Leveraging IPS to provide indoor localization and navigation services

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NOMSTROM
ANALYTICS

Agenda

- **CONTEXT: INDOOR POSITIONING SYSTEMS**
- DATA AND METHODOLOGICAL APPROACH
- RESULTS OF THE ANALYSIS
- CONCLUSIONS AND Q&A

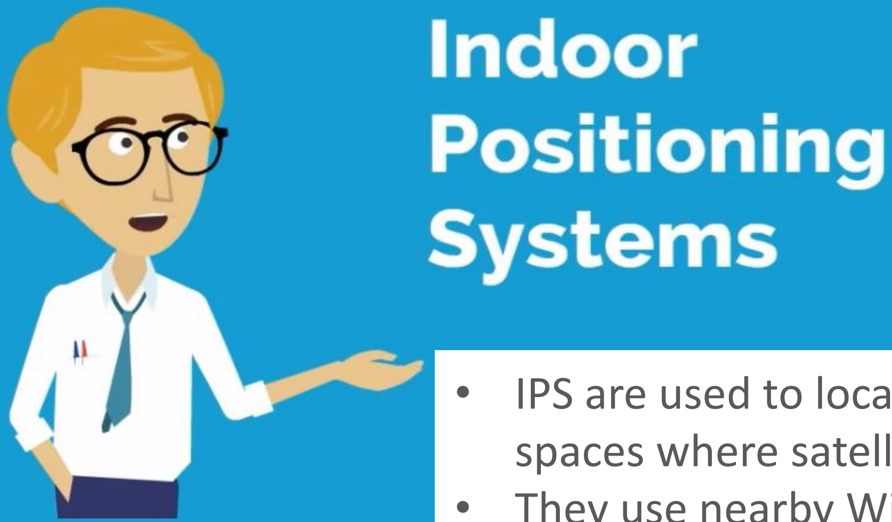
Nowadays, we use the GPS on our mobile-phones to get directions in outdoor environments

Today we use **GPS navigation** when treveling by car, bike or foot BUT there is one big problem: it **doesn't work inside buildings**

GPS – Outdoor

GPS – Indoor

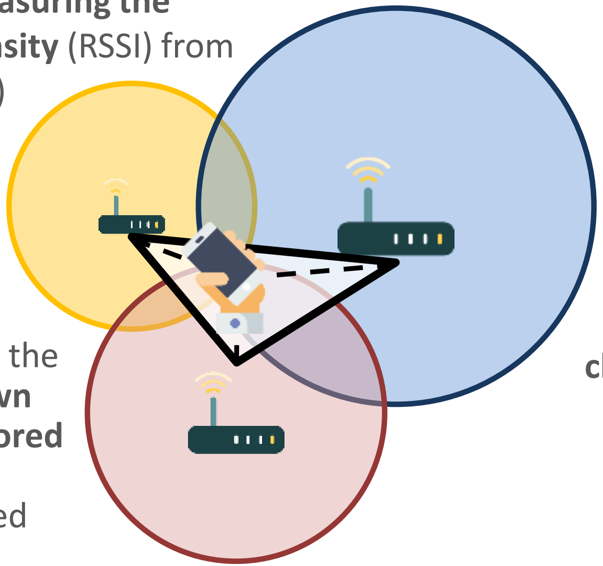
To solve indoor localization problems, «Indoor positioning systems» have been developed



- IPS are used to locate people or objects inside large indoor spaces where satellite navigation through GPS is inadequate
- They use nearby Wi-Fi hotspots and other wireless access points (WAPs) to discover where a device is located

Fingerprinting is one of the most common indoor localization techniques using WiFi APs

1. Fingerprinting is based on **measuring the received signal strength intensity** (RSSI) from Wireless Access Points (WAPs)



2. It is necessary to **record the RSSI from several WAPs** in range and to store this information

in a database **along with the known coordinates of the client device** in an offline phase

3. During the online tracking phase, the **current RSSI vector at an unknown location is compared to those stored in the fingerprint** and the closest match is returned as the estimated user location

The **accuracy** of this technique **depends on the layout of the space** (i.e. shape, furniture, walls, doors), hence any change of the environment impacts the "fingerprint" that corresponds to each location, requiring an update to the database

Fingerprinting is one of the most common indoor localization techniques using WiFi APs

