Indoor Positioning via Wi-Fi Fingerprinting

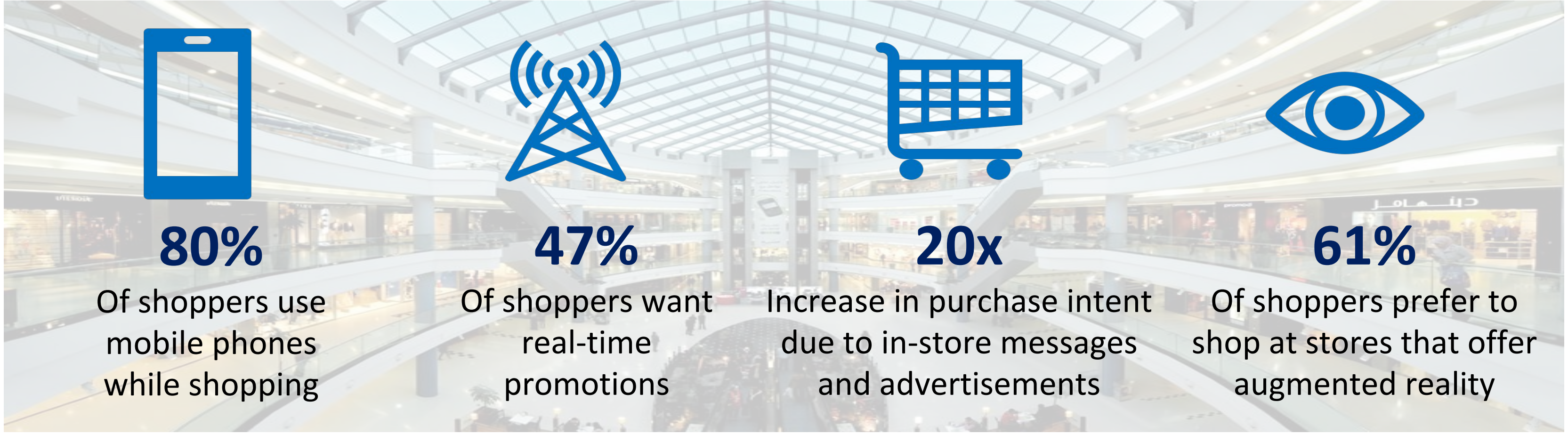
IOT ANALYTICS

Agenda

- Location Intelligence & Analytics
- Project Introduction and Goals
- Data Security & Management
- The Dataset
- Dataset Challenges
- Algorithms & Model Parameters
- Model Comparisons
- Indoor Positioning Systems Compared
- Recommendations / Next Steps

Location Intelligence & Analytics

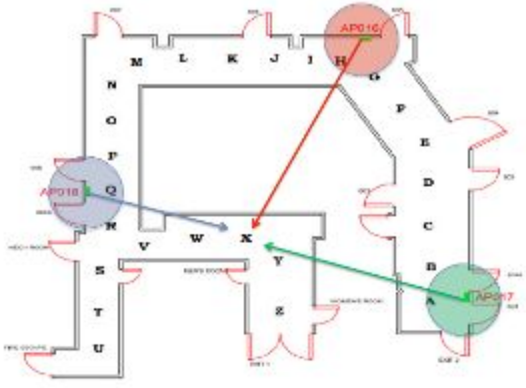
- WAPs (wireless access points) - the enabling technology that facilitates the connectivity of smart devices to a WiFi network
  - Eg. Network of WAPS in a mall facilitates the tracking of smartphones as a customer moves
- The aggregation of tracking data creates a digital footprint known (footfall traffic patterns) - businesses can analyze to gain useful insight into customer traffic patterns and behavior



Project Goals

Client Request: Investigate the feasibility of determining indoor location on large industrial sites using WiFi fingerprinting.

What We Did: Analyzed the data and evaluated the application of various machine learning algorithms to determine if a model could be constructed that would achieve the desired accuracy.



What We Found: We were able to construct a model that predicts indoor location with 90% or greater accuracy. However, other methods may be more accurate and already in production.

Data Security & Management

At IOT we use a combination of the NIST cyber-security framework and IT best practices to manage and protect data.

1. **Identify** - Data, hardware, & software
2. **Protect** - Proper measures to protect data
3. **Detect** - Ability to detect anomalies and cyber-attacks
4. **Response** - Respond to attacks based on policies and tools in place
5. **Recover** - Recover affected areas and return to service promptly

The Dataset

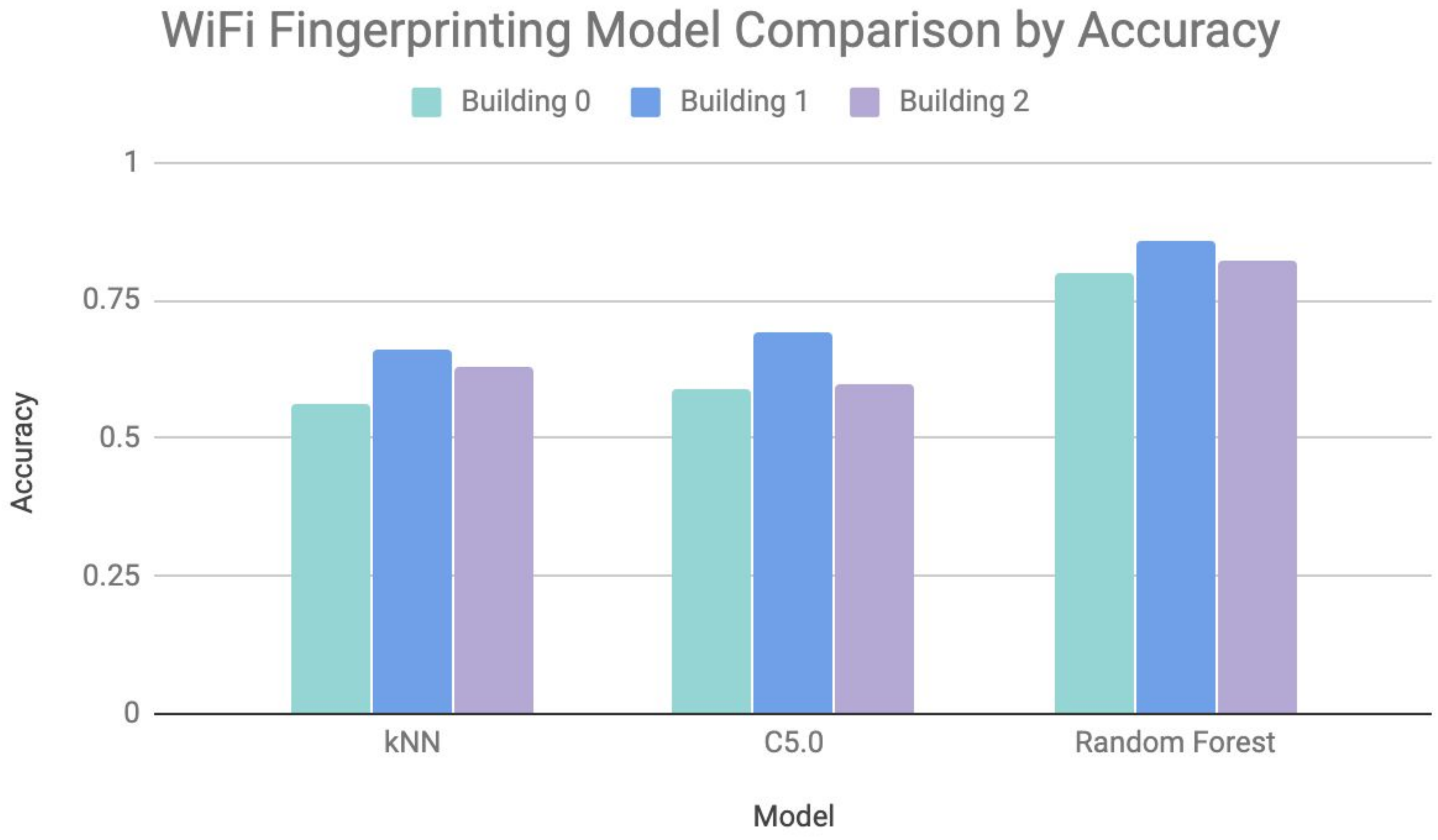
- Covers 3 Buildings of the Universitat Jaume I in Castellón, Spain with 4 or more floors (almost 110k square meters)
- Created in 2013 by more than 20 different users and 25 android devices
- Approximately 20k observations of 529 attributes that captured:
  - WiFi fingerprints - Received Signal Strength Intensity (RSSI) corresponding to each detected Wireless Access Point (WAP)
  - Latitude and longitude
  - Building, floor, and relative space
  - User and timestamp information

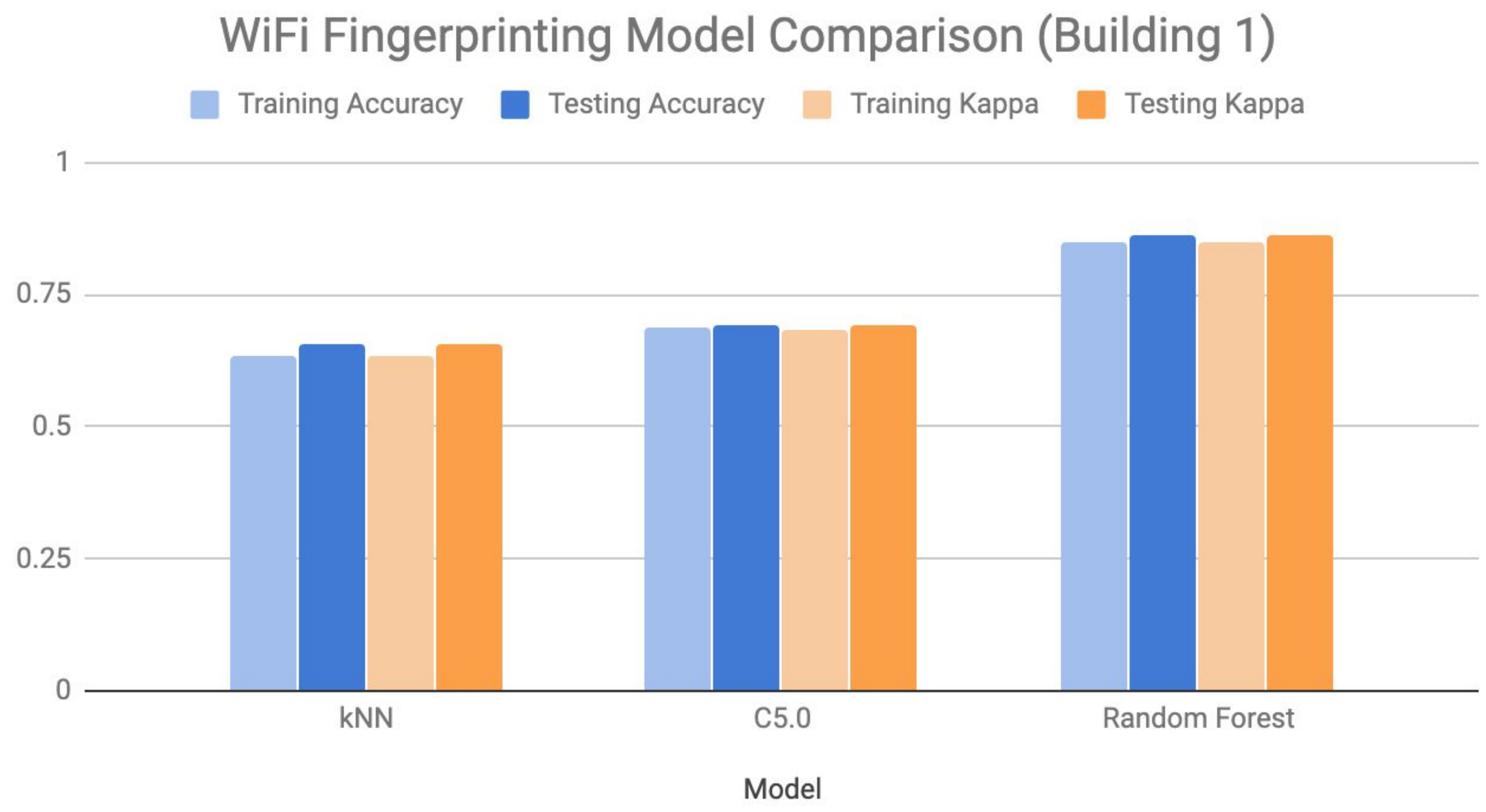
Dataset Challenges

- Number of Features
  - <u>Solution</u>: Eliminate the features that are not useful for predicting the indoor location i.e. Longitude, Latitude, User ID, Phone ID, and Timestamp
- Feature Variance
  - <u>Solution</u>: Identify and remove features with zero variance
- Dependent variable
  - <u>Solution</u>: Create one dependent variable that is a combination of Building, Floor, Space ID, and Relative Position
- Size
  - <u>Solution</u>: Eliminate irrelevant classes in the dependant variable and lower computational cost by dividing the dataset using building ID

Algorithms & Model Parameters

- Each building dataset was partitioned into training/testing datasets using a 75/25 ratio
- A set seed of 123 was used prior to running each model
- The following three classification algorithms were selected:
  - knn: k- Nearest Neighbors (tuning parameter = k)
  - C5.0: C5.0 (tuning parameter = trials, model, winnow)
  - RF: Random Forest (tuning parameter = mtry)
- 10 fold Cross-validation with repeats set to 1 was applied for all the models
- Models were autotuned with Tunelength limited to 5


WiFi Fingerprinting Model Comparison by Accuracy
Building 0
Building 1
Building 2
1
0.75
0.5
0.25
0
Accuracy
kNN
C5.0
Random Forest
Model


WiFi Fingerprinting Model Comparison (Building 1)
Training Accuracy
Testing Accuracy
Training Kappa
Testing Kappa
1
0.75
0.5
0.25
0
kNN
C5.0
Random Forest
Model

Indoor Positioning Systems Compared

ACCURACY / COST →

	Bluetooth	Magnetic Positioning	WiFi Fingerprinting	Acoustics	Visible Light	Ultra Wide Band (UWB)
Pros	- High reception range - Low energy use	- High accuracy - Low cost	- High accuracy - Widely available - Low cost	- Very high accuracy	- Very high room-level accuracy	- Very high accuracy - Immune to interference
Cons	- Low accuracy - Prone to noise	- Local magnetic field is affected by moving metal objects (eg. elevators)	- Prone to noise - Requires complex processing algorithms	- Affected by sound pollution - Requires addtl. Hardware - Expensive to retrofit	- High power consumption - Expensive to retrofit - Does not work well for large open spaces (eg. shopping malls)	- Very high cost - Shorter range - Requires addtl. hardware

Recommendations / Next Steps

- WiFi Fingerprinting strikes a balance between costs and location accuracy for initial location analytics investment
  - Assumes similar building types and accuracy needs across projects
  - Ensure consistent data collection standards in order to see similar results and maintain accuracy
- Existing app Anyplace - free, highly accurate WiFi fingerprinting app
- Best solution is likely a hybrid of WiFi Fingerprinting and MEMS sensors - combines location with direction
- Also recommend deployment of WiFi analytic applications such as Purple and Aisle 411 to monetize acquired WAPS data