ДОМАШНЕЕ ЗАДАНИЕ 2: **Выбор модели**

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Цель работы

1. реализация собственных классов совместимых с библиотекой sklearn
2. использование полиномиальной трансформации в моделях регрессии и классификации
3. использование регуляризации в моделях регрессии и классификации
4. выбор гиперпараметров и интерпретация кривых обучения

Подключение стилей оформления

In [443…

```
%%html
<link href="css/style.css" rel="stylesheet" type="text/css">
```

1. Варианты

К содержанию

Чтобы узнать свой вариант, введите Вашу фамилию в соответвующее поле ниже и запустите ячейку:

In [444…

```
surname = "Овчинникова"  # Ваша фамилия

alph = 'абвгдеёжзийклмнопрстуфхцчшщъыьэюя'
w = [4, 42, 21, 21, 34,  1, 44, 26, 18, 43, 38, 26, 18, 43,  3, 49, 45,
       7, 42, 25,  4,  9, 36, 33, 31, 29,  5, 31,  4, 19, 24, 27, 33]
d = dict(zip(alph, w))
variant =  sum([d[el] for el in surname.lower()]) % 2 + 1
print("Ваш вариант - ", variant)
```

```
Ваш вариант -  2
```

Задание 1:

К содержанию

Реализация класса, предназначенного для оценки параметров линейной регрессии с регуляризацией, совместимого с sklearn. Коэффициент регуляризации (alpha) как параметр, использование метода наименьших квадратов с регуляризацией.

In [445…

```
import pandas as pnd
import matplotlib.pyplot as plt
%matplotlib inline
```

```
from matplotlib.colors import ListedColormap
clrMap = ListedColormap(["blue", "red", "green"])
```

In [446…

```
df = pnd.read_csv("data/Reg_A5.csv")

X = df.drop('Y', axis=1).values
y = df['Y'].values
```

In [447…

```
df.head()
```

Out[447…

	X	Y
0	3.856603	9.209759
1	0.103760	10.409240
2	3.168241	7.643742
3	3.744019	8.453341
4	2.492535	9.317824

In [448…

```
X
```

Out[448…

```
array([[3.85660322],
       [0.10375975],
       [3.16824117],
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       [1.8667038 ],
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```

```
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```

```
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```

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```

```
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```

```
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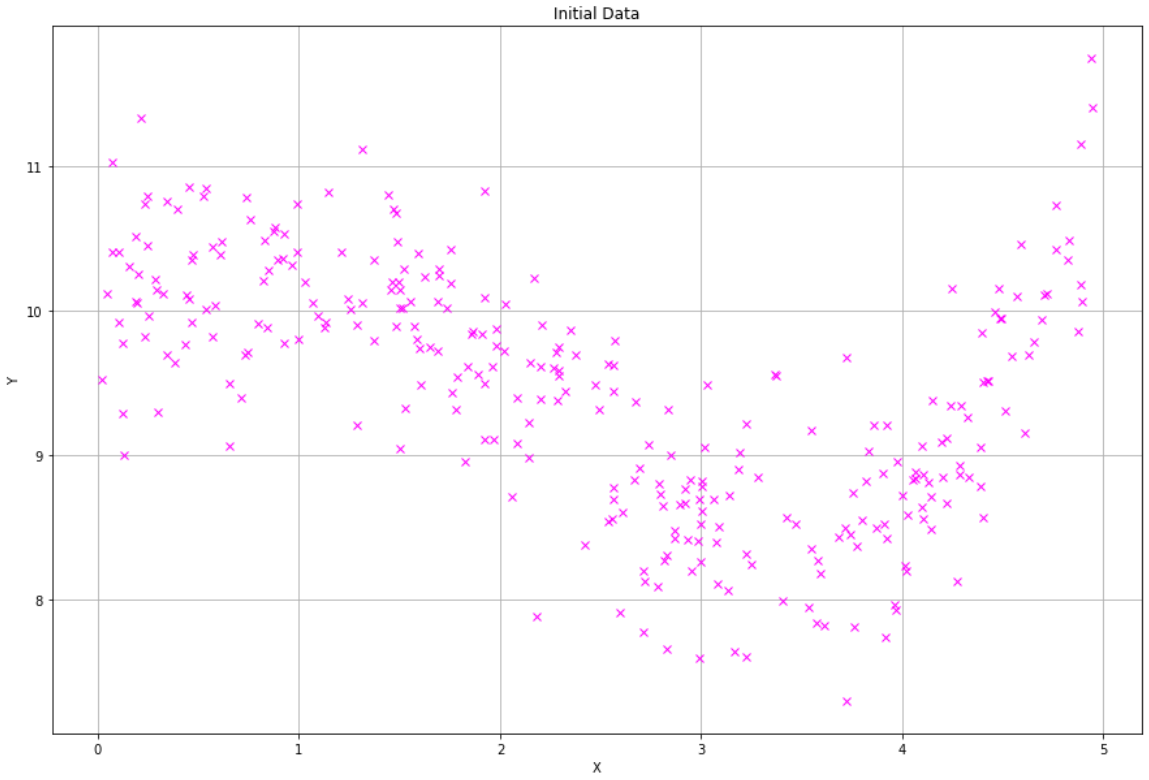
       [4.4039603 ],
       [3.00477104],
       [3.22613873],
       [0.28314101],
       [1.48742048]])
```

In [449…

```
plt.figure(figsize = (15, 10))
plt.title("Initial Data")
plt.xlabel("X")
plt.ylabel("Y")
plt.plot(X, y, "x", color = 'magenta')
plt.grid(True)
plt.show()
```



In [450…

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.
```

In [451…

```
X_train
```

Out[451…

```
array([[0.61254991],
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```

```
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```

```
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```

```
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       [3.7230162 ],
       [3.06263033],
       [2.99127836],
       [0.96626866]])
```

In [452…

```
import numpy as np
from sklearn.base import BaseEstimator, RegressorMixin
from sklearn.utils.validation import check_X_y, check_array, check_is_fi
from sklearn.model_selection import train_test_split

class CustomLinearRegression(RegressorMixin, BaseEstimator):

# Использовать метод наименьших квадратов с регуляризацией
    def __init__(self, alpha, method = 'ols'):
        self.alpha = alpha
        self.method = method

    def fit(self, X, y, alpha = 0):

        X, y = check_X_y(X, y)

# матрица X размером n на p
        X_ = np.c_[np.ones(X.size), X]

        # n = X_.shape[0]
        # p = X_.shape[1]

        A = np.identity(X_.shape[1])

# По условию: A - единичная матрица размера p+1 на p+1, в которой элемен
        A[0,0] = 0

# X - матрица признаков размера n на p+1 (дополнительный первый столбец
        # column = np.ones(n)
        # X_ = np.insert(X_, 0, column, axis=1)

        try:
            self.coef_ = np.linalg.pinv(X_.T @ X_ + alpha * A) @ X_.T @
            print("coef", self.coef_.size)

        except:
            raise ValueError
        return self

    def fit_transform(self, X, y=None):

        return self.fit(X).transform(X)

    def predict(self, X):
        check_is_fitted(self, 'coef_')
        X = check_array(X)

        X_ = np.c_[np.ones(X.size), X]
```

```
        return X_ @ self.coef_
```

In [453…
```
# X_train = X_train.reshape(-1, 1)
# X_test = X_test.reshape(-1, 1)
```

In [454…
```
X_train.shape
```

Out[454…
```
(210, 1)
```

In [455…
```
X_test.shape
```

Out[455…
```
(90, 1)
```

In [456…
```
C = CustomLinearRegression(alpha = 0.5)

C.fit(X_train, y_train, alpha = 0.5)
C.coef_
```

Out[456…
```
coef 2
array([10.15352775, -0.30039683])
```

In [457…
```
y_pred = C.predict(X_test)
y_pred
```

Out[457…
```
array([ 9.48990132,  9.61704641,  9.91442128,  9.96978113,  9.97820187,
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```

Реализация класса для стандартизации признаков в виде трансформации совместимый с sklearn. Передаваемые параметры: 1) has_bias (содержит ли матрица вектор единиц), 2) apply_mean (производить ли центровку)

Transformer is an architecture for transforming one sequence

into another one with the help of two parts (Encoder and Decoder)

In [458…

```
class CustomStandardTransformer():

    def __init__(self, apply_mean, has_bias):
        self.apply_mean = apply_mean
        self.has_bias = has_bias
        # pass

# Performing the operation based upon the training data that yields the
    def fit(self, X, y = None):
        X = check_array(X)
        return self

    # def fit_transform():
    # pass

    def fit_transform(self, X, y=None):

        return self.fit(X).transform(X)

# Transformer method for this transformer: applying passed mean and addi
    def transform(self, X, y=None):

        if self.apply_mean:
            mean_p = X.mean(axis = 0)
            X = X - mean_p

        if not self.has_bias:
            X = np.c_[np.ones(X.size), X]

        return X
```

Используя класс Pipeline, обучаем линейную регрессию для набора данных с коэффициентом регуляризации, равным 0.01.

Defining the steps in the pipeline, orchestrating the flow

In [459…

```
from sklearn.pipeline import Pipeline
```

In [460…

```
pipeline = Pipeline([
    ("standartizer", CustomStandardTransformer(apply_mean=True, has_bias=
    ("regressor", CustomLinearRegression(alpha = 0.01))])
pipeline.fit(X_train, y_train, regressor__alpha=0.01)
```

Out[460…

```
coef 2
Pipeline(steps=[('standartizer',
                 <__main__.CustomStandardTransformer object at 0x0000011B
15EED250>),
                ('regressor', CustomLinearRegression(alpha=0.01))])
```

In [461…

```
# Predicting through pipeline's regressor
y_pred = pipeline.predict(X_test)
y_pred
```

Out[461…