RSSI	Level	Required for
-30 dBm	Exceptional	Any use
-67 dBm	Very good	VoIP, streaming
-70 dBm	Okay	Email, web surfing
-80 dBm	Not good	Basic connectivity
-90 dBm	Unusable	No functionality

IPS can be used to provide different services to people in a variety of large indoor spaces

Possible IPS uses:

- Provide navigation aid
- Market better products to customers
- Provide just-in-time information via audio/video
- Offer augmented reality experiences
- Connect people of interest in proximity to one another

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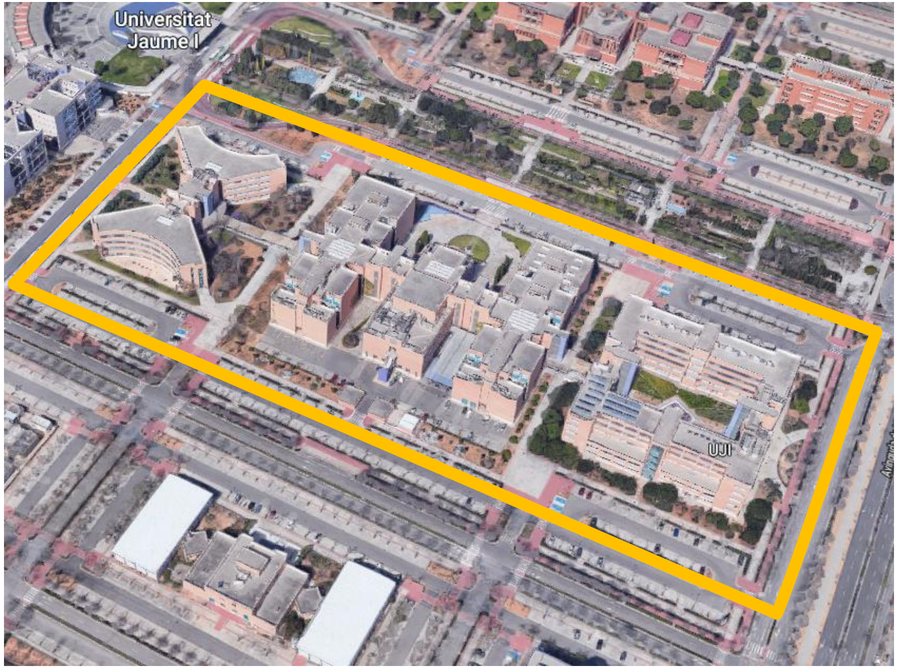
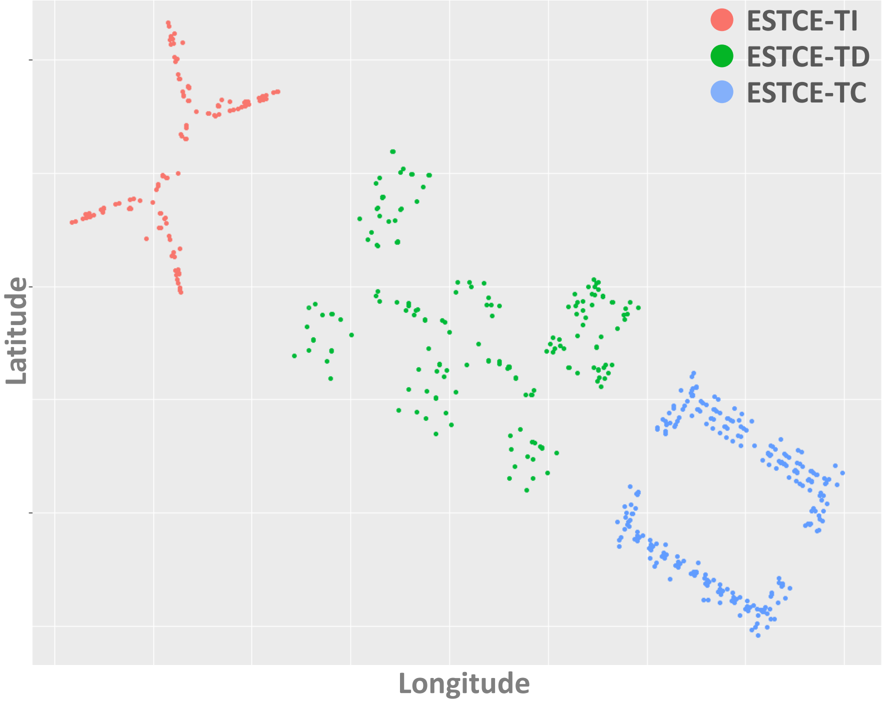
Data were collected at three multi-floor buildings of the Jaume I University in Spain

J. I University – 3D view from Google maps



The university campus covers a surface of almost 110.000 m²

J. I University – Observations from Training set



The DB consists of more than 20k observations and 500+ variables

Features of the DBs

- **Total # nr observations**: 21.049 sampled points: 19.938 for Training set and 1.111 for Validation set
- **Tracking period**: Training fingerprints collected between May-June 2013. Validation fingerprints 3 months later
- **Data collection**: Data acquired by 20+ users using 25 models of mobile devices through two dedicated apps (CaptureLoc and ValidateLoc)

Total # of variables: 529

WAPs
Indicates the RSS level per each wireless access point (WAP)

Building
Indicates the building in which the capture was taken:
- 0 = ESTCE-TI
- 1 = ESTCE-TD
- 2 = ESTCE-TC

Floor
Corresponds to the floor (altitude) where the capture was taken

Latitude
Corresponds to a real world coordinate measured in meters

Longitude
Corresponds to a real world coordinate measured in meters

Space
Identifies the particular space (offices, labs etc.) where the capture was taken

Rel. Position
Denotes if the capture was taken inside or outside the space

User
Represents the different users that recorded the captures

Phone
Indicates the device used in each capture

Time
Represents the time in which the capture was taken

In order to assess the feasibility of the app, several algorithms are tested

GOAL

Assess the **accuracy of** using **WiFi fingerprint** as indoor localization technique and **advise** our **client on the feasibility to incorporate the system** based on this technique **into a smartphone app** for indoor location to help people to navigate a complex, unfamiliar interior space without getting lost

MAIN ALGORITHMS EMPLOYED

KNN

- The position estimation is generally based on the Euclidean distance between compared data points: hence it can be used to estimate the localization by considering the average of its closest K data points
- Accuracy comparable with that one of more complex algorithms
- Fast, simple and flexible

RF - C5.0

- High scalability on large learning set
- Great prediction accuracy
- Long time for training on large dataset

SVM

- Great prediction accuracy
- Long time for training on large dataset

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Prediction model - Building

Pre-process

- Transform RSS values in the range [-30;100] and [-104;-80] in -106 → no signal
- Delete rows and columns with variance = 0
- Make sure that the Training set has the same columns as the Validation set
- Variables employed in the model: WAPs, BuildingID, Floor, Latitude, Longitude

	Accuracy (%)	Kappa (m)
KNN	100%	1
RF	100%	1
C5.0	99,54%	0,99

The system can predict with an accuracy of 100% in which building a person/object is located

Prediction model - Floor 1/4

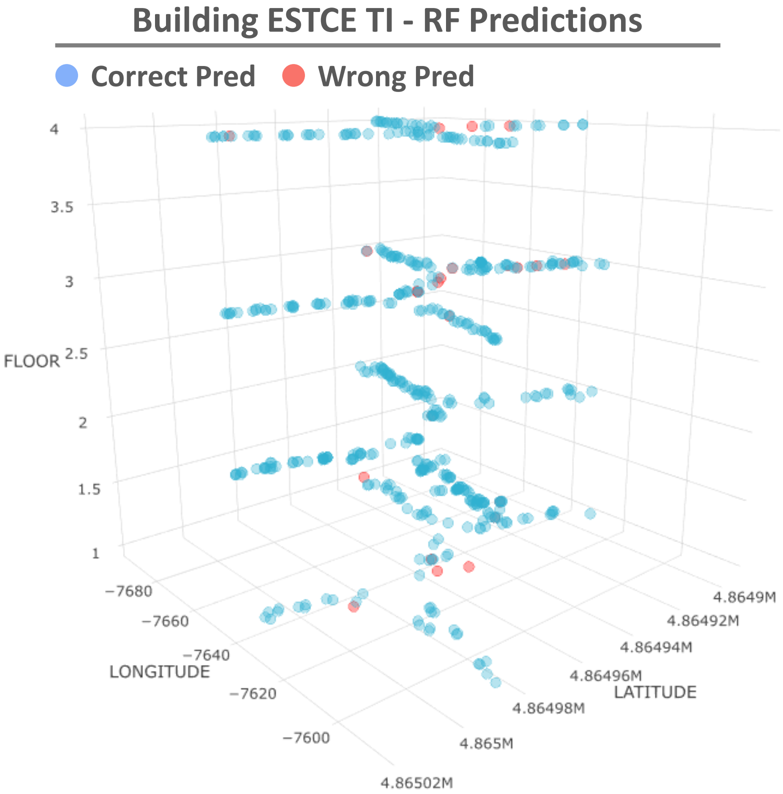
Pre-process

- Transform RSS values in the range [-30;100] and [-104;-80] in -106 → no signal
- Delete rows and columns with variance = 0
- Make sure that the Training set has the same columns as the Validation set
- Variables employed in the model: WAPs, BuildingID, Floor, Latitude, Longitude

	Accuracy (%)	Kappa (m)
KNN	90,79%	0,87
RF	91,25%	0,88
C5.0	85,05%	0,79

In order to try to get better results, it is possible to split the 2 datasets by building using different algorithms

Prediction model - Floor 2/4



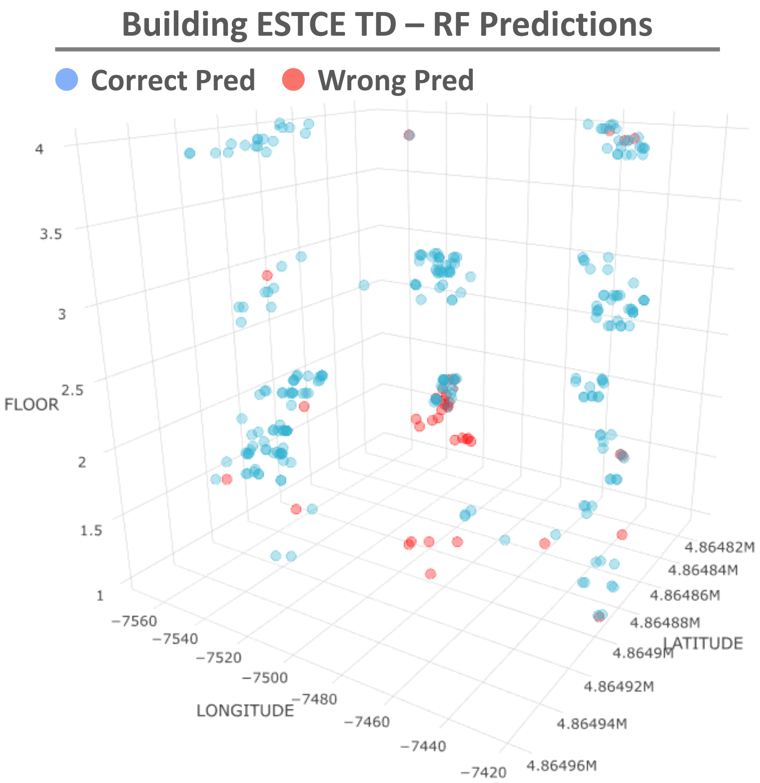
Metrics: RF

Accuracy (%)	Kappa (m)
95,70%	0,94

Errors: possible causes

- Total 23 errors, mainly in the 3° floor (11)
- Predicted one floor above or below
- N° of active WAPs for wrong predictions lower (on average) than the correct ones
- RSS for wrong predictions lower (on average) than the correct ones
- 83% occured on October 4, 2013
- Physical interferences

Prediction model - Floor 3/4



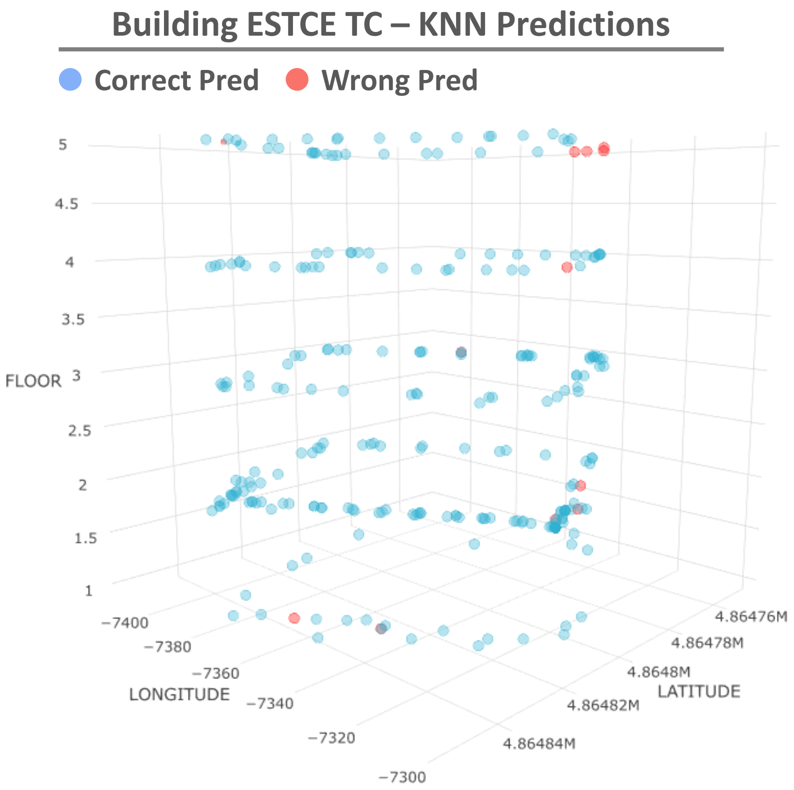
Metrics: RF

Accuracy (%)	Kappa (m)
86,82%	0,81

Errors: possible causes

- Total 39 errors, mainly in the 1° and 2° floor (respectively 9 and 25)
- Mainly predicted one floor above or below
- N° of active WAPs for wrong predictions lower (on average) than the correct ones
- RSS for wrong predictions slightly lower (on average) than the correct ones
- 92% occured on October 4, 2013 Building shape, physical interf., floor usage

Prediction model - Floor 4/4



Metrics: KNN

Accuracy (%)	Kappa (m)
95,11%	0,93

Errors: possible causes

- Total 13 errors, mainly in the 2° and 5° floor (respectively 4 and 5)
- Predicted one floor above or below
- N° of active WAPs for wrong predictions lower (on average) than the correct ones
- 92% occured on October 4, 2013
- Occured in a corner

Prediction model - Latitude

Pre-process

- Transform RSS values in the range [-30;100] and [-104;-80] in -106 → no signal
- Delete rows and columns with variance = 0
- Row normalization
- Make sure that the Training set has the same columns as the Validation set
- Variables employed in the model: WAPs, BuildingID, Latitude

	R2 (%)	MAE (m)
KNN	98,74%	5,04
RF	98,22%	6,53
SVM	94,90%	11,76

The model can predict the latitude localization quite accurately: it may differ from the exact one by a maximum of 5,04 meters

Prediction model - Longitude

Pre-process

- Transform RSS values in the range [-30;100] and [-104;-80] in -106 → no signal
- Delete rows and columns with variance = 0
- Row normalization
- Make sure that the Training set has the same columns as the Validation set
- Variables employed in the model: WAPs, BuildingID, Longitude

	R2 (%)	MAE (m)
KNN	99,42%	5,49
RF	99,43%	6,78
SVM	98,10%	11,90

The model can predict the longitude localization quite accurately: it may differ from the exact one by a maximum of 5,49 meters

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Main findings and recommendations

GOALS

- **Assess** the **accuracy of WiFi fingerprint** as indoor localization technique
- **Advise** our **client on the feasibility to incorporate the WiFi fingerprint system into a smartphone app** for indoor localization

FINDINGS	RECOMMENDATIONS
On average, the nr of active WAPs and their RSS levels were lower in the wrong predictions	Avoid changing WAPs position; if it is needed, make sure the new position still guarantees a good connection coverage
The shape of the building and its intended use can interfere with the level and the speed of the WiFi connection	For big spaces with larger walls and floors the use of Powerline adaptors is advised
Physical objects as well as construction materials can be an obstacle for the wireless communication	Consider to use of materials like wood and glass (e.g. for furniture) and avoid metal and cement
WAPs position is important to guarantee a great, uniform connection	The best position for access points is in the middle of rooms, along corridors, in an elevated position

Q&A: Time for questions

Thanks for your attention

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