MLCap_zhenshox_V3_RF_Lasso

November 4, 2020

[83]:
```
import os
import sys

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import scipy.stats as scs
import statsmodels as smm
import statsmodels.api as sm
import statsmodels.tsa.api as smt
import statsmodels.formula.api as smf
```

1 1. Final Dataset

[84]:
```
train=pd.read_csv('raw_train_daily.csv')
test=pd.read_csv('raw_test_daily.csv')

train=train.iloc[:,1:] #
test=test.iloc[:,1:] #
```

[85]:
```
train=train.drop(labels='Signal',axis=1).dropna() #signal has too many missing␣
↪values
test=test.drop(labels='Signal',axis=1).dropna() #signal has too many missing␣
↪values

train.columns
```

[85]:
```
Index(['Time', 'AM_NetPos', 'FedFunds', '1Y OIS', 'Libor 3 mo', 'Libor 6 mo',
       'Libor 1Y', 'T10Y3M', 'T10Y2Y', 'T10YIE', 'JNK_Price', 'SPX',
       'WILL5000INDFC', 'NASDAQCOM', 'GOLD_price', 'VIX', 'VXVCLS', 'GVZCLS',
       'JPY', 'EUR', 'USDX_Close', 'DTWEXBGS', 'FF_Mkt', 'FF_SMB', 'FF_HML',
       'FF_MOM', 'Lev_NetPos', 'AM_n_L', 'AM_n_S', 'Lev_n_L', 'Lev_n_S',
       'AM_L', 'AM_S', 'Lev_L', 'Lev_S', 'SPY Flows', 'IVV', 'JNK_Volume',
```

```
       'Flag'],
      dtype='object')
```

2 2. Feature Generation

[86]:
```
def feature(train):
    #1. Slope
    train['SPX_1w_chg']=train['SPX']/train['SPX'].shift(-1)-1 #weekly pct change
    train['SPX_2w_chg']=train['SPX']/train['SPX'].shift(-2)-1

    #2. Spread
    train['Spread_Libor_1YOIS']=train['Libor 1Y']-train['1Y OIS']

    #3. Lag: for comtemporary variables
    l=['AM_n_L', 'AM_n_S', 'Lev_n_L', 'Lev_n_S','AM_L', 'AM_S', 'Lev_L',␣
 ↪'Lev_S']
    newl=['last_'+s for s in l]
    train[newl]=train[l].shift(-1)   #TS ARIMA potential
    train=train.drop(labels=l,axis=1)

    #4. Var

    #5. Cumsum

    #Comments: 1.daily signal 2.time series singal

    return train.dropna()
```

[87]:
```
#Benchmark: OLS
train=feature(train)
test=feature(test)

#Since the dataset is already small, train&test set are not splitted yet
X=train.drop(columns = ['Time','AM_NetPos'])
y=train['AM_NetPos']
X_test=test.drop(columns = ['Time','AM_NetPos'])
y_test=test['AM_NetPos']
```

3 3. LASSO

3.1 Lasso Model

[88]:
```
from sklearn import linear_model
model = linear_model.Lasso(alpha=10,max_iter=100000).fit(X, y)
```

[89]:
```
print(model.coef_)
print('\nAll varialbes: ',list(X.columns))
print('\nPicked vars: ',list(X.columns[model.coef_==0]))
print('\nLeft out vars: ',list(X.columns[model.coef_!=0]))
```

```
[ 0.00000000e+00  0.00000000e+00  0.00000000e+00  0.00000000e+00
  0.00000000e+00 -0.00000000e+00 -0.00000000e+00  0.00000000e+00
  5.10137264e+02  8.88015861e+01 -1.42133728e+03  5.33419468e+00
  7.02990471e+00  2.29478471e+03 -2.64568573e+03 -2.77534879e+02
  7.56756033e+01 -0.00000000e+00 -4.55179028e+01  1.50160034e+01
 -0.00000000e+00 -0.00000000e+00 -0.00000000e+00  0.00000000e+00
 -2.56497306e-01 -1.14602417e-01 -1.01329368e+00 -3.07504879e-05
 -2.28256510e+02  3.21670704e+05  4.24416866e+03 -0.00000000e+00
 -1.05382319e+02  1.33533313e+02  6.16103782e+00 -5.07546989e+00
  8.90609455e-01 -8.77559461e-01  2.09000141e-01 -2.62583597e-01]

All varialbes:  ['FedFunds', '1Y OIS', 'Libor 3 mo', 'Libor 6 mo', 'Libor 1Y',
'T10Y3M', 'T10Y2Y', 'T10YIE', 'JNK_Price', 'SPX', 'WILL5000INDFC', 'NASDAQCOM',
'GOLD_price', 'VIX', 'VXVCLS', 'GVZCLS', 'JPY', 'EUR', 'USDX_Close', 'DTWEXBGS',
'FF_Mkt', 'FF_SMB', 'FF_HML', 'FF_MOM', 'Lev_NetPos', 'SPY Flows', 'IVV',
'JNK_Volume', 'Flag', 'SPX_1w_chg', 'SPX_2w_chg', 'Spread_Libor_1YOIS',
'last_AM_n_L', 'last_AM_n_S', 'last_Lev_n_L', 'last_Lev_n_S', 'last_AM_L',
'last_AM_S', 'last_Lev_L', 'last_Lev_S']

Picked vars:  ['FedFunds', '1Y OIS', 'Libor 3 mo', 'Libor 6 mo', 'Libor 1Y',
'T10Y3M', 'T10Y2Y', 'T10YIE', 'EUR', 'FF_Mkt', 'FF_SMB', 'FF_HML', 'FF_MOM',
'Spread_Libor_1YOIS']

Left out vars:  ['JNK_Price', 'SPX', 'WILL5000INDFC', 'NASDAQCOM', 'GOLD_price',
'VIX', 'VXVCLS', 'GVZCLS', 'JPY', 'USDX_Close', 'DTWEXBGS', 'Lev_NetPos', 'SPY
Flows', 'IVV', 'JNK_Volume', 'Flag', 'SPX_1w_chg', 'SPX_2w_chg', 'last_AM_n_L',
'last_AM_n_S', 'last_Lev_n_L', 'last_Lev_n_S', 'last_AM_L', 'last_AM_S',
'last_Lev_L', 'last_Lev_S']
```

3.2 Performance

[90]:
```
def evaluate(y,y_pred,title='Result'):
    mse=np.mean((y-y_pred)**2)
    ape=np.mean(np.abs((y-y_pred)/y))
    print(title,':')
    print('MSE is {}'.format(mse))
    print('Average Percentage Error is {}'.format(ape))
```

[91]:
```
#Train
y_pred=model.predict(X)
y_pred_test=model.predict(X_test)

evaluate(y,y_pred,title='Lasso Train')
```

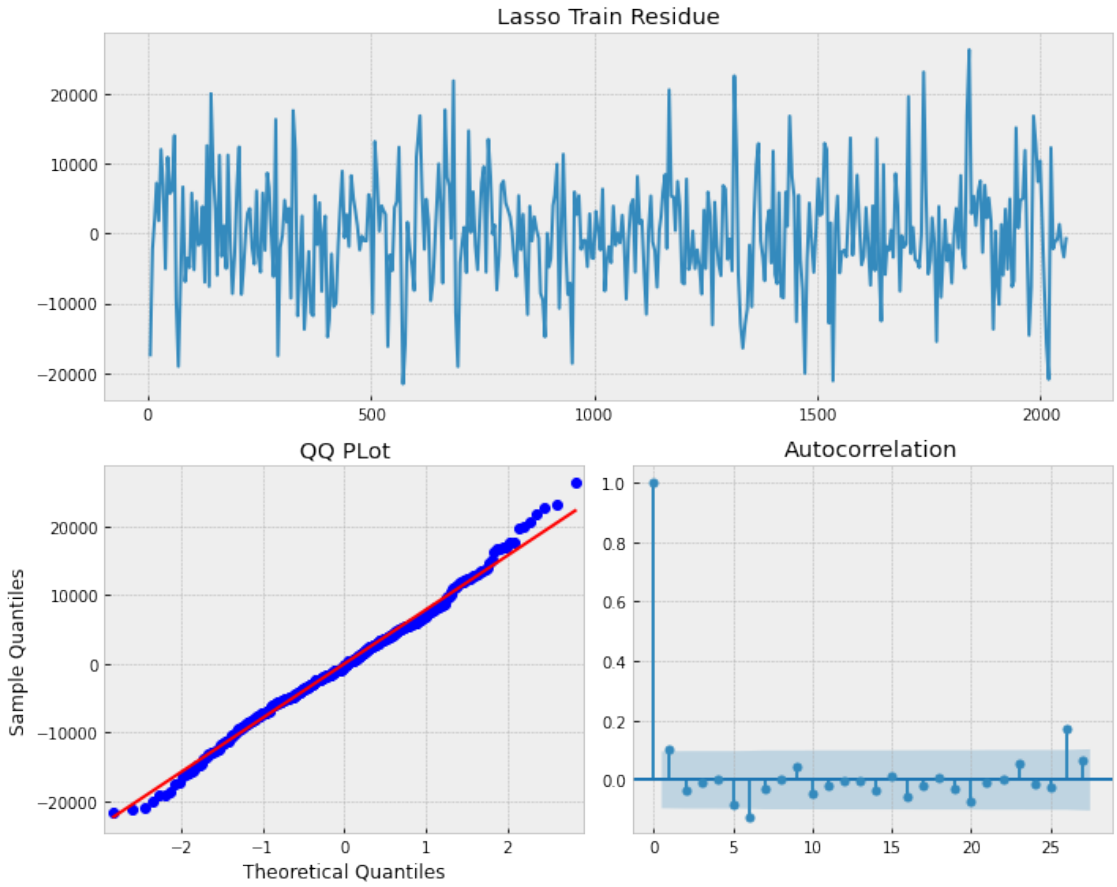
```
print('\n')
evaluate(y_test,y_pred_test,title='Lasso Test')
```

```
Lasso Train :
MSE is 62262773.13616344
Average Percentage Error is 0.04618291056209291


Lasso Test :
MSE is 186662093.51179442
Average Percentage Error is 0.08931963571908069
```

3.3 Residue Plots

[92]:
```
def tsplot(y, lags=None, figsize = (10,8), style = 'bmh',title='Time Series of␣
↪Log Ret'):
    if not isinstance(y, pd.Series):
        y = pd.Series(y)
    with plt.style.context(style):
        fig = plt.figure(figsize=figsize)
        layout = (2,2)
        ts_ax = plt.subplot2grid(layout, (0,0), colspan = 2)
        acf_ax = plt.subplot2grid(layout, (1,1))
        qq_ax = plt.subplot2grid(layout, (1,0))
        y.plot(ax = ts_ax)
        ts_ax.set_title(title)
        smt.graphics.plot_acf(y, lags = lags, ax=acf_ax,alpha = 0.05)
        sm.qqplot(y, line = 's', ax=qq_ax)
        qq_ax.set_title('QQ PLot')
        plt.tight_layout()
    return
```

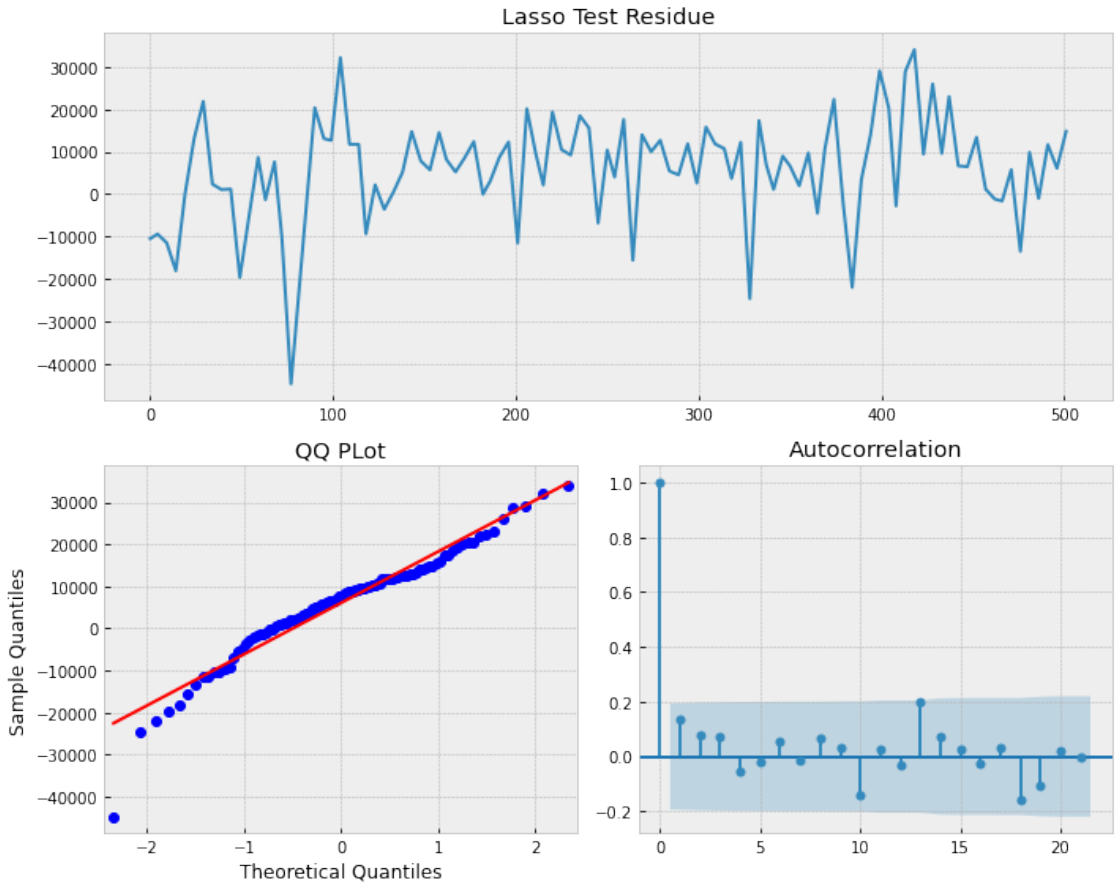
[93]:
```
#look at the residue
tsplot(y-y_pred,title='Lasso Train Residue')
```



Comments:

1. Heavy tail

[94]:
```
tsplot(y_test-y_pred_test,title='Lasso Test Residue')
```



4 4. Random Forest

4.1 RF Model

[95]:
```
from sklearn.ensemble import RandomForestRegressor
model_RF=RandomForestRegressor(n_estimators=20,random_state=0,criterion='mae',
                               min_samples_leaf = 2).fit(X,y)
```

4.2 Performance

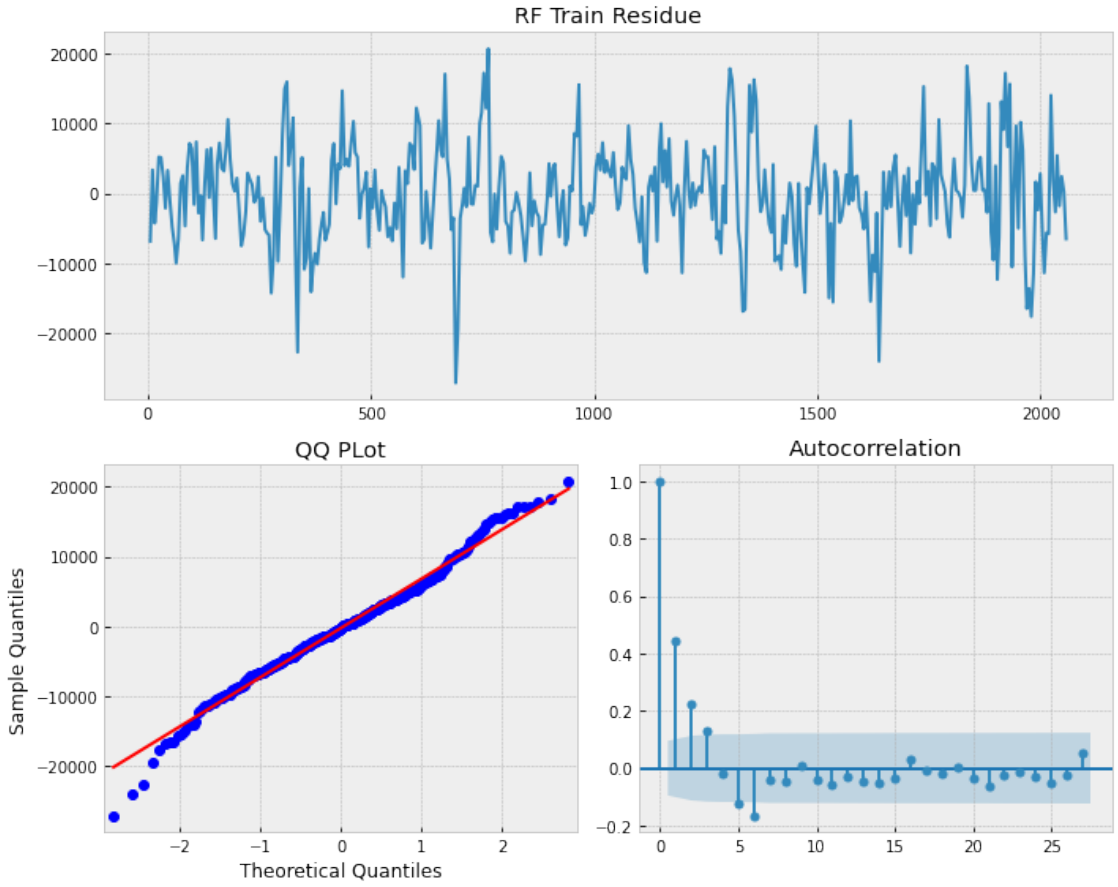
[96]:
```
y_pred=model_RF.predict(X)
y_pred_test=model_RF.predict(X_test)

evaluate(y,y_pred,title='RF Train')
print('\n')
evaluate(y_test,y_pred_test,title='RF Test')
```

```
RF Train :
MSE is 49941067.169101
```

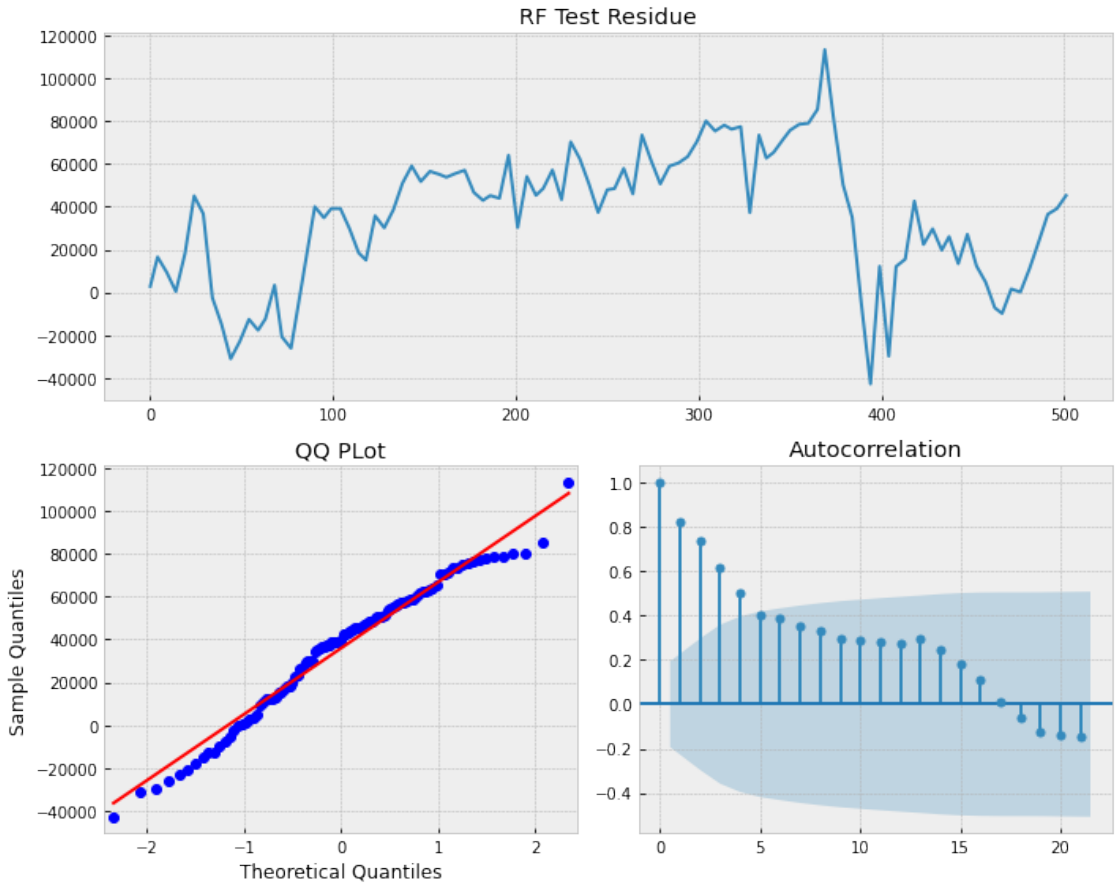
```
Average Percentage Error is 0.0415941753319309


RF Test :
MSE is 2248079665.8610735
Average Percentage Error is 0.28096071084591184
```

4.3 RF Residue Plot

[97]:
```
tsplot(y-y_pred,title='RF Train Residue')
```



[98]:
```
tsplot(y_test-y_pred_test,title='RF Test Residue')
```


RF Test Residue
QQ PLot
Autocorrelation
Sample Quantiles
Theoretical Quantiles

[ ]: