Informatyka 6 semestr

Przewidywanie gatunku piosenek na podstawie ich tekstu

Dane

Zbiór danych użyty w tym projekcie pochodzi ze strony: https://www.kaggle.com/gyani95/380000-lyrics-from-metrolyrics
Z powyższego zestawu używam tylko kolumny 'genre oraz 'lyrics

```
class Lyrics_Data:
    def __init__(self, path):
        self.path = path
        self.data = pd.read_csv(path)#nrows=100000
        self.data = self.data[['genre','lyrics']].dropna()
```

Normalizacja tekstu

Na tekstach piosenek wykonuję:

- usunięcie znaków nowej linii
- usuniecie cyfr
- zmiana na małe litery
- usunięcie interpunkcji
- usunięcie białych znaków
- usunięcie słów pomijanych
- stemming
- lemmatization

Dzielenie Tekstu

```
train_x, valid_x, train_y, valid_y = model_selection.train_test_split(d['lyrics'], d['genre'])
```

Naive Bayes

```
text_clf = Pipeline(
    [('vect', CountVectorizer()),
        ('clf', MultinomialNB(alpha=0.1))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer()),
        ('clf', MultinomialNB(alpha=0.1))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer()),
        ('clf', MultinomialNB(alpha=0.2))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

0.49747899159663866

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer()),
        ('clf', MultinomialNB(alpha=0.08))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer()),
        ('clf', MultinomialNB(alpha=0.15))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

0.5014555822328931

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer(max_df=0.4,min_df=4)),
        ('clf', MultinomialNB(alpha=0.15))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer(max_df=0.4,min_df=4)),
        ('clf', MultinomialNB(alpha=0.05))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

0.5207683073229292

```
text_clf = Pipeline(
    [('vect', TfidfVectorizer(max_df=0.4,min_df=4)),
        ('clf', MultinomialNB(alpha=0.08))])

# train our model on training data
text_clf.fit(train_x, train_y)

# score our model on testing data
predicted = text_clf.predict(valid_x)
np.mean(predicted == valid_y)
```

```
from sklearn.metrics import precision_recall_fscore_support
genres = list(d['genre'].unique())
precision, recall, fscore, support = precision_recall_fscore_support(valid_y, predicted)
for n,genre in enumerate(genres):
    genre = genre.upper()
    print(genre+'_precision: {}'.format(precision[n]))
print(genre+'_recall: {}'.format(recall[n]))
print(genre+'_fscore: {}'.format(fscore[n]))
print(genre+'_support: {}'.format(support[n]))
    print()
POP precision: 0.5503952569169961
POP_recall: 0.15597871744609354
POP_fscore: 0.2430722234344316
POP support: 3571
HIP-HOP_precision: 0.6666666666666666
HIP-HOP recall: 0.02594810379241517
HIP-HOP_fscore: 0.049951969260326606
HIP-HOP support: 2004
NOT AVAILABLE_precision: 0.3150684931506849
NOT AVAILABLE_recall: 0.12387791741472172
NOT AVAILABLE_fscore: 0.17783505154639176
NOT AVAILABLE_support: 557
ROCK_precision: 0.7261219792865362
ROCK recall: 0.7023374145333121
ROCK fscore: 0.7140316844487552
ROCK support: 6289
METAL_precision: 0.83333333333333334
METAL_recall: 0.0063371356147021544
METAL fscore: 0.012578616352201257
METAL_support: 789
OTHER_precision: 0.46534653465346537
OTHER_recall: 0.09073359073359073
OTHER_fscore: 0.1518578352180937
OTHER_support: 2072
COUNTRY_precision: 0.6786274949540255
COUNTRY_recall: 0.5102006407013995
COUNTRY_fscore: 0.5824831568816169
COUNTRY_support: 5931
JAZZ_precision: 0.28781925343811393
JAZZ_recall: 0.19790611279972983
JAZZ fscore: 0.23454072443466079
JAZZ_support: 5922
ELECTRONIC_precision: 0.1690307328605201
ELECTRONIC_recall: 0.11016949152542373
ELECTRONIC_fscore: 0.13339552238805968
ELECTRONIC_support: 1298
FOLK_precision: 0.535012285012285
FOLK_recall: 0.08697823047733173
FOLK_fscore: 0.14963064765504208
FOLK_support: 10014
R&B precision: 0.8235294117647058
R&B_recall: 0.017456359102244388
R&B fscore: 0.034188034188034185
R&B_support: 802
INDIE precision: 0.505897607495399
INDIE_recall: 0.8831367967580592
INDIE_fscore: 0.6432911830015823
```

INDIE_support: 27391

SGD Classifier

0.5115096038415367

Random Forest