Personalized individual trajectory prediction via Meta-Learning

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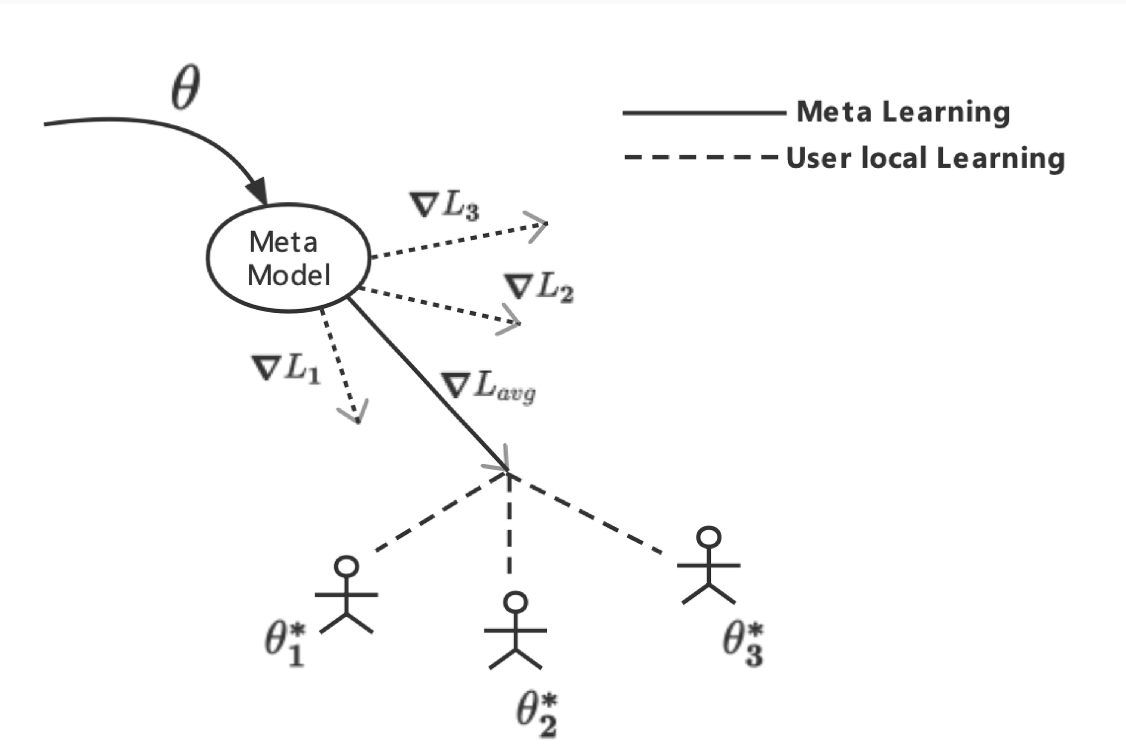
1.Goal:predict personal trajectory

Our goal is to train a meta model θ with a good initialize parameters, which can capture a user's personalize trajectory characteristic quickly. That means if you input a user's history trajectory data into the meta model, it can generate a sub-model θ^i adapted to that user more quickly compared to no-meta-learning model. You can use this sub-model θ^i to predict this user's future trajectory.



