Sentiment Analysis of Financial News Using NLTK and Classification model

Problem statment:

- We have to predict the sentiment of fiancial news using nltk

About Dataset

- This dataset contains 3 csv file
  - cnbc headline (3080, 3)
  - gaurdian headline (17800, 2)
  - reuters headline (32770, 3)

Columns Provided in the Dataset

- **cnbc headline**
  1. time
  2. headlines
  3. Description
- **gaurdian headline**
  1. time
  2. headline
- **reuters headline**
  1. time
  2. headline
  3. description

What is NLTK ?

The Natural Language Toolkit (NLTK) is a platform used for building Python programs that work with human language data for applying in statistical natural language processing (NLP).

It contains text processing libraries for tokenization, parsing, classification, stemming, tagging and semantic reasoning.

https://medium.com/@ODSC/intro-to-language-processing-with-the-nltk-59aa26b9d056 (https://medium.com/@ODSC/intro-to-language-processing-with-the-nltk-59aa26b9d056)

What is sentiment analysis ?

Sentiment analysis is the process of detecting positive or negative sentiment in text. It's often used by businesses to detect sentiment in social data, gauge brand reputation, and understand customers.

https://monkeylearn.com/sentiment-analysis/ (https://monkeylearn.com/sentiment-analysis/)

In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

In [2]:

```
# Import all the required libraries
import re
import pandas as pd
import numpy as np
import os
import datetime as dt
from matplotlib import pyplot as plt
%matplotlib inline
import seaborn as sns
from collections import Counter
import string
!pip install emoji
import emoji
pd.set_option('display.max_rows',500)
import warnings
warnings.filterwarnings("ignore")
#import stopwords and text processing libraries
from collections import Counter
import string
import unicodedata
import nltk
nltk.download('all')
nltk.download('punkt')
nltk.download('stopwords')
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import  TfidfVectorizer
from sklearn.decomposition import NMF
from nltk.stem.porter import *
from nltk.stem.wordnet import WordNetLemmatizer
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: emoji in /usr/local/lib/python3.8/dist-packages (2.2.0)
```

```
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```

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```

```
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[nltk_data]  Done downloading collection all
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [3]:
```
#import machine learning libraries
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import LinearSVC
from sklearn.pipeline import make_pipeline
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.ensemble import GradientBoostingClassifier
import xgboost as xg
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
```

Basic EDA on cnbc_headlines dataset

Read csv file of cnbc headlines using pandas

In [4]:
```
df_cnbc = pd.read_csv('/content/drive/MyDrive/Projects/Sentiment Analysis of Financial News/cnbc_headlines.csv')
df_cnbc.head()
```

Out[4]:

	Headlines	Time	Description
0	Jim Cramer: A better way to invest in the Covi...	7:51 PM ET Fri, 17 July 2020	"Mad Money" host Jim Cramer recommended buying...
1	Cramer's lightning round: I would own Teradyne	7:33 PM ET Fri, 17 July 2020	"Mad Money" host Jim Cramer rings the lightnin...
2	NaN	NaN	NaN
3	Cramer's week ahead: Big week for earnings, ev...	7:25 PM ET Fri, 17 July 2020	"We'll pay more for the earnings of the non-Co...
4	IQ Capital CEO Keith Bliss says tech and healt...	4:24 PM ET Fri, 17 July 2020	Keith Bliss, IQ Capital CEO, joins "Closing Be...

Check the shape of cnbc headline dataset

In [5]:
```
df_cnbc.shape
```

Out[5]:
```
(3080, 3)
```

Check all the columns in the cnbc headline dataset

In [6]:
```
df_cnbc.columns
```

Out[6]:
```
Index(['Headlines', 'Time', 'Description'], dtype='object')
```

Check which columns are having categorical, numerical or boolean values

In [7]:
```
df_cnbc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3080 entries, 0 to 3079
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Headlines    2800 non-null   object
 1   Time         2800 non-null   object
 2   Description  2800 non-null   object
dtypes: object(3)
memory usage: 72.3+ KB
```

Check for missing values in all the columnns of cnbc headline dataset

In [8]:
```
df_cnbc.isnull().sum()
```

Out[8]:
```
Headlines      280
Time           280
Description    280
dtype: int64
```

Observation:

- There is 280 missing values in headlines, description and time

Drop nan values in cnbc headline dataset

In [9]:
```
df_cnbc.dropna(inplace = True)
```

Drop the duplicate rows in the dataset keep the first one

In [10]:
```
df_cnbc.drop_duplicates(keep = 'first', inplace=True)
```

Check the shape of cnbc headline dataset

In [11]:
```
df_cnbc.shape
```

Out[11]:
```
(2800, 3)
```

Reset index

In [12]:
```
df_cnbc.reset_index(drop = True, inplace = True)
```

Basic EDA on Gaurdian headlines dataset

Read csv file of gaurdian headlines using pandas

In [13]:
```
df_guardian = pd.read_csv('/content/drive/MyDrive/Projects/Sentiment Analysis of Financial News/guardian_headlines.csv')
df_guardian.head()
```

Out[13]:

	Time	Headlines
0	18-Jul-20	Johnson is asking Santa for a Christmas recovery
1	18-Jul-20	'I now fear the worst': four grim tales of wor...
2	18-Jul-20	Five key areas Sunak must tackle to serve up e...
3	18-Jul-20	Covid-19 leaves firms 'fatally ill-prepared' f...
4	18-Jul-20	The Week in Patriarchy \n\n\n Bacardi's 'lad...

