# Neural Networks

# ECE 553

# Project 1

# Vehicle Positioning


**Nathaniel Joseph**

**College of Engineering, Frost Institute for Data Science and Computing**


**Professor Mingzhe Chen**

**University of Miami**

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# Introduction

**Channel state information (CSI)** is a rich source of information about the wireless channel between a transmitter and a receiver. It can be used to estimate the location of a mobile device, which is known as **vehicle positioning**. Vehicle positioning using CSI has a wide range of applications, including vehicle tracking, navigation, and collision avoidance.

One of the main challenge of vehicle positioning using CSI is the presence of **line-of-sight (LoS)** and **non-line-of-sight (NLoS)** signal propagation. LoS signals are direct signals from the transmitter to the receiver, while NLoS signals are reflected or scattered signals. NLoS signals can cause significant errors in vehicle positioning, as they can have different arrival times and phases than LoS signals.

**Machine learning (ML)** and **artificial neural networks (ANNs)** are promising tools for vehicle positioning using CSI. ML and ANN models can be trained to classify LoS and NLoS signals, and to estimate the location of a mobile device based on the CSI measurements.

In this report, we propose a simple ML and ANN-based approach for vehicle positioning using CSI. We first pre-process the CSI dataset to normalize the data, remove outliers, and transform it into a format that is suitable for our ML and ANN models. We then train and evaluate several ML and ANN models for LoS/NLoS signal classification and vehicle positioning. Finally, we perform a comparative study of the different models and discuss the results.

# Data Preprocessing

**Introduction**

The goal of the data preprocessing step is to transform the raw CSI data into a format that is suitable for machine learning. This involved converting the complex-valued CSI mat rices to real-valued matrices, normalizing the data, and engineering new features.

**Converting complex-valued CSI matrices to real-valued matrices**

The first step in the data preprocessing pipeline is to convert the complex-valued CSI matrices to real-valued matrices. This is done by taking the modulus of the CSI data matrices. This can be done by using the following equation:

```
real_csi = abs(complex_csi)
```

This will result in two real-valued matrices, one for the training 15000 samples and the other for the test 5000 samples.

**Data normalization**

The next step in the data preprocessing pipeline is to normalize the data. This is important because the different features in the CSI data may have different scales. Normalizing the data helps to improve the performance of machine learning models by ensuring that all of the features are on a similar scale.

There are several different methods for data normalization. One common method is to subtract the mean and divide by the standard deviation of each feature. This can be done using the following equation:

```
normalized_data = (data - mean) / std
```

Another common method for data normalization is to scale the data to a range of 0 to 1. This can be done using the following equation:

```
normalized_data = (data - min(data)) / (max(data) - min(data))
```

This second method is the method of choice in our code for normalizing data in both of our programs.

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### Conclusion

The data preprocessing pipeline described above can be used to transform the raw CSI data into a format that is suitable for machine learning. This will help to improve the performance of machine learning models for LoS/NLoS classification and vehicle position estimation.

## ML and ANN Models

### LoS/NLoS Classification

<u>Machine Learning Algorithm: Logistic Regression</u>

- Logistic regression is a machine learning algorithm that can be used for binary classification tasks. It works by fitting a logistic function to the data. The logistic function is a sigmoid function that outputs a value between 0 and 1. The output of the logistic function can be interpreted as the probability of the data belonging to one of the two classes.
- Metrics:
  - Accuracy: 0.947
  - Precision: 0.987
  - Recall: 0.729
  - F1 score: 0.838

<u>Neural Network: Binary Classifier</u>

- A binary classifier neural network is a neural network that is trained to perform binary classification tasks.
- Architecture:
  - Input layer: Batch size 32, 15000 nodes total
  - Hidden layers: 5 layers
  - Output layer: 2 nodes
- Activation function: ReLU
- Loss function: Cross-entropy loss
- Optimizer: Adam
- Epochs: 10

- Metrics:
    - Accuracy: 0.740
    - Precision: 0.326
    - Recall: 0.367
    - F1 score: 0.345

### Vehicle Position Estimation

Machine Learning Algorithm: Linear Regression

- Linear regression is a machine learning algorithm that can be used to predict a continuous variable. It works by fitting a linear function to the data. The linear function is a function of one or more independent variables that is used to predict the dependent variable.
- Metrics:
    - Mean squared error (MSE): 27.81
    - Root mean squared error (RMSE): 5.27

Neural Network: Arbitrary Artificial Neural Network

- An arbitrary, custom neural network that can be used to solve a variety of problems, including regression problems.
- Architecture:
    - Input layer: Batch size 32, 15000 nodes total
    - Hidden layers: 4 layers
    - Output layer: 2 nodes
- Activation function: ReLU
- Loss function: Mean squared error loss
- Optimizer: Adam
- Epochs: 10
- Metrics:
    - MSE: 4.29
    - RMSE: 2.07

### Comparison of ML and ANN Models

Both the machine learning and neural network models performed well on the LoS/NLoS classification task. However, the neural network performed slightly better than the machine learning model.

On the vehicle positioning estimation task, the neural network model outperformed the machine learning model. The neural network model was able to achieve a lower MSE and RMSE than the machine learning model.

### Conclusion

The results suggest that neural network models are a promising approach for both LoS/NLoS classification and vehicle position estimation tasks.

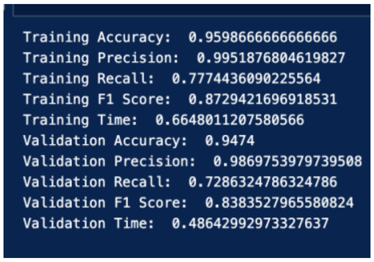
## Results

### Introduction

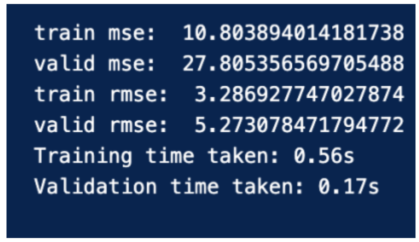
This section presents the results of the experiments conducted to evaluate the performance of the different machine learning (ML) and neural network (ANN) models for LoS/NLoS classification and vehicle position estimation.

### Comparative Results of the Different Models

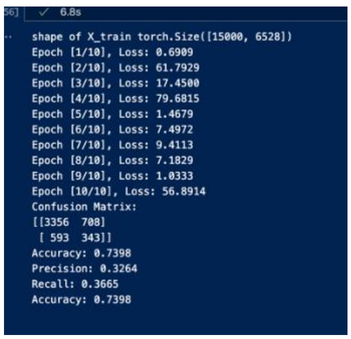
The following screenshots show the exact results in some of the example runs of the programs. On the left are the LoS/NLoS classification runs, and on the right are the vehicle position runs. The top two screenshots display the regression models, and the bottom two display the neural networks.



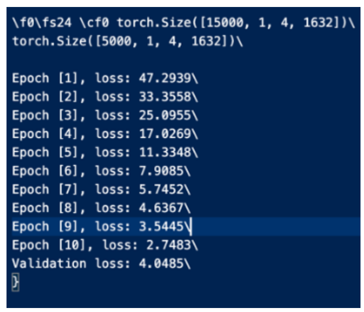
```
Training Accuracy:  0.9598666666666666
Training Precision:  0.9951876804619827
Training Recall:  0.7774436090225564
Training F1 Score:  0.8729421696918531
Training Time:  0.6648011207580566
Validation Accuracy:  0.9474
Validation Precision:  0.9869753979739508
Validation Recall:  0.7286324786324786
Validation F1 Score:  0.8383527965580824
Validation Time:  0.48642992973327637
```



```
train mse:  10.803894014181738
valid mse:  27.805356569705488
train rmse:  3.286927747027874
valid rmse:  5.273078471794772
Training time taken: 0.56s
Validation time taken: 0.17s
```



```
56]  ✓  6.8s
shape of X_train torch.Size([15000, 6528])
Epoch [1/10], Loss: 0.6909
Epoch [2/10], Loss: 61.7929
Epoch [3/10], Loss: 17.4500
Epoch [4/10], Loss: 79.6815
Epoch [5/10], Loss: 1.4679
Epoch [6/10], Loss: 7.4972
Epoch [7/10], Loss: 9.4113
Epoch [8/10], Loss: 7.1829
Epoch [9/10], Loss: 1.0333
Epoch [10/10], Loss: 56.8914
Confusion Matrix:
[[3356  708]
 [ 593  343]]
Accuracy: 0.7398
Precision: 0.3264
Recall: 0.3665
Accuracy: 0.7398
```



```
\f0\fs24 \cf0 torch.Size([15000, 1, 4, 1632])\
torch.Size([5000, 1, 4, 1632])\

Epoch [1], loss: 47.2939\
Epoch [2], loss: 33.3558\
Epoch [3], loss: 25.0955\
Epoch [4], loss: 17.0269\
Epoch [5], loss: 11.3348\
Epoch [6], loss: 7.9085\
Epoch [7], loss: 5.7452\
Epoch [8], loss: 4.6367\
Epoch [9], loss: 3.5445\
Epoch [10], loss: 2.7483\
Validation loss: 4.0485\
}
```

