MacPaw

May 2, 2021

[1]:
```
import os
import pickle

import numpy as np
import pandas as pd

%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.base import BaseEstimator
from sklearn.base import TransformerMixin
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import VotingRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

[2]:
```
pd.set_option("display.max_columns", None)
pd.set_option("max_colwidth", None)
```

[3]:
```
DATA_FOLDER = "./msi2021-data-science/data/"

train_path = os.path.join(DATA_FOLDER, "train.csv")
test_path = os.path.join(DATA_FOLDER, "test.csv")
```

```
data = pd.read_csv(train_path)
X_final = pd.read_csv(test_path)
```

[4]:
```
data
```

[4]:
```
         Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0         1          60       RL         65.0     8450   Pave   NaN      Reg
1         2          20       RL         80.0     9600   Pave   NaN      Reg
2         3          60       RL         68.0    11250   Pave   NaN      IR1
3         4          70       RL         60.0     9550   Pave   NaN      IR1
4         5          60       RL         84.0    14260   Pave   NaN      IR1
…       …          …       …           …       …    …      …       …
1455   1456          60       RL         62.0     7917   Pave   NaN      Reg
1456   1457          20       RL         85.0    13175   Pave   NaN      Reg
1457   1458          70       RL         66.0     9042   Pave   NaN      Reg
1458   1459          20       RL         68.0     9717   Pave   NaN      Reg
1459   1460          20       RL         75.0     9937   Pave   NaN      Reg

     LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0            Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1            Lvl    AllPub       FR2       Gtl      Veenker      Feedr
2            Lvl    AllPub    Inside       Gtl      CollgCr       Norm
3            Lvl    AllPub    Corner       Gtl      Crawfor       Norm
4            Lvl    AllPub       FR2       Gtl      NoRidge       Norm
…          …       …       …          …       …          …
1455         Lvl    AllPub    Inside       Gtl      Gilbert       Norm
1456         Lvl    AllPub    Inside       Gtl       NWAmes       Norm
1457         Lvl    AllPub    Inside       Gtl      Crawfor       Norm
1458         Lvl    AllPub    Inside       Gtl        NAmes       Norm
1459         Lvl    AllPub    Inside       Gtl      Edwards       Norm

     Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0          Norm     1Fam     2Story            7            5       2003
1          Norm     1Fam     1Story            6            8       1976
2          Norm     1Fam     2Story            7            5       2001
3          Norm     1Fam     2Story            7            5       1915
4          Norm     1Fam     2Story            8            5       2000
…         …       …         …           …            …       …
1455       Norm     1Fam     2Story            6            5       1999
1456       Norm     1Fam     1Story            6            6       1978
1457       Norm     1Fam     2Story            7            9       1941
1458       Norm     1Fam     1Story            5            6       1950
1459       Norm     1Fam     1Story            5            6       1965

      YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0             2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
```

```
1             1976     Gable  CompShg     MetalSd     MetalSd       None
2             2002     Gable  CompShg     VinylSd     VinylSd    BrkFace
3             1970     Gable  CompShg     Wd Sdng     Wd Shng       None
4             2000     Gable  CompShg     VinylSd     VinylSd    BrkFace
…              …        …       …          …           …          …
1455          2000     Gable  CompShg     VinylSd     VinylSd       None
1456          1988     Gable  CompShg     Plywood     Plywood      Stone
1457          2006     Gable  CompShg     CemntBd     CmentBd       None
1458          1996       Hip  CompShg     MetalSd     MetalSd       None
1459          1965     Gable  CompShg     HdBoard     HdBoard       None

      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond  \
0          196.0        Gd        TA      PConc       Gd       TA
1            0.0        TA        TA     CBlock       Gd       TA
2          162.0        Gd        TA      PConc       Gd       TA
3            0.0        TA        TA     BrkTil       TA       Gd
4          350.0        Gd        TA      PConc       Gd       TA
…           …        …        …         …       …      …
1455         0.0        TA        TA      PConc       Gd       TA
1456       119.0        TA        TA     CBlock       Gd       TA
1457         0.0        Ex        Gd      Stone       TA       Gd
1458         0.0        TA        TA     CBlock       TA       TA
1459         0.0        Gd        TA     CBlock       TA       TA

     BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
0              No          GLQ         706          Unf           0
1              Gd          ALQ         978          Unf           0
2              Mn          GLQ         486          Unf           0
3              No          ALQ         216          Unf           0
4              Av          GLQ         655          Unf           0
…             …           …          …           …          …
1455           No          Unf           0          Unf           0
1456           No          ALQ         790          Rec         163
1457           No          GLQ         275          Unf           0
1458           Mn          GLQ          49          Rec        1029
1459           No          BLQ         830          LwQ         290

      BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
0           150          856    GasA        Ex          Y      SBrkr
1           284         1262    GasA        Ex          Y      SBrkr
2           434          920    GasA        Ex          Y      SBrkr
3           540          756    GasA        Gd          Y      SBrkr
4           490         1145    GasA        Ex          Y      SBrkr
…          …           …      …       …          …         …
1455        953          953    GasA        Ex          Y      SBrkr
1456        589         1542    GasA        TA          Y      SBrkr
1457        877         1152    GasA        Ex          Y      SBrkr
```

```
1458          0         1078    GasA        Gd          Y      FuseA
1459        136         1256    GasA        Gd          Y      SBrkr

      1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
0          856       854             0       1710             1             0
1         1262         0             0       1262             0             1
2          920       866             0       1786             1             0
3          961       756             0       1717             1             0
4         1145      1053             0       2198             1             0
…          …         …             …         …              …             …
1455       953       694             0       1647             0             0
1456      2073         0             0       2073             1             0
1457      1188      1152             0       2340             0             0
1458      1078         0             0       1078             1             0
1459      1256         0             0       1256             1             0

      FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  \
0            2         1             3             1          Gd
1            2         0             3             1          TA
2            2         1             3             1          Gd
3            1         0             3             1          Gd
4            2         1             4             1          Gd
…          …         …             …             …          …
1455         2         1             3             1          TA
1456         2         0             3             1          TA
1457         2         0             4             1          Gd
1458         1         0             2             1          Gd
1459         1         1             3             1          TA

      TotRmsAbvGrd Functional  Fireplaces FireplaceQu GarageType  GarageYrBlt  \
0                8        Typ           0         NaN     Attchd       2003.0
1                6        Typ           1          TA     Attchd       1976.0
2                6        Typ           1          TA     Attchd       2001.0
3                7        Typ           1          Gd     Detchd       1998.0
4                9        Typ           1          TA     Attchd       2000.0
…              …        …             …          …         …            …
1455             7        Typ           1          TA     Attchd       1999.0
1456             7       Min1           2          TA     Attchd       1978.0
1457             9        Typ           2          Gd     Attchd       1941.0
1458             5        Typ           0         NaN     Attchd       1950.0
1459             6        Typ           0         NaN     Attchd       1965.0

     GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
0             RFn           2         548         TA         TA          Y
1             RFn           2         460         TA         TA          Y
2             RFn           2         608         TA         TA          Y
3             Unf           3         642         TA         TA          Y
```

```
4             RFn           3         836         TA         TA           Y
…             …             …         …           …          …
1455          RFn           2         460         TA         TA           Y
1456          Unf           2         500         TA         TA           Y
1457          RFn           1         252         TA         TA           Y
1458          Unf           1         240         TA         TA           Y
1459          Fin           1         276         TA         TA           Y

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  \
0              0           61              0          0            0
1            298            0              0          0            0
2              0           42              0          0            0
3              0           35            272          0            0
4            192           84              0          0            0
…            …             …             …          …
1455           0           40              0          0            0
1456         349            0              0          0            0
1457           0           60              0          0            0
1458         366            0            112          0            0
1459         736           68              0          0            0

      PoolArea PoolQC  Fence MiscFeature  MiscVal  MoSold  YrSold SaleType  \
0            0    NaN    NaN         NaN        0       2    2008       WD
1            0    NaN    NaN         NaN        0       5    2007       WD
2            0    NaN    NaN         NaN        0       9    2008       WD
3            0    NaN    NaN         NaN        0       2    2006       WD
4            0    NaN    NaN         NaN        0      12    2008       WD
…        …    …      …           …       …      …       …
1455         0    NaN    NaN         NaN        0       8    2007       WD
1456         0    NaN  MnPrv         NaN        0       2    2010       WD
1457         0    NaN  GdPrv        Shed     2500       5    2010       WD
1458         0    NaN    NaN         NaN        0       4    2010       WD
1459         0    NaN    NaN         NaN        0       6    2008       WD

     SaleCondition  SalePrice
0           Normal     208500
1           Normal     181500
2           Normal     223500
3          Abnorml     140000
4           Normal     250000
…             …        …
1455        Normal     175000
1456        Normal     210000
1457        Normal     266500
1458        Normal     142125
1459        Normal     147500
```

```
[1460 rows x 81 columns]
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     1452 non-null   object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
```

```
 39  Heating         1460 non-null   object
 40  HeatingQC       1460 non-null   object
 41  CentralAir      1460 non-null   object
 42  Electrical      1459 non-null   object
 43  1stFlrSF        1460 non-null   int64
 44  2ndFlrSF        1460 non-null   int64
 45  LowQualFinSF    1460 non-null   int64
 46  GrLivArea       1460 non-null   int64
 47  BsmtFullBath    1460 non-null   int64
 48  BsmtHalfBath    1460 non-null   int64
 49  FullBath        1460 non-null   int64
 50  HalfBath        1460 non-null   int64
 51  BedroomAbvGr    1460 non-null   int64
 52  KitchenAbvGr    1460 non-null   int64
 53  KitchenQual     1460 non-null   object
 54  TotRmsAbvGrd    1460 non-null   int64
 55  Functional      1460 non-null   object
 56  Fireplaces      1460 non-null   int64
 57  FireplaceQu     770 non-null    object
 58  GarageType      1379 non-null   object
 59  GarageYrBlt     1379 non-null   float64
 60  GarageFinish    1379 non-null   object
 61  GarageCars      1460 non-null   int64
 62  GarageArea      1460 non-null   int64
 63  GarageQual      1379 non-null   object
 64  GarageCond      1379 non-null   object
 65  PavedDrive      1460 non-null   object
 66  WoodDeckSF      1460 non-null   int64
 67  OpenPorchSF     1460 non-null   int64
 68  EnclosedPorch   1460 non-null   int64
 69  3SsnPorch       1460 non-null   int64
 70  ScreenPorch     1460 non-null   int64
 71  PoolArea        1460 non-null   int64
 72  PoolQC          7 non-null      object
 73  Fence           281 non-null    object
 74  MiscFeature     54 non-null     object
 75  MiscVal         1460 non-null   int64
 76  MoSold          1460 non-null   int64
 77  YrSold          1460 non-null   int64
 78  SaleType        1460 non-null   object
 79  SaleCondition   1460 non-null   object
 80  SalePrice       1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

[6]:
```
data.describe()
```

[6]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000
mean	730.500000	56.897260	70.049958	10516.828082	6.099315
std	421.610009	42.300571	24.284752	9981.264932	1.382997
min	1.000000	20.000000	21.000000	1300.000000	1.000000
25%	365.750000	20.000000	59.000000	7553.500000	5.000000
50%	730.500000	50.000000	69.000000	9478.500000	6.000000
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000
max	1460.000000	190.000000	313.000000	215245.000000	10.000000

	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1
count	1460.000000	1460.000000	1460.000000	1452.000000	1460.000000
mean	5.575342	1971.267808	1984.865753	103.685262	443.639726
std	1.112799	30.202904	20.645407	181.066207	456.098091
min	1.000000	1872.000000	1950.000000	0.000000	0.000000
25%	5.000000	1954.000000	1967.000000	0.000000	0.000000
50%	5.000000	1973.000000	1994.000000	0.000000	383.500000
75%	6.000000	2000.000000	2004.000000	166.000000	712.250000
max	9.000000	2010.000000	2010.000000	1600.000000	5644.000000

	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	46.549315	567.240411	1057.429452	1162.626712	346.992466
std	161.319273	441.866955	438.705324	386.587738	436.528436
min	0.000000	0.000000	0.000000	334.000000	0.000000
25%	0.000000	223.000000	795.750000	882.000000	0.000000
50%	0.000000	477.500000	991.500000	1087.000000	0.000000
75%	0.000000	808.000000	1298.250000	1391.250000	728.000000
max	1474.000000	2336.000000	6110.000000	4692.000000	2065.000000

	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	5.844521	1515.463699	0.425342	0.057534	1.565068
std	48.623081	525.480383	0.518911	0.238753	0.550916
min	0.000000	334.000000	0.000000	0.000000	0.000000
25%	0.000000	1129.500000	0.000000	0.000000	1.000000
50%	0.000000	1464.000000	0.000000	0.000000	2.000000
75%	0.000000	1776.750000	1.000000	0.000000	2.000000
max	572.000000	5642.000000	3.000000	2.000000	3.000000

	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	Fireplaces
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	0.382877	2.866438	1.046575	6.517808	0.613014
std	0.502885	0.815778	0.220338	1.625393	0.644666
min	0.000000	0.000000	0.000000	2.000000	0.000000
25%	0.000000	2.000000	1.000000	5.000000	0.000000
50%	0.000000	3.000000	1.000000	6.000000	1.000000

```
75%       1.000000      3.000000      1.000000      7.000000      1.000000
max       2.000000      8.000000      3.000000     14.000000      3.000000

       GarageYrBlt   GarageCars   GarageArea   WoodDeckSF  OpenPorchSF  \
count  1379.000000  1460.000000  1460.000000  1460.000000  1460.000000
mean   1978.506164     1.767123   472.980137    94.244521    46.660274
std      24.689725     0.747315   213.804841   125.338794    66.256028
min    1900.000000     0.000000     0.000000     0.000000     0.000000
25%    1961.000000     1.000000   334.500000     0.000000     0.000000
50%    1980.000000     2.000000   480.000000     0.000000    25.000000
75%    2002.000000     2.000000   576.000000   168.000000    68.000000
max    2010.000000     4.000000  1418.000000   857.000000   547.000000

       EnclosedPorch    3SsnPorch  ScreenPorch     PoolArea       MiscVal  \
count    1460.000000  1460.000000  1460.000000  1460.000000   1460.000000
mean       21.954110     3.409589    15.060959     2.758904     43.489041
std        61.119149    29.317331    55.757415    40.177307    496.123024
min         0.000000     0.000000     0.000000     0.000000      0.000000
25%         0.000000     0.000000     0.000000     0.000000      0.000000
50%         0.000000     0.000000     0.000000     0.000000      0.000000
75%         0.000000     0.000000     0.000000     0.000000      0.000000
max       552.000000   508.000000   480.000000   738.000000  15500.000000

            MoSold       YrSold      SalePrice
count  1460.000000  1460.000000    1460.000000
mean      6.321918  2007.815753  180921.195890
std       2.703626     1.328095   79442.502883
min       1.000000  2006.000000   34900.000000
25%       5.000000  2007.000000  129975.000000
50%       6.000000  2008.000000  163000.000000
75%       8.000000  2009.000000  214000.000000
max      12.000000  2010.000000  755000.000000
```

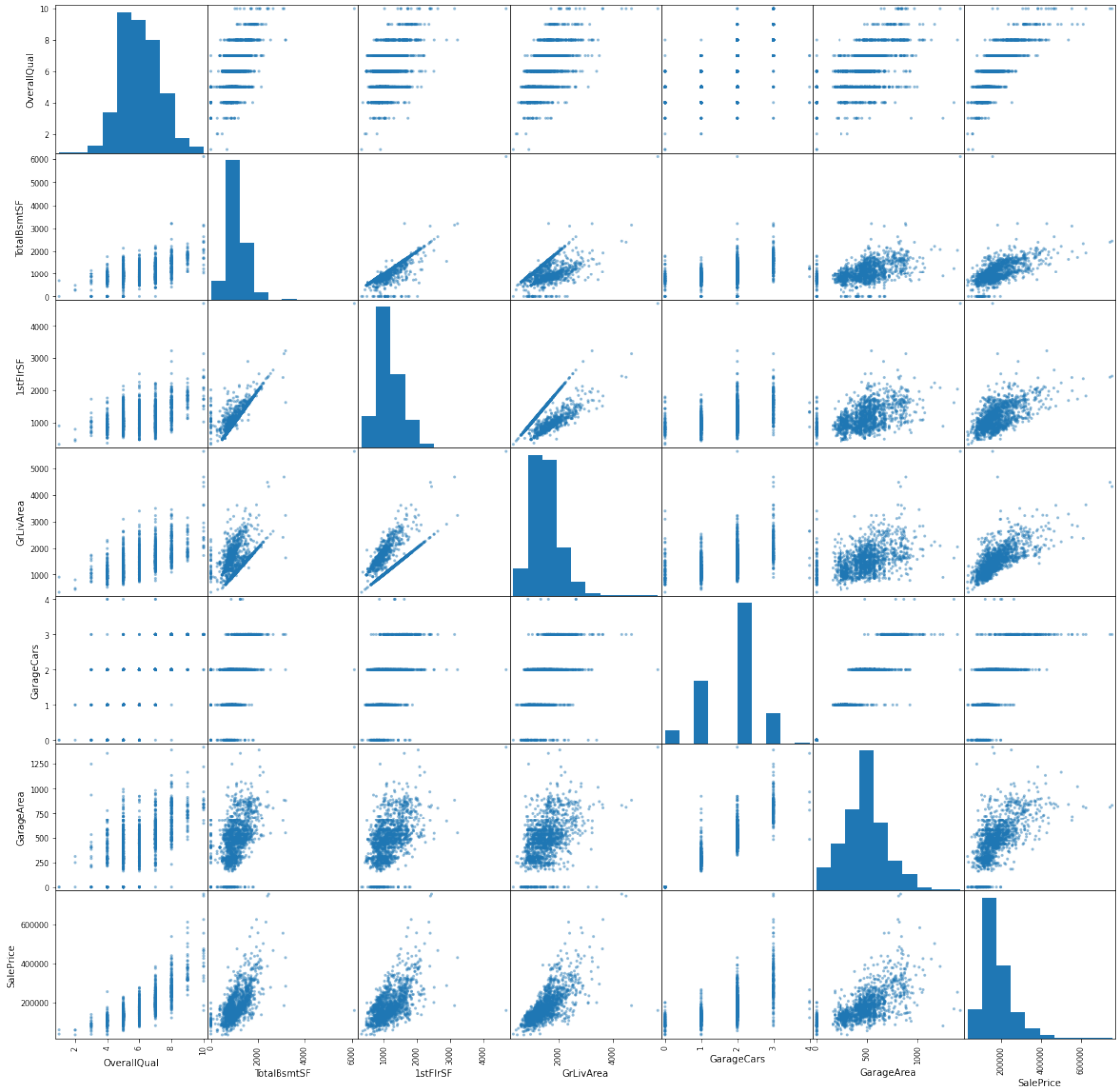
[7]:
```
corr_matrix = data.corr()
corr_matrix["SalePrice"].sort_values(ascending=False)
```

[7]:
```
SalePrice        1.000000
OverallQual      0.790982
GrLivArea        0.708624
GarageCars       0.640409
GarageArea       0.623431
TotalBsmtSF      0.613581
1stFlrSF         0.605852
FullBath         0.560664
TotRmsAbvGrd     0.533723
YearBuilt        0.522897
YearRemodAdd     0.507101
```

```
GarageYrBlt      0.486362
MasVnrArea       0.477493
Fireplaces       0.466929
BsmtFinSF1       0.386420
LotFrontage      0.351799
WoodDeckSF       0.324413
2ndFlrSF         0.319334
OpenPorchSF      0.315856
HalfBath         0.284108
LotArea          0.263843
BsmtFullBath     0.227122
BsmtUnfSF        0.214479
BedroomAbvGr     0.168213
ScreenPorch      0.111447
PoolArea         0.092404
MoSold           0.046432
3SsnPorch        0.044584
BsmtFinSF2      -0.011378
BsmtHalfBath    -0.016844
MiscVal         -0.021190
Id              -0.021917
LowQualFinSF    -0.025606
YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

We can see, that dataset have many high correlating features. Later we will use Random Forest or Decision Tree for prove this results. Also, we will check not only numerical attrubutes. Lets plot with a few best features.

[8]:
```
from pandas.plotting import scatter_matrix

best_corr_attributes = [name for name in corr_matrix.keys()
              if np.fabs(corr_matrix["SalePrice"].loc[name]) >= 0.6]

scatter_matrix(data[best_corr_attributes], figsize=(20, 20))
plt.show()
```



1 Preparing data for algorithms

[9]:
```
train, test = train_test_split(data, test_size=0.2)
```

[10]:
```
drop_na = ["GarageType", "GarageYrBlt", "GarageFinish", "GarageQual",␣
 ↪"GarageCond", "LotFrontage",
                        "MasVnrType", "MasVnrArea", "BsmtQual", "BsmtCond",␣
 ↪"BsmtExposure", "BsmtFinType1",
                        "BsmtFinType2","Electrical"]
drop_columns = ["Alley", "FireplaceQu", "PoolQC", "Fence", "MiscFeature"]

class DataCleaner(BaseEstimator, TransformerMixin):
```

```
    """
    This class remove empty rows or columns

    Methods:
    fit(X, y=None):
        Return self object

    transform(X):
        Remove rows and columns in X

    """
    def __init__(self, drop_na, drop_columns):
        """
        Parameters
        drop_na : list
            Column names in which rows with cells that contains N/A will be␣
↪deleted

        drop_columns : list
            Column names that must be deleted

        """
        self._drop_na = drop_na
        self._drop_columns = drop_columns


    def fit(self, X, y=None):
        return self

    def transform(self, X):
        """
        Remove columns and rows by params that you passed in constrictor

