# FlipItNews

October 26, 2023

### 0.0.1 Objective

- The goal of this project is to use a bunch of news articles extracted from the companies' internal database and categorize them into several categories like politics, technology, sports, business and entertainment based on their content. Use natural language processing and create & compare at least three different models.

[92]:
```
import re
import string
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly_express as px
import nltk

from nltk.corpus import twitter_samples
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import TweetTokenizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.metrics import accuracy_score,precision_score, recall_score
import warnings

warnings.filterwarnings('ignore')
nltk.download('wordnet')
nltk.download('omw-1.4')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\revan\AppData\Roaming\nltk_data…
```

```
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\revan\AppData\Roaming\nltk_data…
[nltk_data]   Package omw-1.4 is already up-to-date!
```

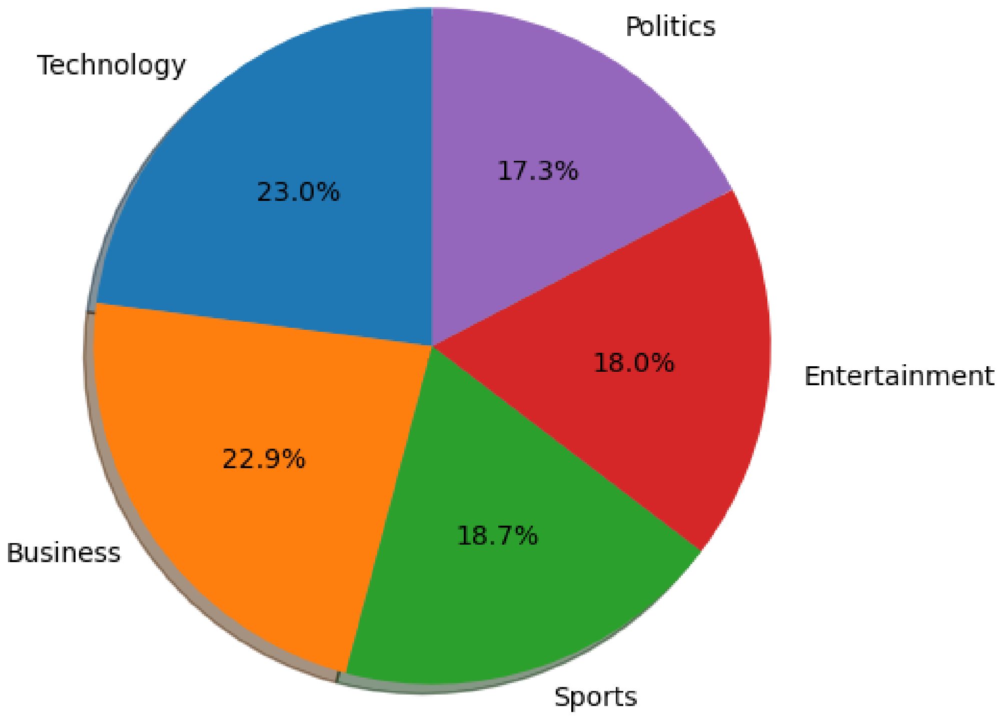
[92]: True

[93]:
```
df = pd.read_csv("flipitnews-data.csv")
```

[94]:
```
fig = px.pie(df, names='Category',hole=0.3, title='Category Pie Chart')
fig.show()
```

[95]:
```
def pie_chart(dataframe):
  # Converting pd object to list of string
  label_types  = dataframe.Category.unique().astype(str)
  # Count tweets for each label
  label_counts = dataframe.Category.value_counts()
  print('Labels in the dataset: ', label_types)
  print(label_counts)
  # labels for the two classes
  labels = label_types #'Positives', 'Negative'
  # Sizes for each slide
  sizes = [count for count in label_counts]
  # Declare a figure with a custom size
  fig = plt.figure(figsize=(5, 5))
  # Declare pie chart, where the slices will be ordered and plotted␣
↪counter-clockwise:
  plt.pie(sizes, labels=labels, autopct='%1.1f%%',
          shadow=True, startangle=90)
  # Equal aspect ratio ensures that pie is drawn as a circle.
  plt.axis('equal')
  # Display the chart
  plt.show()

pie_chart(df)
```

```
Labels in the dataset:  ['Technology' 'Business' 'Sports' 'Entertainment'
'Politics']
Category
Sports           511
Business         510
Politics         417
Technology       401
Entertainment    386
Name: count, dtype: int64
```




### 0.0.2 User defined function to process the textual data

[96]:
```
def process_tweet(tweet):
    lemmatizer = WordNetLemmatizer()
    stopwords_english = stopwords.words('english')
    # remove stock market tickers like $GE
    tweet = re.sub(r'\$\w*', '', tweet)
    # remove old style retweet text "RT"
    tweet = re.sub(r'^RT[\s]+', '', tweet)
    # remove hyperlinks
    tweet = re.sub(r'https?://[^\s\n\r]+', '', tweet)
    # remove hashtags
    # only removing the hash # sign from the word
    tweet = re.sub(r'#', '', tweet)
    # tokenize tweets
    tweet = re.sub(r'[0-9]+', '', tweet)
    # tokenize tweets
    tokenizer = TweetTokenizer(preserve_case=False, strip_handles=True,
                               reduce_len=True)
    tweet_tokens = tokenizer.tokenize(tweet)

    tweets_clean = []
```

```
    for word in tweet_tokens:
        if (word not in stopwords_english and  # remove stopwords
                word not in string.punctuation):  # remove punctuation
            # tweets_clean.append(word)
            lemma_word = lemmatizer.lemmatize(word)  # stemming word
            tweets_clean.append(lemma_word)

    word1 = ""
    for i in tweets_clean:
        word1+= i +" "

    return word1
```

[97]:
```
df["Cleaned_Text"] = df["Article"].apply(process_tweet)
```

[98]:
```
print("Before Preprocess")
print(df["Article"][100])
print("-"*200)
print("After Preprocess")
print(df["Cleaned_Text"][100])
```

```
Before Preprocess
housewives lift channel 4 ratings the debut of us television hit desperate
housewives has helped lift channel 4 s january audience share by 12% compared to
last year.  other successes such as celebrity big brother and the simpsons have
enabled the broadcaster to surpass bbc two for the first month since last july.
bbc two s share of the audience fell from 11.2% to 9.6% last month in comparison
with january 2004. celebrity big brother attracted fewer viewers than its 2002
series.  comedy drama desperate housewives managed to pull in five million
viewers at one point during its run to date  attracting a quarter of the
television audience. the two main television channels  bbc1 and itv1  have both
seen their monthly audience share decline in a year on year comparison for
january  while five s proportion remained the same at a slender 6.3%. digital
multi-channel tv is continuing to be the strongest area of growth  with the bbc
reporting freeview box ownership of five million  including one million sales in
the last portion of 2004. its share of the audience soared by 20% in january
2005 compared with last year  and currently stands at an average of 28.6%.
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
----------------------------------------
After Preprocess
housewife lift channel rating debut u television hit desperate housewife helped
lift channel january audience share compared last year success celebrity big
brother simpson enabled broadcaster surpass bbc two first month since last july
bbc two share audience fell last month comparison january celebrity big brother
attracted fewer viewer series comedy drama desperate housewife managed pull five
million viewer one point run date attracting quarter television audience two
main television channel bbc itv seen monthly audience share decline year year
```

```
comparison january five proportion remained slender digital multi-channel tv
continuing strongest area growth bbc reporting freeview box ownership five
million including one million sale last portion share audience soared january
compared last year currently stand average
```

### 0.0.3 Bag of Words and TF-IDF techniques for vectorizing the data

[99]:
```python
def Text_to_matrix(df,choice):
    cv = CountVectorizer()
    # Learn the vocabulary dictionary and return document-term matrix
    bow_rep = cv.fit_transform(df["Cleaned_Text"]).todense()  #
    bow_dataframe = pd.DataFrame(bow_rep)
    # Get output feature names for dataframe columns.
    bow_dataframe.columns = cv.get_feature_names()
    bow_dataframe["Category"] = df["Category"]

    tfidf_vectorizer = TfidfVectorizer(min_df=5)
    # min_df: ignore terms that have a document frequency strictly lower than␣
 ↪the given threshold.
    tfidf_features = tfidf_vectorizer.fit_transform(df["Cleaned_Text"]).
 ↪todense()  # todense() returns a matrix
    # create dataframe
    tfidf_features_df = pd.DataFrame(tfidf_features)
    tfidf_features_df.columns = tfidf_vectorizer.get_feature_names()  # Get␣
 ↪output feature names for dataframe columns.
    tfidf_features_df["Category"] = df["Category"]
    if choice == "tf":
        return tfidf_features_df
    elif choice == "bow":
        return bow_dataframe
```

[100]:
```python
tf_idf_df = Text_to_matrix(df,choice="tf")
```

### 0.0.4 Train-test split and train a Naive Bayes classifier model using the simple/classical approach.

[101]:
```python
x = tf_idf_df.drop("Category",axis=1)
y = tf_idf_df["Category"]
```

[102]:
```python
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.2)
```

[103]:
```python
print(xtrain.shape,xtest.shape,ytrain.shape,ytest.shape)
```

```
(1780, 8017) (445, 8017) (1780,) (445,)
```

[104]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
ytrain = le.fit_transform(ytrain)
```

```
ytest = le.transform(ytest)
```

[105]:
```
model = MultinomialNB()
model.fit(xtrain,ytrain)
```

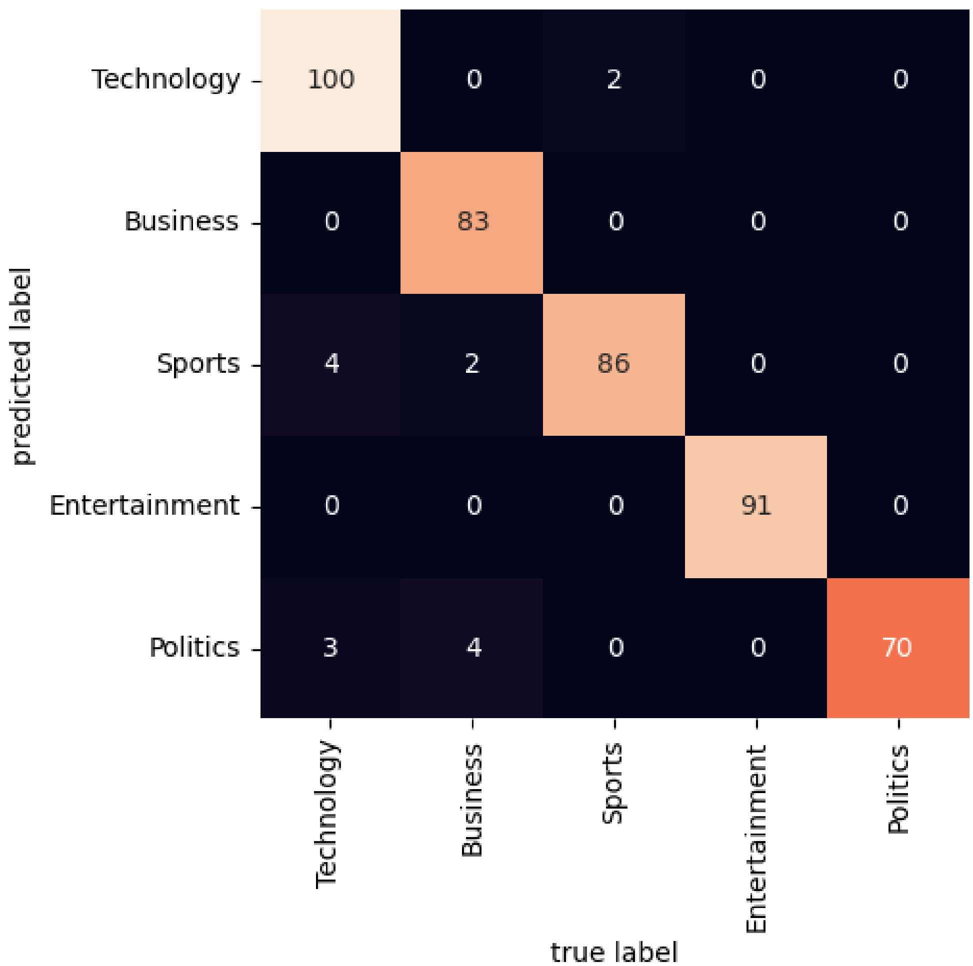
[105]: MultinomialNB()

### 0.0.5 Evaluate the model's performance and plot the Confusion Matrix as well as Classification Report.

[106]:
```
labels = model.predict(xtest)
mat = confusion_matrix(ytest, labels)
print(f"Classification report: {classification_report(ytest, labels)}")
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False,
            xticklabels=df["Category"].unique(), yticklabels=df["Category"].
 ↪unique())
plt.xlabel('true label')
plt.ylabel('predicted label')
```

```
Classification report:               precision    recall  f1-score   support

           0       0.98      0.93      0.96       107
           1       1.00      0.93      0.97        89
           2       0.93      0.98      0.96        88
           3       1.00      1.00      1.00        91
           4       0.91      1.00      0.95        70

    accuracy                           0.97       445
   macro avg       0.96      0.97      0.97       445
weighted avg       0.97      0.97      0.97       445
```

[106]: Text(113.9222222222222, 0.5, 'predicted label')




### 0.0.6 Evaluate three more classifier models (Decision Tree, Nearest Neighbors, Random Forest)

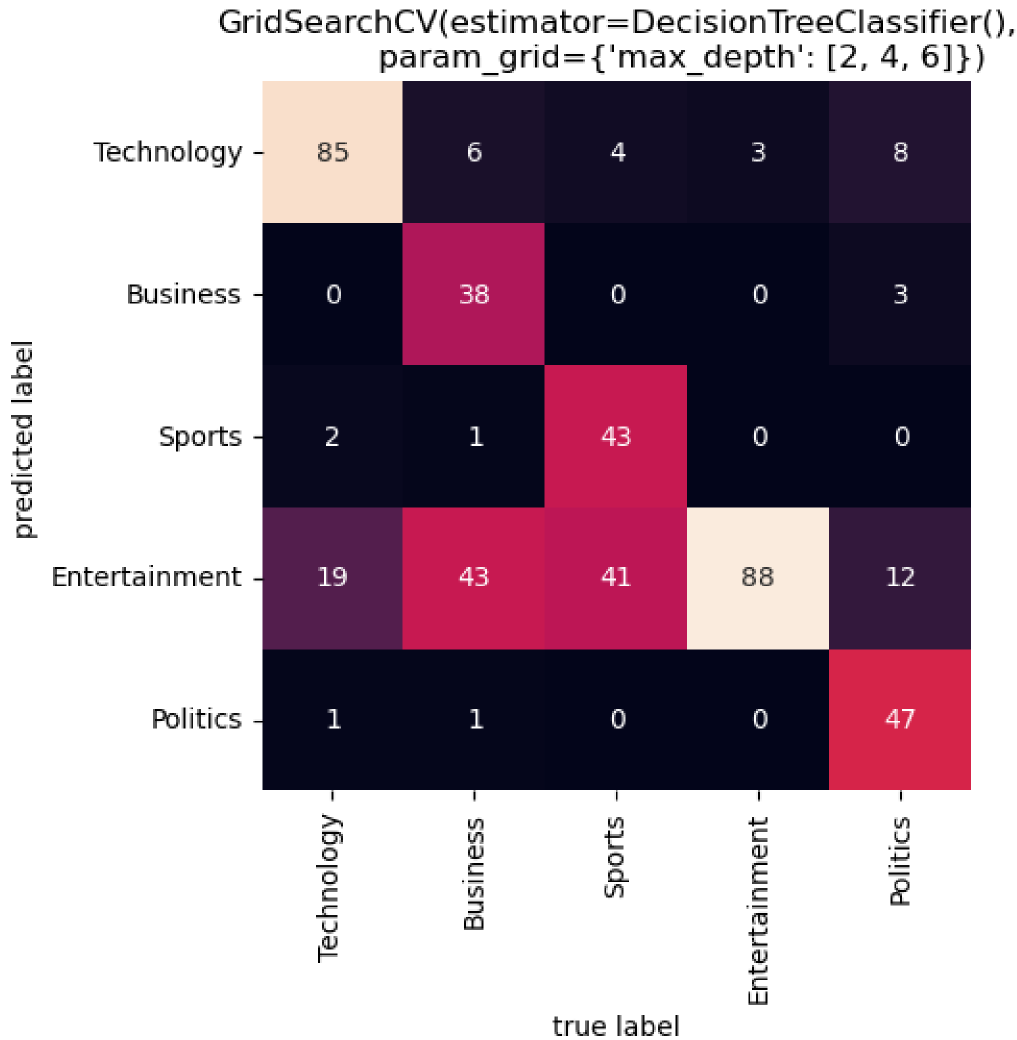
[107]:
```
dtc = DecisionTreeClassifier()
dtc_params = {'max_depth': [2, 4, 6]}
dtc_grid = GridSearchCV(dtc, dtc_params)
dtc_grid.fit(xtrain, ytrain)
dtc_score = dtc_grid.score(xtest, ytest)

# K-Nearest Neighbors Classifier
knn = KNeighborsClassifier()
knn_params = {'n_neighbors': [3, 5, 7]}
knn_grid = GridSearchCV(knn, knn_params)
knn_grid.fit(xtrain, ytrain)
knn_score = knn_grid.score(xtest, ytest)
```

```
# Random Forest Classifier
rfc = RandomForestClassifier()
rfc_params = {'n_estimators': [100, 200], 'max_depth': [2, 4]}
rfc_grid = GridSearchCV(rfc, rfc_params)
rfc_grid.fit(xtrain, ytrain)
rfc_score = rfc_grid.score(xtest, ytest)

print({'Decision Tree': dtc_score,
            'K-Nearest Neighbors': knn_score,
            'Random Forest': rfc_score})
```

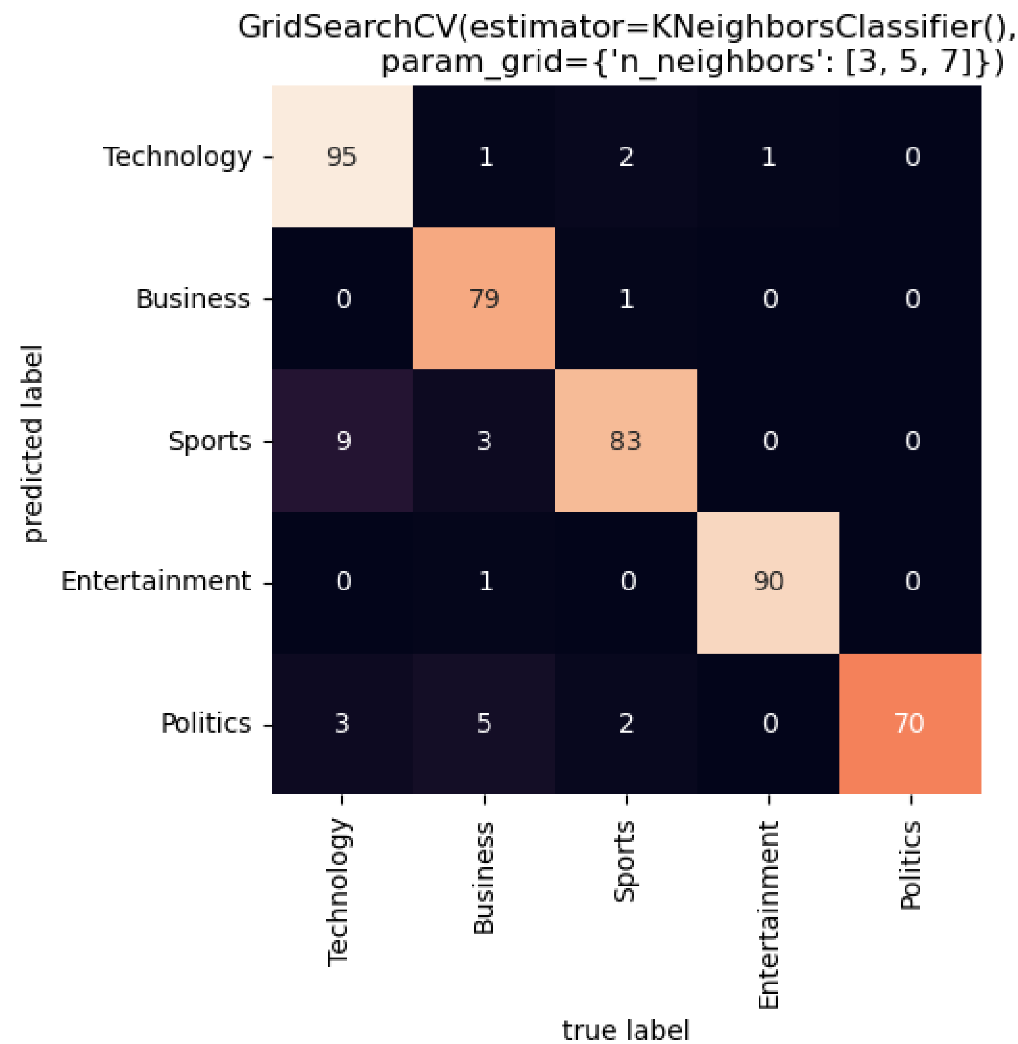
```
{'Decision Tree': 0.6764044943820224, 'K-Nearest Neighbors': 0.9370786516853933,
'Random Forest': 0.8426966292134831}
```

[111]:
```
models = [dtc_grid,knn_grid,rfc_grid]
for model in models:
    labels = model.predict(xtest)
    mat = confusion_matrix(ytest, labels)
    print(f"Classification report: {classification_report(ytest, labels)}")
    plt.title(f"{model}")
    sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False,
                xticklabels=df["Category"].unique(), yticklabels=df["Category"].
 ↪unique())
    plt.xlabel('true label')
    plt.ylabel('predicted label')
    plt.show()
```

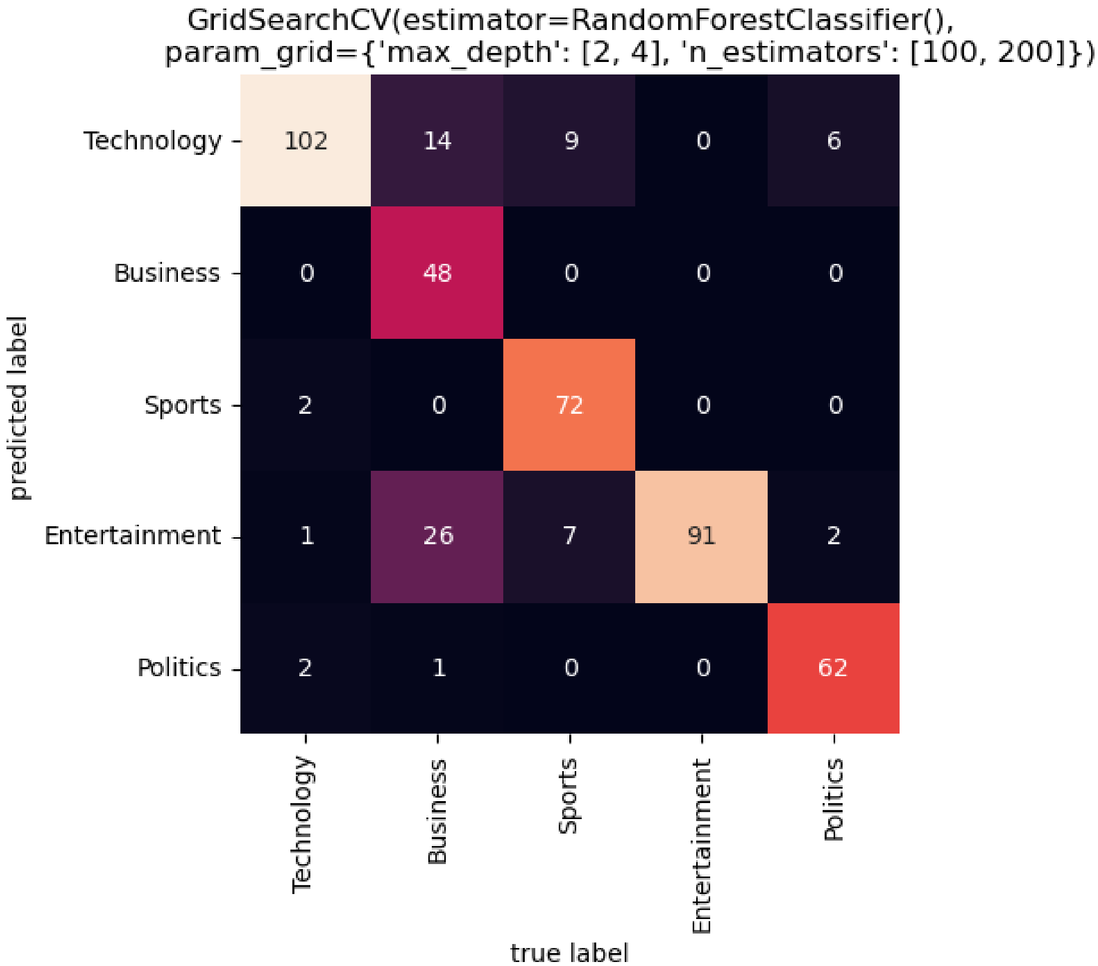
```
Classification report:               precision    recall  f1-score   support

           0       0.80      0.79      0.80       107
           1       0.93      0.43      0.58        89
           2       0.93      0.49      0.64        88
           3       0.43      0.97      0.60        91
           4       0.96      0.67      0.79        70

    accuracy                           0.68       445
   macro avg       0.81      0.67      0.68       445
weighted avg       0.80      0.68      0.68       445
```




```
Classification report:               precision    recall  f1-score   support

           0       0.96      0.89      0.92       107
           1       0.99      0.89      0.93        89
           2       0.87      0.94      0.91        88
           3       0.99      0.99      0.99        91
           4       0.88      1.00      0.93        70

    accuracy                           0.94       445
   macro avg       0.94      0.94      0.94       445
weighted avg       0.94      0.94      0.94       445
```




```
Classification report:               precision    recall  f1-score   support

           0       0.78      0.95      0.86       107
           1       1.00      0.54      0.70        89
           2       0.97      0.82      0.89        88
           3       0.72      1.00      0.83        91
           4       0.95      0.89      0.92        70

    accuracy                           0.84       445
   macro avg       0.88      0.84      0.84       445
weighted avg       0.88      0.84      0.84       445
```




### 0.0.7 Observe and comment on the performances of all the models used

[109]:
```
# Naive bayes model is performing well when compared to other models
# We are clustering groups based on the input features, the clustering␣
↪algorithms are doing better compared to other trees algorithm
# Thats why Naive bayes and Knn algorithm did their jobs better
```