`Context:`

The Gurugram-based company ‘FlipItNews’ aims to revolutionize the way Indians perceive finance, business, and capital market investment, by giving it a boost through artificial intelligence (AI) and machine learning (ML). They’re on a mission to reinvent financial literacy for Indians, where financial awareness is driven by smart information discovery and engagement with peers. Through their smart content discovery and contextual engagement, the company is simplifying business, finance, and investment for millennials and first-time investors

`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.

In [73]:
```
import pandas as pd
import numpy as np
import nltk
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
```

```
'choco' is not recognized as an internal or external command,
operable program or batch file.
```

In [74]:
```
df = pd.read_csv('data\\flipitnews-data.csv')
```

In [75]:
```
df.head()
```

Out[75]:

	Category	Article
0	Technology	tv future in the hands of viewers with home th...
1	Business	worldcom boss left books alone former worldc...
2	Sports	tigers wary of farrell gamble leicester say ...
3	Sports	yeading face newcastle in fa cup premiership s...
4	Entertainment	ocean s twelve raids box office ocean s twelve...

Shape of Data

In [76]:
```
df.shape
```

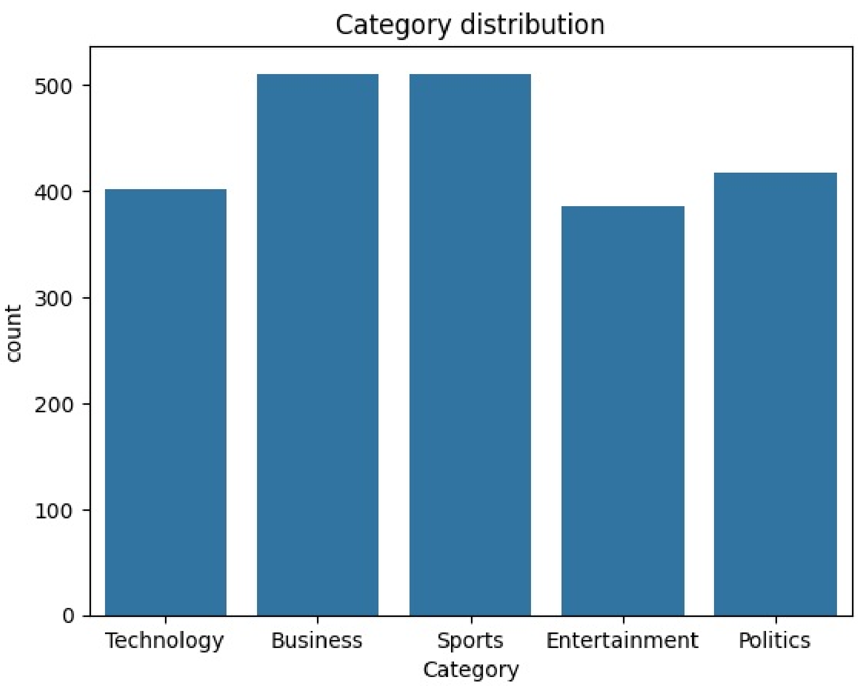
Out[76]:
```
(2225, 2)
```

Null Check

In [77]:
```
df.isna().sum()
```

Out[77]:
```
Category    0
Article     0
dtype: int64
```

In [78]:
```
plt.title("Category distribution")
sns.countplot(x=df['Category'])
plt.show()
```



Text PreProcessing

In [140…

```
from nltk.corpus import stopwords
import pickle
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from string import punctuation
import re
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split as tts
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay, classification_report
```

In [80]:

```
Label_encode = LabelEncoder()
```

In [81]:

```
# print(set(df['Category']))
# print(set(LabelEncoder().fit_transform(df['Category'])))
```

In [82]:

```
test_text = df['Article'][1]
stopword = stopwords.words('english')
stopword.extend(punctuation)
```

In [83]:

```
def get_text_preprocessed(words):
    words = words.lower()
    words = re.sub(r'[^a-zA-Z\s]', '', words)
    words = word_tokenize(words)
    words = [WordNetLemmatizer().lemmatize(word) for word in words if word not in stopword]
    words = " ".join(words)
    return words
```

In [84]:

```
print("Processed")
print(get_text_preprocessed(test_text))
```

```
Processed
worldcom bos left book alone former worldcom bos bernie ebbers accused overseeing bn bn fraud never made accoun
ting decision witness told juror david myers made comment questioning defence lawyer arguing mr ebbers responsi
ble worldcom problem phone company collapsed prosecutor claim loss hidden protect firm share mr myers already p
leaded guilty fraud assisting prosecutor monday defence lawyer reid weingarten tried distance client allegation
cross examination asked mr myers ever knew mr ebbers make accounting decision aware mr myers replied ever know
mr ebbers make accounting entry worldcom book mr weingarten pressed replied witness mr myers admitted ordered f
alse accounting entry request former worldcom chief financial officer scott sullivan defence lawyer trying pain
t mr sullivan admitted fraud testify later trial mastermind behind worldcom accounting house card mr ebbers tea
m meanwhile looking portray affable bos admission pe graduate economist whatever ability mr ebbers transformed
worldcom relative unknown bn telecom giant investor darling late worldcom problem mounted however competition i
ncreased telecom boom petered firm finally collapsed shareholder lost bn worker lost job mr ebbers trial expect
ed last two month found guilty former ceo face substantial jail sentence firmly declared innocence
```

In [85]:

```
print("Unprocessed")
print(word_tokenize(test_text))
```

```
Unprocessed
['worldcom', 'boss', 'left', 'books', 'alone', 'former', 'worldcom', 'boss', 'bernie', 'ebbers', 'who', 'is', '
accused', 'of', 'overseeing', 'an', '$', '11bn', '(', '£5.8bn', ')', 'fraud', 'never', 'made', 'accounting', 'd
ecisions', 'a', 'witness', 'has', 'told', 'jurors', '.', 'david', 'myers', 'made', 'the', 'comments', 'under',
'questioning', 'by', 'defence', 'lawyers', 'who', 'have', 'been', 'arguing', 'that', 'mr', 'ebbers', 'was', 'no
t', 'responsible', 'for', 'worldcom', 's', 'problems', '.', 'the', 'phone', 'company', 'collapsed', 'in', '2002
', 'and', 'prosecutors', 'claim', 'that', 'losses', 'were', 'hidden', 'to', 'protect', 'the', 'firm', 's', 'sha
res', '.', 'mr', 'myers', 'has', 'already', 'pleaded', 'guilty', 'to', 'fraud', 'and', 'is', 'assisting', 'pros
ecutors', '.', 'on', 'monday', 'defence', 'lawyer', 'reid', 'weingarten', 'tried', 'to', 'distance', 'his', 'cl
ient', 'from', 'the', 'allegations', '.', 'during', 'cross', 'examination', 'he', 'asked', 'mr', 'myers', 'if',
'he', 'ever', 'knew', 'mr', 'ebbers', 'make', 'an', 'accounting', 'decision', '.', 'not', 'that', 'i', 'am', 'a
ware', 'of', 'mr', 'myers', 'replied', '.', 'did', 'you', 'ever', 'know', 'mr', 'ebbers', 'to', 'make', 'an', '
accounting', 'entry', 'into', 'worldcom', 'books', 'mr', 'weingarten', 'pressed', '.', 'no', 'replied', 'the',
'witness', '.', 'mr', 'myers', 'has', 'admitted', 'that', 'he', 'ordered', 'false', 'accounting', 'entries', 'a
t', 'the', 'request', 'of', 'former', 'worldcom', 'chief', 'financial', 'officer', 'scott', 'sullivan', '.', 'd
efence', 'lawyers', 'have', 'been', 'trying', 'to', 'paint', 'mr', 'sullivan', 'who', 'has', 'admitted', 'fraud
', 'and', 'will', 'testify', 'later', 'in', 'the', 'trial', 'as', 'the', 'mastermind', 'behind', 'worldcom', 's
', 'accounting', 'house', 'of', 'cards', '.', 'mr', 'ebbers', 'team', 'meanwhile', 'are', 'looking', 'to', 'por
tray', 'him', 'as', 'an', 'affable', 'boss', 'who', 'by', 'his', 'own', 'admission', 'is', 'more', 'pe', 'gradu
ate', 'than', 'economist', '.', 'whatever', 'his', 'abilities', 'mr', 'ebbers', 'transformed', 'worldcom', 'fro
m', 'a', 'relative', 'unknown', 'into', 'a', '$', '160bn', 'telecoms', 'giant', 'and', 'investor', 'darling', '
of', 'the', 'late', '1990s', '.', 'worldcom', 's', 'problems', 'mounted', 'however', 'as', 'competition', 'incr
eased', 'and', 'the', 'telecoms', 'boom', 'petered', 'out', '.', 'when', 'the', 'firm', 'finally', 'collapsed',
'shareholders', 'lost', 'about', '$', '180bn', 'and', '20', '000', 'workers', 'lost', 'their', 'jobs', '.', 'mr
', 'ebbers', 'trial', 'is', 'expected', 'to', 'last', 'two', 'months', 'and', 'if', 'found', 'guilty', 'the', '
former', 'ceo', 'faces', 'a', 'substantial', 'jail', 'sentence', '.', 'he', 'has', 'firmly', 'declared', 'his',
'innocence', '.']
```

In [86]:
```python
df['processd_article'] = df['Article'].apply(get_text_preprocessed)
```

In [87]:
```python
categories = Label_encode.fit(df['Category'])
df['Category_enc'] = categories.transform(df['Category'])
```

In [88]:
```python
df.head()
```

Out[88]:

	Category	Article	processd_article	Category_enc
0	Technology	tv future in the hands of viewers with home th...	tv future hand viewer home theatre system plas...	4
1	Business	worldcom boss left books alone former worldc...	worldcom bos left book alone former worldcom b...	0
2	Sports	tigers wary of farrell gamble leicester say ...	tiger wary farrell gamble leicester say rushed...	3
3	Sports	yeading face newcastle in fa cup premiership s...	yeading face newcastle fa cup premiership side...	3
4	Entertainment	ocean s twelve raids box office ocean s twelve...	ocean twelve raid box office ocean twelve crim...	1

In [89]:
```python
print("Processed   : ",word_tokenize(df['Article'][4]))
print("Unprocessed : ",df['processd_article'][4])
```

```
Processed   :  ['ocean', 's', 'twelve', 'raids', 'box', 'office', 'ocean', 's', 'twelve', 'the', 'crime', 'cape
r', 'sequel', 'starring', 'george', 'clooney', 'brad', 'pitt', 'and', 'julia', 'roberts', 'has', 'gone', 'strai
ght', 'to', 'number', 'one', 'in', 'the', 'us', 'box', 'office', 'chart', '.', 'it', 'took', '$', '40.8m', '(',
'£21m', ')', 'in', 'weekend', 'ticket', 'sales', 'according', 'to', 'studio', 'estimates', '.', 'the', 'sequel'
, 'follows', 'the', 'master', 'criminals', 'as', 'they', 'try', 'to', 'pull', 'off', 'three', 'major', 'heists'
, 'across', 'europe', '.', 'it', 'knocked', 'last', 'week', 's', 'number', 'one', 'national', 'treasure', 'into
', 'third', 'place', '.', 'wesley', 'snipes', 'blade', ':', 'trinity', 'was', 'in', 'second', 'taking', '$', '1
6.1m', '(', '£8.4m', ')', '.', 'rounding', 'out', 'the', 'top', 'five', 'was', 'animated', 'fable', 'the', 'pol
ar', 'express', 'starring', 'tom', 'hanks', 'and', 'festive', 'comedy', 'christmas', 'with', 'the', 'kranks', '
.', 'ocean', 's', 'twelve', 'box', 'office', 'triumph', 'marks', 'the', 'fourth-biggest', 'opening', 'for', 'a'
, 'december', 'release', 'in', 'the', 'us', 'after', 'the', 'three', 'films', 'in', 'the', 'lord', 'of', 'the',
'rings', 'trilogy', '.', 'the', 'sequel', 'narrowly', 'beat', 'its', '2001', 'predecessor', 'ocean', 's', 'elev
en', 'which', 'took', '$', '38.1m', '(', '£19.8m', ')', 'on', 'its', 'opening', 'weekend', 'and', '$', '184m',
'(', '£95.8m', ')', 'in', 'total', '.', 'a', 'remake', 'of', 'the', '1960s', 'film', 'starring', 'frank', 'sina
tra', 'and', 'the', 'rat', 'pack', 'ocean', 's', 'eleven', 'was', 'directed', 'by', 'oscar-winning', 'director'
, 'steven', 'soderbergh', '.', 'soderbergh', 'returns', 'to', 'direct', 'the', 'hit', 'sequel', 'which', 'reuni
tes', 'clooney', 'pitt', 'and', 'roberts', 'with', 'matt', 'damon', 'andy', 'garcia', 'and', 'elliott', 'gould'
, '.', 'catherine', 'zeta-jones', 'joins', 'the', 'all-star', 'cast', '.', 'it', 's', 'just', 'a', 'fun', 'good
', 'holiday', 'movie', 'said', 'dan', 'fellman', 'president', 'of', 'distribution', 'at', 'warner', 'bros.', 'h
owever', 'us', 'critics', 'were', 'less', 'complimentary', 'about', 'the', '$', '110m', '(', '£57.2m', ')', 'pr
oject', 'with', 'the', 'los', 'angeles', 'times', 'labelling', 'it', 'a', 'dispiriting', 'vanity', 'project', '
.', 'a', 'milder', 'review', 'in', 'the', 'new', 'york', 'times', 'dubbed', 'the', 'sequel', 'unabashedly', 'tr
ivial', '.']
Unprocessed :  ocean twelve raid box office ocean twelve crime caper sequel starring george clooney brad pitt j
ulia robert gone straight number one u box office chart took weekend ticket sale according studio estimate sequ
el follows master criminal try pull three major heist across europe knocked last week number one national treas
ure third place wesley snipe blade trinity second taking rounding top five animated fable polar express starrin
g tom hank festive comedy christmas kranks ocean twelve box office triumph mark fourthbiggest opening december
release u three film lord ring trilogy sequel narrowly beat predecessor ocean eleven took opening weekend total
remake film starring frank sinatra rat pack ocean eleven directed oscarwinning director steven soderbergh soder
bergh return direct hit sequel reunites clooney pitt robert matt damon andy garcia elliott gould catherine zeta
jones join allstar cast fun good holiday movie said dan fellman president distribution warner bros however u cr
itic le complimentary project los angeles time labelling dispiriting vanity project milder review new york time
dubbed sequel unabashedly trivial
```

BOW

In [131…
```python
from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
pd.set_option('display.max_rows',None)
```

In [91]:
```python
c_vectorizer = CountVectorizer()
c_vect= c_vectorizer.fit(df['processd_article'])
X_bow = c_vect.transform(df['processd_article']).toarray()
Y = df['Category_enc'].to_numpy()
```

In [92]:
```python
X_bow
```

Out[92]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=int64)
```

In [93]:
```python
X_bow.shape
```

Out[93]:
```
(2225, 27175)
```

In [209…
```python
xtrain,xtest,ytrain,ytest = tts(X_bow,Y,test_size=0.23)
```

In [210…
```python
print(f'train shape {xtrain.shape}  test shape {xtest.shape} , ytrain shape {ytrain.shape} , ytest shape {ytest
```

```
train shape (1713, 27175)  test shape (512, 27175) , ytrain shape (1713,) , ytest shape (512,)
```

In [211…
```python
naive_bs_model = GaussianNB()
naive_bs_model.fit(xtrain,ytrain)
```

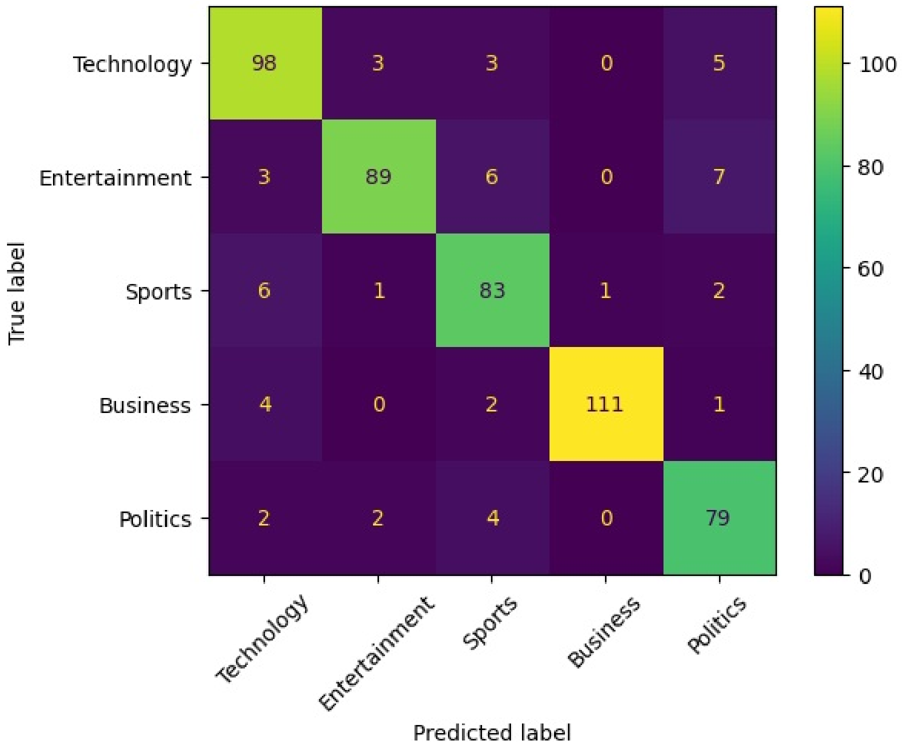
Out[211]:
```
▾ GaussianNB
GaussianNB()
```

In [115…
```python
pred = naive_bs_model.predict(xtest)
```

In [116…
```python
print(classification_report(ytest,pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.90      0.88       109
           1       0.94      0.85      0.89       105
           2       0.85      0.89      0.87        93
           3       0.99      0.94      0.97       118
           4       0.84      0.91      0.87        87

    accuracy                           0.90       512
   macro avg       0.90      0.90      0.90       512
weighted avg       0.90      0.90      0.90       512
```

In [130…
```python
ConfusionMatrixDisplay(confusion_matrix(ytest,pred),display_labels=list(set(Label_encode.inverse_transform(pred
plt.xticks(rotation=45)
plt.show()
```



In [143…
```
print("Model Accuracy with Naive Bayes with BOW : ",naive_bs_model.score(xtest,ytest))
```

```
Model Accuracy with Naive Bayes with BOW :  0.8984375
```

In [121…
```
def test_text_function(text,vector_embed_type='bow'):
    preprocess_text = get_text_preprocessed(text)
    if(vector_embed_type=='bow'):
        cv_vect = c_vect.transform([preprocess_text]).toarray()
    pred = naive_bs_model.predict(cv_vect)
    return(Label_encode.inverse_transform(pred)[0])
```

In [124…
```
test_text_function(df['Article'][2216])
```

Out[124]:
```
'Entertainment'
```

In [125…
```
df.tail(10)
```

Out[125]:

	Category	Article	processd_article	Category_enc
2215	Technology	junk e-mails on relentless rise spam traffic i...	junk email relentless rise spam traffic puttin...	4
2216	Entertainment	top stars join us tsunami tv show brad pitt r...	top star join u tsunami tv show brad pitt robe...	1
2217	Technology	rings of steel combat net attacks gambling is ...	ring steel combat net attack gambling hugely p...	4
2218	Sports	davies favours gloucester future wales hooker ...	davy favour gloucester future wale hooker mefi...	3
2219	Business	beijingers fume over parking fees choking traf...	beijingers fume parking fee choking traffic ja...	0
2220	Business	cars pull down us retail figures us retail sal...	car pull u retail figure u retail sale fell ja...	0
2221	Politics	kilroy unveils immigration policy ex-chatshow ...	kilroy unveils immigration policy exchatshow h...	2
2222	Entertainment	rem announce new glasgow concert us band rem h...	rem announce new glasgow concert u band rem an...	1
2223	Politics	how political squabbles snowball it s become c...	political squabble snowball become commonplace...	2
2224	Sports	souness delight at euro progress boss graeme s...	souness delight euro progress bos graeme soune...	3

Embeddding Using TF-IDF

In [132…
```
tf_vectorizer = TfidfVectorizer()
tf_vect= tf_vectorizer.fit(df['processd_article'])
X_tf = tf_vectorizer.transform(df['processd_article']).toarray()
```

In [134…
```
tf_xtrain,tf_xtest,tf_ytrain,tf_ytest = tts(X_tf,Y,test_size=0.23)
print(f'train shape {tf_xtrain.shape}  test shape {tf_xtest.shape} , ytrain shape {tf_ytrain.shape} , ytest sha
```

```
train shape (1713, 27175)  test shape (512, 27175) , ytrain shape (1713,) , ytest shape (512,)
```

In [135…
```
naive_bs_model_tf = GaussianNB()
naive_bs_model_tf.fit(tf_xtrain,tf_ytrain)
```

Out[135]:

```
GaussianNB
GaussianNB()
```

In [136…

```
tf_pred = naive_bs_model_tf.predict(tf_xtest)
```

In [137…

```
print(classification_report(tf_ytest,tf_pred))
```

```
              precision    recall  f1-score   support

           0       0.93      0.86      0.90       124
           1       0.96      0.91      0.94        89
           2       0.86      0.95      0.90        95
           3       0.99      0.97      0.98       115
           4       0.91      0.97      0.93        89

    accuracy                           0.93       512
   macro avg       0.93      0.93      0.93       512
weighted avg       0.93      0.93      0.93       512
```

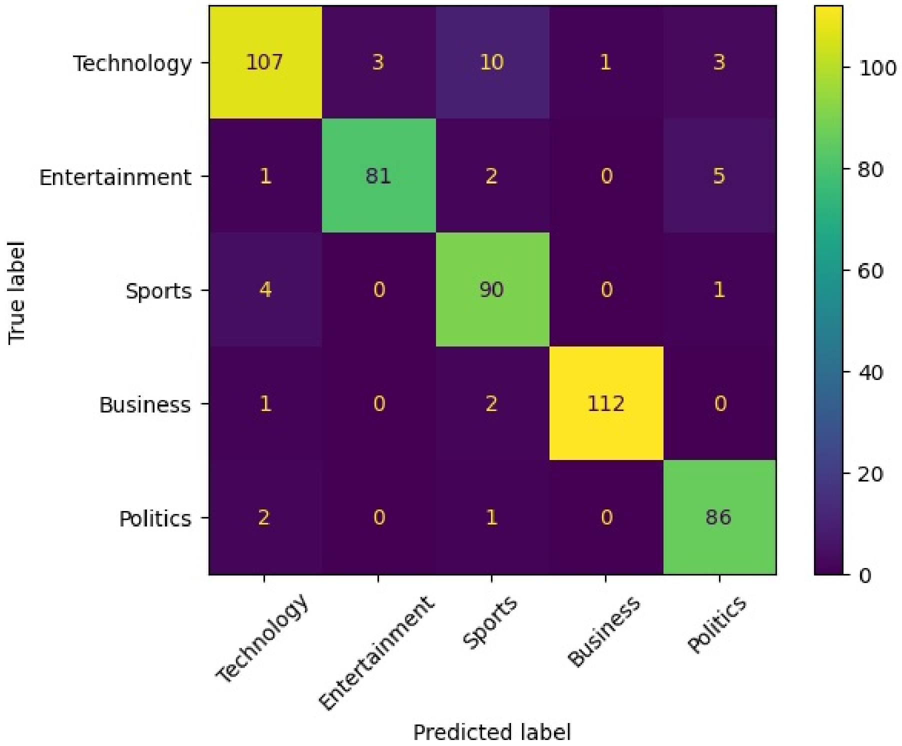
In [142…

```
print("Model Accuracy with Naive Bayes with TF-IDF: ",naive_bs_model_tf.score(tf_xtest,tf_ytest))
```

```
Model Accuracy with Naive Bayes with TF-IDF:  0.9296875
```

In [138…

```
ConfusionMatrixDisplay(confusion_matrix(tf_ytest,tf_pred),display_labels=list(set(Label_encode.inverse_transfor
plt.xticks(rotation=45)
plt.show()
```



In [166…

```
def test_text_function(text,vector_embed_type='bow'):
    " This Function will preprocess and give predictions of text belonging to certain class"
    ans  = None
    preprocess_text = get_text_preprocessed(text)                                   # Preprocessing
    if(vector_embed_type=='bow'):
        with open('naive_bs_model.pkl', 'rb') as file:                              # Loading Model
            naive_bs_model = pickle.load(file)
        cv_vect = c_vect.transform([preprocess_text]).toarray()
        pred = naive_bs_model.predict(cv_vect)                                      # Predicting
        ans = Label_encode.inverse_transform(pred)[0]                               # predicting class
    elif(vector_embed_type=='tf'):
        with open('tf_idf_model.pkl', 'rb') as file:
            naive_bs_model_tf = pickle.load(file)
        tf_vects = tf_vect.transform([preprocess_text]).toarray()
        pred = naive_bs_model_tf.predict(tf_vects)
        ans = Label_encode.inverse_transform(pred)[0]
    else:
        print("Invalid vector embed type")
    return ans
```

Testing model on different text input

In [168…

```
Accutal_class = (df.iloc[2184,:][0])
```

```
print("Accutal class : ",Accutal_class)
pred = test_text_function(df['Article'][2184],'tf')
print("Prediciton : ",pred)
```

```
Accutal class :  Business
Prediciton :  Business
C:\Users\gaura\AppData\Local\Temp\ipykernel_11848\982742917.py:1: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  Accutal_class = (df.iloc[2184,:][0])
```

In [179…

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
```

Using BOW Data training RandomForest

In [180…

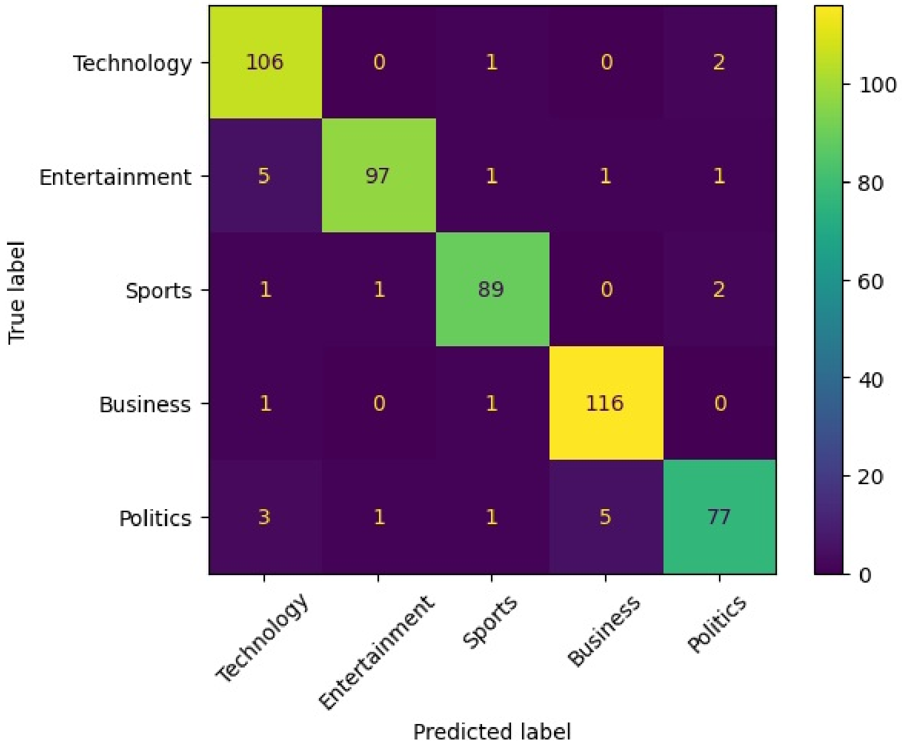
```
random_forest_classifier =RandomForestClassifier()
random_forest_classifier.fit(xtrain,ytrain)
```

Out[180]:

```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [181…

```
random_f_pred = random_forest_classifier.predict(xtest)
ConfusionMatrixDisplay(confusion_matrix(ytest,random_f_pred),display_labels=list(set(Label_encode.inverse_trans
plt.xticks(rotation=45)
plt.show()
```



In [182…

```
print(classification_report(ytest,random_f_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.97      0.94       109
           1       0.98      0.92      0.95       105
           2       0.96      0.96      0.96        93
           3       0.95      0.98      0.97       118
           4       0.94      0.89      0.91        87

    accuracy                           0.95       512
   macro avg       0.95      0.94      0.95       512
weighted avg       0.95      0.95      0.95       512
```

In [183…

```
print("Model Accuracy with Random Forest with BOW: ",round(random_forest_classifier.score(xtest,ytest),2))
```

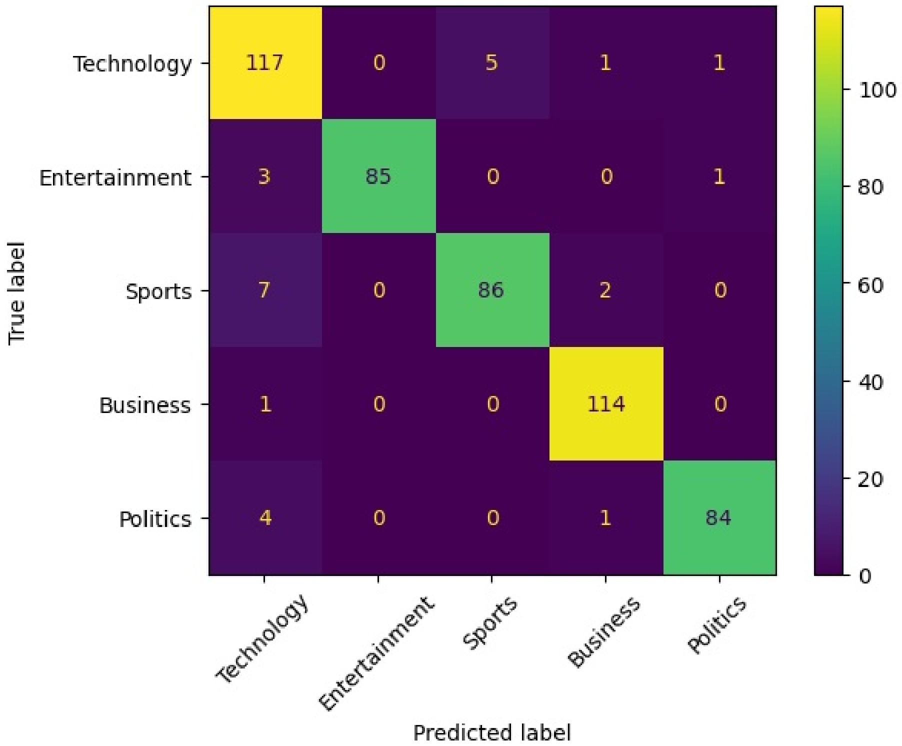
```
Model Accuracy with Random Forest with BOW:  0.95
```

Using TF-IDF Data training RandomForest

In [186…

```
random_forest_classifier_tf =RandomForestClassifier()
random_forest_classifier_tf.fit(tf_xtrain,tf_ytrain)
```

```
random_f_pred_tf = random_forest_classifier_tf.predict(tf_xtest)
ConfusionMatrixDisplay(confusion_matrix(tf_ytest,random_f_pred_tf),display_labels=list(set(Label_encode.inverse_
plt.xticks(rotation=45)
plt.show()
```



In [187…
```
print("Model Accuracy with Random Forest with TF-IDF: ",round(random_forest_classifier_tf.score(tf_xtest,tf_yte
```

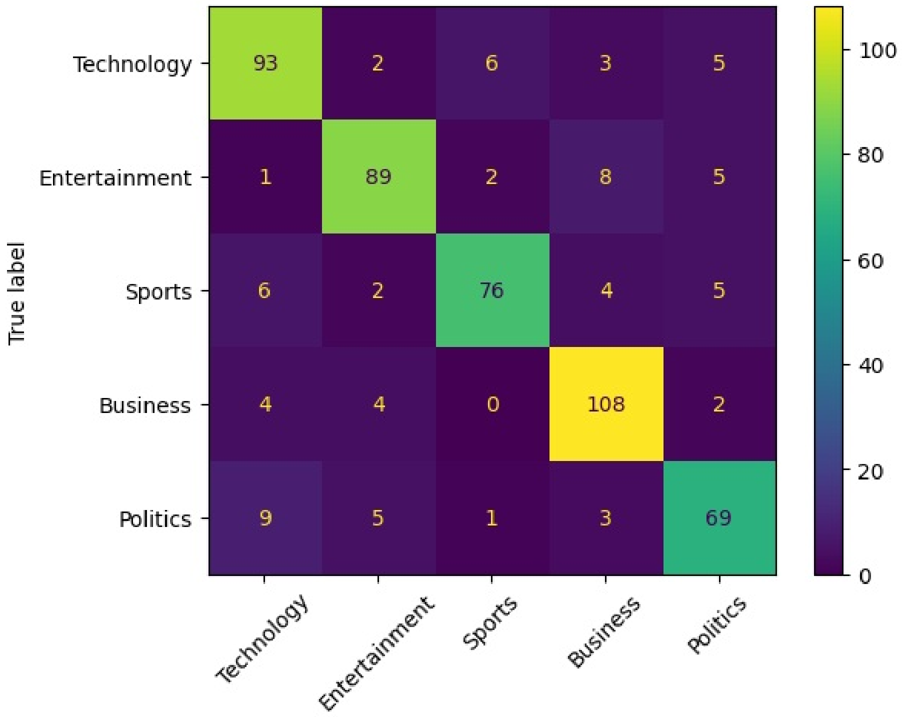
```
Model Accuracy with Random Forest with TF-IDF:  0.95
```

In [188…
```
print(classification_report(tf_ytest,random_f_pred_tf))
```

```
              precision    recall  f1-score   support

           0       0.89      0.94      0.91       124
           1       1.00      0.96      0.98        89
           2       0.95      0.91      0.92        95
           3       0.97      0.99      0.98       115
           4       0.98      0.94      0.96        89

    accuracy                           0.95       512
   macro avg       0.95      0.95      0.95       512
weighted avg       0.95      0.95      0.95       512
```

Using BOW Data training Decision Tree

In [189…
```
DS_classifier = DecisionTreeClassifier()
DS_classifier.fit(xtrain,ytrain)

