

```
1 %load_ext autoreload
2 %autoreload 2
3 %matplotlib inline
4
5 from google.colab import drive
6 drive.mount('/content/drive')
```

```
1 import matplotlib.pyplot as plt
2 #%matplotlib plt.rcParams['figure.figsize'] = (12.0, 6.0)
3 %matplotlib plt.rc('figure', figsize=(20.0, 10.0))
```

```
1 import os, sys
2
3 DATAPATH = '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/data'
4 print(f"DATAPATH:{DATAPATH} contents:{os.listdir(DATAPATH)}")
5
6 MODULEPATH = '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio/nb'
7 print(f"MODULEPATH:{MODULEPATH} contents:{os.listdir(MODULEPATH)}")
8
9 sys.path.append(MODULEPATH)
10 print(f"sys.path:{sys.path}")
11
12 import numpy as np
13 import pandas as pd
14
15 import edhec_risk_kit_109_BBI as erk
```

In order to plot the frontier for portfolios with more than 2 assets, we need to find the weights of the

We start by creating the same sort of function that we already created for the 2 asset case:

```
def plot_ef(n_points, er, cov):  
    """  
    Plots the multi-asset efficient frontier  
    """  
    weights = ??? # we need to implement: optimal_weights(n_points, er, cov)  
    rets = [portfolio_return(w, er) for w in weights]  
    vols = [portfolio_vol(w, cov) for w in weights]  
    ef = pd.DataFrame({  
        "Returns": rets,  
        "Volatility": vols  
    })  
    return ef.plot.line(x="Volatility", y="Returns", style='.-')
```

But let's start by loading up the data as usual:

```
1 %load_ext autoreload  
2 %autoreload 2  
3 %matplotlib inline  
4 import edhec_risk_kit_109_BBI as erk  
5  
6 ind = erk.get_ind_returns(DATAPATH)  
7 er = erk.annualize_rets(ind["1996":"2000"], 12)  
8 cov = ind["1996":"2000"].cov()
```

In order to find the optimal weights, we need a function that will minimize the volatility for a given level of

```

from scipy.optimize import minimize

def minimize_vol(target_return, er, cov):
    """
    Returns the optimal weights that achieve the target return
    given a set of expected returns and a covariance matrix
    """
    n = er.shape[0]
    init_guess = np.repeat(1/n, n)
    bounds = ((0.0, 1.0),) * n # an N-tuple of 2-tuples!
    # construct the constraints
    weights_sum_to_1 = {'type': 'eq',
                        'fun': lambda weights: np.sum(weights) - 1
                       }
    return_is_target = {'type': 'eq',
                        'args': (er,),
                        'fun': lambda weights, er: target_return - erk.portfolio_return(
    )
    weights = minimize(erk.portfolio_vol, init_guess,
                        args=(cov,), method='SLSQP',
                        options={'disp': False},
                        constraints=(weights_sum_to_1, return_is_target),
                        bounds=bounds)

    return weights.x

```

Let's use this to recreate the result we got from frontier for the 2-Asset optimization between "Gam" frontier as we did last time:

```

1 l = ["Games", "Fin"]
2 erk.plot_ef2(20, er[l], cov.loc[l,l])

```

The Efficient Frontier for the portfolio that has a target return of 0.15 is approx 0.056, so let's see if

```
1 weights_15 = erk.minimize_vol(0.15, er[1], cov.loc[1,1])
2 vol_15 = erk.portfolio_vol(weights_15, cov.loc[1,1])
3 vol_15
```

Perfect!

Now that we can find the weights to minimize the vol given a target return, we can plot the efficient

from the highest to the lowest possible return into a grid, and finding the portfolio that targets the targeted rate of return.

Add these:

```
def optimal_weights(n_points, er, cov):  
    """  
    """  
  
    target_rs = np.linspace(er.min(), er.max(), n_points)  
    weights = [minimize_vol(target_return, er, cov) for target_return in target_rs]  
    return weights  
  
def plot_ef(n_points, er, cov):  
    """  
    Plots the multi-asset efficient frontier  
    """  
  
    weights = optimal_weights(n_points, er, cov) # not yet implemented!  
    rets = [portfolio_return(w, er) for w in weights]  
    vols = [portfolio_vol(w, cov) for w in weights]  
    ef = pd.DataFrame({  
        "Returns": rets,  
        "Volatility": vols  
    })  
    return ef.plot.line(x="Volatility", y="Returns", style='.-')
```

```
1 l = ["Smoke", "Fin", "Games", "Coal"]  
2 erk.plot_ef(50, er[l], cov.loc[l,l])
```



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3 DATAPATH = '/content/drive/My Drive/Coursera/EDHEC/investment-portfolio'
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```





In order to plot the frontier for portfolios with more than 2 assets, we need to find the weights of the assets on the efficient frontier.

We start by creating the same sort of function that we already created for the 2 asset case:

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    weights = ??? # we need to implement: optimal_weights(n_points, er, cov)  
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6 ind = erk.get_ind_returns(DATAPATH)  
7 er = erk.annualize_rets(ind["1996":"2000"], 12)  
8 cov = ind["1996":"2000"].cov()
```



In order to find the optimal weights, we need a function that will minimize the volatility for a given level of return.

```

from scipy.optimize import minimize

def minimize_vol(target_return, er, cov):
    """
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    # construct the constraints
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                        'fun': lambda weights, er: target_return - erk.portfolio_return(
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    weights = minimize(erk.portfolio_vol, init_guess,
                        args=(cov,), method='SLSQP',
                        options={'disp': False},
                        constraints=(weights_sum_to_1, return_is_target),
                        bounds=bounds)

    return weights.x

```

Let's use this to recreate the result we got from frontier for the 2-Asset optimization between "Games" and "Fin". Let's plot that efficient frontier as we did last time:

```

1 l = ["Games", "Fin"]
2 erk.plot_ef2(20, er[l], cov.loc[l,l])

```



The Efficient Frontier for the protfolio that has a target return of 0.15 is approx 0.056, so let's see if optimizer is able to locate it.

```
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2 vol_15 = erk.portfolio_vol(weights_15, cov.loc[1,1])
3 vol_15
```



Perfect!

Now that we can find the weights to minimize the vol given a target return, we can plot the efficient

dividing up the range from the highest to the lowest possible return into a grid, and finding the port targets the minimum volatility given a particular targeted rate of return.

Add these:

```
def optimal_weights(n_points, er, cov):
    """
    """

    target_rs = np.linspace(er.min(), er.max(), n_points)
    weights = [minimize_vol(target_return, er, cov) for target_return in target_rs]
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def plot_ef(n_points, er, cov):
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1 l = ["Smoke", "Fin", "Games", "Coal"]
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