Driver-centric Risk Object Identification

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Abstract—A massive number of traffic fatalities are due to driver errors. To reduce fatalities, developing intelligent driving systems assisting drivers to identify potential risks is in urgent need. Risky situations are generally defined based on collision prediction in existing research. However, collisions are only one type of risk in traffic scenarios. We believe a more generic definition is required. In this work, we propose a novel driver-centric definition of risk, i.e., risky objects influence driver behavior. Based on this definition, a new task called risk object identification is introduced. We formulate the task as a cause-effect problem and present a novel two-stage risk object identification framework, taking inspiration from models of situation awareness and causal inference. A driver-centric Risk Object Identification (ROI) dataset is curated to evaluate the proposed system. We demonstrate state-of-the-art risk object identification performance compared with strong baselines on the ROI dataset. In addition, we conduct extensive ablative studies to justify our design choices.

Index Terms—Risk assessment, driving scene understanding, situation awareness, end-to-end driving model, and causal inference

1 INTRODUCTION

More than 1.3 million people die in road accidents worldwide every year, or approximately 3,700 people per day [1]. Road traffic accidents are among the leading causes of non-natural death around the world. The majority of these accidents are due to driver errors, such as lack of awareness [2]. To reduce the number of accidents, developing intelligent driving systems that identify potential hazards is in urgent need. The task has been studied extensively in the risk assessment literature [3]. In the context of intelligent vehicles, the risk is generally defined based on collision prediction. While this definition is widely applied, road collision is only one source of potential hazards in driving [3]. We believe a more generic definition is needed.

We propose a novel driver-centric definition of risk, i.e., risky objects influence driver behavior. Fig. 1 depicts the idea of the proposed definition. While driving toward an intersection, we react to the crossing pedestrian (i.e., slow down). After passing the intersection, we react to the construction cone (i.e., deviate to a clear path). From these examples, we observe that we constantly attend to those traffic participants potentially influencing driver behavior, because we humans are equipped with risk perception. In other words, a dangerous situation would occur if we do not react to them immediately. The proposed definition captures the observation. We believe the definition gives a new perspective to the definition of risk assessment.

A natural question arises: Who changes drivers’ behavior? We propose a new task called risk object identification, which aims to identify the object(s) influencing drivers’ behavior. The proposed task can be approached via three existing tasks: (1) salient object identification learned from human gaze behavior [4]; (2) object importance estimation or risky region localization learned from human annotations [5], [6]; and (3) salient regions/objects identification learned from end-to-end driving models with self-attention mechanisms [7], [8].

First, learning to predict pixel-level driver attention by imitating human gaze behavior has been explored by [4], [9], [10]. This area of research is motivated by psychological studies suggesting that there is a connection between driving, attention, and gaze [11]. Alletto et al., [4] collect a
To address the aforementioned issues, we propose a novel two-stage risk object identification framework based on the proposed definition of risk. Specifically, we formulate the risk object identification as a cause-effect problem \[13\]. The core concept is depicted in Fig. 2. In the first stage, a driving model learns to predict driver response in a given situation. We simplify the response of drivers to be Influenced or Uninfluenced as Stop and Go, respectively. To predict driver response, a novel driving model motivated by the model of situation awareness \([14]\) is proposed. Specifically, the proposed model encapsulates the goal (i.e., driver intention), perception (i.e., elements of the environment), comprehension (i.e., interactions between driver and Thing objects and interactions between driver and Stuff objects in 3D), and projection (i.e., intention-aware interaction forecasting) for driver response prediction. Thing and Stuff objects are defined in Section 5.1.

In the second stage, given a Stop response (i.e., driver behavior is influenced by certain objects), we intervene input video by removing a tracklet at a time and inpainting the removed area in each frame to simulate a scenario without the presence of the tracklet. The same driving model is applied to predict the effect of the removal. The process iterates through all tracklets and records the corresponding effects. Please note that we assume that the cause of driver response change is either vehicles or pedestrians. The tracklet that causes a maximum response change is the risk object.

Our work differs from existing methods \([1, 5, 6, 7, 8]\) in the following three aspects:

1) A novel driver-centric notion of risk, whereby risky objects are defined as those that influence driver behavior, is proposed;
2) An unsupervised framework is introduced as an initial step toward generalization;
3) A causal inference-based framework is proposed to address the issue of "causal misidentification" in end-to-end driving models for risk object identification.

In this work, we make the following substantial extensions to our early results \([15]\):

1) We re-design the driving model substantially to predict driver response by modeling driver decision processes via the model of situation awareness \([14]\);
2) We systematically benchmark three different tasks, i.e., driver response prediction, driver intention prediction, and risk object identification on the proposed driver-centric ROI dataset;
3) We conduct thorough ablative studies to justify the architectural designs.

2 RELATED WORK

Risk Assessment. Living agents can assess risk for decision-making. Earlier attempts have been made to study this problem from different angles, and can be categorized into four categories. First, the works \([16, 17]\) design a set of rules based on the current state of vehicles and contextual states for detecting dangerous situations. These rule-based approaches ignore uncertainties of dynamic driving environments, leading to instabilities in their decisions. Second, risky situations can be determined by the similarity of a pattern between a pair of traffic participants with accident patterns obtained from accident databases \([18, 19]\). However, real-world accident data are hard to obtain. It is also challenging to realistically simulate accident with a simulator. Moreover, it is insufficient to consider pairwise relations in complicated driving scenarios, where multiple traffic participants interact with each other.
Third, a popular risk assessment methodology is to predict all possible colliding future trajectories [20], [21], [22]. Please refer to [3] for a detailed survey of motion prediction and risk assessment in the context of intelligent vehicles. While predicting all possible colliding future trajectories is well-received by this research field, the approach involves a large number of computations since it requires pairwise comparisons. Fourth, Lefèvre et al. [23] define the risk of a situation by detecting conflicts between driver intention and expectation via a probabilistic framework. While this paradigm is very close to our proposed definition of risk, the underlying mechanism for risk object identification is different. Specifically, in [23], a risk object is identified by computing the probability of intention- expectation mismatch for each vehicle based on vehicle states. If the probability exceeds a threshold, the corresponding vehicle is considered to be a “hazard”. In contrast, we discover the risk object based on causal inference, reasoning the effect of an object removal (i.e., intervention).

Vision-based End-to-end Driving Models. The history of vision-based end-to-end driving models can be traced back to 1989 when ALVINN [24], the framework that learns a mapping from images to navigation signals via a shallow neural network, is introduced. Recently, Bojarski et al. [25] demonstrate a similar idea by extending it to modern convolutional neural networks for extracting better visual representations from images. In [26], visual representations are learned with an auxiliary semantic segmentation task to better represent driving scenes.

While significant progress has been demonstrated, neural network-based frameworks lack interpretability, crucial for safety-critical applications. To address the issue, Kim et al. [7], [27] and Wang et al. [8] propose pixel-level and object-level attention mechanisms, respectively. Particularly, Wang et al. [8] propose an object-level attention scoring mechanism as a means to model how certain traffic participants impact actions of driving models.

Interactions modeling between traffic participants is commonly studied in trajectory prediction literature [28], [29], [30], [31]. However, interaction modeling for learning driving policies is under-explored. To address this problem, our method explicitly models the interactions using Graph Convolutional Networks (GCNs). Instead of simply weighting and concatenating objects’ visual representations as interaction modeling [8], we model interaction as message passing that incorporates relative distances between traffic participants and ego-vehicle. Moreover, interactions between the ego-vehicle and road infrastructure (e.g., traffic light) are considered in the proposed framework. We show that the two interaction modelings are essential for driver response prediction. Additionally, the proposed driving model exploits the inductive biases motivated by situation awareness [14]. We empirically demonstrate the effectiveness of these inductive biases for both driver response prediction and risk object identification.

While the aforementioned driving models have shown remarkable advances in following roads and avoiding obstacles, they cannot be guaranteed to achieve a goal (e.g., left turn). Codevilla et al. [32], [33] incorporate navigational commands as an extra input for learning driving policies. Instead of inputting a navigational intention command, the proposed driving model infers drivers’ intention from egocentric videos for driver response prediction.

Causality in Computer Vision. Computer vision research has proliferated over the past decades due to the advance of deep learning algorithms. However, current deep learning models suffer from spurious correlation problems [34] because of ignoring causality in data. Humans perceive causality of the physical world. To address the issue, recent studies [35], [36], [37], [38], [39] explicitly consider the concept of causality into deep learning architectural designs.

Particularly, the authors of [37], [38] propose a novel training objective as a practical approximation for imagina- tive intervention (i.e., do operator proposed in [13]) to eliminate noncausal relations and unobserved confounders for image captioning and visual Q&A. In this work, we also leverage causal intervention but in a different way. Specifically, instead of using an imaginative causal intervention, we explicitly conduct do operator via image inpainting.

To our best knowledge, we are among the first to utilize causal inference for driving scene applications. Kim et al. [7] propose a causality test to verify the effectiveness of inferred attention maps obtained from the proposed driving model. We also employ causal inference similar to the causality test. However, the purpose of causal inference in this work is to identify risk objects. Moreover, we design a simple but effective data augmentation strategy using causal intervention. This leads to a more robust driving model.

Haaan et al. [12] propose to incorporate functional causal models [13] into imitation learning to address the issue of “causal misidentification”. In [40], they overcome the causal misidentification issue by adding noises to inputs. Our work is complementary to [12], [40]. Specifically, the focus of [12], [40] is to improve the robustness of driving models, whereas the proposed framework leverages driving models to determine the response of drivers in a counterfactual situation for risk object identification. We believe the two lines of work should be studied jointly and will leave for future work.

3 Driver-centric ROI Dataset

To study driver-centric risk object identification, a dataset with diverse reactive scenarios (i.e., drivers react to potential hazards while navigating to their goals) is indispensable. For instance, when human drivers intend to turn left at an unprotected intersection, we react (e.g., slowing down or stopping) to certain traffic participants to avoid dangerous situations. We curate a driver-centric Risk Object Identification (ROI) dataset from the Honda Research Institute Driving Dataset (HDD) [41].

3.1 Dataset Annotation

The driver-centric ROI dataset utilizes a two-layer representation — Intention and Response. Fig. 3 illustrates how we construct the proposed driver-centric ROI dataset from the HDD dataset.

The Goal-oriented layer defined in the HDD dataset denotes tactical driver behavior such as right turn, left turn, 1. The dataset is available at https://usa.honda-ri.com/HDD
or lane change. As shown in Fig. 3, each frame is labeled with either a goal-oriented or background action. To obtain the Intention of a n-frame clip (the parameter n is 20 in our implementation), we use the last frame’s label of the Goal-oriented layer as the Intention label. While performing a tactical behavior, drivers might have to stop or deviate due to traffic participants or obstacles. We extend the Stimulus-driven actions, i.e., Stop and Deviate, defined in the HDD dataset as the Response label. Note that both Stop and Deviate are merged into Stop as depicted in Fig. 3. The rest of the frames are labeled as Go. The HDD dataset also annotates a Cause layer to explain the reason for Stop and Deviate actions. We create our Test2 set by selecting frames from the four Cause scenarios, i.e., Congestion, Crossing Pedestrian, Crossing Vehicle and Parked Vehicle. Moreover, in the Test2 set, we provide bounding boxes of risk objects (i.e., object[s] influencing driver’s behavior) for risk object identification benchmarks. We focus on scenarios in which drivers react to vehicles or pedestrians.

### 3.2 Dataset Statistics

The driver-centric ROI dataset has 184,890 frames for training driver response and intention predictors. Two test sets are constructed for driver response prediction and risk object identification, respectively. The Test1 split has 63,314 frames for both driver response and intention benchmarks. The Test2 has 630 frames (i.e., 630 different risk objects) covering four different reactive scenarios, i.e., Congestion, Crossing Pedestrian, Crossing Vehicle, and Parked Vehicle for risk object identification benchmarks. Detailed statistics are shown in Table 1.

| Split   | Intention | Response |
|---------|-----------|----------|
|         | BG        | IP       | LT       | RT       | LLC      | RLC      | LLB      | RLB      | CP       | RP       | MG       | UT       | STP      | G        |
| Train   | 737,949   | 48,932   | 21,819   | 19,824   | 4,815    | 4,386    | 1,833    | 717      | 2,364    | 588      | 1,182    | 2,001    | 184,890  | 661,521  |
| Test1   | 236,622   | 17,772   | 7,017    | 6,195    | 1,098    | 1,212    | 435      | 324      | 432      | 123      | 327      | 432      | 63,314   | 208,675  |
| Test2   | 543       | 20       | 12       | 35       | 10       | 4        | 2        | 35       | 10       | 4        | 2        | 630      |          |
| Cause   |           |          |          |          |          |          |          |          |          |          |          |          |          |
| Congestion | 98       | /        | /        | /        | /        | /        | /        | /        | /        | /        | /        | /        | 99       | /        |
| Crossing Pedestrian | 62   | 15       | 5        | /        | /        | /        | /        | /        | /        | /        | /        | /        | 84       | /        |
| Crossing Vehicle | 263  | 2        | 7        | 35       | /        | /        | /        | 4        | /        | /        | /        | /        | 311      | /        |
| Parked Vehicle | 120  | 3        | /        | /        | 9        | 4        | /        | /        | /        | /        | /        | /        | 136      | /        |
| All     | 543       | 20       | 12       | 35       | 10       | 4        | 2        | 35       | 10       | 4        | 2        | 630      |          |

**TABLE 1**

Statistics (annotated frames) of the proposed driver-centric ROI dataset.
4 PROBLEM FORMULATION

Given a reactive scenario with \( T \) RGB images \( I := \{I_1, I_2, \cdots, I_T\} \), the goal is to identify the object influencing driver response in the last frame. The task is called risk object identification.

We formulate the task as a cause-effect problem \([13]\). Specifically, a two-stage framework is proposed to identify the cause (i.e., the object) of an effect (i.e., driver response) via the proposed Intention-aware Driving Model and Causal Reasoning for Risk Object Identification. We discuss the methodology in the following.

5 INTENTION-AWARE DRIVING MODEL

An overview of the proposed intention-aware driving model is depicted in Fig. 4. To predict the response of a driver, a driving model should capture complicated spatio-temporal interactions between a driver and traffic participants. We propose a novel driving model motivated by the model of situation awareness (SA) \([14]\). Specifically, the proposed model encapsulates the four essential components defined in SA for driver response prediction: goal/objective (i.e., driver intention), perception (i.e., elements of a traffic environment), comprehension (i.e., interactions between driver and Thing objects, and interactions between driver and Stuff objects in 3D), and projection (i.e., intention-aware interaction forecasting). The detail of each component is discussed in the following.

5.1 Perception

Perception plays an essential role in the SA model \([14]\). This component perceives the status, attributes, and dynamics of relevant traffic participants of a traffic environment. Specifically, given \( T \) RGB images, we apply object detection \([12]\) and semantic segmentation \([15]\) to obtain Thing and Stuff objects, respectively. In this work, we distinguish Stuff objects from Thing objects by evaluating whether states of an object can be influenced by other objects. If yes, we categorize the object as a Thing object. For instance, cars stop or yield to pedestrians, but a traffic light turns red or green by itself. In addition to detection and segmentation, we perform object tracking using Deep SORT \([44]\) and depth estimation \([45]\).

5.2 Comprehension

We interpret Comprehension as the spatio-temporal interactions between the driver and Thing objects, and interactions between the driver and Stuff objects in the 3D world. Note that a thorough modeling of Comprehension is beyond the scope of this work. Specifically, we construct two graphs, i.e., Ego-Thing Graphs and Ego-Stuff Graphs. They are modeled with Graph Convolutional Networks (GCNs) \([46]\). The details of each graph are discussed below. Note that the interaction modeling is proposed in \([47]\). We extend the modeling for driver response prediction.

5.2.1 Ego-Thing Graph

The Ego-Thing Graph is designed to model interactions among a driver and Thing objects.

Graph Definition. We denote a sequence of frame-wise Ego-Thing Graphs as \( G^{ET} = \{G^{ET}_t | t = 1, \cdots, T\} \), where \( T \) is the number of frames, and \( G^{ET}_t \in \mathbb{R}^{(K+1) \times (K+1)} \) is the Ego-Thing affinity matrix at frame \( t \) encoding pairwise interactions among Thing objects and Ego. Specifically, \( G^{ET}(i, j) \) denotes the influence of object \( j \) on object \( i \). A Node \( i \) at time \( t \) is represented by two types of features \((x_i^t, p_i^t)\), where \( x_i^t \) represents the appearance feature, and \( p_i^t \in \mathbb{R}^{1 \times 3} \) is the 3D location of the \( i \)-th object in respect to Ego in a local frame.

Node Feature Extraction. Thing objects are car, person, bicycle, motorcycle, bus, train, and truck. Given bounding boxes obtained from object detection \([12]\), we keep \( K \) top-scoring detected boxes. The parameter \( K \) is set to 20. There are \( K + 1 \) objects, where index \( i = 1, 2, \cdots, K \) corresponds to Thing objects, and index \( K + 1 \) corresponds to...
Ego. The appearance feature for \(i\)-th object is denoted as \(x_i^t \in \mathbb{R}^{1 \times D}, i = 1, 2, \ldots, K, K + 1 \). RoAlign \[42\] and max pooling are applied to obtain the appearance features of Thing objects. The appearance of Ego is obtained by the same procedure as Thing objects, but with a frame-size bounding box.

**Relational Modeling.** We consider both appearance features and distance constraints motivated by \[48\] in relational modeling. An edge \(G^{ET}(i, j)\) is defined as:

\[
G^{ET}(i, j) = f_s(p_i^t, p_j^t) \exp(f_a(x_i^t, x_j^t)) / \sum_{j=1}^{K+1} f_s(p_i^t, p_j^t) \exp(f_a(x_i^t, x_j^t)),
\]

where \(f_a(x_i^t, x_j^t)\) indicates an appearance relation, and \(f_s(p_i^t, p_j^t)\) denotes relative distance between \(i\)-th and \(j\)-th object, respectively. The softmax function is used to normalize an affinity matrix \(G^{ET}\). An appearance relation is defined as below:

\[
f_a(x_i^t, x_j^t) = \phi(x_i^t)^T \phi'(x_j^t) / \sqrt{D},
\]

where \(\phi(x_i^t) = wx_i^t\) and \(\phi'(x_j^t) = w'x_j^t\). Both \(w \in \mathbb{R}^{D \times D}\) and \(w' \in \mathbb{R}^{D' \times D}\) are learnable parameters. \(\sqrt{D}\) is a normalization factor.

In addition to appearance relation, we also consider spatial constraint via calculating a relative distance between a pair of objects. Specifically, we unproject the center of a Thing object’s bounding box to 3D space \[45\]. For Ego, we unproject the middle-bottom pixel of the frame to 3D space. Given a 2D coordinate \((u_i^t, v_i^t)\) of \(i\)-th object at time \(t\), the corresponding 3D coordinate \((x_i^t, y_i^t, z_i^t)\) is obtained as follows:

\[
[x_i^t \ y_i^t \ z_i^t \ 1]^T = \delta_{u_i^t, v_i^t} \cdot P^{-1} \begin{bmatrix} u_i^t & v_i^t & 1 \end{bmatrix}^T,
\]

where \(P\) is the camera intrinsic matrix, and \(\delta_{u_i^t, v_i^t}\) is the relative depth at \((u_i^t, v_i^t)\) obtained by \[45\]. The spatial constraint \(f_s\) is formulated as:

\[
f_s(p_i^t, p_j^t) = \mathbb{I}(d(p_i^t, p_j^t) \leq \mu),
\]

where \(p_i^t\) denotes the 3D coordinate of \(i\)-th object at time \(t\), \(\mathbb{I}(\cdot)\) is the indicator function, \(d(p_i^t, p_j^t)\) computes the Euclidean distance between object \(i\) and object \(j\) in the 3D space, and \(\mu\) is the distance threshold. The motivation of spatial constraint is that interactions between two distant objects are usually scarce. In our implementation, we empirically set the value of \(\mu\) to be 3.0.

### 5.2.2 Ego-Stuff Graph

An Ego-Stuff Graph \(G^{ES}\) is constructed in a similar manner as an Ego-Thing Graph \(G^{ET}\) except for node feature extraction.

**Node feature extraction.** We define the following classes as Stuff objects: Crosswalk; Lane Markings; Lane Separator; Road; Service Lane; Traffic Island; Traffic Light and Traffic Sign. Some Stuff classes (e.g., crosswalk obtained from semantic segmentation) cannot be well depicted as rectangular bounding boxes. Thus, RoAlign \[42\] is not applicable. We propose MaskAlign to extract features from a binary mask \(M_i^t\), i.e., the \(i\)-th Stuff object at time \(t\). MaskAlign first downsamples the mask \(M_i^t\) to the same spatial dimension of an intermediate 3D feature map \(X\). Note that the downsampled mask is denoted as \(M_i^{′t}\). A Stuff object feature is obtained as follows:

\[
x_i^t = \frac{\sum_{w=1}^{W} \sum_{h=1}^{H} I_s(x_i^t, w, h) \cdot M_i^{′t}(w, h)}{\sum_{w=1}^{W} \sum_{h=1}^{H} M_i^{′t}(w, h)},
\]

where \(X_i^t \in \mathbb{R}^{1 \times D}\) is a D-dimension feature at location \((w, h)\) for time \(t\), and \(M_i^{′t}(w, h)\) is a binary scalar indicating whether object \(i\) exists at location \((w, h)\).

**Relational Modeling.** We neglect interactions among Stuff objects since they are insusceptible to each other. We only model interactions between Stuff objects and Ego. Hence, we set \(f_s\) (as in Eq. 4) to zeros for every pair of Stuff objects. To model spatial constraint, we unproject every pixel within a downsampled binary mask \(M_i^{′t}\) to the 3D space, and calculate the relative distance between the corresponding 3D coordinates and the 3D coordinate of Ego. We choose the one with the minimum distance within a downsampled mask.

The distance threshold \(\mu\) in Ego-Stuff Graphs is empirically set to be 0.6.

### 5.2.3 Interaction Modeling as Message Passing

In Section 5.2.1 and 5.2.2 two relational modelings are discussed. To predict driver response, we need interaction modeling that captures influences of multiple traffic participants to a driver. We formulate interactions as message passing in GCN that takes a graph as input, passes information through edges, and outputs updated nodes’ features. The message passing process in GCN is written as:

\[
X^{t+1} = GX^tW^l + X^l,
\]

where \(G\) is the affinity matrix discussed in Section 5.2.1 and 5.2.2. The matrix \(X^l \in \mathbb{R}^{(K+1) \times D}\) is the appearance feature matrix for the \(l\)-th layer. \(W^l \in \mathbb{R}^{D \times D}\) is a learnable weight matrix. We also build a residual connection by adding \(X^l\). Layer Normalization \[49\] and ReLU are applied before \(X^{t+1}\) is fed to the next message passing. Note that we use a one-layer GCN to model Ego-Stuff interactions and a two-layer GCN for Ego-Thing interaction modeling.

### 5.3 Projection

The role of Projection is to forecast future actions of elements in the environment. The updated appearance feature \(X^{t+1}\), discussed in the Comprehension section, is processed independently at every frame without considering temporal changes. An encoder-decoder architecture is proposed to capture temporal interactions for forecasting future interactions.

**Encoder-decoder Architecture.** We implement the proposed encoder-decoder architecture based on the Temporal Recurrent Network (TRN) \[50\], which makes use of both accumulated historical evidence and predicted future information to better predict current action. Following \[50\], we use long short-term memory (LSTM) \[51\] as the backbone for both encoder and decoder.

We aggregate updated Ego features from Ego-Stuff Graphs and Ego-Thing Graphs by an element-wise summation. Time-specific updated Ego features are fed into the encoder LSTM
to obtain a $1 \times D$ feature vector called interaction representation. Note that prior works [48], [52], [53] fuse all nodes’ features in a graph, and the fused features are sent to the encoder LSTM. In contrast, we only send updated Ego features in $X^{t+1}$ to the encoder-decoder architecture, because updated Ego features are expected to capture interactions among traffic participants that are key to robust driver response prediction. Unlike typical decoder architectures implemented as other LSTMs, TRN includes an LSTM decoder, a future gate, and a spatiotemporal accumulator (STA). We extend TRN for the predicting driver response, and the corresponding architecture is depicted in Fig. 5. The LSTM decoder learns a feature representation of the evolving interactions. The future gate receives a vector of hidden states from the decoder LSTM and embeds features via the element-wise summation as the future context. The STA concatenates historical, current, and predicted future spatiotemporal features, and estimates driver response occurring in the very next frame.

**Intention-aware Design.** Driver intention is indispensable for planning the next action [32], estimating the importance of road users [54], and assessing risk [55]. Similarly, in our task, driver response (i.e., Go and Stop) is determined not only by interactions among traffic participants but also driver intention (e.g., Left Turn or Right Turn). For instance, a vehicle turning right at an intersection will not stop for pedestrians walking on the left sidewalk. Hence, we treat features extracted from the I3D head as the intention representation. The representation is used to initialize the hidden state of the first decoder LSTM cell. Note that the design differs from [50], which initializes the hidden state $h_0$ with zeros. To acquire a good intention representation, the representation is trained to predict driver intention in a supervised learning manner.

6 Causal Reasoning

The previous section introduces the proposed intention-aware driving model. In this section, we discuss how we utilize intervention, a powerful tool for causal inference, as a means for data augmentation to improve the performance of the driving model (Sec. 6.1) and apply causal inference to identify the risk object (Sec. 6.2).

**Algorithm 1 Driving Model Training**

$T$: Number of frames  
$N$: Number of Thing objects in a given tracklet list  
$A_r$: Ground truth driver response (either Go or Stop)  
**Input:** A sequence of RGB frames $I := \{I_1, I_2, \cdots, I_T\}$  
**Output:** Predicted driver response $a_r$ and intention $a_i$. Notice that $a_r$ consists of confidence scores of Go or Stop. $a_r := \{r^{\text{go}}, r^{\text{stop}}\}$.

1. $O := \text{DetectionAndTracking}(I)$  
   $: = \{O_1, O_2, \cdots, O_N\}$  
2. $S := \text{SemanticSegmentation}(I)$  
   $: = \{S_1, S_2, \cdots, S_T\}$  
3. // Data Augmentation via Intervention (Sec. 6.1)  
4. if $A_r$ is Go and $N > 1$ then  
5. // Randomly remove a tracklet  
   $k := \text{RandomSelect}(N)$  
6. else  
7. $k$ is empty  
8. end if  
9. // Mask out Thing object $k$ on each mask frame  
   $M := \text{MaskGenerator}(I, O_k)$  
10. // Remove a Thing object $k$ from the tracklet list  
    $O' = O - \{O_k\}$  
11. $a_r, a_i := \text{DrivingModelTraining}(I, M, O', S)$ // Discussed in Sec. 6.1  
12. return $a_r, a_i$
the driver’s lane is red. In this situation, the frontal vehicle is labeled as the risk object (cause). However, driver response remains the same if the frontal vehicle were not present because of the red light. Generating Stop scenarios is non-trivial, and we leave it for future works.

To train the intention-aware driving model with the proposed data augmentation strategy, the model should be able to “intervene,” i.e., remove a non-causal object from images. We realize the strategy by replacing standard convolutional layers in I3D with partial convolutional layers \([56], [57]\). Note that a partial convolutional layer is initially introduced for image inpainting. We utilize partial convolutions to simulate a scenario without the presence of an object. A 3D partial convolutional layer takes two inputs, i.e., a sequence of RGB frames and a one-channel binary mask for each frame. The pixel values of a mask are 1 by default. While training the driving model with data augmentation, we set the pixels within the selected object to be 0. In addition, the node of the selected object in a graph is disconnected from the rest of the objects.

The proposed training process is outlined in Algorithm \([1]\). Given training samples in a Go scenario, we randomly select an object \( k \) to intervene, i.e., simulating a situation without the presence of the object. Specifically, given a tracklet \( o_k \), a one-channel binary mask \( M_t \) at time \( t \) is defined as

\[
M_t(i, j) = \begin{cases} 
0, & \text{if } (i, j) \text{ in region } o_k^t \\
1, & \text{otherwise}
\end{cases}, \tag{7}
\]

where \( o_k^t \) is the bounding box of the \( k \)-th object at time \( t \), and \((i, j)\) is a pixel coordinate within the box. Note that \( k \)-th object is discarded from the tracklet list while training the driving model.

**Algorithm 2 Causal Inference for Risk Object Identification**

\( T \): Number of frames  
\( N \): Number of objects  
**Input**: A sequence of RGB frames \( I := \{I_1, I_2, \cdots, I_T\} \) where the ego car stops  
**Output**: Risk object ID

1: \( O := \text{DetectionAndTracking}(I) \)  
2: \( S := \text{SemanticSegmentation}(I) \)  
3: for \( O_k \in O \) do  
4: // Mask out Thing object \( k \) on each frame  
5: \( M := \text{MaskGenerator}(I, O_k) \)  
6: // Remove the Thing object \( k \) from the tracklet list  
7: \( O' = O - \{O_k\} \)  
8: // Predict driver response and intention  
9: without the object \( k \), where \( a_r := \{r^{go}_k, r^{stop}_k\} \)  
10: \( a_r, a_i := \text{DrivingModel}(I, M, O', S) \)  
11: end for
12: return \( \arg \max_k (r^{go}_k) \)

### 6.2 Causal Inference for Risk Object Identification

Given a ‘Stop’ scenario, we aim to identify the corresponding risk object. We deploy the same intervention process discussed in Section 6.1 to identify the risk object. Specifically, the masks of a tracklet and the corresponding video frames are processed by the same driving model. The model outputs the confidence score of Go and Stop without the presence of the tracklet. After iterating through all tracklets, we select the object with the highest Go confidence score to be the risk object. This is because the object causes the most
driver behavior change. Algorithm\(^2\) describes the overall causal inference process.

7 EXPERIMENTS

7.1 Implementation Details

We implement our framework in TensorFlow. All experiments are performed on a server with 4 NVIDIA TITAN-XP cards. The input to the framework is a 20-frame clip with a resolution of \(224 \times 224\) at 3 fps, approximately 6.67s. The framework outputs the predictions of driver intention and response of the next frame. We adopt Inception-v3\(^5\) pre-trained on ImageNet\(^59\) as the backbone, following\(^60\) to inflate 2D convolution into a 3D ConvNet, and finetune it on the Kinetics action recognition dataset\(^61\). The intermediate feature used in RoIAlign and MaskAlign is the Mixed_5c layer, where the number of feature channels is 512. The intention feature is generated from a \(1 \times 1 \times 1\) convolution on the Mixed_5c layer’s feature, and the channel number of the feature is 512. The downsampled binary mask \(M^t\) is \(28 \times 28\). The decoder length is set to be 3. The model is trained in a two-stage training scheme with a batch size of 32. First, we finetune the Kinetics pre-trained branch on the driver-centric ROI dataset for 50,000 iterations without using GCN. Second, we load the weights trained in the first stage and finetune the network with GCN for another 20,000 iterations. Note that we employ the augmentation strategy mentioned in Section 6.1 in the second stage. We use the Adam optimizer\(^62\) with the default parameters. The learning rate is set to be 0.001 and 0.0002 for the first and second stage, respectively.

7.2 Driving Model Performance

7.2.1 Evaluation Setup

The performance of the driving model is evaluated as a discrete feasible action prediction, in accordance with\(^7\),\(^8\),\(^26\),\(^63\). The two discrete actions, Go and Stop are evaluated. We follow the train/test split defined in\(^41\),\(^47\), where 846,411 and 271,989 samples are used for training and testing, respectively. Four evaluation metrics are utilized. First, we report perplexity as in\(^7\),\(^8\),\(^26\),\(^63\). Perplexity calculates the negative log-likelihood of predicted probability of Response given ground truth (lower is better). Second, the macro-averaged accuracy is reported. Note that, in a multi-class classification setup, the micro-averaged accuracy is preferable if the label distribution is imbalanced. In our task, the Go to Stop ratio is approximately 4:1. Therefore, we also report the micro-averaged accuracy as the third metric. Response prediction can be treated as an online action detection task\(^50\),\(^64\). We use per-frame mean average precision (mAP) as the fourth evaluation metric.

7.2.2 Evaluation

Table 2 summarizes the results of the driving models. We compare the following baselines. To compare different models, we keep their backbone network (i.e., Inception-v3) the same. CNN+LSTM. We extract visual features from the Mixed_5c layer of I3D and sequentially input the features at each time step to a two-layer LSTM\(^50\) for temporal modeling. Pixel-level attention. The pixel-level attention module is proposed by\(^7\) to improve model’s interpretability and the performance of driving models. Object-level attention. In\(^8\), the authors propose an object-centric attention mechanism to augment end-to-end policy learning. Both pixel- and object-level attention modules are incorporated into CNN+LSTM.

The following summarizes our proposals.

GCN. The key difference between GCN and three baselines is the input feature to the LSTM module. Specifically, the feature is processed via Graph Convolution Networks and contains interaction among traffic participants and driver.

Multi-head. We add an additional head for driver intention prediction to CNN+LSTM and GCN. A standard cross-entropy loss is used for driver intention prediction. Note that both the interaction and intention features share the same features from the Mixed_5c layer of I3D.

TRN Head. To forecast future interactions, we incorporate TRN\(^50\). We initialize TRN with intention representation (as shown in Fig. 5).

Intervention. The concept of intervention is utilized to augment training data to improve the performance of driver response prediction discussed in Section 6.1.

We show that GCN outperforms baselines, demonstrating the importance of interaction modeling. By incorporat-

| Model | Response | Intention |
|-------|----------|-----------|
|       | Perplexity | Macro Accuracy | Micro Accuracy | Overall mAP |
| 1. CNN + LSTM | 1.00 | 64.37 | 77.95 | 71.07 | / |
| 2. CNN + LSTM + Multi-head | 0.93 | 68.27 | 79.04 | 70.12 | 36.41 |
| 3. Pixel-level Attention\(^7\) | 0.89 | 76.15 | 80.21 | 78.57 | / |
| 4. Object-level Attention\(^8\) | 0.84 | 78.81 | 83.19 | 79.02 | / |
| 5. GCN (ours) | 0.83 | 77.57 | 82.64 | 80.33 | / |
| 6. GCN + Multi-head (ours) | 0.72 | 76.30 | 85.68 | 84.46 | 36.31 |
| 7. GCN + TRN Head (ours) | 0.69 | 79.32 | 86.17 | 83.44 | 36.80 |
| 8. GCN + TRN Head + Data Augmentation (ours) | 0.37 | 87.63 | 92.56 | 95.44 | 36.75 |

Table 2: Results of driver response prediction compared with baselines. Perplexity (lower is better), macro- and micro-average accuracies, and overall mAP are used as metrics for driver response prediction. The unit is % for all metrics except perplexity. The best and second best performances are shown in bold and underlined, respectively. We also report the performance of driver intention prediction using the overall mAP as the metric.
Fig. 7. Visualization of Learned Ego-Thing Graph and Ego-Stuff Graph on egocentric images. The first and second rows show examples from an Ego-Thing Graph and an Ego-Stuff Graph, respectively. Comparing (a) and (b), which have similar traffic configurations, our model attends to objects at different locations based on distinct intentions. In (c) and (d), pedestrians intending to cross the street have a significant influence on ego behavior when turning left or turning right. Fig. (e) illustrates a left turn case when the heat map shows high attention around the traffic light, which is green. In (f)-(h), lane markings show strong influences on the ego’s lane-related behaviors.

| Intention Modeling | Model | Perplexity |
|--------------------|-------|------------|
| Without intention modeling | 0.83  |
| Multi-head         | 0.72  |
| TRN Head           | 0.69  |

| Different Graphs   | Model | Perplexity |
|--------------------|-------|------------|
| Ego-Stuff Graph    | 0.74  |
| Ego-Thing Graph    | 0.80  |
| Ego-Thing Graph + Ego-Stuff Graph | 0.69 |

| Spatial Modeling   | Model | Perplexity |
|--------------------|-------|------------|
| Appearance Relation | 0.73  |
| Appearance + Spatial Relation | 0.69 |

| Data Augmentation | Model | Perplexity |
|-------------------|-------|------------|
| Without Augmentation | 0.69  |
| With Augmentation  | 0.37  |

TABLE 3
Ablative study of our design choices.

An analysis of Intention Modeling. The first section of Table 3 analyzes the influence of intention modeling. The baseline does not consider intention. When intention representation is incorporated into Multi-head and TRN Head, the results are improved by 0.11 and 0.14, respectively.

Variations of Different Graphs. When both Ego-Stuff and Ego-Thing Graphs are considered, the model achieves the best perplexity performance. The results indicate the importance of the proposed interaction modeling of drivers, traffic participants, and road infrastructure.

Importance of Spatial Relation. We study the importance of the spatial relation function (Eq. 4) to the Response prediction. We conduct two experiments, i.e., 1) using only the appearance relations, and 2) appending 3D spatial relation as an additional constraint. Without using the proposed 3D spatial relation, the perplexity increases by 0.04, indicating the need for a spatial constraint.

Data Augmentation via Intervention. We study the impact of data augmentation by comparing the performance of two models trained with and without the data augmentation strategy. The last section in Table 3 showcases the advantage of using augmented data, cutting the perplexity by nearly half. The data augmentation strategy adds variations to the training set that improve the robustness of the proposed driving model.

7.2.4 Visualization
We visualize learned affinity matrices in Ego-Thing Graph and Ego-Stuff Graph to determine if our approach can highlight those objects influencing driver behavior. The visualization results as shown in Fig. 7 provide a strong evidence that the proposed model captures the underlying interactions between traffic participants and driver.

Fig. 7a and 7b showcase similar traffic configurations where the driver approaches a four-way intersection with the presence of other vehicles. Given different intentions, i.e., Left Turn in Fig. 7a and Right Turn in Fig. 7b, our model attends to objects that impact the ego-vehicle navigation. A similar phenomenon is observed in Fig. 7c and 7d. Note that a similar visualization is demonstrated in [47]. Different attention map characteristics are observed. While similar driving model architectures are leveraged, three
Table 4
Comparison with baselines. The methods with * are re-implemented by us to ensure the same backbone is used for fair comparisons. mAcc stands for mean accuracy, and the unit is %. The best and second best performances are shown in bold and underlined, respectively.

| Model                                           | Crossing Vehicle | Crossing Pedestrian | Parked Vehicle | Congestion |
|------------------------------------------------|------------------|---------------------|----------------|------------|
| Random Selection                                | 15.1             | 7.1                 | 6.4            | 5.5        |
| Driver’s Attention Prediction                  | 16.8             | 8.9                 | 10.0           | 21.3       |
| Driver’s Attention Prediction * [7]            | 22.6             | 9.5                 | 22.6           | 40.7       |
| Object-level Attention * [7]                   | 28.0             | 8.1                 | 15.6           | 35.7       |
| Random Selection                                | 27.5             | 13.6                | 26.0           | 51.3       |
| GCN + TRN Head (ours)                          | 29.0             | 13.2                | 27.3           | 52.2       |
| GCN + TRN Head + Data Augmentation (ours)      | 32.5             | 12.9                | 28.4           | 57.5       |

7.3 Risk Object Identification

7.3.1 Evaluation Setup

We evaluate risk object identification in the four reactive scenarios: Congestion; Crossing Pedestrian; Crossing Vehicle; and Parked Vehicle. We use accuracy (number of correct predictions over the number of samples) as the metric. A correct prediction is one that has an Intersection over Union (IoU) score between a selected box and a ground truth box that is larger than a predefined threshold. Similar to [65], [66], accuracies at IoU thresholds of 0.5 and 0.75 are reported. In addition, mean accuracy (mACC) is calculated by using IoU thresholds ranging from 0.5 to 0.95 (in increments of 0.05).

7.3.2 Evaluation

We compare the performance of Risk Object Identification with the following baselines. The results are shown in Table 4.

Random Selection. Random selection randomly picks an object as the risk object from all the detections for a given frame randomly. Note that the method does not process any visual information except object detection. The method is used to contextualize the challenge of this task.

Driver Attention Prediction uses a pre-trained model [9] trained on the BDD-A dataset to predict the driver’s gaze attention maps at each frame. We compute an average attention weight of every detected object region based on a predicted attention map. The risk object is the object with the highest attention weight, indicating the driver’s gaze attends to this region. The model is trained with human gaze signals that are unavailable in the proposed dataset.

The performance of this method is slightly better than Random Selection as reported in the second row of Table 4. We observe that predicted attention maps tend to focus at a vanishing point. Note that this issue has been raised in [10], highlighting the problem as one of the challenges of imitating human gaze behavior.

Object-level Attention Selector. The object-level attention driving model [8] is reformulated for risk object identification. The risk object is the object with the highest object-attention score.

Pixel-level Attention. Kim et al. [7] propose a causality test to search for regions that influence the network’s output behavior. Note that region proposals are formed based on sampling predicted pixel-level attention maps. To identify a risk object, we replace the region proposal strategy used in [7] with object detection, and utilize the inferred pixel-level attention map to filter out detections with low attention values. In the experiments, we set the threshold at 0.002. The modification ensures a fair comparison as region proposals obtained from [7] are not guaranteed to be an object entity. Note that the code of region proposal generation detailed in [7] is not publicly available.

We report favorable risk object identification performance over existing baselines [7], [8] in Table 4 The results indicate the effectiveness of the proposed intention-aware driving model and causal inference for the task. In the next section, we perform ablation studies to examine the contributions of each part of our model. Notice that our evaluation protocol differs from [15]. In [15], the authors train four different driving models and test four scenarios independently, whereas a single intention-aware driving model is trained in this work.

7.3.3 Ablation Study

Three variations are studied to analyze their impacts on the performance of risk object identification: (1) architecture of the driving model, (2) intention modeling and (3) training strategy. The results are summarized in Table 5.

Architecture The completed framework (GCN + TRN Head, reported in the last row of Table 5) boosts the mACCs of GCN by 6.2%, 0.5%, 3.0% and 24.6% in four different scenarios, respectively. The architecture ranks first in three scenarios (Crossing Vehicle, Parked Vehicle, and Congestion). We found interaction modeling is crucial, as it improves performance over a pure CNN+LSTM model.

Intention Modeling Both multi-head and TRN head based intention modelings improve overall performance. While the two modelings have similar risk object identification results, we choose TRN Head because it achieves better performance of the driver response prediction task.

Training with Data Augmentation We observe significant improvement in all scenarios with the proposed data augmentation strategy except Crossing Pedestrian. The results indicate the effectiveness of the proposed training strategy. For Crossing Pedestrian, our conjecture is that vehicles are likely to be chosen because of the natural imbalanced distribution in the training data. Note that the ratio of detected vehicles to pedestrians is approximately 17:1. Our model learns how to identify risk objects under traffic configurations (especially different vehicle configurations) so that the model performs favorably for scenarios that involve...
Driving Model | Data Augmentation | Causal Inference | Crossing Vehicle | Crossing Pedestrian | Parked Vehicle | Congestion
--- | --- | --- | --- | --- | --- | ---
CNN + LSTM | | ✓ | 29.9 29.9 26.3 | 15.5 14.3 12.4 | 33.1 28.7 25.4 | 39.4 35.4 32.9
GCN (ours) | ✓ | ✓ | 31.8 31.5 27.5 | 16.7 15.5 13.6 | 32.4 29.4 26.0 | 56.6 56.6 51.3
GCN + Multi-head (ours) | ✓ | ✓ | 31.8 31.8 28.0 | 17.9 17.9 14.6 | 32.4 29.4 26.3 | 61.6 57.6 53.8
GCN + TRN Head (ours) | ✓ | ✓ | 28.3 29.0 29.0 | 13.1 11.9 9.6 | 22.1 21.3 27.3 | 60.6 56.6 52.2
GCN + TRN Head (ours) | ✓ | ✓ | 37.0 37.0 32.5 | 15.5 15.5 12.9 | 35.3 31.6 28.4 | 66.7 62.6 57.5

**TABLE 5**
Ablation study of the proposed risk object identification framework. The unit is %. The best and second best performances are shown in bold and underlined, respectively.

![Image of driving model data augmentation](image)

**Fig. 8.** Risk object identification results obtained by Causation and Correlation. Note that Causation is the causal inference based approach proposed in the paper. Instead of using causal inference, Correlation determines the risk object by selecting the object with the highest attention weight to Ego in the Ego-Thing Graph. The top row shows an egocentric view where green boxes indicate our Causation results, blue boxes are Correlation results, and ground truth boxes are in red. A bird’s-eye-view representation is presented in the bottom row, providing information including scene layout and intentions of traffic participants.

interacting with vehicles. In contrast, scenarios that involve interacting with pedestrians are less emphasized. To solve this problem, a possible solution is to perform a category-aware intervention so that a balanced distribution can be obtained.

In summary, with the proposed components, i.e., TRN Head, intention modeling, and training with data augmentation, we demonstrate state-of-the-art risk object identification performance. Note that this observation is also found in driver response prediction, discussed in Section 7.2.

**7.3.4 Correlation vs. Causation**
We study the importance of causal modeling for this task. Instead of using causal inference (called Causation) to identify the risk object, the risk object is the object with the highest attention weight between Ego in Ego-Thing Graph. We call this method Correlation. In Table 5, the second to the last row shows the results of Correlation. Our Causation ap-
proach significantly outperforms Correlation in all reactive scenarios. We empirically demonstrate the need of casual modeling for this task.

In Fig. 8 ground truth risk objects are enclosed in red bounding boxes, our Causation results are shown in green, and the Correlation predictions are shown in blue boxes. In addition, we provide a bird’s-eye-view (BEV) pictorial illustration of scenes in the second row. Note that BEVs depict scene layouts, driver intention, and traffic participants’ intentions, with identified risk objects in green boxes. In Fig. 8 (b), three crossing pedestrians with different intentions are depicted. Our Causation approach correctly identifies the left-hand side pedestrian as the risk object while the driver intends to turn left. While Correlation predicts the same result, our method is more explainable because the decision is made by considering driver intention. Fig. 8 (d), (f), (g) and (h) showcase examples where Correlation fails but the proposed framework identifies risk objects successfully.

8 CONCLUSION

In this paper, we propose a novel driver-centric definition of risk, i.e., risky objects influence driver behavior. A new task called risk object identification is introduced and is formulated as a cause-effect problem. We present a novel two-stage risk object identification framework inspired by the model of situation awareness and causal inference. We also create a driver-centric Risk Object Identification (ROI) dataset to evaluate the proposed system. Extensive quantitative and qualitative evaluations are conducted. Favorable performance compared with strong baselines is demonstrated. Future work can leverage road topology explicitly to improve driver intention prediction. Additionally, a single shot risk object identification framework would be interesting to explore for practical applications.

ACKNOWLEDGMENTS

The work is sponsored by Honda Research Institute USA.

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