A Report of Trajectory Prediction based on Deep Learning

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ABSTRACT

Pedestrians trajectories prediction has become a popular topic in recent years. Many approaches can be used to accomplish the prediction, including deterministic and non-deterministic ways. In this report we conduct research and discuss how to use a non-deterministic method, i.e. deep learning methods to solve the prediction problem. The algorithm we are going to use is a combination of SocialGAN and InfoGAN. Firstly, we train a model by the adopted algorithms. Secondly, during the research, we propose our research questions and try to answer them in the report.

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INTRODUCTION

The innate abilities that human beings possess to process complex things effortlessly in daily life are impressive. To translate even the fractional part of one of these abilities of the human being into a machine is a challenging task in itself. One such ability of human beings is to navigate in a social environment. For example, when we walk in a crowded public space we follow a large number of common-sense rules and social etiquette. Which includes respecting the personal space of others, yielding right-of-way, avoiding walking through the people belonging to the same group, taking the shortest or safer path to the destination, and much more.

This ability of ours in the field of technology is commonly known as Human/Pedestrian trajectory prediction. The task of predicting human trajectories is crucial for current and future technological advancements. There are already many applications that make intensive use of modeling the pedestrians motion data and social interactions, e.g. infrastructure design (urban safety, city planning) [5, 9, 12], traffic operations [11], autonomous driving, are just a few to name. Typically, this modeling is performed in an offline manner by gathering the pedestrian motion data beforehand and completing the analysis to make decisions for the improvements in the environment. In modern world applications, however, one needs to perform this in real-time, allowing one to predict the pedestrian moves and infer their short or mid-term intentions in the environment. That allows to take preventive actions and trigger the alarm for the monitoring system in critical real-time decision-making

applications. As in the case of autonomous driving, finding the intention of the pedestrians surrounding the car is of paramount importance in avoiding collisions. The task of modeling social interactions is extremely challenging as there exists no fixed set of rules which govern human motion. Here we refer to this task of predicting the human motion as Pedestrian trajectory prediction.

Helbing and Molnar [10] propose the Social Force model. Yi [16] introduces the factor of a stationary group to the modeling of pedestrians trajectories with an energy map. The aforementioned ways are deterministic ways for prediction, they can not utilize the valuable information in the trajectories data.

Over the last few years, following the widespread usage of machine learning and deep learning methods, researchers use various neural networks to tackle the trajectories prediction problem. Zhou et al. [17] build a linear dynamic system, applying Expectation Maximization (EM) algorithm to estimate parameters, to learn motion patterns in crowded scenes. Altché [2] proposes a method that predicts the trajectory on the highway using Long Short-Term Memory (LSTM). Alahi et al. [1] give a sequence model based on LSTM as well as a social pooling that aggregates the human-human interaction in a scene.

However, these approaches mentioned previously learn only the pattern of human motion from data. Predicting human trajectory is a complex task. This is because both internal and external stimuli, such as intentions and other directly or indirectly observable influences, can affect human motion, as mentioned in the survey [15]. In addition to the location, which is usually recorded in the dataset, many factors that are not explicitly recorded in the dataset, such as speed, direction, or even not recorded, such as route and human intent. Recent researches have shown that Generative Adversarial Network (GAN) can better capture these uncertainties with latent space and thus naturally preserve multimodality. Gupta et al. [8] used GAN and a Pooling Module to predict socially acceptable trajectories and found that certain directions in the latent space are related to direction and velocity. What is more, the study of Amirian et al. [4] has shown that InfoGAN, an information-theoretic extension to the Generative Adversarial Network [6], partly improves the performance on commonly used datasets that have the largest variance in the prediction distribution, while still leaving some room for improvement.

Even though these researches give various effective models that fulfill the prediction task and attempt to encompass hidden aspects that influence the trajectory, they have not disentangled these factors in the latent space. If we know the factors that affect pedestrians' trajectory and apply these factors in specific scenarios, we can obtain better performance of prediction on various distributed

datasets and to mitigate the limitations of the observed data. Therefore, we decide to consider the hidden factors behind different datasets.

In this study, we focus on what factors we can obtain that influence human trajectories and try to develop a model that can be controlled by these factors. we assume that different datasets have different static environments and so the data in a dataset share some specific common features. We consider three factors: obstacles (obstacles information such as the presence of static obstacles and the coordinates), maps (geometry and topology), and semantics (environment semantics such as no-go-zones, crosswalks, sidewalks, or traffic lights) in static environments, which are denoted by the survey [15]. We propose to develop a controllable generation model that is controlled by factor c to have different static environments. We demonstrate that human movement is influenced by these three factors that we consider in a static environment. Also, with inputting different factors in static environments, our model can achieve better performance on different datasets.

1 PROBLEM STATEMENT

In this paper, our goal is to develop a controllable generative model to predict pedestrian trajectories. Consider the problem of predicting the future trajectory of each pedestrian. Let (x_i^t, y_i^t) denote the position of the i pedestrian at time t, and a sequence of coordinates $[(x_i^t, y_i^t), (x_i^{t+1}, y_i^{t+1}), ..., (x_i^{t+n}, y_i^{t+n})]$ denote the trajectory of pedestrians from time t to $t + n$.

Given the observed trajectory of n_{obs} steps $X_i^t = [(x_i^t, y_i^t), (x_i^{t+1}, y_i^{t+1}), ..., (x_i^{t+n_{obs}}, y_i^{t+n_{obs}})]$, with certain controllable factor c and random variable z, we want to fit a function to generate the prediction of trajectory for the next n_{pred} steps $Y_i^t = [(x_i^{t+n_{obs}+1}, y_i^{t+n_{obs}+1}), (x_i^{t+n_{obs}+2}, y_i^{t+n_{obs}+2}), ..., (x_i^{t+n_{obs}+n_{pred}}, y_i^{t+n_{obs}+n_{pred}})]$. That is

$$Y_i^t = f(X_i^t | c, z)$$

The prediction Y_i^t is controllable by the vector c, where consist of (c_1, c_2, c_3). So we can control the factors of obstacles, maps, and semantics respectively. These factors might vary over time.

2 DATA ACQUISITION & PRE-PROCESSING

In this section, we introduce the two publicly accessible datasets we will use for our experiments, ETH [14] and UCY [13]. They are widely used datasets that contain real-world human trajectories. Researchers at ETH and UCY took videos at different locations and manually annotated them with time steps of 0.4 seconds. The datasets of ETH contain 2 subsets: eth (with 365 pedestrians) and hotel (with 420 pedestrians). The UCY datasets contain 3 subsets: zara01 (with 148 pedestrians), zara02 (with 204 pedestrians) and univ (with 850 pedestrians). The UCY datasets contain 3 subsets: zara01 (with 148 pedestrians), zara02 (with 204 pedestrians) and univ (with 850 pedestrians). All these pedestrian trajectories were recorded in 4 different scenarios with different maps, obstacles and times. People have various goals, so there are different directions and velocities.

2.1 Data acquisition

The original datasets can be downloaded directly from the official download links (ETH - BIWI Walking Pedestrians dataset [1], UCY - Crowded Data [2]).

2.2 Data preprocessing

In our experiments, we use the data parsed by SocialWays directly. In our experiments, we use the data parsed by Social Ways directly. For the ETH dataset, the parsing process can be illustrated by the Social Ways project, and for the UCY dataset, the parsing process is currently not included in the project and is not publicly available. But the parsed data is provided by Social Ways and is available for public download [3].

3 MODELLING

Our experiments are based on Social Ways. A major change in Social Ways compared to previously implemented GAN models for trajectory prediction is that it implements the InfoGAN architecture. The results from Social Ways [3] show that InfoGAN can greatly improve the trajectory prediction of multimodal pedestrians, avoiding pattern collapse and degradation. Figure 2 illustrates the architecture.

In the following subsections, we will describe the key methods of Social Ways and our experiments.

3.1 Methodology

3.1.1 Generative Adversarial Networks.

According to the research of Generative Adversarial Nets [7]: a Generative Adversarial Network (GAN) consists of two network components, a discriminator D and a generator G, which compete with each other. G takes the input noise variable z and generates the sample $G(z)$, D takes the generated sample or training data as input x and predicts the probability $D(x)$ that x comes from the data and not generated by G. D is trained to maximize the probability of assigning correct labels to training samples and generated samples, while G is trained to minimize the correctness of D. In other words, D and G play a min-max game with the value function $V(G, D)$.

$$\min_G \max_D V(G, D) = \mathbb{E}_{x \sim p_{data}}[\log(D(x))] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))] \quad (1)$$

In our case, for pedestrian trajectory data, the generator is trained to generate possible future trajectories that have a distribution similar to the training data, given certain previously observed trajectories, while the discriminator learns to distinguish the rationality of the generated paths. These two networks are trained simultaneously. As the discriminators are learned, the generators are improved.

3.1.2 InfoGAN.

The algorithm InfoGAN bases on Generative Adversarial Network(GAN). Even though Generator of GAN can generate fake examples from the noise input **z**, this noise vector is entangled. In other words,

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[1]https://data.vision.ee.ethz.ch/cvl/aem/ewap_dataset_full.tgz
[2]https://graphics.cs.ucy.ac.cy/research/downloads/crowd-data
[3]http://www.dropbox.com/sh/lh1s41d1pqp8cbx/AAD4sB1JAiZIkCL7LHht-S4Ca

we can not deduce any information from the input noise vector and can not control the output of the Generator. What the data the Generator will produce is totally random. Based on GAN, InfoGAN is a way that learning interpretable representation by information. It can deduce meaningful information from the input data. Instead of using single noise input, InfoGAN accepts another input which is called latent code $\mathbf{c}$. This latent code can be discrete or continuous. When it is discrete, a integer vector can be used to represent different factors. During training, the vector should be encoded by one hot code. Generator also contains another neural network Q which is called auxiliary network. It takes the fake data that generated by G and output the decoded latent code $\hat{\mathbf{c}}$. By maximizing the mutual information between $G(\mathbf{z}, \mathbf{c})$ and $\hat{\mathbf{c}}$, G and Q are trained. The system structure of InfoGAN is in 1. The min-max game of InfoGAN is a game with the value function[6]:

$$\min_{G,Q} \max_{D} \mathbf{V_{InfoGAN}}(D, G, Q) = \mathbf{V}_{D,G} - \lambda \mathcal{L}_I(G, Q),$$

where $\mathcal{L}_I(G, Q)$ is the lower bound of the mutual information $\mathbf{I}(c; G(z, c))$.

3.1.3 Description of Latent Code.

Our experiments attempt to disentangle the latent code so that the latent code can correspond to the semantic features of the data. To enrich our expression, we allow two types of latent codes, categorical latent codes and continuous latent codes.

For categorical latent code c, we can use cross entropy as a loss function to maximize the information between the code and the code predicted by Q.

$$\mathcal{L}(c, Q(G(x, c))) = MSE(c, Q(G(x, c)))$$

For a continuous latent code c, we can use the mean squared error as a loss function to maximize the information between the code and the code predicted by Q.

$$\mathcal{L}(c, Q(G(x, c))) = CE(c, Q(G(x, c)))$$

On the basis of categorical latent codes and continuous latent codes, we can introduce a series of semantic factors. For example, velocity and direction can be represented as continuous latent codes and scenes can be expressed as categorical latent codes. For map/obstacle information, the image embedding of the background image (the background image of the video recording trajectory data) can be used as a sequence of continuous latent codes.

3.1.4 Experimental Setup.

In our project, we will train the model using three integer latent codes and three continuous latent codes. At every loop of the training of G, we modify the noise vector as the combination of an one-hot encoded vector with three random integer numbers and another vector with three random float numbers.

After the model is trained, we need to evaluate the latent codes by the method called latent traversal. Assume the discrete codes are $\mathbf{C_1} = c_1, c_2, c_3$ and the continuous codes are $\mathbf{C_2} = c_4, c_5, c_6$. First we fix $\mathbf{C_2}$ and set $c_1 = 1, c_2 = 0, c_3 = 0$, then use the trained G to generate 10 trajectories. Then we draw 10 samples from the generated examples and plot the trajectories as pictures Pic_1. Then fix $\mathbf{C_2}$ and set $c_1 = 0, c_2 = 1, c_3 = 0$ and generate 100 trajectories and take random 10 plot as pictures. We conduct the same process

to each integer variables. Then we observe the trajectories in the picture and infer the possible factor that affects the trajectories. Our guess is speed and direction. We can start inferring from these two factors. If we can find out the pattern in the trajectories, we can match them to the vector of integer latent codes. When evaluate the continuous codes, just fix the other two codes and change the one that is being evaluated by 0.1 every loop, the value of the code value should be in [0.1, 0.3, 0.5, 0.7, 0.9]. There will be $3 \times 5 = 15$ groups of pictures. We observe the picture and try to deduce the factors from the trajectories.

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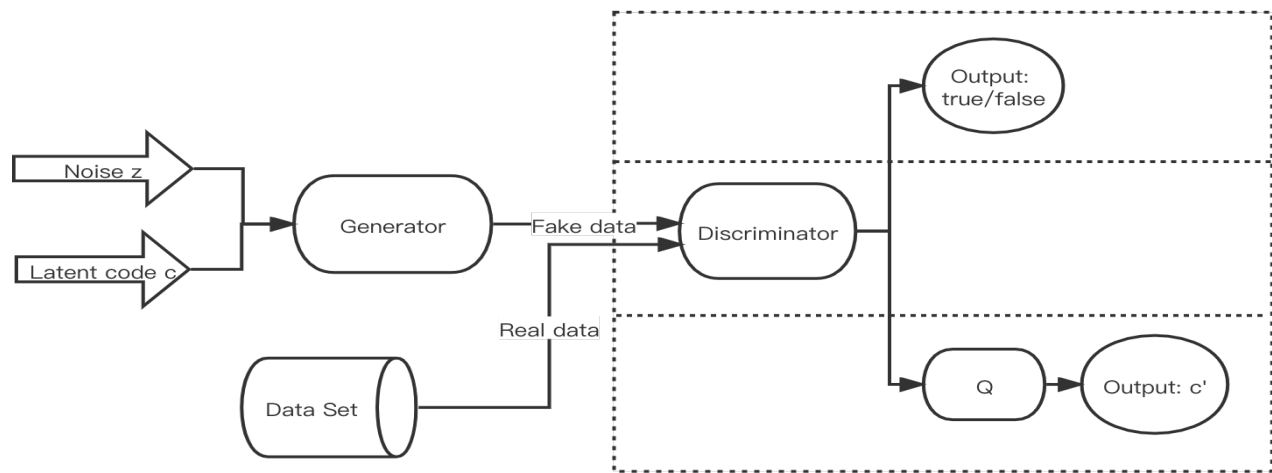
Figure 1: InfoGAN Overview
InfoGAN consists of three parts, Generator G, Discriminator D and auxiliary network Q. D and Q share the network, only their last layers
are different.