Министерство образования и науки Российской Федерации
Федеральное государственное бюджетное образовательное учреждение высшего образования
«Московский государственный технический университет имени Н.Э. Баумана (национальный исследовательский университет)»
(МГТУ им. Н.Э. Баумана)

Методы машинного обучения

Отчёт по рубежному контролю № 2

Выполнил:
студент группы ИУ5 – 23М Крутов Т.Ю.

Преподаватель: Гапанюк Ю.Е.

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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.datasets import load_iris, load_boston
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.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_errc
from sklearn.metrics import roc_curve, roc_auc_score
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")
```

```
df = pd.read_csv('deceptive-opinion.csv')
df
```

	deceptive	hotel	polarity	source	
0	truthful	conrad	positive	TripAdvisor	We stayed for a one night getaway wi
1	truthful	hyatt	positive	TripAdvisor	Triple A rate with upgrade to view roo
2	truthful	hyatt	positive	TripAdvisor	This comes a little late as I'm fina
3	truthful	omni	positive	TripAdvisor	The Omni Chicago really delivers on
4	truthful	hyatt	positive	TripAdvisor	I asked for a high floor away from th
...	...	...	...	...	
1595	deceptive	intercontinental	negative	MTurk	Problems started when I booked the Int
1596	deceptive	amalfi	negative	MTurk	The Amalfi Hotel has a beautiful web
1597	deceptive	intercontinental	negative	MTurk	The Intercontinental Chicago Magnific
1598	deceptive	palmer	negative	MTurk	The Palmer House Hilton, while it loo
1599	deceptive	amalfi	negative	MTurk	As a former Chicagoan, I'm appalled at

1600 rows × 5 columns

```
df.isna().sum()
```

```
deceptive    0
hotel        0
polarity     0
source       0
text         0
dtype: int64
```

```
df.columns
```

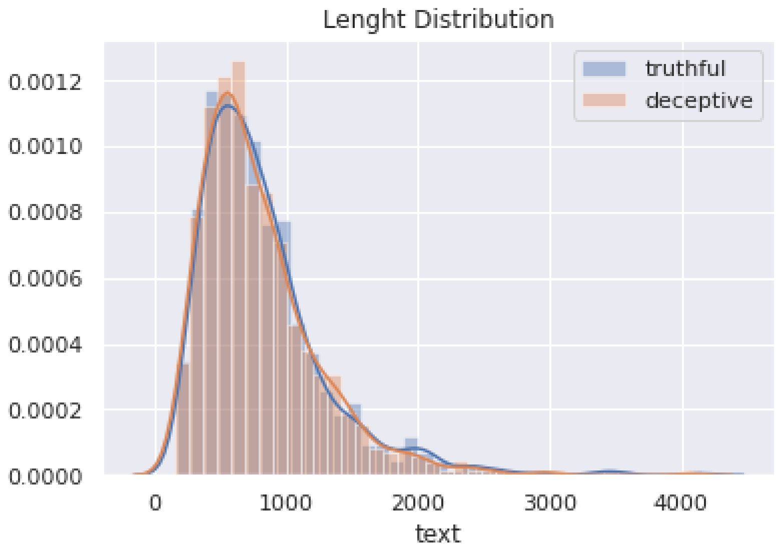
```
Index(['deceptive', 'hotel', 'polarity', 'source', 'text'], dtype='object')
```

```
df['deceptive'].unique()
```

```
array(['truthful', 'deceptive'], dtype=object)
```

```
s1 = df[df.deceptive  == 'truthful'].text.apply(len)
s2 = df[df.deceptive == 'deceptive'].text.apply(len)
sns.distplot(s1,label='truthful')
sns.distplot(s2,label='deceptive')

sns.set()

plt.title('Lenght Distribution')
plt.legend()

print('truthful mean: %s' % s1.mean())
print(f'deceptive mean: {s2.mean()}')
```

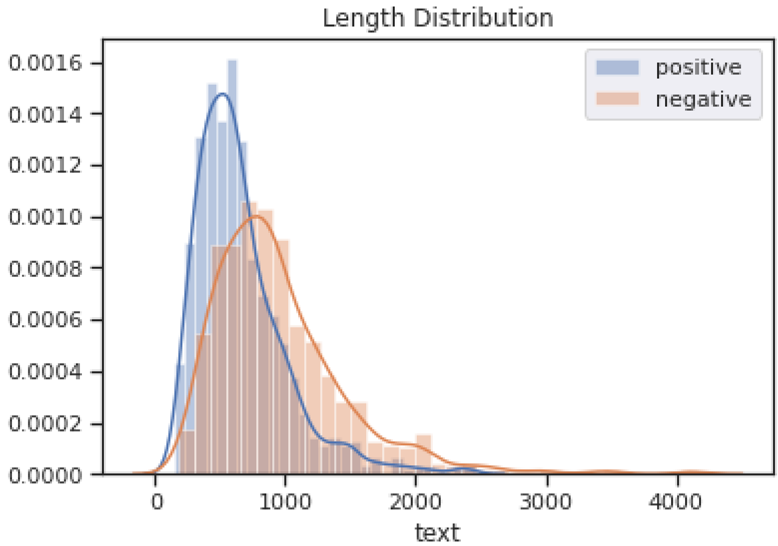
```
truthful mean: 821.015
deceptive mean: 791.4325
```




```
s1 = df[df.polarity  == 'positive'].text.apply(len)
s2 = df[df.polarity == 'negative'].text.apply(len)
sns.distplot(s1,label='positive')
sns.distplot(s2,label='negative')

sns.set()

plt.title('Length Distribution')
```

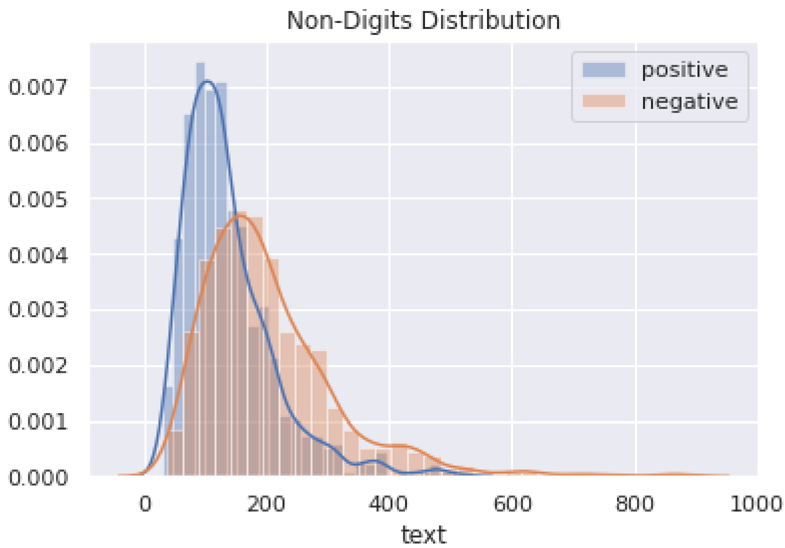
```
plt.legend()

print('positive mean: %s' % s1.mean())
print(f'negative mean: {s2.mean()}')
```

```
positive mean: 656.5275
negative mean: 955.92
```




```
s1 = df[df.polarity == 'positive']['text'].str.replace(r'\w+', '').str.len()
s2 = df[df.polarity == 'negative']['text'].str.replace(r'\w+', '').str.len()

sns.distplot(s1, label='positive')
sns.distplot(s2, label='negative')

plt.title('Non-Digits Distribution')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f6dfbb55390>
```




```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y = df.polarity

y = le.fit_transform(y)
```

```
X = df.drop(columns='polarity')
y
```

```
array([1, 1, 1, ..., 0, 0, 0])
```

```
def accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    """
    Вычисление метрики accuracy для каждого класса
    y_true - истинные значения классов
    y_pred - предсказанные значения классов
    Возвращает словарь: ключ - метка класса,
    значение - Accuracy для данного класса
    """
    # Для удобства фильтрации сформируем Pandas DataFrame
    d = {'t': y_true, 'p': y_pred}
    df = pd.DataFrame(data=d)
    # Метки классов
    classes = np.unique(y_true)
    # Результирующий словарь
    res = dict()
    # Перебор меток классов
    for c in classes:
        # отфильтруем данные, которые соответствуют
        # текущей метке класса в истинных значениях
        temp_data_flt = df[df['t']==c]
        # расчет accuracy для заданной метки класса
        temp_acc = accuracy_score(
            temp_data_flt['t'].values,
            temp_data_flt['p'].values)
        # сохранение результата в словарь
        res[c] = temp_acc
    return res

def roc_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    """
    Вычисление метрики accuracy для каждого класса
    y_true - истинные значения классов
    y_pred - предсказанные значения классов
    Возвращает словарь: ключ - метка класса,
    значение - Accuracy для данного класса
    """
    # Для удобства фильтрации сформируем Pandas DataFrame
    d = {'t': y_true, 'p': y_pred}
    df = pd.DataFrame(data=d)
    # Метки классов
    classes = np.unique(y_true)
    # Результирующий словарь
    res = dict()
    # Перебор меток классов
    for c in classes:
        # отфильтруем данные, которые соответствуют
```

```
        # отфильтруем данные, которые соответствуют
        # текущей метке класса в истинных значениях
        temp_data_flt = df[df['t']==c]
        # расчет accuracy для заданной метки класса
        try:
            temp_acc = roc_auc_score(
            temp_data_flt['t'].values,
            temp_data_flt['p'].values)
        # сохранение результата в словарь
            res[c] = temp_acc
        except ValueError:
            pass

    return res

def print_accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray):
    """
    Вывод метрики accuracy для каждого класса
    """
    accs = accuracy_score_for_classes(y_true, y_pred)
    if len(accs)>0:
        print('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))

def print_roc_auc(y_true: np.ndarray,
    y_pred: np.ndarray):
    accs = roc_score_for_classes(y_true, y_pred)
    if len(accs)>0:
        print('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))


# Сформируем общий словарь для обучения моделей из обучающей и тестовой выборки
vocab_list = df['text'].tolist()
vocab_list[1:15]
```

```
['Triple A rate with upgrade to view room was less than $200 which also included brea
 "This comes a little late as I'm finally catching up on my reviews from the past sev
 "The Omni Chicago really delivers on all fronts, from the spaciousness of the rooms
 "I asked for a high floor away from the elevator and that is what I got. The room wa
 "I stayed at the Omni for one night following a business meeting at another downtowr
 'We stayed in the Conrad for 4 nights just before Thanksgiving. We had a corner room
 'Just got back from 2 days up in Chicago shopping with girlfriends. First time I hav
 "We arrived at the Omni on 2nd September for a 6 day stay. I took ill when I left th
 'On our visit to Chicago, we chose the Hyatt due to its location in downtown, withir
 "I stayed at the Fairmont Chicago for one night - I'm a frequent business traveler a
 'Ok, so first trip to chicago and I was a litlle worried about the hotel and the loc
 "We arrived at 10:30 am on a Friday, and they had a room ready for us by 11:30 am, m
 "My wife and I came to spend the weekend in downtown Chicago for shopping and we fou
 "I got a Sunday night stay for only $50 off of Priceline.com, so it would be hard tc
```

```
vocabVect = CountVectorizer()
```

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

```
Количество сформированных признаков - 9570
```

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

```
stayed=8064
for=3556
one=5865
night=5677
getaway=3769
with=9443
family=3323
on=5863
thursday=8599
```

Векторизация текста

Для векторизации можно использовать простой класс CountVectorizer. Подсчитывает кол
текст

```
test_features = vocabVect.transform(vocab_list)
```

```
test_features
```

```
<1600x9570 sparse matrix of type '<class 'numpy.int64'>'
	with 146467 stored elements in Compressed Sparse Row format>
```

```
test_features.todense()
```

```
matrix([[0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        ...,
        [1, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0]])
```

```
# Размер нулевой строки
len(test_features.todense()[0].getA1())
```

```
9570
```

```
# Непустые значения нулевой строки
[i for i in test_features.todense()[0].getA1() if i>0]
```

```
vocabVect.get_feature_names()[500:530]
```

```
vocabvect.get_feature_names()[300:330]
```

```
['agree',
 'agreeable',
 'agreed',
 'agreement',
 'ah',
 'ahead',
 'ahould',
 'aid',
 'aides',
 'air',
 'airfare',
 'airline',
 'airlines',
 'airplane',
 'airport',
 'airports',
 'airshow',
 'airy',
 'aka',
 'akin',
 'akk',
 'al',
 'alarm',
 'alarmed',
 'alas',
 'albeit',
 'albiet',
 'alcoholic',
 'alcove',
 'alert']
```

Использование N-грамм

```
ncv = CountVectorizer(ngram_range=(1,3))
ngram_features = ncv.fit_transform(vocab_list)
ngram_features
```

```
<1600x257331 sparse matrix of type '<class 'numpy.int64'>'
	with 579998 stored elements in Compressed Sparse Row format>
```

```
len(ncv.get_feature_names())
```

```
257331
```

```
# Теперь признаками являются N-граммы
ncv.get_feature_names()[2000:2020]
```

```
['500 certificate me',
 '500 dollars',
 '500 dollars for',
 '500 night',
 '500 night one',
 '500 paint',
 '500 paint scrape',
 '500 to',
 '500 to fix',
 '50pm',
 '50pm the',
 '50pm the bar',
 '51',
```

```
tfidfv = TfidfVectorizer(ngram_range=(1,3))
tfidf_ngram_features = tfidfv.fit_transform(vocab_list)
tfidf_ngram_features
```

```
<1600x257331 sparse matrix of type '<class 'numpy.float64'>'
	with 579998 stored elements in Compressed Sparse Row format>
```

```
tfidf_ngram_features.todense()
```

```
matrix([[0.        , 0.        , 0.        , ..., 0.        , 0.        ,
         0.        ],
        [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
         0.        ],
        [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
         0.        ],
        ...,
        [0.03880781, 0.        , 0.        , ..., 0.        , 0.        ,
         0.        ],
        [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
         0.        ],
        [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
         0.        ]])
```

```
# Непустые значения нулевой строки
[i for i in tfidf_ngram_features.todense()[0].getA1() if i>0]
```

Решение задачи анализа тональности

С использованием кросс-валидации попробуем применить к корпусу текстов различные вар

```
def VectorizeAndClassify(vectorizers_list, classifiers_list):
    for v in vectorizers_list:
        for c in classifiers_list:
            pipeline1 = Pipeline([("vectorizer", v), ("classifier", c)])
            score = cross_val_score(pipeline1, df['text'], y, scoring='accuracy', cv=3).me
            print('Векторизация - {}'.format(v))
            print('Модель для классификации - {}'.format(c))
            print('Accuracy = {}'.format(score))
            print('===========================')
```

```
vectorizers_list = [CountVectorizer(vocabulary = corpusVocab), TfidfVectorizer(vocabulary
```

```
classifiers_list = [LogisticRegression(C=3.0), LinearSVC(), KNeighborsClassifier()]
VectorizeAndClassify(vectorizers_list, classifiers_list)
```

```
/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)
/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)
Векторизация - CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                lowercase=True, max_df=1.0, max_features=None, min_df=1,
                ngram_range=(1, 1), preprocessor=None, stop_words=None,
                strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None,
                vocabulary={'00': 0, '000': 1, '00a': 2, '00am': 3, '00pm': 4,
                            '03': 5, '04': 6, '05': 7, '06': 8, '07': 9,
                            '08': 10, '0800': 11, '09': 12, '10': 13, '100': 14,
                            '103': 15, '104': 16, '105': 17, '105mph': 18,
                            '107': 19, '10am': 20, '10pm': 21, '10th': 22,
                            '10x': 23, '10yo': 24, '11': 25, '110': 26,
                            '1112': 27, '116': 28, '11am': 29, ...})
Модель для классификации - LogisticRegression(C=3.0, class_weight=None, dual=False, f
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
Accuracy = 0.9187483750377693
===========================
/usr/local/lib/python3.6/dist-packages/sklearn/svm/_base.py:947: ConvergenceWarning:
  "the number of iterations.", ConvergenceWarning)
Векторизация - CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                lowercase=True, max_df=1.0, max_features=None, min_df=1,
                ngram_range=(1, 1), preprocessor=None, stop_words=None,
                strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None,
                vocabulary={'00': 0, '000': 1, '00a': 2, '00am': 3, '00pm': 4,
                            '03': 5, '04': 6, '05': 7, '06': 8, '07': 9,
                            '08': 10, '0800': 11, '09': 12, '10': 13, '100': 14,
                            '103': 15, '104': 16, '105': 17, '105mph': 18,
                            '107': 19, '10am': 20, '10pm': 21, '10th': 22,
                            '10x': 23, '10yo': 24, '11': 25, '110': 26,
                            '1112': 27, '116': 28, '11am': 29, ...})
Модель для классификации - LinearSVC(C=1.0, class_weight=None, dual=True, fit_interce
          intercept_scaling=1, loss='squared_hinge', max_iter=1000,
          multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
          verbose=0)
Accuracy = 0.9162479827045461
===========================
Векторизация - CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                lowercase=True, max_df=1.0, max_features=None, min_df=1,
                ngram_range=(1, 1), preprocessor=None, stop_words=None,
```

```
                strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None,
                vocabulary={'00': 0, '000': 1, '00a': 2, '00am': 3, '00pm': 4,
                            '03': 5, '04': 6, '05': 7, '06': 8, '07': 9,
                            '08': 10, '0800': 11, '09': 12, '10': 13, '100': 14,
                            '103': 15, '104': 16, '105': 17, '105mph': 18,
                            '107': 19, '10am': 20, '10pm': 21, '10th': 22,
                            '10x': 23, '10yo': 24, '11': 25, '110': 26,
                            '1112': 27, '116': 28, '11am': 29, ...})
Модель для классификации - KNeighborsClassifier(algorithm='auto', leaf_size=30, metri
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='uniform')
Accuracy = 0.7031255489737265
===========================
Векторизация - 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,
```

```
X_train, X_test, y_train, y_test = train_test_split(df['text'], y, test_size=0.3, random_s
```

```
def sentiment(v, c):
    model = Pipeline(
        [("vectorizer", v),
         ("classifier", c)])
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print_accuracy_score_for_classes(y_test, y_pred)
    print_roc_auc(y_test, y_pred)
```

```
sentiment(TfidfVectorizer(), LogisticRegression(C=5.0))
```

```
Метка    Accuracy
0        0.9669421487603306
1        0.9243697478991597
```

```
sentiment(TfidfVectorizer(ngram_range=(1,3)), LogisticRegression(C=5.0))
```

```
Метка    Accuracy
0        0.9669421487603306
1        0.9201680672268907
```

```
sentiment(TfidfVectorizer(ngram_range=(2,3)), LogisticRegression(C=5.0))
```

```
Метка    Accuracy
0        0.9214876033057852
1        0.9159663865546218
```

```
sentiment(TfidfVectorizer(ngram_range=(1,4)), LogisticRegression(C=5.0))
```

```
Метка    Accuracy
0        0.9628099173553719
1        0.8991596638655462
```

```
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import Lasso
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.calibration import CalibratedClassifierCV
from sklearn.linear_model import LogisticRegression

tfvectorizer = TfidfVectorizer(sublinear_tf=True, min_df=1, norm='l2',ngram_range=(1, 2),s
text_clf = Pipeline([('tfidf', tfvectorizer),
('MnNB', MultinomialNB()),
])

text_clf2 = Pipeline([('tfidf', tfvectorizer),
                     ('lSVC', CalibratedClassifierCV(LinearSVC())),
])

text_clf3 = Pipeline([('tfidf', tfvectorizer),
                     ('LR', LogisticRegression()),
])
```

MultinomialNB

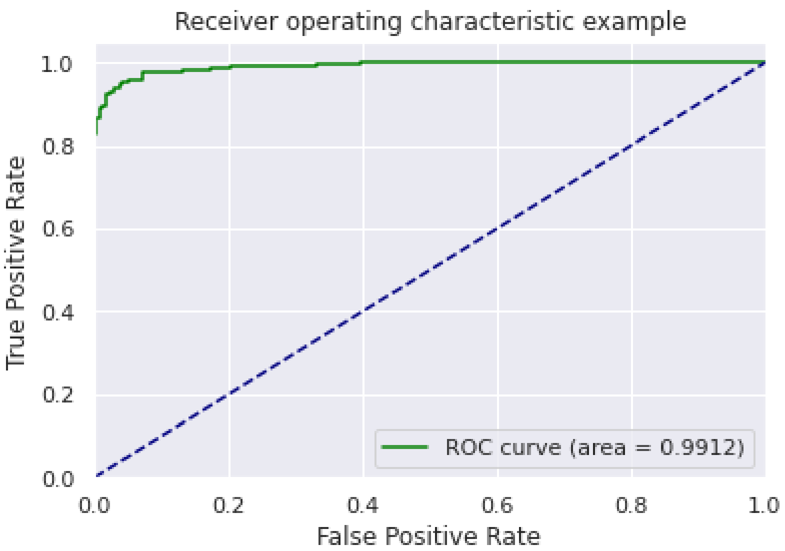
```
%time text_clf.fit(X_train, y_train);
```

```
CPU times: user 324 ms, sys: 8.81 ms, total: 333 ms
Wall time: 334 ms
Pipeline(memory=None,
         steps=[('tfidf',
                 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, 2), norm='l2',
                                 preprocessor=None, smooth_idf=True,
                                 stop_words='english', strip_accents=None,
                                 sublinear_tf=True,
                                 token_pattern='(?u)\\b\\w\\w+\\b',
                                 tokenizer=None, use_idf=True,
                                 vocabulary=None)),
                ('MnNB',
                 MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True))],
         verbose=False)
```

```
from sklearn.metrics import accuracy_score as accuracy, precision_score as precision, reca

print('accuracy train:', accuracy(y_train, text_clf.predict(X_train)))
print('accuracy test :', accuracy(y_test, text_clf.predict(X_test)), '\n')

print('precision train:', precision(y_train, text_clf.predict(X_train)))
print('precision test :', precision(y_test, text_clf.predict(X_test)), '\n')
```

```
print('recall train:', recall(y_train, text_clf.predict(X_train)))
print('recall test :', recall(y_test, text_clf.predict(X_test)), '\n')

from sklearn.metrics import roc_curve, auc
y_pred_prob = text_clf.predict_proba(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob[:,1])
roc_auc= auc(fpr, tpr)
plt.figure()
plt.plot(fpr, tpr, color='green', label='ROC curve (area = %0.4f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
accuracy train: 0.9973214285714286
accuracy test : 0.9520833333333333

precision train: 0.9946902654867257
precision test : 0.9282868525896414

recall train: 1.0
recall test : 0.9789915966386554
```



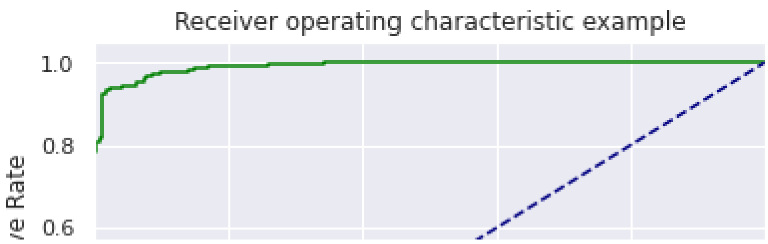
LinearSVC

```
%time text_clf2.fit(X_train, y_train);
```

```
CPU times: user 410 ms, sys: 6.61 ms, total: 417 ms
Wall time: 421 ms
Pipeline(memory=None,
         steps=[('tfidf',
                 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, 2), norm='l2',
                                 preprocessor=None, smooth_idf=True,
                                 stop_words='english', strip_accents=None,
                                 sublinear_tf=True,
                                 token_pattern='(?u)\\b\\w\\w+\\b',
                                 tokenizer=None, use_idf=True,
                                 vocabulary=None)),
                ('lSVC',
                 CalibratedClassifierCV(base_estimator=LinearSVC(C=1.0,
                                                                 class_weight=None,
                                                                 dual=True,
                                                                 fit_intercept=True,
                                                                 intercept_scaling=1,
                                                                 loss='squared_hinge'
```

```
print('accuracy train:', accuracy(y_train, text_clf2.predict(X_train)))
print('accuracy test :', accuracy(y_test, text_clf2.predict(X_test)), '\n')

print('precision train:', precision(y_train, text_clf2.predict(X_train)))
print('precision test :', precision(y_test, text_clf2.predict(X_test)), '\n')

print('recall train:', recall(y_train, text_clf2.predict(X_train)))
print('recall test :', recall(y_test, text_clf2.predict(X_test)), '\n')

from sklearn.metrics import roc_curve, auc
y_pred_prob = text_clf2.predict_proba(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob[:,1])
roc_auc= auc(fpr, tpr)
plt.figure()
plt.plot(fpr, tpr, color='green', label='ROC curve (area = %0.4f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
accuracy train: 1.0
accuracy test : 0.94375

precision train: 1.0
precision test : 0.934156378600823

recall train: 1.0
recall test : 0.9537815126050421
```



Линейная регрессия

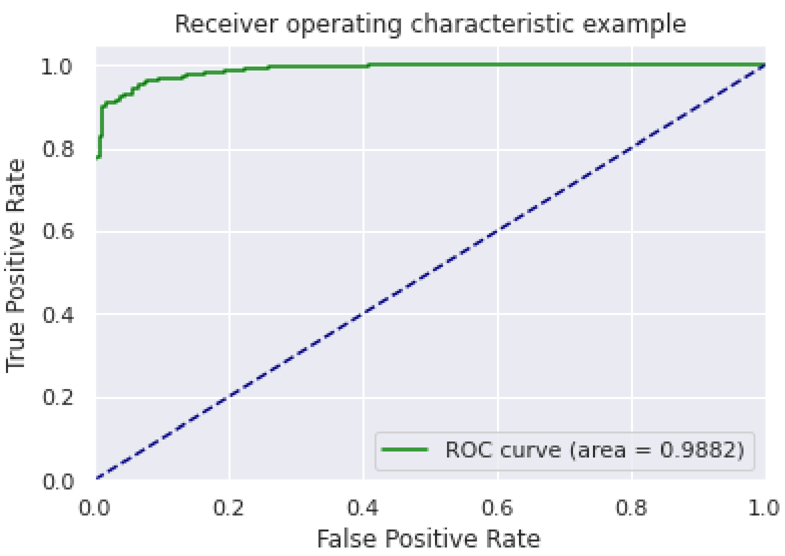
```
%time text_clf3.fit(X_train, y_train)
```

```
CPU times: user 536 ms, sys: 164 ms, total: 701 ms
Wall time: 546 ms
Pipeline(memory=None,
         steps=[('tfidf',
                 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, 2), norm='l2',
                                 preprocessor=None, smooth_idf=True,
                                 stop_words='english', strip_accents=None,
                                 sublinear_tf=True,
                                 token_pattern='(?u)\\b\\w\\w+\\b',
                                 tokenizer=None, use_idf=True,
                                 vocabulary=None)),
                ('LR',
                 LogisticRegression(C=1.0, class_weight=None, dual=False,
                                    fit_intercept=True, intercept_scaling=1,
                                    l1_ratio=None, max_iter=100,
                                    multi_class='auto', n_jobs=None,
                                    penalty='l2', random_state=None,
                                    solver='lbfgs', tol=0.0001, verbose=0,
                                    warm_start=False))],
         verbose=False)
```

```
print('accuracy train:', accuracy(y_train, text_clf3.predict(X_train)))
print('accuracy test :', accuracy(y_test, text_clf3.predict(X_test)), '\n')
print('precision train:', precision(y_train, text_clf3.predict(X_train)))
print('precision test :', precision(y_test, text_clf3.predict(X_test)), '\n')
print('recall train:', recall(y_train, text_clf3.predict(X_train)))
print('recall test :', recall(y_test, text_clf3.predict(X_test)), '\n')

from sklearn.metrics import roc_curve, auc
y_pred_prob = text_clf3.predict_proba(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob[:,1])
roc_auc= auc(fpr, tpr)
```

```
plt.figure()
plt.plot(fpr, tpr, color='green', label='ROC curve (area = %0.4f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```

```
accuracy train: 0.9973214285714286
accuracy test : 0.94375

precision train: 0.9946902654867257
precision test : 0.934156378600823

recall train: 1.0
recall test : 0.9537815126050421
```



Сравним характеристики трёх моделей. На рассмотренном наборе данных наибольшую эф
LinearSVC