Check the shape of gaurdian headline dataset

In [14]:
```
df_guardian.shape
```

Out[14]:
```
(17800, 2)
```

Check columns of gaurdian headline

In [15]:
```
df_guardian.columns
```

Out[15]:
```
Index(['Time', 'Headlines'], dtype='object')
```

Check which columns are having categorical, numerical or boolean values

In [16]:
```
df_guardian.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17800 entries, 0 to 17799
Data columns (total 2 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   Time       17800 non-null  object
 1   Headlines  17800 non-null  object
dtypes: object(2)
memory usage: 278.2+ KB
```

Check null values in gaurdian headlines dataset

In [17]:
```
df_guardian.isnull().sum()
```

Out[17]:
```
Time         0
Headlines    0
dtype: int64
```

Drop duplicate rows in headlines and keep the first one

In [18]:
```
df_guardian.drop_duplicates(keep = 'first', inplace = True)
```

Reset index

In [19]:
```
df_guardian.reset_index(drop = True, inplace = True)
```

Basic EDA on reuters headlines

Read csv file of reuters headlines using using pandas

In [20]:
```
df_reuters = pd.read_csv('/content/drive/MyDrive/Projects/Sentiment Analysis of Financial News/reuters_headlines.csv')
df_reuters.head()
```

Out[20]:

	Headlines	Time	Description
0	TikTok considers London and other locations fo...	Jul 18 2020	TikTok has been in discussions with the UK gov...
1	Disney cuts ad spending on Facebook amid growi...	Jul 18 2020	Walt Disney has become the latest company to ...
2	Trail of missing Wirecard executive leads to B...	Jul 18 2020	Former Wirecard chief operating officer Jan M...
3	Twitter says attackers downloaded data from up...	Jul 18 2020	Twitter Inc said on Saturday that hackers were...
4	U.S. Republicans seek liability protections as...	Jul 17 2020	A battle in the U.S. Congress over a new coron...

Check the shape of reuters headlines dataset

In [21]:
```
df_reuters.shape
```

Out[21]:
```
(32770, 3)
```

Check the columns of reuters headline dataset

In [22]:
```
df_reuters.columns
```

Out[22]:
```
Index(['Headlines', 'Time', 'Description'], dtype='object')
```

Check which columns are having categorical, numerical or boolean values

In [23]:
```
df_reuters.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32770 entries, 0 to 32769
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Headlines    32770 non-null  object
 1   Time         32770 non-null  object
 2   Description  32770 non-null  object
dtypes: object(3)
memory usage: 768.2+ KB
```

Check for missing values in all the columnns of reuters headlines dataset

In [24]:
```
df_reuters.isnull().sum()
```

Out[24]:
```
Headlines      0
Time           0
Description    0
dtype: int64
```

Drop the duplicate rows in reuters headlines dataset and keep the first one

In [25]:
```
df_reuters.drop_duplicates(keep ='first', inplace = True)
```

In [26]:
```
df_reuters.reset_index(drop = True, inplace = True)
```

SENTIMENT ANAYSIS

Making some functions that we will need ahead

Preprocessing

1. **Lowercase** - It is necessary to convert the text to lower case as it is case sensitive.
2. **remove punctuations** - The punctuations present in the text do not add value to the data. The punctuation, when attached to any word, will create a problem in differentiating with other words. so we have to get rid of them.
3. **remove stopwords** - Stopwords include: I, he, she, and, but, was were, being, have, etc, which do not add meaning to the data. So these words must be removed which helps to reduce the features from our data. These are removed after tokenizing the text.
4. **stemming** - A technique that takes the word to its root form. It just removes suffixes from the words. The stemmed word might not be part of the dictionary, i.e it will not necessarily give meaning.
5. **lemmatizing** - Takes the word to its root form called Lemma. It helps to bring words to their dictionary form. It is applied to nouns by default. It is more accurate as it uses more informed analysis to create groups of words with similar meanings based on the context, so it is complex and takes more time. This is used where we need to retain the contextual information.

https://youtu.be/IMQzEk5vht4 (https://youtu.be/IMQzEk5vht4)

https://www.pluralsight.com/guides/importance-of-text-pre-processing (https://www.pluralsight.com/guides/importance-of-text-pre-processing)

Create a function for preprocessing

In [27]:
```
def preprocess(x):
  #convert all to lowercase
  x = x.lower()
  #remove puntuations
  remove_punct = str.maketrans('', '', string.punctuation)
  x = x.translate(remove_punct)
  #remove stopword
  stopwordslist = stopwords.words('english')
  tokens = word_tokenize(x)
  result = [w for w in tokens if not w in stopwordslist]

  #stemming
  ps = PorterStemmer()
  stemwords = [ps.stem(w) for w in result]

  #Lemmitizing
  lemmatizer = WordNetLemmatizer()
  lemmawords = [lemmatizer.lemmatize(w) for w in stemwords]

  return ( " ".join(lemmawords))
```

Import sentiment intensity analyzer

- https://towardsdatascience.com/sentimental-analysis-using-vader-a3415fef7664 (https://towardsdatascience.com/sentimental-analysis-using-vader-a3415fef7664)

In [28]:
```
import nltk
nltk.download('vader_lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer
# create sentiment intensity analyzer object
sid = SentimentIntensityAnalyzer()
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Create fuction to decide sentiment as positive, negative and neutral

In [29]:
```
def polarity(a):
 return sid.polarity_scores(a)['compound']
```

Working with description of cnbc and reuters datasets

Concatenate cnbc headlines dataset and reuters headline dataset

In [30]:
```
df_concatened_d = pd.concat([df_cnbc, df_reuters], axis = 0)
```

Check the shape of this new dataset

In [31]:
```
df_concatened_d.shape
```

Out[31]: (35515, 3)

Make a copy of new dataset

In [32]:
```
df_concatened_d_copy = df_concatened_d.copy()
```

Apply preprocessing to the description of new dataset

In [33]:
```
df_concatened_d['Description'] = df_concatened_d['Description'].apply(lambda x : preprocess(x))
```

Analyze polarity score of values in description and add new column of it in dataset

In [34]:
```
df_concatened_d['ds_score'] = df_concatened_d['Description'].apply(lambda x: polarity(x))
```

Create a function which will assign sentiment based on polarity score

In [35]:
```
def assign_sentiment(x):
  if x > 0:
    return 'Positive'
  if x < 0:
    return 'Negative'
  if x == 0:
    return 'Neutral'
```

Apply the function which decides sentiment to polarity score column

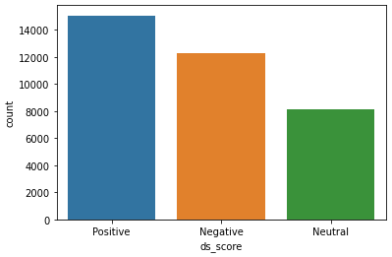
In [36]:
```
df_concatened_d['ds_score'] = df_concatened_d['ds_score'].apply(lambda x : assign_sentiment(x))
```

In [ ]:
```
df_concatened_d.head()
```

Plot a count plot on description score column

In [37]:
```
sns.countplot(df_concatened_d['ds_score'])
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd2dbd4130>



Observation:

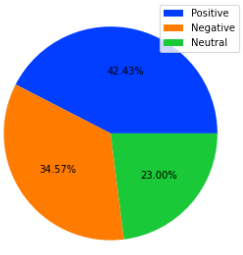
- Descriptions contains approximately:
  - 14000 positive statment
  - 12000 negative statment
  - 8000 neutral statment

Plot a pie plot on description score column

In [38]:
```
# define Seaborn color palette to use
palette_color = sns.color_palette('bright')

# plotting data on chart
plt.figure(figsize = (20,5))
plt.pie(df_concatened_d['ds_score'].value_counts(normalize = True), autopct='%.2f%%', colors=palette_color)
plt.legend(['Positive', 'Negative', 'Neutral'])

# displaying chart
plt.show()
```



Observation:

- Descriptions contains:
  - 42.43 % positive statments
  - 34.57 % negtive statements
  - 23.00 % neutral statments

Spliting in Independent and Dependent Features

In [39]:
```
X = df_concatened_d['Description']
y = df_concatened_d['ds_score']
```

Train test split

- Split the dataset into test and train
- 90% train , 10% test and random state 212

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.10, random_state = 212)
```

Modelling on description of cnbc headlines dataset and reuters headline dataset on datasets

In [41]:
```
'''All Models'''
models = {
1 : make_pipeline(TfidfVectorizer(),LinearSVC(random_state=0, tol=1e-5)),
2 : make_pipeline(CountVectorizer(),TfidfTransformer(),LogisticRegression()),
3 : make_pipeline(CountVectorizer(),TfidfTransformer(),MultinomialNB()),
4 : make_pipeline(CountVectorizer(),TfidfTransformer(),BernoulliNB()),
5 : make_pipeline(CountVectorizer(),TfidfTransformer(),GradientBoostingClassifier()),
6 : make_pipeline(CountVectorizer(),TfidfTransformer(),xg.XGBClassifier()),
7 : make_pipeline(CountVectorizer(),TfidfTransformer(),DecisionTreeClassifier()),
8 : make_pipeline(CountVectorizer(),TfidfTransformer(),KNeighborsClassifier())
}

map_keys = list(models.keys())
```

In [42]:
```
def get_model_building_technique_name(num):
  if num == 1:
    return 'LinearSVC'
  if num == 2:
    return 'LogisticRegression'
  if num == 3:
    return 'MultinomialNB'
  if num == 4:
    return 'BernoulliNB'
  if num == 5:
    return 'GradientBoostingClassifier'
  if num == 6:
    return 'XGBClassifier'
  if num == 7:
    return 'DecisionTreeClassifier'
  if num == 8:
    return 'KNeighborsClassifier'
  return ''
```

In [43]:
```
results = [];
for key_index in range(len(map_keys)):
  try:
    key = map_keys[key_index]
    model = models[key]
    print(key)
    model.fit(X_train, y_train)

    '''Test Accuracy'''
    y_pred = model.predict(X_test)

