Value-Added Services for Local Search: Innovative Recommender Systems and Routing Models

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TIS innovation park

SASA
SOCIETÀ AUTOBUS SERVIZI D'AREA
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Landesverband der
Tourismusorganisationen
Südtirols

Comune di Bolzano
Stadtgemeinde Bozen

Outline

- STS Place Recommendation App
- Comino Routing Engine
- Parking Lot Occupancy Prediction

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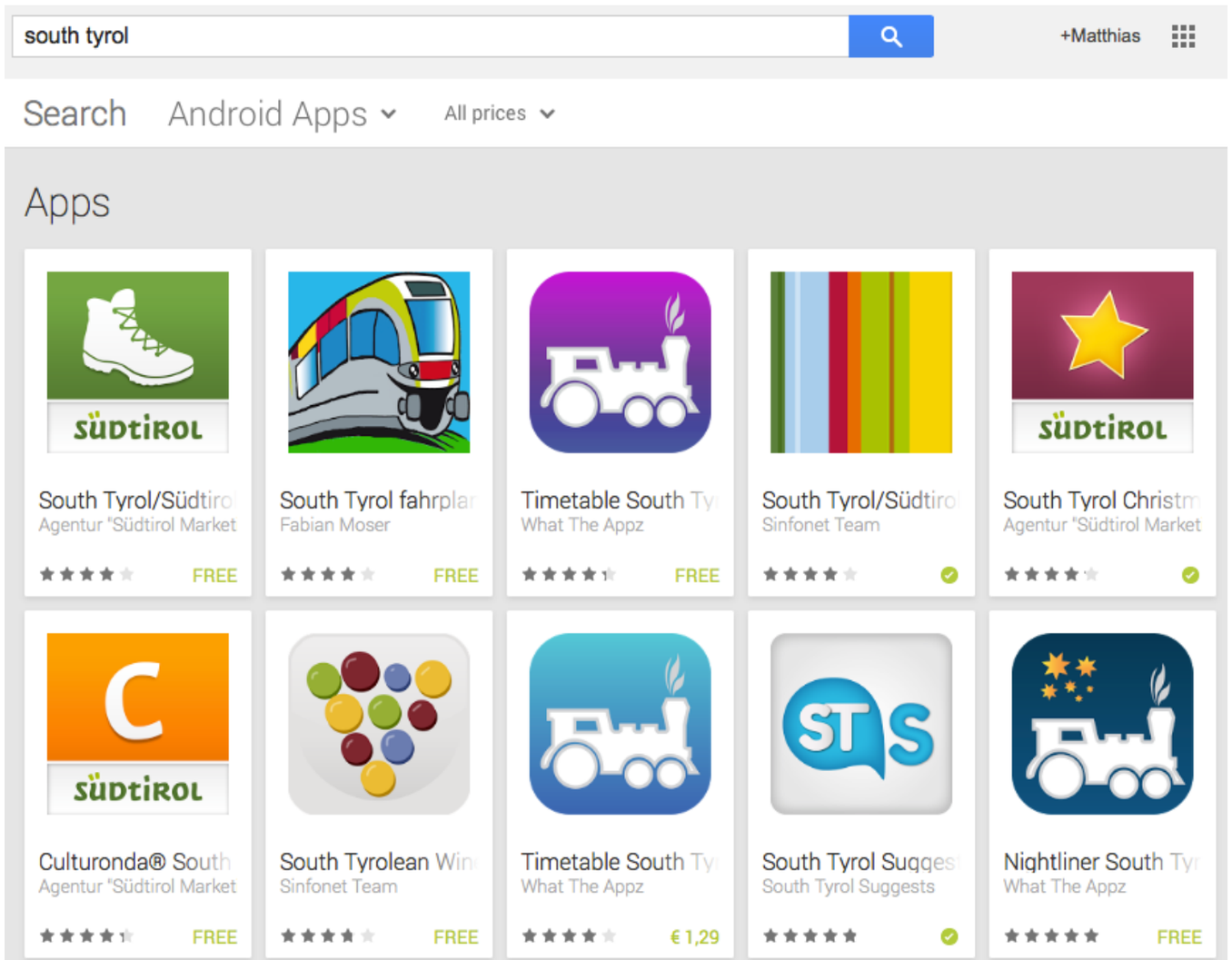
STS (South Tyrol Suggests)

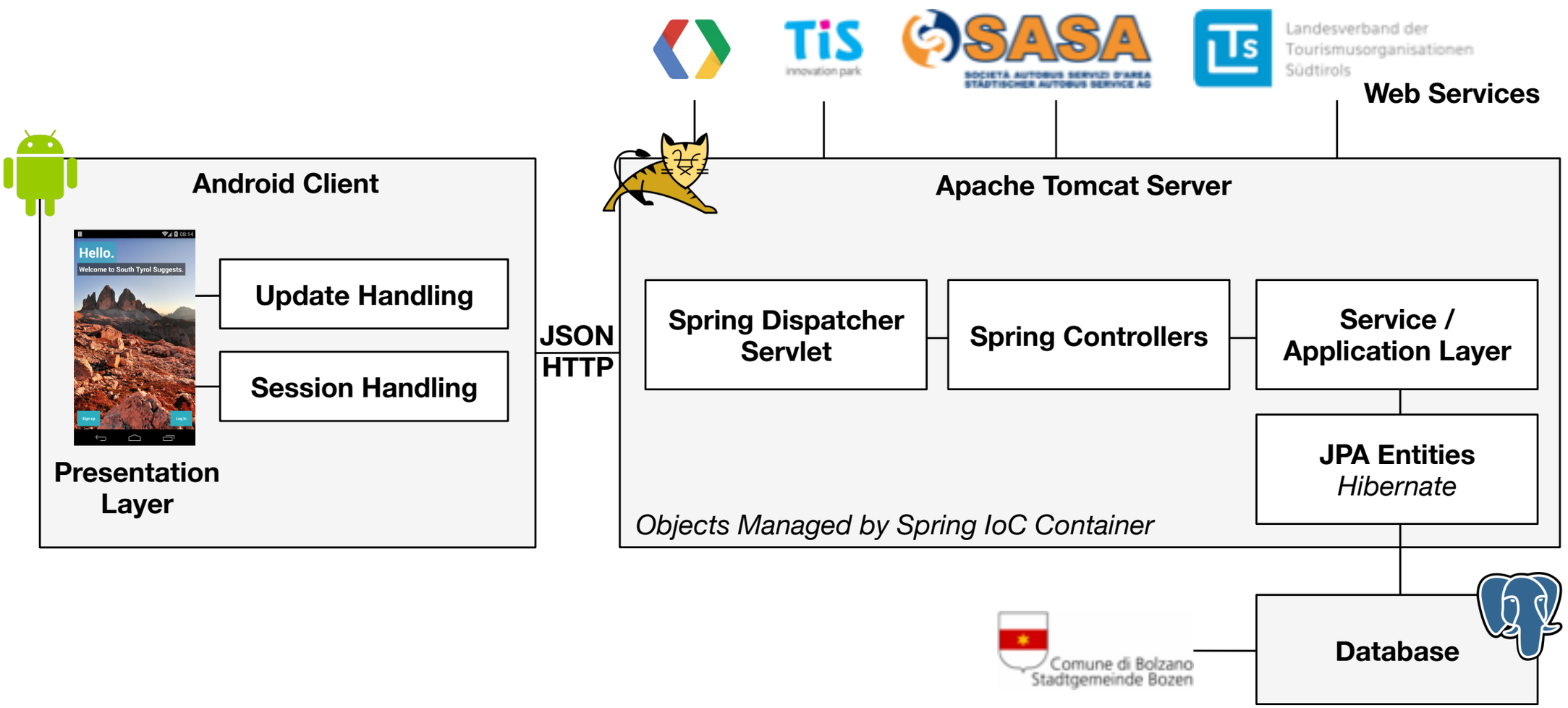
- Our **Android app** on Google Play that supports the following functionalities:
  - Intelligent recommendations for POIs in South Tyrol that are adapted to the current contextual situation of the user (e.g., weather, location, parking status)
  - Eco-friendly routing to selected POIs by public or private transportation means
  - Search for various types of POIs across different data sources (i.e., LTS, Municipality of Bolzano)
  - User personality questionnaire for preference elicitation support

Statistics



- App usually shown in the **top-10 search results**
- Current/total installs: **164 / 575**
- Avg. rating/total #: **4.92 / 13**

Software Architecture and Implementation



Interaction with the System

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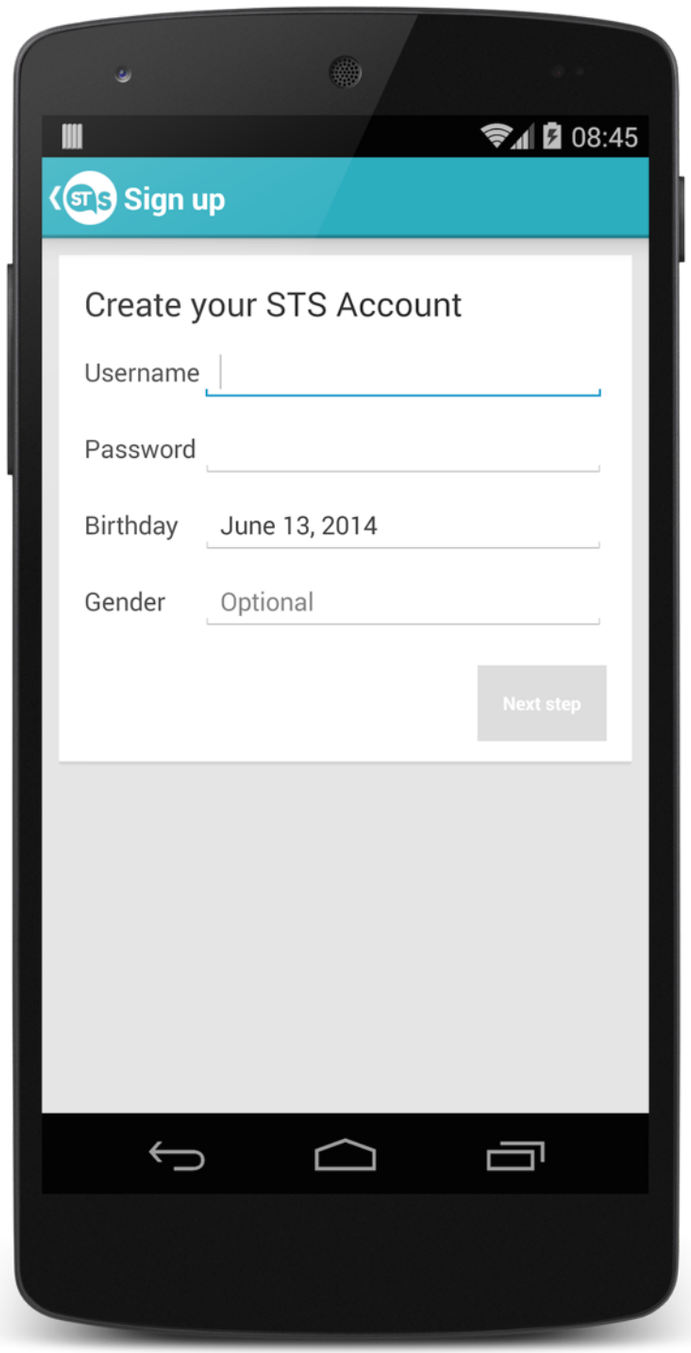

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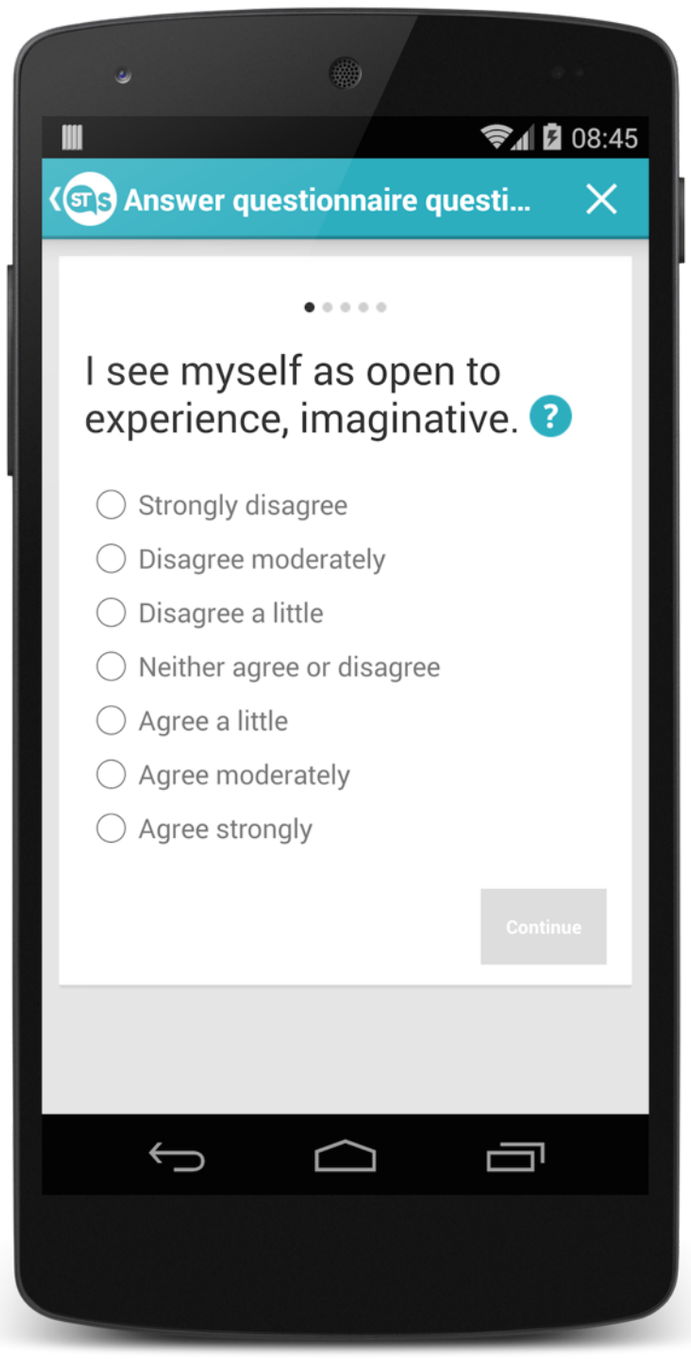

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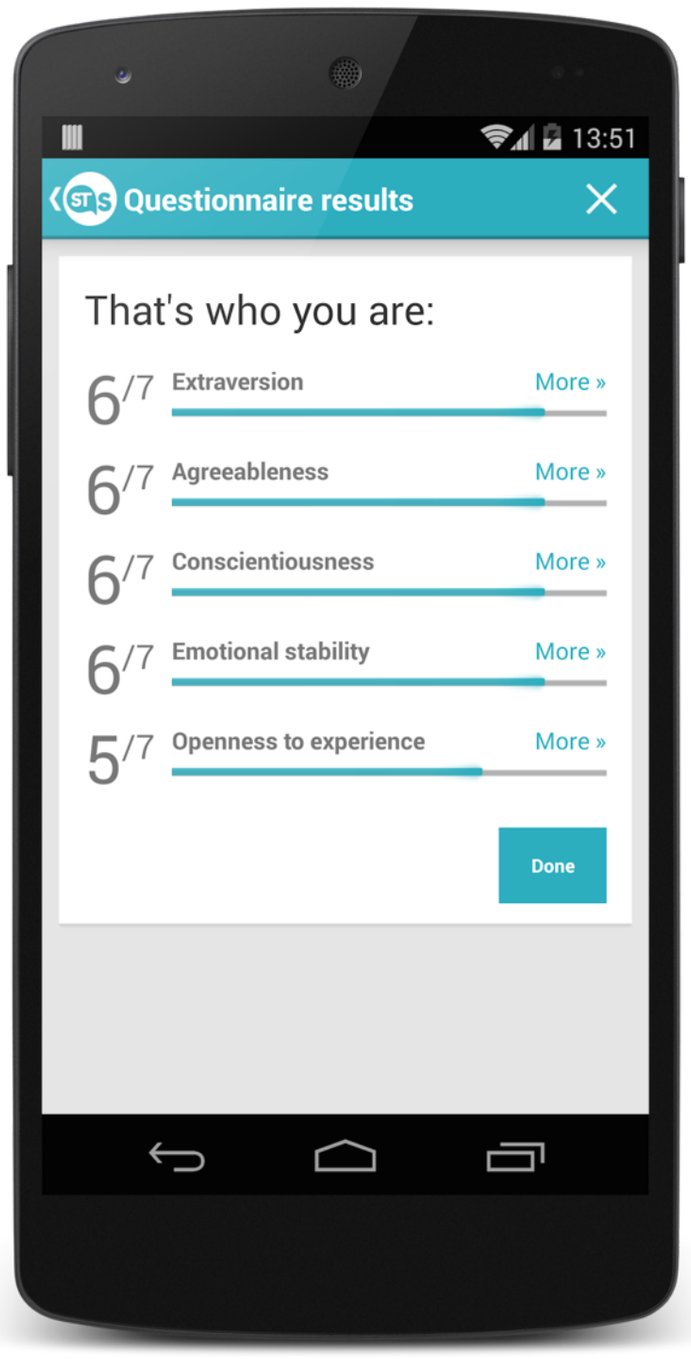

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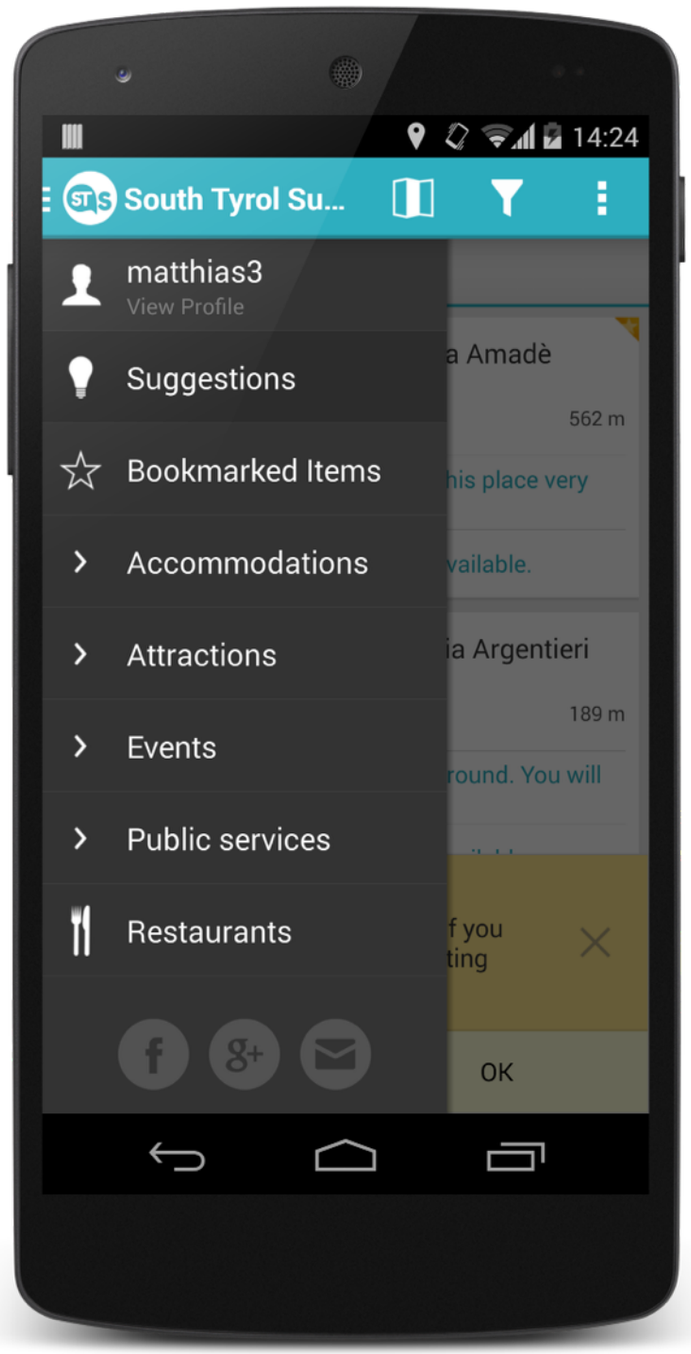

