MDP-based Itinerary Recommendation using Geo-Tagged Social Media

Radhika Gaonkar, **Maryam Tavakol**, Ulf Brefeld
rgaonkar@cs.stonybrook.edu, {tavakol,brefeld}@leuphana.de

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Travel Itinerary

Motivation

Challenges in trip planning:

→ Many decisions to be made at once while planning a trip:

Duration of trip, costs, places to visit, food and many more!

→ The Web provides an overload of information

→ There is no one resource that exhaustively covers all the aspects of travel

Automatically gathering **personalized** trip related information from different sources

Problem Setting

Recommend a sequence of POIs (Point of Interests) given individual user preferences

- A sequential problem
- An instance of constructive learning
- Based on previous visited POIs

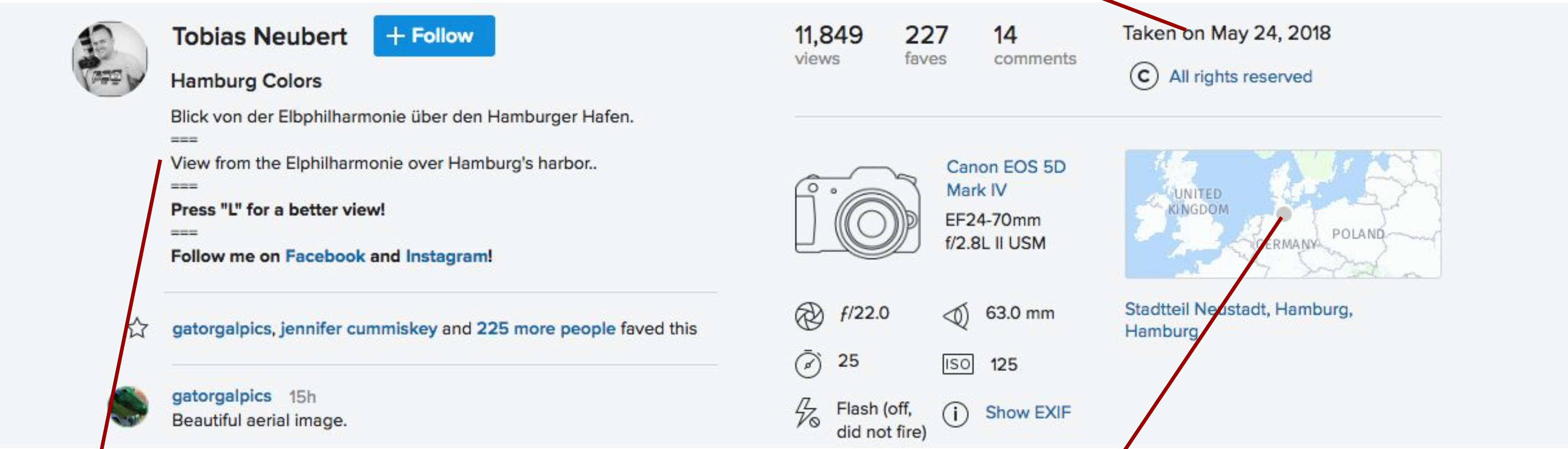
Data Acquisition

Data Acquisition

- We turn a photo-sharing site (Flickr) into a useful resource for reconstructing a user's trip
- The photos include:
    - Geographical coordinate (small-fraction)
    - Timestamp of capturing the photo
    - Semantic data; tags and titles

Example

Time



Semantic data

Geo coordinate

Obtaining POIs

- Photos with location coordinate (small subset)
- Photos without coordinate information
  - Inferring the POI from **Latent Semantic Analysis (LSA)** to compute the semantic similarity between the tags of the geotagged and non-geotagged photos

POIs from Geo-coordinates

48.174135
11.547317

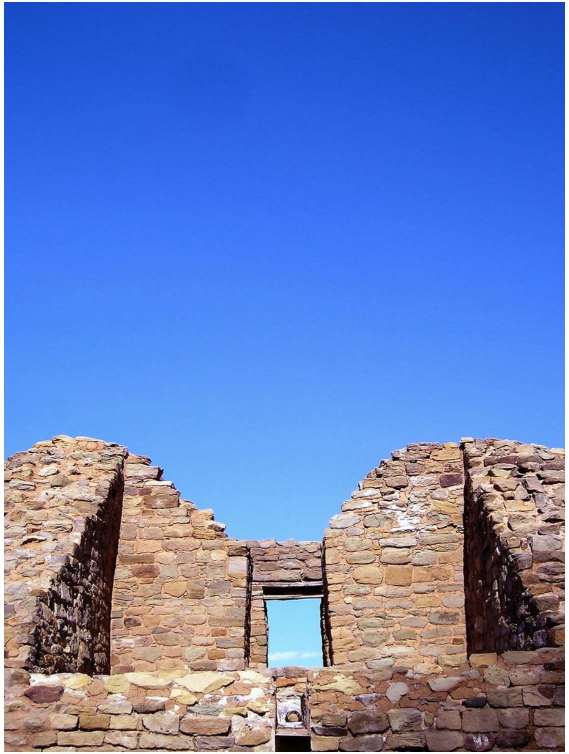
48.177082
11.558003

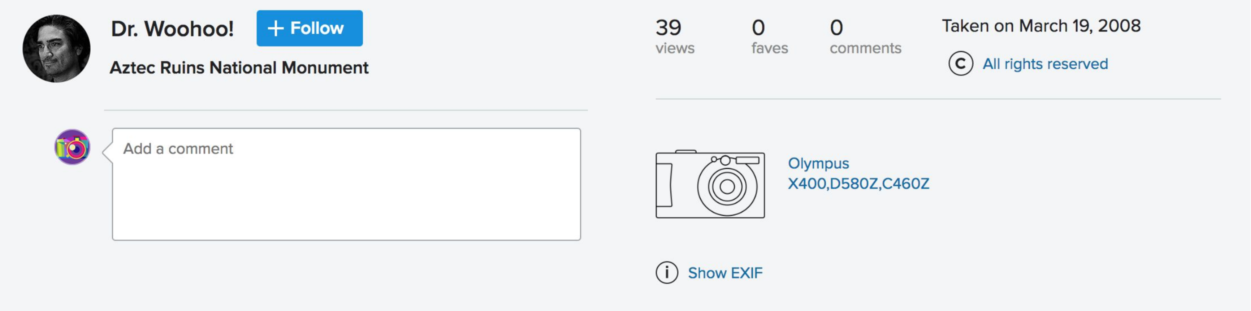
- ➔ Query API with coordinates
- ➔ Limit search radius
- ➔ Fuzzy match place name with tags
- ➔ Assign place with highest match

Olympia Park

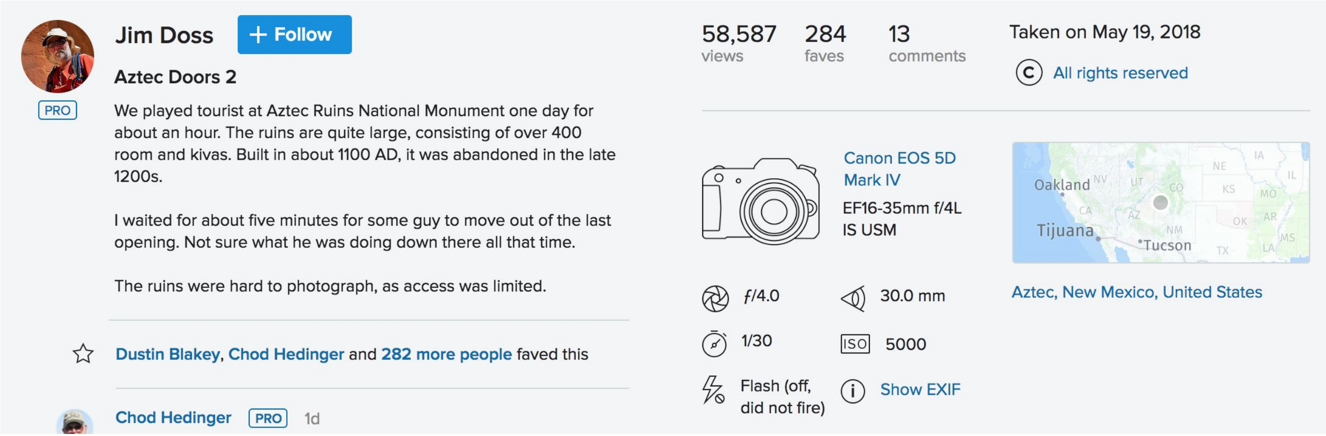
BMW Museum

Non-geotagged Photo

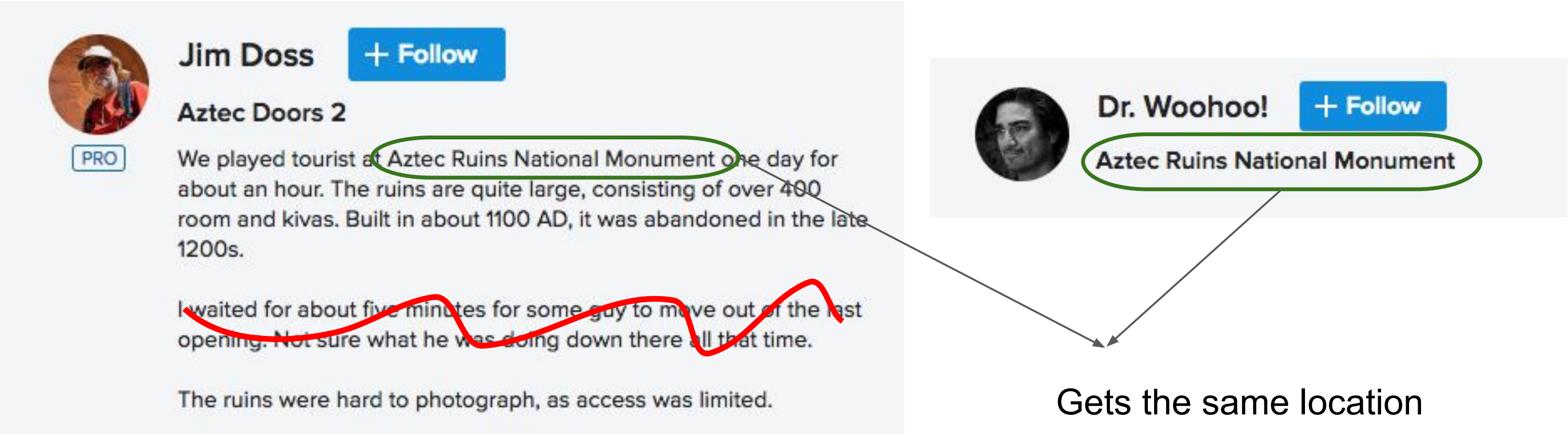




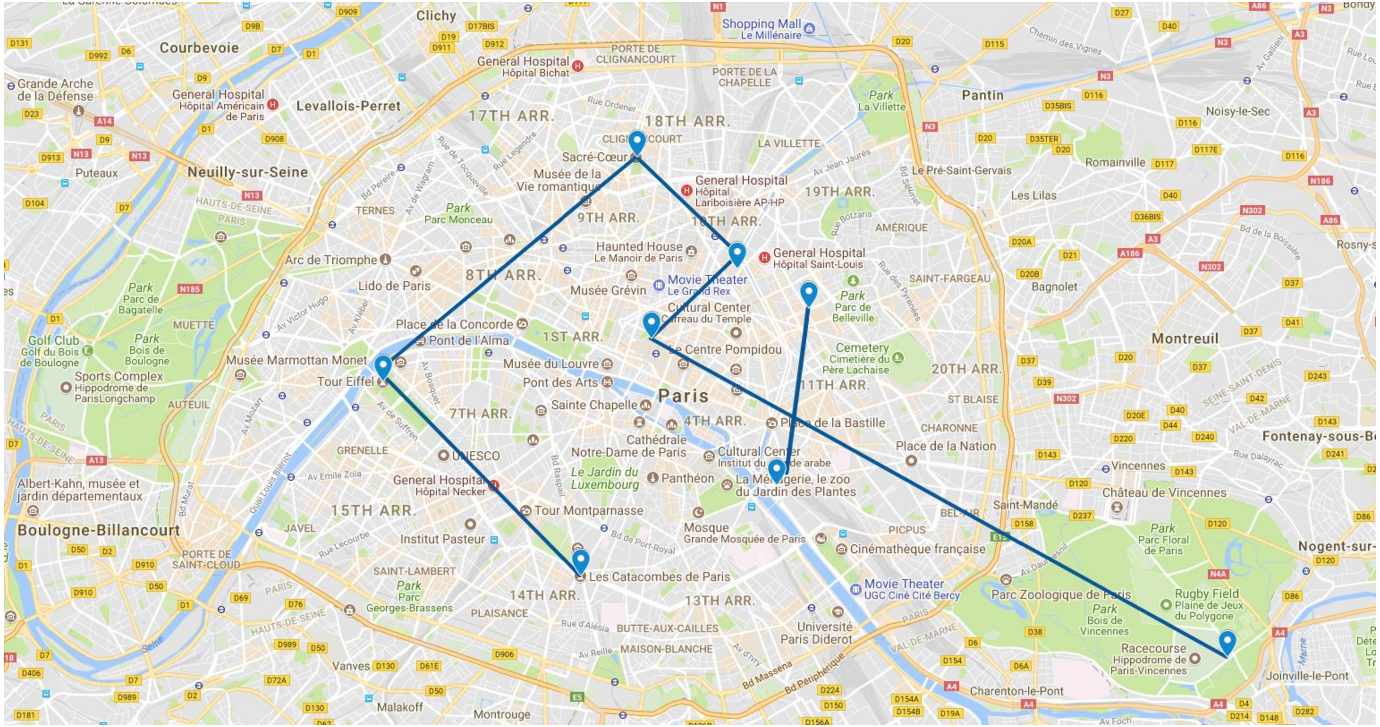
Geotagged Photo



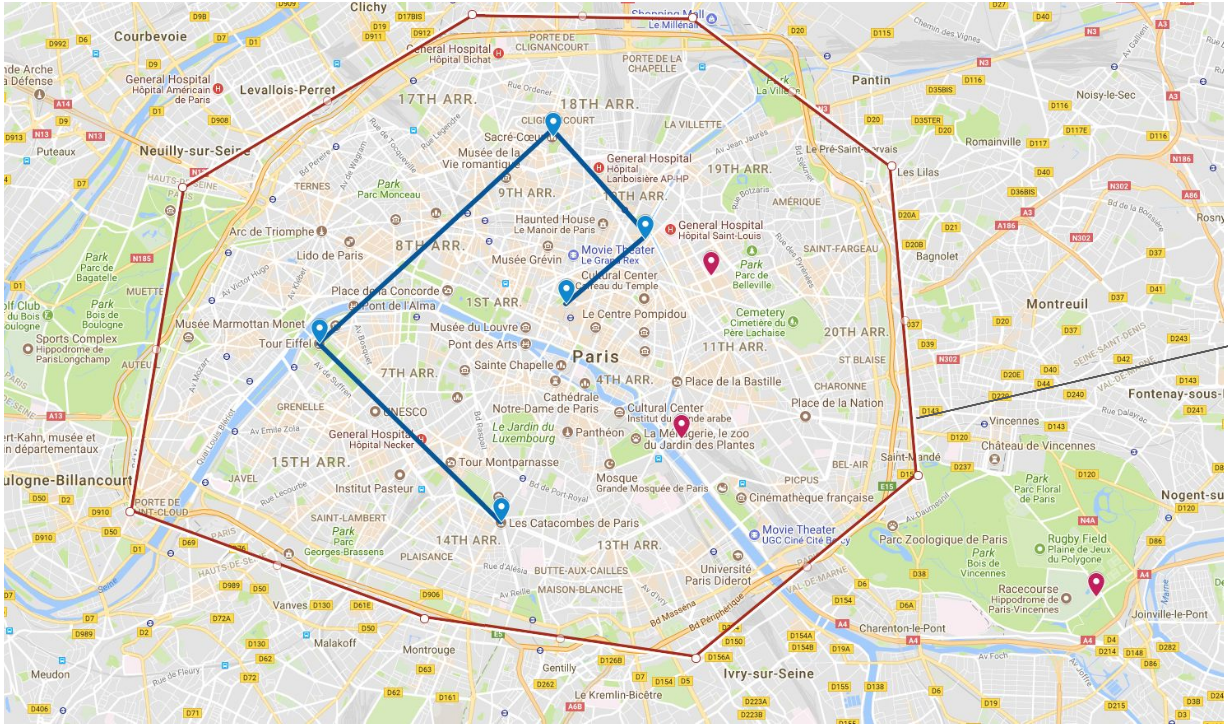
POI from Text Similarity



Resident vs. Tourist



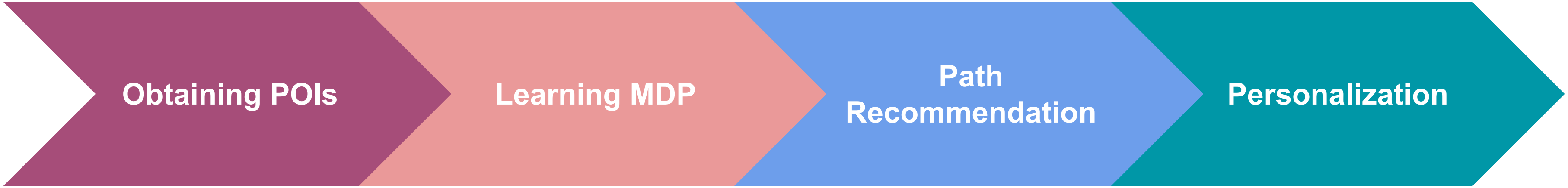
Itinerary Inference



Bounding box of city

Learning the model

Procedure



Obtaining POIs
Learning MDP
Path Recommendation
Personalization

Reinforcement Learning

- A touristic trip is considered a sequential problem
- The photos provide implicit feedback on the user's preferences

⇨ A match for RL-based approaches

Encode the history of previous visits in a Markov model

MDP Definition

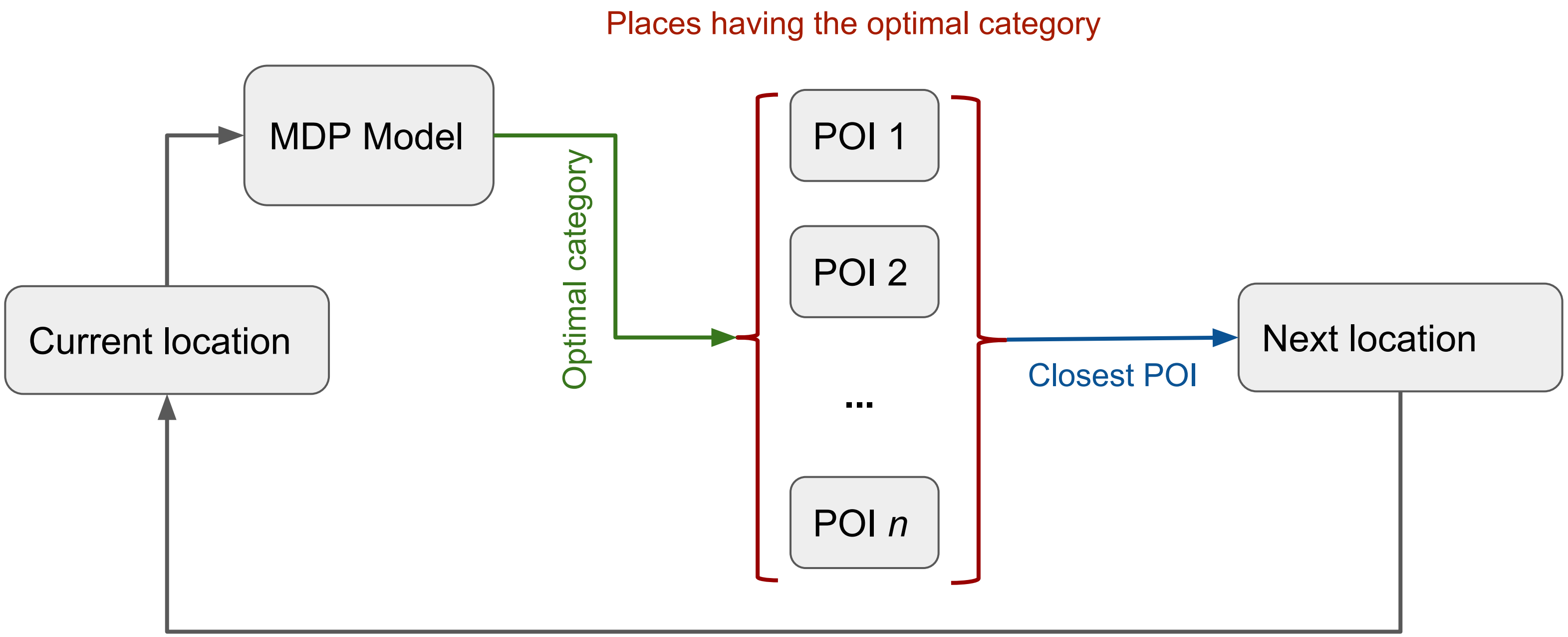
- **State**: a sequence of at most *k* places the user visited up to time *t*
- **Actions**: all POI *categories* present in the city
- **Reward function**: higher reward when the recommended action is taken by the user
- **Transition function**: probability of transition between two states after taking an action

- **Goal**: maximize the sum of discounted reward

Learning the Model

- Estimating the state-transition function & reward function using **maximum-likelihood** method
- Optimizing the MDP via **Value Iteration** algorithm, *V(s)*
- The state-action values, *Q(s, a)*, are obtained from the learned value function
    - The Q-value gives a score for every place category

Path Recommendation



Personalization

Personalization Score

- Duration-based
    - The amount of **time** a user spends on a specific category
    - Spends at least 2 hours in every museum
- Frequency-based
    - The **frequency** of visiting a certain category
    - Often eats at Italian restaurant

Online Personalization

- A POI is recommended based on both distance & personalized preference
- The place in the optimal category:

Weighted(**distance + personalized score**)

Evaluation

Evaluation

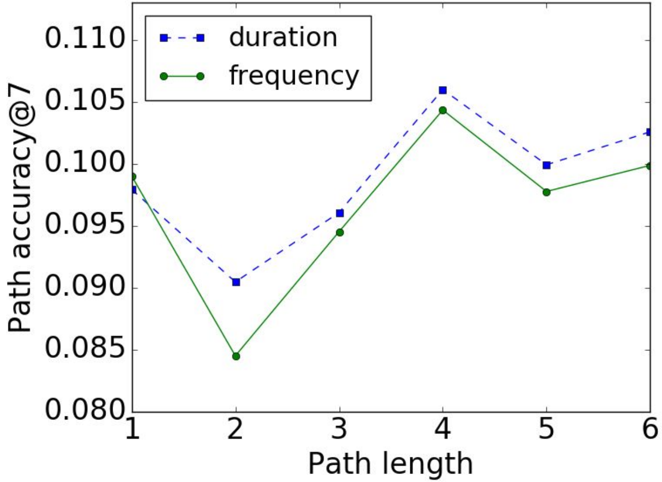
- Photographs of Munich, London, Paris
- Leave-one-out cross-validation method
- Performance measures:
    - Partial path accuracy
    - Exact path accuracy
- Baselines:
    - Breadth first search (BFS), Dijkstra, Heuristic Search, A*

Partial Path Accuracy - Order of Markov Chain

Path Length	1	2	3	4	5	6
1st order	0.041	0.041	0.042	0.042	0.041	0.034
2nd order	**0.098**	**0.090**	**0.096**	**0.106**	**0.100**	**0.103**
3rd order	0.097	**0.090**	0.093	0.105	0.090	0.087
4th order	0.089	0.084	0.083	0.094	0.077	0.060
5th order	0.074	0.071	0.058	0.072	0.070	0.058

- Encoding more history into the state improves the performance

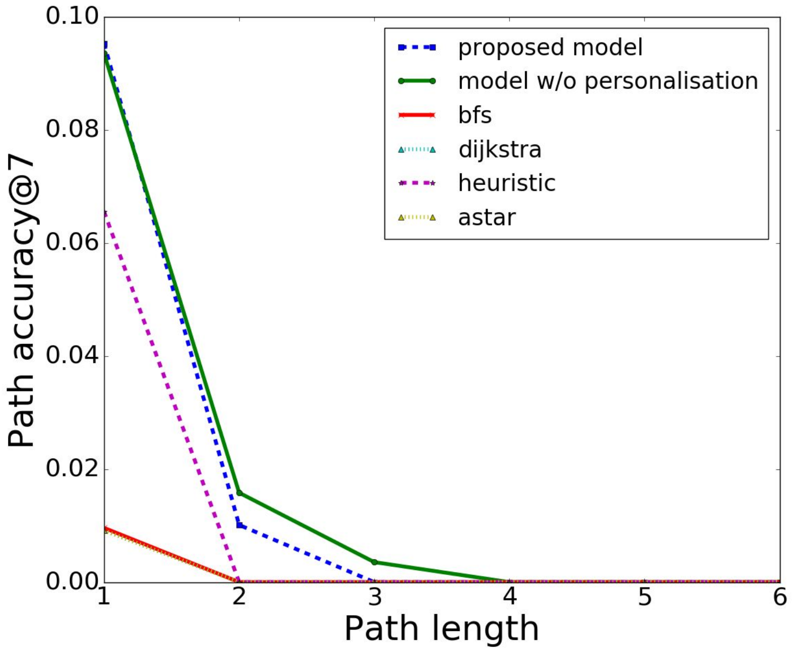
Comparing Personalization Techniques



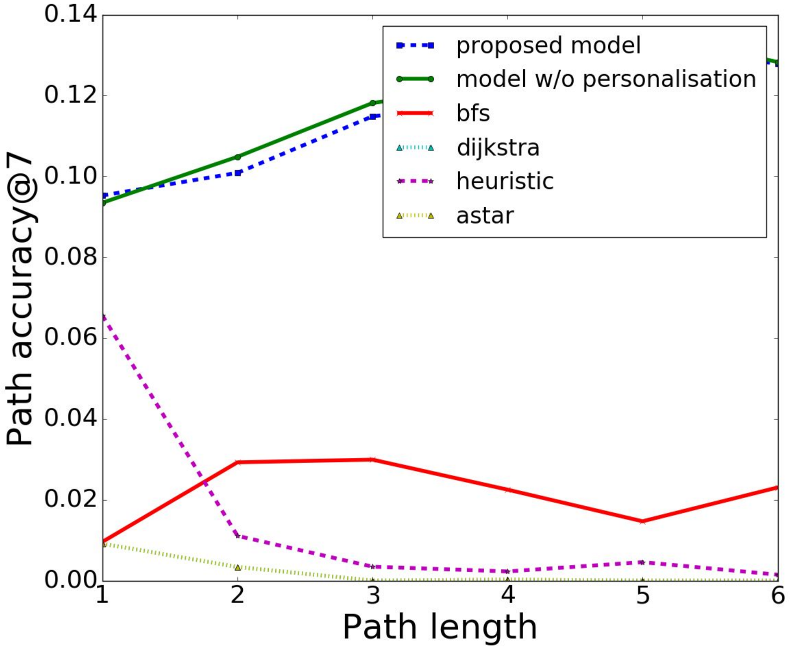
- Duration-based outperforms frequency-based

POI Recommendation vs. Baseline -- Munich

Exact path accuracy

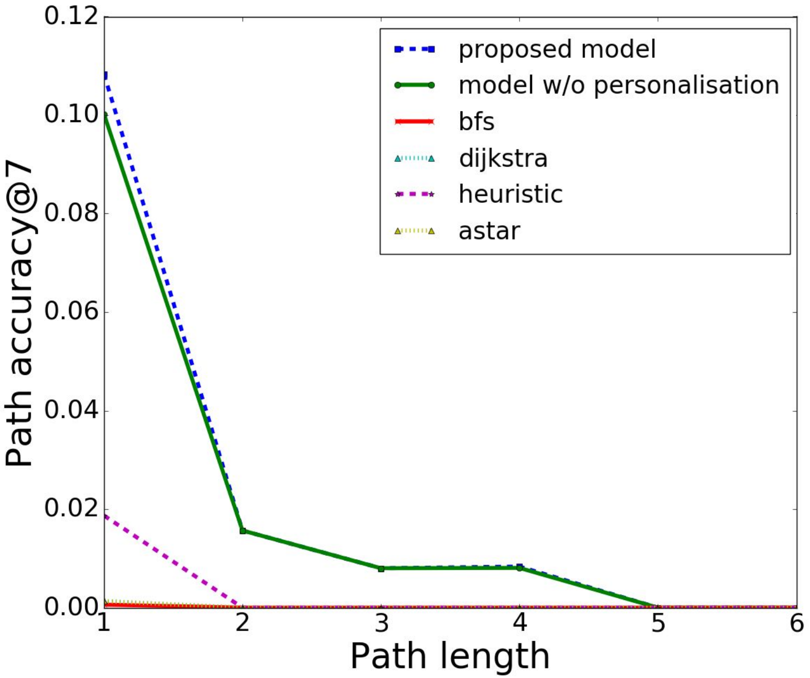


Partial path accuracy

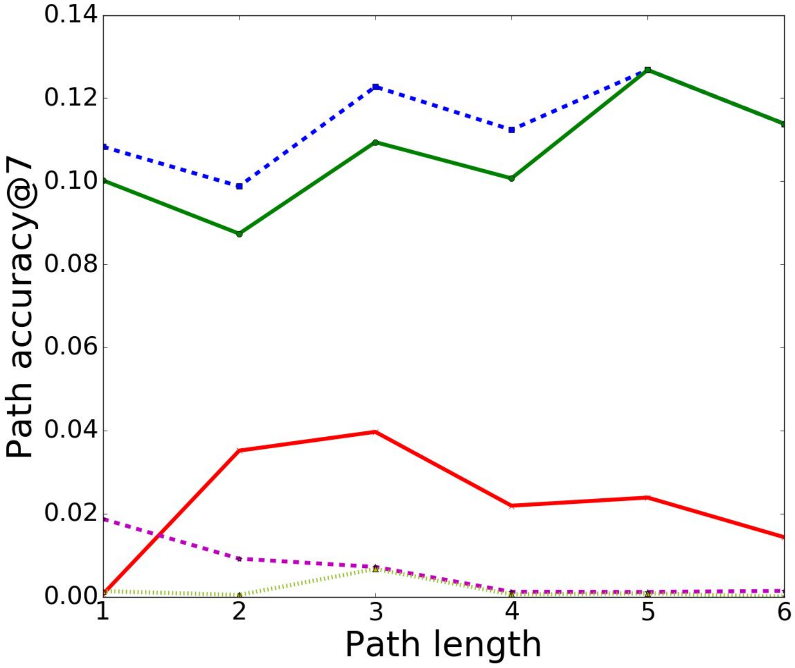


POI Recommendation vs. Baseline -- Paris

Exact path accuracy

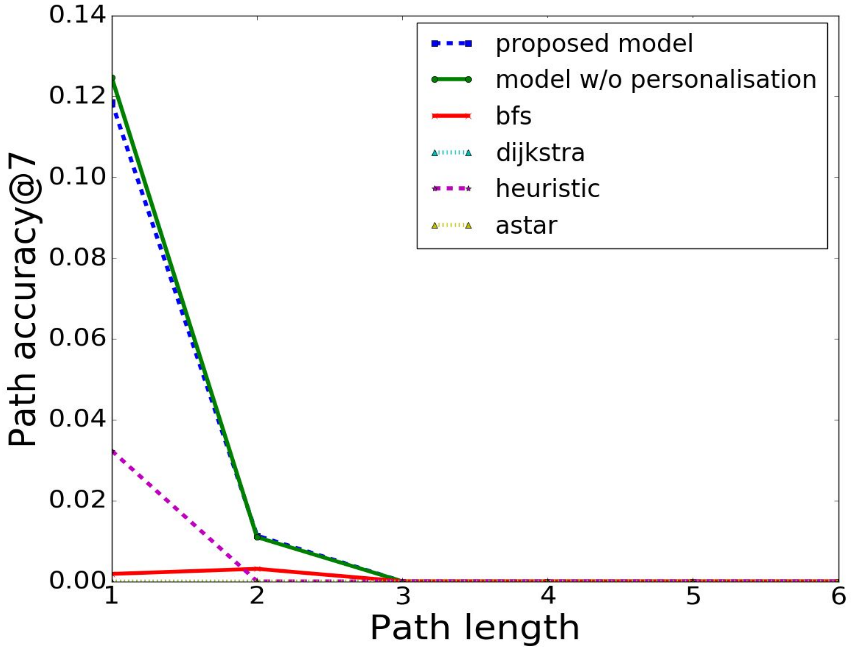


Partial path accuracy

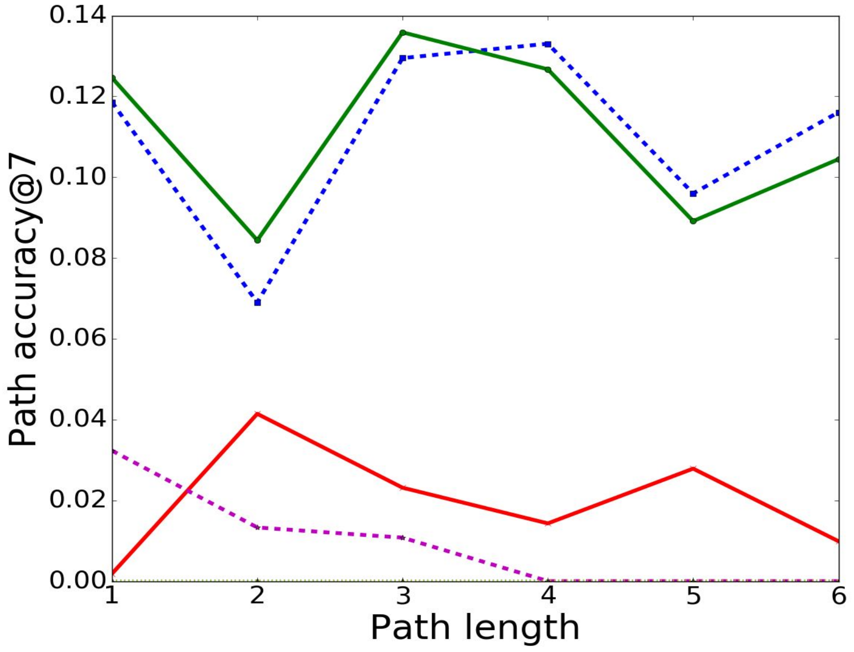


POI Recommendation vs. Baseline -- London

Exact path accuracy



Partial path accuracy



Conclusion

- An RL approach to recommend user itinerary:
    - Utilize freely available data from social media
    - Minimal manual intervention in data creation process
    - Computationally inexpensive
    - Outperforms standard path planning methods

Question?

Thanks for your attention

Currently looking for Postdoc position

Maryam Tavakol
tavakol@leuphana.de

http://ml3.leuphana.de/maryam.html