Exploiting Unlabeled Data in Smart Cities using Federated Learning

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Abstract—Privacy concerns are considered one of the main challenges in smart cities as sharing sensitive data brings threatening problems to people’s lives. Federated learning has emerged as an effective technique to avoid privacy infringement as well as increase the utilization of the data. However, there is a scarcity in the amount of labeled data and an abundance of unlabeled data collected in smart cities, hence there is a need to use semi-supervised learning. We propose a semi-supervised federated learning method called FedSem that exploits unlabeled data. The algorithm is divided into two phases where the first phase trains a global model based on the labeled data. In the second phase, we use semi-supervised learning based on the pseudo labeling technique to improve the model. We conducted several experiments using traffic signs dataset to show that FedSem can improve accuracy up to 8% by utilizing the unlabeled data in the learning process.

Index Terms—Federated Learning, Labeled data, Pseudo-Labeling, Semi-supervised Learning, Smart cities, Traffic Signs, Unlabeled data

I. INTRODUCTION

Given the rapid advancements in technology, the lifestyle of people is requiring smarter instruments. This has brought a challenge and an opportunity to shift towards smart cities. The smart cities provide reliable and robust solutions to many problems with traffic, healthcare, education, security, etc. [1], [2]. They embody a large number of smart devices in various applications. The compelling capabilities of the sensors equipped within these devices generate an unprecedented amount of data [3]. Learning from this data enhances the performance of applications and enables the discovery of the knowledge in order to make intelligent decisions [1]. However, a large chunk of this data is sensitive in nature because it is generated by users and should be stored locally in the devices to protect user’s privacy. In addition, sending the devices’ data to a centralized location is resource hungry which leads to network congestion as too many users attempt to make use of the same resource [4].

Federated learning (FL) has emerged as an efficient technique to avoid privacy infringement while allowing the discovery of the necessary information hidden in the data [5]. FL enables users to share their knowledge without violating their privacy which keeps the sensitive data where it is generated. Users only share their local training model periodically with the coordination of a centralized server which collects these models and builds a new global model [6]. The global model is the result of an averaging algorithm, which considers the individual weights of local models across participants. Thus, terminal devices do not need to transmit local data to a centralized entity. The centralized server coordinates a fleet of participating devices in order to compute aggregations of local models [7]. Sharing the global model among all devices in the network increases the usability of these models [6]. Besides, FL exploits the resources of the terminal devices to do the learning tasks remotely instead of pushing the whole data to the server [9]. Fig. 1 illustrates the federated learning in the disseminated network. Each device uploads its local model to a centralized server and then downloads the global model to do on-device inference using a cloud-distributed model. Thus, the prediction is made directly without a cloud round-trip [10].

In the literature, several works studied federated learning and its applications aiming to address system level and statistical challenges as presented in Section II. However, the assumption is that the generated data is fully labeled which does not reflect the realistic nature of the applications [7]–[9]. In contrast, there is a scarcity in the amount of labeled data and an abundance of unlabeled data collected in smart cities. Exploiting the unlabeled data to enhance the learning performance is crucial. Tackling the aforementioned challenge, we can summarize our contributions as follows:

- We propose semi-supervised federated learning, FedSem can handle the problem of unlabeled data in smart cities while preserving privacy increasing the data utilization.
- We utilize German Traffic Sign Dataset (GTSDB) to evaluate our proposed method under various settings of unlabeled data ratios.
- FedSem enables the use of unlabeled data in federated learning, and the validation accuracy is improved by 8% compared to using only labeled data.
To the best of our knowledge, this is the first work in federated learning that takes into account semi-supervised learning which exploits unlabeled data generated in the smart cities.

The rest of this paper is structured as follows. We review the state of art of similar works in Section II Then, we introduce the system model and our proposed approach in Section III. We present details descriptions of the used datasets, performance metrics, experimental setup and results are provided in Section IV. Finally, we conclude our work with remarks in Section V.

II. RELATED WORK

In order to process large amounts of data, with the evolution of cloud computing techniques, the majority of the works have been devoted to study large-scale distributed learning especially in the data center setting. However, pushing the data directly to the server violates privacy of users for critical applications. Recently, Federated learning has emerged as an effective solution to preserve the privacy and share the knowledge between users due to the rapid growth of computing agents (i.e. smartphones, wearables, and internet-of-things devices). In this approach, it is directly learning the models over the network rather than transmitting the data to the cloud. This technique inspired researchers to pay attention to challenges with heterogeneity, privacy, and disseminated networks.

Focusing on federated learning, many optimization methods have been designed to tackle the statistical and system challenges. These methods showed outstanding improvements compared to conventional approaches such as ADMM methods and mini-batch algorithm. These methods allow for local updates in the edge devices by only activating a subset of them to participate in forming a global model. In addition, with the aim of convergence, the authors in proposed a heuristic method called, multitask learning, to average the local updates received from a set of devices and then broadcast the global model accordingly. The authors proposed to collect raw data in a certain period to improve the model. However, the data is private and this will violate the principle of federated learning which mainly aims to preserve users privacy.

Recently, heuristic methods have been proposed by other researchers to address data statistical heterogeneity in federated learning. For example, Federated Averaging (FedAvg) is a heuristic algorithm based on averaging local Stochastic Gradient Descent (SGD) updates in the primal. In [4], the authors showed the FedAvg method providing empirical outstanding performance. However, FedAvg is challenging to analysis due to its local updating, the only a subset of devices participates at each round, and the issue is that data is distributed in a heterogeneously and non-identically. To tackle this issue, the authors in [8], proposed approaches to periodically send the local data produced by the edge devices to edge-server and then, share the global model to all edge devices. however, these methods are unrealistic because the bandwidth and energy are quickly consumed due to periodic data transmissions and user privacy is violated. On the other side, sharing the edge-device data between all members requires sufficient network resources and powerful computing capabilities to manipulate massive datasets.

In summary, the majority of researchers have studied statistical challenges of federated learning. However, to the best of our knowledge there are no approaches to handle the problem of using unlabeled data collected in smart cities in federated learning by preserving privacy.

III. SYSTEM MODEL

In this work, we consider a swarm of smart vehicles learning traffic signs in smart cities. This system includes a set of autonomous vehicles $K$ passing through different roads. A subset of these vehicles $S$ occasionally is active. The coordination between these nodes is performed by a centralized server that organizes to which individuals will contribute to the global model. Each device trains the local model based on its own data (traffic sign images) locally and sends only gradients and weights to the server. Then, the server applies federated averaging to create a global model using $\omega$. In general, server coordinates to select the number of participants $S$ and the number of rounds $R$ towards convergence.

$$\omega_{t+1} = \frac{1}{K} \sum_{k \in S_t} \omega_{t+1}^k$$

where $w$ is the weights of the global model, $K$ is the total number of devices in the network, and $S_t$ is the subset of devices selected to train the global model.

1) Federated Averaging: (FedAvg) [4]. In FedAvg, the stochastic gradient descent (SGD) is used as a local solver and each vehicle $k$ has a local surrogate to approximate the global objective function. The local solver hyperparameters (i.e. learning rate and local epochs) are assumed to be homogeneous among all vehicles in all rounds $R$. At each round $r$, only a subset of $K$ participants is selected to update the global model. The SGD is run locally for a number of epochs $E$ and $\eta$. A central server repeats these steps until convergence. The steps of this approach are summarized in Algorithm [1].

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**Algorithm 1: FedAvg [4]**

**Input:** $R, K, \eta, \omega^0, S, E$

**for** $r = 1$ to $R$ **do**

1. Server coordinates to choose subset $S$ of $K$ randomly
2. Server broadcasts $\omega^0$ to $S$
3. Device $k_i$ run a local solver for $E$ epochs to update $\omega^t$ with step size $\eta$ to get $\omega^{t+1}$
4. The selected device $k_i$ sends its updated model $\omega^{t+1}$ back to the server
5. Server receive all updates from $S$ and average $\omega'$s as $\omega^{t+1} = \frac{1}{R} \sum_{k \in S_t} \omega^{t+1}_k$

**end**
In this section, we explain the semi-supervised learning in general then, we narrow this definition to federated learning settings. Semi-supervised learning is an approach where unlabeled data is used to gain more understanding of the general structure in general [16]. In other words, training the model is performed by learning features only from a small labeled data set, and fill the unlabeled points by predicting its class with the help of initial model.

A. FedSem

Our proposed learning method which aims to leverage the semi-supervised learning techniques in federated learning. We take advantage of using pseudo-labeling technique to utilize unlabeled data in all devices in the network. In the beginning, the server sends initial model Model-Phase1 with random gradients and weights to available clients which in turn will start training or updating their model using only their labeled data in order to collaboratively design a global model Model-Phase1. This phase aims to capture all labels and features from different devices to assure that the global model can predict all expected labels. Then, the server receives the local models from all participant devices and average weights and gradients to create the global model Model-Phase1. All participant devices and coordinating server repeat this scenario for many rounds until convergence of Model-Phase1. Server evaluates the global model every round to decide if the model can be used in phase two to enable all devices to utilize unlabeled data. In phase two, the data is fully labeled and all devices train their model following the federated supervised learning procedure in order to design the more robust global model Model-Phase2. In Fig.2 explains the proposed method with a flowchart. In addition, Algorithm 2 and Algorithm 3 explain the steps in each phase with details.

**Algorithm 2: Federated Algorithm for Semi-supervised learning Phase-1**

**Input:** Total Participant devices $K$, Subset Participant in each round $S$, Learning rate $\eta$, initial gradients $\omega^0$, Number of epochs in local device $E$, Number of rounds $R$

**for** $i = 1$ to $R$ **do**

- Server coordinates to choose subset $S$ of $K$ randomly
- Server broadcasts $\omega^i$ to $S$

**for** $j = 1$ to $S$ **do**

- Device $k_j$ Start training using only the fully labeled data points for $E$ epochs to update $\omega^i$ with step size $\eta$ to get $\omega^{i+1}$
- The selected device $k_j$ send its updated model $\omega^{i+1}$ back to the server

**end**

- Server receive all updates from $S$ and average $\omega^i$s as $\omega^{i+1} = \frac{1}{K} \sum_{k \in S} \omega^{i+1}_k$

**if** convergence is satisfied **then**

- Save the model ”Model-Phase1”;
- Break;

**end**

B. Key Challenges of Federated Learning

In order to evaluate the proposed method FedSem, we should take into account the following properties of federated learning [4].

- Non-IID: training the data in each device depends on the usage of the device by the user. Consequently, any specific user’s local data doesn’t represent the population distribution [8].
- Unbalanced data: the local training data (e.g. Sign Images) is varied depending on the usage of the service.
Algorithm 3: Federated Algorithm for Semi-supervised learning Phase-2

Input: Total Participant devices $K$, Subset Participant in each round $S$, Learning rate $\eta$, initial gradients $\omega^0$, Number of epochs in local device $E$, Number of rounds $R$

- All $K$ devices use “Model-Phase1” to fill unlabeled data points. for $i = 1$ to $R$ do
  - Server coordinates to choose subset $S$ of $K$ randomly
  - Server broadcasts $\omega^i$ to $S$
    for $j = 1$ to $S$ do
      - Device $k_j$ train its model utilizing labeled and unlabeled data $E$ epochs to update $\omega^i$ with step size $\eta$ to get $\omega^{i+1}$
      - The selected device $k_j$ send its updated model $\omega^{i+1}$ back to the server
    end
  - Server receive all updates from $S$ and average $\omega^i$'s as $\omega^{i+1} = \frac{1}{\vert S \vert} \sum_{k \in S} \omega^{i+1}_k$
  -if convergence is satisfied then
    - Save the model “Model-Phase2”;
    - Break;
  end
end

which in turn is different from the user(e.g. vehicle) to another [7].

- Communication boundaries: Some devices(e.g., smartphones, vehicles) typically are not available all the time or may have slower connections. Also, different users may use different network technologies(i.e. 4G and 5G) [8].

V. NUMERICAL RESULTS

FedSem aims to utilize unlabeled data by splitting the learning process into two-phase. FedSem enables to increase the stability and robustness of learning process by increasing the amount of data used to train the model. FedSem follows the procedure of FedAvg where a part of devices are selected at each round to train and update the model, updates are performed locally, and then it is sent to a server to form a global model.

In this section, the performance of Fedsem method is benchmarked to supervised federated learning under different scenarios. First, we explain the used dataset and its structure, then we present the used model and classifier.

A. Dataset, Performance Metrics, and Experimental Setup

The German Traffic Sign Dataset (GTSDB) has been widely used in similar research for centralized supervised learning [17], [18]. We follow the procedure done in [17], [18] for splitting the dataset. The data is split into 39209 32×32 px color images for training and 12630 images for testing. Each image represents one of 43 distinct classes of traffic signs. Each image is a 32×32×3 array of pixel intensities, represented as [0, 255] integer values in RGB color space. The class of each image is converted to an one-hot encoding scheme. We used a deep neural network classifier as a model following the work done in [17]. This distribution is similar to [7]. For image recognition, we use convolutional neural networks as in [19].

In this work, we use percentage of the labeled data and number of users in the network versus testing loss and testing accuracy as performance metrics to evaluate FedSem. In general, the dataset is split between $n$ devices. In each round, we select a random participants to update the model.

We have implemented FedSem in TensorFlow [20]. We have employed Adam optimizer as a local solver. The sampling scheme is implemented as in algorithms 1 and 2 which is a uniform among devices. The update is performed based on the weights to the local data points as proposed in [4].

For the model training parameters, we adopted the parameters similar to work done in [18]. However, we reduce the batch size to fit the device capabilities. The model has 4 layers comprising of 3 convolutional layers for feature extraction and one fully connected layer as a classifier [18].

Table I illustrates this dataset and how it is split across devices. For experiments setup, the learning rate and a number of chosen devices per round are determined. We have reported results by using the hyperparameters on FedAvg [4]. We have split the data on each device into a training set (80%) and testing set (20%). All matrices are reported depending on the global model.

We summarize the experimental setup in Table II. We started conducting an experiment using only labeled data on the same setting mentioned in Table I. Then we repeat the same experiments with the same settings but we inject the unlabeled data point after finishing the first phase.

| Parameter | Value |
|-----------|-------|
| Library   | TensorFlow GPU |
| Number of local epochs $E$ | 20, 40 and 100 |
| Learning rate $\eta$ | 0.0001 |
| Batch Size | 32 |
| Number of rounds | 50, and 100 |
| Clients per round | 10 and 20 |
| Evaluation Period | every round |
B. Results

In Table III, we summarize the obtained accuracy in both phases using different percentages of labeled data and different number of epochs. We can notice that regardless of the percentage of the labeled data used in the phase one, training the model using unlabeled data helps to increase the accuracy. However, tuning the number of epochs to a large number decreases the accuracy because the participants try to optimize their solution to the internal objective function. However, tuning the number of epochs to an optimal value increases the accuracy as well as decreases the number of rounds that is needed to converge. This helps to reduce the communication costs.

In Fig. 3, we compare the accuracy before and after injecting the unlabeled data points. Unlabeled data helps to increase the testing accuracy. In conclusion, the more labeled data point, the more testing accuracy. We have shown that the percentage of the labeled data points is really important factor for model training. Also, injecting unlabeled data into training after labeling them with prior model increases the accuracy even if the ratio of unlabeled data is high.

VI. CONCLUSIONS

In this work, we propose a federated semi-supervised learning technique to utilize the unlabeled data in smart cities. The proposed approach divides the learning into two phases to assure capturing the information encapsulated within unlabeled data. The global model resulting from Phase-1 is used to label the unlabeled data. We have conducted several experiments using different percentages of labeled data to show how FedSem utilizes the unlabeled data to enhance accuracy. FedSem improves the accuracy of up to 8% compared to using only the labeled data. Overall, utilizing unlabeled data in federated learning increases accuracy.

REFERENCES

[1] N. N. Amma and F. R. Dhanaseelan, “Privacy preserving data mining classifier for smart city applications,” in 2018 3rd International Conference on Communication and Electronics Systems (ICCES), pp. 645–648. IEEE, 2018.
[2] D. Puiu, P. Barnaghi, R. Tönjes, D. Kümpér, M. I. Ali, A. Mileo, J. X. Parreira, M. Fischer, S. Kolozali, N. Farajidavar et al., “Citypulse: Large scale data analytics framework for smart cities,” IEEE Access, vol. 4, pp. 1086–1108, 2016.

[3] T. S. Brisimi, C. G. Cassandras, C. Osgood, I. C. Paschalidis, and Y. Zhang, “Sensing and classifying roadway obstacles in smart cities: The street bump system,” IEEE Access, vol. 4, pp. 1301–1312, 2016.

[4] H. B. McMahan, E. Moore, D. Ramage, S. Hampson et al., “Communication-efficient learning of deep networks from decentralized data,” arXiv preprint arXiv:1602.05629, 2016.

[5] N. H. Tran, W. Bao, A. Zomaya, and C. S. Hong, “Federated learning over wireless networks: Optimization model design and analysis,” in IEEE INFOCOM 2019-IEEE Conference on Computer Communications, pp. 1387–1395. IEEE, 2019.

[6] V. Smith, S. Forte, M. Chenxin, M. Takić, M. I. Jordan, and M. Jaggi, “Cocoa: A general framework for communication-efficient distributed optimization,” Journal of Machine Learning Research, vol. 18, p. 230, 2018.

[7] A. K. Sahu, T. Li, M. Sanjabi, M. Zaheer, A. S. Talwalkar, and V. Smith, “Federated optimization for heterogeneous networks,” 2018.

[8] V. Smith, C.-K. Chiang, M. Sanjabi, and A. S. Talwalkar, “Federated multi-task learning,” in Advances in Neural Information Processing Systems, pp. 4424–4434, 2017.

[9] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, “Federated learning in mobile edge networks: A comprehensive survey,” arXiv preprint arXiv:1909.11875, 2019.

[10] T. Chen, G. Giannakis, T. Sun, and W. Yin, “Lag: Lazily aggregated gradient for communication-efficient distributed learning,” in Advances in Neural Information Processing Systems, pp. 5050–5060, 2018.

[11] S. Boyd, N. Parikh, E. Chu, B. Peleato, J. Eckstein et al., “Distributed optimization and statistical learning via the alternating direction method of multipliers,” Foundations and Trends® in Machine learning, vol. 3, no. 1, pp. 1–122, 2011.

[12] J. Dean, G. Corrado, R. Monga, K. Chen, M. Devin, M. Mao, A. Senior, P. Tucker, K. Yang, Q. V. Le et al., “Large scale distributed deep networks,” in Advances in neural information processing systems, pp. 1223–1231, 2012.

[13] O. Dekel, R. Gilad-Bachrach, O. Shamir, and L. Xiao, “Optimal distributed online prediction using mini-batches,” Journal of Machine Learning Research, vol. 13, no. Jan, pp. 165–202, 2012.

[14] O. Shamir, N. Srebro, and T. Zhang, “Communication-efficient distributed optimization using an approximate newton-type method,” in International conference on machine learning, pp. 1000–1008, 2014.

[15] P. Liu, S. U. Stich, and M. Jaggi, “Don’t use large mini-batches, use local sgd,” arXiv preprint arXiv:1808.07217, 2018.

[16] Z. Li, B. Ko, and H. Choi, “Pseudo-labeling using gaussian process for semi-supervised deep learning,” in 2018 IEEE International Conference on Big Data and Smart Computing (BigComp), pp. 263–269. IEEE, 2018.

[17] P. Sermanet and Y. LeCun, “Traffic sign recognition with multi-scale convolutional networks.” in IJCNN, pp. 2809–2813, 2011.

[18] A. Starovoitov, “Traffic sign classification with a convolutional network,” Pattern Recognition and Image Analysis, vol. 28, no. 1, pp. 155–162, 2018.

[19] J. Li and Z. Wang, “Real-time traffic sign recognition based on efficient cnns in the wild,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 3, pp. 975–984, 2018.

[20] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard et al., “Tensorflow: A system for large-scale machine learning,” in 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16), pp. 265–283, 2016.