Artificial Intelligence II Homework 3

Comments & Model Performance results on Questions 1 & 2

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Basic Execution flow

1. Before creating the train & validation sets, we read the `.csv` files the usual way (with `pd.read_csv`), to check if all the samples have the expected format without missing values, and get the number of samples in the validation set (which will be needed later).

2. We create the Train and Validation sets, using `TabularDataset` objects:

- We preprocess each tweet with `customPreprocessor` and tokenize it using `nltk.TweetVectorizer`.
- We will access the two sets in batches, using `BucketIterator` objects. We initialize the validation set `BucketIterator` with `batch_size` equal to the validation set size, so essentially we access the set in "batch mode" (one batch for the whole set).

3. We create the embeddings matrix, where we store the **GloVe** vector for each word in the train set vocabulary.

4. We initialize the Model. Hyperparameters such as number of epochs, batch size, learning rate, number & size of layers, Dropout probability etc. can be modified on cell #2.
   We use `CrossEntropyLoss` and the `Adam` optimizer.

5. We train the model: We use `numpy` arrays to store several performance stats during training, such as Loss and F1 score on Train and Validation set after each epoch.
   During each epoch:

   - For each batch given by the train set `BucketIterator`:
     - We make predictions on this batch
     - Extract the predicted labels & calculate the accuracy
     - Calculate & store the batch Loss
     - Perform backpropagation
   - After going through all the batches, we calculate the total Loss and the F1 score for the Train set
   - We make predictions on the Validation set
   - Calculate & store the Validation set Loss
   - We extract the predicted labels, calculate the accuracy and store the F1 score

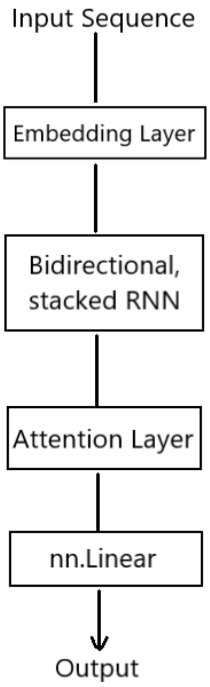
6. Displaying performance results: After the end of training we display:

   - The Confusion Matrices of the final model predictions on the Train and Validation sets.
   - The F1 Learning Curves for both sets, to demonstrate the performance of the model after each epoch of the training phase.
   - The F1, Precision and Recall scores for the final model on both sets.
     We use the corresponding **scikit-learn** routines for calculating the scores. We use `average='micro'` for F1 score and `average='macro'` for Precision & Recall scores.

- Training phase Loss curves for both sets.
- The ROC Curves for the Validation set predictions.
  We mirror the usage of `roc_curve` from **scikit-learn** for multiple classes, as demonstrated here.
  To create the curves, we apply the `softmax` function to the NN output vector, to convert it to possibility values that add-up to 1, and use the `softmax` output to create the curves.
  `roc_curve` applies generated possibility thresholds to create the curves, therefore if we provided it with just the predicted labels, it would only apply 3 thresholds to each result, which is insufficient to create useful ROC curves.

Model types used during development

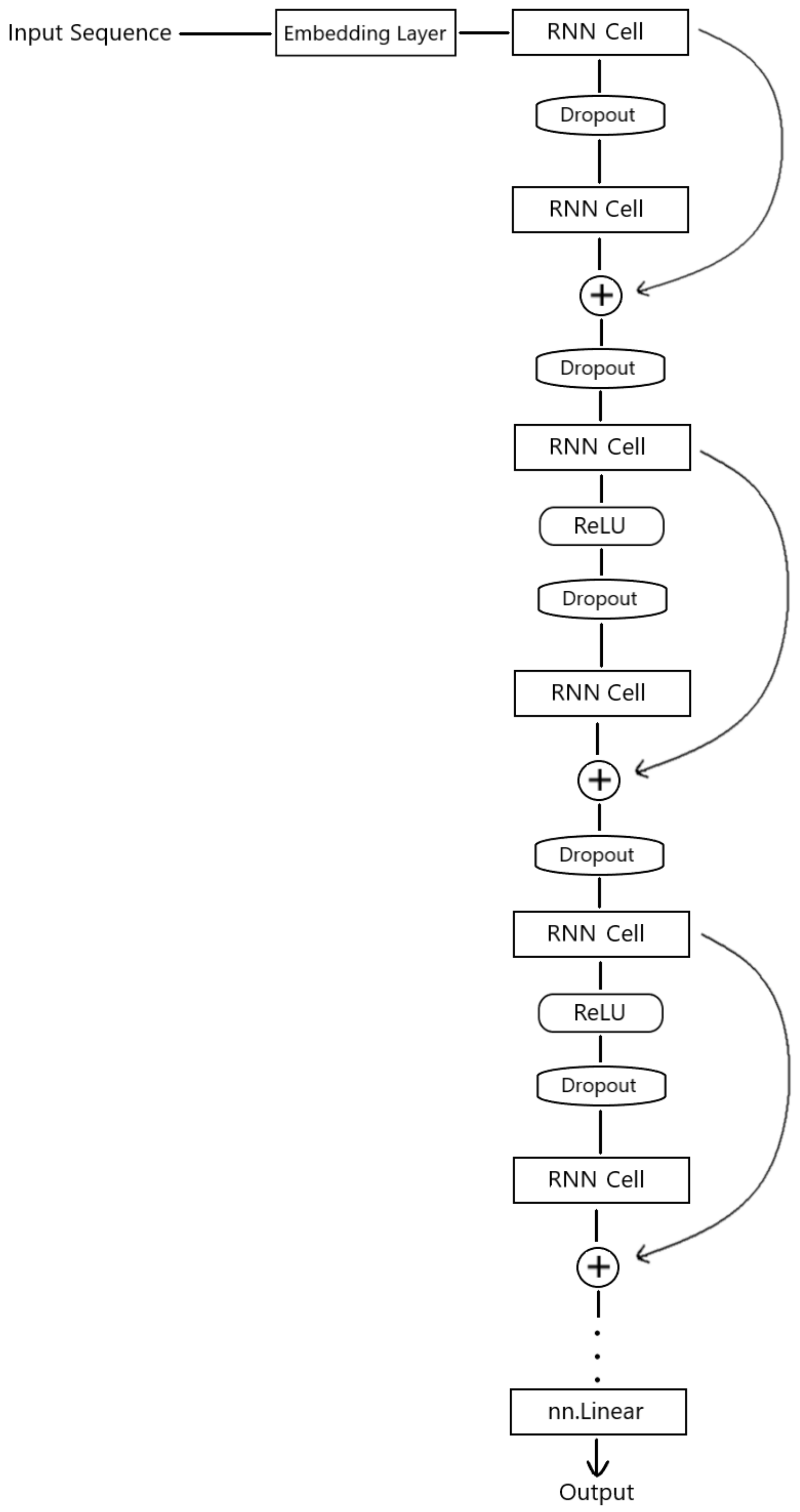
- Models 1, 2 have the following architecture:



(Model 2 does not use attention layer, but other than that the structure is the same.
Model 1 is the chosen model, and can be used with or without attention layer. See the next sections for the performance comaprison.)

  - We use bidirectional, stacked RNN, without skip connections.
  - If desired (optionally in Model 1), we can pass the RNN output through an Attention Layer, to help the model focus in critical parts of each tweet and prevent the vanishing gradient in faraway hidden states.
  - Finally, we add a Linear layer to output a vector of the desired size.

- Models 3, 4 use the following architecture:



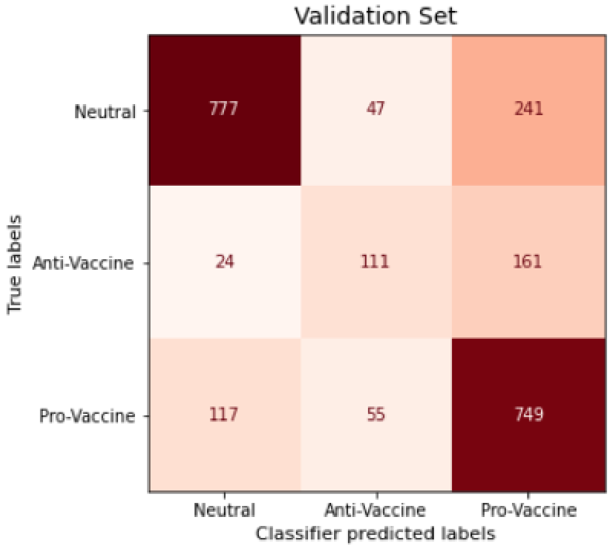
  - We use a stacked RNN, this time with skip connections. We apply a skip connection in every 2 layers (layers 1, 3, 5 etc. have a skip connection, and the output of layers 2, 4, 6 etc. is the destination of a skip connection). Skip connections are implemented simply using `torch.add`
  - Before providing input to any layer (except for the first one) we apply a Dropout layer to it.
  - We apply a `ReLU` layer to the odd layer outputs, except for the first one.
  - Finally, we add a Linear layer to output a vector of the desired size.

Different models performance comparison

Notes on all models:

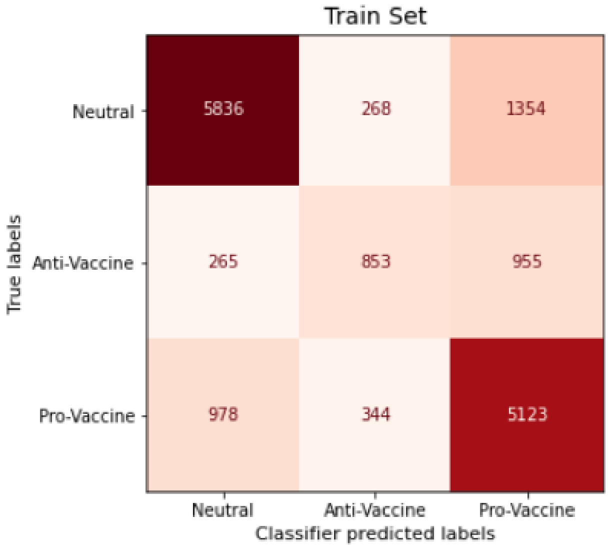
- The performance results displayed below have been produced without using GPU acceleration.
- When not using GPU, the results can be reproduced using `SEED = 42`.
- Unfortunately, GPU-accelerated model results could not be fully reproduced.
- The execution of each model using only CPU takes about 4-5 minutes. In case this is inconvenient, GPU can be enabled in code cell #6, but note that the results for all models will differ from the ones presented bellow.
- All models use the **GloVe** pre-trained word embeddings from `glove.6B.100d.txt`.

1. This is the preselected model in the interactive notebook. For this model, we use:
    - Learning rate: 0.005
    - Batch Size: 256
    - # Epochs: 5
    - RNN: Bidirectional, 4-layer **GRU**, with `hidden_size = 32`
    - Dropout probability: 0.5



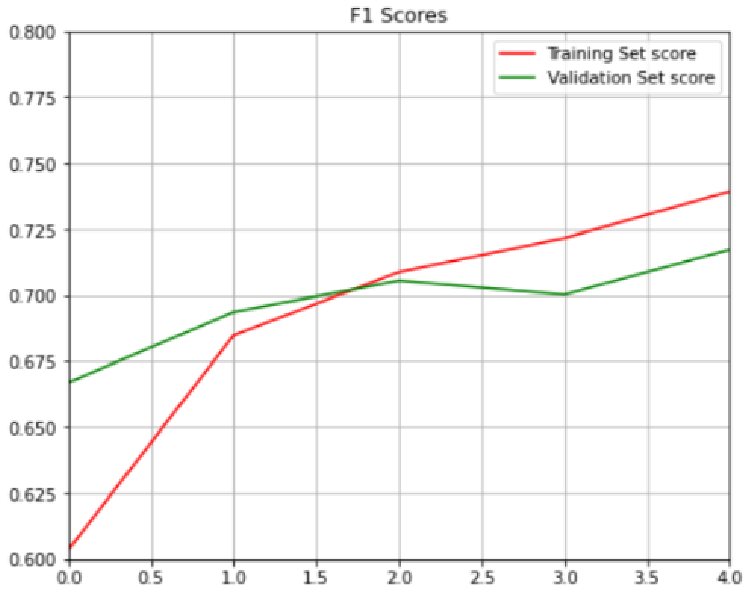
Validation Set

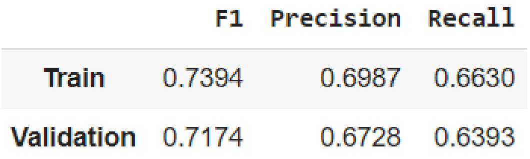
True labels \ Classifier predicted labels	Neutral	Anti-Vaccine	Pro-Vaccine
Neutral	777	47	241
Anti-Vaccine	24	111	161
Pro-Vaccine	117	55	749



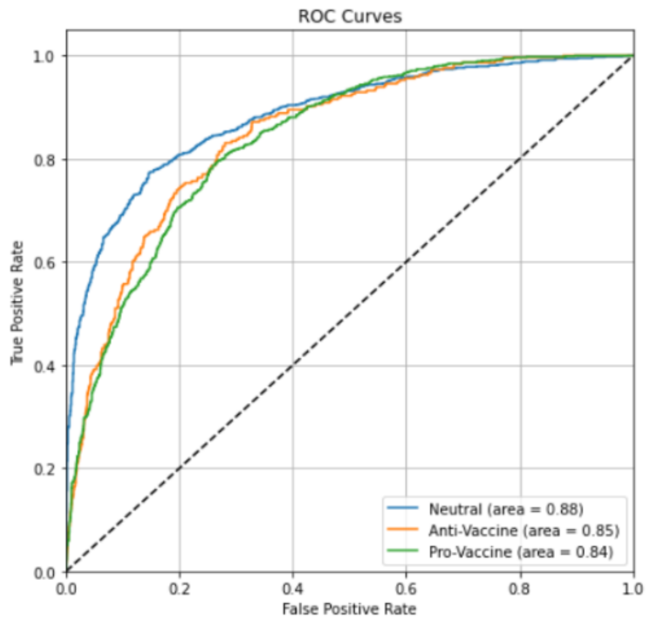
Train Set

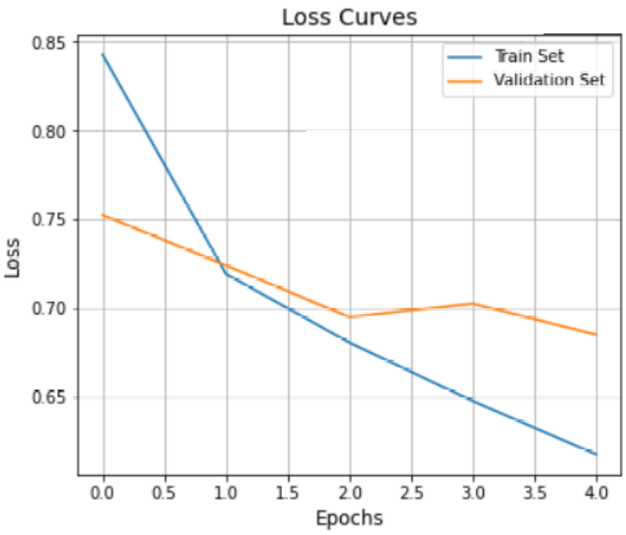
True labels \ Classifier predicted labels	Neutral	Anti-Vaccine	Pro-Vaccine
Neutral	5836	268	1354
Anti-Vaccine	265	853	955
Pro-Vaccine	978	344	5123





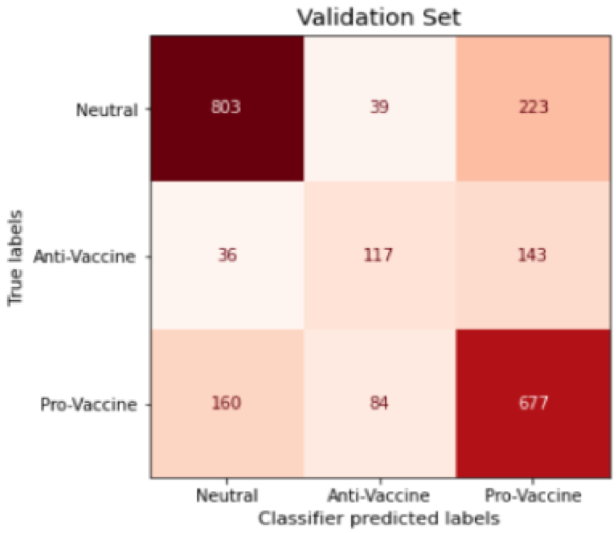
	F1	Precision	Recall
Train	0.7394	0.6987	0.6630
Validation	0.7174	0.6728	0.6393



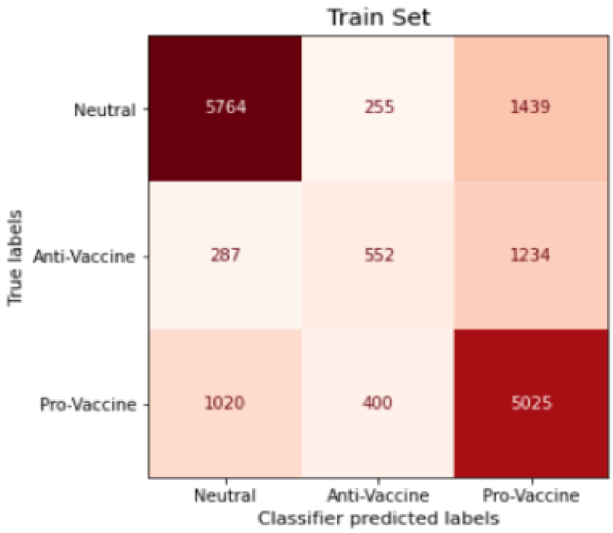


2. For this model, we use:

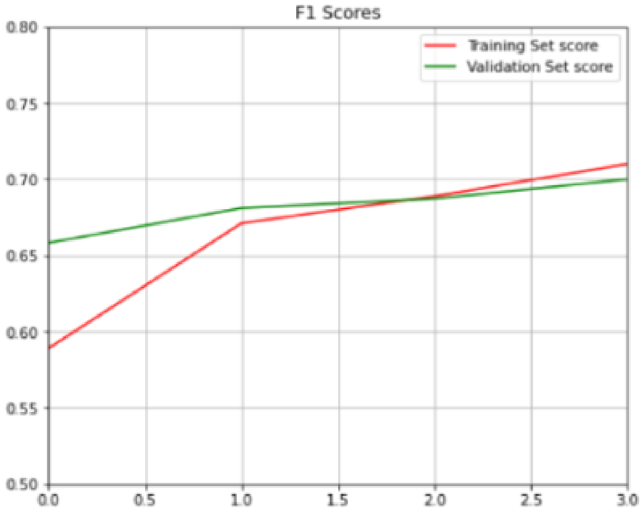
- Learning rate: 0.005
- Batch Size: 128
- # Epochs: 4
- RNN: Bidirectional, 4-layer **LSTM**, with `hidden_size = 32`
- Dropout probability: 0.5

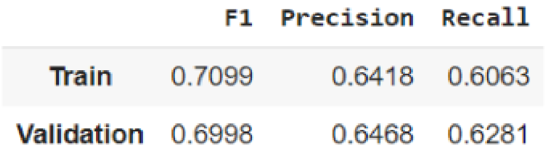

Validation Set

True labels \ Classifier predicted labels	Neutral	Anti-Vaccine	Pro-Vaccine
Neutral	803	39	223
Anti-Vaccine	36	117	143
Pro-Vaccine	160	84	677

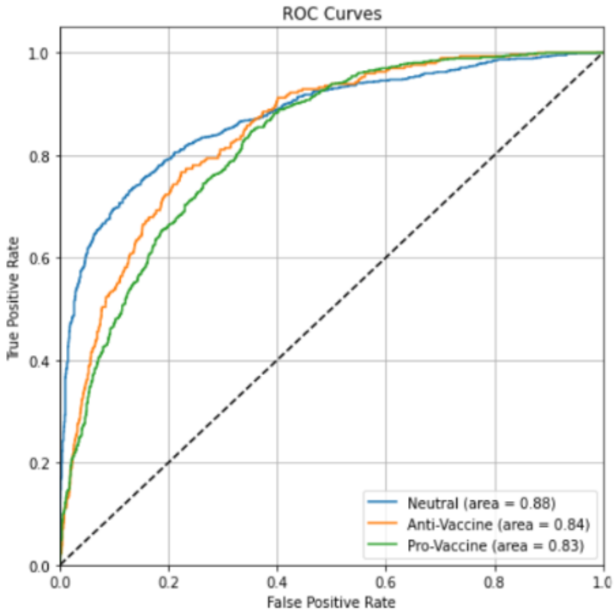

Train Set

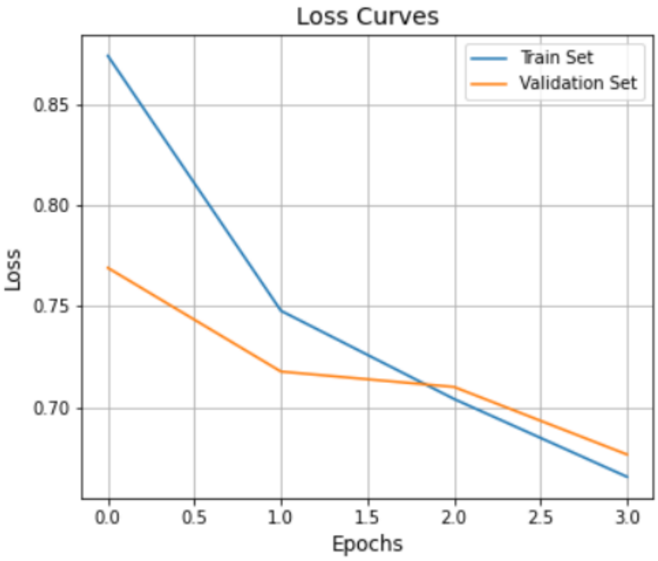
True labels \ Classifier predicted labels	Neutral	Anti-Vaccine	Pro-Vaccine
Neutral	5764	255	1439
Anti-Vaccine	287	552	1234
Pro-Vaccine	1020	400	5025





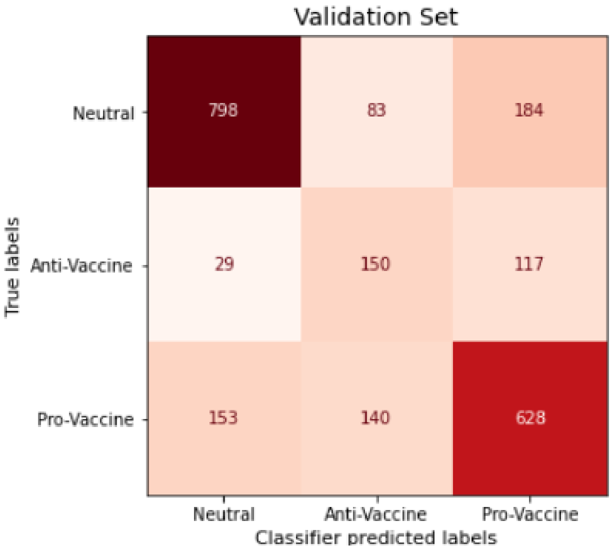
	F1	Precision	Recall
Train	0.7099	0.6418	0.6063
Validation	0.6998	0.6468	0.6281



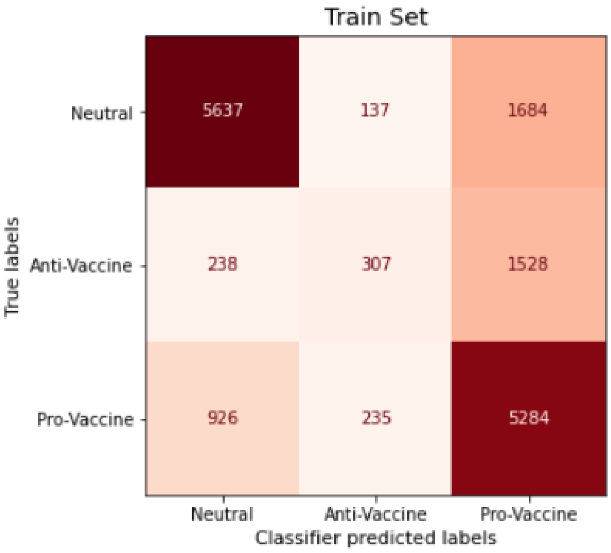


3. In this model, we use:

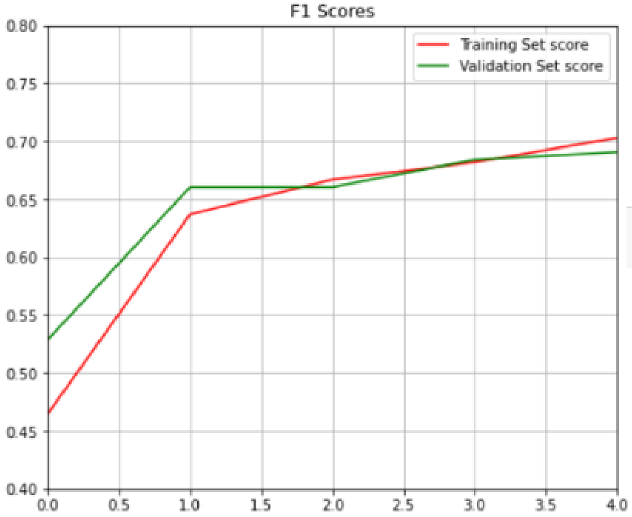
- Learning rate: 0.005
- Batch Size: 128
- # Epochs: 5
- RNN: 6-layer **GRU**, with `hidden_size = 64` and skip connections
- Dropout probability: 0.5

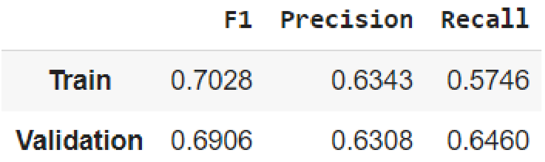


	Neutral	Anti-Vaccine	Pro-Vaccine
Neutral	798	83	184
Anti-Vaccine	29	150	117
Pro-Vaccine	153	140	628



	Neutral	Anti-Vaccine	Pro-Vaccine
Neutral	5637	137	1684
Anti-Vaccine	238	307	1528
Pro-Vaccine	926	235	5284

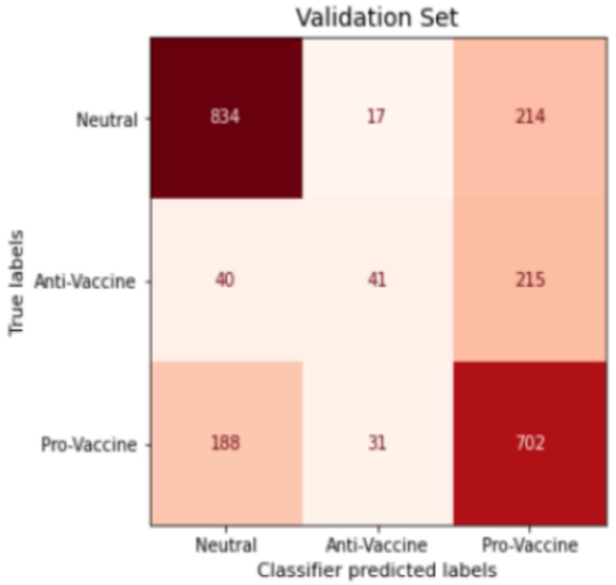


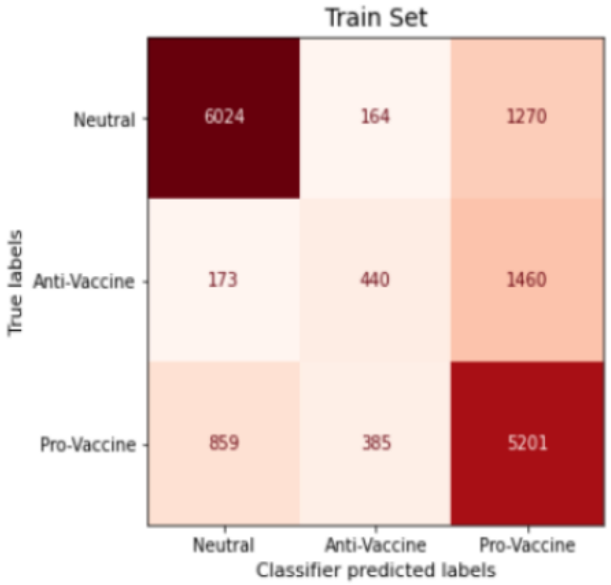


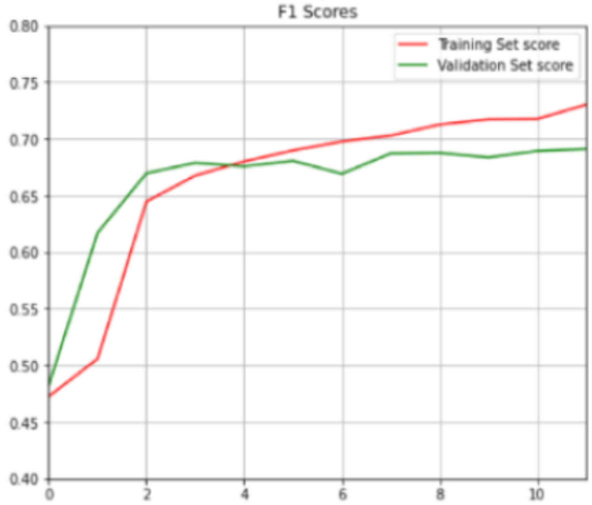
	F1	Precision	Recall
Train	0.7028	0.6343	0.5746
Validation	0.6906	0.6308	0.6460

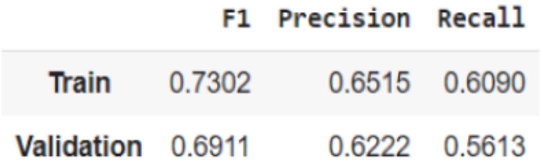
4. In the last model, we use:

- Learning rate: 0.0055
- Batch Size: 256
- # Epochs: 12
- RNN: 3-layer **LSTM**, with `hidden_size = 64` and skip connections
- Dropout probability: 0.5

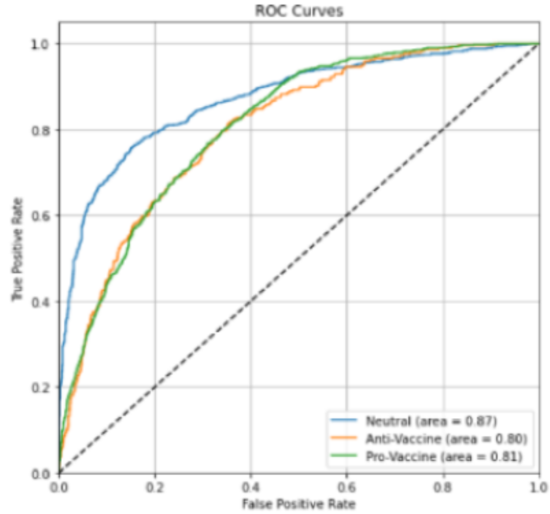


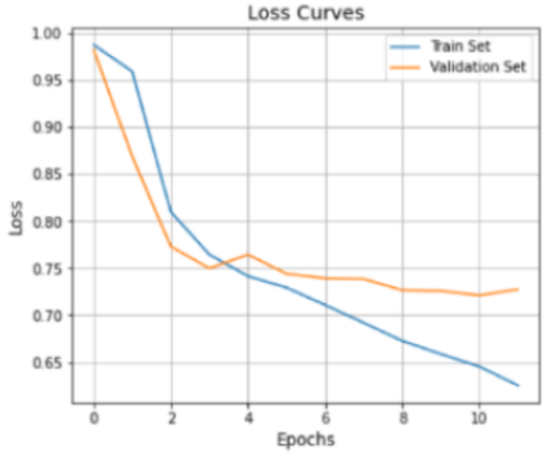






	F1	Precision	Recall
Train	0.7302	0.6515	0.6090
Validation	0.6911	0.6222	0.5613





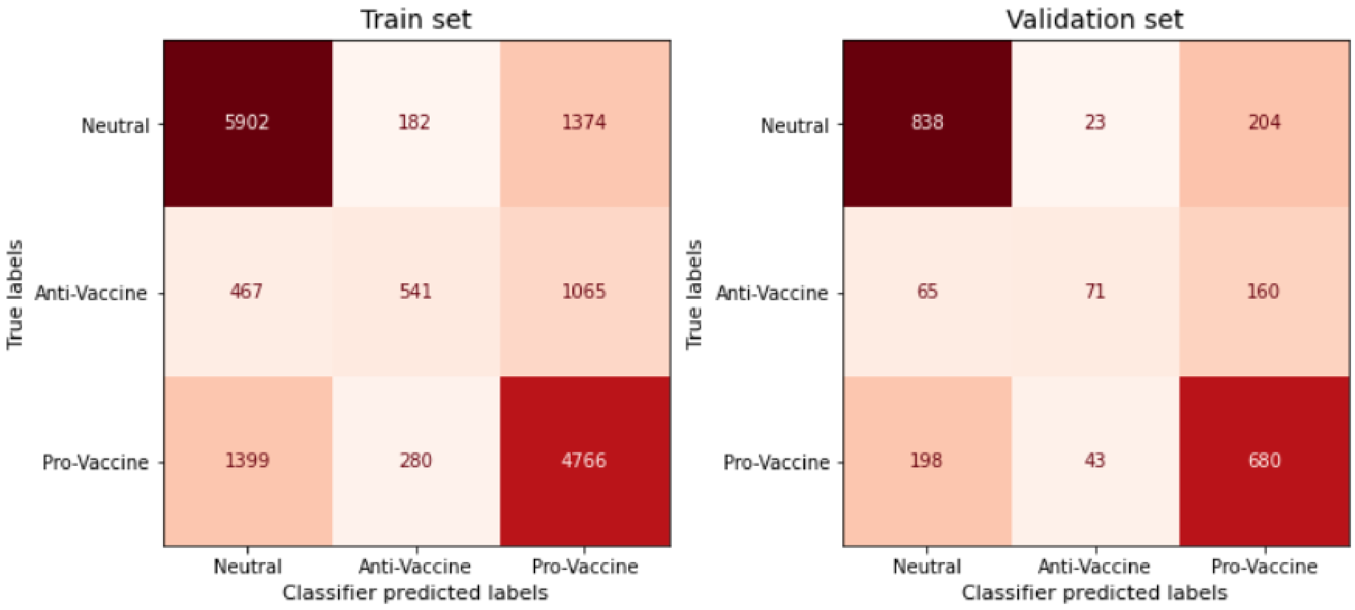
Comments/Observations on the models and their develpoment

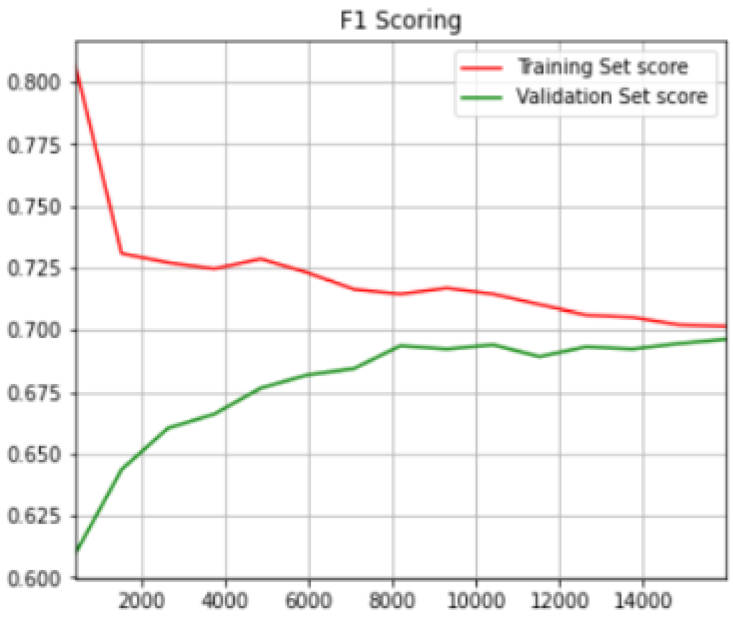
- We notice that bidirectional models tend to perform better. They learn more quickly (in terms of epochs) and perform better in each seperate class, which affects the **Precision** and especially the **Recall** score.
- Skip connections did not seem to have any significant effect in the model performance.
- GRU models achieved slightly better performance, possibly due to their simplicity, which prevents overfitting in comparison to LSTM's.
- Decreasing the Dropout probability and/or the batch size usually resulted in higher tendency for overfitting.
- Using **GloVe** embeddings with vector size = 100 appeared to be just about right. Higher vector size would cause significant overfitting in most cases.
- Just like in the previous 2 homeworks, we see much better performance on `Neutral` and `Pro-Vaccine` tweets in all models, since the vast amount of train set tweets are labeled as such.
- However, the ROC curves show that while the model may have trouble classifying `Anti-Vaccine` tweets correctly, the possibility assigned to this class when the prediction is wrong is not small. In other words, the model may be **misclassifying** the `Anti-Vaccine` tweets, but **it is not very "confident"** in these cases.

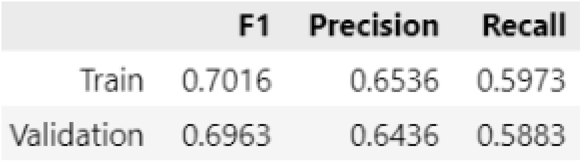
Adding Attention Layer to Model 1

Comparison with HW1 Softmax Regression Model and HW2 Feed-Forward NN Model

Below are the performance results of the model obtained using SoftMax Regression in HW1:







	F1	Precision	Recall
Train	0.7016	0.6536	0.5973
Validation	0.6963	0.6436	0.5883

We can see that the results are not drastically different, probably due to the "naive" use of word vectors in HW2: Simply taking the mean vector of all words in a tweet does not take important factors into account, such as the position of the words, or meaningful word combinations.
Despite that fact, we can see that the NN classifier seems less biased by the the class imbalance in the Train set, since it labels less `Neutral` tweets correctly, and more `Pro-Vaccine` tweets correctly. The performance on the `Anti-Vaccine` tweets might be disappointing, since the imbalance is huge, but as mentioned above, the ROC Curve shows that the model is not that confident when mislabeling `Anti-Vaccine` tweets.

Development

The notebook has been developed mostly in Google Colab, but also in WSL Ubuntu 20.04, using Visual Studio Code & Python 3.8.10.
It has been tested successfully in the Google Colab environment, using both CPU-only and GPU-accelerated runtime engines.