

# Diverse Critical Interaction Generation for Planning and Planner Evaluation

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**Abstract**—Generating diverse and comprehensive interacting agents to evaluate the decision-making modules is essential for the safe and robust planning of autonomous vehicles (AV). Due to efficiency and safety concerns, most researchers choose to train interactive adversary (competitive or weakly competitive) agents in simulators and generate test cases to interact with evaluated AVs. However, most existing methods fail to provide both natural and critical interaction behaviors in various traffic scenarios. To tackle this problem, we propose a styled generative model RouteGAN that generates diverse interactions by controlling the vehicles separately with desired styles. By altering its style coefficients, the model can generate trajectories with different safety levels serve as an online planner. Experiments show that our model can generate diverse interactions in various scenarios. We evaluate different planners with our model by testing their collision rate in interaction with RouteGAN planners of multiple critical levels.

## I. INTRODUCTION

Self-driving vehicles are expected to make transportation systems much more efficient in the future with smart decision-making systems that can avoid irrational behaviors leading to potential dangers. The safety and robustness evaluation of autonomous vehicle planners during online operation remains an essential but unsolved problem. As in all the other engineering fields, one fundamental philosophy to tackle this problem is through comprehensive testing. In reality, it takes hundreds of miles for autonomous vehicles to encounter various safe-critical cases. Such an evaluation process is both time-consuming and risky since we cannot control other traffic participants' behavior on the road. As a result, researchers have proposed multiple evaluation methods in simulator environments, where the key problem degenerates to designing diverse and natural test cases. To take advantage of prior knowledge and collected natural interaction data, researchers propose data-driven and learning methods for planner evaluation. In the testing process, *learned* interactive adversary (competitive or weakly competitive) agents are controlled to interact with the tested vehicle, and we use safety metrics like collision rate to evaluate planners' performance. By varying the environment and adversary agents in test cases, we can figure out possible failure modes and improve the decision-making algorithms. A common approach in previous test case generation methods is to sample diverse initial states of the adversary agents [1], [2].

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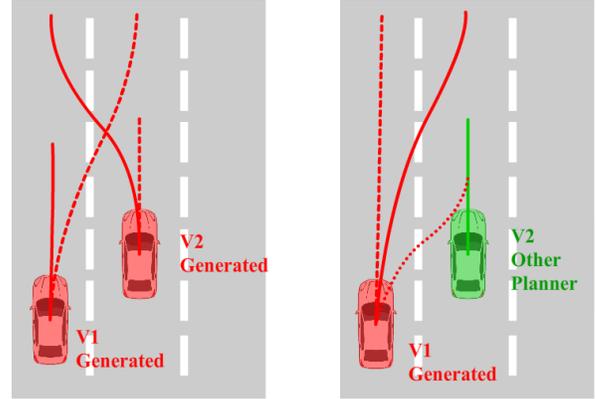


Fig. 1. **Left:** Previous generative methods produce various interactions by generating the trajectory of all the involved vehicles. **Right:** We plan on a single vehicle to generate diverse interactions and allow the other vehicle to use arbitrary planners (including the proposed RouteGAN).

However, one drawback of this approach is that they usually assume over-simplified adversary agents with little reaction to the tested vehicle. In reality, the adversary agents usually alter the speed and orientation based on observation of other vehicles during the interaction. Another popular approach is to train adversary agents with Reinforcement Learning (RL) to minimize the driving performance of tested agent [3]. The trained adversary agents have complex reacting driving behavior, but their reactions are usually not natural since they do not learn from human driving data. Moreover, they cannot be generalized to different road structures. To summarize, our main question is:

*Can we design interactive adversary agents for testing, which have diverse, natural behaviors in various scenarios?*

We notice that some previous data-driven trajectory generation methods can produce diverse, near-authentic trajectories [4], [5]. However, the purpose of these methods is to generate the whole interaction data. In other words, they generate the trajectory of all the agents jointly, rather than controlling a single agent conditioning on its observation on other agents. Therefore, we cannot directly use joint trajectories generation to control adversarial agents for testing case generation. Our proposed method is designed to remove such restrictions and apply data-driven methods to adversary agents training in planner evaluation.

In this paper, we propose RouteGAN, a deep generative model that generates diverse interactive behavior of a controlled vehicle using observations of the surrounding

vehicles. Instead of generating all the trajectories jointly, RouteGAN controls a single vehicle and allows controlling other vehicles with RouteGAN or any other planning modules as shown in Figure 1. To ensure the diversity of generated trajectories, we use a style variable to control the proposed generation process. In particular, one dimension of the style variable represents how critical the generated trajectory is, which allows us to produce safe, near-critical, and critical interactions with the surrounding vehicles. As a result, RouteGAN can be used as a safe planner during planning and planner for adversary agents during planner evaluation.

Our contribution can be summarized as follows.

- We propose RouteGAN, which can produce styled behavior of a single agent in multi-agent interaction scenarios. The proposed model controls the styles of agents separately and iteratively generates the whole interactions.
- Multi-branch safe/critical discriminators and Auxiliary Distribution Network are designed to ensure style control over generated behavior of the interacting vehicle. Experiments show that the model can generate diverse interactions in various scenarios.
- We use RouteGAN as an online opponent vehicle planner to test the performance of different planners. Results show that varying style input of RouteGAN controlled opponent vehicle increases the collision rate for rule-based and data-driven planning models.

## II. RELATED WORK

### A. Trajectory Prediction and Generation

Trajectory prediction aims at predicting the future state of multiple agents such as vehicles and humans, given the past observation of the surrounding environment [6]–[9]. Many researchers propose methods that take advantage of deep learning for trajectory prediction, and we further divide them into two categories: deterministic and non-deterministic prediction. Deterministic prediction outputs a single future trajectory for each agent. They are usually based on supervised learning and fit the expert data in the dataset directly [10]–[13]. One problem of deterministic prediction is that it does not take multi-modality into account. In reality, the driver can take various kinds of actions, which will lead to different outcomes. On the other hand, non-deterministic prediction methods can output multiple possible future trajectories for each agent. These methods usually contain a sampling process from which we can obtain the desired multi-modality trajectories. One line of work models the probability distribution of the future states via Gaussian mixture model (GMM) [14], [15]. Another line of work uses deep generative models to generate diverse behavior, including variational autoencoder (VAE) [4], [5], conditional VAE [16], and generative adversarial network (GAN) [17]. Our proposed method is inspired by these non-deterministic trajectory prediction methods.

### B. Safe-critical Planner Evaluation

There are various kinds of frameworks designed to test the planner performance under safe-critical cases. The purpose of these frameworks is to test if autonomous vehicles can make safe decisions while interacting with unknown drivers in different environments. Creating critical test scenarios for testing is one popular direction [2]. [1], [2] use adaptive sampling to generate multi-modal safe-critical initial conditions in cyclists-vehicle interactions. [18] generates critical scenarios with evolutionary algorithms. Another way to test the planners is to change the behaviors of other participating vehicles. Field Operational Tests (FOT) [19] directly use collected data to simulate opponents, [3] uses reinforcement learning (RL) to learn adversarial agents of critical driving styles. An obvious limitation for data-driven methods like FOT is the rareness of natural critical cases. RL-based methods suffer from poor generalization ability under different environments and unnatural generated behavior affected by reward design. Our work follows the second way but aims to extract diverse and controllable behavior from existing driving datasets.

### C. Path Planning and Trajectory Representation

The goal of path planning in autonomous driving is to find a trajectory (curve) that connects a start position and an end position. Such trajectory should avoid collision with obstacles and have some desired properties like smoothness and small curvature. The planned trajectory is usually represented by parametric models. Common parametric models include polynomials [20], splines [21], [22], clothoids [23], and Bezier curves [24], [25]. [26] provides a review of these methods. We use optimization methods to search for the optimal parameters of models that meet our requirements.

### D. Deep Generative Models

In recent years, researchers have proposed various deep learning based generative models to represent the data distribution. VAE [27] assumes that the latent variable to generate the data follows a Gaussian distribution. VAE is used by recent trajectory methods for latent space interpolation [5]. There are several variants of VAE. One important variant is the CVAE [28] whose generation process is conditioned on a controllable variable. GAN [29] trains a generator network to produce near-authentic data by an adversary process. InfoGAN [30] proposes to maximize the mutual information between latent variables and the generated data. The mutual information maximization in InfoGAN is implemented by introducing an auxiliary distribution network for variational lower bound maximization. InfoGAN is able to learn disentangled and interpretable latent representation. Such property is used in our work to produce data of various styles.

## III. PROBLEM FORMULATION

### A. Trajectory Generation

While trajectory prediction frameworks focus more on predicting future trajectories given historic observations, styled trajectory generation focuses more on generating

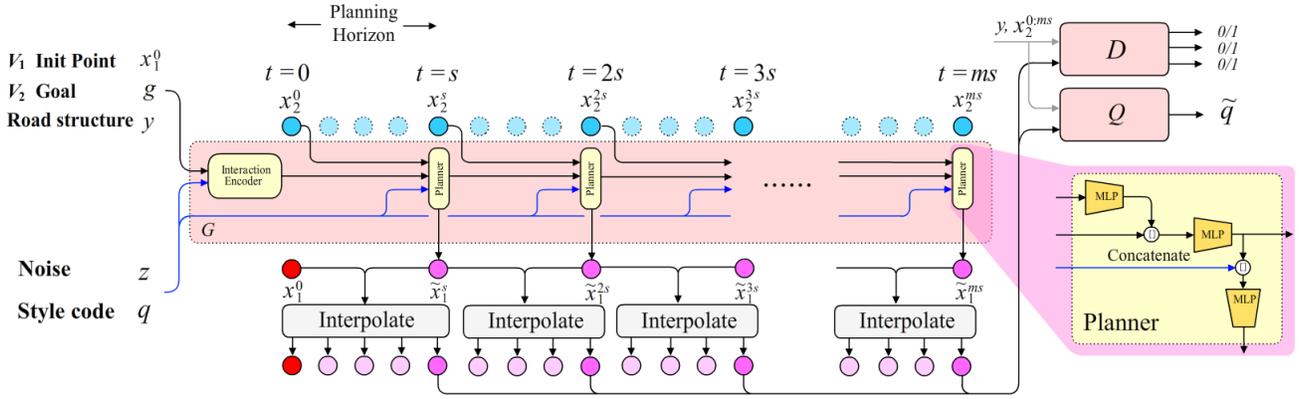


Fig. 2. This figure shows the overview framework of our proposed algorithm. The generator network  $G$  only generates several key waypoints (darker pink circles), and the other intermediate states are from interpolation (lighter pink circles). Our algorithm can be used for  $V_1$ 's planning as follows. At each planning step (i.e.,  $0, s, 2s, \dots, ms$ ), we will use the past and current information of  $V_2$  to generate the next waypoint. Then, we use interpolation to generate all the intermediate points on the trajectory.

interactive trajectories based on initial states and goals of different agents. The reason is that styles can be inferred from historic observations, and they usually remain the same during the whole interaction. We assume that the collected interaction data follow this assumption. As a result, the styled generation problem is formulated as generating trajectories of all  $k$  interacting vehicles  $\{x_i^{1:T}\}_{i=1}^k$  given their initial states  $\{x_i^0\}_{i=1}^k$  and controllable input  $c$  corresponding to different interaction factors (styles, goals, etc). Unlike most previous generation works that jointly produce all vehicles' trajectories, our proposed framework is designed to generate diverse trajectories of one certain vehicle in a finite planning horizon  $s$  based on the current state and goals of all the traffic participants  $\{x_g\}_{i=1}^k$  so as to create various kind of reactions. Instead of control a single variable  $c$  for the whole interaction, we assume different styles for all the vehicles  $\{q_i\}_{i=1}^k$ . The future trajectory of the  $i$ th agent  $x_i^{t:t+s}$  is generated using  $[\{x_i^t\}_{i=1}^k, \{x_g\}_{i=1}^k, y, q_i]$ . The agent plans every  $s$  steps after observing other vehicles' up-to-date states, and the planning horizon  $s$  is a hyperparameter for decision frequency in practice. In this way, we can generate the interacting behaviors of a participating agent with controlled styles. If all vehicles are controlled by their styled generators, we can iteratively generate the joint behavior of multiple vehicles. If we control only the ego vehicle, the generation framework can be directly used as an online planner.

### B. Planning and Planner Evaluation

For simplicity, we consider interactions between two vehicles on the road in the later discussion and denote them as  $V_1$  and  $V_2$  respectively. In the planning setting, as discussed before, the route generator can be used to plan the trajectory of vehicle  $V_1$  given past observations and the estimated goal of an unknown driver  $V_2$ . The first dimension of  $V_1$ 's style variable  $q^{(1)} := q_1^{(1)}$  in our generation model can be used to control the conservative degree of the planner.

We can also perform tests on different planners by using this generator as an opponent agent. Assume  $V_1$  is still controlled by our generator with varying  $q_1$  representing

different driving styles, and  $V_2$  is controlled by a rule-based, data-driven, or human-controlled planner, we can perform a safety evaluation on  $V_2$  planner by changing the style of  $V_1$  from conservative to aggressive. For most planners, we can expect safety metrics like collision rate to increase as we increase the critical factor  $q^{(1)}$  of our RouteGAN controller.

## IV. METHOD

### A. Overview

The proposed framework, RouteGAN, is illustrated in Figure 2. The generator network  $G$  outputs the trajectory as follows. It first encodes  $V_1$ 's initial positions  $x_1^0$ , the final goal  $g$  of  $V_2$ , the road structure  $y$ , the style code  $q$ , and the noise  $z$  into an initial hidden vector  $h^{-s}$ . Here, the road structure  $y$  is represented by a bird-eye view image. The position of  $V_1$  and  $V_2$  is based on such image. We use  $(-1, -1)$  and  $(1, 1)$  to describe the up left corner and bottom right of  $y$  respectively. The final goal  $g$  is the expect position of  $V_2$  in the future and is represented by a coordinate. As is stated above, our planner plans for every  $s$  steps from time  $t = 0$ . At time  $ks$ , the planner module combine previous hidden vector  $h^{(k-1)s}$  with style code  $q$  and current observation of  $V_2$  to produce the next hidden vector  $h^{ks}$  and next key waypoint of  $V_1$ , denoted as  $\tilde{x}_1^{(k+1)s}$ . Then, we use interpolation to generate the trajectory of  $V_1$  between current position  $x_1^{ks}$  (i.e.,  $\tilde{x}_1^{ks}$ ) and the generated key waypoint  $\tilde{x}_1^{(k+1)s}$ :

$$x_1^{ks:(k+1)s} = \text{Interpolate}(\tilde{x}_1^{ks}, \tilde{x}_1^{(k+1)s}), k = 0, 1, \dots, m-1. \quad (1)$$

In order to make the generator produce natural and diverse trajectories, a multi-branch discriminator  $D$  (natural) and an auxiliary distribution network  $Q$  (diverse) are introduced. Our method assumes access to a safe interaction dataset as well as a critical interaction dataset. The discriminator  $D$  should determine whether a trajectory is natural and whether a given interaction is from the safe dataset or the critical dataset. The auxiliary distribution network  $Q$  should reconstruct  $q$  from the generated interaction to ensure that the generated interaction contains the style information.

In the remaining subsections, we introduce the detailed structure of RouteGAN in IV-B, the loss functions and the training process of RouteGAN in IV-C. The interpolation method is introduced in IV-D, and finally in IV-E, we briefly discuss the difference of our methods compared to prior generative methods.

## B. RouteGAN

1) *Generator G*: The generator  $G$  first packs up the environment information of the interaction.

$$z_{scene} = F_{scene}(y), \quad (2)$$

$$z_g = F_g(g), \quad (3)$$

$$z_{init} = F_{init}(x_1^0). \quad (4)$$

In above equations,  $F_{scene}$  is a Convolutional Neural Network (CNN) [31].  $F_g$  and  $F_{init}$  are Multi-Layer Perceptrons (MLP) [31]. Then, we combine these vectors to produce the initial hidden vector.

$$h_{init} = h^{-s} = H_{init}([z_{scene}, z_g, z_{init}, q, z]). \quad (5)$$

$H_{init}$  is an MLP.  $[\cdot]$  refers to vector concatenation. Then, the generative network iteratively uses the style variable  $q$  and current observation of  $V_2$  to update the hidden vector and predict the future position of  $V_1$ . The update of hidden vector is computed as

$$z_2^t = H_2(x_2^t), t = 0, s, 2s, \dots, ms, \quad (6)$$

$$h^t = F_{update}([z_2^{t-s}, h^{t-s}]), t = s, 2s, \dots, ms. \quad (7)$$

$H_2$  and  $F_{update}$  are MLPs. Finally, we use the hidden vector, the style code  $q$ , and noise  $z$  to predict the next key waypoint.

$$\tilde{x}_1^{t+s} = \tilde{x}_{1,q}^{t+s} = F_{trajectory}([h^t, q, z]), t = 0, s, \dots, (m-1)s. \quad (8)$$

$s F_{trajectory}$  is an MLP.  $q$  takes value from  $[-2, 2]^c$ , where  $c$  is the dimension of  $q$ . As we have discussed before, we use the first dimension of  $q$ , denoted as  $q^{(1)}$ , to represent the critical rate of the interaction.  $z$  is a random vector and is sampled from normal distribution.

2) *Discriminator D*: The discriminator is trained to distinguish the fake interactions from the real interactions. To model the style of interaction, we build two extra branches in the discriminator network for safe and critical interactions. The three branches are denoted as  $D_{valid}$ ,  $D_{safe}$ , and  $D_{critical}$  respectively.  $D_{valid}$  takes the key point sequence and the scene as input, and it tries to distinguish generated waypoint-scene pair  $(\tilde{x}_1^{0,s,\dots,ms}, y)$  from real waypoint-scene pairs, which are sampled from the dataset.  $D_{safe}$  takes the interactions (i.e., the key waypoint sequences of an interactive vehicle pair  $(\tilde{x}_1^{0,s,\dots,ms}, \tilde{x}_2^{0,s,\dots,ms})$ ) as input and it tries to distinguish the generated interaction from real, safe interaction pairs drawn from the dataset. Similarly,  $D_{critical}$  takes the interactions as input, and it tries to distinguish the generated interaction from real, critical interaction pairs drawn from the dataset.

3) *Auxiliary Distribution Network Q*: In order to ensure that the style of the generated key waypoint sequence can be controlled by the style variable  $q$ , we use an auxiliary distribution network  $Q$  to maximize the mutual information between  $q$  and  $\tilde{x}_1^{0,s,\dots,ms}$ . This can avoid the case where the model treats style variable  $q$  as a dispensable input and only use past trajectories for future generations. In practice, we train a auxiliary distribution network  $Q$  to reconstruct  $q$  with  $\tilde{x}_1^{0,s,\dots,ms}$ ,  $\tilde{x}_2^{0,s,\dots,ms}$  and  $y$ .

## C. Loss functions

We introduce the following loss functions to train our RouteGAN.

1) *Discriminator loss*: The loss of  $D_{valid}$  is defined as

$$\mathcal{L}_{valid}^D = \mathbb{E}(\log(D_{valid}(x^{0,s,\dots,ms}, y)) + \log(1 - D_{valid}(\tilde{x}_1^{0,s,\dots,ms}, y))).$$

Here,  $x^{0,s,\dots,ms}, y$  is randomly drawn from the dataset. Concretely, we randomly select a trajectory  $x^{0:T}$  in the dataset and extract its key waypoints  $x^{0,s,\dots,ms}$ . Then, we put  $x^{0,s,\dots,ms}$  and its corresponding scene observation  $y$  together to create a real sequence-scene pair. The loss of  $D_{safe}$  is defined as

$$\mathcal{L}_{safe}^D = \mathbb{E}(\log(D_{safe}(\Gamma(x_{safe:1}^{0,s,\dots,ms}, x_{safe:2}^{0,s,\dots,ms}))) + \log(1 - D_{safe}(\Gamma(x_2^{0,s,\dots,ms}, \tilde{x}_1^{0,s,\dots,ms}))) + \log(1 - D_{safe}(\Gamma(x_{critical:1}^{0,s,\dots,ms}, x_{critical:2}^{0,s,\dots,ms}))).$$

In the above equation,  $x_{safe:1}^{0,s,\dots,ms}$  and  $x_{safe:2}^{0,s,\dots,ms}$  are key waypoint sequences extracted from a safe interaction  $(x_{safe:1}^{0:T}, x_{safe:2}^{0:T})$  sampled from the dataset.  $x_{critical:1}^{0,s,\dots,ms}$  and  $x_{critical:2}^{0,s,\dots,ms}$  are key waypoint sequences extracted from a critical interaction  $(x_{critical:1}^{0:T}, x_{critical:2}^{0:T})$  sampled from the dataset.  $\Gamma$  is a differentiable augmentation operation. Such augmentation is a composition of normalization and random rotation transformation defined as

$$\Gamma(x_1, x_2) = (U(x_1 - \mu(x_1, x_2)), U(x_2 - \mu(x_1, x_2))). \quad (9)$$

Here,  $\mu(x_1, x_2)$  is the mean position of the two trajectories,  $U$  is a random rotation matrix. We find that such augmentation step can make RouteGAN provide more diverse and robust results in practice. Minimizing  $\mathcal{L}_{safe}^D$  enforces  $D_{valid}$  network to discriminate critical interactions and fake interactions from the real, safe interactions. Similarly, the loss function of  $D_{critical}$  is defined as

$$\mathcal{L}_{critical}^D = \mathbb{E}(\log(D_{critical}(\Gamma(x_{critical:1}^{0,s,\dots,ms}, x_{critical:2}^{0,s,\dots,ms}))) + \log(1 - D_{critical}(\Gamma(x_2^{0,s,\dots,ms}, \tilde{x}_1^{0,s,\dots,ms}))) + \log(1 - D_{critical}(\Gamma(x_{safe:1}^{0,s,\dots,ms}, x_{safe:2}^{0,s,\dots,ms}))).$$

The loss function of discriminator is the combination of the above losses:

$$\mathcal{L}^D = \mathcal{L}_{valid}^D + \mathcal{L}_{safe}^D + \mathcal{L}_{critical}^D. \quad (10)$$

2) *Generator loss*: The goal of generator is to produce critical interactions as real as possible. The loss function of the generator contains three terms  $\mathcal{L}_{valid}^G, \mathcal{L}_{safe}^G$ , and  $\mathcal{L}_{critical}^G$ . They correspond to the three discriminator loss terms above respectively. They are defined as

$$\mathcal{L}_{valid}^G = \mathbb{E}(\log(D_{valid}(\tilde{x}_1^{0,s,\dots,ms}, y))), \quad (11)$$

$$\mathcal{L}_{safe}^G = \mathbb{E}(\log(D_{safe}(x_2^{0,s,\dots,ms}, \tilde{x}_{1,q^{(1)} < 0}^{0,s,\dots,ms}))), \quad (12)$$

$$\mathcal{L}_{critical}^G = \mathbb{E}(\log(D_{critical}(x_2^{0,s,\dots,ms}, \tilde{x}_{1,q^{(1)} > 0}^{0,s,\dots,ms}))). \quad (13)$$

Then, the loss of generator is defined as

$$\mathcal{L}^G = \alpha \mathcal{L}_{valid}^G + \mathcal{L}_{safe}^G + \mathcal{L}_{critical}^G. \quad (14)$$

Here  $\alpha$  is a hyperparameter balancing the weight of  $\mathcal{L}_{valid}^G$ . This is designed to encourage diversity, since some scenarios in the dataset only provide single mode such as following the straight line. An  $\alpha < 1$  can introduce more possible modes into these scenarios.

3) *Information loss*: The goal of  $Q$  network is to reconstruct the style variable  $q$ . Therefore, we minimize the following  $L_2$  loss.

$$\mathcal{L}^Q = \frac{1}{2} \mathbb{E} \|q - Q(\tilde{x}_{1,q}^{0,s,\dots,ms}, y)\|^2.$$

4) *Road constraint loss*: We also find it useful to add in a road constraint loss. This term can ensure that the generated key points lie within the road. It is defined as follows. First, we use a heat map operation  $\mathbb{R}^2 \rightarrow \mathbb{R}^{w \times h}$  to transform the generated key point onto a 2D map. It is defined as

$$\text{Heatmap}(x)(u, v) = \exp\left(-\frac{(u - x_1)^2 + (v - x_2)^2}{2\sigma^2}\right). \quad (15)$$

Here,  $\sigma$  is a hyperparameter. This mapping is differentiable so we can define the road constraint loss as

$$\mathcal{L}_{road} = \text{mean}\left(\frac{1}{m} \sum_{k=1}^m (1 - y) \cdot (\text{Heatmap}(\tilde{x}_1^{k,s}))\right). \quad (16)$$

The overall optimization process proceeds as follows. For each training step, we optimize  $D$  network using the loss function  $\mathcal{L}^D$  for 4 steps with  $G$  and  $Q$  fixed. Then we fix  $D$  network and optimize  $G$  and  $Q$  using the loss function  $\mathcal{L}^{G,Q}$  defined by

$$\mathcal{L}^{G,Q} = L_G + \lambda_1 L_Q + \lambda_2 L_{road}. \quad (17)$$

Here,  $\lambda_1$  and  $\lambda_2$  are two hyperparameters balancing the weight of each loss term.

#### D. Interpolation

To obtain the trajectory of the vehicle between discrete key waypoints, one simple approach is piecewise linear interpolation. However, piecewise linear interpolation will lead to non-smoothness at each key waypoint. Therefore, we only use linear interpolation for the first two key waypoints  $x_1^0, x_1^1$ . For the interpolation between the latter key waypoints, we use Bezier curve and the process is shown in the Figure 3. Let  $P_0, P_1$  be two consecutive key waypoints.  $D_0$  is the orientation of vehicle at  $P_0$ . Then we determine  $D_1$ , the

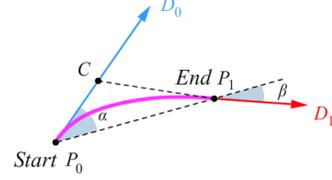


Fig. 3. Bezier curve interpolation used in the proposed method.

orientation of vehicle at  $P_1$  by the following heuristic. Let  $\alpha$  be the angle (with sign) between  $D_0$  and  $P_0P_1$ ,  $\beta$  be the angle (with sign) between  $P_0P_1$  and  $D_1$ . Then we set  $\beta = \alpha k$ .  $k$  is a scaling parameter and is heuristically defined as 0.25. Finally, the control point  $C$  of Bezier curve is set to be the intersection point of the two lines defined by  $(P_0, D_0)$  and  $(P_1, D_1)$ . It is explicitly given by

$$C = P_0 + \frac{(P_{1x} - P_{0x})D_{1y} - (P_{1y} - P_{0y})D_{1x}}{D_{0x}D_{1y} - D_{0y}D_{1x}} D_0. \quad (18)$$

We compute the trajectory  $\gamma$  between  $P_0$  and  $P_1$  using  $P_0, C$  and  $P_1$ , i.e.  $\gamma(t) = P_0(1-t)^2 + 2Ct(1-t) + P_1t^2$ .

#### E. Discussion

There are two main factors that our model differs from the previously proposed learning based trajectory generation models. First, previous methods usually use the generator network to generate the full trajectory. In contrast, our generator network only generates few key waypoints, and we obtain the *full* trajectory by interpolation. We find this modification crucial in experiments as it makes the generation process focus more on the global shape information rather than local details, which can bring out various styles.

Secondly, we split the discriminator into different branches and introduce an augmentation step. This operation can decouple the interaction from a particular viewpoint and avoid mode collapse.

## V. EXPERIMENTS

#### A. Settings

We use the Argoverse dataset [32] and INTERACTION dataset [33] to evaluate RouteGAN. Argoverse is used by the latest interaction generation method CMTS [5]. In our experiments, we adopt the same modified Argoverse trajectory dataset used by CMTS, which contains interaction data in the straight road and intersection scenarios. We also use the interaction data in roundabout scenarios in INTERACTION. Since the number of critical interaction data in these datasets is less than that of safe interactions, we apply some simple data augmentation tricks to generate some pseudo-critical interactions. The tricks include temporal realignment which relabels the timestamps of safe interactions to turn them into critical interactions, and local deformation which slightly alters the trajectory's shape to produce intersections.

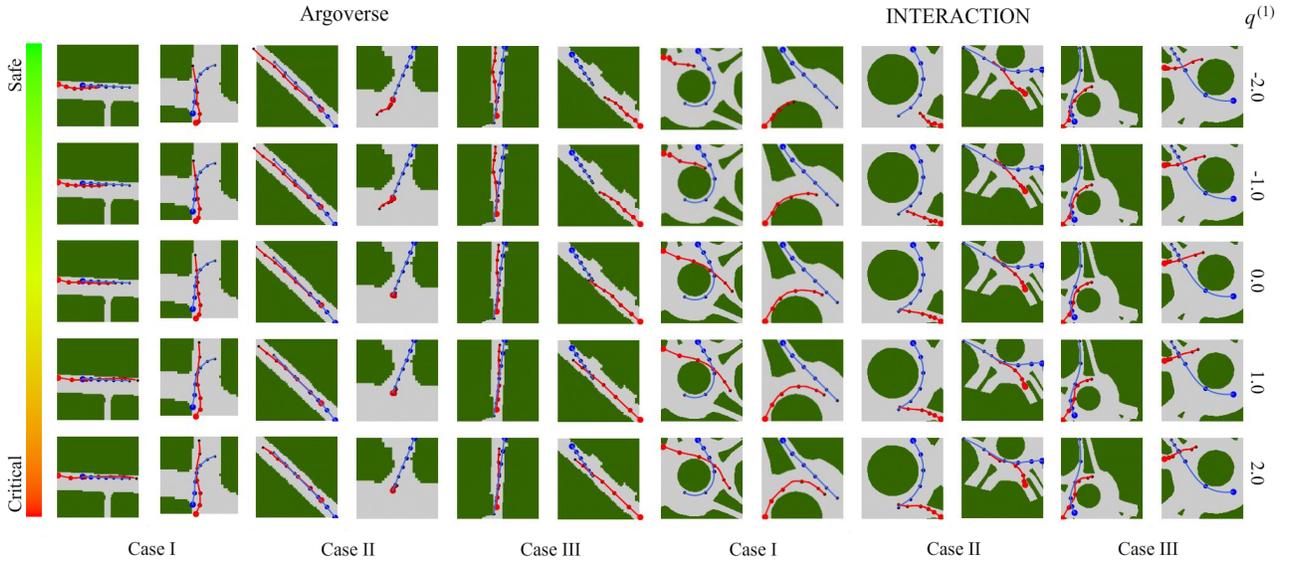


Fig. 4. Generated interaction examples on Argoverse dataset and INTERACTION dataset. Through out the later part of this paper, the red line indicates the trajectory of  $V_1$  (RouteGAN) and the blue line indicates the trajectory of  $V_2$ . The start point is indicated by the largest circle.

### B. Qualitative Case Study

In this part, we visualize some typical generated interactions on Argoverse and INTERACTION. In order to make it easier to understand the effect of  $q^{(1)}$ , which is the first dimension of the style variable of vehicle  $V_1$ , we assume that  $V_2$  simply follows the trajectory in the dataset. We design three common intersection cases:

Case I.  $V_1$  and  $V_2$  go in the same direction. At the beginning,  $V_1$  is behind  $V_2$ .

Case II.  $V_1$  and  $V_2$  go in the same direction. At the beginning,  $V_1$  is ahead of  $V_2$ .

Case III.  $V_1$  and  $V_2$  go in the opposite direction. Note that in the roundabout scenario,  $V_1$  and  $V_2$  can not go in the opposite direction since it is invalid. Therefore this case is substituted by intersection.

The generation interaction results of above cases on two datasets are shown in the Figure 4. We selected 2 different scenarios for each case. From up to down we set  $q^{(1)}$  to  $-2.0, -1.0, 0.0, 1.0, 2.0$  with other dimension of style code  $q$  fixed, which shows a transition from safe interaction into critical interaction. Compared with our method, we find that CMTS can not provide promising results on roundabout scenarios though it is verified on Argoverse. Therefore, we do not display its result here and we refer readers to the paper directly for its result on Argoverse.

1) *Result on Case I:* For the safe interaction,  $V_1$  follows  $V_2$  slowly. As  $q^{(1)}$  increases,  $V_1$  gradually speeds up and hits  $V_2$  from behind.

2) *Result on Case II:* For the safe interaction, the typical result is that  $V_1$  speeds up and avoids collision with  $V_2$ . Another kind of generated interaction is that  $V_1$  turns to another lane and gives its way to  $V_2$ . However, as  $q^{(1)}$  increases,  $V_1$  stops in the center of the road or even goes

backwards, which leads to crashes if  $V_2$  does not slow down in time.

3) *Result on Case III, Argoverse:* For the safe interaction,  $V_1$  turns to a different lane or slow down. As  $q^{(1)}$  increases,  $V_1$  no longer stays away from  $V_2$  and runs into  $V_2$ 's lane.

4) *Result on Case III, INTERACTION:* For the safe interaction,  $V_1$  proceeds based on the priority (i.e.,  $V_2$  go first). But as  $q^{(1)}$  increases,  $V_1$  no longer waits for  $V_2$  and crashes into it regardless of its lower priority.

### C. Joint Generation of Interactions

We also demonstrate that RouteGAN is able to generate interactions jointly as [4], [5], [17]. In this section, both  $V_1$  and  $V_2$  are controlled by RouteGAN and their style codes are denoted as  $q_1$  and  $q_2$  respectively. For a car-following scenario, we sweep  $q_1^{(1)}$  and  $q_2^{(2)}$  in the latent spaces with step size 1.0 and fix  $z$  and all the other dimensions of  $q_1$  and  $q_2$ . The reason for this design is that the  $q_2^{(2)}$  controls the geometry of the leading car  $V_2$  and  $q_1^{(1)}$  controls the interacting style of  $V_1$  in this car-following case. One example is shown in the Figure 5. Similarly, when  $q_1^{(1)}$  increases, the generated  $V_1$ 's trajectories gradually becomes more critical as expected.  $q_2^{(2)}$  controls the 'bending' style of  $V_2$ 's trajectory.

### D. Diversity of Generated Interactions

In this subsection, we verify that RouteGAN is able to generate diverse interactions. Controlling both cars with RouteGAN and sweeping the latent space is more complicated since the vehicles are affecting each other, making comparison between interactions hard. Therefore, we control  $V_1$  here to show diversity of planned trajectories given the same observations. We sweep  $q^{(1)}$  and  $q^{(2)} := q_1^{(2)}$  in the latent space  $[-2.0, 2.0] \times [-2.0, 2.0]$  with step size 1.0 and fix  $z$  and other dimensions of  $q$ . Then, we use these codes to

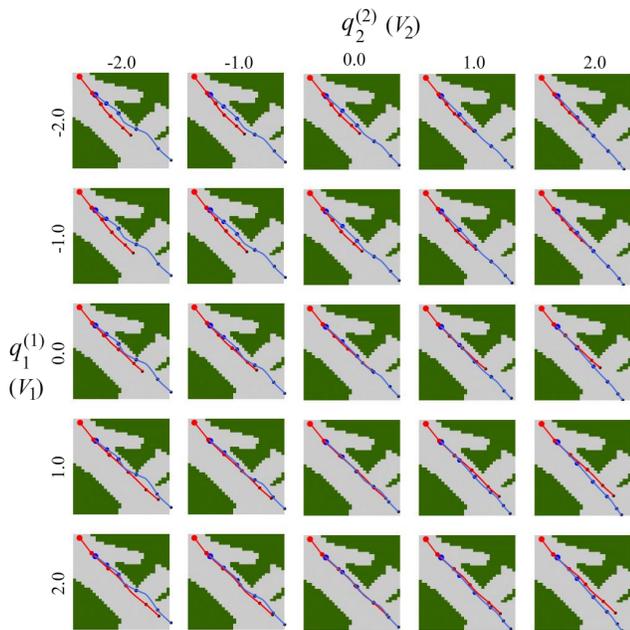


Fig. 5. The result of generating interactions jointly. Both  $V_1$  and  $V_2$  are controlled by RouteGAN.

generate interactions. One example is shown in the Figure 6. When  $q^{(1)}$  increases, the generated  $V_1$ 's trajectory gradually intersects with  $V_2$ 's trajectory as expected. Meanwhile,  $q^{(2)}$  controls the ‘bending’ style of  $V_1$ 's trajectory. As  $q^{(2)}$  varies from  $-2.0$  to  $2.0$ , the trajectory of  $V_1$  will bend upwards and follow  $V_2$  from different directions.

### E. Application: Planner Testing

One direct application of RouteGAN is simulation-based autonomous driving decision system testing. To test a planner's response to various interactions, we can use RouteGAN as its adversary in the interaction. In this experiment, we verify RouteGAN's testing performance. Since  $q^{(1)}$  reflects the level of interaction safety, we expect that the collision rate increases as  $q^{(1)}$  increases. We assume that the tested system is able to carry out perfect control. In other words, the low-level controller can strictly follow the trajectory calculated by the upper-level planners. We choose the following decision-making systems to test.

1) *Data Planner*: Data planner is a dummy planner which only follows the reference trajectory in the dataset.

2) *IDM Planner*: Intelligent driver model (IDM) [34] is a differential dynamic system which models the dynamics of multiple vehicles on an infinitely long line. To apply this model in 2 dimensional planning, we project the coordinate of  $V_1$  onto  $V_2$ 's reference trajectory and use Runge-Kutta 4 method [35] to calculate the future position.

3) *Astar Planner*: Astar [36] is a basic planning baseline in AI and autonomous driving. It will search for optimal acceleration along the reference trajectory at each time step.

The testing result is shown in the Table I. We observe that the collision rate increases as  $q^{(1)}$  goes up. Since data

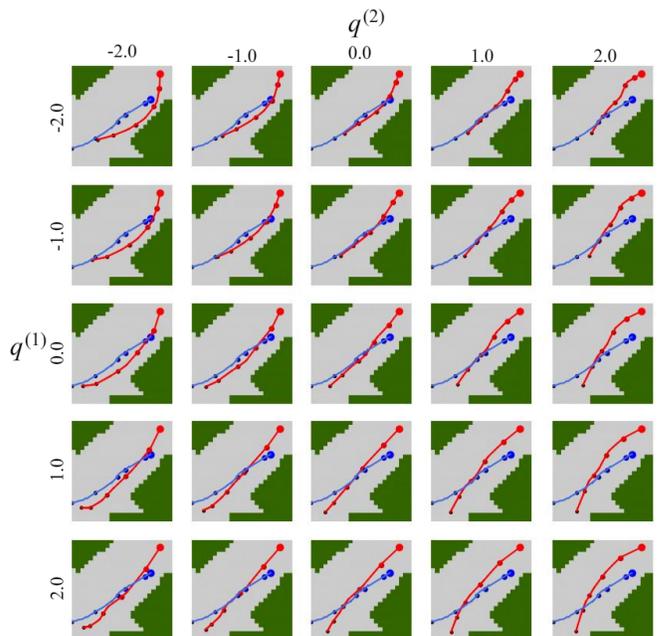


Fig. 6. The result of latent space sweeping.

TABLE I  
THE COLLISION RATES OF PLANNERS INTERACTING WITH DIFFERENT STYLES OF ROUTEGANS

$V_1$	$V_2$	Coefficient $q^{(1)}$				
		-2.0	-1.0	0.0	1.0	2.0
RouteGAN	Data	4.2%	9.1%	47.1%	88.6%	95.3%
RouteGAN	IDM	1.4%	3.0%	8.7%	18.1%	24.4%
RouteGAN	Astar	0.0%	0.0%	1.5%	4.8%	6.5%

planner simply follow the reference regardless of the motion of  $V_1$ , the collision rate of it is high when  $q^{(1)} > 0$ . The collision rate of IDM and Astar planner is in general much lower than that of the data planner. However we find that IDM planner is still not good enough when it comes to intersection cases, since one assumption of IDM planner is that  $V_1$  will move along  $V_2$ 's reference trajectory. Note that the result for RouteGAN itself is not shown in our planner evaluation. This is because we do not put collision as a soft or hard penalty in our model to generate critical cases. Therefore RouteGAN is not the best choice for collision avoidance. From the experiment, we can see that the collision rate in planner evaluation is directly affected by the driving style of adversary agents. Given the same initial conditions, aggressive drivers can better test the robustness of planners in critical cases. Our designed planner evaluation framework can help planners to improve their critical-case performance.

## VI. CONCLUSION

In this work, we investigate the problem of generating diverse interactive behavior of controlled vehicles. We propose RouteGAN, a generative model to solve this problem by controlling a style variable to produce safe or critical interaction behaviors with observations of participating vehicles. We demonstrate the diversity of generated trajectories in different

traffic scenarios, proving its ability to serve as a safe planner. Finally, we use it as an adversary agent to perform safety evaluations on different planners and validate the increase of collision rate by varying the style of the adversary agent.

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