- # News Article Classification Text Preprocessing and NLP models

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- ## Classification of News Articles

It is a notebook for classification of News articles which are having classes numbered 1 to 4,

1 is "World News",

2 is "Sports News",

3 is "Business News" and

4 is "Science-Technology News".

- ## Step 1: Import necessary libraries

```
import numpy as np
import pandas as pd
import nltk
import string as s
from ultk.corpus import stopwords
import seaborn as sns
import re
from skleann.feature_extnaction.text import CountVectonizen, TfidfVectonizen
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\swaraj\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
True
```

- ## Step 2: Load your dataset

```
# Due to large amount of data , not able to run KNN so. ie limited resorces, more memory required
# Specify the number of rows you want to read
# num_rows_to_read = 60000  # Replace this with the desired number of rows

# Read only the specified number of rows
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

```
train.head()
```

	CLass Index	T1t1e	Description
0	3	Wall St. Bears Claw Back Into the Black (Reuters)	Reuters - Short-sellers, Wall Street's dwindli...
1	3	Carlyle Looks Toward Commercial Aerospace (Reu...	Reuters - Private investment firm Carlyle Grou...
2	3	Oil and Economy Cloud Stocks' Outlook (Reuters)	Reuters - Soaring crude prices plus worries\ab...
3	3	Iraq Halts Oil Exports from Main Southern Pipe...	Reuters - Authorities have halted oil export\f...
4	3	Oil prices soar to all-time record, posing new...	AFP - Tearaway world oil prices, toppling reco...

```
test.head()
```

	Class Index	Title	Description
0	3	Fears for T N pension after talks	Unions representing workers at Turner Newall...
1	4	The Race is On: Second Private Team Sets Launc...	SPACE.com - TORONTO, Canada -- A second\team o...
2	4	Ky. Company Wins Grant to Study Peptides (AP)	AP - A company founded by a chemistry research...
3	4	Prediction Unit Helps Forecast Wildfires (AP)	AP - It's barely dawn when Mike Fitzpatrick st...
4	4	Calif. Aims to Limit Farm-Related Smog (AP)	AP - Southern California's smog-fighting agenc...

```
train.info()
```

```
‹class 'pandas.core.frame.DataFrame'›
Rangelndex: 120000 entries, 0 to 119999
Data columns (total 3 columns):
 #   Column       Non-Null Count   Dtype

 0   Class Index  120000 non-null  int64
 1   Title         120000 nou-uull  object
 2   Description  120000 non-null  object
dtypes: int64(1), object(2)
memory usage: 2.7+ MB
```

```
print(train.shape)
 print(test.shape)
```

```
(120000, 3)
(7600, 3)
```

Spliting data into input and label

```
train_x = traiu.Description
test_x = test.Description

trains =  traiu['Class Index']
tests = test['Class Index']
```

Step 3: Preprocessing the dataset

Removal of HTML Tag

```
def striphtml(data):
    p = re.compile(r'‹.*?>')
    netunn  p.sub('', data)
```

```
train_x = train_x.apply(striphtml)
test_x - test_x.apply(striphtml)
```

- ### Removal of URL

```
def remove_url(data):
    return  re.sub(r'\s*(?:https?://)?www\.\S*\.[A-Za-z]{2,5}\s*',       data).strip()
```

```
train_x = train_x.apply(remove_url)
test_x = test_x.apply(remove_url)
```

- ### Tokenization of Data

```
def word_tok(data):
    tokens = re.findall("[\w']+", data)
    return tokens
```

```
  *  <>:4: SyntaxWarning: invalid escape sequence '\w'
     <>:4: SyntaxWarning: invalid escape sequence '\w'
     C:\Users\swaraj\AppData\Local\Temp\ipykernel_18984\882723685.py:4:  SyntaxWarning: invalid escape sequence '\w'
       tokens = re.finda11(“[\w']+“, data)
```

```
train_x = train_x.apply(word_tok)
test_x  =test_x . apply(word_tok)
```

Removal of stopwords

```
def remove_stopwords(data):
    stopWords = stopwords.words('english')
    new_list - []
    for i in data:
        if i.lower() not in stopWords:
            new_list.append(i)
    return new_list
```

```
train_x = train_x.apply(remove_stopwords)
test_x = test_x.apply(remove_stopwords)
```

- Removal of Punctuation Symbols

```
def remove_punctuations(data):
    new_list = []
    for i in data:
        for j in s.punctuation:
            i = i.replace(j,'')
        new_list.append(i)
    return new_list
```

```
train_x  = train_x.apply(remove_punctuations)
test_x =  test_x . apply(renove_punctuat1ons)
```

- Removal of numbers

```
def- remove_number (data):
    no_d ig it_list = [ ]
    new_11st = [ ]

    for i in data:
        for j in s.digits:
            i = i.replace(j,'')
        no_digit_list.append(i)

    for i in no_digit_list:
        if i!='':
            new_list.append(i)
    return new_list
```

```
train_x  = train_x.apply(remove_number)
test_x = test_x.apply(remove_number)
```

- Stemming of dataset

```
import nltk

def stemming(data):
    porter_stemmer = nltk.PorterStemmer()
    roots = [porter_stemmer.stem(i) for i in data]
    return roots
```

```
train_x = train_x.apply(stemming)
test_x = test_x.apply(stemming)
```

Lemmatization of data

```
def   lemmat1zat ton (data) :
    lemmatizer = nltk.stem.WordNetLemmatizer()
    roots = [lemmatizer.lemmatize(i) for i in data]
    return roots


train_x = tnain_x.apply(lemmatization)
test_x = test_x.apply(lemmatization)
```

- ## Remove extra words

```
def nemove_extnaWords(data):
    extra_words  =['href','iii','1t','gt','ii','com','quot']

    new_list = []
    for i in data:
        if i not in extra_words:
            new_list.append(i)
    return new_list


train_x  =  train_x.apply(remove_extraWords)
test_x = test_x.apply(remove_extraWords)


train_x = [“  “.join(map(str, lst)) for 1st in train_x]
test_x = [“ “.join(map(str, 1st)) for 1st in test_x]
```

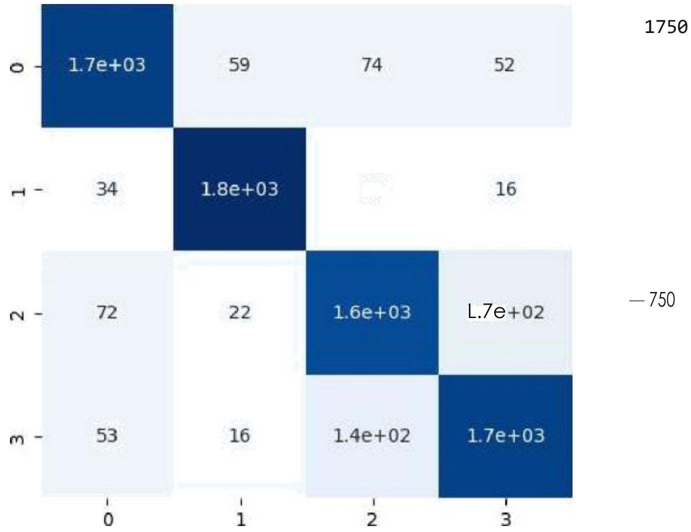
- ## Step 4: Feature Extraction

```
# Vectorizatiou with CountVectorizer
count_vect  = CountVectorizer(min_df=8, ngram_range=(1, 3))
train_count = count_vect.fit_transform(train_x)
test_count  = count_vect.transform(test_x)


# Vectorization  with TfidfVectorizer
tfidf_vect  = TfidfVectorizen(min_df=8, ngram_range=(1, 3))
train_tfidf = tfidf_vect.fit_transfonm(train_x)
test_tfidf  = tfidf_vect.transform(test_x)
```

- ## Step 5: Train and Evaluate the models

```
S Function to train and evaluate models
def train_and_evaluate_model(model, tnain_data, test_data, model_name):
    model.fit(train_data, trains)
    predictions = model.predict(test_data)
    accunacy = accuracy_score(test_y, predictions)
    print(f‟{model_name} Accuracy: {accuracy}‟)
    priut(‟Classification Report:”)
    print(classification_report(test_y, predictions))
    print(‟Confusion Matrix:‟)
    print(confusion_matrix(test_y, predictions))
    sns.heatmap(confusion_matrix(tests, predictions), cmap=‟Blues‟, annot=True)


