Deep Information Fusion-driven POI Scheduling for Mobile Social Networks

Zhiwei Guo, *Member, IEEE,* Keping Yu, *Member, IEEE,* Ali Kashif Bashir, *Senior Member, IEEE,* Di Zhang, *Senior Member, IEEE,* Yasser D. Al-Otaibi, and Mohsen Guizani, *Fellow, IEEE*

***Abstract*—With the growing importance of green wireless communications, point-of-interest (POI) scheduling in the mobile social network (MSN) environment has become important in addressing the high demand for innovative scheduling solutions. To enhance feature expressions for the complicated structures in MSNs, this paper explores a deep information fusion-based POI scheduling system for the MSN environment via the implementation of an edge-cloud deep hybrid sensing (PS-MSN) framework. Cloud sensing modules utilize the explicit contextual real-time information for each user, while edge sensing modules detect the real-time implicit linkages among users. Based on these two types of modules, a deep representation scheme is embedded into the hybrid sensing framework to improve its feature expression abilities. As a result, this type of framework is able to integrate multisource information so that more fine-grained feature spaces are built. In this work, two groups of experiments are conducted on a real-world dataset to evaluate the efficiency, as well as stability, of the designed PS-MSN. Using three benchmark methods to make comparisons, the excellent overall performance of PS-MSN is properly verified.**

***Index Terms*—mobile social networks, wireless communications, deep learning, POI scheduling, hybrid sensing.**

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Zhiwei Guo is with the Chongqing Key Laboratory of Intelligent Perception and BlockChain Technology, Chongqing Technology and Business University, Chongqing 400067, China. (e-mail: zwguo@ctbu.edu.cn).

Keping Yu is with the Global Information and Telecommunication Institute, Waseda University, Tokyo, 169-0072 Japan (email: keping.yu@aoni.waseda.jp).

Ali Kashif Bashir is with the Department of Computing and Mathematics, E-154, John Dolton, Chester Street, M1 5GD, Manchester Metropolitan University, Manchester, United Kingdom and with the School of Electrical Engineering and Computer Science, National University of Science and Technology (NUST), Islamabad, Pakistan (email: dr.alikashif.b@ieee.org).

Di Zhang is with the School of Information Engineering, Zhengzhou University, Zhengzhou 450001, China. (email: dr.di.zhang@ieee.org).

Yasser D. Al-Otaibi is with the Department of Information Systems, Faculty of Computing and Information Technology in Rabigh, King Abdulaziz University, Jeddah 21589, Saudi Arabia (e-mail: yalotaibi@kau.edu.sa).

Mohsen Guizani is with the Machine Learning Department, Mohamed Bin Zayed University of Artificial Intelligence (MBZUAI), UAE (email: mguizani@ieee.org).

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I. Introduction

The past decade has witnessed vigorous development of wireless communication technologies. Advancements in this field have facilitated the popularity of smart mobile terminals as well as wireless networks [1]. Reliable wireless resources are easily available for people to engage in their social activities anytime and anywhere [2]. Because of the prevalence of communication technologies, numerous mobile applications are connected to wireless networks [3]. In this evolving context, mobile social networks (MSNs) are becoming increasingly available [4]. The MSN is essentially a type of network media that enables interconnections among mobile devices [5]. To enrich the user experience, MSNs are currently oriented towards the type of social networks where users are able to engage in location-aware social activities [6]. For instance, the users in these networks can relay location information and share opinions with others [7]. In reality, users usually have no idea how to navigate around in the networks. They are more inclined to resort to existing points of interest (POIs) in the MSNs. Note that POIs refer to the places that attract the interests of users. Predictably, recommendations for possible POIs for users is likely to become a popular demand in MSNs.

In recent years, POI scheduling has been widely investigated in MSNs. Existing studies can be categorized into two types, contextual pattern-based approaches [8]-[10] and semantic pattern-based approaches [11], [12]. The two types of methods construct feature spaces from the perspective of the users and POIs. In addition, they have been proven effective in a number of specific cases. Unfortunately, they utilize only the initial features and shallow features to establish recommendation models, without extracting the deep-level features. Currently, deep learning is a prevalent intelligent computing technology due to its strong feature abstraction and extraction abilities. Although explainability is not an advantage of deep learning, its considerable efficiency when implementing prediction and classification tasks has been widely acknowledged.

To bridge this gap, this work makes the following research contributions: 1) Promotion of POI scheduling in MSNs via two aspects of the exploration efforts; 2) exploration of a deep learning-based **P**OI **S**cheduling system for **M**obile **S**ocial **N**etworks (PS-MSN) where the core is essentially an edge cloud deep hybrid sensing framework; 3) deployment of a deep representative learning scheme to achieve deeper feature abstractions in MSNs; and 4) development of a hybrid sensing framework of clouds and edges to enable reasonable

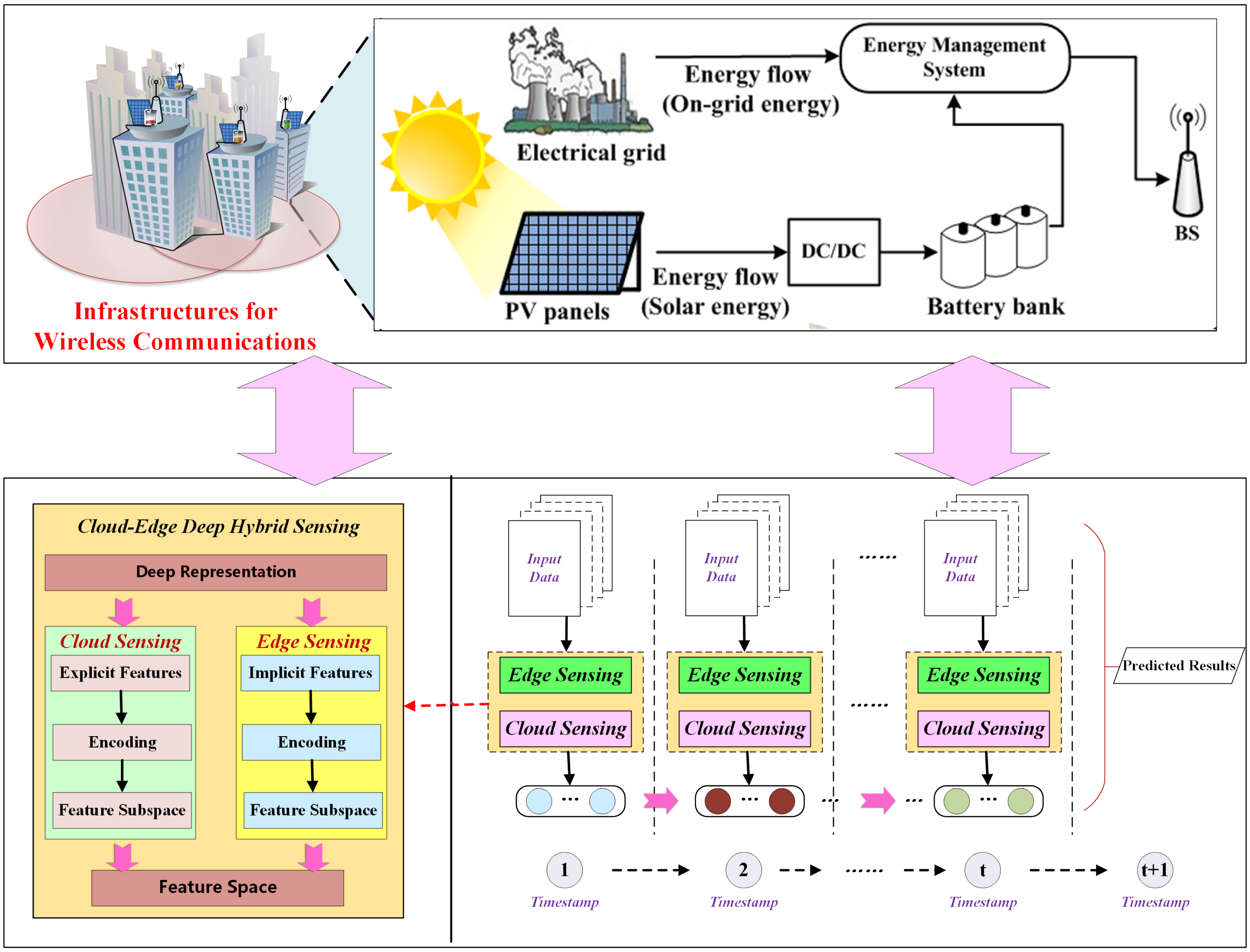


Fig. 1. Illustration of the workflow of solution thoughts.

allocations of communication resources. This research shows that deep feature representations are able to mine more hidden information from the sparse initial records so that the feature vectors can express more implicit content. The cloud sensing captures explicit features, while the edge sensing captures implicit features. This hybrid framework promotes computational efficiency. The combination is likely to become a feasible solution for POI scheduling.

As is shown in Fig. 1, The ideal research platform for this work is a future wireless networks empowered by hybrid energy technologies. Traditional energy-empowered communications infrastructures are energy-hungry and face serious pressures related to sustainable development. Because of these issues, hybrid energy-empowered mobile networks are viewed as a promising solution for the future, which is the anticipated future scenario for this study. It is noted that each base station is equipped with a photovoltaic panel to harvest solar energy. The interaction data of the first t timestamps are viewed as historical records. Preference profiling for users is established by the scheduling system. The system is composed of two major components, the cloud sensing module and edge sensing module. The former locates its primary server in the cloud and senses the real-time explicit contextual information of each user. The latter views each user as a computing unit and detects the real-time implicit linkages between one user and others. On this basis, the deep representation scheme is embedded into the hybrid sensing framework to improve its feature expression abilities. Naturally, the idea of edge-cloud deep hybrid sensing integrates multiple sources of information to construct more fine-grained feature spaces, so the challenges of doing POI scheduling in MSNs can be overcome to some extent. This work serves as the first study of the POI scheduling problem within MSNs.

II. System Model

When the geographical space is divided into cells of the same size, each single cell is called a POI. Before modeling, all the initial geographical coordination data are transformed into a number of POIs. Let u_i denote the set of users and p_j denote the set of POIs. It is assumed that a user can interact with a POI more than once. Fig. 2 displays the system model of a PS-MSN. It contains two types of basic infrastructure, a cloud center and an edge node. A cloud center is a group of base stations that are responsible for the centralized computation tasks of an area; and an edge node is a decentralized data processor located in blank regions that

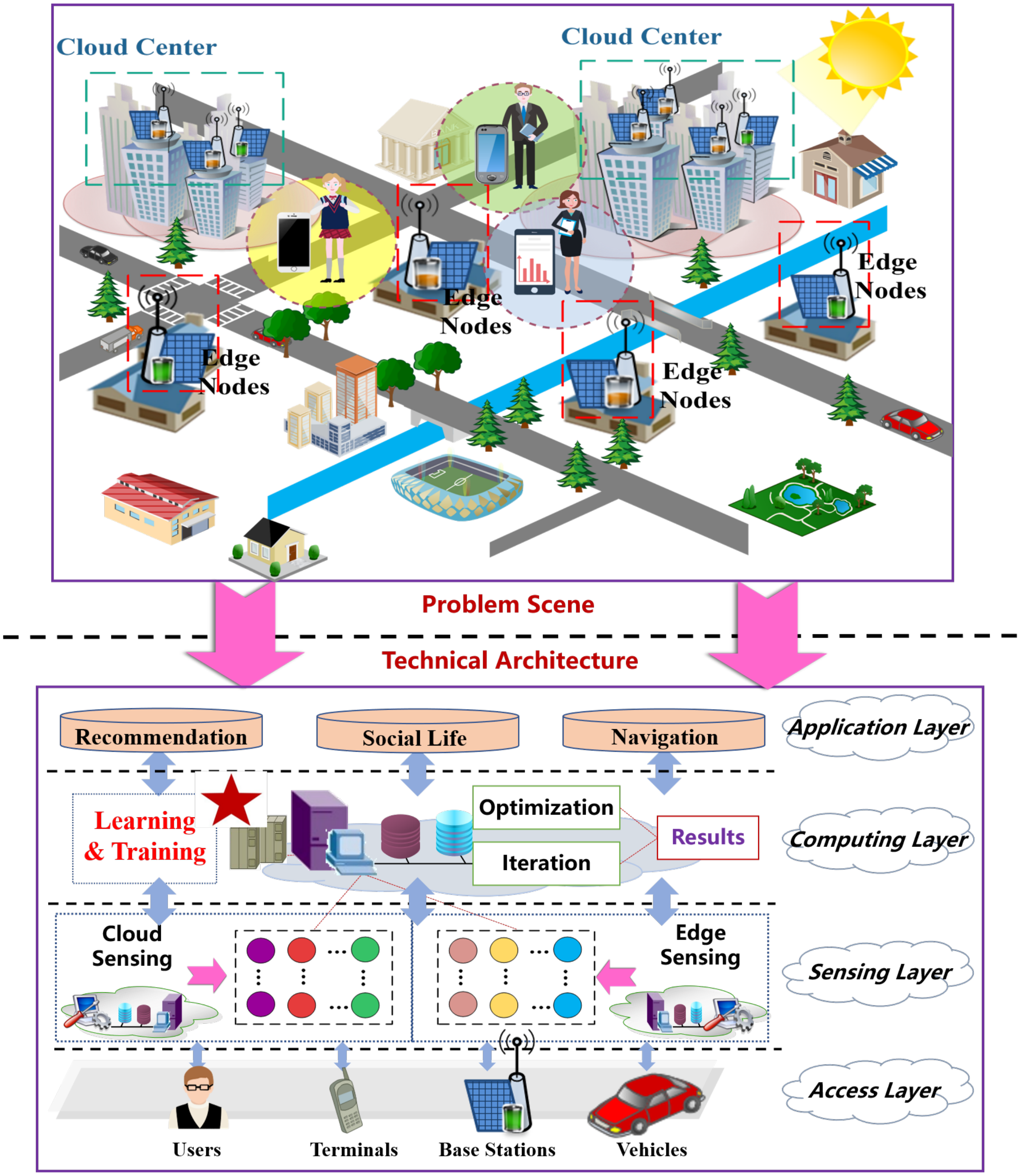


Fig. 2. System model of the designed PS-MSN.

undertakes processing tasks, so that the workflow of the cloud centers can be reduced. Users are allowed to have wireless access to the core network with the aid of mobile terminals. The process of POI scheduling for them is implemented in four layers, the access layer, sensing layer, computing layer and application layer. These layers are described as follows:

- The access layer is mainly responsible for collecting the original data and connecting them to the MSN. It contains several types of entities: users, vehicles, and terminals. Terminals denote the set of vehicular equipment with sensing functions, such as cellphones. Users and vehicles hold the wireless devices that have access to wireless communication media and are used for social activities. All wireless data obtain access to the core networks via base stations.
- Having acquired the initial data, the sensing layer implements two main operations, deep representation and cloud-edge sensing. For the entire feature space, the cloud sensing module and edge sensing module are designed to model explicit subspaces and implicit subspaces, respectively. Their feature expression is based on a deep representation scheme.

- As representative vectors are obtained in the sensing layer, the computing layer is required to carry out a training procedure to learn the model's parameters. All training samples with labels are input to train the model through an iterative optimization process. After that, all the parameters within the model are successfully learned so that the scheduling system is completely formulated.
- In the application layer, the scheduling system is available to users to provide personalized services. It serves as a navigation platform for users to search for places that satisfy their demands. Additionally, it can also be used as a social platform where users share location-based activities with others.

III. Edge-Cloud Deep Hybrid Sensing

This section fully explores the characteristics of MSN scenarios and describes the designed PS-MSN in detail. It is composed of three subsections that give information on the cloud sensing module, the edge sensing module and the training.

A. Cloud Sensing Module

The cloud sensing module manages to formulate explicit feature expressions for each user. Explicit features contain two main parts, the contextual part and semantic part. The two parts are profiles related to the users and POIs. Thus, the main goal of this subsection is to learn a parametric representative vector for the historical interaction records of user u_i who has t interaction records. The workflow of the cloud sensing module is illustrated in Fig. 3.

Contextual features in this research mainly refer to the profiles of users. Users are classified into either an unstructured type or a structured type. The two types of features both need to be encoded into a vectorized form before feeding them into deep neural networks. The latter can be directly transformed into representative vectors, while the former needs the aid of some extraction models. For example, short texts can be represented as a latent topic indicator with the use of a semantics model. Encoding vectors of both types of attributes are integrated into a total vector. After that, it is input into a convolutional neural network (CNN) model to generate a representative vector v_{it}.

Semantic features in this research refer to the textual content associated with POIs. For the j-th POI, all textual information is viewed as a sentence. Sentences can be transformed into vectors via the embedding operation, which is common in natural language processing. The obtained sentence vectors are then input into the bidirectional gated recurrent unit (Bi-GRU) network to model sequential semantic characteristics from both the forward and backward directions. Accordingly, a vector v_{jt} can be deduced to denote the complete semantic feature of the POI. After that, it is input into an attention-based neural mapping procedure to generate the semantic feature vector.

Given the above encoding procedures, the representative vector at the t-th timestamp can be obtained as $C_{ij}^{(t)}$. All of its parameters can be learned in the training process.

B. Edge Sensing Module

The edge sensing module manages to formulate global feature expressions for each user. The global features mainly exploit the implicit relations among users and include two main metrics in this research, social relations and mobile relations. Here, social relations refer to the available real-time connections among users in an MSN. The connections may vary for different timestamps and are time-variant objects. Mobile relations are derived from the location records of users. For the relational vector of user u_i at the t-th timestamp, its elements correspond to the relation status between the user and others. The workflow of the edge sensing module is illustrated in Fig. 3.

At the t-th timestamp, the social relation vector of user u_i can be obtained through binary encoding. Its elements correspond to its social relation status with other users. Each element is set to 1 if a relation exists, and set to 0 if a relation does not exist. To construct another matrix for convolutional operations, each of the three adjacent elements in the vector are selected in turn to construct rows of a matrix. The matrices at each timestamp are input into the long-short term memory (LSTM) model. After t rounds of iterations, the output vector of LSTM at the t-th timestamp, s_{it}, is obtained.

A measurement of mobile relations is implemented by calculating the similarity between the POI sequences of different users. In the first step, the POI sequences of user u_i are encoded into a more abstract feature vector. As the generation of a POI sequence is a sequential process, the feature vector is a parametric expression in terms of POIs at the t-th timestamp and the $(t-1)$-th timestamp. The representative vector for mobile relations between user u_i and user u_z is obtained by conducting neural mapping of the difference between the representative vectors of their POI sequences. After that, the mobile relation between user u_i and user u_z is obtained. It can be further concatenated into the mobile relation vector m_{it} of user u_i.

C. Training

Given the above two representative factors, in terms of the cloud sensing module and edge sensing module, the goal of POI scheduling is to predict the most possible POIs for user u_i at the $(t+1)$-th timestamp. The least square method is introduced here to construct the objective function for training, and the Adam optimizer is selected as the learning method. After training, all the parameters in the representative factors can be successfully learned. Therefore, the most appropriate POIs at the $(t+1)$-th timestamp can be directly calculated.

IV. Evaluation

A. Workflow of Experimental Implementation

In order to make the proposal more understandable and easier for readers to follow, algorithm implementation of the PS-MSN is briefly illustrated in Fig. 4. The whole workflow of experimental implementation includes three parts: deep information fusion, scheduling, and evaluation.

The deep information fusion acts as the foundation of the whole framework, and is composed of two aspects. On the

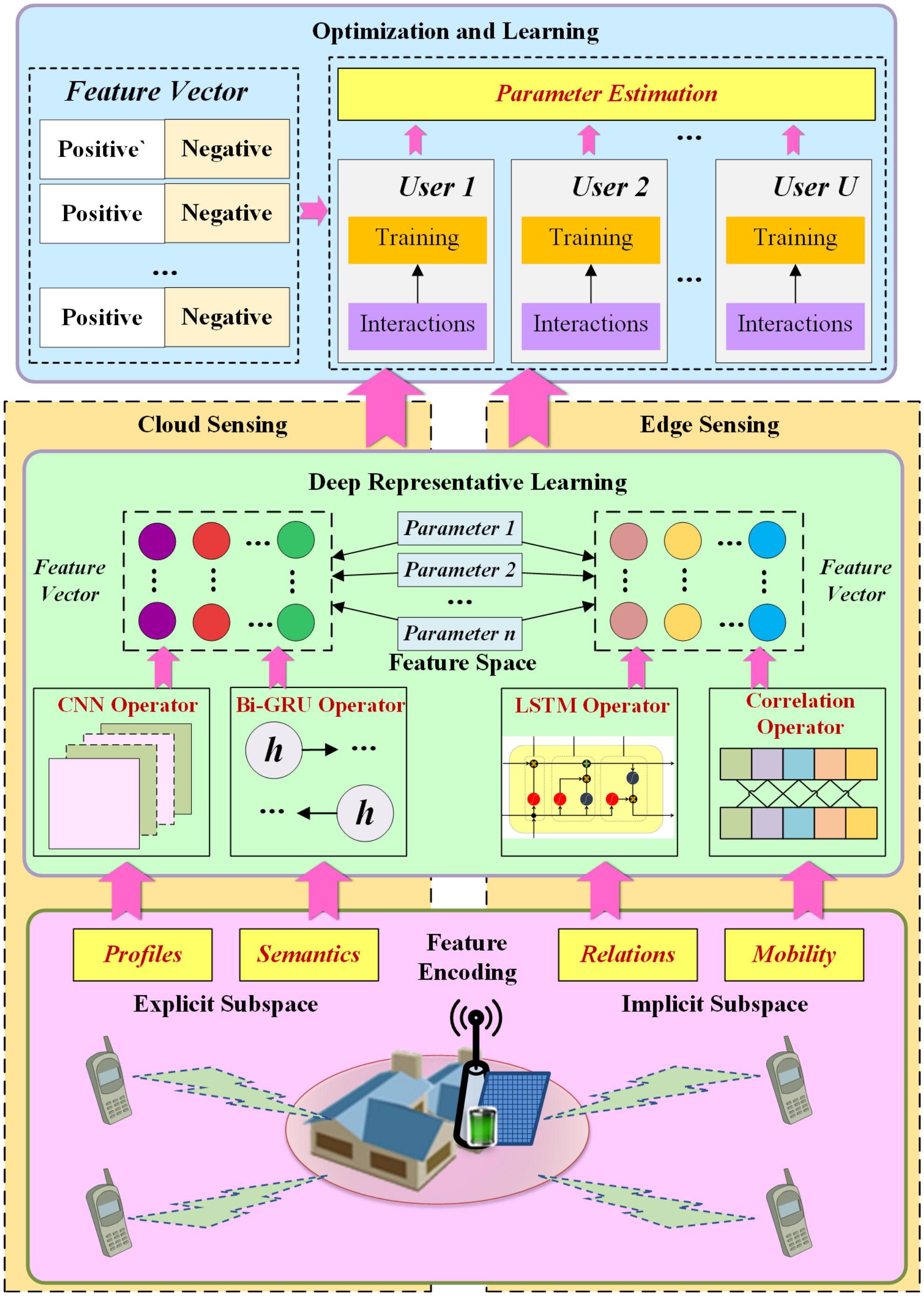


Fig. 3. Roadmap of the cloud-edge deep hybrid sensing framework.

one hand, the cloud sensing contains extraction of contextual features and semantic features. The contextual features are encoded via the generic CNN model, and the semantic features are encoded via the generic Bi-GRU model. The two are concatenated into a new representative vector $C_{ij}^{(t)}$ for clouding sensing part. On the other hand, the edge sensing contains measurement of social relations at different timestamps are encoded via the LSTM model, and mobile relations among users can be realized by calculating mobility similarity. The two are concatenated into a new representative vector $E_{ij}^{(t)}$. The $C_{ij}^{(t)}$ and $E_{ij}^{(t)}$ are deep representation for features at the t-th timestamp.

Then, the logarithmic cross-entropy loss function is formulated as the training objective of models, and backward propagation is introduced as the optimization method. After a number of rounds of iterations, all the parameters can be learned. The model that has been well trained can be used to generate scheduling results. In terms of evaluation, the above described algorithm is implemented on a real-word dataset for evaluation. If the obtained experimental results seem not reasonable enough, the procedure will be back to

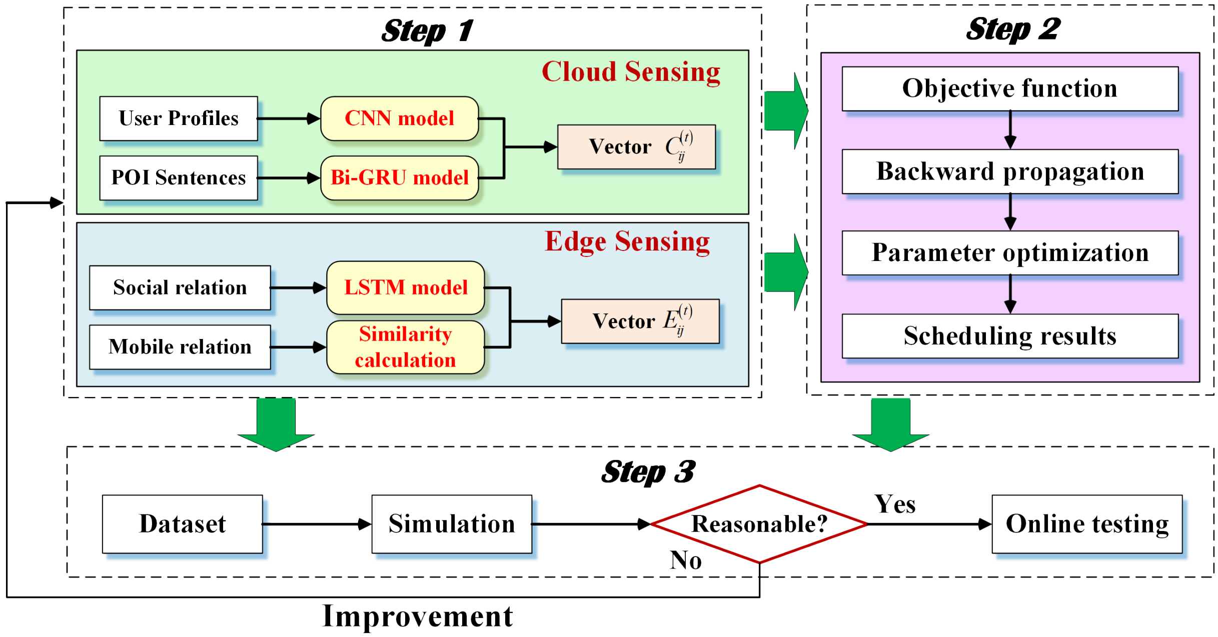


Fig. 4. Illustration for workflow of algorithm implementation.

initial position to improve algorithm. Otherwise, the proposal is going to be embedded into online web prototype systems, in order to be tested in distributed data stream.

B. Simulative Scenario and Setting

To construct a reliable simulative environment, a real-world dataset from a realistic MSN platform is selected for this purpose. *Foursquare*, a very popular location-based MSN application, provides public social media for mobile users to engage in location-aware online activities via geographical check-ins. The dataset is collected from the Twitter platform [13] and includes social check-in data in the United States. For simplicity, the selected dataset is named Foursquare. This dataset contains users, positions, and check-ins. The initial Foursquare dataset has 22534 users, 21762 POIs, 987648 check-ins, and 397854 social links. As the initial dataset is quite sparse, it is necessary to remove low-quality data from the dataset. For example, users and POIs where the number of interaction records is below 15 need to be filtered out. After preprocessing, the final experimental dataset has 4858 users, 4271 POIs, 247592 check-ins and 74035 social links. In addition, each POI is set as a square block of 0.05 (latitude) $\times$ 0.05 (longitude). The textual contents of the POIs can be crawled from two primary sources, the Yelp website [1] and Baidu maps [2].

Traditionally, the experimental dataset is separated into a training part and a testing part. The training part is used to train POI recommendation models, and the testing part is used to assess the performance of the trained models. The recommendation effect can be measured by calculating the repetition rate between the suggested POIs generated by the models and the POIs of the testing part. Naturally, higher repetition rate values indicate a better POI scheduling effect. The specific indexes for the repetition rate selected here are three typical ones, $Precision@C$, $Recall@C$ and $NDCG@C$; where $@C$ denotes the metric values where the recommendation size for each user is C. For simplicity, their descriptions can be found in [14], [15]. To make a comparison, five typical approaches are selected as baseline methods; they are briefly described as follows:

FPMC [14]—adds the Markov chain model into the classical model named matrix factorization to capture long-term interaction activities between users and POIs.

ST-LDA [15]—acts as a probability-based model that is capable of inferring implicit user preferences towards POIs. Social and geographical correlation is employed to reduce data sparsity.

PSG-LSTM—considers auxiliary factors from three aspects, user preferences, social influence and geographical comments. These are fused into the long short-term memory (LSTM) model to enable POI scheduling.

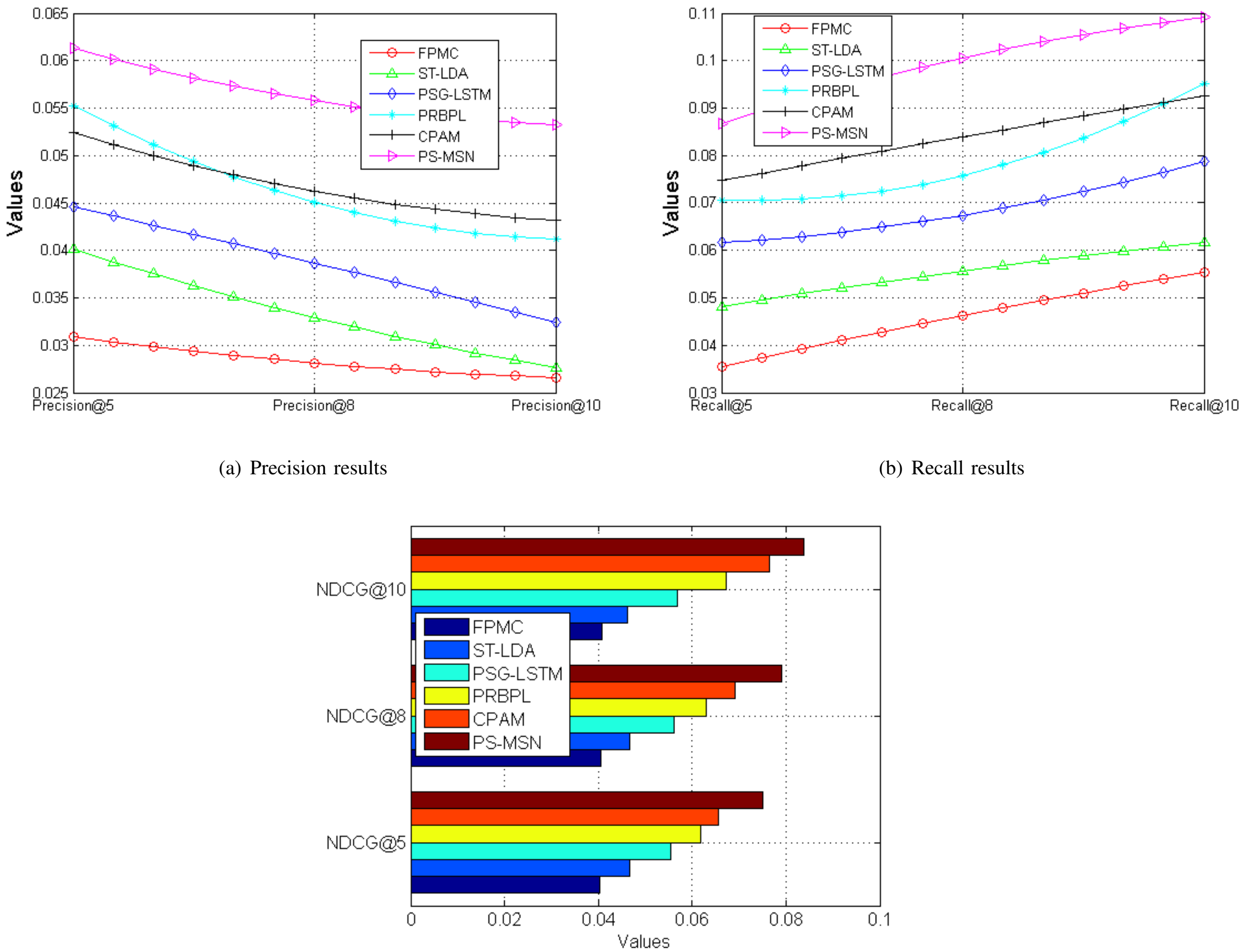
PRBPL [11]—studies representation and mining of user preferences from POI-related check-in data. It jointly considers geographical distance and POI categorical distance so that pairwise user preferences can be obtained from the initial data.

CPAM [12]—incorporates both contextual influences and user preferences into POI recommendations. It uses skip-gram to model POI features and logistic matrix factorization to model user preferences.

C. Results and Analysis

Fig. 5 shows the precision, recall and NDCG results with respect to The scheduling results. It has three subfigures, corresponding to the three results. The precision results and recall

[1] http://www.yelp.com
[2] http://map.baidu.com



(a) Precision results

(b) Recall results

(c) NDCG results

Fig. 5. Precision, recall and NDCG results of PS-MSN and baselines.

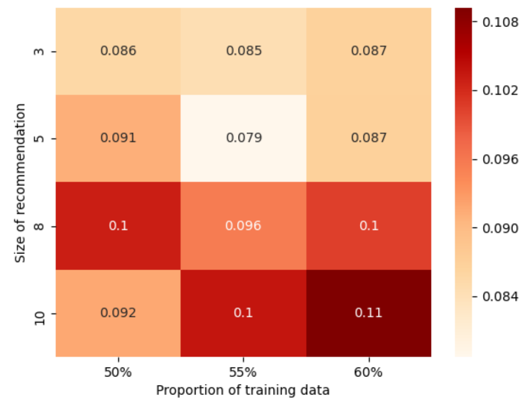
results ascend and descend, respectively, with the increase in the number of suggested POIs. In regards to performance comparisons, three earlier methods, FPMC, ST-LDA and PSG-LSTM, perform relatively worse than others. Two later methods, PRBPL and CPAM, achieve better results. Among all of these approaches, the designed PS-MSN always performs better than the baselines. Even compared with PRBPL, it can still produce an improvement of at least 15%. It is approximately 20% better in regards to the precision results, approximately 26% better in regards to the recall results and approximately 22% better in regards to the NDCG results. Two possible reasons can be deduced to explain the above observations. First, PS-MSN considers both the explicit and implicit feature factors, so a deeper representation for feature spaces can be built. Second, PS-MSN updates two feature subspaces via two different multiround iterations, so the deep representation for feature spaces is reoptimized. The collaborative effect of the above reasons contributes to more effective scheduling.

In addition, another group of experiments was also carried out to test the stability of PS-MSNs by testing its sensitivity to parameter changes. Specifically, the fluctuation tendencies of three metrics are investigated when there are a constantly changing combination of parameters, which are the proportion of training data and the recommendation size. The relevant precision results, recall results and NDCG results are all illustrated in Fig. 6. Although the values of the three different metrics have fluctuations in terms of different scenario settings, the degree of fluctuation is relatively mild. In analyzing the tendency for change of the three metric values, two latent reasons may be deduced for an explanation. Importantly, the feature spaces can be enhanced with consideration of multi-source features, which provides more comprehensive views for feature expressions. Additionally, the role of deep information fusion is significant, as finer feature spaces are more prone to better recommendation effects. Because of these reasons, the designed PS-MSN is not susceptible to parameter changes.

V. Future Research Directions

This work examines importing deep learning into cloud-edge hybrid sensing networks and explores a novel framework to enable POI scheduling. We would like to outline potential future research directions for this field:

(a) Precision results



(b) Recall results

(c) NDCG results

Fig. 6. Parameter sensitivity results of PS-MSN.

1) First, security must be regarded as an indispensable factor when doing POI scheduling because big data analysis is inevitably plagued with user privacy problems. Thus, the balancing of improved recommendation efficiency and privacy demands is an essential consideration for the future. Perhaps the federated learning concept is a promising solution for this purpose.

2) Second, although deep learning has been proven effective in many scenarios, computational complexity and explainability are still known issues that need to be solved. Balancing recommendation efficiency and real-time characteristics is another issue to consider. In addition to improving the hardware performance, finding ways to reduce the running time of soft algorithms is worth investigating.

3) Third, the model in this work is actually an offline learning framework instead of an online learning framework. It utilizes offline data for training, without the use of an online data stream. In fact, online learning is more prevalent in the field of machine learning. Thus, ways to dynamically optimize the algorithm is also a concern that can be addressed in the future.

VI. Conclusion

The rapid development of MSNs has increased the requirement for POI scheduling in these type of networks. However, MSNs have two problematic characteristics, data sparsity and process uncertainty. To remedy this issue, this paper explores PS-MSN, a POI scheduling system for MSN through edge-cloud deep hybrid sensing. It separates entire feature spaces into explicit features and implicit features, which are interrogated by both the cloud sensing module and the edge sensing module, respectively. The modeling of the subspaces is further enhanced by deep representative learning. The deep hybrid sensing framework contributes to a feature space with strong feature expression capabilities. Finally, experiments on a real-world dataset show that the designed PS-MSN outperforms baselines in comparisons across three metrics.

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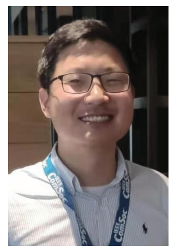
Zhiwei Guo (Member, IEEE) received the Ph.D. degree in Communications and Information Systems from Chongqing University, Chongqing, China, in 2018. He is currently working as an Associate Professor with Chongqing Technology and Business University, Chongqing, China. His research interests focus on data mining and the Internet of Things.

Keping Yu (Member, IEEE) received his Ph.D. degree from Waseda University, Japan, in 2016. He is currently a researcher at Waseda University. He has authored 100+ publications including papers in prestigious journal/conferences such as the IEEE Wireless Communications, ComMag, NetMag, IoTJ, TFS, TII, T-ITS, TVT, TNSE, TGCN, CEMag, IoT-Mag, ICC, GLOBECOM etc. He is an Associate Editor of IEEE Open Journal of Vehicular Technology, Journal of Intelligent Manufacturing, Journal of Circuits, Systems and Computers. His research interests include smart grids, information-centric networking, the Internet of Things, artificial intelligence, blockchain, and information security.

Ali Kashif Bashir (Senior Member, IEEE) is a Reader at the Department of Computing and Mathematics, Manchester Metropolitan University, United Kingdom. He is also University of Electronics Science and Technology of China (UESTC) as an Honorary Professor; with University of Science and Technology, Islamabad (NUST) as an Adjunct Professor, and with University of Guelph, Canada as Special Graduate Faculty. He is a senior member of IEEE, member of IEEE Industrial Electronic Society, member of ACM, and Distinguished Speaker of ACM. He has authored over 200 research articles; and received over 3 Million USD funding as PI and Co-PI. His research interests include internet of things, wireless networks, distributed systems, network/cyber security, network function virtualization, machine learning, etc. He is serving as the Editor-in-chief of the IEEE FUTURE DIRECTIONS NEWSLETTER.



Di Zhang [S’13, M’17, SM’19] is an Associate Professor at Zhengzhou University, Zhengzhou, China. He is editor of IEEE ACCESS, KSII Transactions on Internet and Information Systems and IET Quantum Communication. He has served as guest editor of IEEE WIRELESS COMMUNICATIONS Special Issue on 5GB Remote e-Health, IEEE NETWORK Special Issue on Licensed and Unlicensed Spectrum for Future 5G/B5G Wireless Networks. In 2019, he received the ITU Young Author Award and the IEEE Outstanding Leadership Award. His research interests include information theory, signal processing and Internet of things.

Yasser D. Al-Otaibi (Senior Member IEEE) received the B.Sc in Information Technology, M.Sc. in Information Systems, Grad. Dip. in research studies, and Ph.D. in information systems from Griffith University, Brisbane, QLD, Australia, in 2010, 2012, 2013 and 2018, respectively. He is the recipient of two consecutive Griffith awards for academic excellence (in 2012 and 2013) during his graduate studies at Griffith University. He is currently an Assistant Professor with the Department of Information Systems, Faculty of Computing and Information Technology in Rabigh, King Abdulaziz University, Jeddah, Saudi Arabia. Yasser’s current research interests include IT adoption and acceptance, wireless sensor networks, computer security, and IoT.

Mohsen Guizani (Fellow, IEEE) received his B.S., M.S., and Ph.D. from Syracuse University. He is currently a professor in the Machine Learning Department, Mohamed Bin Zayed University of Artificial Intelligence (MBZUAI), UAE. His research interests include wireless communications and mobile computing, applied machine learning, cloud computing, and security and its application to healthcare systems. He has more than 800 publications in these areas. He was listed as a Clarivate Analytics Highly Cited Researcher in Computer Science in 2019 and 2020. He has won several research awards including the 2015 IEEE Communications Society Best Survey Paper Award as well as four Best Paper Awards from IEEE ICC and GLOBECOM conferences.

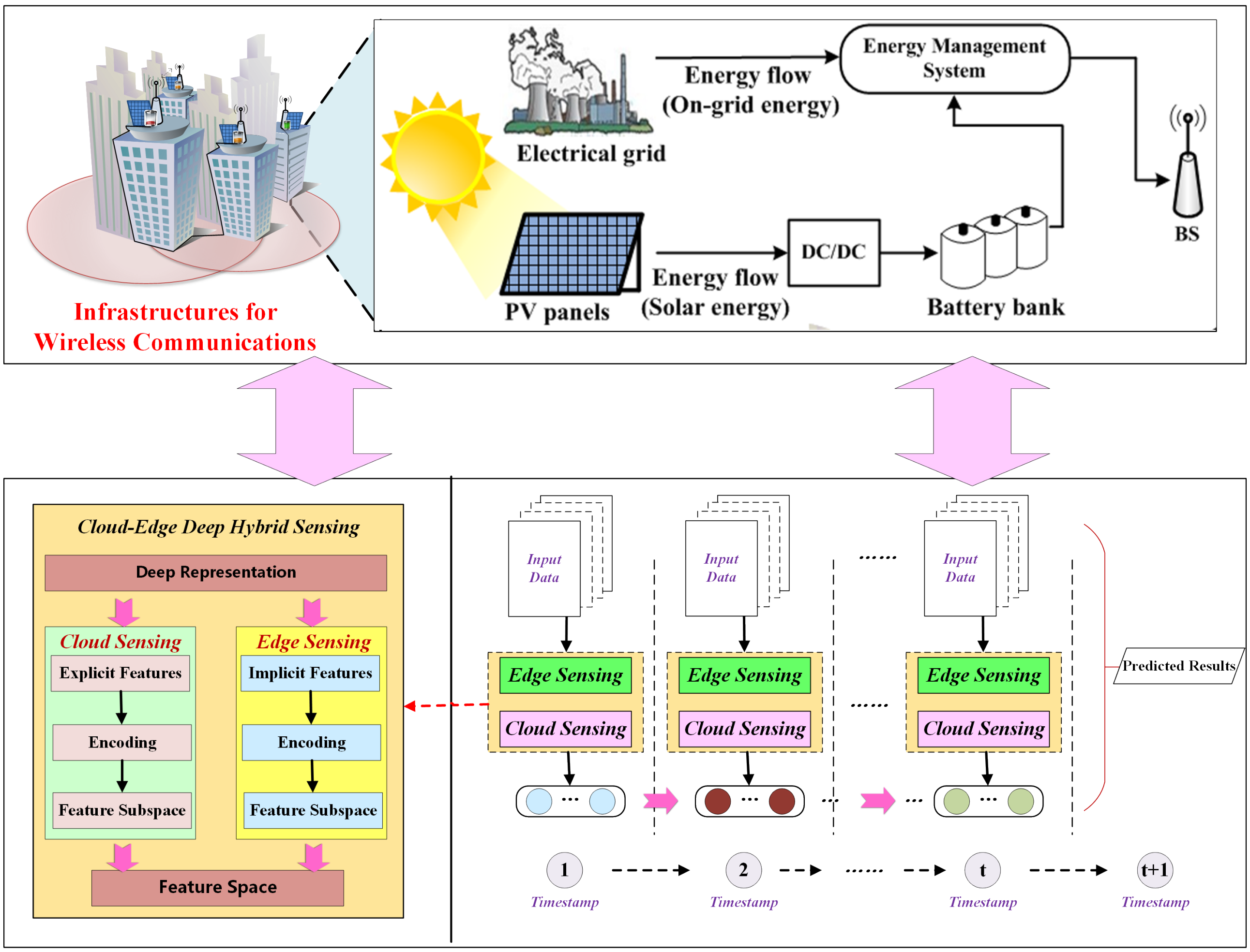


Figure 1. Illustration of the workflow of solution thoughts.

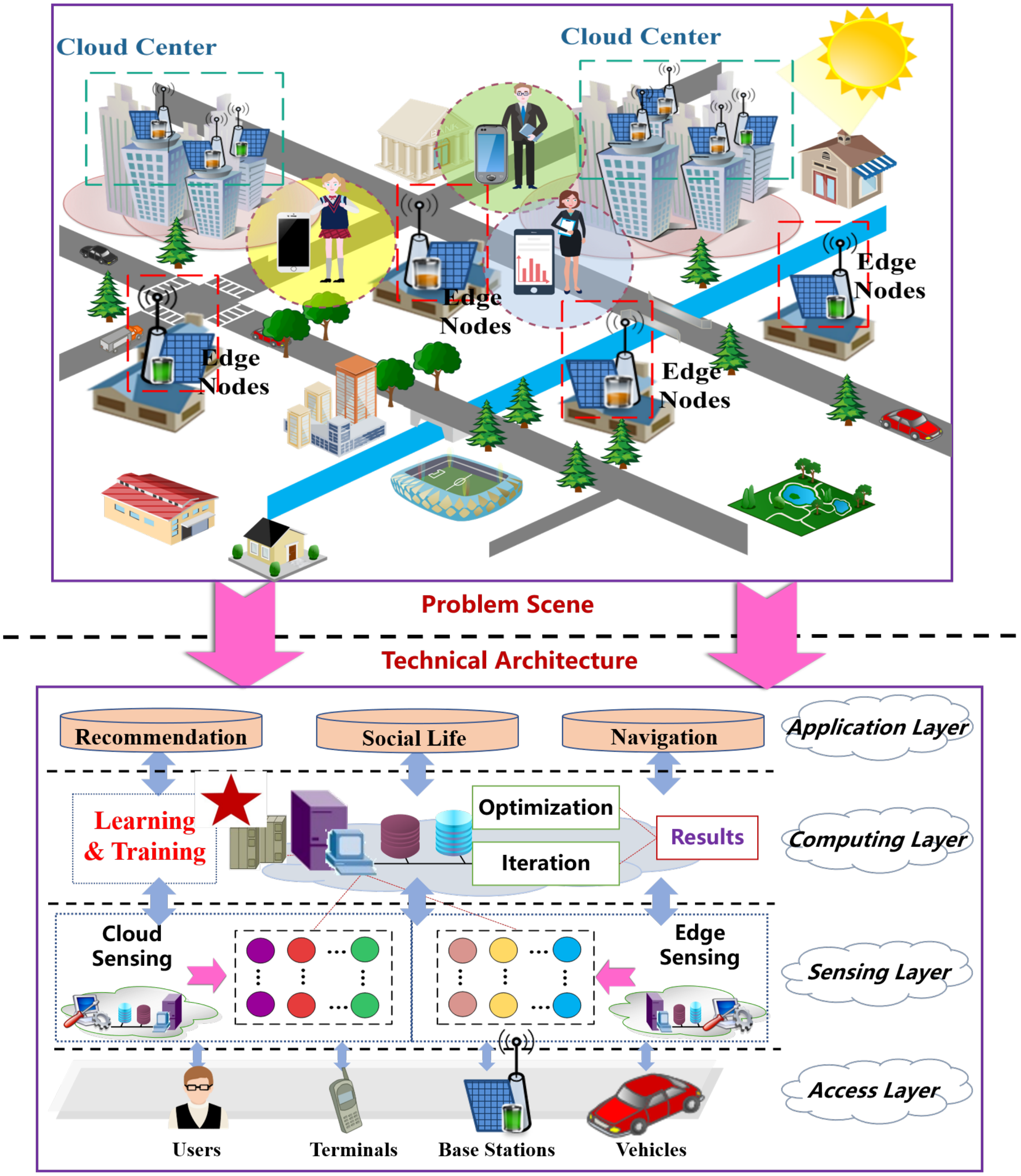


Figure 2. System model of the designed PS-MSN.

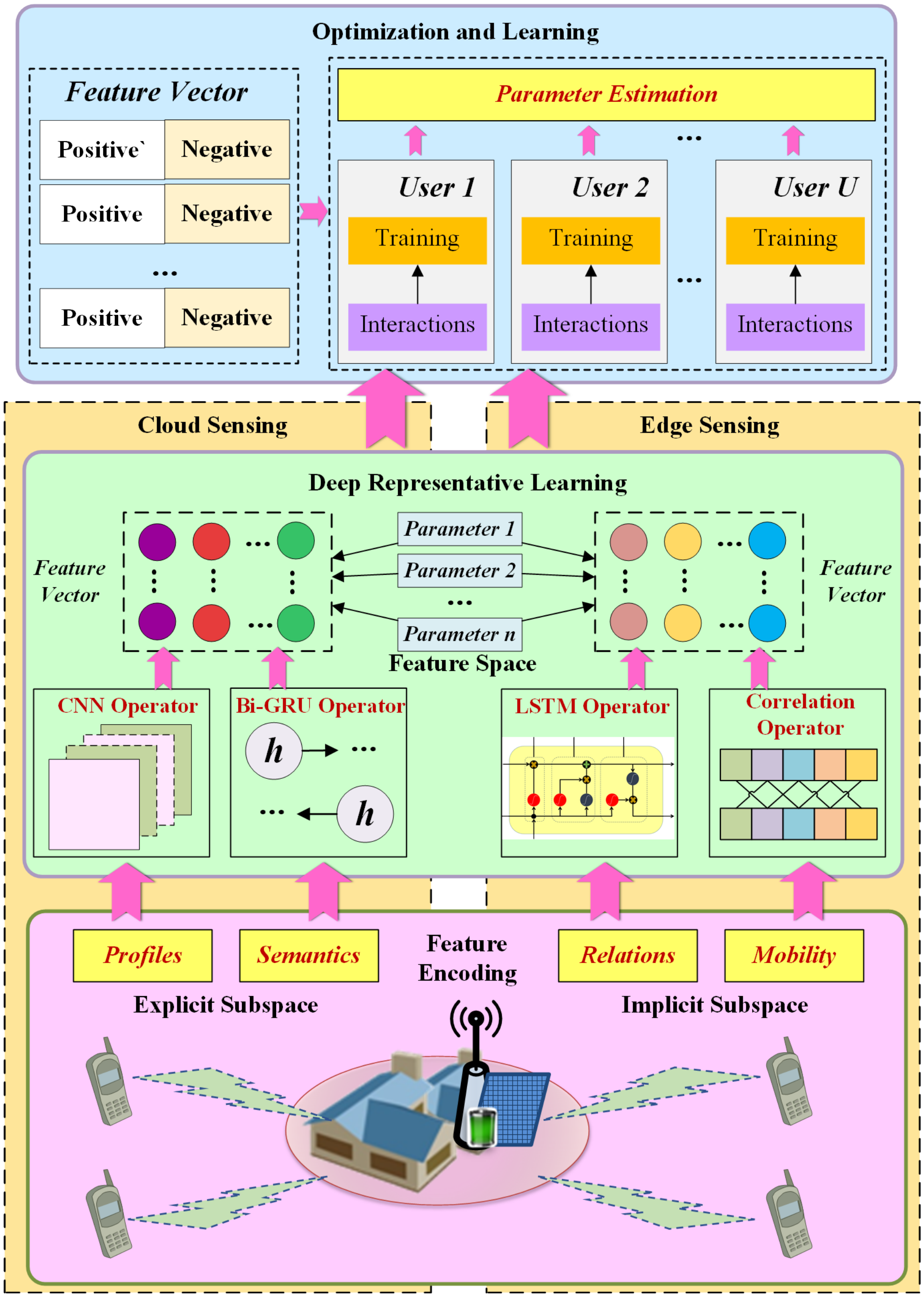


Figure 3. Roadmap of the cloud-edge deep hybrid sensing framework.

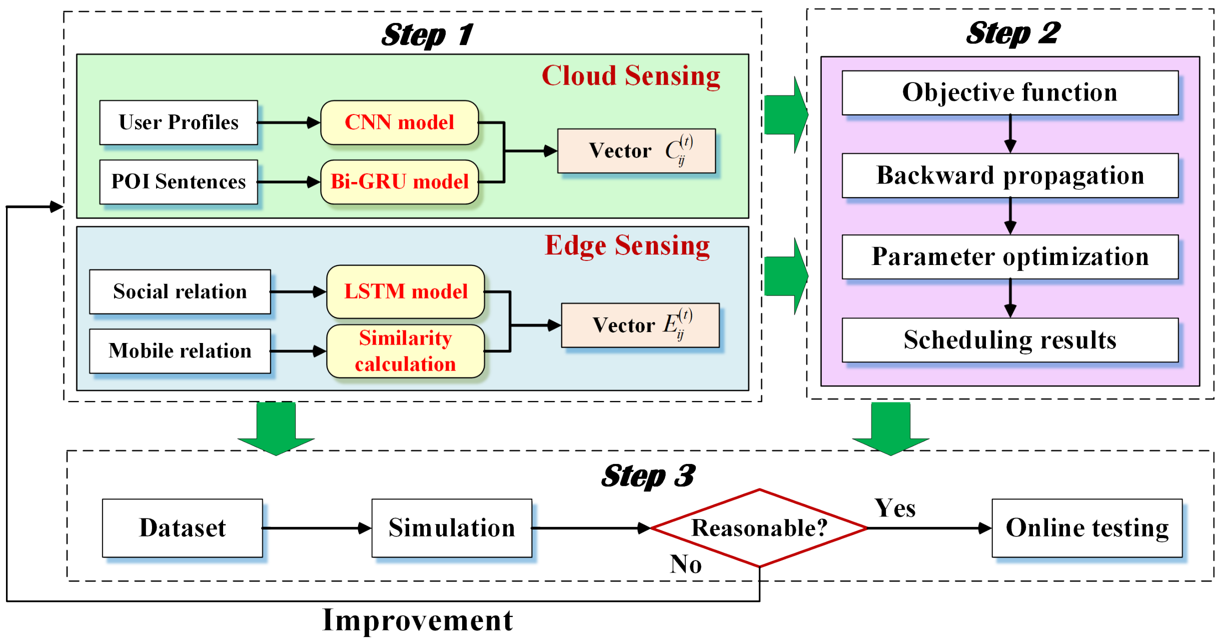
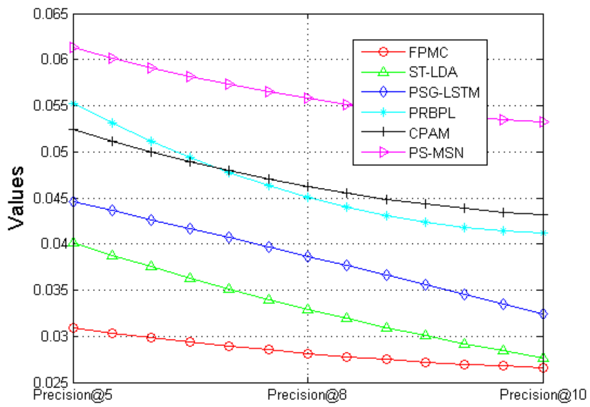
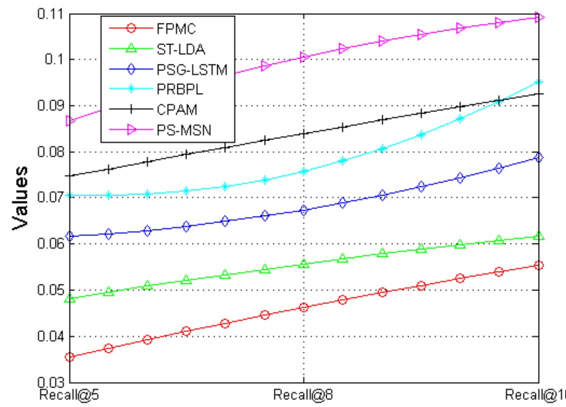


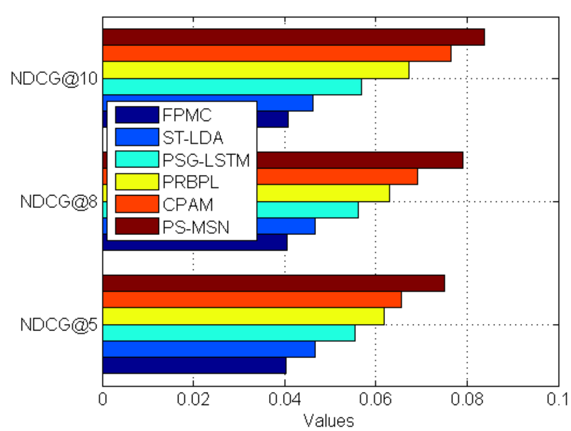
Figure 4. Illustration for workflow of algorithm implementation.



(a) Precision results



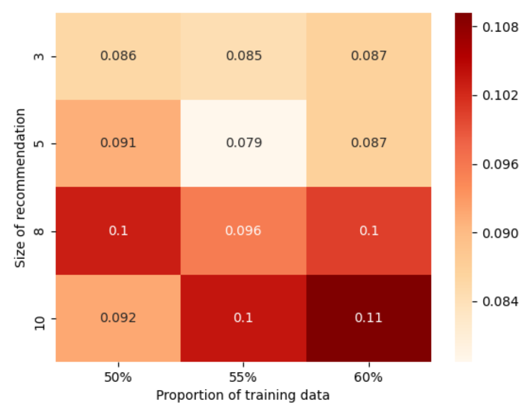
(b) Recall results



(c) NDCG results

Figure 5. Precision, recall and NDCG results of PS-MSN and baselines.

(d) Precision results



(e) Recall results

(f) NDCG results

Figure 6. Parameter sensitivity results of PS-MSN.