A Survey on Machine Learning Based Proactive Caching

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Abstract: The world today is experiencing an enormous increase in data traffic, coupled with demand for greater quality of experience (QoE) and performance. Increasing mobile traffic leads to congestion of backhaul networks. One promising solution to this problem is the mobile edge network (MEN) and consequently mobile edge caching. In this paper, a survey of mobile edge caching using machine learning is explored. Even though a lot of work and surveys have been conducted on mobile edge caching, our efforts in this paper are rather focused on the survey of machine learning based mobile edge caching. Issues affecting edge caching, such as caching entities, caching policies and caching algorithms, are discussed. The machine learning algorithms applied to edge caching are reviewed followed by a discussion on the challenges and future works in this field. This survey shows that edge caching can reduce delay and subsequently the backhaul traffic of the network; most caching is conducted at the small base stations (SBSs) and caching at unmanned aerial vehicles (UAVs) is recently used to accommodate mobile users who dissociate from SBSs. This survey also demonstrates that machine learning approach is the state of the art and reinforcement learning is predominant.

Keywords: mobile edge caching; reinforcement learning; unmanned aerial vehicle

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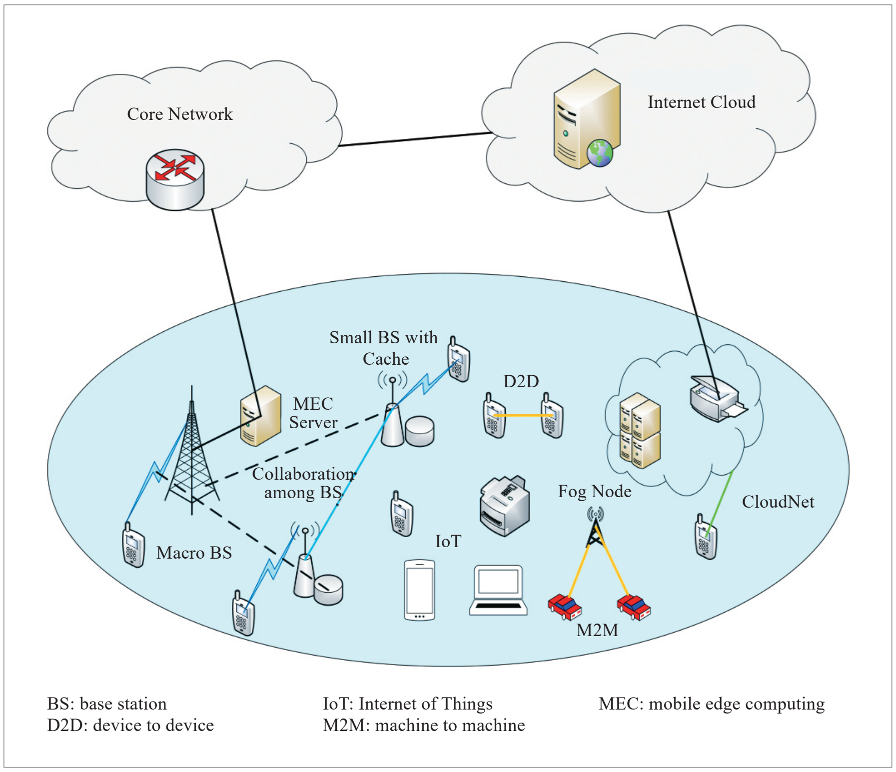
1 Introduction

The world is witnessing an astronomical growth of mobile traffic and an ever-increasing demand from end users for high bandwidth and quality of experience (QoE) because they do almost everything and share vast amounts of data, documents, media, etc. on their mobile devices. Mobile data traffic grew fast between 2011 and 2016 and is estimated to increase to 49.0 exabytes per month by 2021 [1]. Increasing mobile traffic leads to congestion of backhaul networks, which further leads to a higher cost of operation and maintenance, a lower quality of service (QoS), and inhibits data delivery. The increasing demand for bandwidth coupled with greater QoE and performances is beyond the current fourth generation (4G) technologies, and new solutions such as the fifth generation (5G) technologies have emerged. In order to meet the increasing data demands, small-cell networks will be widely deployed, which can achieve much higher throughput and energy efficiency [2]. Mobile edge networks (MENs), as shown in **Fig. 1**, are a promising solution to address the above issues (increasing demand for bandwidth, congestion of backhaul networks, higher cost of operation and maintenance, a lower QoS, demand for greater QoE and performance, etc.). By moving the network functions and resources closer to end users (i.e., the network edge), many benefits can be obtained, such as high data rates, low delay, improved energy efficiency, and flexible network deployment and management [3]. One innovative proposal to overcoming these challenges is caching the content. While the two common locations for caching the content are at the evolved packet core (EPC) and the radio access network (RAN) [4]. Certain popular contents (e.g., on-the-air TV series



▲**Figure 1. Architecture of a mobile edge network.**

and popular music) are frequently requested; such contents can be cached during off-peak times at the network edge, such as at base stations (BSs) and even user devices [5]. Then the contents are distributed to requesters through high-rate and low-cost mobile edge networks rather than transmitted through the backhaul network repeatedly.

There is an emerging paradigm shift towards the use of unmanned aerial vehicles (UAVs) to assist the traditional cellular networks in wireless communications to provide connectivity from the sky to ground users. Such communication from the sky is expected to be a major component of beyond 5G cellular networks. When mobile users move outside the cell coverage areas, the cached contents may not be effectively distributed to the users. In addition, when a user hands over to a new cell, the contents requested may not be cached, leading to extra delay and bandwidth consumption due to the caching in the new BS or long-distance fetch from the content server. Also, in drone cells, the limited fronthaul capacity can hardly satisfy the demands of data-craving services [6]. To alleviate the pressure of small cells and reduce the cost of densely deployed small base stations (SBSs), UAVs can be exploited to assist small cells in providing high-speed transmission due to their low cost and high mobility. UAV-aided wireless networks can establish wireless connections without infrastructure, realize larger wireless coverage, and achieve higher transmission rate. This makes it suitable for many practical applications, such as terrestrial BS offloading [7], emergency response and public safety [8], Internet of Things (IoT) communications [9], [10], and massive machine type communications [11]. A lot of surveys have been conducted on edge caching over the years. In [12], various cache management systems were suggested to enhance the performance of mobile Ad hoc networks (MANETs). The authors of [13] presented a comprehensive overview of the recently proposed in-network caching mechanisms for information centric networks (ICNs). They described each caching mechanism in detail, presented examples to illustrate how it works and extensive simulations, and discussed the remaining research challenges. The authors of [14] provided a review of the caching problems in ICNs, with a focus on on-path caching. To this end, a detailed analysis of the existing caching policies and forwarding mechanisms that complement these policies were given in [14]. The paper [15] grouped the most interesting caching techniques with regard to different architectures, considering the cases and the quality of the solutions.

Additionally, the survey [12] outlined various cooperative caching schemes in wireless sensor networks (WSN) and classified them in distinct categories based on type of approach applied. Maintaining cache consistency is as important as caching data. This paper also gave a brief overview of various cache consistency models. GLASS et al. [16] developed a unique taxonomy for cache discovery, surveyed a representative set of MANET-based cooperative caching schemes, and classified the associated cache discovery techniques within the taxonomy. Using this classification, they then highlighted the various cache discovery techniques that have been utilized, analyzed their potential in addressing the specific challenges that occur when deploying non-safety applications within vehicular Ad hoc networks (VANETs), and identified general pitfalls that should be avoided. In [17], a survey of cache management strategies in ICNs was presented along with their contributions and limitations, and their performance was evaluated in a simulation network environment with respect to cache hit, stretch ratio, and eviction operations. Some unresolved ICN caching challenges and directions for future research in this networking area were also discussed.

The paper [18] provided a systematical survey of the state-of-the-art caching techniques that were recently developed in cellular networks, including macro-cellular networks, heterogeneous networks, device-to-device networks, cloud-radio access networks, and fog-radio access networks. In particular, its authors gave a tutorial on the fundamental caching techniques and introduced caching algorithms from three aspects, i. e. , content placement, content delivery, and joint placement and delivery. They also provided comprehensive comparisons among different algorithms in terms of different performance metrics, including throughput, backhaul cost, power consumption, and network delay; finally, they summarized the main research achievements in different networks and highlighted main challenges and potential research directions. A detailed survey on the emerging technologies to achieve low latency communications was presented in [19], considering three different solution domains: RAN, core network, and caching; a general overview of major 5G cellular network elements such as software defined network (SDN), network function virtualization (NFV), caching, and mobile edge computing (MEC) capable of meeting latency and other 5G requirements was also presented. Finally, [20] presented an overview of caching in wireless networks and then provided a detailed comparison of traditional and popularity-based caching. The attributes of videos and the evaluation criteria of caching policies were discussed, some of the recent works on proactive caching, focusing on prediction strategies, were summarized, and an insight into the potential opportunities and challenges as well as some open research issues enabling the realization of efficient deployment of popularity-based caching as part of the next-generation mobile networks were provided.

· Even though a lot of work and surveys have been done on mobile edge caching [13] – [15], this survey is focused on the study of machine learning based mobile edge caching.

· We discuss the issues that affect caching in mobile edge networks in general and the use of UAVs to cache contents introduced.

· We discuss learning techniques applied to caching in mobile edge networks.

The rest of the paper is organized as follows. Section 2 outlines some of the issues that affect edge caching. Section 3 discusses learning based caching schemes and Section 4 analyzes the challenges and future directions. Conclusions are drawn in Section 5.

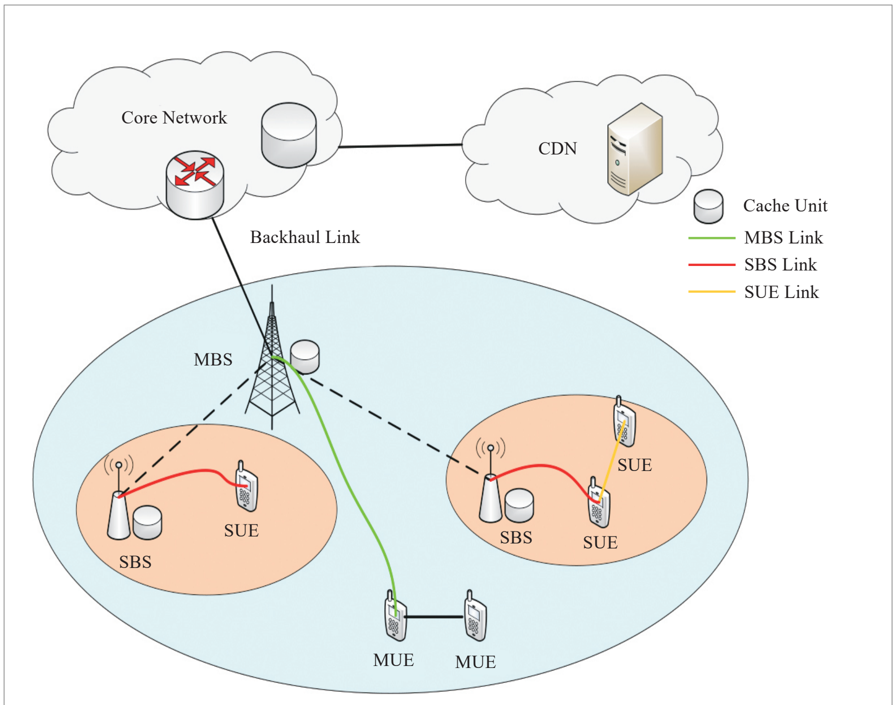
2 Mobile Edge Caching

Many caching schemes pose such questions as where to cache, what to cache, and how to cache. Answers to these questions provide us with better caching solutions. A lot of research work has been done in trying to answer some of the above questions using various methods. Heuristic, stochastic and various optimization techniques have been applied on caching solutions. As the network gets so dynamic and complex, such methods become too difficult and complex to be implemented, hence the introduction of machine learning in the caching solutions to mobile edge caching (architecture shown in **Fig. 2**). In this section, we will survey the research efforts that have been made in the mobile edge networks. The related issues include caching entities, content description, caching policies, content delivery, and so on.

2.1 Caching Entities

Caching units can be deployed in many places of a mobile network, such as the core network, RAN, user devices and current UAVs, to cater for mobile users. Currently the widely deployed places of caching is the EPC [4]. By caching content at the mobile core network, the mobile traffic can be reduced. The caching places at the edge network are discussed as follows.

1) Macro BS (MBS) caching: In heterogeneous networks, MBSs have more coverage areas and can serve more users. Caching at the MBS can obtain better cache hit probability. CAO and CAI in [21] investigated a context-aware proactive caching problem in a heterogeneous network consisting of a single MBS with grid power supply and multiple small-cells with energy harvesting, aiming to maximize the service ratio at the SBSs. The authors of [22] presented Wolpertinger architecture for content caching at the macro base station. The proposed framework aims at maximizing the long-term cache hit rate and it requires no knowledge of the content popularity dis-



▲Figure 2. Architecture of edge caching.

tribution. Furthermore, Context-aware data caching in the heterogeneous small cell networks (HSCNs) with MBS caching was proposed in [23], [35] to reduce the service delay for end users.

2) SBS caching: SBSs are densely deployed in next generation heterogeneous networks. Therefore, caching at SBSs is another good choice since the SBSs are more close to end users and usually provide higher data rates. Many researchers [18], [21], [24] have studied the performance of caching at SBSs.

3) Device caching: device-to-device (D2D) communication is one of the key technologies in 5G networks. The storage resources in mobile devices can be exploited. The QoE of users can be greatly improved by caching contents in mobile devices if the caching strategy is carefully designed. In [25], the D2D caching problem was modeled as a multi-agent multi-armed bandit problem and Q-learning was used to learn how to coordinate the caching decisions. Several D2D caching schemes with the application of learning techniques have been proposed [26]–[29].

4) UAV caching: A new trend of caching entity is the use of UAVs as a flying BS to cache popular contents that would be able to serve mobile users. The authors of [6] solved the problem of content caching with multi UAVs while considering the user mobility by using a novel algorithm based on the machine learning framework of conceptor-based echo state networks. In this framework, the agent is able to learn the mobility patterns and request distributions of the users; based on that, it can predict the contents for caching at the UAVs and the location of the UAVs, and can effectively deliver the contents to the users. Additionally, the liquid state machine is used to maximize the queue stability requirements of users while caching the contents at the UAV [30].

2.2 Caching Policies and Algorithms

To decide what to cache, the caching policies and algorithms are used in the edge networks and the popularity of content should be considered to maximize the hit probability of cache, i. e. , the probability that the content requested by users is cached in the edge networks. Even though content popularity can be grouped into Static [31] and Dynamic [28], [32], the static ones cannot reflect the real content popularity which is time varying so the dynamic one is more realistic and suitable for the learning based caching schemes. The commonly used popularity model is the Zipf model observed in web caching [33].

A host of caching policies and algorithms have been proposed in mobile caching. Some of the conventional caching policies in wired networks are also applicable in wireless networks. In addition, new schemes such as learning based policies and cooperative caching policies are also proposed. The literature [16] reviews in detail the conventional caching policies and forwarding mechanism in information centric networks.

1) Conventional versus learning based caching policies: Content replacement policies such as the least frequently used (LFU) and least recently used (LRU) have been adopted in a large number of caching policies [16]. These strategies are simple and efficient with uniform size objects. However, these policies ignore the download latency and size of objects. Another proactive caching policy used in content delivery networks is the most popular video (MPV) policy, which caches the most popular videos based on the global video popularity distribution [34]. However, the cache size of the RAN is very limited compared to that of CDN. The hit probability achieved by MPV policy could be too low for RAN caches. On the other hand, the content popularity is time-varying and is not known in advance. Therefore, the track and estimation of timely content popularity is an important issue. Based on machine learning technology, learning based caching polices were proposed in [35]. The authors in [35] solved the problem of distributed caching in SBSs from a reinforcement learning view. By adopting coded caching, the caching problem is reduced to a linear program that considers the network connectivity and the coded caching scheme performs better than the uncoded scheme. The authors in [36] solved the cache replacement problem with a Q-learning based strategy.

2) User preference based policies: In [34], the authors proposed a user preference profile (UPP) based caching policy. It is observed that local video popularity is significantly different from national video popularity and users may show strong preferences toward specific video categories. The UPP of each user is defined as the probability that a user requests videos of a specific video category.

3) Non-cooperative versus cooperative caching: Some of the existing caching policies decide the content to cache at each base station without considering the cooperation among BSs. In [34], the proposed scheme makes caching decision based on the UPP of active users in a specific cell without considering the impact of caches in other cells. In [36], the cache replacement problem modeled as Markov Decision Process (MDP) is solved in a distributed way using Q-learning method, without exchanging extra information about cached data between the BSs. This strategy outperforms the conventional ones such as the LFU, LRU and randomized strategy. However, a lot of existing works have studied the cooperation among cache entities when designing the caching policies [26], [37]–[40].

2.3 Caching of Different File Types

The most common file types for caching is multimedia files such as popular videos and audio files [26], [38], [41]. One essential trait of multimedia data is that many users have the same affinity for popular contents, thus caching of such contents aid in improving the hit rate. The Internet of Things is one of the main use cases of the next generation 5G networks. IoT refers to a large number of "things" (devices, objects, humans and animals with unique IDs) connected via the Internet that can share data. Thus the caching of IoT data (sensory and any kind of data including multimedia data) is also important for reducing the total traffic load as the IoT data volume is increasing and IoT data have different characteristics such as short lifespan of the data as compared to multimedia data [42], [43].

2.4 Mobility versus Static User Awareness

User mobility is a unique feature of wireless networks, thus it should be considered in caching at the network edge. Many works have been done on this issue. The authors in [44] proposed a temporal-spatial recommendation policy, which can guide mobile users to request their preferred files in proper time and place, so as to make local popularity peakier. Here the assumption was that the user preference, the impact of the recommendation on request probability, and the mobility pattern are unknown. Hence, they resorted to deep reinforcement learning to optimize the recommendation and caching policy. User mobility in the caching policies was also considered in [29] and [45].

2.5 Impact on System Performance

1) Capacity: Existing works on edge caching have proved that caching at the network edge can significantly improve system capacity. For example, the solution proposed in [34] can improve capacity by 3 times compared to having no cache in the RAN.

2) Delay: Caching at the network edge can significantly reduce content delivery delay due to the proximity of caches to end users. In [26], the reinforcement learning cooperative content caching scheme significantly reduced content downloading latency and improved content cache hit rate when compared with other popular caching schemes. In [39], the authors investigated a delay minimization problem by jointly considering the spatiotemporal variation of content variation, the cost of content sharing between user devices, and the cost of cooperative caching among BSs, using a two-stage multi-armed bandit learning based online cooperative algorithm.

3) Spectral efficiency: a deep reinforcement learning (DRL) based algorithm was developed for coded caching enabled Fog RAN (F-RANs) in [46] to provide high spectral and energy efficiency. With the help of new designed fog access points (F-APs), F-RANs can take the full advantage of local caching capabilities, which relieves the load of fronthaul and reduces transmission delay. In [47], a cache content management policy was proposed, which exploited the popularity of the contents in order to increase the chances of D2D communications. With extensive simulations in [47], it was observed that the proposed Q-learning algorithm indeed learns by reserving near-optimal number of resource blocks (RBs) to serve the data rate requirement at each distributed D2D controller (DDC) and that the one-and two-hop modes of D2D transfer effectively reduces the load on eNB by transferring a maximum 49% of the required data to the user equipment (UE). A summary of the issues affecting edge caching is shown in **Table 1**.

3 Learning Based Caching

The traditional optimization techniques become complex and difficult to solve due to the complex nature of the caching problems. Therefore, the machine learning approaches are introduced into solving these kinds of problems. Machine learn-

▼Table 1. Summary of literatures on edge caching

Work Area	Literature	Key Points
Caching entities	[15], [21], [23], [31], [37], [47], [49], [51] – [53]	Macro base station (MBS)
	[18], [21] – [25], [28], [29], [31], [35] – [38], [41], [43], [44], [46], [49], [50], [52] – [54]	Small base station (SBS)
	[25] – [29], [39], [47], [51], [55]	Device
	[6], [30], [55], [56]	Unmanned aerial vehicle (UAV)
Content popularity	[31]	Static model
	[6], [21], [22], [24], [26] – [29], [32], [34] – [36], [39] – [41], [44], [45], [49], [50] – [52], [54] – [57]	Dynamic model
Caching policies and algorithms	[16], [34], [48]	Conventional caching policies
	[28], [29], [34], [44], [52], [58]	User preference based polices
	[6], [21] – [30], [35] – [41], [43] – [47], [49] – [51], [53] – [57]	Learning based policies
	[34]	Non-cooperative policies
	[22], [23], [26], [28], [30], [37] – [40], [51], [54], [55], [57]	Cooperative policies
Caching file types	[6], [21] – [24], [26] – [30], [32], [34] – [41], [44] – [47], [49] – [51], [53], [55], [57] – [59]	Multimedia data
	[42], [43], [48], [59]	Internet of Things (IoT) data
Mobility awareness	[6], [29], [30], [44], [45], [48], [49], [51], [52]	Spatial and temporal properties of user mobility
Problem	[23], [24], [26], [27], [34], [37] – [39], [41], [43], [46], [50], [52], [55], [58]	Delay
	[22] – [26], [37], [44]	Hit rate
	[35], [36], [39] – [41], [45] – [47]	Backhaul/fronthaul
	[6], [34], [49], [58],	Quality of experience (QoE)

ing techniques are generally grouped into the supervised learning, unsupervised learning, and reinforcement learning. This section will discuss the application of these learning techniques in caching.

3.1 Supervised Learning Based Caching

The majority of practical machine learning uses supervised learning. Supervised learning uses an algorithm to learn the mapping from input variables X to the output variable ($Y = f(X)$) based on example input-output pairs. The goal would be a model that would approximate the mapping function so well that when you have new input data (X), you can predict the output variables (Y) for that data.

VARANASI and CHILUKURI [48] proposed a differentiated edge caching scheme called FlexiCache for vehicle to anything (V2X) communication, aiming at increasing the QoS of the network; kernel ridge regression (KRR) is used to predict the proportion of cache to be allocated to each traffic type, for a desired QoS parameter.

CHEN, et al. [30] used the liquid state machine to solve the problem of joint caching and resource allocation in a network of cache-enabled UAVs that serve wireless ground users over the Long Term Evolution (LTE) licensed and unlicensed bands.

SHEN et al. [49] considered caching selected contents of SBSs in an ultra-dense network (UDN). The cache efficiency problem is formulated as a system backhaul load minimization problem, which is hard to be solved for the highly random content demands. Therefore, the cache strategies based on machine learning (K-means and K-Nearest Neighbour (K-NN)) were proposed to tackle this difficult problem from the perspective of exploiting the potential of mobile traffic data. Other machine learning schemes include [23], [38], [40], [50], etc.

3.2 Unsupervised Learning Based Caching

For unsupervised learning, you only have input data (X) and no corresponding output variables. The goal of unsupervised learning is to learn more about data by modeling the underlying structure or distribution in the data. The algorithms are left to their own devices to discover and present the interesting structure in the data. Examples are found in the literatures [27], [28], [32], and [49].

In [49], the K-means clustering algorithm was used to fully uncover hidden spatio-temporal patterns of content requests at SBSs, and achieve personalized inter-cluster cache and predictive intra-cluster cache. Then, the K-NN classification algorithm was introduced to categorize the constantly emerging new contents and cache them in the corresponding cluster periodically with high accuracy and low complexity.

The authors in [27] proposed an efficient learning-based caching algorithm operating together with a non-parametric estimator to minimize the average transmission delay in D2D-enabled cellular networks. It is assumed that the system does not have any prior information regarding the popularity of the files, and the non-parametric estimator is aimed at learning the intensity function of the file requests. An algorithm was devised to determine the best <file,user> pairs that provide the best delay improvement in each loop to form a caching policy with very low-transmission delay and high throughput. This algorithm was also extended to address a more general scenario, in which the distributions of fading coefficients and the values of system parameters potentially change over time.

In order to learn user preference, the authors of [28] modeled the user request behavior resorting to probabilistic latent semantic analysis and the model parameters are learned by the expectation maximization algorithm. They found that the user preferences are less similar and the activity level and topic preference of each user change slowly over time. Based on this observation, they introduced a prior knowledge-based learning algorithm for user preference, which can shorten the learning time.

Based on SDN, the authors of [32] proposed a deep-learning-based content popularity prediction (DLCPP) to achieve the popularity prediction. DLCPP adopts the switch's computing resources and links in the SDN to build a distributed and recon figurable deep learning network. For DLCPP, they initially determine the metrics that can reflect changes in content popularity. Each network node collects the spatial-temporal joint distribution data of these metrics. Then, the data are used as input to stacked auto-encoders (SAE) in DLCPP to extract the spatiotemporal features of popularity. Finally, the popularity prediction is transformed into a multi-classification problem through discretizing the content popularity into multiple classifications. The Softmax classifier is used to achieve the content popularity prediction.

3.3 Reinforcement Learning Based Caching

In reinforcement learning, an agent is able to learn from its environment and take some action so as to maximize some notion of cumulative reward with or without a model. The authors of [22], inspired by the success of DRL in solving complicated control problems, presented a DRL-based framework with Wolpertinger architecture for content caching at the base station. The proposed framework is aimed at maximizing the long-term cache hit rate, and it requires no knowledge of the content popularity distribution. SUNG et al. [37] applied reinforcement learning (Q-learning) to the content replacement problem in a wireless content delivery network (WCDN) with cooperative caching to maximize the hit ratio based on a multi-agent Q-learning scheme.

CHENG et al. [52] proposed a novel localized deterministic caching framework, based on machine learning techniques. By introducing the concept of the rating matrix, they first proposed a new Bayesian learning method to predict personal preferences and estimate the (individual content request probability) ICRP. This crucial information was then incorporated into their caching strategy for maximizing the system throughput, or equivalently, minimizing the download latency, where a deterministic caching algorithm based on reinforcement learning was proposed to optimize the content placement. The authors of [42] presented fundamentals of caching, major challenges, relevant state of the art, and a description of their current approaches. They showed directions of using machine learning for caching in the IoT.

Additionally, the authors of [58] proposed a multi-agent reinforcement learning (MARL)-based cooperative content caching policy for the MEC architecture when the users' preference is unknown and only the historical content demands can be observed. They formulated the cooperative content caching problem as a multi-agent multi-armed bandit problem and proposed a MARL-based algorithm to solve the problem. In [26], the D2D caching problem is modeled as a multi-agent multi-armed bandit problem and use Q-learning to learn how to coordinate the caching decisions. The user devices can be independent learners if they learn the Q-values of their own actions, or joint action learners if they learn the Q-values of their own actions in conjunction with those of other UEs. The authors of [25] presented Stimulable Neural Network (SNN)-Cache that leverages SNN to utilize the inter-relationships among sequenced requests in caching decision, evaluated SNN-Cache using an ICN simulator, and showed that it decreases the load of content servers significantly compared to a recent size-aware cache replacement algorithm (up to 30. 7%) as well as the traditional cache replacement algorithms.

Furthermore, SADEGHI et al. [57] introduced a novel approach to account for space-time popularity of user requests by casting the caching task in a reinforcement learning (RL) framework for heterogeneous networks (Hetnets). HE et al. [51] formulated an optimization problem to maximize the network operator's utility while considering the trust-based social networks specifically with MEC, in-network caching and D2D communications under the umbrella of a 3C framework using a deep reinforcement learning approach. An integrated framework that can enable dynamic orchestration of networking, caching and computing resources to improve the performance of next generation vehicular networks was studied in [60] and in this framework, the resource allocation strategy is formulated as a joint optimization problem and DRL is used for problem solving. The authors of [61] dealt with an information-centric virtualized network for smart cities with a deep Q learning approach for caching. There are other reinforcement based caching schemes proposed in [26], [29], [43], [44], [46], [50], and [59]. **Table 2** summarizes some of the machine learning techniques applied to mobile edge caching.

4 Challenges and Future Directions

Like traditional networks, wireless networks are faced with similar challenges like communication cost, storage and computation. The major challenge of caching is the limited storage space. Because of this, a caching scheme must carefully consider the caching decision and replacement techniques to overcome the challenge and improve the performance such as backhaul traffic, latency, and throughput of the network.

4.1 Online Caching

Caching has the content placement phase during which the content is placed in the caching unit and the content delivery phase during which the content is actually delivered to the end user (entity). At some point in the life span of the content, the content may require updating. One efficient caching update is update during the content delivery phase rather

▼Table 2. A summary of machine learning techniques applied to edge caching

Type of Machine Learning	Literature	Algorithm
Supervised learning	[6]	Eco state network
	[30]	Liquid state network
	[22], [49]	K-Nearest Neighbour (KNN)
	[48]	Kernel ridge regression (KRR)
	[38], [40], [50]	Deep learning
	[23]	Convolutional neural network (CNN)
	[25]	Stimulable neural network (SNN)
Unsupervised learning	[27], [28], [32], [49]	K-means
	[27], [28]	Greedy based algorithm
	[32]	Stacked auto encoders (SAEs) deep learning
Reinforcement learning	[57]	Q-learning
	[44] – [46], [51]	Deep Q-learning
	[60]	Double-dueling-deep Q-network
	[22], [34], [37], [43]	Actor critic
	[26], [58]	Multi agent Q-learning
	[21]	Post decision state based approximate RL (PDS-ARL)
	[52]	Discrete learning automata (DLA)

than the content placement phase. This is known as online caching. Online caching together with machine learning presents itself as an important direction in the future cache research.

4.2 UAV Caching

A major problem of mobile edge caching is the mobility of users. Mobile users tend to dissociate themselves from their associated base stations. The advent of UAV caching and machine learning techniques in the future 5G networks would help to solve this bottleneck by employing UAVs as flying base stations to help to proactively cache content for such mobile users. The UAV can assist cellular networks or can be a complete UAV network on their own depending on the application.

4.3 Context Awareness

The mobile edge networks are advantageous in exploiting context information (user location, other surrounding users, and resources in the environment). The real time context aware applications could be accomplished with the use of machine learning by collaborations among MEC platforms.

4.4 Virtualization

In the future 5G networks, different service providers would be providing different services with different QoS and QoE. Network infrastructure are expensive, so there is the need for the research into providing virtual networks that would be able to efficiently share and utilize the underlying physical infrastructure.

4.5 Integration

The architecture of mobile edge networks involves resources such as computing, storage and communications. The efficient integration of these resources to achieve the optimal performance for all users and applications is an ongoing research direction that is not concluded. More comprehensive resource allocation schemes need to be developed.

5 Conclusions

This paper surveys and summarizes the research efforts made on the mobile edge caching and communication resources. The related issues of caching are discussed. Additionally, machine learning based caching schemes are discussed and summarized. In this survey, we group the machine learning based caching into reinforcement learning and other learning techniques. We realize that reinforcement learning is more widely used because of its ability to interact and learn from the environment with or without a model. The more recent UAV caching is also introduced which is able to deal with mobile users that request content. Finally, the challenges and future works on mobile edge caching are discussed.

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