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Кафедра «Системы обработки информации и управления»

Лабораторная работа №3
по дисциплине
«Методы машинного обучения»
на тему

«Обработка признаков (часть 2)»

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1. Цель лабораторной работы

Изучение продвинутых способов предварительной обработки данных для дальнейшего формирования моделей.

2. Задание

1. Выбрать один или несколько наборов данных (датасетов) для решения следующих задач. Каждая задача может быть решена на отдельном датасете, или несколько задач могут быть решены на одном датасете. Просьба не использовать датасет, на котором данная задача решалась в лекции.
2. Для выбранного датасета (датасетов) на основе материалов лекций решить следующие задачи:
   i. масштабирование признаков (не менее чем тремя способами);
   ii. обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов);
   iii. обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным);
   iv. отбор признаков:
      1. один метод из группы методов фильтрации (filter methods);
      2. один метод из группы методов обертывания (wrapper methods);
      3. один метод из группы методов вложений (embedded methods).

1.Масштабирование признаков (не менее чем тремя способами);

```
[ ] import pandas as pd
    import matplotlib.pyplot as plt
    import numpy as np
    import seaborn as sns
    from sklearn.datasets import fetch_california_housing
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    from sklearn.preprocessing import MinMaxScaler
    from sklearn.preprocessing import RobustScaler
    from sklearn.preprocessing import MaxAbsScaler
```

```
[ ] housing = fetch_california_housing()
    data = pd.DataFrame(housing.data,
                                          columns=housing.feature_names)
    data['Y'] = housing.target
    data.shape
```

```
(20640, 9)
```

```
data.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	Y
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422

```
[ ] # Нужно ли масштабирование
    data.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	Y
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070655	35.631861	-119.569704	2.068558
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386050	2.135952	2.003532	1.153956
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692308	32.540000	-124.350000	0.149990
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429741	33.930000	-121.800000	1.196000
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818116	34.260000	-118.490000	1.797000
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282261	37.710000	-118.010000	2.647250
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333333	41.950000	-114.310000	5.000010

```
[ ] # DataFrame не содержащий целевой признак
    X_ALL = data.drop('Y', axis=1)
```

```
[ ] # Функция для восстановления датафрейма
    # на основе масштабированных данных
    def arr_to_df(arr_scaled):
        res = pd.DataFrame(arr_scaled, columns=X_ALL.columns)
        return res
```

```
[ ] # Разделим выборку на обучающую и тестовую
    X_train, X_test, y_train, y_test = train_test_split(X_ALL, data['Y'],
                                                        test_size=0.2,
                                                        random_state=1)
    # Преобразуем массивы в DataFrame
    X_train_df = arr_to_df(X_train)
    X_test_df = arr_to_df(X_test)

    X_train_df.shape, X_test_df.shape

((16512, 8), (4128, 8))
```

```
# Построение плотности распределения
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    # первый график
    ax1.set_title(label1)
    sns.kdeplot(data=df1[col_list], ax=ax1)
    # второй график
    ax2.set_title(label2)
    sns.kdeplot(data=df2[col_list], ax=ax2)
    plt.show()
```

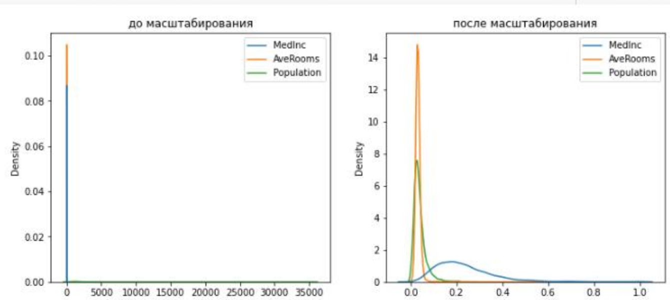
MinMax-масштабирование

```
cs31 = MinMaxScaler()
data_cs31_scaled_temp = cs31.fit_transform(X_ALL)
data_cs31_scaled = arr_to_df(data_cs31_scaled_temp)
data_cs31_scaled.describe()
```

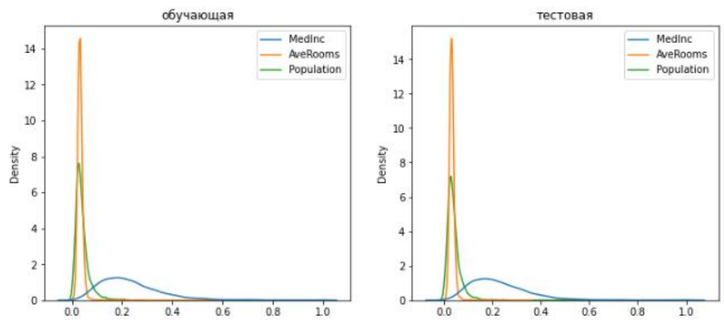
	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	0.232464	0.541951	0.032488	0.022629	0.039869	0.001914	0.328572	0.476125
std	0.131020	0.246776	0.017539	0.014049	0.031740	0.008358	0.226988	0.199555
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.142308	0.333333	0.025482	0.019943	0.021974	0.001398	0.147715	0.253984
50%	0.209301	0.549020	0.031071	0.021209	0.032596	0.001711	0.182784	0.583665
75%	0.292641	0.705882	0.036907	0.022713	0.048264	0.002084	0.549416	0.631474
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

```
[ ] cs32 = MinMaxScaler()
    cs32.fit(X_train)
    data_cs32_scaled_train_temp = cs32.transform(X_train)
    data_cs32_scaled_test_temp = cs32.transform(X_test)
    data_cs32_scaled_train = arr_to_df(data_cs32_scaled_train_temp)
    data_cs32_scaled_test = arr_to_df(data_cs32_scaled_test_temp)
```

```
[ ] draw_kde(['MedInc', 'AveRooms', 'Population'], data, data_cs31_scaled, 'до масштабирования', 'после масштабирования')
```



```
draw_kde(['MedInc', 'AveRooms', 'Population'], data_cs32_scaled_train, data_cs32_scaled_test, 'обучающая', 'тестовая')
```



Масштабирование данных на основе Z-оценки

```
# Обучаем StandardScaler на всей выборке и масштабируем
cs11 = StandardScaler()
data_cs11_scaled_temp = cs11.fit_transform(X_ALL)
# формируем DataFrame на основе массива
data_cs11_scaled = arr_to_df(data_cs11_scaled_temp)
data_cs11_scaled
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	2.344766	0.982143	0.628559	-0.153758	-0.974429	-0.049597	1.052548	-1.327835
1	2.332238	-0.607019	0.327041	-0.263336	0.861439	-0.092512	1.043185	-1.322844
2	1.782699	1.856182	1.155620	-0.049016	-0.820777	-0.025843	1.038503	-1.332827
3	0.932968	1.856182	0.156966	-0.049833	-0.766028	-0.050329	1.038503	-1.337818
4	-0.012881	1.856182	0.344711	-0.032906	-0.759847	-0.085616	1.038503	-1.337818
...	...	...	...	...	...	...	...	...
20635	-1.216128	-0.289187	-0.155023	0.077354	-0.512592	-0.049110	1.801647	-0.758826
20636	-0.691593	-0.845393	0.276881	0.462365	-0.944405	0.005021	1.806329	-0.818722
20637	-1.142593	-0.924851	-0.090318	0.049414	-0.369537	-0.071735	1.778237	-0.823713
20638	-1.054583	-0.845393	-0.040211	0.158778	-0.604429	-0.091225	1.778237	-0.873626
20639	-0.780129	-1.004309	-0.070443	0.138403	-0.033977	-0.043682	1.750146	-0.833696

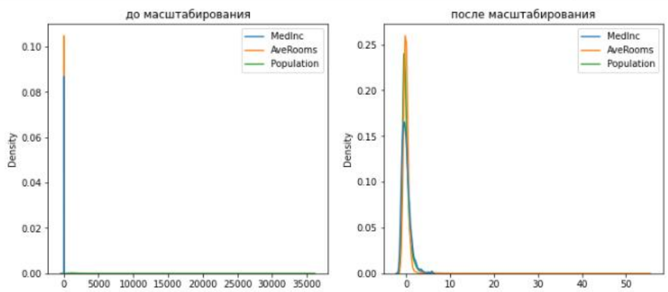
20640 rows × 8 columns

```
data_cs11_scaled.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
count	2.064000e+04	2.064000e+04	2.064000e+04	2.064000e+04	2.064000e+04	2.064000e+04	2.064000e+04	2.064000e+04
mean	6.609700e-17	5.508083e-18	6.609700e-17	-1.060306e-16	-1.101617e-17	3.442552e-18	-1.079584e-15	-8.526513e-15
std	1.000024e+00	1.000024e+00	1.000024e+00	1.000024e+00	1.000024e+00	1.000024e+00	1.000024e+00	1.000024e+00
min	-1.774299e+00	-2.196180e+00	-1.852319e+00	-1.610768e+00	-1.256123e+00	-2.290000e-01	-1.447568e+00	-2.385992e+00
25%	-6.881186e-01	-8.453931e-01	-3.994496e-01	-1.911716e-01	-5.638089e-01	-6.171062e-02	-7.967887e-01	-1.113209e+00
50%	-1.767951e-01	2.864572e-02	-8.078489e-02	-1.010650e-01	-2.291318e-01	-2.431585e-02	-6.422871e-01	5.389137e-01
75%	4.593063e-01	6.643103e-01	2.519615e-01	6.015869e-03	2.644949e-01	2.037453e-02	9.729566e-01	7.784964e-01
max	5.858286e+00	1.856182e+00	5.516324e+01	6.957171e+01	3.025033e+01	1.194191e+02	2.958068e+00	2.625280e+00

```
[ ] # Построение плотности распределения
def draw_kde(col_list, df1, df2, label1, label2):
        fig, (ax1, ax2) = plt.subplots(
                ncols=2, figsize=(12, 5))
        # первый график
        ax1.set_title(label1)
        sns.kdeplot(data=df1[col_list], ax=ax1)
        # второй график
        ax2.set_title(label2)
        sns.kdeplot(data=df2[col_list], ax=ax2)
        plt.show()
```

```
draw_kde(['MedInc', 'AveRooms', 'Population'], data, data_cs11_scaled, 'до масштабирования', 'после масштабирования')
```




```
[ ] # Обучаем StandardScaler на обучающей выборке
# и масштабируем обучающую и тестовую выборки
cs12 = StandardScaler()
cs12.fit(X_train)
data_cs12_scaled_train_temp = cs12.transform(X_train)
data_cs12_scaled_test_temp = cs12.transform(X_test)
# формируем DataFrame на основе массива
data_cs12_scaled_train = arr_to_df(data_cs12_scaled_train_temp)
data_cs12_scaled_test = arr_to_df(data_cs12_scaled_test_temp)
```

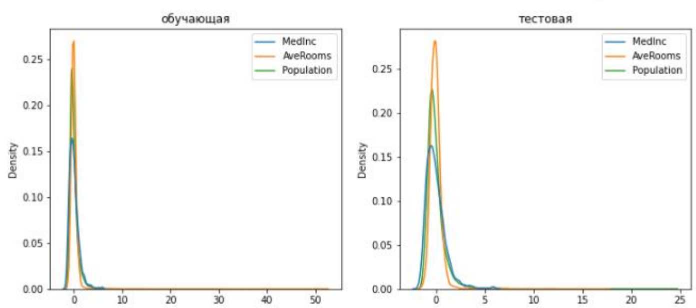
```
data_cs12_scaled_train.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
count	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04
mean	-1.663183e-16	5.239134e-17	1.912768e-16	2.119321e-16	2.280691e-17	1.183377e-18	3.050962e-16	-1.818528e-15
std	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00
min	-1.784934e+00	-2.193326e+00	-1.758064e+00	-1.510898e+00	-1.265666e+00	-2.022041e-01	-1.446964e+00	-2.354008e+00
25%	-6.894428e-01	-8.425832e-01	-3.830692e-01	-1.840409e-01	-5.688744e-01	-5.757397e-02	-7.965259e-01	-1.113670e+00
50%	-1.753078e-01	3.142707e-02	-8.210226e-02	-1.001681e-01	-2.324925e-01	-2.427528e-02	-6.421054e-01	5.401142e-01
75%	4.619818e-01	6.670709e-01	2.359401e-01	-4.655013e-05	2.649611e-01	1.542318e-02	9.722905e-01	7.792156e-01
max	5.880939e+00	1.858903e+00	5.221361e+01	6.500353e+01	3.048505e+01	1.069443e+02	2.956360e+00	2.622289e+00

```
data_cs12_scaled_test.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
count	4128.000000	4128.000000	4128.000000	4128.000000	4128.000000	4128.000000	4128.000000	4128.000000
mean	-0.014481	0.013911	-0.023175	-0.028812	0.000977	-0.010484	-0.000777	0.011417
std	1.021662	0.999880	0.692871	0.604269	1.038310	0.100045	0.997493	0.989980
min	-1.784934	-2.113871	-1.521001	-1.428741	-1.258546	-0.207179	-1.437605	-2.378915
25%	-0.712242	-0.842583	-0.381876	-0.186036	-0.564647	-0.056193	-0.791846	-1.058876
50%	-0.198860	0.031427	-0.076683	-0.101062	-0.220479	-0.021970	-0.642105	0.530152
75%	0.451514	0.667071	0.224293	-0.000800	0.271190	0.019040	0.976970	0.784197
max	5.880939	1.858903	17.369108	18.082473	24.152526	4.165286	2.914245	2.502738

```
# распределения для обучающей и тестовой выборки немного отличаются
draw_kde(['MedInc', 'AveRooms', 'Population'], data_cs12_scaled_train, data_cs12_scaled_test, 'обучающая', 'тестовая')
```



Масштабирование по максимальному значению

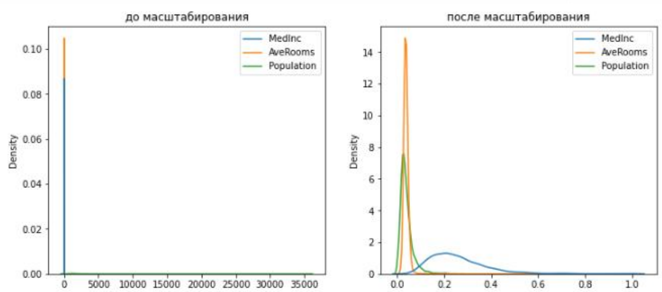
```
[ ] cs51 = MaxAbsScaler()
    data_cs51_scaled_temp = cs51.fit_transform(X_ALL)
    # формируем DataFrame на основе массива
    data_cs51_scaled = arr_to_df(data_cs51_scaled_temp)
    data_cs51_scaled.describe()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	0.258043	0.550759	0.038257	0.032192	0.039949	0.002470	0.849389	-0.961558
std	0.126654	0.242030	0.017435	0.013911	0.031738	0.008353	0.050917	0.016112
min	0.033326	0.019231	0.005963	0.009785	0.000084	0.000557	0.775685	-1.000000
25%	0.170892	0.346154	0.031293	0.029533	0.022056	0.001954	0.808820	-0.979493
50%	0.235652	0.557692	0.036848	0.030786	0.032678	0.002267	0.816687	-0.952875
75%	0.316215	0.711538	0.042650	0.032276	0.048344	0.002640	0.898927	-0.949015
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	-0.919260

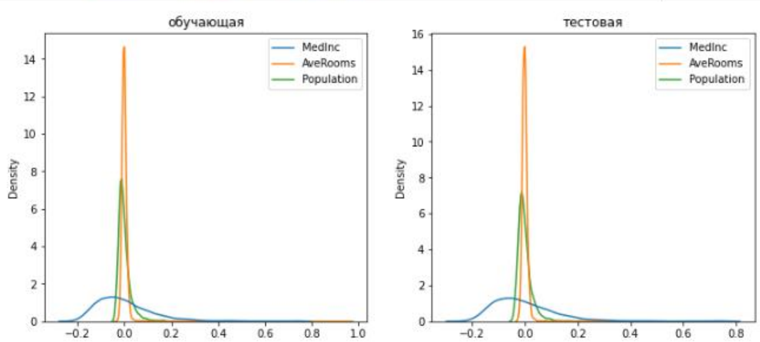
```
[ ] cs52_mas = MaxAbsScaler()
    cs52_mean = StandardScaler(with_mean=True, with_std=False)

    cs52_mas.fit(X_train)
    cs52_mean.fit(X_train)

    data_cs52_scaled_train_temp = cs52_mas.transform(cs52_mean.transform(X_train))
    data_cs52_scaled_test_temp = cs52_mas.transform(cs52_mean.transform(X_test))
    # формируем DataFrame на основе массива
    data_cs52_scaled_train = arr_to_df(data_cs52_scaled_train_temp)
    data_cs52_scaled_test = arr_to_df(data_cs52_scaled_test_temp)
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but MaxAbsScaler was fitted with feature names
  warnings.warn(
/usr/local/lib/python3.9/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but MaxAbsScaler was fitted with feature names
  warnings.warn(
```

```
draw_kde(['MedInc', 'AveRooms', 'Population'], data, data_cs51_scaled, 'до масштабирования', 'после масштабирования')
```




```
draw_kde(['MedInc', 'AveRooms', 'Population'], data_cs52_scaled_train, data_cs52_scaled_test, 'обучающая', 'тестовая')
```



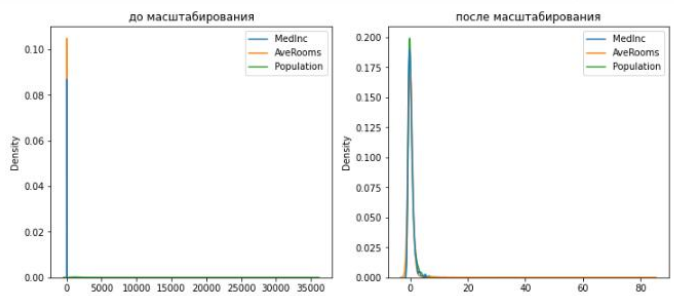
Масштабирование по медиане

```
[ ] cs41 = RobustScaler()
    data_cs41_scaled_temp = cs41.fit_transform(X_ALL)
    # формируем DataFrame на основе массива
    data_cs41_scaled = arr_to_df(data_cs41_scaled_temp)
    data_cs41_scaled.describe()
```

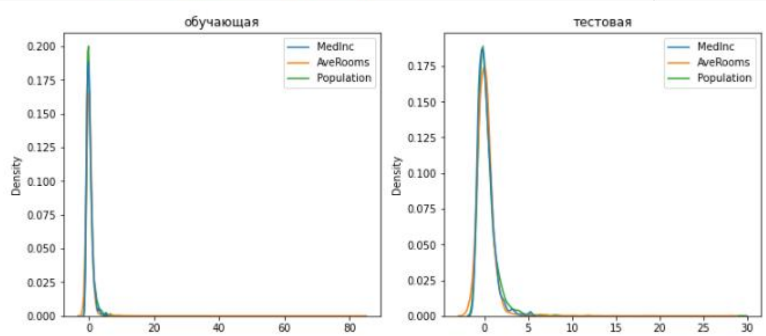
	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
count	2.064000e+04	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	1.540799e-01	-0.018974	0.124015	0.512533	0.276628	0.296227	0.362926	-0.284882
std	8.715378e-01	0.662398	1.535166	5.071439	1.207316	12.182767	0.565067	0.528636
min	-1.392252e+00	-1.473684	-2.719533	-7.656179	-1.239872	-2.493559	-0.455026	-1.546174
25%	-4.456270e-01	-0.578947	-0.489191	-0.456959	-0.404051	-0.455561	-0.087302	-0.873351
50%	1.018608e-16	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	5.543730e-01	0.421053	0.510809	0.543041	0.595949	0.544439	0.912698	0.126649
max	5.259674e+00	1.210526	84.806698	353.332681	36.797441	1455.116059	2.034392	1.102902

```
cs42 = RobustScaler()
cs42.fit(X_train)
data_cs42_scaled_train_temp = cs42.transform(X_train)
data_cs42_scaled_test_temp = cs42.transform(X_test)
# формируем DataFrame на основе массива
data_cs42_scaled_train = arr_to_df(data_cs42_scaled_train_temp)
data_cs42_scaled_test = arr_to_df(data_cs42_scaled_test_temp)
```

```
[ ] draw_kde(['MedInc', 'AveRooms', 'Population'], data, data_cs41_scaled, 'до масштабирования', 'после масштабирования')
```




```
[ ] draw_kde(['MedInc', 'AveRooms', 'Population'], data_cs42_scaled_train, data_cs42_scaled_test, 'обучающая', 'тестовая')
```



2.Обработку выбросов для числовых признаков (по одному способу для удаления выбросов и для замены выбросов)

```
[ ] import numpy as np
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt
    from sklearn.datasets import fetch_california_housing
    import scipy.stats as stats
    from sklearn.svm import SVR
    from sklearn.linear_model import LinearRegression
    from sklearn.neighbors import KNeighborsRegressor
    from sklearn.tree import DecisionTreeRegressor
    from sklearn.ensemble import RandomForestRegressor
    from sklearn.ensemble import GradientBoostingRegressor
    from sklearn.metrics import mean_squared_error
    from sklearn.model_selection import train_test_split
    from IPython.display import Image
    %matplotlib inline
    sns.set(style="ticks")
```

```
[ ] x_col_list = ['AveRooms', 'HouseAge', 'MedInc']
```

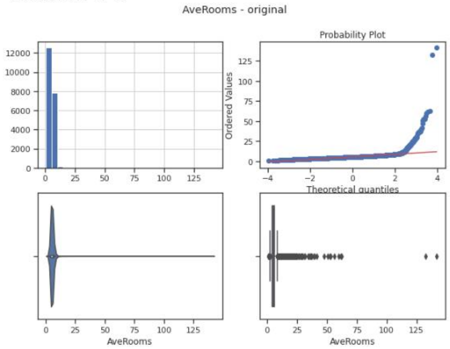
```
housing = fetch_california_housing()
data = pd.DataFrame(housing.data,
                                          columns=housing.feature_names)
data['Y'] = housing.target
data.shape
```

```
(20640, 9)
```

```
[ ] def diagnostic_plots(df, variable, title):
        fig, ax = plt.subplots(figsize=(10,7))
        # гистограмма
        plt.subplot(2, 2, 1)
        df[variable].hist(bins=30)
        ## Q-Q plot
        plt.subplot(2, 2, 2)
        stats.probplot(df[variable], dist="norm", plot=plt)
        # ящик с усами
        plt.subplot(2, 2, 3)
        sns.violinplot(x=df[variable])
        # ящик с усами
        plt.subplot(2, 2, 4)
        sns.boxplot(x=df[variable])
        fig.suptitle(title)
        plt.show()
```

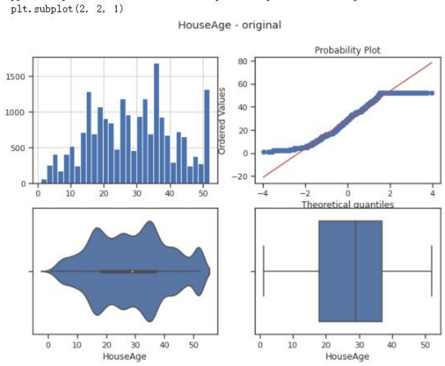
```
[ ] diagnostic_plots(data, 'AveRooms', 'AveRooms - original')
```

```
<ipython-input-27-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlapping axes is deprecated since 3.6 and will be removed two minor releases later; explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```



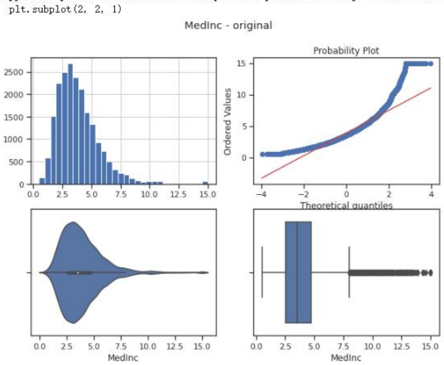

```
diagnostic_plots(data, 'HouseAge', 'HouseAge - original')
```

```
<ipython-input-27-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlapping axes is deprecated since 3.6 and will be removed two minor releases later; explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```




```
diagnostic_plots(data, 'MedInc', 'MedInc - original')
```

```
<ipython-input-27-1fe78d5d2ee2>:4: MatplotlibDeprecationWarning: Auto-removal of overlapping axes is deprecated since 3.6 and will be removed two minor releases later; explicitly call ax.remove() as needed.
  plt.subplot(2, 2, 1)
```




```
[ ] data.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	Y
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422

```
[ ] data.describe().T
```

	count	mean	std	min	25%	50%	75%	max
MedInc	20640.0	3.870671	1.899822	0.499900	2.563400	3.534800	4.743250	15.000100
HouseAge	20640.0	28.639486	12.585558	1.000000	18.000000	29.000000	37.000000	52.000000
AveRooms	20640.0	5.429000	2.474173	0.846154	4.440716	5.229129	6.052381	141.909091
AveBedrms	20640.0	1.096675	0.473911	0.333333	1.006079	1.048780	1.099526	34.066667
Population	20640.0	1425.476744	1132.462122	3.000000	787.000000	1166.000000	1725.000000	35682.000000
AveOccup	20640.0	3.070655	10.386050	0.692308	2.429741	2.818116	3.282261	1243.333333
Latitude	20640.0	35.631861	2.135952	32.540000	33.930000	34.260000	37.710000	41.950000
Longitude	20640.0	-119.569704	2.003532	-124.350000	-121.800000	-118.490000	-118.010000	-114.310000
Y	20640.0	2.068558	1.153956	0.149990	1.196000	1.797000	2.647250	5.000010

```
[ ] #Использование 3 sigma
    def three_sigma(df):
          way = (df.mean() - 3 * df.std() < df) &(df.mean() + 3 * df.std() > df)
          index = np.arange(df.shape[0])[way]
          output= df.iloc[index]
          return output
```

```
for col in data.columns:
      data[col]=three_sigma(data[col])
```

```
[ ] data.describe().T
```

	count	mean	std	min	25%	50%	75%	max
MedInc	20295.0	3.738741	1.604919	0.499900	2.550750	3.507600	4.667050	9.556100
HouseAge	20640.0	28.639486	12.585558	1.000000	18.000000	29.000000	37.000000	52.000000
AveRooms	20507.0	5.301245	1.285753	0.846154	4.435479	5.219810	6.029049	12.808511
AveBedrms	20495.0	1.069311	0.137882	0.333333	1.005747	1.048128	1.098000	2.514610
Population	20298.0	1333.286974	814.376106	3.000000	781.000000	1154.000000	1687.000000	4819.000000
AveOccup	20632.0	2.935397	0.904044	0.692308	2.429301	2.817800	3.281506	33.952941
Latitude	20640.0	35.631861	2.135952	32.540000	33.930000	34.260000	37.710000	41.950000
Longitude	20640.0	-119.569704	2.003532	-124.350000	-121.800000	-118.490000	-118.010000	-114.310000
Y	20640.0	2.068558	1.153956	0.149990	1.196000	1.797000	2.647250	5.000010

Использование межквартильного размаха

```
[ ] # Тип вычисления верхней и нижней границы выбросов
    from enum import Enum
    class OutlierBoundaryType(Enum):
        SIGMA = 1
        QUANTILE = 2
        IRQ = 3
```

```
# Функция вычисления верхней и нижней границы выбросов
def get_outlier_boundaries(df, col, outlier_boundary_type: OutlierBoundaryType):
    if outlier_boundary_type == OutlierBoundaryType.SIGMA:
        K1 = 3
        lower_boundary = df[col].mean() - (K1 * df[col].std())
        upper_boundary = df[col].mean() + (K1 * df[col].std())

    elif outlier_boundary_type == OutlierBoundaryType.QUANTILE:
        lower_boundary = df[col].quantile(0.05)
        upper_boundary = df[col].quantile(0.95)

    elif outlier_boundary_type == OutlierBoundaryType.IRQ:
        K2 = 1.5
        IQR = df[col].quantile(0.75) - df[col].quantile(0.25)
        lower_boundary = df[col].quantile(0.25) - (K2 * IQR)
        upper_boundary = df[col].quantile(0.75) + (K2 * IQR)

    else:
        raise NameError('Unknown Outlier Boundary Type')

    return lower_boundary, upper_boundary
```

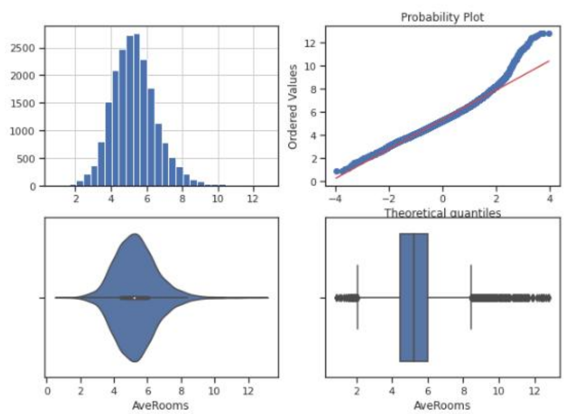
Удаление выбросов

```
[ ] data.shape
```

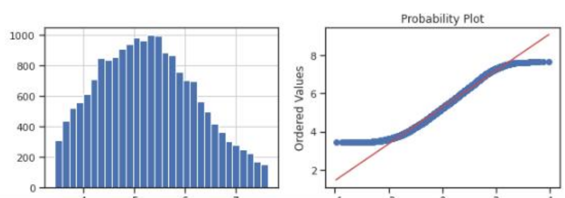
```
(20640, 9)
```

```
for col in x_col_list:
    for obt in OutlierBoundaryType:
        # Вычисление верхней и нижней границы
        lower_boundary, upper_boundary = get_outlier_boundaries(data, col, obt)
        # Флаги для удаления выбросов
        outliers_temp = np.where(data[col] > upper_boundary, True,
                                 np.where(data[col] < lower_boundary, True, False))
        # Удаление данных на основе флага
        data_trimmed = data.loc[~(outliers_temp), ]
        title = 'Поле-{}, метод-{}, строк-{}'.format(col, obt, data_trimmed.shape[0])
        diagnostic_plots(data_trimmed, col, title)
```

Поле-AveRooms, метод-OutlierBoundaryType.SIGMA, строк-20507



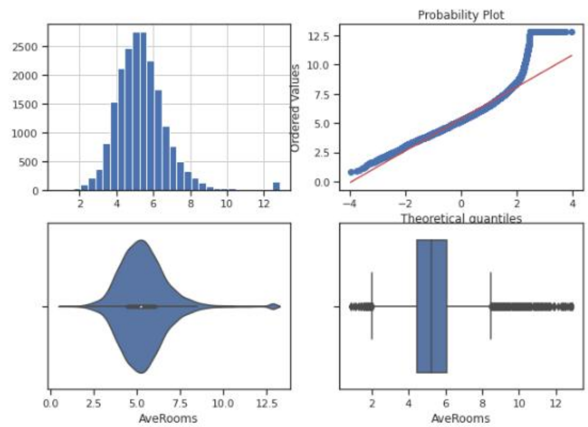
Поле-AveRooms, метод-OutlierBoundaryType.QUANTILE, строк-18576



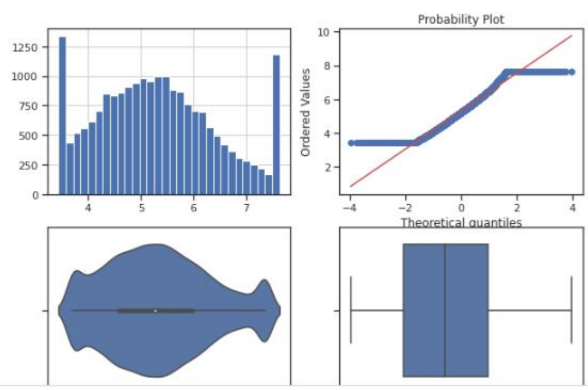
Замена выбросов

```
[ ] for col in x_col_list:
        for obt in OutlierBoundaryType:
            # Вычисление верхней и нижней границы
            lower_boundary, upper_boundary = get_outlier_boundaries(data, col, obt)
            # Изменение данных
            data[col] = np.where(data[col] > upper_boundary, upper_boundary,
                                 np.where(data[col] < lower_boundary, lower_boundary, data[col]))
            title = 'Поле-{}, метод-{}'.format(col, obt)
            diagnostic_plots(data, col, title)
```

Поле-AveRooms, метод-OutlierBoundaryType.SIGMA



Поле-AveRooms, метод-OutlierBoundaryType.QUANTILE



3.Обработку по крайней мере одного нестандартного признака (который не является числовым или категориальным)

```
[ ] import numpy as np
    import pandas as pd
    import seaborn as sns
    import datetime
    import ipaddress
    import tqdm
    from sklearn.preprocessing import LabelEncoder
    from sklearn.preprocessing import MinMaxScaler
    from sklearn.model_selection import cross_val_score, cross_validate
    from sklearn.linear_model import LogisticRegression
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.ensemble import GradientBoostingClassifier
    from sklearn.svm import LinearSVC
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import roc_auc_score
    import matplotlib.pyplot as plt
    %matplotlib inline
    sns.set(style="ticks")
```

```
[ ] data = pd.read_csv('Movies.csv', sep=',')
```

```
[ ] data.shape
```

```
(853, 13)
```

```
[ ] data.head()
```

	index	Title	Release Date	Year	Description	URL	Rating	Runtime	Genres	Votes	Directors	Series	Order
0	0	101 Dalmatians	18-11-1996	1996	NaN	https://www.imdb.com/title/tt0115433/	5.7	103.0	Adventure, Comedy, Crime, Family	98439.0	Stephen Herek	101 Dalmatians	1
1	1	102 Dalmatians	22-11-2000	2000	NaN	https://www.imdb.com/title/tt0211181/	4.9	100.0	Adventure, Comedy, Family	33823.0	Kevin Lima	101 Dalmatians	2
2	2	12 Rounds	19-03-2009	2009	NaN	https://www.imdb.com/title/tt1160368/	5.6	108.0	Action, Crime, Thriller	26828.0	Renny Harlin	12 Rounds	1
3	3	12 Rounds 2: Reloaded	04-06-2013	2013	NaN	https://www.imdb.com/title/tt2317524/	5.3	95.0	Action, Adventure, Thriller	5141.0	Roel Reiné	12 Rounds	2
4	4	21 Jump Street	12-03-2012	2012	NaN	https://www.imdb.com/title/tt1232829/	7.2	109.0	Action, Comedy, Crime	498876.0	Christopher Miller, Phil Lord	21 Jump Street	1

```
[ ] # Целевой признак
    data['Order'].value_counts()
```

```
1     364
2     262
3     113
4      52
5      24
6      14
7       9
8       5
9       3
10      2
11      2
12      1
13      1
14      1
Name: Order, dtype: int64
```

```
[ ] # Закодируем целевой признак
    target_le = LabelEncoder()
    data['order_le'] = target_le.fit_transform(data['Order'])
    data['order_le'].unique(), target_le.inverse_transform(data['order_le'].unique())
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14]))
```

```
data.dtypes
```

```
index             int64
Title            object
Release Date     object
Year              int64
Description     float64
URL              object
Rating          float64
Runtime         float64
Genres           object
Votes           float64
Directors        object
Series           object
Order             int64
order_le          int64
dtype: object
```

Выделение признаков из URL-адреса

```
[ ] # Проверка наличия подстроки в URL
    def substr_in_url(substr):
        lsubstr = substr.lower()
        return data.apply(lambda x: 1 if lsubstr in x['URL'].lower() else 0, axis=1)
```

```
[ ] data['is_get'] = substr_in_url('GET')
    data['is_php'] = substr_in_url('PHP')
    data['is_js'] = substr_in_url('JS')
    data['is_woff'] = substr_in_url('WOFF')
    url_features = ['is_get', 'is_php', 'is_js', 'is_woff']
```

```
[ ] data.head()
```

	index	Title	Release Date	Year	Description	URL	Rating	Runtime	Genres	Votes	Directors	Series	Order	order_le	is_get	is_php	is_js	is_woff
0	0	101 Dalmatians	18-11-1996	1996	NaN	https://www.imdb.com/title/tt0115433/	5.7	103.0	Adventure, Comedy, Crime, Family	98439.0	Stephen Herek	101 Dalmatians	1	0	0	0	0	0
1	1	102 Dalmatians	22-11-2000	2000	NaN	https://www.imdb.com/title/tt0211181/	4.9	100.0	Adventure, Comedy, Family	33823.0	Kevin Lima	101 Dalmatians	2	1	0	0	0	0
2	2	12 Rounds	19-03-2009	2009	NaN	https://www.imdb.com/title/tt1160368/	5.6	108.0	Action, Crime, Thriller	26828.0	Renny Harlin	12 Rounds	1	0	0	0	0	0
3	3	12 Rounds 2: Reloaded	04-06-2013	2013	NaN	https://www.imdb.com/title/tt2317524/	5.3	95.0	Action, Adventure, Thriller	5141.0	Roel Reiné	12 Rounds	2	1	0	0	0	0
4	4	21 Jump Street	12-03-2012	2012	NaN	https://www.imdb.com/title/tt1232829/	7.2	109.0	Action, Comedy, Crime	498876.0	Christopher Miller, Phil Lord	21 Jump Street	1	0	0	0	0	0

Обработка даты

```
data['Release Date']=pd.to_datetime(data['Release Date'])
```

```
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '18-11-1996' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '22-11-2000' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '19-03-2009' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '26-04-2007' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '16-10-2007' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '19-02-1999' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '19-01-2017' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '18-04-2014' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '31-10-1984' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '31-10-1985' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '27-02-1987' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
<ipython-input-134-d5c2ff3090a1>:1: UserWarning: Parsing '19-08-1988' in DD/MM/YYYY format. Provide format or specify infer_datetime_format=True for consistent parsing.
  data['Release Date']=pd.to_datetime(data['Release Date'])
```

Выделение стандартных признаков даты и времени

```
[ ] # День
    data['day'] = data['Release Date'].dt.day
    # Месяц
    data['month'] = data['Release Date'].dt.month
    # Год
    data['year'] = data['Release Date'].dt.year
```

```
[ ] data.head()
```

	index	Title	Release Date	Year	Description	URL	Rating	Runtime	Genres	Votes	...	Series	Order	order_le	is_get	is_php	is_js	is_woff	day	month	year
0	0	101 Dalmatians	1996-11-18	1996	NaN	https://www.imdb.com/title/tt0115433/	5.7	103.0	Adventure, Comedy, Crime, Family	98439.0	...	101 Dalmatians	1	0	0	0	0	0	18	11	1996
1	1	102 Dalmatians	2000-11-22	2000	NaN	https://www.imdb.com/title/tt0211181/	4.9	100.0	Adventure, Comedy, Family	33823.0	...	101 Dalmatians	2	1	0	0	0	0	22	11	2000
2	2	12 Rounds	2009-03-19	2009	NaN	https://www.imdb.com/title/tt1160368/	5.6	108.0	Action, Crime, Thriller	26828.0	...	12 Rounds	1	0	0	0	0	0	19	3	2009
3	3	12 Rounds 2: Reloaded	2013-04-06	2013	NaN	https://www.imdb.com/title/tt2317524/	5.3	95.0	Action, Adventure, Thriller	5141.0	...	12 Rounds	2	1	0	0	0	0	6	4	2013
4	4	21 Jump Street	2012-12-03	2012	NaN	https://www.imdb.com/title/tt1232829/	7.2	109.0	Action, Comedy, Crime	498876.0	...	21 Jump Street	1	0	0	0	0	0	3	12	2012

5 rows × 21 columns

```
# Создадим масштабируемые признаки для дальнейших экспериментов
dt_features = ['year', 'day', 'month']
dt_features_scaled = []
for f in dt_features:
    f_new = str(f + '_scaled')
    dt_features_scaled.append(f_new)
    data[f_new] = MinMaxScaler().fit_transform(data[[f]])
dt_features_scaled
```

```
['year_scaled', 'day_scaled', 'month_scaled']
```

```
[ ] data.head()
```

	index	Title	Release Date	Year	Description	URL	Rating	Runtime	Genres	Votes	...	is_get	is_php	is_js	is_woff	day	month	year	year_scaled	day_scaled	month_scaled
0	0	101 Dalmatians	1996-11-18	1996	NaN	https://www.imdb.com/title/tt0115433/	5.7	103.0	Adventure, Comedy, Crime, Family	98439.0	...	0	0	0	0	18	11	1996	0.6750	0.566667	0.909091
1	1	102 Dalmatians	2000-11-22	2000	NaN	https://www.imdb.com/title/tt0211181/	4.9	100.0	Adventure, Comedy, Family	33823.0	...	0	0	0	0	22	11	2000	0.7250	0.700000	0.909091
2	2	12 Rounds	2009-03-19	2009	NaN	https://www.imdb.com/title/tt1160368/	5.6	108.0	Action, Crime, Thriller	26828.0	...	0	0	0	0	19	3	2009	0.8375	0.600000	0.181818
3	3	12 Rounds 2: Reloaded	2013-04-06	2013	NaN	https://www.imdb.com/title/tt2317524/	5.3	95.0	Action, Adventure, Thriller	5141.0	...	0	0	0	0	6	4	2013	0.8875	0.166667	0.272727
4	4	21 Jump Street	2012-12-03	2012	NaN	https://www.imdb.com/title/tt1232829/	7.2	109.0	Action, Comedy, Crime	498876.0	...	0	0	0	0	3	12	2012	0.8750	0.066667	1.000000

5 rows × 24 columns

4.Отбор признаков

1) один метод из группы методов фильтрации (filter methods)

```
[ ] import numpy as np
    import pandas as pd
    import seaborn as sns
    import matplotlib.pyplot as plt
    from sklearn.datasets import load_iris
    from sklearn.datasets import fetch_california_housing
    import scipy.stats as stats
    from sklearn.svm import SVR
    from sklearn.svm import LinearSVC
    from sklearn.feature_selection import SelectFromModel
    from sklearn.linear_model import Lasso
    from sklearn.linear_model import LogisticRegression
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn.neighbors import KNeighborsRegressor
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.ensemble import GradientBoostingClassifier
    from sklearn.tree import DecisionTreeRegressor
    from sklearn.ensemble import RandomForestRegressor
    from sklearn.ensemble import GradientBoostingRegressor
    from sklearn.metrics import mean_squared_error
    from sklearn.model_selection import train_test_split
    from sklearn.feature_selection import VarianceThreshold
    from sklearn.feature_selection import mutual_info_classif, mutual_info_regression
    from sklearn.feature_selection import SelectKBest, SelectPercentile
    from IPython.display import Image
    %matplotlib inline
    sns.set(style="ticks")
```

```
[ ] iris = load_iris()
    iris_X = iris.data
    iris_y = iris.target
    iris_feature_names = iris['feature_names']
    iris_x_df = pd.DataFrame(data=iris['data'], columns=iris['feature_names'])
```

```
[ ] housing = fetch_california_housing()
    housing_X = housing.data
    housing_y = housing.target
    housing_feature_names = housing['feature_names']
    housing_x_df = pd.DataFrame(data=housing['data'], columns=housing['feature_names'])
```

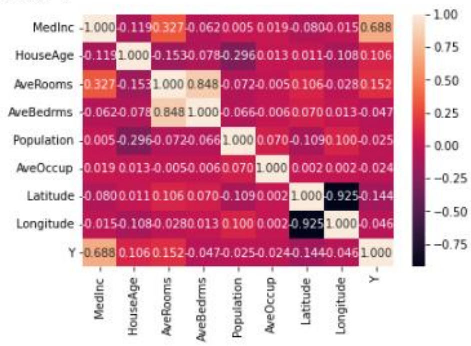
Методы, основанные на корреляции

```
[ ] housing = fetch_california_housing()
    data = pd.DataFrame(housing.data,
                                              columns=housing.feature_names)
    data['Y'] = housing.target
    data.shape
```

```
(20640, 9)
```

```
sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

```
<Axes: >
```




```
[ ] # Формирование DataFrame с сильными корреляциями
    def make_corr_df(df):
          cr = data.corr()
          cr = cr.abs().unstack()
          cr = cr.sort_values(ascending=False)
          cr = cr[cr >= 0.8]
          cr = cr[cr < 1]
          cr = pd.DataFrame(cr).reset_index()
          cr.columns = ['f1', 'f2', 'corr']
          return cr
```

```
[ ] make_corr_df(data)
```

	f1	f2	corr
0	Longitude	Latitude	0.924664
1	Latitude	Longitude	0.924664
2	AveRooms	AveBedrms	0.847621
3	AveBedrms	AveRooms	0.847621

```
[ ] # Обнаружение групп коррелирующих признаков
    def corr_groups(cr):
        grouped_feature_list = []
        correlated_groups = []

        for feature in cr['f1'].unique():
            if feature not in grouped_feature_list:
                # находим коррелирующие признаки
                correlated_block = cr[cr['f1'] == feature]
                cur_dups = list(correlated_block['f2'].unique()) + [feature]
                grouped_feature_list = grouped_feature_list + cur_dups
                correlated_groups.append(cur_dups)
        return correlated_groups
```

```
[ ] # Группы коррелирующих признаков
    corr_groups(make_corr_df(data))
```

```
[['Latitude', 'Longitude'], ['AveBedrms', 'AveRooms']]
```

2)Один метод из группы методов обертывания (wrapper methods)

```
[ ] !pip install mlxtend
    import joblib
    import sys
    sys.modules['sklearn.externals.joblib'] = joblib

    from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS
    knn = KNeighborsClassifier(n_neighbors=3)
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: mlxtend in /usr/local/lib/python3.9/dist-packages (0.14.0)
Requirement already satisfied: pandas>=0.17.1 in /usr/local/lib/python3.9/dist-packages (from mlxtend) (1.4.4)
Requirement already satisfied: matplotlib>=1.5.1 in /usr/local/lib/python3.9/dist-packages (from mlxtend) (3.5.3)
Requirement already satisfied: scikit-learn>=0.18 in /usr/local/lib/python3.9/dist-packages (from mlxtend) (1.2.2)
Requirement already satisfied: setuptools in /usr/local/lib/python3.9/dist-packages (from mlxtend) (57.4.0)
Requirement already satisfied: scipy>=0.17 in /usr/local/lib/python3.9/dist-packages (from mlxtend) (1.10.1)
Requirement already satisfied: numpy>=1.10.4 in /usr/local/lib/python3.9/dist-packages (from mlxtend) (1.22.4)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (4.39.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (0.11.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (2.8.2)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (23.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (8.4.0)
Requirement already satisfied: pyparsing>=2.2.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (3.0.9)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.9/dist-packages (from matplotlib>=1.5.1->mlxtend) (1.4.4)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-packages (from pandas>=0.17.1->mlxtend) (2022.7.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist-packages (from scikit-learn>=0.18->mlxtend) (3.1.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.9/dist-packages (from scikit-learn>=0.18->mlxtend) (1.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-packages (from python-dateutil>=2.7->matplotlib>=1.5.1->mlxtend) (1.15.0)
```

```
efs1 = EFS(knn,
           min_features=2,
           max_features=4,
           scoring='accuracy',
           print_progress=True,
           cv=5)

efs1 = efs1.fit(iris_X, iris_y, custom_feature_names=iris_feature_names)

print('Best accuracy score: %.2f' % efs1.best_score_)
print('Best subset (indices):', efs1.best_idx_)
print('Best subset (corresponding names):', efs1.best_feature_names_)
```

```
Features: 11/11Best accuracy score: 0.97
Best subset (indices): (0, 2, 3)
Best subset (corresponding names): ('sepal length (cm)', 'petal length (cm)', 'petal width (cm)')
```

```
[ ] efs2 = EFS(knn,
               min_features=1,
               max_features=2,
               scoring='accuracy',
               print_progress=True,
               cv=5)

efs2 = efs2.fit(iris_X, iris_y, custom_feature_names=iris_feature_names)

print('Best accuracy score: %.2f' % efs2.best_score_)
print('Best subset (indices):', efs2.best_idx_)
print('Best subset (corresponding names):', efs2.best_feature_names_)
```

```
Features: 10/10Best accuracy score: 0.96
Best subset (indices): (3,)
Best subset (corresponding names): ('petal width (cm)',)
```

3)Один метод из группы методов вложений (embedded methods).

Использование линейных моделей

Линейная регрессия

```
[ ] # Используем L1-регуляризацию
e_ls1 = Lasso(random_state=1)
e_ls1.fit(housing_X, housing_y)
# Коэффициенты регрессии
list(zip(housing_feature_names, e_ls1.coef_))
```

```
[('MedInc', 0.1454692320524941),
 ('HouseAge', 0.005814968844496919),
 ('AveRooms', 0.0),
 ('AveBedrms', -0.0),
 ('Population', -6.372926073320524e-06),
 ('AveOccup', -0.0),
 ('Latitude', -0.0),
 ('Longitude', -0.0)]
```

```
sel_e_ls1 = SelectFromModel(e_ls1)
sel_e_ls1.fit(housing_X, housing_y)
list(zip(housing_feature_names, sel_e_ls1.get_support()))
```

```
[('MedInc', True),
 ('HouseAge', True),
 ('AveRooms', False),
 ('AveBedrms', False),
 ('Population', False),
 ('AveOccup', False),
 ('Latitude', False),
 ('Longitude', False)]
```

Использование моделей на основе решающего дерева

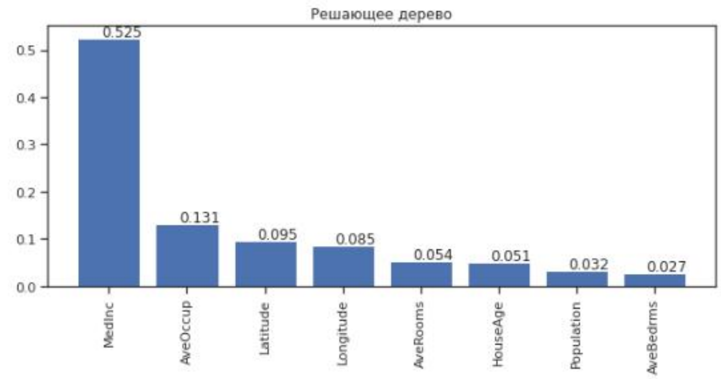
Задача регрессии

```
from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, title, figsize=(7,4)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values, tree_model.feature_importances_))
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse = True)
    # Названия признаков
    labels = [x for x,_ in sorted_list]
    # Важности признаков
    data = [x for _,x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ax.set_title(title)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a,b in zip(ind, data):
        plt.text(a-0.1, b+0.005, str(round(b,3)))
    plt.show()
    return labels, data
```

```
[ ] dtr1 = DecisionTreeRegressor()
    rfr1 = RandomForestRegressor()
    gbr1 = GradientBoostingRegressor()
    dtr1.fit(housing_X, housing_y)
    rfr1.fit(housing_X, housing_y)
    gbr1.fit(housing_X, housing_y)

    # Важность признаков
    dtr1.feature_importances_, sum(dtr1.feature_importances_)
```

```
(array([0.52497546, 0.05076972, 0.05358679, 0.02674551, 0.03229779,
        0.13148761, 0.09481681, 0.0853203 ]), 0.9999999999999998)
```

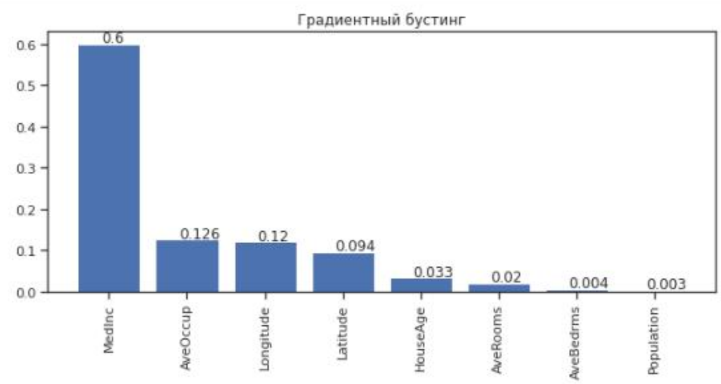
```
[ ] _,_=draw_feature_importances(dtr1, housing_x_df, 'Решающее дерево', figsize=(10,4))
```




```
list(zip(housing_feature_names, SelectFromModel(dtr1).fit(housing_X, housing_y).get_support()))
```

```
[('MedInc', True),
 ('HouseAge', False),
 ('AveRooms', False),
 ('AveBedrms', False),
 ('Population', False),
 ('AveOccup', True),
 ('Latitude', False),
 ('Longitude', False)]
```

```
[ ] _,_=draw_feature_importances(gbr1, housing_x_df, 'Градиентный бустинг', figsize=(10,4))
```



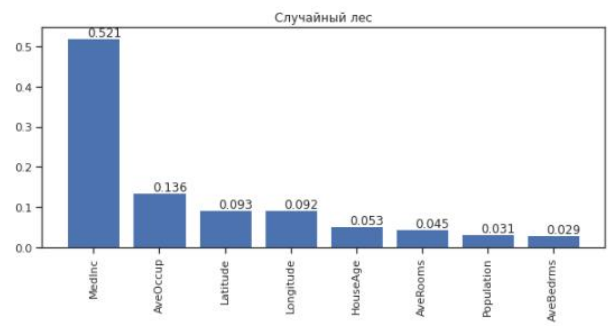
```
[ ] list(zip(housing_feature_names, SelectFromModel(gbr1).fit(housing_X, housing_y).get_support()))
```

```
[('MedInc', True),
 ('HouseAge', False),
 ('AveRooms', False),
 ('AveBedrms', False),
 ('Population', False),
 ('AveOccup', True),
 ('Latitude', False),
 ('Longitude', False)]
```

```
[ ] list(zip(housing_feature_names, SelectFromModel(gbr1, threshold='0.25*mean').fit(housing_X, housing_y).get_support()))
```

```
[('MedInc', True),
 ('HouseAge', True),
 ('AveRooms', False),
 ('AveBedrms', False),
 ('Population', False),
 ('AveOccup', True),
 ('Latitude', True),
 ('Longitude', True)]
```

```
_,_=draw_feature_importances(rfr1, housing_x_df, 'Случайный лес', figsize=(10,4))
```




```
[ ] list(zip(housing_feature_names, SelectFromModel(rfr1).fit(housing_X, housing_y).get_support()))
```

```
[('MedInc', True),
 ('HouseAge', False),
 ('AveRooms', False),
 ('AveBedrms', False),
 ('Population', False),
 ('AveOccup', True),
 ('Latitude', False),
 ('Longitude', False)]
```

```
list(zip(housing_feature_names, SelectFromModel(rfr1, threshold='0.1*mean').fit(housing_X, housing_y).get_support()))
```

```
[('MedInc', True),
 ('HouseAge', True),
 ('AveRooms', True),
 ('AveBedrms', True),
 ('Population', True),
 ('AveOccup', True),
 ('Latitude', True),
 ('Longitude', True)]
```