House Prices: Advanced Regression Techniques

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Problem Statement

It costs a lot to buy a house.People always wish to buy a better house with a lower price.However, the seller and the intermediary agent will be unhappy for this

So we wish to predict the price of the house with using some practical features,such as the location(street), house style, utilities, etc.

Dataset

We have some dataset about the record of the house price compiled by Dean De Cock from https://www.kaggle.com/c/house-prices-advanced-regression-techniques/overview. It describes the sale of individual residential property in Ames,Iowa from 2006 to 2010. It contains 2930 observations and large number of explanatory variables(23 nomonal,23 ordinal,14 discrete and 20 continus) involved in assessing home values. It is divided into two datasets which is the train data set and the test data set.

In summary, it contains:

- sample_submission.csv, A benchmark submission from a linear regression on year and month of sale, lot square footage, and nuMSSubClass: Identifies the type of dwelling involved in the sale. 1459rows x 2columns data

- test.csv,a dataset of 1459rows x 80columns data

- train.csv, a dataset of 1460rows x 81columns data

- data_description.txt,identify what the names of columns stand for

Packages ¶

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import random
import copy
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Lasso, LassoCV
from sklearn.model_selection import validation_curve
from sklearn.model_selection import GridSearchCV #to find the best alpha a
nd score
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.decomposition import PCA
from scipy import stats,special
from scipy.special import inv_boxcox
```

General Info about our data

we can load the traning data and the test data into the project.

In [2]:
```
train_data = pd.read_csv('train.csv',index_col=0)# the first column is ID,
 which can be use as index
test_data = pd.read_csv('test.csv',index_col=0)
```

Have a look about what do those data look like

In [3]:
```
print(train_data.shape)
train_data.head()
```

```
(1460, 80)
```

Out[3]:

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

5 rows × 80 columns

In [4]:
```
print(test_data.shape)
test_data.head()
```

```
(1459, 79)
```

Out[4]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Land(
Id								

1461	20	RH	80.0	11622	Pave	NaN	Reg
1462	20	RL	81.0	14267	Pave	NaN	IR1
1463	60	RL	74.0	13830	Pave	NaN	IR1
1464	60	RL	78.0	9978	Pave	NaN	IR1
1465	120	RL	43.0	5005	Pave	NaN	IR1

5 rows × 79 columns

Here are the explanation of the columns

In [5]:
```
# description = open('data_description.txt','r') #there is a description fi
le in the dataset
# for line in description:#read line by line
#     print(line);
```

It's quite long. Just comment it.

Data cleaning and visualization

Null value

First,we find the columns which may contains null value

In [6]:
```
#columns in train_data contains null value
temp1 = train_data.isnull().any()
index1 = temp1.index.tolist()
columns1 = []
i=0
for t in temp1:
    if(t==True):
        columns1.append(index1[i])
    i +=1
print(columns1)

#columns in test_data contains null value
temp2 = test_data.isnull().any()
index2 = temp2.index.tolist()
columns2 = []
i=0
for t in temp2:
    if(t==True):
        columns2.append(index2[i])
    i +=1
print(columns2)
```

```
['LotFrontage', 'Alley', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCon
d', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'Electrical', 'Firepl
aceQu', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageQual', 'Garag
eCond', 'PoolQC', 'Fence', 'MiscFeature']
```

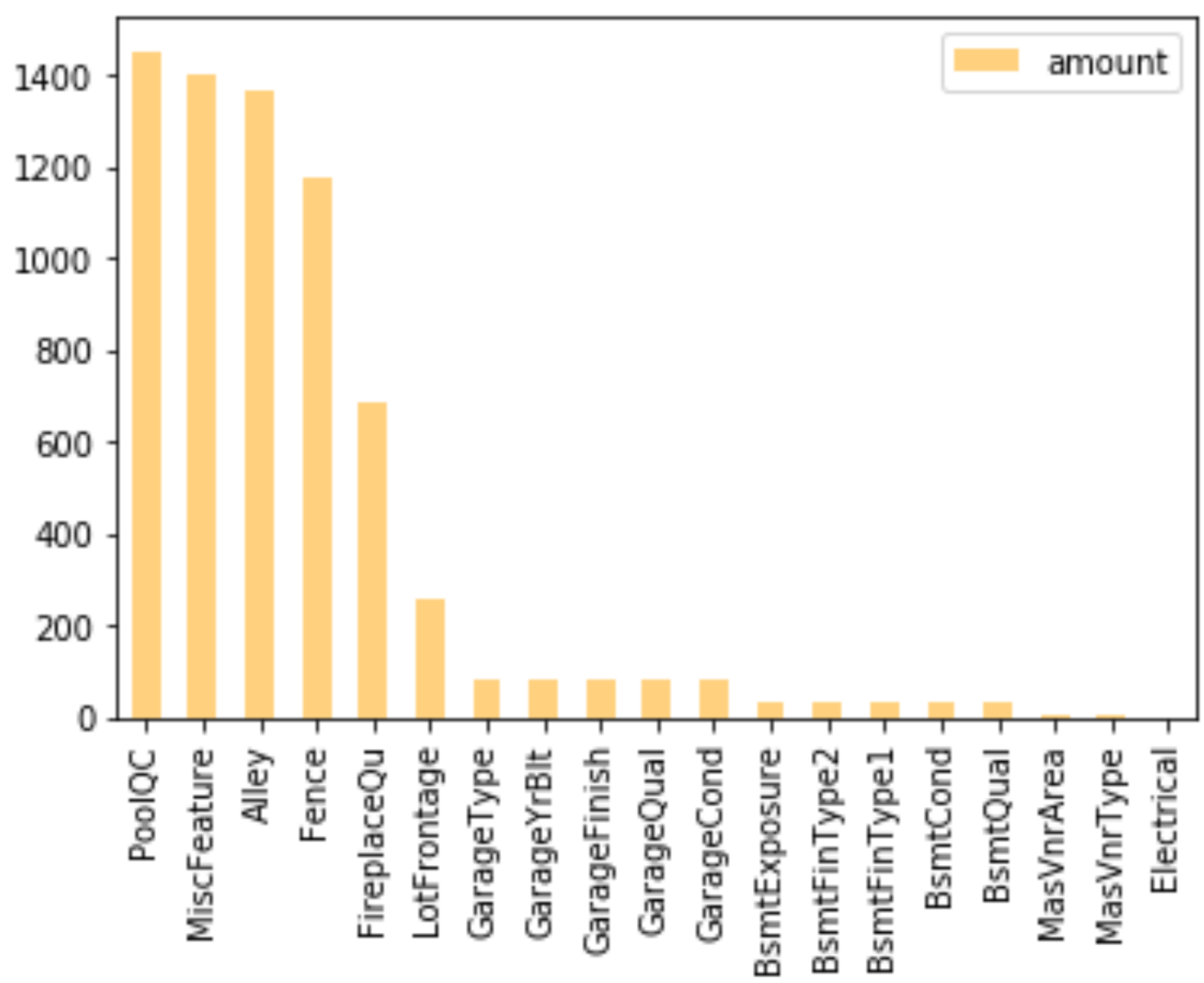
```
['MSZoning', 'LotFrontage', 'Alley', 'Utilities', 'Exterior1st', 'Exterio
r2nd', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond', 'BsmtExposur
e', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfS
F', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath', 'KitchenQual', 'Functi
onal', 'FireplaceQu', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'Garag
eCars', 'GarageArea', 'GarageQual', 'GarageCond', 'PoolQC', 'Fence', 'Mis
cFeature', 'SaleType']
```

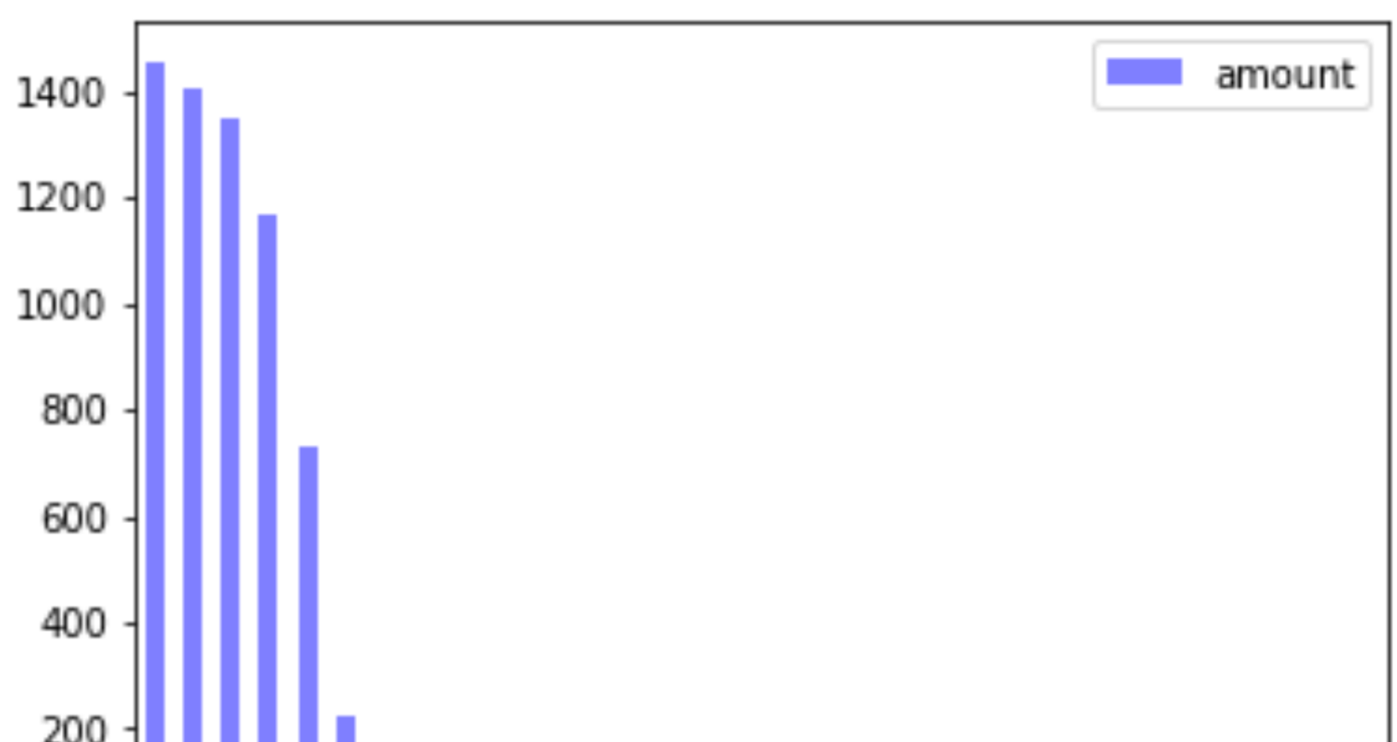
It's not quite straight-forward. Visualize the amount of null value in above column in train data or test data,respectively

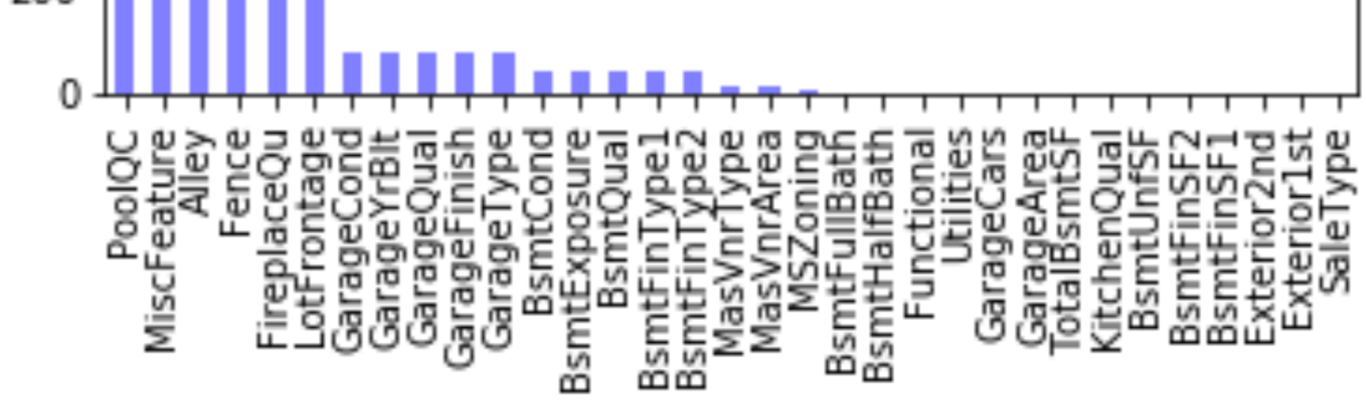
In [7]:
```
check_df1 = train_data[columns1]
num1 = check_df1.isna().sum()
null_value1 = pd.DataFrame({'amount':num1})
null_value1 = null_value1.sort_values(by = 'amount', ascending=False)
null_value1.plot(kind='bar',alpha=0.5, rot=90,color='orange')

check_df2 = test_data[columns2]
num2 = check_df2.isna().sum()
null_value2 = pd.DataFrame({'amount':num2})
null_value2 = null_value2.sort_values(by = 'amount', ascending=False)
null_value2.plot(kind='bar',alpha=0.5, rot=90,color='blue')
```

Out[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f191f5f7b8>
```







Some columns have terrible amount of null value, we must drop this columns

In [8]:
```
train_data = train_data.drop(['PoolQC','MiscFeature','Alley','Fence','Firep
laceQu','LotFrontage'],axis=1)
test_data = test_data.drop(['PoolQC','MiscFeature','Alley','Fence','Firepla
ceQu','LotFrontage'],axis=1)
```

I notice that there are some variables called "Garage**", and we have variable "GarageCars", there is strong relationship among them. so we can drop those columns

In [9]:
```
train_data.drop(['GarageYrBlt','GarageFinish','GarageCond','GarageQual','Ga
rageType'],axis=1, inplace=True)
test_data.drop(['GarageYrBlt','GarageFinish','GarageCond','GarageQual','Gar
ageType'], axis=1, inplace=True)
```

Same as "bsmtxx" and "MasVnrxx"

In [10]:
```
train_data.drop(['BsmtCond','BsmtExposure','BsmtFinType2','BsmtFinType1','M
asVnrType'],axis=1, inplace=True)
test_data.drop(['BsmtCond','BsmtExposure','BsmtFinType2','BsmtFinType1','Ma
sVnrType'], axis=1, inplace=True)
```

In [11]:
```
for i in ['PoolQC','MiscFeature','Alley','Fence','FireplaceQu','LotFrontag
e','GarageYrBlt','GarageFinish','GarageCond','GarageQual','GarageType','Bsm
tCond','BsmtExposure','BsmtFinType2','BsmtFinType1','MasVnrType']:
    columns1.remove(i)
    columns2.remove(i)
#To find the left column with null value
train_data[columns1].head()
```

Out[11]:

	MasVnrArea	BsmtQual	Electrical
Id			
1	196.0	Gd	SBrkr
2	0.0	Gd	SBrkr
3	162.0	Gd	SBrkr
4	0.0	TA	SBrkr
5	350.0	Gd	SBrkr

I decide to fill the discrete null value with the most frequent value in its column and fill the continuous null value with the mean value of its column

In [12]:
```
#since the distribution of each variable are given in Kaggle, i just look up them
train_data['Electrical'].fillna('SBrkr',inplace=True)
train_data['BsmtQual'].fillna('Gd',inplace=True)
#fill with the mean value or zero
train_data['MasVnrArea'].fillna(train_data['MasVnrArea'].mean(),inplace=True)
```

In [13]:
```
test_data[columns2].head()
```

Out[13]:

	MSZoning	Utilities	Exterior1st	Exterior2nd	MasVnrArea	BsmtQual	BsmtFin
Id							
1461	RH	AllPub	VinylSd	VinylSd	0.0	TA	46
1462	RL	AllPub	Wd Sdng	Wd Sdng	108.0	TA	92
1463	RL	AllPub	VinylSd	VinylSd	0.0	Gd	79
1464	RL	AllPub	VinylSd	VinylSd	20.0	TA	60
1465	RL	AllPub	HdBoard	HdBoard	0.0	Gd	26

In [14]:
```
#since the distribution of each variable are given in Kaggle, i just look up them
test_data['MSZoning'] = test_data['MSZoning'].fillna('RL')
test_data['Utilities'] = test_data['Utilities'].fillna('AllPub')
test_data['Exterior1st'] = test_data['Exterior1st'].fillna('VinylSd')
test_data['Exterior2nd'] = test_data['Exterior2nd'].fillna('VinylSd')
test_data['KitchenQual'] = test_data['KitchenQual'].fillna('TA')
test_data['Functional'] = test_data['Functional'].fillna('Typ')
test_data['SaleType'] = test_data['SaleType'].fillna('WD')
test_data['BsmtQual'] = test_data['BsmtQual'].fillna('Gd')
#fill with the mean value or zero
test_data['MasVnrArea'] = test_data['MasVnrArea'].fillna(test_data['MasVnrArea'].mean())
test_data['BsmtFinSF1'] = test_data['BsmtFinSF1'].fillna(test_data['BsmtFinSF1'].mean())
test_data['BsmtFinSF2'] = test_data['BsmtFinSF2'].fillna(test_data['BsmtFinSF2'].mean())
test_data['BsmtUnfSF'] = test_data['BsmtUnfSF'].fillna(test_data['BsmtUnfSF'].mean())
test_data['TotalBsmtSF'] = test_data['TotalBsmtSF'].fillna(test_data['TotalBsmtSF'].mean())
test_data['GarageCars'] = test_data['GarageCars'].fillna(test_data['GarageCars'].mean())
test_data['GarageArea'] = test_data['GarageArea'].fillna(test_data['GarageArea'].mean())
test_data['BsmtFullBath'] = test_data['BsmtFullBath'].fillna(test_data['BsmtFullBath'].mean())
test_data['BsmtHalfBath'] = test_data['BsmtHalfBath'].fillna(test_data['BsmtHalfBath'].mean())
```

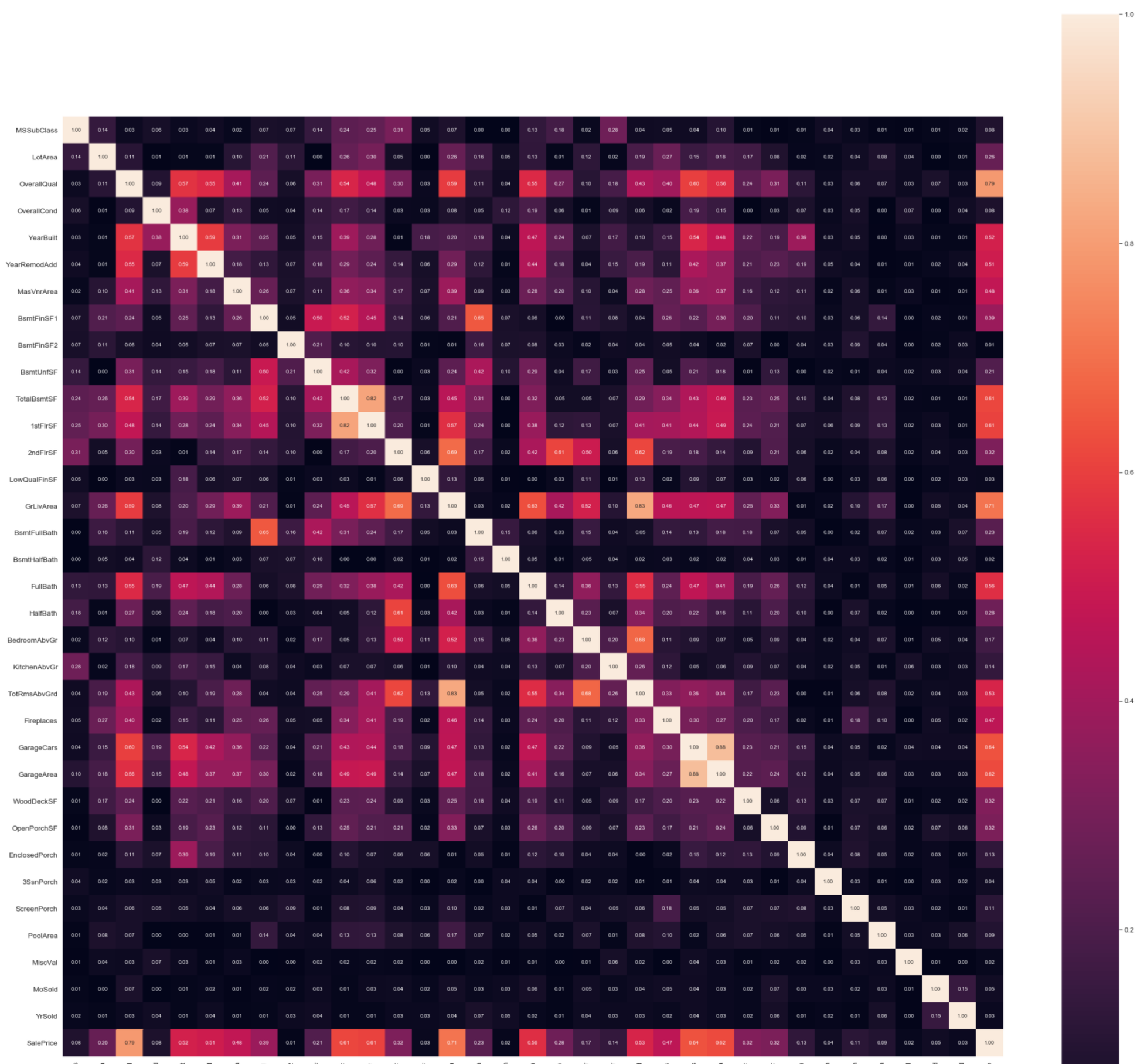
Now,we can see our data again to check whether there is any null value left

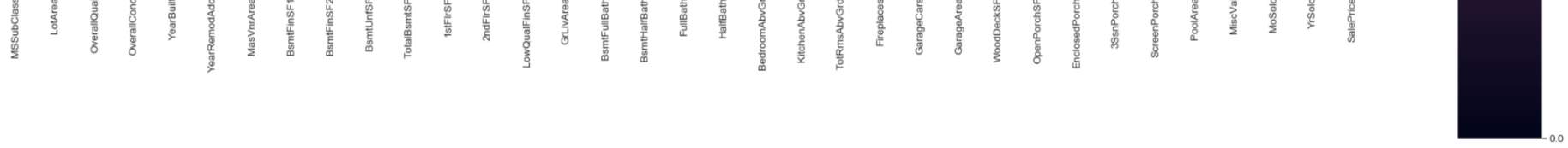
In [15]:
```
#if both the dataset have no null value, nothign should be printed out
for i in train_data.isnull().any():
    if(i==True):
        print(i)
for i in test_data.isnull().any():
    if(i==True):
        print(i)
```

Reduce multillinearity

From the course Regression Analysis,we learn that we should remove variables which have high correlation with another beacause it will cause multillinearity

In [16]:
```
corr = abs(train_data.corr()) #function to get the correlation between ea
ch variable
plt.figure(figsize=[40,40])
cols_first = corr['SalePrice'].index#get the index of all corr matrix
column = abs(np.corrcoef(train_data[cols_first].values.T))#use abosolute
 value to show the strength of correlation
sns.set(font_scale=1.25)
sns.heatmap(column, cbar=True,annot=True, square=True,vmin=0,vmax=1, fmt
='.2f', annot_kws={'size': 10}, yticklabels=cols_first.values, xticklabe
ls=cols_first.values)
plt.show()
```





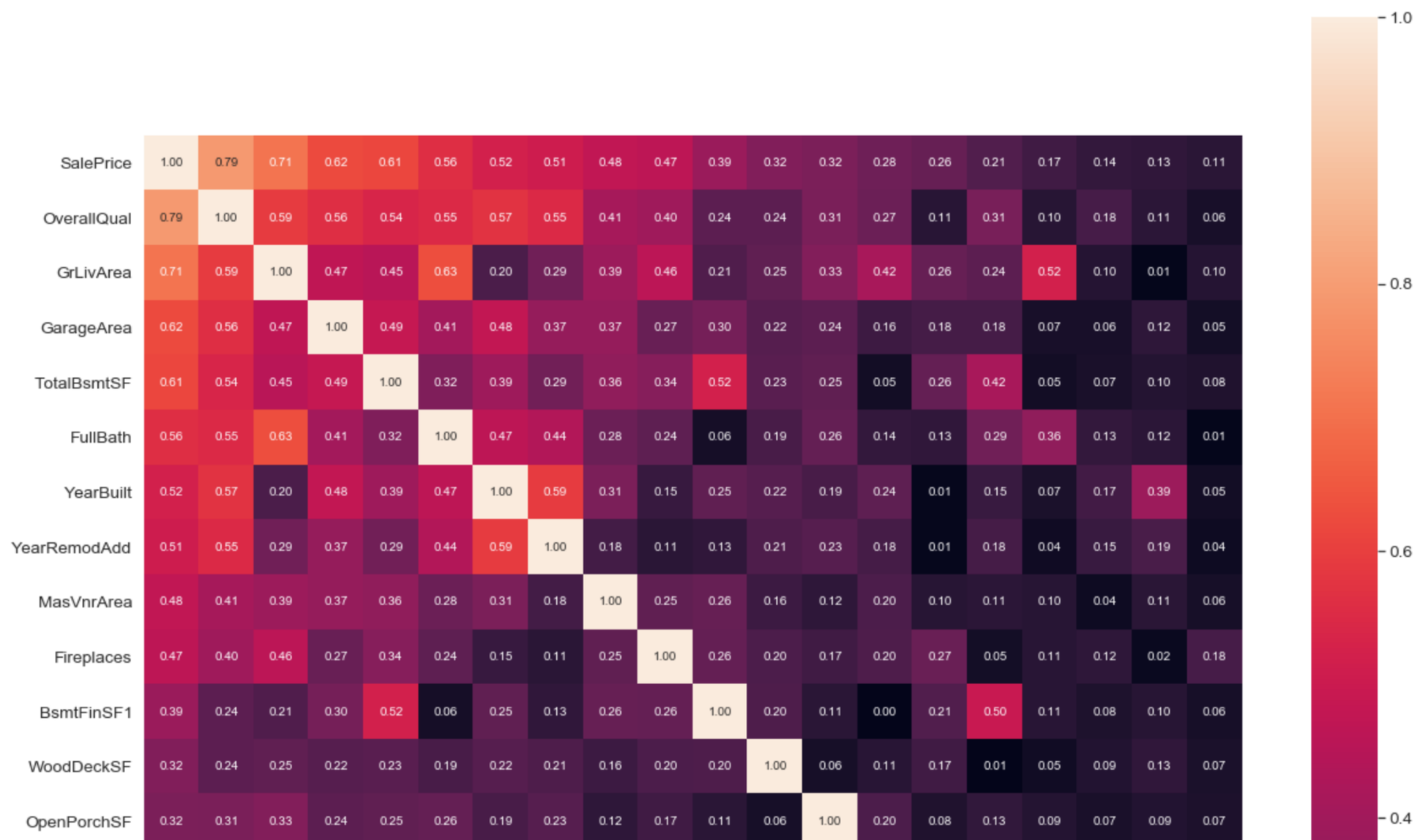
In [17]:
```
# drop = ['GarageCars','1stFlrSF','TotRmsAbvGrd','ExterQual_Gd','SaleCon
dition_Partial','KitchenQual_Gd','Foundation_CBlock','2ndFlrSF','Heating
QC_TA','CentralAir_N','Exterior1st_VinylSd','RoofStyle_Gable','LotShape_
IR1','LotShape_Reg','MSZoning_RL','PavedDrive_N','SaleType_WD','BsmtUnfS
F','Exterior2nd_VinylSd']
drop = ['GarageCars','1stFlrSF','TotRmsAbvGrd','2ndFlrSF','BsmtFullBath'
]
train_data = train_data.drop(drop,axis=1)
test_data = test_data.drop(drop,axis=1)
cols_first = list(cols_first)
for d in drop:
    cols_first.remove(d)
```

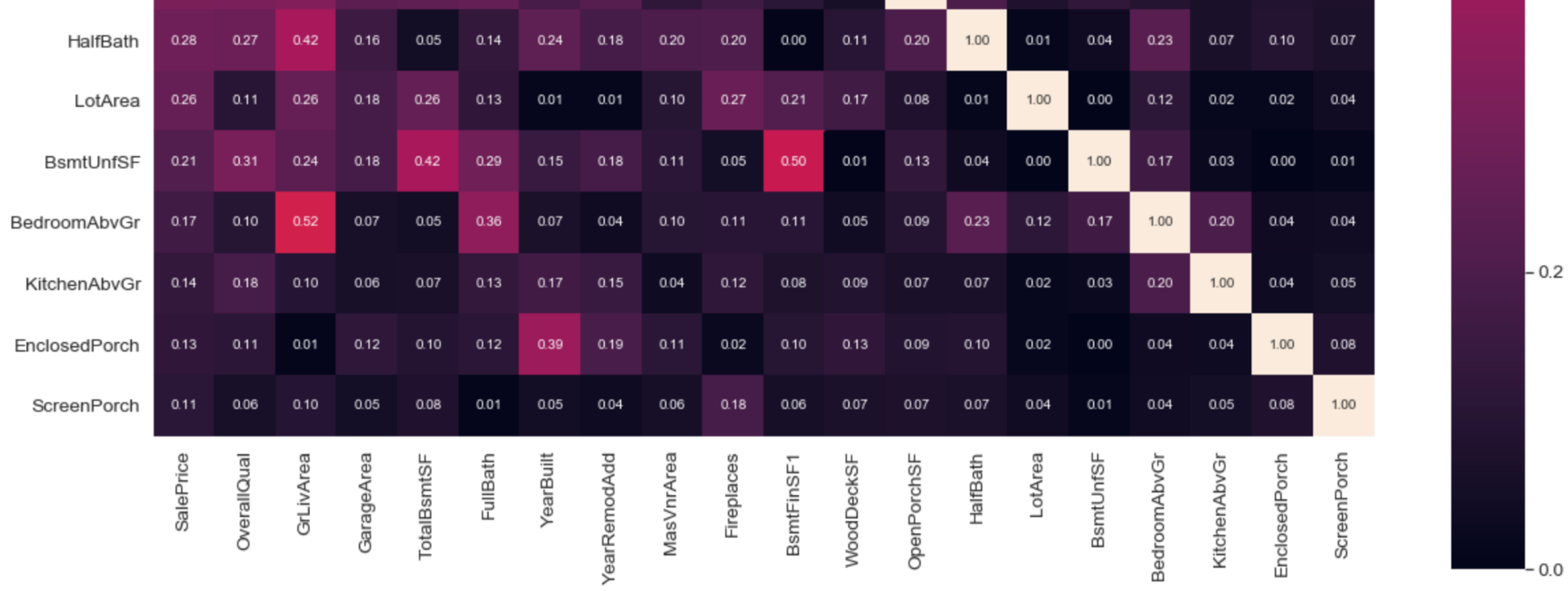
Eliminate the outliers

It's difficult to check all the outliers by looking the relational graph of each variables and sale price.

Therefore, we can delete the outliers by looking the graph of top 30 variables which influence sale price much more

In [18]:
```
corr = abs(train_data.corr()) #function to get the correlation between ea
ch variable
plt.figure(figsize=[20,20])
n = 20
cols_second = corr.nlargest(n,'SalePrice')['SalePrice'].index
column = abs(np.corrcoef(train_data[cols_second].values.T))
sns.set(font_scale=1.25)
sns.heatmap(column, cbar=True,annot=True, square=True,vmin=0,vmax=1, fmt
='.2f', annot_kws={'size': 10}, yticklabels=cols_second.values, xticklab
els=cols_second.values)
plt.show()
```

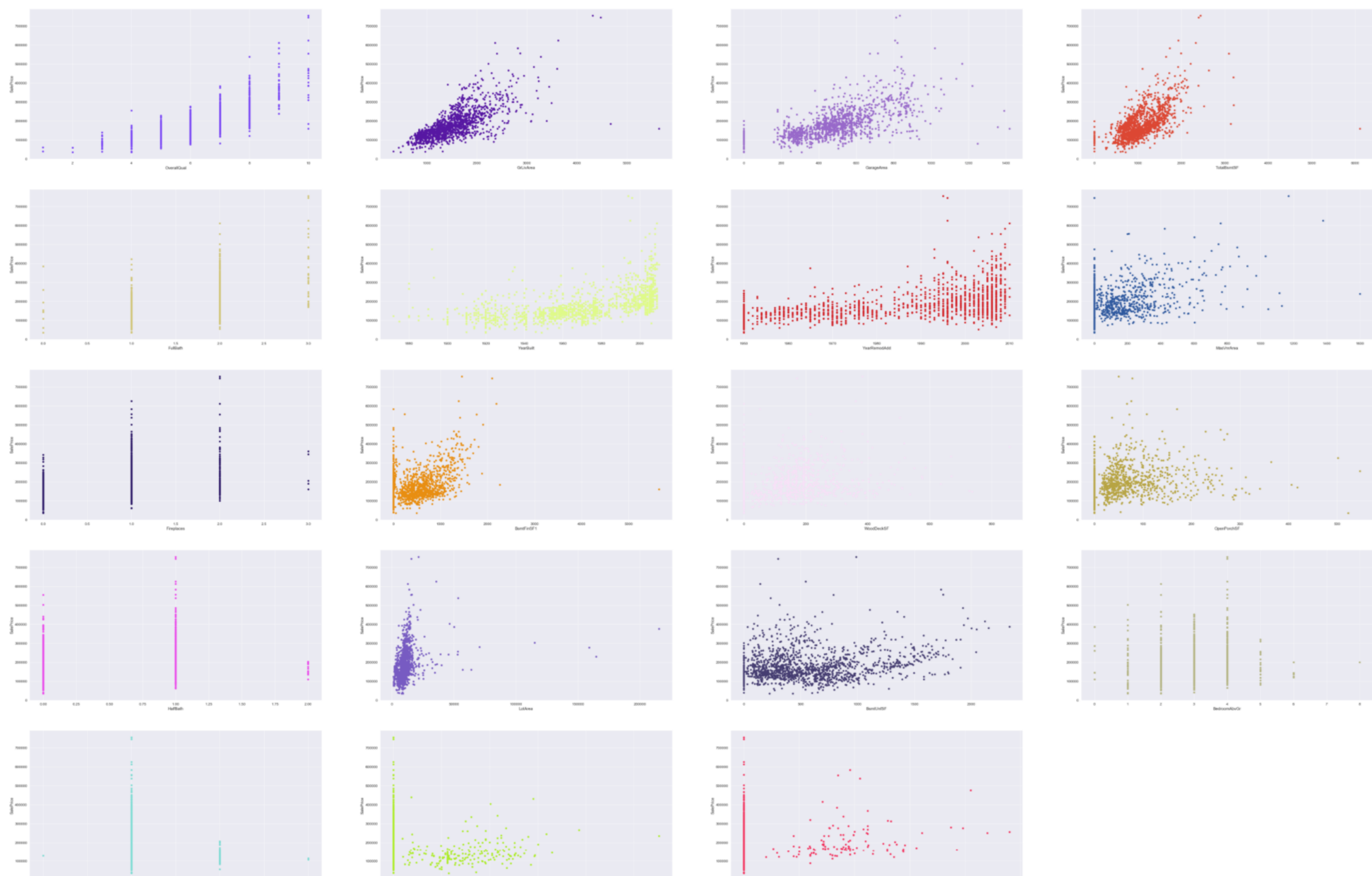




visualize them in the scatter plot

In [19]:
```
#a function to generate random color
def randomcolor():
    colorList = ['1','2','3','4','5','6','7','8','9','A','B','C','D','E'
,'F']
    color = ""
    for i in range(6):
        color += colorList[random.randint(0,14)]
    return "#"+color
```

In [20]:
```
fig = plt.figure(figsize=[90,60])
cols_l = list(cols_second)
cols_l.remove('SalePrice')
y = train_data['SalePrice']
index = 1
for i in cols_l:
    plt.subplot(5,4,index)
    plt.scatter(train_data[i],y,color=randomcolor())#use scatter plot to
 plot it
    plt.xlabel(i)
    plt.ylabel('SalePrice')
    index += 1
```



From the graph above, we can easily find some data are outliers.Fill these value with the mean value

In [21]:
```
train_data.drop(train_data[(train_data['GarageArea']>1200)&(train_data[
"SalePrice"]<300000)].index,inplace=True)
train_data.drop(train_data[(train_data["GrLivArea"]>4000)&(train_data["S
alePrice"]<200000)].index,inplace=True)
train_data.drop(train_data[train_data["TotalBsmtSF"]>5800].index,inplace
=True)
train_data.drop(train_data[(train_data["MasVnrArea"]>1400)].index,inplac
e=True)
train_data.drop(train_data[(train_data["BsmtFinSF1"]>2000)&(train_data[
"SalePrice"]<200000)].index,inplace=True)
train_data.drop(train_data[(train_data["LotArea"]>70000)].index,inplace=
True)
train_data.drop(train_data[(train_data["BsmtUnfSF"]<1000)&(train_data["S
alePrice"]>600000)].index,inplace=True)
train_data.drop(train_data[(train_data["YearBuilt"]<1900)&(train_data["S
alePrice"]>300000)].index,inplace=True)
train_data.drop(train_data[(train_data["OpenPorchSF"]>500)&(train_data[
"SalePrice"]<100000)].index,inplace=True)
```

And some vairables have no relationship with the sale price,we can drop them

In [22]:
```
train_data= train_data.drop(['3SsnPorch'],axis=1)
train_data =train_data.drop(['PoolArea'],axis=1)
#drop those columns in test_data
test_data = test_data.drop(['3SsnPorch'],axis=1)
test_data = test_data.drop(['PoolArea'],axis=1)
```

Select some categorical variables (original)

The correlation matrix only listed variables which are continuous and many categorical varibales are not mentioned.

However,due to my limitation of knowledge, I can not analyze all of them. Therefore, I use box plot to plot all the categorical variables and choose those variables which have obivious correlation with sale price and less outliers

In [23]:
```
cate_col = list(train_data.columns)
for i in cols_first:
    if(i in  cate_col):# I use to debug
        cate_col.remove(i)
index = 1
fig = plt.figure(figsize=[50,90])
for i in cate_col:
    x = train_data[i]
    y = train_data['SalePrice']
    plt.subplot(10,4,index)
    ax = sns.boxplot(x, y)#categorical plot
    ax.set_xticklabels(ax.get_xticklabels(),rotation=50)#rotate the x la
bel for good looking
```

```
    but for good looking
    index += 1
```

choose some variables satisfies above condition

In [24]:
```
#I choose variables which have more than two kinds of variable.
cate_col = ['CentralAir','BsmtQual','KitchenQual','Neighborhood','RoofSt
yle','Functional','SaleCondition','SaleType','ExterCond']
```

According to the plot above, we can infer that all of those categorical variables have some correlation with the sale price. We can keep them in our data set.

In [25]:
```
cols.first.remove('3SsnPorch')
```

In [25]:
```
cols_first.remove('3SsnPorch')
cols_first.remove('PoolArea')
for i in cate_col:
    cols_first.append(i)
train_data = train_data[cols_first]
cols_first.remove('SalePrice')
test_data = test_data[cols_first]
```

One-hot encoding

Some data in the dataframe is str,which is not suitable to do regression. Therefore, we could use one-hot encoding to deal with it.

In [26]:
```
train_data = pd.get_dummies(train_data).astype(float)
test_data = pd.get_dummies(test_data).astype(float)
```

(Original) Since we change the discrete variables to dummy variables, sometimes columns in train data do not appear in test data.

In this case,we need to add those missing columns and assign the value 0

In [27]:
```
list1= list(train_data.columns)
list2 = list(test_data.columns)
c = [l for l in list1 if l not in list2]# find the missing column
c.remove('SalePrice')#sale price is not allowed to appear in test data
for c in c:
    test_data[c] = 0.0
```

Now,we could have a glipse on our data set again

In [28]:
```
train_data.head()
```

Out[28]:

	MSSubClass	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	Mas
Id							
1	60.0	8450.0	7.0	5.0	2003.0	2003.0	
2	20.0	9600.0	6.0	8.0	1976.0	1976.0	
3	60.0	11250.0	7.0	5.0	2001.0	2002.0	
4	70.0	9550.0	7.0	5.0	1915.0	1970.0	
5	60.0	14260.0	8.0	5.0	2000.0	2000.0	

5 rows × 96 columns

In [29]:
```
test_data.head()
```

Out[29]:

	MSSubClass	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	M
Id							
1461	20.0	11622.0	5.0	6.0	1961.0	1961.0	

1461	20.0	11622.0	5.0	6.0	1961.0	1961.0
1462	20.0	14267.0	6.0	6.0	1958.0	1958.0
1463	60.0	13830.0	5.0	5.0	1997.0	1998.0
1464	60.0	9978.0	6.0	6.0	1998.0	1998.0
1465	120.0	5005.0	8.0	5.0	1992.0	1992.0

5 rows × 95 columns

In [30]:
```
# train_data.to_csv('t.csv')
```

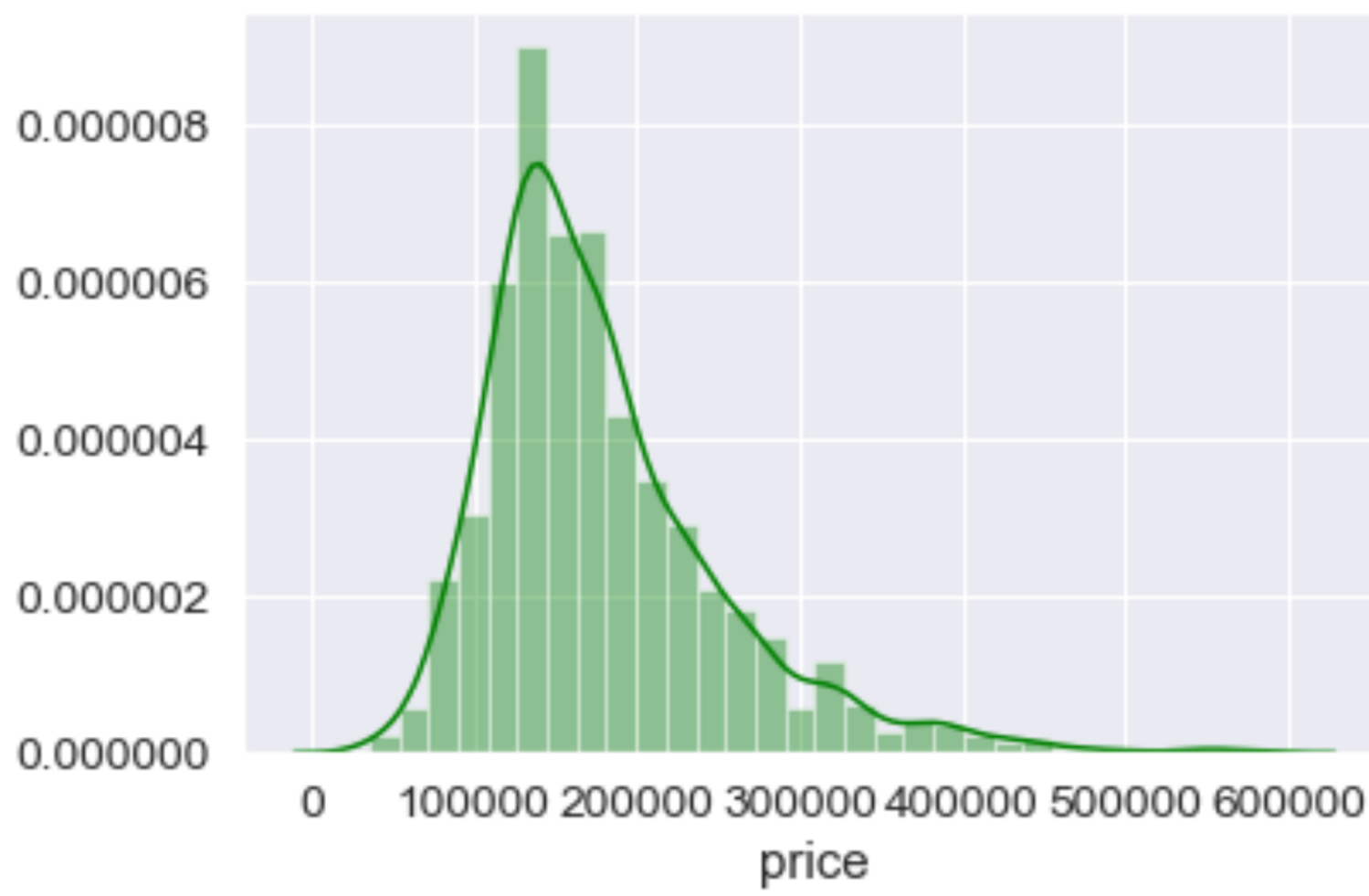
In [31]:
```
# test_data.to_csv('t2.csv')
```

Box-Cox Transformation

Before we take further step,have a look on the distribution of sale price

In [32]:
```
y = train_data['SalePrice']
sns.set_palette("hls")
sns.distplot(y,color="green",bins=30,kde=True)#plot the distribution and
 the line
plt.xlabel('price')
plt.show()
print("The skewness is "+str(y.skew()))
```

```
D:\Anaconda\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning:
Using a non-tuple sequence for multidimensional indexing is deprecated;
use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```




```
The skewness is 1.442601937080809
```

Obviously, the distribution of sale price is skewed and does not follow the normal distribution

normal distribution.

In our regression analysis course, linear regression model makes sense if and only if the random error follows N (0,σ²) . In other words, the sale price should follow normal distribution either.

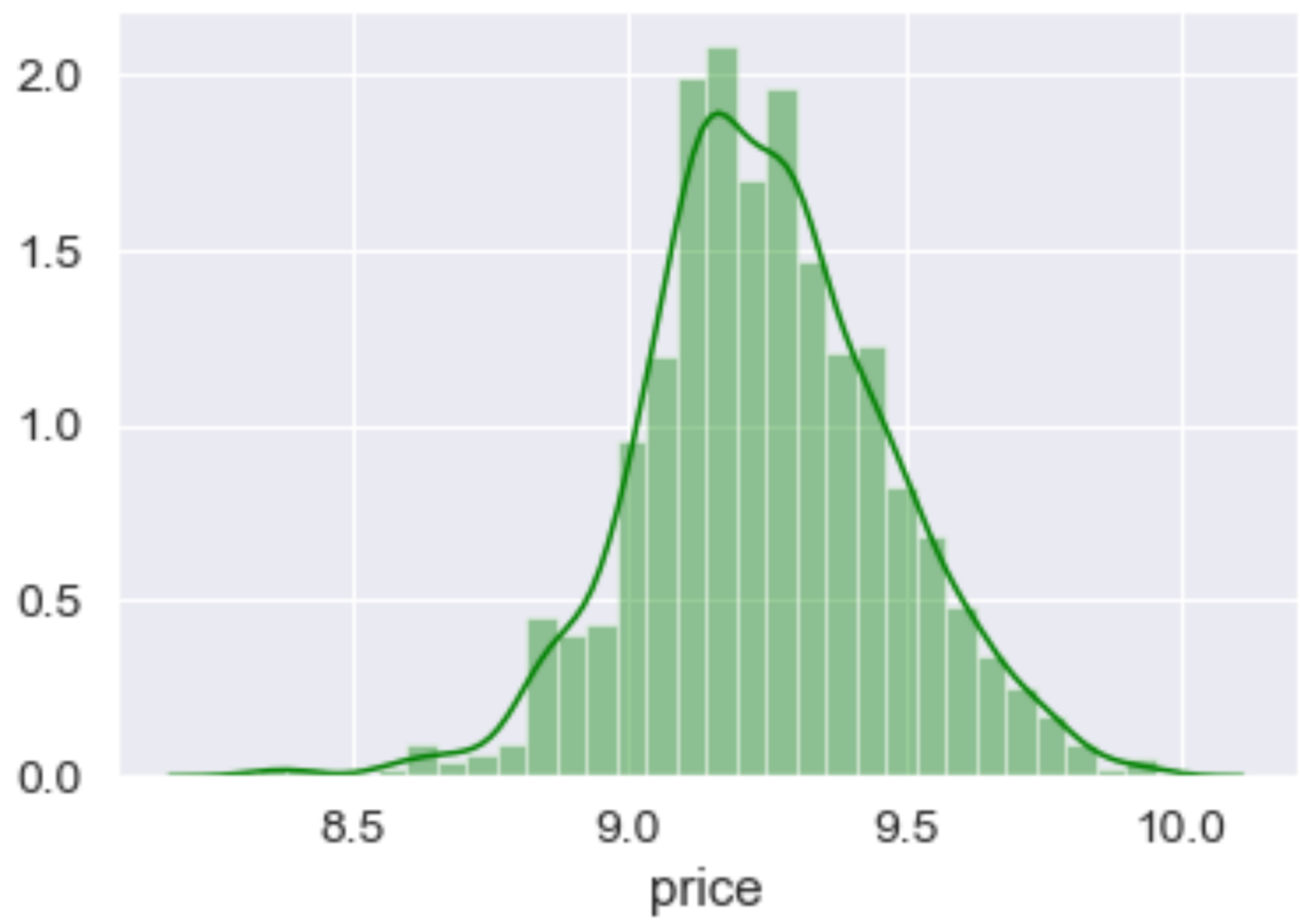
We could use Box-Cox Transformation to make the distribution of sale price more smooth.

I learn some code about how to use this transformation from (http://dataunderthehood.com/2018/01/15/box-cox-transformation-with-python/)

In [33]:
```
useless1, max_log, useless2 = stats.boxcox(y, alpha=0.01)#the function r
eturn three values, however, we only need the second one
#alpha means the (1-α)% confidence interval
print("The best lambda is = {:g}".format(max_log))
```

```
The best lambda is = -0.0456494
```

In [34]:
```
train_data['SalePrice'] = special.boxcox1p(train_data['SalePrice'],max_l
og)#box-cox transformation with best parameter
y_train = train_data['SalePrice']
sns.set_palette("hls")
sns.distplot(y_train,color="green",bins=30,kde=True)#plot the distributi
on and the line
plt.xlabel('price')
plt.show()
print("The skewness is "+str(train_data['SalePrice'].skew()))
```




```
The skewness is -0.003345111165451571
```

After processing, the sale price generally follow normal distribution.

what we should pay attention on is we must take exponent to the data that we predict.

Data Modeling and Validation

Data Modeling and Validation

Model building and model validation

since we have lots of variables, simple linear regression probably have terrible performance

Here I use polynomial regression,ridge regression ,and lasso regression

In [35]:
```
# create some function to build different model
def PolynomialRegression(degree=2, **kwargs):
    return make_pipeline(PolynomialFeatures(degree),
                         LinearRegression(**kwargs))
def poly(X,Y):
    degree = np.arange(0,4)#My computer has poor memory
    train_score, val_score = validation_curve(PolynomialRegression(), X,
Y,'polynomialfeatures__degree', degree, cv=5)
    plt.plot(degree, np.median(train_score, 1), color='blue', label='tra
ining score')
    plt.plot(degree, np.median(val_score, 1), color='red', label='valida
tion score')
    plt.legend(loc='best')
    plt.ylim(0,1)
    plt.xlabel('degree')
    plt.ylabel('score');

def ridge(X,Y):
    ridge = Ridge(max_iter=1000,tol=0.001)
    #fit_intercept means we assume it do not cross the original point,tol
 is precision,solver is a method
    parameters = {'alpha':[1e-8,1e-7,1e-6,1e-5,1e-4,1e-3,1e-2,1e-1],'nor
malize':[True,False],
                  'fit_intercept':[True,False],
                 'solver':['auto','svd','cholesky','lsqr','sparse_cg','sa
g','saga'],'random_state':[None,0,1,2]}
    #select a series of alpha to input in the model and find which is the
 best parameter
    model=GridSearchCV(ridge,parameters,n_jobs=-1,scoring='neg_mean_squa
red_error',cv=5,return_train_score=True)
    #find the best alpha,n_jobs=-1 means we use all the processor,scoring
 means the criteria is nmse
#     scores = cross_val_score(model, X, Y, cv=5) be caution! it takes lo
ts of time
    model.fit(X,Y)
#     print(pd.DataFrame(model.cv_results_)) too messy,useless
    print("best parameters:")
    print(model.best_params_)
    print("best score:")
    print(model.best_score_)
    return model.best_score_
#     print('scores:'+str(scores))
def lasso(X,Y):
    lasso =Lasso(max_iter=1000,tol=0.001)
    parameters = {'alpha':[1e-8,1e-7,1e-6,1e-5,1e-4,1e-3,1e-2,1e-1],'nor
malize':[True,False],
```

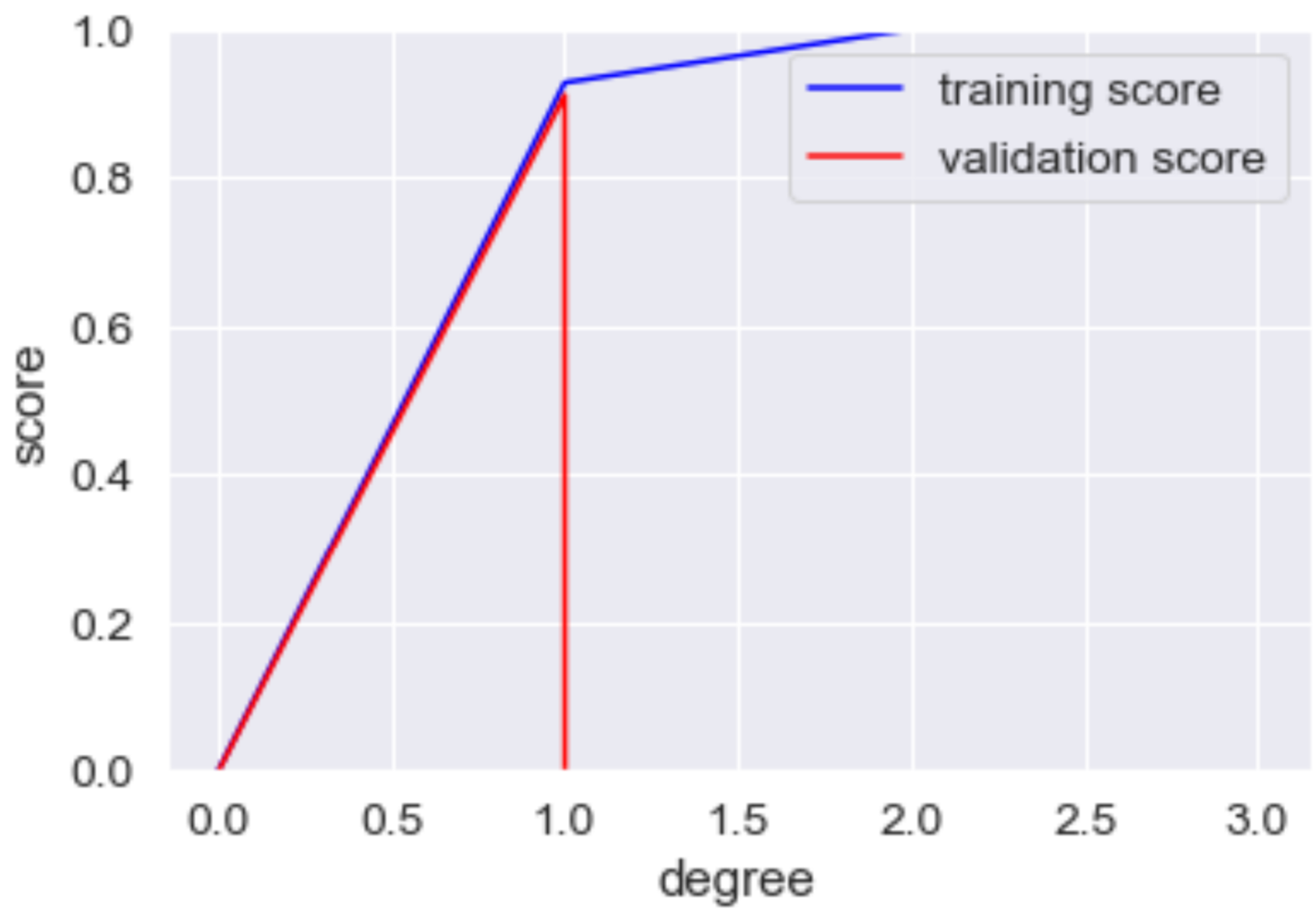
```
                    'fit_intercept':[True,False],
                    'precompute':[True,False],'warm_start':[True,False],
                   'selection':['random','cyclic'],'random_state':[None,0,1
,2]}
    #select a series of alpha to input in the model and find which is the
 best parameter
    model=GridSearchCV(lasso,parameters,n_jobs=-1,scoring='neg_mean_squa
red_error',cv=5,return_train_score=True)
    #find the best alpha,n_jobs=-1 means we use all the processor,scoring
 means the criteria is nmse
#     scores = cross_val_score(model, X, Y, cv=5) be caution! it takes lo
ts of time
    model.fit(X,Y)
#     print(pd.DataFrame(model.cv_results_)) too messy,useless
    print("best parameters:")
    print(model.best_params_)
    print("best score:")
    print(model.best_score_)
    return model.best_score_
#     print('scores:'+str(scores))
```

Define the X and Y

In [36]:
```
X = train_data.loc[:,train_data.columns!='SalePrice']
Y = train_data['SalePrice']
```

We could test the polynomial regression first

In [37]:
```
poly(X,Y)
```



It seems that degree=1 is the only choice!

In [38]:
```
modelp = PolynomialRegression(1,fit_intercept=True,normalize = False,n_j
obs=-1)
modelp.fit(X,Y)
predict = modelp.predict(test_data)
p = copy.deepcopy(test_data)
```

```
p = copy.deepcopy(test_data)
p['predicted'] = inv_boxcox(predict,max_log)#take exponent to multiple t
he data
```

Then we test the ridge regression model and lasso regression model

In [39]:
```
print("ridge:")
scorer = ridge(X,Y)
print("lasso:")
scorel = lasso(X,Y)
```

```
ridge:
best parameters:
{'alpha': 0.01, 'fit_intercept': True, 'normalize': True, 'random_stat
e': 1, 'solver': 'saga'}
best score:
-0.004605889773119084 5
lasso:
best parameters:
{'alpha': 0.0001, 'fit_intercept': True, 'normalize': False, 'precomput
e': False, 'random_state': 2, 'selection': 'random', 'warm_start': Tru
e}
best score:
-0.004468540266831057
```

```
D:\Anaconda\lib\site-packages\sklearn\model_selection\_search.py:841: D
eprecationWarning: The default of the `iid` parameter will change from
True to False in version 0.22 and will be removed in 0.24. This will ch
ange numeric results when test-set sizes are unequal.
  DeprecationWarning)
```

Use both model to make a prediction

In [40]:
```
modelr = Ridge(alpha=1e-2,fit_intercept=True,normalize=True,max_iter=100
00,tol=0.0001,solver='saga',random_state=1)#build the model with best pa
rameter
modelr.fit(X,Y)
predict = modelr.predict(test_data)
r = copy.deepcopy(test_data)
r['predicted'] = inv_boxcox(predict,max_log)#inverse the box-cox transfo
rmation before
```

In [41]:
```
modell = Lasso(alpha=1e-4,fit_intercept=True,normalize=False,max_iter=10
000,tol=0.0001,precompute=False,random_state=2,selection='random',warm_s
tart=True)
modell.fit(X,Y)
predict = modell.predict(test_data)
l = copy.deepcopy(test_data)
l['predicted'] = inv_boxcox(predict,max_log)#inverse the box-cox transfo
rmation before
```

Visualize the prediction

plot the predictied data

In [42]:

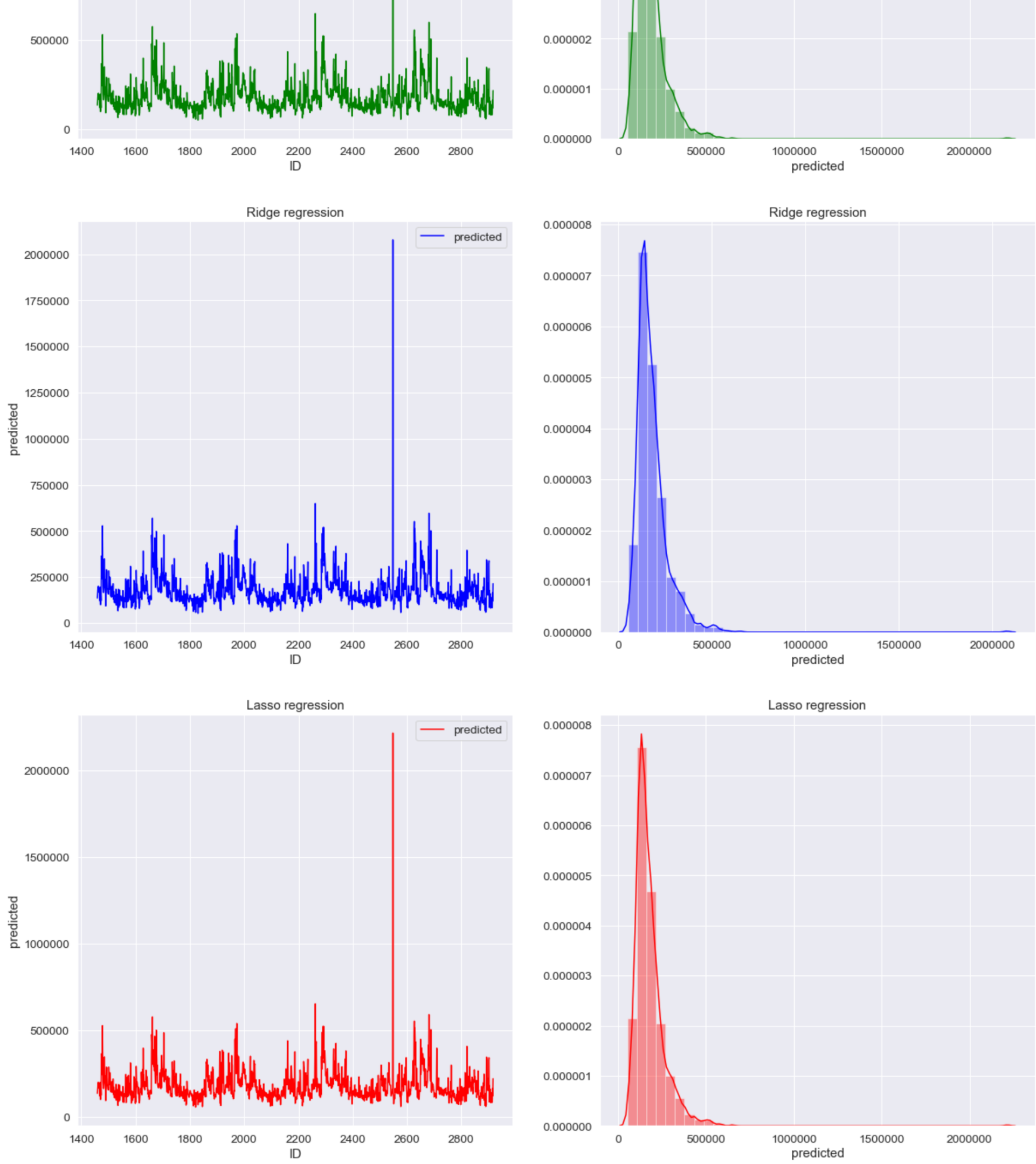
```
x = np.linspace(1459,2917,1459)#similuate the test id
fig = plt.figure(figsize=[20,30])
plt.subplot(3,2,1)
plt.plot(x,p['predicted'],color='green')
plt.xlabel('ID')
plt.ylabel('predicted')
plt.legend()
plt.title('Polynomial regression')
plt.subplot(3,2,2)
sns.distplot(l['predicted'],color="green",bins=40,kde=True)
plt.title('Polynomial regression')
print("the skewness of Polynomial regression is :"+str(p['predicted'].sk
ew()))

plt.subplot(3,2,3)
plt.plot(x,r['predicted'],color='blue')
plt.xlabel('ID')
plt.ylabel('predicted')
plt.legend()
plt.title('Ridge regression')
plt.subplot(3,2,4)
sns.distplot(r['predicted'],color="blue",bins=40,kde=True)
plt.title('Ridge regression')
print("the skewness is of Ridge regression :"+str(r['predicted'].skew
()))

plt.subplot(3,2,5)
plt.plot(x,l['predicted'],color='red')
plt.xlabel('ID')
plt.ylabel('predicted')
plt.legend()
plt.title('Lasso regression')
plt.subplot(3,2,6)
sns.distplot(l['predicted'],color="red",bins=40,kde=True)
plt.title('Lasso regression')
print("the skewness is of Lasso regression:"+str(l['predicted'].skew()))
```

```
D:\Anaconda\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning:
Using a non-tuple sequence for multidimensional indexing is deprecated;
use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be
interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
the skewness of Polynomial regression is :7.158444716327397
the skewness is of Ridge regression :6.80393565464841
the skewness is of Lasso regression:7.696147598945272
```



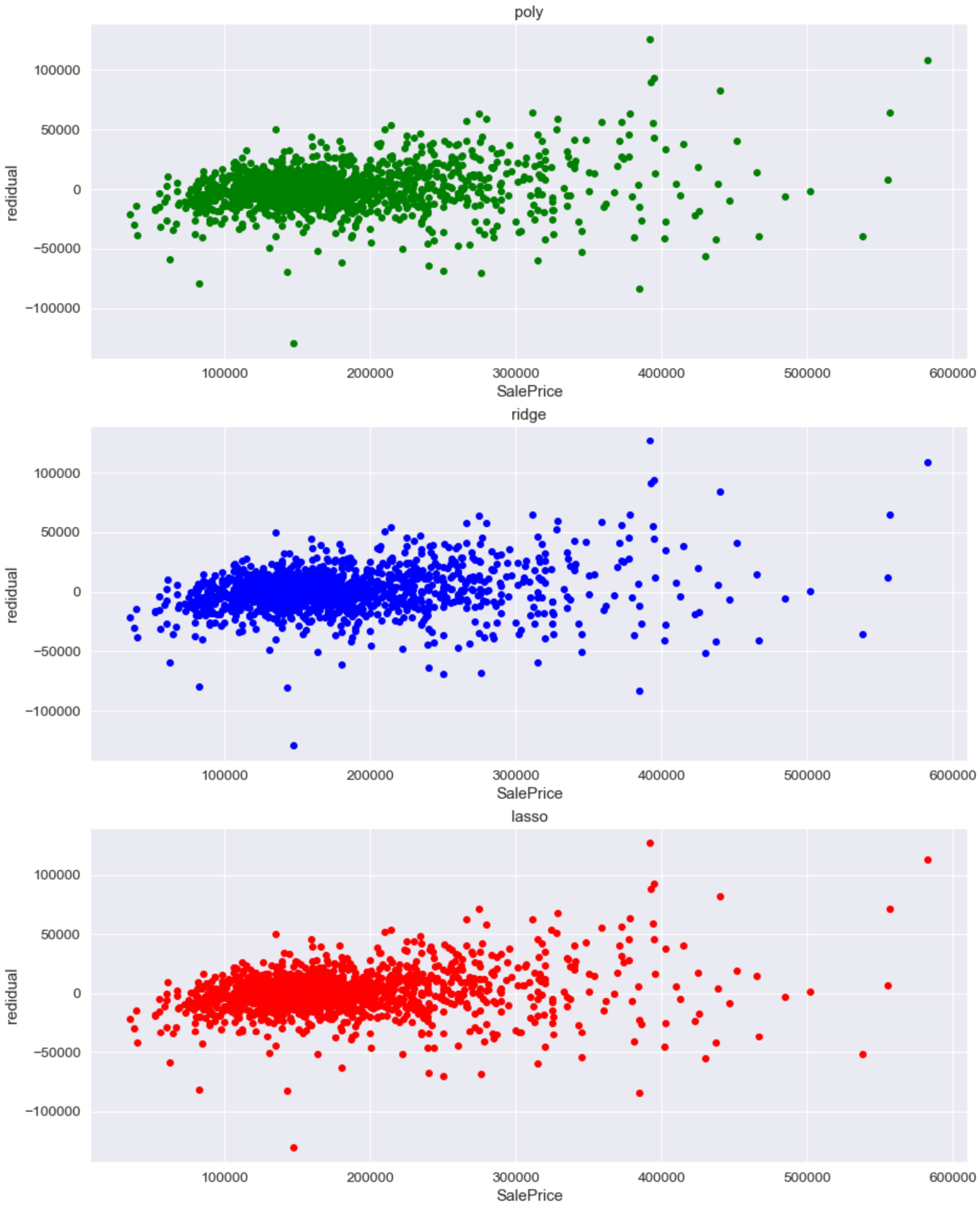
Residual plot

Have a look on the residual v.s. each Yi

In [43]:
```
#use the original trian data set to predict
predict_p = modelp.predict(X)
predict_r = modelr.predict(X)
predict_l = modell.predict(X)

resid = [inv_boxcox(Y,max_log) - inv_boxcox(predict_p,max_log),inv_boxco
x(Y,max_log) - inv_boxcox(predict_r,max_log),inv_boxcox(Y,max_log) - inv
_boxcox(predict_l,max_log)]
title = ['poly','ridge','lasso']
color = ['green','blue','red']
fig = plt.figure(figsize=[15,20])
for i in range(1,4):
    plt.subplot(3,1,i)
    plt.scatter(inv_boxcox(Y,max_log),resid[i-1],color=color[i-1])
    plt.ylabel('redidual')
    plt.xlabel('SalePrice')
```

```
    plt.title(title[i-1])
```



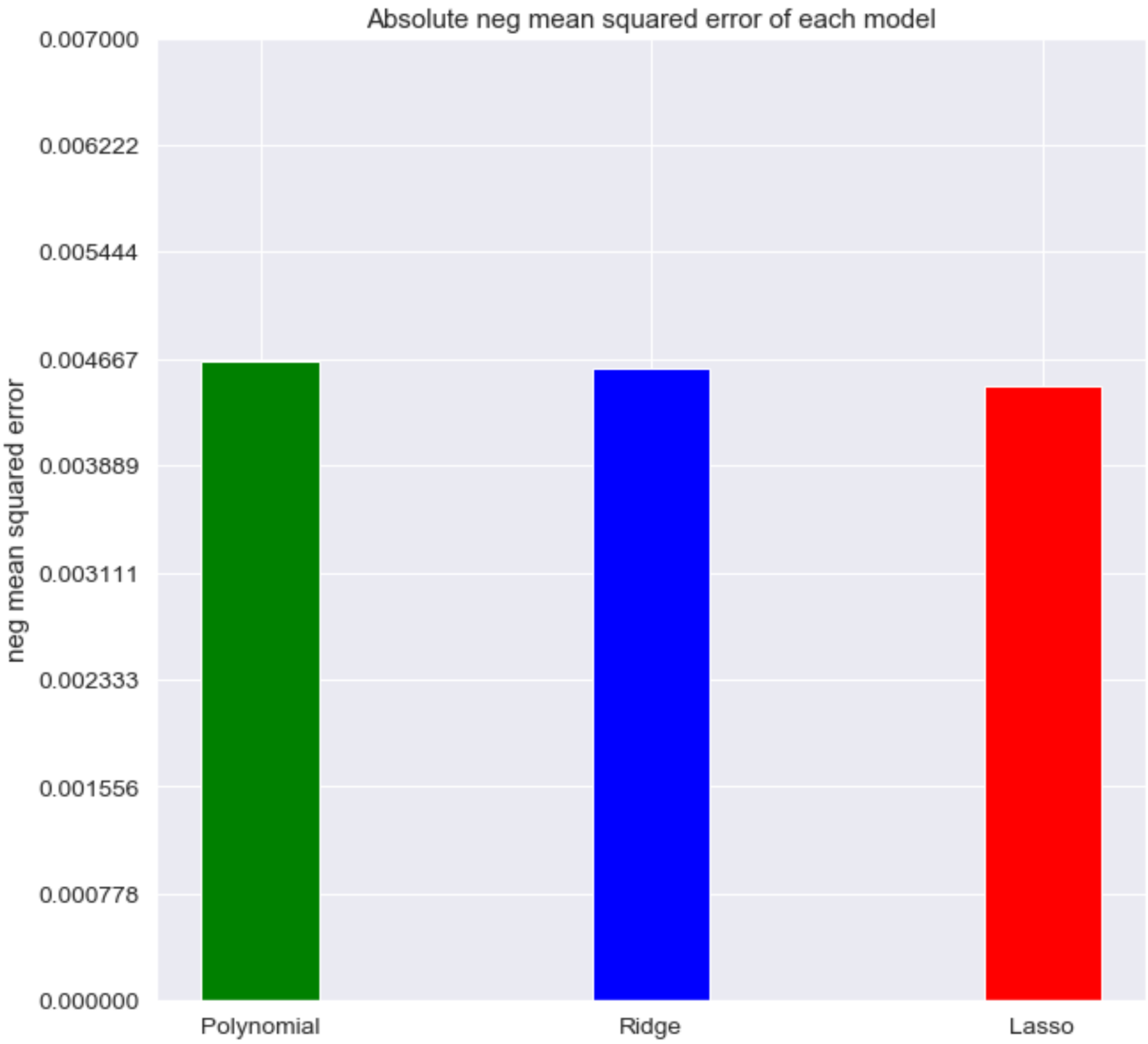
It seems that the residual randomly distributed , linearly distributed and has constant variance

Compare the score

Compare the score basis on the priciple 'neg mean squared error'

In [44]:
```
x =['Polynomial','Ridge','Lasso']
y = [(abs(np.mean(cross_val_score(modelp, X, Y, cv=5,scoring='neg_mean_s
quared_error',n_jobs=-1)))),abs(scorer),abs(scorel)]
fig = plt.figure(figsize=[10,10])
plt.bar(x,y,width=0.3,color=['green','blue','red'])
plt.ylabel('neg mean squared error')
plt.title('Absolute neg mean squared error of each model')
plt.xticks(np.linspace(0,0.007,10));
```

```
plt.yticks(np.linspace(0,0.007,10));
```



Submit to Kaggle

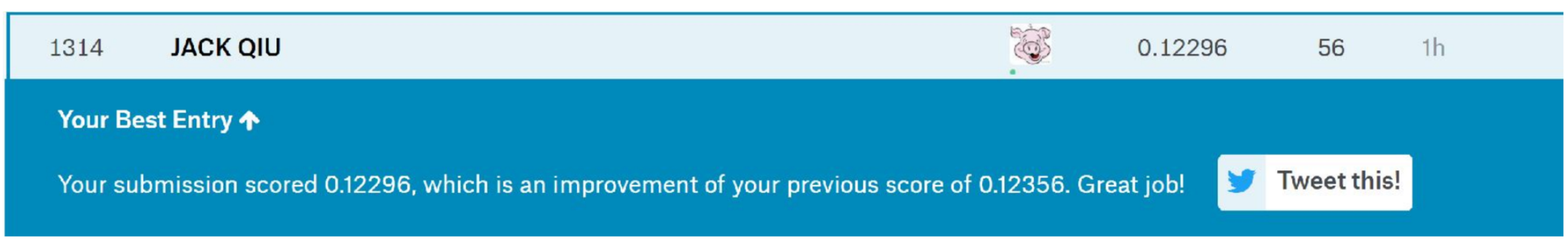
From the plot above, it seems that lasso model has better performance than others(not too much),we can choose lasso model as our final model

Finally, We can export our data to csv file and submit online!

In [45]:
```
result = pd.DataFrame()
result['SalePrice'] = l['predicted']#using lasso model
result.index = test_data.index
result.to_csv('submission.csv')
```

Grade --- Top 29%

My performance is OK



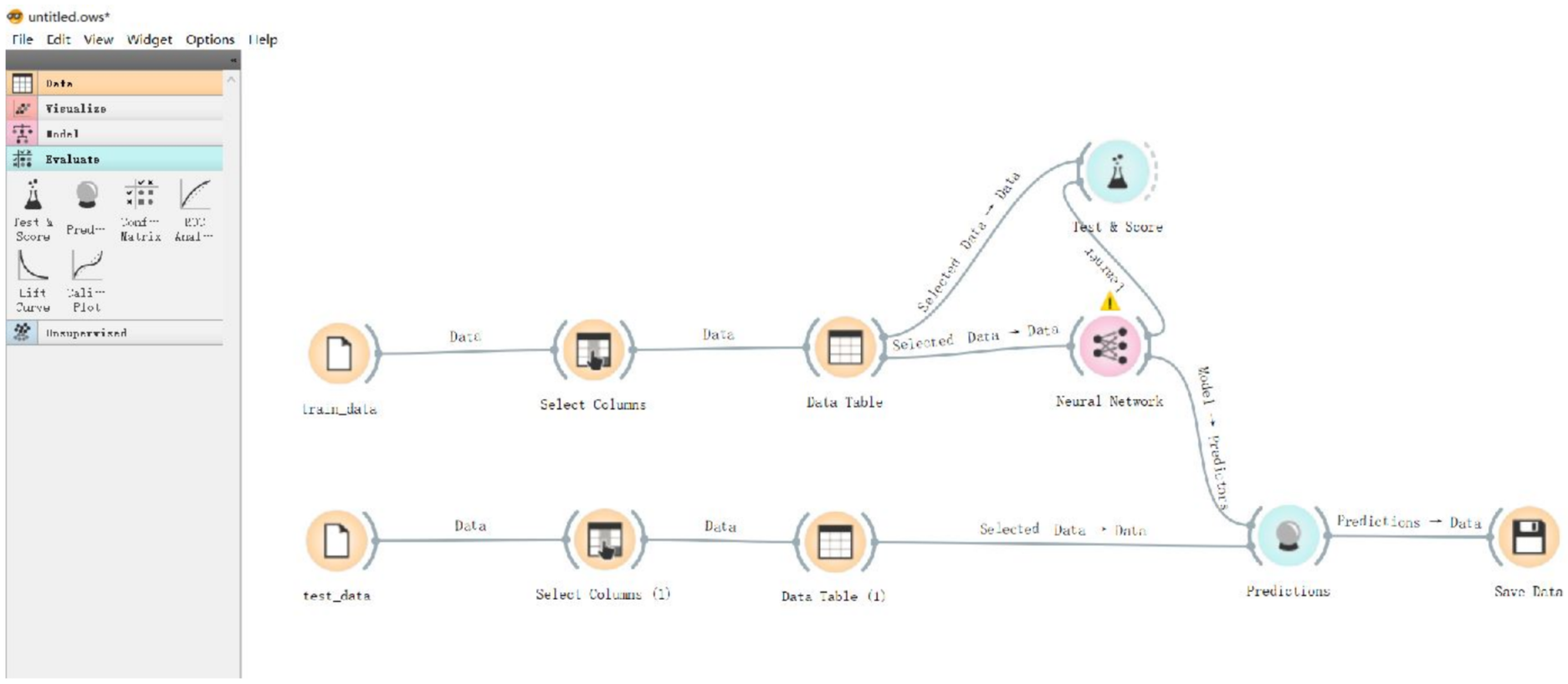
House Prices: Advanced Re...
Ongoing·Top 29%

1,314th
of 4552

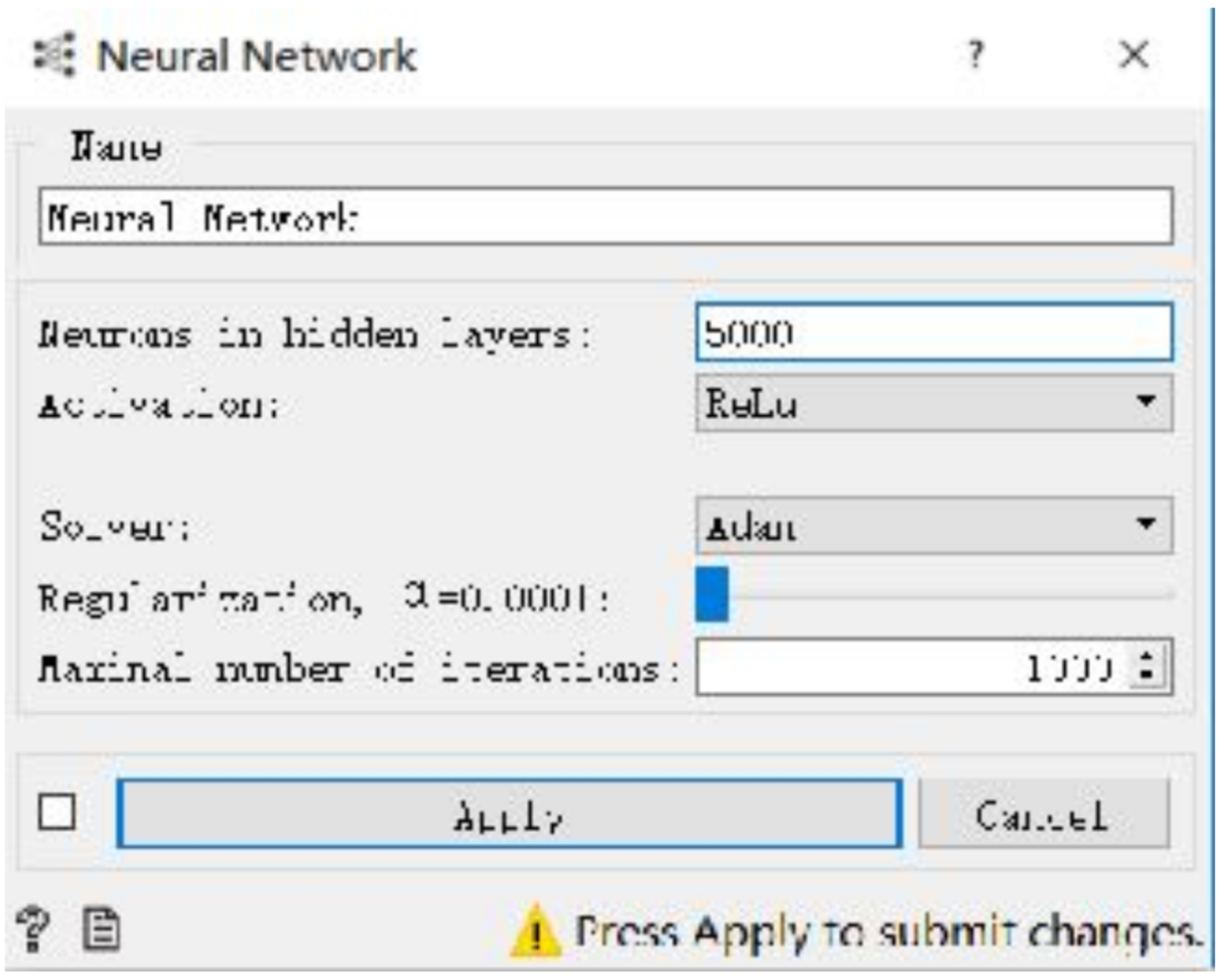
Possible improvement

It's quite difficult to use linear model to fit a data set which contains over one hundreds dimensions. Using neural network model probably is a good try

For example, Orange is a useful and user-friedly tool to build a naive neural network by yourself. It provides a GUI to building a model,do a cross validation and predict the data.



Setting some unknown parameters randomly



However, it performs not as well as my previous job. Increasing the amount of hidden layers may be one of solutions

sample_submission.csv
a day ago by JACK QIU
0.15693

a day ago by chen qiu

add submission details