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МЕТОДЫ МАШИННОГО ОБУЧЕНИЯ

Отчёт по рубежному контролю № 2

«Задача классификация текстов на основе методов наивного Байеса»

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```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from IPython.display import Image
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classification_report
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_erro
from sklearn.metrics import roc_curve, roc_auc_score, auc
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR, LinearSVR
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

```
# В качестве набора данных будем использовать отзывы с сайта amazon
mob = pd.read_csv('Amazon_Unlocked_Mobile.csv', sep=",", encoding='ISO-8859-1')
mob.head()
```

	Product Name	Brand Name	Price	Rating	
0	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...	Samsung	199.99	5	I feel s
1	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...	Samsung	199.99	4	nice ph
2	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...	Samsung	199.99	5	
3	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...	Samsung	199.99	4	It wor
4	"CLEAR CLEAN ESN" Sprint EPIC 4G Galaxy SPH-D7...	Samsung	199.99	4	Great

```
mob.shape
```

```
(413840, 6)
```

PromptCloud extracted more than 400 thousand reviews of unlocked mobile phones sold on Ama
reviews, ratings, price and their relationships.

```
# Уникальные значения признака Review Votes
mob['Review Votes'].unique()
```

```
array([  1.,   0.,   2.,   6.,  19.,  12.,  13.,  17.,   4.,   9.,   3.,
         5.,  16.,   7.,  11.,  15.,   8.,  23.,  14.,  20.,  24.,  nan,
        18.,  10.,  41.,  59.,  42., 116.,  22.,  57.,  21.,  32.,  54.,
        30.,  77., 115.,  39.,  31.,  64., 124.,  36., 100., 125.,  28.,
        86.,  25.,  43.,  27., 120.,  72., 121.,  48.,  33.,  75.,  40.,
        37., 249.,  38., 130., 112., 157.,  51.,  58.,  63., 107.,  52.,
        34.,  46.,  45.,  85., 105., 366.,  29., 138.,  67.,  62.,  35.,
        47., 177.,  80.,  66.,  68.,  84., 152.,  53., 113., 151., 141.,
       159., 128.,  94.,  79.,  56.,  78.,  55.,  61.,  50.,  76., 127.,
        96., 119.,  87.,  60., 192.,  44.,  49., 126.,  26.,  81.,  88.,
       158.,  92., 155., 154., 156., 106., 175., 103., 172., 118.,  83.,
       296., 136.,  73.,  74.,  90.,  65., 283., 282., 288., 285., 270.,
       265., 478., 462., 465., 171.,  98.,  99., 169., 213., 110., 183.,
        71., 109., 114., 182., 221., 487., 170.,  93., 166., 137., 108.,
       219., 123., 218.,  91.,  69., 185., 226., 122., 146., 190., 246.,
       250.,  82., 150., 214., 133., 274., 101., 257., 129., 215., 104.,
       140., 134., 200., 297., 204., 176., 232., 227., 263., 102.,  89.,
        70., 173., 153., 404., 339., 131., 524., 518., 331.,  95., 519.,
       287., 187., 197., 117., 264., 186., 142., 193., 145., 147., 191.,
       207., 383., 251., 240., 139., 305., 304., 174., 132., 308.,  97.,
       279., 216., 160., 178., 111., 428., 423., 205., 356., 645., 165.,
       168., 212., 371., 295., 364., 163., 201., 272., 162., 350., 335.])
```

```
# Уникальные значения признака Rating
# Будем использовать этот признак для определения характеристик текста
mob['Rating'].unique()
```

```
array([5, 4, 1, 2, 3])
```

```
mob.isna().sum()
```

```
Product Name        0
Brand Name      65171
Price            5933
Rating              0
Reviews            62
Review Votes    12296
dtype: int64
```

```
# Удалим строки с пропусками данных,
# так как их количество существенно меньше размера датасета и не отразится на качестве мод
mob.dropna(inplace=True)
```

```
mob.shape
```

```
(334335, 6)
```

Рассмотрим, как рейтинг мобильных устройств влияет на длину отзывов

```
s1 = mob[mob.Rating == 1].Reviews.apply(len)
s2 = mob[mob.Rating == 2].Reviews.apply(len)
s3 = mob[mob.Rating == 3].Reviews.apply(len)
s4 = mob[mob.Rating == 4].Reviews.apply(len)
s5 = mob[mob.Rating == 5].Reviews.apply(len)
```

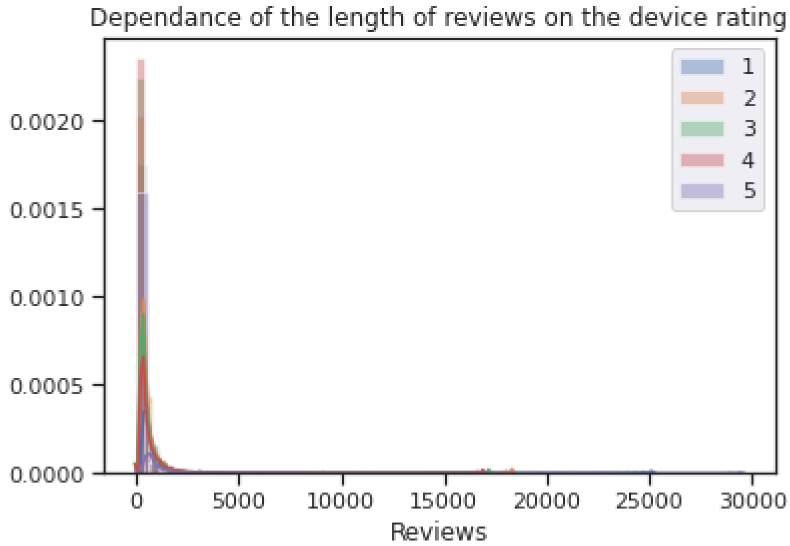
```
sns.distplot(s1,label='1')
sns.distplot(s2,label='2')
sns.distplot(s3,label='3')
sns.distplot(s4,label='4')
sns.distplot(s5,label='5')

sns.set()

plt.title('Dependance of the length of reviews on the device rating')
plt.legend()

print('1 - mean: %s' % s1.mean())
print('2 - mean: %s' % s2.mean())
print('3 - mean: %s' % s3.mean())
print('4 - mean: %s' % s4.mean())
print('5 - mean: %s' % s5.mean())
```

```
1 - mean: 247.22681845832972
2 - mean: 330.6330476380307
3 - mean: 296.54532197405786
4 - mean: 274.9803058249539
5 - mean: 169.16030246375928
```



Как видно из графика, негативные отзывы (для товаров с рейтингом 1,2) превышают поло: рейтингом 4,5) по длине.

```
# Разделим данные на обучающую и тестовую выборки
X = mob.Reviews
y = mob.Rating
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

```
# Сформируем общий словарь для обучения моделей из обучающей и тестовой выборки
vocab_list = mob['Reviews'].tolist()
vocab_list[1:10]
```

```
['nice phone, nice up grade from my pantach revue. Very clean set up and easy set up.
 'Very pleased',
 'It works good but it goes slow sometimes but its a very good phone I love it',
 'Great phone to replace my lost phone. The only thing is the volume up button does n
 'I already had a phone with problems... I know it stated it was used, but dang, it d
 'The charging port was loose. I got that soldered in. Then needed a new battery as w
 "Phone looks good but wouldn't stay charged, had to buy new battery. Still couldn't 
 'I originally was using the Samsung S2 Galaxy for Sprint and wanted to return back t
```

```
vocabVect = CountVectorizer()
vocabVect.fit(vocab_list)
corpusVocab = vocabVect.vocabulary_
print('Количество сформированных признаков - {}'.format(len(corpusVocab)))
```

```
Количество сформированных признаков - 63516
```

```
for i in list(corpusVocab)[1:10]:
    print('{}={}'.format(i, corpusVocab[i]))
```

```
so=52056
lucky=34179
to=56818
have=27444
found=24315
this=56266
used=59467
phone=41769
us=59365
```

Проведём векторизацию текста

```
# Класс TfidfVectorizer вычисляет специфичность текста в корпусе текстов на основе метрики
tfidfv = TfidfVectorizer(ngram_range=(1,3))
tfidf_ngram_features = tfidfv.fit_transform(vocab_list)
tfidf_ngram_features
```

```
<334335x4204950 sparse matrix of type '<class 'numpy.float64'>'
	with 33222615 stored elements in Compressed Sparse Row format>
```

В качестве классификаторов будем использовать Multinomial Naive Bayes (MNB) и LogisticR

```
clf1 = Pipeline([('tfidfv', tfidfv), ('MultinomNB', MultinomialNB()),])
clf2 = Pipeline([('tfidfv', tfidfv), ('LogRegr', LogisticRegression()),])
```

Multinomial Naive Bayes (MNB)

```
%time
clf1.fit(X_train, y_train)
```

```
CPU times: user 2 µs, sys: 0 ns, total: 2 µs
Wall time: 44.1 µs
Pipeline(memory=None,
         steps=[('tfidfv',
                 TfidfVectorizer(analyzer='word', binary=False,
                                 decode_error='strict',
                                 dtype=<class 'numpy.float64'>,
                                 encoding='utf-8', input='content',
                                 lowercase=True, max_df=1.0, max_features=None,
                                 min_df=1, ngram_range=(1, 3), norm='l2',
                                 preprocessor=None, smooth_idf=True,
                                 stop_words=None, strip_accents=None,
                                 sublinear_tf=False,
                                 token_pattern='(?u)\\b\\w\\w+\\b',
                                 tokenizer=None, use_idf=True,
                                 vocabulary=None)),
                ('MultinomNB',
                 MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True))]
```

Метрики точности accuracy_score, precision_score, recall_score

```
print('accuracy_score (train):', accuracy_score(y_train, clf1.predict(X_train)))
print('accuracy_score (test):', accuracy_score(y_test, clf1.predict(X_test)))
```

```
accuracy_score (train): 0.6868831024551988
accuracy_score (test): 0.6610901187425848
```

```
print('precision_score (train):', precision_score(y_train, clf1.predict(X_train), average=
print('precision_score (test):', precision_score(y_test, clf1.predict(X_test), average='mi
```

```
precision_score (train): 0.6868831024551988
precision_score (test): 0.6610901187425848
```

```
print('recall_score (train):', recall_score(y_train, clf1.predict(X_train), average='micro
print('recall_score (test):', recall_score(y_test, clf1.predict(X_test), average='micro'))
```

```
recall_score (train): 0.6868831024551988
recall_score (test): 0.6610901187425848
```

LogisticRegression

```
%time
clf2.fit(X_train, y_train)
```

```
CPU times: user 2 µs, sys: 0 ns, total: 2 µs
Wall time: 5.48 µs
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: Converg
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
Pipeline(memory=None,
         steps=[('tfidfv',
                 TfidfVectorizer(analyzer='word', binary=False,
                                 decode_error='strict',
                                 dtype=<class 'numpy.float64'>,
                                 encoding='utf-8', input='content',
                                 lowercase=True, max_df=1.0, max_features=None,
                                 min_df=1, ngram_range=(1, 3), norm='l2',
                                 preprocessor=None, smooth_idf=True,
                                 stop_words=None, strip_accents=None,
                                 sublinear_tf=False,
                                 token_pattern='(?u)\\b\\w\\w+\\b',
                                 tokenizer=None, use_idf=True,
                                 vocabulary=None))
```

Метрики точности accuracy_score, precision_score, recall_score

```
                                  fit intercept=True, intercept scaling=1,
```

```
print('accuracy_score (train):', accuracy_score(y_train, clf2.predict(X_train)))
print('accuracy_score (test):', accuracy_score(y_test, clf2.predict(X_test)))
```

```
accuracy_score (train): 0.841189741661468
accuracy_score (test): 0.7975992263287505
```

```
print('precision_score (train):', precision_score(y_train, clf2.predict(X_train), average=
print('precision_score (test):', precision_score(y_test, clf2.predict(X_test), average='mi
```

```
precision_score (train): 0.841189741661468
precision_score (test): 0.7975992263287505
```

```
print('recall_score (train):', recall_score(y_train, clf2.predict(X_train), average='micro
print('recall_score (test):', recall_score(y_test, clf2.predict(X_test), average='micro'))
```

```
recall_score (train): 0.841189741661468
recall_score (test): 0.7975992263287505
```

Таким образом, на основании полученных с помощью метрик accuracy, precision_score и rec
классификаций, можно сделать вывод о том, что для выбранного набора данных классифи
более качественную классификацию данных.