        Parameters
        X : pandas.core.frame.DataFrame
            Input data

        Returns
        pandas.core.frame.DataFrame
            Data with removed rows and cols that you passed in constrictor
        """

        new_X = X.drop(self._drop_columns, axis=1)
        new_X = new_X.dropna(subset=self._drop_na)

        return new_X
```

[11]:
```
train_temp = train.copy()

train_temp = DataCleaner(drop_na, drop_columns).fit_transform(train_temp)
train_temp.head()
```

[11]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape
965	966	60	RL	65.0	10237	Pave	Reg
621	622	60	RL	90.0	10800	Pave	Reg
429	430	20	RL	130.0	11457	Pave	IR1
1374	1375	60	FV	85.0	10625	Pave	Reg
45	46	120	RL	61.0	7658	Pave	Reg

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1
965	Lvl	AllPub	Inside	Gtl	Gilbert	RRAn
621	Lvl	AllPub	Inside	Gtl	NWAmes	Norm
429	Lvl	AllPub	Corner	Gtl	Timber	Norm
1374	Lvl	AllPub	Inside	Gtl	Somerst	Norm
45	Lvl	AllPub	Inside	Gtl	NridgHt	Norm

	Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt
965	Norm	1Fam	2Story	6	5	2005
621	Norm	1Fam	2Story	6	7	1974
429	Norm	1Fam	1Story	6	5	1988
1374	Norm	1Fam	2Story	7	5	2005
45	Norm	TwnhsE	1Story	9	5	2005

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType
965	2007	Gable	CompShg	VinylSd	VinylSd	None
621	1997	Gable	CompShg	HdBoard	HdBoard	None
429	1988	Gable	CompShg	HdBoard	HdBoard	None
1374	2005	Gable	CompShg	CemntBd	CmentBd	None
45	2005	Hip	CompShg	MetalSd	MetalSd	BrkFace

	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond
965	0.0	Gd	TA	PConc	Gd	TA
621	0.0	TA	TA	CBlock	TA	TA
429	0.0	TA	TA	CBlock	Gd	TA
1374	0.0	Gd	TA	PConc	Gd	TA
45	412.0	Ex	TA	PConc	Ex	TA

	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2
965	No	Unf	0	Unf	0
621	No	ALQ	956	Rec	182
429	Mn	GLQ	1005	Unf	0
1374	No	Unf	0	Unf	0
45	No	GLQ	456	Unf	0

```
      BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
965         783          783    GasA        Ex          Y      SBrkr
621         384         1522    GasA        TA          Y      SBrkr
429         387         1392    GasA        TA          Y      SBrkr
1374       1026         1026    GasA        Ex          Y      SBrkr
45         1296         1752    GasA        Ex          Y      SBrkr

      1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
965        783       701             0       1484             0             0
621       1548      1066             0       2614             0             0
429       1412         0             0       1412             1             0
1374      1026       932             0       1958             0             0
45        1752         0             0       1752             1             0

      FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  \
965          2         1             3             1          Gd
621          2         1             4             1          TA
429          2         0             3             1          Gd
1374         2         1             3             1          Gd
45           2         0             2             1          Ex

      TotRmsAbvGrd Functional  Fireplaces GarageType  GarageYrBlt  \
965              8        Typ           1     Attchd       2005.0
621              9        Typ           1     Attchd       1974.0
429              6        Typ           1     Attchd       1988.0
1374             9        Typ           1     Attchd       2005.0
45               6        Typ           1     Attchd       2005.0

     GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
965           Fin           2         393         TA         TA          Y
621           RFn           2         624         TA         TA          Y
429           Unf           2         576         TA         TA          Y
1374          Fin           3         936         TA         TA          Y
45            RFn           2         576         TA         TA          Y

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  \
965            0           72              0          0            0
621           38          243              0          0            0
429            0            0            169          0            0
1374         154          210              0          0            0
45           196           82              0          0            0

      PoolArea  MiscVal  MoSold  YrSold SaleType SaleCondition  SalePrice
965          0        0       7    2007      New       Partial     178900
621          0        0       6    2008       WD        Normal     240000
429          0        0       3    2009       WD        Normal     175000
1374         0        0       7    2008       WD        Normal     250000
```

```
45          0         0       2    2010        WD         Normal     319900
```

[12]:
```python
class DataColumnSplitter(BaseEstimator, TransformerMixin):
    """
    This class stplit input data to data without column that you indicate␣
↪(data_ field) and
    indicated column (column_ filed)

    Attributes
    data_ : pandas.core.frame.DataFrame
        Inputed data without labels

    column_ : pandas.core.series.Series
        Removed column

    target_column_ : str
        Name of column that you indicate

    Methods
    fit(X, y=None)
        Return self object

    transfrom(X)
        Remove selected column from DataFrame and save removed column in calss␣
↪field named column_
    """
    def __init__(self, target_column):
        """
        Parameters:
        target_column : str
            Name of column
        """
        self.target_column_ = target_column
        self.data_ = None
        self.column_ = None

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        """
        Remove selected column from DataFrame and save removed column in calss␣
↪field named column_

        Parameters
        X : pandas.core.frame.DataFrame
            Input data
```

```
        Returns
        pandas.core.frame.DataFrame
            Data without selected column
        """

        if self.target_column_ in X.columns:
            data = X.drop(self.target_column_, axis=1)
            self.column_ = X[self.target_column_].copy()
            self.data_ = data
        else:
            self.data_ = X
        return self.data_
```

[13]:
```
X_train, y_train = None, None

dcs = DataColumnSplitter("SalePrice")
X_train = dcs.fit_transform(train_temp)
y_train = dcs.column_
```

[14]:
```
X_train.head()
```

[14]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	\
965	966	60	RL	65.0	10237	Pave	Reg	
621	622	60	RL	90.0	10800	Pave	Reg	
429	430	20	RL	130.0	11457	Pave	IR1	
1374	1375	60	FV	85.0	10625	Pave	Reg	
45	46	120	RL	61.0	7658	Pave	Reg	

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	\
965	Lvl	AllPub	Inside	Gtl	Gilbert	RRAn	
621	Lvl	AllPub	Inside	Gtl	NWAmes	Norm	
429	Lvl	AllPub	Corner	Gtl	Timber	Norm	
1374	Lvl	AllPub	Inside	Gtl	Somerst	Norm	
45	Lvl	AllPub	Inside	Gtl	NridgHt	Norm	

	Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt	\
965	Norm	1Fam	2Story	6	5	2005	
621	Norm	1Fam	2Story	6	7	1974	
429	Norm	1Fam	1Story	6	5	1988	
1374	Norm	1Fam	2Story	7	5	2005	
45	Norm	TwnhsE	1Story	9	5	2005	

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType	\
965	2007	Gable	CompShg	VinylSd	VinylSd	None	
621	1997	Gable	CompShg	HdBoard	HdBoard	None	
429	1988	Gable	CompShg	HdBoard	HdBoard	None	

```
1374          2005     Gable  CompShg     CemntBd     CmentBd       None
45            2005       Hip  CompShg     MetalSd     MetalSd    BrkFace

      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond  \
965          0.0        Gd        TA      PConc       Gd       TA
621          0.0        TA        TA     CBlock       TA       TA
429          0.0        TA        TA     CBlock       Gd       TA
1374         0.0        Gd        TA      PConc       Gd       TA
45         412.0        Ex        TA      PConc       Ex       TA

     BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
965            No          Unf           0          Unf           0
621            No          ALQ         956          Rec         182
429            Mn          GLQ        1005          Unf           0
1374           No          Unf           0          Unf           0
45             No          GLQ         456          Unf           0

      BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
965         783          783    GasA        Ex          Y      SBrkr
621         384         1522    GasA        TA          Y      SBrkr
429         387         1392    GasA        TA          Y      SBrkr
1374       1026         1026    GasA        Ex          Y      SBrkr
45         1296         1752    GasA        Ex          Y      SBrkr

      1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
965        783       701             0       1484             0             0
621       1548      1066             0       2614             0             0
429       1412         0             0       1412             1             0
1374      1026       932             0       1958             0             0
45        1752         0             0       1752             1             0

      FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  \
965          2         1             3             1          Gd
621          2         1             4             1          TA
429          2         0             3             1          Gd
1374         2         1             3             1          Gd
45           2         0             2             1          Ex

      TotRmsAbvGrd Functional  Fireplaces GarageType  GarageYrBlt  \
965              8        Typ           1     Attchd       2005.0
621              9        Typ           1     Attchd       1974.0
429              6        Typ           1     Attchd       1988.0
1374             9        Typ           1     Attchd       2005.0
45               6        Typ           1     Attchd       2005.0

     GarageFinish  GarageCars  GarageArea GarageQual GarageCond PavedDrive  \
965           Fin           2         393         TA         TA          Y
```

```
621          RFn          2         624         TA         TA          Y
429          Unf          2         576         TA         TA          Y
1374         Fin          3         936         TA         TA          Y
45           RFn          2         576         TA         TA          Y

      WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  \
965            0           72              0          0            0
621           38          243              0          0            0
429            0            0            169          0            0
1374         154          210              0          0            0
45           196           82              0          0            0

      PoolArea  MiscVal  MoSold  YrSold SaleType SaleCondition
965          0        0       7    2007      New       Partial
621          0        0       6    2008       WD        Normal
429          0        0       3    2009       WD        Normal
1374         0        0       7    2008       WD        Normal
45           0        0       2    2010       WD        Normal
```

[15]:
```
y_train
```

[15]:
```
965     178900
621     240000
429     175000
1374    250000
45      319900
         …
1456    210000
1062     90000
1302    290000
1204    153500
83      126500
Name: SalePrice, Length: 878, dtype: int64
```

[16]:
```
def get_better_numeric_columns(importances_features, threshold):
    """
    Leaves the best attributes, by threshold

    Parameters
    importances_features : pandas.core.frame.DataFrame
        Table with indices as data column names and importances values in first␣
↪column for all indices

    threshold : float
        All rows whose importances values are less that threshold will be␣
↪removed
```

```
    Returns
    list
        Column names whose importances values are gtrater that threshold

    """
    sorted_features = importances_features.sort_values(ascending=False)
    columns = None

    if isinstance(threshold, float) and 0. < threshold < 1.:
        columns = [name for name in sorted_features.index if sorted_features.
↪loc[name] > threshold]

    elif isinstance(threshold, int) and threshold > 0:
        columns = sorted_features.iloc[:threshold].index

    elif isinstance(threshold, float) and not 0. < threshold < 1.:
        raise ValueError("Threshold as float must be in segment (0, 1)")

    elif isinstance(threshold, float) and threshold <= 0:
        raise ValueError("Threshold as int must be positive (> 0)")

    else:
        raise ValueError("Invalid variable 'threshold' data type. It must be␣
↪int or float")

    return list(columns)

class BestAttributesSelector(BaseEstimator, TransformerMixin):
    """
    Select best attributes by corr matrix, tree, random forest or other

    Methods
    fit(X, y=None)
        Return self

    transform(self, X)
        Select best attrubutes
    """

    def __init__(self, importance_attrs, numbersonly=False):
        """
        Patameters
        importance_attrs : list
            List with most importance column names

        """
        self._importance_attrs = importance_attrs
```

```
    def fit(self, X, y=None):
        return self

    def transform(self, X):
        """
        Select best attributes in input series

        Patameters
        X : pandas.core.frame.DataFrame
            Input data

        Returns
        pandas.core.frame.DataFrame
            DataFrame with best attributes
        """
        new_X = X[self._importance_attrs]

        return new_X
```

[17]:
```
get_better_numeric_columns(corr_matrix["SalePrice"], 5)
```

[17]:
```
['SalePrice', 'OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea']
```

[18]:
```
class ColumnNamesSaver(BaseEstimator, TransformerMixin):
    """
    Save column names

    Attributes
    column_names_ : list
        Column names

    Methods
    fit(X, y=None)
        Return self

    transform(self, X)
        Save column names
    """
    def __init__(self):
        self.column_names_ = None

    def fit(self, X, y=None):
        return self

    def transform(self, X):
```

```
        """
        Save column names

        Parameters
        X : pandas.core.frame.DataFrame
            Input data

        Returns
        X : pandas.core.frame.DataFrame
            Not transformed input data
        """
        self.column_names_ = list(X.columns)
        return X
```

[19]:
```
class CathgoricalEncoder(BaseEstimator, TransformerMixin):
    """
    Transform cathegorical attributes to numerical columns

    Methods
    fit(X, y=None)
        Return self

    transfrom(X)
        Transfrom cathegorical attributes to numerical columns
    """
    def __init__(self):
        self._encoder = OneHotEncoder()

    def fit(self, X, y = None):
        return self

    def transform(self, X):
        """
        Select cathegirical attributes from input DataFrame, use sklearn.
↪OneHotEncoder to transfrom data and
        merge transfromed data with numerical attributes

        Parameters
        X : pandas.core.frame.DataFrame
            Input data

        Returns
        pandas.core.frame.DataFrame
            Prepared data
        """
        cat_attributes = [name for name in X.dtypes.keys()
                  if str(X[name].dtype) == "object"]
```

```
        cat_matrix = self._encoder.fit_transform(X[cat_attributes])
        encoded_part = pd.DataFrame(cat_matrix.toarray(), columns=self.
↪_get_new_column_names(cat_matrix, cat_attributes, self._encoder))

        new_X = X.drop(cat_attributes, axis=1)
        new_X.reset_index(drop=True, inplace=True)
        encoded_part.reset_index(drop=True, inplace=True)

        new_X = pd.concat([new_X, encoded_part], axis=1)

        return new_X

    @staticmethod
    def _get_new_column_names(matrix, cathegorical_attributes, encoder):
        new_column_names = []
        for column_name, values in zip(cathegorical_attributes, encoder.
↪categories_):
            for value in values:
                new_column_names.append(f"{column_name}_{value}")
        return new_column_names
```

[20]:
```
ce = CathgoricalEncoder().fit_transform(X_train)
ce.head()
```

[20]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	\
0	966	60	65.0	10237	6	5	
1	622	60	90.0	10800	6	7	
2	430	20	130.0	11457	6	5	
3	1375	60	85.0	10625	7	5	
4	46	120	61.0	7658	9	5	

	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	\
0	2005	2007	0.0	0	0	783	
1	1974	1997	0.0	956	182	384	
2	1988	1988	0.0	1005	0	387	
3	2005	2005	0.0	0	0	1026	
4	2005	2005	412.0	456	0	1296	

	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	\
0	783	783	701	0	1484	0	
1	1522	1548	1066	0	2614	0	
2	1392	1412	0	0	1412	1	
3	1026	1026	932	0	1958	0	
4	1752	1752	0	0	1752	1	

```
   BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr  TotRmsAbvGrd  \
0             0         2         1             3             1             8
1             0         2         1             4             1             9
2             0         2         0             3             1             6
3             0         2         1             3             1             9
4             0         2         0             2             1             6

   Fireplaces  GarageYrBlt  GarageCars  GarageArea  WoodDeckSF  OpenPorchSF  \
0           1       2005.0           2         393           0           72
1           1       1974.0           2         624          38          243
2           1       1988.0           2         576           0            0
3           1       2005.0           3         936         154          210
4           1       2005.0           2         576         196           82

   EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  MiscVal  MoSold  YrSold  \
0              0          0            0         0        0       7    2007
1              0          0            0         0        0       6    2008
2            169          0            0         0        0       3    2009
3              0          0            0         0        0       7    2008
4              0          0            0         0        0       2    2010

   MSZoning_C (all)  MSZoning_FV  MSZoning_RH  MSZoning_RL  MSZoning_RM  \
0               0.0          0.0          0.0          1.0          0.0
1               0.0          0.0          0.0          1.0          0.0
2               0.0          0.0          0.0          1.0          0.0
3               0.0          1.0          0.0          0.0          0.0
4               0.0          0.0          0.0          1.0          0.0

   Street_Grvl  Street_Pave  LotShape_IR1  LotShape_IR2  LotShape_IR3  \
0          0.0          1.0           0.0           0.0           0.0
1          0.0          1.0           0.0           0.0           0.0
2          0.0          1.0           1.0           0.0           0.0
3          0.0          1.0           0.0           0.0           0.0
4          0.0          1.0           0.0           0.0           0.0

   LotShape_Reg  LandContour_Bnk  LandContour_HLS  LandContour_Low  \
0           1.0              0.0              0.0              0.0
1           1.0              0.0              0.0              0.0
2           0.0              0.0              0.0              0.0
3           1.0              0.0              0.0              0.0
4           1.0              0.0              0.0              0.0

   LandContour_Lvl  Utilities_AllPub  LotConfig_Corner  LotConfig_CulDSac  \
0              1.0               1.0               0.0                0.0
1              1.0               1.0               0.0                0.0
2              1.0               1.0               1.0                0.0
3              1.0               1.0               0.0                0.0
```

```
4              1.0               1.0               0.0                0.0

   LotConfig_FR2  LotConfig_FR3  LotConfig_Inside  LandSlope_Gtl  \
0            0.0            0.0               1.0            1.0
1            0.0            0.0               1.0            1.0
2            0.0            0.0               0.0            1.0
3            0.0            0.0               1.0            1.0
4            0.0            0.0               1.0            1.0

   LandSlope_Mod  LandSlope_Sev  Neighborhood_Blmngtn  Neighborhood_Blueste  \
0            0.0            0.0                   0.0                   0.0
1            0.0            0.0                   0.0                   0.0
2            0.0            0.0                   0.0                   0.0
3            0.0            0.0                   0.0                   0.0
4            0.0            0.0                   0.0                   0.0

   Neighborhood_BrDale  Neighborhood_BrkSide  Neighborhood_ClearCr  \
0                  0.0                   0.0                   0.0
1                  0.0                   0.0                   0.0
2                  0.0                   0.0                   0.0
3                  0.0                   0.0                   0.0
4                  0.0                   0.0                   0.0

   Neighborhood_CollgCr  Neighborhood_Crawfor  Neighborhood_Edwards  \
0                   0.0                   0.0                   0.0
1                   0.0                   0.0                   0.0
2                   0.0                   0.0                   0.0
3                   0.0                   0.0                   0.0
4                   0.0                   0.0                   0.0

   Neighborhood_Gilbert  Neighborhood_IDOTRR  Neighborhood_MeadowV  \
0                   1.0                   0.0                   0.0
1                   0.0                   0.0                   0.0
2                   0.0                   0.0                   0.0
3                   0.0                   0.0                   0.0
4                   0.0                   0.0                   0.0

   Neighborhood_Mitchel  Neighborhood_NAmes  Neighborhood_NPkVill  \
0                   0.0                 0.0                   0.0
1                   0.0                 0.0                   0.0
2                   0.0                 0.0                   0.0
3                   0.0                 0.0                   0.0
4                   0.0                 0.0                   0.0

   Neighborhood_NWAmes  Neighborhood_NoRidge  Neighborhood_NridgHt  \
0                  0.0                   0.0                   0.0
1                  1.0                   0.0                   0.0
```

```
2                  0.0                   0.0                   0.0
3                  0.0                   0.0                   0.0
4                  0.0                   0.0                   1.0

   Neighborhood_OldTown  Neighborhood_SWISU  Neighborhood_Sawyer  \
0                   0.0                 0.0                  0.0
1                   0.0                 0.0                  0.0
2                   0.0                 0.0                  0.0
3                   0.0                 0.0                  0.0
4                   0.0                 0.0                  0.0

   Neighborhood_SawyerW  Neighborhood_Somerst  Neighborhood_StoneBr  \
0                   0.0                   0.0                   0.0
1                   0.0                   0.0                   0.0
2                   0.0                   0.0                   0.0
3                   0.0                   1.0                   0.0
4                   0.0                   0.0                   0.0

   Neighborhood_Timber  Neighborhood_Veenker  Condition1_Artery  \
0                  0.0                   0.0                0.0
1                  0.0                   0.0                0.0
2                  1.0                   0.0                0.0
3                  0.0                   0.0                0.0
4                  0.0                   0.0                0.0

   Condition1_Feedr  Condition1_Norm  Condition1_PosA  Condition1_PosN  \
0               0.0              0.0              0.0              0.0
1               0.0              1.0              0.0              0.0
2               0.0              1.0              0.0              0.0
3               0.0              1.0              0.0              0.0
4               0.0              1.0              0.0              0.0

   Condition1_RRAe  Condition1_RRAn  Condition1_RRNe  Condition1_RRNn  \
0              0.0              1.0              0.0              0.0
1              0.0              0.0              0.0              0.0
2              0.0              0.0              0.0              0.0
3              0.0              0.0              0.0              0.0
4              0.0              0.0              0.0              0.0

   Condition2_Artery  Condition2_Feedr  Condition2_Norm  Condition2_PosA  \
0                0.0               0.0              1.0              0.0
1                0.0               0.0              1.0              0.0
2                0.0               0.0              1.0              0.0
3                0.0               0.0              1.0              0.0
4                0.0               0.0              1.0              0.0

   Condition2_PosN  Condition2_RRNn  BldgType_1Fam  BldgType_2fmCon  \
```

```
0              0.0              0.0            1.0              0.0
1              0.0              0.0            1.0              0.0
2              0.0              0.0            1.0              0.0
3              0.0              0.0            1.0              0.0
4              0.0              0.0            0.0              0.0

   BldgType_Duplex  BldgType_Twnhs  BldgType_TwnhsE  HouseStyle_1.5Fin  \
0              0.0             0.0              0.0                0.0
1              0.0             0.0              0.0                0.0
2              0.0             0.0              0.0                0.0
3              0.0             0.0              0.0                0.0
4              0.0             0.0              1.0                0.0

   HouseStyle_1.5Unf  HouseStyle_1Story  HouseStyle_2.5Fin  HouseStyle_2.5Unf  \
0                0.0                0.0                0.0                0.0
1                0.0                0.0                0.0                0.0
2                0.0                1.0                0.0                0.0
3                0.0                0.0                0.0                0.0
4                0.0                1.0                0.0                0.0

   HouseStyle_2Story  HouseStyle_SFoyer  HouseStyle_SLvl  RoofStyle_Flat  \
0                1.0                0.0              0.0             0.0
1                1.0                0.0              0.0             0.0
2                0.0                0.0              0.0             0.0
3                1.0                0.0              0.0             0.0
4                0.0                0.0              0.0             0.0

   RoofStyle_Gable  RoofStyle_Gambrel  RoofStyle_Hip  RoofStyle_Mansard  \
0              1.0                0.0            0.0                0.0
1              1.0                0.0            0.0                0.0
2              1.0                0.0            0.0                0.0
3              1.0                0.0            0.0                0.0
4              0.0                0.0            1.0                0.0

