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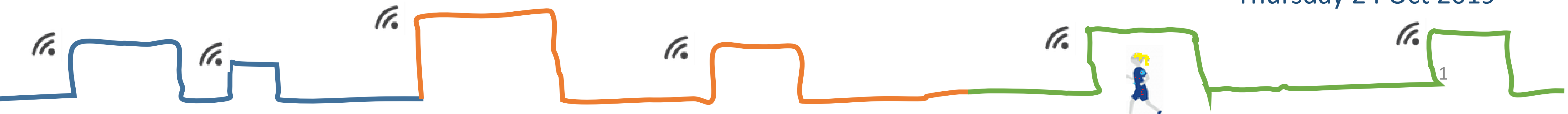
The Life Cycle of Urban Analytics

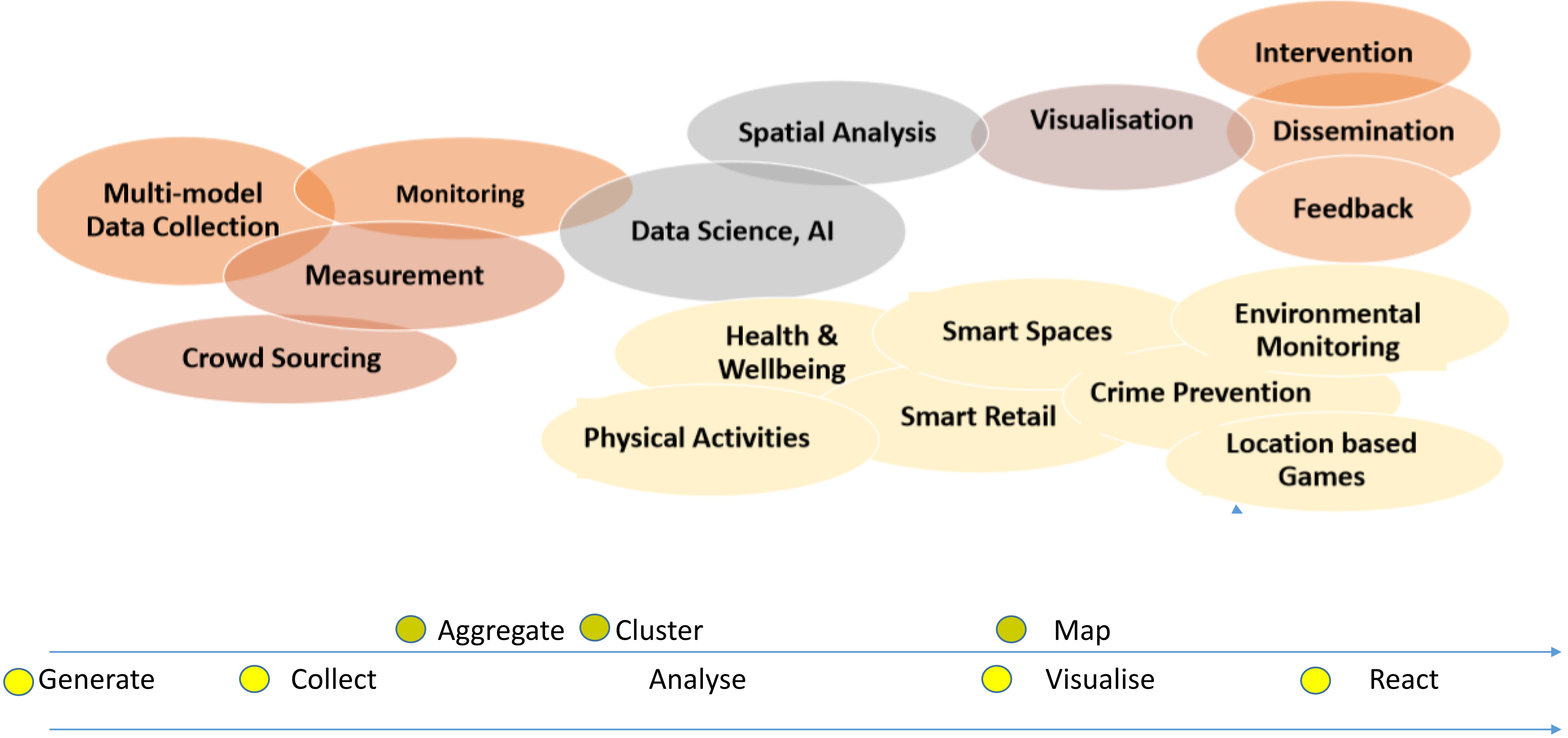
Urban Analytics Workshop
Birmingham
Thursday 24 Oct 2019



Overview

- Building Blocks of Urban Analytics
- Data Types
- Data Collection
- Data Labelling
- Data Analytics
- Data Mapping & Visualisation

Urban Data Analytics: Building Blocks



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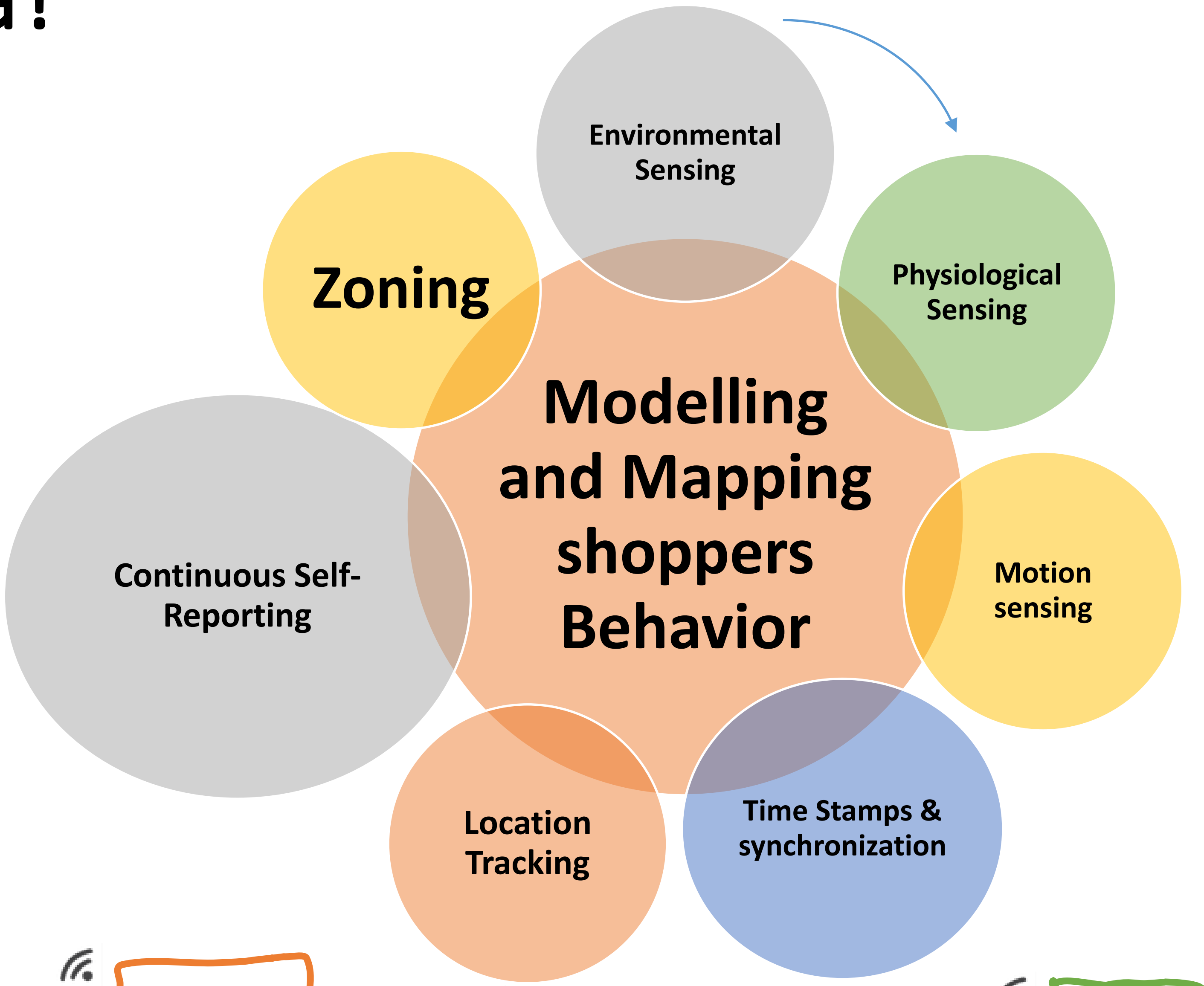
What Data?



Which Sensors?

Data collection tools

Wearables

Smartphones

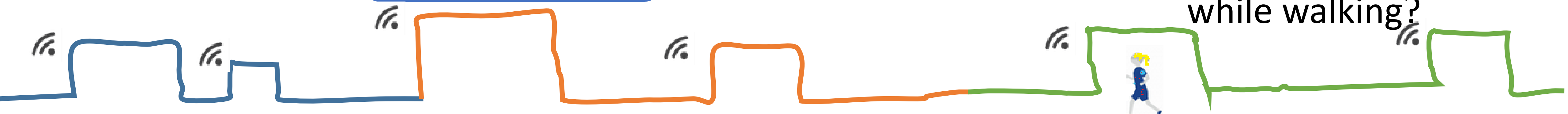
Fixed sensors

Portable sensors

How can the participants wear on-body sensing belts?

Is there a sensing infrastructure in everyday places?

How many can the users carry with them while walking?



