МОСКОВСКИЙ ГОСУДАРСТВЕННЫЙ ТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ
им. Н.Э. Баумана

Кафедра «Систем обработки информации и управления»

РК 2

по дисциплине

«Методы машинного обучения»

ИСПОЛНИТЕЛЬ: Чечнев А.А.
ФИО

группа ИУ5-
23М

_____
подпись

"__"_____2020 г.

ПРЕПОДАВАТЕЛЬ: Гапанюк Ю. Е.
ФИО

_____
подпись

"__"_____2020 г.

Москва – 2020

Рубежный контроль №2

Необходимо подготовить отчет по рубежному контролю и разместить его в Вашем репозитории. Вы можете использовать титульный лист, или в начале ноутбука в текстовой ячейке указать Ваши Ф.И.О. и группу.

Тема: Методы построения моделей машинного обучения. В рамках рубежного контроля Вы можете решить на выбор или 1) задачу классификации текста или 2) задачу классификации/регрессии/ кластеризации данных (по вариантам).

Задача 1. Классификация текстов на основе методов наивного Байеса.

Данный вариант выполняется на основе материалов лекции часть 1 и часть 2.

Необходимо решить задачу классификации текстов на основе любого выбранного Вами датасета (кроме примера, который рассматривался в лекции). Классификация может быть бинарной или многоклассовой. Целевой признак из выбранного Вами датасета может иметь любой физический смысл, примером является задача анализа тональности текста.

Необходимо сформировать признаки на основе CountVectorizer или TfidfVectorizer.

В качестве классификаторов необходимо использовать два классификатора, не относящихся к наивным Байесовским методам (например, LogisticRegression, LinearSVC), а также Multinomial Naive Bayes (MNB), Complement Naive Bayes (CNB), Bernoulli Naive Bayes.

Для каждого метода необходимо оценить качество классификации с помощью хотя бы двух метрик качества классификации (например, Accuracy, ROC-AUC).

Сделате выводы о том, какой классификатор осуществляет более качественную классификацию на Вашем наборе данных.

In [1]:

```
import pandas as pd
pd.set_option('display.max.columns', 100)
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.set_option('display.max_colwidth', -1)
sns.set()
```

```
C:\Users\als\Anaconda3\lib\site-packages\ipykernel_launcher.py:7: FutureWarn
ing: Passing a negative integer is deprecated in version 1.0 and will not be
supported in future version. Instead, use None to not limit the column widt
h.
  import sys
```

Датасет - спам/не спам

In [2]:

```
df = pd.read_csv('data/spam.csv', encoding = 'latin-1')
```

In [3]:

```
df.shape
```

Out[3]:

```
(5572, 5)
```

In [4]:

```
df.head()
```

Out[4]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only in bugis n great world la e buffet... Cine there got amore wat...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup final tkts 21st May 2005. Text FA to 87121 to receive entry question(std txt rate)T&C's apply 08452810075over18's	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives around here though	NaN	NaN	NaN

In [5]:

```
df.describe()
```

Out[5]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
count	5572	5572	50	12	6
unique	2	5169	43	10	5
top	ham	Sorry, I'll call later	bt not his girlfrnd... G o o d n i g h t . . .@"	GE	GNT:-)"
freq	4825	30	3	2	2

In [6]:

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

Out[6]:

```
v1            0
v2            0
Unnamed: 2    5522
Unnamed: 3    5560
Unnamed: 4    5566
dtype: int64
```

У столбцов 2,3,4 слишком много пустых, поэтому попросту избавимся от них

In [7]:

```
df.columns
```

Out[7]:

```
Index(['v1', 'v2', 'Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], dtype='objec
t')
```

In [8]:

```
df.drop(columns=['Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], inplace=True)

df = df.rename(columns = {'v1': 'target','v2': 'text'})

df.target.value_counts()
```

Out[8]:

```
ham     4825
spam    747
Name: target, dtype: int64
```

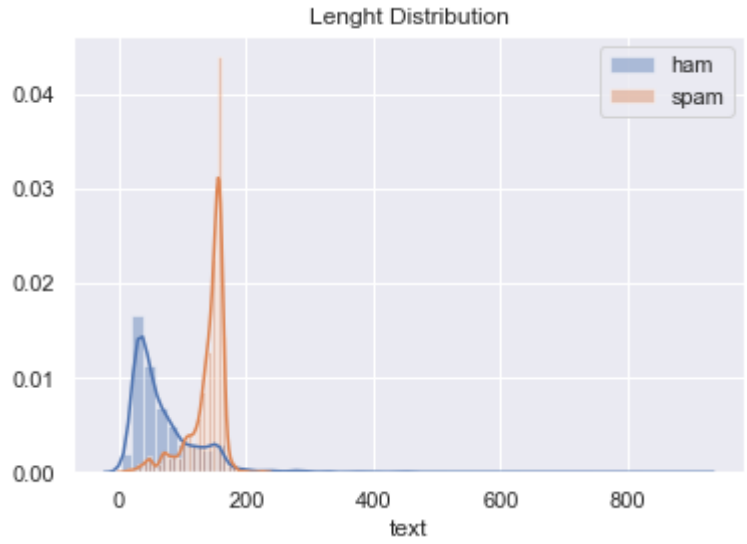
Классы несбалансированны поэтому будум использовать метрики (precission recall roc_auc)

Посмотрим на распределение длины сообщений в зависимости от класса

In [9]:

```
s1 = df[df.target == 'ham'].text.apply(len)
s2 = df[df.target == 'spam'].text.apply(len)

sns.distplot(s1,label='ham')
sns.distplot(s2,label='spam')

sns.set()

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

print('ham mean: %s' % s1.mean())
print(f'spam mean: {s2.mean()}')
```

```
ham mean: 71.02362694300518
spam mean: 138.8661311914324
```

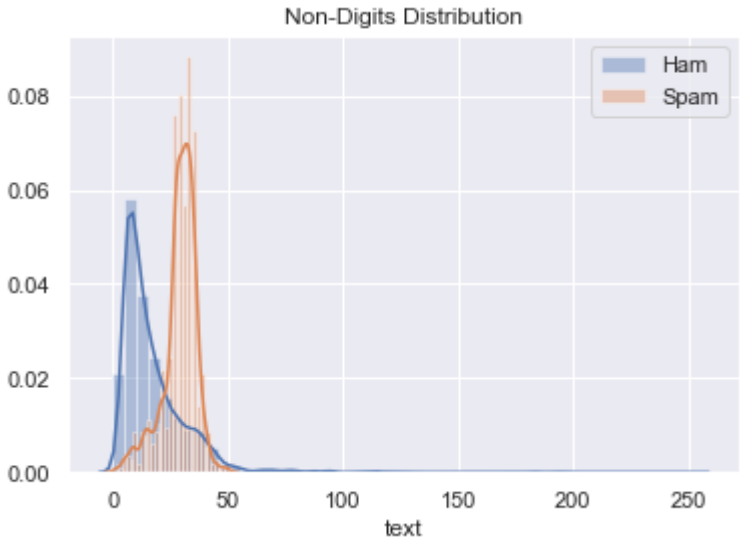


In [11]:

```
s1 = df[df['target'] == 'ham']['text'].str.replace(r'\w+', '').str.len()
s2 = df[df['target'] == 'spam']['text'].str.replace(r'\w+', '').str.len()

sns.distplot(s1, label='Ham')
sns.distplot(s2, label='Spam')

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

Out[11]:

```
<matplotlib.legend.Legend at 0x2ad2eb68320>
```



Подготовим выборки для использования в модели и разделим датасет на тренировочный и тестовый

In [12]:

```
from sklearn.preprocessing import LabelEncoder
```

In [13]:

```
X = df.text
la = LabelEncoder()
y = df.target
y = la.fit_transform(y)
```

In [14]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

Построим модели

In [22]:

```
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


tfidf = TfidfVectorizer(sublinear_tf=True, min_df=1, norm='l2',
                                                ngram_range=(1, 2),
                                                stop_words='english')


text_clf = Pipeline([('tfidf', tfidf),
                     ('MnNB', MultinomialNB()),
])

