visualization

September 13, 2019

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

from numpy.random import seed
seed(1)

import statsmodels.api as sm
from statsmodels import regression,stats
import statsmodels.stats.diagnostic as smd
import scipy

import math

import warnings
warnings.filterwarnings("ignore")

from sklearn import preprocessing

from keras.layers import Input, Dense,Conv1D, Conv2D, MaxPooling2D, UpSampling2D,dot,Re
from keras.layers import BatchNormalization,LeakyReLU
from keras.models import Model
from keras.callbacks import EarlyStopping
from keras import regularizers
from keras import backend as K

from tensorflow import set_random_seed
set_random_seed(2)
```

```
Using TensorFlow backend.
```

0.1 Get r_square data and loss data

0.2 auto_one_r_square is the r_square of the autoencoders who has one dense in beta side network, but four or five or six or seven or eight factors in the bottleneck layer.

In [2]:
```
auto_one_r_square=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_one_
auto_one_r_square.rename(columns = {'Unnamed: 0':'portfolio'},inplace=True)
auto_one_r_square.set_index('portfolio',drop=True,inplace=True)

auto_one_loss=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_one_four_
auto_one_loss.drop(columns='Unnamed: 0',inplace=True)

auto_one_mse=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_one_four_
auto_one_mse.drop(columns='Unnamed: 0',inplace=True)
```

In [3]:
```
auto_one_loss.tail()
```

Out[3]:
```
     history_1_4_loss  history_1_5_loss  history_1_6_loss  history_1_7_loss  \
995          0.000009          0.000007          0.000006          0.000006
996          0.000009          0.000007          0.000006          0.000006
997          0.000009          0.000007          0.000006          0.000006
998          0.000009          0.000007          0.000006          0.000006
999          0.000009          0.000007          0.000006          0.000005

     history_1_8_loss
995          0.000004
996          0.000004
997          0.000004
998          0.000004
999          0.000004
```

In [4]:
```
auto_two_r_square=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_two_
auto_two_r_square.rename(columns = {'Unnamed: 0':'portfolio'},inplace=True)
auto_two_r_square.set_index('portfolio',drop=True,inplace=True)

auto_two_loss=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_two_four_
auto_two_loss.drop(columns='Unnamed: 0',inplace=True)

auto_two_mse=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_two_four_
auto_two_mse.drop(columns='Unnamed: 0',inplace=True)
```

In [5]:
```
auto_three_r_square=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_th
auto_three_r_square.rename(columns = {'Unnamed: 0':'portfolio'},inplace=True)
auto_three_r_square.set_index('portfolio',drop=True,inplace=True)

auto_three_loss=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_three_
auto_three_loss.drop(columns='Unnamed: 0',inplace=True)

auto_three_mse=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\auto_three_f
auto_three_mse.drop(columns='Unnamed: 0',inplace=True)
```

0.3 Below is linear regression results by four Famm and French factors

```
In [6]: F_F_r_square=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\F_F_r_square.cs
        F_F_r_square.rename(columns = {'Unnamed: 0':'portfolio'},inplace=True)
        F_F_r_square.set_index('portfolio',drop=True,inplace=True)
```

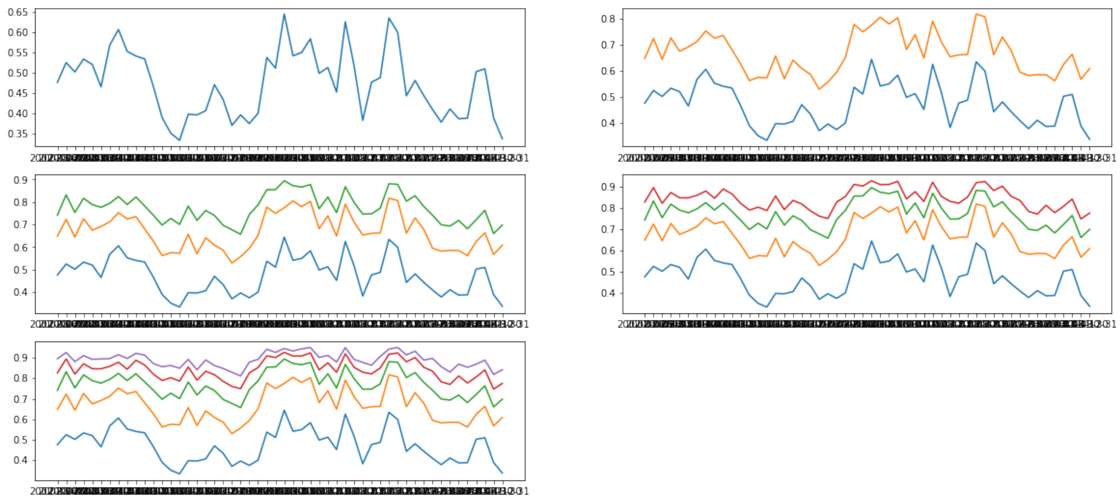
0.4 Below is Principal component analysis results by four Famm and French factors

```
In [44]: PCA_r_square=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\PCA_r_square.c
         PCA_r_square.rename(columns = {'Unnamed: 0':'portfolio'},inplace=True)
         PCA_r_square.set_index('portfolio',drop=True,inplace=True)

         PCA_r_square_stand=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\PCA_r_sq
         PCA_r_square_stand.rename(columns = {'Unnamed: 0':'portfolio'},inplace=True)
         PCA_r_square_stand.set_index('portfolio',drop=True,inplace=True)

         pct_per_one=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\pct_per_one.csv
         pct_per_one.rename(columns = {'Unnamed: 0':'date'},inplace=True)
         pct_per_one.set_index('date',drop=True,inplace=True)

         pct_per_two=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\pct_per_two.csv
         pct_per_two.rename(columns = {'Unnamed: 0':'date'},inplace=True)
         pct_per_two.set_index('date',drop=True,inplace=True)

         pct_per_three=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\pct_per_three
         pct_per_three.rename(columns = {'Unnamed: 0':'date'},inplace=True)
         pct_per_three.set_index('date',drop=True,inplace=True)

         pct_per_four=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\pct_per_four.c
         pct_per_four.rename(columns = {'Unnamed: 0':'date'},inplace=True)
         pct_per_four.set_index('date',drop=True,inplace=True)

         pct_per_five=pd.read_csv(r'F:\capstone\xz\0711\0724\autoencoder\outcome\pct_per_five.c
         pct_per_five.rename(columns = {'Unnamed: 0':'date'},inplace=True)
         pct_per_five.set_index('date',drop=True,inplace=True)
```

0.5 Below is the volatility percentage that can be explained by PCA

```
In [8]: plt.figure(figsize=(20,9))
        plt.subplot(3, 2, 1)
        plt.plot(pd.DataFrame(pct_per_one))

        plt.subplot(3, 2, 2)
        plt.plot(pd.DataFrame(pct_per_two))

        plt.subplot(3, 2, 3)
        plt.plot(pd.DataFrame(pct_per_three))
```

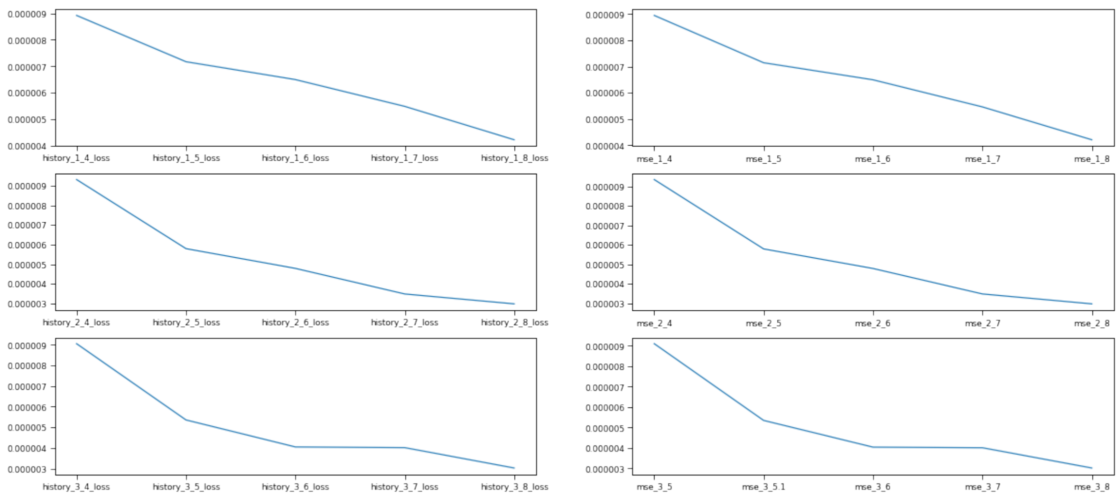
```
plt.subplot(3, 2, 4)
plt.plot(pd.DataFrame(pct_per_four))

plt.subplot(3, 2, 5)
plt.plot(pd.DataFrame(pct_per_five))


plt.show()
```



0.6 Below is the loss by autoencoder and the mse calculated by hand. We can see that they are very close, showing that the target of autoencoder model is just what we want

In [40]:
```
plt.figure(figsize=(20,9))
plt.subplot(3, 2, 1)
plt.plot(auto_one_loss.iloc[-1])

plt.subplot(3, 2, 2)
plt.plot(auto_one_mse.iloc[-1])

plt.subplot(3, 2, 3)
plt.plot(auto_two_loss.iloc[-1])

plt.subplot(3, 2, 4)
plt.plot(auto_two_mse.iloc[-1])

plt.subplot(3, 2, 5)
plt.plot(auto_three_loss.iloc[-1])

plt.subplot(3, 2, 6)
```

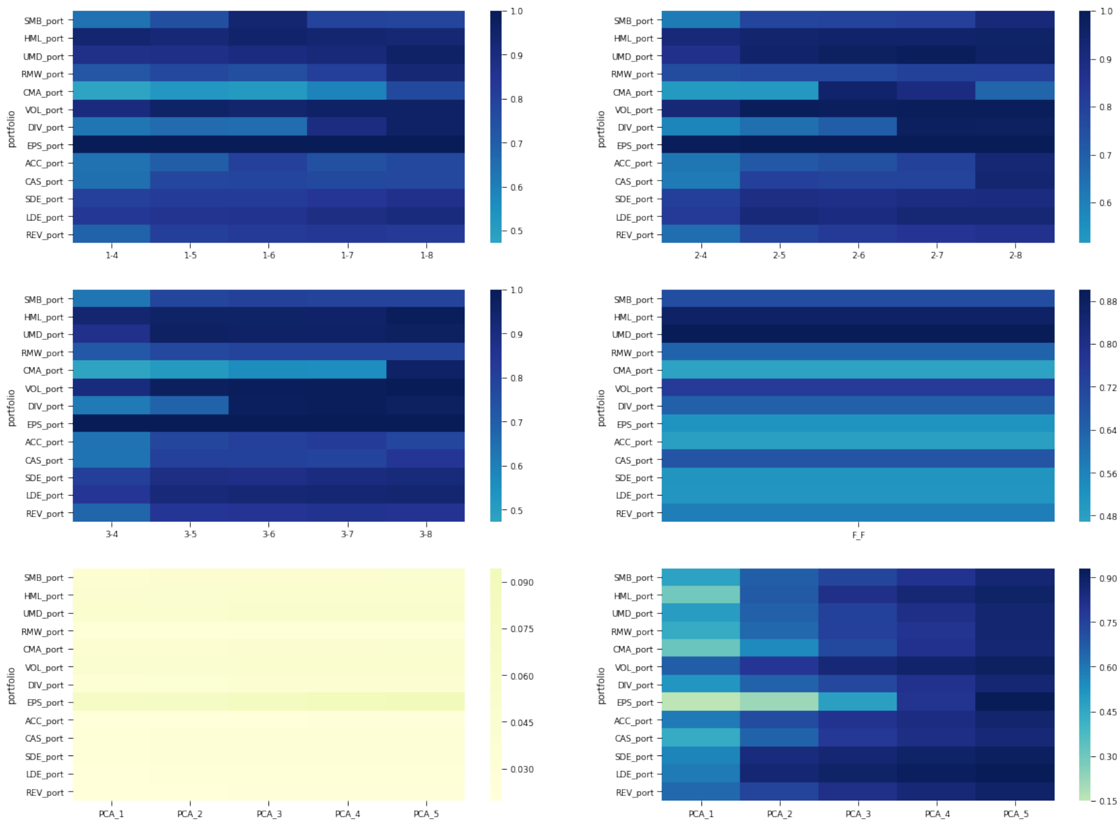
```
plt.plot(auto_three_mse.iloc[-1])

plt.show()
```



1 plot the r squre of different models

1.1 For example, 1-4 means one dense in beta side network and four factor in bottle-neck layer.

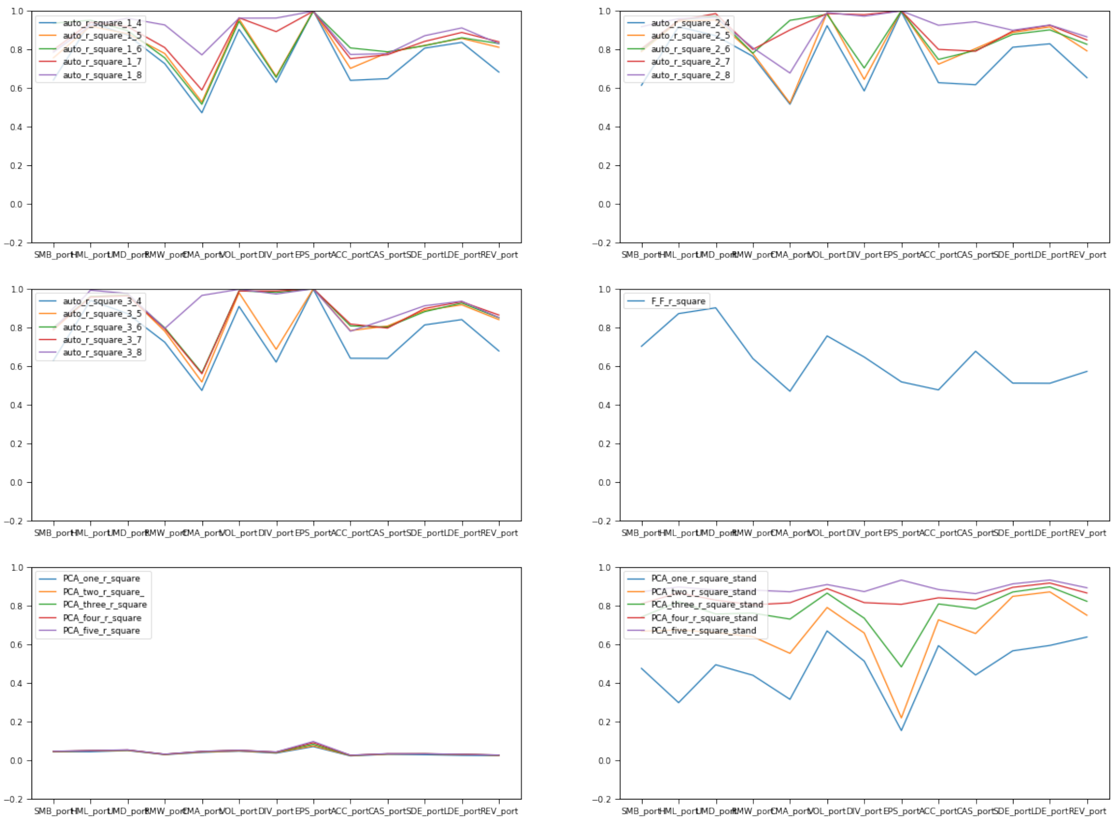
In [46]:
```
plt.figure(figsize=(20,15))
sns.set_context("paper")
plt.subplot(3, 2, 1)
sns.heatmap(auto_one_r_square,cmap="YlGnBu",xticklabels=['1-4','1-5','1-6','1-7','1-8

plt.subplot(3, 2, 2)
sns.heatmap(auto_two_r_square,cmap="YlGnBu",xticklabels=['2-4','2-5','2-6','2-7','2-8

plt.subplot(3, 2, 3)
sns.heatmap(auto_three_r_square,cmap="YlGnBu",xticklabels=['3-4','3-5','3-6','3-7','3-

plt.subplot(3, 2, 4)
sns.heatmap(F_F_r_square,cmap="YlGnBu",xticklabels=['F_F'],center=0.4)