Data Collection

Active data which refers to data that requires active input from the users to be generated (e.g. self-report data), whereas

Passive data: data that are collected without requiring any active participation from the user (e.g.sensor data and phone usage patterns)

Data Labelling

Labelling Technique		Data collection	Related work	Description	Accuracy	Time	Cost
Human	In House Labelling	Video	Activity recognition - [15]	Labelling carried out by in house trained team	High	Long	Low
	Crowd Sourcing	Video	reCAPTCHA - [12]	Labelling carried out by external third parties (not trained)	Low	Long	High
	Labelling at the Point of Collection	Mobile	Mobile app - [26] [27]	Labelling carried out by the user in-situ and in real-time	High	Short	Low
Automatic		Sensor / video	Fujitsu - [28]	Generating time-series data automatically from a previous extended data collection period	Low	Short	Low
Synthetic data		Sensor / video	GAN - [29]	Generating synthetic labelled dataset with similar attributes recently using Generative Adversarial Networks	Very Low	Short	Low

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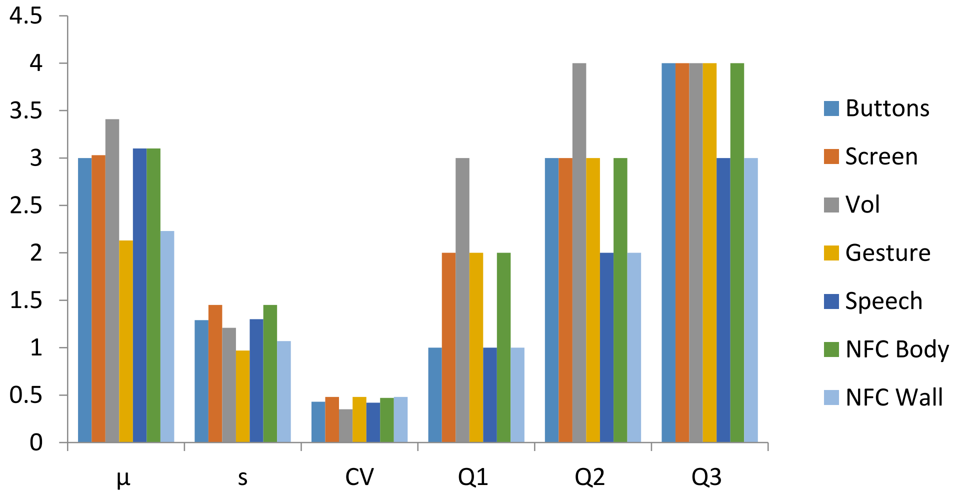
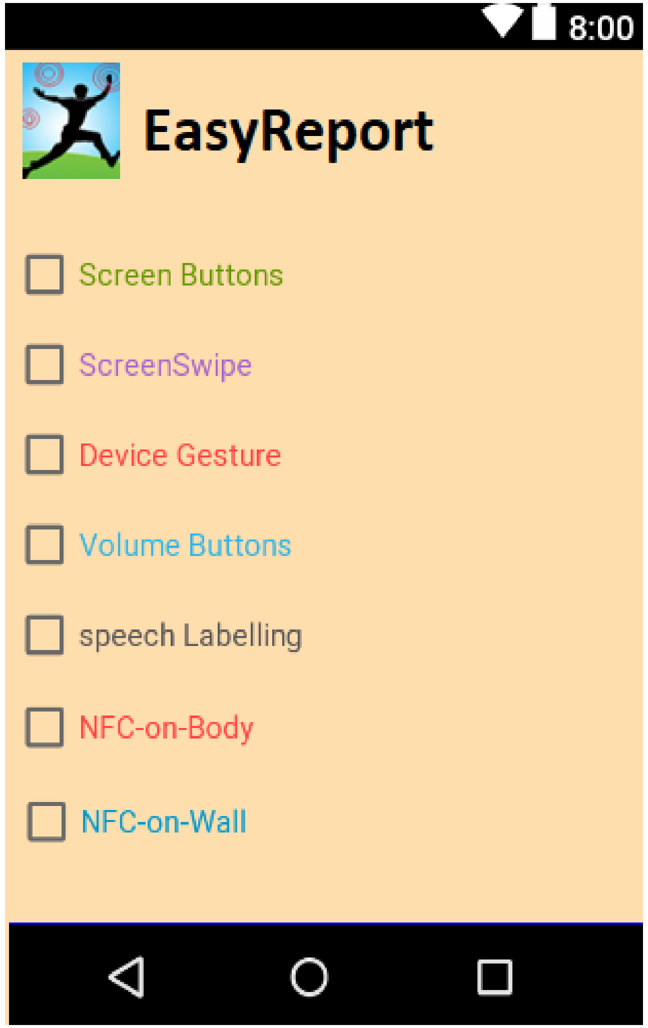
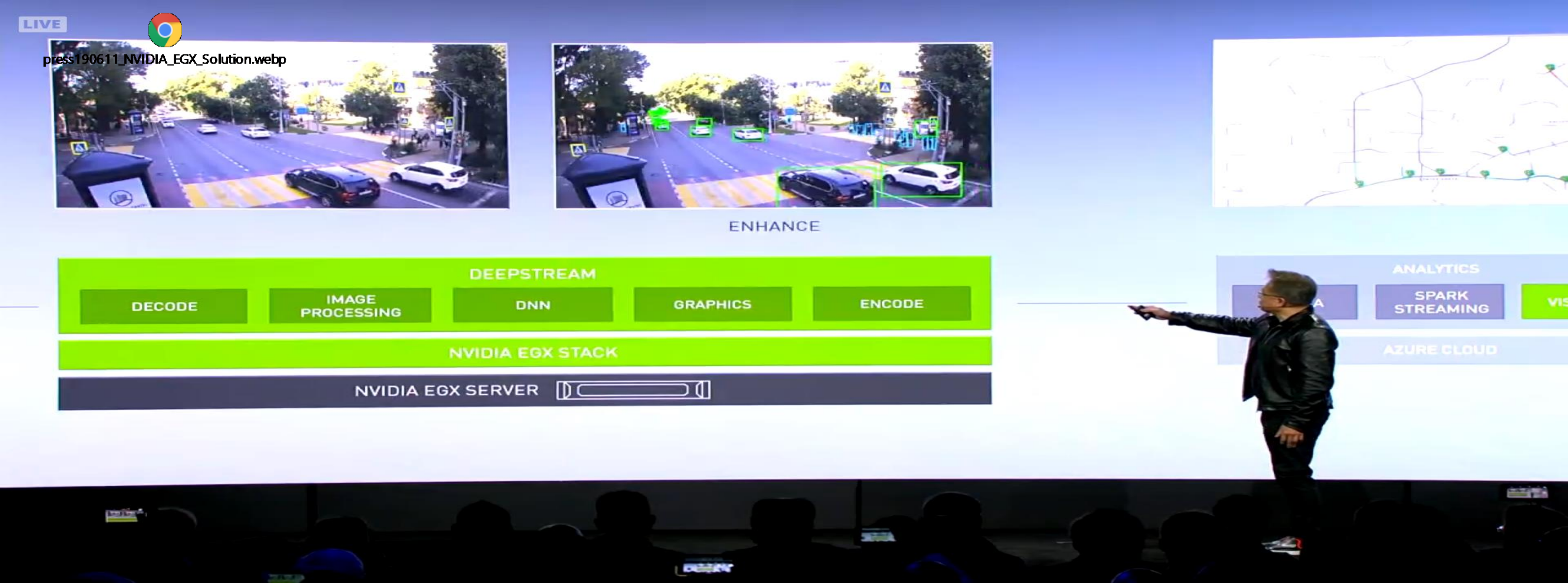
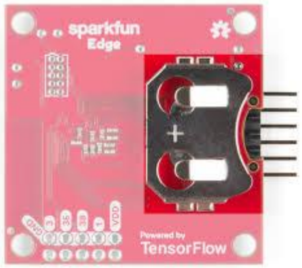
Self-Reporting techniques for Crowdsrourcing Data Mobile Phone Data Labelling





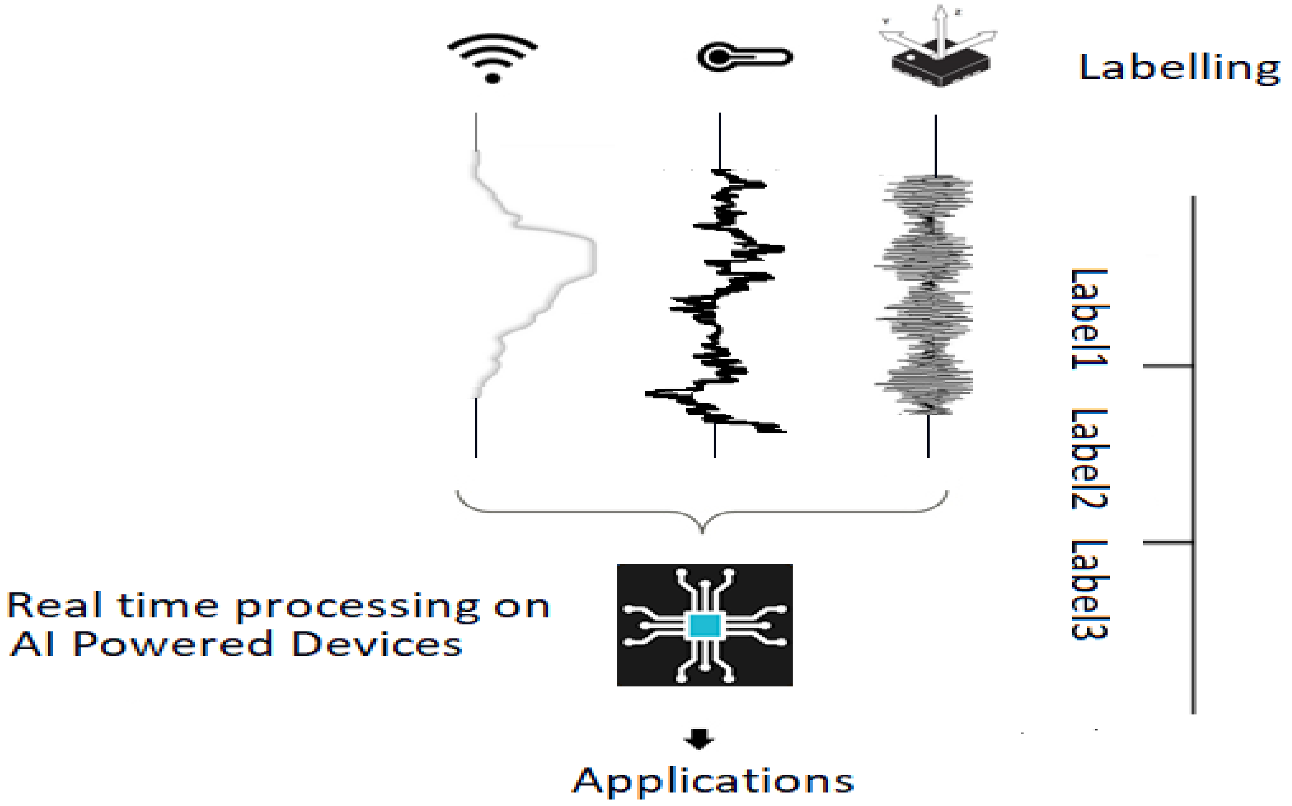
Eman M. G. Younis, Eiman Kanjo, Alan Chamberlain:
Designing and evaluating mobile self-reporting techniques: crowdsourcing for citizen science. Personal and Ubiquitous Computing 23(2): 329-338 (2019)





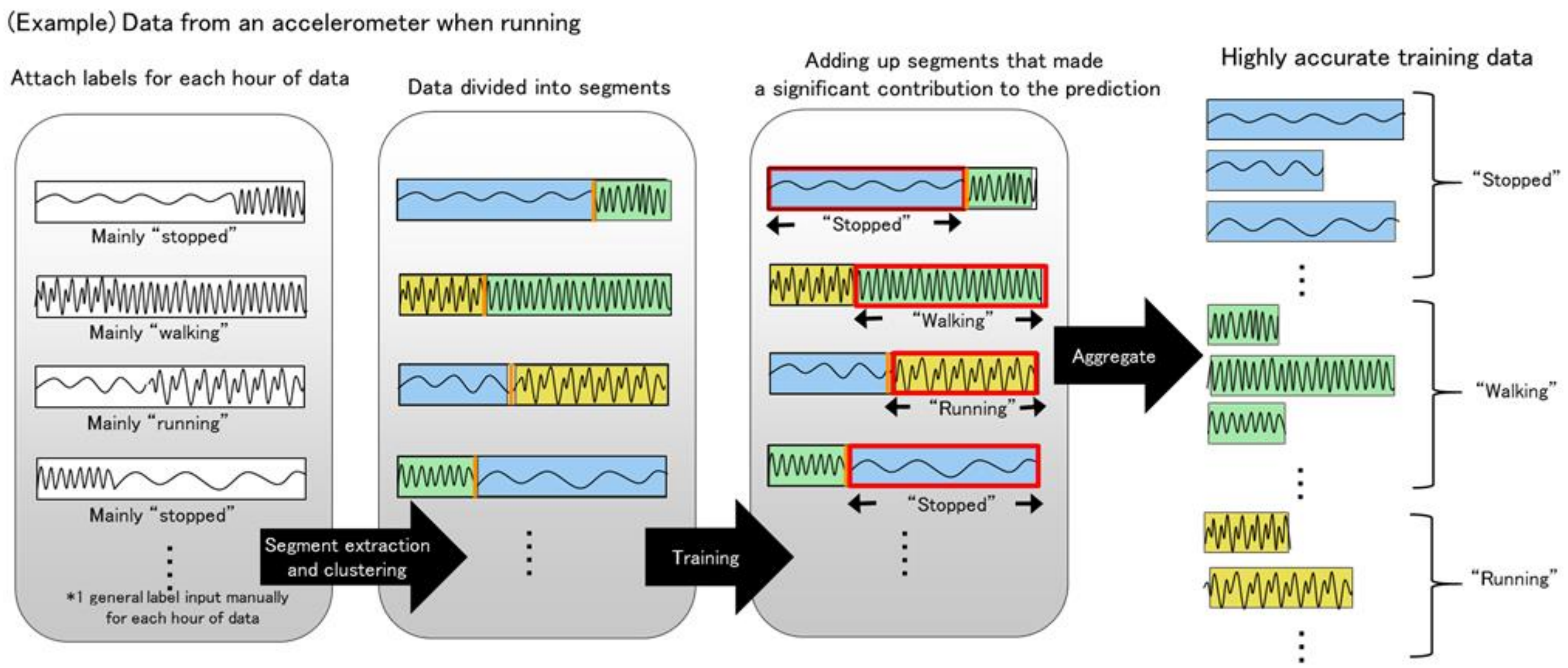
Edge Computing

Mutli-Model Sensor Data Labelling



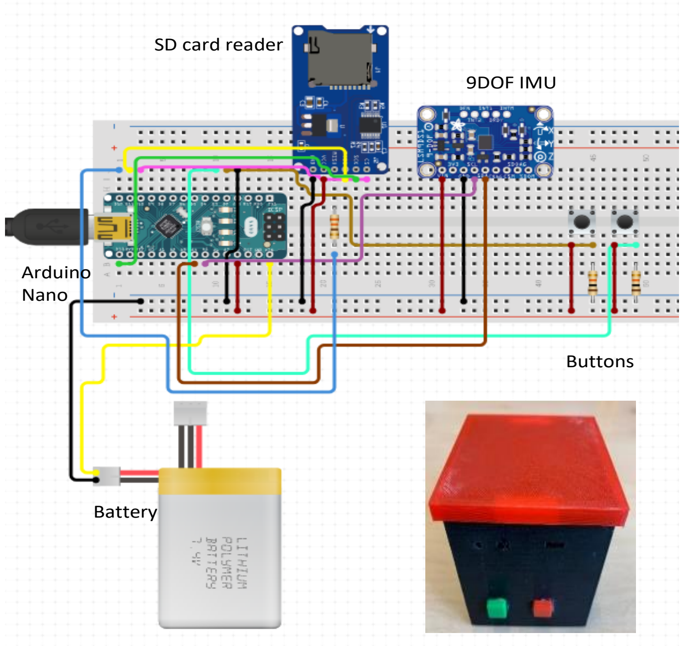
Kieran Woodward, Eiman Kanjo, Andreas Oikonomou, “LabelSens: Enabling Real-time Sensor Data Labelling at the point of Collection on Edge Computing”. CoRR abs/1910.01400 , 2019.

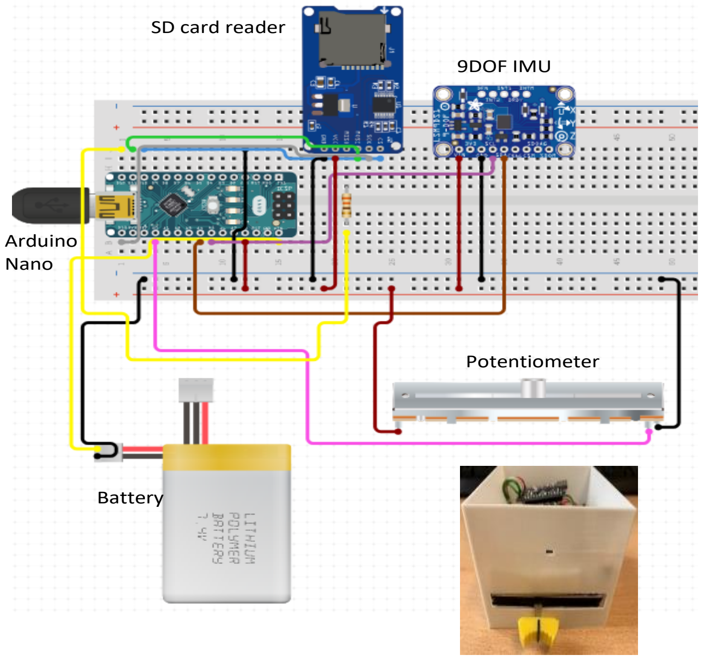
Automatic Data Labelling

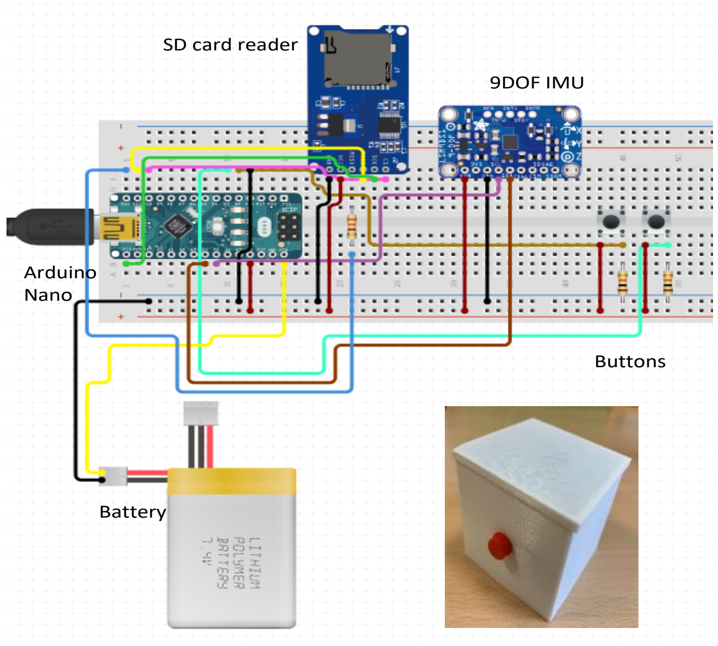


https://www.fujitsu.com/global/about/resources/news/press-releases/2019/0510-01.html

