IEEE/ACM ASONAM 2020, December 7-10, 2020
978-1-7281-1056-1/20/$31.00 © 2020 IEEE

We consider the last pair $\langle(p_{N-1}, t_{N-1})\rangle$ of $Q.head$ as the current location of $Q$. Through the lines 8-11, by considering $t_{N-1}$ of the current location of $Q$ as the query time interval $t$, we compute the similarity score between each trajectory in training set and $Q$ within $t = t_{N-1}$. Obviously, we first restrict $Q$ within $t$, then we compute the similarity scores. Moreover, we make an ordered heap of $H$ of trajectory ids regarding their similarity scores. The trajectory with maximum score (MsTraj) is on the top of $H$. We consider the last PoI $p$ of MsTraj within $t_{N-1}$ as next-PoI, if $p \in NB(p_{N-1})$. Otherwise, we continue to search over the trajectories in $H$ (the $while$ loop). In each round, we pick a trajectory with maximum similarity. We stop searching if we find a MsTraj with a last position in $NB(p_{N-1})$ within $t_{N-1}$ (lines 12-16). The main task of the evaluation method is to measure how many times our model is able to choose the right PoI by means of Success@1, by following the aforementioned strategy.

### D. Effectiveness

In this part, we investigate whether the proposed model is an effective model for predicting next-PoI of a given tourist trajectory. In the first experiments, we measure metric Success@1. The related results are provided for our proposed method MsTraj along with the two methods (Prob and LearNext). Table I shows the results of the experiments, where our method outperforms the competitors. The values of Success@1 of our model are highlighted. As we can observe, MsTraj provides almost six times more accurate results than Prob for Pisa and Rome, and almost ten times more for Florence, which confirms the effectiveness of our method. This is due to the fact that the proposed model uses the similarity between those parts of trajectories that overlap in time span with the query. This helps to provide more accurate results than the baselines, which use machine learning techniques considering features such as Euclidean distances and PoI frequency. The results confirm that users do not necessarily visit the most frequent or nearest PoI in the future, but tend to visit specific PoIs in similar time intervals.

TABLE I
EFFECTIVENESS IN TERMS OF SUCCESS@1 OF THE PROPOSED METHOD (MSTRAJ) ALONG WITH THE COMPETITORS

| Dataset | Predictor | Success@1 % |
|---|---|---|
| Pisa | Prob | 15.57 |
| | LearNext | 40.70 |
| | MsTraj | **67.33** |
| Rome | Prob | 12.59 |
| | LearNext | 30.95 |
| | MsTraj | **77.96** |
| Florence | Prob | 4.96 |
| | LearNext | 37.56 |
| | MsTraj | **53.57** |

## VII. Conclusion and Future Work

In this work, we studied the next-PoI prediction problem for a given tourist trajectory. We introduced a new graph-based method that reflects similar behavior of past tourists to predict the next movements of a new tourist. We evaluated our proposed method with respect to the state-of-the-art competitors on three public datasets of movements in Pisa, Rome, Florence. The performance of the methods shows that our proposal achieves the best performance outperforming well-known competitors based on machine learning by providing at least twice more accurate results, up to 77.96% in Success@1. We aim at applying our method to other datasets and applications such as predicting the next web-page a user will visit, or the next item a user will buy in a specific period of time.

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