

The Dark Side(-Channel) of Mobile Devices: A Survey on Network Traffic Analysis

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Abstract—In recent years, mobile devices (e.g., smartphones and tablets) have met an increasing commercial success and have become a fundamental element of the everyday life for billions of people all around the world. Mobile devices are used not only for traditional communication activities (e.g., voice calls and messages) but also for more advanced tasks made possible by an enormous amount of multi-purpose applications (e.g., finance, gaming, and shopping). As a result, those devices generate a significant network traffic (a consistent part of the overall Internet traffic). For this reason, the research community has been investigating security and privacy issues that are related to the network traffic generated by mobile devices, which could be analyzed to obtain information useful for a variety of goals (ranging from fine-grained user profiling to device security and network optimization).

In this paper, we review the works that contributed to the state of the art of network traffic analysis targeting mobile devices. In particular, we present a systematic classification of the works in the literature according to three criteria: (i) the goal of the analysis; (ii) the point where the network traffic is captured; and (iii) the targeted mobile platforms. In this survey, we consider points of capturing such as Wi-Fi access points, software simulation, and inside real mobile devices or emulators. For the surveyed works, we review and compare analysis techniques, validation methods, and achieved results. We also discuss possible countermeasures, challenges, and possible directions for future research on mobile traffic analysis and other emerging domains (e.g., Internet of Things). We believe our survey will be a reference work for researchers and practitioners in this research field.

Index Terms—Internet traffic, machine learning, mobile device, network traffic analysis, smartphone, tablet computer.

I. INTRODUCTION

THE last decade has been marked by the rise of mobile devices which are nowadays widely spread among people. The most diffused examples of such mobile devices are smartphones and tablets. When compared with traditional cell phones, smartphones and tablets (henceforth also referred as *mobile devices*) have an enormously increased computational power, more available memory, a larger display, and Internet connectivity via both Wi-Fi and cellular networks. Moreover, such devices run mobile operating systems which are able to experience multimedia contents, as well as to run mobile applications (also called *apps*). Combined together, these

elements enable both smartphones and tablets to have the same functionalities typically offered by laptops and desktop computers.

According to the statistics reported in [1], smartphone users were 25.3% of the global population in 2015, and this percentage is expected to grow till 37% in 2020. Similarly, the statistics about tablets reported in [2] indicate a global penetration of 13.8% in 2015, expected to reach 19.2% in 2020. The driving forces of this tremendous success are the ubiquitous Internet connectivity, thanks to the worldwide deployment of cellular and Wi-Fi networks, and a large number of apps available in the official (and unofficial) marketplaces. A mobile device typically hosts a lot of sensitive information about its owner, such as contacts, photos and videos, and GPS position. Such information must be properly protected, especially when it is transmitted to remote services. Since an important fraction of the overall Internet traffic is due to mobile devices, it is not surprising that attackers and network traffic analysts have soon started to target them. For this reason, the research community investigates network traffic analysis techniques to improve both security and privacy on mobile devices.

Network traffic analysis (henceforth simply referred as *traffic analysis*) is the branch of computer science that studies inferential methods which take the network traces of a group of devices (from a few to many thousands) as input, and give information about those devices, their users, their apps, or the traffic itself as output. Network traces can be captured at different layers (e.g., data-link layer, application layer), different points (e.g., within a Wi-Fi network, within the devices), and their content is often encrypted (making analysis even more challenging). Typically, researchers follow two different approaches to analyze mobile network traffic: (i) taking pre-existent methods designed for traditional Internet traffic, and adapting them to the mobile scenario; or (ii) developing new methods tailored to mobile Internet traffic properties. It is worth to underline that this survey focuses on Internet traffic only. We do not consider other types of mobile traffic (e.g., Call Detail Records) or data transmission technologies (e.g., Bluetooth, infrared).

Contributions – In this paper, we survey the state of the art of network traffic analysis on mobile devices, giving the following contributions:

- We categorize each work according to three criteria:
 - 1) the goal of the analysis;
 - 2) the point where the network traffic is captured (henceforth simply referred to as *point of capturing*); and
 - 3) the targeted mobile platforms.

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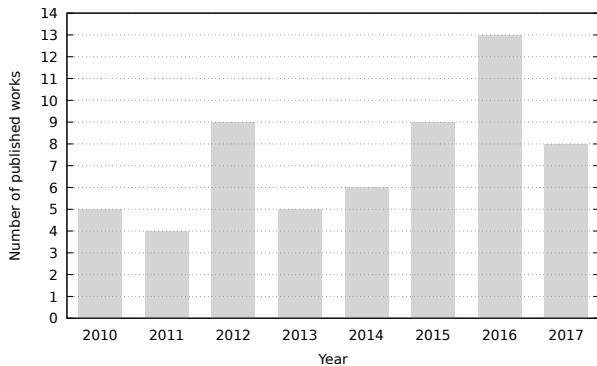


Fig. 1. Number of published works that we identified and considered relevant to this survey, sorted by year of publication.

Moreover, we provide further insights on the models and methods that can be used to perform traffic analysis targeting mobile devices.

- The objective of this survey is three-fold. On the one hand, we provide a systematic classification of state-of-the-art techniques for the analysis of the network traffic of mobile devices. On the other hand, we provide an overview of methodologies adopted for the analyses and information about the datasets used for validating the obtained results. We also discuss possible countermeasures to thwart mobile traffic analysis and provide meaningful insights about challenges and pitfalls related to the topics that have been investigated, as well as identify possible future research directions. We believe that our work will both help new researchers in this field and foster future research trends.
- To the best of our knowledge, we are the first to survey the works that analyze datasets of mobile traffic that are either: (i) logged on one or more mobile devices; (ii) extracted from wired network traces; (iii) sniffed at one or more access points of a Wi-Fi network; (iv) eavesdropped by one or more Wi-Fi monitors; (v) produced by one or more mobile device emulators; or (vi) generated via a software simulation. The work by Naboulsi et al. [3] is the only published survey that reviews the works in which the analyzed datasets are collected within the network infrastructure of one or more cellular providers (e.g., 3G and HSDPA). In fact, our survey is complementary to the one in [3], and together they provide a complete treatment of the research field of traffic analysis targeting mobile devices.

Overall, we survey 59 works, published between 2010 and 2017. Figure 1 shows that the number of publications in the considered research field has significantly increased in the last years. We believe that this amount of work will grow in the future as the global spreading of mobile devices is increasing and their contribution to the worldwide Internet traffic is becoming more significant.

Organization – The rest of the document is organized as follows. Section II provides a road-map of the survey that helps the reader with understanding the classifications adopted to report the surveyed works. In the following sections, we survey the works according to three criteria: in Section III, the goal of the analysis performed on the mobile traffic; in Section IV,

the point of capturing used to collect the mobile traffic; and, in Section V, the targeted mobile platforms. In Section VI, we review the models and methods applied in the surveyed works to perform traffic analysis targeting mobile devices. In Section VII, we describe the validation datasets used in the evaluation and discuss the obtained results. We discuss the effect of network traffic encryption and other countermeasures in Section VIII. In Section IX, we outline the current situation in the field of traffic analysis targeting mobile devices, as well as the trends that are likely to drive research in the next future. Finally, we conclude the paper in Section X.

II. CATEGORIZATION OF WORK

In this section, we present an overview of the classification criteria we follow to categorize the works considered in our survey: the goal of the analysis performed on the mobile traffic (Section II-A); the point of capturing of the mobile traffic (Section II-B); and the targeted mobile platform (Section II-C). In Table I, we report the surveyed works according to these criteria. For each work, we also indicate whether the proposed analyses are still applicable in case of traffic encryption via either SSL/TLS or IPsec (see Section IV for more details about how traffic encryption affects the analyses presented in the surveyed works). It is worth to notice that a few works (i.e., Wei et al. [4], Le et al. [5], Alan et al. [6], Tadrous and Sabharwal [7], and Wang et al. [8]) propose multiple traffic analysis techniques, each affected by traffic encryption in a different way.

A. Classification by Goal of the Analysis

The first classification takes into account the goal of the analysis performed on the captured mobile traffic. For each surveyed work, Table I provides this information in the *Goal of the Analysis* column. We survey more in detail the works according to this classification in Section III.

Overall, we are able to identify thirteen goals. In Figure 2, we depict such goals by their field of pertinence: apps, mobile users, and mobile devices. In what follows, we list and briefly describe each goal, sorted by the number of works:

- **Traffic characterization** (*Characterization* in Table I): to infer the network properties of mobile traffic. The knowledge of such properties is crucial to effectively deploy and configure resources in cellular networks, as well as in Wi-Fi networks serving mobile devices. More details in Section III-A.
- **App identification** (*App* in Table I): to identify the network traffic belonging to a specific mobile app. This type of analysis can help network administrators in resource planning and management, as well as in app-specific policy enforcement (e.g., forbidding a social network app within an enterprise network). Moreover, app identification can be employed to uncover the presence of sensitive apps (e.g., dating, health, religion) in the mobile device of a target user. See Section III-B.
- **Usage study** (*Usage* in Table I): to infer the usage habits of mobile users (e.g., which are the most frequently used apps). As an example, the knowledge of the places where

TABLE I
ALL SURVEYED WORKS.

Year	Paper	Goal of the Analysis	Point of Capturing	Targeted Mobile Platform	SSL/TLS	IPsec
2010	Afanasyev et al. [9]	Characterization, Usage	APs, Wired	Platform-independent	X	X
	Falaki et al. [10]	Characterization, Usage	Devices	Android, Windows Mobile	✓	X
	Husted et al. [11]	Position	Simulator	Platform-independent	✓	✓
	Maier et al. [12]	Characterization, Usage	Wired	Platform-independent	X	X
	Shepard et al. [13]	Characterization	Devices	iOS	✓	X
2011	Finamore et al. [14]	Characterization, Usage	Wired	Platform-independent	X	X
	Gember et al. [15]	Characterization, Usage	APs	Platform-independent	X	X
	Lee et al. [16]	App	Wired	Android, iOS	X	X
		Characterization, Usage		Platform-independent	X	X
Rao et al. [17]	Characterization	Wired	Android, iOS	X	X	
2012	Baghel et al. [18]	Characterization	Wired	Android	✓	X
	Chen et al. [19]	Characterization	Wired	Platform-independent	X	X
	Ham et al. [20]	Usage	Devices	Android	✓	✓
	Musa et al. [21]	Position	Monitors	Platform-independent	✓	✓
	Shabtai et al. [22]	Malware	Devices	Android	✓	✓
	Stevens et al. [23]	PII Leakage	APs	Android	X	X
	Su et al. [24]	Malware	Devices	Android	✓	X
	Wei et al. [25]	Malware	Wired	Android	X	X
	Wei et al. [4]	Characterization	Devices	Android	✓	✓/X
		Sociological	Monitors	Platform-independent	✓	✓
2013	Barbera et al. [26]	Sociological	Monitors	Platform-independent	✓	✓
	Kuzuno et al. [27]	PII Leakage	Devices	Android	X	X
	Qazi et al. [28]	App	APs, Devices	Android	✓	X
	Rao et al. [29]	App, PII Leakage	Wired	Android, iOS	✓	X
	Watkins et al. [30]	User Actions	APs	Android	✓	✓
2014	Chen et al. [31]	OS	APs	Android, iOS	✓	X
		Tethering	Monitors, Wired	Platform-independent	✓	X
	Coull et al. [32]	User Actions, OS	Devices	iOS	✓	✓
	Crussell et al. [33]	Ad Fraud	Emulators	Android	X	X
	Lindorfer et al. [34]	Characterization	Emulators	Android	X	X
	Shabtai et al. [35]	Malware	Devices	Android	✓	✓
	Verde et al. [36]	User Fingerprinting	Wired	Platform-independent	✓	✓
2015	Chen et al. [37]	Characterization	Wired	Android	X	X
	Fukuda et al. [38]	Characterization, Usage	Devices	Android, iOS	✓	✓
	Le et al. [5]	App, PII Leakage	Devices	Android	✓/X	X
	Park et al. [39]	User Actions	Wired	Android	✓	X
	Soikkeli et al. [40]	Usage	Devices	Platform-independent	✓	✓
	Song et al. [41]	PII Leakage	Devices	Android	✓	X
	Wang et al. [42]	App	Monitors	iOS	✓	✓
	Yao et al. [43]	App	APs, Emulators	Android, iOS, Symbian	X	X
	Zaman et al. [44]	Malware	Devices	Android	X	X
2016	Alan et al. [6]	App	APs	Android	✓	✓/X
	Conti et al. [45]	User Actions	Wired	Android	✓	X
	Fu et al. [46]	User Actions	APs	Android	✓	✓
	Mongkolluksamee et al. [47]	App	Devices	Android	✓	X
	Narudin et al. [48]	Malware	Devices, Emulators	Android	X	X
	Nayam et al. [49]	Characterization	Wired	Android, iOS	X	X
	Ren et al. [50]	PII Leakage	Wired	Android, iOS, Windows Phone	✓	✓
	Ruffing et al. [51]	OS	Monitors	Android, iOS, Windows Phone, Symbian	✓	✓
	Saltaformaggio et al. [52]	User Actions	APs	Android, iOS	✓	✓
	Spreitzer et al. [53]	Website Fingerprinting	Devices	Android	✓	✓
	Tadrous et al. [7]	Characterization	APs	Android, iOS	✓	✓/X
	Vanrykel et al. [54]	PII Leakage, User Fingerprinting	Wired	Android	X	X
	Wang et al. [8]	Malware	Wired	Android	✓/X	X
	2017	Arora et al. [55]	Malware	Devices	Android	✓
Chen et al. [56]		App	Emulators	Android	X	X
Cheng et al. [57]		PII Leakage	Wired	Android	✓	X
Continella et al. [58]		PII Leakage	Wired	Android	✓	X
Espada et al. [59]		Characterization	Devices	Android	✓	X
Malik et al. [60]		OS	APs	Android, iOS, Windows Phone	✓	✓
Taylor et al. [61]		App	Wired	Android	✓	X
Wei et al. [62]		Characterization, Usage	Wired	Platform-independent	X	X

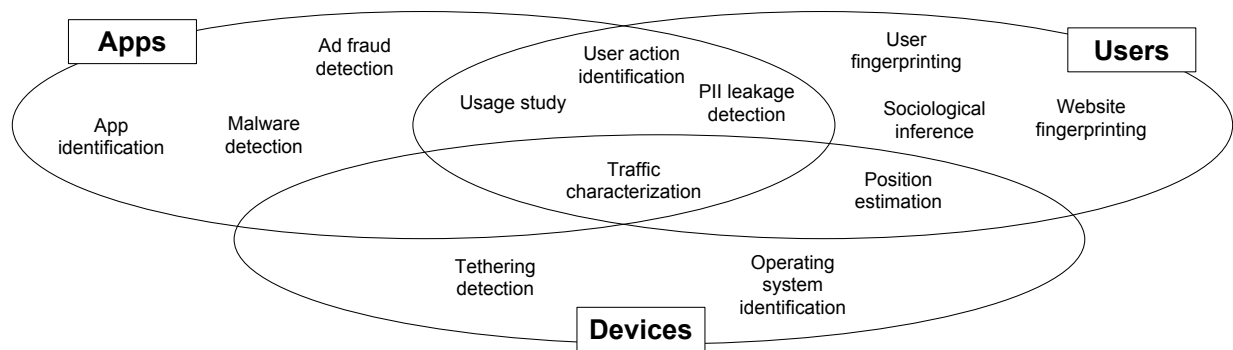


Fig. 2. The goals of traffic analysis targeting mobile devices, and their pertinence to apps, mobile users, and mobile devices.

mobile devices are mostly used can drive the deployment of cellular stations and Wi-Fi hotspots. See Section III-C.

- PII leakage detection** (*PII Leakage* in Table I): to detect and/or prevent the leakage of a mobile user's Personal Identifiable Information (PII). This type of analysis can be employed to assess the behavior of a mobile app from a privacy point of view, by checking which PII it actually discloses to remote hosts. Detecting PII leakage is also the first step to prevent such problem, since it is then possible to block network transmissions carrying PII, or replace sensitive information with bogus data. See Section III-D.
- Malware detection** (*Malware* in Table I): to detect whether a mobile app behaves maliciously (e.g., downloading and installing malicious code from the network). This type of analysis can be used to assess the security of an app submitted by a developer to a mobile marketplace. In such case, the result of the security tests decides whether the app can be released to the public. Moreover, malware detection algorithms can be embedded into anti-virus apps that mobile users can use to check whether an installed app is malicious. See Section III-E.
- User action identification** (*User Actions* in Table I): to identify a specific action that a mobile user performed on her mobile device (e.g., uploading a photo on Instagram), or to infer some information about that specific action (e.g., the length of a mobile user's message sent through an instant messaging app). Researchers can employ such analysis to discover the identity behind an anonymous social network profile. This can be accomplished by verifying whether there is a match between the events reported on that profile's page, and the actions a suspect performed while using the mobile app of that social network. Alternatively, it is possible to build behavioral profiles of mobile users, which are useful for user reconnaissance within networks and, in aggregated form, for marketing studies. See Section III-F.
- Operating system identification** (*OS* in Table I): to discover the operating system of a mobile device. This type of analysis is usually a preliminary phase for more advanced attacks against mobile devices: the adversary tries to infer the operating system of the target mobile device in order to subsequently exploit an ad hoc vulnerability for that specific OS. Moreover, operating system identification carried out on a large mobile user population can be a starting point
- for other types of analysis not directly related to computer science (e.g., sociological studies). See Section III-G.
- Position estimation** (*Position* in Table I): to estimate the position and/or the trajectory (i.e., the movements) of a mobile device within a geographical area. This type of analysis helps infer social status, interests, and habits of the owner of a mobile device. As a further step, the profiles of several mobile users can be aggregated for marketing, as well as sociological studies. Besides, position estimation can aid road traffic prediction along urban streets, by leveraging the most frequent trajectories followed by the citizens that move along the city. See Section III-H.
- User fingerprinting** (*User Fingerprinting* in Table I): to detect the traffic belonging to a specific mobile user. This type of analysis can be employed to trace a mobile user, by approximating her position with the location of the Wi-Fi hotspot or cellular station to which her mobile device is connected. From this information, it is then possible to build a behavioral profile of that mobile user. Alternatively, it is possible to examine a mobile traffic dataset in order to extract and group together the network traces generated by a specific mobile user. Such data can be subsequently used for other types of traffic analysis targeting that user. See Section III-I.
- Ad fraud detection** (*Ad Fraud* in Table I): to detect ad fraud by a mobile app, i.e., to recognize whether a mobile app is trying to trick the advertising business model (e.g., fabricating false user clicks on ads). This type of analysis is valuable to ad providers, which can rely on it to protect themselves from dishonest app developers. See Section III-J.
- Sociological inference** (*Sociological* in Table I): to infer some kind of sociological information about mobile users (e.g., language, religion, health condition, sexual preference, wealth), from one or more properties related to their mobile devices (e.g., list of installed apps, associated Wi-Fi networks). See Section III-K.
- Tethering detection** (*Tethering* in Table I): to detect whether a mobile device is tethering, i.e., it is sharing its Internet connectivity with other devices, for which it acts as an access point. Tethering constitutes a problem for cellular network providers, since it significantly increases the volume of network traffic generated by a single client. Such providers are therefore interested in tethering detection

techniques that can be used to prevent their customers from sharing their Internet connectivity, or simply require them to pay an extra fee to do that. See Section III-L.

- **Website fingerprinting** (*Website Fingerprinting* in Table I): to infer which websites and/or webpages are visited by a mobile user while navigating via the web browser of her mobile device. Similarly to sociological inference, this type of analysis can reveal interests, social habits, religious belief, as well as sexual and political orientations of a mobile user. See Section III-M.

B. Classification by Point of Capturing

The second classification considers where and how the mobile traffic is captured. For each surveyed work, Table I provides this information in the *Point of Capturing* column. It is worth to notice that: (i) we focus on the (hardware and/or software) equipment that captures the traffic; and (ii) we report the point of capturing only for those datasets for which the authors give enough details about the collection process. We survey more in detail the works according to this classification in Section IV.

Overall, we identify six different points of capturing. In what follows, we list and briefly describe each of them, sorted by the number of works in which a point of capturing is employed:

- At one or more wired network equipments (*Wired* in Table I). The size of the population of monitored mobile devices varies according to the type of considered network equipments: thousands of mobile users in the case of edge routers (i.e., routers connecting customers to the ISP's backbone) and Internet gateways; from tens to a few hundreds in the case of VPN servers and forwarding servers (i.e., traditional desktop computers set up to log all traffic traversing a wired link that connects a Wi-Fi hotspot serving mobile devices to the Internet). More details in Section IV-A.
- Within one or more mobile devices, i.e., client-side (*Devices* in Table I). This type of point of capturing is particularly useful if we want to target a specific mobile app (e.g., Facebook), or a particular network interface (e.g., cellular). We specify that this category also includes the case of a network traffic logger installed within either: (i) a mobile device emulator; and (ii) a machine to which the mobile traffic is mirrored using a remote virtual network interface. See Section IV-B.
- At one or more access points of a Wi-Fi network (*APs* in Table I). This type of point of capturing allows the number of monitored mobile devices to vary from tens to a few thousands, and it is suitable to capture the traffic of mobile devices while their users are performing network-intensive tasks (e.g., watching streaming videos, updating apps). See Section IV-C.
- At one or more machines running virtual mobile devices, i.e., emulators (*Emulators* in Table I). Running multiple virtual instances of mobile devices and controlling them via automated tools make possible to collect network traffic on a large-scale. On real mobile devices, same data collection

would be far more expensive. It is important to highlight that the traffic logging is performed by the host machines or their virtualization managers. We do not consider the case in which the traffic logging takes place within the emulated mobile devices (such case is covered by the *Devices* category). See Section IV-D.

- At one or more Wi-Fi monitors (*Monitors* in Table I). Researchers usually employ this type of capturing devices to focus the network traffic collection process on a specific geographical area of interest (e.g., a train station). Such approach is often the only viable solution whether it is not possible to directly access a target mobile device, or the network to which it is connected. See Section IV-E.
- At one or more virtual capturing points within a simulated environment generated and managed by a software program (*Simulator* in Table I). This point of capturing can help study particular deployments of mobile devices that are not observable in a real-world scenario because of technical, economical, or legal constraints. See Section IV-F.

C. Classification by Targeted Mobile Platform

The third classification considers the mobile platforms that are targeted by the traffic analysis. For each surveyed work, Table I provides this information in the *Targeted Mobile Platform* column. It is worth to specify that we classify a work as *platform-independent* if its authors do not provide information about the targeted mobile platforms, or such information is not relevant to the analysis they perform on the mobile traffic (we discuss this type of works in Section V-E). We survey more in detail the works according to this classification in Section V.

Overall, we find four distinct mobile platforms (in what follows, listed by their popularity in the surveyed works): Android, Google's open-source mobile operating system (we discuss it in Section V-A); iOS, the operating system of Apple's mobile devices (Section V-B); Windows Mobile/Phone, the mobile counterpart of Microsoft's desktop operating system (Section V-C); and Symbian, the first released modern mobile operating system (Section V-D).

III. GOALS OF TRAFFIC ANALYSIS TARGETING MOBILE DEVICES

In this section, we survey the works according to the goal of the analysis that is performed on the mobile traffic. Table II summarizes the goals of the surveyed works. As shown in Figure 3, the most frequently pursued goal is traffic characterization (eighteen works), followed by app identification and usage study (ten works each), PII leakage detection (nine works), malware detection (eight works), user action identification (six works), operating system identification (four works), and position estimation and user fingerprinting (two works each). Each of the following goals counts one work only: ad fraud detection, sociological inference, tethering detection, and website fingerprinting. As shown in Table II, twelve works pursue two goals, and one work even three.

In the following sections, we present the goal(s) and achieved results for each surveyed work. For each goal, we report relevant aspects and findings in the state of the art, and

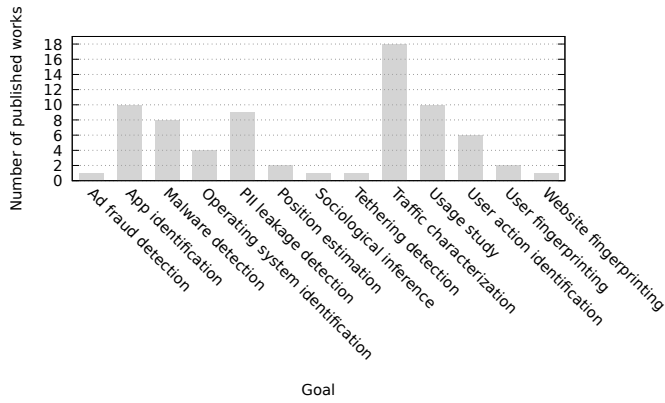


Fig. 3. Number of published works contributing traffic analysis methods targeting mobile devices, sorted by goal of the analysis.

we discuss whether the proposed analyses work on encrypted network traffic. For the sake of simplicity, encryption methods that make TCP headers and IP headers unavailable to the analysis are referred as to SSL/TLS and IPsec, respectively. We enter in more detail about encryption as a countermeasure against mobile traffic analysis in Section VIII-A. The treatment of each goal takes place in its own section, and all sections are ordered by goal popularity in the surveyed works.

A. Traffic Characterization

Network management can benefit from knowing the properties of the Internet traffic that traverses the network. Such information can be used to efficiently deploy the hardware equipments, as well as to setup them in order to provide the best Quality of Service (QoS) to the users. This statement particularly holds for networks serving mobile devices, since such devices generate traffic with peculiar properties. In light of the rapid evolution of mobile devices, the characterization of their Internet traffic is crucial to provide network administrators the information they need for resource planning, deployment, and management.

We define as *traffic characterization* the analysis of the network traffic generated by mobile devices in order to infer its properties. In Table III, we group the works that study the mobile traffic according to the scope of the analysis:

- The works that study the network traffic of specific apps and/or mobile services. We survey nine works belonging to this category. Rao et al. in [17] study the Android and iOS native apps of two video streaming services, namely Netflix and YouTube. YouTube is targeted also by Finamore et al. in [14]. The Android apps of Facebook and Skype are considered in [18]. In [4], Wei et al. focus on 27 Android apps (19 free and 8 paid). The analysis by Lindorfer et al. in [34] covers over 1,000,000 unique Android apps. In [37], Chen et al. analyze 5560 malicious Android apps (from 177 malware families). In [49], Nayam et al. study 63 Android and 35 iOS free apps, all belonging to the “Health & Fitness” category. The work presented by Tadrous et al. in [7] focuses on five interactive apps for both Android and iOS. In [59], Espada et al. present a framework for traffic

TABLE II
THE SURVEYED WORKS BY GOAL OF THE ANALYSIS PERFORMED ON THE MOBILE TRAFFIC.

Year	Paper	Ad Fraud Detection	App Identification	Malware Detection	Operating System Identification	PII Leakage Detection	Position Estimation	Sociological Inference	Tethering Detection	Traffic Characterization	Usage Study	User Action Identification	User Fingerprinting	Website Fingerprinting	
2010	Afanasyev et al. [9]														
	Falaki et al. [10]														
	Husted et al. [11]						✓				✓	✓			
	Maier et al. [12]										✓	✓			
	Shepard et al. [13]										✓	✓			
2011	Finamore et al. [14]										✓	✓			
	Gember et al. [15]										✓	✓			
	Lee et al. [16]		✓								✓	✓			
2012	Rao et al. [17]										✓	✓			
	Baghel et al. [18]										✓	✓			
	Chen et al. [19]										✓	✓			
	Ham et al. [20]											✓			
	Musa et al. [21]						✓								
	Shabtai et al. [22]			✓											
	Stevens et al. [23]					✓									
	Su et al. [24]			✓											
	Wei et al. [25]			✓											
	Wei et al. [4]										✓				
2013	Barbera et al. [26]							✓							
	Kuzuno et al. [27]					✓									
	Qazi et al. [28]		✓												
	Rao et al. [29]		✓			✓									
	Watkins et al. [30]												✓		
2014	Chen et al. [31]				✓			✓					✓		
	Coull et al. [32]												✓		
	Crussell et al. [33]		✓												
	Lindorfer et al. [34]									✓					
2015	Shabtai et al. [35]			✓											
	Verde et al. [36]													✓	
	Chen et al. [37]										✓	✓			
	Fukuda et al. [38]										✓	✓			
	Le et al. [5]			✓		✓									
	Park et al. [39]												✓		
	Soikkeli et al. [40]											✓	✓		
	Song et al. [41]					✓									
	Wang et al. [42]			✓											
	Yao et al. [43]			✓											
2016	Zaman et al. [44]			✓											
	Alan et al. [6]		✓												
	Conti et al. [45]												✓	✓	
	Fu et al. [46]												✓	✓	
	Mongkolluksamee et al. [47]		✓												
	Narudin et al. [48]			✓											
	Nayam et al. [49]										✓				
	Ren et al. [50]														
	Ruffing et al. [51]					✓									
	Saltaformaggio et al. [52]												✓		
	Spreitzer et al. [53]													✓	✓
	Tadrous et al. [7]									✓					
2017	Vanrykel et al. [54]					✓				✓			✓		
	Wang et al. [8]			✓											
	Arora et al. [55]			✓											
	Chen et al. [56]		✓												
	Cheng et al. [57]														
	Contimella et al. [58]					✓									
	Espada et al. [59]									✓					
	Malik et al. [60]					✓									
Taylor et al. [61]		✓													
Wei et al. [62]										✓	✓				

TABLE III
THE SURVEYED WORKS THAT DEAL WITH TRAFFIC CHARACTERIZATION.

