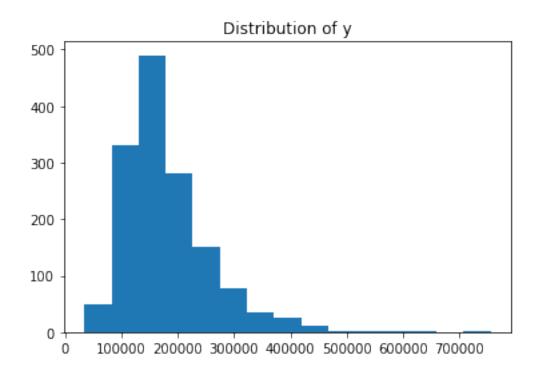
remove outliers and log chang y to improve performance

May 24, 2019

I try to remove some outliers in X for better performance. Also use log transfer y. Fit in Ridge and Lasso with clean data. Use grid search to improve performance.

```
In [1]: import numpy as np
        import pandas as pd
        from matplotlib import pyplot as plt
        import seaborn as sns
        %matplotlib inline
In [2]: clean_data = pd.read_csv('clean_data.csv')
        clean_data.head()
Out[2]:
           {\tt Id\ MSSubClass\ LotFrontage\ LotArea\ OverallQual\ OverallCond\ YearBuilt}
        0
                        60
                                    65.0
                                              8450
                                                               7
                                                                             5
                                                                                      2003
             1
            2
                        20
                                    80.0
                                              9600
                                                                             8
        1
                                                               6
                                                                                      1976
                                                               7
                                                                             5
            3
                        60
                                    68.0
                                             11250
                                                                                      2001
                                                               7
        3
            4
                                                                             5
                        70
                                    60.0
                                              9550
                                                                                      1915
                                    84.0
                                                                             5
                        60
                                             14260
                                                                                      2000
           YearRemodAdd ExterQual ExterCond
                                                                           SaleType_ConLI
        0
                    2003
                                   3
                                               2
                                                                                         0
        1
                    1976
                                   2
                                               2
                                                                                         0
        2
                    2002
                                   3
                                               2
                                                                                         0
        3
                    1970
                                   2
                                               2
                                                                                         0
                    2000
                                   3
                                               2
        4
                                                                                         0
           SaleType_ConLw
                             SaleType_New
                                            SaleType_Oth
                                                           SaleType_WD
        0
                         0
                                         0
                                                        0
                                                                      1
        1
                         0
                                         0
                                                        0
                                                                      1
        2
                         0
                                         0
                                                        0
                                                                      1
                                         0
        3
                         0
                                                        0
                                                                      1
        4
                                         0
                                                        0
           SaleCondition_AdjLand SaleCondition_Alloca SaleCondition_Family
        0
                                 0
                                                         0
        1
                                 0
                                                         0
                                                                                0
        2
                                 0
                                                         0
                                                                                0
```

```
3
                               0
                                                      0
                                                                             0
        4
                                0
                                                      0
           SaleCondition_Normal SaleCondition_Partial
        0
        1
                               1
                                                      0
        2
                              1
                                                      0
                              0
                                                      0
        4
                                                      0
                               1
        [5 rows x 534 columns]
In [3]: clean_data.columns
Out[3]: Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
               'OverallCond', 'YearBuilt', 'YearRemodAdd', 'ExterQual', 'ExterCond',
               'SaleType_ConLI', 'SaleType_ConLw', 'SaleType_New', 'SaleType_Oth',
               'SaleType_WD', 'SaleCondition_AdjLand', 'SaleCondition_Alloca',
               'SaleCondition_Family', 'SaleCondition_Normal',
               'SaleCondition_Partial'],
              dtype='object', length=534)
In [4]: y=clean_data['SalePrice']
        clean_data=clean_data.drop(['SalePrice'],axis=1) #drop the y in clean_data
        X = clean data.iloc[:,1:] # drop the id column
        X.shape
Out[4]: (1459, 532)
In [5]: y.describe()
Out[5]: count
                   1459.000000
        mean
                 180930.394791
        std
                  79468.964025
        min
                  34900.000000
        25%
                 129950.000000
        50%
                 163000.000000
        75%
                 214000.000000
                 755000.000000
        max
        Name: SalePrice, dtype: float64
In [6]: plt.hist(y,bins=15)
        plt.title('Distribution of y')
        # Basically the first and last 9 bins have little samples,
        #it's hard to predict these small groups of data, so drop it first.
Out[6]: Text(0.5,1,'Distribution of y')
```



