```
import numpy as np
import pandas as pd
from typing import Dict, Tuple
from scipy import stats
from IPython.display import Image
from sklearn.externals.six import StringIO
from IPython.display import Image
import graphviz
import pydotplus
from sklearn.datasets import load iris, load boston
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import accuracy_score, balanced_accuracy_score
from sklearn.metrics import precision_score, recall_score, f1_score, classification_report
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_graphviz
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.ensemble import ExtraTreesClassifier, ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingClassifier, GradientBoostingRegressor
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_squared_log_erro
from sklearn.metrics import roc_curve, roc_auc_score
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR, LinearSVR
%matplotlib inline
sns.set(rc={'figure.figsize':(16,8)})
for col in df.columns:
    count = df[df[col].isnull()].shape[0]
    print('{} - {}'.format(col, count))
print ('{} - размер датасета'.format(df.shape))
 [→ longitude - 0
     latitude - 0
     housing_median_age - 0
     total rooms - 0
     total_bedrooms - 0
     population - 0
     households - 0
     median income
     median house value -
     ocean proximity - 0
     (20433, 10) - размер датасета
df = pd.read csv('housing.csv', error bad lines=False, comment='#')
df = df.dropna(axis=0, how='any')
```

```
for col in df.columns:
    count = df[df[col].isnull()].shape[0]
    print('{} - {}'.format(col, count))
print ('{} - pasмep датасета'.format(df.shape))
#df.drop(columns='id', inplace = True);
#df.drop(columns='Cabin', inplace= True)
```

Description of the content of the c

df

₽		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
	0	-122.23	37.88	41.0	880.0	129.0	322
	1	-122.22	37.86	21.0	7099.0	1106.0	240
	2	-122.24	37.85	52.0	1467.0	190.0	496
	3	-122.25	37.85	52.0	1274.0	235.0	55{
	4	-122.25	37.85	52.0	1627.0	280.0	56
	20635	-121.09	39.48	25.0	1665.0	374.0	84
	20636	-121.21	39.49	18.0	697.0	150.0	356
	20637	-121.22	39.43	17.0	2254.0	485.0	1007
	20638	-121.32	39.43	18.0	1860.0	409.0	74
	20639	-121.24	39.37	16.0	2785.0	616.0	1387

20433 rows × 10 columns

df.reset_index(drop=True, inplace=True)

Кодируем категориальные признаки

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
le = LabelEncoder()
df['ocean_proximity'].unique()
```

₽		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
	0	-122.23	37.88	41.0	880.0	129.0	322
	1	-122.22	37.86	21.0	7099.0	1106.0	240
	2	-122.24	37.85	52.0	1467.0	190.0	496
	3	-122.25	37.85	52.0	1274.0	235.0	558
	4	-122.25	37.85	52.0	1627.0	280.0	56
	20428	-121.09	39.48	25.0	1665.0	374.0	84!
	20429	-121.21	39.49	18.0	697.0	150.0	356
	20430	-121.22	39.43	17.0	2254.0	485.0	1007
	20431	-121.32	39.43	18.0	1860.0	409.0	74 ⁻
	20432	-121.24	39.37	16.0	2785.0	616.0	1387

20433 rows × 10 columns

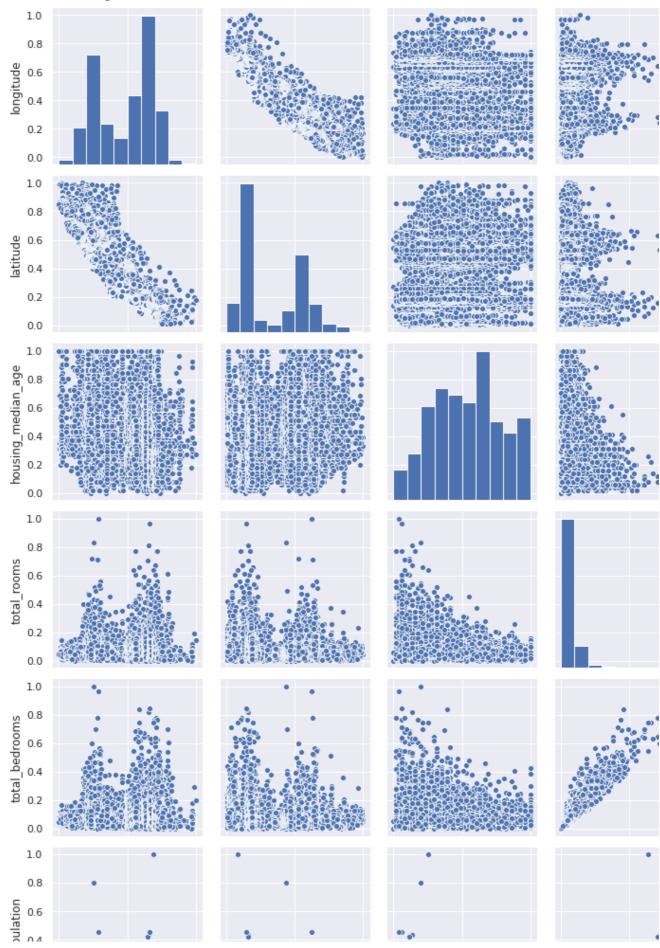
from sklearn.preprocessing import MinMaxScaler
features

С>

		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati	
	0	-122.23	37.88	41.0	880.0	129.0	322	
	1	-122.22	37.86	21.0	7099.0	1106.0	240	
	2	-122.24	37.85	52.0	1467.0	190.0	496	
Построим парные статистики								
	4	-122.25	37.85	52.0	1627.0	280.0	568	
<pre>sns.pairplot(df)</pre>								

₽

<seaborn.axisgrid.PairGrid at 0x7ff4174d4f60>

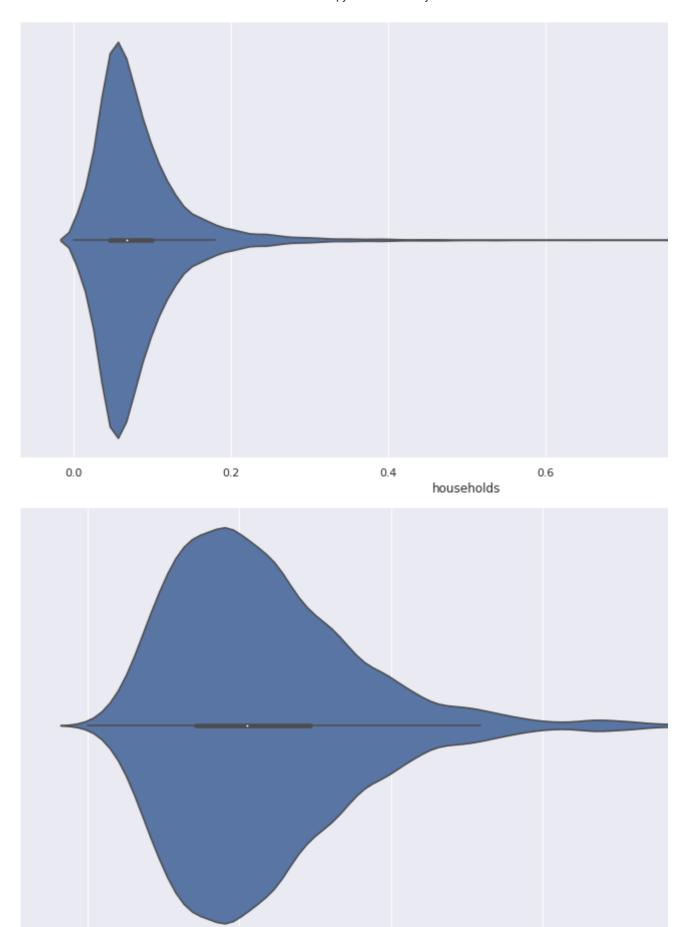


Скрипичные диаграммы для числовых колонок

for col in ['households', 'median_income', 'median_house_value','ocean_proximity']:
 sns.violinplot(x=df[col])

plt.show()

₽



Произведем масштабирование

```
scal= MinMaxScaler()
s = scal.fit_transform(df)
https://colab.research.google.com/drive/1gQoYg28XNA-nBku6gWsQYLPR4CDgmExi#scrollTo=3le2QAz7Xema
```

d+ = pd.DataFrame(s, columns= ['longitude', 'latitude', 'housing_median_age', 'total_rooms
df

₽		longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
	0	0.211155	0.567481	0.784314	0.022331	0.019863	0.0089
	1	0.212151	0.565356	0.392157	0.180503	0.171477	0.0672
	2	0.210159	0.564293	1.000000	0.037260	0.029330	0.0138
	3	0.209163	0.564293	1.000000	0.032352	0.036313	0.0155
	4	0.209163	0.564293	1.000000	0.041330	0.043296	0.0157
	20428	0.324701	0.737513	0.470588	0.042296	0.057883	0.0235
	20429	0.312749	0.738576	0.333333	0.017676	0.023122	0.0098
	20430	0.311753	0.732200	0.313725	0.057277	0.075109	0.0281
	20431	0.301793	0.732200	0.333333	0.047256	0.063315	0.0206
	20432	0.309761	0.725824	0.294118	0.070782	0.095438	0.0387

features = df.drop(columns='median_house_value')
target = df.median_house_value

20433 rows × 10 columns

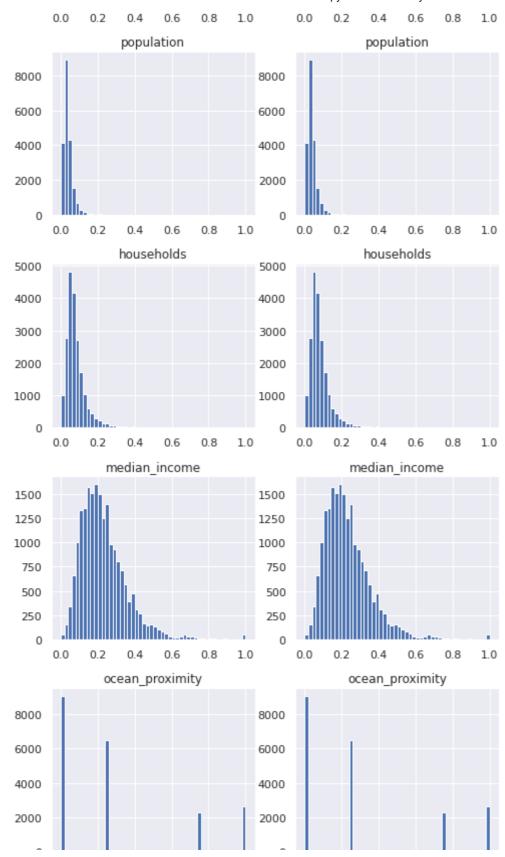
```
0
             0.902266
Гэ
    1
             0.708247
    2
             0.695051
    3
             0.672783
             0.674638
    20428
             0.130105
    20429
             0.128043
             0.159383
    20430
    20431
             0.143713
             0.153403
    20432
    Name: median_house_value, Length: 20433, dtype: float64
```

```
# Проверим, что масштабирование не повлияло на распределение данных for col in features:
    col_scaled = col

fig, ax = plt.subplots(1, 2, figsize=(8,3))
    ax[0].hist(features[col], 50)
    ax[1].hist(features[col_scaled], 50)
    ax[0].title.set_text(col)
    ax[1].title.set_text(col_scaled)
    plt.show()
```

С→





X_train, X_test, y_train, y_test = train_test_split(
 features, target, test_size=0.2, random_state = 1)

```
target_df = pd.DataFrame(target, columns=['median_house_value'])
df_merge = features.join(target_df)
df_merge
```

С→

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
0	0.211155	0.567481	0.784314	0.022331	0.019863	0.0089
1	0.212151	0.565356	0.392157	0.180503	0.171477	0.0672
2	0.210159	0.564293	1.000000	0.037260	0.029330	0.0138
3	0.209163	0.564293	1.000000	0.032352	0.036313	0.0155
4	0.209163	0.564293	1.000000	0.041330	0.043296	0.0157
20428	0.324701	0.737513	0.470588	0.042296	0.057883	0.0235
20429	0.312749	0.738576	0.333333	0.017676	0.023122	0.0098
20430	0.311753	0.732200	0.313725	0.057277	0.075109	0.0281
20431	0.301793	0.732200	0.333333	0.047256	0.063315	0.0206
20432	0.309761	0.725824	0.294118	0.070782	0.095438	0.0387

fig, ax = plt.subplots(figsize=(10,5))
sns.heatmap(df_merge.corr(), annot=True, fmt='.2f')

C→ <matplotlib.axes._subplots.AxesSubplot at 0x7ff409489be0>



regr_X_train = X_train

regr_X_test = X_test

regr_Y_train = y_train

regr Y test = v test

[#] Выборки для задачи регресии

```
regr_X_train.shape, regr_X_test.shape, regr_Y_train.shape, regr_Y_test.shape
    ((16346, 9), (4087, 9), (16346,), (4087,))
class MetricLogger:
    def __init__(self):
        self.df = pd.DataFrame(
            {'metric': pd.Series([], dtype='str'),
            'alg': pd.Series([], dtype='str'),
            'value': pd.Series([], dtype='float')})
    def add(self, metric, alg, value):
        Добавление значения
        # Удаление значения если оно уже было ранее добавлено
        self.df.drop(self.df[(self.df['metric']==metric)&(self.df['alg']==alg)].index, inp
        # Добавление нового значения
        temp = [{'metric':metric, 'alg':alg, 'value':value}]
        self.df = self.df.append(temp, ignore_index=True)
    def get_data_for_metric(self, metric, ascending=True):
        Формирование данных с фильтром по метрике
        temp_data = self.df[self.df['metric']==metric]
        temp_data_2 = temp_data.sort_values(by='value', ascending=ascending)
        return temp_data_2['alg'].values, temp_data_2['value'].values
    def plot(self, str_header, metric, ascending=True, figsize=(5, 5)):
        Вывод графика
        array labels, array metric = self.get data for metric(metric, ascending)
        fig, ax1 = plt.subplots(figsize=figsize)
        pos = np.arange(len(array_metric))
        rects = ax1.barh(pos, array metric,
                         align='center',
                         height=0.5,
                         tick_label=array_labels)
        ax1.set_title(str_header)
        for a,b in zip(pos, array_metric):
            plt.text(0.5, a-0.05, str(round(b,3)), color='white')
        plt.show()
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export_graphviz
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR, NuSVR, LinearSVR
from sklearn.ensemble import ExtraTreesClassifier, ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingClassifier, GradientBoostingRegressor
```

Построим несколько моделей МО

- 1. Линейная регрессия
- 2. Метод ближайших соседей
- 3. Метод опорных векторов
- 4. Случайный лес
- 5. Решающее дерево
- 6. Градиентный бустинг

```
for model_name, model in regr_models.items():
    regr_train_model(model_name, model, regrMetricLogger)
```

round(mae, 3), round(mse, 3), round(r2, 3)))

 \Box

```
****************
LinearRegression(copy X=True, fit intercept=True, n jobs=None, normalize=False)
MAE=0.104, MSE=0.02, R2=0.645
*****************
*****************
KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
                metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                weights='uniform')
MAE=0.085, MSE=0.016, R2=0.714
***************
****************
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma='scale',
   kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
MAE=0.085, MSE=0.015, R2=0.741
***************
***************
DecisionTreeRegressor(ccp alpha=0.0, criterion='mse', max depth=None,
                  max_features=None, max_leaf_nodes=None,
                  min_impurity_decrease=0.0, min_impurity_split=None,
                  min_samples_leaf=1, min_samples_split=2,
                  min_weight_fraction_leaf=0.0, presort='deprecated',
                  random_state=None, splitter='best')
MAE=0.087, MSE=0.019, R2=0.671
*****************
******************
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                  max depth=None, max features='auto', max leaf nodes=None,
                  max_samples=None, min_impurity_decrease=0.0,
                  min_impurity_split=None, min_samples_leaf=1,
                  min_samples_split=2, min_weight_fraction_leaf=0.0,
                  n_estimators=100, n_jobs=None, oob_score=False,
                  random_state=None, verbose=0, warm_start=False)
MAE=0.063, MSE=0.01, R2=0.827
******************
*****************
GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                     init=None, learning rate=0.1, loss='ls', max depth=3,
                     max features=None, max leaf nodes=None,
                     min impurity decrease=0.0, min impurity split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=100,
                     n_iter_no_change=None, presort='deprecated',
                     random state=None, subsample=1.0, tol=0.0001,
                     validation fraction=0.1, verbose=0, warm start=False)
```

▼ Подбор гиперпараметров

KNeighbors

```
n_range = np.array(range(1,100,5))
tuned_parameters = [{'n_neighbors': n_range}]
tuned parameters
```

```
[\{'n\_neighbors': array([1, 6, 11, 16, 21, 26, 31, 36, 41, 46, 51, 56, 61, 66, 71, 7, 6, 61, 66, 71, 7, 6, 6, 7]]
              86, 91, 96])}]
regr_gs_KN = GridSearchCV(KNeighborsRegressor(), tuned_parameters, cv=5, scoring='neg mean
regr_gs_KN.fit(regr_X_train, regr_Y_train)
 GridSearchCV(cv=5, error_score=nan,
                  estimator=KNeighborsRegressor(algorithm='auto', leaf_size=30,
                                                 metric='minkowski',
                                                 metric_params=None, n_jobs=None,
                                                 n_neighbors=5, p=2,
                                                 weights='uniform'),
                  iid='deprecated', n_jobs=None,
                  param_grid=[{'n_neighbors': array([ 1, 6, 11, 16, 21, 26, 31, 36, 41, 4
            86, 91, 96])}],
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='neg_mean_squared_error', verbose=0)
# Лучшая модель
regr_gs_KN.best_estimator_
     KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
                         metric_params=None, n_jobs=None, n_neighbors=11, p=2,
                         weights='uniform')
# Лучшее значение параметров
regr_gs_KN.best_params_
 「→ {'n_neighbors': 11}
# Изменение качества на тестовой выборке в зависимости от К-соседей
plt.plot(n range, regr gs KN.cv results ['mean test score'])
 C→
```

L→

```
[<matplotlib.lines.Line2D at 0x7ff406bf5630>]
      -0.017
      -0.018
DecisionTree
       0.015
n_range = np.array(range(1,50,3))
tuned_parameters = [{'max_depth': n_range}]
tuned_parameters
    [{'max_depth': array([ 1, 4, 7, 10, 13, 16, 19, 22, 25, 28, 31, 34, 37, 40, 43, 46,
regr_gs_DT = GridSearchCV(DecisionTreeRegressor(), tuned_parameters, cv=5, scoring='neg_me
regr_gs_DT.fit(regr_X_train, regr_Y_train)
   GridSearchCV(cv=5, error_score=nan,
                  estimator=DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse',
                                                   max_depth=None, max_features=None,
                                                   max_leaf_nodes=None,
                                                   min impurity decrease=0.0,
                                                   min_impurity_split=None,
                                                   min_samples_leaf=1,
                                                   min_samples_split=2,
                                                   min_weight_fraction_leaf=0.0,
                                                   presort='deprecated',
                                                   random_state=None,
                                                   splitter='best'),
                  iid='deprecated', n_jobs=None,
                  param_grid=[{'max_depth': array([ 1, 4, 7, 10, 13, 16, 19, 22, 25, 28,
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='neg_mean_squared_error', verbose=0)
# Лучшая модель
regr_gs_DT.best_estimator_
 □→ DecisionTreeRegressor(ccp alpha=0.0, criterion='mse', max depth=10,
                           max features=None, max leaf nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min samples leaf=1, min samples split=2,
                           min_weight_fraction_leaf=0.0, presort='deprecated',
                           random_state=None, splitter='best')
# Лучшее значение параметров
regr_gs_DT.best_params_
    {'max depth': 10}
#Изменение качества на тестовой выборке в зависимости от глубины
plt.plot(n_range, regr_gs_DT.cv_results_['mean_test_score'])
```

[<matplotlib.lines.Line2D at 0x7ff406a82f28>]



SVM

```
n_range1 = np.array(range(1,5,1))
n_{range2} = np.array(range(1,10,1))*0.1
tuned_parameters = [{'degree': n_range1}, {'gamma' : n_range2}]
tuned_parameters
    [{'degree': array([1, 2, 3, 4])},
      {'gamma': array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9])}]
regr_gs_SVR = GridSearchCV(SVR(), tuned_parameters, cv=5, scoring='neg_mean_squared_error'
regr_gs_SVR.fit(regr_X_train, regr_Y_train)
 GridSearchCV(cv=5, error_score=nan,
                  estimator=SVR(C=1.0, cache size=200, coef0=0.0, degree=3,
                                epsilon=0.1, gamma='scale', kernel='rbf',
                                max iter=-1, shrinking=True, tol=0.001,
                                verbose=False),
                  iid='deprecated', n_jobs=None,
                  param_grid=[{'degree': array([1, 2, 3, 4])},
                              {'gamma': array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='neg_mean_squared_error', verbose=0)
# Лучшая модель
regr_gs_SVR.best_estimator_
```

```
С⇒
    SVR(C=1.0, cache size=200, coef0=0.0, degree=1, epsilon=0.1, gamma='scale',
         kernel='rbf', max iter=-1, shrinking=True, tol=0.001, verbose=False)
# Лучшее значение параметров
regr_gs_SVR.best_params_
 □→ {'degree': 1}
#Изменение качества на тестовой выборке в зависимости от глубины
plt.plot(n_range1, regr_gs_SVR.cv_results_)
RandomForestRegressor max_depth
n_range = np.array(range(1,10,1))
tuned_parameters = [{'max_depth': n_range}]
tuned parameters
    [{'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}]
regr_gs_RFR = GridSearchCV(RandomForestRegressor(), tuned_parameters, cv=5, scoring='neg_m
regr_gs_RFR.fit(regr_X_train, regr_Y_train)
 GridSearchCV(cv=5, error_score=nan,
                  estimator=RandomForestRegressor(bootstrap=True, ccp_alpha=0.0,
                                                  criterion='mse', max_depth=None,
                                                  max features='auto',
                                                  max leaf nodes=None,
                                                  max_samples=None,
                                                  min impurity decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min samples split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  n estimators=100, n jobs=None,
                                                  oob_score=False, random_state=None,
                                                  verbose=0, warm start=False),
                  iid='deprecated', n_jobs=None,
                  param_grid=[{'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}],
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='neg_mean_squared_error', verbose=0)
# Лучшая модель
regr gs RFR.best estimator
     RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                           max_depth=9, max_features='auto', max_leaf_nodes=None,
                           max_samples=None, min_impurity_decrease=0.0,
                           min impurity split=None, min samples leaf=1,
                           min_samples_split=2, min_weight_fraction_leaf=0.0,
                           n estimators=100, n jobs=None, oob score=False,
                           random_state=None, verbose=0, warm_start=False)
```

regr_gs_RFR.best_params_

GradientBoostingRegresso

```
n_range = np.array(range(1,10,1))
tuned parameters = [{'max depth': n range}]
tuned parameters
    [{'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}]
regr_gs_GBR = GridSearchCV(GradientBoostingRegressor(), tuned_parameters, cv=5, scoring='n
regr_gs_GBR.fit(regr_X_train, regr_Y_train)
GridSearchCV(cv=5, error score=nan,
                  estimator=GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0,
                                                       criterion='friedman_mse',
                                                       init=None, learning_rate=0.1,
                                                       loss='ls', max_depth=3,
                                                       max features=None,
                                                      max leaf nodes=None,
                                                      min_impurity_decrease=0.0,
                                                       min impurity split=None,
                                                      min_samples_leaf=1,
                                                       min_samples_split=2,
                                                      min_weight_fraction_leaf=0.0,
                                                       n estimators=100,
                                                       n_iter_no_change=None,
                                                       presort='deprecated',
                                                       random_state=None,
                                                       subsample=1.0, tol=0.0001,
                                                       validation_fraction=0.1,
                                                       verbose=0, warm_start=False),
                  iid='deprecated', n jobs=None,
                  param_grid=[{'max_depth': array([1, 2, 3, 4, 5, 6, 7, 8, 9])}],
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='neg_mean_squared_error', verbose=0)
regr gs GBR.best estimator
    GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                               init=None, learning_rate=0.1, loss='ls', max_depth=9,
                               max features=None, max leaf nodes=None,
                               min impurity decrease=0.0, min impurity split=None,
                               min samples leaf=1, min samples split=2,
                               min_weight_fraction_leaf=0.0, n_estimators=100,
                               n iter no change=None, presort='deprecated',
                               random_state=None, subsample=1.0, tol=0.0001,
                               validation fraction=0.1, verbose=0, warm start=False)
regr_gs_GBR.best_params_
    {'max depth': 9}
```

LinearRegression

```
n_{range} = np.array(range(1,10,1))*0.1
tuned_parameters = [{'n_jobs': n_range}]
tuned parameters
[{'n_jobs': array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9])}]
regr_gs_LR = GridSearchCV(LinearRegression(), tuned_parameters, cv=5, scoring='neg_mean_sq
regr_gs_LR.fit(regr_X_train, regr_Y_train)
   GridSearchCV(cv=5, error_score=nan,
                  estimator=LinearRegression(copy_X=True, fit_intercept=True,
                                             n jobs=None, normalize=False),
                  iid='deprecated', n jobs=None,
                  param_grid=[{'n_jobs': array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring='neg_mean_squared_error', verbose=0)
regr_gs_LR.best_estimator_

    LinearRegression(copy_X=True, fit_intercept=True, n_jobs=0.1, normalize=False)

regr_gs_LR.best_params_
┌→ {'n_jobs': 0.1}
```

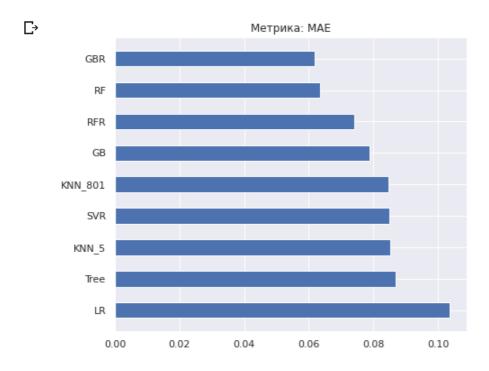
▼ Повторение построения базового решения для задачи регресии

```
regr_models_grid = {'KNN_801':regr_gs_KN.best_estimator_,
                    'LR':regr_gs_LR.best_estimator_,
                    'SVR':regr_gs_SVR.best_estimator_,
                    'RFR':regr_gs_RFR.best_estimator_,
                    'GBR' : regr_gs_GBR.best_estimator_,
                    'LR' : regr gs LR.best estimator
                    }
for model_name, model in regr_models_grid.items():
    regr train model(model name, model, regrMetricLogger)
 С→
```

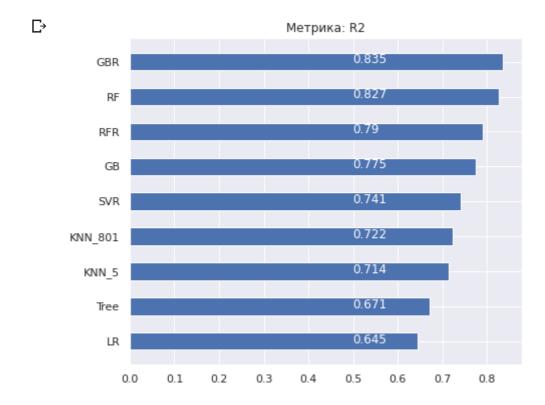
```
***************
    KNeighborsRegressor(algorithm='auto', leaf size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=11, p=2,
                    weights='uniform')
    MAE=0.085, MSE=0.016, R2=0.722
    ***************
    *****************
    LinearRegression(copy_X=True, fit_intercept=True, n_jobs=0.1, normalize=False)
    MAE=0.104, MSE=0.02, R2=0.645
    ***************
    ***************
    SVR(C=1.0, cache_size=200, coef0=0.0, degree=1, epsilon=0.1, gamma='scale',
       kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
    MAE=0.085, MSE=0.015, R2=0.741
    ***************
    ***************
    RandomForestRegressor(bootstrap=True, ccp alpha=0.0, criterion='mse',
                      max_depth=9, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
    MAE=0.074, MSE=0.012, R2=0.79
    ******************
Решение задачи регрессии
                         may features = None may leaf nodes = None
# Метрики качества модели
regr_metrics = regrMetricLogger.df['metric'].unique()
regr_metrics
    array(['MAE', 'MSE', 'R2'], dtype=object)
```

Double-click (or enter) to edit

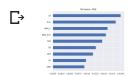
regrMetricLogger.plot('Метрика: ' + 'MAE', 'MAE', ascending=False, figsize=(7, 6))



regrMetricLogger.plot('Метрика: ' + 'R2', 'R2', ascending=True, figsize=(7, 6))



regrMetricLogger.plot('Метрика: ' + 'MSE', 'MSE', ascending=True, figsize=(7, 6))



Как видно из гистограмм наилучшим методом будет линейная регрессия либо градиентны

!apt-get install texlive texlive-xetex texlive-latex-extra pandoc
!pip install pypandoc

cp "/content/drive/My Drive/Colab Notebooks/Untitled.ipynb" ./

Reading package lists... Done
Building dependency tree
Reading state information... Done
pandoc is already the newest version (1.19.2.4~dfsg-1build4).
texlive is already the newest version (2017.20180305-1).
texlive-latex-extra is already the newest version (2017.20180305-1).
0 upgraded, 0 newly installed, 0 to remove and 31 not upgraded.
Requirement already satisfied: pypandoc in /usr/local/lib/python3.6/dist-packages (1.
Requirement already satisfied: wheel>=0.25.0 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: pip>=8.1.0 in /usr/local/lib/python3.6/dist-packages (
The google.colab import drive drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m