Personalized Ranking Metric Embedding for Next New POI Recommendation

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1 Problem being addressed

Predict next new Point of Interest in location based data. Use sequential data, personalization and geographical data. Make use of appropriate temporal constraints (eg: time window threshold be no more than 6 hours.)

2 Key ideas and contributions

- Develops a novel PRME algorithm (personalized, ranking metric embedding) that ranks potential POIs using a low dimensional Euclidean latent space. The distance between two POIs measures the strength of their transition (or sequential relation.)
  Use of a pair-wise metric embedding algorithm to model the sequential transition of POIs. Only considers next new recommendation (N^2- POI recommendation problem.

- Suggesting new POIs is meaningful as users look for new POIs (eg: restaurants) to explore. (Explore more than exploit, here)

- The transition probability $P(l_j|l_i)$ fits a Boltzmann distribution. But since we consider pair-wise ranking, we only need to calculate the Euclidean distances in the k-dimensional latent space.

- Uses a linear interpolation (mixture model) to personalize this ranking.
  $D_{u,l^c,l} = \alpha D^P_{u,l} + (1-\alpha) D^S_{l^c,l}$ where l^c is the current location and l is the POI. S is the Sequential transition latent space for item similarity. P is the personalized latent space for user and item similarity.

- Incorporates geographical and time0based thresholds easily.

- **Training data** - FourSquare, Gowalla (1 year dataset)
  Optimization - MAP analogous to BPR
  Evaluation metric - Recall, Precision
  Baselines Most Popular, User based CF, MF, MC, FPMC, PME

3 Strong points

- Can capture transitive information- $X_i \rightarrow X_j$ & $X_j \rightarrow X_k$ implies $X_i \rightarrow X_k$, something FPMC cannot (as the factorization is independent)

- Can handle data sparsity and generalize over unobserved data (due to pairwise ranking)
- Successfully demonstrate that sequential modelling is more important than user preference modelling. $\alpha = 0.2$
- **Directionality** :From a sequential transition space, the directionality is actually ignored, since the Euclidean distance is the same for $a \rightarrow b$ and $b \rightarrow a$. The algorithm works well because the given a current location l_c, we don't need to worry about coming from another location to l_c. This is also another reason why data sparsity is not an issue.
- Can learn if 2 items are geographically far apart, but have a train connecting them, they are brought together in the latent space.

4 Weak Points

- **Temporal Dynamics**: Time is only considered from a thresholding perspective, and not as an integral aspect of the sequence (session based, time gaps etc)
- Unconvincing geographical influence modelling. No design decisions explained as to the choice of the weighting factor.

5 Questions

1. [**E**] Use α_u instead of α. Personalize the weighting as well.
2. [**E**] How would you handle repeat consumption?
3. Uses only current location. Transitivity exists. Do we still need to model something similar to higher order MCs?
4. "we assume that the observed next POI is more related to current POI than the unobserved POI." Is this because it is better than being random? What if a user is currently in an Italian restaurant a, and his observed POI is a Thai restaurant b of pure exploration, but the unobserved POI is an Italian restaurant c? The likelihood that a and c are closer in the metric space should be more than that of a and b

6 Misc

Easy, quick read. Creative.
ACM ref:
Shanshan Feng, Xutao Li, Yifeng Zeng, Gao Cong, Yeow Meng Chee, and Quan Yuan. 2015. Personalized ranking metric embedding for next new POI recommendation. In Proceedings of the 24th International Conference on Artificial Intelligence (IJCAI'15), Qiang Yang and Michael Wooldridge (Eds.). AAAI Press 2069-2075