

**Bachelor's thesis**

# **Machine Learning-based User Movement Prediction in Layer 2 Networks**

**Vorhersage von Benutzerbewegungen in Layer 2 Netzwerken basierend auf  
Maschinellem Lernen**

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## **Abstract**

- human movement not considered when roaming of mobile devices appears
- could lead to many unnecessary handovers and thus to bad performance
- this thesis proposes a machine learning-based approach to predict the Access Point (AP) a user will be nearest to based on the Received Signal Strength Indication (RSSI) of the APs
- the chosen machine learning model is Long Short-Term Memory (LSTM) and is trained on real-world data from a dataset of a competition by Microsoft Research
- the dataset analysis showed that interpolation is necessary to ensure that Wireless Fidelity (Wi-Fi) and waypoint data together are used in the prediction
- many APs are deployed in the buildings of the dataset, which makes the prediction task hard
- one building and one floor were chosen to be the dataset for this thesis
- the evaluation of the model shows that the mode predicts the AP a user is nearest to with a top 3 accuracy of about 71%
- too many classes, which makes prediction too hard and top 3 accuracies too low
- with fewer classes, the model could predict better
- in the future, data explicitly generated for this purpose could be used to predict the top k access points so that the location of the access points is known and can be considered in prediction



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# 1 Introduction

In large-scale Wi-Fi environments such as office buildings, shopping malls, and airports, where multiple APs are required, people often move around indoors with their mobile devices. To maintain a stable connection to the Service Set Identifier (SSID), the station must remain in the range of the AP or may roam to another AP with the same SSID. However, the current roaming process in 802.11k/r[8][7] does not consider human movement. For example, if a user's station is moving away from AP<sub>1</sub> towards AP<sub>2</sub> and further towards AP<sub>3</sub>. AP<sub>3</sub> does not initiate the roaming process, but instead the station will connect to AP<sub>2</sub> first and then to AP<sub>3</sub>, which increases the number of handovers. It would be ideal if the movement from AP<sub>1</sub> to AP<sub>3</sub> was detected and a roam from AP<sub>1</sub> to AP<sub>3</sub> was initiated. An AP may instruct a client device to roam based on signal strength, but currently without considering the device's trajectory or the user's likely destination. Real time applications such as video conferencing are particularly sensitive to these hand-offs, which may result in dropped connections and unsatisfied users.

Therefore, this thesis will explore if a time series Machine Learning (ML) model can predict the nearest AP a station may connect to next. Because of the many APs in large-scale Wi-Fi environments, this prediction is a multi-class classification problem with many classes, how many exactly will be discovered in Chapter 3. This leads to a hard prediction task, as the model needs to predict the next AP out of many APs. To make the prediction task easier, the model will predict the top 3 APs the station may connect to next. So the nearest station needs to be in the top 3 of the predictions to be considered a correct prediction.

A time series ML model requires time series data as input. There are two possible data sources: generate new or utilize existing data. Data generation needs a comprehensive plan for accounting data setup and collection. As this process is time-consuming and needs a lot of planning and evaluation beforehand, this thesis will not generate data. Thus, this thesis will use a pre-existing dataset with sensor data such as acceleration, waypoint data and Wi-Fi data from large-scale environments. The only dataset which I found with these requirements is from a 2021 competition by Microsoft Research [9] on kaggle [13]. The data will be analyzed in Chapter 3 to determine what parts of the data I will use for the ML model.

After that, I will discuss the suitability of some pre-selected time series ML models for the task in Chapter 4. Because of findings in Chapter 3, this thesis will preprocess the data and implement the LSTM model for one site and floor of the competition in Chapter 5. Finally, in Chapter 6, I will evaluate the model's performance and, in Chapter 7, conclude if this prediction could be useful in the future.





## 2 Background

### 2.1 Machine Learning

#### 2.1.1 Classification

Classification ML models predict specific categories or classes for input data. By training on input features and labels, these models categorize unseen data. They find use in many domains, producing outputs such as spam or not spam, positive or negative sentiment, and malignant or benign tumors. A specific type of classification is multi-class classification which categorizes more than two classes. [1, pp.179-182] In this thesis, a chosen classification model will predict the next AP a user will be nearest to based on the RSSI of the APs and the trajectory of the user.

#### 2.1.2 Time Series Prediction

Time series prediction is a type of supervised learning problem where a model is trained on a sequence of observations and learns to predict the next value in the sequence. Those sequences consist of data points arranged chronologically, prevalent in numerous domains like stock prices. Due to its inherent temporal dependencies, where subsequent data points influence previous ones, specific machine learning techniques are applied. These include Multilayer Perceptron (MLP), Hidden Markov Model (HMM), and Recurrent Neural Network (RNN) models such as LSTM. Each model is designed to capture and leverage temporal patterns within the data, predicting future trends based on historical observations. [16]

#### 2.1.3 Univariate and Multivariate Time Series

A time series is univariate, if one observation recorded sequentially over time, e.g., temperature or stock prices. The focus of using ML is to understand and forecast a single variable's behavior. In the dataset observed in this thesis, has more than just one value which is recorded sequentially over time such as RSSI, waypoint and sensor data. Therefore, the dataset has multiple observations were recorded over the same time intervals, ML allows for the analysis of interrelationships and interdependencies between these variables, e.g., temperature, humidity, uv-index and wind speed. The focus here is on delving into understanding dynamic interactions and co-movements between multiple variables

#### **2.1.4 Multilayer Perceptron**

MLP, also known as a feedforward artificial neural network, is a class of deep learning models primarily used for supervised learning tasks. An MLP consists of multiple layers of nodes in a directed graph, each fully connected to the next one. Each node in one layer is connected with certain weights to every node in the following layer. MLPs apply a series of transformations, typically nonlinear, to the input data using activation functions, such as the sigmoid or Rectified Linear Unit (ReLU), facilitating the model's ability to model complex patterns and dependencies in the data [5].

#### **2.1.5 Hidden Markov Model**

HMM is a statistical model that assumes the system being modeled is a Markov process with unobserved (hidden) states[21]. HMMs are mainly known for their application in temporal pattern recognition, such as speech and handwriting. They describe the probability of a sequence of observable data, which is assumed to result from a sequence of hidden states, each producing an observable output according to a particular probability distribution.

#### **2.1.6 Recurrent Neural Networks**

RNN is an artificial neural network well-suited to sequential data because of its intrinsic design. Unlike traditional feedforward neural networks, an RNN possesses loops in its topology, allowing information to persist over time. This unique characteristic enables the model to use its internal state (memory) to process sequences of inputs, making it ideally suited for tasks involving sequential data such as speech recognition, language modeling, and time series prediction[4].

