Syracuse University

IST664 – Natural Language Processing

Twitter Emotion Recognition using RNN

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Goal and Motivation

Emotions are expressed in nuanced ways, which varies by collective or individual experiences, knowledge, and beliefs. Therefore, to understand emotion, as conveyed through text, a robust mechanism capable of capturing and modeling different linguistic nuances and phenomena is needed.

We aimed to predict emotion of various Tweets using Recurrent Neural Network approach.

Data Description

We are using the default English Twitter messages dataset from the HuggingFace Hub □with six basic emotions: anger, fear, joy, love, sadness, and surprise.

```
{'train': Dataset(features: {'text': Value(dtype='string', id=None), 'label': Value(dtype='string', id=None)}, num_ro
ws: 16000),
 'validation': Dataset(features: {'text': Value(dtype='string', id=None), 'label': Value(dtype='string', id=None)}, n
um_rows: 2000),
 'test': Dataset(features: {'text': Value(dtype='string', id=None), 'label': Value(dtype='string', id=None)}, num_row
s: 2000)}
```

Inside the dataset, here are three separated datasets: train, validation, and test, which are ready for us to use. There are 20000 tweets in total, and 16000, 2000, 2000 records for train, validation and test respectively.

Missing Values

Let us take a closer look into the quality of data. First, we need to check if there are any missing values. After examinations on there datasets, it is obvious to see that there is no missing values within this dataset.

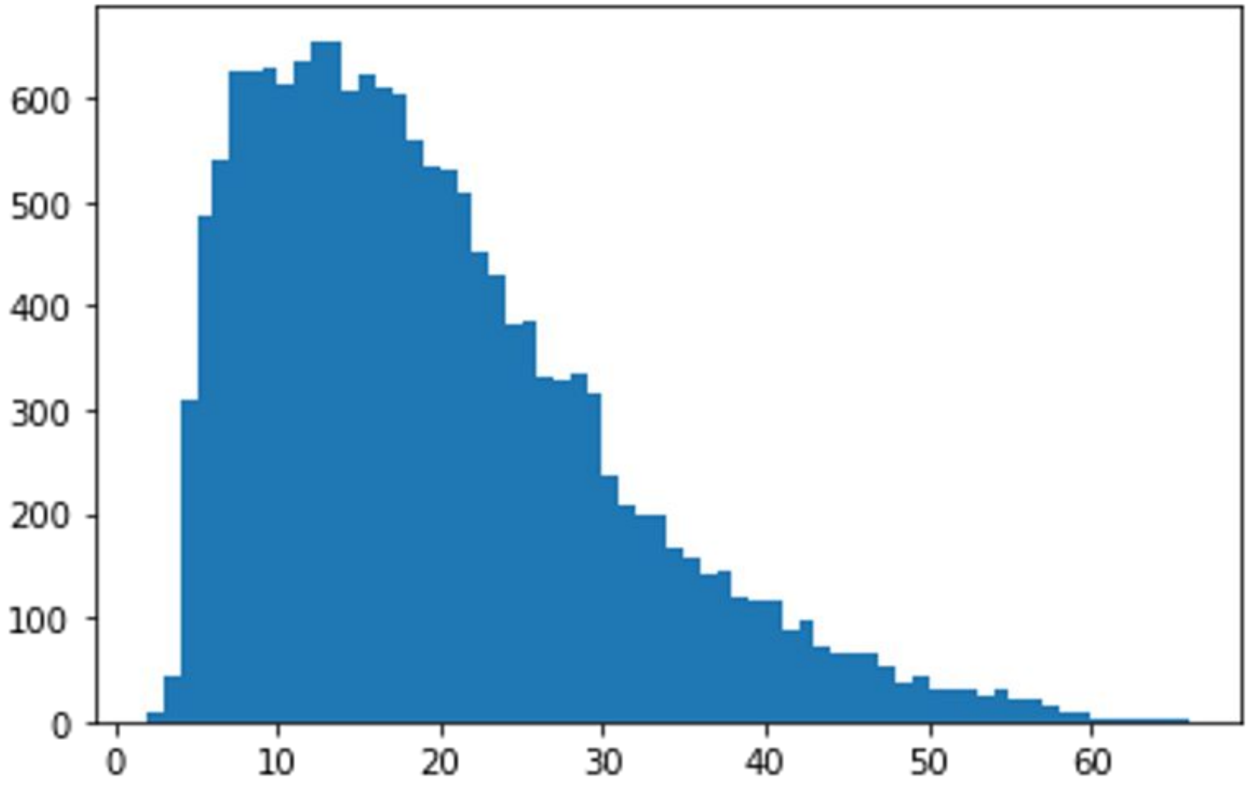
```
label     0
text      0
dtype: int64
```

Exploratory Data Analysis

Lengths of tweets

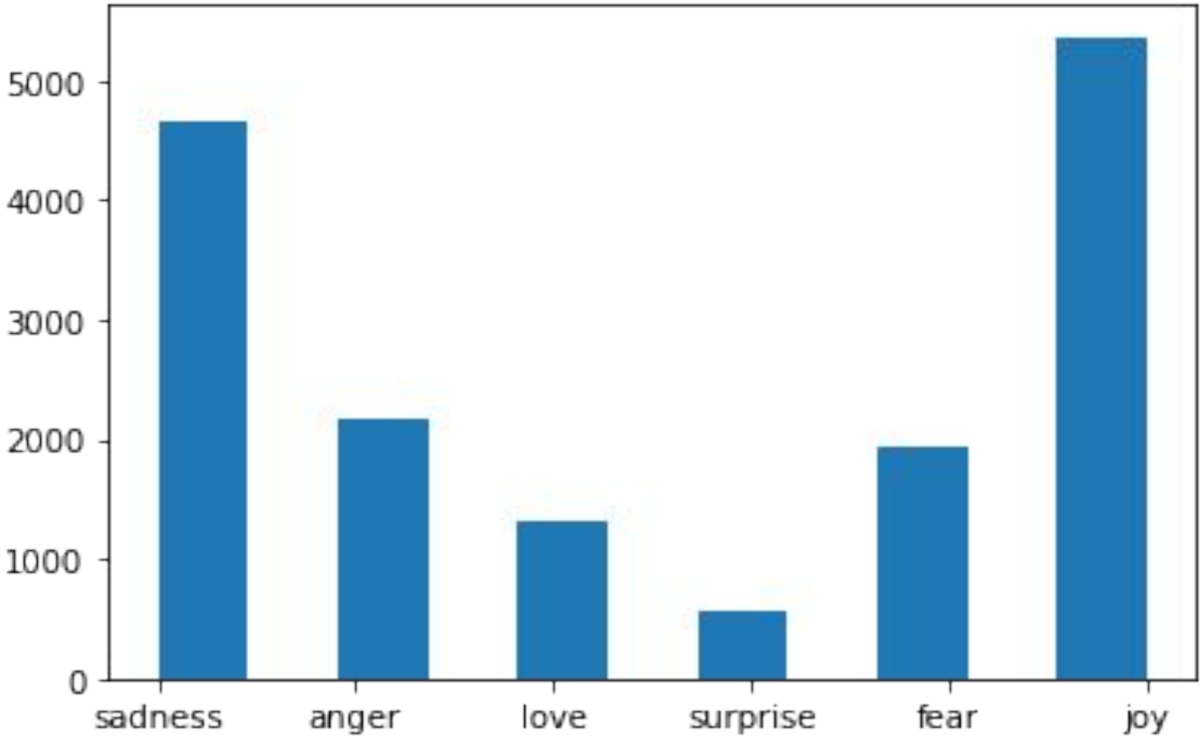
Average: 19.1663125

Median: 17



Exploratory Data Analysis

Count of different labels in the dataset



Data Preprocessing

Tokenizing

For RNN model, we first need to convert each unique word to unique number to feed model.

Texts to sequences

Example:

('i didnt feel humiliated’)

After converting:

[[2, 139, 3, 679]]

Data Preprocessing

Padding and Truncating Sequences

The input of model requires fixed shape. Therefore we need set max-lengths argument to a number. The words of tweets exceeds this number will be chopped off at the end. For words of tweets within this number will be padded with zeros.

Example:

Maxlens = 50

```
array([  2, 139,   3, 679,   0,   0,   0,   0,   0,   0,   0,   0,   0,
         0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
         0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
         0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0], dtype=int32)
```

Data Preprocessing

Preparing labels

{'fear': 0, 'joy': 1, 'surprise': 2, 'anger': 3, 'love': 4, 'sadness': 5}

Train-test Split

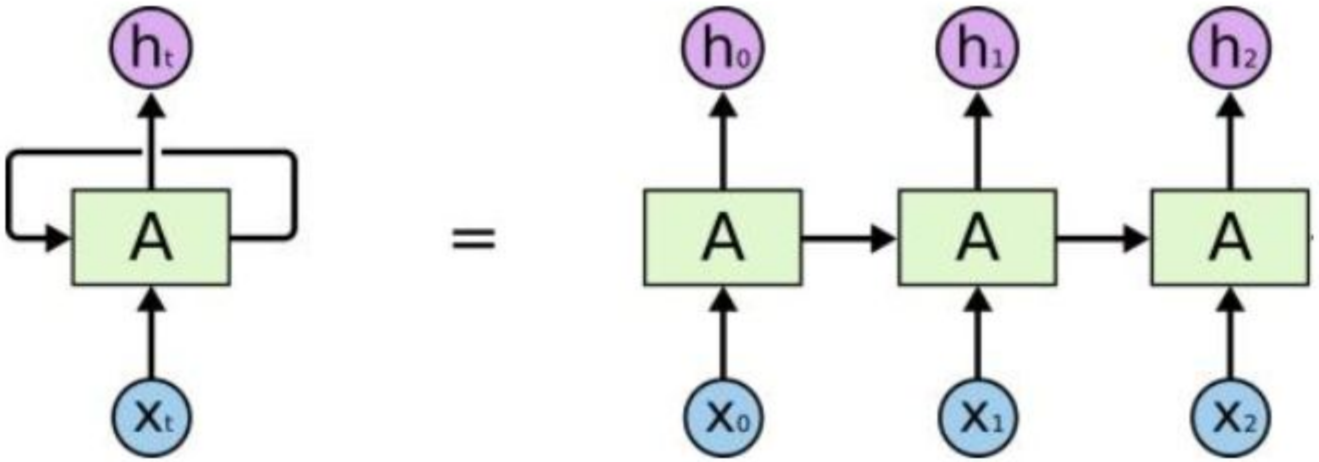
Dataset already split into training, validation, and test sets.

We plan to mix up the validation set and training set to create our own training and validation set to get multiple model accuracy and choose the average accuracy as the general accuracy of our model.

Training Set	Validation Set	Test Set
16000	2000	2000

Models

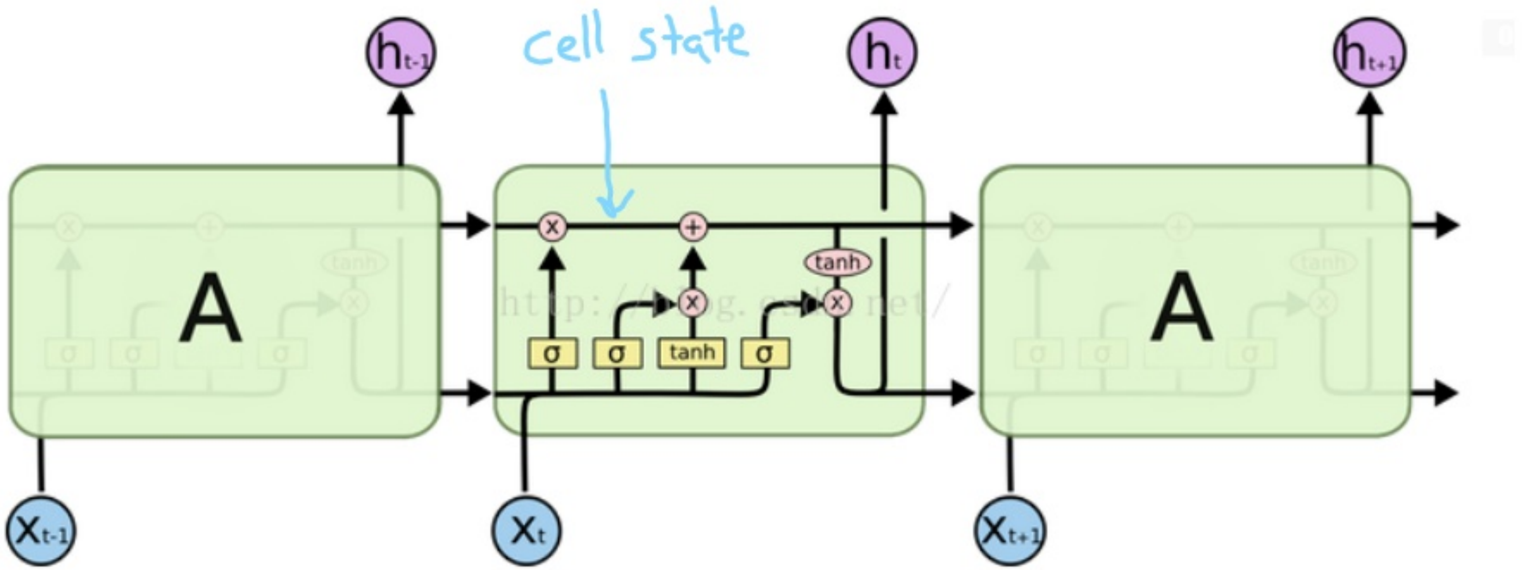
RNN



$$h_t = \sigma(x_t \times w_{xt} + h_{t-1} \times w_{ht} + b)$$

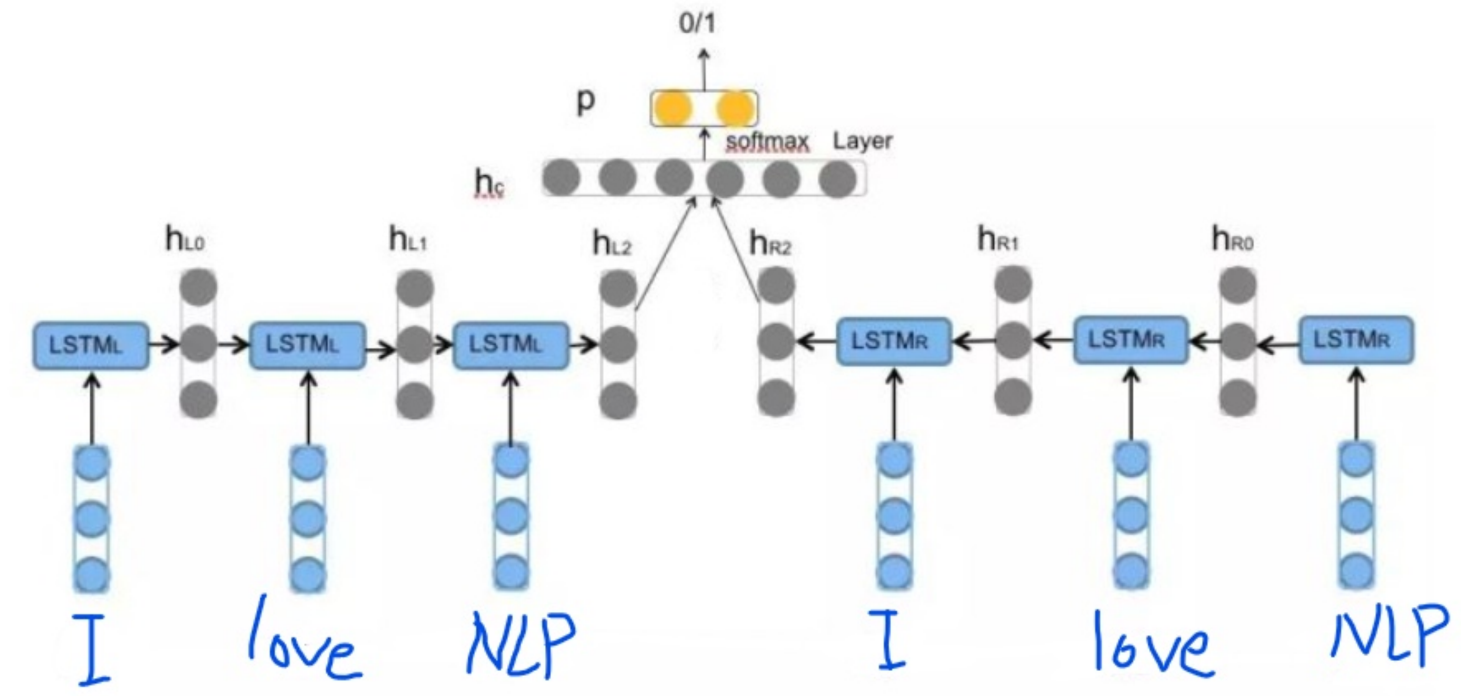
Models

LSTM



Models

BiLSTM



Models

BiLSTM

Embedding layer: input dimension: 10,000, output dimension: (16, 50)

First Bidirectional LSTM layer: 20 cells with return sequence set to True. (Returns a output in every timestamp or every cell)

Second Bidirectional LSTM layer: 20 cells

Output layer: 6 emotion classe, using activation function softmax.

