Mobile and Social Sensing for real-time problems

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Overview

What is Mobile sensing

- Motivation
- Types of sensors
- Sensing scales

Safety and Crowd Monitoring in mobile sensing

- Issues and examples

Challenges

Mobile sensing

*use of mobile **phone** sensors to collect information*

Smartphones & microsensors

NFC

GPS

Ambient Light Sensor

WiFi

Barometer

Camera(s)

Bluetooth

Magnetometer

Microphone(s)

Gyroscope

Water Sensor

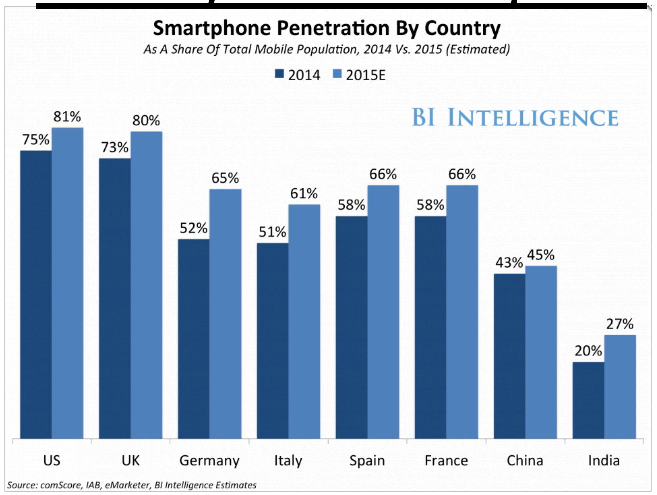
Accelerometer

Proximity Sensor

Motion Coprocessor

Social Sensor (online social networks)

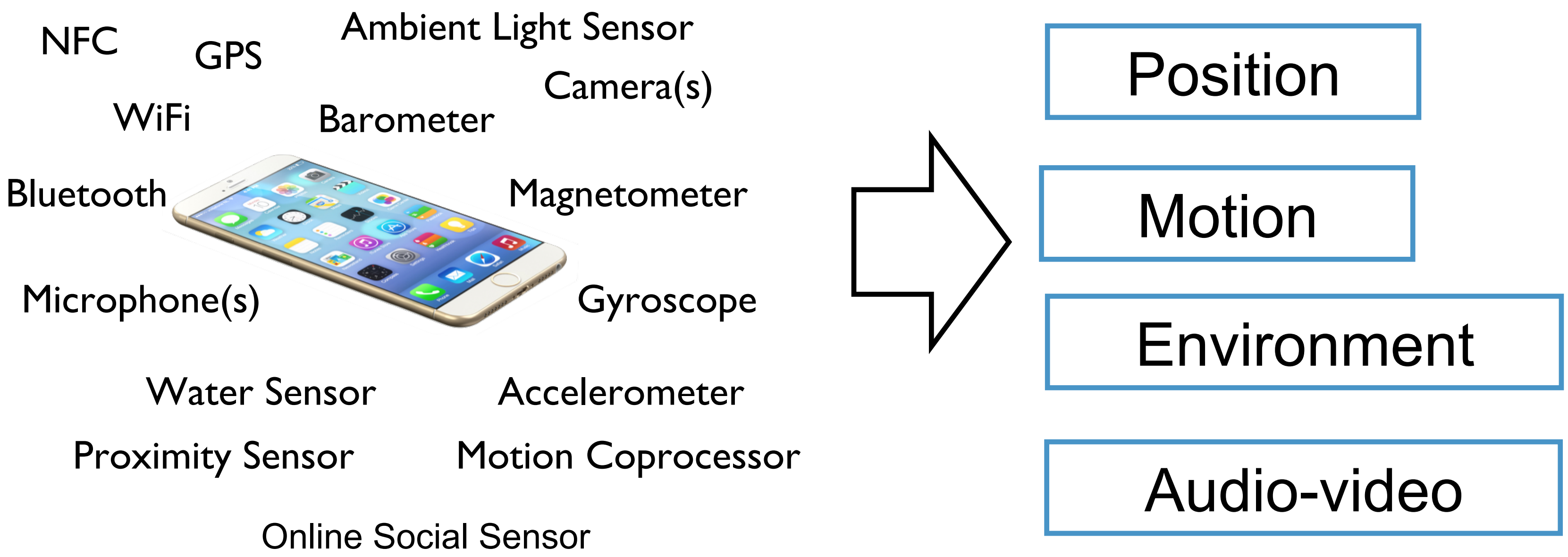
Smartphone adoption



http://uk.businessinsider.com/smartphone-adoption-platform-and-vendor-trends-in-major-mobile-markets-around-world-2015-3?r=US&IR=T

Sensor overview

Sensors : a type of transducer that converts some physical phenomenon such as heat, light, sound into electrical signals.



Bluetooth®

Wireless networking technology for exchanging data over short distances. (~10 meters for Class 2 radios)

Can also be used for indoor positioning.

Very useful for spatial-temporal data gathering (participant mobility and social interactions).

Bluetooth LE, marketed as Bluetooth Smart, has very low battery consumption.

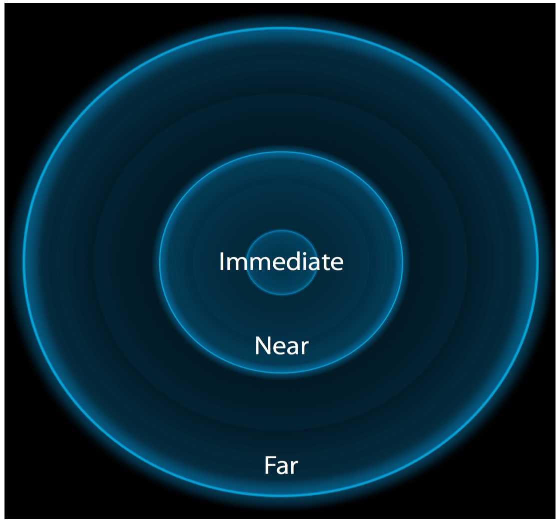
iBeacon technology

Apple's implementation of Bluetooth Smart, used as an indoor positioning system.

Classifies the location of the device as Immediate, Near, Far or Unknown.

All devices can be iBeacon transmitters, receivers (or both), but the technology is also open to third-party hardware.

Also available in Android using an [open source library from RadiusNetworks](#).



Wireless networking technology.

Can been used as an indoor positioning system (IPS) by triangulating the Received Signal Strength Indication (RSSI) of other Wi-Fi hot-spots.

Some mobile devices combine GPS, cell tower triangulation and WiFi-based location to improve accuracy.

Read “Survey of Wireless Indoor Positioning Techniques and Systems” by Hui Liu et al.

Satellite Navigation Systems (GPS)

It calculates the location (latitude and longitude), altitude, and speed of the device based on the distance from at least four satellites (trilateration).

Average accuracy is ~3m.

Not suitable for indoor positioning.

GPS is the most popular one, but others are available or coming in the future (GLONASS, COMPASS, Galileo, IRNSS).

Compass

A compass is a navigational instrument that measures directions in a frame of reference that is stationary relative to the surface of the earth.

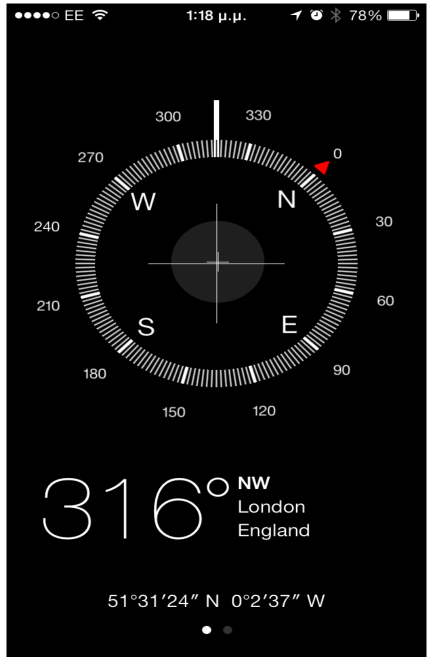
Compass can be used to determine geographic direction of the phone.

Together with GPS positioning can provide real time navigation services.

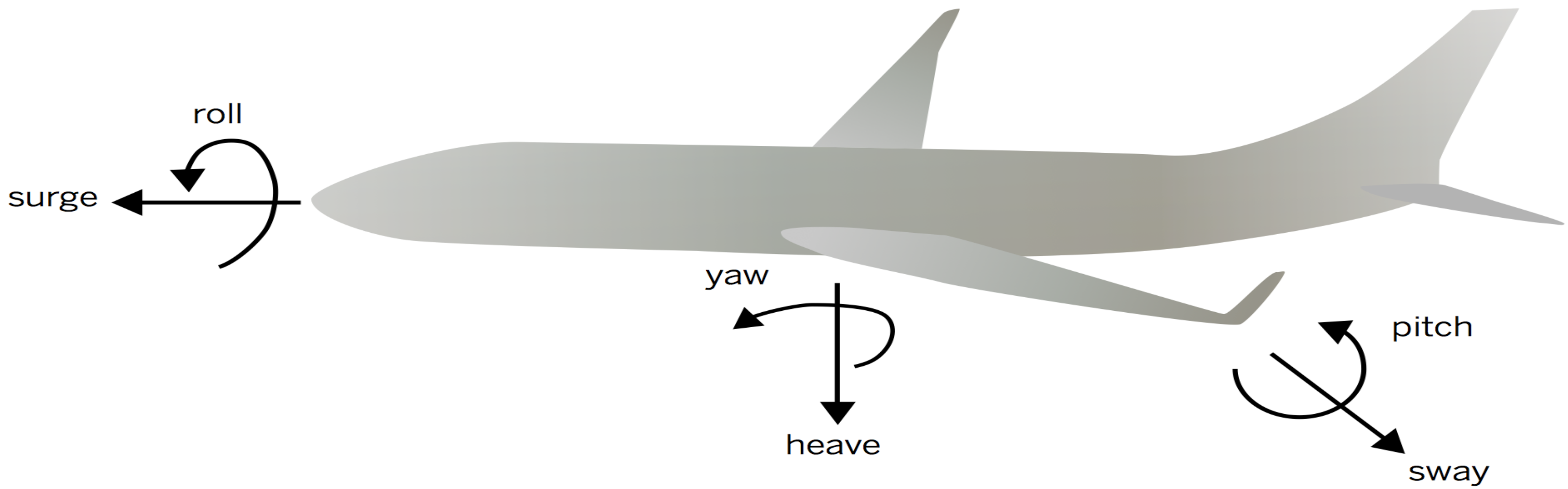
Magnetometer

Magnetic field sensor.
Tells you the actual orientation of the device relative to the magnetic north (not the true north).
Three axis magnetometer:
x, y, z (East, North, Up)

Requires calibration and sensitive to magnetic fields coming from metal objects, electric motors



Some terminology



Six degrees of freedom (3D Translation & 3D Rotation)

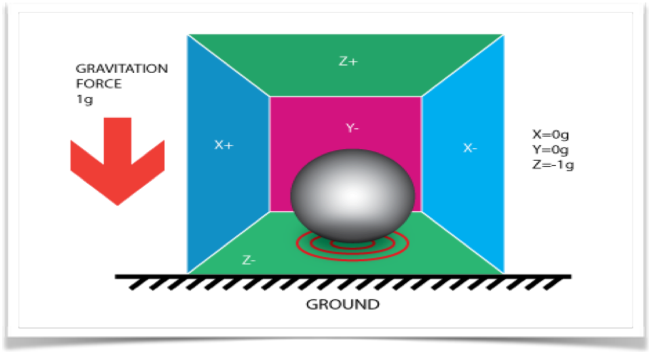
Accelerometer

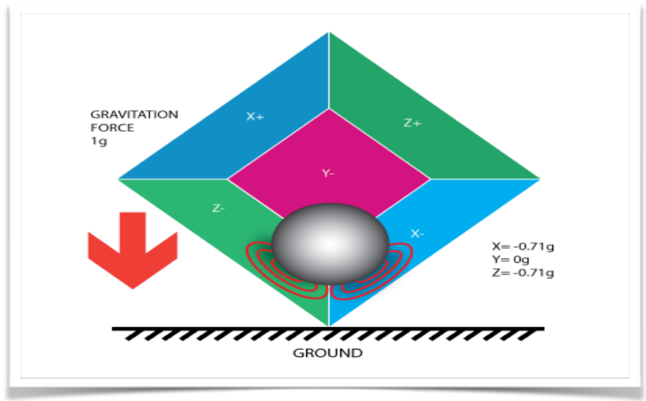
A sensor that measures the force of acceleration of the device.

3 axis accelerometer:
x, y, z (Surge, Heave, Sway)

Can also calculate Pitch and Roll (but not Yaw!) using trigonometric calculations.

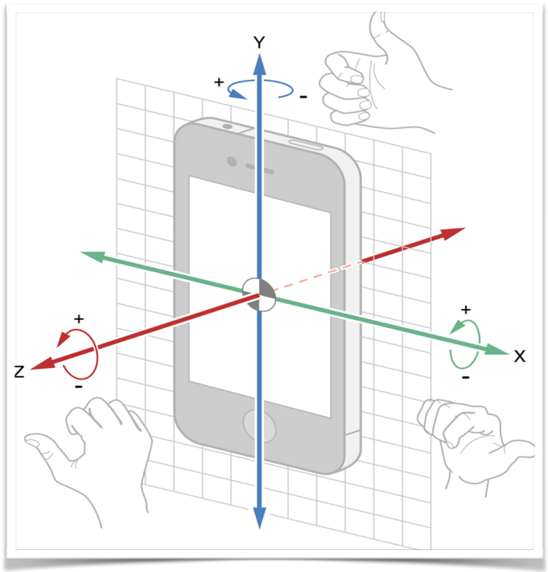
Also used to understand the device orientation, by measuring the acceleration caused by the gravity.





Gyroscope

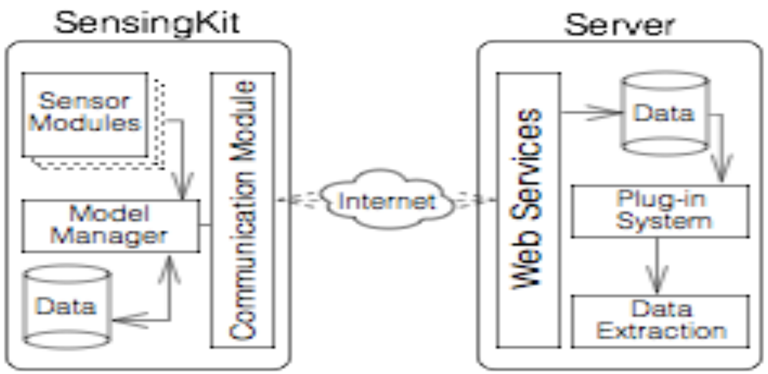
3 axis gyroscope:
x, y, z (Pitch, Roll, Yaw)
Tells you how much your device is being rotated over time.
Less computationally expensive Pitch and Roll.
Also provides Yaw.



SensingKit: A Multi-Platform Mobile Sensing Framework for Large-Scale Experiments

Platform Characteristics

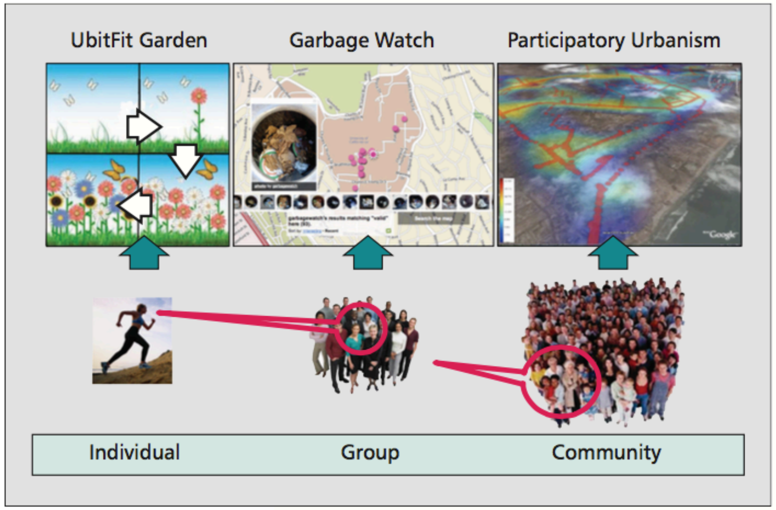
- Works in Android and iOS mobile systems.
- Captures Motion, Location, Proximity, Environment data.
- Power efficient using Bluetooth Smart (4.0).
- Easily extensible using a modular design.
- Automated time sync and data processing on the server.
- Available in open-source under the GNU LGPL v3.0.



For more info, check www.sensingkit.org

Mobile Sensing Scales

- Personal
- Group
- Community

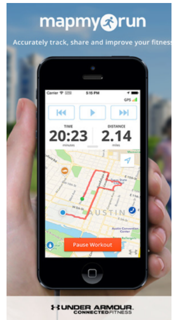


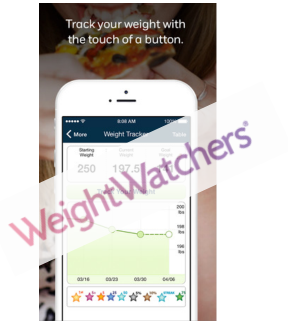
[Lane et al, 2011]

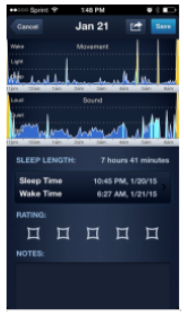
Individual Sensing

"the quantified self"

- Exercise
- Health
- Sleep
- Carbon footprint







Data collected by and about the self.

Group Sensing

- Sensing tied to a specific group
- Users share common interest
- Results shared with the group
- Limited access

Examples: UCLA’s GarbageWatch (2010)

- Users uploaded photos of recycling bins to improve recycling program on campus

Community Sensing aka *Mobile Crowdsensing*

"individuals with sensing and computing devices collectively sharing information to measure and map phenomena of common interest" [Ganti et al, 2011]

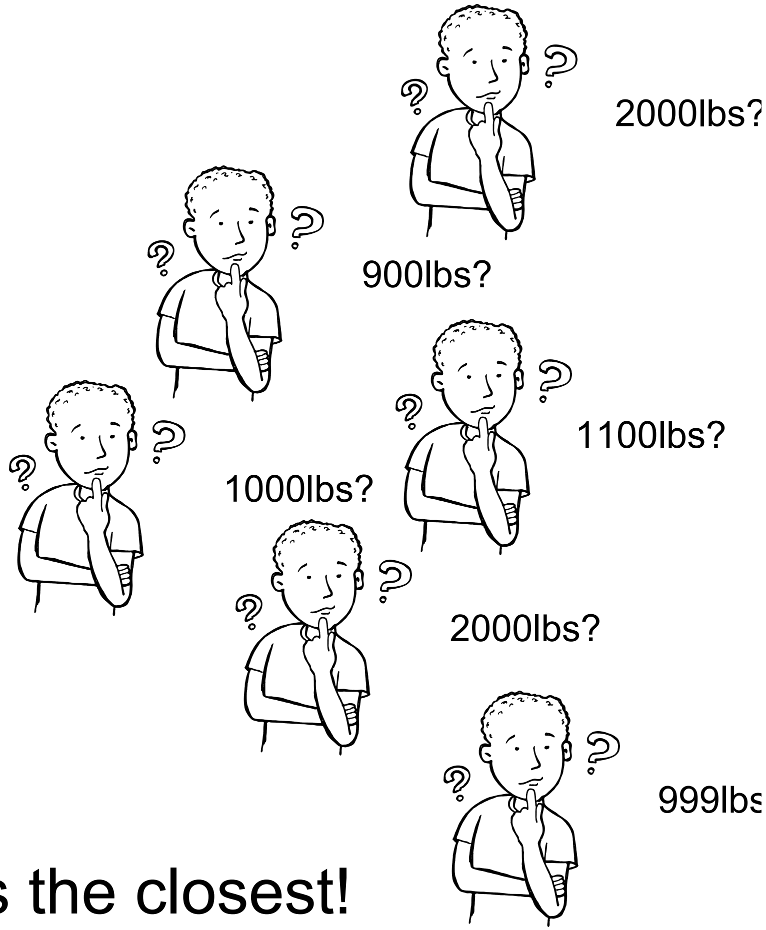
https://phone-lab.org/

http://www.slate.com/articles/technology/webhead/2004/07/art_mobs.html

"a new sensing paradigm that empowers ordinary citizens to contribute data sensed or generated from their mobile devices, aggregates and fuses the data in the cloud for crowd intelligence extraction and people-centric service delivery." [Guo et al, 2014]

Why crowdsourced?

how much?



Average of everyone’s guesses was the closest!

Typology of crowdsensing

User involvement

Participatory Sensing — *high* … *low* — Opportunistic Sensing

Participatory Sensing
- *User takes measurement with phone*
- *User engages with activity (incentives required)*

Opportunistic Sensing
- *Minimal interaction*
- *Background data collection*
- *Constant collection*

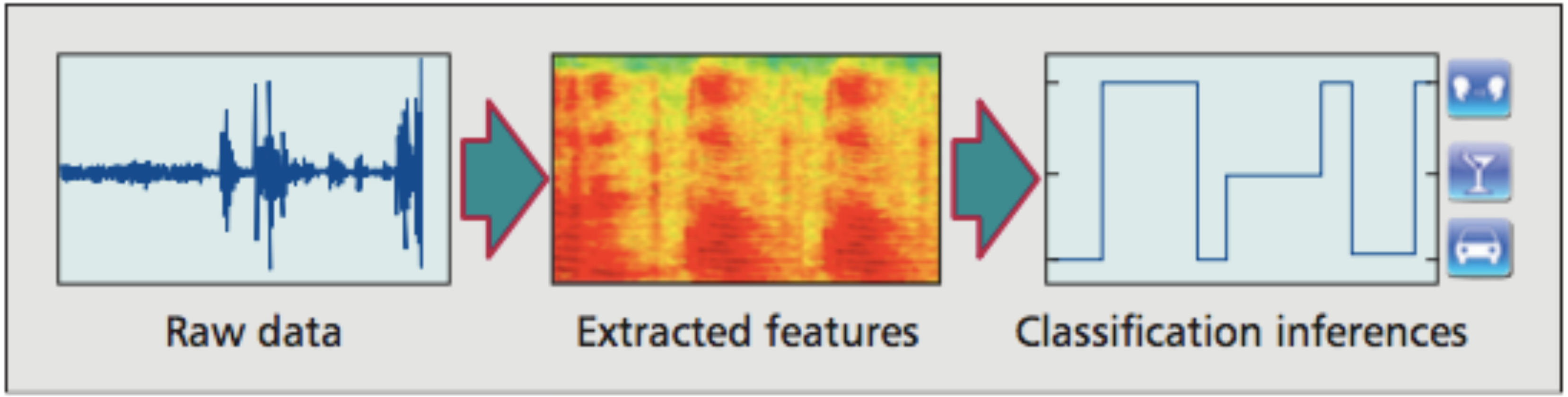
Data Collection

Explicit — Implicit

- Environmental: eg. air pollution, water levels, wildlife habits.
- Infrastructure: eg. transport congestion, parking availability
- Social: share and compare ➔ exercise, bike routes, eating habits

Sensing steps

Collect. Extract. Classify.



1. Data Capture from sensors

2. Data Analysis, e.g., Feature extraction

3. Data classification using Machine Learning

Mobility State using an Accelerator

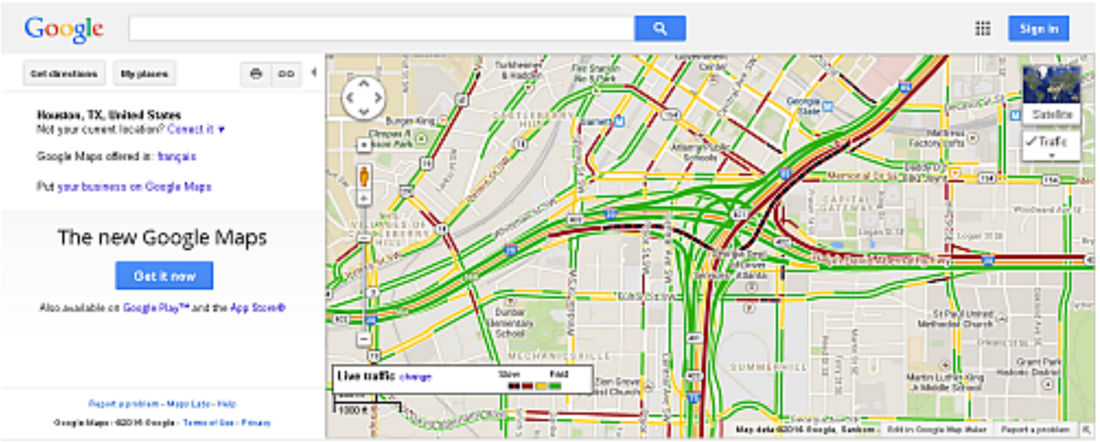
[Oshin et al, 2015]

- *Use 4Hz Accelerometer samples over 2 sec samples*
- *Look for Peaks and Troughs as features*

Urban human mobility states	*mm*	T_{PT}	P_{mm}	T_{mm}
Stationary (no movement)	0.3	(0,1)		
Stationary (slight movements)	1.4	(0,2)	(0,1.1)	
Light rail train	7	(3,5)	(0.07,1.7)	(0.5,2.6)
Underground train	2	(3,5)	(0.7,2.3)	(1.03,1.9)
Car	8	(3,5)	(3,4)	(2,6)
Bus	12	(3,5)	(1.3,6)	(4,8)
Cycling	21	(3,5)	(9.2,21.5)	(1.1,15)
Walking	19	(5,6)	(3.9,11.9)	(5.9,20.9)
Jogging	30	(4,5)	(5.4,12.4)	(8.3,14.6)

Google maps:

You are likely already a participant in vehicle routing:

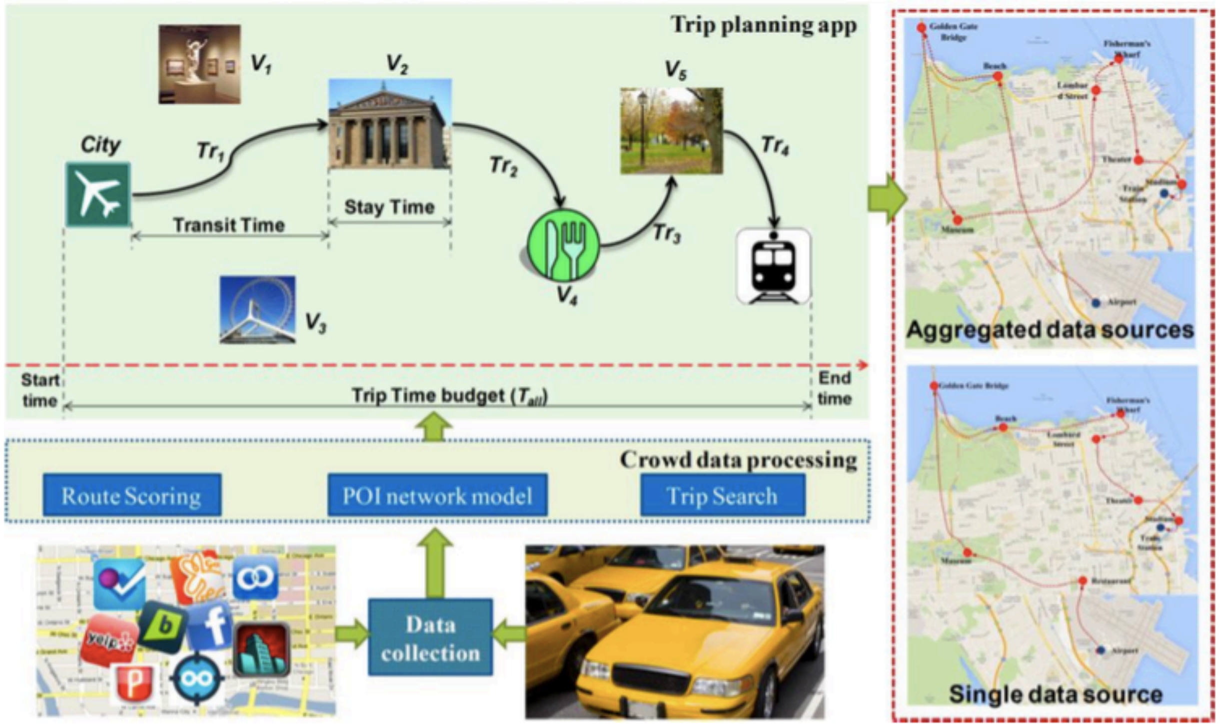


https://en.wikipedia.org/wiki/File:Google_Traffic_screenshot.png#/media/File:Google_Traffic_screenshot.png

Trip planning

[Guo et al, 2014]

- taxi GPS trace data
- Foursquare (OSN)



Safety and Crowd Monitoring in mobile sensing

Safety and Crowd monitoring

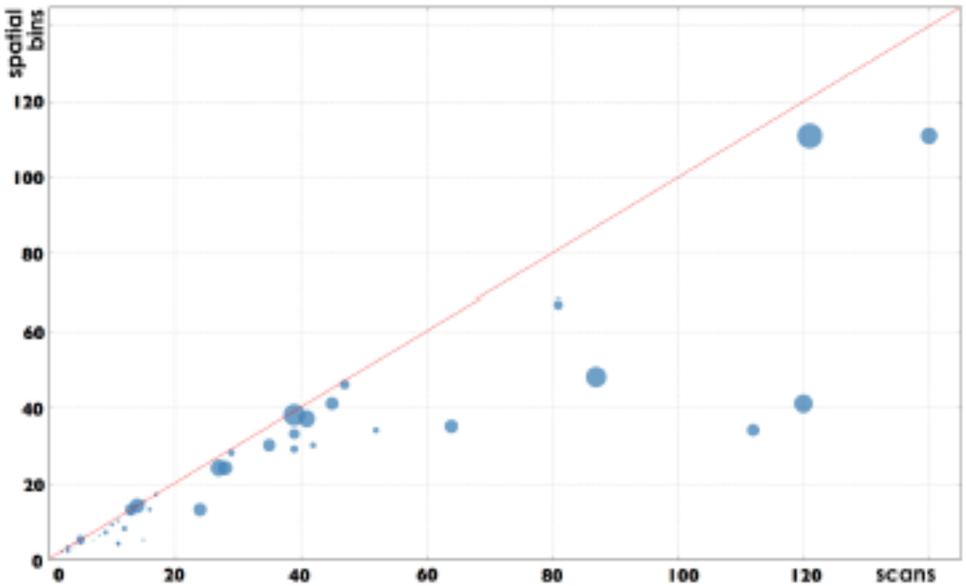
Issues:

- Size
- Type
- Density
- Groups within groups,
- Turbulence
- real-time data-collection/cleaning/processing often required

Bluetooth based mobility and interaction

[Stopczynski et al, 2013]

- 130,000 participants with small subset (155) of “sensors” (via an app) used as scanners.



Crowd topography

[Wirz et al, 2012]

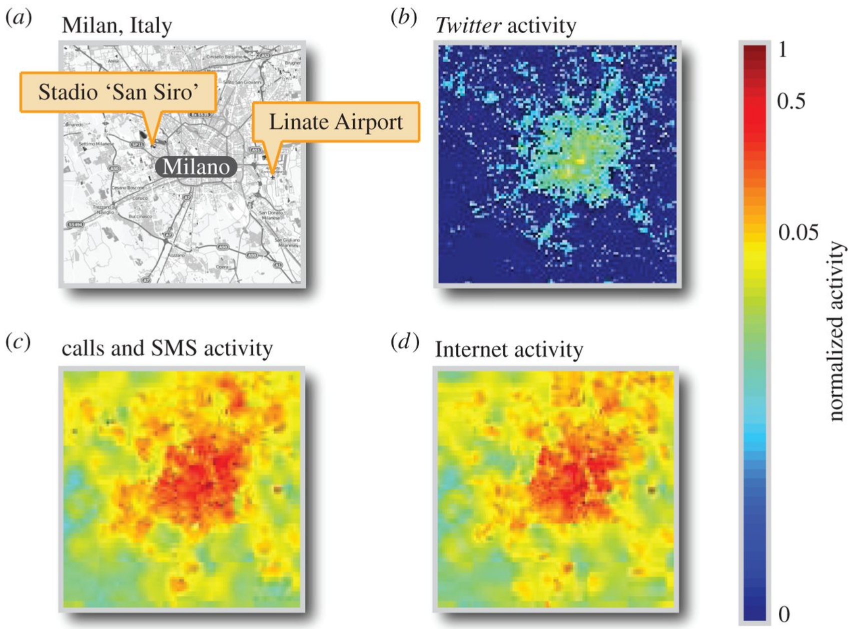
Use mathematical methods based on pedestrian-behavior models to infer and visualize crowd conditions from pedestrians' *GPS location traces and WiFi/GSM-fingerprinting*

(a) Density distribution (b) Crowd movement velocity (c) Turbulence (d) Crowd pressure

Quantifying crowd size

[Botta et al, 2015]

Twitter, calls and SMS, and Internet activity in Milan.



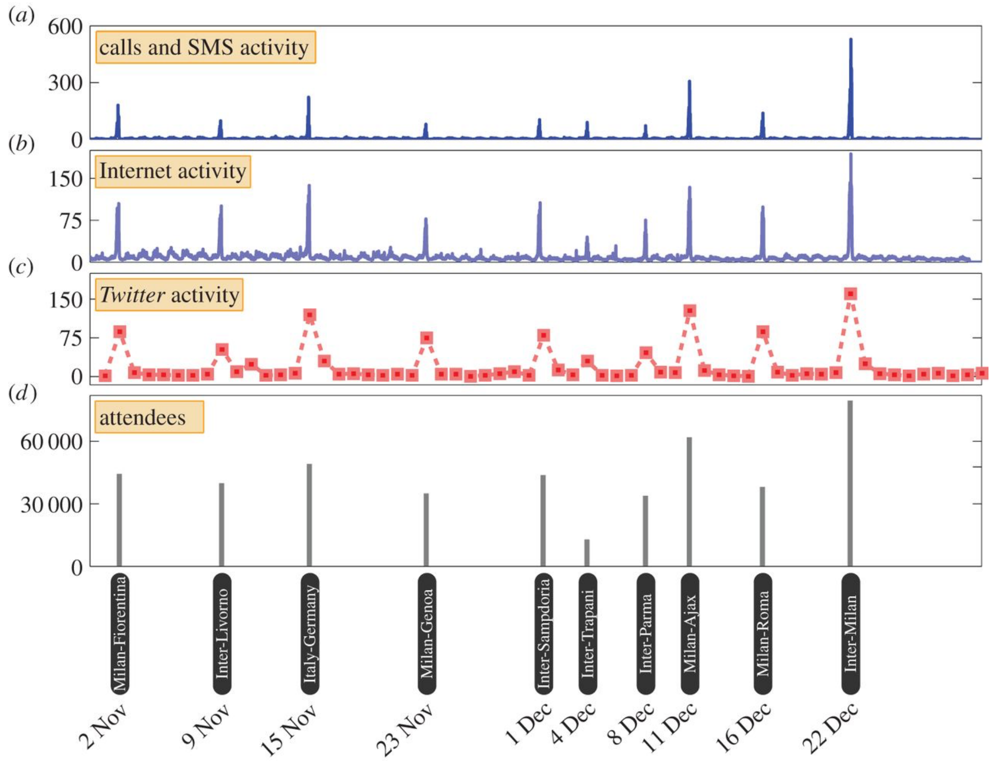
Can data from mobile phone usage and Twitter usage be used to estimate the number of people in an area at a given time?

Yes!

Stadio San Siro

Choose an area – Stadio San Siro:

- 10 spikes in all three data sets on match days
- Relative sizes show strong similarity to relative sizes of actual attendance counts.



Sensing “crowd events” in OSNs
[Wang et al, 2013 and 2014]

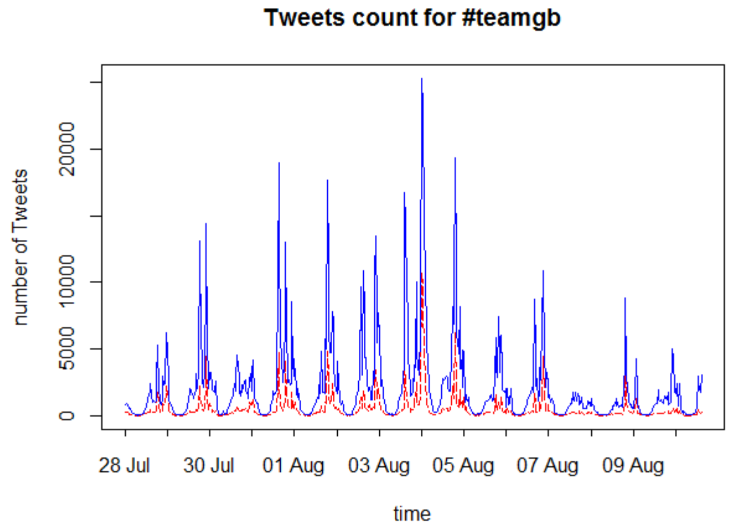
Sensing **crowd sentiment or sub-events** relies on a good and representative collection of social media documents.

Matching a few search keywords

- Selection of words is subjective
- New words arise in the midst

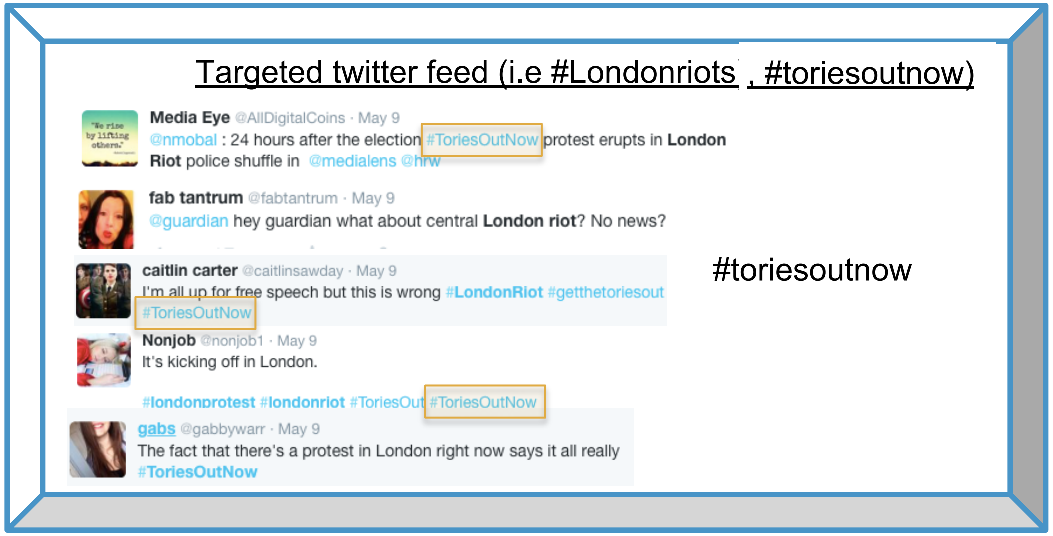
Goal! Aaron Ramsey. Penalty. GB 1-1 Korea. **#football #olympic**

And just like that **#FIFA** awards **#GBR** a penalty. **#GBRvKOR**



Adaptive event data collection

- Adaptive crawling to collect an **extended** set of event Tweets by **automatically** identifying **extra** search terms as filter criteria



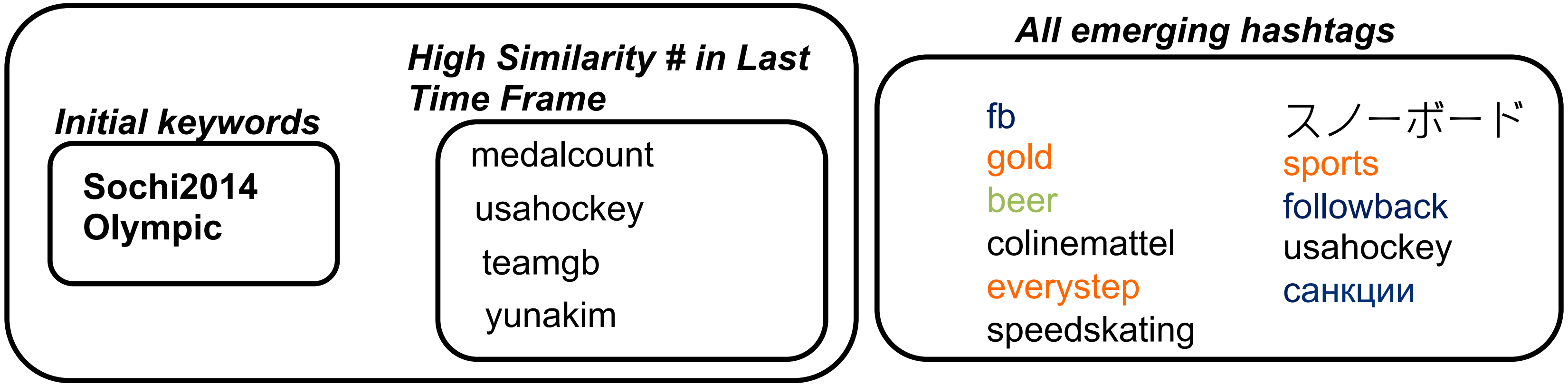
CETRe Keyword Adaptation Algorithm

For each timeframe:

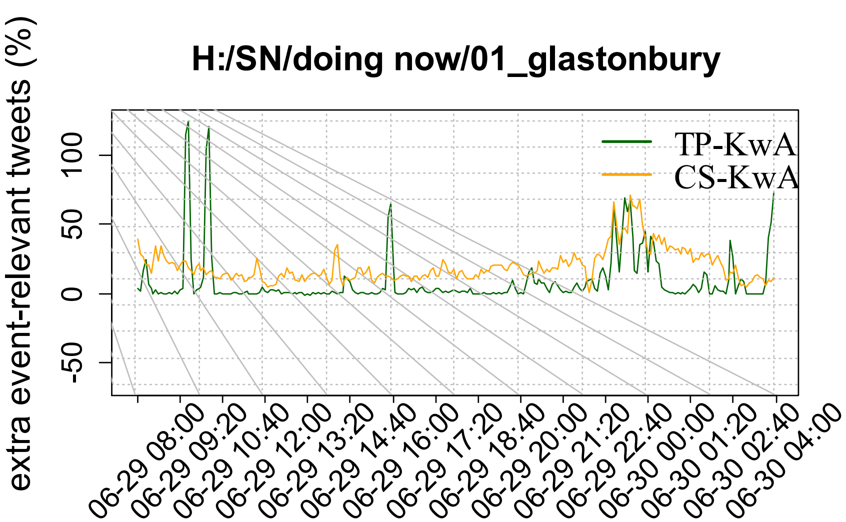
The base seed set

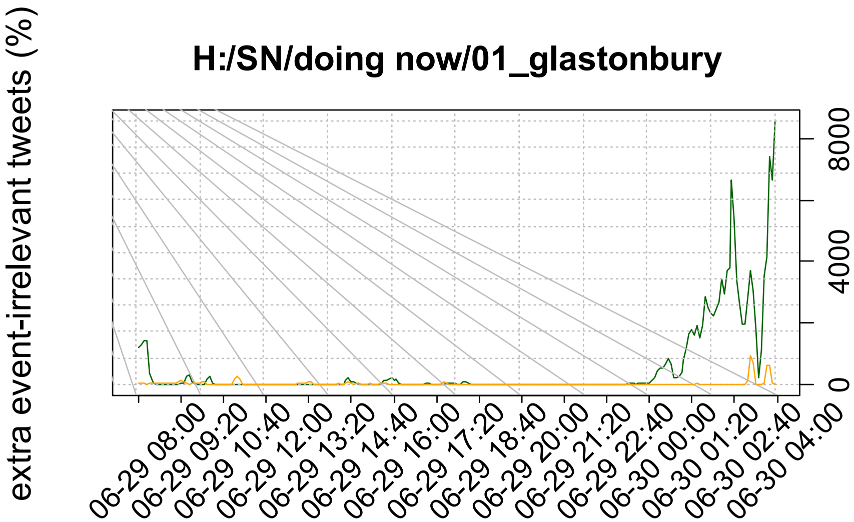
Initial + high similarity hashtags in last time frame

Add top similar hashtags to the base seed set (dist < 0.5)



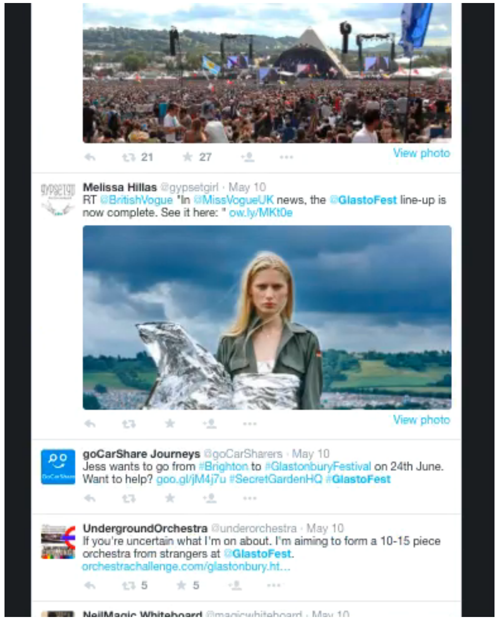
Extra information collected





Use of Online Social Networks

- Real-time sub-event detection during event scenarios from social media data.



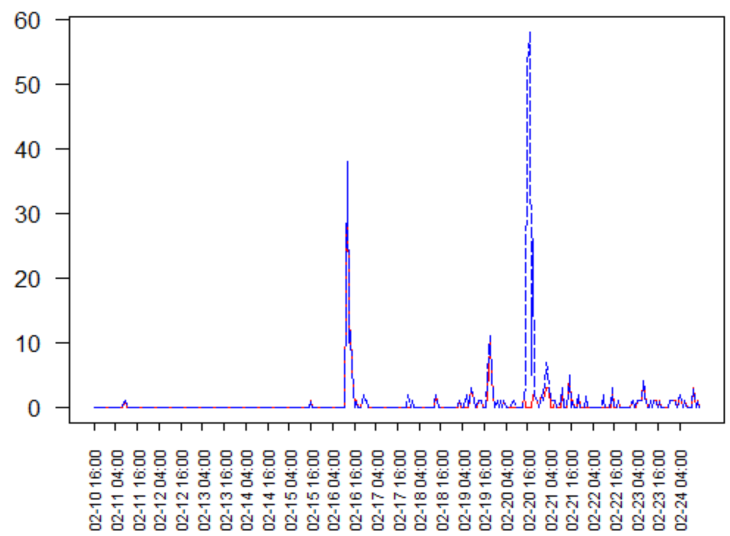
Sub-events

The who headliners glastonbury festival

Professor Steven Hawking to "play" Glastonbury Festival

Bursts & Event Detection (Sochi2014: #maoasada)

	Baseline	CETRe	Gain
average			
Number of bursts	5.8	12.6	+5.3
Number of event	5.2	6.8	+2.3
#maoasada			
Number of bursts	7	11	+4
Number of event	3	4	+1



Pedestrian Flocks

- Flocks prefer to move together as a unit.
- They walk side by side as long as the space is not crowded.
- Typically, individuals in the same group will walk at the same speed and follow the same trajectories.
- They quickly reform after they become separated.
- Very often, they synchronise their gate!

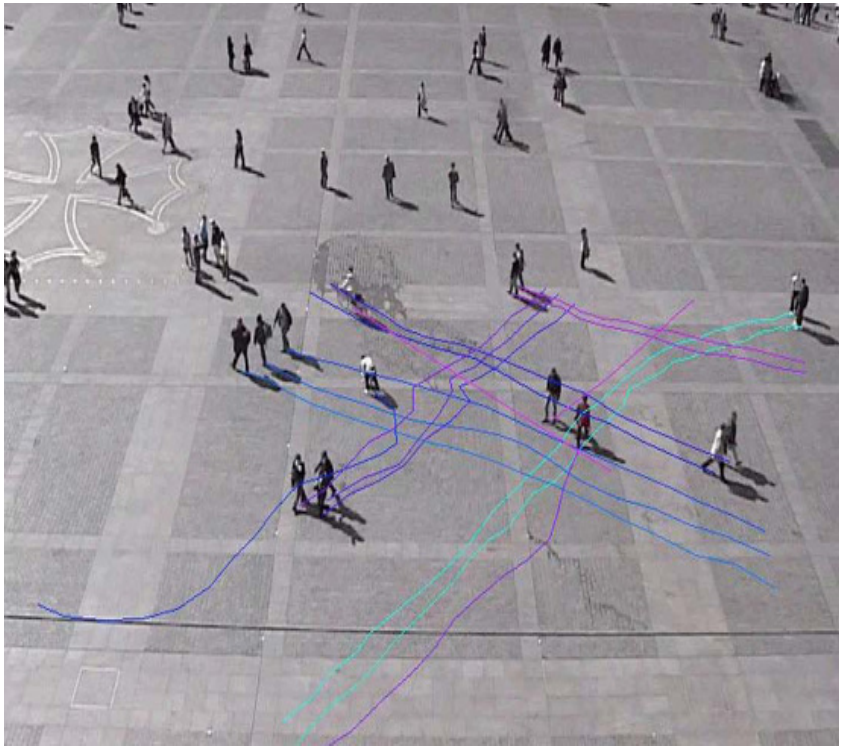


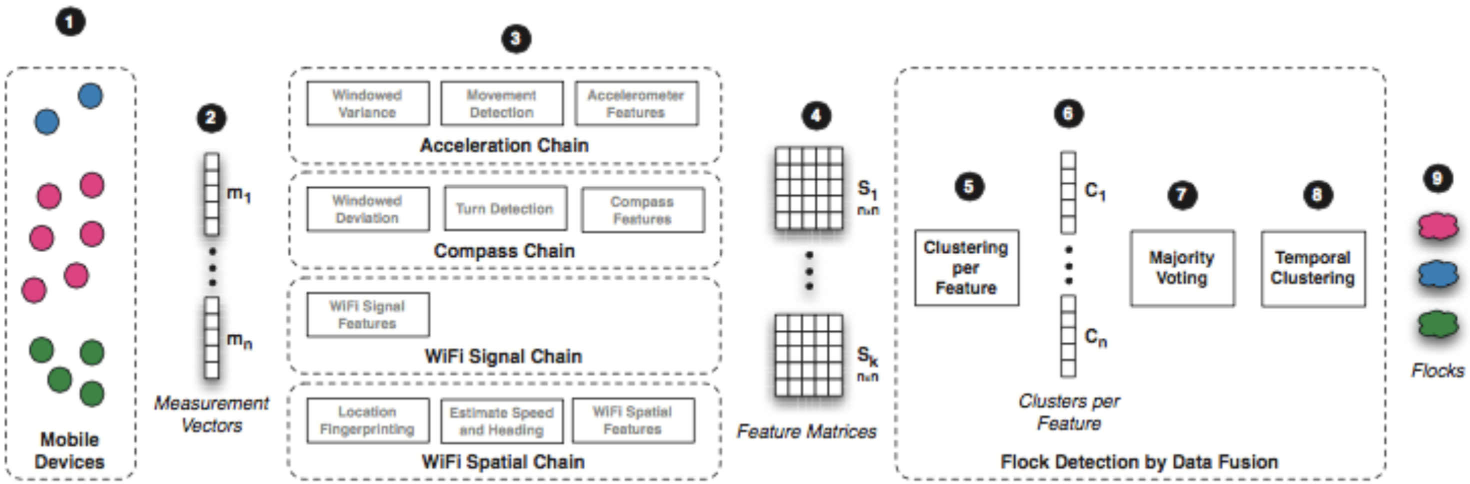
Image by CRCA / CNRS / University of Toulouse

Detecting Flocks

[Kjærgaard et al, 2012]

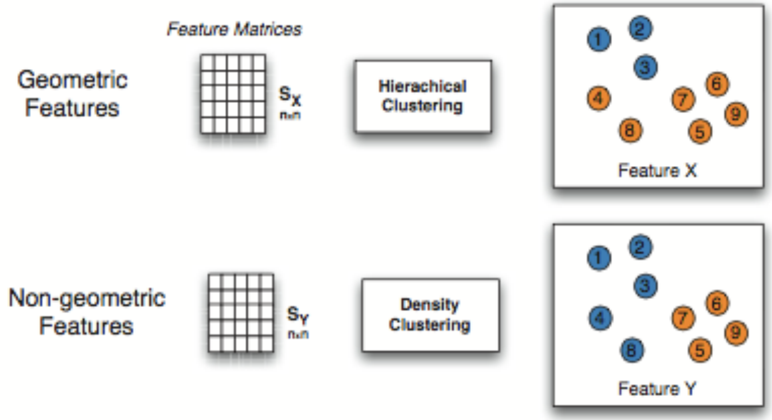
A pedestrian flock F is a moving cluster that exists for the duration $t \geq \tau$ and consists of more than $n \geq \nu$ people where τ and ν are application specific.

- Wifi, Compass, Accelerometer



3 kinds of clustering

- Agglomerative hierarchical clustering for wifi data.
- Density joint clustering for accelerometer and compass.
- Use majority voting to fuse clusters and perform temporal clustering to get flocks.



Towards sensing groups in Crowds

[Katevas et al, 2015]

- Use of mobile sensors (proximity, accelerometer, etc) to detect social groups in crowd *without* video.

