DIGITAL PRIVACY UNDER ATTACK: CHALLENGES AND ENABLERS

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ABSTRACT. Users have renewed interest in protecting their private data in the digital space. When they don't believe that their privacy is sufficiently covered by one platform, they will readily switch to another. Such an increasing level of privacy awareness has made privacy preservation an essential research topic. Nevertheless, new privacy attacks are emerging day by day. Therefore, a holistic survey to compare the discovered techniques on attacks over privacy preservation and their mitigation schemes is essential in the literature. We develop a study to fill this gap by assessing the resilience of privacy-preserving methods to various attacks and conducting a comprehensive review of countermeasures from a broader perspective. First, we introduce the fundamental concepts and critical components of privacy attacks. Second, we comprehensively cover major privacy attacks targeted at anonymous data, statistical aggregate data, and privacy-preserving models. We also summarize popular countermeasures to mitigate these attacks. Finally, some promising future research directions and related issues in the privacy community are envisaged. We believe this survey will successfully shed some light on privacy research and encourage researchers to entirely understand the resilience of different existing privacy-preserving approaches.

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1. INTRODUCTION

Data privacy has been expected to be the most critical issue of next-generation technologies [92, 93]. This is more evident with the increasing adoption of machine learning (ML), where algorithms are being fed reams of data [79]. Along with the explosion of big data and advances in computing, communications, and storage capabilities, the evolution toward transforming the technological landscape for data privacy preservation and analytics has already been evident [111, 93].

In recent years, the volume of sensitive personal data and the motivation of malicious actors have increased dramatically [125]. Information extracted from the personal data is valuable for achieving the data-driven experience and developing a new private environment. For example, location-based service combines users' location data with smart applications to provide services on demand [41]. Private genomic data being collected for molecular analysis, contributes substantially to the improvement of human health and medical analytics [104]. Gartner's prediction also reflects that privacy lawsuit claims related to biometric information and cyber-physical systems will exceed \$8 billion by 2025. ¹

Nevertheless, such trends were not accompanied by sufficient awareness of privacy preservation, which the people are most concerned about. As more and more organizations and individuals share their data, it gives rise to the risk of leaking sensitive information that users may never want to disclose. The (unwanted) motivations towards revealing private information and diminishing the utility of private data, several privacy attacks have been reported in the recent decade. For instance, personal location data confided to the proximity services have been used to locate users [95].

Incidents such as the famous *Hugo Awards* 2015 attack [27] have already raised alarming concerns about privacy. Korolova [66] exploited the micro-targeting feature of Facebook's advertisement system to infer private user information easily from data visible to "only me", including *inference from impressions* and *inference from clicks*.

From all listed above, though private information is not explicitly stated, privacy could be violated by analyzing the data. Failure to fully guarantee privacy will prevent users from sharing their personal data with others, which will significantly hinder the expected evolution of data science, digital society, and innovations across several sectors including health and other public applications [60].

For a long time, researchers attempt the privacy issues from a wider perspective and investigate various strategies to protect sensitive information against privacy attacks. After 2012, numerous emerging issues have been extensively studied on privacy preservation, as illustrated in Figure 1, which led to several valuable surveys, tutorials, and important research articles [135, 69, 175, 148, 51, 26, 123, 156, 79, 161, 8]. As shown in Figure 1, Vatsalan et al. [135] provided a detailed review on the *privacy-preserving linkage techniques* (PPRL) that balance the data utility and privacy. Lei Xu et al. [69] reviewed the *privacy-preserving data mining* (PPDM) technology at different stages of the *knowledge discovery from the data* (KDD) process. Zhu et al. [175] summarized the common issues on data publishing and data analysis in the context of *differential privacy* (DP), and Yang et al. [156] discussed *local differential privacy* (LDP) mechanism in different application scenarios.

^{−1}February 15, 2022, *https://www.* [(None)]-(None) ((None))

2013 Privacy preserving linkage techniques [134]	2014 Location privacy attacks [147]	Diff priv publi data an	2017 Terential acy data shing and alysis [176]	20 Cre netv user id linkag	917 oss- vork lentify je [122]	202 ML-aided protecti ML-basec attack	21 l privacy on and l privacy : [79]	2 Privacy in user online	022 problems -oriented services [8]
2014 Privacy preserving dat mining [69]	2(E ta anonyr attac graph ()16)e- nization :ks on]ata [51]	2017 Reconstruc attacks/Tra attacks [2	ction cing [4]	2 L diffe pr applica	020 ocal erential ivacy tions [155]	202 Privacy risk feder learnin	21 leakage s in ated g [160]	2023 Attacks on privacy protection techniques[This work]

FIGURE 1. Evolution of the surveys on privacy preservation and attacks in the past decade

Machine learning (ML) has been used profoundly in privacy research in recent years, as discussed and compared extensively in the recent survey article [79]. As a distributed learning framework, federated learning (FL) can protect local data privacy without sharing it globally in the network. Yin et al. [161] surveyed privacy leakage risks in the FL and introduced several privacy-preserving techniques. Moreover, Barth et al. [8] reviewed the current approaches to privacy issues for online service by visualizations and design guidelines.

In addition, cryptography is also a vital privacy-preserving tool with advanced technologies such as general secure multi-party computing (SMPC), privacy-preserving set operations, and homomorphic encryption (HE). These technologies have been developed for a long time and been systematically summarized by numerous privacy researchers [40]. Acar et al. [1] introduced the classic homomorphic encryption techniques, together with partially homomorphic encryption (PHE) and some what homomorphic encryption (SWHE), and systematically discussed the basic knowledge and future extensions. Martins et al. [94] summarized the performance and security features of more powerful fully homomorphic encryption (FHE) from an engineering perspective. Zhang et al. [168] introduced Attribute-based encryption (ABE) from various dimensions such as classification standards, functions, and structures in the cloud computing access control environment. Zhang et al. [167] reviewed the privacy-preserving deep learning exploiting multi-party secure computing and data encryption technology in the cloud server outsourcing environment, and was committed to providing some promising research directions. Although these works provided effective privacy-preserving ideas, cryptography involving more encryption with mathematical approaches is out of the scope of this survey. Moreover, of particular relevance to this survey, we now develop a high-level view of the notable milestones investigating several essential aspects of privacy (except encryption), which is the central focus of this work.

Wernke et al. [148] extensively reviewed existing location privacy attacks categorized based on the attackers' knowledge, including the *temporal information* and the *context information*. Ji et al. [51] discussed the de-anonymization attacks on graph data, as well as their quantifications. They also analyzed the impact on the data utility and privacy achieved after the graph anonymization operation. Dwork et al. [26] focused on privacy attacks on the aggregate data and mainly summarized reconstruction attacks and tracing attacks. Possible DP applications against these attacks were discussed as well. Shu et al. [123] reviewed the major achievements [(None)]-(None) ((None)) 4 Committed by: (None) in the process of exploring cross-network user identity linkage, providing its formal definition along with a unified and widely applicable framework. Liu et al. [79] analyzed the relevance of machine learning and privacy from a unique perspective, and elaborated ML-aided privacy protection and ML-based privacy attack based on different roles of machine learning technology.

A comprehensive survey on [26] summarized theoretical and practical analysis of reconstruction attacks and tracing attacks till 2017. Another privacy attacks survey [116] investigated the attacks against the machine learning approach using the taxonomy of attacks. Other works mainly focused on one specific privacy attack method or one specific attack field, such as the de-anonymization of graph data [51], social network attacks [121], IoT attacks [163], blockchain attacks [15] and location privacy attacks [148]. After several years of theoretical and practical development, new privacy attacking methods keep emerging, and some are also followed with innovative defense methods [170, 136]. However, despite the aforementioned work, form the lens of privacy attacks, no recent comprehensive review is available with a rigorous review of privacy preservation and attacks. This paper attempts to fill the void by analyzing the latest and commonly adopted privacy attacking techniques. It is important to provide a comprehensive survey with meaningful references and a better understanding of privacy resilience for researchers in information security and privacy preservation. In this survey paper, we provide an extensive discussion on privacy attacks, together with corresponding mitigation measures, future research directions and challenges.

Two major contributions in this survey are enlisted as follows.

- (1) We categorize existing research works on privacy attacks based on several criteria, and identify detailed trends through comparing and analyzing the features of breakthrough research works for resilience to privacy attacks (see Section 2).
- (2) We develop a systematic framework to explore and exploit the principles, methods, preservation measures, and future research directions considering various types of privacy attacks. We aim to provide a holistic understanding of the current development trends for the advances in data privacy research (see Section 3 to Section 5).

2. BACKGROUND AND OVERVIEW

Before diving into the details of privacy attacks, the notion of success from the adversary's perspective needs to be explored. In particular, we need to answer the question: 'what do we mean by privacy violation?' Generally speaking, privacy violation is a situation when an adversary obtains additional information beyond any published data from the system. Most importantly, privacy violation often incurs certain harmful consequences. Dwork and Roth [22] provided several convincing statements. For example, the quasi-identifiers (QI) can be used to match anonymized records with non-anonymized records across multiple databases in what we call the *linkage attack*. It may not only reveal the user's membership in certain databases, but also disclose the private information of the individuals. For summary statistics, they [22] discuss the reconstruction attacks. In the statistical database, each individual has a "secret bit" to be preserved, the goal of an adversary is to increase his chance of guessing the "secret bit" of individuals, so as to rebuild the whole database. Besides, we know that, we are the ones who define the privacy (None)]-(None) ((None)) 5 Committed by: (None)

threshold for what constitutes a privacy violation, such as "Correctly match 90% of anonymous records" or "Successfully reconstruct more than 80% of the secret bits of individuals in the database". Typically, only when the attack goal is achieved as well as the threshold on given databases protected by some privacy techniques are crossed, we believe that a privacy violation of a certain degree has occurred. Privacy attack refers to the process of exploiting seemingly harmless released data to discern the sensitive information of individuals [26]. We show the privacy possibilities in the various links of data sharing and transmission in the digital age in Figure 2. At the same time, we provide an abstract view of the privacy attack process in Figure 3.



FIGURE 2. Digital pipeline for data and private sharing.

From these, we can observe how motivation, methodology, information and target interact with each other during the attack process and realize that privacy is also an aspect that cannot be ignored when sharing information and data in the digital age.

2.1. **Components of Privacy Attack.** Four key components are involved in the privacy attack process:

- Adversary: The adversary represents individuals or organizations who maliciously conduct privacy attack algorithms or private queries according to an attack strategy designed to compromise privacy. For the adversary, the auxiliary information or accessible resources need to be specified, including the background knowledge, some specific query mechanisms and partially available public data. In most cases, one key premise for privacy violations is that the adversary needs to master some auxiliary information of the targeted user, also commonly known as background knowledge or external information, which can be obtained from different channels or through different means. For instance, the public Facebook profiles together with voter registration records were exploited to launch a linkage attack [97]. However, with the research development in the privacy attack, it has been proven that even without any auxiliary information, certain harmful privacy attacks are still possible [109, 133].
- Motivation:
 The likelihood of an attack is closely related to the motivation of the adversary to commit violations of privacy, which is elusive and hard to quantify as it depends on specific situations [144], let alone those targeted [(None)]-(None) ((None))

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FIGURE 3. The main components of the privacy attack process.

attacks with high levels of attention. Consider one scenario: the arrival of a celebrity may prompt a completely kind and innocent hospital staff member to turn into an adversary, who has the motivation to abuse his/her access to patient records, thus resulting in a privacy violation. Similar scenarios are common in this era of big data since data publishing and sharing have also become common. The adversary will launch privacy attacks for the discovery of privacy attributes, membership inference, or any other purpose that may be in his favor. But we should know that privacy risks may sometimes occur as a collateral effect under many circumstances [108].

- **Target:** The *attack target* includes private data and private model, in general, not only sensitive attributes but also all information that people are reluctant to disclose can become a target in the attack process. Such as the genetic information tied to diseases [46], users' behaviour patterns [47] and the sensitive relationships [137]. In the current privacy-preserving field, common methods include anonymization, statistical aggregation publishing, privacy-preserving (encrypted) machine learning models etc., all of which might naturally become the priority attack targets.
- Methodology: The *attack methodology* adopted by the adversary is the core of the privacy attack. From a generalized perspective, the attack methodology can also represent a certain attack method or an attack algorithm. Although research works on privacy-preserving are constantly evolving, novel privacy attacks are emerging at the same time. Recent studies show that many advanced privacy-preserving algorithms are highly vulnerable to specific privacy attacks [48, 179]. Our focus is to deeply understand the characteristics of these attack methodologies and their resilience so as to provide references for better research on privacy.

Over the years, research works on privacy attacks have been focused on these components, resulting in different classification criteria derived from the whole process of privacy attack, as summarized in Table 1. Towards enabling a greater contribution to privacy-preserving, in this paper, we summarize the classic and state-of-the-art privacy attacks. We adopt a multi-layer classification framework, [(None)]-(None) ((None)) 7 Committed by: (None)

as shown in fig. 4, and classify privacy attacks according to the attack target. The adversary can launch an attack on the anonymous data, statistically aggregated data, and published privacy-preserving ML model. Then, in the second layer, we assort each privacy attack by the motivation of attacking such as membership inference and attributes inference. In the last layer, we discuss the different attack methods. The summary and comparison of privacy attacks against different targets (anonymous data, statistically aggregated data, and privacy-preserving ML model) is presented in section 3, section 4 and section 5 respectively. Each section includes many subsections to introduce the detailed classification from the second layer and the third layer.

Summarizing various privacy attacks, it's anticipated to provide a deeper understanding of the resilience of existing privacy-preserving methods to various privacy attacks. Section 6 introduces the countermeasures for different attacks. section 7 proposes several future research directions for potential privacy-preserving work.

Components	Classification criteria
Adversary	With Auxiliary Information, Without Auxiliary Information
Target	Anonymous Data, Statistically Aggregated Data, Privacy-preserving ML Model
Motivation	Re-identification, Membership Inference, Attributes Inference,
Methodology	Attacks (Reconstruction, Linkage, Differential, Structural, Model Extraction, \dots)

TABLE 1. Classification Criteria of Privacy Attacks



FIGURE 4. High-level hierarchical view of privacy attacks

2.2. **Privacy Utility Tradeoff.** In the privacy research community, the irreconcilable contrast between enhancing privacy and increasing utility is well noted [37]. It is indeed true that the greater the amount of privacy in data collection to be maintained, the higher increasing value of the commercial value generated. At the same time, it will also bury increased danger of privacy risks. To effectively ensure privacy, data curators shall choose to add a certain amount of noise to the sensitive features of the data. However, such an approach will inevitably undermine the utility and eventually degrades the performance of the system. This phenomenon is commonly known as 'privacy-utility trade-off', which is illustrated in Figure 5. We can observe that the analytical value of the data is the main reason for the privacy utility trade-off (discussed later in Section 4.1.1).



FIGURE 5. Privacy-Utility Trade-off: increase in privacy gains decreases utility

To this end, Liao et al. [78] designed a adjustable measurement method for information leakage and explored its applications in privacy-utility tradeoff. Li et al. [70] proposed a framework that extracts an intermediate representation from the original data to achieve the removal of private information while retaining the discriminate features required.

For privacy-preserving methods based on noise addition, the privacy utility tradeoff has been extensively studied and well understood in the literature. Most works focused on several kinds of DP environments, and more toward balancing the impact of the privacy vs. utility for different private queries [44]. In several traditional privacy attacks such as reconstruction attacks, the privacy utility trade-off is also an aspect that has been widely and well-studied. We will discuss this part with more details in section 4.1.1.

3. Attacks on Anonymous Data

It is worth noting that various agencies and research groups may collect and publish data sets about individuals for various reasons, including satisfying business obligations, encouraging reproducible scientific studies, and meeting legal constraints [17, 64]. To this end, for preventing the sensitive and confidential personal information contained or presented within the original data from being leaked or misused, and to alleviate public concerns about privacy disclosure, we have been employing various methods to anonymize the data sets before making them public. *Anonymization* always increases the difficulty in extracting individual information from records, so that individuals' identities and sensitive attributes will be mostly hidden from adversaries.

It is believed that records with private information could be "de-identified" that appear to be private by simply modifying or deleting *personally identifiable information* (PII). The records without PII are called *anonymous data*. One common approach is to delete the *explicit identifiers*, including common attributes such as ID number and name, to obtain *de-identified* data. However, many research works have discovered that the combinations of a few characteristics can uniquely or nearly uniquely re-identify individuals [130, 99]. Such combinations nominally rely [(None)]-(None) ((None)) **9** Committed by: (None)

(a) Ori	ginal I	Data	(1	5)	Naïve A	Anonyi	mized Data
Name	Age	Sex	Disease	Ι	d	Age	\mathbf{Sex}	Disease
Alice	26 25	F M	COVID-19	1		26 25	F M	COVID-19
Cathy	$\frac{25}{26}$	F	Diabetes	3		$\frac{25}{26}$	F	Diabetes
David Eve	$25 \\ 27$	M M	Diabetes AIDS	4 5		$25 \\ 27$	M M	Diabetes AIDS

TABLE 2. Anonymous Data

on *quasi-identifiers* (QIDs), serving as important indicators to directly or indirectly recognize the specific entities.

We consider a simple example, in which the information on patients of a hospital is shown in Table 2(a). Table 2(b) was published by a curator, after deleting PIIs, in the hospital. When the *explicit identifiers* (i.e. name) are removed, *Alice* and *Cathy* can not be distinguished. However, if we know one of our neighbors, a 27-year-old man, has also visited the hospital, it can be concluded that he could be the one diagnosed with AIDS. Here, (Age, Sex) serves as QIDs.

In general, any information attained by the adversary that can distinguish one individual from another as accurately as possible can be exploited to achieve the re-identification of anonymous data [101]. It's well-known that QIDs include not only the common attributes of databases but also the target's unique auxiliary information gained by the adversary. Examples include large-scale re-identification exploiting movie viewing histories [99] and the unique structure of social networks to re-identify targeted users [100].

3.1. Linkage Attack. As one obvious fact, though every anonymized dataset individually may help prevent the leaking of private information, exploiting the combinations of multiple sanitized datasets, which is known as *linkage attack*, weakens such a guarantee. In the linkage attacks against relational data, the adversary (re)identifies individuals by linking the anonymized tables with some external tables representing auxiliary information of individuals. One example of the linkage attack is provided in Figure 6. It should be considered that the uniqueness of such linkages determines the possibility of uniquely identifying the entities.



FIGURE 6. Linking to (re)identify: 87% US population have unique combination (gender, postcode, birth date)

As a common privacy attack method exploited by malicious adversaries, linkage attacks against anonymous data have been discussed in many research works [126, [(None)]-(None) ((None)) 10 Committed by: (None) 129, 97]. As far as we know, Sweeney [126] introduced the linkage attack for reidentification, firstly, demonstrating the potential privacy risks of publishing Naïve anonymized data. According to a famous statistical report of census data [127], researchers can uniquely identify 87% of the US population by the combinations of *DOB* (date of birth), *ZIP code*, and *gender* with great possibility and feasibility. Zang and Bolot [164] correlated the "top N" locations inferred from call records with some publicly available information to identify users in the anonymized location data. Re-identification on the *Personal Genome Project (PGP)* was achieved in [130], which also identified the participants based on demographics. When databases do not share the full *date of birth* with the public, Sweeney [129] further investigated the possibility of matching known patients to anonymous health records exploiting News stories data. In addition, both online and offline data sources - such as detailed Facebook information and numerous voter records - have been combined to enrich residents' profiles [97].

As we can see from the above, the basic principle of a linkage attack is to find common features hidden in data from different sources, so as to obtain more comprehensive private information. We should believe that some sufficiently unique auxiliary information will leak privacy. Some data that appears harmless in our daily lives can also be exploited for linkage attacks. A few examples of data sources that can easily be linked are discussed as follows.

- Social networks: The combo of personal information within multiple social networks is usually referred to as online social footprint [89]. Several researchers have focused on the social network matching exploiting these combinations. Due to the limitations of getting overlapping datasets and heavy calculations, "pseudonyms" have been used to match profiles across multiple online social networks (OSNs) [9]. The automated identity theft attacks were discussed, in which a novel scoring system with a threshold created to determine whether two specific accounts correspond to the same user. After that, Shen et al. [121] presented the first countermeasure against user identity linkage attacks, developing a novel greedy algorithm to prevent identities from being linked on different OSNs.
- **Trajectory:** The characteristics of trajectory data include high dimensionality, sparseness and sequentiality, and the data itself can be expressed in the form of a sequence of Spatio-temporal doublets. While collecting high-quality trajectory data is essential for effective data mining, it usually contains detailed private information about individuals' lifestyles or moves. When the adversary exploits partially known trajectory data as the auxiliary knowledge, the moving individuals' privacy may be at risk. The absolute uniqueness of human mobility was demonstrated by de Montjoye et al. [18], they proposed a formal formula, given the revolution and the known Spatio-temporal points, to represent the uniqueness and provide the trajectory privacy bounds. Ghasemi Komishani et al. [33] introduced similarity attack via trajectory data as well. Generally speaking, the subtrajectory information attained by the adversary here acts as QIDs used for privacy attacks. Xu et al. [153] proved that check-in data which seems to be "private", if combined with information containing other mobility data. will have a high risk of re-identification.

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Others: In addition to those discussed above, we should also know that auxiliary information itself may leak privacy in many circumstances to some extent because of its uniqueness and distinguishability. Vu et al. [137] introduced *social link mining* to reveal potential social relationships among travelers through check-in information, increasing awareness of privacy in LBSM among travelers. Adithia and Yudhistira [2] regarded shopping receipts data as auxiliary knowledge and used data mining to construct customer profiles.

All the above series of research works about different data sources assume a priori that the known auxiliary information is only limited to a specific set of QIDs. Unlike these works focusing on simple cross-database correlation, Narayanan and Shmatikov [99] presented a more powerful and extensive de-anonymization attacks aiming to compromise high-dimensional databases with micro-data from individuals, such as movie ratings or transaction data. Even if the released databases have been sanitized, the attack still works effectively and can tolerate some noises existing within the adversary's auxiliary information. Motivated by the findings of Merener [96], we realized that when auxiliary knowledge contains rare attributes, the de-anonymization works far better [99]. Moreover, when some auxiliary information corresponds to a rare attribute, the size of the information that is needed for de-anonymization could be reduced further to 50%. Given the potential risks of these attacks, the *Netflix prize* discontinued [124], and this further illustrates that just publishing anonymized data is insufficient to prevent identities and privacy from being disclosed through linkage attacks.

From a broader perspective, there are many privacy risks with similar principles of linkage attacks, such as attacks using amplification, minimality, composition or isolation, which have been concerned by privacy-preserving researchers for a long time. Methods that may help resist such linkage attacks have been the focus of extensive privacy investigations in recent years. To thwart privacy threats attributed to QIDs as much as possible, k-anonymity was presented by Sweeney [128] for the first time, which provided a guarantee that even in the same database, it is impossible to distinguish any individual clearly from at least k-1 other individuals. After that, several variants including 1-diversity [87] and t-closeness [75] have been presented for better assessing the privacy guarantees on a sanitized dataset. Due to the attempt inherent in these privacy mechanisms to minimize information loss, Wong et al. [149] firstly presented the minimality attack and proved its feasibility on various anonymization models.

In the modern Internet environment, with the rapid development of big data, people need to consider the possibility of linkage attacks while fully enjoying the convenience brought by data sharing. Zheng et al. [171] discussed the linkages between data collected from different dimensions, different devices, and different participants in the smart *Internet of Things* environment, which shows huge privacy threats under it. The de-anonymization attacks that exist in the payment process using online virtual currency have been discussed by Zhang et al. [169], and they explained that combining digital and physical transaction flows can achieve high-accuracy transaction linkage attacks.

To protect data in the blockchain, *Blockchain-based Privacy-Preserving Record* Linkage (BC-PPRL) [106] developed a protocol to guarantee computational auditability. Furthermore, Christen et al. [16] proposed linkage attack based on the [(None)]-(None) ((None)) 12 Committed by: (None)

References	Resources				
Sweeney [126][127] Zang and Bolot [164] Sweeney et al. [130] Sweeney [129] Narayanan and Shmatikov [99] Minkus et al. [97] Xu et al. [153] Zheng et al. [171]	Anonymous medical data Anonymous location data Anonymous genomic data Anonymous hospital data Netflix Prize databases Public Facebook profiles Check-in records Contents from different dimensions	Public census data Public census data Voter & public records News stories & Public data Public IMDB Voter registration records Additional mobility data Contents from different participants			
Zhang et al. [169] Christen et al. [16]	Digital transaction flows Bloom filter encoding	Physical transaction flows Sets of Bloom filters			

TABLE 3. Existing works and dimension of linkage attacks

pattern-mining to identify the encoded records by using the small exchanged piece of information and Nóbrega et al. [107] further studied this attack to ameliorate the limitation of BC-PPRL. Table 3 describes the auxiliary information or resources exploited in some famous linkage attacks.

3.2. Structural Attack. Nowadays, graph data has spanned lots of domains and exploded in popularity, ranging from mobility traces to online social network data. These graph data from different fields are usually publicly and regularly shared to achieve many different goals, such as academic research or business cooperation. Since there may exist lots of sensitive information within the published graph data, various anonymization techniques which may compromise the data utility need to be applied before releasing them.

As shown above, graph data can usually be represented as G = (V, E), in which V is the vertex set representing different individuals and $E \subseteq V \times V$ is the edge set corresponding to the relationships between different individuals. The so-called graph de-anonymization refers to the process of reconstructing the original graph or recovering part of the original graph from the anonymized graph. According to some special properties of nodes or edges in the anonymous graph, the specific node positions are determined in the corresponding original graph, which is the basic idea of de-anonymization.

Improper anonymization of graph data will lead to the degradation of data utility, because it will greatly reduce the information values contained in nodes and edges during graph analysis [49]. Other attack methods aim to re-identity the anonymized users from the anonymized graph, so-called *structural attack* [51]. In recent years, numerous structural approaches of de-anonymization attacks based on graph theory have emerged [51, 72]. The key concept is to re-identity the anonymized subjects through their uniquely distinguishable structural features and some specific external auxiliary knowledge about the anonymized graph. The following summarizes these attacks systematically.

3.2.1. Structure information-based de-anonymization. To achieve the attack purpose of re-identifying the anonymized vertex, the adversary also needs some auxiliary information, with which they may conduct different kinds of attacks against graph data privacy. Zhou et al. [173] defined six types of auxiliary information in graph data: attributes of vertices, vertex degrees, link relationships, individuals neighborhoods, embedded subgraphs and graph metrics.

Hay et al. [42] introduced three kinds of effective adversary knowledge used to attack the naively anonymized networks, including vertex refinement queries (local [(None)]-(None) ((None)) 13 Committed by: (None) expanding structural queries), subgraph queries (edge counts queries) and hub fingerprint queries (node's connection to network hubs). Zhou and Pei [172] proposed neighbourhood attacks, in which the adversary exploits the background knowledge about some target individuals' neighbors and the relationships among the neighbors, to re-identify the victims. Zhu et al. [176] proposed n-hop neighFNR, which relied on the regional characteristic of the cumulative degree of n-hop neighbors and learned from the simulated annealing-based graph matching algorithm, to conduct re-identification. Qian et al. [113] introduced knowledge graphs to strengthen the auxiliary information available in social networks, making the ability of deanonymization and inference attacks to a higher level. Zhang et al. [165] believed that user attributes in social networks also have a significant impact on the attack effect. The multipartite graph is obtained by quantifying the diversity of user attribute values, and network mapping is performed on this basis.

In addition to the above-mentioned structural attacks based on the information of the graph structure, in the era of big data, if other auxiliary information related to the anonymized graph network is maliciously exploited, can more powerful privacy attacks be conducted? We believe that the answer is *YES*! and this requires further investigation.

3.2.2. Seed-based de-anonymization. One of the first works to study structure-based de-anonymization attacks discussed active and passive attacks using small subgraphs designed to violate social network users' privacy [5]. Although providing an important reference, owing to the limitations of practicality and effectiveness, Narayanan and Shmatikov [100] introduced a classic and widely applied approach to de-anonymization, which modeled the process of de-anonymization as two steps: seed identification and propagation. The seed represents a node in a graph that can provide some individual auxiliary information. The method conducted 'network alignment', which matches the anonymized graph's nodes with the auxiliary graph's nodes that have known identities as accurately as possible. Figure 7 illustrates the process of seed-based de-anonymization.



FIGURE 7. An example of seed-based de-anonymization where 1) *Seed identification*: mapping some seeds between two networks through unique subgraph pattern search; 2) *Propagation*: expanding the set of matched users by comparing and mapping the neighbors of previously matched seeds incrementally.

More importantly, motivated by this work, a series of seed-based de-anonymization attacks emerged [158, 100, 147]. Yartseva and Grossglauser [158] further improved [(None)]-(None) ((None)) 14 Committed by: (None)

Representative work	Method	Contribution	Limitation
Zhu et al. [175]	Neighborhood attacks	Adversary exploits the	Can be defended by DP
		background knowledge about	
		neighbors	
Backstrom et al. [5]	Design active attacks (disturb the	Adopt neighboring information to	Not scalable and can be defensed
	links to neighbors) and passive	identify matching pairs effectively	
	attacks (de-anonymize the		
	neighbors) to graph data		
Yartseva and	Percolation graph matching	Adopt neighboring information to	Wrong matching by only relying
Grossglauser [158]	(PGM)	identify matching pairs effectively	on local information
Zhang et al. [166]	Personalized PageRank-based	Apply Personalized PageRank	The dependence of seed
	Graph Matching (PPRGM)	(PPR) to quantify the pair of	
		nodes' matching score	
Pedarsani et al. [109]	Bayesian method for approximate	Seed-free attack	Performance decreases
	graph matching		significantly as the graph density
			increases

TABLE 4. Comparison of the Methods of Structural Attacks and Limitations

the attack in [100], and presented a simple *percolation-based* de-anonymization algorithm. It tried to match every pair of nodes from the auxiliary and anonymized graphs incrementally, in which both nodes have at least r neighboring mapped pairs. Wei Peng et al. [147] introduced a two-stage algorithm called *Seed-and-Grow* to achieve the re-identification of anonymous individuals within social networks, two stages of which were based on the graph structure and overlapping user bases among different social networks, respectively. Similar to [100], their attack consisted of two phases: initial landmarks selection and extended mappings. For improving accuracy and efficiency, Zhang et al. [166] introduced a new framework to match the node by quantifying the matching score of a pair, which employing higher-order neighboring information.

However, these seed-based de-anonymization techniques require large numbers of seeds, and they have difficulty effectively mapping nodes of the large-scale anonymized graph.

To overcome these deficiencies, Nilizadeh et al. [105] proposed a communityenhanced de-anonymization attack with the nature of "divide-and-conquer". It performs the mapping at the community level for the first time, after which the heuristic network mapping method [100] is applied to nodes within de-anonymized communities, finally to the entire graph. A Bayesian attacking framework focusing on seed-free graph de-anonymization was considered by Pedarsani et al. [109], not requiring any side information or initially mapped nodes. Table 4 compares some representative works on structural attacks with their contributions and limitations. Shao et al. [120] proposed a seedless de-anonymization method called *RoleMatch*, which uses node similarity and neighborhood matching to achieve efficient node matching. A practical unified similarity (US) measurement applied in the mapping propagation step was defined by Ji et al. [50], and a US-based de-anonymization framework was generalized to an adaptive framework, which eliminates the necessity for the adversary to obtain auxiliary information about the size of the overlap between auxiliary dataset and anonymous dataset.

4. ATTACKS ON STATISTICAL DATA

Nowadays, due to the massive size of the data collected, many databases contain confidential information. The data curator may be reluctant to publish the original data directly or fully share them with untrusted parties for the sake of privacypreserving. For instance, data curators may only allow statistical and aggregate [(None)]-(None) ((None)) 15 Committed by: (None) queries on these sensitive databases [132], or more cautiously, choose to publish noisy or encrypted databases [103]. In recent years, considerable research works have demonstrated that the adversary who monitors different query results of the databases might get private information, including inferring the sensitive values of data or even reconstructing them. Upholding the confidentiality requirement by statistical aggregate publishing, although protecting privacy to a certain extent, usually poses great challenges. That is because various statistics or query results released by the well-intentioned curator refer to how the sensitive information is potentially related to public information, which may inadvertently disclose private information, resulting in privacy violations.

Considering the above observations, many questions naturally pop up: Can we publish valuable statistical aggregate information about individuals while preserving their privacy? Is it practical to infer sensitive information only from the statistical aggregate data published? Under what conditions can the adversary exploit these aggregated releases or query results to reconstruct all or most of the sensitive bits of databases? Is it absolutely private to conduct encrypted queries on a strictly encrypted database? Driven by these issues, recent years have seen tremendous interest in *reconstruction attacks* [26, 56], *differential attacks* [?] and *membership inference attacks* [112] against statistical aggregation of the data sets. In this section, we will review a series of reconstruction attacks based on different statistical querying conditions, differential attacks based on the query result difference, as well as membership inference attacks posing privacy threats in multiple fields.

4.1. **Reconstruction Attacks.** Dinur and Nissim [20] firstly reported the reconstruction attack, which attempts to reconstruct the statistical database from the private query results of linear statistics. After that, a large number of follow-up works investigated the reconstruction attack [26, 22], which provides favorable guidance in the theoretical development of a rigorous approach to the private publishing of statistical aggregate data.

With the continuous advancements and research interests in the field, reconstruction attacks on several different types of original data, such as social links [33], encrypted data [56] or image data [88], are prevalent. Next, we aim to summarize the privacy-aware reconstruction of the statistical database. The reconstruction attack can be defined as follows [20, 26].

Definition 1 (Reconstruction Attack). Consider an *n*-row database of *n* individuals, each row contains a unique identifier and information (x_i, s_i) . The sensitive bit denoted by s_i is with some private information, while the remaining parts of the row are represented by x_i can be regarded as available and public. Considering that *s* is represented as the column vector of the sensitive bits in the database, the goal of the reconstruction attack is to generate a vector s' of all *n* bits that agree with *s* as much as possible.

From Definition 1, it can be concluded that reconstruction attack attempts to determine the sensitive bits of individuals in the database on which the private queries are conducted. By Using several query methods to infer the sensitive value, reconstruction attack methods can be mainly divided into linear query and range query, as discussed later in Section 4.1.1 and Section 4.1.2 respectively. In addition to the two mainstream methods, there are other ML-based reconstruction attack methods. Based on *Generative Adversarial Network* (GAN), Hitaj et al. [45] can [(None)]-(None) ((None)) **16** Committed by: (None)

generate the prototype samples of the training set even if with the protection of differential privacy. Besides, Phong et al. [110] launched a reconstruction attack by inspecting the similarity between local model which is uploaded to the server and the original global model. But these works suffer from the adversary with rich auxiliary information or all records are analogous in the ML model, hence these methods have not been adopted widely.

4.1.1. Linear Query for Reconstruction Attacks. By executing noisy statistical queries on the database of n entries along with using the results to create a set of mathematical constraints, the reconstruction attacks can be transformed into the task of solving simultaneous equations. That is, there usually exists a linear program that can reconstruct most of the fraction of database [32]. Dwork et al. [26] considered the released statistics q as the approximation to Bs for some matrix B, whose rows respectively correspond to queries. That is, understanding reconstruction attacks based on linear statistics can be boiled down to understanding when the *B*-reconstruction problem can be solved.

The general settings and notations considered in the related papers are as follows: consider a database with an attribute and n records denoted by $d = (d_1, ..., d_n) \in \{0, 1\}^n$. Common statistical queries can be initiated by naming a subset of rows $q \in [n]$, and the accurate answer a_q of this query is all database entries' sum specified by q, i. e. $a_q = \sum_{i \in q} d_i$, where d_i is the bit of the *i*-th row, $1 \leq i \leq n$. The form of statistical database D = (d, A) can generally be used to represent the query-answer mechanism. In many query mechanisms, the efficiency of database query algorithm A can also be determined according to the magnitude of its perturbation to the answer: if the result satisfies $-a_q \cdot A(q) - \leq \varepsilon$, the answer A(q) of algorithm A is considered to be disturbed by ϵ perturbation.

1. The Game Between Utility And Privacy In the seminal study of Dinur and Nissim [20], a polynomial-time algorithm M was introduced to reconstruct a good approximation of the statistical database with low error and a high probability of success. However, due to the elusive hidden connotation of privacy, Dinur and Nissim [20] initially did not attempt to clearly define what privacy is, but defined what is called as *blatant non-privacy* from a simpler and more novel perspective [22]:

Definition 2 (Blatant Non-privacy). If the adversary has a high probability of constructing a candidate database that matches 99.99% of the entries in the real database D or, more accurately, matches $n \cdot o(n)$ entries in the n-row database, then we can infer that the mechanism or the database querying system is blatantly non-private [22].

A pivotal conclusion was drawn: to prevent blatant non-privacy defined above, it is necessary to add the perturbation of magnitude $\Omega(\sqrt{n})$ to the output perturbation sanitiser, which possibly deteriorates the database utility completely. Table 5 summarizes the main results of this pioneering work. In summary, Dinur and Nissim [20] demonstrated the trade-off between data utility and privacy when computing statistics on sensitive information of the confidential database.

After that, a series of studies have been done on the effects of the perturbation added to the answers of querying, the limitations of adversary queries and the computational time complexity on the success of the reconstruction attacks [24, 23]. Dwork et al. [24] introduced a slightly extreme situation where the curators [(None)]-(None) ((None)) 17 Committed by: (None)

TABLE 5.	Perturbation	and Privacy
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Perturbation of A	Privacy of D	Adversary
o(n)	$\exp(n)$ -non-private	Exponential Adversary
$o(\sqrt{n})$	poly(n)-non-private	Polynomially Bounded Adversary
$o(\sqrt{T(n)})$	$(T(n),\delta)$ -private ¹	Time- T Bounded Adversary

¹ $T(n) > polylog(n), \delta > 0.$

TABLE 6. Main Features of Representative Reconstruction Attacks

References	Query	Runtime	Noise
Dinur and Nissim [20]	$O(n \log^2 n)$	$O(n^5 \log^4 n)$	$O(\sqrt{n})$
Dwork et al. [24]	O(n)	$O(n^5)$	0.239: arbitrarily inaccurate
Dwork and Yekhanin [23]	O(n)	$O(n \log n)$	$O(\sqrt{n})$
Dwork and Yekhanin [23]	$O(n \log n)$	$Poly(\frac{e}{\varepsilon})$	$\frac{1}{2} - \epsilon$: arbitrarily inaccurate

give completely incorrect answers to a small fraction of queries, by combining the reconstruction attacks with *LP Decoding* for error correction. They demonstrated that any database query mechanism which

- provides arbitrarily inaccurate answers on a 0.239 fraction of randomly generated privacy weighted subset-sum queries; and
- adds additional $O(\sqrt{n})$ error to any reasonable number of answers

may be non-private.

Dwork and Yekhanin [23] introduced a class of more powerful attacks requiring only *n* deterministically chosen queries. For those queries, adding arbitrary perturbation to a $(\frac{1}{2} - \varepsilon)$ fraction of responses can not defend against an adversary who runs within time regardless of the database size. The *No-free-lunch* theorem [62] pointed out that the released statistics query answers will provide evidence of data participation, so the subsequent noise queries will not be sufficient to protect privacy. From above, we should know that the accuracy of reconstruction attacks depend on the magnitude of the perturbation, the number of queries and the size of the database. Table 6 summarized the main features of the above representative reconstruction attacks.

