

Statistics Methods in Finance

Homework 3

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DUE 2020/10/15 00:00

Outline (HW3 questions)

- Use the 3 daily-return data you obtained in the second week.

1.(30%) Mean-Variance Portfolio: No Risk-Free Assets

- Suppose these 3 stocks are the only assets you got. Draw the efficient frontier.

2.(30%) Mean-Variance Portfolio: Risk-Free Assets

- Suppose now you have a risk-free asset with (annual) return 2%. Construct the capital market line, and determine the market portfolio.

3.(40%) CAPM

- Based on the previous 2 problems, run the CAPM regression for these three assets. Please report the estimated betas and R-square.
 - Do NOT be afraid of getting a low R-square.

1. Mean-Variance Portfolio: No Risk-Free Assets

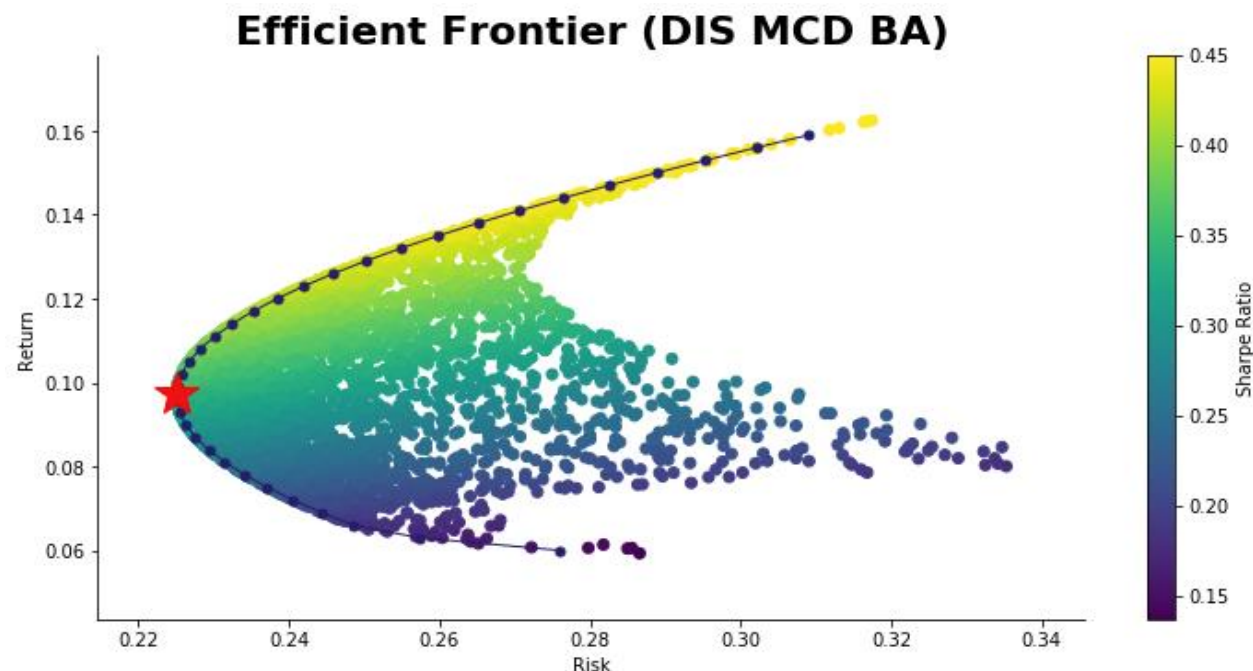
In the following website, I choose **DIS**, **MCD**, and **BA** as the three firms in the historical components of the Dow Jones Industrial Average during 2000/1/1 to 2006/12/31

https://www.wikiwand.com/en/Historical_components_of_the_Dow_Jones_Industrial_Average

個股平均收益(6年): DIS:0.081 MCD:0.0583 BA:0.1651
(權重均等)投資組合預期報酬率為: 0.1015
(權重均等)投資組合風險為: 0.2293

Constraint optimization for finding efficient frontier

```
def standard_deviation(weights):  
    return np.sqrt(reduce(np.dot, [weights, covariance_matrix, weights.T]))  
  
'''效率前緣(Efficient Frontier)'''  
x0 = stocks_weights #變量的初始猜測值  
bounds = tuple((0, 1) for x in range(total_stock))  
  
efficient_fronter_return_range = np.arange(0.06, 0.16, .003)  
efficient_fronter_risk_list = []  
  
for i in efficient_fronter_return_range:  
    constraints = [{ 'type': 'eq', 'fun': lambda x: sum(x) - 1},  
                   { 'type': 'eq', 'fun': lambda x: sum(x * stocks_expected_return) - i}]  
    efficient_fronter = solver.minimize(standard_deviation, x0=x0,  
                                       constraints=constraints, bounds=bounds)  
    efficient_fronter_risk_list.append(efficient_fronter.fun)
```



The star point means:

風險最小化投資組合預期報酬率為:0.097
風險最小化投資組合風險為:0.225
DIS 佔投資組合權重 : 0.2340
MCD 佔投資組合權重 : 0.4530
BA 佔投資組合權重 : 0.3130

2. Mean-Variance Portfolio: Risk-Free Assets

Constraint optimization for finding CML and tangency portfolio

```
'''效率前線(Efficient Frontier)'''
x0 = stocks_weights
bounds = tuple((0, 1) for x in range(total_stock))

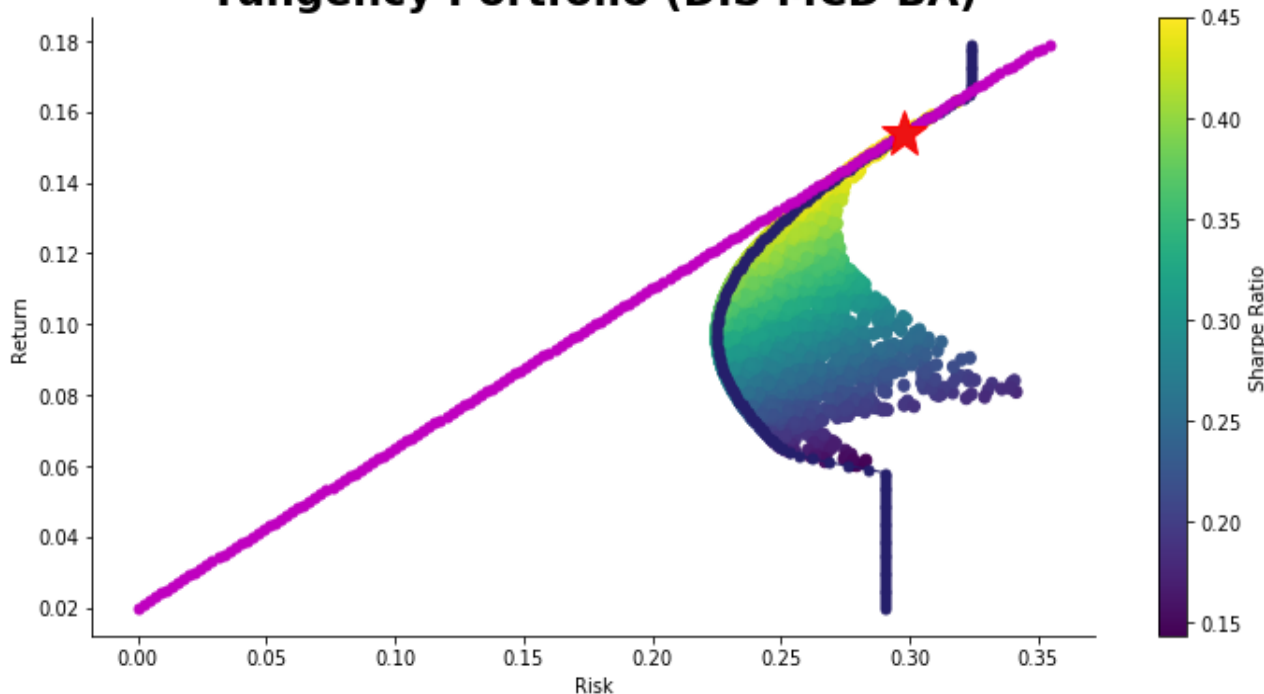
efficient_fronter_return_range = np.arange(0.02, 0.18, .001)
efficient_fronter_risk_list = []
portfolio_weights = []
for i in efficient_fronter_return_range:
    constraints1 = [{'type': 'eq', 'fun': lambda x: sum(x) - 1},
                    {'type': 'eq', 'fun': lambda x: sum(x * stocks_expected_return) - i}]
    efficient_fronter = solver.minimize(standard_deviation, x0=x0,
                                       constraints=constraints1, bounds=bounds)
    efficient_fronter_risk_list.append(efficient_fronter.fun)
    portfolio_weights.append(efficient_fronter.x)

'''資本市場線(Capital Market Line)'''
x0 = stocks_weights
bounds = tuple((0, 1) for x in range(total_stock))
CML_risk_list = []
for i in efficient_fronter_return_range:
    constraints2 = [{'type': 'eq',
                    'fun': lambda x: 0.02 + sum(x * (stocks_expected_return - 0.02)) - i}]
    efficient_fronter = solver.minimize(standard_deviation, x0=x0,
                                       constraints=constraints2, bounds=bounds)
    CML_risk_list.append(efficient_fronter.fun)

'''切點(Tangency Portfolio)'''
TP_idx = np.argmin(abs(np.array(CML_risk_list) - np.array(efficient_fronter_risk_list)))
[TP_x, TP_y] = [CML_risk_list[TP_idx], efficient_fronter_return_range[TP_idx]]

print('切點投資組合預期報酬率為:' + str(round(TP_y, 3)))
print('切點投資組合風險為:' + str(round(TP_x, 3)))
for i in range(total_stock):
    print(str(returns.columns[i]) + ' 佔投資組合權重 : ' + str(round(portfolio_weights[TP_idx][i], 4)))
```

Tangency Portfolio (DIS MCD BA)

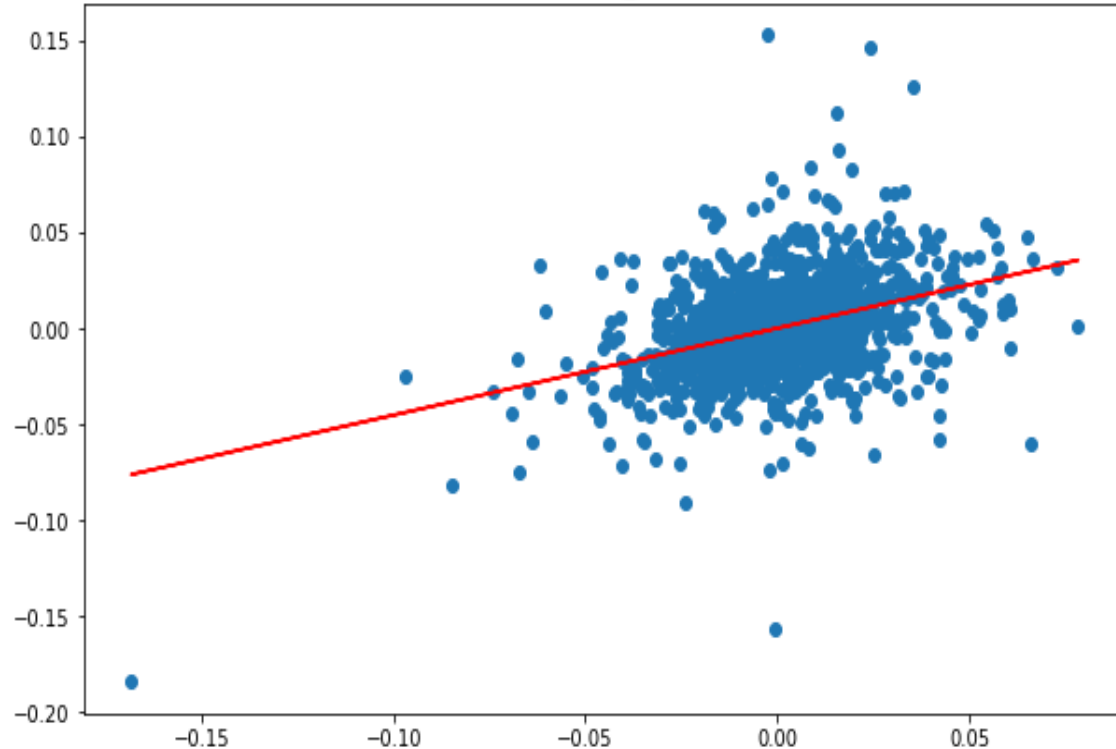


The star point shows the determined market portfolio:

切點投資組合預期報酬率為:0.154
切點投資組合風險為:0.298
DIS 佔投資組合權重 : 0.0642
MCD 佔投資組合權重 : 0.0534
BA 佔投資組合權重 : 0.8824

3. Run the CAPM regression for the asset DIS

CAPM Linear Regression (DIS)



OLS Regression Results						
=====						
Dep. Variable:	DIS	R-squared:	0.148			
Model:	OLS	Adj. R-squared:	0.147			
Method:	Least Squares	F-statistic:	304.7			
Date:	Mon, 12 Oct 2020	Prob (F-statistic):	4.77e-63			
Time:	23:12:16	Log-Likelihood:	4351.7			
No. Observations:	1758	AIC:	-8699.			
Df Residuals:	1756	BIC:	-8689.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

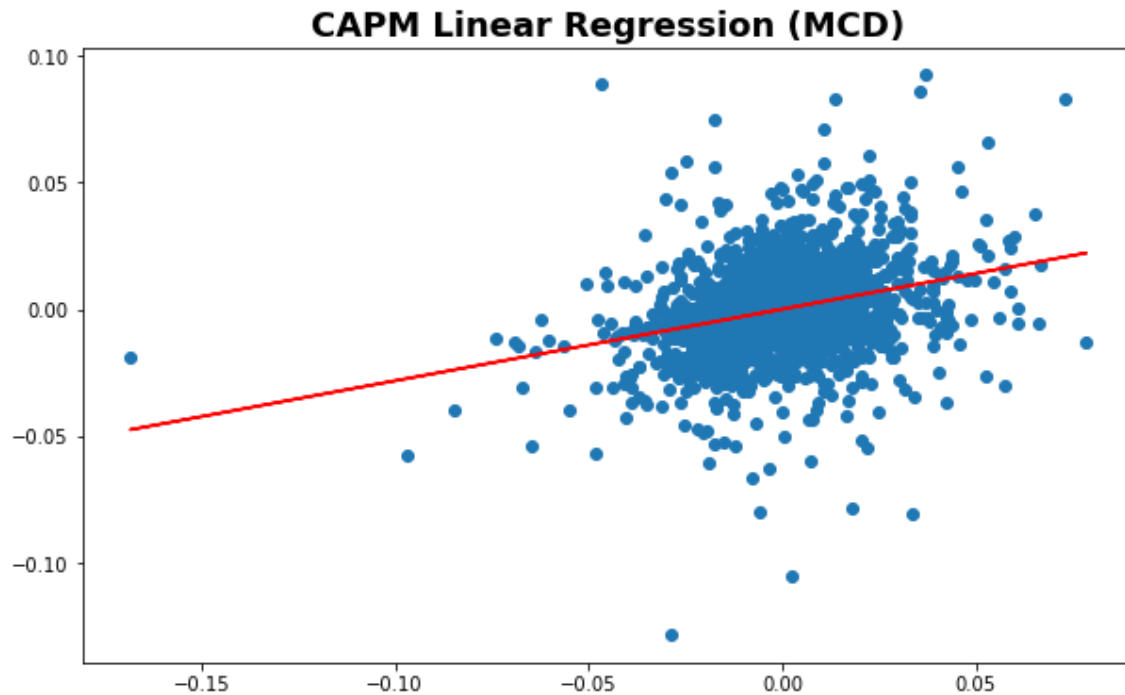
const	1.46e-06	0.000	0.003	0.998	-0.001	0.001
0	0.4525	0.026	17.456	0.000	0.402	0.503
=====						
Omnibus:	290.596	Durbin-Watson:	2.062			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3846.910			
Skew:	0.328	Prob(JB):	0.00			
Kurtosis:	10.217	Cond. No.	53.4			
=====						

Therefore the $\beta=0.4525$ and the R-square=0.148

Therefore the linear regression for CAPM model is:

$$R_i - R_f \approx \beta_i(R_m - R_f) \rightarrow R_i - R_f \approx 0.4525(R_m - R_f)$$

3. Run the CAPM regression for the asset MCD



OLS Regression Results						
=====						
Dep. Variable:	MCD	R-squared:	0.084			
Model:	OLS	Adj. R-squared:	0.083			
Method:	Least Squares	F-statistic:	160.6			
Date:	Mon, 12 Oct 2020	Prob (F-statistic):	2.80e-35			
Time:	23:25:17	Log-Likelihood:	4617.4			
No. Observations:	1758	AIC:	-9231.			
Df Residuals:	1756	BIC:	-9220.			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

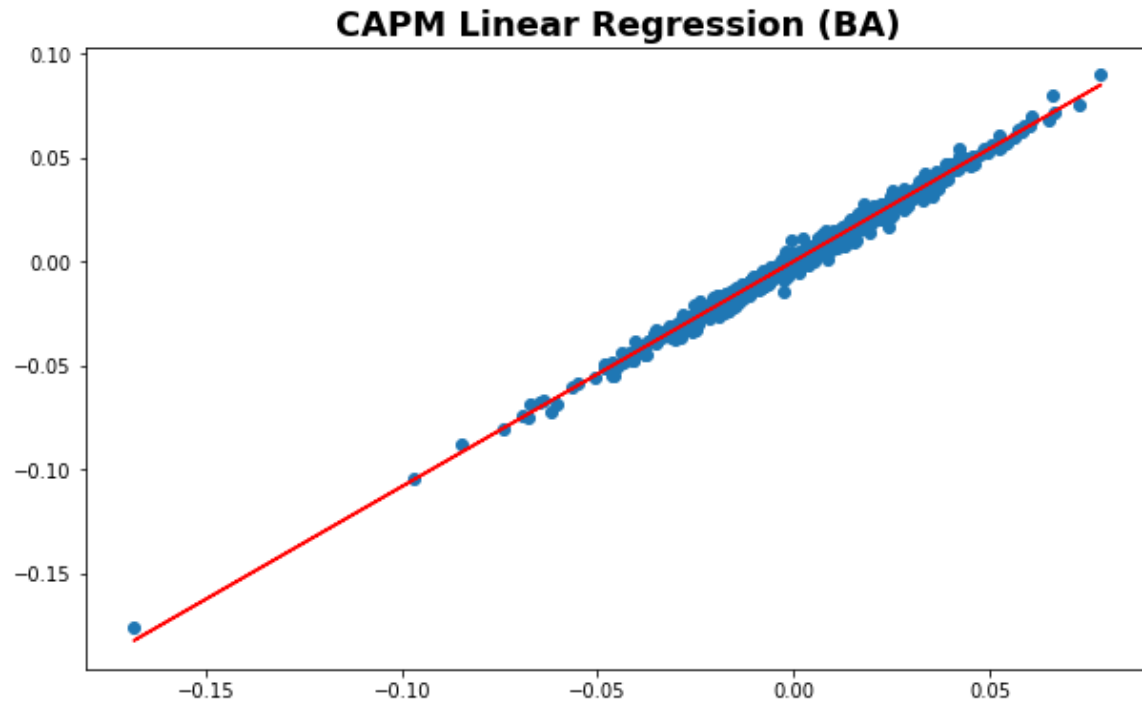
const	1.702e-06	0.000	0.004	0.997	-0.001	0.001
θ	0.2824	0.022	12.672	0.000	0.239	0.326
=====						
Omnibus:	201.132	Durbin-Watson:	2.015			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1795.542			
Skew:	-0.089	Prob(JB):	0.00			
Kurtosis:	7.948	Cond. No.	53.4			
=====						

The $\beta=0.2824$ and the R-square=0.084

Therefore the linear regression for CAPM model is:

$$R_i - R_f \approx \beta_i(R_m - R_f) \rightarrow R_i - R_f \approx 0.2824(R_m - R_f)$$

3. Run the CAPM regression for the asset BA



OLS Regression Results						
=====						
Dep. Variable:	BA	R-squared:	0.991			
Model:	OLS	Adj. R-squared:	0.991			
Method:	Least Squares	F-statistic:	1.922e+05			
Date:	Mon, 12 Oct 2020	Prob (F-statistic):	0.00			
Time:	23:26:59	Log-Likelihood:	8484.2			
No. Observations:	1758	AIC:	-1.696e+04			
Df Residuals:	1756	BIC:	-1.695e+04			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	-2.091e-07	4.63e-05	-0.005	0.996	-9.11e-05	9.06e-05
0	1.0832	0.002	438.461	0.000	1.078	1.088
=====						
Omnibus:	150.281	Durbin-Watson:	2.002			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	840.164			
Skew:	-0.148	Prob(JB):	3.64e-183			
Kurtosis:	6.374	Cond. No.	53.4			
=====						

Therefore the $\beta=1.0832$ and the R-square=0.991

Therefore the linear regression for CAPM model is:

$$R_i - R_f \approx \beta_i(R_m - R_f) \rightarrow R_i - R_f \approx 1.0832(R_m - R_f)$$