Sensing devices with different Physical Labelling widgets

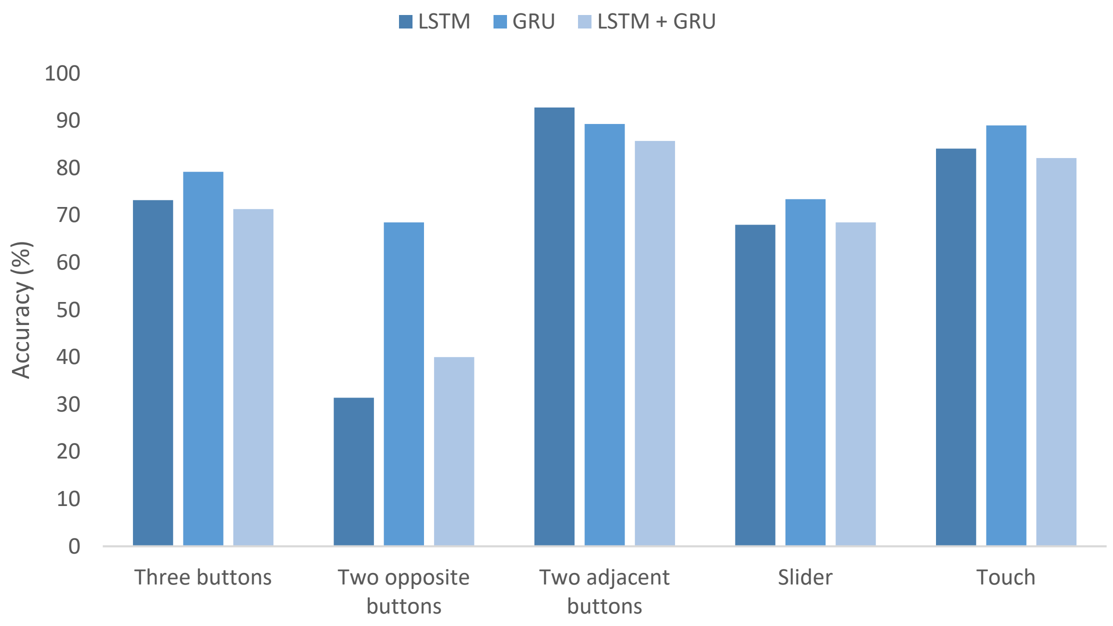


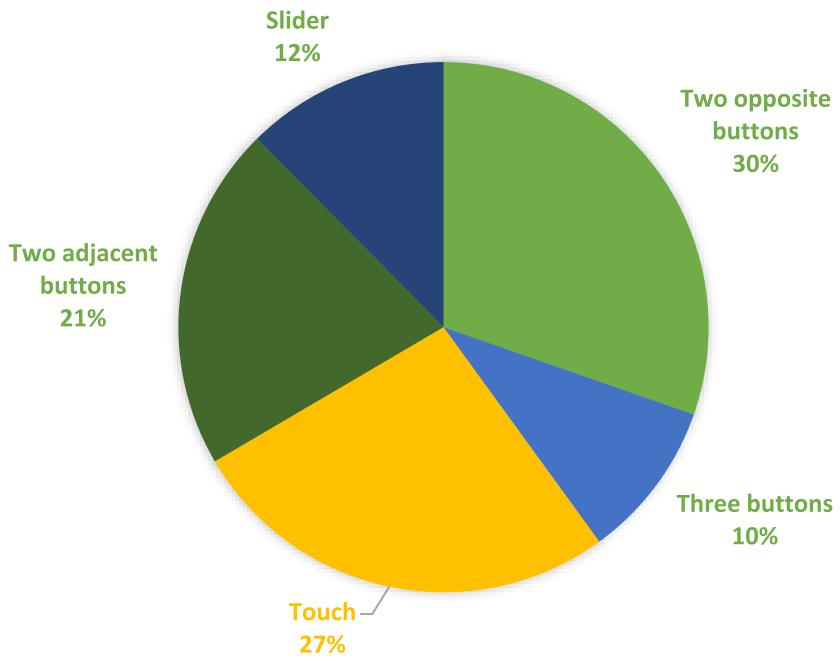




Kieran Woodward, Eiman Kanjo, Andreas Oikonomou, “LabelSens: Enabling Real-time Sensor Data Labelling at the point of Collection on Edge Computing”. CoRR abs/1910.01400 , 2019.

Comparison of deep learning techniques on the combined data collected from each device



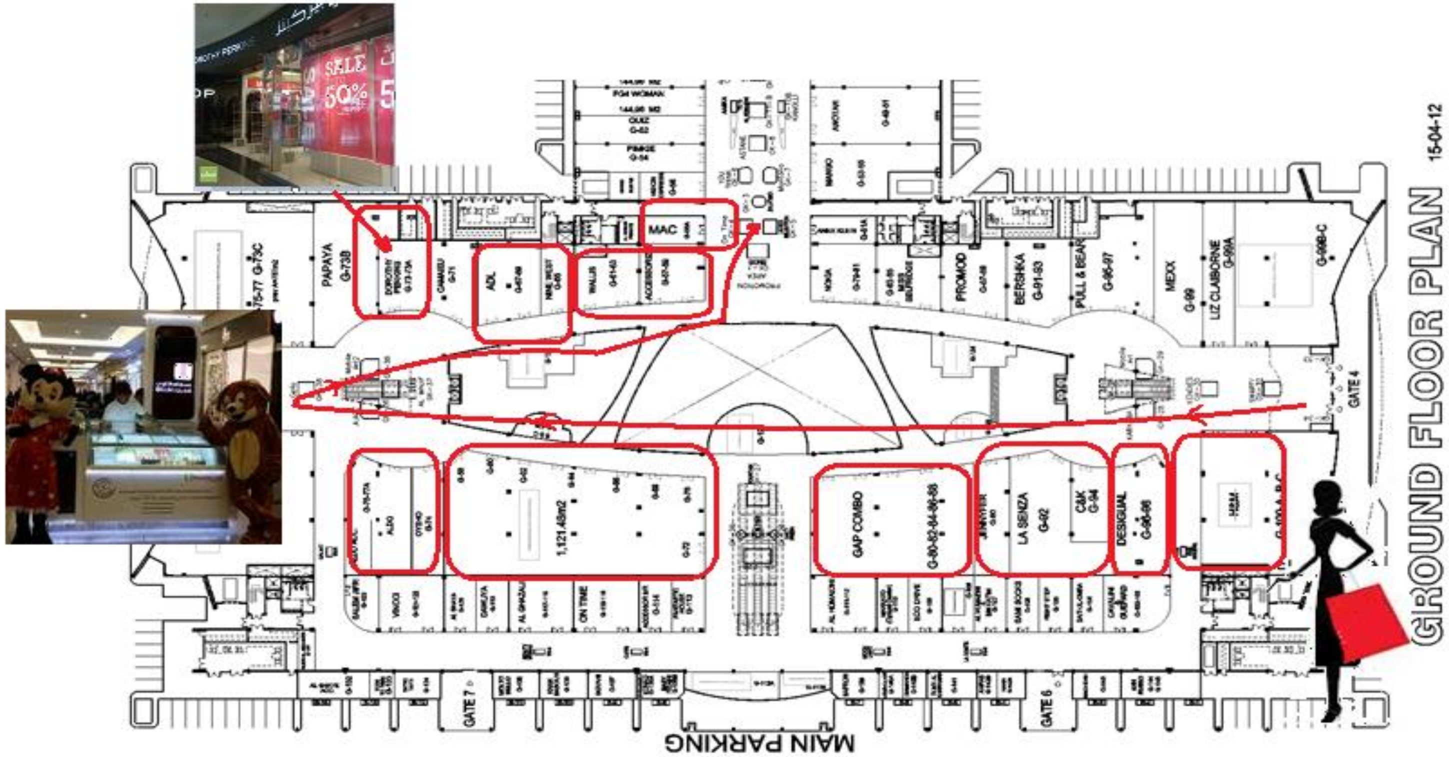


Total in-situ labelling rate per device

Kieran Woodward, Eiman Kanjo, Andreas Oikonomou, “LabelSens: Enabling Real-time Sensor Data Labelling at the point of Collection on Edge Computing”. CoRR abs/1910.01400 , 2019.

Zoning

Zoning divides a physical space into zones or places, e.g. Shops, clusters of shops or areas.



Zoning: Near Field Communications (NFC)

Near Field Communication is a method of wireless data transfer that detects and then enables technology in close proximity to communicate with each other.

- To Unlock mobile content
- NFC around the house or hospital
- On-Body NFC

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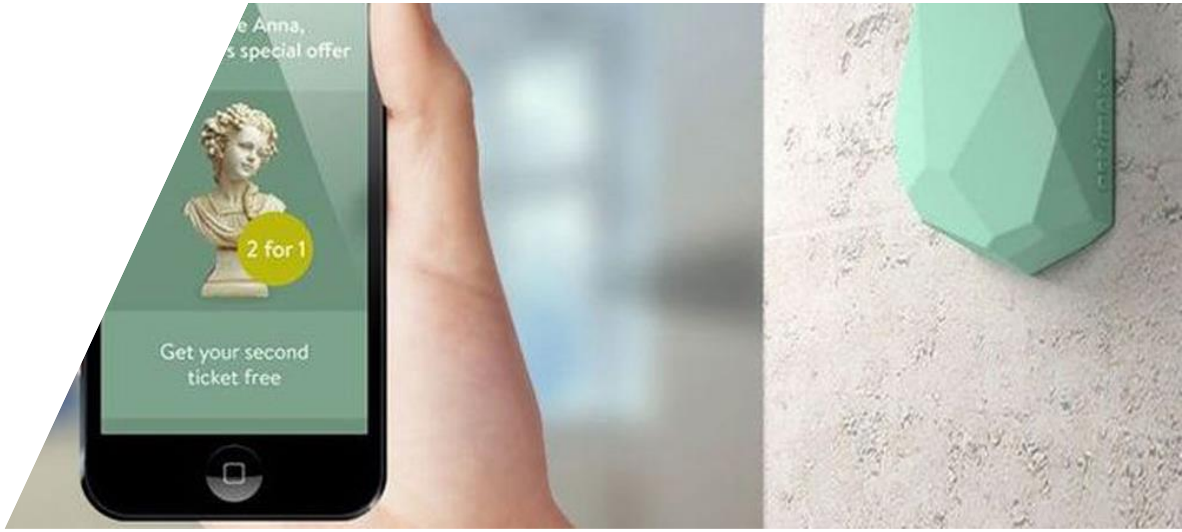
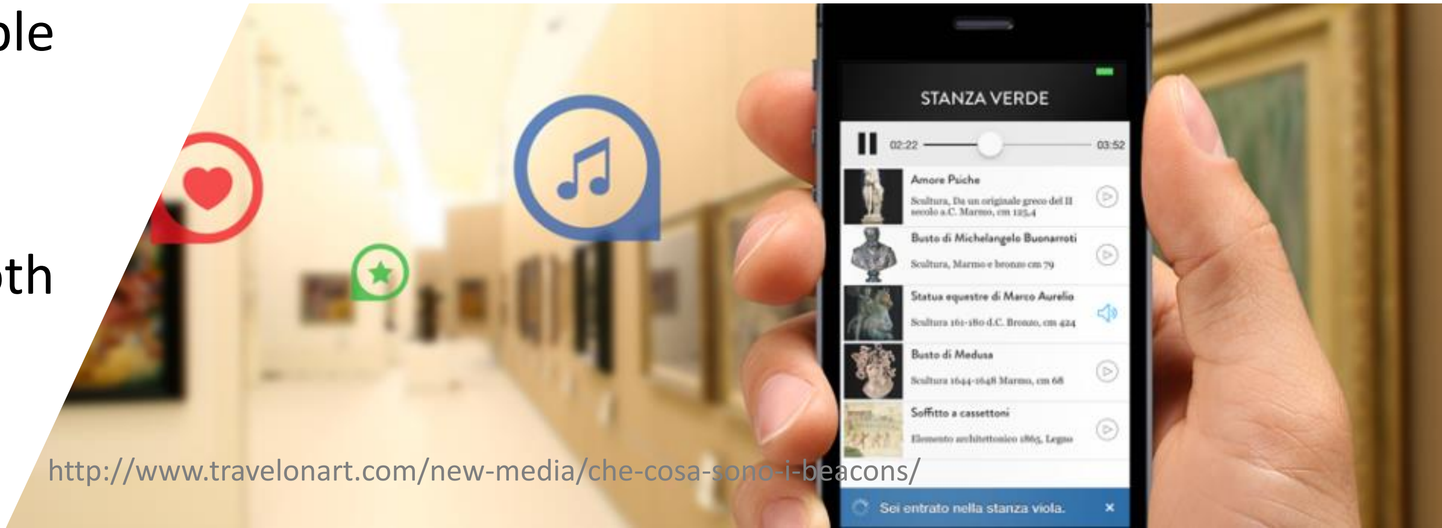
Short Range Communications

