Federated Learning in Vehicular Networks

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***Abstract*—Machine learning (ML) has already been adopted in vehicular networks for such applications as autonomous driving, road safety prediction and vehicular object detection, due to its model-free characteristic, allowing adaptive fast response. However, the training of the ML model brings significant overhead for the data transmission between the parameter server and the edge devices in the vehicles. Federated learning (FL) framework has been recently introduced as an efficient tool with the goal of reducing this transmission overhead while also achieving privacy through the transmission of only the model updates of the learnable parameters rather than the whole dataset. In this article, we investigate the usage of FL over ML in vehicular network applications to develop intelligent transportation systems. We provide a comprehensive analysis on the feasibility of FL for the ML based vehicular applications. Then, we identify the major challenges from both learning perspective, i.e., data labeling and model training, and from the communications point of view, i.e., data rate, reliability, transmission overhead/delay, privacy and resource management. Finally, we highlight related future research directions for FL in vehicular networks.**

***Index Terms*—Machine learning, federated learning, vehicular networks, edge intelligence, edge efficiency.**

I. Introduction

As vehicles evolve with advanced safety features and eventually self-driving capabilities, massive amounts of data are generated by a variety of sensors on board, such as camera, RADAR and LIDAR as well as proximity and temperature sensors [1]. For instance, an autonomous vehicle is expected to generate about one gigabyte of data per second. However, currently, these data are not systematically processed, stored, or analyzed for better inference. Recently, machine learning (ML) algorithms have been developed to learn from sensor measurements due to several advantages, including low computational complexity when solving optimization-based or combinatorial search problems and the ability to extrapolate new features from a limited set of features contained in a training set.

The current trend in the usage of ML in vehicular networks focuses on centralized algorithms, where a powerful learning algorithm, often a neural network (NN), is trained on the massive dataset collected from the edge devices on the vehicles, as illustrated in Figure 1. NN model provides a non-linear mapping between the input, which contains mostly vehicle sensor data, and the output, which can be the labels of the sensor data. This mapping is constructed by training the NN through the collection of the local sensor data from the edge devices, which is a supervised learning scheme. Once model training is completed, the model parameters are sent back to the edge devices for prediction purposes. However, the size of the generated data is huge when we need to build wider and deeper NN architectures for successful training. Thus, training a model with data transmission from the edge devices to the cloud center in a reliable manner may be too costly in terms of bandwidth, introduce unacceptable delays, and infringe user privacy.

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Federated learning (FL) has been recently introduced with the goal of bringing ML down to the edge level [2], as illustrated in Figure 2. In FL, instead of the local datasets, the edge devices only send the gradients of the learnable parameters derived from these local datasets to the cloud server. The cloud server aggregates these gradients and determine the model parameters, which are then transmitted to the edge devices. This procedure continues iteratively, until the learning model is trained. The training procedure is similar to that of ML, except that FL does not involve the transmission of the whole dataset. This enables reducing both the complexity of ever growing datasets at the edge devices in the vehicles and the transmission overhead of these datasets to the cloud servers. Hence, FL is a promising approach to efficiently train the learning models by preserving the privacy of raw data and reducing the transmission overhead in wireless communications. While FL has already received great research interest in the wireless networks [2], imparting FL to the vehicular networks is more challenging due to the dynamic nature of the channel characteristics of the vehicular networks [3]. Furthermore, previous works [2, 3] approach FL from the communications point-of-view. The main contribution of this article is to provide a comprehensive analysis on FL by considering both learning and communications aspects, based on the description and analysis of several learning-based vehicular applications.

This article aims to provide a comprehensive grasp on how vehicular networks can benefit from FL. First, we discuss ML based vehicular network applications in the context of vehicle management and traffic management. We present the advantages of the usage of FL over ML for training the models in these vehicular network applications. Then, we provide an extensive discussion on both FL- and communications-related research challenges in a broad perspective. FL-related challenges include data diversity, labeling and model training, whereas communication-related challenges are transmission overhead, communication delay, privacy, scheduling and resource allocation. Finally, we provide an extensive discussion on the major research issues and future research directions in making FL feasible in vehicular networks.

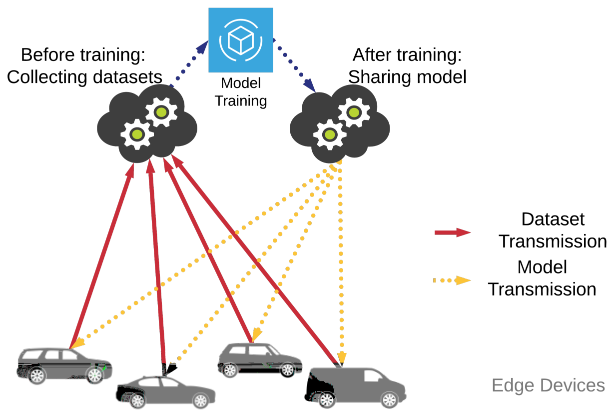

Fig. 1. Model training for ML in a vehicular network.

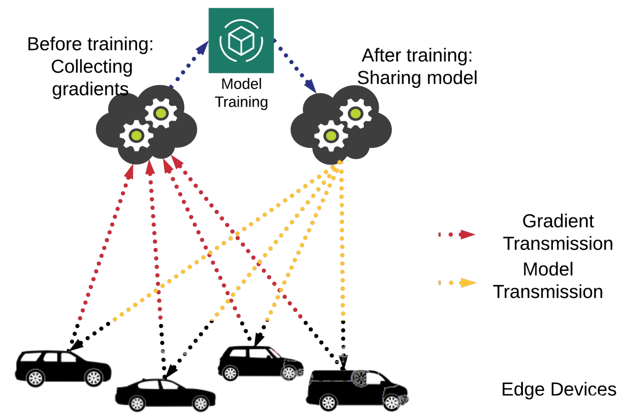

Fig. 2. Model training for FL in a vehicular network.

II. Machine Learning for Vehicular Applications

ML-based techniques have become significantly useful in vehicular applications with the increase in the amount as well as diversity of the data generated by the sensors. Specifically, ML originates from the imitation of the human brain containing billions of neurons forming a neural network, hence, is mostly called as artificial NN. There are mainly three types of ML, namely, supervised, unsupervised and reinforcement learning. In a supervised learning model, the NN learns on a labeled dataset where an answer key is provided beforehand. In contrast, unsupervised learning studies the clustering of the unlabeled data by exploiting the hidden features/patterns derived from the dataset. Reinforcement learning (RL) also uses unlabeled data and the model parameters are learned based on the award and penalty mechanism, which are formulated as a function of varying environment characteristics.

In the following, we present the ML based vehicular applications and the related challenges in two categories: vehicle management and traffic management.

A. *Vehicle Management: Autonomous Driving*

The aim of autonomous driving is to navigate a vehicle through a road environment without collisions. To achieve this, the vehicle needs to detect, identify, localize and track surrounding objects, such as pedestrians, trees and other vehicles relative to its own frame of reference, and adjust its driving dynamics accordingly. The layered nature of this end-to-end autonomous driving task, depicted in Figure 3, renders conventional methods that use an ensemble of hand-crafted computer vision techniques for each layer sub-optimal. Deep neural networks that are trained in an end-to-end manner on a huge amount of RADAR/LIDAR/camera sensor data, such as convolutional neural networks (CNNs), have emerged in recent years as a better alternative [4].

In [5], a human-like decision-making method is proposed for autonomous driving by using CNNs. The input of CNN is the LIDAR data collected from multiple vehicles to provide depth information, whereas the output of the CNN is the decision regarding the speed and steering of the vehicle. While this demonstrates the advantage of using trained CNNs for autonomous driving, CNNs require a large amount of precisely labeled data for accurate prediction. Therefore, the training is usually conducted in a cloud data server in an offline manner. The main drawback in offline training is that the trained model cannot adapt to the environment dynamics. The usage of FL can provide the adaptation to the environmental changes, such as feature learning in different geographical locations. However, FL utilizes gradient computation on the edge device, which necessitates immediate and accurate labeling of online data. Therefore, the higher layers of the autonomous driving ML application stack shown in Figure 3, such as intent estimation and driving decisions can get higher benefit from FL strategies rather than the lower layers such as object detection and tracking.

B. *Traffic Management: Infotainment and Route Planning*

Infotainment and route planning are crucial for preventing traffic jams, sustaining an efficient distribution of resources during normal traffic, and enabling effective emergency response during extreme situations. Data-driven ML solutions are superior to conventional model-based approaches for these applications since they can easily adapt to the random changes in the system dynamics over time caused by human involvement, which can be difficult to model mathematically. For instance, in [6], a deep learning based resource management scheme, which learns the hidden patterns in data traffic over a vehicular software-defined network (SDN), is shown to improve packet traffic efficiency compared to the conventional methods. Similar solutions exist for route planning and efficient management of vehicle traffic. While these applications benefit from versatile ML solutions, they rely on frequent model retraining due to the ever-changing dynamics of the systems. Since the data generated for training the models for these applications can accurately and quickly be labeled on the vehicle, FL strategies can benefit the retraining of these models, speeding up the deployment and improving the overall performance of the application.

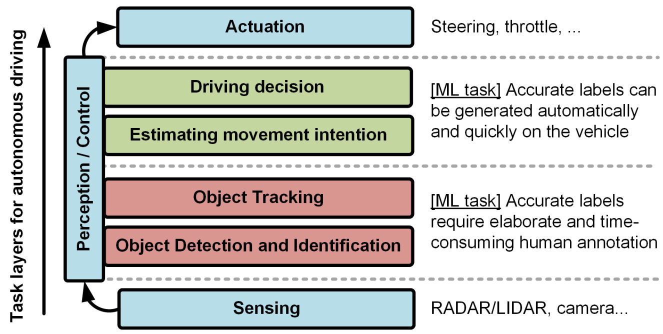

Fig. 3. The hierarchical structure of tasks for autonomous driving.

III. Federated Learning for Distributed Training in Vehicular Networks

Conventional approaches for training ML models in vehicular applications consider a central server, which collects the raw data from vehicular edge devices, computes gradients according to the current state of the model and the incoming data, then updates the model parameters accordingly. However, this approach cannot easily yield a model that can adapt to local changes as required by the applications. Many of the nodes in a given vehicular network cannot comply with the requirements for high transmission overhead and raw data privacy due to the highly dynamic and harsh communication channel, hindering the local adaptation capability of the model since the local data from those nodes cannot participate in the model training to better represent the distribution in the global dataset. Distributed training with an FL scheme enables adaptation to the data distribution since the gradients are computed on the edge device based on the local dataset, and the gradients themselves, instead of the much larger raw data, are transmitted to the central server. This not only reduces transmission overhead, but also does preserve raw data privacy. Thus, it enables more nodes to participate in model training, which results in a model that better adapts to the local changes inside the global dataset.

The proposition of FL, which enables it to adapt to local changes, is based on the "mini-batch learning" technique in conventional ML model training, where the dataset is partitioned into smaller sub-blocks that are used for parameter updates rather than the whole dataset. The gradients are computed for each of these sub-blocks, i.e., mini-batches, and then a combination of these gradients, typically the average, is used as the gradient value for a parameter update step, which is repeated iteratively until convergence. Since the computation of the gradients for different mini-batches are independent, FL schemes can exploit the local processing capabilities of the edge devices in the vehicles to compute and transmit these in parallel, as illustrated in Figure 2. The central server then simply combines the collected gradients and performs model update, then transmits the new model parameters to each vehicle. This reduces the transmission overhead and preserves privacy since the much larger and vulnerable raw data are not transmitted, enabling significantly more nodes to participate in the model training, thus, increasing the local adaptivity of the ML model.

Although FL has its advantages over centralized learning (CL), not all applications can benefit from FL strategies for model training. Using FL is advantageous for applications and environments that satisfy three conditions:

1) The application requires a model that adapts to new conditions, which constantly change on the edge, and retraining/update-from-server/deployment for each edge device needs to happen fast.
2) Data gathered by the edge device cannot be transmitted to a cloud server in relevant time, either because they are too large and/or need to be transmitted immediately and/or need excessive measures for raw data privacy.
3) Data gathered by the edge device can be quickly and accurately labeled on the same device for gradient computation.

As a new emerging field still in its infancy, there are a very limited number of works considering FL in vehicular applications that satisfy these three conditions [7, 8]. In [7], FL has been considered in a vehicular network, where the communication between the data center and the edge devices is assisted by road side units to ensure low latency for gradient data transmission. Specifically, a Lyapunov optimization based approach is proposed to minimize the delays incurred by the transmission of gradient data in FL. In [8], the authors propose a selective model aggregation approach, where the data center collects the gradient data from only "fine" edge clients in a vehicular network, such as the devices with high data quality and power capability. Then, the performance of FL is compared to that of ML based on both MNIST and BelgiumTSC image classification datasets, which are composed of the images of the numbers and traffic signs, respectively. While these works demonstrate the above-mentioned advantages of using FL over CL for a constrained set of applications, they are not directly applicable for realistic ML-based vehicular applications. FL still faces significant open challenges for use in such realistic applications like autonomous driving and traffic management via infotainment and route planning.

IV. Research Challenges and Future Directions

The main challenges to be addressed for using FL in vehicular environments and utilizing its promises for reduced transmission overhead, raw data privacy and more adaptive and scalable ML models, are summarized in Figure 4. Even though the transmission overhead is reduced, successfully training ML models over vehicular networks with FL is still challenging since the communication channel varies dynamically in the vehicular environment due to high vehicle mobility and varying weather conditions, resulting in frequent drop-outs and hand-overs. Moreover, transmission overhead reduction comes at the cost of increased computation overhead at the vehicular edge devices: The edge devices need to compute gradients, which typically necessitates powerful processors so that all devices can complete the computation and transmit the update in relevant time. Furthermore, the number of edge devices participating in the FL model update in vehicular networks will

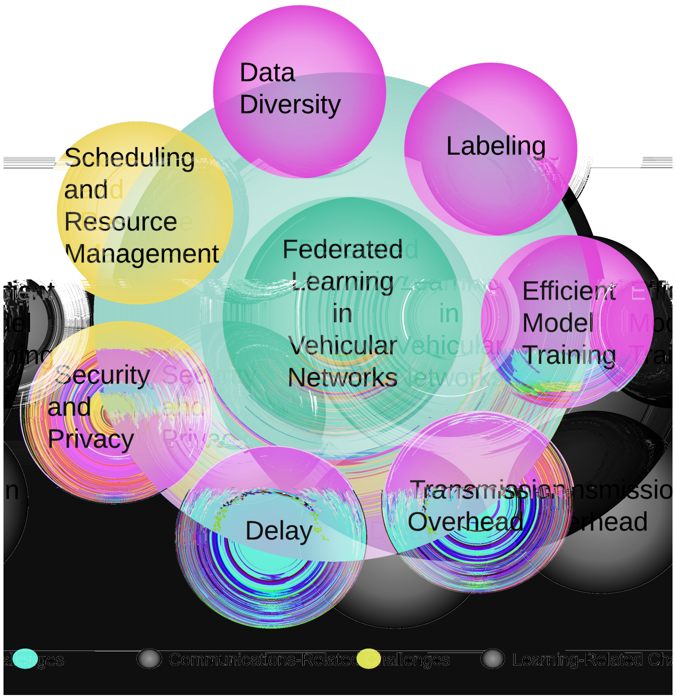

Fig. 4. Summary of the design and research challenges for federated learning in vehicular networks.

typically be much lower than that in regular wireless networks simply because vehicles need larger physical space between each other compared to humans with laptops/phones. This may cause an undersampling phenomenon for the dataset as seen by the model since there is typically high variety in local data gathered by each edge device. These challenges need to be addressed in detail in order to leverage the advantages of FL for ML-based vehicular networks applications.

In this section, we provide an extensive discussion on both learning-related and communications-related research challenges, for FL in vehicular networks. In addition, we highlight possible future research directions related to these challenges.

A. FL-Related Research Challenges

1) Data Diversity: In FL, the training data are located at the edge devices, which causes data diversity due to the non-uniform distribution of the datasets at the edge devices. For example, in autonomous driving scenario, the image data obtained from vehicles in different locations have different distributions. Data diversity causes large variances in the averaged gradient data, and therefore, decreases the convergence rate for the learning models. For example, the features of the collected image data in different locations increases the diversity of the dataset, which makes NN unable to perform feature-extraction and feature-representation well. Furthermore, the number of edge devices in vehicular networks is smaller than general wireless networks due to the large distance among the vehicles. This leads to the model aggregation from less number of edge devices, which also makes model training a challenging task in vehicular applications. To improve the model training performance against data diversity caused by either non-uniform data distribution or insufficient number of edge devices, one possible solution is to increase the model size, i.e., enlarging the width and the depth of the NN model so that the NN can provide robust feature representation, as demonstrated for the beamformer design problem in [9]. However, the design of larger and deeper NN models need further investigation to provide robustness in vehicular networks, which have more diversity in the data than conventional wireless networking applications.

2) Labeling: ML techniques are mostly supervised, i.e., the dataset is labeled. For example, an image dataset of vehicles includes ant025(we)252lt267(ar(autonoar(auu

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to be developed to make FL model training more feasible in vehicular network applications.

B. Communications-Related Research Challenges

Communications-related challenges for FL have received significant attention recently for regular wireless/cellular networks. However, these existing studies consider applications that have no practical significance in the vehicular domain (e.g., handwritten character recognition) and they are specifically tuned to the network topology and dynamics of the regular wireless/cellular networks, which typically have high node density but relatively low node mobility. On the contrary, vehicular networks and applications have relatively low node density and very high node mobility. Therefore, an overall re-evaluation of the results in these works for the vehicular environment and the relevant applications is necessary in the context of FL. We group these challenges into four main categories: Transmission overhead, delay, security and privacy, and finally, scheduling and resource management.

1) Transmission Overhead: Compared to the CL based techniques, FL allows us to reduce the transmission overhead by replacing raw data transmission with model update parameter transmission. However, the size of the model update parameter set is directly proportional to the size of the learning model. Thus, the transmission of model parameters may become a bottleneck if the model involves massive number of learnable parameters.

The solution is either to reduce the transmission overhead or increase the reliability of the channel. There are two ways of reducing the transmission overhead in FL-based framework: compressed sensing and model compression. In compressed sensing, the sparsity of the gradients, i.e., most of the gradients being zero, is exploited to reduce the amount of transmitted data [12]. While this approach reduces the transmission overhead, it increases encoding/decoding complexity at the parameter server and edge devices in a vehicular network for reliable performance. Hence, further investigation of lower computation complexity solutions is needed. Model compression is another approach to reduce the number of NN parameters. In [13], quantized NN parameters are used for this purpose in sensor selection problem. In order to apply model compression techniques such as quantized/tensorized NN models in vehicular applications, the application-specific design of hyperparameter optimization stage and NN model is required to obtain the optimum model architecture.

Alternatively, channel reliability can be improved to facilitate faster convergence to more accurate models. For example, the authors in [12] attempt to design an FL-friendly communication protocol from scratch based on the exploitation of the broadcast/multiple-access nature of the downlink/uplink channels in an FL framework. Using analog links in noisy band-limited channels for both uplink and downlink rather than digital links has been demonstrated to provide higher reliability at lower transmit power, especially when the local data among edge devices are not uniformly distributed. While this strategy can enable a near-optimal rate and reliability for a given vehicular FL scenario, such customization may not be realistic for general vehicular use. Development of environment-aware heterogeneous architectures combining the strengths of different standard-compliant vehicular communication technologies, e.g., choosing between IEEE 802.11p, millimeter-wave and visible light communications based on road/channel conditions, is a promising future research direction for improving the overall network reliability of FL-based vehicular frameworks.

2) Delay: During FL based training, model convergence rate is determined by the execution time of each model update iteration and the number of iterations. Model convergence rate is an important parameter in the fast and accurate deployment of FL-based applications. In [14], a delay-minimizing FL scheme is formulated as the solution of a joint learning and communication optimization problem for regular wireless/cellular networks. However, this solution is not directly applicable to vehicular networks, in which drop-outs, handovers and varying channel conditions happen much more frequently and rapidly than regular wireless networks due to the much higher mobility and less spatial density of nodes. The effects of such intermittent and extreme network topology/capability changes on FL in vehicular networks need to be investigated as further research.

3) Security and Privacy: During FL training, different types of devices may participate in the learning stage. Thus, untrusted devices can join the network more easily, which brings security and privacy issues. The security and privacy of the devices in the network can be achieved through the use of reputation management (reward and punishment) based approaches. In [8], authors propose a method, where each edge device receives a reward in exchange for their computation of power and data quality. However, [8] considers a simple FL framework with a single server. In a realistic vehicular network scenario, there can be multiple access points acting like servers in FL, increasing the dimension of the reputation management problem. As a result, their usage in vehicular networks requires further research for multi-server FL architectures.

4) Scheduling and Resource Management: The availability of wireless communication resources and the packet error performance of each node in a wireless network vary greatly among nodes due to both device heterogeneity and spatial distribution. Since FL convergence rate is directly affected by the performance of the communication link between each edge device and the central FL controller, scheduling and resource management of nodes participating in an FL scheme need to be explicitly optimized with the objective of maximizing the FL convergence rate. However, this problem becomes ill-defined for vehicular networks where the links between the vehicular edge devices on the road are usually intact whereas the links to the central controller from each device experiences frequent and sporadic handovers and drop-outs. A "collaborative" FL solution where the vehicular edge devices instead utilize multiple hops between neighbouring vehicular edge devices to reach the central controller can decrease the sensitivity of the FL framework performance to such network-related shortcomings. While such a framework is proposed in [15], it is specifically tuned to the network topology and dynamics of regular wireless/cellular networks, which are significantly different from vehicular networks. Therefore, further research on scheduling and resource management strategies for FL, focusing on the low-density / high-mobility network topology in the vehicular environment, is needed.

V. Conclusions

In this article, we present an FL based framework for the distributed training of ML models, as an efficient learning scheme for vehicular networks and edge intelligence, in contrast to the classical ML techniques based on the centralized training on cloud servers. We enlist several applications of vehicular networks for the usage of ML and FL, such as autonomous driving, infotainment and route planning. We identify the major research challenges of FL in vehicular networks, presented from both learning perspective, i.e., data labeling and model training, and the communications point of view, i.e., data rate, reliability, transmission overhead/delay, privacy and resource management, along with the related future research directions.

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