Prediction of House Sale Price in Boston

In [ ]:

```
# Проект построен следующим образом.
# Сначала определяются ф-ции, для последующего запуска генетического алгоритма по по
# гиперпараметров для модели регрессии XGBoost (градиентного бустинга)
# 1. Data Parsing - обработка сырых данных:
# 1.1 Очистка данных
# 1.2 Определение ф-ций для последующей трансформации категориальных признаков, а та
# 1.3 Проведение непосредственно самой трансформации/разделения признаков
# 2. Применение линейной регрессионной модели ElasticNet с предварительным подбором
# 3. Применение регрессора XGBoost
# 3.0 Подбор гиперпараметров вручную
# 3.1 Подбор гиперпараметров на основе генетического алгоритма (точность по кросс-ва
# 4. Применение модели регрессии RandomForest (макс. точность 85%)
# 4. Применение модели регрессии BaggingRegressor (точность 84%)
# 4. Применение модели регрессии Support Vector Regressor (точность 83%)
#
# В итоге регрессор XGBoost с подбором гиперпараметров при помощи генетического алго
# 89% по кросс-валидации
```

In [108…

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import ElasticNet
from sklearn import linear_model
from sklearn import ensemble, model_selection, metrics, tree
import xgboost as xgb
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import accuracy_score, mean_absolute_error
from numpy.random import randint
from numpy.random import randn,random
import random as rnd

from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR

import warnings

%matplotlib inline
```

Define functions for further Genetics run

In [109…

```
'''
    Function of getting of the survived botes of the population
        Input parameters:
        - popul - the population
        - val - the current values of the prediction error MAE on the botes for the
        - nsurv - the number of the survived botes
'''
def getSurvPopul(
        popul,
        val,
        nsurv,
```

```
        ):
    newpopul = [] # 2-dimension matrix for new population
    sval = sorted(val, reverse=1) # Sort the val-values on descending
    for i in range(nsurv): # Finally, the best nsurv-botes will be written in a new
        index = val.index(sval[i]) # Get the index in list 'val' for the value=sval[
        newpopul.append(popul[index]) # Add the bote from the current population wit
    return newpopul, sval # Return new population ('nsurv' elements) and the sorted

'''
    Function to get parents from the survived botes of the population
        Input parameters:
        - curr_popul - the current survived population
        - nsurv - the number of survived botes
'''
def getParents(
        curr_popul,
        nsurv
        ):
    indexp1 = rnd.randint(0, nsurv - 1) # The random index of the first parent from
    indexp2 = rnd.randint(0, nsurv - 1) # The random index of the second parent from
    botp1 = curr_popul[indexp1] # Get the first parent-bote based on index 'indexp1'
    botp2 = curr_popul[indexp2] # Get the second parent-bote based on index 'indexp2
    return botp1, botp2 # Return the both parents-botes

'''
    Function of crossing of two parents
        Input parameters:
        - botp1 - the first parent-bote
        - botp2 - the second parent-bote
        - j - number of the feature
'''
def crossPointFrom2Parents(
        botp1,
        botp2,
        j
        ):
    pindex = rnd.random() # random number from 0 to 1
    if pindex < 0.5:
        x = botp1[j]
    else:
        x = botp2[j]
    return x
```

In [110…

```
'''
    Function of initialization of population of botes. Each bote contents 6 hyperpar

    n_estimators - the number of trees
    learning_rate - gradient step
    max_depth - max depth of the each tree (increasing this value will make the mode
                overfit)
    gamma - Minimum loss reduction required to make a further partition on a leaf no
            the more conservative the algorithm will be
    min_child_weight - Minimum sum of instance weight (hessian) needed in a child. I
                       in a leaf node with the sum of instance weight less than min_
                       will give up further partitioning. In linear regression task,
                       number of instances needed to be in each node. The larger min
                       the algorithm will be.
    subsample - ratio of the training instances. Setting it to 0.5 means that XGBoos
                training data prior to growing trees and this will prevent overfitti
                every boosting iteration.
'''
def initilialize_poplulation(num_botes):
    learningRate = np.empty([num_botes, 1])
```

```
    nEstimators = np.empty([num_botes, 1], dtype = np.uint8)
    maxDepth = np.empty([num_botes, 1], dtype = np.uint8)
    minChildWeight = np.empty([num_botes, 1])
    gammaValue = np.empty([num_botes, 1])
    subSample = np.empty([num_botes, 1])
    for i in range(num_botes):
        learningRate[i] = round(rnd.uniform(0.01, 1), 2)
        nEstimators[i] = rnd.randrange(10, 1500, step = 25)
        maxDepth[i] = int(rnd.randrange(1, 10, step= 1))
        minChildWeight[i] = round(rnd.uniform(0.01, 10.0), 2)
        gammaValue[i] = round(rnd.uniform(0.01, 10.0), 2)
        subSample[i] = round(rnd.uniform(0.01, 1.0), 2)
    population = np.concatenate((learningRate, nEstimators, maxDepth, minChildWeight
    return population
```

In [111…

```
'''
    Function of mutation
        Input parameters:
            param_n - feature index
            param_val - the value of the feature
            num_of_pars - the number of features in each bote
'''
def mutation(param_n,param_val,num_of_pars):
    #the borders for the each feature
    minMaxValue = np.zeros((num_of_pars, 2))
    minMaxValue[0, :] = [0.01, 1.0] #min/max learning rate
    minMaxValue[1, :] = [10, 2000] #min/max n_estimator
    minMaxValue[2, :] = [1, 15] #min/max depth
    minMaxValue[3, :] = [0, 10.0] #min/max child_weight
    minMaxValue[4, :] = [0.01, 10.0] #min/max gamma
    minMaxValue[5, :] = [0.01, 1.0] #min/max subsample

    # First set the change of the feature
    if param_n == 0: #learning_rate
        mutationValue = round(np.random.uniform(-0.5, 0.5), 2)
    if param_n == 1: #n_estimators
        mutationValue = np.random.randint(-200, 200)
    if param_n == 2: #max_depth
        mutationValue = np.random.randint(-5, 5)
    if param_n == 3: #min_child_weight
        mutationValue = round(np.random.uniform(5, 5), 2)
    if param_n == 4: #gamma
        mutationValue = round(np.random.uniform(-2, 2), 2)
    if param_n == 5: #subsample
        mutationValue = round(np.random.uniform(-0.5, 0.5), 2)

    # new feature value = old feature value + change of the feature
    mutated_param = param_val + mutationValue
    # keep the new feature value within the borders
    if(mutated_param > minMaxValue[param_n, 1]):
        mutated_param = minMaxValue[param_n, 1]
    if(mutated_param < minMaxValue[param_n, 0]):
        mutated_param = minMaxValue[param_n, 0]
    return mutated_param
```

1. Data Parsing

'houses_train.csv' - the data which should be used for model creation 'houses_test.csv' - the data which should be used for model testing

In [112…

```
data = pd.read_csv('Data\houses_train.csv', sep=',')
data_test = pd.read_csv('Data\houses_test.csv', sep=',')
data.head()
```

Out[112...

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPu

5 rows × 81 columns

1.1 Data Cleaning

In [4]:

```
data.describe()
```

Out[4]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuil
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	1460.00000(
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.26780
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112799	30.20290
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.00000(
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000000	1954.00000(
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000000	1973.00000(
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	2000.00000(
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.00000(

8 rows × 38 columns

In [4]:

```
data_test.describe()
```

Out[4]:

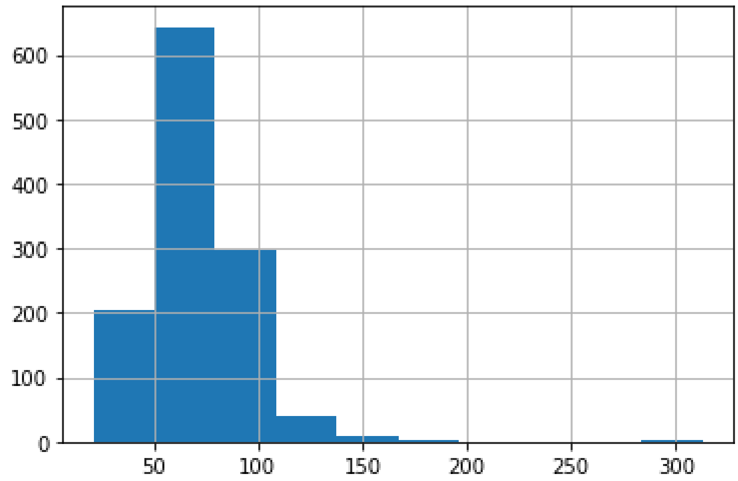
	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt
count	1459.000000	1459.000000	1232.000000	1459.000000	1459.000000	1459.000000	1459.000000
mean	2190.000000	57.378341	68.580357	9819.161069	6.078821	5.553804	1971.357779
std	421.321334	42.746880	22.376841	4955.517327	1.436812	1.113740	30.390071
min	1461.000000	20.000000	21.000000	1470.000000	1.000000	1.000000	1879.000000
25%	1825.500000	20.000000	58.000000	7391.000000	5.000000	5.000000	1953.000000
50%	2190.000000	50.000000	67.000000	9399.000000	6.000000	5.000000	1973.000000
75%	2554.500000	70.000000	80.000000	11517.500000	7.000000	6.000000	2001.000000
max	2919.000000	190.000000	200.000000	56600.000000	10.000000	9.000000	2010.000000

8 rows × 37 columns

1.1.1 LotFrontage (Linear feet of street connected to property)

In [113...

