

Pervasive AI for IoT Applications: Resource-efficient Distributed Artificial Intelligence

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Abstract—Artificial intelligence (AI) has witnessed a substantial breakthrough in a variety of Internet of Things (IoT) applications and services, spanning from recommendation systems and speech processing applications to robotics control and military surveillance. This is driven by the easier access to sensory data and the enormous scale of pervasive/ubiquitous devices that generate zettabytes (ZB) of real-time data streams. Designing accurate models using such data streams, to predict future insights and revolutionize the decision-taking process, inauguates pervasive systems as a worthy paradigm for a better quality-of-life. The confluence of pervasive computing and artificial intelligence, Pervasive AI, expanded the role of ubiquitous IoT systems from mainly data collection to executing distributed computations with a promising alternative to centralized learning, presenting various challenges, including privacy concerns, scalability, and latency requirements. In this context, a wise cooperation and resource scheduling should be envisaged among IoT devices (e.g., smartphones, smart vehicles) and infrastructure (e.g. edge nodes, and base stations) to avoid communication and computation overheads and ensure maximum performance. In this paper, we conduct a comprehensive survey of the recent techniques and strategies developed to overcome these resource challenges in pervasive AI systems. Specifically, we first present an overview of the pervasive computing, its architecture, and its intersection with artificial intelligence. We then review the background, applications and performance metrics of AI, particularly Deep Learning (DL) and online learning, running in a ubiquitous system. Next, we provide a deep literature review of communication-efficient techniques, from both algorithmic and system perspectives, of distributed inference, training and online learning tasks across the combination of IoT devices, edge devices and cloud servers. Finally, we discuss our future vision and research challenges.

Index Terms—Pervasive computing, deep learning, distributed inference, federated learning, online learning.

I. INTRODUCTION

DIVEN by the recent development and prevalence of computing power, algorithms, Internet of Things (IoT) systems, and big data, a booming era of AI has occurred, covering a wide spectrum of applications including natural language processing [1], speech recognition [2], computer vision [3], and robotics [4]. Owing to these breakthroughs, AI has achieved unprecedented improvements in multiple sectors of academia, industry, and daily services in order to improve

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the humans' productivity and lifestyle. As an example, multiple intelligent IoT applications have been designed such as shopping recommenders, smart assistants, self-driving cars, disease mapping services, smart home appliances, manufacturing robots, and surveillance systems. In this context, studies estimate that AI will have higher impact on the global Gross Domestic Product (GDP) by 2030, accounting for \$ 13 trillion additional gains compared to 2018 [5]. The high performance of AI systems applied to multiple fields comes at the expense of a huge memory requirement and an intensive computational load to perform both training and inference phases. More specifically, training an intelligent model is computationally expensive because of the large number of parameters, reaching millions for deep networks, that need to be repetitively fine-tuned over hundreds of iterations. Similarly, the inference phase is computationally intensive due to the high dimension of raw data (e.g., high resolution images) and millions of tasks (e.g., multiplications and max-pooling) in deep networks [6], [7]. To this end, the resource consumption has been adopted as an important parameter to assess the performance of AI models.

The popularity of AI is also related to the abundance of storage and computing devices, ranging from server clusters in the cloud to personal phones and computers, further, to wearables and IoT units. In fact, the unprecedented amount of data generated by the massive number of ubiquitous devices opens up an attractive opportunity to provide intelligent IoT services that can transform all aspects of our modern life and fuel the continuous advancement of AI. Statistics forecast that, by 2025, the number of devices connected to the internet will reach more than 500 billion [8] owing to the maturity of their sensing capabilities and affordable prices. Furthermore, reports revealed that these devices will generate enormous data reaching more than 79 ZB by 2025 and will increase the economic gains up to 11 trillion by the same year. Particularly, 40% of this economic impact is related to the healthcare market, 33% corresponds to the industrial applications, 7% corresponds to the energy sector, whereas the rest is related to other domains such as agriculture, security, and retail [9].

With the rapid evolution of AI and the enormous bulks of data generated by pervasive devices, conventional wisdom resorts to centralized cloud servers for analytics. However, this approach is no longer sustainable as it introduces several challenges: (1) the appearance of a new breed of services and the advent of delay-sensitive technologies spanning from self-driving cars to Virtual and Augmented Reality (VR/AR), make the cloud-approaches inadequate for AI tasks due to the long

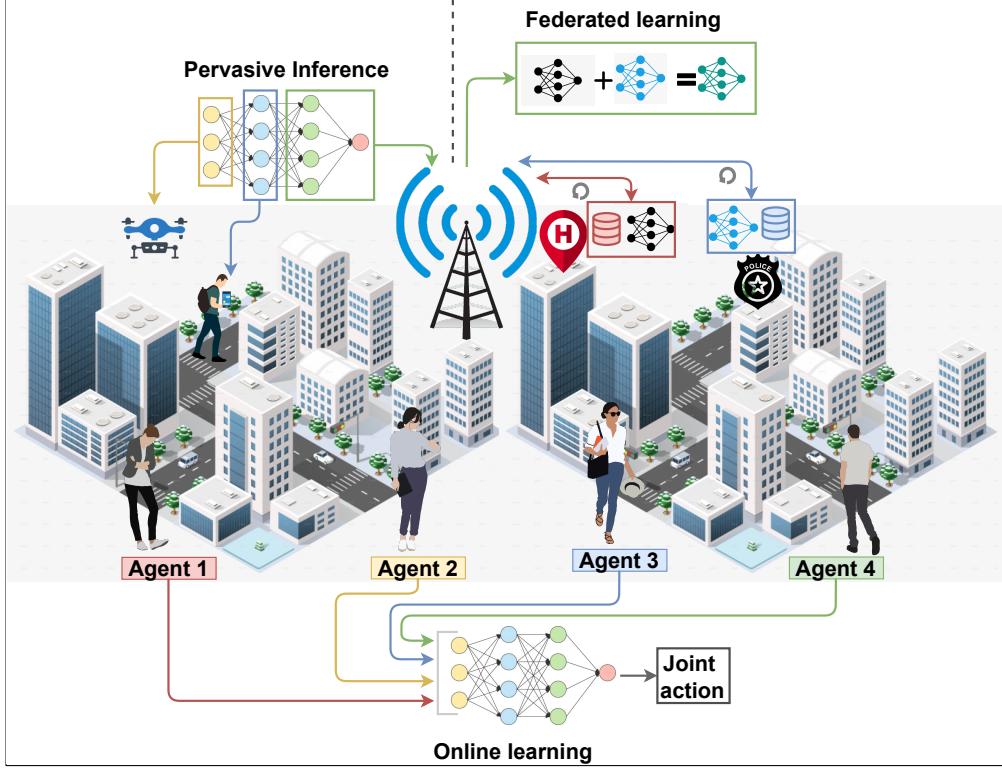


Fig. 1: Illustration of pervasive AI.

transmission delays. More precisely, the aforementioned applications are real-time and cannot allow any additional latency or connectivity loss. For example, autonomous cars sending camera frames to remote servers need to receive prompt inferences to detect potential obstacles and apply brakes [10], [11]. Besides, the delay variance is also very important in interactive IoT applications such as visuo-haptic perceptions and VR to avoid motion sickness [12]. Other examples are the voice assistant applications (e.g., Siri and Alexa) that should parse the user's request and answer its query instantly, and the Unmanned Aerial Vehicles (UAVs) that should sense and react rapidly in hazardous environments, even if the network is unavailable [13]. Sending data to cloud servers may not satisfy the latency requirements of the real-time applications. Particularly, experiments in [14] demonstrated that executing a computer vision task on a camera frame offloaded to an Amazon server takes more than 200 ms. (2) In addition to latency, privacy presents a major concern for cloud-based AI approaches. In fact, end-users are typically reluctant to upload their private data to cloud servers (e.g., photos or audios), as they can be highly exposed to cyber risks, malicious attacks, or disclosures. Among the most popular breaches reported in the 21st century, we can cite the Marriott attack revealed in 2018 and affecting 500 million customers and Equifax breach recorded in 2017 and affecting 147 million users [15]. (3) A tremendous number of AI tasks, involving unstructured and bandwidth-intensive data, needs to be transferred across the Wide Area Network (WAN), which poses huge pressure on the network infrastructure having varying quality. (4) In the same context, offloading the data to remote servers encounters

also scalability issues, as the access to the cloud can become a bottleneck when the number of data sources increases, particularly if some devices import irrelevant and noisy inputs. (5) Nowadays, Explainable AI (XAI) [16] has become extremely popular, aiming to enhance the transparency of learning and detect prediction errors. However, consigning AI tasks to the cloud makes the whole process a black-box vis-a-vis the end-user, and prevents model decomposability and debugging.

Pushing AI to the network edge has been introduced as a viable solution to face latency, privacy, and scalability challenges described earlier. As such, the large amount of computational tasks can be handled by edge devices without exchanging the related data with the remote servers, which alleviates the traffic load and guarantees agile IoT services owing to the physical proximity of computing devices to the data sources [17]. In the case when the AI tasks can only be executed at the cloud datacenters, the edge devices can be used to pre-process the data and polish it from noisy inputs in order to reduce the transmission load [18]. Furthermore, the edge network can play the role of a firewall that enhances user privacy by discarding sensitive information prior to data transfer. A variety of edge devices can be candidate for executing different AI tasks with different computation requirements, ranging from edge servers provisioned with GPUs, to smartphones with strong processors and even small IoT wearables with Raspberry Pi computing. These edge devices have been continuously improving to fit for deep AI models. In this context, researchers have proposed various strategies from diverse angles, covering new hardware designs and novel AI models. More specifically, when designing a learning

technique for resource constrained units, a reduced number of parameters can be used to decrease the memory demand and the execution time, e.g., SqueezeNet [19] and MobileNets [20]. Additionally, to speed up the learning process, vendors have produced custom integrated circuits designed for deep learning tasks, such as the Tensor Processing Unit (TPU) of Google [21]. Also, manufacturers have provided libraries and software tools to leverage the CPU/GPU in order to parallelize AI tasks. As an example, iPhone is currently issued with A12 Bionic chip dedicated to AI-based applications [22]. In spite of this technological advancement, a large range of pervasive devices used in countless fields of our daily life still suffers from limited power and memory, such as smart home IoT appliances, sensors, and gaming gears. Furthermore, privacy remains a challenge, even if local computing naturally improves the security of data.

Given the limited resources of edge-devices, computing the full AI model in one device may be infeasible, particularly when the task requires high computational load, e.g., Deep Neural Networks (DNN). A promising solution is to adopt pervasive computing, where different data storages and processing capacities existing everywhere and including distributed cloud datacenters, edge servers, and IoT devices cooperate to accomplish AI tasks that need large memory and intensive computation. This marriage of pervasive computing and AI has given rise to a new research area, namely “*Pervasive AI*”, which garnered considerable attention from both academia and industry. Formally, pervasive AI focuses on how to intelligently distribute the inference or the training of the AI model across devices, to minimize the latency, and improve privacy and scalability. Specifically, tech giants started to implement pilot projects to assess the efficiency of pervasive computing in crafting the way to better govern the AI applications. For example, Google designed a framework to distribute the training of language DNNs on clients’ devices to predict the next-word in virtual keyboards [23]. Notably, the research and practice on this emerging intersection is still in its infancy. The pervasive AI was firstly introduced to solve the described challenges of centralized approaches (e.g., on-cloud or on-device computation). (1) Thus, to preserve privacy and reduce the huge overhead of data collection and the complexity of training an astronomical dataset, *Federated Learning (FL)* is proposed, where raw data are stored in their source entities and the model is trained collaboratively. Particularly, each entity computes a local model using its collected data, then sends the results to a fusion server to aggregate the global model. Such an approach covers the distribution of data and the assembly of the trained AI models. (2) To cope with the limited resources provided by edge devices and simultaneously avoid latency overheads caused by cloud transmissions, the inference task is distributed among ubiquitous devices located at the proximity of the source. The basic idea is to divide the trained model into segments and subsequently, each segment is assigned to a participant. Each participant shares the output to the next one until generating the final prediction. In other words, the *Pervasive Inference* covers the distribution of the established model resulting from the training phase. (3) Some AI techniques are inherently distributed such as Multi-Agent Reinforcement

Learning (MARL) or Multi-agent Bandits (MAB) classified as *Online Learning*, where agents cooperate to build and improve a policy in real-time enabling them to take on-the-fly decisions/actions based on the environment status. In this case, the distribution covers the online creation and update of the Reinforcement Learning (RL) policy. The pervasive AI concept is illustrated in Fig. 1.

The pervasive AI exploits the on-device computation capacities to collaboratively achieve learning tasks, which requires a careful scheduling to wisely use the available resources without resorting to remote computing. Yet, some intensive AI tasks can only be performed by involving the cloud servers, which results in higher communication costs. Therefore, leveraging the small and ubiquitous resources and managing the enormous communication overheads present a major bottleneck for the pervasive AI.

I.A. Our scope

In this survey, we focus on the confluence of the two emerging paradigms: pervasive computing and artificial intelligence, which is named *Pervasive AI*. The pervasive AI is a promising research field, in which the system design is highly correlated to the resource constraints of the ubiquitous participants (e.g., memory, computation, bandwidth, and energy.) and the communication overheads between them. More specifically, the size of some deep AI models, their computational requirements and their energy consumption may exceed the memory or the battery level of some devices, which restricts them from participating in the collaborative system. Furthermore, the process of decentralized training or inference may involve a big number of participants that potentially communicate over wireless links, which creates new challenges related to channels capacities and conditions, the delay performance, and the privacy aspect. Therefore, the pervasive AI should rely on various parameters, including the optimal AI partitioning, the wise design of architectures and algorithms managing the distributed learning, and the smart selection and scheduling of pervasive participants supported by efficient communication protocols, while accounting for the channel dynamics and communication overheads. Not only that, all the on-device constraints should be taken into consideration such as the memory, the computation, the energy, not to mention the privacy requirements of the system. Finally, the load of real-time inferences (e.g., an area that needs 24/7 surveillance), the pace of data collection (e.g., weather monitoring) and the dynamics of the studied environment should also be considered as they highly impact the number of selected participants and the parallelization strategies. In this paper, we survey the aforementioned challenges in deploying pervasive AI models and algorithms. Particularly, we provide a deep study of resource-efficient distributed learning for the training phase, the inference tasks, and the online learning involving real-time training and decision process. We start by identifying the motives behind establishing a pervasive AI system for IoT applications and its corresponding communication and resource challenges.

TABLE I: Comparison with existing surveys.

Refs	Summary	AI/pervasivity		Scope		AI technique			Topic		
		AI on pervasive networks	AI for pervasive networks	cloud	edge servers	IoT	DI	FL	MARL	Deployment: hardware, software techniques, protocols.	Management: communication, resource allocation, and algorithms
[24], [25] (2020-2021)	Deep Learning applications for the Mobile Edge computing networks	✗	✓ 5G, wireless networks	✓	✓	✓	✓	✓	✗	✓	✗
[26] (2019)	Efficient usage of IoT hardware and software for AI applications	✓	✗	✗	✗	✓	✗	✗	✗	✓	✗
[27]–[31] (2019-2020)	Enabling AI on edge networks	✓	✓	✗	✓	✓	✓	✓	✗	✓	✗
[32] (2018)	Enabling AI on edge networks	✓	✗	✗	✓	✓	✓	✗	✗	✓	✗
[33]–[35] (2018-2020)	Decision making in multi-agent systems and related applications	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
[36] (2020)	Deep RL for IoT systems	✓	✓	✗	✗	✓	✗	✗	✗	✓	✓
[37] (2020)	Deep RL for wireless networks	✓	✓ wireless networks	✗	✓	✓	✗	✗	✓	✓	✗
[38] (2019)	Communication for ML and ML for communication	✓	✓ wireless networks	✗	✓	✓	✗	✓	✗	✗	✓
[39] (2020)	Communication efficient edge AI	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
[40] (2019)	AI on mobile and wireless networks	✓	✓ 5G, wireless networks	✗	✓	✓	✗	✗	✗	✓	✓
[41] (2020)	Enabling protocols, technologies for federated learning	✓	✓	✓	✓	✓	✗	✓	✗	✓	✗
[42]–[44] (2020)	Architecture, design and applications of centralized, distributed and federated learning	✓	✓	✓	✓	✓	✗	✓	✗	✓	✓
[45] (2020)	Enabling protocols, technologies for federated learning	✓ Vehicular IoT	✗	✗	✓	✓	✗	✓	✗	✓	✗
Our paper	Pervasive AI	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓

I.B. Related surveys

The intersection of pervasive computing and AI is still in its early stage, which attracts the researchers to review the existing works and provide useful and innovative insights, as illustrated in Table I. First, many efforts discussed the applications of artificial intelligence that support edge networks composed of ubiquitous devices, in order to meet the networking requirements. Multiple edge contexts are explored such as healthcare, smart cities, and grid energy. As an example, two recent surveys [24], [25] provided an in-depth discussion of the usage of AI in wireless and 5G networks to empower caching and offloading, resource scheduling and sharing, virtual edge orchestration, and network privacy. Additionally, they discussed the standardizations that increased the potential of AI to solve communication and wireless issues. These surveys touched upon the pervasive AI, particularly federated learning and distributed inference. However, the distribution was discussed briefly as one of the techniques that further enables AI for the edge. In our survey, the applications

of AI for pervasive networks are not the main topic. Instead, the deployment of AI on pervasive devices is the scope of this paper. Authors in [26] presented an overview about hardwares, softwares, and run-time optimizations enabling the deployment of AI on pervasive devices, which include CPU accelerators, samples reduction, and computation reduction through AI compression. Enabling the complex AI techniques in resource-constrained devices is one of the arms of this survey. However, we cover only the distribution approach to fit the complex models on small devices. Still, our study is not restricted nor to small devices neither to the distribution motivated by resource scarcity. Indeed, we define the pervasive AI as “*the distribution of AI tasks among any type of devices existing anywhere in order to handle different types of systems (e.g., IoT systems, privacy-aware systems, and inherently decentralized systems)*”.

The surveys in [27]–[32] conducted a comprehensive review on the systems, architectures, frameworks, softwares, technologies, and algorithms that enable the AI on edge networks

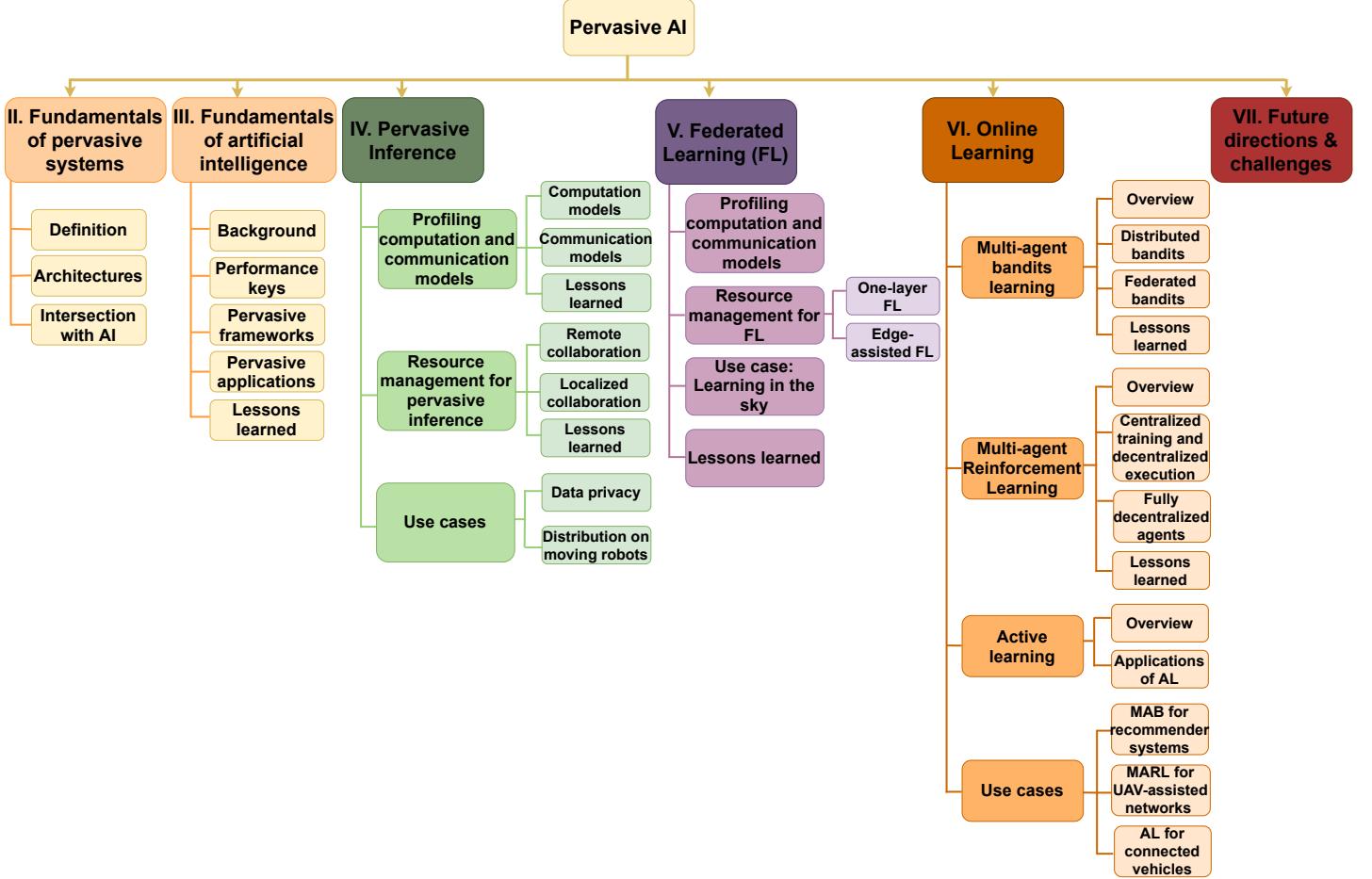


Fig. 2: Pervasive AI survey roadmap.

and discussed the advantages of edge computing to support the AI deployment compared to cloud approaches. However, even though they dedicated a short part for distributed AI, these efforts did not discuss the resource and communication challenges of pervasive systems nor the splitting techniques of AI. Moreover, they did not consider the cloud computing as indispensable part of the distributed system. Therefore, unlike the previous surveys [27]–[32], we present an in-depth review that covers the resources, communication and computation challenges of distributed AI among ubiquitous devices. More specifically, applying the same classical communication and computation techniques adopted in centralized approaches for pervasive AI is not trivial. As an alternative, both pervasive computing system and distributed AI techniques are tailored to take into consideration the heterogeneous resources of participants, the AI model, the requirements of the system to reduce the communication and computation overhead during the training and inference phases. These customized strategies for pervasive AI are the main focus of our survey.

The previous papers discussed the distribution as one of the approaches enabling AI deployment on the edge. Particularly, they briefly examined the distributed inference and federated learning. However, the multi-agent online learning including Multi-Agent Reinforcement and bandit learning has not been reviewed by any one of them. Multiple papers

surveyed the single agent and multi-agents reinforcement learning, such as [33]–[37]. In these tutorials, the authors conducted comprehensive studies of applications of distributed RL for networking problems and presented an overview of the evolution of cooperative and competitive MARL, in terms of rewards optimization, policy convergence, agents connection, and performance improvement. To the best of our knowledge, we are the first to cover the computation and communication issues witnessed by cooperative agents while achieving a consensus on the distributed RL policy.

Finally, the authors in [38]–[40] provided a deep review of communication challenges of AI-based applications on edge networks. Specifically, the survey in [40] provided insights about allocating mobile and wireless networks resources for AI learning tasks. However, the distribution of AI techniques was not targeted in this latter paper. The surveys in [38], [39] are considered the closer ones to our topic as they explored the communication-efficient AI distribution. However, they mainly focused on the training phase, i.e., federated learning, whereas the pervasive inference and online learning were ignored as the literature about these topics was too small. The inference distribution is briefly discussed in [38] from a communication angle, however, without discussing other constraints such as the memory and computation nor presenting the partitioning strategies (i.e., splitting of the trained model), which highly

impact the distribution process, the parallelization technique, and participants orchestration. Our paper represents a holistic survey that covers all AI tasks that require cooperation between pervasive devices guided by the system design, the AI model, and the application requirements.

I.C. Contributions and structure of the paper

The contributions of this paper are summarized as follows:

- We present an overview of the pervasive systems and introduce its architecture and potential participants.
- We provide a brief background of artificial intelligence, particularly deep learning and online learning. We, also, describe the frameworks that support AI tasks and the metrics that assess their performance. Furthermore, we present multiple IoT applications, in which pervasive AI can be useful.
- For each phase of the AI (e.i., training, inference, and online learning), we profile the communication and computation models and review the state-of-the-art. A comparison between different existing works, lessons learned, in addition to recent use cases, are also provided.
- We conclude by an elaborative discussion of our future vision and we identify some open challenges that may arouse new promising research ideas.

The rest of this paper is organized as follows: Sections II and III present the fundamentals of pervasive systems and artificial intelligence, respectively. In section IV, we present a deep study of the *pervasive inference*. Particularly, we review the state-of-the-art approaches adopting different splitting strategies and managing the existing pervasive resources to distribute the inference. Next, we compare the performance of these works and discuss the learned lessons and potential use cases. Section V presents the related studies that investigated the potential of *federated learning* schemes in different domains. Moreover, it highlights the use of FL within UAV swarms for cooperative target recognition as a case study. Section VI investigates diverse *online learning* schemes, which are multi-agent bandits, reinforcement learning, and active learning. Indeed, we review state-of-art algorithms that tackle the pervasive systems perspective on online learning. Specifically, we focus on the algorithms that study the trade-off between the consumed communication resources and the performance, offering a novel viewpoint on the strengths and weaknesses of the discussed approaches. We discuss the future vision and open challenges, in section VII. Finally, we conclude in section VIII. More details about the road map of the paper are illustrated in Fig. 2. Additionally, the list of acronyms is presented in Table II.

TABLE II: List of Acronyms

AC	Actor-Critic
AE	Auto-Encoder
AI	Artificial Intelligence
AL	Active Learning
AR	Augmented Reality
BM	Bolzman Machines
BS	Base Station
CNN	Convolutional Neural Network
Conv	Convolutional

CTDE	Centralized Training and Decentralized Execution
DAG	Directed Acyclic Graph
DB	Distributed Bandits
DDPG	Deep Deterministic Policy Gradient
DL	Deep Learning
DNN	Deep Neural Network
DPPO	Distributed Proximal Policy Optimization
DQL	Deep Q-Learning
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
ECG	Electrocardiogram
EEG	Electroencephalogram
FANET	Flying Ad-hoc Network
FB	Federated Bandit
Fc	Fully connected
FL	Federated Learning
FNN	Feed forward Neural Network
GAN	Generative Adversarial Networks
GDP	Gross Domestic Product
IID	Independent and Identically Distributed
IoT	Internet of Things
IoV	Internet of Vehicles
LSTM	Long Short Term Memory
MAB	Multi-Agent Bandit
MADDPG	Multi-Agent Deep Deterministic Policy Gradient
MARL	Multi-Agent Reinforcement Learning
MDP	Markov Decision Process
MEC	Mobile Edge Computing
MLP	Multi-Layer Perceptron
NN	Neural Network
PAC	Probably Approximately Correct
PAIaaS	Pervasive AI as a service
POMDP	Partially Observable Markov Decision Process
POMG	Partially Observable Markov Game
ppb	part per billion
ppm	part per million
PPO	Proximate Policy Optimization
QoE	Quality of Experience
QoS	Quality of Service
RL	Reinforcement Learning
rMSE	regularized Maximum Likelihood Estimation
RNN	Recurrent Neural Network
SGD	Stochastic Gradient Descent
SINR	Signal to Interference plus Noise Ratio
TPU	Tensor Processing Unit
UAV	Unmanned Aerial Vehicle
UCB	Upper Confidence Bound
UE	User Equipment
VR	Virtual Reality
WAN	Wide Area Network
XAI	Explainable AI
6G, 5G, 4G	Sixth, Fifth, Fourth Generations

II. FUNDAMENTALS OF PERVERSIVE SYSTEMS

II.A. Definition

The pervasive computing [46], [47], named also ubiquitous computing, is the growing trend to embed computational capabilities in all devices in order to enable them to communicate efficiently and accomplish any computing task, while minimizing their resource consumptions e.g. battery, memory, cpu time, etc. The pervasive computing can occur in any device, at any format, in any place and any time. More

specifically, it can span from resource-constrained devices to highly performant servers and can involve cloud datacenters, mobile edge computing servers, mobile devices, wearable computers, embedded systems, laptops, tablets, pair of intelligent glasses, and even a refrigerator or a TV. These ubiquitous devices are constantly connected and available for any task, Ubiquitous computing is supported by different technologies including operating and middleware systems, sensor networks, distributed systems, mobile protocols and networks, human-computer interaction, smart home technologies, and artificial intelligence.

To illustrate the pervasive computing where participants hand tasks one to another, we can cite the example of an Apple watch that notifies the user of an incoming phone call and allows him to start the conversation from his mobile device and complete it from the smart watch. Another example is the Audible application of Amazon, where a user can read a book on his/her tablet in the park and continue listening to it using Amazon Echo or Alexa at home. To summarize, we are not talking anymore about devices acting on a passive data. Instead, the pervasive systems are able to collect, process, communicate any data type or size, understand its surroundings, adapt to the input context, and enhance humans' experiences and lifestyles.

II.B. Ubiquitous participants

The pervasive systems are characterized by highly heterogeneous devices (see Fig. 3), where the critical challenge is to design a scalable infrastructure able to dynamically discover different components, manage their interconnection and interaction, interpret their context, and adapt rapidly to the deployment of new softwares and user interfaces. A pervasive system can be composed of:

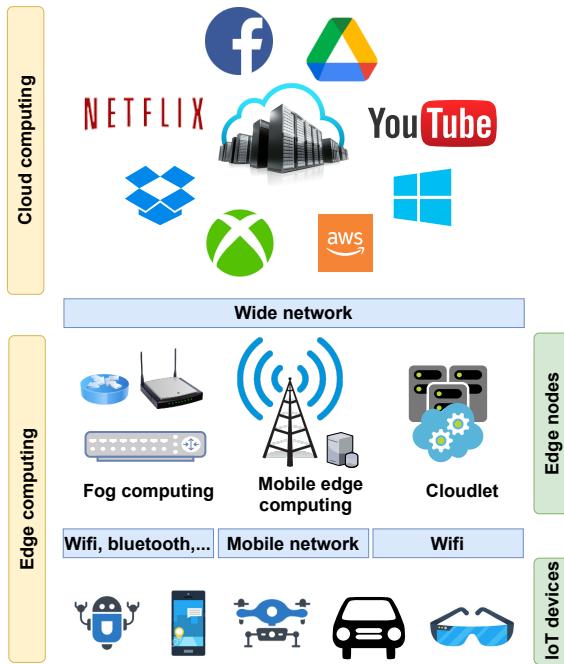


Fig. 3: Ubiquitous participants.

II.B.1. Data center and cloud computing

Cloud computing [48]–[52] is defined as delivering on-demand services from storage, management, and computation to artificial intelligence and natural language processing on pay-as-you-go basis. Hence, instead of owning computing servers, companies, operators, and end-users can exploit the high-performance facilities offered by the cloud service provider. In this way, they can benefit from better computational capacities, while reducing the cost of owning and maintaining a computation infrastructure, and paying only for their requested services. Cloud computing underpins a broad number of services, including data storage, cloud back-up of photos, video streaming services, and online gaming.

II.B.2. Mobile Edge Computing (MEC)

Edge computing is introduced as a solution to bring cloud facilities at the vicinity of users in order to minimize the services perceived latency, relieve the data transmission, and ease the cloud congestion. In another word, the edge computing has become an essential complement to the cloud and even a substitute in some scenarios. Services and computing capabilities equipped at the edge of cellular networks are called Mobile Edge Computing (MEC) facilities [53]–[55]. Deploying MEC servers within the edge Base Stations (BSs) allows providing location and context awareness, deploying new services quickly and flexibly, and enhancing the Quality of Service (QoS).

II.B.3. Cloudlets

Cloudlets [56] are the network components that connect cloud computing to mobile computing. This network part presents the middle layer of the three-tier hierarchical architecture composed of mobile devices, micro-clouds, and cloud data centers. The role of cloudlets is to define the algorithms and implement the functionalities that support low latency edge-cloud tasks offloading.

II.B.4. Fog computing

The fog [57] and cloud computing share the same set of services provided to end-users, such as storage, networking, computing, and artificial intelligence. However, the cloud architecture is composed of fully distributed large-scale data centers. Meanwhile, fog services focus on IoT devices in a specific geographical area and target applications requiring real-time response such as live streaming, interactive applications, and online collective gaming.

II.B.5. Edge devices

In most of the studies, the interpretation of edge devices (i.e., edge nodes and IoT devices) is still ambiguous [58], which means the difference between end or IoT devices and edge nodes is still unclear. Yet, common consensus defines the end-devices/IoT as ubiquitous gadgets, such as smartphones and smart gadgets and the edge nodes, as devices in higher levels including fog nodes, MEC servers, and cloudlets. The edge nodes are expected to possess higher storage and computation capacities and to offer high-quality networking and

processing services at the proximity of IoT devices with a lower response time compared to the cloud remote servers.

Driven by the expansion and pervasiveness of the computing devices, we believe that the heterogeneity of ubiquitous systems will increase in the future. These devices have to interact seamlessly and coherently, despite their difference in terms of software and hardware capacities.

II.C. Architecture and intersection with AI

Fig. 4 illustrates the hierarchical architecture of a pervasive system [47], which is composed of three layers:

- Data source layer: the data is collected from different monitored sources generating information of physical world or human activities, multimedia data such as images and audio, and social media information.
- Data management layer: this layer involves the storage and integration of heterogeneous data incoming from pervasive sources, the cleaning and pre-processing that tailor the context of the system, and the data analytics that convert the raw information into useful and personalized insights using multiple approaches, such as business and artificial intelligence.
- Application layer: to this end, the insights generated from the previous layer are used to offer multiple intelligent applications, such as health advisor and smart home applications.

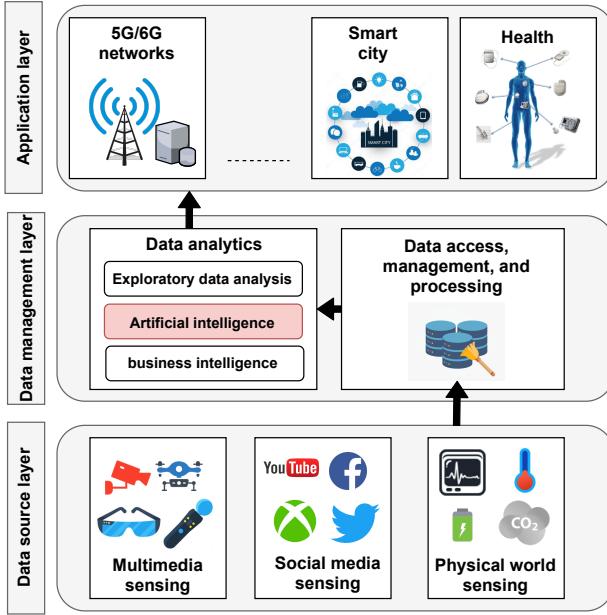


Fig. 4: Pervasive architecture.

In our paper, we focus only on the data management layer, specifically the data analytics using artificial intelligence. The data source layer is thoroughly discussed in [59], whereas the application layer can be found in [9].

III. FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE

Since approaches and techniques reviewed in this survey rely on artificial intelligence and deep neural networks, we start first by providing a brief background of deep learning. A deeper and detailed review of AI can be found in the reference book in [60].

III.A. Background

Even though AI has recently gained enormous attention, it is not a new term and it was initially coined in 1956. In fact, AI is a computation paradigm that aims to teach machines how to act, react, learn, reason, plan, solve problems, and behave like humans. Particularly, by absorbing the knowledge from the real-world data, the AI agent makes decisions without being previously programmed. Multiple techniques and procedures fall under this broad umbrella, such as rule-based systems, expert systems, blackboard architectures, control systems, and well-known machine learning algorithms. Machine learning generally includes three categories, which are supervised, unsupervised and online learning. An important branch of machine learning is deep learning that can be supervised or unsupervised and it is based on simulating the biological nervous system and performing the learning through subsequent layers transformation. As most of the pervasive applications are led by deep learning techniques and recently online learning, the crossover between the above-mentioned domains (shown in Fig. 5) defines the scope of this paper.

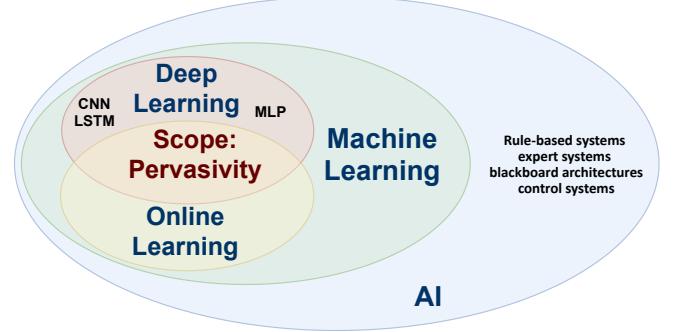


Fig. 5: Relation between AI, machine learning, deep learning, and online learning. This survey mainly focuses on pervasive deep and online learning.

III.A.1. Deep learning and Deep Neural Networks

In the following, we briefly present an overview of the most common deep learning networks.

Neural networks consist of a first input layer, multiple hidden layers, and a last output layer, as shown in Fig. 6. When the neural network contains a high number of sequential layers, it can be called Deep Neural Network (DNN). The DNN layers include smaller units, namely neurons. Each neuron performs a weighted summation and a bias over all received inputs, the obtained sum is then fed to an activation function to generate the output. Fig. 7 illustrates the structure of the neuron. During the training process, the weights and bias vector related to each layer are optimized to enhance the accuracy of the model. Most commonly, the output of one

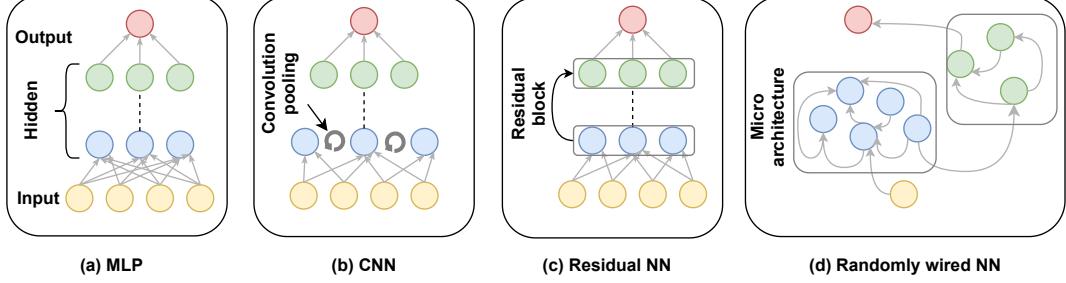


Fig. 6: NN structures: (a) Multilayer Perceptron (MLP), (b) Convolutional Neural Network (CNN), (c) Residual Neural Network, (d) Randomly Wired Neural Network.

layer is the input of the next layer and the output of the final layer is either a classification or a feature. The correctness of the prediction is assessed by the loss function that calculates the error between the true and predicted values. To adjust the weights of different neurons, an optimization algorithm calculating the gradient of the loss function is used. The widely used optimizers are Stochastic Gradient Descent (SGD) [61] and its variants including ADAM [62]. The error rate is propagated back across the network until the input layer. This process, known as the backpropagation, is repeated multiple rounds, while balancing the weights for each neuron at each round. The DNN is considered trained and ready for inference, when the error rate falls below the desired threshold.

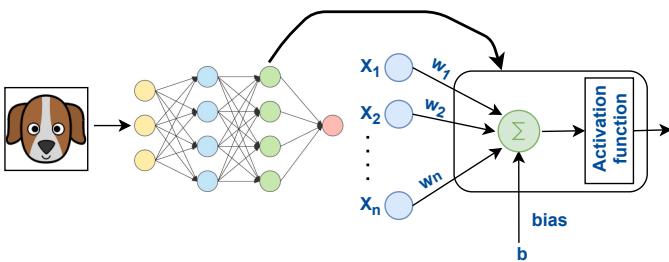


Fig. 7: MLP composed of multiple neurons: Each neuron has several inputs and trainable weights and bias.

The DNN networks have various structures. Hence, we introduce the fundamentals of the most known types as follows:

a) Multilayer Perceptron (MLP): If the output of one layer is fed forward to the subsequent layer, the Neural Network (NN) is termed as the Feed Forward NN (FNN). The baseline FNN is called MLP or Vanilla. As shown in Fig. 6 (a), each layer is Fully connected (Fc) to the next one and the output is sent to the next layer's perceptron without any additional computation or recursion other than the activation function. Even though the structure of MLP is simple, it is able to distinguish non-linearly separable data, as long as the NN model size is sufficiently large.

b) Convolutional Neural Networks (CNN): Processing vision-based tasks (e.g., image data), using MLP, potentially requires a deep model with a huge number of perceptrons, as for each data pixel a perceptron is assigned, which makes the network hard to train and scale. One of the successors of MLP is CNN that is introduced to solve this problem by defining

additional pre-processing layers, (i.e., convolutional (conv) and pooling layers), as shown in Fig. 6 (b). In the convolutional layer, the 2D input data (e.g., speech signal and image) is processed by extracting high-level features and compressing the information. Furthermore, the convolutional layer includes a set of learning parameters, namely filters that have the same number of channels as the data feature maps with smaller dimensions. Each filter channel passes through the length and width of the corresponding input feature map and calculates the inner product to the data. The summation of all the outputs produces one feature map. Finally, the number of output feature maps equals the number of filters, as illustrated in Fig. 8. The second basic component of the CNN network is the pooling task, which has an objective to reduce the spatial size of the input feature maps and minimize the computation time. For example, Maxpooling aiming at partitioning the input data into a grid and picking the maximum value of each grid cell, is widely used in state-of-the-art CNNs. The main difference between the Fc and the conv layers is that each neuron in Fc networks is connected to the entire input, which is not the case of CNN that is connected to only a subset of the input.

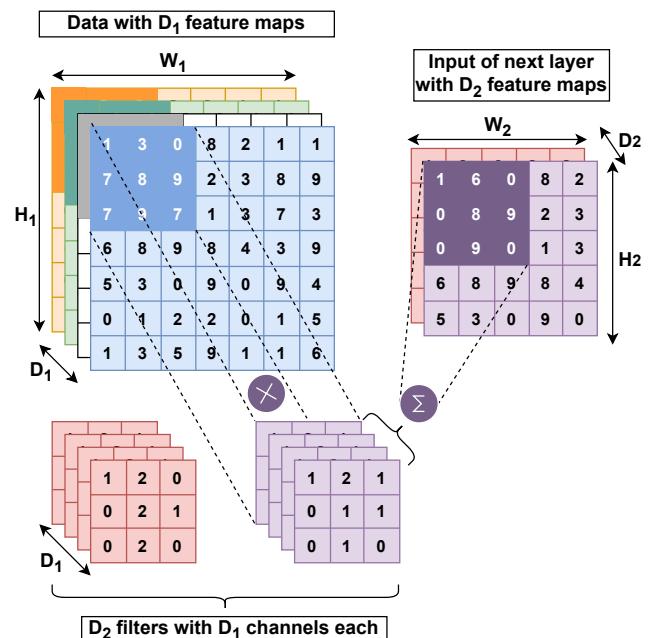


Fig. 8: Convolutional task.

TABLE III: Parameters comparison of state-of-the-art DNNs trained on ImageNet [63], in terms of flops¹.
MACC: Multiply-ACCumulate operations.

Model	Comp	Add	Div	MACC	Activations	params	size (Mb)	pros	cons
VGG 16 [7]	196.85 M	10 K	10 K	154.7 G	288.03 M	138.36 M	512.2	- Spatial exploitation. - Simple and homogeneous topology.	- Computationally expensive fully connected layers.
AlexNet [64]	17.69 M	4.78 M	9.55 M	7.27 G	20.81 M	60.97 M	217	- Spatial exploitation. - Low, medium, and high feature extraction. - Introduces regularization in CNN.	- Inactive neurons in the first layers. - Large filter size that causes artifacts aliasing in the output feature maps.
GoogleNet [65]	161.07 M	8.83 M	16.64 M	16.04 G	102.19 M	7 M	40	- Spatial exploitation. - Multi-scale layers. - Reduces number of params by using bottleneck and average pooling layers.	- Potential lose of important information because of representational bottleneck.
ResNet 50 [3]	10.89 M	16.21 M	10.59 M	3.87 G	46.72 M	25.56 M	97.7	- Depth and Multi-path. - Introduce residual learning. - Solve the vanishing gradient problem.	- Complex architecture. - Multiple layers have no contribution for the inference. - Potential re-learning of redundant feature maps.
ResNet 152 [3]	22.33 M	35.27 M	22.03 M	11.3 G	100.11 M	60.19 M	230		
Inception v3 [6]	16.53 M	25.94 M	8.97 M	5.72 G	41.33 M	23.83 M	91	- Depth and width. - Reduce computational load by using asymmetric filters.	- Complex architecture. - Problem of homogeneity.
Inception v4 [66]	21.87 M	53.42 M	15.09 M	12.27 G	72.56 M	42.71 M	163	- Depth and width. - Deep hierarchy of features.	- Learning is slow.
SqueezeNet [19]	9.67 M	226 K	1.51 M	861.34 M	12.58 M	1.25 M	4.7	- Squeezes non-important features.	- Lower accuracy.

A milestone for CNN applied to computer vision problems is the design of AlexNet, which revolutionized the ImageNet visual recognition challenges in 2012 [64]. AlexNet is composed of 5 conv layers and 3 Fc layers, it contains 61 million weights to classify 227x227 images, and requires 217 Mb to be stored. Another representative example of the state-of-the-art Deep Neural Network that has demonstrated unprecedented performance in visual recognition tasks is VGG. VGG-16 [7] presents a deeper network of 13 conv layers and 3 Fc layers and includes more than 138 million parameters for 224x224 images. VGG can only be executed on powerful devices as deploying it on end-devices presents intolerable classification latency, reaching over 16 seconds [67]. To reduce the computation of the inference, Google introduced a model called GoogleNet or inception model [65]. While achieving a better accuracy, GoogleNet is composed of 7 million weights and requires only 7 million operations for 224x224 images.

c) *Deep Residual Networks*: Following the victory of AlexNet and VGG, the deep residual networks have achieved a new breakthrough in the computer vision challenges during the recent years. Particularly, the residual networks paved the way for the deep learning community to train up to hundreds and even thousands of layers, while achieving high performance. In fact, designing a deep network does not work by only stacking sequential layers, as the training becomes difficult due to the vanishing gradient problem where the backpropagation is inefficient. As a result, when the network goes deeper, its performance starts to saturate and degrade quickly. To tackle the vanishing gradient, an auxiliary loss can be added in

an intermediate layer as extra supervision [65]; however, the performance improvement is not significant. ResNet [3] is the state-of-the-art variant of the residual network. This model uses the so called shortcut/skip connections that skip multiple nodes and feed the intermediate output to a destination layer (see Fig. 6 (c)), which serves as a memory to the model. A similar idea is applied in the Long Short Term Memory (LSTM) networks [68], where a forget gate is added to control the information that will be fed to the next time step. LSTM belongs to the Recurrent Neural Networks (RNN) family.

d) *Randomly Wired Networks*: The aforementioned networks focus more on connecting operations such as convolutional tasks through wise and sequential paths. Unlike previous DNNs, the randomly wired networks [69] arbitrarily connect the same operations throughout the sequential micro-architectures, as shown in Fig. 6 (d). Still, some decisions are required to design a random DNN, such as the number of stages to down-sample feature maps using Maxpooling and the number of nodes to deploy in each stage. The edge of the randomly wired networks over the other models is that the training is faster, the number of weights is reduced and the memory footprint is optimized.

Table III summarizes the parameters of some state-of-the-art DNNs trained on ImageNet dataset [63]. Other state-of-the-art structures achieved unprecedented performance in multiple deep learning applications [70], [71], including Recurrent Neural Networks (RNNs) [72], Auto-Encoders (AEs) [73], and Generative Adversarial Networks (GANs) [74]; however, detailed overview of all models falls outside the scope of this paper.

¹<http://dgschwend.github.io/netscope/quickstart.html>
<https://machinethink.net/blog/how-fast-is-my-model/>

III.A.2. Online Learning

Online learning, also known as sequential decision making, refers to techniques that update the model/policy at each step, when receiving each new instance of data. This sequential learning handling real-time incoming data is opposed to offline learning or batch learning, where multiple instances of the data are collected first, and then the model is trained once by consuming the whole batch, although it can be updated later if the data distribution changes. The batch learning is the most common way to train deep neural networks as it avoids the problem of *catastrophic forgetting* occurring in online techniques where previous learning may be forgotten upon learning new information. On the other hand, the advantage of the online learning is that it is adaptable, as it does not have any knowledge or assumption about the data distribution. In this way, if the trend of data drifts or morphs, the policy or the model can adapt to the changes on-the-fly. To update the model in offline learning, the data have to be retrained every time. The online learning is also data efficient as once the input is digested, it is no longer needed and it can be removed, which is not the case of offline learning that stores the whole data for training. The mini-batch learning imposed by resource constraints is the halfway point between offline and online learning.

a) *Bandit learning*: The bandit problem represents the simplest online learning formulation, where an agent interacts with an environment by performing actions at discrete time steps. Each of these actions results in a feedback signal that is referred to as reward, which describes the goodness of that action. Consider a website that wants to maximize the engagement and relevance of articles presented to users. When a new user arrives, the website needs to decide on an article header to show and observe whether or not the user interacts with this article. In this example, the selected action is the article to display, and the reward is binary, 1 if clicked, 0 otherwise. Many recommendation-based systems can be modeled similarly, such as movie-recommender systems where actions are which movie to recommend, and web search where the actions are which results to show. In these scenarios, the reward is assessed according to the users' satisfaction. This is fundamentally different from supervised learning, where the true values of the trained data are known and the aim is to learn a model capable of classifying the inference data samples or forecasting targeted features. More specifically, a perfect model that describes the environment is used in the latter, whereas the bandit online model is only estimated from trials.

Agents, in bandit learning, aim to quickly discover the best action (also referred to as arm) across a group of actions by only observing the rewards obtained by executing each one. There are multiple extensions to this basic definition, e.g., linear bandits, adversarial bandits, and combinatorial bandits, where different assumptions regarding how the actions generate the reward, are made. There are optimal algorithms for the stochastic bandit problem in the single-agent case, like successive-elimination and Upper Confidence Bound (UCB). In successive-elimination, actions are tried for a fixed number of times before being eliminated. Analysis can show that sub-

optimal actions can not be selected more than logarithmic factor on the horizon. In UCB, actions with the highest plausible expected reward are selected (utilizing confidence bounds related to the distribution, also known as concentration bounds). The same logarithmic upper bound on sub-optimal action selection is shown in [75]. Note that a critical assumption in bandits is that actions do not have any effect on the agent other than causing a sample of a reward signal. In cases where actions may transform the environment from a well-described state to another, the formulation is known as reinforcement learning.

b) *Reinforcement Learning (RL)*: The RL concept is based on learning how to map situations and environment states to actions in order to maximize the long-term reward signal. The RL-agent is not apprised which action to choose; instead, it discovers the actions that achieve the highest reward by trying different combinations and receiving immediate gains and penalties, which can be modeled as a Markov Decision Process (MDP). Different from the bandit learning, the RL chosen action does not impact only the direct reward, but also all subsequent situations and related rewards. These two features, trial and error, and search and delayed reward assignment, are the key characteristics of the RL enabling it to learn by interacting with its environment and then adapting to it. This principle is illustrated in Fig. 9. Deep Reinforcement Learning (DRL) [76], [77] combines reinforcement learning and the deep learning. The DRL is well-suited and even indispensable, when the environment is highly dynamic and dimensional and the number of states is large or continuous. In such a scenario, the traditional RL cannot perform efficiently. Hence, the powerful ability representation of DNN is used to solve the continuous or huge state-action space problem. Using the DRL becomes a powerful solution in numerous fields, including robotics, 5G networks, and security, even though applications are still in their infancy.

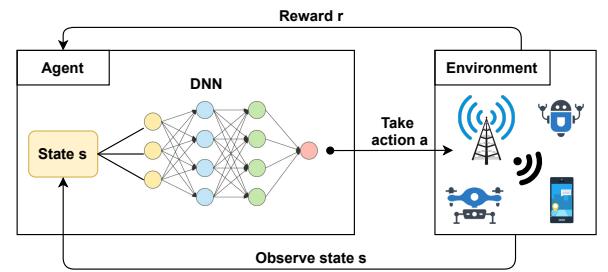


Fig. 9: Deep Reinforcement Learning (DRL) design.

Variants of DRL include the deep policy gradient RL [78], the Deep Q-Networks (DQN) [79], Distributed Proximal Policy Optimization (DPPO) [80], and Asynchronous Advantage Actor-Critic [81]. In this survey, we only discuss two representative techniques, which are the DQN and the policy gradient DRL:

- Deep Q-Networks (DQN): The DQN is a representative of the value-based DRL that leverages the powerful ability of DNN to map the high-dimensional states set to action values. Other variants of DQN include the Double Deep Q-Learning (Double-DQL) [82] which handles the

problem of the overestimation of Q-actions, and Dueling Deep Q-Learning (Dueling-DQL) [83] that finds the most valuable states without experiencing their impact on the actions.

- Policy-gradient-based DRL: Another commonly used DRL strategy is policy-gradient that includes Deep Deterministic Policy Gradient (DDPG) [84] and Proximate Policy Optimization (PPO) [80]. The policy-gradient is trained by continuously calculating the gradient of policy expectation reward and updating its parameters. Besides, a well-known approach in policy-gradient DRL is the Actor-Critic (AC) framework, which is composed of policy and action-value functions. The policy function plays the role of the actor that takes decisions and interacts with the environment, whereas the action-value function is called a critic that is responsible to evaluate the performance of the actor.

III.B. Performance metrics

The assessment of the DNN performance depends on the proximity-aware IoT application where deep learning is used. For example, for object detection, face authentication, or self-driving car, the accuracy is of an ultrahigh importance. Yet, some performance metrics are general and not specific to any application, including latency, memory footprint, and energy consumption. An overview of different performance metrics is presented as follows:

III.B.1. Latency

The latency is defined as the required time to perform the whole inference/training process, which includes the data pre-processing, data transmission, the classification process or the model training, and the post processing. Real-time applications led by artificial intelligence (e.g., drones, autonomous vehicles, AR/VR gaming, and intelligent wearable devices) have usually stringent latency constraints, of around 100 ms [26]. Hence, the near-processing is advantageous for fast inference response. Furthermore, specialized accelerators should be wisely designed to efficiently perform deep learning for edge applications and meet the latency requirements. The latency metric is affected by different factors, such as the size of the DNN model, the computational capacity of the host device, and the transmission efficiency.

III.B.2. Accuracy vs efficiency

The accuracy refers to the percentage of data samples that receive the right prediction compared to the total number of input data. This metric mainly reflects the performance of the trained model. In addition to the capability of the deep network, accuracy is also impacted by the speed of feeding the data to the model. Particularly, the fast feeding of images is a serious issue encountered by the video analytics applications in resource-constrained devices because of the potential skipping of some data samples, which causes accuracy drop. Therefore, for ultrahigh accuracy, the computing device has to fit the extremely intensive memory and computation requirements of the DNN model. Recently, some approaches have resorted to compressing the deep network in order to deploy it in small

IoT devices, with an objective to maintain the accuracy as high as possible. Pervasive AI, which is the scope of this survey, is an efficient solution to perform edge inference without changing the accuracy.

III.B.3. Energy efficiency

Unlike the cloud and edge servers, the IoT devices are battery-limited (e.g., commercial drones.). Moreover, the communication and computation overhead caused by the deep model training/inference incurs huge energy consumption. Hence, the energy efficiency is of a large importance in the context of edge AI and it primarily depends on the size of the DNN and the capabilities of the computing device.

III.B.4. Computation and memory footprint

To perform DNN training/inference, significant cycles are executed for memory data transfer to/from computational array, which makes it a highly intensive and challenging task. For example, VGG 16 and AlexNet require respectively 512 Mb and 217 Mb of memory to store more than 136 M and 60 M of weights and perform respectively 154.7 G and 7.27 G multiplications to classify a single ImageNet input, which is illustrated in Table III. Such amount of memory and computational tasks is infeasible to be executed in power and resource constrained devices with a real-time response. Therefore, optimizing the size of the DNN is very necessary (see squeezeNet in Table III). Additionally, the way to load the tremendous DNN parameters has a significant impact on the computation requirements of the learning tasks, which encourages for network re-designing (e.g., pruning [85] and quantization [86]). While the model squeezing approaches are based on features' removal, the high accuracy of the DNN requires millions of parameters. This paves the way for introducing efficient data distribution and parallelization that do not affect the performance of the system.

III.B.5. Communication Overhead

The communication overhead impacts the performance of the system, when the DNN computation is offloaded to the cloud or other edge participants. Hence, it is indispensable to minimize this overhead, particularly in costly network infrastructure. The data overhead mainly depends on how the model is designed, i.e., types and configuration of the layers that determine the output size, in addition to the communication technology. Another important performance metric related to offloading DNN tasks is the consistency of parameters and computations distributed across all machines. Furthermore, the fault-tolerance should be guaranteed to deal with communication failures efficiently.

III.B.6. Privacy

IoT devices produce and offload a massive amount of data every second, which can result in serious privacy vulnerabilities and security attacks such as black-box attacks [87], white-box attacks [88], data poisoning [89], membership attacks [90], and targeted mis-classification [91]. Guaranteeing the robustness and privacy of the DNN system has become

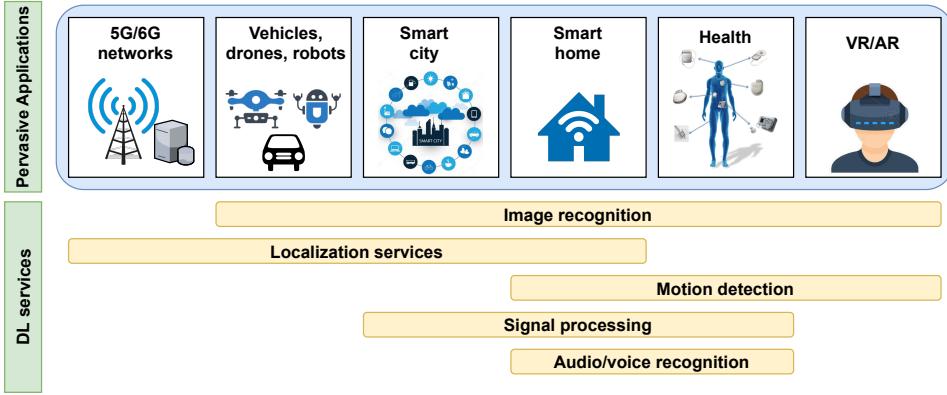


Fig. 10: AI pervasive application and the related foundational DL services reviewed in this survey.

a primary concern for the deep learning community. The traditional wise resorts to data encryption, pre-processing, and watermarking. Yet, all these solutions can be neutralized using model stealing attacks. Hence, more sophisticated defenses need to be designed to secure the DNN training and execution, through data distribution.

To design an efficient deep learning network or select the adequate one for the targeted application, a large number of hyperparameters need to be considered. Therefore, understanding the trade-off between these parameters (e.g., latency, accuracy, energy, privacy, and memory.) is essential before designing the model. Recently, automated machine learning frameworks responsible for DNN selection and parameters tuning, have been introduced, such as Talos [92].

III.C. Pervasive frameworks for AI

Several hardware and open source software libraries are publicly available for pervasive devices, particularly resource-limited ones, to enable DNN training and inference. As a first example, Google TensorFlow [93] is an open source deep learning framework released in 2015 to execute DNN tasks on heterogeneous distributed systems based on their estimated computational and communication times. In 2017, an optimized version of TensorFlow, namely TensorFlowLite [94], was specially designed for resource constrained devices, such as Raspberry Pi. This new version was further enhanced by enabling mobile GPU support, in 2019. However, TensorFlowLite was not designed to process the training phase but only to compress pre-trained DNN models and perform inference tasks with minimum latency. Another lightweight deep learning framework developed by Facebook is Caffe2 [95]. Caffe2 provides a straightforward way to experiment deep learning algorithms with an easy update, high flexibility, and ability to enable heterogeneous models on low-power devices. In 2019, this framework was merged with the well-known deep learning platform, PyTorch [96], for research and production purposes. Core ML [97] and DeepLearningKit [98] are two machine learning frameworks commercialized by Apple to support pre-trained models on iPhone/iPad devices. More specifically, Core ML was designed to leverage the CPU/GPU endowed with the end-device for deep learning

applications such as natural language and image processing, while minimizing the energy consumption and memory footprint. On the other hand, DeepLearningKit supports more complex networks such as CNNs and it is coined to utilize the GPU more efficiently for iOS based applications. Equipping end-devices with GPUs is important for an efficient inference and model training. In this context, IoT-specific development kits are provided to experiment AI in edge computing. One of the recent powerful kits is the NVIDIA Jetson Nano developer kit [99], which is a powerful small device that enables running multiple DNNs in parallel for intensive applications including object recognition. The Intel Edison kit [100] is another popular AI platform designed for IoT experiments.

III.D. Pervasive AI for IoT Applications

Deep learning methods have brought substantial breakthroughs in a broad range of IoT applications, spanning from signal and natural language processing to image and motion recognition. Recently, because of the revolution of pervasive computing, the DL paradigm has been re-designed to target a wide variety of proximity-aware IoT applications, use cases and verticals. In this section, we review the accomplishments of deep learning in different domains where pervasive computing is needed, including intelligent vehicles and robots, smart homes and cities, health and well-being, energy and smart grid, virtual reality and augmented reality, and 5G/6G intelligent networks. Besides, we identify several types of foundational DL services on which pervasive applications are built, such as vision and image classification, and motion and speech recognition. The common metric that groups different DL services is the need for prompt response and fast analytic mode of data that should not be piled for later processing. Fig. 10 illustrates different foundational DL services and the related pervasive applications/domains reviewed in this paper. Note that each application may require more DL services beyond the ones summarized in this survey.

III.D.1. Intelligent vehicles, robots, and drones

Recently, DNNs have been widely used to lead a variety of mobile platforms such as drones, robots, and vehicles, in order to achieve critical tasks such as autonomous navigation

and human safety monitoring. In this context, intelligent transportation systems have become an important source of ubiquitous data, e.g., Internet of Vehicles (IoV). For example, authors in [101]–[104] used the GPS data from taxis and bikes as an input to their CNN models to forecast the traffic flow and predict the potential congestions. Learning from GPS data can be categorized as outdoor localization, which is also called location aware DL services. Motivated by the revolutionary development of image processing DL services, applications such as driving assistance, autonomous driving, and mobility mapping have become more reliable and commonly used in intelligent mobile systems. As an example, in [105], the captured image from the vehicle front facing camera is used to decide the steering angle and keep the car in the middle of the lane. Authors in [106] designed a traffic sign recognition system that outperforms the humans' detection by 0.62% and boosts self-driving efficiency. The ever-improving online learning techniques are broadly exploited for UAVs/robots guidance, including the works in [107], [108] where drones learn how to navigate and avoid obstacles while searching target objects. Several start-ups are using DL for their self-driving systems, such as prime-air UAVs of Amazon used to deliver packages [109], Uber self-navigating cars [110], and the smart delivery robots widely used in many hospitals during the Covid-19 pandemic to avoid contact with patients [111]. Finally, the distinctive performance of drones/robots encouraged the emergence of more critical and sophisticated missions; many of them were not even envisaged a couple of decades ago, including military border surveillance, oil/gas offshore inspection, and forest fire detection [112] based on image processing DL services.

III.D.2. Smart homes and cities

The concept of a smart home covers a large range of applications, that contribute to enhance the productivity, convenience, and life quality of the house occupants. Nowadays, many smart appliances are able to connect to the internet and offer intelligent services, such as smart air conditioners, smart televisions, and lighting control systems. Most of these appliances require the deployment of wireless controllers and sensors in walls, floors, and corners to collect data for motion recognition DL services. Speech/voice DL recognition services are also involved for a better home control. Well-known examples are Amazon Alexa [113], Apple siri [114], and Microsoft Cortana [115] applications that interact with the vocal requests of users. Combined with image recognition DL services, Cortana can also be used to gather information from smart refrigerators and define food items [116].

Compared to smart homes, smart city services are more relevant to the deep learning community as the data collected from different ubiquitous participants is huge and highly heterogeneous, which allows high-quality analysis. Examples involve waste management and garbage classification [117], air quality and pollution level estimation [118], energy consumption and smart grid [119], pedestrian traffic and crowd moving prediction [120], parking control [121], human activity monitoring using their wearable devices [122], and even analyzing the time passengers spend to look at the ads. These

aforementioned applications are based on image recognition, localization, and signal processing DL services.

III.D.3. Health and well-being

Deployed on wearable and personal devices, the DL services have been used as health care solutions for individual users and communities. For instance, some mobile applications can monitor the dietary regime by recognizing food images, the portion size and related relevant information, using image processing DL services [123], [124]. Furthermore, handwritten images can help to identify Parkinson's disease [125], electrocardiogram (ECG) and electroencephalogram (EEG) signals processing contributes to early detection of seizures and QRS complex [126], [127], and voice/motion monitoring can give some insights to diagnose psychological disorders [128].

III.D.4. Virtual Reality (VR) and Augmented Reality (AR)

VR is designed to create an artificial environment, where users are placed into a 3D experience simulating their different senses such as vision, touch, and hearing. AR can be defined as a VR that inserts artificial objects into the real environment. In AR, sensors are used to control the orientation and position of the camera. Popular examples of applications using AR/VR include the tactile internet and holographic telepresence [129], and multi-players VR games. The latency of the virtual reality systems is measured in terms of “motion-to-photons” metric, which is defined as the delay starting from moving the headset to updating the display according to the movement. This motion-to-photons latency should be in the range of tens to hundreds of milliseconds [130]. Offloading the VR/AR computation to the remote cloud servers may incur higher latencies exceeding the required constraints. Hence, on-device computation is indispensable to achieve real-time performance.

III.D.5. 5G/6G intelligent networks

The potential applications of DNN aiming to enhance networking performance are countless, particularly after the emergence of the sixth generation (6G). Different from previous generations, the 6G paradigm is based on supporting a wider variety of AI services spanning from high-performance servers to resource-limited devices, making “connected things” evolve into “connected intelligence”. Applications of DL in the new generation networks involve adaptive resource allocation to serve users in real-time [131], device-to-device (D2D) task offloading using online learning and localization services [132], proactive caching to minimize remote communication and reduce latency [133], network energy efficiency [134], and privacy and data security [135].

III.E. Lessons learned

In this section, we reviewed state-of-the-art deep learning and online learning techniques, examined their performance metrics, and presented some of their applications that may require pervasive deployment. In this context, multiple conclusions can be stated:

- The AI proximity-aware IoT applications have different requirements and each one has its distinctive performance

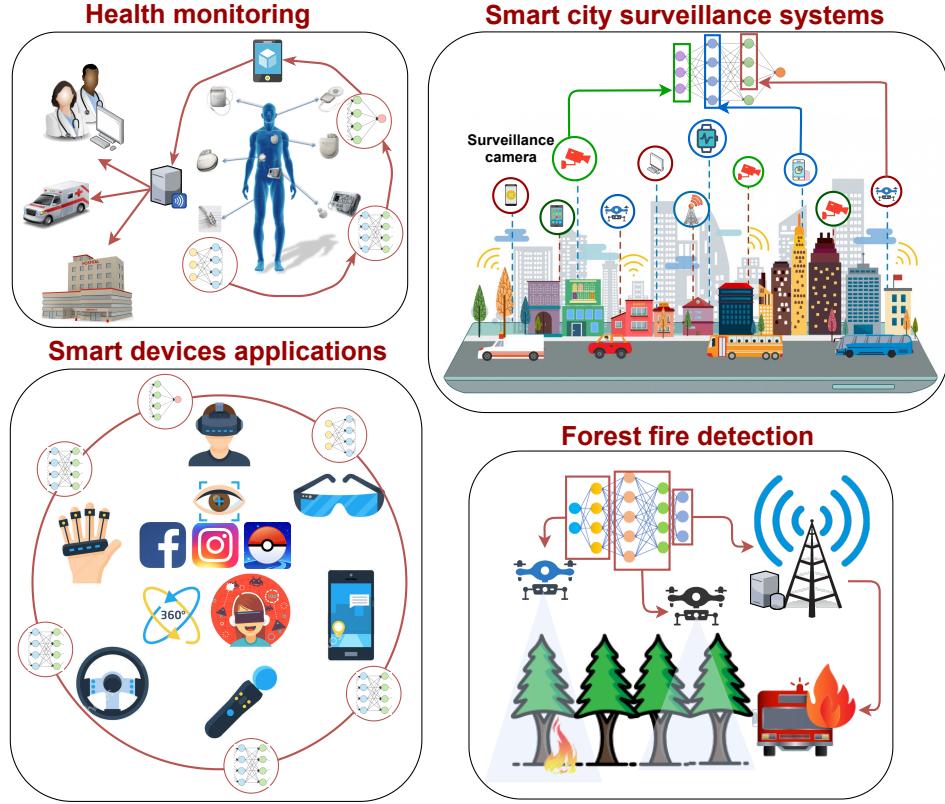


Fig. 11: Pervasive inference system in multiple scenarios.

keys. For example, VR/AR is highly sensitive to delays and cannot tolerate any motion sickness. Meanwhile, the applications relying on UAVs and moving robots have stringent requirements in terms of energy to accomplish their missions. For the surveillance applications, the accuracy is paramount whereas health services require strict privacy constraints. However, such requirements come with other costs. More specifically, lower delays and energy consumption can be achieved using small DL networks that generate fast inference and can be deployed locally. On the other hand, high accuracy cannot be attained using these models. Instead, deep networks can be adopted, while incurring higher memory and computation requirements and consequently higher communication overheads for remote execution. Privacy imposes local training and inference, that requires robust devices issued with GPUs. Therefore, understanding the requirements of the targeted application and the trade-off between different hyper-parameters is crucial for selecting the adequate AI model and the processing device.

- The common characteristic for most of AI applications, particularly for IoT applications that require real-time data collection, is the need for prompt response and fast analytics that should not be piled for later processing. Hence, centralized solutions such as cloud-based data analytics are not feasible anymore, due to the communication overheads. Pervasive computation has emerged as a solution that enables the deployment of AI at the proximity of the data source for latency-sensitive

applications, and in collaboration with high-performance servers for better computational resources.

- Understanding the application requirements and the pervasive environment and wisely selecting the data shape and the adopted AI technique, is critical for determining the distribution mode. More specifically, the privacy constraints and the size of the data open the doors for federated learning where each entity trains its data locally. The low latency requirements and the limited resources imposed by some pervasive systems, push for the partitioning of inference where the AI model is split into smaller segments. Finally, the dynamics of the system, the unavailability of labeled data and the inherently decentralized architectures call for the online learning where agents are distributed.

After understanding the motivations for *pervasive AI* and the requirements of the IoT applications and their related AI models, we present different distribution modes and their communication and computation models in the subsequent sections. We start by the distributed inference and federated learning. Next, we discuss online learning, including multi-agent bandit, multi-agent RL, and active learning.

IV. PERVASIVE INFERENCE

In this section, we discuss the pervasive inference, where the trained model is partitioned and different segments are distributed among ubiquitous devices. Fig. 11 illustrates different scenarios, where the distribution can solve the challenges presented by the centralized approaches. In the following

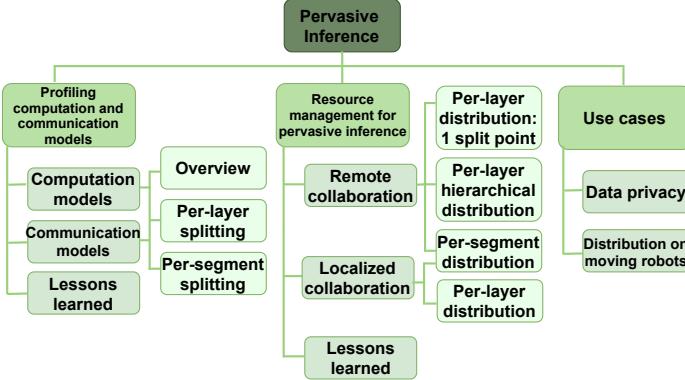


Fig. 12: Outline of pervasive inference section.

subsections, the communication and computation components of the pervasive inference are introduced. Then, the resource management approaches for the distribution are reviewed and two use cases are described. Fig. 12 presents different branches of this section.

IV.A. Profiling computation and communication models

The computation and communication models present the mechanisms to formulate different operations and functions into an optimization problem in order to facilitate the theoretical analysis of DNN distribution. More specifically, we discuss the computational requirements of different DNN tasks, the wireless communication latency between different pervasive participants and their energy consumption.

IVA.1. Computation models

Various parameters play a critical role to model the computational tasks of different segments of the DNN network including latency, generality, scalability and context awareness. In this subsection, we describe the computation models of two popular splitting strategies adopted in the literature, which are the per-layer and per-segment splitting. These models are presented after introducing some definitions.

a) Overview and definitions:

Binary offloading: Relatively simple or highly complex tasks that cannot be divided into sub-tasks and have to be computed as a whole either locally at the source devices or sent to the remote servers because of resource constraints, are called binary offloading tasks. These tasks can be denoted by the three-tuple notation $T(K, \tau, c)$. This commonly used notation illustrates the size of the data to be classified presented by K and the constraint τ (e.g., completion deadline, the maximum energy, or the required accuracy). The computational load to execute the input data of the DNN task is modeled as a variable c , defined as the number of multiplications per second [136]. Using these parameters not only depicts the key proprieties of the AI application, such as the memory and computation requirements, but also allows a better evaluation of the energy consumption performance, accuracy and classification latency. Although binary offloading has been widely studied in the literature, we note that it is out of the scope of this survey covering the pervasity and distribution of AI tasks.

Partial offloading: In practice, DNN classification is composed of multiple subtasks (e.g., layers execution, multiplication tasks, and feature maps creation), which allows to implement fine-grained (partial) computations. More specifically, the AI task can be split into two or more segments, where the first one can be computed at the source device and the others are offloaded to pervasive participants (either remote servers or neighboring devices).

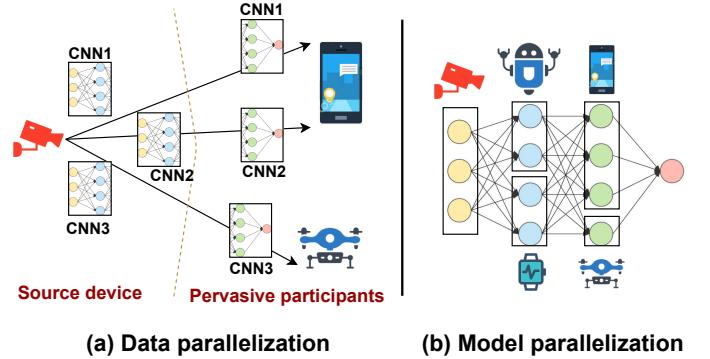


Fig. 13: Inference parallelization: data and model parallelization

Data parallelization: The most manageable task of partial offloading is the data parallelization, where duplicated offloaded segments are independent and can be arbitrarily divided into different groups and executed by different participants of the pervasive system, e.g., segments from different classification requests (as shown in Fig. 13 (a)). We highlight that the input data to parallel segments are independent and can be different or akin.

Model parallelization: A more sophisticated partial offloading pattern is the model parallelization, where the execution of one task is split across multiple pervasive devices. Accordingly, the input data is also split and fed to different parallel segments. Then, their outputs are merged again. In this offloading pattern, the dependency between different tasks cannot be ignored as it affects the execution of the inference. Particularly, the computation order of different tasks (e.g., layers) cannot be determined arbitrarily because the outputs of some segments serve as the inputs of others (as shown in Fig. 13 (b)). In this context, the inter-dependency between different computational parts of the DNN model needs to be defined. It is worth mentioning that many definitions of data and model parallelism are presented in the literature, which are slightly different. In our paper, we opted for the definitions presented in [137].

Typical dependencies: Different DNN networks can be abstracted as task-call graphs. These graphs are generally presented by Directed Acyclic Graphs (DAGs), which have a finite directed structure with no cycles. Each DNN graph is defined as $G(V, E)$, where the set of vertices V presents different segments of the network, while the set of edges E denotes their relations and dependencies. Typically, three types of dependencies contribute to determining partitions' strategies, namely the sequential dependency which includes the conventional CNN network with sequential layers and without

any residual block (e.g., VGG [7]), the parallel dependency which includes the relation between different tasks in the same layer (e.g., feature maps transformation), and the general dependency including general DNN models (e.g., randomly wired CNN [69]). Different dependencies are depicted in Fig. 14. The required computation workload and memory are specified for each vertex V and the amount of the input and output data can be defined on the edges.

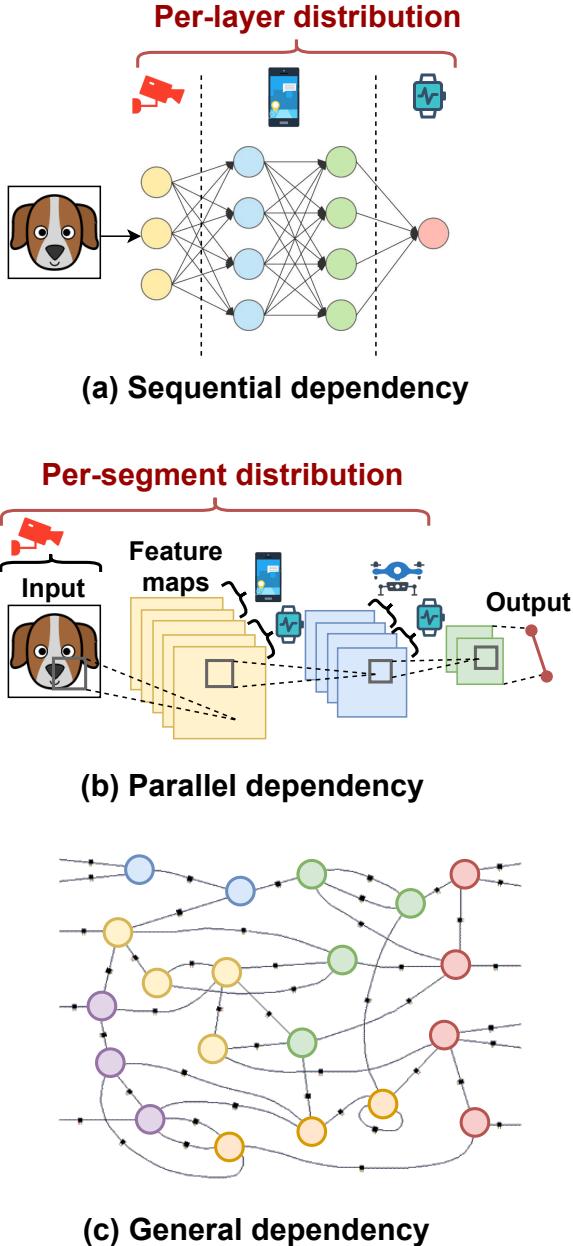


Fig. 14: Typical typologies of DNNs and partitioning strategies.

Based on the presented dependencies, two partition strategies can be introduced, namely per-layer and per-segment partitioning (see Fig. 14). Per-layer partitioning defines dividing the model into layers and allocating each set of layers within a pervasive participant (e.g., IoT device or remote servers). On the other hand, per-segment partitioning denotes segmenting

the DNN model into smaller tasks such as feature maps transformations, multiplication tasks and even per-neuron segmentation.

Computation latency: The primary and most common engine of the pervasive devices to perform local computation is the CPU. The performance of the CPU is assessed by cycle frequency/ clock speed f [138] or the multiplication speed e [139]. In the literature, authors adopt the multiplication speed to control the performance of the devices executing the deep inference. In practice, e is bounded by a maximum value e_{max} reflecting the limitation of the device computation capacity. Based on the model introduced for binary offloading, the computation latency of the inference task $T(K, \tau, c)$ is calculated as follows [139]:

$$t^c = \frac{c}{e}. \quad (1)$$

Importantly, a higher computational capacity e_{max} is desirable to minimize the computation latency at the cost of energy consumption. As end-devices are energy constrained, the energy consumption of the local computation is considered as a key measure for evaluating the inference efficiency. More specifically, a high amount of energy consumed by AI applications is not desirable by end-devices due to their incurred cost. Similarly, significant energy consumption of edge nodes (e.g., access points or MEC servers.) increases the cost envisaged by the service providers.

Computation energy: If the inference is executed at the data-generating source, the consumed energy is mainly associated to the task computation. In contrast, if the task is delegated to remote servers or to neighboring devices, the power consumption consists of the required energy to transfer the data between participants, the amount of energy consumed for the computation of different segments, and the energy required to await and receive the classification results. Suppose that the inference task/sub-task T_i takes a time t_i^c to be computed locally in the device participating in the pervasive inference and let P_i denote the processing power to execute the task per second. The energy consumed to accomplish an inference task T_i locally at the computing device is equal to [140]:

$$e_i^{local} = t_i^c \times P_i. \quad (2)$$

Next, we profile the DNN partitioning strategies presented in the literature, in terms of computation and memory requirements first and then in terms of communicated data to offload the output of segments. The key idea of partitioning a DNN network is to evenly or unequally distributing the computational load and the data weights across pervasive devices intending to participate in the inference process, while minimizing the classification latency. A partitioning can be achieved by simply segmenting the model per-layer or set of layers (see Fig. 13 (a)) or by splitting the layers' tasks (see Fig. 13 (b)). Then, each part is mapped to a participant.

b) Per-layer splitting: As previously mentioned, the computational load of each layer is measured as the number of multiplications required to accomplish the layer's goal [141].

TABLE IV: Characteristics of different splitting strategies:

A: After, B: Before, N_{Fc} : number of fully connected layers, n : number of input neurons (Fc), m : number of output neurons (Fc), H_1, W_1, D_1 : dimensions of the input data (Conv), H_2, W_2, D_2 : dimensions of the output data (Conv), H_f, W_f, D_1 : dimensions of the filter (Conv), k/D_2 : number of filters, d_x, d_y : dimensions of the spatial splitting (Conv), N : Number of participants, k'_i : Number of segments per participant.

Partitioning strategy	N^o of smallest segments	Activation task	Inputs per segment	Filters weights per device	Outputs per segment	Computation per segment	Transmitted data per layer	Merging strategy
Per-layer: Fully-connected (Fc)	N_{Fc}	A	n	X	m	$n \times m$	$n + m$	Seq
Per-segment: Output splitting for Fc layers	$\sum_{i=1}^{N_{Fc}} m_i$	B/A	n	X	1	n	$n \times N + m$	Concat
Per-segment: Input splitting for Fc layers	$\sum_{i=1}^{N_{Fc}} n_i$	A	1	X	m	m	$N \times m + n$	Sum
Per-layer: Convolution (Conv)	N_{Conv}	A	$H_1 \times W_1 \times D_1$	$k \times D_1 \times (H_f \times W_f)$	$H_2 \times W_2 \times k$	$\frac{cp}{k} = D_1 \times (W_f \times H_f) \times k \times (W_2 \times H_2)$	$H_1 \times W_1 \times D_1 + H_2 \times W_2 \times k$	Seq
Per-segment: channel splitting for Conv	$\sum_{i=1}^{N_{Conv}} k_i$	B/A	$H_1 \times W_1 \times D_1$	$k'_i \times D_1 \times (H_f \times W_f)$	$H_2 \times W_2$	$\frac{cp}{k} = \frac{(N \times H_1 \times W_1 \times D_1)}{(K \times H_2 \times W_2)}$	$(N \times H_1 \times W_1 \times D_1) + (K \times H_2 \times W_2)$	Concat
Per-segment: spatial splitting for Conv	$\sum_{i=1}^{N_{Conv}} \frac{H_1^i \times W_1^i}{d_x^i \times d_y^i}$	B/A	$\frac{H_1 \times W_1 \times D_1}{d_x \times d_y} + padding$	$k \times D_1 \times (H_f \times W_f)$	$\frac{H_2 \times W_2 \times k}{d_x \times d_y}$	$\frac{cp}{d_x \times d_y} = \frac{H_1 \times W_1 \times D_1}{d_x \times d_y} + H_2 \times W_2 \times k + N \times padding$	$H_1 \times W_1 \times D_1 + H_2 \times W_2 \times k + N \times padding$	Concat
Per-segment: filter splitting for Conv	$\sum_{i=1}^{N_{Conv}} D_1^i \times k_i$	A	$H_1 \times W_1$	$(H_f \times W_f)$	$H_2 \times W_2$	$\frac{cp}{D_1 \times k}$	$(D_1 \times H_1 \times W_1) + (N \times H_2 \times W_2 \times k)$	Sum+concat

Fully-connected layers: The computation requirement of a fully-connected layer can be calculated as follows:

$$c^{Fc} = n \times m, \quad (3)$$

where n represents the number of the input neurons and m is the number of the output neurons.

Convolutional layers: The computation load of a convolution layer can be formulated as follows [141]:

$$c^{conv} = D_1 \times (W_f \times H_f) \times D_2 \times (W_2 \times H_2). \quad (4)$$

We remind that D_1 is the number of input channels of the convolutional layer which is equal to the number of feature maps generated by the previous layer, $(W_f \times H_f)$ denotes the spatial size of the layer's filter, D_2 represents the number of filters and $(W_2 \times H_2)$ represents the spatial size of the output feature map (see Fig. 8).

The computational load introduced by pooling and ReLU layers can be commonly neglected, as it does not require any multiplication task [141]. We highlight that the per-layer splitting is motivated by the sequential dependency between layers. This dependency does not permit the model parallelism nor the latency minimization. Instead, it allows the resource-constrained devices to participate in the AI inference.

c) Per-segment splitting:

Fully-connected layers: We start by profiling the fully-connected layer partitioning. More specifically, the computations of different neurons y_i in a fully-connected layer are independent. Hence, their executions can be distributed, and model parallelism can be applied to minimize the inference latency. Two methods are introduced in the literature (e.g., [142], [143]), which are the output and input partitioning as shown in Fig. 15.

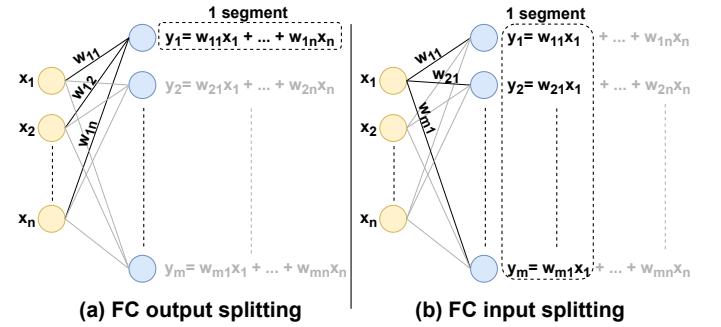


Fig. 15: Partitioning of fully connected layers.

- **Output splitting:** the computation of each neuron y_i is performed in a single participant that receives all input data $\{x_1, x_2, \dots, x_n\}$, as highlighted in Fig. 15 (a). Later, when the computation of all neurons is done, results are merged by concatenating the output of all devices in the correct order. The activation function can be applied on each device or after the merging process.
- **Input splitting:** each participant computes a part of all output neurons y_i . Fig. 15 (b) illustrates an example, where each device executes $\frac{1}{n}$ of the required multiplications. By adopting this partitioning method, only a part of the input, x_i , is fed to each participant. Subsequently, when all participants accomplish their tasks, summations are performed to build the output neurons. However, in contrast to the output-splitting method, the activation function can only be applied after the merging process.

Convolutional layers: Next, we illustrate different partitioning strategies of the convolutional layer. As described in the previous section III-A1b, each filter is responsible to create one of the feature maps of the output data (Fig. 8). We remind that the dimensions of the input data are $H_1 \times W_1 \times D_1$, the dimensions of the k filters are $H_f \times W_f \times D_f$, and the dimensions of the output feature maps are defined by $H_2 \times W_2 \times D_2$. We note that by definition D_1 is equal to

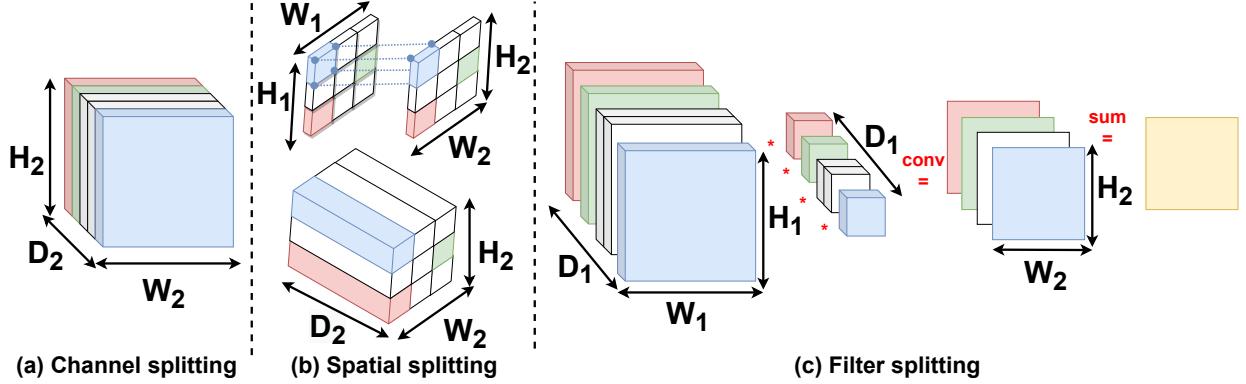


Fig. 16: Partitioning of convolutional layer: (a) is an output splitting, and (b) and (c) are input splittings.

D_f and k is equal to D_2 . Furthermore, each filter contains $D_1 \times (H_f \times W_f)$ weights and performs $D_1 \times (H_f \times W_f)$ multiplications per output element. Similarly to the fully connected layers, two partitioning strategies characterize the convolutional layer, namely the input and output splitting. In this context, the output splitting includes the channel partitioning, meanwhile, the input splitting consists of the spatial and filter partitioning strategies (see Fig. 16). These splitting strategies are introduced and adopted by multiple recent works, including [67], [142], [144], for which we will thoroughly review the resource management techniques in the following section.

- *Channel splitting*: each participant computes one or multiple non-overlapping output feature maps, which serve as input channels for the next layer. This implies that each device i possesses only $1 \leq k'_i \leq k$ filters responsible to generate k'_i feature maps, where $\sum_i k'_i = k$. In addition to the k'_i filters, the entire input data is fed to each device to compute different outputs. In this way, filters' weights are distributed across participants, $(k'_i \times D_1 \times H_f \times W_f)$ each, and the total number of multiplications is equal to $D_1 \times (H_f \times W_f) \times k'_i \times (W_2 \times H_2)$ per device. The channel partitioning strategy allows model parallelization, and consequently inference acceleration. At the end, when all devices finish their tasks, different feature maps are concatenated depth-wise, with a complexity equal to $O(k)$. We emphasize that the activation function can be applied before merging at each device or once at the concatenation device. Fig. 16 (a) shows an example of channel partitioning.
- *Spatial splitting*: this fine-grained splitting divides the input spatially, in the x or y axis, in order to jointly assemble the output data, as shown in Fig. 16 (b). Let d_x and d_y define the split dimensions on the x-axis and y-axis, respectively. Therefore, the input data are partitioned into segments of size $(d_x \times d_y)$, and each group of segments can be transmitted to a device. Furthermore, each part allocated to a participant needs to be extended with overlapping elements from the neighboring parts, so that the convolution can be performed on the borders. Compared to the latter splitting, in which all the input data should be copied to all participants with parts of

the filters, the spatial splitting distributes only parts of the data with all the filters to each device. It means, in addition to the segment of the input data, an amount of $(k \times D_1 \times W_f \times H_f)$ weights should be transmitted and stored at each device. Note that storing the filters is considered as a one-time memory cost, as they will be used for all subsequent inferences. Also, the total number of multiplications is reduced per-device and each one executes only $\frac{1}{(d_x \times d_y)}$ of the computational load per segment. When all computations are done, the output data is concatenated spatially with a complexity of $O(\frac{H_2 \times W_2}{d_x \times d_y})$, and the activation function can be applied before or after the merging process. Note that for simplicity, we presented, for spatial splitting, the case where filters do not apply any size reduction.

- *Filter splitting*: in this splitting strategy, both filters and input data are split channel wise on a size of k'_i for each participant i . Figure 16 (c) illustrates the convolution of the input data by one filter in order to produce one feature map. In this example, the input channels and one of the filters are divided into 4 devices, which implies that each device saves only its assigned channels of the input data and the filter, so the memory footprint is also divided. The computational load is also reduced, in such a way each participant executes $k'_i \times (H_f \times W_f) \times (W_2 \times H_2)$ multiplications. In the end, all final outputs are summed to create one feature map and the activation function can only be applied after the merging process. A concatenation task is performed, when all features are created. Note that the complexity of this partitioning is equal to the number of devices contributing in the distribution.

Table IV summarizes the computation and memory characteristics of different splitting strategies. In this table, we present the number of smallest segments per model, the input, output and computation requirements for each small segment, the weights of filters assigned to each device owing k'_i segments, and the transmitted data per layer when having N participants.

IV.A.2. Communication models

The latency is of paramount importance, in AI applications. Hence, minimizing the communication delay and the data transmission by designing an efficient DNN splitting is the

main focus of pervasive inference.

a) Overview:

Communication latency: In the literature, the communication channels between different pervasive devices are abstracted as bit-pipes with either constant rates or random rates with a defined distribution. However, this simplified bit-pipe model is insufficient to illustrate the fundamental properties of wireless propagation. More specifically, wireless channels are characterized by different key aspects, including: (1) the multi-path fading caused by the reflections from objects existing in the environment (e.g., walls, trees, and buildings); (2) the interference with other signals occupying the same spectrum due to the broadcast nature of the wireless transmissions, which reduces their Signal-to-Interference-plus-Noise-Ratios (SINRs) and increases the probability of errors; (3) bandwidth shortage, motivating the research community to exploit new spectrum resources, design new spectrum sharing and aggregation, and propose new solutions (e.g., in-device caching and data compression). Based on these characteristics, the communication/upload latency between two devices, either resource-constrained devices or high-performant servers, can be expressed as follows:

$$t^u = \frac{K}{\rho_{i,j}}, \quad (5)$$

where K is the size of the transmitted data and $\rho_{i,j}$ is the achievable data rate between two participants i and j , defined as follows:

$$\rho_{i,j} = B_i \times \log_2(1 + \Gamma_{i,j}), \quad (6)$$

B_i denotes the bandwidth of the device i . Furthermore, the average SINR of the link between i and j , namely $\Gamma_{i,j}$, is given by:

$$\Gamma_{i,j} = \frac{P_{i,j} h_{i,j}}{\sum_{q,q \neq j} I_{q,j} \sigma^2}, \quad (7)$$

where $P_{i,j}$ and $h_{i,j}$ are the transmit power and the channel gain between i and j , σ^2 is the Gaussian noise, and $\sum_{q,q \neq j} I_{q,j}$ is the total interference power at the receiver j resulting from neighboring devices transmitting over the same channel.

The total transmission latency t^T of the entire inference is related to the type of dependency between different layers of the model. This latency is defined in eq. (8), if the dependency is sequential (e.g., layers) and in eq. (9) if the dependency is parallel (e.g., feature maps). In case the dependency is general (e.g., randomly wired networks), we formulate the total latency as the sum of sequential communication and the maximum of parallel transmissions.

$$t^T = \sum_{s=1}^S t_s^u. \quad (8)$$

$$t^T = \max(t_s^u, \forall s \in \{1 \dots S\}). \quad (9)$$

Communication energy: The energy consumption to offload the inference sub-tasks to other participants consists of the amounts of energy consumed on outwards data transmissions and when receiving the classification results generated

by the last segment of the task T . This energy is formulated as follows [138] [140]:

$$e_i^{offd} = t_i^u \cdot P_i + \sum_s \sum_k \sum_j \frac{K_s}{\rho_{k,j}} \cdot P_s \cdot X_{k,s} X_{j,s+1}, \quad (10)$$

where t_i^u is the upload delay to send the original data/task i to the first participant, K_s is the output of the segment s (e.g., layers or feature maps), $\rho_{k,j}$ denotes the data rate of the communication, and $X_{k,s}$ is a binary variable indicating if the participant k executes the segment s .

Using only the onboard battery and resources, the source-generating device may not be able to accomplish the inference task within the required delays and the energy constraint. In such a case, partitioning the task among neighboring devices or offloading the whole inference to the remote servers are desirable solutions.

b) Per-layer splitting: Per-layer partitioning is characterized by a simple dependency between different segments and a higher data transmission per device. Indeed, the computation of one Fc layer per participant costs the system a total communication overhead equal to $(n + m)$. Meanwhile, the allocation of a convolutional layer requires a transmission load equal to $(H_1 \times W_1 \times D_1) + (H_2 \times W_2 \times k)$.

c) Per-segment splitting: The per-segment partitioning requires a higher total transmission load with less computation and memory footprint per device. Meaning, this type of partitioning trades communication with the memory. More details are illustrated in Table IV, where the output and input of the fully-connected layers have a total communication overhead of $n \times (N - 1)$ and $m \times (N - 1)$ respectively compared to the per-layer distribution. Hence, depending on the input and output sizes, namely n and m , the optimal partition strategy can be selected. Regarding the convolutional layers, the channel splitting has an overhead of $(N - 1) \times H_1 \times W_1 \times D_1$ since a copy of the entire input data needs to be broadcasted to all participants, the spatial splitting pays an overhead of the padding equal to $N \times padding$, and the filter splitting has an overhead of $(N - 1) \times H_2 \times W_2 \times k$ incurred in the merging process.

IV.A.3. Lessons learned

The main lessons acquired from the review of the splitting strategies are:

- The performance of model parallelism is always better than that of data parallelism in terms of latency minimization, as it allows computing multiple sub-tasks simultaneously. Meanwhile, the data parallelism pays the high costs of merging and transmitting the same inputs, either for fault-tolerance purposes or to handle multiple concurrent requests.
- The choice of the parallelism mode, highly depends on the partitioning strategy and the dependency between different segments. For example, in the per-layer splitting with a sequential dependency, the model parallelism cannot be applied to compute different fragments. On the other hand, the general and parallel dependencies pave the way to distribute concurrent segments.

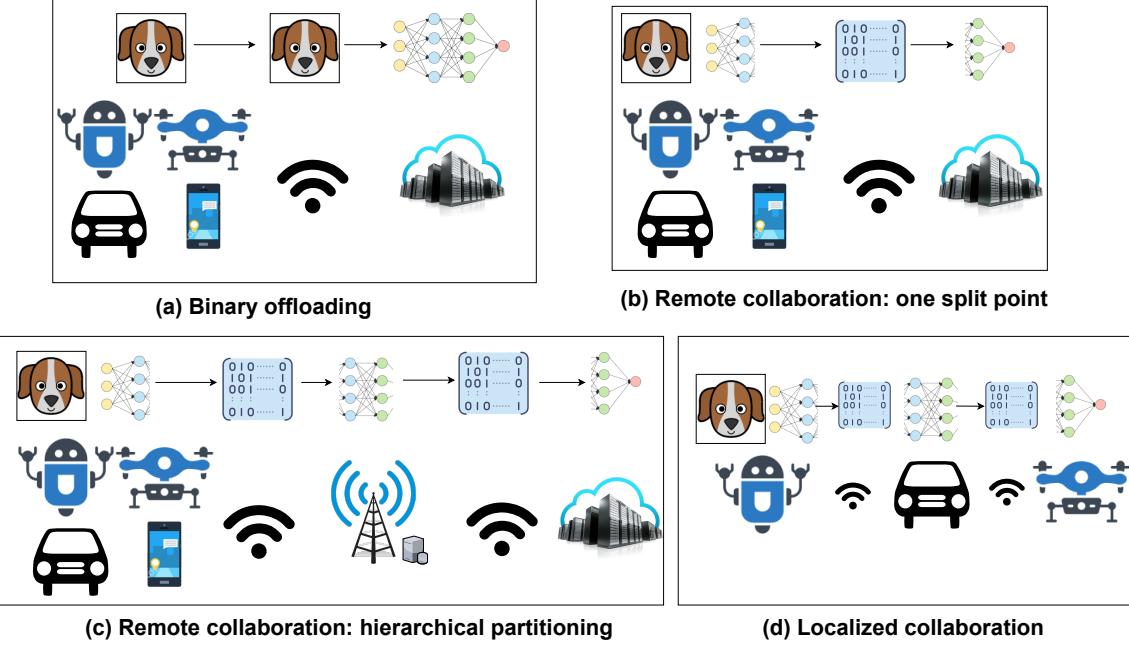


Fig. 17: Resource management for distributed inference.

- Data parallelism is highly important for AI applications with a high load of inference requests, such as 24/7 monitoring systems and VR/AR applications. In such scenarios, the classifications and feature learning are required every short interval of time, measured sometimes in terms of “motion-to-photons” latency. Generally, source devices do not have sufficient resources to compute this huge load of inferences. In this case, distributing the requests within neighboring devices and parallelizing their computations, contribute to minimizing the queuing time.
- Understanding the characteristics of the pervasive system is compulsory for selecting the partition strategy. More specifically, the per-layer distribution is more adequate for systems with a lower number of participants and higher pervasive capacities. For example, VGG19 has 19 layers and accordingly needs a maximum of 19 participants. More importantly, these devices are required to be able to accommodate the computation demand of convolutional layers. Meanwhile, opting for fine-grained partitioning results in small fragments that fit in resource-limited devices, such as sensors. However, a high number of sensors (e.g., $\sum_i^{N_{conv}} D_i^k \times k_i$ segments using filter splitting.) should be involved to accomplish the inference.
- Choosing the most optimal partitioning for the per-segment strategy highly depends on the properties of the DNN network, including the channel sizes, the number of filters, the size of feature maps, and the number of neurons. Particularly, for Fc splitting, m and n are the decisive variables for choosing input or output partitioning. For convolutional layers, the size of the channels and filters, and the capacities of participants are the decisive parameters to select the strategy. In terms of memory requirements, the channel splitting requires copying the whole input channels to all devices along with a part of

the filters. Meanwhile, the spatial splitting copies all the filters and a part of the data, whereas the filter splitting needs only a part of the channels and filters. In terms of transmission load, the spatial splitting has less output data per segment compared to channel and filter strategies. Finally, the channel splitting has a higher computational load. Still, it incurs less dependency between segments.

IV.B. Resource management for distributed inference

The joint computational and transmission resource management plays a key role in achieving low inference latency and efficient energy consumption. In this section, we conduct a comprehensive review of the existing literature on resource management for deep inference distribution and segments allocation on pervasive systems. We start by discussing the remote collaboration, which consists of the cooperation between the data source and remote servers to achieve the DNN inference. In this part, we determine the key design methodologies and considerations (e.g., partitioning strategies and number of split points) in order to shorten the classification delays. Subsequently, more complex collaboration, namely localized collaboration, is examined, where multiple neighboring devices are coordinated to use both computational and wireless resources and accomplish the inference tasks with optimized energy, delays, and data sharing.

IV.B.1. Remote collaboration

The remote collaboration encompasses two approaches, the binary and the partial offloading defined in the previous section. The binary offloading consists of delegating the DNN task from a single data-generating device to a single powerful remote entity (e.g., edge or cloud server), with an objective to optimize the classification latency, accuracy, energy, and cost (see Fig. 17 (a)). The decision will be whether to

offload the entire DNN or not, depending on the hardware capability of the device, the size of the data, the network quality, and the DNN model, among other factors. Reference papers covering binary offloading of deep learning include DeepDecision [145], [146] and MCDNN [147]. The authors of these papers based their studies on empirical measurements of trade-offs between different aforementioned parameters. The binary offloading has been thoroughly investigated in the literature for different contexts. However, the DNN offloading has a particular characteristic that distinguishes it from other networking tasks, namely the freedom to choose the type, the parameters, and the depth of the neural network, according to the available resources.

As the scope of this survey, is the pervasive AI, we focus on the partial offloading that covers the per-layer distribution applying one or multiple splitting points along with the per-segment distribution.

a) Per-layer distribution - one split point: The partial offloading leverages the unique structure of the deep model, particularly layers, to allow the collaborative inference between the source device and the remote servers. More specifically, in such an offloading approach, some layers are executed in the data-generating device whereas the rest are computed by the cloud or the edge servers, as shown in Fig. 17 (b). In this way, latency is potentially reduced owing to the high computing cycles of the powerful remote entities. Furthermore, latency to communicate the intermediate data resultant from the DNN partitioning should lead to an overall classification time benefit. The key idea behind the per-layer partitioning is that after the shallow layers, the size of the intermediate data is relatively small compared to the original raw data thanks to the sequential filters. This can speed up the transmission over the network, which motivates the partition after the initial layers. Fig. 18 shows the size of data transmitted between different layers of AlexNet trained with images-sized 224x224 RGB and with the parameters defined in [148]. It is clear that the intermediate data size decreases, as the network goes deeper.

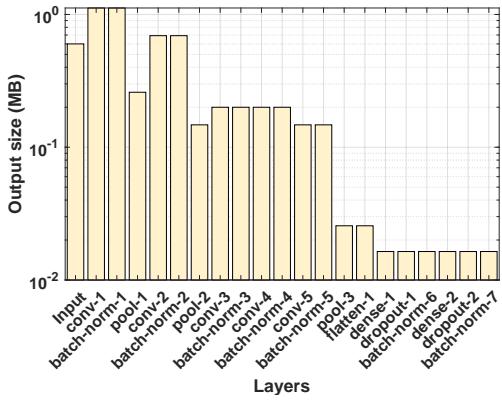


Fig. 18: The size of data transmitted between different layers of the AlexNet network.

Neurosurgeon [149] is one of the first works that investigated layer-wise partitioning, where the split point is decided intelligently depending on the network conditions. Particularly, the authors examined deeply the status quo of the cloud and

in-device inference and confirmed that the wireless network is the bottleneck of the cloud approach and that the mobile device can outperform the cloud servers only when holding a GPU unit. As a next step, the authors investigated the layer-level performance in terms of computing and output data size of multiple state-of-the-art DNNs over multiple types of devices and wireless networks and concluded that layers have significantly different characteristics. Based on the computation and data transmission latency of the DNN layers, the optimal partition points that minimize the energy consumption and end-to-end latency are identified. Finally, after collecting these data, Neurosurgeon is trained to predict the power consumption and latency based on the layer type and network configuration and dynamically partition the model between the data source and the cloud server.

However, while the DNN splitting significantly minimizes the inference latency by bending the computational resources of the mobile device and the remote server, this strategy is constrained by the characteristics of intermediate layers that can still generate high-sized data, which is the case of VGG 16 illustrated in Fig. 19.

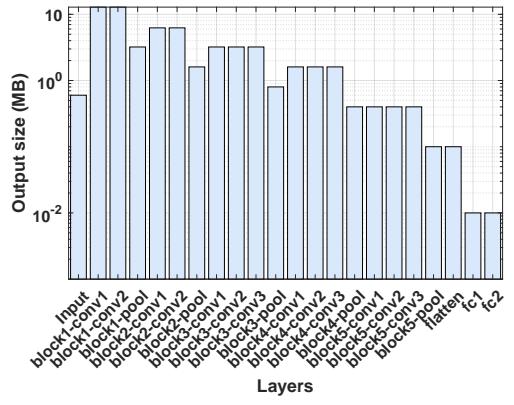


Fig. 19: The transmitted data size between different layers of the VGG16 network.

The work in [150] followed the same steps of the previous work, including testing the performance of different layers and training a regression model that predicts the optimal split point. Moreover, to further reduce the latency and tackle the problem of sized intermediate data, the authors proposed to combine the early-exit strategy, namely BranchyNet [151], with their splitting approach. The objective is to execute only few layers and exit the model without resorting to the cloud, if the accuracy is satisfactory. In this way, the model inference is accelerated, while sacrificing the accuracy of the classification. We note that BranchyNet is a model trained to tailor the right size of the network with minimum latency and higher accuracy. Accordingly, both models cooperate to select the optimal exit and split points. The authors extended the work by replacing both trained models with a reinforcement learning strategy [152], namely Boomerang. This RL approach offers a more flexible and adaptive solution to real-time networks and presents less complex and more optimal split and exit points' selection. The early-exit strategy is also proposed along with the layer-wise partitioning by the ADDA approach [153],

where authors implemented the first layers on the source device and encouraged the exit point before the split point to use only local computing and eliminate the transmission time. Similarly, authors in [154], formulated the problem of merging the exit point selection and the splitting strategy, while aiming to minimize the transmission energy, instead of focusing on latency.

In addition to using the early-exit to accelerate the inference, other efforts adopted compression combined with the partitioning to reduce the shared data between collaborating entities. Authors in [155] introduced a distribution approach with feature space encoding, where the edge device computes up to an intermediate layer, compresses the output features (loss-less or lossy), and delegates the rest of the inference on the compressed data to a host device in order to enhance the bandwidth utilization. To maintain high accuracy, the authors proposed to re-train the DNN with the encoded features on the host side. The works in [156], [157] also suggested compressing the intermediate data through quantization, aiming at reducing the transmission latency between edge and cloud entities. The authors examined the trade-off between the output data quantization and the model accuracy for different partitioning scenarios. Then, they designed accordingly a model to predict the edge and cloud latencies and the communication overhead. Finally, they formulated an optimization problem to find the optimal split layer constrained by the accuracy requirements. To make the solution adaptive to runtime, an RL-based channel-wise feature compression, namely JALAD, is introduced by the authors in [156]. Pruning is another compression technique proposed in [158] to be joined with the partitioning strategy. The authors introduced a 2-step pruning framework, where the first step mainly focuses on the reduction of the computation workload and the second one handles the removal of non-important features transmitted between collaborative entities, which results in less computational and offloading latency. This can be done by pruning the input channels, as their height, length, and number impact directly the size of the output data and the computing requirements, which we illustrated in Table IV.

b) Per-layer distribution - back and forth, and hierarchical distribution: Solely offloading the deep learning computation to the cloud can violate the latency constraints of the AI application requiring real-time and prompt intervention. Meanwhile, using only the edge nodes or IoT devices can deprive the system from powerful computing resources and potentially increase the processing time. Hence, a judicious selection of multiple cuts and distribution between different resources, i.e., IoT device – edge server – cloud, contribute to establishing a trade-off between minimizing the transmission time and exploiting the powerful servers. Additionally, the layers of the DNN model are not always stacked in a sequential dependency. More specifically, layers can be arranged in a general dependency as shown in Fig. 14 (c), where some of them can be executed in parallel or do not depend on the output of the previous ones. In this case, adopting an optimized *back and forth* distribution strategy, where the end-device and the remote servers parallelize the computation of the layers and merge the output, can be beneficial for the inference

latency. Authors in [159] designed a Dynamic Adaptive DNN Surgery (DADS) scheme that optimally distributes complex structured deep models, presented by DAG graphs, under variable network conditions. In case the load of requests is light, the min-cut problem [160] is applied to minimize the overall delay to process one frame of the DNN structure. When the load condition is heavy, scheduling the computation of multiple requests (data parallelization) is envisaged using the 3-approximation ratio algorithm [161] that maximizes the parallelization of the frames from different requests. Complex DNN structures were also the focus in [162], where the authors used the shortest path problem to formulate the allocation of different frames of the DNN *back and forth* between the cloud and the end-device. The path, in this case, is defined as latency or energy of the end-to-end inference.

On the other hand, *hierarchical architecture* for sequential structures is very popular as a one way distribution solution to establish a trade-off between transmission latency and computation delay (see Fig. 17 (c)). The papers in [163]–[165] proposed to divide the trained DNN over a hierarchical distribution, comprising “IoT-edge-cloud” resources. Furthermore, they leveraged the state-of-the-art work BranchyNet [151] to early exit the inference if the system has a good accuracy. In this way, fast, private, and localized inference of only shallow layers becomes possible at the end and edge devices, and an offloading to the cloud is only performed when additional processing is required. Hierarchical distribution can also be combined with compressing strategies to reduce the size of the data to be transmitted and accordingly minimize the communication delay and the time of the entire inference, such as using the encoding technique as done in [166]. Authors in [167], [168] also opted for hierarchical offloading, while focusing primarily on fault-tolerance of the shared data. Particularly, authors in [167] considered two fault-tolerance methods, namely reassigning and monitoring, where the first one consists of assigning all layers tasks at least once, and then the unfinished tasks are reassigned to all participants regardless of their current state. This method, is generating a considerable communication and latency overhead related to allocating redundant tasks, particularly to devices with limited-capacities. Hence, a second strategy is designed to monitor the availability of devices before the re-assignment. Meanwhile, the work in [168] proposed to add skip blocks [3] to the DNN model and include at least one block in each partition, to enhance the robustness of the system in case the previous layer connection fails.

c) Per-segment distribution: The per-segment partitioning is generally more popular when distributing the inference among IoT devices with limited capacities, as some devices, such as sensors, cannot execute the entire layer of a deep network. Furthermore, per-segment partitioning creates a huge dependency between devices, and consequently, multiple communications with remote servers are required. However, few works adopted this strategy for inference collaboration between end devices and edge/fog servers, including [169]. Authors in [169] proposed a spatial splitting (see Fig. 16 (b)) that minimizes the communication overhead per device. Then, a distribution solution is designed based on the matching

TABLE V: Performance of distribution strategies compared to: ○ cloud only; ● on-device only; ○ edge-server only.

Refs	Latency	Bandwidth	Energy	computation/ memory	throughput	Inference rate
Neurosurgeon [149]	$3.1 \times \rightarrow 40.7 \times$	✗	59.5 % → 94.7%	✗	$1.5 \times \rightarrow 6.7 \times$	✗
Edgent [150]	$2.3 \times$	✗	✗	✗	✗	✗
Boomerang [152]	$1.2 \times \rightarrow 2 \times$	✗	✗	✗	✗	✗
ADDA [153]	$1.7 \times \rightarrow 3 \times$	✗	✗	✗	✗	✗
[155]	✗	✗	$15.3 \times$	✗	$16.5 \times$	✗
[155]	✗	✗	$2.3 \times$	✗	$2.5 \times$	✗
JALAD [156]	$1.1 \times \rightarrow 11.7 \times$	✗	✗	✗	✗	✗
JointDNN [162]	$3 \times$	✗	$7 \times$	✗	✗	✗
DADS [159]	$8.08 \times$	✗	✗	$14.01 \times$	✗	✗
DADS [159]	$6.45 \times$	✗	✗	$8.31 \times$	✗	✗
Auto tuning [157]	$1.13 \times \rightarrow 1.7 \times$	✗	✗	85% → 99%	✗	✗
DDNN [163]	✗	$20 \times$	✗	✗	✗	✗
COLT-OPE [164]	$2 \times$	✗	✗	✗	✗	✗
4 ×	✗	✗	✗	✗	✗	✗
[165]	48.11 %	✗	✗	✗	✗	✗
[165]	39.75 %	✗	70%	✗	✗	✗
DINA [169]	$2.6 \times \rightarrow 4.2 \times$	✗	✗	✗	✗	✗
MoDNN [67]	$2.17 \times \rightarrow 4.28 \times$	✗	✗	✗	✗	✗
AAIoT [170]	$1 \times \rightarrow 10 \times$	✗	✗	✗	✗	✗
DeepWear [171]	$5.08 \times \rightarrow 23 \times$	✗	53.5% → 85.5%	✗	✗	✗
[142]	$2 \times \rightarrow 6 \times$	✗	✗	✗	✗	✗
[172]	✗	✗	✗	✗	✗	$1.7 \times \rightarrow 4.69 \times$
DeepThings [144]	$0.6 \times \rightarrow 3 \times$	✗	✗	68%	✗	✗

- The results in the table present the enhancement of the proposed strategies compared to the baseline approaches.

- ✗ stands for the number of times the metric is improved, i.e., how many times the latency, bandwidth usage, energy, computation, and memory are reduced, and how many times the throughput and inference rate are increased compared to the baselines.

theory [173] and the swap matching problem [174], to jointly accomplish the DNN inference. The matching theory is a mathematical framework in economics that models interactions between two sets of selfish agents, each one is competing to match agents of the other set. The objective was to reduce the total computation time while increasing the utilization of the resources related to the two sets of IoT devices and fog nodes.

IV.B.2. Localized collaboration

Another line of work considers the distribution of DNN computation across multiple edge participants, as shown in Fig. 17 (d). These participants present neighboring nodes that co-exist in the same vicinity, e.g., IoT devices or fog nodes. The model distribution over neighboring devices can be classified into two types: the per-layer distribution where each participant performs the computation of one layer or more and the per-segment allocation where smaller segments of the model are allocated to resource-limited devices.

a) *Per-layer distribution*: The layer-wise partitioning can itself be classified under two categories, the one splitting point strategy where only two participants are involved and multiple splitting points where two or more devices are collaborating. For example, the DeepWear [171] approach splits the DNN into two sub-models that are separately computed on a wearable (e.g., smart watch) and a handheld device. First, the authors conducted in-depth measurements on different devices and for multiple models to demystify the performance of wearable-side DL and study the potential gain from the partial offloading. The derived conclusions are incorporated into a lightweight online scheduling algorithm based on a prediction

model that judiciously determines how, and when to offload, in order to minimize latency and energy consumption of the inference. On the other hand, authors in [139] proposed a methodology for optimal placement of CNN layers among multiple IoT devices, while being constrained by their computation and memory capacities. This methodology minimizes the latency of decision-making, which is measured as the total of processing times and transmissions between participants. Furthermore, this proposed technique can be applied both to CNNs in which the number of layers is fixed and CNNs with an early-exit. Similarly, authors in [170] proposed a CNN multi-splitting approach to accelerate the inference process, namely AAIoT. Unlike the above-mentioned efforts, AAIoT deploys the layers of the neural network on multi-layer IoT architecture. More specifically, the lower-layer device presents the data source, and the higher-layer devices have more powerful capacities. Offloading the computation to higher participants implies sacrificing the transmission latency to reduce the computation time. However, delivering the computation to lower participants does not bring any benefits to the system. An optimal solution and an online algorithm that uses dynamic programming are designed to make the best architectural offloading strategy. Other than capacity-constrained IoT devices, the distribution of the inference process over cloudlets in a 5G-enabled MEC system is the focus of the work in [140], where authors proposed to minimize the energy consumption, while meeting stringent delay requirements of AI applications, using a RL technique.

b) *Per-segment distribution*: The per-segment distribution is defined as allocating fine-grained partitioned DNN on lightweight devices such as Android devices or Raspberry

Pis. The partitioning strategy is based on the system configuration and the pervasive network characteristics, including the memory, computation, and communication capabilities of the IoT devices and their number. The segmentation of the DNN models varies from neurons partitioning to channels, spatial, and filters splitting, as discussed in section IV-A. For example, the work in [67] opted for the spatial splitting (see Fig. 16 (b)), where the input and the output feature maps are partitioned into a grid and distributed among lightweight devices. The authors proposed to allocate the cells along the longer edge of the input matrix (rows or columns) to each participant, in order to reduce the padding overhead produced by the spatial splitting. Different segments are distributed to IoT devices according to the load-balancing principles using the MapReduce model. The same rows/columns partitioning is proposed in [175], namely the data-lookahead strategy. More specifically, each block contains data from other blocks within the same layer such that its connected blocks in subsequent layers can be executed independently without requesting intermediate/padding data from other participants. The spatial splitting is also adopted in [144], where authors proposed a Fused Tile Partitioning (FTP) method. This method fuses the layers and divides them into a grid. Then, cells connected across layers are assigned to one participant, which largely reduces the communication overhead and the memory footprint.

The previous works introduced homogeneous partitioning, where segments are similar. Unlike these strategies, authors in [172], [176] proposed a heterogeneous partitioning of the input data to be compatible with the IoT system containing devices with different capabilities ranging from small participants that fit only few cells to high capacity participants suitable for layer computation. For the same purpose, authors in [177] jointly conducted per-layer and per-segment partitioning, where the neurons and links of the network are modeled as a DAG. In this work, grouped convolutional techniques [178] are used to boost the model parallelization of different nodes of the graph. The papers in [142], [143], [179], [180] studied different partitioning strategies of the convolutional layers (channel, spatial and filters splitting) and fully connected layers (output and input splitting). Next, they emphasized that an optimal splitting depends greatly on the parameters of the CNN network and that the inference speedup depends on the number of tasks to be parallelized, which is related to the adopted splitting method. Hence, one partitioning approach cannot bring benefits to all types of CNNs. Based on these conclusions, a dynamic heuristic is designed to select the most adequate splitting and model parallelism for different inference scenarios.

Table V shows the performance of these techniques in terms of latency, bandwidth, energy, computation, memory, and throughput, whereas Table VI presents a comparison between different distributed inference techniques introduced in this section.

IV.B.3. Lessons learned

The lessons acquired from the literature review covering the DNN distribution can be summarized as follows:

- In per-layer strategies, selecting the split points depends on multiple parameters, which are the capacity of the end device that constrains the length of the first segment, the characteristics of the network (e.g., wi-fi, 4G, or LTE) that impact the transmission time, and the DNN topology that determines the intermediate data size.
- The deep neural networks with a small-reduction capacity of pooling layers or with fully-connected layers of similar sizes undergo small variations in the per-layer latency and data size. In this case, remote collaboration is not beneficial for data transmission. Hence, compression (e.g., quantization, pruning, and encoding) can be a good solution to benefit from remote capacity with the minimum of communication overhead.
- Recently, many efforts have focused on the localized inference through per-segment distribution that allows to involve resource-limited devices and avoid transmission to remote servers. This kind of works targeted the model parallelization and aimed to maximize the concurrent computation of different segments within the same request. However, fewer works covered data parallelization and real-time adaptability to the dynamic of requests. Particularly, the load of inferences highly impacts the distribution of segments to fit them to the capacity of participants.
- Adopting a mixed partitioning strategy is advantageous for heterogeneous systems composed of high and low-capacity devices and multiple DNNs, which allows to fully utilize the pervasive capacities while minimizing the dependency and data transmission between devices.

IV.C. Use cases

The DNN distribution is applied in multiple AI-governed use cases, including healthcare [182], object detection [183], and intelligent connected vehicles [184]. In this section, we review the literature of two applications that impose extra constraints to the system, namely data privacy and the distribution on moving robots, which presents challenges in managing the battery life, the connection with other participants and the dynamic model selection to enhance the accuracy of the data captured in harsh environments.

IV.C.1. Data privacy

The data captured by end-devices and sent to remote servers (e.g., from cameras or sensors to cloud servers) may contain sensitive information such as camera images, GPS coordinates of critical targets, or vital signs of patients. Exposing these data has become a big security concern for the deep learning community. This issue is even more concerning when the data is collected from a small geographical area (e.g., edge computing) involving a set of limited and cooperating users. In fact, if an attacker reveals some data (even public or slightly sensitive), a DL classifier can be trained to automatically infer the private data of a known community. These attacks, posing severe privacy threats, are called inference attacks that analyze trivial or available data to illegitimately acquire knowledge about more robust information without accessing it, by only capturing their statistical correlations. An example of a popular

TABLE VI: Comparison between Distributed Inference techniques.

Refs	Year	End-Device	No. of end Devices	Localized inference	Context	Real-time processing	Partitioning mechanism	No. of partitions	Model or data parallelism	other techniques	Runtime adaptability
Neurosurgeon [149]	2017	Tegra TKI	1	X	X	X	Per-layer	1	X	X	X
DDNN [163]	2017	X	Many	X	X	✓	Per-layer	Many	Data	Early exit	X
MoDNN [67]	2017	LG Nexus 5	4	✓	X	X	Per-segment	Many	Model	X	X
Edgent [150]	2018	Raspberry Pi 3	1	X	X	✓	Per-layer	1	X	Early exit	X
[155]	2018	X	1	X	X	X	Per-layer	1	X	Compression	X
DeepThings [144]	2018	Raspberry Pi 3	Many	✓	X	✓	Per-segment	Many	Model	X	X
Collaborative robots [137]	2018	Raspberry Pi	12	✓	Robots and image recognition	✓	Per-segment	Many	Both	X	✓
Musical chair [179], [180]	2018	Raspberry Pi	Many	✓	object/action recognition	✓	Per-segment	Many	Both	X	✓
HDDNN [167]	2018	X	Many	X	X	✓	Per-layer	Many	Data	Encryption	X
Auto tuning [157]	2018	Jetson TX2	Many	X	X	X	Per-layer	Many	X	Quantization	X
JALAD [156]	2018	GPU Quadro k620	1	X	X	X	Per-layer	1	X	Quantization	✓
KLP [172], [176]	2018 2019	STM32F469	Many	✓	X	X	Per-segment	Many	Model	X	X
ADDA [153]	2019	Raspberry Pi 3	1	X	X	X	Per-layer	1	X	Early exit	X
Boomerang [152]	2019	Raspberry Pi 3	1	X	X	✓	Per-layer	1	X	Early exit	✓
[181]	2019	Krait CPU	12	✓	sensors fault tolerance	✓	X	Many	Model	X	✓
[139]	2019	Raspberry Pi STM32H7	Many	✓	X	X	Per-layer	Many	Data	X	X
DADS [159]	2019	Raspberry Pi 3 model B	1	X	X	✓	Per-layer	Many	X	X	✓
COLT-OPE [164]	2019	X	1	X	X	X	Per-layer	Many	X	Early exit	✓
EDDL [177]	2019	Fog nodes	Many	✓	X	X	Per-layer Per-segment	Many	Model	Sparsification Early exit	X
[154]	2019	GPU GTX1080	1	X	X	✓	Per-layer	1	X	X	✓
[143]	2019	X	7	✓	X	X	Per-layer Per-segment	Many	Model	X	X
deepFogGuard [168]	2019	X	Many	X	X	X	Per-layer	Many	X	X	X
2steps-pruning [158]	2019	X	2	X	X	X	Per-layer	1	X	pruning	X
JointDNN [162]	2019	jetson tx2	1	X	X	X	Per-layer	1	X	X	✓
AAIoT [170]	2019	Raspberry Pi, Mobile PC, Desktop PC, Server	Many	✓	X	X	Per-layer	Many	X	X	X
MWWP [182]	2020	X	Many	X	health care multi-view	✓	Per-layer	Many	Data	X	✓
[183]	2020	Raspberry Pi	Many	✓	object detection	X	Per-segment	Many	Model	Compression	X
CONVENE [175]	2020	X	1	X	Parallel data sharing on antennas	X	Per-segment	Many	Model	X	✓
DINA [169]	2020	X	Many	X	Intelligent Connected Vehicles	✓	X	Many	Both	X	✓
[184]	2020	X	Many	✓	augmented reality in 5G	✓	Per-layer	1	X	X	X
[166]	2020	X	1	X	Visual based applications	X	Per-layer	2	Data	Early-exit	✓
[165]	2020	Huawei	1	X	Wearable devices	✓	Per-layer	1	X	Compression	✓
[142]	2020	Raspberry Pi 3	Many	✓	5 G	✓	Per-layer	Many	Data	X	X
Deep Wear [171]	2020	Android wear	2	✓	Cloudlet	✓	Per-layer	1	X	Compression	✓
[140]	2021	Cloudlet	Many	✓	Data privacy	✓	Per-segment	Many	Both	X	✓
DistPrivacy [185]	2021	Raspberry Pi STM32H7 LG Nexus 5	Many	✓						X	✓

inference attack is the Cambridge Analytica scandal in 2016, where public data of Facebook users were exploited to predict their private attributes (e.g., political view and location). Some well-known inference attacks are summarized in Table VII.

TABLE VII: Examples of inference attacks.

Inference attacks	Exposed data	Sensitive data
Side-channel attacks [186]	Processing time, power consumption.	Cryptographic keys
Location inference attacks [187]	smartphones' sensor data.	Location
Feature inference attacks [188]	Prediction results, partial features of the DNN model.	DNN structure
Membership inference attacks [189]	confidence level of classes, gradients.	membership of a sample to a dataset.
attribute inference attacks [190]	social data, likes, friends.	Gender, ages, preferences.

Edge computing naturally enhances privacy of the sensitive information by minimizing the data transfer to the cloud through the public internet. However, additional privacy techniques should be adopted to further protect the data from eavesdroppers. In this context, in addition to its ability to allow the pervasive deployment of neural networks, the DNN splitting was also used for privacy purposes. Meaning, by partitioning the model, partially processed data is sent to the untrusted party instead of transmitting raw data. In fact, in contrast to the training data that belongs to a specific dataset and generally follows a statistical distribution, the inference samples are random and harder to be reverted. Furthermore, the model parameters are independent from the input data, which makes the inference process reveal less information about the sample [88]. While preserving privacy, the inevitable challenge of DNN partitioning that remains valid, is selecting the splitting point that preserves the latency requirements of the system.

Authors in [191] proposed to extract the features sufficient and necessary to conduct the classification from the original image or from one of the layers' outputs using an encoder and transmit these data to the centralized server for inference. This approach prevents the exposure of irrelevant information to the untrusted party that may use it for unwanted inferences. Nevertheless offloading only extracted features contributes to minimizing the transmission overhead, this work focused only on the privacy perspective. The work in [192] also proposed feature extraction for data privacy, while achieving a trade-off between on-device computation, the size of transmitted data, and security constraints. In fact, selecting the split layer from where the data will be extracted intrinsically presents a security compromise. Particularly, as we go deeper in the DNN network, the features become more task specific and the irrelevant data that can involve sensitive information are mitigated [197]. Hence, if the split is performed in a deep layer, the privacy is more robust and the transmission overhead is lower. However, a higher processing load is imposed on the source device. The latter work [192], along with the work in [88], advised to perform deep partition in case the source device has enough computational capacity. If the source device is resource-constrained, the model should be partitioned in the

shallow layers, although most of the output features are not related to the main task. Authors in [192] proposed a solution based on Siamese fine-tuning [198] and dimensionality reduction to manipulate the intermediate data and send only the primary measures without any irrelevant information. In addition to enhancing privacy, this mechanism contributes to reducing the communication overhead between the end-device and the remote server.

However, to this end, the arms race between attacks and defenses for DNN models has come to a forefront, as the amount of extracted features can be sufficient for adversary approaches to recover the original image. Whereas, less shared features may also result in low classification accuracy. The works in [88], [199], [200] proposed adversarial attacks to predict the inference input data (or the trained model), using only available features from shared outputs between participants. Authors in [88] focused particularly on the privacy threats presented by the DNN distribution; and accordingly, designed a white-box attack assuming that the structure of the trained model is known and the intermediate data can be inverted through a regularized Maximum Likelihood Estimation (rMSE). Additionally, a black-box attack is also proposed, where the malicious participant only has knowledge about his segment and attempts to design an inverse DNN network to map the received features to the targeted input and recover the original data. Authors demonstrated that reversing the original data is possible, when the neural system is distributed into layers. Numerous countermeasures have been considered to strengthen the robustness of deep networks, including adding noise to the intermediate data to obfuscate it, differential privacy, and cryptographic techniques that train the model on encrypted samples.

Adding noise to the intermediate data is adopted in [193]. In this paper, the authors proposed to perform a simple data transformation in the source-device to extract relevant features and add noise. Next, these features extracted from shallow layers are sent to the cloud to complete the inference. To maintain a high classification accuracy, the neural network is re-trained with a dataset containing noisy samples. However, adding noise to the intermediate data costs the system additional energy consumption and computational overhead. Therefore, the splitting should be done at a layer where the output size is minimal. Though, the latter work did not describe the partition strategy. The Shredder approach [194] resolved this dilemma by considering the computation overhead during the noise injection process. The idea is to conduct an offline machine learning training to find the noise distribution that strikes a balance between privacy (i.e., information loss) and accuracy drop. In this way, the DNN model does not require retraining with the noisy data and the network can be cut at any point to apply directly the noise distribution. The partitioning decision is based on the communication and computation cost. A higher privacy level and lower communication overhead are guaranteed, when the split is performed at deep layers; however, the allocation at the end-device becomes less scalable. Adding noise or extracting task-specific data can be included under the umbrella of differential privacy, which at a high level ensures that the model does not receive any information

TABLE VIII: Comparison between privacy-aware distribution strategies.
(H: High, M: Medium, L: Low).

Privacy-aware strategy	Privacy level	Accuracy preserving	DNN re-training	Compatibility with IoT and DNNs	Partitioning strategy	Communication overhead	Computation overhead on source-device
Deep split [88]	H	✓	✗	✓	per-layer	L	H
Feature extraction [191], [192]	L	✗	✗	✓	per-layer	L	M
Noise addition [193]–[195]	M	✗	✓	✗	per-layer	M	H
Cryptography [196]	H	✗	✓	✗	per-layer	M	H
Privacy-aware partitioning [185]	M	✓	✗	✓	Filter splitting	H	L

about the private input data, while still presenting satisfactory classification. The performance of differential privacy is assessed by a privacy budget parameter ϵ that denotes the level of distinguishability. Authors in [195] conducted theoretical analysis to minimize ϵ , while considering accuracy and the communication overhead to offload the intermediate features among fog participants.

Cryptography is another technique that can be used to protect the distributed inference. The main idea is to encrypt the input data and process it using a model trained on encrypted dataset, in a way the intermediate data cannot be used by a malicious participant. Little research, including [196], investigated the encrypted DNN distribution, as this approach suffers from a prohibitive computation and communication overhead that exacerbates the complexity of the inference process, particularly when executed in resource-constrained devices.

All the previous techniques applied additional tasks to secure the shared data, e.g., feature extraction, adding noise, and encryption, which overloads the pervasive devices with computational overhead. Different from previous works, DistPrivacy [185] used the partitioning scheme to guarantee privacy of the data. In fact, all the existing privacy-aware approaches adopted the per-layer distribution of the DNN model. This partitioning strategy incurs an intermediate shared information that can be reverted easily using adversarial attacks. The main idea in [185] is to divide the data resulting from each layer into small segments and distribute it to multiple IoT participants, which contributes to hiding the properties of the original image and preventing untrusted devices from recovering the data. Particularly, the authors adopted the filter splitting strategy, in such a way that each device computes a part of the feature maps. However, as stated in section IV-A, this partitioning strategy results in large data transmission between participants. Therefore, the authors formulated an optimization that establishes a trade-off between privacy and communication overhead.

Fig. 20 illustrates different privacy-aware strategies for distributed inference existing in the literature.

Table VIII shows the performance of different privacy-aware distribution strategies. We can see that choosing the adequate strategy depends on the requirements of the pervasive system, as multiple trade-offs need to be established, such as the security level and accuracy, or the computation and

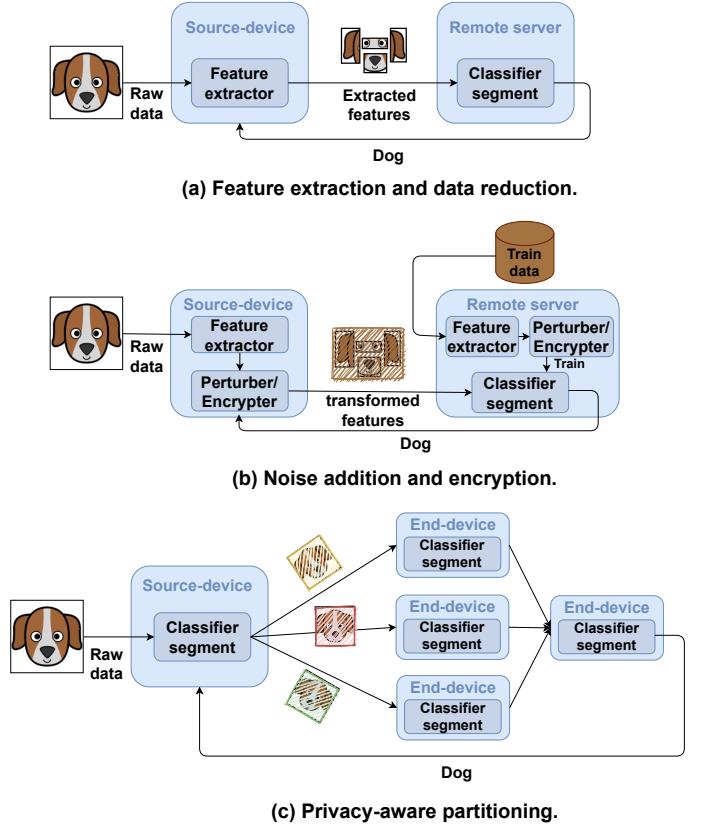


Fig. 20: Privacy-aware distribution strategies.

communication loads.

IV.C.2. Distribution on moving robots

Currently, robotic systems have been progressively converging to computationally expensive AI networks for tasks like path planning and object detection. However, resource-limited robots, such as low power UAVs, have insufficient on-board power-battery or computational resources to scalably execute the highly accurate neural networks.

In surveillance applications, the aim is to monitor specific objects or identify threats within the target region. Moving devices are the most suitable technology to provide information about the target object from different angles, which makes the identification more accurate. These data-generating devices are only responsible for collecting the data, while servers with higher capacities generate the identification re-

sults. The traditional wisdom resorts to cloud or edge servers to compute heavy tasks. However, due to the harsh environments where robots move (e.g., military border zones, forests, and offshore oil reserves), the communication with remote servers is strongly affected by the weather. Also, the processing might be difficult or even impossible because of the interference resulting from the UAV altitude or the underground environment (e.g., high-rise building effect on path loss). Furthermore, as surveillance devices send high-resolution images to cloud/edge servers at each small interval of time and knowing that incidents rarely occur, the large data volume transmitted by source units has become problematic, particularly for such systems characterized by an unstable bandwidth availability. Because of this tremendous amount of data obtained during the robots mission, AI should be integrated within the design of the devices. However, moving robots come with distinct features, often understated, such as that communicating with the remote servers while moving incurs unstable latency, more energy consumption, and potential loss of data.

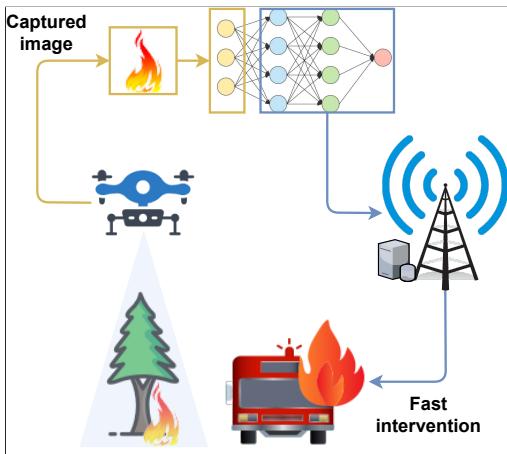


Fig. 21: A fire detection scenario with distributed DNN.

The work in [201], [202] examined the case of per-layer distribution with one split point between one UAV and one MEC server (see Fig. 21). More specifically, the authors proposed a framework for AI-based visual target tracking system, where low-level layers of the DNN classifier are deployed in the UAV device and high-level layers are assigned to the remote servers. The classification can be performed using only the low-level layers, if the image quality is good. Otherwise, the output of these layers should be further processed in the MEC server, for higher accuracy. In this context, the authors formulated a weighted-sum cost minimization problem for binary offloading and partial offloading, while taking into consideration the error rate/accuracy, the data quality, the communication bandwidth, and the computing capacity of the MEC and the UAV. The offloading probability is derived for the binary offloading and the offloading ratio (i.e., the segment of DNN to execute in the MEC) is obtained for the partial offloading scheme. In this model, the mobility of the UAVs (i.e., the distance between the UAV and the server) is involved through the transmission data rate between the device and the MEC, as presented in Eq. (6) in the previous section IV-A. Additionally, the distance

between the UAV and the target impacts the quality of the image and consequently impacts the offloading decisions. In the proposed framework, multiple trade-offs are experienced:

- The accuracy is achieved at the expense of delay and transmitted data: if most of the images have bad quality, the system is not able to accomplish low average latency as on-board inference is not sufficient. For this reason, different inferences should be extended wisely using the segment allocated in the MEC, particularly if the environment is challenging such as bad weather or when the target is highly dynamic.
- A trade-off exists also between the accuracy and latency, and the position of the UAVs: when the device is close to the target, high resolution images can be taken, which allows obtaining good accuracy on-board and avoiding the data offloading. Being close to the targets is not always possible, particularly in harsh environments or when the surveillance should be hidden.
- The battery life is increased at the expense of the inference latency: the battery can be saved, if processing coefficient is decreased, which enlarges the computation time of the classification.
- The split point selection: if the intermediate data is smaller than the raw data, the offloading is encouraged to enhance the accuracy.

An online solution of this offloading trade-off using reinforcement learning is presented in [203].

The previous works adopted the per-layer wise with one split point and remote collaboration approach. This strategy is more adequate for flying devices that can enhance their link quality by approaching the MEC stations. However, for ground robots, offloading segments of the inference to remote servers costs the system a large transmission overhead and high energy consumption. Authors in [204] studied the distribution of the DNN network among ground robots and profiled the energy consumed for such tasks, when moving or being in idle mode. Several conclusions are stated:

- When the robot is idle, the DNN computation and offloading increase the power consumption of the device by 50%.
- If the device is moving, the DNN execution causes high spikes in power consumption, which may limit the device to attain a high performance as this variation incurs a frequent change of the power saving settings in the CPU.
- Distributing the inference contributes to reducing the energy consumed per device, even-though the total power consumption is higher. This is due to the reduced computation and memory operations per device and the idle time experienced after offloading the tasks.

Based on the energy study of moving robots, the authors proposed to distribute the DNN model into smaller segments among multiple low-power robots to achieve an equilibrium of performance in terms of energy and number of executed tasks [137]. Still, the distribution of the model into small segments (e.g., filter splitting) requires the intervention of a large number of robots that are highly dependent, which is not realistic.

V. FEDERATED LEARNING FOR DISTRIBUTED TRAINING

Despite the great potential of deep learning in different applications, it still has major challenges that need to be addressed. These challenges are mainly due to the massive amount of data needed for training deep learning models, which imposes severe communication overheads in both network design and end-users. Moreover, the conventional way of transferring the acquired data to a central server for training comes with many privacy concerns that several applications may not tolerate. In this context, the need for intelligent and on-device DL training has emerged. More specifically, instead of moving the data from the users to a centralized data center, pervasive data-sources engage the server to broadcast a pre-trained model to all of them. Then, each participant deploys and personalizes this generic model by training it on its own data locally. In this way, privacy is guaranteed as the data is processed within the host. The on-device training has been widely used in many applications [42], such as the medical field, assistance services, and smart education. However, this no-round-trip training technique precludes the end-devices to benefit from others' experiences, which limits the performance of the local models. To this end, Federated Learning (FL) has been advanced, where end-users can fine-tune their learning models while preserving privacy and local data processing. Then, these local models (i.e., model updates) are aggregated and synchronized (averaged) at a centralized server, before being sent back to the end-users. This process repeats several times (i.e., communication rounds) until reaching converge. Accordingly, each participant builds a model from its local data and benefits from other experiences, without violating privacy constraints. FL is proposed by Google researchers in 2016 [205], and since then, it has witnessed unprecedented growth in both industry and academia.

For the sake of completeness, we present in this section an overview for this emerging pervasive learning technique, i.e., Federated Learning. In particular, we introduce the computation and communication models of the FL techniques. Then, we present a brief summary of the related works in the literature, while highlighting a use case that considers the application of FL within UAV swarms. It is worth mentioning that the FL can be used for both online and offline learning (i.e., the training can be performed on static datasets at once, or continuously training on new data received by different participants). In this paper, we focus on studying the communication models of the pervasive FL, which are valid for offline and online learning; and for this reason we chose not to include it under the umbrella of the online learning section. Fig. 22 summarizes the main subsections presented in what follows.

V.A. Profiling computation and communication models

Generally, the FL system is composed of two main entities, which are the data-sources (i.e., owners of data or pervasive participants) and the centralized server (i.e., model owner). Let N denote the number of data-sources. Each one of these devices has its own dataset D_i . This private data is used to train the local model m_i , and then the local parameters are sent to the centralized server. Next, the local models are collected and aggregated onto a global model $m_G = \bigcup_{i=1}^N m_i$.

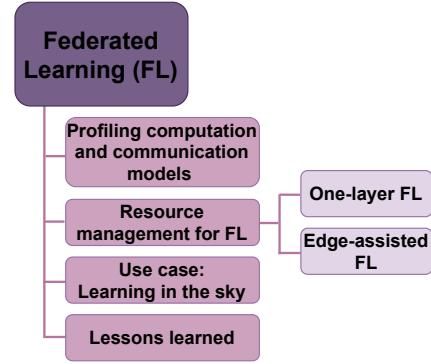


Fig. 22: Outline of federated learning.

The FL is different from training in the remote server, where the distributed data are collected and aggregated first, i.e., $D_G = \bigcup_{i=1}^N D_i$, and then one model m is trained centrally. We assume that data-sources are honest and submit their real data or their true local models to the centralized server. Otherwise, control and incentive techniques are used to guarantee the reliability of FL, including [206].

Typically, the life cycle of FL is composed of multiple communication rounds that are completed when the centralized model reaches a satisfactory accuracy. Each round includes the following steps:

- *Initialization of FL*: The centralized server fixes the training task, the data shape, the initial model parameters, and the learning process (e.g., learning rate). This initial model m_G^0 is broadcasted to the selected participants
- *Training and updating the local models*: Based on the current global model m_G^t , each data-source i utilizes its own data D_i to update the local model m_i^t . We note that t presents the current round index. Hence, at each step t , the goal of each participant is to find the optimal parameters minimizing the loss function $L(m_i^t)$ defined as:

$$m_i^{t*} = \operatorname{argmin}_{m_i^t} L(m_i^t) \quad (11)$$

Subsequently, the updated parameters of the local models are offloaded to the server by all selected participants.

- *Global model aggregation*: The received parameters are aggregated into one global model m_G^{t+1} , which will be sent back in its turn to the data owners. This process is repeated continuously, until reaching convergence. The server goal is to minimize the global loss function presented as follows:

$$L(m_G^t) = \frac{1}{N} \sum_{i=1}^N L(m_i^t) \quad (12)$$

The aggregation of the global model is the most important phase of FL. A classical and straightforward aggregation technique, namely FedAvg, is proposed by Google reference paper [205] and presented in Algorithm 1.

Algorithm 1 summarizes the aforementioned steps, where the centralized server tries to minimize the global loss function by averaging the aggregation following the equation in line 11. The FL system is iterated continuously until the convergence

Algorithm 1 FederatedAveraging (FedAvg) [205]

```

1: Input:  $N$ : participants,  $D_i$ : dataset of the device  $i$ ,  $B$ : local mini-batches,  $E$ : number of local epochs,  $T$ : number of rounds,  $\rho$ : learning rate,  $c$ : fraction of participants.
2: Output: Global model  $m_G$ .
3: Initialization of FL: initialize  $m_G^0$ 
4: Global model aggregation:
5: for  $t=1..T$  do
6:    $NP \leftarrow \max(c.N, 1)$ 
7:    $P \leftarrow$  select random  $NP$  participants
8:   for  $i \in P$  in parallel do
9:      $m_i^{t+1} \leftarrow$  Local model update ( $i, m_G^t$ )
10:    end for
11:     $m_G^{t+1} = \sum_{i=1}^N \frac{|D_i|}{\sum_{j=1}^N |D_j|} m_i^{t+1}$  % Averaging aggregation
12:   end for
13:   Local model update ( $i, m$ ):
14:    $d \leftarrow$  split  $D_i$  into batches of size  $B$ 
15:   for  $j=1..E$  do
16:     for samples  $b \in d$  do
17:        $m \leftarrow m - \rho \Delta L(m, b)$  %  $\Delta L$  is the gradient of  $L$ 
18:     end for
19:   end for

```

of the global loss function or reaching a desirable accuracy. A major challenge in FL is the large communication and energy overhead related to exchanging the models updates between different end-users, and the centralized server [207], [208]. Such overheads depend on multiple parameters, including the models' updates size, the number of participating users, the number of epochs per user, and the number of communication rounds required to maintain the convergence. Particularly, the energy consumed by an FL participant i characterized by a frequency f , a local dataset D_i , and a number of local epochs E , is given by [209], [210]:

$$e_i^c = E \times (\phi \gamma |D_i| f^2), \quad (13)$$

where ϕ is the number of CPU cycles required to compute one input instance, and γ is a constant related to the CPU. The latency required to compute the local model can be expressed as:

$$t_i^c = E \times \left(\frac{\phi |D_i|}{f} \right). \quad (14)$$

From the equations (13) and (14), we can see that a trade-off exists between the local training latency and the consumed energy. More specifically, for a fixed accuracy determined by the number of local epochs and a fixed frequency, the latency is accelerated depending on the size of the private data. If the data size and the accuracy are fixed, increasing the CPU frequency can help to minimize the local model computation. However, minimizing the latency comes at the expense of energy consumption that increases to the square of the operating frequency.

The transmission time to share the model updates between the centralized servers and different FL participants mainly

depends on the channel quality, the number of devices and the number of global rounds, illustrated as follows:

$$t^T = T \times \sum_{i=1}^N \frac{K}{\rho_i}, \quad (15)$$

where K is the models' parameters size shared with the server and ρ is the data rate of the participant i . On the other hand, the total energy consumed during the federated learning process using the local transmit powers P_i is equal to:

$$e^T = T \times \sum_{i=1}^N \frac{KP_i}{\rho_i}, \quad (16)$$

From the above equations, we can see that the local iterations E and the global communication rounds T are very important to optimize the energy, computation, and communication costs. Particularly, for a relative local accuracy θ_l , E can be expressed as follows [211]:

$$E = \alpha \times \log\left(\frac{1}{\theta_l}\right), \quad (17)$$

where α is a parameter that depends on the dataset size and local sub-problems. The upper bound on the number of global rounds to reach the targeted accuracy θ_G can be presented as [211]:

$$T = \frac{\zeta \log\left(\frac{1}{\theta_G}\right)}{1 - \theta_l}. \quad (18)$$

We note that $\zeta \log\left(\frac{1}{\theta_G}\right)$ is used instead of $O(\log\left(\frac{1}{\theta_G}\right))$, where ζ is a positive constant. From equations (17) and (18), we can see that the computation cost depending on the local iterations E and the communication cost depending on the global rounds T are contradictory. It means, minimizing E implies maximizing T and consequently increasing the convergence latency.

To summarize, FL pervasiveness aspects that are being tackled by different studies, to reduce communication and energy overheads, may include:

- 1) reducing communication frequency, i.e., number of communication rounds;
- 2) reducing the number of local iterations;
- 3) selecting minimum number of participating users in the training process;
- 4) optimizing local devices operating frequencies;
- 5) minimizing the entropy of the models updates by using lossy compression schemes;
- 6) using efficient encoding schemes in communicating models updates.

In what follows, we categorize different presented FL schemes in the literature, based on the system architecture, namely one-layer FL and edge-assisted FL. The former refers to user-cloud architecture, where different users share their learning models with a cloud or centralized server for aggregation, while the latter refers to user-edge-cloud architecture, where edge nodes are leveraged to reduce communication overheads and accelerate FL convergence (see Figure 23).

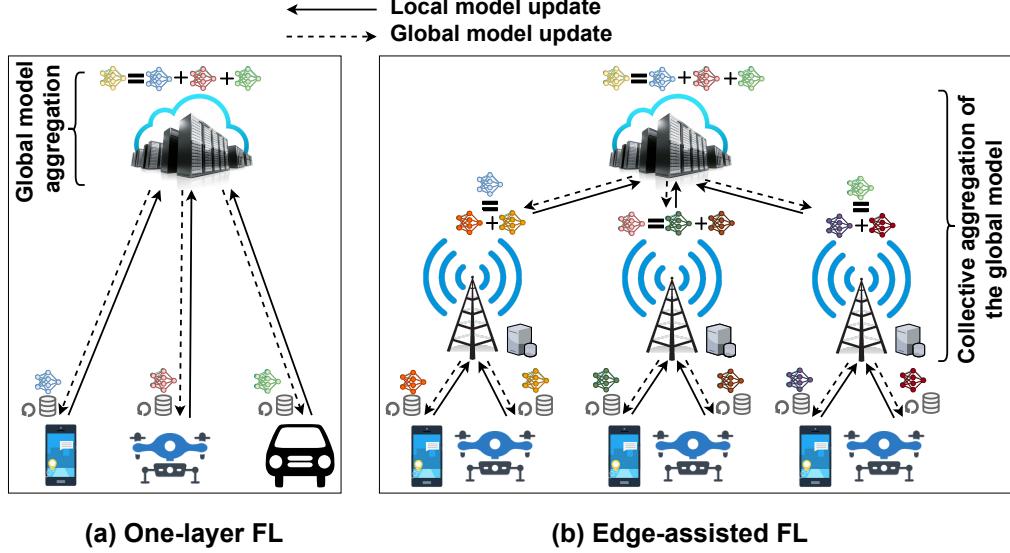


Fig. 23: The FL architectures considered in the literature: (a) one-layer FL, (b) edge-assisted FL.

V.B. Resource management for Federated learning

V.B.1. One-layer Federated Learning

The concept of FL was first proposed in [205] by Google, with its efficiency demonstrated through experiments on different datasets. The presented model in [205] considered a one-layer FL, where the users exchange their updated models with a centralized server that aggregates and forms an updated global model with a fixed frequency.

Afterward, several extensions have been proposed to the original FL. The investigated problems/approaches in FL, considering one-layer architecture, can be categorized into:

- analyzing the convergence of distributed gradient descent and federated learning algorithms from a theoretical perspective, and optimizing the learning process given computation and communication resource budget [212]–[215];
 - considering partial user participation for the FL aggregation process in a resource-constrained environment while balancing between the model accuracy and communication cost [216]–[219];
 - developing communication-efficient techniques to reduce the amount of exchanged data in FL communications by adopting various sparsification and compression techniques [220]–[222].

The effect of non-Independent and Identically Distributed (non-IID) data on the performance of FL has been studied in [212]. It has been shown, theoretically and empirically, that highly skewed non-IID data (i.e., the local data at different users are not identically distributed) can significantly reduce the accuracy of the global learning model by up to 55%. As a solution to enhance the training on non-IID data, the authors proposed to share globally a small subset of data between all users. Combining this data with the local data of each user turns it to be less biased or skewed. However, exchanging data between different users is not always feasible due to the privacy constraint and communication overhead of sharing

such data. In [213], the authors analyzed the convergence rate of FedAvg on non-IID data for strongly convex and smooth problems. In [214], the authors studied the adaptation of global aggregation frequency for FL, while considering a fixed resource budget. Indeed, they analyzed the convergence bound of gradient-descent based FL on non-IID data from a theoretical perspective. Then, they used this convergence bound to build a control algorithm that adapts the frequency of global aggregation in real-time to minimize the learning loss under a fixed resource budget. A new FL algorithm, named FEDL, is presented in [215]. This algorithm used a local surrogate function that enables each user to solve its local problem approximately up to a certain accuracy level. The authors presented the linear convergence rate of FEDL as a function of the local accuracy and hyper-learning rate. Then, a resource allocation problem over wireless networks was formulated, using FEDL, to capture the trade-off between the training time of FEDL and user's energy consumption.

It is shown in [213] that the participation of all users in the FL process enforces the central server to wait for *stragglers*, i.e., users who have low-quality wireless links that can significantly slow down the FL process, which turns the FL to be unrealistic. Thus, to mitigate the impact of *stragglers*, the authors in [216] proposed a method to select a subset of users for the FL synchronization (or aggregation) process in a resource-constrained environment. They demonstrated the advantages of such a technique on improving the FL learning speed. This work has been extended in [217], where a control scheme is proposed, based on reinforcement learning, to accelerate the FL process by actively selecting the best subset of users in each communication round that can counterbalance the bias introduced by non-IID data. In [218], a joint optimization framework for sample selection and user selection was studied to keep a balance between the model accuracy and cost. However, the distribution distance between different users was optimized in this framework by adjusting the local batch size, which might lead to the under-

utilization of data in strongly skewed users. In [219], the problem of users selection to minimize the FL training time was investigated on cell-free massive multiple-input multiple-output (CFmMIMO) networks.

Alternatively, sparsification schemes have been studied to reduce the entropy of the exchanged data (i.e., models' updates) in FL communications. The authors in [220] presented an approach that accelerates the distributed stochastic gradient descent by exchanging sparse updates instead of dense updates. Indeed, they fixed the sparsity rate by only communicating the fraction of entries with the biggest magnitude for each gradient. In [221], the authors proposed a sparse ternary compression scheme that was designed to maintain the requirements of the FL environment. The proposed scheme compressed both the upstream and downstream communications of FL leveraging sparsification, ternarization, error accumulation, and optimal Golomb encoding. This study demonstrated the effect of communications compression and data distributions on the obtained performance. However, it neither considered the wireless resources allocation nor the edge-assisted FL architecture. In [222], the FedAvg scheme was adjusted to use a distributed form of Adam optimization, along with the sparsification and quantization, in order to propose a communication-efficient FedAvg.

V.B.2. Edge-assisted Federated Learning

Few studies have been proposed so far to address the problem of non-IID data in edge-assisted FL architecture. For instance, the authors in [223] extended the work in [214] to analytically prove the convergence of the edge-assisted federated averaging algorithm. This work was further extended in [224] considering probabilistic users selection to avoid the impact of *stragglers*. In [225], a self-balancing FL framework, along with two strategies to prevent the bias of training caused by imbalanced data distribution, was proposed. The first strategy aimed to, before training the model, perform data augmentation in order to alleviate global imbalance. The second strategy exploited some mediators (which can be considered as edge nodes) to reschedule the training of the users based on the distribution distances between the mediators. In [226], the effect of the skewed data in edge-assisted FL was studied and compared to the centralized FL. Indeed, this work identified the major parameters that affect the learning performance of edge-assisted FL. However, this work ignored the resource allocation and wireless communications constraints, such as bandwidth, energy consumption, and latency.

Table IX presents the taxonomy of the federated learning techniques described in this section.

V.C. Use case: Learning in the sky

Nowadays, deep learning has been widely used in Flying Ad-hoc Network (FANET). Different tasks can be executed using DL techniques at UAV swarms, such as coordinated trajectory planning [233] and jamming attack defense [234]. However, due to the related massive network communication overheads, forwarding the generated large amount of data from the UAV swarm to a centralized entity, e.g., ground base stations, makes implementing centralized DL challenging.

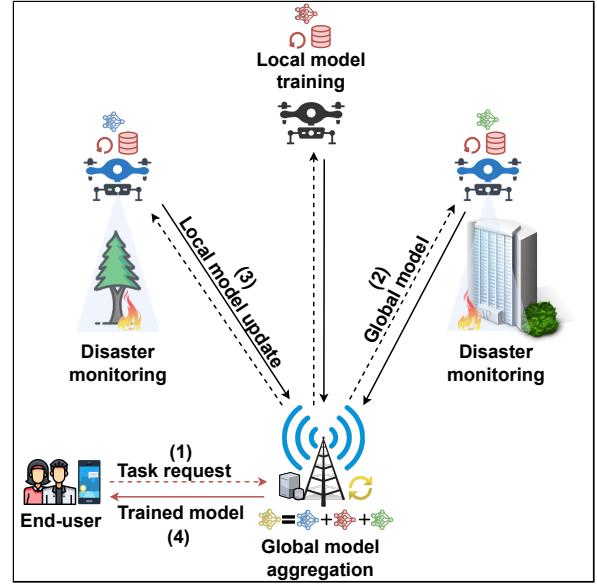


Fig. 24: An example of FL applications in UAV-assisted environment.

As a promising solution, FL was introduced within a UAV swarm in several studies [233], [234], [236], [237] to avoid transferring raw data, while forwarding only local trained models' updates to the centralized entity. Models aggregation and generation of a global FL model is the responsibility of the centralized entity, who will also send this global model to the end-user and all participants over the intra-swarm network (see Fig. 24).

In [233], the authors present a FL framework for the swarm of wirelessly connected UAVs flying at the same altitude. The considered swarm includes a leader UAV and a set of followers UAVs. It is assumed that each follower collects data while flying and implements FL for executing inference tasks such as trajectory planning and cooperative target recognition. Hence, each follower exploits its gathered data to train its own learning model, then forwarding its model's updates to the leading UAV. All received models are then aggregated at the leading UAV to generate a global FL model, that will be used by the following UAVs in the next iteration. Interestingly, [233] investigates the impact of wireless factors (such as fading, transmission delay, and UAV antenna angle deviations) on the performance of FL within the UAV swarms. The authors present the convergence analysis of FL while highlighting the communication rounds needed to obtain FL convergence. Using this analysis, a joint power allocation and scheduling optimization problem is then formulated and solved for the UAV swarm network in order to minimize the FL convergence time. The proposed problem considers the resource limitations of UAVs in terms of: (1) the strict energy limitations due to the energy consumed by learning, communications, and flying during FL convergence; and (2) delay constraints imposed by the control system that guarantees the stability of the swarm.

TABLE IX: Taxonomy of federated learning techniques.

Refs	Year	FL devices	Architecture	Trained model	Aggregation algorithm	Dataset	Targeted metrics
[205]	2017	Mobile devices	One-layer	- 2NN - CNN - LSTM	FedAvg	- CIFAR-10 [227] - MNIST [228]	- Accuracy vs rounds
[212]	2018	Mobile and IoT devices	One-layer	- CNN	Enhanced FedAvg	- CIFAR-10 - MNIST - KWS [229]	- Accuracy vs rounds - Shared data - Weight divergence
[213]	2019	End-users	One-layer	- Logistic regression	FedAvg	- MNIST	- Global loss vs rounds - Rounds vs local epochs
[214]	2019	Edge nodes	One-layer	- Squared-SVM - Linear regression, - K-means - CNN	FedAvg	- MNIST - Energy [230] - User Knowledge Modeling [231] - CIFAR-10	- Loss vs nodes - Accuracy vs nodes
[215]	2019	End-users	One-layer	X	Non-weighted averaging	X	- Communication vs computation time - Learning time vs energy
[216]	2019	End-users	One-layer	- CNN	Averaging	- CIFAR-10 - Fashion-MNIST [232]	- Accuracy vs time - Number of participants
[217]	2020	Mobile devices	One-layer	- CNN	FedAvg with users selection Favor	- MNIST - Fashion-MNIST - CIFAR-10	-Accuracy vs rounds
[218]	2020	End-users	One-layer	- MLP - CNN	FedAvg	- MNIST	- Accuracy vs rounds
[219]	2020	Mobile devices	One-layer	X	X	X	- Transmission time - Loss
[221]	2020	Mobile devices	One-layer	- VGG11 - CNN - LSTM - Logistic regression	Weighted averaging with Top-k sparsified communication	- CIFAR - KWS - MNIST - Fashion-MNIST	- Communication delay - Accuracy
[222]	2020	IoT devices	One-layer	- 2NN - CNN	communication-efficient FedAvg (CE-FedAvg)	- CIFAR-10 - MNIST	- Uploaded data - communication rounds - convergence time
[233]	2020	UAVs	One-layer	X	FedAvg	X	- Rounds vs bandwidth
[234]	2020	UAVs	One-layer	- FCN	FedAvg	CRAWDAD [235]	- Accuracy vs rounds - local learning time
[236]	2020	UAVs	One-layer	- CNN	FedAvg	- MNIST	- Utility of participants
[237]	2020	UAVs	One-layer	- LSTM - GRU - AQNet [238]	FedAvg	- Ground and aerial Sensing Data collected by authors	- Energy consumption
[223]	2020	End-users	Edge-assisted	- CNN	Hierarchical FedAvg	- CIFAR-10 - MNIST	- Accuracy vs epochs - Training time - Energy consumption
[224]	2020	End-users	Edge-assisted	- FCN - LeNet-5	Weighted averaging with Effective Data Coverage (EDC)	- MNIST - Aerofoil [239]	- Accuracy vs rounds - Training time - Energy consumption
[225]	2021	Mobile devices	Edge-assisted	- CNN	FedAvg	- EMNIST [240] - CINIC-10 [241] - CIFAR-10	- Accuracy vs rounds - Accuracy vs epochs - Storage requirement
[226]	2021	End-users	Edge-assisted	- FCN - CNN	FedAvg	- MNIST - Fashion-MNIST - CIFAR-10	- Accuracy vs rounds - Accuracy vs edge distance distribution - Speed

V.D. Lessons learned

Despite the prompt development of diverse DL techniques in different areas, they still impose a major challenge, which is: How can we efficiently leverage the massive amount of data generated from pervasive IoT devices for training DL models if these data cannot be shared/transferred to a centralized server?

- FL has emerged as a promising privacy-preserving collaborative learning scheme to tackle this issue by enabling multiple collaborators to jointly train their deep learning models, using their local-acquired data, without the need of revealing their data to a centralized server [221]. However, a major dilemma in FL is the large communication overhead associated with transferring the models' updates. Typically, by following the main steps

of FL protocol, every node or collaborator has to send a full model update in every communication round. Such update follows the same size of the trained model, which can be in the range of gigabytes for densely-connected DL models [242]. Given that large number of communication rounds may be needed to reach the FL convergence on big datasets, the overall communication cost of FL can become unproductive or even unfeasible. Thus, minimizing the communication overheads associated with the FL process is still an open research area.

- We also remark that despite the considerable presented studies that have provided significant insights about different FL scenarios and user selection schemes from the theoretical perspective, optimizing the performance and

wireless resources usage for edge-assisted FL is still missing. Most of the existing schemes for FL suffer from slow convergence. Also, considering FL schemes in highly dynamic networks, such as vehicular networks, or resource-constraint environments, such as healthcare systems, is still challenging.

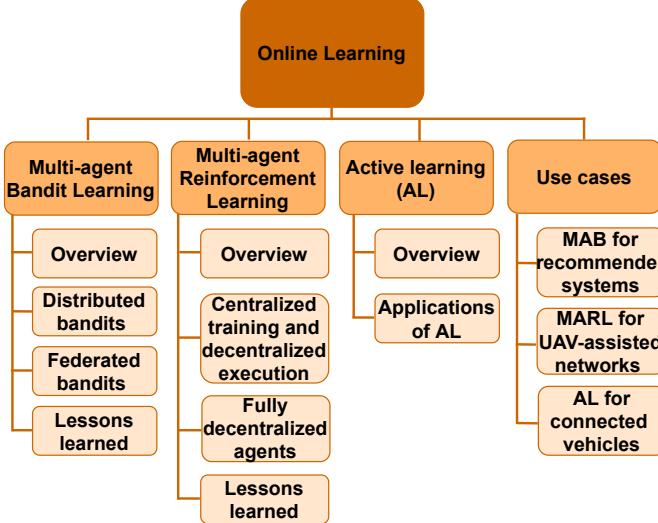


Fig. 25: Outline of online learning.

VI. ONLINE LEARNING

In this section, we discuss three prominent online learning formulations: Multi-agent Reinforcement Learning (MARL), Multi-agent Bandit (MAB) problem, and Active Learning (AL). The "Multi-agent" prefix indicates the existence of multiple collaborative agents² that are aiming to optimize a specific criterion through learning from past experience (i.e., past interactions). We note that MARL and bandits were originally proposed to model a single agent interacting with the environment and aiming to maximize its reward. However, in pervasive systems, where there are numerous but resource-limited agents (i.e., devices), collaboration becomes essential to leverage the potential of the collective experience of these devices. Motivated by the prevalence of collaboration in pervasive systems, we review in this section distributed MAB and MARL algorithms from a resource utilization perspective. We also highlight that AL can be performed both as an offline and online learning, although the latter is considered as the edge of the AL technique. Thus, in this paper, we focus on the online execution of AL, where the trained dataset is updated progressively in real-time.

As has been the case throughout the paper, we are interested in the performance/resource-management trade-offs. Specifically, we propose a taxonomy based on the obtained performance with specific resource budgets (e.g., communication rounds). Fig. 25 shows the taxonomy of the online learning discussed in this section.

²Note that while competitive settings can also be modeled, the focus of this section is on systems that aim to jointly optimize an objective function with minimum resource utilization (pervasive AI systems). Thus, competitive and zero-sum games will not be deeply surveyed.

VI.A. Multi-agent multi-arm bandit learning

In this section, we first provide technical definitions of the single-agent bandit problem and then explain its multi-agent version.

VI.A.1. Overview

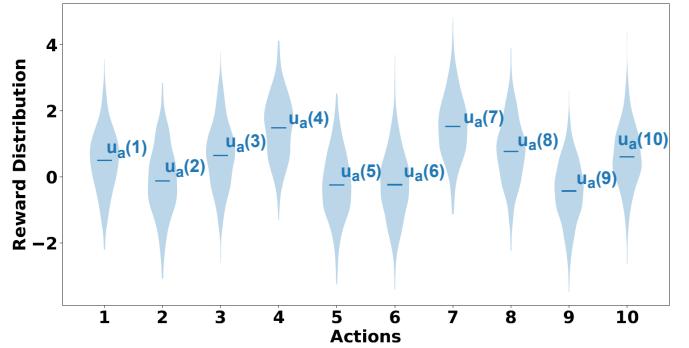


Fig. 26: The basic bandit problem: a set of actions corresponding to different reward distributions.

The Bandit problem, introduced earlier in section III, is given in Algorithm 2, and visually illustrated in Fig. 26. Fundamentally, there exists a set of actions \mathcal{K} (10 actions in the figure), where each action a results in a reward sampled from a distribution \mathcal{D}_a (Gaussians in the example illustrated in Fig. 26).

Algorithm 2 Basic bandit problem

Input: The set of K actions (arms) \mathcal{K} ,

- 1: **for** each round $t \in [T]$:
 - 2: Algorithm picks an action a_t
 - 3: Environment returns a reward $r_t \sim \mathcal{D}_{a_t}$
-

The problem instance is fully specified by the time horizon T and mean reward vector (the vector of the expected reward for each action/arm) $\mu = u_a, a \in \mathcal{K}$, where $u_a = \mathbb{E}[\mathcal{D}_a]$. The optimal policy is simply choosing the action whose expected value is the highest, i.e., $a_* = \arg \max_a u_a$. However, as this action is not known a priori (\mathcal{D}_a is not known), it has to be estimated online from samples. Thus, it is inevitable that some sub-optimal actions will be picked, while building certainty on the optimal one. A reasonable performance measure is the *Regret*, which is defined as the difference between the optimal policy's cumulative rewards, and the cumulative rewards achieved by a solution algorithm

$$R_T = \underbrace{u_* \times T}_{\text{Optimal policy's cumulative rewards}} - \underbrace{\sum_{t=1}^T u_{a_t}}_{\text{An algorithm's cumulative rewards}} \quad (19)$$

In other words, the regret R_T is the sum of *per-step regrets*. A per-step regret at time step t is simply the difference between the best action's expected reward u_* and the expected reward of the action chosen by an algorithm $u_{a,t}$ (i.e., a is selected by the algorithm we are following). Thus, it represents how much

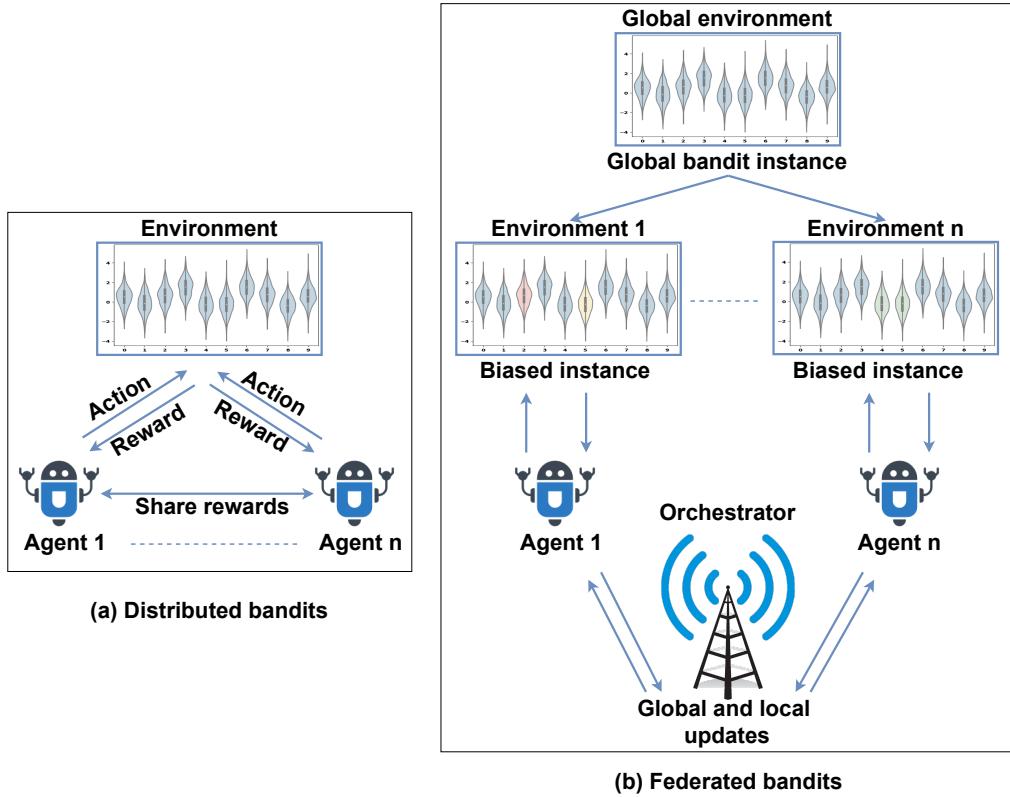


Fig. 27: Multi-agent bandits formulations: (a) Distributed Bandits: each agent collaborates with others to identify the best action in the same environment (b) Federated bandits: each agent collaborates with others to identify the best global action using biased local samples. In this example, the local environments were generated (e.g., sampled) from a global one.

rewards are missed because the best action is not found and has to be estimated from samples. Solution algorithms typically prove sub-linear regret growth (i.e., this difference goes to zero as time progresses. In this way, learning is achieved). The best achievable regret bound for the described bandit problem was proven to be $O(\log T)$ [243].

Several solution algorithms with optimal performance guarantees have been proposed in the literature [243], which fall generally into two categories, explore-then-commit and optimism-based algorithms. Explore-then-commit class, such as successive elimination algorithm, acts in phases and eliminates arms using increasingly sensitive hypothesis tests. On the other hand, the optimism algorithm, such as Upper Confidence Bound (UCB) algorithm, builds confidence for the reward of each action and selects the action with the highest upper bound. The asymptotic performance of both classes is similar. Note that performance guarantees are also classified into instance-dependent bound that depends on the problem information such as the difference between the best and second-best arms, and instance-independent regret (i.e., worst-case regret). These algorithms are recently being extended to model pervasive systems through two main MAB formulations: *distributed* and *federated* bandits, as shown in Fig. 27.

In distributed bandits, agents aim to solve the same bandits instance (i.e., quickly discover the best action), represented by the action set and their generating distributions. Meanwhile, in the federated bandit settings, agents handle different bandits

instances and utilize each others' experiences to solve them. While the terms used to describe the exact problem is sometimes ambiguous in the literature (i.e., distributed, federated, and decentralized were sometimes used interchangeably), in this work, we adopt the recent convention on reserving the term *federated* for the case where each agent faces a different (but related to others) problem instance, while keeping the term *distributed* for the case where the instance is the same but the decision making is distributed across other agents.

VI.A.2. Distributed Bandits Formulations

In many bandit problem instances, it is appealing to employ more agents to learn collaboratively and concurrently to speed up the learning process. In the distributed bandit problem, there exists a set of agents $[M]$ collaborating to solve the *same* bandit instance (the K arms are the same). These agents communicate according to some networking topologies. In many contexts, the sequential decision-making problem at hand is distributed by nature. For example, we can consider a recommender system deployed over multiple servers in different locations. While every server aims to always recommend the best item, it is intuitive to reuse each other's experiences and cut the time needed to learn individually. Furthermore, since their communication may violate the latency constraints, it is desirable that this collaboration and reuse of experience require minimum communication overhead.

While the classical single-agent bandit algorithm has been

proposed since the 2002, its multi-agent counterpart is much more recent, with new state-of-the-art algorithms being currently proposed. The work in [244] initiated the interest in the communication-regret trade-off. The authors established a non-trivial bound on the regret, given an explicitly stated bound on the number of exchanged messages. However, they focused on the full-information setting assuming that the agents observe the rewards of all actions at each round, and not only the one picked, which is the case in bandit settings. Nonetheless, this work initiated the interest in studying the same trade-off under the bandit settings. The authors of [245] considered the partial feedback (i.e., bandit settings) and presented an optimal trade-off between performance and communication. This work did not consider regret as the performance criterion, but rather assumed the less common “best arm identification” setup, where the goal is to purely explore in order to eventually identify the best arm with high probability after some number of rounds. The authors in [246] studied the regret of distributed bandits with a gossiping-based P2P communication specialized to their setup, where at every step, each agent communicates only with two other agents randomly selected. [247] studied the regret under the assumption that the reward obtained by each agent is observable by all its neighbors. [248] proposed a collaborative UCB algorithm on a graph-network of agents and studied the effect of the communication graph topology on the regret bound. [249] improved this line of work as the approach requires less global information about the communication graph by removing the graph dependent factor multiplying the time horizon in the regret bound.

Other works go beyond merely studying the effect of the network topology on the regret bound and explicitly accounting for the communication resources to use. The authors in [250] deduced an upper bound on the number of needed communicated bits, proving the ability to achieve the regret bound in [249] with a finite number of communication bits. However, the interesting question, particularly from the perspective of pervasive system design, is whether the use of communication resources can also be bounded, i.e., can the order of optimal regret bound be guaranteed with a maximum number of communicated bits / communicated messages ?

The work in [251] established the first logarithmic upper bound on the number of communication rounds needed for an optimal regret bound. The authors considered a complete graph network topology, wherein a set of agents are initialized with a disjoint set of arms. As time progresses, a gossiping protocol is used to spread the best performing arm with agents. The authors showed that, with high probability, all agents will be aware of the best arm while progressively communicating at less (halving) periods. The authors generalized this work with a sequel formulation [252], which relaxes the assumption of a complete graph, and introduces the option for agents to pull information. However, this approach is still using the same gossiping style of communication. According to [253], this dependence on pair-wise gossiping communication results in a sub-optimal instance-independent regret bound. The authors in [254] focused on the regret-communication trade-off in the distributed bandit problem. The networking model utilizes a central node that all agents communicate with. Initially,

agents work independently to eliminate bad arms. Then, they start communicating with the central node at the end of each epoch, where epochs’ duration grows exponentially, leading to a logarithmic bound on the number of needed messages.

The work in [253] presents a state of the art distributed bandit learning algorithm. The authors proposed algorithms for both fully connected and partially connected graphs (i.e., assuming that every agent can broadcast to everyone and assuming that agents can communicate with a subset of the others). Similar to elimination-based algorithms, the proposed algorithm proceeds with epochs of doubling lengths, only communicating at the end of an epoch, thus guaranteeing a logarithmic need for communication resources. The communicated messages are only the ID of the action played most often. Furthermore, the regret is proved to be optimal even in instance independent problems, for reasonable values of the time horizon (i.e., $\log(T) > 2^{14}$). During each epoch, agents maintain a set of arms that are recommended by other agents at the end of previous epochs and implement a UCB algorithm among these.

VI.A.3. Federated Bandits Formulation

The federated bandit formulation, shown in Fig. 27 (b), is a recently emerging framework akin to the federated learning framework discussed earlier. In this formulation, there exists a set of agents, each one is facing a *different* instance of the bandit (but the instances are related to each other). This is different from the distributed bandit formulation discussed in the previous sub-section, where a set of agents collaborate to solve the *same* instance of the multi-arms bandits. Recall that a bandit instance is determined by the mean vector μ . Thus, in the federated bandit settings, the local bandit instance is a *noisy* and potentially *biased* observation of the mean vector. In addition, the collaboration is necessary, as even perfect local learning algorithms might not perform adequately due to their biased observations.

The setting of federated bandits is first proposed by [255] (although not under the same term). The authors proposed an algorithm, where agents agree on the best global arm, and they all play it at the beginning of each round. In this way, communication is needed at the beginning of each round. Recently, [256] studied this federated setting, where the global arm mean vector is the average of the local ones. Although the authors did not propose a bound on the number of messages needed to be exchanged, the communication model considered a partially connected graph, where each agent communicates only with neighbors but with focus on constrained communication resources. The algorithm contains two main steps: First, each agent shares a set of local information with other neighbors (the number of times an arm was sampled and its sampled mean) . Second, a gossip update is performed, where each agent incorporates information received from neighbors in updating its estimate of each arm’s mean.

[258] presented a more general formulation, where the global mean vector is not necessarily the average of the local ones. Instead, the local means are themselves *samples* from a distribution whose mean is unknown. The local observation for each agent is, in turn, samples from the local distributions.

TABLE X: Multi-agent stochastic bandit learning literature.

Refs	Problem Formulation	Communication Model	Communication Guarantee	Regret Guarantee	Method
P2P- ϵ -Greedy [246]	DB	Two Neighbors on a graph	$O(T)$	$O(T)$	Gossiping arms estimates.
coop-UCB2 [248]	DB	Neighbors on a graph	$O(T)$	$O(\log T)$	A running Consensus on the estimates of arms total rewards.
UCB-Network [247]	DB	Multiple (Graph and centralized)	$O(T)$	$O(\log T)$	Identifying and utilizing dominating sets in the network.
DDUCB [249]	DB	Neighbors on a graph	$O(T)$	$O(\log T)$ (with improved constants)	A running Consensus on the estimates of arms total rewards.
[251]	DB	Single neighbors on a complete graph	$O(\text{constant})$	$O(\log T)$	Gossiping among different local Poisson clocks.
GosInE [252]	DB	Neighbors on a complete graph	$\Omega(T)$	$O(\log T) + C_G$	Gossiping and information pulling.
DPE2 [250]	DB	Neighbors on a graph	$O(\text{constant})$	$O(\log T)$	Leader-election to handle exploration (exploration is centralized).
DEMAB [254]	DB	Centralized coordinator	$O(\log T)$	$O(\log T)$	Utilizing public randomness to divide arms among clients.
LCC-UCB [253]	DB	Multiple (Graph and centralized)	$O(\log T)$	$O(\log T)$	communicating after doubling-epochs with maintaining fixed.
[255]	FB	Neighbors on a graph	$O(\log T)$	$O(\log T + C_G)$	Selecting the best arm according to voting.
GossipUCB [256]	FB	Neighbors on a graph	$O(T)$	$O(\max\{\log T, \log_{C_G} N\})$	Maintaining local belief that is updated through gossiping.
[257]	FB	Centralized coordinator	$O(\log T)$	$O(\log T)$	Aggregating estimates through the controller until a fixed point of time.
[258]	FB	Centralized coordinator	$O(\log T)$	$O(\log T)$	Mixed target learning objective based on local and global objectives.
[259]	FB	Neighbors on a graph	$O(T)$	$O(\log T)$	Agent uses estimates of their neighbors weighted by a similarity metric.

The communication model is similar to supervised federated learning, where agents communicate periodically with an orchestrator that updates the estimates of arms payoffs and instructs the agents on which arms to keep and which to eliminate. Although the communication is periodic, the total number of communication rounds is bounded (logarithmic with respect to the horizon T). This is because the number of agents incorporated in the learning process decays exponentially with time. Such an approach works since the average of clients' local means concentrates exponentially fast around that global mean (a known result from probability concentration analyses).

A setting that is slightly different from the federated bandits was studied in [259]. The difference is that although agents have similar yet not identical local models, the reward for each agent is actually sampled from its local distribution. Thus, each agent of them is trying to identify the best arm in its local instance through using information from other ones on arms that are similar. This is in contrast with other works presented here where the agents' rewards are sampled from a *global* distribution that they are collaboratively trying to estimate from biased local observations.

Table X summarizes the works in MAB problems. It lists the problem formulation: distributed Bandits (DB) or federated Bandits (FB), the communication model (i.e., the network topology), the communication guarantee (i.e., number of messages needed to achieve the performance), the regret guarantee (i.e., the growth of the regret with respect to the time horizon), and the method (i.e., the main principle behind the algorithms). C_G denotes a constant related to the communication graph or gossiping matrix.

VI.A.4. Lessons Learned

- Communication-cognizant Multi-agent Bandit formulations: Online-learning systems need to account for the communication resources. Thus, recent works do not only analyze regret but explicitly reason about the necessary communication resources. This is manifested through two main observations. First, the derived regret guarantees are always affected by the networking topology (e.g., parameters representing the connectivity of a communication graph, number of involved agents, or number of exchanged messages). Second, accompanied by every regret guarantee, an upper bound on communication resource usage is also provided (e.g., the maximum number of exchanged messages or exchanged bits).
- Towards the federation of the bandit framework: When the bandit instances faced by each agent are local biased instances, the federated bandits framework arises. In such situation, agents need to learn with the help of a logically centralized controller, similar to supervised federated learning, in order to estimate the true global instance and the true best action [258]. However, if agents are not interested in solving a hidden global instance but rather only their own, they may reuse their peers' experience and an instance-similarity metric to help them solve their own instances [259].

VI.B. Multi-agent reinforcement learning

This section presents an overview of Multi-agent Reinforcement Learning (MARL) from a pervasive system perspective. We specifically focus on the *communication-performance* trade-off and classify previous works according to their approach to handle this trade-off. We note that our perspective

is different from previous surveys (i.g., [260], [261]), which studied the technical merits and demerits of the learning algorithms. Instead, we are interested in the *systems* aspects of the considered works. That is, what are the communication topology and protocol used between agents and how do these choices affect the performance (rewards obtained by all agents).

VI.B.1. Overview

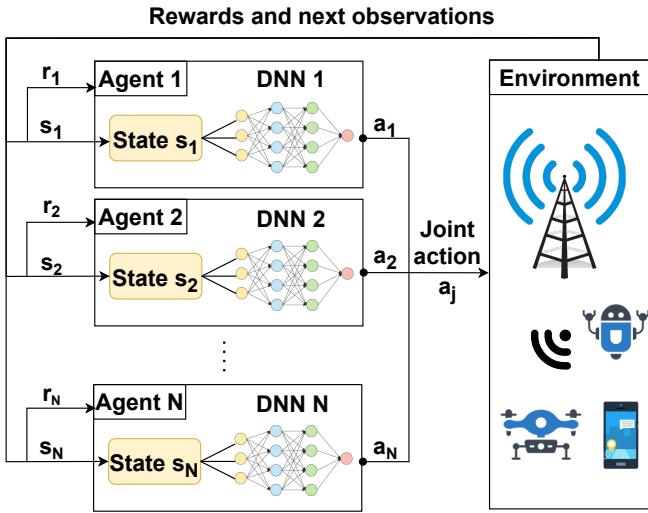


Fig. 28: MARL Framework: multiple autonomous agents act on an environment and observe (parts) of its state, and a, potentially different, reward signal.

Unlike MAB formulations, in reinforcement learning, we have a *state space*, which is a set of all possible states (i.e., configuration) the environment might be in, along with a *transition operator* which describes the distribution over the next states given the current state and performed actions. Therefore, agents need to not only detect the best actions, which maximize the reward (bandits objective) but also to account for the possible next state, as it might be arbitrarily bad/good regardless of the current one. Hence, in MARL, the collaborative agents aim to maximize the current and *future* expected sum of rewards.

MARL problems, visualized in Fig. 28, are often modeled as a Partially Observable Markov Game (POMG) [262], which is a multi-agent extension for Partially Observable Markov Decision Process (POMDP). POMGs are represented by the tuple $(\mathcal{N}, \mathcal{S}, \mathcal{A}, \mathcal{O}, \mathcal{T}, \mathcal{R}, \gamma)$, where:

- \mathcal{N} is the set of all agents.
- $s_t \in \mathcal{S}$ is a possible configuration of all the agents at time t .
- $a_t \in \mathcal{A}$ is a possible action vector for the agents, where $\mathcal{A} = \mathcal{A}_1 \times \mathcal{A}_2 \times \dots \times \mathcal{A}_N$.
- $o_t \in \mathcal{O}$ is a possible observation of the agents, where $\mathcal{O} = \mathcal{O}_1 \times \mathcal{O}_2 \times \dots \times \mathcal{O}_N$.
- $\mathcal{T} : \mathcal{O} \times \mathcal{A} \mapsto \mathcal{O}$ is the state transition probability.
- \mathcal{R} is the set of rewards for all the agents $r_i : \mathcal{O} \times \mathcal{A} \mapsto \mathbb{R}$.
- γ is the reward discount factor.

Each agent aims to find a policy π_n that maximizes its own reward. In cooperative scenarios, the policy aims at maximizing the total reward. If the rewards are not the same for all agents, the framework is referred as mixed Decentralized-POMDP. When the rewards are similar for all agents (i.e., $r_n = r \quad \forall n \in \mathcal{N}$), the POMG is collaborative. In the following, we discuss algorithms that might work on one or both settings. The main focus will be, on the communication aspects (i.e., topology and cost) of MARL algorithms.

There exist results on the hardness of solving the POMG under several settings. We can cite the case of a tabular representation of the spaces and the cases where function approximation is used (linear or nonlinear). The main solution approaches are policy gradient, value-based methods [263]. Policy gradient methods parametrize agents' policies within a class and utilize gradient descent to optimize an objective function (i.e., reward obtained by the policy). Value-based methods aim to generalize the famous Q-learning algorithm to the multi-agent settings, either through making each agent learn its own Q-function and treating others as a part of a non-stationary environment , or through learning a global Q-function.

The optimization in policy gradient methods is done on the objective function: $J(\theta \doteq v_{\pi_\theta}(s_0))$, which is the cost of starting from the initial state s_0 , and following the parametrized policy π_θ thereafter. The gradient of this function can be written as:

$$(G_t - b(S_t)) \frac{\nabla \pi(A_t | S_t, \theta_t)}{\pi(A_t | S_t, \theta_t)}. \quad (20)$$

As shown in the policy gradient algorithm [263], b is any function of the state, referred to as the baseline. If it is the zero function, the resulting equation represents the “reinforce” algorithm. Another popular option is the value function of the state. If this state value function is updated through bootstrapping, the resulting method is called Actor-critic. Thus, Actor-critic methods are policy gradients that use the state value function as a baseline ($b(s) = V(s)$) and update this function through bootstrapping. Readers may refer to [264] for more details and comparison between these approaches. As will be clarified next, each work tunes different parts of these main solution approaches according to the application.

VI.B.2. Centralized training and Decentralized Execution (CTDE)

The Centralized Training and Decentralized Execution (CTDE) approach is originally proposed in [265]. This approach leverages the assumption that, in most application scenarios, the initial training is done on centralized simulators, where agents can communicate with each other with no communication cost. This phase is denoted as centralized training. Then, at deployment, agents are assumed not to communicate at all, or conduct limited communication with each other, and they rely on their “experience” at the training phase to actually execute their collaborative policies.

a) *Communication only at training*: The advantage of such an approach is that it does not require communication between agents upon deployment and thus incurs no communication cost. However, this comes at the cost of losing adaptability,

which is the major motivation behind online learning. Such loss might occur in case of a major shift in the environment model between the training and deployment, where the learned coordinated policies are no longer performant, and new coordination is needed. The main workaround is to monitor the agents' performance and re-initiating the centralized training phase to learn new coordinated policies whenever needed.

This approach has been popularized by recent methods such as VDN [266], QMIX [267], and QTRAN [268]. These works adopt *value function factorization* technique, where factorizations of the global value function in terms of individual (i.e., depending only on local observations) value function are learned during centralized training. Then, the global function (i.e., neural network) can be discarded at execution time, and each individual agent utilizes only the local function. When each agent acts greedily according to its local network, the global optimality can still be guaranteed since, at the training phase, these local networks were trained according to gradient signals with respect to the global reward.

Another approach to solving POMG is actor-critic. The CTDE version of actor-critic approaches is represented by learning a centralized critic, which evaluates the global action, and decentralized policy network, which outputs an action based only on local observation. During training, the actor-critic networks are jointly learned, and hence the global critic "guides" the training of the actors. Then, at execution, the global critic may be discarded, and only actors can be used. The works in [269] present a deep deterministic policy gradient method that follows the described approach, where each agent learns a centralized critic and decentralized actor. Similarly, [270] follows the same approach, but all agents learn the same critic. Multiple other variations are done on the same DDPG algorithm aiming to either enhance performance [271] through incorporating an attention-mechanism, or limit the use of communication resources (limited budget on the number of messages used, or a message is (a part of) an agent's state). [272].

b) Learned communication: An important line of work within the MARL community is the study of learned communication between agents. In these settings, agents are allowed to send arbitrary bits through a communication channel to their peers in order to convey useful information for collaboration. These agents need to learn *what* to send, and *how* to interpret the received messages so that they inform each other of action selection. Thus, the agents are effectively learning communication protocols, which is a difficult task [281].

While the learned communication can be trained centrally and executed in a decentralized fashion, agents can still communicate at the execution phase through a limited bandwidth channel. Hence, we distinguish this setting from the works discussed in the previous subsection. Yet, similar approaches can be followed. For example, discarding the critic in execution (sometime used interchangeably with the term CTDE) but still maintaining the learned communication [276] and parameter sharing and gradient pushing in [281], where in execution, these messages are discretized.

The authors in [282] aimed to learn to schedule communication between agents in a wireless environment and

focused only on collision avoidance mechanism in the wireless environment. In [273], information theoretic approach was used to compress the content of the message. In addition, source and destination are also learned through a scheduler. On the other hand, a popular line of work concentrated on designing so-called *gating mechanism* techniques in order to accomplish the efficiency of the learned communication protocols. In this line of work, agents train a gating network, which generates a binary action to specify whether the agent should communicate with others or not at a given time step, limiting the number of communicated bits/messages needed to realize a certain desirable behavior. [274] investigates the adaptability of these communication protocols and demonstrates the importance of communicating only with selected groups. Specifically, agents cannot distinguish messages that are particularly important to them (i.e., have implications on their actions) from the messages of all other agents. Thus, they introduce an attention scheme within each agent where an attention unit receives encoded local observation and action intention of the agent to decide whether a communication with others in its observable field is needed. The communication group dynamically changes and persists only when necessary.

The authors in [275] looked at *communication at scale* and proposed an Individualized Controlled Continuous Communication Model (IC3Net), where agents are trained according to their own rewards (hence the approach can work for competitive scenarios also). Then, they demonstrated that their designed gating mechanism allows agents to block their communication, which is useful in competitive scenarios and reduces communication in cooperative scenarios by opting out from sending unnecessary messages. However, the effect of the gate on communication efficiency was not thoroughly studied, and the focus was instead on the emerging behavior. The work in [276] presents the state-of-the-art on efficient learned communication. The authors introduced Actor-Critic Message Learner (ACML), wherein the gate adaptively prunes less beneficial messages. To quantify the benefit of an action, Gated-ACML adopts a global Q-value difference as well as a specially designed threshold. Then, it applies the gating value to prune the messages, which do not hold value. The authors showed that surprisingly, not only the communication-efficiency significantly increases, but in specific scenarios, even the performance improves as a result of well-tuned communication. The reason behind this is that, since the communication protocol is learned, it is probable to hold redundant information that agents do not decode successfully. The proposed gating mechanism can also be integrated with several other learned communication methods.

VI.B.3. Fully Decentralized Agents

In fully decentralized reinforcement learning, there is no distinction between training and testing environments. Thus, the communication model stays the same throughout the agents' interaction with the environment. Under these settings, we recognize two extreme cases. First, agents do not communicate with each other, and learn to coordinate solely through the obtained rewards. In the case of no communication, the major challenge faced by the agents is the non-stationarity

TABLE XI: Communication-Cognizant Multi-Agent Reinforcement Learning literature.

Refs	Framework	Learning algorithm	Communication scheme	Communication decision
VDN [266], QMIX [267], QTRAN [268]	CTDE	Value-based	NA	Always during training, None at execution.
MADDPG [269], COMA [270]	CTDE	Actor-critic-based	NA	Always during training, None at execution.
[273] IMAC	CTDE with learned comm.	Policy gradient	Learned source and destination	At every step (limited size)
[274] ATOC	CTDE with learned comm.	Actor-critic based	Gated communication with neighbors	When network topology changes.
[275] IC3Net	CTDE with learned comm.	Policy gradient	Gated communication with neighbors	Communicate when necessary, possibly many messages per round.
[276] ACML	CTDE with learned comm.	Actor-critic based	Gated communication with neighbors	Communicate when necessary, respecting a limited bandwidth.
[277]	Fully decentralized	Value-based	Indirect	No message passing.
[278]	Fully decentralized	actor-critic-based	With neighbors	At every step.
[279]	Fully decentralized	actor-critic-based	With neighbors	At every step (limited size).
[280]	Fully decentralized	Policy gradient	Broadcast to all through central controller	At every step.

of the environment. A non-stationary environment from the perspective of the agents is when the distribution of the next states varies for the same current state and action pairs. The fully decentralized DRL was recently popularized by [277]. In [277], the authors proposed a 3-dimensional reply buffer whose axes are the episode index, timestep index, and agent index. It was illustrated that conditioning on data from that buffer helps agents the perceived non-stationarity of the environment.

On the other extreme, agents can be modeled to be able to communicate at every step. Specifically, the problem of graph networked agents is investigated in [278]. In this paper, agents are connected via a time-varying and possibly sparse communication graph. The policy of each agent takes actions that are based on the local observation and the neighbors' messages to maximize the globally averaged return. The authors fully decentralized actor-critic algorithms and provided convergence guarantees when the value functions are approximated by linear functions. However, a possible disadvantage of this algorithm is that the full parameter vector of the value function is required to be transmitted at each step. This has been addressed in [279], where also graph-networked agents are assumed, but each agent broadcasts only one (scaled) entry of its estimate of parameters. This significantly reduces communication cost (given that it occurs at every iteration). The paper also does not assume a bidirectional communication matrix and deals with only unidirectional ones, which is a more general formulation that appeals to more applications. The decentralized actor-critic-based algorithm also solves the distributed reinforcement learning problem for strongly connected graphs with linear value function approximation.

[280] considered the communication efficiency in fully decentralized agents, but with the assumption of a centralized controller. The paper utilizes policy gradient solution methods, where the controller aggregates the gradients of the agents to update the policy parameters. This process is akin to federated learning clients selection. The authors propose a process to determine which clients should communicate to the controller based on the amount of progress in their local optimization. They also propose a methodology to quantify

the importance of local gradient (i.e., the local optimization progress) and then only involve agents who are above a certain threshold. Following this approach, the authors showed that the performance (i.e., cumulative reward) is similar to the case where all clients are participating, with considerable communication round savings.

Table XI summarises the works discussed above according to their communication model and the approach in handling the communication-performance tradeoff. We first identify the framework CTDE, CTDE with learned communication, or fully decentralized) as well as the learning algorithm (value, policy gradient, or actor-critic). Then, we list two important columns. First, the communication scheme, which states *how* agents communicate with each other. In CTDE, the training is done in simulation. Thus, agents are logically centralized and do not communicate. If no messages are passed between agents and their collaboration is solely learned through rewards, then the communication scheme is *indirect*. Otherwise, it is either (*gated*) with neighbors directly or through a *central controller*. Lastly, the communication decision columns state *when* the communication is made, which can be at every step (with optimized message size or not), or according to other conditions as detailed in the discussion.

VI.B.4. Lessons Learned

- *CTDE-a practical middle ground:* CTDE algorithm leverages the fact that training is often done in simulators, where there is no communication cost, and agents may share experience tuples, network parameters, and observations freely, in order to train policies that can be executed later on, based on only local observations. This approach seems to model most of the pervasive systems applications where agents do not need to start training while being decentralized. In this framework, the actor-critic-based algorithms are more popular, where a centralized critic network that uses the observations of all agents guides the training of a decentralized policy network that uses only the local observations. The critic network can be discarded at execution time, enabling decentralized execution. The framework is emerging as

a possible alternative to the fully decentralized extremes, which either communicate at every step or do not communicate at all and try to indirectly and independently learn collaborative policies [269], [272].

- *Scheduling for efficient learned communication:* In learned communication, agents learn to encode and decode useful messages. In this area, gating mechanisms are the main tools towards efficient communication [274]–[276]. In gate design, agents learn when to send and refrain from sending a message by quantifying the benefit (i.e., reward) of actions following this communication. More general *schedulers* modules investigate the design of communication module that learn to minimize the content of the messages as well (i.e., compressing the communication messages) [273]. Overall, scheduling mechanisms are being increasingly used in MARL settings with learned communication, in order to face the limited bandwidth problems often encountered in practical scenarios.

VI.C. Active Learning (AL)

As far as online learning schemes have been tackled, AL has emerged as a promising and effective concept. Herein, we first present a brief overview for the concept of AL, then we discuss some recent applications of AL presented in the literature.

VI.C.1. Overview

The main idea behind AL is that an active learner is allowed to actively select over time the most informative data to be added to its training dataset in order to enhance its learning goals [283], [284]. Hence, in AL framework, the training dataset is not static, which means that the training dataset and learning model are progressively updated in order to continuously promote the learning quality [285]. Specifically, the main steps of AL are: (1) acquiring new data from the contiguous nodes; (2) picking out the most informative data to append to the training dataset; (3) retraining the learning model using newly-acquired data. Hence, the communication overheads associated with different AL schemes will depend on:

- 1) Type and amount of exchanged data between the contiguous nodes. We remark here that contiguous nodes can exchange labels, features, or samples. Hence, based on the type and amount of changed data there will be always a tradeoff between enhancing the performance and decreasing communication overheads.
- 2) Number of selecting nodes that will be considered in the AL process.

It is worth mentioning also that FL allows multiple nodes to cooperatively train a global model without sharing their local data, which differs from AL in many ways. In particular, FL seeks for obtaining a synchronization between different cooperative nodes, in addition to the presence of a centralized node (or server) to generate the global model. Thus, AL and FL are addressing orthogonal problems – the former leverages the newly-acquired data from the contiguous nodes to retrain its model, while the latter trains its model in a distributed

manner by sharing the model’s updates with the contiguous nodes [286].

VI.C.2. Applications of AL

Traditionally, AL algorithms depend on the presence of an accurate classifier that generates the ground-truth labels for unlabeled data. However, this assumption becomes hard to maintain in several real-time applications, such as crowdsourcing applications and automated vehicles. Specifically, in crowdsourcing, many sources are typically weak labelers, which may generate noisy data, i.e., data that may be affected by errors due to low resolution and age of information problems. However, most of the existing studies on AL investigate the noisy data (or imperfect labels) effect on the binary classification problems [287], [288], while few works consider the general problem of multi-class or multi-labeled data [289]–[291].

One of the main problems in crowdsourcing is how to collect large amount of labeled data with high quality, given that the labeling can be done by volunteers or non-expert labelers. Hence, the process of acquiring large amount of labeled data turned to be challenging, computationally demanding, resource hungry, and often redundant. Moreover, crowdsourced data with cheap labels comes with its own problems. Despite being labels cheap, it is still expensive to handle the problem of noisy labels. Thus, when data/labelers are not selected carefully, the acquired data may be very noisy [292], [293], due to many reasons such as varying degrees of competence, labelers biases, and disingenuous behavior, which significantly affects the performance of supervised learning. Such challenges have encouraged the researcher to design innovative schemes that can enhance the quality of the acquired data from different labelers. For instance, [289] tackles the problem of demanding deep learning techniques to large datasets by presenting an AL-based solution that leverages multiple freely accessible crowdsourced geographic data to increase datasets’ size. However, in order to effectively deal with the noisy labels extracted from these data and avoid performance degradation, the authors have proposed a customized loss function that integrates multiple datasets by assigning different weights to the acquired data based on the estimated noise. [291] enhances the performance of supervised learning with noisy labels in crowdsourcing systems by introducing a simple quality metric and selecting the ϵ -optimal labeled data samples. The authors investigate the data subset selection problem based on the Probably Approximately Correct (PAC) learning model. Then, they consider the majority voting label integration method and propose two data selection algorithms that optimally select a subset of k samples with high labelling quality. In [290], the authors investigate the problem of imbalanced noisy data, where the acquired labeled data are not uniformly distributed across different classes. The authors therein aim to label training data given received noisy labels from diverse sources. Then, they used their learning model to predict the labels for new unlabeled data, and update their learning model until some conditions are met (e.g., the performance of the learned model meets a predefined requirement, or it cannot be improved any more). Specifically, for labeled data, they

implement a label integration and data selection scheme that considers data uncertainty and class imbalance level, while classifying the unlabeled data using the trained model before adding them to the training dataset. Hence, the proposed framework presents two core procedures: label integration and sample selection. In the label integration procedure, a Positive LAbel Threshold (PLAT) algorithm is used to infer the correct label from the received noisy labels of each sample in the training set. After that, three sample selection schemes are proposed to enhance the learning performance. These schemes are respectively based on the uncertainty derived from the received-noisy labels, the uncertainty derived from the learned model, and the combination method.

A different application of AL is investigated in [285], where AL is exploited for incremental face identification. Conventional incremental face recognition approaches, such as incremental subspace approaches, have limited performance on complex and large-scale environment. Typically, the performance may drastically drop when the training data of face images is either noisy or insufficient. Moreover, most of existing incremental methods suffer from noisy data or outliers when updating the learning model. Hence, the authors in [285] present an active self-paced learning framework, which combines: active learning and Self-Paced Learning (SPL). The latter refers to a recently developed learning approach that mimics the learning process of humans by gradually adding to the training set the easy to more complex data, where easy data being those with high classification confidence. In particular, this study aims to solve the incremental face identification problem by building a classifier that progressively selects and labels the most informative samples in an active self-paced way, then adds them to the training set.

AL has been also considered in various applications of intelligent transportation systems. For instance, the authors in [294] investigate the vehicle type recognition problem, in which labeling a sufficient amount of data in surveillance images is very time consuming. To tackle this problem, this work leveraged fully labeled web data to decrease the required labeling time of surveillance images using deep transfer learning. Then, the unlabeled images with high uncertainty are selected to be queried in order to be added later to the training set. Indeed, the cross-domain similarity metric is linearly combined with the entropy in the objective function of the query criteria to actively select the best samples. Ultimately, we highlight that most of the presented studies so far consider in their AL framework specific classifiers (or learning models), which cannot be easily used in other learning models [295]. Accordingly, obtaining an optimal label integration and data selection strategy that can be used with a generic multi-class classification techniques is still worth further investigation.

VI.D. Use Cases

VI.D.1. MAB for recommender systems

Online learning systems are fundamental tools in recommender systems, which are, in turn, a cornerstone in the development of current intelligent user applications, from social media application feeds to content caching across net-

works. Due to the recent growth in data generation, local geo-distributed servers are often used to support applications that utilize recommender systems. Furthermore, privacy concerns sometimes limit the ability of these local servers to share data with other servers. In [258], the authors motivate the use of federated bandits by explaining how they can model such a critical use case. In the discussed example, a set of servers run a recommender system for their prospective clients. The goal of each one is to recommend the most popular content across all servers. However, due to latency constraints, communication at every decision-making step is infeasible. Besides, sharing individual samples of rewards violates privacy, as all servers will learn about a particular user's choice and preference. Due to these reasons, the authors proposed and utilized a federated bandits algorithm (Fed-UCB) which only communicates $\log T$ times in a T horizon to minimize recommendation latency. At each round, only the sample *means* are communicated, preserving a certain level of privacy (additional improvements are also discussed). Finally, the performance of the system is shown to be near-optimal; thus, achieving the goal of recommending the best item across all servers while meeting the privacy and communication constraints.

VI.D.2. MARL for UAV-assisted networks

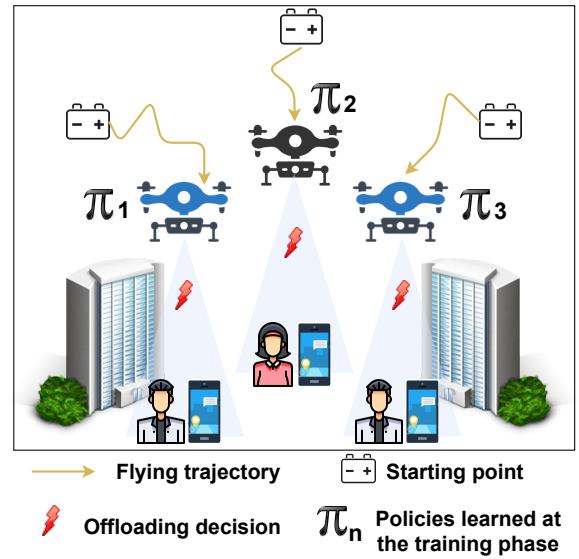


Fig. 29: UAV-assisted networks: UAV agents are trained to deduce a collaborative policies for providing compute/communication resources for on ground equipment.

UAVs have provided new potentials for extending communication coverage and even compute capabilities of devices in areas where full networking infrastructure is not present. This is done through wireless communication between UAV and on-ground equipment, enabling those equipment to extend their connectivity and potentially offload tasks to a broader network relayed by the UAV. The work in [296] aims at utilizing UAVs to provide intermittent compute/communication resource support for user equipments (UEs) on the ground. The benefits of such UAV-assisted scenarios are numerous, including creating

dynamic networking graphs without the need for full networking infrastructure, which can be of extreme value in catastrophes response for example. Nonetheless, the UAVs need to optimize their trajectory paths so that they cover the widest areas with minimum movement (i.e., energy consumption) and maximum utility (i.e., providing the resources to the UE that needs it the most). However, such optimization is shown to be intractable. Thus, the authors opted for learning-assisted (i.e., data-driven) methods. Since a centralized training was possible in their tackled scenario is available, they used a CTDE algorithm, specifically Multi-Agent DDPG (MADDPG). In MADDPG, agents aim to jointly optimize the UE-load of each UAV while minimizing the overall energy consumption experienced by UEs, that depends on the UAV's trajectory and offloading decisions. Following the MADDPG algorithm, the UAVs observations were *communicated* among them to deduce the collaborative policy at training. At execution, no message sharing was needed. This resulted in a satisfactory performance due to the accurate simulator. However, as discussed earlier, environments that are expected to change might necessitates the use of other algorithms that maintain periodic, learned, or persistent communication after deployment.

We note that the application of reinforcement learning in resource-constrained environments (e.g., IoT devices), requiring the design of communication-aware techniques, is still scarce. Most testing for these methods is done on artificial testing environments like Open AI's Particle environments [297], or video games like StarCraft II [298], which is a typical practice in the RL community since success in these environments is often indicative of broader applicability.

VI.D.3. AL for Connected Vehicles

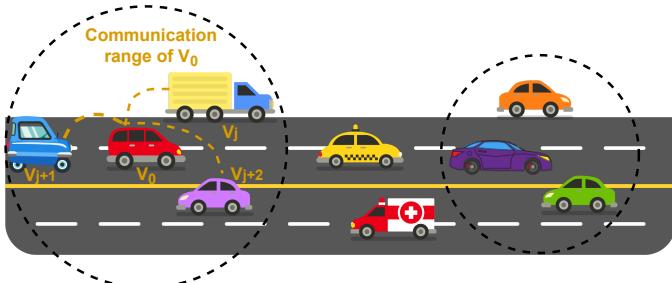


Fig. 30: AL for time-varying vehicular network.

Traditional machine learning models require massive, accurately labeled datasets for training in order to ensure high classification accuracy for new data as it arrives [299]. This assumption cannot be guaranteed in many real-time applications, such as connected and autonomous vehicles. Indeed, vehicles are typically weak labelers (i.e., data sources that generates label with low classification confidence). Hence, they may acquire/generate noisy data, e.g., data generated by cameras in the presence of fog or rain. Also, in a highly dynamic environment like vehicular network, not only the generated data by the vehicles' classifiers can have low classification accuracy, but also the data received from neighboring vehicles may be prone to noise and communication errors. Hence, the

authors in [300] have tackled these challenges by proposing a cooperative AL framework for connected vehicles. The main goal of this work is two-fold: (1) selecting the optimal set of labelers, those considered to be the most reliable ones; as well as (2) selecting a maximally diverse subset of high quality data that are locally-generated and/or received from neighboring vehicles to be used for updating the learning model at each vehicle.

In [300], the time-varying vehicular network shown in Figure 30 is considered. It is assumed that each vehicle can communicate and exchange information only with the neighboring vehicles that are located within its communication range. For instance, the set $\mathcal{N}_{v_0}(t) = \{v_j, v_{j+1}, v_{j+2}\}$ at time t means that there are only three vehicles staying in the communication range of vehicle v_0 . Furthermore, this framework considers two types of data: multiple-labeled online dataset and offline/historical labeled dataset. The online dataset is considered as sequences of samples that arrive from neighboring vehicles or generated at vehicle v_0 within time T (i.e., refers to the period of time during which a vehicle v_0 is exposed to a certain road view). At time T , vehicle v_0 receives a sequence of training samples/labels that contains input features and associates with multiple noisy labels generated from the vehicles sending data to v_0 . The presented framework in [300] includes five main stages, as described below:

- 1) **Offline Learning:** Initially, each vehicle with its own offline/historical training data generates an initial learning model with a certain accuracy level.
- 2) **Online labeling:** The vehicle starts to collect new information through its local sensors or from neighboring vehicles. These information can be labels, features, or samples, depending on the adopted operational mode.
- 3) **Label integration:** After acquiring the new information, each vehicle obtains an aggregated label for the received data using different proposed label integration strategies.
- 4) **Labeler selection:** After monitoring the behavior of the neighboring vehicles, each vehicle selects a subset of high-quality labelers, based on their reputation values that are estimated from the past interactions using subjective logic model.
- 5) **Data selection and models update:** Finally, each vehicle selects the maximally diverse collection of high-quality samples to update its learning model.

The proposed AL framework in [300] depicts its efficiency for connected automated vehicles, as follows: (1) it allows for increasing the amount of acquired data at different vehicles during the training phase; (2) it accounts for the labelers' accuracy, data freshness, and data diversity while selecting the optimal subset of labelers and data to be included in the training set; (3) Using different real-world datasets, it could provide 5 – 10% increase in the classification accuracy compared to the state-of-the-art approaches that consider random data selection, while enhancing the classification accuracy by 6% compared to random labelers selection approaches.

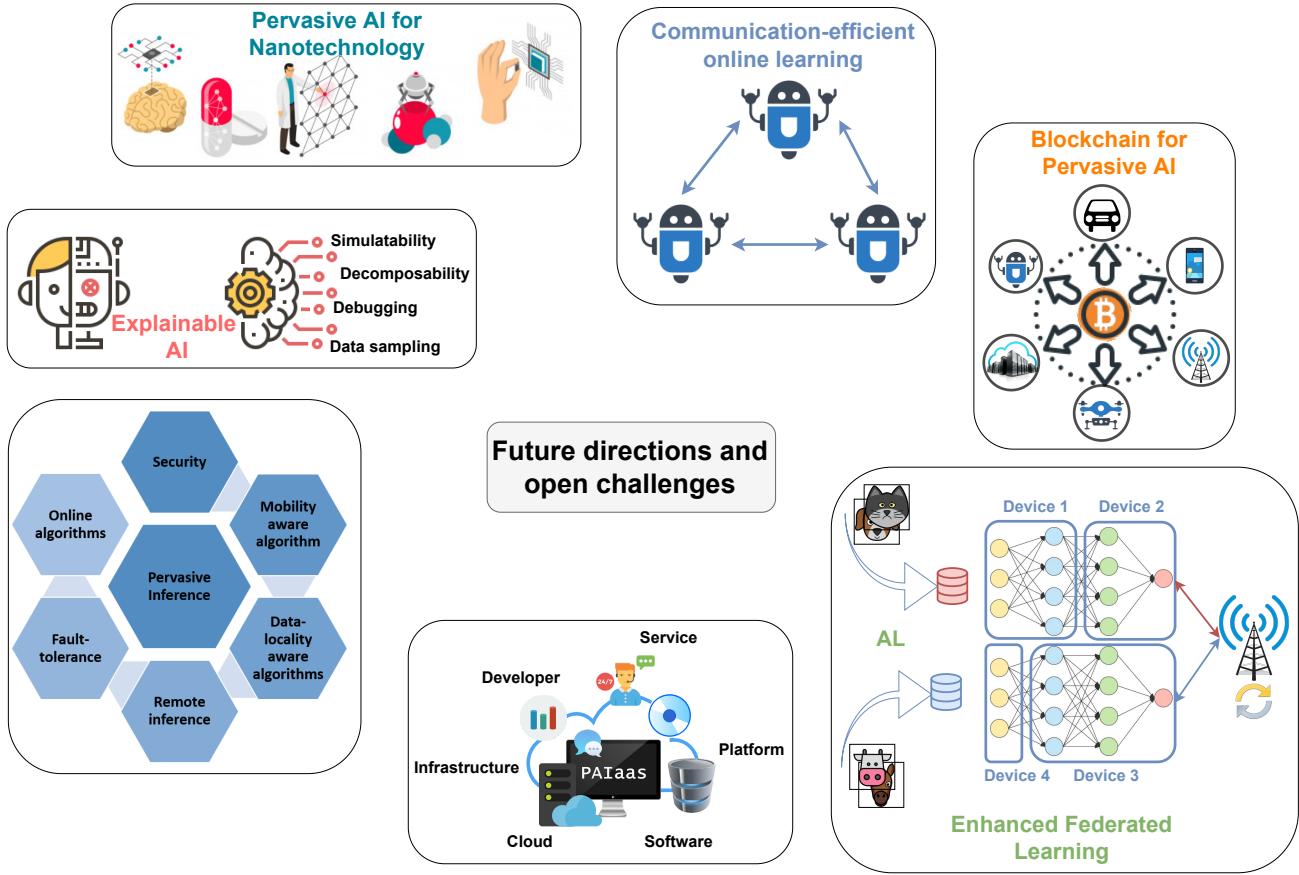


Fig. 31: Future directions and open challenges.

VII. FUTURE DIRECTIONS AND OPEN CHALLENGES

In this section, we present a list of open challenges and issues facing the pervasive AI systems, and we propose some promising ideas to mitigate these issues. Specifically, we introduce the opportunities to integrate the pervasive AI in emerging systems, and we suggest some future directions for efficient distributed inference and enhanced federated learning algorithms. Finally, we present some innovative ideas related to the new concepts of online learning. Fig. 31 presents a brief of the proposed directions.

VII.A. Deployment of Pervasive AI in emerging systems

VII.A.1. Pervasive AI-as-a-service

While the 5G main goal is to provide high speed mobile services, the 6G pledges to establish next-generation softwarization and improve the network configurability in order to support pervasive AI services deployed on ubiquitous devices. However, the research on 6G is still in its infancy, and only the first steps are taken to conceptualize its design, study its implementation, and plan for use cases. Toward this end, academia and industry communities should pass from theoretical studies of AI distribution to real-world deployment and standardization, aiming at instating the concept of Pervasive AI-as-a-service (PAIaaS). PAIaaS allows the service operators and AI developers to be more domain-specific and focus on enhancing users' quality of experience, instead of worrying

about tasks distribution. Moreover, it permits to systemize the mass-production and unify the interfaces to access the joint software that gathers all participants and applications.

VII.A.2. Incentive and trusty mechanism for distributed AI using blockchain

The distribution of heavy and deep neural networks on ubiquitous and resource-limited devices contributes to minimizing the latency of the AI task and guarantees the security of the data. However, even though pervasive systems are composed of computing units existing everywhere, anytime, and not belonging necessarily to any operator, the distribution is based on the assumption that pervasive devices are consenting to participate in the collaborative system. In this context, several considerations should be examined first: (1) The design of an incentive mechanism to motivate different nodes to take over AI tasks and sacrifice their memory, energy, communication, and computation resources to gain some rewards (e.g., monetary remuneration and free access to services); (2) In addition to the security of the private data to be processed by the pervasive devices, the security of the participants' information should be guaranteed (e.g., locations, identifiers, and capacities). Recently, blockchain [301] has gained large popularity as a decentralized dataset managing transaction records across distributed devices, while ensuring trusty communication. Moreover, the aforementioned incentivizing mechanism can also be handled by blockchain

systems. More specifically, all source devices and pervasive nodes have to first register to the blockchain system to benefit from the distributed AI or to participate in the computation. Then, data-generating devices request help to accomplish a task and submit at the same time a transaction application to the blockchain with a reward. Next, when the joining devices complete the offloaded tasks, they return the results to the source device and validate the completion of the transaction. Finally, the recorded participants are awarded according to their contribution to the blockchain transaction. The edge-based blockchain has a promising potential to prevent the security threats of transferring data between heterogeneous, decentralized, and untrusted devices. However, this approach is still in its infancy. Particularly, deploying it in resource-constrained devices is challenging due to the huge energy and computation load of blockchain mining [302].

VII.A.3. Explainable AI (XAI)

The AI-based applications are increasingly involved in many fields, where the decisions are very critical to lives and personal wellness, such as smart health applications and autonomous drones used during wars. However, most of the users do not have visibility on how the AI is making decisions. This lack of explainability prevents us to fully trust the predictions generated by AI systems. Finding reasons and logical explanations for decisions made by AI is called Explainable AI (XAI) [16], [303], [304]. XAI is an emerging field that is expected to answer some questions, including: Why are some predictions chosen, and why others not? When does an AI model succeed in taking the right decision, and when it fails?

Various techniques are used to explain the AI: (1) One of these techniques is decomposability, which stands for the ability to describe each part of the model, extract features of the output, and analyze them using clustering methods. The pervasive AI system is the most adequate environment to empower XAI by improving the ability to interpret, understand, and explain the behavior of the model. More specifically, by distributing the inference, the model becomes algorithmically transparent, and each segment can be interpreted and clustered by its importance for the prediction. (2) Moreover, among the most important directions supporting the XAI is model debugging. Debugging a DNN allows to detect errors and understand their sources and their influence on misleading the prediction. A distributed model produces fine-grained outputs, that help to follow the inference process and localize the errors before reaching the prediction layer. (3) A third direction to explain the AI is the extraction of data samples that are highly correlated with the results generated by the model. In fact, similarly to human behaviors when trying to understand some processes, examples are analyzed to grasp the inner correlation that is derived by the AI model. Federated learning is based on clustering data entries and training local models. This technique permits us to narrow the examples search and enables the detection of the most influencing inputs on the model behavior. Research on XAI is still in its infancy, and pervasive DNN computing looks like a promising environment to track the AI process and interpret the results.

VII.B. Efficient algorithms for pervasive inference

VII.B.1. Online resource orchestration

The pervasive systems are characterized by an extremely dynamic environment, where the available computing resources are volatile, and the load of requests may follow some statistical distributions. More specifically, ubiquitous nodes can join and leave the pervasive system randomly, which makes it hard to estimate the available resources. Moreover, the load of requests depends on the IoT application. For example, surveillance systems require frequent image processing (e.g., face recognition and crowd monitoring) every small interval of time. On the other hand, other applications, such as weather, air quality, and pollution level estimation, have to gather a specific amount of data before requesting the inference, which makes the load of requests lower. Additionally, the quality of the collected data may affect the depth of the adopted DL and consequently the computation requirements of the tasks. As an example, capturing high quality images allows to have a good prediction using smaller networks. In this scenario, early-exit techniques or squeezed models can be adopted. Having such data quality depends on the source device (e.g., UAV, professional camera, mobile phone, etc.) and the dynamic of the targets (e.g., fixed or moving).

Because of this network's dynamics, the pervasive systems deploying distributed inference need a well-designed online resource orchestration and participants selection strategy to support the large number of AI services with minimum latency. Meanwhile, heterogeneous and limited resources, and high dimensional parameters should be taken into consideration. In section IV, we have introduced existing theoretical approaches to split different DNN networks and distribute the resultant segments into pervasive devices to optimize pervasive computing. Nonetheless, most of them focused on how to partition the model in order to maximize the data parallelism and minimize the dependency between participants. Yet, there is no relevant work that deeply studied the performance of DNN distribution and reported the bottleneck and gain of such an approach in long-term online resource orchestration, with different loads of requests and a dynamic behavior of participants and sources. In other words, the model parallelism is not well investigated in the literature, where sources can generate multiple requests at the same time and offload them to neighboring devices. In this scenario, the critical decision is to choose whether to process the same task from different requests while minimizing the memory to store the filters' weights or to compute sequential tasks from the same request while reducing the transmission among participants. Furthermore, the age-aware inference is an important factor that can be foreseen in online model parallelization. In fact, some requests are highly sensitive to delays and need to be processed timely, such as self-driving cars, whereas others are less critical, including machine translation and recommendation systems. Thus, prioritizing urgent tasks and assigning better resources and intensive data parallelization to them is of high importance. We believe that pervasive AI computing should focus more on the online configuration to implement the above vision.

VII.B.2. Privacy-aware distributed inference

Guaranteeing the privacy of the data shared between collaborative devices is one of the main concerns of pervasive systems, since untrusted participants may join the inference and observe critical information. Because of this heterogeneity of ubiquitous devices, the trained models are subject to malicious attacks, such as black-box and white-box risks, by which the original inputs may be in jeopardy. In this case, privacy-aware mechanisms should be enhanced to ensure the security of the distributed inference process. Many efforts have been conducted in this context, such as noise addition and cryptography. Even though these techniques succeeded in hiding features of the data from untrusted devices, most of them suffer from computation overhead and incompatibility with some end-devices or DNNs. More specifically, noisy or encrypted data need to be re-trained to preserve the accuracy of the prediction, and each input has to be obfuscated, which adds a computation overhead. Moreover, encryption may not be applicable for all DNN operations nor possible in some end-devices due to the crypto key management requirements. A notable recent work [185] proposed to use the distribution for data privacy, without applying any additional task requiring computation overhead. In fact, per-segment splitting leads by design to assigning only some features of the input data to participants. Authors, of this work, applied filter partitioning and conducted empirical experiments to test the efficiency of black-box attacks on different segments' sizes (i.e., number of feature maps per device). The lower the number of feature maps per device, the higher the privacy. However, filter partitioning incurs high communication load and dependency between devices. This study is still immature. Other partitioning strategies (e.g., channel and spatial.) can be examined to identify the optimal partitioning and distribution that guarantee satisfactory privacy and minimum resource utilization per participant.

VII.B.3. Trajectory optimization of moving robots for latency-aware distributed inference

The usage of robots (e.g., UAVs) proved its efficiency to improve services in critical and hard-reaching regions. Recently, moving robots have been used for real-time image analysis, such as highway inspection, search and rescue operations, and border surveillance missions. These devices have numerous challenges, including energy consumption and unstable communication with remote servers. Recent works [137], [204] proposed to avoid remote AI inferences and leverage the computation capacity of ground robots to accomplish the predictive tasks. However, existing works did not cover the distribution of the inference among flying drones, characterized by their faster navigation, higher power consumption, and ability to reach areas with high interferences (e.g., high-rise buildings) compared to ground devices. Moreover, recent efforts did not cover the path planning for different moving robots to complete their assigned missions, while performing latency-aware predictions. More specifically, the time period between capturing the data to the moment when tasks from all the points are collected, should be minimized by optimizing the devices' trajectories, and planning close paths for participants

handling subsequent segments. Furthermore, the trajectories of devices with available resources should cross the paths of the nodes offloading the tasks, because of resource constraints.

VII.B.4. Remote inference of non-sequential DNN models

A major part of pervasive inference literature analyzes the remote collaboration, where the source device computes the shallow layers of the model, while the cloud handles the deep layers. In this context, the split point is chosen based on the size of the shared data, the resource capability of the end-device, and the network capacity. This DNN partitioning approach may work well for the standard sequential model, where filters are sequentially reducing the size of the intermediate data. However, state-of-the-art networks do not only include sequential layers with reduced outputs. Indeed, generative models (GAN) [74] proved their efficiency for image generation, image quality enhancement, text-to-image enhancement, etc. Auto-encoders also showed good performance for image generation, compression, and denoising. These types of networks have large-sized inputs and outputs. Hence, despite the reduced intermediate data, the cloud servers have to return the high-sized results to the source device, which implies high transmission overhead. Another family of efficient neural networks is the RNN (see section III-A1c), used mostly for speech recognition and natural language processing. These networks include loops in their structures and multiple outputs of a single layer, which imposes multiple communications with remote servers in case of partitioning. Other complex DNN structures prevent remote collaboration wisdom, such as the randomly wired networks and Boltzmann Machines (BM) having a non-sequential dependency. Keeping up with ever-advancing deep learning designs is a major challenge for per-layer splitting, particularly for remote collaboration. Based on these insights, the scheduling of DNN partitioning should have various patterns depending on the model structure.

VII.B.5. Fault-tolerance of distributed inference

When a deep neural network is split into small segments and distributed among multiple physical devices, the risk of nodes failure is increased, which leads to performance drop and even inference abortion. The typical networking wisdom resorts to re-transmission mechanisms along with scheduling redundant paths. These failure management techniques inevitably consume additional bandwidths. The DNNs are characterized by a unique structure that may enclose skip connections, convolutional neural connections, and recurrent links. These features of state-of-the-art networks implicitly increase the robustness and resiliency of the joint inference. More specifically, skip blocks allow receiving information from an intermediate layer in addition to the data fed from the previous one. These connections, serving as a memory for some DL models (e.g., ResNet), can play the role of fault-tolerant paths. If one of the devices fails or leaves the joint system, information from a prior participant can still be propagated forward to the current device via the skip blocks, which adds some failure resiliency. The skip connections proved an unprecedented ability to enhance the accuracy of deep models,

in addition to its potential to strengthen the fault-tolerance of pervasive computing. However, transmission overheads are experienced, particularly for failure-free systems. Thus, a trade-off between accuracy, resilience, and resource utilization should be envisaged. Another vision to be investigated is to train the system without skip connections and use them only in case of failures. This idea is inspired from the Dropout [305] technique that is used to reduce the data overfitting problem. It is based on randomly dropping some neurons during the training and activating them during the inference. Studying the impact of cutting off some transmissions during the inference for different splitting strategies while re-thinking the dropout training is interesting to strengthen the fault-tolerance of pervasive computing. Very recent works [168], [306] started to discuss such insights; however, they are still immature.

VII.B.6. Data-locality-aware algorithms

Most of the efforts, studying the pervasive inference, focus on splitting and parallelizing the DNN tasks related to a predictive request. Next, based on the requirements of these tasks and the available resources in the joint system (e.g., computation and energy), tasks are distributed and assigned to the participants. However, in terms of memory, only the weight of the input data is considered, whereas the weights to store the DNN structure are never taken into account. In section III, we showed in Table III that state-of-the-art DNN models are very sized and require high memory availability. For example, VGG-16 model has 138 M parameters and requires 512 Mb to store its filters. What worsens the situation is that some partitions impose copying the filters to all participants (e.g., spatial splitting.). Moreover, if the intelligent application is led by multiple DNN models and different segments are assigned to each device, a huge memory burden is experienced. Therefore, data-locality-aware algorithms should be designed. More specifically, the distribution system has to account for the past tasks assigned to each participant and try to maximize the re-usability of previously-stored weights, with consideration to the capacity of the devices. Minimizing the number of weights assigned to each participant, not only contributes to reduce the memory usage, but also guarantees the privacy of the structure against white-box attacks [307].

VII.B.7. Pervasive inference for nanotechnology applications

Nanotechnology is the field of innovation and research that focuses on creating particles (e.g., devices and materials) in the scale of atoms. These particles can be used in multiple domains, such as Nanomedicine that studies new ways of detecting and curing diseases. One of the interesting examples of Nanomedicine is the detection of diabetes through analyzing human's breaths. In fact, our body chemistry and our breaths change when we are sick, although our noses are not strong enough to detect it. More specifically, specific biomarkers are released in case of sickness, giving a huge opportunity to detect the disease just by sniffing out the breath. However, a big challenge is faced, as these biomarkers exist at a very low concentration equal to parts-per-million (ppm). In the context

of diabetes, Acetone is produced such as patients have 2 ppm Acetone concentration, whereas healthy people have only 1 ppm. Meaning, the difference of the biomarker concentration between healthy and patients is equal to 1 ppm. In order to detect this ppm or even part-per-billion (ppb) in the human breath rather than blood, the design of super-sensitive sensors is mandatory. Before nanotechnology, it was not possible to precisely detect such nano concentration. Nowadays, intelligent and invisible nano-sensors can be trained to sniff human breath. However, reaching the full potential of Nanomedicine (e.g., drug delivery systems and precision cancer medicine) is still yet to be fully realized.

To guarantee that Nano particles achieve the targeted objectives, large amount of data and computational analysis is expected. While the traditional techniques opt for an in-depth understanding of biological and chemical knowledge, the AI only requires data training. Thus, it is highly interesting to integrate the AI to evaluate and formulate the nanoscale particles [308], [309]. However, these particles suffer from small energy capacity that limits their communication with remote devices (e.g., handheld mobiles and computers). Hence, the distribution of inference within the nano-sensors can provide localized processing and minimize the data transmission. In this context, new partitioning strategies should be envisaged, as the existing ones do not fit the extremely limited computational resources of the particles. Particularly, even neuron, spatial, or filter splitting involving numerous multiplications are considered complex tasks. Thus, per-multiplication partitioning and the related dependency between millions of nano-participants have to be investigated to ensure the practicality of this futuristic convergence between pervasive AI and nanotechnology.

VII.C. Enhanced federated learning algorithms

VII.C.1. Active Federated Learning

Given the main limitations of FL in terms of communication overheads and slow convergence, combining AL concept with emerging FL schemes would be of great interest. Since most of the existing schemes for FL suffer from slow convergence, a novel active FL solution would be needed, which exploits the distributed nature of FL, while coping with highly dynamic environments and ensuring adequately fast convergence. Indeed, heterogeneity of the local training data at distributed participating nodes and considering all nodes in the FL process can significantly slow down the convergence. Full nodes participation renders the centralized server to wait for the stragglers. Thus, we envision that: (1) exchanging some side information between different participating nodes (e.g., the unique data samples or class distribution) can significantly help in tackling the data heterogeneity problem; (2) considering partial node participation by proposing efficient user selection schemes can play an important role in decreasing communication overheads and accelerating the convergence.

VII.C.2. Blending inter and intra data parallelism for federated learning

Deep neural networks require intensive memory and computational loads. This challenge is compounded, when the model

is larger and deeper, as it becomes infeasible to acquire training results from a single resource-limited device. Triggered by this challenge, federated learning is proposed to train deep models over tens and even hundreds of CPUs and GPUs, by taking advantage of *inter-data parallelism*. At present, federated learning techniques split the data to be trained among pervasive nodes while copying the whole DL model to all of them. Still, small devices cannot participate in such a process due to their limited capacities. Hence, blending the *inter-data parallelism* where the trained data is distributed and the *intra-data parallelism* where the intermediate data and segments of the model are partitioned, can be a feasible solution to enable training within non-GPU devices. Certainly, the practicality, gains and bottleneck of such an approach are to be examined and studied, as the backpropagation characterizing the training phase imposes huge dependency and communication between devices.

VII.D. Communication-efficient online learning

VII.D.1. Demonstrated applications

Since most of the MAB algorithms discussed in this paper are recent, it remains interesting to see their implications on practical applications. For example, quantifying the effect of bounded communication resources or energy used in wearable devices and congestion between edge nodes. Similarly, quantifying the improvement in regret bounds on actual and Quality of Experience (QoE) metrics can be promising.

VII.D.2. More general forms of MABs

The state of art algorithms in the distributed and federated setup adapt the finite-actions, and the stochastic case of the multi-agent settings. However, there exist many more general forms of the bandit problem that are yet to be studied under the multi-agent settings. These include but are not limited to adversarial-bandits, linear bandits, pure exploration, and non-stationary bandits. Investigating potential regret improvements and communication resource utilization in the MAB settings of non-stochastic and infinite-action bandits remains to be tackled.

VII.D.3. Heterogeneity of Bandit agents

In MAB settings, agents might not only differ in the instance each is trying to solve, but also in their computational capabilities. Different computational capabilities mean that agents interact with their environments at different rates, collecting an additional amount of samples and hence different quality estimates. While the effect of this computational heterogeneity is heavily studied in supervised federated learning, it is not yet investigated either in distributed or federated bandits.

VII.D.4. MARL performance/communication tradeoff

Methods that train in a logically centralized server and then execute in a decentralized manner (CTDE) are able to communicate less (even not at all) at execution while being able to learn good joint policy due to the central training phase, as illustrated earlier. However, their adaptability is not guaranteed when dealing with a non-stationary environment,

and they might require re-training again to adapt to the new environment. On the other hand, fully decentralized agents can continue the learning throughout their deployment but need to communicate more often to reason about their joint action. Otherwise, learning can be challenging and might diverge [310]. A natural goal is to design adaptable methods yet communicate conservatively, which is the main motivation behind scheduling in learned communication. Thus, more work is needed to address the question of adaptable and communication-cognizant MARL.

VII.D.5. MARL under networking constraints

Several communication characteristics have not been investigated under the MDP and POMG settings. For example, while delay, noise, failure, and time-varying topologies are vital factors in today's practical networks, they were not considered in most of MARL papers. These factors were, however, considered in other optimization frameworks like multi-agent (distributed) convex optimization [311]. Some of the works surveyed here started to study bandwidth and multiple-access aspects [273], [276]. Yet, it is important to study the performance of emerging policies of MARL under realistic networking constraints.

VIII. CONCLUSION

Recently, AI and pervasive computing have drawn the attention of academia and industrial verticals, as their confluence has proved a high efficiency to enhance human's productivity and lifestyle. Particularly, the computing capacities offered by the massive number of ubiquitous devices open up an attractive opportunity to fuel the continuously advancing and pervasive IoT services, transforming all aspects of our modern life. In this survey, we presented a comprehensive review of the resource allocation and communication challenges of pervasive AI systems, enabling to support a plethora of latency-sensitive applications. More specifically, we first presented the fundamentals of AI networks, applications and performance metrics, and the taxonomy of pervasive computing and its intersection with AI. Then, we summarized the resource management algorithms for the distributed inference, training, and online learning. In this context, partitioning strategies, architectures, and communication issues and solutions were extensively reviewed. Additionally, relevant use cases were described and futuristic applications were discussed.

Multiple challenges remain to be addressed, to further improve the performance, as well as the resource management, privacy, and avant-garde applications. Therefore, we presented our vision of technical challenges and directions that may emerge in the future, along with some opportunities for innovation. We hope that this survey will elicit fruitful discussion and inspire new promising ideas.

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