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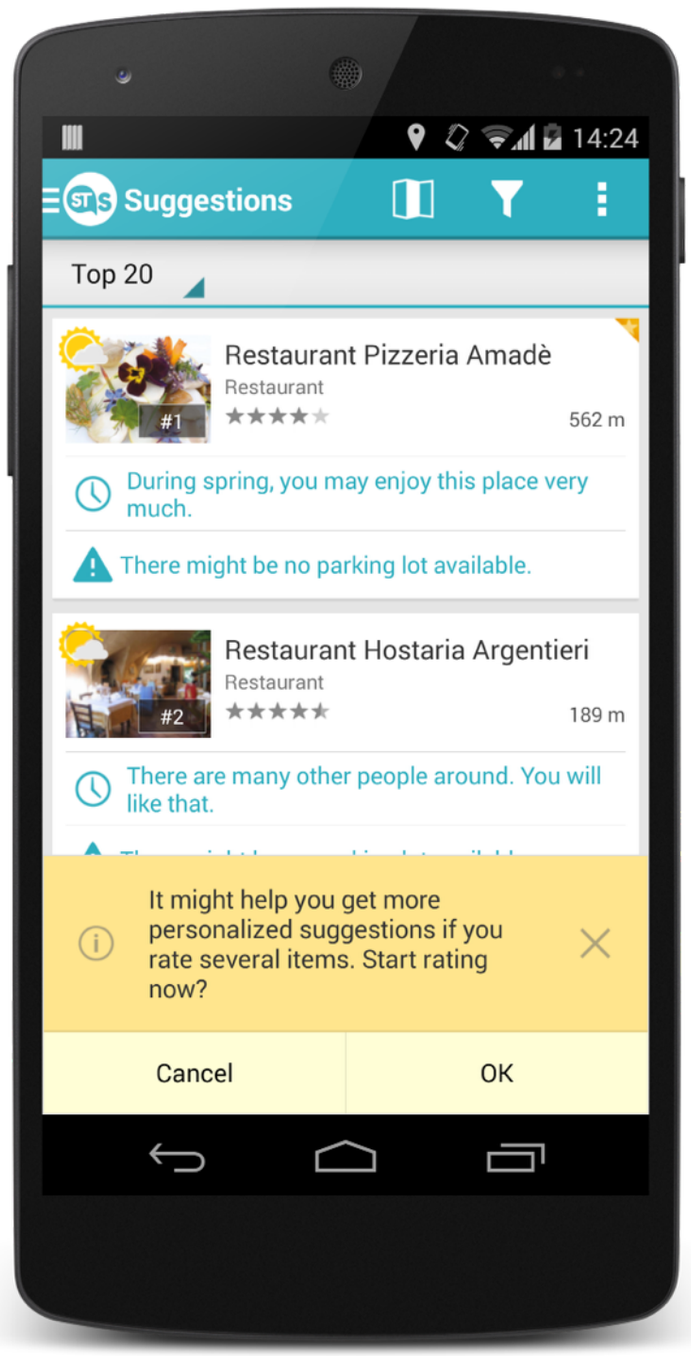

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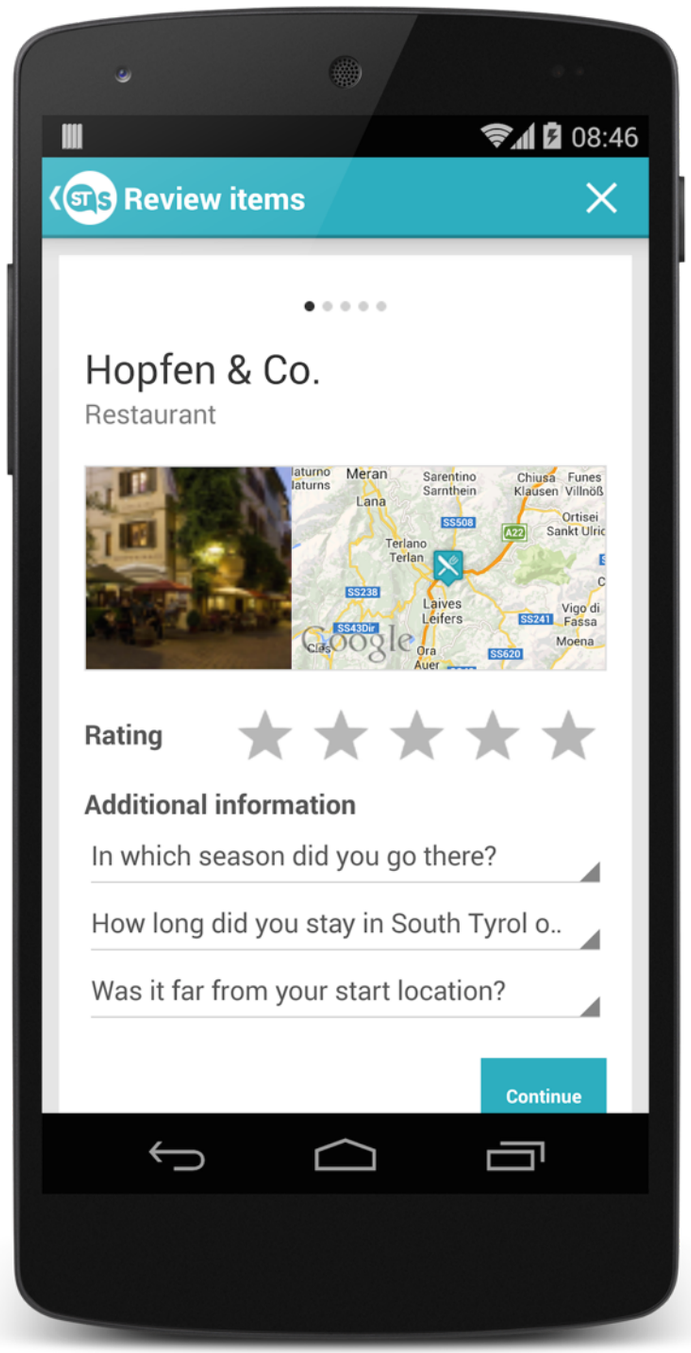

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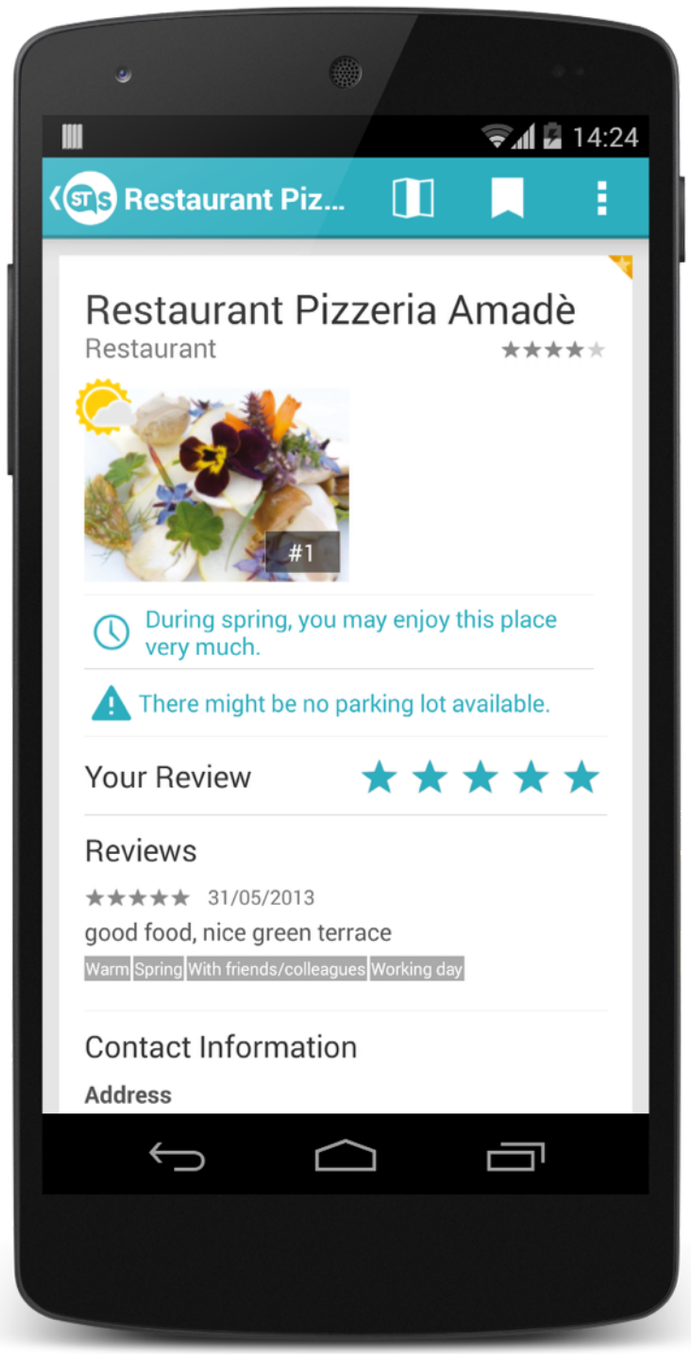

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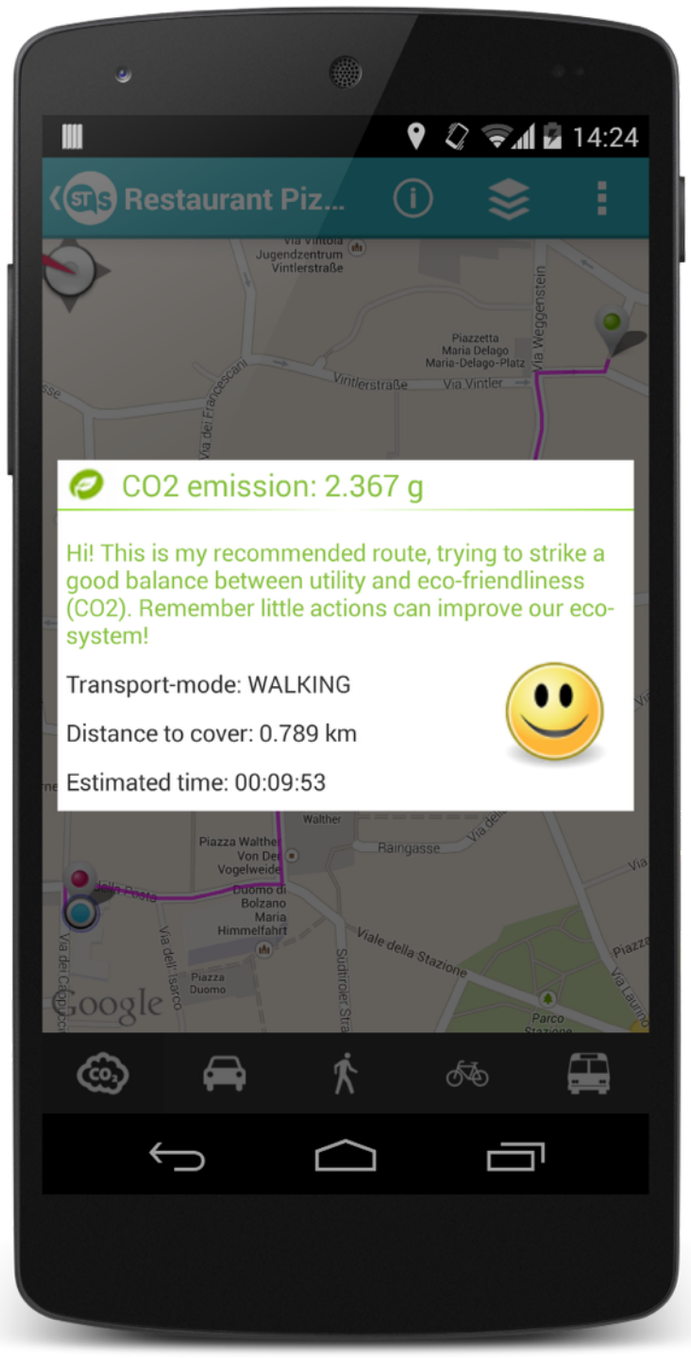

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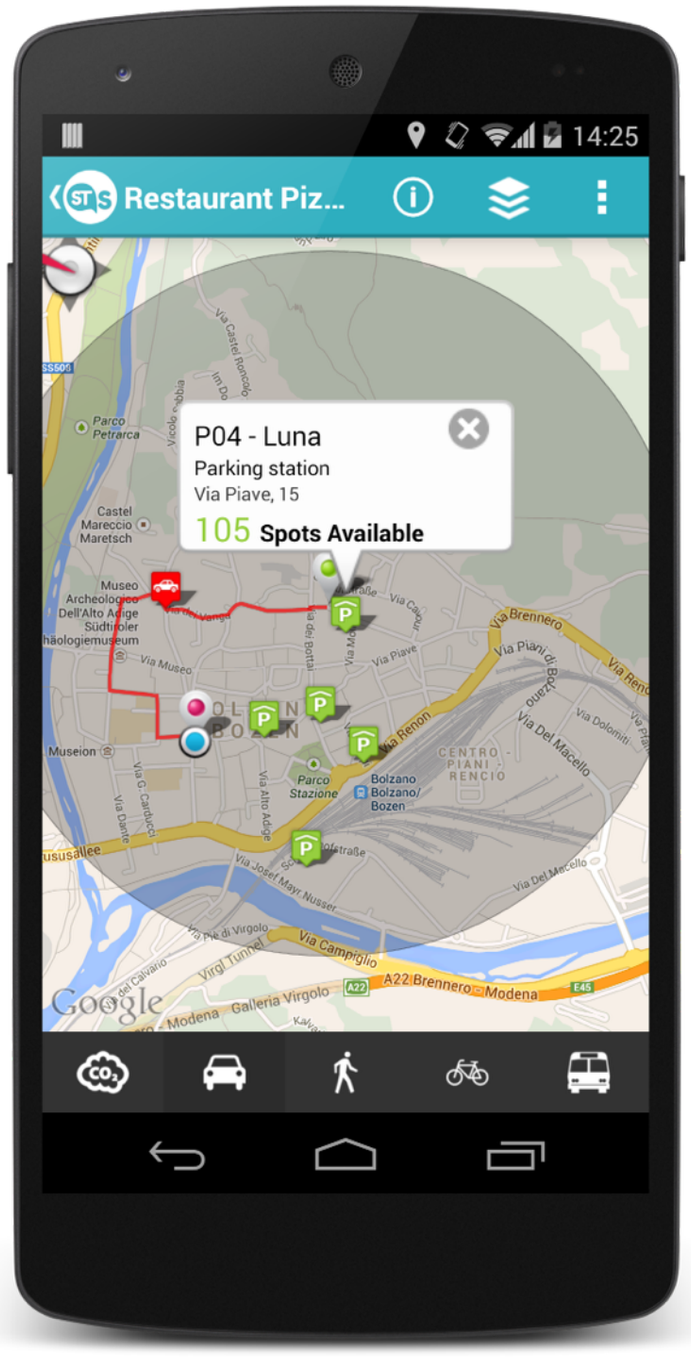

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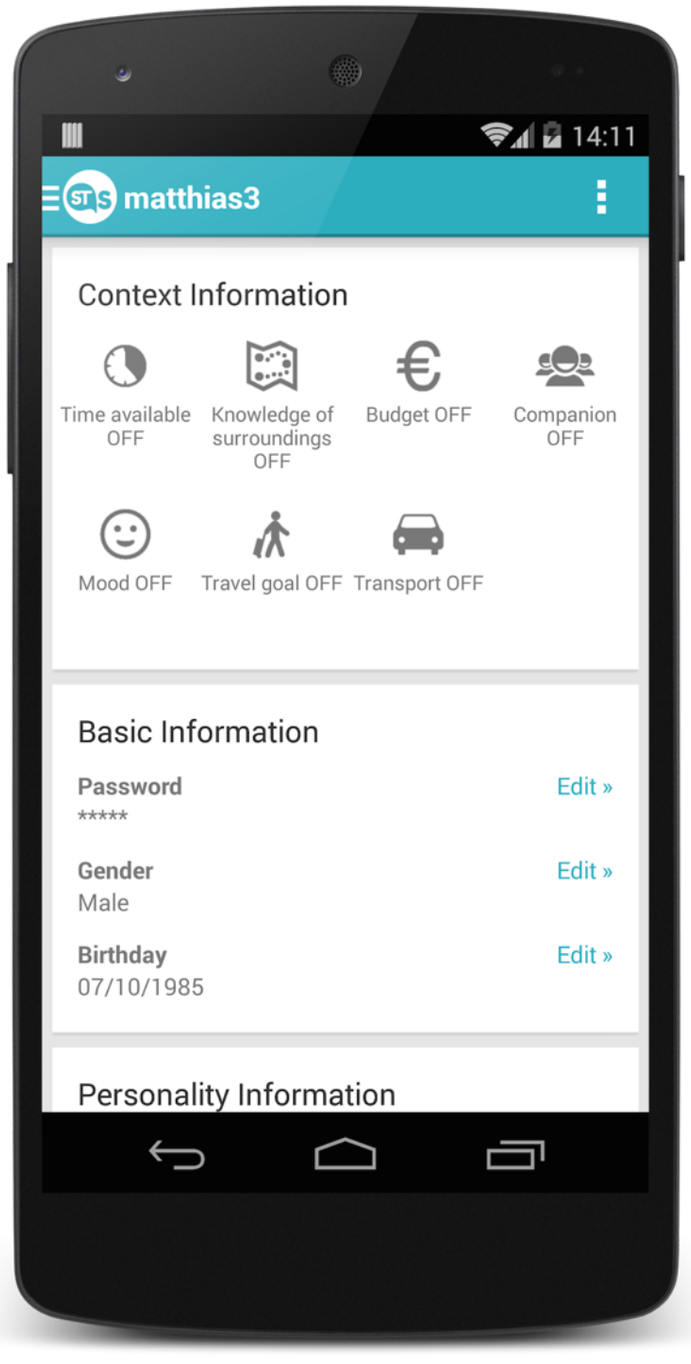

Recommendation Task

- Core computations of recommender systems:
  - **Collection of user preferences (ratings):** collect user feedback (ratings) on items to learn the user preferences
  - **Rating prediction:** a model must be built to predict ratings for items not currently rated by the user
  - **Item selection:** a model must be built that selects the N most relevant items for the user

Rating Prediction Algorithm (1/2)

- Rating prediction algorithm is based on **Matrix Factorization (MF)**
  - **Basic idea of MF:** predict unknown ratings by discovering some latent features that determine how a user rates an item; features associated with the user should match with the features associated with the item

r
5 x 4 matrix

r_{11}	r_{12}	r_{13}	r_{14}
r_{21}	r_{22}	r_{23}	r_{24}
r_{31}	r_{32}	r_{33}	r_{34}
r_{41}	**r_{42}**	r_{43}	r_{44}
r_{51}	r_{52}	r_{53}	r_{54}

=

q
5 x 3 matrix

a	**b**	**c**

p
3 x 4 matrix

	x		
	y		
	z		

$$r_{42} = (a, b, c) \cdot (x, y, z) = a * x + b * y + c * z$$

Rating prediction

$$\hat{r}_{ui} = q_i^T p_u$$

User preference factor vector

Item preference factor vector

Rating Prediction Algorithm (2/2)

- **Context-Aware Matrix Factorization (CAMF):** extends standard MF by incorporating baseline parameters for each contextual condition and item pair to capture the deviation of the rating for an item produced by the contextual conditions

$$\hat{r}_{uic_1,\ldots,c_k} = q_i^T (p_u + \sum_{a \in A(u)} y_a) + \bar{i} + b_u + \sum_{j=1}^{k} b_{ic_j}$$

Captures the rating deviation due to context (e.g., weather, parking)

Rating = 4

Item average	User bias	Context bias	Preference factor (user-demographics-item-interaction)

c_j	contextual condition j
q_i	latent factor vector of item i
p_u	latent factor vector of user u
A(u)	set of user attributes
y_a	latent factor vector of user attribute a
$\bar{i}$	average rating of item i
b_u	baseline for user u
b_{ic_j}	baseline for item-contextual condition ic_j

Evaluation

- **Several user studies** involving > 100 test users
  - Test users were students, colleagues, or other people recruited at the Klimamobility Fair and Innovation Festival
- **Obtained results:**
  - Recommendation model successfully exploits the weather conditions at POIs and leads to a higher user's perceived recommendation quality and choice satisfaction
  - Implemented active learning strategy increases the number of acquired ratings and recommendation accuracy
  - Users largely accept to follow the supported human-computer interaction and find the user interface clear, user-friendly and easy to use

Next Steps

- Integration of the **Comino routing engine**
- Allow users to plan **future visits** to POIs
- Provide users with **push recommendations**
- Exploit **activity and emotion information** inferred from wearable devices in the recommendation process

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Comino

- **Multimodal routing engine** that combines several transportation networks
  - Walking
  - Public transport system
  - Car
  - Bicycle
- Shall be used as a service by the STS and SASAbus apps

Comino API

- **Beta version** available at http://comino.inf.unibz.it
  - Computes point-to-point shortest path for a given arrival/departure time
  - Simple GUI
  - RESTful API in JSON
- **Limitations:**
  - Bus schedules must be updated
  - Not scalable for large networks and massive parallel requests

Next Steps

- Access and integrate **current bus schedules**
- **Improve performance** to efficiently serve many parallel requests for large networks
- **Support additional modalities:** bicycle, car
- **Provide additional functionalities:** top-k shortest routes, limit the number of changes between modalities, maximum time for walking (e.g., elderly people)

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Parking Lot Occupancy Prediction

- **Information about parking lot occupancy in the near future can be very useful**
  - Plan a journey appropriately
  - Save time when looking for a parking lot
  - Reduce the traffic in a city

Occupancy Prediction: Architecture (1/2)

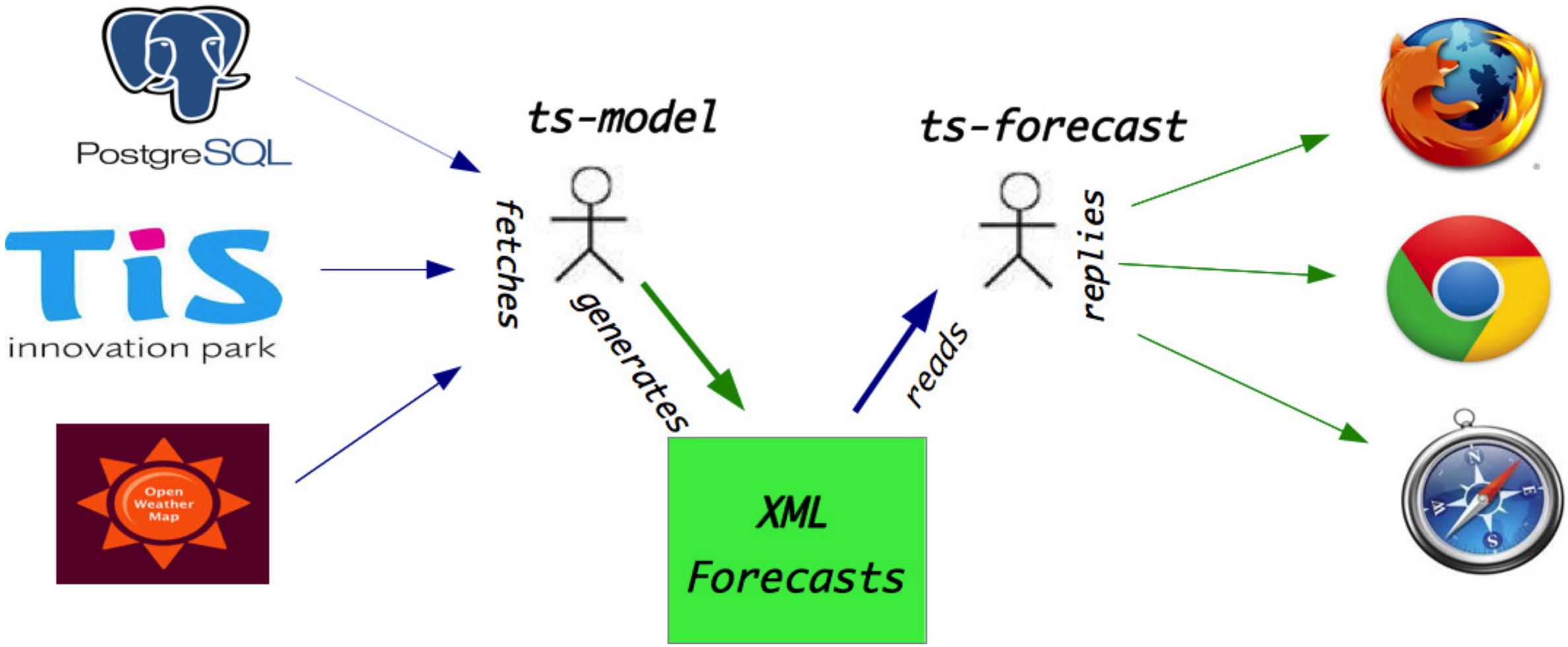
1. Collect historical information (parking lots, weather, holidays, etc.)

2. Build models for estimating parking occupancy

3. Generate and store predictions

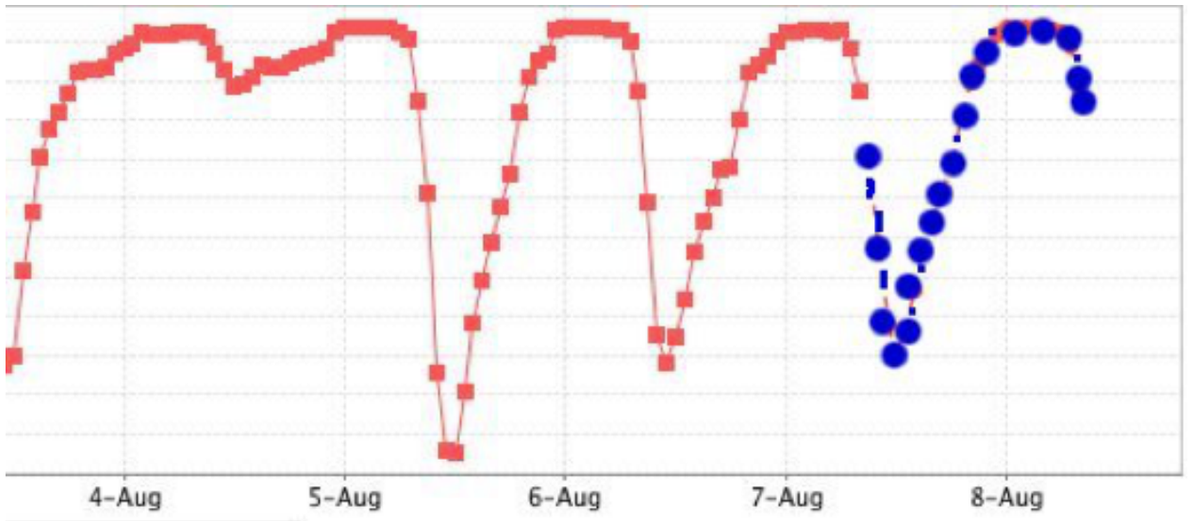
4. Reply to web service requests

Occupancy Prediction: Architecture (2/2)

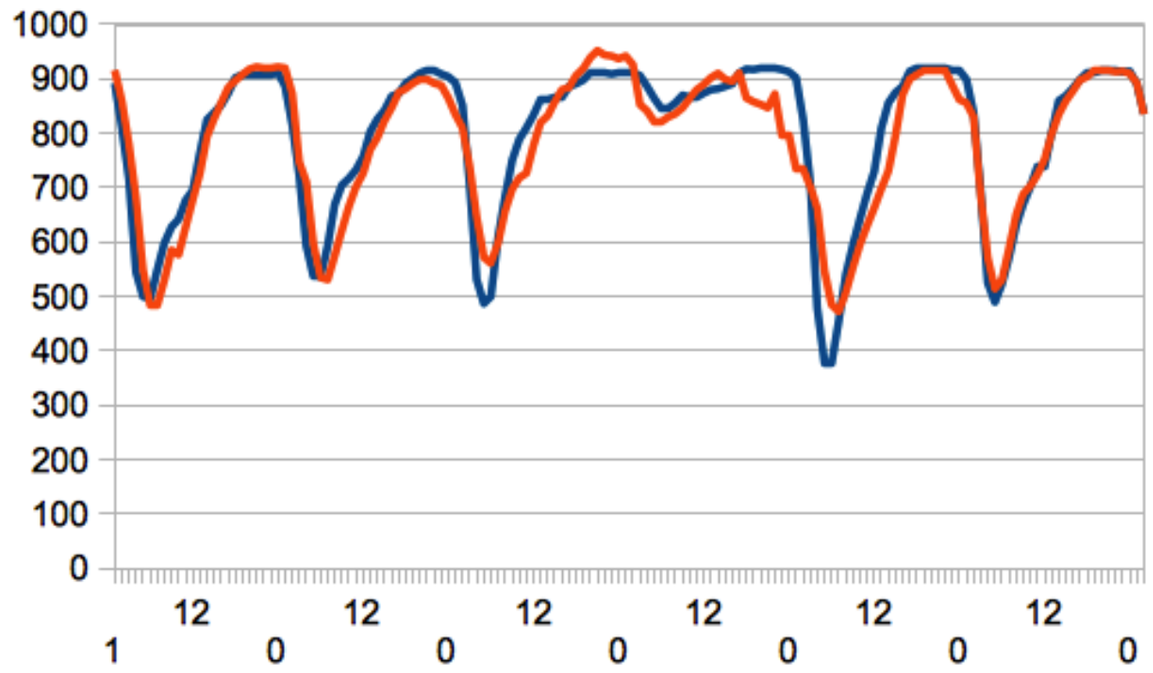


Occupancy Prediction: Example

- Parking lot 108
  - Observed free slots
  - 24 hours prediction



- Comparison
  - Real values (red)
  - Predicted values (blue)



Next Steps

- Evaluate and improve the forecasting algorithm
- Exploit the forecasts in various tools and services
- Apply prediction approach to other fields (e.g., traffic prediction)