

MDP-based Itinerary Recommendation using Geo-Tagged Social Media

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Den Bosch - Oct 24, 2018

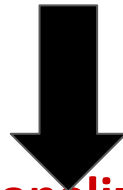
Travel Itinerary



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 →



Tobias Neubert [+ Follow](#)

Hamburg Colors

Blick von der Elbphilharmonie über den Hamburger Hafen.

====

View from the Elbphilharmonie over Hamburg's harbor..


====

Press "L" for a better view!

====

Follow me on [Facebook](#) and [Instagram](#)!


☆ [gatorgalpics](#), [jennifer cummiskey](#) and **225 more people** faved this

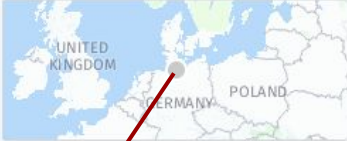
 [gatorgalpics](#) 15h
Beautiful aerial image.

11,849 views 227 faves 14 comments

Taken on May 24, 2018

© All rights reserved

 **Canon EOS 5D Mark IV**
EF24-70mm f/2.8L II USM

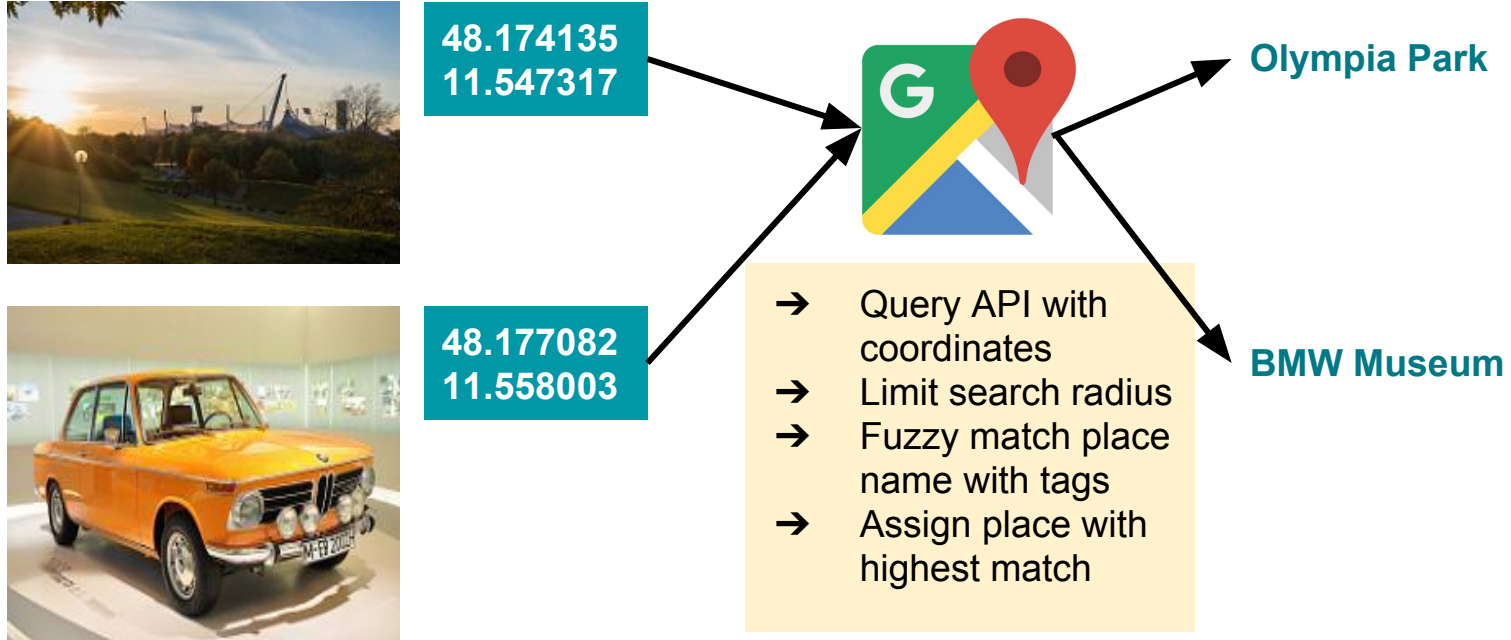
 **Stadtteil Neustadt, Hamburg, Hamburg**

f/22.0 63.0 mm
25 ISO 125
Flash (off, did not fire) [Show EXIF](#)

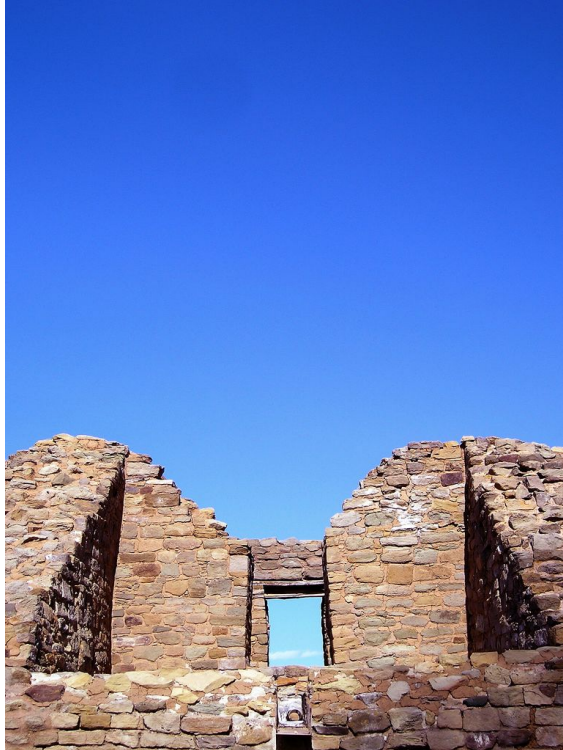
Obtaining POIs


- 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



Non-geotagged Photo



**Dr. Woohoo!** [+ Follow](#)


Aztec Ruins National Monument


39
views

0
faves


0
comments

Taken on March 19, 2008


 [All rights reserved](#)



Add a comment



Olympus
X400,D580Z,C460Z

 [Show EXIF](#)

Geotagged Photo



Jim Doss

+ Follow

Aztec Doors 2

PRO

We played tourist at Aztec Ruins National Monument one day for about an hour. The ruins are quite large, consisting of over 400 room and kivas. Built in about 1100 AD, it was abandoned in the late 1200s.

I waited for about five minutes for some guy to move out of the last opening. Not sure what he was doing down there all that time.

The ruins were hard to photograph, as access was limited.



Dustin Blakey, Chod Hedinger and 282 more people faved this



Chod Hedinger

PRO

1d

58,587

views

284

faves

13

comments

Taken on May 19, 2018

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Canon EOS 5D
Mark IV
EF16-35mm f/4L
IS USM



f/4.0



30.0 mm



1/30



5000



Flash (off,
did not fire)

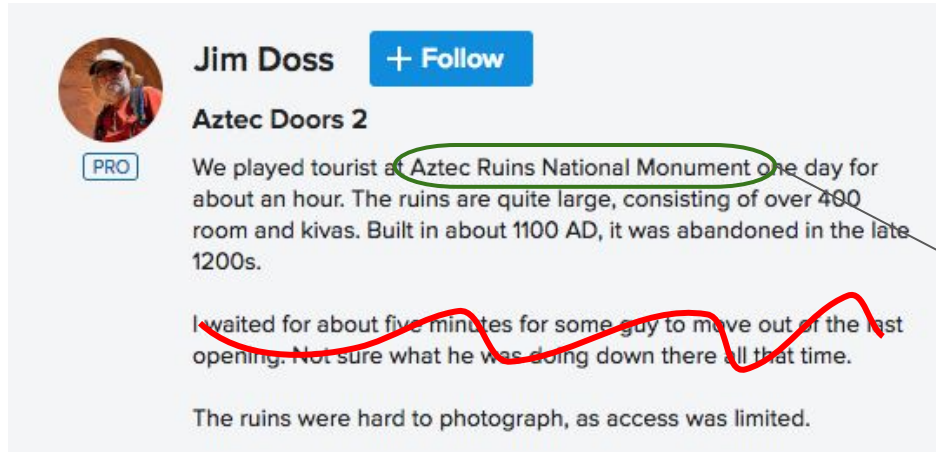


Show EXIF



Aztec, New Mexico, United States

POI from Text Similarity



Jim Doss + Follow

Aztec Doors 2

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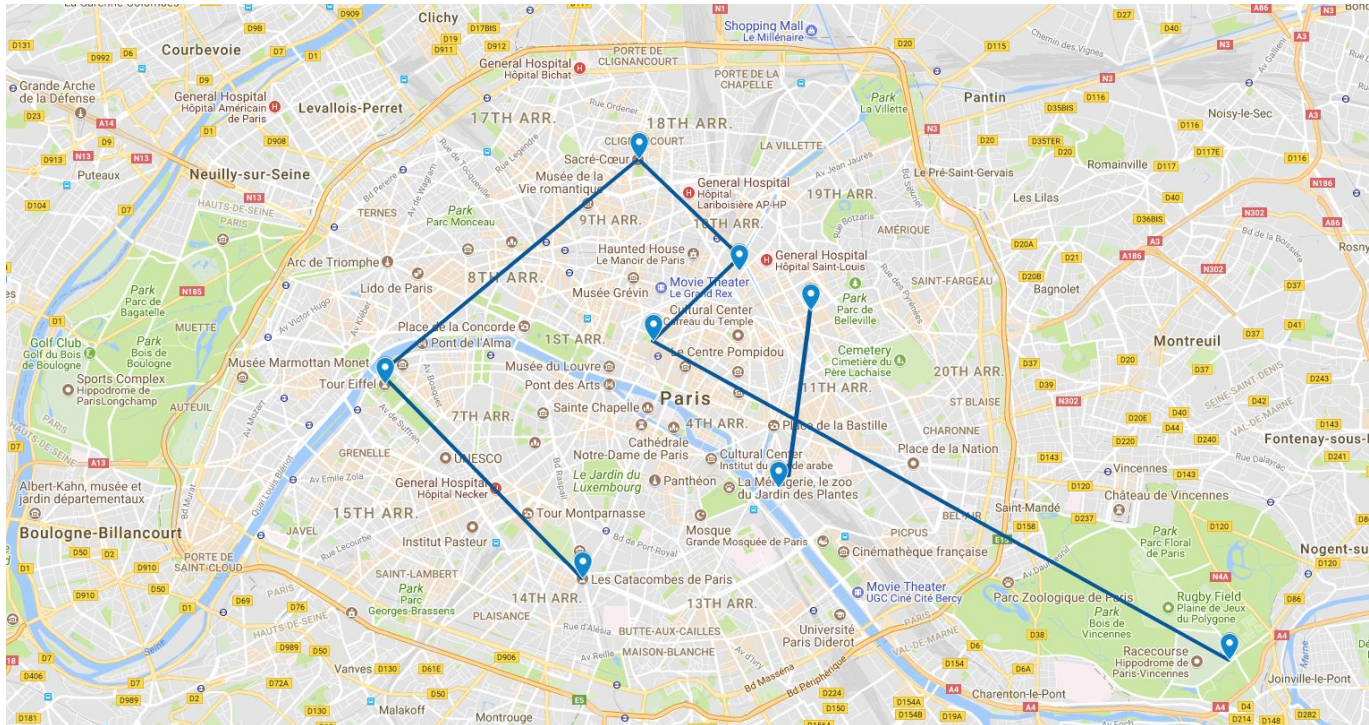


Dr. Woohoo! + Follow

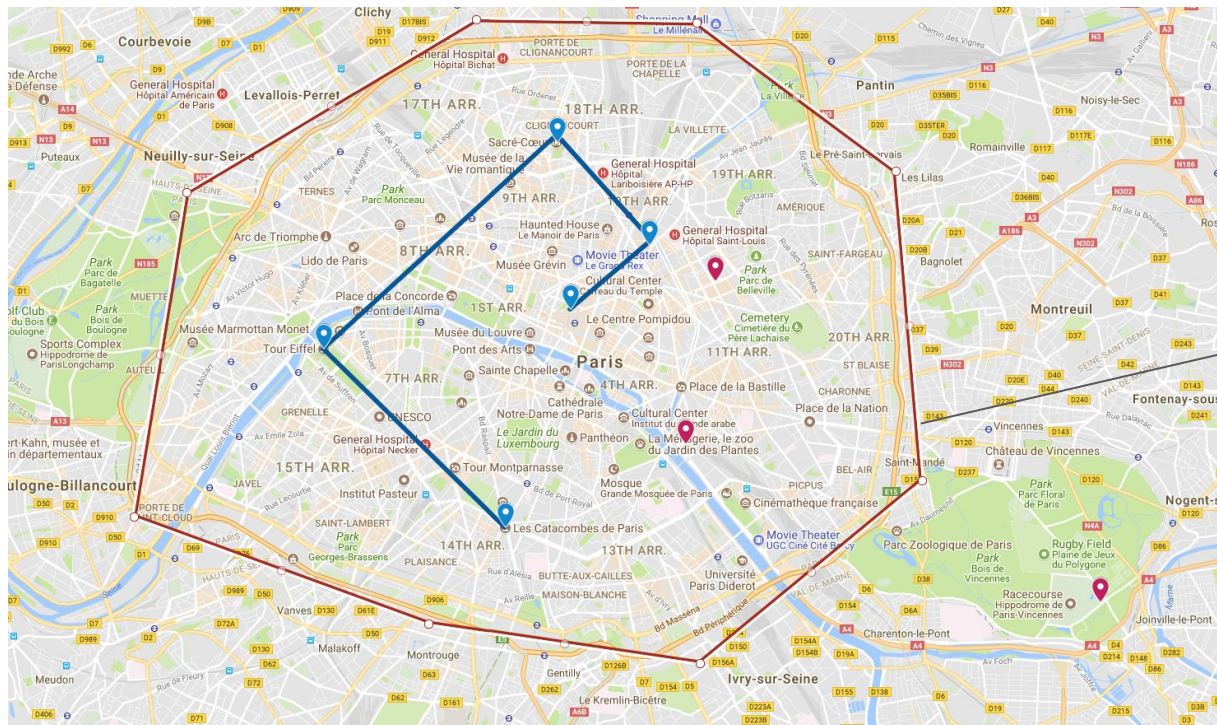
Aztec Ruins National Monument

Gets the same location

Resident vs. Tourist



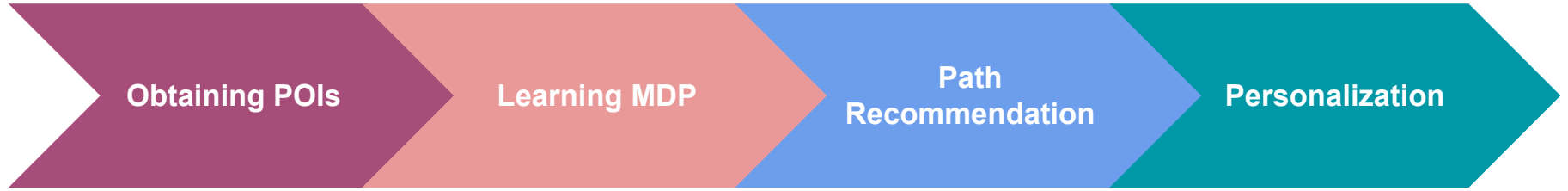
Itinerary Inference



Bounding box of city

Learning the model

Procedure



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

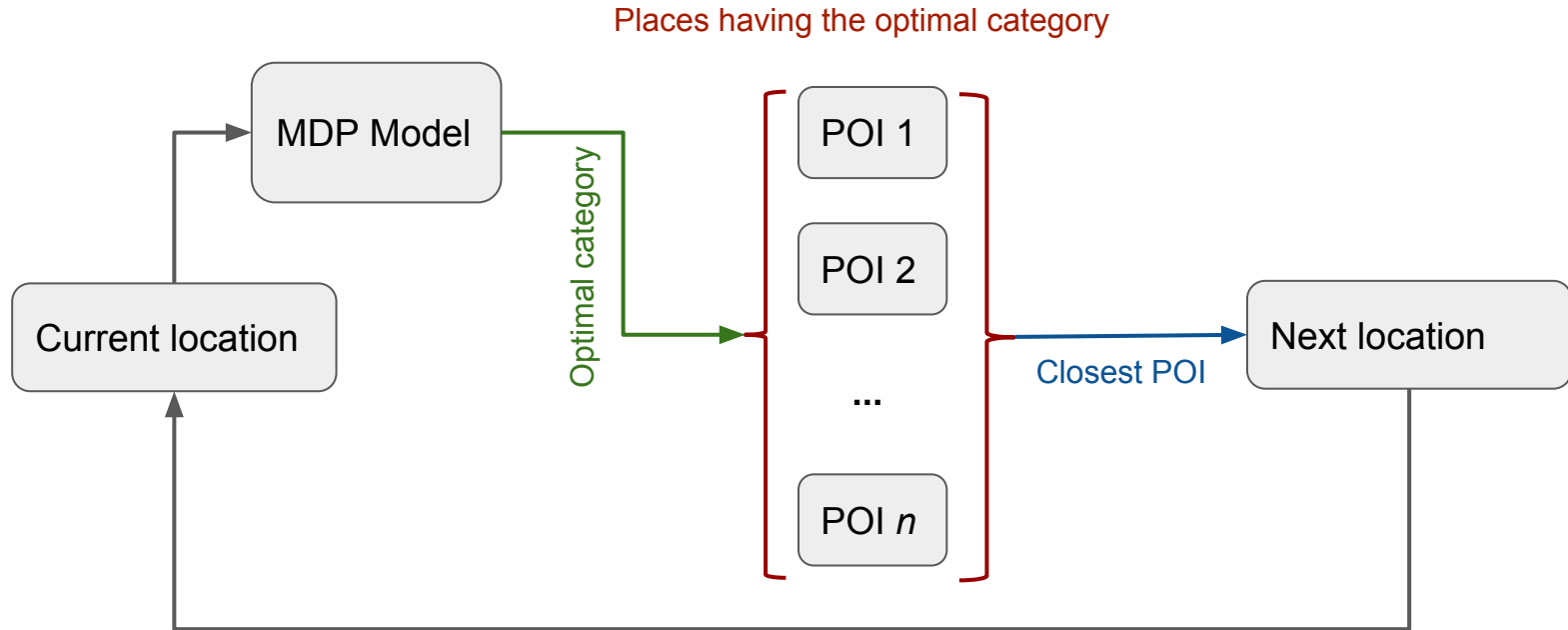
MDP Definition

- **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

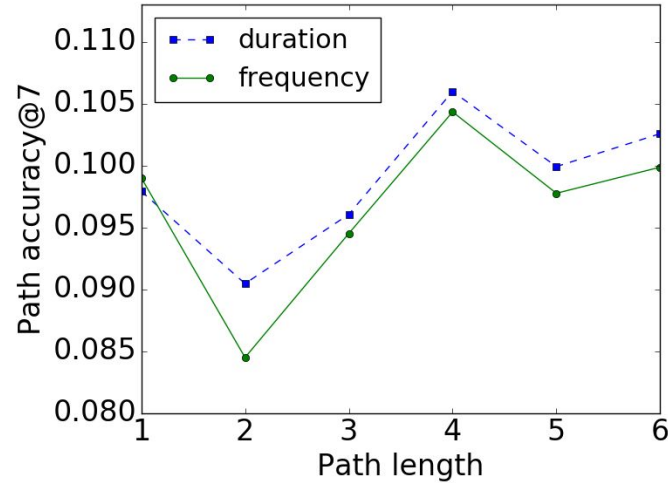
- Photographs of Munich, London, Paris
- Leave-one-out cross-validation method
- Performance measures:
 - Partial path accuracy
 - Exact path accuracy
- Baselines:
 - Breadth first search (BFS), Dijkstra, Heuristic Search, A*

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

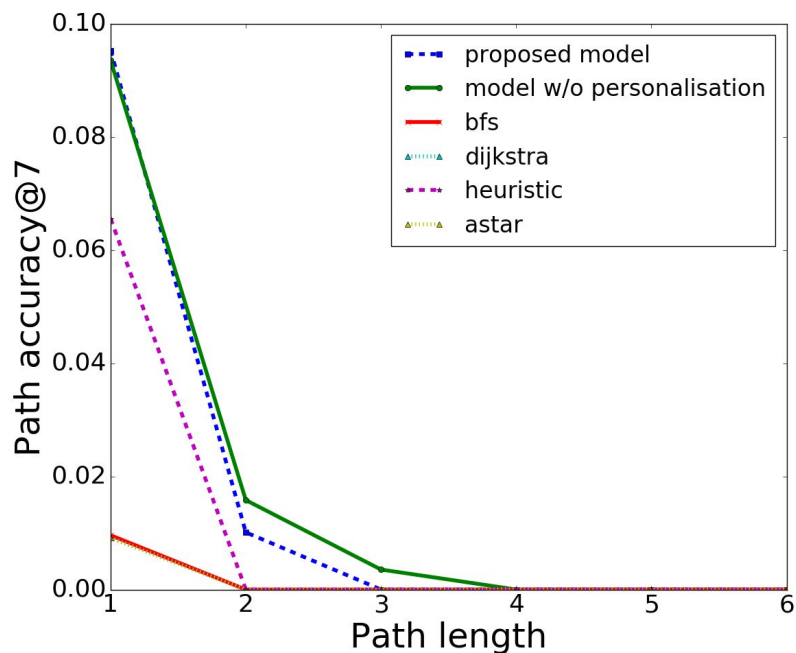
Comparing Personalization Techniques



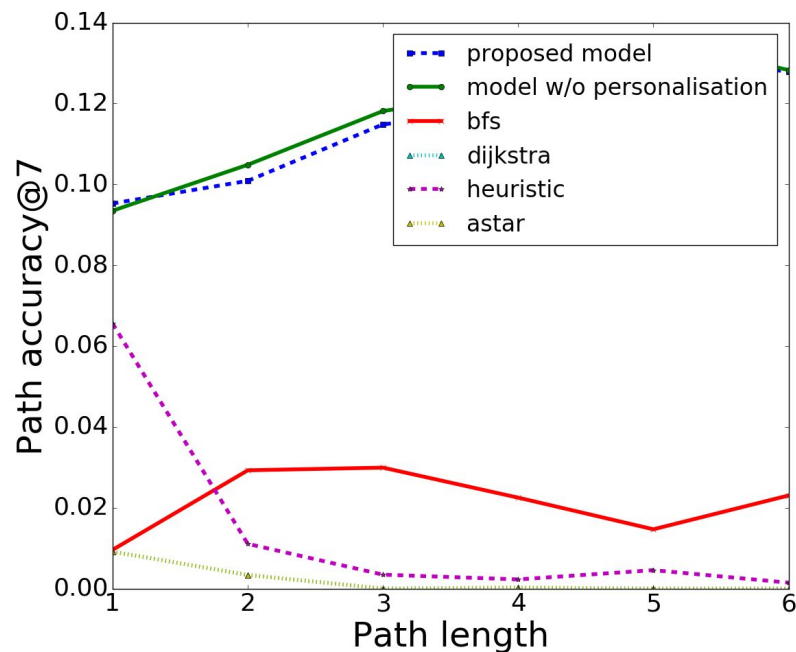
- Duration-based outperforms frequency-based

POI Recommendation vs. Baseline -- Munich

Exact path accuracy

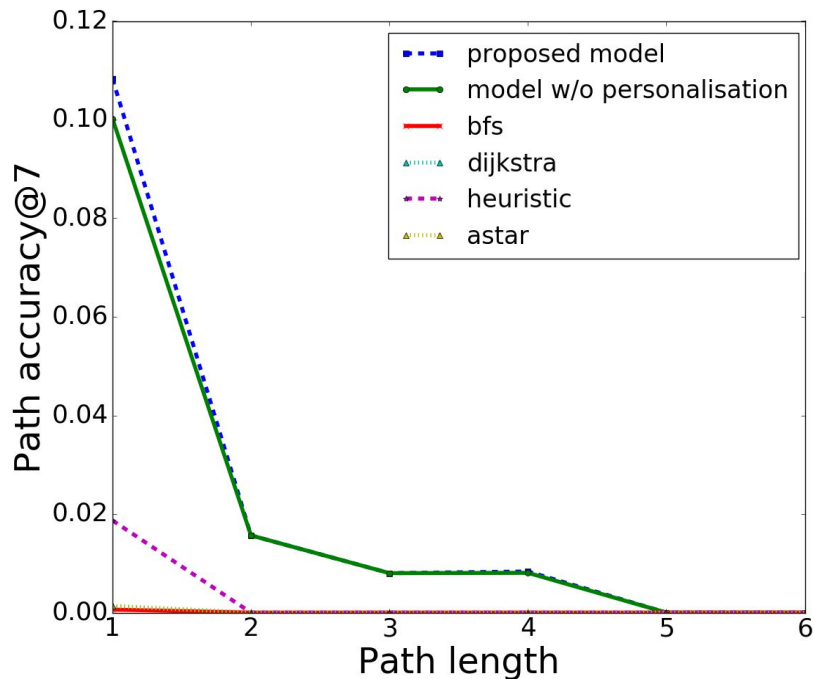


Partial path accuracy

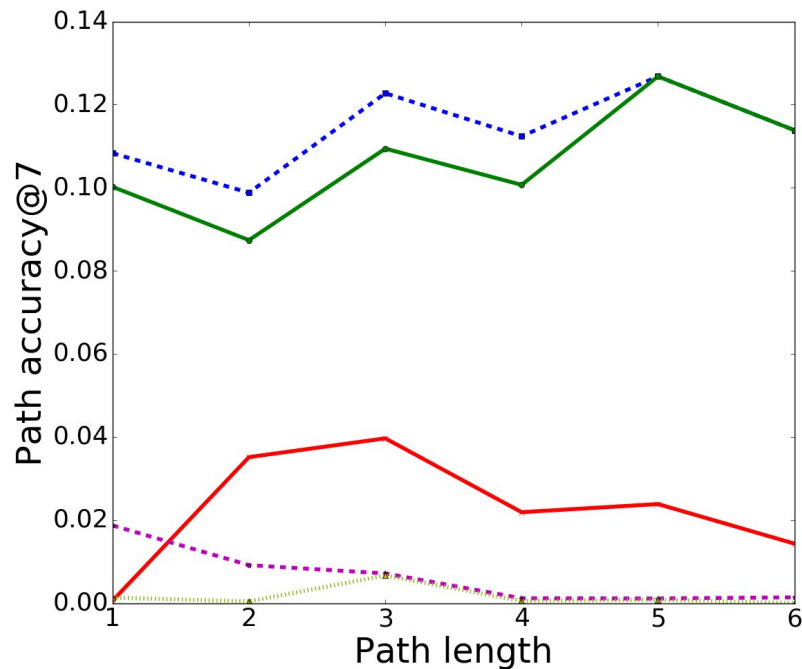


POI Recommendation vs. Baseline -- Paris

Exact path accuracy

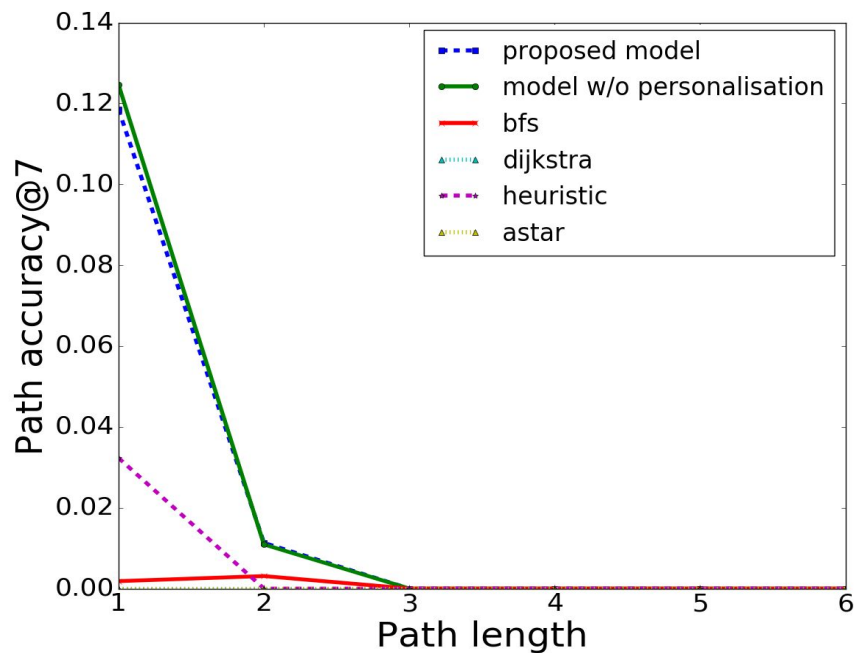


Partial path accuracy

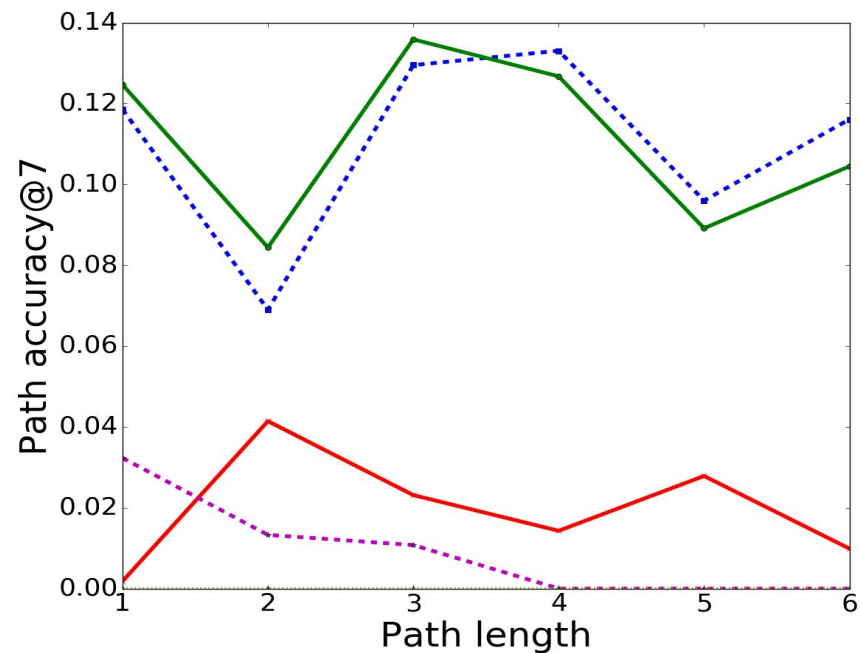


POI Recommendation vs. Baseline -- London

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

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