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Intelligent Framework for Fog Infrastructures in Internet of Vehicles Using Context-Aware Data-Driven Approach

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ABSTRACT: Internet of Vehicles (IoV) is the evolution of vehicular ad-hoc networks and intelligent transportation systems focused on reaping the benefits of data generated by various sensors within these networks. The IoV is further empowered by a centralized cloud and distributed fog-based infrastructure. The myriad amounts of data generated by the vehicles and the environment have the potential to enable diverse services. These services can benefit from both variety and velocity of the generated data. This paper focuses on the data at the edge nodes to enable fog-based services that can be consumed by various IoV safety and non-safety applications. This paper emphasizes the challenges involved in offering the context-aware services in an IoV environment. In order to overcome these challenges, this paper proposes a data analytics framework for fog infrastructures at the fog layer of traditional IoV architecture that offers context-aware real time, near real-time and batch services at the edge of a network. Finally, the appropriateness of the proposed framework is verified through different use cases in the IoV environment.

KEYWORDS: Intelligent Framework, Fog Infrastructures, Internet of Vehicles Using Context-Aware Data-Driven

I. INTRODUCTION

The Internet of Things is an emerging global Internet-based information infrastructure, which is now positioned as the de facto platform for ubiquitous sensing and personalized service delivery. It promises a new information infrastructure in which all objects around us are connected to the Internet, possessing the capability to communicate with one another with minimal conscious interventions. IoT allows people and things to connect at any time, and anywhere, with anything and anyone, ideally using any network to facilitate global exchange and delivery of intelligent and relevant services [1]. It is the new Internet where things and humans become addressable and readable counterparts. The IoT infrastructure consists of heterogeneous physical and virtual objects that can cooperate on social interactions, where each entity is capable of producing or consuming intelligent services. With this revolutionary and innovative development, it is now possible for our everyday objects to understand our needs: what we want or prefer and where and when we need them [2]. However, for practical deployment of intelligent applications on this infrastructure, one of the associated problems that need to be addressed is how to find relevant services. A recent and an excellent proposal is context-aware recommendation system that exploits contextual information obtained from devices to learn the user preferences to provide services of interest. CARs are an extension of traditional recommendation systems, which are generally categorized into three main types: the collaborative filtering (CF), the content-based filtering (CBF), and the hybrid recommendation (HR) systems. On one hand, the traditional CF systems rely on the similarity (or the so-called correlation) between each pair of service consumers, who have consumed or rated the same items, to predict preferences of the target user. If the system predicts the preferences of the target user accurately, then it can suggest relevant and interesting services that the target user has not yet seen or consumed. On the other hand, the CBF systems use information about the user's consumption history to provide new and relevant services that the user has not yet seen or consumed. The hybrid recommender system is a combination of both CF and CBF, where the strengths of both are harnessed to address their peculiar weaknesses [3]. The most important step therefore in the recommendation process,

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depending on the recommendation algorithm, is either the determination of the target user's neighbors and the aggregation of the preference information of each neighbor to generate a predicted preference or the determination of services that are similar to the ones the target user has consumed in the past. Note that, in the case of collaborative recommendation, every neighbor must have rated some services in order to participate in the preference prediction process. This means that if none of the neighbors has rated the service, the rating prediction cannot be computed. This problem is referred to as cold start problem. Similarly, one key problem of CBF is overspecialization. An overspecialized CBF system always tends to suggest items or services that are similar to those consumed in the past by the user. However, these problems have been addressed by various excellent proposals. And of late, context-aware recommendation. The traditional recommendation systems consider user preferences and assume that these preferences do not change as users move from one location to another engaging in various activities. However, in addition to user preferences, CARSs use contextual information such as location, activities, environment situations, traffic information, device characteristics, and network conditions to provide relevant recommendations according to the user preferences in those contextual situations. Despite their widely reported success, CARSs are limited in the type of contextual information they can use and the knowledge they can infer from such context information. In addition, even though CARSs have been explored to understand diverse preferences of users to suggest relevant services, nevertheless, apart from the user's mobile phones, some existing CARSs have not taken into consideration other context sources such as everyday objects with which users interact in the IoT environment. Therefore, we argue that existing CARSs lack the adequate capability to provide dynamic and flexible context information required for making dynamic and intelligent recommendation decisions. Thus, the IoT is a novel computing paradigm for developing a new ubiquitous and pervasive network of addressable interconnected heterogeneous everyday objects that can provide dynamic sources of context information. Since IoT objects interact with the environment and other objects, for example, object-to-object and object-to-human interactions sharing vast volume of data, value-added services based on these data can be delivered to users, providing impressive user experience [4]. The IoT possesses the potentials to take context awareness to the next level considering that massive and dynamic data coming from diverse IoT objects can be exploited, via available software interfaces, to build more dynamic and intelligent CARSs.

Efficient Transportation systems are essential to increase the productivity of a nation. The estimations show that population's time spent on the roads is increasing. This dependency on the transportation systems, however, poses several challenges. First of all, the congestion is surging because of the increasing number of vehicles on the road. The congestion is a key source of air pollution in metropolitans around the world due to increases in the fuel consumption. Furthermore, the congestion poses many safety issues such as risk of accidents. The performance of transportation systems plays a key role in the economic strength of a country, so effective technologies are required to address the inherent challenges [5].

VANETs have seen significant advancements in recent years. IoV is the latest development for VANETs that enables each entity of the network to be connected to the Internet for sharing information with other entities. IoV endorses strong interaction between vehicles, infrastructure and humans by empowering them with connectivity, computing and processing capabilities through Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I), Vehicle to Sensor (V2S), Vehicle to Human (V2H), and Vehicle to Device (V2D) and Infrastructure to Infrastructure (I2I). With technological advancements, IoV is expected to provide vehicles, drivers and passengers with unprecedented safety and convenience such as, accident warnings, vacant car parking notifications, restaurants' discount vouchers, dangerous road warnings, emergency vehicle caveats, internet and multimedia sharing, traffic light management and road safety messages etc.

An IoT-based infrastructure is a potential platform to address CARS context problem because it provides an important infrastructure to collect information from various objects that users interact with. This context information can then be exploited to address many challenges of context-aware personalized recommendation systems. There are two main advantages of IoT as a solution to CARS problem. Firstly, IoT provides ubiquitous sensing functionality allowing better understanding of object and human environments. This understanding can be used to gain useful insights into user preferences in a way traditional recommendation approaches, including CARS, have not been able to achieve.

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Secondly, as illustrated in Figure 1, IoT also allows, for example, collaborative recommendation algorithms, to exploit social characteristics of IoT objects to learn about those objects or humans with similar interests and preferences. However, collecting data, such as context data, from IoT devices poses a new challenge in terms of security and reliability. Thus, trust management is emerging as a powerful tool that can be used to address reliability of not only context data itself but also that of context providers, context information consumers, users, and services [6].