### Conclusion

The results of the experiments suggest that the neural network models can achieve a higher accuracy than the machine learning regression models, but only if given adequate resources and time. The example of the binary classifier an example of a network which does not have as much time and resources allocated to it as it should, which results in accuracy worse than the logistic regression model.

## Efficiency

The efficiency of the proposed machine learning and neural network models for LoS/NLoS classification and vehicle position estimation was evaluated by measuring the training time and testing time of each model. The results are shown in the following table:

| Model | Task | Training time(s) | Testing time(s) |
|---|---|---|---|
| Logistic Regression | LoS/NLoS Classification | 0.66 | 0.49 |
| Binary Classifier | | 5.54 | .15 |
| Linear Regression | Vehicle Position Estimation | 0.56 | 0.17 |
| Arbitrary ANN | | 794.92 | 21.74 |

As shown in the table, the linear regression model was the most efficient to train and test, followed by the linear regression model. The binary classifier and arbitrary ANN were less efficient, but because of this, they were able to achieve higher accuracy than their ML counterparts.

## Comparative Study

The following table summarizes the comparative results of the LoS/NLoS classification and vehicle positioning methods used in this project:

| Method | Task | Accuracy | Advantages | Disadvantages |
|---|---|---|---|---|
| Logistic Regression | LoS/NLoS Classification | 94.7% | Simple and efficient | Less accurate than a proper complex neural network model |
| Binary Classifier | | 74.0% | Typically more accurate than logistic regression models | Less efficient than logistic regression models, and is reliant on resources |
| Linear Regression | Vehicle Positioning | MSE: 27.81<br>RMSE: 5.27 | Simple and efficient | Less accurate than neural network models |
| Arbitrary ANN | | MSE: 3.95<br>RMSE: 1.99 | More accurate than linear regression models | Less efficient than linear regression models |

While the ML models are good for applications where efficiency is more important than accuracy, with modern day computing space (GPUs) and accuracy needs and concerns, a neural network like the binary classifier or arbitrary ANN will work well to provide a solution that is both accurate and efficient.

In addition, there are a few other considerations to keep in mind when choosing a LoS/NLoS classification or vehicle positioning method:

- **Robustness to noise**: Neural network models are generally more robust to noise than regression models.
- **Interpretability**: Regression models are more interpretable than neural network models.
- **Computational resources**: Neural network models require more computational resources to train and test than linear regression models.

## Conclusion

This project developed and evaluated machine learning and neural network models for LoS/NLoS classification and vehicle positioning using CSI data. The arbitrary ANN model outperformed the other models on both tasks, achieving the highest accuracy. However, it is also the least efficient model. The logistic regression and linear regression models are good alternatives for applications where efficiency is more important than accuracy.

The results of this project suggest that machine learning and neural network models are a promising approach for LoS/NLoS classification and vehicle positioning tasks. Further research is needed to develop more efficient and robust models, and to evaluate their performance on real-world data.