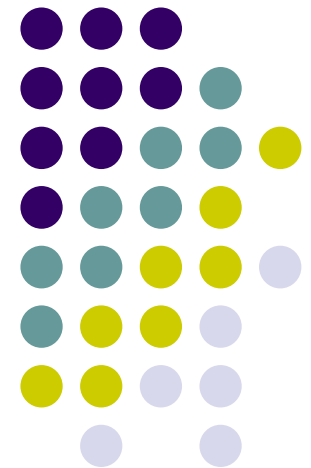


Advanced Computer Graphics CS 525M: Crowds replace Experts: Building Better Location-based Services using Mobile Social Network Interactions

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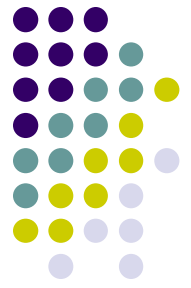
Liviu Iftode



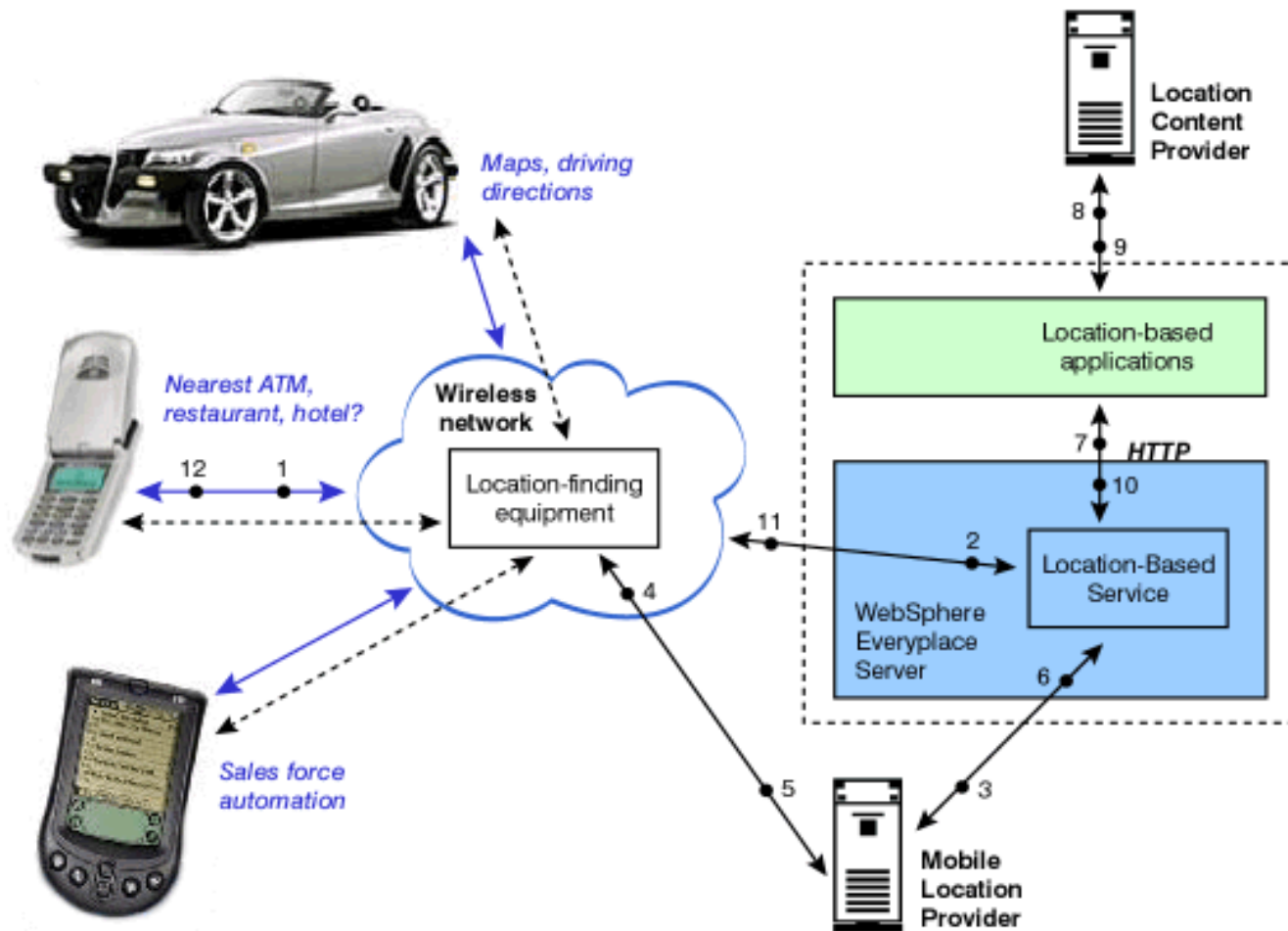
Motivation

What is the location-based services?





Motivation





Motivation

Location-based services

- Are growing in popularity
- Face two challenges
 - Collect up-to-date information about places
 - Rank places

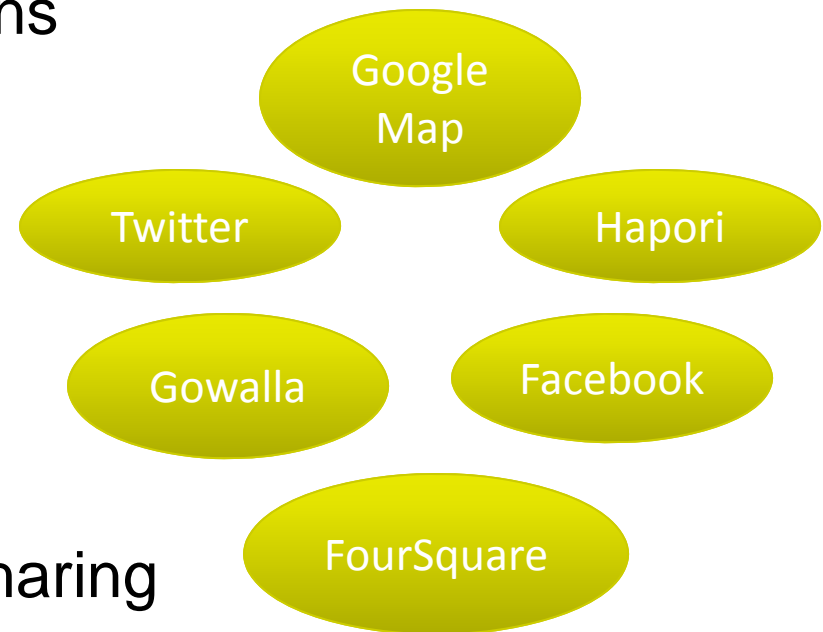
Can we build a location-based service by making use of mobile social network interactions?

SocialTelescope



Related work

- Leveraging social interactions
- Crowdsourcing
- Geo-social networks
- Location-based services
- Privacy issues in location sharing



SocialTelescope Design - Motivating Scenario



- A tourist carrying a smartphone reached New York
- Make several queries to a location-based services
- Indulge in some tourism
 - > a good seafood places
 - > a bar that plays good live music
- No friends to ask for, no luxury of time to visit



SocialTelescope Design - Architecture

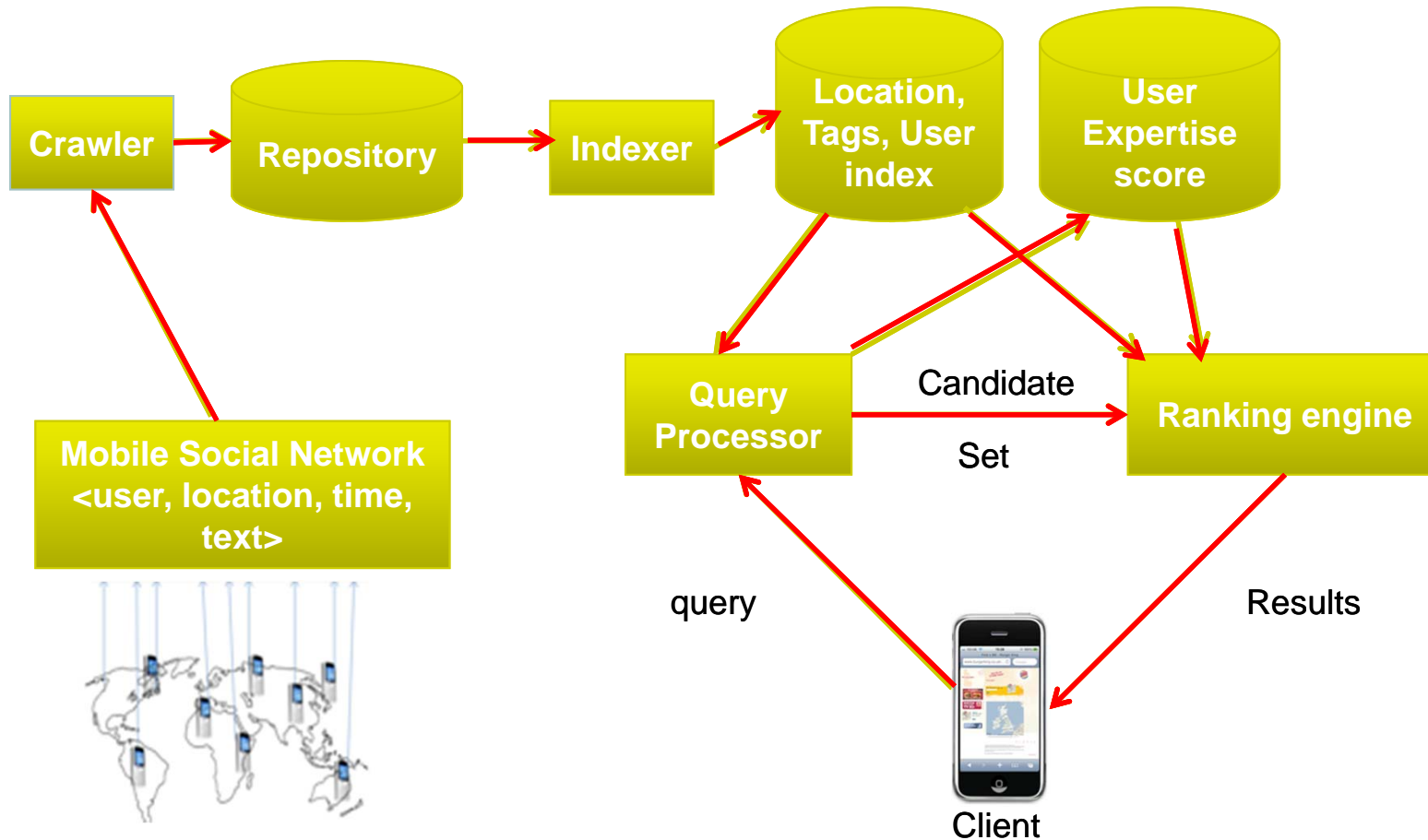


Figure1. High-level Architecture of SocialTelescope

SocialTelescope Design - Architecture cont.



Crawling

- Record all public user interactions in mobile social networks, and store them in a repository
- Social network services typically provide well-defined APIs for external applications to crawl their public data

Indexing

- Text entered by a user is converted into a set of tags
- Three entities : locations, tags, users
- Find a user's mobility profile, interests profile and location's profile



SocialTelescope Design - Architecture cont.

Query Processing and Ranking Algorithm

- The fraction of total visits by user u to places matching search term q is computed as:

$$F(q, u) = \frac{n_{q,u}}{\forall i \in Q n_{i,u}}$$

- The relative importance of search term q is computed as:

$$I(q) = \log \frac{|Q|}{\forall j \in U n_{q,j}}$$

- We define the user expertise score, $S_{q,u}$ as :

$$S_{q,u} = F(q, u) \cdot I(q)$$

- 1: Get the list of places L matching search keyword q
- 2: Foreach user u :
- 3: Compute user expertise score $S_{q,u}$
- 4: Order each place in L by number of user visits weighted by $S_{q,u}$
- 5: Return the top k results in L

Algorithm1: SocialTelescope Ranking Algorithm

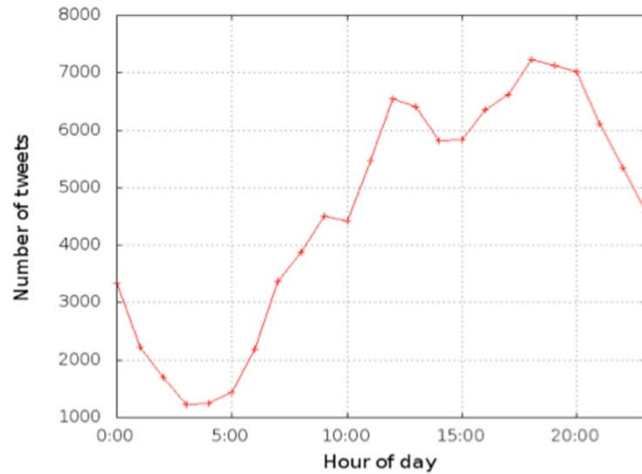


Mobile Social Network Dataset

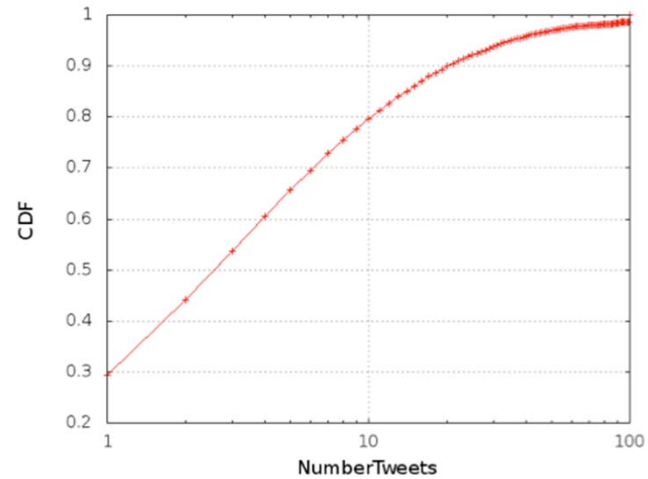
Start date	June 14,2010
End Date	August 20, 2010
Bounding box for geo-tweets	(40.703,-74.022),(40.879,-73.899)
Total geo-tweets in the region	198919
Total number of distinct users	15659
Total FourSquare checkins corresponding to the geo-tweets	43461
Total number of distinct FourSquare users	6451

Table1 details of the SocialTelescope dataset.

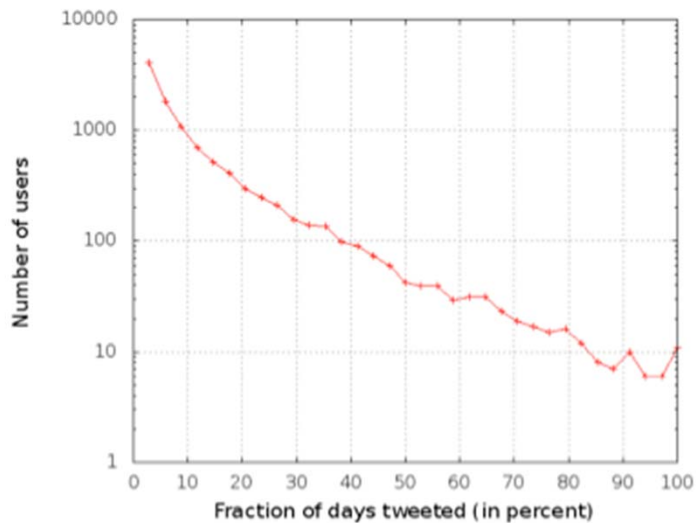
Mobile Social Network Dataset cont.



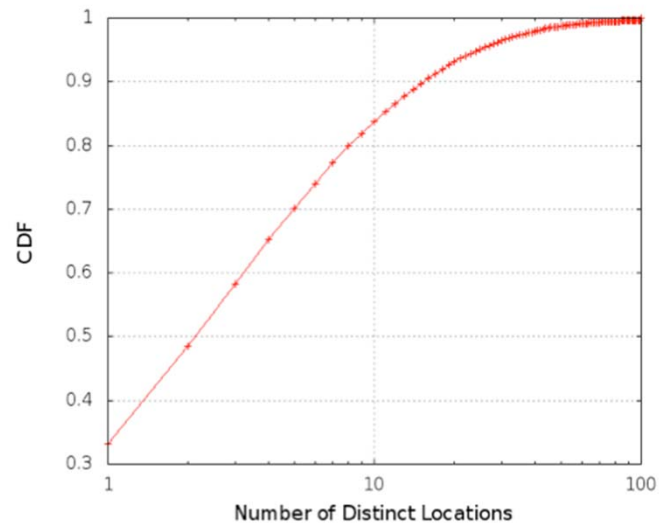
Hourly trends: number of tweets during different hours of day across the entire dataset



