# Big Data Driven Vehicular Networks

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Abstract-Vehicular communications networks (VANETs) enable information exchange among vehicles, other end devices and public networks, which plays a key role in road safety/infotainment, intelligent transportation system, and selfdriving system. As the vehicular connectivity soars, and new onroad mobile applications and technologies emerge, VANETs are generating an ever-increasing amount of data, requiring fast and reliable transmissions through VANETs. On the other hand, a variety of VANETs related data can be analyzed and utilized to improve the performance of VANETs. In this article, we first review the VANETs technologies to efficiently and reliably transmit the big data. Then, the methods employing big data for studying VANETs characteristics and improving VANETs performance are discussed. Furthermore, we present a case study where machine learning schemes are applied to analyze the VANETs measurement data for efficiently detecting negative communication conditions.

## I. INTRODUCTION

With the development of automobile technologies, vehicles are expected to be not only safer, but also greener, more comfortable and entertaining, while self-driving is also a defining requirement of the future vehicles. As a promising technology to meet such expectations, vehicular communication networks (VANETs) enable automobiles to communicate with each other through vehicle-to-vehicle (V2V) communication and the network through vehicle-to-infrastructure (V2I) communication, and exchange information efficiently and reliably through the V2V and V2I communications, or more generally, vehicle-to-everything (V2X) communications. VANETs can facilitate a variety of useful applications, such as road safety enhancement, traffic management, vehicular mobile data services, and self-driving assistance [1], [2].

Due to the ever-increasing demand of mobile services and the fast development of self-driving technologies, the data volume required, generated, collected, and transmitted by VANETs has seen an exponential escalation, which is known as big data [3]. As explained in [4], the data in VANETs can well match the "5Vs" of big data characteristics, i.e., volume, variety, velocity, value, and veracity, which justifies that the

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Shan Zhang is with the Department of Computer Science and Technology, Beihang University, Beijing, 100083, P.R. China (email: zhangshan\_2011@outlook.com) VANETs data can be treated as big data and can be solved by big data techniques.

Relying on the big data, the future VANETs will enable a variety of promising applications and services, such as smart city and Intelligent Transportation System (ITS) applications, and significantly change many aspects of the society, including the transportation system, telecommunication, business, government, as well as the human life style. The VANETs big data and enabled applications are shown in Fig. 1. For example, road traffic information can be collected by vehicles and roadside units, and reported to the ITS cloud server. Based on large-scale traffic information, real-time traffic prediction and management functions are conducted, so as to detect the road anomaly, alleviate traffic jam, and reduce emission and pollution. Self-driving vehicles will consume or generate multiple Giga Bytes (GB) data per second, typically from outfitted high-quality cameras, LiDARs and Radars [5]. Through the data fusion, analysis and integration of the cloud data such as weather and road traffic information, and information from other vehicles, self-driving vehicles can make decisions on actuating the vehicle for driving autonomously, on a planned route, and eliminate traffic fatalities. As a potential impact of self-driving technologies, the vehicles will be more like home or offices, and thus people will focus on the mobile applications and services that can better support the in-vehicle activities, rather than driving the vehicle. Therefore, the future VANETs will evolve to satisfy the big mobile data demands, and support a wide variety of promising applications and services.

The trend of big data can bring new challenges and opportunities for VANETs. On one hand, the VANETs big data is with a significantly large amount, from heterogeneous sources, and having various requirements. To efficiently support the big data, VANETs should be capable of providing extremely high data rate, large network capacity, heterogeneous network integration, and differentiated quality of service (QoS) guarantee. In addition, besides data communication, the future VANETs are envisioned to play a critical role in data collection, storage, and computation. On the other hand, the VANETs big data such as GPS, vehicle mobility trace, road traffic information, and network measurements, contains rich valuable network information. If properly utilized, such big data can reveal a lot of network characterizations, evaluate the network performance, and optimize the network management, by applying advanced techniques such as big data mining, analysis, and machine learning mechanisms. The purpose of this article is to investigate the impacts of big data on VANETs, introduce the new challenges and opportunities, and discuss corresponding solutions. We focus on two related topics, i.e., efficiently supporting big data in VANETs, and utilizing big data for better understanding and improving VANETs. Furthermore, we study a case where machine learning schemes are applied to analyze the VANETs measurement data for efficiently detecting negative communication conditions.

# II. BIG DATA IN VANETS

The VANETs big data come from multiple heterogeneous sources, presenting diversified characteristics, such as volume, structure, value, requirements for processing delay, etc. We classify the VANETs big data according to the sources of the data as follows.

- Vehicle sensing data: Modern vehicles have equipped various sensors (speedometer, tire pressure sensor, etc.) to collect vehicle and environmental information. Rich information from such sensors can enable a wide range of applications, such as online vehicle diagnosis, road safety improvement, smart charging planning, accident detection, and so forth.
- **GPS data:** GPS devices can provide accurate and structured location-related information of vehicles, including longitude, latitude, altitude, and speed. GPS data can be used for diversified goals, such as navigation, traffic management, communication routing optimization, vehicular content caching and sharing, etc. In addition, the datasets of large-scale vehicle trajectories, generated by tracing the long-time GPS data of vehicles in a geographical area, can be investigated to analyze the VANETs characteristics, such as network connectivity, and design efficient mechanisms, such as routing protocol for delay-tolerant vehicular network, and radio access network deployment.
- Self-driving related data: The autonomous vehicle will make big data even bigger. Self-driving technology requires the accurate perception and understanding of the environment to make proper decisions to control the vehicle. Since traditional sensors have limited capability, and cannot provide necessary information such as real-time road vision, accurate distance, and 3D map, advanced devices like cameras and light detection and ranging (LiDAR) sensors are equipped for a better perception. However, the high-definition cameras and LiDAR will produce a huge amount of data as they continuously collect high-definition data such as high-quality videos.
- Vehicular mobile service data: In-vehicle infotainment is becoming more crucial for improving the experience of both drivers and passengers. Mobile applications such as video/audio streaming, online gaming, social networks, and user generated contents (UGC) require or generate a huge amount of data.

## **III. SUPPORTING BIG DATA IN VEHICULAR NETWORKS**

For big data system to efficiently function, four essential parts need to be well supported, i.e., data aggregation, storage, transmission, and computation. In VANETs, the raw data can be gathered by vehicle sensors, and stored in on-board storage. Since the raw data contain redundancy, data processing is conducted to extract valuable information. After accumulating the data (either raw or processed), there is a demand to transmit the data to appropriate data storage systems (such as cloud/edge servers) for further analysis and process. Therefore, VANETs should be capable of effectively supporting these big data functions.

Traditional VANETs employ the IEEE 802.11p based dedicated short-range communication (DSRC) technologies, where data transmission mainly relies on distributed medium access control (MAC) and multi-hop routing protocols [6]. However, the traditional VANETs technologies can hardly satisfy the harsh requirements of big data applications due to the decentralized protocols and bandwidth limitations, which leads to the lack of network resources and flexibility to support the big data with diversified QoS requirements. Moreover, issues such as energy efficiency, caching, and computation capabilities are not well considered in current VANETs, which are also essential in supporting the big data. In this section, we discuss some promising VANETs technologies to better support the big data, including 5G technologies and opportunistic data offloading mechanisms. As shown in Fig. III, the 5G macro cells can provide ubiquitous communication support, while 5G small cells, Wireless Local Area Networks (WLANs), cognitive radio networks (CRNs) and device-to-device (D2D) communications offer cost-effective data pipes for VANETs big data.

## A. 5G Technologies

An intuitive solution to support the VANETs big data is the pervasive cellular network. As the 4G LTE network is struggling to support the ever-increasing data volume and the emerging mobile services with differentiated QoS requirements, 5G networks, the next-generation networks, are building a way to solve the issues. Based on software-defined network (SDN) related technologies, 5G networks are designed to serve as a platform to provide satisfying services for vertical fields, including telecommunication, transportation, agriculture, economics, government, education, etc [7]. According to the key performance indicators, 5G networks are capable of offering a 10 Gb/s data rate with less than 1 ms endto-end latency [8]. Moreover, machine-type communications with low power consumption and high reliability requirements are well supported for the emerging Internet of Things (IoT) applications.

To better characterize and support different services, 5G defines three categories of use cases, i.e., enhanced mobile broadband (eMBB), ultra-reliable and low-latency communication (URLLC), and massive machine-type communication (mMTC), and the performance indicators of each categories. These three categories, together with the well-defined key technologies, can provide guaranteed performance to VANETs big data gathering and transmission tasks.

• eMBB: In VANETs, the exponentially increasing big data demands of the vehicular mobile data services requires a



Figure 1. VANETs big data and applications.

![](_page_2_Figure_2.jpeg)

Figure 2. Supporting Big Data Through VANETs

high-capacity network that can provide extremely high date rates. Enabled by promising network technologies, such as advanced channel coding, mmWAVE, and ultradense small cell networks, eMBB can provide peak data rate of 10 Gb/s and mobile data volume of 10 Tb/s/km<sup>2</sup>. Therefore, with 5G networks, the emerging data-craving vehicular data applications can be better supported, and many more will come to reality.

• URLLC: The mission-critical data services in VANETs, such as safety message transmission, require very low latency and very high reliability. The requirements fall into the category of URLLC in 5G, which can provide less than 5 ms latency and higher than 99.999% reliability.

• mMTC: Relying on potential technologies such as machine-to-machine communication and narrow-band IoT (NB-IoT), mMTC aims to support ubiquitous machine-type connections with low energy consumption and low latency. A large amount of VANETs big data is generated by the densely deployed light weight devices, such as sensors equipped in vehicles or deployed along the roads. 5G technologies can accommodate such massive concurrent connectivity, provide reliable data transmission, and prolong the device battery life, and therefore facilitate the big data gathering services.

5G also defines enhanced vehicle-to-everything (eV2X) use case for supporting the vertical field of vehicular communication and data services [9]. The requirements for typical V2X scenarios are defined, including vehicle platooning, advanced driving, extended sensors, and remote driving.

# B. Opportunistic Data Pipes

Although the 5G networks can significantly improve the network capacity, the ever-increasing big data will still put a severe burden on the network, resulting in possible network congestions. In addition, the commercialization and deployment of 5G networks will start in year 2020, and will be a long-time process. Therefore, in the near future, the 4G LTE networks with relatively small capacity will be straining to accommodate the big data. Moreover, usually using the cellular network to transmit a large amount of data will incur prohibitive costs. As a result, alternative data pipes for supporting the big data are required. WLANs, CRNs and D2D communications can be employed to offload the VANETs big data from the cellular network in a cost-effective way.

1) WiFi Offloading: WiFi, operating on unlicensed spectrum, is a popular solution to deliver data content at low cost. The feasibility of WiFi for outdoor Internet access at vehicular mobility, referred to as drive-thru Internet, has been demonstrated in [10]. Different from the fully covered cellular network, WiFi only provides intermittent small coverage areas along the road. Therefore, although WiFi operates on unlicensed spectrum, it is spatially/temporal opportunistic for vehicles to employ due to the vehicle mobility. Therefore, employing the mobility feature is an important issue in vehicular WiFi offloading. One example is prediction-based delayed offloading. Based on the mobility prediction and priori knowledge of WiFi deployment, the future opportunities of WiFi access and corresponding throughput can be predicted. Then, according to the delay tolerance of different users or applications, offloading decision can be made whether to wait for WiFi offloading or directly transmit through cellular networks.

2) Cognitive Radio Technology: Cognitive radio is envisioned as a promising spectrum-sharing technology which enables unlicensed users opportunistically exploit spatially and/or temporally vacant licensed radio spectrum bands which are allocated to licensed systems. The CR technology can employ the vast underutilized spectrum resources to support the big data transmissions. However, in VANETs, the high mobility of vehicles may require excessively frequent spectrum sensing to protect the primary transmissions [11]. The TV white spaces (TVWS) have been suggested for wireless broadband access due to the abundant and currently underutilized spectrum resources at VHF/UHF bands and its superb penetration property. Unlike other licensed system, the spectrum usage of TV broadcasting system is highly stable and predictable, and can be inquired from a database. Therefore, the TVWS is envisioned as a potential solution to CR-enabled VANETs [12].

3) Device-to-Device Communication: By utilizing the proximity, mobile users can communicate directly with each other using the cellular spectrum (or other spectrum bands) without traversing the base station or the backhaul networks, named device-to-device D2D communications. Therefore, D2D communications can increase the overall spectral efficiency and reduce communication delay for mobile users, which may be applied to many VANETs applications such as video streaming, location-aware advertisement, safety related applications, and so forth. However, incorporating D2D communication in vehicular environment introduces several new challenges. For example, a full channel state information, which is usually needed in resource allocation schemes for D2D communication, is hard to track and easy to be outdated in VANETs. In addition, the topology of VANETs makes the interference pattern more difficult to model than a general cellular network where a Poison point process (P.P.P.) can be applied to model the user spatial distribution.

## IV. EMPLOYING BIG DATA IN VEHICULAR NETWORKS

As mentioned above, big data in VANETs can provide valuable insights of VANETs, which can be employed to characterize and evaluate the performance of VANETs, and design new protocols with big data intelligence. In this section, we show the utilization of two typical data sets in VANETs, i.e., vehicle mobility trace data and VANETs measurements data. An overview of big data employment in VANETs is shown in Fig. 3. The two data sets can be employed to extract practical channel model and mobility model, and predict vehicle movement. With such knowledge, VANETs characterization and intelligent protocol design can be achieved.

## A. Vehicle Mobility Trace Data

Admittedly, the high mobility of vehicles leads to challenges to VANETs. However, the mobility can also have benefits on the network, e.g., mobility-aware protocols and delay-tolerant data dissemination. Through the analysis of the datasets of vehicle mobility, an amount of valuable information can be obtained, such as the practical mobility model, network connectivity, spatial and temporal density distribution, etc. There are several databases that stores real and large-scale taxi mobility trace data from different cities, including San Francisco, Shanghai, and Shenzhen [13]. Main content of the trace data includes time stamp, vehicle velocity, driving direction and vehicle location, which can be used for further study on VANETs.

Mobility model is widely used in VANETs location-based protocol design and performance evaluation. Due to the time intervals of vehicles reporting their trace, the trace data is always error-prone and has gaps between locations in two consecutive records. Therefore, some data preprocessing mechanism is needed. For instance, due to the predictability property of vehicle mobility, it is possible to fill the gap by predicting the route through analyzing road map, traffic signs and the past vehicle trace. Then, a realistic mobility model can be generated from the modified trace data. Position-based routing schemes and MAC protocols are designed to adapt to the high mobility and frequently changing topology of VANETs. The mobility model and network characteristics can be obtained by analyzing the mobility trace data and network measurement data, which are taken into consideration in the design of routing schemes and MAC protocols. For instance, position-based routing schemes can exploit the real-time position and predict vehicle movement to improve the transmission performance. Position-based MAC protocols can predict potential packet collisions due to the vehicle mobility and make effort to avoid them. The historical mobility trace data can also be used in simulations to evaluate the designed MAC and routing protocols.

Furthermore, mobility trace data is also useful in analyzing and improving the connectivity of VANETs. Network connectivity metrics can be evaluated from the mobility trace data, including link duration, average hops, number of connected vehicle pairs, and interconnect time distribution. Improvement of connectivity can also be achieved with the aid of trace data. The prediction methods of vehicle movement can be developed to make seamless handoff possible for communication between vehicles and infrastructures. In addition, through investigating the real-time trace data generated in VANETs, information of vehicle traffic flow can be obtained. Then, unmanned aerial vehicles (UAVs) can be deployed in order to improve the network connectivity.

## B. VANETs Measurement Data

Measurement of VANETs communication plays a vital role in VANETs characterization, since in VANETs, many influencing factors are difficult to model, such as mobile channels, pedestrians, terrain, and obstacles. In order to obtain realistic measurement data, communication devices using IEEE 802.11p protocol are deployed on vehicles and roadside units (RSUs) during experiment. These experiments are conducted in various environments such as urban, suburban, rural, open fields and freeway, and different measurement data is collected depending on the characteristics of interest.

WiFi offloading is envisioned as a potential solution to data explosion problem in cellular networks. However, high mobility of vehicles makes WiFi offloading in VANETs distinguished from static WiFi offloading. Measurement data like connection establishment time, connection time, interconnection time, max rate and transferable data volume in once drive-thru is collected to analyze WiFi offloading performance. Then, a three-phase feature is observed as an important WiFi offloading characteristic, including entry, production, and exit phases. It shows that in entry and exit phases, the connection quality is weaker and data rate is lower than production phase, which provides guidance to researchers about how to improve the offloading performance, e.g., reducing the association and authentication time in order to maximize data transfer in production phase.

Unlike static or low-mobility wireless channels, the vehicular channel is more complicated due to the shadowing by nearby vehicles, high Doppler shifts, and inherent nonstationary [14]. Therefore, building an accurate and practical channel model is crucial for VANETs performance analysis, protocol design, and simulation experiments. This can be done by studying the real communication measurement data, including both V2V measurements and V2I measurements in different important environments. The resulting channel models characterize the vehicular channel from different channel metrics, including pathloss, signal fading, delay spread, Doppler spread, and angular spread.

## V. CASE STUDY

In this section, we study a case where big data and machine learning schemes are employed to support efficient protocol design in VANETs communications.

## A. Online NLoS Detection

In VANETs, packets related to safety information should be delivered perfectly (with transmission chance and without packet loss). However, it is found that non-line-of-sight (NLoS) condition is a key factor of V2V link performance degradation [15]. Inspired by the intuition that blindly sending more packets in harsh NLoS conditions can hardly succeed but incur resource wasting and increase interference to other neighboring vehicles, we propose an innovative scheme to detect NLoS conditions online by learning the V2V measurement data. Given that the NLoS condition can be detected, more robust protocols can be devised, e.g., allocating scarce wireless channel resources to those vehicles under line-of-sight (LoS) conditions or seeking helper vehicles to relay packets for those vehicles under NLoS conditions. In the sequel, we will elaborate the scheme in two parts, i.e., measurement data collection and building detection model using machine learning methods.

## B. Collecting V2V Communication Measurement Data Sets

We collect V2V communication trace data by two experimental vehicles each mounted with a Arada LocoMateTM OBU (DSRC module) on the roof. The transmitter vehicle sends a 300-bytes packet every 100 ms to the receiver vehicle, which consists of a sequence number, the latitude, the longitude, the altitude and the speed information of the transmitter. Meanwhile, both the transmitter and the receiver log all the packets transmitted and received. In addition, we deploy two cameras on each vehicle with one mounted on the front glass and the other fixed on the rear glass, which record the whole process for off-line analysis. Fig. 4 (a) shows the data collection devices.

We conduct data collection campaigns including three major road types in a city, i.e., highway, suburban, and urban. Each data set contains following three types information: 1) communication trace: by comparing packet's sequence number at sender and receiver, each packet can be marked as received or dropped and we can compute the packet delivery ratio (PDR) throughout all experiment time; 2) GPS trace: both vehicles have logged GPS trace, which can provide speed, altitude and distance information; 3) recorded videos: it can be

![](_page_5_Figure_0.jpeg)

Figure 3. Employing big data in VANETs.

![](_page_5_Picture_2.jpeg)

(a) Data collection devices

![](_page_5_Picture_4.jpeg)

(c) A LoS condition

![](_page_5_Picture_6.jpeg)

(b) Data collection scenarios

![](_page_5_Picture_8.jpeg)

(d) A NLoS condition

Figure 4. Illustration of the data collection campaign

utilized to check the communicating environments, e.g., types of road, traffic conditions, surrounding obstacles and so on. Three types of data are within time synchronization for better observation and comparison. The overall campaign lasts for over two months with an accumulated distance of over 1,500 kilometers and a total size up to 110GB. We run our testbed within areas of the above three road types in Shanghai as shown in Fig. 4 (b). We denote three data sets by  $\mathcal{H}$  (highway),  $\mathcal{S}$  (suburban), and  $\mathcal{U}$  (urban).

## C. Supervised Machine Learning

In this subsection, we use two classic supervised machine learning methods, i.e., *Naive Bayes (NB)* and *Support Vector Machines (SVM)*, to detect NLoS conditions.

Labeling NLoS conditions: Before using machine learning techniques, we first label out all NLoS conditions. Since the whole data collection campaigns are recorded by cameras, we mark all NLoS situations when two vehicles cannot visually see each other. Although NLoS conditions found by cameras are not necessarily to be NLoS for RF radios, those visually NLoS conditions are still good approximations of real radio NLoS conditions and valuable for learning. Fig. 4(c) and Fig. 4(d) show examples of a LoS condition and a NLoS condition, where vehicle 1 and vehicle 2 are communicating vehicles, but vehicle 2 is blocked by obstacles in the NLoS condition and cannot be found in Fig. 4(d).

**Feature Extraction:** When machine learning algorithms are processed, representative tuple of features rather than raw data is a more effective input. Thus, it is necessary to extract effective features from raw data set. According to the analysis in the work [15], PDRs are heavily influenced by LoS/NLoS conditions and LoS/NLoS durations are with memories due to the power law distributions. Therefore, we can use history PDR values as features for training. At this point, we select three features, i.e., PDR value of the previous 1 second, PDR value of the previous 5 seconds and PDR value of the previous 10 seconds.

Machine learning with NB and SVM: After feature extracting, we obtain samples in the form of <3-dimensional features, label>. We then use parts of samples to train NB and SVM models. NB methods are a set of supervised learning algorithms based on applying Bayes' theorem. Given a label variable y and a tuple of feature vectors  $x_1$  to  $x_n$ , Maximum A Posteriori (MAP) estimation is used to estimate P(y) and  $P(x_i|y)$ . NB learners and classifiers can be extremely fast compared to some sophisticated methods. The cores in SVM are the kernel and the similarity function. A kernel is a landmark, and the similarity function computes the similarity between an input example and the kernels.

## D. Performance Evaluation

To evaluate the performance of machine learning methods, we define the following metrics based on the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN): 1) *accuracy:* the probability that the identification of a condition is the same as the ground truth; 2) *precision:* the probability that the identifications for NLoS conditions are exactly NLoS conditions in ground truth; 3) *recall:* the probability that all NLoS conditions in ground truth are identified as NLoS conditions; 4) *false positive rate (FPR):* the probability that a LoS condition is identified as a NLoS condition.

We first evaluate the learning results under different scenarios. For more robust model evaluation, we adopt the crossvalidation scheme to validate training models. In specific, for each data set, i.e.,  $\mathcal{H}$  with 16425 samples,  $\mathcal{S}$  with 16033 samples and  $\mathcal{U}$  with 27439 samples, we first split them to 10 subsets, then cross validate the learning models by using *i*-th subset, for  $i \in \{1, 2, ..., 10\}$ , as validation set and the remaining subsets together as training sets. Fig. 5(a) shows the accuracy of NLoS detection under different scenarios with NB and SVM methods. We have the following two main observations. First, both NB and SVM methods can achieve superb accuracy values. For instance, with NB method, the accuracy can reach about 92.5%, 96.9% and 97.4% in highway, suburban and urban, respectively, while with SVM, the values can be about 93.7%, 98.3% and 98.3%, respectively. Second, the performance of SVM can slightly outperform the performance of NB. Table I shows other metric values and similar observations can be obtained.

With the accuracy promise, we then investigate the robustness of the learning models, i.e., the performance of the models with different sizes of training data. We first split each sample set into two subsets, one subset (occupying 10% proportion) as validation set and the other subset (occupying 90% proportion) as training set. The training set is evenly split into 10 subsets and for j-th training, for  $j \in \{1, 2, ..., 10\}$ , the union of the first to j-th subsets behave as the training set. Fig. 5(b) shows the accuracy of NLoS detection with different sizes of training data under different scenarios. We have the following two main observations. First, for NB method, to achieve a very high accuracy, it requires high diversity training data to cover all situations in validation set. When the accuracy performance reaches a supreme value (about 96.5% in the figure), increasing the training size cannot further improve the performance. For instance, in the highway scenario, the accuracy increases from 84.3% to 90.9% then to 96.4% with training data size 0.1, 0.2 and 0.3, respectively; with more training data, the accuracy will oscillate around 96.4%. It is noted that different subsets of training data may have varied impacts on the model performance, which explains that in the highway scenario, the accuracy increases significantly with the 2nd and 3rd subsets of training data, while in the suburban scenario, the accuracy increase more obviously with the 5th subset of training data. Second, SVM method is not as sensitive to the training data size as NB method does. For instance, the accuracy of SVM in highway scenario oscillates around 97% regardless of the training data size. Similar observations can also be obtained in suburban and urban scenarios. As the results are tightly close to the highway results which may confuse the figure, they are not shown in the figure.

## VI. CONCLUSIONS

In this article, we have discussed two important issues in VANETs in the big data era, i.e., efficiently supporting the big data through VANETs, and employing the big data to improve VANETs. For the former one, a framework combining 5G cellular network and alternative opportunistic data pipes is introduced, and is envisioned to provide efficient, reliable, and flexible support of the VANETs big data. For the latter one, the mechanisms which analyze and learn typical big data for characterizing VANETs and designing intelligent protocols for VANETs are discussed. Furthermore, we have shown a case study in which urban VANETs measurement data is used to detect NLoS conditions through machine learning schemes.

## VII. ACKNOWLEDGMENT

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![](_page_7_Figure_0.jpeg)

Figure 5. NLoS detection accuracy.

Table I LEARNING RESULTS

Scenarios	Accuracy(%)		Precision(%)		Recall(%)		FPR(%)	
	NB	SVM	NB	SVM	NB	SVM	NB	SVM
Highway	0.9247	0.9367	0.9578	0.9393	0.9359	0.9832	0.0606	0.0189
Suburban	0.9690	0.9831	0.9958	0.9867	0.9715	0.9943	0.0280	0.0035
Urban	0.9735	0.9828	0.9925	0.9851	0.9773	0.9971	0.0216	0.0037

#### REFERENCES

- S. Al-Sultan, M. M. Al-Doori, A. H. Al-Bayatti, and H. Zedan, "A comprehensive survey on vehicular ad hoc network," *Elsevier J. Netw. Comput. Appl.*, vol. 37, pp. 380–392, 2014.
- [2] N. Lu, N. Cheng, N. Zhang, X. Shen, and J. W. Mark, "Connected vehicles: Solutions and challenges," *IEEE Internet Things J.*, vol. 1, no. 4, pp. 289–299, 2014.
- [3] M. Chen, S. Mao, and Y. Liu, "Big data: A survey," Springer Mobile Netw. Appl., vol. 19, no. 2, pp. 171–209, 2014.
- [4] P. Bedi and V. Jindal, "Use of big data technology in vehicular ad-hoc networks," in *Proc. IEEE ICACCI*, Delhi, India, 2014, pp. 1677–1683.
- [5] M. Maurer, J. C. Gerdes, B. Lenz, and H. Winner, Autonomous driving: technical, legal and social aspects. Springer, 2016.
- [6] M. Hadded, P. Muhlethaler, A. Laouiti, R. Zagrouba, and L. A. Saidane, "TDMA-based MAC protocols for vehicular ad hoc networks: A survey, qualitative analysis, and open research issues," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2461–2492, 2015.
- [7] W. Quan, Y. Liu, H. Zhang, and S. Yu, "Enhancing crowd collaborations for software defined vehicular networks," *IEEE Commun. Mag.*, vol. 55, no. 8, pp. 80–86, 2017.
- [8] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, "What will 5g be?" *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1065–1082, 2014.
- [9] 3GPP, "3GPP TS 22.186: Enhancement of 3GPP support for V2X scenarios," 3GPP, Tech. Rep., June 2017.
- [10] V. Bychkovsky, B. Hull, A. Miu, H. Balakrishnan, and S. Madden, "A measurement study of vehicular Internet access using in situ Wi-Fi networks," in *Proc. of ACM MobiCom*, Los Angeles, USA, Sep. 2006, pp. 50–61.
- [11] N. Cheng, N. Zhang, N. Lu, X. Shen, J. Mark, and F. Liu, "Opportunistic Spectrum Access for CR-VANETs: A Game-Theoretic Approach," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 237–251, 2014.
- [12] H. Zhou, N. Zhang, Y. Bi, Q. Yu, X. Shen, D. Shan, and F. Bai, "TV white space enabled connected vehicle networks: Challenges and solutions," *IEEE Netw.*, vol. 31, no. 3, pp. 6–13, 2017.

- [13] C. Celes, F. Silva, A. Boukerche, R. Andrade, and A. Loureiro, "Improving VANET simulation with calibrated vehicular mobility traces," *IEEE Trans. Mobile Comput.*, vol. 16, no. 12, pp. 3376–3389, 2017.
- [14] C. F. Mecklenbrauker, A. F. Molisch, J. Karedal, F. Tufvesson, A. Paier, L. Bernadó, T. Zemen, O. Klemp, and N. Czink, "Vehicular channel characterization and its implications for wireless system design and performance," *Proc. IEEE*, vol. 99, no. 7, pp. 1189–1212, 2011.
- [15] F. Lv, H. Zhu, H. Xue, Y. Zhu, S. Chang, M. Dong, and M. Li, "An empirical study on urban ieee 802.11 p vehicle-to-vehicle communication," in *Proc. IEEE SECON*, London, UK, Jun. 2016, pp. 1–9.

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