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Recent advances, challenges, and opportunities

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Wireless recommendations for internet of vehicles: Recent advances, challenges, and opportunities

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Abstract: Internet of Vehicles (IoV) is a distributed network of connected cars, roadside infrastructure, wireless communication networks, and central cloud platforms. Wireless recommendations play an important role in the IoV network, for example, recommending appropriate routes, recommending driving strategies, and recommending content. In this paper, we review some of the key techniques in recommendations and discuss what are the opportunities and challenges to deploy these wireless recommendations in the IoV.

Key words: Internet of Vehicles (IoV); wireless recommendations; interactions between communication and computation; edge computing

1 Introduction

Internet of Vehicles (IoV) is a distributed network that consists of connected cars, roadside infrastructures, wireless communication networks, and central servers to support data transmission, content sharing, and information provision.

IoV is regarded as an important scenario for Internet of Things (IoT)[1,2] and is intended to play an essential role in the next generation Intelligent Transportation System (ITS)[3,4]. IoV enables us to collect real-time information of vehicles on the road, to enhance on-time delivery rate, and to optimize the dispatch and fleet management aiming at improving the operating performance and reducing manpower and fuel costs. Recent advances in wireless communications, distributed systems, Artificial Intelligence (AI), Cyber Physical Systems (CPS), including electronic vehicles, and autonomous cars, are key enablers of the development of IoV. Gathering and exchanging information and data among different vehicles, roadside units, and central cloud platforms, IoV has the potential to create new valuable applications, such as the automatic navigation, the content caching and sharing among vehicles and the cloud, the accident alert, and the automatic fleet management. An overview of the IoV network is shown in Fig. 1. The ultimate objective of the IoV is to achieve a more efficient, safe, and green world of transportation.

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1.1 Key enabler

In this subsection, we discuss the key enablers of the IoV.

- **Wireless communication**

The recent development of wireless communication technologies[5], such as 5G, edge computing, and IoT, will offer more connectivity options for the vehicle to enable real-time communication with human drivers, pedestrians, other vehicles, roadside infrastructures, and central management systems. The future IoV is expected to support various Vehicle to Everything (V2X)[6] communications. Several V2X communications are listed as below.

– Intra-vehicle communication can monitor the

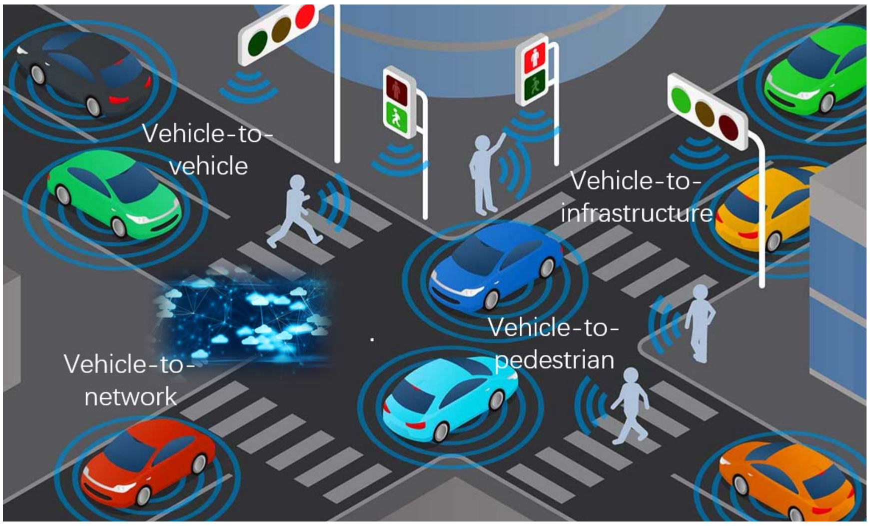


Fig. 1 An overview of the IoV network.

vehicle's internal performance through On Board Units (OBUs) and a number of equipped sensors.

– Vehicle to Vehicle (V2V)[7] communication allows exchange of information between vehicles. Information may include the speed, surrounding environment, and position of nearby vehicles.

– Vehicle to Network (V2N) communication supports the wireless exchange of information between a vehicle and the Internet. Vehicles are enabled access to diverse Internet services.

– Vehicle to Internet (V2I)[8] communication enables the vehicle to access additional information from the internet through wireless networks such as 5G.

– Vehicle to Pedestrian (V2P)[9] communication supports awareness for vulnerable road users like pedestrians and cyclists.

- **Distributed system**

The IoV network is in essence a distributed system. Vehicles, roadside units, sensors are regarded as distributed nodes. These distributed nodes not only have communication capability, but also are able to perform local computations. Thus, the development of distributed systems, such as edge computing framework, interactions between communication and computation, will enhance the deployment of IoV[10]. For example, the proliferation of cloud and edge computing[11] capabilities will enable an easy and seamless way of using the vehicle as an integrated part of the cloud and-edge based services. Understanding the interactions between communication and computation could help to build a fundamental framework for IoV.

- **Artificial intelligence**

In the past decade, artificial intelligence grows extremely fast. Artificial intelligence refers to machines that can mimic cognitive functions that humans associate with, such as learning and problem-solving. Artificial intelligence is a main driving force of IoV. When data are gathered in the IoV network, from sensors equipped on the vehicles or roadside units or from driver generated data (such as mobile apps), one immediate challenge is how to process and utilize the data. Artificial intelligence is a vital tool to process the data. For example, how to detect an anomaly and send an alert; how to analyze the sensor data and make decisions/suggestions on how to drive; and how to incorporate vehicles' data to predict the road congestion status and navigate to an appropriate route[12, 13].

- **Cyber-physical system**

Cyber-physical systems comprise digital, physical, and human components engineered for function through integrated physics and logic. Examples of CPS include smart grids, autonomous automobile systems, medical monitoring, industrial control systems, and robotics systems. In the IoV network, physical components (such as sensors and cameras), data, humans, and computational components need to be deeply intertwined and coordinated[14, 15].

1.2 Application scenario and major benefit

The IoV network brings a great number of benefits to the entire society and our daily lives. Some of the major benefits are as follows.

- **Safe driving**

In each year, millions of casualties are caused by road accidents due to human errors, such as fatigue or negligence of potential danger. The implementation of IoV has the potential to correct errors and make vehicle transportation safer.

The IoV network can use sensors and cameras to gather data and information from various vehicles and roadside entities, such as the lamp post and traffic lights, to detect and predict possible collisions and accidents. This will then trigger a warning and an alert will be sent to the drivers[16].

With the help of the IoV network, periodical messages about the vehicle's information and notifications of possible emergencies can also be generated, such as traffic jams, dangerous road conditions, or accidents[17].

- **Remote vehicle service**

IoV can connect, access, and control vehicles remotely. This enables the driver to control the vehicle without approaching it. More convenient services become available, like remote door lock, tracking the trail of vehicles[18], finding the vehicle in a parking lot[19], and tracing a stolen vehicle. For example, a logistic company can track the fleet in real time, such that it can provide a more accurate estimation of the good delivery time.

With the help of GPS signals and other sensors' data, the transportation agencies are able to get information of the real-time traffic, transit, and parking lot, making it easier to manage transportation systems to improve the efficiency of transportation.

- **Emergency response**

IoV can bring some fundamental changes to urban emergency response and accident management. In the IoV, when an emergency occurs, for example, car accidents, dangerous road conditions, the connected cars, or roadside units can automatically send real-time data via IoV about the emergency along with the location information to the emergency management system[20, 21]. The emergency management system can automatically respond to this (for example, send a warning to nearby vehicles) or make a request for human emergency team involvement (for example, human emergency team will ask police and ambulances to handle the case). This can reduce the emergency response time and save lives in an emergency scenario.

- **Entertainment**

IoV can also bolster the advanced information systems. Connected cars and roadside infrastructures can get access to the wireless communication networks, such as 5G, and thus, can provide entertainment content and online services, and can enable live streaming music, media, or other information[22] through the dashboard. These can be shared among the connected vehicles.

To provide all these services and realize the aforementioned benefits, wireless recommendation techniques are a core component of the system; while the IoV network serves as the fundamental infrastructure to support the wireless recommendations, and hence various applications related to traffic, vehicles, drivers, and passengers. Multi-dimensional data are collected from different sensors, including traffic information, vehicle positions, and trajectories. Leveraging such data, wireless recommendation systems can provide route recommendations, driving strategy recommendations, and content recommendations. The major benefits of IoV, such as safe driving, remote vehicle services, emergency response, and entertainment, would be realized via these data-intensive applications, for example, recommending appropriate driving strategies could help to improve the safety in driving, recommending new routes in an emergence situation could help to reduce the commute time, or recommending popular music/movies to neighboring vehicles could entertain the drivers and passengers. In a word, IoV networks collect the underlying data, based on which the recommendation systems could make decisions; and as a result, the combination of the two will bring a number of benefits. Table 1 shows the possible benefits of deploying wireless recommendation systems in the IoV.

In this paper, we will review some of the key techniques in recommendations, how wireless

Table 1 Benefits of recommendation systems in the IoV.

Category	Benefit
IoV system information	-Traffic/road information -Vehicles' speed, direction, and position information -Users' historical trace -Users' content requests information
Possible recommendation	-Route recommendation -Parking pot search -Warnings or alerts for dangers -Music/video recommendation
Promising benefit	-Safe driving -Reduced traffic congestion -Remote vehicle services -Emergency response -Personalized entertainment

recommendations are used in IoV networks, and the main challenges and opportunities.

Recommendations have become fundamental to any modern information processing systems — in effect, they allow users to find various contents, options, strategies, etc. based on their *intent* rather than *explicitly searching* for pre-specified ones. The applications of recommendation range from multimedia recommendations (e.g., movies, music, and news), product recommendations, ads recommendations, tourism recommendations, and transportation route recommendations, to healthcare diagnostic recommendations. With content almost in majority consumed over wireless devices and the increasing trend of pushing computation to edge devices, wireless recommendations become very important.

In wireless recommendation systems for IoV networks, there are many wireless features to be taken into account. For example, bandwidth constraints can affect the user experience and the performance of the recommendations; the data are kept locally in distributed servers and federated recommendations may need to be made; and the content and vehicles are time-varying with high dynamics.

Unlike most traditional learning or communication systems, where the focuses are on how to learn some specific parameters or communicate at a maximum rate, the IoV network is a joint framework that spans across the areas of machine learning and information theory/communications, which brings many new challenges and opportunities at the same time. In this paper, we will discuss these aspects.

The paper is organized as follows. In Section 2, we review some classic and advanced techniques of recommendations. In Section 3, we talk about the wireless recommendation application scenarios in IoV networks. In Section 4, we discuss the key challenges and opportunities of deploying wireless recommendation systems in the IoV network. In Section 5, we present our first results. In Section 6, we conclude the paper.

2 Review of the recommendation technique

In this section, we will review several classical and advanced recommendation techniques and discuss their strengths and weaknesses.

Usually, in a recommendation system, there are users, items, and ratings. The recommendation system will recommend items to users based on their interests, which are reflected as the ratings. In the IoV network, the users may be vehicles and drivers; the items may be the routes, driving strategies, and content; and the ratings may be the preference or reward of users on each route, driving strategy, or content.

We will focus on some widely used recommendation system techniques, which are summarized as Table 2, and give examples about how they can be used in the IoV as well as the possible challenges they face.

2.1 Classical collaborative filtering and matrix factorization

Collaborative filtering is the mainstream technique in recommendation systems. In a general sense, collaborative filtering refers to methods that can make predictions about the preferences of a user on items (filtering) by learning knowledge from global user-item interactions (collaborating).

The first category of collaborative filtering is heuristic methods, such as user-based[23] or content/item-based[24–26] models. In user-based models[23], collaborative filtering algorithm aims at filtering out items that a user might like on the basis of reactions by similar users. In content/item-based

Table 2 Summary of recommendation system techniques.

Category	Method	Advantage	Disadvantage
Classical technique	-Collaborative filtering User-based method[23] Item-based method[24–26] -Similarities evaluation[27–29]	-Ability to recommend similar items -Ability to learn from similar users -Personalized recommendation	-Sparsity -Cold-start -Lack of diversity[30]
	-Matrix factorization[31,32] SVD++[33], SVD[34], and FM[35] -Feedback and side information[36,37]	-Better representations with dense embeddings and better rating estimation with the inner product	-Poor inner-product-based predication[38,39] -Ambiguous representations[40]
Deep learning-based technique	-Neural CF[40–43] -Deep neural network[44] -GNN and graph embedding[45,46]	-Better representation ability for high dimensional features	-Require large amounts of samples and hardware resources for training
Reinforcement learning-based technique	-Contextual MAB[47–49] -Markov Decision Process[50] -Upper Confidence Bound[51–53] -Thompson Sampling[54]	-Online learning -Diverse recommendation -Reasonable exploration -Solving the cold-start problem	-Unstable training -Difficult to converge -Low learning efficiency

models[24–26], collaborative filtering algorithm tries to predict a user's interest on an item based on the user's interests on similar items/contents.

One key question is how to evaluate the similarities between users or items. Usually when calculating the similarities between two users or item, we commonly used similarity measures, like cosine-similarity or Person-correlation-based similarity[24], which are studied and shown a good performance. To further enhance the similarity accuracy, Ref. [27] used tags as features in computing similarities; Ref. [28] utilized trust network to enhance the model. Sometimes, explicit ratings (feedback) are not available or costly to the system. In this case, implicit feedback[29] can be estimated/learned to yield personalized rankings.

These heuristic methods form the rudiment of the recommendation system. However, there are a number of problems for the simple models, for example, sparsity, cold-start, inaccuracy, and lack of diversity[30]. A more sophisticated method is the Matrix Factorization (MF) technique, which shows a great performance raise in the Netflix Recommendation Contest[31] and has made a deep impact on the industry.

Formally, the MF technique can be described as follows. Let $\boldsymbol{R}$ denote the $m \times n$ incomplete user-item rating matrix. Here, each row represents a user; each column represents an item; and each entry represents either the rating of the corresponding user given to the corresponding item or it is an unknown value indicating an unrated user-item pair. Usually the number of users and items m, n are large, so each user and each item are represented by a large vector (i.e., a row or a column in the matrix). The MF technique tries to map each user/item into a low-dimensional ($d \ll m, n$) vector space, which is also referred to as latent space. By convention, $\boldsymbol{p}_u$ stands for a user latent factor and $\boldsymbol{q}_i$ stands for an item latent factor. Then the goal of MF is to minimize the mismatch between $\boldsymbol{p}_u^{\mathrm{T}}\boldsymbol{q}_i$ and the corresponding real rating $r_{u,i}$ aggregated among all rated elements in the rating matrix $\boldsymbol{R}$.

For instance, a music recommendation system has been deployed in the IoV using collaborative filtering[32]. The MF method is also widely used in the field of signal processing and representation learning. There are also many variants of the MF algorithms, such as SVD++[33], SVDFeature[34], and FM[35], which further boost performances by adding implicit feedback and side information[36,37].

MF models provide a better solution for building CF models, because (1) dense embeddings are more expressive than simple sparse representations; and (2) the inner product is shown to be a better rating estimation function than simple weighted sum or similarity calculation. However, in recent years, researchers have pointed out several problems in the MF models: difficulty of maximizing inner-product[38], inaccuracy in inner product-based predication[39], and ambiguous representations[40].

2.2 Deep learning-based technique

In recent years, deep learning has made a great improvement in the field of computer science. Researchers of recommendation system have started to pay more attention to deep learning techniques so as to achieve better performance in recommendation tasks. As discussed in previous subsections, we can see that the deficiencies in user, poor item representation ability, and lack of good estimation functions restrict the ability of traditional Collaborative Filtering (CF) and MF models. Deep learning is a promising alternative to solve these problems.

From the perspective of deep learning, MF methods can actually be viewed as a two-layer shallow neural network: inputs are the sparse one-hot encoding of users and items; the first embedding layer transforms sparse vector into low-dimensional embedding vectors; outputs are the inner product of user and item vectors to predict the rating. Thus, we can stack more neural layers after embedding layer to approximate sophisticated non-linear rating functions instead of inner products.

Following this idea, Ref. [40] proposed a Neural Collaborative Filtering (NCF) model and a combined model of NCF and MF, by replacing the inner product function with a multi-layer tower-shaped deep structure as the prediction function, which achieves a much better performance than conventional works. Similarly, Ref. [41] achieved outstanding performance gain over conventional methods, by adding embedding transformation layers before user/item embedding layers for a fine modeling of features. References [42, 43] also showed promising results by applying deep neural networks in recommendations. In Ref. [44], an intelligent vehicle audio system in the IoV was proposed to make driving strategy recommendations based on deep learning techniques. More recently, graph embedding[45] and graph neural networks[46] have also attention in the design of recommendation systems due to that they are more suitable to capture discrete or sequential inputs.

By utilizing powerful neural structures, the prediction functions have a strong ability in handing non-linear relations and can capture user-item interactions far better than simple inner product function. We can see that the application of deep learning has greatly helped to improve the conventional CF or MF models and has become recent advances in the industry, for example, being applied by YouTube, Amazon, and Facebook.

2.3 Reinforcement learning-based technique

Reinforcement learning, such as contextual bandit algorithms[47–49] and Markov decision process[50], is suitable for online learning tasks in which data become available in a sequential order. For recommendation tasks, it is used to update the best recommendation results for users at each step, as opposed to batch learning techniques which generate the best results by learning on the entire training dataset at once. Reinforcement learning is also a major optimization approach to diversified recommendation[48]. Among that, contextual bandits play a crucial role, with applications ranging from news[47], ads, to movie recommendations[48], and can diversify results by balancing the tradeoff between exploration (recommending seemingly suboptimal items but learning new knowledge about user preference) and exploitation (recommending the best possible items based on the knowledge so far).

Multi-Armed Bandit (MAB) problem is a mature sequential decision making model and please refer to Ref. [51] for a general description of the MAB problem and algorithms. The contextual bandit problem is a variation of the conventional MAB problem by taking into account contexts that can influence the user preference over items, such as the time, location, user profile, and browsing history. Various techniques have been proposed to solve the contextual bandit problem: Upper Confidence Bound (UCB)-based (such as LinUCB)[52, 53], Thompson Sampling[54], epoch-based, etc.

Noted that it is not easy to directly deploy those techniques that we have introduced in this section in the IoV system, whether the classic CF/MF or the advanced deep learning-based recommendation technologies. There are a number of challenges that need to be addressed when the proposed strategies are being implemented in the IoV. One key challenge is the high dynamics of vehicles. When a vehicle is moving across areas covered by different Road-Side Units (RSUs), multiple RSUs will need to cooperate to deliver the content. One straightforward solution is to predict the vehicle's trajectory so as to assist the content delivery and caching at different RSUs. Another challenge is the noisy communication environment of vehicles, which may result in erasures or errors when delivering the content. To tackle the above challenges, wireless communication techniques and specifically tailored algorithms may need to be proposed. In the next section, we will introduce several scenarios to show how wireless recommendations are deployed in the IoV system.

3 Wireless recommendation for internet of vehicles

In this section, we talk about several applications of recommendations over wireless on the IoV network.

3.1 Route recommendation

Route recommendation is an important part of the IoV and intelligent transportation systems since route navigation becomes a basic requirement for people. It plays a positive role in alleviating urban congestion and improving travel efficiency. In this section, we will discuss several examples of route recommendations. An illustration of route recommendation is shown in Fig. 2.

3.1.1 Personalized route recommendation

Traditional route recommendation services generally consider a certain metric, such as the shortest distance or traveling time, and provide the shortest or quickest path between an origin and a destination. However,

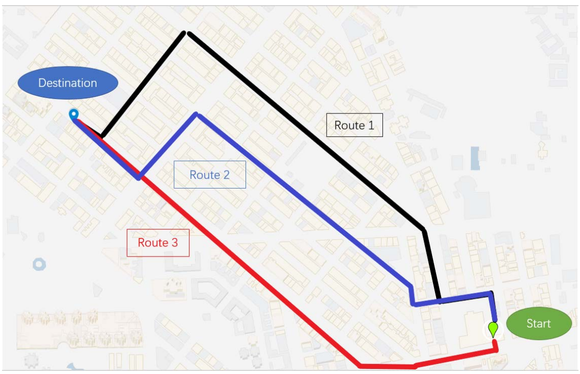


Fig. 2 Route recommendation strategy.

these methods ignore some factors, such as road safety and traffic jam, thus cannot make a comprehensive consideration of the route situation. On the other hand, traditional route planning does not take the drivers' preferences into consideration but only provide generic recommendations. In practice, different drivers may select different routes between the same source and destination because they may have different driving preferences (e.g., time-efficient driving or fuel-efficient driving). Reference [32] proposed two personalized route recommendation methods. Both of them utilize collaborative filtering techniques to estimate users' behavior from Global Positioning System (GPS) trajectories. Then a route with the maximum probability generated by the Naive Bayes model will be recommended. Similarly, Ref. [55] also studied how to recommend personalized routes using big trajectory data. They recommend the shortest route in the small graph, that is constructed with appropriate edge weights reflecting how the driver would like to use the edges based on the selected trajectories.

3.1.2 Machine learning-based route recommendation

More and more artificial intelligence and deep learning methods are applied to this route recommendation problem. Convolution Neural Network (CNN), which is widely used in image processing, is utilized to detect and recognize road surface for route recommendation[56]. Rrecurrent Neural Network (RNN)[57] based default logic is proposed for route planning to improve the accuracy of default reasoning in a dynamic environment. Besides, reinforcement learning is proved to be an effective way for decision-making problem. Interaction between the vehicles and the environment can be formulated as a Markov Decision Process (MDP), then Q-learning algorithm[58,59] can be performed to optimize the route recommendation results for real-time navigation.

3.1.3 V2X communication based cooperative route recommendation

In addition to route recommendation for single vehicle, cooperative route recommendation can benefit from ongoing V2X communication techniques in IoV system. The V2V communication system proposed in Ref. [60]

can gather information regarding of other vehicles and real-time traffic information, then a genetic algorithm is adopted to an appropriate route. In Ref. [61], the virtual vehicle concept was applied which adapts the cooperation approach via strategic concession game, trying to minimize both the individual and global driving time.

3.2 Driving strategy recommendation

Driving strategy is another emergent requirement for drivers. At present, early warning systems have made positive contributions to avoiding accidents. Appropriate driving strategy (such as distance alarms, automatic braking according to sensing and monitoring surrounding environments) recommendations and reminders can help drivers respond in time to reduce the probability of accidents. In this section, we will discuss a variety of driving strategy recommendations works. Reminders can help drivers respond in time to reduce the probability of accidents. An illustration of the driving strategy recommendation is shown in Fig. 3.

3.2.1 Review of driving control strategies

Common driving control strategies include functions, such as forward-collision warning, blind-spot warning, lane-departure warning, lane-change or merge warning, intersection collision warning, pedestrian detection and warning, backup warning, rear-impact warning, and rollover warning for heavy vehicles[62]. A special category of collision warning is driver monitoring, to detect and warn of drowsiness or other impairments that prevent the driver from safely operating the vehicle.

3.2.2 Drivers' characteristics based driving strategy recommendation

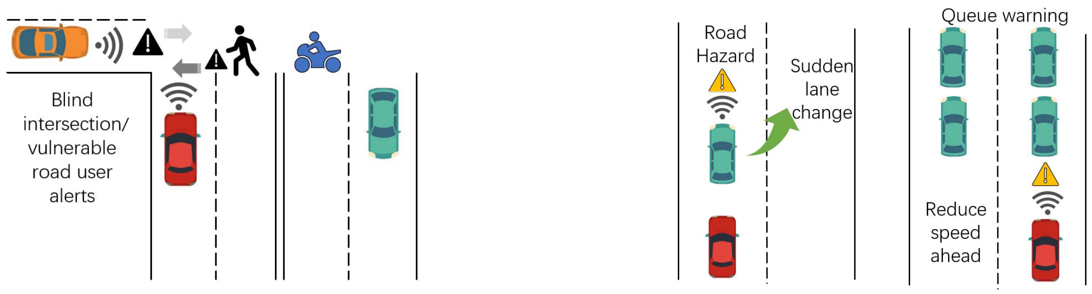
Individual driving style may vary considerably among users. Some users might prefer driving with high accelerations, others might prefer a more stable style. Typically, a large number of parameters, such as acceleration profiles, distances to other cars, speed during lane changes, etc., characterize a driver's style. To capture these features, Ref. [63] modeled the individual style as a cost function and performed feature-based inverse reinforcement learning to find the model parameters which fit the style well. Other deep learning techniques, like deep sparse auto-encoder[64], is also used to extract hidden features for visualization of driving behavior. Once the behavior model has been learned, it can be used to compute and recommend adaptive driving strategies[65–67].

3.2.3 V2X communication based collaborative driving strategy recommendation

The driving strategy recommendation will be more accurate using information of other vehicles. Reference [68] investigated the V2V communications and real-time databases to decrease collision risks and enhance safety. Similarly, a V2V based lane change warning system has been studied in Ref. [69]. Artificial intelligent methods are also utilized for cooperative decision-making in a decentralized way[70,71]. Moreover, Ref. [72] first considered secure and privacy preserving in 5G fog based IoV, which is another emergent as we must face privacy leaks when collaboratively solve problems.

3.3 Content recommendation

With the increasing demand for vehicle travel, entertainment information services have received more and more attention in IoV. Such emerging applications improve user experience while also greatly increase the pressure on storage and transmission of IoV systems. In



(a) Blind intersection and vulnerable road user alserts (b) Lane charge warning and deceleration warning for vehicles ahead

Fig. 3 Examples of driving strategy recommendation.

the cellular access network, content requests from vehicles must transfer to the base station firstly, then enter the Internet. However, the physical location between the vehicle and the content server will cause a large transmission delay. In practical scenarios, a large number of vehicles often request for popular contents in the same hot-spot areas, which will cause huge pressure on the network. In addition, the repeated transmission of the same content will waste communication resources. In this section, we will discuss the content recommendation in IoV system. An illustration of content recommendation is shown in Fig. 4.

3.3.1 Vehicle content recommendation

Reference [73] first considered the in-vehicle multimedia recommendation for group users by taking care of personalized preferences. User identification and profile aggregation and merging are performed before generating recommendation strategy. Reference [74] proposed a weighted interest degree recommendation algorithm using association rules for intelligence in the IoV. User interest score is predicted by establishing an association between user interests and recommend personalized service. With assistant of social networking and big data analysis, Ref. [75] proposed a reliable recommendation system model for IoV. Reference [76] also made use of social big data studies how to combine both the physical and social layer information for realizing content dissemination in Device-to-Device Vehicle-to-Vehicle (D2D-V2V)-based IoV networks.

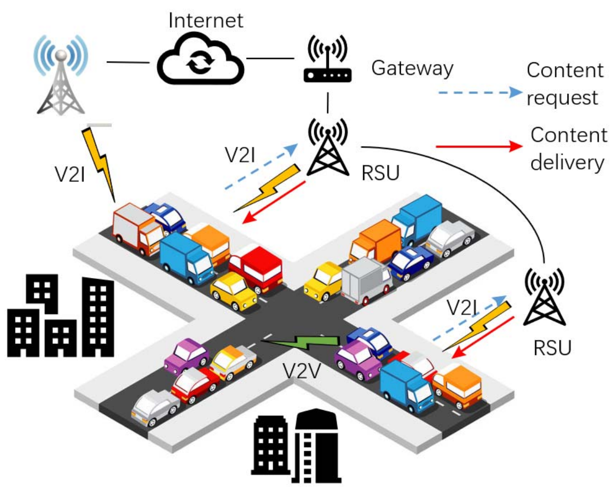


Fig. 4 Content recommendation.

3.3.2 Vehicle content delivery

Content delivery is a key functionality for developing the IoV and there have been huge number of studies in this area. Different delivery strategies are designed under different network architectures, such as Content Delivery Networks (CDN)[77], Information-Centric Networks (ICN)[78], content-centric networks[79], Named Data Networks (NDN)[80], etc. From a big data perspective, the vehicular data can be classified into location-centric, user-centric, and vehicle-centric[81]. Then different types of information can be used for different tasks through data analysis. Reference [82] proposed a content delivery solution based on vehicular cloud and aimed to take advantage of the name-based mechanism to reduce the content delivery cost and latency. Except for vehicular cloud, vehicular edge computing[83, 84] is also a promising paradigm to enable massive multimedia content to be cached in proximity to vehicles, aiming to minimize content delivery latency in IoV.

3.3.3 Vehicle content C^3

Communication, caching, and computing (C^3) problems are always jointly considered for optimal operation in vehicular networks. In Ref. [85], a new cooperative edge caching architecture for 5G networks was proposed. Smart vehicles are taken as collaborative caching agents for sharing content cache tasks with base stations. Reference [86] proposed a cross-entropy-based dynamic content caching scheme to cache the contents at the edge of VCNs based on the requests of vehicles and the cooperation among the RSUs. AI-based algorithms are made full use of to improve system utility facing high mobility of vehicles. For example, deep reinforcement learning methods were used to dynamically orchestrate edge computing and caching resources in Refs. [87, 88]. Blockchain techniques[89] were used to address security issues since the vehicles may not be willing to cache content to their untrusted vehicles.

4 Challenge and opportunity

As we have discussed, there are numerous benefits and applications of recommendation systems to assist the IoV. In this section, we will discuss the challenges and opportunities.

As the number of sensors on vehicles and roadside units grows rapidly, these wireless nodes become a major information acquisition and processing points. As such, the conventional cloud computing infrastructure for information processing is moving towards edge computing infrastructure where more data are kept locally and more computations are processed in close proximity to end users. This new paradigm brings many new challenges for computation tasks. As an important information filtering application, edge computing-based wireless recommendations need to be specifically redesigned and to address the new challenges that emerge. Some of the key challenges and opportunities are organized as follows.

- **Distributed operation**

Recommendation systems are starting to pervade IoV applications, such as vehicles collaboratively recommending trajectories to peers, or vehicles in close proximity running crowd sourcing tasks. We cannot necessarily rely on a central server storing all content, learning all preferences, and making all decisions. Instead, we need distributed operations. Also given delay constraints, power constraints, storage constraints, computation constraints, and communication constraints, how can we perform tasks in IoV efficiently in a distributed manner is a big challenge.

To tackle this challenge, we may need to combine knowledge and tools from different domains, such as distributed computing, artificial intelligence, communication, and embedding systems, to jointly solve the problems and optimize the system performance[90].

- **Wireless challenges that restrict data transmission**

There are many wireless challenges on the road conditions, such as noise, interference, dynamic network structures, and limited bandwidth[91]. How to successfully design corresponding data processing schemes over wireless remain a significant challenge. The possible solutions may include wireless coordinated decision making, federated reinforcement learning.

- **High dynamics and uncertainty**

In many wireless recommendations in the IoV network, the user information can be unknown and fast changing (unknown vehicles passing-by as opposed to long-term Netflix subscribers) and the feature information is harder to get, compared with the static scenario where user profile and item features can be obtained by the server. The network topology is changing rapidly overtime when vehicles are moving; and also the network size is changing from time to time[92], as different time in a day the road condition varies dramatically.

Thus, we may need to explore the unobserved latent structures of users and items, for example, we know that users/items have similarities and they can be clustered into different types. We may need to use dynamic graphs or just neighboring information to make recommendations.

- **Security and privacy**

In IoV networks, one immediate challenge is the security and privacy problem[93–95]. In traditional centralized systems, we can apply security measures to defend the system against various attacks. In stark contrast, in the IoV, there are a number of wireless nodes involving in the communication and computation process and some of them are vulnerable and may be prone to get attacked (e.g., security software was not installed on all edge devices)[5, 96]. It is often hard to take uniform measures to ensure that all distributed nodes are fully protected against attacks. Therefore, we may try to solve this problem from a different perspective, by actively designing robust algorithms that can address the adversary attack problem.

Another big concern is the privacy on individual user data[97, 98]. In the IoV, each vehicle has its own personal data and may not want to share with other vehicles, roadside units, or the central platforms. The secrecy attacks often steal data by eavesdropping or interception. To protect user privacy, we may need to actively take measures, such as encryption, transmitting parameters instead of raw data, etc. to design algorithms that are suitable in the IoV network. Some promising techniques, like Intrusion Detection System (IDS)[99], Honeypot[100], and Secure Routing Protocols[101] have been shown to be effective.

Such challenges bring to the forefront the need for bridging artificial intelligence with communications / information theory. Although designing recommendation systems and data transmission networks has attracted significant research efforts in separate communities, understanding the optimal design of both recommendations and how we utilize the wireless medium can be a good opportunity.

5 First attempt in wireless recommendations for IoV

In this section, we will talk about our first attempts of our recent works in wireless recommendations for the IoV. It is a noteworthy that this is a pretty new field and we only scratch the surface. There are huge opportunities in this area from both the academic and industrial perspectives.

- **Bandwidth-aware wireless recommendation**

In wireless recommendations for the IoV network, bandwidth is usually a very scarce resource. Thus, a straightforward question is how should we make recommendations in wireless IoV networks in view of the limited bandwidth. Traditional recommendations only take into account the user preference. In stark contrast to this, in Ref. [102], we considered to jointly optimize the user preference and data transmission efficiency, as it is the case over IoV networks.

We formulated the bandwidth-aware recommendation problem over IoV networks in the context of index coding*.

In the bandwidth-aware recommendation problems, we consistently found that although the optimization problems are in general Non-deterministic Polynomal (NP)-hard, significant bandwidth savings are possible even when restricted to polynomial time algorithms[102]. We also found that there is a tradeoff between user preference and bandwidth usage, as shown in Fig. 5.

In addition, we had two more works that consider the tradeoff behavior between the user preference learning and the broadcasting bandwidth[104, 105] for IoV networks. In Ref. [104], we proposed a bandwidth-aware reinforcement learning based algorithm to efficiently learn user preference given a limited broadcast bandwidth. In Ref. [105], we proposed a graph theory based coded reinforcement learning technique to balance the user preference learning rate and bandwidth.

*Index coding is a canonical problem in broadcasting networks where a transmitter aims to make broadcast transmissions to multiple receivers, each with different requests and/or side information[103].

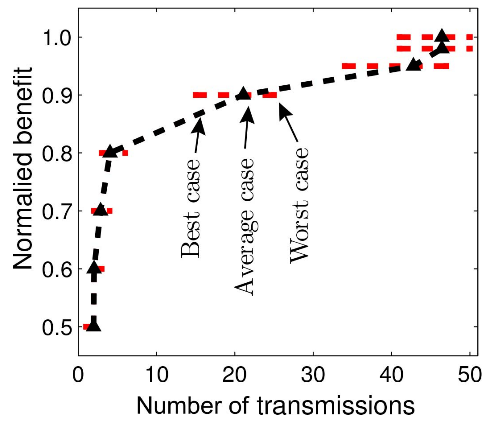


Fig. 5 Trade-off between bandwidth and benefit (user preference) in Ref. [102], where the bandwidth is described by the number of transmissions (horizontal axis); and the benefits are aggregated by summing up all users preferences (vertical axis). The three arrows in the middle point to the three points of the red line, representing the best, average, and worst cases obtained after multiple simulations. The other points and red lines reflect the interval of values obtained after multiple simulations.

- **Wireless content caching and delivery**

In our second category of work, we studied the wireless content caching, delivery, and recommendations based on user preferences[106, 107].

Content caching and delivery at the network edge of the IoV, such as wireless caching stations equipped on the roadside unit, are important techniques to provide content-based services (such as music, video, and radio). The spatial-temporal diversity of content popularity requires different contents to be cached in different Wireless Caching Stations (WCSs) and periodically updated to adapt to temporal changes and user preferences. In Refs. [106, 107], we proposed reinforcement learning and content caching schemes to learn the user preference for different contents and recommend caching strategies on wireless caching stations. In addition, we showed a tradeoff between the user preference changing speed and the communication cost, as shown in Fig. 6. In Ref. [108], we designed caching strategies for mobile users when the network scale is large and content popularity is arbitrary.

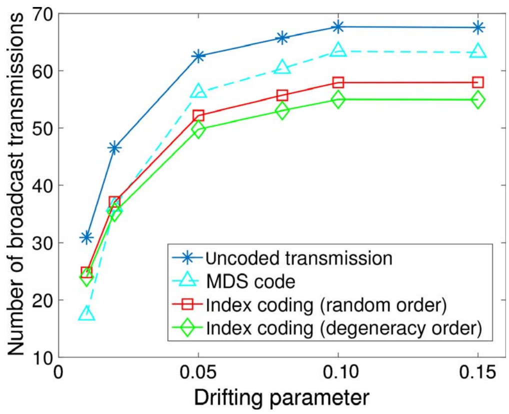


Fig. 6 Performance comparison under different user preference changing speeds (represented by the drifting parameter) in Ref. [107]. It shows that more communication cost (bandwidth) is needed when the user preference is changing faster.

- **Privacy and security for IoV**

In our recent work, we have studied the privacy issues and security issues in wireless distributed systems[109–113].

In Ref. [109], we proposed a coding based framework to protect the privacy of users when many users are in the same broadcast domain. In Ref. [110], we studied an anomaly detection problem in the federated learning framework where many distributed nodes are trying to protect the privacy of their local data against others. We proposed a corresponding privacy protection scheme and showed the tradeoff between learning performance the privacy protection level at each node, as shown in Fig. 7. XGboost is a common classification algorithm, and F1-score is an metric used to measure the classification results. Higher F1-score means higher classification accuracy.

In Refs. [112, 113], we studied how to combat the Byzantine attacks for wireless distributed systems, such as the IoV. Since wireless distributed nodes are usually prone to be attacked due to many nodes and non-uniform protection schemes, we would like to design a strategy to make the distributed computation robust, even with the existence of Byzantine attackers, namely, those nodes that can send arbitrarily bad intermediate messages to others when performing some computation tasks. We proposed a coding based scheme to tackle this problem and showed the effectiveness in theory and practice. In Ref. [111], we studied the Byzantine attack problem

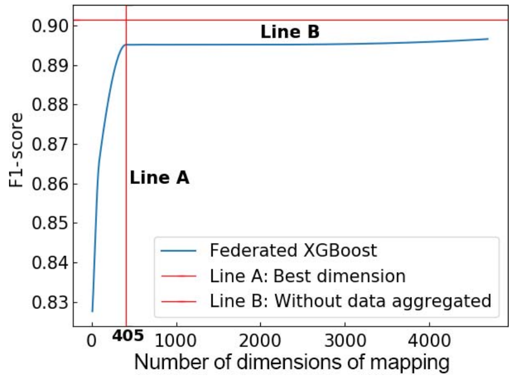


Fig. 7 F1-score of federated XGBoost framework for anomaly detection in Ref. [110], where the commonly used F1-score (the harmonic mean of the precision and recall) is used to measure the performance (vertical axis) of the anomaly detection, with a higher F1-score representing a better performance; and the dimension of mapping is used to describe the level of privacy protection, with a less number of dimensions representing a higher level of privacy protection. We can see a tradeoff behavior between the level of privacy protection and the performance of the anomaly detection.

in a game theory framework and a defending strategy was proposed to defend corresponding distributed nodes when many wireless nodes performing a joint task are prone to be attacked.

6 Conclusion

In this paper, we have reviewed the wireless recommendation applications in the IoV network, for example, recommending appropriate routes, recommending driving strategies, and recommending content. We have analyzed several key challenges and opportunities for the deployment of wireless recommendation systems in the IoV. We believe that incorporating knowledge and tools from different domains, such as artificial intelligence, communications, distributed systems, and cyber-physical systems, will help to tackle emerging system problems and improve the system performance.

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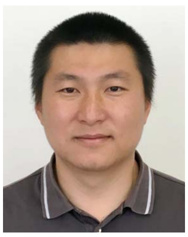

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