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

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

result_df = pd.DataFrame()
```

MultinomialNB

In [23]:

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

```
Wall time: 171 ms
```

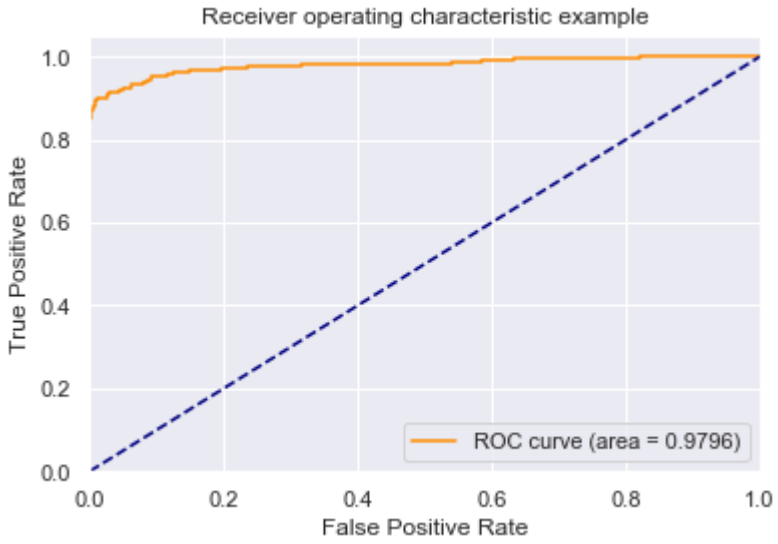
Out[23]:

```
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=No
ne,
                                 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=Tru
e))],
         verbose=False)
```

In [24]:

```
from sklearn.metrics import accuracy_score as AS, precision_score as PS, recall_score as RS

result_df.loc['Multinomial', 'AS train'] = AS(y_train, text_clf.predict(X_train))
result_df.loc['Multinomial', 'PS train'] = PS(y_train, text_clf.predict(X_train))
result_df.loc['Multinomial', 'RS train'] = RS(y_train, text_clf.predict(X_train))

result_df.loc['Multinomial', 'AS test'] = AS(y_test, text_clf.predict(X_test))
result_df.loc['Multinomial', 'PS test'] = PS(y_test, text_clf.predict(X_test))
result_df.loc['Multinomial', 'RS test'] = RS(y_test, text_clf.predict(X_test))


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

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

print('recall train:', RS(y_train, text_clf.predict(X_train)))
print('recall test :', RS(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='darkorange', 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: 0.9797435897435898
accuracy test : 0.9557416267942583

precission train: 1.0
precission test : 1.0

recall train: 0.8447937131630648
recall test : 0.6890756302521008
```


Receiver operating characteristic example
True Positive Rate
False Positive Rate
ROC curve (area = 0.9796)
0.0
0.2
0.4
0.6
0.8
1.0

LinearSVC

In [25]:

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

```
Wall time: 265 ms
```

Out[25]:

```
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=No
ne,
                                 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_weigh
t=None,
                                                                 dual=True,
                                                                 fit_interce
pt=True,
                                                                 intercept_s
caling=1,
                                                                 loss='squar
ed_hinge',
                                                                 max_iter=10
00,
                                                                 multi_class
='ovr',
                                                                 penalty='l
2',
                                                                 random_stat
e=None,
                                                                 tol=0.0001,
                                                                 verbose=0),
                                        cv=None, method='sigmoid'))],
         verbose=False)
```

In [26]:

```
from sklearn.metrics import accuracy_score as AS, precision_score as PS, recall_score as RS

result_df.loc['LinearSVC', 'AS train'] = AS(y_train, text_clf2.predict(X_train))
result_df.loc['LinearSVC', 'PS train'] = PS(y_train, text_clf2.predict(X_train))
result_df.loc['LinearSVC', 'RS train'] = RS(y_train, text_clf2.predict(X_train))
result_df.loc['LinearSVC', 'AS test']  = AS(y_test , text_clf2.predict(X_test))
result_df.loc['LinearSVC', 'PS test']  = PS(y_test , text_clf2.predict(X_test))
result_df.loc['LinearSVC', 'RS test']  = RS(y_test , text_clf2.predict(X_test))



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

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

print('recall train:', RS(y_train, text_clf2.predict(X_train)))
print('recall test :', RS(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='darkorange', 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: 0.9994871794871795
accuracy test : 0.9796650717703349

precission train: 0.9960861056751468
precission test : 0.925

recall train: 1.0
recall test : 0.9327731092436975
```

LogisticRegression

In [27]:

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

```
Wall time: 333 ms
```

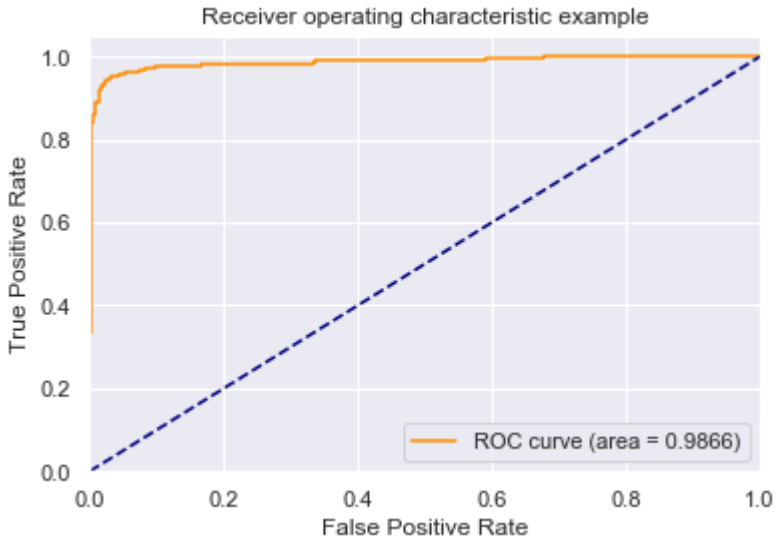
Out[27]:

```
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=No
ne,
                                 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)
```

In [28]:

```
from sklearn.metrics import accuracy_score as AS, precision_score as PS, recall_score as RS


result_df.loc['Logistic_regression', 'AS train'] = AS(y_train, text_clf3.predict(X_train))
result_df.loc['Logistic_regression', 'PS train'] = PS(y_train, text_clf3.predict(X_train))
result_df.loc['Logistic_regression', 'RS train'] = RS(y_train, text_clf3.predict(X_train))

result_df.loc['Logistic_regression', 'AS test'] = AS(y_test, text_clf3.predict(X_test))
result_df.loc['Logistic_regression', 'PS test'] = PS(y_test, text_clf3.predict(X_test))
result_df.loc['Logistic_regression', 'RS test'] = RS(y_test, text_clf3.predict(X_test))


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

print('precission train:', PS(y_train, text_clf3.predict(X_train)))
print('precission test :', PS(y_test, text_clf3.predict(X_test)), '\n')

print('recall train:', RS(y_train, text_clf3.predict(X_train)))
print('recall test :', RS(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='darkorange', 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: 0.9476923076923077
accuracy test : 0.9461722488038278

precission train: 0.9935275080906149
precission test : 0.9868421052631579

recall train: 0.6031434184675835
recall test : 0.6302521008403361
```



Сравнение моделей

In [29]:

```
result_df
```

Out[29]:

	AS train	PS train	RS train	AS test	PS test	RS test
Multinomial	0.979744	1.000000	0.844794	0.955742	1.000000	0.689076
LinearSVC	0.999487	0.996086	1.000000	0.979665	0.925000	0.932773
Logistic_regression	0.947692	0.993528	0.603143	0.946172	0.986842	0.630252

Вывод: Сравнивая метрики моделей видим, что модель с LinearSVC немного уступает остальным по точности, одако значительно выигрывает по полноте