```
data.LotFrontage.hist()
# Replace all NaN values of LotFrontage to the mean value
data['LotFrontage'] = data['LotFrontage'].fillna((data['LotFrontage'].mean()))
data_test['LotFrontage'] = data_test['LotFrontage'].fillna((data_test['LotFrontage']
```



1.1.2 MasVnrArea (Masonry veneer area in square feet)

In [114...

```
data[data.MasVnrArea.isnull()][['MasVnrType','MasVnrArea']]
```

Out[114...

	MasVnrType	MasVnrArea
234	NaN	NaN
529	NaN	NaN
650	NaN	NaN
936	NaN	NaN
973	NaN	NaN
977	NaN	NaN
1243	NaN	NaN
1278	NaN	NaN

In [115...

```
# As MasVnrArea is always NaN when the house has no corresponding type, replace MasV
data['MasVnrArea'] = data['MasVnrArea'].fillna(0.0)
data_test['MasVnrArea'] = data_test['MasVnrArea'].fillna(0.0)
```

1.1.3 GarageYrBlt (Year garage was built)

In [116...

```
# Replace NaN GarageYrBlt to the earliest year - 1900
data['GarageYrBlt'] = data['GarageYrBlt'].fillna(1900)
data_test['GarageYrBlt'] = data_test['GarageYrBlt'].fillna(1900)
```

1.1.4 Replace (BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, BsmtFullBath, BsmtHalfBath, GarageCars, GarageArea) NaN to 0

In [117…

```
data_test['BsmtFinSF1'] = data_test['BsmtFinSF1'].fillna(0.0)
data_test['BsmtFinSF2'] = data_test['BsmtFinSF2'].fillna(0.0)
data_test['BsmtUnfSF'] = data_test['BsmtUnfSF'].fillna(0.0)
data_test['TotalBsmtSF'] = data_test['TotalBsmtSF'].fillna(0.0)
data_test['BsmtFullBath'] = data_test['BsmtFullBath'].fillna(0.0)
data_test['BsmtHalfBath'] = data_test['BsmtHalfBath'].fillna(0.0)
data_test['GarageCars'] = data_test['GarageCars'].fillna(0.0)
data_test['GarageArea'] = data_test['GarageArea'].fillna(0.0)
```

1.1.5 MasVnrType - Replace NaN to the existing 'None' category

In [118…

```
data['MasVnrType'] = data['MasVnrType'].fillna('None')
data_test['MasVnrType'] = data_test['MasVnrType'].fillna('None')
```

1.1.6 FullBath (Full bathrooms above grade)

In [119…

```
print('Unique train data')
print(data.FullBath.unique())
print('Unique test data before transformation')
print(data_test.FullBath.unique())

# As train data values have maximum 3 - replace 4 in test data to 3

data_test.loc[data_test['FullBath'] > 3, 'FullBath'] = 3
print('Unique test data after transformation')
print(data_test.FullBath.unique())
```

```
Unique train data
[2 1 3 0]
Unique test data before transformation
[1 2 3 4 0]
Unique test data after transformation
[1 2 3 0]
```

1.1.7 Typo errors fixing in 'Exterior2nd' column

In [120…

```
print('Before fixing:')
print('Exterior1st(train):',list(data.Exterior1st.unique()))
print('Exterior2nd(train):',list(data.Exterior2nd.unique()))
print('Exterior1st(test):',list(data_test.Exterior1st.unique()))
print('Exterior2nd(test):',list(data_test.Exterior2nd.unique()))

# Fix the values in Exterior2nd 'Wd Shng' to 'WdShing', 'Brk Cmn' to 'BrkComm' and '

data.loc[data['Exterior2nd'] == 'Wd Shng', 'Exterior2nd'] = 'WdShing'
data_test.loc[data_test['Exterior2nd'] == 'Wd Shng', 'Exterior2nd'] = 'WdShing'
data.loc[data['Exterior2nd'] == 'Brk Cmn', 'Exterior2nd'] = 'BrkComm'
data_test.loc[data_test['Exterior2nd'] == 'Brk Cmn', 'Exterior2nd'] = 'BrkComm'
data.loc[data['Exterior2nd'] == 'CmentBd', 'Exterior2nd'] = 'CemntBd'
data_test.loc[data_test['Exterior2nd'] == 'CmentBd', 'Exterior2nd'] = 'CemntBd'

# Replace the nan values in 'Exterior1st' and 'Exterior2nd' for data_test to 'Other'

data_test['Exterior1st'] = data_test['Exterior1st'].fillna('Other')
data_test['Exterior2nd'] = data_test['Exterior2nd'].fillna('Other')
print('\n','After fixing:')
print('Exterior2nd(train):',list(data.Exterior2nd.unique()))
print('Exterior2nd(test):',list(data_test.Exterior2nd.unique()))

# In the function body which will be introduced further we will use data_train.Exter
# also 'Other' value versus 'data_train.Exterior1st.unique()'
```

```
Before fixing:
Exterior1st(train): ['VinylSd', 'MetalSd', 'Wd Sdng', 'HdBoard', 'BrkFace', 'WdShin
g', 'CemntBd', 'Plywood', 'AsbShng', 'Stucco', 'BrkComm', 'AsphShn', 'Stone', 'ImStu
cc', 'CBlock']
Exterior2nd(train): ['VinylSd', 'MetalSd', 'Wd Shng', 'HdBoard', 'Plywood', 'Wd Sdn
g', 'CmentBd', 'BrkFace', 'Stucco', 'AsbShng', 'Brk Cmn', 'ImStucc', 'AsphShn', 'Sto
ne', 'Other', 'CBlock']
Exterior1st(test): ['VinylSd', 'Wd Sdng', 'HdBoard', 'Plywood', 'MetalSd', 'CemntB
d', 'WdShing', 'BrkFace', 'AsbShng', 'BrkComm', 'Stucco', 'AsphShn', nan, 'CBlock']
Exterior2nd(test): ['VinylSd', 'Wd Sdng', 'HdBoard', 'Plywood', 'MetalSd', 'Brk Cm
n', 'CmentBd', 'ImStucc', 'Wd Shng', 'AsbShng', 'Stucco', 'CBlock', 'BrkFace', 'Asph
Shn', nan, 'Stone']

 After fixing:
Exterior2nd(train): ['VinylSd', 'MetalSd', 'WdShing', 'HdBoard', 'Plywood', 'Wd Sdn
g', 'CemntBd', 'BrkFace', 'Stucco', 'AsbShng', 'BrkComm', 'ImStucc', 'AsphShn', 'Sto
ne', 'Other', 'CBlock']
Exterior2nd(test): ['VinylSd', 'Wd Sdng', 'HdBoard', 'Plywood', 'MetalSd', 'BrkCom
m', 'CemntBd', 'ImStucc', 'WdShing', 'AsbShng', 'Stucco', 'CBlock', 'BrkFace', 'Asph
Shn', 'Other', 'Stone']
```

1.2 Functions for data transformation

In [121…

```python
# Transform each categorical column to multiple columns
def to_categorical(arg,vect_len):
    vect = np.zeros(vect_len)
    vect[int(arg)] = 1.0
    return vect
```

1.2.1 Function to transfer data to categorial

In [122…

```python
#d - input original value (string)
#dVar - np-array of all variants for that data
def categ_trans(d, dVar):
    dVar = list(dVar)
    #Find an index of the value in all variants array
    if d in dVar:
        ind = dVar.index(d)
        #one hot encoding
        ind = to_categorical(ind, len(dVar))
    else:
        ind = np.zeros(len(dVar))
    return ind
```

1.2.2 Function to transfer multiple-choice data to categorial

In [123…

```python
def categ_mult_trans(d,dVar):
    dVar = list(dVar)
    vect = np.zeros(len(dVar))
    for val in d:
        vect[dVar.index(val)] = 1
    return vect
```

1.2.3 Function to transfer original construction date (YearBuilt) into several categories

In [124…

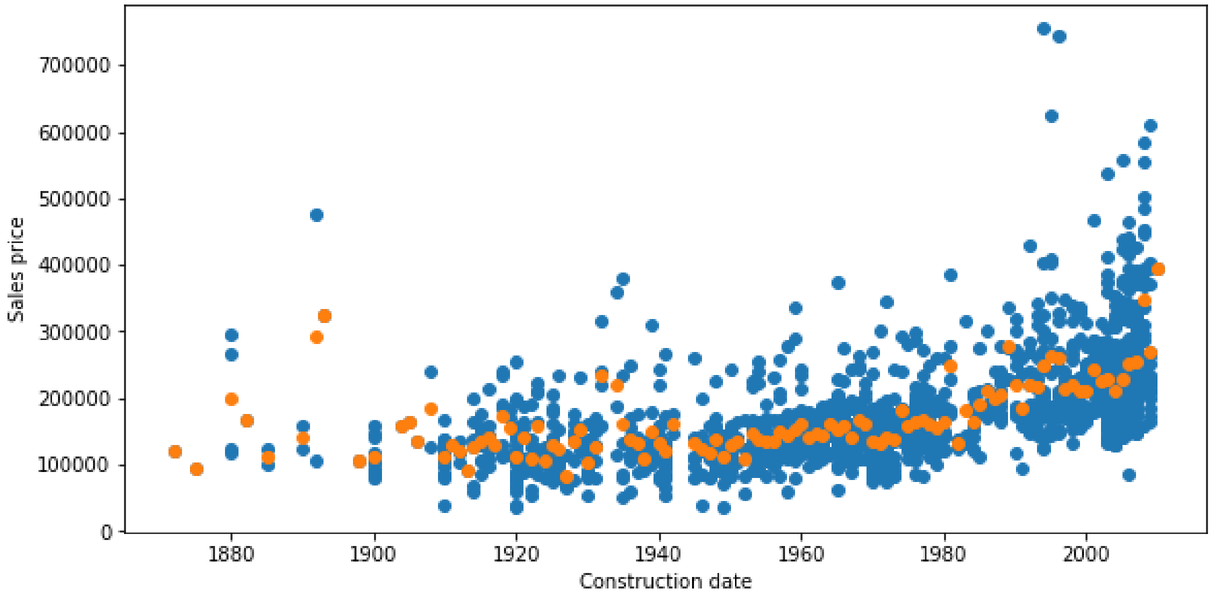
```python
#First, look on the data
plt.figure(figsize=(10,5))

# mean sale price within each constrution year
y_mean = []
x_mean = list(data.YearBuilt.unique())
```

```
for year in x_mean:
    y_mean.append(data[data.YearBuilt == year].SalePrice.mean())

y = data.SalePrice
x = data.YearBuilt
plt.scatter(x, y)
plt.scatter(x_mean, y_mean)
plt.xlabel('Construction date')
plt.ylabel('Sales price')
plt.xlim(plt.xlim())
plt.ylim(plt.ylim())
plt.show()

# According to the graph below, let's create the following 13 categories
def year_categ(year):
    if year <= 1900:
        return [1.0,0,0,0,0,0,0,0,0,0,0,0,0]
    if (year >= 1901) & (year <= 1930):
        return [0,1.0,0,0,0,0,0,0,0,0,0,0,0]
    if (year >= 1931) & (year <= 1950):
        return [0,0,1.0,0,0,0,0,0,0,0,0,0,0]
    if (year >= 1951) & (year <= 1957):
        return [0,0,0,1.0,0,0,0,0,0,0,0,0,0]
    if (year >= 1958) & (year <= 1967):
        return [0,0,0,0,1.0,0,0,0,0,0,0,0,0]
    if (year >= 1968) & (year <= 1972):
        return [0,0,0,0,0,1.0,0,0,0,0,0,0,0]
    if (year >= 1973) & (year <= 1975):
        return [0,0,0,0,0,0,1.0,0,0,0,0,0,0]
    if (year >= 1976) & (year <= 1981):
        return [0,0,0,0,0,0,0,1.0,0,0,0,0,0]
    if (year >= 1982) & (year <= 1985):
        return [0,0,0,0,0,0,0,0,1.0,0,0,0,0]
    if (year >= 1986) & (year <= 1989):
        return [0,0,0,0,0,0,0,0,0,1.0,0,0,0]
    if (year >= 1990) & (year <= 1999):
        return [0,0,0,0,0,0,0,0,0,0,1.0,0,0]
    if (year >= 2000) & (year <= 2006):
        return [0,0,0,0,0,0,0,0,0,0,0,1.0,0]
    if year >= 2007:
        return [0,0,0,0,0,0,0,0,0,0,0,0,1.0]
```



1.2.4 Function to transfer Remodel date (YearRemodAdd) into several categories

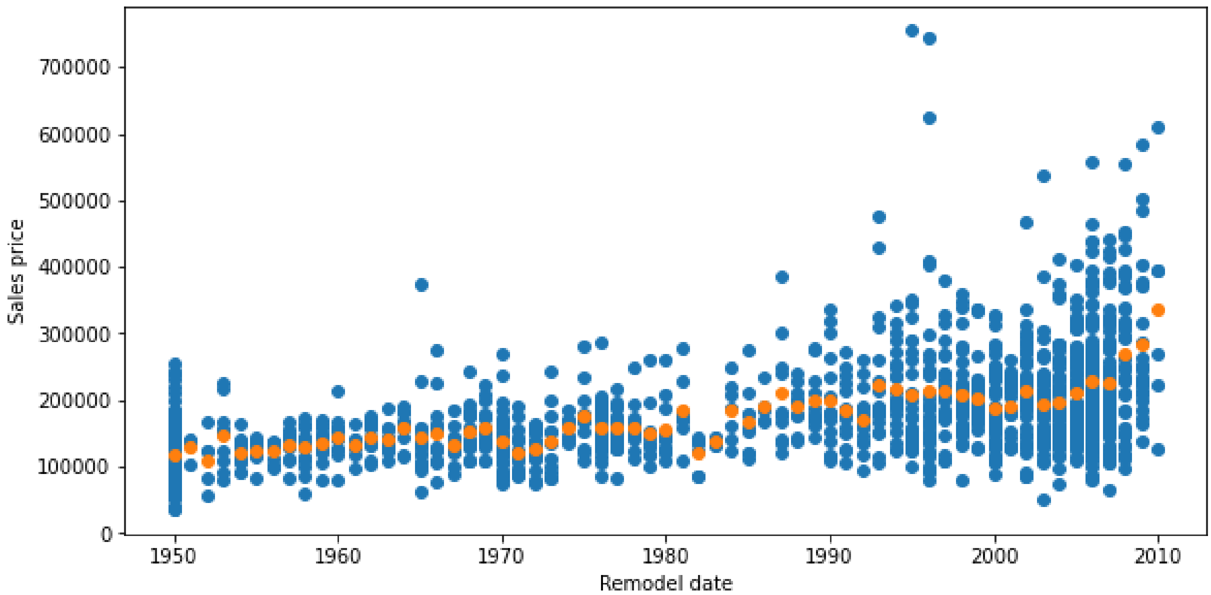
In [125…

```
#First, look on the data
plt.figure(figsize=(10,5))

# mean sale price within each remodel year
y_mean = []
x_mean = list(data.YearRemodAdd.unique())
for year in x_mean:
    y_mean.append(data[data.YearRemodAdd == year].SalePrice.mean())

y = data.SalePrice
x = data.YearRemodAdd
plt.scatter(x, y)
plt.scatter(x_mean, y_mean)
plt.xlabel('Remodel date')
plt.ylabel('Sales price')
plt.xlim(plt.xlim())
plt.ylim(plt.ylim())
plt.show()

# According to the graph below, let's create the following 4 categories
def Ryear_categ(year):
    if year <= 1980:
        return [1.0,0,0,0]
    if (year >= 1981) & (year <= 1990):
        return [0,1.0,0,0]
    if (year >= 1991) & (year <= 2000):
        return [0,0,1.0,0]
    if year >= 2001:
        return [0,0,0,1.0]
```



1.2.5 Function to transfer Total rooms above grade excluding bathrooms (TotRmsAbvGrd) into several categories

In [126…

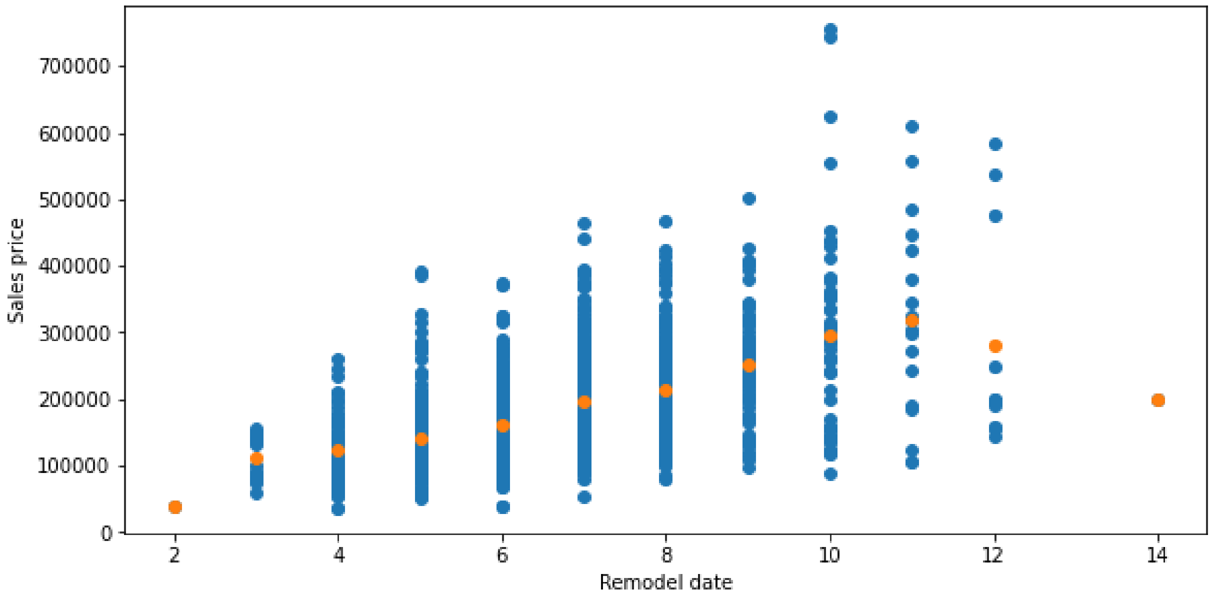
```
#First, look on the data
plt.figure(figsize=(10,5))

# mean sale price within each number of rooms
y_mean = []
x_mean = list(np.sort(data.TotRmsAbvGrd.unique()))
for room in x_mean:
    y_mean.append(data[data.TotRmsAbvGrd == room].SalePrice.mean())

y = data.SalePrice
x = data.TotRmsAbvGrd
plt.scatter(x, y)
```

```
plt.scatter(x_mean, y_mean)
plt.xlabel('Remodel date')
plt.ylabel('Sales price')
plt.xlim(plt.xlim())
plt.ylim(plt.ylim())
plt.show()

# According to the graph below, let's create the following 10 categories
def Rooms_categ(room):
    if room == 2:
        return [1.0,0,0,0,0,0,0,0,0,0,0]
    if room == 3 or room == 4:
        return [0,1.0,0,0,0,0,0,0,0,0,0]
    if room == 5:
        return [0,0,1.0,0,0,0,0,0,0,0,0]
    if room == 6:
        return [0,0,0,1.0,0,0,0,0,0,0,0]
    if room == 7:
        return [0,0,0,0,1.0,0,0,0,0,0,0]
    if room == 8:
        return [0,0,0,0,0,1.0,0,0,0,0,0]
    if room == 9:
        return [0,0,0,0,0,0,1.0,0,0,0,0]
    if room == 10:
        return [0,0,0,0,0,0,0,1.0,0,0,0]
    if room == 11:
        return [0,0,0,0,0,0,0,0,1.0,0,0]
    if room >= 12:
        return [0,0,0,0,0,0,0,0,0,1.0,0]
```



1.2.6 Function to transfer Number of fireplaces (Fireplaces) into several categories

In [127…

```
def Fire_categ(arg):
    if arg == 0:
        return [1.0, 0, 0, 0]
    if arg == 1:
        return [0, 1.0, 0, 0]
    if arg == 2:
        return [0, 0, 1.0, 0]
    if arg >= 3:
        return [0, 0, 0, 1.0]
```

1.2.7 Function to transfer Year garage was built (GarageYrBlt) into several categories

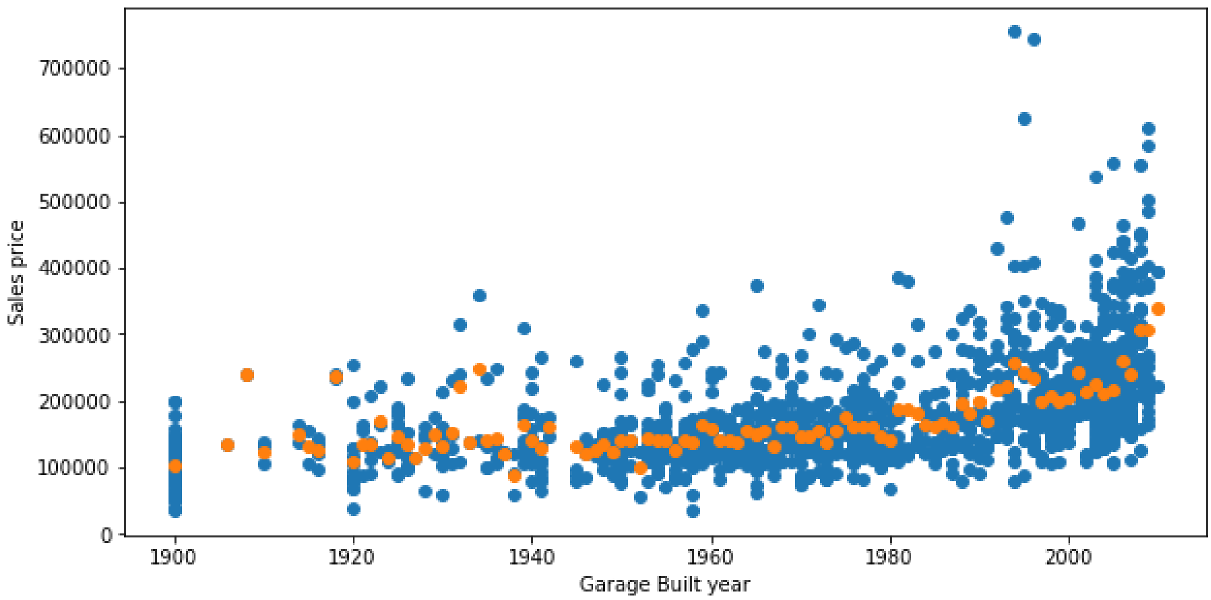
In [128…

```
#First, look on the data
plt.figure(figsize=(10,5))

# mean sale price within each remodel year
y_mean = []
x_mean = list(data.GarageYrBlt.unique())
for year in x_mean:
    y_mean.append(data[data.GarageYrBlt == year].SalePrice.mean())

y = data.SalePrice
x = data.GarageYrBlt
plt.scatter(x, y)
plt.scatter(x_mean, y_mean)
plt.xlabel('Garage Built year')
plt.ylabel('Sales price')
plt.xlim(plt.xlim())
plt.ylim(plt.ylim())
plt.show()

# According to the graph below, let's create the following 6 categories
def Gar_year_categ(year):
    if year <= 1960:
        return [1.0,0,0,0,0,0]
    if (year >= 1961) & (year <= 1980):
        return [0,1.0,0,0,0,0]
    if (year >= 1981) & (year <= 1990):
        return [0,0,1.0,0,0,0]
    if (year >= 1991) & (year <= 2000):
        return [0,0,0,1.0,0,0]
    if (year >= 2001) & (year <= 2005):
        return [0,0,0,0,1.0,0]
    if year >= 2006:
        return [0,0,0,0,0,1.0]
```



1.2.8 Function to transfer Size of garage in car capacity (GarageCars) into several categories

In [129…

```
def Gar_car_categ(arg):
    if arg == 0:
        return [1.0, 0, 0, 0, 0]
    if arg == 1:
        return [0, 1.0, 0, 0, 0]
    if arg == 2:
        return [0, 0, 1.0, 0, 0]
    if arg == 3:
```

```
        return [0, 0, 0, 1.0, 0]
    if arg > 3:
        return [0, 0, 0, 0, 1.0]
```

1.2.9 Function to join all transformed parameters together

In [130…

```
def getAllParameters(d):
    MSSubClass = categ_trans(d.MSSubClass,data.MSSubClass.unique())
    MSZoning = categ_trans(d.MSZoning,data.MSZoning.unique())
    Street = categ_trans(d.Street,data.Street.unique())
    Alley = categ_trans(d.Alley,data.Alley.unique())
    LotShape = categ_trans(d.LotShape,data.LotShape.unique())
    LandContour = categ_trans(d.LandContour,data.LandContour.unique())
    Utilities = categ_trans(d.Utilities,data.Utilities.unique())
    LotConfig = categ_trans(d.LotConfig,data.LotConfig.unique())
    LandSlope = categ_trans(d.LandSlope,data.LandSlope.unique())
    Neighborhood = categ_trans(d.Neighborhood,data.Neighborhood.unique())
    Condition = categ_mult_trans([d.Condition1] + [d.Condition2],data.Condition1.uni
    BldgType  = categ_trans(d.BldgType,data.BldgType.unique())
    HouseStyle = categ_trans(d.HouseStyle,data.HouseStyle.unique())
    OverallQual = categ_trans(d.OverallQual,np.sort(data.OverallQual.unique()))
    OverallCond = categ_trans(d.OverallCond,np.sort(data.OverallCond.unique()))
    YearBuilt = year_categ(d.YearBuilt)
    YearRemodAdd = Ryear_categ(d.YearRemodAdd)
    RoofStyle = categ_trans(d.RoofStyle,data.RoofStyle.unique())
    RoofMatl = categ_trans(d.RoofMatl,data.RoofMatl.unique())
    Exterior = categ_mult_trans([d.Exterior1st] + [d.Exterior2nd],data.Exterior2nd.u
    MasVnrType = categ_trans(d.MasVnrType,data.MasVnrType.unique())
    ExterQual = categ_trans(d.ExterQual,data.ExterQual.unique())
    ExterCond = categ_trans(d.ExterCond,data.ExterCond.unique())
    Foundation = categ_trans(d.Foundation,data.Foundation.unique())
    BsmtQual = categ_trans(d.BsmtQual,data.BsmtQual.unique())
    BsmtCond = categ_trans(d.BsmtCond,data.BsmtCond.unique())
    BsmtExposure = categ_trans(d.BsmtExposure,data.BsmtExposure.unique())
    BsmtFinType1 = categ_trans(d.BsmtFinType1,data.BsmtFinType1.unique())
    BsmtFinType2 = categ_trans(d.BsmtFinType2,data.BsmtFinType2.unique())
    Heating = categ_trans(d.Heating,data.Heating.unique())
    HeatingQC = categ_trans(d.HeatingQC,data.HeatingQC.unique())
    CentralAir = categ_trans(d.CentralAir,data.CentralAir.unique())
    Electrical = categ_trans(d.Electrical,data.Electrical.unique())
    BsmtFullBath = categ_trans(d.BsmtFullBath,np.sort(data.BsmtFullBath.unique()))
    BsmtHalfBath = categ_trans(d.BsmtHalfBath,np.sort(data.BsmtHalfBath.unique()))
    FullBath = categ_trans(d.FullBath,np.sort(data.FullBath.unique()))
    HalfBath = categ_trans(d.HalfBath,np.sort(data.HalfBath.unique()))
    BedroomAbvGr = categ_trans(d.BedroomAbvGr,np.sort(data.BedroomAbvGr.unique()))
    KitchenAbvGr = categ_trans(d.KitchenAbvGr,np.sort(data.KitchenAbvGr.unique()))
    KitchenQual = categ_trans(d.KitchenQual,data.KitchenQual.unique())
    TotRmsAbvGrd = Rooms_categ(d.TotRmsAbvGrd)
    Functional = categ_trans(d.Functional,data.Functional.unique())
    Fireplaces = Fire_categ(d.Fireplaces)
    FireplaceQu = categ_trans(d.FireplaceQu,data.FireplaceQu.unique())
    GarageType = categ_trans(d.GarageType,data.GarageType.unique())
    GarageYrBlt = Gar_year_categ(d.GarageYrBlt)
    GarageFinish = categ_trans(d.GarageFinish,data.GarageFinish.unique())
    GarageCars = Gar_car_categ(d.GarageCars)
    GarageQual = categ_trans(d.GarageQual,data.GarageQual.unique())
    GarageCond = categ_trans(d.GarageCond,data.GarageCond.unique())
    PavedDrive = categ_trans(d.PavedDrive,data.PavedDrive.unique())
    PoolQC = categ_trans(d.PoolQC,data.PoolQC.unique())
    Fence = categ_trans(d.Fence,data.Fence.unique())
    MiscFeature = categ_trans(d.MiscFeature,data.MiscFeature.unique())
    MiscVal = categ_trans(d.MiscVal,data.MiscVal.unique())
    MoSold = categ_trans(d.MoSold,data.MoSold.unique())
```

```
    YrSold = categ_trans(d.YrSold,np.sort(data.YrSold.unique()))
    SaleType = categ_trans(d.SaleType,data.SaleType.unique())
    SaleCondition = categ_trans(d.SaleCondition,data.SaleCondition.unique())

    out = list(MSSubClass)
    out.extend(MSZoning)
    out.append(d.LotFrontage)
    out.append(d.LotArea)
    out.extend(Street)
    out.extend(Alley)
    out.extend(LotShape)
    out.extend(LandContour)
    out.extend(Utilities)
    out.extend(LotConfig)
    out.extend(LandSlope)
    out.extend(Neighborhood)
    out.extend(Condition)
    out.extend(BldgType)
    out.extend(HouseStyle)
    out.extend(OverallQual)
    out.extend(OverallCond)
    out.extend(YearBuilt)
    out.extend(YearRemodAdd)
    out.extend(RoofStyle)
    out.extend(RoofMatl)
    out.extend(Exterior)
    out.extend(MasVnrType)
    out.append(d.MasVnrArea)
    out.extend(ExterQual)
    out.extend(ExterCond)
    out.extend(Foundation)
    out.extend(BsmtQual)
    out.extend(BsmtCond)
    out.extend(BsmtExposure)
    out.extend(BsmtFinType1)
    out.append(d.BsmtFinSF1)
    out.extend(BsmtFinType2)
    out.append(d.BsmtFinSF2)
    out.append(d.BsmtUnfSF)
    out.append(d.TotalBsmtSF)
    out.extend(Heating)
    out.extend(HeatingQC)
    out.extend(CentralAir)
    out.extend(Electrical)
    out.append(d['1stFlrSF'])
    out.append(d['2ndFlrSF'])
    out.append(d.LowQualFinSF)
    out.append(d.GrLivArea)
    out.extend(BsmtFullBath)
    out.extend(BsmtHalfBath)
    out.extend(FullBath)
    out.extend(HalfBath)
    out.extend(BedroomAbvGr)
    out.extend(KitchenAbvGr)
    out.extend(KitchenQual)
    out.extend(TotRmsAbvGrd)
    out.extend(Functional)
    out.extend(Fireplaces)
    out.extend(FireplaceQu)
    out.extend(GarageType)
    out.extend(GarageYrBlt)
    out.extend(GarageFinish)
    out.extend(GarageCars)
    out.append(d.GarageArea)
```

```
    out.extend(GarageQual)
    out.extend(GarageCond)
    out.extend(PavedDrive)
    out.append(d.WoodDeckSF)
    out.append(d.OpenPorchSF)
    out.append(d.EnclosedPorch)
    out.append(d['3SsnPorch'])
    out.append(d.ScreenPorch)
    out.append(d.PoolArea)
    out.extend(PoolQC)
    out.extend(Fence)
    out.extend(MiscFeature)
    out.extend(MiscVal)
    out.extend(MoSold)
    out.extend(YrSold)
    out.extend(SaleType)
    out.extend(SaleCondition)
    return out
```

In [131…

```
# Check of the final function getAllParameters() which join all transformed paramete

testlist = getAllParameters(data.iloc[2])
col_list = list(data.columns)
col_list.remove('Id')
#remove number-type noncategorial columns
col_list.remove('LotFrontage')
col_list.remove('LotArea')
col_list.remove('MasVnrArea')
col_list.remove('BsmtFinSF1')
col_list.remove('BsmtFinSF2')
col_list.remove('BsmtUnfSF')
col_list.remove('TotalBsmtSF')
col_list.remove('1stFlrSF')
col_list.remove('2ndFlrSF')
col_list.remove('LowQualFinSF')
col_list.remove('GrLivArea')
col_list.remove('GarageArea')
col_list.remove('WoodDeckSF')
col_list.remove('OpenPorchSF')
col_list.remove('EnclosedPorch')
col_list.remove('3SsnPorch')
col_list.remove('ScreenPorch')
col_list.remove('PoolArea')
#remove double columns
col_list.remove('Condition2')
col_list.remove('Exterior1st')
#remove columns where the original data was transformed to categorial
col_list.remove('FullBath')
col_list.remove('YearBuilt')
col_list.remove('YearRemodAdd')
col_list.remove('TotRmsAbvGrd')
col_list.remove('Fireplaces')
col_list.remove('GarageYrBlt')
col_list.remove('GarageCars')
#remove the target column
col_list.remove('SalePrice')

# Removed colums give the total dimension:
add_dim = 18 + 4 + 13 + 4 + 10 + 4 + 6 + 5
# Calculate the total dimension of the rest columns
dim = 0
for col in col_list:
    dim += data[col].unique().shape[0]
```

```
# Are the dimensions the same?
dim+add_dim == len(testlist)
```

Out[131…
```
True
```

1.3 Make the transformation of all the data

In [24]:
```
# X,y     = data taken from data_train.csv
# X_pred = data taken from data_test.csv
```

In [132…
```
%%time
i = 0
X = []
X_pred = []
for i in range(max(data.shape[0],data_test.shape[0])):
    if i < data.shape[0]:
        X.append(getAllParameters(data.iloc[i]))
    if i < data_test.shape[0]:
        X_pred.append(getAllParameters(data_test.iloc[i]))
    i += 1

# Make a column of the target feature
y = data.SalePrice

print(len(X[123]))
print(len(X_pred[123]))
```

```
402
402
Wall time: 44.6 s
```

In [133…
```
# Split the data which are targeted for building a model into test and train dataset
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state =
```

In [134…
```
# Normalization of the data
xScaler = StandardScaler()
xScaler.fit(X_train)
X_train_scl = xScaler.transform(X_train)
X_test_scl = xScaler.transform(X_test)
X_scl = xScaler.transform(X)

yScaler = StandardScaler()
yScaler.fit(np.array(y_train).reshape(-1,1))
y_train_scl = yScaler.transform(np.array(y_train).reshape(-1,1)).flatten()
y_test_scl = yScaler.transform(np.array(y_test).reshape(-1,1)).flatten()
y_scl = yScaler.transform(np.array(y).reshape(-1,1)).flatten()
```

In [135…
```
print("The mean value of some standartized column of X-matrix: ",np.mean(X_test_scl[
print("The mean value of standartized y: ",np.mean(y_test_scl))
print("The standard deviation of some standartized column of X-matrix: ",np.std(X_te
print("The standard deviation of standartized y: ",np.std(y_test_scl))
```

```
The mean value of some standartized column of X-matrix:  -0.013069817382308425
The mean value of standartized y:  0.059598526916780366
The standard deviation of some standartized column of X-matrix:  0.968852710487984
The standard deviation of standartized y:  1.0315398340950754
```

2. Linear Regression Model: ElasticNet

In [ ]:

```
%%time
warnings.filterwarnings('ignore')
# Fit the optimal model parameters
alphas = np.arange(0.1,1.1,0.1)
l1_ratios = np.arange(0.0,1.1,0.1)
min_err = np.inf
for alpha in alphas:
    for L1r in l1_ratios:
        regressor = ElasticNet(alpha=alpha, l1_ratio=L1r)
        regressor.fit(X_train_scl, y_train_scl)
        prediction = regressor.predict(X_test_scl)
        # denormalization of the prediction
        y_predict = yScaler.inverse_transform(prediction).flatten()
        # prediction error
        diff = np.abs(y_predict - y_test)
        pred_err = diff.sum()
        if pred_err < min_err:
            min_err = pred_err
            best_par = [alpha, L1r]
            best_model = regressor
        print("Alpha: {:.1f}, L1 ratio: {:.1f}, prediction abs error: {:.0f}".format
```

In [33]:

```
print("The best model of ElasticNet has alpha =",best_par[0],"and L1 ratio =",best_p
```

```
The best model of ElasticNet has alpha = 0.1 and L1 ratio = 0.1
```

In [34]:

```
regressor = ElasticNet(alpha=best_par[0], l1_ratio=best_par[1], max_iter=10000)
regressor.fit(X_train_scl, y_train_scl)
# make prediction on the test dataset
prediction = regressor.predict(X_test_scl)
# prediction de-scaling
y_predict = yScaler.inverse_transform(prediction).flatten()
```

In [35]:

```
mean_price = np.mean(y_test)
mean_delta = np.mean(abs(y_predict - y_test))
print('The mean house price on the test dataset: ', round(mean_price))
print('The mean prediction error on the test dataset: ', round(mean_delta))
print('The mean relative error: ', round(100*mean_delta/mean_price), '%', sep='')
```

```
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  15906
The mean relative error: 9%
```

In [36]:

```
# Predict on the estimated dataset
X_pred_scl = xScaler.transform(X_pred)
y_pred_estimated_unscaled = regressor.predict(X_pred_scl)
y_pred_estimated = yScaler.inverse_transform(y_pred_estimated_unscaled).flatten()
```

In [35]:

```
# Put the result in file to upload to KAGGLE
Final_table = pd.DataFrame(columns=["Id","SalePrice"])
for i in range(1461,2920):
    Final_table.loc[i-1461] = [int(i), y_pred_estimated[i-1461]]
Final_table = Final_table.astype({"Id": int})
Final_table.set_index('Id',inplace=True)
```

```
Final_table.head()
Final_table.to_csv('Data\HousesSale_Regr.csv',sep=',',header=True)
```

Out[35]:

	SalePrice
Id	
1461	123765.655348
1462	162727.703856
1463	188766.689191
1464	195219.206672
1465	209246.406694

3. The gradient boosting XGBoost

3.0 Select the hyperparameters manually

In [37]:

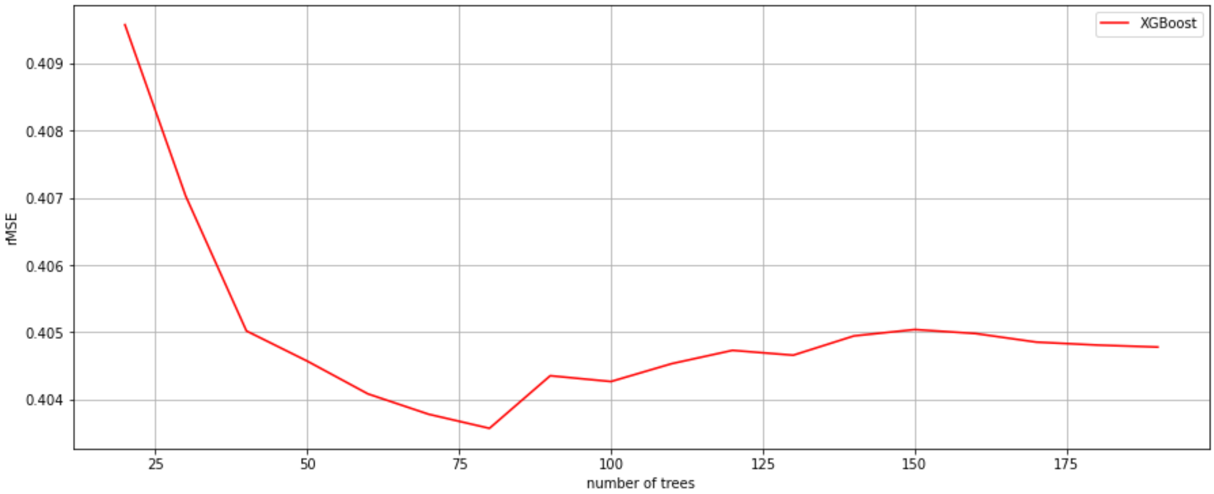
```
%%time
# First seek the enough number of Trees

n_est = np.arange(20, 200, 10)
score = []
for n in n_est:
    print(n)
    est = xgb.XGBRegressor(max_depth=5, n_estimators=n)
    answer = model_selection.cross_val_predict(estimator=est, X=X_train_scl, y = y_t
    score.append(metrics.mean_squared_error(y_train_scl, answer)**0.5)
```

```
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
190
Wall time: 2min 57s
```

In [38]:

```
plt.figure(figsize=(15,6))
plt.plot(n_est, score, color='r', label="XGBoost")
plt.legend()
plt.xlabel("number of trees")
plt.ylabel("rMSE")
plt.grid()
```

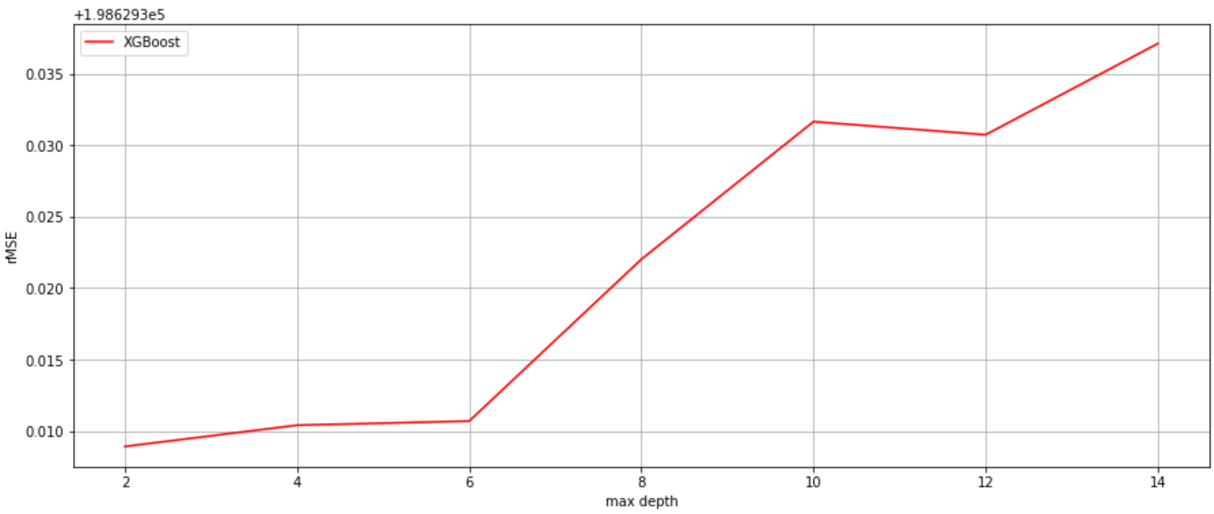


In [39]:
```
# You can see that the optimal number of Trees is ~80
```

In [40]:
```
%%time
# Now seek the optimal depth on the selected above number of Trees
len = np.arange(2, 16, 2)
score = []
for d in len:
    print(d)
    est = xgb.XGBRegressor(max_depth=d, n_estimators=80)
    ans = model_selection.cross_val_predict(estimator=est, X=X_train_scl, y=y_train_
    score.append(metrics.mean_squared_error(y_train, ans)**0.5)
```

```
2
4
6
8
10
12
14
Wall time: 2min 57s
```

In [41]:
```
plt.figure(figsize=(15,6))
plt.plot(len, score, color='r', label="XGBoost")
plt.legend()
plt.xlabel("max depth")
plt.ylabel("rMSE")
plt.grid()
```



In [37]:
```
# early_stopping_rounds - overwork prevention: early break if there is no improvemen
# learning_rate - control the input of each Tree in the ensamble
# subsample - the percentage of random subsample used for training of each Tree
def XGB_fit(max_depth=4, n_estimators=80, learning_rate = 0.12, subsample=1.0):
    XGB_opt = xgb.XGBRegressor(max_depth=max_depth, n_estimators=n_estimators, learn
    XGB_opt.fit(X_train_scl, y_train_scl)
    prediction = XGB_opt.predict(X_test_scl)
    y_predict = yScaler.inverse_transform(prediction).flatten()

    mean_price = np.mean(y_test)
    mean_delta = np.mean(abs(y_predict - y_test))
    print('The mean house price on the test dataset: ', round(mean_price))
    print('The mean prediction error on the test dataset: ', round(mean_delta))
    print('The mean relative error: ', round(100*mean_delta/mean_price), '%', sep=''
```

In [38]:
```
# prediction de-scaling
for ss in np.arange(0.1,1.1,0.1):
    print("Subsample: {:.2f}".format(ss))
    XGB_fit(learning_rate = 0.09, subsample=ss)
```

```
Subsample: 0.10
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  19059
The mean relative error: 10%
Subsample: 0.20
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18827
The mean relative error: 10%
Subsample: 0.30
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  19688
The mean relative error: 11%
Subsample: 0.40
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18610
The mean relative error: 10%
Subsample: 0.50
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  17572
The mean relative error: 10%
Subsample: 0.60
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18506
The mean relative error: 10%
Subsample: 0.70
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18672
The mean relative error: 10%
Subsample: 0.80
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18441
The mean relative error: 10%
Subsample: 0.90
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18201
The mean relative error: 10%
Subsample: 1.00
The mean house price on the test dataset:  184683
The mean prediction error on the test dataset:  18536
The mean relative error: 10%
```

3.1 Select hyperparameters based on Genetics

In [175…

```
%%time
n = 40 # the population size
nsurv = int(0.2*n) # the size of the survived botes in population
nnew = n - nsurv # the number of new botes (after keeping the best 'nsurv' botes)
l = 6 # the length of bote (number of features)
epohs = 30 # number of epochs (how many times we change population)

popul = initilialize_poplulation(n) # Creates random population: [n, l] matrix

for it in range(epohs):
    val = [] # 1-dimension array of the model precision (or error for regression pro

    for i in range(n):
        bot = popul[i] # the current bote

        # run the model on the features from the current bote
        XGB_i = xgb.XGBRegressor(
            learning_rate=bot[0],
            n_estimators=int(bot[1]),
            max_depth=int(bot[2]),
            min_child_weight=bot[3],
            gamma=bot[4],
            subsample=bot[5])
        XGB_i.fit(X_train_scl, y_train_scl)

        #prediction = XGB_i.predict(X_test_scl)
        #y_predict = yScaler.inverse_transform(prediction).flatten()
        #val.append(round(mean_absolute_error(y_predict, y_test),1))

        # Make cross-validation of the builded model
        kfold = model_selection.KFold(n_splits=10,random_state=1,shuffle=True)
        K_results = model_selection.cross_val_score(XGB_i,X_scl,y_scl,cv=kfold)
        # calculate the mean accuracy on the cross-validation
        accuracy = np.mean(abs(K_results))
        if accuracy > 1:
            print('ups...accuracy=',accuracy)
            accuracy = 0.2
        # add the prediction score for the current bote based on cross-validation ac
        val.append(round(accuracy,4))

    newpopul, sval = getSurvPopul(popul, val, nsurv) # Get the survived botes of pop
    print(it, " ", [round(s,8) for s in sval[0:6]]) # print scores for 6 best botes

    for i in range(nnew): # run cycle 'n-nsurv' times to fill the rest of the new po
        botp1, botp2 = getParents(newpopul, nsurv) # Get from the survived botes-pop
        newbot = [] # set new bote which will be borned from the choosen parents abo
        # each feature of the new bote is crossing the features of the parents
        for j in range(l):
            # j-th feature of the new bote:
            x = crossPointFrom2Parents(botp1, botp2, j)
            newbot.append(x)
        #Introduce mutation in a random feature of the borned bote
        j_mut = np.random.randint(0, l)
        newbot[j_mut] = mutation(j_mut,newbot[j_mut],l)
        newpopul.append(newbot) # Add this bote in new population of the survived bo
        #so we finally add 'n-nsurv' new borned botes to the survived botes

    popul = newpopul # Write the new created population in 'popul'
```

```
0   [0.8772, 0.8513, 0.8495, 0.8207, 0.8205, 0.8172]
1   [0.8772, 0.8631, 0.8573, 0.8523, 0.8513, 0.8495]
2   [0.8772, 0.8719, 0.8692, 0.8676, 0.8673, 0.8672]
3   [0.8772, 0.8754, 0.8753, 0.8749, 0.8742, 0.8736]
4   [0.8787, 0.8786, 0.8772, 0.8766, 0.8764, 0.8763]
```

```
5   [0.8787, 0.8786, 0.8781, 0.8779, 0.8773, 0.8772]
6   [0.8802, 0.8799, 0.8791, 0.8787, 0.8786, 0.8781]
7   [0.8837, 0.8815, 0.8813, 0.8802, 0.8799, 0.8793]
8   [0.8837, 0.8837, 0.8836, 0.8833, 0.8818, 0.8815]
9   [0.8837, 0.8837, 0.8837, 0.8836, 0.8833, 0.8829]
10   [0.8847, 0.8842, 0.8839, 0.8837, 0.8837, 0.8837]
11   [0.8847, 0.8846, 0.8842, 0.8839, 0.8838, 0.8837]
12   [0.885, 0.8847, 0.8846, 0.8846, 0.8846, 0.8842]
13   [0.885, 0.8849, 0.8847, 0.8846, 0.8846, 0.8846]
14   [0.8861, 0.8855, 0.885, 0.8849, 0.8847, 0.8846]
15   [0.8861, 0.8861, 0.8855, 0.885, 0.8849, 0.8847]
16   [0.8885, 0.8867, 0.8867, 0.8861, 0.8861, 0.8861]
17   [0.8885, 0.8867, 0.8867, 0.8867, 0.8861, 0.8861]
18   [0.8885, 0.8885, 0.8884, 0.8876, 0.8871, 0.8871]
19   [0.8885, 0.8885, 0.8884, 0.8876, 0.8871, 0.8871]
20   [0.8885, 0.8885, 0.8885, 0.8885, 0.8884, 0.8876]
21   [0.8887, 0.8887, 0.8886, 0.8885, 0.8885, 0.8885]
22   [0.8887, 0.8887, 0.8887, 0.8887, 0.8887, 0.8886]
23   [0.8887, 0.8887, 0.8887, 0.8887, 0.8887, 0.8887]
24   [0.8888, 0.8888, 0.8888, 0.8887, 0.8887, 0.8887]
25   [0.8888, 0.8888, 0.8888, 0.8888, 0.8888, 0.8887]
26   [0.8888, 0.8888, 0.8888, 0.8888, 0.8888, 0.8888]
27   [0.8888, 0.8888, 0.8888, 0.8888, 0.8888, 0.8888]
28   [0.8888, 0.8888, 0.8888, 0.8888, 0.8888, 0.8888]
29   [0.8888, 0.8888, 0.8888, 0.8888, 0.8888, 0.8888]
Wall time: 1d 3h 38min 51s
```

In [176…

```
#print the features of the best bote
best_bot = popul[0]
print("Learning rate = ",best_bot[0])
print("Trees number = ",best_bot[1])
print("Max depth = ",best_bot[2])
print("min_child_weight = ",best_bot[3])
print("gamma = ",best_bot[4])
print("subsample = ",best_bot[5])
```

```
Learning rate =  0.06
Trees number =  907.0
Max depth =  5.0
min_child_weight =  8.71
gamma =  0.01
subsample =  0.73
```

In [177…

```
# run the model on the features of the best bote
XGB_best = xgb.XGBRegressor(
            learning_rate=best_bot[0],
            n_estimators=int(best_bot[1]),
            max_depth=int(best_bot[2]),
            min_child_weight=best_bot[3],
            gamma=best_bot[4],
            subsample=best_bot[5])
XGB_best.fit(X_train_scl, y_train_scl)

kfold = model_selection.KFold(n_splits=10,random_state=1,shuffle=True)
K_results = model_selection.cross_val_score(XGB_best,X_scl,y_scl,cv=kfold)
accuracy = np.mean(abs(K_results))
print("Accuracy on cross-validation for the best model: ",accuracy)
```

```
Accuracy on cross-validation for the best model:  0.888770301559821
```

In [136…

```
# run the model on the default features (for comparison)
XGB_default = xgb.XGBRegressor()
```

```
XGB_default.fit(X_train_scl, y_train_scl)

kfold = model_selection.KFold(n_splits=10,random_state=1,shuffle=True)
K_results = model_selection.cross_val_score(XGB_default,X_scl,y_scl,cv=kfold)
accuracy = np.mean(abs(K_results))
print("Accuracy on cross-validation for the default model: ",accuracy)
```

```
Точность по кросс-валидации:  0.8583988745747231
```

In [178…

```
# Prediction on the data from KAGGLE competition
X_pred_scl = xScaler.transform(X_pred)
y_pred_estimated_unscaled = XGB_best.predict(X_pred_scl)
y_pred_estimated = yScaler.inverse_transform(y_pred_estimated_unscaled).flatten()
Final_table = pd.DataFrame(columns=["Id","SalePrice"])
for i in range(1461,2920):
    Final_table.loc[i-1461] = [int(i), y_pred_estimated[i-1461]]
Final_table = Final_table.astype({"Id": int})
Final_table.set_index('Id',inplace=True)
Final_table.head()
```

Out[178…

	SalePrice
Id	
1461	123965.960938
1462	169039.906250
1463	190272.546875
1464	193199.031250
1465	186994.890625

In [179…

```
Final_table.to_csv('Data\HousesSale_XGB_gen.csv',sep=',',header=True)
```

4. RandomForest

In [176…

```
# Ф-ция создания случайного бота (для мутаций)

# Создаем м-цу: numberOfParents x 6 (6 - кол-во элементов бота)
# criterion - критерии ошибки для минимизации (в классификации “gini” и “entropy”)
# max_depth - максимальная глубина деревьев
# min_samples_leaf - ограничение на число объектов в листьях
# min_samples_split - минимальное число объектов, при котором выполняется расщеплени
# max_features - число признаков для выбора расщепления
# n_estimators - число деревьев

def createRandomBot():
    maxfeatureslist = ['auto', 'sqrt','log2', None]
    criterionlist = ['mse', 'mae']

    maxFeatures = maxfeatureslist[int(rnd.randrange(0, 4, step= 1))]
    nEstimators = rnd.randrange(10, 1500, step = 25)
    maxDepth = int(rnd.randrange(1, 20, step= 1))
    minSamplesLeaf = rnd.randrange(4, 14, step = 1)
    minSamplesSplit = rnd.randrange(5, 15, step = 1)
    criterion = criterionlist[int(rnd.randrange(0, 2, step= 1))]
    bot = [maxFeatures, nEstimators, maxDepth, minSamplesLeaf, minSamplesSplit, crit
    return bot
```

In [194…

```
%%time
n = 40 # Размер популяции
nsurv = int(0.2*n) # Количество выживших (столько лучших переходит в новую популяцию
nnew = n - nsurv # Количество новых (столько новых ботов создается)
l = 6 # Длина бота
epohs = 20 # Количество эпох

popul = [] # Массив популяции
#Создаём случайных ботов
for i in range(n):
    popul.append(createRandomBot())
val = [] # Одномерный массив значений этих ботов

for it in range(epohs): # Пробегаемся по всем эпохам
    val = [] # Создаем пустой список для значений ботов

    for i in range(n): # Проходим по всей длине популяции
        bot = popul[i] # Берем очередного бота

        # запускаем модель на параметрах текущего бота popul[i]
        #maxFeatures, nEstimators, maxDepth, minSamplesLeaf, minSamplesSplit, criter
        RFR_i = ensemble.RandomForestRegressor(
            max_features=bot[0],
            n_estimators=bot[1],
            max_depth=bot[2],
            min_samples_leaf=bot[3],
            min_samples_split=bot[4],
            criterion=bot[5])
        RFR_i.fit(X_train_scl, y_train_scl)
        # делаем предсказания на тестовой выборке
        prediction = RFR_i.predict(X_test_scl)
        # денормализация предсказания
        y_predict = yScaler.inverse_transform(prediction).flatten()
        # добавляем ошибку предсказания в список на эпоху
        val.append(round(mean_absolute_error(y_predict, y_test),1))

    newpopul, sval = getSurvPopul(popul, val, nsurv) # Получаем новую популяцию и со
    print(it, " ", [round(s,8) for s in sval[0:6]]) # Выводим значения ф-ции ошибки

    for i in range(nnew): # Проходимся в цикле nnew-раз
        botp1, botp2 = getParents(newpopul, nsurv) # Из newpopul(новой популяции) по
        newbot = [] # Массив для нового бота
        # проходимся по длине бота и осуществляем смешивание/скрещивание от родителе
        for j in range(l): # Проходим по всей длине бота
            # Получаем значение для j-ого компонента бота
            x = crossPointFrom2Parents(botp1, botp2, j)
            newbot.append(x) # Добавялем новое значение в бот

        #Создаем случайный дополнительный бот для мутаций
        bot4Mut = createRandomBot()
        #Вносим мутацию в случайную компоненту текущего бота
        j_mut = np.random.randint(0, l)
        newbot[j_mut] = bot4Mut[j_mut]

        newpopul.append(newbot) # Добавляем бота в новую популяцию
        #(таким образом к nsurv-лучших ботов предыдущей популяции добавится nnew-но

    popul = newpopul # Записываем в popul посчитанную новую популяцию
```

```
0   [20779.2, 20971.2, 21776.0, 21865.9, 22177.3, 22195.0]
1   [20770.8, 20840.0, 20952.1, 21018.8, 21028.7, 21033.4]
2   [20193.1, 20676.8, 20765.3, 20781.8, 20792.4, 20815.6]
```

```
3   [19707.3, 19715.0, 20668.5, 20763.3, 20805.6, 20815.5]
4   [19468.1, 19469.4, 19484.5, 19544.5, 19548.5, 19601.8]
5   [19455.6, 19474.4, 19494.9, 19534.5, 19536.9, 19579.2]
6   [19398.8, 19476.2, 19496.3, 19499.0, 19503.8, 19505.0]
7   [19472.3, 19483.0, 19488.5, 19497.6, 19508.8, 19518.2]
8   [19407.8, 19441.4, 19473.9, 19493.2, 19494.8, 19519.5]
9   [19377.2, 19390.1, 19413.6, 19447.7, 19483.3, 19489.2]
10   [19316.4, 19407.4, 19477.8, 19486.9, 19487.9, 19500.7]
11   [19373.2, 19392.5, 19416.4, 19444.2, 19458.9, 19506.8]
12   [19410.3, 19410.4, 19415.1, 19427.8, 19511.4, 19513.5]
13   [19330.6, 19344.4, 19372.8, 19416.2, 19428.1, 19445.2]
14   [19354.8, 19415.5, 19432.2, 19437.6, 19448.3, 19496.3]
15   [19395.5, 19397.5, 19432.5, 19451.2, 19462.1, 19499.2]
16   [19448.3, 19457.8, 19480.8, 19481.8, 19482.8, 19487.3]
17   [19354.0, 19445.2, 19465.5, 19478.0, 19479.8, 19494.1]
18   [19390.5, 19454.5, 19462.9, 19463.2, 19474.7, 19488.9]
19   [19376.7, 19423.4, 19425.2, 19431.7, 19466.7, 19467.0]
Wall time: 9h 56min 42s
```

In [195…

```
best_bot = popul[0]
print("max_features = ",best_bot[0])
print("n_etimators = ",best_bot[1])
print("max_depth = ",best_bot[2])
print("min_samples_leaf = ",best_bot[3])
print("min_samples_split = ",best_bot[4])
print("criterion = ",best_bot[5])
```

```
max_features =  sqrt
n_etimators =  210
max_depth =  17
min_samples_leaf =  4
min_samples_split =  7
criterion =  mse
```

In [186…

```
# Оценка модели на тестовых данных
#print("Точность на тренировочных данных: ",model.score(X_train_scl, y_train_scl))
#print("Точность на тестовых данных: ",model.score(X_test_scl, y_test_scl))
```

In [187…

```
# Вычисление MSE
#y_test_pred = model.predict(X_test_scl)
#metrics.mean_squared_error(y_test_scl,y_test_pred)
```

In [196…

```
# запускаем модель на параметрах наилучшего бота
RFR_best = ensemble.RandomForestRegressor(
            max_features=best_bot[0],
            n_estimators=best_bot[1],
            max_depth=best_bot[2],
            min_samples_leaf=best_bot[3],
            min_samples_split=best_bot[4],
            criterion=best_bot[5])
RFR_best.fit(X_train_scl, y_train_scl)

# Стандартизируем исходные данные для кросс-валидации
X_scl = xScaler.transform(X)
y_scl = yScaler.transform(np.array(y).reshape(-1,1)).flatten()

# Проводим кросс-валидацию построенной модели
k = 10
kfold = model_selection.KFold(n_splits=k,random_state=1,shuffle=True)
K_results = model_selection.cross_val_score(RFR_best,X_scl,y_scl,cv=kfold)
```

```
# и считаем точность по кросс-валидации
accuracy = np.mean(abs(K_results))
print("Точность по кросс-валидации: ",accuracy)
```

```
Точность по кросс-валидации:  0.8250211439050444
```

In [185…

```
# для сравнения запускаем модель с параметрами по умолчанию
RFR_standard = ensemble.RandomForestRegressor()
RFR_standard.fit(X_train_scl, y_train_scl)

# Проводим кросс-валидацию построенной модели
K_results = model_selection.cross_val_score(RFR_standard,X_scl,y_scl,cv=kfold)
# и считаем точность по кросс-валидации
accuracy = np.mean(abs(K_results))
print("Точность по кросс-валидации: ",accuracy)
```

```
Точность по кросс-валидации:  0.8519049241394392
```

5. Bagging Regressor

In [215…

```
# запускаем модель с параметрами по умолчанию
BR_standard = ensemble.BaggingRegressor()
BR_standard.fit(X_train_scl, y_train_scl)

# Проводим кросс-валидацию построенной модели
k = 10
kfold = model_selection.KFold(n_splits=k,random_state=1)
K_results = model_selection.cross_val_score(BR_standard,X_scl,y_scl,cv=kfold)
# и считаем точность по кросс-валидации
accuracy = np.mean(abs(K_results))
print("Точность по кросс-валидации: ",accuracy)
```

```
C:\anaconda3\lib\site-packages\sklearn\model_selection\_split.py:293: FutureWarning:
Setting a random_state has no effect since shuffle is False. This will raise an erro
r in 0.24. You should leave random_state to its default (None), or set shuffle=True.
  warnings.warn(
Точность по кросс-валидации:  0.8358407546752996
```

6. Support Vector Regressor

In [218…

```
# запускаем модель с параметрами по умолчанию
SVR_standard = SVR(kernel='linear')
SVR_standard.fit(X_train_scl, y_train_scl)

# Проводим кросс-валидацию построенной модели
k = 10
kfold = model_selection.KFold(n_splits=k,random_state=1)
K_results = model_selection.cross_val_score(SVR_standard,X_scl,y_scl,cv=kfold)
# и считаем точность по кросс-валидации
accuracy = np.mean(abs(K_results))
print("Точность по кросс-валидации: ",accuracy)
```

```
C:\anaconda3\lib\site-packages\sklearn\model_selection\_split.py:293: FutureWarning:
Setting a random_state has no effect since shuffle is False. This will raise an erro
r in 0.24. You should leave random_state to its default (None), or set shuffle=True.
  warnings.warn(
Точность по кросс-валидации:  0.830490403153979
```

In [ ]: