Sensing...

Everything!!!

A data-driven approach to improving everyday experiences.

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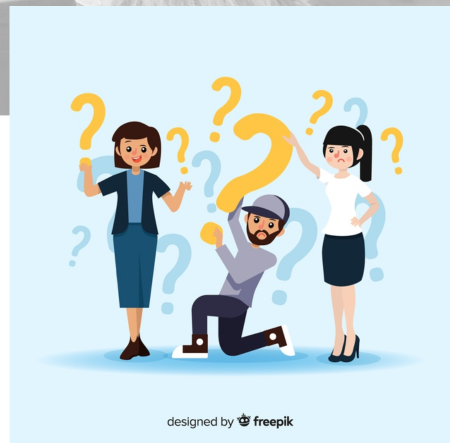


A whistle stop tour through some of the things you can do with data..


GLASTONBURY


POKéMON
GO

NFC

GPS

Ambient Light Sensor

Camera(s)

WiFi

Barometer

Bluetooth

Magnetometer

Microphone(s)

Gyroscope

Water Sensor

Accelerometer

Proximity Sensor

Motion Coprocessor

Social Sensor (online social networks)

Social sensors and sub-events

Color ALIVE

Social Networks and Social data

- Adaptive event data collection and real-time sub-event detection during event scenarios from social media data.

Wang X., Tokarchuk L and Poslad S (2014). 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.

Wang X, Tokarchuk L, Cuadrado F, and Poslad S. (2013) Exploiting Hashtags for Adaptive Microblog Crawling. IEEE/ACM. International Conference on Advances in Social Networks Analysis and Mining. ASONAM 2013.

How do you get meaningful content?

- How you collect these extra tags is important:
  - **Term frequency (TF-KwAA) -> garbage**
  - **Statistical correlation (TP-KwAA) --> still lots of garbage**
  - Content Similarity (CS-KwAA) -> Hooray!

- More content without overloading AND it is relevant :

	Baseline	TF-KwAA	TP-KwAA	CS-KwAA
Event Relevant Tweets	201,683 (97.64%)	191,096 (5.47%)	232,797 (42.60%)	260,897 (90.82%)
Event Irrelevant Tweets	4,875 (2.36%)	3,301,592 (94.53%)	326,814 (58.40%)	26,356 (9.18%)

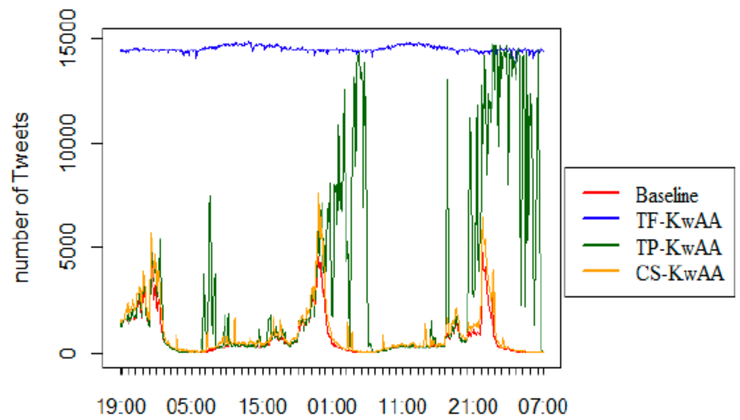
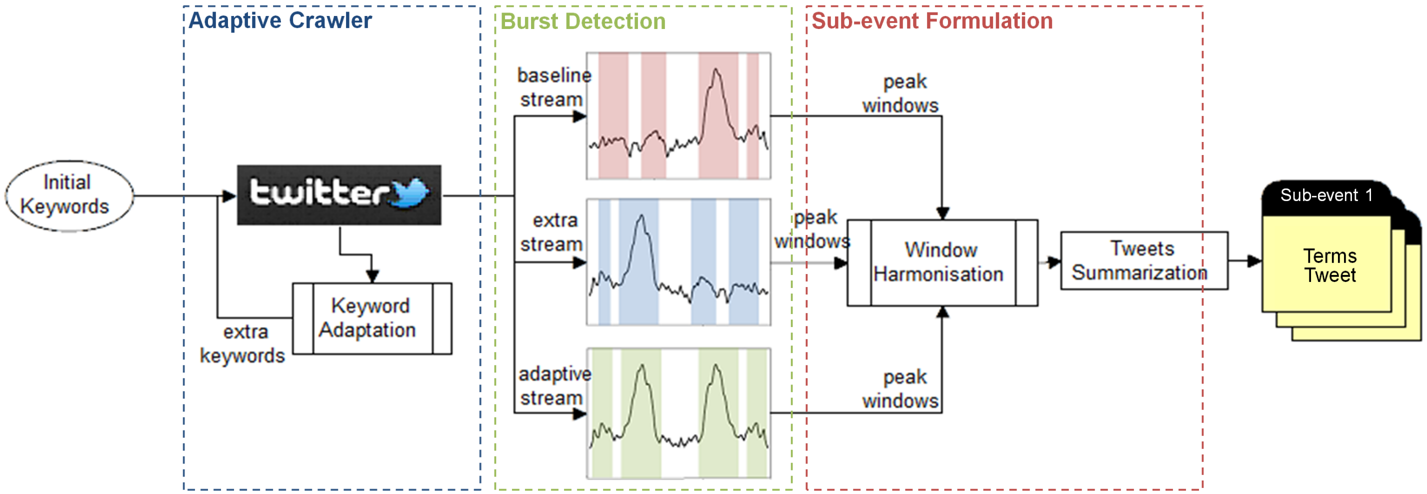


FIGURE 3.8: Tweet Volume for 2013 Glastonbury Music Festival

Piecing together a (sub) event

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



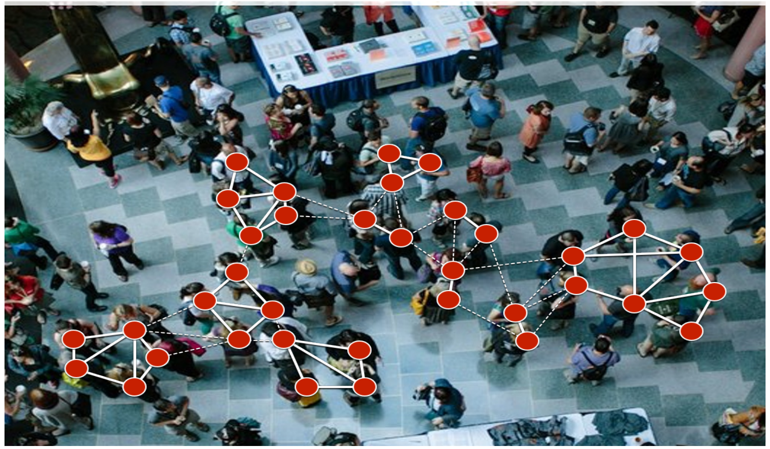
Sub-event	Time span	Summary tweet	Descriptive terms
Ben Howard	16:20 to 16:50	@benhowardmusic is some guy #amazing #lovehit	[#amazing] [#jealous] [#wow] [#lovehim] [howard]
Laura Mvula	15:55 to 16:20	Laura Mvula looks stunning! #glastonbury	[heatwave] [#sebheupdate] [laura] [mvula] [6pm]
	18:55 to 19:35	#Glastoshout please stop laura mvula	[#festival] [#jealous] [laura] [manch] [#glastoshout]
Tibetan Monk Throat Singing	16:20 to 17:20	Tibetan monk throat singing......I think you''d have to have been there #glastonbury	[heatwave] [alongside] [#silverhayes] [haircut] [monk]
Elvis Costello	17:20 to 18:05	Olivers Army are on their way #elviscostello #glastonbury	[deborah] [8ish] [hoop] [tenda] [vanessa]
Noah and the Whale	16:20 to 17:20	Noah and The Whale!<3 #glastonbury #wishiwasthere	[noah] [whale] [heatwave] [heading] [#jealous]
	18:55 to 19:55	Noah and the whale #glastonbury #lovethem	[noah] [whale] [belongings] [door] [johnny]
Primal Scream	19:35 to 19:55	The crowd during @screamofficial #stonesglasto #primalscream #therollingstones	[whale] [#primalscream] [noah] [#goodtimes] [#noahandthewhale]
Maverick Sabre	20:25 to 20:55	Maverick Sabre #wow	[maverick] [sabre] [#wow] [wonderwall] [#amazing]
Glastonbury founder supports badger cull	19:55 to 21:15	#glastonbury badger badger badger badger badger badger	[badger] [sabre] [maverick] [wonderwall] [1965]
	21:15 to 21:40	Wonder will Eavis get "BADGERED" tomorrow at #Glastonbury? - "BADGER BADGER BADGER!"	[badger] [switch] [rudiment] [1965] [petition
Two Door Cinema Club	21:10 to 21:35	Two Door Cinema rock and they look like they could do your accounts...#bbcglasto	[cinema] [door] [margaret] [#leftfield] [invite]
Example	21:35 to 22:05	is there anybody, completely off their nut? #example	[#example] [#proud] [#nffc] [#jealous] [cinema]
Rollingstones	22:15 to 23:30	Oh dear the #Stones at #glastonbury look like a Wonga TV ad	[wonga] [#stones] [#glastonbury2013live] [careworker] [#physiotherapy]

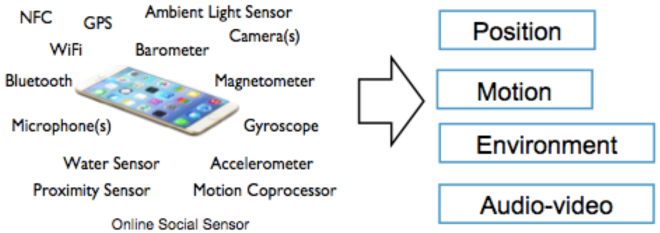
Tokarchuk L, Wang X, Poslad S (2017) Piecing together the puzzle: Improving event content coverage for real-time sub-event detection using adaptive microblog crawling. PLOS ONE 12(11): e0187401. https://doi.org/10.1371/journal.pone.0187401

Mobile Sensing and Groups/Crowds

Color ALIVE

Mobile Sensing of Groups

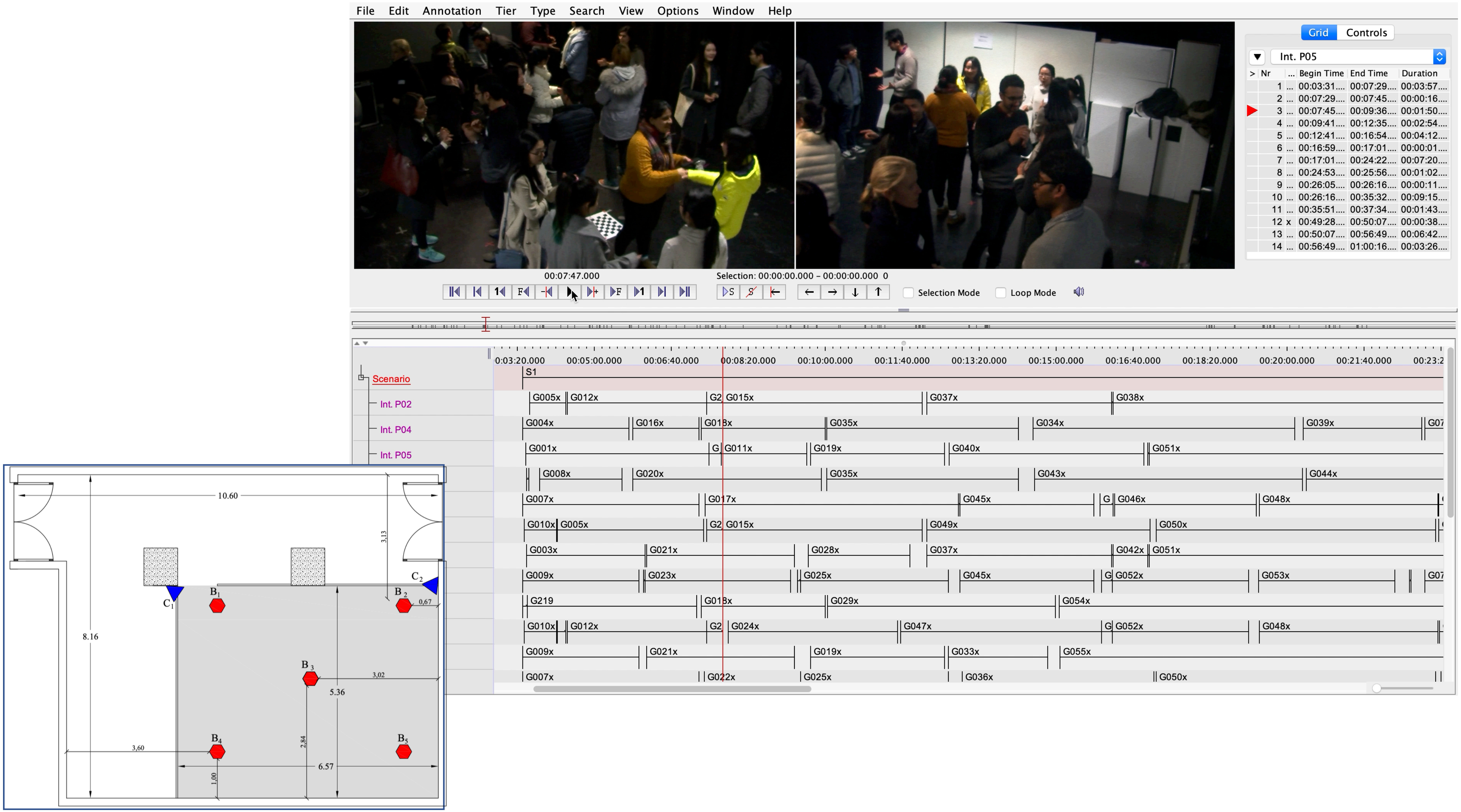




- Use of mobile sensors (proximity, accelerometer, etc) to detect social groups in crowd *without* video.
- **Build proximity graphs and detect group composition (number, size and trajectory) based on only mobile sensors.**
- SensingKit **http://www.sensingkit.org/ : A Multi-Platform Mobile Sensing Framework for Large-Scale Experiments**

✓ *Used in crowd detection experiments, health platforms and mobile sensing games.*

Katevas K., Haddadi H. and Tokarchuk L. (2014). Poster: SensingKit–A Multi-Platform Mobile Sensing Framework for Large-Scale Experiments. ACM MobiCom.
Katevas K., Haddadi H., Tokarchuk L and Clegg R (2016). "Detecting Group Formations using iBeacon Technology", 4th International Workshop on Human Activity Sensing Corpus and Application (HASCA2016) in conjunction with UbiComp2016, September 2016, Heidelberg, Germany.


File Edit Annotation Tier Type Search View Options Window Help
Grid Controls
Int. P05
Nr Begin Time End Time Duration
1 00:03:31.... 00:07:29.... 00:03:57....
2 00:07:29.... 00:07:45.... 00:00:16....
3 00:07:45.... 00:09:36.... 00:01:50....
4 00:09:41.... 00:12:35.... 00:02:54....
5 00:12:41.... 00:16:54.... 00:04:12....
6 00:16:59.... 00:17:01.... 00:00:01....
7 00:17:01.... 00:24:22.... 00:07:20....
8 00:24:53.... 00:25:56.... 00:01:02....
9 00:26:05.... 00:26:16.... 00:00:11....
10 00:26:16.... 00:35:32.... 00:09:15....
11 00:35:51.... 00:37:34.... 00:01:43....
12 x 00:49:28.... 00:50:07.... 00:00:38....
13 00:50:07.... 00:56:49.... 00:06:42....
14 00:56:49.... 01:00:16.... 00:03:26....
00:07:47.000
Selection: 00:00:00.000 – 00:00:00.000 0
Selection Mode
Loop Mode
Scenario
Int. P02
Int. P04
Int. P05
S1
10.60
3.13
8.16
5.36
6.57
3,02
3,60
2,84
1,00
0,67
C1
C2
B1
B2
B3
B4
B5

Traditional Machine Learning Pipeline

time consuming

Input Data (raw) → Feature Extraction → Classical Machine Learning

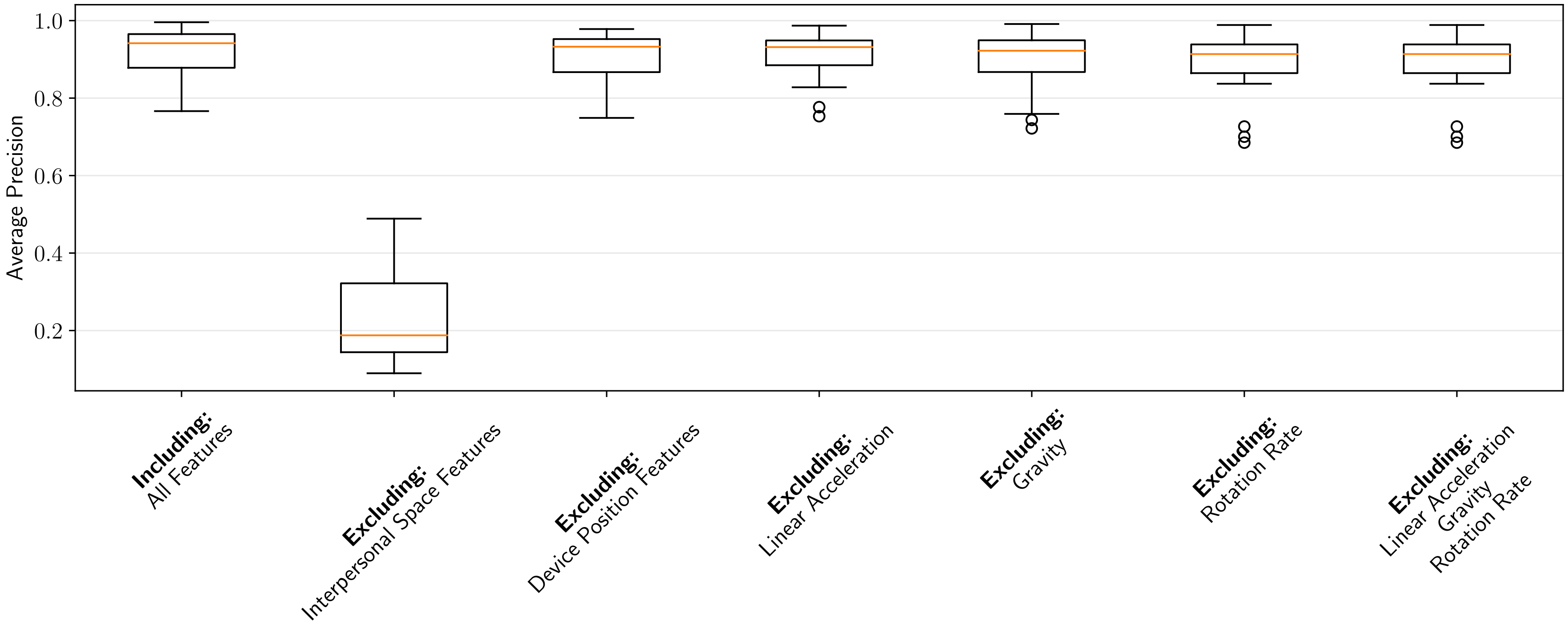
- *Accelerometer*
- *Battery level*
- *Network data activity*
- *Noise level*
- *Call logs*
- *Location*
- *Screen Status*
- *…*

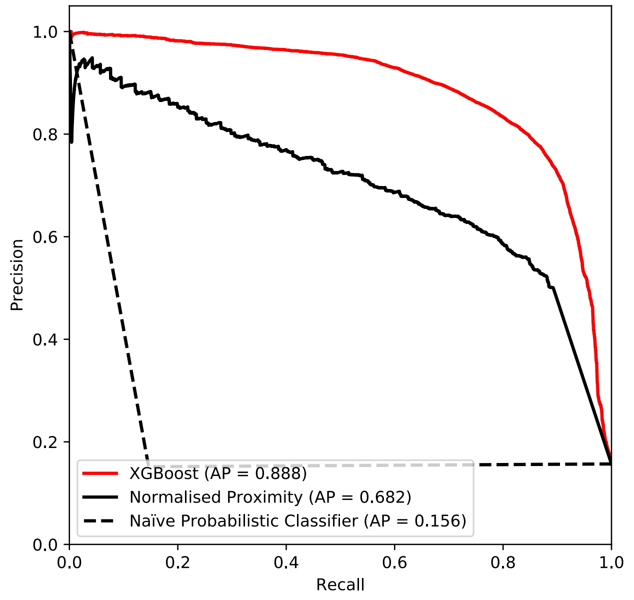
- Mean and Max Acceleration
- Battery drain levels in the last hour
- Data received during the day
- Average ambient noise level during the last five minutes
- Time since the last outgoing call
- Current distance from home
- Number of device unlocks
- …

- Logistic Regression
- SVM
- Random Forests
- XGBoost
- …

231 combinations of the participant pairs!

Features features everywhere…





Detecting Social Interactions

XGBoost (consistently outperformed all others tested)

- maximize Average Precision (AP) performance
- Predicts, for all pairs, if they are interacting.

Community Detection

G(V, E(w)) (E(w) edges weighted by **XGBoost prediction)**

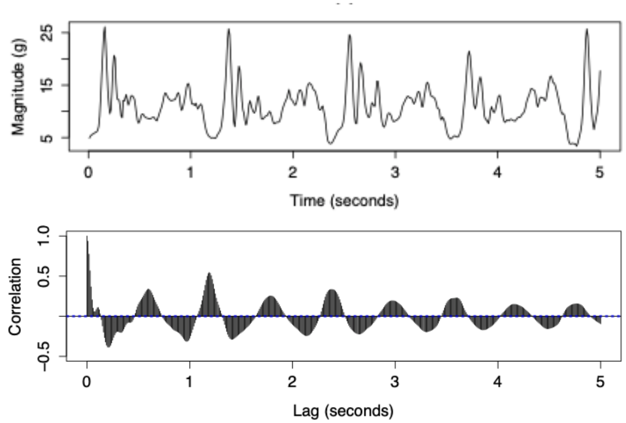
- Detects: interactive groups of various sizes
  (77.8% precision, 86.5% recall and 94.0 accuracy).
- 77.8% of participants the model discovered as interacting were correctly detected
- 86.5% of all interactions that actually took place during the event were detected by the model.

Katevas, Kleomenis; Hänsel, Katrin; Clegg, Richard; Leontiadis, Ilias; Haddadi, Hamed; Tokarchuk, Laurissa; Finding Dory in the Crowd: Detecting Social Interactions using Multi-Modal Mobile Sensing; [arXiv preprint arXiv:1809.00947](arXiv:1809.00947)*; 2018.*

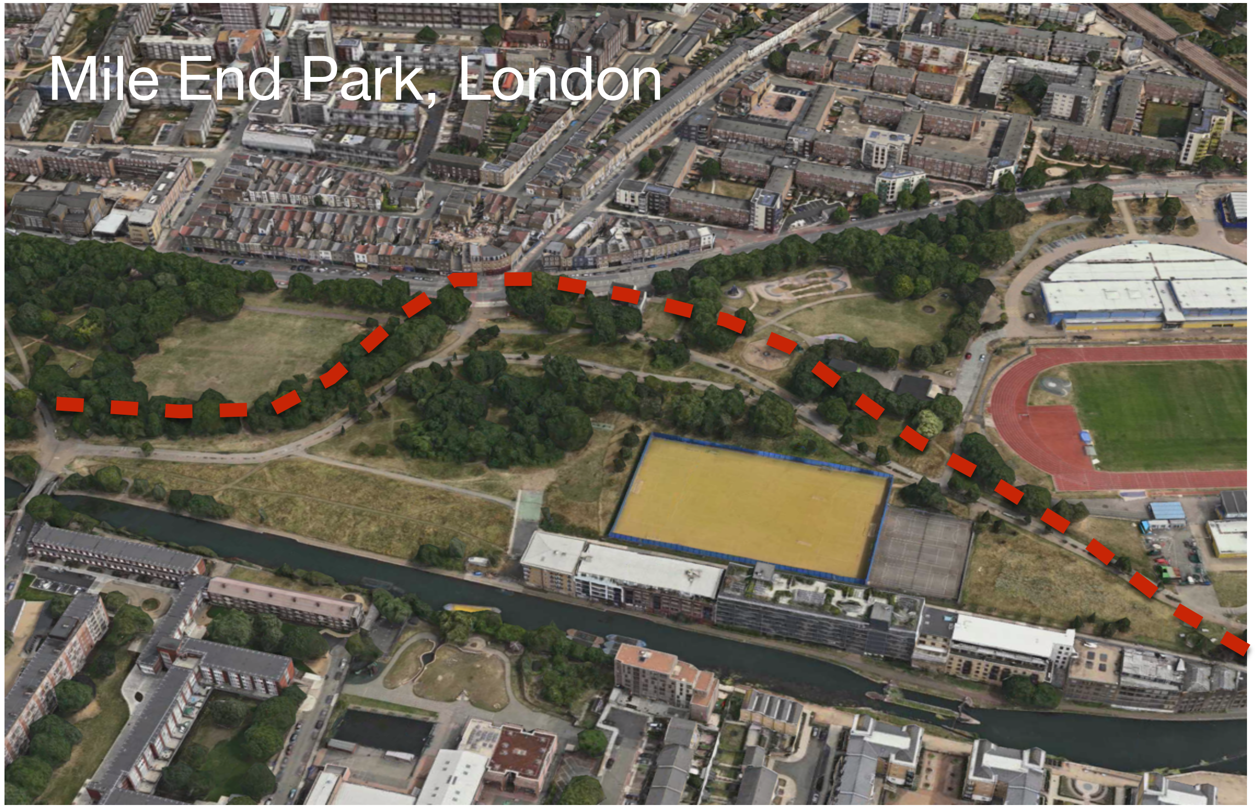
Mobile Sensors and Synchrony

Gait Synchronization and Accelerometers

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



- Is there detectable synchronization? Yes



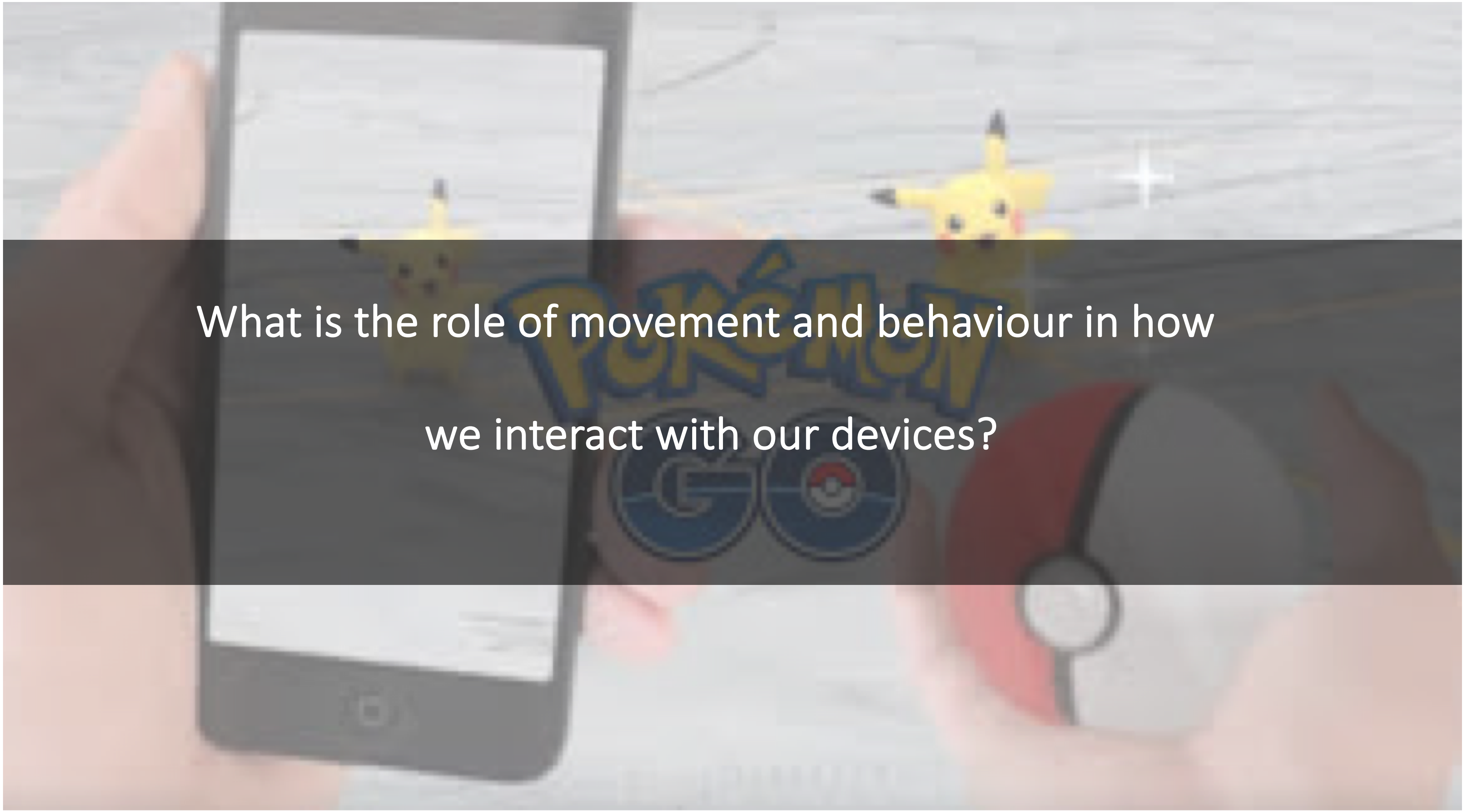
Katevas K., Haddadi H., Tokarchuk L and Clegg R (2015). Walking in Sync: Two is Company, Three's a Crowd. *ACM MobiSys 2nd Workshop on Physical Analytics (WPA)*. Florence, Italy, May 2015.


14:15:09:22
Royal Institution Christmas Lectures at BBC Four.

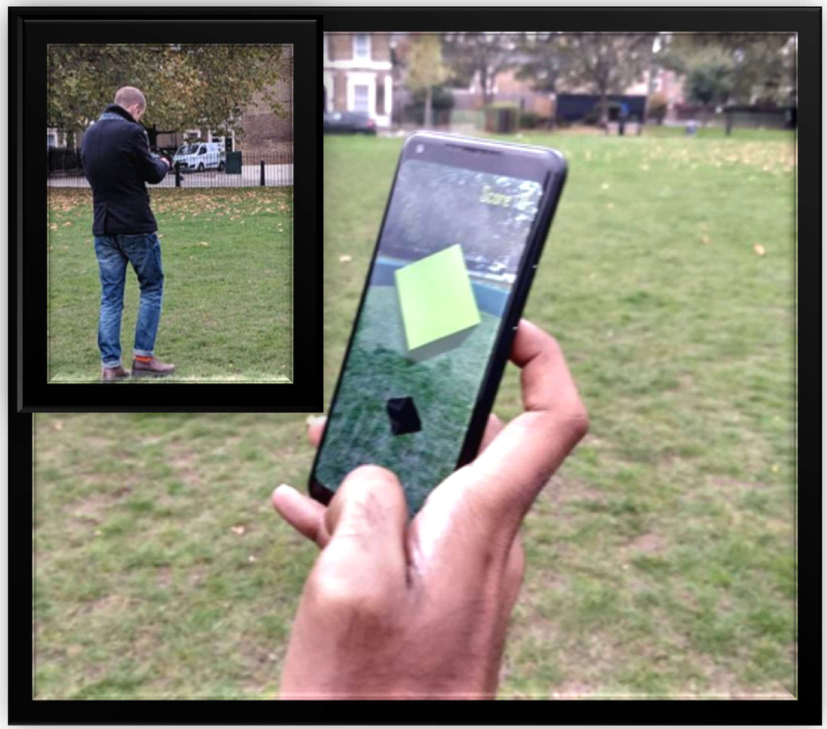
2
1
Acceleration
208
210
212
214
Time

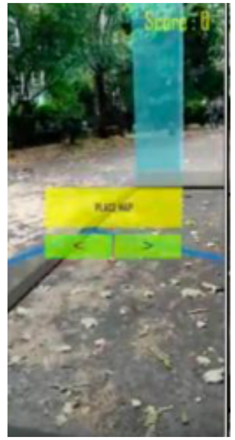
Sensors and Behaviour

Color ALIVE


What is the role of movement and behaviour in how
we interact with our devices?

Augmented Reality (AR) and sensors





Treasure Hunter:

- Collect AR treasure (puzzle pieces)
- Solve puzzle.
- Games differ on amount of treasure and size

Data Collected:

- Pairwise Comparison questionnaire
  (4AFC protocol)
- Player Movement data during the game
  (@64Hz)
- Player Score through the game.

People are greedy and lazy!

Challenge and Frustration —> Highly Accurate

Boredom, Excitement and Fun —> Show signs of overfitting

- Players like large amount of rewards,
- They do not like to walk a lot for this

Questions

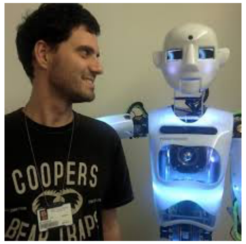
- Can player experience predict their enjoyment?
- Can we determine what kind of person (player) they are?
- Can we use player behavioral characteristics to tailor content?

Warriar, Vivek; Woodward, John Tokarchuk, Laurissa. Modelling Player Preference in AR Mobile Games. To appear: IEEE Conference on Games (2019)

Image credit: justiniskandar.com

Collaborators

- **Xinyue Wang**
  (CSC and EU FP 7 Tridec project)



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- **Vivek Warriar**
  (MAT CDT)