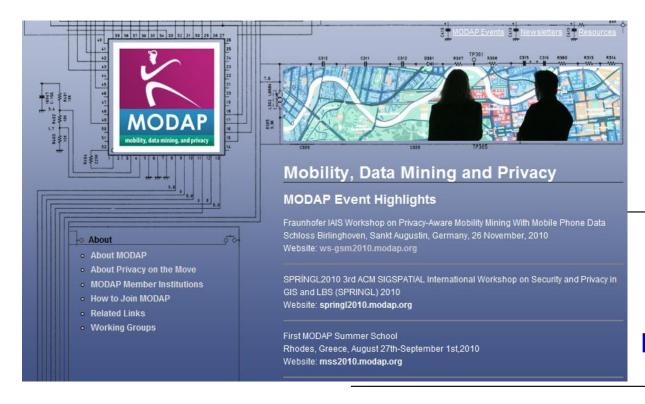
Privacy Issues in Geospatial Visual Analytics



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http://geoanalytics.net/and





Privacy issues

- Lots of personal data containing locations can be (automatically) collected and are actually collected:
 - Mobile phone use, car tracking, video observation, use of bank cards, ...
- People can also make their locations known to others through Web2.0:
 - Georeferenced photos in flickr and Panoramio, Twitter messages, ...
- These data can be (and often should be or need to be) analyzed and are actually analyzed
- The analyses may disclose potentially sensitive personal information
- Visual analytics approaches can aggravate the problem
 - Enables human-computer collaboration where each side applies its unique capabilities
 - Humans use their knowledge, experience, common sense; can easily relate pieces of information; do not require formal representations





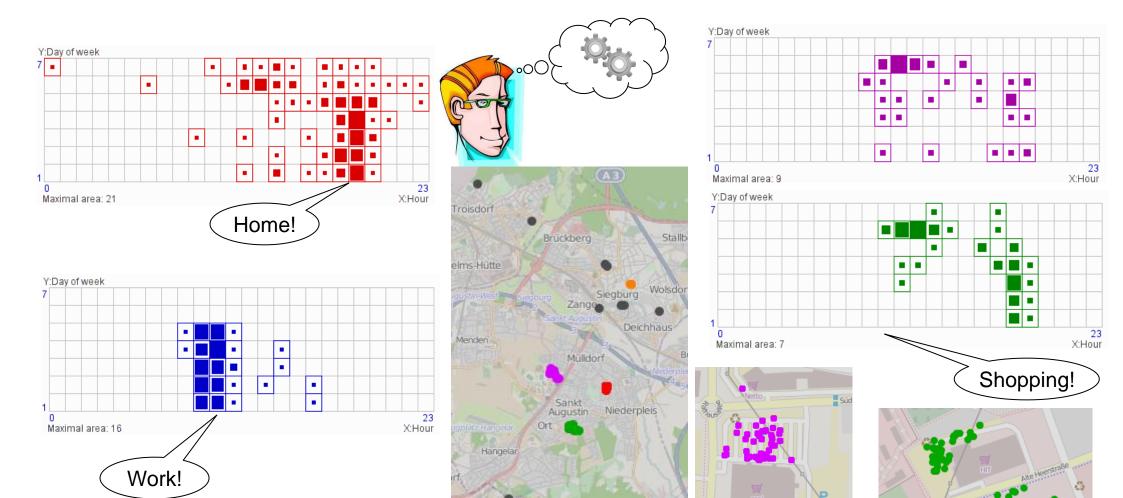
Example 1: GPS tracks of a personal car







Spatial clusters of stops for >=30 minutes



echlinghoven Heidebergen





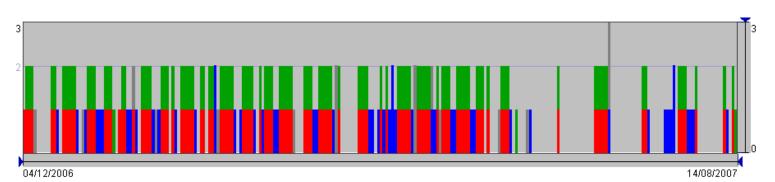
Birlinghoven

What was learned about the car owner:

- The places where the person lives, works, and shops and the places the person sometimes visits
- The durations of the stops; the times spent in the shopping areas
- The usual times of the trips and stops
- The typical routes and their distribution over time (daily and weekly patterns)

Other inferred personal information:

The person has a flexible work schedule, has no small children, is often away or sick

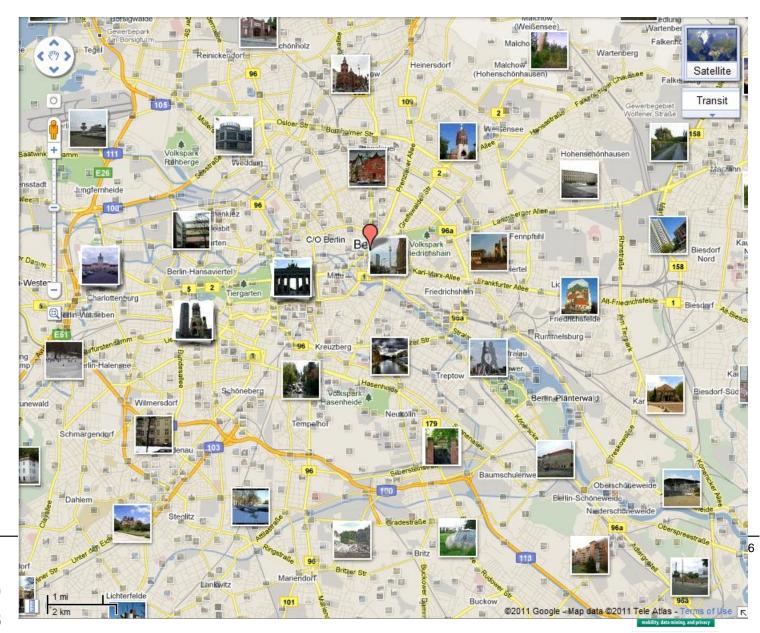


green: home to work red: work to home blue: home – home





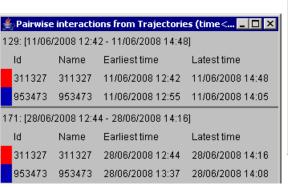
Example 2: Photos in flickr or Panoramio

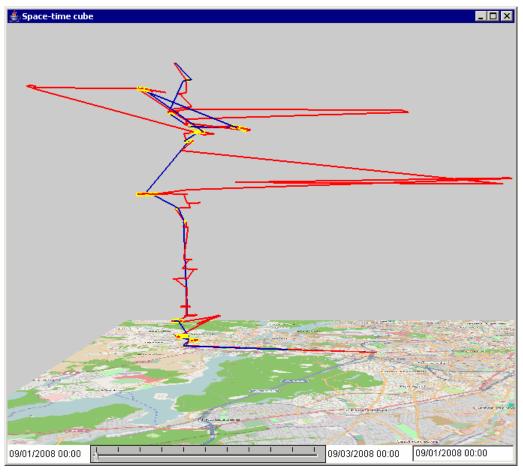


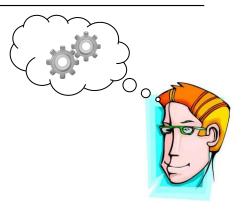


Repeated meetings of people

□ identifiers	Overall frequency		Frequency after filtering	
311327;953473		67		67
311327;1367968		50		50
953473;1367968		26		26
1592718;1620799		24		24
311327;2038072		8		8
953473;2038072		5		5
1367968;2038072		3		3
899174;953473		2		2
899174;1367968		2		2
1690654;2038072		2		2 2 2 2
1592718;1962862		2		2
1038820;2044833		2		2
986555;1592718		1		1
953473;1690654		1		1
953473;1258045		1		1
953473;1178121		1		1
687113;1620799		1		1







Users 311327, 953473, and 1367968 frequently meet each other in Berlin and sometimes meet also user 2038072.

Users 1592718 and 1620799 frequently meet.

. . .





Example 3: the iPhone case

- Availability of important but challenging spatio-temporal data sets (geospatial imagery, sensors, GPS and movement tracking, geo-tagging, flickr, wiki, ...)
 - Sometimes {unintentionally}
 breaking
 personal privacy

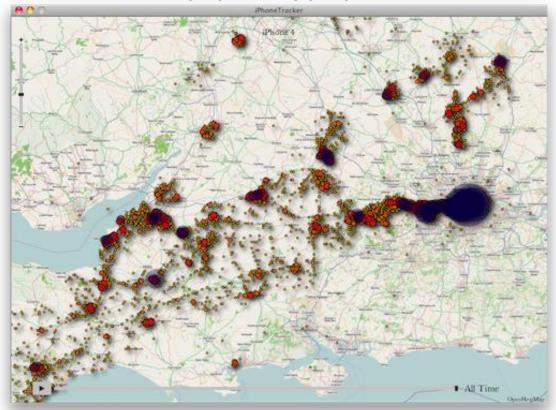


Image courtesy of http://petewarden.github.com/iPhoneTracker/

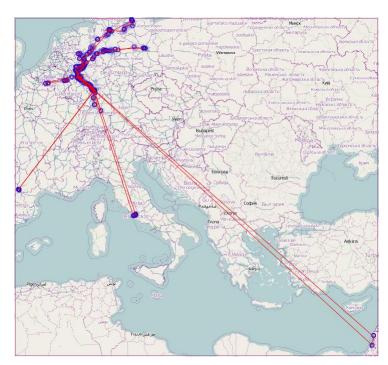


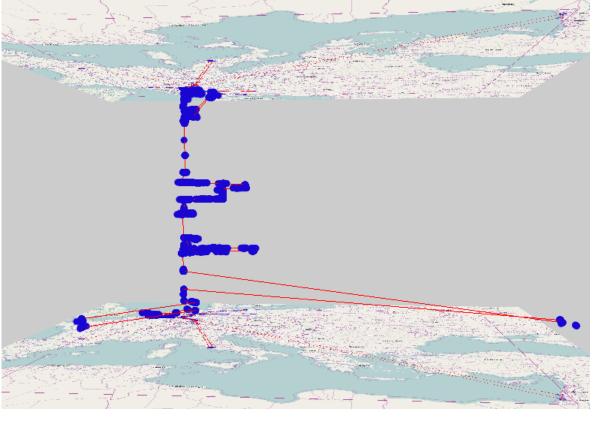


Are iPhone data really dangerous for {my} personal privacy?

At large scale: definitely YES – show which cities have been visited and

when



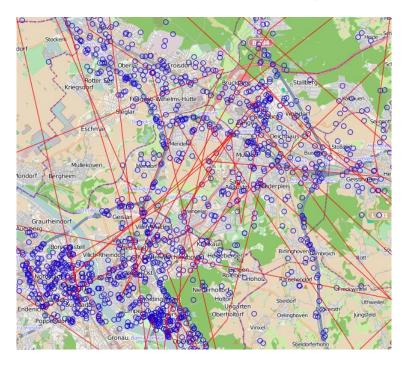


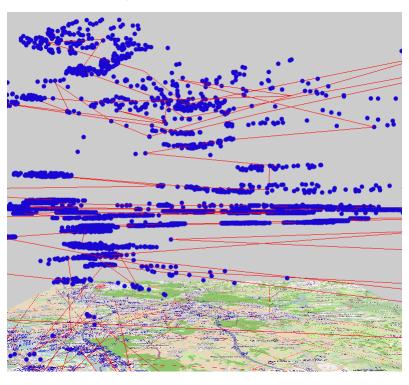




Are iPhone data really dangerous for {my} personal privacy?

At small scale: probably NO – real mobility patterns are not visible









iPhone data: cross-checking with other data sources (positions of photos) ospatial Visual Analytics November 2011

What is special about human's involvement in analysis?

- A human flexibly links data and extracted patterns to context
 - Spatial (geographic) context: properties of places, spatial objects and their properties, spatial relationships
 - *Temporal context*: properties of time moments and intervals, temporal objects (events and processes) and their properties, temporal relationships
 - Conceptual context: general and domain-specific concepts and their relationships
- The context does not need to be formally or even explicitly represented
- A human flexibly infers new information by linking pieces of known information

Hence, how can (geo)visual analytics contribute to privacy protection?

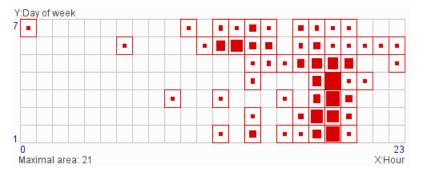
- Try to describe the context
- Try to describe the possible inferences

to inform and direct the privacy protection research



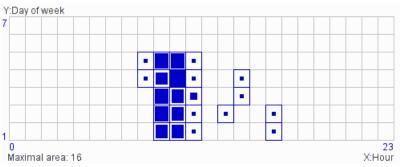


Examples of describing context and inferences



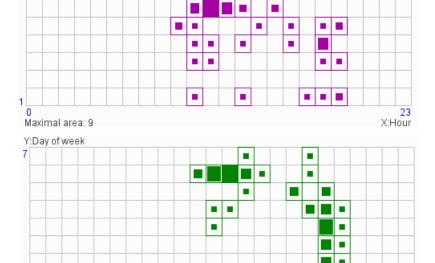


- days of the week
- times of the day



Conceptual context:

- activities of people
- typical days and times of the activities
- typical durations
- typical places

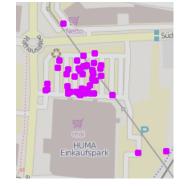


Long stops in the evenings of the working days and at any time in the weekends ⇒ Home!

Long stops in the mornings of the working days

Spatial context:

• shopping areas



Maximal area: 7

Y:Day of week





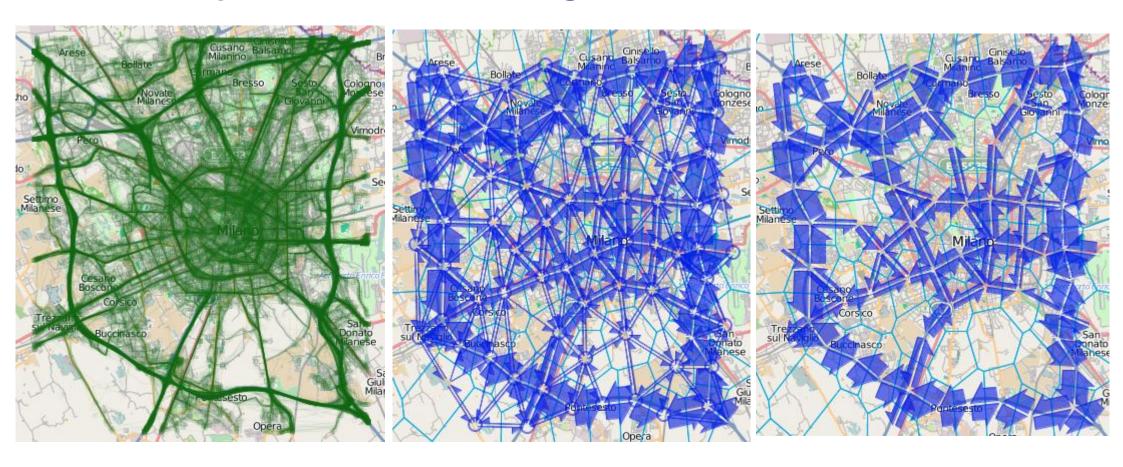
Shopping!

and no stops in the weekends ⇒ Work!

Stops >= 30 minutes in shopping areas ⇒



Another possible contribution: generalization



Generalization and aggregation are used to visualize large amounts of data and avoid display clutter.



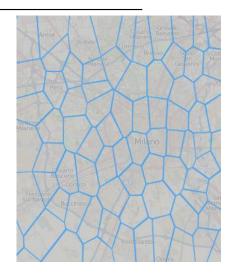


Generalization as an approach to privacy protection







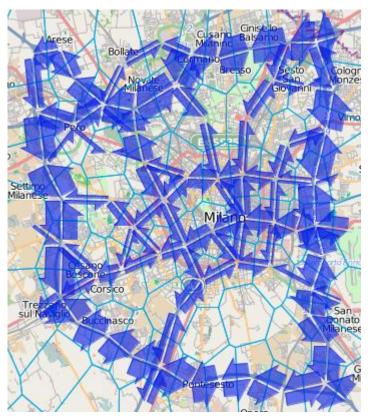


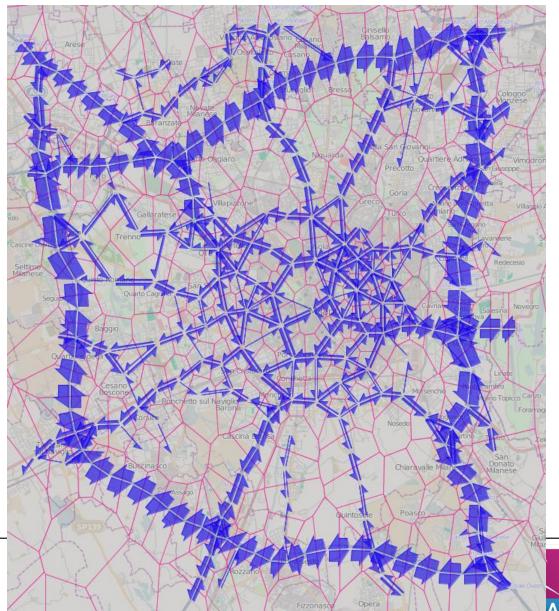






Variable generalization level depending on data density





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Inter-disciplinary collaboration needed

Geovisual analytics + privacy protection research

Positive example:

A.Monreale, G.Andrienko, N.Andrienko, F.Giannotti, D.Pedreschi, S.Rinzivillo, S.Wrobel **Movement Data Anonymity through Generalization**

Transactions on Data Privacy, 2010, v.3 (3), pp. 91-121

http://www.tdp.cat/issues/abs.a045a10.php





Conclusion

- Space- and time-referenced data may allow extraction of sensitive personal information
- Geovisual analytics enables humans to establish links and make inferences
- Humans can do this more flexibly than computers
 - Do not require formal representation, can deal with incomplete information, can use previous knowledge and experience, ...
- Researchers on privacy protection focus on automated analysis methods and may overlook the capabilities of human analysts
- Geovisual analytics should collaborate with privacy research
 - to identify potential risks to personal privacy from involving humans in analysis
 - to use visual analytics approaches for privacy protection





http://www.modap.org

