Floor Localization

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Introduction

Location services are one of the most used applications today on smartphones and devices. In emergencies, accurate and fast localization proves to be of vital importance to pinpoint the location of the person in distress. We focused on the indoor floor localization problem where the target is to determine the floor that the user is currently in inside a building. While GPS proved as a powerful means for localization, it has some shortcomings such as battery consumption and poor indoors accuracy. Some effort in the localization domain have been put into exploiting cellular networks to create low-cost-low-overhead localization systems. Using Here, We present a GSM fingerprinting-based floor localization system that has virtually no setup cost using deep neural networks. Our work serves as an extension to [4]

Approach

Our work uses a fingerprinting approach which is divided into two phases

- Offline phase: A fingerprint for the building of interest is constructed by collecting samples onsite from the different floors of the building. This data is then used to train a model to predict the floor from which a sample was picked up. Samples collected contain the received signal strength received (RSS) by the phones used in collection from all cell towers detected in the area. These samples are labelled with the floor number they were picked from and undergo pre-processing before being used in constructing the model.
- Online phase: The trained model is deployed and is given unlabeled samples and outputs the predicted floor for each given sample.

The problem is modelled a classification problem where the input is a sample s represented as a vector $(s_1, s_2, \ldots s_q)$ where each si represents the RSS picked up in this sample from tower i for all q towers detected in the are. The output f represents the floor number from which a sample was collected and our target is to produce floor predictions for samples collected in the online phase.

Dataset

Due to the lack of proper datasets, we decided to collect our own by selecting a building on campus and collecting RSS samples using a set of phones. The process of collection involves starting an RSS logging app that can scan access the cellular API of the phone and produce RSS logs in a file. These logs are then tagged with the floor they were tagged from and processed to generate our training and test datasets. The data we collected was from the Electrical Engineering building in the Faculty of Engineering, Alexandria University which has 6 floors. Five different phones on two carriers were used in the collection process. Collected data undergoes the same pre-processing mentioned in [2] to produce RSS vectors used in training during the offline phase and for testing in the online phase .

Models

Several models were constructed in an effort to find a suitable architecture for the problem. The first architecture we experimented on was a simple fully connected network.

We then re-formalized our problem as sequence model, where the a sequence of subsequent samples used to estimate the user's floor instead of just one. The motive was to leverage potential information in the user's history to produce more accurate predictions. We experimented with several time series convolutional neural network (CNN) architectures. Architectures we experimented with include:

1. Time series CNN model that we constructed
2. SeriesNet [3] which is time series forecasting model that we adapted for our use. It is constructed as a dilated causal CNN based on the WaveNet architecture. We adapted this model for our purposes and modified it to function as a classifier
3. Inception Time [1] which is a time series architecture resembling the Inception network.
4. 1D variant of the ResNet architecture.

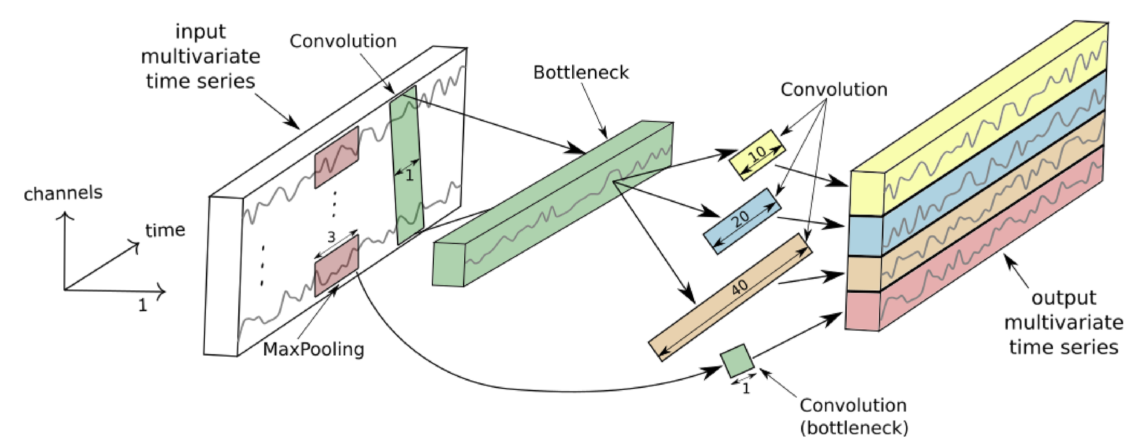

Fig. 1: Inception Time building block

Results

For evaluation, we tested our models against the SkyLoc system[4] from literature. We start by evaluating our models against homogeneous datasets, i.e datasets train and test data are both sampled from the same collection/distribution (Either from the data of one mobile phone or from a shuffled collection from several phones). Accuracies of SkyLoc and the FC architecture are shown in the following table.

Dataset	SkyLoc	FC
HTC X9	100	99.8
Moto G5	100	99.8
Oneplus 6	100	100
Combined Dataset	99.9	99.8

Table 1: Accuracy of SkyLoc and FC models under homogeneous datasets from different devices

We then proceeded to experiment with heterogeneous datasets where train and test data are collected from different phones. We used a "leave on out" approach where we train our model using data from all phones except one, and use unseen data from that remaining phone for validation and test.Results are summarized in Table 2 and the plot in Figure 2 showing within-k-floors accuracy at different values of k.

Within-k-floors	SkyLoc	FC	CNN	SeriesNet	Inception	ResNet
0	34.6	43.8	50.2	44.4	47.8	50.2
1	63.3	67.8	79.3	76.7	80.7	78.6
2	79.4	88.9	93.8	92.7	96.1	93.5
3	93.2	95.9	96.4	96.2	99.2	96.5
4	99.1	99	98.3	98.9	99.7	99.5

Table 2: Within-k-floors accuracy of different models under heteregenous datasets

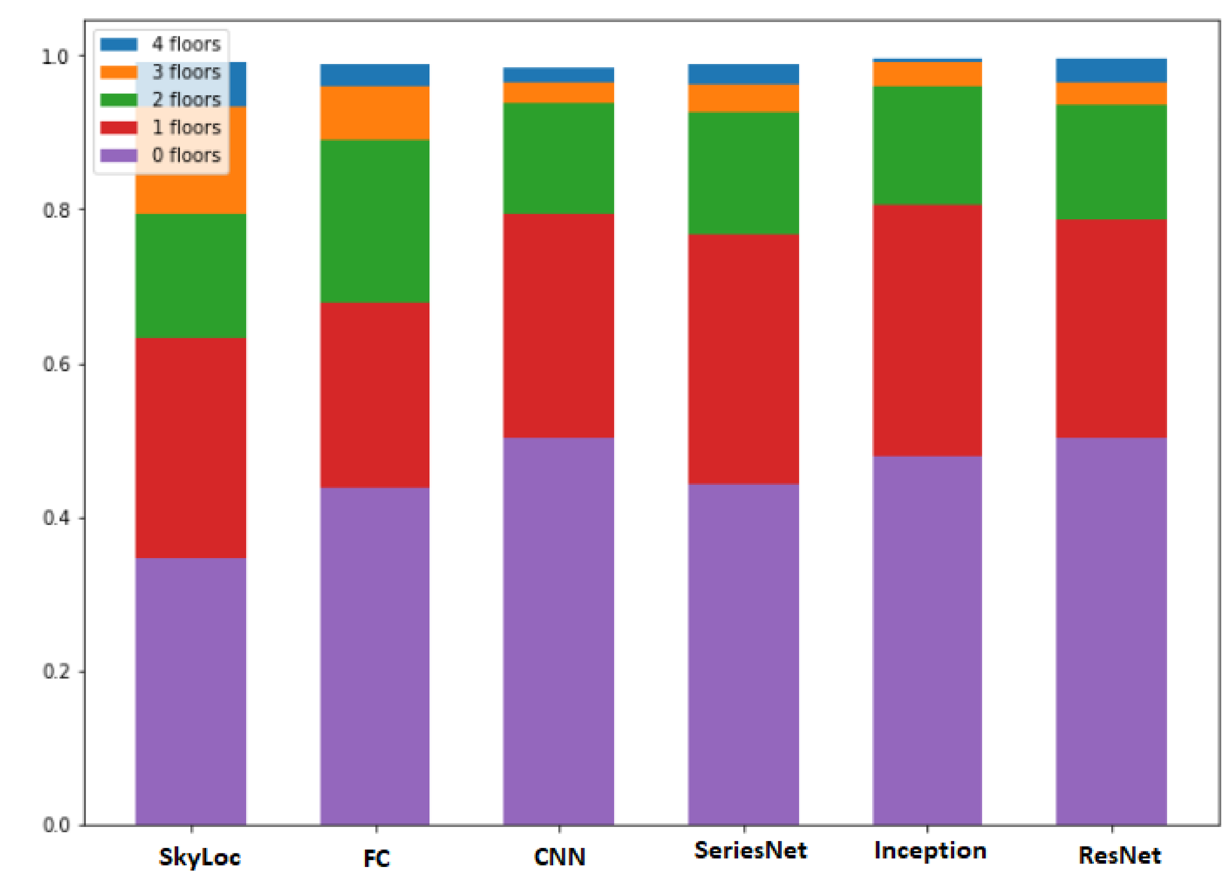

Fig. 2: Plot of within-k-floors accuracy of different models under heteregenous datasets

Future Work

We have recently collected more data from the same building as well as from another building (Administration building in the Faculty of Engineering). We aim to use this data to further investigate the behavior of scanned RSS samples and generate more insights to help us produce better-performing models.

References

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[3] Z. Shen et al. "SeriesNet:A Generative Time Series Forecasting Model". In: *2018 International Joint Conference on Neural Networks (IJCNN)*. 2018, pp. 1–8.

[4] Alexander Varshavsky et al. "The SkyLoc Floor Localization System". In: Jan. 2007, pp. 125–134. DOI: 10.1109/PERCOM.2007.37.