Sentiment Analysis Using Nueral Networks

Part I: Research Question

1. Research Question

Can positive or negative sentiment be predicted for future customers using a neural network and natural language processing (NLP)?

2. Goals

The goal of this analysis is to build a neural network that can predict positive or negative sentiment of future customers using previous customer reviews. This will lead to greater understanding of which products customers prefer and can help with future marketing decisions.

3. Neural Network Type

A recurrent neural network (RNN) will be used for this analysis. RNN considers that the next word depends on the previous words in the review. This is a many to one RNN. There are many inputs that lead to a single output, in this analysis, if the sentiment is positive or negative. (Saeed, 2021) The model will be built using a sequential neural network utilizing the TensorFlow and Keras libraries. A sequential model is used when the data is not 'independently and identically distributed' (Lendave, 2021). The data is not independent because the order of the words matter. If the order was changed, the meaning changes.

Part II: Data Preparation

1. Exploratory data analysis

Import packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tensorflow import keras
import warnings
warnings.filterwarnings('ignore')
```

Load Datasets

```
In [2]:
          amazon_df = pd.read_csv('amazon_cells_labelled.txt', names = ['review', 'labe
          yelp_df = pd.read_csv('yelp_labelled.txt', names = ['review', 'label'], sep =
          imdb_df = pd.read_csv('imdb_labelled.csv',names = ['review', 'label'], sep =
        Look at Dataframes and size
In [3]:
          amazon df.head()
Out[3]:
                                              review label
         0
               So there is no way for me to plug it in here i...
                                                         0
                             Good case, Excellent value.
          1
                                                         1
          2
                                  Great for the jawbone.
                                                         1
         3 Tied to charger for conversations lasting more...
                                                         0
          4
                                      The mic is great.
In [4]:
          amazon df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1000 entries, 0 to 999
         Data columns (total 2 columns):
               Column Non-Null Count Dtype
               review 1000 non-null
                                          object
                      1000 non-null
                                          int64
         dtypes: int64(1), object(1)
         memory usage: 15.8+ KB
In [5]:
          yelp df.head()
Out [5]:
                                                review label
         0
                                  Wow... Loved this place.
                                                           1
          1
                                       Crust is not good.
                                                           0
          2
                     Not tasty and the texture was just nasty.
             Stopped by during the late May bank holiday of...
         4 The selection on the menu was great and so wer...
                                                           1
In [6]:
          yelp df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1000 entries, 0 to 999
         Data columns (total 2 columns):
              Column Non-Null Count Dtype
          0
              review 1000 non-null
                                        object
              label 1000 non-null
                                        int64
          1
         dtypes: int64(1), object(1)
         memory usage: 15.8+ KB
In [7]:
         imdb_df.head()
Out[7]:
                                             review label
         0
             A very, very, very slow-moving, aimless movie ...
                                                       0
         1
             Not sure who was more lost - the flat characte...
                                                       0
         2
             Attempting artiness with black & white and cle...
         3
                   Very little music or anything to speak of.
         4 The best scene in the movie was when Gerardo i...
In [8]:
         imdb df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1000 entries, 0 to 999
         Data columns (total 2 columns):
              Column Non-Null Count Dtype
         ___ ____
          0
              review 1000 non-null
                                        object
              label 1000 non-null
                                        int64
         dtypes: int64(1), object(1)
         memory usage: 15.8+ KB
        Merge 3 dataframes into one.
        code from: https://stackoverflow.com/questions/53877687/how-can-i-concat-multiple-
        dataframes-in-python
In [9]:
         df list = [amazon_df, yelp_df, imdb_df]
         df = pd.concat(df_list, ignore_index = True)
         df.head()
```

```
Out[9]:
                                               review label
          0
                So there is no way for me to plug it in here i...
                                                          0
           1
                              Good case, Excellent value.
           2
                                   Great for the jawbone.
                                                          1
          3 Tied to charger for conversations lasting more...
                                                          0
          4
                                       The mic is great.
                                                          1
In [10]:
           # Check size of new dataset. Should have two columns with 3000 rows.
           df.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 3000 entries, 0 to 2999
          Data columns (total 2 columns):
                Column Non-Null Count
                                           Dtype
           0
                review 3000 non-null
                                           object
           1
                label
                         3000 non-null
                                           int64
          dtypes: int64(1), object(1)
          memory usage: 47.0+ KB
          Get descriptive statistics to look at min and max. Should be between 0 and 1.
In [11]:
           df.describe()
Out[11]:
                        label
          count 3000.000000
                    0.499667
           mean
                    0.500083
             std
                    0.000000
            min
           25%
                    0.000000
           50%
                    0.000000
           75%
                     1.000000
                     1.000000
            max
          Check for missing data
In [12]:
           df.isnull().sum()
          review
                      0
Out[12]:
          label
                      0
          dtype: int64
          Make all words lower case
```

```
In [13]: df['review'] = df['review'].str.lower()
    df.head()
```

```
Out[13]:
                                                          review label
             0
                   so there is no way for me to plug it in here i...
                                                                       0
                                     good case, excellent value.
             1
                                                                       1
             2
                                           great for the jawbone.
                                                                       1
             3 tied to charger for conversations lasting more...
                                                                       0
             4
                                                 the mic is great.
                                                                       1
```

Remove all puncuation

```
In [14]:
    df['review'] = df['review'].str.replace(r'[^\w\s]+', '')
    df.head()
```

```
Out [14]:

o so there is no way for me to plug it in here i...

pood case excellent value

great for the jawbone

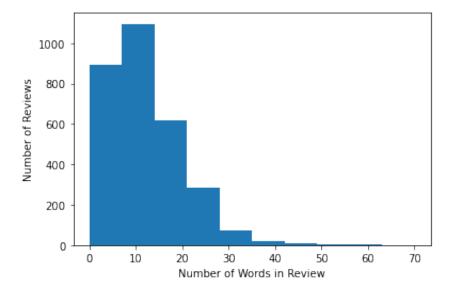
tied to charger for conversations lasting more...

the mic is great

the mic is great
```

Remove special characters code from: https://towardsdatascience.com/simplify-your-dataset-cleaning-with-pandas-75951b23568e

```
Out[15]:
                                                 review label
           0
                so there is no way for me to plug it in here i...
                                                            0
           1
                                 good case excellent value
           2
                                     great for the jawbone
                                                            1
           3 tied to charger for conversations lasting more...
                                                            0
           4
                                          the mic is great
                                                            1
          Remove digits from dataset
In [16]:
            df['review'] = df['review'].str.replace('\d+', '')
          Count number of words in each reviw and add count column
In [17]:
            def word count(string):
                 words = string.split()
                 return len (words)
            df['count'] = df['review'].apply(word count)
In [18]:
            df.head()
Out[18]:
                                                 review label count
           0
                so there is no way for me to plug it in here i...
                                                                   21
                                                            0
           1
                                 good case excellent value
                                                                   4
           2
                                     great for the jawbone
                                                                   4
           3 tied to charger for conversations lasting more...
                                                                   10
                                          the mic is great
                                                                   4
          Find total number of words
In [19]:
            df['count'].sum()
           35119
Out[19]:
          Historgram of review lengths
In [20]:
            plt.hist(df['count'])
            plt.xlabel('Number of Words in Review')
            plt.ylabel('Number of Reviews')
            plt.show()
```



Find length of longest review

```
In [21]: df['count'].max()
Out[21]: 70
```

Remove stopwords

code from: https://towardsdatascience.com/how-to-clean-text-data-639375414a2f

```
import nltk
stopwords = nltk.corpus.stopwords.words('english')

df['review_nostop'] = df['review'].apply(lambda x: ' '.join([word for word in word not in (stop) df.head()
```

review_nostop	count	label	review	2]:	Out[22]:
way plug us unless go converte	21	0	so there is no way for me to plug it in here i	0	
good case excellent value	4	1	good case excellent value	1	
great jawbone	4	1	great for the jawbone	2	
tied charger conversations lasting minutesmajo	10	0	tied to charger for conversations lasting more	3	
mic grea	4	1	the mic is great	4	

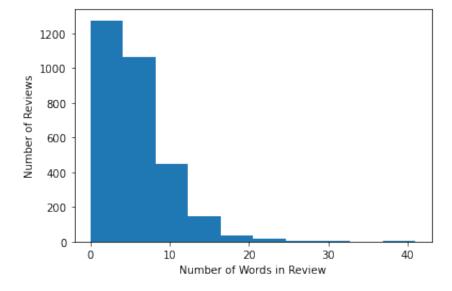
Count number of words in review_nostop and create new column

```
In [23]:
    df['nostop_count'] = df['review_nostop'].apply(word_count)
    df.head()
```

Out[23]:		review	label	count	review_nostop	nostop_count
	0	so there is no way for me to plug it in here i	0	21	way plug us unless go converter	6
	1	good case excellent value	1	4	good case excellent value	4
	2	great for the jawbone	1	4	great jawbone	2
	3	tied to charger for conversations lasting more	0	10	tied charger conversations lasting minutesmajo	6
	4	the mic is great	1	4	mic great	2

Histogram of review length after stop word removal

```
plt.hist(df['nostop_count'])
   plt.xlabel('Number of Words in Review')
   plt.ylabel('Number of Reviews')
   plt.show()
```



Length of longest review after removing stop words

```
In [25]: df['nostop_count'].max()
Out[25]: 41
```

Find the size of the vocabulary

```
In [26]:
    vocab = []
    reviews = df['review_nostop'].tolist()

    for review in reviews:
        for word in review.split(' '):
            if not word in vocab:
                  vocab.append(word)
    print(len(vocab))
```

5181

The proposed word embedding length was found using the formula: 4th root of the number of categories. (Introducting TensorFlow Feature Columns, 2017) In this analysis, every word in the vocabulary is its own category. Based on this formula, a word embedding length of 8 dimension will be used.

```
In [27]: emb_size = len(vocab)**0.25
    emb_size

Out[27]: 8.484053491799331
```

2. Tokenize the DataFrame

Tokenization is the process of separating text into smaller units known as tokens. For this analysis, the token size is word. These tokens are used to create the vocabulary, the set of unique tokens. Each of the words are then become an integer. (Aravindpai, 2020) This process is necessary because Keras cannot process text.

code from:https://towardsdatascience.com/a-complete-step-by-step-tutorial-on-sentiment-analysis-in-keras-and-tensorflow-ea420cc8913f

Set the tokenizer function

```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
tokenizer = Tokenizer(oov_token='<00V>')
```

Splti the dataset into 70/30

```
In [29]:
    split = round(len(df)*.7)
    train_review = df['review_nostop'][:split]
    train_label = df['label'][:split]
    test_review = df['review_nostop'][split:]
    test_label = df['label'][split:]
```

Convert the reviews to string format.

Set terms for tokenize and padding

```
In [31]:
    vocab_size = 5180
    embedding_dim = 8
    max_length = 50
    trunc_type = 'post'
    oov_tok = '<00V>'
    padding_type = 'post'
```

Tokenize the words

```
tokenizer = Tokenizer(num_words = vocab_size, oov_token = oov_tok)
tokenizer.fit_on_texts(training_reviews)
word_index = tokenizer.word_index
```

Print word_index

```
In [33]: print(word_index)
```

{'<00V>': 1, 'good': 2, 'great': 3, 'phone': 4, 'food': 5, 'place': 6, 'servic e': 7, 'like': 8, 'time': 9, 'back': 10, 'one': 11, 'really': 12, 'would': 13, 'quality': 14, 'dont': 15, 'well': 16, 'best': 17, 'product': 18, 'go': 19, 'i ve': 20, 'also': 21, 'works': 22, 'ever': 23, 'nice': 24, 'headset': 25, 'batt ery': 26, 'im': 27, 'get': 28, 'use': 29, 'sound': 30, 'even': 31, 'love': 32, 'excellent': 33, 'recommend': 34, 'work': 35, 'could': 36, 'never': 37, 'bette r': 38, 'ear': 39, 'first': 40, 'made': 41, 'bad': 42, 'price': 43, 'much': 44 , 'pretty': 45, 'case': 46, 'disappointed': 47, 'got': 48, 'worst': 49, 'frien dly': 50, 'think': 51, 'came': 52, 'way': 53, 'money': 54, 'going': 55, 'new': 56, 'enough': 57, 'still': 58, 'definitely': 59, 'minutes': 60, 'restaurant': 61, 'two': 62, 'experience': 63, 'amazing': 64, 'say': 65, 'poor': 66, 'happy' : 67, 'delicious': 68, 'right': 69, 'didnt': 70, 'make': 71, 'thing': 72, 'won t': 73, 'us': 74, 'far': 75, 'car': 76, 'terrible': 77, 'vegas': 78, 'movie': 79, 'waste': 80, 'little': 81, 'everything': 82, 'item': 83, 'worked': 84, 'al ways': 85, 'charger': 86, 'comfortable': 87, 'long': 88, 'went': 89, 'people':
90, 'want': 91, 'buy': 92, 'used': 93, 'cant': 94, 'staff': 95, 'eat': 96, 'bo ught': 97, 'piece': 98, 'times': 99, 'impressed': 100, 'bluetooth': 101, 'lot' : 102, 'easy': 103, 'awesome': 104, 'ordered': 105, 'worth': 106, 'stars': 107 , 'doesnt': 108, 'fine': 109, 'since': 110, 'found': 111, 'know': 112, 'look':

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3. Padding Process

Neural networks requires that all inputs be the same size and shapes. This is accomplished by adding zeros to the beginning or ending of the sequence. (Caner, 2020) Here, zeroes are added to the end of the sequence.

```
In [34]:
          sequences = tokenizer.texts_to_sequences(training_reviews)
          padded = pad_sequences(sequences, maxlen = max_length, truncating=trunc_type,
                                  padding = 'post')
          testing_reviews = tokenizer.texts_to_sequences(testing_reviews)
          testing padded = pad sequences(testing reviews, maxlen = max length, padding
In [35]:
          padded[0]
          array([
                   53,
                        183,
                                74,
                                     420,
                                             19, 1335,
                                                                       0,
                                                                             0,
                                                                                    0,
Out[35]:
                    0,
                          0,
                                0,
                                       0,
                                             0,
                                                    0,
                                                          0,
                                                                 0,
                                                                             0,
                                                                                    0,
                                       0,
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                    0,
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                    0,
                          0,
                                 0,
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                                                          0,
                                                                 0,
                                                                       0,
                                                                                    0,
                    0,
                           0,
                                 0,
                                       0,
                                              0,
                                                    0], dtype=int32)
```

4. Categories of Sentiment and Activation Function

There are two categories of sentiment: 1 – positive, 2 – negative. The sigmoid activation function will be used in the final dense layer because the outputs are binary.

5. Steps to Prepare Data

The steps used to prepare the data are as follows:

- Import packages
- Load datasets
- · Inspect datasets size
- Merge the datasets into one DataFrame
- Remove special characters and digits
- · Remove stop words
- Create a vocabulary
- Find the embedding size
- Split the data into training and test sets using a 70/30 split
- Tokenize the DataFrame
- Pad the reviews to standardize the lengths

6. Copy of prepared data

```
In [36]: df.to_csv('prepared_sentiment_data.csv')
```

Part III: Network Architecture

code from:https://towardsdatascience.com/a-complete-step-by-step-tutorial-on-sentiment-analysis-in-keras-and-tensorflow-ea420cc8913f

Build the model

2022-03-14 11:33:44.329186: I tensorflow/core/platform/cpu_feature_guard.cc:14 5] This TensorFlow binary is optimized with Intel(R) MKL-DNN to use the follow ing CPU instructions in performance critical operations: SSE4.1 SSE4.2 AVX AV X2 FMA

To enable them in non-MKL-DNN operations, rebuild TensorFlow with the appropri ate compiler flags.

2022-03-14 11:33:44.329542: I tensorflow/core/common_runtime/process_util.cc:1 15] Creating new thread pool with default inter op setting: 12. Tune using int er_op_parallelism_threads for best performance.

Compile the model

```
In [38]: model.compile(loss='binary_crossentropy', optimizer = 'adam', metrics = ['acc']
```

1. Summary of model

```
In [39]: model.summary()
```

Model: "sequential"

Layer (type)	Output	Shape	Param #
embedding (Embedding)	(None,	50, 8)	41440
global_average_pooling1d (Gl	(None,	8)	0
dense (Dense)	(None,	10)	90
dense_1 (Dense)	(None,	5)	55
dense_2 (Dense)	(None,	1)	6
Total parame. Al 501			

Total params: 41,591
Trainable params: 41,591
Non-trainable params: 0

2. Discuss the number of layers, the type of layers, and the total number of parameters

The first layer is the Embedding layer. This layer converts each word to a fixed length vector of a stated size. The parameters used in the layer are the vocabulary size, embedding dimension, and the maximum length of each review. The second layer is GlobalAveragePooling1D() which flattens the vector from three dimensions to two dimension. The third layer is a Dense layer with 10 nodes and the activation function relu. The fourth layer has 5 nodes and uses the relu activation function. The final layer is a Dense layer with 1 node and activation function sigmoid. The sigmoid activation function was chosen because the output is binary.

Convert labels to arrays

```
In [40]:
    training_labels_final = np.array(training_labels)
    testing_labels_final = np.array(testing_labels)
```

3. Justify the choice of hyperparameters

Activation Functions: relu – chosen because it only returns positive numbers or 0. Sigmoid – chosen because the outcome is binary.

Number of Nodes per Layer – The nodes of the first layer are equal to the number of words in the vocabulary. The second node of 10 is a number that is between the first layer and the last layer. The third node of 5 was chosen because it reduces the number of nodes from the previous layer but is more than the final layer. The last layer has 1 node since the output of the model is binary.

Loss Function – The loss function used in the model was Binary Crossentropy. It was chosen because there are two possible outputs.

Optimizer – the Adaptive Moment Estimation, Adam, optimizer was chosen because it is efficient and requires less memory. The Adam optimizer combines the strength of gradient descent with momentum and root means square propagation. (Intuition of Adam Optimizer, 2020)

Stopping Criteria – Early stopping is used during the fitting of the model. The model will stop based on validation loss. Validation loss shows how well the model fits new data.

Evaluation Metric – Accuracy is the percent of correct predictions to the set of targets. It was chosen because of its ease of interpretation.

Part IV: Model Evaluation

Fit the model with 25 epochs

```
Train on 2100 samples, validate on 900 samples
Epoch 1/25
accuracy: 0.5038 - val_loss: 0.6931 - val_accuracy: 0.4944
Epoch 2/25
accuracy: 0.5629 - val loss: 0.6925 - val accuracy: 0.6489
Epoch 3/25
accuracy: 0.6686 - val_loss: 0.6910 - val_accuracy: 0.7122
Epoch 4/25
accuracy: 0.7600 - val_loss: 0.6864 - val_accuracy: 0.7422
Epoch 5/25
accuracy: 0.8186 - val_loss: 0.6755 - val_accuracy: 0.7378
```

```
Epoch 6/25
2100/2100 [============== ] - 0s 127us/sample - loss: 0.6412 -
accuracy: 0.8586 - val loss: 0.6566 - val accuracy: 0.6800
Epoch 7/25
accuracy: 0.8657 - val loss: 0.6310 - val accuracy: 0.7256
2100/2100 [============== ] - 0s 116us/sample - loss: 0.5273 -
accuracy: 0.9000 - val loss: 0.5959 - val accuracy: 0.7489
2100/2100 [=============] - 0s 129us/sample - loss: 0.4577 -
accuracy: 0.9114 - val loss: 0.5687 - val accuracy: 0.7444
Epoch 10/25
2100/2100 [=============== ] - 0s 118us/sample - loss: 0.3862 -
accuracy: 0.9219 - val loss: 0.5432 - val accuracy: 0.7444
Epoch 11/25
2100/2100 [=============== ] - 0s 121us/sample - loss: 0.3290 -
accuracy: 0.9305 - val loss: 0.5280 - val accuracy: 0.7444
Epoch 12/25
2100/2100 [==============] - 0s 123us/sample - loss: 0.2846 -
accuracy: 0.9295 - val_loss: 0.5209 - val_accuracy: 0.7511
Epoch 13/25
accuracy: 0.9433 - val loss: 0.5063 - val accuracy: 0.7611
Epoch 14/25
accuracy: 0.9448 - val_loss: 0.5107 - val_accuracy: 0.7533
Epoch 15/25
accuracy: 0.9538 - val loss: 0.5056 - val accuracy: 0.7644
Epoch 16/25
accuracy: 0.9533 - val loss: 0.5237 - val accuracy: 0.7600
Epoch 17/25
accuracy: 0.9652 - val loss: 0.5211 - val accuracy: 0.7611
Epoch 18/25
accuracy: 0.9657 - val loss: 0.5249 - val accuracy: 0.7667
Epoch 19/25
accuracy: 0.9671 - val loss: 0.5355 - val accuracy: 0.7611
Epoch 20/25
accuracy: 0.9695 - val_loss: 0.5360 - val_accuracy: 0.7578
Epoch 21/25
accuracy: 0.9729 - val loss: 0.5512 - val accuracy: 0.7633
Epoch 22/25
accuracy: 0.9738 - val loss: 0.5528 - val accuracy: 0.7600
Epoch 23/25
accuracy: 0.9719 - val_loss: 0.5627 - val_accuracy: 0.7556
Epoch 24/25
accuracy: 0.9757 - val_loss: 0.5810 - val_accuracy: 0.7700
```

1. Stopping Criteria

Stopping criteria is used to prevent overfitting. It does this by stopping the training of the model as soon as the validation error reaches a minimum. The patience parameter is used to ensure that the training does not stop at a local minimum but reaches the true minimum.

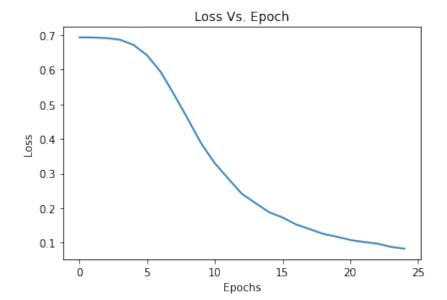
code from: https://towardsdatascience.com/a-practical-introduction-to-early-stopping-in-machine-learning-550ac88bc8fd

```
In [42]:
      from tensorflow.keras.callbacks import EarlyStopping
      early stopping = EarlyStopping(monitor = 'val loss', patience = 5, mode = 'mi
In [43]:
      history = model.fit(padded, training labels final, epochs = 25,\
                  validation_data = (testing_padded, testing_labels_final),
     Train on 2100 samples, validate on 900 samples
     Epoch 1/25
     accuracy: 0.9795 - val loss: 0.5912 - val accuracy: 0.7678
     Epoch 2/25
     accuracy: 0.9810 - val_loss: 0.6254 - val_accuracy: 0.7589
     Epoch 3/25
     accuracy: 0.9790 - val_loss: 0.6092 - val_accuracy: 0.7611
     Epoch 4/25
     accuracy: 0.9805 - val loss: 0.6202 - val accuracy: 0.7489
     Epoch 5/25
     accuracy: 0.9795 - val_loss: 0.6318 - val_accuracy: 0.7511
     accuracy: 0.9795 - val loss: 0.6366 - val accuracy: 0.7600
```

2. Visualizations of the model's training process

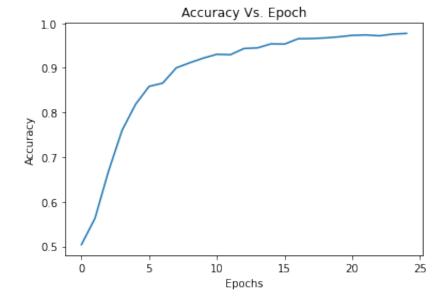
Graph of loss

```
In [44]:
    plt.plot(history_ns.history['loss'])
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title('Loss Vs. Epoch')
    plt.show()
```



Graph of accuracy

```
In [45]:
    plt.plot(history_ns.history['accuracy'])
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.title('Accuracy Vs. Epoch')
    plt.show()
```

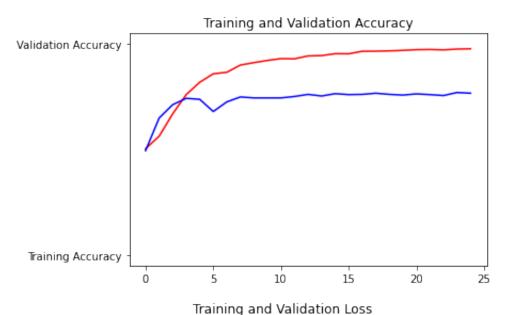


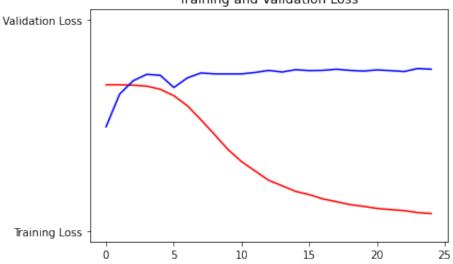
Graphs of training and validation

code from: https://towardsdatascience.com/a-complete-step-by-step-tutorial-on-sentiment-analysis-in-keras-and-tensorflow-ea420cc8913f

```
In [46]:
    acc = history_ns.history['accuracy']
    val_acc = history_ns.history['val_accuracy']
    loss = history_ns.history['loss']
    val_loss = history_ns.history['val_loss']
    epochs = range(len(acc))
    plt.plot(epochs, acc, 'r', 'Training Accuracy')
    plt.plot(epochs, val_acc, 'b', 'Validation Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.figure()
    plt.plot(epochs, loss, 'r', 'Training Loss')
    plt.plot(epochs, val_acc, 'b', 'Validation Loss')
    plt.title('Training and Validation Loss')
    plt.figure()
```

Out[46]: <Figure size 432x288 with 0 Axes>





<Figure size 432x288 with 0 Axes>

3. Model Fitness

The model accuracy improves over the first 6 epochs. After this point the model starts to overfit the training data. While having a large accuracy percentage may seem good, it can be a sign that the model will not handle new data well. To reduce the chance of overfitting, early stopping was used.

4. Predictive Accuracy

The predictive accuracy of the model is 76%. The model can predict customer sentiment about 76% of the time. This is fairly high accuracy.

Part V: Summary and Recommendations

E. Code to save trained model

code from: https://www.kdnuggets.com/2021/02/saving-loading-models-tensorflow.html

In [47]:

model.save('SentimentAmalysis.h5')

F. Functionality of neural network

This model is very functional. It has a high predictive accuracy. One recommendation would be to try the model with more layers. This might improve the accuracy.

G. Recommendations

A recommend course of action is to use the model to reach out to customers who are predicted to have poor sentiment towards the product. The company can use this opportunity to correct any problems with the product or gather feedback on how to improve. This will help to improve sentiments towards the company if not the product.

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In []:	
In []:	