Load data and preprocess

This code is for loading the data from kaggle, performing any necessary transformations, and storing the modified results in a .csv file for easier access

In [1]:
```
# Automatically load changes in dependency files (may be unnecessary here, but usef
%load_ext autoreload
%autoreload 2
```

First need to download the dataset from Kaggle

I moved the dataset to a local directory for better access to it, since the default installed in .cache/kagglehub

In [2]:
```
# %conda install kagglehub
import kagglehub

# May have to install transformers and gensim for tokenization later, uncomment if
# !pip install gensim
# !pip isntall transformers

# Download latest version
path = kagglehub.dataset_download("goyaladi/twitter-bot-detection-dataset")

print("Path to dataset files:", path)
```

```
c:\Users\maden\anaconda3\envs\COSC325\Lib\site-packages\tqdm\auto.py:21: TqdmWarnin
g: IProgress not found. Please update jupyter and ipywidgets. See https://ipywidget
s.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
Warning: Looks like you're using an outdated `kagglehub` version, please consider up
dating (latest version: 0.3.11)
Path to dataset files: C:\Users\maden\.cache\kagglehub\datasets\goyaladi\twitter-bot
-detection-dataset\versions\2
Path to dataset files: C:\Users\maden\.cache\kagglehub\datasets\goyaladi\twitter-bot
-detection-dataset\versions\2
```

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import LabelEncoder, MinMaxScaler


import os
```

In [4]:
```
# Recursive find for bot data from current directory
path = None
for dirpath, dirnames, filenames in os.walk("."):
    for filename in filenames:
        if filename == "bot_detection_data.csv":
            path = os.path.join(dirpath, filename)

assert path is not None, "bot_detection_data.csv not found in current directory or
print(f"Path to csv file: {path}")
```

```
Path to csv file: .\data\bot_detection_data.csv
```

In [5]:
```
# Read in data into dataframe and get some preliminary information about dataset
df = pd.read_csv(path)

print(df.dtypes)

df.head()
```

```
User ID             int64
Username           object
Tweet              object
Retweet Count       int64
Mention Count       int64
Follower Count      int64
Verified             bool
Bot Label           int64
Location           object
Created At         object
Hashtags           object
dtype: object
```

Out[5]:

	User ID	Username	Tweet	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Lo
0	132131	flong	Station activity person against natural majori...	85	1	2353	False	1	Adl
1	289683	hinesstephanie	Authority research natural life material staff...	55	5	9617	True	0	Sanc
2	779715	roberttran	Manage whose quickly especially foot none to g...	6	2	4363	True	0	Harri
3	696168	pmason	Just cover eight opportunity strong policy which.	54	5	2242	True	1	Martin
4	704441	noah87	Animal sign six data good or.	26	3	8438	False	1	Camac

In [6]:

```
# An issue right off the bat, created at should be Unix epoch time. Convert to date
df["Created At"] = pd.to_datetime(df["Created At"]).astype("int64") // 10**9 # Conv
df["Location"] = df["Location"].astype(str)
df["Hashtags"] = df["Hashtags"].astype(str)

print(df.dtypes)
```

```
User ID              int64
Username            object
Tweet               object
Retweet Count        int64
Mention Count        int64
Follower Count       int64
Verified              bool
Bot Label            int64
Location            object
Created At           int64
Hashtags            object
dtype: object
```

In [7]:
```
# Check for NaN values in the dataset
print(df.isna().sum())
```

```
User ID            0
Username           0
Tweet              0
Retweet Count      0
Mention Count      0
Follower Count     0
Verified           0
Bot Label          0
Location           0
Created At         0
Hashtags           0
dtype: int64
```

In [8]:
```
'''
Looks like data is already fairly clean, the only NaN column is hashtags
We want our model to generalize, so it should not include the User ID or Username a
The bot label will need to be dropped before feeding data to the model.
'''

df = df.drop(["User ID", "Username"], axis=1)
df.head()
```

Out[8]:

	Tweet	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Location	Created At	Ha
0	Station activity person against natural majori...	85	1	2353	False	1	Adkinston	1589210990	
1	Authority research natural life material staff...	55	5	9617	True	0	Sanderston	1669439890	bo
2	Manage whose quickly especially foot none to g...	6	2	4363	True	0	Harrisonfurt	1659928614	
3	Just cover eight opportunity strong policy which.	54	5	2242	True	1	Martinezberg	1628980025	
4	Animal sign six data good or.	26	3	8438	False	1	Camachoville	1586813061	f m

In [9]:
```
'''Our biggest problem now is the string labels - they can't be one-hot-encoded, so
First, create lists of the items, since Tfidf vectorizer requires an iterable.
This works for hashtags and tweets, but not locations - we will have to one-hot enc
'''

txt_data = df["Tweet"] + ' ' + df["Hashtags"]
```

In [10]:
```
''' Initialize vectorizer and fit

 Also this site helped me understand how to use this library and what it does:
 https://kavita-ganesan.com/tfidftransformer-tfidfvectorizer-usage-differences/
 '''
vectorizer = TfidfVectorizer()

txt_data_matrix = vectorizer.fit_transform(txt_data)

print(txt_data_matrix[0])

# More interesting case -- a lot of these which are only one word long have a score
print(txt_data_matrix[1])
```

```
  (0, 799)	0.2835294682766055
  (0, 10)	0.28377526964993016
  (0, 605)	0.2854437101326405
  (0, 20)	0.2861260608232863
  (0, 530)	0.28336623111754666
  (0, 473)	0.2851900744232126
  (0, 545)	0.2826378164501514
  (0, 292)	0.28707885767072966
  (0, 761)	0.28903737666080176
  (0, 275)	0.28967601591872344
  (0, 760)	0.2856985642728896
  (0, 481)	0.28427031555777604
  (0, 527)	0.14805443620650166
  (0, 530)	0.2863499012090043
  (0, 69)	0.2868462995680757
  (0, 692)	0.29010161940964224
  (0, 452)	0.28709623307322024
  (0, 482)	0.28759962306049996
  (0, 791)	0.2896618249846389
  (0, 664)	0.28709623307322024
  (0, 166)	0.2894869124648654
  (0, 648)	0.2865975258513498
  (0, 65)	0.2938508641068884
  (0, 108)	0.2899252684619582
  (0, 460)	0.2893996697446291
```

In [11]:

```
''' The support vector machine will expect lists of fixed size. Currently,
values are stored in a dense matrix, since most entries in the vocabulary are 0.
We'll drop these columns from the DataFrame and work on preprocessing the rest of t
'''

# Save columns first if we need to add them back later (BERT Encoding)
twt_col = df["Tweet"]
hashtag_col = df["Hashtags"]

df = df.drop(['Tweet', 'Hashtags'], axis=1)

txt_data_matrix = txt_data_matrix.astype('float64')
```

In [12]:

```
# Now need to one-hot encode Location
label_encoder = LabelEncoder()

'''Print the length of Location before. We can see that some locations are repeated
 but there are still 25k unique values. Some more preprocessing may be necessary he

'''
print(f"{len(df['Location'])}")

df["Location"] = label_encoder.fit_transform(df["Location"])

df["Location"].unique()
```

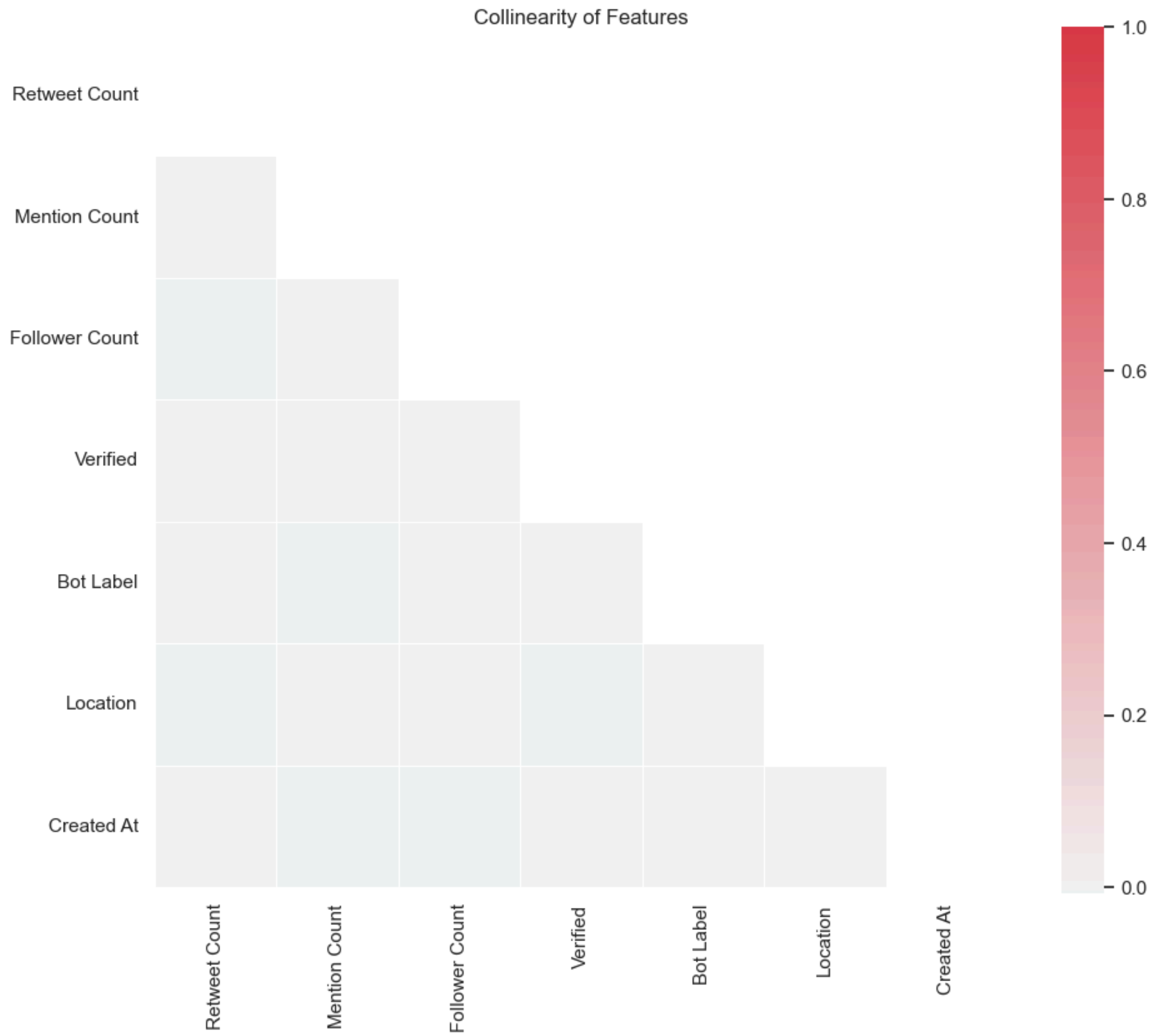
```
50000
```

Out[12]:

```
array([   85, 19263,  6482, ..., 23730,  9388,  2938])
```

```
In [13]: # Next, we check for collinearity among these features
         # Source: https://medium.com/5-minute-eda/5-minute-eda-correlation-heatmap-b57bbb7b
         sns.set_theme(style="white")
         corr = df.corr()
         mask = np.zeros_like(corr, dtype=bool) # Array of 0s with same size and dtype as co
         mask[np.triu_indices_from(mask)] = True # Upper triangle set to True
         f, ax = plt.subplots(figsize=(11, 9))
         cmap = sns.diverging_palette(220, 10, as_cmap=True)
         sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0, square=True, linewidth=.5
         ax.set_title("Collinearity of Features")
```

```
Out[13]: Text(0.5, 1.0, 'Collinearity of Features')
```




```
In [14]: # Normalize values in DataFrame
         scaler = MinMaxScaler()

         cols_to_scale = ["Retweet Count", "Mention Count", "Follower Count", "Location", "C

         for col in cols_to_scale:
             df[col] = scaler.fit_transform(df[[col]])
```

In [15]:
```python
# Combine our text data with df
df_columns = df.columns.tolist()

txt_cols = []
for i in range(1, 971):
    txt_cols.append(f"w{i}")

df_columns.extend(txt_cols)
df = df.to_numpy().astype('float64')

# Convert to dense matrix for stacking
txt_data_matrix = txt_data_matrix.toarray()
print(f"txt_data_matrix.shape: {txt_data_matrix.shape}")
print(f"df.shape: {df.shape}")
combined_data = np.hstack((df, txt_data_matrix))

# Convert back to DataFrame for storage
df = pd.DataFrame(combined_data, columns=df_columns)
df.head()
```

```
txt_data_matrix.shape: (50000, 970)
df.shape: (50000, 7)
```

Out[15]:

	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Location	Created At	w1	w2	w3	...	w96
0	0.85	0.2	0.2353	0.0	1.0	0.003373	0.105605	0.0	0.0	0.0	...	0.
1	0.55	1.0	0.9617	1.0	0.0	0.764465	0.850671	0.0	0.0	0.0	...	0.
2	0.06	0.4	0.4363	1.0	0.0	0.257243	0.762343	0.0	0.0	0.0	...	0.
3	0.54	1.0	0.2242	1.0	1.0	0.432733	0.474930	0.0	0.0	0.0	...	0.
4	0.26	0.6	0.8438	0.0	1.0	0.067188	0.083336	0.0	0.0	0.0	...	0.

5 rows × 977 columns

In [16]:
```python
# Most features don't seem highly correlated, so no need to drop any (no risk here

# Save dataset to csv file

#df.to_csv('data/preprocessed_data.csv', index=True)

# Try parquet, it is allegedly faster and will preserve data types (namely, the lis
df.to_parquet('data/preprocessed_data.parquet')
```

In [17]:
```python
# That data did not seem to work well. Using BERT or Word2Vec, we will revisit the
from transformers import BertTokenizer, BertConfig

tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")

# Example of how it works
text = "the quick brown fox jumps over the lazy dog"
tokens = tokenizer.tokenize(text)
```

```python
token_ids = tokenizer.convert_tokens_to_ids(tokens)
print("Tokens: ", tokens)
print("Token ids: ", token_ids)

# We'll use this one since it adds special tokens like [SEP]
tokens = tokenizer.encode(text)
token_ids = tokenizer.convert_tokens_to_ids(tokens)
print("Encoded: ", tokens)
```

```
None of PyTorch, TensorFlow >= 2.0, or Flax have been found. Models won't be availab
le and only tokenizers, configuration and file/data utilities can be used.
Tokens:  ['the', 'quick', 'brown', 'fox', 'jumps', 'over', 'the', 'lazy', 'dog']
Token ids:  [1996, 4248, 2829, 4419, 14523, 2058, 1996, 13971, 3899]
Encoded:  [101, 1996, 4248, 2829, 4419, 14523, 2058, 1996, 13971, 3899, 102]
```

In [18]:

```python
# Restrict columns to all except for text data
df = df[["Retweet Count", "Mention Count", "Follower Count", "Verified", "Bot Label

df = pd.concat([df, twt_col, hashtag_col], axis=1)

df.head()
```

Out[18]:

	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Location	Created At	Tweet	Hashtags
0	0.85	0.2	0.2353	0.0	1.0	0.003373	0.105605	Station activity person against natural majori...	nan
1	0.55	1.0	0.9617	1.0	0.0	0.764465	0.850671	Authority research natural life material staff...	both live
2	0.06	0.4	0.4363	1.0	0.0	0.257243	0.762343	Manage whose quickly especially foot none to g...	phone ahead
3	0.54	1.0	0.2242	1.0	1.0	0.432733	0.474930	Just cover eight opportunity strong policy which.	ever quickly new I
4	0.26	0.6	0.8438	0.0	1.0	0.067188	0.083336	Animal sign six data good or.	foreign mention

In [19]:

```
# After tokenization, use Word2Vec to embed words: https://tedboy.github.io/nlps/ge
# Padding to make it easier when flattening out into columns
encoded_twt = tokenizer(df["Tweet"].tolist(), padding=True)
df["Tweet"] = encoded_twt["input_ids"]

encoded_hashtags = tokenizer(df["Hashtags"].tolist(), padding=True)
df["Hashtags"] = encoded_hashtags["input_ids"]

import gensim
from gensim.models import Word2Vec

def get_sentence_embedding(tokens, model):
    valid_tokens = [token for token in tokens if token in model.wv]
    if not valid_tokens:
        return np.zeros(model.vector_size)

    # Return mean for embedding of the sentence
    return np.mean(model.wv[valid_tokens], axis=0)
```

```
twt_model = Word2Vec(encoded_twt["input_ids"], min_count=1, vector_size=100, seed=4
hashtag_model = Word2Vec(encoded_hashtags["input_ids"], min_count=1, vector_size=10

df["Tweet"] = df["Tweet"].apply(lambda tokens: get_sentence_embedding(tokens, twt_m
df["Hashtags"] = df["Hashtags"].apply(lambda tokens: get_sentence_embedding(tokens,

df.head()
```

Out[19]:

	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Location	Created At	Tweet	Hash
0	0.85	0.2	0.2353	0.0	1.0	0.003373	0.105605	[0.58442277, -0.44875756, 0.22199216, -0.08359...	[-0.3500 -0.1687 0.135 -0.02
1	0.55	1.0	0.9617	1.0	0.0	0.764465	0.850671	[0.6030587, -0.5392003, 0.2610763, -0.05339244...	[-0.2099 -0.3096 0.2264 -0.0
2	0.06	0.4	0.4363	1.0	0.0	0.257243	0.762343	[0.6021777, -0.5444441, 0.25941738, -0.0580339...	[-0.2025 -0.3181 0.2269 -0.0
3	0.54	1.0	0.2242	1.0	1.0	0.432733	0.474930	[0.62992066, -0.66145974, 0.31215787, -0.02632...	[-0.0573 -0.3561 0.267 -0.04
4	0.26	0.6	0.8438	0.0	1.0	0.067188	0.083336	[0.6314546, -0.7026064, 0.3262894, -0.01022859...	[-0.2017 -0.3091 0.2165 -0.0

In [ ]:

In [20]:

```
df["Hashtags"].head()
```

Out[20]:

```
0    [-0.35002995, -0.16879569, 0.1357387, -0.02084...
1    [-0.20993058, -0.30967736, 0.22648755, -0.0622...
2    [-0.20259608, -0.31819913, 0.22690043, -0.0617...
3    [-0.05733835, -0.35614485, 0.2676731, -0.04486...
4    [-0.20172688, -0.30911303, 0.21654083, -0.0558...
Name: Hashtags, dtype: object
```

In [21]:

```
# Padding looks correct, now flatten out into columns
col_names = df.columns[:-2].tolist()

# The text data all has the same length, so we can flatten them
for i in range(1, len(df["Tweet"].iloc[0])+1):
    col_names.append(f"twt_{i}")
```

```python
for i in range(1, len(df["Hashtags"].iloc[0])+1):
    col_names.append(f"hashtag_{i}")

twt_col = np.vstack(df["Tweet"].values)
hashtag_col = np.vstack(df["Hashtags"].values)
df = df.drop(["Tweet", "Hashtags"], axis=1)

df = np.array(df)
twt_col = np.array(twt_col)
hashtag_col = np.array(hashtag_col)

df = np.hstack((df, twt_col, hashtag_col))

df = pd.DataFrame(df, columns=col_names)
df.head()
```

Out[21]:

	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Location	Created At	twt_1	twt_2	
0	0.85	0.2	0.2353	0.0	1.0	0.003373	0.105605	0.584423	-0.448758	0
1	0.55	1.0	0.9617	1.0	0.0	0.764465	0.850671	0.603059	-0.539200	0
2	0.06	0.4	0.4363	1.0	0.0	0.257243	0.762343	0.602178	-0.544444	0
3	0.54	1.0	0.2242	1.0	1.0	0.432733	0.474930	0.629921	-0.661460	0
4	0.26	0.6	0.8438	0.0	1.0	0.067188	0.083336	0.631455	-0.702606	0

5 rows × 207 columns

In [22]:

```python
# Save and retrain
df.to_parquet('data/bert_encoded_data.parquet')
```

In [23]:

```python
# Now Load dataset and process
# From here on out is a second jupyter notebook appended to this one
```

In [24]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score


import os

RANDOM_STATE = 42
```

In [25]:

```python
import os

# Recursive find for bot data from current directory
path = None
```

```python
for dirpath, dirnames, filenames in os.walk("."):
    for filename in filenames:
        if filename == "bert_encoded_data.parquet":
            path = os.path.join(dirpath, filename)

assert path is not None, "bot_detection_data.csv not found in current directory or
print(f"Path to csv file: {path}")
```

```
Path to csv file: .\data\bert_encoded_data.parquet
```

In [26]:
```python
df = pd.read_parquet(path)

df.head()
```

Out[26]:

	Retweet Count	Mention Count	Follower Count	Verified	Bot Label	Location	Created At	twt_1	twt_2	
0	0.85	0.2	0.2353	0.0	1.0	0.003373	0.105605	0.584423	-0.448758	0
1	0.55	1.0	0.9617	1.0	0.0	0.764465	0.850671	0.603059	-0.539200	0
2	0.06	0.4	0.4363	1.0	0.0	0.257243	0.762343	0.602178	-0.544444	0
3	0.54	1.0	0.2242	1.0	1.0	0.432733	0.474930	0.629921	-0.661460	0
4	0.26	0.6	0.8438	0.0	1.0	0.067188	0.083336	0.631455	-0.702606	0

5 rows × 207 columns

In [27]:
```python
# Get our data X and y before splitting into train and test sets
# We drop the text columns for now to see if the model even needs them for successf
y = df['Bot Label']

X = df[["Retweet Count", "Mention Count", "Follower Count", "Verified", "Location",

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At
0    0.105605
1    0.850671
2    0.762343
3    0.474930
4    0.083336
```

In [28]:
```python
# Check for potential class imbalance, may need to adjust loss function weights
print(len(df[df['Bot Label'] == 1]))
print(len(df[df["Bot Label"] == 0]))
```

```
25018
24982
```

In [29]:
```
# Training
model = svm.SVC(kernel='linear', random_state=RANDOM_STATE)
model.fit(X_train, y_train)
```

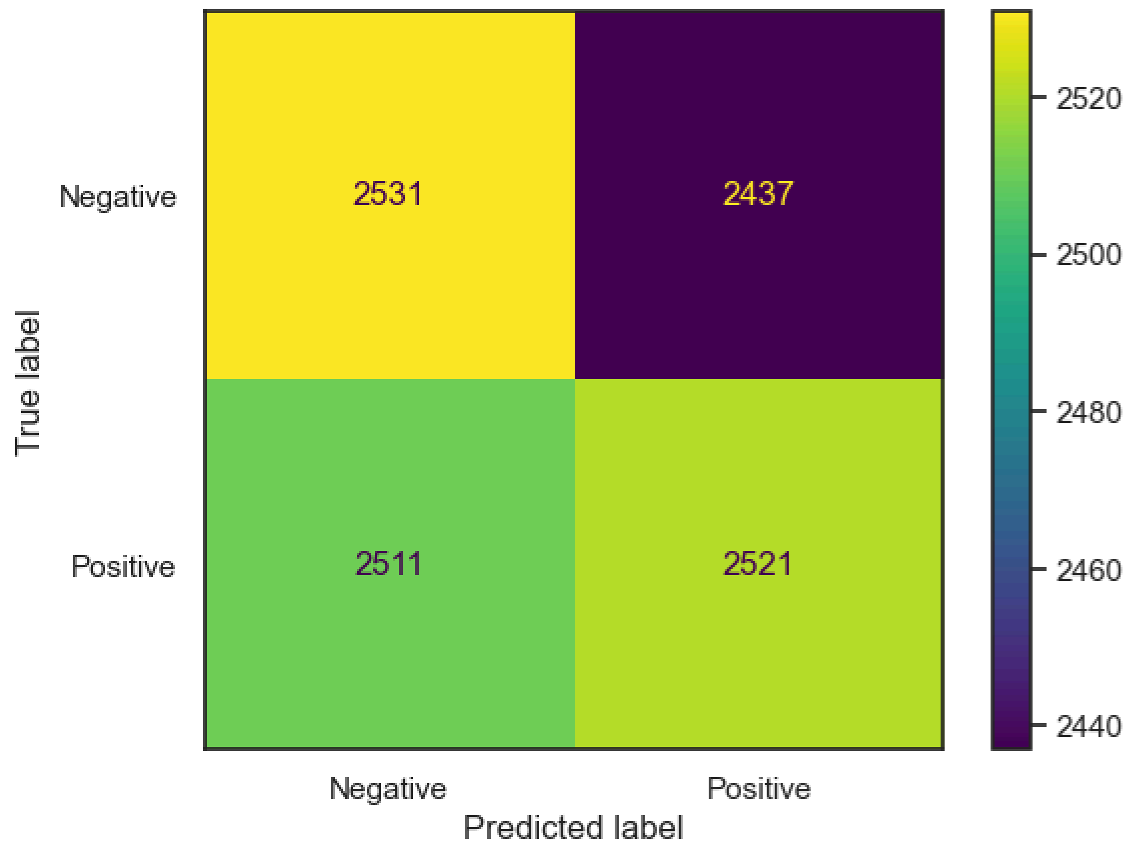
Out[29]:

SVC

```
SVC(kernel='linear', random_state=42)
```

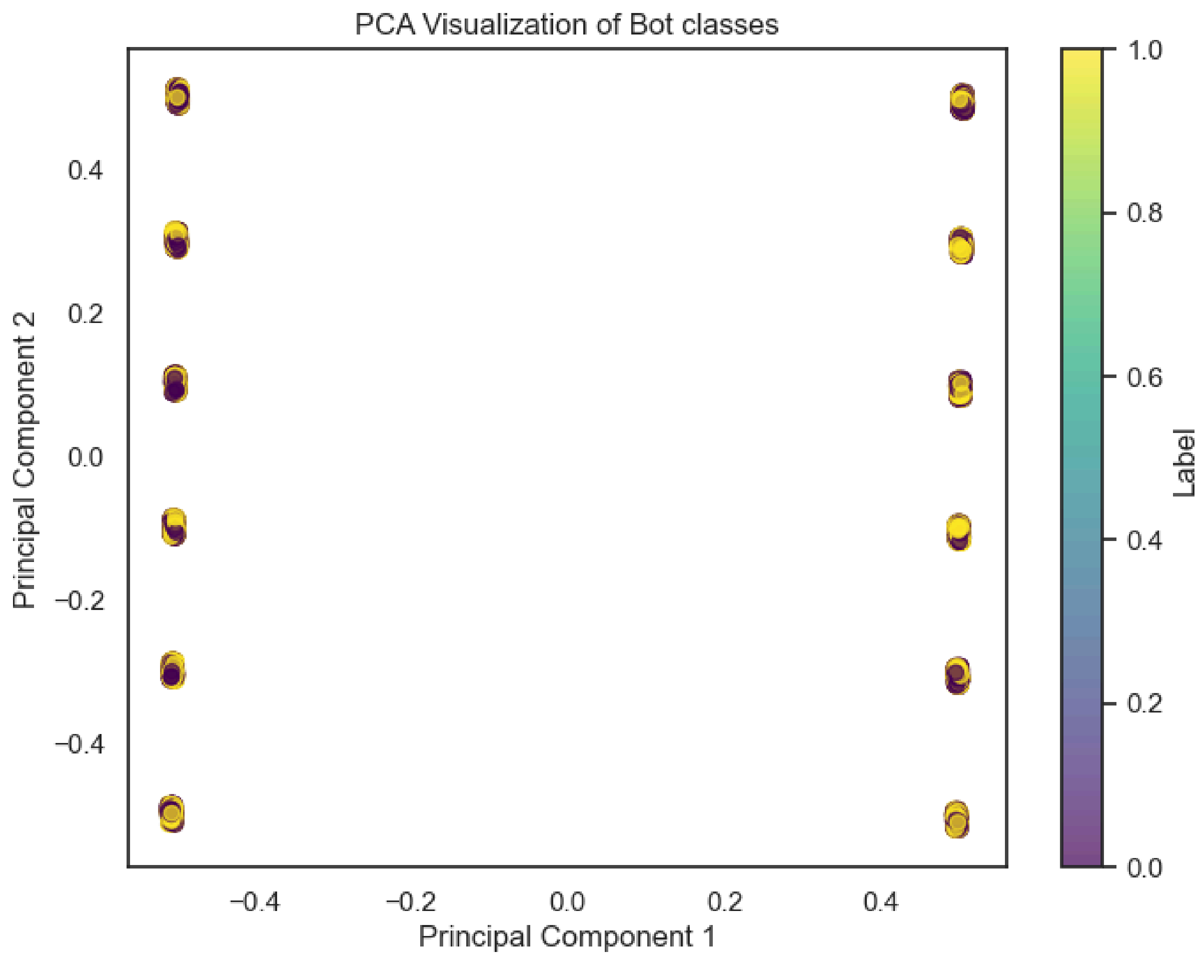
In [30]:
```
# Evaluation
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
y_hat = model.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

```
Accuracy: 0.51
F1 Score: 0.50
Precision: 0.51
Recall: 0.50
```



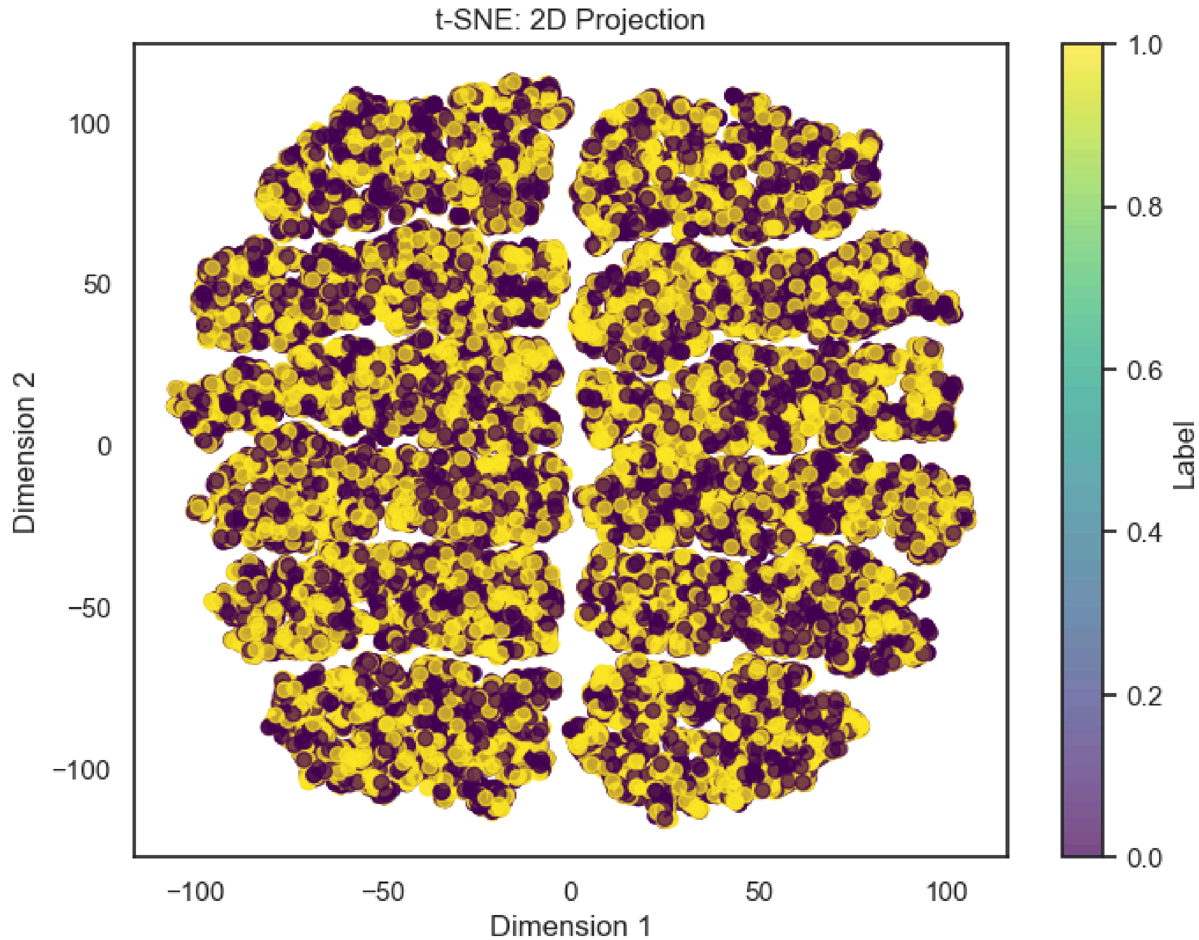
In [31]:

```
# Inspiration: https://www.datacamp.com/tutorial/introduction-t-sne
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA

# PCA reduces feature space by finding directions that capture the most variance
pca = PCA(n_components=3, random_state=RANDOM_STATE)
X_pca = pca.fit_transform(X)

plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis', alpha=0.7)
plt.title("PCA Visualization of Bot classes")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.colorbar(label='Label')
plt.show()
```



In [32]:

```
# Interesting, but doesn't preserve local structure very well, let's look at t-SNE
from sklearn.manifold import TSNE
X_tsne = TSNE(n_components=2, random_state=RANDOM_STATE).fit_transform(X)

plt.figure(figsize=(8, 6))
plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=y, cmap='viridis', alpha=0.7)
plt.title("t-SNE: 2D Projection")
plt.xlabel("Dimension 1")
plt.ylabel("Dimension 2")
plt.colorbar(label='Label')
plt.show()
```



In [33]:

```
# Try training with the text columns

X = df.drop('Bot Label', axis=1)

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373   
1           0.55            1.0          0.9617       1.0  0.764465   
2           0.06            0.4          0.4363       1.0  0.257243   
3           0.54            1.0          0.2242       1.0  0.432733   
4           0.26            0.6          0.8438       0.0  0.067188   

   Created At     twt_1     twt_2     twt_3     twt_4  ...  hashtag_91  \
0    0.105605  0.584423 -0.448758  0.221992 -0.083593  ...    0.125355   
1    0.850671  0.603059 -0.539200  0.261076 -0.053392  ...   -0.117175   
2    0.762343  0.602178 -0.544444  0.259417 -0.058034  ...   -0.124059   
3    0.474930  0.629921 -0.661460  0.312158 -0.026327  ...   -0.214849   
4    0.083336  0.631455 -0.702606  0.326289 -0.010229  ...   -0.122647   

   hashtag_92  hashtag_93  hashtag_94  hashtag_95  hashtag_96  hashtag_97  \
0    0.294862    0.243294   -0.232206    0.374747   -0.269184   -0.382470   
1    0.335634    0.013350   -0.247745    0.262996   -0.240250   -0.224535   
2    0.338809    0.000209   -0.249944    0.263091   -0.238794   -0.226714   
3    0.362426   -0.035149   -0.292454    0.239671   -0.153282   -0.110559   
4    0.329823   -0.002046   -0.246382    0.260587   -0.231789   -0.229471   

   hashtag_98  hashtag_99  hashtag_100  
0    0.024018    0.018229     0.061237  
1    0.108484   -0.118404     0.086830  
2    0.108327   -0.122253     0.091454  
3    0.135174   -0.244549     0.098680  
4    0.106929   -0.122275     0.088122  

[5 rows x 206 columns]
```

In [34]:
```python
# Training
model = svm.SVC(kernel='linear', random_state=RANDOM_STATE)
model.fit(X_train, y_train)
```

Out[34]:

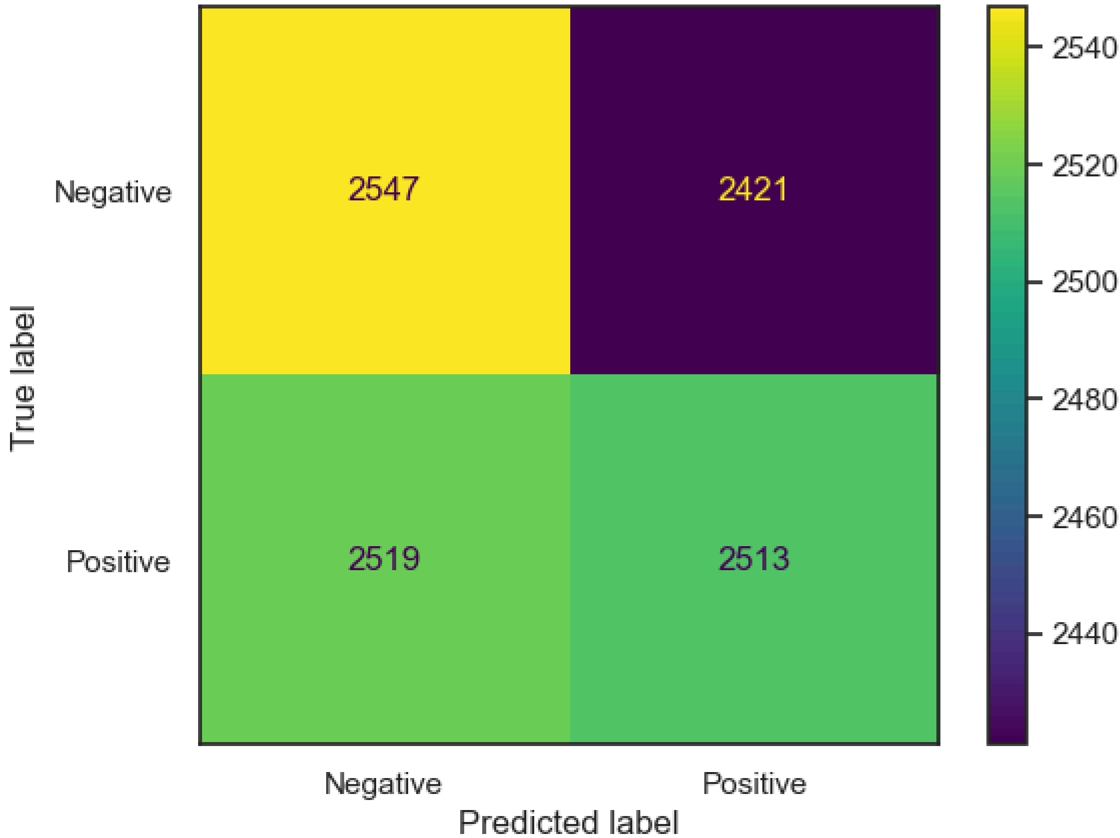
SVC

```
SVC(kernel='linear', random_state=42)
```

In [35]:
```python
# Evaluation
y_hat = model.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))
cm_test = confusion_matrix(y_test, y_hat)
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

```
Accuracy: 0.51
F1 Score: 0.50
Precision: 0.51
Recall: 0.50
```



In [36]:
```
# We'll try with a Random Forest now
from sklearn.ensemble import RandomForestClassifier

X = df[["Retweet Count", "Mention Count", "Follower Count", "Verified", "Location",

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

rf_model = RandomForestClassifier(random_state=RANDOM_STATE)

rf_model.fit(X_train, y_train)
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At
0    0.105605
1    0.850671
2    0.762343
3    0.474930
4    0.083336
```

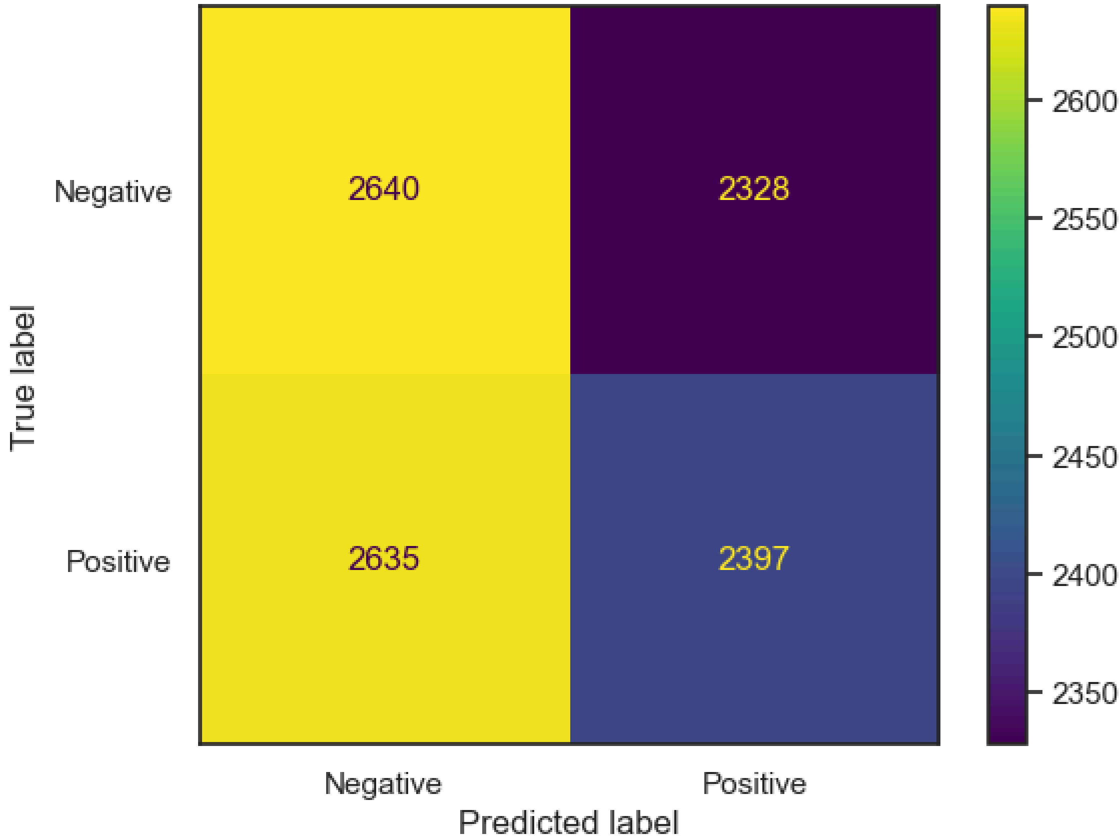
Out[36]:

```
RandomForestClassifier

RandomForestClassifier(random_state=42)
```

In [37]:

```python
y_hat = rf_model.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

```
Accuracy: 0.50
F1 Score: 0.49
Precision: 0.51
Recall: 0.48
```



In [38]:

```
# With text now
X = df.drop('Bot Label', axis=1)

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

rf_model = RandomForestClassifier(random_state=RANDOM_STATE)

rf_model.fit(X_train, y_train)
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373   
1           0.55            1.0          0.9617       1.0  0.764465   
2           0.06            0.4          0.4363       1.0  0.257243   
3           0.54            1.0          0.2242       1.0  0.432733   
4           0.26            0.6          0.8438       0.0  0.067188   

   Created At     twt_1     twt_2     twt_3     twt_4  ...  hashtag_91  \
0    0.105605  0.584423 -0.448758  0.221992 -0.083593  ...    0.125355   
1    0.850671  0.603059 -0.539200  0.261076 -0.053392  ...   -0.117175   
2    0.762343  0.602178 -0.544444  0.259417 -0.058034  ...   -0.124059   
3    0.474930  0.629921 -0.661460  0.312158 -0.026327  ...   -0.214849   
4    0.083336  0.631455 -0.702606  0.326289 -0.010229  ...   -0.122647   

   hashtag_92  hashtag_93  hashtag_94  hashtag_95  hashtag_96  hashtag_97  \
0    0.294862    0.243294   -0.232206    0.374747   -0.269184   -0.382470   
1    0.335634    0.013350   -0.247745    0.262996   -0.240250   -0.224535   
2    0.338809    0.000209   -0.249944    0.263091   -0.238794   -0.226714   
3    0.362426   -0.035149   -0.292454    0.239671   -0.153282   -0.110559   
4    0.329823   -0.002046   -0.246382    0.260587   -0.231789   -0.229471   

   hashtag_98  hashtag_99  hashtag_100  
0    0.024018    0.018229     0.061237  
1    0.108484   -0.118404     0.086830  
2    0.108327   -0.122253     0.091454  
3    0.135174   -0.244549     0.098680  
4    0.106929   -0.122275     0.088122  

[5 rows x 206 columns]
```

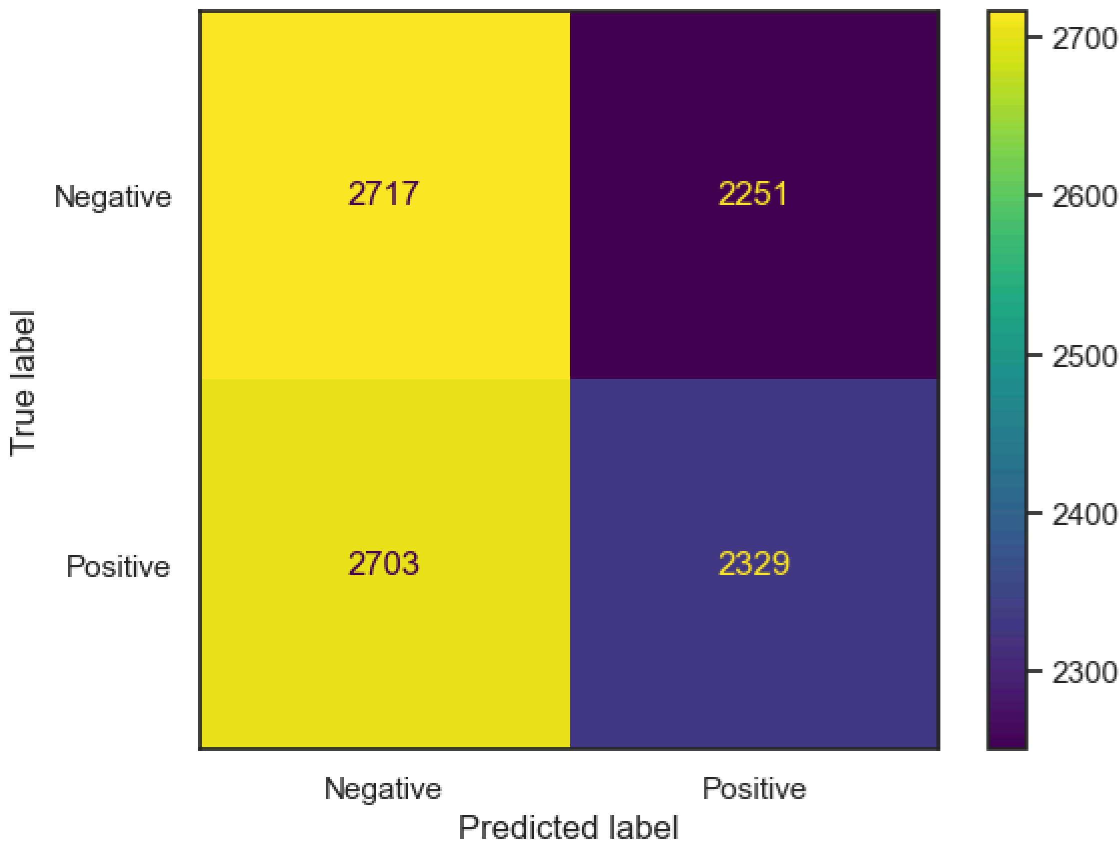
Out[38]:

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In [39]:

```python
y_hat = rf_model.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

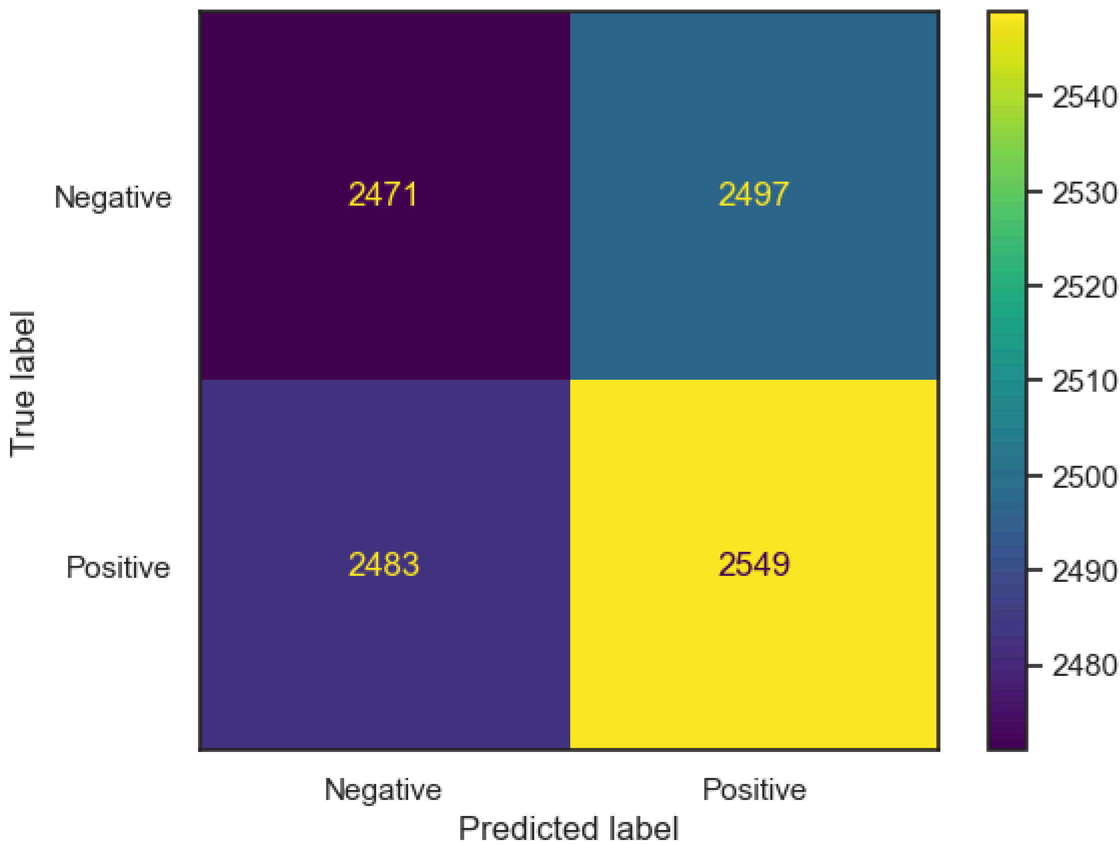
```
Accuracy: 0.50
F1 Score: 0.48
Precision: 0.51
Recall: 0.46
```



In [40]:

```
# Decision Tree (without text data)
from sklearn.tree import DecisionTreeClassifier

X = df[["Retweet Count", "Mention Count", "Follower Count", "Verified", "Location",

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

tree = DecisionTreeClassifier(random_state=RANDOM_STATE)
tree.fit(X_train, y_train)

y_hat = tree.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At
0    0.105605
1    0.850671
2    0.762343
3    0.474930
4    0.083336
Accuracy: 0.50
F1 Score: 0.51
Precision: 0.51
Recall: 0.51
```

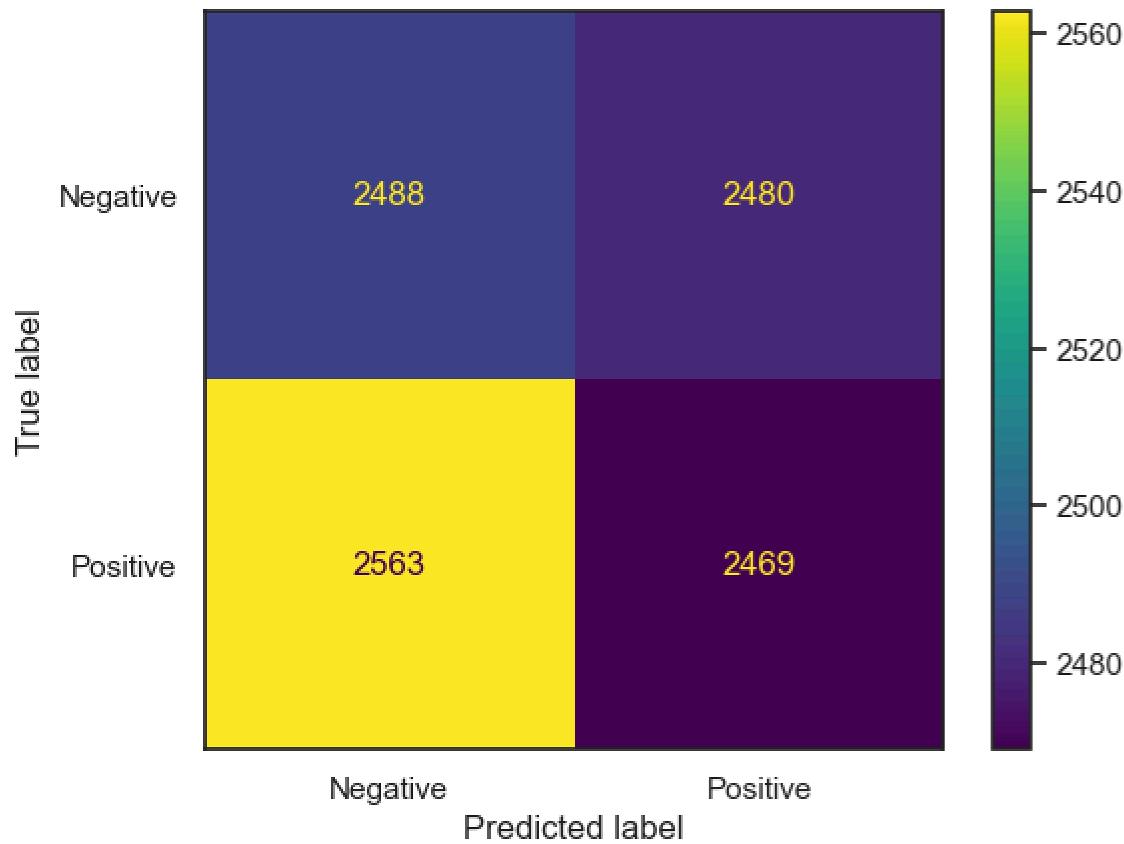


In [41]:

```
# Decision Tree (with text)
X = df.drop('Bot Label', axis=1)

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

tree = DecisionTreeClassifier(random_state=RANDOM_STATE)
tree.fit(X_train, y_train)

y_hat = tree.predict(X_test)

# Metrics
```

```python
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
```

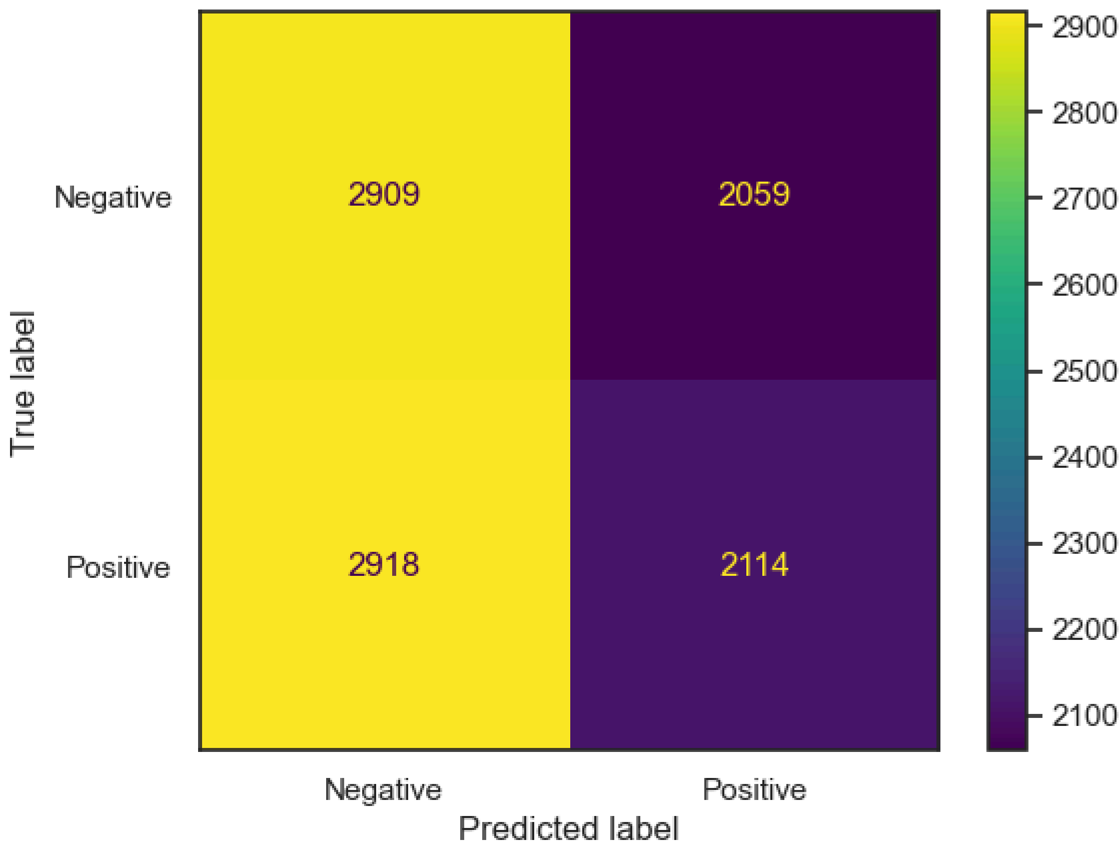
```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At     twt_1     twt_2     twt_3     twt_4  ...  hashtag_91  \
0    0.105605  0.584423 -0.448758  0.221992 -0.083593  ...    0.125355
1    0.850671  0.603059 -0.539200  0.261076 -0.053392  ...   -0.117175
2    0.762343  0.602178 -0.544444  0.259417 -0.058034  ...   -0.124059
3    0.474930  0.629921 -0.661460  0.312158 -0.026327  ...   -0.214849
4    0.083336  0.631455 -0.702606  0.326289 -0.010229  ...   -0.122647

   hashtag_92  hashtag_93  hashtag_94  hashtag_95  hashtag_96  hashtag_97  \
0    0.294862    0.243294   -0.232206    0.374747   -0.269184   -0.382470
1    0.335634    0.013350   -0.247745    0.262996   -0.240250   -0.224535
2    0.338809    0.000209   -0.249944    0.263091   -0.238794   -0.226714
3    0.362426   -0.035149   -0.292454    0.239671   -0.153282   -0.110559
4    0.329823   -0.002046   -0.246382    0.260587   -0.231789   -0.229471

   hashtag_98  hashtag_99  hashtag_100
0    0.024018    0.018229     0.061237
1    0.108484   -0.118404     0.086830
2    0.108327   -0.122253     0.091454
3    0.135174   -0.244549     0.098680
4    0.106929   -0.122275     0.088122

[5 rows x 206 columns]
Accuracy: 0.50
F1 Score: 0.49
Precision: 0.50
Recall: 0.49
```



In [42]:

```
# Naive-Bayes (without text)
from sklearn.naive_bayes import GaussianNB

X = df[["Retweet Count", "Mention Count", "Follower Count", "Verified", "Location",

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

bayes_model = GaussianNB()
bayes_model.fit(X_train, y_train)

y_hat = bayes_model.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

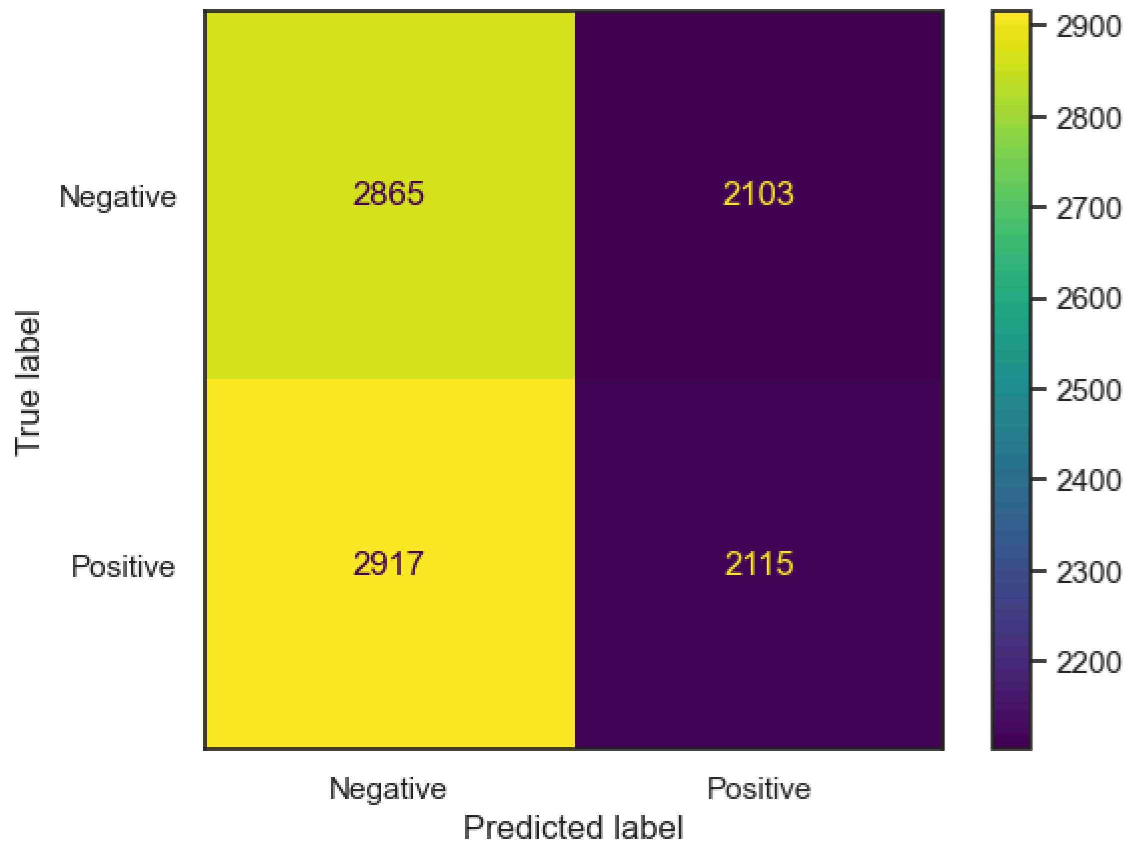
```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At
0    0.105605
1    0.850671
2    0.762343
3    0.474930
4    0.083336
Accuracy: 0.50
F1 Score: 0.46
Precision: 0.51
Recall: 0.42
```



In [43]:
```python
# Naive-Bayes (with text)
X = df.drop('Bot Label', axis=1)

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

bayes_model = GaussianNB()
bayes_model.fit(X_train, y_train)

y_hat = bayes_model.predict(X_test)

# Metrics
```

```python
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
```

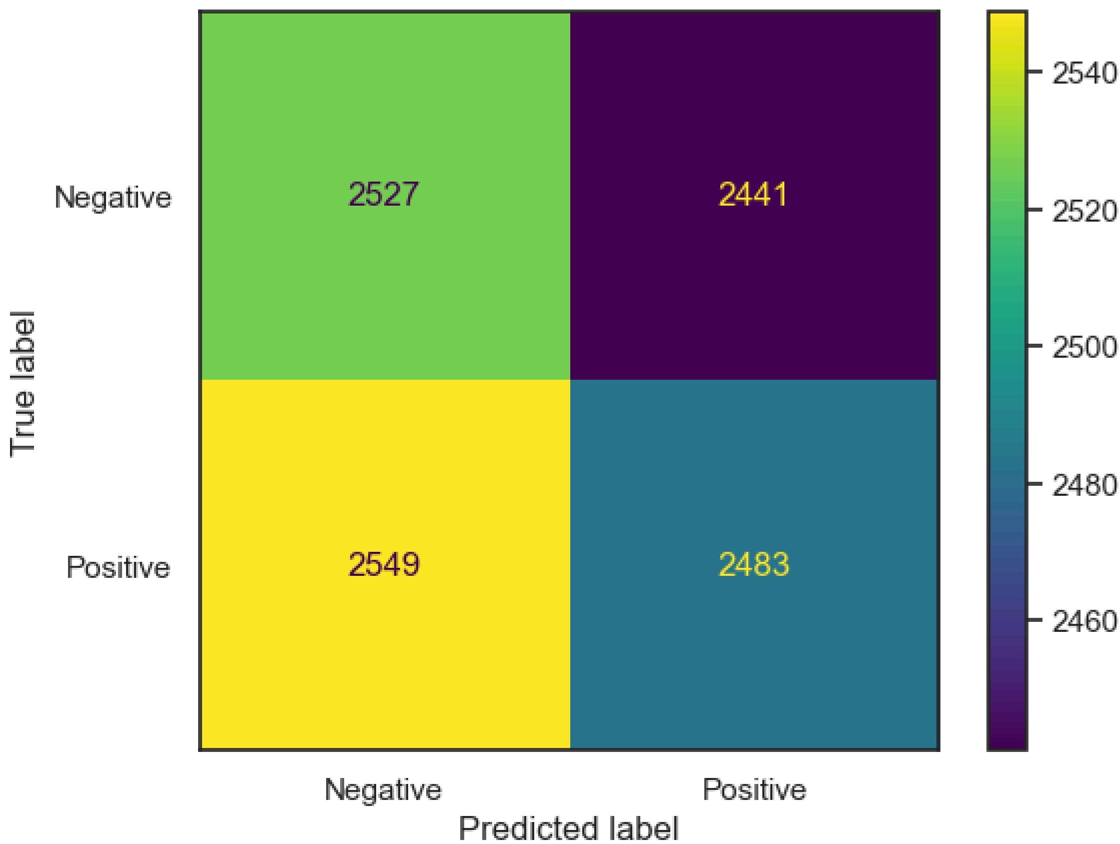
```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At     twt_1     twt_2     twt_3     twt_4  ...  hashtag_91  \
0    0.105605  0.584423 -0.448758  0.221992 -0.083593  ...    0.125355
1    0.850671  0.603059 -0.539200  0.261076 -0.053392  ...   -0.117175
2    0.762343  0.602178 -0.544444  0.259417 -0.058034  ...   -0.124059
3    0.474930  0.629921 -0.661460  0.312158 -0.026327  ...   -0.214849
4    0.083336  0.631455 -0.702606  0.326289 -0.010229  ...   -0.122647

   hashtag_92  hashtag_93  hashtag_94  hashtag_95  hashtag_96  hashtag_97  \
0    0.294862    0.243294   -0.232206    0.374747   -0.269184   -0.382470
1    0.335634    0.013350   -0.247745    0.262996   -0.240250   -0.224535
2    0.338809    0.000209   -0.249944    0.263091   -0.238794   -0.226714
3    0.362426   -0.035149   -0.292454    0.239671   -0.153282   -0.110559
4    0.329823   -0.002046   -0.246382    0.260587   -0.231789   -0.229471

   hashtag_98  hashtag_99  hashtag_100
0    0.024018    0.018229     0.061237
1    0.108484   -0.118404     0.086830
2    0.108327   -0.122253     0.091454
3    0.135174   -0.244549     0.098680
4    0.106929   -0.122275     0.088122

[5 rows x 206 columns]
Accuracy: 0.50
F1 Score: 0.46
Precision: 0.50
Recall: 0.42
```



In [44]:

```
# k-Nearest Neighbors (without text)
from sklearn.neighbors import KNeighborsClassifier

X = df[["Retweet Count", "Mention Count", "Follower Count", "Verified", "Location",

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)

y_hat = knn.predict(X_test)

# Metrics
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
plt.show()
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373   
1           0.55            1.0          0.9617       1.0  0.764465   
2           0.06            0.4          0.4363       1.0  0.257243   
3           0.54            1.0          0.2242       1.0  0.432733   
4           0.26            0.6          0.8438       0.0  0.067188   

   Created At  
0    0.105605  
1    0.850671  
2    0.762343  
3    0.474930  
4    0.083336  
Accuracy: 0.50
F1 Score: 0.50
Precision: 0.50
Recall: 0.49
```

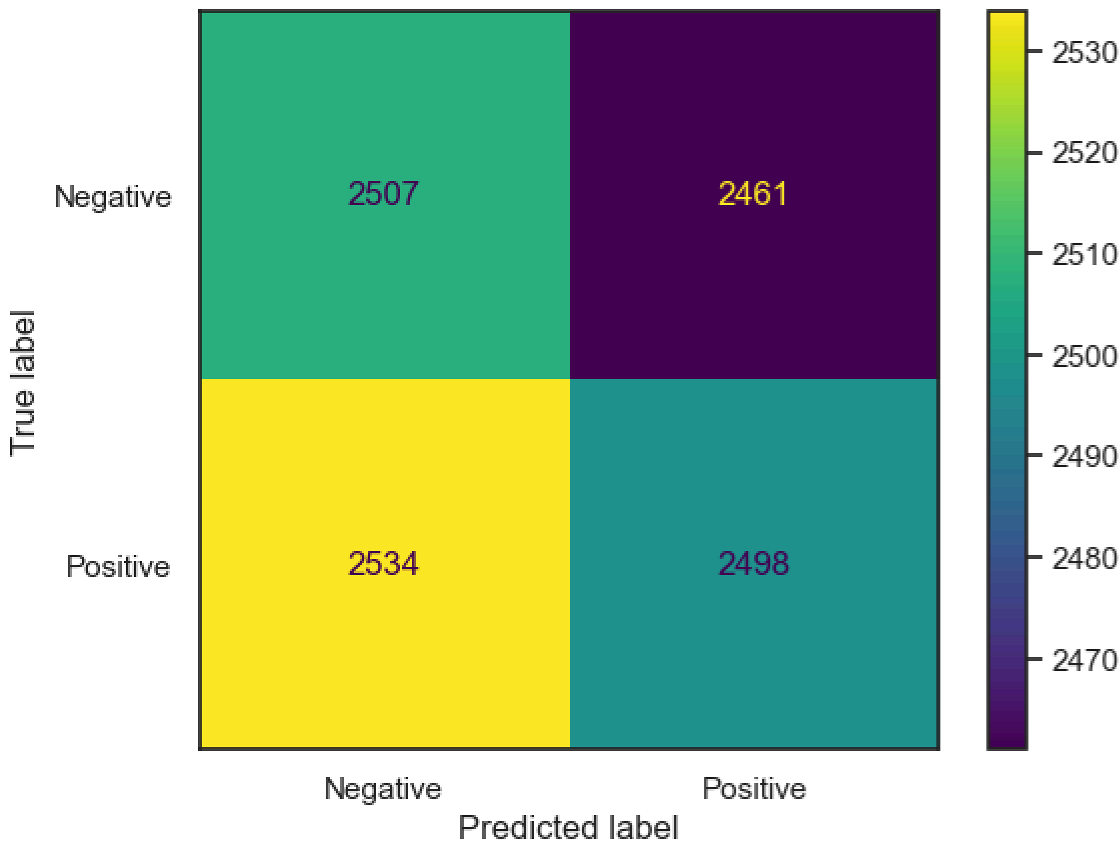


In [45]:

```python
# k-Nearest Neighbors (with text)
X = df.drop('Bot Label', axis=1)

print(X.head())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)

y_hat = knn.predict(X_test)

# Metrics
```

```
accuracy = accuracy_score(y_test, y_hat)
f1 = f1_score(y_test, y_hat, average='binary')  # use average='macro' or 'weighted'
precision = precision_score(y_test, y_hat, average='binary')
recall = recall_score(y_test, y_hat, average='binary')

print("Accuracy: {:.2f}".format(accuracy))
print("F1 Score: {:.2f}".format(f1))
print("Precision: {:.2f}".format(precision))
print("Recall: {:.2f}".format(recall))

cm_test = confusion_matrix(y_test, y_hat)

disp = ConfusionMatrixDisplay(confusion_matrix=cm_test, display_labels=['Negative',
```

```
   Retweet Count  Mention Count  Follower Count  Verified  Location  \
0           0.85            0.2          0.2353       0.0  0.003373
1           0.55            1.0          0.9617       1.0  0.764465
2           0.06            0.4          0.4363       1.0  0.257243
3           0.54            1.0          0.2242       1.0  0.432733
4           0.26            0.6          0.8438       0.0  0.067188

   Created At     twt_1     twt_2     twt_3     twt_4  ...  hashtag_91  \
0    0.105605  0.584423 -0.448758  0.221992 -0.083593  ...    0.125355
1    0.850671  0.603059 -0.539200  0.261076 -0.053392  ...   -0.117175
2    0.762343  0.602178 -0.544444  0.259417 -0.058034  ...   -0.124059
3    0.474930  0.629921 -0.661460  0.312158 -0.026327  ...   -0.214849
4    0.083336  0.631455 -0.702606  0.326289 -0.010229  ...   -0.122647

   hashtag_92  hashtag_93  hashtag_94  hashtag_95  hashtag_96  hashtag_97  \
0    0.294862    0.243294   -0.232206    0.374747   -0.269184   -0.382470
1    0.335634    0.013350   -0.247745    0.262996   -0.240250   -0.224535
2    0.338809    0.000209   -0.249944    0.263091   -0.238794   -0.226714
3    0.362426   -0.035149   -0.292454    0.239671   -0.153282   -0.110559
4    0.329823   -0.002046   -0.246382    0.260587   -0.231789   -0.229471

   hashtag_98  hashtag_99  hashtag_100
0    0.024018    0.018229     0.061237
1    0.108484   -0.118404     0.086830
2    0.108327   -0.122253     0.091454
3    0.135174   -0.244549     0.098680
4    0.106929   -0.122275     0.088122

[5 rows x 206 columns]
Accuracy: 0.50
F1 Score: 0.50
Precision: 0.50
Recall: 0.50
```



Negative
Positive
True label
2507
2461
2534
2498
Negative
Positive
Predicted label
2530
2520
2510
2500
2490
2480
2470