```
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
import nltk
import sklearn


from tensorflow import keras
from keras.preprocessing.text import text_to_word_sequence
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import roc_auc_score
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier


dataset = pd.read_csv('/content/BBC News.csv')
test_set = pd.read_csv("/content/BBC News.csv")


dataset.head( )
```

	ArticleId	Text	Category
0	1833	worldcom ex-boss launches defence lawyers defe...	business
1	154	german business confidence slides german busin...	business
2	1101	bbc poll indicates economic gloom citizens in ...	business
3	1976	lifestyle governs mobile choice faster bett...	tech
4	917	enron bosses in $168m payout eighteen former e...	business

```
target_category = dataset['Category'].unique( )
print(target_category)
```

```
['business' 'tech' 'politics' 'sport' 'entertainment']
```

```
dataset['categoryId'] = dataset['Category'].factorize()[0]
dataset.head()
```

	ArticleId	Text	Category	categoryId
0	1833	worldcom ex-boss launches defence lawyers defe...	business	0
1	154	german business confidence slides german busin...	business	0
2	1101	bbc poll indicates economic gloom citizens in ...	business	0
3	1976	lifestyle governs mobile choice faster bett...	tech	1
4	917	enron bosses in $168m payout eighteen former e...	business	0

```
category = dataset[["Category","categoryId"]].drop_duplicates().sort_values('categoryId')
category
```

	Category	categoryId
0	business	0

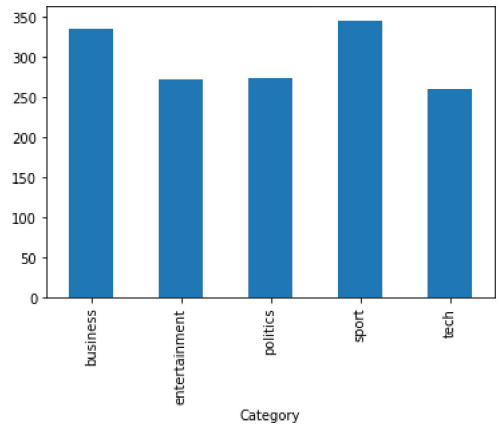
```
dataset.groupby('Category').categoryId.count()
```

```
Category
business       336
entertainment  273
politics       274
sport          346
tech           261
Name: categoryId, dtype: int64
```

DATA VISUALIZATION

```
dataset.groupby('Category').categoryId.count().plot.bar(ylim=0)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1571138a60>
```




```
text = dataset["Text"]
text.head()
```

```
0    worldcom ex-boss launches defence lawyers defe...
1    german business confidence slides german busin...
2    bbc poll indicates economic gloom citizens in ...
3    lifestyle  governs mobile choice  faster  bett...
4    enron bosses in $168m payout eighteen former e...
Name: Text, dtype: object
```

```
category = dataset["Category"]
category.head()
```

```
0    business
1    business
2    business
3        tech
4    business
Name: Category, dtype: object
```

DATA PREPROCESSING

```
def preprocessDataset(train_text):

  #word tokenization using text-to-word-sequence
  train_text= str(train_text)
  tokenized_train_set = text_to_word_sequence(train_text,filters='!"#$%&()*+,-./:;<=>?@[\\]^_`{|}~\t\n',lower=True,split=" ")

  #stop word removal
  stop_words = set(stopwords.words('english'))
  stopwordremove = [i for i in tokenized_train_set if not i in stop_words]


  #join words into sentence
  stopwordremove_text = ' '.join(stopwordremove)
```

```
    #remove numbers
    numberremove_text = ''.join(c for c in stopwordremove_text if not c.isdigit())

    #--Stemming--
    stemmer= PorterStemmer()

    stem_input=nltk.word_tokenize(numberremove_text)
    stem_text=' '.join([stemmer.stem(word) for word in stem_input])


    lemmatizer = WordNetLemmatizer()

    def get_wordnet_pos(word):
        """Map POS tag to first character lemmatize() accepts"""
        tag = nltk.pos_tag([word])[0][1][0].upper()
        tag_dict = {"J": wordnet.ADJ,
                    "N": wordnet.NOUN,
                    "V": wordnet.VERB,
                    "R": wordnet.ADV}

        return tag_dict.get(tag, wordnet.NOUN)

    lem_input = nltk.word_tokenize(stem_text)
    lem_text= ' '.join([lemmatizer.lemmatize(w, get_wordnet_pos
(w)) for w in lem_input])

    return lem_text
```