   RoofMatl_ClyTile  RoofMatl_CompShg  RoofMatl_Roll  RoofMatl_Tar&Grv  \
0               0.0               1.0            0.0               0.0
1               0.0               1.0            0.0               0.0
2               0.0               1.0            0.0               0.0
3               0.0               1.0            0.0               0.0
4               0.0               1.0            0.0               0.0

   RoofMatl_WdShake  RoofMatl_WdShngl  Exterior1st_AsbShng  \
0               0.0               0.0                  0.0
1               0.0               0.0                  0.0
2               0.0               0.0                  0.0
3               0.0               0.0                  0.0
4               0.0               0.0                  0.0
```

```
   Exterior1st_BrkComm  Exterior1st_BrkFace  Exterior1st_CBlock  \
0                  0.0                  0.0                 0.0
1                  0.0                  0.0                 0.0
2                  0.0                  0.0                 0.0
3                  0.0                  0.0                 0.0
4                  0.0                  0.0                 0.0

   Exterior1st_CemntBd  Exterior1st_HdBoard  Exterior1st_ImStucc  \
0                  0.0                  0.0                  0.0
1                  0.0                  1.0                  0.0
2                  0.0                  1.0                  0.0
3                  1.0                  0.0                  0.0
4                  0.0                  0.0                  0.0

   Exterior1st_MetalSd  Exterior1st_Plywood  Exterior1st_Stone  \
0                  0.0                  0.0                0.0
1                  0.0                  0.0                0.0
2                  0.0                  0.0                0.0
3                  0.0                  0.0                0.0
4                  1.0                  0.0                0.0

   Exterior1st_Stucco  Exterior1st_VinylSd  Exterior1st_Wd Sdng  \
0                 0.0                  1.0                  0.0
1                 0.0                  0.0                  0.0
2                 0.0                  0.0                  0.0
3                 0.0                  0.0                  0.0
4                 0.0                  0.0                  0.0

   Exterior1st_WdShing  Exterior2nd_AsbShng  Exterior2nd_AsphShn  \
0                  0.0                  0.0                  0.0
1                  0.0                  0.0                  0.0
2                  0.0                  0.0                  0.0
3                  0.0                  0.0                  0.0
4                  0.0                  0.0                  0.0

   Exterior2nd_Brk Cmn  Exterior2nd_BrkFace  Exterior2nd_CBlock  \
0                  0.0                  0.0                 0.0
1                  0.0                  0.0                 0.0
2                  0.0                  0.0                 0.0
3                  0.0                  0.0                 0.0
4                  0.0                  0.0                 0.0

   Exterior2nd_CmentBd  Exterior2nd_HdBoard  Exterior2nd_ImStucc  \
0                  0.0                  0.0                  0.0
1                  0.0                  1.0                  0.0
2                  0.0                  1.0                  0.0
```

```
3                  1.0                  0.0                  0.0
4                  0.0                  0.0                  0.0

   Exterior2nd_MetalSd  Exterior2nd_Other  Exterior2nd_Plywood  \
0                  0.0                0.0                  0.0
1                  0.0                0.0                  0.0
2                  0.0                0.0                  0.0
3                  0.0                0.0                  0.0
4                  1.0                0.0                  0.0

   Exterior2nd_Stone  Exterior2nd_Stucco  Exterior2nd_VinylSd  \
0                0.0                 0.0                  1.0
1                0.0                 0.0                  0.0
2                0.0                 0.0                  0.0
3                0.0                 0.0                  0.0
4                0.0                 0.0                  0.0

   Exterior2nd_Wd Sdng  Exterior2nd_Wd Shng  MasVnrType_BrkCmn  \
0                  0.0                  0.0                0.0
1                  0.0                  0.0                0.0
2                  0.0                  0.0                0.0
3                  0.0                  0.0                0.0
4                  0.0                  0.0                0.0

   MasVnrType_BrkFace  MasVnrType_None  MasVnrType_Stone  ExterQual_Ex  \
0                 0.0              1.0               0.0           0.0
1                 0.0              1.0               0.0           0.0
2                 0.0              1.0               0.0           0.0
3                 0.0              1.0               0.0           0.0
4                 1.0              0.0               0.0           1.0

   ExterQual_Fa  ExterQual_Gd  ExterQual_TA  ExterCond_Ex  ExterCond_Fa  \
0           0.0           1.0           0.0           0.0           0.0
1           0.0           0.0           1.0           0.0           0.0
2           0.0           0.0           1.0           0.0           0.0
3           0.0           1.0           0.0           0.0           0.0
4           0.0           0.0           0.0           0.0           0.0

   ExterCond_Gd  ExterCond_TA  Foundation_BrkTil  Foundation_CBlock  \
0           0.0           1.0                0.0                0.0
1           0.0           1.0                0.0                1.0
2           0.0           1.0                0.0                1.0
3           0.0           1.0                0.0                0.0
4           0.0           1.0                0.0                0.0

   Foundation_PConc  Foundation_Stone  Foundation_Wood  BsmtQual_Ex  \
0               1.0               0.0              0.0          0.0
```

```
1              0.0              0.0              0.0          0.0
2              0.0              0.0              0.0          0.0
3              1.0              0.0              0.0          0.0
4              1.0              0.0              0.0          1.0

   BsmtQual_Fa  BsmtQual_Gd  BsmtQual_TA  BsmtCond_Fa  BsmtCond_Gd  \
0          0.0          1.0          0.0          0.0          0.0
1          0.0          0.0          1.0          0.0          0.0
2          0.0          1.0          0.0          0.0          0.0
3          0.0          1.0          0.0          0.0          0.0
4          0.0          0.0          0.0          0.0          0.0

   BsmtCond_Po  BsmtCond_TA  BsmtExposure_Av  BsmtExposure_Gd  \
0          0.0          1.0              0.0              0.0
1          0.0          1.0              0.0              0.0
2          0.0          1.0              0.0              0.0
3          0.0          1.0              0.0              0.0
4          0.0          1.0              0.0              0.0

   BsmtExposure_Mn  BsmtExposure_No  BsmtFinType1_ALQ  BsmtFinType1_BLQ  \
0              0.0              1.0               0.0               0.0
1              0.0              1.0               1.0               0.0
2              1.0              0.0               0.0               0.0
3              0.0              1.0               0.0               0.0
4              0.0              1.0               0.0               0.0

   BsmtFinType1_GLQ  BsmtFinType1_LwQ  BsmtFinType1_Rec  BsmtFinType1_Unf  \
0               0.0               0.0               0.0               1.0
1               0.0               0.0               0.0               0.0
2               1.0               0.0               0.0               0.0
3               0.0               0.0               0.0               1.0
4               1.0               0.0               0.0               0.0

   BsmtFinType2_ALQ  BsmtFinType2_BLQ  BsmtFinType2_GLQ  BsmtFinType2_LwQ  \
0               0.0               0.0               0.0               0.0
1               0.0               0.0               0.0               0.0
2               0.0               0.0               0.0               0.0
3               0.0               0.0               0.0               0.0
4               0.0               0.0               0.0               0.0

   BsmtFinType2_Rec  BsmtFinType2_Unf  Heating_GasA  Heating_GasW  \
0               0.0               1.0           1.0           0.0
1               1.0               0.0           1.0           0.0
2               0.0               1.0           1.0           0.0
3               0.0               1.0           1.0           0.0
4               0.0               1.0           1.0           0.0
```

```
   Heating_Grav  Heating_OthW  HeatingQC_Ex  HeatingQC_Fa  HeatingQC_Gd  \
0           0.0           0.0           1.0           0.0           0.0
1           0.0           0.0           0.0           0.0           0.0
2           0.0           0.0           0.0           0.0           0.0
3           0.0           0.0           1.0           0.0           0.0
4           0.0           0.0           1.0           0.0           0.0

   HeatingQC_Po  HeatingQC_TA  CentralAir_N  CentralAir_Y  Electrical_FuseA  \
0           0.0           0.0           0.0           1.0               0.0
1           0.0           1.0           0.0           1.0               0.0
2           0.0           1.0           0.0           1.0               0.0
3           0.0           0.0           0.0           1.0               0.0
4           0.0           0.0           0.0           1.0               0.0

   Electrical_FuseF  Electrical_FuseP  Electrical_Mix  Electrical_SBrkr  \
0               0.0               0.0             0.0               1.0
1               0.0               0.0             0.0               1.0
2               0.0               0.0             0.0               1.0
3               0.0               0.0             0.0               1.0
4               0.0               0.0             0.0               1.0

   KitchenQual_Ex  KitchenQual_Fa  KitchenQual_Gd  KitchenQual_TA  \
0             0.0             0.0             1.0             0.0
1             0.0             0.0             0.0             1.0
2             0.0             0.0             1.0             0.0
3             0.0             0.0             1.0             0.0
4             1.0             0.0             0.0             0.0

   Functional_Maj1  Functional_Maj2  Functional_Min1  Functional_Min2  \
0              0.0              0.0              0.0              0.0
1              0.0              0.0              0.0              0.0
2              0.0              0.0              0.0              0.0
3              0.0              0.0              0.0              0.0
4              0.0              0.0              0.0              0.0

   Functional_Mod  Functional_Typ  GarageType_2Types  GarageType_Attchd  \
0             0.0             1.0                0.0                1.0
1             0.0             1.0                0.0                1.0
2             0.0             1.0                0.0                1.0
3             0.0             1.0                0.0                1.0
4             0.0             1.0                0.0                1.0

