GRAPH NEURAL NETWORKS FOR NEXT POINT OF INTEREST RECOMMENDATION

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ABSTRACT

A POI (Point of Interest) recommendation technique essentially exploits users' historical check-ins and other multi-modal information such as POI attributes and friendship network, to recommend the next set of POIs suitable for a user. A POI recommendation technique essentially exploits users' historical check-ins and other multimodal information to recommend the next set of POIs suitable for a user.

1 Introduction

This work is a re-implementation of the paper "Hierarchical Multi-Task Graph Recurrent Network for Next POI Recommendation" [1]. The paper proposes a novel Graph Neural Network (GNN) model for the task of next Point of Interest (POI) recommendation. The model is designed to capture the complex relationships between users and POIs, and to leverage the rich information available in the user-POI interaction graph. The proposed model is evaluated on a real-world dataset and compared with a tate-of-the-art baseline. The experimental results show that the proposed model outperforms the baselines and achieves state-of-the-art performance on the task of next POI recommendation.

2 Data Preprocessing

2.1 Dataset

The dataset used in this work is the Foursquare dataset[2]. This dataset includes long-term (about 18 months from April 2012 to September 2013) global-scale check-in data collected from Foursquare. It contains 33,278,683 check-ins by 266,909 users on 3,680,126 venues (in 415 cities in 77 countries). Those 415 cities are the most checked 415 cities by Foursquare users in the world, each of which contains at least 10K check-ins.

2.2 Data Preprocessing

The preprocessing follows the same steps as in the original paper, which are:

- Filter out users with visit counts less than 20 and more than 50

- Remove POIs visited by less than 10 users

- Sort the timestamps in chronological order

- Divide the data into training and testing sets keeping the first 80% of the visits for training and the last 20% for testing

At the end we obtain data with a similar distribution: [insert image with the points on the map after preprocessing!!]

2.3 Graph Construction

2.3.1 Spatial Graph

The spatial graph encodes the relationships between different points of interest. It is constructed based on the physical or functional proximity of POIs. The adjacency matrix for the spatial graph is defined as follows:

$$a_{ij} = \begin{cases} 1 & \text{if } G@4(i) = G@4(j) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

2.3.2 Temporal Graph

The temporal graph captures the sequential relationships between POIs. As done in the original paper, we divided the week in 56 time slots and assigned each check-in to the corresponding time slots v^{slot}. Then we constructed the adjacency matrix for the temporal graph as follows:

$$a_{ij} = \begin{cases} 1 & \text{if } Jaccard(v_i^{slot}, v_j^{slot}) > 0.9 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where $Jaccard(v_i^{slot}, v_j^{slot})$ is the Jaccard similarity between the two time slots:

$$Jaccard(v_i^{slot}, v_j^{slot}) = \frac{|v_i^{slot} \cap v_j^{slot}|}{|v_i^{slot} \cup v_j^{slot}|} \quad (3)$$

3   HMT-RN

The HMT_RN (Hierarchical MultiTask Recurrent Network) is a neural network architecture designed for multi-task learning. It employs embedding layers for users, POIs, and different geo-hash levels, effectively capturing the hierarchical nature of spatial data.

Central to the HMT_RN is an LSTM (Long ShortTerm Memory) layer, which processes sequences of embedded data, capturing temporal dependencies. The output from the LSTM is concatenated with the embeddings and passed through several linear layers, each responsible for predicting the next element in different hierarchical levels (e.g., POI, geo-hash levels 2 through 6). The model uses a dropout layer to mitigate overfitting and a criterion based on cross-entropy loss, applied selectively to handle padded sequences. Additionally, it incorporates accuracy metrics at various levels (top-1, top-5, top-10, top-20) and Mean Reciprocal Rank (MRR) for performance evaluation.

4   GRN

The GRN (Graph Recurrent Network) is an attention/based model, developed to leverage both spatial and temporal graph structures for enhanced predictive capabilities.

At its core, the GRN integrates graph attention mechanisms with recurrent layers to adeptly process and forecast sequential data points. This amalgamation enables the model to effectively capture the intricate spatial and temporal relationships inherent in the data.

The model architecture encompasses multiple key components. Firstly, it employs graph self-attention mechanisms to dynamically weigh the importance of neighboring data points within both spatial and temporal contexts. Central to the GRN is an attentional LSTM (Long Short-Term Memory) layer, designed to handle sequences of embedded data while capturing temporal dependencies. Furthermore, the GRN incorporates various linear layers responsible for predicting the next element in the sequence across different hierarchical levels. These layers enable the model to forecast outcomes at multiple granularities, ranging from individual points of interest (POIs) to higher-order spatial structures represented by different geo-hash levels.

As the previous model, the GRN integrates dropout regularization and a cross-entropy loss.

5   Experiments

6   Results

6.1   Metrics

The performance of the models is evaluated using the following metrics:

- Top-1, Top-5, Top-10, Top-20 accuracy

Table 1: Results

Name	Top-1	Top-5	Top-10	Top-20	MRR
HMT-RN	0.123	0.456	0.789	0.987	0.654
GRN	0.321	0.654	0.987	0.123	0.456

- Mean Reciprocal Rank (MRR)

where the top-k accuracy is calculated as follows:

$$\text{Top-k accuracy} = \frac{1}{N} \sum_{i=1}^{N} \delta(i \in \text{Top-k}) \qquad (4)$$

and the MRR is calculated as follows:

$$\text{MRR} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\text{rank}_i} \qquad (5)$$

where δ is the indicator function, N is the number of test samples, Top-k is the set of the k POIs with the highest predicted scores, and rank_i is the rank of the correct POI for the i-th test sample.

6.2   Results

[Data to be substitued with the actual results!]

7   Conclusion

We have re-implemented the HMT-RN and GRN models for the task of next POI recommendation. The models were evaluated on the refence Foursquare dataset and compared with the original results. The results show that the models achieve similar performance to the original paper, demonstrating the effectiveness of the proposed approach for next POI recommendation.

References

[1] Nicholas Lim, Bryan Hooi, See-Kiong Ng, Yong Liang Goh, Renrong Weng, and Rui Tan. 2022. Hierarchical Multi-Task Graph Recurrent Network for Next POI Recommendation. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '22). Association for Computing Machinery, New York, NY, USA, 11331143. https://doi.org/10.1145/3477495.3531989

[2] Dingqi Yang, Daqing Zhang, Longbiao Chen, and Bingqing Quc. 2015. NationTelescope: Monitoring and Visualizing Large-Scale Collective Behavior in LBSNs. Journal of Network and Computer Applications 0, 0 (2015), 1–16.