Abstract

To plan a safe and efficient route, an autonomous vehicle should anticipate future motions of other agents around it. Motion prediction is an extremely challenging task which recently gained significant attention of the research community. In this work, we present a simple and yet strong baseline for uncertainty aware motion prediction based purely on transformer neural networks, which has shown its effectiveness in conditions of domain change. While being easy-to-implement, the proposed approach achieves competitive performance and ranks 1st on the 2021 Shifts Vehicle Motion Prediction Competition.

1 Introduction

Driving a car is a complex activity that requires drivers to understand the involved multi-actor scenes in real time and actions in a rapidly changing environment in a fraction of second. To be able to fully rely on autonomous vehicles to drive autonomously, desirable to correctly assess the confidence of the algorithm in its predictions, including situations under the condition of distributional shifts, e.g. in a unseen (new to algorithms) roads, cities, countries.

In order to fully rely at autonomous vehicles, it is necessary to be confident of a high level of generalization of all algorithms used for autonomous driving.

The motivation to understand and predict human motion is immense and it has a deep impact in related topics, such as, decision making, path planning, autonomous navigation, surveillance, tracking, scene under-standing, anomaly detection, etc.

The problem of forecasting where cars will be in the near future is, however, ill-posed by nature: human beings tend to be unpredictable on their decisions and car driving is neither exempt of it. These random nature in motion brings an open challenge to prediction algorithms, where algorithms are desired to be accurate and correctly grasp the uncertainty associated with their predictions.

The contributions of this work are summarized as follows: 1) we propose a unified transformer-based motion prediction framework for both multi-modal trajectory prediction and uncertainty estimation. 2) Our proposed approach achieves state-of-the-art performance, and ranks 1st on the Shifts Vehicle Motion Prediction Competition.

2 Related Work

The motion prediction task is one of the most important in the field of autonomous driving and has recently attracted a lot of attention from both academia and industry [1] [9] [8] [2] [17] [15]. Broadly, modern motion prediction methods can be divided in two classes:

1) Models where scene context information are processed from vectorized maps (HD maps) [7] [10].

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2) Models where high-definition maps and surroundings of each vehicle in cars’s vicinity rasterized to image representation, thus providing complete context and information necessary for accurate prediction of future trajectory [4] [14] [6].

Recently models based at transformers architectures, have shown theirs applicability both at computer vision tasks [5] [11], and at sequence to sequence tasks [16], [3], which opens a high potential of applicability Transformer based approaches for motion prediction task.

3 Method

We assume that object detections and tracks are provided by perception stack (running on the Yandex self driving car (SDC) fleet [13]) and focus only on the motion prediction.

The proposed method goal is to predict the most-likely movement trajectory of vehicles at time $T \in (0, 5]$ seconds in the future and model’s scalar uncertainty estimates, which can later be used in subsequent SDC pipeline algorithms as an estimate of the forecast uncertainty with a scene context that is particularly familiar or low risk in the case of low estimated uncertainty, or unfamiliar or high risk in the case of high estimated uncertainty.

In this section we describe the architecture of our model, the loss function used for training and implementation details.

The future is ambiguous and human motion is unpredictable and multimodal by nature. In order to account for such multimodal nature, we aim to produce up to $K=5$ different hypotheses (proposals) and their probabilities for the future trajectory which will be evaluated against the ground truth trajectory.

3.1 Input representation

Context information about the state of dynamic objects (i.e., vehicles, pedestrians), described by its position, velocity, linear acceleration, and orientation together with context information about the HD map including lane information (e.g., traffic direction, lane priority, speed limit, traffic light association), road boundaries, crosswalks, and traffic light states are rasterized into multi-channel images which are passed to transformer based model.

3.2 Model architecture

Our method can be represented as an image-based regression, model architecture shown at Fig 1 consists of two main stages:
• Transformer-based image processing encoder, namely modified ViT\(^5\) (modified in accordance to process multi-channel images) acts as a current state estimation for single vehicle. ViT uses multi-head self-attention\(^{18}\) removing image-specific inductive biases compared to CNN approaches and self-attention layers in ViT allows it to integrate information globally across the entire image so ViT doesn’t suffer from lacks of a global understanding of the images.

• Transformer based decoder which predicts \(K\) different hypothesis (proposals) for the future trajectory with the corresponding confidence values \(c_1^{1..5}\) which are normalized using softmax operator such that \(\sum c^{1..5} = 1\). Apart of predicting multi-trajectory plans proposed model predicts overall scene uncertainty score, which is described in more details later.

Multi channel images are initially split into fixed-size patches and processed further by visual transformer model. Dense encoded latent state produced by ViT later repeated \(N\) times, according to number of desired trajectories to be predicted.

Each of \(K\) latent state concatenated with \(S \sim \mathcal{N}(0,1)\), samples from Normal distribution, which is according to our internal experiments gives minor improvements in metrics comparing to sinusoidal Positional Encoding \(^{18}\), that can be interpreted by the absence of a relative or absolute positional correlation between sequential states. On the other hand samples from Normal distribution, concatenated with repeated latent state, helps decoder to transform repeated latent state to more diverse trajectories.

At the same time, property of multi-head attention attend globally, therefore, learning long-range relationships provides more opportunities for a correct assessment of uncertainties.

### 3.3 Loss function

We model possible future trajectories as the mixture of \(K\) Gaussian distributions, as it is allows model to predict multi-modal distribution, comparing to widely spread ADE loss, examples of model’s predictions are shown at Fig \(^2\) In this case our network outputs the means positions of the Gaussians \(\hat{x}_i\) while we fix the covariance of every Gaussian in the mixture to be equal to the identity matrix \(\sigma = I\), and for each trajectory model predicts trajectory probability \(c^k\) which are normalized using softmax operator such that \(\sum c^k = 1\). Then, given predicted \(\hat{x}_i, \sigma_i, c_i\) for the loss function we can use negative log-likelihood (NLL) of mixture of Gaussians defined by the predicted proposals given the ground truth coordinates \(X^{gt}\).

\[
X^{gt} = [(x_1, y_1), ..., (x_T, y_T)]
\]

\[
\hat{X} = [(\hat{x}_1, \hat{y}_1), ..., (\hat{x}_T, \hat{y}_T)], k = 1, ..., K
\]

where \(T\) is a prediction horizon, \(K\) - number of hypotheses.

We compute negative log probability of the ground truth trajectory under the predicted mixture of Gaussians with the means equal to the predicted trajectories and the identity matrix I as covariance:

\[
L_{\text{pose}} = -\log \sum_{k=1}^{K} c_k \mathcal{N}(X^{gt}; \mu = \hat{X}; \sigma = I)
\]

In order to evaluate model uncertainty, we propose to use second loss which is basically Root Mean Squared Error between predicted uncertainty measure and trajectory NLL value.

\[
L_{\text{uncertainty}} = \text{RMSE}(L_{\text{pose}}, \hat{U})
\]

where \(U\) - predicted uncertainty score, RMSE - Root Mean Squared Error function.

### 3.4 Implementation details

The output of our model is \(K = 5\) trajectories, each containing \(T = 25\) two dimensional coordinates. We train our model using AdamW \(^{12}\) optimizing for 40 full epochs of training set provided by shifts
Examples of multi-modality of predicted trajectories

Negative example with high average displacement error.

Figure 2: Qualitative results of Transformer based trajectory prediction on Shifts Vehicle Motion Prediction validation set. Bold olive line represents ground truth trajectory, other colored lines represents trajectories predicted by proposed model, legend shows probability of each predicted trajectory, and ADE (error) of that trajectory.

4 Experiments

We evaluate the effectiveness of Transformer based trajectory prediction method on the Shifts Vehicle Motion Prediction Challenge [13]. As shown in Table 1, our method ranks 1st on the leaderboard. The Shifts Motion Prediction Challenge main metric is R-AUC cNLL [13], which provides a full picture of the models performance incorporating both uncertainty estimation and predicted trajectories accuracy. It can be seen that despite the fact that according to R-AUC cNLL metric second method gives slightly better trajectories accuracy in terms of ADE, FDE, cNLL, our transformer-based approach produces more reliable uncertainties which reflect in better overall R-AUC cNLL.

5 Conclusions

In this work, we propose an fully transformer-based trajectory prediction model. It outperforms previous cnn-based and graph-based methods at the task of uncertainty aware motion prediction. Our model achieves state-of-the-art performance and ranks 1st on the Shifts Motion Prediction Challenge.
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