WhereTo: a Travel Recommendation System

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Motivation & Introduction

- Learn more about Recommendation Systems

- Travel Recommendations
    - iGSLR: personalized geo-social location recommendation: a kernel density estimation approach (Chow and Zhang)
    - Blurring-Sharpening Process Models for Collaborative Filtering (Choi, et al.)
    - Spatio-Temporal Transformer Recommender: Next Location Recommendation with Attention Mechanism by Mining the Spatio-Temporal Relationship between Visited Locations (Huang, et al.)

- **Problem Statement**: build a recommendation system that recommends certain travel locations to the user, given historical spatio-temporal check-ins of users

Datasets

2 Datasets: **Gowalla** and **Foursquare**

- ❖ Publicly available datasets crawled from Gowalla and Foursquare websites
- ❖ Contain spatio-temporal check-ins of users across the globe for various time-frames
  - ❖ Gowalla: 6,442,890 check-ins for 196,591 users from Feb. 2009 - Oct. 2010
  - ❖ Foursquare: 22,809,624 check-ins for 114,324 from Apr. 2012 - Jan. 2014

Dataset Properties

- Also contain social links for the users to establish friendships
- The check-in statistics for both datasets are quite similar
- However, the social links greatly vary across the two datasets

Table 1: Dataset Raw Statistics

Metric	Gowalla	Foursquare
No of Users	196,591	114,324
No of Check-ins	6,442,890	22,809,624
No of Social Links	950,327	607,333
No of Locations	1,280,969	3,820,891
Timeframe	Feb. 2009 - Oct. 2010	Apr. 2012 - Jan. 2014
Friends per User		
Mean	9.67	6.97
Median	3	3
Range	1-14,730	1-1200
Check-ins per Location		
Mean	5.03	5.97
Median	2	2
Range	1-5,811	1-23,520

Dataset Preparation

❖ Datasets were thoroughly cleaned by dropping duplicates, converting the given utc time and offsets to regional timestamps, and removing the outliers

❖ Users with check-ins less than 5 were also removed in order to have sufficient information per user

❖ Method 1 required aggregations for user and location pairs and Method 2 required sorting users per timestamps

Model 1: Blurring-Sharpening Process Models for Collaborative Filtering (**BSPM**) **(Choi, et al. 2017)**

- ❖ Blurring and Sharpening processes to model user preferences
- ❖ Blurring using Heat Equation and Ideal Low Pass Filter
- ❖ Outperforms existing CF models and GCNs in terms of Recall
- ❖ Significantly faster than other baselines

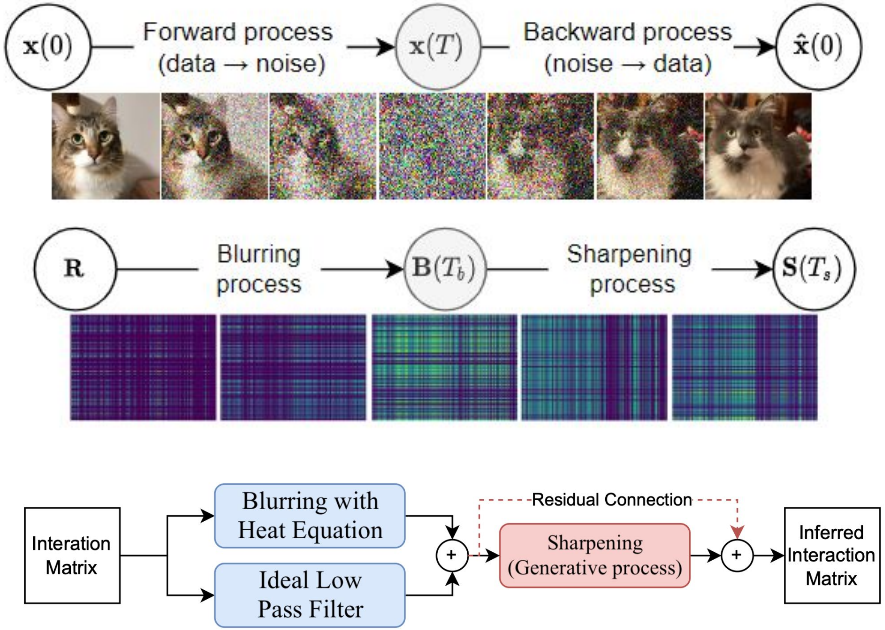

Figure 1: The comparison between SGMs and BSPMs; BSPM workflow

Model 1 (BSPM) Experiments & Evaluation

Experiment Setup:

- Interaction Matrix, some values are hidden as test values.
- 70/30 - train/test split
- System Settings:
  MacBook Pro M1 - 8GB RAM

Evaluation Metrics:

- **Recall@K**: probability that there are correct POIs (which are not present in the training set) in the first K recommended POIs.

Model 1 (BSPM) Results - Recall @ 20

RECALL@20	Gowalla			Foursquare		
idl factor	k=200	k=448	k=600	k=200	k=448	k=600
0.1	0.02792	0.02642	0.03621	0.01440	0.01924	0.01965
0.2	0.02892	0.02871	0.03471	0.01749	0.02215	0.02492
0.4	0.02971	0.03279	0.03563	0.01695	0.02305	0.02522
0.5	0.02871	0.03213	0.03563	0.01683	0.02605	0.02668
0.8	0.02904	0.03504	0.04192	0.01900	0.02764	0.02686

Table 2

Figure 2.1

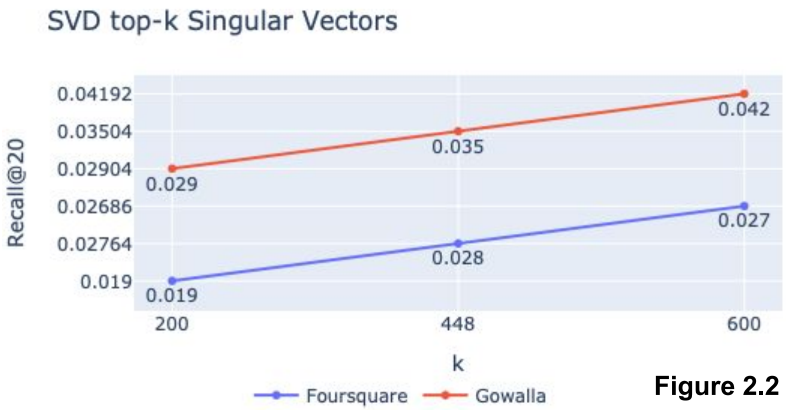

Figure 2.2

Model 1 (BSPM) Results - Time

Time (s)	Gowalla			Foursquare		
Time	**k=200**	**k=448**	**k=600**	**k=200**	**k=448**	**k=600**
Training	30.38600	98.91800	362.86500	30.35300	95.06800	268.12200
Test	21.49100	28.03000	33.45600	21.37200	26.99000	32.15900

Table 3

Model 2: Spatio-temporal Transformer Recommender (**STTR**) **(Huang, et al. 2017)**

- ❖ Determines the Spatio-Temporal patterns within the users trajectories and visited locations to predict the next POI (Point of Interest).
- ❖ Spatio-temporal Relationship explored using 2 ways:
  - ❖ Spatio-Temporal Aggregation
  - ❖ Long-Term preferences of User Trajectory(including user profile, location visited, timestamp, check ins, etc)
- ❖ Captures patterns/dependencies even when the data is spatially distant and temporally irregular.

Parameters
Embedding Dimension
of Negative Samples
Length of User History
Learning Rate
Dropout

Table 4: STTR Model Parameters

Model 2 STTR Model Architecture

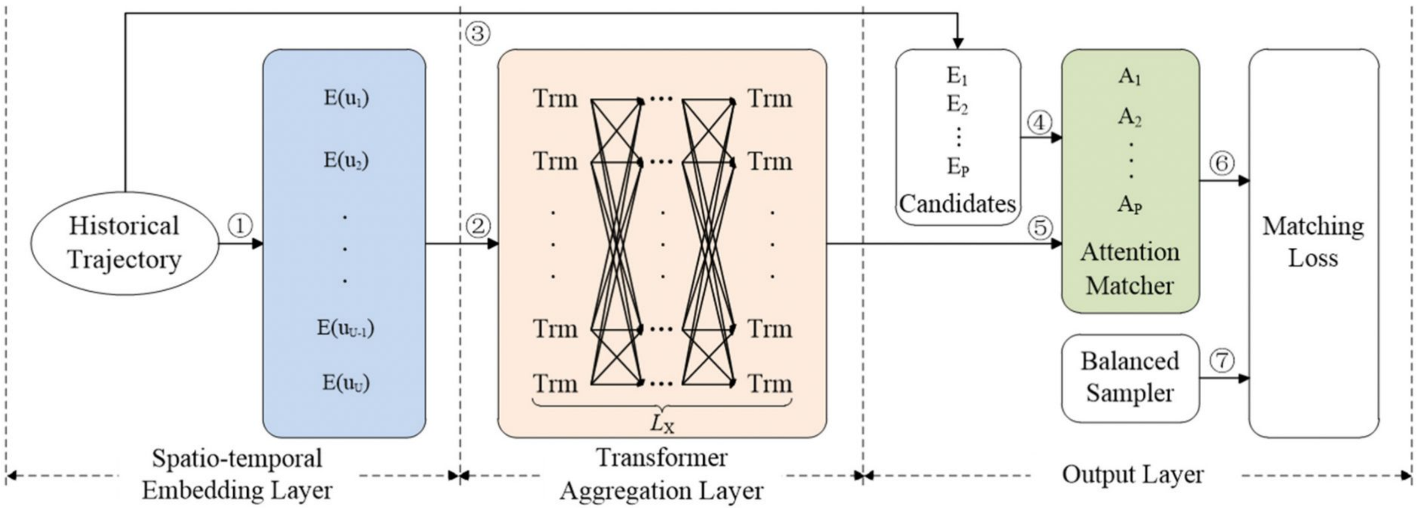

Figure 3.1: STTR Model Architecture

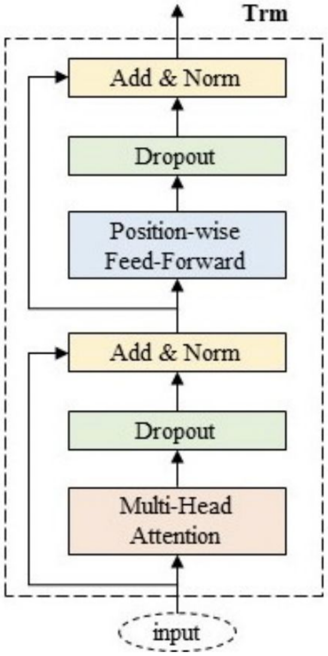

Figure 3.2: Transformer Unit Architecture

Model 2 (STTR) Experiments & Evaluation

Experiment Setup:

- Sequence of check-ins were split by interaction: 98 train, 1 validation, 1 test check-in
- System Settings: CoC Pace Clusters & Colab standard GPU was utilized
  - RAM: 12 GB
  - GPU: Nvidia K80

Evaluation Metrics:

- **Recall@K**: probability that there are correct POIs in the first K recommended POIs.
- **Normalized Discounted Cumulative Gain (NDCG@K)**: measures the quality of Top K ranking list depending on the ranks.

Model 2 (STTR) Results - Embedding Dimension

- Tuned embedding dimension while keeping other parameters consistent
- Higher the dimensions, better the model performance

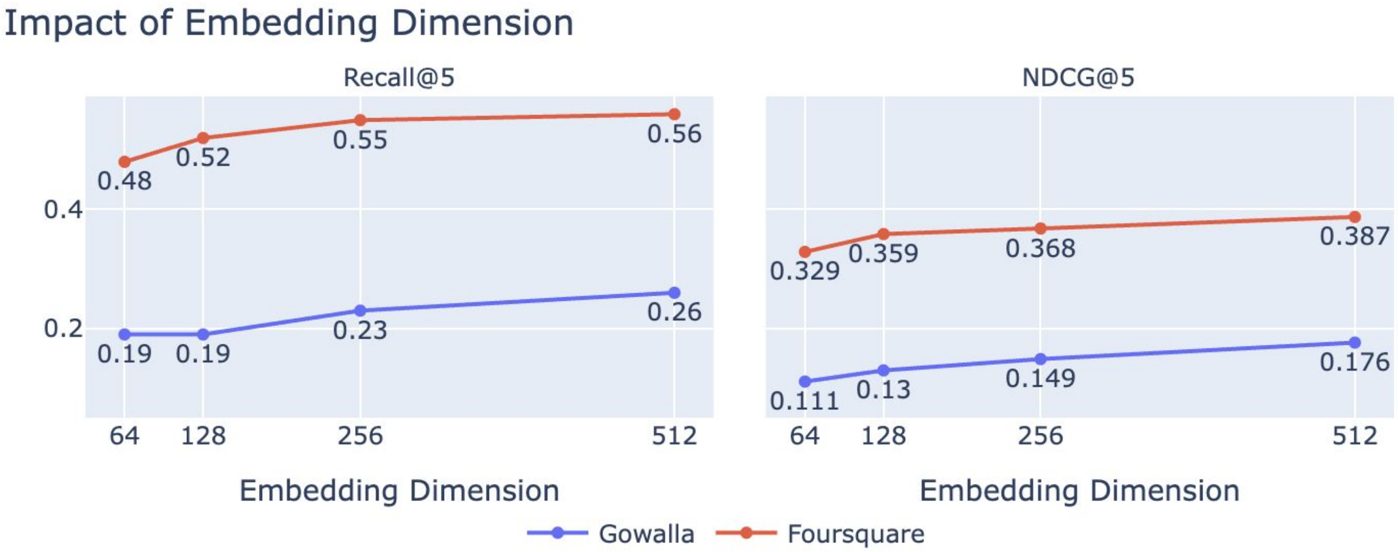

Figure 4: Impact of Embedding Dimension

Model 2 (STTR) Results - # of Negative Samples

- Tuned Number of Negative Samples keeping other parameters consistent
- Reaches best performance at 15 and decreases further

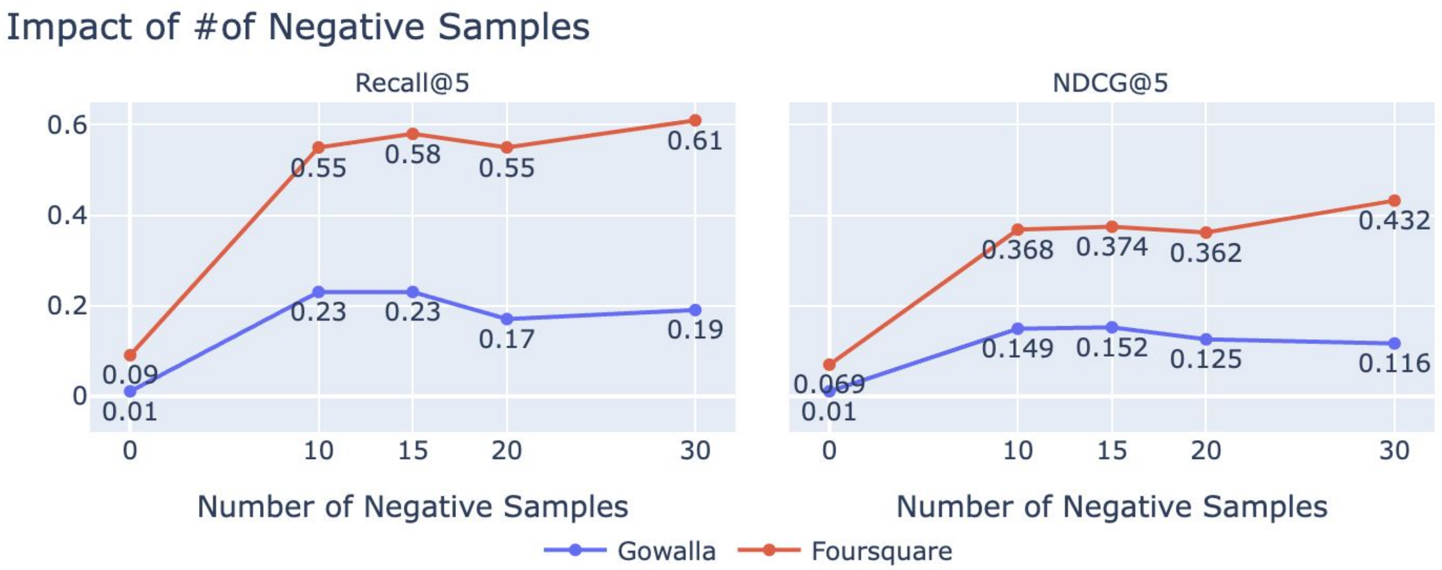

Figure 5: Impact of # of Negative Samples

Model 2 (STTR) Results - Historical Trajectories

- ❖ Tuned the length of user history considered for each user
- ❖ Higher recall for lower values; however this is due to overfitting
- ❖ Overall with increase in length, performance increases

Figure 6: Impact of User History Length

Model 2 (STTR) Results

- Below configuration gave the best results:
  - Embedding Dimension = 256
  - # of Negative Samples = 10
  - Length of Historical Trajectory = 100
  - Learning Rate = 3e-3
  - Dropout = 0.2
  - Epochs = 100

- With the above configuration, we compared the results from the original paper

	Gowalla			NYC		
	Recall@5	Recall@10	Recall@20	Recall@5	Recall@10	Recall@20
STTR - paper	0.35	0.43	0.53	0.53	0.65	0.73
Our Implementation	0.39	0.47	0.58	0.55	0.67	0.79

Table 5: Recommendation Performance Comparison with Reference

Conclusion

- Method 1 is observed to be significantly faster as it allows us to save trained matrix and then tune during testing
- Method 2 captures complex spatio-temporal patterns for users interactions and also captures long term dependencies for visited locations
- Due to the significant difference in natures of the two methods, it is difficult to compare them and their evaluation metrics

Future Work

- ❖ Incorporate emotion and personality (user profile)
  - ➢ User tweets for emotion acquisition
  - ➢ User activity on social platforms for personality acquisition
- ❖ Incorporate user’s social interactions and social activity
- ❖ Incorporate locations unique features

Thank You !