ds_f_pred = DS_classifier.predict(xtest)
ConfusionMatrixDisplay(confusion_matrix(ytest,ds_f_pred),display_labels=list(set(Label_encode.inverse_transform
plt.xticks(rotation=45)
plt.show()
```



In [190…
```
print("Model Accuracy with Decision Tree with BOW: ",round(DS_classifier.score(xtest,ytest),2))
```

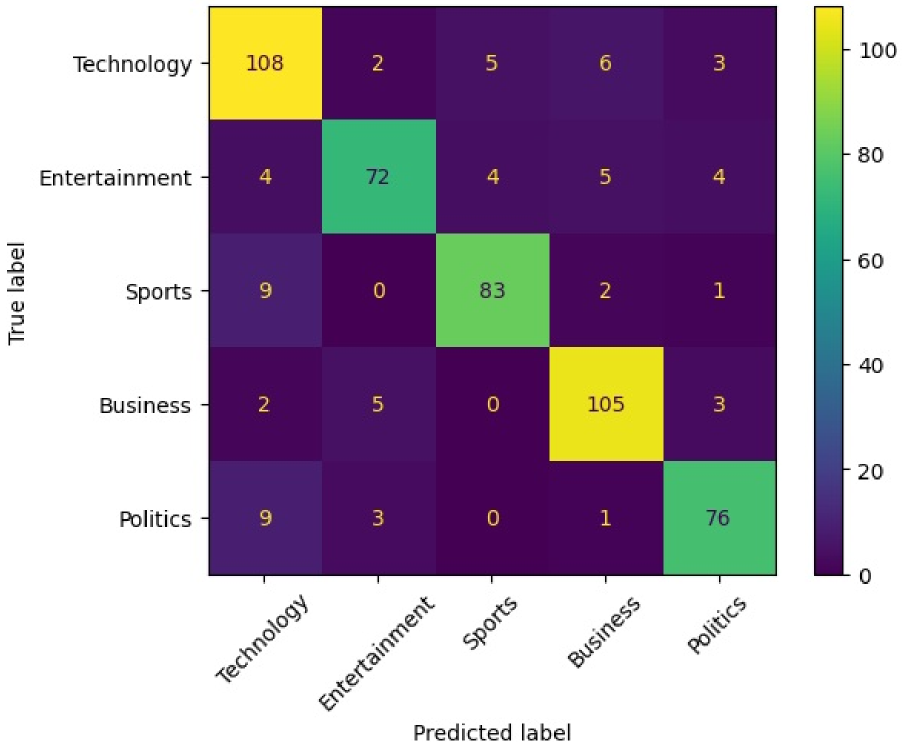
```
Model Accuracy with Decision Tree with BOW:  0.85
```

In [191…
```
print(classification_report(ytest,ds_f_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.85      0.84       109
           1       0.87      0.85      0.86       105
           2       0.89      0.82      0.85        93
           3       0.86      0.92      0.89       118
           4       0.80      0.79      0.80        87

    accuracy                           0.85       512
   macro avg       0.85      0.85      0.85       512
weighted avg       0.85      0.85      0.85       512
```

Using TF-IDF Data training Decision Tree

In [192…
```
DS_classifier_tf =DecisionTreeClassifier()
DS_classifier_tf.fit(tf_xtrain,tf_ytrain)

DS_f_pred_tf = DS_classifier_tf.predict(tf_xtest)
ConfusionMatrixDisplay(confusion_matrix(tf_ytest,DS_f_pred_tf),display_labels=list(set(Label_encode.inverse_tra
plt.xticks(rotation=45)
plt.show()
```



In [193…

```
print("Model Accuracy with Decision Tree with BOW: ",round(DS_classifier_tf.score(tf_xtest,tf_ytest),2))
```

```
Model Accuracy with Decision Tree with BOW:  0.87
```

In [194…

```
print(classification_report(tf_ytest,DS_f_pred_tf))
```

```
              precision    recall  f1-score   support

           0       0.82      0.87      0.84       124
           1       0.88      0.81      0.84        89
           2       0.90      0.87      0.89        95
           3       0.88      0.91      0.90       115
           4       0.87      0.85      0.86        89

    accuracy                           0.87       512
   macro avg       0.87      0.86      0.87       512
weighted avg       0.87      0.87      0.87       512
```

Consolidating Metrics

In [195…

```
model_metrics = pd.DataFrame()
```

In [196…

```
model_metrics['model_name'] = ['NaiveBayes','NaiveBayes','RandomForest','RandomForest', 'DecisionTree','Decisio
```

In [198…

```
model_metrics['Vectorize_technique'] = ['BOW','TF-IDF','BOW','TF-IDF','BOW','TF-IDF']
```

In [202…

```
model_metrics['Accuracy(%)'] = [90,93,95,95,85,87]
```

In [205…

```
model_metrics
```

Out[205]:

	model_name	Vectorize_technique	Accuracy(%)
0	NaiveBayes	BOW	90
1	NaiveBayes	TF-IDF	93
2	RandomForest	BOW	95
3	RandomForest	TF-IDF	95
4	DecisionTree	BOW	85
5	DecisionTree	TF-IDF	87

Questionnaire:

How many news articles are present in the dataset that we have? `5 Articles`

Most of the news articles are from `sports` category.

Only `401` no. of articles belong to the ‘Technology’ category.

What are Stop Words and why should they be removed from the text data?

`Ans :  Words like "a","an" are known as stopword, it is important to remove them because they dont contribute more in prediction.`

Explain the difference between Stemming and Lemmatization.

`Ans : Stemming convert words to there root form without having proper human readble meaning, whereas Lemmatization convert words to root form with meaning full context.`

Which of the techniques Bag of Words or TF-IDF is considered to be more efficient than the other?

`Ans : Tf-IDF is more efficient than Bag of Words , because they dont consider all words with same importance as it is done in BOW.`

What's the shape of train & test data sets after performing a 75:25 split.

`Ans :  train shape (1668, 27175)  test shape (557, 27175) , ytrain shape (1668,) , ytest shape (557,)`

Which of the following is found to be the best performing model..

`Ans  : Random Forest`

According to this particular use case, both precision and recall are equally important. (T/F)

`Ans  : T`

In [ ]: