5-Class Sentiments Analysis using Random Forest

May 16, 2020

Data Exploration

[1]:
```
# importing require libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:
```
# Reading dataset of train and test
train_df = pd.read_csv('data/sentiment_5_class_train.csv')
test_df = pd.read_csv('data/sentiment_5_class_test.csv')
```

[3]:
```
train_df.head()
```

[3]:
```
                                              Phrase  Sentiment
0                                       the prisoner          2
1  The sheer joy and pride they took in their wor…          3
2  has never made a more sheerly beautiful film t…          3
3  the story has the sizzle of old news that has …          3
4                                       far superior          4
```

[4]:
```
test_df.head()
```

[4]:
```
                                              Phrase  Sentiment
0  makes for a touching love story , mainly becau…          3
1                               a truly magical movie          4
2                                               check          3
3     is a remarkably accessible and haunting film .          4
4                                        are too cute          3
```

[5]:
```
# checking the shape of dataset
print('train_df shape: ', train_df.shape)
print('test_df shape: ', test_df.shape)
```

```
train_df shape:  (14711, 2)
test_df shape:  (3678, 2)
```

```
[6]: # checking the null values
     train_df.isnull().sum()
```

```
[6]: Phrase       0
     Sentiment    0
     dtype: int64
```

```
[7]: test_df.isnull().sum()
```

```
[7]: Phrase       0
     Sentiment    0
     dtype: int64
```

```
[8]: # checking the number of sentiments
     train_df.Sentiment.unique()
```

```
[8]: array([2, 3, 4, 0, 1])
```

Here, above sentiments represents:
0 : Very Bad
1 : Bad
2 : Normal
3 : Good
4 : Very Good

```
[9]: # checking if there is empty phrase or not
     empty_train = train_df[train_df.Phrase.apply(lambda x: len(x.split()) == 0)]
     empyt_test = test_df[test_df.Phrase.apply(lambda x: len(x.split()) == 0)]

     print('Empty train Phrase: \n', empty_train)
     print('Empty test Phrase: \n', empyt_test)
```

```
Empty train Phrase:
       Phrase  Sentiment
6189                  1
Empty test Phrase:
 Empty DataFrame
Columns: [Phrase, Sentiment]
Index: []
```

Here, we have empty `Phrase` at training set but not in test set.

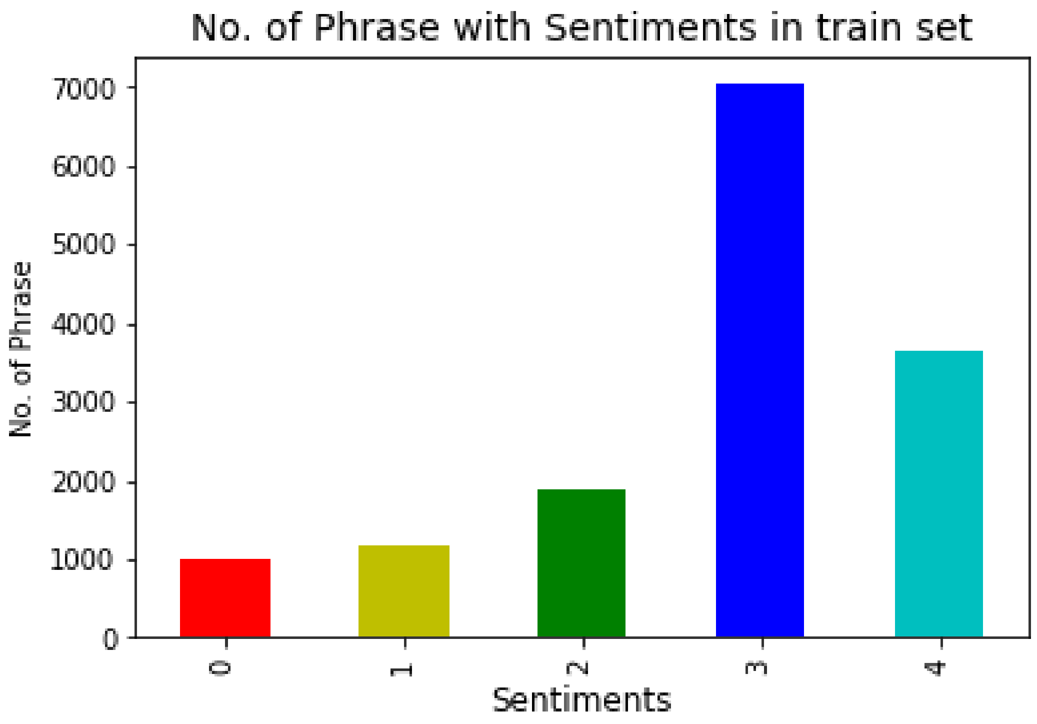
```
[10]: # removing empty Phrase index
      train_df.drop(empty_train.index, inplace=True)
```

```
[11]: # Total number of Phrase with sentiments in train set
      sentiments_collection_train = train_df.groupby('Sentiment').size()
      sentiments_collection_test = test_df.groupby('Sentiment').size()
```

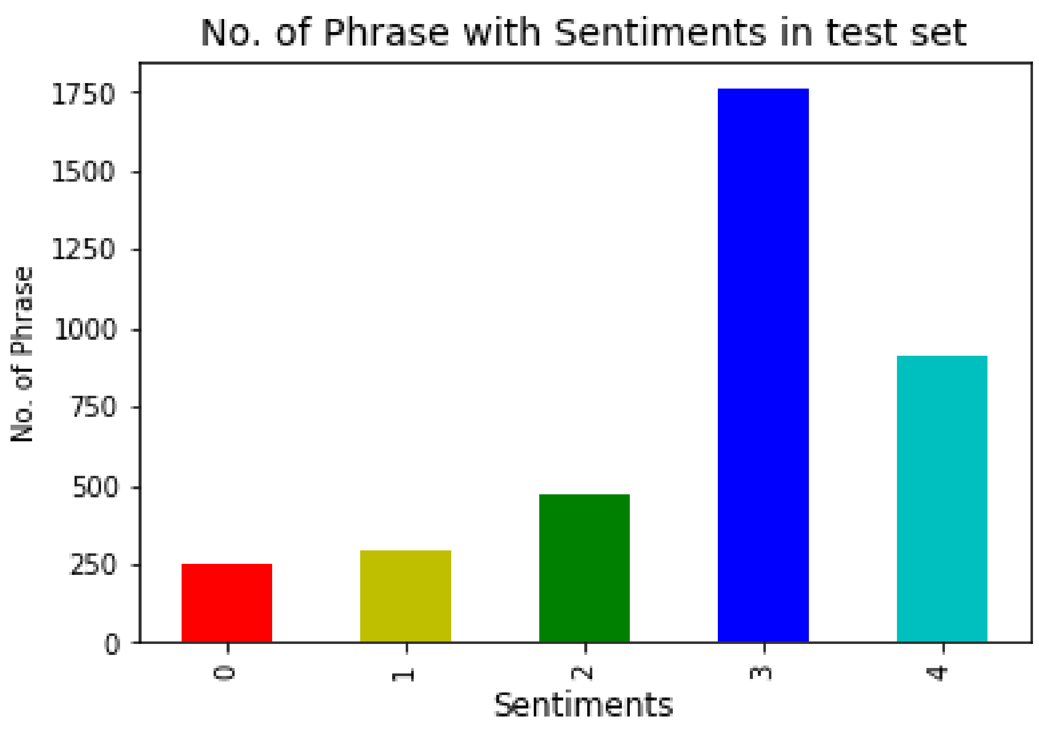
```
print('In train set: \n', sentiments_collection_train)
print('\n In test set: \n', sentiments_collection_test)
```

```
In train set:
 Sentiment
0     988
1    1164
2    1876
3    7033
4    3649
dtype: int64

 In test set:
 Sentiment
0     247
1     291
2     469
3    1759
4     912
dtype: int64
```

```
[12]: # barplot of no.of phrase with sentiments in train set
sentiments_collection_train.plot(kind='bar', color=['r', 'y', 'g', 'b', 'c'])

plt.title('No. of Phrase with Sentiments in train set', fontsize=14)
plt.xlabel('Sentiments', fontsize=12)
plt.ylabel('No. of Phrase')

plt.show()
```

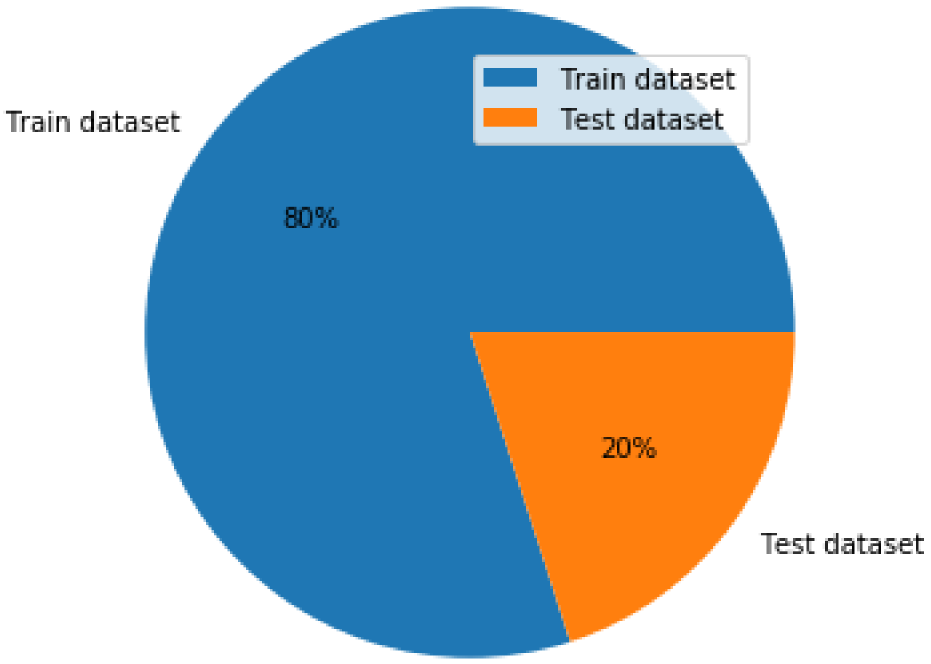


[13]:
```
# barplot of no.of phrase with sentiments in test set
sentiments_collection_test.plot(kind='bar', color=['r', 'y', 'g', 'b', 'c'])

plt.title('No. of Phrase with Sentiments in test set', fontsize=14)
plt.xlabel('Sentiments', fontsize=12)
plt.ylabel('No. of Phrase')

plt.show()
```



This diagram shows that, we have more number of positive phrase than the negative phrase. We can also observe that the data is inbalanced because label 3 is higer than other. so, to make a balanced dataset we can use SMOOTEING method.

[14]:
```
# lets check the distribution of train and test set
train_len = len(train_df)
test_len = len(test_df)

plt.pie(x=[train_len, test_len], labels=['Train dataset', 'Test dataset'],␣
 ↪autopct='%1.0f%%', radius=1.4)
plt.legend()

plt.show()
```



Feature Extraction and Preprocessing

Splitting train and test set.

```
[15]: X_train = train_df['Phrase'].tolist()
      y_train = train_df['Sentiment']

      X_test = test_df['Phrase'].tolist()
      y_test = test_df['Sentiment']

      print('X_train length: ', len(X_train))
      print('X_test length: ', len(X_test))
      print('\n')

      print('y_train length: ', len(y_train))
      print('y_test length: ', len(y_test))
```

```
X_train length:  14710
X_test length:  3678


y_train length:  14710
y_test length:  3678
```

Using `Term Frequency - Inverse Dense Frequency (TF-IDF)` for vectorizatioin.

[16]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer()
vectorizer.fit(X_train)
```

[16]:
```
TfidfVectorizer()
```

[17]:
```
X_train_v = vectorizer.transform(X_train)
X_test_v = vectorizer.transform(X_test)

print('X_train_v shape: ', X_train_v.shape)
print('X_test_v shape: ', X_test_v.shape)
```

```
X_train_v shape:  (14710, 7115)
X_test_v shape:  (3678, 7115)
```

We, know that the data is imbalanced. So, we are using `SMOOTE Oversampling` to make the data balanced.

[18]:
```
from collections import Counter
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42, sampling_strategy='auto')
X_train_smote, y_train_smote = smote.fit_resample(X_train_v, y_train)
```

```
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.neighbors.base module is  deprecated in version 0.22 and will be removed
in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.neighbors. Anything that cannot be imported from
sklearn.neighbors is now part of the private API.
  warnings.warn(message, FutureWarning)
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.ensemble.bagging module is  deprecated in version 0.22 and will be
removed in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.ensemble. Anything that cannot be imported from
sklearn.ensemble is now part of the private API.
  warnings.warn(message, FutureWarning)
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.ensemble.base module is  deprecated in version 0.22 and will be removed
in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.ensemble. Anything that cannot be imported from
sklearn.ensemble is now part of the private API.
  warnings.warn(message, FutureWarning)
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
```

```
sklearn.ensemble.forest module is  deprecated in version 0.22 and will be
removed in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.ensemble. Anything that cannot be imported from
sklearn.ensemble is now part of the private API.
  warnings.warn(message, FutureWarning)
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.utils.testing module is  deprecated in version 0.22 and will be removed
in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.utils. Anything that cannot be imported from sklearn.utils
is now part of the private API.
  warnings.warn(message, FutureWarning)
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:143: FutureWarning: The
sklearn.metrics.classification module is  deprecated in version 0.22 and will be
removed in version 0.24. The corresponding classes / functions should instead be
imported from sklearn.metrics. Anything that cannot be imported from
sklearn.metrics is now part of the private API.
  warnings.warn(message, FutureWarning)
/home/code_monkey/anaconda3/lib/python3.7/site-
packages/sklearn/utils/deprecation.py:86: FutureWarning: Function safe_indexing
is deprecated; safe_indexing is deprecated in version 0.22 and will be removed
in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[19]:
```
Counter(y_train_smote)
```

[19]:
```
Counter({2: 7033, 3: 7033, 4: 7033, 0: 7033, 1: 7033})
```

Now, our dataset is balanced.

Grid Search

[20]:
```
grid_params={
    'n_estimators':(5,8,11,13),
    'max_depth':(3, 5, 7, 9, 11, 13),
    'min_samples_split': (2, 4, 6, 8, 10),
    'random_state':(1,42),
}
```

[21]:
```
from sklearn.svm import SVC
from sklearn.metrics import make_scorer,f1_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

scorer = make_scorer(f1_score, average='micro')
clf = GridSearchCV(RandomForestClassifier(), grid_params, scoring=scorer)
clf.fit(X_train_smote, y_train_smote)
```

[21]:
```
GridSearchCV(estimator=RandomForestClassifier(),
             param_grid={'max_depth': (3, 5, 7, 9, 11, 13),
                         'min_samples_split': (2, 4, 6, 8, 10),
                         'n_estimators': (5, 8, 11, 13),
                         'random_state': (1, 42)},
             scoring=make_scorer(f1_score, average=micro))
```

[22]:
```
best_score = clf.best_score_

print(best_score)
```

```
0.5197781885397412
```

[23]:
```
best_params = clf.best_params_

print(best_params)
```

```
{'max_depth': 13, 'min_samples_split': 8, 'n_estimators': 13, 'random_state':
42}
```

[24]:
```
print('The best score is: {} with params {}'.format(best_score, best_params))
```

```
The best score is: 0.5197781885397412 with params {'max_depth': 13,
'min_samples_split': 8, 'n_estimators': 13, 'random_state': 42}
```

Model Evaluation

[25]:
```
from sklearn import metrics


model=RandomForestClassifier(random_state=1,n_estimators=13,max_depth=13,min_samples_split=6)
model.fit(X_train_smote, y_train_smote)

y_pred = model.predict(X_test_v)
print(metrics.classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.29      0.34      0.32       247
           1       0.30      0.21      0.25       291
           2       0.20      0.84      0.32       469
           3       0.60      0.12      0.21      1759
           4       0.48      0.42      0.45       912

    accuracy                           0.31      3678
   macro avg       0.37      0.39      0.31      3678
weighted avg       0.47      0.31      0.29      3678
```

```
[ ]:
```