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Fake-News-Classification / Main_Notebook.ipynb

moscatena added link to other notebooks and markdown

1 contributor

2.43 MB

Fake News Detection

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Image Source.jpg)

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Overview

Fake news has become increasingly more common in the past decades. It's effectiveness cannot be misjudged, as it can aid people in not taking responsability, in winning

arguments or, in a bigger scale, elections. In 2016 hundreds of teenagers in Europe were hired to write false stories about the US election. Their stories would be retweeted or shared on social media or direct message hundreds and thousands of times, reaching millions of people. It's hard to quantify how much those stories could influence an outcome, but nearing the end of the election, fake news had a higher engagement count than mainstream news.
Stories like this are not only recent though. One can easily look at las century history when some say Hitler Pioneered 'Fake News', but this has happened for milenia, with counts in 1274 bce, where Ramses's II accounts of The Battle of Kadesh have been gravely misconstrued.

Business Problem

Detecting fake news is a very challenging task. If the platform where it is being broadcasted can be biased, and one simply can't have access to the source material, how can you attest to it's truthness? We also have to take into consideration that out of those fake news, some of them could have been written as parody, some completely fabricated, some manipulated or making false connections.
To better understand how to assess if a news is fake or true, I'll be using Natural Language Processing.

Data Understanding

With the idea of trying to improve fake news classification, the LIAR dataset was created in 2017, containing 12.8 thousand manually labeled short statements from the last decade gathered from PolitiFact.com, which provides detailed analysis report and links to source document to each case. This is the most accuratly labeled dataset on the subject and became a benchmark for it.
The data consists of 12.8k rows with 14 different features containing: Statement ID, Label, Statement, Speaker, Speaker's job title, State, Speaker's party affiliation, the statement credit count (from pants on fire to true), Venue or Location of statement and the Justification for the labeling. I'll explore all the metadata but will create my models using only the 'statement' and 'label' features, since I want to see if the models can be used in broader situations.
Link to dataset.

I. Data Exploration

To start with, we load the dataset and explore its values.

In [208…

```
# Load required libraries

#Exploratory
import pandas as pd
import numpy as np

#Data Visualization
```

```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from wordcloud import WordCloud

# sklearn
from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer,
from sklearn.metrics import accuracy_score, recall_score, plot_confusion_matr
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import FunctionTransformer

#Preprocessing
import nltk
from nltk.corpus import stopwords
from nltk.collocations import *
from nltk import word_tokenize
from nltk.stem.wordnet import WordNetLemmatizer
import string
import re

#Data Modeling
from sklearn.linear_model import LogisticRegression, SGDClassifier, PassiveAg
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifi
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier

#Data Evaluation
from imblearn.over_sampling import RandomOverSampler
from imblearn.pipeline import Pipeline as imbpipe
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import cross_validate , GridSearchCV, Randomized

# Ignore any warnings
import warnings;
warnings.filterwarnings('ignore')
```

In [2]:

```
col_names = ['ID', 'label', 'statement', 'subject', 'speaker', 'speaker\'s ti
raw_train = pd.read_csv('data/train2.tsv', sep='\t', names=col_names)
raw_test = pd.read_csv('data/test2.tsv', sep='\t', names=col_names)
raw_val = pd.read_csv('data/val2.tsv', sep='\t', names=col_names)
```

In [6]:

```
raw_train.head()
```

Out[6]:

	ID	label	statement	subject	speaker	speaker's title	state	
0.0	2635.json	false	Says the Annies List political group supports ...	abortion	dwayne-bohac	State representative	Texas	repu
1.0	10540.json	half-true	When did the decline of coal start? It started...	energy,history,job-accomplishments	scott-surovell	State delegate	Virginia	de

2.0	324.json	mostly-true	Hillary Clinton agrees with John McCain "by vo...	foreign-policy	barack-obama	President	Illinois	de
3.0	1123.json	false	Health care reform legislation is likely to ma...	health-care	blog-posting	NaN	NaN	
4.0	9028.json	half-true	The economic turnaround started at the end of ...	economy,jobs	charlie-crist	NaN	Florida	de

In [7]:
```
raw_train['label'].value_counts()
```

Out[7]:
```
half-true       2114
false           1995
mostly-true     1962
true            1676
barely-true     1654
pants-fire       839
Name: label, dtype: int64
```

In [8]:
```
raw_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Float64Index: 10242 entries, 0.0 to 10268.0
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   ID              10240 non-null  object 
 1   label           10240 non-null  object 
 2   statement       10240 non-null  object 
 3   subject         10238 non-null  object 
 4   speaker         10238 non-null  object 
 5   speaker's title  7343 non-null  object 
 6   state           8032 non-null   object 
 7   party           10238 non-null  object 
 8   barely true     10238 non-null  float64
 9   false           10238 non-null  float64
 10  half true       10238 non-null  float64
 11  mostly true     10238 non-null  float64
 12  pants on fire   10238 non-null  float64
 13  context         10138 non-null  object 
 14  justification   10154 non-null  object 
dtypes: float64(5), object(10)
memory usage: 1.3+ MB
```

In [11]:
```
raw_train.isna().sum()
```

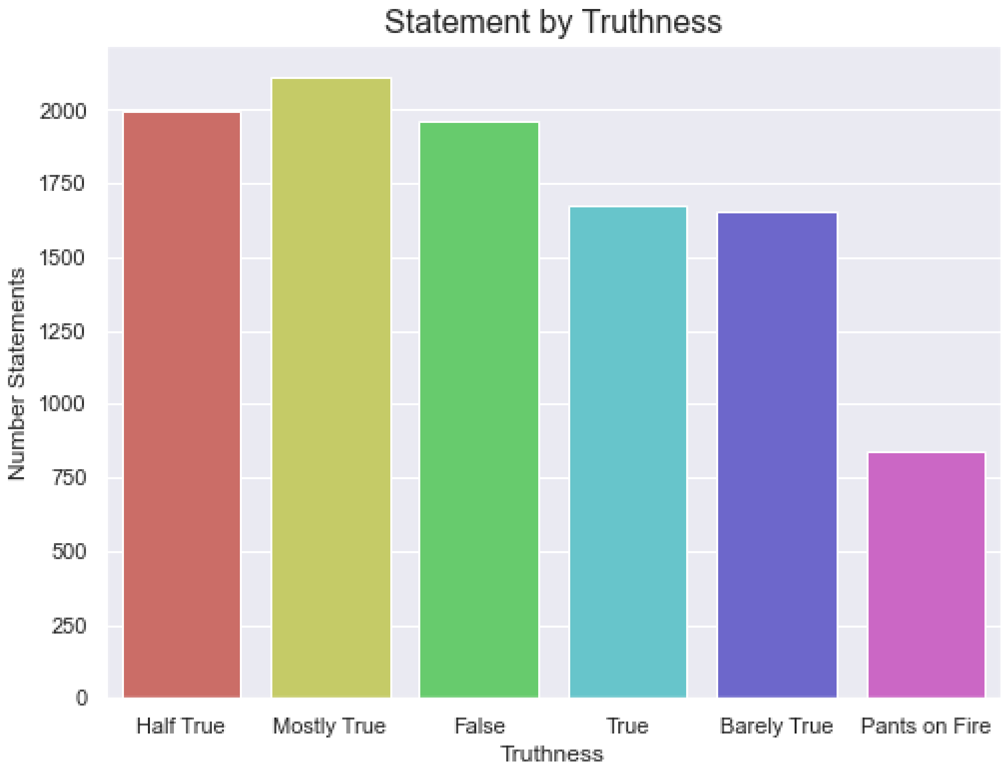
Out[11]:
```
ID                   2
label                2
statement            2
```

```
subject              4
speaker              4
speaker's title   2899
state             2210
party                4
barely true          4
false                4
half true            4
mostly true          4
pants on fire        4
context            104
justification       88
dtype: int64
```

We can see some features with lots of missing values, but the Label and Statement features are almost full.

In [30]:

```
# Visualize the count of classes of target variable
fig, ax = plt.subplots(figsize=(8, 6))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x='label', data=raw_train, palette='hls')
ax.set_title('Statement by Truthness', fontsize=16)
ax.set_xlabel('Truthness', fontsize=12)
ax.set_xticklabels(['Half True', 'Mostly True', 'False', 'True', 'Barely True
ax.set_ylabel('Number Statements', fontsize=12);
```

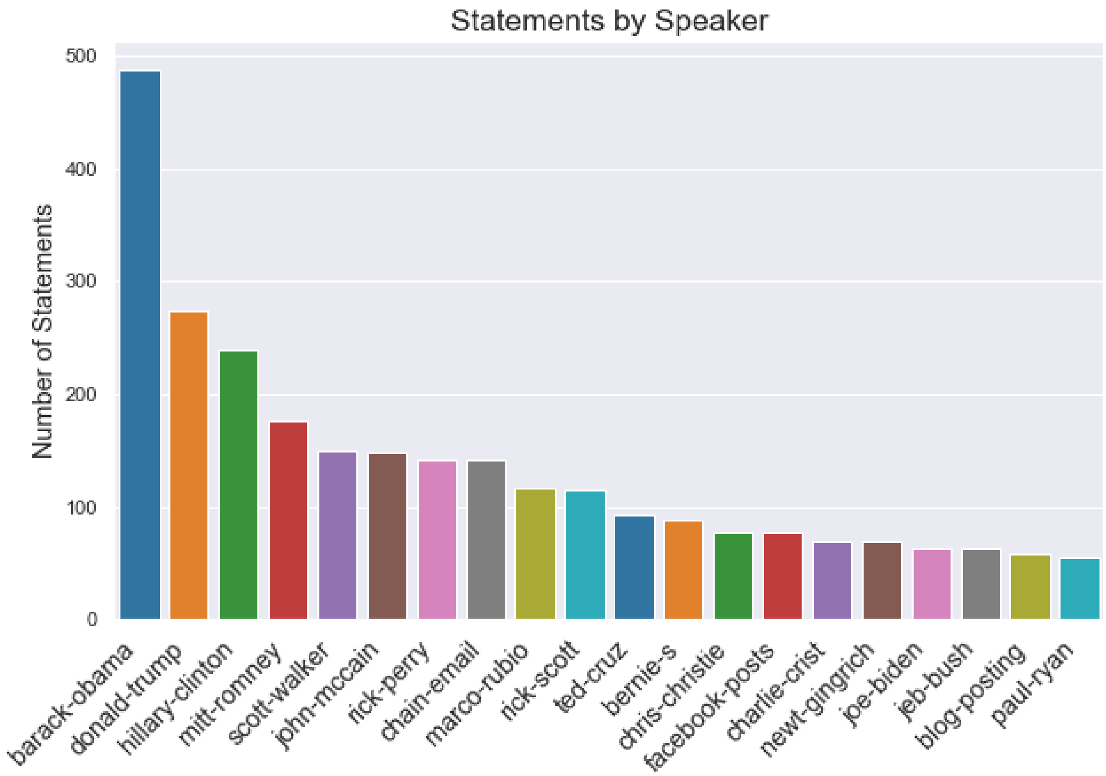


Apart from 'Pants on Fire', the data seems to be fairly balanced.

In [45]:

```
#visualize the counts of statements by speaker

fig, ax = plt.subplots(figsize=(10,6))

ax = sns.countplot(
    data=raw_train,
    x="speaker", order=raw_train["speaker"].value_counts()[:20].index,
    palette='tab10')

ax.set_title('Statements by Speaker', fontsize='x-large')
```

```
ax.set_xlabel(' ')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignment='ri
ax.set_ylabel('Number of Statements',fontsize='large');
```

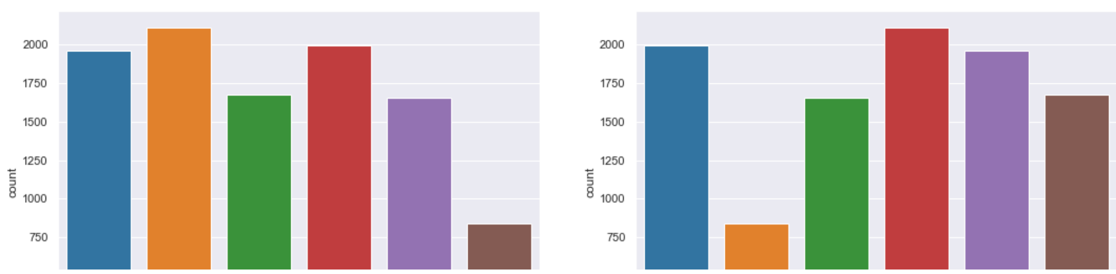


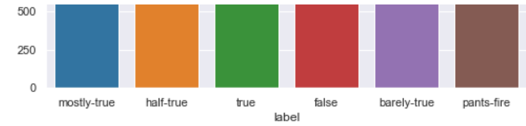
Barack Obaba has the highest number of statements in the dataset, followed by Donald Trump and Hillary Clinton.

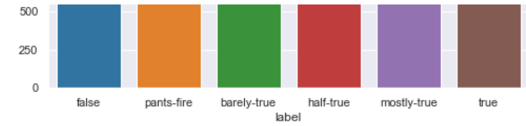
In [60]:

```
#visualize the counts of true statements by speaker Obama / Trump

fig, axes = plt.subplots(ncols=2, figsize=(18,6))

sns.countplot(
    data=raw_train,
    x="label", order=raw_train[raw_train['speaker']=='barack-obama']['label']
    palette='tab10', ax=axes[0])

sns.countplot(
    data=raw_train,
    x="label", order=raw_train[raw_train['speaker']=='donald-trump']['label']
    palette='tab10', ax=axes[1])


# ax[0].set_title('True Statements by Speaker', fontsize='x-large')
# ax[0].set_xlabel(' ')
# ax[0].set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignmen
# ax[0].set_ylabel('Number of Statements',fontsize='large');
```

Out[60]: <AxesSubplot:xlabel='label', ylabel='count'>

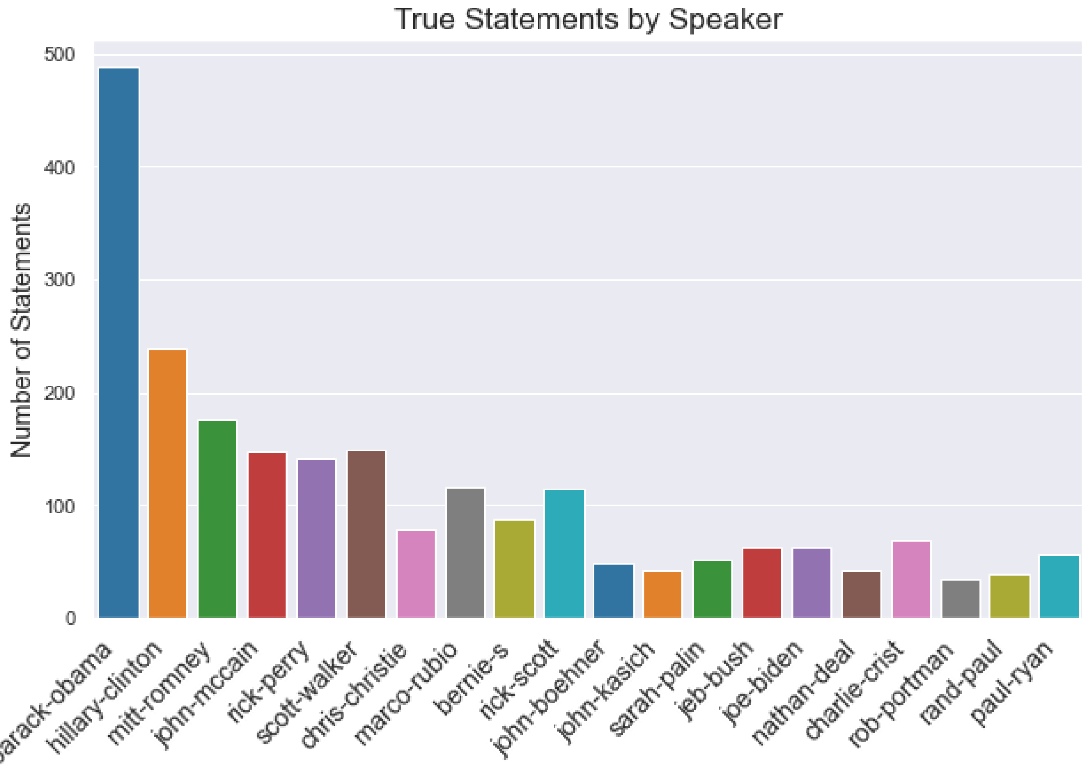






In [47]:

```
#visualize the counts of true statements by speaker

fig, ax = plt.subplots(figsize=(10,6))

ax = sns.countplot(
    data=raw_train,
    x="speaker", order=raw_train["speaker"][raw_train['label']=='true'].value
    palette='tab10')

ax.set_title('True Statements by Speaker', fontsize='x-large')
ax.set_xlabel(' ')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignment='ri
ax.set_ylabel('Number of Statements',fontsize='large');
```



In [54]:

```
raw_train[raw_train['speaker']=='barack-obama']['label'].value_counts()
```

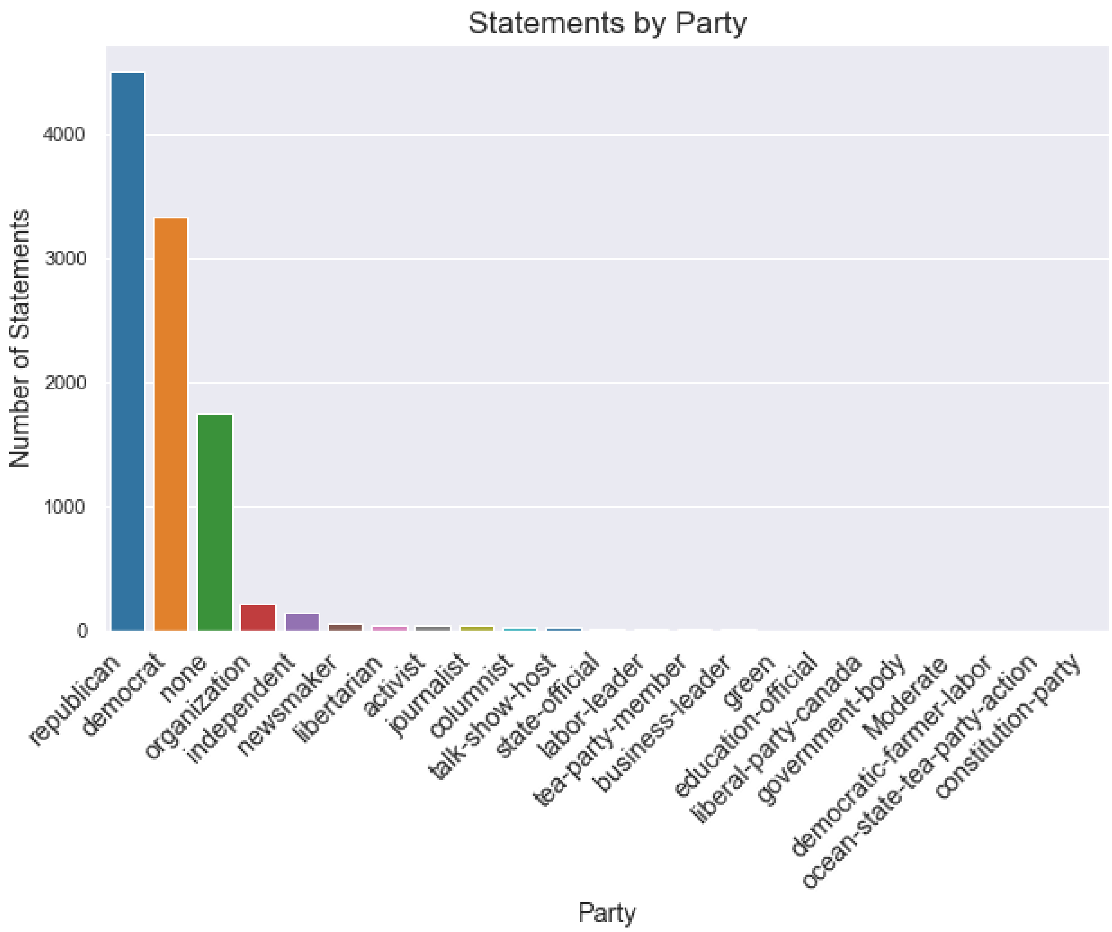
Out[54]:

```
mostly-true    130
half-true      124
true           103
false           67
barely-true     56
pants-fire       8
Name: label, dtype: int64
```

In [21]:

```
#visualize the counts of statements by party

fig, ax = plt.subplots(figsize=(10,6))

ax = sns.countplot(
    data=raw_train,
    x="party", order=raw_train["party"].value_counts().index,
```

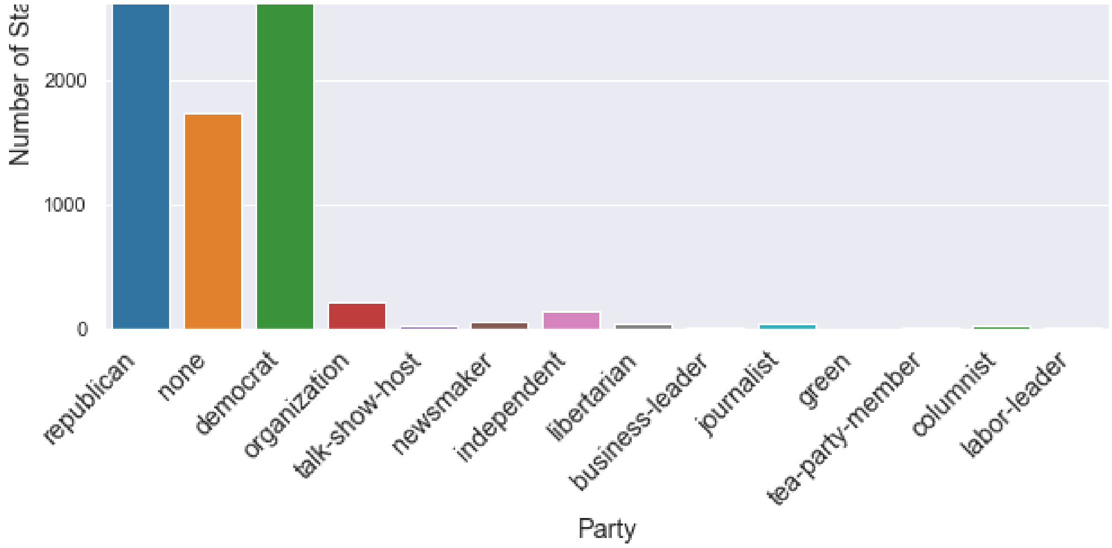
```
    palette='tab10')

ax.set_title('Statements by Party', fontsize='x-large')
ax.set_xlabel('Party',fontsize='large')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignment='ri
ax.set_ylabel('Number of Statements',fontsize='large');
```



There are many parties or professions that the statement orator could belong. The vast majority though are Republicans, Democrats or have no political association.

In [22]:

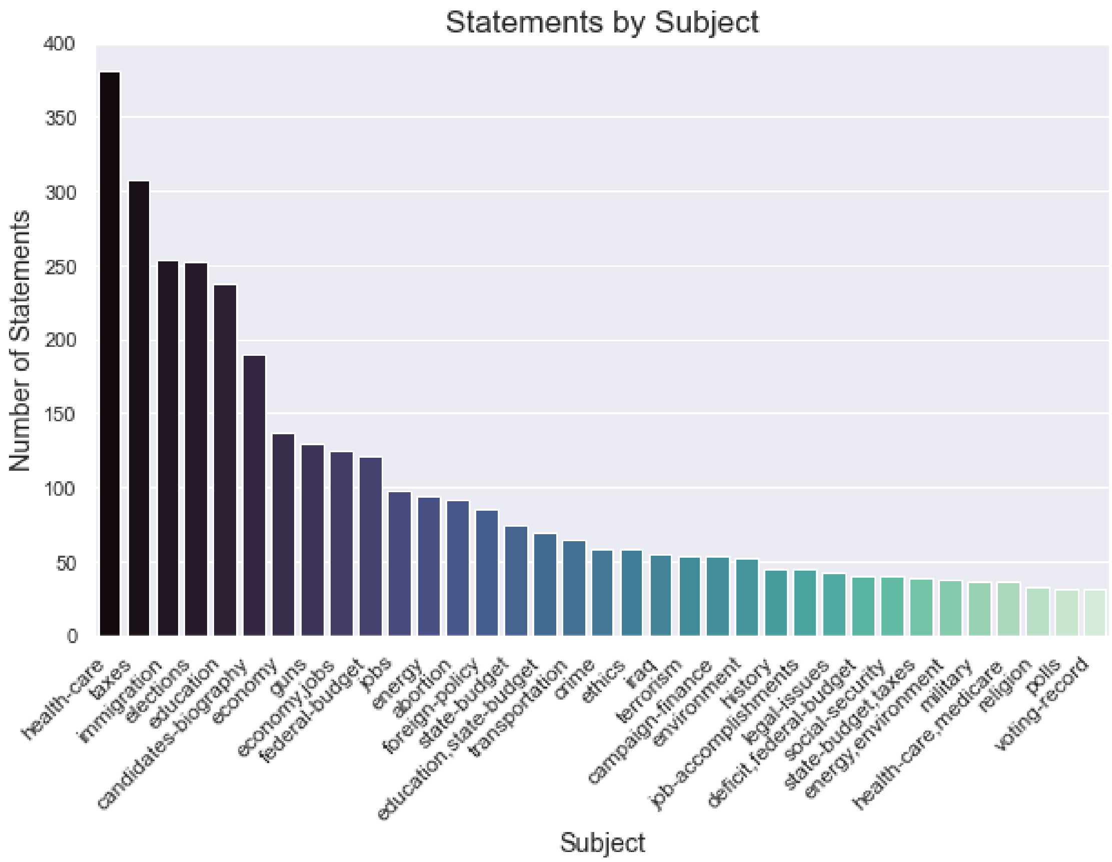
```
#visualize the counts of statements by party

fig, ax = plt.subplots(figsize=(10,6))

ax = sns.countplot(
    data=raw_train,
    x="party", order=raw_train['party'][raw_train['label']=='pants-fire'].val
    palette='tab10')

ax.set_title('Pants on Fire Statements by Party', fontsize='x-large')
ax.set_xlabel('Party',fontsize='large')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignment='ri
ax.set_ylabel('Number of Statements',fontsize='large');
```



Here we see Republicans have the majority of the Pants on Fire statements, but they also have the majority of statements overall, so this graph by itself could be misleading.

In [26]:

```
#visualize the counts of statements by Subject

fig, ax = plt.subplots(figsize=(10,6))

top_35_subjects = raw_train['subject'].value_counts()[:35].index.tolist()
ax = sns.countplot(
    data=raw_train,
    x="subject", order=top_35_subjects,
    palette='mako')

ax.set_title('Statements by Subject', fontsize='x-large')
ax.set_xlabel('Subject',fontsize='large')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignment='ri
ax.set_ylabel('Number of Statements',fontsize='large');
```



Health Care leads as the most talked about subject. It'll be interesting to note if we visualize this information again when performing nlp techniques.

In [280…

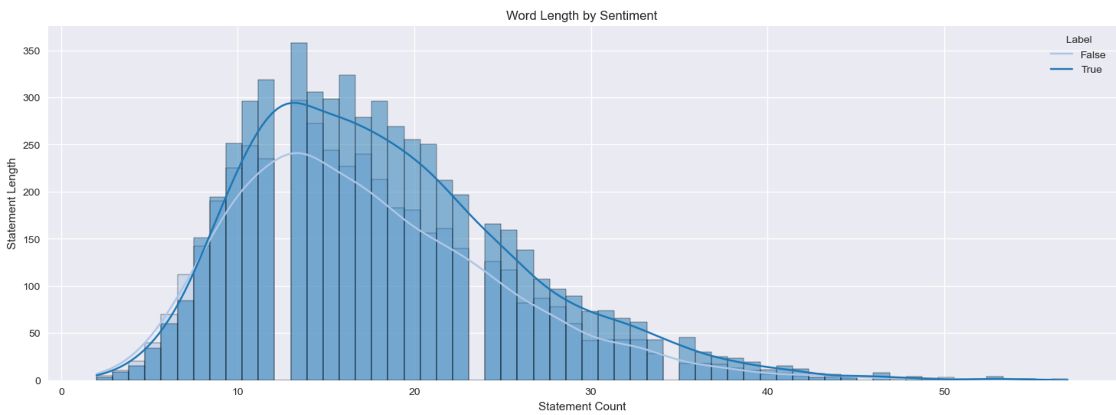
```
# Create new column measuring the length of statements
raw_train['words'] = raw_train['statement'].apply(lambda x: len(x.split() if
```

In [ ]:

```
# Cleaning the dataset a bit to be able to execute graph
raw_train_copy = raw_train.copy()
raw_train_copy = raw_train_copy.fillna(' ')
raw_train_copy = raw_train_copy.reset_index(drop=True)
raw_train_copy = raw_train_copy[raw_train_copy['words']<60]
def label(df):
    df['label'] = df['label'].map({'true': 1,
                                    'mostly-true': 1,
                                    'half-true': 1,
                                    'false': 0,
                                    'barely-true': 0,
                                    'pants-fire': 0})
    return df
raw_train_copy = label(raw_train_copy)
```

In [302…

```
# Visualize the difference between length of true or false statements

plt.style.use('seaborn')

fig, ax = plt.subplots(figsize=(18, 6))

sns.histplot(x='words', data=raw_train_copy, bins='auto', kde=True, hue='labe
ax.set_title('Word Length by Sentiment')
ax.set_xlabel('Statement Count')
ax.set_ylabel('Statement Length')
ax.legend(['False', 'True'], title='Label')

plt.show()
```



The distribution of false and true statements seem to follow the same pattern, with peaks occuring at above 250 words. The difference in the distribution might very easily be caused by the fact that we have more True than False statements, So I don't think this can give me any insights for classification.

Cleaning

To perform Categoral Encoding, the data has to be cleaned in a specific way. All sentences here are lower cased, stripped of stopwords, including additional ones specific for this dataset, other non word characters are removed, as well as punctuation, and the words are lemmetized (remove the inflectional ending of words so they can be classified together). I'll also drop nan values, duplicates, reset the index, and change my labels to binary according to their truthness.

In [157…

```
# Drop rows with nan values in the 'statement' feature
def drop_na(df):
    df = df.dropna(subset=['statement'], axis=0)
    return df
```

In [158…

```
# Drop duplicated rows
def drop_duplicated(df):
    df = df.drop_duplicates()
    return df
```

In [159…

```
# Encode label as binary
def label(df):
    df['label'] = df['label'].map({'true': 1,
                                   'mostly-true': 1,
                                   'half-true': 1,
                                   'false': 0,
                                   'barely-true': 0,
                                   'pants-fire': 0})
    return df
```

In [180…

```
# Lower case, remove stopwords, characters, punctuation and lemmatize words
def clean(text):
    text=text.lower()
    stp=set(stopwords.words("english"))
    stp.update(['say', 'percent', 'state', 'year',
           'said', 'people', 'one'])
    placesp = re.compile('[/(){}\[\]\|@,;]')
    removech= re.compile('[^0-9a-z #+_]')
    st=WordNetLemmatizer()
    text=re.sub(placesp,' ',text)
    text=re.sub(removech,' ',text)
    text=text.split()
    text=[w for w in text if not w in stp]
    text=[st.lemmatize(w) for w in text]
    text=[w for w in text if not w in stp]
    text=" ".join(text)
    text = text.translate(str.maketrans("", "", string.punctuation))
    return text
```

In [181…

```
# Runs the above function in each row of dataframe
def clean_df(df):
    df['statement'] = df['statement'].apply(lambda x: clean(x))
    return df
```

In [162…

```
# Drops all features apart from 'statement' and 'label'
def drop_features(df):
    df = df[['statement','label']]
    return df
```

In [163…

```
# Resets index of dataframe
```

```
# Resets index of dataframe
def reset_index(df):
    df = df.reset_index(drop=True)
    return df
```

In [182…

```
# Pipeline to ensure everything goes according to order
cleaning_pipeline = Pipeline(steps=[
    ('drop_na', FunctionTransformer(drop_na)),
    ('drop_duplicated', FunctionTransformer(drop_duplicated)),
    ('label', FunctionTransformer(label)),
    ('clean', FunctionTransformer(clean_df)),
    ('drop_features', FunctionTransformer(drop_features)),
    ('reset_index', FunctionTransformer(reset_index))
])
```

In [183…

```
# Clean all datasets
df_train_clean = cleaning_pipeline.fit_transform(raw_train)
df_val_clean = cleaning_pipeline.transform(raw_val)
df_test_clean = cleaning_pipeline.transform(raw_test)
```

In [35]:

```
# %store df_train_clean
# %store df_val_clean
# %store df_test_clean
```

```
Stored 'df_train_clean' (DataFrame)
Stored 'df_val_clean' (DataFrame)
Stored 'df_test_clean' (DataFrame)
```

In [184…

```
# Creates X variable and y target for all data
X_train_clean = df_train_clean['statement']
y_train_clean = df_train_clean['label']
X_val_clean = df_val_clean['statement']
y_val_clean = df_val_clean['label']
X_test_clean = df_test_clean['statement']
y_test_clean = df_test_clean['label']
```

In [185…

```
df_train_clean.head()
```

Out[185…

	statement	label
0	annies list political group support third trim...	1
1	decline coal start started natural gas took st...	0
2	hillary clinton agrees john mccain voting give...	0
3	health care reform legislation likely mandate ...	1
4	economic turnaround started end term	0

In [34]:

```
df_train_clean['label'].value_counts(normalize=True)
```

Out[34]:

```
0    0.561719
1    0.438281
Name: label, dtype: float64
```

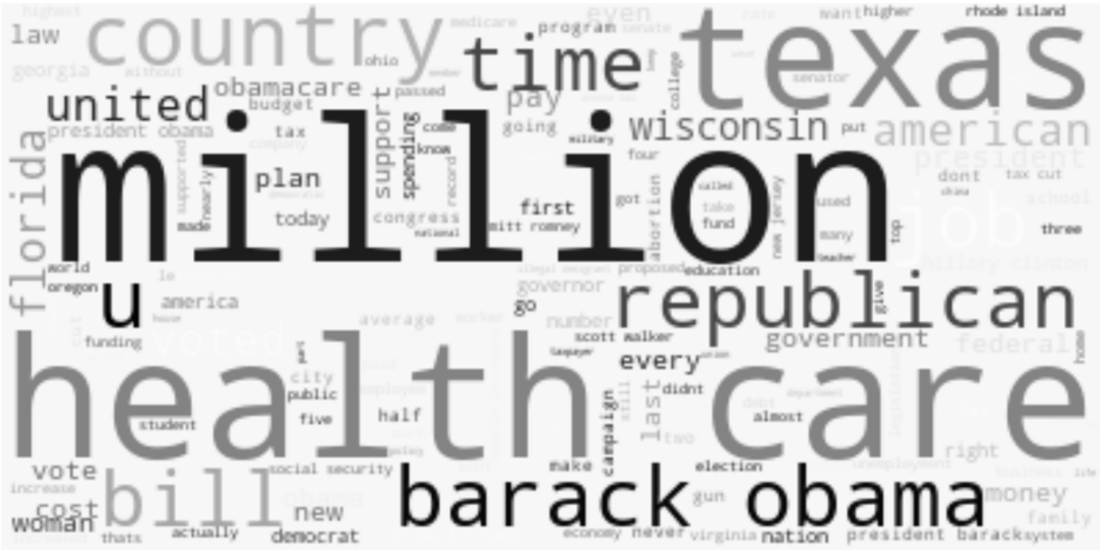
The target is fairly balanced. I will perform random oversampling in some models, but don't expect it to cause major changes.

Word Clouds

Word clouds are a visual display of the data fed to them. The bigger a word appear in them, the more common it appears in the data.
The first one I'll generate is using all the statements in the train data.

In [308…

```
text = ' '.join(df_train_clean['statement'])

# Create and generate a word cloud image:
plt.figure(figsize=(14,10))
wordcloud = WordCloud(background_color='#f7f7f7', colormap='Greys_r', random_

# Display the generated image:
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
```



Below we see the word cloud consisting of all the words in statements in the train data that have been labeled as True.

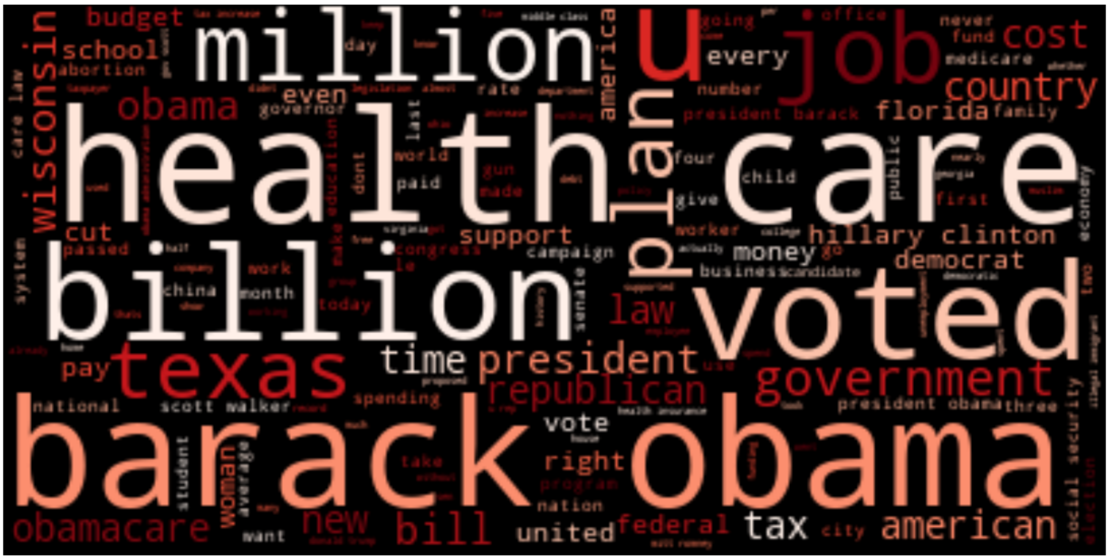
In [306…

```
text = ' '.join(df_train_clean[df_train_clean['label']==0]['statement'])

# Create and generate a word cloud image:
plt.figure(figsize=(14,10))
wordcloud = WordCloud(background_color='Black', colormap='Greens', random_sta

# Display the generated image:
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
```

Below we see the word cloud consisting of all the words in statements in the train data that have been labeled as False.

In [307…

```
text = ' '.join(df_train_clean[df_train_clean['label']==1]['statement'])

# Create and generate a word cloud image:
plt.figure(figsize=(14,10))
wordcloud = WordCloud(background_color='Black', colormap='Reds', random_state

# Display the generated image:
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
```



There isn't much to be gained from trying to analyse these clouds given this dataset and what it's trying to classify. I'll perform other techniques for word and feature extractions throughout the notebook.

II. Data Modeling

Create pipelines and helper functions to train several models at the same time.
The first models will use CountVectorizer as their vectorizer.

