reddit_predicting_political_lean

December 8, 2023

[ ]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer,  CountVectorizer
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report
import tensorflow as tf
import tensorflow_hub as hub
```

0.1 Exploratory Data Analysis

We will be working with the "Liberals vs Conservatives on Reddit [13000 posts]" dataset from Kaggle (Gajare, 2022).

After the initial text exploration we determined it will be beneficial to combine Reddit post `Title` and `Text` columns into a single column `Combined_Text` to use for machine learning.

Additionally we performed the data cleaning and removed special characters and URLs from the text, that step is stored in the `Cleaned_Text` column.

[ ]:
```
dataset_url = "https://raw.githubusercontent.com/AAI-501/aai_501_project/main/
↪cleaned_reddit_data.csv"
```

[ ]:
```
df = pd.read_csv(dataset_url)
display(df.head(5))
```

```
                                               Title Political Lean  Score  \
0  No matter who someone is, how they look like, …        Liberal      1
1    Biden speech draws 38.2 million U.S. TV viewers        Liberal      6
2                                State of the union        Liberal      1
3             We Should Just Give Poor People Money        Liberal      7
4                                 Do it for the Dew        Liberal      6
```

```
       Id            Subreddit  \
0  t5fybt            socialism
1  t5fqdn            democrats
2  t5fj9a  DemocraticSocialism
3  t5f7n9      SocialDemocracy
4  t5es2c            democrats

                                                 URL  Num of Comments  \
0                    https://v.redd.it/ng5fyl7hp2l81                 0
1  https://www.reuters.com/world/us/biden-speech-…                 1
2  https://www.reddit.com/r/DemocraticSocialism/c…                 1
3                        https://youtu.be/a80kRjpubG0                 3
4                https://i.redd.it/drmunn90f2l81.jpg                 1

                                                Text  Date Created  \
0                                                NaN  1.646272e+09
1                                                NaN  1.646271e+09
2  Who watched the state of the union last night …  1.646270e+09
3                                                NaN  1.646270e+09
4                                                NaN  1.646268e+09

                                      Combined_Text  \
0  No matter who someone is, how they look like, …
1   Biden speech draws 38.2 million U.S. TV viewers
2  State of the union Who watched the state of th…
3            We Should Just Give Poor People Money
4                                Do it for the Dew

                                       Cleaned_Text
0  no matter who someone is how they look like wh…
1      biden speech draws 382 million us tv viewers
2  state of the union who watched the state of th…
3            we should just give poor people money
4                                do it for the dew
```

[ ]:
```
df.describe()
```

[ ]:
```
              Score  Num of Comments  Date Created
count  12854.000000     12854.000000  1.285400e+04
mean     118.558270        19.055936  1.622576e+09
std      498.888034        60.381567  6.112838e+07
min        0.000000         0.000000  1.231048e+09
25%        3.000000         1.000000  1.632132e+09
50%       12.000000         3.000000  1.642030e+09
75%       65.000000        15.000000  1.645107e+09
max    25055.000000      2150.000000  1.646272e+09
```

The target column for this dataframe is `Political Lean`, so let's group the data by political lean

and see the results.

[ ]:
```
df.groupby(['Political Lean']).size()
```

[ ]:
```
Political Lean
Conservative    4535
Liberal         8319
dtype: int64
```

We have more rows representing `Liberal` political lean, compared to `Concervative`.

[ ]:
```
df.dtypes
```

[ ]:
```
Title               object
Political Lean      object
Score                int64
Id                  object
Subreddit           object
URL                 object
Num of Comments      int64
Text                object
Date Created       float64
Combined_Text       object
Cleaned_Text        object
dtype: object
```

[ ]:
```
df = df.dropna(subset=['Cleaned_Text']).loc[df['Cleaned_Text'] != '']
df['Date Created'] = pd.to_datetime(df['Date Created'],unit='s')
df
```

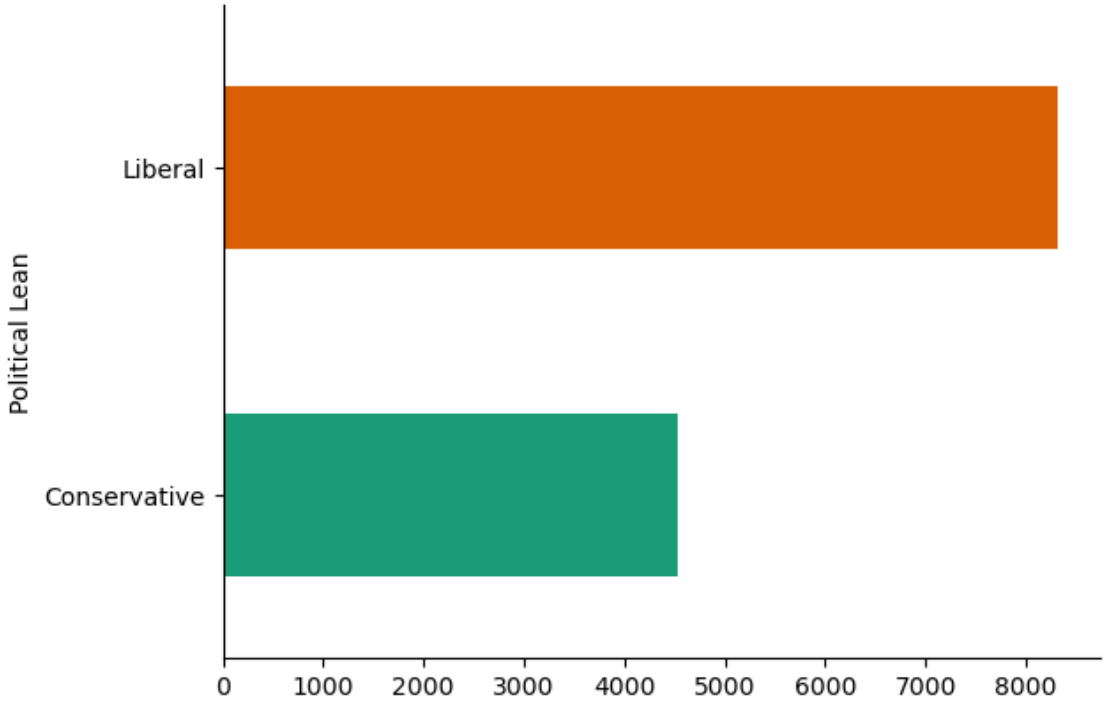
[ ]:
```
                                                   Title Political Lean  \
0      No matter who someone is, how they look like, …        Liberal
1        Biden speech draws 38.2 million U.S. TV viewers        Liberal
2                                     State of the union        Liberal
3                  We Should Just Give Poor People Money        Liberal
4                                    Do it for the Dew        Liberal
…                                                    …            …
12849  Ron Paul’s Spirited Defense of WikiLeaks & Fre…   Conservative
12850  "Anarcho-capitalism, in my opinion, is a doctr…   Conservative
12851  Mises Wiki is a wiki project dedicated to the …   Conservative
12852  Fireman Protection Monopoly - Is This Failed C…   Conservative
12853      Can this Wikipedia Article be Better Written?   Conservative

       Score      Id            Subreddit  \
0          1  t5fybt            socialism
1          6  t5fqdn            democrats
2          1  t5fj9a  DemocraticSocialism
3          7  t5f7n9      SocialDemocracy
```

```
4          6  t5es2c            democrats
…      …      …                 …
12849      2   em7rm    anarchocapitalism
12850      2   ei98o    anarchocapitalism
12851      2   e6x22    anarchocapitalism
12852      2   e4vtd    anarchocapitalism
12853      2   e00j6    anarchocapitalism
```

```
                                                    URL  Num of Comments  \
0                          https://v.redd.it/ng5fyl7hp2l81                 0
1      https://www.reuters.com/world/us/biden-speech-…                 1
2      https://www.reddit.com/r/DemocraticSocialism/c…                 1
3                             https://youtu.be/a80kRjpubG0                 3
4                    https://i.redd.it/drmunn90f2l81.jpg                 1
…                                                    …               …
12849  http://www.deathandtaxesmag.com/40485/ron-paul…                 1
12850  http://www.pressaction.com/news/weblog/full_ar…                 1
12851               http://wiki.mises.org/wiki/Main_Page                 0
12852  http://www.csmonitor.com/Business/Mises-Econom…                 0
12853  https://www.reddit.com/r/anarchocapitalism/com…                 0

                                                  Text        Date Created  \
0                                                  NaN 2022-03-03 01:42:57
1                                                  NaN 2022-03-03 01:31:48
2      Who watched the state of the union last night … 2022-03-03 01:21:28
3                                                  NaN 2022-03-03 01:05:08
4                                                  NaN 2022-03-03 00:43:03
…                                                  …                   …
12849                                              NaN 2010-12-15 13:54:29
12850                                              NaN 2010-12-08 12:53:14
12851                                              NaN 2010-11-16 12:17:27
12852                                              NaN 2010-11-12 01:00:34
12853  I go to the mises.org and listen to the writin… 2010-11-02 12:49:10

                                          Combined_Text  \
0      No matter who someone is, how they look like, …
1       Biden speech draws 38.2 million U.S. TV viewers
2      State of the union Who watched the state of th…
3                 We Should Just Give Poor People Money
4                                   Do it for the Dew
…                                                   …
12849  Ron Paul’s Spirited Defense of WikiLeaks & Fre…
12850  "Anarcho-capitalism, in my opinion, is a doctr…
12851  Mises Wiki is a wiki project dedicated to the …
12852  Fireman Protection Monopoly - Is This Failed C…
12853  Can this Wikipedia Article be Better Written? …
```

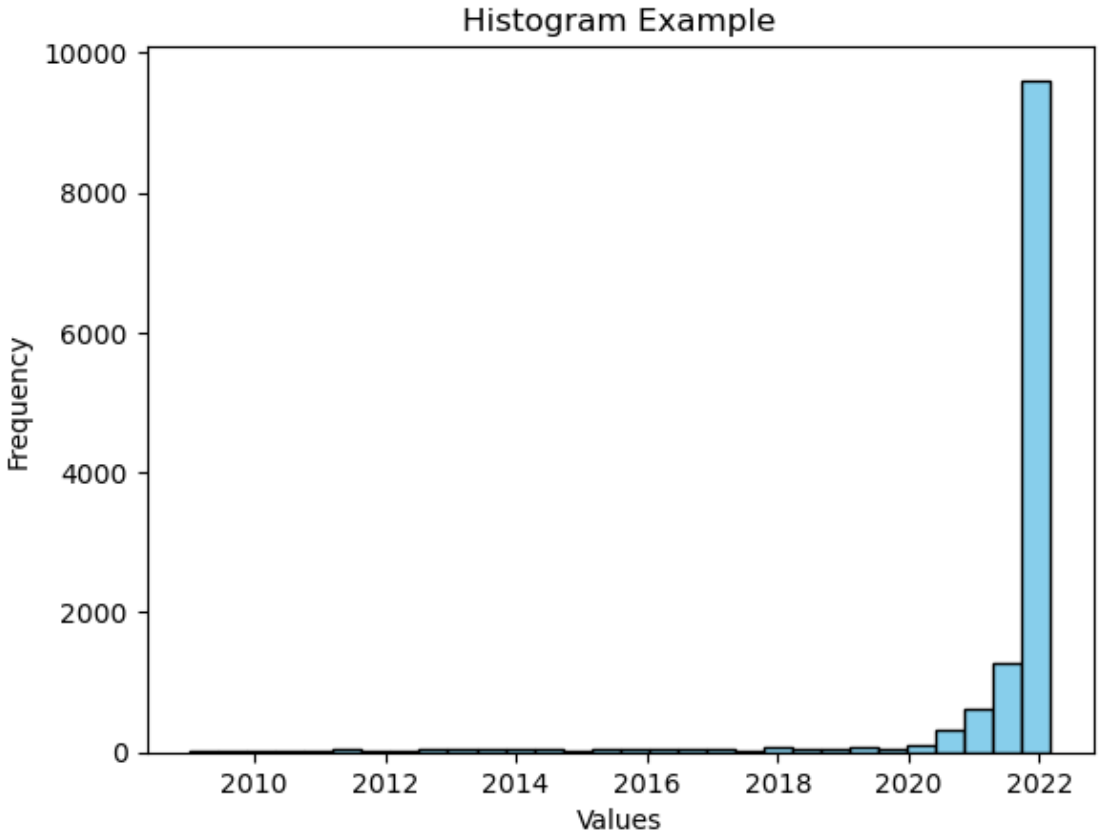
```
                                                Cleaned_Text
0       no matter who someone is how they look like wh…
1           biden speech draws 382 million us tv viewers
2       state of the union who watched the state of th…
3                   we should just give poor people money
4                                    do it for the dew
…                                                     …
12849   ron pauls spirited defense of wikileaks  free …
12850   anarchocapitalism in my opinion is a doctrinal…
12851   mises wiki is a wiki project dedicated to the …
12852   fireman protection monopoly  is this failed ca…
12853   can this wikipedia article be better written i…

[12854 rows x 11 columns]
```

[ ]:
```
df.groupby('Political Lean').size().plot(kind='barh', color=sns.palettes.
 ↪mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```



[ ]:
```
# Plotting the histogram
plt.hist(df['Date Created'], bins=30, color='skyblue', edgecolor='black')

# Adding labels and title
```

```
plt.title('Histogram Example')
plt.xlabel('Values')
plt.ylabel('Frequency')

# Display the plot
plt.show()
```



[ ]:
```
display(df['Score'].sum())
```

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0.2 Comparative Vectorization and Model Analysis

[ ]:
```
def train_and_evaluate_logit(X_train, X_test, y_train, y_test, random_state=42):
    logreg = LogisticRegression(random_state=random_state)
    logreg.fit(X_train, y_train)
    y_pred = logreg.predict(X_test)

    report_df = pd.DataFrame(classification_report(y_test, y_pred,␣
 ↪output_dict=True)).transpose()
```

```
    return report_df

def train_and_evaluate_svm(X_train, X_test, y_train, y_test, random_state=42):
    svm_classifier = SVC(random_state=random_state)
    svm_classifier.fit(X_train, y_train)
    y_pred = svm_classifier.predict(X_test)

    report_df = pd.DataFrame(classification_report(y_test, y_pred,␣
 ↪output_dict=True)).transpose()
    return report_df

def train_and_evaluate_nb(X_train, X_test, y_train, y_test):
    # Training a Multinomial Naive Bayes classifier

    # Find the minimum value in the training set
    min_val = np.min(X_train)

    # Shift the data to make all values non-negative
    if min_val < 0:
        X_train += abs(min_val)
        X_test += abs(min_val)

    # Create and train the classifier
    nb_classifier = MultinomialNB()
    nb_classifier.fit(X_train, y_train)

    # Make predictions and evaluate
    y_pred = nb_classifier.predict(X_test)
    report = classification_report(y_test, y_pred, output_dict=True)

    return pd.DataFrame(report).transpose()

def train_and_evaluate_knn(X_train, X_test, y_train, y_test, n_neighbors=5):
    knn_classifier = KNeighborsClassifier(n_neighbors=n_neighbors)
    knn_classifier.fit(X_train, y_train)
    y_pred = knn_classifier.predict(X_test)

    report_df = pd.DataFrame(classification_report(y_test, y_pred,␣
 ↪output_dict=True)).transpose()
    return report_df


def train_and_evaluate_rand_forest(X_train, X_test, y_train, y_test):
    rand_forest_classifier = RandomForestClassifier()
    rand_forest_classifier.fit(X_train, y_train)
    y_pred = rand_forest_classifier.predict(X_test)
```

```
    report_df = pd.DataFrame(classification_report(y_test, y_pred,␣
 ↪output_dict=True)).transpose()
    return report_df


results = {
    'TfidfVectorizer': {},
    'CountVectorizer':{},
    'USE':{}
}
```

[ ]:
```
# X is the 'Cleaned_Text' column, y is the 'Political Lean' column
X = df['Cleaned_Text']
y = df['Political Lean']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# TfidfVectorizer
vectorizer = TfidfVectorizer()
X_train_vectorized = vectorizer.fit_transform(X_train)
X_test_vectorized = vectorizer.transform(X_test)

# CountVectorizer
vectorizer_count = CountVectorizer()
X_train_count = vectorizer_count.fit_transform(X_train)
X_test_count = vectorizer_count.transform(X_test)

# Universal Sentence Encoder
embed = hub.load("https://tfhub.dev/google/universal-sentence-encoder/4")
X_train_embeddings = embed(X_train)
X_test_embeddings = embed(X_test)
```

1 Models

[ ]:
```
# SVM + TfidfVectorizer
results['TfidfVectorizer']['SVM'] = train_and_evaluate_svm(X_train_vectorized,␣
 ↪X_test_vectorized, y_train, y_test)
display(results['TfidfVectorizer']['SVM'])
```

	precision	recall	f1-score	support
Conservative	0.815356	0.488499	0.610959	913.000000
Liberal	0.769269	0.939083	0.845736	1658.000000
accuracy	0.779074	0.779074	0.779074	0.779074
macro avg	0.792313	0.713791	0.728347	2571.000000
weighted avg	0.785635	0.779074	0.762363	2571.000000

[ ]:
```
# SVM + CountVectorizer
results['CountVectorizer']['SVM'] = train_and_evaluate_svm(X_train_count,␣
 ↪X_test_count, y_train, y_test)
display(results['CountVectorizer']['SVM'])
```

	precision	recall	f1-score	support
Conservative	0.724138	0.069003	0.126000	913.000000
Liberal	0.657810	0.985525	0.788991	1658.000000
accuracy	0.660054	0.660054	0.660054	0.660054
macro avg	0.690974	0.527264	0.457495	2571.000000
weighted avg	0.681364	0.660054	0.553553	2571.000000

[ ]:
```
# SVM + Universal Sentence Encoder
results['USE']['SVM'] = train_and_evaluate_svm(X_train_embeddings.
 ↪numpy(),X_test_embeddings.numpy(), y_train, y_test)
display(results['USE']['SVM'] )
```

	precision	recall	f1-score	support
Conservative	0.756469	0.544359	0.633121	913.000000
Liberal	0.782654	0.903498	0.838746	1658.000000
accuracy	0.775963	0.775963	0.775963	0.775963
macro avg	0.769561	0.723929	0.735933	2571.000000
weighted avg	0.773355	0.775963	0.765725	2571.000000

[ ]:
```
# Naive Bayes + TfidfVectorizer
results['TfidfVectorizer']['NB']  = train_and_evaluate_nb(X_train_vectorized,␣
 ↪X_test_vectorized, y_train, y_test)
display(results['TfidfVectorizer']['NB'] )
```

	precision	recall	f1-score	support
Conservative	0.907834	0.215772	0.348673	913.00000
Liberal	0.695837	0.987937	0.816550	1658.00000
accuracy	0.713730	0.713730	0.713730	0.71373
macro avg	0.801835	0.601855	0.582611	2571.00000
weighted avg	0.771120	0.713730	0.650400	2571.00000

[ ]:
```
# Naive Bayes + CountVectorizer
results['CountVectorizer']['NB']  = train_and_evaluate_nb(X_train_count,␣
 ↪X_test_count, y_train, y_test)
display(results['CountVectorizer']['NB'])
```

	precision	recall	f1-score	support
Conservative	0.693333	0.626506	0.658228	913.000000
Liberal	0.804696	0.847407	0.825499	1658.000000
accuracy	0.768961	0.768961	0.768961	0.768961
macro avg	0.749015	0.736956	0.741864	2571.000000
weighted avg	0.765150	0.768961	0.766099	2571.000000

[ ]:
```
# Naive Bayes + Universal Sentence Encoder
results['USE']['NB']  = train_and_evaluate_nb(X_train_embeddings,␣
 ↪X_test_embeddings , y_train, y_test)
display(results['USE']['NB'])
```

```
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1469: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

	precision	recall	f1-score	support
Conservative	0.000000	0.000000	0.000000	913.000000
Liberal	0.644885	1.000000	0.784110	1658.000000
accuracy	0.644885	0.644885	0.644885	0.644885
macro avg	0.322443	0.500000	0.392055	2571.000000
weighted avg	0.415877	0.644885	0.505661	2571.000000

[ ]:
```
# KNN + TfidfVectorizer
results['TfidfVectorizer']['KNN'] = train_and_evaluate_knn(X_train_vectorized,␣
 ↪X_test_vectorized, y_train, y_test)
display(results['TfidfVectorizer']['KNN'])
```

	precision	recall	f1-score	support
Conservative	0.422456	0.572837	0.486285	913.000000
Liberal	0.707427	0.568758	0.630558	1658.000000
accuracy	0.570206	0.570206	0.570206	0.570206
macro avg	0.564941	0.570797	0.558422	2571.000000
weighted avg	0.606229	0.570206	0.579325	2571.000000

[ ]:
```
# KNN + CountVectorizer
results['CountVectorizer']['KNN']  = train_and_evaluate_knn(X_train_count,␣
 ↪X_test_count, y_train, y_test)
display(results['CountVectorizer']['KNN'])
```

	precision	recall	f1-score	support
Conservative	0.457847	0.386637	0.419240	913.000000
Liberal	0.688889	0.747889	0.717178	1658.000000
accuracy	0.619603	0.619603	0.619603	0.619603

```
macro avg      0.573368  0.567263  0.568209  2571.000000
weighted avg   0.606842  0.619603  0.611376  2571.000000
```

[ ]:
```
# KNN + Universal Sentence Encoder
results['USE']['KNN'] = train_and_evaluate_knn(X_train_embeddings.numpy(),␣
 ↪X_test_embeddings.numpy(), y_train, y_test)
display(results['USE']['KNN'])
```

```
              precision    recall  f1-score     support
Conservative   0.671217  0.646221  0.658482   913.00000
Liberal        0.809102  0.825694  0.817313  1658.00000
accuracy       0.761960  0.761960  0.761960     0.76196
macro avg      0.740159  0.735957  0.737898  2571.00000
weighted avg   0.760137  0.761960  0.760910  2571.00000
```

[ ]:
```
#  Logistic Regression + TfidfVectorizer
results['TfidfVectorizer']['LR'] = train_and_evaluate_logit(X_train_vectorized,␣
 ↪X_test_vectorized, y_train, y_test)
display(results['TfidfVectorizer']['LR'])
```

```
              precision    recall  f1-score      support
Conservative   0.773050  0.477547  0.590386   913.000000
Liberal        0.762332  0.922799  0.834925  1658.000000
accuracy       0.764683  0.764683  0.764683     0.764683
macro avg      0.767691  0.700173  0.712655  2571.000000
weighted avg   0.766138  0.764683  0.748086  2571.000000
```

[ ]:
```
# Logistic Regression + CountVectorizer
results['CountVectorizer']['LR'] = train_and_evaluate_logit(X_train_count,␣
 ↪X_test_count, y_train, y_test)
display(results['CountVectorizer']['LR'])
```

```
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/sklearn/linear_model/_logistic.py:460: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
              precision    recall  f1-score      support
Conservative   0.710561  0.596933  0.648810   913.000000
Liberal        0.796009  0.866104  0.829578  1658.000000
accuracy       0.770517  0.770517  0.770517     0.770517
macro avg      0.753285  0.731518  0.739194  2571.000000
```

```
weighted avg   0.765665  0.770517  0.765385  2571.000000
```

[ ]:
```
# Logistic Regression + Universal Sentence Encoder

results['USE']['LR'] = train_and_evaluate_logit(X_train_embeddings.numpy(),␣
 ↪X_test_embeddings.numpy(), y_train, y_test)
display(results['USE']['LR'])
```

```
              precision    recall  f1-score      support
Conservative   0.649148  0.500548  0.565244   913.000000
Liberal        0.755758  0.851025  0.800567  1658.000000
accuracy       0.726566  0.726566  0.726566     0.726566
macro avg      0.702453  0.675786  0.682906  2571.000000
weighted avg   0.717899  0.726566  0.717001  2571.000000
```

[ ]:
```
# Random Forest + TfidfVectorizer
results['TfidfVectorizer']['RF'] =␣
 ↪train_and_evaluate_rand_forest(X_train_vectorized, X_test_vectorized,␣
 ↪y_train, y_test)
display(results['TfidfVectorizer']['RF'] )
```

```
              precision    recall  f1-score      support
Conservative   0.781469  0.489595  0.602020   913.000000
Liberal        0.766883  0.924608  0.838392  1658.000000
accuracy       0.770128  0.770128  0.770128     0.770128
macro avg      0.774176  0.707101  0.720206  2571.000000
weighted avg   0.772063  0.770128  0.754453  2571.000000
```

[ ]:
```
# Random Forest + CountVectorizer
results['CountVectorizer']['RF'] =␣
 ↪train_and_evaluate_rand_forest(X_train_count, X_test_count, y_train, y_test)
display(results['CountVectorizer']['RF'])
```

```
              precision    recall  f1-score      support
Conservative   0.791667  0.520263  0.627892   913.000000
Liberal        0.777778  0.924608  0.844861  1658.000000
accuracy       0.781019  0.781019  0.781019     0.781019
macro avg      0.784722  0.722435  0.736376  2571.000000
weighted avg   0.782710  0.781019  0.767812  2571.000000
```

[ ]:
```
# Random Forest + Universal Sentence Encoder
results['USE']['RF'] = train_and_evaluate_rand_forest(X_train_embeddings.
 ↪numpy(), X_test_embeddings.numpy(), y_train, y_test)
display(results['USE']['RF'])
```

```
              precision    recall  f1-score      support
Conservative   0.804938  0.357065  0.494689   913.000000
Liberal        0.728994  0.952352  0.825837  1658.000000
accuracy       0.740957  0.740957  0.740957     0.740957
```

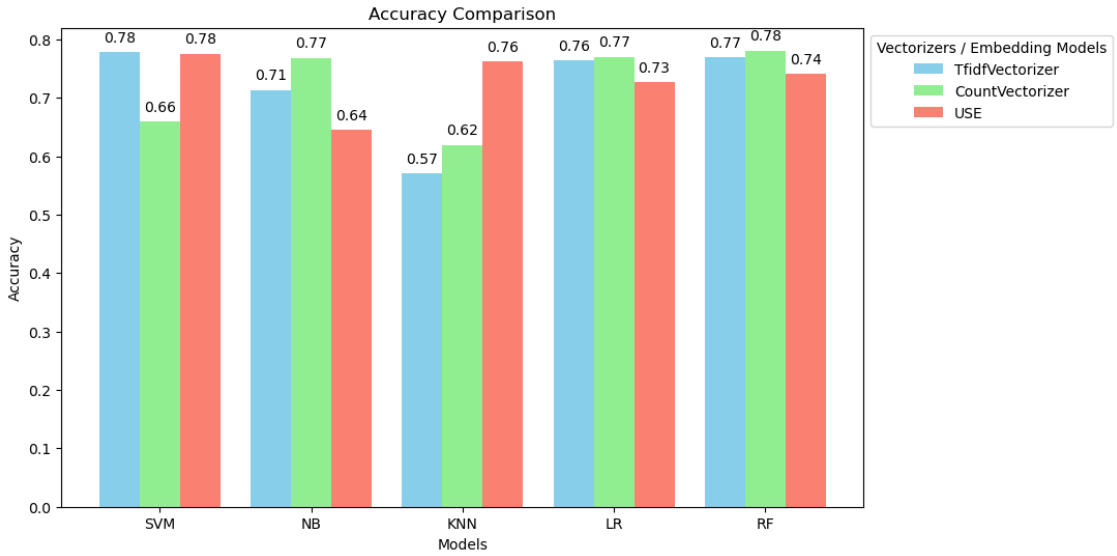
```
macro avg       0.766966  0.654708  0.660263  2571.000000
weighted avg    0.755963  0.740957  0.708241  2571.000000
```

2 Accuracy Check

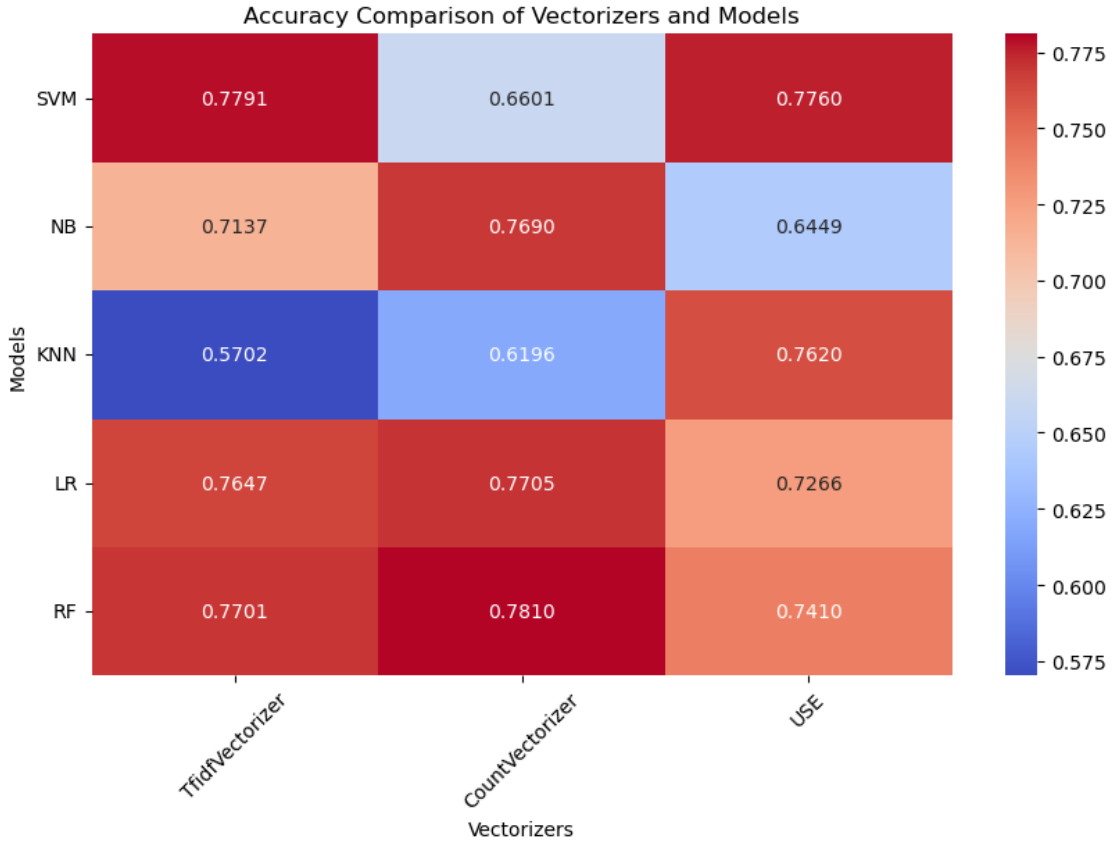
[ ]:
```python
def extract_accuracies(data):
    """
    Extract accuracies from a nested dictionary where the innermost elements␣
 ↪are DataFrames.
    """
    accuracies = {}
    for vectorizer, models in data.items():
        accuracies[vectorizer] = {}
        for model, df in models.items():
            # Extracting the accuracy value
            accuracy = df.loc['accuracy', 'support']
            accuracies[vectorizer][model] = accuracy
    return accuracies


accuracy_dict_from_df = extract_accuracies(results)
accuracy_df_full = pd.DataFrame(accuracy_dict_from_df)

ax = accuracy_df_full.plot(kind='bar', figsize=(10, 6), width=0.8,␣
 ↪color=['skyblue', 'lightgreen', 'salmon'])

ax.set_title('Accuracy Comparison')
ax.set_ylabel('Accuracy')
ax.set_xlabel('Models')
ax.legend(title='Vectorizers / Embedding Models', loc='upper left',␣
 ↪bbox_to_anchor=(1, 1))

# Adding numbers on top of each bar
for p in ax.patches:
    ax.annotate(f"{p.get_height():.2f}", (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                ha='center', va='center', xytext=(0, 10), textcoords='offset␣
 ↪points')

plt.xticks(rotation=0)
```

[ ]:
```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'SVM'),
  Text(1, 0, 'NB'),
  Text(2, 0, 'KNN'),
  Text(3, 0, 'LR'),
```

```
Text(4, 0, 'RF')])
```



[ ]:
```python
plt.figure(figsize=(10, 6))
ax = sns.heatmap(accuracy_df_full, annot=True, fmt=".4f", cmap="coolwarm")

# Setting the title and labels
ax.set_title('Accuracy Comparison of Vectorizers and Models')
ax.set_xlabel('Vectorizers')
ax.set_ylabel('Models')

# Adjust layout
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.show()
```



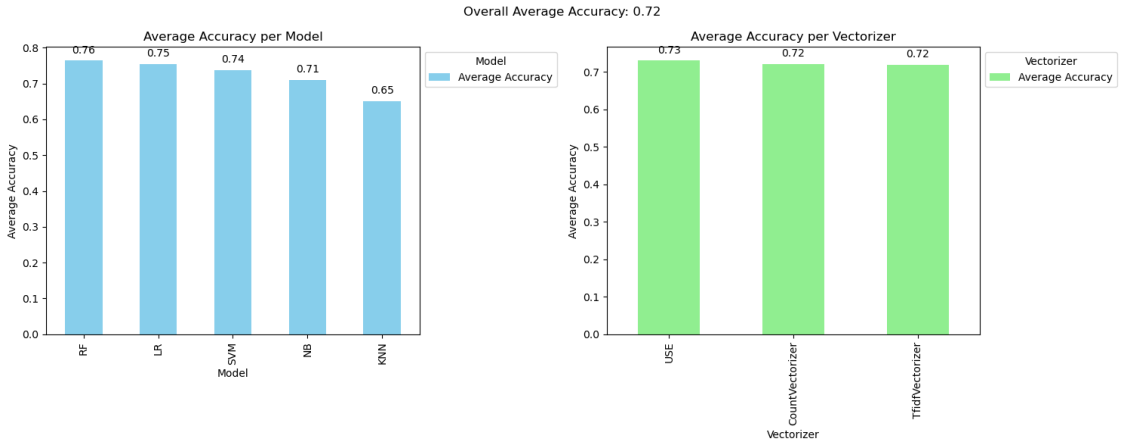
[ ]:
```
accuracy_series = accuracy_df_full.stack()

top_5_accuracies = accuracy_series.sort_values(ascending=False).head(5)
top_5_list = list(top_5_accuracies.index)

top_5_accuracies_print = "\n".join([
    f"{idx + 1}. {model} with {vectorizer}\n\t Accuracy: {accuracy:.4f}%"
    for idx, ((vectorizer, model), accuracy) in enumerate(top_5_accuracies.
 ↪items())
])

print(top_5_accuracies_print)
```

```
1. CountVectorizer with RF
        Accuracy: 0.7810%
2. TfidfVectorizer with SVM
        Accuracy: 0.7791%
3. USE with SVM
        Accuracy: 0.7760%
4. CountVectorizer with LR
        Accuracy: 0.7705%
```

5. TfidfVectorizer with RF
   Accuracy: 0.7701%

[ ]:
```
# Correct calculations for average accuracies

# Average accuracy for each model across all vectorizers
average_accuracy_per_model_corrected = accuracy_df_full.mean(axis=1)

# Average accuracy for each vectorizer across all models
average_accuracy_per_vectorizer_corrected = accuracy_df_full.mean(axis=0)

# Overall average accuracy across all models and vectorizers
overall_average_accuracy_corrected = accuracy_df_full.stack().mean()

# Preparing data for visualization
model_averages_df = average_accuracy_per_model_corrected.reset_index()
model_averages_df.columns = ['Model', 'Average Accuracy']

vectorizer_averages_df = average_accuracy_per_vectorizer_corrected.reset_index()
vectorizer_averages_df.columns = ['Vectorizer', 'Average Accuracy']

# Sorting data
model_averages_df_sorted = model_averages_df.sort_values(by='Average Accuracy',␣
 ↪ascending=False)
vectorizer_averages_df_sorted = vectorizer_averages_df.sort_values(by='Average␣
 ↪Accuracy', ascending=False)

# Plotting with numbers on bars
fig, ax = plt.subplots(1, 2, figsize=(15, 6))

# Plot for models
model_averages_df_sorted.plot(x='Model', y='Average Accuracy', kind='bar',␣
 ↪ax=ax[0], color='skyblue')
ax[0].set_title('Average Accuracy per Model')
ax[0].set_ylabel('Average Accuracy')
ax[0].set_xlabel('Model')
ax[0].legend(title='Model', loc='upper left', bbox_to_anchor=(1, 1))
# Adding numbers on top of each bar for models
for p in ax[0].patches:
    ax[0].annotate(f"{p.get_height():.2f}", (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                   ha='center', va='center', xytext=(0, 10), textcoords='offset␣
 ↪points')

# Plot for vectorizers
vectorizer_averages_df_sorted.plot(x='Vectorizer', y='Average Accuracy',␣
 ↪kind='bar', ax=ax[1], color='lightgreen')
```

```
ax[1].set_title('Average Accuracy per Vectorizer')
ax[1].set_ylabel('Average Accuracy')
ax[1].set_xlabel('Vectorizer')
ax[1].legend(title='Vectorizer', loc='upper left', bbox_to_anchor=(1, 1))
# Adding numbers on top of each bar for vectorizers
for p in ax[1].patches:
    ax[1].annotate(f"{p.get_height():.2f}", (p.get_x() + p.get_width() / 2., p.
 ↪get_height()),
                   ha='center', va='center', xytext=(0, 10), textcoords='offset␣
 ↪points')

plt.suptitle(f'Overall Average Accuracy: {overall_average_accuracy_corrected:.
 ↪2f}')
plt.tight_layout()
plt.show()
```



2.1 Model Selection

Based on the model performances, the best performing candidate is: - `Support Vector Machine` with `TfidfVectorizer`.

These are surprising results, since `TfidVectorizer` does not reflect the semantics of the Reddit posts. However, vectors created with `TfidVectorizer` reflect the importance of the word in the corpus.

2.2 Conclusion

None of the techiques created the execptional results - i.e. accuracy for all the classification algorithms was below 80%

`Support Vector Machine` algorithm performed the best for classification Reddit posts and for predicting `Political Lean`.