

Locating Phones Indoors with WiFi Fingerprint

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Agenda

Background

Modelling

- Model Building

- Model Performance

Conclusion

Background

- ▶ Mission: Locate device by its WiFi fingerprint
- ▶ Area to cover:
 - ▶ Three buildings of Universitat Jaume I with 4 or more floors and almost 110.000 m²
 - ▶ More than 20 different users and 25 Android devices, with widely varying signal strengths
 - ▶ Area covered by 520 different WiFi access-points



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Data Processing

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- ▶ No scaling was done as all the models used were tree based
- ▶ Outlier dropping was tried, but this led to worse performance, so all observations were kept in the analysis

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 3. Lastly the just predictions from the second layer were given to a last layer of 4 models that made the final prediction

Model Evaluation

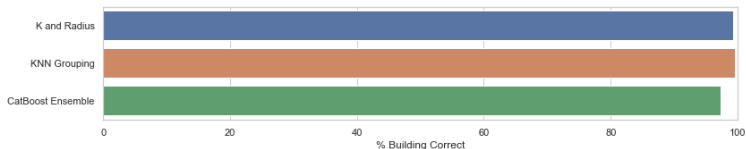
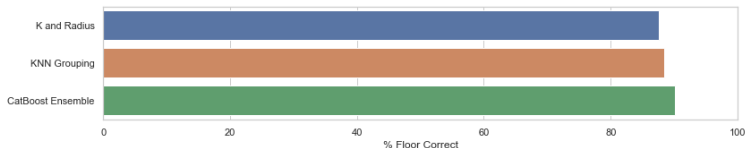
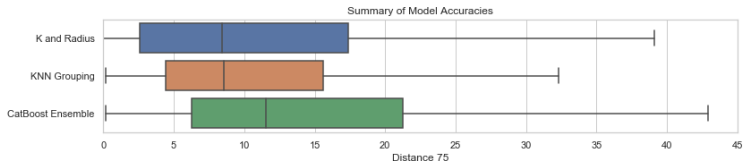
Models were evaluated by a single scoring metrics named Distance 75 that combines all the 4 target values. This metric calculates the manhattan distance between prediction and actual values in 3D space and adds an additional penalty for getting the building wrong:

Distance75 =

$$\begin{aligned} & \frac{1}{n} * \sum_{n=1}^n (|longitude_{predicted} - longitude_{actual}| \\ & + |latitude_{predicted} - latitude_{actual}| \\ & + 4 * |floor\ number_{predicted} - floor\ number_{actual}| \\ & + 50 * |building\ number_{predicted} - building\ number_{actual}|) \end{aligned} \quad (1)$$

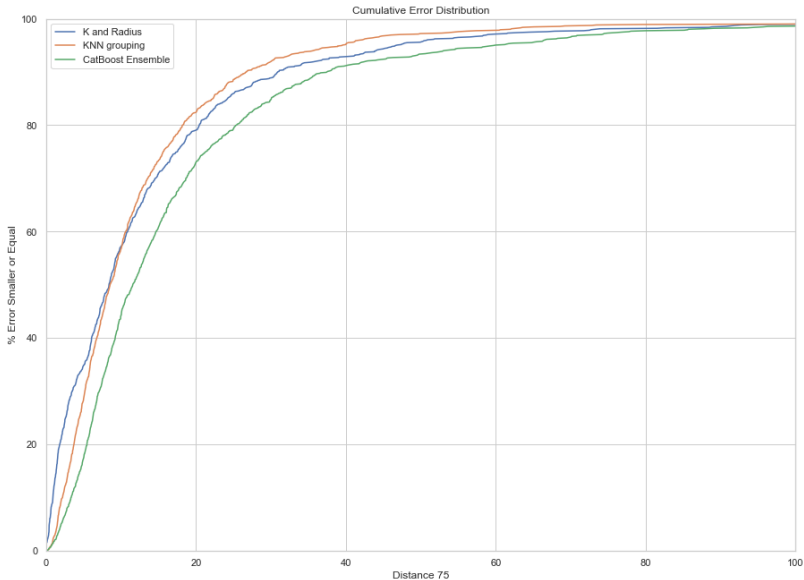
Overall Performance

- ▶ KNN models perform clearly much better than CatBoost
- ▶ Building is easy to predict, but floor is not



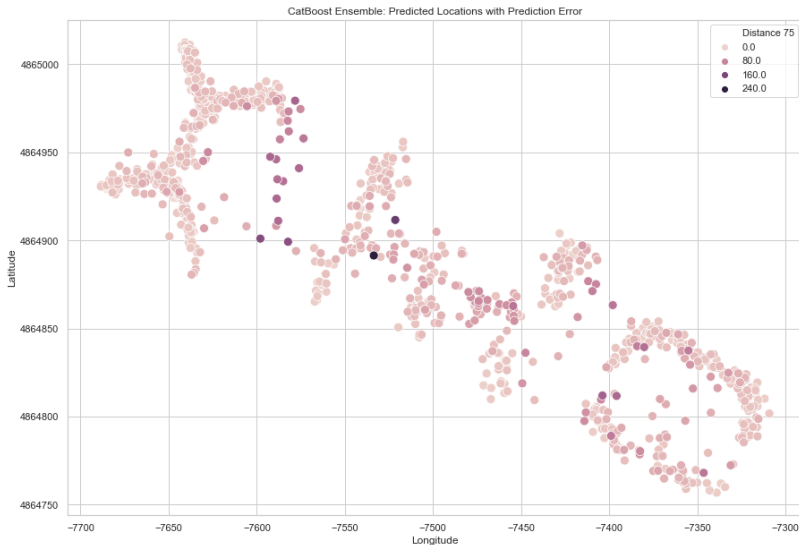
Error distribution

- K and radius model has a fatter tail than KNN grouping in errors



KNN models vs. CatBoost

- CatBoost makes predictions that are outside the buildings



KNN models vs. CatBoost

- KNN keeps to already observed values and makes no stupid errors



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4. If we have identifiers for unique locations (e.g. rooms and hallways) in the final training data, then KNN model with grouping is the best choice. It is also smaller than normal KNN model (less points to consider) by an order or magnitude and so much faster with its predictions
5. If the final training data does not have identifiers for unique locations or we get more training data in the future that does not have these labels, then K and radius model is the best choice

The End

Questions?