Economic News Identification Using an LSTM Neural Network Approach

Jan Maciejowski, Fabian Perez, Ali Rammal, Louis Golding, Abdullah Ghosheh, Ayah El Barq

Introduction

In an era where information is abundant, researchers, policy makers and executives face an extreme task of distinguishing economically relevant articles. This goal is the primary objective of our project with the use of the dataset (US-Economic_news.csv), our goal is to create a classification model that can identify documents based on how relevant they are to modern economy.

The dataset we have contains several attributes such as positivity, relevance, date and headline and displays various articles. These attributes are pivotal for the project and for the model, it helps us categorize the news based on relevancy.

To start with the project, we have to conduct an in-depth analysis on the attributes to check their efficiency towards the articles and to assess whether they're going to be important for building the model or not, by doing so we can receive insights on the attributes efficiency. Secondly, with such insights we continue to build the classification model that can assess articles and determining whether they're relevant or not.

In [18]:
```
import pandas as pd
from ydata_profiling import ProfileReport
import matplotlib.pyplot as plt
```

1: EDA and Preprocessing

Initial EDA

This notebook contains the code to load the "US economy news" dataset

In [2]:
```
df_news = pd.read_csv('US-Economic-News.csv', delimiter=',', encoding = 'ISO-885
print(df_news.columns)
print()
print(df_news.shape)
```

```
Index(['_unit_id', '_golden', '_unit_state', '_trusted_judgments',
       '_last_judgment_at', 'positivity', 'positivity:confidence', 'relevance',
       'relevance:confidence', 'articleid', 'date', 'headline',
       'positivity_gold', 'relevance_gold', 'text'],
      dtype='object')

(8000, 15)
```

In [ ]:
```
df_news.head(20)
```

In [4]:
```
profile = ProfileReport(df_news, title="News Profile Report")
profile.to_file('your_report.html')
profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

Overview

Dataset statistics

Number of variables	15
Number of observations	8000
Missing cells	26805
Missing cells (%)	22.3%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	882.9 KiB
Average record size in memory	113.0 B

Variable types

Numeric	4
Boolean	1
Categorical	3
DateTime	2
Text	3
Unsupported	2

Alerts

Out[4]:

From our data profiling, we can see that we have missing values in our dataset. 22.3% of our data is missing. Exploring our dataset will help us understand the nature of the variables available and help us decide what to do in terms of preprocessing

```
target variable:
    relevance: relevance is the variable that is either yes or
no, which is either economically relevant or irrelevant

id:
    The unit_id refers to the file id of obtained features of
determining the relevance of an article.

constants:
    Golden is a constant variable so we should not include it in
our data for the model.
    _unit_state is also a constant variable so it would not
provide useful information in our models.
    _trusted_judgments is another constant variable that does
not provide variance

    We would assume that relevance gold and positivity gold are
connected to golden. They are missing and corrupt, and removing
golden because of this other reason seems correct

variables:
    positivity: highly correlated with the target variable,
however there are 82.2% missing values. In the profile, the
histogram shows that curve is not normal, so imputing with the
mean could be a good strategy. At the same time, we do not know
what this variable means. We thought it could mean the positive
words in the article, or whether the article was liked as higher
scores = relevant. Leaving this variable out of the features for
the model would be a better idea as we would save more time and
be efficient. A neural network is able to consume text and make
classifications solely based on that, through the use of
different text processing libraries and methodologies

    positivity confidence: there was no information to conclude
the value of this data. it is also missing, so it would be best
to keep it out of the features.

    relevance confidence: there is no correlation and the
context of this data is not understood. We will not include it
in our features

    date: we will not use the date of publication as there is no
correlation to relevance-no patterns identified.

    article id: article identifier
```

From this, we will only be using the text and headlines as features for our model building. We will explore different models with an endgoal of building a neural network that is able to classify whether a new article is economically relevant or not. In our preprocessing, we can try unique ways of tokenizing and vectorizing the text, decide to keep headlines only or include the whole text. There are a number of methodologies that can be pursued to produce a capable neural network with high accuracy on test set.

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Introduction

The model leverages Natural Language Processing (NLP) techniques and a Recurrent Neural Network (RNN) architecture to learn these distinguishing features from the text. RNNs are particularly suited for this task due to their ability to process sequences of data, like sentences and paragraphs, capturing the contextual information essential for understanding textual content

The main objective of this project is to create a machine learning model that can automatically classify a given piece of text as either a news article or a non-news article with a high degree of accuracy. This classification is achieved by training the model on a labeled dataset, where each instance of text is pre-identified as either a news article or not. The model learns to recognize patterns and features unique to news writing, enabling it to generalize and make accurate predictions on unseen data.

This capability is crucial for applications such as content filtering, media analysis, and information retrieval, where distinguishing between journalistic content and other types of text is necessary. By automating this process, the model aims to assist in efficiently managing and categorizing large volumes of textual data, enhancing the effectiveness of digital content management systems, and providing valuable insights into the nature and distribution of information across various media platforms.

Preprocess

Primary Steps

Packages & NLTK Data Downloads

Aside from the essential packages for data handling and visualization (pandas, numpy, matplotlib), tensorflow keras libraries are used for the completion of the objective, involving tokenizer and pad_sequences. Furthermore, the NLTK library is used for the text cleaning phase in order to fit text into vectorization. Packages such as Punkt - which divides a text into a list of sentences by using an unsupervised algorithm to build a model for abbreviation words, collocations, and words that start sentences; Stopwords - removes words that frequently appear in any language or corpus; Wordent - a lexical database of English which helps find conceptual relationships between words such as hypernyms, hyponyms, synonyms, antonyms etc.

Variable Selection and Cleaning

As the dataset originally contains 14 variables in total, the most viable decision is to emphasize on the string variables which offer the context for economic newspaper detection. Furthermore, variables 'text' and 'headline' (the only ones used for model training) offer the needed context for a great generalizable model, while the rest of the variables strongly lack any relevance that facilitates proper predictions due to biased metrics based on low number of survey samples.

The 'relevance' variable (originally in string type of data) was transformed into a binary variable where (1) = economic newspaper article & (0) = any other. Then, the dataset was reduced into a 50:50 ratio of relevant and non-relevant articles from merging a random sample of non-relevant articles with size length equal to all relevant articles. Headlines and the full text were embedded together into a single string. The training text data was cleaned through extra symbol removal, and split into words for the removal of the stop words and lemmatization. From this point, the text data is classified as clean string data.

Tokenization & Padding

This step, also called vectorization, is performed through the tokenizer function form tensorflow turns each string into a sequence of numbers for the model to identify relevant articles with higher frequency of words related to the field of interest. By default, all punctuation is removed, turning the texts into space-separated sequences of words. These sequences are then split into vectorized lists of tokens. They will then be indexed or vectorized. After this process is performed, the train data is prepared for padding.

The step of padding the vectorized sequences is required since the model expects similar observation sizes, and the text of each newspaper article is different from each other. For this, the padding process involves identifying the longest sequence and setting all observations to that longest size. Any extra space per observation is deemed a zero.

From this point, our data was split into training, testing, and validation sets for the maximum assurance of our model's generalizability towards new data. All these steps are seen below.

First, we must read in all necessary packages.

In [85]:
```
import pandas as pd
import numpy as np
import re
import matplotlib.pyplot as plt

import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
```

```
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout, Bidirection
from tensorflow.keras.callbacks import EarlyStopping

from sklearn.metrics import confusion_matrix

from tensorflow.keras.optimizers import Adamax
from tensorflow.keras.optimizers import Nadam
import tensorflow_addons as tfa
```

```
C:\Users\majon\AppData\Local\Programs\Python\Python310\lib\site-packages\tensorfl
ow_addons\utils\tfa_eol_msg.py:23: UserWarning:

TensorFlow Addons (TFA) has ended development and introduction of new features.
TFA has entered a minimal maintenance and release mode until a planned end of lif
e in May 2024.
Please modify downstream libraries to take dependencies from other repositories i
n our TensorFlow community (e.g. Keras, Keras-CV, and Keras-NLP).

For more information see: https://github.com/tensorflow/addons/issues/2807

  warnings.warn(
C:\Users\majon\AppData\Local\Programs\Python\Python310\lib\site-packages\tensorfl
ow_addons\utils\ensure_tf_install.py:53: UserWarning: Tensorflow Addons supports
using Python ops for all Tensorflow versions above or equal to 2.12.0 and strictl
y below 2.15.0 (nightly versions are not supported).
 The versions of TensorFlow you are currently using is 2.15.0 and is not supporte
d.
Some things might work, some things might not.
If you were to encounter a bug, do not file an issue.
If you want to make sure you're using a tested and supported configuration, eithe
r change the TensorFlow version or the TensorFlow Addons's version.
You can find the compatibility matrix in TensorFlow Addon's readme:
https://github.com/tensorflow/addons
  warnings.warn(
```

In addition to that we need some NLTK datasets with english stopword, that must be removed and lemmatized.

In [2]:
```
# Ensure you have downloaded the necessary NLTK data
# nltk.download('punkt')
# nltk.download('stopwords')
# nltk.download('wordnet')
```

Reading the data

In [3]:
```
df = pd.read_csv("./US-Economic-News.csv", delimiter=',', encoding= 'ISO-8859-1'

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8000 entries, 0 to 7999
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   _unit_id                8000 non-null   int64  
 1   _golden                 8000 non-null   bool   
 2   _unit_state             8000 non-null   object 
 3   _trusted_judgments      8000 non-null   int64  
 4   _last_judgment_at       8000 non-null   object 
 5   positivity              1420 non-null   float64
 6   positivity:confidence   3775 non-null   float64
 7   relevance               8000 non-null   object 
 8   relevance:confidence    8000 non-null   float64
 9   articleid               8000 non-null   object 
 10  date                    8000 non-null   object 
 11  headline                8000 non-null   object 
 12  positivity_gold         0 non-null      float64
 13  relevance_gold          0 non-null      float64
 14  text                    8000 non-null   object 
dtypes: bool(1), float64(5), int64(2), object(7)
memory usage: 882.9+ KB
```

In [4]:
```
df.head(5)
```

Out[4]:

	_unit_id	_golden	_unit_state	_trusted_judgments	_last_judgment_at	positivity	p
0	842613455	False	finalized	3	12/5/15 17:48	3.0	
1	842613456	False	finalized	3	12/5/15 16:54	NaN	
2	842613457	False	finalized	3	12/5/15 1:59	NaN	
3	842613458	False	finalized	3	12/5/15 2:19	NaN	
4	842613459	False	finalized	3	12/5/15 17:48	3.0	

Removing unneccessary columns.

In [6]:
```
df = df[['headline', 'text', 'relevance']]

# We drop all irrelavant features to only keep headline and text for 2 reasons:
# The other features seem either irrelevant or we lack documentation
# With headline and text only, our final model will be more generalizable. We co
```

Balancing the dataset to 50% relevant and 50% not relevant.

In [7]:
```
import pandas as pd
import numpy as np

df_yes = df[df['relevance'] == 'yes']
df_no = df[df['relevance'] == 'no']

df_no_sampled = df_no.sample(n=len(df_yes), random_state=42)

# Concatenate the sampled 'no' rows with all 'yes' rows
df_balanced = pd.concat([df_yes, df_no_sampled])

print(df_balanced['relevance'].value_counts())
```

```
relevance
yes    1420
no     1420
Name: count, dtype: int64
```

In [8]:
```
df = df_balanced
```

Cleaning Strings

Here we merge the title and the full text into one string, we will process in whole.

In [9]:
```
df['whole_txt'] = df['headline']+ ' ' + df['text']
```

In [10]:
```
wtxt_train = np.array(df['whole_txt'])
```

Removing of special signs, number ect.

In [11]:
```
for i in range(len(wtxt_train)):
    # Taking out '<br>' in the 'whole_text' column
    wtxt_train[i] = re.sub(r'</?br>', ' ', wtxt_train[i])
    # Deletion of non-latin alfabet signs, also numbers
    wtxt_train[i] = re.sub(r'[^a-zA-Z]', ' ', wtxt_train[i])
    # Removing single letter works like 'a'.
    wtxt_train[i] = re.sub(r"\s+[a-zA-Z]\s+", ' ', wtxt_train[i])
    # Removing double spaces
    wtxt_train[i] = re.sub(r'\s+', ' ', wtxt_train[i])
    # Lower case
    wtxt_train[i] = wtxt_train[i].lower()
```

Split the words.

We split the string into many strings representing words encoded here as elements of a list.

In [12]:
```
for i in range(len(wtxt_train)):
    wtxt_train[i] = word_tokenize(wtxt_train[i])
```

Removing stop words.

We are removing stop words like for example: the, they, them, for. Those are words that bring no meritorical value to the articles topic since they are just a non meaning bringing punctuation necessary in the language. By removing them we can also save on size and therefore computational power.

In [13]:
```
stop_words = set(stopwords.words('english'))

for i in range(len(wtxt_train)):
    wtxt_train[i] = [word for word in wtxt_train[i] if word not in stop_words]
```

In [14]:
```
wtxt_train[0]
# stop_words
```

Out[14]:
```
['yields',
 'cds',
 'fell',
 'latest',
 'week',
 'new',
 'york',
 'yields',
 'certificates',
 'deposit',
 'offered',
 'major',
 'banks',
 'dropped',
 'tenth',
 'percentage',
 'point',
 'latest',
 'week',
 'reflecting',
 'overall',
 'decline',
 'short',
 'term',
 'interest',
 'rates',
 'small',
 'denomination',
 'consumer',
 'cds',
 'sold',
 'directly',
 'banks',
 'average',
 'yield',
 'six',
 'month',
 'deposits',
 'fell',
 'week',
 'ended',
 'yesterday',
 'according',
 'bank',
 'survey',
 'banxquote',
 'money',
 'markets',
 'wilmington',
 'del',
 'information',
 'service',
 'three',
 'month',
 'consumer',
 'deposits',
 'average',
 'yield',
 'sank',
 'week',
```

```
 'according',
 'banxquote',
 'two',
 'banks',
 'banxquote',
 'survey',
 'citibank',
 'new',
 'york',
 'corestates',
 'pennsylvania',
 'paying',
 'less',
 'threemonth',
 'small',
 'denomination',
 'cds',
 'declines',
 'somewhat',
 'smaller',
 'five',
 'year',
 'consumer',
 'cds',
 'eased',
 'banxquote',
 'said',
 'yields',
 'three',
 'month',
 'six',
 'month',
 'treasury',
 'bills',
 'sold',
 'monday',
 'auction',
 'plummeted',
 'fifth',
 'percentage',
 'point',
 'previous',
 'week',
 'respectively']
```

Lemmatization

That means bringing the words with different endings to their initial meaning and form.

In [15]:
```
lemmatizer = WordNetLemmatizer()
for i in range(len(wtxt_train)):
    wtxt_train[i] = [lemmatizer.lemmatize(word) for word in wtxt_train[i]]
```

In [16]:
```
df['whole_txt'] = wtxt_train
df = df.drop(['headline', 'text'], axis = 1)
```

In [17]:
```
df.head(5)
```

Out[17]:

	relevance	whole_txt
0	yes	[yield, cd, fell, latest, week, new, york, yie...
4	yes	[currency, trading, dollar, remains, tight, ra...
5	yes	[stock, fall, bofa, alcoa, slide, stock, decli...
9	yes	[u, dollar, fall, currency, decline, softened,...
12	yes	[defending, deflation, author, james, stewart,...

Data preparation

- Initial Data Processing: Our first step is to encode the relevance label into both the Relevant (1) and non-Relevant labels (0). Then, we make it into a np.array to feed into the model.
- Then, we begin to clean text data into pad sequences.

In [18]:
```
df.update(df["relevance"].apply(lambda x: 0 if x == "no" else 1))
```

In [19]:
```
df.head(5)
```

Out[19]:

	relevance	whole_txt
0	1	[yield, cd, fell, latest, week, new, york, yie...
4	1	[currency, trading, dollar, remains, tight, ra...
5	1	[stock, fall, bofa, alcoa, slide, stock, decli...
9	1	[u, dollar, fall, currency, decline, softened,...
12	1	[defending, deflation, author, james, stewart,...

Tokenization

First, we need to "tokenize" our sentences, i.e., convert them to sequences of numbers. For this task, we are going to use the `Tokenizer` from Tensorflow (documentation here)

In [20]:
```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(wtxt_train)   # fit our tokenizer on the dataset (i.e., a
                                     # dictionary with the correspondence of each

# see the language dictionary and the total number of words (please note that nu
word_index = tokenizer.word_index
total_words = len(word_index) + 1
```

In [21]:
```
word_index
```

Out[21]:

```
{'year': 1,
 'rate': 2,
 'market': 3,
 'said': 4,
 'stock': 5,
 'price': 6,
 'new': 7,
 'economy': 8,
 'economic': 9,
 'month': 10,
 'federal': 11,
 'would': 12,
 'interest': 13,
 'percent': 14,
 'last': 15,
 'week': 16,
 'inflation': 17,
 'bank': 18,
 'billion': 19,
 'fed': 20,
 'dollar': 21,
 'bond': 22,
 'point': 23,
 'growth': 24,
 'investor': 25,
 'one': 26,
 'company': 27,
 'million': 28,
 'index': 29,
 'since': 30,
 'york': 31,
 'quarter': 32,
 'average': 33,
 'first': 34,
 'time': 35,
 'tax': 36,
 'increase': 37,
 'reserve': 38,
 'may': 39,
 'government': 40,
 'president': 41,
 'report': 42,
 'business': 43,
 'day': 44,
 'rose': 45,
 'say': 46,
 'consumer': 47,
 'also': 48,
 'yesterday': 49,
 'two': 50,
 'economist': 51,
 'dow': 52,
 'sale': 53,
 'many': 54,
 'job': 55,
 'fund': 56,
 'share': 57,
 'could': 58,
 'high': 59,
 'gain': 60,
```

```
'higher': 61,
'trading': 62,
'cut': 63,
'deficit': 64,
'state': 65,
'analyst': 66,
'decline': 67,
'money': 68,
'spending': 69,
'fell': 70,
'mr': 71,
'recession': 72,
'financial': 73,
'term': 74,
'treasury': 75,
'policy': 76,
'even': 77,
'rise': 78,
'good': 79,
'industrial': 80,
'level': 81,
'unemployment': 82,
'much': 83,
'american': 84,
'department': 85,
'today': 86,
'trade': 87,
'low': 88,
'cent': 89,
'lower': 90,
'expected': 91,
'washington': 92,
'cost': 93,
'still': 94,
'plan': 95,
'budget': 96,
'jones': 97,
'three': 98,
'nation': 99,
'official': 100,
'house': 101,
'labor': 102,
'recent': 103,
'security': 104,
'home': 105,
'people': 106,
'next': 107,
'long': 108,
'exchange': 109,
'oil': 110,
'recovery': 111,
'make': 112,
'record': 113,
'news': 114,
'industry': 115,
'end': 116,
'investment': 117,
'back': 118,
'credit': 119,
'number': 120,
```

```
'second': 121,
'income': 122,
'profit': 123,
'past': 124,
'issue': 125,
'chairman': 126,
'data': 127,
'strong': 128,
'board': 129,
'short': 130,
'big': 131,
'according': 132,
'le': 133,
'chief': 134,
'service': 135,
'friday': 136,
'administration': 137,
'major': 138,
'late': 139,
'like': 140,
'world': 141,
'reported': 142,
'yield': 143,
'drop': 144,
'currency': 145,
'well': 146,
'mortgage': 147,
'loan': 148,
'earlier': 149,
'group': 150,
'firm': 151,
'fall': 152,
'inc': 153,
'earnings': 154,
'street': 155,
'rising': 156,
'per': 157,
'loss': 158,
'country': 159,
'worker': 160,
'way': 161,
'work': 162,
'central': 163,
'another': 164,
'co': 165,
'third': 166,
'get': 167,
'move': 168,
'future': 169,
'early': 170,
'wall': 171,
'sign': 172,
'national': 173,
'bill': 174,
'program': 175,
'january': 176,
'figure': 177,
'congress': 178,
'bush': 179,
'part': 180,
```

```
'annual': 181,
'capital': 182,
'take': 183,
'see': 184,
'trader': 185,
'close': 186,
'likely': 187,
'change': 188,
'made': 189,
'june': 190,
'demand': 191,
'among': 192,
'housing': 193,
'half': 194,
'july': 195,
'pay': 196,
'nearly': 197,
'nasdaq': 198,
'little': 199,
'march': 200,
'system': 201,
'result': 202,
'debt': 203,
'come': 204,
'raise': 205,
'problem': 206,
'concern': 207,
'rally': 208,
'show': 209,
'four': 210,
'standard': 211,
'committee': 212,
'product': 213,
'small': 214,
'corp': 215,
'keep': 216,
'foreign': 217,
'forecast': 218,
'corporate': 219,
'ago': 220,
'continued': 221,
'u': 222,
'april': 223,
'city': 224,
'yen': 225,
'real': 226,
'global': 227,
'greenspan': 228,
'meeting': 229,
'help': 230,
'however': 231,
'employment': 232,
'sector': 233,
'fear': 234,
'far': 235,
'value': 236,
'based': 237,
'despite': 238,
'ahead': 239,
'including': 240,
```

'poor': 241,
'hit': 242,
'executive': 243,
'several': 244,
'go': 245,
'might': 246,
'survey': 247,
'volume': 248,
'period': 249,
'current': 250,
'session': 251,
'benefit': 252,
'measure': 253,
'put': 254,
'order': 255,
'large': 256,
'pace': 257,
'public': 258,
'set': 259,
'added': 260,
'area': 261,
'japan': 262,
'compared': 263,
'think': 264,
'increased': 265,
'start': 266,
'going': 267,
'commerce': 268,
'biggest': 269,
'tuesday': 270,
'five': 271,
'better': 272,
'need': 273,
'fiscal': 274,
'pressure': 275,
'international': 276,
'continue': 277,
'white': 278,
'finance': 279,
'united': 280,
'thursday': 281,
'energy': 282,
'largest': 283,
'least': 284,
'six': 285,
'percentage': 286,
'revenue': 287,
'though': 288,
'general': 289,
'mark': 290,
'growing': 291,
'february': 292,
'sell': 293,
'sharply': 294,
'crisis': 295,
'august': 296,
'latest': 297,
'ended': 298,
'dropped': 299,
'monday': 300,

'buy': 301,
'came': 302,
'deal': 303,
'october': 304,
'best': 305,
'wednesday': 306,
'member': 307,
'already': 308,
'office': 309,
'senate': 310,
'previous': 311,
'slightly': 312,
'december': 313,
'enough': 314,
'november': 315,
'export': 316,
'technology': 317,
'around': 318,
'risk': 319,
'manager': 320,
'began': 321,
'euro': 322,
'yet': 323,
'supply': 324,
'composite': 325,
'lost': 326,
'health': 327,
'whether': 328,
'weak': 329,
'top': 330,
'buying': 331,
'september': 332,
'boost': 333,
'clinton': 334,
'wage': 335,
'face': 336,
'outlook': 337,
'thing': 338,
'making': 339,
'right': 340,
'showed': 341,
'look': 342,
'falling': 343,
'monetary': 344,
'reagan': 345,
'estimate': 346,
'war': 347,
'closed': 348,
'activity': 349,
'force': 350,
'america': 351,
'lowest': 352,
'action': 353,
'expect': 354,
'declined': 355,
'although': 356,
'hour': 357,
'highest': 358,
'return': 359,
'gold': 360,

```
'effort': 361,
'private': 362,
'fourth': 363,
'management': 364,
'banking': 365,
'republican': 366,
'run': 367,
'total': 368,
'mean': 369,
'food': 370,
'effect': 371,
'maker': 372,
'import': 373,
'advance': 374,
'retail': 375,
'almost': 376,
'worry': 377,
'post': 378,
'indicator': 379,
'amount': 380,
'sharp': 381,
'key': 382,
'selling': 383,
'political': 384,
'expectation': 385,
'production': 386,
'without': 387,
'question': 388,
'want': 389,
'coming': 390,
'manufacturing': 391,
'hope': 392,
'released': 393,
'domestic': 394,
'note': 395,
'become': 396,
'confidence': 397,
'law': 398,
'every': 399,
'overall': 400,
'chip': 401,
'director': 402,
'computer': 403,
'auto': 404,
'soon': 405,
'vice': 406,
'slow': 407,
'call': 408,
'strength': 409,
'gained': 410,
'employee': 411,
'blue': 412,
'support': 413,
'decade': 414,
'leader': 415,
'jobless': 416,
'cash': 417,
'give': 418,
'led': 419,
'view': 420,
```

'taking': 421,
'offer': 422,
'research': 423,
'university': 424,
'democrat': 425,
'open': 426,
'full': 427,
'old': 428,
'car': 429,
'surge': 430,
'called': 431,
'seen': 432,
'proposal': 433,
'insurance': 434,
'industrials': 435,
'line': 436,
'account': 437,
'power': 438,
'net': 439,
'amid': 440,
'p': 441,
'adjusted': 442,
'care': 443,
'reason': 444,
'turn': 445,
'near': 446,
'trend': 447,
'head': 448,
'retailer': 449,
'contract': 450,
'later': 451,
'europe': 452,
'asset': 453,
'lead': 454,
'monthly': 455,
'japanese': 456,
'longer': 457,
'remain': 458,
'senior': 459,
'slowdown': 460,
'lot': 461,
'saving': 462,
'control': 463,
'find': 464,
'hold': 465,
'option': 466,
'social': 467,
'purchase': 468,
'school': 469,
'expansion': 470,
'european': 471,
'county': 472,
'toward': 473,
'association': 474,
'decision': 475,
'left': 476,
'told': 477,
'mixed': 478,
'reduce': 479,
'china': 480,

'believe': 481,
'election': 482,
'slowing': 483,
'target': 484,
'output': 485,
'performance': 486,
'secretary': 487,
'bad': 488,
'evidence': 489,
'announced': 490,
'store': 491,
'gross': 492,
'unit': 493,
'important': 494,
'case': 495,
'producer': 496,
'must': 497,
'recently': 498,
'productivity': 499,
'john': 500,
'leading': 501,
'took': 502,
'helped': 503,
'claim': 504,
'held': 505,
'life': 506,
'family': 507,
'council': 508,
'region': 509,
'following': 510,
'statement': 511,
'hand': 512,
'condition': 513,
'summer': 514,
'push': 515,
'campaign': 516,
'away': 517,
'congressional': 518,
'talk': 519,
'obama': 520,
'robert': 521,
'lending': 522,
'remains': 523,
'within': 524,
'meanwhile': 525,
'alan': 526,
'broad': 527,
'place': 528,
'begin': 529,
'looking': 530,
'agency': 531,
'grew': 532,
'jumped': 533,
'union': 534,
'impact': 535,
'district': 536,
'raising': 537,
'institution': 538,
'due': 539,
'payroll': 540,

'payment': 541,
'reduction': 542,
'banker': 543,
'former': 544,
'operation': 545,
'personal': 546,
'seven': 547,
'great': 548,
'factor': 549,
'individual': 550,
'local': 551,
'development': 552,
'steel': 553,
'posted': 554,
'mutual': 555,
'holding': 556,
'know': 557,
'study': 558,
'rule': 559,
'statistic': 560,
'rather': 561,
'generally': 562,
'democratic': 563,
'charge': 564,
'party': 565,
'signal': 566,
'prospect': 567,
'gdp': 568,
'conference': 569,
'estate': 570,
'climbed': 571,
'buyer': 572,
'found': 573,
'steady': 574,
'morgan': 575,
'hard': 576,
'fact': 577,
'reached': 578,
'modest': 579,
'across': 580,
'card': 581,
'others': 582,
'equity': 583,
'stimulus': 584,
'fixed': 585,
'black': 586,
'adviser': 587,
'getting': 588,
'course': 589,
'used': 590,
'mid': 591,
'followed': 592,
'raised': 593,
'instead': 594,
'revised': 595,
'often': 596,
'history': 597,
'especially': 598,
'jump': 599,
'beginning': 600,

```
'manufacturer': 601,
'final': 602,
'probably': 603,
'predicted': 604,
'example': 605,
'chicago': 606,
'customer': 607,
'significant': 608,
'sold': 609,
'minute': 610,
'seems': 611,
'closing': 612,
'given': 613,
'traded': 614,
'step': 615,
'center': 616,
'building': 617,
'benchmark': 618,
'commodity': 619,
'german': 620,
'package': 621,
'gap': 622,
'improvement': 623,
'shift': 624,
'position': 625,
'construction': 626,
'maryland': 627,
'virginia': 628,
'range': 629,
'advanced': 630,
'weakness': 631,
'cutting': 632,
'meet': 633,
'turned': 634,
'use': 635,
'started': 636,
'factory': 637,
'defense': 638,
'comment': 639,
'rebound': 640,
'single': 641,
'airline': 642,
'agreement': 643,
'rest': 644,
'act': 645,
'straight': 646,
'agreed': 647,
'attack': 648,
'sept': 649,
'list': 650,
'noted': 651,
'west': 652,
'got': 653,
'quickly': 654,
'heavy': 655,
'trillion': 656,
'side': 657,
'bear': 658,
'borrowing': 659,
'inventory': 660,
```

```
'moving': 661,
'possible': 662,
'idea': 663,
'try': 664,
'grow': 665,
'taken': 666,
'slump': 667,
'crash': 668,
'ford': 669,
'unchanged': 670,
'press': 671,
'strategist': 672,
'provide': 673,
'really': 674,
'clear': 675,
'uncertainty': 676,
'something': 677,
'proposed': 678,
'cause': 679,
'crude': 680,
'journal': 681,
'known': 682,
'continuing': 683,
'fee': 684,
'middle': 685,
'afternoon': 686,
'holiday': 687,
'initial': 688,
'bernanke': 689,
'finished': 690,
'hurt': 691,
'financing': 692,
'morning': 693,
'strategy': 694,
'largely': 695,
'ever': 696,
'officer': 697,
'worst': 698,
'pushed': 699,
'moved': 700,
'household': 701,
'light': 702,
'along': 703,
'plant': 704,
'c': 705,
'commission': 706,
'oct': 707,
'huge': 708,
'moderate': 709,
'motor': 710,
'utility': 711,
'carter': 712,
'stronger': 713,
'slower': 714,
'warned': 715,
'living': 716,
'employer': 717,
'whose': 718,
'declining': 719,
'discount': 720,
```

```
'aid': 721,
'behind': 722,
'increasing': 723,
'downturn': 724,
'break': 725,
'showing': 726,
'project': 727,
'bit': 728,
'relatively': 729,
'commercial': 730,
'expects': 731,
'drug': 732,
'suggests': 733,
'upward': 734,
'continues': 735,
'boom': 736,
'working': 737,
'dividend': 738,
'author': 739,
'easing': 740,
'fuel': 741,
'remained': 742,
'information': 743,
'changed': 744,
'eight': 745,
'balance': 746,
'positive': 747,
'sent': 748,
'saying': 749,
'available': 750,
'particularly': 751,
'certain': 752,
'tech': 753,
'basis': 754,
'seasonally': 755,
'saw': 756,
'class': 757,
'dealer': 758,
'portfolio': 759,
'different': 760,
'faster': 761,
'reading': 762,
'book': 763,
'focus': 764,
'response': 765,
'potential': 766,
'add': 767,
'equipment': 768,
'greater': 769,
'governor': 770,
'vote': 771,
'smaller': 772,
'issued': 773,
'additional': 774,
'event': 775,
'peak': 776,
'thought': 777,
'regulator': 778,
'jan': 779,
'slide': 780,
```

```
'matter': 781,
'paul': 782,
'seem': 783,
'never': 784,
'lender': 785,
'fallen': 786,
'david': 787,
'chance': 788,
'weekly': 789,
'legislation': 790,
'free': 791,
'climb': 792,
'needed': 793,
'retirement': 794,
'california': 795,
'trust': 796,
'related': 797,
'estimated': 798,
'analysis': 799,
'rail': 800,
'reform': 801,
'appears': 802,
'larger': 803,
'bureau': 804,
'active': 805,
'economics': 806,
'drive': 807,
'college': 808,
'kind': 809,
'worse': 810,
'corporation': 811,
'speech': 812,
'suggest': 813,
'offering': 814,
'ground': 815,
'deposit': 816,
'bring': 817,
'consecutive': 818,
'running': 819,
'surplus': 820,
'george': 821,
'serious': 822,
'core': 823,
'limit': 824,
'bet': 825,
'soared': 826,
'barrel': 827,
'went': 828,
'improved': 829,
'ease': 830,
'sluggish': 831,
'bull': 832,
'regional': 833,
'source': 834,
'debate': 835,
'trying': 836,
'inflationary': 837,
'direction': 838,
'broader': 839,
'mostly': 840,
```

```
'attention': 841,
'prime': 842,
'able': 843,
'william': 844,
'expert': 845,
'caused': 846,
'process': 847,
'weekend': 848,
'paid': 849,
'indicated': 850,
'review': 851,
'hiring': 852,
'pushing': 853,
'wholesale': 854,
'gas': 855,
'aug': 856,
'flat': 857,
'stay': 858,
'double': 859,
'similar': 860,
'attempt': 861,
'paper': 862,
'common': 863,
'risen': 864,
'presidential': 865,
'whole': 866,
'partner': 867,
'associated': 868,
'community': 869,
'let': 870,
'sen': 871,
'release': 872,
'difficult': 873,
'indeed': 874,
'worth': 875,
'received': 876,
'broker': 877,
'word': 878,
'widely': 879,
'anticipated': 880,
'robust': 881,
'machine': 882,
'answer': 883,
'spring': 884,
'warning': 885,
'temporary': 886,
'organization': 887,
'asia': 888,
'suggested': 889,
'negative': 890,
'germany': 891,
'gave': 892,
'main': 893,
'season': 894,
'track': 895,
'opportunity': 896,
'student': 897,
'conservative': 898,
'plunge': 899,
'game': 900,
```

```
'name': 901,
'ending': 902,
'include': 903,
'seemed': 904,
'brokerage': 905,
'sure': 906,
'bottom': 907,
'page': 908,
'tokyo': 909,
'asked': 910,
'dec': 911,
'finally': 912,
'adding': 913,
'th': 914,
'correction': 915,
'trouble': 916,
'weaker': 917,
'failed': 918,
'feel': 919,
'fight': 920,
'series': 921,
'cap': 922,
'sense': 923,
'surged': 924,
'seek': 925,
'closely': 926,
'nine': 927,
'always': 928,
'check': 929,
'special': 930,
'ap': 931,
'offered': 932,
'doubt': 933,
'fast': 934,
'canada': 935,
'done': 936,
'south': 937,
'situation': 938,
'wide': 939,
'men': 940,
'appeared': 941,
'keeping': 942,
'rapidly': 943,
'tell': 944,
'difference': 945,
'texas': 946,
'imf': 947,
'quarterly': 948,
'layoff': 949,
'picture': 950,
'san': 951,
'easy': 952,
'bigger': 953,
'brother': 954,
'taxpayer': 955,
'woman': 956,
'either': 957,
'actually': 958,
'beyond': 959,
'using': 960,
```

```
 'spokesman': 961,
 'giving': 962,
 'consider': 963,
 'addition': 964,
 'forecaster': 965,
 'volatility': 966,
 'losing': 967,
 'item': 968,
 'bid': 969,
 'nothing': 970,
 'kept': 971,
 'increasingly': 972,
 'boston': 973,
 'client': 974,
 'slowed': 975,
 'passed': 976,
 'projected': 977,
 'optimism': 978,
 'role': 979,
 'edged': 980,
 'boosted': 981,
 'usually': 982,
 'consensus': 983,
 'richard': 984,
 'volcker': 985,
 'interview': 986,
 'voter': 987,
 'military': 988,
 'competition': 989,
 'spend': 990,
 'indicate': 991,
 'possibility': 992,
 'gasoline': 993,
 'tumbled': 994,
 'appear': 995,
 'finish': 996,
 'institute': 997,
 'approved': 998,
 'accounting': 999,
 'asian': 1000,
 ...}
```

In [22]:
```
total_words
```

Out[22]:
```
20936
```

Padding Sequences

Sentences and sequences tend to have different lengths, however our model is expecting equally sized observations. Here we want to convert our texts to sequences and make them of the same length (in general, the lenght of the longest of our sequences). We are going to use here `pad_sequences` from Tensorflow (documentation here), to add zeroes to the tokenized sentences until they all reach the same length.

In [23]:
```
sequences = tokenizer.texts_to_sequences(wtxt_train)
padded_sequences = pad_sequences(sequences)
```

In [24]:
```
sequences[0]
```

Out[24]:
```
[143,
 2582,
 70,
 297,
 16,
 7,
 31,
 143,
 2405,
 816,
 932,
 138,
 18,
 299,
 2041,
 286,
 23,
 297,
 16,
 1055,
 400,
 67,
 130,
 74,
 13,
 2,
 214,
 7581,
 47,
 2582,
 609,
 1698,
 18,
 33,
 143,
 285,
 10,
 816,
 70,
 16,
 298,
 49,
 132,
 18,
 247,
 6514,
 68,
 3,
 12016,
 3663,
 743,
 135,
 98,
 10,
 47,
 816,
 33,
 143,
 1832,
 16,
```

```
132,
6514,
50,
18,
6514,
247,
3307,
7,
31,
12017,
3308,
1042,
133,
12018,
214,
7581,
2582,
67,
1020,
772,
271,
1,
47,
2582,
1165,
6514,
4,
143,
98,
10,
285,
10,
75,
174,
609,
300,
1056,
2042,
1110,
286,
23,
311,
16,
2406]
```

In [25]:
```
padded_sequences
```

Out[25]:
```
array([[    0,     0,     0, ...,   311,    16,  2406],
       [    0,     0,     0, ...,   239,   232,    42],
       [    0,     0,     0, ...,   325,   326,    23],
       ...,
       [    0,     0,     0, ...,   203,  4375,    59],
       [    0,     0,     0, ...,   159,     9,   169],
       [    0,     0,     0, ..., 12015,  7108,  7444]])
```

In [26]:
```
df['pad_seq'] = padded_sequences.tolist()
```

In [27]:
```
df.drop(['whole_txt'], axis = 1)
```

Out[27]:

	relevance	pad_seq
0	1	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
4	1	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
5	1	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
9	1	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
12	1	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
...	...	...
7810	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
677	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
4794	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
5869	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
2977	0	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...

2840 rows × 2 columns

Here we end up with padded sequences and the binarly encoded relevance.

In [28]:
```
df.head(5)
```

Out[28]:

	relevance	whole_txt	pad_seq
0	1	[yield, cd, fell, latest, week, new, york, yie...	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
4	1	[currency, trading, dollar, remains, tight, ra...	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
5	1	[stock, fall, bofa, alcoa, slide, stock, decli...	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
9	1	[u, dollar, fall, currency, decline, softened,...	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
12	1	[defending, deflation, author, james, stewart,...	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...

Train-Test Split

Over here we do the Train-Test Split, we designate the X and y variables using the padded sequences and revelance respectively. The split is done in proportions 80% to 20% using a random state, in order to mix the relevant and non relevant cases more less equaly by each split. Then from the product of the training split we create another split into the true train part of the data and the validation set, by 80-20% as well. At the end we finish with 3 sets train, validation and test. The sizes of each array are given below. The arrays for the y variable are turned into numpy arrays and they contain only integer values, since those are the only ones tensorflow will accept given a binary crossentropy.

In [29]:
```
X = padded_sequences
y = df['relevance']
```

In [30]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,  test_size=0.2, random
```

In [31]:
```
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,  test_size=0
```

In [32]:
```
X_train
```

Out[32]:
```
array([[   0,    0,    0, ...,   61,  362,   66],
       [   0,    0,    0, ..., 4569, 6281, 1252],
       [   0,    0,    0, ..., 3415,   95,    4],
       ...,
       [   0,    0,    0, ...,  479,   96,   64],
       [   0,    0,    0, ...,   27,  246,  609],
       [   0,    0,    0, ...,   10,  391,   24]])
```

In [33]:
```
X_train.shape
```

Out[33]:
```
(1817, 404)
```

In [34]:
```
y_train
```

Out[34]:
```
6965    1
2156    0
1103    0
7486    1
5865    1
       ..
2245    1
1956    1
3711    0
506     1
3821    1
Name: relevance, Length: 1817, dtype: object
```

In [35]:
```
y_train.shape
```

Out[35]:
```
(1817,)
```

In [36]:
```
y_val.shape
```

Out[36]:
```
(455,)
```

In [37]:
```
y_test.shape
```

Out[37]:
```
(568,)
```

In [ ]:
```

```

In [38]:
```
y_train = np.array(y_train)
y_val = np.array(y_val)
y_test = np.array(y_test)
```

In [39]:
```
y_train = y_train.astype('int')
y_val = y_val.astype('int')
```

```
y_test = y_test.astype('int')
```

Building the model

We are going to build multiple models that include:

- `Embedding` layer with an output representation of each word as a vector of dim 100, 200 or 300
- `LSTM` with an intermediate state of 100 nodes, though this number can vary depending on the model in subject
- An output layer `Dense` that connects the output of the LSTM and creates an output of 1. It either activates if found relevant or not if otherwise. It uses a sigmoid activation which traverses between a 0 and a 1.
- `Dropout` a function that drops a given percentage of links in a random manner after layer training, a good option to try to limit the overfitting effects.
- `Bidirectional` a both way LSTM layer, by that it captures both past and future information to train on.

Early Stopping

Early Stopping allows us to stop training in order to aviod overfitting as soon as we are getting same or worse loss scores on the validation set. Such a stop is executed when the loss drop occures 3 times in a row. For a poorer accuracy, it restores the previous better weights.

In [40]:
```
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weig
```

Training the models

Model Building

Regarding model building, we first tried to create a solid model through in depth hyperparameter tuning, but our results were always roughly the same; slightly better than random. We were obtaining training accuracy of 1.0 and test accuracy of 0.83 at most. These results may seem satisfying at first, but we actually had an imbalanced dataset. In fact, our y variable contained 82% of articles that were “economically irrelevant” and only 18% of relevant. Our first intuition was to use 100, 200 or 300 words for the final model in training and to make an excel to keep track of the model parameters used, training parameters and results.

We then decided to employ regularization methods to reduce over-fitting. We also used graphs to see the loss and what happens at each epoch by defining a history variable and then plotting history when training is done. We did all of this to gain insights and these steps helped us figure out the deeper problem: the imbalance of the y variable in our original dataset. Thus, we finally chose to balance our original dataset by using as many relevant as irrelevant articles, while keeping all of the relevant ones of which we only had 18% in our original dataset. So our final dataset consists of 50% of irrelevant articles and 50% of relevant ones. We then re-ran all our code and models on this new dataset and our results drastically improved, as you can see below.

Other models were run along in different files, using different configurations, however the document you are reading worked the best for our given task, those incluse:

- The original 80 - 20 % Full Text modeling (Worst Performing)
- The 50 - 50 % Full Text modeling (Best Performing, DESCRIBED HERE)
- The 50 - 50 % Headlines Only modeling (Worse Performance by around ~ 10%)
- The 50 - 50 % Headlines + First N Words of Text modeling (Slightly Worse Performance Highly Dependant on the Value of N)
- The 50 - 50 % Full Text 'word2vec' modeling (Depending on model, slightly better or worse)

In the word2vec case we decided to keep it out due to computation complications, not much better results often slightly worse, longer waiting times and over all it increased vastly the model complexity, which we wanted to avoid.

All files can be found on GitHub, some of them are not described and in a more 'dirty' format.

https://github.com/Majon911/EconNewsMLIdent

MODEL 1 (The base model)

- Our base model defines LSTM as a great foundation for its usability in sequence data such as NLP
- On the other side, we come with ideally the final output from a classification of all outputs from the LSTM, and use the dense layer to reduce to that one most likely prediction; hence the '1' of output dimension. Finally, the adam optimizer was initialized with, which would tend to overfit through the model training.
- At 56% validation accuracy, this model overfits at 99%.

In [41]:
```
# We are going to build our model with the Sequential API
model = Sequential()
model.add(Embedding(total_words,      # number of words to process as input
                    100,     # output representation
                    input_length=len(padded_sequences[0])))    # total length of
model.add(LSTM(100, return_sequences=False))
model.add(Dense(1, activation='sigmoid'))  # Change activation based on the numb

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy']
```

```
WARNING:tensorflow:From C:\Users\majon\AppData\Local\Programs\Python\Python310\li
b\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprec
ated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\majon\AppData\Local\Programs\Python\Python310\li
b\site-packages\keras\src\optimizers\__init__.py:309: The name tf.train.Optimizer
is deprecated. Please use tf.compat.v1.train.Optimizer instead.
```

In [42]:
```
model(padded_sequences)
```

Out[42]:
```
<tf.Tensor: shape=(2840, 1), dtype=float32, numpy=
array([[0.49838775],
       [0.49697223],
       [0.49766093],
       ...,
       [0.49778345],
       [0.4963791 ],
       [0.5038256 ]], dtype=float32)>
```

In [43]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 404, 100)          2093600

 lstm (LSTM)                 (None, 100)               80400

 dense (Dense)               (None, 1)                 101

=================================================================
Total params: 2174101 (8.29 MB)
Trainable params: 2174101 (8.29 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [44]:
```
hist = model.fit(X_train, y_train, epochs=10, validation_data = (X_val, y_val))
```

```
Epoch 1/10
WARNING:tensorflow:From C:\Users\majon\AppData\Local\Programs\Python\Python310\li
b\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorV
alue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\majon\AppData\Local\Programs\Python\Python310\li
b\site-packages\keras\src\engine\base_layer_utils.py:384: The name tf.executing_e
agerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly
_outside_functions instead.

57/57 [==============================] - 13s 195ms/step - loss: 0.6880 - accurac
y: 0.5498 - val_loss: 0.6759 - val_accuracy: 0.6484
Epoch 2/10
57/57 [==============================] - 9s 162ms/step - loss: 0.5424 - accuracy:
0.7870 - val_loss: 0.6902 - val_accuracy: 0.5978
Epoch 3/10
57/57 [==============================] - 9s 163ms/step - loss: 0.2517 - accuracy:
0.9086 - val_loss: 0.9096 - val_accuracy: 0.6066
Epoch 4/10
57/57 [==============================] - 10s 172ms/step - loss: 0.0673 - accurac
y: 0.9818 - val_loss: 1.2419 - val_accuracy: 0.5824
Epoch 5/10
57/57 [==============================] - 10s 172ms/step - loss: 0.0200 - accurac
y: 0.9961 - val_loss: 1.4963 - val_accuracy: 0.5670
Epoch 6/10
57/57 [==============================] - 9s 152ms/step - loss: 0.0251 - accuracy:
0.9950 - val_loss: 1.3650 - val_accuracy: 0.5604
Epoch 7/10
57/57 [==============================] - 9s 159ms/step - loss: 0.0163 - accuracy:
0.9950 - val_loss: 1.8727 - val_accuracy: 0.5868
Epoch 8/10
57/57 [==============================] - 9s 158ms/step - loss: 0.0078 - accuracy:
0.9978 - val_loss: 1.6632 - val_accuracy: 0.5736
Epoch 9/10
57/57 [==============================] - 10s 169ms/step - loss: 0.0045 - accurac
y: 0.9989 - val_loss: 2.0763 - val_accuracy: 0.5978
Epoch 10/10
57/57 [==============================] - 10s 178ms/step - loss: 0.0041 - accurac
y: 0.9989 - val_loss: 1.6814 - val_accuracy: 0.5692
```

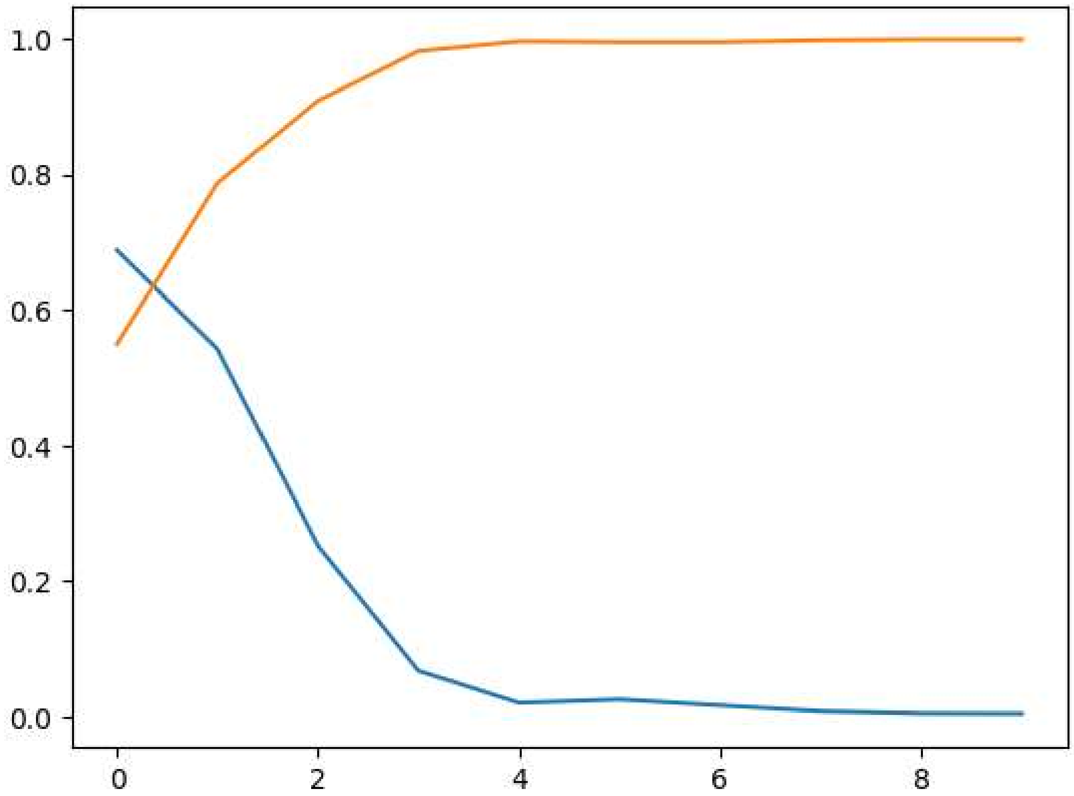
In [46]:

```
hist.history
```

Out[46]:
```
{'loss': [0.6879979968070984,
  0.5423904061317444,
  0.25165560841560364,
  0.0672721192240715,
  0.01998290978372097,
  0.02507256343960762,
  0.01631668023765087,
  0.007824108004570007,
  0.004535376559942961,
  0.004056017845869064],
 'accuracy': [0.5498073697090149,
  0.7870115637779236,
  0.9086406230926514,
  0.9818381667137146,
  0.9961475133895874,
  0.9950467944145203,
  0.9950467944145203,
  0.9977985620498657,
  0.9988992810249329,
  0.9988992810249329],
 'val_loss': [0.675902247428894,
  0.6902332901954651,
  0.9096015691757202,
  1.2418750524520874,
  1.4963206052780151,
  1.3650264739990234,
  1.8727422952651978,
  1.663246750831604,
  2.076326608657837,
  1.6813592910766602],
 'val_accuracy': [0.6483516693115234,
  0.5978022217750549,
  0.6065934300422668,
  0.5824176073074341,
  0.5670329928398132,
  0.5604395866394043,
  0.58681321144104,
  0.5736263990402222,
  0.5978022217750549,
  0.5692307949066162]}
```

In [47]:
```
plt.plot(hist.history['loss'])
plt.plot(hist.history['accuracy'])
```

Out[47]:
```
[<matplotlib.lines.Line2D at 0x2cebedc3880>]
```



In [111…
```
loss, accuracy = model.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 58ms/step - loss: 1.6814 - accuracy:
0.5692
```

As we can see the model using Adam optimizer, vastly overfits as we can see on the graph, the loss line drops dramatically to nealy 0 just after the first 3 epochs. That had to be changed because with such an agressive rate, we will often overfit and the scores on the validation set were not much better.

Model 1 Testing

For comparision reasons, we decided to run a test using this model, the test set accuracy is given below and does not stand away from the validation accuracy. The threshold is set to 0.5, that means >0.5 means a positive case, below means a negative case.

In [267…
```
loss, accuracy = model.evaluate(X_test, y_test)
```

```
18/18 [==============================] - 1s 64ms/step - loss: 1.6087 - accuracy:
0.5757
```

In [268…
```
#Prection and Confusion Matrix
y_pred = model.predict(X_test)
bin_y_pred = (y_pred > 0.5).astype(int)
```

```
18/18 [==============================] - 1s 56ms/step
```

In [269…
```
bin_y_pred = np.squeeze(bin_y_pred)
```

In [270…
```
bin_y_pred
```

Out[270…

```
array([0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0,
       0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1,
       0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0,
       1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0,
       1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0,
       0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0,
       0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1,
       0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0,
       0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0,
       1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0,
       0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0,
       0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1])
```

In [271…

```python
y_true = y_test
y_pred = bin_y_pred

cm = confusion_matrix(y_true, y_pred)

TN, FP, FN, TP = cm.ravel()

print(f"{'':<20}{'Predicted No':<20}{'Predicted Yes':<20}")
print(f"{'Actual No':<20}{TN:<20}{FP:<20}")
print(f"{'Actual Yes':<20}{FN:<20}{TP:<20}")

print("\nPrecision:", round(TP/(TP + FP), 4))
print("Recall:", round(TP/(TP + FN), 4))
print("Accuracy:", round((TP+TN)/(TP + TN + FP + FN), 4))
```

```
                    Predicted No        Predicted Yes
Actual No           152                 130
Actual Yes          111                 175

Precision: 0.5738
Recall: 0.6119
Accuracy: 0.5757
```

The precision for the base model is 0.57, above we can see its confusion matrix and precision and recall values.

MODEL 2

- In this model, the idea of the Dropout layer's implementation is aimed at the reduction of parameter memorization to make the model reduce overfitting with the train data, the 0.2 drops around 20% of the output parameters from the LSTM layer before feeding the Dense layer. This model showed great improvement with 65% validation acuracy.

In [124…
```
# We are going to build our model with the Sequential API
model2 = Sequential()

model2.add(Embedding(total_words,       # number of words to process as input
                     50,     # output representation
                     input_length=len(padded_sequences[0])))    # total length of

model2.add(LSTM(50, return_sequences=False))

model2.add(Dropout(0.2))

model2.add(Dense(1, activation='sigmoid'))

model2.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'
```

In [125…
```
model2.summary()
```

```
Model: "sequential_12"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_12 (Embedding)    (None, 404, 50)           1046800

 lstm_13 (LSTM)              (None, 50)                20200

 dropout_8 (Dropout)         (None, 50)                0

 dense_12 (Dense)            (None, 1)                 51

=================================================================
Total params: 1067051 (4.07 MB)
Trainable params: 1067051 (4.07 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

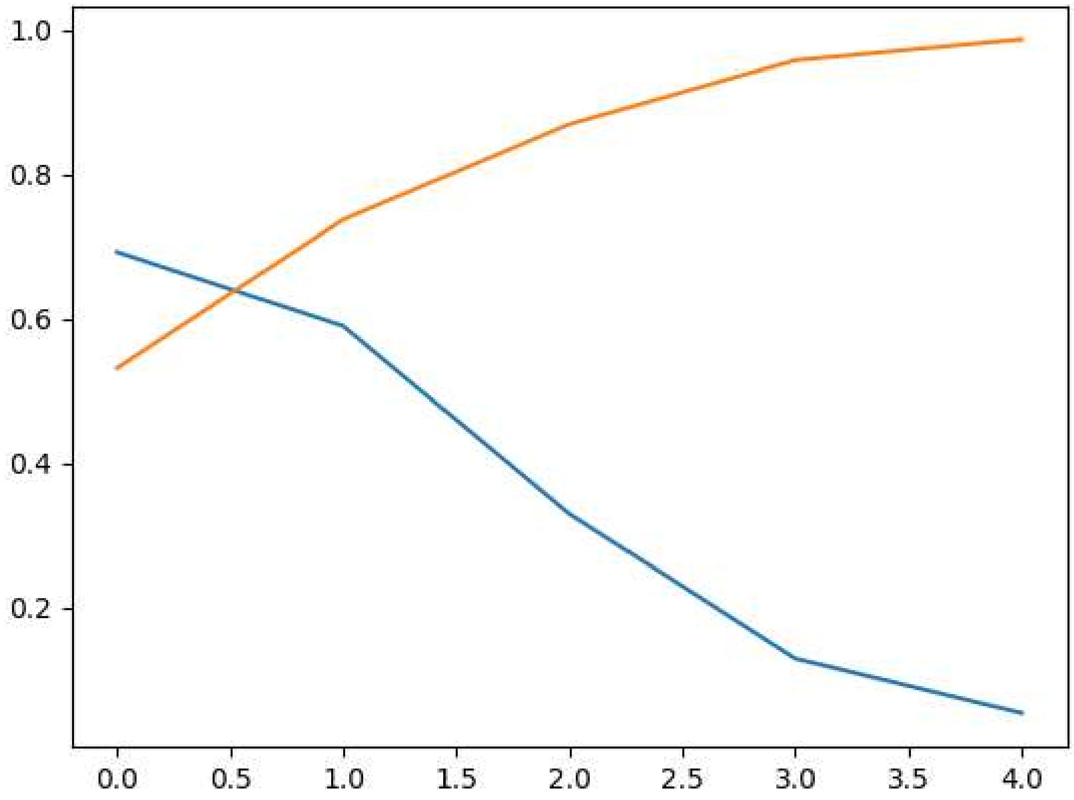
In [126…
```
hist2 = model2.fit(X_train, y_train, epochs=10, validation_data = (X_val, y_val)
```

```
Epoch 1/10
57/57 [==============================] - 11s 151ms/step - loss: 0.6919 - accurac
y: 0.5311 - val_loss: 0.6797 - val_accuracy: 0.6659
Epoch 2/10
57/57 [==============================] - 7s 123ms/step - loss: 0.5895 - accuracy:
0.7369 - val_loss: 0.6224 - val_accuracy: 0.6593
Epoch 3/10
57/57 [==============================] - 7s 125ms/step - loss: 0.3292 - accuracy:
0.8690 - val_loss: 0.8046 - val_accuracy: 0.5978
Epoch 4/10
57/57 [==============================] - 7s 127ms/step - loss: 0.1286 - accuracy:
0.9576 - val_loss: 1.1220 - val_accuracy: 0.5824
Epoch 5/10
57/57 [==============================] - 7s 126ms/step - loss: 0.0530 - accuracy:
0.9862 - val_loss: 1.2956 - val_accuracy: 0.5670
```

In [127…
```
plt.plot(hist2.history['loss'])
plt.plot(hist2.history['accuracy'])
```

Out[127…

```
[<matplotlib.lines.Line2D at 0x2cfaa981480>]
```



In [128…

```
loss, accuracy = model2.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 42ms/step - loss: 0.6224 - accuracy: 
0.6593
```

Thanks to the dropout layer, we reduced the effects of overfitting, and increased our accuracy by a good 5% on validation data. In here we also reduced the number of nodes in the LSTM layer to 50 to try to reduce the effects of overfitting.

MODEL 3

- Model 3, along with the following models begins to explore the optimization of parameters, given the increase of output representation and a reduction of nodes at the dropout layer. Accuracy: 62%

In [113…

```
model3 = Sequential()

model3.add(Embedding(total_words,       # number of words to process as input
                    200,     # output representation
                    input_length=len(padded_sequences[0])))     # total length of

model3.add(LSTM(200, return_sequences=False))

model3.add(Dropout(0.2))

model3.add(Dense(1, activation='sigmoid'))

model3.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'
```

In [114…
```
model3.summary()
```

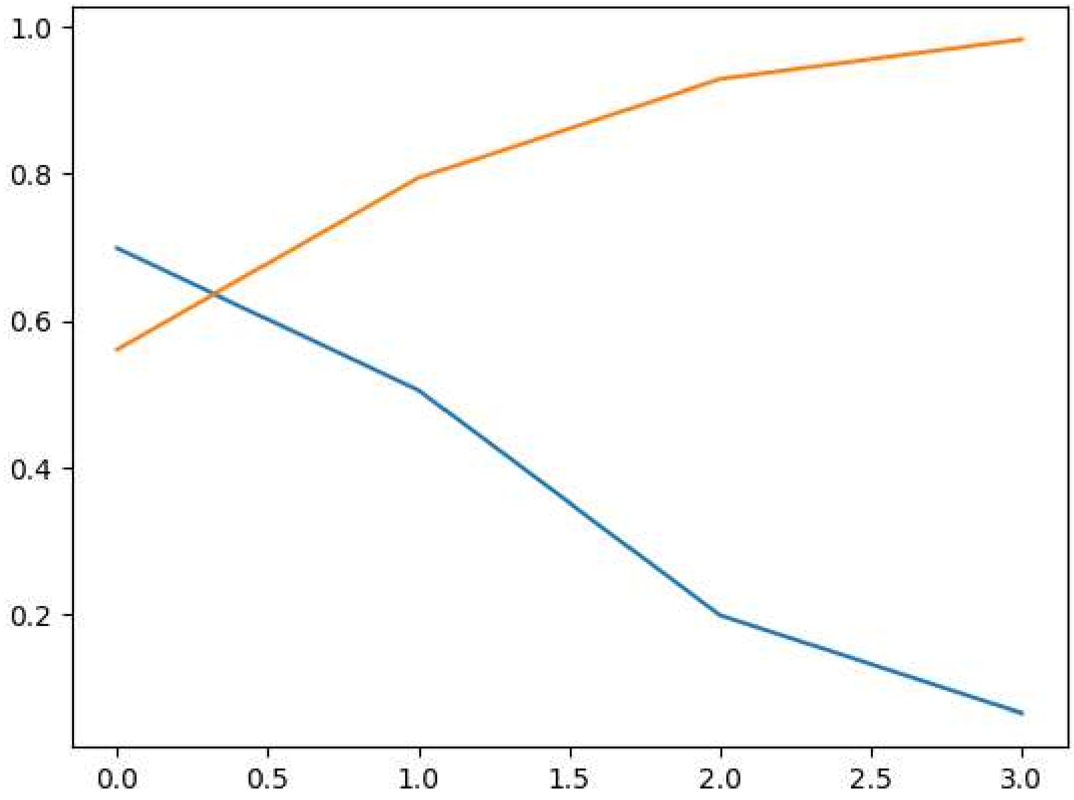
```
Model: "sequential_11"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_11 (Embedding)    (None, 404, 200)          4187200

 lstm_12 (LSTM)              (None, 200)               320800

 dropout_7 (Dropout)         (None, 200)               0

 dense_11 (Dense)            (None, 1)                 201

=================================================================
Total params: 4508201 (17.20 MB)
Trainable params: 4508201 (17.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [115…
```
hist3 = model3.fit(X_train, y_train, epochs=10, validation_data = (X_val, y_val)
```

```
Epoch 1/10
57/57 [==============================] - 34s 566ms/step - loss: 0.6986 - accurac
y: 0.5608 - val_loss: 0.6696 - val_accuracy: 0.6220
Epoch 2/10
57/57 [==============================] - 36s 629ms/step - loss: 0.5054 - accurac
y: 0.7947 - val_loss: 0.6990 - val_accuracy: 0.5978
Epoch 3/10
57/57 [==============================] - 34s 606ms/step - loss: 0.1986 - accurac
y: 0.9290 - val_loss: 0.9651 - val_accuracy: 0.6110
Epoch 4/10
57/57 [==============================] - 36s 635ms/step - loss: 0.0652 - accurac
y: 0.9829 - val_loss: 1.4469 - val_accuracy: 0.6022
```

In [116…
```
plt.plot(hist3.history['loss'])
plt.plot(hist3.history['accuracy'])
```

Out[116…
```
[<matplotlib.lines.Line2D at 0x2cfa29a9810>]
```



In [117…

```
loss, accuracy = model3.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 2s 152ms/step - loss: 0.6696 - accuracy:
0.6220
```

The increase of the LSTM nodes and the output representation to 200, proved to be a step in the wrong direction, with a 2-3% lower accuracy then model 2.

MODEL 4

- Model's 4 change of model compile modifies the type of optimizer to 'sgd' since adam might have given a high learning rate to the model. Accuracy: 49%. The stochastic gradient descent proved to be not a good fit for our model.

In [73]:

```
model4 = Sequential()

model4.add(Embedding(total_words,       # number of words to process as input
                    100,     # output representation
                    input_length=len(padded_sequences[0])))     # total length of

model4.add(LSTM(100, return_sequences=False))

model4.add(Dense(1, activation='sigmoid'))

model4.compile(optimizer='sgd', loss='binary_crossentropy', metrics=['accuracy']
```

In [74]:

```
model4.summary()
```

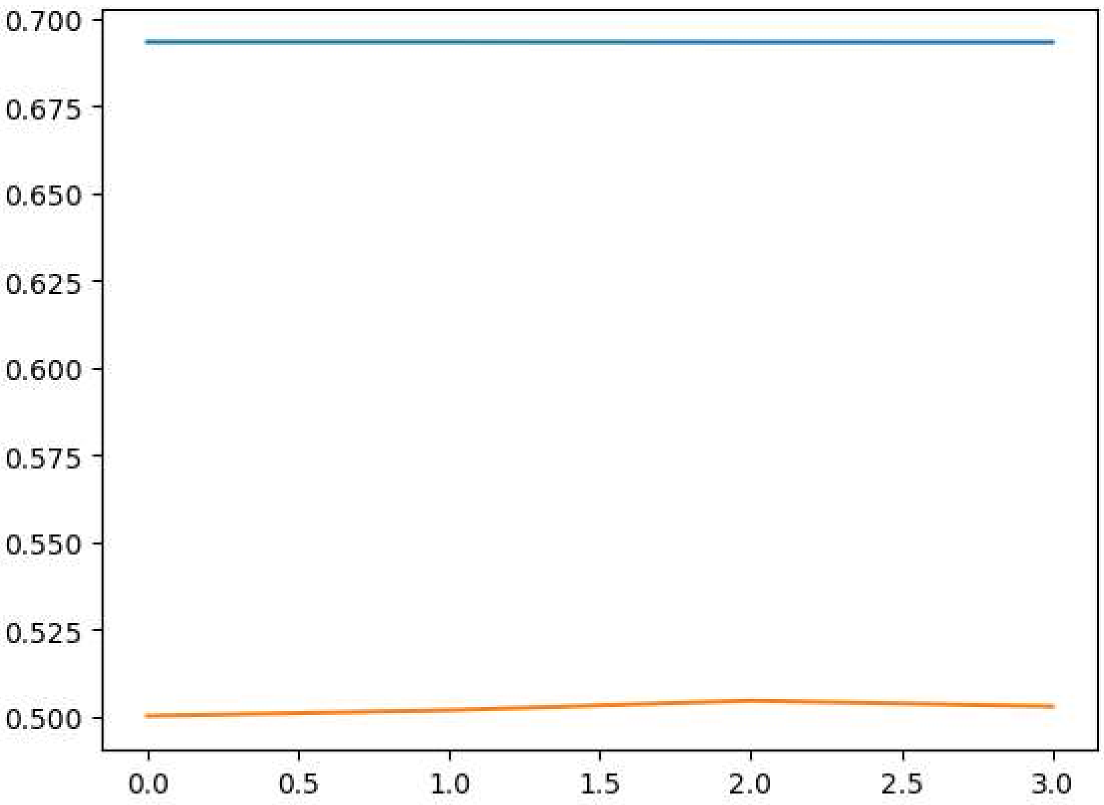
```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_5 (Embedding)     (None, 404, 100)          2093600   
                                                                 
 lstm_5 (LSTM)               (None, 100)               80400     
                                                                 
 dense_5 (Dense)             (None, 1)                 101       
                                                                 
=================================================================
Total params: 2174101 (8.29 MB)
Trainable params: 2174101 (8.29 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [75]:
```python
hist4 = model4.fit(X_train, y_train, epochs=10, validation_data = (X_val, y_val)
```

```
Epoch 1/5
57/57 [==============================] - 10s 148ms/step - loss: 0.6932 - accurac
y: 0.5003 - val_loss: 0.6930 - val_accuracy: 0.4967
Epoch 2/5
57/57 [==============================] - 8s 139ms/step - loss: 0.6932 - accuracy:
0.5019 - val_loss: 0.6930 - val_accuracy: 0.4879
Epoch 3/5
57/57 [==============================] - 8s 137ms/step - loss: 0.6931 - accuracy:
0.5047 - val_loss: 0.6930 - val_accuracy: 0.4901
Epoch 4/5
57/57 [==============================] - 8s 134ms/step - loss: 0.6931 - accuracy:
0.5030 - val_loss: 0.6930 - val_accuracy: 0.4857
```

In [76]:
```python
plt.plot(hist4.history['loss'])
plt.plot(hist4.history['accuracy'])
```

Out[76]: [<matplotlib.lines.Line2D at 0x2cf79f2c3d0>]



In [118…
```
loss, accuracy = model4.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 72ms/step - loss: 0.6930 - accuracy: 0.4967
```

MODEL 5 (Top Performer)

- Model 5, deemed to as the Steroid Model, is significantly the best model with a validation `accuracy of 71.9%`. This model is very particular due to its transfer of output dimensions that are back checked from interaction between multiple layers in the model. There are 2 bidirectoinal layers that is filtered through a dropout layer and returned for further refinement. Overall, the data outputs traverse the dropout layer 3 times, which give room to find the keywords perhaps more efficiently than other models.
- Different values of the output representation, LSTM layer nodes, learning rates and dropout values have been tested, using different optimizers. Adamax with the default learning rate of 0.001, has been found the best performing.
- 100 in the LSTM layer has been found to be the most efficent.
- This method also dramatically overfits reaching the train accuracy of 90 at 4th or 5th epoch, but has been found to still capture the most information, out of all tested models.
- The dropout rate has been set to 0.2, since more strickter dropout rates did not improve the performance.
- Bidirectional Layers proved to be better performing then one way ones.

In [78]:
```
adamax_opt = Adamax(learning_rate = 0.001)
```

In [79]:
```
model5 = Sequential()

model5.add(Embedding(total_words,       # number of words to process as input
                     100,     # output representation
                     mask_zero = True,
                     input_length=len(padded_sequences[0])))     # total length of

model5.add(Bidirectional(tf.keras.layers.LSTM(100, return_sequences=True)))

model5.add(Dropout(0.2))

model5.add(Bidirectional(tf.keras.layers.LSTM(100, return_sequences=False)))
#model5.add(LSTM(100, return_sequences=False))

model5.add(Dropout(0.2))

model5.add(Dense(1, activation='sigmoid'))

model5.compile(optimizer=adamax_opt, loss='binary_crossentropy', metrics=['accur
```

In [80]:
```
model5.summary()
```

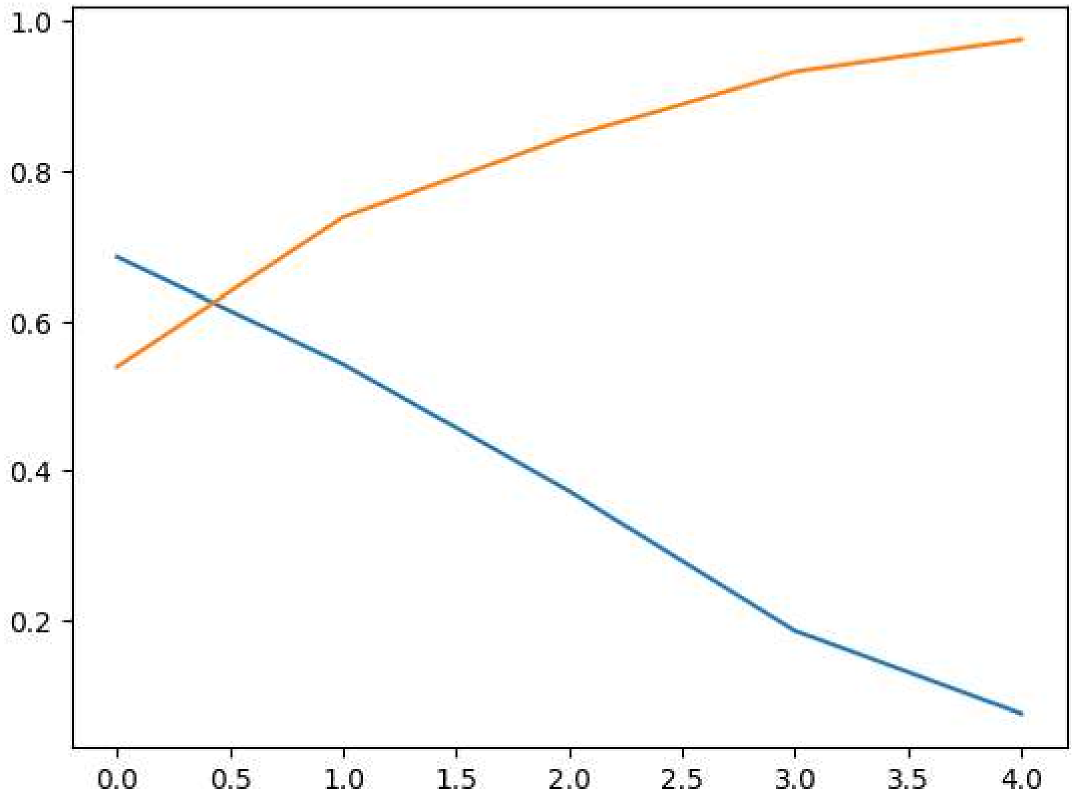
```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_6 (Embedding)     (None, 404, 100)          2093600   
                                                                 
 bidirectional (Bidirection  (None, 404, 200)          160800    
 al)                                                             
                                                                 
 dropout_1 (Dropout)         (None, 404, 200)          0         
                                                                 
 bidirectional_1 (Bidirecti  (None, 200)               240800    
 onal)                                                           
                                                                 
 dropout_2 (Dropout)         (None, 200)               0         
                                                                 
 dense_6 (Dense)             (None, 1)                 201       
                                                                 
=================================================================
Total params: 2495401 (9.52 MB)
Trainable params: 2495401 (9.52 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [81]:
```
hist5 = model5.fit(X_train, y_train, epochs=10, validation_data = (X_val, y_val)
```

```
Epoch 1/10
57/57 [==============================] - 47s 638ms/step - loss: 0.6855 - accurac
y: 0.5394 - val_loss: 0.6210 - val_accuracy: 0.6901
Epoch 2/10
57/57 [==============================] - 35s 609ms/step - loss: 0.5429 - accurac
y: 0.7386 - val_loss: 0.5775 - val_accuracy: 0.7187
Epoch 3/10
57/57 [==============================] - 35s 611ms/step - loss: 0.3732 - accurac
y: 0.8465 - val_loss: 0.7202 - val_accuracy: 0.6967
Epoch 4/10
57/57 [==============================] - 34s 592ms/step - loss: 0.1863 - accurac
y: 0.9329 - val_loss: 0.7666 - val_accuracy: 0.6571
Epoch 5/10
57/57 [==============================] - 33s 574ms/step - loss: 0.0759 - accurac
y: 0.9758 - val_loss: 1.0978 - val_accuracy: 0.6615
```

In [82]:
```
plt.plot(hist5.history['loss'])
plt.plot(hist5.history['accuracy'])
```

Out[82]:
```
[<matplotlib.lines.Line2D at 0x2cf95a358d0>]
```



In [119…

```
loss, accuracy = model5.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 3s 206ms/step - loss: 0.5775 - accuracy:
0.7187
```

We can see that the loss graph is way more streched out, reducing the previous effects we had using the normal adam optimizer and no dropout. We have less of an overfitting situation.

MODEL 6

- Model 6 eplores the modification to improve the hyperparameters of models with output dmension of 50, and and regularized learning rate of adamW optimizer at 0.001.
- Accuracy: 60%
- AdamW is a weight decay technique that penalizes large weigths, in order to prevent the effects of overfitting.
- The 50 nodes in LSTM and output representation have been restored in this case, since they performed the best.

In [86]:

```
adamw_optimizer = tfa.optimizers.AdamW(learning_rate=1e-2, weight_decay=1e-4)
```

In [87]:

```
# We are going to build our model with the Sequential API
model6 = Sequential()

model6.add(Embedding(total_words,      # number of words to process as input
                     50,     # output representation
                     input_length=len(padded_sequences[0])))     # total length of
```

```
model6.add(LSTM(50, return_sequences=False))

model6.add(Dropout(0.2))

model6.add(Dense(1, activation='sigmoid'))

model6.compile(optimizer= adamw_optimizer, loss='binary_crossentropy', metrics=[
```

In [88]:
```
model6.summary()
```

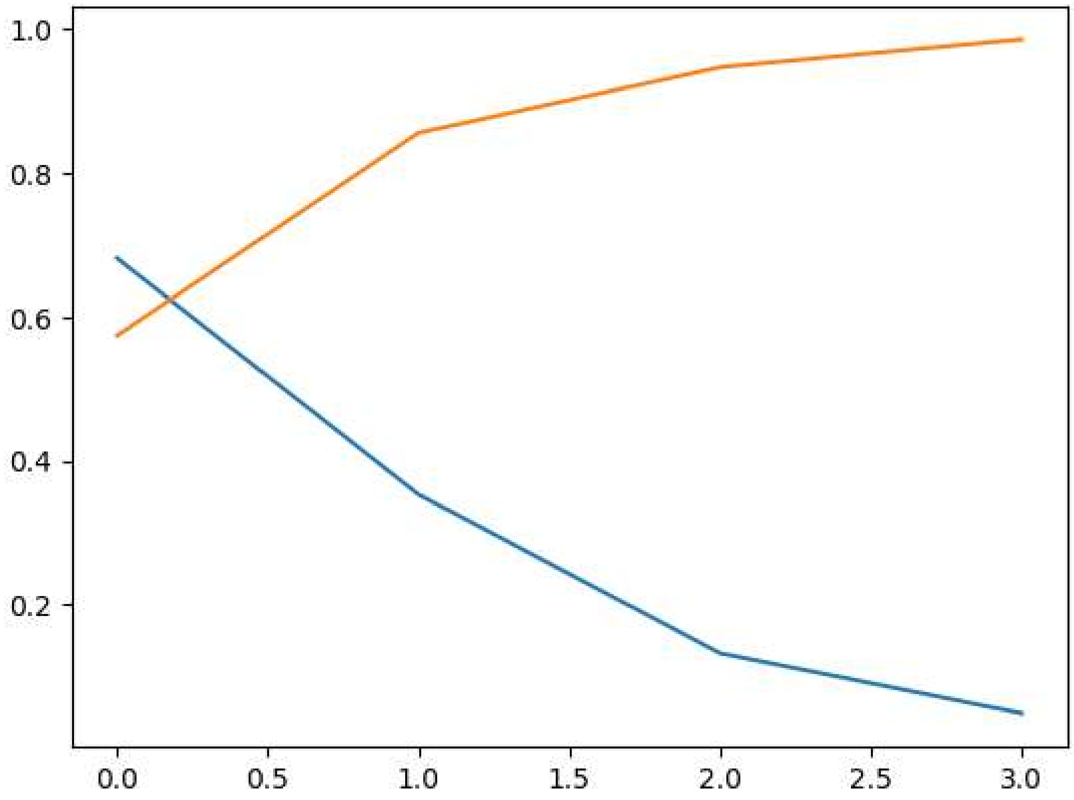
```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_7 (Embedding)     (None, 404, 50)           1046800   
                                                                 
 lstm_8 (LSTM)               (None, 50)                20200     
                                                                 
 dropout_3 (Dropout)         (None, 50)                0         
                                                                 
 dense_7 (Dense)             (None, 1)                 51        
                                                                 
=================================================================
Total params: 1067051 (4.07 MB)
Trainable params: 1067051 (4.07 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [89]:
```
hist6 = model6.fit(X_train, y_train, epochs=10, validation_data = (X_val, y_val)
```

```
Epoch 1/10
57/57 [==============================] - 9s 124ms/step - loss: 0.6816 - accuracy:
0.5740 - val_loss: 0.6954 - val_accuracy: 0.6044
Epoch 2/10
57/57 [==============================] - 6s 114ms/step - loss: 0.3534 - accuracy:
0.8558 - val_loss: 0.9911 - val_accuracy: 0.5495
Epoch 3/10
57/57 [==============================] - 7s 115ms/step - loss: 0.1327 - accuracy:
0.9466 - val_loss: 1.2453 - val_accuracy: 0.5758
Epoch 4/10
57/57 [==============================] - 7s 117ms/step - loss: 0.0496 - accuracy:
0.9851 - val_loss: 1.3434 - val_accuracy: 0.5604
```

In [90]:
```
plt.plot(hist6.history['loss'])
plt.plot(hist6.history['accuracy'])
```

Out[90]:
```
[<matplotlib.lines.Line2D at 0x2cf9bdffd60>]
```



In [120…

```
loss, accuracy = model6.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 47ms/step - loss: 0.6954 - accuracy: 0.6044
```

The effects of overfitting are not as well handled as in model 5, as seen in the graph above.

MODEL 7

- This model once again explores the further regularization of the adamax optimizer at 0.001
- Accuracy: 67%
- The thought is simple, we want to see how the Adamax optimizer performs on a simpler model.
- The 100 in LSTM and output representation / embedding layers proved to work better then 50 for this optimizer.
- Adamax is a much less agressive optimizer with adaptive learning rates, an adress made to the flaws of the original Adam optimizer.

In [92]:

```
adamax_opt = Adamax(learning_rate = 0.001)
```

In [93]:

```
# We are going to build our model with the Sequential API
model7 = Sequential()

model7.add(Embedding(total_words,       # number of words to process as input
                     100,     # output representation
                     input_length=len(padded_sequences[0])))     # total length of
```

```
model7.add(LSTM(100, return_sequences=False))
#model7.add(Bidirectional(LSTM(100, return_sequences=False)))

model7.add(Dropout(0.2))

model7.add(Dense(1, activation='sigmoid'))

model7.compile(optimizer= adamax_opt, loss='binary_crossentropy', metrics=['accu
```

In [94]:

```
model7.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_8 (Embedding)     (None, 404, 100)          2093600   
                                                                 
 lstm_9 (LSTM)               (None, 100)               80400     
                                                                 
 dropout_4 (Dropout)         (None, 100)               0         
                                                                 
 dense_8 (Dense)             (None, 1)                 101       
                                                                 
=================================================================
Total params: 2174101 (8.29 MB)
Trainable params: 2174101 (8.29 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [95]:

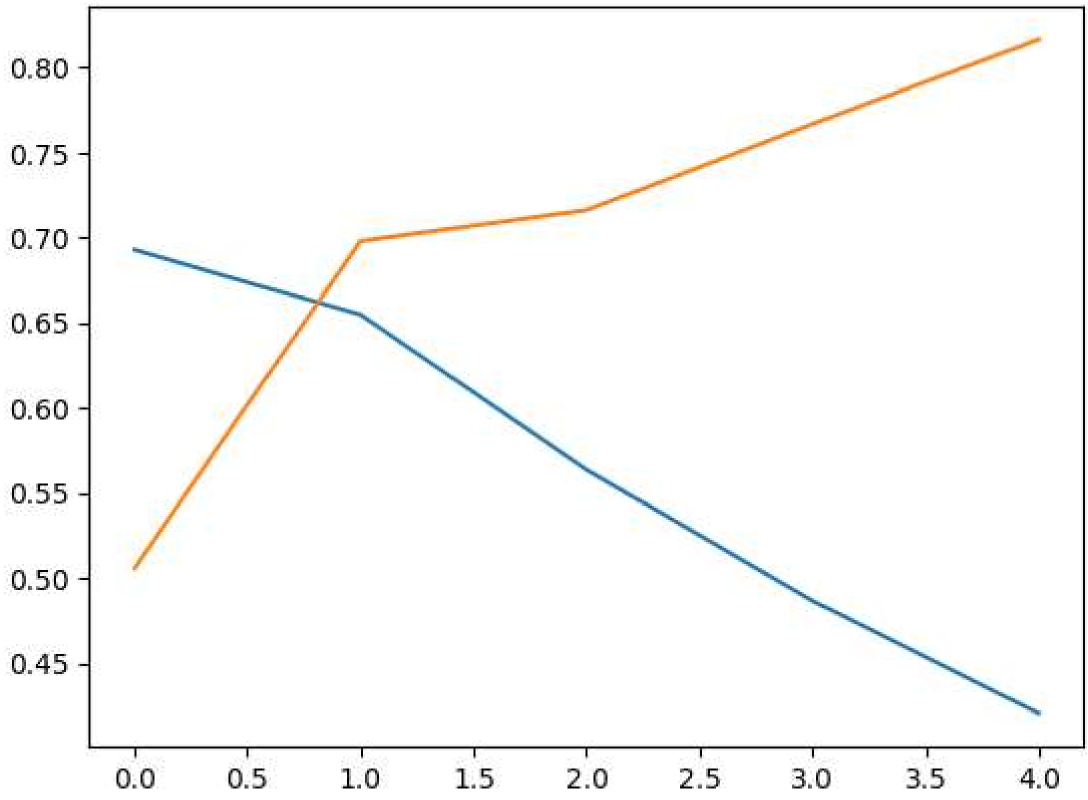
```
hist7 = model7.fit(X_train, y_train, epochs=20, validation_data = (X_val, y_val)
```

```
Epoch 1/50
57/57 [==============================] - 12s 173ms/step - loss: 0.6927 - accurac
y: 0.5058 - val_loss: 0.6913 - val_accuracy: 0.5692
Epoch 2/50
57/57 [==============================] - 10s 171ms/step - loss: 0.6547 - accurac
y: 0.6979 - val_loss: 0.6336 - val_accuracy: 0.6615
Epoch 3/50
57/57 [==============================] - 10s 178ms/step - loss: 0.5636 - accurac
y: 0.7160 - val_loss: 0.6363 - val_accuracy: 0.6703
Epoch 4/50
57/57 [==============================] - 10s 183ms/step - loss: 0.4867 - accurac
y: 0.7666 - val_loss: 0.6562 - val_accuracy: 0.6637
Epoch 5/50
57/57 [==============================] - 10s 181ms/step - loss: 0.4207 - accurac
y: 0.8162 - val_loss: 0.7302 - val_accuracy: 0.6747
```

In [96]:

```
plt.plot(hist7.history['loss'])
plt.plot(hist7.history['accuracy'])
```

Out[96]: [<matplotlib.lines.Line2D at 0x2cf9dcba560>]



In [121…

```
loss, accuracy = model7.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 64ms/step - loss: 0.6336 - accuracy:
0.6615
```

This model performs slightly better then Adam for this exact configuration.

MODEL 8

- In this model we are testing yet another optimizer, this time the Nadam one.
- Nadam is an optimizer combining two different ones the Nesterov Accelerated Gradient (momentum incorporated) and Adam. NAG updates the parameters using a combination of the current gradient and a fraction of the previous update.
- Accuracy: 65.71%

In [98]:

```
nadam_opt = Nadam(learning_rate = 0.001)
```

In [99]:
```
# We are going to build our model with the Sequential API
model8 = Sequential()

model8.add(Embedding(total_words,       # number of words to process as input
                     100,     # output representation
                     input_length=len(padded_sequences[0])))     # total length of

model8.add(LSTM(100, return_sequences=False))

model8.add(Dropout(0.2))

model8.add(Dense(1, activation='sigmoid'))

model8.compile(optimizer= nadam_opt, loss='binary_crossentropy', metrics=['accur
```

In [100…
```
model8.summary()
```

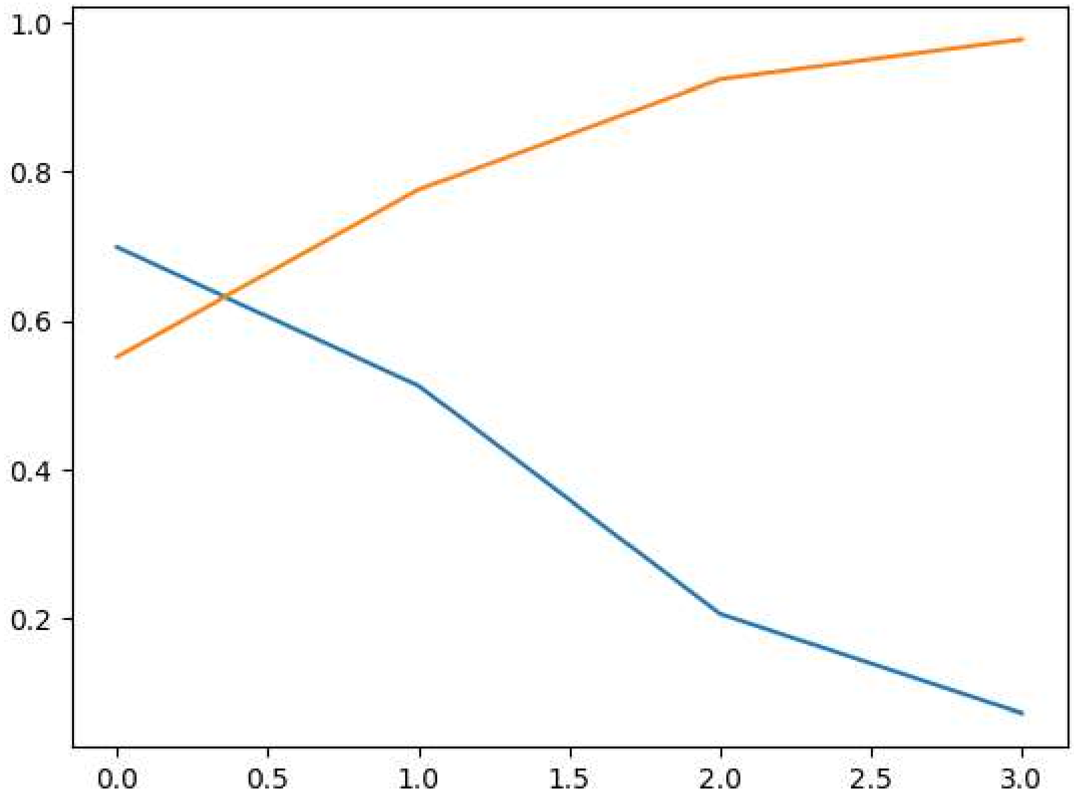
```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_9 (Embedding)     (None, 404, 100)          2093600

 lstm_10 (LSTM)              (None, 100)               80400

 dropout_5 (Dropout)         (None, 100)               0

 dense_9 (Dense)             (None, 1)                 101

=================================================================
Total params: 2174101 (8.29 MB)
Trainable params: 2174101 (8.29 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [101…
```
hist8 = model8.fit(X_train, y_train, epochs=20, validation_data = (X_val, y_val)
```

```
Epoch 1/20
57/57 [==============================] - 13s 194ms/step - loss: 0.6985 - accurac
y: 0.5515 - val_loss: 0.6736 - val_accuracy: 0.6571
Epoch 2/20
57/57 [==============================] - 10s 176ms/step - loss: 0.5126 - accurac
y: 0.7760 - val_loss: 0.6824 - val_accuracy: 0.6352
Epoch 3/20
57/57 [==============================] - 10s 177ms/step - loss: 0.2061 - accurac
y: 0.9241 - val_loss: 1.0434 - val_accuracy: 0.6242
Epoch 4/20
57/57 [==============================] - 10s 177ms/step - loss: 0.0726 - accurac
y: 0.9774 - val_loss: 1.2087 - val_accuracy: 0.5868
```

In [102…
```
plt.plot(hist8.history['loss'])
plt.plot(hist8.history['accuracy'])
```

Out[102…
```
[<matplotlib.lines.Line2D at 0x2cf9e25c610>]
```



In [122…

```
loss, accuracy = model8.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 65ms/step - loss: 0.6736 - accuracy:
0.6571
```

Its performance does not stand out from a normal adam optimizer.

MODEL 9

- In model 9 we try to containing the simplest best performing model with Adamax 0.001 and try to introduce the Bidirectional layer to the model.
- Accuracy: 68%

In [104…

```
adamax_opt = Adamax(learning_rate = 0.001)
```

In [105…

```
# We are going to build our model with the Sequential API
model9 = Sequential()

model9.add(Embedding(total_words,       # number of words to process as input
                     100,     # output representation
                     input_length=len(padded_sequences[0])))     # total length of

#model9.add(LSTM(100, return_sequences=False))
model9.add(Bidirectional(LSTM(100, return_sequences=False)))

model9.add(Dropout(0.2))

model9.add(Dense(1, activation='sigmoid'))

model9.compile(optimizer= adamax_opt, loss='binary_crossentropy', metrics=['accu
```

In [106…
```
model9.summary()
```

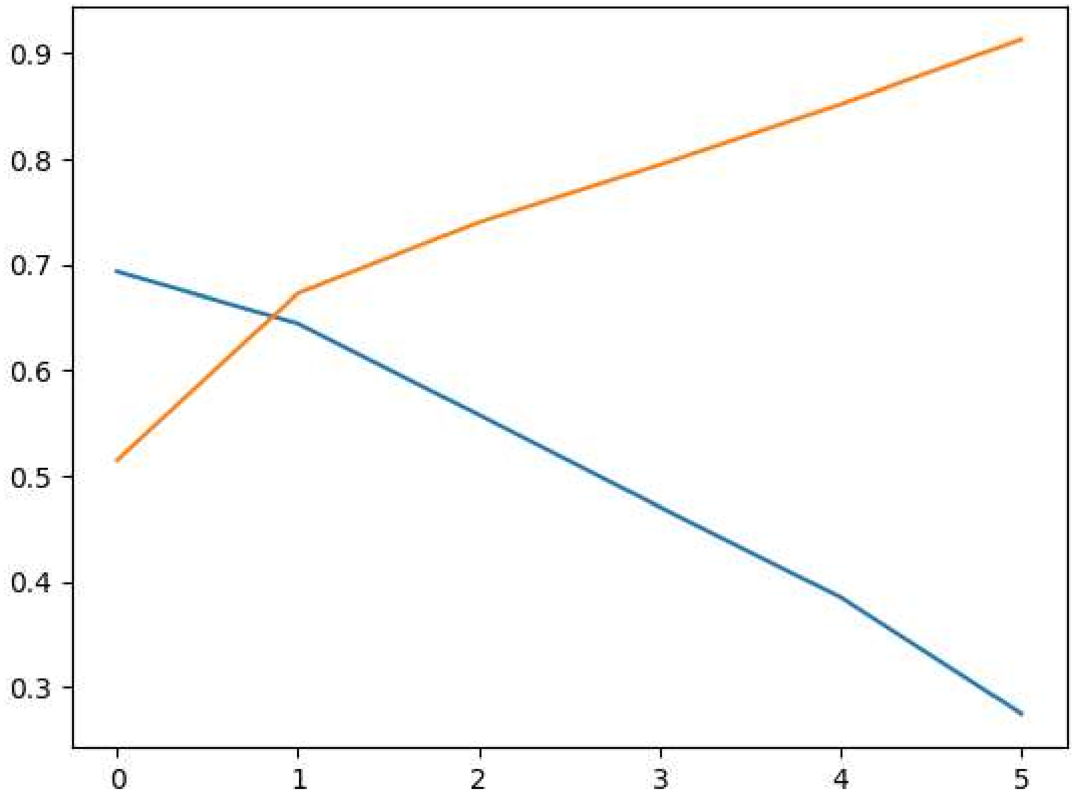
```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_9 (Embedding)     (None, 404, 100)          2093600   
                                                                 
 lstm_10 (LSTM)              (None, 100)               80400     
                                                                 
 dropout_5 (Dropout)         (None, 100)               0         
                                                                 
 dense_9 (Dense)             (None, 1)                 101       
                                                                 
=================================================================
Total params: 2174101 (8.29 MB)
Trainable params: 2174101 (8.29 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [107…
```
hist9 = model9.fit(X_train, y_train, epochs=20, validation_data = (X_val, y_val)
```

```
Epoch 1/50
57/57 [==============================] - 16s 223ms/step - loss: 0.6931 - accurac
y: 0.5146 - val_loss: 0.6911 - val_accuracy: 0.5780
Epoch 2/50
57/57 [==============================] - 12s 208ms/step - loss: 0.6441 - accurac
y: 0.6725 - val_loss: 0.6356 - val_accuracy: 0.6835
Epoch 3/50
57/57 [==============================] - 12s 209ms/step - loss: 0.5578 - accurac
y: 0.7397 - val_loss: 0.6029 - val_accuracy: 0.6857
Epoch 4/50
57/57 [==============================] - 13s 222ms/step - loss: 0.4707 - accurac
y: 0.7942 - val_loss: 0.6156 - val_accuracy: 0.6835
Epoch 5/50
57/57 [==============================] - 12s 220ms/step - loss: 0.3854 - accurac
y: 0.8514 - val_loss: 0.7752 - val_accuracy: 0.6659
Epoch 6/50
57/57 [==============================] - 12s 218ms/step - loss: 0.2752 - accurac
y: 0.9125 - val_loss: 0.7378 - val_accuracy: 0.6725
```

In [108…
```
plt.plot(hist9.history['loss'])
plt.plot(hist9.history['accuracy'])
```

Out[108…
```
[<matplotlib.lines.Line2D at 0x2cfa24b9c60>]
```



In [123…
```
loss, accuracy = model9.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 87ms/step - loss: 0.6029 - accuracy:
0.6857
```

We can see an improvement in the model performance after introducing the Bidirectional Layers.

MODEL 10

- Here we try a variation of the best model yet with a change in the LSTM bidirectional layers to 50.
- The performace drops slightly, we will remain with the previous version.
- Accuracy: 68%

In [134…
```
adamax_opt = Adamax(learning_rate = 0.001)
```

In [135…
```
model10 = Sequential()

model10.add(Embedding(total_words,      # number of words to process as input
                    100,     # output representation
                    mask_zero = True,
                    input_length=len(padded_sequences[0])))     # total length of

model10.add(Bidirectional(tf.keras.layers.LSTM(50, return_sequences=True)))

model10.add(Dropout(0.2))

model10.add(Bidirectional(tf.keras.layers.LSTM(50, return_sequences=False)))
#model5.add(LSTM(100, return_sequences=False))
```

```
model10.add(Dropout(0.2))

model10.add(Dense(1, activation='sigmoid'))

model10.compile(optimizer=adamax_opt, loss='binary_crossentropy', metrics=['accu
```

In [136…

```
model10.summary()
```

```
Model: "sequential_15"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_15 (Embedding)    (None, 404, 100)          2093600

 bidirectional_7 (Bidirecti  (None, 404, 100)          60400
 onal)

 dropout_13 (Dropout)        (None, 404, 100)          0

 bidirectional_8 (Bidirecti  (None, 100)               60400
 onal)

 dropout_14 (Dropout)        (None, 100)               0

 dense_15 (Dense)            (None, 1)                 101

=================================================================
Total params: 2214501 (8.45 MB)
Trainable params: 2214501 (8.45 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [137…

```
hist10 = model10.fit(X_train, y_train, epochs=20, validation_data = (X_val, y_va
```

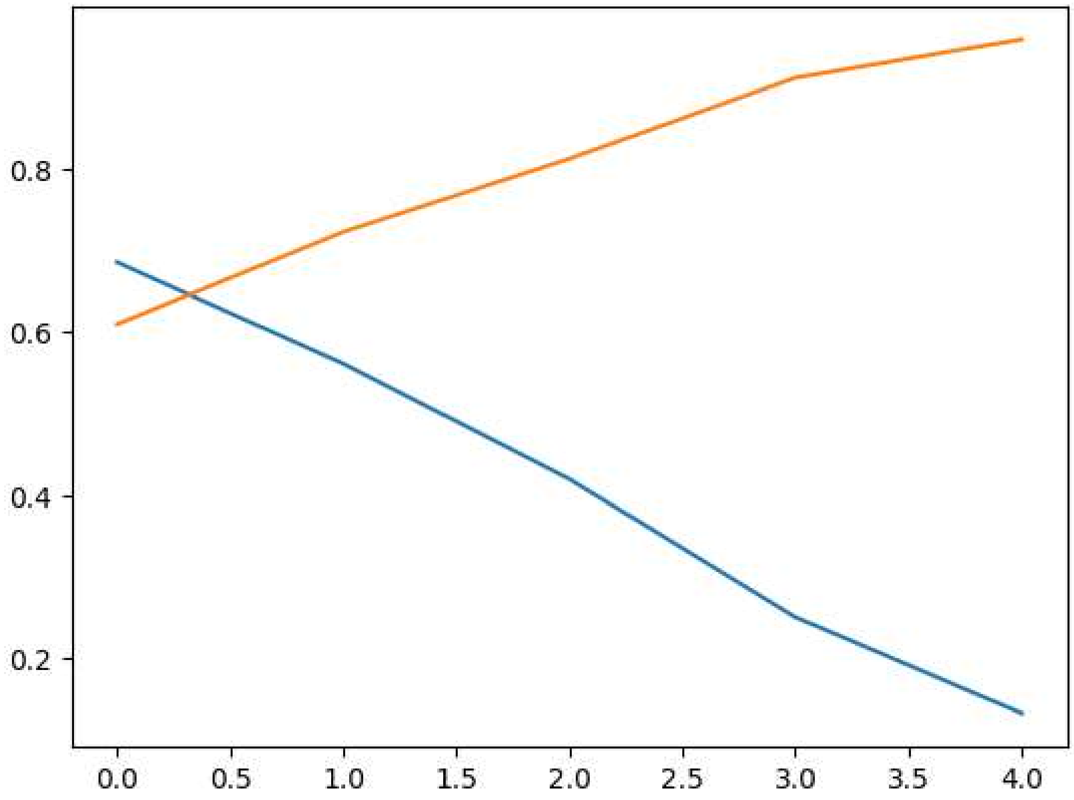
```
Epoch 1/20
57/57 [==============================] - 41s 490ms/step - loss: 0.6856 - accurac
y: 0.6098 - val_loss: 0.6623 - val_accuracy: 0.6659
Epoch 2/20
57/57 [==============================] - 23s 403ms/step - loss: 0.5616 - accurac
y: 0.7226 - val_loss: 0.5920 - val_accuracy: 0.6791
Epoch 3/20
57/57 [==============================] - 23s 403ms/step - loss: 0.4203 - accurac
y: 0.8123 - val_loss: 0.6416 - val_accuracy: 0.6813
Epoch 4/20
57/57 [==============================] - 23s 402ms/step - loss: 0.2511 - accurac
y: 0.9114 - val_loss: 0.7972 - val_accuracy: 0.6440
Epoch 5/20
57/57 [==============================] - 23s 411ms/step - loss: 0.1336 - accurac
y: 0.9582 - val_loss: 0.9629 - val_accuracy: 0.6220
```

In [138…

```
plt.plot(hist10.history['loss'])
plt.plot(hist10.history['accuracy'])
```

Out[138…

```
[<matplotlib.lines.Line2D at 0x2cfcedb8040>]
```



In [139…

```
loss, accuracy = model10.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 2s 101ms/step - loss: 0.5920 - accuracy:
0.6791
```

MODEL 11

- Another variation of model 5, here we are trying to adress the overfitting problem by reducing the learning rate.
- Accuracy: 0.71%

In [149…

```
adamax_opt = Adamax(learning_rate = 0.0001)
```

In [150…

```
model11 = Sequential()

model11.add(Embedding(total_words,      # number of words to process as input
                      100,    # output representation
                      mask_zero = True,
                      input_length=len(padded_sequences[0])))     # total length of

model11.add(Bidirectional(tf.keras.layers.LSTM(100, return_sequences=True)))

model11.add(Dropout(0.2))

model11.add(Bidirectional(tf.keras.layers.LSTM(100, return_sequences=False)))
#model11.add(LSTM(100, return_sequences=False))

model11.add(Dropout(0.2))

model11.add(Dense(1, activation='sigmoid'))
```

```
model11.compile(optimizer=adamax_opt, loss='binary_crossentropy', metrics=['accu
```

In [151…

```
model11.summary()
```

```
Model: "sequential_19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_19 (Embedding)    (None, 404, 100)          2093600   
                                                                 
 bidirectional_15 (Bidirect  (None, 404, 200)          160800    
 ional)                                                          
                                                                 
 dropout_21 (Dropout)        (None, 404, 200)          0         
                                                                 
 bidirectional_16 (Bidirect  (None, 200)               240800    
 ional)                                                          
                                                                 
 dropout_22 (Dropout)        (None, 200)               0         
                                                                 
 dense_19 (Dense)            (None, 1)                 201       
                                                                 
=================================================================
Total params: 2495401 (9.52 MB)
Trainable params: 2495401 (9.52 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [152…

```
hist11 = model11.fit(X_train, y_train, epochs=20, validation_data = (X_val, y_va
```

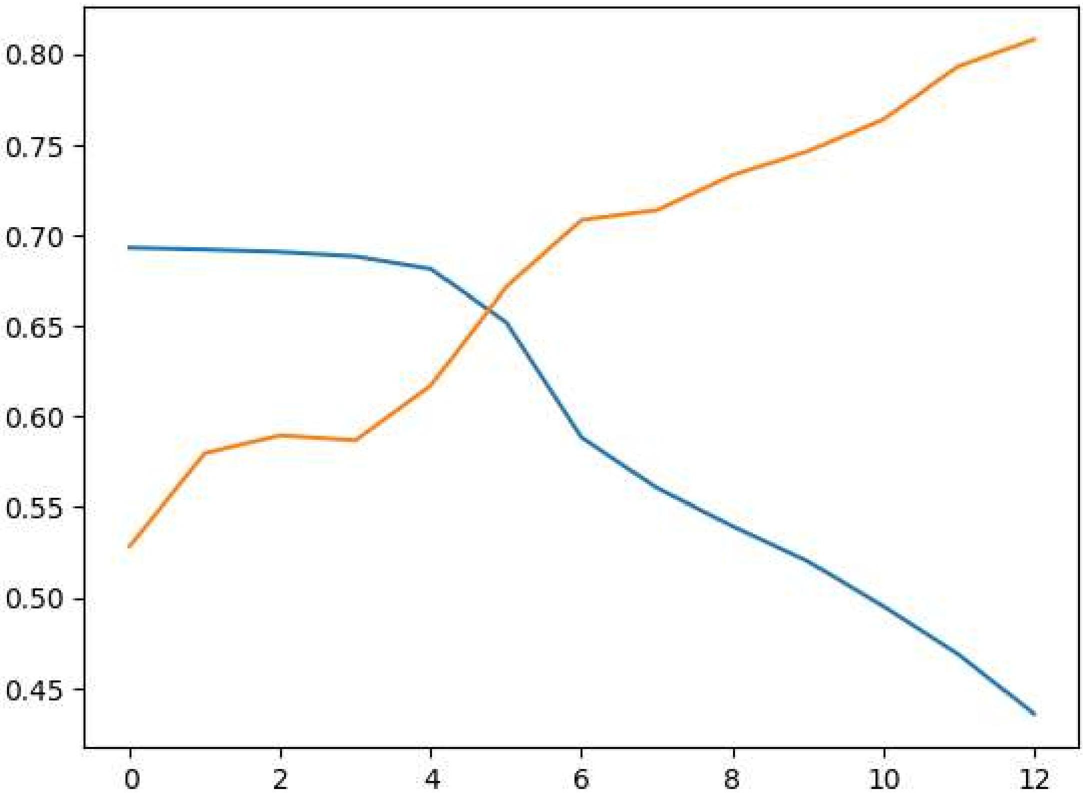
```
Epoch 1/20
57/57 [==============================] - 50s 659ms/step - loss: 0.6930 - accurac
y: 0.5283 - val_loss: 0.6927 - val_accuracy: 0.5319
Epoch 2/20
57/57 [==============================] - 31s 549ms/step - loss: 0.6920 - accurac
y: 0.5795 - val_loss: 0.6923 - val_accuracy: 0.5253
Epoch 3/20
57/57 [==============================] - 31s 550ms/step - loss: 0.6907 - accurac
y: 0.5894 - val_loss: 0.6914 - val_accuracy: 0.5341
Epoch 4/20
57/57 [==============================] - 31s 547ms/step - loss: 0.6882 - accurac
y: 0.5867 - val_loss: 0.6890 - val_accuracy: 0.5714
Epoch 5/20
57/57 [==============================] - 31s 539ms/step - loss: 0.6813 - accurac
y: 0.6170 - val_loss: 0.6808 - val_accuracy: 0.5802
Epoch 6/20
57/57 [==============================] - 31s 553ms/step - loss: 0.6519 - accurac
y: 0.6714 - val_loss: 0.6339 - val_accuracy: 0.7033
Epoch 7/20
57/57 [==============================] - 31s 553ms/step - loss: 0.5884 - accurac
y: 0.7083 - val_loss: 0.6056 - val_accuracy: 0.6791
Epoch 8/20
57/57 [==============================] - 32s 558ms/step - loss: 0.5603 - accurac
y: 0.7138 - val_loss: 0.6003 - val_accuracy: 0.7121
Epoch 9/20
57/57 [==============================] - 32s 560ms/step - loss: 0.5395 - accurac
y: 0.7331 - val_loss: 0.5960 - val_accuracy: 0.7011
Epoch 10/20
57/57 [==============================] - 33s 572ms/step - loss: 0.5202 - accurac
y: 0.7463 - val_loss: 0.5958 - val_accuracy: 0.7121
Epoch 11/20
57/57 [==============================] - 32s 557ms/step - loss: 0.4953 - accurac
y: 0.7639 - val_loss: 0.6112 - val_accuracy: 0.7055
Epoch 12/20
57/57 [==============================] - 32s 556ms/step - loss: 0.4686 - accurac
y: 0.7931 - val_loss: 0.6228 - val_accuracy: 0.7077
Epoch 13/20
57/57 [==============================] - 33s 574ms/step - loss: 0.4359 - accurac
y: 0.8079 - val_loss: 0.6151 - val_accuracy: 0.6857
```

In [153…

```
plt.plot(hist11.history['loss'])
plt.plot(hist11.history['accuracy'])
```

Out[153…

```
[<matplotlib.lines.Line2D at 0x2cfd1721b40>]
```



In [154…

```
loss, accuracy = model11.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 2s 156ms/step - loss: 0.5958 - accuracy:
0.7121
```

As we can see with this learning rate we do not achieve better performance then with its default value, also there are many hills sygnifying problems with using this learning rate. The loss function at first sees not much improvement to then dramatically fast decrease. That is not an appriciated effect.

MODEL 12

- For the last model we try different output representation values of 200 and 300, only to see worse performace.
- Accuracy for 300: 67%

In [161…

```
adamax_opt = Adamax(learning_rate = 0.001)
```

In [162…

```
# We are going to build our model with the Sequential API
model12 = Sequential()

model12.add(Embedding(total_words,       # number of words to process as input
                     300,     # output representation
                     input_length=len(padded_sequences[0])))     # total length of

#model12.add(LSTM(100, return_sequences=False))
model12.add(Bidirectional(LSTM(100, return_sequences=False)))

model12.add(Dropout(0.2))

model12.add(Dense(1, activation='sigmoid'))
```

```
model12.compile(optimizer= adamax_opt, loss='binary_crossentropy', metrics=['acc
```

In [163…

```
model12.summary()
```

```
Model: "sequential_21"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_21 (Embedding)    (None, 404, 300)          6280800

 bidirectional_18 (Bidirect  (None, 200)               320800
 ional)

 dropout_24 (Dropout)        (None, 200)               0

 dense_21 (Dense)            (None, 1)                 201

=================================================================
Total params: 6601801 (25.18 MB)
Trainable params: 6601801 (25.18 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [164…

```
hist12 = model12.fit(X_train, y_train, epochs=20, validation_data = (X_val, y_va
```

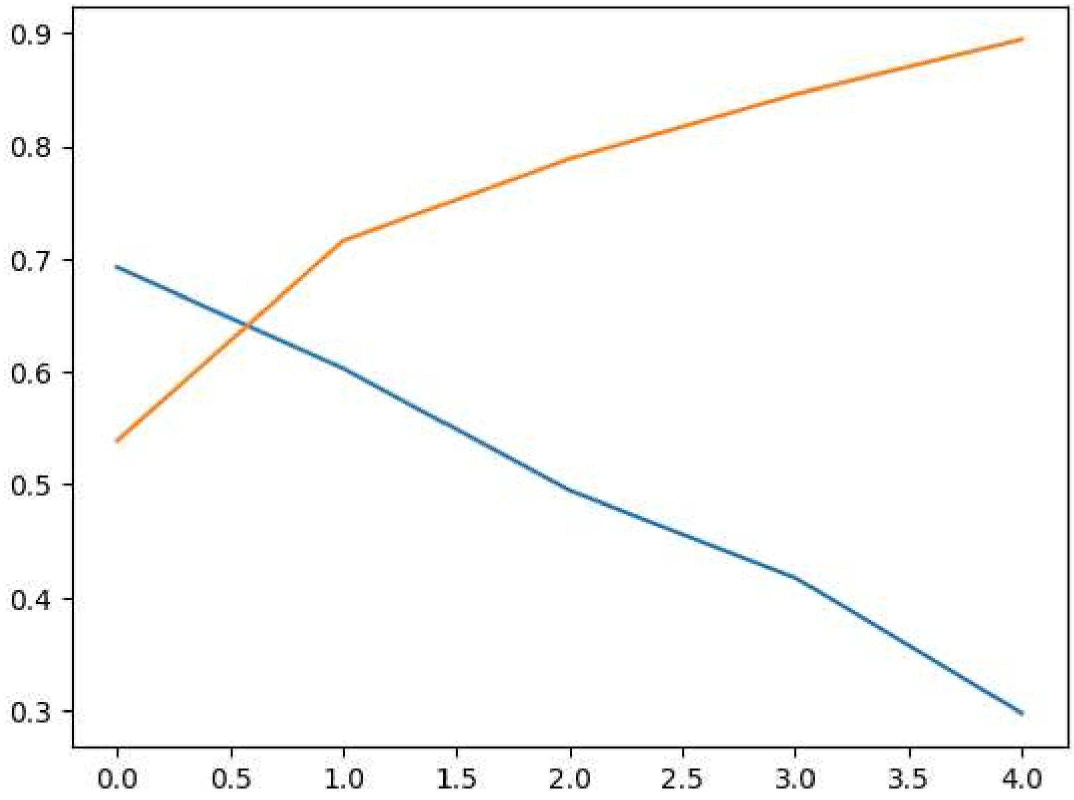
```
Epoch 1/20
57/57 [==============================] - 21s 318ms/step - loss: 0.6926 - accurac
y: 0.5388 - val_loss: 0.6801 - val_accuracy: 0.6813
Epoch 2/20
57/57 [==============================] - 17s 295ms/step - loss: 0.6032 - accurac
y: 0.7160 - val_loss: 0.5951 - val_accuracy: 0.6791
Epoch 3/20
57/57 [==============================] - 17s 303ms/step - loss: 0.4948 - accurac
y: 0.7887 - val_loss: 0.6057 - val_accuracy: 0.6901
Epoch 4/20
57/57 [==============================] - 17s 299ms/step - loss: 0.4176 - accurac
y: 0.8459 - val_loss: 0.6326 - val_accuracy: 0.6681
Epoch 5/20
57/57 [==============================] - 17s 303ms/step - loss: 0.2975 - accurac
y: 0.8943 - val_loss: 0.6705 - val_accuracy: 0.6879
```

In [165…

```
plt.plot(hist12.history['loss'])
plt.plot(hist12.history['accuracy'])
```

Out[165…

```
[<matplotlib.lines.Line2D at 0x2cffae30ca0>]
```



In [166…

```
loss, accuracy = model12.evaluate(X_val, y_val)
```

```
15/15 [==============================] - 1s 79ms/step - loss: 0.5951 - accuracy:
0.6791
```

Link to an excel SpreadSheet containing model performance, also with No 50-50 split and title only. Word2vec proved to work similar, depending on the model, 2-3% better or arpund the same worse, therefore we decided to leave it out and use lemmatization.

https://docs.google.com/spreadsheets/d/1Vcnnh5MvkoVpfSyF4jWzxz93QvzuRA8cQcuvnS_G

Testing Our Best Performing Model

As shown above the 5th model proves to be the best performer, we will now proceed to the testing process, where we first check its performance of the test set to then predict the test results, and create a confusion matrix resembling its predictive performance. The threshold is yet again set to 0.5.

In [167…

```
loss, accuracy = model5.evaluate(X_test, y_test)
```

```
18/18 [==============================] - 3s 153ms/step - loss: 0.5891 - accuracy:
0.6937
```

In [169…

```
#Prection and Confusion Matrix
y_pred = model5.predict(X_test)
bin_y_pred = (y_pred > 0.5).astype(int)
```

```
18/18 [==============================] - 7s 148ms/step
```

In [170…
```
bin_y_pred = np.squeeze(bin_y_pred)
```

In [171…
```
y_true = y_test
y_pred = bin_y_pred
```

In [189…
```
cm = confusion_matrix(y_true, y_pred)

TN, FP, FN, TP = cm.ravel()

print('Test Set Results:\n')

print(f"{'':<20}{'Predicted No':<20}{'Predicted Yes':<20}")
print(f"{'Actual No':<20}{TN:<20}{FP:<20}")
print(f"{'Actual Yes':<20}{FN:<20}{TP:<20}")

print("\nPrecision:", round(TP/(TP + FP), 4))
print("Recall:", round(TP/(TP + FN), 4))
print("Accuracy:", round((TP+TN)/(TP + TN + FP + FN), 4))
```

```
Test Set Results:

                    Predicted No        Predicted Yes
Actual No           194                 88
Actual Yes          86                  200

Precision: 0.6944
Recall: 0.6993
Accuracy: 0.6937
```

In the results above we can see a much more imporved model, with better metrics when compared to the base model. Nearly 70% accuracy, recall and precision. Makes this a well performing model. Especially when compared to others we checked. The test accuracy does not fall out of bounds with the validation result, signaling the validity of the performance of our model outside of the train set, and a good balance of each cases in each of the splits made.

Custom Text Import And Prediction

To prove the performance of the model and simply to check its real life purpose, we have checked real recent articles from Bloomberg and CNBC, in both classes of relevancy. First, we created a function in which 3 arguments are provided - the headline string, the text string and the length of padded sequences to set a max article length of 404 words our model can intake.

- The strings are combined into a single string, then the cleaning process is done, along with removing the stopwords, and lemmatization.
- An error will be brought out if the length of the given article is > 404 words or the padded sequence length.
- If however this is not the case we proceed into turning the text into sequences and padding them given the max length given as an argument.
- As the last step a prediction is made and later classified as Economic or Non Economic depending if the value is smaller or bigger then the threshold of 0.5.

- The demonstration of the function in work with real articles is given below.

In [250…

```
def is_txt_econ(headline, text, max_l):
    whole_txt = headline + ' ' + text

    # Taking out '<br>' in the 'whole_text' column
    whole_txt = re.sub(r'</?br>', ' ', whole_txt)
    # Deletion of non-latin alfabet signs, also numbers
    whole_txt = re.sub(r'[^a-zA-Z]', ' ', whole_txt)
    # Removing single letter works like 'a'.
    whole_txt = re.sub(r"\s+[a-zA-Z]\s+", ' ', whole_txt)
    # Removing double spaces
    whole_txt = re.sub(r'\s+', ' ', whole_txt)
    # Lower case
    whole_txt = whole_txt.lower()
    whole_txt = word_tokenize(whole_txt)
    whole_txt = [word for word in whole_txt if word not in stop_words]
    whole_txt = [lemmatizer.lemmatize(word) for word in whole_txt]

    if len(whole_txt) > max_l:
        print('ERROR, Article lenght must be < 404')
    else:
        sequences = tokenizer.texts_to_sequences([whole_txt])
        padded_sequences = pad_sequences(sequences, maxlen=max_l)

        predictions = model5.predict(padded_sequences)
        if predictions < 0.5:
            return(predictions, 'Non Economic')
        else:
            return(predictions, 'Economic')
```

In [261…

```
# Bloomberg Article - Economic Relevance, debatable, about changing structures i
# https://www.bloomberg.com/news/articles/2023-12-03/ubs-s-ermotti-to-find-poten
is_txt_econ('UBS’s Ermotti to Find Potential Successor Within Three Years', 'Ser
```

```
1/1 [==============================] - 0s 118ms/step
```

Out[261…

```
(array([[0.22238688]], dtype=float32), 'Non Economic')
```

In [262…

```
# CNBC - Surely Non Economic, regarding a terrorist attack in Paris
# https://www.cnbc.com/2023/12/03/one-dead-two-injured-after-tourists-attacked-n
is_txt_econ('One dead, two injured after man attacks tourists near Paris Eiffel
```

```
1/1 [==============================] - 0s 119ms/step
```

Out[262…

```
(array([[0.14373618]], dtype=float32), 'Non Economic')
```

In [263…

```
# CNBC, article about rising gold prices due to FED policies.
# https://www.cnbc.com/2023/12/01/gold-set-for-3rd-weekly-gain-as-cooler-data-ce
is_txt_econ('Gold hits record high on bets for March start to Fed rate cuts', 'G
```

```
1/1 [==============================] - 0s 100ms/step
```

Out[263…

```
(array([[0.5134268]], dtype=float32), 'Economic')
```

In [264…

```
# CNBC Oil Prices Article
# https://www.cnbc.com/2023/12/01/oil-prices-set-to-rise-in-2024-after-opec-volu
is_txt_econ('Oil prices could reach $100 a barrel in 2024 if OPEC+ members fulfi
```

```
1/1 [==============================] - 0s 103ms/step
```

Out[264…

```
(array([[0.7161325]], dtype=float32), 'Economic')
```

As we can see the algorithm mostly correctly predicts the articles. However, we can see some limitations of such model.

- It can be debatable for some content to be classified as either economic or not for a human, how is a machine supposed to react to that.
- The words that were not in the initial dictionary before training are just simply ignored and their context is not taken into consideration.

As for the recommendations for the future...

- More data, with more economic news, we only had 1420 cases of economic news out of 8000.
- This would allow for a better glossary, therefore likely better predictions.
- Recognize news brands, we only had the Wall Street Journal and the Washington Post. Some brands are strictly financial, while others are not.