

Supporting mobility analysis with crowd-sourced data - Opportunities and challenges

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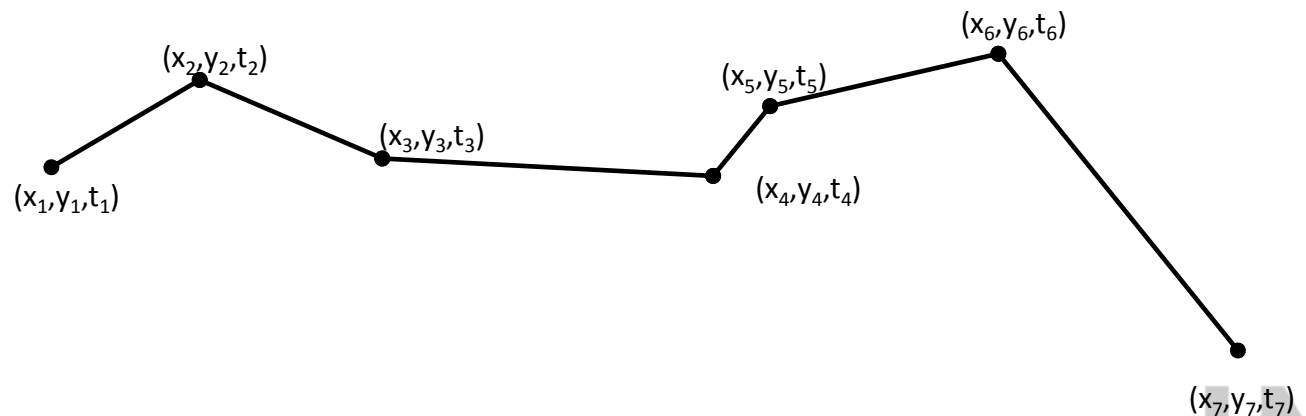
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Problem and objective (1)

Mobility in real world



Individual trajectory



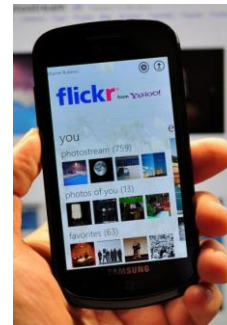
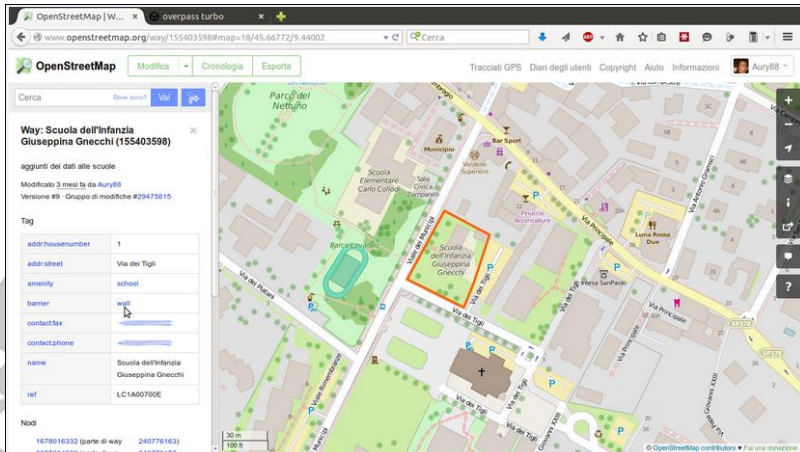
Problem and objective (2)

- Mobility data are used in many applications
 - Transportation: traffic management, routing
 - Urban planning: land use and infrastructure utilisation monitoring
 - Environment: air pollution and noise pollution control
 - Business: advertisement, choice of new business location
 - ...
- However, such applications require high level information:
 - characteristics of places visited
 - events that took place at the time of visit
 - characteristics of the geographic space where the movement took place
 - ...
- Surveys are expensive to deliver such information
- Manual annotation by the moving individuals is not feasible
- What about crowd-sourcing?

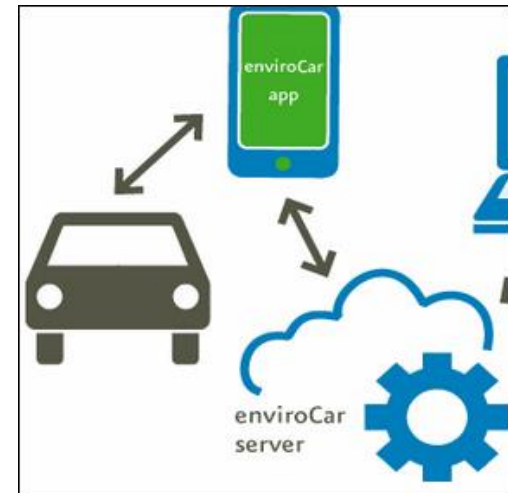


Opportunities (1)

- Increasing people's participation to producing geo-referenced crowdsourced data



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Opportunities (2)

- Produced crowdsourced data are rich in semantics
 - social network data
 - main data + social structure
 - Social structure given a high importance
 - Example:
 - check-ins (<https://foursquare.com/>)
 - mainly text (<http://www.twitter.com/>)
 - mainly text (<http://www.facebook.com/>)
 - photos (<http://www.flickr.com/>)
 - contribution-focused data
 - main data (+ social structure)
 - If available, social structure given low importance
 - Example:
 - noise level data (<http://www.noisetube.net/#&panel1-1>)
 - vehicle emission data (<https://www.envirocar.org/>)
 - pleasantness of urban locations (<http://urbangems.org/>)
 - geo-referenced pages (http://en.wikipedia.org/wiki/Main_Page)
 - geographic features (<http://www.openstreetmap.org>)



Opportunities (3)

- Availability of APIs for accessing crowd-sourced data

- **Root**
- **Friends**
 - /users/:username/friends
 - /users/:username/friends/:friend
- **Tracks**
 - /tracks
 - /tracks/:trackid
 - /users/:username/tracks
 - /users/:username/tracks/:trackid
- **Phenomenons**
 - /phenmenons
 - /phenmenons/:phenomenon
- **Sensors**
 - /sensors
 - /sensors/:sensor

The Flickr API is available for non-commercial use by outside developers. Commercial use is possible by prior arrangement.

Read these first:

- [Developer Guide](#)
- [Overview](#)
- [Encoding](#)
- [User Authentication](#)

- [Dates](#)
- [Tags](#)
- [URLs](#)
- [Buddyicons](#)

- [Flickr APIs Terms of Use](#)

- [API Keys](#)
- [Developers' mailing list](#)

API Methods

activity

- [flickr.activity.userComments](#)
- [flickr.activity.userPhotos](#)

auth

- [flickr.auth.checkToken](#)
- [flickr.auth.getFrob](#)
- [flickr.auth.getFullToken](#)
- [flickr.auth.getToken](#)

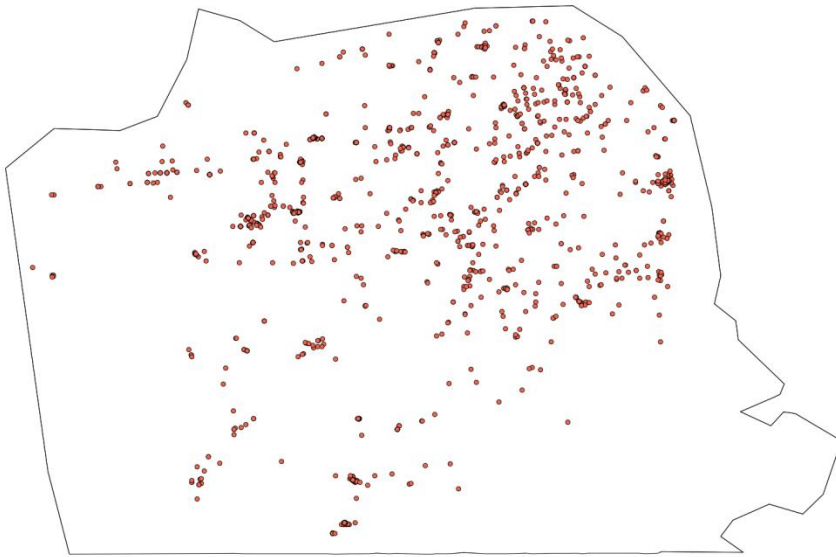
auth.oauth

- [flickr.auth.oauth.checkToken](#)
- [flickr.auth.oauth.getAccessToken](#)



Challenges (1)

- Data sparsity
- Data representativeness



Challenges (2)

- Limitations associated with the available APIs, e.g:
 - In Foursquare, view friends of an individual but can not view the check-ins of a specific user
 - In Flickr, limit at 3600 queries per hour and per key
 - Motivation
 - contribution-focused data may require:
 - acquisition of specific devices (e.g. sensors)
 - more efforts
 - for social network data
 - Establishing and maintaining a network is a one motivation
- Need for (further) motivation



Challenges (3)

- Incompleteness due to limited quality control
- Location uncertainty due to:
 - accuracy of the device used for location recording
 - processing done at the crowdsourcing platform that can filter or modify geographic information
 - the credibility of the user generating the data who can change geographic coordinates intentionally
 - the difference between user and content locations
e.g. a Flickr photo showing Mount Everest with coordinates on a another mountain



Addressing the challenges (1)

- Collaborative filtering (CF) for addressing data sparsity
 - commonly used in recommendation systems
 - idea behind: similar users make ratings in a similar manner for similar items.
 - similarity is determined between users and between items, a prediction can be made to the rating of a user about future items (Nakamura and Abe, 1998)
- Data pre-processing for addressing the uncertainty
 - *Filtering* outlying data items and those of obviously wrong locations or values
 - *density of contributions* as one indicator of the level of certainty



Addressing the challenges (2)

- Integrating data from multiple sources for addressing data representativeness, incompleteness, and sparsity
 - But addressing also the problems due to the integration
 - e.g. Conflicting information solved by a voting strategy (Li et al. 2013)
 - Evaluate different integration approaches to choose most effective and best performing



Addressing the challenges (3)

- **Implementing incentive mechanisms** for addressing the motivation challenge:
 - Choose suitable incentive mechanisms from available proposals (examples in Quinn and Bederson, 2011)
 - Further examples:
 - Crowd-sourcing platforms imparting reputation to contributors indirectly
 - Providing interesting applications based on contributed data with additional features for contributors, and advertising these features



Conclusion

- Crowd-sourced data have a high potential to support mobility analysis.
- However, several challenges need to be addressed.
- Our future work will concentrate on challenges related to integrating data from multiple sources:
 - Applying ontological modelling approaches for simplifying the integration
 - Integrating social network activities of a user from different social platforms to fill the gap caused by using only one source



Thank you for your attention



References (1)

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References (2)

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