# UNIVERSITY OF ATHENS DEPARTMENT OF INFORMATICS AND TELECOMMUNICATIONS

# Deep Learning for NLP - HW2

Student name: *Dimitrios Chrysos* sdi: 2100275

Course: Artificial Intelligence II ( $\Upsilon \Sigma 19$ ) Semester: Spring Semester 2024-2025

# **Contents**

1	Abstract							
2	Data processing and analysis							
	2.1	Pre-pr	rocessing		2			
	2.2	Data r	partitioning for train, test and validation		2			
	2.3	Vector	rization		2			
3	Alg	Algorithms and Experiments						
	3.1		riments		3			
	3.2	-						
	3.3		nization techniques		20			
	3.4	_	uation					
		3.4.1	ROC curve		21			
		3.4.2	Learning Curve					
			Confusion matrix		23			
4	Res	esults and Overall Analysis						
			ts Analysis		23			
		4.1.1	Best trial		24			
	4 2		parison with the first project		25			

#### 1. Abstract

The task is to perform sentiment analysis using PyTorch with Word2Vec word embeddings as input to the model. The project is written in Python for a given Englishlanguage Twitter dataset. Three datasets will be used: train\_dataset, val\_dataset, and test\_dataset, which are used for training, validation, and testing, respectively.

# 2. Data processing and analysis

### 2.1. Pre-processing

The data cleaning and pre-processing were done using regular expressions and Python methods and applied to the three provided datasets. The following steps were used:

- 1. To ensure uniformity, all text is converted to lowercase
- 2. Common spelling mistakes, contractions, slang words, and informal abbreviations are corrected to improve standardization and prevent misinterpretations during feature extraction.
- 3. Removal of URLs, Hashtags, Emails, Mentions, Numbers, Emojis, Non-ASCII characters, Single-Letter Words, and Special Characters because they provide close to no value for sentiment analysis.
- 4. Sequences of three or more identical letters are reduced for standardization.
- 5. Excess whitespace is replaced with a single space for readability purposes.

Applying these techniques ensures that the text data is clean, structured, and suitable for sentiment analysis. This preprocessing step improves model accuracy by eliminating noise and standardizing input text.

### 2.2. Data partitioning for train, test and validation

• The data was already portioned.

#### 2.3. Vectorization

- The technique uses the pre-trained Word2Vec model "GoogleNews-vectors-negative300" to map each word to a high-dimensional vector.
- A tweet is tokenized, and each token is replaced with its corresponding Google News vector (or a zero vector if absent).
- The total representation of the tweet is then calculated by averaging these word vectors, producing a semantically meaningful embedding of fixed size.

# 3. Algorithms and Experiments

# 3.1. Experiments

- 1. First Experiment glove.6B.50d.txt
  - The first experiment used the following configuration:
    - Glove glove.6B.50d.txt for the embeddings.
    - batch\_size=128 for the data-loaders.
    - A model architecture of two hidden layers that both used ReLu as an activation function, batch normalization for regularization, and dropout to reduce overfitting.
    - num\_epochs=10 to get a starting understanding of the metrics.
    - nn.CrossEntropyLoss() for the loss function.
    - Adam optimizer.
    - The three variables that follow were generated using optuna optimization in previous discarded experiments and are the base for most of the following experiments.
      - (a) dropout\_prob=0.3125125247127012
      - (b) lr=0.0019524310388177159
      - (c) weight\_decay=5.263544573640884e-06
  - This configuration produced the following results:

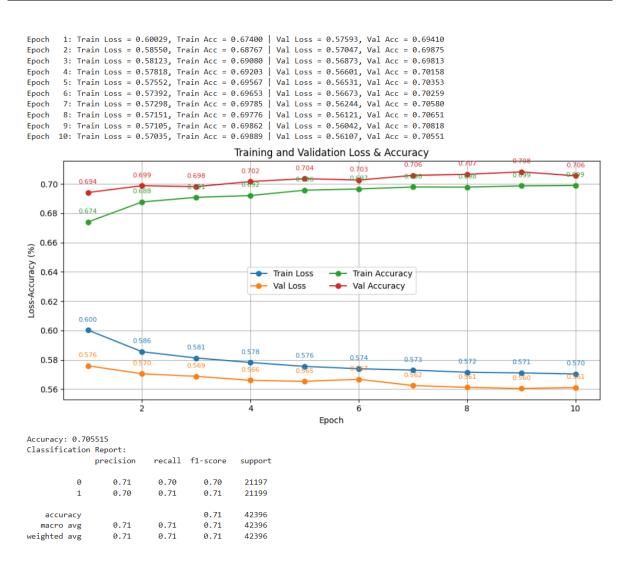


Figure 1: Experiment 1

# 2. Second Experiment - Self Trained Vectors

- For the second experiment, only the vectorization strategy changed.
  - The vectors used here are **trained** from the **training dataset**.
  - The rest of the configuration is the same as **Experiment 1**
  - This configuration produced the following results:

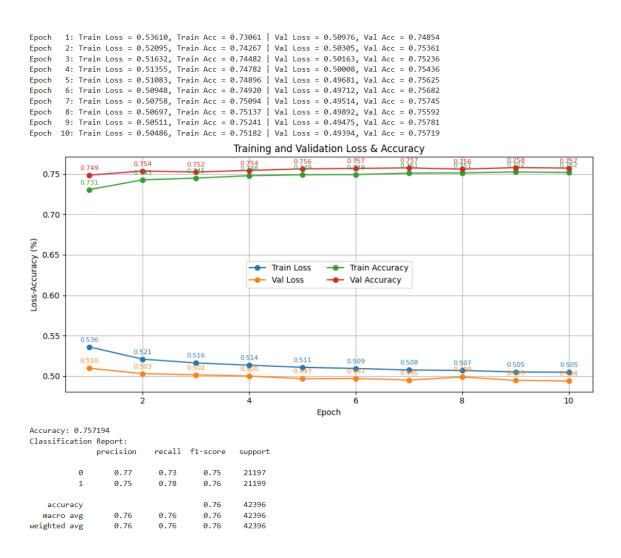


Figure 2: Experiment 2

- The accuracy of the evaluation dataset increased significantly.
- 3. Third Experiment Google News Vectors
  - Following **Experiment 2**, the third experiment again changed only the vectorization strategy.
    - The vectors used here are from the GoogleNews-vectors-negative300.bin file.
    - The rest of the configuration is the same as **Experiment 1**
    - This configuration produced the following results:

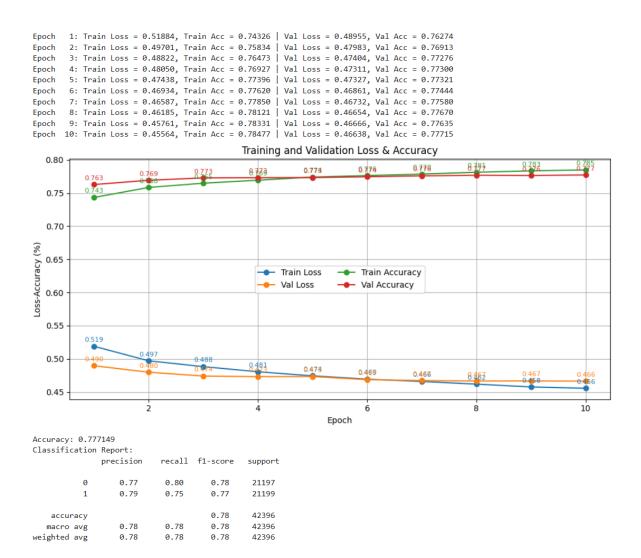


Figure 3: Experiment 3

- The accuracy of the evaluation dataset again increased significantly.
- 4. Fourth Experiment glove.twitter.27B.200d.txt
  - Again following the two previous experiments, the fourth experiment changed only the vectorization strategy.
    - The vectors used here are from the glove.twitter.27b.200d.txt file.
    - The rest of the configuration is the same as **Experiment 1**
    - This configuration produced the following results:

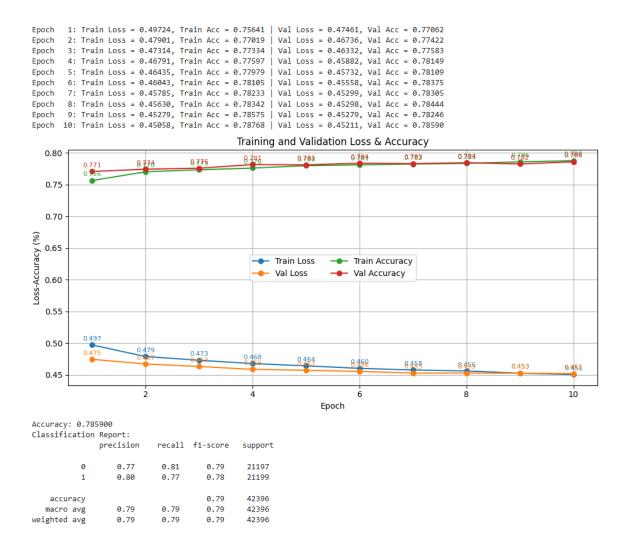


Figure 4: Experiment 4

- The accuracy of the evaluation dataset again increased significantly.
- 5. Fifth Experiment Try removing most frequent words
  - From this experiment and the experiments moving forward, the model from **Experiment 4** will be used.
  - The purpose of this experiment is to discover whether the removal of words that are included in 15% (or more) of the tweets increases the accuracy of the evaluation dataset.
  - The rest of the configuration is the same as Experiment 4
  - This change in the preprocessing step produced the following results:

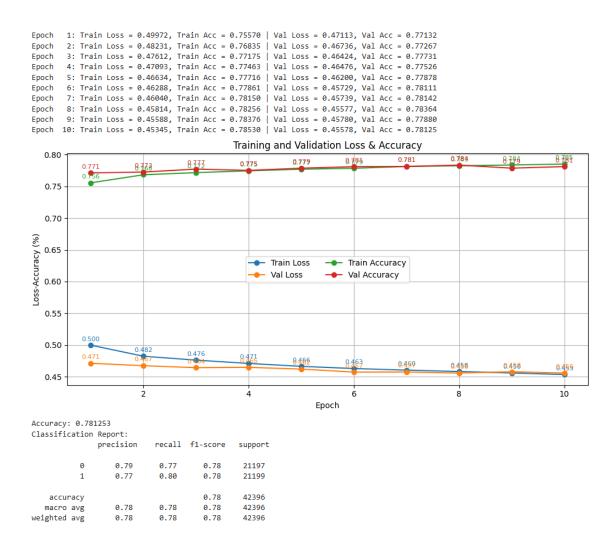


Figure 5: Experiment 5

- The metrics across the board got worse compared to **Experiment 4**. For this reason, this technique will not be used in the next experiments.
- 6. Sixth Experiment Try not using dropout
  - The purpose of this experiment was to understand the impact of **dropout**.
  - For this reason the experiment runs with dropout\_prob=0
  - The rest of the configuration is the same as **Experiment 4**
  - The following are the results:

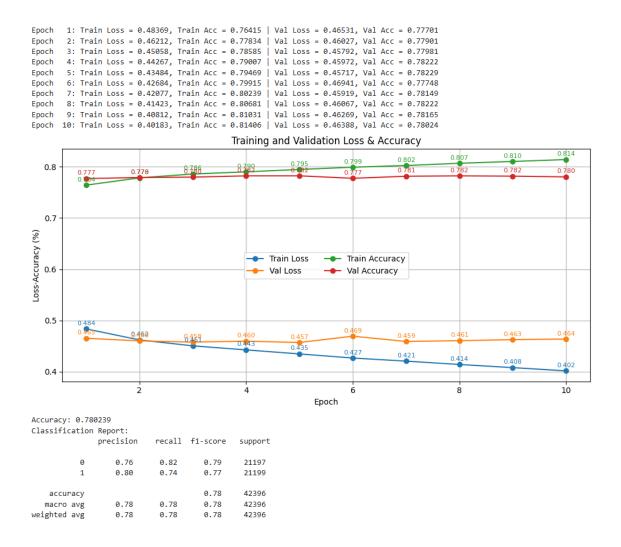


Figure 6: Experiment 6

- The results clearly show both a decrease in accuracy and also a significant increase in overfitting that can be spotted by looking at the differences between the curves Train Accuracy-Val Accuracy and Train Loss-Val Loss.
- For the above reason, the next experiments will use dropout.
- **Experiment 4** is the best so far.
- 7. Seventh Experiment Try using an 1 hidden layer architecture
  - For this experiment, the network architecture changes from two hidden layers to one.
  - The rest of the configuration is the same as **Experiment 4**
  - This change in the architecture produced the following results:

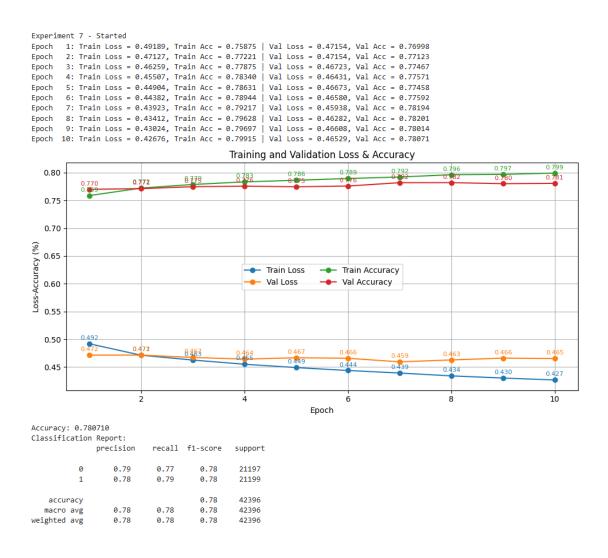


Figure 7: Experiment 7

- Although the difference is smaller, we are having the same problem with overfitting the **Experiment 6** had.
- The classification report metrics are also decreased compared to **Experiment 4**.
- Experiment 4 is still the best performing.
- 8. Eighth Experiment Try using a 3 hidden layers architecture
  - In contrast with the previous experiment, this one uses more hidden layers.
  - The architecture changes from two hidden layers to three.
  - Other configuration changes are num\_epochs=30 and dropout\_prob=0.4125125247127012 (to regularize the model), those changes are needed to understand if this more complex model is indeed better than the one of **Experiment 4**.
  - Results:

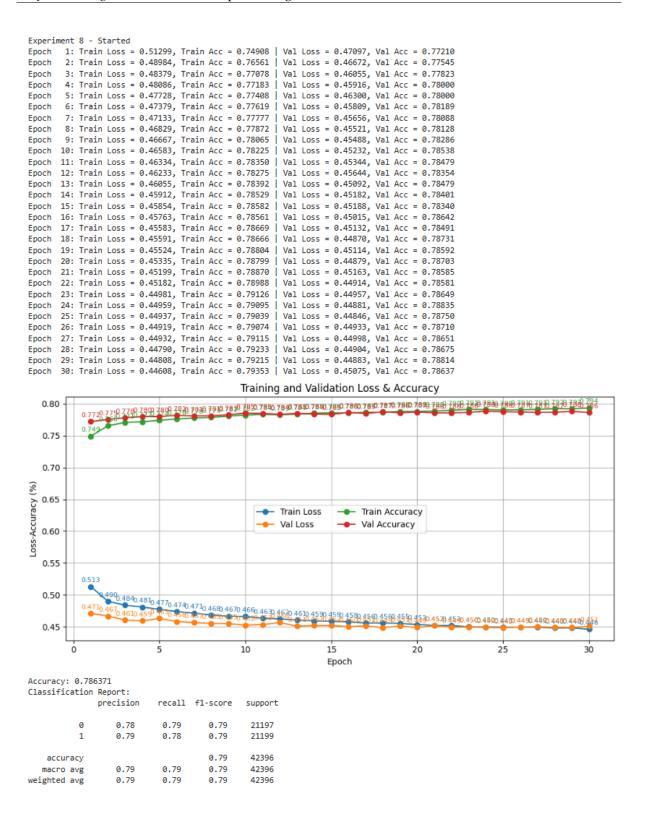


Figure 8: Experiment 8

The results indicate better performance on the curves and more stable metrics in the classification report. To have a confident answer, the next experiment is the model with the architecture of Experiment 4 but with the configuration changes of this experiment.

