

#### ST-MoE-BERT: A Spatial-Temporal Mixtureof-Experts Framework for Long-Term Cross-City Mobility Prediction

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#### Outline



#### 1. Motivation & Problem Definition

Human Mobility Prediction Challenge (HuMob Challenge) 2024



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**Urban Planning** 

**Emergency Response** 

### 1. Motivation & Problem Definition

Challenges in Human Mobility Prediction

- Data quality: Sparse and unevenly distributed spatially and temporarily
- Complexity of human mobility patterns
- Transfer model between different cities

#### 1. Motivation & Problem Definition



Figure from <a href="https://wp.nyu.edu/humobchallenge2024">https://wp.nyu.edu/humobchallenge2024</a>





#### Embeddings





#### BERT



Figure from [1]

[1] Devlin, Jacob. "Bert: Pre-training of deep bidirectional transformers for language understanding." *arXiv preprint arXiv:1810.04805* (2018).



#### Mixture-of-Experts



FFN: Feed-forward network



Transfer Learning

Adapt learned representations from a large-scale mobility dataset of one city to predict mobility patterns in different cities.

#### **Differential Learning Rates:**

- **Spatial embeddings:** Higher learning rate (10x the base rate) to quickly adapt to unique spatial characteristics of a new city.
- **General Parameters:** Lower learning rate to retain broad knowledge from the initial training phase.





[1] Yabe, Takahiro, et al. "YJMob100K: City-scale and longitudinal dataset of anonymized human mobility trajectories." *Scientific Data* 11.1 (2024): 397.



Average number of user records per **A** day, **B** timewindow



City	Α	В	С	D
Number of Users	100,000	25,000	20,000	6,000



Accuracy

• the percentage of correct location predictions

**GEO-BLEU** 

• evaluates the similarity of geospatial sequences on place n-gram accuracy

Dynamic Time Wrapping (DTW)

• Minimize the cumulative distance over all points, adjusted for temporal shift



#### Results

Historical frequency (HF): predicts future locations using historical visit patterns based on time and weekday Naïve BERT

Method		А		В			С			D		
	GEO-BLEU↑	DTW $\downarrow$	Acc. ↑									
HF	0.266	80.3	20.4%	0.265	56.4	21.0%	0.251	42.4	20.8%	0.295	80.0	21.0%
BERT	0.256	35.7	23.8%	0.284	20.6	27.0%	0.253	65.6	18.2%	0.253	65.6	18.2%
ST-MoE-BERT	0.286	30.2	27.9%	0.297	29.3	28.7%	0.297	19.7	28.9%	0.300	48.1	26.5%





#### Ablation study

Impact of Transfer Learning on Prediction Performance

Method		А			В			С			D	
	GEO-BLEU↑	$\mathrm{DTW}\downarrow$	Acc. ↑	GEO-BLEU↑	DTW $\downarrow$	Acc. ↑	GEO-BLEU↑	DTW $\downarrow$	Acc. ↑	GEO-BLEU↑	DTW $\downarrow$	Acc. ↑
ST-MoE-BERT w/o PT	0.286	30.2	27.9%	0.286	28.2	27.5%	0.294	20.7	27.9%	0.250	67.6	21.4%
ST-MoE-BERT	-	-	-	0.297	29.3	28.7%	0.297	19.7	28.9%	0.300	48.1	26.5%

#### 

### 3. Experiments

#### Hyperparameters

Pretrained Model					
Learning Rate	0.0003				
Weight Decay	0.001				
Number of Hidden Layers	12				
Hidden Size	768				
Number of Attention Heads	16				
Number of Experts	8				
Dropout	0.1				
Day Embedding Size	64				
Time Embedding Size	64				
Day of Week Embedding Size	64				
Weekday Embedding Size	32				
Location Embedding Size	256				
Fine-Tuned Model					
Learning Rate	0.00005				
Location Embedding Learning Rate	0.0005				



#### **Our Contribution**

- We introduce ST-MoE-BERT, a transformer-based method that combines BERT with an MoE layer to predict long-term cross-city mobility
- Transfer learning strategy that employs different learning rates, enhancing prediction accuracy in different cities
- We demonstrate that ST-MoE-BERT outperforms the baseline methods with an average improvement of 8.29%



# Thank you!

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