```
array([ 9.45154139,  9.57884515,  9.87659114,  9.93202007,  9.94045132,
        8.84615918,  9.73796485,  9.75194812,  9.23765857,  9.6330438 ,
        9.83798135,  8.82741433,  9.80627594,  9.53833106,  9.34721049,
        9.18696183,  8.85238287,  8.81432727,  9.60667048,  9.60806078,
        8.88116922,  9.64937318,  9.74211795, 10.05692177,  8.99582577,
       10.055903  , 10.09364862,  9.52434929,  9.58096471,  9.77496096,
        8.78668055,  9.86605147,  9.46330033, 10.09398721,  8.90754285,
       10.03083519,  8.96319798,  9.63735871,  8.92146751,  8.79272802,
       10.04286635,  9.86323828,  8.66642594,  9.24656057,  9.0394876 ,
        9.97547488,  8.64537381,  9.23470182,  9.94457964,  9.08531176,
        9.89527646,  9.34551789,  8.76661386,  9.56653875,  9.29870144,
        9.67411489,  9.47122065,  9.20529299,  9.20892419,  8.63074696,
        9.66378564,  9.3002903 ,  8.76549444,  9.04137508,  8.83957487,
       10.01358733, 10.01937149,  8.75826472,  9.77793363,  9.70349538,
        8.86869281,  8.98434818, 10.04008472,  8.66334945,  9.58782056,
        8.71603024,  9.97364219,  9.98048821,  9.94461581,  9.21763352,
        8.94139129,  8.95226467,  9.90219235,  9.51980348,  8.79546284,
        9.21510682,  9.86783542,  9.92017588,  9.12987572,  8.87362408])
```

Реализуйте функции для расчета MSE и R^2 при отложенной выборке (run_holdout) и кросс-валидации (run_cross_val). Для кросс-валидации используйте только класс KFold. Выходными значениями должны быть MSE и R^2 для обучающей и тестовой частей.

In [462…

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error as mse, r2_score as r2s
```

In [463…

```
# The hold-out method for training a machine learning model is the proce
# and using one split for training the model and other splits for valida
#The hold-out method is used for both model evaluation and model selecti
```

In [464…

```
def run_holdout(model_name, X, y, train_size, random_state, custom_flag)

    # splitting the data
    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=

    # training on one split

    if custom_flag == 0:
        model_name.fit(X_train, y_train)
    else:
        model_name.fit(X_train, y_train, regressor__alpha=0.01)

    y_pred_train = model_name.predict(X_train)
    y_pred_test = model_name.predict(X_test)

    metrics = []
    mse_hold_train = mse(y_train, y_pred_train)
    # metrics.append(mse_hold_train)

    mse_hold_test = mse(y_test, y_pred_test)
    # metrics.append(mse_hold_test)
```

```
    r2_hold_train = r2s(y_train, y_pred_train)
    # metrics.append(r2_hold_train)

    r2_hold_test = r2s(y_test, y_pred_test)
    # metrics.append(r2_hold_test)

    metrics = {'mse trained': mse_hold_train,
               'mse tested': mse_hold_test,
               'r2 trained': r2_hold_train,
               'r2 tested': r2_hold_test
              }

    return metrics
```

In [465…

```
# Cross-validation is a resampling method that uses different portions o
# on different iterations. It is mainly used in settings where the goal
# and one wants to estimate how accurately a predictive model will perfo
```

In [466…

```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error as mse, r2_score as r2s
import pandas as pd

def run_cross_val(model_name, X, y, n_splits, shuffle, random_state, cus

    X_train, X_test, y_train, y_test = train_test_split(X, y, train_size

    # Dividing the data with KFold
    kf = KFold(n_splits = n_splits, shuffle = shuffle, random_state = ra
    blocks = kf.split(X_train, y_train)

    mse_train = []
    mse_test = []
    r2_train = []
    r2_test = []
    metrics_n = []

    # Separating features and target variables
    for train_index, test_index in blocks:

        if custom_flag == 0:
            model_name.fit(X_train[train_index], y_train[train_index])
        else:
            model_name.fit(X_train[train_index], y_train[train_index], r

    # Training the model on separated features
        y_pred_train = model_name.predict(X_train)
        y_pred_test = model_name.predict(X_test)

        mse_train.append(mse(y_train, y_pred_train))
        mse_test.append(mse(y_test, y_pred_test))
        r2_train.append(r2s(y_train, y_pred_train))
        r2_test.append(r2s(y_test, y_pred_test))


    # metrics_n.append(np.mean(mse_train))
    # metrics_n.append(np.mean(mse_test))
    # metrics_n.append(np.mean(r2_train))
    # metrics_n.append(np.mean(r2_test))

    # metrics = pd.DataFrame({
```

```
    #         'metrics': ['mse trained', 'mse tested', 'r2 trained', 'r2
    #         'means': [np.mean(mse_train), np.mean(mse_test), np.mean(r2_
    # })
    metrics = {'mse trained': np.mean(mse_train),
               'mse tested': np.mean(mse_test),
               'r2 trained': np.mean(r2_train),
               'r2 tested': np.mean(r2_test)
              }
    return metrics
```

In [467…

```
run_holdout(pipeline, X, y, train_size=0.75, random_state = 0, custom_fl
```

Out[467…

```
coef 2
{'mse trained': 0.5246791769800708,
 'mse tested': 0.6628343974372327,
 'r2 trained': 0.2631672557692607,
 'r2 tested': 0.11599357781438557}
```

In [468…

```
run_cross_val(pipeline, X, y, n_splits = 4, shuffle = True, random_state
```

Out[468…

```
coef 2
coef 2
coef 2
coef 2
{'mse trained': 0.5257066149797427,
 'mse tested': 0.6641420624742496,
 'r2 trained': 0.2617243741112111,
 'r2 tested': 0.11424957615234144}
```

Задание 2. Регрессия и кросс-валидация

⚠️ Замечание:

```
Используйте ранее реализованные классы и функции
Разбейте исходные данные на обучающее и тестовое
подмножества в соотношении 70 на 30, random_state=0
Для выбора гиперпараметров используйте два подхода: 1) с
отложенной выборкой, 2) с кросс-валидацией
Параметры разбиения для выбора гиперпараметров используйте
те, что в п.4 задания 1
```

Дано множество наблюдений (см. набор данных к заданию), модель - линейная регрессия (без регуляризации). Найти степень полинома с минимальной ошибкой на проверочном подмножестве, определить среднеквадратическую ошибку на тестовом подмножестве (степень полинома от 1 до 25). Сделать заключение о влиянии степени полинома регуляризации.

Построить:

```
диаграмму разброса исходных данных
график зависимости среднеквадратической ошибки (MSE) от
степени полинома для обучающего и проверочного подмножеств
график зависимости коэффициента детерминации (R^2) от
```

степени полинома для обучающего и проверочного подмножеств
функцию регрессии (наилучший случай) + исходные данные

In [469…
```
new_df = pnd.read_csv("data/Reg_A5.csv")
```

In [470…
```
X = df.drop('Y', axis=1).values
y = df['Y'].values
```

In [471…
```
X
```

Out[471…
```
array([[3.85660322],
       [0.10375975],
       [3.16824117],
       [3.74401941],
       [2.49253506],
       [1.12398323],
       [0.99031432],
       [3.80265356],
       [0.84555418],
       [0.44169907],
       [3.42679909],
       [4.76696673],
       [0.01974133],
       [2.56096132],
       [4.06310481],
       [3.06263033],
       [3.60877659],
       [1.45938034],
       [4.58887061],
       [3.57287892],
       [2.71272184],
       [0.71085024],
       [1.8667038 ],
       [3.37066808],
       [2.20916587],
       [2.17006997],
       [3.08883489],
       [2.56569121],
       [3.25198591],
       [3.00519477],
       [4.02611598],
       [2.60823576],
       [4.5432444 ],
       [1.59618044],
       [0.45229675],
       [1.50350028],
       [0.56992181],
       [4.14340663],
       [0.2344816 ],
       [3.13143574],
       [2.73793078],
       [4.09643498],
       [0.9947377 ],
       [4.28425151],
       [1.7582632 ],
       [3.77323846],
       [1.47980853],
       [4.4196824 ],
       [1.62755819],
```

```
[0.82507949],
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[0.46730187],
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[0.7557601 ],
[1.92057224],
[4.72130356],
[4.93812737],
[2.28152274],
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[1.25687067],
[2.98685824],
[4.5141588 ],
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[2.95100681],
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[1.50435654],
[0.12699891],
[1.5153128 ],
[1.21037938],
[2.78789094],
[2.8275351 ],
[2.37566124],
[1.46398988],
[0.3212553 ],
[4.89409573],
[1.69853922],
[2.47524315],
[4.88540363],
[2.20386912],
[1.59136403],
[2.59898493],
[2.89068215],
[4.26966875],
[0.34048637],
[2.32265404],
[3.90974559],
[3.59301405],
[2.9301099 ],
[0.18547207],
[1.75328196],
[2.81595342],
[1.49864936],
[2.56167077],
```

```
[3.36733463],
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[4.42913548],
[1.82682486],
[1.09384675],
[3.76248085],
[0.53439792],
[3.7230162 ],
[2.34892647],
[2.99127836],
[0.73810096],
[0.92017411],
[3.22536063],
[0.24314003],
[1.24306254],
[2.71204258],
[1.13386672],
[1.90705767],
[4.61116393],
[4.62678436],
[2.83374962],
[2.66735442],
[0.07430012],
[4.88949632],
[2.86514452],
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[2.8077868 ],
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[2.92097914],
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[2.14225369],
[3.46945033],
[0.52309872],
[2.19802619],
[0.83101074],
[2.53489315],
[4.09517932],
[0.45053367],
[4.00034375],
[2.82563177],
[2.94673856],
[0.99050329],
[2.18059128],
[1.47951881],
[0.18778838],
[0.1534242 ],
[2.265525  ],
[3.72432038],
[2.78647703],
[1.925568  ],
[0.84036399],
[4.1913066 ],
[2.99525899],
[3.91357409],
[4.24254591],
[3.01581488],
[3.90530309],
[3.07868438],
```

```
[0.10582596],
[3.75232305],
[0.88021067],
[2.29257103],
[2.56561354],
[2.42010445],
[4.22192897],
[0.87406947],
[0.07317438],
[4.24382036],
[3.71337289],
[2.28348768],
[2.08449204],
[0.58364755],
[1.69339566],
[0.4732952 ],
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[1.02975129],
[2.86888116],
[1.46915778],
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[0.46720188],
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[3.92433359],
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[4.32239597],
[1.92015384],
[1.28651444],
[4.1470096 ],
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[2.53800454],
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[1.3714741 ],
[3.54552982],
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[4.22309431],
[2.69073759],
[2.79543258],
[0.61254991],
[1.88820959],
[2.14373665],
```

```
       [2.55604323],
       [4.45881285],
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       [1.98220939],
       [3.96636617],
       [2.06138039],
       [0.92433775],
       [4.20123658],
       [2.846357  ],
       [0.30025103],
       [4.94458487],
       [1.14391167],
       [3.07350856],
       [1.8401334 ],
       [4.01387968],
       [3.13780926],
       [4.10608238],
       [1.44126569],
       [1.37397566],
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       [4.69257099],
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       [0.61167961],
       [2.29362115],
       [4.8740625 ],
       [3.40287187],
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       [4.13951588],
       [4.81950261],
       [2.99468225],
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       [1.86014451],
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       [1.60571016],
       [3.19017541],
       [0.04610551],
       [2.71732519],
       [1.68877323],
       [4.49012154],
       [4.70353519],
       [1.92060925],
       [1.98058896],
       [4.48639972],
       [0.29411184],
       [2.02689644],
       [0.6508777 ],
       [0.43484704],
       [3.91982143],
       [1.52286678],
       [2.92027936],
       [4.39233089],
       [4.4039603 ],
       [3.00477104],
       [3.22613873],
       [0.28314101],
       [1.48742048]])
```

In [472…
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
```

In [473…
```
max_degree = 25

hold_metrics_mse_train = []
hold_metrics_mse_test = []
hold_metrics_r2_train = []
hold_metrics_r2_test = []

cv_metrics_mse_train = []
cv_metrics_mse_test = []
cv_metrics_r2_train = []
cv_metrics_r2_test = []

deg_range = range(1, max_degree + 1)
for deg in deg_range:

    pf = PolynomialFeatures(degree = deg)
    features = pf.fit_transform(X)
    lr = LinearRegression(fit_intercept = False)

    hold_metrics = run_holdout(lr, features, y, train_size=0.75, random_
    cv_metrics = run_cross_val(lr, features, y, n_splits=4, shuffle=True

    hold_metrics_mse_train.append(hold_metrics['mse trained'])
    hold_metrics_mse_test.append(hold_metrics['mse tested'])
    hold_metrics_r2_train.append(hold_metrics['r2 trained'])
    hold_metrics_r2_test.append(hold_metrics['r2 tested'])

    cv_metrics_mse_train.append(cv_metrics['mse trained'])
    cv_metrics_mse_test.append(cv_metrics['mse tested'])
    cv_metrics_r2_train.append(cv_metrics['r2 trained'])
    cv_metrics_r2_test.append(cv_metrics['r2 tested'])

best_mse_hold = np.argmin(hold_metrics_mse_test)
best_mse_cv = np.argmin(cv_metrics_mse_test)
best_r2_hold = np.argmax(hold_metrics_r2_test)
best_r2_cv = np.argmax(cv_metrics_r2_test)
# cv_metrics_mse_test
```

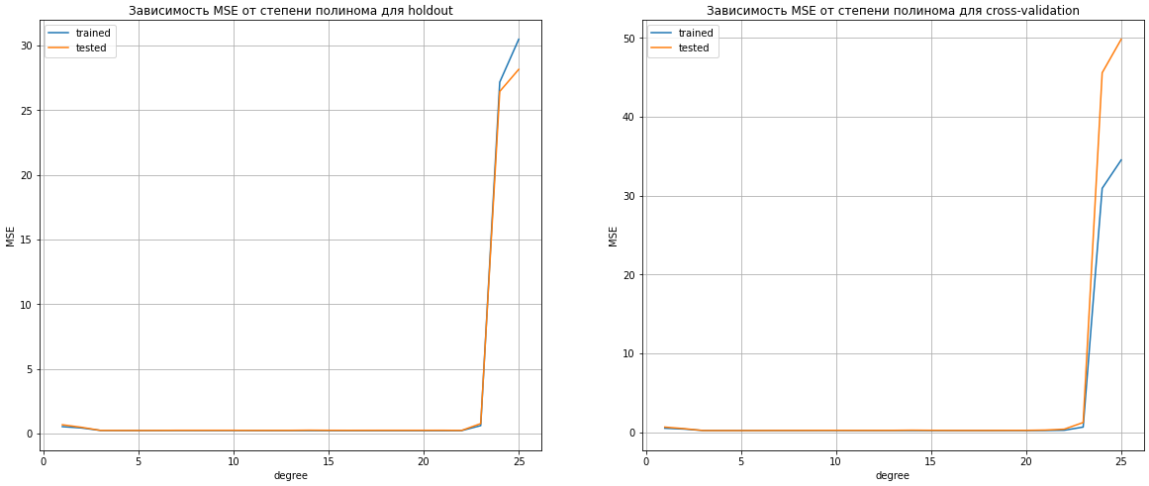
In [474…
```
fig, ax = plt.subplots(1, 2, figsize = (20, 8))

ax[0].plot(deg_range, hold_metrics_mse_train, label = 'trained')
ax[0].plot(deg_range,  hold_metrics_mse_test, label='tested')
ax[0].set_title('Зависимость MSE от степени полинома для holdout')
ax[0].set_xlabel('degree')
ax[0].set_ylabel('MSE')
ax[0].grid()
ax[0].legend()

ax[1].plot(deg_range, cv_metrics_mse_train, label = 'trained')
ax[1].plot(deg_range,  cv_metrics_mse_test, label='tested')
ax[1].set_title('Зависимость MSE от степени полинома для cross-validatio
ax[1].set_xlabel('degree')
ax[1].set_ylabel('MSE')
ax[1].grid()
ax[1].legend()
```

```
<matplotlib.legend.Legend at 0x11b11c5a4c0>
```

Out[474…



In [475…

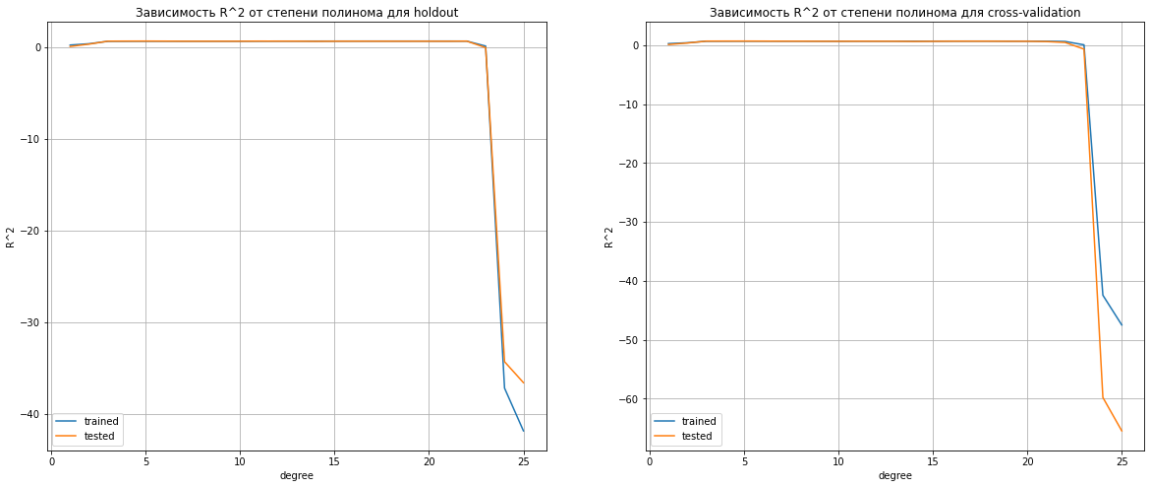
```
fig, ax = plt.subplots(1, 2, figsize = (20, 8))

ax[0].plot(deg_range, hold_metrics_r2_train, label = 'trained')
ax[0].plot(deg_range,  hold_metrics_r2_test, label='tested')
ax[0].set_title('Зависимость R^2 от степени полинома для holdout')
ax[0].set_xlabel('degree')
ax[0].set_ylabel('R^2')
ax[0].grid()
ax[0].legend()

ax[1].plot(deg_range, cv_metrics_r2_train, label = 'trained')
ax[1].plot(deg_range,  cv_metrics_r2_test, label='tested')
ax[1].set_title('Зависимость R^2 от степени полинома для cross-validatio
ax[1].set_xlabel('degree')
ax[1].set_ylabel('R^2')
ax[1].grid()
ax[1].legend()
```

Out[475…

```
<matplotlib.legend.Legend at 0x11b11d6af40>
```



In [476…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7

# Can't implement custom linear model, fixing not iterable LR
X_poly_train = PolynomialFeatures(degree = best_mse_hold + 1).fit_transf
X_poly_test = PolynomialFeatures(degree = best_mse_hold + 1).fit_transfo
# poly_transf = PolynomialFeatures(degree = best_mse_hold + 1).fit_trans
# transformer =  CustomStandardTransformer(apply_mean = False, has_bias=
lrn = LinearRegression(fit_intercept=True)
```

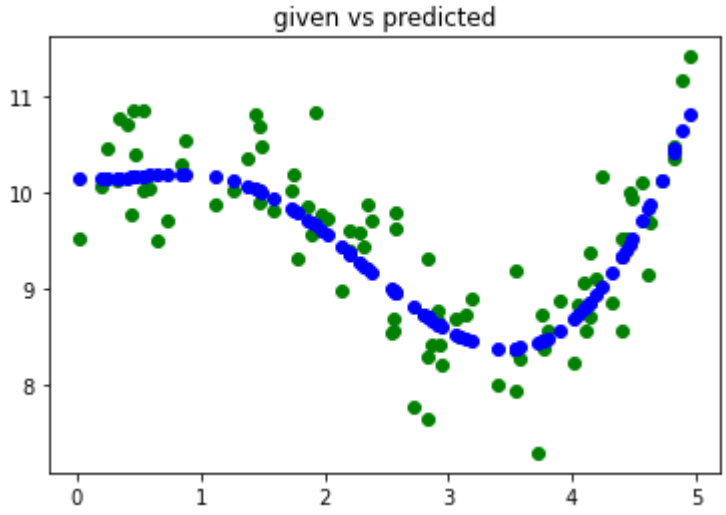
```
lrn.fit(X_poly_train, y_train)
y_pred = lrn.predict(X_poly_test)
```

In [477…

```
f_x_d = np.linspace(X_poly_test.min(), X_poly_test.max(), 100)
```

In [478…

```
plt.title("given vs predicted")
plt.scatter(X_test, y_test, color="green", label='started')
plt.scatter(X_test, y_pred, color="blue", label='prediction')
# plt.plot(f_x_d, y_pred, color="red", lw=5, label='prediction')
plt.show()
```



In [479…

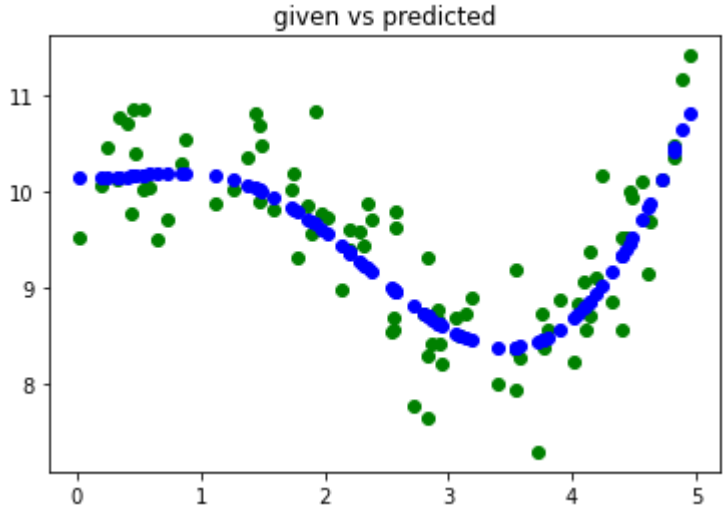
```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7

# Can't implement custom linear model, fixing not iterable LR
X_poly_train = PolynomialFeatures(degree = best_mse_cv + 1).fit_transfor
X_poly_test = PolynomialFeatures(degree = best_mse_cv + 1).fit_transform
lrn = LinearRegression(fit_intercept=True)

lrn.fit(X_poly_train, y_train)
y_pred = lrn.predict(X_poly_test)
```

In [480…

```
plt.title("given vs predicted")
plt.scatter(X_test, y_test, color="green", label='started')
plt.scatter(X_test, y_pred, color="blue", label='prediction')
# plt.plot(f_x_d, y_pred, color="red", lw=5, label='prediction')
plt.show()
```



Заключение:

С возрастанием степени полинома возрастает вероятность переобучения. На высоких степенях полином нестабилен

Задание 3

! Замечание:

```
Используйте класс логистической регрессии из sklearn со
следующими параметрами:
    penalty='l2'
    fit_intercept=True
    max_iter=100
    C=1e5
    solver='liblinear'
    random_state=12345
Разбейте исходные данные на обучающее и тестовое
подмножества в соотношении 70 на 30, random_state=0
Для выбора гиперпараметров используйте два подхода: 1) с
отложенной выборкой, 2) с кросс-валидацией
Для кросс-валидации можно использовать функцию
cross_validate из sklearn
Параметры разбиения для выбора гиперпараметров используйте
те, что в п.4 задания 1
```

Дано множество наблюдений (см. набор данных к заданию), классификатор - логистическая регрессия. Найти степень полинома с минимальной ошибкой на проверочном подмножестве, определить долю правильных классификаций на тестовом подмножестве. Сделать заключение о влиянии степени полинома регуляризации.

Построить:

```
диаграмму разброса исходных данных
график зависимости доли правильных классификаций от степени
```

полинома для обучающего и проверочного подмножеств
график зависимости доли правильных классификаций от количества итераций для обучающего и проверочного подмножеств для наилучшего случая
результат классификации для наилучшего случая (степень полинома) для обучающего и тестового подмножеств

In [481…

```
import requests
url = 'https://raw.githubusercontent.com/MLMethods/Assignments/master/da
res = requests.get(url, allow_redirects=True)
with open('dfv2.csv','wb') as file:
    file.write(res.content)
dfv2 = pd.read_csv('dfv2.csv')
dfv2
```

Out[481…

	X1	X2	Y
0	5.712051	4.420663	0
1	4.658783	6.312037	1
2	4.211528	4.934160	0
3	5.440266	5.688972	0
4	5.109973	7.006561	1
...	...	...	...
495	4.782801	5.331527	0
496	3.469108	5.801888	1
497	6.357797	4.195166	1
498	5.261725	4.757229	0
499	5.393892	4.049974	0

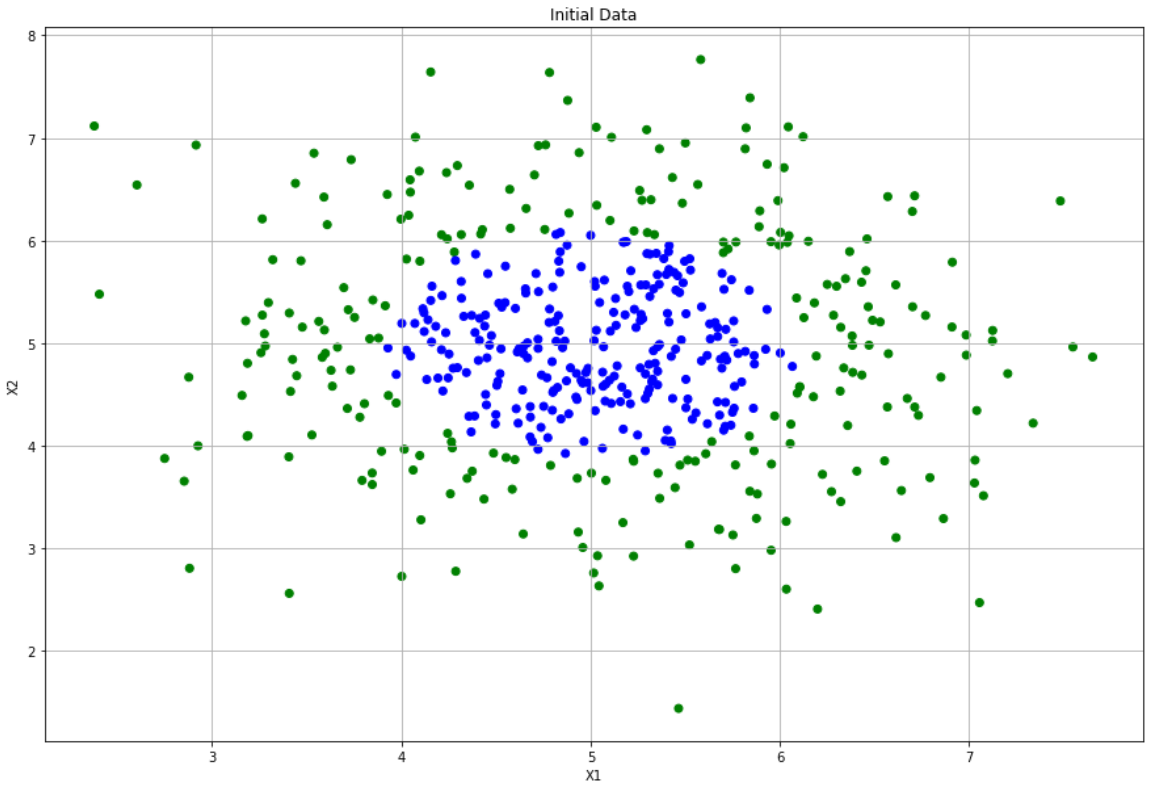
500 rows × 3 columns

Initial data

In [482…

```
x1 = dfv2.X1.values
x2 = dfv2.X2.values
y = dfv2.Y.values

plt.figure(figsize = (15, 10))
plt.xlabel("X1")
plt.title("Initial Data")
plt.ylabel("X2")
plt.scatter(dfv2.X1, dfv2.X2, c = dfv2.Y, cmap = clrMap)
plt.grid(True)
plt.show()
```



In [483…

```
X = dfv2.drop('Y', axis=1).values
```

In [484…

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
# from sklearn.model_selection import cross_validate
from sklearn.metrics import accuracy_score
```

In [485…

```
# Splitting data to training, evaluating and testing

X_train_init, X_test, y_train_init, y_test = train_test_split(X, y, trai

# Splitting the data to evaluating, train_size from exercise 1 // holdou

x_train, x_val, y_train, y_val = train_test_split(X_train_init, y_train_
```

In [486…

```
# logistic regression with parameters

logr = LogisticRegression(penalty='l2',
                          fit_intercept = True,
                          max_iter = 100,
                          C = 1e5,
                          solver = 'liblinear',
                          random_state = 12345)
```

In [487…

```
max_deg = 25
degree_range = range(1, max_deg + 1)
degree = 0
accr = 0
mse_ch = 100
mse_data = []
accuracy_data = []
```

```
accuracy_data_tr = []

for deg in degree_range:

    pf = PolynomialFeatures(degree = deg)

    x_train_holdout = pf.fit_transform(x_train)

    x_test_holdout = pf.fit_transform(x_val)

    x_test_pf = pf.fit_transform(X_test)

    # using holdout for initial data
    # hold_metrics = run_holdout(logr, x_train_holdout, y_train, train_s

    # using cross-validation for initial data
    # cv_metrics = run_cross_val(logr, X_train_init, y_train_init, n_spl

    logr.fit(x_train_holdout, y_train)

    # holdout with tested/initial data
    y_pred_test_holdout = logr.predict(x_test_holdout)

    # holdout with training data
    y_pred_train_holdout = logr.predict(x_train_holdout)
    y_pred_test_pf = logr.predict(x_test_pf)

    # calculating mse for each step

    mse_data.append(mse(y_pred_test_holdout, y_val))

    # calculating accuracy for the plot, evaluated data

    accuracy_data.append(accuracy_score(y_pred_test_holdout, y_val))

    # calculating accuracy for the plot, training data
    accuracy_data_tr.append(accuracy_score(y_train, y_pred_train_holdout

    # mse_ch is a chosen mse value. at each step we compare the chosen b
    if mse(y_pred_test_holdout, y_val) < mse_ch:
        mse_ch = mse(y_pred_test_holdout, y_val)
        degree = deg
    # accr is a chosen accuracy value
    if accr < accuracy_score(y_pred_test_holdout, y_val):
        accr = accuracy_score(y_pred_test_holdout, y_val)

    # adding!! accuracy with holdout
    hd_accrs = []
    hd_accrs.append(accuracy_score(y_pred_test_pf, y_test))
    hd_accr = 0

    if hd_accr < accuracy_score(y_pred_test_pf, y_test):
        hd_accr = accuracy_score(y_pred_test_pf, y_test)
```

In [488…

```
#
accr, mse_ch, hd_accr, degree
```

Out[488…

```
(1.0, 0.0, 0.84, 2)
```

In [489…

```
# y_pred_test_holdout
```

In [490…
```
# y_val
```

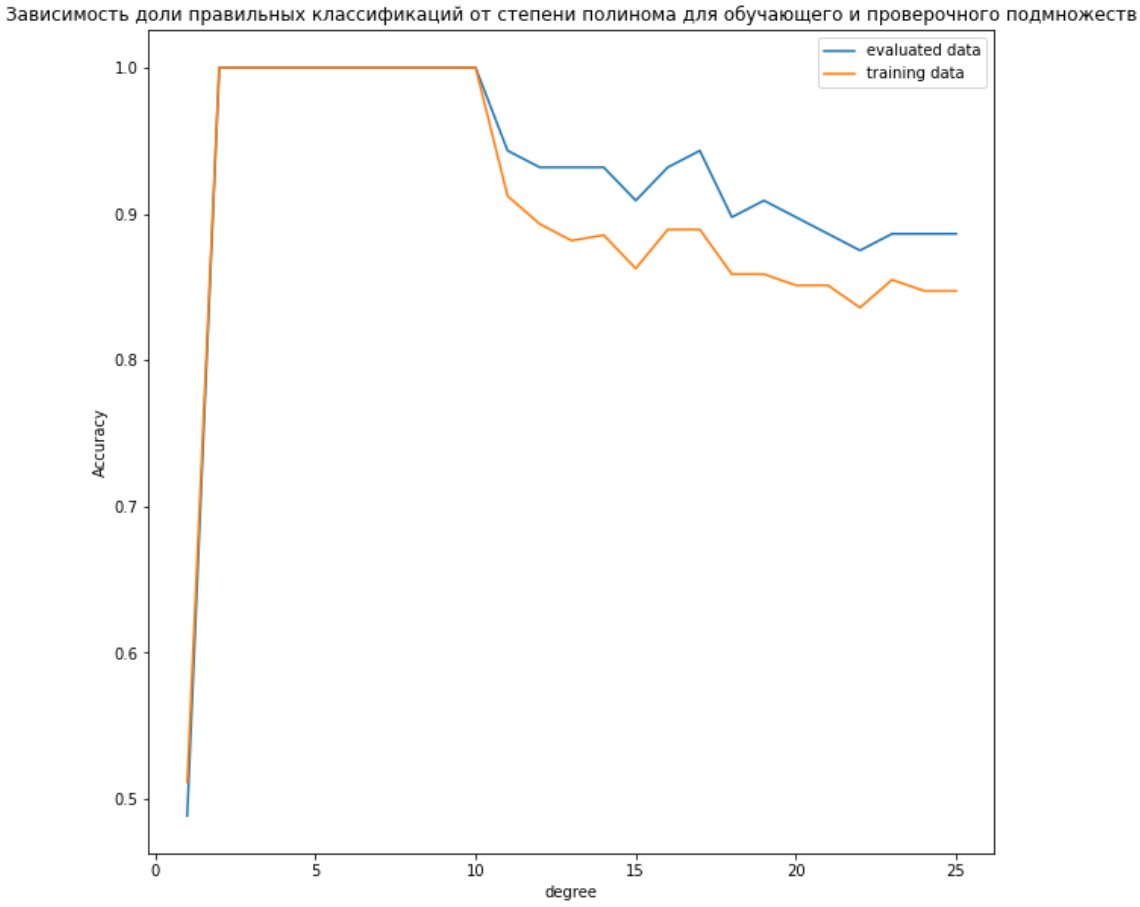
In [491…
```
# LogisticRegression?
```

In [492…
```
# accuracy_score?
```

In [493…
```
# LogisticRegression().score
```

In [494…
```
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
ax.plot(range(1, max_deg + 1), accuracy_data, label='evaluated data')
ax.plot(range(1, max_deg + 1), accuracy_data_tr, label='training data')
ax.set_title('Зависимость доли правильных классификаций от степени полин
ax.set_xlabel('degree')
ax.set_ylabel('Accuracy')
ax.legend()
```

Out[494…
```
<matplotlib.legend.Legend at 0x11b11e91b50>
```



In [495…
```
pf = PolynomialFeatures(degree = degree)
X_train_holdout = pf.fit_transform(x_train)
X_test_holdout = pf.fit_transform(x_val)
X_test_pf = pf.fit_transform(X_test)
```

In [496…
```
accuracy_data_it = []
```

```
accuracy_data_tr_it = []
```

In [497…

```
iterations = 500
for i in range(1, iterations):

    pf = PolynomialFeatures(degree = degree)

    # logistic regression with more iterations

    logr_i = LogisticRegression(penalty='l2',
                                fit_intercept = True,
                                max_iter = i,
                                C = 1e5,
                                solver = 'liblinear',
                                random_state = 12345)


    logr_i.fit(X_train_holdout, y_train)

    # holdout with tested/initial data
    y_pred_test_holdout = logr_i.predict(X_test_holdout)

    # holdout with training data
    y_pred_train_holdout = logr_i.predict(X_train_holdout)
    y_pred_test_pf = logr_i.predict(X_test_pf)

    # calculating accuracy for the plot, evaluated data

    accuracy_data_it.append(accuracy_score(y_pred_test_holdout, y_val))

    # calculating accuracy for the plot, training data
    accuracy_data_tr_it.append(accuracy_score(y_train, y_pred_train_hold
```

```
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: Conv
ergenceWarning: Liblinear failed to converge, increase the number of iter
ations.
  warnings.warn("Liblinear failed to converge, increase "
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```

```
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C:\Users\blueb\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: Conv
ergenceWarning: Liblinear failed to converge, increase the number of iter
```

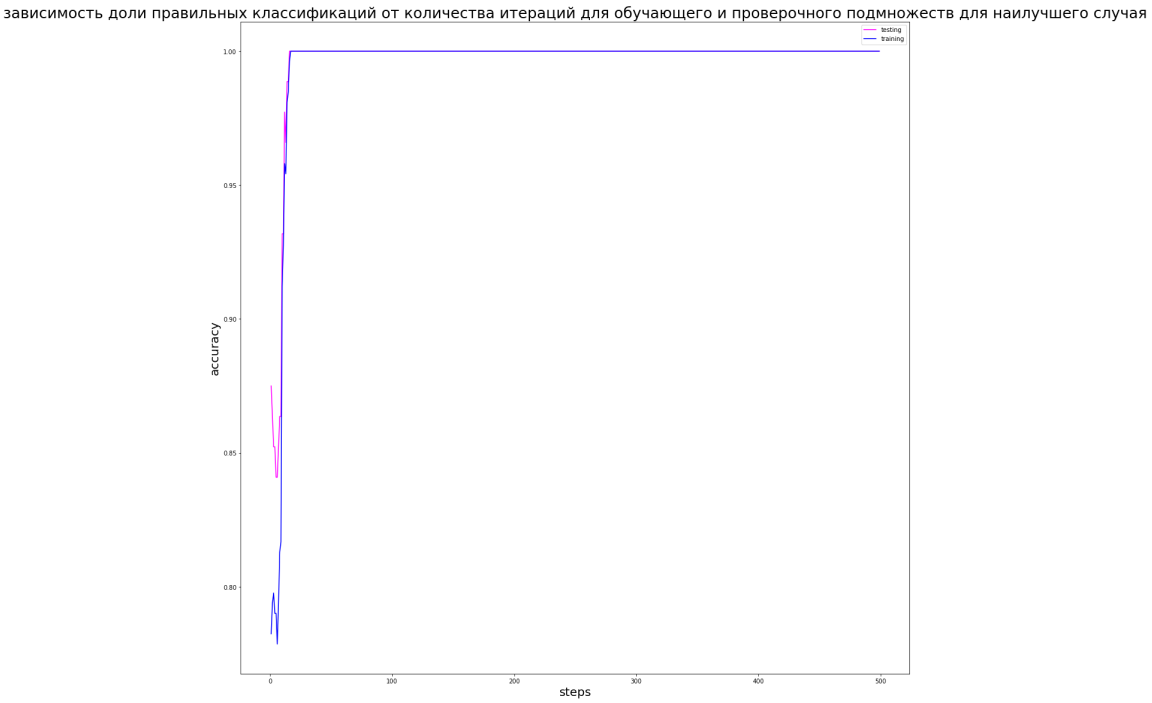
```
ations.
  warnings.warn("Liblinear failed to converge, increase "
```

In [498…

```
fig,ax = plt.subplots(1, 1, figsize=(20, 20))
ax.plot(range(1, iterations), accuracy_data_it, color = 'magenta', label
ax.plot(range(1, iterations), accuracy_data_tr_it, color = 'blue', label
ax.set_xlabel('steps', fontsize=20)
ax.set_ylabel('accuracy', fontsize=20)
ax.set_title('зависимость доли правильных классификаций от количества ит
ax.legend()
```

Out[498…

```
<matplotlib.legend.Legend at 0x11b12665910>
```



Cross-validation

In [499…

```
from sklearn.model_selection import cross_validate
import sklearn.metrics as skm
```

In [500…

```
# Splitting data to training, evaluating and testing

X_train_init, X_test, y_train_init, y_test = train_test_split(X, y, trai

# Splitting the data to evaluating, train_size from exercise 1 // holdou

x_train, x_val, y_train, y_val = train_test_split(X_train_init, y_train_
```

In [501…

```
skm.SCORERS.keys()
```

Out[501…

```
dict_keys(['explained_variance', 'r2', 'max_error', 'neg_median_absolute_
error', 'neg_mean_absolute_error', 'neg_mean_absolute_percentage_error',
'neg_mean_squared_error', 'neg_mean_squared_log_error', 'neg_root_mean_sq
uared_error', 'neg_mean_poisson_deviance', 'neg_mean_gamma_deviance', 'ac
curacy', 'top_k_accuracy', 'roc_auc', 'roc_auc_ovr', 'roc_auc_ovo', 'roc_
auc_ovr_weighted', 'roc_auc_ovo_weighted', 'balanced_accuracy', 'average_
precision', 'neg_log_loss', 'neg_brier_score', 'adjusted_rand_score', 'ra
nd_score', 'homogeneity_score', 'completeness_score', 'v_measure_score',
```

```
'mutual_info_score', 'adjusted_mutual_info_score', 'normalized_mutual_inf
o_score', 'fowlkes_mallows_score', 'precision', 'precision_macro', 'preci
sion_micro', 'precision_samples', 'precision_weighted', 'recall', 'recall
_macro', 'recall_micro', 'recall_samples', 'recall_weighted', 'f1', 'f1_m
acro', 'f1_micro', 'f1_samples', 'f1_weighted', 'jaccard', 'jaccard_macr
o', 'jaccard_micro', 'jaccard_samples', 'jaccard_weighted'])
```

In [502…

```
max_deg = 25
kf = KFold(n_splits = 4, shuffle=True, random_state=0)
degree_range = range(1, max_deg + 1)
degree = 0
accr = 0
mse_ch = 100
mse_data = []
accuracy_data = []
accuracy_data_tr = []

for deg in degree_range:

    pf = PolynomialFeatures(degree = deg)

    Xx_train_holdout = pf.fit_transform(x_train)

    Xx_test_holdout = pf.fit_transform(x_val)

    Xx_test_pf = pf.fit_transform(X_test)


    # using cross-validation for initial data
    cv_sc = cross_validate(logr, Xx_train_holdout, y_train, cv = kf,
                           scoring=['neg_mean_squared_error', 'accurac
                           return_train_score=True)

    mse_data.append(abs(cv_sc["test_neg_mean_squared_error"]).mean())

    if mse_ch > abs(cv_sc["test_neg_mean_squared_error"]).mean():
        mse_ch = abs(cv_sc["test_neg_mean_squared_error"]).mean()
        degree = deg

    accuracy_data.append(cv_sc["test_accuracy"].mean())

    if accr < cv_sc["test_accuracy"].mean():
        accr = cv_sc["test_accuracy"].mean()

    accuracy_data_tr.append(cv_sc["train_accuracy"].mean())
```

In [503…

```
# mse_data,

mse_ch, degree, accr
```

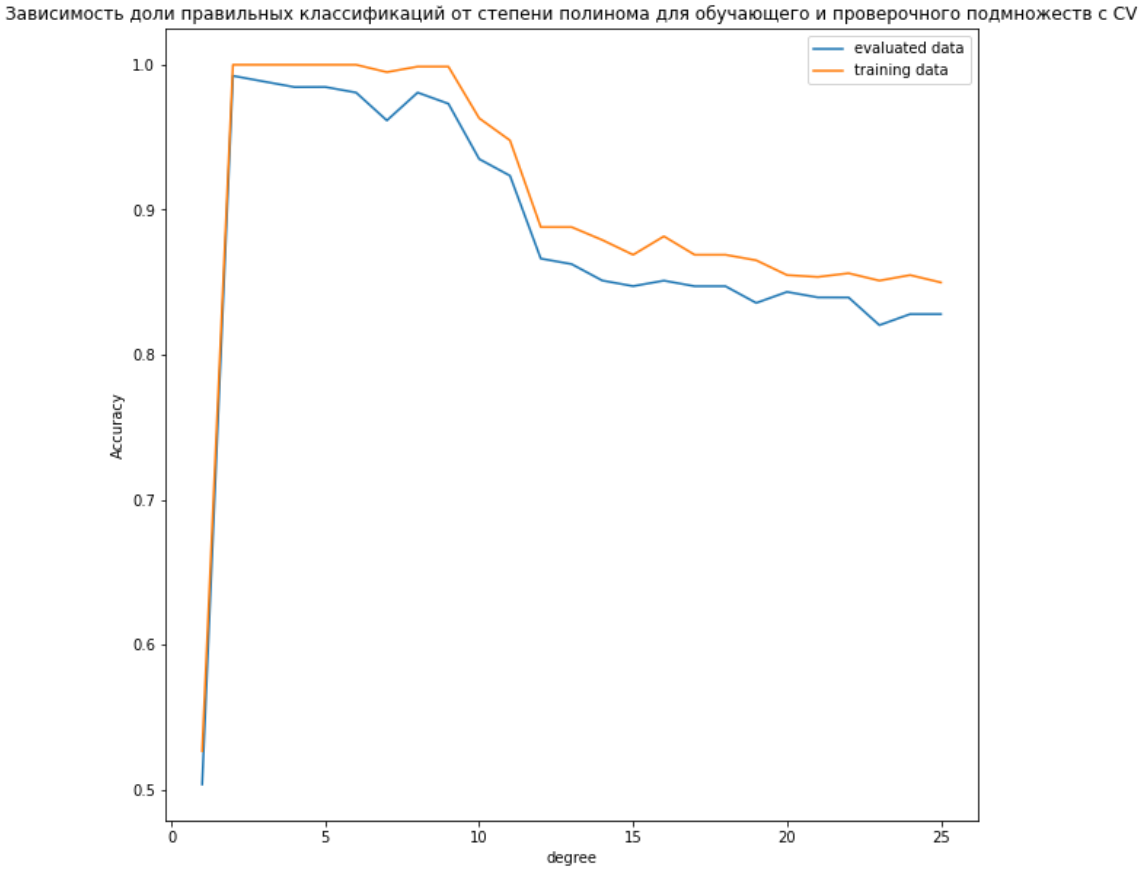
Out[503…

```
(0.007634032634032634, 2, 0.9923659673659674)
```

In [504…

```
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
ax.plot(range(1, max_deg + 1), accuracy_data, label='evaluated data')
ax.plot(range(1, max_deg + 1), accuracy_data_tr, label='training data')
ax.set_title('Зависимость доли правильных классификаций от степени полин
ax.set_xlabel('degree')
ax.set_ylabel('Accuracy')
ax.legend()
```

Out[504… <matplotlib.legend.Legend at 0x11b126e1f10>



In [505…
```
pf = PolynomialFeatures(degree = degree)
X_train_holdout = pf.fit_transform(x_train)
X_test_holdout = pf.fit_transform(x_val)
X_test_pf = pf.fit_transform(X_test)
```

In [506…
```
accuracy_data_it = []
accuracy_data_tr_it = []
```

In [507…
```
iterations = 500
for i in range(1, iterations):

    pf = PolynomialFeatures(degree = degree)

    # logistic regression with more iterations

    logr_i = LogisticRegression(penalty='l2',
                                fit_intercept = True,
                                max_iter = i,
                                C = 1e5,
                                solver = 'liblinear',
                                random_state = 12345)


    logr_i.fit(X_train_holdout, y_train)

    # holdout with tested/initial data
    y_pred_test_holdout = logr_i.predict(X_test_holdout)

    # holdout with training data
```

```python
    y_pred_train_holdout = logr_i.predict(X_train_holdout)
    y_pred_test_pf = logr_i.predict(X_test_pf)

    # calculating accuracy for the plot, evaluated data

    accuracy_data_it.append(accuracy_score(y_pred_test_holdout, y_val))

    # calculating accuracy for the plot, training data
    accuracy_data_tr_it.append(accuracy_score(y_train, y_pred_train_hold
```

```
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: Conv
ergenceWarning: Liblinear failed to converge, increase the number of iter
ations.
  warnings.warn("Liblinear failed to converge, increase "
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ations.
  warnings.warn("Liblinear failed to converge, increase "
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: Conv
ergenceWarning: Liblinear failed to converge, increase the number of iter
ations.
  warnings.warn("Liblinear failed to converge, increase "
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ations.
  warnings.warn("Liblinear failed to converge, increase "
```

```
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: Conv
ergenceWarning: Liblinear failed to converge, increase the number of iter
ations.
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  warnings.warn("Liblinear failed to converge, increase "
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  warnings.warn("Liblinear failed to converge, increase "
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\svm\_base.py:985: Conv
ergenceWarning: Liblinear failed to converge, increase the number of iter
ations.
  warnings.warn("Liblinear failed to converge, increase "
```
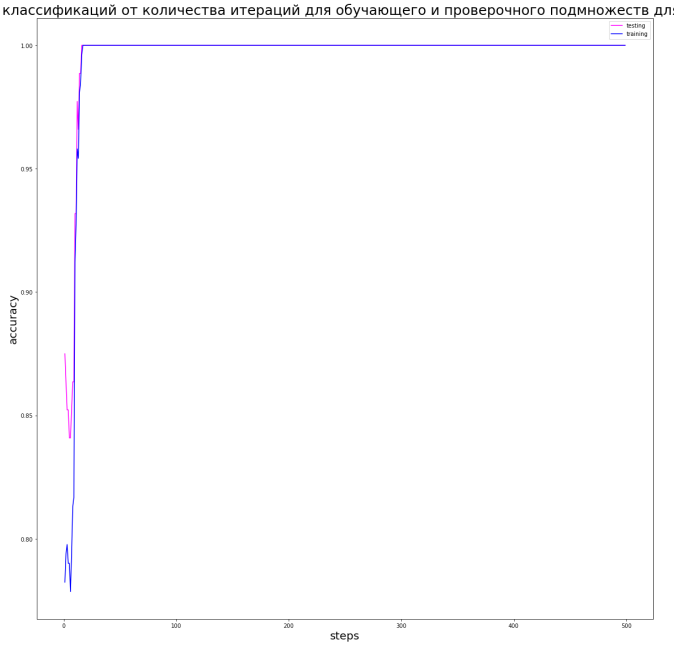

In [508…

```
fig,ax = plt.subplots(1, 1, figsize=(20, 20))
ax.plot(range(1, iterations), accuracy_data_it, color = 'magenta', label
ax.plot(range(1, iterations), accuracy_data_tr_it, color = 'blue', label
ax.set_xlabel('steps', fontsize=20)
ax.set_ylabel('accuracy', fontsize=20)
ax.set_title('зависимость доли правильных классификаций от количества ит
ax.legend()
```

Out[508…

```
<matplotlib.legend.Legend at 0x11b127593d0>
```

зависимость доли правильных классификаций от количества итераций для обучающего и проверочного подмножеств для наилучшего случая в случае CV



Заключение:

С возрастанием степени полинома возрастает вероятность переобучения. На высоких степенях полином нестабилен

Задание 4. Регрессия и регуляризация

Дано множество наблюдений (см. набор данных к заданию), модель - линейная регрессия с L2 регуляризацией. Найти коэффициент регуляризации с минимальной ошибкой на проверочном подмножестве, определить среднеквадратическую ошибку на тестовом подмножестве. Для выбора гиперпараметров использовать кросс-валидацию (параметры см. задание 2). Сделать заключение о влиянии коэффициента регуляризации.

Коэф. регуляризации

alphas = np.append([0.0], np.logspace(-8, 1, 20, base=10))

Построить:

```
матрицу корреляций
график зависимости среднеквадратической ошибки от
коэффициента регуляризации для обучающего и проверочного
подмножеств
график зависимости R-квадрата от коэффициента регуляризации
для обучающего и проверочного подмножеств
график предсказанные значения (y_pred) - действительные
значения (y_true) для итоговой модели
```

In [509…

```
url = 'https://raw.githubusercontent.com/MLMethods/Assignments/master/da
res = requests.get(url, allow_redirects=True)
with open('reg_df.csv','wb') as file:
    file.write(res.content)
```

```
reg_df = pd.read_csv('reg_df.csv')
reg_df
```

Out[509…

	X1	X2	X3	X4	X5	X6	X7
0	3.856603	14.873388	57.360757	221.217682	853.148822	3290.256492	1.268921e+04
1	0.103760	0.010766	0.001117	0.000116	0.000012	0.000001	1.294799e-07
2	3.168241	10.037752	31.802020	100.756468	319.220791	1011.368453	3.204259e+03
3	3.744019	14.017681	52.482471	196.495391	735.682558	2754.409777	1.031256e+04
4	2.492535	6.212731	15.485450	38.598027	96.206935	239.799159	5.977078e+02
...	...	...	...	...	...	...	...
295	4.403960	19.394866	85.414221	376.160841	1656.597410	7295.589233	3.212949e+04
296	3.004771	9.028649	27.129023	81.516502	244.938425	735.983886	2.211463e+03
297	3.226139	10.407971	33.577559	108.325862	349.474260	1127.452444	3.637318e+03
298	0.283141	0.080169	0.022699	0.006427	0.001820	0.000515	1.458880e-04
299	1.487420	2.212420	3.290798	4.894801	7.280627	10.829354	1.610780e+01

300 rows × 17 columns

In [510…
```
X = reg_df.drop('Y', axis=1).values
y = reg_df['Y'].values
```

In [511…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7
```

In [512…
```
alphas = np.append([0.0], np.logspace(-8, 1, 20, base=10))
alphas
```

Out[512…
```
array([0.00000000e+00, 1.00000000e-08, 2.97635144e-08, 8.85866790e-08,
       2.63665090e-07, 7.84759970e-07, 2.33572147e-06, 6.95192796e-06,
       2.06913808e-05, 6.15848211e-05, 1.83298071e-04, 5.45559478e-04,
       1.62377674e-03, 4.83293024e-03, 1.43844989e-02, 4.28133240e-02,
       1.27427499e-01, 3.79269019e-01, 1.12883789e+00, 3.35981829e+00,
       1.00000000e+01])
```

In [513…
```
import seaborn as sn
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error, r2_score
```

In [514…
```
covM = reg_df.cov()
covM
```

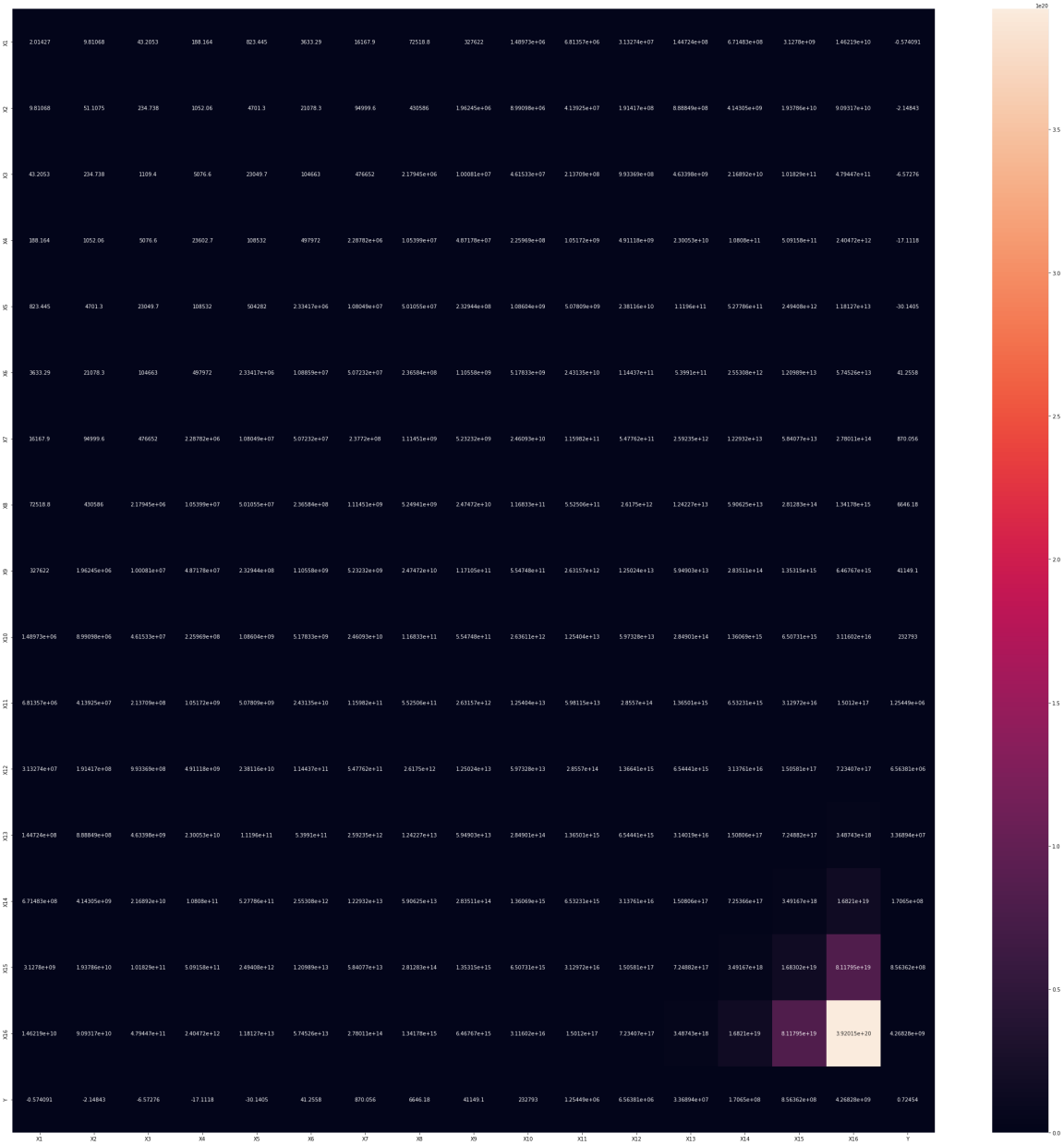
Out[514…

	X1	X2	X3	X4	X5	X
X1	2.014265e+00	9.810682e+00	4.320531e+01	1.881641e+02	8.234451e+02	3.633286e+0
X2	9.810682e+00	5.110754e+01	2.347375e+02	1.052060e+03	4.701302e+03	2.107832e+0
X3	4.320531e+01	2.347375e+02	1.109401e+03	5.076602e+03	2.304972e+04	1.046627e+0
X4	1.881641e+02	1.052060e+03	5.076602e+03	2.360274e+04	1.085317e+05	4.979720e+0
X5	8.234451e+02	4.701302e+03	2.304972e+04	1.085317e+05	5.042822e+05	2.334168e+0

X6	3.633286e+03	2.107832e+04	1.046627e+05	4.979720e+05	2.334168e+06	1.088588e+0
X7	1.616785e+04	9.499959e+04	4.766522e+05	2.287823e+06	1.080491e+07	5.072316e+0
X8	7.251878e+04	4.305857e+05	2.179447e+06	1.053987e+07	5.010547e+07	2.365844e+0
X9	3.276224e+05	1.962455e+06	1.000811e+07	4.871781e+07	2.329436e+08	1.105579e+0
X10	1.489734e+06	8.990978e+06	4.615333e+07	2.259686e+08	1.086042e+09	5.178330e+0
X11	6.813569e+06	4.139246e+07	2.137092e+08	1.051719e+09	5.078086e+09	2.431352e+1
X12	3.132738e+07	1.914168e+08	9.933686e+08	4.911176e+09	2.381158e+10	1.144374e+1
X13	1.447241e+08	8.888486e+08	4.633979e+09	2.300535e+10	1.119597e+11	5.399102e+1
X14	6.714827e+08	4.143048e+09	2.168920e+10	1.080802e+11	5.277861e+11	2.553083e+1
X15	3.127797e+09	1.937863e+10	1.018293e+11	5.091576e+11	2.494079e+12	1.209890e+1
X16	1.462187e+10	9.093170e+10	4.794468e+11	2.404721e+12	1.181274e+13	5.745260e+1
Y	-5.740914e-01	-2.148434e+00	-6.572758e+00	-1.711184e+01	-3.014055e+01	4.125584e+0

In [515…

```
plt.figure(figsize = (40, 40))
sn.heatmap(covM, annot=True, fmt='g')
plt.show()
```



In [522…

```
# L2 regularization
l2 = Ridge()
```

In [529…

```
X_train_init, X_test, y_train_init, y_test = train_test_split(X, y, trai
x_train, x_val, y_train, y_val = train_test_split(X_train_init, y_train_
```

In [537…

```
alpha = {
    "alpha": alphas
}

grid_class_parameters = {
    "estimator": lr,
    "param_grid": alpha,
    "cv": KFold(n_splits = 4, shuffle=True, random_state=0),
    "scoring": ['neg_mean_squared_error','r2'],
    "return_train_score": True
}

l2cv = GridSearchCV(l2, alpha, cv = 4, scoring=['neg_mean_squared_error'
                            refit='neg_mean_squared_error', return_train_
```

```
l2cv.fit(x_train, y_train)

y_train_pred = l2cv.predict(X_train_init)
y_test_pred = l2cv.predict(X_test)
Y_test = l2cv.predict(x_val)

# training mse and r2
mse_tr = mean_squared_error(y_train_init, y_train_pred)
r2_tr = r2_score(y_train_init, y_train_pred)

# val mse and r2
mse_trv = mean_squared_error(Y_test, y_val)
r2_trv = r2_score(Y_test, y_val)

# testing mse and r2
mse_trt = mean_squared_error(y_test, y_test_pred)
r2_trt = r2_score(y_test, y_test_pred)
```

```
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=4.73158e-27): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=3.81005e-26): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=7.59785e-25): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=7.3671e-25): result m
ay not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=2.00517e-24): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=4.34289e-24): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=6.25515e-24): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=6.23433e-24): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=1.71553e-23): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=4.47365e-23): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=4.7738e-23): result m
ay not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
```

```
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=7.45607e-24): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=2.37697e-24): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=1.44946e-22): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
C:\Users\blueb\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.p
y:147: LinAlgWarning: Ill-conditioned matrix (rcond=3.23561e-23): result
may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True,
```

In [535…

```
mse_tr, r2_tr
```

Out[535…

```
(0.2312283654423648, 0.6703461783977429)
```

l2.fit(x_train, y_train)

y_train_pred = l2.predict(X_train_init) y_test_pred = l2.predict(X_test) y_test_holdout_pred = l2.predict(x_val)

In [563…

```
l2cv.best_params_
```

Out[563…

```
{'alpha': 3.359818286283774}
```

In [547…

```
mse_tr_test = np.array([abs(l2cv.cv_results_["mean_test_neg_mean_squared
                        abs(l2cv.cv_results_["mean_train_neg_mean_square
                       ])
columns = ["abs test mse", "abs train mse"]
```

In [570…

```
r2_tr_test = np.array([abs(l2cv.cv_results_["mean_test_r2"]),
                       abs(l2cv.cv_results_["mean_train_r2"])
                      ])
columnsr = ["r2 test mse", "r2 train mse"]
```

In [560…

```
df_mse = pd.DataFrame(mse_tr_test, index = columns)
df_mse = df_mse.T
df_mse
```

Out[560…

	abs test mse	abs train mse
0	0.307453	0.208261
1	0.286323	0.212123
2	0.285664	0.212329
3	0.284913	0.212528
4	0.284333	0.212698
5	0.283883	0.212821
6	0.283530	0.212986

7	0.283327	0.213215
8	0.283091	0.213398
9	0.282595	0.213521
10	0.281817	0.213650
11	0.280761	0.213809
12	0.306491	0.222284
13	0.279934	0.214734
14	0.276804	0.215363
15	0.276859	0.215900
16	0.277487	0.216527
17	0.272522	0.216662
18	0.273225	0.216961
19	0.265377	0.217270
20	0.556281	0.494994

In [561…

```
df_mse["abs test mse"]
```

Out[561…

```
0     0.307453
1     0.286323
2     0.285664
3     0.284913
4     0.284333
5     0.283883
6     0.283530
7     0.283327
8     0.283091
9     0.282595
10    0.281817
11    0.280761
12    0.306491
13    0.279934
14    0.276804
15    0.276859
16    0.277487
17    0.272522
18    0.273225
19    0.265377
20    0.556281
Name: abs test mse, dtype: float64
```

In [571…

```
df_r2 = pd.DataFrame(r2_tr_test, index = columnsr)
df_r2 = df_r2.T
df_r2
```

Out[571…

	r2 test mse	r2 train mse
0	0.553066	0.698291
1	0.576759	0.692413
2	0.577809	0.692110
3	0.579014	0.691822

4	0.579901	0.691579
5	0.580505	0.691400
6	0.580916	0.691155
7	0.581135	0.690815
8	0.581482	0.690543
9	0.582297	0.690363
10	0.583579	0.690177
11	0.585263	0.689949
12	0.556303	0.676330
13	0.587358	0.688623
14	0.591272	0.687735
15	0.591318	0.686956
16	0.589383	0.686058
17	0.597206	0.685834
18	0.595481	0.685427
19	0.607632	0.684960
20	0.064685	0.303510

In [554…

```
# график зависимости среднеквадратической ошибки от коэффициента регуляр
alphas_x = np.asarray(alphas, dtype = "float")
alphas_x
```

Out[554…

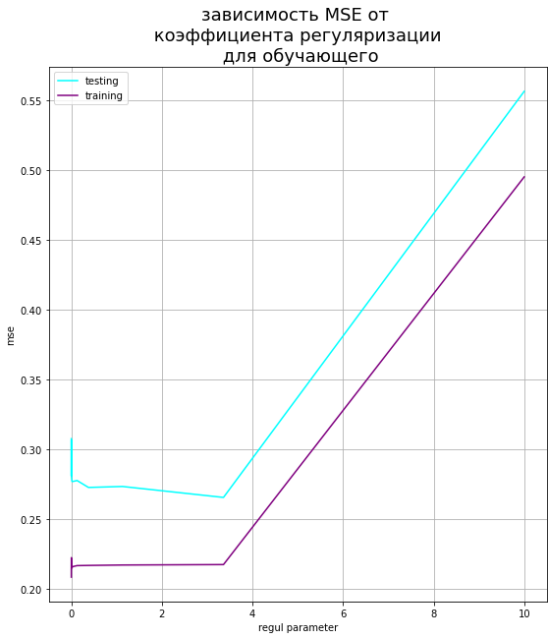
```
array([0.00000000e+00, 1.00000000e-08, 2.97635144e-08, 8.85866790e-08,
       2.63665090e-07, 7.84759970e-07, 2.33572147e-06, 6.95192796e-06,
       2.06913808e-05, 6.15848211e-05, 1.83298071e-04, 5.45559478e-04,
       1.62377674e-03, 4.83293024e-03, 1.43844989e-02, 4.28133240e-02,
       1.27427499e-01, 3.79269019e-01, 1.12883789e+00, 3.35981829e+00,
       1.00000000e+01])
```

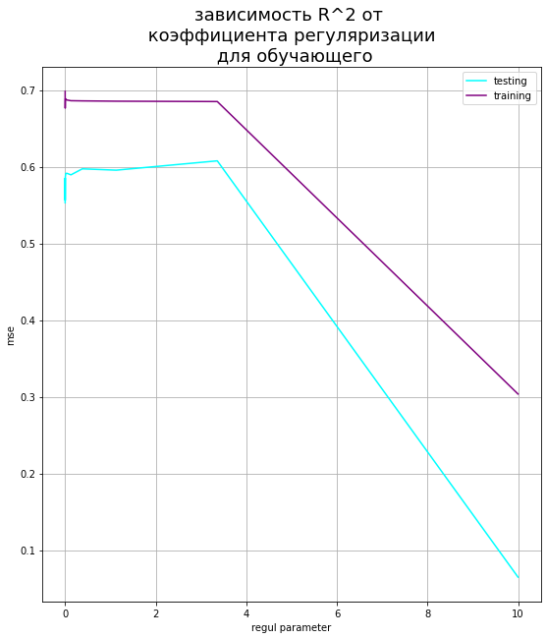
In [582…

```
fig,ax = plt.subplots(1, 2, figsize = (20, 10))

ax[0].plot(alphas, df_mse["abs test mse"], color = 'cyan', label = "test
ax[0].plot(alphas, df_mse["abs train mse"], color = 'purple', label = "t
ax[0].set_xlabel('regul parameter', fontsize = 10)
ax[0].set_ylabel('mse', fontsize = 10)
ax[0].set_title('зависимость MSE от \n коэффициента регуляризации \n для
ax[0].grid(True)
ax[0].legend()

ax[1].plot(alphas, df_r2["r2 test mse"], color = 'cyan', label = "testin
ax[1].plot(alphas, df_r2["r2 train mse"], color = 'purple', label = "tra
ax[1].set_xlabel('regul parameter', fontsize = 10)
ax[1].set_ylabel('mse', fontsize = 10)
ax[1].set_title('зависимость R^2 от \n коэффициента регуляризации \n для
ax[1].grid(True)
ax[1].legend()
```

Out[582…

```
<matplotlib.legend.Legend at 0x11b1f7d2970>
```

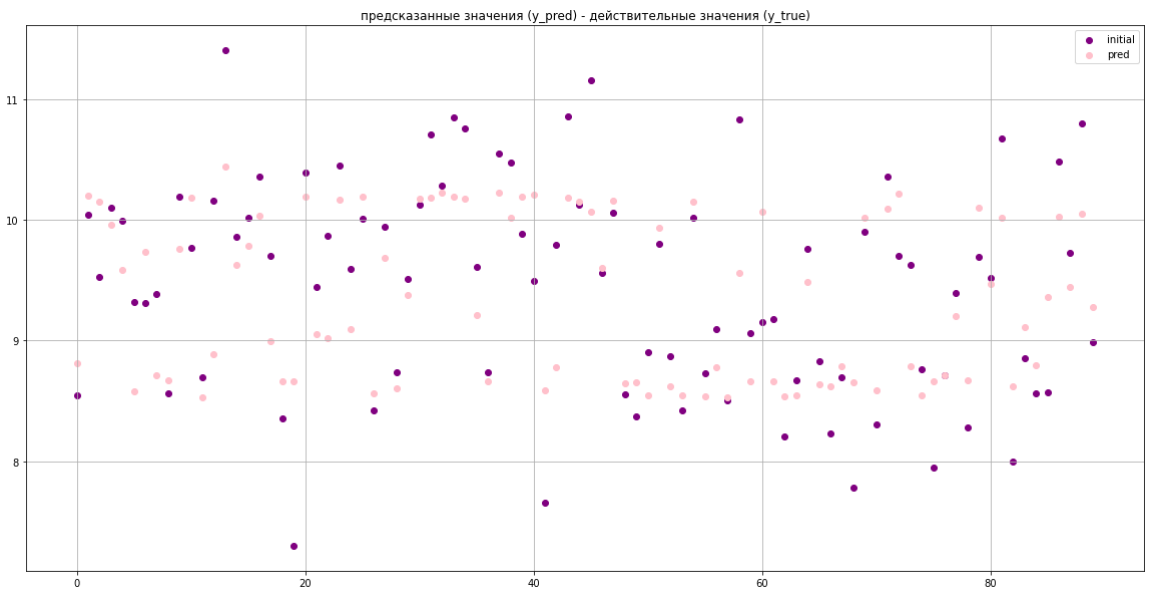




In [ ]:
```
# график предсказанные значения (y_pred) - действительные значения (y_tr
```

In [585…
```
plt.figure(figsize = (20, 10))
plt.scatter(range(len(y_test)), y_test, color = 'purple', label = "initi
plt.scatter(range(len(y_test_pred)), y_test_pred, color = 'pink', label =
plt.title('предсказанные значения (y_pred) - действительные значения (y_
plt.grid(True)
plt.legend()
```

Out[585…
```
<matplotlib.legend.Legend at 0x11b1fba31c0>
```



Заключение

Регуляризация ничего не может с выбросами: с ростом коэффициента регуляризации решение отклоняется по количеству выбросов