2. Bring Reconstruction Attacks Into Practice To further confirm the practical feasibility and effectiveness of common reconstruction attacks and understand the resilience of statistical aggregate publishing to these attacks, numerous research works have considered the possibility of bringing reconstruction attacks into practice. Recently, the severe harm caused by reconstruction attacks has been witnessed, which poses a potential threat to some privacy statistics query systems.

Apart from binary databases, the case of databases with health statistical data were discussed by Vaidya et al. [134]. They proposed a possible identifying inference attack through HCUPnet, a free, online, privacy query system based on health statistical data from HUCP. They combined the results of privacy statistical queries with integer programming technology, and then successfully realized the [(None)]-(None) ((None)) 18 Committed by: (None)

reconstruction attacks against healthcare databases. Furthermore, with the continuous update and optimization of some NP-hard solvers and the great improvement in the computer speed, it is not just a theoretical risk to conduct reconstruction attacks on larger and more complex databases. Garfinkel et al. [32] considered reconstructing census databases by encoding the constraints and exploiting SAT solvers to solve a set of constrained equations from census statistical results.

4.1.2. Range Query for Reconstruction Attacks. In addition to data aggregation releases, a popular way to deal with the aggregate accumulation of massive data is to outsource the data to *third-party servers*. To protect sensitive information that may exist in outsourced data (e.g. medical or financial), cryptographic techniques can be employed to ensure confidentiality while the server is allowed to process efficient and practical encrypted queries for some encrypted responses [157].

Nevertheless, it is elusive to achieve a satisfactory compromise between privacy and efficiency [56, 37]. Recent research works have shown that this confidentiality would be violated when the adversary was given some auxiliary information, such as large numbers of encrypted queries and their encrypted results [77].

TABLE 7.	\mathbf{C}	omparisons	of	Two	Types	of	Reconstruction	Attacks:
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	Reconstruction Attacks based On Linear Querying	Reconstruction Attacks based On Range Querying
Adversary	Honest but Curious Adversary	Persistent Passive Adversary
Motivation	Reconstruct the Sensitive Bits	Crack Encrypted Information
Target	Perturbed Statistical Database	Encrypted Database
Methods	Exploit query results of linear statistics	Exploit special results of range querying

Different from reconstruction attacks based on linear querying as discussed in section 4.1.1, only when a significant fraction of encrypted data can be reconstructed accurately with high probability in polynomial time, it can be claimed that the reconstruction attacks based on range querying are successful. Table 7 compares and summarizes these two kinds of reconstruction attacks. The latest series of reconstruction attacks based on range queries have greatly increased the privacy risks of personal data stored in the encrypted databases [37, 90].

1. Setting and Notation The general settings and notations considered in reconstruction attacks based on range querying are as follows: assume that the targeted encrypted database is a set of n records, in which every record is identified as (r, i), including a unique *identifier* $r \in R$ and the value i = val(r), ranging in the integer interval I = [1, ..., N], which represents the database values' universe. If v_i represents the exact number of records with value i, the vector $v = (v_1, v_2, ..., v_N)$ can be respectively represented as the counts of the individual labels in the encrypted database.

Correspondingly, a *dense database* means that for all $i \in I$, the database contains some records (r, i) satisfying var(r) = i. Considering that multiple records may exist in the database having the same value, the *range query* defined below can be conducted on most encrypted databases.

Definition 3 (Range Query). A range query [a, b] initiated on an encrypted database will return an *identifier* set $M = \{r \in R : var(r) \in [a, b]\}$, where both a and b are integers, and $a \leq b$.

۵	[(None)]-(None)	((None))
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From above, it can be concluded that databases supporting the *range query* are especially vulnerable because the results returned by range queries are also likely to leak various private information about the encrypted data accessed by these queries.

2. Volume Reconstruction Attacks Given Definition 3 above, we first discuss the volume attacks, in which the adversary can only get the exact number of records returned by these queries. Namely, the attack corresponds to the full reconstruction of database counts. Although volume attacks can not exact match every record to its value, the accurate database record counts reconstructed by the attack may indeed mean serious leakage in practice. For example, the accurate count may reflect the distributions of different credit levels among bank customers or the salary levels of core employees in a company. As we all know, publishing accurate database record counts will bring potential undetectable privacy risks, which further promotes the progress of modern privacy research.

The work by Kellaris et al. [56] is the first systematic research on the volume attacks and full database reconstruction arising from range queries. However, owing to the limited uniformity assumption and the need for a massive number of queries, their attack was less practical and severely inefficient, and it stayed more at the conceptual level. Grubbs et al. [35] mainly focused on volume attacks exploiting volume leakage of *range queries*. In more detail, they simplified the reconstruction of the database counts to the clique searching problem in the graph, and the graph is constructed by exploiting the volume leakage. Moreover, the related assumptions required are much weaker than those in [56]. Gui et al. [37] discussed a more versatile and robust volume attack which tolerates spurious queries, fake answers and noise added to leaked information.

These works show that attacks exploiting the volume leakage often contain potential risks in practice and should be paid more attention to by researchers. Simply hiding the access patterns is far from enough and novel privacy countermeasures need to be contained.

3. Reconstruction Attacks Exploiting Multiple Leakage Apart from the volume reconstruction attacks exploiting volume leakage, many other information leakages can be exploited to achieve encrypted database reconstruction under different query conditions.

Lacharite et al. [67] discussed the conditions in which the adversary's auxiliary information is bounded in access pattern leakage and rank information leakage. Within this auxiliary information, three types of reconstruction attacks were presented. Grubbs et al. [36]'s work combined the ideology of statistical learning theory, introducing ε -approximate database reconstruction ($\varepsilon - ADR$) and ε -approximate order reconstruction ($\varepsilon - AOR$). These research works greatly improved the efficiency of reconstruction and conducted more robust attacks over previous work [56, 35]. However, to some extent, they all considered some additional assumptions of the encrypted databases. For example, Grubbs et al. [36] assumed the existence of points at specific intervals and a minimum distance is always imposed between these points. In addition to single-dimensional databases, higher-dimensional databases are easy to disclose privacy (2D range query attack [28]). Markatou et al. [91]

References	[56]	[35]	[67]	[37]	[36]	[90]
Assumptions						
Access Pattern Leakage	\checkmark		\checkmark		~	√
Volume Leakage	\checkmark	\checkmark		\checkmark		
Search Pattern Leakage						\checkmark
Rank Information			\checkmark			
Leakage						
Limited Distribution	\checkmark	\checkmark			\checkmark	
Dense Database	\checkmark	\checkmark			\checkmark	
Attack						
FOR ¹	$O(N^2 \log N)$				$O(N \log N)$	$O(N^2 \log N)$
FDR^2	$O(N^4 \log N)$		$N \log N + O(N)$		$O(N^2 \log N)$	$O(N^2 \log N)$
ADR^3	,		O(N)		,	,
Volume Attacks	$O(N^4 \log N)$	$O(N^2 \log N)$				

TABLE 8. Range Querying: contributions and features of reconstruction attacks

¹ full ordering reconstruction (FOR)

² full database reconstruction (FDR)

³ approximate database reconstruction (ADR)

demonstrated order reconstruction attack for higher-dimensional databases by inferring the geometry of data. The common and strict assumption that all range queries have to satisfy is that they are issued uniformly in a random fashion [56, 36] or required some auxiliary information [91]. Such schemes are difficult to be realized in practical applications. For example, in [91], the correct order reconstruction needs some information such as statistical information of the database (e.g., the centroid) or several known records, which are hard to get in reality.

To tackle the aforementioned problems, Markatou and Tamassia [90] exploited the search pattern leakage combined with the access pattern leakage to successfully achieve full database reconstruction. They made further use of PQ-tree [10], and did not require queries from any particular distribution. Kornaropoulos et al. [65] developed the first reconstruction attack on encrypted one-dimensional databases supporting advanced k-nearest neighbour (KNN) queries, proving the possibility of exploiting novel querying to achieve reconstruction. Table 8 presented the main contributions and features of the latest reconstruction attacks based on the range querying discussed above.

4.2. **Differential Attack.** One major criterion for privacy is that the evidence of whether an individual has participated should be confidentially hidden in the whole data generation process [62], which is different from the simple presence or absence of one tuple. For example, when an edge in the social network is deleted, it will influence all other edges in the communities. From this, we should know that whether an individual participates or not will have a subtle effect on the entire community. Such a situation can inadvertently violate privacy. Based on this observation, we will discuss *differential attacks* in the following.

Differential attack is one traditional privacy attack, whose principle is to infer a specific record's attribute or participation by the query result difference when the targeted record is inserted or removed in the statistical aggregates [?]. For example, considering the following two statistical queries to a medical database for a potential attack target Amy:

- How many patients have been diagnosed with AIDS?
- How many patients not named Amy have been diagnosed with AIDS?

From the querying result difference, we may infer whether Amy has AIDS, so as to achieve the purpose of privacy attacks. With further related research works, differential attacks involve more and more content, and their applied field has also [(None)]-(None) ((None)) 21 Committed by: (None)

expanded. In the following, differential attacks in the background of smart grids have been summarized emphatically, which exploit the aggregate measurements of smart grids to deduce the existence of a certain individual data record, thus achieving privacy violations for users.

In recent years, research on the smart grid and smart metering has attracted increasing attention from both industry and academia. Due to the application requirements, protecting the privacy of users' metering data while revealing the valuable overall statistical information in some specific regions is essential in research works on smart grids. Since the readings in the smart meters are sent to power suppliers or centralized database regularly, what needs to be strictly guaranteed is the privacy and confidentiality of these data so as to prevent accidental leakage and unnecessary privacy risks. Recently, privacy-preserving data aggregation of smart meters has aroused the interest of a large number of researchers, and it is regarded as a popular research topic in smart grids. For example, different kinds of encryption schemes, anonymization techniques and obfuscation approaches through noise addition have been presented [7].

However, the potential risks of privacy disclosure still exist in the field of smart grids. Related research works have proved that users' behavior or private information can be successfully inferred through electricity consumption readings [68]. Rottondi et al. [118] presented a *decision attack* against meters' aggregation with data perturbation, which exploited the time correlation of the meter measurement data to infer whether a targeted record exists or not. That is, the adversary aimed to infer whether the aggregate measurement contains the targeted record or not. After that, Jia et al. [52] introduced a novel *human-factor-aware differential aggregation* (HDA) attack, in which the adversary may infer a targeted user's meter readings through his presence or absence information. By exploiting the estimated measurement result, users' behavior patterns may be inferred and monitored, thus creating serious privacy concerns and risks.

4.3. Membership Inference Attack. In some sensitive domains, such as the medical and financial industries, membership in the database is usually regarded as confidential. Because of this, some curators or data owners often choose to publish statistics as opposed to raw data. Publishing statistical aggregate data is generally considered to be a practical and simple privacy-preserving method to prevent personal information leakage. However, even so, the adversary may end up compromising the privacy of some objects who are part of the aggregation by accessing the relevant aggregate statistical information. This may lead to another common privacy attack, membership inference attack, which is also known as tracing attacks [26], attempting to deduce the presence of target individuals within the specified database. In the membership inference attacks, the adversary aims to infer whether the target is included in the published sensitive statistical data or not.

Numerous related research works have shown that even in the form of aggregation, statistical data may accurately reveal sensitive information about the involved individuals. Wang et al. [142] proved that even with a relatively small and less precise set of statistics, e.g. test statistics such as *p*-value and r^2 , the presence of individuals within which can be identified. When the statistics are distorted by [(None)]-(None) ((None)) **22** Committed by: (None) measurement error or noise introduced, Dwork et al. [25] presented a robust tracing attack applied to all mechanisms producing estimates of the statistics. Membership inference over aggregate location time-series was introduced by Pyrgelis et al. [112] for the first time, which instantiated the inference task using the ML classifier trained in advance on the adversary's prior auxiliary information. Apart from inferring membership, Xu et al. [152] verified the possibility of recovering exact trajectories of individuals in the group from their aggregated mobility data, not require any prior information, which further proved that the uniqueness and regularity inherent in the statistical data may incur a great privacy risk.

5. Attacks on Privacy-preserving Models

Accompanied by the rapid improvement and development of technology and science, machine-learning has made considerable progress and attracted more attention from the public. Owing to the sensitive training data or great commercial value, machine learning models may be deemed confidential within many common and practical scenarios, such as medical diagnoses and facial recognition. The increasing deployment of machine learning in these scenarios brings convenience and efficiency, but also increases the risks of numerous privacy attacks, including model inversion attacks [29], model stealing attacks [133] and some adversarial attacks [179]. Therefore, there exists a pressing and broad call to advance the security and privacy behind machine learning. Such appeals have not been ignored, numerous research works have been conducted to understand the risks, attacks and defenses on privacy-preserving machine learning systems.

5.1. Extraction Attack. In recent years, various private ML models have been deployed with public access to querying interfaces, such as the popular ML-as-aservice (MLaaS), which allows users to train and get private models using confidential data or conduct queries on private models without disclosing any private information related to the ML models themselves. As the growing tension between public access and model confidentiality, the potential attack aiming to "steal" the functionality of ML models with little prior knowledge of training data or parameters has been motivated — which is referred to as the model extraction attack. In model extraction attacks, the adversary strives to copy or steal secret model parameters by sending repeated queries to these prediction APIs, to compromise model confidentiality and steal an equivalent or near-equivalent private ML model, with which the subsequent model inversion attacks or malicious evasion attacks can be possible or more efficient. Apart from that, due to the huge training cost, the extraction of sensitive ML models may incur huge commercial losses. Figure 8 reveals the situation where the adversary accesses a private black-box model f trained through *MLaaS* and tries to "steal" an approximated model f'.

Many researchers have demonstrated the feasibility of model extraction attacks in real-world applications, fully reflecting the risk of privacy model leakage. Tramer et al. [133] presented equation-solving model extraction attacks and decision tree extraction attacks using class labels along with high-precision confidence values returned by ML prediction APIs. Wang and Gong [140] observed the fact that when the target parameters are obtained, the objective function's gradient is close to $\mathbf{0}$, thus introducing the hyper-parameter stealing attacks against various machine learning algorithms. Yan et al. [155] presented an adaptive query-flooding for duplication attack by extracting model information using black-box access. Zhu et al. $\mathbf{0}$ [(None)]-(None) ((None)) **23** Committed by: (None)



FIGURE 8. The process of ML model extraction attacks: The adversary has known part of the model structure or the label information, and attempts the unknown parameters via multiple queries to the target.

[177] proposed *Hermes Attack*, a new model-extraction attack using a large-scale reverse engineering and semantic reconstruction. Luo et al. [84] verified that the adversary could extract the model parameters and reconstruct the model features from a model with Shapely value.

On the whole, the *model extraction attack* may violate the training-set privacy, destroy model monetization and promote model evasion. At the same time, when the model is successfully extracted, it can be further exploited together with white-box inversion attacks [29] or membership inference attacks [122], which poses a greater privacy threat.

5.2. Membership Inference Attack. When the machine learning models are associated with sensitive domains, such as financial services [61] or medical research [4], not only the models themselves, but the membership information in the training sets may motivate the privacy risks of individuals. So another branch of research related to membership inference attacks focuses on the field of machine learning, unlike what discussed in Section 4.3, aiming at determining whether a targeted individual-related record is part of a specific sensitive training dataset.

As we know, in the process of constructing machine learning models, numerous sensitive data, including individuals' transactions and preferences, medical health records, locations or face images, are used as training data. There is a certain possibility that black-box models or white-box models may unintentionally disclose secrets of private training data by either the specific predictive behavior or the details of their structures and parameters. In the background of machine learning, the black-box setting is referred to as the condition where the adversary can only obtain the model's output results under given inputs, while the white-box setting represents the condition where the adversary can obtain almost all the secret parameters and internal structure of the model, and both are common in practical application scenarios. Figure 9 shows the visual difference between above two settings.

Many researchers in the privacy field believe that the privacy-preserving machine learning models have the risks of disclosing the training set membership in both settings. Shokri et al. [122] firstly verified the possibility of successfully implementing member inference attacks on the ML models under ML-as-a-service (MLaaS), known as a popular black-box API. They innovatively proposed a novel shadow training technique, which can help train a special attacking model so as to conduct membership inference according to the targeted model's output without any auxiliary information, namely, quantifying the membership information disclosure [(None)]-(None) ((None)) 24 Committed by: (None)



FIGURE 9. Black-box vs White-box. The former represents a model with unknown model parameters, and the latter represents a model with known internal parameters and structure.

through the model prediction outputs. However, owing to the assumption that the target model to be attacked and the generated shadow model are consistent in both structure and training data, the scope of their membership inference attack was largely reduced. Liu et al. [81] presented more effective membership inference attacks called *SocInf*, building the mimic model based on neural networks and generative adversarial networks to disclose the prediction differences. Through repeated queries, the adversary can attain the highest possible membership inference attack performance on the targeted models by reconstructing the posterior vectors from the prediction labels.

Considering the problem of inadequate data for training the attack model, Bai et al. [6] developed *GANMIA* to generate synthetic data. But the above works all discussed membership inference attacks against ML models conducted under the *black-box settings*, in which adversaries can only obtain model predictions. Such attacks may be inefficient against deep-learning models with large sets of parameters.

Rahman et al. [114] conducted membership inference against an advanced differentially private deep model under the white-box settings for the first time. Nasr et al. [102] designed a novel white-box inference attack exploiting the *stochastic* gradient descent (SGD) the algorithm's privacy vulnerability. They also discussed and evaluated the attack in all major scenarios with different criteria, such as prior knowledge or model training architecture. Sablayrolles et al. [119] proposed an optimal membership inference strategy beyond with mild assumptions on the parameters' distribution, which depended only on the loss function rather than the parameters. They also demonstrated that the state-of-the-art membership inference methods can closely substitute the optimal strategy [122, 160]. Besides, Azadmanesh et al. [3] applied generative adversarial network (GAN) models and launch a white box membership inference attack for improving performance.

5.3. Model Inversion Attack. It is generally believed that membership inference and attribute inference have some connections. Yeom et al. [160] discussed the issue and further supported the relationships among privacy risks of ML models, over-fitting, and influence [150], including their effects on membership inference and attribute inference. In the attribute inference attack targeted at ML models, the models and incomplete information of some records are exploited to infer the missing sensitive attribute of the targeted record. Specifically, the adversary aims to infer the exact value of the hidden sensitive attributes of specifically targeted records by analyzing the released data together with models, which is considered a successful when the inference is correct with sufficient probability.

One major research topic related to attribute inference attack against ML models was *model inversion attacks*, in which the adversary leverages the predictions of ML [(None)]-(None) ((None)) **25** Committed by: (None)

-	Model extraction attack	Model inversion attack	Membership inference attack
Representative work	Tramer et al. [133]	Fredrikson et al. [29]	Shokri et al. [122]
Motivation	Construct approximate models	Infer the hidden input features	Infer membership
Attack target	Model parameters/structure	Unknown sensitive attributes	Target training data
Auxiliary information	×	\checkmark	Both
Countermeasures	Rounding/DP	Rounding/DP	Rounding/DP/Regularization

TABLE 9. Three Model Attacks

models to infer sensitive attributes used as input to the models. The initial research on model inversion attacks exploiting *maximum a posterior* (MAP) estimator was launched by Fredrikson et al. [30], in which the adversary was given incomplete auxiliary information about a patient's historical medical data and the main purpose is to infer the genotype of the targeted patient accurately through ML predictive model trained in advance on similar medical history datasets. They intended to seek the correlations among the attack target, the model output and other attributes, while providing a general inversion algorithm. However, their attack was limited by the fact that the inferred sensitive features could only come from a small domain. In order to show the broader risk of inversion attacks, Fredrikson et al. [29] presented the novel white-box inversion attack exploiting the confidence information revealed by MLaaS APIs, which represents the likelihood from the model's intermediate layer. Wu et al. [150] formally characterized model invertibility and "invertibility interference", as well as proved the computational power of the restricted channels between the multi-layer models under the white-box setting.

For FL, Zhu et al. [174] demonstrated how can we obtain the training data from shared gradients by developing a Deep Leakage from the gradients. Luo et al. [85] presented another idea of gradient inversion by reconstructing training data. Using transfer learning, Ye et al. [159] proved that the inversion attacks fall apart when we target the student model. However, this will recover the training data successfully when targeting the teacher model. Table 9 summarized such classic model attacks where privacy researchers are most concerned about and compared them with several different aspects.

6. Countermeasures and Enablers

In this section, based on our classification in earlier sections, we provide an overview of existing countermeasures for each of the aforementioned attacks and shed some light on potential enablers to resilience. It is worth noting that these attacks present far-reaching challenges for businesses and corporates, from navigating the immediate operational issues to assessing notification obligations. It is also for defending against ensuing regulatory investigations and litigation focused on the adequacy of businesses and their data privacy. Unfortunately, the nature of the privacy-preservation mechanism is not a one-size-fits-all approach. Measures against various attacks originating from different types of data are summarized in Section 6.1, Section 6.2, and Section 6.3. Table 10 demonstrates the main types of privacy attacks discussed in this review and the corresponding possible countermeasures.

6.1. Preserving Anonymous Data. In addition to minimizing the hidden risks of privacy disclosure, higher re/de-identification standards may result in de-identified research data, thus decreasing the analytical capability of the data. The deviation [(None)]-(None) ((None))
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Attack Target	Attack Method	Possible Countermeasures	Representative Literature	
An anna Data	Linkage Attack	Perturbation (Generalization/Bucketization/Suppression)	[33], [13]	
Anonymous Data	Structural Attack	Partitioning and Clustering	()/ ()	
		(K-anonymity and its variants)	[53]	
		Query AuditingModifying		
	Reconstruction Attack	Query Processing	[59],[83],[35],[76]	
Statistical Data		Adding Noise (Output noise injection)		
	Differential Attack	Disclosure Avoidance	[134], [32]	
	Membership Inference Attack	Adding Noise	[11]	
		(Differential privacy/Output noise injection)	[11]	
	Extraction Attack	Differential Privacy	[199]	
Deine er en en in e Madala		Rounding	[133]	
Privacy-preserving Models	Membership Inference Attack	Reduce Overfitting		
		Regularization and Dropout	[98], [73]	
		Model Stacking		
Inversion Attack		Differential Privacy	[20]	
	Inversion Attack	Rounding	[29]	

TABLE 10. Attacks vs Countermeasures

of the analytical research results using de-identified databases on the edX platform were proved in Daries et al. [17]. Because of the tensions between open data and privacy, compared with anonymous datasets, better solutions are desperately needed. Current research works have identified many best practices to prevent re-identification; see [53, 141] and the references therein.

6.1.1. *Perturbation*. Earlier efforts of privacy-aware anonymization focused on data perturbation to reduce the precision. *Generalization* (combining granular values into categories), *bucketization*, and *suppression* are all widely used anonymization mechanisms. To this end, Ghasemi Komishani et al. [33] combined generalization of sensitive attributes and local suppression of trajectories to preserve privacy as much as possible. In terms of the graph data, modification methods including modifying (including adding or deleting) vertices and edges in graphs to anonymize them and defend against de-anonymization attacks. However, what matters most when we conduct data perturbation is striking a balance between data privacy and utility; see [178, 117, 13] for more details.

A two-step perturbation-based utility-aware privacy-preserving data publishing framework was proposed by Zhuang and Chang [178], which emphasizes utility as important as privacy. An irreversible data perturbation algorithm called *PABIDOT* is proposed by Chamikara et al. [13], which exploits the principle of geometric transformation to protect data privacy while preserving data utility.

6.1.2. Partitioning and Clustering. In order to decrease the possibility of using quasi-identifiers to match particular individuals, partition-based methods focus on dividing the database into different disjoint groups which satisfy specific criteria, such as K-anonymity and its variants. K-anonymity mandates each record to be indistinguishable, because at least k records have the same attributes [128]. Its variants include 1-diversity [87], t-closeness [75], etc, with the idea of data desensitization.

Although these schemes may help protect against re-identification, it has been noted that they are vulnerable to *composition attacks* [31] because of the released exact information. Following the same principle, in order to protect individuals' private information in the graph data, clustering-based methods attempt to cluster vertices and edges in the graph into different groups, as well as anonymizing the subgraphs into super-vertices [53].

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6.1.3. Randomization. The success of re-identification is related with how unique the quasi-identifiers are. So randomly introducing uncertainty into raw data or quasi-identifiers, such as randomized response and local DP [22], may prevent deanonymization attacks. For example, Wang et al. [141] demonstrated how they adopt local DP with the small noise for online social networks.

6.2. **Preserving Statistical Data.** Attacks targeted at statistical aggregate data summarized earlier demonstrates that combining a certain number of specific private query results with database-related auxiliary knowledge can bring the risks of privacy leakage to a certain extent. Here, we discuss some generic kinds of countermeasures which help restrain the possibility of conducting successful attacks, thus improving the resilience of statistical aggregate publishing against these attacks.

6.2.1. *Disclosure Avoidance*. Intuitively, releasing less statistical data or carefully processed data will be a reasonable countermeasure against reconstruction attacks. For example, *bucketization*, *generalization* and *cell suppression* [154]. However, just as discussed above, those methods with certain limitations fail to protect privacy against powerful adversaries effectively [32].

6.2.2. Adding Noise. Curators can choose adding noise to the original data or the published statistical data, which are called *input noise injection* and *output noise injection*, respectively. Similarly, dummy records can be added to databases. But we need to keep a balance between data utility and data privacy while perturbing the databases, as what has been discussed above. More formal privacy models, such as DP [22], can add noises or dummy records without significantly affecting the statistical characteristics of the privacy, database to be protected. A large number of research works have proved that DP is a more principled way to achieve strict and provable privacy guarantees in released statistics by adding random noise into the exact statistical values. Bose [11] proposed to encrypt and secure data from multiple sources to provide query services, so as to preserve the privacy of the data being queried. Specifically, it was to exchange data through commutative encryption. In a sense, DP is more like a condition that the data publishing mechanism meets, instead of the characteristics of the released dataset itself.

6.2.3. Query Auditing. In an attempt to achieve effective privacy-preserving, privacy statistical queries issued by the adversary should be checked continually to prevent information leakage. If given the privacy definition and the answers to past queries, any new query that leads to private information disclosure should be denied. A quantitative privacy metric called *PriDe* is proposed by Khan et al. [59], serving as a tool to calculate the privacy risk score when querying a private database, which can be deployed in an interactive query environment to monitor and protect data privacy. As a popular customizable technology and analysis platform, *SAIL DATABANK* also uses the idea of a privacy governance model to provide anonymous data for reference in various fields after rigorous auditing disclosing risks [54]. But we should know that query denials themselves can also leak privacy [57], and sometimes, the denials will also reduce the data utility. As a result, more efficient *non-deniable auditing* has been proposed [83], which serves as a starting point for privacy research and provides an important reference for future related

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6.2.4. Modifying Query Processing. Certain limitations on private queries may also reduce the efficiency of reconstruction attacks. For instance, if the server batches some queries together instead of processing them individually, it can prevent each query's volume from disclosing, thus preventing volume attacks successfully [35]. Another feasible practice is setting a lower limit on the width of range queries, which can also prevent the reconstruction of exact counts of individual records. The query algorithms with privacy-preserving features are also promising research directions. Li and Liu [76] proposed a privacy-preserving dynamic conjunctive query framework that satisfies adaptive security, scalable index size and effective query processing at the same time. In order to solve the problem of low query efficiency and query security in the hybrid cloud environment, an improved retrieval method combining geometric disturbance, k-means and R-Tree index was proposed by Vulapula and Malladi [138].

6.3. Securing Privacy-preserving Models. The attacks targeted at privacypreserving models discussed above fully illustrate that simply hiding private parameters or model structures is far from sufficient to fully achieve robust privacypreserving. In the following, we conclude some common approaches to effective defensive strategies against different kinds of model privacy attacks, so as to guide future research towards more efficient and strong privacy-preserving ML algorithms.

6.3.1. Perturbation of Gradients. The inaccuracy in gradients often brings difficulties for the adversaries to infer the real attribute. There are several successful methods to perturb the gradients [162, 155]. For example, Yin et al. [162] replaced the updated gradients with their average value. Along with data balance and data confusion, the such defensive method can also resist attacks from various adversaries. Another most commonly used technique to gradient perturbation is the DP. Indeed, DP has been considered as an increasingly successful approach to reduce unnecessary privacy leakage by injecting calibrated (random) noise to the sensitive data. Following DP definition, it provides the possibility of maximizing the accuracy of data query results while offering guarantees as much as possible to minimize the privacy loss on individuals who contributed to the data. Membership inference attacks essentially need to exploit the true state of input/output, which happens to be the essence of *DP*. Therefore, DP can prevent the inferring of whether a specific record is included in the training dataset when the model's outputs change slightly, so as to avoid privacy violations as much as possible. When applied to the model parameters, DP may mitigate model extraction attacks in a sense. Yan et al. [155] proposed a defense model called monitoring-based DP to defend adaptive query-flooding parameter duplication attacks. They designed an adaptive allocation strategy for the DP budget, which can improve the model's performance elegantly.

However, the current DP mechanisms cannot guarantee a balance between privacy and utility [30]. If not handled properly, the added noise may sometimes decrease the efficiency of some anomaly detection system [34]. What should be widely noticed is that specific privacy-preserving mechanisms might leak privacy inadvertently because of their special nature under certain scenarios [34, 82].

6.3.2. Reduce Overfitting. The success of most privacy attacks targeted at privacy-preserving ML models is largely due to the inevitable over-fitting characteristics inherent in the ML models, which will increase the prediction difference between [(None)]-(None) ((None))
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data that the targeted models have never "met" before and data on which the models are trained. It's believed that exploiting this difference may greatly increase the privacy violation risks. Mukherjee et al. [98] developed an effective GAN model privacy-preserving architecture called privGAN, which proved that preventing overfitting can largely prevent membership inference attacks. Li et al. [73] found that the attack accuracy was closely related to the model generalization gap and proposed that when reasonably reducing the training accuracy and combining the mix-up training method, the model's defense against membership inference can be strengthened. As a result, leveraging some regularization techniques to avoid over-fitting will defend against such attacks effectively [98, 73, 160].

6.3.3. Rounding. The basic intuition is that the lower the prediction accuracy, the less information the ML models leak. Thus, the rounding can be used to confuse model outputs' confidence scores or coarsen precision of the prediction vector, thus defending against the model inversion attacks [29] and the model stealing attacks [133] introduced above. Along this line, Tramer et al. [133] further proved that the potential model extraction attacks were still possible even by omitting the confidence values, which highlights the urgency for privacy ML model deployment and for more powerful countermeasures in the future.

7. FUTURE RESEARCH DIRECTIONS

Although some potential privacy risks have been identified in previous sections, this section is devoted to the emerging issues related to other privacy attacks which require further research attention. At the same time, we highlight the privacy issues which are considered as the future research directions of data privacy.

7.1. **Privacy Attack on Differential Privacy.** *Differential privacy* (DP) is the most successful privacy-preserving mathematical framework due to its lightweight and easy implementation without prior knowledge. Recent research works [39, 14] on DP open a feasible way to achieve strong and provable privacy guarantees. DP limits what can be learned from aggregated query results over privacy statistical databases, as well as reduces the possibility of privacy violations by ensuring that any record's presence in the database has a statistically negligible effect. Even so, due to its complicated nature, rigorous privacy standards and unpredictable prior knowledge of the adversary, the general DP initially proposed has been shown to be insufficient against some special privacy attacks [80, 74].

Haeberlen et al. [39] summarized that some DP querying systems, such as *PINQ* and *Airavat*, are vulnerable to varieties of inevitable *convert-channel attacks*, including *timing attacks*, state attacks and privacy budget attacks. Liu et al. [80] explored the privacy risks implied by the assumption of independence between records under the background of DP, and they exploited the inherent natural dependence in real databases to present a practical inference attack which violated the DP guarantee. The risks of DP mechanism in practice were clarified by Li et al. [74]. They argued that existing differential private database querying systems cannot defend against repeated attacks effectively owing to the setting and selection of the privacy budget.

As a popular and promising privacy-preserving framework, we anticipate that privacy attacks on DP will receive more attention in the future. In addition to the *centralized DP* (CDP), *local DP* (LDP) has been applied on numerous large distributed systems in various fields for collecting and analyzing sensitive user data, [(None)]-(None) ((None)) **30** Committed by: (None) such as Google's *RAPPOR*, *Prochlo* and Apple's *iOS*. The first systematic research work on *data poisoning attacks* against LDP for heavy-hitter, identification was conducted in [12]. The above work reinforced the importance of deploying LDP by efficient and safe cryptographic techniques, as well as highlighting the urgency of new defenses.

7.2. Privacy Attack on Spatio-temporal Data. With the development of locationaware technology and the outbreak of the COVID-19 epidemic, people's trajectories and whereabouts are collected and released for various reasons. Besides, in recent years, many location-based applications and services have continued to collect and share human mobility traces for traffic forecasting, urban road planning, or offering other real-time life-enriching experiences [86]. If these trajectory data are revealed, it will pose a great threat to privacy, such as disclosing travel records or sensitive locations visited. Hence, the privacy-preserving of location mobility traces increasingly become popular and attract major concerns. At present, the more popular countermeasures include trajectory data release based on virtual trajectory and DP.

A vast majority of past research works on location privacy-preserving conducted traditional pointed-based perturbations of locations that obfuscate or perturb each location point by using a fake location or a cloaked region, which is vulnerable to inference attacks and has trouble ensuring space utility. Li et al. [71] proved the possibility of inferring sensitive demographics from shared users' locations by matching them with the real mobility traces and checking similar POIs. Gursoy et al. [38] presented a Bayesian inference attack, partial sniffing attack and outlier linkage attack against trajectory data. Zhao et al. [170] explored the limitation of location k-anonymity owing to *location injection attacks* and presented a useful framework called *ILLIA*. The privacy risks and challenges in *space crowdsourcing*, a popular platform to collect and disseminate Spatio-temporal information, have been emphasized by Tahmasebian et al. [131]. Using FL, Khalfoun et al. [58] proposed a privacy-preserving method for mobility data, which can select the best location protection mechanism automatically and make a better trade-off between privacy and utility.

However, it needs to be emphasized that the existing methods of protecting user privacy have serious losses in data utility. It is also very important to explore how to achieve higher-quality trajectory data release and strike a balance between the conflicting goals of data utility and data privacy. The privacy attacks on spatiotemporal trajectory data are closely related to daily life. Due to its nature of irregularity and sparsity, it also deserves further attention in the future.

7.3. **Privacy Attack over Existing ML.** Nowadays, for improving the efficiency of machine learning or protecting privacy involved in the training process better, various machine learning methods have been emerging, such as *multi-view learning*, *federated learning*, etc. However, while pursuing an optimized model, there still exist many hidden privacy risks requiring much attention.

Compared to the common single-view learning, the privacy-preserving of multiview learning, which is ubiquitous and popular in the big data era, has not been fully studied and explored so far. Xian et al. [151] presented a framework for deanonymizing network data on the basis of *Multi-View Low-Rank Coding* (MVLRC), [(None)]-(None) ((None)) **31** Committed by: (None) showing that traditional privacy-preserving techniques are inefficient when applying to multi-view data. Extensive research works on secure *multi-party machine learning* have been developed too. Hayes and Ohrimenko [43] introduced the *contamination attacks* for *multi-party machine learning*, in which the malicious artificial connection between sensitive attributes and labels was learned by models.

Federated learning (FL) is also regarded as the latest breakthrough within the scope of privacy-preserving machine learning research works, in which models are trained in a decentralized manner by independent data curators, preventing their private data from being disclosed to others. However, many existing FL frameworks have been proven to be vulnerable to privacy risks and it may not always offer sufficient privacy guarantees. The attack from malicious servers against the FL has been discussed by [143], which explored the user-level privacy leakage for the first time. Wei et al. [146] discussed the gradient leakage attacks targeted at the federated server, thus violating the client's privacy regarding its training data. Ren et al. [115] pointed out that the proposed Generative Regression Neural Network can recover the image data in the FL framework.

Therefore, DP has been used in FL to perturb the gradients [63]. However, such a straightforward method deteriorates model performance [145]. It is thus of paramount importance to be aware of the implications of developing more robust privacy-preserving FL algorithms in the future.

7.4. Towards Detecting Privacy Violation. Despite the significant effort by the privacy research community to develop and improve privacy violation detection methods, it is still unclear whether latent leakages of private information can be found effectively or not.

Researchers have proposed detection methods for different privacy risks [21, 19, 55]. Dou and Coulondre [21] focused on detecting whether a set of published relational views broke the traditional k-anonymity, presenting a sound and practical means for privacy violation detection under multi-view publishing. With further research works on DP, various sophisticated privacy-preserving DP algorithms have emerged. However, many algorithms claim to meet DP have errors or loopholes which violate what they claim, so effective evaluation and detection mechanisms are urgently needed to verify the effectiveness of the DP algorithms. Ding et al. [19] presented a counterexample generator and effectively detected DP violations by classic statistical tests. Juuti et al. [55] proposed *PRADA*, effective and generic detection of DNN model extraction attacks, which focuses on analyzing the distributions of the successive queries on prediction APIs from clients and identifies the existence of deviations. Moreover, how to measure the risk of privacy leakage is also one important topic. In a detailed survey [139], existing privacy metrics were comprehensively discussed from different perspectives, which can serve as a general reference framework for measuring the privacy levels.

It is generally believed that privacy violation detection will receive more attention in future. After all, only if the risks of privacy leakage are discovered in time and effectively, privacy-preserving can be further improved and the resilience against various privacy attacks is strengthened.

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8. Conclusive Remarks

We developed a holistic survey of research works on privacy attacks, particularly a summary of recent literature on attacks against anonymous data, statistical aggregate data, and privacy-preserving models. To introduce different privacy attacks and better understand the resilience of standard privacy-preserving methods to these attacks, we first explained the intrinsic processes of privacy attacks. We then developed an overview of fundamental concepts and critical components in privacy attacks. After that, we presented a categorization of attacks that compromise some privacy-preserving methodologies. We discussed impending privacy attacks against anonymous data, statistical aggregate data, and privacy-preserving models. We found different privacy violation risks incurred over these common attack targets when having different attack motivations or conducting different attack methodologies. We also reviewed some celebrated and widely applicable countermeasures to mitigate these attacks.

We built a comprehensive knowledge of privacy-preserving measures by summarizing numerous privacy assaults. To that goal, we set out to combat the threats mentioned above while also identifying research gaps in existing privacy-protection methods. By reviewing previous research, we can see that privacy is highly vulnerable to invasion. Individuals who want to profit from new technology must unavoidably exchange knowledge and data in this era of big pervasive data. The availability of enormous volumes of private data raises the possibility of privacy breaches even higher. A challenging but crucial topic is how to create a balance between data sharing and privacy risk control so that individuals are ready to participate and contribute to the evolutionarily robust big data realization with high confidence. Overall, one can observe that the essence of this problem lies in how to achieve a subtle privacy-utility trade-off – a virtuous cycle.

In addition, we demonstrate how resilience against privacy attacks has been a bottleneck research challenge in recent years. The detailed literary analysis in this article will help resolve new privacy challenges and explore innovative directions for future research.

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