Mandatory Assignment 1

2024-01-03

0.1 Exercise 1:

We only show the first five tickers from now on.

	AAPL	AMGN	AXP	BA	CAT
2000-01-31	-0.04815	0.04007	0.05377	0.10907	-0.12240
2000-02-29	0.11067	0.08429	-0.19467	-0.17208	-0.18199
2000-03-31	0.19977	-0.06783	0.11283	0.03200	0.13094
2000-04-30	-0.06786	-0.07010	0.01858	0.05965	0.01596
2000-05-31	-0.37306	0.14168	0.08888	-0.00730	-0.02631

```
We have 27 tickers in our downloaded data.
```

0.2 Exercise 2:

Preview of the downloaded data.

	AAPL	AMGN	AXP	BA	CAT
AAPL	0.01249	0.00122	0.00272	0.00178	0.00254
AMGN	0.00122	0.00510	0.00127	0.00127	0.00138
AXP	0.00272	0.00127	0.00736	0.00435	0.00426
BA	0.00178	0.00127	0.00435	0.00897	0.00318
CAT	0.00254	0.00138	0.00426	0.00318	0.00847

	Mean	Std
AAPL	0.02553	0.11177
AMGN	0.01034	0.07143
AXP	0.01139	0.08577
BA	0.01317	0.09472

	Mean	Std
CAT	0.01518	0.09204

	Sharpe
UNH	0.289325

We see that UNH has the highest sharpe ratio.

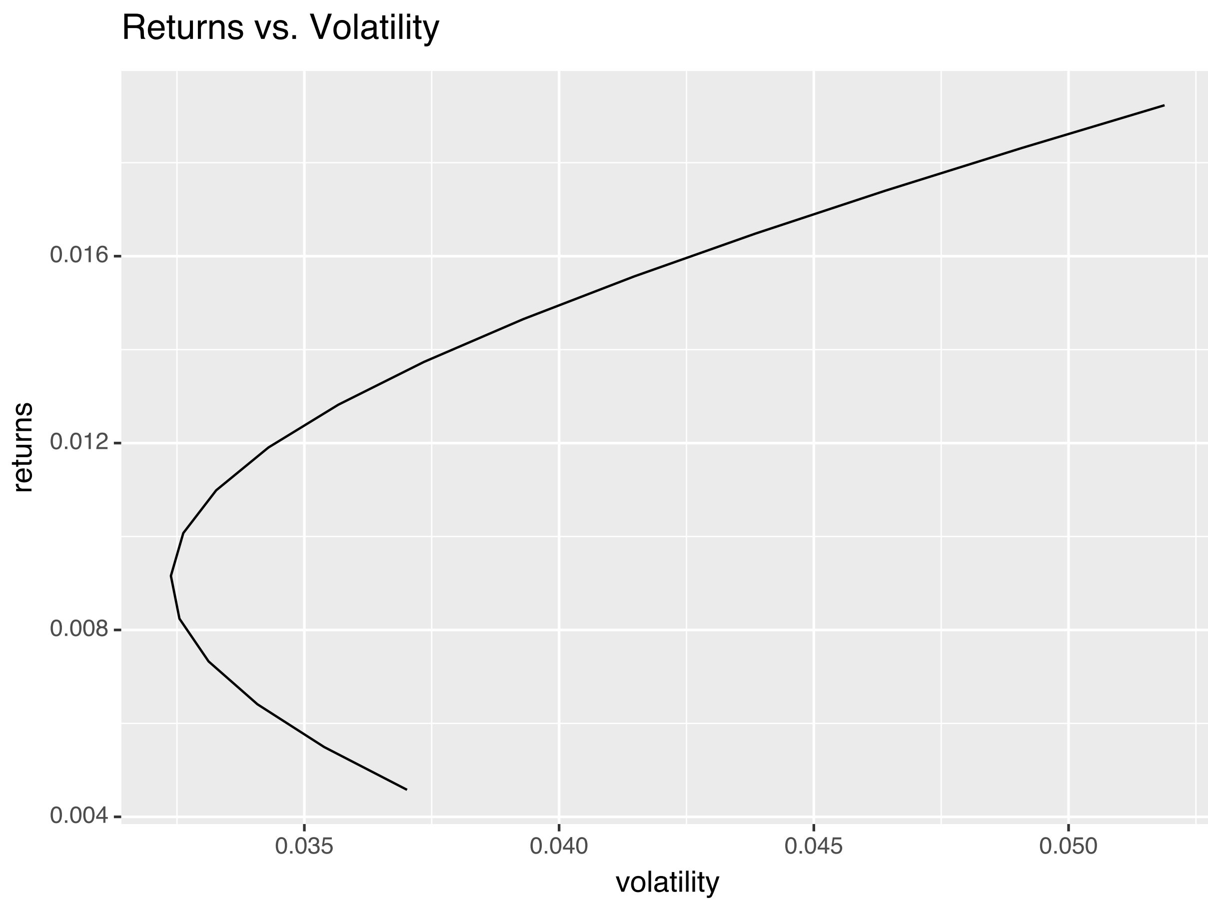
0.3 Exercise 3:

Our function is called minimize_risk_return and takes these paramates as variables: port_covariance, portfolio_returns, x0, and bounds. Where x0 is the initial guess for the minimizer, while bounds is defined as the bounds of the minimizer. It returns the optimal portfolio choise that gives the double return of mvp.

0.4 Exercise 3.3:

	returns	volatility	sharpe_ratio
c			
-0.1	0.019231	0.051884	0.370645
0.0	0.018315	0.049081	0.373154
0.1	0.017399	0.046397	0.375004
0.2	0.016483	0.043854	0.375873
0.3	0.015568	0.041477	0.375337

0.5 Exercise 3:




```
returns         0.016483
volatility      0.043854
sharpe_ratio    0.375873
Name: 0.20000000000000004, dtype: float64
```

0.6 Exercise 4:

	Weights
AAPL	23.26
AMGN	3.51
AXP	0.00
BA	0.00
CAT	0.31

The portfolio doesn't seem very balanced, since you go very long in some stocks, such as AAPL, while you go very short in other stocks. In addition, some of these weights are so close to zero that they are not viable for an actual real life portfolio.

The sharpe ratio should be higher than for the individaul assets, as we try to minimize volatitilty. #If there was a single asset with a higher sharpe ratio then the optimal portfolio would exist of only that asset.

0.7 Exercise 5

The function uses np.random.multivariate_normal, which uses this notation random.multivariate_normal(mea cov, size=None, check_valid='warn', tol=1e-8) This means that it uses the expected returns of the stocks we have given as it's mean, the covariance as it covariance and then it simulates returns based on 200 simulated periods

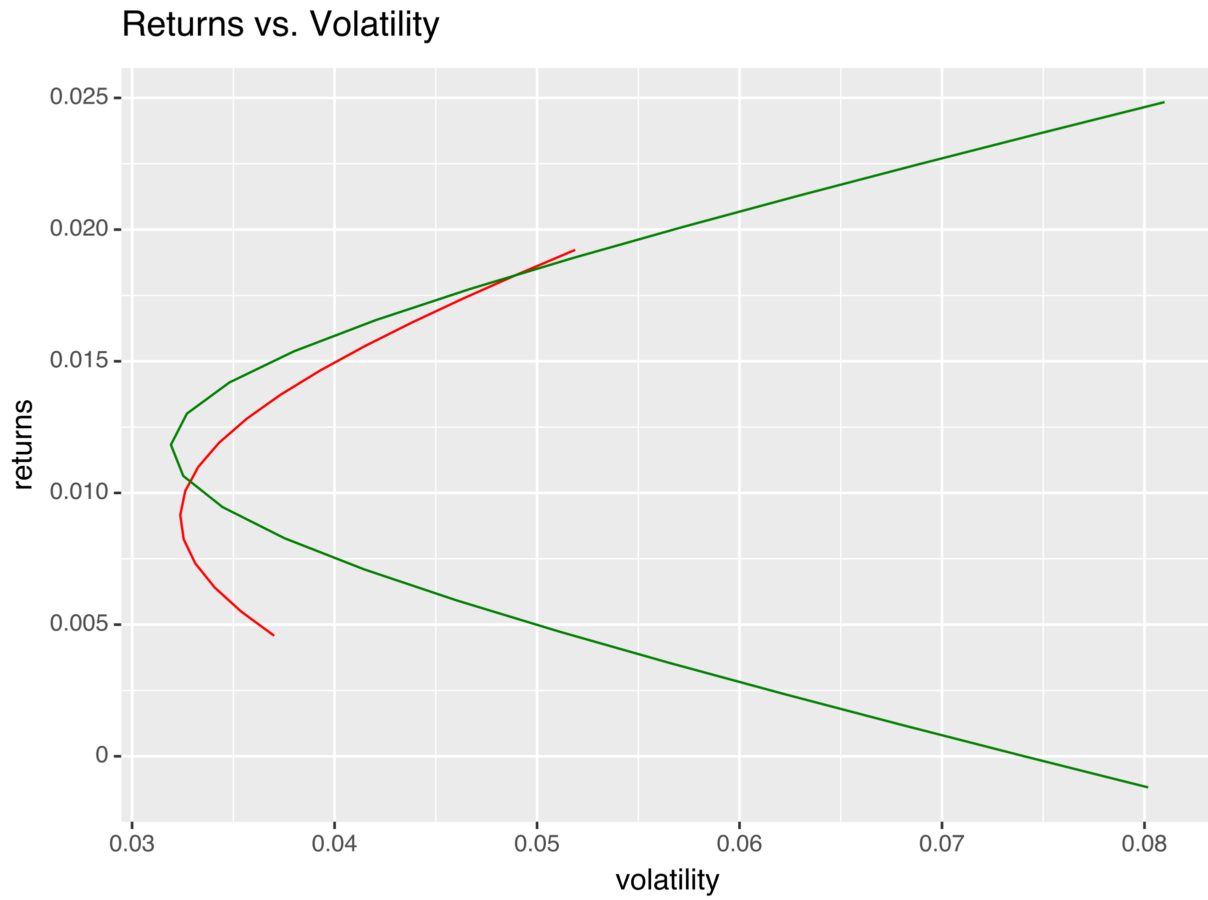
0.8 Exercise 6

Preview of simulated results.

	AAPL	AMGN	AXP	BA	CAT
0	0.015120	-0.057691	-0.006611	0.080148	-0.033693
1	0.033759	-0.075823	-0.045468	-0.178705	0.054748
2	-0.062710	-0.016043	-0.018889	0.040807	-0.107210
3	-0.103275	-0.020033	0.077986	0.005862	0.006434
4	-0.091726	-0.083570	-0.072075	-0.058844	-0.086443

	0
AAPL	5.459894e-03
AMGN	7.093821e-02
AXP	0.000000e+00
BA	4.878910e-18
CAT	9.093746e-18

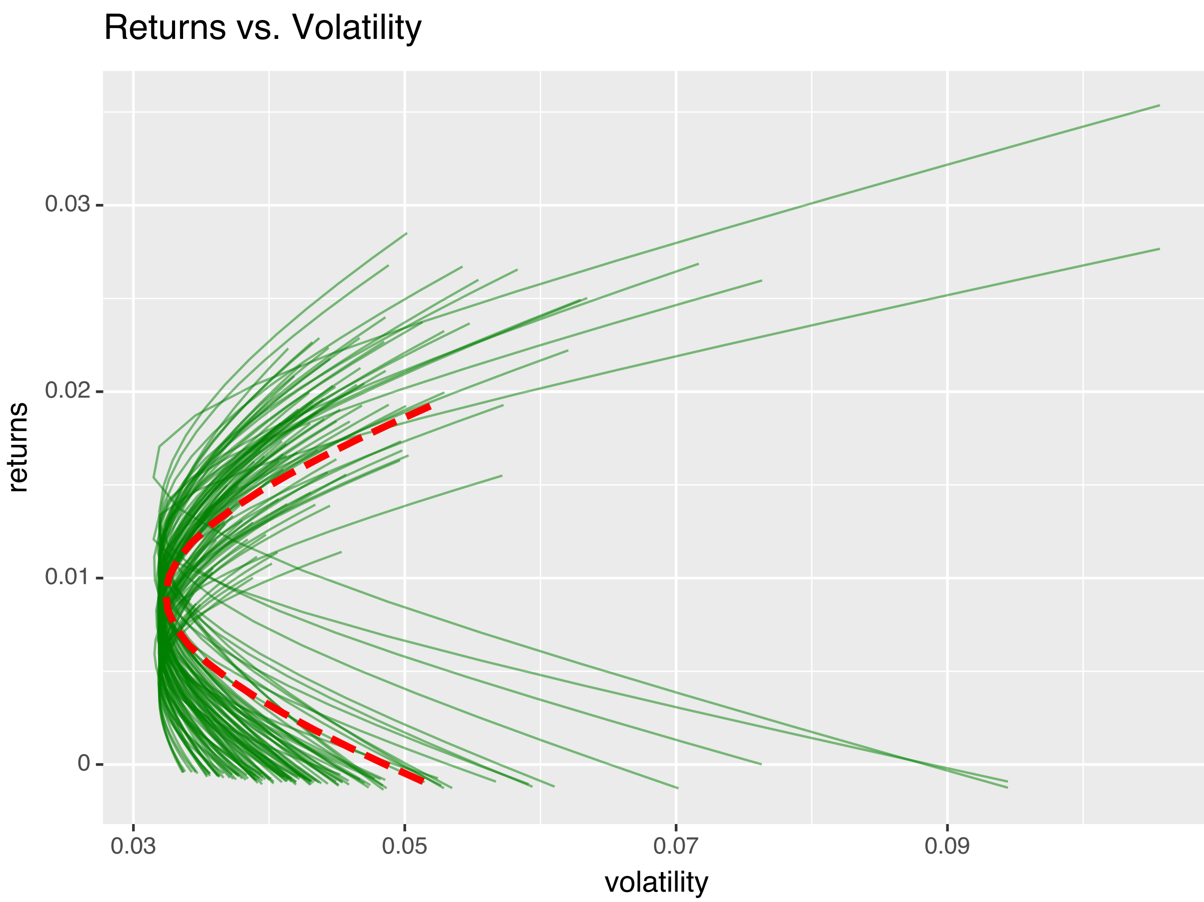
	returns	volatility	sharpe_ratio
c			
-0.1	0.024842	0.080991	0.306721
0.0	0.023659	0.074855	0.316061
0.1	0.022476	0.068830	0.326542
0.2	0.021293	0.062947	0.338269
0.3	0.020110	0.057250	0.351267



The red curve is the theoretical efficient frontier and the green curve is our simulated frontier.

The simulated one deviates since the sample size is rather small (just 200 periods). As one period is one day, it

0.9 Exercise 7:



It can be concluded that most of the simulations revolve around the theoretical efficient frontier. There are also larger outliers than we saw with one simulation. The simulations create random returns based on the true means and covariance. Therefore, it is expected that deviations are present.

We tried simulating with 20,000 periods, where the simulated frontier converged towards lower Sharpe ratios than the ones in the theoretical frontier with the given seed. We also tried changing the seed, where the simulations showed to converge towards different values. Thus, the amount of outliers is caused by a small number of runs and the point of convergence is caused by the seed given to the simulation.

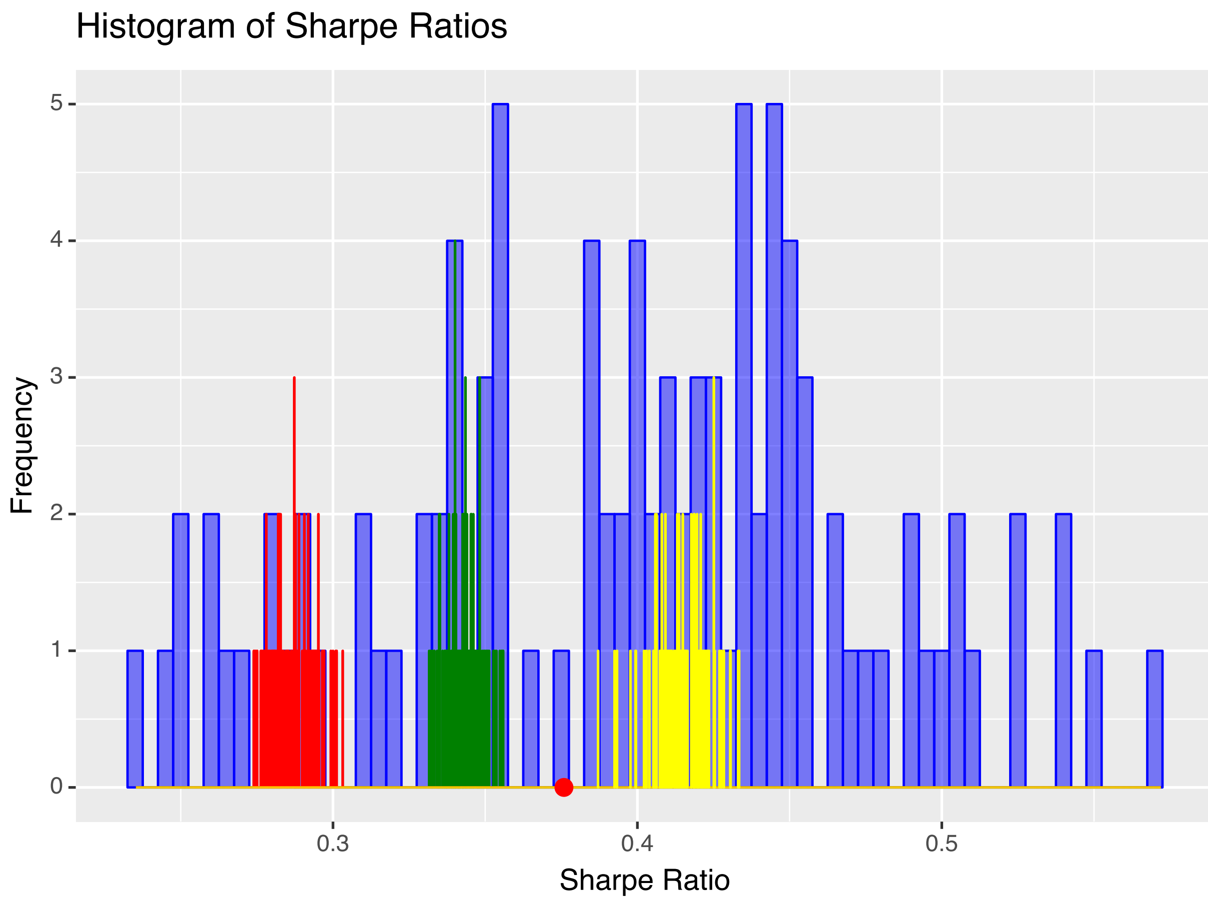
0.10 Exercise 8

We show the first five sharpe ratios.

	sharpe_ratio
0	0.497879
1	0.450513
2	0.334510

	sharpe_ratio
3	0.437499
4	0.245432

0.11 Exercise 9 and 10



The blue histogram shows the sharpe ratios with 200 obersavations. The green histogram shows the sharpe ratios of 20.000 observations. The red histogram shows the sharpe ratios based on geometric mean with 20.000 oberservations. The yellow histogram shows the sharpe ratios where shorting is posible.

From the blue histogram we see that the sharpe ratios are scattered across the axis, compared to the three other plots which are much more densily placed around a single value. from the green histogram we notice that observation field of Sharpe ratios becomes much more narrow, but it is lower than the true Sharpe ratio. The results from the geometric mean allocation strategy, where we have simulated with the geometric mean of the stocks, turned out to perform worse than the original allocation strategy. Finanly the yellow histogram shows the result of an allocation strategy where shorting is permitted. Hence, the stocks' weights can be negative. The Sharpe ratios achieved by this strategy are higher than the efficient tangency portfolio with true parameters.

Although, none of these two alternative strategies improve upon the benchmark, it can be argued that and alocation with shorting is to be prefered to the therotical one since its sharpe values revoles around a higher value.