```
#PACKAGES
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from IPython.display import display
dp = '{:.4f}'
pd.options.display.float_format = dp.format

#FUNCTIONS FROM GITHUB
def maxdrawdown(returns):
    cum_returns = (1 + returns).cumprod()
    rolling_max = cum_returns.cummax()
    drawdown = (cum_returns - rolling_max) / rolling_max

    max_drawdown = drawdown.min()
    end_date = drawdown.idxmin()
    summary = pd.DataFrame({'Max Drawdown': max_drawdown, 'Bottom':
end_date})

    for col in drawdown:
        summary.loc[col, 'Peak'] = (rolling_max.loc[:end_date[col],
col]).idxmax()
        recovery = (drawdown.loc[end_date[col]:, col])
        try:
            summary.loc[col, 'Recover'] =
pd.to_datetime(recovery[recovery >= 0].index[0])
        except:
            summary.loc[col, 'Recover'] = pd.to_datetime(None)

        summary['Peak'] = pd.to_datetime(summary['Peak'])
        try:
            summary['Duration (to Recover)'] = (summary['Recover'] -
summary['Peak'])
        except:
            summary['Duration (to Recover)'] = None

        summary = summary[['Max Drawdown', 'Peak', 'Bottom',
'Recover', 'Duration (to Recover)']]

    return summary

def performanceMetrics(returns,annualization = 12, quantile = .05):
    metrics = pd.DataFrame(index=returns.columns)
    metrics['Mean'] = returns.mean() * annualization
    metrics['Vol'] = returns.std() * np.sqrt(annualization)
    metrics['Sharpe'] = (returns.mean() / returns.std()) *
np.sqrt(annualization)
```

```
    metrics['Min'] = returns.min()
    metrics['Max'] = returns.max()
    return metrics

def tailMetrics(returns, quantile=.05, relative=False, mdd=True):
    metrics = pd.DataFrame(index=returns.columns)
    metrics['Skewness'] = returns.skew()
    metrics['Kurtosis'] = returns.kurtosis() - 3

    VaR = returns.quantile(quantile)
    CVaR = (returns[returns < returns.quantile(quantile)]).mean()

    if relative:
        VaR = (VaR - returns.mean())/returns.std()
        CVaR = (CVaR - returns.mean())/returns.std()

    metrics[f'VaR ({quantile})'] = VaR
    metrics[f'CVaR ({quantile})'] = CVaR

    if mdd:
        mdd_stats = maximumDrawdown(returns)
        metrics = metrics.join(mdd_stats)

        if relative:
            metrics['Max Drawdown'] = (metrics['Max Drawdown'] - 
returns.mean())/returns.std()

    return metrics

#IMPORTING DATA
desc = pd.read_excel('hw2_data.xlsx', 'descriptions').rename(columns = 
{'Unnamed: 0':'Symbol'}).set_index('Symbol')
dataset2=funds = 
pd.read_excel('hw2_data.xlsx','hedge_fund_series').set_index('date')
dataset3=mlf = 
pd.read_excel('hw2_data.xlsx','merrill_factors').set_index('date')
other = pd.read_excel('hw2_data.xlsx','other_data').set_index('date')

#QUESTION 1
dataset2_index=['HFRIFWI', 'MLEIFCTR', 'MLEIFCTX', 'HDG', 'QAI']
dataset2_mean=dataset2.mean()*12
dataset2_vol=dataset2.std()*(12**0.5)
dataset2_sharpe=dataset2_mean/dataset2_vol
dataset2_max=dataset2.max()
dataset2_min=dataset2.min()

q1_data=list(zip(dataset2_index,dataset2_mean,dataset2_vol,dataset2_sh
arpe,dataset2_max,dataset2_min))
```

```
q1_table=pd.DataFrame(q1_data, columns=['Index','Expected
Return','Volatility','Sharpe Ratio','Maximum Return', 'Minimum
Return'])
display(q1_table)
```

```
      Index  Expected Return  Volatility  Sharpe Ratio  Maximum Return
\
0   HFRIFWI           0.0508      0.0615        0.8257          0.0586

1  MLEIFCTR           0.0388      0.0538        0.7209          0.0589