In [225…

```
mnb = Pipeline([('Vectorizer', CountVectorizer()),
                ('mnb', MultinomialNB())])

lr = Pipeline([('Vectorizer', CountVectorizer()),
               ('LogisticReg', LogisticRegression())])

dtc = Pipeline([('Vectorizer', CountVectorizer()),
                ('DecisionTree', DecisionTreeClassifier())])

rf = Pipeline([('Vectorizer', CountVectorizer()),
               ('RandomFor', RandomForestClassifier())])

etc = Pipeline([('Vectorizer', CountVectorizer()),
                ('ExtraTrees', ExtraTreesClassifier())])
```

```
                ('ExtraTrees', ExtraTreesClassifier())])

gbc = Pipeline([('Vectorizer', CountVectorizer()),
               ('gradiendboosting', GradientBoostingClassifier())])

svc = Pipeline([('Vectorizer', CountVectorizer()),
                ('SupportVec', SVC())])

sgd = Pipeline([('Vectorizer', CountVectorizer()),
                ('StochGrad', SGDClassifier())])

pac = Pipeline([('Vectorizer', CountVectorizer()),
                ('PassAgress', PassiveAggressiveClassifier())])

mlp = Pipeline([('Vectorizer', CountVectorizer()),
                ('MultiLayerPerc', MLPClassifier())])
```

In [226…

```
models1 = [('MultiNomBa', mnb),
          ('LogisticReg', lr),
          ('DecTreeClass', dtc),
          ('RandomFor', rf),
          ('ExtraTrees', etc),
          ('GradBoost', gbc),
          ('SupportVec', svc),
          ('StochGrad', sgd),
          ('PassAgress', pac),
          ('MultiLayerPerc', mlp)]
```

In [227…

```
def fit_models(models, X, y):
    '''
    Inputs a list of (name, model), X, y
    Fits data into models
    '''
    for name, model in models:
        model.fit(X, y)
    return None
```

In [244…

```
def print_cm_with_labels(y_true,
                         y_pred):
    '''
    Takes the true values and predicted values of a classifier and
    plots a confusion matrix (normalized by predictions) using
    a list of given display labels.
    '''
    disp_labels = ['True', 'Fake']
    cm = confusion_matrix(y_true, y_pred, normalize='true')
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=disp_la

    fig, ax = plt.subplots(figsize=(6,6))
    disp.plot(ax=ax)
    ax.grid(False)
    disp.ax_.set_xticklabels(disp_labels)
    return None
```

In [245…

```
def cross_validate_models(models, X, y, cv=5, scoring='accuracy', cm=False):
    '''
    Input: Models (name, model), X, y
    Optional: cross validation (cv), scoring, confusion matric (cm)
    Output: mean of models scores
```

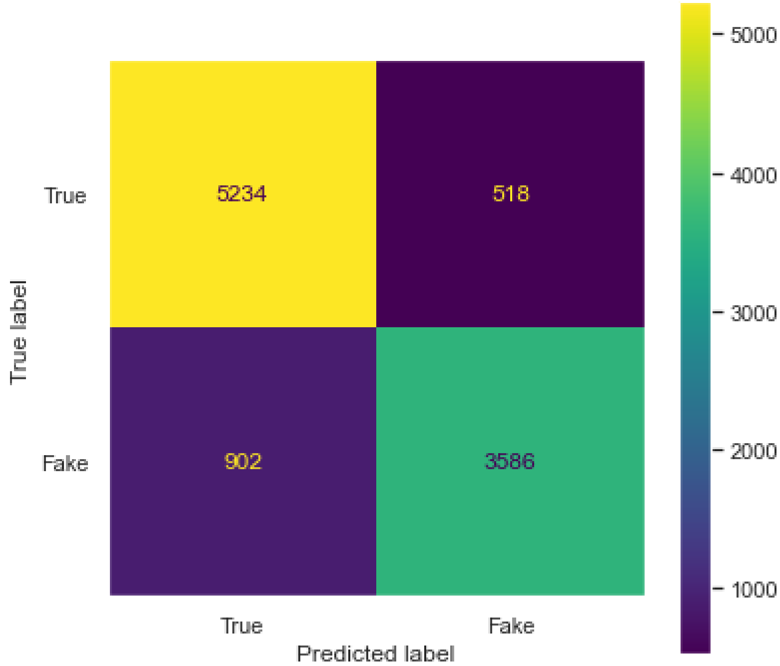
```
    Default cross validation = 5
    Default scoring='accuracy'
    If cm=True, print models confusion matrices. Default=False
    '''
    fit_models(models, X, y)
    results = [(name, cross_validate(model, X, y, scoring=scoring, cv=cv)) fo
    scores = [(result[0], result[1]['test_score'].mean()) for result in resul
    if cm==True:
        for index, model in enumerate(models):
            print(f'{model}')
            print(f'Accuracy: {results[index][1]}')
            print_cm_with_labels(y, model[1].predict(X))
    return scores
```

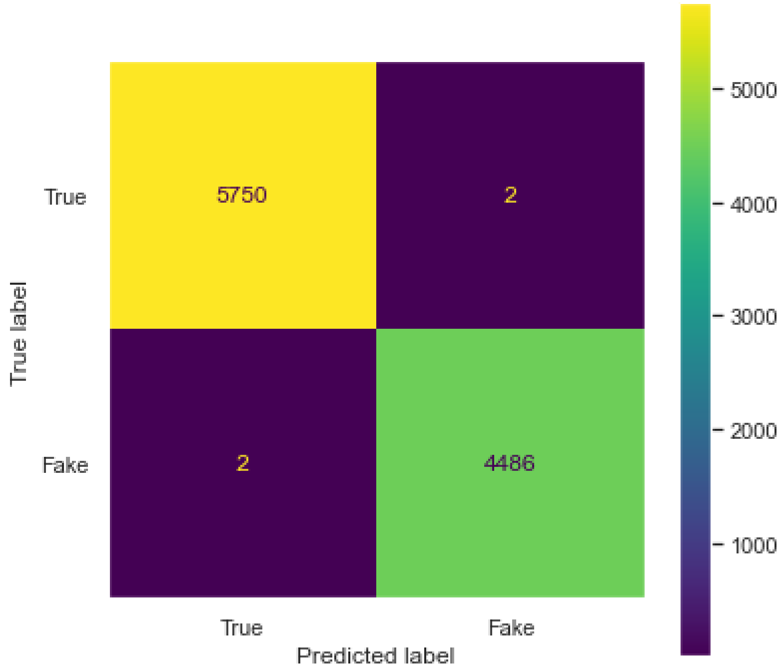
In [50]:

```
scores1 = cross_validate_models(models1, X_train_clean, y_train_clean, cv=2,
```

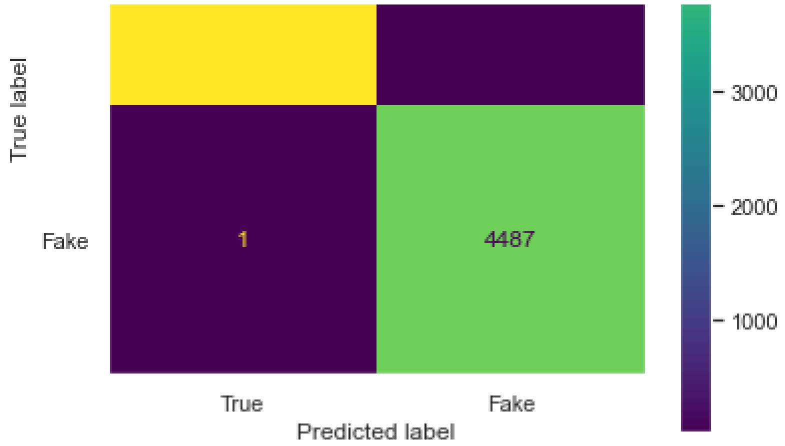
```
('MultiNomBa', Pipeline(steps=[('cv', CountVectorizer()), ('mnb', Multinomial
NB())]))
Accuracy: {'fit_time': array([0.1639967 , 0.11591935]), 'score_time': array
([0.07800412, 0.11352849]), 'test_score': array([0.59902344, 0.59238281])}
('LogisticReg', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('LogisticReg', LogisticRegression())]))
Accuracy: {'fit_time': array([0.37039828, 0.28338933]), 'score_time': array
([0.1532228 , 0.07814908]), 'test_score': array([0.58710938, 0.57832031])}
('DecTreeClass', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('DecisionTree', DecisionTreeClassifier())]))
Accuracy: {'fit_time': array([1.0517242 , 1.05138612]), 'score_time': array
([0.10976958, 0.12790418]), 'test_score': array([0.5640625 , 0.57246094])}
('RandomFor', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('RandomFor', RandomForestClassifier())]))
Accuracy: {'fit_time': array([4.54556251, 4.72434187]), 'score_time': array
([0.51054597, 0.54418159]), 'test_score': array([0.60546875, 0.60234375])}
('ExtraTrees', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('ExtraTrees', ExtraTreesClassifier())]))
Accuracy: {'fit_time': array([7.73035979, 7.5283339 ]), 'score_time': array
([0.622576  , 0.61666083]), 'test_score': array([0.59746094, 0.59863281])}
('GradBoost', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('gradiendboosting', GradientBoostingClassifier())]))
Accuracy: {'fit_time': array([1.68400359, 1.70053792]), 'score_time': array
([0.11409664, 0.11342096]), 'test_score': array([0.59160156, 0.57734375])}
('SupportVec', Pipeline(steps=[('Vectorizer', CountVectorizer()), ('SupportVe
c', SVC())]))
Accuracy: {'fit_time': array([4.99297929, 5.22642541]), 'score_time': array
([4.65467954, 3.80260515]), 'test_score': array([0.60449219, 0.60898438])}
('StochGrad', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('StochGrad', SGDClassifier())]))
Accuracy: {'fit_time': array([0.14897466, 0.17407441]), 'score_time': array
([0.12687755, 0.11644864]), 'test_score': array([0.56210938, 0.55703125])}
('PassAgress', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('PassAgress', PassiveAggressiveClassifier())]))
Accuracy: {'fit_time': array([0.20667052, 0.18715477]), 'score_time': array
([0.12542081, 0.11729622]), 'test_score': array([0.55898437, 0.53867188])}
('MultiLayerPerc', Pipeline(steps=[('Vectorizer', CountVectorizer()),
                ('MultiLayerPerc', MLPClassifier())]))
Accuracy: {'fit_time': array([139.25722003, 108.48316097]), 'score_time': arr
ay([0.14162731, 0.119519  ]), 'test_score': array([0.57265625, 0.55839844])}
```

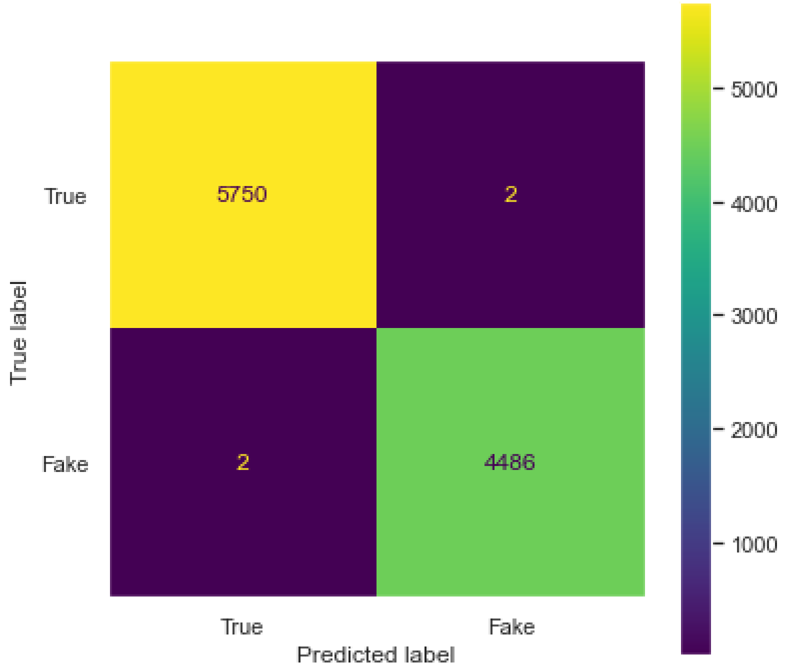

True label
Fake
1375
3113
True
Fake
Predicted label
3500
3000
2500
2000
1500
1000

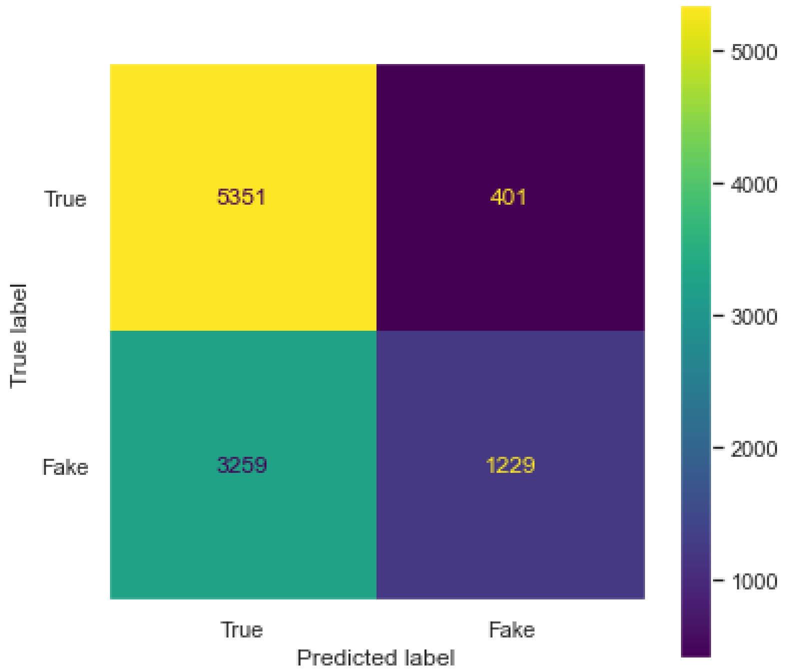

True label
True
Fake
5234
518
902
3586
True
Fake
Predicted label
5000
4000
3000
2000
1000


True label
True
Fake
5750
2
2
4486
True
Fake
Predicted label
5000
4000
3000
2000
1000

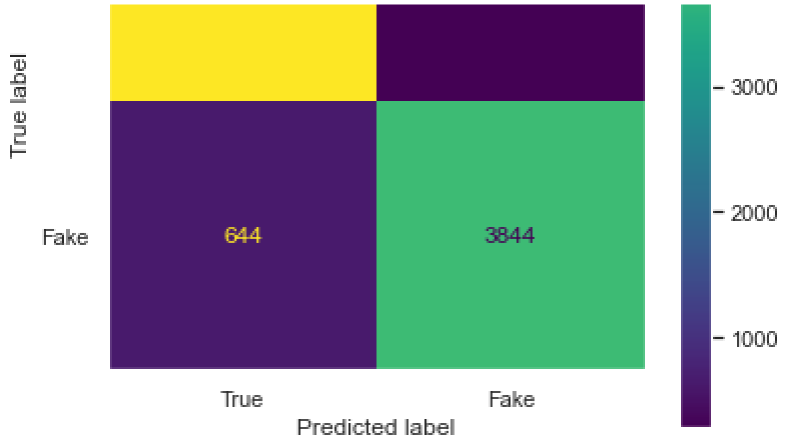

True
5749
3
5000
4000

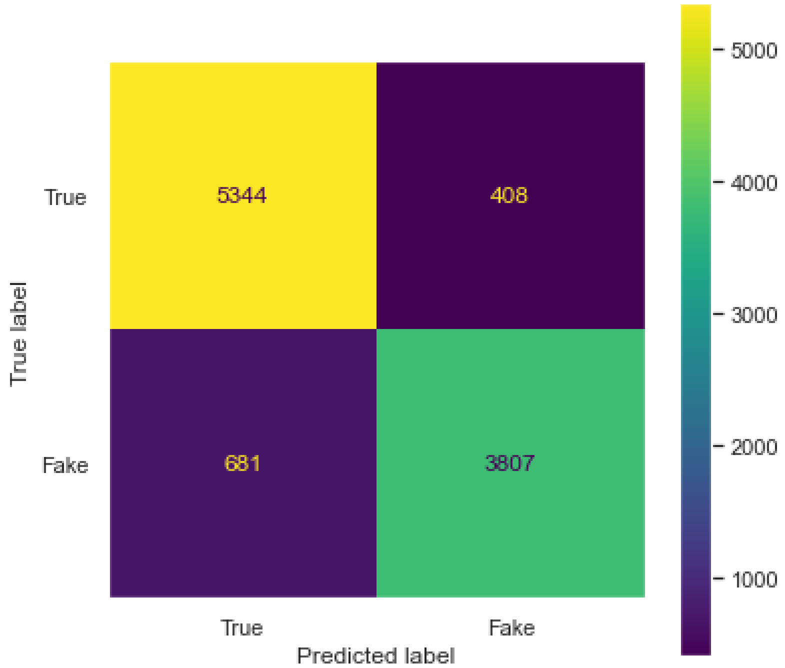

True label
Fake
1
4487
True
Fake
Predicted label
3000
2000
1000

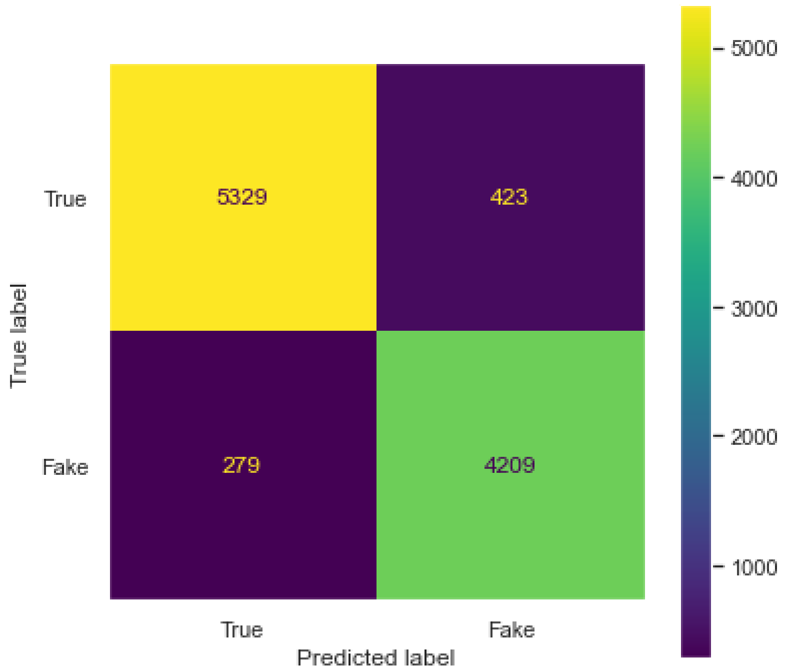

True label
True
Fake
5750
2
2
4486
True
Fake
Predicted label
5000
4000
3000
2000
1000


True label
True
Fake
5351
401
3259
1229
True
Fake
Predicted label
5000
4000
3000
2000
1000

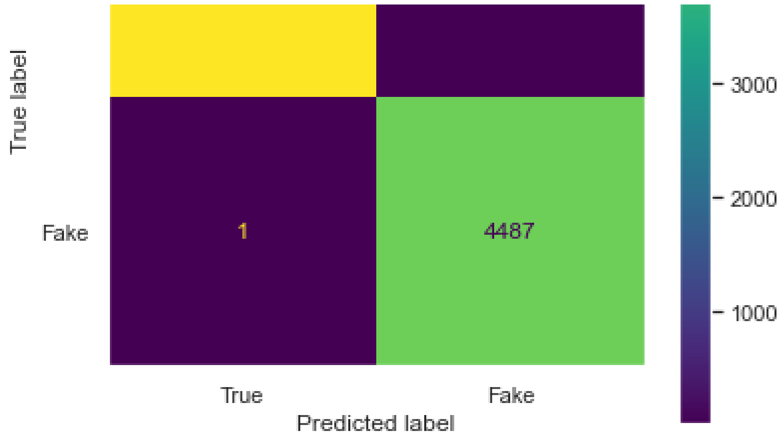

True
5474
278
5000
4000


True label
Fake
644
3844
True
Fake
Predicted label
3000
2000
1000


True label
True
Fake
5344
408
681
3807
True
Fake
Predicted label
5000
4000
3000
2000
1000


True label
True
Fake
5329
423
279
4209
True
Fake
Predicted label
5000
4000
3000
2000
1000


True
5749
3
5000
4000



In [51]:

```
scores1
```

Out[51]:

```
[('MultiNomBa', 0.595703125),
 ('LogisticReg', 0.58271484375),
 ('DecTreeClass', 0.5682617187500001),
 ('RandomFor', 0.60390625),
 ('ExtraTrees', 0.598046875),
 ('GradBoost', 0.58447265625),
 ('SupportVec', 0.60673828125),
 ('StochGrad', 0.5595703125),
 ('PassAgress', 0.548828125),
 ('MultiLayerPerc', 0.5655273437499999)]
```

Trhe accuracy of the models range from around 54% to around 60%. The majority of the confusion matrices displayed look really overfit. That's something I'll try to address during the hyperparameter tuning stage.

I'll now use Tfidf vectorizer for the same models to see if there's an improvement.

In [52]:

```
mnb_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                ('mnb', MultinomialNB())])

lr_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                ('LogisticReg', LogisticRegression())])

dtc_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                ('DecisionTree', DecisionTreeClassifier())])

rf_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                ('RandomFor', RandomForestClassifier())])

etc_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                ('ExtraTrees', ExtraTreesClassifier())])

gbc_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                ('gradiendboosting', GradientBoostingClassifier())])

svc_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                 ('SupportVec', SVC())])

sgd_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                 ('StochGrad', SGDClassifier())])

pac_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                 ('PassAgress', PassiveAggressiveClassifier())])

mlp_tfidf = Pipeline([('Vectorizer', TfidfVectorizer()),
                 ('MultiLayerPerc', MLPClassifier())])
```

In [53]:

```
models2 = [('MultiNomBa', mnb_tfidf),
          ('LogisticReg', lr_tfidf),
          ('DecTreeClass', dtc_tfidf),
          ('RandomFor', rf_tfidf),
          ('ExtraTrees', etc_tfidf),
          ('GradBoost', gbc_tfidf),
          ('SupportVec', svc_tfidf),
          ('StochGrad', sgd_tfidf),
          ('PassAgress', pac_tfidf),
          ('MultiLayerPerc', mlp_tfidf)]
```

In [54]:

```
scores2 = cross_validate_models(models2, X_train_clean, y_train_clean, cv=2)
```

In [55]:

```
scores2
```

Out[55]:

```
[('MultiNomBa', 0.5951171875000001),
 ('LogisticReg', 0.6005859375),
 ('DecTreeClass', 0.55810546875),
 ('RandomFor', 0.59990234375),
 ('ExtraTrees', 0.5960937500000001),
 ('GradBoost', 0.5801757812499999),
 ('SupportVec', 0.6017578125),
 ('StochGrad', 0.58095703125),
 ('PassAgress', 0.55),
 ('MultiLayerPerc', 0.5570312500000001)]
```

Trhe accuracy of the models did not increase by changing only the vectorizer alone. Since we have many variables to try in the different models (different hyper parameters, vectorizers and n-gram range), I chose to adapt my function to evaluate a model at a time, but now we can specify those variables as arguments. This should save me time since I won't go through the whole pipeline everytime when wanting to evaluate a model.

I'll also be using the validation data to check the models accuracy from now on.

In [246…

```
def cross_validate_model(model_name, vectorizer, X, y, cm=False, params=False
    '''
    Input: Model name (str), Vectorizer (str) X, y
    Optional: confusion matric (cm), gridsearch parameters (params), gridsear
              random over sampling (ros), ngram range (ngram_range)
    Output: model validation accuracy
    If cm=True, print models confusion matrices. Default=False
    If params, performs gridsearch for best parameters
    If params_rs, performs randomized gridsearch for best parameters
    gs_cv specifies the split of X that will be use to gridsearch and to vali
    If ros, performs random over sampling
    ngram_range gives the model which ngram range to use with the vectorizer
                default is for unigrams only (1,1), (1,2) considers unigrams
                (2,2) considers just bigrams, (2,3) considers just bigrams an
    '''
    # instantiate model
    if model_name == 'mnb':
        model = MultinomialNB()
    elif model_name == 'lr':
        model = LogisticRegression()
    elif model_name == 'dtc':
        model = DecisionTreeClassifier()
    elif model_name == 'rf':
```

```
        model = RandomForestClassifier()
    elif model_name == 'etc':
        model = ExtraTreesClassifier()
    elif model_name == 'gbc':
        model = GradientBoostingClassifier()
    elif model_name == 'svc':
        model = SVC()
    elif model_name == 'sgd':
        model = SGDClassifier()
    elif model_name == 'pac':
        model = PassiveAggressiveClassifier()
    elif model_name == 'mlp':
        model = MLPClassifier()

    # create pipeline given vectorizer
    if vectorizer == 'cv':
        pipe = Pipeline([('cv', CountVectorizer(ngram_range=ngram_range)),
               (model_name, model)])
    elif vectorizer == 'tfidf':
        pipe = Pipeline([('tfidf', TfidfVectorizer(ngram_range=ngram_range)),
               (model_name, model)])
    elif vectorizer == 'hash':
        pipe = Pipeline([('hash', HashingVectorizer(ngram_range=ngram_range))
               (model_name, model)])

    # perform random over sampling if ros
    if ros:
        ros = RandomOverSampler()
        X, y = ros.fit_resample(np.array(X).reshape(-1, 1), y)
        X = pd.DataFrame(X).iloc[:,0]

    # fit the data
    pipe.fit(X, y)

    # performs gridsearch if params
    if params:
        grid_search = GridSearchCV(pipe, params, cv=gs_cv)
        grid_search.fit(X, y)
        print(model)
        print(grid_search.best_params_)

        y_pred = grid_search.predict(X)
        acc = accuracy_score(y, y_pred)
        print(f'Training Accuracy: {round(acc, 4)}')
        y_pred_val = grid_search.predict(X_val_clean)
        acc_val = accuracy_score(y_val_clean, y_pred_val)
        print(f'Validation Accuracy: {round(acc_val, 4)}')
        if cm==True:
            print_cm_with_labels(y, grid_search.predict(X))
    elif params_rs:
        grid_search = RandomizedSearchCV(pipe, params_rs, cv=gs_cv)
        grid_search.fit(X, y)
        print(model)
        print(grid_search.best_params_)

        y_pred = grid_search.predict(X)
        acc = accuracy_score(y, y_pred)
        print(f'Training Accuracy: {round(acc, 4)}')
        y_pred_val = grid_search.predict(X_val_clean)
        acc_val = accuracy_score(y_val_clean, y_pred_val)
        print(f'Validation Accuracy: {round(acc_val, 4)}')
        if cm==True:
            print_cm_with_labels(y, grid_search.predict(X))
    else:
        print(model)
```

```
        print(model)
        y_pred = pipe.predict(X)
        acc = accuracy_score(y, y_pred)
        print(f'Training Accuracy: {round(acc, 4)}')
        y_pred_val = pipe.predict(X_val_clean)
        acc_val = accuracy_score(y_val_clean, y_pred_val)
        print(f'Validation Accuracy: {round(acc_val, 4)}')
        if cm==True:
            print_cm_with_labels(y, pipe.predict(X))
    return acc_val
```

Baseline Model

The first model I'll use is Logistic Regression. It is a common classification model to classify binary classes, and a good fit for a baseline model. I'll feed it the raw dataset, in which the texts are not processed.

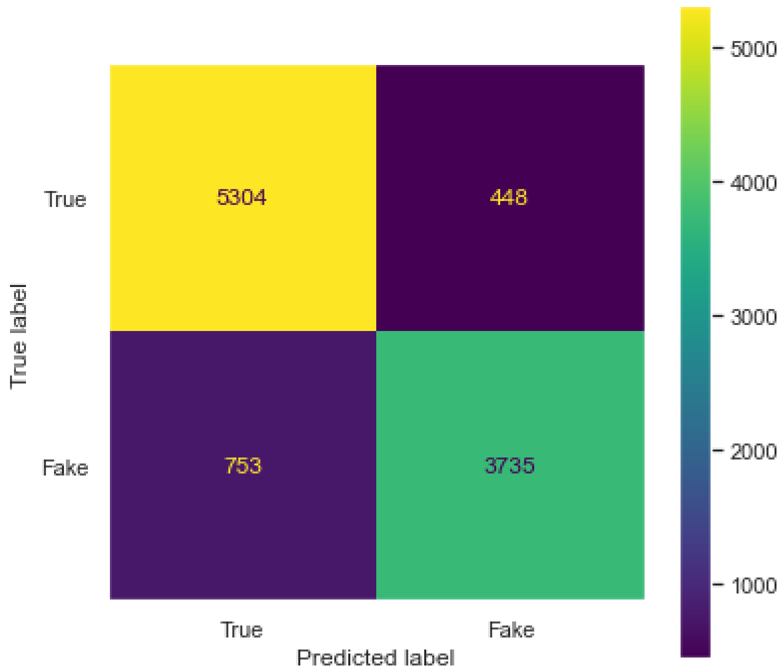
In [58]:

```
# Change the train data enough so the model can run
baseline_train_df = raw_train.copy()
baseline_train_df = baseline_train_df.dropna(subset=['statement'], axis=0)
baseline_train_df = label(baseline_train_df)
baseline_X_train = baseline_train_df['statement']
baseline_y_train = baseline_train_df['label']
```

In [60]:

```
baseline = cross_validate_model('lr', 'cv', baseline_X_train, baseline_y_trai
```

```
LogisticRegression()
Training Accuracy: 0.8827
Validation Accuracy: 0.5802
```



The baseline model has a training accuracy or around 88%, but the cross validation score is around 58%. That probably means that the model is overfit in the training data. Hyperparameter tuning should help to solve that issue in my newer models.

Classification Models

To improve on the baseline model I'll use the preprocessed data, change the vectorizer, add different n-grams, apply random over sampling and perform hyperparameter tuning

add different n-grams, aply random over sampling and perform hyperparameter tuning.
I chose accuracy as a metric to evaluate the model's performance, since both false negatives and false positives can be problematic. I'll also run more complex classification models, tune their hyperparameters, and make use of a neural networks in a separate notebook.
For every model I'll chose a variaty of variables based on the results from the previous ones and from the hyperparameter tuning.

Naive Bayes

In [62]:
```
mnb_params_1 = [{'mnb__alpha':[.001, .01, .05, .1, .2, .4, .6, .8, 1]}]

Mnb_1 = cross_validate_model('mnb', 'cv', X_train_clean, y_train_clean, param
```

```
MultinomialNB()
{'mnb__alpha': 1}
Training Accuracy: 0.7873
Validation Accuracy: 0.6036
```

In [64]:
```
Mnb_2 = cross_validate_model('mnb', 'tfidf', X_train_clean, y_train_clean, pa
```

```
MultinomialNB()
{'mnb__alpha': 1}
Training Accuracy: 0.9876
Validation Accuracy: 0.6121
```

There seem to be a lot of improvement that can be gained by fine tuning, but the Naive Bayes model seem to overfit a lot.
Next I'll try with different models.

Logistic Regression

In [65]:
```
lr_params_1 = [{
    'lr__C':[0.001, 0.1, 1],
    'lr__solver':['lbfgs', 'saga', 'newton-cg', 'liblinear', 'sag'],
    'lr__fit_intercept':[True, False],
    'lr__penalty':['l1', 'l2', 'elasticnet', None],
    'lr__class_weight': ['balanced',  None],
}]

lr_1 = cross_validate_model('lr', 'cv', X_train_clean, y_train_clean, params=
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.744
Validation Accuracy: 0.6168
```

In [232…
```
lr_params_2 = [{
    'lr__C':[0.1],
    'lr__solver':['saga'],
    'lr__fit_intercept':[False],
    'lr__penalty':['l2'],
    'lr__class_weight': [None],
}]
```

In [68]:
```
lr_2 = cross_validate_model('lr', 'tfidf', X_train_clean, y_train_clean, ros=
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.6972
Validation Accuracy: 0.6277
```

In [69]:

```
lr_3 = cross_validate_model('lr', 'tfidf', X_train_clean, y_train_clean, ros=
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.7763
Validation Accuracy: 0.6324
```

In [70]:

```
lr_4 = cross_validate_model('lr', 'hash', X_train_clean, y_train_clean, ros=T
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.6681
Validation Accuracy: 0.6231
```

In [71]:

```
lr_5 = cross_validate_model('lr', 'hash', X_train_clean, y_train_clean, ros=T
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.6977
Validation Accuracy: 0.6207
```

In [72]:

```
lr_6 = cross_validate_model('lr', 'hash', X_train_clean, y_train_clean, ros=T
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.7182
Validation Accuracy: 0.6176
```

For Logistic Regression, the best model uses a tfidf vectorizer with bigram range of (1,2) and ros.

Decision Tree Classifier

In [73]:

```
dtc_params_1 = [{
    'dtc__criterion':['gini', 'entropy'],
    'dtc__max_depth':[1, 2, 5, 8, 12, 16, 22],
    'dtc__ccp_alpha':[.001, .01, .1, .5],
    'dtc__splitter':['random', 'best'],
    'dtc__class_weight': ['balanced',  None]
}]

dtc_1 = cross_validate_model('dtc', 'cv', X_train_clean, y_train_clean, param
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0.001, 'dtc__class_weight': None, 'dtc__criterion': 'entro
py', 'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.5933
Validation Accuracy: 0.5732
```

We can notice a closer proximity between the training and the validation accuracies, suggesting less overfitting of the training data. The number are still very low and need more tuning.

In [74]:
```
dtc_params_2 = [{
    'dtc__criterion':['entropy'],
    'dtc__max_depth':[16],
    'dtc__ccp_alpha':[0],
    'dtc__splitter':['random'],
    'dtc__class_weight': [None]
}]
```

In [75]:
```
dtc_2 = cross_validate_model('dtc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.5993
Validation Accuracy: 0.535
```

In [76]:
```
dtc_3 = cross_validate_model('dtc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.6099
Validation Accuracy: 0.546
```

In [77]:
```
dtc_4 = cross_validate_model('dtc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.5947
Validation Accuracy: 0.5553
```

In [78]:
```
dtc_5 = cross_validate_model('dtc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.5341
Validation Accuracy: 0.5405
```

In [79]:
```
dtc_6 = cross_validate_model('dtc', 'hash', X_train_clean, y_train_clean, ros
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.6139
Validation Accuracy: 0.5654
```

In [80]:
```
dtc_7 = cross_validate_model('dtc', 'hash', X_train_clean, y_train_clean, ros
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.5997
Validation Accuracy: 0.5467
```

In [81]:
```
dtc_8 = cross_validate_model('dtc', 'hash', X_train_clean, y_train_clean, ros
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.6047
Validation Accuracy: 0.5405
```

In [82]:
```
dtc_9 = cross_validate_model('dtc', 'hash', X_train_clean, y_train_clean, ros
```

```
DecisionTreeClassifier()
{'dtc__ccp_alpha': 0, 'dtc__class_weight': None, 'dtc__criterion': 'entropy',
'dtc__max_depth': 16, 'dtc__splitter': 'random'}
Training Accuracy: 0.5425
Validation Accuracy: 0.5421
```

The decision tree models don't seem to work really well for this.

Random Forest Classifier

Gridsearches are not optimal for this amount of models, so I'll start using Randomized search to save time.

In [83]:
```
rf_params_1 = [{
    'rf__criterion':['gini', 'entropy'],
    'rf__max_depth':[1, 2, 5, 8, 12, 16, 22],
    'rf__ccp_alpha':[.001, .01, .1, .5],
    'rf__n_estimators':[100, 500, 1000],
    'rf__class_weight': ['balanced',  None],
    'rf__max_features': ['auto',  'sqrt', 'log2']
}]

rf_1 = cross_validate_model('rf', 'cv', X_train_clean, y_train_clean, params_
```

```
RandomForestClassifier()
{'rf__n_estimators': 500, 'rf__max_features': 'sqrt', 'rf__max_depth': 22, 'r
f__criterion': 'entropy', 'rf__class_weight': 'balanced', 'rf__ccp_alpha': 0.
001}
Training Accuracy: 0.6419
Validation Accuracy: 0.602
```

In [84]:
```
rf_params_2 = [{
    'rf__criterion':['entropy'],
    'rf__max_depth':[22],
    'rf__ccp_alpha':[.001],
    'rf__n_estimators':[500],
    'rf__class_weight': ['balanced'],
    'rf__max_features': ['sqrt']
}]
```

In [85]:
```
rf_2 = cross_validate_model('rf', 'cv', X_train_clean, y_train_clean, ngram_r
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.6575
Validation Accuracy: 0.6121
```

In [86]:
```
rf_3 = cross_validate_model('rf', 'cv', X_train_clean, y_train_clean, ros=Tru
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.6526
Validation Accuracy: 0.6067
```

In [87]:

```
rf_4 = cross_validate_model('rf', 'cv', X_train_clean, y_train_clean, ros=Tru
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.6671
Validation Accuracy: 0.6199
```

In [88]:

```
rf_5 = cross_validate_model('rf', 'tfidf', X_train_clean, y_train_clean, ngra
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.7047
Validation Accuracy: 0.6137
```

In [89]:

```
rf_6 = cross_validate_model('rf', 'tfidf', X_train_clean, y_train_clean, ros=
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.6825
Validation Accuracy: 0.6067
```

In [90]:

```
rf_7 = cross_validate_model('rf', 'tfidf', X_train_clean, y_train_clean, ros=
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.708
Validation Accuracy: 0.6129
```

In [91]:

```
rf_8 = cross_validate_model('rf', 'hash', X_train_clean, y_train_clean, ngram
```

```
RandomForestClassifier()
{'rf__ccp_alpha': 0.001, 'rf__class_weight': 'balanced', 'rf__criterion': 'en
tropy', 'rf__max_depth': 22, 'rf__max_features': 'sqrt', 'rf__n_estimators':
500}
Training Accuracy: 0.646
Validation Accuracy: 0.6137
```

For Random Forests, the best model uses count vectorizer, bigram range of (1,2) and ros.

Extra Trees Classifier

In [94]:

```
etc_params_1 = [{
    'etc__criterion':['gini', 'entropy'],
```

```
    'etc__max_depth':[1, 2, 5, 8, 12, 16, 22],
    'etc__ccp_alpha':[0, .001, .01, .1, .5],
    'etc__n_estimators':[100, 500, 1000],
    'etc__class_weight': ['balanced',  'balanced_subsample', None],
    'etc__max_features': ['auto',  'sqrt', 'log2']
}]

etc_1 = cross_validate_model('etc', 'cv', X_train_clean, y_train_clean, param
```

```
ExtraTreesClassifier()
{'etc__n_estimators': 500, 'etc__max_features': 'sqrt', 'etc__max_depth': 16,
'etc__criterion': 'entropy', 'etc__class_weight': 'balanced', 'etc__ccp_alph
a': 0}
Training Accuracy: 0.7406
Validation Accuracy: 0.602
```

In [96]:

```
etc_params_2 = [{
    'etc__criterion':['entropy'],
    'etc__max_depth':[16],
    'etc__ccp_alpha':[0],
    'etc__n_estimators':[500],
    'etc__class_weight': ['balanced'],
    'etc__max_features': ['sqrt']
}]
```

In [97]:

```
etc_2 = cross_validate_model('etc', 'cv', X_train_clean, y_train_clean, ngram
```

```
ExtraTreesClassifier()
{'etc__ccp_alpha': 0, 'etc__class_weight': 'balanced', 'etc__criterion': 'ent
ropy', 'etc__max_depth': 16, 'etc__max_features': 'sqrt', 'etc__n_estimator
s': 500}
Training Accuracy: 0.713
Validation Accuracy: 0.5522
```

In [98]:

```
etc_3 = cross_validate_model('etc', 'tfidf', X_train_clean, y_train_clean, ng
```

```
ExtraTreesClassifier()
{'etc__ccp_alpha': 0, 'etc__class_weight': 'balanced', 'etc__criterion': 'ent
ropy', 'etc__max_depth': 16, 'etc__max_features': 'sqrt', 'etc__n_estimator
s': 500}
Training Accuracy: 0.7426
Validation Accuracy: 0.5654
```

In [395…

```
# etc_4 = cross_validate_model('etc', 'hash', X_train_clean, y_train_clean, n
```

In [99]:

```
etc_5 = cross_validate_model('etc', 'cv', X_train_clean, y_train_clean, ngram
```

```
ExtraTreesClassifier()
{'etc__ccp_alpha': 0, 'etc__class_weight': 'balanced', 'etc__criterion': 'ent
ropy', 'etc__max_depth': 16, 'etc__max_features': 'sqrt', 'etc__n_estimator
s': 500}
Training Accuracy: 0.7715
Validation Accuracy: 0.6153
```

In [100…

```
etc_6 = cross_validate_model('etc', 'cv', X_train_clean, y_train_clean, ros=T
```

```
ExtraTreesClassifier()
{'etc__ccp_alpha': 0, 'etc__class_weight': 'balanced', 'etc__criterion': 'ent
ropy', 'etc__max_depth': 16, 'etc__max_features': 'sqrt', 'etc__n_estimator
s': 500}
```

```
s': 500}
Training Accuracy: 0.7725
Validation Accuracy: 0.6114
```

In [101…

```
etc_7 = cross_validate_model('etc', 'tfidf', X_train_clean, y_train_clean, ng
```

```
ExtraTreesClassifier()
{'etc__ccp_alpha': 0, 'etc__class_weight': 'balanced', 'etc__criterion': 'ent
ropy', 'etc__max_depth': 16, 'etc__max_features': 'sqrt', 'etc__n_estimator
s': 500}
Training Accuracy: 0.7959
Validation Accuracy: 0.6106
```

In [102…

```
etc_8 = cross_validate_model('etc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
ExtraTreesClassifier()
{'etc__ccp_alpha': 0, 'etc__class_weight': 'balanced', 'etc__criterion': 'ent
ropy', 'etc__max_depth': 16, 'etc__max_features': 'sqrt', 'etc__n_estimator
s': 500}
Training Accuracy: 0.7887
Validation Accuracy: 0.6083
```

In [401…

```
# etc_9 = cross_validate_model('etc', 'hash', X_train_clean, y_train_clean, n
```

In [402…

```
# etc_10 = cross_validate_model('etc', 'hash', X_train_clean, y_train_clean,
```

For extra trees, the best model uses count vectorizer and unigrams and bigrams.

Gradient Boosting Classifier

In [103…

```
gbc_params_1 = [{
    'gbc__learning_rate':[0.05, 0.1],
    'gbc__n_estimators':[40, 70]
}]

gbc_1 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, param
```

```
GradientBoostingClassifier()
{'gbc__learning_rate': 0.1, 'gbc__n_estimators': 70}
Training Accuracy: 0.6283
Validation Accuracy: 0.5701
```

In [104…

```
gbc_params_2 = [{
    'gbc__learning_rate':[0.05, 0.1],
    'gbc__n_estimators':[70, 100, 500]
}]

gbc_2 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, param
```

```
GradientBoostingClassifier()
{'gbc__learning_rate': 0.05, 'gbc__n_estimators': 500}
Training Accuracy: 0.6818
Validation Accuracy: 0.5911
```

In [105…

```
gbc_params_3 = [{
    'gbc__learning_rate':[0.005, 0.01],
    'gbc__n_estimators':[500, 1000]
}]
```

```
gbc_3 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, param
```

```
GradientBoostingClassifier()
{'gbc__learning_rate': 0.01, 'gbc__n_estimators': 1000}
Training Accuracy: 0.6373
Validation Accuracy: 0.5709
```

In [106…

```
gbc_params_4 = [{
    'gbc__learning_rate':[0.001, 0.01],
    'gbc__n_estimators':[1000, 2000]
}]

gbc_4 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, param
```

```
GradientBoostingClassifier()
{'gbc__learning_rate': 0.01, 'gbc__n_estimators': 2000}
Training Accuracy: 0.6655
Validation Accuracy: 0.5841
```

In [107…

```
gbc_params_5 = [{
    'gbc__learning_rate':[0.02, 0.01],
    'gbc__n_estimators':[3000, 2000]
}]

gbc_5 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, param
```

```
GradientBoostingClassifier()
{'gbc__learning_rate': 0.02, 'gbc__n_estimators': 2000}
Training Accuracy: 0.7136
Validation Accuracy: 0.5997
```

In [108…

```
gbc_params_6 = [{
    'gbc__learning_rate':[0.02],
    'gbc__n_estimators':[2000],
    'gbc__loss':['deviance', 'exponential'],
    'gbc__max_features': ['sqrt',  'log2', None]
}]

gbc_6 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, param
```

```
GradientBoostingClassifier()
{'gbc__learning_rate': 0.02, 'gbc__loss': 'deviance', 'gbc__max_features': No
ne, 'gbc__n_estimators': 2000}
Training Accuracy: 0.713
Validation Accuracy: 0.6036
```

In [110…

```
# gbc_params_7 = [{
#     'gbc__criterion':['mae', 'friedman_mse'],
#     'gbc__loss':['deviance'],
#     'gbc__learning_rate':[0.02],
#     'gbc__n_estimators':[2000]
# }]
# gbc_7 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, par
```

In [112…

```
# gbc_params_8 = [{
#     'gbc__loss':['deviance'],
#     'gbc__learning_rate':[0.02],
#     'gbc__n_estimators':[2000],
#     'gbc__max_features': [None],
#     'gbc__subsample': [1, 0.8],
#     'gbc__max_depth': [3, 5, 7, 12]
```

```
#     'gbc__max_depth': [3, 5, 7, 12],
#     'gbc__min_samples_leaf': [1, 5, 15, 25],
# }]
# gbc_8 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, par
```

In [ ]:

```
# gbc_7 = cross_validate_model('gbc', 'cv', X_train_clean, y_train_clean, par
```

Gradient Boosting isn't increasing our validation accuracy

C-Support Vector Classification

In [113…

```
svc_params_1 = [{
    'svc__C':[0.5, 1, 1.5],
    'svc__shrinking':[True, False]
}]

svc_1 = cross_validate_model('svc', 'cv', X_train_clean, y_train_clean, param
```

```
SVC()
{'svc__shrinking': True, 'svc__C': 1}
Training Accuracy: 0.91
Validation Accuracy: 0.6254
```

In [114…

```
svc_params_2 = [{
    'svc__C':[1],
    'svc__gamma':['scale', 'auto'],
    'svc__tol':[0.001, 0.0001],
    'svc__shrinking':[True]
}]

svc_2 = cross_validate_model('svc', 'cv', X_train_clean, y_train_clean, param
```

```
SVC()
{'svc__tol': 0.001, 'svc__shrinking': True, 'svc__gamma': 'scale', 'svc__C':
1}
Training Accuracy: 0.91
Validation Accuracy: 0.6254
```

In [115…

```
svc_params_3 = [{
    'svc__C':[1],
    'svc__gamma':['scale'],
    'svc__tol':[0.01, 0.001],
    'svc__shrinking':[True],
    'svc__class_weight': ['balanced', None]
}]

svc_3 = cross_validate_model('svc', 'cv', X_train_clean, y_train_clean, param
```

```
SVC()
{'svc__tol': 0.001, 'svc__shrinking': True, 'svc__gamma': 'scale', 'svc__clas
s_weight': None, 'svc__C': 1}
Training Accuracy: 0.91
Validation Accuracy: 0.6254
```

In [116…

```
svc_params_4 = [{
    'svc__C':[1],
    'svc__gamma':['scale'],
    'svc__tol':[0.001,],
    'svc__shrinking':[True],
    'svc__class_weight': [None]
}]
```

```
}]
```

In [117…

```
svc_4 = cross_validate_model('svc', 'cv', X_train_clean, y_train_clean, ros=T
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.9292
Validation Accuracy: 0.6168
```

In [118…

```
svc_5 = cross_validate_model('svc', 'cv', X_train_clean, y_train_clean, ros=T
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.9625
Validation Accuracy: 0.6246
```

In [119…

```
svc_6 = cross_validate_model('svc', 'cv', X_train_clean, y_train_clean, ros=T
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.9895
Validation Accuracy: 0.5958
```

In [120…

```
svc_7 = cross_validate_model('svc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.9988
Validation Accuracy: 0.5919
```

In [121…

```
svc_8 = cross_validate_model('svc', 'tfidf', X_train_clean, y_train_clean, ro
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.9987
Validation Accuracy: 0.5888
```

In [122…

```
svc_9 = cross_validate_model('svc', 'hash', X_train_clean, y_train_clean, ngr
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.995
Validation Accuracy: 0.574
```

In [123…

```
svc_10 = cross_validate_model('svc', 'hash', X_train_clean, y_train_clean, ro
```

```
SVC()
{'svc__C': 1, 'svc__class_weight': None, 'svc__gamma': 'scale', 'svc__shrinki
ng': True, 'svc__tol': 0.001}
Training Accuracy: 0.9969
Validation Accuracy: 0.5771
```

The best svc model uses count vectorizer, unigrams and has a validation accuracy of around 62.54%.

around 62.34%.

Stochastic Gradient Descent Classifier

In [124…

```
sgd_params_1 = [{
    'sgd__loss':['hinge', 'log'],
    'sgd__alpha':[0.01, 0.001, 0.0001],
    'sgd__early_stopping': [True]
}]

sgd_1 = cross_validate_model('sgd', 'cv', X_train_clean, y_train_clean, param
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__loss': 'hinge'}
Training Accuracy: 0.6495
Validation Accuracy: 0.6121
```

In [125…

```
sgd_params_2 = [{
    'sgd__loss':['log'],
    'sgd__penalty':['l1', 'l2'],
    'sgd__alpha':[0.1, 0.01],
    'sgd__early_stopping': [True]
}]

sgd_2 = cross_validate_model('sgd', 'cv', X_train_clean, y_train_clean, param
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__loss': 'log', 'sgd__p
enalty': 'l2'}
Training Accuracy: 0.6617
Validation Accuracy: 0.6207
```

In [126…

```
sgd_params_3 = [{
    'sgd__loss':['log'],
    'sgd__penalty':['l2'],
    'sgd__alpha':[0.01],
    'sgd__fit_intercept':[True, False],
    'sgd__learning_rate': ['optimal', 'constant', 'invscaling', 'adaptive'],
    'sgd__early_stopping': [True]
}]

sgd_3 = cross_validate_model('sgd', 'cv', X_train_clean, y_train_clean, param
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.6616
Validation Accuracy: 0.6238
```

In [127…

```
sgd_params_4 = [{
    'sgd__loss':['log'],
    'sgd__penalty':['l2'],
    'sgd__alpha':[0.01],
    'sgd__fit_intercept':[False],
    'sgd__learning_rate': ['optimal'],
    'sgd__early_stopping': [True]
}]

sgd_4 = cross_validate_model('sgd', 'cv', X_train_clean, y_train_clean, param
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
```

```
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.662
Validation Accuracy: 0.6285
```

In [128…

```
sgd_5 = cross_validate_model('sgd', 'tfidf', X_train_clean, y_train_clean, pa
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.6274
Validation Accuracy: 0.5724
```

In [129…

```
sgd_6 = cross_validate_model('sgd', 'hash', X_train_clean, y_train_clean, par
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.6213
Validation Accuracy: 0.5896
```

In [130…

```
sgd_7 = cross_validate_model('sgd', 'tfidf', X_train_clean, y_train_clean, ro
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.6627
Validation Accuracy: 0.6254
```

In [131…

```
sgd_8 = cross_validate_model('sgd', 'cv', X_train_clean, y_train_clean, ros=T
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.6633
Validation Accuracy: 0.6207
```

In [132…

```
sgd_9 = cross_validate_model('sgd', 'tfidf', X_train_clean, y_train_clean, ng
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.672
Validation Accuracy: 0.5818
```

In [133…

```
sgd_10 = cross_validate_model('sgd', 'cv', X_train_clean, y_train_clean, ngra
```

```
SGDClassifier()
{'sgd__alpha': 0.01, 'sgd__early_stopping': True, 'sgd__fit_intercept': Fals
e, 'sgd__learning_rate': 'optimal', 'sgd__loss': 'log', 'sgd__penalty': 'l2'}
Training Accuracy: 0.7182
Validation Accuracy: 0.6269
```

The best validation accuracy for SGD classifier is 62.85%, and is from a model with cv as vectorizer and uses unigrams only.

Passive Aggressive Classifier

In [134…

```
pac_params_1 = [{
    'pac__C':[0.5, 1.0, 1.5, 2.0],
    'pac__fit_intercept':[True,False]
```

```
}]

pac_1 = cross_validate_model('pac', 'cv', X_train_clean, y_train_clean, param
```

```
PassiveAggressiveClassifier()
{'pac__C': 1.5, 'pac__fit_intercept': True}
Training Accuracy: 0.9261
Validation Accuracy: 0.56
```

In [135…

```
pac_params_2 = [{
    'pac__C':[1.5],
    'pac__fit_intercept':[True],
    'pac__class_weight': ['balanced', None],
    'pac__average': [True, False, 5, 10]
}]

pac_2 = cross_validate_model('pac', 'cv', X_train_clean, y_train_clean, param
```

```
PassiveAggressiveClassifier()
{'pac__C': 1.5, 'pac__average': 10, 'pac__class_weight': None, 'pac__fit_inte
rcept': True}
Training Accuracy: 0.9536
Validation Accuracy: 0.5561
```

It doesn't seem like the valdiation accuracy will improve for these models, so I'll stop the tuning here.

Multi-layer Perceptron Classifier

In [135…

```
# mlp_params_1 = [{
#     'mlp__activation':['identity', 'logistic', 'tanh', 'relu']
# }]

# mlp_1 = cross_validate_model('mlp', 'cv', X_train_clean, y_train_clean, par
```

```
KeyboardInterrupt
```

In [ ]:

```
# mlp_params_2 = [{
#     'mlp__activation':['identity', 'logistic', 'tanh', 'relu'],
#     'mlp__alpha':[0.01, 0.001, 0.0001],
#     'mlp__learning_rate': ['constant', 'invscaling', 'adaptive'],

# }]
```

The Multi-Layer Perceptron models were taking too long to run and were interupted because of time constrainsts.

Embedding

Word embedding in NLP consists in adding meaning to a word by breaking it down into n-dimensional vectors in such a way that vectors that are close in that space share meaning or context. I've done exploration of several techniques using word embeddings, starting with Word2Vec and Glove, which can be found on the Word2Vec_Glove Notebook.

In [261…

```
#
```

```
#
#
#
```

Clustering

The work regarding Clustering can be found in the Clustering Notebook.

In [264…

```
#
#
#
```

Latent Dirichlet Analisys

The topic exploration of this work is within the LDA Notebook.

In [265…

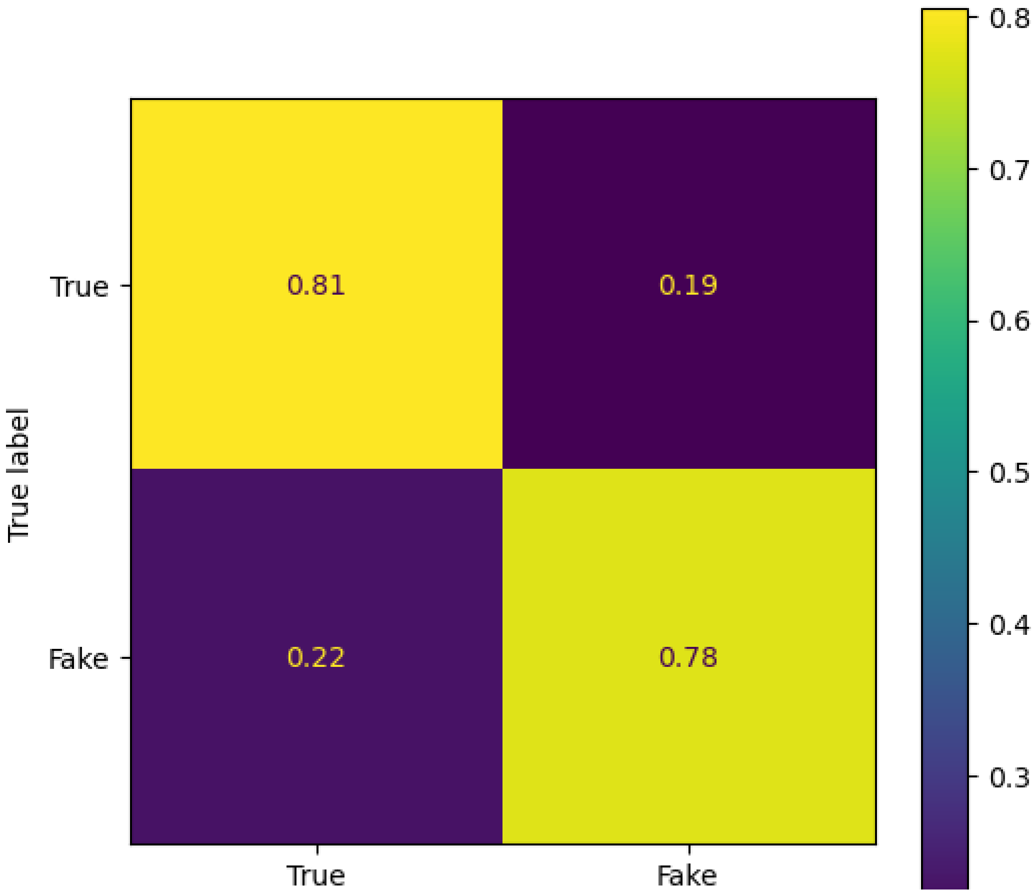
```
#
#
#
```

III. Final Model

In [247…

```
lr_best = cross_validate_model('lr', 'tfidf', X_train_clean, y_train_clean, r
```

```
LogisticRegression()
{'lr__C': 0.1, 'lr__class_weight': None, 'lr__fit_intercept': False, 'lr__pen
alty': 'l2', 'lr__solver': 'saga'}
Training Accuracy: 0.7907
Validation Accuracy: 0.6371
```



The model with the highest accuracy is the ...

In [266...

```
# Show library with accuracies
# Show confusion matrix of best model
# Show model performance graph
#
```

IV. Results

Now it's time to run our final model against the test set:

In [ ]:

```
# Create model again
# Give test accuracy
# Print test Confusion Matrix
```

In [ ]:

```

```

V. Reccommendations

In [267...

```
#
#
#
```

Next Steps

For further development, I propose:

- Create models for different languages
  - Different languages have different semantic structures. If this model is to be reproduced for a different language, we'd need fo find pre-trained embeddings in that language to use in our vocabulary
- Use the Metadata
  - The person making the statement, their political affiliation, other characteristics may affect how the model operates. If we have that information for new statements, it could give us a more accurate classification

Contact

For any further questions, feel free to reach me:

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Github

LinkedIn

References:

Reimche, Roman. (2018). Comparison of the diffusion of real and fake news in social networks.. 10.13140/RG.2.2.35221.22243.
"Liar, Liar Pants on Fire": A New Benchmark Dataset for Fake News Detection (Wang, ACL 2017)
Where is Your Evidence: Improving Fact-checking by Justification Modeling (Alhindi et al., 2018)
Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation.

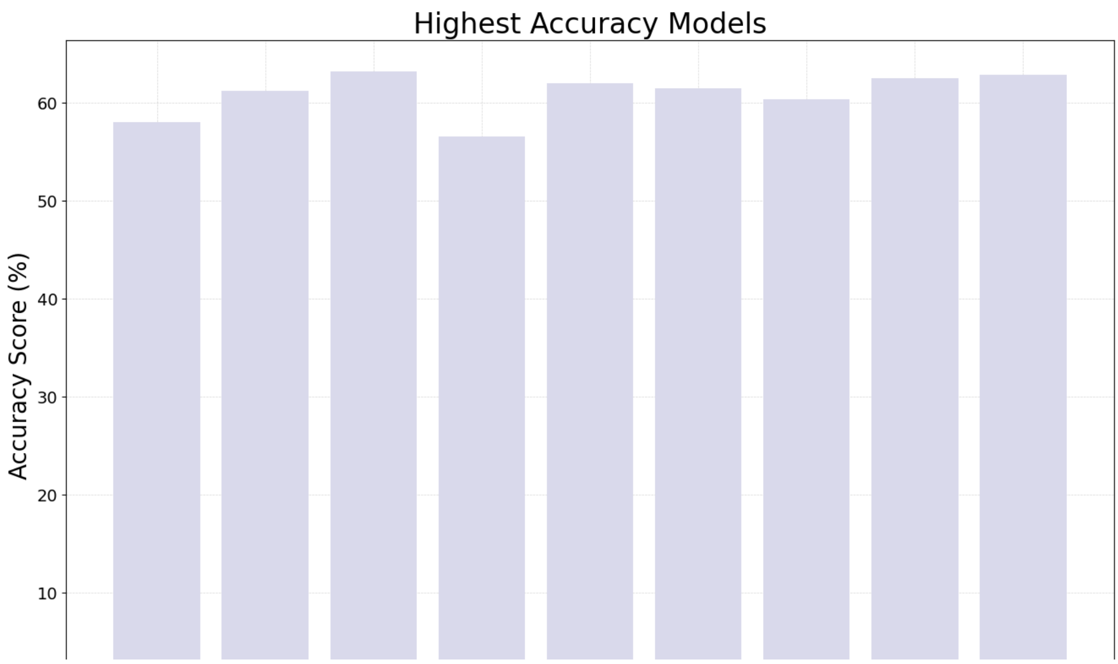
In [ ]:

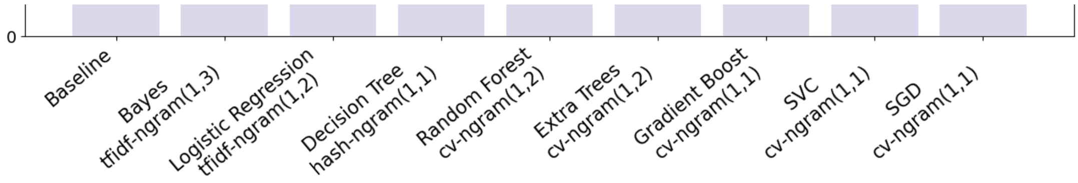
In [220…

```
skyler_graph = {'Baseline': 58.02, 'Bayes        \ntfidf-ngram(1,3)': 61.21,
                'Decision Tree    \nhash-ngram(1,1)': 56.54, 'Random Forest\nc
                'Gradient Boost\ncv-ngram(1,1)': 60.36, 'SVC        \ncv-ngram
```

In [224…

```
# Visualize the chages from baseline to tuned models
plt.style.use('default')

fig, ax = plt.subplots(figsize=(16, 10))

c = ['#d9d9eb', '#d9d9eb', '#d9d9eb', '#d9d9eb',
     '#d9d9eb', '#d9d9eb', '#d9d9eb', '#d9d9eb', '#d9d9eb']

model_names = [model_name for model_name, value in skyler_graph.items()]
model_scores = [value for model_name, value in skyler_graph.items()]

plt.bar(model_names, model_scores, color=c, zorder=3)

ax.set_title('Highest Accuracy Models', fontsize=24)
plt.xticks(rotation=40, ha='right', fontsize=16)
plt.yticks(fontsize=14)
ax.set_ylabel('Accuracy Score (%)', fontsize=20)

plt.grid(linestyle = '--', linewidth = 0.5, alpha=.5, zorder=0)
plt.show()
# plt.savefig('./images/skyler_graph_01')
```






```
<Figure size 640x480 with 0 Axes>
```

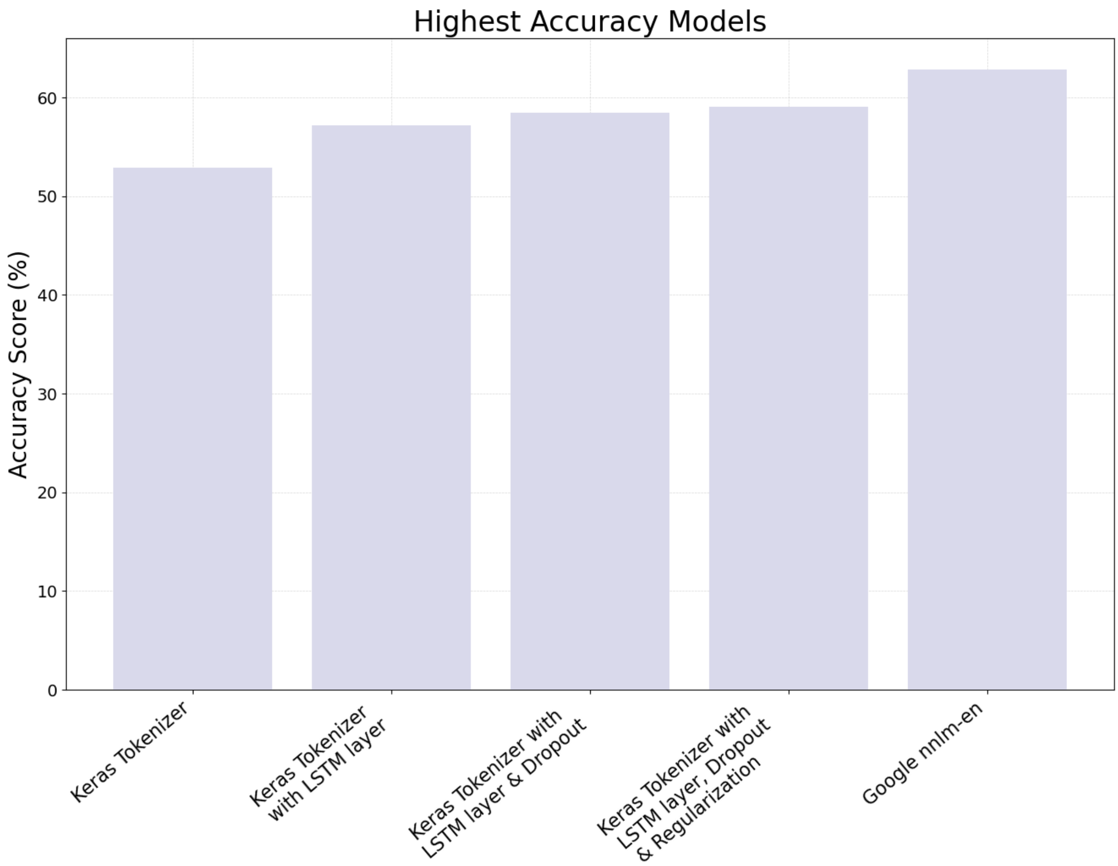
Best Accuracies

In [256…

```
skyler_graph2 = {'Keras Tokenizer': 52.85,  'Keras Tokenizer \n with LSTM lay
                'Keras Tokenizer with \n      LSTM layer, Dropout\n & Regular
```

In [257…

```
# Visualize the chages from baseline to tuned models
plt.style.use('default')

fig, ax = plt.subplots(figsize=(16, 10))

c = ['#d9d9eb', '#d9d9eb', '#d9d9eb', '#d9d9eb', '#d9d9eb']

model_names_nn = [model_name for model_name, value in skyler_graph2.items()]
model_scores_nn = [value for model_name, value in skyler_graph2.items()]

plt.bar(model_names_nn, model_scores_nn, color=c, zorder=3)

ax.set_title('Highest Accuracy Models', fontsize=24)
plt.xticks(rotation=40, ha='right', fontsize=16)
plt.yticks(fontsize=14)
ax.set_ylabel('Accuracy Score (%)', fontsize=20)

plt.grid(linestyle = '--', linewidth = 0.5, alpha=.5, zorder=0)
plt.show()
# plt.savefig('./images/skyler_graph_01')
```



In [ ]:

In [ ]:

In [ ]:

In [ ]: