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# Exploring nonlinear spatiotemporal effects for personalized next point-of-interest recommendation



**Key words:** Point-of-interest recommendation; Spatiotemporal effects; Long short-term memory (LSTM); Attention mechanism

Corresponding author: Zhimin LV
E-mail: lvzhimin@nercar.ustb.edu.cn
ORCID: https://orcid.org/0000-0002-7313-5796

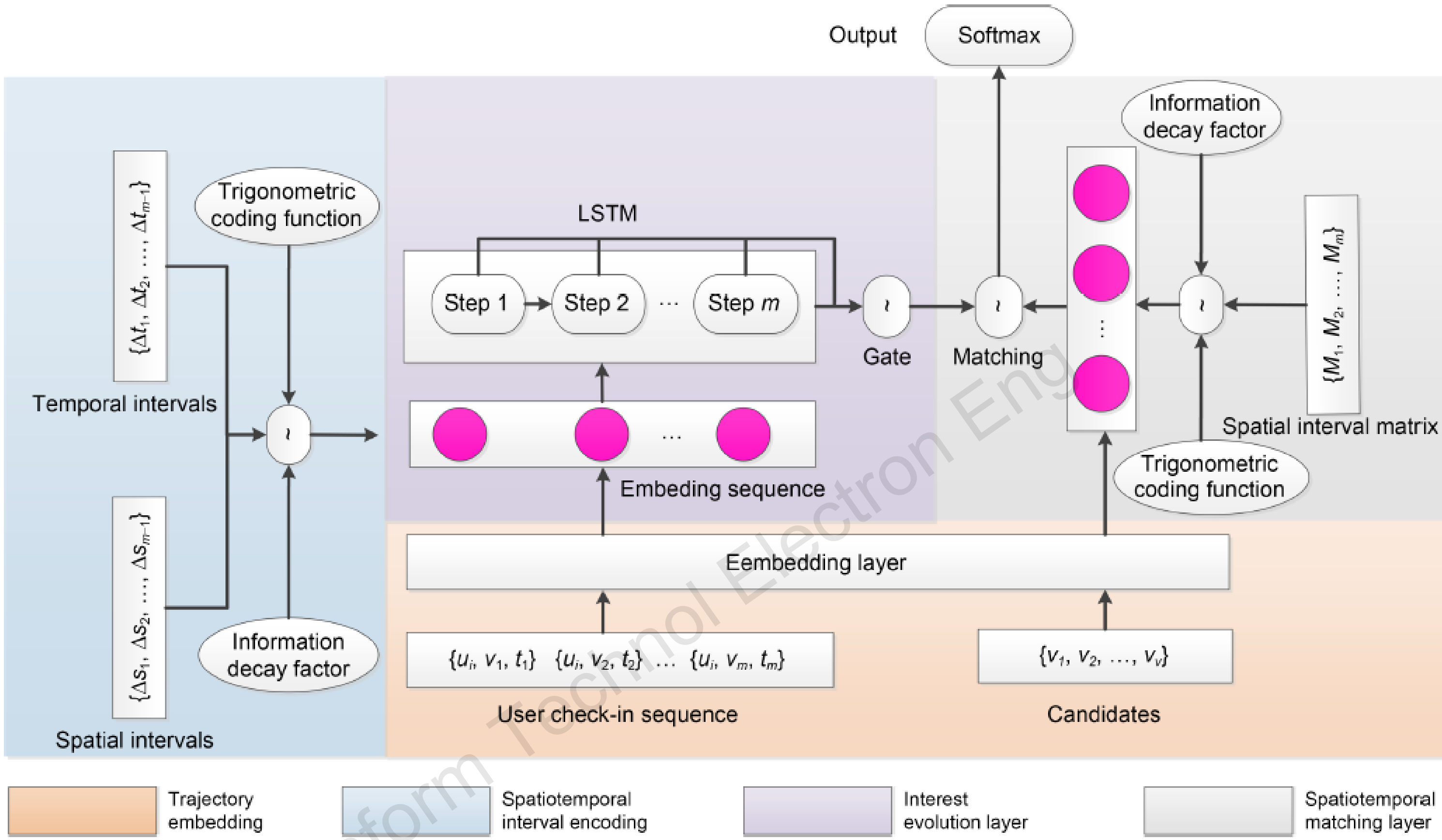
# Motivation

1. From a temporal perspective, user’s travel trajectories are periodic not only in the short term but also in the long term. From a spatial perspective, user’s check-in’s are generally concentrated around one or more central points, and the density decreases rapidly with increasing distance from the central location, indicating that the user’s check-in preferences are subject to nonlinear influences by geographical distance. Moreover, the decay of user interest over time is usually also a nonlinear process.
2. Previous models ignore the spatiotemporal correlation between user’s check-in trajectories and the candidate location sets. However, a user’s current preference is not only related to his/her historical behavior but also limited by time and region.

# Main contributions

1. We propose the spatiotemporal trajectory (STT) model, an improved form of the long short-term memory (LSTM) model with an attention mechanism (AM), to fully consider the spatiotemporal information of user's historical trajectories for aggregating relevant locations.
2. We introduce an information decay factor, which can be used as a weight in the process of spatiotemporal encoding. The decay factor can attenuate the information that is less relevant to the current spatiotemporal situation of the user, allowing the model to focus on more valuable information in a nonlinear fashion.
3. We design a spatiotemporal matching (STM) architecture for the spatiotemporal correlation of user historical trajectories with all candidate locations. This architecture matches the latent feature of the user STT with all the spatial representations of the candidate sets, and thus, it can find the most suitable point-of-interest (POI).

# Model






- Components of our model
  1. **The interest extractor layer** extracts the representation of user's STT.
  2. **The interest evolution layer** learns sequential preference by LSTM and AM.
  3. **The STM layer** measures the correlation between user's STTs and candidate sets and then calculates the softmax probability of user preference for candidate POIs.

# Recommendation performance

- The results of all baseline models on four datasets.

**Table 2 Evaluation of baseline models in terms of Recall@5 and Recall@10 on four datasets**

| Model | Recall@5 | | | | Recall@10 | | | |
|---|---|---|---|---|---|---|---|---|
| | NYC | TKY | SIN | Gowalla | NYC | TKY | SIN | Gowalla |
| STRNN | 23.65% | 18.36% | 17.91% | 16.64% | 28.02% | 27.91% | 20.16% | 25.67% |
| DeepMove | 32.68% | 26.84% | 23.89% | 19.59% | 40.14% | 35.09% | 31.55% | 26.99% |
| STGN | 24.39% | 19.40% | 22.92% | 15.28% | 30.15% | 27.10% | 27.27% | 24.22% |
| ARNN | 19.70% | 18.52% | 18.17% | 18.10% | 34.83% | 26.96% | 25.38% | 27.45% |
| LSTPM | 27.91% | 25.68% | 25.79% | 20.15% | 35.64% | 33.10% | 33.27% | 27.01% |
| TiSASRec | 36.64% | 30.31% | 29.63% | 24.11% | 50.20% | 36.93% | 37.53% | 35.46% |
| GeoSAN | 40.06% | 29.57% | 33.97% | 27.64% | 52.67% | 37.40% | 39.43% | 36.45% |
| STAN | 46.69% | 34.61% | 37.51% | 30.16% | 59.62% | 42.64% | 43.01% | 39.98% |
| STT | 62.42% | 37.28% | 37.83% | 31.23% | 72.88% | 46.41% | 45.42% | 41.74% |
| Improvement* | 33.69% | 7.71% | 0.85% | 3.55% | 22.24% | 8.84% | 5.60% | 4.40% |

NYC: New York City; TKY: Tokyo City; SIN: Singapore. * Recall@5 and Recall@10 of our STT model compared with those of STAN

- Our STT model outperforms all baselines on all datasets and gains 11.45% Recall@5 and 10.27% Recall@10 improvements on average against the strongest baseline STAN.

# Ablation study

- The performance of variant STT models on all four datasets.

Table 3 Ablation analysis (Recall@5 and Recall@10) on four datasets

| Variant | Recall@5 | | | | Recall@10 | | | |
|---|---|---|---|---|---|---|---|---|
| | NYC | TKY | SIN | Gowalla | NYC | TKY | SIN | Gowalla |
| Default | 62.42% | 37.28% | 37.83% | 31.23% | 72.88% | 46.41% | 45.42% | 41.74% |
| Remove TDF | 62.01% | 36.92% | 37.72% | 30.25% | 71.24% | 45.83% | 44.26% | 41.32% |
| Remove SDF | 61.10% | 33.27% | 35.97% | 30.19% | 71.09% | 45.10% | 43.72% | 41.20% |
| Remove TIE | 59.78% | 32.62% | 35.18% | 29.88% | 69.67% | 44.56% | 43.46% | 40.46% |
| Remove SIE | 57.91% | 30.98% | 34.81% | 27.94% | 69.64% | 43.34% | 42.34% | 38.05% |
| Remove AM | 54.69% | 30.25% | 31.55% | 21.33% | 63.33% | 39.37% | 39.38% | 35.47% |
| Remove STM | 34.76% | 13.43% | 20.37% | 15.44% | 41.71% | 17.92% | 29.45% | 26.56% |

NYC: New York City; TKY: Tokyo City; SIN: Singapore



- The interplay between different parts of the model suggests that we have captured the nonlinear influence of spatiotemporal information on users.

# Conclusions

- We propose a novel next POI recommendation method called STT that effectively considers the nonlinear spatiotemporal influence on user trajectories.
- We design an encoding method to introduce temporal and spatial interval sequences into our model. During the encoding process, we introduce a decay factor to help the model focus on valuable spatiotemporal information in a nonlinear way.
- We perform comprehensive parameter filtering, ablation study, and comparisons with baseline models in the experimental section. Experimental results demonstrate that our STT model improves the accuracy to a great extent compared with state-of-the-art models.

Xi SUN received his MS degree in School of Economics and Management from University of Science and Technology Beijing (USTB), China, in 2019. He is currently an PhD candidate in USTB. His current research interests include recommendation systems and industrial anomaly diagnosis.



Zhimin LV is currently a full professor of University of Science and Technology Beijing and deputy director of Steel Manufacturing Execution System Technology Engineering Research Center, Ministry of Education. He is mainly engaged in the research of product quality modeling and industrial big data application, production planning and scheduling theory, and enterprise information platform technology.