ML for Economic Analysis Project 1 - Peru

Mingmin Feng; Jingyan Yang; Yu Pan; Rachid Ben Maatoug; Nataell Cornu

1 Problem Description

This report is a replication and extension of Hanna and Olken's study about predicting per-capita consumption by using information of observable assets for per household in Peru. We add new assets features which are not used by Hanna and Olken and also create more than four thousands interactions specifically for Lasso. We use machine learning techniques such as K-nearest Neighbors, Support Vector Machine Regression, Light Gradient Boosting Machine and Neural Network to predict the poverty status of households on the testing sample. We find that Lasso and Light Gradient Boosting Machine preform better than other models after comparing their MSE. In the end, we also replicate the welfare analysis with the new proxy-means test and compare it to the original one.

In [1]:
```
# install packages
# !pip install scikit-neuralnetwork
# !pip install lightgbm
# ! pip install mlxtend
# ! pip install yellowbrick
```

In [2]:
```
# Ignore  the warnings
import warnings
warnings.filterwarnings('always')
warnings.filterwarnings('ignore')
#Import everything
import pandas as pd
import numpy as np
from numpy.linalg import inv
from numpy.random import normal as rnorm
import itertools
import time
import statsmodels.api as sm
import random

# for plot
import seaborn as sns
#stata-like output
import statsmodels.api as sm
import statsmodels.formula.api as smf

#for missing values
import missingno as msno
from sklearn.impute import SimpleImputer
```

In [3]:
```
 #regression
from sklearn.linear_model import LinearRegression,Ridge,Lasso,RidgeCV
from sklearn.ensemble import RandomForestRegressor,BaggingRegressor,GradientBoostingRegressor,Ada
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import LassoCV
from sklearn.linear_model import RidgeCV
from sklearn import neural_network
from sklearn.neural_network import MLPRegressor
from lightgbm import LGBMRegressor

#model selection
from sklearn.model_selection import train_test_split,cross_validate
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from mlxtend.feature_selection import SequentialFeatureSelector as SFS

#preprocessing
from sklearn.preprocessing import MinMaxScaler,StandardScaler,LabelEncoder
from sklearn.impute import SimpleImputer

#evaluation metrics
from sklearn.metrics import mean_squared_log_error,mean_squared_error, r2_score,mean_absolute_err
from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score  # for classific
import sklearn.metrics as metrics
from sklearn.metrics import mean_squared_error
```

In [4]:
```
# Import matplotlib for graphs
import matplotlib.pyplot as plt
from mlxtend.plotting import plot_sequential_feature_selection as plot_sfs
# import yellowbrck for graphs
from yellowbrick.datasets import load_credit
from yellowbrick.features import Rank2D
from yellowbrick.regressor import AlphaSelection
from yellowbrick.regressor.alphas import alphas

# Set global parameters
%matplotlib inline
plt.style.use('seaborn-white')
plt.rcParams['lines.linewidth'] = 3
plt.rcParams['figure.figsize'] = (10,6)
plt.rcParams['figure.titlesize'] = 20
plt.rcParams['axes.titlesize'] = 18
plt.rcParams['axes.labelsize'] = 14
plt.rcParams['legend.fontsize'] = 14
```

2 Data Preprocessing

We check the missing value of data, visulize the data to get a "feel", impute the missing value with median, and split the data into trainning and test set.

2.1 Dataset acquisition

we use pd.read_csv to read the csv file as dataframe data type.

In [5]:
```
# Peru data
peru = pd.read_csv('datasets/Project1_CompletaData_96.csv')
peru.head()
# Overview of all variables
peru.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46305 entries, 0 to 46304
Columns: 105 entries, lnpercapitaconsumption to percapitahat_OLS
dtypes: float64(41), int64(64)
memory usage: 37.1 MB
```

2.2 Cleaning the Data

We check our dataset by detecting whether it contains null, Nan values or missing values.

In [6]:
```
peru.isnull().sum()
```

Out[6]:
```
lnpercapitaconsumption      0
d_fuel_other                0
d_fuel_wood                 0
d_fuel_coal                 0
d_fuel_kerosene             0
                         ...
h_hhsize                    0
id_for_matlab               0
hhid                        0
lncaphat_OLS              927
percapitahat_OLS          927
Length: 105, dtype: int64
```

In [7]:
```
columnNames = peru.columns.values.tolist()
columnNames[2]
```

Out[7]:
```
'd_fuel_wood'
```

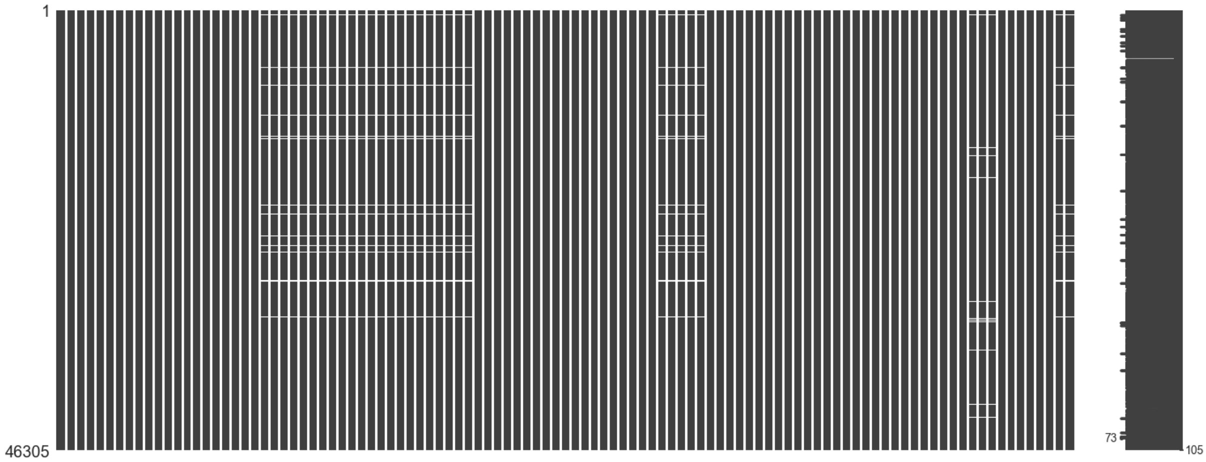
In [8]:
```
peru.loc[25:26,columnNames[22:30]]
```

Out[8]:

	d_wall_woodmat	d_wall_stonemud	d_wall_quincha	d_wall_tapia	d_wall_adobe	d_wall_stonecement	d_\
25	NaN	NaN	NaN	NaN	NaN	NaN	
26	0.0	0.0	0.0	1.0	0.0	0.0	

In [9]:
```
# Visualize no missing values
msno.matrix(peru)
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1e880bf64c8>



In [10]:
```
# Visualize the distribution of each feature to get an overview of the dataset.
peru.describe(include='all')
```

Out[10]:

	lnpercapitaconsumption	d_fuel_other	d_fuel_wood	d_fuel_coal	d_fuel_kerosene	d_fuel_gas	d_
count	46305.000000	46305.000000	46305.000000	46305.000000	46305.000000	46305.000000	4
mean	5.856564	0.104244	0.307202	0.025656	0.004557	0.518734	
std	0.744232	0.305580	0.461339	0.158108	0.067350	0.499654	
min	2.110213	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	5.344724	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	5.876649	0.000000	0.000000	0.000000	0.000000	1.000000	
75%	6.360625	0.000000	1.000000	0.000000	0.000000	1.000000	
max	9.663810	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 105 columns

2.3 Split Train-test dataset

In [11]:
```
trainNaN = peru[peru['training']==1]
# train = trainNaN.dropna()
train=trainNaN.dropna(axis=0, how='any', inplace=False)
# train.isnull().sum().sum()

# train.to_csv(r'Path where you want to store the exported CSV file\File Name.csv', index = False)

#train.to_csv(r'E:\ML for EconAna\Peru\train_py.csv',index=True ,header=True)
```

In [12]:
```
test = peru[peru['training']==0]
test.head()
```

Out[12]:

	lnpercapitaconsumption	d_fuel_other	d_fuel_wood	d_fuel_coal	d_fuel_kerosene	d_fuel_gas	d_fuel_elect
0	5.351858	0	1	0	0	0	
1	5.768755	0	0	0	0	1	
2	5.968277	0	0	0	0	1	
3	5.654599	0	0	0	0	1	
4	4.771289	0	1	0	0	0	

5 rows × 105 columns

In [13]:
```
x_train = train.iloc[:,1: 97]
x_train1 = train.iloc[:,1: 97]
x_test = test.iloc[:,1: 97]
x_train.head()
```

Out[13]:

	d_fuel_other	d_fuel_wood	d_fuel_coal	d_fuel_kerosene	d_fuel_gas	d_fuel_electric	d_fuel_none	d_
23152	0	1	0	0	0	0	0	
23153	0	0	0	0	1	0	0	
23154	0	1	0	0	0	0	0	
23155	0	1	0	0	0	0	0	
23156	1	0	0	0	0	0	0	

5 rows × 96 columns

In [14]:
```
y_train = train.loc[:,'percapitaconsumption']
lny_train = train.loc[:,'lnpercapitaconsumption']
y_test = test.loc[:,'percapitaconsumption']
lny_test = test.loc[:,'lnpercapitaconsumption']
```

##impute the missing values and export it to the current directory imr = SimpleImputer(missing_values=np.nan, strategy='median') imr = imr.fit(x_test) x_test = pd.DataFrame(imr.transform(x_test)) x_test.to_csv(r'Datasets\x_test_96.csv',index=True ,header=True)

In [15]:
```
# import x_test data
x_test = pd.read_csv('datasets/x_test_96.csv')
x_test1 = pd.read_csv('datasets/x_test_96.csv')
x_test.head()
```

Out[15]:

	d_fuel_other	d_fuel_wood	d_fuel_coal	d_fuel_kerosene	d_fuel_gas	d_fuel_electric	d_fuel_none	d
0	0	1	0	0	0	0	0	
1	0	0	0	0	1	0	0	
2	0	0	0	0	1	0	0	
3	0	0	0	0	1	0	0	
4	0	1	0	0	0	0	0	

5 rows × 96 columns

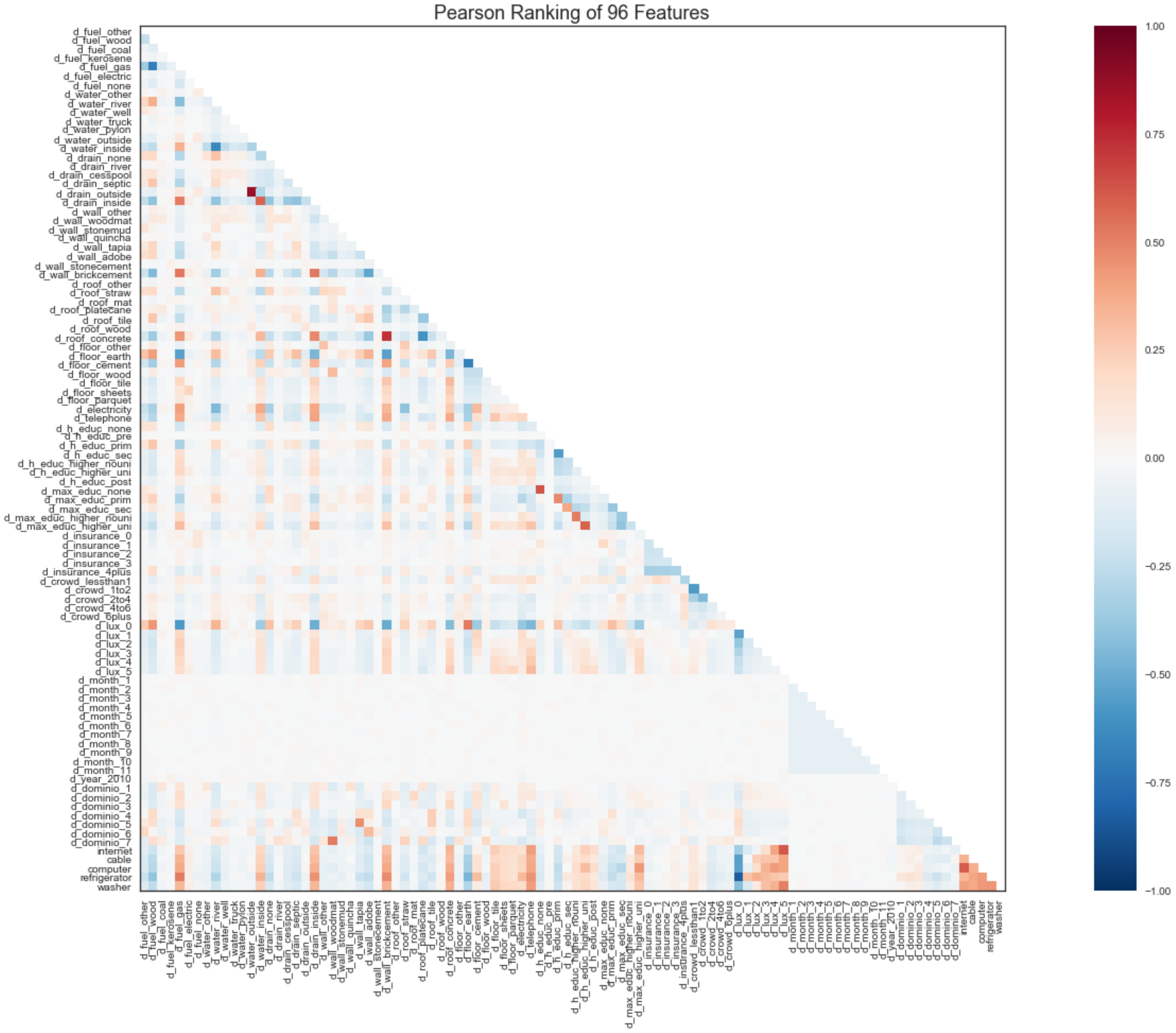
In [16]:
```
print(np.any(np.isnan(x_test)))
print(np.all(np.isfinite(x_test)))
print(np.any(np.isinf(x_test)))
```

```
False
True
False
```

In [17]:
```
x_test.isnull().sum()
```

Out[17]:
```
d_fuel_other        0
d_fuel_wood         0
d_fuel_coal         0
d_fuel_kerosene     0
d_fuel_gas          0
                   ..
internet            0
cable               0
computer            0
refrigerator        0
washer              0
Length: 96, dtype: int64
```

In [18]:
```python
# Instantiate the visualizer with the Pearson ranking algorithm
visualizer = Rank2D(algorithm='pearson')
fig=plt.gcf()
fig.set_size_inches(30,15)
visualizer.fit(x_train, y_train)           # Fit the data to the visualizer
visualizer.transform(x_train)        # Transform the data
visualizer.show()
```



Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1e880edc648>

In [19]:
```
x_test.shape
```
Out[19]: (23152, 96)

In [20]:
```
x_train.shape
```
Out[20]: (22191, 96)

3 Model implementation

3.1.1 Replicate the original paper(Peru): OLS

In [21]:
```
# add constant for train_x
x_train_72 = train.iloc[:,1: 73]
x_test_72 = x_test.iloc[:,0: 72]
one = np.ones(np.shape(x_train_72))
x_train_withcons = np.concatenate([one,x_train_72],axis=1)
# add constant for test_x
one = np.ones(np.shape(x_test_72))
x_test_withcons = np.concatenate([one,x_test_72],axis=1)
```

In [22]:
```
x_train_72.head()
```
Out[22]:

	d_fuel_other	d_fuel_wood	d_fuel_coal	d_fuel_kerosene	d_fuel_gas	d_fuel_electric	d_fuel_none	d_
23152	0	1	0	0	0	0	0	
23153	0	0	0	0	1	0	0	
23154	0	1	0	0	0	0	0	
23155	0	1	0	0	0	0	0	
23156	1	0	0	0	0	0	0	

5 rows × 72 columns

In [23]:
```
x_test_72.head()
```
Out[23]:

	d_fuel_other	d_fuel_wood	d_fuel_coal	d_fuel_kerosene	d_fuel_gas	d_fuel_electric	d_fuel_none	d_wate
0	0	1	0	0	0	0	0	
1	0	0	0	0	1	0	0	
2	0	0	0	0	1	0	0	
3	0	0	0	0	1	0	0	
4	0	1	0	0	0	0	0	

5 rows × 72 columns

In [24]:
```
# linear regression with constant
linreg = LinearRegression()
ols = linreg.fit(x_train_withcons,y_train)
```

In [25]:
```
ols.coef_
```

Out[25]:
```
array([-3.12256229e+10, -5.03391773e+15,  2.99299831e+15,  6.10481641e+15,
       -4.16245416e+15,  8.83051527e+15, -2.56013196e+15,  5.64440096e+14,
       -1.45623568e+15,  4.01206398e+14, -4.51309780e+14,  1.86113021e+15,
        1.40745341e+15, -1.67251797e+15, -1.76925109e+15,  1.60586686e+15,
       -3.00027099e+14, -4.13841222e+14,  1.46717124e+14,  2.04521644e+14,
       -5.81132430e+14,  4.22871475e+14, -2.96690516e+14, -1.19893161e+15,
        3.97251228e+14,  1.14321197e+15,  4.78978085e+13,  7.75875956e+14,
        9.10229697e+14,  7.52377309e+14,  6.25624845e+14, -2.94743112e+14,
        1.07649475e+14, -3.44936365e+14, -2.61241543e+14,  3.62813631e+14,
       -1.69939942e+14, -2.99010871e+14,  3.74617224e+14, -1.48977457e+14,
        7.59097342e+13,  2.98900125e+14,  6.18257541e+14,  7.22708745e+14,
       -3.98493008e+14,  6.18409144e+14,  4.92349361e+14,  1.06247324e+14,
        2.05091041e+14,  1.17193528e+14, -3.27338199e+13, -1.88755098e+14,
       -6.41510459e+13, -7.14184091e+13, -3.20778787e+13,  3.41620675e+13,
        1.31142642e+14, -1.13335800e+14, -7.85267880e+13,  1.63962952e+13,
        1.08539007e+14, -2.32325870e+14,  5.32119129e+13,  5.57211445e+13,
       -6.89050152e+12, -5.00000000e-01, -4.00000000e+00, -2.50000000e+00,
       -2.50000000e-01,  0.00000000e+00,  2.00000000e+00, -7.50000000e-01,
       -1.16383753e+15, -1.16383753e+15, -1.16383753e+15, -1.16383753e+15,
       -1.16383753e+15, -1.16383753e+15, -1.16383753e+15, -1.48041694e+14,
       -1.48041694e+14, -1.48041694e+14, -1.48041694e+14, -1.48041694e+14,
       -1.48041694e+14, -1.48041694e+14, -1.30000000e+01, -1.39375000e+01,
        4.00000000e+00, -5.62500000e-01, -6.00000000e+00,  7.25000000e+00,
        3.88972454e+14,  3.88972454e+14,  3.88972454e+14,  3.88972454e+14,
        3.88972454e+14,  3.88972454e+14,  3.88972454e+14,  3.88972454e+14,
       -8.26631694e+14, -8.26631694e+14, -8.26631694e+14, -8.26631694e+14,
       -8.26631694e+14, -8.26631694e+14, -8.26631694e+14, -2.58379012e+14,
       -2.58379012e+14, -2.58379012e+14, -2.58379012e+14, -2.58379012e+14,
       -2.58379012e+14, -2.58379012e+14, -2.50000000e-01,  3.55000000e+01,
       -3.19522374e+14, -3.19522374e+14, -3.19522374e+14, -3.19522374e+14,
       -3.19522374e+14, -3.19522374e+14, -3.19522374e+14, -1.46625000e+02,
       -5.28750000e+01, -3.15000000e+01, -3.75000000e+01, -3.72500000e+01,
       -1.46212999e+15, -1.46212999e+15, -1.46212999e+15, -1.46212999e+15,
       -1.46212999e+15,  8.76020318e+14,  8.76020318e+14,  8.76020318e+14,
        8.76020318e+14,  8.76020318e+14, -5.41301136e+14, -5.41301136e+14,
       -5.41301136e+14, -5.41301136e+14, -5.41301136e+14, -5.41301136e+14])
```

In [26]:
```
ols_estimate_y = ols.predict(x_train_withcons)
ols_estimate_y
```

Out[26]:
```
array([445., 805., 199., ..., 389., 329., 758.])
```

In [27]:
```
ols_pred_y = ols.predict(x_test_withcons)
```

In [28]:
```
# Linear regression by using Stata Model
x = sm.add_constant(x_train)
model2=sm.OLS(y_train, x)
results=model2.fit()
results.summary().tables[1]
```

Out[28]:

	coef	std err	t	P>|t|	[0.025	0.975]
const	271.5376	14.141	19.203	0.000	243.821	299.254
d_fuel_other	-100.4283	8.378	-11.987	0.000	-116.851	-84.006
d_fuel_wood	-89.2030	7.219	-12.357	0.000	-103.353	-75.053
d_fuel_coal	-40.1382	11.701	-3.430	0.001	-63.073	-17.203
d_fuel_kerosene	-57.9007	25.350	-2.284	0.022	-107.588	-8.213
d_fuel_gas	-15.6770	6.562	-2.389	0.017	-28.540	-2.814
d_fuel_electric	436.4550	20.089	21.726	0.000	397.079	475.831
d_fuel_none	138.4298	11.108	12.462	0.000	116.658	160.202
d_water_other	34.2105	9.082	3.767	0.000	16.408	52.013
d_water_river	15.3014	6.012	2.545	0.011	3.518	27.085
d_water_well	24.5248	9.045	2.711	0.007	6.796	42.254
d_water_truck	70.6472	13.216	5.345	0.000	44.742	96.552

3.1.2 Calculate MSE-OLS

In [29]:
```
#calculate MSE for the training dataset (from the estimation of original paper)
from sklearn import metrics

metrics.mean_squared_error(train.lncaphat_OLS, train.lnpercapitaconsumption)
```

Out[29]: 0.1919835924821717

In [30]:
```
#calculate MSE for the training dataset (Original Paper)
metrics.mean_squared_error(train.percapitahat_OLS, train.percapitaconsumption)
```

Out[30]: 77167.47406692483

In [31]:
```
#calculate MSE for y in the testing dataset (Original Paper)
original_pred_y = pd.DataFrame(test.percapitahat_OLS)
NaNy = original_pred_y.join(y_test)
NaNy=NaNy.dropna(axis=0, how='any', inplace=False)
NaNy.head()
print(NaNy.shape)
mse_ols_y = metrics.mean_squared_error(NaNy.percapitahat_OLS,NaNy.percapitaconsumption)
print(mse_ols_y)
```

```
(22704, 2)
89689.4794288619
```

In [32]:
```
#calculate MSE for lny in the testing dataset (Original Paper)
original_pred_lny = pd.DataFrame(test.lncaphat_OLS)
NaNlny = original_pred_lny.join(lny_test)
NaNlny=NaNlny.dropna(axis=0, how='any', inplace=False)
NaNlny.head()
print(NaNlny.shape)
mse_ols_lny = metrics.mean_squared_error(NaNlny.lncaphat_OLS,NaNlny.lnpercapitaconsumption)
print(mse_ols_lny)
```

```
(22704, 2)
0.1908680255424893
```

In [33]:
```
#calculate MSE for the training dataset (my calculation)
metrics.mean_squared_error(ols_estimate_y,y_train)
```

Out[33]:
```
77192.08104485337
```

In [34]:
```
#calclulate MSE for the testing dataset (my calculation)
metrics.mean_squared_error(ols_pred_y, y_test)
```

Out[34]:
```
6.358591436402691e+26
```

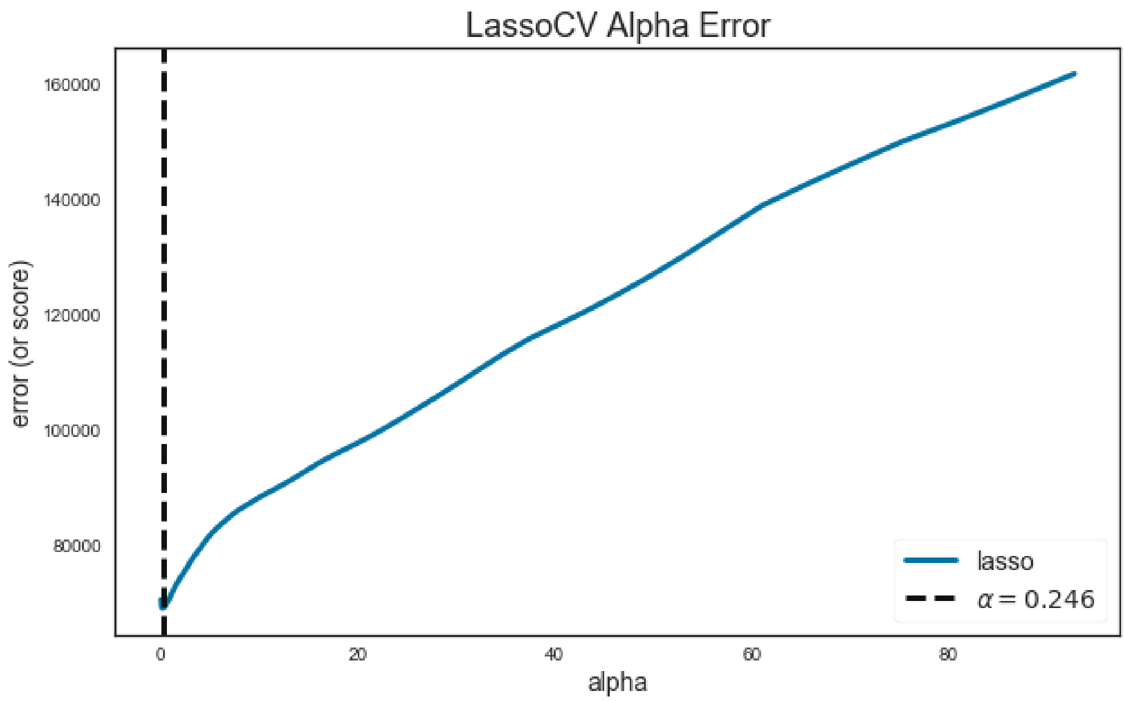
3.2 Model - Lasso

In [67]:
```
## Create new variables specifically for Lasso
#interact each of two variables in x_train, we get 4560 interactions with 96 old features.

for i in range(0,96):
    a=i
    for j in range(a+1,96):
            x_train1['interaction'+str(i)+str('t')+str(j)]=x_train1.iloc[:,i]* x_train1.iloc[:,j]
```

In [68]:
```
#interact each of two variables in x_train, we get 4560 interactions with 96 old features.
for i in range(0,96):
    a=i
    for j in range(a+1,96):
            x_test1['interaction'+str(i)+str('t')+str(j)]=x_test1.iloc[:,i]* x_test1.iloc[:,j]
```

In [69]:
```
alphas(LassoCV(random_state=0), x_train1, y_train)
```



Out[69]:
```
AlphaSelection(ax=<matplotlib.axes._subplots.AxesSubplot object at 0x000001E88CBA2588>,
               is_fitted='auto', model=None)
```

In [70]:
```
lassocv = LassoCV(alphas = [0.185,0.19,0.193,0.2,0.21,0.24],cv=10)
lassocv.fit(x_train1, y_train)
```

Out[70]:
```
LassoCV(alphas=[0.185, 0.19, 0.193, 0.2, 0.21, 0.24], copy_X=True, cv=10,
        eps=0.001, fit_intercept=True, max_iter=1000, n_alphas=100, n_jobs=None,
        normalize=False, positive=False, precompute='auto', random_state=None,
        selection='cyclic', tol=0.0001, verbose=False)
```

In [71]:
```
lassocv.alpha_
```

Out[71]:
```
0.21
```

In [72]:
```
lasso_estimate_y = lassocv.predict(x_train1)
metrics.mean_squared_error(lasso_estimate_y,y_train)
```
Out[72]:
```
61528.5635551761
```
In [73]:
```
lasso_pred_y = lassocv.predict(x_test1)
mse_lasso_y = metrics.mean_squared_error(lasso_pred_y,y_test)
print(mse_lasso_y)
```
```
80288.03171922367
```
In [74]:
```
# lny
ln_lassocv = LassoCV(alphas = [0.0001,0.001,0.1,0.2,0.5],cv=10)
ln_lassocv.fit(x_train1, lny_train)
```
Out[74]:
```
LassoCV(alphas=[0.0001, 0.001, 0.1, 0.2, 0.5], copy_X=True, cv=10, eps=0.001,
        fit_intercept=True, max_iter=1000, n_alphas=100, n_jobs=None,
        normalize=False, positive=False, precompute='auto', random_state=None,
        selection='cyclic', tol=0.0001, verbose=False)
```
In [75]:
```
ln_lassocv.alpha_
```
Out[75]:
```
0.001
```
In [76]:
```
lasso_pred_lny = ln_lassocv.predict(x_test1)
```
In [77]:
```
# mse_lasso_lny
mse_lasso_lny = metrics.mean_squared_error(lasso_pred_lny,lny_test)
print(mse_lasso_lny)  ## alpha 0.001 mse: 0.18047432116868548
```
```
0.18047432116868548
```

3.3 Model-KNN Regression

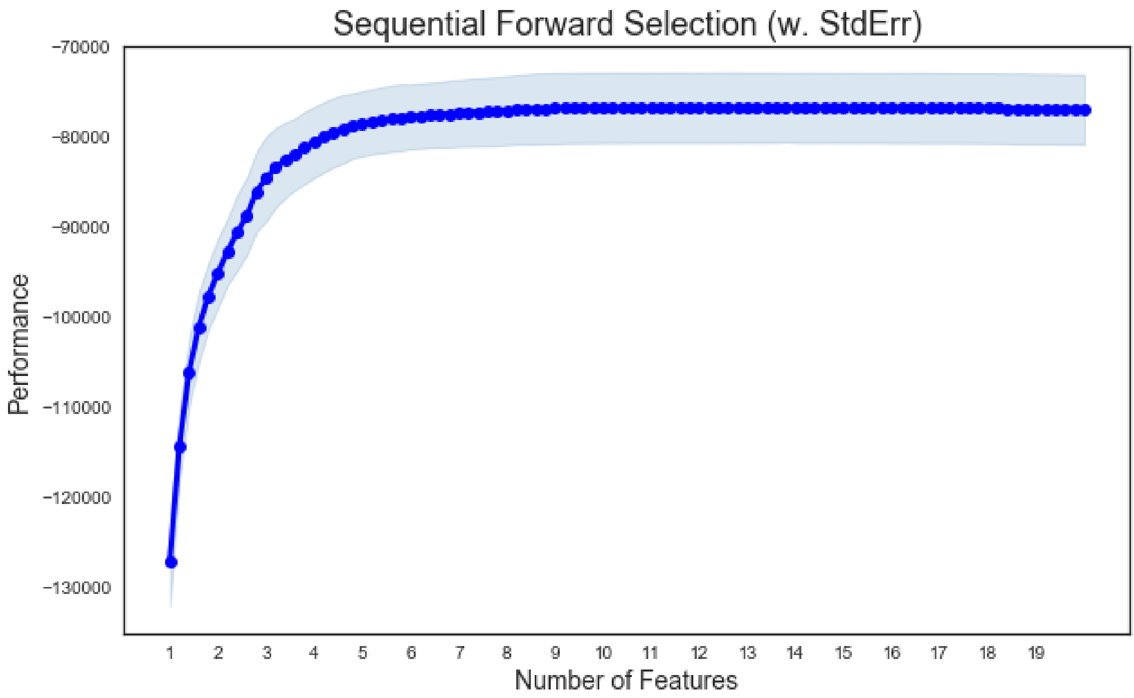
Not sure if it is a suitable algorithm for our dataset since all the features are dummies, and it is hard to define/calculate the "distance". But we will see...

In [60]:
```
random.seed(30)
sfs = SFS(LinearRegression(),
         k_features= (30, 96),
         forward=True,
         floating=False,
         scoring='neg_mean_squared_error',
         cv=5)
sfs.fit(x_train, y_train)
sfs.k_feature_names_
```

Out[60]:
```
('d_fuel_other',
 'd_fuel_wood',
 'd_fuel_coal',
 'd_fuel_gas',
 'd_fuel_electric',
 'd_fuel_none',
 'd_water_river',
 'd_water_truck',
 'd_water_pylon',
 'd_water_outside',
 'd_water_inside',
 'd_drain_river',
 'd_drain_septic',
 'd_drain_inside',
 'd_wall_other',
 'd_wall_stonemud',
 'd_wall_tapia',
 'd_wall_adobe',
 'd_roof_straw',
 'd_roof_mat',
 'd_roof_tile',
 'd_roof_wood',
 'd_floor_earth',
 'd_floor_tile',
 'd_floor_sheets',
 'd_floor_parquet',
 'd_telephone',
 'd_h_educ_pre',
 'd_h_educ_prim',
 'd_h_educ_sec',
 'd_h_educ_higher_nouni',
 'd_h_educ_higher_uni',
 'd_h_educ_post',
 'd_max_educ_none',
 'd_max_educ_prim',
 'd_max_educ_higher_nouni',
 'd_insurance_0',
 'd_insurance_1',
 'd_insurance_3',
 'd_insurance_4plus',
 'd_crowd_lessthan1',
 'd_crowd_1to2',
 'd_crowd_2to4',
 'd_lux_0',
 'd_lux_1',
 'd_lux_2',
 'd_lux_3',
 'd_lux_4',
 'd_lux_5',
 'd_month_3',
 'd_month_6',
 'd_month_8',
 'd_month_9',
 'd_year_2010',
 'd_dominio_1',
 'd_dominio_2',
 'd_dominio_3',
```

```
 'd_dominio_4',
 'd_dominio_5',
 'd_dominio_6',
 'd_dominio_7',
 'internet',
 'cable',
 'refrigerator',
 'washer')
```

In [61]:
```
fig1 = plot_sfs(sfs.get_metric_dict(), kind='std_dev')
plt.title('Sequential Forward Selection (w. StdErr)')
ticks = np.arange(1, 96, 5)
plt.xticks(ticks)
plt.show()
```



In [62]:
```
x_train_sfs = sfs.transform(x_train)
x_test_sfs = sfs.transform(x_test)
```

In [63]:
```
x_train_knn = pd.DataFrame(x_train_sfs)
x_test_knn = pd.DataFrame(x_test_sfs)
```

In [64]:
```
# create a knn regression model (best-fitted parameter is k=37)
param_dict = {'n_neighbors':[37], 'weights': ['distance'], 'metric':['hamming']}
knn_gscv = GridSearchCV(estimator=KNeighborsRegressor(), param_grid = param_dict,scoring='neg_mea
knn_gscv.fit(x_train_knn, y_train)
knn_gscv.best_params_
```

Out[64]:
```
{'metric': 'hamming', 'n_neighbors': 37, 'weights': 'distance'}
```

In [65]:
```
train_knn_pred = knn_gscv.predict(x_train_knn)
print(metrics.mean_squared_error(train_knn_pred, y_train))
```

```
3057.958463518474
```

In [66]:
```
# mse for y
knn_pred_y = knn_gscv.predict(x_test_knn)
mse_knn_y = metrics.mean_squared_error(knn_pred_y, y_test)
print(mse_knn_y)
```

90780.47927757952

In [88]:
```
# create a knn regression model
param_dict = {'n_neighbors':[17, 37, 57], 'weights': ['distance'], 'metric':['hamming']}
ln_knn_gscv = GridSearchCV(estimator=KNeighborsRegressor(), param_grid = param_dict,scoring='neg_m
ln_knn_gscv.fit(x_train_knn, lny_train)
ln_knn_gscv.best_params_
```

Out[88]: {'metric': 'hamming', 'n_neighbors': 37, 'weights': 'distance'}

In [89]:
```
# mse for lny
knn_pred_lny = ln_knn_gscv.predict(x_test_knn)
mse_knn_lny = metrics.mean_squared_error(knn_pred_lny, lny_test)
print(mse_knn_lny)
```

0.20991093774748923

3.4 SVM Regression (SVR)

```
#Code for CV:
params_dict={'C':[10,100,300],'gamma':[0.01,0.1,1],'kernel':['rbf']}
params_dict={'C':[300],'gamma':[0.1],'kernel':['rbf']}
svr_gscv=GridSearchCV(estimator=SVR(),param_grid=params_dict,scoring='neg_mean_squared_error',cv
=5)
```

In [37]:
```
# After using CV, we have found the best-fitted parameter,
# so we directly use the selected parameter in the later programing for saving time

svr_gscv=SVR(C = 300, gamma = 0.1, kernel = 'rbf')
svr_gscv.fit(x_train,y_train)
```

Out[37]:
```
SVR(C=300, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma=0.1,
    kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

In [38]:
```
# MSE for the training set
svr_estimate_y = svr_gscv.predict(x_train)
metrics.mean_squared_error(svr_estimate_y,y_train)
```

Out[38]: 56010.9428618192

In [39]:
```
# predict for x_test
svr_pred_y = svr_gscv.predict(x_test)
# calculate MSE from the prediction for x_test and y_test
mse_svr_y = metrics.mean_squared_error(svr_pred_y, y_test)  ##300 and 0.1 mse:  ## 84657.0160
print(mse_svr_y)
```

84657.01604518267

```
#lny; Code for CV:
params_dict={'C':[1,10,300],'gamma':[0.01,0.1,1,10],'kernel':['rbf']}
svr_gscv=GridSearchCV(estimator=SVR(),param_grid=params_dict,scoring='neg_mean_squared_error',cv
=5)
svr_gscv.fit(x_train,lny_train)
```

```
print(svr_gscv.best_params_)
```

In [102]:
```
#lny;

# After using CV, we have found the best-fitted parameter,
# so we directly use the selected parameter in the later programing for saving time
lny_svr_gscv=SVR(C = 100 , gamma = 0.001, kernel = 'rbf')
lny_svr_gscv.fit(x_train,lny_train)

# predict for x_test
svr_pred_lny = lny_svr_gscv.predict(x_test)

# calculate MSE from the prediction for x_test and lny_test
mse_svr_lny = metrics.mean_squared_error(svr_pred_lny, lny_test)  ##
print(mse_svr_lny)
```

```
0.17923064710220138
```

3.5 LightGBM

In [41]:
```
x_try = x_train.iloc[0:22673,]
y_try = y_train.iloc[0:22673,]
```

```
#code for cv:
params_dict={'num_leaves':[5,10,15,20,25,31],'n_estimators':[20, 40, 60, 80, 97, 
100],'learning_rate':[0.01, 0.1, 0.3, 0.5, 0.7]}
```

In [42]:
```
# After using CV, we have found the best-fitted parameter,
# so we directly use the selected parameter in the later programing for saving time
params_dict={'num_leaves':[31],'n_estimators':[97],'learning_rate':[0.01, 0.1, 0.3]}
lgbm_gscv=GridSearchCV(estimator=LGBMRegressor(),param_grid=params_dict,scoring='neg_mean_squared_
lgbm_gscv.fit(x_try, y_try)
lgbm_gscv.best_params_
```

Out[42]:
```
{'learning_rate': 0.1, 'n_estimators': 97, 'num_leaves': 31}
```

In [43]:
```
lgbm_pred_y = lgbm_gscv.predict(x_test)
```

In [44]:
```
mse_lgbm_y = metrics.mean_squared_error(lgbm_pred_y, y_test)
print(mse_lgbm_y)
```

```
80546.35227972006
```

In [95]:
```
#prediction for lny
lny_try = lny_train.iloc[0:22673,]
params_dict={'num_leaves':[5,10,20,25],'n_estimators':[20,100,500,1000,1500],'learning_rate':[0.02
lgbm_gscv=GridSearchCV(estimator=LGBMRegressor(),param_grid=params_dict,scoring='neg_mean_squared_
lgbm_gscv.fit(x_try, lny_try)
print(lgbm_gscv.best_params_)
lgbm_pred_lny = lgbm_gscv.predict(x_test)

# mse for lny
mse_lgbm_lny = metrics.mean_squared_error(lgbm_pred_lny, lny_test)
print(mse_lgbm_lny)
```

```
{'learning_rate': 0.04, 'n_estimators': 1500, 'num_leaves': 10}
0.17864507664424056
```

3.6 Neural Network

```
#code for cv:
params_dict={'hidden_layer_sizes':[(5),(10),(20),(10,8),(10,10),(20,10)]}
clf_nn =GridSearchCV(estimator = neural_network.MLPRegressor(activation="relu",
                         solver='adam', alpha=0.0001,
                         batch_size='auto', learning_rate="constant",
                         learning_rate_init=0.001, power_t=0.5, max_iter=500 ,tol=1e-
4),param_grid=params_dict,cv=5)
```

In [40]:
```
# After using CV, we have found the best-fitted parameter,
# so we directly use the selected parameter in the later programing for saving time
clf_nn = MLPRegressor(random_state=1, max_iter=500).fit(x_train, y_train)
nn_estimate_y=clf_nn.predict(x_train)
print(metrics.mean_squared_error(nn_estimate_y, y_train))

nn_pred_y=clf_nn.predict(x_test)
mse_nn_y = metrics.mean_squared_error(nn_pred_y, y_test)
print(mse_nn_y)
```

```
60146.973467169766
81377.09921569008
```

In [113]:
```
#prediction for lny
params_dict={'hidden_layer_sizes':[(5),(10),(10,10),(20,10)]}
clf_nn =GridSearchCV(estimator = neural_network.MLPRegressor(activation="relu",
                 solver='adam', alpha=0.3,
                 batch_size='auto', learning_rate="constant",
                 learning_rate_init=0.005, power_t=0.5, max_iter=500 ,tol=1e-4),param_grid=params_
clf_nn.fit(x_train,lny_train)
print(clf_nn.best_params_)
nn_pred_lny = clf_nn.predict(x_test)
mse_nn_lny = metrics.mean_squared_error(nn_pred_lny, lny_test)
print(mse_nn_lny)
```

```
{'hidden_layer_sizes': (10, 10)}
0.18699041083015602
```

4 Evaluation of different variables

In [114]:
```
model_names=['OLS','Lasso','KNN','SVR','LGBM','NN']
mse_pred_y=(mse_ols_y,mse_lasso_y,mse_knn_y,mse_svr_y,mse_lgbm_y,mse_nn_y)
d={'Modelling Algo':model_names,'MSE':mse_pred_y}
d
```

Out[114]:
```
{'Modelling Algo': ['OLS', 'Lasso', 'KNN', 'SVR', 'LGBM', 'NN'],
 'MSE': (89689.4794288619,
  80288.03171922367,
  90780.47927757952,
  84657.01604518267,
  80546.35227972006,
  81377.09921569008)}
```

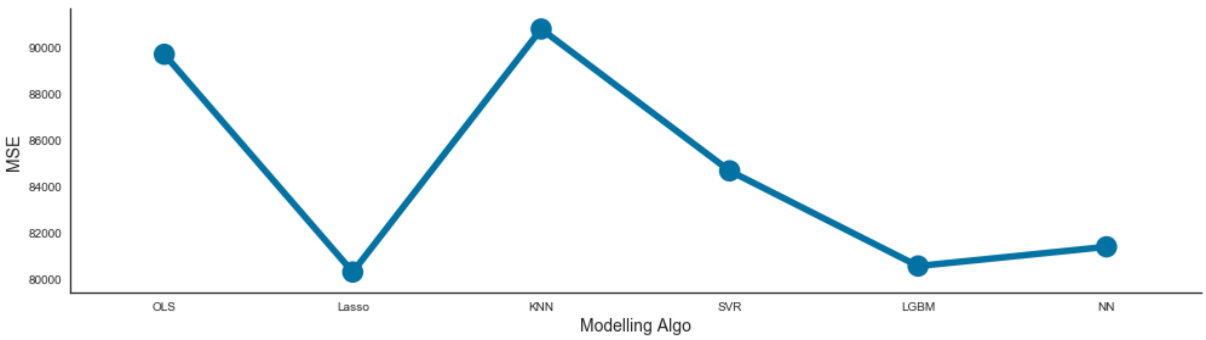
In [115]:
```
acc_frame=pd.DataFrame(d)
acc_frame
```

Out[115]:

	Modelling Algo	MSE
0	OLS	89689.479429
1	Lasso	80288.031719
2	KNN	90780.479278
3	SVR	84657.016045
4	LGBM	80546.352280
5	NN	81377.099216

In [116]:
```
sns.factorplot(x='Modelling Algo',y='MSE',data=acc_frame,kind='point',size=4,aspect=3.5)
```

Out[116]: <seaborn.axisgrid.FacetGrid at 0x1e88aaeee48>



In [117]:
```
# for lny
model_names=['OLS','Lasso','KNN','SVR','LGBM','NN']
mse_pred_lny=(mse_ols_lny,mse_lasso_lny,mse_knn_lny,mse_svr_lny,mse_lgbm_lny,mse_nn_lny)
d2={'Modelling Algo':model_names,'MSE_lny':mse_pred_lny}
d2
```

Out[117]:
```
{'Modelling Algo': ['OLS', 'Lasso', 'KNN', 'SVR', 'LGBM', 'NN'],
 'MSE_lny': (0.1908680255424893,
  0.18047432116868548,
  0.20991093774748923,
  0.17923064710220138,
  0.17864507664424056,
  0.18699041083015602)}
```

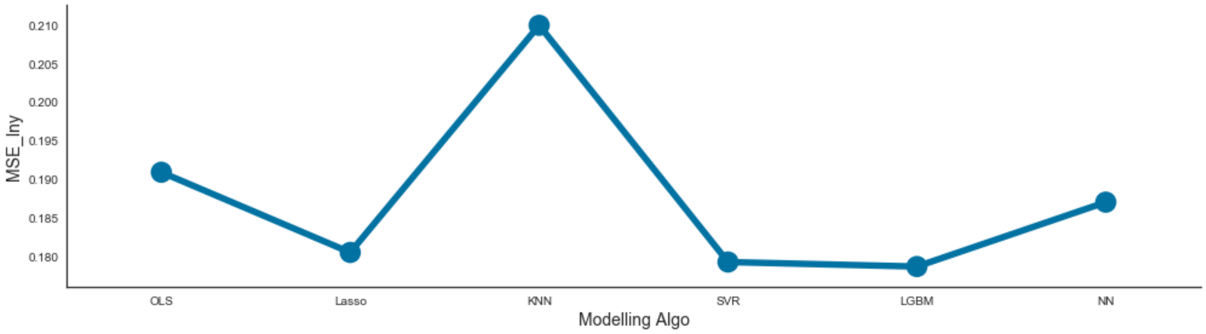
In [118]:
```
acc_frame2=pd.DataFrame(d2)
acc_frame2
```

Out[118]:

	Modelling Algo	MSE_lny
0	OLS	0.190868
1	Lasso	0.180474
2	KNN	0.209911
3	SVR	0.179231
4	LGBM	0.178645
5	NN	0.186990

In [143]:
```
sns.factorplot(x='Modelling Algo',y='MSE_lny',data=acc_frame2, kind='point',style="whitegrid", co
```

Out[143]: <seaborn.axisgrid.FacetGrid at 0x1e896299048>



5 Export Prediction

In [144]:
```
#combine the original test dataset and the precise predicted y
lasso_pred_y = pd.DataFrame(lasso_pred_y)
lasso_out = lasso_pred_y.join(test)
lasso_out.to_csv(r'Datasets\lasso_out.csv',index=True ,header=True)

knn_pred_y = pd.DataFrame(knn_pred_y)
knn_out = knn_pred_y.join(test)
knn_out.to_csv(r'Datasets\knn_out.csv',index=True ,header=True)

svr_pred_y = pd.DataFrame(svr_pred_y)
svr_out = svr_pred_y.join(test)
svr_out.to_csv(r'Datasets\svr_out.csv',index=True ,header=True)

lgbm_pred_y = pd.DataFrame(lgbm_pred_y)
lgbm_out = lgbm_pred_y.join(test)
lgbm_out.to_csv(r'Datasets\lgbm_out.csv',index=True ,header=True)

nn_pred_y = pd.DataFrame(nn_pred_y)
nn_out = nn_pred_y.join(test)
nn_out.to_csv(r'Datasets\nn_out.csv',index=True ,header=True)
```

In [145]:
```
lasso_pred_lny = pd.DataFrame(lasso_pred_lny)
lasso_out_lny = lasso_pred_lny.join(test)
lasso_out_lny.to_csv(r'Datasets\lasso_out_lny.csv',index=True ,header=True)

knn_pred_lny = pd.DataFrame(knn_pred_lny)
knn_out_lny = knn_pred_lny.join(test)
knn_out_lny.to_csv(r'Datasets\knn_out_lny.csv',index=True ,header=True)

svr_pred_lny = pd.DataFrame(svr_pred_lny)
svr_out_lny = svr_pred_lny.join(test)
svr_out_lny.to_csv(r'Datasets\svr_out_lny.csv',index=True ,header=True)

lgbm_pred_lny = pd.DataFrame(lgbm_pred_lny)
lgbm_out_lny = lgbm_pred_lny.join(test)
lgbm_out_lny.to_csv(r'Datasets\lgbm_out_lny.csv',index=True ,header=True)

nn_pred_lny = pd.DataFrame(nn_pred_lny)
nn_out_lny = nn_pred_lny.join(test)
nn_out_lny.to_csv(r'Datasets\nn_out_lny.csv',index=True ,header=True)
```