- 9. Ninth Experiment 2 hidden layers with more epochs and dropout\_prob
  - This experiment will prove if the previous one is indeed better than Experiment 4.
  - We will understand this by having the same architecture as **Experiment 4** but with the configuration changes of **Experiment 8**.
  - Results:

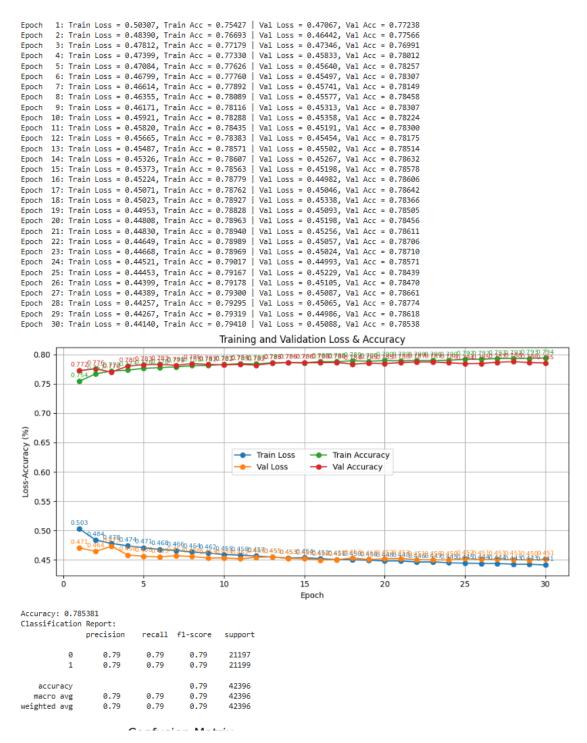


Figure 9: Experiment 9

- The results are almost identical between the two experiments.
- For this reason and because it has a lower complexity **Experiment 9** is considered the best.
- 10. Tenth Experiment Try using GELU with 2 layers
  - The parameter that changes here is the activation function used, now the two hidden layers use the GELU activation function.
  - Results:

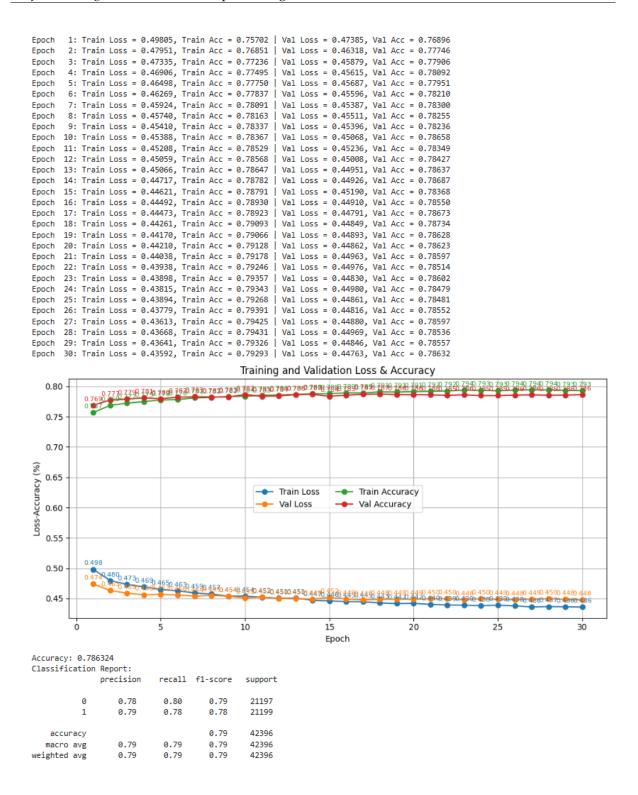


Figure 10: Experiment 10

• Similar results with **Experiment 9**, but with a bit less stable metrics in the classification report. ReLu is also considered a more efficient approach for shallow networks.

#### 11. Eleventh Experiment - Reduce Batch Size

This experiment uses the same configuration as Experiment 9 but with

batch\_size=64 instead of batch\_size=128.

• Results:

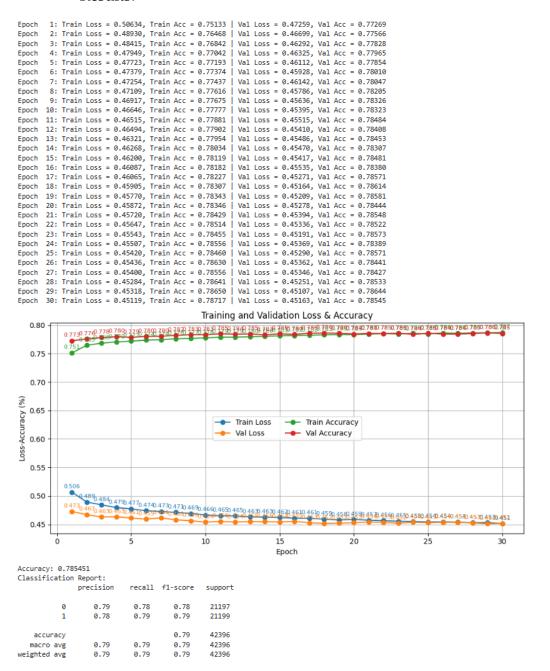


Figure 11: Experiment 11

 The results indicate similar metrics for the accuracy and classification report, as a larger batch size means faster training Experiment 9 is still considered the best.

## 12. Twelfth Experiment - Increase Batch Size

 This experiment uses the same configuration as Experiment 9 but with batch\_size=256 instead of batch\_size=128.

#### • Results:

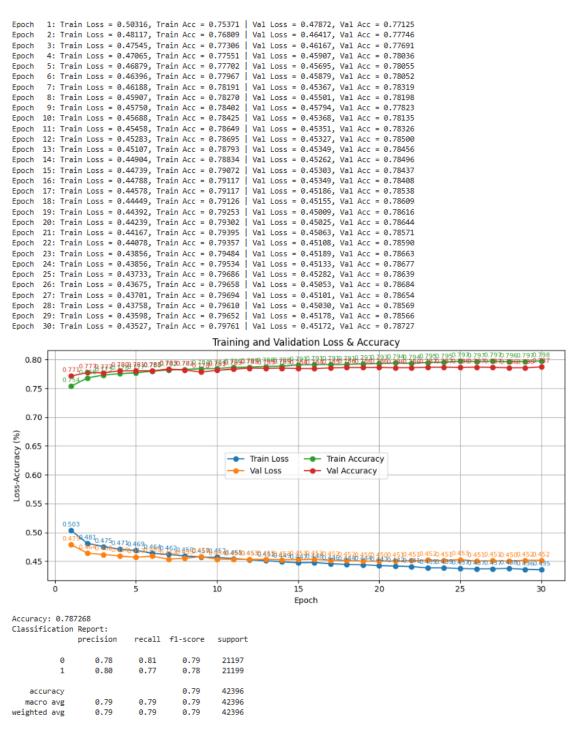


Figure 12: Experiment 12

• The results indicate similar accuracy metrics, but the classification report is less stable. **Experiment 9** is still considered the best.

# 13. Thirteen Experiment - Optimization

• To optimize the hyper-parameters of **Experiment 9** the framework **Optuna** was used for 50 runs of 20 epochs.

- The following are the parameters tested by Optuna:
  - (a) optimizer\_name -> ["Adam", "AdamW"]
  - (b) learning\_rate -> floats between 1e-3 and 1e-1
  - (c) weight\_decay -> floats between 1e-6 and 1e-4
  - (d) dropout\_prob -> floats between 0.25 and 0.5
- The value ranges were selected using a combination of previous draft runs of Optuna and manual testing.
- Optimization results:

```
Epoch 19: Train Loss = 0.44887, Train Acc = 0.78990 | Val Loss = 0.45679, Val Acc = 0.78132
[I 2025-04-15 11:12:04,795] Trial 48 finished with value: 0.45539774117340526 and parameters: {'optimizer_name': 'AdamW', 'learning_rat
 ': 0.0125469966707564, 'weight_decay': 1.8716483219033318e-05, 'dropout_prob': 0.35991237149788785}. Best is trial 34 with value: 0.45
30378578298063.
Epoch 20: Train Loss = 0.44942, Train Acc = 0.78840 | Val Loss = 0.45540, Val Acc = 0.78257
Epoch 1: Train Loss = 0.50117, Train Acc = 0.75442 | Val Loss = 0.47672, Val Acc = 0.76757
        2: Train Loss = 0.48346, Train Acc = 0.76712
                                                           Val Loss = 0.46545, Val Acc = 0.77500
        3: Train Loss = 0.47710, Train Acc = 0.77141 |
4: Train Loss = 0.47280, Train Acc = 0.77348 |
                                                           Val Loss = 0.46526, Val Acc = 0.77753
                                                           Val Loss = 0.45901, Val Acc = 0.77941
Epoch
        5: Train Loss = 0.46847, Train Acc = 0.77731 |
                                                           Val Loss = 0.45891, Val Acc = 0.78047
        6: Train Loss = 0.46529, Train Acc = 0.77826 | Val Loss = 0.46217, Val Acc = 0.77852 7: Train Loss = 0.46167, Train Acc = 0.78050 | Val Loss = 0.45864, Val Acc = 0.77970
Epoch
        8: Train Loss = 0.45898, Train Acc = 0.78145 | Val Loss = 0.45780, Val Acc = 0.77939
Epoch
        9: Train Loss = 0.45671, Train Acc = 0.78247 | Val Loss = 0.45710, Val Acc = 0.78111
Epoch 10: Train Loss = 0.45490, Train Acc = 0.78336 | Val Loss = 0.45596, Val Acc = 0.78201

Epoch 11: Train Loss = 0.45275, Train Acc = 0.78507 | Val Loss = 0.45611, Val Acc = 0.78250
Epoch 12: Train Loss = 0.45071, Train Acc = 0.78567 | Val Loss = 0.45508, Val Acc = 0.78314
Epoch 13: Train Loss = 0.44888, Train Acc = 0.78787 | Val Loss = 0.45640, Val Acc = 0.78342
Epoch 14: Train Loss = 0.44845, Train Acc = 0.78762 | Val Loss = 0.45387, Val Acc = 0.78529
Epoch 15: Train Loss = 0.44450, Train Acc = 0.78952
                                                           Val Loss = 0.45591, Val Acc = 0.78205
Epoch 16: Train Loss = 0.44440, Train Acc = 0.78973 | Val Loss = 0.45536, Val Acc = 0.78356
Epoch 17: Train Loss = 0.44251, Train Acc = 0.79236 | Val Loss = 0.45422, Val Acc = 0.78411
Epoch 18: Train Loss = 0.44156, Train Acc = 0.79149
                                                           Val Loss = 0.45592, Val Acc = 0.78385
Epoch 19: Train Loss = 0.44054, Train Acc = 0.79226 | Val Loss = 0.45428, Val Acc = 0.78290
[I 2025-04-15 11:13:36,214] Trial 49 finished with value: 0.4588513873427747 and parameters: {'optimizer name': 'AdamW', 'learning rat
 ': 0.002864222029302957, 'weight_decay': 2.7453163998042397e-05, 'dropout_prob': 0.3296590440397862}. Best is trial 34 with value: 0.4
530378578298063.
Epoch 20: Train Loss = 0.43902, Train Acc = 0.79371 | Val Loss = 0.45885, Val Acc = 0.78130
numbers of the finished trials: 50
the best params: {'optimizer_name': 'AdamW', 'learning_rate': 0.0010291927407311168, 'weight_decay': 8.018811458914011e-06, 'dropout_pr
ob': 0.35537187034206433
the best value: 0.4530378578298063
Optimization Process - Finished
```

Figure 13: Optimization Results

• Results:

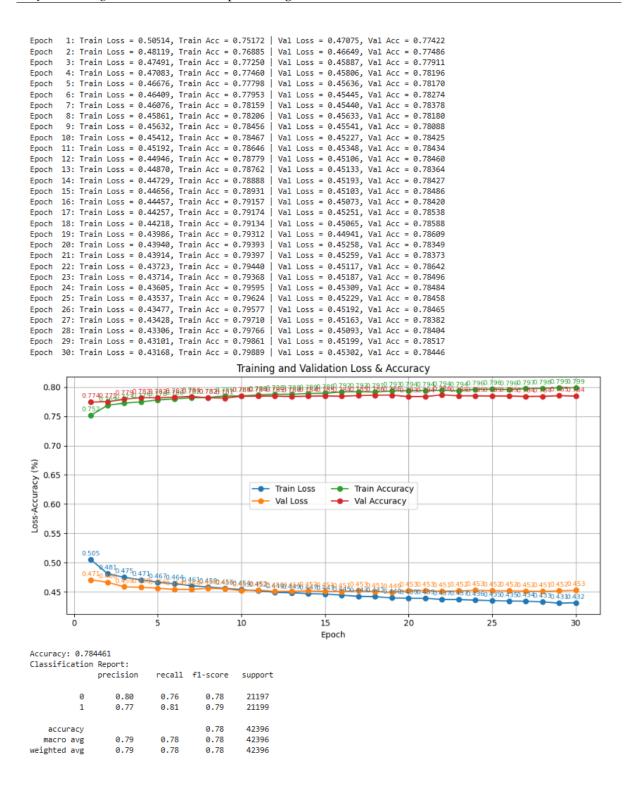


Figure 14: Experiment 13

• The results show a clear imbalance in the classification report metrics and overall lower values, for this reason, the best model of the experiments will be considered the one of **Experiment 9**.

#### 3.2. Hyper-parameter tuning

#### 1. Final Results:

• The best results are the ones of Experiment 9.

```
Train and Evaluate Best Model - Started
       1: Train Loss = 0.50387, Train Acc = 0.75216 | Val Loss = 0.46909, Val Acc = 0.77479
Fnoch
       2: Train Loss = 0.48481, Train Acc = 0.76723
                                                     | Val Loss = 0.46415, Val Acc = 0.77755
       3: Train Loss = 0.47918, Train Acc = 0.77018
                                                      | Val Loss = 0.46190, Val Acc = 0.77972
Epoch
       4: Train Loss = 0.47392, Train Acc = 0.77365
                                                       Val Loss = 0.45934, Val Acc = 0.77934
Epoch
       5: Train Loss = 0.47088, Train Acc = 0.77485
                                                       Val Loss = 0.45783, Val Acc = 0.78085
Epoch
Epoch
       6: Train Loss = 0.46796, Train Acc = 0.77766
                                                       Val Loss = 0.46000, Val Acc = 0.78038
       7: Train Loss = 0.46659, Train Acc = 0.77823
                                                       Val Loss = 0.45498, Val Acc = 0.78272
Epoch
       8: Train Loss = 0.46400, Train Acc = 0.77963
                                                     | Val Loss = 0.45526, Val Acc = 0.78305
Epoch
       9: Train Loss = 0.46213, Train Acc = 0.78122
                                                      | Val Loss = 0.45462, Val Acc = 0.78305
Epoch 10: Train Loss = 0.45867, Train Acc = 0.78277
                                                       Val Loss = 0.45270, Val Acc = 0.78481
Epoch 11: Train Loss = 0.45814, Train Acc = 0.78363
                                                       Val Loss = 0.45548, Val Acc = 0.78401
      12: Train Loss = 0.45763, Train Acc = 0.78310
                                                       Val Loss = 0.45371, Val Acc = 0.78448
Epoch 13: Train Loss = 0.45494, Train Acc = 0.78592
                                                       Val Loss = 0.45403, Val Acc = 0.78394
Epoch 14: Train Loss = 0.45440, Train Acc = 0.78607
                                                       Val Loss = 0.45203, Val Acc = 0.78562
Epoch 15: Train Loss = 0.45331, Train Acc = 0.78584
                                                       Val Loss = 0.45319, Val Acc = 0.78441
Epoch 16: Train Loss = 0.45164, Train Acc = 0.78737
                                                      | Val Loss = 0.45172, Val Acc = 0.78432
Epoch 17: Train Loss = 0.45174, Train Acc = 0.78664
                                                       Val Loss = 0.45333, Val Acc = 0.78540
Epoch 18: Train Loss = 0.45030, Train Acc = 0.78906
                                                       Val Loss = 0.45080, Val Acc = 0.78614
      19: Train Loss = 0.44937, Train Acc = 0.78926
                                                       Val Loss = 0.45039, Val Acc = 0.78496
Epoch 20: Train Loss = 0.44817, Train Acc = 0.78932
                                                     | Val Loss = 0.45260, Val Acc = 0.78533
Epoch
      21: Train Loss = 0.44834, Train Acc = 0.79005
                                                       Val Loss = 0.45071, Val Acc = 0.78500
Epoch
      22: Train Loss = 0.44642, Train Acc = 0.79017
                                                       Val Loss = 0.45133, Val Acc = 0.78654
Epoch 23: Train Loss = 0.44692, Train Acc = 0.78913
                                                       Val Loss = 0.45300, Val Acc = 0.78529
      24: Train Loss = 0.44560, Train Acc = 0.79009
                                                       Val Loss = 0.45187, Val Acc = 0.78618
Epoch
Epoch 25: Train Loss = 0.44502, Train Acc = 0.79159
                                                       Val Loss = 0.45190, Val Acc = 0.78588
      26: Train Loss = 0.44423, Train Acc = 0.79196
                                                       Val Loss = 0.45149, Val Acc = 0.78491
      27: Train Loss = 0.44366, Train Acc = 0.79129
                                                       Val Loss = 0.45177, Val Acc = 0.78576
Epoch
Epoch 28: Train Loss = 0.44371, Train Acc = 0.79292
                                                      | Val Loss = 0.45212, Val Acc = 0.78319
Epoch
      29: Train Loss = 0.44198, Train Acc = 0.79312
                                                      | Val Loss = 0.45056, Val Acc = 0.78540
      30: Train Loss = 0.44275. Train Acc = 0.79297 | Val Loss = 0.45130, Val Acc = 0.78616
Epoch
                                              Training and Validation Loss & Accuracy
   0.80
   0.70
   0.65
Loss-Accuracy
                                                                   - Train Accuracy
                                                  Train Loss
                                                      Val Loss

    Val Accuracy

  0.60
   0.55
   0.50
                                                                   530,4520,4520,4500,4808,4530,4538,4538,453
   0.45
         0
                                              10
                                                                                   20
                                                                                                      25
                                                                                                                         30
                                                                 Epoch
Accuracy: 0.786159
Classification Report:
              precision
                            recall f1-score
                                               support
           0
                             0.78
                                       0.78
                                                21197
          1
                   0.78
                             0.80
                                       0.79
                                                21199
                                       0.79
                                                42396
   accuracy
                             0.79
                                       0.79
                                                42396
   macro avg
weighted avg
                                                42396
```

Figure 15: Best Model - Results

• The results seem to get around the same value of 0.79 for all metrics, this

demonstrates a balanced performance and indicates an effective classification without significant bias. The insignificant amount of overfitting can also be observed by the small Delta between the Train and Val curves of the plot above.

# 2. Model Configuration:

- The final configuration is the following:
  - batch\_size -> 128
  - network architecture -> Two hidden layers with ReLu as an activation function, batch optimization, and dropout.
  - $num_epochs -> 30$
  - loss\_func -> nn.CrossEntropyLoss()
  - optimizer\_name -> Adam
  - learning\_rate -> 0.0019524310388177159
  - $weight_decay -> 5.263544573640884e-06$
  - dropout\_prob -> 0.4125125247127012

# 3. Under-Fitting & Over-Fitting:

- No under-fitting was observed in all of the experiments.
- The Delta between the train and val accuracies is small enough to not be considered as overfitting.

#### 3.3. Optimization techniques

- 1. Optuna, an optimization framework, was used to run multiple times with different hyperparameters for a number of epochs to find the best match (lowest val loss), although not far from the best experiment, the results of Optuna were rejected for the reasons described above. More info about the use of Optuna on Experiment 13.
- 2. Batch normalization was done by normalizing the outputs of each layer to keep the values stable during training, which makes learning faster and more reliable.
- 3. Dropout was done by randomly turning off a percentage of neurons during training, helping to reduce overfitting by preventing the network from relying on specific neurons too much.

#### 3.4. Evaluation

• I evaluated the predictions using accuracy, precision, recall, F1-score, and Plots.

- All the metrics reached around 78%, showing the general stability and good performance of the model. These results, and especially the F1-score, which can be described as the harmonic mean of the precision and recall of a classification model, reveal a good performance in recognizing positive cases while minimizing false positives and false negatives.
- Learning curves were plotted to analyze model performance across different experiments, helping to detect overfitting or underfitting trends.
- The following table shows the average metrics between the two classes of each experiment.

Experiment	Accuracy	Precision	Recall	F1-Score
1	0.71	0.71	0.71	0.71
2	0.76	0.76	0.76	0.76
3	0.78	0.78	0.78	0.78
4	0.79	0.79	0.79	0.79
5	0.78	0.78	0.78	0.78
6	0.78	0.78	0.78	0.78
7	0.78	0.78	0.78	0.78
8	0.79	0.79	0.79	0.79
9	0.79	0.79	0.79	0.79
10	0.79	0.79	0.79	0.79
11	0.79	0.79	0.79	0.79
12	0.79	0.79	0.79	0.79
13	0.79	0.79	0.79	0.79

Table 1: Experiments

#### 3.4.1. ROC curve.

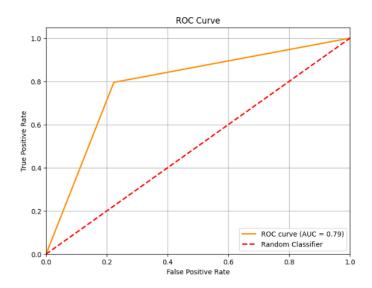


Figure 16: Best Model - ROC Curve

- The ROC (Receiver Operating Characteristic) curve shows that the classifier achieves a TPR (True Positive Rate) of about 0.80 at a FPR (False Positive Rate) of around 0.20-0.25, rising well above the "random" baseline classifier.
- An overall AUC (Area Under the ROC Curve) of 0.79 indicates that the model
  has good discrimination ability between positive and negative tweets, correctly
  ranking a randomly chosen positive example above a negative one roughly 79%
  of the time.

# 3.4.2. Learning Curve.

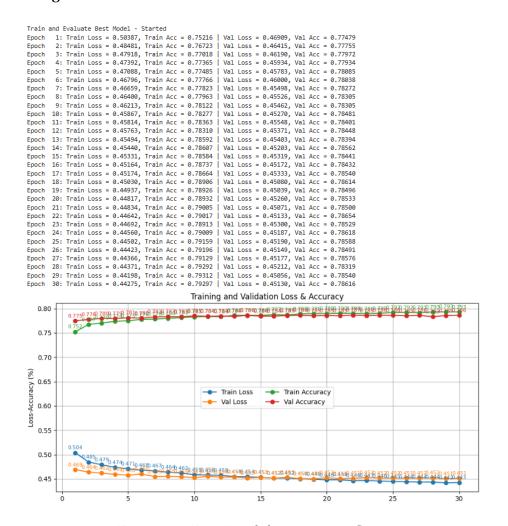


Figure 17: Best Model - Learning Curve

- The **training curves** show a steady drop in **loss** from about **0.50** to **0.44** over **30** epochs, with **training accuracy** climbing from around **75%** up to **79%**.
- The **validation curves** mirror this trend, **val loss** falls from around **0.47** to **0.45** and **val accuracy** rises from around **77%** to **79%**, both show most improvement at roughly the first **10 epochs**, improvement is still present afterwards but with a slower rate.
- The small but persistent gap (**training acc** around **79**% vs. **validation acc** around **78.5**%) indicates only mild overfitting, and the fact that both **losses** continue to

decrease alongside each other suggests the model is well-tuned and not underfitting.

## 3.4.3. Confusion matrix.

• True Negatives (TN): 16.474

• False Positives (FP): 4.723

• False Negatives (FN): 4.343

• True Positives (TP): 16.856

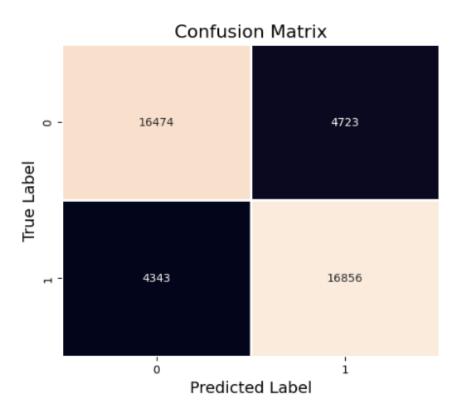


Figure 18: Best Model - Confusion Matrix

• The model performs well overall, as the numbers for correct predictions (TP & TN) are significantly higher than incorrect ones.

# 4. Results and Overall Analysis

## 4.1. Results Analysis

• My final results show an accuracy of around 78.5%, meaning that the model makes a correct sentiment prediction 78.5% of the time. Metrics such as precision, recall, and f1-score, alongside the Learning Curves plot, also show that the model is balanced.

• More experiments I would make would be to run the Optuna optimization for a number of times and epochs for each one of the experiments made.

## 4.1.1. Best trial.

• Results of best trial:

Accuracy: 0.786159													
Classification Report:													
		precision	recall	f1-score	support								
	0	0.79	0.78	0.78	21197								
	1	0.78	0.80	0.79	21199								
accur	racy			0.79	42396								
macro	avg	0.79	0.79	0.79	42396								
weighted	avg	0.79	0.79	0.79	42396								

Figure 19: Best Trial - Classification Report

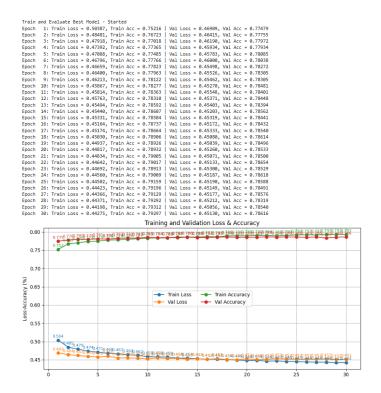


Figure 20: Best Trial - Learning Curve

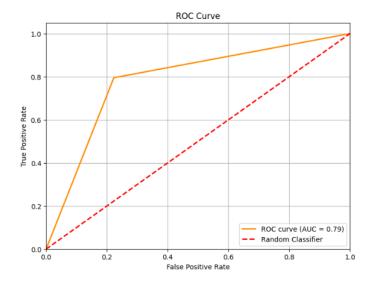


Figure 21: Best Trial - ROC Curve

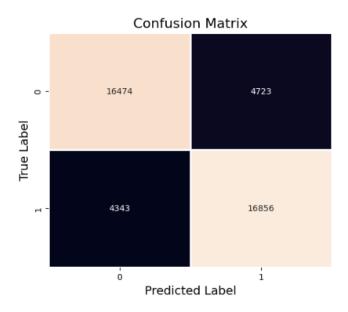


Figure 22: Best Trial - Confusion Matrix

• Look at **Experiment 9** and **3.2. Hyper-parameter tuning** for more information.

# 4.2. Comparison with the first project

- Overall, the neural-network model in Project 2 achieves a final accuracy of about 78.6% (with precision/recall/F1 all around 0.79), whereas the simpler logistic-regression baseline in Project 1 topped out closer to 80% validation accuracy (and the other metrics).
- That small gap in accuracy between then two procjects probably stems largely from the input vectors.

- More precisely, averaging Word2Vec embeddings smooths away the fine-grained n-gram signals that TF–IDF feeds into logistic regression.
- The two-layer network has far more parameters and a tougher, and more complex training landscape, so it usually needs either more data or more careful hyperparameter tuning to outperform a simple logistic regression, which has fewer parameters and a single, easy-to-find optimum.