SPLIT TRAIN SET

```
X_train, X_test, Y_train, Y_test = train_test_split(text,category, test_size = 0.3, random_state = 60,shuffle=True, stratify=category)

print(len(X_train))
print(len(X_test))
```

```
1043
447
```

MULTINOMIAL NAIVE BAYES

```
nb = Pipeline([('tfidf', TfidfVectorizer()),
               ('clf', MultinomialNB()),
              ])
nb.fit(X_train,Y_train)

test_predict = nb.predict(X_test)

train_accuracy = round(nb.score(X_train,Y_train)*100)
test_accuracy =round(accuracy_score(test_predict, Y_test)*100)


print("Naive Bayes Train Accuracy Score : {}% ".format(train_accuracy ))
print("Naive Bayes Test Accuracy Score  : {}% ".format(test_accuracy ))
print()
print(classification_report(test_predict, Y_test, target_names=target_category))
```

```
Naive Bayes Train Accuracy Score : 98%
Naive Bayes Test Accuracy Score  : 96%

                precision    recall  f1-score   support

      business       0.98      0.94      0.96       105
          tech       0.89      1.00      0.94        73
      politics       0.94      0.92      0.93        84
         sport       1.00      0.98      0.99       106
 entertainment       0.95      0.94      0.94        79

      accuracy                           0.96       447
     macro avg       0.95      0.96      0.95       447
  weighted avg       0.96      0.96      0.96       447
```

DECISION TREE

```
dt = Pipeline([('tfidf', TfidfVectorizer()),
               ('dt', DecisionTreeClassifier()),
              ])

dt.fit(X_train, Y_train)

test_predict = dt.predict(X_test)

train_accuracy = round(dt.score(X_train,Y_train)*100)
test_accuracy =round(accuracy_score(test_predict, Y_test)*100)

print("Decision Tree Train Accuracy Score : {}% ".format(train_accuracy ))
print("Decision Tree Test Accuracy Score  : {}% ".format(test_accuracy ))
print()
print(classification_report(test_predict, Y_test, target_names=target_category))
```

```
Decision Tree Train Accuracy Score : 100%
Decision Tree Test Accuracy Score  : 76%

                precision    recall  f1-score   support

      business       0.68      0.73      0.71        94
          tech       0.68      0.74      0.71        76
      politics       0.78      0.76      0.77        84
         sport       0.91      0.79      0.84       121
 entertainment       0.73      0.79      0.76        72

      accuracy                           0.76       447
     macro avg       0.76      0.76      0.76       447
  weighted avg       0.77      0.76      0.77       447
```

RANDOM FOREST CLASSIFIER

```
rfc = Pipeline([('tfidf', TfidfVectorizer()),
               ('rfc', RandomForestClassifier(n_estimators=100)),
              ])

rfc.fit(X_train, Y_train)

test_predict = rfc.predict(X_test)

train_accuracy = round(rfc.score(X_train,Y_train)*100)
test_accuracy =round(accuracy_score(test_predict, Y_test)*100)

print("K-Nearest Neighbour Train Accuracy Score : {}% ".format(train_accuracy ))
print("K-Nearest Neighbour Test Accuracy Score  : {}% ".format(test_accuracy ))
print()
print(classification_report(test_predict, Y_test, target_names=target_category))
```

```
K-Nearest Neighbour Train Accuracy Score : 100%
K-Nearest Neighbour Test Accuracy Score  : 93%

                precision    recall  f1-score   support

      business       0.97      0.88      0.92       112
          tech       0.88      1.00      0.94        72
      politics       0.85      0.93      0.89        75
         sport       1.00      0.93      0.96       112
 entertainment       0.92      0.95      0.94        76

      accuracy                           0.93       447
     macro avg       0.93      0.94      0.93       447
  weighted avg       0.94      0.93      0.93       447
```

TEST SET

```
test_set.head()
```

	ArticleId	Text	Category
0	1833	worldcom ex-boss launches defence lawyers defe...	business
1	154	german business confidence slides german busin...	business
2	1101	bbc poll indicates economic gloom citizens in ...	business
3	1976	lifestyle governs mobile choice faster bett...	tech
4	917	enron bosses in $168m payout eighteen former e...	business

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