Personalized individual trajectory prediction via Meta-Learning

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Abstract

Individual trajectory prediction is a sequential forecasting task, which uses a moving agent's past trajectory to predict possible future trajectories. Existing work trains one predictor for all users, while few studies consider a personalized predictor that automatically extracts the personal trajectory characteristics for each individual. Also, individual trajectories are highly random and in-homogeneous, resulting in some real target locations are not in the training data set totally, making the model difficult to converge. To address above difficulties, we propose a pre-trained trajectory prediction model via meta-learning, which not only can learn a more generalized initialization parameters to extract the trajectory features of multiple individuals, but also solve the problem of in-homogeneous distribution using pre-trained grid-based classification.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**.

Keywords: Trajectory forecasting , Meta-Learning , Negative Sampling

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1 Introduction

Individual trajectory prediction is the cornerstone of navigation systems, location-based recommendation systems and other travel apps. For example, some apps will recommend the ads appealing to you based on the predicted location when you are wandering around the mall. However, to predict Individual's trajectories is still a challenging task due to some characteristic of individual trajectory.

Figure 1. Visualization of trajectories from different individuals. (identities are indicated by colors).

Firstly, individual trajectories are personalized, causes trained model can only be applied to specific individual. It is cost to retrain a new model if the predicted individual is replaced. However, few existing work considers to build a generalization model which extracts the multiple individuals' trajectory features simultaneously. In this study, we use the meta-learning method to train the trajectory prediction model to get a better initialization parameters, which can be adapt to a moving agent's trajectory features quickly with few trajectory data of the same user.
Another characteristic of individual trajectory is highly random and in-homogeneous. As shown in Figure 1, 3 individuals' trajectories are totally different and are concentrated in certain locations (black, red, yellow regions), while we do not have access to geographical information about other area (white region) which has a large impact on prediction. It causes that some real target locations are not in data-set totally, making the model difficult to converge or not converge at all. We propose a grid-based classification model with negative sampling pre-trained transforms individual trajectory forecasting into a classification problem to improve the accuracy.

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2 Personalized Trajectory Learning

2.1 Classification Model with Negative Sampling Pre-train

In Geo-life data-set, a person P has a set of trajectory data $\mathcal{D} = \{d_1, ..., d_n\}$, where d is a GPS point(longitude and latitude). We firstly partition the predicting region into small grids g, mark all the GPS points in this range with the same index, then transform the GPS data-set $\mathcal{D}$ to Gird data-set $\mathcal{G} = \{g_1, ..., g_n\}$ with a word dictionary $dict$ (Pre-train it with Negative Sampling based on spatial continuity). We sampling from Gird data-set $\mathcal{G}$ with a sliding window of equal length l in time series, then generating a lot of segments $\mathcal{S} = \{s_1, ..., s_m\}$, we define a segment s_i as a contiguous sub-sequence of Gird data-set $\mathcal{G}$ with l length $s = \{g_{t+1}, g_{t+2} ..., g_{t+l}\}$. A personalized trajectory prediction model f_θ is trained to produce a prediction location $Y = g_t$, where is the last one of a segment s, conditioned on $X = \{g_1, ..., g_{t-1}\}$, where is previous $t-1$ trajectory data of a segment s:

$$f_\theta(Y|X;\theta) = P(g_t|g_{1:t-1};\theta)$$

Our idea is to borrow from Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017)[1], which aims to learn the initial parameters of meta prediction model that can quickly adapt to the person after trained with few segment sample from its. We name it User-Agnostic Meta-Learning (**UAML**).

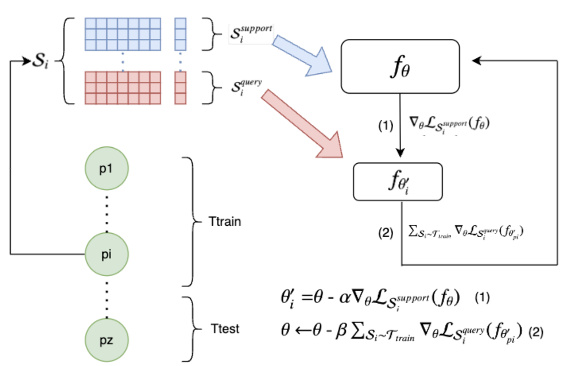

Figure 2. Visualization of UMAL.

2.2 User-Agnostic Meta-Learning.

Every person has a segment set S, therefore the meta data-set can be defined as $\mathcal{T} = \{S_1, ...S_z\}$, where z is the total number of person, which can be split into into $\{\mathcal{T}_{train}, \mathcal{T}_{test}\}$. For each train epoch, model sample a batch of person's segment set $\mathcal{S}_i$ from $\mathcal{T}_{train}$, then let few segments of it as support set $\mathcal{S}_i^{support}$ to train the sub-model f_θ then get $f_{\theta'_i}$, and other as query set $\mathcal{S}_i^{query}$ to test the $f_{\theta'_i}$ then get the query loss $\mathcal{L}_{\mathcal{D}_p^{valid}}(f_{\theta'_i})$. Finally use the gradient of query loss $\nabla_\theta \mathcal{L}_{\mathcal{D}_i^{valid}}(f_{\theta'_i})$ of each person in the batch to update the model. A summary of the training procedure is shown in Algorithm 1 and Figure 2.

Algorithm 1 User-Agnostic Meta-Learning

Require: $\mathcal{T}_{train}$
Require: α, β: step size hyperparameters
Randomly initialize θ
while not done **do**
  Sample batch of persona $\mathcal{S}_i \sim \mathcal{T}_{train}$
  for all $\mathcal{S}_i$ **do**
    Split $\mathcal{S}_i$ into $\mathcal{S}_i^{support}$, $\mathcal{S}_i^{query}$
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{S}_i^{support}}(f_\theta)$ using $\mathcal{S}_i^{support}$
    Compute adapted parameters with gradient descent: $\theta'_i = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{S}_i^{support}}(f_\theta)$
  end for
  $\theta \leftarrow \theta - \beta \sum_{\mathcal{S}_i \sim \mathcal{T}_{train}} \nabla_\theta \mathcal{L}_{\mathcal{S}_i^{query}}(f_{\theta'_{pi}})$
end while

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3 Experiment and Results

We utilized three metrics to quantitatively evaluate our methods:

$$MRR = \frac{1}{|N|}\sum_{i=1}^{|N|}\frac{1}{rank_i} \qquad Acc@K = \frac{1}{|N|}\sum_{i=1}^{|N|} rank_i \leq K$$

where mean reciprocal rank (MRR) is focused more on the top-ranked, $rank_i$ is the ranking of the real movement, $|N|$ is the number of samples.

Also, we use $Distance$ (Geodesic Distance between two GPS points) as the third metric. The experimental results are shown at Table 1 illustrate better performance of **UAML** model compared to **GRU** model with 3 train epochs using the same data-set.

Table 1. Quantitative evaluation

	MRR	*Acc@5*	*Acc@10*	*Distance*
UAML	0.15	0.22	0.29	3.5
GRU	0.06	0.10	0.13	5.4

4 Conclusion

UAML use grid-based classification model with negative sampling pre-trained transforms individual trajectory forecasting into a classification problem, and improve the performance about generalization of the model among different individuals. We tested our proposed model and the training paradigm using real-world GPS big data-set Geo-life data-set [2], and outperforms non-meta-learning baselines using some evaluation metrics.

References

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