2  MLEIFCTX           0.0373      0.0537        0.6954          0.0588

3       HDG           0.0281      0.0564        0.4984          0.0583

4       QAI           0.0255      0.0455        0.5604          0.0341


   Minimum Return
0         -0.0908
1         -0.0532
2         -0.0524
3         -0.0592
4         -0.0563
```

```
#QUESTION 2

def skew():scipy.stats.skew()
def kurt(): scipy.stats.kurtosis()



#skewness,kurtosis, value at risk, conditional VaR and maximum
drawdown
dataset2_skew= dataset2.skew()
dataset2_kurtosis=dataset2.kurt()-3
dataset2_quantile5=dataset2.quantile(.05)

dataset2_cvar=dataset2[dataset2<=dataset2_quantile5]

dataset2_CVaR=dataset2_cvar.mean()
dataset2_maxdraw=maxdrawdown(dataset2)

q2_data=list(zip(dataset2_index,dataset2_skew,dataset2_kurtosis,datase
t2_quantile5,dataset2_CVaR))

q2_table=pd.DataFrame(q2_data, columns=['Index','Skewness','Kurtosis
(-3)','Value at Risk','Conditional VaR'])
display(q2_table)
```

```
dataset2_maxdraw

      Index  Skewness  Kurtosis (-3)  Value at Risk  Conditional VaR
0   HFRIFWI   -1.1092         3.7301        -0.0253          -0.0388
1  MLEIFCTR   -0.1867        -0.5705        -0.0255          -0.0328
2  MLEIFCTX   -0.1716        -0.6244        -0.0256          -0.0327
3       HDG   -0.1796        -0.4183        -0.0285          -0.0348
4       QAI   -0.5451        -0.3304        -0.0162          -0.0263

                Max Drawdown       Peak     Bottom    Recover  \
HFRIFWI Index        -0.1155 2019-12-31 2020-03-31 2020-08-31
MLEIFCTR Index       -0.0845 2019-12-31 2020-03-31 2020-11-30
MLEIFCTX Index       -0.0837 2019-12-31 2020-03-31 2020-11-30
HDG US Equity        -0.0882 2020-01-31 2020-03-31 2020-11-30
QAI US Equity        -0.0756 2019-12-31 2020-03-31 2020-07-31

               Duration (to Recover)
HFRIFWI Index               244 days
MLEIFCTR Index              335 days
MLEIFCTX Index              335 days
HDG US Equity               304 days
QAI US Equity               213 days
```

```
#QUESTION 3

for regressand in funds.columns:
    x = sm.add_constant(pd.DataFrame(mlf['SPY US Equity']))
    y = pd.DataFrame(funds[regressand])
    model = sm.regression.linear_model.OLS(y, x).fit()
    print(model.summary(), '\n')
    var_res = model.resid.std()
    alpha = model.params[0]
    beta = model.params[1]
    ir = dp.format(alpha * np.sqrt(12) / var_res)
    tr = dp.format(funds[regressand].mean() * 12 / beta)
    print('beta =', dp.format(beta))
    print('information ratio =', ir)
    print('treynor ratio = ', tr)
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:          HFRIFWI Index   R-squared:
0.753
Model:                            OLS   Adj. R-squared:
0.751
Method:                 Least Squares   F-statistic:
366.0
Date:                Tue, 28 Jun 2022   Prob (F-statistic):
```

```
2.98e-38
Time:                        03:04:11   Log-Likelihood:
404.50
No. Observations:                 122   AIC:
-805.0
Df Residuals:                     120   BIC:
-799.4
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const            -0.0006      0.001     -0.733      0.465      -0.002
0.001
SPY US Equity     0.3943      0.021     19.131      0.000       0.354
0.435
======================================================================
========
Omnibus:                       19.652   Durbin-Watson:
1.472
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
92.695
Skew:                          -0.217   Prob(JB):
7.44e-21
Kurtosis:                       7.248   Cond. No.
25.7
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

beta = 0.3943
information ratio = -0.2420
treynor ratio =  0.1288
                            OLS Regression Results

======================================================================
========
Dep. Variable:          MLEIFCTR Index   R-squared:
0.816
Model:                             OLS   Adj. R-squared:
0.815
Method:                  Least Squares   F-statistic:
```

```
532.7
Date:                Tue, 28 Jun 2022   Prob (F-statistic):
5.91e-46
Time:                        03:04:11   Log-Likelihood:
438.72
No. Observations:                 122   AIC:
-873.4
Df Residuals:                     120   BIC:
-867.8
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const            -0.0012      0.001     -1.863      0.065      -0.002
7.44e-05
SPY US Equity     0.3594      0.016     23.081      0.000       0.329
0.390
======================================================================
========
Omnibus:                        7.133   Durbin-Watson:
1.428
Prob(Omnibus):                  0.028   Jarque-Bera (JB):
12.641
Skew:                           0.093   Prob(JB):
0.00180
Kurtosis:                       4.566   Cond. No.
25.7
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

beta = 0.3594
information ratio = -0.6153
treynor ratio =  0.1080
                            OLS Regression Results

======================================================================
========
Dep. Variable:         MLEIFCTX Index   R-squared:
0.815
Model:                            OLS   Adj. R-squared:
```

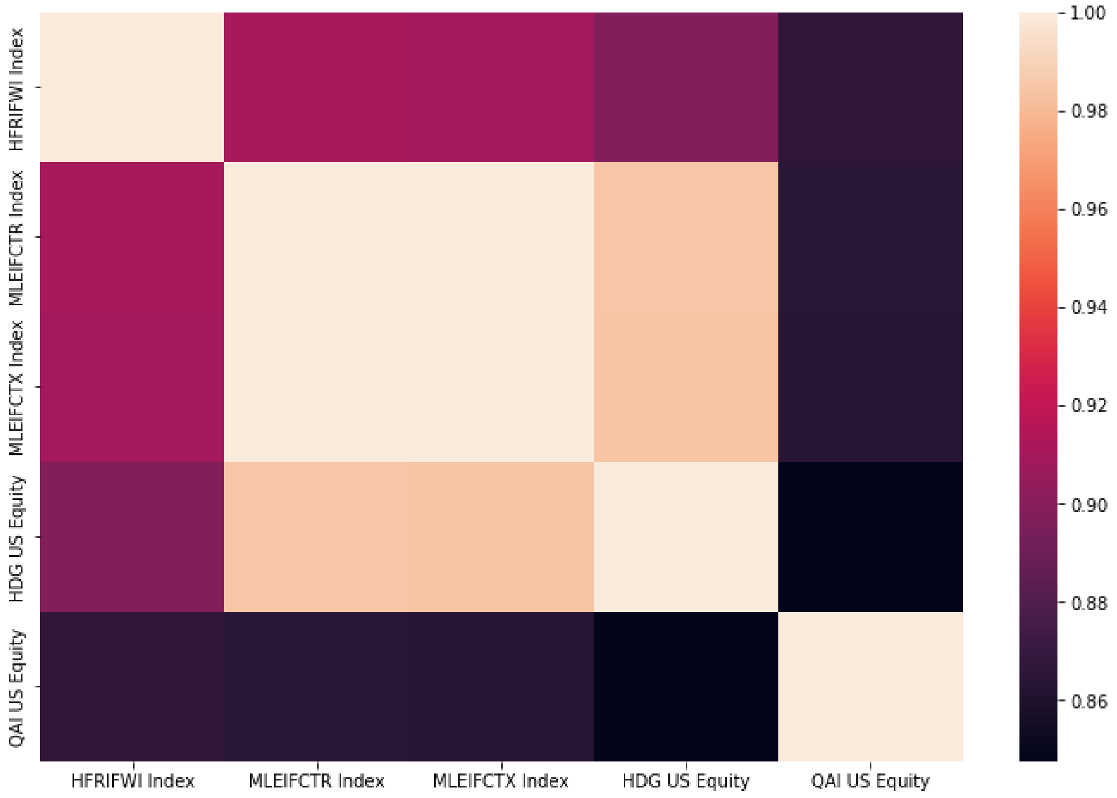
```
0.814
Method:                 Least Squares   F-statistic:
528.8
Date:                Tue, 28 Jun 2022   Prob (F-statistic):
8.49e-46
Time:                        03:04:11   Log-Likelihood:
438.73
No. Observations:                 122   AIC:
-873.5
Df Residuals:                     120   BIC:
-867.8
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const            -0.0013      0.001     -2.032      0.044      -0.003
-3.34e-05
SPY US Equity     0.3580      0.016     22.996      0.000       0.327
0.389
======================================================================
========
Omnibus:                        7.244   Durbin-Watson:
1.425
Prob(Omnibus):                  0.027   Jarque-Bera (JB):
12.641
Skew:                           0.124   Prob(JB):
0.00180
Kurtosis:                       4.557   Cond. No.
