A Knowledge Networking Approach for AI-driven Roundabout Risk Assessment

Duncan Deveaux[†], Takamasa Higuchi[‡], Seyhan Uçar[‡], Jérôme Härri[†], Onur Altintas[‡]

[†]EURECOM, 450 route des Chappes, 06904 Sophia-Antipolis, France
E-mail: {deveaux,haerri}@eurecom.fr
[‡]InfoTech Labs, Toyota Motor North America R&D, Mountain View CA, USA
E-mail: {takamasa.higuchi,seyhan.ucar,onur.altintas}@toyota.com

***Abstract*—Smart applications in vehicular networks, such as highly-automated driving, require knowledge to support complex decision making which is highly dependent on the current driving context, for example, through machine learning based object recognition. Unlike information, the pertinence of a knowledge model depends on its context of use, rather than its date of creation. In turn, the existing information sharing mechanisms in vehicular networks, optimized for fast information delivery, must be adapted to support rich contextual queries, and let vehicles discover the right knowledge for the right context. Moreover, networking of knowledge models has the potential to alleviate the redundant transmission and computation of similar information. Through a case of vehicle exit probability knowledge distribution in a roundabout, we show the impact and potential of a context-based dissemination of knowledge in terms of accuracy, delay, and overhead compared to context-agnostic approaches.**

***Index Terms*—context,distribution,knowledge,vehicular**

I. Introduction

VEHICULAR networking has originally been defined as an enabler of information sharing between vehicles, infrastructure, and connected road users. Information storage and dissemination mechanisms have been defined to support infotainment and safety applications on board vehicles. For example, the ETSI CAM [1] was standardized to convey information about the kinematics of a vehicle. Due to the highly dynamic topology of the vehicular environment, such safety messages quickly expire and must be stored and disseminated with critical delay constraints.

On the other hand, *knowledge* can be defined as an abstracted model obtained from the analysis of information and defined using Artificial Intelligence (AI) technologies, of which Machine Learning (ML) is a popular instance. Knowledge has been increasingly used by Connected and Autonomous Vehicles (CAVs) to support smart applications, which require complex decision-making based on a form of experience. For example, after receiving the information of the presence of a conflicting vehicle on the road from a CAM, how should a CAV react to avoid the associated risk? Depending on the context, e.g., the location of the vehicle or the current traffic conditions, the decision of which evasive maneuver to perform requires complex and highly context-dependent processing, which we refer to as *knowledge*.

The existing information storage and dissemination mechanisms for vehicular safety applications are optimized for low delay delivery. On the contrary, the relevance of a knowledge model depends on its *context of use* rather than its age. For example, let us consider a model to recognize and classify objects on the road from camera images and LiDAR point clouds, as defined in [2]. If the model has been trained from images and point clouds sensed in clear weather, it will lose accuracy when applied in rainy weather, as discussed in [3]. As an alternative example, the accuracy of models to predict the exit probability pattern of vehicles on roundabouts may vary based on the geometrical shape of the considered roundabout. Due to the highly mobile topology of vehicular networks, the driving context of each vehicle is likely to evolve dynamically. As such, rather than critically low delay, a key factor of knowledge distribution in vehicular networks is to ensure that the right knowledge is delivered in the right context.

In turn, knowledge networking has the potential to reduce redundancy, both by mitigating the independent computation of similar models by distinct organizations, and by favoring the transmission of precomputed knowledge rather than larger sets of source information. Existing works have considered the networking of knowledge in vehicular networks. [4] described the concept of a knowledge networking architecture involving knowledge composition, storage, and distribution. [5] defined a knowledge networking framework specialized for the composition and exchange of deep learning models. Yet, to the best of our knowledge, no mechanism has been defined which considers a generic context-based distribution of knowledge in vehicular networks, such that the context of use of knowledge can be defined and used to provide knowledge in the right context.

In [6], we introduced the Vehicular Knowledge Networking (VKN) framework. It describes an architecture for knowledge description, storage and dissemination in vehicular networks. In this paper, we use the VKN framework to evaluate the potential impact of context-based knowledge networking in vehicular networks. Through the case of roundabout exit probability estimation knowledge, we define a packet-level simulation in which vehicles can request for the creation of knowledge which is adapted to their current driving context. The contributions of this paper are as follows:

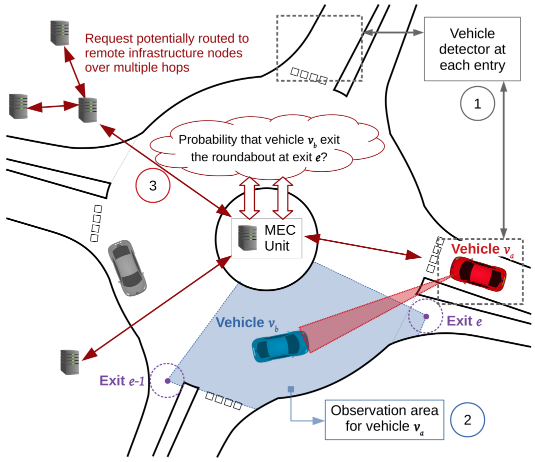

Fig. 1: The Exit Probability Knowledge Creation Case Study

- A packet-level networking simulation is contributed which implements context-based knowledge distribution over existing vehicular networking protocols. It implements the complementary aspects of knowledge description, storage, and dissemination mechanisms.
- The obtained results show that context-based knowledge networking can significantly improve the accuracy of knowledge, and that context-aware knowledge caching reduces the overhead and delay of knowledge access. This opens perspectives on future context-aware vehicular knowledge networking.

The rest of the article is organized as follows: Section II introduces the considered roundabout exit probability use case. Then, Section III describes the implementation of knowledge description, storage, and dissemination through VKN for this use case. Section IV describes the packet-level simulation setup to evaluate the VKN context-based knowledge distribution. Lastly, Section V discusses the obtained results, while Section VI summarizes the article.

II. Risk-based Roundabout Entry

The assessment of risk by CAVs is a key enabler of safe highly automated driving. As considered in [7], several factors may jeopardize self-driving abilities and cause slow downs or a human *take-over*. The unexpected behavior of human road users is listed as a key risk factor, especially when negotiation is required, as in unsignalized intersections. For example, entering a roundabout may require estimating the intentions of vehicles which are already in the roundabout, to avoid a collision between circulating and entering vehicles.

A report by the Transportation Research Board indicated that roundabout entry conflicts involve, respectively, 36.6%, 50.8%, and 71.1% of roundabouts crashes in France, Queensland (Australia), and the United Kingdom [8]. In turn, to evaluate the accuracy of context-based knowledge networking in vehicular networks, we consider the networking of roundabout risk knowledge for safe CAV entry.

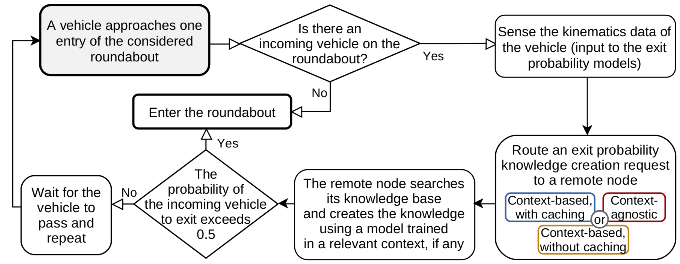

Fig. 2: Flow Chart of the Roundabout Entry Procedure

A. Scenario Definition

Figure 1 illustrates the considered scenario. The red-colored CAV v_a approaches an entry of a roundabout R, but senses a blue-colored incoming vehicle v_b, which is a traditional human-driven vehicle and, as such, cannot share information about its future trajectory. To enter the roundabout safely while avoiding the formation of queues at the entry, the entering CAV v_a aims to obtain the knowledge of the probability of the incoming vehicle v_b to exit the roundabout.

Models to estimate exit probability values are stored in remote nodes, i.e., a central Mobile Edge Computing (MEC) unit, or infrastructure nodes accessible through multihop wireless communication. Yet, no exit probability estimation model was trained specifically for the roundabout R. In turn, v_a wishes to express a request for the creation of exit probability knowledge using a model which, albeit not trained directly on tracks extracted from R, was trained in a similar context.

The safe roundabout entry use case, as described in Figure 2, is leveraged to implement and evaluate a packet-level simulation of the dissemination of context-relevant knowledge among vehicular nodes. Three scenarios are compared to evaluate the performance of context-based knowledge networking:

- In *context-based knowledge networking with knowledge caching*, roundabout exit probability models which have been trained in a relevant context are cached in the MEC unit in the center of the roundabout.
- In *context-based knowledge networking without knowledge caching*, models with relevant contexts are not cached in the central MEC unit. As such, context-based knowledge creation requests must be forwarded to other infrastructure nodes which possess the right knowledge through multihop communications, as shown in Figure 1.
- In *context-agnostic knowledge networking*, i.e., the baseline approach, models which were not trained in a relevant context are cached in the central MEC unit. This is because, in this case, the context of usage of roundabout exit probability models is not taken into account, as it has not been studied or defined. As such, there is no clear better option considering which model to cache.

