Improving Diversity of Multiple Trajectory Prediction based on Map-adaptive Lane Loss

Sanmin Kim, Hyeongseok Jeon, Junwon Choi, and Dongsuk Kum*

Abstract—Prior arts in the field of motion predictions for autonomous driving tend to focus on finding a trajectory that is close to the ground truth trajectory. Such problem formulations and approaches, however, frequently lead to loss of diversity and biased trajectory predictions. Therefore, they are unsuitable for real-world autonomous driving where diverse and road-dependent multimodal trajectory predictions are critical for safety. To this end, this study proposes a novel loss function, Lane Loss, that ensures map-adaptive diversity and accommodates geometric constraints. A two-stage trajectory prediction architecture with a novel trajectory candidate proposal module, Trajectory Prediction Attention (TPA), is trained with Lane Loss to encourage multiple trajectories to be diversely distributed, covering feasible maneuvers in a map-aware manner. Furthermore, considering that the existing trajectory performance metrics are focusing on evaluating the accuracy based on the ground truth future trajectory, a quantitative evaluation metric is also suggested to evaluate the diversity of predicted multiple trajectories. The experiments performed on the Argoverse dataset show that the proposed method significantly improves the diversity of the predicted trajectories without sacrificing the prediction accuracy.

Index Terms—Autonomous Vehicle, Motion Prediction, Trajectory Forecasting, Multimodal Prediction, Diverse Prediction

I. INTRODUCTION

FORECASTING the future trajectory of dynamic agents in a multi-agent environment is a fundamental task for mobile robotics such as autonomous driving. To preemptively take action for the uncertain future, the future motion prediction of nearby agents is necessary. However, Future motions of nearby agents are highly uncertain, and therefore, it is insufficient to predict their future deterministically (e.g., selecting a single trajectory with the most likelihood). Suppose that the prediction output of the surrounding agent provides both future trajectories of lane-keeping and turns with the probability of 0.8 and 0.2 each. In this case, the planner can take action for the lane-keeping prediction while proactively preparing for the turn. In contrast, if the prediction model only returns lane-keeping results, the planner cannot have contingency plan for the turning case in advance since there is only one predicted maneuver or trajectory. For this reason, predictions that can cover a wide range of uncertain futures, even those less likely to happen, are required in order for the decision/planning module to guarantee safety at all times so that an autonomous agent can beware of it.

However, developing a reliable prediction model that can generate multiple trajectories with diverse maneuvers is challenging due to several issues. First, there is only a single ground truth modality per scenario in datasets. The lack of diverse ground truth for a given scenario poses a huge barrier for multiple trajectory prediction. Second, most of the trajectory datasets have a highly imbalanced distribution in which the lane-keeping trajectory is highly dominant compared to other maneuvers such as lane changes/turns. For example, in Argoverse motion forecasting dataset, which is one of the largest trajectory dataset, more than 90 percents of target agents’ maneuver is going straight as presented in table I. Such imbalance in the distribution of datasets leads to biased prediction results (prediction results are overwhelmed by lane-keeping). Third, a driving environment such as a road map is various and hardly generalized. Because vehicles should follow the lanes, trajectories are distinct in different road geometry. Therefore, the prediction model should be able to handle various road geometry adaptively to work in the diverse road shapes adequately.

In the literature on motion predictions, previous works [1]–[11] have proposed several multimodal prediction models with decent prediction accuracy in terms of final and average distance errors (FDE and ADE). In particular, many of them leverage road information to output multiple predictions. However, the multimodality in these models cannot address...
the diversity problem because they are trained based on the ground truth that represents only a single modality among various possible maneuvers. Especially, going straight amounted to the majority of the ground truth maneuver. In addition, multimodal prediction models trained with the imbalanced dataset tend to output multiple trajectories distributed longitudinally, increasing prediction accuracy in imbalanced validation and test set even if outputs are not diverse. Furthermore, most of conventional works evaluate prediction results based on FDE and ADE, which cannot measure the diversity of prediction results quantitatively or qualitatively. Thereby, they can cause critical failure cases by preventing the decision/planning module from proactively taking action with a contingency plan for unexpected futures.

In this work, we present a simple yet effective method to improve the diversity of multiple trajectory predictions in a map-adaptive manner. Our novel Lane Loss leverages map information to make multiple trajectory outputs cover diverse maneuvers including ones that have never been observed in the ground truth of datasets. We first find multiple feasible reference lanes from the map information and encourage the outputs to be spread over those reference lanes. With Lane Loss, the prediction model can output diverse future trajectories overcoming the imbalance problem and the limitation of unimodal annotation in trajectory datasets. Thereby, downstream motion planners can reckon with uncertain futures in their planning. Moreover, since Lane loss utilizes map information adaptively, it makes the prediction model generalizable for various road environments. It is worth noting that the Lane Loss only works in the training phase, and there is no additional burden in inference.

Furthermore, we propose a two-stage prediction architecture with Trajectory Proposal Attention (TPA), which generates trajectory candidates inspired by a two-stage object detection framework that leverages region proposals for more accurate detection results. TPA generates trajectory proposals in the middle of the prediction model so that the rest of the network can leverage trajectory proposals to output more accurate final prediction results. TPA not only improves prediction accuracy but also allows Lane loss to be applied twice for both trajectory candidates and final predictions to enhance the prediction results’ diversity.

Lastly, we propose a quantitative evaluation metric, min-LaneFDE, that can evaluate both the diversity and feasibility at the same time. Since the conventional metrics such as Average Distance Error (ADE) and Final Distance Error (FDE) only measure errors from the ground truth future trajectory, they are impractical for evaluating the diversity of outputs, especially within the imbalanced dataset. To address this problem, minLaneFDE leverages available map information and measures a minimum error between a set of possible lane candidates (feasible maneuvers) and a set of multiple predicted trajectories.

To summarize, this work mainly has three contributions as follow:

- We devise a new loss function, Lane Loss, that encourages the multiple outputs to be diverse and feasible, considering maneuver candidates based on map information so that multiple outputs can cover uncertain futures which should be handled by motion planner in downstream.
- A new two-stage prediction architecture is proposed, which generates trajectory candidates first and leverages them for the final predictions, boosting the effect of Lane loss.
- We suggest a quantitative evaluation metric, minLaneFDE, to assess the quality of diversity in multiple outputs in a map-adaptive way. Our model significantly improves the quality of diversity of multiple trajectory predictions without sacrificing conventional accuracy.

The remainder of this paper is organized as follows: In section III previous works that are closely related to our work are discussed. In section IV we will give our problem formulation. Then, the proposed method including Lane loss and Trajectory Proposal Attention is described in Section V. In Section VI experiment details such as dataset, implementation details, and results are presented. Finally, Section VII provides the conclusions.

II. RELATED WORK

The problem of future motion prediction for dynamic agents has been addressed in many studies, and we review the papers about several trajectory prediction models and loss functions for trajectory prediction in this section.

A. Single(Deterministic) Trajectory Prediction

In the early stage of motion prediction research, the majority of works [4], [12]–[18] output a single prediction result and put their effort into making it as close as possible to the ground truth. Various methods such as the kinematic-based model [12], [13], Gaussian Mixture Model [18], or Recurrent Neural Network [4], [14], [17] have been employed for the single trajectory prediction. Among them, [4], [18] generate probabilistic outputs to take into account uncertainty that increase by the prediction time horizon. However, those works output only one maneuver even a target vehicle is at an intersection, which can cause a critical failure such as collision.

B. Multiple Trajectory Prediction

Feature-based multimodal trajectory regression models: [1], [3], [19]–[23] extract features from the past and environmental context and then predict multiple trajectories using those features. [2], [3], [23] use simple CNN to encode rasterized map images, while [10], [19], [22], [26], [28] use lane-level map data to handle the complex topology of map

| Maneuver               | Training     | Validation  |
|-----------------------|--------------|-------------|
| Going straight        | 191024 (92.75%) | 34958 (90.70%) |
| Left turn             | 7860 (3.82%)  | 1880 (4.88%)  |
| Right turn            | 4757 (2.31%)  | 1238 (3.21%)  |
| Left lane change      | 1084 (0.53%)  | 284 (0.74%)   |
| Right lane change     | 1217 (0.59%)  | 184 (0.48%)   |

TABLE I DISTRIBUTION OF TARGET AGENTS’ MANEUVER IN ARGOVERSE TRAJECTORY FORECASTING DATASET
data. However, they train with only a single modality of ground truth, underestimating the importance of diversity. Even though several approaches [29]–[31] have targeted the diversity of outputs, their diversities do not consider a map [29], [30] or only depend on the distribution of the data [31], which is highly imbalanced.

Candidate-based trajectory forecasting approaches: [6]–[11], [32] first propose multiple trajectory candidates or goal points, followed by classification and regression to find the most likely candidate. TNT [6] suggested the candidates of goal points of the agent in advance, and then the classification and regression for the trajectory to that goal point follow. On the other hand, CoverNet [7] generates a set of trajectories to cover all possible motions before classifying the most likely trajectory among them. Even though the previous methods show outstanding performance in prediction accuracy, they are trained with a given ground truth future trajectory representing only a single modality among all possible maneuvers. Therefore, they fail to capture diversity of predictions. Moreover, they suffer from a massive number of candidates, which is necessary to provide sufficient solution space.

To overcome the limitations in previous works, we introduce Trajectory Proposal Attention (TPA) with Lane Loss to generate feasible multiple future trajectory proposals with the lane-level map information as the pseudo ground truth that is impossible to obtain from the dataset.

C. Auxiliary Loss for Trajectory Prediction

In order to handle limitations of distance error based loss function and to improve the quality of predictions, several auxiliary loss terms [2], [3], [33]–[38] have been introduced. However, these approaches focus on improving the feasibility of trajectories instead of diversity by penalizing outputs that lie out of the drivable area [38] or have improper heading angles [33]–[35]. Even though DATF [37] introduced a loss term for diverse predictions, it only considers a drivable area that is less informative.

In contrast to the above methods that have been tried to teach "Where can not go", the proposed Lane Loss focuses on training "Where can go" by considering reference lanes extracted from a map. To this end, Lane Loss encourages the outputs to be feasible and diverse enough to cover every possible maneuver. With Lane Loss, the model can generate diverse maneuvers in a map-adaptive way even if a ground truth represents only a single modality among all possible modalities in the scenario.

III. PROBLEM FORMULATION

We represent the sequences of observed states for agents in the scene at the current time as $S_o = \{s_i(t)\}_{i=1}^N$ and $S_o = \{s_i(t)\}_{i=t_o-t_o+1}^{t_o+1}$ where $i$ is the agent index, $N$ denotes the number of agents, $s_i(t)$ denotes 2d coordinate at time $t$ with the origin at the current position of the agent $(x_i(t), y_i(t))$, and $t_o$ denotes the observation time horizon. The set of possible future sequences is denoted as $Y = \{y_{i,m}\}_{i=1}^N, m=1,\ldots,M$ and $Y^{i,m} = \{y_{i,l}\}_{l=1}^M$ where $y_{i,l,m} = \{x_{i,l}, y_{i,l}\}$ is a 2d coordinate of $m$-th modality, and $M$, $t_f$ denotes the number of modalities and the prediction time horizon. Here, $Y$ includes the annotated ground truth $Y_{gt}$ because the ground truth is one of the possible future trajectory. The map information at current time is represented as $C$. We define the whole input as briefly $X = \{S_o, C\}$.

The objective of the conventional trajectory prediction is to find the model that can well represent $p(Y_{gt}|X)$ for given information $X$. In contrast to that, our objective is to find a model for $p(Y|X)$, where $Y$ is the set of possible trajectories that denote not only the ground truth $Y_{gt}$ but also other unseen maneuvers ($Y_{gt} \in Y$). Following this problem definition, the model that can represent $p(Y|X)$ is able to cover all possible motions that can happen and therefore, it is possible to provide helpful information about uncertain future to downstream path planners.

IV. METHODOLOGY

A. Model Architecture

As depicted in Figure 2, our model consists of mainly two parts: Baseline network and Trajectory Proposal Attention (TPA). In the feature extractor of the baseline network, the historical trajectories of surrounding agents $S_o$ are encoded into actor features, and the map information $C$ is encoded using GCN. (details are described in LaneGCN [22].) The output of the feature extractor $h_{obs}$ is processed by TPA, which will be explained in detail. Then, the output of TPA $h$ is fed into Interaction Network (FusionNet in LaneGCN) to consider the interaction among agents and maps. Finally, the prediction header makes the multiple future trajectories of agents and their scores.

The baseline network can be replaceable with any trajectory prediction model consisting of a feature extractor and prediction header. TPA serves as a neck of the overall architecture. In this work, we adopt one of state-of-the-art models LaneGCN [22] as a baseline network.

B. Baseline Network

LaneGCN [22] is a motion forecasting model that constructs a lane graph from vectorized map data using Graph Convolutional Network [49] and then fuses the information of agents in the traffic and map feature considering interactions among agents and maps. LaneGCN consists of four modules: ActorNet, MapNet, FusionNet and Prediction Header. ActorNet is the module for extracting features from trajectories of agents. The network has the structure of 1D CNN and Feature Pyramid Network (FPN) for multi-scale features. MapNet encodes structured map information into a feature representation. In LaneGCN, the map data is converted into a graph structure, Lane Graph, in which nodes represent the centerline of lane segments and edges represent connectivity. Then the multi-scale LaneConv operation to aggregate the topology information of the lane graph is applied. FusionNet is a network that considers the interaction among agents and maps using attention mechanism. Especially, FusionNet takes into account all kinds of fusion such as agents-lanes, lanes-lanes, lanes-agents, and agents-agents. Lastly, Prediction Header is the final network for generating multiple future
trajectories and confidence scores of each trajectory. Both the regression and scoring network has a residual block and a linear layer.

We have employed parts of LaneGCN in both Baseline Network. In our Baseline Network, the Feature Extractor is consists of ActorNet, MapNet. ActorNet and MapNet process trajectories of agents and map information each, and then fuse the map and trajectory information. Interaction Network and Prediction Header in the Baseline Network have the same network as FusionNet and Prediction Header in LaneGCN. Therefore our model also outputs multiple future trajectories with scores for each trajectory.

C. Trajectory Proposal Attention

Trajectory Proposal Attention (TPA) is the first stage of the two-stage trajectory prediction framework. It aims to output multiple trajectory proposals that are geometrically feasible based on historical observations and map data. Then, the proposals are aggregated into a joint representation through Proposal Attention. TPA consists of three modules: proposal header, proposal encoder, and proposal attention, which will be explained.

Proposal Header takes the feature extracted from observable past trajectories and map data as the input and generates trajectory proposals.

\[ \mathbf{Z} = f_{\theta}^{P_{H}}(h_{\text{obs}}) \]  

(1)

where \( \mathbf{Z} \in \mathbb{R}^{k \times t \times 2} \) is the trajectory proposals, \( k \) is the number of proposals, and \( \theta \) is the parameters for the proposal header. In other words, the proposal header can be analyzed as a region proposal network (RPN) in two-stage object detection models. Similar to RPN, the output of our proposal header is recursively used in the downstream network to provide physical and geometrical clues. For the consistency in generating trajectories among proposal header and prediction header, we adopt the same network on both proposal header and prediction header. Headers are consist of three MLPs with a residual connection after the second layer, ReLU, and a GroupNorm layer. The trajectory proposals are trained with the same loss function as the final outputs to make proposals. Details of Loss function will be explained later.

Proposal Encoder is an embedding layer that encodes trajectory proposals into feature vectors.

\[ \mathbf{g} = \{ g_i = f_{\phi}^{P_{E}}(z_i) | z_i \in \mathbf{Z}, i = 1, \ldots, k \} \]  

(2)

where \( \mathbf{g} \in \mathbb{R}^{k \times 128} \) represents embedding features of trajectory proposals and \( \phi \) is parameters for proposal encoder. Since the purpose of the proposal encoder is to make embedding for trajectory-shaped input, it has the same architecture as ActorNet in the baseline network, and it consist of 1D CNN and feature pyramid network. The functions to encode each proposal share their weight.

Proposal Attention is a module to aggregate features from multiple proposals representing different maneuvers or behaviors. Because all of proposals (candidates) can not be ignored, Multi-head attention network \([40]\) is employed in order to aggregate all features of proposals. The future feature \( h_{\text{fut}} \) is generated using the observation feature \( h_{\text{obs}} \) and proposal feature \( g \). Proposal Attention takes the observation feature as the query, and the proposal features are used as the key and the value.

\[ \text{head}_i = \text{Attention}(h_{\text{obs}}w_{i}^{Q}, g^{K}_i, g^{V}_i) \]  

(3)
where $W$ is an attention mechanism instead of averaging or summation to help the future feature take more important future maneuvers while also keeping others. Then, each agent’s $h_{obs}$ and $h_{fut}$ are concatenated into $h$. The combined feature $h$ can be interpreted as the feature that takes into account both the observable historical information such as the past trajectory, and future information. $h$ is fed as the input signal to the interaction network and prediction header to generate final prediction outputs.

D. Loss Function

The proposed model is trained in an end-to-end manner and we use a summation of three losses: scoring loss, regression loss for final prediction, and regression loss for proposals.

$$L_{total} = \alpha_{score}L_{score} + \alpha_{pred}L_{pred}^{reg} + \alpha_{prop}L_{prop}^{reg}$$

(5)

where $\alpha_{score}$, $\alpha_{pred}$, and $\alpha_{prop}$ are the weighting factors.

For scoring multiple trajectories, we adopted a hinge loss to maximize a trajectory score closest to the ground truth while suppressing scores for other modalities as described in equation 6

$$L_{score} = \sum_{m \neq m^*} \max(0, p_m + \epsilon - p_{m^*})$$

(6)

where $M$ is the number of predicted trajectories (the number of modalities) for each agent. $p$ denotes a score output and $\epsilon$ is the margin.

$L_{pred}^{reg}$ and $L_{prop}^{reg}$ are regression losses for reducing the prediction error, where the superscript $prop$ and $pred$ denote proposals and predictions. Each regression loss consists of two terms: Winner-Takes-All loss $L_{WTA}$ and Lane Loss $L_{Lane}$.

**Winner-Takes-All Loss:** Winner-Takes-All (WTA) loss is widely employed for multiple trajectory prediction [2], [3], [22] to overcome the mode collapse problem inherent in the Mixture-of-Experts (ME) loss which is defined as,

$$L_{ME} = \sum_{m} p_m\text{dist}({\hat{Y}^m, Y})$$

(7)

where $\text{dist}({\hat{Y}^m, Y})$ denotes distance loss term such as RMSE and MAE. $Y$ and $\hat{Y}^m$ denote the ground truth and $m$-th modality of predictions.

To address the problem of ME loss, WTA loss selects the winner mode based on the Euclidean distance of the position between the ground truth trajectory and predicted trajectories instead of summing all distance losses across all modalities. Then the loss is calculated only for the selected mode (the winner) based on a distance function.

$$L_{WTA} = \sum_{m} u_{m}^{wta}\text{dist}({\hat{Y}^m, Y})$$

(8)

$$u_{i}^{wta} = \delta(i = \arg\min_{m} \|\hat{Y}^m_{tf} - y_{tf}\|)$$

(9)

where $\delta$ is the Kronecker delta, returning 1 for the condition is true and 0 otherwise. WTA loss makes the predicted
trajectories updated for the one closest to the ground truth, while the scores are updated for all modalities. It allows each prediction output to specialize for typical maneuvers, successfully overcoming the mode collapse problem.  

However, for WTA loss to work successfully, the ground truth trajectories should be well distributed over various maneuvers (e.g., turning or going straight). Because WTA loss updates only one modality, it is highly affected by the distribution of the ground truth trajectories. Therefore, the performance of the model that trained with WTA loss and the imbalanced dataset is limited, especially for generating diverse output, which is critical for safe motion planning. However, for WTA loss to work successfully, the ground truth trajectories should be well distributed over various maneuvers (e.g., turning or going straight).

Even though several works [41]–[44] have been proposed to improve WTA loss, they focused on the problem of the diluted probability density function of the output compared to the ground truth, assuming that the distribution of ground truth is sufficiently diverse. Considering the fact that the ground truth in trajectory datasets is not diverse since there is a single ground truth per scenario, which is dominated by a lane-keeping maneuver in almost all cases, those works fail to overcome the fundamental drawback of WTA loss. To address this problem, we introduce a new loss function, Lane Loss, which utilizes the lane-level map information as the pseudo ground truth for the unrevealed modality in the dataset.

**Lane Loss:** Despite only a single observed ground truth in each situation, the prediction results should be able to cover other maneuvers that do not align with the maneuver of the ground truth. In other words, it should not ignore the minor portions of situations regardless of the numeric value of likelihood in order for safe driving in the uncertain future. Even though several approaches [33]–[38] use map data in the loss function, they focus on enhancing feasibility by penalizing outputs out of the drivable area instead of improving diversity to cover enough possible future motions. For example, let us assume a model outputs six multiple future trajectories which are precisely the same and perfectly stick to the lane centerline, which is in a drivable area but not diverse and undesirable for multimodal prediction. In this case, additional losses in previous approaches do not penalize anything because every output is feasible even though they are the same. However, in contrast to other losses, Lane Loss penalizes trajectories not to be the same but to cover all possible maneuvers as much as possible. To this end, we introduce Lane Loss, which helps the multiple trajectories be diverse in a map-adaptive manner covering various feasible maneuvers, including cases that are unlikely to happen but crucial for safety.

Lane Loss calculates the distance error of predicted trajectories from the feasible reference lane candidates to encourage diverse predictions. These possible reference lanes are acquired directly from the map data. Similar to WTA loss, Lane Loss chooses the winner mode for each reference lane candidate based on Euclidean distance from a lane candidate and the predicted trajectories.

$$L_{lane} = \frac{1}{L} \sum_{l} \sum_{m \neq m^*} \sum_{u \in \mathcal{M}} dist(Y_{tf}^m, R_l)$$

$$u_i^m = \delta(i = \arg \min_m \|d_{R_i}(y_{tf}^m)\|)$$

where $L$ is the number of the reference lanes, $R_l \in \mathbb{R}^{M \times 1 \times 2}$ denotes the $l$-th reference lane with a structure of trajectory, $\delta$ denotes the Kronecker delta, and $|d_{R_i}(y_{tf}^m)|$ means the normal distance of the $m$-th predicted trajectory at the final prediction time $t_f$ from the $l$-th reference lane $R_l$ in the Frenet-Serret Frame.

The reference lanes for the Lane loss are extracted from the map data. In Arogoverse API, there is a function for getting lane candidates [45]. However, lane candidates from that function have various lengths independent of the given past trajectory or the ground truth. Therefore, we process these lane candidates into reference lane trajectories to use them for the loss function. The reference lanes are processed as follows: 1) start point: find the nearest point of the current position (the last point of the past trajectory) 2) end point: find the nearest point on the lane candidate with the travel distance based on the constant velocity. 3) interpolate between the start point and the end point based on the lane candidates. Then, a loss for each reference lane is computed and we set the number of reference lanes as 3 which can cover most cases.

Consequently, the regression loss is the mean of the summation of WTA loss and Lane Loss for all agents in the scene.

$$L_{reg}^i = \frac{1}{N} \sum_{i} (L_{WTA}^i + L_{Lane}^i)$$

where $L_{WTA}^i$ and $L_{Lane}^i$ denotes losses for $i$-th agent.

Algorithm 1 presents the pseudocode for calculating regression loss. As explained in the code, WTA loss first finds

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**Algorithm 1** Regression loss: Lane loss and WTA loss

1. **input:** predicted trajectories $\hat{Y} \in \mathbb{R}^{M \times L \times 1 \times 2}$, ground truth trajectory $Y \in \mathbb{R}^{L \times 1 \times 2}$, reference lanes $R \in \mathbb{R}^{L \times L \times 2}$ where $M, L, \text{and } L$ denotes number of prediction outputs (modalities), prediction time steps, and number of reference lanes for each agent
2. **output** regression loss $L_{reg}$
3. for $m$ in $\{1, 2, \ldots, M\}$ do
4. $d_{wta}^m \leftarrow$ Euclidean distance between $\hat{Y}^m_{tf}$ and $Y_{tf}$
5. end for
6. $m^* = \arg \min_m d_{wta}^m$
7. $L_{WTA} \leftarrow$ Smooth L1 loss between $\hat{Y}^{m^*}$ and $Y$
8. for $l$ in $\{1, 2, \ldots, L\}$ do
9. for $m$ in $\{1, 2, \ldots, M\} \backslash m^*$ do
10. $d_{lane}^m \leftarrow$ Normal dist. of $\hat{Y}^m_{tf}$ in Frenet frame of $R_l$
11. end for
12. $m^{**} = \arg \min_m d_{lane}^m$
13. $L_{lane} \leftarrow$ Smooth L1 loss between $\hat{Y}^{m^{**}}$ and $R_l$
14. $L_{lane} \leftarrow L_{lane} + L_{lane}$
15. end for
16. $L_{reg} = L_{WTA} + \ell L_{lane}$
17. return $L_{reg}$
the one trajectory that is the most similar to the ground truth based on the Euclidean distance and calculates a loss. Then, the selected trajectory is excluded from the set of outputs, and Lane loss works similarly. For Lane loss, we find the closest trajectory based on the normal distance of the endpoint in the Frenet frame of each reference lane. Since reference lanes have a waypoint structure, an interpolation-based approximation is applied for the normal distance in the Frenet frame. The reference lane is upsampled into 500 waypoints, and the minimum distance between upsampled waypoints and the endpoint of trajectory is considered as the normal distance.

V. EXPERIMENTS

A. Dataset

Argoverse motion forecasting dataset [47] is a real-world driving trajectory dataset with over 324k sequences collected in the USA. It has 205942, 39472, and 78143 sequences for each training, validation, and testing. Each sequence consists of 5 seconds of time horizon (2 seconds for the past trajectory and 3 seconds for the future trajectory) with 10Hz of the sampling rate. It also provides the locations of the centroid of the target and surrounding agents and HD-map data.

B. Metric

We employ minimum Average/Final Displacement Error (minADE/minFDE) as the multimodal evaluation metrics [47].

There are several parameter variations on Argoverse motion forecasting validation set.

The results of several parameter variations on Argoverse motion forecasting validation set are as follows:

The results of Argoverse motion forecasting test set are as follows:

Although these metrics are widely used in the motion forecasting task, minADE and minFDE only depend on the error from the ground truth, neglecting the other possible maneuvers. Therefore, they are impossible to evaluate the diversity of the multiple outputs fairly. Accordingly, a metric that can evaluate the diversity of multiple predictions is required in addition to minADE/minFDE.

In this sense, we define a new performance metric, minimum LaneFDE (minLaneFDE), that captures both the quantity and quality of diversity of multiple outputs based on the map data, specifically the centerlines of reference lanes. Even though [37] proposed a metric for the diversity, only a drivable area is considered, while minLaneFDE focuses on the diversity of covering possible future maneuvers. minLaneFDE denotes the minimum value among the lateral displacement errors between centerlines of possible lane candidates (we employ Argoverse map API [47] to get the lane candidates) and each multiple predicted trajectory. In other words, minLaneFDE evaluates the error of the closest prediction from each lane candidate. Thus, even if the multiple trajectories are diverse, minLaneFDE will increase if none of them are around the reference lanes. minLaneFDE can evaluate how much the multiple trajectories can cover the possible lanes on the map.

\[
\text{minADE}_k = \min_{m=1,2,...,k} \frac{1}{f} \sum_{t} \| y_{t,f}^{n,m} - y_{t}^{n} \|_2 \quad (13) 
\]

\[
\text{minFDE}_k = \min_{m=1,2,...,k} \| y_{t,f}^{n,m} - y_{t}^{n} \|_2 \quad (14) 
\]

where \(k\) denotes the number of modality that is used for the evaluation. \(\text{minADE}\) and \(\text{minFDE}\) are the average of all target agents in the dataset.

\[
\text{minLaneFDE}\:
\]

\[
\text{minLaneFDE} = \frac{1}{NL} \sum_{i} \sum_{m=1,...,M} \min_{l=1,...,L} |d_{R_i}(y_{l}^{i,m})| \quad (15) 
\]

where \(N\) is the number of agents, \(L\) is the number of reference lanes, \(M\) is the number of estimated trajectories, and \(t_f\) denotes the final time index. \(|d_{R_i}(y_{l}^{i,m})|\) denotes the normal
Fig. 4. Visualization of prediction results. Top: Results of LaneGCN, which is the baseline of our model. LaneGCN fails to predict the target trajectory and returns all multiple similar trajectories in cases where it is difficult to infer the future maneuver from the given historical information. Middle: Prediction results of trajectory proposals of our proposed model. Distinct trajectories represent not only going straight even if they are not accurate. Bottom: Final prediction results of our model. Our model can predict accurate and diverse multiple future trajectories.

distance of \( m \)-th prediction in the Frenet-Serret Frame of \( l \)-th lane candidate for \( i \)-th agent.

Although \( \text{minLaneFDE} \) can evaluate the diversity of multiple trajectories appropriately, evaluation for scenarios such as an intersection where more diverse maneuvers are possible can be underestimated since the validation or test dataset is overwhelmed by the straight scenarios. Hence, we make an intersection subset from the validation set to evaluate on the complex road shape. It is described in Table II as \( \text{LaneFDE}(a) \) - total dataset, \( \text{LaneFDE}(b) \) - intersection subset. We sampled the intersection subset (4652 cases) from the validation set based on the map information, in which the target agent is approaching the intersection or already in the intersection.

C. Implementation Details

The time steps of past trajectory \( t_o \) is 20 with 10Hz (2 seconds) and the time steps for future trajectory \( t_f \) is 30 with 10Hz (3 seconds). We choose the number of proposals and the predictions as 6 (\( M = 6 \)). For Lane Loss and minLaneFDE, we use maximum 3 reference lanes (\( L = 3 \)). Lastly, as the weighting factors for each loss function, \( \alpha_{\text{score}} = 1.0 \), \( \alpha_{\text{pred}} = 1.0 \), \( \alpha_{\text{prop}} = 0.1 \) is used.

For training on Argoverse Motion Forecasting dataset, we implement models using the Pytorch and use the Adam optimizer (beta1=0.9, beta2=0.999) with the batch size of 128. We initialize the training with the learning rate as 0.0001 and is annealed by a factor of 10 after 32 epochs. Although we employ an existing model as the baseline, we did not use a pre-trained model and trained the whole mode. We train the model on 4 Nvidia RTX 3090 GPUs for a total of 40 epochs and it takes about 24 hours.

D. Quantitative Results

Ablation Study: To demonstrate the contributions of each component of our model, the results of ablation studies
using LaneGCN as the baseline are summarized in Table II. The model with the TPA module trained by Lane Loss shows the best performance, especially for the diversity that minLaneFDEs evaluate, while the prediction accuracy is conserved. By comparing the baseline and the baseline + Lane Loss, we can verify that Lane Loss significantly improves the diversity through minLaneFDE. Even though minADE/minFDE is slightly increased, the performance in terms of the diversity shows remarkable improvement. We claim the reason of increase in minADE/minFDE comes from the imbalance distribution in the validation set. Since the lane-keeping is dominant in the validation set, minADE/minFDE of diverse outputs cannot help worsen for fewer outputs are on the lane-keeping compared to baseline of which outputs are mostly lane keeping. However, the minor disadvantage in minADE/minFDE can be recovered by TPA successfully since the model with TPA can refine the final output based on trajectory proposals and improve prediction accuracy. Conclusively, by training the network with TPA and Lane Loss together, the prediction model can generate diverse outputs in a map-adaptive manner with the outstanding advance in both minLaneFDE(a) and minLaneFDE(b) without sacrificing the prediction accuracy, represented by minADE/minFDE.

In Table III we show the results of experiments for various future feature aggregation methods and the number of trajectory proposals. From the table, we can find that among three aggregation methods: Average, Summation, Attention (Multi-Head Attention), Attention method shows the best performance in minADE/minFDE, while not much difference in minLaneFDE. With this result, we can verify that Attention-based future features can improve prediction accuracy. In addition, the result of a different number of trajectory proposals that proposal header outputs show that a larger number of proposals have a positive effect on diversity.

Comparison with state-of-the-art: We compare our model with state-of-the-art methods in the test set of the Argoverse Motion Forecasting dataset, and the results are presented in Table IV ("min" is dropped since the lack of space). It includes the Argoverse official baseline and other candidate-based trajectory prediction approaches like the proposed architecture. The results show that the proposed model performs better than other models. Even if the performance margin is insignificant, considering that our model improves the diversity of prediction output remarkably, it is an outstanding achievement.

E. Qualitative Results

We visualize qualitative results of several case studies on the Argoverse validation set compared with the baseline model LaneGCN in Figure 4 and 5. The gray lines represent road lanes around the target vehicle, the yellow line denotes the observed past trajectory of the target, the green lines are multiple predictions which are the output of the model, the red line is ground truth future trajectory, and the magenta lines are other agents’ future trajectories. In Figures, there are three rows. The first row is the output of LaneGCN, which is the baseline model, the second row denotes trajectory proposals that are the output of Proposal Header, and the last row represents the final prediction of our model.

As Figure 4 describes, it is impossible to distinguish whether the target agent will go straight or take a turn with the given past trajectory (yellow). In these cases, the baseline model tends to predict the future motion of the target as going straight while ignoring the possibility of other maneuvers because the baseline model trained with an imbalanced dataset without any technique for the diversity. Therefore, it fails to predict the future motion of the agent correctly. However, our model can suggest both straight and turning maneuvers, including the correct prediction. Especially, as can be verified from the results of the proposals (middle), our proposed model can predict the diverse future motions from the stage of trajectory proposals even if they are not accurate compared to the final prediction.

On the other hand, in Figure 5, outputs of both baseline and our model (left) contain the trajectory close to the ground truth. However, these cases have interesting results in some points. In Figure 5 (e), even though the baseline model accurately predicts future trajectory, all predicted trajectories are near the ground truth. In contrast, our model can predict accurately and have the prediction output of a different maneuver, providing a possible future even it is less likely. In Figure 5 (f), the
prediction results of LaneGCN show dispersed outputs which include infeasible trajectories. Even though LaneGCN uses the map data as graph representation, it fails to generate map-dependent predictions explicitly. However, since ours are trained with the Lane loss by leveraging reference lanes, the predictions can stick to the lanes, making them more feasible and even more diverse. In figure 5 (g), it seems LaneGCN generates diverse prediction results. However, it is impossible to make a left turn if you look closely. (There is no lane segment for the left turn.) Thus it is a false diversity, whereas our model only predicts possible maneuvers.

VI. CONCLUSION

In this work, we propose a new loss function that encourages the multimodal prediction outputs to be dispersed, leveraging the reference lanes obtained from the map data in order to cover diverse maneuvers. Furthermore, we developed a new two-stage trajectory prediction framework based on Trajectory Proposal Attention (TPA). The proposed model trained with Lane loss achieved outstanding performance in the evaluation metric minLaneFDE, which measures the diversity of outputs without sacrificing prediction accuracy. In conclusion, our model can provide valuable information on uncertain futures so that the decision/planning can proactively take action. Furthermore, since it works in a map-adaptive manner, it is applicable to a continuously changing driving environment.

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Hyunseok Jeon received the B.S. degree in mechanical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2015, and the M.S. degree from the Vehicular System Design and Control (VDC) Laboratory, Graduate School of Green Transportation, KAIST, in 2018. He is currently pursuing the Ph.D. degree with the VDC Laboratory. His research interests include artificial intelligent and deep learning in trajectory prediction for the autonomous driving vehicles.

Junwon Choi received the B.S. and M.S. degrees from the Electrical Engineering Department, Seoul National University, and the Ph.D. degree in electrical computer engineering from the University of Illinois at Urbana–Champaign. In 2010, he joined Qualcomm, San Diego, USA, where he participated in research on advanced signal processing technology for next-generation wireless systems. Since 2013, he has been with the Electrical Engineering Department, Hanyang University, as a Faculty Member. His research area includes signal processing, machine learning, intelligent vehicles, and wireless communications.

Dongsuk Kum received the Ph.D. degree in mechanical engineering from the University of Michigan, Ann Arbor, MI, USA, in 2010. He was a Visiting Research Scientist with the General Motors Research and Development Propulsion Systems Research Laboratory, Warren, MI, USA, where he was focused on the advanced propulsion system technologies, including hybrid electric vehicles, fly-wheel hybrid, and waste heat recovery systems. He is currently an Associate Professor with the Graduate School of Green Transportation, Korea Advanced Institute of Science and Technology, where he is also the Director of the Vehicular Systems Design and Control Laboratory. His research centers on the modeling, control, and design of the advanced vehicular systems with particular interests in hybrid electric vehicles and autonomous vehicles.

Sanmin Kim received the B.S degree in Mechanical Engineering and the M.S degree in the Graduate School of Green Transportation from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2018 and 2020, respectively. He is currently pursuing the Ph.D. degree in the Graduate School of Green Transportation, KAIST. His research interests include deep learning for perception and prediction in autonomous driving vehicles.