plt.subplot(3, 2, 5)
sns.heatmap(PCA_r_square,cmap="YlGnBu",xticklabels=['PCA_1','PCA_2','PCA_3','PCA_4','I

plt.subplot(3, 2, 6)
sns.heatmap(PCA_r_square_stand,cmap="YlGnBu",xticklabels=['PCA_1','PCA_2','PCA_3','PC

plt.show()
```



```
In [12]: name=['SMB', 'HML', 'UMD', 'RMW', 'CMA', 'VOL','DIV', 'EPS', 'ACC', 'CAS', 'SDE', 'LDI
```

```
In [47]: plt.figure(figsize=(20,15))
         plt.subplot(3, 2, 1)
         plt.plot(auto_one_r_square)
         plt.legend(auto_one_r_square.columns,loc=2)
         plt.ylim((-0.2,1))

         plt.subplot(3, 2, 2)
         plt.plot(auto_two_r_square)
         plt.legend(auto_two_r_square.columns,loc=2)
         plt.ylim((-0.2,1))

         plt.subplot(3, 2, 3)
         plt.plot(auto_three_r_square)
         plt.legend(auto_three_r_square.columns,loc=2)
         plt.ylim((-0.2,1))

         plt.subplot(3, 2, 4)
         plt.plot(F_F_r_square)
         plt.legend(F_F_r_square.columns,loc=2)
```

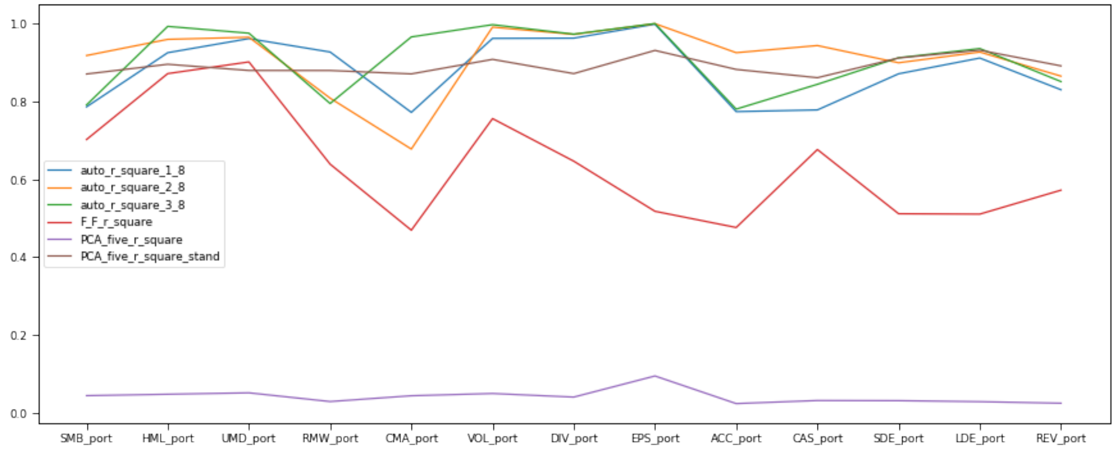
```
plt.ylim((-0.2,1))

plt.subplot(3, 2, 5)
plt.plot(PCA_r_square)
plt.legend(PCA_r_square.columns,loc=2)
plt.ylim((-0.2,1))

plt.subplot(3, 2, 6)
plt.plot(PCA_r_square_stand)
plt.legend(PCA_r_square_stand.columns,loc=2)
plt.ylim((-0.2,1))

plt.show()
```



1.2 According to the plot above, auto_one_four, auto_two_four, auto_three_four perform the best.

```
In [53]: pred_best=pd.concat((auto_one_r_square.iloc[:,4],auto_two_r_square.iloc[:,4],auto_thre
                    F_F_r_square,PCA_r_square.loc[:,'PCA_five_r_square'],
                    PCA_r_square_stand.loc[:,'PCA_five_r_square_stand']),axis=1)
```

In [54]:
```
plt.figure(figsize=(15,6))
plt.plot(pred_best)
plt.legend(['auto_r_square_1_8','auto_r_square_2_8','auto_r_square_3_8','F_F_r_square
            'PCA_five_r_square_stand'])
plt.show()
```



1.3 According to the plot above, we can see that autoencoder has done a good job of predicting returns.