B. Exit Probability Models

The considered knowledge networking scenarios require the definition of semantics to describe the interface and context of usage of the considered roundabout exit probability models

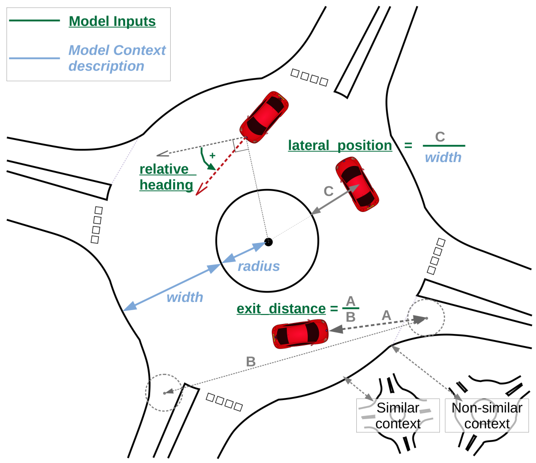

Fig. 3: Input and Context Description of the Considered Exit Probability Models

in an interoperable language shared by nodes. In this section, we describe a semantic description of the inputs, outputs, and context of usage of such models, based on existing works. In [9], we originally defined the interface of a model to assess the probability of a vehicle to exit a roundabout. ML models were trained to associate the kinematics of a vehicle with its probability of exiting at the next available exit. As illustrated by Figure 3 in dark green underlined text, the inputs to predict the probability of a vehicle to exit at the next exit are:

- The heading of the vehicle, relatively to the curvature of the roundabout, `relative_heading` $\in [-180, 180]°$.
- The straight-line distance to the next exit, normalized by the distance between the next and the previous exit, `exit_distance` $\in [0, 1]$.
- The lateral position of the vehicle in the roundabout, normalized by the width of the driveable area, `lateral_position` $\in [0, 1]$.

In [9], an exit probability model with 91% vehicle exit prediction accuracy was trained from vehicle tracks in a single roundabout, extracted from the RounD dataset [10]. In turn, to evaluate the accuracy of exit probability models in other roundabouts, i.e., other driving contexts, a more complex analysis was performed in [11].

On the one hand, a roundabout exit probability model was trained for multiple distinct roundabouts: The three roundabouts of the RounD dataset [10] and the five roundabouts of the INTERACTION dataset [12]. On the other hand, through an information theoretic similarity-based analysis as detailed in [11], we determined the contextual features which influence the similarity of exit probability models: (i) The number of entry legs, (ii) radius, and (iii) width of their roundabouts of training, as illustrated by the light blue italic text in Figure 3. For example, the bottom-right roundabout features a non-similar context to the main roundabout, due to a differing number of entries. Table I summarizes the roundabouts for which an exit probability model was trained and their associated context.

TABLE I: Considered Roundabouts and Associated Contexts

Dataset / Roundabout	**Entry Legs**	**Radius** (m)	**Width** (m)
Interaction / CHN_LN	4	23	9
Interaction / DEU_OF	3	8.75	4.5
Interaction / USA_EP	4	6.75	6.75
Interaction / USA_FT	7	9	9
Interaction / USA_SR	4	13.5	4.5
RounD / 0	4	15	9
RounD / 1	4	8	4.5
RounD / 2	3 (see [11])	6.75	4.5

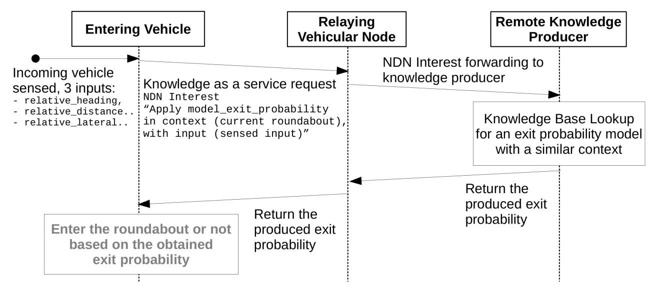

Fig. 4: Sequence of the Knowledge Dissemination Procedure

III. Vehicular Knowledge Networking Integration

In this work, we implement the roundabout entry procedure as shown in Figure 2 through VKN. VKN is a framework which allows the description of AI-based knowledge models to, in turn, support the definition of interoperable knowledge creation, storage, and dissemination mechanisms. In this section, we define VKN-supported (i) knowledge description, (ii) storage, and (iii) dissemination mechanisms to support the distribution of exit probability knowledge in an unknown roundabout, using existing exit probability models trained in similar contexts. In turn, we describe the implemented (iv) knowledge creation and (v) utilization approaches.

Figure 4 shows the implemented knowledge distribution aspects. It illustrates the overall flow of the exit probability knowledge networking through VKN. Namely, entering vehicles formulate requests to compute the exit probability of any incoming vehicle. The request is forwarded to a knowledge producer which takes the driving context of the crossed roundabout into account to produce the knowledge.

A. Knowledge Description

To allow the storage and dissemination of exit probability knowledge between vehicles in an interoperable manner, well-defined semantics must be defined such that the nodes which consume the knowledge share a common understanding of its structure and context of use with the nodes which produce it. In turn, nodes can discover and use new knowledge without requiring hard-coded updates for their on-board computing units to apprehend it. As part of VKN, we divide the semantic description of knowledge in four complementary sections to efficiently describe the exit probability knowledge models:

1) Ontology Description: To begin with, we provide a description of the variables which are used to describe the input, output, and context description elements of a knowledge model. Table II defines the list of named objects which are used as part of the exit probability model descriptions, as introduced in Section II.

2) Meta Model Description: The named objects defined in Table II provide a basis for the description of the generic class of exit probability models. We refer to this aspect as the exit probability *meta model* description. The meta model description defines the input and output interface of a class of exit probability models, as listed in the 'Role' column of Table II. It provides a list of named objects which can be used to describe the context of usage of models which are part of this class of models, here, (i) the number of entries, (ii) radius, and (iii) width of the roundabout of training. Moreover, the meta model description defines a *condition of context similarity* which outputs whether two contexts are similar. For example, Equation 1 is a condition of similarity which was considered in our preliminary work [11], and illustrated in Figure 3. Following Equation 1, `RounD/2` and `DEU_OF` were trained in contexts which are similar. On the contrary, due to a differing number of entries, the contexts associated with `USA_FT` and `CHN_LN` are not similar.

$$(\Delta Entries = 0) \land (\Delta Radius \leq 6.0m) \tag{1}$$

3) Model Description: Several models may belong to the class of exit probability models as defined by the exit probability *meta model description*. For example, an exit probability model trained in `DEU_OF` and another trained in `CHN_LN` share the same input/output interface, and variables to describe their context of use. As such, they implement the exit probability model meta-description. Yet, they each feature a different context of usage, as shown in Table I.

As such, exit probability model descriptions implement the exit probability meta-model in a specific context. Namely, the exit probability meta-model states that the context of usage of exit probability models can be described using the entry number, radius, and width of a roundabout. In turn, the description of the model associated with DEU_OF states that it has been trained in a 3-entry roundabout of radius 8.75m and width 4.5m. Figure 5 summarizes the semantic description of exit probability models, exposing the relationship between ontology, meta-model, and model descriptions.

4) Model Bytecode: Finally, the bytecode associated with a model description is the machine code which can be executed to perform output creation from well-formed input. In this study, the exit probability models are executed in a Python environment and stored as Python *pickle* files. They contain the exit probability logistic regression models trained using the *scikit-learn* library [13].

B. Knowledge Storage

1) Generic Architecture: To store knowledge in vehicular networks, we define a VKN knowledge base module, which matches the architecture of the knowledge description defined in Section III-A. Namely, four distinct KBs are defined and interconnected:

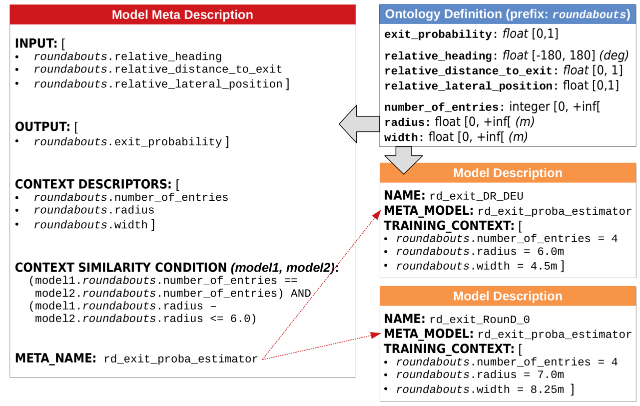

Fig. 5: Exit Probability Knowledge Semantic Description

1. The definition of ontologies and named objects is contained in an *ontology knowledge base*.
2. The description of meta-models, e.g., the exit probability meta-model as defined in Figure 5, are contained in a *meta knowledge base*. Meta models refer to the *ontology knowledge base* to describe their interface and context.
3. The description of models is stored in a *model description base*. Each model description implements a specific meta-model described in the *meta knowledge base*.
4. Model bytecodes are stored in specific database. Each model is connected with its semantic description in the *model description base*.

2) Application to Roundabout Exit Knowledge: In this paper, which implements context-based exit probability knowledge distribution as described in Section II, both the vehicles and infrastructure units are provided with a KB module, containing the aforementioned databases. In the KB module of the simulated vehicles, the ontology KB contains the ontology description as defined in Table II and the top-right corner of Figure 5. What is more, the exit probability meta-model, i.e., `rd_exit_proba_estimator` as defined in the left side of Figure 5 is contained in the meta KB of vehicles. Yet, the vehicles are not aware of the description nor bytecode of any model implementing the `rd_exit_proba_estimator` meta-description.

The KB modules of the infrastructure units contain the same ontology and meta KB as vehicles. Additionally, their model description KB and model bytecode KB contain descriptions and bytecodes of models implementing the `rd_exit_proba_estimator` meta-model:

- In *context-based knowledge networking with knowledge caching*, models with relevant contexts are cached in the KB of the MEC unit in the center of the roundabout. For example, if the considered roundabout is `DEU_OF`, the `rd_exit_RounD_2` model is integrated, as it has been trained in a similar context.
- In *context-based knowledge networking without knowledge caching*, models with relevant contexts are not stored in the central MEC unit but in several remote infrastructure nodes. In turn, knowledge creation requests

TABLE II: Semantic Description of the Exit Probability Model Variables

Named object	Type	Role	Description
`relative_heading`	$float \in [-180, 180]\ (deg)$	Input	The heading of a vehicle relatively to the curvature of a roundabout.
`exit_distance`	$float \in [0, 1]$	Input	The relative distance to the next exit.
`lateral_position`	$float \in [0, 1]$	Input	The relative lateral position in the roundabout.
`exit_probability`	$float \in [0, 1]$	Output	A value of exit probability.
`entry_number`	$int > 0$	Context	The number of entry legs of a roundabout.
`radius`	$float > 0\ (m)$	Context	The radius of a roundabout.
`width`	$float > 0\ (m)$	Context	The total width of the driveable circular lanes of a roundabout.

from vehicles need to be routed to knowledge producers in the right context through multi-hop communications.

- In the baseline *context-agnostic knowledge networking*, models trained in a non-relevant context are added to the KB of the central MEC unit. They are used to produce knowledge, as context is not considered in this approach.

Vehicles are provided with a meta-model description of the exit probability class of models. In practice, it can be obtained through a VKN knowledge discovery request, e.g., to fetch the description of available meta models which produce a roundabout exit probability as an output. Additionally, mechanisms are required to let vehicles express and route requests for the creation of exit probability knowledge to remote infrastructure nodes, which own relevant models in a context which is similar to that of the crossed roundabout.

C. Knowledge Dissemination

As illustrated by Figure 4, each vehicle is provided with the knowledge of the `rd_exit_proba_estimator` meta-model. In turn, entering CAVs sensing the presence of an incoming vehicle can formulate a request for the creation of exit probability knowledge (i) using the input sensed from the incoming vehicle, (ii) in the context of the crossed roundabout. The request is wirelessly forwarded to a remote knowledge producer, which owns a model implementing the `rd_exit_proba_estimator` interface. After it was produced, the knowledge is returned to the entering vehicle.

In this case study, entering CAVs are not aware of the exact location and host address in which relevant knowledge models are stored and available. In turn, we make the choice to implement networking operations using Information-Centric Networking (ICN). ICN is a paradigm in which content is uncoupled from its host. As such, rather than addressing a specific host which is known beforehand to host relevant knowledge, entering vehicles directly disseminate a knowledge creation request to neighboring nodes. Named Data Networking (NDN) is an implementation of ICN, which uses hierarchical names to refer to content, and routes 'interests' for named content from consumers to producers.

To formulate knowledge creation requests to be disseminated over NDN, we encapsulate VKN knowledge creation requests in a NDN interest name. As illustrated by Figure 6, we set the `/vkn/model_apply` prefix to indicate that the interest is a knowledge creation request. Then, two keywords are integrated to the interest name, i.e., `__input__` and `__context__` to indicate the upcoming definition of slash-separated $(key, value)$ elements describing, respectively, (i)

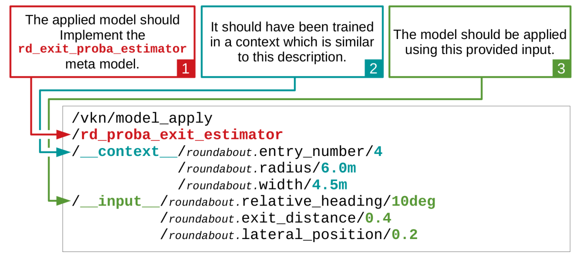

Fig. 6: Knowledge Creation Requests over NDN

the inputs to use, and (ii) the driving context which should be matched when selecting the models to use.

D. Knowledge Creation

As a knowledge producer receives the request, it creates the exit probability knowledge as illustrated in Figure 4, and following the procedure described in Algorithm 1. From line 7 to 13, the model KB is searched for exit probability models which have been trained in a similar context than the requested context of application. In turn, in line 11, matching models are used to predict values of exit probability based on the provided input. Lastly, in line 14, the obtained probabilities are averaged. This technique is an instance of ensemble voting, as surveyed in [14]. It alleviates the impact of potential outliers in the obtained probability values, as discussed in the preliminary study in [11]. If no model with the right context is found, the algorithm fails, or falls back to using a model with a non-similar context in the baseline *context-agnostic* approach.

Algorithm 1 Knowledge Creation Request Processing

1: $KB\_meta \leftarrow MetaKB()$ ▷ The Meta KB.
2: $KB\_model \leftarrow ModelKB()$ ▷ The Model KB.
3: ▷ Treat an exit probability knowledge creation request encoded as a NDN interest.
4: **procedure** $treat\_request(interest\_name)$
5: $matching\_models\_predictions \leftarrow list()$
6: $(meta\_model, inputs, context) \leftarrow parse(interest\_name)$
7: **for each** $model$ **in** KB_model **do**
8: **if** $model.meta\_model = meta\_model$ **and**
9: $meta\_model.is\_similar(model.context, context)$ **then**
10: $matching\_models\_predictions.add(model.apply\_to(inputs))$
11: **end if**
12: **end for**
13: **if not** $matching\_models\_predictions.empty()$ **then**
14: **return** $matching\_models\_predictions.average()$
15: **else**
16: **return** $no\ matching\ model$
17: ▷ In the *context-agnostic knowledge networking* case, the knowledge creation falls back to selecting a non context relevant model
18: **end if**
19: **end procedure**

TABLE III: Simulation Parameters

Parameter	Value
Considered Roundabouts	Table I, except USA_FT and CHN_LN
Infrastructure Nodes	1 (Local MEC) + 50 (Remote Static Nodes)
Node Placement Area	$200 \times 200m^2$
Protocol stack	IEEE 802.11p & IEEE 1609.4 & NDN
Three Log Distance Model	Distance=(1, 200, 500)m, Exponents=(1.9, 3.8, 3.8), Reference Loss=46.67dB
Nakagami Model	Distance=(80, 200)m, Exponents=(1.5, 0.75, 0.75)
NDN Hop Limit	10

E. Knowledge Utilization

As illustrated by Figure 4, CAVs receiving the exit probability knowledge could use it in real applications to take routing or entering decisions. Yet, as this study aims at demonstrating the impact of context-based knowledge networking, the mobility of vehicles is not modified as a result of the received exit probability, which is left as future work. Rather, at the end of the simulation, the exit probability values received by vehicles are scored.

Namely, accuracy scores are computed for the exit probability values obtained by CAVs. Probabilities exceeding 0.5 are associated with a prediction of exit. In turn, the exit predictions are compared with the actual observed behavior of incoming vehicles. We consider (i) *accuracy*, i.e., $\frac{number\ of\ correct\ predictions}{number\ of\ predictions}$, and (ii) *precision*, i.e., $\frac{TP}{TP+FP}$, with TP and FP the number of true and false positives.

IV. Simulation Setup

We run several ns-3 simulations of vehicles crossing a roundabout R which request the creation of exit probability knowledge to remote knowledge producers, based on the driving context in that roundabout. Simulations are run for each roundabouts listed in Table I which feature at least one other roundabout with a similar context, according to the similarity condition of Equation 1, i.e., excluding `USA_FT` and `CHN_LN`. Namely, in each simulation, we consider that no exit probability model has been trained for the considered roundabout R. In turn, existing models which have been trained in other roundabouts listed in Table I must be used.

A. Topology

A MEC unit is placed in the center of the roundabout. Moreover, a set of 50 additional static nodes are generated in a square area of $200m$ side centered on the roundabout. They represent infrastructure units or static connected objects. Their position are uniformly sampled, following the condition that each added infrastructure node must be located within $30m$ of at least one other infrastructure unit. Then, the mobility of vehicles is replicated from real vehicle tracks extracted from the RounD and INTERACTION dataset recordings.

B. Protocol Stack

Communications between the vehicles and infrastructure units are wireless, implemented in ns-3 using existing protocols adapted to the vehicular environment. The physical layer implements the IEEE 802.11p standard [15]. Specifically, it uses a 10MHz frequency band of the licensed 5.9 GHz band of Intelligent Transportation Systems (ITS). In turn, the Medium Access Control (MAC) layer uses IEEE 802.11p, with the WAVE IEEE 1609.4 extension [16]. Moreover, a *Three Log Distance* propagation loss and *Nakagami* fading model are added to the physical IEEE 802.11p channel, with the default ns-3 parameters as listed in Table III.

The networking layer of vehicles and infrastructure units implements the NDN protocol, which we simulate in ns-3 through the ndnSIM 2.8 library [17]. On the one hand, entering vehicles are *consumers* for exit probability knowledge content, and express interest messages for its creation. On the other hand, depending on the scenario, a specific set of simulated infrastructure nodes are defined as *producers* of exit probability knowledge. Interests are routed from entering vehicles to producers through multicast and potentially multihop wireless communications, with a limit of 10 hops.

In this work, no changes are applied to the networking and lower layer protocols. Instead, context-aware knowledge networking is implemented as an overlay application. Knowledge producers leverage their KBs to create exit probability knowledge as described in Algorithm 1.

C. Evaluation

Finally, we evaluate the performance of context-based knowledge networking considering the (i) delay, (ii) average hop count, and (iii) overhead associated with exit probability knowledge dissemination, as well as (iv) the accuracy of the obtained knowledge. These metrics are compared for the three knowledge networking scenarios introduced in Section II-A:

- In *context-based knowledge networking with knowledge caching*, exit probability models with a relevant training context are cached in the central MEC unit, close to the vehicles, and defined as the only knowledge producer.
- In *context-based knowledge networking without knowledge caching*, a set of 5 infrastructure units, distinct from the central MEC unit, are randomly selected as knowledge producers and provided with relevant context knowledge. In turn, multiple hops may be required to route knowledge interests from vehicles to producers.
- In *context-agnostic knowledge networking*, only the central MEC unit is defined as a knowledge producer. Yet, its KB is populated with models which were not trained in a relevant context for the considered roundabout R. As such, while the exit probability can be computed close to the vehicles, the accuracy of the obtained knowledge may be reduced compared to the proposed context-aware approaches.

V. Results & Discussion

In this section, we present and discuss the obtained results through two main aspects, i.e., the accuracy of context-based knowledge creation and the networking performance of knowledge dissemination.

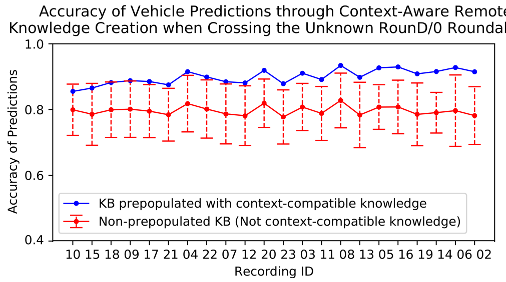

Fig. 7: Accuracy Score on RounD/0 Exit Predictions using Context-Based Knowledge Networking

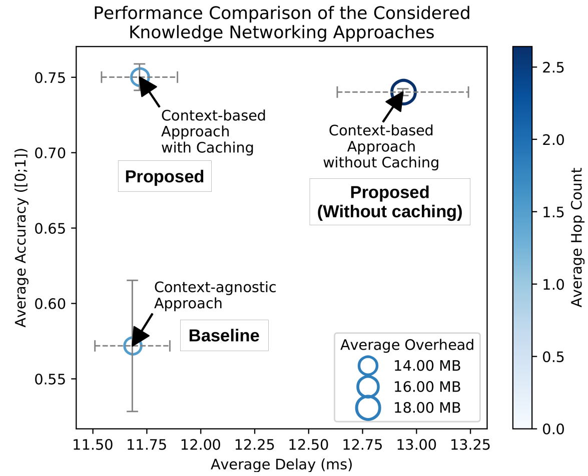

Fig. 8: Networking Performance Evaluation

A. Knowledge Accuracy

To begin with, we evaluate the impact of context-based knowledge networking on the accuracy of the knowledge which is disseminated in vehicular networks. For each vehicle track recording of each considered roundabout, the accuracy of knowledge produced through the two *context-based* approaches, i.e., the *proposed* approach, is compared with the *context-agnostic* alternative, i.e., the *baseline* approach.

Figure 7 illustrates, for each vehicle track recording of the `RounD/0` roundabout, the accuracy of predictions obtained through the *proposed* context-based knowledge networking in blue, i.e., when remote infrastructure units have produced knowledge using models which have been trained in a relevant context, similar to that of `RounD/0`. It is compared with the accuracy of predictions obtained through the *baseline* context-agnostic knowledge networking in red, which are bounded by 95% confidence intervals, obtained by considering accuracy scores related to the various models trained in a non-similar context to that of `RounD/0`. The recordings are ordered by average accuracy improvement of the context-based approach.

In `RounD/0,1,2` and `DEU_OF`, significant accuracy improvements are obtained for the proposed context-based knowledge networking. Even in a context-agnostic approach where knowledge is created from a random model implementing the right interface, the spread of the confidence intervals would force vehicles to take conservative entering decisions, based on the lower bounds of the prediction accuracy.

On the other hand, the accuracy of context-based and context-agnostic approaches remained stable for the `USA_SR` and `USA_EP` roundabouts, potentially because of an overly permissive similarity condition in Equation 1. Nonetheless, for these roundabouts, the precision score associated with the proposed context-based knowledge networking was improved significantly compared to the baseline context-agnostic approach. Precision is relevant in this use case as it penalizes false positives, i.e., when a vehicle was predicted to but did not exit the roundabout, which may induce collisions.

B. Networking Performance

In parallel, we consider the impact of the proposed context-based knowledge networking on networking performance metrics, i.e., the delay, number of hops, and overhead required to distribute knowledge in the considered wireless topology. As these network metrics are independent from the specific exit probability model which is used to produce the exchanged knowledge, we focus on a recording extracted from the `DEU_OF` roundabout, as a case study. Figure 8 compares network performance indicators for the three considered scenarios, i.e, the proposed *context-based* knowledge networking, with and without caching, and the baseline *context-agnostic* knowledge networking. For each scenario, the considered `DEU_OF` recording is simulated 20 times with different random infrastructure unit locations. Four metrics are compared:

- The average delay between the sending of an interest and the reception of the knowledge with 95% confidence intervals, as well as the average associated hop count.
- The average accuracy of the exit probability knowledge over a simulation with 95% confidence intervals, as well as the average overhead associated with a simulation.

While the baseline *context-agnostic* approach allows knowledge delivery with a lower delay and overhead than the *context-based* approach without caching, it significantly decreases the accuracy of the produced knowledge, as discussed in Section V-A. Namely, in the baseline context-agnostic approach, models have been cached in the central MEC unit, yet without considering context-relevant knowledge. In turn, due to the proximity of entering vehicles, the knowledge can be disseminated with a relatively low hop count, delay, and overhead. On the other hand, it is significantly less accurate than approaches which route knowledge requests to producers possessing context-relevant models.

The simulated topology ensures the presence of a knowledge producer in the vicinity of the entering vehicles, i.e., within a few hops at most. In a setup featuring a more scarce distribution of knowledge producers, the deterioration of network performance could increase due to the lack of caching. To conciliate both high networking performance and knowledge accuracy, the proposed *context-based knowledge networking with caching* stores knowledge where its context is relevant. Then, accurate knowledge can be accessed efficiently.

The obtained results illustrate the potential and impact of context-based knowledge networking, and open perspectives on the need to take context into account for every aspect of knowledge networking in vehicular networks. Namely, knowledge should be cached in locations which feature a context in which it can be applied, such that it can be accessed by vehicles in a relevant context. Similarly, knowledge is typically built by an organization for the exclusive use of its fleet of vehicles. Through semantic-supported dissemination mechanisms which allow the transmission of requests for the creation of knowledge in a specific context, knowledge networking could be opened to all nodes of vehicular networks, while maintaining the accuracy of models.

VI. Conclusion

Existing content caching and dissemination approaches in vehicular networks take various parameters such as the popularity or age of content into account. While this is adapted for safety information delivery, which has strict delay constraints and local relevance, knowledge is relevant indefinitely as long as it is applied in the right context. As such, mechanisms are required which take the context of usage of knowledge into account for knowledge networking operations. Through rich knowledge semantic description, vehicles can describe their driving context, as well as the relevant context of usage of knowledge models. In this paper, we showed the potential and impact of context-based knowledge networking in a packet-level simulation, where vehicles request the creation of roundabout exit probability knowledge in various roundabouts, i.e., driving contexts. This opens perspectives for context-based knowledge networking applied to other types of vehicular knowledge, which would make the knowledge accessible to a greater number of vehicles, while maintaining its accuracy by ensuring it is cached and used in the right context.

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