Characterizing User Association Patterns for Optimizing Small-Cell Edge System Performance

Fan Wu, Feng Lyu, Huaqing Wu, Ju Ren, Yaoxue Zhang, and Xuemin (Sherman) Shen

Abstract

Edge computing is a promising paradigm to support multifarious time-sensitive applications. In this article, we shed light on data-driven approaches to optimize edge system performance via mining user association patterns in the wireless local area network (WLAN). Particularly, we first describe the association traces (containing more than 50,000 users) that are collected in one operational WLAN network. We then conduct the data analytics to mine user association patterns that have impacts on edge system performance. To leverage our findings, we propose three data-driven approaches to optimize the edge system performance, that is, efficient edge resource deployment, mobility-aware user service migration, and distributed cooperative learning for edge intelligence. Finally, we cast a case study on distributed learning by devising a cooperation scheme, named co-location time scheme (*CoLo*) (e.g., C-Located learning), which can leverage the user association patterns to distribute learning tasks. Extensive data-driven experiments corroborate the efficacy of *CoLo* in comparison with state-of-the-art schemes.

Introduction

According to the latest IDC's forecast, there will be more than 100 billion terminals and devices connected globally in 2022, and more than 40 percent of data will be analyzed, processed, and stored at the network edge [1]. Edge computing is a promising paradigm to support multifarious time-sensitive applications with providing computing resources, communication capabilities, and storage resources via small-cell networks (e.g., WiFi). For instance, IEEE 802.11 (WiFi) wireless local area networks (WLAN) have become a popular technology to provide Internet access services for widely dispersed wireless users. However, in the small-cell edge system, enormous users have various mobility patterns and diversified traffic demands for different applications, for example, AR/VR, HD map, mobile gaming, and Live show, and the unbalanced workload distribution among different access points (APs) can pose significant challenges in the edge facility deployment. In this case, it means that user association patterns change in real time and can lead to unbalanced network load as user demand changes. In addition, the current edge system cannot adjust resources dynamically for different APs since the future traffic demands of mobile users are unknown ahead. Due to the mobility and resource-constrained characteristics of mobile users, the service qualities of users vary from one physical environment to another, requiring service migration technologies to compensate for the impact of changes in network connectivity. Moreover, as user size and mobility increase, the network becomes more dynamic, making the service migration challenging in the WLAN edge system. Besides, some intelligent algorithms require distributed cooperations among users, while the heterogeneous characteristics and mobility of users may lead to algorithm failures, which can affect the edge system performance significantly. Therefore, the current edge computing technologies have some limitations in edge facility deployment, service migration, and distributed intelligence, and how to improve the performance of small-cell edge to meet the various types of user demand is an open issue.

In the literature, edge computing has been extensively studied in terms of edge facility deployment, server migration, and distributed intelligence. Firstly, some edge mechanisms have been proposed to improve system performance, including edge cache deployment and allocation, edge resource sharing, and scheduling schemes [2]. Secondly, most works on service migration try to find the best trade-off between resource allocation and service delay in mobile edge computing [3, 4]. For example, to understand the impact of user dynamic requests, authors of [3] adopted the Lyapunov technology to decompose the long-term optimization problem into a series of real-time optimization sub-problems, which can improve the mobile edge service performance efficiently. Lastly, the problem of how to deploy intelligence algorithms on the edge side has been studied in [5, 6] to improve the system performance. To explore user mobility patterns, some data analytic works have been conducted to model user behavior in the WLAN and cellular operators systems [7–9]. For instance, the authors [7] propose a user association scheme to improve resource utilization for WLAN, which considers signal quality, AP loads, and traffic requirements.