Year	Paper	Apps/ Services	Mobile Devices	
			Comparison with non-mobile	Only Mobile
2010	Afanasyev et al. [9]		✓	
	Falaki et al. [10]			✓
	Maier et al. [12]		✓	
	Shepard et al. [13]			✓
2011	Finamore et al. [14]	✓		
	Gember et al. [15]		✓	
	Lee et al. [16]		✓	
	Rao et al. [17]	✓		
2012	Baghel et al. [18]	✓		
	Chen et al. [19]			✓
	Wei et al. [4]	✓		
2014	Lindorfer et al. [34]	✓		
2015	Chen et al. [37]	✓		
	Fukuda et al. [38]			✓
2016	Nayam et al. [49]	✓		
	Tadrous et al. [7]	✓		
2017	Espada et al. [59]	✓		
	Wei et al. [62]			✓

characterization of Android apps, and choose Spotify as case study.

- The works that study the network traffic generated by a population of mobile devices. We can further divide such works into two subsets:
 - The works that compare mobile traffic with non-mobile one. We survey four works belonging to this subcategory. The work in [12] focuses on the network traffic of mobile devices when they are connected to home Wi-Fi networks, while the works in [9], [15], [16] carry out the same analysis for campus Wi-Fi networks.
 - The works that only consider mobile traffic. We survey five works belonging to this subcategory. The works in [19], [62] target campus Wi-Fi networks, while the works in [10], [13], [38] leverage client-side measurements collected through logging apps.

The aforementioned works provide interesting results and observations about mobile network traffic characteristics. In what follows, we highlight the main properties that emerged from the works we survey:

- Compared to residential broadband traffic, the daily volume of traffic per mobile user is roughly one order of magnitude smaller [10].
- Mobile devices generate more downlink than uplink traffic, clearly following a client-server behavior [10], [4], [38], [7].
- At the network layer, IP flows of mobile devices have a shorter duration, a much higher number of packets, and a much smaller packets, compared to IP flows of non-mobile devices [16].
- Most of the transport-layer traffic is carried over TCP [10], [15], [19], and more than half of the overall TCP traffic is encrypted [10]. Transfers within TCP connections are small in size [10], [15], causing a high overhead for lower-layer protocols, particularly when transport-layer encryption is in place [10].
- Most of the application-layer traffic is carried over HTTP or HTTPS [10], [15], [16], [19], [34], [37], [62]. Moreover, the

analysis carried out by Chen et al. in [19] highlights that: (i) the adoption of HTTPS is increasing (a trend confirmed by Nayam et al. in [49] and by Wei et al. in [62]); and (ii) Akamai and Google servers serve nearly 40% of the global mobile traffic.

- Mobile devices contact a less diverse set of hosts compared to non-mobile devices [15], [19].
- Mobile devices experience a low loss rate on Wi-Fi networks [19]. Instead, mobile traffic on cellular networks suffers high delays and losses, as well as low throughputs [10].
- An important fraction of mobile traffic is due to video streaming [12], [15], mainly on the YouTube platform [14].
- Android apps typically do not encrypt their network traffic (i.e., they simply rely on HTTP), they connect to several different hosts, and part of their network traffic is toward Google’s services [4].
- A significant part of the network traffic generated by Android and iOS free apps is due to advertisement and tracking services [49].
- Netflix and YouTube apps for Android tend to periodically buffer large portions of the video to be played, while their counterparts for iOS tend to initially buffer a large amount of data, then periodically buffer small portion of the video to keep playback ongoing (although the YouTube app employs large-block buffering under favorable network conditions) [17]. Moreover, Netflix and Youtube apps for iOS create a large number of TCP flows to provide a single video to cope with TCP timeouts caused by the delays of cellular networks. This causes an overhead that is not necessary when mobile devices are connected to Wi-Fi networks [17], [19].

B. App Identification

The Internet connectivity and multi-purpose apps are two key aspects of the success and widespread adoption of mobile devices. Most of the apps can send and receive data through the network interfaces of mobile devices (i.e., Wi-Fi and cellular), and often this capability is mandatory for apps to work properly.

The network traffic patterns related to an app (or type of app) constitute a behavioral network fingerprint which can be recognized in unseen network traces. We refer to this analysis as *app identification*. It is worth to notice that this approach also takes into consideration the network traffic generated by an app that is not directly related to any user actions (e.g., the data exchanged because of background activities).

App identification brings several benefits to network management, but it also has privacy implications:

- The knowledge of the apps used by the clients of a network can help the administrators to tune the network equipments and parameters in order to deliver the best achievable Quality of Service (QoS).
- In an enterprise network where some particular apps is not allowed to be used (e.g., Facebook, Twitter), app detection can help the administrators enforce such policy by blocking traffic belonging to the forbidden apps.
- It is possible to target a high profile user and discover whether she uses privacy-sensitive (e.g., health, dating) apps.

TABLE IV
TARGETED MOBILE PLATFORMS AND NUMBER OF CONSIDERED APPS IN
THE SURVEYED WORKS THAT DEAL WITH APP IDENTIFICATION.

Year	Paper	Number of Targeted Apps		
		Android	iOS	Symbian
2011	Lee et al. [16]	50	50	None
2013	Qazi et al. [28]	40	None	None
	Rao et al. [29]	832	209	None
2015	Le et al. [5]	70	None	None
	Wang et al. [42]	None	13	None
	Yao et al. [43]	651,000	68,000	10,000
2016	Alan et al. [6]	1,595	None	None
	Mongkolluksamee et al. [47]	5	None	None
2017	Chen et al. [56]	5,000	None	None
	Taylor et al. [61]	110	None	None

- Knowing the set of apps installed on a mobile device can reveal sensitive information about the user such as relationship status, spoken languages, country, and religion [63].

In Table IV, we report the surveyed works that deal with app identification [16], [28], [29], [5], [42], [43], [6], [47], [56], [61]. The number of apps selected for profiling and fingerprinting varies from less than ten to many thousands.

Despite the core topic of the work by Lee et al. in [16] is a comparison between smartphone traffic and traditional Internet traffic, the authors also perform app identification targeting the Android and iOS platforms. Indeed, they select the top 50 apps of both Apple App Store and Google Play Store, generate their payload signatures, and use such signatures to recognize the traffic generated by such apps in network traces. Unfortunately, this approach is based on payload signatures, thus it cannot deal with the apps that encrypt their network traffic.

Qazi et al. in [28] present the Atlas framework, which incorporates application identification into Software-Defined Networking (SDN). Prototyped on HP Labs wireless network, the identification performance of Atlas is tested on the top 40 popular Android apps from Google Play Store. Since it requires to inspect transport-layer information, Atlas cannot process network traffic protected by IPsec.

Rao et al. in [29] present Meddle, a cross-platform system for collecting and analyzing the network traffic of mobile devices. The idea is to leverage VPN tunnels (which are natively supported by modern mobile OSes) to redirect the network traffic of the target mobile devices to the Meddle proxy server, where software middleboxes are responsible for traffic processing and analysis. Thanks to this man-in-the-middle approach, Meddle can inspect the network traffic protected by SSL/TLS, but it cannot work with data transmissions encrypted via IPsec. The authors employ Meddle for app identification (and also PII leakage detection, see Section III-D for details) based on fields of HTTP messages (i.e., Host and User-Agent).

Le et al. in [5] propose AntMonitor, a system for collecting and analyzing network traffic from Android devices. Among other types of analysis, AntMonitor can perform app identification. The authors select 70 Android apps to evaluate the performance of their solution. Among the considered features, there are the flags of TCP segments, which are hidden if IPsec is employed, thus the proposed framework does not work if network-layer encryption is in place.

The app identification framework proposed by Wang et al. in [42] is based on extracting side-channel information from Wi-Fi traffic belonging to a target mobile device. The authors depict a passive adversary as follows: (i) she is able to sniff the traffic on the same WLAN channel as the access point to which the target device is connected; (ii) leveraging the MAC address of the target device, she can elicit its traffic from the collected network traces; and (iii) she cannot break the encryption scheme of the sniffed traffic (i.e., the app identification can also target secure WLANs). To evaluate their solution, the authors choose the iOS platform, considering thirteen popular apps from a wide range of different app categories.

Yao et al. in [43] present SAMPLES (Self Adaptive Mining of Persistent LEXical Snippets), an app identification framework that leverages the occurrences of app identifiers within HTTP headers (thus it cannot handle network traffic protected by IPsec or SSL/TLS). SAMPLES models such occurrences into generalized conjunctive rules, which are used to identify the app that generated a given network flow. To evaluate their system, the authors consider over 700,000 apps from Google Play Store, Apple App Store, and Nokia OVI Store (details are given in Table IV).

Alan and Kaur in [6] investigate the feasibility of identifying Android apps from their launch-time network traffic by only leveraging the information available in TCP/IP headers. The authors collect the launch-time traffic of 1,595 apps. This work proposes three different methods that can handle network traffic encrypted via SSL/TLS, but only two of them can also deal with IPsec encryption.

Mongkolluksamee et al. in [47] (which is an extended version of a previous work by the same authors [64]) apply machine learning to build an app identification system for Android apps. The authors leverage graphlet- and histogram-based features, and employ a random forest classifier (more details in Section VI-B2). However, this analysis requires to access TCP and UDP headers, which is infeasible for apps that employ IPsec to encrypt their network traffic. It is worth to notice that despite this work focuses on 3G traffic, the actual capturing of the network traffic is performed within a mobile device via tcpdump (more details in Section IV-B).

Chen et al. in [56] present an innovative method to identify the invariant tokens (e.g., URLs, key-value pairs, developer IDs) that are present in the network traffic of a specific app; such tokens can then be exploited to carry out app identification via deep packet inspection (which is applicable to unencrypted traffic only). The described framework requires to perform an advanced static analysis on the targeted app in order to find the parts of code that trigger network activities; compared to dynamic analysis and UI fuzzing, this method permits to cover almost all (98.54%) of the app's network activities in a very short period of time (less than twenty seconds). The authors focus on the Android platform, and evaluate their solution on 2,500 apps from Google Play Store and other third-party Android marketplaces, and 2,500 malicious apps from VirusTotal.

Taylor et al. in [61] (which is an extension of a previous work by the same authors [65]) propose AppScanner, an app identification system based on machine learning (more details

in Section VI-B2). The authors profile 110 popular Android apps crawled from Google Play Store and re-identify them in real-time. Moreover, the authors study how the classification performance is affected by varying the duration of the network traffic capturing, the mobile device that generates the collected data, and the version of the fingerprinted apps. AppScanner leverages the information within IP and TCP headers, thus being able to process the network traffic encrypted via SSL/TLS, but not the one protected by IPsec.

C. Usage Study

The habits of mobile users have significantly changed with the evolution of cellphones toward smartphones and tablets. First of all, the adoption of the touchscreen display has revolutionized the human-device interaction. Moreover, the development of mobile operating systems supporting multi-tasking and third-party apps has enhanced the capabilities of mobile devices well beyond the requirements for communication activities. In this scenario, many researchers investigate how mobile users interact with their mobile devices. This to improve the usability of mobile OSes and apps, as well as to properly set up networks serving mobile devices. For instance, the knowledge of places where mobile devices are mostly used can drive the deployment of free Wi-Fi hotspots to reduce the traffic load on cellular networks.

We define as *usage study* the analysis of the network traffic of mobile devices that aims at inferring the usage habits of mobile users. The works we review in this section leverage network-side measurements [9], [12], [14], [15], [16], [62], as well as data collected within mobile devices [10], [20], [38], [40]. In Table V, we show the three analysis perspectives adopted by the surveyed works that investigate the usage habits of mobile users:

- *The network.* As an example, observing the time in which users are active during the day (i.e., sending and receiving data), duration of activity, amount of traffic generated, and most frequently used network interfaces (i.e., Wi-Fi or cellular).
- *The apps and/or mobile services.* For instance, analyzing which are the most frequently used apps/services, and which is the traffic volume of a specific app.
- *The geographical positions and mobility patterns.* As an example, studying the locations where mobile devices are most frequently used, and where they generate most of their traffic.

In what follows, we summarize their findings reported by the works in usage study:

- The most frequently used apps are the ones related to multimedia content (e.g., YouTube, Spotify) and web browsers [10], [12], [15], [16], [20], [38]. Nonetheless, social network and instant messaging apps are also popular [38].
- The predominance of cellular over Wi-Fi network traffic observed for mobile devices by Ham et al. in [20] in 2012 is gradually disappearing. As reported in [38], in 2015 more than half of mobile traffic is carried over Wi-

TABLE V
THE SURVEYED WORKS THAT DEAL WITH USAGE STUDY.

Year	Paper	Network	Apps/ Services	Geography/ Mobility
2010	Afanashev et al. [9]	✓	✓	✓
	Falaki et al. [10]		✓	
	Maier et al. [12]		✓	
2011	Finamore et al. [14]		✓	
	Gember et al. [15]		✓	
	Lee et al. [16]	✓	✓	
2012	Ham et al. [20]	✓	✓	
2015	Fukuda et al. [38]	✓		
	Soikkeli et al. [40]	✓		✓
2017	Wei et al. [62]	✓		

Fi. In particular, mobile users prefer switching to Wi-Fi connectivity whenever a Wi-Fi access point is available [38].

- The usage of mobile devices is low at nighttime and high in daytime [9], [16], [20], [40].
- Cellular traffic peaks during commute times, while Wi-Fi traffic peaks in the evening [38]. Cellular traffic is lighter on weekends than weekdays, while Wi-Fi traffic follows the opposite trend [38].
- Mobile users tend to generate more network traffic when they are out of home, and when their devices have high battery level [40].
- The volume of traffic generated by the mobile users of a Wi-Fi network varies greatly, from less than 100 MB to several GBs, according to users' habits and needs [62].
- According to Finamore et al. in [14], YouTube mobile users: (i) similarly to non-mobile users, they prefer short videos (40% of the watched videos are shorter than three minutes, and only 5% are longer than ten minutes); (ii) similarly to non-mobile users, they rarely change video resolution and, whenever they do that, it is to switch to a higher resolution (although full screen mode is not frequently used); and (iii) more frequently than non-mobile users, they early stop watching the video (within the first fifth of its duration for 60% of the videos).

D. PII Leakage Detection

As we introduced in Section I, a mobile device is a source of sensitive information about its owner (e.g., phone number, contacts, photos, videos, GPS position). In addition to that, apps often require to access such information to deliver their services. As an example, an instant messaging app (e.g., WhatsApp, Telegram, WeChat) requires to access the contacts saved in the device's address book. As another example, a social network app (e.g., Facebook, Instagram) requires to inspect the device's memory to find photos.

To disclose sensitive information to a remote host, an app must be authorized to: (i) access some kind of sensitive information (e.g., the GPS position); and (ii) connect to the Internet. The disclosure of such information can be either allowed or illicit, depending on three factors: (i) the level of sensitivity of the disclosed information; (ii) the reason why the app transmits such information to a remote host; and (ii) whether the user is aware of this transmission of sensitive data.

In this section, we focus on *Personal Identifiable Information (PII)*, which is information that can be used to identify, locate, or contact an individual. In the domain of mobile devices, we can identify four types of PII:

- Information related to mobile devices, such as IMEI (International Mobile Equipment Identity, a unique identifier associated to each mobile device), Android Device ID (an identifier randomly generated on the first boot of any Android device), and MAC address (a unique identifier assigned to each network interface).
- Information related to SIM cards, such as IMSI (International Mobile Subscriber Identity, a unique identifier assigned to each subscriber of a cellular service), and SIM Serial ID (the identifier assigned to each SIM card).
- Information related to users, such as name, gender, date of birth, address, phone number, and email.
- Information about user’s location, such as GPS position and ZIP code.

We define as *PII leakage detection* the analysis of the network traffic of a mobile device in order to detect the leakage of a user’s PII. Once a PII leakage is detected, it is possible to apply suitable countermeasures, such as blocking the network flows carrying the PII, or substituting the sensitive information with bogus data. The latter approach is a good solution for mobile users who want to protect their privacy while being able to enjoy the functionalities of the apps.

In Table VI, we present the surveyed works that deal with PII leakage detection [23], [27], [29], [5], [41], [50], [54], [57], [58]. For each work, we summarize the targeted mobile platforms, and whether the PII leaks are simply detected or also prevented.

Stevens et al. in [23] present a comprehensive study on thirteen popular ad providers for Android. In particular, part of this study focuses on the analysis of ad traffic in order to detect the transmission of the user’s PII. The authors observe that at the time of writing only one of the considered ad providers leverage encryption to protect its network traffic. For this reason, they choose to perform a deep packet inspection to identify the leakage of the user’s private information. The results show that several types of PII (e.g., age, gender, GPS position) are leaked in clear by ad libraries. Moreover, the authors highlight that although none of the considered ad providers is able to build a complete user profile, the UDIDs in ad-related traffic can be exploited by an external adversary to correlate sensitive information from different ad providers and build a complete user profile.

Kuzuno and Tonami in [27] investigate the leakage of sensitive information by the advertisement libraries embedded into free Android apps. They focus on both original and hashed identifiers unique to mobile devices (i.e., IMEI and Android ID) and SIM cards (i.e., IMSI and SIM Serial ID), as well as on the name of the cellular operator (CARRIER). To carry out their analysis, the authors develop two components: (i) a server application; and (ii) a mobile app that can be installed on an Android device. The server application takes as input the network traffic of a set of apps that leak sensitive information, and applies a clustering method (see Section VI-B3 for details) to generate traffic signatures. The mobile app

leverages such signatures to identify the sensitive information leaked by the other apps installed on the device. To evaluate their solution, the authors employ the network traffic of 1,188 free Android apps and achieve the following results: 94% of HTTP messages containing sensitive information are correctly detected, with 5% false negatives (i.e., undetected HTTP messages carrying sensitive information), and less than 3% false positives (i.e., HTTP messages without sensitive information, incorrectly identified as sensitive). Since the signature generation phase requires to inspect HTTP messages looking for sensitive information, the system cannot work on encrypted traffic (i.e., neither SSL/TLS nor IPsec).

Rao et al. in [29] and Ren et al. in [50] present ReCon, a cross-platform system that allows mobile users to control the PII leaked in the network traffic of their devices. ReCon is based on Meddle (we described it in Section III-B), therefore it can inspect mobile traffic even if it is encrypted at transport layer, but cannot cope with data transmissions protected by IPsec. Moreover, ReCon offers a web interface through which the user can visualize in real time which PII is leaked, and optionally modify such PII or block the connection carrying it. In [29], Rao et al. target Android and iOS OSes, and the PII leakage detection mechanism is based on a domain blacklist. In [50], Ren et al. also include Windows Phone among the considered OSes, and PII leaks are detected using properly trained machine learning classifiers (more details in Section VI-B3). The works in [29], [50] expose an extensive leakage of sensitive information belonging to all the types of PII we listed above, as well as the transmission of usernames and passwords in both plain-text (HTTP) and encrypted (HTTPS) traffic.

Le et al. in [5] present AntMonitor, a system for collecting and analyzing network traffic from Android devices (we already mentioned it in Section III-B). Among other types of analysis, AntMonitor can perform PII leakage detection. The authors capture the network traffic of nine Android users for a period of five weeks, then inspect the collected dataset searching the following PII: IMEI, Android Device ID, phone number, email address, and device location. Overall, 44% and 66% of the analyzed apps leak IMEI and Android Device ID, respectively, while PII related to the user is rarely disclosed to remote hosts. It is worth to notice that the proposed analysis requires to inspect application-layer data, which is infeasible in case of traffic encryption, neither at network (IPsec) nor transport layer (SSL/TLS).

Song and Hengartner in [41] develop PrivacyGuard, an open-source Android app that leverages the `VPNService` class of the Android API for eavesdropping the network traffic of the apps installed on the device. The authors employ PrivacyGuard to investigate the leakage of PII related to mobile users (e.g., phone number) and devices (e.g., IMEI) by Android apps. In an evaluation conducted using 53 Android apps, PrivacyGuard detects more PII leaks than TaintDroid [66]. The proposed app can optionally replace the leaked information with bogus data. Moreover, it can inspect transmission protected by SSL/TLS (through a man-in-the-middle approach), but cannot deal with traffic encrypted via IPsec.

TABLE VI
WORKS THAT DEAL WITH PII LEAKAGE DETECTION.

Year	Paper	Targeted Mobile Platform			Action on PII Leaks	
		Android	iOS	Windows Phone	Detection	Prevention
2012	Stevens et al. [23]	✓			✓	
2013	Kuzuno et al. [27]	✓			✓	
	Rao et al. [29]	✓	✓		✓	✓
2015	Le et al. [5]	✓			✓	
	Song et al. [41]	✓			✓	✓
2016	Ren et al. [50]	✓	✓	✓	✓	✓
	Vanrykel et al. [54]	✓			✓	
2017	Cheng et al. [57]	✓			✓	
	Continella et al. [58]	✓			✓	

Vanrykel et al. in [54] investigate the leakage of sensitive identifiers in the unencrypted network traffic of Android apps. The authors develop a framework that automatically executes apps, collects their network traffic, inspects the HTTP data, and detects the identifiers that are transmitted in clear. The analysis of 1,260 Android apps (from 42 app categories) shows that: (i) the Android ID and Google Advertising ID are the most frequently leaked identifiers, while the SIM serial number, the IMSI, the device serial number, and the email of the registered Google account are less common in apps' network traffic; (ii) there is an extensive leakage of app-specific identifiers; and (iii) certain apps leak the user's phone number, email address, or position.

Cheng et al. in [57] present a framework for the detection of PII leaks by Android apps. Such framework leverages the information available in IP and TCP headers; for this reason, it works even if the apps employ SSL/TLS to encrypt their network transmissions, and it can be blocked only using IPsec. Overall, the idea is to model the network traffic related to a user-app interaction into a sequence of packet sizes, then convert such sequences into feature vectors to be used for training and evaluating a machine learning classifier. The authors consider seven Android apps (i.e., BaiduYun, Evernote, QQ, QQMail, TouTiao, WeChat, and Weibo), plus a self-developed Android malware, called Moledroid, that implements several techniques employed by malicious apps to leak PII.

Continella et al. in [58] develop Agrigento, an open-source framework for the analysis of Android apps in order to detect PII leakage. Agrigento is based on differential analysis, and its workflow consists of two phases. In the first phase, the app under scrutiny is executed several times on a physical device to collect: (i) its network traffic; and (ii) additional system- and app-level information that is contextual to the execution (e.g., randomly-generated identifiers, timestamps). Subsequently, the collected information is aggregated to model the network behavior of the app. In the second phase, a specific PII within the operating system of the mobile device is set to a different value. The app is then executed once again to collect its network traffic and the contextual information. Finally, a PII leak is reported if the collected data does not conform to the model learned before. Evaluated on 1,004 Android apps, Agrigento detects more privacy leaks than currently available state-of-the-art solutions (e.g., ReCon [50]), while limiting the number of false positives. The proposed framework requires to inspect HTTP messages and leverages a man-in-the-middle

approach to deal with HTTPS traffic. However, Agrigento does not work on network traffic encrypted via IPsec.

E. Malware Detection

As happened for personal computers, the success and widespread adoption of mobile devices have attracted the interest of malware developers. Mobile devices, and particularly smartphones, are an ideal target for attackers since: (i) they are ubiquitous, i.e., the population of potential targets is large; (ii) they host sensitive information about their owners (e.g., identity, contacts, GPS position); and (iii) they have networking capabilities and they are usually connected to the Internet.

We define as *malware detection* the attempt to understand whether a mobile app is malicious through the analysis of the network traffic it generates. In this section, we present the state of the art techniques for such kind of traffic analysis. We point out that we do not report the works that study the properties of the network traffic generated by malicious apps, because in such case the analysis is more related to traffic characterization (see Section III-A). From the surveyed works, we elicit three kinds of actor that actually perform malware detection task: (i) an app marketplace [24]; (ii) a security company [25], [44], [48], [8], [55]; or (iii) a mobile user [22], [35].

Shabtai et al. in [22] present an anomaly-based malware detection app for Android devices. The proposed app monitors several aspects of the device (e.g, memory, network, power) and extracts different features, some of which are related to network traffic (e.g., the number of received packets). A properly trained machine-learning-based classifier is then employed to check whether an installed app is malicious. The proposed solution is evaluated using 40 benign and 4 malicious Android apps. The authors consider different classifiers (e.g., decision tree, Bayesian networks), as well as different metrics for feature selection (e.g., Fisher score, information gain). Moreover, the authors investigate how the detection accuracy is affected when: (i) the testing apps are not used in the training phase; and (ii) training and testing are performed on different devices.

Su et al. in [24] propose a framework that allows an Android marketplace to detect whether an app submitted by a mobile developer is malicious or benign. The system consists of two components: (i) servers, where developers can upload their new apps for verification; and (ii) physical Android devices,

where apps are actually executed while monitoring their system calls and network traffic. The gathered information is sent to a central server, which classifies each app as safe or malicious according to the response of two classifiers. In particular, a classifier bases its decision on system call statistics, while the other considers network traffic features. The network traffic classifier is trained with data from 49 malicious apps (from 22 malware families) and 60 benign apps, and tested with data from 50 malicious apps (from 22 malware families) and 70 benign apps (from eleven app categories). It is worth to notice that such classifier cannot process network traffic encrypted via IPsec, since one of the features it leverages is the average TCP session duration, which is not computable without accessing TCP headers.

Wei et al. in [25] present a framework for Android malware detection. Using network traffic generated by malicious Android apps, the system learns the network behavior of Android malware with regard to the resolution of domain names. Then, the system is employed to automatically analyze the DNS traffic produced by a given app and state whether that app is safe or malicious. The authors evaluate their solution using malicious apps from a public dataset of Android malware and benign apps from the official Android marketplace. A weakness of this framework is that it requires the access to the DNS traffic of apps, which can be hidden by IPsec or SSL/TLS encryption.

Shabtai et al. in [35] design an anomaly-based malware detection app for Android devices. Such app analyzes the network behavior of the apps installed on the device in order to identify self-updating malware (i.e., benign apps that after being installed on the device, they download a malicious payload from the Internet) and popular apps republished with additional malicious code. The idea is to model the normal network behavior of each installed app as a set of traffic patterns, and subsequently detect any deviation from those patterns. The system is evaluated on several benign apps, ten self-updating malicious apps developed by the authors, and the infected version of five of the chosen benign apps. The system works even with apps that encrypt their network traffic, since it needs to know only their amount of transmitted/received bytes and its percent out of the total device traffic.

The work by Zaman et al. [44] stems from the observation that malicious apps usually send the user's sensitive information to accomplice remote hosts. The idea is to log all communications with remote hosts for each app installed on the mobile device. Leveraging a list of known malicious domains, it is possible to label the apps that contacted them as malware. This approach requires to inspect the URLs within HTTP messages, therefore it does not work on encrypted network traffic. The authors evaluate their solution on *DroidKungFu* and *AnserverBot* samples (i.e., two Android malware) being able to detect only the former one.

Narudin et al. in [48] investigate whether an anomaly-based IDS (Intrusion Detection System) can successfully detect malicious Android apps by relying on traffic analysis. To build a comprehensive dataset of network traces, the authors run benign apps on a physical Android device and malicious apps on dynamic analysis platforms available online. The collected

network traffic is then sent to a central server, where several machine learning classifiers (e.g., random forest, multi-layer perceptron) are trained and evaluated. Unfortunately, such classifiers cannot process encrypted traffic, since they need to inspect HTTP messages.

Wang et al. in [8] present TrafficAV, an Android malware detection system based on machine learning. The proposed framework offers two distinct detection models, which rely on TCP- and HTTP-related network features, respectively. We give more details about considered features and classifiers in Section VI-B4. The authors evaluate their models on the network traffic of 8,312 benign apps and 5,560 malware samples. While the HTTP feature-based model cannot work on traffic encrypted with SSL/TLS since it requires to perform Deep Packet Inspection (DPI), both the proposed models cannot cope with apps that employ IPsec.

Arora and Peddoju in [55] (which is an extension and refinement of a previous work by the same authors [67]) also apply machine learning to detect Android malware. They collect the network traffic of malware samples from eleven families, extract 22 network-layer features (e.g., average time interval between received packets, per-flow sent bytes), and train a naive Bayes classifier. They evaluate their proposal on the network traffic of malware samples from six families (different from the ones used for training). Moreover, the authors present a feature selection algorithm that reduces the number of features to be used, while limiting the drop in detection accuracy. The proposed framework is encryption-agnostic, although the same authors admit that encryption may be a possible solution to evade detection. We provide more details about the features and the algorithm to select them in Section VI-B4.

F. User Action Identification

As we stated in Section III-B, most of the apps can leverage the Wi-Fi and cellular network interfaces of mobile devices to send and receive data. Since users perform several actions while interacting with apps, it is likely that most of such actions generate data transmissions. The network traffic trace of a given action typically follows a pattern that depends on the nature of the user-app interaction of that action. As a practical example, browsing a user's profile on Facebook will likely produce a different traffic pattern compared to posting a message on Twitter. These patterns can be used to recognize specific user actions related to a particular app of interest in generic network traces. Moreover, it is often possible to infer specific information about a given user action (e.g., the length of the message sent via an instant messaging app). We refer to these types of traffic analysis as *user action identification*.

The possibility to identify actions of mobile users can be useful in several scenarios:

- It is possible to profile the habits of a mobile user (e.g., checking emails in the morning, watching YouTube videos in the evening). The user's behavioral profile can be used to later recognize the presence of that user in a network. Moreover, profiles of thousands of mobile users can be aggregated in order to infer some information for marketing or intelligence purposes.

TABLE VII
APP CATEGORIES COVERED IN THE SURVEYED WORKS THAT DEAL WITH
USER ACTION IDENTIFICATION.