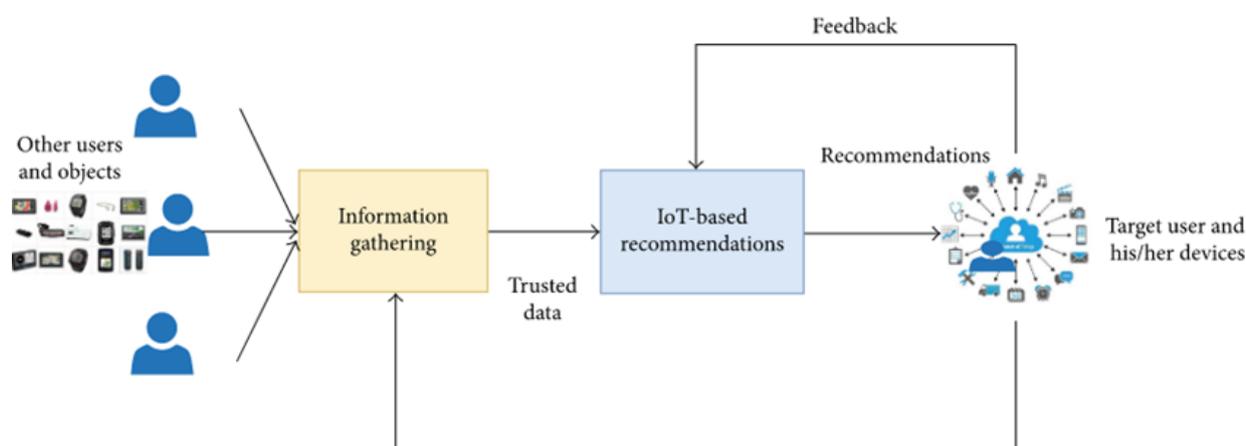


Figure 1: A high-level view of IoT-based recommendation system[3].

The aim of this article is fourfold as illustrated by the high-level functional architecture of the proposed system in Figure 2:(1)It proposes a conceptual context-aware framework that can collect, analyze, and infer high-level context information from IoT objects. The high-level context is a complex contextual information obtained by combining more than one atomic context using cognitive reasoning or machine intelligence; for example, from “*activity = walking*” and “*location = gym,*” a more complex context such as “*walking to the gym*” or “*walking in the gym*” can be inferred.(2)It provides suggestions to users based on their current and historical context information, taking into account the contextual preferences of the users.(3)It proposes an extended contextual profile model for entities to manage their service consumption preferences.(4)It presents how trust can be incorporated into context-aware personalized recommendations [7].

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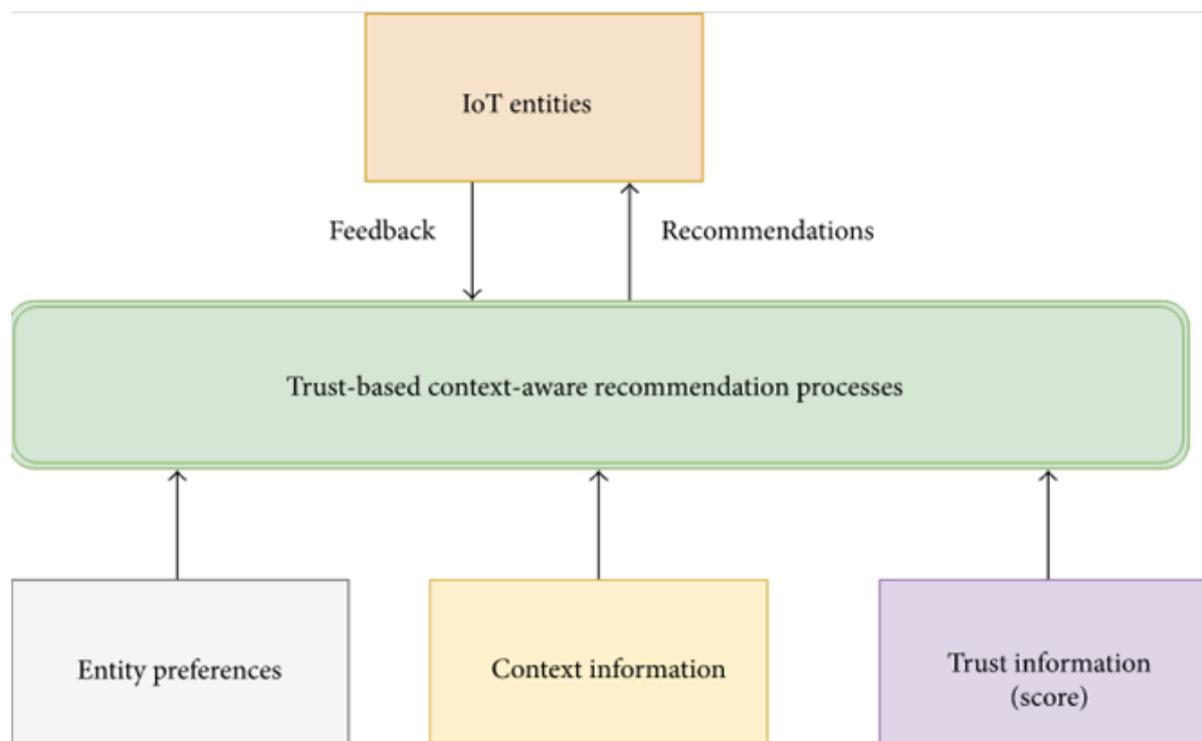


Figure 2: A high-level architecture of the proposed trust-based context-aware recommender systems[7].

Thus, in Section 3, the article presents a conceptual framework addressing these fourfold issues. The framework can collect, analyze, and infer context information from mobile sources such as IoT devices. The analyzed context information can be exploited to gain useful insights into the preferences of an entity in an IoT environment in terms of what services they consume or can provide in diverse contextual situations thus satisfying the first aim of the proposed framework. To realize the second aim, the framework provides the components for recommendation processes that can use the inferred contextual information to provide personalized and relevant suggestions [8]. Thirdly, a contextual preference model capable of capturing entity user preferences, contexts in which such preferences have been expressed, and the level of confidence in such contextual preferences, measured through trust evaluation, is also presented. Finally, we discuss how to incorporate contexts and trust information to improve the relevance of recommendations. The contribution of the current article is a conceptual framework for the provisioning of relevant service recommendations in IoT-based infrastructure [9].

In Section 2, we discuss background and related work. Section 3 presents the proposed system and its components. In Section 4, we present the experimental setup, evaluations, and results. In Section 5, we discuss the results and provide some insights about our findings. In Section 6, we conclude the article and discuss the future direction of our work [10].

There are different technologies used to provide the required infrastructure to collect, process, and analyze the generated data to enable data-driven intelligence. Vehicular Cloud computing (VCC) has empowered the ITS systems to enable range of different applications from safety to traffic management. This paradigm requires all the sensed data from vehicles and environments to be sent towards a centralized cloud. The integration of cloud computing with ITS

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provides the required infrastructure to store, process and analyze mammoth amounts of data. VCC also orchestrates various services for different applications such as traffic congestion management and traffic predictions [11].



Figure 3: Data-driven intelligence system[8].

These applications are required to interact with a centralized cloud to consume offered services. This paradigm offers a great platform for offering services based on long-term data. However, this centralized paradigm struggles to deal with delay-sensitive applications such as Traffic Light Management, Vehicle Tracking, Road Safety Messages, Accident Warnings, Emergency Vehicle Warning, Commercial Advertisement, Alternate Routes, etc. On the other hand, Fog computing offers a distributed cloud model to enable the delay-sensitive applications. In this paradigm, all the sensed data is gathered by the designated fog servers in the vicinity of the vehicles and the environment. To reduce delay and increase energy efficiency, the data should travel just one hop before it can be processed and analyzed. All the fog servers in different areas orchestrate their own services to enable range of delay sensitive applications. Figure 1 shows a data-driven intelligence system in action that collects data and analyzes it to produce useful analytics for different applications of IoV [12].

II. REVIEW OF LITERATURE

Ahmed et al. Reviewed the role of big data analytics for IoT systems. They also have covered the detail of recent advances in big data analytics and related platforms and solutions. The general requirements of IoT environments and open research challenges to enable data-driven intelligence are also presented by the authors. Furthermore, few IoT applications, along with Smart transportation, are assessed by the authors to highlight the potential benefits of big data analytics. Similarly,

Qin et al. Presented a data-centric perspective of IoT. They have reviewed recent techniques for data stream processing, storage models, event processing and searching in IoT. However, these papers only provide reviews of the potential of big data analytics in IoT but do not provide a framework to avail the benefits. A data-centric framework is proposed in to support the development of cloud-based IoT applications. The framework is composed of three components: Data Source Manager, Cloud Manager and Application Manager. Data Source manager interact with multiple data sources and provides the interface for applications.

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Cloud Manager is responsible for the provision of resources based on the applications' requirements and monitoring of the cloud's performance. Finally, Application Manager facilitates users to execute their applications in the cloud. These papers, however, only either address the general IoT requirements or mostly focused on centralized cloud based solutions and are not focused on IoV scenarios. VCC based efforts focused on enabling data-driven intelligence based on vehicular data gathered at a centralized cloud.

Sookhaket al. Have reviewed the current Cloud Computing technologies and discussed the taxonomy of vehicular networking. They have also analyzed the technologies in the context of VCC. Moreover, authors presented general architecture, security and key management issues, and potential vehicular applications. Their paper also highlighted the open research issues such as context-based routing mobility and unstable communication links. An IoT based Vehicular Data Cloud architecture is proposed in to provide on-demand services to customers through vehicular cloud. The layered architecture integrates various information and communication services made available to users using Service-Oriented architecture (SOA) based cloud services. SOA also abstracts the implementation details by integrating various middleware systems. Furthermore, it is argued that these SOA-based services ease the process of creating new application for developers by organizing, aggregating and packaging different business application services. The paper also highlighted the related future challenges and opportunities. These papers partially address the IoV requirements, because the papers have only focused on the data-driven intelligence at a centralized cloud server.

There are few efforts that cover distributed data-driven intelligence in IoT environments. Fog Computing paradigm aims to create large distributed cloud-based services by deploying fog nodes at the edge of various networks. The fog nodes are allowed to have different configurations and capabilities. Applying Fog Computing paradigm in IoT has several benefits such as reduced latency, efficiency and agility.

Bonomiet al. Have examined the potential of fog-based big data analysis to enable disruptive business models. The authors discussed few IoT use-cases to illustrate the requirements of fog computing. Furthermore, they proposed a high-level software architecture, to realize different applications, that has three layers: Abstraction layer, Service Orchestration layer, and Application layer. The Abstraction Layer integrates the heterogeneous IoT devices by providing an abstraction API. Then, the Orchestration layer contains a Fog let that acts as a resource manager, a distributed storage for policies and other data, and a messaging bus to deliver messages for resource management and service orchestration. Finally, the Application layer provides Data and Control APIs to enable applications to utilize the distributed data store and define the deployment configurations. Another effort discussed a general architecture for the provision of consumer centric IoT services. These papers cover the fog based data-driven intelligence, but the IoV requirements are only partially addressed.

Fog computing paradigm is also applied to vehicular network in few articles. The case study of connected vehicles is briefly explored to highlight how fog-based semantic data analytics can offer services for the discovery and management of the vehicles. The term Vehicular Fog Computing is coined in by considering vehicles as fog nodes. Different application scenarios are considered such as moving and parked vehicles as infrastructure units of the fog paradigm.

However, the paper also emphasized different open challenges to be tackled before some useful applications can be realized.

Zhang et al. Considered offloading computation to local fog servers to reduce latency and increase scalability. The authors also proposed a regional cooperative fog computing- based intelligent vehicular network (CFC-IoV) to manage the big data generated by IoV in a smart city environment. Another approach has proposed a new fog-based VANET architecture by following the Software Defined Networking (SDN) paradigm in order to offer preprocessed services at a low latency. Another similar effort considers vehicles as IoT resources, but briefly mentioned the data related layer. A Pub/Sub-based fog computing architecture is also proposed for IoV in. Another survey paper reviewed the role of fog computing in IoV and proposed an abstract architecture based on the lambda architecture. This architecture is further augmented with domain-based semantic ontology. These efforts are more focused on general architecture to realize fog

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computing and have not addressed the data-centric perspective in detail to enable intelligence. Context-awareness and Content Centric Networking (CCN) has been studied in context of VANETs by different authors.

Wan et al. Proposed a multi-layer context aware architecture for vehicular networks with mobile cloud support. The authors have divided the applications and services of context-aware cyber-physical systems into three computational layers; vehicle, location and cloud. In vehicular computational layer, vehicle is expected to provide data about vehicle sensors, environment, driver and passengers. In location computational layer, Road Side Equipment (RSE) can exchange context-aware information with On-Board Equipment (OBE) of vehicles. Context-aware information exchange between RSE and vehicles can help in generating real time information, e.g., traffic information. Besides proposing architecture, authors analyzed two service components, e.g., vehicular social networks and context-aware vehicular security. Finally, a context-aware application scenario of dynamic car parking services has been exemplified to evaluate the proposed architecture. Due to high mobility in VANETs, context-awareness plays a vital role for content generation and consumption.

Duarte et al. Have analyzed the efficiency of approaches combining CCN, Floating Content (FC) and Software Defined Networking (SDN) for adaptive VANET architecture to assimilate periodic connectivity, varying node density and mobility patterns in ensuring high QoS. The major contribution of this article is to highlight the potential of SDN in VANETs to ensure optimized content dissemination in a network, by analyzing the factors that affect CCN and FC based content dissemination and investigation of reduction in content retrieval time by utilizing technologies like Wi-Fi and LTE in vehicles. Context and social relationship management in VANETs have been explored by some researchers.

Nassaret al. Have provided an overview of context-aware processing and communication gateway associated with VANETs. Context-aware system architecture for VANETs has been discussed along with the challenges involved in knowledge querying and information dissemination in VANETs. A context-aware VANET system is layered into smart dissemination, context processing and context collection and modeling layers. Finally, smart dissemination is used as a mechanism to disseminate relevant information to the nodes. The factors that help in choosing the appropriate communication include, type of service and relevance of the service to nodes' context.

Shin and Byun et al. have proposed a Social Enabler (S-Enabler). In order to demonstrate its working, they applied S-Enabler to a vehicle to ensure context-aware and energy saving services. Middleware architecture for S-Enabler is designed that comprises of six management modules; context management, the cooperation management module, the social management module, the session management module, service management module and a knowledge repository. The authors have also proposed energy saving algorithm based on social behavior. The experiments performed to evaluate the performance of energy saving in vehicles illustrated reduction in fuel consumption by 31.7%. Based on the literature, there has been significant work done in the domains of big data, IoT, IoV and Fog Computing. However, there is a gap in the provision of context-aware and delay-sensitive services. This paper aims to this gap by proposing a framework to enable context aware data-driven intelligence in IoV environments

III. PROPOSED SYSTEM

3.1 Proposed System Architecture

Software Defined Networking (SDN), characterized by the decoupled control plane and data plane, provides comprehensive network control. The communication between the data plane and the control interrupts the flow of the packet, resulting in an increase in both cost and delay in communication. Thus, SDN focuses on minimizing the communication between data plane and control plane [16]. The SDN controller can also make informed management decisions based on the real-time central global information. Therefore, it is popular in complex network management.

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SDN provides the controller an overall picture of the network via a programmable control plane and interacts with forwarding devices and offers a programming interface for network management applications. As a result, it helps in the dynamic network deployment and agile network management without interfering with other networks. It also contributes to faster application innovation and optimal resource utilization [17]. With the help of SDN control plane configuration, the network can not only adapt to the changes in the network dynamics but also respond to the emergency situations (e.g., in case of accidents)[16]. The SDN accompanies the edge computing and complements the intelligent transportation system in order to deal with the complexity of a heterogeneous and massive number of vehicles, humongous data flow, and frequent topology change to provide immediate vehicle mobility to extend driving safety.

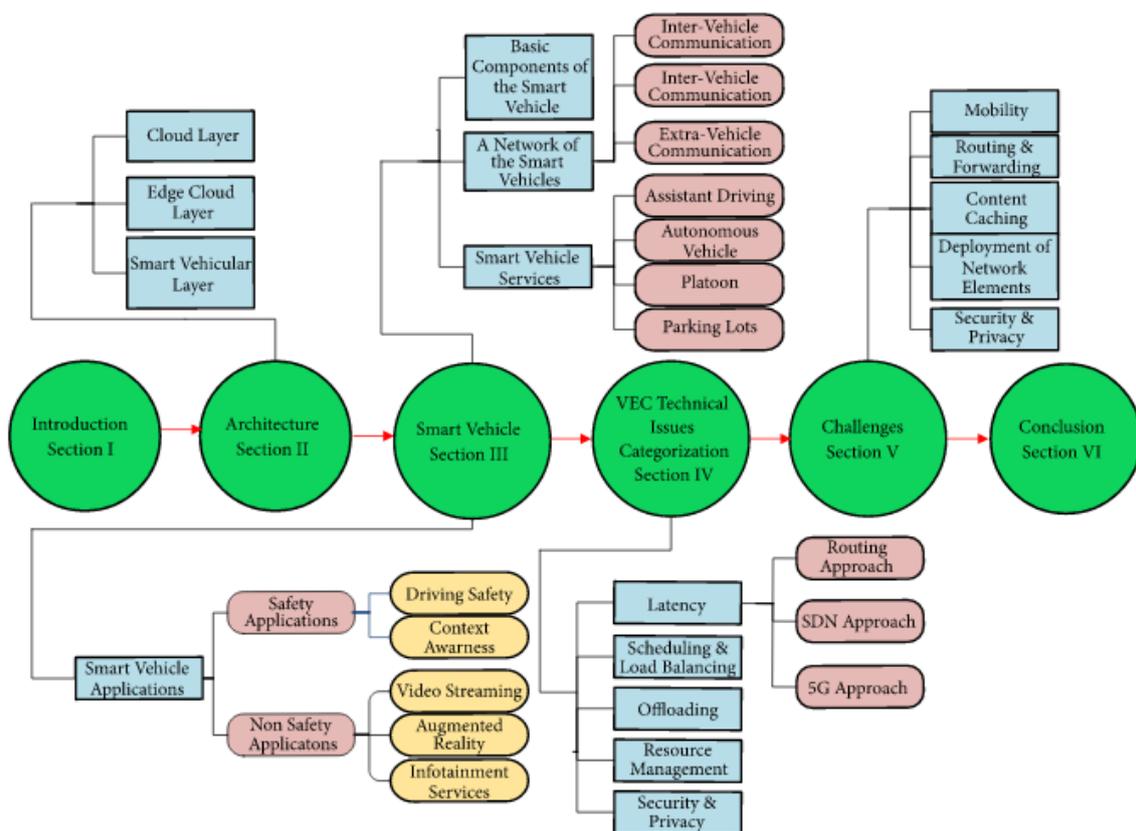


Fig. Proposed System Architecture [9]

3.2. IoT context abstraction layers

In this section, we present an overview of the proposed conceptual framework for context-aware personalized service delivery in IoT. The predicted deployment of billions of devices and their global access require layered architecture for the management of information from the physical devices to the cloud computing. IoT will take the concept of Ambient Intelligence to the next level as it supports the concrete realization of building a digital ecosystem that is fully aware of the environments without conscious human intervention [1].

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To realize such technological development, some key features must be present:

1. TheIoT-based systems should be adaptive, and they should change in response to contextual situations.
2. They should be dynamic by anticipating preferences of entities or users.
3. They should be context aware to recognize the environment, objects, or entity’s situational contexts.
4. The IoT-based systems should support tailoring of services to the users’ contextual preferences
5. The sources of information and information itself must be reliable. Thus, we propose trust as a means for improving the reliability of personalized recommendations by using feedback from users to compute trust after consuming services in specific contexts.

Firstly, we give a high-level overview of a typical IoT platform, such as the one being developed by the Wise-IoT project consortium. Wise-IoT project is an EU H2020 funded project, being executed by leading European research and academic institutes and their counterparts in South Korea. Wise-IoT aims to provide a worldwide interoperable IoT that utilizes a large variety of different IoT systems and combines them with contextualized information from various data sources. Such an IoT platform can be viewed broadly as a three-layered architecture as illustrated.

The OneM2M standard is a global IoT standard that addresses communication issues for a common IoT service layer and interoperability on the IoT connectivity layer. This sensor layer is also responsible for the IoT management. Management layer and can be considered as the cloud layer responsible for the acquisition, aggregation, and processing of context data. Furthermore, low-level context data from the physical layer are preprocessed for cognitive inference purposes using various techniques such as data mining or machine-learning algorithms as well as semantic web models for context reasoning, consisting of a context knowledge base and query and inference engines [3].

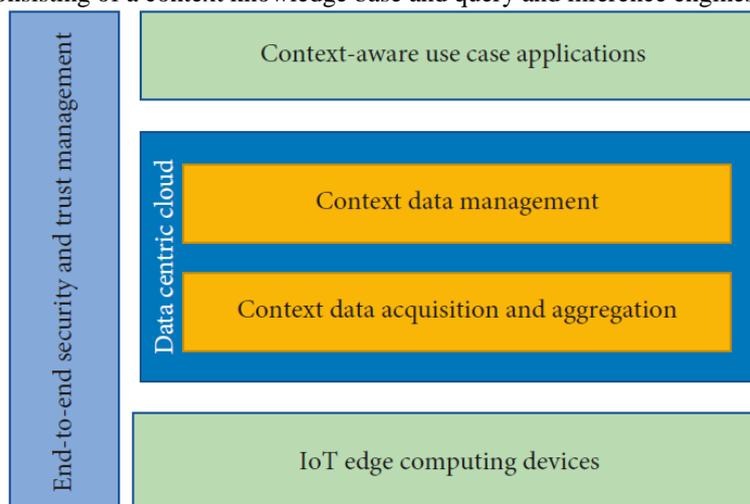


Figure 5: IoT context abstraction layers [10].

Furthermore, low-level context data from the physical layer are preprocessed for cognitive inference purposes using various techniques such as data mining or machine-learning algorithms as well as semantic web models for context reasoning, consisting of a context knowledge base and query and inference engines. One of the current and popular implementations of this layer is the FIWARE context broker, which is based on the NGSI standard [4].

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FIWARE provides the capabilities to obtain IoT context data in addition to context information obtained directly from the user's mobile devices. Nevertheless, presently, these context brokers such as the one developed in the FIWARE project; do not provide the capability for context classification and knowledge processing and logical inference last and the upper most layer is the application layer where context information is exploited to deliver intelligent services. Different kinds of applications can be deployed at this layer, for example, car parking or route recommendation applications.

We also have a contextual profile model, recommendation manager, feedback manager, and contextual profile manager. Contextual profile model is responsible for learning the entity's preferences in contexts of service consumption. Recommendation manager is responsible for using the contextual preferences to candidate services and suggest the most relevant ones to the users [5].

3.3. Context Information Access and Processing.

This section introduces the context awareness component that we have designed, for deployment on the IoT platform to process context data obtained from IoT context brokers and other IoT platforms such as the FIWARE broker. Each of these components will be discussed in the next sections. The framework consists of various processing modules to be incorporated into our trust-based platform for intelligent service delivery in the IoT environment. The context framework has been designed to provide the capability for high-level context classification, using machine learning and ontologies for context classification, semantic processing, and reasoning. In we have described in detail context sensing, context classification, and reasoning using the neural network algorithm and various statistical features to identify the context in IoT. In this section, we only provide various steps for context classification and reasoning. However, we extend the concepts developed in that paper by providing here the cognitive model of context information and inference using ontologies, reasons, and Semantic Web Rule Language (SWRL) [6].

3.3.1. Context Sensing and Preprocessing.

The ability of a system to identify contextual situations and to make informed decisions is one of the most important functions of any context-aware system. However, sensors emit data that are in low-level formats, which are not suitable for decision-making by mobile applications. Context recognition process collects raw data from sensors and transforms them into information that can be used to build intelligent applications. To provide accurate context information about service consumers, the proposed framework uses the context recognition process to identify contextual information such as user activities, from smartphone-embedded and IoT sensors (obtained in the form of Web Services APIs from IoT platforms). The framework's sensing module gathers events from these sensors such as accelerometer, gyroscope, rotation vector, orientation, proximity, microphone, light sensors, and other sensing devices, preprocesses the data, and then uses classification algorithm(s) to derive more meaningful context information. It collects sample data from each sensor in predetermined time intervals overlapping the next predetermined time space. In the data preprocessing phase, the framework removes the data outliers. This is achieved by eliminating samples from the beginning and ending of each example to reduce the influence of noise in the streams of sensor data [7].

3.3.2. Feature Extraction.

The user's dynamic contexts, such as activities, occur in relatively long period, in seconds or minutes, compared to the sampling rate of the sensors. This sampling rate usually does not provide sufficient data to describe user activities. Foregoer, activities are usually identified on time window basis rather than sampling rate basis. Comparing a series of time windows to identify activities is almost impossible even if the signals being compared come from the same user performing the same activity context. The feature extraction process addresses this problem by • filtering relevant data and obtaining quantitative data from each time window. Many approaches have been explored in literature such as statistical and structural properties of the sensor signals. Structural features such as Fourier transform are quite complex and require more computational resources [8].

This may not be ideal for an energy-starved smart device. On the other hand, statistical features are simple and require less computational resources. Thus, this process uses simple labeled statistical features (e.g., range, maximum, minimum, mean, and standard deviation), which have been validated in our previous work to be very effective to

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discriminate between time windows. Features are extracted into feature vectors that are then used in the next process [9].

3.3.3. Context Classification.

After extracting the time window features from the raw sensor signals, without deriving the context knowledge from them, the example features are limited in how they can be used. The context classification uses supervised machine learning algorithms such as the neural network (NN) to derive high-level context from the statistical features. Details of the modeling and evaluations can be found in [10]. These models are integrated into the recognition service to obtain independent future activities and contexts of the users [10].

3.3.4. High-Level Context/Contextual Situations: Context

Inference of the context information obtained from context recognition and classification processes is not able to provide cognitive meaning of complex context information, in addition to not being able to recognize complex context information. Thus, it is important to develop a cognitive model based on semantic web technologies that can infer higher-level contextual situation from. For example, it is important to know what a user is presently doing, when, and where he/she is doing it. Nevertheless, without relating this information to provide more high-level contexts, this information will not be useful to the application. This is one of the weaknesses of some of the existing work [11]. The proposed context framework thus uses the knowledge-based model on top of the classification process to relate different atomic context information to obtain contextual information at a higher semantic level. For example, having known that a user sitting at home is in the living room, if we know that the TV is on, and then it is important to relate this information and conclude that the user is watching TV. For example, having known that a user located at home is sitting in the living room, if we know that her TV is on, then it is important to relate this information and conclude that the user is watching TV. The user is watching TV, obtained from sitting, home, living room, TV, and so on, and is inferred using the knowledge-based cognitive process. The details of this process can be found in [12]. It can also determine complex context such as a user is "jogging at the sport arena." is kind of information is crucial to offering rich quality of experience to users [12].

(1) Ontology Concepts: In this section, we introduce the design of the ontology model in the proposed framework for the inference of higher or complex contextual information from the atomic context classified by the context recognition model. To infer higher-level or complex contextual situation from the recognized and classified contexts from the previous section, we have developed semantic web-based ontology reasoning for context in the IoT environment. We have provided some important concepts from which the ontology was designed and developed [13].

To infer high-level contexts from those concepts, context reasons and context rules have been used. The conceptual context framework incorporates nine generic interrelated concepts, which were defined for providing context information for the context-aware media recommendation domain. Eight of the core concepts are based on our previous context representation model in but now extended to incorporate trust as an additional concept that relates with other core concepts as a property. The ontology is being developed using OWL DL with adequate provision for adaptation decisions, relying on various rule-based mechanisms, which support an automatic knowledge inference from contextual information. Activity, Time, Trust, Adaptation, and Network [14].

The concepts in this domain are generic and are valid for many application scenarios. The second layer incorporates specific domain ontologies, integrating reasoning and rules for inferring contexts specific to each domain. The specific or lower domain ontology is designed based on the combination of user specific activities and locations and other contextual situations. For example, the user home domain activity and the related contexts determine contextual information that characterizes the user's activities when at home. We define the primary concepts of the context model as follows:

- **User:** the central focus of any context-aware recommendation system is the user. In these systems, information such as location, activities, and preferences is very crucial to building a system that adapts to the user's needs. This contextual information influences the user's preferences for service consumption, and

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therefore, when recommending service items to the user, it is important that this information be incorporated into the recommendation process.

- **Time:** the time concept is primarily used to capture the “when question” of the other concepts. Time duration, start time, end time, and so on are some of the elements of this concept. These elements of the time concept are used to infer, for instance, high-level time information such as weekdays or weekends which is subsequently used in addition to location information to infer a user’s contextual situation including her activity contexts.
- **Device:** the characteristics and capabilities of IoT devices can have significant impact on the personalized recommendation process. The device characteristics can be used to adapt recommendations to the user’s device. For example, the device battery level can be used to determine the appropriate format to present recommended items. In fact, it may present the item such as streaming video in a format that requires less power such as in text form. If the battery level is low, the recommendation system could decrease the brightness or lower the spatiotemporal resolution of the content in case of an audiovisual content. In addition, this concept also describes the capabilities of the devices.
- **Environment:** another important concept of the ontology is the natural environment. This concept influences the kind of items users would prefer to consume depending on the environmental condition or situational contexts. It provides information about the environment in which a user interacts with the recommendation system or his device. There are two groups of fundamental concepts related to the environment
- **Concepts:** location, including logical (e.g., city and street) and physical (e.g., GPS coordinates), and environment conditions (e.g., noise level, illumination, and weather information). For example, information about the current weather can be used to provide more relevant media recommendations to users, that is, the category and genre of contents preferred by the users can be influenced by weather information.
- **Activity:** user activities can be used in addition to the other context information by the recommendation process, given that they have a strong impact on the preferences and needs of mobile users, as previously stated. As explained in the previous sections, to address this problem, low-level data obtained from device-embedded sensors are channeled to a context recognition model running on the device, which recognizes high-level activity being performed by the user.
- **Network:** the network concept describes the conditions and characteristics of the network connection of the user.

IV. TRADITIONAL IOV ARCHITECTURE

IoV is an emerging field that has the potential of utilizing various state-of-the-art concepts like IoT, Big Data Analytics, Wireless Communications, Safety and non-safety application and Security etc. Recently, there have been some efforts in developing a generic IoV architecture that provides overall frame of reference for future researches in this area. A generic IoV architecture comprises of a data source layer, communication layer, fog layer, cloud layer, application and security layer. Each layer of the architecture is responsible for performing certain tasks. At Data Source layer, data is collected from various sensors, e.g., vehicle sensors and environmental sensors incorporated into Road Side Units (RSUs) [1].

Communication layer is responsible for data transmission between different entities of the system, e.g., vehicles, RSUs, passengers, drivers, pedestrians and cloud etc. One of the major responsibilities of Fog layer is to ensure the required scalability with the provision of fog-based decentralized architecture in an IoV network through huge amount of data generated by different entities of the network. The Cloud layer provides resources to perform complex computations, store enormous amounts of data, and a place to make system-wide decisions. Application layer is responsible for providing safety and non-safety application through V2V, V2I, V2S, V2H and V2D communication. Finally, Security layer is responsible for securing the data throughout the IoV architecture. This article is expected to explore the capabilities of the Fog layer in IoV systems to ensure offering of context-aware services in an IoV environment by proposing a framework that enables delay sensitive applications [2].

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V. IOV CHALLENGES

IoV system faces various challenges due to its dynamic nature and real-time data requirements. Several researches are under process to improve the overall efficiency of IoV systems [4]. A comprehensive review of literature assisted in summarizing the following major challenges faced by IoV system for their design, development and deployment [3].

A. Heterogeneity and Interoperability

An IoV system involves communication between diverse entities of the system like vehicles, RSUs and drivers and passengers' handheld devices etc. Each entity of the system requires disparate communication scheme and is capable of generating distinct type of data. For example, in a V2I communication, if a vehicle can communicate through a cellular technology, e.g., 2G, 3G or 4G etc. and a RSU can only communicate through Dedicated Short Range Communication (DSRC); the communication might never occur due to unsupported communicating technologies [5].

In a V2V communication, vehicles supporting DSRC might still not be able to communicate with each other if data sent by one vehicle is unrecognizable by another vehicle due to different encryption techniques used by the manufacturers of the vehicles. Due to scalable and dynamic nature of IoV, the network is expected to grow significantly with discrete nodes that might be different from each other in communication protocols, security algorithms, data sharing mechanisms and other supporting technologies. Hence a mechanism is required that enables heterogeneous entities to socialize with each other [6].

B. Real Time Data

One of the major requirements of IoV system is dissemination and gathering of real time data to and from its distinct entities. In some cases, processing of the data before dissemination and gathering requires real time analysis to ensure appropriate actions. For example, an ambulance carrying a patient in critical condition to the hospital would require real time information of the traffic to avoid jams and congestions to ensure timely delivery of patient to the hospital. A slight miscalculation in data delivery of traffic information in this case might result in ambulance being stuck in a traffic jam that would end up in compromising the life of the patient. In IoV, mostly safety and non-safety applications need data analysis in the cloud that depends upon many factors like available bandwidth, cloud processing, computing and storage capabilities, complexity of encryption algorithm and amount of data etc. An IoV system requires an efficient technique that ensures real time data delivery to enable delay sensitive applications [7].

C. Context-Awareness

A vital feature in IoV is to empower vehicles to be context aware, e.g., to be cognizant of their surroundings particularly the ones that are of high relevance. Context-awareness in IoV starts with gathering data through in-vehicle or environmental sensors, converting this sensing information in to high level contextual information and finally taking an action based on this contextual information. For example, in a smart vehicle, a camera installed above the driver seat might constantly monitor the driver to measure the fatigue level through algorithms that use driver face expressions to calculate driver fatigue. This information from the camera (sensing component) is then converted in to high level contextual information by gathering other information like vehicle speed, road type, vehicle movement and inter-vehicle distance to finally alarm the driver of the situation or suggesting the driver to take a break. Context-awareness in IoV is extremely useful as it can assist drivers in understanding their own driving behavior; improve fuel efficiency by providing less traffic routes, enables authorities in managing parking slots and govern traffic rules in highly populated urban areas. An IoV system entails systematic context awareness process that ensures effective decision making for autonomous entities [8].

D. Quality of Service (QoS)

IoV enables plethora of applications based on V2S, V2V and V2I communication. These applications have diverse QoS requirements in terms of latency, throughput and jitter, etc. The provision of required QoS depends on many factors such as vehicle's speed, density of vehicles in the vicinity, application's data requirements, location of sources, characteristics of the communication technologies involved, and the processing requirements. For example, it is easy to

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meet real-time requirements of an application that only requires data from a sensor with peer to peer (P2P) connection in a vehicle. However, it is quite challenging to provide QoS to an application that requires data from a source that is located multiple hops away. Moreover, the heterogeneity of the involved communication technologies further augments the issue of meeting QoS requirements. The provision of QoS becomes extremely challenging in case of IoV applications with high QoS requirements, for example, some applications demand low latency, but require video data to be processed from multiple sources. All these challenges make the provision of QoS a daunting task in IoVs. A data driven intelligent framework needs to consider these diverse QoS requirements of various applications to aid those applications to run efficiently and effectively [9].

E. Data Quality

IoV data-centric applications assume that the quality of data will be up to some acceptable level, so the efficacy can be guaranteed. The data generated in IoV is prone to errors due to multifarious reasons such as data source issue, unreliable communication link, noise, etc. The data source can malfunction due to technical reason that can result in inaccurate data. These data can severely impact the outcome of an application and increase the possibility of serious incidents in the context of safety applications. The heterogeneity of communication technologies can negatively impact the end-to-end reliability of the data and needs to be taken in to account by anIoV data centric framework. To tackle with noise related issues there are several solutions available in the literature that analyze the data to detect and eliminate different types of noise. An intelligent IoV framework may decide to offer a best-effort approach by reducing the number of dimensions depending on the context and QoS requirement of an application [10].

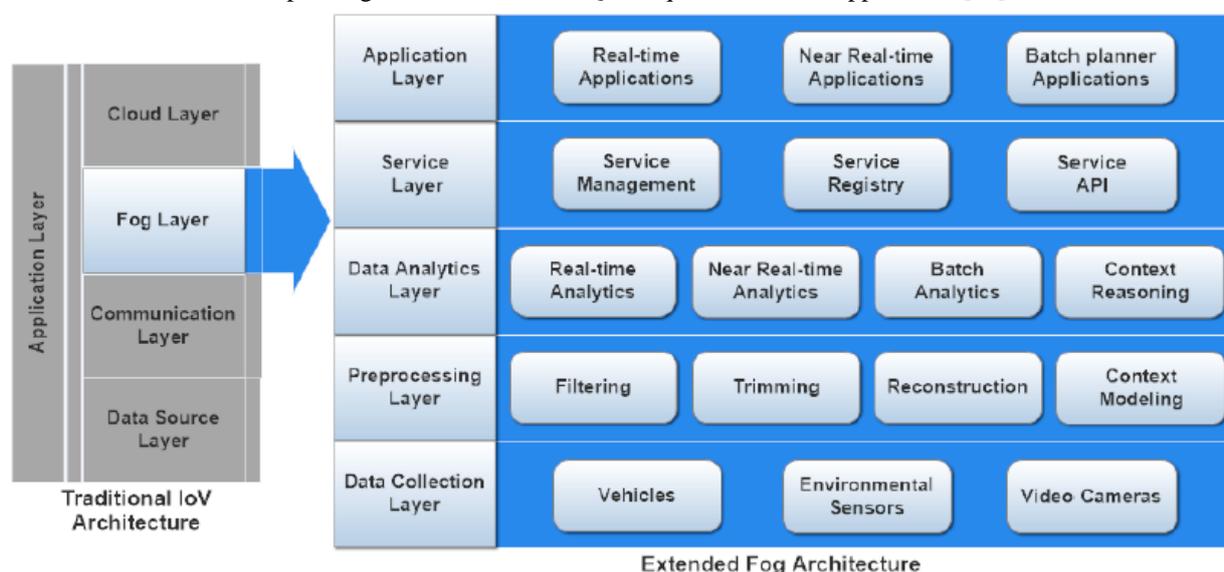


Figure6: Proposed data-driven-intelligent framework [11].