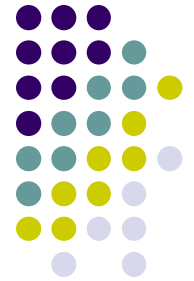
Distribution of number of tweets per year



Distribution of active days per user. An active Day refers to a day when a user at least one tweet



Mobility profile per user: number of distinct locations where a user tweeted from



Mobile Social Network Dataset cont.



User tags for locations in the form of a tag cloud

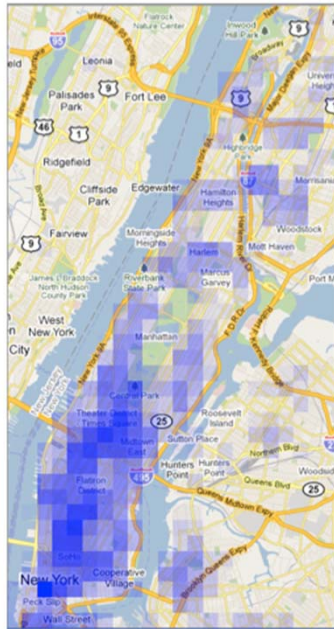
bar	385
coffee	376
douchebag	355
pizza	340
beer	242
food	223
restaurant	206
brunch	181
gym	166
brooklyn	162

Top ten most popular User tags for locations

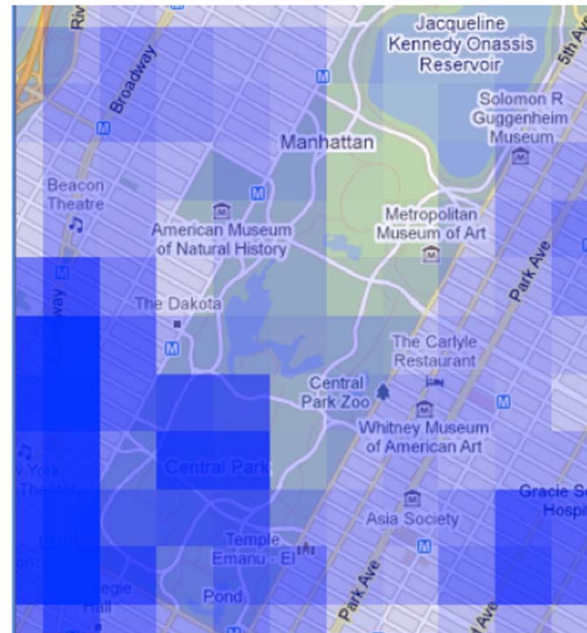
Trends in user tags for location



Mobile Social Network Dataset cont.



Heatmap of the entire region



Heatmap zoomed in to Central Park to show Trends at a finer granularity

Heatmap of the New York city region based on geo-tweets



Evaluation - Goals and Metrics

- Goal
 - Return relevant results efficiently
- Key measures of the quality
 - **Coverage**
 - How complete and up-to-date is information about different locations
 - **Relevance**
 - How relevant are the top results to the query

Evaluation - Methodology



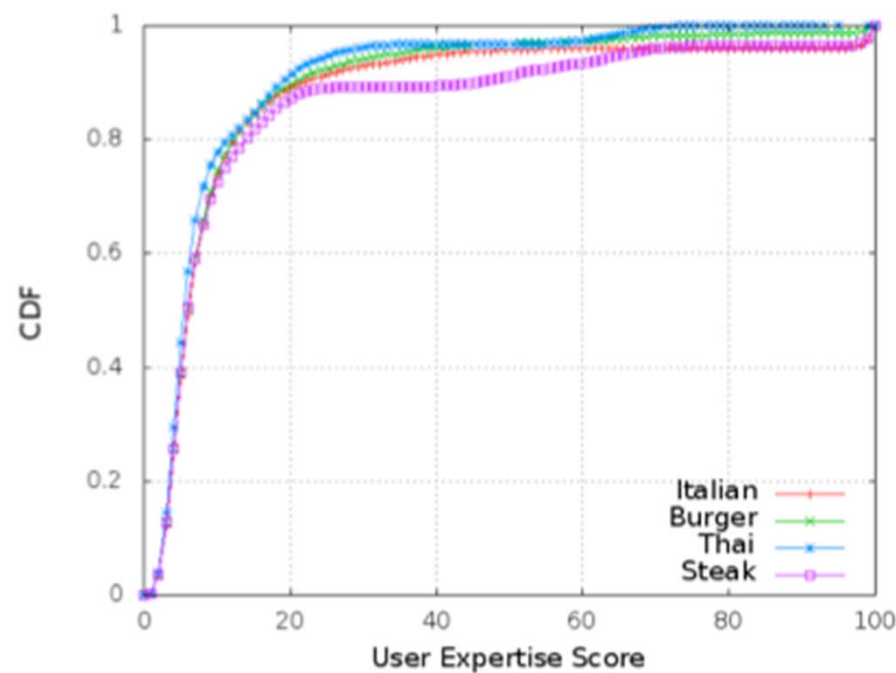
- Focus on restaurant search
- Compare between user-review based & page-rank based
- User feedback

Evaluation - coverage and Relevance Results



Query	#Matches	#Experts
Barbecue	65	116
Burger	166	238
Japanese	237	182
Indian	70	61
Seafood	85	60
Mexican	212	140
Chinese	165	84
Steak	78	28
Thai	102	31
Italian	332	175

Number of place and expert matches
In dataset for the 10 test queries

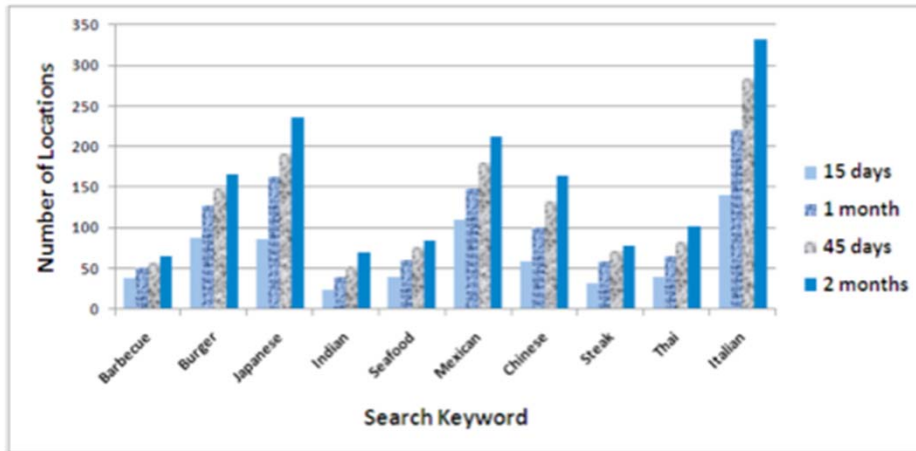


Distribution of User Expertise Score for
Different queries

Details of test queries using Zagat Top Places

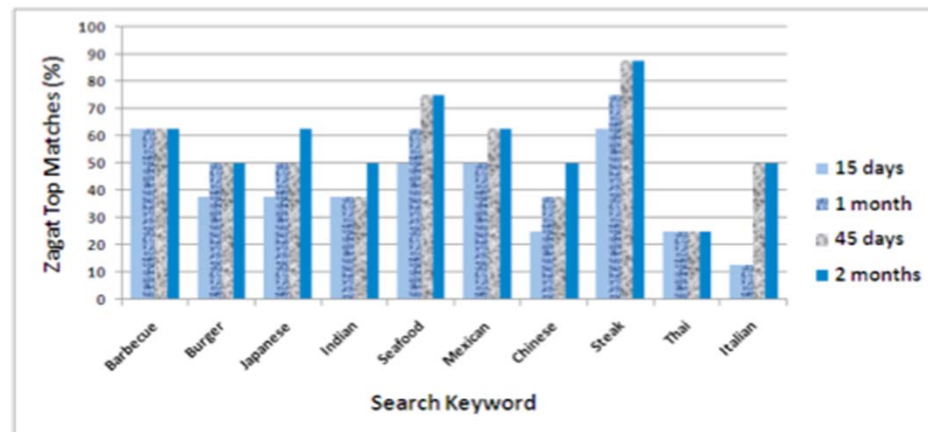


Evaluation – Coverage and Relevance Results cont.

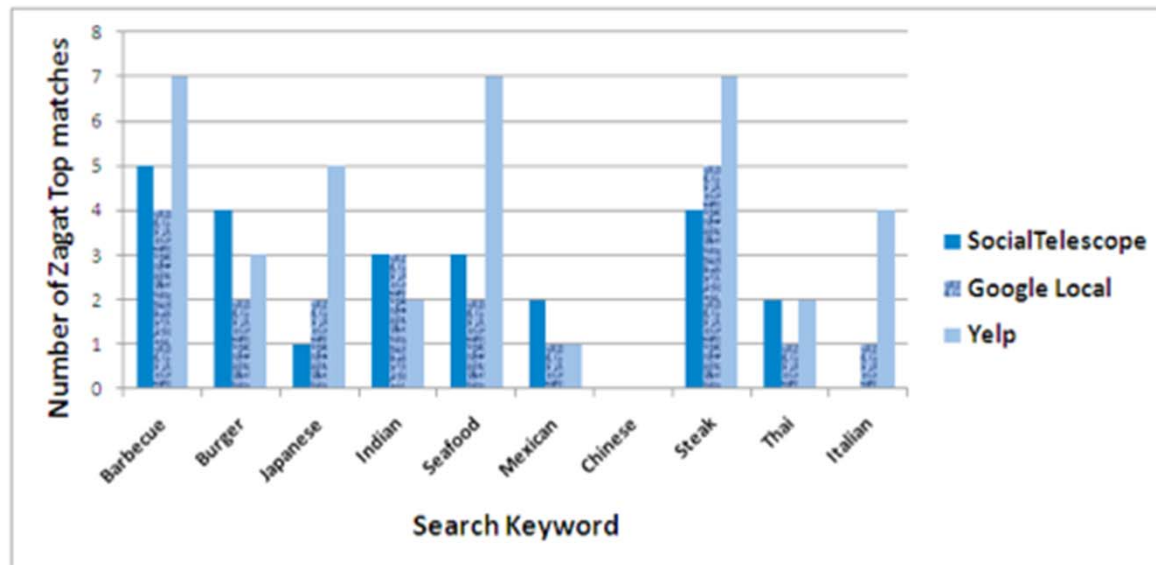


Total number of matches in SocialTelescope, for each of the test queries

Relevance of results returned by SocialTelescope, measured as fraction of Zagat Top Places that are contained in the result set



Evaluation – Coverage and Relevance Results cont.



Comparison of ranking results of SocialTelescope, Google Local Search and Yelp, by assuming the Zagat Top Places list to be the ground truth



Evaluation – user feedback

- Test to 8 users
- Three sets of results
 - SocialTelescope & Google Local Search & Yelp
- Reports from the feedback
 - SocialTelescope performs better for queries that are subjective in nature
 - When a user wanted only places with a speciality cuisine, SocialTelescope did not perform well



Discussion

- Spoofing locations

Validating a mobile user's location

- Improvements to the ranking algorithm

Better infer user preference for a place based on the text they enter
In social networks

- Cost of building and updating a location-based service

Cost less than the existing approach on collecting and updating information

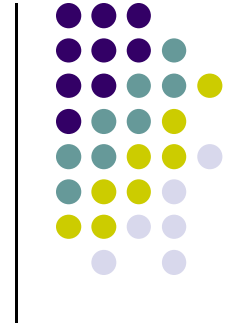
- Personalized results

Reveal no personal information



Conclusion

- Show how a location-based service can be built
- Introduce an algorithm for ranking places
- Present results from an evaluation
- Compare the approach to existing approaches



Thank you !