# CS6375 Assignment 1

https://github.com/as567-code/CS6375_Assignment_1

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March 16, 2025

## 1 Introduction and Data

This project focuses on performing sentiment analysis using two neural network architectures: a Feedforward Neural Network (FFNN) and a Recurrent Neural Network (RNN). The goal is to predict Yelp review ratings (ranging from 1 to 5 stars) based on the review text. To achieve this, I used two models that process the text data and aim to classify the sentiment accurately into one of the five classes. The data consists of Yelp reviews that are labeled by their star rating. The dataset is divided into three sets:

- Training Data

- Validation Data

- Test Data

Wrote a small code/file called **"Length_of_Data.ipynb** to find the length of the datasets. Below is the summary of the statistics of the datasets.

| Datasets | Number of Examples |
|---|---|
| Training | 8000 |
| Validation | 800 |
| Test | 800 |

Table 1: Data Statistics

## 2 Implementations

### 2.1 FFNN

Forward Function: This function shows how the data flows through the network.

- **hidden _ layer = self.activation(self.W1(input _vector))**: The input vector is passed through the first linear layer, producing a hidden layer representation.

- **output _layer = self.W2(hidden layer)**: The hidden is the passed through a second linear layer, producing the output layer representation.

- **predicted _vector = self.softmax(output layer)**: The predicted output is passed through a LogSoftMax function, which converts the score into log probabilities.

Libraries/Tools used:

- **nn.Module:** Base class for all neural networks.

- **nn.Linear:** A linear transformation layer, which is fully connected.

- **nn.ReLU:** This is the Rectified Linear Unit, which is an activation function. This introduces non linearity to the neural network.

- **nn.LogSoftMax:** Computes log probabilities.

- **nn.NLLLoss:** The negative log likelihood loss function for classification tasks.

Optimizers and Initializations:

- **Optimizer:**The code uses Stochastic Gradient Descent (SGD) with momentum for updating the model weights during training.

- **Weight Initialization:** self.W1 and self.W2 are the weight initializations. Pytorch uses a uniform distribution to initialize weight and biases of the linear layers.

```python
def forward(self, input_vector):
    # [to fill] obtain first hidden layer representation
    hidden_layer = self.activation(self.W1(input_vector))
    # [to fill] obtain output layer representation
    output_layer = self.W2(hidden_layer)
    # [to fill] obtain probability dist.
    predicted_vector = self.softmax(output_layer)
    return predicted_vector
```

Figure 1: FFNN forward function

Added a small piece of code to check the testing accuracy.

```
def forward(self, inputs):
    # [to fill] obtain hidden layer representation (https://pytorch.org/docs/stable/generated/torch.nn.RNN.html)
    # [to fill] obtain output layer representations
    output, hidden = self.rnn(inputs)
    # [to fill] sum over output
    output_sum = output[-1]
    # [to fill] obtain probability dist.
    predicted_vector = self.W(output_sum)
    predicted_vector = self.softmax(predicted_vector)
    return predicted_vector
```

Figure 2: RNN forward function

## 2.2   RNN

In the forward function, I write output sum = output[-1]. This is the hidden
state corresponding to the last token in the sequence. In this case, instead of
using a command like output.sum() to sum all the hidden states, we rather
only consider the last token. In this case, the last state carries information
from all the previous tokens, thus making it better than using the output.sum()
command. Libraries/Tools used:

- **nn.Module:** Base class for all neural networks.

- **nn.RNN:** This initializes the RNN and the parameters define the struc-
  ture of the RNN.

- The other libraries are similar to that of FFNN.

- RNN processes inputs as sequences and maintains the hidden states, whereas
  the FFNN processes inputs independently.

- RNN works in a way such that the next output is dependent on the pre-
  vious input.

# 3   Experiments and Results

## 3.1   Evaluations

1. Evaluation Process: During the training phase, the model is evaluated at
   the end of each epoch. This involves both calculating the training accuracy
   and validating the model against a separate validation dataset. I can
   observe this in the results.

2. Metrics used:

   - The primary metric used for evaluating the model is accuracy, which
     measures the proportion of correctly predicted instances out of the
     total instances evaluated.

   - Although accuracy is the main metric, the implementation also tracks
     the loss during training and validation. The loss function used is Neg-
     ative Log Likelihood Loss (NLLLoss), which is particularly suitable

for multi-class classification tasks. The loss quantifies how well the model's predicted probabilities align with the actual labels, providing insight into the model's performance beyond just accuracy.

3. During training, the model iterates through the training dataset in mini-batches, predicting the class labels for each input vector. The predicted labels are compared with the actual labels to calculate the number of correct predictions and compute the accuracy for that epoch. The same procedure is done for the validation dataset.

## 3.2 Results

Results of ffnn.py:

- Taking 2 hidden dimensions and 2 epochs:

```
100%|
Training completed for epoch 1
Training accuracy for epoch 1: 0.524125
Training time for this epoch: 2.6117641925811768
Validation started for epoch 1
100%|
Validation completed for epoch 1
Validation accuracy for epoch 1: 0.56
Validation time for this epoch: 0.12484097480773926
Training started for epoch 2
100%|
Training completed for epoch 2
Training accuracy for epoch 2: 0.573625
Training time for this epoch: 1.6113970279693604
Validation started for epoch 2
100%|
Validation completed for epoch 2
Validation accuracy for epoch 2: 0.57125
Validation time for this epoch: 0.06160306930541992
```

Figure 3: FFNN with 2 hidden dimensions and 2 epochs

- Taking 64 hidden dimensions and 20 epochs:

```
100%|
Training completed for epoch 19
Training accuracy for epoch 19: 0.91275
Training time for this epoch: 38.80930709838867
Validation started for epoch 19
100%|
Validation completed for epoch 19
Validation accuracy for epoch 19: 0.57875
Validation time for this epoch: 0.6203410625457764
Training started for epoch 20
100%|
Training completed for epoch 20
Training accuracy for epoch 20: 0.93125
Training time for this epoch: 36.29905366897583
Validation started for epoch 20
100%|
Validation completed for epoch 20
Validation accuracy for epoch 20: 0.6025
Validation time for this epoch: 0.6333768367767334
```

Figure 4: FFNN with 64 hidden dimensions and 20 epochs

Results of rnn.py:

```
Training started for epoch 1
100%|
tensor(1.0860)
Training completed for epoch 1
Training accuracy for epoch 1: 0.411625
Validation started for epoch 1
100%|
Validation completed for epoch 1
Validation accuracy for epoch 1: 0.4
Training started for epoch 2
100%|
tensor(1.0747)
Training completed for epoch 2
Training accuracy for epoch 2: 0.419875
Validation started for epoch 2
100%|
Validation completed for epoch 2
Validation accuracy for epoch 2: 0.43625
```

Figure 5: Accuracy for RNN with 2 hidden dimensions and 2 epochs

- Taking 2 hidden dimensions and 2 epochs

- Taking 64 hidden dimensions and 20 epochs

```
========= Loading data =========
========= Vectorizing data =========
Training started for epoch 1
100%|
tensor(1.0868)
Training completed for epoch 1
Training accuracy for epoch 1: 0.4045
Validation started for epoch 1
100%|
Validation completed for epoch 1
Validation accuracy for epoch 1: 0.40375
Training started for epoch 2
100%|
tensor(1.0817)
Training completed for epoch 2
Training accuracy for epoch 2: 0.422625
Validation started for epoch 2
100%|
Validation completed for epoch 2
Validation accuracy for epoch 2: 0.41125
```

Figure 6: Initial accuracy for RNN

```
Training done to avoid overfitting!
Best validation accuracy is: 0.43625
```

Figure 7: Final accuracy for RNN

## 4  Analysis

Some error examples are:

- "Bartender needs an attitude adjustment". True label is 1, predicted label is 3. The model couldn't understand the sarcasm.

- "Oh great, another 45-minute wait for my cold food. Just what I wanted." True label is 1, predicted label is 4. The model couldnt understand the sarcasm

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- "I have no problem paying for service when I receive value for it, but when it is just gouging, that's not worth it." True label is 2, Predicted label is 4, the model couldn't understand the subtle negativity at the end of the sentence.

## 5    Conclusion and Others

Feedback for the assignment:

- The assignment took around 20 hours, mostly debugging the results.

- The RNN was more difficult compared to the FFNN, especially when fine-tuning the model. Handling the data structure and optimizing performance took more time than expected.

- The assignment could include how to upload large files into github, although it was easily available online(using git lfs install).