Models

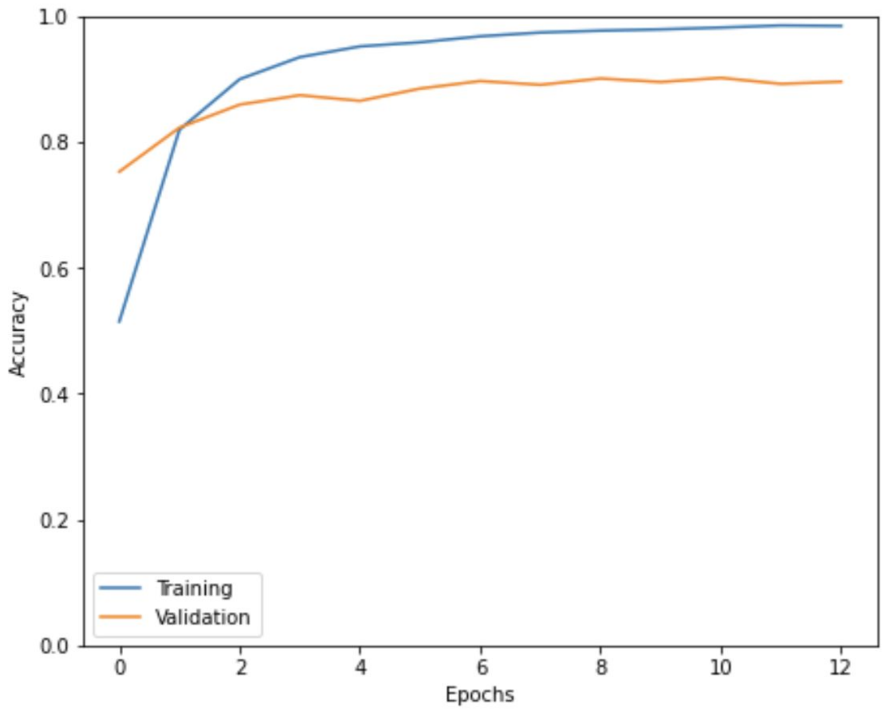
BiLSTM

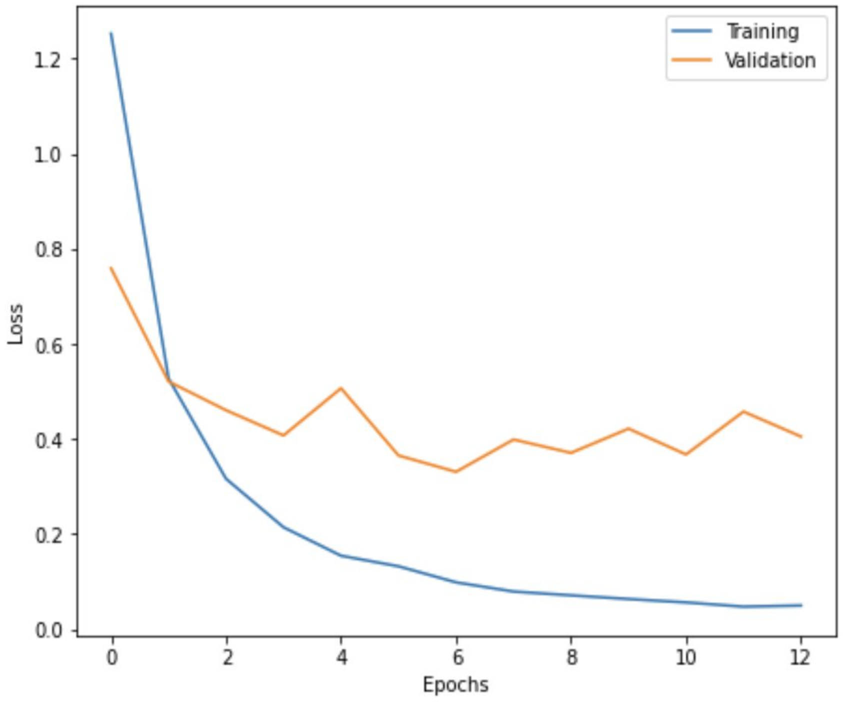
Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 50, 16)	160000
bidirectional_2 (Bidirection	(None, 50, 40)	5920
bidirectional_3 (Bidirection	(None, 40)	9760
dense_1 (Dense)	(None, 6)	246

Total params: 175,926
Trainable params: 175,926
Non-trainable params: 0

Model Evaluation

Visualization of training history:





Results

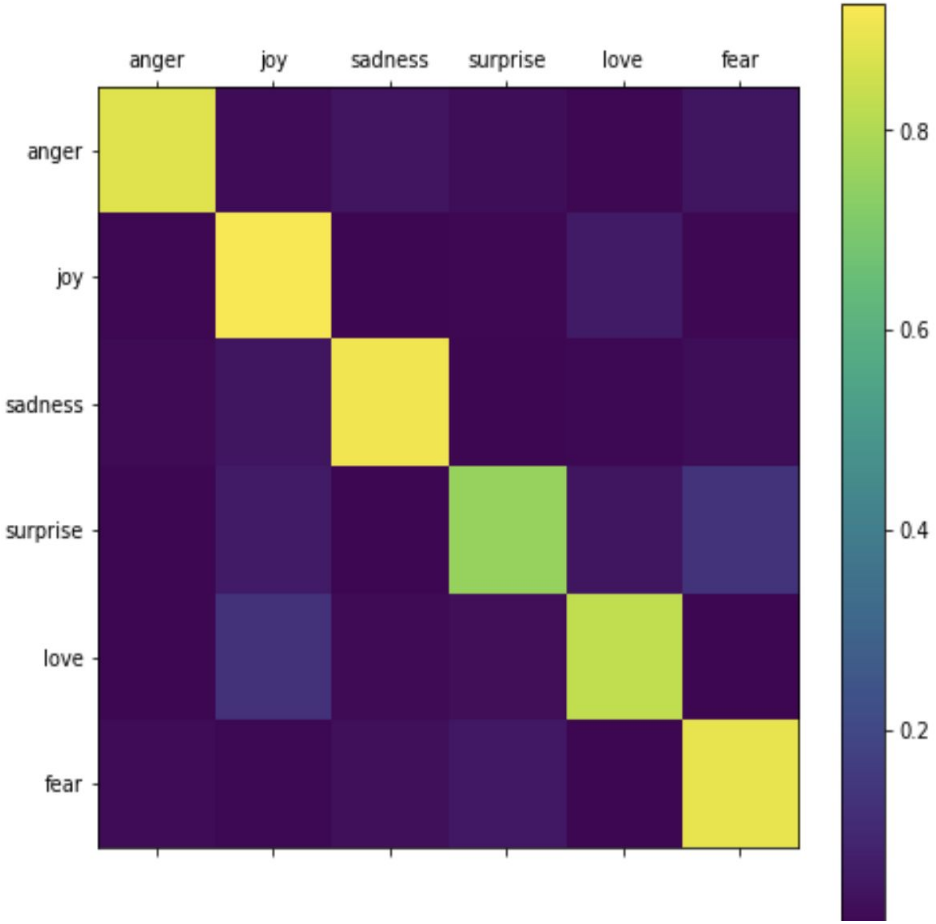
Predicted emotions and the display of confusion matrix:

x axis: test labels

y axis: predicted emotions

Classes: set of labels

```
Sequence: i can t help feeling lucky little do i know
Emotion: joy
Predicted Emotion: joy
```



Future Work

- To learn the performance difference between different NN model, we plan to implement a CNN to replace with the LSTM model. Then we will compare the performance of these two models.

- Also, we plan to mix the given test, validation and train sets to create these sets by ourselves. We might change the percentage of these three sets to see the difference of model's performance.

Conclusion

- RNN model for the emotion recognition gave us the more accurate predictions and we were able to get high prediction accuracy.

- BiLSTM-based approach to detecting the user's emotion expression in tweets.

- Model prediction accuracy:

  Accuracy – 0.8985

  Loss – 0.4029

References

[1] Elvis Saravia, Hsien- Chi Toby Liu, Yen-Hao Huang, Junlin Wu, Yi-Shin Chen, “Contextualized Affect Representations for Emotion Recognition”

Thank You!