# Logistic  Regression
lr = LogisticRegression(max_iter=200)
print(“Logistic  Regression  with CountVectorizer")
train_and_evaluate_model(
    lr, train_count, test_count, ”Logistic  Regression with CountVectorizer”
```

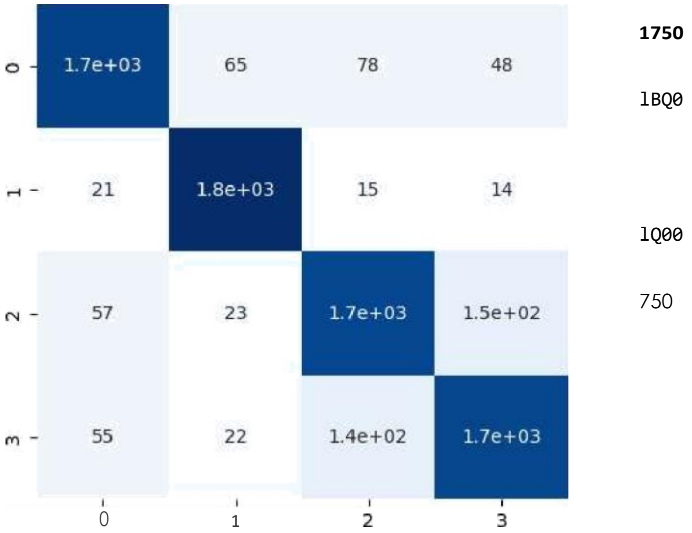
```
Logistic Regression with CountVectorizer
Logistic Regression with CountVectorizer Accuracy: 0.9035526315789474
Classification Report:
              precision    recall  f1-score   support

           1       0. 92      0.90      0.91      1900
           2       0. 95      0.96      0.96      1900
           3       0.87      0.86      0.87      1900
           4       B.87      0.89      0.88      1900

    accuracy                           0.9B      7600
   macro avg       0.90      0.90      0.90      7600
weighted avg       0.9B      0.90      0.90      7600

Confusion Matrix:
[[1715    59    74    52]
 [   34 1833    17    16]
 [   72    22 1632   174]
 [   53    16   144 1687]]
```



[redacted]

```
print("Logistic Regression with TfidfVectorizer")
train_and_evaluate_model(
    lr, train_tfidf, test_tfidf, "Logistic  Regression  with  TfidfVectorizer"
```

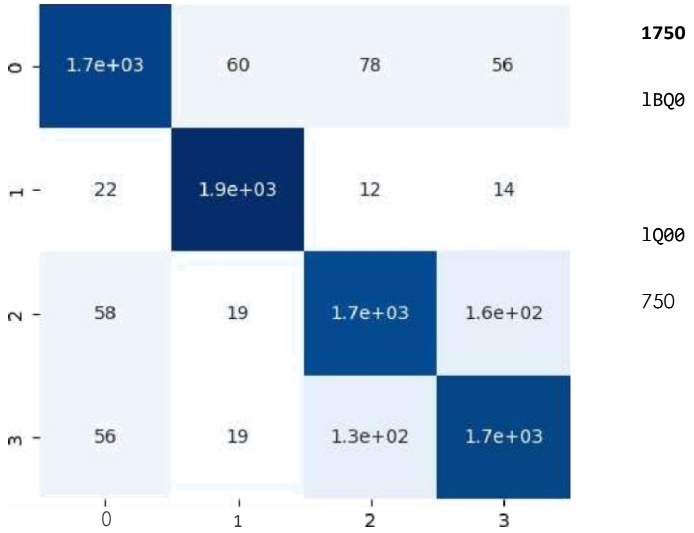
```
Logistic  Regression  with  TfidfVectorizer
Logistic Regression with TfidfVectorizer Accuracy: 0.9090789473684211
Classification Report:
                 precision    recall  fl-score   support

              1       0.93      0.98      0.91      1900
              2       0.94      0.97      0.96      1900
              3       0.88      0.88      0.88      1900
              4       0.89      0.89      0.89      1900

       accuracy                           0.91      7600
      nacro avg       0.91      0.91      0.91      7600
   weighted avg       0.91      6.91      0.91      7600

Confusion Matrix:
[[1709   65   78   48]
 [  21 1850   15   14]
 [  57   23 1666  154]
 [  55   22  139 1684]]
```



- Support Vector Classifier (SVC)

```
svc = SVC()
print("SVC with CountVectorizer")
train_and_evaluate_model(svc, train_count, test_count, "SVC with CountVectorizer")
```

```
SVC  with  CountVec ton  zer
SVC with CountVectorizer Accuracy: 0.9096052631578947
Classification Report:
              precision    recall  fl-score   support

           1       0.93      0.98      0.91      1900
           2       0. 95     0.97      0.96      1900
           3       0.88      0.87      0.88      1900
           4       0.88      0.89      0.89      1900

    accuracy                           0.91      7600
   nacro avg       0.91      0. 91     0.91      7600
weighted avg       0.91      6. 91     0.91      7600

Confusion Matrix:
[[1706   60   78   56]
 [   22 1852   12   14]
 [   58   19 1659  164]
 [   56   19  129 1696]]
```



```
print(“SVC with TfidfVectorizer“)
train_and_evaluate_model(svc, train_tfidf, test_tfidf, “SVC with TfidfVectorizer“)
```

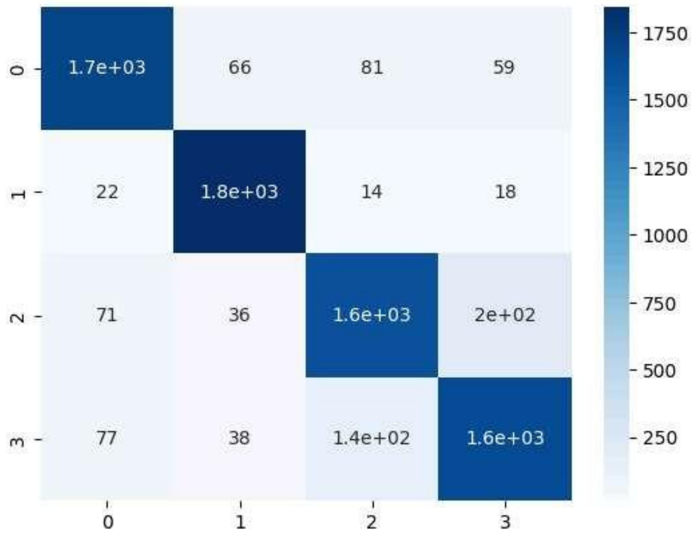
```
SVC with TfidfVectorizer
SVC with TfidfVectorizer Accuracy: 0.9132894736842105
Classification Report:
              precision    recall  fl-score   support

           1       0.93      0.90      0.92      1900
           2       0.95      0.98      0.96      1900
           3       0.89      0.88      0.88      1900
           4       0.88      0.90      0.89      1900

    accuracy                           0.91      7600
   nacro avg       0.91      0.91      0.91      7600
weighted avg       0.91      6.91      0.91      7600
```

Random Forest

```
Confusion Matrix:
[[1708   61   79   52]
```

```
rf = R ndggFggggtCl§gsif}gg(n_estimators=100, random_state=42)
print({Rajjom §grQg#7Wit8s§ountVectorizer“)
train_gnd gvalQgte Qgdgt86]]
    rf, train_count, test_count, "Random Forest with CountVectorizer”
```

```
Random Forest with CountVectorizer
Random Forest with CountVectorizer Accuracy: 0.8914473684210527
Classification Report:
              precision    recall  fl-score   support

           1       0.91      0.89      0.90      1900
           2       0.93      0.97      0.95      1900
           3       0.87      0.84      0.85      1900
           4       0.86      0.86      0.86      1900

    accuracy                           0.89      7600
   nacro avg       0.89      0.89      0.89      7600
weighted avg       0.89      0.89      0.89      7600

Confusion Matrix:
[[1694   66   81   59]
 [  22 1846   14   18]
 [  71   36 1593  200]
 [  77   38  143 1642]]
```



```
print(“\nRandom Forest with TfidfVectorizer")
train_and_evaluate_model(
    rf, train_tfidf, test_tfidf, ”Random Forest with TfidfVectorizer“
```