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Deep Learning for Internet of Things Infrastructure

EDITED BY

Uttam Ghosh, Mamoun Alazab,
Ali Kashif Bashir, and
Al-Sakib Khan Pathan

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Typeset in Times
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Dedicated to

my loving wife Pushpita and darling children
Upadhriti and Shriyan – Uttam Ghosh

my family – Mamoun Alazab

my parents, wife, and children – Ali Kashif Bashir

my family – Al-Sakib Khan Pathan

Contents

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1 Data Caching at Fog Nodes under IoT Networks

Review of Machine Learning Approaches

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CONTENTS

1.1 INTRODUCTION

In recent years, small devices embedded with sensors produce a large amount of data by sensing real-time information from the environment. The network of these devices communicating with each other is recognized as the Internet of Things (IoT), sometimes called as Internet of Everything [1]. The data produced by the IoT devices need to be delivered to the users using IoT applications after processing and analyzing. Further, data produced by the IoT devices are transient, which means that generated data have a particular lifetime, and after that lifetime, the data become useless and hence discarded [2]. Therefore, it is required to store the data somewhere near the IoT devices [3]. Simultaneously, suppose the data produced by the IoT devices are stored at the cloud server. In that case, it adds communication overhead, as the IoT users need to contact the cloud server whenever they require any data.

Fog computing is a decentralized approach to bring the advantages and intelligence of cloud computing such as storage, applications, and computing services near the end devices somewhere between the cloud and the end devices [4,5]. Fog nodes can be anything such as servers, networking devices (routers and gateways), cloudlets, and base stations. These nodes are aware of their geographical distribution as well as the logical location in the cluster. They can operate in a centralized or in a distributed manner and can also act as stand-alone devices. These nodes receive inputs from the data generators (IoT devices), process them, and provide temporary storage to the data. Fog nodes are intelligent devices that decide what data to store and what to send to the cloud for historical analysis. These devices can be either software or hardware, arranged in a hierarchy, and used to filter data transmitted by the sensors devices. These devices should have less latency, high response time, optimal bandwidth, optimal storage, and decision-making capability. At fog nodes, intelligent algorithms are embedded to store data, computing, and forward data between various layers. The member function of the fog node in the fog-cloud network is depicted in Figure 1.1. In this figure, the *compute* module is responsible for processing data and calculating the desired result. The *storage* module is responsible for storing data reliably so that robustness can be achieved. Further, various *accelerator* units such as digital signal processors and graphics processing units are used in critical tasks to provide additional power. In contrast, the *network* module is responsible for the guaranteed delivery of data.

Fog computing only complements cloud computing by providing short-term analytics, unlike cloud computing which offers long-term analytics. However, it is to be mentioned that fog computing does not replace cloud computing [6]. There are prominent six characteristics that differentiate fog computing from other computing paradigms [7,8].

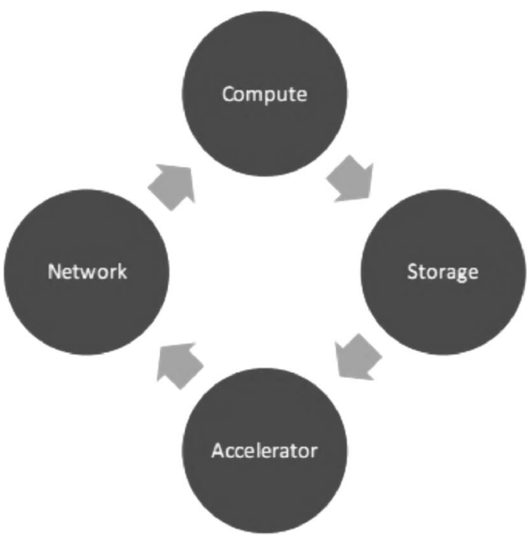

FIGURE 1.1 Functions of fog nodes.

a. **Awareness and Low Latency**: Fog nodes are aware of their logical location in the whole system and offer very low latency and communication costs. Fog nodes are frequently placed near the edge devices, and hence they can return reply and other analysis much faster than the cloud nodes.
b. **Heterogeneity**: Fog nodes generally collect different forms of data and from other types of devices through various kinds of networks.
c. **Adaptive**: In many situations, fog computing deals with uncertain load patterns of various requests submitted by different IoT applications. Adaptive and scaling features of fog computing help it to deal with the scenario mentioned earlier.
d. **Real-Time Interaction**: Unlike cloud computing, which supports batch processing, fog computing supports real-time interaction. The real-time data, which is time -sensitive, is processed and stored at fog nodes and is sent back to the users whenever required. On the contrary, the data which is not time -sensitive and whose life cycle is long is sent to the cloud for processing.
e. **Interoperability**: Because fog computing supports real-time interaction, it requires the cooperation of various providers leading to the interoperable property of fog computing.
f. **Geographically Distributed**: Unlike a centralized cloud, the applications serviced by fog nodes are geographically distributed, like delivering seamless quality videos to the moving vehicles.

Further, the processing time of fog nodes is significantly less (millisecond to subsecond). This technique avoids the need for costly bandwidth and helps the cloud by handling the transient data. To facilitate fog computing, the node should exhibit autonomy (property to take decision independently without the intervention of other nodes), heterogeneity, manageability, and programmability. Figure 1.2 shows fog computing architecture where IoT devices are connected to fog nodes, and then fog nodes are further connected to the cloud nodes [9].

The architecture of fog computing consists of three layers [10]:

a. **Terminal Layer**: This is the lowermost layer and consists of the IoT devices such as mobile phones and sensors, which detect the information from the environment by sensing it and then transmit the detected information to the upper layer. The information is transmitted in the form of data streams. The IoT data streams are the sequence of values emitted by the IoT devices or produced by one application module for another application module and sent to the higher layer for processing.
b. **Fog Layer**: This layer consists of various switches, portals, base stations, and specific servers. This layer lies between the IoT devices and the cloud and is used to process data near the IoT devices. If fog nodes cannot fulfill the terminal layer's request, then the request is forwarded to the cloud layer.
c. **Cloud Layer**: This layer consists of high-performance servers used for the storage of data and performing powerful computing.

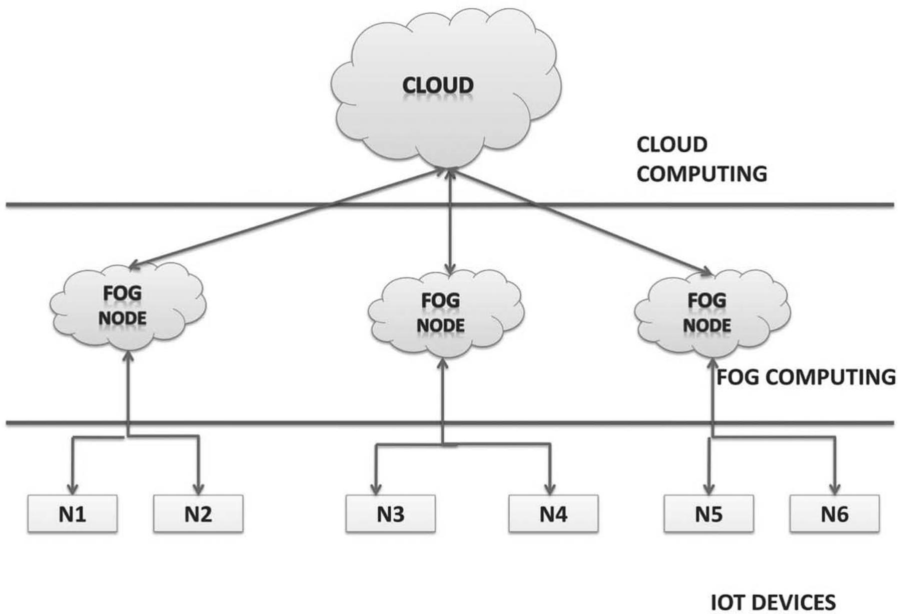

FIGURE 1.2 An architecture of fog computing.

Generally, IoT devices do not have processing power and storage, due to which they suffer from many problems such as performance, reliability, and security [11]. Fog nodes are capable of performing operations that require a large number of resources on behalf of IoT devices which are generally resource-constrained. This makes end devices less complex and also reduces power consumption. Further, fog computing also supports real-time interactions between the IoT devices and fog nodes. The data is available to the IoT devices quickly, unlike cloud computing where batch processing is mostly used. IoT devices are resource-constrained and generally do not have security features for which fog nodes act like proxy servers and provide extra security features. Fog nodes regularly update the software and security credentials and check the safety status of these devices.

Fog computing also offers the implementation of various service models such as Software as a Service (SaaS), Platform as Service (PaaS), and Infrastructure as a Service (IaaS) [12,13]. Due to such advantages, various frameworks such as Google App Engine, Microsoft Azure, and Amazon Web Services using cloud computing have also started supporting fog computing for providing solutions to advanced distributed applications that are geographically dispersed and require low-latency computational resources. They are also using dedicated nodes with low-latency computational power, also called mist nodes (lightweight fog nodes), and are sometimes placed closer to the IoT devices than fog nodes [14,15]. Hence, the integration of IoT with fog computing brings many such advantages.

1.1.1 Importance of Caching at Fog Nodes

The IoT devices do not have to contact the remote server, i.e., cloud, whenever they require some data. The IoT devices first check data in the cache of fog nodes. If required data is present, then the fog nodes return the data to the IoT devices; otherwise, they contact the cloud for the needed data. Hence, caching of data at fog nodes reduces the transactional latency. Moreover, fog computing requires lesser bandwidth to transfer the data [16]. As fog computing supports hierarchical processing, the amount of the data needed to be transferred from the IoT devices to the clouds is more petite. In contrast, the amount of data transmitted per unit of time from the fog node to the IoT devices is more, which leads to improvement in overall throughput. Hence, caching data at fog nodes decreases the general operational expenses. Data is stored in the distributed manner at fog nodes which can be deployed anywhere according to the requirements.

Further, caching of data at fog nodes helps reduce load at the cloud servers as the data whose frequency of interest is more among IoT devices and the probability of reusing the same data is also high is cached at fog nodes. Hence, only selected data is transferred for storage and processing to the cloud, which reduces the latency of contacting the remote server, which is far away from the IoT devices/sensors. Further, storing data at fog nodes ensures continuous services to the IoT devices irrespective of intermittent network connectivity.

Along with the advantages, some challenges need to be addressed to cache data at fog nodes. The biggest challenge of this technique is to decide what to store in the cloud and what to cache at fog nodes. The decision to cache the data at the fog node should be taken so that the hit rate of data at the fog node should be maximized such that the overall throughput is maximized [17,18]. Further, the storage capacity of fog nodes is limited, and they can only store the selected data. Therefore, it is necessary to predict the future demand of the users such that the data frequently required by the users in the future can be stored at the fog node to maximize the hit rate. However, it is difficult to predict the future requirement of the users.

Another challenge that needs to be addressed is maintaining synchronization between the data cached at the fog node or different fog nodes and data at the cloud nodes. Further, the security of data at fog nodes and the selection of ideal fog nodes are also issues of concern [19]. Various machine learning and deep learning techniques can be used to protect the data from attackers. In [20], various deep learning applications for cybersecurity are discussed, which can also be used in fog computing. Further, in [21], the stability of smart grids is predicted using a multidirectional extended short-term memory technique. The cooperation among sensor nodes is exploited in [22] to accelerate the signature verification and provide authentication in a wireless sensor network. The author in [23] also classifies the behavior of various malicious nodes and proposes a detection method of malicious nodes based on similarity in sequences and frequencies of API calls. Further, the authors in [24] also discuss the various trends in malware occurrences in the banking system. Apart from this, the authors in [25,26] also discuss the detection of intruders in the cyber system using machine learning.

Further, the mobility of nodes or virtual machines, which requires maintenance, balancing, and power management, is also a challenge that needs to be addressed. Each fog node may have one or more virtual machines depending upon requests and traffic conditions. The computation and communication required for the process of hand-off and its effect on caching are very much complicated and expensive [27,28].

As discussed above, this chapter focuses on an essential aspect of caching, which is to predict the future demands of the IoT users such that effective caching of data can be done at fog nodes. To address this problem, various machine learning techniques are discussed, which help learn the behavior and pattern of demands of IoT devices and add autoprocessing and auto computing capability to fog nodes. Also, the caching techniques used in wireless networks can be used in fog computing. However, these techniques cannot predict the future demands of the end -users. Hence, directly applying these techniques to fog nodes makes the system less efficient. Therefore, machine learning techniques are used to predict the users' future demand and make caching at the fog more efficient. Before exploring the machine learning techniques, in the next section, various applications of caching at fog nodes and the life cycle of fog data are discussed.

The rest of the chapter is organized as follows. Section 1.2 represents the applications of data caching at fog nodes for IoT devices. Section 1.3 describes the life cycle of fog nodes, and Section 1.4 discusses the machine learning techniques for data caching and replacement. The future research directions are discussed in Section 1.5, followed by the conclusion in the last section.

1.2 APPLICATIONS OF DATA CACHING AT FOG NODES FOR IoT DEVICES

In this section, some real scenarios are discussed where data caching at fog nodes can be very useful [29–36].

a. **Dynamic Content Delivery and Video Streaming**: With the increase in multimedia content, the conventional network suffer from congestion. Further, video traffic acquires half of the traffic, and frames to play the video are required faster, such that there is no interruption. Hence caching of data at fog nodes is a suitable approach for faster delivery of the multimedia contents [37].
b. **Virtual Reality and Online Gaming**: Virtual reality and online gaming require real-time data. In virtual reality, it is required to provide the status of the user as well as the location of the users. Hence, it is required to process the data and provide data to the user as soon as possible, where fog computing seems to be the promising approach for this purpose [38].
c. **Smart Cities**: In smart cities, various IOTs are connected to share data . These IoTs generate a large amount of data that need to be processed near the IoTs. For example, in smart traffic lights, data can be stored and processed at fog nodes and used to send warning signals to the approaching vehicles [39].

d. **Smart Grids**: The data generated by intelligent grids contain complex parameters that are hard to analyze. Fog nodes have the power to investigate and process complex data to perform heavy computations. Hence, fog nodes can be used to store and process the local data generated by smart grids and various IoT devices used in smart cities [40].
e. **Smart Healthcare**: Real-time data processing makes smart healthcare more efficient and faster. Hence fog computing can be used in healthcare in order to make its working more efficient. For example, fog computing may be used to detect falling of the stroke patients [41].
f. **Intensive Computation Systems**: The systems which require intensive computations require low processing and latency time. Hence the data produced by these systems must be processed and stored at fog nodes and provided to the systems whenever needed [42].
g. **Internet of Vehicles**: Fog computing plays a vital role in vehicle-to-vehicle communication and taking safety measures on the road by providing data to the vehicles required to take decisions for traffic control and smart parking. Fog nodes obtain data from the sensors deployed and take decisions for traffic control measures [30].
h. **Wireless Sensors Systems**: The data produced by wireless sensor systems such as oil and gas industries and chemical factories are transient which need to be stored near the users. Hence the data produced by these systems should be cached at fog nodes to improve the performance of the methods [43,44].

In the scenarios mentioned earlier, it is suitable to store the real-time or dynamic contents near the users that are generating data and may also require them in the near future. This requirement can be easily fulfilled by caching the data at fog nodes located near the users or IoT devices.

1.3 LIFE CYCLE OF FOG DATA

As discussed in the introduction section, depending upon the various layers in fog computing, fog data goes through various steps from acquiring data at the terminal layer to processing data and the execution of tasks to constitute a life cycle. The life cycle of the data is shown in Figure 1.3, and various steps involved during the life cycle are explained as follows [45–50]:

a. **Data Acquisition**: The sensors present in the device layer/terminal layer sense the environment and collect data. The acquired data are either sent to the sink node or directly transferred to the fog node for processing.
b. **Lightweight Processing**: This is done at the fog layer and hence includes various tasks such as filtering of data, cleaning of data, eliminating the unwanted data, lightweight manipulation of data, compression/decompression of data, and encryption/decryption of data. Some data are stored at this layer to support real-time processing, and the rest of the data are transferred to the cloud layer for further processing. Further, the feedback and the data are exchanged by the fog layer, as shown in Figure 1.3

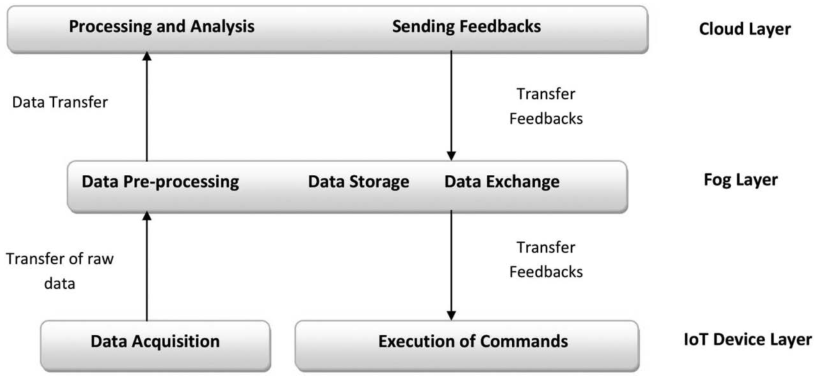

FIGURE 1.3 Life cycle of fog data.

c. **Processing and Analysis**: The data received from the fog layer are processed using different types of analysis to extract the crucial data. The data are permanently stored at the cloud server. According to the processing performed at the data received from the fog layer, reports are generated. Various technologies such as map -reduce are used for data processing in the cloud.
d. **Sending Feedback**: Based on reports generated during data processing, the cloud server sends feedback such as data required by the end devices and proper commands to the device layer to perform the necessary action.
e. **Command Execution**: Based on the feedback received from the cloud server, the actuators perform the respective action, and then required steps are performed on the environment.

It is evident from the above sections that caching played a significant role in fog computing. Efficient caching will help achieve low latency requirements and maintain high QoS and QoE of 5G. Caching is classified as reactive caching, where data caching is done on request, and proactive caching, where prefetching of data is done. To achieve higher spectrum efficiency, proactive caching is better if prediction errors are nearly zero [51]. Therefore, it is crucial to design various techniques to predict the users' future requests, which can be cached at fog nodes such that repetitive requests to the cloud can be avoided.

Various techniques have been used in the literature for data prediction and caching, like fog-to-fog (F2F) caching [52], where multi-agent cooperation is used. The authors in [53] proposed a location customized regression-based caching algorithm to predict the future content demands. According to various activity levels, the authors in [54] distinguished requests on three different popularity levels and then strategically cached data at fog nodes. Apart from caching at fog nodes, device-to-device (D2D) caching has also been done in the fog computing environment where direct communication between the nodes (IoT devices) takes place at a short distance without any infrastructure [55,56]. Whenever data is required by the device, it checks its local cache for the data. If information is not available, it broadcasts the request to the other instruments. The other IoT devices present at the ground tier in hierarchy check

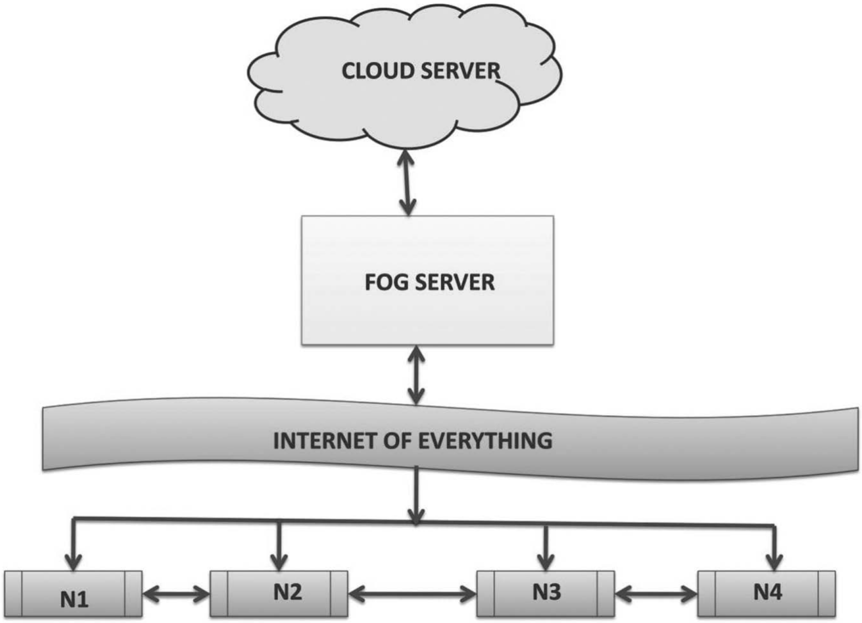

FIGURE 1.4 Caching using D2D technique.

for the data. If the data are present, the respective device replies with the data to the requesting device; otherwise, it replies with the negative acknowledgment. They are then requesting device requests for the data at the fog servers. As stated earlier, if data are not available at the fog server, then it sends the request to the cloud server. Cloud server, in return, sends the data to the fog server, and then the fog server sends data to the requesting nodes. Figure 1.4 shows the interaction between various IoT devices and the interaction between IoT devices and fog nodes.

As mentioned before, the content placement problem relies on the prediction accuracy of the user requirement, the popularity of the content, and caching strategy design. To predict the data content demand , much available data related to similar interests – social and geographic data and history data of users – can be used to predict user demand [57] better. This is effectively implemented using machine learning schemes. In the following section, various machine learning techniques used for data caching at fog nodes are investigated.

1.4 MACHINE LEARNING FOR DATA CACHING AND REPLACEMENT

Caching at fog nodes is influenced by various factors like the varying interest of different IoT users, which changes with different contexts, changed locations, network topology, and so on. Therefore, the future content request is highly unknown before making any caching decision [66]. Machine learning–based algorithms enable each fog node having limited storage to make the right decision in selecting the suitable contents to cache such that the caching performance of the fog node is maximized. Machine learning is used for predicting users' demand and mapping users' input to the output actions. Machine learning is a promising approach for improving network efficiency by predicting users' need and is used to discover early knowledge from large data streams [57]. In the machine learning approach, many data are exploited to determine the content popularity and helpful in filtering the data and knowledge [67–70]. The further processing of these data is valuable for analyzing the correlation between the features and the respective output of the data [71]. Further, machine learning techniques can be categorized into two types: unsupervised learning and supervised learning. In supervised learning, learning systems are provided with learning algorithms with known quantities that help these algorithms make future judgments. On the other hand, in unsupervised learning, the learning system is equipped with unlabeled data, and the algorithm is allowed to act upon it without any guidance. Machine learning can be used at any layer of fog computing, i.e., the terminal layer, the fog layer, or the cloud. At the terminal layer, machine learning is used for data sensing. There are various methods used for the sensing of data and are described in Table 1.1. The complex features of datasets like videos, vibrations, and different modeled readings from the IoT devices can be recognized by machine learning methods [72–77]. Various machine learning algorithms such as recurrent neural network (RNN), convolutional neural network (CNN), and generative adversarial network (GAN) have been used recently [76].

At the fog layer, machine learning is used for data storage and resource management [78]. Using machine learning algorithms, data are sampled from the IoT devices, compressed, and aggregated at fog nodes for further processing. Figure 1.5 shows the data analysis methods for the data produced by the IoT devices and various machine learning techniques that can be used to analyze the data and then decide that what to cache at fog nodes.

TABLE 1.1
Machine Learning Methods Used at Terminal Layer for Data Sensing

Sr. No.	Techniques	Description
1	Residual nets [58]	In this method, in order to reduce the difficulty of training models, shortcut connections are introduced into the convolutional neural networks. Visual inputs are mainly focused on residual nets
2	Long-term recurrent convolutional network [59]	In this method, convolutional neural networks are applied in order to extract the features. In the video, frame sequences are combined with the long short-term memory [60]. Further, the spatial and temporal relationships are exploited between inputs.
3	Restricted Boltzman machine [61]	The performance of human activities is improved by the deep Boltzman machine. In the case of multi-restricted Boltzman machine, performance is improved by multi-nodal DBM [62]
4	IDNET [63]	A convolutional neural network is applied by IDNET for biometric analysis tasks.
5	DeepX [64] and RedEye [65]	In these methods, on the basis of hardware and software, the energy consumption of the deep neural network is reduced

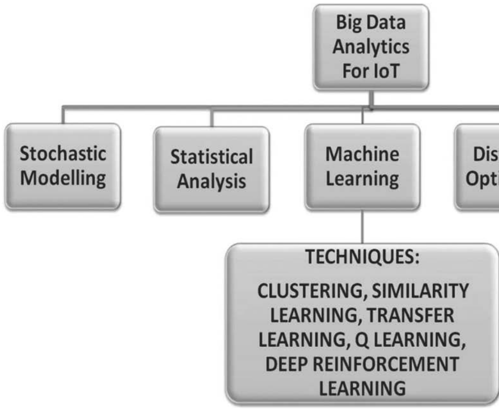

FIGURE 1.5 Big data analytics for the wireless network.

Various machine learning techniques used by the researchers in the literature for data caching at fog nodes are as follows:

1. **Clustering of Fog** Servers: Clustering is a technique used in unsupervised learning in which the information is not guided. In this technique, fog servers are clustered to fulfill the demands of IoT devices [30]. Data are stored at various fog servers after being coded into segments. When the user raises the content request, it is served by the group of fog servers which are clustered based on content stored in them. Suppose the requested content is cached at fog servers . In that case, the IoT device fetches the data from fog servers in ascending order of transmission distance until the obtained segments are sufficient for decoding. Further, if the received components are not enough, the nearest fog server contacts the cloud for the data, fetches the remaining data from the cloud and delivers it to the IoT device. Further, cluster size influences the system's efficiency as the benefit of cooperative caching has vanished if the size of the cluster is immense. However, at the same time, IoT devices can fetch the data from various nodes and increase the cache diversity. Therefore, cluster size should be optimal, which balances the trade-off.
2. **Similarity Learning Approach**: In this approach, fog nodes are given with a pair of similar IoT devices and a pair of less similar devices. From the given set of IoT devices, the intelligent fog node finds the similarity function (or the distance metric function) between the pair of similar devices by learning about their various features [57]. In this technique, two parameters, i.e., common interest and physical relations (link quality), are considered to find the similarity between IoT devices. A one-to-one matching scheme is also used for the pairing of IoT devices. With the help of this function, the intelligent fog node finds whether the new device is similar or not and hence finds the future interest of a new device whose interests are unknown.
3. **Transfer Learning Approach**: In this approach, the intelligent fog node gains knowledge while solving the problem and stores it. It then translates

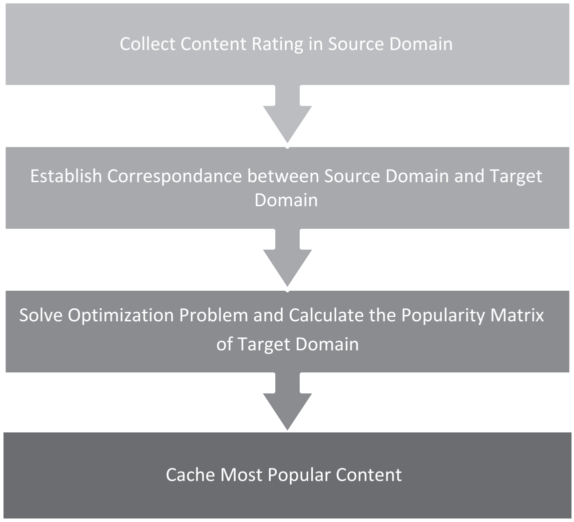

FIGURE 1.6 Training using transfer learning.

the new problem by exploiting the knowledge obtained from the data of existing tasks [79]. The fog node makes use of two domains for training: the source domain and the target domain. The source domain refers to the knowledge obtained from the interactions of IoT devices, while the target domain refers to the pattern of requests made by the IoT devices. The source domain consists of IoT devices and the data requested by machines in the past. Additionally, the source domain contains a popularity matrix (the number of times the particular data is asked by the IoT devices). This technique smartly borrows the user-data relationship from the source domain to understand the target domain by establishing correspondence between both. The correspondence is set to identify the similarly rated content in both disciplines. Further, an optimization problem is formulated by combining both domains to evaluate the popularity matrix of the target domain [80]. According to the values present in the popularity matrix of the target domain, the most popular content is cached at the fog node. Figure 1.6 illustrates the proposed transfer learning caching procedure.

The only problem with this technique is that it cannot give appropriate results if the relation between the source domain and the target domain is not efficient, which means that if the information demanded by the IoT devices is not related to the present information in the system, then transfer learning is not able to take an accurate decision for caching.

4. **Recommendation via Q Learning**: In existing local caching systems, the users do not know about the cached data. Therefore, they cannot send their request even though the requested file is available in the cache, decreasing the system's efficiency considerably. Hence to improve the efficiency

of the system, a recommender algorithm is used [81]. In this system, the fog server broadcasts an abstract to the users to gain knowledge about the presently cached files. An abstract contains one line introduction about the file and the ranking of the file in terms of the number of requests to the file. The value of the abstract also influences the decision of the user to request the file since the request rate of a file and the arrival and departure rate of the IoT devices is unknown in advance. To conquer this problem, Q learning is used, which is a form of deep learning approach used to improve the system's performance by reducing the latency and improving the throughput. It shows perfect accuracy in determining the future demand of the nodes by selecting the Q value. Multiple layers are used in this network, and these layers are used to process data and predict the future demand of the users. Since more data are generated and processed by the lower layers than the higher layers, more layers should be deployed near the users to reduce the network traffic and improve the system's performance.

The requested rate for the *i*th file depends upon the number of IoT devices present in the system and the number of IoT devices that arrived at that particular amount of time. As a result, an unknown number of requests to the *i*th file depends upon the caching action in the previous and present interval. During the learning process, the Q value is selected for each state-action pair which maximizes the reward. Then remaining IoT devices are counted in order to choose the action to the current interval. At the end of the gap, the bonus for the respective action is calculated, and the next state is observed. Then using these values, a new Q value is calculated [81]. This approach increases the long-term reward of the system and hence improves performance.

5. Deep Reinforcement Learning:

According to history, the deep reinforcement learning approach intelligently perceives the environment and automatically learns about the caching policy [82,83]. The emergence of deep neural networks has made it feasible to learn from raw and possibly high-dimensional data automatically. Learning-based caching techniques can be categorized into two approaches: popularity prediction and reinforcement learning approach. In the popularity prediction approach, first content popularity is predicted, and then according to popularity predictions, caching policy is devised. This approach is summarized in Figure 1.7 [66].

Various information like traffic patterns and context information is used to predict the content's popularity. Content popularity is expected in [84] by using user–content correlations and users' social ties through D2D communication. The authors in [85–87] have used various online learning algorithms to predict the content popularity. After the popularity prediction procedure, various caching policies and algorithms can be devised after solving optimization problems by combining estimated popularity with a few network constraints or traditional caching algorithms. However, these caching problems are usually complex and are NP-hard.

In the second approach, which is the reinforcement learning (RL) approach, in place of separating popularity prediction and content placement, the RL-based approach considers both as a single entity and is shown in Figure 1.8.

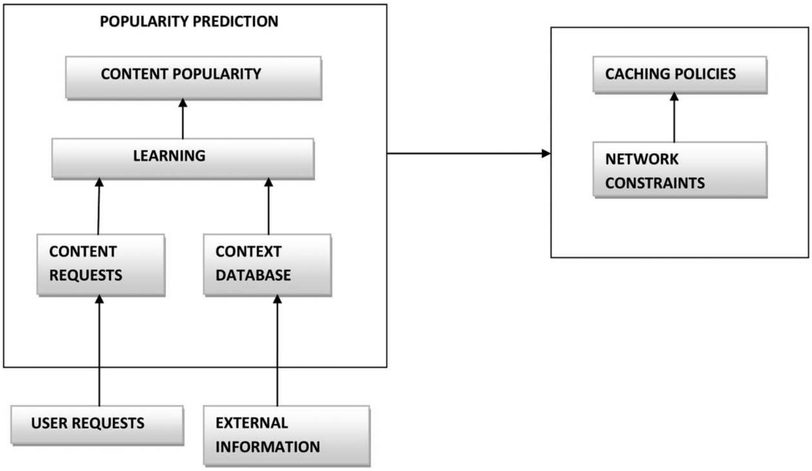

FIGURE 1.7 Popularity prediction approach.

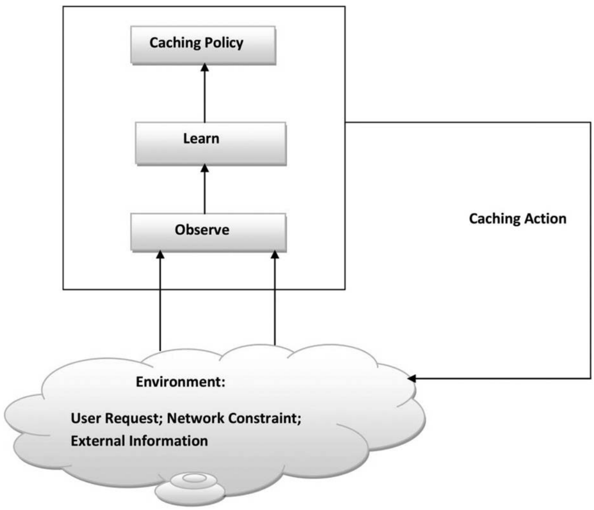

FIGURE 1.8 Reinforcement learning approach.

The RL agent train caching policy with observations based upon its action like QoE or offloaded traffic. This also avoids handling other factors affecting caching performance like node mobility or network topology. Various RL algorithms have been applied for designing fog nodes caching schemes. The advantage of RL-based approaches is that RL agents can be trained directly on raw and high dimensional observations.

One of the RL-based caching schemes is proposed by Zhu et al. [82]. The authors defined the action space where each action indicates the data item to be replaced in the cache. Initially, the fog node observes the environment, and according to the environment, it will obtain the state of the domain. Then according to the caching policy used, it takes the required action and attains the corresponding state. The action vector is represented as follows:

$$A_n = \left\{a_0, a_1, a_2, \ldots\ldots a_c\right\}$$

where c is the number of files present in the cache, a0 represents no caching action took place, av represents the new file is cached at the *v*th position, and the corresponding state vector is defined as follows:

$$S_n = \{s_1, s_2, s_3, \ldots\ldots s_n\}$$

After the action is taken, the system attains the reward, which is fed back to the edge node and the process is repeated. Further, each data item is associated with two data fields: (a) the time-stamp field and (b) the lifetime field. The time-stamp field tgen is used to indicate the time when data is created or generated, while the lifetime field tlife indicates the time up to which the value is valid in the item. The age of the data tage is predicted by finding the difference between the current time and the time generated. If tage < tlife, then the requested data is available at the cache and is fresh, and then data is directly returned to the user from the cache; otherwise, the data available at the cache is not fresh. When data is not fresh and if data is not available, then the node fetches fresh data from the cloud and returns it to the IoT device. Deep reinforcement learning aims at maximizing the reward when the agent takes action at a particular state. Figure 1.9 illustrates the application of deep reinforcement learning at fog nodes and knows the IoT devices' future demands.

6. **Federated Learning**: Conventional machine learning approaches depend upon the data and processing in a central entity. However, this is not always possible as the private data is not sometimes accessible, and also it requires great communication overhead to transmit initial data that is generated by a large number of IoT devices to the central machine learning processors [88–92]. Therefore, federated learning is the decentralized machine learning approach that keeps the data at the generation point itself, and then locally trained models are only transmitted to the central processor. These algorithms also significantly reduce overall energy consumption and network bandwidth by only sharing features rather than the whole data stream. It also responds in real -time to reduce the latency. These machine learning algorithms exploit on-device processing power and efficiently use private data as model training is performed in a distributed manner and keep the data in place, i.e., place of generation. In the content popularity approaches discussed above, direct access to private user data for differentiating content may not be feasible. Till now, federated learning has not been explored for caching in the fog computing environment. The authors in [88] have successfully demonstrated that content popularity prediction can be made with the help of federated learning.

Pros and cons of various machine learning techniques discussed above are summarized in Table 1.2.

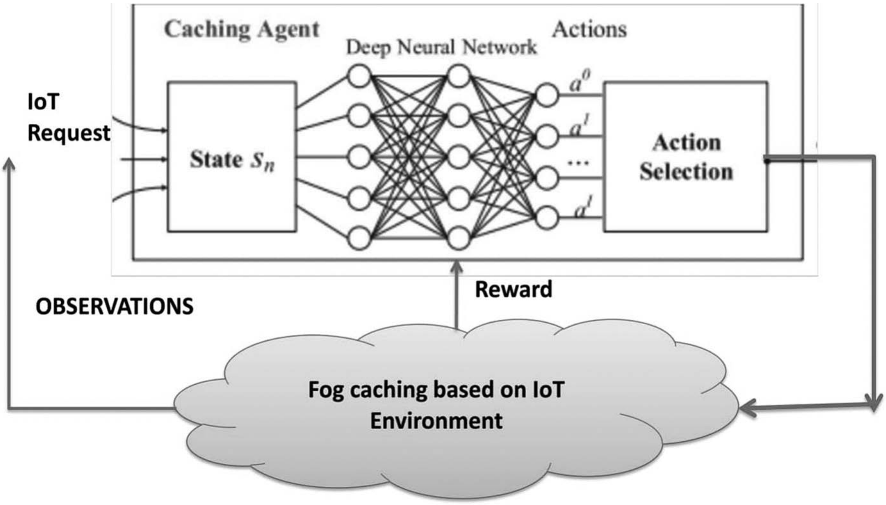

FIGURE 1.9 Applying DRL to fog caching.

TABLE 1.2
Pros and Cons of Machine Learning Algorithms

Techniques	Pros	Cons
Clustering	1. Coded caching is used which improves efficiency 2. Load balancing	1. If the size of the cluster is large, then efficiency is compromised
Similarity learning	1. Use only previous knowledge to find the similarity 2. Efficient if similar device arrives	1. Can't predict demand if a completely new node arrives
Transfer learning	1. Solve the new problem by exploiting existing knowledge	1. Difficult to find the correspondence between the source domain and the target domain
Q Learning	1. End devices know which data is cached and where it is cached and use a priority of data in caching, which improves the efficiency. 2. Extra space is needed for storing priority of the data	1. Delay in forecasting abstract 2. Better accuracy in predicting demands
Deep learning reinforcemen	1. Long-term cost of user fetching data is reduced 2. Overlapping coverage of fog nodes is considered	1. Cooperative caching is not considered 2. Better accuracy in predicting demands
Federated learning	1. Able to use the private data 2. Reduced communication overhead	1. Complex machine learning technique may have to be applied at various levels

1.5 FUTURE RESEARCH DIRECTIONS

In this section, various research issues related to fog nodes caching are discussed. These points may help readers for their future research directions in the area of fog nodes caching.

a. **Lack of Memory Space**: To implement a machine learning -based system, it is necessary to have sufficient data at the learning system for learning purposes. However, fog nodes do not have enough memory space; hence, it is of profound importance to investigate an effective machine learning technique that can learn from limited available data. As discussed before, the reader may explore federated learning, which is not exploited for content prediction in caching.
b. **Heterogeneous IoT Devices**: Most of the time, IoT devices are heterogeneous; e.g., in smart homes, various types of sensors for light and temperature may be installed, which generate a lot of different kinds of traffic. Hitherto, the impact of heterogeneity of IoT devices is not well addressed. In this kind of scenario, network connectivity methods, protocols to handle these devices, and communication methods are not discussed, which increases the latency while communicating with fog nodes.
c. **Synchronization Among Fog Nodes**: In the current research, the synchronization of data present at various fog servers and cloud servers is not discussed. Since the data produced by IoT devices is transient and becomes useless after some time, it is necessary to address the problem of synchronization of data at various fog servers and also with the cloud server.
d. **Game -Theoretic/Auction Models**: In various business models, fog nodes earn by serving the IoT Devices. In this kind of system, fog nodes may not cooperate with each other and may act selfishly. Therefore, various game theory–based or auction-based theories may be applied to solve non-cooperation among fog nodes.

1.6 CONCLUSION

IoT devices generate a lot of data that are stored and processed at cloud servers. To reduce the latency, fog computing has been introduced. However, there is a need for caching data at fog nodes to reduce further communication with cloud nodes. This chapter introduces various advantages of storing data of IoT devices at the fog nodes and subsequently the challenges faced to store data at fog nodes. Further, the life cycle of fog data as well as the architecture of fog computing is discussed. The application of caching data at fog nodes is also discussed in this chapter. This chapter also describes how various machine learning techniques are used to predict the future demand of IoT devices and store the most requested data at fog nodes. The chapter is then concluded with future research directions for readers.

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Data Caching at Fog Nodes under IoT Networks

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Deep Neural Network–Based Security Model for IoT Device Network

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