/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: DataCoreturn self.partial_fit(X, y)

/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarnizeturn self.fit(X, **fit_params).transform(X)

/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:8: DataConversionWesternel_

```
ConvergenceWarning)
Out [8]: 33069.93524702181
In [9]: # grid search to get the best hyperparameter.
        from sklearn.model_selection import GridSearchCV
       parameters = { 'max_iter':[1000,2000,5000], 'alpha':[1, 10,100,1000,10000]}
        ls = Lasso(random_state=42)
        clf = GridSearchCV(ls, parameters, cv=5)
        clf.fit(X_train_sc,y_train)
        y_test_pred = clf.predict(X_test_sc)
        y_train_pred = clf.predict(X_train_sc)
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.
  ConvergenceWarning)
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.
```

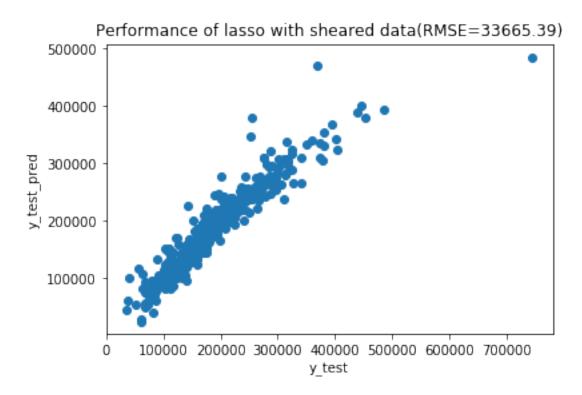
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.

```
ConvergenceWarning)
```

/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.greenceWarning)

/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.g
ConvergenceWarning)

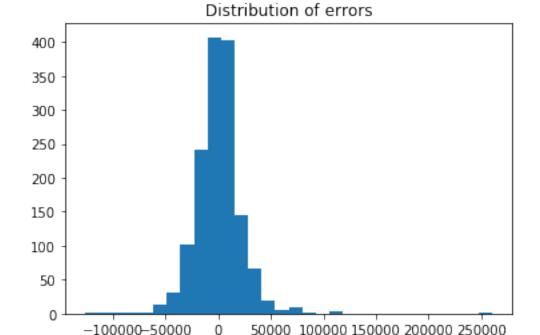
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_search.py:841: DeprecationWarning)



In [12]: clf.best_score_
R2

Out[12]: 0.8037315767569586

0.1 Remove outliers in X



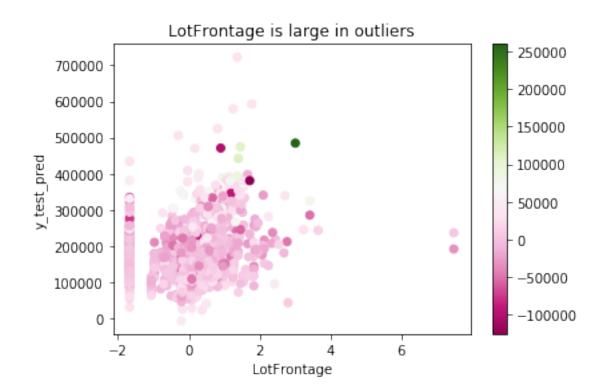
```
Out[18]:
               MSSubClass
                            LotFrontage
                                           LotArea
                                                     OverallQual
                                                                   OverallCond YearBuilt
         700
                  0.052093
                              -1.673021
                                          0.148034
                                                       -0.090550
                                                                      1.328141
                                                                                  0.176179
         1064
                 -0.881004
                                          0.191906
                                                                     -0.494482
                                                                                  1.197285
                                1.196449
                                                        1.376930
         1094
                                                                     -0.494482
                 -0.881004
                                0.259479 -0.175261
                                                       -0.824290
                                                                                 -0.647293
         1152
                 -0.881004
                                0.903646
                                          0.075925
                                                        1.376930
                                                                     -0.494482
                                                                                  1.098468
         1167
                 -0.881004
                                1.723495
                                          0.265211
                                                        1.376930
                                                                     -0.494482
                                                                                  1.131407
         1173
                 -0.881004
                              -1.673021
                                          2.028113
                                                       -0.090550
                                                                     -2.317105
                                                                                 -0.482598
         1218
                  0.285367
                              -0.209006 -0.194760
                                                       -1.558029
                                                                     -1.405794
                                                                                 -1.701337
         1299
                               0.230199
                 -0.881004
                                          1.331579
                                                       -0.824290
                                                                      2.239452
                                                                                -0.120270
                              ExterQual
                                                      BsmtQual
                                                                                         \
               YearRemodAdd
                                          ExterCond
         700
                              -0.692465
                                                      0.577925
                    0.492087
                                           2.661743
         1064
                                2.756348
                    1.165509
                                          -0.217113
                                                      1.689151
         1094
                   -1.576280
                              -2.416871
                                          -0.217113 -0.533302
         1152
                    1.021204
                                1.031941
                                          -0.217113
                                                      1.689151
         1167
                    1.021204
                                1.031941
                                          -0.217113
                                                      0.577925
         1173
                   -0.469944
                                1.031941
                                          -0.217113 -0.533302
                   -1.672484
                              -0.692465
                                          -3.095969 -0.533302
         1218
         1299
                    0.876900
                              -0.692465
                                          -0.217113 -0.533302
                                                                          . . .
               SaleType_ConLI
                                 SaleType_ConLw
                                                  SaleType_New
                                                                 SaleType_Oth
                                                                                SaleType_WD
         700
                     -0.031311
                                      -0.044302
                                                     -0.309020
                                                                    -0.031311
                                                                                   0.393672
         1064
                     -0.031311
                                      -0.044302
                                                      3.236033
                                                                    -0.031311
                                                                                  -2.540188
                                                                    -0.031311
         1094
                     -0.031311
                                      -0.044302
                                                     -0.309020
                                                                                   0.393672
         1152
                     -0.031311
                                      -0.044302
                                                      3.236033
                                                                    -0.031311
                                                                                  -2.540188
         1167
                     -0.031311
                                      -0.044302
                                                     -0.309020
                                                                    -0.031311
                                                                                   0.393672
                                                     -0.309020
                                                                    -0.031311
         1173
                     -0.031311
                                      -0.044302
                                                                                   0.393672
         1218
                     -0.031311
                                      -0.044302
                                                     -0.309020
                                                                    -0.031311
                                                                                   0.393672
                                                     -0.309020
         1299
                     -0.031311
                                      -0.044302
                                                                    -0.031311
                                                                                   0.393672
               SaleCondition_AdjLand
                                        SaleCondition_Alloca
                                                                SaleCondition_Family
         700
                             -0.062715
                                                    -0.076885
                                                                           -0.126176
         1064
                             -0.062715
                                                    -0.076885
                                                                           -0.126176
         1094
                            -0.062715
                                                    13.006409
                                                                           -0.126176
                            -0.062715
                                                    -0.076885
         1152
                                                                           -0.126176
         1167
                             -0.062715
                                                    -0.076885
                                                                           -0.126176
         1173
                             -0.062715
                                                    13.006409
                                                                           -0.126176
         1218
                             -0.062715
                                                    -0.076885
                                                                           -0.126176
                             -0.062715
                                                    -0.076885
         1299
                                                                           -0.126176
               SaleCondition_Normal
                                       SaleCondition_Partial
         700
                            0.470417
                                                    -0.310918
         1064
                           -2.125775
                                                     3.216278
         1094
                           -2.125775
                                                    -0.310918
         1152
                           -2.125775
                                                     3.216278
         1167
                            0.470417
                                                    -0.310918
         1173
                           -2.125775
                                                    -0.310918
         1218
                            0.470417
                                                    -0.310918
```

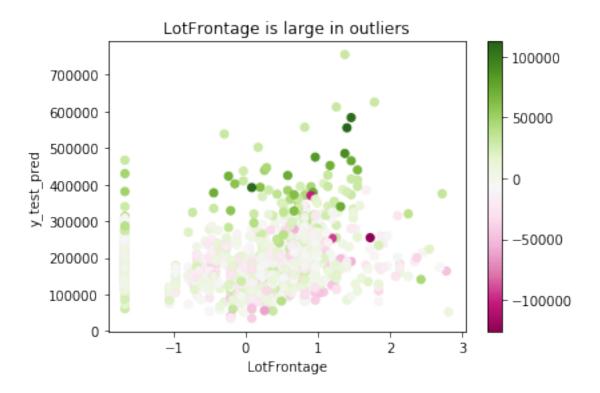
1299 -2.125775 3.216278

[8 rows x 532 columns]

Out[19]:	390 446 491 554 1316 1379	MSSubClass I -0.881004 0.052093 0.402004 -0.881004 0.052093 0.052093	1.401411 1.459972 0.962207 0.083797 1.372131 3.011828	LotArea 0.442724 0.301082 1.134291 -0.232562 0.266775 0.460384	0verallQua 2.8444 2.1106 2.8444 1.3769 2.1106 2.8444	-0.494482 7 -0.494482 1 3.150764 3 0.416829 7 -0.494482	1.197285 1.197285 -2.623626 1.164346 1.197285	\
		YearRemodAdd	ExterQual	ExterCond	BsmtQual		\	
	390	1.117407	2.756348	-0.217113	1.689151			
	446	1.165509	2.756348	-0.217113	1.689151			
	491	0.395884	1.031941		-0.533302			
	554	1.069306	1.031941	-0.217113				
	1316	1.165509	2.756348	-0.217113	1.689151			
	1379	0.540189	1.031941	-0.217113	1.689151			
		SaleType_ConL	.I SaleType	_ConLw Sa	leType_New	SaleType_Oth	SaleType_WD	\
	390	-0.03131	.1 -0.	044302	-0.309020	-0.031311	0.393672	
	446	-0.03131	1 -0.	044302	3.236033	-0.031311	-2.540188	
	491	-0.03131	1 -0.	044302	-0.309020	-0.031311	0.393672	
	554	-0.03131	1 -0.	044302	3.236033	-0.031311	-2.540188	
	1316	-0.03131	1 -0.	044302	3.236033	-0.031311	-2.540188	
	1379	-0.03131	1 -0.	044302	-0.309020	-0.031311	0.393672	
		SaleCondition_AdjLand SaleCond					•	
390		-0.062715		-0.076885		-0.126176		
	446	-0.062715		-0.076885		-0.126176		
	491		0.062715		-0.076885		126176	
	554 -0.062715 1316 -0.062715				-0.076885	-0.126176		
	1316			-0.076885	-0.126176			
	1379	_	0.062715		-0.076885	-0.	126176	
SaleCondition Normal SaleCondition Partial								
	390	-			-0.310918			
	446		2.125775		3.216278			
	491		.470417		-0.310918			
	554		2.125775		3.216278			
	1316		2.125775		3.216278			
	1379		2.125775		-0.310918			

[6 rows x 532 columns]





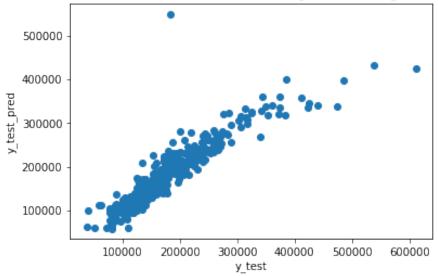
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.g
ConvergenceWarning)

```
Out [22]: 35317.15079537594
```

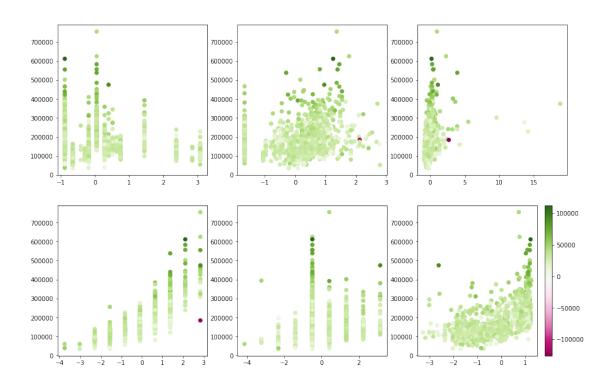
```
In [23]: parameters = { 'max_iter':[1000,2000,5000],'alpha':[1, 10,100,1000,10000]}
    ls = Lasso(random_state=42)
    clf = GridSearchCV(ls, parameters, cv=5)
    clf.fit(X_train,y_train)
    y_test_pred = clf.predict(X_test)
    y_train_pred = clf.predict(X_train)
    mse = mean_squared_error(y_test, y_test_pred)
    sqrt(mse)
```

```
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.
  ConvergenceWarning)
Out [23]: 30570.689624112565
In [24]: y.shape[0]-y_filted.shape[0] # 7 data points removed
Out[24]: 7
In [25]: plt.scatter(y_test, y_test_pred)
         plt.title('Performance of lasso with sheared data according to LotFrontage(RMSE=30570
         plt.xlabel('y_test')
         plt.ylabel('y_test_pred')
Out[25]: Text(0,0.5,'y_test_pred')
```

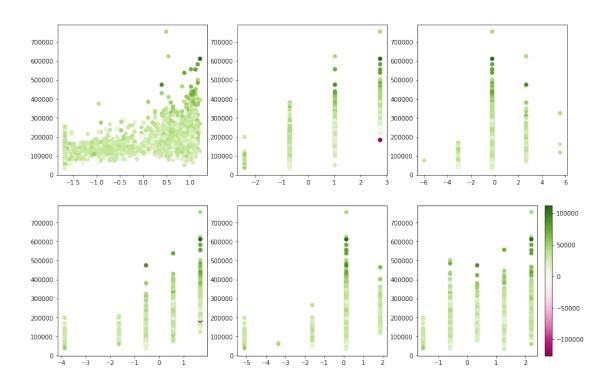
Performance of lasso with sheared data according to LotFrontage(RMSE=30570.68)



```
In [26]: # combine data for some EDA and find more outliers
        y_filted = np.hstack([y_train,y_test])
        X_true_comb = np.vstack([X_train,X_test])
        X_filted = pd.DataFrame(X_true_comb,columns=X.columns)
        y pred = clf.predict(X filted)
         error_filted =y_filted-y_pred
         error_filted
Out[26]: array([ 5.21606840e+03, -9.47065676e+03, 5.37606815e+03, ...,
                -1.64250998e+02, -1.62202384e+01, 1.63888821e+04])
In [27]: i = 0
        fig, axes = plt.subplots(2, 3, figsize=(15,10))
         axes[0, 0].scatter(X_filted.iloc[:,i+0],y_filted , c=error_filted, cmap=cm)
         axes[0, 1].scatter(X_filted.iloc[:,i+1],y_filted , c=error_filted, cmap=cm)
         axes[0, 2].scatter(X_filted.iloc[:,i+2],y_filted , c=error_filted, cmap=cm)
         axes[1, 0].scatter(X_filted.iloc[:,i+3],y_filted , c=error_filted, cmap=cm)
         axes[1, 1].scatter(X_filted.iloc[:,i+4],y_filted , c=error_filted, cmap=cm)
        axes[1, 2].scatter(X_filted.iloc[:,i+5],y_filted , c=error_filted, cmap=cm)
        plt.colorbar(sc)
Out[27]: <matplotlib.colorbar.Colorbar at 0x1a257a4b00>
```

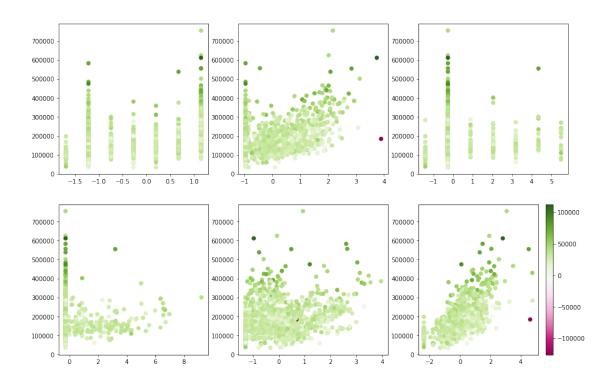


Out[28]: <matplotlib.colorbar.Colorbar at 0x1a13b234e0>

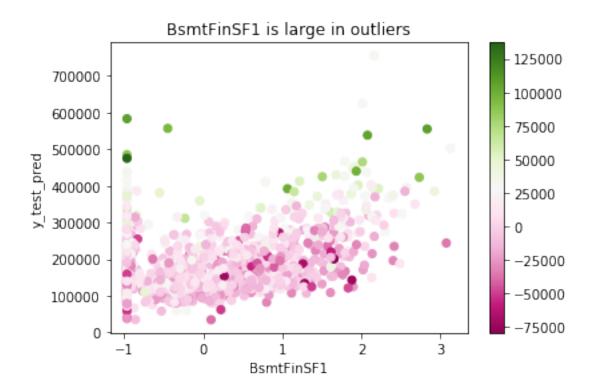


```
In [29]: i = 12
    fig, axes = plt.subplots(2, 3, figsize=(15,10))
    axes[0, 0].scatter(X_filted.iloc[:,i+0],y_filted , c=error_filted, cmap=cm)
    axes[0, 1].scatter(X_filted.iloc[:,i+1],y_filted , c=error_filted, cmap=cm)
    axes[0, 2].scatter(X_filted.iloc[:,i+2],y_filted , c=error_filted, cmap=cm)
    axes[1, 0].scatter(X_filted.iloc[:,i+3],y_filted , c=error_filted, cmap=cm)
    axes[1, 1].scatter(X_filted.iloc[:,i+4],y_filted , c=error_filted, cmap=cm)
    axes[1, 2].scatter(X_filted.iloc[:,i+5],y_filted , c=error_filted, cmap=cm)
    plt.colorbar(sc)
```

Out [29]: <matplotlib.colorbar.Colorbar at 0x1a13df9198>



```
In [30]: # find some outliers in feature BsmtFinSF1
         import heapq
         print(heapq.nlargest(3, X_filted.iloc[:,13]))
[3.8974066763514945, 3.7424466786490984, 3.131215576600758]
In [31]: X_filted.columns[13]
Out[31]: 'BsmtFinSF1'
In [33]: # remove according to BsmtFinSF1.
         X_filted2 = X_filted[X_filted['BsmtFinSF1'] < 3.6]</pre>
         y_filted2 = y_filted[X_filted['BsmtFinSF1'] < 3.6]</pre>
         error_filted2 = error_filted[X_filted['BsmtFinSF1'] < 3.6]</pre>
         cm = plt.cm.get_cmap('PiYG')
         sc = plt.scatter(X_filted2.iloc[:,13],y_filted2 , c=error_filted2, cmap=cm) # LotFron
                                                                                #Linear feet of s
         plt.colorbar(sc)
         plt.title('BsmtFinSF1 is large in outliers')
         plt.xlabel('BsmtFinSF1')
         plt.ylabel('y_test_pred')
Out[33]: Text(0,0.5,'y_test_pred')
```



/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.greenceWarning)

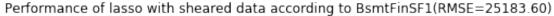
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.greenceWarning)

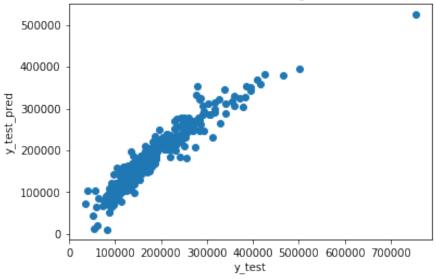
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.grayscore.gr

```
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.
  ConvergenceWarning)
```

Out[45]: 25183.600856565372

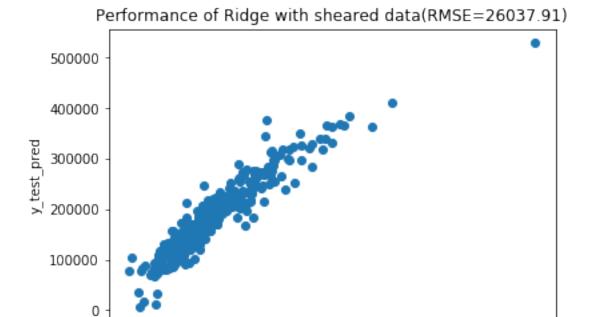
0.2 After remove the outliers in X, the root mean squared error droped to 25183.60





0.3 fit into Ridge

```
In [48]: parameters = { 'max_iter':[1000,2000,5000], 'alpha':[1, 10,100,1000,10000]}
         from sklearn.linear_model import Ridge
         ls = Ridge(random_state=42)
         clf = GridSearchCV(ls, parameters, cv=5)
         clf.fit(X_train,y_train)
         y_test_pred = clf.predict(X_test)
         y_train_pred = clf.predict(X_train)
In [49]: mse_test = mean_squared_error(y_test, y_test_pred)
         sqrt(mse_test)
Out [49]: 26037.908039527552
In [50]: clf.best_score_
Out [50]: 0.8699814937005034
In [51]: plt.scatter(y_test, y_test_pred)
         plt.title('Performance of Ridge with sheared data(RMSE=26037.91)')
         plt.xlabel('y_test')
        plt.ylabel('y_test_pred')
Out[51]: Text(0,0.5,'y_test_pred')
```

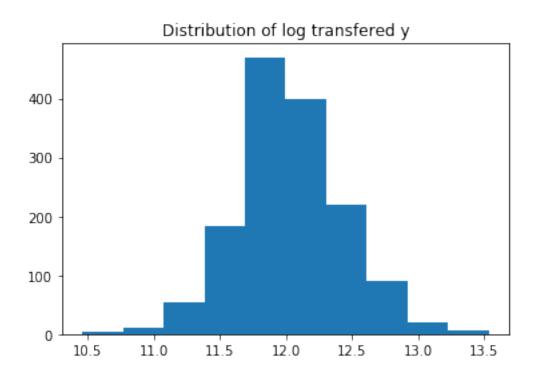


100000 200000 300000 400000 500000 600000 700000

y_test

0.4 log transfered y

0

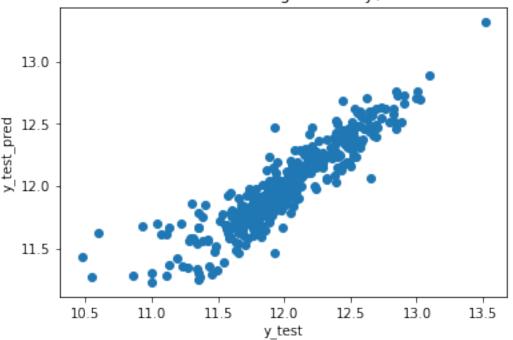


0.5 fit into lasso

ConvergenceWarning)

```
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/coordinate_descent.
  ConvergenceWarning)
/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_search.py:841:
  DeprecationWarning)
In [64]: mse_test = mean_squared_error(y_test, y_test_pred)
         sqrt(mse_test)
Out [64]: 0.18036476431273618
In [65]: clf.best_params_
Out[65]: {'alpha': 1, 'max_iter': 500}
In [66]: clf.best_score_
Out [66]: 0.6492490027698465
In [68]: plt.scatter(y_test, y_test_pred)
         plt.title('Performance of Lasso with log transfer y(RMSE=0.180365)')
         plt.xlabel('y_test')
        plt.ylabel('y_test_pred')
Out[68]: Text(0,0.5,'y_test_pred')
```



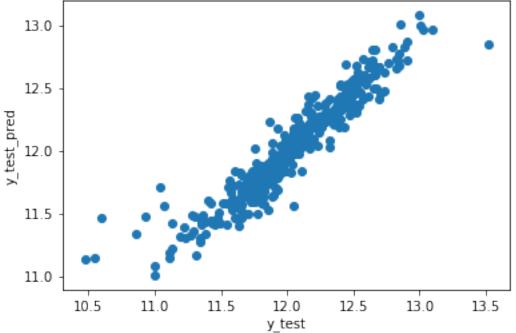


0.6 fit into Ridge

```
In [69]: parameters = { 'max_iter':[10,50,100,500],'alpha':[0.001,0.01,0.1,1, 10,100,1000]}
    rg = Ridge(random_state=42)
    clf = GridSearchCV(rg, parameters, cv=5)
    clf.fit(X_train,y_train)
    y_test_pred = clf.predict(X_test)
    y_train_pred = clf.predict(X_train)
```

/Users/fanwenyu/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_search.py:841: DeprecationWarning)

Performance of Ridge with log transfer y(RMSE=0.134803)



Out[71]: 0.1375474209000953

In [72]: clf.best_score_

Out[72]: 0.6234102765983629