Year	Paper	Covered App Categories										
		Communication	Dating	Gaming	Health	Maps	Media	News	Productivity	Shopping	Social	Utility
2013	Watkins et al. [30]			✓								✓
2014	Coull et al. [32]	✓										
2015	Park et al. [39]	✓										
2016	Conti et al. [45]	✓							✓		✓	
	Fu et al. [46]	✓										
	Saltaformaggio et al. [52]	✓	✓		✓	✓	✓	✓		✓	✓	

- It is possible to perform *user de-anonymization*. Suppose a national agency is trying to discover the identity of a dissident spreading anti-government propaganda on a social network. It is possible to monitor a suspect and detect when she posts messages via the social network mobile app. The inferred posting timestamps can be matched with the time of the messages on the dissident social profile in order to understand whether the suspect is actually the dissident.

In Table VII, we show the app categories covered by the surveyed works that perform user action identification [30], [32], [39], [45], [46], [52]. As we can notice from Table VII, almost all the works target communication apps, which belong to the most privacy-sensitive app category. This category includes both instant messaging apps (e.g., iMessage, KakaoTalk, WhatsApp) and email clients (e.g., Gmail, Yahoo Mail). Another sensitive category is social (e.g., Facebook, Twitter, Tumblr), which is targeted in [45], [52]. Apps related to multimedia contents (e.g., YouTube) are considered in [30], [52]. Moreover, Saltaformaggio et al. in [52] also focus on other categories of apps: dating (e.g., Tinder), health (e.g., HIV Atlas), maps (e.g., Yelp), news (e.g., CNN News), and shopping (e.g., Amazon). The works in [30], [45] cover productivity apps (e.g., Dropbox), and Watkins et al. in [30] also consider mobile games (e.g., Temple Run 2) and utility apps (e.g., ZArchiver).

Watkins et al. in [30] develop a framework that exploits the inter-packet time of responses to ICMP packets (i.e., pings) to infer the type of action that the target user is performing on her mobile device. In particular, the authors focus on three types of user action: (i) CPU intensive; (ii) I/O intensive; and (iii) non-CPU intensive. First of all, the authors check the feasibility of their approach for the Android and iOS platforms, showing that unfortunately their solution does not work on iOS since such OS does not use CPU throttling. Subsequently, they evaluate their framework using six Android apps. Since the proposed solution exploits the timing of packets, it is not affected by traffic encryption.

Coull and Dyer in [32] target iMessage, Apple’s instant messaging service, which is available as an app for iOS or a computer application for OS X. The proposed analysis leverages the sizes of the packets exchanged between the target user and Apple’s servers, thus it works despite all

iMessage communications are encrypted. The authors focus on five user actions: “start typing”, “stop typing”, “send text”, “send attachment”, and “read receipt”. The authors also aim to infer the language (among six languages: Chinese, English, French, German, Russian, and Spanish) and length of the exchanged messages. The authors make two assumption necessary by their methods to work correctly: (i) for user actions identification, they assume to have correctly inferred that the target mobile device is running iOS; and (ii) for language and message length inference, they also assume to have correctly identified an iMessage action.

Park and Kim in [39] target KakaoTalk, an instant messaging service widely used in Korea. They consider eleven actions that a user can perform on the Android app (e.g., join a chat room, send a message, add a friend). For each action, the proposed framework learns its traffic pattern as a sequence of packets. Such sequence is then used to recognize that specific action in unseen network traces. The proposed solution works despite KakaoTalk traffic is encrypted using SSL/TLS, but it does not work in presence of IPsec encryption.

Conti et al. in [45] present an identification framework which leverages the information available in IP and TCP headers (e.g., source and destination IP addresses) and therefore it works even if the network traffic is encrypted via SSL/TLS. However, the proposed approach does not work on an IPsec scenario, since it relies on (IP address, TCP port) pairs to separate traffic flows. The authors target seven popular Android apps (namely Dropbox, Evernote, Facebook, Gmail, Google+, Tumblr, and Twitter). The authors also compare their proposal with websites fingerprinting algorithms by Liberatore and Levine [68] and Herrmann et al. in [69], outperforming them.

Fu et al. in [46] propose CUMMA, a framework for user action identification that targets messaging apps. The authors focus their analysis on the Android platform, and consider the WeChat and WhatsApp apps. For each targeted app, several user actions are chosen for identification, such as sending a text message or sharing the GPS position. Since the network traffic of messaging apps is usually encrypted to protect the privacy of their users, CUMMA is designed to overcome such limitation by exploiting only the size and timing of the packets exchanged between the app and the servers of the service provider. The proposed framework leverages machine learning by employing a classifier that is trained and evaluated on the feature vectors extracted from the captured information. The authors also develop a clustering method based on hidden Markov model to deal with the fact that the same network flow can likely contain the network data related to multiple user actions (see Section VI-B5).

Saltaformaggio et al. in [52] present NetScope, a user action identification system that can be deployed at Wi-Fi access points or other network equipments. Since it leverages IP headers/metadata, NetScope can be employed even if the network traffic is protected by IPsec. The authors evaluate their solution by considering 35 user actions from 22 apps across two platforms (i.e., Android and iOS) and eight app categories.

TABLE VIII
TARGETED MOBILE OSES IN THE SURVEYED WORKS THAT DEAL WITH
OPERATING SYSTEM IDENTIFICATION.

Year	Paper	Android	iOS	Windows Phone	Symbian
2014	Chen et al. [31]	✓	✓		
	Coull et al. [32]		✓		
2016	Ruffing et al. [51]	✓	✓	✓	✓
2017	Malik et al. [60]	✓	✓	✓	

G. Operating System Identification

We define as *operating system identification* the attempt to discover the operating system of a mobile device by analyzing its network traffic. This type of analysis has several applications:

- An adversary can identify the operating system of a target mobile device, and tailor her subsequent attack to that OS (e.g., by choosing a proper security exploit). In such case, the operating system identification is a preparatory task for more advanced and focused attacks. Moreover, the overall attack strategy can be more effective if the adversary is able to infer not only the operating system of the target mobile device, but also the version of that OS.
- It is possible to expose the adoption of mobile operating systems among a crowd of people. This can be a starting point for marketing, as well as sociological studies (we consider the latter in Section III-K).

In this section, we survey four works [31], [32], [51], [60]. Table VIII reports the mobile operating systems they consider.

Chen et al. in [31] develop a probabilistic classifier that leverages the information available in IP and TCP headers. Therefore, their method works unless IPsec is employed to hide the content of IP packets. Such classifier is evaluated using network traces captured at a Wi-Fi access point to which Android and iOS mobile devices, as well as Windows laptops are connected.

Coull and Dyer in [32] target iMessage, Apple’s instant messaging service. They leverage the sizes of the encrypted packets exchanged between the target user and Apple’s servers, in order to determine whether she is using iMessage on iOS or OS X. The proposed classifier needs to observe only five packets to successfully identify the OS.

The work by Ruffing et al. [51] stems from the observation that the timing of the network traffic generated by a mobile device depends on its operating system. The idea is to analyze the frequency spectrum of packet timing in order to identify the frequency components that are related to OS features, and filter out the ones that bring noise. Since this approach does not require to inspect the content of packets, it can be successfully applied even if encryption is in place. The authors evaluate their solution using network traffic captured from smartphones running the following operating systems: Android, iOS, Windows Phone, and Symbian. The authors also evaluate whether their approach is suitable to discriminate different versions of the same OS, and they choose Android and iOS for such analysis.

Malik et al. in [60] present a framework that exploits the inter-packet time of packets coming from a target mobile

device in order to infer its operating system. In particular, the authors focus on two types of packet: (i) the response to an ICMP packet sent to the target mobile device (active measurement); and (ii) an IP packet related to a video stream involving the target mobile device (passive measurement). In both cases, the proposed solution effectively discriminates among three mobile operating systems, namely Android, iOS, and Windows Phone. Moreover, such approach is not hindered by traffic encryption, since it exploits the timing of packets. However, we must point out that the authors’ testbed includes only three devices, one for each of the considered mobile operating systems. Therefore, it is not clear whether the mobile device model and the OS version may affect the accuracy in identifying the OS.

H. Position estimation

The set of places frequently visited by a person tells a lot about her social status, interests, and habits. Such information can be exploited for commercial purposes (e.g., targeted advertisement), as well as intelligence activities (e.g., police investigations). Since most of people own a mobile device and keep it with them all day long, locating the smartphone/tablet of a target user becomes a simple yet effective way to know her position. Multiple position detections can be then aggregated to build a profile of the subject or reconstruct its movements. The movements of several mobile users can be aggregated as well, for example to aid traffic prediction along urban streets.

We define as *position estimation* the inference of the position and/or trajectory (i.e., movements) of a mobile device in a geographical area, by analyzing the network traffic that device generates. In this section, we survey the works that propose this type of traffic analysis. We point out that we do not consider the works in which: (i) the mobile traffic is analyzed to detect the leakage of GPS coordinates (we consider this kind of works in Section III-D); and (ii) the analysis performed on the network traffic is device-agnostic, i.e., it does not take into account the fact that the target devices are smartphones/tablets (this kind of works is excluded since it is too generic).

Husted and Myers in [11] investigate whether a malnet (i.e., a colluding network of malicious Wi-Fi devices) can successfully determine the location of a mobile device. Each malicious node looks for probe requests carrying the MAC address of the target mobile device, and uploads its findings to a central server where the data coming from all nodes is used for trilateration. Through a software simulation of a metropolitan population of users equipped with 802.11g mobile devices, the authors show that 10% of tracking population is sufficient to track the position of the remaining users. Besides, the tracking benefits from extending the broadcasting range of the mobile devices. This suggests that the adoption of newer 802.11 standards can make it feasible to build a geolocating malnet.

Musa and Eriksson in [21] present a system for passively tracking mobile devices by leveraging the Wi-Fi probe requests they periodically transmit. The idea is to employ a number of Wi-Fi monitors, which look for probe requests from mobile devices and report each detection to a central server, where the

detections of the same mobile device are turned into a spatio-temporal trajectory. To evaluate their system, the authors set up three deployments and leverage GPS ground truth to measure the accuracy of the inferred trajectories. The mean error is under 70 meters when the distance among the monitors is over 400 meters.

I. User Fingerprinting

Mobile users interact actively with their devices, leveraging the nearly ubiquitous Internet connectivity and the capabilities of the apps available in the marketplaces. To each mobile user, it is possible to associate a set of preferred (i.e., most frequently used) apps and, for each of these apps, a set of preferred actions (i.e., most frequently executed). Since most of the mobile apps are able to connect to the Internet, and many user actions within them trigger data transmission through the network, it becomes clear that the network traffic generated by a user is likely to present a fairly constant pattern across different devices, as well as across different networks. We define as *user fingerprinting* the attempt to exploit such pattern in order to recognize the network traffic belonging to a specific mobile user. This type of analysis can be applied to:

- Recognize the presence of a specific mobile user within a network. Once the network is identified, it is then possible to approximate the geographical position of that user with the location of the Wi-Fi hotspot or cellular station to which her mobile device is connected.
- Partition the network traces of a mobile traffic dataset by user. Once the transmissions related to a specific mobile user have been separated and grouped together, it is then possible to apply other types of traffic analysis targeting that user.

In this section, we review the works that deal with mobile user fingerprinting.

Verde et al. in [36] present a system being able to accurately infer when a target user is connected to a given network and her IP address, even though she is hidden behind NAT among thousands of other users. To achieve this objective, a machine learning classifier is trained with the NetFlow records of the target user's traffic, and then employed to analyze the NetFlow records of a given network in order to detect the presence of the target user within it (more details on the classifier are provided in Section VI-B8). The system is evaluated as follows:

- Cross-validation is applied to the NetFlow records of the traffic generated by 26 different mobile users connecting to the Internet through the same Wi-Fi access point.
- The authors enroll five mobile users and ask them to connect their devices to a Wi-Fi access point to then try to detect the presence of such users within a real-world large metropolitan Wi-Fi network.

It is worth to notice that the proposed solution is encryption-agnostic, since NetFlow records can be extracted even from encrypted traffic.

Vanrykel et al. in [54] investigate how mobile unencrypted traffic can be exploited for user surveillance. The authors develop a framework to automatically execute apps, collect

their network traffic, inspect the HTTP data, and identify the sensitive identifiers that are transmitted in clear. Moreover, the authors present a graph building technique that exploits such identifiers to extract the network traces generated by a specific mobile user from a traffic dataset (more details in Section VI-C2). The authors analyze 1,260 Android apps (from 42 app categories) showing that their proposed solution can link 57% of a mobile user's unencrypted network traffic. In addition, the authors observe the limited effectiveness of ad-blocking apps in preventing the leakage of sensitive identifiers.

J. Ad Fraud Detection

Mobile apps can be partitioned into two macro categories: paid and free apps. To cover the cost of developing and maintaining a free app, developers usually rely on advertisement, which applies the following business model:

- The ad provider yields a library that can be embedded in the app. Such library fetches ad contents and displays them on the app's user interface.
- The ad provider pays according to the amount of times the ads are displayed to the user (*impressions*) and/or clicked by the user (*clicks*).

We define as *ad fraud detection* the analysis of network traffic in order to uncover apps that trick the business model described above and let their developers illicitly earn money. Unfortunately, despite the economic impact that such research brings in the market of mobile advertisements, only one work has been published on this topic.

Crussell et al. in [33] focus on the Android platform. They identify two fraudulent app behaviors:

- To request ads while the app is running in background. This generates impressions without actually displaying ads to the user.
- To click on ads without any user interaction, which is achievable in the following ways: (i) the app can trick the ad library by simulating a user click on the ad with a touch event; and (ii) the app extracts the click URL from the ad request (i.e., the web page that will be opened when the user clicks on the ad), then makes an HTTP request to the click URL to simulate a user click.

The authors propose MAdFraud, a tool being able to automatically run Android apps in emulators and analyze their application-layer traffic in order to expose ad fraud. The system is employed to analyze 130,339 Android apps crawled from nineteen different marketplaces, and 35,087 Android apps that probably contain malware (provided by an unspecified security company). The authors report that 30% of apps generate fake impressions (i.e., they request to display an ad while running in the background), while 27 apps generate fake clicks (i.e., they contact a click URL without any user interaction). Unfortunately, MAdFraud cannot process encrypted traffic, since it relies on the HTTP and DNS data generated by apps. However, the authors' analysis covers most of the available ad libraries. This means that such libraries do not usually employ any form of encryption for their data transfers (i.e., they simply rely on plain HTTP).

K. Sociological Inference

A property of a mobile device (e.g., the list of installed apps, the Wi-Fi networks to which the device associated) characterizes its owner. Sociologists can leverage this kind of information to study a population of mobile users. In this section, we review the works that deal with *sociological inference*, which we define as the analysis of the network traffic generated by mobile devices in order to infer some kind of sociological information about their users.

Barbera et al. in [26] investigate whether sociological information about a large crowd can be inferred by inspecting the Wi-Fi probe requests generated by the mobile devices of those people. First of all, the authors: (i) devise a methodology to convert a dataset of Wi-Fi probe requests into a social graph representing the owners of the monitored mobile devices; and (ii) develop an automatic procedure to infer the language of a given SSID. Subsequently, they target gatherings of people at urban, national, and international scale, as well as a mall, a train station, and a campus. As a result of their analysis, the authors report some findings: (i) the social graph of all the targeted events has social-network properties; (ii) the distributions of languages and mobile device vendors match the nature of the monitored crowds; and (iii) socially interconnected people tend to adopt mobile devices of the same vendor, and appear in the same time slot.

L. Tethering Detection

The ability to connect to cellular networks lets mobile devices have nearly ubiquitous Internet connectivity. Moreover, mobile devices are able to share such connectivity with other devices that cannot leverage cellular networks (e.g., laptops). This practice is commonly referred to as *tethering*, and can be carried out in many ways, such as via a USB cable, via Bluetooth, or establishing a WLAN (hotspot) for which the mobile device acts as a router.

In this section, we report the works that deal with *tethering detection*, which we define as the analysis of the network traffic generated by a mobile device in order to discover whether it is sharing its Internet connection with other devices. This type of analysis can be valuable for a cellular network provider, since tethering can significantly increase the amount of traffic its network infrastructure has to sustain. An effective detection method would let the cellular ISP prevent users from sharing their mobile Internet connection, or require them to pay an extra fee.

Chen et al. in [31] develop a probabilistic classifier being able to detect tethering by leveraging several network features (e.g., the number of distinct TTLs in the packets coming from the same IP address). To evaluate their solution, the authors use publicly available Wi-Fi traces collected at two conferences, as well as a dataset of Wi-Fi traffic from a campus network. The authors simulate tethering by randomly mix packets from different IP addresses, then modifying source IP addresses accordingly. Since the proposed solution requires to inspect the content of TCP headers, it cannot work whether the captured network traffic is protected by IPsec.

M. Website Fingerprinting

The Internet has a central role in people's everyday life, and surfing the Web has become a common task that can be performed from desktop computers, as well as in mobility using laptops and smartphones/tablets, thanks to the increasing deployment of cellular and Wi-Fi networks. From a privacy point of view, the set of websites frequently visited by a user is a sensitive information, since it can disclose her interests, social habits, religious belief, sexual preference, and political orientation.

In the field of traffic analysis, *website fingerprinting* generally indicates the attempt to infer the website or even webpage visited by a user surfing the Internet with her mobile device, by analyzing the network traffic generated by the mobile web browser. This type of analysis has been extensively treated in the domain of personal computers, where machine learning techniques have been proved to be very effective [68], [69], [70]. Since we focus on mobile devices, in this section we survey the works that target users navigating through the web browser of their mobile devices.

Spreitzer et al. in [53] develop an Android app being able to capture the data-usage statistics of the browser app, and leverage them to fingerprint the mobile webpages visited by the user of the mobile device on which that app is installed. This solution is not affected by encryption, since it only requires to know the amount of data transmitted and received by the browser app (which is easily obtainable in Android). The proposed app is evaluated on a set of 500 possible pages that the user can visit. The authors also evaluate their fingerprinting app when the network traffic is protected by Tor (in particular, by using the Orbot proxy and the Orweb browser).

IV. POINTS OF CAPTURING FOR TRAFFIC ANALYSIS TARGETING MOBILE DEVICES

Another meaningful categorization of the work is based on the point where the network traces are captured in order to build the traffic dataset(s). In Table IX, we report the point(s) of capturing for each surveyed work. As shown in Figure 4, the most common points of capturing are wired network equipments (twenty two works), followed by mobile devices themselves (twenty works), Wi-Fi access points (twelve works), and mobile devices emulators and Wi-Fi monitors (five works each). In one work, the mobile traffic is simulated via software. As shown in Table IX, four works leverage two different types of point of capturing, and one work even three. In the following sections, we provide a definition for and discuss each of the points of capturing we encountered in the surveyed work. For each point of capturing, we also point out pro, cons, and relevant aspects that have to be taken into account, as a guideline to properly design a network traffic collection environment for mobile devices.

A. Wired Network Equipments

In this section, we review the works in which the mobile traffic is captured at one or more wired network equipments. Such equipments can be deployed into two types of network:

TABLE IX
THE SURVEYED WORKS BY WHERE THE MOBILE TRAFFIC IS CAPTURED.

Year	Paper	Mobile Devices (Emulated)	Mobile Devices (Real)	Network Simulators	Wired Network Equipments	Wi-Fi Access Points	Wi-Fi Monitors
2010	Afanasyev et al. [9]				✓	✓	
	Falaki et al. [10]		✓				
	Husted et al. [11]			✓			
	Maier et al. [12]				✓		
	Shepard et al. [13]		✓				
2011	Finamore et al. [14]				✓		
	Gember et al. [15]				✓	✓	
	Lee et al. [16]				✓		
	Rao et al. [17]				✓		
2012	Baghel et al. [18]				✓		
	Chen et al. [19]				✓		
	Ham et al. [20]		✓				
	Musa et al. [21]						✓
	Shabtai et al. [22]		✓				
	Stevens et al. [23]					✓	
	Su et al. [24]		✓				
2013	Wei et al. [25]				✓		
	Wei et al. [4]		✓				
	Barbera et al. [26]						✓
	Kuzuno et al. [27]		✓				
	Qazi et al. [28]		✓			✓	
2014	Rao et al. [29]				✓		
	Watkins et al. [30]					✓	✓
	Chen et al. [31]				✓	✓	✓
	Coull et al. [32]		✓				
	Crussell et al. [33]	✓					
	Lindorfer et al. [34]	✓					
2015	Shabtai et al. [35]		✓				
	Verde et al. [36]				✓		
	Chen et al. [37]				✓		
	Fukuda et al. [38]		✓				
	Le et al. [5]		✓				
	Park et al. [39]		✓		✓		
	Soikkeli et al. [40]		✓				
	Song et al. [41]		✓				
2016	Wang et al. [42]						✓
	Yao et al. [43]	✓				✓	
	Zaman et al. [44]		✓				
	Alan et al. [6]					✓	
	Conti et al. [45]				✓		
2017	Fu et al. [46]					✓	
	Mongkolluksamee et al. [47]		✓				
	Narudin et al. [48]	✓	✓				
	Nayam et al. [49]				✓		
	Ren et al. [50]				✓		
	Ruffing et al. [51]						✓
	Saltaformaggio et al. [52]					✓	
	Spreitzer et al. [53]		✓				
	Tadrous et al. [7]					✓	
	Vanrykel et al. [54]				✓		
	Wang et al. [8]				✓		
2018	Arora et al. [55]		✓				
	Chen et al. [56]	✓					
	Cheng et al. [57]				✓		
	Continella et al. [58]				✓		
	Espada et al. [59]		✓				
	Malik et al. [60]					✓	
	Taylor et al. [61]				✓		
Wei et al. [62]				✓			

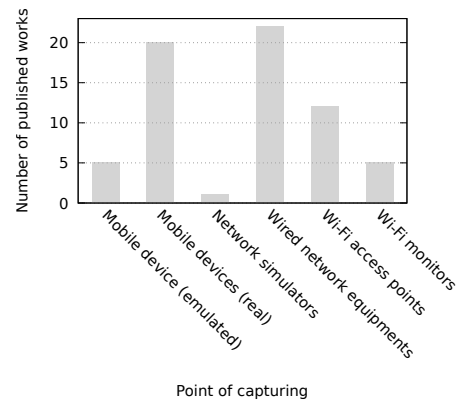


Fig. 4. Number of published works contributing traffic analysis methods targeting mobile devices, sorted by point of capturing.

- Small-scale networks, serving a reduced number of mobile users (from one single mobile device to a few tens). Researchers often deploy such networks to collect the traffic they need in a controlled environment. The equipments associated to this type of network are small Internet gateways [36], VPN servers [29], [50], [54], and traditional desktop computers that log all the traffic traversing the wired link between the APs to which the mobile devices are associated and the Internet [17], [18], [25], [37], [39], [45], [49], [8], [57], [58], [61]. The user population typically consists only of the targeted mobile devices (i.e., there is no need to filter out non-mobile traffic from the captured traces).
- Large-scale networks, serving thousands of users. In such case, the considered network equipments are edge routers (i.e., routers that connect customers to their ISP's backbone) [12], top-level routers [16], [19], [36], Internet gateways [9], [31], [62], switches [31], or generic points of presence within national ISPs and campus networks [14]. The user population typically includes also non-mobile users (e.g., laptop users), and the network traffic they generate must be removed from the captured traces.

In Table X, we present the works in which the collected mobile traffic comes from one or more wired network equipments serving a small number of mobile devices. For each work, we report the network equipments at which the mobile traffic is logged, the targets of the analysis, additional details about the capturing process, and the information leveraged for the analysis. We use the term *forwarding server* to indicate a device that logs all the traffic traversing the wired link between the APs to which the monitored mobile devices are connected and the Internet.

In Table XI, we present the works in which the mobile traffic is extracted from traces captured at one or more wired network equipments serving large-scale networks with thousands of users. In the following, we provide additional information about the mobile data extraction process for each work.

Afanasyev et al. in [9] leverage the Organizationally Unique Identifier (OUI) of the MAC address to discriminate between mobile and non-mobile devices. This approach has the disadvantage that an OUI can be associated to devices of both

TABLE X
THE SURVEYED WORKS IN WHICH THE MOBILE TRAFFIC IS EXTRACTED FROM TRACES CAPTURED AT ONE OR MORE WIRED NETWORK EQUIPMENTS SERVING A SMALL NUMBER OF MOBILE DEVICES.

Year	Paper	Network Equipment(s)	Target(s)	Capturing Details	Leveraged Information
2011	Rao et al. [17]	Forwarding server	Android and iOS clients for Netflix and YouTube	180 seconds for each video playback	HTTP messages
2012	Baghel et al. [18]	Forwarding server	Facebook Android app Skype Android app	90 minutes, no user interaction Five hours, no user interaction	Layer-2+ data
	Wei et al. [25]	Forwarding server	102 malicious Android apps from a public Android malware dataset, and popular Android apps from Google Play Store	No details	DNS data
2013	Rao et al. [29]	VPN server	The top-100 free Android apps in Google Play Store, and 209 free iOS apps from Apple App Store	Up to ten minutes of manual interaction	Layer-3+ data
			732 free Android apps from a third-party Android marketplace	Android Debug Bridge (ADB) scripting and Monkey are leveraged to execute 100,000 actions for each app	
2014	Verde et al. [36]	Gateway router	26 mobile devices	One month of monitoring	NetFlow records
2015	Chen et al. [37]	Forwarding server	5560 malicious Android apps (from 177 malware families)	Each app is stimulated for five minutes using Monkeyrunner	Layer-2+ data
	Park et al. [39]	Forwarding server	Eleven user actions from KakaoTalk Android app	Each user action is automatically executed 100 times	IP headers, TCP headers
2016	Conti et al. [45]	Forwarding server	58 user actions from seven Android apps	Android Debug Bridge (ADB) scripting is leveraged to execute 220 sequences of actions for each app	IP headers, TCP headers
	Nayam et al. [49]	Forwarding server	63 Android and 35 iOS free apps, all belonging to the "Health & Fitness" category	Three 30-minutes-long runs per app, driven using automated scripts (Appium for Android and Silk Mobile for iOS)	HTTP messages
	Ren et al. [50]	VPN server	The top-100 free apps from Google Play Store (Android), Apple App Store (iOS), and Windows Phone Store (Windows Phone)	Five minutes of manual interaction	Layer-3+ data
			850 of the top 1,000 free apps from a third-party Android marketplace	Android Debug Bridge (ADB) scripting and Monkey are leveraged to execute 10,000 actions for each app	
	Vanrykel et al. [54]	Two VPN servers	1,260 Android apps from Google Play Store	User interactions are simulated using The Monkey	HTTP messages
	Wang et al. [8]	Forwarding server	8,312 benign Android apps from Google Play Store, and 5,560 malicious Android apps	Each app is stimulated using Monkeyrunner	TCP- and HTTP-related data
2017	Cheng et al. [57]	Forwarding server	Seven Android apps, plus a self-developed PII-leaking Android app	Manual interaction	IP headers, TCP headers
	Continella et al. [58]	Forwarding server	1,004 Android apps from Google Play Store	Each app is stimulated for ten minutes using Monkey	HTTP messages
	Taylor et al. [61]	Forwarding server	110 of the top-200 Android apps from Google Play Store	Android Debug Bridge (ADB) scripting is leveraged to simulate user-app interactions	IP headers, TCP headers

TABLE XI
THE SURVEYED WORKS IN WHICH THE MOBILE TRAFFIC IS EXTRACTED FROM TRACES CAPTURED AT ONE OR MORE WIRED NETWORK EQUIPMENTS SERVING THOUSANDS OF USERS.

Year	Paper	Targeted Network Equipment(s)	Number of Monitored Users	Capturing Period	Leveraged Information	Methodology Applied to Extract Mobile Data
2010	Afanasyev et al. [9]	Central Internet gateway of an urban Wi-Fi network	Over 2500 simultaneous	5 days	Layer-3+ headers (excluding DHCP data ⁴) of the first packet of each flow for the first quarter of each hour	Leverage RADIUS logs from the APs of the network to map each IP address observed at the gateway to a MAC address, then inspect the Organizationally Unique Identifier (OUI) of the MAC address
	Maier et al. [12]	Edge router of an ISP's network	Over 20,000	4 days over 11 months	Anonymized DSL data	Inspect the User-Agent field of HTTP messages or, for non-HTTP traffic, inspect the Time-To-Live (TTL) field of IP packets
2011	Finamore et al. [14]	Five points of presence within national ISPs and campus networks	Unspecified	1 week	IP packets	Inspect the URL requests, looking for <code>app=youtube_gdata</code> or <code>app=youtube_mobile</code>
	Lee et al. [16]	Top-level router of a campus network	Unspecified	6 days	IP packets	Inspect packet headers, looking for information related to mobile operating systems
2012	Chen et al. [19]	Gateway router of a campus network	Unspecified	3 days, 1 day	Up to 900 bytes of each incoming/outgoing packet, including IP, TCP, and application-level headers	Inspect the IP address (since separate IP pools are used for Ethernet and WLAN), then inspect the User-Agent field of HTTP messages
2014	Chen et al. [31]	Wired switch serving the APs of a Wi-Fi network	Unspecified	Unspecified	Layer-2+ headers, plus DHCP and DNS payloads (all data are anonymized)	None
	Verde et al. [36]	Internet gateways of a campus Wi-Fi network	12,600	1 week	IP packets	None
2017	Wei et al. [62]	Tier-2 router of a metropolitan Wi-Fi network	200,000	1 day	NetFlow records	None
		Internet gateway of a campus Wi-Fi network	6,482	1 month	Layer-3+ data	Inspect the IP address to check whether it belongs to the WLAN IP address pool, leverage the DHCP logs from the DHCP server to map the IP address to a MAC address, and inspect the Organizationally Unique Identifier (OUI) of the MAC address

⁴The DHCP requests are handled by the APs of the network, thus they do not reach the central Internet gateway.

types (e.g., several OUIs belonging to Apple are associated to iPhones and MacBooks as well). Maier et al. in [12] and Chen et al. in [19] inspect the User-Agent field of HTTP messages, which can be misleading and it is not present in non-HTTP mobile traffic. In such case, the authors in [12] inspect the Time-To-Live (TTL) field of IP packets. Finamore et al. in [14] leverage the peculiar characteristics of YouTube traffic from mobile devices, while Lee et al. in [16] inspect the packet headers, looking for information related to mobile operating systems (without clarifying the nature of such information). Chen et al. in [31] do not elicit mobile traffic from the gathered network traces because they simply merge such data with traffic from other sources (see Section IV-E for details), then simulate tethering by modifying the source IP address of packets. Verde et al. in [36] do not need to extract the traffic of mobile devices from the collected network data because identifying such traffic is just the goal of their user fingerprinting method. Wei et al. in [62] inspect the IP address to check whether it belongs to the IP address pool of the target WLAN, then leverage the DHCP logs from the DHCP server of the network to map the IP address to a MAC address, and finally inspect the Organizationally Unique Identifier (OUI) of the MAC address.

B. Mobile Devices (Real)

The most direct way to collect mobile traffic is to place the point of capturing *within* the mobile devices, leveraging their modern operating systems to run a full-fledged logging app that is able to gather the required information. This approach has several implications:

- The covered set of mobile devices tends to be small compared to network-side measurements, since the logging app has to be installed on the mobile device of each volunteer.
- The strongest advantage of this point of capturing is that the traffic is logged directly on the mobile device, therefore we are sure that everything is captured belongs to that mobile device. In case of network-side logging, instead, the mobile traffic needs to be separated from the transmissions generated by other kinds of device, such as laptops and desktop computers. This process is error-prone, since some network information could be potentially misclassified. Moreover, it lacks completeness, because traffic that is not classified for some reason will be discarded even if it belongs to a mobile device.
- The logging app must have the proper permissions to capture traffic on the mobile device.
- The logging app must be lightweight. This means that it has to: (i) impose a negligible computational burden on the mobile device's CPU; (ii) occupy as few memory as possible to store traffic logs (this problem is easy resolvable if the logging app is allowed to periodically upload the logs to a remote server); and (iii) cause minor battery consumption, which is a major concern for mobile users.
- It is possible to focus on the traffic generated by specific mobile apps, or the one transiting through a specific network interface (i.e., Wi-Fi or cellular).

In Table XII, we present the works in which the mobile traffic is captured within one or more mobile devices. For each work, we show the targeted mobile platforms, the number of mobile devices employed, the tool used to capture the network traffic, and the information leveraged for the analysis.

Android is the most targeted mobile platform, mainly because its open nature makes it easy to develop a traffic logger from scratch, or simply port one of the available desktop solutions. Nevertheless, Fukuda et al. in [38] and Shepard et al. in [13] show that effective traffic loggers can be successfully deployed also on iOS devices. Packet sniffing tools such as Shark for Root and the networking module of DELTA logging tool [71] are based on tcpdump, while tPacketCapturePro leverages the `VPNService` class of the Android libraries. This class is also used in the custom logging apps by Le et al. in [5], and Song and Hengartner in [41].

The number of targeted devices is a meaningful information, especially for works which carry out mobile traffic characterization [10], [13], [4], [38], [59], or study the usage habits of mobile users [10], [20], [38], [40]. With regard to such works, we observe that only Fukuda et al. in [38] leverage a suitable population (over 1500 mobile devices), while the others count from a few tens to slightly more than a hundred of mobile devices. We point out that the problem is less relevant for the works in [4], [59], since the focus of the analysis is on the apps, rather than mobile devices.

C. Wi-Fi Access Points

As reported in [38], mobile users are increasingly offloading their traffic demands to Wi-Fi networks. This practice has become very common at home, where Wi-Fi modems are employed to make the wired Internet connection of the house available to laptops and mobile devices. Moreover, free Wi-Fi networks are often deployed in shops and public places (e.g., parks, malls, train stations), as well as at social events (e.g., meetings, conferences, concerts).

A Wi-Fi network typically consists of two types of hardware equipments: (i) access points (APs), which leverage the 802.11 standard to provide network connectivity to the associated wireless devices; and (ii) gateways, which forward the network traffic coming from the APs to the Internet (or to a higher-level gateway, in case of a hierarchical network infrastructure), and vice versa. It is worth to notice that these two categories are not mutually exclusive, since a hardware equipment can act as both access point and gateway (e.g., Wi-Fi modems). In this section, we survey the works that apply analysis methods to mobile traffic captured at one or more Wi-Fi access points (we dealt with traffic capturing at gateways in Section IV-A).

From an analysis point of view, we make the following observations:

- Compared with cellular networks, Wi-Fi networks cover a smaller geographical area, as well as much less users. For this reason, the mobile traffic captured at the APs of a Wi-Fi network is representative of a more restricted user population (e.g., the customers of a shop, the students of a campus), enabling fine-grained analysis.
- Since Wi-Fi networks are typically free of charge, mobile users can carry out intensive network activities (e.g.,

TABLE XII
THE SURVEYED WORKS IN WHICH THE MOBILE TRAFFIC IS CAPTURED WITHIN ONE OR MORE REAL MOBILE DEVICES.

Year	Paper	Mobile Platform(s)	Number of Devices	Capturing Tool	Leveraged Information
2010	Falaki et al. [10]	Android	33	Custom logging app	Per-app Tx/Rx bytes
			2	tcpdump	Layer-2+ data
	Windows Mobile	8	Netlog		
	Shepard et al. [13]	iOS	25	Custom logging app	Per-interface Tx/Rx bytes, IP headers/packets
2012	Ham et al. [20]	Android	10	Custom logging app	Per-process/Per-interface Tx/Rx bytes/packets
	Shabtai et al. [22]	Android	2	Custom logging app	Per-app cellular/Wi-Fi Tx/Rx bytes/packets
	Su et al. [24]	Android	Unspecified	tcpdump	Layer-2+ data
	Wei et al. [4]	Android	2	tcpdump	Layer-2+ data
2013	Kuzuno et al. [27]	Android	1	tcpdump	Layer-2+ data
	Qazi et al. [28]	Android	5	netstat	netstat logs
2014	Coull et al. [32]	iOS	Unspecified	Unspecified (on a Mac, by using the iOS Remote Virtual Interface)	Packet sizes within iMessage's APNS connection
	Shabtai et al. [35]	Android	1	Custom logging app	Per-app Tx/Rx bytes and percent out of total Tx/Rx bytes
2015	Fukuda et al. [38]	Android	Over 800	Custom logging app	Per-app/Per-interface Tx/Rx bytes/packets
		iOS	Over 700		
	Le et al. [5]	Android	9	Custom logging app	Per-app IP headers/packets
	Soikkeli et al. [40]	Unspecified	120	Custom logging app	Tx/Rx bytes
	Song et al. [41]	Android	1	Custom logging app	IP packets
	Zaman et al. [44]	Android	1	Shark for Root netstat	Layer-2+ data netstat logs
2016	Mongkolluksamee et al. [47]	Android	1	tcpdump	Layer-2+ data
	Narudin et al. [48]	Android	1	tPacketCapturePro	Per-app layer-2+ data
	Spreitzer et al. [53]	Android	Unspecified	Custom logging app	Tx/Rx TCP bytes of the browser app
2017	Arora et al. [55]	Android	1	Unspecified	IP packets
	Espada et al. [59]	Android	1	tcpdump	Layer-2+ data

watching videos from a streaming platform). Such kind of activities are hard to observe in cellular networks due to the fees applied to Internet traffic by network providers.

- Wi-Fi networks usually serve not only mobile devices, but also other kinds of device, such as desktop computers and laptops. Therefore, if the analysis targets mobile devices, the network traffic belonging to non-mobile devices must be properly filtered out from the collected network traces.
- If the monitored Wi-Fi network employs several access points, the information gathered at each AP must be properly combined with the one from the other APs, in order to produce a comprehensive network trace. This process can be tricky whenever the APs (or the traffic sniffers deployed at the APs) are not perfectly synchronized, causing timestamps from different sources to be staggered.

In Table XIII, we present the surveyed works in which the mobile traffic is captured at one or more Wi-Fi access points. We can identify two distinct experimental settings: in the former, the authors monitor few access points, deployed in a controlled environment to provide Internet connectivity to a small number of mobile devices [23], [28], [30], [31], [43], [6], [46], [52], [7], [60]; in the latter, several APs of a real Wi-Fi network serving a large number of users are monitored [9], [15].

In the case of multiple APs in a real deployment, it is fundamental to separate the network traffic related to mobile devices from the one related to other types of device (e.g., laptops). Afanasyev et al. in [9] leverage encryption-agnostic data-link- and network-layer information from the RADIUS logs collected by the over 500 APs of the Google Wi-Fi net-

work in Mountain View (California, USA), and discriminate among desktop computers, laptops, and mobile devices by relying on the Organizationally Unique Identifier (OUI) of the MAC address. Gember et al. in [15] carry out a comparison between mobile and non-mobile devices with regard to network traffic properties and habits of users. To discriminate between the two types of device, they apply the following methodology: (i) for a device generating HTTP traffic, the User-Agent field of the HTTP messages is compared with a list of strings clearly related to mobile devices, in order to determine whether the device is a mobile one (match) or not (mismatch); (ii) for a device that does not generate HTTP traffic, the Organizationally Unique Identifier (OUI) of its MAC address is inspected to determine whether it is a mobile or non-mobile device.

D. Mobile Devices (Emulated)

As for their desktop counterparts, apps must be properly tested not only throughout their development process, but also before their final submission to a marketplace. The simplest testing methodology consists of installing the mobile app on one or more physical mobile devices. However, this approach has two shortcomings: (i) the number of different test configurations (each consisting of a hardware device and a version of a compatible mobile operating system) is limited, while the number of configurations available on the market is large; and (ii) the difficulty in automating the tests within the mobile devices, due to lack of tools and resource constraints.

An alternative solution is to install the app to be tested in a mobile device emulator, which is a virtual machine that is

TABLE XIII
THE SURVEYED WORKS IN WHICH THE MOBILE TRAFFIC IS CAPTURED AT ONE OR MORE WI-FI ACCESS POINTS.

Scale of the Targeted Wi-Fi Network(s)	Year	Paper	Leveraged Information
Few APs in controlled environment	2012	Stevens et al. [23]	HTTP messages
	2013	Qazi et al. [28]	Network- and transport-layer information
		Watkins et al. [30]	Inter-packet time of ICMP responses
	2014	Chen et al. [31]	IP headers, TCP headers
	2015	Yao et al. [43]	HTTP messages
	2016	Alan et al. [6]	IP headers, TCP headers
		Fu et al. [46]	Size and timing of IP packets
		Saltaformaggio et al. [52]	IP headers
	Tadrous et al. [7]	802.11 frames	
2017	Malik et al. [60]	Inter-packet time of ICMP responses or IP packets related to video streaming	
Multiple APs in real deployment	2010	Afanasyev et al. [9]	Data-link- and network-layer information from RADIUS logs
	2011	Gember et al. [15]	Layer 2+ data

TABLE XIV
THE SURVEYED WORKS IN WHICH THE MOBILE TRAFFIC IS CAPTURED AT ONE OR MORE MACHINES RUNNING MOBILE DEVICE EMULATORS.

Year	Paper	Number of Apps Run in Mobile Device Emulator(s)		
		Android	iOS	Symbian
2014	Crussell et al. [33]	165,426	None	None
	Lindorfer et al. [34]	Over 1M	None	None
2015	Yao et al. [43]	651,000	68,000	10,000
2016	Narudin et al. [48]	1,030	None	None
2017	Chen et al. [56]	5,000	None	None

able to simulate the components and operations of a mobile operating system. This approach has several implications:

- The Software Development Kit (SDK) of a mobile platform typically provides a mobile device emulator for testing purposes. Therefore, the developers can cut the expense for physical mobile devices and simply buy a machine to run the emulator (or, even better, run the emulator directly on the machine where the code is written, without any additional expenditure).
- If properly endowed with computational power and memory, the testing machine can run multiple mobile device emulators in parallel, speeding up the overall testing process or letting the developers increment the set of tests to be executed on the app.
- A mobile device emulator can be quite easily controlled from the outside, helping test automation and thus reducing human intervention.
- There are important limitations on which components and operations of a mobile operating system can be emulated. Such limitations reduce the types of test that can be actually executed on a given app.

Since a machine running a mobile device emulator is responsible for forwarding the network traffic from the emulator to the Internet and vice versa, it constitutes an ideal point of capturing for mobile traffic. This approach is particularly useful if the focus of the analysis is on the network traffic of a specific mobile app. In Table XIV, we present the targeted mobile platforms and number of considered apps for the surveyed works in which the mobile traffic is captured at one or more machines running mobile device emulators.

Crussell et al. in [33] carry out ad fraud detection on two sets of Android apps: (i) 130,339 apps crawled from nineteen different marketplaces; and (ii) 35,087 apps that probably are malware (provided by an unspecified security company). The authors apply the following modus operandi for capturing the network traffic of a given app: (i) the app is installed on a newly created Android emulator image; (ii) a logger starts to capture the emulator's network traffic; and (iii) the app is first run in the foreground for 60 seconds, then it runs in the background for another 60 seconds.

Lindorfer et al. in [34] present ANDRUBIS, a publicly available system for the analysis of Android apps. For each submitted app, ANDRUBIS applies both static and dynamic analysis techniques in order to study how the app behaves. Moreover, during the 240 seconds of the dynamic analysis, the network traffic generated by the app running in the sandbox is captured for a later analysis focused on high-level protocols (e.g., DNS, HTTP, IRC).

Yao et al. in [43] carry out app identification on three mobile platforms, namely Android, iOS, and Symbian. To capture network traffic from the selected apps, the authors run them in mobile device emulators and trigger their network behavior using UI automation tools (the framework also supports the capturing at a Wi-Fi access point, see Section IV-C).

Narudin et al. in [48] leverage machine learning to build a classifier being able to detect malware on the Android platform. They consider two sets of Android apps: (i) the top twenty free (benign) apps available in the Google Play Store; and (ii) 1,000 malicious apps from 49 malware families, provided by the Android Malware Genome Project, as well as 30 new (in 2013) malicious apps from fourteen malware families, collected by the authors. To capture the traffic of the malicious apps, two online dynamic analysis platforms, namely Anubis and SandDroid, are leveraged (the traffic of the benign apps is logged on a real device, see Section IV-B).

Chen et al. in [56] carry out app identification targeting the Android platform, and evaluate their solution on 2,500 apps from Google Play Store and seven other third-party Android marketplaces, and 2,500 malicious apps from VirusTotal. The considered apps are run in emulators for five minutes, and stimulated via an automatic UI exploration tool; such tool first randomly explore the possible interactions with the app,

then heuristically generates new interactions from the ones that have been already explored.

E. Wi-Fi Monitors

We define as *Wi-Fi monitor* a hardware equipment that is able to scan the Wi-Fi radio bands (i.e., 2.4 and 5 GHz) in order to capture the transiting IEEE 802.11 frames. The most common configuration consists of a traditional Wi-Fi device (e.g., a Peripheral Component Interconnect (PCI) card in a desktop computer) set in monitor mode, i.e., the device passively listens the nearby Wi-Fi transmissions. To effectively eavesdrop the network traffic of a Wi-Fi device, the monitor must be within the target's range of transmission. Such range depends on many factors, including the selected radio band, the power of the Wi-Fi module, and the surrounding buildings.

Wi-Fi monitors can be easily deployed at a low cost, and let oversee a good number of Wi-Fi devices. However, there are a few issues that have to be addressed in order to effectively use Wi-Fi monitors for eavesdropping:

- In case more than one monitor is deployed, an IEEE 802.11 frame can be eavesdropped by multiple distinct monitors if they are too close to each other. When traffic traces provided by different monitors are merged, the duplicate captures must be properly deleted.
- The timestamp of each eavesdropped IEEE 802.11 frame depends on the internal clock of the Wi-Fi monitor that captured it. Since the network data collected by distinct monitors are merged to build a comprehensive dataset, it is crucial to consider internal clock differences between monitors (unless they are synchronized in some way).

In Table XV, we provide information about the capturing process carried out in the works that employ one or more Wi-Fi monitors to collect the network traffic of mobile devices. A typical concern related to the mobile traffic analysis is to filter out from the captured network traces the traffic generated by non-mobile devices. In [21] and [26] the traffic capturing takes place in a location and time such that the collected traffic only belongs to mobile devices. In [42] and [51] the network data generated by non-mobile devices is filtered out since the MAC address of each targeted mobile device is known.

F. Network Simulators

Among the surveyed works, one in particular does not capture the mobile traffic from real or emulated mobile devices, but instead generate it via a software simulator. This approach can be useful to study particular deployments of mobile devices that are not observable in a real-world scenario due to technical difficulties, economical constraints, or limits imposed by law. If the simulation is realistic, the resulting network traces will be really close to the ones that are collected on real or emulated mobile devices.

Network traffic simulation typically works as follows:

- 1) The information about the simulated environment (e.g., geographical extension, buildings, streets) is provided to the system.
- 2) The information about the actors (e.g., mobile devices, laptops, access points) is provided to the system. For each

actor, such information includes its technical specifications, its position within the simulated environment, and its network behavior. If the actor is used by a human user, her sociological characteristics and behavioral patterns are also provided.

- 3) The points of capturing are positioned within the simulated environment.
- 4) The network transmissions of the actors are simulated according to realistic physical laws and social dynamics.

Husted and Myers in [11] develop a 3D simulation of a large population of mobile devices deployed in a dense metropolis where no other Wi-Fi devices (e.g., access points) are present. A fraction of the mobile devices act as trackers (i.e., they are the points of capturing) and scan the air in order to capture Wi-Fi probe requests transmitted by the rest of the population (i.e., the trackees). The system properly simulates the propagation of probe requests (which are transmitted in clear) in the environment, and takes into account the diurnal behavior of mobile users (e.g., go to work in the morning, come home in the evening). The resulting network traffic dataset is leveraged for position estimation (more details in Section III-H).

V. TARGETED MOBILE PLATFORMS IN TRAFFIC ANALYSIS

The network traffic of a mobile device depends on its operating system. Since each mobile OS has its own implementation of the network protocol stack, it generates data transmissions with peculiar network properties. Exploiting such properties is fundamental to devise effective methods for the analysis of mobile traffic. For example, the TCP window size scale option (i.e., the value that is negotiated during the TCP three-way handshake to increase the TCP receiver window size beyond 65,535 bytes) is always 16 for iOS, while it can be either 2, 4, or 64 for Android. Chen et al. in [31] exploit this distinction (together with other differences with regard to network traffic) to successfully recognize whether a target mobile device is running one of those OSes.

In this section, we present the surveyed works according to the mobile platforms they target. As shown in Figure 5, only thirteen works propose analyses that are platform-independent, i.e., they do not take into account the platform which the targeted mobile devices belong to (it is worth to notice that two of them, namely Lee et al. in [16] and Chen et al. in [31], also present other types of analysis that are instead tailored to specific mobile platforms). Among the other works, Android is the most targeted mobile platform (45 works), followed by iOS (fifteen works), Windows Mobile/Phone (four works), and Symbian (two works). As shown in Table XVI, nine works target two mobile platforms, three works target three platforms, and one work even four. We present the targeted mobile platforms, sorted by the the number of works involved: Android in Section V-A, iOS in Section V-B, Windows Mobile/Phone in Section V-C, and Symbian in Section V-D. Each of the above-mentioned sections is organized in three parts: the first part provides an overview of the system architecture; the second part describes the apps specific for that platform; and the third part reviews the works that carry out traffic analysis

TABLE XV
THE SURVEYED WORKS IN WHICH THE MOBILE TRAFFIC IS CAPTURED USING ONE OR MORE WI-FI MONITORS.

Year	Paper	Number of Wi-Fi Monitors	Capturing Duration	Targeted Population	Leveraged Information
2012	Musa et al. [21]	5	9 months	People along the streets near an university campus	802.11 probe requests
		6	12 hours	People along fairly busy roads of a city	
		7	12 hours	People along an arterial road of a city	
2013	Barbera et al. [26]	5	From 40 minutes to 7 hours	People at two political meetings, two Pope's masses, a big mall, and a train station	802.11 probe requests
		1	6 weeks	People at an university campus	
		1	Unspecified	People at streets and aggregation places of a city	
2014	Chen et al. [31]	9	2 days	People at OSDI 2006	Size and header of IP packets
		8	5 days	People at SIGCOMM 2008	
2015	Wang et al. [42]	1	Unspecified	One iOS device	Size and timing of (possibly encrypted) 802.11 frames
2016	Ruffing et al. [51]	1	3 months	Two Android devices, two iOS devices, a Windows Phone device, and a Symbian device	Timing of (possibly encrypted) 802.11 frames

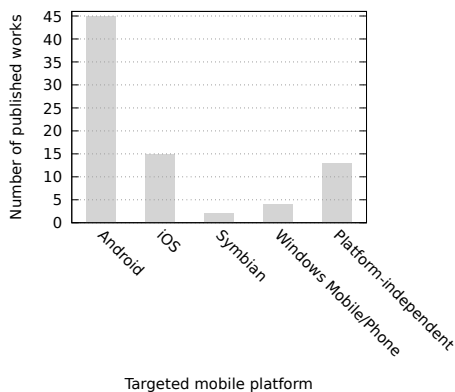


Fig. 5. Number of published works contributing traffic analysis methods targeting mobile devices, sorted by mobile platform.

targeting that platform. Finally, we discuss the works that do not belong to any specific mobile platform in Section V-E.

A. Android

Android is an open-source mobile operating system developed by Google. Android is also promoted by the Open Handset Alliance (OHA), a consortium of 84 firms (including Google, as well as several important actors of the mobile market, like HTC, Samsung, and LG) which is devoted to the development of open standards for mobile devices. Android was unveiled at the end of 2007, and the first batch of commercial Android devices appeared a year later. Many mobile device manufacturers soon started deploying Android on their flagship products, and the popularity of the operating system rapidly increased. Nowadays, Android is the dominant mobile operating system, with a market share of 68.4% in June 2016, according to the statistics reported in [72].

1) *System Architecture*: As shown in Figure 6a, the architecture of the Android operating system consists of a stack of four abstraction layers:

- 1) At the first layer, a Linux kernel provides system services (e.g., memory, power, and process management), preemptive multitasking, a network stack, and drivers for hardware devices (e.g., display, camera).

- 2) The second layer contains the Android Runtime (ART), which is the application runtime environment. Before Android 5.0 (Lollipop), the execution of Android apps is managed by the Dalvik virtual machine process. Android apps and services are typically written in Java and executed in a Dalvik Virtual Machine after being converted from Java Virtual Machine to Dalvik bytecode. ART adopts a different approach: the Dalvik bytecode is translated into native instructions to be later executed on the runtime environment of the device. This solution increases efficiency and reduces power consumption. This layer also includes native libraries that provide several functionalities (e.g., 2D/3D graphics, encryption, SQLite database management).
- 3) The third layer is the application framework, i.e., the environment that runs and manages Android apps. Among the available services that compose such environment, (i) the Activity Manager manages app lifecycle and activity stack; (ii) the Content Providers allow apps to share data with other apps; (iii) the Telephony Manager interfaces with telephony services available on the device; (iv) the Notifications Manager prompts the user with notification or alerts raised by apps; and (v) the Location Manager provides the apps with periodic updates regarding the location of the device.
- 4) The fourth layer is constituted by the apps, which can be native (e.g., web browser, email client) or provided by a third party.

- 2) *Apps*: Android apps run in a sandbox and their access to each system's resource is regulated by a specific permission that has to be given by the user. Before Android 6.0 (Marshmallow), an app's required permissions are presented to the user at the beginning of the installation process. The user must grant all the required permissions in order to install the app on her device. From Android 6.0 on, permissions are managed individually, and users can grant or revoke each permission according to their usability and security needs.

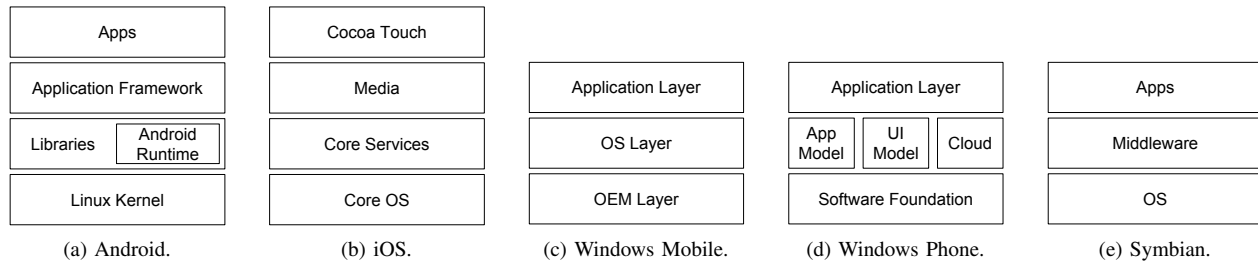


Fig. 6. System architectures of mobile operating systems.

TABLE XVI
TARGETED MOBILE PLATFORMS IN THE SURVEYED WORKS.

Year	Paper	Android	iOS	Symbian	Windows Phone
2010	Falaki et al. [10]	✓			✓
	Shepard et al. [13]		✓		
2011	Lee et al. [16]	✓	✓		
	Rao et al. [17]	✓	✓		
2012	Baghel et al. [18]	✓			
	Ham et al. [20]	✓			
	Shabtai et al. [22]	✓			
	Stevens et al. [23]	✓			
	Su et al. [24]	✓			
	Wei et al. [25]	✓			
	Wei et al. [4]	✓			
2013	Kuzuno et al. [27]	✓			
	Qazi et al. [28]	✓			
	Rao et al. [29]	✓	✓		
	Watkins et al. [30]	✓			
2014	Chen et al. [31]	✓	✓		
	Coull et al. [32]	✓	✓		
	Crussell et al. [33]	✓			
	Lindorfer et al. [34]	✓			
	Shabtai et al. [35]	✓			
2015	Chen et al. [37]	✓			
	Fukuda et al. [38]	✓	✓		
	Le et al. [5]	✓			
	Park et al. [39]	✓			
	Song et al. [41]	✓			
	Wang et al. [42]	✓	✓		
	Yao et al. [43]	✓	✓	✓	
2016	Zaman et al. [44]	✓			
	Alan et al. [6]	✓			
	Conti et al. [45]	✓			
	Fu et al. [46]	✓			
	Mongkolluksamee et al. [47]	✓			
	Narudin et al. [48]	✓			
	Nayam et al. [49]	✓	✓		
	Ren et al. [50]	✓	✓		
	Ruffing et al. [51]	✓	✓	✓	✓
	Saltaformaggio et al. [52]	✓	✓		
	Spreitzer et al. [53]	✓			
	Tadrous et al. [7]	✓	✓		
	Vanrykel et al. [54]	✓			
Wang et al. [8]	✓				
2017	Arora et al. [55]	✓			
	Chen et al. [56]	✓			
	Cheng et al. [57]	✓			
	Continella et al. [58]	✓			
	Espada et al. [59]	✓			
	Malik et al. [60]	✓	✓		✓
	Taylor et al. [61]	✓			

A third-party Android app is shipped in an APK (Application Package Kit) file, which can be downloaded from the developer's website and manually installed on the device. To simplify the process, Android users typically rely on the app stores, or app marketplaces, which are programs that allow them to browse the available apps, as well as to install, update, and remove them. Google Play Store (formerly Android Market) is the primary app store installed on Android devices, and hosts over 2,500,000 apps [73] distributed by both Google itself and third-party developers under Google's license and compatibility requirements. However, the openness of Android has allowed the birth of a number of other third-party app marketplaces (e.g., GetJar, F-Droid, the app store by Amazon), which release apps under policies different from Google's one.

3) *Traffic Analysis*: Since mobile apps are a key component of the success of the Android operating system, it is not surprising that most of the surveyed works focus their analysis on the network traffic generated by Android apps. The achieved results show that it is possible to successfully fingerprint an Android app (or type of app) [16], [28], [29], [5], [43], [6], [47], [56], [61], as well as an action performed by a mobile user on her Android device [30], [39], [45], [46], [52]. In [29], [5], [41], [50], [54], [57], [58], it is reported that Android apps extensively leak the PII of mobile users, and the works in [23], [27] highlight that an important role in this phenomenon is played by the embedded ad libraries. Regarding mobile advertisement, Crussell et al. in [33] prove that many Android apps trick the advertisement business model in order to let their developers illicitly earn money. In [54], the authors exploit the sensitive identifiers that are present in mobile traffic to fingerprint Android users. In [53], the network statistics of Android's default web browser are leveraged for website fingerprinting. Finally, several works aim at detecting malicious Android apps: in [25], [44], [48], [8], [55], automated detection frameworks that can be employed by marketplaces and security companies are presented; instead, the authors in [22], [35] present apps that can enable malware detection directly within the mobile devices of the end users.

In light of its market share, we argue that Android is the reference operating system for many mobile users, and Android devices are responsible for an important fraction of the worldwide mobile Internet traffic. For this reason, it is not surprising that many works aim at studying the properties of the network traffic generated by Android devices [10], [17], [18], [4], [34], [37], [38], [49], [7], [59], as well as the usage habits of Android users [10], [20], [38]. Moreover, Android

plays an important role in the works that deal with mobile OS identification [31], [51], [60].

B. iOS

iOS is a proprietary mobile operating system developed by Apple. Such OS is exclusively deployed in Apple's mobile devices. iOS was officially released with the name iPhone OS in 2007. Later, this mobile OS was extended to support other Apple's mobile devices: iPod Touch (Apple's multimedia player) in 2007 and iPad (Apple's tablet) in 2010. According to the statistics reported in [72], iOS is the second most popular mobile operating system, with a market share of 20.32% in June 2016.

1) *System Architecture*: As shown in Figure 6b, the architecture of the iOS operating system consists of a stack of four abstraction layers, each providing different services and technologies:

- The Core OS layer contains: (i) the kernel; (ii) the device drivers; (iii) the interfaces to access the low-level features of the operating system (e.g., file system, memory, concurrency, networking); and (iv) the interfaces to access the frameworks that provide several core functionalities (e.g., support for external hardware, Bluetooth, authentication, cryptography, support for VPN tunnels).
- The Core Services layer includes the mandatory system services for running apps. These services provide core functionalities (e.g., account management, location services, cellular network services), as well as high-level features (e.g., P2P, data protection, file sharing, SQLite, XML).
- The Media layer contains technologies leveraged by developers to implement multimedia content in their apps (i.e., audio, video, and graphic).
- The Cocoa Touch layer provides the key frameworks which define the appearance of apps and grant the access to high-level system services (e.g., push notifications, touch-based input, multi-tasking).

2) *Apps*: Apple distributes the iOS Software Development Kit (SDK), which contains the tools needed to develop, test, and deploy native iOS apps. Apps are written in Objective-C or Swift, and leverage the iOS system frameworks. Such frameworks provide the interfaces that developers need to write software for the iOS platform. Apps are physically installed on the devices, and run directly on their operating system.

Third-party iOS apps are available to users in the App Store, Apple's digital distribution platform, which was launched in 2008. The apps are developed with the iOS SDK and released after Apple's approval. The review process aims at assessing that the distributed apps fulfill precise usability and security requirements. According to the statistics reported in [74], the App Store hosts about two million apps, available for various iOS devices (e.g., iPhone, iPad). It is worth to notice that there exist also unofficial marketplaces that distribute iOS apps (e.g., Cydia), but they all require a jailbroken iOS device. In a jailbroken iOS device, software vulnerabilities have been exploited to remove the restrictions imposed by Apple on iOS. This practice is required to allow the download and installation

of apps, extensions, and themes that are unavailable through the official Apple App Store.

3) *Traffic Analysis*: Mobile apps are a fundamental building block of the iOS user experience. For this reason, several solutions have been proposed to effectively fingerprint them [16], [29], [42], [43], as well as to detect the interactions between an iOS user and a specific app installed on her mobile device [32], [52]. The authors in [29], [50] investigate the disclosure of sensitive information by iOS apps, discovering that many of them leak the PII of the user. Regarding OS identification, Coull et al. in [32] discriminates between iOS and OS X, while the frameworks presented in [31], [51], [60] consider iOS among the targeted mobile operating systems. Finally, a few works study the properties of the network traffic generated by iOS devices [13], [17], [38], [49], [7], and the usage habits of iOS users [38].

C. Windows Mobile/Phone

In the early 1990s, Microsoft began to develop a new operating system for minimalist computers and embedded systems. This OS, later called Windows CE and officially released in 1996, was the basis for the operating systems that make Microsoft enter into the mobile market at the beginning of 2000s. The first batch of mobile devices running a Microsoft's OS were Windows Mobile smartphones. They became available in 2003 and targeted business users at first. The lifecycle of Windows Mobile lasted for approximately seven years, ending in 2010 with the release of its successor, Windows Phone, which had a new user interface and aimed at the consumer market. The last iteration of this OS was Windows Phone 8.1, released in 2014 and succeeded by Windows 10 Mobile at the end of 2015. Overall, Microsoft's mobile OSes struggle to acquire a relevant market share and seem not to threaten the duopoly by Android and iOS (a trend confirmed by the fact that, according to the statistics reported in [72], only 1.94% of mobile devices were Windows Phone ones in June 2016).

1) *System Architectures*: As shown in Figure 6c, the architecture of the Windows Mobile operating system follows a stack model, consisting of three abstraction layers:

- The Original Equipment Manufacturer (OEM) layer is positioned at the bottom of the stack. This layer directly communicates with the underlying hardware components (e.g., microprocessor, RAM, ROM, digital signal processors, input/output modules).
- The Operating System (OS) layer includes the kernel, the core DLLs, the object store (which offers file system, registry, and database persistent storage), multimedia technologies, the device manager, communication and networking services, and the Graphic Windowing and Events Subsystem (GWES). The later one provides an interface between the OS, the app, and the user.
- The Application layer consists of the apps, from either Microsoft itself or third parties.

As shown in Figure 6c, the architecture of the Windows Phone operating system is different, although it maintains the three-levels stack:

- At the bottom of the stack, the Software Foundation layer includes: (i) the kernel, which manages security, networking, and storage; and (ii) the interfaces that mediate the access to the underlying hardware components (e.g., sensors, camera).
- The intermediate layer is composed by three elements: (i) the App Model, which is the component providing first-class access to several functionalities that are important for apps (e.g., isolation, licensing, software updates, data sharing); (ii) the UI Model, which manages the user interface of the operating system; and (iii) the components that enable the integration with Microsoft's cloud services.
- The Application layer includes the frameworks available to developers for building the user interface and logic of their apps.

2) *Apps*: Apps for Windows Mobile are developed using the official Software Development Kit (SDK) released by Microsoft, and can be written either in C++ ("native" apps) or C#/Basic ("managed" apps). At the end of 2009, Microsoft set up a digital distribution platform, called Windows Marketplace for Mobile, to organize and centralize the release of apps for the Windows Mobile platform. With the advent of Windows Phone, Microsoft started to progressively abandon Windows Mobile, by ending support and closing Windows Marketplace for Mobile in 2012.

Although the SDK and libraries are different, the apps for Windows Phone are written with the same languages used for Windows Mobile apps (i.e., C++, C#, and Basic), plus HTML5 and JavaScript for web-based apps. The official software distribution platform for Windows Phone, called Windows Phone Marketplace (and later renamed Windows Phone Store), was launched by Microsoft at the end of 2010, and subsequently merged into the Windows Store (i.e., Microsoft's universal software marketplace) in 2015.

3) *Traffic Analysis*: Only a few works we survey target Microsoft's mobile OSes. Falaki et al. in [10] deploy a custom logging app on Windows Mobile devices to capture their network traffic and study its properties. Ren et al. in [50] investigate PII leaks through network traffic generated by devices running several mobile operating systems, including Windows Phone. Finally, the works in [51], [60] deal with mobile OS identification, and Windows Phone is among the operating systems that the proposed frameworks are able to recognize.

D. Symbian

Symbian is a mobile operating system originally developed for PDAs in 1998, and subsequently moved into cellphones and smartphones in the following years. Running exclusively on ARM processors, Symbian requires an additional middleware to form a complete operating system and to provide a user interface. During the 2000s, Symbian became the most popular mobile OS, since many mobile manufacturers, particularly Nokia, chose it to power their devices. A non-profit organization, the Symbian Foundation, was created in 2008 to drive the development of the operating system and promote the adoption of Nokia's middleware, namely S60. However, with the advent of Android and iOS, and Nokia

adopting Windows Phone for its devices, the popularity of the Symbian platform rapidly decreased. The Symbian Foundation closed in 2010, and the development of the OS ended in that period. According to the statistics reported in [72], Symbian is almost disappeared, with a market share of only 2.22% in June 2016.

1) *System Architecture*: As shown in Figure 6e, the architecture of the Symbian operating system consists of a stack of three abstraction layers:

- The OS layer is the core of a Symbian system, and contains the kernel, which provides the interfaces to access the underlying hardware, and several essential services (e.g., communications, text and data handling, graphics).
- The Middleware layer provides a software platform which consists of higher-level generic APIs available to the apps of the upper layer. These APIs include the native UI frameworks, as well as frameworks for app lifecycle, higher-level protocols, and data handling. Different platforms are not compatible, i.e., apps developed for a platform cannot run on the others.
- The Apps layer includes apps that interact with the user and background services that provide functionalities to the apps.

2) *Apps*: As we already explained in Section V-D1, all Symbian devices share a common core, on top of which different software platforms are built to provide an execution environment for user apps (actually implementing the Middleware layer shown in Figure 6e). Backed by different groups of mobile device manufacturers, three software platforms were created for Symbian:

- S60 (Series 60) was the most popular Symbian platform, officially supported by the Symbian Foundation and deployed in the products of several mobile device manufacturers, including Nokia, Samsung, and LG. S60 was able to run apps developed in Java MIDP, C++, Python, and Adobe Flash. Third-party developers had to distribute their apps by either releasing them in the marketplaces (the most important stores were run by Nokia and Opera Software), or pre-installing them in the mobile devices of some manufacturers.
- UIQ (User Interface Quartz) was developed by UIQ Technology, and supported by Sony Ericsson and Motorola. The platform was able to run native apps written in C++ using the Symbian/UIQ Software Development Kit (SDK), as well as Java apps. The development of UIQ stopped in 2008, when the Symbian Foundation was established and chose S60 as its reference Symbian platform.
- MOAP (Mobile Oriented Applications Platform) was the platform chosen by NTT DoCoMo, a major Japanese cellular operator, for its FOMA (Freedom of Mobile Multimedia Access) service, which was a W-CDMA-based 3G telecommunications service. Supported by a few Japanese companies, like Fujitsu and Sharp, MOAP did not spread outside of Japan. It was not an open development platform, i.e., there were no third-party apps.

3) *Traffic Analysis*: Only two works target the Symbian operating system. The first work by Ruffing et al. [51] deals with the identification of the OS of mobile devices, and Symbian is among the operating systems that the proposed

framework is able to recognize. The second work by Yao et al. [43] presents an app identification system which is trained and evaluate on, among others, 10,000 Symbian apps from the Nokia OVI Store.

E. Platform-independent Works

We survey several works in which the analysis performed on the network traffic is generic, which means that it is not specific for a particular mobile platform. Some of these works leverage the 802.11 probe requests that are sent by mobile devices of any platform to discover if an already known Wi-Fi access point is nearby: in [26], sociological information is inferred from the probe requests of a population of mobile users, while in [19], [21] probe requests are exploited to estimate a mobile device’s geographical position and movements, respectively. Besides, some works simply group together mobile devices of different platforms and consider them as a unique category. In [19], [62], the properties of the network traffic generated by mobile devices in a campus Wi-Fi network are studied. In [9], [12], [15], mobile and non-mobile devices are compared on network traffic properties and users’ usage habits, and the same is done in [14] but limited to the YouTube service. Finally, Verde et al. in [36] present a user fingerprinting method that is successfully used to recognize the presence of some target mobile users within a small test network and a large Wi-Fi one.

VI. MODELS AND METHODS IN TRAFFIC ANALYSIS TARGETING MOBILE DEVICES

In the literature, researchers leverage several different models and methods to carry out the analysis of the network traffic of mobile devices. The application of such instruments is strictly correlated with the point of listening (as described in Section IV), as well as the information extracted from the captured traffic. Being able to capture packet-level unencrypted data (e.g., HTTP messages) constitutes the most optimistic scenario since all the information enclosed in the network packets (e.g., the URLs that has been contacted) is available in clear. Under these conditions, it is possible to effectively apply Deep Packet Inspection (DPI) techniques. Unfortunately, such types of analysis cannot be carried out if the information available in the network traffic is affected by the following factors: (i) the presence of encrypted traffic at different layers (i.e., IPsec at network layer, SSL/TLS at transport layer); and (ii) the application of traffic aggregation or sampling (e.g., NetFlow, IPFIX). For this reason, network traffic analysts have to rely on mathematical models and methods to cope with the lack of available information whenever such difficulties are in place. According to their goals, researchers can still apply techniques to analyze the mobile network traffic. For example, it is possible to rely on statistical-based techniques to perform traffic characterization. Among those techniques, machine learning provides several approaches to classify and cluster network traffic.

In this section, we provide a deeper insight into the models and methods leveraged in the state of the art to devise solutions for the analysis of mobile devices’ network traffic.

In particular, we provide an overview of the methodology followed to perform traffic analysis with machine learning in Section VI-A, describing each step in the procedure. In Section VI-B, instead, we deal with application of machine learning to several types of traffic analysis targeting mobile devices.

A. Overview and Elements on Machine Learning

Machine learning (ML) is the branch of artificial intelligence that studies algorithms that can be used to learn from and make predictions on data. Such algorithms are typically adopted to solve problems for which a traditional algorithmic solution (i.e., a finite sequence of instructions) is hard, if not impossible to find.

In this section, we provide an introduction on the basic concepts of machine-learning-based analysis. This is also mean to be a guideline that reports the principal steps that have to be followed to properly train a machine learning model (summarized in Figure 7). For each step, we define its purpose and describe the different methods used by the surveyed works.

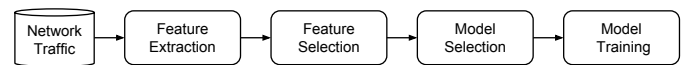


Fig. 7. Procedure for a machine learning analysis.

1) *Features extraction from network traffic*: As a first step, the network traffic collected from a capturing point (See Section IV) has to be transformed into a format that can be used by a machine learning technique. This step is called *feature extraction* and typically takes a network entity as an input (e.g., packets, flows) and provides a fixed-sized vector for features that represent the properties of such entity. A good feature extraction has to enclose in such output vector as much as possible the information available from the network traffic collected according to the final target of the analysis. Some examples of feature extraction methods used in the surveyed work are:

- Time Series (TS) are sequence of entities ordered by the time in which they occur [75]. As an example time series, a flow of packets can be represented as a sequence of packet sizes. Since time series related to network traffic do not have a fixed length, an additional transformation is necessary to obtain a fixed size vector.
- Statistical Feature Extraction (SFE) consists in applying statistical primitives (e.g., mean, standard deviation) along the data dimensions. As an example, from a sequence of packet sizes it is possible to extract a feature vector in which each element corresponds to a statistical primitive.
- Histograms are used for feature extraction to represent the distribution of values, by aggregating them into a fixed number of bins. Each bin corresponds to a range of values and it counts the occurrences of values within that range.
- Bag-of-Word (BoW) is a model that first identify distinguishable entities (i.e., words) and then counts the frequency of occurrence of each specific entity in the input data. This model is broadly used in document classification.

Moreover, in Section VI-C we describe into detail two other feature extraction and analysis methods that rely on dictionaries and graphs. At the end of the feature extraction, we obtain a dataset that can be seen as a matrix in which each row corresponds to an entity (a.k.a., observation) and a column to a feature (a.k.a., dimension). Optionally, it is possible to normalize the whole dataset by column to a specific interval of values (e.g., from 0 to 1).

2) *Feature Selection*: Given the dataset obtained from the previous step, it is often necessary to select a subset of features which are meaningful to describe the reality to be modeled. Indeed, a high-dimensional dataset may present a phenomena called *curse of dimensionality*. The target of a model is to identify similarities within observations belonging to the same class, and such similarities need to be statistically significant to not mislead during the training of a model. Hence, the amount of observations needed to prove that a similarity is not due to sparsity grows exponentially with the number of features of the dataset. Thus, a dataset with an unbalanced amount of observations among classes (e.g., the unbalance between the number of malicious and benign traffic traces in malware analysis) and a high-dimensionality may be not able to prove whether the features are statistically significant. Moreover, the high amount of features also increase the computational cost to train a model. In order to cope with that, it is possible to apply feature selection (or feature reduction) techniques, among which:

- Analysis of Variance (ANOVA) [76] is a statistical method to analyze the difference between the mean values of features in a dataset. ANOVA evaluates the statistical significance of features in the dataset running a statistical test (i.e., a *t*-test that aims to reject the null hypothesis) generalized to work on multiple means.
- Principal Components Analysis (PCA) [77] and Independent Component Analysis (ICA) [78] are used in signal processing to identify the components of a signal, but they are also used for feature selection tasks. PCA aims to find and remove correlated features in order to reduce the dimensionality of a dataset. To do so, PCA decomposes the feature set into a set of orthogonal components that show a high variance (i.e., covariance matrix's eigenvectors of the original dataset). Similarly to PCA, ICA removes correlated features by finding statistically independent components.
- Relative Mutual Information (RMI) measures the mutual dependence between couples of features. In practice, RMI quantifies the amount of information expressed by a feature evaluating the conditional entropy of that feature given another one [79].

3) *Model Selection and Training*: Once the features set is defined, the learning process can proceed with the actual training of a model. A model has to be selected taking into account two main factors: (i) the goal of the analysis; and (ii) the availability of labeled data. For this reason, it is necessary to carry out some preliminary analysis to understand which model is the most suitable for the available data. These factors also determine whether the outcome result has to be a binary or multi-labels classification, or a clustering task. Once the

candidate models have been selected according the available dataset and the goal that has to be achieved, it is possible to evaluate the performance of such models varying their hyper-parameters. This procedure is called *model selection*, and it is a good practice to carry it out before training a final model. It is possible to run this evaluation on a dataset portion (i.e., training set) leaving the remainder of the dataset (i.e., testing set) for the evaluation of the final model. For the sake of simplicity, here we only mention the so called *holdout method*, but we describe in detail this and other dataset partitioning methods in Section VII-A3.

In what follows, we introduce two main machine learning approaches used in mobile traffic analysis: supervised and unsupervised learning.

a) *Supervised Learning*: The most frequently used machine learning methods in traffic analysis follow the supervised learning paradigm. This paradigm permit to extract knowledge from labeled datasets. This category of learning also comprehends semi-supervised learning, which allow the presence of unlabeled data.

- *Support Vector Machines (SVM)* classifier is a method that aim at separate observations into classes relying on a hyperplane (which is identified by three observations, i.e., vectors). Since observations may not be separable by an hyperplane (i.e., *linear SVM*), it is possible to apply kernel functions, such as *Polynomial Kernel (PK)* and *Radial Basis Function (RBF)*, to make the observations linearly separable by projecting them to a high dimensional feature.
- *Decision Trees* classifier is a simple method that relies on tree structures. The components of these structures are: (i) nodes, each representing a condition on a feature; (ii) leaves, each representing a feature vector. Among the possible algorithms to generate a decision tree, the most popular are *ID3*, *C4.5*, and *J48*.
- *Ensemble Methods* combine the results of many weak classifiers into a more powerful one. This combination of results follows a strategy such as Boosting or Bootstrap aggregation. An example of ensemble methods is *Random Forest (RF)* classifier which usually relies on decision trees as weak learners.
- The *Probabilistic Learning* methods leverage Directed Acyclic Graphs (DAGs) to represent the probability between variables, each represented by a node. For each edge that connects a node *A* from to a node *B*, it is associated with a probability function that, given an input, outputs the probability to have a transition from *A* to *B*. *Bayesian network (BN)* is an example of method that assumes each variable is conditionally independent from the others, i.e., *Naïve Bayes (NB)*. As another example, *Hidden Markov Model (HMM)* assumes a conditional probability distribution among hidden variables (i.e., unobservable states) respecting the Markov property. HMM is often applied in pattern and speech recognition.
- *Regression* methods consist of explaining through a function the relation between a dependent variable (i.e., class) given an independent variable (i.e., data). An example is the *Linear Regression (LiReg)*, which aims to fit the data with a linear model. Another example is the *Logistic Regression*

(*LoReg*) which is a linear regression that gives in output not a continuous value, but a binary value instead.

- *k-Nearest Neighbors (kNN)* method simply consists of mapping labeled observations into a space. During the classification of an unlabeled example X , the algorithm assigns the most recurrent class label among the k nearest neighbors of X (with k fixed beforehand).
- *Artificial Neural Networks (NN)* are learning methods based on nodes (i.e., neurons) connected to each other and arranged into layers. Each neuron applies a propagation function to its incoming connections and generates an output. The connections between neurons are weighted, and during the training such weights are updated using a back-propagation algorithm (e.g., gradient descent). Traditional neural networks have three kinds of neuron, according to the location (i.e., input, hidden, or output layer). In particular, a neural network without cycles (i.e., feed-forward) with more than one layer of hidden neurons is called *Multilayer Perceptron (MLP)*. Some other variants that allow cycles and multiple layers of hidden neurons are *Convolutional (CNN)* and *Recurrent (RNN)* neural networks. Another example of neural network is the *Neural-Fuzzy classifier (NFz)*. Neural networks can be also used for unsupervised and reinforced learning.

b) Unsupervised Learning: This machine learning approach aims to group observations into clusters according to their similarity. This task is called *unsupervised* because it does not need any previous knowledge about observations. Indeed, unsupervised learning is useful in goals of analysis that do not rely on a labeled datasets, such as traffic characterization.

Clustering methods rely on distance metrics to measure the similarity between observations. Such metrics are particularly useful when network entities (e.g., packets, flows) and sets are involved. Examples of distance metrics used in the surveyed work are *Euclidean* and *Compression* distances, the optimal warping path of *Dynamic Time Warping (DTW)* [80], and *Jaccard's Index (JI)* [81].

Hierarchical Clustering (HC) is a clustering method that aims to build a hierarchy of clusters according to a specific strategy. The *agglomerative* strategy starts with a cluster for each observation and iteratively merges clusters according to their similarity (keeping trace of the hierarchy among clusters), until all observations are aggregated in a single cluster (a.k.a., Bottom-up strategy). The hierarchy of clusters resulting from this process can be represented through a dendrogram. By setting a *cut-off* parameter, it is possible to cut the resulting hierarchy at a specific height to obtain a set of clusters.

k-Means Clustering (kMeans) is a method that aims to group observations into k clusters. Such method is initialized with a preliminary division of the observations according to their position in the feature space. Then, it iterates on each observation alternating two steps: “assignment” and “update”. The “assignment” step associates an observation to the cluster whose centroid (i.e., mean of all cluster elements) is the nearest (i.e., having the shortest distance centroid-observation). The “update” step recomputes the centroids of clusters given the observation’s new assignment. The algorithm converges

when the assignment step does not move any observation from the previous iteration.

B. Machine Learning Applications by Goal of the Analysis

Machine learning is effectively applied in most of the works we survey to perform such type of analysis targeting mobile devices. In the following sections, we review the applications of machine learning according to the popularity of the goal of the analysis (in the same order used in Section III).

1) *Traffic Characterization:* Nayam et al. in [49] study the network behavior of 63 Android and 35 iOS free apps. To find similarities between the apps, the authors apply the following methodology:

- The TCP and UDP traffic of each analyzed app is partitioned according to the type of domains to which it is related: (i) advertisement; (ii) tracking; (iii) popular services (e.g., Google, Facebook); and (iv) other domains.
- For each app, the following attributes are computed: (i) total number of sessions; (ii) session rate for each type of domain; and (iii) percentage of sessions for each type of domain.
- k -means clustering is applied to group together the apps that show a similar network behavior.

In Table XVII, we report the resulting app classification.

2) *App Identification:* Supervised learning is applied for app identification in [28], [5], [42], [6], [47], [61]. The methodology followed to build the app classifier is the same in all such works: (i) the network traffic of the selected mobile apps is captured; (ii) for each mobile app, feature vectors are extracted from its network traces and labeled with the name/type of that app; and (iii) the chosen classifier is trained on the labeled feature vectors. In Table XVIII, we report the leveraged features and employed classifiers for each of the surveyed works in which machine learning is applied for app identification. Moreover, in the following we provide additional information about the reinforced-learning-based method that Taylor et al. propose in [61] to cope with the problem of *ambiguous* networks flows, i.e., network flows that are not useful in order to uniquely identify an app. Generated by third-party libraries (e.g., ad libraries) which can be embedded in different apps, such flows hinder the training of a classifier. To tackle the problem, the authors propose a method composed of four stages: (i) a preliminary classifier is trained using a preliminary training set; (ii) the preliminary classifier is evaluated using a preliminary testing set; (iii) samples which are wrongly labeled by the preliminary classifier are re-labeled as “ambiguous”; and (iv) a reinforced classifier is trained using the re-labeled dataset, including “ambiguous” as a new class.

3) *PII Leakage Detection:* Machine learning is applied for PII leakage detection in [27], [50], [57]. In particular, the authors of such works leverage hierarchical clustering [27], C4.5 decision tree [50], and random forest [57].

Kuzuno and Tonami in [27] investigate the leakage of sensitive information due to ad libraries embedded into free Android apps. The proposed framework works as follows:

- The HTTP traffic of the target mobile apps is captured.
- The payloads of HTTP messages are inspected, and each message is labeled according to the fact that it contains sensitive information or not.

TABLE XVII
CLASSIFICATION OF THE APPS ACCORDING TO THEIR NETWORK BEHAVIOR (NAYAM ET AL. [49]).

Cluster	Network behavior	Classification
0	Excessive ad-related traffic, and excessive number of sessions	Suspicious
1	Excessive ad- and tracking-related traffic, and excessive number of sessions	
2	Excessive ad-related traffic, excessive traffic related to other domains, and excessive number of sessions	
3	Excessive tracking-related traffic, and excessive number of sessions	
4	Excessive ad-related traffic, but very low network activity	
5	High portion of traffic related to popular services, but very low use of them and very low network activity	Innocuous
6	High use of popular services, but very low network activity	
7	High portion of traffic related to other domains, but very low tracking-related traffic and very low use of popular services	Potentially suspicious
8	High portion of traffic related to other domains, but very low use of them and very low portion of tracking-related traffic	
9	High portion of traffic related to other domains, but very low use of them	

TABLE XVIII
THE SURVEYED WORKS IN WHICH MACHINE LEARNING IS APPLIED FOR APP IDENTIFICATION.

Year	Paper	Features	Classifier
2013	Qazi et al. [28]	N/A	C5.0 decision tree
2015	Le et al. [5]	84 network-level features belonging to five typologies (packet length statistics, payload length statistics, inter-arrival time statistics, bursts timing, overall flow statistics, and TCP flags)	Linear SVM
	Wang et al. [42]	Average and standard deviation of the size/time of all the transmitted/received 802.11 frames, and average size/time of the low 20%, mid 60%, and high 20%	Random forest
2016	Alan et al. [6]	Burst sizes (rounded to the nearest 32 bytes) of the first 64 IP packets	Based on Jaccard index
		Sizes of the first 64 IP packets (using the minus sign for incoming packets)	Gaussian NB
	Sizes of the first 64 IP packets (using the minus sign for incoming packets), modified by term frequency – inverse document frequency transformation and normalization	Multinomial NB	
	Mongkolluksamee et al. [47]	35 graphlet- and 24 histogram-based features extracted from network information (source/destination IP address, protocol, source/destination port, size)	Random forest
2017	Taylor et al. [61]	18 statistics (minimum, maximum, mean, median, absolute deviation, standard deviation, variance, skew, kurtosis, percentiles from 10% to 90%, and number of values) computed on the transmitted/received/both IP packet sizes within TCP flows	Random forest

- The HTTP messages containing sensitive information are clustered using hierarchical clustering. The following metrics are employed:

- The HTTP message destination distance d_{dst} , which is defined as:

$$d_{dst}(p_x, p_y) = d_{ip}(p_x, p_y) + d_{port}(p_x, p_y) + d_{host}(p_x, p_y) \quad (\text{VI-B3.1})$$

where $p_n = \{ip_n, port_n, host_n\}$ with ip_n a destination IPv4 address, $port_n$ a port number, $host_n$ a HTTP host, and the distances are defined as:

$$\begin{aligned} d_{ip}(p_x, p_y) &= lmatch(ip_x, ip_y)/32 \\ d_{port}(p_x, p_y) &= match(port_x, port_y) \\ d_{host}(p_x, p_y) &= \frac{ed(host_x, host_y)}{\max(len(host_x), len(host_y))} \end{aligned} \quad (\text{VI-B3.2})$$

where $lmatch()$ returns the number of common upper bits in two IP addresses, $match()$ returns 1 on matching ports and 0 otherwise, $ed()$ returns an edit distance, $len()$ returns the length of a character string, and $max()$ returns the greater of its two arguments. In particular, the values of distances d_{ip} , d_{port} and d_{host} are within an interval $[0, 1]$.

- The HTTP message content distance d_{header} , which is defined as:

$$d_{header}(p_x, p_y) = d_{rline}(p_x, p_y) + d_{cookie}(p_x, p_y) + d_{body}(p_x, p_y) \quad (\text{VI-B3.3})$$

where $p_n = \{rline_n, cookie_n, body_n\}$ with $rline_n$ a request line, $cookie_n$ a cookie, $body_n$ a message body, and the distance is defined as:

$$d_i(p_x, p_y) = ncd(i_x, i_y) \in [0, 1] \quad (\text{VI-B3.4})$$

where $i \in \{rline, cookie, body\}$ and $ncd(k, z)$ is the normalized compression distance of the strings k and z .

- Given C_x and C_y two clusters of HTTP messages, the linkage criterion is the following:

$$d(C_x, C_y) = \frac{\sum_{\substack{p_x \in C_x \\ p_y \in C_y}} d_{msg}(p_x, p_y)}{|C_x| * |C_y|} \quad (\text{VI-B3.5})$$

where:

$$d_{msg}(p_x, p_y) = d_{dst}(p_x, p_y) + d_{header}(p_x, p_y) \quad (\text{VI-B3.6})$$

- The conjunction signature set resulting from the clustering is employed to detect sensitive information leakage in mobile HTTP traffic.

Ren et al. in [50] focus on the mobile apps for Android, iOS, and Windows Phone. The presented framework is composed of three steps:

- The collected network traffic (which consists of HTTP/HTTPS flows) is inspected looking for the PII related to the target mobile devices. Each flow is labeled according to the fact that it leaked PII or not.
- In the feature extraction phase, a bag-of-words model is used, with the flows being the documents and the structured data being the words. More in detail, each flow is partitioned into words (using tokens), then it becomes a vector of binary values. In such vector, each word is set to 1 if it appears in the flow, otherwise it is set to 0.
- For each destination domain (identified using the `Host` field of the HTTP header), the framework selects the features (i.e., the words) that are more suitable for classification. Finally, a C4.5 decision tree is trained on the feature vectors associated to that destination domain.

The framework presented by Cheng et al. in [57] for detecting the PII leaks of Android apps consists of three phases:

- In the pre-processing phase, the network traffic of the targeted apps is partitioned into flows according to the information available in IP and TCP headers. Moreover, among the flows of each app, the flow with the minimum overall distance (computed using Dynamic Time Warping) from the other flows of the app is elected as leader. Finally, the flows are converted into time series of packet sizes.
- In the feature extraction phase, each time series is converted into a feature vector by computing the following features: the distance (computed using Dynamic Time Warping) of the series from the nearest leader, the weight of the behavior that generated the series (i.e., click, swipe, or other), the series duration, the number of packets in the series, the average packet size of the series, and the average packet interval of the series.
- In the classification phase, a random forest classifier is trained using the feature vectors.

4) *Malware Detection*: Researchers have effectively employed machine learning techniques to detect mobile malware from the network traffic of mobile devices. In particular, they have applied both supervised learning [22], [24], [35], [48], [8], [55] and unsupervised learning [25].

a) *Malware Detection via Supervised Learning*: In Table XIX, for each of the surveyed works in which supervised learning is applied for malware detection, we report the leveraged features and employed classifiers.

Regarding the work by Shabtai et al. in [22], the features reported in Table XIX are only the ones related to network traffic.

Regarding the work by Arora and Peddoju in [55], the authors present a feature selection algorithm to find the minimal set of features that achieves the best detection performance (the first that is reported in Table XIX). Given a set of features

$\{F_1, \dots, F_n\}$, the proposed algorithm is composed of the following steps:

- Rank the features according to different metrics. Each metric produces a different ranking. The authors uses the following metrics: (i) the *information gain* of a feature F , which is the reduction of entropy after observing F ; and (ii) the chi-squared test, which expresses the difference between the expected and observed values.
- For $k = 1$ up to n :
 - Extract the top- k features from each ranking, and keep only the ones that are present in all the rankings;
 - Use the selected features to perform a classification using a naive Bayes classifier, and compute the achieved F-measure;
 - If the F-measure computed above is greater than the one achieved in the previous steps, update the minimal set of features with the currently selected features.

b) *Malware Detection via Unsupervised Learning*: The framework proposed by Wei et al. in [25] works as follows:

- A monitor collects DNS response messages.
- The IP addresses within the answer and additional sections of the DNS response messages are mapped to geographical coordinates.
- Independent Component Analysis (ICA) is used to compute the spatial uniform distribution of hosts (i.e., uniformity degree in the geographic distribution of hosts) and their spatial service relationship (which describes the relationship between a provider and a consumer by a service distance, and tends to be zero for a benign domain). Both of these metrics are leveraged to label mobile apps as benign or malicious.

5) *User Action Identification*: Machine learning is applied for user action identification in [30], [32], [39], [45], [46], [52]. In these works, the authors leverage several techniques: in the field of unsupervised learning, agglomerative hierarchical clustering and k -means clustering; in the field of supervised learning, linear regression, naive Bayes, random forest, and support vector machine.

Watkins et al. in [27] employ a neural-fuzzy classifier that exploits the inter-packet time of responses to ICMP packets (i.e., pings) to infer the type of action that the target user is performing on her mobile device. In particular, the authors focus on three types of user action: (i) CPU intensive; (ii) I/O intensive; and (iii) non-CPU intensive.

Coull and Dyer in [32] try to infer the language (among six possible choices: Chinese, English, French, German, Russian, and Spanish) and length of the messages exchanged between iMessage clients (on both iOS and OS X) and Apple's servers. For the language, a multinomial naive Bayes classifier is used with the count of each length/direction pair observed (direction indicates whether the data is going to or coming from Apple's servers). For the length, linear regression (with least squares estimation) is employed using the payload length as the explanatory variable and the message size as the dependent variable.

TABLE XIX
THE SURVEYED WORKS IN WHICH SUPERVISED LEARNING IS APPLIED FOR MALWARE DETECTION.

Year	Paper	Features	Classifier
2012	Shabtai et al. [22]	Cellular/Wi-Fi sent/received bytes/packets	Bayesian networks
			J48 decision tree
			Histograms
			k -means
2012	Su et al. [24]	Average and standard deviation of the number of sent/received packets, average and standard deviation of the number of sent/received bytes, and average session duration	Logistic regression
			Naive Bayes
			J48 decision tree
2014	Shabtai et al. [35]	Average sent/received bytes, average received bytes in percent out of total amount of transmitted bytes, inner/outer average send/receive interval, and average sent/received data in percent out of total transmitted data	Random forest
			Decision tree
2016	Narudin et al. [48]	Source/Destination IP address, source/destination port, frame length/number, HTTP request type, number of frames received by unique source/destination in the last t seconds from the same destination/source, and number of packets flowing from source to destination and vice versa	BN with/without feature selection
			MLP with/without feature selection
			J48 with/without feature selection
			k NN with/without feature selection
			RF with/without feature selection
2016	Wang et al. [8]	Per-TCP-flow sent/received bytes, sent/received packets, and average sent/received packet size Per-HTTP-message Host, Request-URI, Request-Method, and User-Agent	C4.5 decision tree
2017	Arora et al. [55]	Sent/Received packets per second/flow, ratio of incoming to outgoing bytes, maximum/average packet size, and minimum time interval between sent/received packets	Naive Bayes
		Sent/Received bytes/packets per second/flow, ratio of incoming to outgoing bytes/packets, first sent/received packet size, maximum/average packet size, minimum/maximum/average time interval between sent/received packets, average flow duration, and ratio of number of connections to number of destination IPs	

Conti et al. in [45] combine unsupervised and supervised learning to fingerprint several user actions of popular Android apps. The proposed framework works as follows:

- The network traffic generated by each user action is partitioned into flows (each flow is a time-ordered sequence of TCP segments exchanged during a single TCP session). Each flow is converted into three time series of packet sizes (with negative sizes for incoming traffic). One series is for incoming traffic, one is for outgoing traffic, and one combines traffic in both directions.
- The flows are clustered using the agglomerative hierarchical clustering with the following linkage criterion:

$$d(u, v) = \sum_{\substack{1 \leq i \leq n \\ 1 \leq j \leq m}} \frac{\text{distance}(u[i], v[j])}{|u| * |v|} \quad (\text{VI-B5.1})$$

where $\text{distance}()$ is a distance function, and u and v are clusters of n and m elements, respectively. The distance function is defined as follows:

$$\text{distance}(f_i, f_j) = \sum_{k=1}^n w_k \times \text{DTW}(T_k^i, T_k^j) \quad (\text{VI-B5.2})$$

where f_i is a flow consisting of a set of n time series $\{T_1^i, \dots, T_n^i\}$, w_k is a weight assigned to the k^{th} time series, and $\text{DTW}(x, y)$ is the optimal warping path between the time series x and y .

- For every user action, each flow f is assigned to the cluster that minimizes the distance between f and the leader of the cluster (which is the flow that has the minimum overall distance from the other flows of the cluster). The k^{th} feature

indicates the number of flows that have been assigned to the k^{th} cluster after the execution of that user action.

- The final classification is performed using a random forest classifier.

The systems for user action identification developed by Park and Kim in [39] and Saltaformaggio et al. in [52] are similar to the one by Conti et al. [45]. However, there are a few differences:

- In [39], each flow is represented by a single time series including both incoming and outgoing traffic. As a consequence, the clustering is applied to time series (in [45], the authors consider sets of time series). Moreover, the distance function in the formula of the linkage criterion is simply $\text{DTW}()$.
- In [52], the IP traffic is partitioned into server transactions, each containing the IP headers (ordered by time) of the packets exchanged with a specific remote host. The server transactions are converted into feature vectors by the following 26 features: (i) send/receive average inter-packet time; (ii) the ratio of the number of packets sent/received to/from the server over the total number of packets exchanged with the server; (iii) the ratio of the size of the data sent/received to/from the server over the size of the total data exchanged with the server; and (iv) the number of packets sent/received within each of ten size ranges, normalized by the total number of sent/received packets. The feature vectors are then clustered using k -means clustering (following an incremental approach to find a suitable value for k), and the final classification is performed using a multi-class support vector machine.

The framework proposed by Fu et al. in [46] is based on supervised learning and consists of the following steps:

- The captured network flows are partitioned into sessions, then hierarchical clustering is applied to group together the sessions that are related to the same user action (the authors call such groups of sessions as *dialogs*).
- The dialogs are converted into feature vectors by extracting features that are related to the size (e.g., median, standard deviation, percentage of packets in a given range) and timing (e.g., median, standard deviation) of IP packets. Each feature vector is labeled with the user action that generated the corresponding dialog.
- A classifier is trained and evaluated on the feature vectors. The authors consider the following classifiers: random forest, gradient boosted trees, support vector machine, naive Bayes, and k -nearest neighbors.
- The dialogs related to multiple user actions, which have been classified as “unknown” in the previous step, are split into sub-dialogs that are then classified using a trained hidden Markov model.

6) *Operating System Identification*: Supervised learning techniques are applied for operating system identification in [31], [32], [51], [60].

Chen et al. in [31] present a naive Bayes classifier that leverages the following binary features:

- $TTL = 128$ (Windows) and $TTL \neq 128$ (Windows, Android, or iOS), where TTL is the Time-To-Live (TTL) field of the IP header.
- $ID_{mvr} < 0.05$ (mostly Windows, rarely Android), $ID_{mvr} \in [0.05, 0.40]$ (mostly Android, rarely Windows), and $ID_{mvr} > 0.40$ (mostly iOS, rarely Android), where ID_{mvr} is the monotonicity violation ratio of the identification (ID) field in the IP headers.
- $TS_{ratio} < 0.05$ (Windows) and $TS_{ratio} \geq 0.05$ (Android or iOS), where TS_{ratio} is the ratio of segments with TCP timestamp option.
- $WS = 4$ (mostly Windows, rarely Android), $WS = 16$ (iOS), $WS = 64$ (mostly Android, rarely Windows), and $WS = 256$ (Windows), where WS is the TCP window size scale option.
- $clock_{SD} \leq 3$ (mostly Android, rarely iOS and Windows) and $clock_{SD} > 3$ (iOS), where $clock_{SD}$ is the standard deviation of a device clock frequency, estimated using packets coming from its IP address.

Coull and Dyer in [32] leverage the sizes of encrypted packets exchanged between a target iMessage user and Apple’s servers. The aim of this analysis is to determine whether the iMessage client is running on iOS or OS X. The authors use a binomial naive Bayes classifier with one class for each of the four possible (OS, direction) pairs, with direction indicating whether the packet is going to or coming from Apple’s servers. The classifier operates on a binary feature vector of (size, direction) pairs, where the value for a given feature is 1 if the corresponding pair is observed and 0 otherwise.

The framework presented by Ruffing et al. in [51] combines together supervised learning and analysis of the frequency

spectrum of packet timing. The proposed methodology is composed of two phases:

- Training phase:
 - Each traffic trace, which is labeled with the operating system that generated it, is converted into a frequency spectrum.
 - Frequency components are extracted from the frequency spectra generated in the previous step.
 - A genetic algorithm is applied to separate the frequency components that are related to OS features from those that bring noise. The former are promoted features.
- Identification phase:
 - A new traffic trace x is converted into a feature-extracted frequency spectrum F^x .
 - The identified operating system is provided by the following formula:

$$\operatorname{argmax}_{os \in OS} \frac{1}{n_{os}} \sum_{i=1}^{n_{os}} \operatorname{corr}(F^x, F_i^{os}) \quad (\text{VI-B6.1})$$

where OS is the set of the considered mobile OSEs, n_{os} is the number of feature-extracted frequency spectra of the mobile operating system os , F_i^{os} is the i^{th} feature-extracted frequency spectrum of the mobile operating system os , and $\operatorname{corr}(X, Y)$ is a function that computes the correlation between the frequency spectra X and Y .

Malik et al. in [60] carry out OS identification by exploiting the inter-packet time of packets coming from the target mobile device. In particular, the authors focus on two types of packet: (i) the response to an ICMP packet sent to the target mobile device (active measurement); and (ii) an IP packet related to a video stream involving the target mobile device (passive measurement). The presented framework consists of a random forest classifier that is trained and evaluated on the inter-packet times of three mobile devices running Android, iOS, and Windows Phone, respectively.

7) *Position Estimation*: Musa and Eriksson in [21] present a system for converting the detections of the Wi-Fi probe requests periodically transmitted by a target mobile device into a highly likely spatiotemporal trajectory within the monitored area.

The position estimation problem is formulated using a hidden Markov model (HMM): (i) each street of the covered area is partitioned into segments, and each segment represents a rectangular area in which a mobile device may be located; and (ii) a state of the HMM is assigned to each segment, and transition probabilities are used to model the behavior of mobile devices at intersections (i.e., go straight, turn left, or turn right). For each detection det_i of the target mobile device and each state s_i of the HMM, the emission probability $p(det_i | s_i)$, which represents the probability of making the detection det_i if the current state is s_i , is computed. Finally, the Viterbi’s map-matching algorithm is applied to find the maximum-probability path, which is represented by a sequence of hidden states visited in the Markov model.

8) *User Fingerprinting*: Verde et al. in [36] present a framework for fingerprinting mobile users from NetFlow

records. The proposed solution is based on supervised learning and hidden Markov model (HMM):

- Feature vectors are extracted from the NetFlow records of the target user, and then partitioned into subsets. Each subset is related to a specific network service. For each service, several HMMs are created by varying the number of states and the subset of features, and setting up their parameters via the k -means algorithm. The HMMs are trained in parallel, and subsequently converted into binary classifiers using a probability threshold t (i.e., if the observation has a probability lower than t , it will be classified as 0, otherwise it will be classified as 1). Finally, the best performing HMM is selected for that network service.
- Feature vectors are extracted from the NetFlow records captured at the monitored network, and subsequently partitioned according to the network service they belong to. Each feature vector is classifier with the HMM corresponding to its service. For each time interval, the results are aggregated into a new record that contains, for each HMM h , the number of feature vectors recognized by h as belonging to the target user during the interval, times the weight of h (which is computed during the training phase). Finally, a machine learning classifier is used to determine whether, during each of the time intervals, the network traffic contains data transmissions from the target user. The framework supports the following classifiers: support vector machine, random forest, RIPPER, multi-layer perceptron, and naive Bayes.

9) *Ad Fraud Detection*: Crussell et al. in [33] present a system being able to automatically run Android apps in emulators and analyze their application-layer traffic in order to detect whether they: (i) request ads while being in the background (i.e., ads are not displayed to the user); and (ii) click on ads without user interaction (i.e., false user clicks are simulated). The framework is based on supervised learning:

- The HTTP and DNS traffic of each analyzed app is extracted from its network traces, then causally related HTTP requests are linked to form request trees.
- For each request page (identified by the host and path names of its URL), all the related HTTP requests are aggregated. After that, the authors extract 33 features as follows:
 - Ten features derive from query parameters:
 - * For each query parameter, it is computed the ratio of distinct values found for that parameter over the total number of times the parameter appeared in a request, as well as the ratio of distinct values found for that parameter over the total number of distinct apps. Each ratio is segmented into several intervals and the number of query parameters whose ratio is in each interval is counted. These counts contribute six features.
 - * It is also computed the entropy of each query parameter. The entropy is considered high if it is greater than 216 bits, low otherwise. The number of query parameters that have, respectively, high and low entropy contribute two features.
 - * The last two features are the average and the total number of query parameters.

- Sixteen features derive from the request trees. Such features are related to their structure (e.g., average height and depth of trees containing the page), number of children, their MIME types, and types of edge that connect the children to their parent.
- Seven features derive from HTTP headers (e.g., status codes, requests' length, replies' length).
- The authors train a random forest classifier to classify each request page as ad-related (ARQ) or not (NARQ).
- The ad request pages (i.e., the ARQ pages) and the HTTP request trees are leveraged to extract and verify ad impressions (i.e., displaying) and clicks.

10) *Tethering Detection*: Chen et al. in [31] apply supervised learning to detect whether a target mobile device is tethering its Internet connection to other devices. The proposed probabilistic classifier leverages the following binary features:

- $n_{OS} = 1$ (no tethering) and $n_{OS} > 1$ (tethering), where n_{OS} is the number of operating systems identified from the packets coming from the same IP address (also the OS identification framework is based on machine learning, see Section VI-B6 for details).
- $n_{TTL} = 1$ (no tethering with high probability) and $n_{TTL} > 1$ (tethering with high probability), where n_{TTL} is the number of distinct TTLs in the packets coming from the same IP address.
- $ts_{mvr} \leq 0$ and $ts_{mvr} > 0$, where ts_{mvr} is the violation ratio of the TCP timestamp monotonicity of the segments coming from the same device (the idea is to exploit the fact that segments generated by the same device tend to monotonically increase TCP timestamp values, whereas segments from different devices tend to have mixed TCP timestamp values).
- $clock_{SD} \leq 35$ and $clock_{SD} > 35$, where $clock_{SD}$ is the standard deviation of the clock frequency estimated using the packets coming from the same IP address (a large standard deviation is likely due to tethering).
- $boot_{SD} \leq 1455$ and $boot_{SD} > 1455$, where $boot_{SD}$ is the standard deviation of the boot time inferred from the TCP timestamp values in the segments coming from the same device (the idea is to exploit the fact that different devices have distinct boot times and distinct initial TCP timestamp values).

11) *Website Fingerprinting*: Spreitzer et al. in [53] fingerprint the websites visited by an Android user via the web browser of her mobile device, by leveraging the data-usage statistics of the browser app. The proposed framework is based on supervised learning:

- Each considered website w_i is opened in the web browser of an Android device. At the same time, the TCP bytes transmitted and received by the browser app are sampled at a frequency f for a period of t seconds. The readings constitute a sample of the website w_i . The sampling process stops after collecting n samples, which constitute the signature of the website w_i . All the generated signatures are included in a database T .
- T is loaded into an unprivileged Android app that is installed on the target mobile device. When the user opens a website

within the web browser of the device, the app samples the transmitted and received TCP bytes of the browser app, and builds a signature s . For each signature s_i in T , the similarity (which is a function based on the Jaccard index) between s and s_i is computed; the app returns the website corresponding to the signature s_i that maximizes the similarity with s .

C. Other Analysis Methods

Some traffic analyses does not require machine learning techniques to achieve their goals. In this section, we report two alternative methods. In Section VI-C1, we describe a way to turn a dictionary¹ into an effective classifier. In Section VI-C2, we report two methodologies that rely on graphs.

1) *Dictionary*: A dictionary can be used as a one-feature classifier whether: (i) the keys are the values that the feature can take; and (ii) a set of class labels is associated to each key. This solution is suitable to solve classification problems in which there is a single feature, which takes a limited set of values.

Coull and Dyer in [32] target iMessage, Apple’s instant messaging service, which is available as a mobile app for iOS or a traditional computer program for OS X. The objective is to fingerprint five distinct user actions (i.e., start typing, stop typing, send text, send attachment, and read receipt) by leveraging the size of the packets exchanged between the target iMessage client and Apple’s servers. The authors study the packet sizes corresponding to the considered user actions, and notice that each user action has two distinctive packet sizes: (i) one when a message is sent to Apple’s servers; and (ii) one when a message is received from Apple’s servers. This property can be exploited to build a classifier that takes the form of a dictionary in which one or more user action labels are associated to each packet size observed in the training data. When a new packet arrives, the dictionary is queried to retrieve the user action label(s) for its payload length: if only one label is found, the packet is given that label; if two or more labels are returned, the user action most frequently associated to that payload size during training is chosen.

2) *Graph Analysis*: In this section, we highlight a few works in which graph theory is leveraged for mobile traffic analysis.

Barbera et al. in [26] combine graph theory and traffic analysis to carry out sociological inference targeting mobile users (their findings are reported in Section III-K). More precisely, they present a methodology to build the social network² of a group of mobile users from the probe requests sent by their mobile devices. The proposed procedure consists of the following steps:

- The dataset of collected probe requests is turned into an *affiliation network*. An affiliation network $G = (V_1, V_2, E)$ is a bipartite graph in which V_1 is a set of *actors*, V_2 is a

¹We use the term *dictionary* to indicate a collection of (key, value) pairs, such that each key appears at most once in the collection, and a value can be either a single value or an unordered set of values.

²In a social network, the nodes correspond to the individuals, while the edges model the relationships between them.

set of *groups* the actors belong to, and each edge $e \in E$ connecting an actor $v_1 \in V_1$ to a group $v_2 \in V_2$ represents a group membership. In the work by Barbera et al. [26], V_1 is the set of mobile devices (identified by their MAC address) that sent at least one probe request, V_2 is the set of SSIDs contained in the collected probe requests, and an edge $e \in E$ connecting a mobile device $v_1 \in V_1$ to an SSID $v_2 \in V_2$ represents v_1 having v_2 in its Preferred Network List (PNL), which is the list of the SSIDs of the Wi-Fi networks v_1 connected to in the past.

- A *similarity measure* $f : V_1 \times V_1 \rightarrow R$ is chosen to represent the strength of the social relationship between the users of each pair of mobile devices u and v . Based on the Adamic-Adar similarity measure [82], Barbera et al. [26] define the f function as:

$$f(u, v) = \sum_{w \in N(u) \cap N(v)} \frac{1}{\log_2(|M(w)|)} \quad (\text{VI-C2.1})$$

where $N(u)$ is the PNL of the mobile device u , and $M(w)$ is the set of mobile devices that have the SSID w in their PNL.

- The affiliation network G is turned into a social network $G' = (V_1, E')$ by applying the following rule:

$$\forall u, v \in V_1 : (u, v) \in E' \Leftrightarrow f(u, v) > t \quad (\text{VI-C2.2})$$

where t is a minimum similarity threshold.

Vanrykel et al. in [54] present a graph building technique that processes a mobile traffic dataset in order to partition the network traces it contains by user. The idea is to exploit the sensitive identifiers that are typically present in the network traffic generated by mobile devices. The proposed methodology consists of the following steps:

- Through the analysis of TCP timestamps, the packets that belong to the same app session (therefore to the same mobile user) are grouped together into a node. Alternatively, it is possible to partition the packets by TCP session.
- For each node, the sensitive identifiers present in HTTP messages are extracted according to host-specific rules.
- To cluster the nodes into components, each one representing the network traffic related to a specific mobile user, the following rules are iteratively applied to all nodes:
 - If the node’s identifiers (or their hashed/encoded values) match the identifiers of an existing component, add the node to that component and merge their identifiers.
 - If the node’s identifiers (or their hashed/encoded values) match the identifiers of multiple existing components, merge those components together, add the node to the resulting component, and merge their identifiers.
 - If the node’s identifiers (or their hashed/encoded values) do not match the identifiers of any existing component, make the node a component on its own.

VII. VALIDATION METHODS AND RESULTS FOR TRAFFIC ANALYSIS TARGETING MOBILE DEVICES

In this section, we critically evaluate and compare the results achieved by the surveyed works in the field of traffic analysis targeting mobile devices. Such results are linked to

the analyzed datasets and presented by the goal of the analysis. To help the reader, we also devote an initial section (VII-A) to describe: (i) the evaluation metrics for the analyses that can be considered as a *classification* problem, as well as those metrics that are specific of a particular goal; (ii) the dataset partitioning techniques for the analyses that follow the supervised learning paradigm; and (iii) the conventions that we will follow in the tables.

To offer a clear comparison among works, for each goal of the analysis (sorted by popularity as in Section III) we summarize with tables the information about validation in terms of datasets, methods, and results. Moreover, we discuss interesting aspects of validation and we comment the obtained results.

A. Preliminaries

1) *Evaluation Metrics for Classification Problems*: In a classification problem, given a set of $n \geq 2$ classes (or labels) $C = \{C_1, \dots, C_n\}$ and a new instance x , the goal is to infer which class x belongs to (i.e., which is the index i such that $x \in C_i$). We distinguish between two types of classification: *binary* and *multi-class*.

In a binary classification problem, we have only two classes (i.e., $n = 2$): a *positive* one, which represents a given property P , and a *negative* one, which represents the negation of that property (\bar{P}). The goal is to infer whether P holds for the new instance x . Under such conditions, we define as *true positives* the correctly classified positive instances, as *false positives* the negative instances incorrectly classified as positive, as *true negatives* the correctly classified negative instances, and as *false negatives* the positive instances incorrectly classified as negative.

In a multi-class classification problem, instead, we have at least three classes (i.e., $n \geq 3$). In such scenario, given two (possibly equal) class indexes i and j ($1 \leq i, j \leq n$), we define as $c_{i,j}$ the number of instances belonging to the class C_i that are classified as belonging to the class C_j . As a consequence of the above definition, $c_{i,i}$ represents the number of instances belonging to the class C_i that are correctly classified.

To evaluate the results achieved in the surveyed works that present traffic analyses we can consider as classification problems, we use four performance metrics: accuracy, precision, recall, and F-measure.

Accuracy — We define as *accuracy* the number of correctly classified instances (i.e., the number of true positives TP plus the number of true negatives TN) over the total number of classified instances (i.e., the sum of the number of true positives TP , the number of false positives FP , the number of true negatives TN , and the number of false negatives FN):

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (\text{VII-A1.1})$$

Accuracy measures how much the considered instances have been correctly classified, and ranges from 0.0 (none of the instances has been correctly classified) to 1.0 (all the instances have been correctly classified).

Precision — We define as *precision* the number of true positives TP over the total number of instances that have been

classified as positive (i.e., the number of true positives TP plus the number of false positives FP):

$$precision = \frac{TP}{TP + FP} \quad (\text{VII-A1.2})$$

Precision measures how much the instances classified as positive have been correctly classified, without any insight into the positive instances that could have been missed. Precision ranges from 0.0 (none of the instances classified as positive is positive) to 1.0 (all the instances classified as positive are positive).

Recall — We define as *recall* the number of true positives TP over the total number of instances that belong to the positive class (i.e., the number of true positives TP plus the number of false negatives FN):

$$recall = \frac{TP}{TP + FN} \quad (\text{VII-A1.3})$$

Recall measures how much the instances belonging to the positive class have been correctly classified, without any insight into the negative instances that could have been classified as positive. Recall ranges from 0.0 (none of the instances belonging to the positive class have been correctly classified) to 1.0 (all the instances belonging to the positive class have been correctly classified).

F-measure — We define as *F-measure* the harmonic average of precision and recall:

$$F\text{-measure} = 2 \times \frac{precision \times recall}{precision + recall} \quad (\text{VII-A1.4})$$

The F-measure provides a single score to express the performance in a classification task, and ranges from 0.0 (precision and recall are both 0.0) to 1.0 (precision and recall are both 1.0).

2) *Goal-specific Evaluation Metrics*: To evaluate the results achieved in the surveyed works that deal with app identification and user fingerprinting, we use additional performance metrics that are specific of those types of analysis: app matching rate and app identification rate for app identification; data aggregation rate for user fingerprinting.

App Matching Rate (AMR) — We define as *app matching rate* the ratio between the number of network transmissions that are successfully matched with one of the targeted apps (n_{match}), over the total number of captured network transmissions (n_{total}):

$$AMR = \frac{n_{match}}{n_{total}} \quad (\text{VII-A2.1})$$

The app matching rate measures how much the captured network transmissions belong to the targeted apps, and ranges from 0.0 (none of the transmissions belong to the targeted apps) to 1.0 (all transmissions belong to the targeted apps). The app matching rate is often used when no ground truth is available, i.e., the apps that actually generated the captured network transmissions are unknown.

App Identification Rate (AIR) — We define as *app identification rate* the ratio between the number of identified apps ($n_{identify}$), over the total number of targeted apps (n_{total}):

$$AIR = \frac{n_{identify}}{n_{total}} \quad (\text{VII-A2.2})$$

The app identification rate measures how many of the targeted apps have been successfully identified, and ranges from 0.0 (none of the targeted apps have been identified) to 1.0 (all the targeted apps have been identified).

Data Aggregation Rate (DAR) — We define as *data aggregation rate* the percentage of network data related to a mobile user that is correctly linked to that mobile user. The data aggregation rate ranges from 0.0 (none of the network data related to the mobile user has been linked to that mobile user) to 1.0 (all the network data related to the mobile user have been linked to that mobile user).

3) *Dataset Partitioning Techniques for Supervised Learning*: To evaluate the performance of a supervised-learning-based analysis, it is necessary to partition the dataset. The *holdout* method is the fundamental method to partition the dataset in order to get the data for training and testing, respectively. This method first creates two empty sets: training set and testing set. Then it randomly assigns each observation in a dataset to one of those sets according to a given pre-determined parameter $S_{training}$. This parameter indicates the proportion in terms of the number of elements that the training set include compared to the total elements of the dataset. As an example, with $S_{training} = 0.7$ the training set will include the 70% of the total elements of the dataset, while the testing set will include the remaining 30%. Such proportion can also be expressed using two integers n and m that stand as the number of equipotent parts in which the dataset is partitioned and the number of parts used as testing set, respectively. As an example, with $n = 5$ and $m = 2$ a dataset is partitioned into five equipotent parts of which three used as training set and two as testing set.

All model selection and training processes must be done exclusively using the training set, without involving the testing set in any case. Indeed, it is possible to further partition a training set and use part of it as a reduced testing set (i.e., validation set) to perform model selection and hyper-parameter tuning. The testing set has to be used for the only purpose of evaluating the performance of the trained model.

In multi-class classification, it is useful to ensure that training and testing sets hold the same proportion of observations belonging to a class. This option is called *stratification* and is used to avoid imbalance of class representation between training and testing sets.

Another method to evaluate a learning model is to perform a *cross-validation*. The cross-validation method consists in partitioning a dataset into k folds (i.e., complementary and equipotent subsets) and iteratively training and testing a given model for k times. For each run, one fold is considered as a testing set and the remaining $k - 1$ folds as training set. The overall results are obtained by aggregating the results of each run. As for multi-class holdout method, the dataset can be partitioned in folds using the stratification option. Cross-validation can also be used on the training set only to perform model selection and hyper-parameter tuning. A variant of cross-validation called *leave-p-out cross-validation* allows specifying the exact number of observations p to holdout as a testing set at each run (the case in which $p = 1$ is called *leave-one-out cross-validation*).

4) *Table Conventions*: To uniquely identify the datasets that have no name in a given work, we will use arbitrary names of the form “[yy].[author]_[n]”, where [yy] is the last two digits of the publication year of the work, [author] is the surname of the first author of the work, and [n] is a progressive number, starting from zero.

Moreover, since we are space-constrained, we will shrink the content of the tables by using the following shortenings:

- We will use the character “#” to shorten the word “number”.
- Given a number n , we will write “ $n+$ ” for “over n ”.
- We will write “Tx” and “Rx” for “transmitted” and “received”, respectively.
- To reference a given OSI layer, we will use the corresponding ordering number (e.g., “layer 2” for the data-link layer, “layer 3” for the network layer, “layer 4” for the transport layer, “layer 7” for the application layer). To reference a given OSI layer and the layers above it, we will add the character “+” to the ordering number of the bottom layer (e.g., “layer 3+” for layers from network to application).
- Given two decimal numbers $S_{training}$ and S_{test} such that $S_{training} + S_{test} = 1$, we will write “ $S_{training}/S_{test}$ ” to indicate the holdout dataset partitioning technique with $S_{training}$ of the data reserved to the training set, and S_{test} of the data reserved to the test set (e.g., “0.7/0.3”).
- Given two integer numbers n and m such that $m < n$, we will write “out(n, m)” to indicate the holdout dataset partitioning technique with m parts out of n reserved to the test set, and the remaining ones reserved to the training set (e.g., “out(10, 2)”).
- Given an integer number k , we will write “kCross(k)” to indicate the k -fold cross-validation.

B. Traffic Characterization

In this section, we focus on the datasets used for traffic characterization works, since we have already summarized the findings of these works in Section III-A.

In Table XX we provide information about the datasets analyzed in the surveyed works that deal with traffic characterization targeting specific apps and/or mobile services. As we can notice, most of these works rely on data from the data-link layer and above. Four out of nine works consider only one or two apps in their analysis (e.g., Skype, Youtube). Two works focus on a specific category of apps: Chen et al. in [37] on malware, and Nayam et al. in [49] on apps related to health and fitness. Moreover, Lindorfer et al. in [34] study a set of one million apps.

In Table XXI, we report the information about the datasets of the works that focus their analysis on a population of mobile devices. Most of the works consider more than two hundred devices (five out of nine), among which three works on more than two thousand devices. Unfortunately, Chen et al. in [19] and Lee et al. in [16] do not specify the number of devices involved in their analysis.

C. App Identification

In Table XXII, we summarize the information about validation for works that deal with app identification. Since this goal

TABLE XX

THE DATASETS OF THE SURVEYED WORKS THAT DEAL WITH TRAFFIC CHARACTERIZATION TARGETING SPECIFIC APPS AND/OR MOBILE SERVICES.

Year	Paper	Mobile Platform(s)	App(s)/Mobile Service(s)	Dataset	Point of Capturing	Content
2011	Finamore et al. [14]	Platform-independent	YouTube	US-Campus	Wired (within a campus network, one week)	IP packets
				EU1-Campus		
				EU1-ADSL	Wired (within an ISP's network, one week)	
				EU2-ADSL		
2011	Rao et al. [17]	Android, iOS	Netflix	NetMob	Wired (forwarding server, 180 seconds per video)	Layer-2+ data
			YouTube	YouMob		
2012	Baghel et al. [18]	Android	Facebook	12.Baghel_0	Wired (forwarding server, 90 minutes)	Layer-2+ data
			Skype	12.Baghel_1	Wired (forwarding server, five hours)	
	Wei et al. [4]	Android	19 free and 8 paid apps	12.Wei_0	Devices (two devices)	Layer-2+ data
2014	Lindorfer et al. [34]	Android	Over 1,000,000 apps	14.Lindorfer_0	Emulators (240 seconds per app)	Layer-2+ data
2015	Chen et al. [37]	Android	5560 malicious apps (from 177 malware families)	15.Chen_0	Wired (forwarding server, five minutes per app)	Layer-2+ data
2016	Nayam et al. [49]	Android	63 free apps ("Health & Fitness" category)	16.Nayam_0	Wired (forwarding server, three 30-minutes-long runs per app)	HTTP messages
		iOS	35 free apps ("Health & Fitness" category)			
	Tadrous et al. [7]	Android, iOS	Five apps (common to the targeted mobile platforms)	16.Tadrous_0	APs (one AP, 300 sessions per app)	802.11 frames
2017	Espada et al. [59]	Android	Spotify	17.Espada_0	Devices (one device)	Layer-2+ data

TABLE XXI

THE DATASETS OF THE SURVEYED WORKS THAT DEAL WITH TRAFFIC CHARACTERIZATION TARGETING A POPULATION OF MOBILE DEVICES.

Year	Paper	Dataset	Point of Capturing	# Mobile Devices	Content
2010	Afanasyev et al. [9]	10.Afanasyev_0	APs (28 days)	2500 simultaneous	Layer-2 and -3 data from RADIUS logs
		10.Afanasyev_1	Wired (central Internet gateway, five days)		Layer-3+ headers (no DHCP data) of the first packet of each flow for the first quarter of each hour
	Falaki et al. [10]	Dataset1	Devices	Two Android, eight Windows Mobile	Layer-2+ data
		Dataset2		33 Android	Per-app Tx/Rx bytes
	Maier et al. [12]	SEP08	Wired (an ISP's edge router, one day)	200+	Anonymized DSL data
		APR09		400+	
AUG09a		500+			
	AUG09b	500+			
	Shepard et al. [13]	10.Shepard_0	Devices	25 iOS	IP packets
2011	Gember et al. [15]	Net1	APs (campus network, three days)	32,166	Layer-2+ data
		Net2		112	
	Lee et al. [16]	11.Lee_0	Wired (top-level router of a campus network, six days)	N/A	IP packets
2012	Chen et al. [19]	12.Chen_0	Wired (gateway router of a campus Wi-Fi network, three days)	N/A	Up to 900 bytes of each incoming/outgoing packet (including IP, TCP, and application-level headers)
		12.Chen_1	Wired (gateway router of a campus Wi-Fi network, one day)	N/A	
2015	Fukuda et al. [38]	2013	Devices	800+ Android, 700+ iOS	Per-app/Per-interface Tx/Rx bytes/packets
		2014			
		2015			
2017	Wei et al. [62]	Traffic-May	Wired (Internet gateway of a campus network, one month)	10,756 Android, 11,328 iOS, 618 BlackBerry	Layer-3+ data

involves multi-label classification, we also provide results of traffic analysis proposals. Eight works out of ten consider a reasonable sample of apps (i.e., more than 40), while Wang et al. in [42] and Mongkolluksamee et al. in [47] only consider thirteen and five apps, respectively. Most of the works provide accuracy as a metric to evaluate their proposal, but recall and precision would have provided a better understanding of the performance.

In what follows, we provide some additional observations about these works. We observe that Lee et al. in [16] and the *mobUser* dataset by Rao et al. [29] have no ground truth, therefore only app matching rate is provided as a result. Alan et al. in [6] provide two additional findings: (i) a performance drop when trained classifiers are tested on updated versions of the same apps; (ii) a performance drop when training and testing involve different devices, which introduces a possible bias towards a specific OS or vendor. Although it is not clearly stated, the results reported in the Table XXII for this work seem to be the ones using network traffic from the same app versions and installed on the same devices.

Regarding the work by Mongkolluksamee et al. in [47], we underline that "16.Mongkolluksamee_0" dataset (which the reported metrics refer to) is filtered out of background network traffic of Android OS and other apps. The authors observe a performance drop if such background traffic is kept, and mitigate that drop by removing short-lived flows.

Taylor et al. in [61] further investigate other aspects with additional experiments (not reported in the table): (i) the effect of training on a dataset older than the testing one; (ii) the effect of performing training and testing on datasets from different devices, with different app versions, and both; and (iii) the effect of the proposed reinforced learning approach to deal with ambiguous flows.

D. Usage Study

In Table XXIII we provide information about the datasets analyzed in the surveyed works that deal with usage study. We can notice that eight works out of ten that deal with usage study also deal with traffic characterization (Tables XX and XXI). Nonetheless, Table XXIII is meant to offer a proper comparison also with works that purely deal with usage study. An evident difference is that pure usage studies employ fewer devices when compared with other works. Indeed, while most of the other works employ more than two hundred devices, Ham et al. in [20] and Soikkeli et al. in [40] validate their finding on only ten Android and 120 (unspecified) devices, respectively. Moreover, it is interesting to notice that both these works just rely on transmitted and received bytes.

E. PII Leakage Detection

In Table XXIV, we summarize the validation methods used by works that deal with PII leakage detection. Most of the works on PII leakage detection focus on providing findings and observations about user private information transmission (in clear) to third-party services (summarized in detail in Section III-D), rather than provide actual results from a classification task. Despite this, Kuzuno et al. in [27] and Ren

et al. in [50] report results in terms of accuracy since they are the only ones that rely on machine learning methods. It is worth noticing that Kuzuno et al. in [27] only report classification accuracy without providing any additional finding.

As an overall consideration about datasets, five works out of eight carry out an analysis on more than one thousand apps. Besides, Song et al. in [41] consider only 53 apps and Le et al. in [5] do not specify the number of considered apps. Moreover, Stevens et al. in [23] carry out their analysis on a custom app that includes thirteen popular Android ad libraries.

F. Malware Detection

We present the validation methods and results for works that deal with malware detection in Table XXV. It is worth noticing that five works out of eight validate their proposals on datasets collected from less than two devices. Moreover, only Wei et al. in [25] and Wang et al. in [8] rely on a forwarding server, while the other datasets are collected directly from devices. Surprisingly, Narudin et al. in [48] are the only that rely on emulators to collect malware traffic, despite the use of emulators-based sandboxes is a common practice in mobile malware analysis.

In what follows, we provide some additional observations regarding the validation of malware detection works. The results of the work by Shabtai et al. in [22] are referred to their experiment I. Since experiment I provides two sub-experiments (i.e., gaming apps and tool apps), we averaged the results for each metric. Moreover, the authors carry out three other experiments: in experiment II, the authors evaluate the effect of testing on apps not used in training; in experiment III, the authors evaluate the effect of performing training and testing on different devices; and in experiment IV, the authors evaluate the combination of both. The authors also evaluate three metrics for feature selection: chi-square, Fisher score, and information gain.

Regarding the datasets used by Shabtai et al. in [35], the "14.Shabtai_0" dataset refers to the experiments with the infected versions of the benign apps, while "14.Shabtai_1" and "14.Shabtai_2" refer to the experiments with the self-updating malware.

Despite Zaman et al. in [44] rely on DPI on HTTP messages and only focus on two malware samples, their proposal is able to identify only one malware out of two (i.e., Droid-KungFu), thus having an accuracy of 0.5. Moreover, their dataset involves traffic collected from a single device. Clearly, this proposal cannot be considered effective and well validated.

Narudin et al. in [48] validate their proposal on two datasets, namely "Ds1000" and "Priv". In particular, the authors argue that applying feature selection on "Ds1000" dataset slightly improves classifiers performance (except for multi-layer perceptron which has a performance drop).

G. User Action Identification

In Table XXVI, we compare the validation methods and results of works that aim at identifying user actions. Given the nature of this goal and the difficulty to build a ground truth, all the works leverage their own dataset to validate their analysis.

TABLE XXIII
THE DATASETS OF THE SURVEYED WORKS THAT DEAL WITH USAGE STUDY.

Year	Paper	Dataset	Point of Capturing	# Mobile Devices	Content
2010	Afanasyev et al. [9]	10.Afanasyev_0	APs (28 days)	2500 simultaneous	Layer-2 and -3 data from RADIUS logs
		10.Afanasyev_1	Wired (central Internet gateway, five days)		Layer-3+ headers (no DHCP data) of the first packet of each flow for the first quarter of each hour
	Falaki et al. [10]	Dataset1	Devices	Two Android, eight Windows Mobile	Layer-2+ data
		Dataset2		33 Android	Per-app Tx/Rx bytes
	Maier et al. [12]	SEP08	Wired (an ISP's edge router, one day)	200+	Anonymized DSL data
		APR09		400+	
AUG09a		500+			
AUG09b		500+			
2011	Finamore et al. [14]	US-Campus	Wired (within a campus network, one week)	N/A	IP packets
		EU1-Campus			
		EU1-ADSL	Wired (within an ISP's network, one week)		
		EU1-FTTH			
		EU2-ADSL			
	Gember et al. [15]	Net1	APs (campus network, three days)	32,166	Layer-2+ data
Net2			112		
Lee et al. [16]	11.Lee_0	Wired (top-level router of a campus network, six days)	N/A	IP packets	
2012	Ham et al. [20]	12.Ham_0	Devices	Ten Android	Per-process/Per-interface bytes/packets Tx/Rx
2015	Fukuda et al. [38]	2013	Devices	800+ Android, 700+ iOS	Per-app/Per-interface Tx/Rx bytes/packets
		2014			
		2015			
	Soikkeli et al. [40]	15.Soikkeli_0	Devices	120	Tx/Rx bytes
2017	Wei et al. [62]	Traffic-May	Wired (Internet gateway of a campus network, one month)	10,756 Android, 11,328 iOS, 618 BlackBerry	Layer-3+ data

Among such works, only one relies on dictionaries (i.e., Coull et al. in [32]), while the others use machine learning techniques. In what follows, we provide additional observations about datasets, considered actions, and experiments.

Watkins et al. in [30] do not consider actual actions for their analysis. More precisely, they focus on the resource consumption of actions, dividing these into three categories: (i) CPU intensive; (ii) I/O intensive; and (iii) non-CPU intensive. The reported accuracy is the average accuracy across the two employed devices (i.e., 93% and 95%, respectively).

Coull et al. in [32] consider only the iMessage app and choose the following actions: “start typing”, “stop typing”, “send text”, “send attachment”, and “read receipt”. The reported result (i.e., accuracy > 0.99) is related to the identification of such actions, except “read receipt” which is often confused with “start typing”. Moreover, that results assume that traffic from iMessage app has been correctly detected. The authors carry out other experiments related to message attributes which are not reported in Table XXVI:

- The first experiment aims to infer the language (among six languages: Chinese, English, French, German, Russian, and Spanish) of the exchanged messages. It uses a multinomial naive Bayes classifier with 10-fold cross-validation. Assuming to have correctly identified an iMessage action on a mobile device running iOS, the language classification achieves more than 80% accuracy by considering the first 50 packets.
- The second experiment aims to infer the length of the exchanged messages. It uses linear regression and 10-fold cross-validation. This method is able to achieve an average

error of 6.27 characters for text messages, and an absolute error of at most 10 bytes for attachment transfers.

Park et al. in [39] consider eleven user actions performed on the KakaoTalk app: “join a chat room”, “leave the chat room”, “receive a message”, “send a message”, “add a friend”, “hide a friend”, “block a user”, “unblock a blocked user”, “re-add a blocked friend”, “view a user’s profile”, and “synchronize friend list”. The precision, recall, and F-measure reported in Table XXVI are the average across all the considered user actions. The results achieved by Fu et al. in [46] refer to the best-performing classifier (i.e., the random forest).

H. Operating System Identification

In Table XXVII, we report datasets and results for the works that deal with operating system identification. As we can notice, all four works employ supervised learning techniques.

Coull et al. in [32] aim at determining whether the user is using iMessage on iOS (i.e., mobile) or OS X (i.e., desktop) and they are able to distinguish such operating systems with a perfect accuracy (i.e., 100%) after observing only five packets.

In their experiments, Ruffing et al. in [51] observe that, in case of heavy multitasking, the OS detection accuracy can reach 100% with only 30 seconds of network traffic. Considering Android and iOS, the authors also evaluate whether their approach is suitable to discriminate different versions of the same OS. Moreover, the OS detection accuracy can reach 98% and 50% on fifteen-minutes-long traces from the Skype and Youtube apps, respectively.

TABLE XXIV
THE ACHIEVED RESULTS IN THE SURVEYED WORKS THAT DEAL WITH PII LEAKAGE DETECTION.

Year	Paper	Selected Apps	Dataset	Point of Capturing	Content	Analysis Technique	Accuracy	Precision	Recall	F-measure
2012	Stevens et al. [23]	One custom Android app with embedded ad libraries	12.Stevens_0	APs (one access point, one Android device)	HTTP messages	Deep packet inspection	N/A	N/A	N/A	N/A
	Kuzuno et al. [27]	1,188 free Android apps	13.Kuzuno_0	Devices (one Android device)	Layer-2+ data	Machine learning (hierarchical clustering)	0.940	N/A	N/A	N/A
2013	Rao et al. [29]	The top-100 free Android apps from Google Play Store, and 732 Android apps from a free third-party marketplace	13.Rao_0	Wired (VPN server, lab deployment, two Android devices and one iOS device)	Layer-3+ data	Deep packet inspection	N/A	N/A	N/A	N/A
		209 free iOS apps from Apple App Store	13.Rao_1				N/A	N/A	N/A	N/A
		99 malicious Android apps	13.Rao_2				N/A	N/A	N/A	N/A
		The top-100 free apps from Google Play Store (Android), 732 apps from a free third-party marketplace (Android), and 209 free apps from Apple App Store (iOS)	mobUser	Wired (VPN server, real deployment, eleven Android and fifteen iOS devices)			N/A	N/A	N/A	N/A
2015	Le et al. [5]	Unspecified set of Android apps	15.Le_0	Devices (nine Android devices)	Per-app IP headers/packets	Deep packet inspection	N/A	N/A	N/A	N/A
	Song et al. [41]	53 Android apps from Google Play Store	15.Song_0	Devices (one Android device)	IP packets	Deep packet inspection	N/A	N/A	N/A	N/A
2016	Ren et al. [50]	Top-100 free Android apps from Google Play Store, 850 of the top-1,000 free Android apps from a third-party Android marketplace, top-100 free iOS apps from Apple App Store, and top-100 free Windows Phone apps from Windows Phone Store	16.Ren_0	Wired (VPN server)	Layer-3+ data	Machine learning (bag-of-words model, C4.5 decision tree)	0.981	N/A	N/A	N/A
		1260 Android apps from Google Play Store	16.Vanrykel_0	Wired (two VPN servers)	HTTP messages	Deep packet inspection	N/A	N/A	N/A	N/A
2017	Cheng et al. [57]	Seven Android apps, plus a self-developed PII-leaking malicious Android app	17.Cheng_0	Wired (forwarding server, one Android device)	IP and TCP headers	Machine learning (random forest, both incoming and outgoing traffic)	N/A	0.952	0.947	0.948
						Machine learning (random forest, incoming traffic only)	N/A	0.981	0.981	0.980
	Contininella et al. [58]	1,004 Android apps from Google Play Store	17.Continella_0	Wired (forwarding server, six Android devices)	HTTP messages	Deep packet inspection, differential analysis	N/A	0.991	0.990	0.990

TABLE XXV
THE ACHIEVED RESULTS IN THE SURVEYED WORKS THAT DEAL WITH MALWARE DETECTION.

Year	Paper	Selected Apps	Dataset	Point of Capturing	Content	Analysis Technique	Analysis Details	Accuracy	Precision	Recall	F-measure	
2012	Shabtai et al. [22]	40 benign (20 games and 20 tools) and 4 malicious Android apps	From 12.Shabtai_0 to 12.Shabtai_9 (ten datasets)	Devices (two Android devices)	Per-app cellular/Wi-Fi Tx/Rx bytes/packets	Machine learning (random 0.8/0.2 on each dataset, one classifier run on each dataset per device, average)	Bayesian networks	0.992	N/A	0.984	N/A	
							J48 decision tree	0.999	N/A	0.999	N/A	
							Histograms	0.931	N/A	0.949	N/A	
							k-means	0.793	N/A	0.689	N/A	
							Logistic regression	0.999	N/A	0.998	N/A	
							Naive Bayes	0.954	N/A	0.913	N/A	
	Su et al. [24]	(Android) 49 malicious apps (from 22 malware families) and 60 benign apps for training, 50 malicious apps (from 22 malware families) and 70 benign apps for testing	12.Su_0 (training) and 12.Su_1 (testing)	Devices	Layer-2+ data	Machine learning (supervised learning)	J48 decision tree	0.916	N/A	N/A	N/A	
	Wei et al. [25]	102 malicious Android apps from a public Android malware dataset, and popular Android apps from Google Play Store	12.Wei_0	Wired (forwarding server)	DNS data	Machine learning (unsupervised learning, kCross(10))	Independent Component Analysis (ICA)	1.000	1.000	N/A	N/A	
2014	Shabtai et al. [35]	Several benign Android apps, ten self-updating malicious Android apps, and the infected version of five of the chosen benign apps	14.Shabtai_0 14.Shabtai_1 14.Shabtai_2	Devices (one Android device)	Per-app bytes percent out of total Tx/Rx bytes	Machine learning (supervised learning)	Decision tree	N/A	N/A	0.926	N/A	N/A
							Inspect HTTP messages for the URLs of malicious domains	N/A	N/A	0.954	N/A	N/A
							Bayesian network	N/A	N/A	0.824	N/A	N/A
2015	Zaman et al. [44]	Two Android malware samples (DroidKungFu and AnserverBot)	15.Zaman_0	Devices (one Android device)	Layer-2+ data and netstat logs	Malicious domain blacklisting	Multi-layer perceptron	0.500	N/A	N/A	N/A	
							J48 decision tree	N/A	N/A	0.883	0.880	N/A
2016	Narudin et al. [48]	The top-twenty free (benign) Android apps from Google Play Store, and 1,000 malicious Android apps (from 49 malware families)	Ds1000	Devices (one Android device, for benign apps), emulators (for malicious apps)	Per-app layer-2+ data	Machine learning (supervised learning, feature selection, kCross(10))	k-nearest neighbors	N/A	N/A	1.000	0.997	0.997
							Random forest	N/A	N/A	1.000	1.000	1.000
							Bayesian network	N/A	N/A	0.841	0.756	0.750
							Multi-layer perceptron	N/A	N/A	0.880	0.840	0.839
							J48 decision tree	N/A	N/A	0.836	0.738	0.730
2016	Wang et al. [8]	8,312 benign Android apps from Google Play Store, and 5,560 malicious Android apps	Priv	Wired (forwarding server)	TCP- and HTTP-related data	Machine learning (supervised learning, unspecified holdout)	k-nearest neighbors	N/A	N/A	0.884	0.846	0.845
							Random forest	N/A	N/A	0.837	0.741	0.734
							C4.5 decision tree on TCP-related features	N/A	N/A	0.982	N/A	N/A
2017	Arora et al. [55]	Benign and malicious (from eleven families) Android apps for training, benign and malicious (from six families) Android apps for testing (different from those used for training)	17.Arora_0 (training) and 17.Arora_1 (testing)	Devices (one Android device)	IP packets	Machine learning (supervised learning)	C4.5 decision tree on HTTP-related features	N/A	N/A	0.997	N/A	
							Naive Bayes, 22 network-layer features (no feature selection)	N/A	N/A	N/A	0.873	N/A
							Naive Bayes, 9 network-layer features chosen by feature selection	N/A	N/A	N/A	0.833	

TABLE XXVI
THE ACHIEVED RESULTS IN THE SURVEYED WORKS THAT DEAL WITH USER ACTION IDENTIFICATION.

Year	Paper	Dataset	Point of Capturing	Content	Analysis Technique	Platform	App(s)	# Actions	Accuracy	Precision	Recall	F-measure	
2013	Watkins et al. [30]	13.Watkins_0	APs (one access point, two Android devices)	Inter-packet time of ICMP responses	Machine learning (0.5/0.5, neural-fuzzy classifier)	Android	Adobe Reader	3	0.940	N/A	N/A	N/A	
							Angry Birds						
2014	Coull et al. [32]	14.Coull_0	Devices	Packet sizes within APNS connection	Dictionary, kCross(10)	iOS	iMessage	5	0.990+	N/A	N/A	N/A	
							AppMgr III						
2015	Park et al. [39]	15.Park_0	Wired (forwarding server, one Android device)	IP and TCP headers	Machine learning (agglomerative hierarchical clustering, random forest, kCross(10))	Android	KakaoTalk	11	0.997	0.976	0.977	0.977	
							Music Player						
2016	Conti et al. [45]	16.Conti_0	Wired (forwarding server, one Android device)	IP and TCP headers	Machine learning (agglomerative hierarchical clustering, random forest)	Android	Dropbox	9	N/A	0.950	0.920	0.920	0.920
							Evernote	7	N/A	1.000	1.000	1.000	1.000
							Facebook	8	N/A	0.990	0.980	0.990	0.990
							Gmail	5	N/A	0.830	0.850	0.860	0.860
							Google+	11	N/A	0.900	0.940	0.920	0.920
							Tumblr	11	N/A	0.990	0.990	0.990	0.990
							Twitter	7	N/A	0.980	0.970	0.970	0.970
Fu et al. [46]	16.Fu_0	16.Fu_1	APs (one virtual access point per device, fifteen Android devices)	Size and timing of IP packets	Machine learning (hierarchical clustering, random forest, hidden Markov model)	Android	WeChat	8	0.960+	N/A	N/A	N/A	
			APs (one virtual access point per device, five Android devices)	IP headers	Machine learning (k-means clustering, multi-class support vector machine)	Android	WhatsApp	6	0.976	N/A	N/A	N/A	
Saltaformaggio et al. [52]	16.Saltaformaggio_0	APs (one access point, two iOS and five Android devices)	IP headers	IP headers	Machine learning (k-means clustering, multi-class support vector machine)	Android, iOS	22 popular apps available on both platforms	35	N/A	0.780	0.760	N/A	

I. Position Estimation

In Table XXVIII we summarize the information related to the datasets used by the works that deal with position estimation.

Husted et al. in [11] show that, in a metropolitan population of users equipped with 802.11g mobile devices, having only 10% of tracking population is sufficient to track the position of the remaining 90% of users. Besides, the tracking benefits from extending the broadcasting range of the mobile devices (better with newer 802.11 standards).

Musa et al. in [21] evaluate the accuracy of their trajectory estimation method by considering three deployments of monitors and leveraging GPS as ground truth. Using monitors spaced over 400 meters apart, the proposed system achieves a mean error of less than 70 meters.

J. User Fingerprinting

In Table XXIX, we report validation methods and results of the two works about user fingerprinting. Despite the common goal, these two analyses are quite different. Indeed, Verde et al. in [36] collect datasets of NetFlow records, while Vanrykel et al. in [54] rely on a dataset of HTTP messages. Besides, the former work employ machine learning techniques while the latter performs a graph-based analysis.

Regarding Verde et al. in [36], the results achieved on the “14.Verde_0” dataset refers to the best performing classifier (i.e., random forest). On the other hand, the results achieved on the “14.Verde_1” dataset are the average across the five targeted mobile users. To build a reliable profile for those users, their network traffic is captured from a Wi-Fi access point (under the control of the authors). Vanrykel et al. in [54] are able to link 57% of the unencrypted mobile traffic collected to a specific user/device using graph-based analysis on HTTP messages.

K. Ad Fraud Detection

The only work that investigates ad fraud is the one by Crussell et al. in [33]. The authors validate their proposal on a dataset of network traffic (i.e., layer-2+) collected from mobile device emulators on which they run 130,339 Android apps from nineteen marketplaces, and 35,087 Android apps that probably contain malware. To build the ground truth, the authors manually labeled the page requests of the domains related to ad providers. The authors used a random forest classifier applying a three-fold cross-validation on such labeled dataset. The achieved results are an accuracy of 0.859 and a recall of 0.718. As an additional finding, the authors discover that around 30% of apps with ads request to display an ad while running in the background, and 27 apps generate clicks without user interaction.

L. Sociological Inference

In this section, we report the datasets used for validation by Barbera et al. in [26], the only work that carries out sociological inference. The authors collect datasets containing

802.11 probe requests. The datasets are related to an event or place in which the monitor(s) are deployed:

- Datasets *P1* and *P2* at a political meeting (five monitors);
- Datasets *V1* and *V2* at a Pope’s mass (five monitors);
- Dataset *M* at a big shopping mall (five monitors);
- Dataset *TS* at a train station (five monitors);
- Dataset *U* at a university’s campus (one monitor);
- Dataset *others* at city streets and squares (one monitor).

Relying on these datasets, the authors provide the findings that are discussed in Section III-K.