   GarageType_Basment  GarageType_BuiltIn  GarageType_CarPort  \
0                 0.0                 0.0                 0.0
1                 0.0                 0.0                 0.0
2                 0.0                 0.0                 0.0
3                 0.0                 0.0                 0.0
```

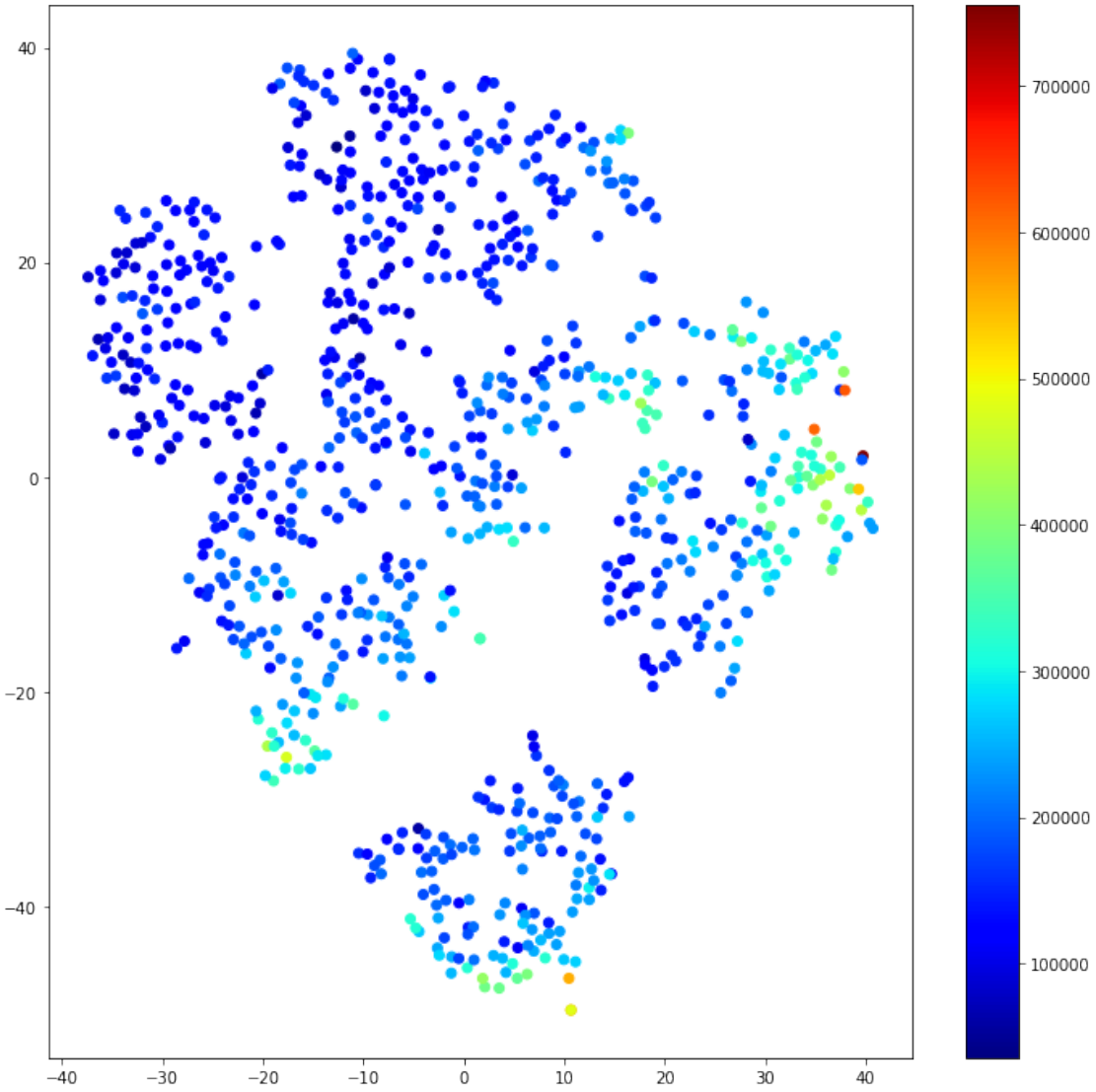
```
4                 0.0                 0.0                 0.0

   GarageType_Detchd  GarageFinish_Fin  GarageFinish_RFn  GarageFinish_Unf  \
0                0.0               1.0               0.0               0.0
1                0.0               0.0               1.0               0.0
2                0.0               0.0               0.0               1.0
3                0.0               1.0               0.0               0.0
4                0.0               0.0               1.0               0.0

   GarageQual_Ex  GarageQual_Fa  GarageQual_Gd  GarageQual_Po  GarageQual_TA  \
0            0.0            0.0            0.0            0.0            1.0
1            0.0            0.0            0.0            0.0            1.0
2            0.0            0.0            0.0            0.0            1.0
3            0.0            0.0            0.0            0.0            1.0
4            0.0            0.0            0.0            0.0            1.0

   GarageCond_Ex  GarageCond_Fa  GarageCond_Gd  GarageCond_Po  GarageCond_TA  \
0            0.0            0.0            0.0            0.0            1.0
1            0.0            0.0            0.0            0.0            1.0
2            0.0            0.0            0.0            0.0            1.0
3            0.0            0.0            0.0            0.0            1.0
4            0.0            0.0            0.0            0.0            1.0

   PavedDrive_N  PavedDrive_P  PavedDrive_Y  SaleType_COD  SaleType_CWD  \
0           0.0           0.0           1.0           0.0           0.0
1           0.0           0.0           1.0           0.0           0.0
2           0.0           0.0           1.0           0.0           0.0
3           0.0           0.0           1.0           0.0           0.0
4           0.0           0.0           1.0           0.0           0.0

   SaleType_Con  SaleType_ConLD  SaleType_ConLI  SaleType_ConLw  SaleType_New  \
0           0.0             0.0             0.0             0.0           1.0
1           0.0             0.0             0.0             0.0           0.0
2           0.0             0.0             0.0             0.0           0.0
3           0.0             0.0             0.0             0.0           0.0
4           0.0             0.0             0.0             0.0           0.0

   SaleType_Oth  SaleType_WD  SaleCondition_Abnorml  SaleCondition_AdjLand  \
0           0.0          0.0                    0.0                    0.0
1           0.0          1.0                    0.0                    0.0
2           0.0          1.0                    0.0                    0.0
3           0.0          1.0                    0.0                    0.0
4           0.0          1.0                    0.0                    0.0

   SaleCondition_Alloca  SaleCondition_Family  SaleCondition_Normal  \
0                   0.0                   0.0                   0.0
1                   0.0                   0.0                   1.0
```

```
2                   0.0                   0.0                   1.0
3                   0.0                   0.0                   1.0
4                   0.0                   0.0                   1.0

   SaleCondition_Partial
0                    1.0
1                    0.0
2                    0.0
3                    0.0
4                    0.0
```

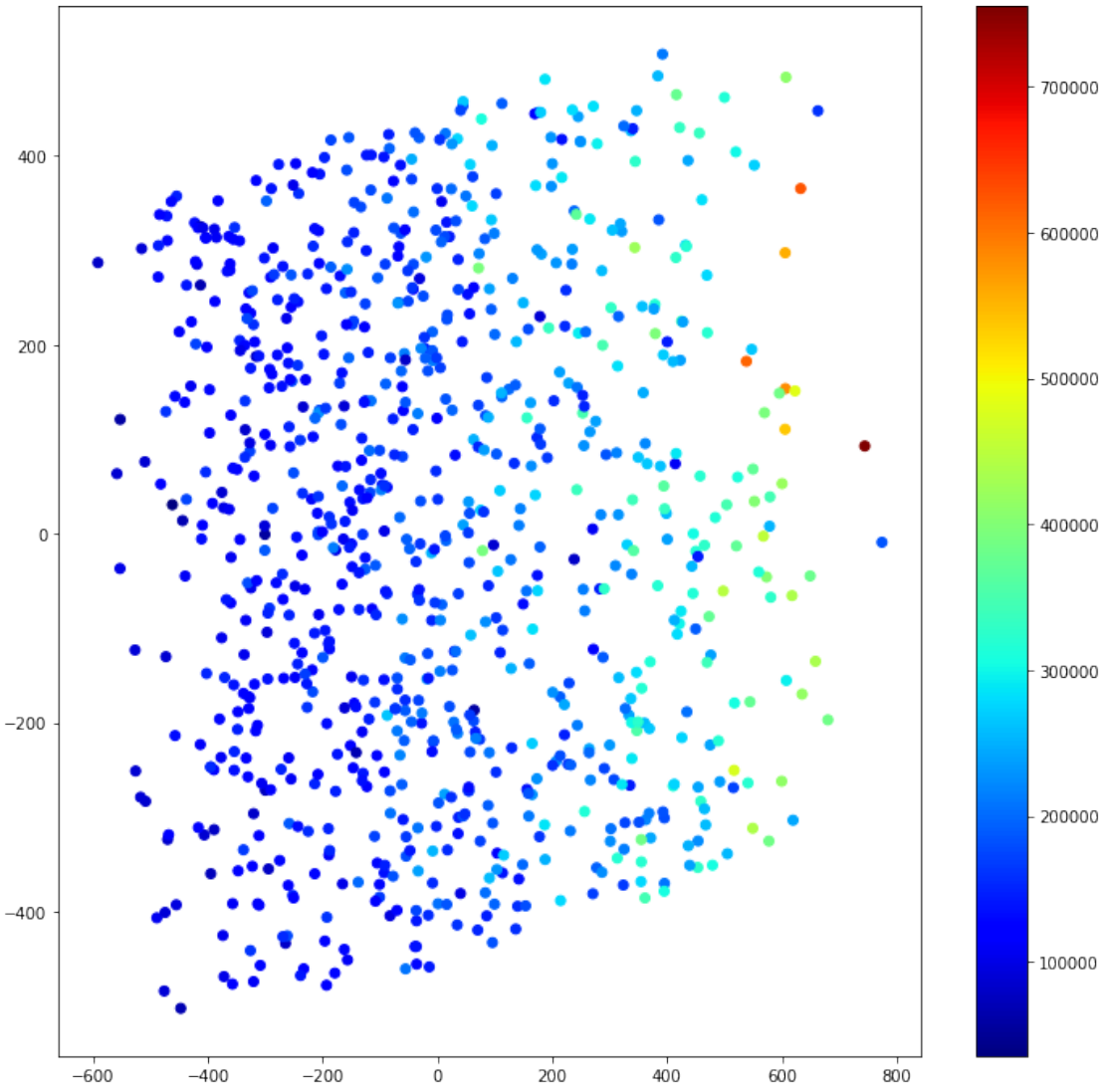
[21]:
```
oe = OrdinalEncoder()
print(X_train.shape)
encoded = oe.fit_transform(X_train)
```

```
(878, 75)
```

[22]:
```
tsne = TSNE(n_components=2)
X_reduced_tsne = tsne.fit_transform(encoded)

plt.figure(figsize=(12, 12))
plt.scatter(X_reduced_tsne[:, 0], X_reduced_tsne[:, 1], c=y_train, cmap="jet")
plt.colorbar()
plt.show()
```



[23]:
```
pca = PCA(n_components=2)
X_reduced_pca = pca.fit_transform(encoded)

plt.figure(figsize=(12, 12))
plt.scatter(X_reduced_pca[:, 0], X_reduced_pca[:, 1], c=y_train, cmap="jet")
plt.colorbar()
plt.show()
```



Many vectors of expensive houses concentrated near. The farther from the core of concentration, then home is more expensive. This fact confirm correlation. (For numerical attributes)

[24]:
```
X_train, y_train = None, None

pipeline = Pipeline([
    ("cleaner", DataCleaner(drop_na, drop_columns)),
    ("labels_splitter", DataColumnSplitter("SalePrice")),
    ("encoder", CathgoricalEncoder()),
    ("scaler", StandardScaler())
])

X_train = pipeline.fit_transform(train)
y_train = pipeline.named_steps["labels_splitter"].column_
```

```
X_test = pipeline.fit_transform(test)
y_test = pipeline.named_steps["labels_splitter"].column_
```

[25]:
```
X_train.shape
```

[25]: (878, 259)

[26]:
```
X_test.shape
```

[26]: (216, 219)

Oh no, we are losing some cathegorical attributes in test set. We have 3 ways: 1) Hardcode some magical constant (list with all cathegorical attributes, and fill empty columns zeros)

2) Delete cahtegorical attributes with many cathegories.

3) Try OriginalEncoder

We have wery small dataset and too many attributes. So, at the first lets try to change OneHotEncoder. Many algorithms are sensetives to attributes, for example, a neighbor with a good attribute will also be considered good. So, OneHotEncoder will be better, but, they create many atributes…… So we not have a choise….

[27]:
```
def remove_column(data, column_name):
    """
    Remove column by name

    Parameters
    data : list
        Column names
    column_name : str
        Column name that must be deleted

    Returns
    list
        data without selected name
    """
    if column_name in data:
        data.remove(column_name)
```

[28]:
```
X_train, y_train = None, None

column_names = None

best_attributes = get_better_numeric_columns(corr_matrix["SalePrice"], 0.3)
remove_column(best_attributes, "SalePrice")
remove_column(best_attributes, "Id")
```

```
# best_attributes += ["Neighborhood", "GarageType", "BsmtQual", "WoodDeckSF",␣
 ↪"MasVnrArea"]

best_attributes += ["Neighborhood", "GarageType", "BsmtQual"]

pipeline = Pipeline([
    ("cleaner", DataCleaner(drop_na, drop_columns)),
    ("labels_splitter", DataColumnSplitter("SalePrice")),
    ("id_splitter", DataColumnSplitter("Id")),
    ("best_selecter", BestAttributesSelector(best_attributes)),
    ("column_names_saver", ColumnNamesSaver()),
    ("encoder", OrdinalEncoder()),
    ("scaler", StandardScaler())
])

X_train = pipeline.fit_transform(train)
y_train = pipeline.named_steps["labels_splitter"].column_

X_test, y_test = None, None
X_test = pipeline.fit_transform(test)
y_test = pipeline.named_steps["labels_splitter"].column_

column_names = pipeline.named_steps["column_names_saver"].column_names_
```

[29]:
```
X_train.shape, y_train.shape
```

[29]:
```
((878, 21), (878,))
```

[30]:
```
X_test.shape, y_test.shape
```

[30]:
```
((216, 21), (216,))
```

2 Model selection

In our dataset we have small amount of instances and attributes, so all models will be fast.

We have regression problem, so we need to calculate distance between prediction and label vectors. For this goal we can use Mean Absolute Error, or Root Mean Squared Error. This two functions most useful in regression problems.

If we use RMSE, then we must minimize this function, because RMSE return heigher value for large error value (use Euclidian norm). If we know, that dataset have many outlier, that we can use MAE (use Manhettan norm). RMSE more sensitive to outlies taht MAE.

Looking at plot with best correlationg features, we can see, that we have some outlies, but not more. So, we will use RMSE.

[31]:
```
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
lin_predictions = lin_reg.predict(X_test)

lin_mse = mean_squared_error(lin_predictions, y_test)
lin_rmse = np.sqrt(lin_mse)
lin_rmse
```

[31]:
```
39404.84690783668
```

[32]:
```
sgd_reg = SGDRegressor()

sgd_params = {
    "eta0": np.arange(0.001, 0.004, 0.0001)
}

sgd_grid_search = GridSearchCV(sgd_reg, sgd_params,␣
 ↪scoring="neg_mean_squared_error", cv=4,
                               return_train_score=True, n_jobs=-1)
sgd_grid_search.fit(X_train, y_train)
```

[32]:
```
GridSearchCV(cv=4, estimator=SGDRegressor(), n_jobs=-1,
             param_grid={'eta0': array([0.001 , 0.0011, 0.0012, 0.0013, 0.0014,
0.0015, 0.0016, 0.0017,
       0.0018, 0.0019, 0.002 , 0.0021, 0.0022, 0.0023, 0.0024, 0.0025,
       0.0026, 0.0027, 0.0028, 0.0029, 0.003 , 0.0031, 0.0032, 0.0033,
       0.0034, 0.0035, 0.0036, 0.0037, 0.0038, 0.0039])},
             return_train_score=True, scoring='neg_mean_squared_error')
```

[33]:
```
sgd_grid_search.best_estimator_
```

[33]:
```
SGDRegressor(eta0=0.002700000000000001)
```

[34]:
```
sgd_results = sgd_grid_search.cv_results_
for mean, params in sorted(zip(sgd_results["mean_test_score"],␣
 ↪sgd_results["params"]), reverse=True, key=lambda x: x[0])[:10]:
    print(np.sqrt(-mean), params)
```

```
36994.72631333194 {'eta0': 0.002700000000000001}
37004.31821847448 {'eta0': 0.003200000000000001}
37016.111822182225 {'eta0': 0.002800000000000001}
37017.06071801622 {'eta0': 0.0039000000000000016}
37017.20925029402 {'eta0': 0.003100000000000001}
37019.82404425921 {'eta0': 0.0018000000000000004}
37022.103826862054 {'eta0': 0.0016000000000000003}
37024.38324526432 {'eta0': 0.0022000000000000006}
37029.87101654565 {'eta0': 0.0014000000000000002}
37030.3860922398 {'eta0': 0.002300000000000001}
```

[35]:
```
forest_reg = RandomForestRegressor()
forest_reg.fit(X_train, y_train)
forest_predictions = forest_reg.predict(X_test)

forest_mse = mean_squared_error(forest_predictions, y_test)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

[35]:
```
33645.06927132211
```

[36]:
```
forest_reg.feature_importances_
```

[36]:
```
array([0.58823225, 0.11004969, 0.0082771 , 0.01660683, 0.02723705,
       0.02355151, 0.04106352, 0.02031146, 0.01715481, 0.01422024,
       0.00875766, 0.01160133, 0.0046584 , 0.03395242, 0.01675045,
       0.00652791, 0.02578713, 0.00791443, 0.00830762, 0.00389306,
       0.00514512])
```

[37]:
```
dtypes = [str(name) for name in data[column_names].dtypes]

for (dtype, name), importance in sorted(
                                zip(zip(dtypes, column_names), forest_reg.
 ↪feature_importances_),
                                reverse=True,
                                key=lambda x: x[1]):
    print(f"{dtype}\t{name} \t-> {importance}")
```

```
int64   OverallQual     -> 0.5882322514896561
int64   GrLivArea       -> 0.11004968985362837
int64   FullBath        -> 0.04106352286343453
int64   BsmtFinSF1      -> 0.03395241955154119
int64   TotalBsmtSF     -> 0.02723705469307356
int64   2ndFlrSF        -> 0.025787129794985555
int64   1stFlrSF        -> 0.0235515055510849
int64   TotRmsAbvGrd    -> 0.02031145953124797
int64   YearBuilt       -> 0.01715481344790636
float64 LotFrontage     -> 0.016750445812492843
int64   GarageArea      -> 0.01660683072203185
int64   YearRemodAdd    -> 0.014220236499537879
float64 MasVnrArea      -> 0.011601326974580495
float64 GarageYrBlt     -> 0.008757660976443107
object  Neighborhood    -> 0.008307619852309819
int64   GarageCars      -> 0.008277100861151668
int64   OpenPorchSF     -> 0.007914431991969203
int64   WoodDeckSF      -> 0.006527912649930745
object  BsmtQual        -> 0.005145120543566297
int64   Fireplaces      -> 0.00465840283317669
```

```
object  GarageType      -> 0.0038930635062509166
```

[38]:
```
corr_matrix["SalePrice"].sort_values(ascending=False)
```

[38]:
```
SalePrice        1.000000
OverallQual      0.790982
GrLivArea        0.708624
GarageCars       0.640409
GarageArea       0.623431
TotalBsmtSF      0.613581
1stFlrSF         0.605852
FullBath         0.560664
TotRmsAbvGrd     0.533723
YearBuilt        0.522897
YearRemodAdd     0.507101
GarageYrBlt      0.486362
MasVnrArea       0.477493
Fireplaces       0.466929
BsmtFinSF1       0.386420
LotFrontage      0.351799
WoodDeckSF       0.324413
2ndFlrSF         0.319334
OpenPorchSF      0.315856
HalfBath         0.284108
LotArea          0.263843
BsmtFullBath     0.227122
BsmtUnfSF        0.214479
BedroomAbvGr     0.168213
ScreenPorch      0.111447
PoolArea         0.092404
MoSold           0.046432
3SsnPorch        0.044584
BsmtFinSF2      -0.011378
BsmtHalfBath    -0.016844
MiscVal         -0.021190
Id              -0.021917
LowQualFinSF    -0.025606
YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

[39]:
```
tree_reg = DecisionTreeRegressor()
tree_reg.fit(X_train, y_train)
tree_predictions = tree_reg.predict(X_test)
```

```
tree_mse = mean_squared_error(tree_predictions, y_test)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

[39]:
```
55807.300247393956
```

[40]:
```
tree_reg = DecisionTreeRegressor()

tree_params = {
    "min_samples_leaf": np.arange(1, 10, 1),
    "max_leaf_nodes": np.arange(50, 100, 2),
    "max_depth": np.arange(5, 15, 1),
    "max_features": np.arange(1, 10, 1),

}

tree_search = GridSearchCV(tree_reg, tree_params,␣
 ↪scoring="neg_mean_squared_error", cv=4,
                           return_train_score=True, n_jobs=-1)
tree_search.fit(X_train, y_train)
```

[40]:
```
GridSearchCV(cv=4, estimator=DecisionTreeRegressor(), n_jobs=-1,
             param_grid={'max_depth': array([ 5,  6,  7,  8,  9, 10, 11, 12, 13,
14]),
                         'max_features': array([1, 2, 3, 4, 5, 6, 7, 8, 9]),
                         'max_leaf_nodes': array([50, 52, 54, 56, 58, 60, 62,
64, 66, 68, 70, 72, 74, 76, 78, 80, 82,
       84, 86, 88, 90, 92, 94, 96, 98]),
                         'min_samples_leaf': array([1, 2, 3, 4, 5, 6, 7, 8,
9])},
             return_train_score=True, scoring='neg_mean_squared_error')
```

[41]:
```
tree_results = tree_search.cv_results_
for neg_mean, params in sorted(zip(tree_results["mean_test_score"],␣
 ↪tree_results["params"]), key=lambda x: x[0], reverse=True)[:10]:
    print(np.sqrt(-neg_mean), params)
```

```
38606.112750110624 {'max_depth': 11, 'max_features': 9, 'max_leaf_nodes': 76,
'min_samples_leaf': 6}
38644.470198613475 {'max_depth': 10, 'max_features': 6, 'max_leaf_nodes': 82,
'min_samples_leaf': 8}
38718.16504550667 {'max_depth': 12, 'max_features': 9, 'max_leaf_nodes': 76,
'min_samples_leaf': 2}
38753.61181033075 {'max_depth': 12, 'max_features': 7, 'max_leaf_nodes': 78,
'min_samples_leaf': 8}
38857.20067171636 {'max_depth': 11, 'max_features': 7, 'max_leaf_nodes': 88,
'min_samples_leaf': 4}
39003.50273130473 {'max_depth': 7, 'max_features': 9, 'max_leaf_nodes': 52,
```

```
'min_samples_leaf': 7}
39007.33269771466 {'max_depth': 6, 'max_features': 9, 'max_leaf_nodes': 82,
'min_samples_leaf': 4}
39018.18211249786 {'max_depth': 13, 'max_features': 9, 'max_leaf_nodes': 72,
'min_samples_leaf': 9}
39074.179146271956 {'max_depth': 7, 'max_features': 8, 'max_leaf_nodes': 94,
'min_samples_leaf': 7}
39142.51799601221 {'max_depth': 6, 'max_features': 7, 'max_leaf_nodes': 50,
'min_samples_leaf': 2}
```