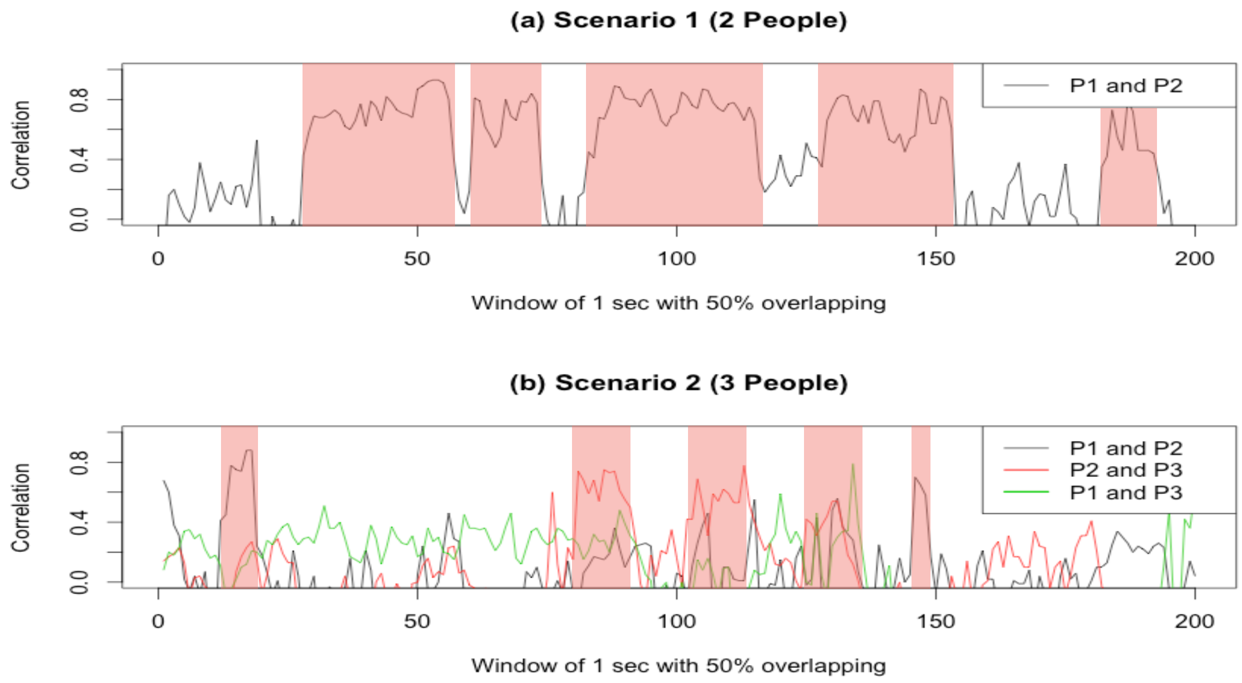
- Aim to detect group composition (number, size and trajectory) based on only mobile sensors.

- SensingKit http://www.sensingkit.org/

Gait Synchronization and Accelerometers

Analyse this phenomenon in pedestrians existing in a group of two or three people.

Is there detectable synchronization? Yes



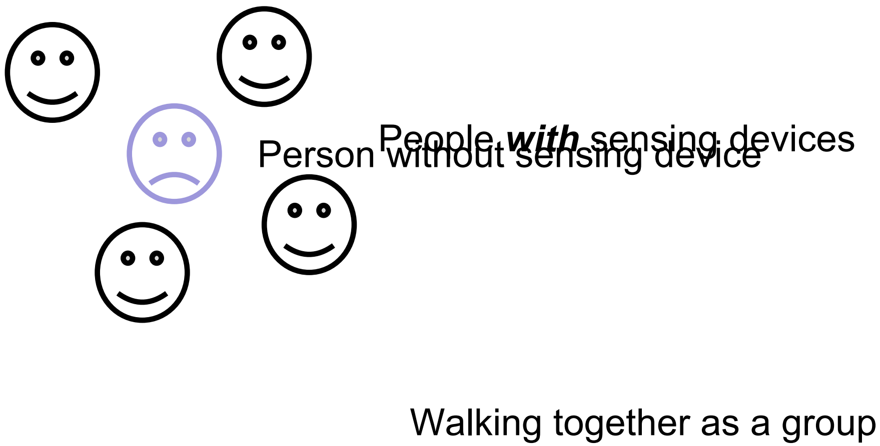
Pearson Correlation applied to windows of 1 sec (with 50% overlap) for Scenario 1 (a) and Scenario 2 (b).

Gait and Accelerometer

- Rich information about individuals' relationships, through analyses of subconscious actions such as gait synchronisation.
- Availability of highly sensitive smartphones enables us to capture these interactions with high accuracy.
- Non-verbal social signals such as **gaze**, **head orientation** and **gestures** between individuals play a significant factor in gait synchronisation.
- A third person can distort the synchronisation.

Incorporating other sensor and detecting "Invisible" people?

- Use of multiple sensors (e.g. iBeacon/Bluetooth Smart, Gyroscope, Magnetometer).
- Detection of presence and number of people not present for the data (not carrying a sensing device).



Building proximity graphs

Some Challenges

Privacy and Trust

- Users not willing to disclose all or some sensor information. Need hard guarantees on privacy.
- Trust on the quality of the information provided by such “crowdsourced” information.

Battery life

- Sensor usage is expensive and resource intensive. Sensing applications have heavy demands on sensors.

Architectural Issues

- Centralized vs decentralized processing (can also have privacy implications)..

Sensor fusion

- Accurately combing sensor inputs.
- Collecting and processing microsensors data AND sensor data.

User acceptance

- Incentive user to install app or face data sparsity for ambiently sensed data

References

R. K. Ganti, F. Ye, and H. Lei. Mobile crowdsensing: current state and future challenges. IEEE Communications Magazine, 49(11), 2011.

Bin Guo, Zhiwen Yu, Daqing Zhang, Xingshe Zhou. From Participatory Sensing to Mobile Crowd Sensing. The Second IEEE International Workshop on Social and Community Intelligence, 2014.

Lane, N.D.; Miluzzo, E.; Hong Lu; Peebles, D.; Choudhury, T.; Campbell, A.T., "A survey of mobile phone sensing," in *Communications Magazine, IEEE* , vol.48, no.9, pp.140-150, Sept. 2010. doi: 10.1109/MCOM.2010.5560598

Oshin, T.O., Poslad S. Zhang, Z. Energy-Efficient Real-Time Human Mobility State Classification Using Smartphones. IEEE Transactions on Computers, 2015, 64(6):1680-1693

F Botta, H Moat and T Preis. Quantifying crowd size with mobile phone and Twitter Data. R. Soc. Open sci. 2: 150162.

Arkadiusz Stopczynski, Jakob Eg Larsen, Sune Lehmann, Lukasz Dynowski, Marcos Fuentes. Participatory Bluetooth Sensing: A Method for Acquiring Spatio-Temporal Data about Participant Mobility and Interactions at Large Scale Events. International Workshop on the Impact of Human Mobility in Pervasive Systems and Applications 2013, Xinyue Wang, Laurissa Tokarchuk, and Stefan Poslad. Identifying Relevant Event Content for Real-time Sub-Events Detection. Exploiting Hashtags for Adaptive Microblog Crawling. IEEE/ACM. International Conference on Advances in Social Networks Analysis and Mining. ASONAM 2014

Xinyue Wang, Laurissa Tokarchuk, Félix Cuadrado, and Stefan Poslad. Exploiting Hashtags for Adaptive Microblog Crawling. IEEE/ACM. International Conference on Advances in Social Networks Analysis and Mining. ASONAM 2013.

Mikkel Baun Kjærgaard, Martin Wirz, Daniel Roggen and Gerhard Tröster. Detecting Pedestrian Flocks by Fusion of Multi-Modal Sensors in Mobile Phones. UbiComp. 2012.

Kleomenis Katevas, Hamed Haddadi, Laurissa Tokarchuk, Richard Clegg, "Walking in Sync: Two is Company, Three’s a Crowd”, ACM MobiSys 2nd Workshop on Physical Analytics (WPA), Florence, Italy, May 2015.