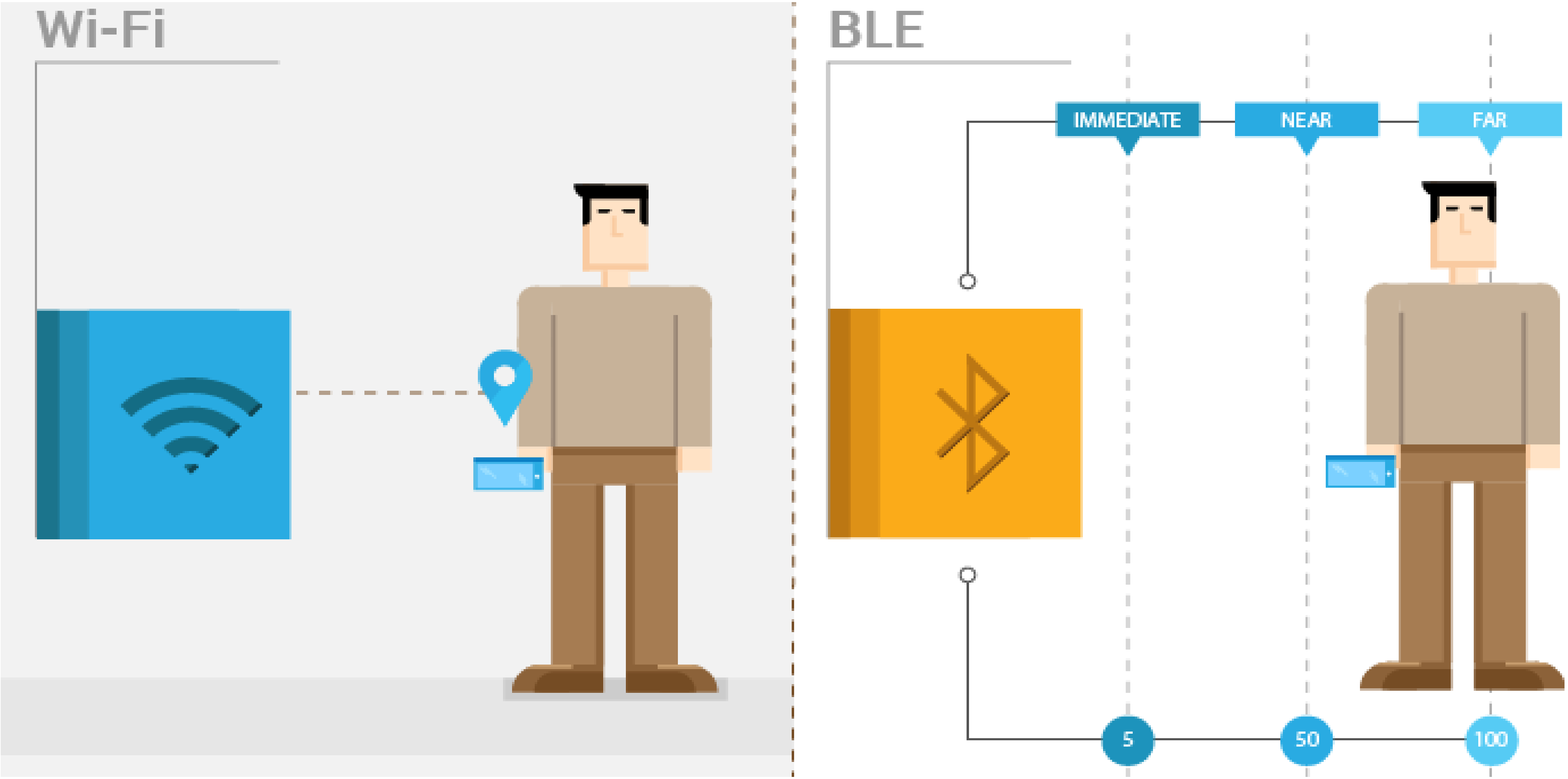
- **Bluetooth beacons** are hardware transmitters - a class of Bluetooth low energy (LE) devices that broadcast their identifier to nearby portable electronic devices. The technology enables smartphones, tablets and other devices to perform actions when in close proximity to a beacon.
- iBeacon introduced by Apple in 2013 to enable retail/location based payment.
- Then few versions of Beacons have followed.
- **Eddystone** is a Google's standard for Bluetooth beacons (released by Google in July 2015





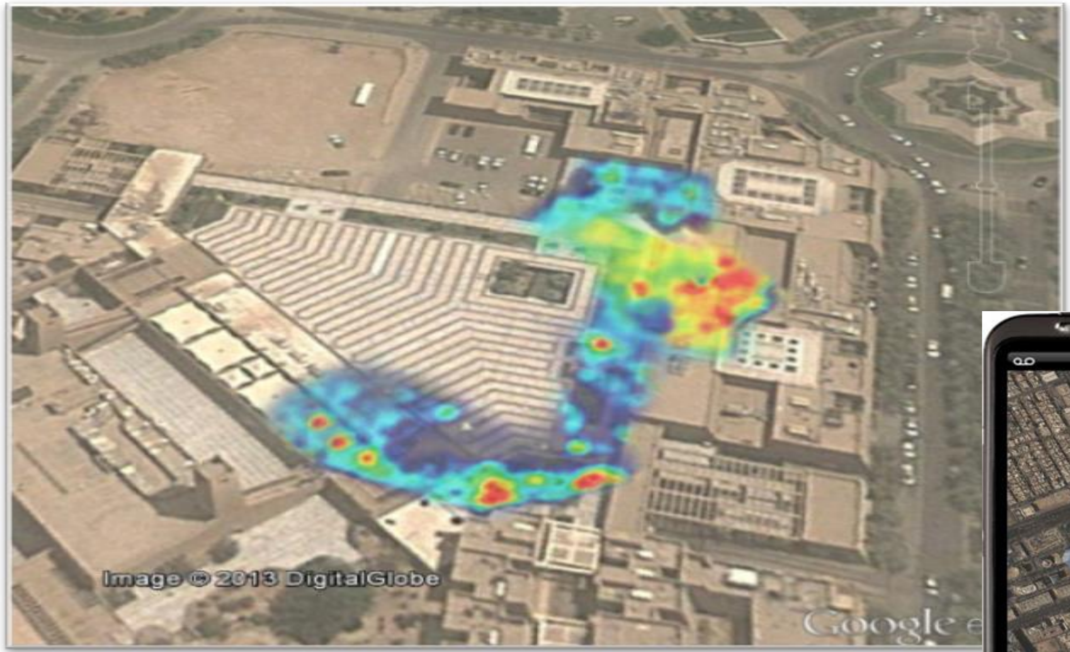
http://www.travelonart.com/new-media/che-cosa-sono-i-beacons/

Proximity based Zoning

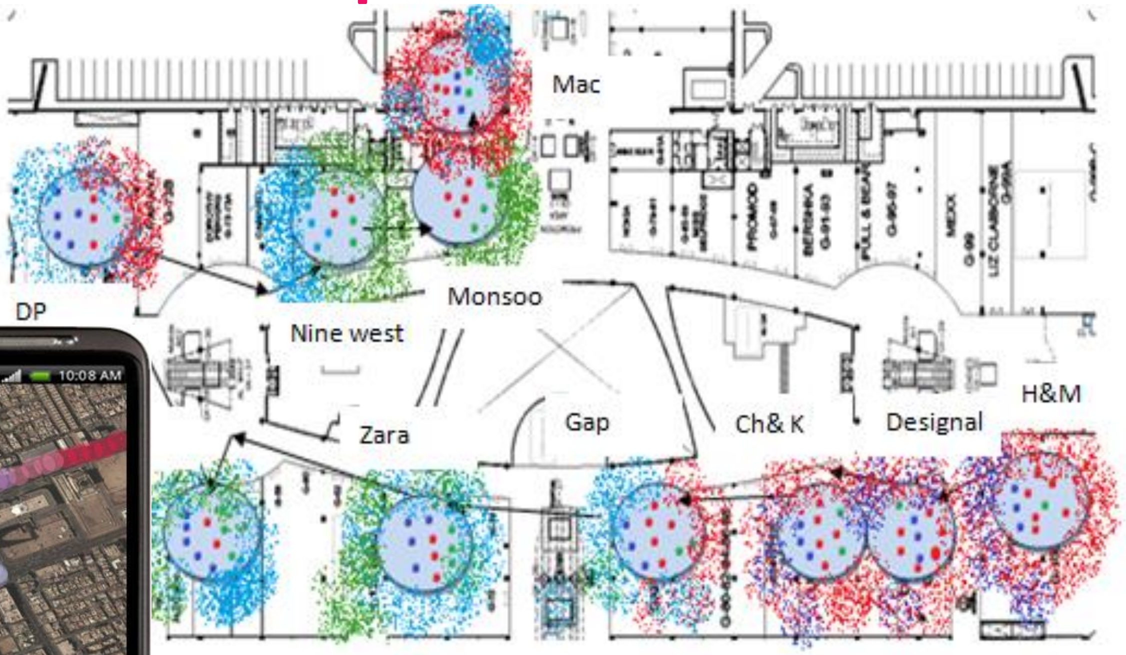


Zoning

NeuroPlace



ShopMobia



Lulwah Al-Barrak, Eiman Kanjo: NeuroPlace: making sense of a place. AH 2013: 186-189

Data Analytics

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Modelling Behaviour from Multi-model Sensor Fusion

Collected **environmental** and **health sensors** data as well as **continuous self-reports of emotions.**

Each line of data is timestamped along with **GPS location**.

50 users/customers

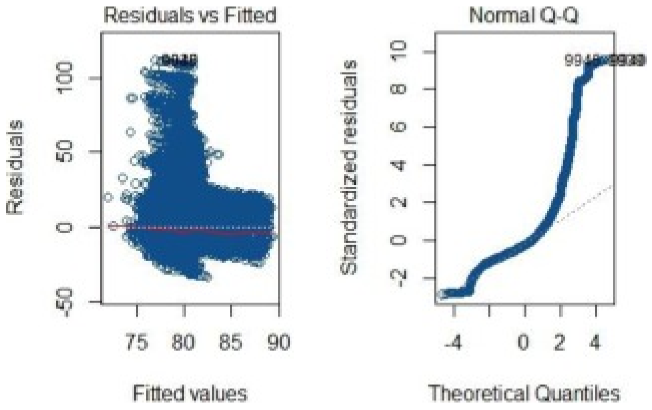
Each Shopper visited 20 shops

45 minutes Shopping journey around the same shopping street.

Eiman Kanjo, Eman M. G. Younis, Nasser Sherkat:
Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach. Information Fusion 40: 18-31 (2018)

Multivariate regression

The comprehensive model above was evaluated using the diagnostic regression curves shown in Fig. 8 shows the relation between the fitted values against the model residual values (i.e. goodness of fit). The model is statistically significant based on (p <0.001).



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HR Diagnostic regression curves: (Left) represents residuals curve, and (Right) represents the Q-Q curve.

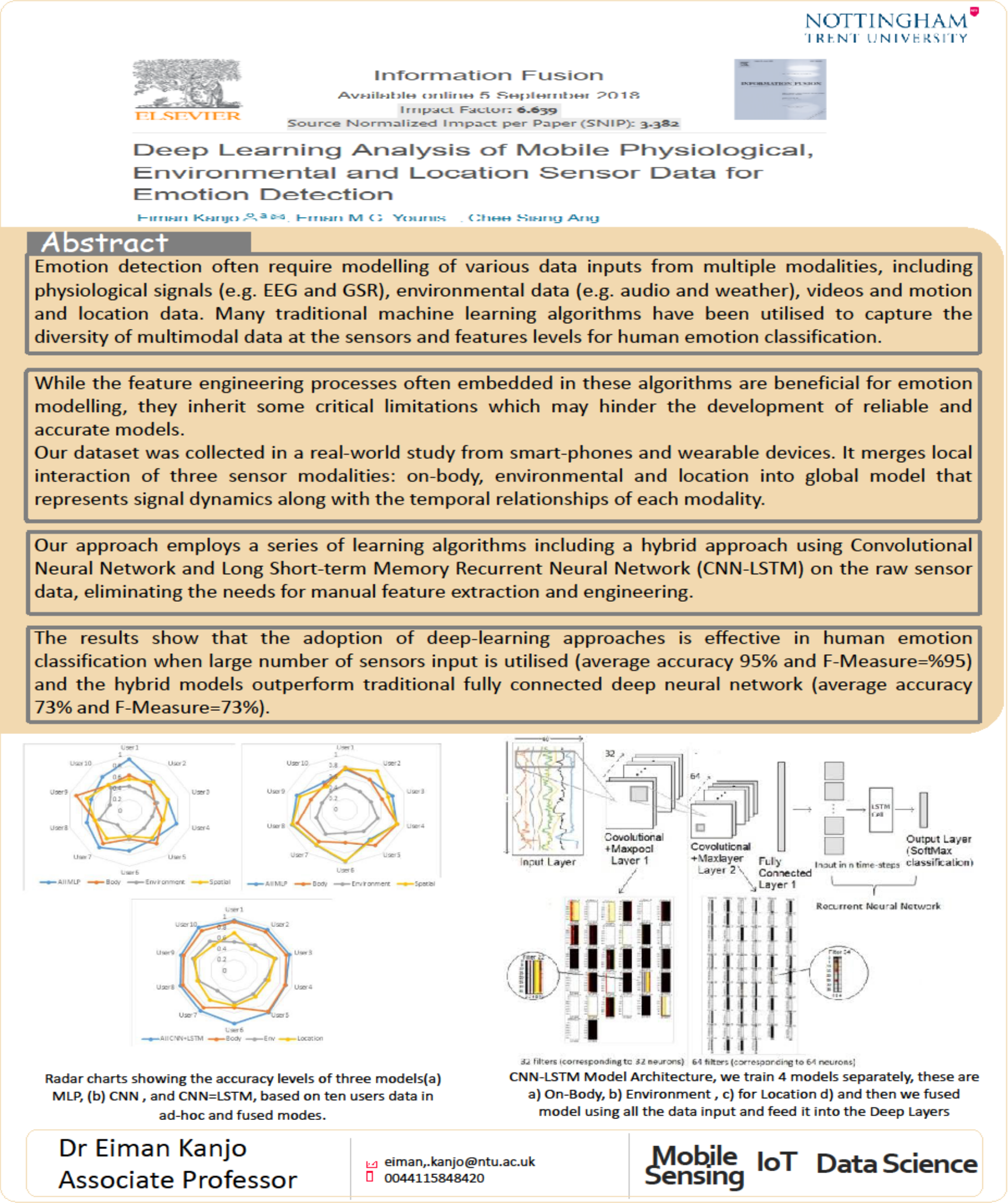
SUNDAY EXPRESS

Do you live in a noisy town? You could be at greater risk of a heart attack

PEOPLE who live in noisy town centres could be at greater risk of a heart attack, according to a new scientific study

By SARAH O'GRADY

Deep Learning for Multimodel Sensor Fusion


NOTTINGHAM TRENT UNIVERSITY

Information Fusion
Available online 5 September 2018
Impact Factor: 6.639
Source Normalized Impact per Paper (SNIP): 3.382

Deep Learning Analysis of Mobile Physiological, Environmental and Location Sensor Data for Emotion Detection

Abstract

Emotion detection often require modelling of various data inputs from multiple modalities, including physiological signals (e.g. EEG and GSR), environmental data (e.g. audio and weather), videos and motion and location data. Many traditional machine learning algorithms have been utilised to capture the diversity of multimodal data at the sensors and features levels for human emotion classification.

While the feature engineering processes often embedded in these algorithms are beneficial for emotion modelling, they inherit some critical limitations which may hinder the development of reliable and accurate models.
Our dataset was collected in a real-world study from smart-phones and wearable devices. It merges local interaction of three sensor modalities: on-body, environmental and location into global model that represents signal dynamics along with the temporal relationships of each modality.

Our approach employs a series of learning algorithms including a hybrid approach using Convolutional Neural Network and Long Short-term Memory Recurrent Neural Network (CNN-LSTM) on the raw sensor data, eliminating the needs for manual feature extraction and engineering.

The results show that the adoption of deep-learning approaches is effective in human emotion classification when large number of sensors input is utilised (average accuracy 95% and F-Measure=%95) and the hybrid models outperform traditional fully connected deep neural network (average accuracy 73% and F-Measure=73%).

Radar charts showing the accuracy levels of three models(a) MLP, (b) CNN , and CNN=LSTM, based on ten users data in ad-hoc and fused modes.

CNN-LSTM Model Architecture, we train 4 models separately, these are a) On-Body, b) Environment , c) for Location d) and then we fused model using all the data input and feed it into the Deep Layers

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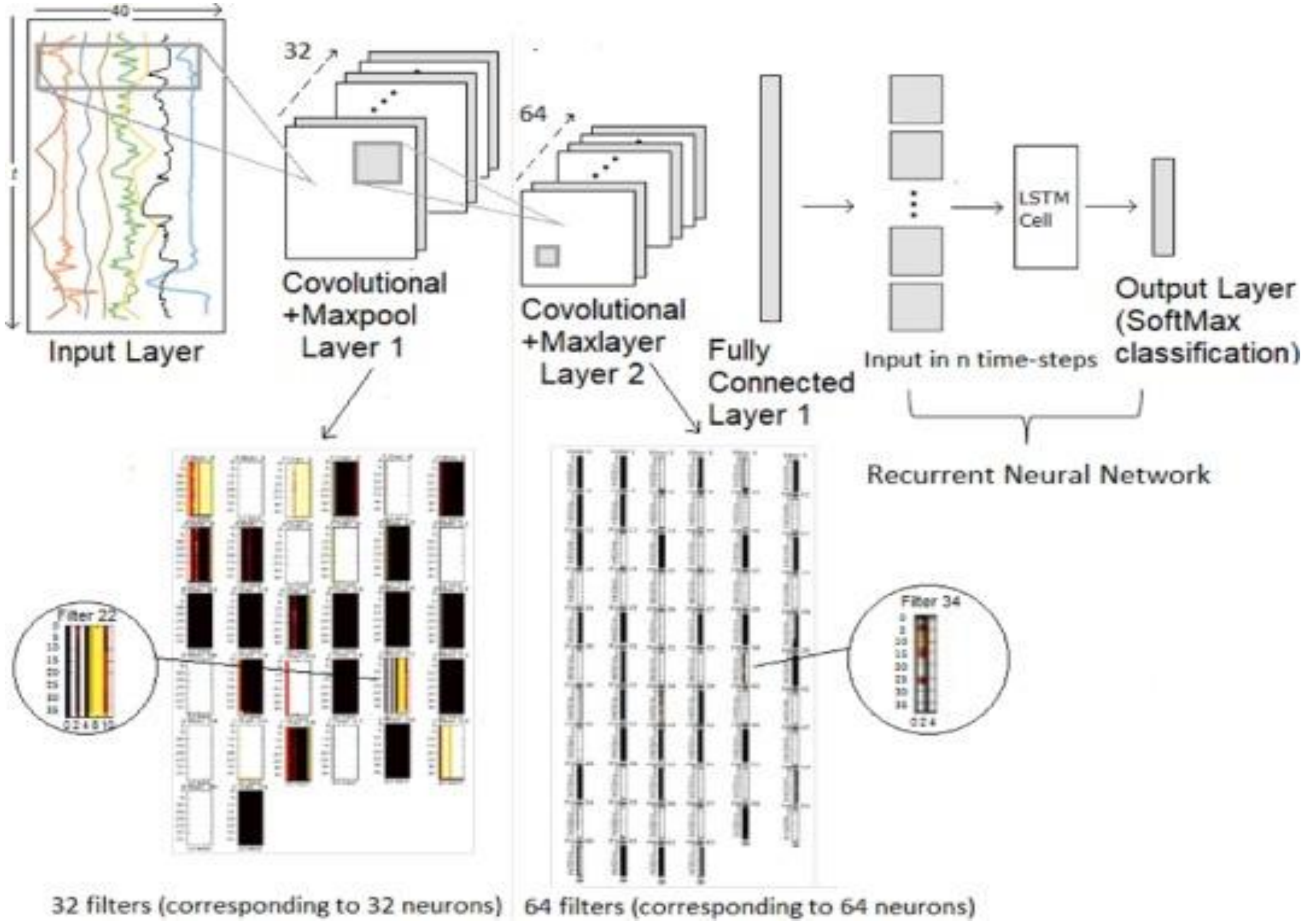
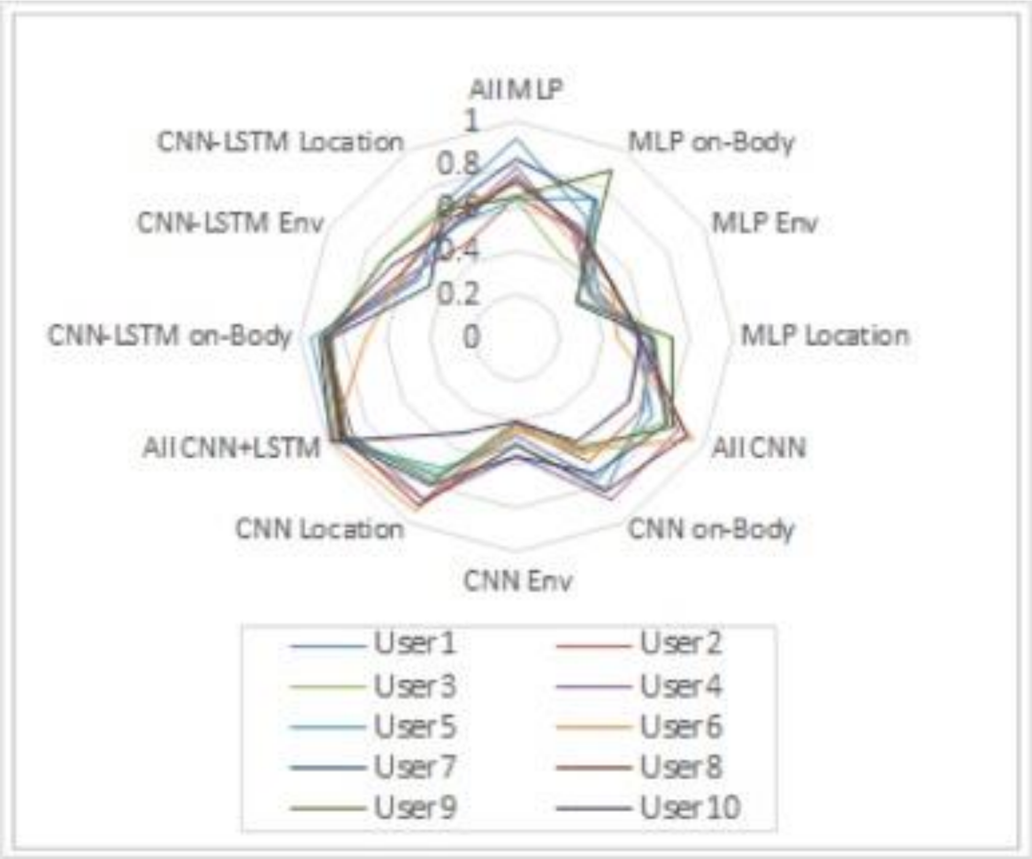
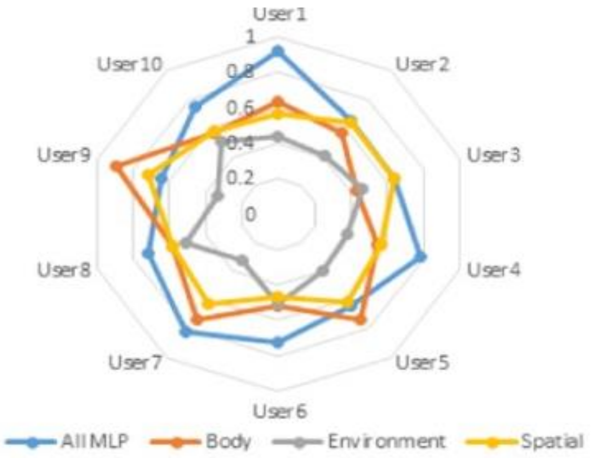
Mobile Sensing IoT Data Science

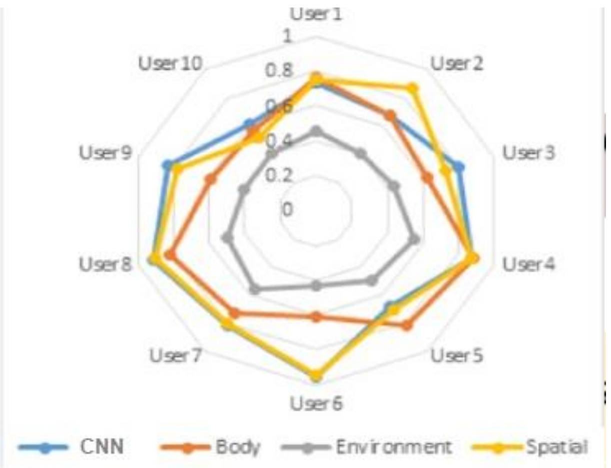


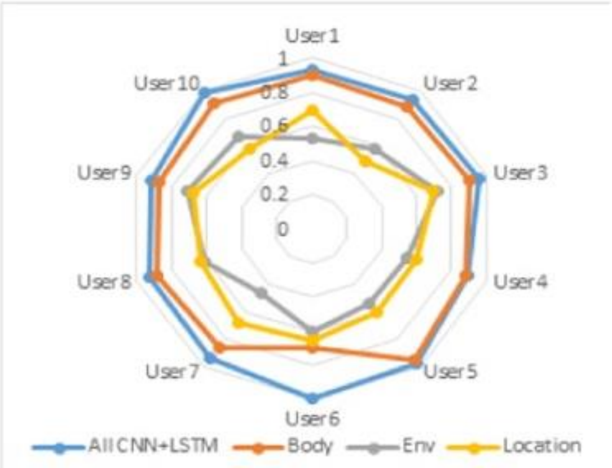
Eiman Kanjo, Eman M. G. Younis, Chee Siang Ang: Deep learning analysis of mobile physiological, environmental and location sensor data for emotion detection. Information Fusion 49: 46-56 (2019)

The accuracy levels of users across all the models in ad-hoc and fused modes.









Data Visualisations & Mapping

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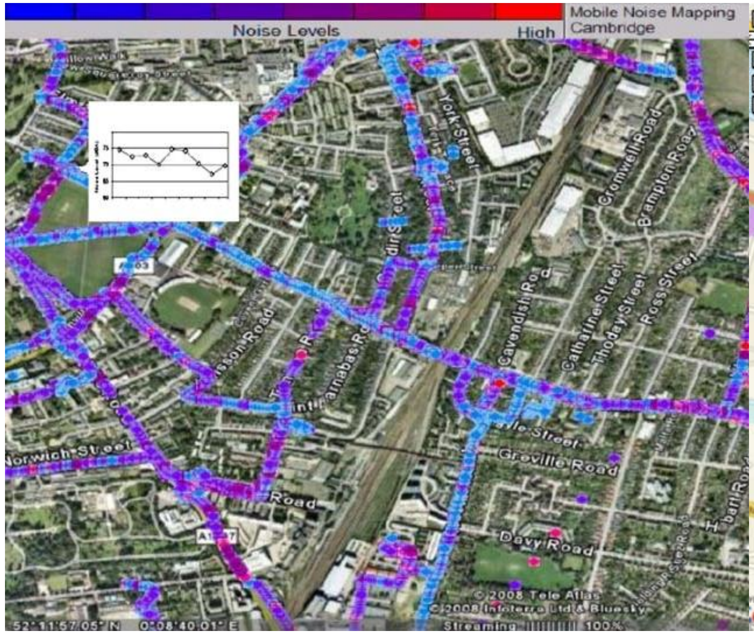
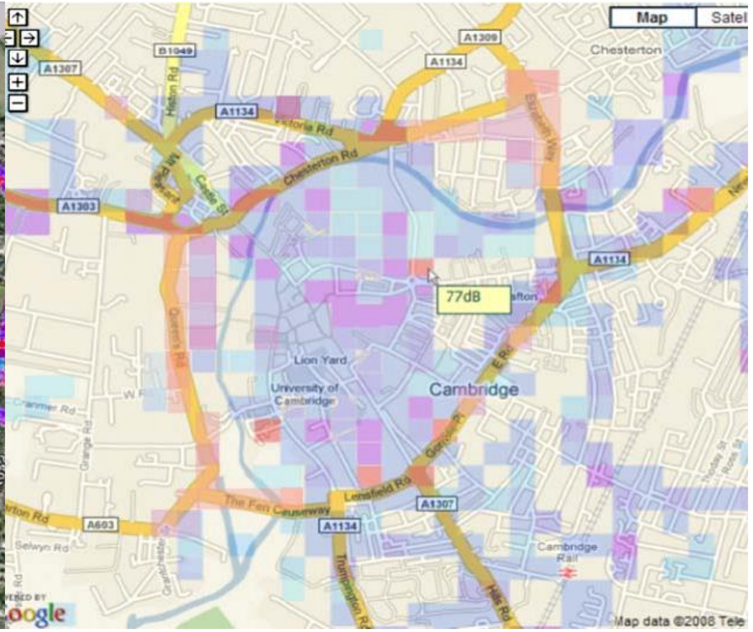
Pollution measurements a trial in Cambridge





$$W_{A1} = 10Log\left[\frac{1.562339 f^4}{(f^2 + 107.65265^2)(f^2 + 737.86223^2)}\right]$$

Eiman Kanjo: NoiseSPY: A Real-Time Mobile Phone Platform for Urban Noise Monitoring and Mapping. MONET 15(4): 562-574 (2010)
Eiman Kanjo, Jean Bacon, David Roberts, Peter Landshoff: MobSens: Making Smart Phones Smarter. IEEE Pervasive Computing 8(4): 50-57 (2009)

Heat Maps

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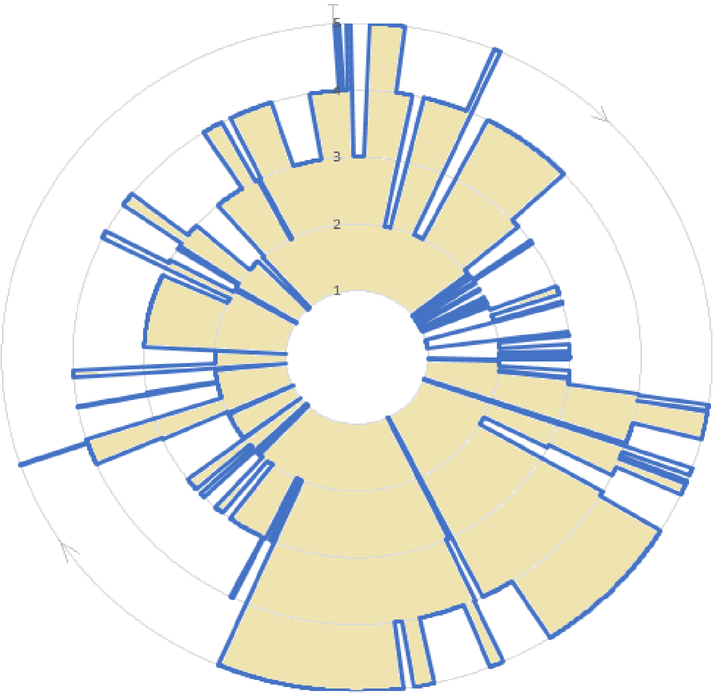
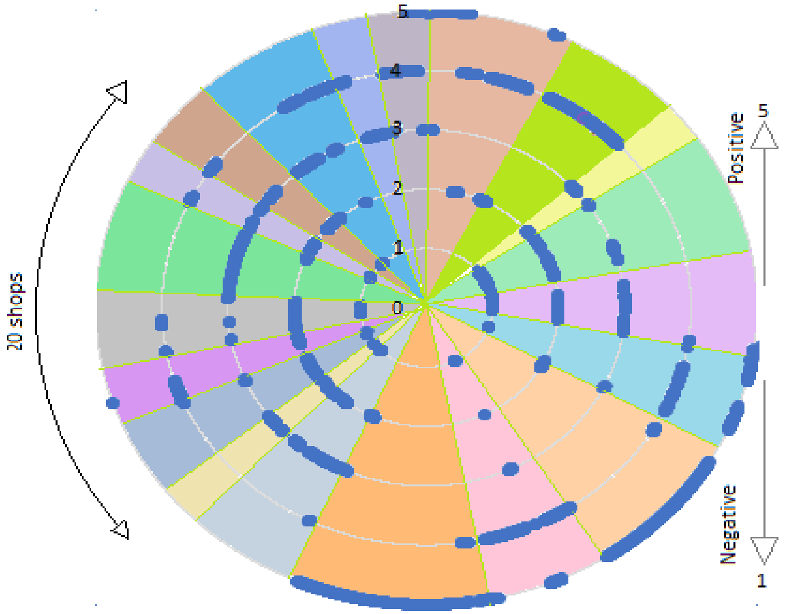
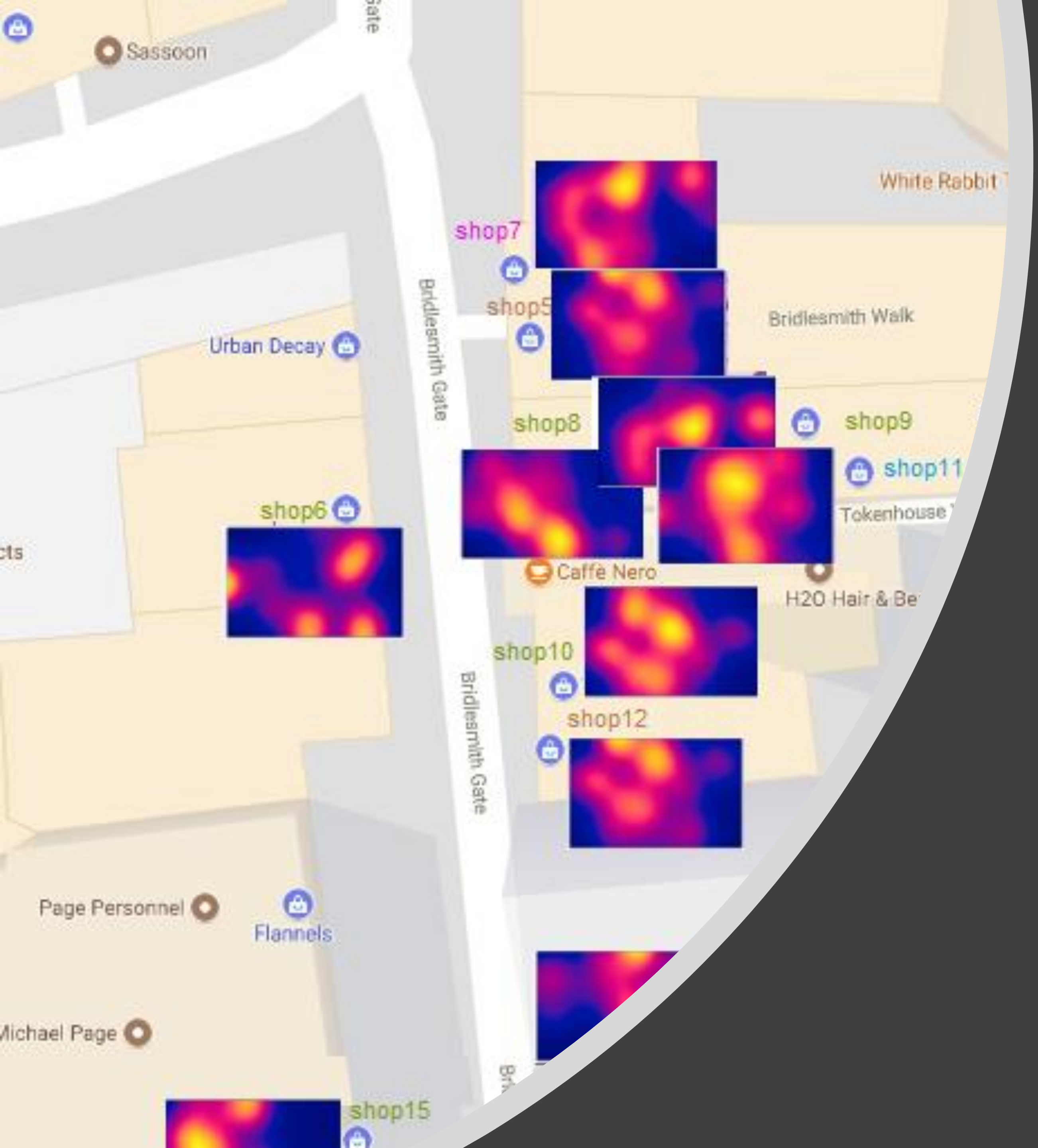


Accumulative Time spent in each shop



Label distribution around 20 shops based on one user journey



Comparing Places/Zones

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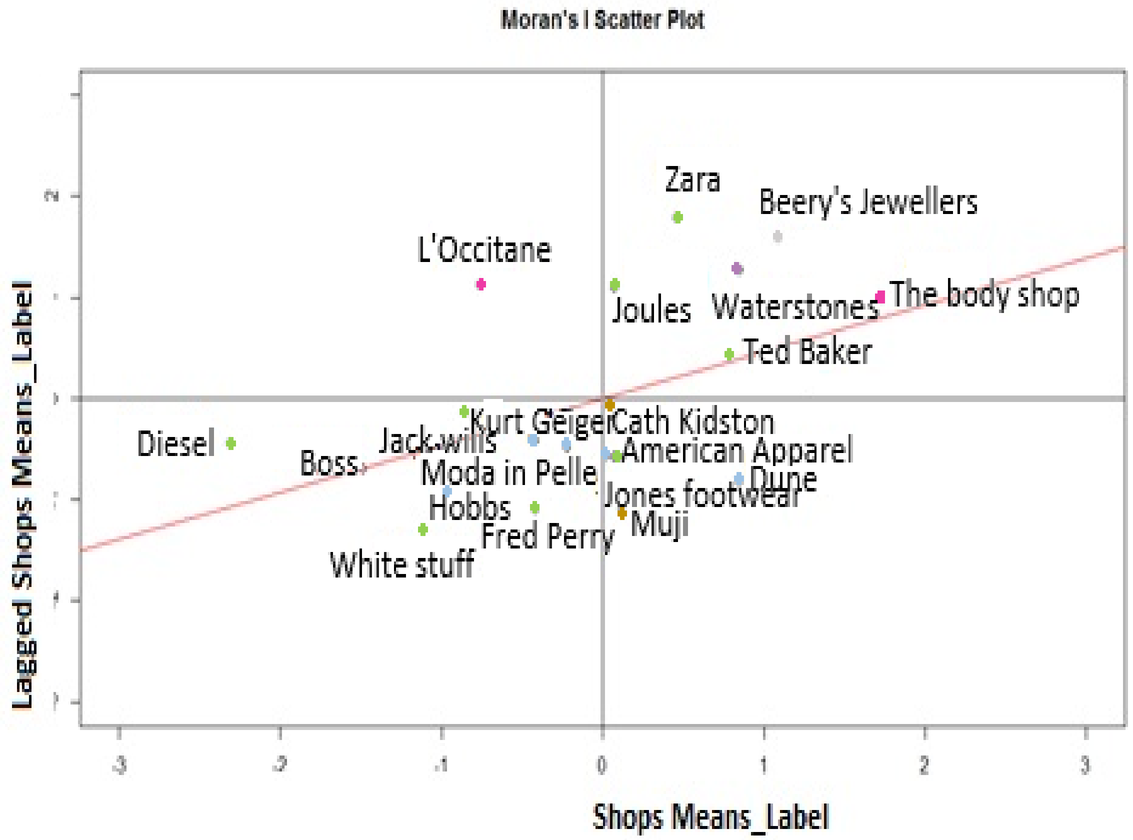
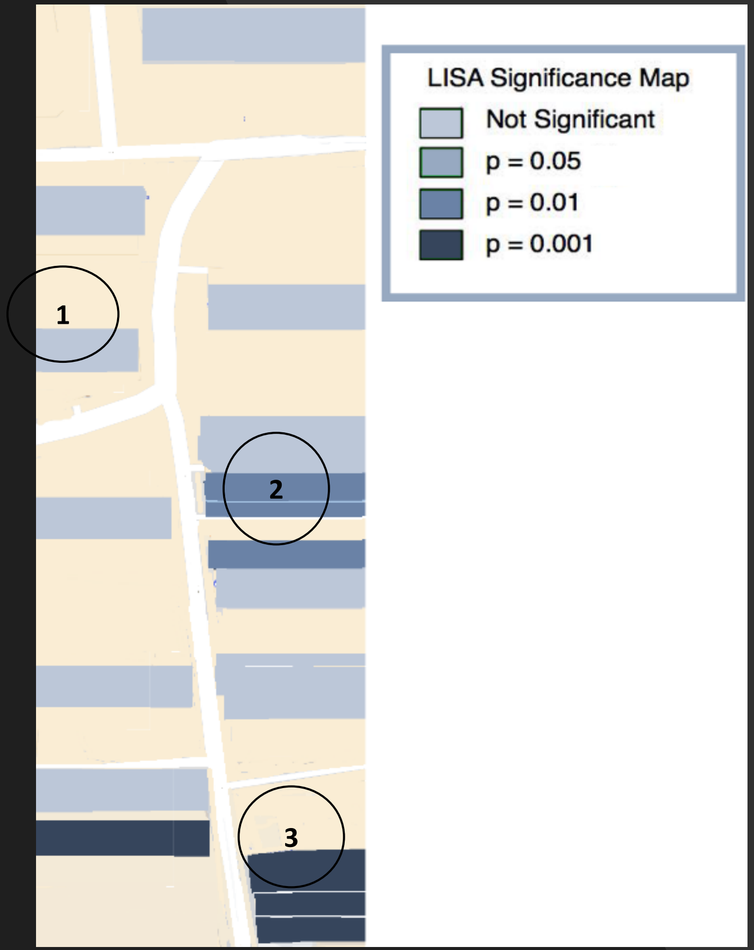
Spatial Autocorrelation Statistics



Moran Scatter Plot



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