[42]:
```
forest_reg = RandomForestRegressor()
forest_reg.fit(X_train, y_train)
forest_predictions = forest_reg.predict(X_test)

forest_mse = mean_squared_error(forest_predictions, y_test)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

[42]:
```
35542.43865830903
```

[43]:
```
forest_reg = RandomForestRegressor()

forest_params = {
    "n_estimators": np.arange(1, 300, 5),
    "max_features": np.arange(1, 15, 1),
    "min_samples_leaf": np.arange(1, 10, 1),
    "max_leaf_nodes": np.arange(2, 100, 1),
}

forest_search = RandomizedSearchCV(forest_reg, forest_params, n_iter=1000,␣
 ↪scoring="neg_mean_squared_error", cv=4,
                                return_train_score=True, n_jobs=-1)
forest_search.fit(X_train, y_train)
```

[43]:
```
RandomizedSearchCV(cv=4, estimator=RandomForestRegressor(), n_iter=1000,
                   n_jobs=-1,
                   param_distributions={'max_features': array([ 1,  2,  3,  4,
5,  6,  7,  8,  9, 10, 11, 12, 13, 14]),
                                        'max_leaf_nodes': array([ 2,  3,  4,  5,
6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17, 18,
       19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35,
       36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52,
       53, 54, 55, 56, 57, 58, 59, 60…
       87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99]),
                                        'min_samples_leaf': array([1, 2, 3, 4,
5, 6, 7, 8, 9]),
                                        'n_estimators': array([  1,   6,  11,
16,  21,  26,  31,  36,  41,  46,  51,  56,  61,
```

```
        66,  71,  76,  81,  86,  91,  96, 101, 106, 111, 116, 121, 126,
       131, 136, 141, 146, 151, 156, 161, 166, 171, 176, 181, 186, 191,
       196, 201, 206, 211, 216, 221, 226, 231, 236, 241, 246, 251, 256,
       261, 266, 271, 276, 281, 286, 291, 296])},
                  return_train_score=True, scoring='neg_mean_squared_error')
```

[44]:
```
forest_results = forest_search.cv_results_
for mean, params in sorted(zip(forest_results["mean_test_score"],␣
 ↪forest_results["params"]), key=lambda x: x[0], reverse=True)[:10]:
    print(np.sqrt(-mean), params)
```

```
32332.883909712382 {'n_estimators': 211, 'min_samples_leaf': 1,
'max_leaf_nodes': 82, 'max_features': 13}
32374.79879517793 {'n_estimators': 36, 'min_samples_leaf': 1, 'max_leaf_nodes':
85, 'max_features': 11}
32445.063016777378 {'n_estimators': 71, 'min_samples_leaf': 1, 'max_leaf_nodes':
88, 'max_features': 12}
32458.666252668456 {'n_estimators': 166, 'min_samples_leaf': 1,
'max_leaf_nodes': 57, 'max_features': 9}
32485.758419087906 {'n_estimators': 266, 'min_samples_leaf': 1,
'max_leaf_nodes': 97, 'max_features': 5}
32586.466475484063 {'n_estimators': 91, 'min_samples_leaf': 1, 'max_leaf_nodes':
95, 'max_features': 8}
32607.29412467637 {'n_estimators': 246, 'min_samples_leaf': 1, 'max_leaf_nodes':
52, 'max_features': 14}
32630.50291754739 {'n_estimators': 131, 'min_samples_leaf': 1, 'max_leaf_nodes':
72, 'max_features': 9}
32644.38933035375 {'n_estimators': 66, 'min_samples_leaf': 1, 'max_leaf_nodes':
40, 'max_features': 7}
32687.17644824022 {'n_estimators': 261, 'min_samples_leaf': 1, 'max_leaf_nodes':
77, 'max_features': 9}
```

[45]:
```
svm_reg = SVR()
svm_reg.fit(X_train, y_train)
svm_predictions = svm_reg.predict(X_test)

svm_mse = mean_squared_error(svm_predictions, y_test)
svm_rmse = np.sqrt(svm_mse)
svm_rmse
```

[45]:
```
87023.67584778993
```

[46]:
```
svm_reg = SVR()

svm_params = [

    {
        'kernel': ['linear'],
```

```
        'C': np.arange(35000, 37000, 10)
    },

    {
        'kernel': ['rbf'],
        'C': np.arange(9000, 10000, 50),
        'gamma': np.arange(0.001, 0.03, 0.005)
    },
]

svm_search = GridSearchCV(svm_reg, svm_params, cv=4,␣
↪scoring='neg_mean_squared_error', n_jobs=-1)
svm_search.fit(X_train, y_train)
```

[46]:
```
GridSearchCV(cv=4, estimator=SVR(), n_jobs=-1,
             param_grid=[{'C': array([35000, 35010, 35020, 35030, 35040, 35050,
35060, 35070, 35080,
       35090, 35100, 35110, 35120, 35130, 35140, 35150, 35160, 35170,
       35180, 35190, 35200, 35210, 35220, 35230, 35240, 35250, 35260,
       35270, 35280, 35290, 35300, 35310, 35320, 35330, 35340, 35350,
       35360, 35370, 35380, 35390, 35400, 35410, 35420, 35430, 35440,
       35450, 35460,…
       36800, 36810, 36820, 36830, 36840, 36850, 36860, 36870, 36880,
       36890, 36900, 36910, 36920, 36930, 36940, 36950, 36960, 36970,
       36980, 36990]),
                          'kernel': ['linear']},
                         {'C': array([9000, 9050, 9100, 9150, 9200, 9250, 9300,
9350, 9400, 9450, 9500,
       9550, 9600, 9650, 9700, 9750, 9800, 9850, 9900, 9950]),
                          'gamma': array([0.001, 0.006, 0.011, 0.016, 0.021,
0.026]),
                          'kernel': ['rbf']}],
             scoring='neg_mean_squared_error')
```

[47]:
```
svm_results = svm_search.cv_results_
for neg_mean, params in sorted(zip(svm_results["mean_test_score"],␣
↪svm_results["params"]), reverse=True, key=lambda x: x[0])[:10]:
    print(np.sqrt(-neg_mean), params)
```

```
37830.43817857638 {'C': 36990, 'kernel': 'linear'}
37830.43822357741 {'C': 36960, 'kernel': 'linear'}
37830.438236216556 {'C': 36940, 'kernel': 'linear'}
37830.438241229196 {'C': 36950, 'kernel': 'linear'}
37830.438280162816 {'C': 36920, 'kernel': 'linear'}
37830.43830373701 {'C': 36900, 'kernel': 'linear'}
37830.43830694255 {'C': 36880, 'kernel': 'linear'}
37830.43834921379 {'C': 36980, 'kernel': 'linear'}
37830.438349719756 {'C': 36860, 'kernel': 'linear'}
```

```
37830.43835137828 {'C': 36970, 'kernel': 'linear'}
```

[48]:
```
svm_reg = SVR(**svm_search.best_params_)
tree_reg = DecisionTreeRegressor(**tree_search.best_params_)

voting_reg = VotingRegressor(
    estimators=[("svr", svm_reg), ("tree", tree_reg)]
)

voting_reg.fit(X_train, y_train)

voting_predictions = voting_reg.predict(X_test)
voting_mse = mean_squared_error(voting_predictions, y_test)
voting_rmse = np.sqrt(voting_mse)
voting_rmse
```

[48]:
```
36360.63444781546
```

[49]:
```
gbrt = GradientBoostingRegressor(**tree_search.best_params_)

gbrt_params = {
    "n_estimators": np.arange(1, 20, 5),
    "learning_rate": np.arange(0.1, 1.1, 0.1)
}

gbrt_search = GridSearchCV(gbrt, gbrt_params, cv=4,␣
 ↪scoring='neg_mean_squared_error', n_jobs=-1)
gbrt_search.fit(X_train, y_train)
```

[49]:
```
GridSearchCV(cv=4,
             estimator=GradientBoostingRegressor(max_depth=11, max_features=9,
                                                 max_leaf_nodes=76,
                                                 min_samples_leaf=6),
             n_jobs=-1,
             param_grid={'learning_rate': array([0.1, 0.2, 0.3, 0.4, 0.5, 0.6,
0.7, 0.8, 0.9, 1. ]),
                         'n_estimators': array([ 1,  6, 11, 16])},
             scoring='neg_mean_squared_error')
```

[50]:
```
gbrt_results = gbrt_search.cv_results_
for neg_mean, params in sorted(zip(gbrt_results["mean_test_score"],␣
 ↪gbrt_results["params"]), reverse=True, key=lambda x: x[0])[:10]:
    print(np.sqrt(-neg_mean), params)
```

```
33537.89400598131 {'learning_rate': 0.2, 'n_estimators': 16}
34344.60063157056 {'learning_rate': 0.2, 'n_estimators': 11}
34660.10611490735 {'learning_rate': 0.30000000000000004, 'n_estimators': 11}
34728.67668878038 {'learning_rate': 0.4, 'n_estimators': 16}
```

```
35156.68872817922 {'learning_rate': 0.4, 'n_estimators': 6}
35510.783950863624 {'learning_rate': 0.30000000000000004, 'n_estimators': 16}
35921.18230331537 {'learning_rate': 0.30000000000000004, 'n_estimators': 6}
36614.38298823303 {'learning_rate': 0.1, 'n_estimators': 16}
37188.29115126182 {'learning_rate': 0.4, 'n_estimators': 11}
37259.31791068092 {'learning_rate': 0.5, 'n_estimators': 6}
```

So, random forest is better estimator.

[51]:
```
best_estimator = forest_search.best_estimator_
```

[52]:
```
X_test, y_test = None, None
X_test = pipeline.fit_transform(data)
y_test = pipeline.named_steps["labels_splitter"].column_

best_estimator.fit(X_train, y_train)
best_estimator_predictions = best_estimator.predict(X_test)

best_estimator_mse = mean_squared_error(best_estimator_predictions, y_test)
best_estimator_rmse = np.sqrt(best_estimator_mse)
best_estimator_rmse
```

[52]:
```
21382.912401353307
```

[53]:
```
id_column = None

X_final_prepared = pipeline.fit_transform(X_final)
id_column = pipeline.named_steps["id_splitter"].column_

print(id_column)
```

```
0       1461
1       1462
2       1463
3       1464
4       1465
        …
1451    2912
1452    2913
1455    2916
1456    2917
1458    2919
Name: Id, Length: 1111, dtype: int64
```

[54]:
```
y_final_pred = best_estimator.predict(X_final_prepared)
y_final_pred
```

[54]:
```
array([127358.1140728 , 153112.6896274 , 180095.17425648, …,
       108303.41865008, 153866.85982141, 256508.31296077])
```

[55]:
```
y_final_pred.shape
```

[55]:
```
(1111,)
```

[56]:
```
results = pd.DataFrame({
    "Id": id_column,
    "SalePrice": y_final_pred
})
results
```

[56]:

	Id	SalePrice
0	1461	127358.114073
1	1462	153112.689627
2	1463	180095.174256
3	1464	181726.435847
4	1465	216642.003449
…	…	…
1451	2912	152384.004743
1452	2913	110421.163725
1455	2916	108303.418650
1456	2917	153866.859821
1458	2919	256508.312961

[1111 rows x 2 columns]

[57]:
```
results.to_csv("prediction.csv", index=False)
```

[ ]:
```

```