

# Vehicle Lane Change Prediction based on Knowledge Graph Embeddings and Bayesian Inference

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**Abstract**—Prediction of vehicle lane change maneuvers has gained a lot of momentum in the last few years. Some recent works focus on predicting a vehicle's intention by predicting its trajectory first. This is not enough, as it ignores the context of the scene and the state of the surrounding vehicles (as they might be risky to the target vehicle). Other works assessed the risk made by the surrounding vehicles only by considering their existence around the target vehicle, or by considering the distance and relative velocities between them and the target vehicle as two separate numerical features. In this work, we propose a solution that leverages Knowledge Graphs (KGs) to anticipate lane changes based on linguistic contextual information in a way that goes well beyond the capabilities of current perception systems. Our solution takes the Time To Collision (TTC) with surrounding vehicles as input to assess the risk on the target vehicle. Moreover, our KG is trained on the HighD dataset using the *TransE* model to obtain the Knowledge Graph Embeddings (KGE). Then, we apply Bayesian inference on top of the KG using the embeddings learned during training. Finally, the model can predict lane changes two seconds ahead with 97.95% f1-score, which surpassed the state of the art, and three seconds before changing lanes with 93.60% f1-score.

**Index Terms**—Lane Change Prediction, Knowledge Graph Embeddings, Bayesian Inference, Bayesian Reasoning

## I. INTRODUCTION

Accidents occur every day in our daily lives, and the number of deaths due to vehicle crashes is increasing every year. Based on statistics published in 2023 by the National Highway Traffic Safety Administration (NHTSA), the number of deaths in motor vehicle traffic crashes in the United States of America (USA) in 2021 is 42000. Which is a 10% increase in the number of deaths compared to 2020, and a 17.3% increase compared to 2019 [1]. Lane-changing maneuvers are one of the causes of vehicle crashes, as a report indicated that 33% of all road crashes happen due to the existence of a vehicle that changes its lane. Also, the NHTSA indicated the fact that 94% of vehicle crashes are the driver's fault [2]. That's why the government put some constraints on the road and the driver, like wearing seat belts and being committed to the road speed limit. Also, researchers started to focus on implementing different models to predict the vehicle lane-changing intention to reduce the number of accidents/crashes on the road. Most of the recently proposed models are based on target vehicle trajectory data and certain relative measurements with the surrounding vehicles (e.g. relative distances and velocities).

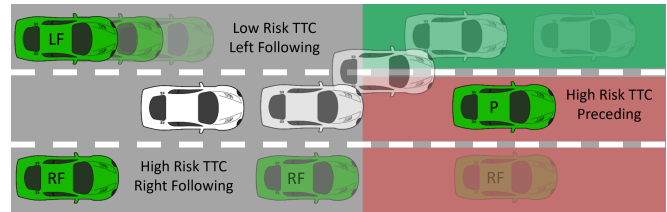


Figure 1. Target (white) vehicle will make left lane-changing maneuver based on the risk assessment of the surrounding (green) vehicles.

Furthermore, these models are based on numerical input values, which makes them act like a black box. This makes reasoning and interpreting the model outputs difficult. Also, it is challenging to explain the model and its outputs to others who may not be familiar with the underlying algorithms. So, this work focuses on addressing the following points:

- 1) Lane change prediction is carried out based on contextual information, not merely using kinematic information learned from previous experiences. This goes beyond the capabilities of current perception systems and allows to generalize and make predictions agnostic to the physical aspect of the road environment.
- 2) Predictions are based on knowledge graphs and, consequently, they are interpretable and explainable, contributing to developing trustworthy systems.
- 3) Bayesian inference is carried out as a downstream task on the grounds of the learned embeddings, allowing the implementation of a fully inductive reasoning system based on KGEs.

The inputs that are fed to the model can describe the risk situation around the target vehicle in a linguistic manner so everyone can understand and reason why the target vehicle took a certain maneuver. For example, Figure 1 shows a scenario of a white target vehicle that will make a left lane change because there is high-risk TTC with the preceding vehicle (P) and high-risk TTC with the right following vehicle (RF) as well. Still, there is low-risk TTC with the left following vehicle (LF). So, the target vehicle will avoid lane keeping or right lane changing in order to avoid collisions/risks with the preceding vehicle and the right following vehicle, respectively. Instead, the target vehicle will execute the left lane changing maneuver. The rest of this article is organized as follows. Section II presents the state of the

art. Section III contains a brief introduction to the Highway Drone (HighD) dataset and Knowledge Graphs (KGs). Then, our proposed methodology will be discussed in detail in Section IV. In Section V, results will be presented. Finally, Section VI concludes the work.

## II. STATE OF THE ART

Recently, different works have focused on predicting vehicle lane changes using different inputs (including target vehicle position, speed, acceleration, and surrounding vehicles' states) and methods (like rule-based algorithms and data-driven models). Rule-based algorithms define certain rules at which the vehicle makes a lane change, such as the gap acceptance model, which assumes that the vehicle will make a lane change when it achieves the least possible distance between it and the front/rear vehicles in the same lane as in [3]. Data-driven models are based on training a model on certain inputs to obtain a certain complex equation that maps these inputs to a certain output. The models can be some traditional machine learning models like Support Vector Machine (SVM) and logistic regression, or deep learning models like Artificial Neural Networks (ANN) and Recurrent Neural Networks (RNN) with all its variations. In 2018, [4] utilized a Long Short-Term Memory (LSTM) model to predict vehicle lane changes by considering the vehicle's past trajectory and neighbors' states. The models take different inputs extracted from the NGSIM dataset. The inputs were the vehicle's lateral and longitudinal global positions with respect to the lane, the vehicle's acceleration, the existence of right/left lane vehicles, and the longitudinal distance between the target vehicle and (front/rear)(left, center, right) surrounding vehicles. Work [5] in 2019 utilized two machine learning models to predict lane changes of surrounding vehicles on highways. The inputs were extracted from the NGSIM dataset. The inputs were longitudinal/lateral velocities, longitudinal/lateral accelerations, distance to left/right lane markings, yaw angle, and yaw rate related to the road. These inputs were trained and tested on SVM and ANN models. In 2019, authors in [6] predicted lane-changing intentions of surrounding vehicles using two different methodologies and by only using visual information provided by the PREVENTION dataset. The first method was Motion History Image - Convolutional Neural Network (MHI-CNN), where temporal and visual information was obtained from the MHI, and then fed to the CNN model. The second model was the GoogleNet-LSTM model, in which a feature vector was obtained from a GoogleNet CNN model and then fed to the LSTM model to learn temporal patterns. The used inputs were the RGB image, center (X, Y), and the bounding box's dimensions (W, H). The results showed that the GoogleNet-LSTM model outperformed the MHI-CNN model. In 2020, [7] trained LSTM and RNN models on the PREVENTION dataset to predict surrounding vehicles' lane-changing intentions by tracking the vehicles' positions (centroid of the bounding box). Sequences of 10, 20, 30, 40, and 50 frames of (X, Y) coordinates of the target vehicle were considered for comparison. It was concluded that RNN models performed better on short sequence lengths and the

LSTM model outperformed RNN at long sequences. The work implemented in [8] in 2022 utilized eXtreme Gradient Boosting (XGBoost) and LSTM to predict the vehicle lane change decision and trajectory prediction, respectively in scenarios in the HighD dataset. The models were based on the traffic flow (traffic density) level, the type of vehicle, and the relative trajectory between the target vehicle and surrounding vehicles. At first, the traffic flow and vehicle type models were separately implemented. The traffic flow  $y_t$  model took the longitudinal velocity  $v_{lon}$  and acceleration  $a_{lon}$  of the target vehicle, Headway, and the relative velocity between the target vehicle and the (left/front/right preceding, and left/right following vehicles). The vehicle type  $y_v$  model took all the inputs stated previously concatenated with the angle between the target vehicle trajectory and road vertical line  $\varphi$ . Then, the lane change decision prediction was achieved utilizing the XGBoost model. The model took the following inputs:  $v_{lon}$ ,  $a_{lon}$ ,  $\varphi$ , lateral velocity  $v_{lat}$  and acceleration  $a_{lat}$  of the target vehicle, Headway and the relative velocity between the target vehicle and the mentioned five surrounding vehicles,  $y_t$ , and  $y_v$ . Finally, vehicle trajectory prediction occurred based on historical trajectories and the predicted lane-changing decision. In 2023, [9] built a dual transformer which contained two transformer models. One was for lane change prediction, while the other was for trajectory prediction. The first model used the target vehicle's historical lateral trajectory information and the surrounding vehicles' states, including the longitudinal distance and velocity between the target vehicle and (the left/front/right preceding vehicle and the left/right following vehicles). The intention prediction output obtained from the first model was fused with the target vehicle's historical lateral trajectory information and fed to the second model to establish the connection between the intentions and the trajectories. The dual transformer was trained and validated on the HighD and NGSIM datasets. Finally, this research assumed that the ego vehicle sensors can obtain all the information regarding the position and speed of the target vehicle and all the surrounding vehicles. After closely examining the previous literature, the following research gaps can be identified, which are covered throughout this work.

- 1) Lane change prediction based on contextual linguistic information, not only using trajectory numerical information learned from previous experiences.
- 2) Predictions are interpretable and explainable as they are based on KGs.
- 3) Enabling a fully inductive reasoning system using Bayesian inference built on top of the KGEs.

## III. PRELIMINARY

This section briefly introduces the dataset used in this work (HighD), and the foundation model (KG and KGE) used to develop the lane change prediction system.

### A. HighD Dataset

The HighD dataset [10] is a German dataset that records naturalistic top-view scenes on German highway roads using

a camera integrated into a drone. The dataset is recorded in six locations and includes 60 tracks ( $\approx 15$  minutes each) containing more than 110,500 vehicles. For each vehicle in the dataset, much information is provided, including but not limited to vehicle position, speed, acceleration, TTC with the preceding (front) vehicle, whether a left/center/right preceding, left/right side, or left/center/right following (rear) vehicle exists, and the vehicle's current lane. The dataset can be reached through the following link: <https://levelxdata.com/highd-dataset/>.

### B. Knowledge Graph and Knowledge Graph Embedding

A graph is a type of database that represents complex data in a structured way, which is human-interpretable and can be easily observed and analyzed. It stores information in the form of entities (nodes) and their relationships (edges). Each relation connects two nodes and acts as the relationship between them. The relation can be directed ( $x$  isFatherOf  $y$ ) or undirected ( $x$  isFriendWith  $y$ ,  $y$  isFriendWith  $x$ ) [11]. A knowledge graph is a directed heterogeneous (nodes can have different types) multigraph (each pair of nodes can be connected with more than one relation). In the context of KGs, a triple  $\langle s, r, o \rangle$  consists of subject and object entities connected by a relation. For example,  $\langle \text{vehicle}, \text{INTENTION\_IS}, \text{leftLaneChanging} \rangle$ . The subject is *vehicle*, the relation is *INTENTION\_IS*, and the object is *leftLaneChanging* [11]. KGE is a supervised machine learning task that learns to represent (embed) the knowledge graph entities and relations into a low-dimensional vector space while preserving semantic meaning. There are several KGE models, such as DistMult, TransE, RotatE, ComplEx, and HolE. Each model's unique scoring function measures the distance between two entities using the relation between them. The purpose of the scoring function is to make entities connected by a relation close to each other in the vector space, while entities that do not belong to this relation should be far apart [11], [12].

## IV. METHODOLOGY

### A. Architecture Overview

Figure 2 shows the pipeline of our proposed methodology. The pipeline consists of three phases. Phase one is the linguistic input generation phase, in which the numerical input variables are converted to linguistic input categories using some threshold limits. Phase two is the KGE phase in which the KG will be generated as triples in a CSV file and embedded (trained) using the Ampligraph library [12]. The third phase is the Bayesian inference and prediction phase. This phase is responsible for calculating the probability that a vehicle will make a *LLC*, *LK*, and *RLC* given the linguistic inputs generated from phase one. And the highest probability is the model prediction. The calculation of these probabilities is based on the formation of triples and the evaluation of these triples using the embeddings obtained from phase two and the Bayesian reasoning in phase three. The KG ontology and input structure will be stated in the next section. Then, each of the three phases is discussed in detail.

### B. Knowledge Graph Ontology and Input Definition

The KG ontology is a formal (general) representation of the entities and their relationships in the KG. In KGs, ontologies are important because they act as a schema for constructing the KG so that they can ensure consistency and explainability of the KG. Also, It is worth mentioning that we apply a number of reifications on the given inputs to get reified triples. For example, if the target vehicle has a preceding vehicle, and the TTC with this preceding vehicle is at high risk, then, the reified triple is  $\langle \text{vehicle}, \text{PRECEDING\_TTC\_IS}, \text{highRiskPreceding} \rangle$  where *vehicle* in that triple points to the target vehicle. Table I shows the ontology for our lane change prediction KG model. The table shows all the input/output classes in the first column, a description in the second column, a set of possible reified linguistic instances (categories) for each class in the third column, a description of that instance (if needed) in the fourth column, and the name of the relation pointing to that class after reification in the fifth column. Figure 3 shows a KG instance based on the formed ontology. For example, it can be observed that the generic entity *vehicle* has a child with ID 638, and this child has *latVelocity* class assigned to *movingStraight* instance. Also, this child has *highRiskPreceding* TTC. *vehicle 638* intention is *LLC*. The same applies to all the entities in the graph for this child and any other child. Note that the entity *vehicle* is connected to all other children, which forms a large KG where numerous instances are interconnected via this general entity as shown in Figure 4 and Figure 5. Such that Figure 4 contains KG for only 10 vehicles (instances), and Figure 5 contains KG instances for 2000 vehicles. It is worth mentioning that the total number of instances used for training and validation is 39304, which is hard to fit into one figure.

### C. Linguistic Input Generation Phase

The used inputs to the model are vehicle lateral (velocity and acceleration), TTC to (preceding, left preceding, right preceding, left following, right following) vehicles. The dataset directly provides the first three inputs. The TTC inputs for the preceding/following left and right vehicles are extracted based on Equation 1. That  $d$  is the distance between the two vehicles, and  $v$  represents the velocity. The sub-letters  $p$  and  $f$  refer to preceding and following vehicles, respectively.

$$TTC_p = d_p / (v_{target} - v_p), \quad TTC_f = d_f / (v_f - v_{target}) \quad (1)$$

After extracting the needed features, all the numerical data is converted to linguistic 'string' categories. The conversion from numerical value to a linguistic category is done by converting each feature to a string based on some threshold limits obtained from statistics and literature. For example, the *latVelocity* feature numerical values (shown in Figure 6) can be separated into three linguistic categories  $\{\text{movingLeft}, \text{movingStraight}, \text{movingRight}\}$ . The challenge here is to choose the numerical threshold limit values that separate the three linguistic categories accurately. These values are

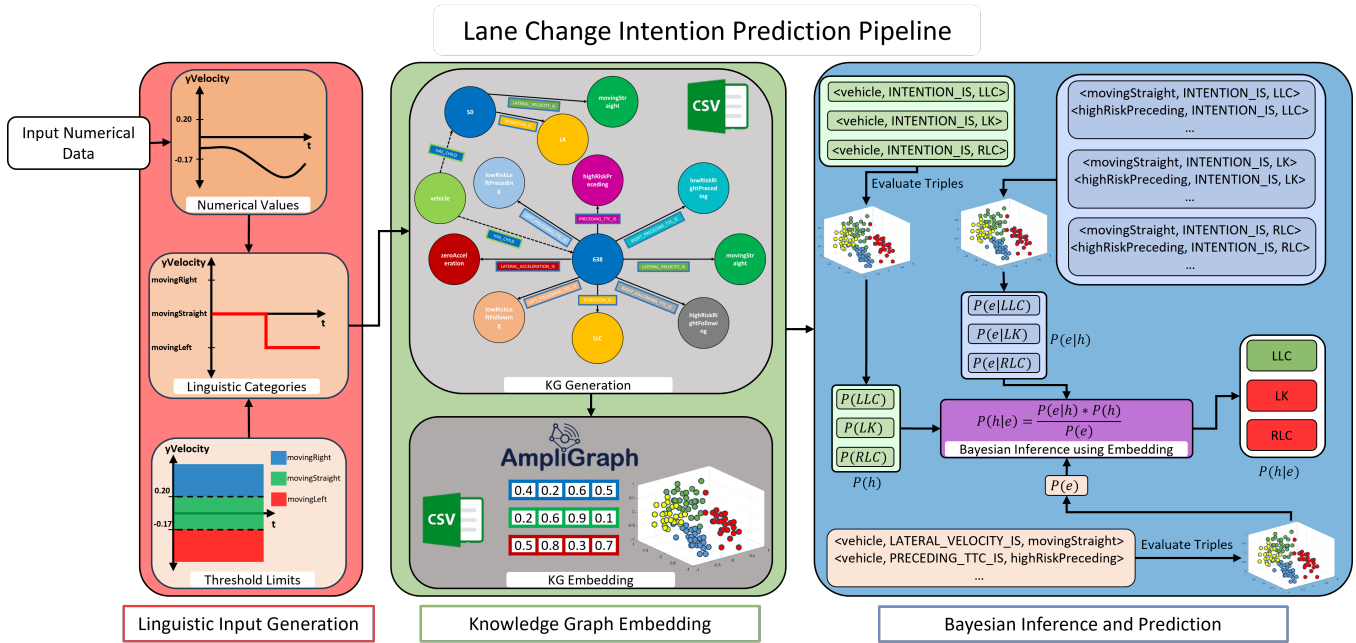


Figure 2. The pipeline for anticipating lane changes consists of three phases: Linguistic Input Generation, Knowledge Graph Embedding, and Bayesian Inference and Prediction.

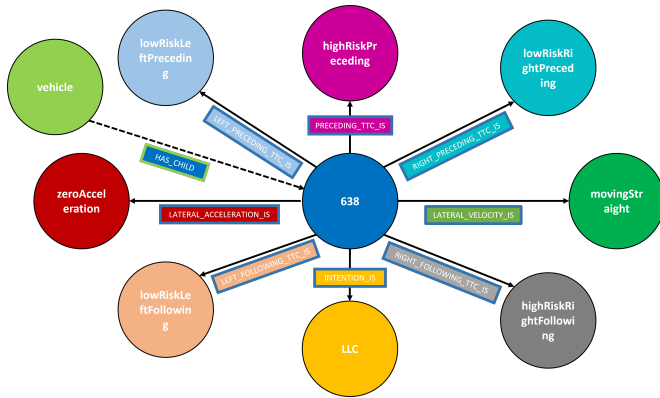


Figure 3. One KG instance where every entity (class) is assigned to its unique instance.

obtained for lateral velocity based on the normal distribution of the data shown in Figure 6. Based on the standard deviation  $\sigma$  and mean  $\mu$  for the data of each lane changing category, the  $\mu \pm 2\sigma$  values represent the threshold limit of each linguistic variable. So, in this case, the *movingStraight* linguistic variable has a threshold limit  $[\mu - 2\sigma, \mu + 2\sigma]$ , *movingLeft*  $(-\infty, \mu - 2\sigma)$ , and *movingRight*  $(\mu + 2\sigma, \infty)$ . The same category separation criterion is applied to obtain the lateral acceleration linguistic categories. Regarding the TTC variables, [13] indicated that there is no definitive value for TTC threshold limits to enable classification between safe and unsafe maneuvering situations. That is because of the fact that drivers' behavior is inconsistent in different situations. [14] stated that TTC values can be divided into three-time segments that show the correlation between the TTC values and the driver braking behavior which is used in risk assessment of the situation. TTC values between zero and

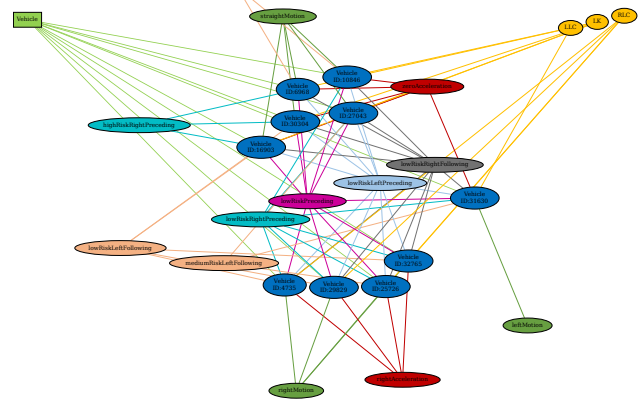


Figure 4. KG with 10 instances where the vehicle generic entity is connected to 10 child vehicles.

four seconds indicate high correlation, TTC values between four and 16 seconds indicate low correlation, and TTC values larger than 16 indicate negligible correlation. [13] used TTC values between 0.5 and 10 seconds to discriminate between safe and unsafe car-following situations during the study of improving the TTC formulation. So, in this work, the selected TTC thresholds for each surrounding vehicle location are based on the TTC with preceding vehicle values provided by the mentioned works. Therefore,  $TTC \in [0, 4]$  is *high-risk*,  $TTC \in (4, 10)$  is *medium-risk*, and any other positive or negative TTC value is *low-risk*.

#### D. Knowledge Graph Embedding Phase

After the linguistic input generation phase, the KG is formed in a CSV file in the form of triples. Then, trained

TABLE I  
Ontology table which includes the definition of all entities (classes), their instances, and possible relations that can be connected to them.

Class	Class Description	Instance	Instance Description	Possible Relation
intention	Lane changing intention of the vehicle	LLC LK RLC	Left Lane Changing Lane Keeping Right Lane Changing	INTENTION_IS
latVelocity	Vehicle lateral velocity	movingLeft movingStraight movingRight	- - -	LATERAL_VELOCITY_IS
latAcceleration	Vehicle lateral acceleration	leftAcceleration zeroAcceleration rightAcceleration	- No lateral acceleration -	LATERAL_ACCELERATION_IS
ttcPreceding	TTC with the preceding (front) vehicle	highRiskPreceding mediumRiskPreceding lowRiskPreceding	- - -	PRECEDING_TTC_IS
ttcLeftPreceding	TTC with the left preceding (front) vehicle	highRiskLeftPreceding mediumRiskLeftPreceding lowRiskLeftPreceding	- - -	LEFT_PRECEDING_TTC_IS
ttcRightPreceding	TTC with the right preceding (front) vehicle	highRiskRightPreceding mediumRiskRightPreceding lowRiskRightPreceding	- - -	RIGHT_PRECEDING_TTC_IS
ttcLeftFollowing	TTC with the left following (rear) vehicle	highRiskLeftFollowing mediumRiskLeftFollowing lowRiskLeftFollowing	- - -	LEFT_FOLLOWING_TTC_IS
ttcRightFollowing	TTC with the right following (rear) vehicle	highRiskRightFollowing mediumRiskRightFollowing lowRiskRightFollowing	- - -	RIGHT_FOLLOWING_TTC_IS
vehicleID	Child vehicle ID which changes every frame	vehicle ID number (e.g. '638')	-	HAS_CHILD
vehicle	Generic entity pointing to every child vehicle	-	-	Any

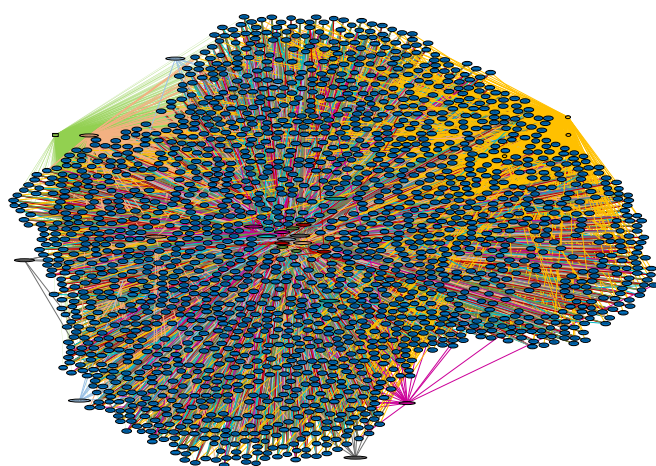


Figure 5. Large KG with 2000 instances from a total of 39304 instances.

using the Ampligraph library.

1) *Knowledge Graph Generation*: As mentioned, the KG is generated in the form of triples in a CSV file. The file contains three columns and many rows. Each row represents an entity and its relationship with another entity. The structure of each row consists of three parts: subject (first column), predicate (second column), and object (third column). Re-

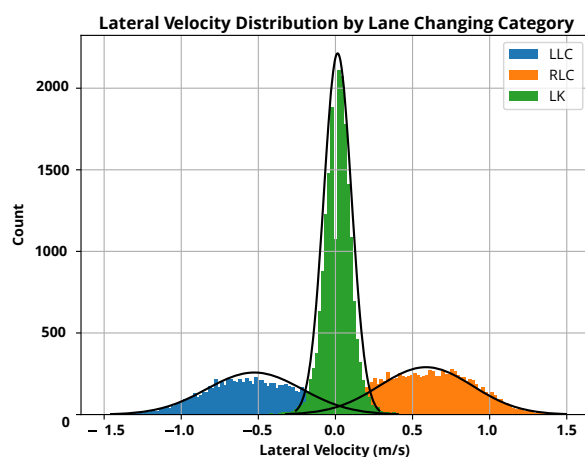


Figure 6. Histogram shows the relation between lateral velocity numerical values and the lane-changing labels.

turning to the example in Figure 3, the triples CSV file will have the following structure.  $\langle \text{vehicle}, \text{HAS\_CHILD}, 638 \rangle$ , this is the first row.  $\langle 638, \text{INTENTION\_IS}, \text{LLC} \rangle$ , this is the second row. Then, the formation of the triple will go by using the same procedure with the other nodes. Note that each vehicle will have a new ID in each frame even if it is the

same vehicle. So, in the next frame,  $\langle \text{vehicle}, \text{HAS\_CHILD } 639 \rangle$ . 638 and 639 are IDs for the same vehicle, but during triples and KG generation, they are considered as IDs of two different vehicles. This graph can be extended to all the indicated seven inputs and to any number of vehicles by following the same structure.

2) *Knowledge Graph Embedding*: After producing the triples CSV file, Ampligraph 2.0.1 library [12] is used for KGE. Training/validation and testing data are separated based on tracks to ensure that the vehicles' behavior is not overlapping, as vehicles from the same track can have similar behavior (e.g. track has a right exit at the end of the road). So, The first 48 (80%) tracks in the dataset are used for training and validation. The other 12 (20%) tracks are kept for testing. Different numbers of triples are used for validation (500, 1K, 2K, 4K, and 10K). However, they all had the same results during testing. So, only 2K triples are considered for validation. These triples are provided by using the *train\_test\_split\_no\_unseen* function provided by the Ampligraph library. The numbers of triples are 351736, 2000, and 12222 for training, validation, and testing, respectively. Two scoring models were tested: *TransE* and *ComplEx*. Training parameters are fixed for fair comparison: embedding size  $k=100$ , five negative triples are generated for each positive triple where both the subject and the object of triples are corrupted, Adam optimizer with learning rate = 0.0005, SelfAdversarialLoss, batch size of 10000, validation burn in = 5, validation freq. = 5, validation batch size = 100. Finally, the early stopping criterion is used to monitor the validation Mean Reciprocal Rank (MRR) metric with the patience of 5 validation epochs.

### E. Bayesian Inference and Prediction Phase

Our proposed solution is intended to allow for inductive reasoning. For that purpose, we implement some reifications in the graph (at the ontology level) and we carry out Bayesian inference on the learned embeddings. After obtaining the embeddings, we can compute the probabilities of the reified triples using the KGE evaluation method provided by the AmpliGraph library. These triples have the form  $P(h, r, t)$ , where  $h$  is the head (or subject entity),  $r$  is the relation, and  $t$  is the tail (or object entity). Based on that,  $P(h|e)$  ( $h$  stands for hypothesis and  $e$  stands for evidence) is computed using Bayes rule as follows Equation 2:

$$P(h|e) = \frac{P(h)P(e|h)}{P(e)} \quad (2)$$

where hypothesis  $h$  is the event or entity that we want to predict (lane change category), and evidence  $e$  is the information that we have measured with onboard sensors for the current frame, which are the inputs given by the HighD dataset in that case. For example, hypothesis: vehicle intention is left lane change, evidence: the vehicle TTC with the preceding vehicle is risky and the vehicle is accelerating laterally to the left. Computation of  $P(h)$  takes place by evaluating a single triple after reification as in this example: (vehicle intention is

left lane change) can be reified to  $\langle \text{vehicle}, \text{INTENTION\_IS}, \text{LLC} \rangle$ .  $P(e)$  is computed using the following equation:

$$P(e) = P(e_1) \times \dots \times P(e_n) \quad (3)$$

where each  $P(e_i)$  can also be computed by reification in the graph. For example, evidence 1 ( $e_1$ ), which says that the vehicle TTC with the preceding vehicle is risky, can be reified as  $\langle \text{vehicle}, \text{PRECEDING\_TTC\_IS}, \text{highRiskPreceding} \rangle$ ; evidence 2 ( $e_2$ ) which says that vehicle is accelerating laterally to the left can be reified as  $\langle \text{vehicle}, \text{LATERAL\_ACCELERATION\_IS}, \text{leftAcceleration} \rangle$ . All pieces of evidence are reified following this philosophy. Regarding the computation of  $P(e|h)$ , it can be rewritten as the following:

$$\begin{aligned} P(e|h) &= P(e_1, \dots, e_n|h) = P(e_1|h) \times \dots \times P(e_n|h) \\ &= P(e_{1c}) \times \dots \times P(e_{nc}) \end{aligned} \quad (4)$$

where  $P(e_{ic})$  stands for the probability of  $e_i$  given that the hypothesis  $h$  is true. Also, conditioned pieces of evidence are reified. For the given example,  $e_{1c}$  is: what is the probability of having a *highRiskPreceding* vehicle, given that the hypothesis is that the target vehicle makes *LLC*. This can be reified to the triple  $\langle \text{highRiskPreceding}, \text{INTENTION\_IS}, \text{LLC} \rangle$ . It means that we take it for granted that the object entity is a vehicle, and it is for sure changing its lane to the left lane. In such conditions, the probability that such a vehicle in such circumstances will have a risky preceding vehicle will be computed. Same applies to  $e_{2c}$ ,  $\langle \text{leftAcceleration}, \text{INTENTION\_IS}, \text{LLC} \rangle$ . Then,  $e_{1c}$  is multiplied by  $e_{2c}$  to get  $P(e|h)$  as in Equation 4. Finally,  $P(h|e)$  can be calculated using Equation 2 given that all these individual probabilities are computable from the graph using the embeddings.

## V. RESULTS

After embedding the KG and utilizing Bayesian reasoning to get the predictions, the model is tested on the last 12 tracks in the HighD dataset. Testing started by comparing the f1-score of the *TransE* model and the *ComplEx* model three seconds before changing lanes. The *TransE* model has 93.60% f1-score, and the *ComplEx* model scores 12% f1-score. So, the *TransE* model worked better and all the upcoming experiments and discussions will be based on using the *TransE* model. Testing takes place at different instances before crossing the lane line starting with 0.5 seconds till four seconds with a step of 0.5 seconds. Table II shows the results at one, two, three, and four seconds. It can be observed that the model maintains the f1-score percentage over 90% for the first three seconds. Then, the performance drops until it reaches 66.52% f1-score four seconds before changing lanes. Then, the model is compared in terms of f1-score with other recent works that used the HighD dataset as shown in Table III. The table shows that [8], and [9] have an average of 1% score margin with the proposed model at 0.5 and 1 seconds. Starting from 1.5 seconds, our model still maintains its performance with approximately the same f1-score and passes both models as their scores start to decrease.

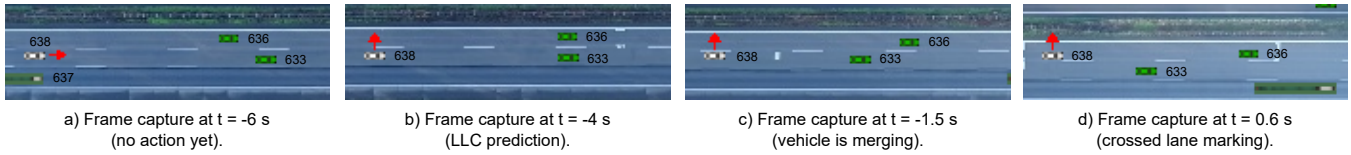


Figure 7. Scene explanation through four different frame captures.

TABLE II

Precision, recall, and f1-score metrics of the predictions obtained from our proposed model at different instants.

1 Second	Precision (%)	Recall (%)	F1-score (%)
LK	98.33	96.96	97.64
LLC	97.98	97.50	97.74
RLC	97.00	99.42	98.19
Macro avg	97.77	97.96	97.86
2 Seconds	Precision (%)	Recall (%)	F1-score (%)
LK	98.86	96.96	97.95
LLC	97.50	99.15	98.32
RLC	96.52	98.66	97.58
Macro avg	97.66	98.25	97.95
3 Seconds	Precision (%)	Recall (%)	F1-score (%)
LK	92.53	96.96	94.70
LLC	95.71	91.77	93.70
RLC	95.46	89.50	92.38
Macro avg	94.56	92.74	93.60
4 Seconds	Precision (%)	Recall (%)	F1-score (%)
LK	69.63	96.96	81.05
LLC	91.30	46.00	61.16
RLC	88.75	42.39	57.37
Macro avg	83.22	61.78	66.52

TABLE III

Comparison with other models using the f1-score (%) metric.

Pred. time	0.5 Seconds	1 Second	1.5 Seconds	2 Seconds
[8]	98.20	97.10	96.61	95.19
[9]	<b>99.18</b>	<b>98.98</b>	97.56	91.76
Ours	97.72	97.86	<b>98.11</b>	<b>97.95</b>

Figure 7 and Figure 8 show a left lane-changing scenario, where Figure 7 shows different captures at different instants for the white target vehicle and its surrounding green neighbors in that scenario. While Figure 8 shows a graph for the numerical values and linguistic categories of the inputs that are fed to the KG model for the same scene. The upper sub-figure is for the lateral velocity, followed by the lateral acceleration, and then the TTC with left/right following vehicles. After that, the TTC with the left/center/right preceding vehicles. Finally, the last sub-figure is for the prediction probabilities throughout the scene. The focus here is to show that the model uses human/machine interpretable and explainable linguistic inputs to get a reasonable prediction. The scene starts with Figure 7a at  $-6$  seconds before changing the lane. By observing the plots in Figure 8, the target vehicle is (*movingStraight*), without lateral acceleration, and low-risk TTC with all surrounding vehicles. At this moment, human reasoning says that the

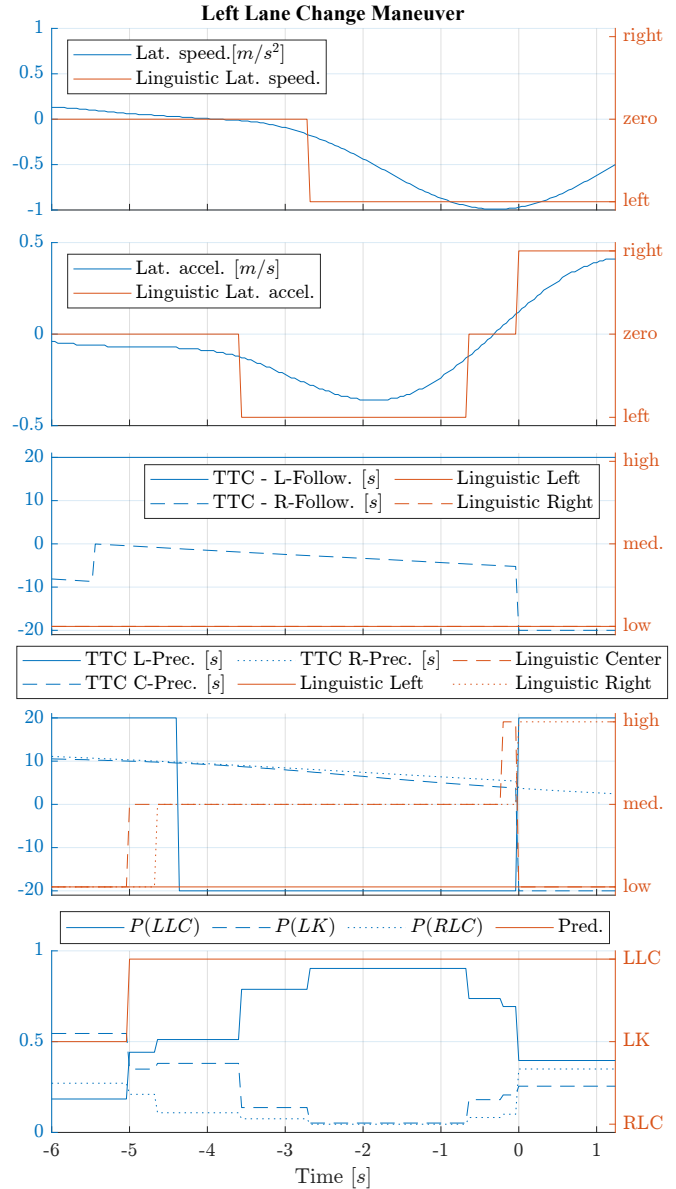


Figure 8. Temporal sequence of numerical variables and linguistic categories.

vehicle is keeping its lane. Using Bayesian reasoning, the model is asked to compute the probability of *LLC* given the generated linguistic inputs, the same question is addressed for *LK* and *RLC*, and the prediction with the highest probability will be the model's prediction. The model uses the KGE to get all the triples probabilities after reification as mentioned earlier in section IV and Figure 2. During this instant, the model prediction is *LK* as it has a higher probability than *LLC* and *RLC*. Moving on to the second instant which is

described in Figure 7b at  $-4$  seconds before changing lanes. Despite having zero lateral velocity and acceleration, the model gives an LLC prediction (represented by a red arrow pointing to the left) because of a medium-risk TTC with the preceding vehicle. Moreover, focusing on the interval  $t=[-5, -4]$ , it is shown that the right preceding vehicle TTC risk changed from low to medium, which makes the *RLC* probability decrease, causing an increase in the *LK* and *LLC* probabilities. After that, in the third captured frame represented in Figure 7c. The target vehicle starts to accelerate in the left direction, moving with lateral velocity in the left direction as well. So, the vehicle started moving to merge and was about to change lanes. The model *LLC* probability increased approximately to 90%. Then, in the last capture after crossing the lane lines in Figure 7d. The target vehicle is merging with right acceleration while moving left, and high-risk right preceding vehicle. Moreover, by comparing the locations of the surrounding vehicles with respect to our target vehicle in Figure 7c and Figure 7d. It can be observed that the preceding vehicle with high-risk before changing lanes becomes the right preceding high-risk vehicle after the left lane changing. Also, the left preceding vehicle becomes the preceding vehicle. The same applies to all other target vehicle neighbors which causes a high change in the TTC values. Finally, Table IV contains links for some multimedia videos that provide results of different scenes including the scene discussed in this section.

TABLE IV  
Different Multimedia for Better Visualisation.

Scenario	Link
Left Lane Change	<a href="https://youtu.be/jPFj3YstBzs">https://youtu.be/jPFj3YstBzs</a>
Left Lane Change	<a href="https://youtu.be/F7BSMsAyerI">https://youtu.be/F7BSMsAyerI</a>
Lane Keeping	<a href="https://youtu.be/zavuxrz33KY">https://youtu.be/zavuxrz33KY</a>
Right Lane Change	<a href="https://youtu.be/7xzeycfmRkc">https://youtu.be/7xzeycfmRkc</a>
Right Lane Change	<a href="https://youtu.be/wLfE8PfAUgU">https://youtu.be/wLfE8PfAUgU</a>

## VI. CONCLUSION

In this work, the problem of vehicle lane change prediction is addressed using explainable contextual linguistic information that describes the target vehicle state and introduces risk awareness by considering the TTC risk with the surrounding vehicles. The proposed solution consists of three phases: linguistic input generation, knowledge graph embedding, and Bayesian inference and prediction. The first phase generates linguistic input categories from numerical values based on some threshold limits. The second phase takes the linguistic inputs and forms a knowledge graph reified triples in the form of a CSV file and uses the Ampligraph library for knowledge graph embedding. In the third, the implementation of a fully inductive reasoning system based on KGEs is carried out using Bayesian inference. This phase uses the embeddings from phase two to calculate the probabilities of different reified triples which are used for Bayesian reasoning to generate the final prediction. The proposed model is evaluated

at different instants before the target vehicle changes lanes. The results showed that the model can predict lane-changing intention two seconds earlier with an f1-score of 97.95%, and three seconds earlier with an f1-score of 93.60%. This shows the reliability and robustness of the model to keep the f1-score higher than 90% for three seconds before changing lanes. Moreover, the model surpassed other recent works that used the HighD dataset, especially after 1.5 seconds when the other models' scores started to decrease, and our model kept its high score without decreasing.

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