M. Tethering Detection

Only one work aims to detect tethering and it is proposed by Chen et al. in [31]. The authors build the first dataset using several points of capturing: a wired network equipment (i.e., a network switch), Wi-Fi monitors (i.e., nine monitors for two days at OSDI 2006, eight monitors for five days at SIGCOMM 2008), and an access point. In particular, they capture DHCP and DNS payloads, and layer-2+ headers from the network switch; size and header of IP packets from monitors; and IP and TCP headers from the access point. The second dataset contains one week of network traffic (i.e., IP packets) collected at the Internet gateway of a campus Wi-Fi network serving 12,600 users.

The authors develop an ad hoc probabilistic classifier to carry out their analysis. The achieved results on the first dataset are 0.68-0.85 recall with precision fixed at 0.95, and 0.78-0.89 recall with precision stable at 0.8. Besides, the results on the second dataset are 0.86 precision, 0.74 recall, and 0.8 F-measure.

N. Website Fingerprinting

The work by Spreitzer et al. in [53] deal with website fingerprinting. This work relies on a dataset containing statistics provided by a mobile browser in terms of transmitted and received bytes of TCP connections. The authors develop a fingerprinting system that employs a machine learning classifier based on Jaccard’s index. Under a normal Internet connection, such fingerprinting system can correctly infer 97% of 2,500 page visits out of a set of 500 monitored pages. Instead, with the traffic routed through Tor by using the Orbot proxy combined with the Orweb browser, the proposal identifies 95% of 500 page visits out of a set of 100 monitored pages.

VIII. COUNTERMEASURES AGAINST MOBILE TRAFFIC ANALYSIS

In this section, we present possible countermeasures proposed in the literature to thwart mobile traffic analysis. In the first instance, we discuss how encryption on different layers can affect the surveyed work in Section VIII-A. We will show that part of the surveyed work is able to cope with encryption. Hence, we survey the state-of-the-art countermeasures and their effectiveness and limitations in Section VIII-B.

TABLE XXVII
THE ACHIEVED RESULTS IN THE SURVEYED WORKS THAT DEAL WITH OPERATING SYSTEM IDENTIFICATION.

Year	Paper	Dataset	Point of Capturing	Content	Analysis Technique	Analysis Details	Platform	Accuracy	Precision	Recall	F-measure
2014	Chen et al. [31]	14.Chen_0	Wired (switch), monitors (nine monitors for two days at OSDI 2006, eight monitors for five days at SIGCOMM 2008), APs (one access point)	Layer-2+ headers plus DHCP and DNS payloads (switch), size and header of IP packets (monitors), IP and TCP headers (APs)	Machine learning (supervised learning)	Naive Bayes	Android	N/A	1.000	0.800	N/A
			Devices	Packet sizes within APNS connection	Machine learning (supervised learning)	Binomial naive Bayes, kCross(10)	iOS	N/A	1.000	1.000	N/A
2016	Ruffing et al. [51]	16.Ruffing_0	Monitors (one monitor for three months, two Android devices, two iOS devices, a Windows Phone device, and a Symbian device)	Timing of 802.11 frames	Machine learning (supervised learning, frequency spectrum analysis)	Consider only the traces lasting five minutes or more	Android, iOS, Windows Phone, Symbian	0.700	N/A	N/A	N/A
			APs (one access point, one Android device, one iOS device, one Windows Phone device)	Inter-packet time of ICMP responses Inter-packet time of IP packets related to video streaming	Machine learning (supervised learning)	Random forest, kCross(10)	Android, iOS, Windows Phone	0.752	N/A	N/A	N/A
2017	Malik et al. [60]	17.Malik_0 17.Malik_1									

TABLE XXVIII
THE DATASETS AND ANALYSIS TECHNIQUES OF THE SURVEYED WORKS THAT DEAL WITH POSITION ESTIMATION.

Year	Paper	Dataset	Point of Capturing	Content	Analysis Technique
2010	Husted et al. [11]	10.Husted_0	Simulator (3D simulation, mobile devices in dense metropolis)	802.11 probe requests	Trilateration
		12.Musa_0	Monitors (five monitors, nine months, streets near a campus)		Machine learning (hidden Markov model, Viterbi's map-matching algorithm)
2012	Musa et al. [21]	12.Musa_1	Monitors (six monitors, twelve hours, fairly busy city roads)		
		12.Musa_2	Monitors (seven monitors, twelve hours, arterial city road)	802.11 probe requests	

TABLE XXIX
THE ACHIEVE RESULTS IN THE SURVEYED WORKS THAT DEAL WITH USER FINGERPRINTING.

Year	Paper	Dataset	Point of Capturing	Content	Analysis Technique	Accuracy	Precision	Recall	F-measure	DAR
2014	Verde et al. [36]	14.Verde_0 14.Verde_1	Wired (gateway router, 26 mobile users on same Wi-Fi AP, one month)	NetFlow records	Machine learning (hidden Markov model, supervised learning)	N/A	0.950	0.930	0.940	N/A
			Wired (tier-2 router of metropolitan Wi-Fi network, 200,000 users, one day)				N/A	0.958	0.956	0.954
2016	Vanrykel et al. [54]	16.Vanrykel_0	Wired (two VPN servers)	HTTP messages	Graph building	N/A	N/A	N/A	N/A	0.570

A. Encryption

The first countermeasures in place are network traffic encryption methods. Such methods aim to guarantee users' privacy against information leaks and DPI. Encryption can be applied at different levels of network protocol stack, such as network (e.g., IPsec) and transport (e.g., SSL/TLS) layers. From the network analysis perspective, the primary effect of the encryption at a given layer is to make unavailable the information of the above layers. This means that SSL/TLS encryption will hide the transport-layer payloads, but TCP/UDP headers will be still available; IPsec encryption, instead, will also hide the TCP/UDP headers, leaving only IP headers for analysis. It is worth noticing that for the sake of simplicity we use the term "IPsec encryption" to refer all the methods that make available IP headers only, such as IPsec (in both transport and tunnel mode), Virtual Private Networks (VPNs) and Tor (The Onion Routing).

As a preliminary overview, for each surveyed work we listed in Table I, we pointed out whether its analyses were applicable in presence of the aforementioned encryption methods. In what follow, we discuss in detail whether encryption affects or not the network analysis techniques adopted by the surveyed work. On one hand, 40 works in this survey are still able to carry out their analysis if SSL/TLS encryption is in place. On the other hand, only 21 works do not rely on information that is hidden by IPsec encryption. The effect of encryption on the analysis strictly depends on the point of capturing. For this reason, for each point of capturing (ordered by the number of related works, as in Section II-B) we report which analysis and why is affected by which type of encryption. In particular, given a point of capturing we discuss the works by year of publication.

1) *Wired networks*: In this section, we discuss the impact of encryption when the point of capturing is wired networks. We divide the presentation of the works into small and large scale networks.

a) *Small Scale*:

- Rao et al. in [17] study the network traffic of the Android and iOS apps for Netflix and YouTube. They successfully inspect the HTTP messages to get the encoding rate of the videos, therefore both services stream videos in clear (at least, they did so at the time the authors collected their datasets).
- The analysis carried out by Baghel et al. in [18] needs to inspect the transport-layer headers, therefore it does not work if IPsec is employed to hide the payload of IP packets. The Android malware detector by Wei et al. [25] requires to access DNS data, which is not possible if the traffic is encrypted.
- To carry out PII leakage detection, Rao et al. in [29] and Ren et al. in [50] inspect HTTP traffic, which is sent in clear, and also HTTPS traffic, which is decrypted using SSLsplit. This approach cannot work, however, if the traffic of a given app is protected by IPsec.
- Chen et al. in [37] focus on the properties of the network traffic of malicious Android apps, and their findings are mainly related to the application layer. For this reason, such

findings are limited to the data that the analyzed apps sent in clear during the capturing process.

- The user action identification frameworks developed by Conti et al. in [45], and Park and Kim in [39], the app identification solution proposed by Taylor et al. in [61] and the PII leakage detection method by Cheng et al. in [57] leverage the information available in IP and TCP headers. As a consequence, such approaches are by design resilient against SSL/TLS, but cannot cope with encryption via IPsec.
- To study the network behavior of several Android and iOS free apps, Nayam et al. in [49] inspect the HTTP messages, and employ a proxy server to deal with HTTPS traffic. Although such approach does not work with apps that employ IPsec to hide their network transmissions, it seems that all the analyzed apps do not leverage such type of encryption.
- The PII leakage detection and user fingerprinting framework proposed by Vanrykel et al. in [54] is focused on unencrypted mobile traffic only, since it requires to inspect HTTP messages.
- Wang et al. in [8] present two Android malware detection models which leverage TCP- and HTTP-related information, respectively. The latter cannot work for apps that encrypt their network traffic using SSL/TLS, and both cannot cope with apps that employ IPsec for their data transmissions.
- The PII leakage detection solution by Continella et al. [58] requires to access the HTTP messages. Although a man-in-the-middle approach is adopted to deal with HTTPS traffic, the framework cannot cope with network traffic protected by IPsec.

b) *Large Scale*:

- Afanasyev et al. in [9] focus part of their analysis on the applications that generate mobile and non-mobile traffic. In particular, they need to inspect transport- and application-layer headers. For this reason, the reported findings do not cover the encrypted traffic present in the collected network traces. The same holds for the mobile traffic characterization by Chen et al. [19].
- The analysis carried out by Maier et al. in [12] requires to access transport- and application-layer information, therefore it cannot deal with encrypted traffic.
- The study by Finamore et al. in [14] focuses on YouTube traffic carried over HTTP and does not consider the users that watch videos via a secure connection (i.e., HTTPS).
- The app identification via payload signatures proposed by Lee et al. in [16] cannot work with apps that encrypt their network traffic. Moreover, in case of encryption the authors' studies of mobile traffic characteristics and mobile users' habits are severely limited.
- The tethering detection technique proposed by Chen et al. in [31] requires to inspect the information available in TCP headers, therefore it does not work if IPsec is employed to hide the payload of IP packets.
- As we previously mentioned in Section IV-A, the mobile user fingerprinting framework by Verde et al. in [36] is encryption-agnostic even in their experiment carried out on a large-scale network, since it takes NetFlow records as input.

- A few of the findings about mobile traffic reported by Wei et al. in [62] are based on application-layer information, which is unavailable in case of traffic encryption.

2) *Mobile Devices*: Regarding the works that capture network traffic directly within mobile devices, we provide the following observations about the effect of encryption.

- Network traffic statistics (e.g., the amount of received bytes through the cellular network) are not affected by encryption, therefore the methods that leverage them are encryption-agnostic. These works are the ones proposed by Ham and Choi in [20], Shabtai et al. in [22], Shabtai et al. in [35], Fukuda et al. in [38], Soikkeli and Riikonen [40], Spreitzer et al. in [53], and Arora and Peddoju in [55]. It is worth to notice that this assertion is not trivial for the work in [53] since its authors leverage the TCP bytes sent/received by the browser app, which it is still available even if the traffic is encrypted via IPsec.
- Falaki et al. in [10] carry out both traffic characterization (Section III-A) and usage study (Section III-C). The former is focused on the TCP protocol, therefore it does not cover the traffic protected by IPsec, whenever present in the collected network traces. The latter leverages the per-app transmitted/received bytes, which are network traffic statistics (i.e., they are not affected by encryption).
- Shepard et al. in [13] provide a few findings about the network traffic of iOS devices. Their analysis is focused on the TCP protocol, hence it does not cover the network traffic protected by IPsec.
- Su et al. in [24] propose a classifier for Android malware detection that cannot process the network traffic encrypted via IPsec since one of the leveraged features is the average TCP session duration, which is not computable without accessing TCP headers.
- To identify Android apps, Wei et al. in [4] perform the following operations: (i) inspect the IP addresses of the captured packets; (ii) compute the amount of transmitted/received data; and (iii) discriminate between HTTP and HTTPS traffic. The first two operations are encryption-agnostic, while the third one is not possible in case an app communicates through IPsec.
- To apply clustering for PII leakage detection, Kuzuno and Tonami in [27] use two metrics that are based on information within HTTP messages which are not accessible when any form of encryption is in place.
- To evaluate their solution for Android app identification, Qazi et al. in [28] set up a monitored access point serving a few mobile devices. The network traffic flowing through the AP is captured, and netstat logs from the devices are gathered. Such logs are then used to match the network flows observed at the AP with the TCP transmissions from the mobile devices, hence this methodology does not work if IPsec is employed.
- The user action and OS identification methods devised by Coull and Dyer in [32] are designed to work with the network traffic of iMessage (Apple’s instant messaging service), which uses encryption by default.

- Le et al. in [5] carry out both app identification (see Section III-B) and PII leakage detection (see Section III-D). The former requires to access the flags of TCP segments, which are hidden if IPsec is employed. The latter needs to inspect application-layer data, which is infeasible if the traffic is encrypted.
- The app for PII leakage detection by Song and Hengartner [41] employs a man-in-the-middle approach to inspect TLS traffic, but it cannot deal with IP packets whose payloads are encrypted by IPsec.
- The Android malware detection solution by Zaman et al. [44] needs to access the URLs within HTTP messages, which are not available if the traffic is encrypted.
- Mongkolluksamee et al. in [47] extract the TCP and UDP data from the collected network traffic of the apps to be profiled. After that, they inspect the headers to reconstruct the captured network flows and compute their statistics (e.g., per-flow total amount of transferred bytes). This approach cannot be applied to apps that encrypt their network traffic using IPsec.
- The malware detection framework by Narudin et al. [48] requires to inspect HTTP messages, therefore it cannot work with encrypted traffic.
- By employing the mobile traffic characterization framework proposed by Espada et al. [59], it is possible to check whether the network traffic of an Android app satisfies a given property. The effect of encryption on the analysis depends on the properties to be verified. Regarding the presented case study (Spotify), the authors successfully access HTTP headers and compute traffic statistics (e.g., number of sent/received TCP segments).

3) *Wi-Fi Access Points*: In this section we consider works in which network traffic is captured from access points in a controlled or not controlled environment. We provide the following observations about the effect of encryption.

APs in a controlled environment — Stevens et al. in [23] study thirteen popular ad libraries for Android. For each library, the authors build a simple app that makes ad requests, then they execute it on a mobile device while capturing the network traffic at the access point to which that device is associated. Since only one of the considered ad libraries leverages encryption to protect its network traffic, the authors apply deep packet inspection to investigate the leakage of the user’s PII. Qazi et al. in [28] set up a wireless access point running OpenFlow and instruct it to extract features from the network traffic of the associated mobile devices. Since it requires to inspect transport-layer information, the proposed framework cannot process network traffic protected by IPsec.

The framework for user action identification presented by Watkins et al. in [30] exploits the inter-packet time of the responses to ICMP packets sent to the target mobile device by a laptop connected via cable to the same network, therefore it is not affected by traffic encryption. The OS identification method by Chen et al. [31] needs to access the headers of TCP segments, so it cannot work if IPsec is employed to hide the payload of IP packets. The app identification solution by Yao et al. [43] requires to access HTTP messages, which is not possible if the traffic is encrypted. The app identification

framework proposed by Alan and Kaur [6] provides three different classifiers. Two of them only leverage the size of IP packets, thus they can take encrypted traffic as input. Instead, the other classifier requires to inspect the content of TCP headers, therefore it works on network traffic encrypted via SSL/TLS, but it does not via IPsec.

The solutions proposed by Saltaformaggio et al. in [52] (user action identification), as well as Tadrous and Sabharwal in [7] (traffic characterization), are encryption-agnostic: the former requires only to inspect IP headers; the latter needs only the size and header information of 802.11 frames. The framework for OS identification presented by Malik et al. in [60] exploits the inter-packet time of the packets (either ICMP responses or IP packets related to video streaming) coming from the target mobile device, therefore it is not affected by traffic encryption. Finally, the proposal by Fu et al. in [46] rely on IP headers only, thus it is resilient to traffic encryption.

APs in a uncontrolled environment — Gember et al. in [15] carry out a comparison between mobile and non-mobile devices with regard to network traffic properties and habits of users. Since the analysis is mainly focused on transport and application layers, most of the authors' findings are related to non-encrypted traffic. Whenever the encryption at network (IPsec) or transport layers (SSL/TLS) is employed, the HTTP information becomes inaccessible, thus making the discrimination process (if not the entire analysis) infeasible.

4) *Wi-Fi Monitors*: As we discuss in Section IV-E, Wi-Fi monitors scan radio bands to capture IEEE 802.11 frames which can be encrypted at data-link layer using Wired Equivalent Privacy (WEP) or Wi-Fi Protected Access (WPA).

The attacks by Musa and Eriksson in [21] and Barbera et al. in [26] cannot be affected by encryption because they rely on probe requests. Due to their nature, probe requests are transmitted in clear. The analyses carried out by Wang et al. in [42] and Ruffing et al. in [51] are encryption-agnostic since they leverage only size and/or timing of the captured 802.11 frames. However, this statement does not hold for Chen et al. in [31], since their analysis requires to access IP payloads.

5) *Mobile Device Emulators*: Mobile device emulators are employed as sandboxes for ad fraud detection and malware analysis. All the three works that rely on emulators aim to inspect HTTP messages, thus the proposed solutions would not work anymore if encryption is applied.

Crussell et al. in [33] carry out ad fraud detection relying on emulators. The proposed framework is not resilient to encryption since it needs to inspect the HTTP and DNS data generated by apps. However, the authors' analysis covers most of the available ad libraries. This means that such libraries do not usually employ any form of encryption for their data transfers, and simply rely on plain HTTP.

The ANDRUBIS framework proposed by Lindorfer et al. in [34] relies on Android emulators to carry out dynamic malware analysis. Such framework focuses its analysis on high-level protocols (e.g., DNS, HTTP, IRC), which is not feasible if the analyzed app encrypts its network traffic. Yao et al. in [43] propose an app identification method on three mobile platforms (i.e., Android, iOS, and Symbian). Unfortu-

nately, since the system requires to inspect HTTP messages, it does not work if an app leverages HTTPS or lower-layers encryption.

Narudin et al. in [48] and Chen et al. in [56] propose machine learning to detect Android malware and a method for app identification, respectively. Both these works rely on HTTP messages inspection, hence they cannot cope with encrypted network traffic.

6) *Network Simulators*: The work on position estimation by Husted and Myers in [11] is the only work that relies on software network simulators to generate mobile traffic. This work is not affected by encryption since it focuses on propagation of probe requests, which are not encrypted.

B. Other Countermeasures

As a countermeasure to privacy invasive mobile traffic analyses (i.e., app identification, user action identification, website fingerprinting, and user fingerprinting), encryption alone is not enough to neutralize them. Indeed, such analyses often focus on network flows behavior or packets exchange patterns. A research field that provides solutions to thwart these kinds of analysis is the one that investigates countermeasures against websites fingerprinting. In this research field, researchers consider an adversary that is able to observe timing, direction, and size of packets within an encrypted connection when a browser loads a webpage [68], [69], [70], [83]. Similarly to our IPsec scenario, the considered attacks rely on IP headers only since they assume to carry out traffic analysis in presence of an anonymity network such as a VPN or Tor. Under these settings, the countermeasures proposed to tackle traffic analysis can be divided in two categories: padding- and distribution-based countermeasures. In what follows, we describe such kind of countermeasures. Moreover, we discuss what impact their application could bring on mobile network traffic.

a) *Padding-based Countermeasures*: This category of countermeasures considers an active modification of the network traffic at packet level. Packet padding is a technique that consists in appending extra information to a packet payload in order to obfuscate its original size. Implementations of SSL 3.0 and TLS 1.0+ already apply a random padding between 0 and 255 bytes to encrypted packets. Unfortunately, SSL/TLS padding provides a limited protection since a padding of at most 255 bytes, compared with the Maximum Transmission Unit (MTU) does not introduce a significant level of noise. For this reason, other padding techniques propose to add dummy bytes to reach a packet size that is multiple of 128 bytes (i.e., linear padding), the nearest power of two (i.e., exponential padding), or MTU.

Researchers propose more sophisticated techniques that not only apply padding on packets' sizes, but also to timing. Dyer et al. in [84] present BuFLO (Buffered Fixed-Length Obfuscation), which apply padding in such a way that packets are sent with a fixed size. Moreover, BuFLO also fixes the packet transmission rate to cope with timing attacks. Cai et al. in [85] propose Tamaraw which is based on BuFLO, but apply a different padding according to the direction of the packet. More recently, Wang et al. in [86] present Walkie Talkie which

modify a web browser to buffer packets, add padding, and transmit them in bursts (i.e., half-duplex mode).

b) Distribution-based Countermeasures: A different approach to counter traffic analysis aims to intervene on the distribution of packets in a network flow. Wright et al. in [87] proposed *traffic morphing*, a distribution-based countermeasure which transforms the original distribution of network packets to a pre-defined target distribution. In practice, traffic morphing reshapes network flows by truncating and padding packets, not only modifying packets sizes but also changing the very number of packets.

Another example of traffic morphing is called *Glove*, which is proposed by Nithyanand et al. in [88]. In first instance, *Glove* regroups websites which network flows are similar into clusters. Hence, *Glove* applies the minimum dummy traffic in such a way that all websites in a cluster will have the same shape, thus they cannot be distinguished from each other. This means that an attacker cannot identify a specific website, but only the cluster to which it belongs.

c) Countermeasures Applied to Mobile Traffic: In the mobile scenario, we have to take into account that we are considering devices that are powered by batteries. Another aspect that has to be considered is that mobile users have a limited volume of Internet traffic given the subscription with a telephonic company (usually a fixed amount of gigabytes). On one hand, the aforementioned padding-based countermeasures generate a bandwidth overhead that ranges between 31% and 145%, with a time overhead that ranges between 34% and 180% for [86] and [84], respectively. On the other hand, distribution-based countermeasures change the shape of a network flow. This procedure has computational costs due to packets aggregation and segmentation while still relying in part on padding.

Countermeasures that introduce a high overhead in terms of bandwidth, time, and computational cost are not feasible on mobile device since such overhead directly result in additional monetary cost, worse user experience, and increased battery consumption. Among the considered countermeasures, the most mobile friendly seems to be *Walkie Talkie* [86], since it offers a reasonable trade off between bandwidth and time overhead. Another possible solution is to deploy a countermeasure (even with high overhead) on the access point rather than on the mobile device, offloading to the access point the padding and computational burdens. Unfortunately, this solution does not protect from attacks that eavesdrop the traffic between mobile devices and access points.

IX. CHALLENGES AND FUTURE OF TRAFFIC ANALYSIS TARGETING MOBILE DEVICES

In this section, we first provide an overall discussion about today's challenges and pitfalls that emerged from the surveyed works in Section IX-A. Then, we outline possible future research directions of mobile traffic analysis in Section IX-B.

A. Challenges and Pitfalls

In state-of-the-art works on mobile traffic analysis, researchers encounter several challenges while devising their

analyses. A first challenge involves the discrimination between mobile and non-mobile traffic in large-scale networks. As a common practice to overcome this challenge, researchers leverage the information available from network traffic. In case of unencrypted traffic, HTTP messages contain the *user-agent* field from which it is possible to obtain information such as mobile device and operating system [12], [14], [19]. In presence of traffic encryption, it is still possible to rely on the default Time-To-Live (TTL) value of IP packets. Another method uses DHCP logs to map an assigned IP address with a MAC address, then to identify mobile devices by extracting the Organizationally Unique Identifier (OUI) from those MAC addresses. In the aforementioned methods, researchers assume that user-agent fields and MAC addresses are not spoofed, and TTL values are the default ones given by the operating systems.

Another challenge is collecting a dataset that includes a solid ground truth, a fundamental task to obtain truthful results. While dataset collection process and data format strictly depend on the point of listening, network traffic labeling requires additional information that has to be retrieved from a different source. For some specific goals of the analysis, traffic labeling can be simple but, especially when it considers real mobile devices, it can become challenging.

In general, it is possible to build a solid ground truth whether one of these two conditions occur: (i) the goal of the analysis is related to the property of the device itself; (ii) the researchers can gain full control of the experiment. On one hand, the former condition can be applied to operating system identification and user fingerprinting. In fact, knowing the pre-assigned IP address or the MAC address of a mobile device is enough to label the traffic as belonging to a specific user or operating system. On the other hand, two examples of the latter condition are works that perform app identification and user action identification, since the goal of these analyses is related to OS internal processes and human-device interaction. For this reason, researchers need to acquire full control of the experiment in order to build a reliable ground truth. While for user action identification tasks researchers have to provide a solid time correlation between a user action and the resulting network traffic, building the ground truth for app identification tasks is more challenging, since they need to know exactly which app generated which network packet or flow. To cope with this problem, a good practice on Android devices is to rely on a logging app (e.g., *NetworkLog* [89], *DELTA* [71]) that associates the Process ID (PID) of an app to each network packet or flow it generates.

Common pitfalls of mobile traffic analysis are mostly related to the experimental design and data collection. In app identification tasks, researchers have to take into account that apps often rely on common third-party libraries (e.g., ad libraries in free apps), thus some traffic patterns generated by an app are not useful to discriminate it among the other considered apps. Hence, the analysis has to cope with such ambiguous traffic and filter it out.

A possible error is not considering enough data sources in order to build a representative dataset for the goal of the analysis. The work by Malik et al. in [60] is a clear

example of this kind of pitfall. In this work, the authors aim at distinguishing between three operating systems but they collect network traffic of only three devices (i.e., one for each targeted operating system). The collected dataset is not representative enough for operating system identification because the traffic may be influenced by both device model and OS version (i.e., bias on the data). Hence, the accuracy is related to the recognition of a specific device (i.e., device model, OS, and its version altogether) among the three considered ones.

Another similar pitfall is to perform an analysis under a close-world assumption. This assumption does not consider aspects or possible events in the real world. This means that in a classification task it must be taken into account not only the classes on which the analysis is focused, but also other possible classes. As an example, in app identification it has to consider, in addition to the targeted apps, the other applications on the market (e.g., as a stand-alone class). Another pitfall is related to mobile malware detection. Proposed works on this topic use emulators instead of real devices. Unfortunately, emulators can be detected using sandbox detection techniques. Hence a malware that detects a sandbox could not execute its malicious payload, thus evading malware analysis [90].

B. Possible Future Directions

In this survey, we can observe an imbalance in terms of the number of works per goal of the analysis. Indeed, some goals are not covered enough by the state of the art of mobile traffic analysis. This makes room for interesting research directions that could have severe economic and privacy implications.

Research on user fingerprinting, sociological inference, and position estimation could be vastly improved since those fields are seriously related to user privacy. Indeed, information obtained from such types of analysis can be used to track the user's movements and infer user sensible information (e.g., nationality, relationships). Surprisingly, only one work investigates ad fraud detection. Ad providers are economically affected by such frauds since they result in a financial loss. Another interesting research direction could be investigating whether there exist differences between mobile and desktop websites in terms of network traffic.

Solutions proposed for mobile traffic analysis can also be applied to the emerging Internet of Things (IoT) paradigm. IoT devices are interconnected and they can both sense the real-world status (i.e., sensors) and intervene to change it (i.e., actuators). Similarly to mobile devices, the communications between IoT devices generate network traffic and they are carried through the same protocol stack. For this reason, we believe that the surveyed analyses on network traffic of mobile devices can become valuable in the IoT domain. As an example, user action identification techniques could be applied to infer information about the real world from the actions performed by an actuator. Moreover, OS or app identification techniques could be used to infer an IoT device's model or firmware version.

X. CONCLUSIONS

In this paper, we surveyed the state of the art of the methods for analyzing the network traffic generated by mobile devices. In particular, we are the first that surveyed the works in which the mobile traffic is captured from alternative sources to cellular networks: Wi-Fi monitors and access points; wired networks; logging apps installed on mobile devices; and networks of mobile devices simulated via software. For each point of capturing, we described its characteristics, the number of mobile users that it monitors, as well as the issues related to the capturing process. Moreover, we observed that the most frequently used approach to capture mobile traffic is logging at either wired networks or mobile devices themselves.

We provide a systematic classification of the state of the art according to the goal of the analysis that targets the network traffic of mobile devices. In particular, we realized that most of the works focus on studying the features of the network traffic generated by mobile devices. Other popular goals are app and user action identification, usage study, and Personal Identifiable Information (PII) leakage and malware detection. While a lot of work has been done on such goals, promising topics, such as user fingerprinting and sociological inference, still offer much room for further investigation.

We also categorized the works on mobile traffic analysis according to the targeted mobile platforms. We observed that Android is not only the most popular mobile platform, but also the most targeted by the analysis methods (i.e., 42 out of 45 works which are not platform-independent). In fact, we demonstrated that the openness of the Android platform is a double-edged sword: on the one hand, it provides mobile users with a large number of apps that enable the most disparate functionalities; on the other hand, it helps malicious developers distribute malware, and more generally, apps that behave ambiguously with regard to the security of mobile devices and the privacy of mobile users.

We observed that most of the surveyed works rely on machine learning techniques, thus we outline the procedure to carry out a machine-learning-based analysis as a tutorial for new researchers. In particular, we also observed a prevalence of frameworks based on supervised learning, clustering, or a combination of both. For each framework, we reported and discussed actual application and performance. We also report possible countermeasures to tackle against mobile traffic analysis and preserve user privacy. Finally, we discuss challenges, pitfalls, and possible future research directions in the field of mobile traffic analysis.

ACKNOWLEDGMENT

Mauro Conti is supported by a Marie Curie Fellowship funded by the European Commission (agreement PCIG11-GA-2012-321980). This work is partially supported by the EU Tag-ItSmart! Project (agreement H2020-ICT30-2015-688061), the EU-India REACH Project (agreement ICI+/2014/342-896), the grant n. 2017-166478 (3696) from Cisco University Research Program Fund and Silicon Valley Community Foundation, and by the grant "Scalable IoT Management and Key security aspects in 5G systems" from Intel. QianQian Li is supported by Fondazione Cassa di Risparmio di Padova e Rovigo.

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