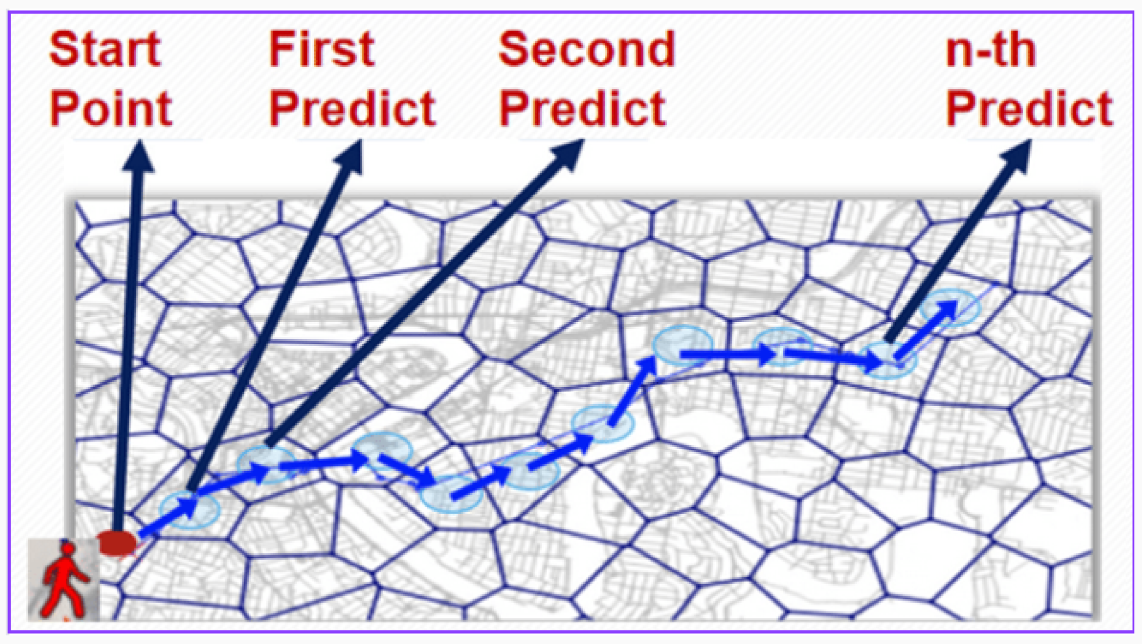
2.Two main challenges

The first challenge is that individual trajectories are personalized, causing that trained model can only be applied to specific individual. It is cost to retrain a new model if the predicted individual is replaced.

Another challenge is that characteristic of individual trajectory is highly random and in-homogeneous. As shown in the Figure , 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.

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



Algorithm

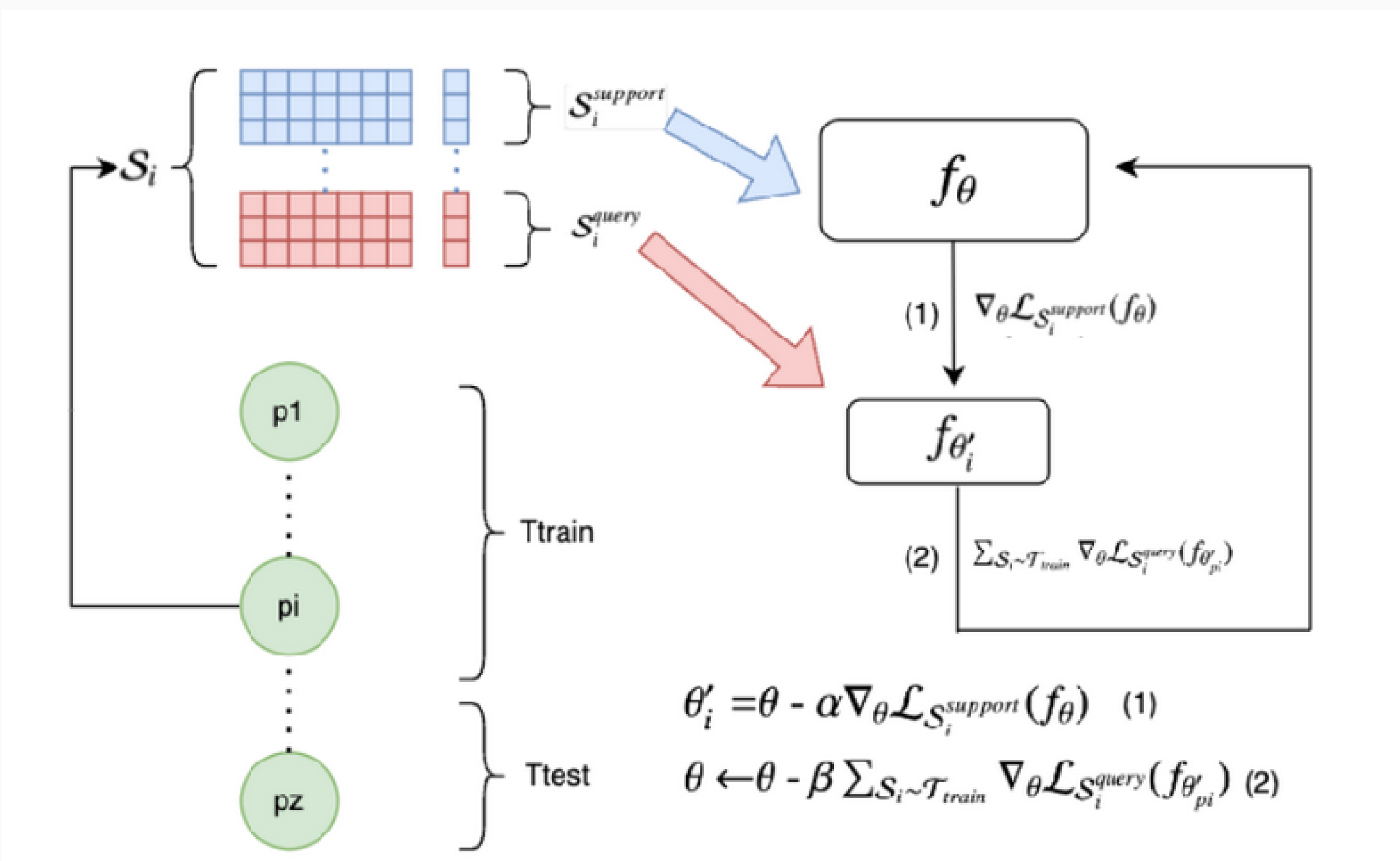
Our idea is to borrow from Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017), which aims to learn the initial parameters of meta prediction model that can quickly adapt to the person after trained with few segment sample from its. We name it User-Agnostic Meta-Learning (**UAML**)

Algorithm 1 User-Agnostic Meta-Learning

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

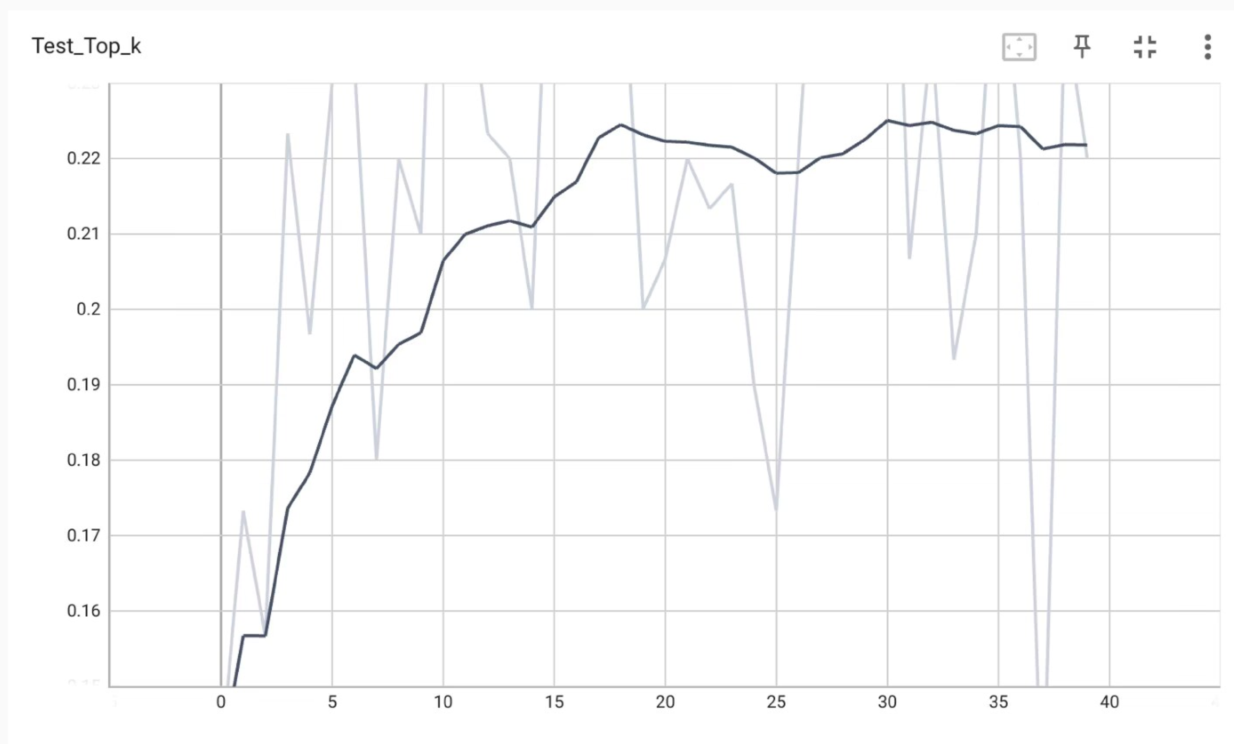
4.novel method:User-Agnostic Meta-Learning (UAML)

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.



5.Results and experiments

We compare our result with *GRU*, a classic model for trajectory predicting, and utilized three metrics to quantitatively evaluate our methods: *MRR* focus more on the top-ranked. *ACC@N* means that the accuracy of *TopN* prediction. Also, we use *Distance* (Geodesic Distance between two GPS points) as the third metric. And the result are as follows.



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