##### **2.1.6.1 Long Short-Term Memory**

LSTM is a special kind of RNN, capable of learning long-term dependencies, which Hochreiter and Schmidhuber introduced in 1997[6]. LSTMs were designed to combat the "vanishing gradient" problem in traditional RNNs. This problem made it difficult for other neural networks to learn from data where relevant events occurred with significant gaps between them. The key to the ability of the LSTMs is its cell state and the accompanying gates (input, forget, and output gate), which regulate the flow of information in the network.

#### **2.1.7 Hyperparameter tuning**

In machine learning, hyperparameters play a vital role in model development. These are parameters such as the learning rate, neural network layers, and the number of windows or batch sizes. Proper selection of hyperparameters, known as hyperparameter tuning or optimization, is crucial to optimize model performance. This iterative procedure involves exploring various hyperparameter combinations for the configuration that yields the most accurate predictions. Hyperparameters can be tuned by, e.g., random search, which can

be done manually or using libraries. This thesis will use keras-tuner[18] to tune the hyperparameters of the LSTM model.

## 2.2 Related Work

Montavont et al. [17] propose a handover decision algorithm based on the Global Positioning System (GPS) location of the mobile device. Khan et al. [15] address the problem of handover prediction and AP selection in dense Wi-Fi networks with Software Defined Networking (SDN). They use ML models such as Support Vector Regression (SVR) and MLP for estimating the throughput of the network to. The predictions outperform the current approaches of strongest received signal first by 9.2% and least loaded signal first by 8%.

Both approaches do not consider the trajectory of the mobile device in the handover or AP selection. Furthermore, in large-scale and dense Wi-Fi environments, GPS may not be available or not accurate enough for indoor trajectories. While Khan et al. focuses on using ML for throughput estimation of the network and accordingly choose the best AP to roam to, they do not consider the trajectory of the mobile device in the AP selection or use ML for the AP selection process directly. Lastly, these approaches do not use user generated data, but synthesized data.

This thesis however will use user generated data, instead of synthesized, and will use ML to predict the next AP a user will be nearest to based on the RSSI of the APs and the trajectory of the user. The prediction will be difficult, because we do not know the location of the APs, and factors such as walls and other obstacles may influence the RSSI. Additionally, there is no information about the throughput or load an access point has, so the predictions cannot be use this information.

These predictions can be used to improve the handover process in Wi-Fi networks initiated by a mobile device, because the predictions use real-world user generated data. This thesis has a different approach, so the results of this thesis cannot be compared to the related work.



## 3 Dataset analysis and preparation

As mentioned in Chapter 1, the dataset used in this thesis is the Indoor Location & Navigation from kaggle [13], which was part of a competition of Microsoft Research in 2021 [9]. The company XYZ<sup>10</sup> recorded the data in shopping malls and was provided by Microsoft Research for this competition. The goal for the competition was to give a file with a path of a shopping mall and predict the floor and waypoint locations at a timestamp given in the submission files for that shopping mall. The following will analyze and prepare the dataset and data for the ML model.

### 3.1 Components of the dataset

As noted in the kaggle notebook “Indoor Navigation: Complete Data Understanding” [11] the data consists of 3 parts:

- a train folder with train path files, organized by site and floor
- a test folder with test path files, organized by site and floor but without waypoint data
- a metadata folder with floor metadata, organized by site and floor, which includes floor images, further information, and a geojson map

The train folder contains 204 subfolders representing each site where the data was recorded. In each site folder are a minimum of one and a maximum of twelve subfolders, which represent the floors of the site; the median is five floors. Overall, there are 26,925 files, each containing the movement of one person for a specific site and floor. Per floor, there are between one and 284 files with a median of 14. The floor F1 of the site 银泰城(城西店) (Yintai City (Chengxi Branch)) which was hashed as “5d27075f03f801723c2e360f” in the train folder of the competition, has the most files.

For this thesis, the submission files and the test folder will not be used. Instead, we will generate our test set out of the train data because our goal is not to predict the floor and site name for a specific timestamp but to predict the Basic Service Set Identifier (BSSID) to which a device may connect next, which is an entirely different task. Therefore, we will not analyze the content of the test and metadata folders in detail.

### 3.2 File structure

Each file in each floor folder is a `.txt` file. The first two lines and the last are denoted with “#”. The first contains the start time of the recording, the second site information SiteID as hash, SiteName, FloorId as hash, and FloorName. The last line contains the end time of the recording. The main part of the data consists of the collected data. Each line contains

a UNIX timestamp in milliseconds, followed by a data type and the data itself, which are all separated by a tabulator. The GitHub repository of the competition [10] shows that the data type in the second column followed by its data can be one of the following:

- (1) TYPE\_ACCELEROMETER with x, y and z acceleration and an accuracy value
- (2) TYPE\_MAGNETIC\_FIELD with x, y and z magnetic field and an accuracy value
- (3) TYPE\_GYROSCOPE with x, y and z gyroscope and an accuracy value
- (4) TYPE\_ROTATION\_VECTOR with x, y and z rotation vector and an accuracy value
- (5) TYPE\_MAGNETIC\_FIELD\_UNCALIBRATED with x, y and z magnetic field and an accuracy value
- (6) TYPE\_GYROSCOPE\_UNCALIBRATED with x, y and z gyroscope and an accuracy value
- (7) TYPE\_ACCELEROMETER\_UNCALIBRATED with x, y and z acceleration and an accuracy value
- (8) TYPE\_WIFI with SSID, BSSID, RSSI, frequency, and last seen timestamp of the access point. The SSID and BSSID are hashed.
- (9) TYPE\_BEACON with Universally Unique Identifier (UUID), Major Identifier (MajorID), Minor Identifier (MinorID), Transmission Power (TxPower), RSSI, distance to the device measured by the beacon, Media Access Control (MAC) address and a timestamp as padding data. The MajorID and MinorID are hashed.
- (10) TYPE\_WAYPOINT with x and y coordinates which are the ground truth location labeled by the surveyor