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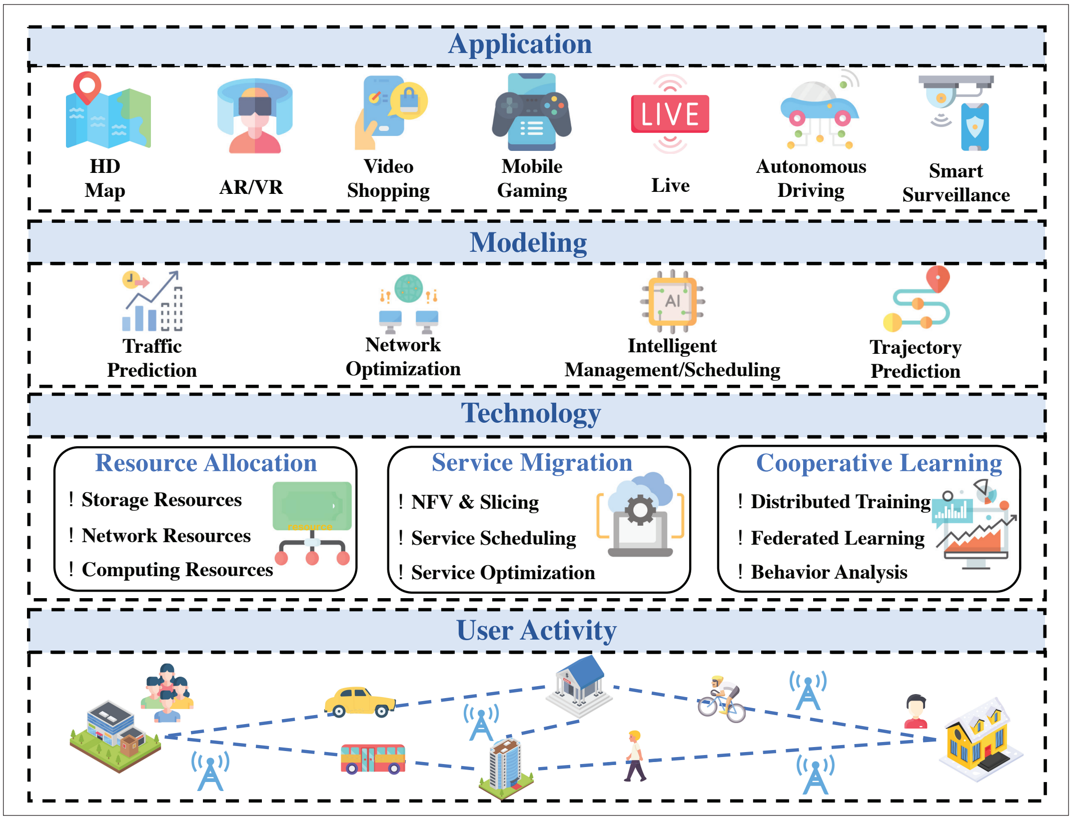

FIGURE 1. Overview of architecture in WLAN edge systems.

However, the current schemes do not systematically characterize user association patterns to efficiently optimize the edge system performance, which motivates us to design a data-driven architecture for performance optimization solutions.

Different from the existing works, in this article, we investigate data-driven approaches to optimize the overall performance of small-cell edge systems by characterizing user association patterns. We first describe user association traces from more than 50,000 users and 8,000 APs over seven weeks at a campus WLAN system. Then we mine the user association patterns based on data analytics, that is, revealing highly-skewed user association distribution, understanding user mobility regularity, and characterizing user face-to-face sociability. To improve the performance of WLAN edge systems, we elaborate on three major optimization approaches: efficient edge facility deployment, mobility-aware user service migration, and distributed cooperative learning for edge intelligence. In the case study, we propose a common location time cooperation scheme, named *CoLo*, to distribute learning tasks by using the user association information, which selects the users with common time in the same AP. The extensive data-driven experiments demonstrate that *CoLo* can reduce the training time and communication overhead significantly.

The rest of this article is organized as follows: We first present the preliminaries on the WLAN edge system. Then we mine the user association patterns based on data analytics, and elaborate on the optimization approaches for the WLAN edge system. Finally, we carry out a case study to demonstrate the efficacy of *CoLo*, which is followed by the conclusion.

Preliminaries on the WLAN Edge System

WLAN Edge System

Figure 1 shows the architecture overview of a WLAN edge system, which consists of user activity layer, technology layer, modeling layer, and application layer. In the user activity layer, users may move along different trajectories by different means of transportation (e.g., car, bus, and bicycle), which may lead to various service demands in different locations. In the technology layer, resource allocation and service migration are two important approaches to improve the performance of WLAN edge systems. In addition, machine learning methods can be utilized to model user behavior, which can guide resource allocation and service migration methodologies in WLAN edge systems. In the modeling layer, different modeling approaches, such as traffic prediction, network optimization, intelligent management and scheduling, and trajectory prediction, can be leveraged to meet various user requirements. In the user application layer, multifarious applications (e.g., AR/VR, HD map, mobile gaming, and Live show) pose stringent requirements on the performance of WLAN edge systems, which may go beyond the capability of current technologies.

Association Data Description

In this article, we adopt the association data of users from a large-scale campus WiFi system (The data set is available at https://github.com/Intelligent-WiFi/DataSet.). The dataset records the details information of the user's associated AP, which can help capture fine-grained user behavior patterns in the WiFi system. For instance, each

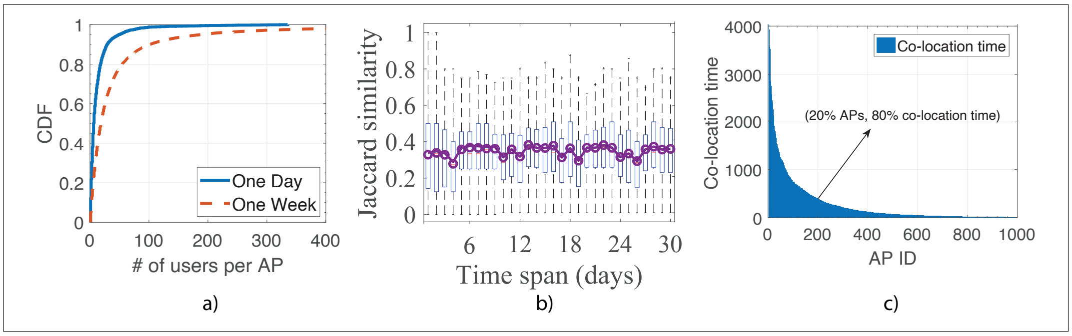

FIGURE 2. User association patterns: : a) user association distribution; b) user mobility from different APs; and c) user face-to-face sociability.

