

# Learning the Popularity of Items for Mobile Tourist Guides

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# Agenda

- Related Work
- Context Model
- Process Model
- System Design
- Data Aggregation
- App Prototype
- User Study Key Results
- $\circ \quad \text{Conclusion} \quad$





# **Related Work - Academic**

#### A Context-Aware Model for Proactive Recommender Systems in

#### the Tourism Domain

Matthias Braunhofer, Francesco Ricci, Béatrice Lamche and Wolfgang Wörndl

#### A Study on Proactive Delivery of Restaurant Recommendations

#### for Android Smartphones

Daniel Gallego Vico, Wolfgang Wörndl and Roland Bader

#### A Situation-Aware Proactive Recommender System

Punam Bedi and Sumit Agarwal



# Related Work - Industry











# **Related Work - Industry**



Pilgrim's Location Detection Using Different Signals (Source: foursquare.com)



## **Overall Research Question**

# How can we learn (infer) the popularity of POIs for a context-sensitive recommender system?



# **Context Model**

- User context
- Temporal context
- Geographic context
- Social context

Two-step recommendation process:

- Phase 1: Analyze the current situation
- Phase 2: Examine the suitability of particular items

This allows for both a proactive and passive recommender system.

Based on: A model for proactivity in mobile, context-aware recommender systems. Woerndl et.al. In Proceedings of the fifth ACM conference on Recommender systems. 2011



# **Process Model**





# System Overview





## Server - Dashboard





## Server - Data Explorer





## Server - Data Explorer





## Server - Inferred Popularities

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		Sights (loca	il)							
ParsApp Dashboard Data Explorer -	APIs - Jobs						Logg	ed in as P	atrick Hie	sel Logout
Sights (local)	Days (Mon-Sun)	Days (Weekda	y/Weekend	d) Ho	ur of Day	Seaso	n We	ather (con	dition)	Weather (temp)
Name			Mon	Tue	Wed	Thu	Fri	Sat	Sun	# Checkins
Burghausen			0.051	0.523	0.097	0.114	0.021	0.097	0.097	237
Burghausen - Burg			0.055	0.378	0.076	0.078	0.034	0.261	0.117	563
Altötting			0.18	0.075	0.057	0.203	0.109	0.232	0.144	439
Amberg			0.051	0.035	0.358	0.195	0.021	0.083	0.257	374
Rothenburg ob der Tauber			0.15	0.139	0.117	0.162	0.09	0.142	0.199	7196
Rothenburg ob der Tauber - Stadtmauer			0.15	0.139	0.117	0.162	0.09	0.142	0.199	7196
Dinkelsbühl			0.057	0.158	0.058	0.16	0.119	0.106	0.342	954
Ansbach			0.146	0.143	0.042	0.144	0.072	0.302	0.15	972
Ansbach - Markgräfliche Residenz			0.146	0.143	0.042	0.144	0.072	0.302	0.15	972
Wolframs-Eschenbach			0.247	0.194	0.032	0.011	0.097	0.022	0.398	93
Aschaffenburg			0.146	0.144	0.102	0.066	0.147	0.228	0.167	2896
Aschaffenburg - Schloss Johannisburg			0.142	0.159	0.108	0.065	0.153	0.219	0.154	3375
Aschaffenburg - Pompejanum			0.143	0.155	0.102	0.067	0.155	0.221	0.157	3106
Aschaffenburg - Schloss Schönbusch			0.026	0.022	0.016	0.048	0.772	0.031	0.086	688
Schloss Mespelbrunn			0.081	0.159	0.037	0.106	0.191	0.24	0.187	246



# **Check-in Analysis: Temporal Context**





## Check-in Analysis: Hotspots





Neuschwanstein Castle (Source: https://pixabay.com/en/neuschwanstein-castle-bavaria-526967, CC0 Public Domain) Heatmap of Check-ins for Neuschwanstein Castle



# Data Aggregation - Key Results

#### ltems

- 20.981 Foursquare POIs
- o 15.3675 Yelp POIs
- 176 Quermania POIs

### **Check-ins**

- 29m Tweets (25m Places, 14m geo-located)
- 249.000 Flickr images

### Total

• ~ 15GB of Data



# **Inference Results**

Seasonal Popularity

POI Name	Spring	Summer	Fall	Winter
Bad Tölz	0.215	0.202	0.215	0.368
Nürnberg	0.238	0.242	0.295	0.226
Walchensee	0.076	0.456	0.291	0.177
Kehlsteinhaus	0.044	0.572	0.35	0.034
Starnberger See	0.003	0.932	0.045	0.019
Kloster Andechs	0.314	0.253	0.365	0.067
Königssee	0.193	0.367	0.305	0.135

Excerpt of Inferred Seasonal Popularity: p(V | s, P).  $\mu = 1,660$  Check-ins



# **Inference Results**

Weather Popularity

POI Name	Sunny	Cloudy	Rainy	Snowy	Unkn.	
Munich	0.532	0.138	0.324	0.005	0.001	
Andechs	0.711	0.072	0.209	0.006	0.002	
Roseninsel	0.796	0.127	0.072	0.005	0	
Almbachkl.	0.907	0	0.093	0	0	

Excerpt of Inferred Weather Condition Popularity: p(V | wc, P).  $\mu = 1,750$ 



# App Prototype



# App Prototype









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# **User Study Results**

The popularity graphs for the weekday (Mon-Sun) were useful and would have influence on my decision to visit a place.

The popularity graphs for the time of day (0-24h) were useful and would have influence on my decision to visit a place.



Number of Users

# **User Study Results**

The popularity graphs for the weather condition (Sunny-Snowy) were useful and would have influence on my decision to visit a place. The popularity graphs for the temperature (Hot-Freezing) were useful and would have influence on my decision to visit a place.



# **User Study Results**

Would you use such an app to get recommendations for weekend trips?

## Would you use such an app to get recommendations for restaurants or bars?



# Future Work

- Association of Check-ins and POIs
  - Inspect data/meta data
  - Evidence-based clustering
  - Versatile approach for different data types
- Improve applicability for cities
- Evaluate the effectiveness of traffic data
- Include ratings into learner/recommender
- Summarize key facts about POI using natural language



# Q & A



# Backup



# Analysis: Inference Model

p(P|C)

p(P|wd = Monday, V = Walhalla) = p(wd = Monday|V = Walhalla)

$$p(wd = Monday | V = Walhalla) = \frac{\sum_{CheckinsForPOIOnMonday}}{\sum_{CheckinsForPOI}}$$



# **Analysis: Prediction Model**

Weighted Additive Scoring

$$S(C,V) = \sum_{i \in [wc,t,d,s,h]} \alpha_i \, p(i,V)$$



# **Analysis: Prediction Model**

**Bayes** Theorem

 $p(wd = Monday|V) \rightarrow p(V|wd = Monday)$ 

$$p(V = Walhalla|wd = Monday) = \frac{p(wd = Monday|V = Walhalla)p(V = Walhalla)}{p(wd = Monday)}$$

p(wd = Monday|V = Walhalla) (as obtained in the previous section)

$$p(V = Walhalla) = \frac{\sum_{CheckInsAtWalhalla}}{\sum_{AllCheckIns}}$$

$$p(wd = Monday) = rac{\sum_{AllCheckInsOnMonday}}{\sum_{AllCheckIns}}$$