HSE 2023: Mathematical Methods for Data Analysis

Homework 3

Warning 1: some problems require (especially the lemmatization part) significant amount of time, so **it is better to start early (!)**

Warning 2: it is critical to describe and explain what you are doing and why, use markdown cells

```
from typing import Tuple, List

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import string
from sklearn.datasets import make_classification
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsOneClassifier
import zipfile
import random
import re
%matplotlib inline

sns.set(style="darkgrid")
```

PART 1: Logit model

We consider a binary classification problem. For prediction, we would like to use a logistic regression model. For regularization we add a combination of the l_2 and l_1 penalties (Elastic Net).

Each object in the training dataset is indexed with i and described by pair: features $x_i \in R^K$ and binary labels y_i. The model parametrized with bias $w_0 \in R$ and weights $w \in R^K$. Note: Bias is included in w vector

The optimization problem with respect to the w_0, w is the following (Logistic loss with Elastic Net regularizers):

$$L(w, w_0) = \sum_{i=1}^{N} - y_i \log \sigma(w^\top x_i) - (1 - y_i) \log \left(1 - \sigma(w^\top x_i)\right) + \gamma \| w \|_1 + \beta \| w \|_2^2$$

1. [0.5 points] Find the gradient of the Elastic Net loss and write its formulas (better in latex format). Remember what derivative sigmoid has (gradient in fact is a lot simpler than you may get using automatic tools like sympy, matlab or whatever)

$$\nabla_w L = \sum_{i=1}^{N} \left(\sigma(x_i^T w) - y_i\right) x_{i\,j} + \gamma \operatorname{sign}(w) + 2\beta w$$

{w}]

2. [0.25 points] Implement the Elastic Net loss (as a function)

```
def loss(X, y, w: List[float], gamma=1., beta=1.) -> float:
    loss = 0
    for i in range(len(X)):
        dot_pr = np.dot(X[i], w)
        sg = 1 / (1+np.exp(-dot_pr))
        loss += -y[i] * np.log(sg) - (1-y[i]) * np.log(1 - sg)
    loss += gamma * np.sum(np.abs(w))
    loss += beta * np.sum(np.square(w))
    return loss
```

3. [0.25 points] Implement the gradient (as a function)

```
def get_grad(X, y, w: List[float], gamma=1., beta=1.) ->
Tuple[List[float], float]:
    grad_w = []
    for j in range(len(w)):
        grad = 0
        for i in range(len(X)):
            dot_pr = np.dot(X[i], w)
            sg = 1 / (1+np.exp(-dot_pr))
            grad += (sg-y[i]) * X[i][j]
        grad += gamma * np.sign(w[j])
        grad += 2*beta * w[j]
        grad_w.append(grad)
    return grad_w
```

Check yourself

```
np.random.seed(42)
X = np.random.multivariate_normal(np.arange(5), np.eye(5), size=10)
X = np.c_[np.ones(X.shape[0]), X]
y = np.random.binomial(1, 0.42, size=10)
w = np.random.normal(size=5 + 1)

grad_w = get_grad(X, y, w)
print(grad_w)
```

```
assert(np.allclose(grad_w,
                   [-3.99447493, -1.84786723,  0.64520104,
1.67059973, -5.03858487, -5.21496336],
                   rtol=1e-2)
)
```

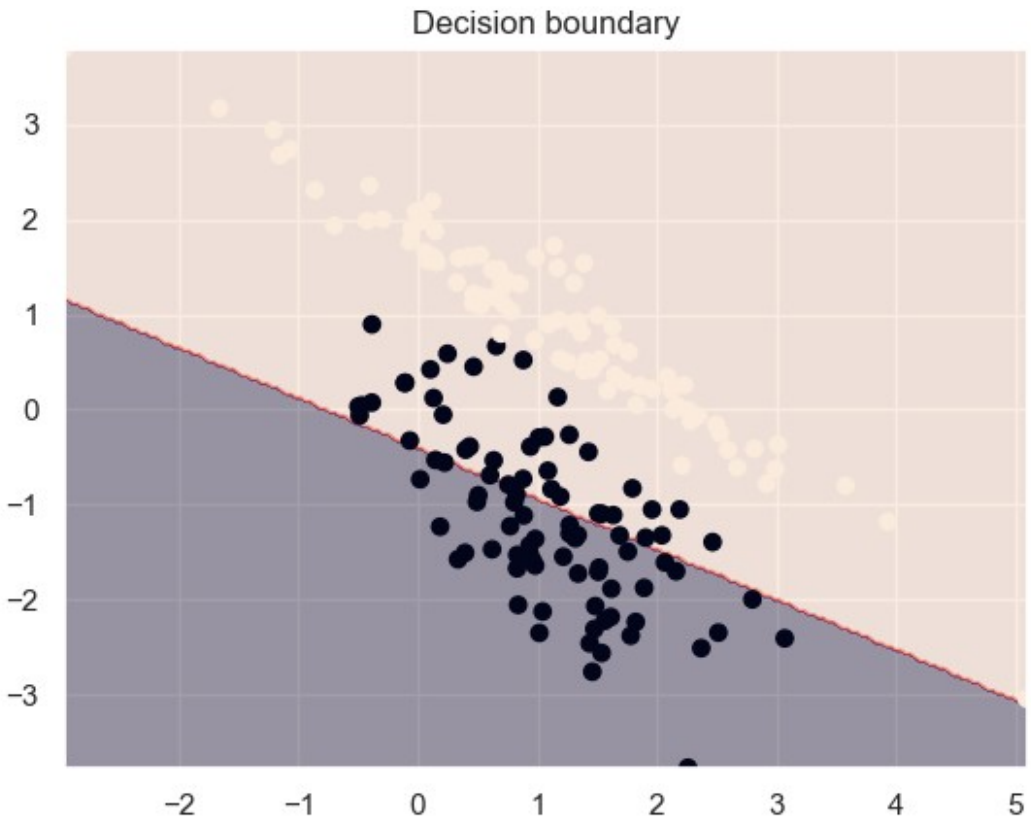
```
[-3.994474929359763, -1.8478672277855601, 0.6452010421087129,
1.6705997291223378, -5.0385848672792095, -5.214963362606359]
```

4. [1 point] Implement gradient descent which works for both tol level and max_iter stop criteria and plot the decision boundary of the result

The template provides basic sklearn API class. You are free to modify it in any convenient way.

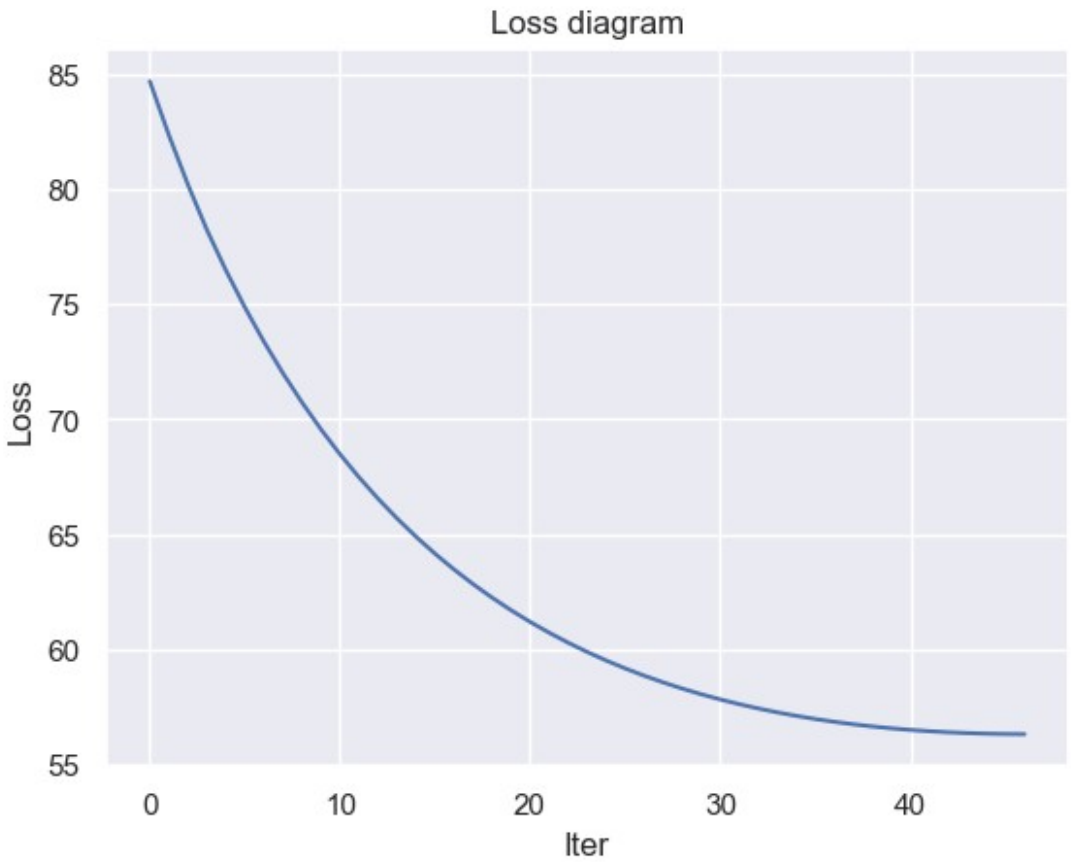
```
from sklearn.base import BaseEstimator, ClassifierMixin

class Logit(BaseEstimator, ClassifierMixin):
    def __init__(self, beta=1.0, gamma=1.0, lr=1e-3, tolerance=0.01,
max_iter=1000, random_state=42):
        self.beta = beta
        self.gamma = gamma
        self.tolerance= tolerance
        self.max_iter= max_iter
        self.lr = lr
        self.random_state = random_state
        self.w = None
        # you may additional properties if you wish
        self.loss_history = []

    def fit(self, X, y):
        # add weights and bias and optimize Elastic Net loss over
(X,y) dataset
        # save history of optimization steps

        # your code here
        np.random.seed(self.random_state)
        N, k = X.shape
        self.w = np.random.randn(k + 1)
        for _ in range(self.max_iter):
            grad_w0, grad_w = get_grad(X, y, self.w[1:]) # finding the
gradient
            self.w[0] -= self.lr*grad_w0 # new weights
            self.w[1:] -= self.lr*grad_w
            loss_curr = loss(X, y, self.w[1:])
            self.loss_history.append(loss_curr)
            if (len(self.loss_history) > 1) and
(abs(self.loss_history[-1] - self.loss_history[-2]) < self.tolerance):
                break
        return self
```

```
    def predict(self, X):
        # return vector of predicted labels (0 or 1) for each object
from X
        # your code here
        return np.round(self.predict_proba(X))

    def predict_proba(self, X):
      # return vector of probabilities for each object from X
        return 1 / (1+np.exp(-np.dot(X,self.w[1:])-self.w[0]))

# sample data to test your model
from sklearn.datasets import make_classification
X, y = make_classification(n_samples=180, n_features=2, n_redundant=0,
n_informative=2,
                           random_state=42,
n_clusters_per_class=1)

# a function to plot the decision boundary
def plot_decision_boundary(model, X, y):
    fig = plt.figure()
    X1min, X2min = X.min(axis=0)
    X1max, X2max = X.max(axis=0)
    x1, x2 = np.meshgrid(np.linspace(X1min, X1max, 200),
                         np.linspace(X2min, X2max, 200))
    ypred = model.predict(np.c_[x1.ravel(), x2.ravel()])
    ypred = ypred.reshape(x1.shape)

    plt.contourf(x1, x2, ypred, alpha=.4)
    plt.scatter(X[:,0], X[:,1], c=y)
    plt.title('Decision boundary')

model = Logit(0, 0)
model.fit(X, y)
plot_decision_boundary(model, X, y)
```



5. [0.25 points] Plot loss diagram for the model, i.e. show the dependence of the loss function from the gradient descent steps

```
plt.plot(range(len(model.loss_history)), model.loss_history)
plt.title('Loss diagram')
plt.xlabel('Iter')
plt.ylabel('Loss')
plt.show()
```



PART 2: Support Vector Machines

6. [2 point] Using the same dataset, train SVM Classifier from Sklearn.

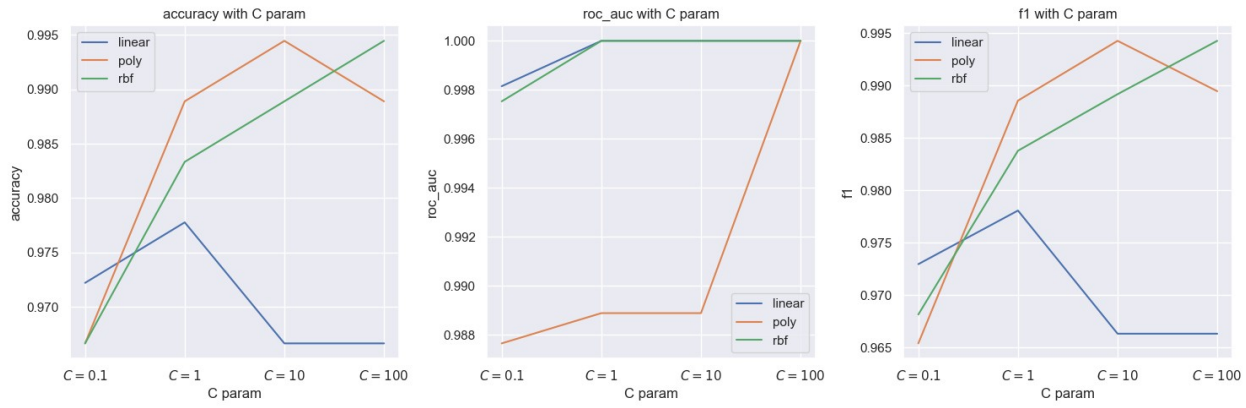
Investigate how different parameters influence the quality of the solution:

- Try several kernels: Linear, Polynomial, RBF (and others if you wish). Some Kernels have hypermeters: don't forget to try different.
- Regularization coefficient

Show how these parameters affect accuracy, roc_auc and f1 score. Make plots for the dependencies between metrics and parameters. Try to formulate conclusions from the observations. How sensitive are kernels to hyperparameters? How sensitive is a solution to the regularization? Which kernel is prone to overfitting?

```
def evaluate_model(X, y, clf):
    acc = cross_val_score(clf, X, y, scoring='accuracy', cv=5).mean()
    ra = cross_val_score(clf, X, y, scoring='roc_auc', cv=5).mean()
    f1 = cross_val_score(clf, X, y, scoring='f1', cv=5).mean()
    return acc, ra, f1

X, y = make_classification(n_samples=180, n_features=2, n_redundant=0,
n_informative=2, random_state=42, n_clusters_per_class=1)
```

```
kernels = ['linear', 'poly', 'rbf'] # various kernels from the task
C_values = [0.1, 1, 10, 100]
metrics = {'accuracy': [], 'roc_auc': [], 'f1': []}
for kernel in kernels:
    for C_value in C_values:
        clf = SVC(kernel=kernel, C=C_value)
        acc, ra, f1 = evaluate_model(X, y, clf)
        metrics['accuracy'].append(acc)
        metrics['roc_auc'].append(ra)
        metrics['f1'].append(f1)
# Plotting
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(15, 5))
parameters = ['$C=0.1$', '$C=1$', '$C=10$', '$C=100$']
for i, metric in enumerate(metrics):
    axes[i].plot(parameters, metrics[metric][:4])
    axes[i].set_xlabel('C param')
    axes[i].set_ylabel(metric)
    axes[i].set_title(f'{metric} with C param')
    axes[i].legend(kernels)
for i, metric in enumerate(metrics):
    axes[i].plot(parameters, metrics[metric][4:8])
    axes[i].set_xlabel('C param')
    axes[i].set_ylabel(metric)
    axes[i].set_title(f'{metric} with C param')
    axes[i].legend(kernels)
for i, metric in enumerate(metrics):
    axes[i].plot(parameters, metrics[metric][8:12])
    axes[i].set_xlabel('C param')
    axes[i].set_ylabel(metric)
    axes[i].set_title(f'{metric} with C param')
    axes[i].legend(kernels)
plt.tight_layout()
plt.show()
```



PART 3: Natural Language Processing

7. [1.75 point] Form the dataset

We are going to form a dataset that we will use in the following tasks for binary and multiclass classification

1. Choose **six** authors that you like (specify who you've chosen) and download the relevant data from **prose** section

2. Build your own dataset for these authors:

   - divide each text into sentences such that we will have two columns: *sentence* and *target author*, each row will contain one sentence and one target
   - drop sentences where N symbols in a sentence < 15
   - fix random state and randomly choose sentences in the folowing proportion "5k : 15k : 8k : 11k : 20k : 3k" for the authors respectively

   sample data may look like:

   sentence author Несколько лет тому назад в одном из своих поместий жил старинный русской барин, Кирила Петрович Троекуров. Пушкин Уже более недели приезжий господин жил в городе, разъезжая по вечеринкам и обедам и таким образом проводя, как говорится, очень приятно время. Гоголь ... ... Я жил недорослем, гоняя голубей и играя в чехарду с дворовыми мальчишками. Пушкин

3. Preprocess (tokenize and clean) the dataset

   - tokenize, remove all stop words (nltk.corpus.stopwords), punctuation (string.punctuation) and numbers
   - convert to lower case and apply either stemming or lemmatization of the words (on your choice)
   - vectorize words using both **bag of words** and **tf-idf** (use sklearn)
   - observe and describe the difference between vectorized output (what do numbers look like after transformations and what do they represent?)

```
# First of all, I'll kindly ask you to download the zip archives from
here: https://github.com/ouzel/hw3_authors/tree/main

# Here is the process how I created them.
# I opened the zip archive using the github link provided in the task.
# Then I went to the prose folder and converted each of the folders to
a zip archive, so it will be easier for me to upload them to jupyter.
# To sup up, these zip archives have exactly the same information as
in the original github provided in the task.

def extract_data(zip_file, author):
```

```
    sentences = []
    targets = [] # for target authors
    with zipfile.ZipFile(zip_file, 'r') as zip: # opening the zip
archives
        for file in zip.namelist():
            if file.endswith('.txt'): # to get rid of info.csv in each
folder
                with zip.open(file) as f:
                    text = f.read().decode('utf-8')
                    sentences1 = re.split(r'(?<!\w\.\w.)(?<![A-Z][a-
z]\.)(?<=\.|\?)\s', text) # splitting into sentences
                    for sentence in sentences1:
                        if len(sentence.strip()) >= 15: # checking the
number of symbols
                            sentences.append(sentence)
                            targets.append(author)
    df = pd.DataFrame({'sentence': sentences, 'author': targets}) #
sentence - author
    return df

# Extracting data by author
# Chosen authors: Herzen, Tolstoy, Turgenev, Bryusov, Gorky, Lermontov
df_herzen = extract_data('Herzen.zip', 'Herzen')
df_tolstoy = extract_data('Tolstoy.zip', 'Tolstoy')
df_turgenev = extract_data('Turgenev.zip', 'Turgenev')
df_bryusov = extract_data('Bryusov.zip', 'Bryusov')
df_gorky = extract_data('Gorky.zip', 'Gorky')
df_lermontov = extract_data('Lermontov.zip', 'Lermontov')
df = pd.concat([df_herzen, df_tolstoy, df_turgenev, df_bryusov,
df_gorky, df_lermontov], ignore_index=True)
random.seed(123)

proportions = [5000, 15000, 8000, 11000, 20000, 3000]
# proportions = [50, 150, 80, 110, 200, 30] -- this is a light version
for testing

sampled_sentences = []
sampled_targets = []
for i in range(len(proportions)):
    sampled = random.sample(df[df['author'] == df['author'].unique()
[i]]['sentence'].tolist(), proportions[i]) # according to the given
proportions
    sampled_sentences.extend(sampled)
    sampled_targets.extend([df['author'].unique()[i]] *
proportions[i])
df_sampled = pd.DataFrame({'sentence': sampled_sentences, 'author':
sampled_targets}) # final version of a dataframe with proportions
display(df_sampled) # to see an extract of a dataframe
df_sampled = df_sampled.sample(frac=1).reset_index(drop=True) #
shuffling so that sentences will be in random order (not grouped by
```

```
authors)
df_sampled.to_csv('sampled_data.csv', index=False) # saving the
dataframe to a file
```

```
                                                  sentence     author
0      Ни радоваться, ни удивляться; Ломбардия не мог...     Herzen
1      \n     Веселая  сельская  жизнь  Степана  Степ...     Herzen
2      Немощь, хилость старого общественного устройст...     Herzen
3                               Итак, биография дядюшки.     Herzen
4       Ему  было\nсемнадцать  лет,  когда  он  лишил...     Herzen
...                                                  ...        ...
61995  Посмотрите, доктор: видите ли вы, на скале  на...  Lermontov
61996  "Смотрите наверх! - шепнул  я\nей, - это ничег...  Lermontov
61997                          Ему это показалось странно.  Lermontov
61998  Вдали вилась пыль - Азамат  скакал  на  лихом ...  Lermontov
61999   "Воды,  воды!.."  -  говорила  она  хриплым  ...  Lermontov

[62000 rows x 2 columns]
```

```
import nltk
from nltk.corpus import stopwords

nltk.download()
# Kindly asking you to download from All packages -> punkt, stopwords,
wordnet.
# Do not forget to close NLTK downloader so that the following code
will work.
```

```
showing info https://raw.githubusercontent.com/nltk/nltk_data/gh-
pages/index.xml

True
```

```
df_sampled["words"] = df_sampled["sentence"].apply(nltk.word_tokenize)
# tokenizing
stop_words = set(stopwords.words("english"))
punctuation = set(string.punctuation) # unfortunately — and -- were
not extracted with this, so I added them separately
punctuation.add('—')
punctuation.add('--')
df_sampled["words"] = df_sampled["words"].apply(lambda x:
[word.lower() for word in x if word.lower() not in stop_words and
word.lower() not in punctuation and not word.isdigit()])

# Stemming could be added like this (commented code):
#stemmer = nltk.stem.PorterStemmer()
#df_sampled["stemmed_words"] = df_sampled["words"].apply(lambda x:
[stemmer.stem(word) for word in x])

lemmatizer = nltk.stem.WordNetLemmatizer()
df_sampled["lemmatized_words"] = df_sampled["words"].apply(lambda x:
```

```
[lemmatizer.lemmatize(word) for word in x])
display(df_sampled)
```

```
                                                  sentence    author  \
0      «И в самом деле, имение-то все сестрино!» — пр...  Turgenev
1                          Маньковского // Наше наследие.   Bryusov
2                                    Он не скоро придет.   Tolstoy
3                              Тотчас раздалось три удара.   Bryusov
4      Мать обнял страх возможного столкновения, она ...     Gorky
...                                                  ...       ...
61995  Они легко всплывали из глубины ее сердца и сла...     Gorky
61996    Есть я или нет меня, вам все равно — наплевать.     Gorky
61997  — Ну, брат, потешил! — кричал Обалдуй, не выпу...  Turgenev
61998     Не в огне, а в грязи кипящей варить вас будут.     Gorky
61999     Марья Павловна улыбнулась своей милой детск...   Tolstoy

                                                   words  \
0      [«, и, в, самом, деле, имение-то, все, сестрин...
1                      [маньковского, //, наше, наследие]
2                                 [он, не, скоро, придет]
3                           [тотчас, раздалось, три, удара]
4      [мать, обнял, страх, возможного, столкновения,...
...                                                  ...
61995  [они, легко, всплывали, из, глубины, ее, сердц...
61996  [есть, я, или, нет, меня, вам, все, равно, —, ...
61997  [ну, брат, потешил, кричал, обалдуй, не, выпус...
61998  [не, в, огне, а, в, грязи, кипящей, варить, ва...
61999  [марья, павловна, улыбнулась, своей, милой, де...

                                        lemmatized_words
0      [«, и, в, самом, деле, имение-то, все, сестрин...
1                      [маньковского, //, наше, наследие]
2                                 [он, не, скоро, придет]
3                           [тотчас, раздалось, три, удара]
4      [мать, обнял, страх, возможного, столкновения,...
...                                                  ...
61995  [они, легко, всплывали, из, глубины, ее, сердц...
61996  [есть, я, или, нет, меня, вам, все, равно, —, ...
61997  [ну, брат, потешил, кричал, обалдуй, не, выпус...
61998  [не, в, огне, а, в, грязи, кипящей, варить, ва...
61999  [марья, павловна, улыбнулась, своей, милой, де...

[62000 rows x 4 columns]
```

```
from sklearn.feature_extraction.text import CountVectorizer,
TfidfVectorizer

# Bag of Words
vectorizer_bow = CountVectorizer()
bow_matrix =
```

```
vectorizer_bow.fit_transform(df_sampled['lemmatized_words'].apply(lamb
da x: ' '.join(x)))
# TF-IDF
vectorizer_tfidf = TfidfVectorizer()
tfidf_matrix =
vectorizer_tfidf.fit_transform(df_sampled['lemmatized_words'].apply(la
mbda x: ' '.join(x)))

# Comparison of vectorizing
print("bag of words:")
print(bow_matrix[:10, :10].toarray().astype(float)) # displaying part
of matrix (full version is too big)
print("tf-idf:")
print(tfidf_matrix[:10, :10].toarray().astype(float))  # displaying
part of matrix (full version is too big)
```

```
bag of words:
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
tf-idf:
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

Binary classification

8. [2 point] Train model using Logistic Regression (your own) and SVC (SVM can be taken from sklearn)

- choose *two* authors from the dataset that you have formed in the previous task
- check the balance of the classes
- divide the data into train and test samples with 0.7 split rate (don't forget to fix the random state)
- using GridSearchCV - find the best parameters for the models (by F1 score) and use it in the next tasks

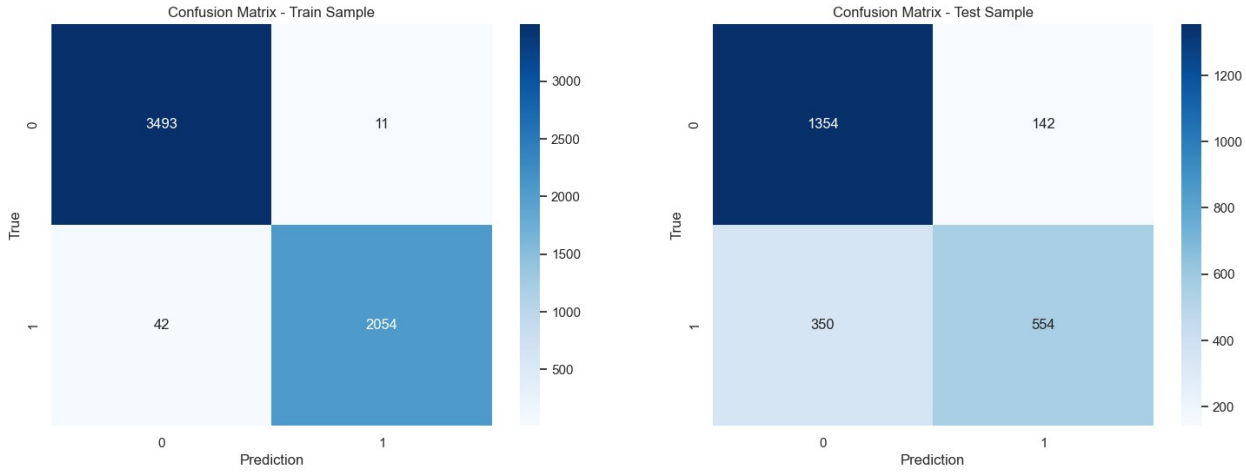
- make several plots to address the dependence between F1 score and parameters
- plot confusion matrix for train and test samples
- compute some relevant metrics for test sample (useful to check the seminars 5 and 6, use sklearn)
- make conclusions about the performance of your models

```
from sklearn.model_selection import ParameterGrid
from sklearn.model_selection import KFold
from sklearn.metrics import f1_score

class MyGridSearchCV: # Custom GridSearchCV for my model
    def __init__(self, estimator, param_grid, scoring, cv):
        self.estimator = estimator
        self.param_grid = list(ParameterGrid(param_grid))
        self.scoring = scoring
        self.cv = cv

    def fit(self, X, y):
        best_score = None
        best_params = None

        for params in self.param_grid:
            self.estimator.init(**params)
            scores = []

            for train_index, test_index in
KFold(n_splits=self.cv).split(X):
                X_train, X_test = X[train_index], X[test_index]
                y_train, y_test = y[train_index], y[test_index]

                self.estimator.fit(X_train, y_train)
                y_pred = self.estimator.predict(X_test)
                score = f1_score(y_test, y_pred)
                scores.append(score)

            mean_score = np.mean(scores)

            if best_score is None or mean_score > best_score:
                best_score = mean_score
                best_params = params

        self.best_params_ = best_params

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import SVC
from sklearn.metrics import f1_score, confusion_matrix,
classification_report
import warnings

warnings.filterwarnings('ignore')
vectorizer_tfidf = TfidfVectorizer()
```

```
author1 = 'Herzen'
author2 = 'Lermontov'
df_authors = df_sampled[(df_sampled['author'] == 'Herzen') |
(df_sampled['author'] == 'Lermontov')]
class_balance = df_authors['author'].value_counts()
print(class_balance) #Checking the balance

X =
vectorizer_tfidf.fit_transform(df_authors['lemmatized_words'].apply(la
mbda x: ' '.join(x)))
y = np.where(df_authors['author'] == 'Herzen', 0, 1) # for binary
classification we'll need to convert authors to 0 and 1.
print("0 stands for Herzen, 1 stands for Lermontov")
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Training models
logit = Logit()
param_grid_logit = {'beta': [0.1, 1, 10], 'gamma': [0.1, 1, 10], 'lr':
[1e-3, 1e-2, 1e-1]}
grid_search_logit = MyGridSearchCV(logit, param_grid_logit,
scoring='f1', cv=5)
param_grid = {'C': [0.1, 1, 10, 100], 'gamma': [1, 0.1, 0.01, 0.001],
'kernel': ['rbf', 'linear']}
grid_search = GridSearchCV(SVC(), param_grid, scoring='f1', cv=5)
grid_search.fit(X_train, y_train)
best_params = grid_search.best_params_
model = SVC(**best_params)
model.fit(X_train, y_train)
#Predictions
y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)
f1_train = f1_score(y_train, y_pred_train, pos_label=0)
f1_test = f1_score(y_test, y_pred_test, pos_label=0)
print(f'F1 score for trained: {f1_train}')
print(f'F1 score for test: {f1_test}')
# Plotting results
fig, ax = plt.subplots(1, 2, figsize=(18, 6))
sns.heatmap(confusion_matrix(y_train, y_pred_train), annot=True,
fmt='d', cmap='RdPu', ax=ax[0])
ax[0].set_title('Confusion Matrix - Train Sample')
ax[0].set_xlabel('Prediction')
ax[0].set_ylabel('True')
sns.heatmap(confusion_matrix(y_test, y_pred_test), annot=True,
fmt='d', cmap='RdPu', ax=ax[1])
ax[1].set_title('Confusion Matrix - Test Sample')
ax[1].set_xlabel('Prediction')
ax[1].set_ylabel('True')
```

```
plt.show()
print(classification_report(y_test, y_pred_test))
```

```
author
Herzen       5000
Lermontov    3000
Name: count, dtype: int64
0 stands for Herzen, 1 stands for Lermontov
F1 score for trained: 0.9924705213808781
F1 score for test: 0.84625
```




```
              precision    recall  f1-score   support

           0       0.79      0.91      0.85      1496
           1       0.80      0.61      0.69       904

    accuracy                           0.80      2400
   macro avg       0.80      0.76      0.77      2400
weighted avg       0.80      0.80      0.79      2400
```

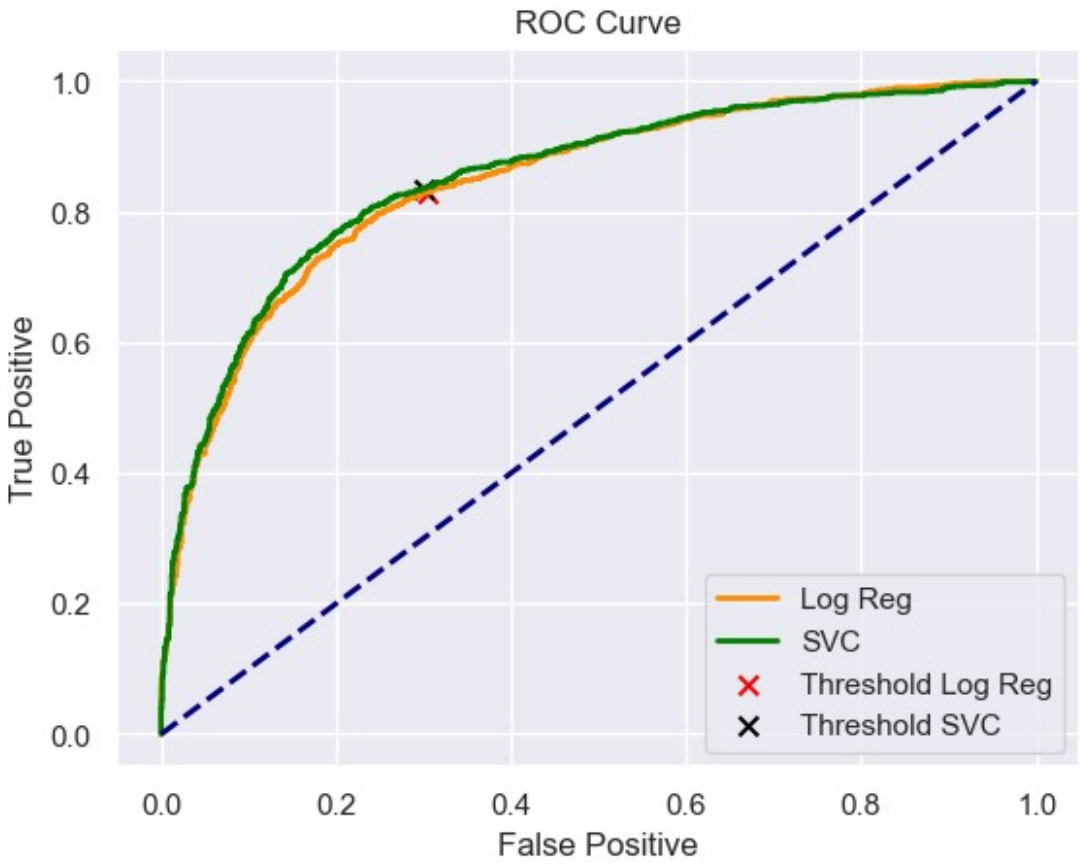
9. [1 point] Analysing ROC AUC

It is possible to control the proportion of statistical errors of different types using different thresholds for choosing a class. Plot ROC curves for Logistic Regression and SVC, show the threshold on ROC curve plots. Choose such a threshold that your models have no more than 30% of false positive errors rate. Pay attention to `thresholds` parameter in sklearn roc_curve

```
from sklearn.svm import SVC
from sklearn.metrics import roc_curve, auc

lr = LogisticRegression()
lr.fit(X_train, y_train)
y_score_lr = lr.decision_function(X_test)
```

```
fpr_lr, tpr_lr, thresholds_lr = roc_curve(y_test, y_score_lr)
roc_auc_lr = auc(fpr_lr, tpr_lr)
svc = SVC(probability=True)
svc.fit(X_train, y_train)
y_score_svc = svc.decision_function(X_test)
fpr_svc, tpr_svc, thresholds_svc = roc_curve(y_test, y_score_svc)
roc_auc_svc = auc(fpr_svc, tpr_svc)

# Plotting
plt.figure()
plt.plot(fpr_lr, tpr_lr, color='darkorange', lw=2, label='Log Reg')
plt.plot(fpr_svc, tpr_svc, color='green', lw=2, label='SVC')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive')
plt.ylabel('True Positive')
plt.title('ROC Curve')
plt.legend()

# Thresholds
thr_index_lr = np.argmax(fpr_lr > 0.3)
thr_lr = thresholds_lr[thr_index_lr]
thr_index_svc = np.argmax(fpr_svc > 0.3)
thr_svc = thresholds_svc[thr_index_svc]
plt.scatter(fpr_lr[thr_index_lr], tpr_lr[thr_index_lr], s=50, c='red',
marker='x', label='Threshold Log Reg')
plt.scatter(fpr_svc[thr_index_svc], tpr_svc[thr_index_svc], s=50,
c='black', marker='x', label='Threshold SVC')
print('Threshold for Log Reg = %0.2f' % thr_lr)
print('Threshold for SVC = %0.2f' % thr_svc)
plt.legend()
plt.show()
```

```
Threshold for Log Reg = -0.70
Threshold for SVC = -0.46
```



Multiclass logit

10. [1 point] Take the One-VS-One classifier (use sklearn) and apply to Logit model (one you've made in the 4th task) in order to get multiclass linear classifier

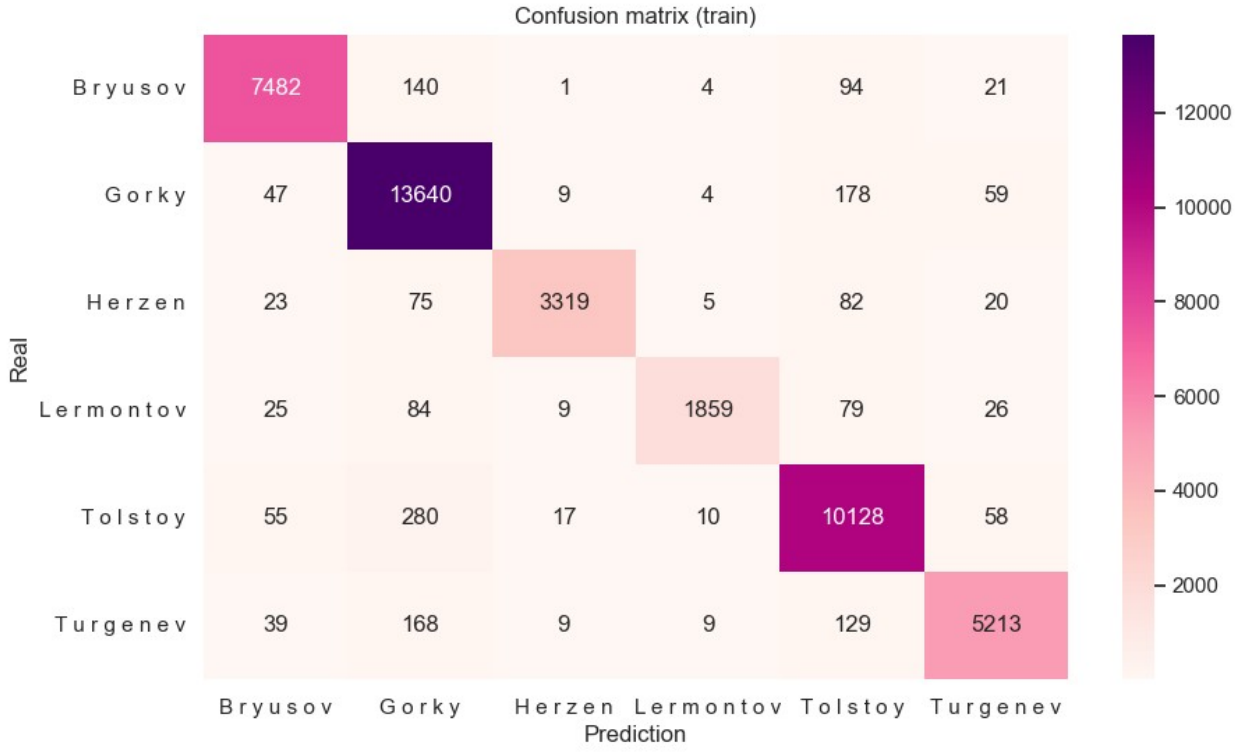
It is possible to use sklearn model instead of your own one but with a penalty of 0.5

OneVsOneClassifier

- use the data you got at the previous step for 6 authors
- divide the data into train and test samples with 0.7 split rate
- using GridSearchCV - find the best parameters for the models (by F1 score)
- plot confusion matrix for train and test samples
- compute relevant metrics for test sample (use sklearn)

```
import warnings
warnings.filterwarnings('ignore')
X = tfidf_matrix
y = df_sampled['author'].apply(lambda x: ' '.join(x))
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)
ovo_classifier = OneVsOneClassifier(LogisticRegression())
param_grid = {'estimator__C': [0.1, 1, 10], 'estimator__solver':
```

```
['newton-cg', 'lbfgs', 'liblinear']}
grid_search = GridSearchCV(ovo_classifier, param_grid,
scoring='f1_macro', cv=5)
grid_search.fit(X_train, y_train)
best_params = grid_search.best_params_
best_model = ovo_classifier.set_params(**best_params)
best_model.fit(X_train, y_train)

def plot_confusion_matrix(model, X, y, title):
    y_pred = model.predict(X)
    cm = confusion_matrix(y, y_pred)
    plt.figure(figsize=(10, 6))
    plt.title(title)
    sns.heatmap(cm, annot=True, fmt='d', cmap='RdPu',
xticklabels=model.classes_, yticklabels=model.classes_)
    plt.xlabel('Prediction')
    plt.ylabel('Real')
    plt.show()

plot_confusion_matrix(best_model, X_train, y_train, 'Confusion matrix
(train)')
plot_confusion_matrix(best_model, X_test, y_test, 'Confusion matrix
(test)')
y_pred = best_model.predict(X_test)
print('OneVsOne Log Reg:')
print(classification_report(y_test, y_pred))
```



OneVsOne Log Reg:

	precision	recall	f1-score	support
Bryusov	0.68	0.65	0.66	3258
Gorky	0.64	0.83	0.72	6063
Herzen	0.63	0.29	0.40	1476
Lermontov	0.73	0.24	0.36	918
Tolstoy	0.59	0.66	0.62	4452
Turgenev	0.64	0.44	0.52	2433
accuracy			0.63	18600
macro avg	0.65	0.52	0.55	18600
weighted avg	0.64	0.63	0.62	18600