**Listing 3.1:** A snippet from the dataset of the file 5daa9e38df065a00069be79.txt of the floor F4

```
#   startTime:1571462193934
#   SiteID:5d27099303f801723c32364d SiteName:银泰百货(庆春
    店) FloorId:5d27099303f801723c323650 FloorName:4F
1571462193944   TYPE_WAYPOINT   57.885998   69.501526
1571462194071   TYPE_ACCELEROMETER   -0.95254517   0.7944031   8.928757   2
1571462194071   TYPE_MAGNETIC_FIELD   -25.65918   -4.4784546   -28.201294   3
1571462194071   TYPE_GYROSCOPE   -0.22373962   -0.07733154   -0.16847229   3
1571462194071   TYPE_ROTATION_VECTOR   0.04186145   -0.02101801   -0.72491926   3
1571462194071   TYPE_MAGNETIC_FIELD_UNCALIBRATED   -4.8568726   10.406494   -387.44965   20.802307
    14.884949   -359.24835   3
1571462194071   TYPE_GYROSCOPE_UNCALIBRATED   -0.22218323   -0.068359375   -0.1628418   0.0026245117
    9.765625E-4   -7.6293945E-4   3
1571462194071   TYPE_ACCELEROMETER_UNCALIBRATED   -0.95254517   0.7944031   8.928757   0.0 0.0 0.0 3
...
1571462194883   TYPE_WIFI   b06c4e327882fab58dfa93ea85ca373a54e887b5   9
    f967858afccb907af6e5adef766c7e7b936ef07   -63 2462   1571462190744
1571462194883   TYPE_WIFI   8204870beb9d02995dab3f08aad97af5eab723cc   0413
    b35df78fc865af15b4721d5aeb33ff57da45   -64 2447   1571462188686
...
1571462194020   TYPE_BEACON   07efd69e3167537492f0ead89fb2779633b04949
    b6589fc6ab0dc82cf12099d1c2d40ab994e8410c   76e907e391ad1856762f70538b0fd13111ba68cd   -57 -71
    5.002991815535578   1b7e1594febd760b00f1a7984e470867616cee4e   1571462194020
...
1571462195943   TYPE_WAYPOINT   59.72475   69.02152
#   endTime:1571462195976
```

Each file contains a different amount of waypoints and sensor data. The first and last data type in each file is a (10). Lines with types from (1) to (7) occur every 20 ms and are measured at the same time. (8) occurs about every 1800-2200 ms. (10) data is not evenly distributed. An assumption for this is that the recording of the waypoint data is triggered by an exterior event, e.g., a button press. As seen in Listing 3.1, the data are measured separately from each other, so there are no combinations of the data types.

A prediction of the next BSSID will only work per site due to the different APs and therefore, BSSIDs per site. Still, the prediction could be difficult for a whole site because the APs are different on each floor, which may result in many APs for the prediction. To better predict, we will focus on a single floor of a site, and use the data from the fourth floor of the shopping mall in Yintai City (Chengxi Branch). To further know, how many data we have for the model, Table 3.1 shows a more detailed analysis.

**Table 3.1:** Summary of data for F1 of site Yintai City (Chengxi Branch)

Information	Value
Total data points	7,157,081
Average data points per file	25,201
Number of waypoints	2,027
Lines of each (1) to (7) data	746,689
Lines of Wi-Fi data	1,862,044
Lines of beacon data	66,187
Number of BSSIDs	4,795
Number of APs	4,795
Number of SSIDs	1,421
RSSI range	-93 to -13 dBm

### 3.3 Preprocessing data for an ML model

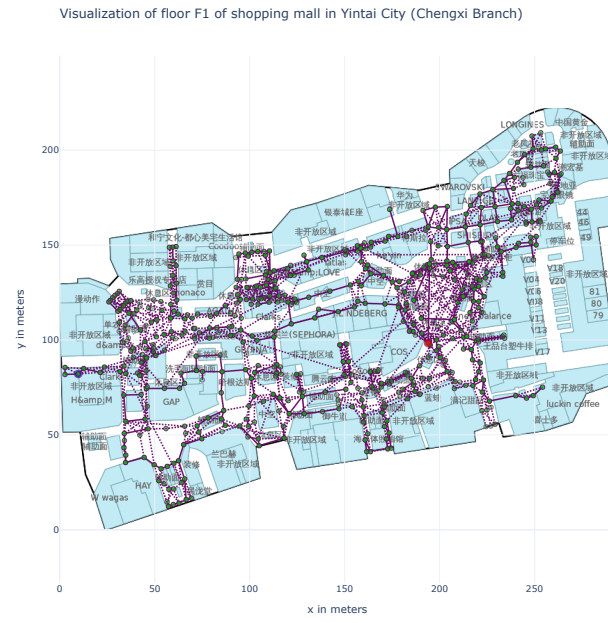
As seen in previous sections, a location for the time of TYPE\_WIFI data points is not provided. Also, we have 2,027 waypoints for this floor but 1,862,044 lines of Wi-Fi data, as seen in Table 3.1. The visualization of the waypoints can be seen in Figure 3.1.

Further human movement may have occurred between TYPE\_WAYPOINT and TYPE\_WIFI data points. Therefore, we cannot combine the data points directly, in order to get a location for the Wi-Fi data points. But, they can be combined using linear interpolation.

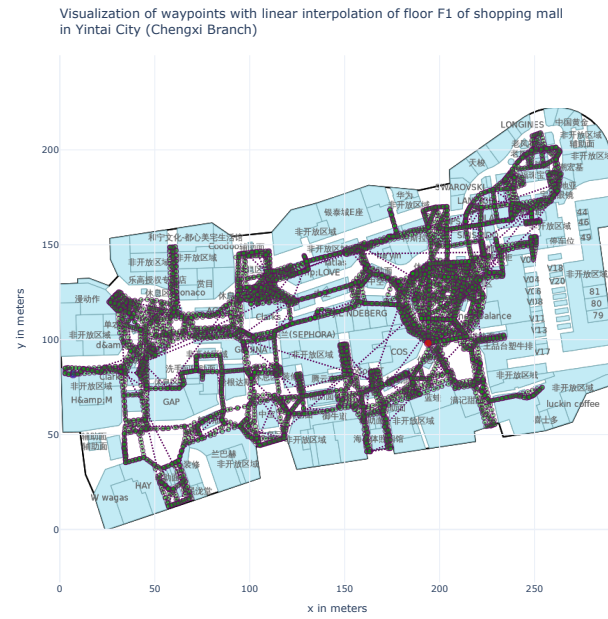
Therefore, an interpolation of TYPE\_WAYPOINT data for TYPE\_WIFI timestamps will be done, in order to get a location for the Wi-Fi. With this interpolation, we have a combination of TYPE\_WAYPOINT and TYPE\_WIFI data as well as more data, we could use for the prediction. The interpolation results in 6549 waypoints which is three times more than the original amount of waypoints, as seen in Figure 3.2.

Furthermore, we will also interpolate TYPE\_ACCELEROMETER data for TYPE\_WIFI timestamps because, if the timestamps do not match for TYPE\_WIFI and TYPE\_ACCELEROMETER we will interpolate for a small time range, which may not change the acceleration values significantly and may result in a more accurate prediction. Now we have a multivariate

### 3 Dataset analysis and preparation



**Figure 3.1:** Visualization of the 2,027 waypoints of the site Yintai City (Chengxi Branch) on floor F1



**Figure 3.2:** Visualization of the interpolated waypoints for site Yintai City (Chengxi Branch) on floor F1



time series with TYPE\_WAYPOINT and TYPE\_ACCELEROMETER data for TYPE\_WIFI timestamps out of the original data as one file, which will be used for the machine learning model. A further interpolation of the other data such as TYPE\_GYROSCOPE is possible, but this thesis only utilizes the data mentioned above.

### 3.3.1 Peculiarities of the data

The analysis of the dataset revealed some peculiarities, which are described in the following.

The data is collected by different devices at different timestamps and days. A problem for the time series is that the waypoint data were measured irregularly. As in Figure 3.1 shows, some waypoints seem to be very distant from the next one, which can be detected by the dotted lines which go all across the floor. Listing 3.2 shows the top 10 pairs of waypoints with the most significant metric differences, where 174.77 meters is the most significant difference.

**Listing 3.2:** Top 10 pairs with the most significant metric differences of data from floor F1 of site Yintai City (Chengxi Branch)

1. Point 1: (247.96523998265695, 168.7631635050295), Point 2: (117.92375106521739, 51.997759545341616), Metric Difference: 174.77113148839442
2. Point 1: (98.66346, 127.5971), Point 2: (258.75049789436116, 181.23350740899357), Metric Difference: 168.83342057049657
3. Point 1: (189.58672, 71.454666), Point 2: (89.73448203762376, 102.255128190099), Metric Difference: 104.49467879858156
4. Point 1: (223.49295, 145.0939), Point 2: (174.26284532732006, 78.86335505811792), Metric Difference: 82.52325908119289
5. Point 1: (34.864815, 35.45561), Point 2: (33.284438514193546, 110.76117936967742), Metric Difference: 75.32215057954856
6. Point 1: (50.31085719185683, 92.03105531572366), Point 2: (114.97229034709193, 123.04521228267667), Metric Difference: 71.71456525741291
7. Point 1: (150.91972285390713, 145.15169976783693), Point 2: (222.23440919809525, 146.11043967333333), Metric Difference: 71.32113060360388
8. Point 1: (64.64140228107132, 25.345204272946134), Point 2: (34.47475562023909, 84.44615420072283), Metric Difference: 66.35471990088624
9. Point 1: (56.83799274253731, 74.52090035349569), Point 2: (94.43750948519768, 125.97292215289488), Metric Difference: 63.72624425248555
10. Point 1: (172.3439286324042, 56.200716101045295), Point 2: (212.4478039192399, 99.33967479470648), Metric Difference: 58.90068395354572

This difference is too high for a human to walk in 1.8 to 2.2 seconds, which is the time between two waypoints. A human's gait speed has its maximum at about 2.53 meters per second, according to [2]. So in 2.2 seconds a human can walk 5.57 meters, which is much less than each of the values in the top 10 in Listing 3.2. Therefore, waypoints which are more than about 5.57 meters apart, are defined as "to apart from each other" to walk in this time and therefore, we will split the path there and will generate separated files. This results in 147 files with data interpolation, which will be used for the ML model. But the data in those interpolated files do not contain any information about the BSSID and corresponding RSSI values, which are needed for the prediction. This will be solved in Section 3.3.2.

### **3.3.2 Received Signal Strength Indicators for each timestamp**

It is obvious, that for a waypoint we have not all RSSI values for each AP because the AP may be out of range. In order to use the RSSI in the prediction and treat each BSSID as a class for the ML model, we need to have a RSSI value for each AP for each timestamp.

First, we will gather all BSSID of the site by iterating over all Wi-Fi data and save it in one file. Every line contains the timestamp and each column header is the BSSID of the AP and each value of the line is the RSSI value of the BSSID at the timestamp. If an AP is not present, we add a very low value  $-999$  into the field. Then we will use this Wi-Fi file and iterate over each file with interpolated data and for each timestamp the BSSID and the corresponding RSSI value. At each timestamp with `TYPE_WIFI` timestamps the RSSI value for each BSSID is now saved. These files will be used to train the ML model.

## 4 Suitable Machine Learning Model

As seen in Chapter 3, we have many data for one floor. We want to predict the next BSSID out of many BSSIDs, so we have multi-class classification problem with supervised learning, as we know, which BSSID is the next one. In the following, we will discuss some pre-chosen models and decide which will be implemented in Chapter 5.

### 4.1 Discussion of Classification Models

As mentioned in Chapter 3, the floor analyzed there has 4795 BSSIDs. So we have 4795 classes for the classification problem. The selection of a suitable model for this task is even more critical. We will discuss the classification models by the following topics: Temporal Dependency Handling, Capacity and Complexity, Multivariate Data, Flexibility and Integration, and Regularization and Overfitting.

#### Temporal Dependency Handling:

- MLPs have no loop [20], making them less suitable for time series data where temporal dependencies are crucial.
- While HMMs can handle temporal dependencies to some extent, they often struggle with longer sequences and multivariate data due to their Markovian assumption [21], which limits their memory to the most recent state.
- Standard RNNs were designed to handle temporal dependencies, but they suffer the vanishing gradient problem, making them less effective in capturing long-term dependencies compared to LSTMs [19].
- LSTMs, by design, are equipped to handle long-term temporal dependencies. Their unique cell state and gating mechanisms allow them to store, modify, and access information over extended periods, making them adept at capturing patterns from long sequences. [6]

#### Capacity and Complexity:

- MLPs can also scale their capacity by adding more hidden layers and units. They are capable of modeling complex relationships within data through their nonlinear activations.
- HMMs have limitations in handling the complexity of multi-class and multivariate problems due to their inherent Markovian assumptions and discrete state representations.
- traditional RNNs suffer from the vanishing gradient problem, especially in longer sequences, which limits their ability to capture long-term dependencies effectively. [19]

- With 4,795 classes, the model needs a considerable capacity to differentiate between the subtle differences in patterns that might exist among them. LSTMs, being deep learning models, can scale effectively in terms of capacity by adding more layers or units while still maintaining their ability to handle temporal data.

**Multivariate Data:**

- While MLPs can also handle multivariate data, they treat each feature and time step independently, often missing out on the interdependencies.
- HMMs are primarily designed for univariate data. Extending them to multivariate scenarios requires additional complexities and assumptions.
- RNNs and LSTMs can seamlessly handle multivariate time series data. Their recurrent nature allows them to effectively process each time step with multiple features.

**Flexibility and Integration:**

- MLPs are very flexible and can be used generally to learn a mapping from inputs to outputs. [3] As we want to learn, which BSSID is the next one, this may be a good fit.
- HMMs are primarily designed for capturing state transitions in sequential data and may not be suitable for tasks requiring the integration of spatial and temporal information. Their rigid assumptions about state transitions limit their flexibility in capturing complex patterns. [21]
- Traditional RNNs can capture short-term dependencies and are relatively simpler to integrate with other architectures due to their sequential nature.
- LSTMs can be easily integrated with other deep learning architectures, such as Convolutional Neural Networks (CNNs), to capture both temporal and spatial features. This flexibility is advantageous when dealing with complex and varied data sources.

**Regularization and Overfitting:**

- dropouts may be used to prevent overfitting for each model[22].
- RNNs are prone to vanishing gradient issues, which can increase overfitting in general. [19]

In conclusion, while MLPs, HMMs, and traditional RNNs have their strengths and have been successful in many applications, they have problems with multivariate time series classification with many classes. This problem demands a model that can efficiently capture intricate temporal patterns, scale in capacity, and handle multivariate data. LSTMs, with their unique architecture and properties, can deal with this challenge, making them the preferred choice for this task and the selected model for our implementation.

## 5 Implementation

All the code for this implementation can be found in the GitHub repository [23].

### 5.1 Preprocessing

- Preprocessing with numpy and pandas
- Use data from Chapter 3 for preprocessing
- Explain what was done to the .txt files in preprocessing part (see [23] preparation.ipynb)
- Explain preprocessing of model (see [23] lstm.ipynb)
- Load data from files of floor with most files
- Create a target variable (based on RSSIs of BSSIDs)
- Normalize the data.
- Create sequences of data based on window\_size variable.
- Encode the target variable, which is a variable with 4795, where 1 means the class is the nearest AP and 0 means the class is not the nearest AP, which results in a one-hot encoding.
- Split the data into training and testing set. (80/20)

### 5.2 LSTM Training and Testing

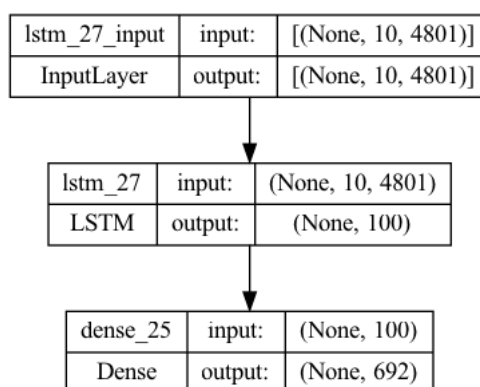
- Use Keras library for implementation [14]
- Model: LSTM layer, Dense layer with softmax activation

Sequences are of length sliding window\_size for each entry in the dataset

- sliding window size will be  $25 * 0.25 = 6.25$ , so we choose 6 seconds as the sliding window size, as our dataset has Wi-Fi timestamps for every about 2 seconds, we set window\_size = 3 [12]

Inputs are (window\_size, number\_of\_features (which are 6 + number of BSSIDs)), see Figure 5.1

- Generate predictions on the test set
- Get class with the highest probability as prediction
- Get top 3 predictions for the test set and check if the target variable is in the top 3 predictions.



**Figure 5.1:** An example LSTM Network with Input, LSTM and Dense Layer with 4801 Features and window\_size of 10.

### 5.3 Tuning model and hyperparameters

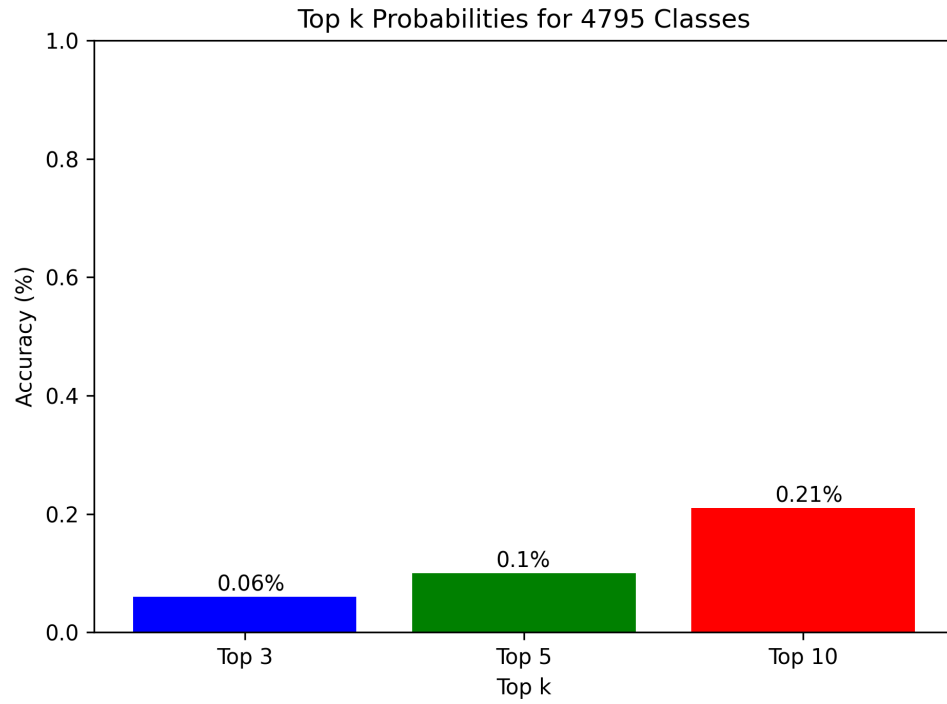
- try out different hyperparameters also in combination
  - Number of units in the LSTM layer = {100, 150, 200, 350, 500, 1000, 2000}
  - batch size = {16, 32, 64}
  - window size = {3, 5, 10, 20}

## 6 Evaluation

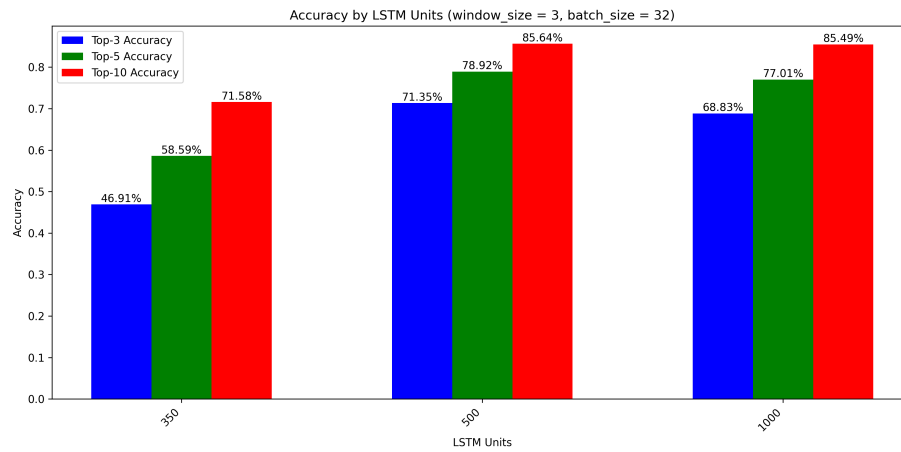
- Top k: predicted class is within the top k predictions
- calculation for top k:

$$\frac{\binom{NUM\_CLASSES-1}{k-1}}{\binom{NUM\_CLASSES}{k}} = \frac{k}{NUM\_CLASSES}$$

- for the floor with most files: NUM\_CLASSES = 4795
- Probabilities to pick one random BSSID, and it is the right one in top 3, 5 or 10, see Figure 6.1
- Accuracy of the model's prediction with a batch\_size of 32, see Figure 6.2, Figure 6.3, Figure 6.4 and Figure 6.5
- Accuracy of the model's prediction with a batch\_size of 16, see Figure 6.6
- Accuracy of the model's prediction with a batch\_size of 64, see Figure 6.7
- Comparison with random selection of classes: lstm always better than random selection
- TODO: describing the plots
- best performance: 71%, see Figure 6.8
- Reasons:
  - data contains too many classes, with fewer classes to predict the model could have performed better
  - discussion could have missed a better model
  - model very simple, could be improved by using other layers in between LSTM and Dense layers

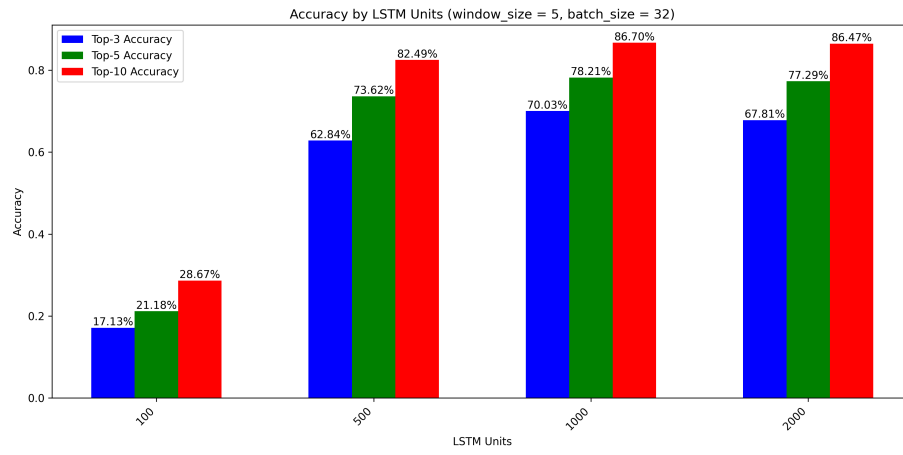


**Figure 6.1:** Probabilities that the predicted class falls within the top k randomly selected classes.

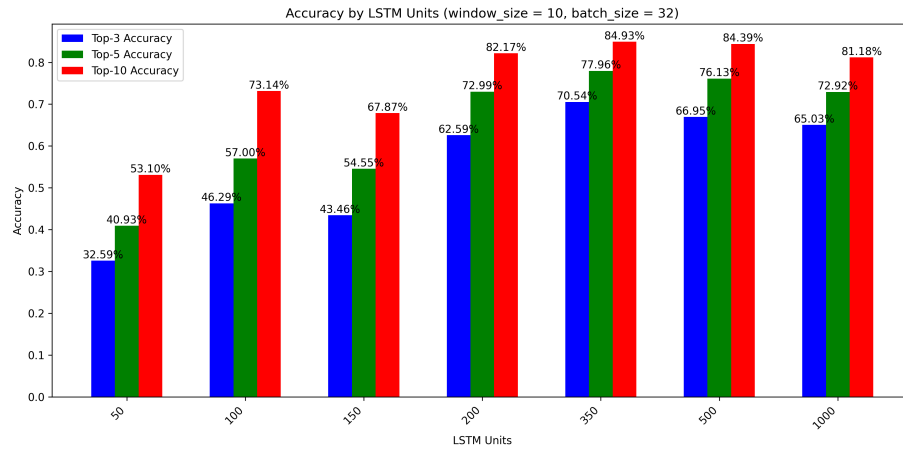


**Figure 6.2:** Accuracy of the model with window size of 3, batch size of 32 and 100, 500 and 1000 units in the LSTM layer.



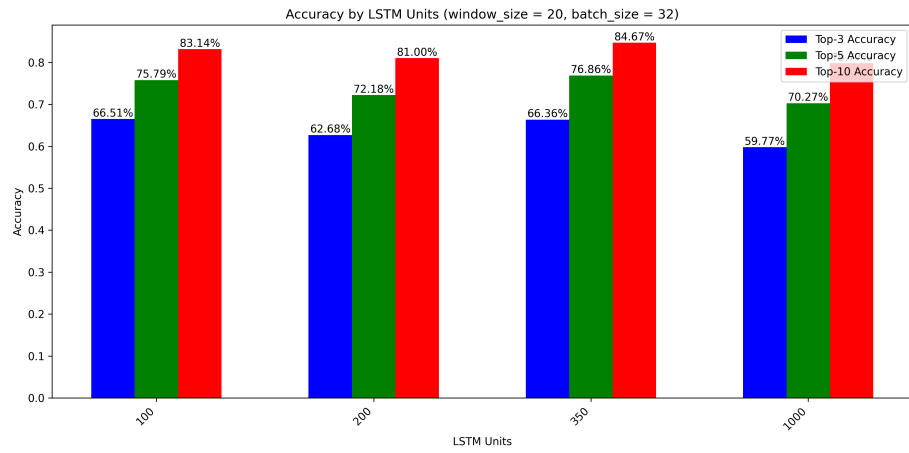


**Figure 6.3:** Accuracy of the model with window size of 5, batch size of 32 and 100, 500 and 1000 units in the LSTM layer.

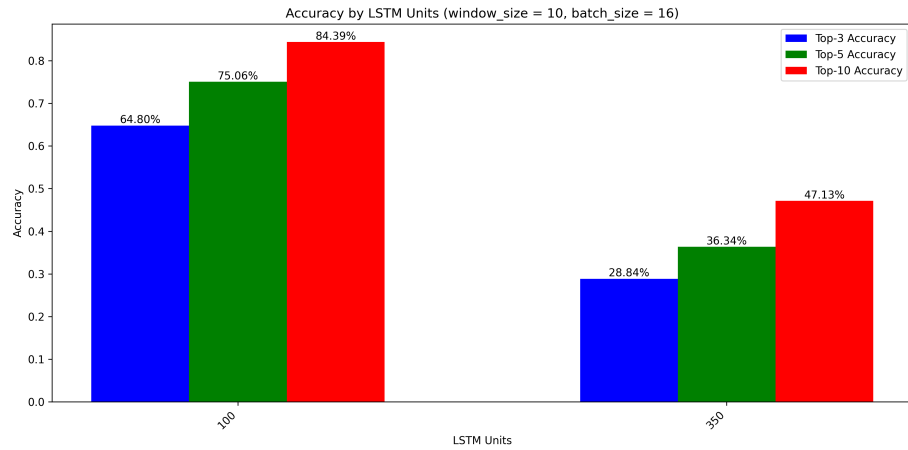


**Figure 6.4:** Accuracy of the model with window size of 10, batch size of 32 and 100, 500 and 1000 units in the LSTM layer.

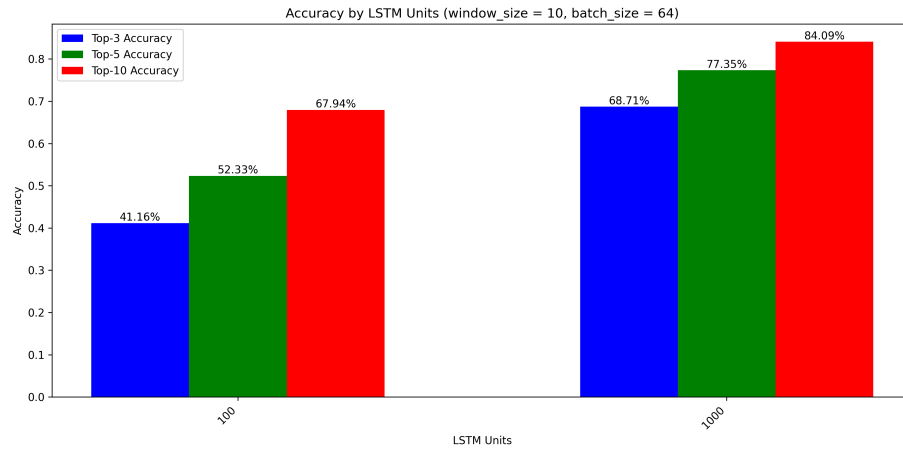
## 6 Evaluation



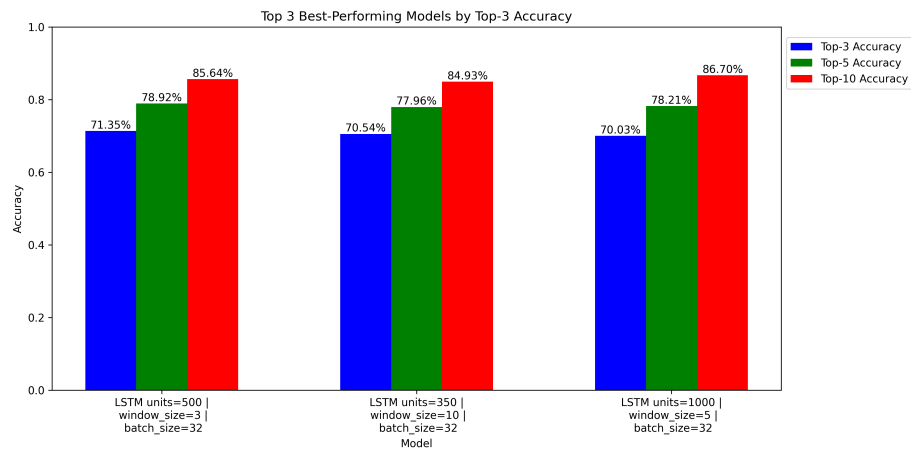
**Figure 6.5:** Accuracy of the model with window size of 20, batch size of 32 and 100, 500 and 1000 units in the LSTM layer.



**Figure 6.6:** Accuracy of the model with window size of 10, batch size of 16 and 100, 500 and 1000 units in the LSTM layer.



**Figure 6.7:** Accuracy of the model with window size of 10, batch size of 64 and 100, 500 and 1000 units in the LSTM layer.



**Figure 6.8:** Accuracy of the three best performing models of the implementation



## 7 Conclusion

- indoor human movement prediction is a hard task with many classes
- although LSTM is the best choice for this task, the prediction accuracy is 70%
- with lesser classes, model could predict better, which could be a reason why ML model
- future work: use LSTM with fewer classes
  - or generate data from mobile devices, so complete setup is known
  - or generate data from APs to predict human movement
  - could than be integrated in AP software like OpenWrt



# Bibliography

- [1] *Bishop - Pattern Recognition and Machine Learning.pdf*. URL: <https://docs.google.com/viewer?a=v&pid=sites&srcid=aWFtYW5kaS5ldXpc2N8Z3g6MjViZDk1NGI1NjQzOWZiYQ> (visited on July 21, 2023).
- [2] R. W. Bohannon. "Comfortable and Maximum Walking Speed of Adults Aged 20-79 Years: Reference Values and Determinants". In: *Age and Ageing* 26.1 (Jan. 1997), pages 15–19. ISSN: 0002-0729. DOI: 10.1093/ageing/26.1.15.
- [3] Jason Brownlee. *When to Use MLP, CNN, and RNN Neural Networks*. URL: <https://machinelearningmastery.com/when-to-use-mlp-cnn-and-rnn-neural-networks/> (visited on Aug. 23, 2023).
- [4] Jeffrey L. Elman. "Finding Structure in Time". en. In: *Cognitive Science* 14.2 (Mar. 1990), pages 179–211. ISSN: 03640213. DOI: 10.1207/s15516709cog1402\_1. URL: [http://doi.wiley.com/10.1207/s15516709cog1402\\_1](http://doi.wiley.com/10.1207/s15516709cog1402_1) (visited on Aug. 6, 2023).
- [5] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. eng. OCLC: 987005922. Cambridge, Massachusetts: The MIT Press, 2016. ISBN: 9780262337434.
- [6] Sepp Hochreiter and Jürgen Schmidhuber. "Long Short-Term Memory". In: (1997). URL: <https://papers.baulab.info/Hochreiter-1997.pdf>.
- [7] "IEEE Standard for Information technology– Local and metropolitan area networks– Specific requirements– Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 2: Fast Basic Service Set (BSS) Transition". In: *IEEE Std 802.11r-2008 (Amendment to IEEE Std 802.11-2007 as amended by IEEE Std 802.11k-2008)* (July 2008). Conference Name: IEEE Std 802.11r-2008 (Amendment to IEEE Std 802.11-2007 as amended by IEEE Std 802.11k-2008), pages 1–126. DOI: 10.1109/IEEESTD.2008.4573292.
- [8] "IEEE Standard for Information technology– Local and metropolitan area networks– Specific requirements– Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 1: Radio Resource Measurement of Wireless LANs". In: *IEEE Std 802.11k-2008 (Amendment to IEEE Std 802.11-2007)* (June 2008). Conference Name: IEEE Std 802.11k-2008 (Amendment to IEEE Std 802.11-2007), pages 1–244. DOI: 10.1109/IEEESTD.2008.4544755.
- [9] *Indoor Location & Navigation | Kaggle*. <https://www.kaggle.com/competitions/indoor-location-navigation>. (Visited on July 11, 2023).
- [10] *indoor-location-navigation-20*. URL: <https://github.com/location-competition/indoor-location-competition-20> (visited on July 31, 2023).
- [11] *Indoor Navigation: Complete Data Understanding*. <https://kaggle.com/code/andradaolteanu/indoor-navigation-complete-data-understanding>. (Visited on Apr. 25, 2023).

- [12] Milagros Jaén-Vargas, Karla Miriam Reyes Leiva, Francisco Fernandes, Sérgio Barroso Gonçalves, Miguel Tavares Silva, Daniel Simões Lopes, and José Javier Serrano Olmedo. "Effects of Sliding Window Variation in the Performance of Acceleration-Based Human Activity Recognition Using Deep Learning Models". In: *PeerJ Computer Science* 8 (Aug. 2022), e1052. ISSN: 2376-5992. DOI: 10.7717/peerj-cs.1052. (Visited on Aug. 27, 2023).
- [13] *Kaggle: Your Home for Data Science*. <https://www.kaggle.com/>. (Visited on July 23, 2023).
- [14] *Keras: The high-level API for TensorFlow*. URL: <https://www.tensorflow.org/guide/keras> (visited on Aug. 18, 2023).
- [15] Muhammad Asif Khan, Ridha Hamila, Adel Gastli, Serkan Kiranyaz, and Nasser Ahmed Al-Emadi. "ML-Based Handover Prediction and AP Selection in Cognitive Wi-Fi Networks". In: *Journal of Network and Systems Management* 30.4 (Aug. 2022), page 72. ISSN: 1573-7705. DOI: 10.1007/s10922-022-09684-2. (Visited on Apr. 26, 2023).
- [16] Joos Korstanje. *How to Select a Model For Your Time Series Prediction Task*. URL: <https://neptune.ai/blog/select-model-for-time-series-prediction-task> (visited on Aug. 23, 2023).
- [17] J. Montavont and T. Noel. "IEEE 802.11 Handovers Assisted by GPS Information". In: *2006 IEEE International Conference on Wireless and Mobile Computing, Networking and Communications*. June 2006, pages 166–172. DOI: 10.1109/WIMOB.2006.1696358.
- [18] Tom O'Malley, Elie Bursztein, James Long, François Chollet, Haifeng Jin, Luca Invernizzi, et al. *KerasTuner*. <https://github.com/keras-team/keras-tuner>. 2019. (Visited on Aug. 21, 2023).
- [19] Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. *On the Difficulty of Training Recurrent Neural Networks*. Feb. 2013. arXiv: 1211.5063 [cs]. (Visited on Aug. 17, 2023).
- [20] Marius-Constantin Popescu, Valentina Balas, Liliana Perescu-Popescu, and Nikos Mastorakis. "Multilayer perceptron and neural networks". In: *WSEAS Transactions on Circuits and Systems* 8 (July 2009).
- [21] L.R. Rabiner. "A tutorial on hidden Markov models and selected applications in speech recognition". In: *Proceedings of the IEEE* 77.2 (Feb. 1989), pages 257–286. ISSN: 00189219. DOI: 10.1109/5.18626. URL: <http://ieeexplore.ieee.org/document/18626/> (visited on Aug. 6, 2023).
- [22] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting". In: *Journal of Machine Learning Research* 15.56 (2014), pages 1929–1958. URL: <http://jmlr.org/papers/v15/srivastava14a.html>.
- [23] Lina Wilske. *GitHub Repository for bachelor thesis*. URL: <https://github.com/linaScience/ba-implementation>.



## Acronyms

<b>AP</b>	Access Point
<b>BSSID</b>	Basic Service Set Identifier
<b>GPS</b>	Global Positioning System
<b>HMM</b>	Hidden Markov Model
<b>LSTM</b>	Long Short-Term Memory
<b>MAC</b>	Media Access Control
<b>MajorID</b>	Major Identifier
<b>MinorID</b>	Minor Identifier
<b>ML</b>	Machine Learning
<b>MLP</b>	Multilayer Perceptron
<b>ReLU</b>	Rectified Linear Unit
<b>RNN</b>	Recurrent Neural Network
<b>RSSI</b>	Received Signal Strength Indication
<b>SDN</b>	Software Defined Networking
<b>SSID</b>	Service Set Identifier
<b>SVR</b>	Support Vector Regression
<b>TxPower</b>	Transmission Power
<b>UUID</b>	Universally Unique Identifier
<b>Wi-Fi</b>	Wireless Fidelity



### **Zusammenfassung**

To-do: translate english abstract to german



### **Eidesstattliche Erklärung**

Hiermit versichere ich, dass meine Bachelor's thesis "Machine Learning-based User Movement Prediction in Layer 2 Networks" ("Vorhersage von Benutzerbewegungen in Layer 2 Netzwerken basierend auf Maschinellern Lernen") selbstständig verfasst wurde und dass keine anderen Quellen und Hilfsmittel als die angegebenen benutzt wurden. Diese Aussage trifft auch für alle Implementierungen und Dokumentationen im Rahmen dieses Projektes zu.

Potsdam, den 29. August 2023,

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(Lina Wilske)