

Machine Learning Systems for Intelligent Services in the Internet of Things: A Survey

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Machine learning (ML) technologies are emerging in the Internet of Things (IoT) to provision intelligent services. This survey moves beyond existing ML algorithms and cloud-driven design to investigate the less-explored systems, scaling and socio-technical aspects for consolidating ML and IoT. It covers the latest developments (up to 2020) on scaling and distributing ML across cloud, edge, and IoT devices. With a multi-layered framework to classify and illuminate system design choices, this survey exposes fundamental concerns of developing and deploying ML systems in the rising cloud-edge-device continuum in terms of functionality, stakeholder alignment and trustworthiness.

CCS Concepts: • **Computing methodologies** → **Machine learning**; • **Computer systems organization** → **Embedded and cyber-physical systems**.

Additional Key Words and Phrases: Internet of Things, machine learning systems, intelligent services, cyber-physical systems, survey, review

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1 INTRODUCTION

Internet of Things (IoT) applications have permeated industries and society in sectors ranging from energy and agriculture, to child care, conservation and manufacturing. Many recent applications of IoT describe themselves as being *smart* to emphasize the use of technology to enhance service provision, for example smart cities or smart health [160]. The push towards smart services is further motivated by complex and expanding urban environments, in which technology plays a fundamental role to support social inclusion, economic development and environmental sustainability [12].

Smartness implies a notion of intelligence embedded within the system and the services it offers. The concept of intelligence typically refers to the ability of computational system components to perform data processing tasks [75]. Intelligence has become integral to the IoT, and the successes of machine learning make it a natural candidate for providing the data processing capabilities that enable smart services. Yet, while running machine learning models on readily available datasets has become easy, deploying them in real-life, large-scale production environments is difficult [129]. When used on a daily basis to serve millions of users in a variety of settings, predictive accuracy alone is insufficient to measure a model's performance. Deployment concerns, cost issues and accessibility are calling for systems approaches that consider machine learning from an integrated software and hardware perspective. In IoT applications, algorithms and

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models are subject to the requirements of the cyber system and the physical environment in which they are deployed. This raises new design concerns, which must be considered alongside deployment, scaling and distribution requirements.

The computational capabilities of many IoT devices are limited. Cloud technologies, which provide elastic and unlimited computational power, are an essential extension of the IoT to enable machine learning and other data processing techniques, to provide data storage and support auxiliary services [13]. However, the cloud is not a panacea, as the wireless communication link between devices and the cloud introduces delays, costs, security risks and privacy concerns. Alternative approaches are thus required to scale and distribute machine learning systems across heterogeneous computing resources in the IoT. Recent advances to scaling machine learning in data centers draw on distributed computing paradigms to parallelize training and inference tasks. Edge computing is extending the data processing continuum from devices to gateways, edge servers and the cloud.

1.1 Survey Highlight

This survey presents a comprehensive review of the challenges and opportunities of using machine learning to enable intelligent services in the IoT. We aim to provide a detailed and holistic, systems-level view of the multi-layered technical considerations that collectively enable intelligence in the IoT. The survey brings together current applications and architectures of machine learning for IoT and also the application analysis methodologies from cyber physical systems (CPS) domain. We summarize the vast experience of the machine learning systems community in deploying machine learning systems in production so to equip researchers and system engineers with a better understanding of the underlying problems resulting from the intersection of machine learning and the IoT. Furthermore, we present the advances made in distributed machine learning and edge computing, and highlight their potential for scaling and distributing machine learning in the IoT. Finally, we show how the design concerns and diverse technology layers can be structured and conceptualized to steer emerging research, and discuss open challenges. To the best of our knowledge, this is the first comprehensive survey to expose the fundamental concerns of developing and deploying machine learning systems in the rising cloud-edge-device continuum in terms of functionality, stakeholder alignment and trustworthiness.

1.2 Complementary Surveys

There are a number of related surveys that are complementary to this one. Samie et al. [139] provide an overview of machine learning in the IoT from an embedded computing point of view, with emphasis on applications and machine learning approaches. Mahdavinejad et al. [104] also review machine learning for IoT data analysis, with a focus on smart cities and data characteristics. Jagannath et al. [76] take a functional perspective and review the application of machine learning for wireless communication in the IoT. These surveys cover algorithms and applications, but do not survey machine learning systems and distributed computing concerns. Diaz et al. [46] review integration issues for the IoT and cloud computing, but do not focus on machine learning. Dias et al. [45] survey prediction-based data reduction in wireless sensor networks, but do not focus on machine learning specifically, or applications beyond data reduction.

Chen and Ran [33] and Zhou et al. [183] survey the intersection of deep learning and edge computing, with a particular focus on distributing deep neural network architectures. For distributed systems, Verbraeken et al. [161] present a detailed survey on distributed machine learning. Mayer and Jacobsen [110] focus their survey on deep learning from the perspective of scalable distributed systems. Neither of these two surveys considers the IoT context.

1.3 Structure of the Survey

This review starts by introducing the IoT and machine learning in Section 2. Section 3 presents machine learning applications in and design aspects of the IoT, as well as the state of the art architectures for deploying machine learning in the IoT. Key challenges of machine learning systems in production are discussed in Section 4. Considerations for scaling and distributing machine learning systems are outlined in Section 5. Section 6 presents emerging technologies that are enabling the development of machine learning systems for the IoT. Section 7 highlights open problems for machine learning systems for smart services in the IoT and Section 8 concludes the review.

2 PRELIMINARY: MACHINE LEARNING IN THE INTERNET OF THINGS

2.1 The Internet of Things and Cyber Physical Systems

The Internet of Things (IoT) extends the digital realm of the Internet and the Web to the physical world of objects [61]. Objects, or things, in the IoT must have at least one of the following capabilities: to be uniquely identified, know their precise location, be able to obtain data about their state or the environment and modify the environment through remotely controlled actuation [75]. In addition, things may have the capability of processing information. In parallel to the IoT, Cyber Physical Systems (CPS) which are comprised of technical and computational systems, have emerged out of the fields of systems engineering and control. Technical systems process, transport and transfer materials and energy in the physical world. Computational systems process information. An embedded system is a computational (cyber) system that is a fixed component of a technical (physical) system [143]. CPS connect embedded systems through communication technology. Sensors and actuators are components of CPS that link the physical and cyber realms by providing information through sensor observations and action through actuation [39]. CPS have the capabilities of collecting data about the physical environment through sensors, of transporting data using communication technology like bluetooth and the Internet, of processing data on local processors or cloud servers, and of receiving messages to perform an action to alter the state of the physical environment. Human users and operators can interact with CPS.

The definitions of IoT and CPS have been converging over time towards a common understanding of systems that integrate logical components such as network connectivity and computation, with physical components through the use of transducing components, which are sensors and actuators [61]. Perspectives in the two fields differ on four key issues: system-level control, whether the one is a platform for the other, Internet connectivity and machine-human interactions. However, Greer et al. [61] argue that the practical benefits of a common definition outweigh the differences in perspective. This paper takes a unified perspective on the two fields to retain focus on the integration of machine learning systems with systems of hybrid physical-logical nature. Unless specified otherwise, the term IoT refers to systems that are either classified as IoT or CPS.

2.2 Overview of Machine Learning

Machine learning methods fit complex functions over data to discover patterns and correlations which can be exploited for building Models and making predictions [67]. Models learned from data are distinguished from knowledge-based Models by capitalising the latter. A model is learned from a training dataset by approximating a useful function that transforms input variables to an output. Once such a function has been approximated, it can be used to calculate an output value for a new input value. In practice, fitting a function over training data is called model training, while using a model to make predictions is called inference [10]. The test for a model is its ability to produce the correct output for a new input. Models are only useful if they can generalise beyond the training data [47]. Machine learning approaches are promising

if well understood Models are not available or if they are too complex to design manually [117]. Similarly, if Models describe a changing process or context and are required to evolve over time, learning from data provides a mechanism for model updates within a changing context.

Two broad categories of machine learning approaches exist: supervised and unsupervised learning. Supervised learning requires that each training sample is labelled, meaning that for each input value there is a known output. Supervised model training uses the labelled training data as guide to find the parameterized function that minimizes the error between the model's predicted output values and the real output values (i.e. the labels). The goal of unsupervised machine learning is to discover structure in the input data in the absence of training labels that are otherwise used to approximate the error for each observation [67]. Typical tasks that machine learning algorithms perform are clustering, classification and regression, which can be used to group data based on characteristic attributes, to detect patterns and anomalies in the data, to make recommendations, discover trends, make forecasts, and emulate audio and visual perception. In particular, Deep Neural Networks, which are commonly referred to as deep learning, is seen as a promising technology to process the data generated by sensors in the IoT [33][165][164]. This multi-layered, neural network based, supervised machine learning approach has provided state of the art results for many perception based tasks [93]. Deep convolutional neural networks are now widely used for image, video, speech and audio processing, while recurrent neural networks have been successfully used for sequential data, like text.

Machine learning methods scale to very large datasets and improve with more data [117]. This has made them successful in analysing the extreme quantities of data produced by digital, online services and applications. Paired with the flexible and accessible computing infrastructure made available through the cloud and open source software, machine learning has become an essential technology for extracting value from data in modern, digital environments [152]. In a static machine learning work flow, raw data is processed and transformed, and then used to train a model. After sufficient evaluation, the model can be used for inference with new data samples. For many models, parameters can be optimized alongside model training to better suit the data [67]. Arriving at a good model depends as much on the training data as on the optimization and evaluation functions [47]. Feature engineering is used in data processing to ensure that the data input contains independent variables that are correlated to the output. It is usual to train and evaluate more than one model, and ensembles of models usually perform better than any one model. Training machine learning models is an optimization problem and has considerably greater computational cost and time requirements than inference [31]. In dynamic environments, model updates are required over time. This can be done explicitly by retraining the model with new data, or implicitly by using online learning algorithms over streaming data [57].

3 DEPLOYING MACHINE LEARNING IN THE IOT

3.1 Machine Learning Applications in the IoT

Machine learning technologies are used for behavioural profiling, monitoring, prediction, planning and perception in the IoT in diverse sectors like agriculture [51], health [52], home [138], building [119], electricity [182][59][166], water [167], wearables [55] and transport [100][133]. While differences exist between sectors, many of the tasks that machine learning technologies can perform have application across domains. For example, in the electricity and water sectors, clustering smart meter data enables behavioural profiling to model and predict the consumption behaviour of customers [7][50]. Human activity recognition is used to identify physical user activity from wearable and mobile data [163]. Similar approaches are used for appliance-level load disaggregation in the electricity sector [179]. Pattern recognition approaches are used to discover anomalous events [127] such as electricity theft [121] and health incidents such as falls [42]. In home

and building systems, scheduling and optimization can be used to automate appliance usage to achieve various objectives, for example least cost or maximum comfort [138]. In transport systems it is desirable to predict real-time traffic flow to optimize routes for an objective, like minimal delay [154]. Computer vision based perception applications are used in autonomous vehicles [107] and security applications.

3.2 Design Aspects and Stakeholder Concerns

The physical world is not entirely predictable [94]. Yet, engineered systems are designed to deliver reliable, predictable and robust performance [64], which is of utmost importance in systems that are critical to human life. The hybrid nature of the IoT imposes more stringent requirements than what would be the case for purely physical or solely cyber systems. Several national, regional and global initiatives have been actively formalising the requirements of IoT systems and producing standards pertaining to aspects of these systems. Examples are the IEEE 2413-2019 Standard for an Architectural Framework for the Internet of Things (IoT) and the oneM2M TS-0001-V3.20.0 Functional Architecture. The Cyber Physical Systems Framework, developed as an analysis methodology by the US National Institute of Standards and Technology [39], defines system concepts that are of interest to one or more stakeholders as *CPS concerns*. At a higher level, the framework groups related concerns into nine *aspects*, as summarised in Table 1. Concerns are related and typically present trade-offs. For example, in considering the uncertainty concern, the latency imposed by specifying and managing uncertainty must also be considered. Not all concerns are relevant within a particular application and stakeholders may prioritize concerns differently. Requirements can be used to specify properties of the system that address the concerns. Given the conceptual similarity of the IoT and CPS, the CPS Framework can provide insights into application concerns of smart services and requirements of machine learning systems in the IoT.

Aspects	Concerns
functional	actuation, communication, controllability, functionality, manageability, monitorability, performance, physical, physical context, sensing, states, uncertainty
business	enterprise, cost, environment, policy, quality, regulatory, time to market, utility
human	human factors, usability
trustworthiness	privacy, reliability, resilience, safety, security
timing	logical time, synchronization, time awareness, time-interval and latency
data	data semantics, identity, operations on data, relationship between data, data velocity, data volume
boundaries	behavioural, networkability, responsibility
composition	adaptability, complexity, constructivity, discoverability
lifecycle	deployability, disposability, engineerability, maintainability, operability, procurability, producibility

Table 1. CPS aspects and concerns as defined in [39]

Machine learning systems for smart service applications are part of the logical system in the IoT. Unlike the low risk analytical settings in which statistical machine learning has been developed, the hybrid physical-logical nature of the IoT thus introduces real-world, potentially life-threatening consequence to system malfunction or failure. As with other software systems, specifying the target system behaviour during a requirements analysis process is thus essential [143][128]. Traditionally, predictive performance has been the key concern of machine learning research. Likewise, in IoT the focus of machine learning implementations has been on functional aspects such as algorithm selection and parameter optimization for various application domains [104][132]. Increasingly however, challenges such as privacy, security, big

data and latency are raised as important [158][140][54]. Other context specific challenges that have been highlighted in various domains are summarized in Table 2. Despite recognizing these challenges, only few domains, like wearables, incorporate explicit requirements analysis processes to specify system requirements upfront [55]. Some individual works such as Akbar et al. [5] consider error estimation and the scalability of the architecture in their evaluation, but generally metrics beyond performance are not yet designed for or evaluated.

IoT Application	Challenges
Smart grids [59][157][123]	data heterogeneity, data integration, data storage, data velocity, data volume, implementability, interoperability, latency, privacy, reliability, resilience, security, visualisation
Agriculture [51]	appropriate technology selection, business model, cost, data ownership, ease of use, interoperability, localisation, privacy, regulation, reliability, resource optimization (hardware and software), roaming, scalability, security
Health [52][148]	adaptability, complexity, data heterogeneity, human interaction, latency, longitudinal analysis, multidisciplinary interaction, noisy data, personalisation, privacy, scalability, visualisation
Mobility [133] [107]	cooperation, deployability, latency, liability, mobility (location updates), privacy, reliability, resource management (hardware), resource optimization (hardware), safety, scheduling, security, trust, uncertainty, validation
Wearables [120][55]	comfort, connectivity, data volume, efficiency, human physiology, latency, interoperability, power consumption, privacy, programming effectiveness, reliability, safety, sustainability, usability, user acceptance, time variations

Table 2. Examples of domain-specific IoT application challenges

3.3 Cloud-based System Architecture

The IoT has become synonymous with big data [84][75], a concept that embodies the business opportunities and challenges entailed in extracting value from high volume, high velocity and high variety data. Large scale data processing, analytics and storage are prerequisites for gaining insights from big data. Cloud platforms have made data processing and storage ubiquitous and convenient by providing unlimited, on-demand computing resources without upfront user commitment, and by allowing users to pay for use as needed, for as long as needed [82]. The cloud is seen as essential for analysing and mining big data. It is thus no surprise that cloud technologies are viewed as integral to the implementation of smart services in many domains [51][59][177].

State of the art architectures for IoT applications are similar and characterised by their reliance on cloud technologies for data processing and machine learning [13][149][140]. They are designed to facilitate the flow of data from tags and sensors that collect observations, over local communication networks and the Internet to the processing and storage facilities of the cloud. In the cloud the data can be processed and fused with other datasets, machine learning models can be trained, inference can be done and the data is stored for future use. The processed data can then be used in applications via APIs, user interfaces or visualisations to support decision making. The outputs of the inference process can also be transmitted over the communication network back to actuator devices to affect a change in the physical environment. Figure 1 shows how devices, communication networks and the cloud collect, transmit and process raw data from sensors for applications, and how processed data can be returned to devices for actuation.

Many open source technologies that support this kind of architecture exist, and have been discussed in detail [46][84]. Both open source software and commercially available cloud platforms are making it easy to launch new IoT applications with machine learning capabilities. The high computational demands of deep learning place further reliance on cloud computing resources [118]. Despite the success of cloud architectures, IoT applications face challenges of both large-scale machine learning, and computing challenges due to the scale and distributed nature of the IoT. These need to be overcome to deliver data processing capabilities that meet smart service requirements.

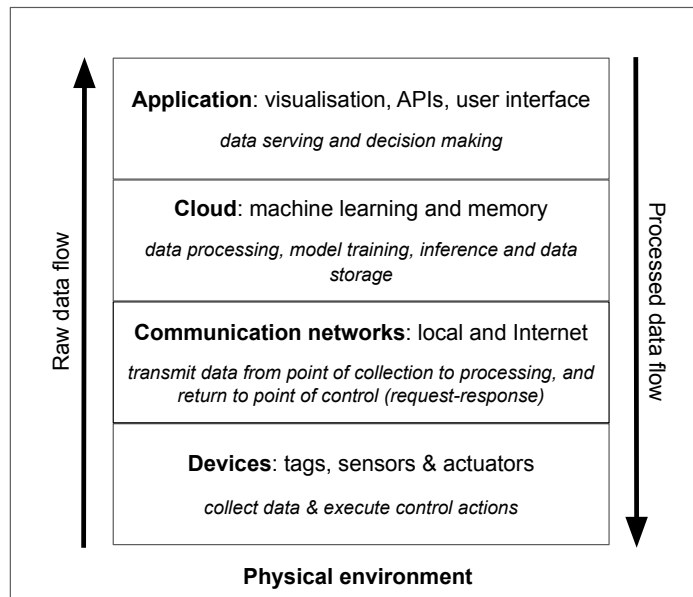


Fig. 1. General overview of a cloud architecture for machine learning in the IoT

4 MACHINE LEARNING SYSTEMS IN PRODUCTION

This section highlights challenges of machine learning systems in production environments which will prevail in IoT applications. Table 3 presents a summary of these challenges at different stages of the machine learning life cycle: data provenance, model training, inference and ongoing machine learning operations.

Data Provenance	Model Training	Inference	Software Engineering
Dirty data	Availability of training data	Efficient inference	System synergy
Data errors	Learning under uncertainty	Inference quality assurance	Data & model management
Data dependencies	Resource-performance trade-off	Interpretable inference	Model boundaries & limitations
Attacks on data	Training malicious models	Protecting private information	Designing for change

Table 3. Summary of system challenges during the machine learning lifecycle

4.1 Data Provenance

4.1.1 Dirty data.

Machine learning approaches are successful where manual processes of creating models are laborious or not possible, and functions can be approximated from data instead (see Section 2.2). Just like code is the foundation of software, data is the foundation of machine learning [10][131]. Due to data's central role in machine learning, missing values [20][141], data redundancy and noise [183] significantly impact model performance and continue to be researched to improve data preprocessing and cleaning.

4.1.2 Data errors.

In addition to impurities that occur in raw data, performance degrading data errors that are generated during preprocessing

and feature generation can propagate through the entire machine learning work flow. As an extension of the software metaphor, such data errors are like bugs in code [23]. Data errors can be created by the data-generating code, for example by dropping features, by inconsistently changing the representation of some features or by creating improbable feature values. Feature skew and training skew are the result of variations in and inconsistent distributions of feature values between training and serving time. Scoring or serving skew refers to the selective serving of model outputs, which results in a self-reinforcing training set. Finally, mismatches can exist between the assumptions made in the training code and the expected data, resulting in impossible data values (e.g. negative log values).

4.1.3 Data dependencies.

The concept of technical debt was introduced by Ward Cunningham in 1992 to consider the long term cost of moving quickly in software engineering. In software engineering, code dependency increases complexity and is classified as technical debt. In machine learning systems, unstable and underutilised data dependencies present technical debt that arises when model input signals change over time and when features are correlated, become redundant or add no value to the model [145]. These data dependencies are often hidden and can have unexpected effects that make machine learning systems brittle and error diagnosis expensive.

4.1.4 Security attacks on data.

Machine learning systems are offering new attack surfaces that jeopardise system security. Poisoning and evasion attacks in particular exploit the dependence of machine learning systems on data. Poisoning attacks pollute the training data in either a targeted manner by influencing specific model outputs, or in an untargeted manner by lowering the model's predictive accuracy. Evasion attacks happen during inference when an adversary modifies the input data to induce incorrect model outputs [79].

4.2 Model Training

The essential resource requirements for model training are (labelled) input data, computing power, electricity to power the computing resources and memory to store training data and models. Most challenges of model training relate to constraints around or lack of one of these resources.

4.2.1 Availability of training data.

Supervised learning relies on high fidelity labelled training data to learn models. Accumulating and labelling sufficient training data is often the most expensive and time consuming aspect of applying machine learning [130]. While some existing IoT applications have collected training data that may be readily labelled retrospectively, for many applications the cost and availability of data labelling presents significant challenges [175].

4.2.2 Learning under uncertainty.

Noise in data are values that obscure the underlying signal. Noise can result from random or systematic errors in the observations, or from data that has been tampered with. Hidden stratification, where training data contains unrecognised categories that are not represented in the labels but that affect predictive outcomes, presents an additional challenge [124]. Learning under label noise [122] and adversarial machine learning [71], which studies the behaviour of machine learning techniques when subjected to the malicious attack of an adversary, have been well studied in the statistical and theoretical machine learning communities. Developing machine learning systems that exhibit robust behaviour in the presence of noisy and adversarial input is viewed as a particular challenge for deploying machine learning in critical applications [152]. This includes systems that can handle inputs for which they were not trained, and models that decline to make

predictions of which they are not confident. In the IoT the multi-layered hardware architecture introduces additional uncertainties such as connectivity loss and latency due to the wireless communication network. Developing machine learning systems that can provide sensing quality assurance and guaranteed results in unstable operating conditions is thus important [2].

4.2.3 Resource-performance trade-off.

The AlphaGo Zero programme [150], which has learned Go playing abilities, was trained on 29 million self-play games over a period of 40 days. For each iteration of self-play, a neural network was trained using 64 GPU workers and 19 CPU parameter servers. The superhuman game playing performance that AlphaGo Zero exhibits has come at an exceptionally large cost of computing power. This is the trend. Since 2012, the computing power required to produce the best models has increased by 300 000 times [11]. This is happening at a time where processors can no longer deliver increased computing power at the same rate as in the past, due to the ending of Moore's law [152]. Understanding the trade-off between computing power, memory and energy consumption on the one hand, and model performance on the other hand is an ongoing research challenge [2]. A simple heuristic is that the availability of storage, compute resources and communication overhead all increase as distance to the remote data center decreases. Large storage and compute are desirable, while communication overheads are not.

4.2.4 Training malicious models.

Due to the complexity and large training cost of learning deep neural network models, many applications rely on readily available machine learning services offered online, or pre-trained, primitive models for download from online repositories. While the availability of pre-trained models enables the development of new applications and increases access to machine learning technologies, they also pose security risks. Backdoor attacks on neural network classifiers occur when a pre-trained model works well on regular inputs, but provides spurious outputs for specific inputs that are only known by the attacker. Gu et al. [63] show that networks trained with such backdoors retain their effectiveness even when used in new settings after undergoing transfer learning. Ji et al. [79] consider a more general class of model reuse attacks in which malicious models are trained to provide predictably incorrect outputs for target input values. These types of attacks are characterised as being effective, evasive, elastic and easy. They pose a significant risk to using machine learning systems where robust performance is required.

4.3 Inference

4.3.1 Efficient inference.

The resource requirements for training models are much greater than those required for inference. In the case of AlphaGo Zero, the trained model uses 4 TPUs on one machine at match time [150], a fraction of the computing power required to train it. However, the scale of model serving and thus inference requirements in modern data centers necessitates optimized inference pipelines with high throughput and low latency [88] to provide a seamless user experience. With the shift towards using deep learning on mobile [80] and embedded devices [137], efficient inference is becoming an important challenge to address due to on-device energy and computing power constraints.

4.3.2 Inference with quality assurance.

Several machine learning models have been found to produce incorrect predictions when input data contain slight perturbations [60]. This can be abused by adversaries in evasion attacks. In general, models that are easy to optimize are easy to perturb. Linear models, ensembles and models that model the input distribution are not resistant to adversarial

examples. Adversarial examples aside, achieving predictable performance with regards to model throughput and latency, as well as the correctness of results, is essential in all operating conditions for critical applications. To provide high quality inference, developing methods that are capable of guaranteeing model outputs is an important challenge [2]. This requires reliable uncertainty estimates that can be calculated at run-time, as well as an understanding of how results are affected by resource availability. In the IoT, methods for calculating uncertainty estimates must be resource efficient.

4.3.3 Interpretable inference.

Efficient and reliable inference strengthen the systems level performance of machine learning, but this alone is not enough. Many popular machine learning techniques, like neural networks, are considered black-box methods [135], meaning that the model output cannot be explained easily in relation to properties of the model input. While models may exhibit predictive performance as good as, or exceeding that of human experts, they are prone to making errors that no human would make and that defy common sense [124]. This erodes the value of the model for real-world decision making. Model interpretability is often likened to the ability of humans to understand how a model works. Lipton [101] categorises the techniques used to render models interpretable into two categories, transparency and post hoc explanations. Transparency comprises simulatability, decomposability and algorithmic transparency. Explanations provide justification for model predictions, irrespective of whether the model is transparent. Where trust, causal reasoning, transferability, informativeness, fair and ethical decision making are necessary, model interpretability is considered important [101].

4.3.4 Protecting private information.

Alongside explainability, safe-guarding data confidentiality is critical, amongst other reasons to comply with regulatory frameworks such as the General Data Protection Regulation in Europe. Reducing the granularity of data representation is a typical approach to preserving privacy, but comes at the cost of some loss of algorithmic effectiveness [3]. Differential privacy can provide privacy guarantees and has become one of the leading approaches to ensuring private computation [169]. However, by introducing noise into computations, differential privacy presents a trade-off between accuracy and privacy during inference [152]. Furthermore, differential privacy assumes independent and identically distributed data, which does not hold true when data are temporally correlated [29], as is the case with timeseries. While user-level privacy is not affected in this case, event-level privacy (i.e. privacy related to each time point) may deteriorate over time.

4.4 Software Engineering for Machine Learning

4.4.1 System synergy.

Sculley et al. [145] analyse the hidden technical debt that arises when teams move fast to develop machine learning products without considering the long term maintainability of the systems they produce. The actual machine learning code, that is the code responsible for training and inference, is only a small component in the greater system which includes configuration, data collection, data verification, feature extraction, machine resource management, analysis tools, process management tools, serving infrastructure and monitoring. Within this complex setup of code and components, it is difficult to enforce strong abstraction boundaries and models become entangled. This creates scenarios where oftentimes hidden dependencies exist between components. Small changes cascade down the entire user chain and can have unintended and unnoticed consequences. Data dependencies, feedback loops and configuration code create further dependencies that production teams must manage.

4.4.2 Data and model management.

Since the study done by Sculley et al. [145] at Google, researchers and software engineers at other companies have

documented and expanded on the software engineering challenges of machine learning systems. Lwakatere et al. [103] interviewed 12 experts, from various companies in different domains, with experience in software engineering for machine learning. From the experiences described by the interviewees, the authors created a taxonomy of challenges experienced in different phases of the machine learning lifecycle (i.e. dataset assembly, model creation, model training and evaluation, model deployment) based on the maturity of the machine learning system within its commercial application (i.e. prototyping, non-critical deployment, critical deployment, cascading deployment). In a study conducted at Microsoft, Amershi et al. [10] interviewed 14 software engineers, with different levels of experience and on different teams, involved within the company's artificial intelligence ecosystem. They found that the top challenge experienced across respondents, irrespective of experience level and team, was data discovery and management. Tracking and versioning model input data as projects grow is particularly challenging, as datasets are often taken from different schemas. Convenient tools that (automatically) codify the knowledge of individual engineers that gather and process data are necessary to do this. However, heterogeneity in coding languages, technical skill levels of end users and application use cases pose challenges to a one-size-fits-all approach [141].

4.4.3 *Model boundaries and limitations.*

Models are not modular in the way that software is. Due to dependencies, individual models are not extensible and multiple models interact in non-obvious ways. Customisation and reuse present further challenges. Taking a step back, even defining a model is difficult [141]. In the most narrow sense, a model consists of the algorithm that specifies the machine learning task and the parameters obtained after training. However, input data must be transformed into features, and machine learning pipelines can be used to combine and track the combination of feature transformations and parameters [115]. Still, the model depends on the data it was trained on, as well as the assumptions of the underlying data distribution. Capturing and managing these implicit assumptions is difficult. While a model may be simple to reuse in the same domain, it can require significant changes when used in a different context. Defining a model becomes even more difficult when considering an ensemble of models, or meta-models such as neural architecture searches. While systems for extracting and managing model metadata have been developed [142], there exists no declarative abstraction for the whole machine learning pipeline (i.e. the machine learning equivalent of SQL) [141].

4.4.4 *Designing for change.*

Models evolve as data changes, methods improve or software dependencies change, thus making ongoing model validation critical [141]. However, comparing model performance is challenging. Training and evaluation must happen on the same data, while avoiding overfitting. For data like timeseries, that are not independent and identically distributed, standard train/validation/test splits are invalid. The same code must be used to compute evaluation metrics throughout and evaluations must track the information on which they depend. Still, in complex, long-running experiments it is difficult to determine the exact reason for performance changes and to preserve backward compatibility of trained models. Detecting change in data and deciding when to retrain a model is necessary to retain model integrity over time. Keeping humans in the loop is important for auditing predictions when training data is noisy, but brings its own challenges.

5 SCALING AND DISTRIBUTING MACHINE LEARNING SYSTEMS

In the traditional, centralized cloud architecture discussed in Section 3.3, individual sensor and actuator nodes send and receive data (via gateways) to the cloud, which functions as a central server that performs all the computing tasks. The cloud provides the advantage of elastic computing resources but presents challenges to scaling machine learning in the IoT, as the communication links that transfer data from devices to the cloud can be a major bottleneck [147]. Decentralized

and distributed structures are two alternative network architectures [16] that have been proposed for networked control systems [58] and communication in the IoT [116], making distributed computing a logical consideration. Distributed machine learning is already an active area of research for scaling machine learning in the cloud, and holds similar relevance for distributing machine learning in the IoT. Edge computing is emerging as an area of research to facilitate distributed machine learning across the cloud, edge and devices. Table 4 summarises the cloud challenges, considerations for distributed computing and for edge computing, to scale and distribute machine learning in the IoT. They are discussed in greater detail in the remainder of this section.

Cloud challenges	Distributed computing	Edge computing
Data transfer & intermittency	Parallelisation	Digital devices for smart services
Privacy	Synchronization	On-device storage & processing
Network security	System architectures	Wireless communication networks
	System optimization	Edge architectures
	Fault tolerance	

Table 4. Considerations for scaling and distributing machine learning in the IoT

5.1 The Cloud is not Enough

In 2018 an estimated 17.8 billion connected devices were reported in use [91]. This number is projected to almost double by 2025. The bandwidth requirements to transfer data from and to devices to enable centralized machine learning systems are enormous [178]. Processing data locally, and discarding it immediately where possible, would reduce the data transfer burden. In mobile and multi-media IoT applications where deep learning has become essential for perception related tasks such as language, speech and vision services, distributing machine learning workloads is already an active area of research [96][33][183]. Generally, when applications require low latency, user privacy and uninterrupted service, a centralized cloud-only approach is insufficient due to intermittency, durability and security challenges introduced by data transfer.

5.1.1 Data transfer and intermittency.

Cloud-based architectures rely on wireless data transfer, which is constrained by the system bandwidth. Latency and system downtime affect the quality of service that can be provided. Furthermore, high data traffic volumes can incur significant financial costs [147]. Devices that predominantly upload or download control traffic, for example home automation sensors, work appliances, health and wearable devices, account for a smaller portion of traffic volume [112] and are more likely to be affected by latency than bandwidth constraints. Applications that upload or download media content, like smart cameras, game consoles and smart TVs, place a greater burden on traffic volumes and are much more affected by bandwidth constraints. Historically, broadband networks have more downstream bandwidth than upstream bandwidth. At scale, content-heavy IoT applications are likely to saturate the upload bandwidth [178], creating data transfer bottlenecks. At present Internet downtimes are common [62]. Web users typically tolerate them, but in the IoT the temporary unavailability of sensors or actuators will directly impact the physical world. While service level agreements from cloud providers can provide compensation for poor service quality [44], a single cloud provider may not be able to provide the required service guarantees [13].

5.1.2 Privacy.

Cloud-based machine learning applications cede control of the flow of information of billions of connected devices to centralized platforms, creating a threat to privacy in the process [136]. Aspects of privacy that require consideration are anonymity, control and trust. Privacy leakage of user information pertaining to data values, location and usage compromises

the anonymity of data providers [8]. Location-based services can infer device location based on communication patterns, while usage data can reveal sensitive temporal activity patterns [112]. For example, home occupancy and fine-grained appliance usage can be inferred from electric smart meter data [179]. The privacy of data collections that are analysed at a later stage or archived must also be considered. As the cloud is out of users' control, there is no effective way of verifying that data has been completely destroyed [178], even if a user revokes access. In cloud architectures, both data providers and information consumers must completely trust the central entity. Roman et al. [136] consider two dimensions of trust. Firstly, IoT systems require trust between all collaborating entities in their current and future interactions. Secondly, they require system level trust, so that the user does not feel subjected to external control. If users trust the central entity, encryption can protect data privacy during transfer. However, if the central entity does not hold the secret key required for decryption, it acts either only as a storage service, or advanced cryptographic mechanisms are required to do computations on encrypted data [22]. Resource constrained connected devices may lack the ability to encrypt and decrypt generated data [8], or provision the necessary computing power and energy for cryptographic computation [172].

5.1.3 Network security.

Sending data over public communication infrastructure like the Internet poses security risks [136]. Broadly speaking, network layer security risks aim to prevent data from reaching its destination, steal data on devices and in transit, or hijack data and devices to gain control over system components. Exhaustion attacks such as Denial of Service (DoS) flood network resources with redundant requests. In the IoT such attacks can be initiated both from within or from outside the system. Due to the pervasive nature of devices, DoS can also be achieved by physically damaging or destroying devices. Node capture and storage attacks extract and alter user information stored on devices or the cloud, while eavesdropping extracts information from data traffic and Man-in-The-Middle attacks intercept and alter messages in transit. Exploit attacks steal information on a system to gain control of it [27]. Other types of attacks may also be launched to gain partial or full system control, with the impact of an attack being determined by the importance of the data managed and services rendered by an entity [136]. Network security issues are not unique to cloud-based IoT systems. While distributing machine learning can reduce vulnerabilities linked to the centralization of resources and information flow, it presents new opportunities for attack, as distributed system components are more difficult to protect.

5.2 Distributed Computing Considerations

Distributed machine learning applies high performance computing theory to optimize machine learning training and inference across cloud servers [161]. For large scale distributed machine learning, the impetus is usually to distribute model training, as it is computationally expensive [31]. Many of the advances have been driven by research in deep learning, where the need to scale data processing has been pressing [18]. Key questions when distributing computations are:

- (1) Which system components can be executed concurrently?
- (2) When should the outputs of concurrent operations be synchronized?
- (3) How should concurrent operations be distributed?
- (4) How can system performance be optimized?
- (5) How does the system recover when computations are interrupted?

5.2.1 Parallelisation.

Efficiencies in distributed machine learning are gained by executing computational tasks concurrently. Parallelisation

considers *which* system components can be executed at the same time. Common strategies are data, model and pipeline parallelism, as well as hybrids that combine different approaches [17]. Data parallelism partitions the input samples into minibatches and distributes the batches across worker nodes, which apply the same model to different datasets. Once trained, the model parameters of each worker need to be synchronized. This approach works well for compute-intensive operations with few parameters, but is limited by synchronization requirements when the number of parameters is large [110]. Increasing the batch size can alleviate synchronization challenges, but reduces model convergence. Assumptions for data parallel training are that the data is independent and identically distributed (i.i.d.), and that the model fits onto a single device. In the IoT both of these can pose a challenge. Model parallelism, in contrast, partitions the model by the architectural structure. This reduces the memory storage required for each worker, allowing for larger models to be used. Training data is passed to the model input layer, and then transferred to different workers that execute different parts of the model. Finding the optimal way of splitting models is hard [111] and model partitioning does not necessarily reduce the training time. Passing model outputs between workers also introduces communication overheads. Pipeline parallelism like Huang et al. [72]’s GPipe combines data and model parallelism. Thus, instead of waiting for all the data to pass through each partition of a split model, the data is also partitioned into micro-batches. Once a worker has computed the outputs for its model partition, the micro-batch is immediately propagated to the next worker. Successful examples of hybrid parallelism are Project Adam [37] and DistBelief [43].

5.2.2 Synchronization.

Where parallelisation distributes tasks, synchronization reassembles the outputs of the tasks. An important consideration is thus *when* to synchronize the outputs of concurrent operations and how to manage dependencies between tasks. Common strategies that are applied are synchronous, asynchronous and bounded asynchronous approaches [110]. Synchronous approaches gather and aggregate updates from workers after each iteration. A worker can only start a new iteration after the newly aggregated global update has been received. This ensures that models are always in sync, but introduces a synchronization barrier and straggler problem [31] where convergence can take a long time due to the time spent waiting for the slowest workers. This becomes particularly problematic with slow network connections and when failures are frequent. In asynchronous approaches, models are updated independently of each other. This gives workers great flexibility and removes the straggler problem, but introduces a new challenge of staleness as workers may be computing updates that lag behind the global model. This results in slower convergence and reduced training performance. Bounded asynchronous approaches aim to find a middle ground by leveraging the approximate nature of machine learning models to allow workers a degree of freedom that is only curbed when a model becomes too stale [38].

5.2.3 System architectures.

Machine learning system architectures determine *how* to distribute computing operations that can occur concurrently. The choice of architecture depends on computation and communication requirements and constraints, such as the desired fault tolerance, bandwidth, communication latency and, in the case of deep neural networks, the network topology and parameter update frequency [17]. The key architectural objectives are firstly to provide scalability to allow a large number of parallel workers to regularly compute, send and receive model updates. Secondly, the system should be easy to configure and thirdly, it should optimally exploit existing lower-level primitives for tasks such as communication [110]. Centralized, decentralized and distributed systems are standard topologies, defined by the degree of distribution that the system implements. Parameter servers are used in centralized architectures to aggregate parameter updates and maintain a central view on the state of the model [110][17]. In a decentralized architecture, nodes exchange parameters directly.

The effectiveness of the decentralized architecture depends on the communication patterns between worker nodes. In a fully-connected allreduce structure, each worker communicates with all other workers. Ring topologies on the other hand only require communication updates between neighbours. While this reduces the communication overhead, it takes longer to propagate the updated parameters to all workers. Decentralized architectures have the advantages that they do not require the implementation, resource allocation and tuning of a parameter server and that fault tolerance can be achieved more easily, because there is no single point of failure. A potential limitation is however the cost of synchronization. Both centralized and decentralized approaches applied in distributed machine learning assume balanced, i.i.d. training data, and a network with homogeneous, high bandwidth [110]. In the IoT these assumptions generally do not hold.

5.2.4 System optimization.

The primary objective of distributed machine learning is to minimise the time required to execute computing tasks [111]. While parallelisation and distributed architectures increase the available computing resources, applying them naively can harm, rather than improve system performance [171]. For model training, the system optimization, resource allocation and scheduling challenges essentially are concerned with determining how to partition a model, where to place model parts and when to train which part of the model [110] in the shortest possible time, fully utilising available computing resources. Deep learning tasks in particular have the challenges that frameworks are typically not designed with dependability in mind, that training tasks are long running, relying heavily on GPUs that generate excessive heat and that burden communication networks in data centers [77]. When data transfer exceeds available bandwidth, communication becomes the bottleneck in the overall training process and compute resources are underutilised [110]. Efficiency gains from additional computing power thus do not translate to the desired reduction in training time. Communication strategies can be designed for continuous communication to manage bursts, to avoid message overlaps that exceed bandwidth capacity, or to prioritise specific messages over others. To optimize system performance, scheduling and synchronizing communication with computing operations across servers [31], and scheduling and optimally allocating computing tasks to processing resources [111] is necessary.

Managing the complexity of large-scale, distributed machine learning systems is challenging, as it requires tuning both system-level configurations and machine learning parameters [30]. Automatically mapping tasks to hardware resources, scheduling and balancing workloads and determining the task execution order is thus important. Recent efforts have investigated adaptive, dynamic load balancing [97], optimal resource allocation and dynamic scheduling [171], and automated, dependence-aware scheduling [168] to improve training speed and system response to varying loads. Meta-optimizations that can be automated to improve model and system performance are parameter search, hyper-parameter search and neural architecture search [17].

5.2.5 Fault tolerance.

Failures in large scale computing systems are common [144]. Jeon et al. [78] categorise failures in deep learning training workloads as being infrastructure, AI engine and user related. Despite the frequency of failures, many existing machine learning frameworks, like Caffe2, Horovod, Pytorch and PaddlePaddle, do not implement approaches for fault tolerance to handle process and hardware errors [9][161]. Instead, users need to include checkpoints in their code from which the system can resume after failure [77]. Design choices can however be made to build fault tolerant systems. Reactive approaches, like checkpointing, replication and logging, respond to a failure. Proactive approaches employ pre-emptive measures or detect failure patterns, like predictive fault tolerance which mitigates failures by observing related errors. Generally, decentralized and asynchronous systems are considered to be less failure-prone. In decentralized systems there is no single point of failure [110]. Asynchronous systems do not suffer from synchronization barriers and are

designed to tolerate stragglers and worker failure [161]. DistBelief [43], which has been succeeded by Tensorflow [1], is an asynchronous system with a sharded parameter server, that presents one of the earliest fault tolerant deep learning implementations. It combines data and model parallelism, and uses asynchronicity on two levels to achieve redundancy by running both the parameter server shards and the model replicas independently. Fault tolerance may come at some performance cost, but this may be a worthwhile trade-off for a dependable and cost-effective execution environment [77].

5.3 Extending Machine Learning to the Edge

In the IoT, digital technologies that are located at the periphery of the Internet are called the edge. Edge technologies vary in processing capabilities and connectivity [139]. At the lowest level, sensing and actuator devices observe and control the environment. Their embedded microcontrollers can be exploited for computation, but processing and memory resources are scarce and power consumption is severely restricted, especially if devices are battery operated [53]. Gateways typically have more computational power than devices and are used to settle the heterogeneity between diverse protocols of different networks and the Internet. Smartphones can act as gateways, and gateways can be used to perform data processing. Finally, fogs are servers that extend the cloud computing paradigm [139] by distributing computation, communication, control and storage closer to the end users [35]. Shi et al. [147] define edge computing as the enabling technologies that allow computation to be performed at the edge of the network, including any computing and network resources along the path between data sources and cloud data centers. Distributed machine learning achieves scale by combining the localised computational power of many processors. In the IoT, edge computing can extend the computing power of the cloud to the observation endpoints [151], thus creating a geographically distributed network of processors that can be used for model training and inference. While local model training and inference reduce data transfer challenges, they introduce constraints due to the low computing power and energy requirements of devices. Deep learning applications for mobile phones and wearables have been driving the development of more efficient and lightweight machine learning approaches, as on-device memory and processing power, energy and bandwidth are testing the limits of complex, large deep learning models in low resource environments [33][180][153].

5.3.1 *Digital devices for smart services.*

Devices collect data to enable services that serve the objectives of application domains. For example, assisted living applications can use wearable devices to recognise human activities and provide services to infer abnormal behaviour or detect emergency situations [19]. Four different configurations can be used to map devices to services: one-to-one, one-to-many, many-to-one and many-to-many [139]. While shared devices reduce the cost of hardware and maintenance, they introduce new challenges of timing, resource constraints and allocation. When many devices operate in close proximity, interference can affect data transmission, which may increase the energy consumption of devices, reduce the service quality and delay real-time applications. It is necessary to consider the devices-to-service relationship in the scheduling of training jobs. Single-tenant scheduling provisions the resources for a single training job, while multi-tenant scheduling requires resource schedulers to allocate multiple training jobs over shared resources [110].

5.3.2 *On-device data storage and processing.*

The objective of an application determines the quality and rate at which data must be acquired and transferred by devices to deliver a desired service. Devices acquire data by sensing the physical environment, process data, execute control actions, store and transmit data to and from upstream technologies and communicate with devices around them [69]. All these operations require processing power and consume energy, meaning that the processing and connectivity capabilities of devices determine the smart services that can be delivered. In general, both computation and communication present

trade-offs between quality of service and energy consumption constraints. The device capabilities are determined by the hardware and software technologies included in the device [139]. For typical IoT devices, processing [53], memory [175] and power [69] are limited, especially for battery-powered devices. The instantaneous power consumed by a device depends on the underlying hardware technology, voltage, frequency and power settings (like active, sleep and off states) and the efficient execution of software implementations. The quality of collected data depends on the resolution and sampling rate of the sensor [139]. The data generation rate varies based on the type of sensor, and thus type of data that is generated. Figure 2 shows the bit per second data generation rate for different categories of sensors. The power consumption of a sensor increases with increased data generation rates, but also with increased quality requirements. Error detection, encryption and transmission further increase energy consumption. Energy efficiency is a prerequisite for enabling further processing, like machine learning, on devices [53] and approaches for profiling, reducing, scheduling and optimizing data flows and energy consumption are required. Due to the heterogeneity of devices and machine learning frameworks, portability of models [161] and performance benchmarks of machine learning systems in the IoT are a challenge and an emerging area of research [15].

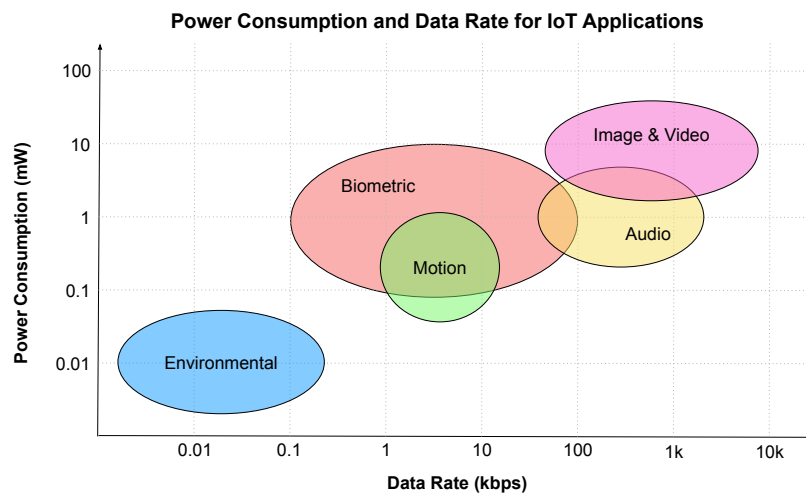


Fig. 2. Power consumption and data generation rates for IoT applications [139][53]

5.3.3 Wireless communication networks.

To distribute machine learning in the IoT, devices need to perform computations locally, or offload computations onto edge and cloud servers. Offloading offers access to greater computing power at higher levels, but presents a trade-off against communication cost, uncertainty and latency [140], which impedes the realisation of real-time applications [154]. Moreover, wireless communication links are lossy and noisy [6], resulting in variability in latency that affects the quality of supply and presents a risk of completely losing connectivity [2]. The choice of wireless communication technology constrains the range over which, and rate at which data can be transferred [139]. Wireless networks connect devices either as a local network, or they connect individual devices and local networks to the Internet [139]. Common topologies in communication networks are star, peer-to-peer and cluster-tree topologies [6]. In addition to the network topology, routing schemes significantly impact the energy efficiency, scalability, latency and adaptivity of wireless networks in

the IoT. Data compression, data fusion and approaches for minimising communication cost have been studied in routing schemes to improve communication performance and reduce on-device energy consumption [102]. Besides the data path, the timing of data transfer matters for managing bottlenecks and the power consumption of devices. Timing schemes can accommodate continuous, sporadic and on-demand data transfer. On-demand timing can either happen on user request, or when an event is detected. Key challenges for machine learning systems are how to reduce the amount of data to be transferred over the wireless network and how to handle the uncertainty and unpredictability introduced by wireless communication [139]. Furthermore, on-device processing and computation offloading present a trade-off, raising the questions of when to switch between local and remote processing and what that decision should be based on [2].

5.3.4 System architectures for edge computing.

Data processing, model training and inference in the IoT can be device, gateway, fog or cloud centric [139]. As discussed, the key question for device centric computation is whether and when to offload computation, which is more challenging if the decision must be made at runtime. Gateway centric computation requires wireless communication, which introduces unpredictable latencies that affect availability and quality of service as devices transmitting data to the gateway increase. Fogs provide greater computational power than devices and gateways, and less latency than transmitting data to the cloud. Finally, cloud centric approaches deliver a high quality of service, offer unlimited storage and processing resources, but come with communication overheads. In the edge computing context, cloud-only computation is considered to be centralized, whereas decentralized architectures implement local training and inference on fogs, gateways or devices [183]. For ease of reference this section refers to gateways and fogs as edge servers.

Hybrid architectures that distribute training and inference across the cloud, edge and devices are an active area of research [33]. Figure 3 presents example architectures that distribute model training and inference across the cloud, edge and devices in different configurations. The architectures are named by training-inference location. From top left to bottom right both processing power and communication overheads decrease, as inference moves from the cloud to devices, and training is distributed to the edge. Figure 3a) is a typical cloud-only architecture. In Figure 3b), the simplest hybrid scenario, a *cloud-edge* architecture trains models in the cloud and downloads trained models onto edge servers which perform local inference with reduced latency, on data offloaded from nearby devices. Baharani et al. [14] use this type of architecture to perform model training in the cloud and inference on an edge server. By reducing the data and energy footprint required for inference, computation can be moved downstream onto devices with reduced processing capacity, thus further reducing latency [153][175]. The typical architecture for mobile inference and wearables is shown in Figure 3c). For sensitive data with privacy concerns and for applications where communication costs are prohibitive, federated learning offers strategies for distributing training across edge servers and the cloud [83]. Figure 3e) is the common setup for federated learning with training distributed between the cloud and some mobile devices. Architectures d) and e) introduce additional complexities due to parallelisation and synchronization requirements. A fully distributed architecture as shown in Figure 3f) is only possible if an application has no requirements for real-time, remote monitoring.

The main challenge with distributing computing across the IoT is to find the optimal balance between local processing and computation offloading, and to find the best timing for offloading, while taking the constraints posed by heterogeneous devices and communication technologies into consideration [139]. The cost, latency and variability of wireless data transfer must be considered in relation to the frequency and size of training updates, privacy and real-time requirements when designing an architecture.

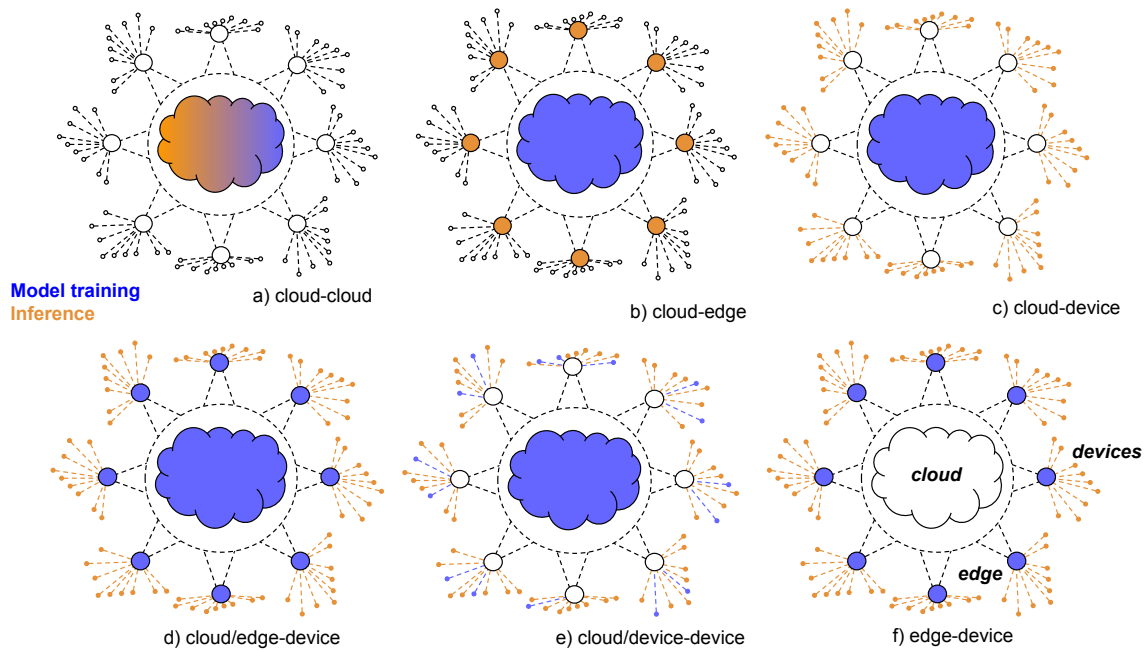


Fig. 3. Examples of machine learning topologies in distributed device, edge and cloud environments

6 EMERGING TRENDS

Smart service applications in the IoT consist of interdependent machine learning, communication and computing technologies with cross-cutting concerns. Figure 4 consolidates the challenges and considerations for developing intelligent applications in the IoT, as discussed in the preceding sections. At the highest level, the application objective determines system requirements for a smart service. Based on the objective, an application may consist of a single or multiple devices, which again can be specific to one or several applications. On the lowest level the device hardware – the sensors and actuators, the processor, memory, connectivity protocols, communication network and the power sources – constrain device capabilities. The software implementations on devices manage data acquisition, processing, storage, transfer and control actions. Achieving synergy between hardware and software implementations across heterogeneous devices is important for high system performance. Depending on the device capabilities and the rate of data generation, data processing, training and inference can be done locally on devices, or offloaded to more powerful upstream servers. Offloading requires data transfer over wireless communication networks. The efficiency and quality of offloading depends on message timing, the communication network topology and throughput, which is strongly dependent on network bandwidth.

To distribute computations across devices, edge nodes and cloud servers, workloads must be parallelized and synchronized. These processes are closely tied to the system architecture and are further affected by the quality and latency of data transfer. Improved scheduling, resource allocation and communication strategies must be considered alongside computation requirements for system optimization. Network interruptions are bound to affect computation and fault tolerance is a necessary consideration. Finally, the machine learning system requires considerations for model training and inference, alongside mechanisms to ascertain data provenance and sound software engineering practices. The class of learning problem is determined by the characteristics of the data distribution, and the application objective.

ML Sys.	Comp. Layer	Challenge addressed	Work	Sec.	Approach	Year
DP	C	dirty data	DataWig [20]		imputation software for missing values	2019
DP	C	data errors	Breck et al. [23]		proactive code validation	2019
T	C	training data availability	Koller et al. [86]	6.2	multi-stream sequence constraints for weak supervision	2019
T	C	training data availability	Osprey [25]	6.2	high level interface for weak supervision over imbalanced data	2019
T	C	training data availability	Ratner et al. [130]	6.2	data programming with labeling functions	2016
T	C	learning under uncertainty	BlinkML [126]		quality assurance: bounded approximate models	2019
T	C	learning under uncertainty	DeepSense [174]		deep learning framework for noisy & feature customization	2016
T	C	quality assurance	CCU [114]		mathematical guarantees for out-of-distribution detection	2020
T	C	resources vs performance	Yuan et al. [176]		hybrid parallelism with independent subnets	2020
T	C	resources vs performance	Dziedzic et al. [49]		resource usage control with band-limited training	2019
T	C	resources vs performance	Pan et al. [125]		data parallelism with backup workers	2017
T	C	resources vs performance	gossiping SGD [81]		decentralized, asynchronous data parallelism	2016
T	C	resources vs performance	SqueezeNet [74]	6.1	model pruning & compression for improved training efficiency	2016
T	C	protecting private info.	PPAN [155]		data release with data-driven, optimal privacy-utility tradeoff	2019
T	C	protecting private info.	v.d. Hoeven [159]	6.3	local differential privacy with user-defined guarantees	2019
T	C	training malicious models	AggregaThor [41]		robust gradient aggregation for Byzantine resilience	2019
T	C	system optimization	Gandiva _{fair} [32]	6.2	gang-aware scheduling with load balancing & GPU trading	2020
T	C	system optimization	AlloX [92]	6.2	min-cost bipartite matching for job scheduling	2020
T	C	system optimization	Xie et al. [170]	6.2	randomly wired neural nets from stochastic network generators	2019
T	C	system optimization	Cirrus [30]		serverless computing	2019
T	C	system optimization	Zoph and Le [184]	6.2	neural architecture search	2017
T	C	system optimization	Omnivore [65]	6.2	centralized, asynchronous data parallelism	2016
T	C	context adaptation	Li and Hoiem [99]		learning without forgetting, using only new data	2018
T	C/D	system architectures	Koloskova et al. [87]		decentralized training with gradient compression	2019
T	C/D	protecting private info.	FedProx [98]	6.3	FedAvg permitting partial work	2020
T	C/D	protecting private info.	Seif et al. [146]	6.3	wireless federated learning with local differential privacy	2020
T	C/D	protecting private info.	Truex et al. [156]	6.3	federated learning, diff. privacy & secure multiparty comput.	2019
T	C/D	protecting private info.	FURL [26]	6.3	locally trained user representations in a federated mobile setup	2019
T	C/D	protecting private info.	FedAvg [24]	6.3	synchronous, data parallel training on mobile devices	2017
T	C/D	synchronization	ADSP [70]		online search to optimize parameter update rate	2019
T	C/D	context adaptation	RILOD [97]		incremental learning for object detection	2019
T	E/D	context adaptation	DeepCham [95]		context-aware adaptation learning	2016
I	C	system optimization	Willump [88]		feature computation compiler optimization	2020
I	C	efficient inference	Clipper [40]		prediction serving with caching, batching & model selection	2017
I	C	efficient inference	SERF [171]		interference-aware, queuing-based scheduler	2016
I	C	protecting private info.	Dwork et al. [48]	6.3	differential privacy - calibrating noise to sensitivity	2016
I	C	protecting private info.	Bost et al. [22]	6.3	classification over encrypted data	2015
I	C/D	protecting private info.	RAE [106]	6.3	AutoEncoder for feature-based replacement of sensitive data	2018
I	C/D	protecting private info.	GEN [105]		framework to trade-off app utility & user privacy	2018
I	C/D	throughput	FilterForward [28]		application specific microclassification to reduce data transfer	2019
I	D	efficient inference	DeepMon [73]		computation offloading onto mobile GPUs	2017
I	D	on-device proc. & stor.	TinyML [15]	6.1	performance benchmark for ultra-low-power devices	2020
I	D	on-device proc. & stor.	ShrinkBench [21]	6.1	standardized evaluation of pruned neural networks	2020
I	D	on-device proc. & stor.	Rusci et al. [137]	6.1	rule-based, iterative mixed-precision model compression	2020
I	D	on-device proc. & stor.	AMC [68]	6.1	reinforcement learning for model compression	2018
I	D	on-device proc. & stor.	DeepEye [108]		caching & model compression	2017
I	D	hard/software co-design	Serenity [4]	6.1	dynamic prog. for memory-optimized compiler schedules	2020
I	D	hard/software co-design	SkyNet [181]		hardware-aware neural architecture search	2020
I	D	hard/software co-design	HAQ [165]	6.1	hardware-aware, automated mixed-precision quantization	2019
I	D	hard/software co-design	DeepX [90]	6.1	automatic model decomposition & runtime compression	2016
SE	C	lifecycle management	Kang et al. [85]	6.2	model assertions to monitor, validate & continuously improve	2020
SE	C	lifecycle management	ease.ml/ci [134]	6.2	continuous integration for machine learning	2019
SE	D	hard/software co-design	TVM [34]	6.1	deep learning workload compilation & optimization	2018
SE	D	hard/software co-design	CMSIS-NN [89]	6.1	library of software kernels for neural nets on Cortex-M cores	2018
SE	D	on-device proc. & stor.	PoET-BiN [36]	6.1	look-up tables for tiny binary neurons	2020
SE	D	on-device proc. & stor.	Riptide [56]	6.1	optimized neural network binarization	2020

Machine Learning System (ML Sys.): Data Provenance (DP), Training (T), Inference (I), Software Engineering (SE)
 Computing Layer (Comp. Layer): Cloud (C), Cloud/Device (C/D), Edge/Device (E/D), Device (D)

Table 5. Emerging technologies

Design constraint	Smart Services				
Application Objective	Requirements Analysis and Engineering		Device(s)-to-Service Relationship		
Characteristics of Data Distribution	Machine Learning System				
	Data Provenance	Model Training	Inference	Software Engineering	
	Dirty Data	Training Data Availability	Efficient Inference	System Synergy	
	Data Errors	Learning under Uncertainty	Quality Assurance	Data + Model Management	
	Data Dependencies	Resources vs Performance	Interpretable Inference	Model Boundaries + Limits	
	Security Attacks on Data	Protecting Private Information		Lifecycle Management	
		Training Malicious Models			
		Context Adaptation			
Workload	Distributed Computing				
	Parallelisation	Synchronization	System Architectures	System Optimization	Fault Tolerance
Data Generation Rate	Offloading				
	Timing		Network Topology	Throughput	
Software	Devices				
	Data Acquisition	Data Processing	Data Storage	Data Transfer	
Hardware	Sensors/Actuators	Processor	Memory	Connectivity	Power Source

Fig. 4. Challenges and design considerations for smart services in the Internet of Things

Based on the design considerations in Figure 4, Table 5 lists emerging research that cuts across challenges and considerations. The first column in the table specifies the machine learning system component that is targeted in the research. The second column specifies the compute location where machine learning components are executed. The third column maps to Figure 4 and specifies the design consideration or challenge addressed in the work. Figure 4 can be used to systematically discover emerging research at the intersection of technology layers and design considerations to expand Table 5, which is open to further additions. The remainder of this section highlights three emerging research areas that have particular significance for machine learning systems in the IoT: on-device inference, automation and optimization, and privacy-preserving machine learning.

6.1 On-device inference

Most of the recent technology developments have been focused on deep learning workloads. Combining cloud training with on-device inference is a major trend for latency and privacy sensitive settings. Recent research has focused on making deep learning models fit on devices with limited memory, executing inference efficiently in low power and memory-constrained environments, and approaches for inference on heterogeneous devices.

The two key techniques used for model compression to reduce model size are quantization, which reduces the floating point precision of parameters and gradients, and pruning, which eliminates insignificant parameters. SqueezeNet [74] is a convolutional neural network architecture for image processing, that uses model pruning and quantization to reduce the model size of AlexNet, the benchmark against which it compares, by 510x and the number of parameters by 50x, while retaining model performance. The authors use principled design space exploration on a micro and macro level to evaluate the effect of the organization and dimensionality of individual network layers, and the network structure

as a whole. He et al. [68] use reinforcement learning to provide the optimal model pruning policy for several image models for mobile devices. They found their automated AMC approach to offer improvements in terms of accuracy and inference latency. Rusci et al. [137] use a rule-based, mixed bitwidth low-precision quantization to select the optimal bitwidth for each layer of a MobilenetV1 image processing network. They use quantization-aware retraining to improve performance and successfully deploy their model on a memory-constrained microcontroller device with 512kB RAM and 2MB FLASH memory. The hardware-aware automated quantization (HAQ) framework developed by Wang et al. [165] also allows for quantization with mixed precision on different neural network layers on the two MobilenetV1/2 image models. HAQ uses reinforcement learning to determine the optimal quantization policy, and takes feedback from the hardware accelerator into consideration. The approach has the ability to adapt to different hardware architectures, shows a reduction in latency and energy consumption, and negligible accuracy loss compared to a fixed 8-bit quantized network. Riptide [56] is an end-to-end system for training and deploying high-speed binarized networks. It performs extreme quantization by reducing bitwidth to 1, 2 or 3 bit precision and achieves superior efficiency and speedups without degrading accuracy. PoET-BiN [36] maps binary neural networks to look-up tables on Field Programmable Gateway Arrays (FPGAs) to reduce energy consumption and compute time significantly on the CIFAR-10, MNIST and SVHN datasets.

The results obtained for on-device processing are promising, but challenging to compare across research papers. Blalock et al. [21] note that despite its popularity, model pruning lacks adequate performance benchmarks which makes it impossible to confidently compare competing techniques. They introduce ShrinkBench, an open-source framework to standardize the evaluation of pruned neural networks. The TinyML benchmark [15] is being developed to enable performance comparison for ultra-low-power devices and forms part of the larger suite of MLPerf benchmarks [109]. In addition to benchmarks, software tools are being developed to facilitate the deployment of deep learning workloads. TVM [34] is a compiler that can be used with popular high-level machine learning frameworks, like TensorFlow, PyTorch and Keras, to train and deploy models on diverse hardware backends. Serenity [4] optimizes compiler schedules for irregularly wired neural networks by using dynamic programming to adhere to on-device memory constraints. CMSIS-NN [89] is an optimized library of software kernels to enable the deployment of neural networks on Cortex-M cores. DeepX [90] is a software accelerator that offers runtime resource control through neural network layer compression and by automatically decomposing a deep learning model across available processors while accounting for dynamic resource constraints of mobile devices.

6.2 Automation and Optimization

To manage complex configuration, deployment and maintenance tasks across multiple technologies, automation and optimization are increasingly relied on throughout the distributed machine learning development lifecycle. Neural architecture search automates and optimizes the process of finding good network architectures for deep learning models. The original approach to neural architecture search proposed by Zoph and Le [184] uses a recurrent neural network as controller to generate hyperparameters, and reinforcement learning to train the controller, in order to arrive at a state-of-the-art convolutional neural network architecture. The concept of exploring a search space for optimal network architectures has since been extended. For example, Xie et al. [170] propose the use of network generators to sample potential architectures from a distribution, and have discovered that randomly wired neural networks can produce competitive results to conventional structures.

While deep learning models are producing state-of-the-art results, their reliance on labelled training data is a constraint. Advances in weak supervision are providing mechanisms for automating label generation. Ratner et al. [130] propose data

programming for programmatically creating training datasets with an extraction framework called Snorkel. Rather than labeling individual data points, Snorkel allows subject matter experts to define labeling functions to describe the processes by which data points could be labeled. The labeling functions are then used as programs to label the data. Osprey [25] extends Snorkel and provides a high level interface for non-programmers to specify complex labeling functions. Koller et al. [86] apply weak supervision to sequence learning problems with parallel sub-problems in multi-stream video processing. They exploit temporal sequence constraints within independent streams and combine them by explicitly imposing synchronization points. In the context of continuous improvement, Kang et al. [85] use model assertions to monitor and validate machine learning models, and to provide weak supervision. The assertions validate the consistency of model outputs and present correction rules that propose new training labels for data that fail the assertions. ease.ml/ci [134], on the other hand, is a continuous integration system that aims to reduce the amount of labels required to a practical amount. The system enables users to state integration conditions with reliability constraints. Optimization techniques are then used to reduce the number of training labels while providing performance guarantees that meet production requirements.

Allocating and scheduling distributed workloads across computing resources can be optimized to meet diverse resource utilization objectives. Hadjis et al. [65] study trade-off factors to minimize the training time of convolutional neural networks. Based on their findings, they present Omnivore, an optimizer for asynchronous, data parallel training. Gandiva_{fair} [32] is a GPU cluster scheduler that guarantees fair allocation of compute resources amongst users, while maximizing the efficiency of the cluster by limiting idle resources. The scheduler uses a gang-aware approach that allocates GPUs in an all-or-nothing manner to a job, distributes jobs evenly through the cluster by using a load balancer and finally implements an automated GPU trading strategy to ensure user-level fairness. AlloX [92] also addresses fair resource allocation amongst users, but aims to simultaneously optimize performance to reduce the average job completion time.

6.3 Privacy-preserving machine learning

Recent work on privacy-preserving machine learning is predominantly focused on retaining the anonymity of data providers both during training and inference. Differential privacy [48] adds random noise that is generated according to a chosen distribution to a data query before returning the result to the user. This approach has provable privacy guarantees and has become the standard for protecting sensitive data in machine learning. v.d. Hoeffen [159] generalize this approach by allowing the data provider to control the noise distribution and by implication the privacy guarantees, while keeping the parameters of the distribution hidden during training.

On-device processing reduces the risk of data leakage. While feasible for inference, the larger resource requirements for training have given rise to federated learning [24], which keeps sensitive data on mobile devices and performs global parameter aggregation on the cloud. Thus privacy is preserved and large data transfer between devices and the cloud is prevented. The Federated Averaging, or FedAvg [24] algorithm does data parallel training on mobile devices and synchronously averages parameter updates on a central server. Many extensions have been proposed to federated learning. FedProx [98] is an adaptation of FedAvg that permits partial work from straggling devices to be committed for averaging. While keeping data on devices improves privacy protection, communicating the update parameters and model over the wireless network presents security risks. Adding differential privacy has been proposed in [113] and integrated into the Tensorflow Private library. Truex et al. [156] proposes federated learning with differential privacy and secure multiparty computation to improve model accuracy by reducing the added noise without sacrificing privacy, as the number of participating devices increases. Seif et al. [146] show that interference in the wireless communication channel can provide

strong guarantees for local differential privacy and improved bandwidth efficiency for federated learning. To allow for personalization, FURL [26] splits parameters into local, private parameters that remain on a mobile device and federated parameters that are averaged on a central server.

For privacy-preserving inference on the cloud, Bost et al. [22] present an approach for classification over encrypted data. To limit sensitive inference on application data accessed by third parties, the Replacement AutoEncoder (RAE) algorithm proposed by Malekzadeh et al. [106] differentiates between black-listed (i.e. sensitive), grey-listed (i.e. not useful) and white-listed (i.e. desired information) predictions. RAE learns to replace black-listed predictions with values from grey-listed predictions. The Guardian-Estimator-Neutralizer (GEN) framework [105] uses feature learning and data reconstruction to trade off the utility that an application provides based on the data it has access to, and the sensitive user information that is revealed.

7 OPEN PROBLEMS

Machine learning has enabled dramatic progress in realising smart services within the IoT. However, many challenges remain to ensure that the deployment of intelligence moves from fragile, cloud-based algorithms to fully functional, trustworthy and business-aligned systems. This section discusses some of the open challenges.

7.1 Full Stack Machine Learning Support

End-to-end software support for machine learning systems in the IoT must facilitate the development, testing, configuration, deployment, management and maintenance of all technologies that affect data provenance, model training and inference. Due to the scale and distribution of devices in the IoT, many of the required tasks will need to be automated. As noted by Hartsell et al. [66], traceability and reproducibility are necessary at every development step for safety and mission-critical applications typical in CPS and the IoT. Machine learning systems embedded within the IoT are no exception, and must be traceable and transparent to human users. Data history and quality are of particular importance, as they replace traditional analytical Models in machine learning systems. Extending and adapting data provenance and software engineering tools developed for cloud technologies to the device-edge-cloud continuum can serve as a starting point. Necessary tasks include automated data validation, catching data errors, making implicit assumptions about data explicit, detecting anomalies between training and serving data, performance profiling and deciding when to retrain a model. The scarcity of labelled training data needs to be overcome and alternatives to supervised learning will need to be explored. Within the context of the IoT, traditional semi-supervised learning with general adversarial networks presents challenges due to increased model complexity, training instability and performance degradation in multi-modal sensing applications [173]. Automated labelling is viewed as promising for addressing the challenge of accumulating sufficient training data [2], but its limitations still need to be explored. Many smart services will need to respond to changing, local conditions. Context adaptation, personalization, incremental learning and continual learning present promising avenues to evolve models in dynamic environments.

7.2 Comprehensive Approach to Trustworthiness

Predictions in the IoT must cater for open world assumptions. New categories, unseen examples, black swan events and foreign attack models require an extension of existing machine learning privacy and robustness considerations to broader trustworthiness concerns that arise within the IoT context. These should include reliability, resilience, safety and security concerns, together with comprehensive trustworthiness guarantees. A nuanced treatment of privacy that extends beyond anonymity to trust and control is necessary. Designing systems that can learn on encrypted data, that can train on devices,

and that can provide sufficient and efficient inference performance with coarser and less data, will improve anonymity, control and trust of machine learning systems in the IoT. Machine learning systems must anticipate network security attacks that can result in altered, noisy and missing data and models. Proactive approaches to dealing with attacks include finding ways to measure data provenance, devising mechanisms for learning under uncertainty, declining predictions, verifying data and model authenticity, providing inference with quality assurance and developing systems that are resilient under attack. Intermittent and unreliable data transfer over wireless channels will result in missing values that can limit inference quality and affect system level predictive performance. This requires machine learning systems that can handle data dropouts, that are fault tolerant and that provide reliable results in unstable communication environments. Issues of fairness, accountability and transparency that have emerged in the machine learning community [162] need to be accounted for in machine learning systems in IoT applications. To incorporate trustworthiness concerns within system requirements and design, mechanisms for specifying and measuring them, and for evaluating trade-offs presented by trustworthiness concerns are needed.

7.3 Socio-Technical Perspective of Smart Services

Smart services in the IoT can be viewed as socio-technical systems involving complex, interacting and interdependent cyber-physical technical components and networks of independent actors consisting, for example, of users, data generators, network providers, data processors and service providers. Important research directions lie at the intersection of the different enabling technologies highlighted in Figure 4, within the contexts provided by the design aspects and concerns outlined in Table 1. The technical system design demands interdisciplinary expertise, and an expanded understanding of the interacting design considerations of distributed machine learning systems and IoT communication, hardware and device technologies. Domain experts need a nuanced understanding of the availability and limitations of machine learning systems and cloud technologies. Moreover, the multi-stakeholder environment gives rise to conflicting requirements and priorities between actors. To apply a systems approach to the development of smart services, frameworks and processes are needed to navigate conflicting design concerns and the trade-offs between stakeholder requirements that they represent. Providing an overview of available technologies and design choices with explicitly specified limitations, quality of service guarantees and uncertainty estimates at each design step can help in negotiating requirements trade-offs and technology choices amongst stakeholders.

8 CONCLUSION

This article presents a structured review of considerations and concerns for deploying machine learning systems in the IoT to enable smart services with intelligence. Four key perspectives have emerged through the review process. Firstly, a unified view of cyber-physical systems and the IoT can benefit the development of machine learning systems for smart services of hybrid logical-physical nature. Particularly, sharing approaches across these two communities enables IoT applications to draw on solid frameworks developed for cyber-physical systems to identify IoT specific design aspects and stakeholder concerns. Secondly, our review highlights the challenges presented by state-of-the-art cloud architectures for machine learning systems in the IoT, and the rising demand to consider alternative architectures. Thirdly, many machine learning systems have been deployed in production and the challenges for ongoing operations are known. These challenges will prevail in IoT applications as well, and require a system-perspective that appraises machine learning technologies beyond algorithms. Finally, advances in distributed computing and edge computing are promising for scaling and distributing machine learning in the IoT, and will be integral to the future architectures of smart services.

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