    Accuracy_Test = accuracy_score(y_test, y_pred)
    conf_mat_Test = confusion_matrix(y_test, y_pred)
    true_positive_Test = conf_mat_Test[0][0]
    false_positive_Test = conf_mat_Test[0][1]
    false_negative_Test = conf_mat_Test[1][0]
    true_negative__Test = conf_mat_Test[1][1]
    Precision_Test = true_positive_Test /(true_positive_Test + false_positive_Test)
    Recall_Test = true_positive_Test/(true_positive_Test + false_negative_Test)
    F1_Score_Test = 2*(Recall_Test * Precision_Test) / (Recall_Test + Precision_Test)
    # AUC_Test = roc_auc_score(y_test, y_pred)

    '''Train Accuracy'''
    y_pred_train = model.predict(X_train)

    Accuracy_Train = accuracy_score(y_train, y_pred_train)
    conf_mat_Train = confusion_matrix(y_train, y_pred_train)
    true_positive_Train = conf_mat_Train[0][0]
    false_positive_Train = conf_mat_Train[0][1]
    false_negative_Train = conf_mat_Train[1][0]
    true_negative__Train = conf_mat_Train[1][1]
    Precision_Train = true_positive_Train /(true_positive_Train + false_positive_Train)
    Recall_Train = true_positive_Train/(true_positive_Train + false_negative_Train)
    F1_Score_Train = 2*(Recall_Train * Precision_Train) / (Recall_Train + Precision_Train)
    # AUC_Train = roc_auc_score(y_train, y_pred_train)

    results.append({
        'Model Name' : get_model_building_technique_name(key),
        'Trained Model' : model,
        'Accuracy_Test' : Accuracy_Test,
        'Precision_Test' : Precision_Test,
        'Recall_Test' : Recall_Test,
        'F1_Score_Test' : F1_Score_Test,
        # 'AUC_Test' : AUC_Test,
        'Accuracy_Train' : Accuracy_Train,
        'Precision_Train' : Precision_Train,
        'Recall_Train' : Recall_Train,
        'F1_Score_Train' : F1_Score_Train
        # 'AUC_Train' : AUC_Train
        })
  except:
    print('Error')
```

```
1
2
3
4
5
6
7
8
```

In [44]:
```
result_df = pd.DataFrame(results)
result_df['difference_f1_score'] = abs(result_df['F1_Score_Test'] - result_df['F1_Score_Train'])
# result_df_test = result_df.iloc[: , [0,2,3,4,5]]
# result_df_train = result_df.iloc[: , [0,6,7,8,9]]
result_df
```

Out[44]:

	Model Name	Trained Model	Accuracy_Test	Precision_Test	Recall_Test	F1_Score_Test	Accuracy_Train	Precision_Train	Recall_Train	F1_Score_Train	difference_f1_score
0	LinearSVC	(TfidfVectorizer(), LinearSVC(random_state=0, ...	0.932151	0.961407	0.981611	0.971404	0.987141	0.997710	0.992799	0.995248	0.023844
1	LogisticRegression	(CountVectorizer(), TfidfTransformer(), Logist...	0.894426	0.932921	0.967949	0.950112	0.953415	0.975596	0.986419	0.980978	0.030865
2	MultinomialNB	(CountVectorizer(), TfidfTransformer(), Multin...	0.639921	0.990196	0.843424	0.910936	0.716516	0.994617	0.871009	0.928718	0.017783
3	BernoulliNB	(CountVectorizer(), TfidfTransformer(), Bernou...	0.739302	0.942564	0.871090	0.905419	0.827019	0.960318	0.919350	0.939388	0.033969
4	GradientBoostingClassifier	(CountVectorizer(), TfidfTransformer(), ([Deci...	0.842061	0.842644	0.989071	0.910005	0.846573	0.844690	0.992226	0.912534	0.002528
5	XGBClassifier	(CountVectorizer(), TfidfTransformer(), XGBCla...	0.802646	0.802669	0.987104	0.885384	0.809843	0.811252	0.992166	0.892635	0.007251
6	DecisionTreeClassifier	(CountVectorizer(), TfidfTransformer(), Decisi...	0.877252	0.979808	0.989320	0.984541	1.000000	1.000000	1.000000	1.000000	0.015459
7	KNeighborsClassifier	(CountVectorizer(), TfidfTransformer(), KNeigh...	0.550957	0.827586	0.761194	0.793003	0.707599	0.900781	0.837077	0.867761	0.074759

Save best model

In [45]:
```
Best_Model_Name = result_df[result_df['difference_f1_score'] == min(result_df['difference_f1_score'])]['Trained Model'].values[0]
import pickle
with open('financial_news_model_d.sav', 'wb') as best_model_pickle:
 pickle.dump(Best_Model_Name, best_model_pickle)
```

Working with test dataset

Perform the prediction on the test dataset

In [46]:
```
loaded_model_cr = pickle.load(open('financial_news_model_d.sav', 'rb'))
result = loaded_model_cr.predict(X_test)
pd.DataFrame(result)
```

Out[46]:

	0
0	Negative
1	Neutral
2	Neutral
3	Positive
4	Neutral
...	...
3547	Negative
3548	Positive
3549	Neutral
3550	Positive
3551	Neutral

3552 rows × 1 columns

Working with headlines + description of cnbc and reuters datasets

Creating copy of orifioriginalngal

In [47]:
```
df_concatened_d_copied = df_concatened_d.copy()
```

Merge headlines and description of new dataset and name it info

In [48]:
```
df_concatened_d['info'] = df_concatened_d['Headlines'] + ' ' + df_concatened_d['Description']
```

Only keep info and time column . drop all remaining columns

In [49]:
```
df_concatened_d.drop(['Headlines', 'Description', 'ds_score'], axis = 1, inplace = True)
```

Apply preprocessing on info column

In [50]:
```
df_concatened_d['info'] = df_concatened_d['info'].apply(lambda x : preprocess(x))
```

Analyze polarity score of values in info and add new column of it in dataset

In [51]:
```
df_concatened_d['ds_score_info'] = df_concatened_d['info'].apply(lambda x: polarity(x))
```

Apply the function which decides sentiment to polarity score column

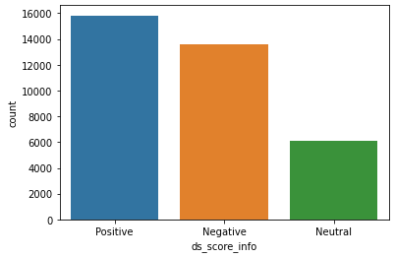
In [52]:
```
df_concatened_d['ds_score_info'] = df_concatened_d['ds_score_info'].apply(lambda x : assign_sentiment(x))
```

In [ ]:
```
df_concatened_d.head()
```

Create a count plot on info_score column

In [53]:
```
sns.countplot(df_concatened_d['ds_score_info'])
```

Out[53]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbd2ba6e940>
```

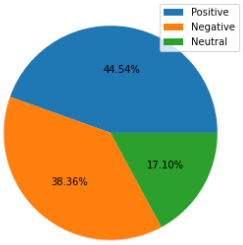


Observation:

- Headlines & Descriptions contains approximatley:
  - 15500 positive statment
  - 13000 negative statment
  - 6500 neutral statment

Create a pie chart on info_score column

In [54]:
```
# plotting data on chart
plt.figure(figsize = (20,5))
plt.pie(df_concatened_d['ds_score_info'].value_counts(normalize = True), autopct='%.2f%%')
plt.legend(['Positive', 'Negative', 'Neutral'])
# displaying chart
plt.show()
```



Observation:

- Headlines & Descriptions contains:
  - 44.5 % positive statments
  - 38.36 % negtive statements
  - 17.10 % neutral statments

Spliting in Independent and Dependent Features

In [55]:
```
X = df_concatened_d['info']
y = df_concatened_d['ds_score_info']
```

Train test split

- Split the dataset into test and train
- 90% train , 10% test and random state 212

In [56]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.10, random_state = 212)
```

Modelling on headlines + description of cnbc and reuters datasets

In [57]:
```
'''All Models'''
models = {
1 : make_pipeline(TfidfVectorizer(),LinearSVC(random_state=0, tol=1e-5)),
2 : make_pipeline(CountVectorizer(),TfidfTransformer(),LogisticRegression()),
3 : make_pipeline(CountVectorizer(),TfidfTransformer(),MultinomialNB()),
4 : make_pipeline(CountVectorizer(),TfidfTransformer(),BernoulliNB()),
5 : make_pipeline(CountVectorizer(),TfidfTransformer(),GradientBoostingClassifier()),
6 : make_pipeline(CountVectorizer(),TfidfTransformer(),xg.XGBClassifier()),
7 : make_pipeline(CountVectorizer(),TfidfTransformer(),DecisionTreeClassifier()),
8 : make_pipeline(CountVectorizer(),TfidfTransformer(),KNeighborsClassifier())
}

map_keys = list(models.keys())
```

In [58]:
```
def get_model_building_technique_name(num):
  if num == 1:
    return 'LinearSVC'
  if num == 2:
    return 'LogisticRegression'
  if num == 3:
    return 'MultinomialNB'
  if num == 4:
    return 'BernoulliNB'
  if num == 5:
    return 'GradientBoostingClassifier'
  if num == 6:
    return 'XGBClassifier'
  if num == 7:
    return 'DecisionTreeClassifier'
  if num == 8:
    return 'KNeighborsClassifier'
  return ''
```

In [59]:
```
results = [];
for key_index in range(len(map_keys)):
  try:
    key = map_keys[key_index]
    model = models[key]
    print(key)
    model.fit(X_train, y_train)

    '''Test Accuracy'''
    y_pred = model.predict(X_test)

    Accuracy_Test = accuracy_score(y_test, y_pred)
    conf_mat_Test = confusion_matrix(y_test, y_pred)
    true_positive_Test = conf_mat_Test[0][0]
    false_positive_Test = conf_mat_Test[0][1]
    false_negative_Test = conf_mat_Test[1][0]
    true_negative__Test = conf_mat_Test[1][1]
    Precision_Test = true_positive_Test /(true_positive_Test + false_positive_Test)
    Recall_Test = true_positive_Test/(true_positive_Test + false_negative_Test)
    F1_Score_Test = 2*(Recall_Test * Precision_Test) / (Recall_Test + Precision_Test)
    # AUC_Test = roc_auc_score(y_test, y_pred)

    '''Train Accuracy'''
    y_pred_train = model.predict(X_train)

    Accuracy_Train = accuracy_score(y_train, y_pred_train)
    conf_mat_Train = confusion_matrix(y_train, y_pred_train)
    true_positive_Train = conf_mat_Train[0][0]
    false_positive_Train = conf_mat_Train[0][1]
    false_negative_Train = conf_mat_Train[1][0]
    true_negative__Train = conf_mat_Train[1][1]
    Precision_Train = true_positive_Train /(true_positive_Train + false_positive_Train)
    Recall_Train = true_positive_Train/(true_positive_Train + false_negative_Train)
    F1_Score_Train = 2*(Recall_Train * Precision_Train) / (Recall_Train + Precision_Train)
    # AUC_Train = roc_auc_score(y_train, y_pred_train)

    results.append({
        'Model Name' : get_model_building_technique_name(key),
        'Trained Model' : model,
        'Accuracy_Test' : Accuracy_Test,
        'Precision_Test' : Precision_Test,
        'Recall_Test' : Recall_Test,
        'F1_Score_Test' : F1_Score_Test,
        # 'AUC_Test' : AUC_Test,
        'Accuracy_Train' : Accuracy_Train,
        'Precision_Train' : Precision_Train,
        'Recall_Train' : Recall_Train,
        'F1_Score_Train' : F1_Score_Train
        # 'AUC_Train' : AUC_Train
        })
  except:
    print('Error')
```

```
1
2
3
4
5
6
7
8
```

In [60]:
```
result_df = pd.DataFrame(results)
result_df['difference_f1_score'] = abs(result_df['F1_Score_Test'] - result_df['F1_Score_Train'])
# result_df_test = result_df.iloc[: , [0,2,3,4,5]]
# result_df_train = result_df.iloc[: , [0,6,7,8,9]]
result_df
```

Out[60]:

	Model Name	Trained Model	Accuracy_Test	Precision_Test	Recall_Test	F1_Score_Test	Accuracy_Train	Precision_Train	Recall_Train	F1_Score_Train	difference_f1_score
0	LinearSVC	(TfidfVectorizer(), LinearSVC(random_state=0, ...	0.901464	0.961875	0.968026	0.964940	0.983950	0.998019	0.993263	0.995635	0.030695
1	LogisticRegression	(CountVectorizer(), TfidfTransformer(), Logist...	0.870777	0.963533	0.936220	0.949681	0.939868	0.985091	0.975645	0.980345	0.030665
2	MultinomialNB	(CountVectorizer(), TfidfTransformer(), Multin...	0.668919	1.000000	0.855864	0.922335	0.717486	0.999682	0.867905	0.929145	0.006810
3	BernoulliNB	(CountVectorizer(), TfidfTransformer(), Bernou...	0.719313	0.955366	0.878603	0.915378	0.811032	0.968690	0.929815	0.948855	0.033477
4	GradientBoostingClassifier	(CountVectorizer(), TfidfTransformer(), ([Deci...	0.720439	0.975075	0.995927	0.985390	0.738979	0.983230	0.992881	0.988032	0.002642
5	XGBClassifier	(CountVectorizer(), TfidfTransformer(), XGBCla...	0.684403	1.000000	0.995722	0.997856	0.692207	1.000000	0.992188	0.996079	0.001778
6	DecisionTreeClassifier	(CountVectorizer(), TfidfTransformer(), Decisi...	0.834741	0.970776	0.980627	0.975677	1.000000	1.000000	1.000000	1.000000	0.024323
7	KNeighborsClassifier	(CountVectorizer(), TfidfTransformer(), KNeigh...	0.562218	0.881373	0.798401	0.837838	0.703407	0.937659	0.850832	0.892138	0.054300

Save Best Model

In [61]:
```
Best_Model_Name = result_df[result_df['difference_f1_score'] == min(result_df['difference_f1_score'])]['Trained Model'].values[0]
import pickle
with open('financial_news_model_hd.sav', 'wb') as best_model_pickle:
 pickle.dump(Best_Model_Name, best_model_pickle)
```

Working with test dataset

Perform the prediction on the test dataset

In [62]:
```
# Perform the prediction on the test dataset
best_model_hd = pickle.load(open('financial_news_model_hd.sav', 'rb'))
result = best_model_hd.predict(X_test)
pd.DataFrame(result)
```

Out[62]:

	0
0	Negative
1	Positive
2	Positive
3	Positive
4	Positive
...	...
3547	Negative
3548	Positive
3549	Positive
3550	Positive
3551	Positive

3552 rows × 1 columns

Working on headlines of cnbc, reuters and guardian datasets

From the dataset you have copied before delete the column of description

In [63]:
```
df_concatened_d_copied = df_concatened_d_copied.drop(['Description'], axis = 1)
df_concatened_d_copied = df_concatened_d_copied.drop(['ds_score'], axis = 1)
```

Concatenate the gaurdian headlines dataset and copy of dataset to get all headlines together

In [65]:
```
df_concatened_h = pd.concat([df_guardian,df_concatened_d_copied], axis = 0).reset_index(drop = True)
```

Check the shape of all headlines dataset

In [66]:
```
df_concatened_h.shape
```

Out[66]: (53315, 2)

Apply preprocessing to the headlines column in the new dataset

In [67]:
```
df_concatened_h['Headlines'] = df_concatened_h['Headlines'].apply(lambda x : preprocess(x))
df_concatened_h.head()
```

Out[67]:

	Time	Headlines
0	18-Jul-20	johnson ask santa christma recoveri
1	18-Jul-20	' fear worst ' four grim tale work life upend ...
2	18-Jul-20	five key area sunak must tackl serv econom rec...
3	18-Jul-20	covid19 leav firm ' fatal illprepar ' nodeal b...
4	18-Jul-20	week patriarchi bacardi ladi vodka latest long...
...	...	...
53310	Mar 20 2018	malaysia say never hire british data firm cent...
53311	Mar 20 2018	prosecutor search volkswagen headquart new emi...
53312	Mar 20 2018	mcdonald set greenhous ga reduct target
53313	Mar 20 2018	pratt whitney deliv spare a320neo engin soon i...
53314	Mar 20 2018	uk alway consid way improv data law pm may spo...

53315 rows × 2 columns

Analyze polarity score of values in headlines and add new column of it in dataset

In [68]:
```
df_concatened_h['ds_score_headlines'] = df_concatened_h['Headlines'].apply(lambda x: polarity(x))
```

Apply the function which decides sentiment to polarity score column

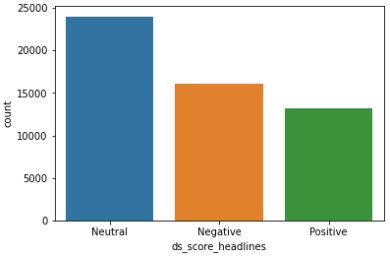
In [69]:
```
df_concatened_h['ds_score_headlines'] = df_concatened_h['ds_score_headlines'].apply(lambda x : assign_sentiment(x))
```

In [ ]:
```
df_concatened_h.head()
```

Create a countplot on headline score column

In [70]:
```
sns.countplot(df_concatened_h['ds_score_headlines'])
```

Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd2db9e280>

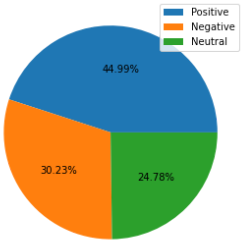


Observation:

- Headlines contains approximately:
  - 14000 positive statment
  - 16000 negative statment
  - 24000 neutral statment

Create a pie digram on headline score column

In [71]:
```
# plotting data on chart
plt.figure(figsize = (20,5))
plt.pie(df_concatened_h['ds_score_headlines'].value_counts(normalize = True), autopct='%.2f%%')
plt.legend(['Positive', 'Negative', 'Neutral'])
# displaying chart
plt.show()
```



Observation:

- Headlines contains:
  - 24.8% positive statments
  - 30.3% negtive statements
  - 44.9% neutral statments

Spliting in Independent and Dependent Features

In [72]:
```
X = df_concatened_h['Headlines']
y = df_concatened_h['ds_score_headlines']
```

Train test split

- Split the dataset into test and train
- 90% train , 10% test and random state 212

In [73]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.10, random_state = 212)
```

