CTP-NET FOR CROSS-DOMAIN TRAJECTORY PREDICTION

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ABSTRACT

Deep learning based trajectory prediction methods rely on large amount of annotated future trajectories, but may not generalize well to a new scenario captured by another camera. Meanwhile, annotating trajectories for training a network for this new scenario is time-consuming and expensive, therefore it is desirable to adapt the model trained with the annotated source domain trajectories to the target domain.

To tackle domain adaptation for trajectory prediction, we propose a Cross-domain Trajectory Prediction Network (CTP-Net), in which LSTMs are used to encode the observed trajectories of both domain, and their features are aligned by a cross-domain feature discriminator. Further, considering the consistency between the observed trajectories and the predicted trajectories in the target domain, a target domain offset discriminator is utilized to adversarially regularize the future trajectory predictions to be consistent with the observed trajectories. Extensive experiments demonstrate the effectiveness of the proposed domain adaptation for trajectory prediction setting as well as our method on domain adaptation for trajectory prediction.

Index Terms— Trajectory prediction; Domain adaptation; Cross-domain feature discriminator

1. INTRODUCTION

Pedestrian trajectory prediction is attracting more and more attention these years due to its potential applications in autonomous driving \cite{1}, abnormal detection \cite{2}, safety monitoring \cite{3}, socially-aware robots \cite{4}, etc. However, existing deep learning based trajectory prediction methods \cite{5,6,7,8,9} need huge amounts of annotated data. When applied to a new scenario with different trajectory distribution, the model trained on the original scenario probably cannot generalize well and the performance degrades. However, annotating the future trajectories for the new scenario is time-consuming and expensive. Therefore, in this paper, we propose to study a cross-domain trajectory prediction task where only the observed trajectories with annotated future trajectories in a existing scenario (\textit{i.e.}, source domain) and the observed trajectories without future trajectory annotations in a new scenario (\textit{i.e.}, target domain) with different trajectory distribution is available. We aim to improve the performance of the model on the target domain without any future trajectory annotation. To the best of our knowledge, it is the first work to consider domain adaptation for trajectory prediction task.

To tackle domain adaptation for trajectory prediction, we propose a Cross-domain Trajectory Prediction Network (CTP-Net). Our proposed CTP-Net consists of two parts for domain adaptation: the feature-level cross-domain alignment by a cross-domain feature discriminator and the target domain trajectory alignment by a target domain offset discriminator. The feature-level cross-domain adaptation aims to align the feature from the source domain and the target domain while the target domain trajectory alignment targets at regularizing the consistency between the predicted future trajectories and the observed trajectories on the target domain.

Specifically, we first pre-train a source encoder and a decoder to predict the future trajectories with supervision under the standard training pipeline on the source domain. The source encoder encodes the coordinates of trajectories into a latent feature space and the source decoder decodes the encoded feature to predict offset of the future time-steps. The parameters of the source encoder-decoder are fixed in further training. We then implement the feature-level cross-domain alignment by training a target encoder with a cross-domain feature discriminator. The discriminator aims to distinguish between the source feature of the observed source trajectories by the fixed source encoder and the target feature of the observed target trajectories by the trainable target encoder. The adversarial objective for the target encoder is to fool domain discriminator. Therefore, the source feature and the target feature are adversarially aligned. After training the target encoder, the target domain trajectory alignment is imposed by training a target decoder with a target domain offset discriminator. The purpose of the target domain offset discriminator is to distinguish between the offset of the observed trajectories and the predicted offset of the future trajectories outputted by the target decoder on the target domain. The target decoder is composed of the fixed source decoder and a trainable offset adapter implemented with a multi-layer perception (MLP) transforms the predicted offset by the source decoder to be in the target domain. The offset adapter is adversarially trained.
to fool the target domain offset discriminator therefore the predicted offset of the future trajectory is imposed to be consistent with the offset of the observed trajectory on the target domain.

The main contributions of this paper can be summarized as follows: i.) the domain adaptation setting is first proposed for trajectory prediction; ii.) a Cross-domain Trajectory Prediction Network (CTP-Net) is proposed to adapt the model from the annotated source domain to the target domain by the proposed feature-level cross-domain alignment and the target domain trajectory alignment; iii.) extensive experiments demonstrate the effectiveness of the proposed domain adaptation for trajectory prediction setting as well as our method on domain adaptation for trajectory prediction.

2. RELATED WORK

We only briefly discuss recent works on domain adaptation and deep-learning-based trajectory prediction.

**Trajectory prediction.** With the development of neural networks, many trajectory prediction methods\cite{10,5,7,11,12} based on deep learning has been proposed. Early works\cite{13,14} regarded person motions in the scene as points to model them independently. Gradually, these researchers\cite{10,5} realized the importance of human-human interactions and how they affect each other for trajectory prediction. Recently, there are a variety of approaches to consider trajectory prediction from different perspectives, such as Multi-future prediction methods\cite{11,12}, Imitative Decision Learning (IDL) method\cite{15}. First-Person methods\cite{16,17}, Inverse Reinforcement Learning (IRL) method\cite{18}, and Constant Velocity method\cite{19}, etc. Different from these previous works, we present a cross-domain trajectory prediction network (CTP-Net), which utilizes feature-level cross-domain alignment and the observation-future consistency to adjust the model from the labeled source domain to the unlabeled target domain.

**Domain adaptation.** Domain adaption is one of the research focuses on Transfer Learning. The main task of it is to enhance models performance on test (target) data by minimizing the marginal distribution difference between training (source) data space and the test data space. Traditional methods, including the TCA\cite{20} and JDA\cite{21}, tend to minimize a distribution distance metric, such as the Maximum Mean Discrepancy (MMD), and the JS-discrepancy with algebraic methods. After the success of deep learning, the idea of leveraging neural networks to assist future extraction and automatic future adaptation came out. Many representative works, such as the DDC\cite{22}, DAN\cite{23}, and DIRL\cite{24} are proposed. Recently, with the development of Generative Adversarial Networks (GAN), such as the Wasserstein-GAN\cite{25}, adversarial domain adaption is becoming increasingly popular. Many classical structures, such as the DANN\cite{26}, DSN\cite{27} have justified the rationality of their back stone idea: to minimize the difference between the source and target domain until the adversary domain discriminator could not distinguish them. Inspired by the achievement of Domain adaption, we proposed a task-oriented Cross-domain Trajectory Prediction Network (CTP-Net) to conduct trajectory prediction. To the best of our knowledge, our work is the first to successfully use domain adaptation in trajectory prediction.

3. METHOD

3.1. Problem formulation

In practice, pedestrian trajectory data comes from 2 domains: the Source domain ($\mathbb{S}$), which has ground truth, and the Target domain ($\mathbb{T}$), which is unlabeled. Given this setting, the goal of Trajectory Prediction is to predict the future trajectory of target domain data ($F_t \in \mathbb{R}^{f \times 2}$) when given the target domain observation data ($O_l \in \mathbb{R}^{l \times 2}$).

Previous trajectory prediction models are firstly trained on the source domain ($O_s$ & $F_s$). Afterward, they will be directly applied to the target domain, which might miss the abundant information from the target domain. However, in our task, with the assistance of Encoder-Decoder structure, as well as the Domain Adaption method, we hope to construct a network that could successfully map the target data into the source trajectory feature domain ($M_s$), then project the prediction trajectory back to the target domain. Specifically, instead of predicting absolute coordinate, we set the coordinate offset($\mathbb{C}$), which is the changing values between two consecutive coordinates, as our predicting stuff.

3.2. Cross-domain Trajectory Prediction Net

The Cross-domain Trajectory Prediction Net (CTP-Net) contains two domain adaptation steps: the first is to align the Cross-domain feature space, and the second one is to align...
the coordinate offset space within the target domain. The whole pipeline of CTP-Net architecture is illustrated in Fig. 1. Roughly speaking, CTP-Net is composed of 3 components: 1. The source encoder-decoder; 2. The Cross-domain feature discriminator and the target encoder; 3. The coordinate offset adaptor, and the target domain offset discriminator.

With this framework, we first pre-train the source encoder-decoder with a standard training pipeline on the source domain to predict the future trajectories. Afterward, we fix the source encoder-decoder parameters. Then use the Cross-domain feature discriminator and the target encoder to achieve feature-level cross-domain alignment. The purpose of this discriminator is to estimate the distribution distance between the source and the target feature domain. Next, we adversarially train the target domain offset discriminator and the coordinate offset adaptor to align the coordinate offset within the target domain.

3.2.1. Source Domain training

This step is aimed to constructing a trajectory prediction model on the source domain, which has an Encoder-Decoder structure.

When it comes to our method, we implement both Encoder and Decoder as the combination of a step embedding (SEB) and an LSTM. Specifically, for the \(i^{th}\) person, the Encoder part is (\(k \in [1 : l0]\)):

\[
h^i_{sk}, out^i_{sk} = LSTM(h^i_{sk(k-1)}, SEB(o^i_{sk}); \theta_{se})
\]

\[
m^i_s = h^i_{slo}
\]

Where \(o^i_s \in \Omega_s\) is the \(i^{th}\) observation data from the source domain, \(\theta_{se}\) is the source encoder parameters, \(h^i_{slo}\) is the final hidden state of the encoder, and \(m^i_s \in \mathbb{M}_s\) is the trajectory feature of the \(i^{th}\) person. Moreover, the design of the Target Encoder (TE) is the same as the Source Encoder (SE), but with different parameters \(\theta_{te}\).

The decoder part is composed of a step embedding, an LSTM and an MLP (\(\psi(\cdot)\)). Specially, both the input and output of decoder are coordinate offsets (\(k \in [l0 + 1 : l0 + l_f]\)):

\[
h^i_{sk}, out^i_{sk} = LSTM(h^i_{sk(k-1)}, SEB(\Delta o^i_{slo}/\Delta f^i_{s(k-1)}); \theta_{sd})
\]

\[
\Delta f^i_{s(k)} = \psi(out^i_{sk}; \theta_{sd})
\]

3.2.2. Wasserstein-distance

The same as the KL-divergence, the Wasserstein-distance (W-distance) is a kind of metric to evaluate the difference between two distributions. First being proposed by [25], the W-distance has shown the advantages on adversary learning. The W-distance [28] could be calculated by:

\[
W(\mathbb{P}_r, \mathbb{P}_g) = \frac{1}{K} \sum_{||D||_L \leq K} \mathbb{E}_{x \sim \mathbb{P}_r}[D(x)] - \mathbb{E}_{x \sim \mathbb{P}_g}[D(x)]
\]

(4)

Where \(D(x)\) is a K-Lipschitz function. Therefore, by solving the problem:

\[
\max_{w:||D_w||_L \leq K} \mathbb{E}_{x \sim \mathbb{P}_r}[D_w(x)] - \mathbb{E}_{x \sim \mathbb{P}_g}[D_w(x)]
\]

(5)

People could estimate \(\hat{D}(x)\), which could assist them to calculate the W-Distance between \(\mathbb{P}_r\) and \(\mathbb{P}_g\).

3.2.3. Trajectory Feature Domain Adaption

The purpose of this step is to map the trajectory feature from the target domain into the source domain. Therefore, we adapt it to a Domain Adaption task, which means the task of this step is to minimize the distribution difference between \(\mathbb{M}_s\) and \(\mathbb{M}_t\). Therefore, with the target decoder, we could estimate \(Pr(m_s|o_t)\).

To achieve this goal, we employ the W-distance-based Adversarial Domain Adaptation. Specifically, this step needs to train the target encoder with parameter \(\theta_{te}\), and the Cross-domain feature discriminator with parameter \(\theta_{dA}\).

According to Eq. (4), denoting the data distribution on \(\mathbb{M}_s\) and \(\mathbb{M}_t\) as \(\mathbb{P}_{ms}\) and \(\mathbb{P}_{mt}\), the W-distance between \(\mathbb{P}_{ms}\) and \(\mathbb{P}_{mt}\) could be estimated by:

\[
W(\mathbb{P}_{ms}, \mathbb{P}_{mt}) = \mathbb{E}_{x \sim \mathbb{P}_{ms}}[\hat{D}_w(x)] - \mathbb{E}_{x \sim \mathbb{P}_{mt}}[\hat{D}_w(x)]
\]

(6)

where \(\hat{D}_w(x)\), could be estimated by solving the problem:

\[
\min_{w:||D_w||_L \leq 1} L_{wd} = \mathbb{E}_{x \sim \mathbb{P}_{ms}}[D_w(x)] - \mathbb{E}_{x \sim \mathbb{P}_{mt}}[D_w(x)]
\]

(7)

Moreover, to enforcing the constraint of Lipschitz Function, [29] proposed to enforce the Gradient Penalty:

\[
L_{gp} = \mathbb{E}_{x \sim \mathbb{P}_s}[(||\nabla x \hat{D}(x)||_2^2 - 1)^2]
\]

(8)

\(\mathbb{P}_s\) is uniformly distributed on the straight line between pairs of points sampled from \(\mathbb{P}_{ms}\) and \(\mathbb{P}_{mt}\).

Eventually, we should solve the problem:

\[
\min_{D(x; \theta_{dA})} L_{wd} - \lambda L_{gp}
\]

(9)

After getting the estimation of the distribution distance, the task of the target decoder is to minimize the distribution difference between \(\mathbb{M}_s\) and \(\mathbb{M}_t\), i.e.

\[
\min_{\theta_{de}} (-\mathbb{E}_{x \sim \mathbb{P}_s}[\hat{D}(TE_{\theta_{de}}(x))])
\]

(10)

The detailed algorithm to train the Cross-domain feature discriminator (\(D_{\theta_{dA}}\)), and the Target Encoder(TE) is shown as [Algorithm 1].
3.2.4. Coordinate offset Domain Adaption

The task of the Coordinate offset Adaptor (CA) is to project the coordinate offset from the source domain to the target domain. Therefore, we also treat this step as a Domain Adaption task, and employed a similar structure of the previous part.

Instead of the absolute pedestrian coordinate, we select the coordinate offset as the input and the output of both the decoder and the CA. Both the theoretical and experimental analysis demonstrate the rationality of this setting. To be specific, on one hand, in most circumstances, it is reasonable to assume that the distribution of the coordinate offset is an symmetric distribution with mean zero. Because pedestrians could go both up/down, right/left freely. On the contrary, the variation of starting coordinates will significantly enlarge the sample space and complicate the absolute coordinate distribution. Accordingly, coordinate offset space is more suitable for domain adaption tasks. On another hand, the ablation experiment also justifies this setting.

Since the $lo$ is usually different from $lf$ (in our experiment, $lo = 8$, $lf = 12$), given the requirement of training target domain offset discriminator, the input frame length of CA might not be 12. In our model, we set the CA input as the concatenation of 6 consecutive frames.

3.2.5. Inference

Previous sections described our approach to construct a CTP-Net, that could both map the trajectory feature from the target domain to the source domain, as well as project the coordinate offset from the source domain to the target domain. Afterward, when finish training, the inference procedure on the target domain is: Target Encoder $\rightarrow$ Source Decoder $\rightarrow$ Coordinate Projector

4. EXPERIMENTS

4.1. Datasets and Evaluation Metrics

Datasets: We evaluate our proposed model on the following publicly available datasets: ETH [30] and UCY [31]. ETH and UCY dataset are widely used for the pedestrian trajectory prediction. The ETH dataset contains two scenes named UNIV and HOTEL, while The UCY dataset contains three scenes named ZARA01, ZARA02 and UNIV. Specifically, we set the observation frame length as 8, and the prediction frame length as 12.

Evaluation metrics: Following previous works [30][10], we adopt two common metrics for testing. (1) Average Displacement Error (ADE) is the mean squared error (MSE) between the ground truth and our prediction over all estimated time steps. (2) Final Displacement Error (FDE) is the Euclidean distance between the predicted final points and the ground truth points at the final prediction. They are defined as:

$$ ADE = \frac{1}{N} \sum_{i=1}^{N} \sqrt{\sum_{t=0}^{N-1} (\hat{F}_t^i - F_{t+1}^i)^2} $$

$$ FDE = \frac{1}{N} \sum_{i=1}^{N} \sqrt{|\hat{F}_{t_f}^i - F_{t_f}^i|^2} $$

Here $N$ is the number of predicted points, $lf$ is the number of predicted frames, $lo$ is the number of observed frames, $\hat{F}_{t+1}^i$ is the predicted coordinates of the trajectory of the $i^{th}$ pedestrian at time $t+1$, and $F_{t+1}^i$ is the corresponding ground truth coordinates.

4.2. Setting

We construct 4 group of experiments:
1. Source: UCY-zara02; Target: ETH-univ.
2. Source: ETH-univ; Target: UCY-zara02.
3. Source: UCY-univ; Target: ETH-hotel.
4. Source: ETH-hotel; Target: UCY-univ.

For each source domain data set, we separate the **training : validation** as 8 : 2; For each target domain data set, we separate the **training : test** set as 4 : 6. Accordingly,
Table 1. Comparative experiment results between our model and baselines. *val*: validation result on source encoder-decoder; *source-only*: source encoder-decoder result; *fine-tuning*: fine-tuning based on trained source encoder-decoder; *target encoder*: replace source encoder with target encoder. *Target encoder & offset adaptor*: final CTP-Net inference path.

| Component                        | Performance (ADE/FDE) |
|----------------------------------|-----------------------|
|                                 | eth-zara | zara-eth | stu-hotel | hotel-stu |
|                                 | social-lstm | fine-tuning | social-lstm | fine-tuning | social-lstm | fine-tuning | CTP-Net | social-lstm | fine-tuning | CTP-Net |
| *val*                           | 4.01/6.32 | 1.73/3.06 | 0.92/1.47 | 0.88/1.46 | 1.17/2.07 | 0.81/1.55 | 1.00/1.52 | 0.74/1.26 |
| source-only                     | 1.27/1.83 | 2.76/4.89 | 3.65/6.10 | 2.90/5.28 | 2.17/3.86 | 2.76/5.14 | 2.01/3.30 | 4.63/8.46 |
| fine-tuning                     | 3.61/5.55 | 2.98/5.08 | 2.56/5.11 | 2.50/3.85 | 3.34/5.65 | 2.60/4.85 | 2.79/5.19 | 3.89/7.30 |
| target encoder                  | 1.42/2.73 | 4.40/3.35 | 1.59/2.79 | 1.61/2.93 |
| Target encoder & offset adaptor | 1.42/2.73 | 4.40/3.35 | 1.59/2.79 | 1.61/2.93 |

Table 2. Ablation experiment results.

| Component                        | Ablation Performance (ADE/FDE) |
|----------------------------------|--------------------------------|
|                                 | eth-zara | zara-eth | stu-hotel | hotel-stu |
|                                 | coordinate | offset | coordinate | offset | coordinate | offset | coordinate | offset |
| *val*                           | 2.32/2.90 | 1.73/3.06 | 1.18/1.36 | 0.88/1.46 | 0.79/1.41 | 0.81/1.55 | 1.20/1.51 | 0.74/1.26 |
| source-only                     | 3.90/5.65 | 2.76/4.89 | 3.24/4.63 | 2.90/5.28 | 3.90/4.72 | 2.76/5.13 | 10.39/10.37 | 4.63/8.46 |
| target encoder                  | 4.12/5.70 | 3.34/5.65 | 3.36/4.45 | 2.61/4.85 | 4.01/4.44 | 2.79/5.19 | 11.02/12.48 | 3.89/7.06 |
| Target encoder & offset adaptor | 4.52/4.83 | 4.40/3.35 | 3.47/3.90 | 1.59/2.79 | 4.66/5.55 | 1.61/2.93 |

4.3. Implementation

In our experiment, we use MLPs to conduct step embedding with the embedding size as 32, the LSTM hidden size as 512, the layer amount of the source decoder MLP is 3. Moreover, all the offset adaptor, the target domain offset discriminator, and the Cross-domain feature discriminator are constructed by MLP with ReLU functions, and the layer amounts for them are: 2, 10, 5.

4.4. Baseline

We compared the performance of our model with 2 baseline, the results of baseline is shown in Table 1:

1. Social-lstm [10]: With the assistance of pooling layer, the Social-LSTM vectorizes and utilizes the interaction between pedestrians.
2. The Fine-tuning model: this model is fine-tuned on the target training set. Specifically, after training the source encoder-decoder, this model takes the first 4 frames from the target observation as input to predict the next 4 frames.

4.5. Ablation & Visualization

In the ablation experiments, we compared the performance of using offset, and coordinate as prediction stuff. And the performance demonstrates our setting of offset. All results are shown in Table 2.

To intuitively verify the effectiveness of NPT-Net, we visualized the sample ground truth offsets, source-only prediction and NPT-Net prediction offsets in Fig. 2.

5. CONCLUSION

In this work, we propose the domain adaptation setting for trajectory prediction, where only the observed trajectories with annotated future trajectories on the source domain and the observed trajectories without future trajectory annotations on the target domain are available. To adapt the annotated source domain future trajectories to the target domain, we propose the Cross-domain Trajectory Prediction Network (CTP-Net). In CTP-Net, the feature-level cross-domain alignment is proposed to align the feature from the source and target domain observed trajectories. To make the predicted future trajectories consistent with the observed trajectories on the target...
domain, the target domain trajectory alignment is further introduced in CTP-Net. Experiments validate the effectiveness of the proposed domain adaptation for trajectory prediction setting as well as the CTP-Net on domain adaptation for trajectory prediction.

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