user logs into the campus WiFi system with a unique user name, and the system collects the user's access time, departure time, usage data, and associated AP ID information. APs are deployed in various places on the campus, covering all buildings (e.g., laboratories, libraries, gymnasiums, and dormitories) to provide network access services for all users. We focus on user connection data on 8255 APs in 163 buildings from April 26, 2019 to June 3, 2019, including a total number of 18,834,772 records generated from 55,131 MAC addresses (users).

Mining User Association Patterns

In this section, we introduce the user association patterns from three major perspectives to characterize user mobility in the WLAN edge system, that is, highly-skewed user association distribution, user mobility regularity, and user face-to-face sociability.

Highly-Skewed User Association Distribution

The information on user-AP associations cannot only show the user's own spatial-temporal characteristics, but also reflect the user's mobility and sociability. Figure 2a shows the cumulative distribution function (CDF) of the number of users per AP. Specifically, we count the number of users associated with each AP during one day and one week, respectively, to extract user association information from the trace data. We can observe an increase in the number of users associated with an AP as the time period changes from one day to one week. For instance, we can see that the probabilities that more than 50 users are associated with the same AP in one day and one week are 0.05 and 0.22, respectively, as shown in Fig. 2a. In addition, it can be seen that the median and mean are 0.97 and 0.9 in one day, and 0.98 and 0.95 in one week, respectively. Skewness is a way to describe the symmetry of a distribution. In a left skewed distribution, the mean is less than the median. It indicates that the user association distribution is highly skewed and affected by the associated AP and time period. When a user is associated with different APs, the various stay time and traffic consumption reflects the user's preferences for different APs.

Understanding User Mobility Regularity

In the wireless scenario, user mobility has been extensively studied [10, 11], such as by using GPS trajectories. In the WLAN system, a user's movement can be inferred from the user association record showing that the user switches among different APs. In this case, the user's trajectory can be represented by the list of its associated APs, and the trajectory similarity can reflect the regularity of user behavior [12]. It means that the user's trajectory similarity can be represented by the similarity of the user's associated APs, and we can use Jaccard similarity to model the user association similarity. Therefore, we can use user association similarity to characterize the similarity of user activities in different time periods. In Fig. 2c, we present the box plots of Jaccard similarity for the top 200 active users in a month by using the user association record. Particularly, for a user on a given day, the user association Jaccard similarity is calculated by comparing the associated AP set of the current day with that of the previous day. We can see that user association Jaccard similarity is relatively small and varies for different days, which means that user trajectory has a low level of regularity. For instance, the median user Jaccard similarity is around 0.3 and the 75th percentile is below 0.5, which indicates that the user trajectory varies differently each day. On the other hand, when the Jaccard similarity of user associations increases, it means that the user trajectory shows a higher level of regularity.

Characterizing User Face-to-Face Sociability

Generally, user association characteristics differ at different APs. To understand the user's face-to-face sociability, we define the co-location time during which users associate with the same AP, where a user can only associate with one AP at a time. We can use the co-location time as a metric to measure how close multiple users are. For example, when the co-location time of two users increases, we can infer the common location event for the users, for example, conversations, course learning, dining, meeting, etc. When two users are associated with the same AP over 15 minutes, we count the overlapping time as a co-location time, that is, a co-location time slot is 15 minutes in this article. Then we count the total co-location time for users associated with each AP in a day, and sort APs based on the co-location time. In Fig. 2c, we plot a histogram for co-location time in top 1000 APs. It shows that more than 80 percent of the user's co-location time is spent on 20 percent of the APs, which suggests that most users are associated with a limited number of APs. Therefore, we can use the user co-location time to detect social interaction among users.

Data-Driven Optimizing Approaches

With the unprecedented number of edge devices in WLAN scenarios, edge infrastructure deployment and resource allocation should be scalable and adaptive to users' mobility patterns. In Fig. 3, we present a three-layer data-driven architecture to characterize user mobility in WLAN edge systems. The architecture consists of user mobility layer, characteristics layer, and abstraction layer, to fully describe user mobility patterns from different dimensions. Particularly, in the user mobility layer, users can take various types of transportation (e.g., bus, taxi, car, and cycling) to get to their destinations and connect to nearby wireless APs to access the network. In the characteristics layer, we can capture user mobility characteristics by calculating the stay time, co-location time, and flight time[1] based on user association records. For instance, a user's stay time and the corresponding network traffic consumption on an AP reflect the user's preference for the AP. Moreover, the potential face-to-face sociability can be inferred based on the co-location time. We can also describe the user's trajectory by utilizing the flight time in different APs. In the abstraction layer, user mobility patterns are further extracted and modelled. Specifically, machine learning-based approaches can be leveraged for the modelling and prediction of user mobility patterns.

In the large-scale WLAN edge system, the three-layer data-driven architecture can effectively discover underlying patterns and hidden logical relationships, which can guide application and model design in mobility scenarios, especially with enormous data volume. In addition, due to the loose coupling relationship between layers, the layer-based data-driven architecture enables flexible design of learning-based models and algorithms by characterizing user movement patterns, without considering the various number of users. In the following, we show three major optimization approaches to improve the WLAN edge system performance, that is, efficient edge facility deployment, mobility-aware user service migration, and distributed cooperative learning for edge intelligence.

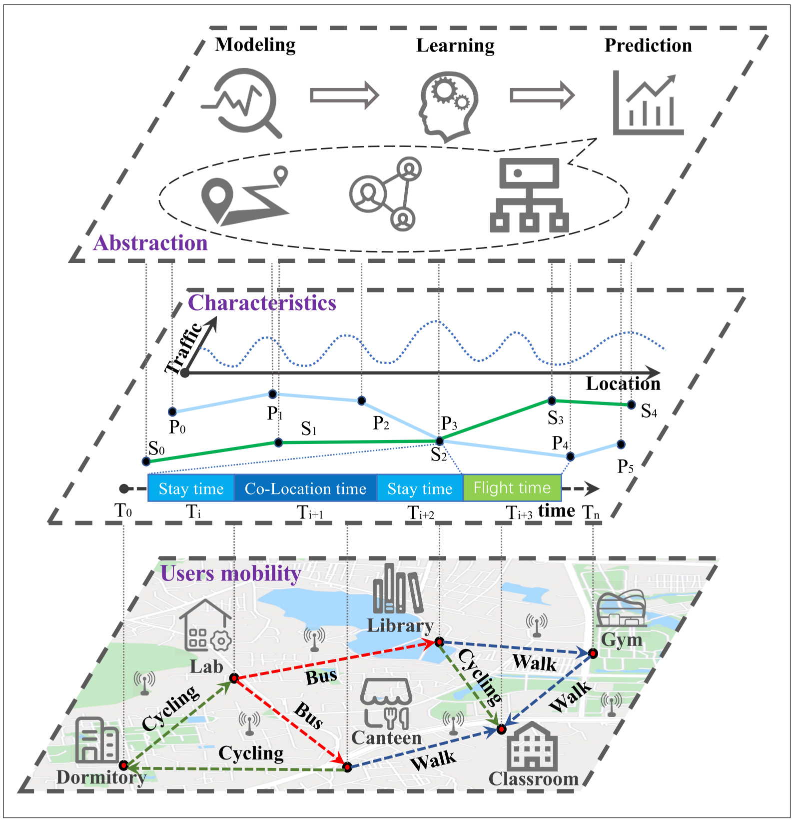

FIGURE 3. Data-driven architecture for user mobility characterization in WLAN edge systems.

Efficient Edge Facility Deployment

Edge facility deployment directly affects the user's service response time and the overall performance of the edge system [1, 13]. Most of the existing research work is carried out from the perspective of model optimization. The impact of the data request law and user mobility law on the deployment of edge facility has rarely been considered. In the WLAN edge system, user behaviors (e.g., user mobility and service request variation) will cause edge service load variation. Therefore, how to use user behavior patterns to guide edge node deployment is a valuable research direction. Figure 4a shows a typical cloud-edge-device scenario, which consists of a cloud server, multiple edge nodes, and users in WLAN. To achieve maximum benefits in the WLAN edge system, we focus on the following research issues for edge node deployment. Firstly, through the association distribution and traffic consumption variation, we can analyze users' preferences for different APs, which can be further utilized to facilitate the design of the edge node deployment scheme. For example, the importance of APs can be evaluated based on user preferences, and then edge servers can be deployed on important APs to improve the edge system performance. Secondly, the relationship between the AP traffic consumption volume and the number of associated users can be explored and utilized to empower efficient resource management. To make the case more general, we can further extend the system by considering different user requirements in various scenarios (e.g., mobile game, tasks training, and live show). Last but not least, by analyzing user mobility patterns, we can find users with similar moving trajectories and users with frequent movement, which can guide edge node deployment to reduce service migration caused by user mobility. In short, user behavior patterns can be comprehensively leveraged based on the three-layer data-driven architecture to improve edge facility deployment efficiency.

Mobility-Aware User Service Migration

User mobility and diversified service requests may cause unbalanced load of edge servers and network congestion, which will seriously reduce the quality of service (QoS) for users. Although edge service migration technology has the potential to ensure continuous services for users and balance the workload among edge servers, it is limited by the communication capabilities, computing resources, and storage capacity of mobile edge networks. Therefore, how to quickly and efficiently migrate edge services according to the real-time user location information has become one of the

[1] The stay time is the duration a user stays in an AP, and the flight time measures how long it takes a user to move from the current associated AP to another AP.

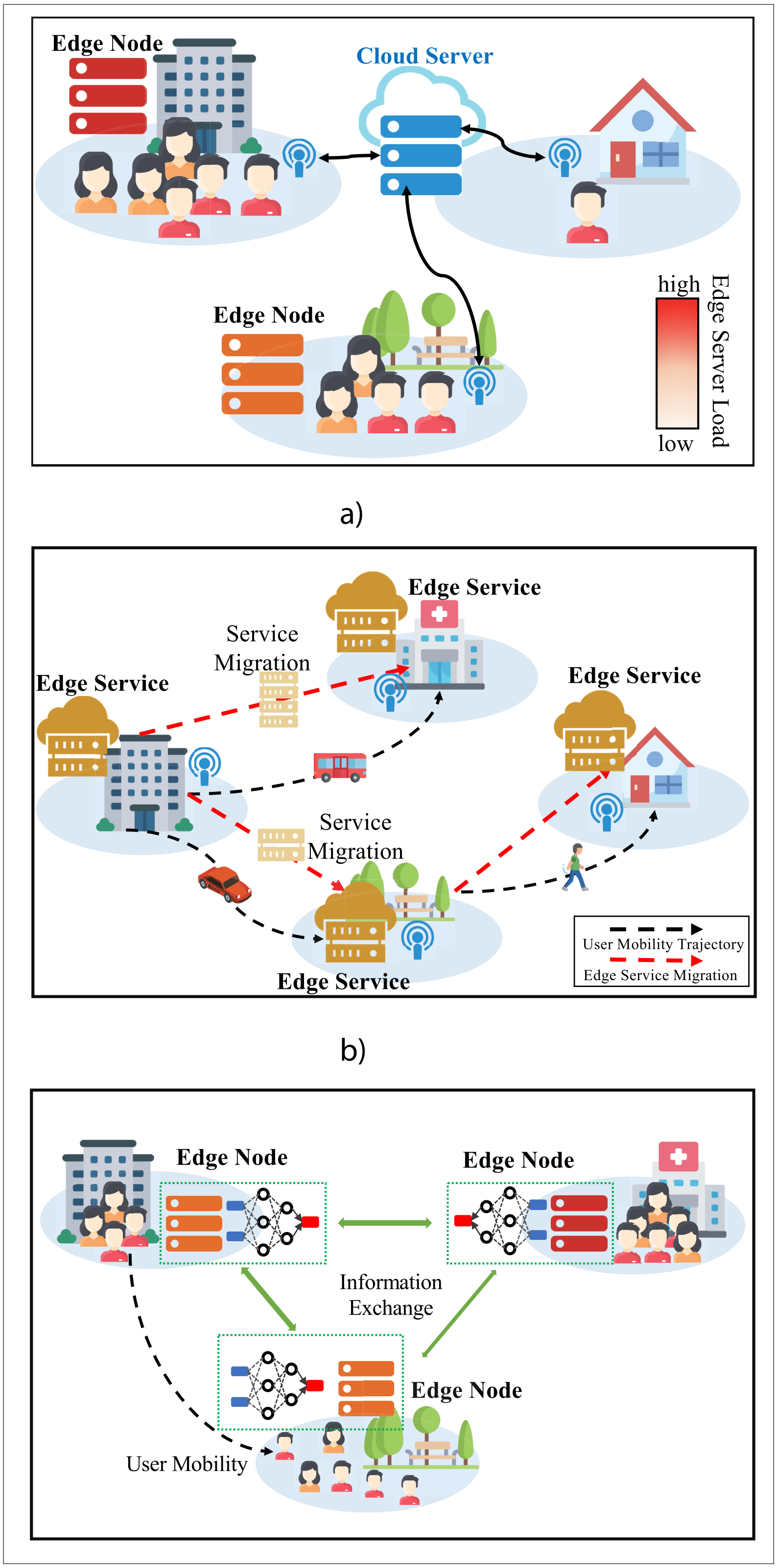

FIGURE 4. Optimization approaches of WLAN edge systems; a) efficient edge facility deployment; b) mobility-aware user service migration; c) and distributed cooperative learning for edge intelligence.

key issues to be solved in mobile edge networks. In Fig. 4b, when a user switches among different APs, the user's movement trajectory can be represented by the switching sequence of APs. To understand the user mobility patterns, it is essential to conduct deep data analytics of user association information in the WLAN edge system. Therefore, we can investigate the following issues for mobility-aware user service migration: Firstly, service migration schemes should be customized for users with diversified mobility patterns. For example, service migration can be conducted proactively to push the desired content to the predicted next user location based on the user mobility regularity. Secondly, user request uncertainty will exacerbate load imbalance in the edge system and thus degrade system performance, especially in a large-scale network scenario. Therefore, we can design a reinforcement learning-based mobility-aware service migration scheme to adapt to the network uncertainty with a low service response time.

Distributed Cooperative Learning for Edge Intelligence

As the computing and storage capacities of edge devices improve, more and more intelligent algorithms are deployed in edge nodes to improve the overall performance of edge systems. For example, intelligent algorithms can be implemented to process real-time data at the edge to improve the decision-making efficiency and accuracy, which can reduce the communication overhead caused by data transmission to cloud services. However, the contradiction between the resource requirements of intelligent algorithms and the limited resources in edge devices is becoming more and more prominent. Therefore, how to utilize user behaviors and mobility patterns to design a distributed cooperative learning scheme for edge intelligence is a crucial research problem in the WLAN edge system. Figure 4c shows a typical distributed cooperative learning scenario for edge intelligence, which consists of mobile users, edge nodes, and intelligent algorithms (deployed in edge nodes). To improve the overall performance of edge computing systems, we focus on the following research issues for distributed cooperative learning. Firstly, we can deploy intelligent algorithms with different resource requirements to edge nodes with different service loads. For example, we can assign training tasks to edge nodes with a low service load and many associated users to reduce the training time. Secondly, to reduce the communication overhead caused by edge data transmission, we can design a distributed model aggregation scheme to update the model parameters in the deployed intelligent algorithms (e.g., federated learning [14]). For example, each device can train a model by using the local data, and then model parameter updates are aggregated at edge nodes without uploading the local data. The model aggregation pattern and frequency can be tailored by considering the users' diversified computing capabilities and dynamic network conditions. Moreover, the edge node can exchange its local model with other edge nodes to refine the model parameters for updating a global model.

In the distributed cooperative learning, the learning tasks should be prudently assigned to mobile users to improve the training efficiency and reduce the training time. In this article, we propose a *CoLo* to distribute learning tasks by analyzing the user mobility behaviors in the WLAN edge system. Specifically, tasks are distributed to users with co-location time to enable parallel training, which can significantly reduce training time. In addition, to reduce the communication overhead, the proposed *CoLo* scheme

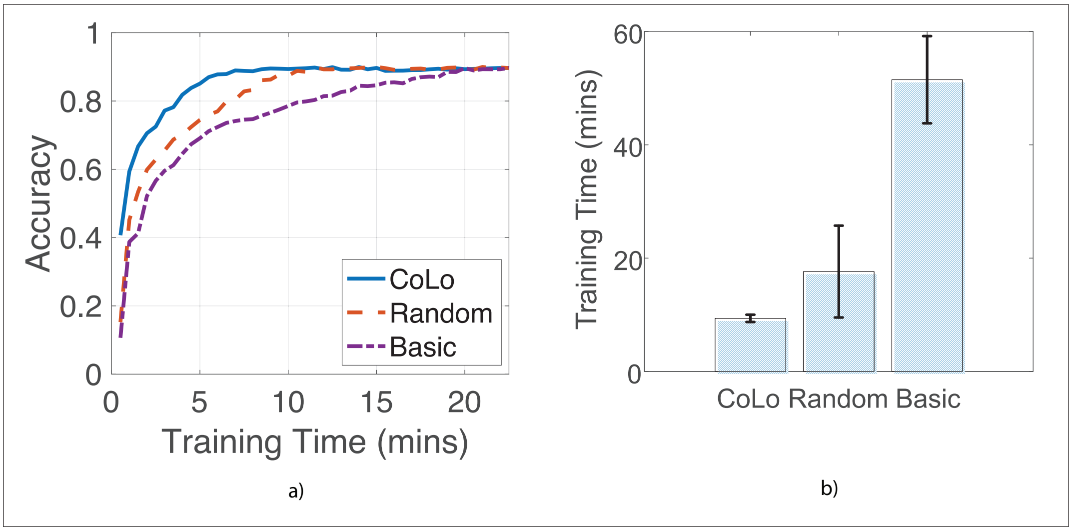

FIGURE 5. Performance evaluation in model accuracy and training time: a) the FedAvg model accuracy; b) the FedAvg model training time.

only synchronizes model parameters to the server without uploading local data by using the federated learning architecture.

Case Study

In this section, we carry out a case study to demonstrate the efficacy of the proposed *CoLo* scheme in the WLAN edge system.

Methodology

Simulation Setup: We consider a distributed learning paradigm to evaluate the proposed *CoLo* by using the widely-used open-source FedML [15] architecture. We consider two common learning models in FedML (i.e., FedAvg and FedGKT) to evaluate the performance of *CoLo*. FedAvg is a baseline federated learning algorithm based on iterative model averaging. In FedAvg, the client updates the local training model to the server and then the server aggregates the local models by weighted coordinate-wise averaging to obtain a global model and updates the global model back to all clients. FedGKT designs a variant of the alternating minimization approach to train a small neural network (e.g., convolutional neural network, CNN) on edge nodes and periodically transfers their knowledge by knowledge distillation to a large server-side neural network. The above models are trained with two common data sets: CIFAR-10 and MNIST. CIFAR-10 consists of training color images and test color images in 10 classes, and MNIST is a data set of handwritten digits. In this article, the default training data set is CIFAR-10 and the training model is FedAvg, and the training is conducted in a server with 8 GPUs and 2 CPUs (8 x NVIDIA V GPU (12GB/GPU); RAM: 1024G; CPU: 2 x Intel Xeon Gold 5218 16C 2.30GHz 22MB 125W). We consider that there are multiple APs connected to the cloud server and each AP acts as an edge node. The training tasks can be assigned to one or multiple users. In addition, the bandwidth for a user-AP connection is set to be 100 Mb/s, and the simulated actual download rate is 30 percent to 35 percent of the bandwidth and follows a uniform distribution.

Baselines: To evaluate the performance of the proposed *CoLo*, we have the following two benchmarks:
- *Random scheme*. In this benchmark, the training tasks are randomly assigned to users without using any association information. In this case, the selected users may have some co-location time in the APs. In addition, Random scheme does not use the centralized training method instead of the federated learning approach to update the model parameters.
- *Basic scheme*. In this benchmark, the training tasks are assigned to the users who have a long association time to APs by using the association information. In addition, we consider that the users can only execute training tasks one by one without parallel training. Basic scheme also adopts the centralized training method.

Performance Metrics: We define the following three metrics for performance evaluation:
- *Accuracy:* Basically, a higher accuracy of model training in FedML is desired. When the model accuracy is stable, it means that the model converges.
- *Training time:* This is the total time for task training until the model converges.
- *Communication cost:* This is the total time used for all users to transmit data during the whole training process.

Performance Comparison

Accuracy: During the training process, we set the default iteration period to be 0.5 minutes. To evaluate the proposed *CoLo*, we plot the average model accuracy results after running 50 iterations for different schemes, as shown in Fig. 5a. We have two major observations. First, in the training process, the model average accuracy of *CoLo* can outperform the other schemes when using the FedAvg algorithm. Second, as the training time increases, all three schemes converge with a model accuracy of around 0.89. The *CoLo*, Random, and Basic schemes converge after about 6 minutes, 12 minutes, and 20 minutes, respectively.

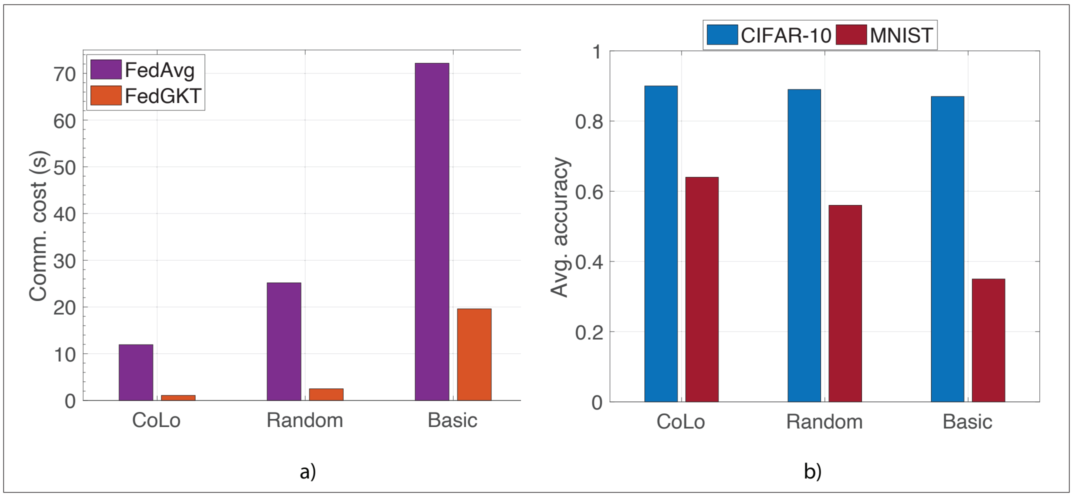

FIGURE 6. Performance comparison with different models and data sets: a) communications cost with different models (i.e., FedAvg and FedGKT); b) the average FedAvg model accuracy with different data sets.

Training Time: Figure 5b shows the training time (mins) for different schemes using the FedAvg model. We have two major observations. First, compared with Random and Basic schemes, the proposed *CoLo* can significantly reduce training time for the same task and FedAvg model. For instance, the average training time is 9.37 mins, 17.63 mins, and 51.5 mins for *CoLo*, Random, and Basic schemes, respectively. In addition, the training time standard deviation of *CoLo* is about 0.64, which increases to 8.1 and 7.6 by adopting Random and Basic schemes, respectively. Second, compared with Basic scheme, Random scheme can achieve a lower average training time in the same training task. The main reason is that Random scheme enables parallel training when users have co-location time, while Basic scheme performs without parallel training. *CoLo* can select all users with co-location time for parallel training by using the user association information and mobility patterns. Therefore, *CoLo* can guarantee the training time performance with high robustness.

Communication Cost: Figure 6a shows the impact of the training model on the communication cost performance of different schemes. We have three major observations:

- *CoLo* scheme outperforms other benchmark schemes significantly in spite of the used training model.
- *CoLo* and Random schemes can significantly reduce the communication cost
- All schemes show a lower communication cost in the FedGKT model, compared with the FedAvg model.

CoLo and Random schemes can significantly reduce the communication cost by using the federated learning approach to update the model parameters, which avoids the communication overhead of transferring training data. In addition, the design of the FedGKT model further helps reduce communication costs, while the federated learning architecture design is still an open research problem.

Impact of Data Sets: Figure 6b shows the impact of data sets on the average model accuracy for different schemes, where the training model is FedAvg. We can easily observe that all schemes perform better when using the CIFAR-10 data set. However, our proposed *CoLo* can significantly outperform the two benchmarks even with the MNIST data set. For instance, when using the MNIST data set, the average model accuracy is about 0.64, 0.56, and 0.35, for *CoLo*, Random, and Basic schemes, respectively.

Conclusion

In this article, we have investigated the data-driven approaches to optimize the edge system performance via mining user association patterns in small-cell networks. By analyzing the user networking traces, we have obtained several user association patterns that can affect the edge computing performance significantly. We have then proposed three data-driven approaches to optimize the small-cell edge computing system, that is, efficient edge facility deployment, mobility-aware user service migration, and distributed cooperative learning for edge intelligence. For the case study, we have devised a scheme named *CoLo* to enhance the distributed learning performance, and conducted extensive data-driven experiments to demonstrate the efficacy of *CoLo*. For the future work, we will investigate the joint task offloading and load balancing problem to further improve the overall performance of the small-cell system.

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References

[1] J. Ren *et al.*, "A Survey on End-Edge-Cloud Orchestrated Network Computing Paradigms: Transparent Computing, Mobile Edge Computing, Fog Computing, and Cloudlet," *ACM Comput. Surv.*, vol. 52, no. 6, Oct. 2019.

[2] H. Wu *et al.*, "Optimal UAV Caching and Trajectory in Aerial-Assisted Vehicular Networks: A Learning-Based Approach," *IEEE JSAC*, vol. 38, no. 12, Dec. 2020, pp. 2783–97.
[3] T. Ouyang, Z. Zhou, and X. Chen, "Follow Me at the Edge: Mobility-Aware Dynamic Service Placement for Mobile Edge Computing," *IEEE JSAC*, vol. 36, no. 10, Sep. 2018, pp. 2333–45.
[4] S. Wang *et al.*, "Dynamic Service Migration in Mobile Edge Computing Based on Markov Decision Process," *IEEE/ACM Trans. Netw.*, vol. 27, no. 3, 2019, pp. 1272–88.
[5] X. Wang *et al.*, "Convergence of Edge Computing and Deep Learning: A Comprehensive Survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, Jan. 2020, pp. 869–904.
[6] J. Park *et al.*, "Wireless Network Intelligence at the Edge," *Proc. IEEE*, vol. 107, no. 11, Oct. 2019, pp. 2204–39.
[7] S. Bayhan *et al.*, "User-AP Association Management in Software-Defined WLANs," *IEEE Trans. Netw. Serv. Manage.*, vol. 17, no. 3, 2020, pp. 1838–52.
[8] G. Xue *et al.*, "Characterizing Sociality for User-Friendly Steady Load Balancing in Enterprise WLANs," *IEEE Netw.*, vol. 29, no. 6, 2015, pp. 26–32.
[9] F. Wu *et al.*, "Boosting Internet Card Cellular Business via User Portraits: A Case of Churn Prediction," *Proc. IEEE INFOCOM*, pp. 640–49.
[10] C. Song *et al.*, "Limits of Predictability in Human Mobility," *Science*, vol. 327, no. 5968, 2010, pp. 1018–21.
[11] L. Alessandretti, U. Aslak, and S. Lehmann, "The Scales of Human Mobility," *Nature*, vol. 587, no. 7834, 2020, pp. 402–07.
[12] S. Shang *et al.*, "Trajectory Similarity Join in Spatial Networks," *Proc. VLDB Endow.*, vol. 10, no. 11, 2017, pp. 1178–89.
[13] Y. Zhang *et al.*, "Efficient Computing Resource Sharing for Mobile Edge-Cloud Computing Networks," *IEEE/ACM Trans. Networking*, vol. 28, no. 3, Mar. 2020, pp. 1227–40.
[14] Y. Deng *et al.*, "AUCTION: Automated and Quality-Aware Client Selection Framework for Efficient Federated Learning," *IEEE Trans. Parallel Distrib. Syst.*, vol. 33, no. 8, 2022, pp. 1996–2009.
[15] C. He *et al.*, "FedML: A Research Library and Benchmark for Federated Machine Learning," arXiv preprint arXiv:2007.13518, 2020.

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