Modeling on headlines

In [74]:
```
'''All Models'''
models = {
1 : make_pipeline(TfidfVectorizer(),LinearSVC(random_state=0, tol=1e-5)),
2 : make_pipeline(CountVectorizer(),TfidfTransformer(),LogisticRegression()),
3 : make_pipeline(CountVectorizer(),TfidfTransformer(),MultinomialNB()),
4 : make_pipeline(CountVectorizer(),TfidfTransformer(),BernoulliNB()),
5 : make_pipeline(CountVectorizer(),TfidfTransformer(),GradientBoostingClassifier()),
6 : make_pipeline(CountVectorizer(),TfidfTransformer(),xg.XGBClassifier()),
7 : make_pipeline(CountVectorizer(),TfidfTransformer(),DecisionTreeClassifier()),
8 : make_pipeline(CountVectorizer(),TfidfTransformer(),KNeighborsClassifier())
}

map_keys = list(models.keys())
```

In [75]:
```
def get_model_building_technique_name(num):
  if num == 1:
    return 'LinearSVC'
  if num == 2:
    return 'LogisticRegression'
  if num == 3:
    return 'MultinomialNB'
  if num == 4:
    return 'BernoulliNB'
  if num == 5:
    return 'GradientBoostingClassifier'
  if num == 6:
    return 'XGBClassifier'
  if num == 7:
    return 'DecisionTreeClassifier'
  if num == 8:
    return 'KNeighborsClassifier'
  return ''
```

In [76]:
```
results = [];
for key_index in range(len(map_keys)):
  try:
    key = map_keys[key_index]
    model = models[key]
    print(key)
    model.fit(X_train, y_train)

    '''Test Accuracy'''
    y_pred = model.predict(X_test)

    Accuracy_Test = accuracy_score(y_test, y_pred)
    conf_mat_Test = confusion_matrix(y_test, y_pred)
    true_positive_Test = conf_mat_Test[0][0]
    false_positive_Test = conf_mat_Test[0][1]
    false_negative_Test = conf_mat_Test[1][0]
    true_negative__Test = conf_mat_Test[1][1]
    Precision_Test = true_positive_Test /(true_positive_Test + false_positive_Test)
    Recall_Test = true_positive_Test/(true_positive_Test + false_negative_Test)
    F1_Score_Test = 2*(Recall_Test * Precision_Test) / (Recall_Test + Precision_Test)
    # AUC_Test = roc_auc_score(y_test, y_pred)

    '''Train Accuracy'''
    y_pred_train = model.predict(X_train)

    Accuracy_Train = accuracy_score(y_train, y_pred_train)
    conf_mat_Train = confusion_matrix(y_train, y_pred_train)
    true_positive_Train = conf_mat_Train[0][0]
    false_positive_Train = conf_mat_Train[0][1]
    false_negative_Train = conf_mat_Train[1][0]
    true_negative__Train = conf_mat_Train[1][1]
    Precision_Train = true_positive_Train /(true_positive_Train + false_positive_Train)
    Recall_Train = true_positive_Train/(true_positive_Train + false_negative_Train)
    F1_Score_Train = 2*(Recall_Train * Precision_Train) / (Recall_Train + Precision_Train)
    # AUC_Train = roc_auc_score(y_train, y_pred_train)

    results.append({
        'Model Name' : get_model_building_technique_name(key),
        'Trained Model' : model,
        'Accuracy_Test' : Accuracy_Test,
        'Precision_Test' : Precision_Test,
        'Recall_Test' : Recall_Test,
        'F1_Score_Test' : F1_Score_Test,
        # 'AUC_Test' : AUC_Test,
        'Accuracy_Train' : Accuracy_Train,
        'Precision_Train' : Precision_Train,
        'Recall_Train' : Recall_Train,
        'F1_Score_Train' : F1_Score_Train
        # 'AUC_Train' : AUC_Train
        })
  except:
    print('Error')
```

```
1
2
3
4
5
6
7
8
```

In [77]:
```
result_df = pd.DataFrame(results)
result_df['difference_f1_score'] = abs(result_df['F1_Score_Test'] - result_df['F1_Score_Train'])
# result_df_test = result_df.iloc[: , [0,2,3,4,5]]
# result_df_train = result_df.iloc[: , [0,6,7,8,9]]
result_df
```

Out[77]:

	Model Name	Trained Model	Accuracy_Test	Precision_Test	Recall_Test	F1_Score_Test	Accuracy_Train	Precision_Train	Recall_Train	F1_Score_Train	difference_f1_score
0	LinearSVC	(TfidfVectorizer(), LinearSVC(random_state=0, ...	0.971305	0.980557	0.996050	0.988243	0.989330	0.996589	0.995965	0.996277	0.008034
1	LogisticRegression	(CountVectorizer(), TfidfTransformer(), Logist...	0.932858	0.922324	0.995070	0.957317	0.962674	0.957902	0.996266	0.976707	0.019390
2	MultinomialNB	(CountVectorizer(), TfidfTransformer(), Multin...	0.839460	0.871979	0.961123	0.914384	0.907780	0.935338	0.978988	0.956666	0.042282
3	BernoulliNB	(CountVectorizer(), TfidfTransformer(), Bernou...	0.886159	0.958051	0.920078	0.938681	0.936915	0.982733	0.951118	0.966667	0.027986
4	GradientBoostingClassifier	(CountVectorizer(), TfidfTransformer(), ([Deci...	0.792386	0.654557	0.996982	0.790271	0.804597	0.668318	0.997536	0.800395	0.010124
5	XGBClassifier	(CountVectorizer(), TfidfTransformer(), XGBCla...	0.753938	0.579224	0.996606	0.732640	0.763729	0.592407	0.997712	0.743406	0.010765
6	DecisionTreeClassifier	(CountVectorizer(), TfidfTransformer(), Decisi...	0.946174	0.984942	0.994471	0.989684	1.000000	1.000000	1.000000	1.000000	0.010316
7	KNeighborsClassifier	(CountVectorizer(), TfidfTransformer(), KNeigh...	0.605026	0.650266	0.667577	0.658808	0.749245	0.795404	0.811792	0.803515	0.144707

In [78]:
```
Best_Model_Name = result_df[result_df['difference_f1_score'] == min(result_df['difference_f1_score'])]['Trained Model'].values[0]
import pickle
with open('financial_news_model_h.sav', 'wb') as best_model_pickle:
 pickle.dump(Best_Model_Name, best_model_pickle)
```

Working with test dataset

Perform the prediction on the test dataset

In [79]:
```
best_model_h = pickle.load(open('financial_news_model_h.sav', 'rb'))
result = best_model_h.predict(X_test)
pd.DataFrame(result)
```

Out[79]:

	0
0	Positive
1	Positive
2	Negative
3	Neutral
4	Negative
...	...
5327	Neutral
5328	Negative
5329	Positive
5330	Neutral
5331	Neutral

5332 rows × 1 columns

Prediction

- You can check the result on real time news headlines
- Here i have used two fiancial news headlines and predicted its sentiment
- You can try more

In [80]:
```
sent1 = ['GST officers detect Rs 4,000 crore of ITC fraud in April-June']
y_predict = best_model_h.predict(sent1)
y_predict
```

Out[80]:
```
array(['Negative'], dtype=object)
```

In [81]:
```
sent2 = ["Finance Ministry releases Rs 9,871 crore to 17 states as grant"]
y_predict = best_model_h.predict(sent2)
y_predict
```

Out[81]:
```
array(['Positive'], dtype=object)
```

Conclusion

- We learn about NLTK and classification ML model, sentiment analysis in this assigment.
- We conclude that using nltk it is easy to classify financial news and more we improve the traning data more we can get accurate

Congratulation for completing the assignment.

You have learned a lot while doing this assignment.