25.7
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

beta = 0.3580
information ratio = -0.6713
treynor ratio =  0.1043
                            OLS Regression Results

======================================================================
========
Dep. Variable:          HDG US Equity   R-squared:
```

```
0.786
Model:                           OLS   Adj. R-squared:
0.784
Method:                Least Squares   F-statistic:
440.0
Date:               Tue, 28 Jun 2022   Prob (F-statistic):
5.89e-42
Time:                       03:04:11   Log-Likelihood:
423.77
No. Observations:                122   AIC:
-843.5
Df Residuals:                    120   BIC:
-837.9
Df Model:                          1

Covariance Type:           nonrobust

=====================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
---------------------------------------------------------------------
-----------
const            -0.0022      0.001     -3.060      0.003      -0.004
-0.001
SPY US Equity     0.3692      0.018     20.977      0.000       0.334
0.404
=====================================================================
========
Omnibus:                       7.300   Durbin-Watson:
1.665
Prob(Omnibus):                 0.026   Jarque-Bera (JB):
11.094
Skew:                         -0.232   Prob(JB):
0.00390
Kurtosis:                      4.403   Cond. No.
25.7
=====================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

beta = 0.3692
information ratio = -1.0106
treynor ratio =  0.0761
                            OLS Regression Results

=====================================================================
========
Dep. Variable:          QAI US Equity   R-squared:
0.719
Model:                            OLS   Adj. R-squared:
0.717
Method:                 Least Squares   F-statistic:
307.6
Date:                Tue, 28 Jun 2022   Prob (F-statistic):
6.59e-35
Time:                        03:04:11   Log-Likelihood:
433.52
No. Observations:                 122   AIC:
-863.0
Df Residuals:                     120   BIC:
-857.4
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const            -0.0014      0.001     -2.081      0.040      -0.003
-6.7e-05
SPY US Equity     0.2850      0.016     17.539      0.000       0.253
0.317
======================================================================
========
Omnibus:                       13.799   Durbin-Watson:
1.910
Prob(Omnibus):                  0.001   Jarque-Bera (JB):
18.709
Skew:                          -0.606   Prob(JB):
8.66e-05
Kurtosis:                       4.488   Cond. No.
25.7
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

beta = 0.2850
information ratio = -0.6873
treynor ratio =  0.0894
```

```
#QUESTION 4

#a) They all under perform against the SPY as they all have negative
alpha.
#the other metrics also indicate poor relative performance hence low
TR and IR<0, for all of them.

#b)They are similar but QAI has better performance on all three ratios
(TR,IR,SR) thus I will say QAI is better.

#c) I would say somewhat as the R squared stat is relatively high for
all, but lower for HFRI.
#Also I would say that they do not really capture the features as the
alpha of HFRI is quite different from the ML series

#QUESTION 5

corr_matrix = dataset2.corr()

print("")
print('CORRELATION MATRIX')
display(corr_matrix)
print("")

plt.figure(figsize = (12,8))
sns.heatmap(corr_matrix)
plt.show()

#The ML series have the strongest correlation of essentially 1.00 with
each other.
#HDG and QAI have the lowest correlation at 0.85 which is still
relatively high.
```

```
CORRELATION MATRIX

                HFRIFWI Index  MLEIFCTR Index  MLEIFCTX Index  HDG US
Equity  \
HFRIFWI Index          1.0000          0.9104          0.9101
0.8977
MLEIFCTR Index         0.9104          1.0000          0.9999
0.9846
MLEIFCTX Index         0.9101          0.9999          1.0000
0.9845
HDG US Equity          0.8977          0.9846          0.9845
1.0000
QAI US Equity          0.8667          0.8644          0.8637
0.8476

                QAI US Equity
```

```
HFRIFWI Index        0.8667
MLEIFCTR Index       0.8644
MLEIFCTX Index       0.8637
HDG US Equity        0.8476
QAI US Equity        1.0000
```



```
#QUESTION 6

y=dataset2['HFRIFWI Index']
X=dataset3
X=sm.add_constant(X)


merril_reg=sm.OLS(y,X).fit()

print(merril_reg.summary())

#alpha=0.0011
#R squared= 0.856

q6_betas=[['SPY',0.072],['USGG3M', -0.4006],['EEM',0.0722],['EFA',
0.1063],['EUO',0.0224],['IWM',0.1309]]
```

```
q6_table=pd.DataFrame(q6_betas,columns=['Security','Beta'])

display(q6_table)
```

```
                            OLS Regression Results                            
======================================================================
========
Dep. Variable:          HFRIFWI Index   R-squared:                       
0.856
Model:                            OLS   Adj. R-squared:                  
0.848
Method:                 Least Squares   F-statistic:                     
113.7
Date:                Tue, 28 Jun 2022   Prob (F-statistic):           
5.84e-46
Time:                        03:04:11   Log-Likelihood:                 
437.27
No. Observations:                 122   AIC:                            
-860.5
Df Residuals:                     115   BIC:                            
-840.9
Df Model:                           6                                         

Covariance Type:            nonrobust                                         

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025      
0.975]
----------------------------------------------------------------------
-----------
const             0.0011      0.001      1.387      0.168      -0.000       
0.003
SPY US Equity     0.0720      0.042      1.725      0.087      -0.011       
0.155
USGG3M Index     -0.4006      0.953     -0.420      0.675      -2.289       
1.488
EEM US Equity     0.0722      0.023      3.083      0.003       0.026       
0.119
EFA US Equity     0.1063      0.038      2.768      0.007       0.030       
0.182
EUO US Equity     0.0224      0.018      1.245      0.216      -0.013       
0.058
IWM US Equity     0.1309      0.025      5.139      0.000       0.080       
0.181
======================================================================
========
Omnibus:                       25.081   Durbin-Watson:                   
1.987
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
91.558
Skew:                          -0.600   Prob(JB):
1.31e-20
Kurtosis:                       7.071   Cond. No.
1.52e+03
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.52e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.

  Security    Beta
0      SPY  0.0720
1   USGG3M -0.4006
2      EEM  0.0722
3      EFA  0.1063
4      EUO  0.0224
5      IWM  0.1309
```

```
#Now we need to report the weights as a proportion of the the sum of
the betas

base=0.0720-0.4006+0.0722+0.1063+0.0224+0.1309

q6_weights=[['SPY',0.072/base],['USGG3M', -0.4006/base],
['EEM',0.0722/base],['EFA', 0.1063/base],['EUO',0.0224/base],
['IWM',0.1309/base]]

q6_table2=pd.DataFrame(q6_weights,columns=['Security','Weight'])

display(q6_table2)

#As you can see, we get VERY unreasonable long-short positions.

exp_return= np.dot(dataset3,[0.072/base,-0.4006/base,0.0722/base,
0.1063/base, 0.0224/base, 0.1309/base])

track_err=np.std(exp_return-dataset2["HFRIFWI Index"])*np.sqrt(12)

#The tracking error or portfolio volatility appears to be 177% !!

print(track_err)
```

```
  Security    Weight
0      SPY   22.5000
```

```
1   USGG3M -125.1875
2      EEM   22.5625
3      EFA   33.2188
4      EUO    7.0000
5      IWM   40.9063

17.651795400072185
```