VI. PROPOSED DATA DRIVEN INTELLIGENT FRAMEWORK

IoV networks are highly scalable with nodes capable of dynamically changing network topologies. However, IoV poses unique set of challenges for designing a data analytical framework due to its peculiar characteristics. Fast moving vehicles require brisk computation and processing of information without any delay to avoid miscommunication that can cause serious inconvenience on the road to not only the entity requesting the information but to other entities

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related to it. As the entities in IoV are highly dynamic in nature, the context of the information is of utmost importance as a slight change in the context might result in providing[1].

Inappropriate information to the vehicles on road. Proposed data-driven-intelligent framework for providing context-aware applications and services for IoV. The proposed framework is an extension of Fog layer of the traditional IoV architecture presented in Figure 2. This section provides the details of responsibilities of each layer of the architecture. Furthermore, Figure 4 provides a holistic view of the proposed data-driven intelligent framework for a better understanding of the working of each layer of the framework [2].

Table 1: Protocols at physical world layer.

Data Source(s)	Technology	Protocol	Type	Description
Vehicle Sensors	V2I/V2S	CIP	Control and Information Protocol	Collects data from vehicles sensors
Vehicle Controller	Intra-Vehicle	I2C	Commination Protocol	Assists in communication between vehicle sensors and on board unit(OBU)
Environmental Sensors	V2I/I2I	I2C	Connection Protocol	Contributes in interfacing various RSU Modules
Handheld Devices	I2P/V2P	TCP/IP	Communication Protocol	Helps in collecting data to and from handheld
Cloud	I2C(Infrastructure to cloud)	TCP/IP	Communication Protocol	Supports in fetching data to and from cloud

A. Data Collection Layer

This layer deals with the collection of data at the fog layer of the IoV system, e.g., RSUs that can provide computation, processing, storage and networking services. In IoV systems, the data can be collected from distinct sources like vehicles, road sensors and handheld devices of drivers, passengers and pedestrians. Besides data collected from the sensors, this layer is also responsible for collecting data from other peer sources like neighboring RSUs and if required from cloud as well. The type of data collected from other sources can be driver profile, vehicle details, traffic information, weather data, empty parking slots and alternate routes etc. The context acquisition process at this stage evaluates context information from collected data based on the source, sensor types and their responsibilities the data is expected to be collected by a fog node [3].

e.g., RSU and is kept till further processing. Furthermore, the proposed framework requires the fog nodes to collect data based on the context.

Fog based distributed information collection proposed by the framework helps in reducing the burden on each fog node and eventually the entire system. Each fog node is responsible for updating the collected data dynamically [4].

The information from fog nodes can be combined to provide contextual information to the entities of the system. It is worth noting here that Data Collection layer at Fog units is not like Data Source layer of a typical IoV architecture. The major difference between the two is that Data Source layer of IoV architecture is responsible for physicality of the sources like vehicle and environmental sensors; however, the Data Collection layer is more of a container of the data acquired from various sources like sensors, handheld device and at times from cloud as well [4].

The data driven intelligence based on the context provided by the proposed framework helps the system in smartly collecting the data from various sources that ensures less burden and provides better efficiency to the entire IoV system [5].

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B. Pre-Processing Layer

This layer of the architecture is responsible for data filtering (extraction), trimming, reconstruction and modeling. In the proposed data-driven intelligent framework, this layer is considered extremely important as it collects the raw data from the data collection layer and gives it a specific direction for above layers to analyze and convert the data into meaningful information. Below are the details of the features provided by this layer?

1) Filtering (Extraction)

One of the major responsibilities of the pre-processing layer is to filter the data from enormous amount of data collected from various sources in data collection layer. In IoVs, entities are feeding the system with data that can serve the purpose for diverse types of safety and non-safety applications. The filtering component of the pre-processing layer ensures that relevant data is extracted based on the application or service requesting the data from the system. Filtering or extraction of data from large chunk of collected data eases the process of analysis, storage and communication by providing only relevant data for specific applications and services [6].

2) Trimming

In pre-processing layer, it is of utmost importance to trim the unnecessary information from the collected data to avoid redundant utilization of resources at fog units due to their limited computing, processing, and storage and communication capabilities. The trimming component of pre-processing layer ensures circumvention of duplicate, incomplete and faulty data. Duplicated data is merged to get the most recent information; incomplete and faulty data is requested again to avoid inaccuracy of information. Trimming serves as a successor to the filtering component of the pre-processing layer as it will trim only the filtered or extracted data relevant to requested application [7].

3) Reconstruction

In order for the analytical layer of the framework to analyze the data, it should be complete, clean, error-free and contextual in nature. The reconstruction module of the pre-processing layer ensures the accurate information for analytical layer by reconstructing the trimmed data in an analytical layer readable manner. This module also assists in segregating the actual required data, metadata and any additional information required by the actual data.

The context information is modeled to understand its details such as properties of IoV entities and their mutual relationships.

The modeling of context information is done using different modeling methods such as key-value pairs, objects, graphical objects, ontology based, and hybrid context modeling. The Key-value pair scheme is the simplest form of modeling that is flexible and easy to understand, however, it's not suitable to explain complex structures with relationships [8].

The object based scheme uses object oriented principles to classify context in classes and define relationships between the vehicular entities. This scheme requires specification for validation and can increase complexity of the reasoning stage. The graphical object scheme takes one step further and uses XML to explain different objects of IoV system.

A semantic ontology of context is created by ontology based modeling to represent it using semantic ontology languages such as Resource Description Framework (RDF) and WebOntology Language (OWL). This modeling technique is more sophisticated and used by databases and semantic web to provide required interoperability to IoV system. However, its complexity can be a hurdle in its employment on a constrained fog node. The hybrid modeling uses multiple modeling scheme to reap the advantages of each modeling technique. A fog node of IoV selects a modeling scheme based on its capabilities [9].

The aim of the pre-processing layer is to make the raw data collected from data collection layer useful for above layers. In IoV, due to highly dynamic nature of the system, analysis of data is expected to be done in a swift and efficient manner and hence filtering, trimming and reconstruction of data is paramount. Figure 5 illustrates a scenario that further highlights the role of pre-processing layer in IoV systems [10].

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C. Analytics Layer

This layer fulfills the main aim of fog-based system to bring the data intelligence at the edge of a network. This intelligence is realized by analytics and can support both delay sensitive and delay-tolerant applications at the intermediate nodes. The data received at this layer is collected and preprocessed by other layers and made ready to be analyzed. Moreover, the current context information is also received at this layer. Based on general lambda architecture, we assume three levels of data analytics to be performed at this layer: Real time analytics, near real time analytics and Batch analytics. The capabilities of a fog node determine whether it can support all kind of analytics [11].

1) Real-Time Analytics

The real-time analytics is essential for fog nodes. Each fog node is required to support some form of real-time analytics. Real-time analytics aids applications that are delay sensitive and require the necessary complex processing to be done within certain amount of time. There are many IoV applications that demand such a QoS such as safety applications. For example, a fog node may assist an autonomous car to perform complex video processing from the surrounding cameras to know whether a pedestrian is about to appear from a street. Real-time analytics are performed on elements of a data stream that need to be processed in real-time to get useful information from it. The real-time processing is limited by the constraints such as available main memory to run an in-memory algorithm. Therefore, these constraints determine whether an approximation will be preferable using sliding windows instead of a refined solution. The real-time analytics employ different algorithms to estimate Cardinality, estimate quintiles and moments, count inversions, find sub sequencing, path analysis, anomaly detection, discover temporal pattern analysis, data prediction, clustering and graph analysis. Table 3 illustrates the examples of these algorithms and relates the output to different IoV applications. The cardinality estimation algorithms such as Hyperloglog are used to analyze a data set and count the unique elements in it, and some algorithms are used to estimate quintile of constrained memory node. The moment's estimation algorithms are used to estimate the frequency of different elements. The discovery of inversions and anomalies in a data stream is performed by algorithms such as inversion counter and Anomaly detector. Some algorithms are used to discover patterns and subsequences in traffic such as Temporal Pattern detectors and subsequence evaluators. The graph analysis based algorithms analyze dynamic graph to determine useful IoV information such as determine a path between different nodes; find a vertex cover of the current traffic. The predictive real-time algorithms create clusters from a data stream; predict missing values and size of a stream [12].

Table 3: Algorithms for real-time analytics.

Category	Algorithms	Sample Outcome	Application
Counters	Cardinality counter	Total Number of entities such vehicles	Traffic management
	Inversions Counter	Whether the received vehicles data is sorted	Safety application
Basic Estimators	Quintiles estimator	Aggregative quintile of heavy vehicles in vicinity	Route planner
	Moments estimator	How many pedestrians are passing	Pedestrian crossing light planner
Pattern Detection	Anomaly detector	Vehicle shared data has irregularities	Rogue node detection
	Patterns matcher	Pattern of traffic congestion	Congestion management
	Subsequences detector	Unsafe driver on the road	Safety application
Graph Analysis	Path locator	Path between two vehicles	Live Traffic
	Graph analyzer	Path analysis between multiple vehicles	Live traffic safety
Predication	Clustering	Cluster data to create an image or video shared by a vehicle	Offloading processing
	Data Predictor	Predict a missing attribute in the data shared by a vehicle	Traffic signal Planner
	Size Predictor	Dynamic size of the graph of current vehicles	Congestion management

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2) Near Real-Time Analytics

The near real-time analytics requires data that can span up to seconds or minutes. The applications that rely on these analytics such as Complex Event Processing (CEP) applications can tolerate delay for some time because of their data requirements. It uses the similar real-time algorithms but on historic data that is gathered from multiple sources [13]. For example, a traffic light signaling control application will require data of the number of vehicles exited and entered the road within last minute to decide when to change the traffic signal. The outcome of these analytics is more granular and gives a bigger picture of the fog vicinity compared to real-time analytics. The analyzed data is stored for a while in cache memory using Memcached and Redis, or the local database depending on the size of data before it can be discarded.

3) Batch Analytics

Only few highly capable fog nodes can perform batch analytics, because of its high processing and memory requirements. The batch analytics support applications that require historic data from hours to days about the vicinity. For example, road-work related information may be shared with every user entering the vicinity of a fog node. Similarly, a road traffic management application can update the traffic light scheduling algorithm based on the trend of the past hour. These analytics can utilize advanced machine learning techniques such as Deep Learning and Deep Reinforcement Learning (DRL) to offer more sophisticated analysis. The key benefits of using these platforms include provision resilient analytics even when the data is out of order or some values are missing and distribute processing across processors and fog nodes to provide required scalability. These are designed for cloud based real-time batch analytics but can work on capable fog nodes [14].

4) Context Reasoning

The received and modeled context information is reasoned to extract useful information by all levels of analytics to enhance the analysis. To perform reasoning, the modeled context information is first of all validated to check it for missing data, and outliers. Then, context information provided by different entities is infused to get a more reliable and higher-level inference from it. At the final stage specific reasoning technique is employed that analyzes the infused information to get high-level context information. There are different reasoning schemes available such as fuzzy reasoning, k-nearest neighbors, and naïve bayes classifiers, probabilistic reasoning, supervised learning and unsupervised learning.

D. Service Layer

The service layer is responsible to stores, manage and expose the results of analytics to IoV applications. The data analytics layer passes its analysis and context information to service layer. The received data is analyzed and classified by the service layer. If the data is required a new service to expose based on its context information than service layer creates a new service and updates its service registry. Otherwise, the data is stored in relation to an existing service. There are two most popular approaches to expose services to users: Service-Oriented Architecture (SOA) based and Representational state transfer (REST) based web services. The SOA based web services uses Simple Object Access Protocol (SOAP) XML messages and offer transactional reliability. However, REST based (RESTfull) web services are more flexible and offer variety of data formats while exposing them using standard GET, PUT, POST and DELETE methods. Therefore, we advocate using RESTfull web services to expose data to application layer. The service layer also performs service composition to provide value-added services to applications [7].

E. Application Layer

There is plethora of applications with different QoS requirements running at application layer. The applications can consume the web services from service layer using push, pull or publish/subscribe based strategies. The push strategy requires the service layer to push updates directly to applications, whereas pull-based applications pull information from service layer them. The publish/subscribe strategy access allow application to subscribe their interests and

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The list of subscribers is notified about the service updates. These applications can be categorized in real-time, near real-time and batch data requirement-based applications. The real-time applications require real-time QoS such as process offloading, and safety applications [8].

VI. USE CASE SCENARIOS

The proposed context-aware and data-driven framework allows fog nodes to gather, analyze and reason with the data collected from multi-sources in IoV. There are several applications that can be enabled by this framework. This section discusses the use-case scenarios that are enriched by the context-aware fog-based services.

A. Real Time Use Case Scenario

Iain travels back from his work around 5 pm daily on his smart car that takes him 45 minutes. After a busy and hectic day, he was travelling back to his home. Suddenly, he received a notification from his car to slow down, so he followed the caution. In few moments, he saw a kid unanticipated appeared on the road from a street while running after a ball [1].

He could fully stop at the right time because of his reduced speed. At the next traffic light, he noticed that his route is updated based on the feedback of the network. He was informed by the route-planner application that the route was updated because of the sudden congestion that may be caused by a delivery truck that is stuck on the road. Few miles before his home, he received an advertisement from a local petrol station that was offering free car cleaning with every full refueling. He decided to avail the offer as his car required a refueling.

B. Near Real Time Use Case Scenario

Dubai downtown is the busiest area in Dubai that gets maximum traffic in the peak work hours. Drivers are facing traffic jams for long times. Frequent accidents are occurring in the area due to heavy traffic. Road and Traffic Authority (RTA) in Dubai have to depute traffic wardens on regular basis besides having traffic signals to ease the flow of traffic. In case of an emergency vehicle, the situation gets worse due to traffic jams and emergency vehicles are stuck in the jams that cause serious inconveniences at times [4].

RTA decided to use Adaptive Traffic Signal Management utilizing Fog units. The fog units are deployed at each traffic signal in the area to collect and store GPS coordinates of the vehicles, and motion sensor readings.

VII. CONCLUSION

The advent of latest technologies has enabled connected vehicles paradigm that offers range of real-time safety and other applications. This connectivity aids collaboration between vehicles and available network infrastructure to generate and share data. This diverse user and context data have potential to provide information for decision making. The traditional centralized cloud-based intelligence in VCC provides the capabilities require dealing with the big data analytics, storage and management. However, it fails to meet the real-time or near real-time requirements of novel applications due to delay caused by multi-hop communication. These novel applications such as adaptive signal scheduling and safety applications require response in real-time or near real-time. These requirements become more challenging in IoV system due to high mobility of its entities. The proposed data-driven framework deals with these issues by collecting, preprocessing and analyzing data based on its context at fog layer of IoV architecture. The analyzed data is made available to applications using RESTfull web services. The frameworks employs push, pull or publish/subscribe based service consumption strategies to support real-time, near real-time, and batch data based IoV applications.

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