Problem 1

Use the data in problem1.csv. Fit a Normal Distribution and a Generalized T distribution to this data. Calculate the VaR and ES for both fitted distributions.

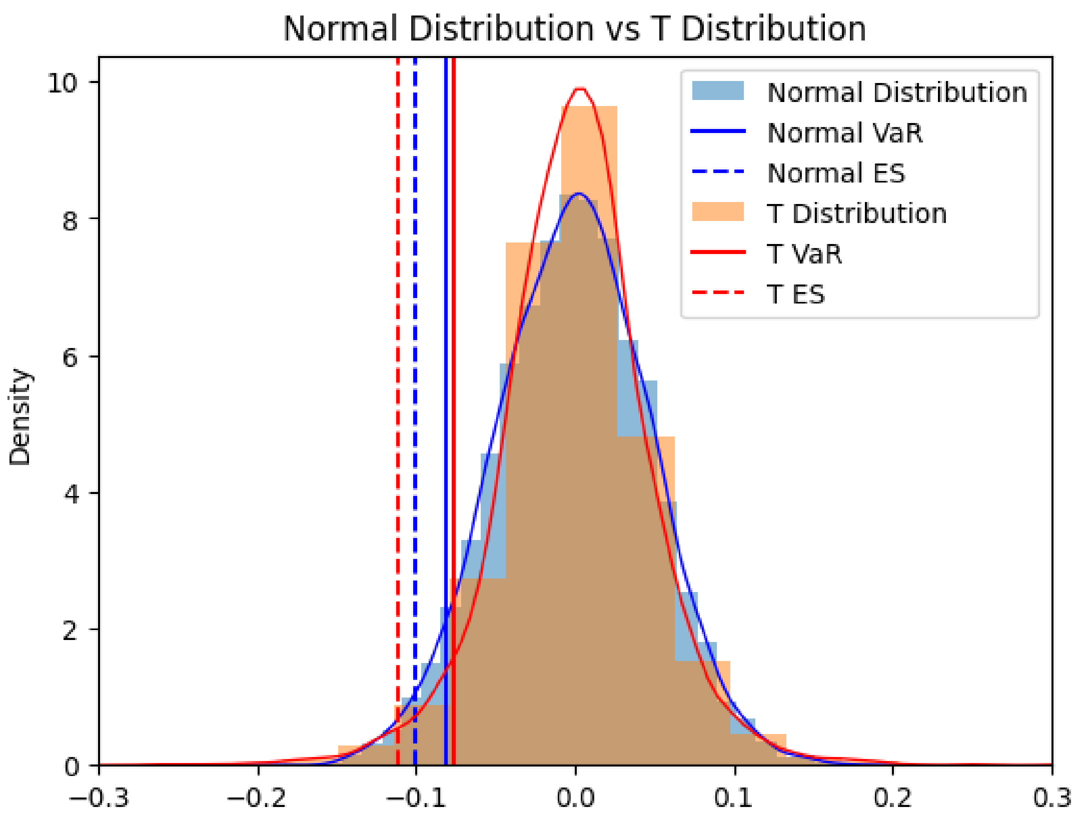
Overlay the graphs the distribution PDFs, VaR, and ES values. What do you notice? Explain the differences.

Analysis

Firstly, I fitted a normal distribution and a Generalized T distribution to this data and the results are:

	Normal Distribution	T Distribution
VaR	0.0808	0.0764
ES	0.1006	0.1116

Then, I overlaid the graphs of distribution PDFs, VaR and ES values.



It can be seen from the table and the graph, Normal Distribution has larger VaR, but smaller ES, while Generalized T distribution has smaller VaR, but larger ES. For the difference between the Var and ES, T distribution's is larger and Normal distribution's is smaller.

The reason for the difference may be that normal distribution and T distribution have different shape. It can be seen from the PDFs that in this example, T distribution has more extreme values (Fat Tail), and Normal distribution are more concentrated. So, ES of fitted T distribution are larger. But for the VaR, I think it depends. For this case, T distribution is concentrated expect the less-than-5%'s fat tail, so, normal distribution has larger VaR.

Problem 2

In your main repository, create a Library for risk management. Create modules, classes, packages, etc as you see fit. Include all the functionality we have discussed so far in class. Make sure it includes

1. Covariance estimation techniques.
2. Non PSD fixes for correlation matrices
3. Simulation Methods
4. VaR calculation methods (all discussed)
5. ES calculation

Create a test suite and show that each function performs as expected.

Analysis

I built my library named *ml_quant_risk*, *MC* and *VaR* packages are included. To run my code, "pip install ml_quant_risk" is needed. I have test all my functions working well in library in my code.

Problem 3

Use your repository from #2.

Using Portfolio.csv and DailyPrices.csv. Assume the expected return on all stocks is 0.

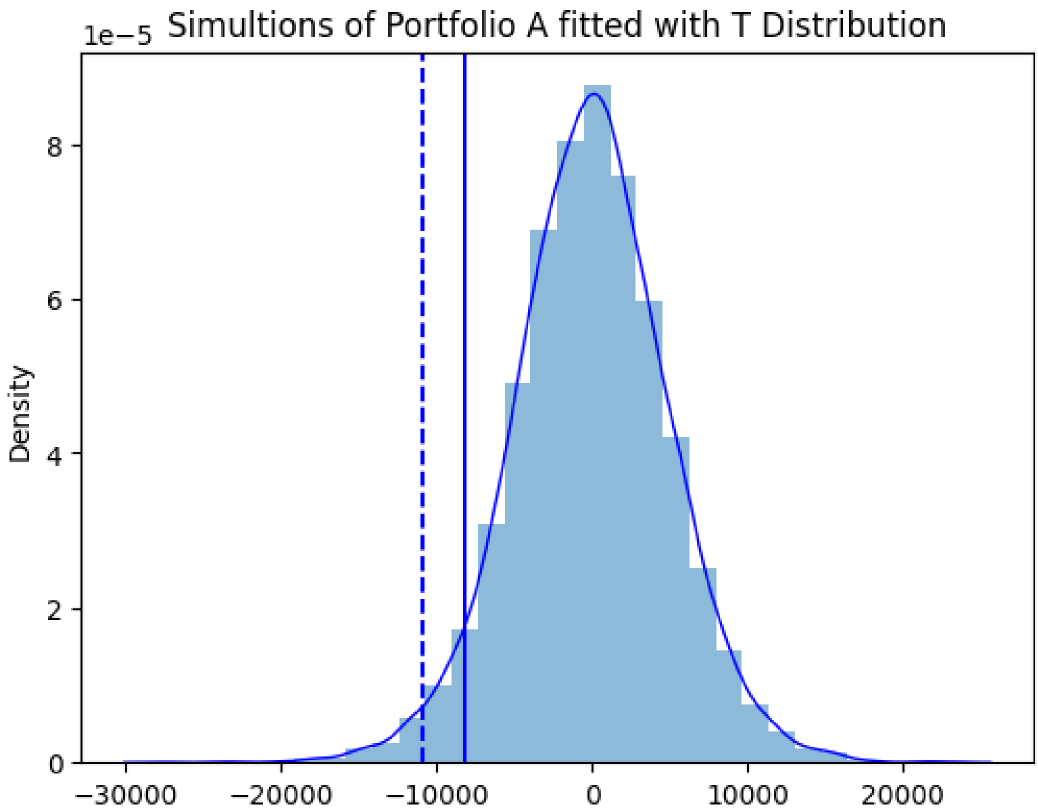
This file contains the stock holdings of 3 portfolios. You own each of these portfolios.

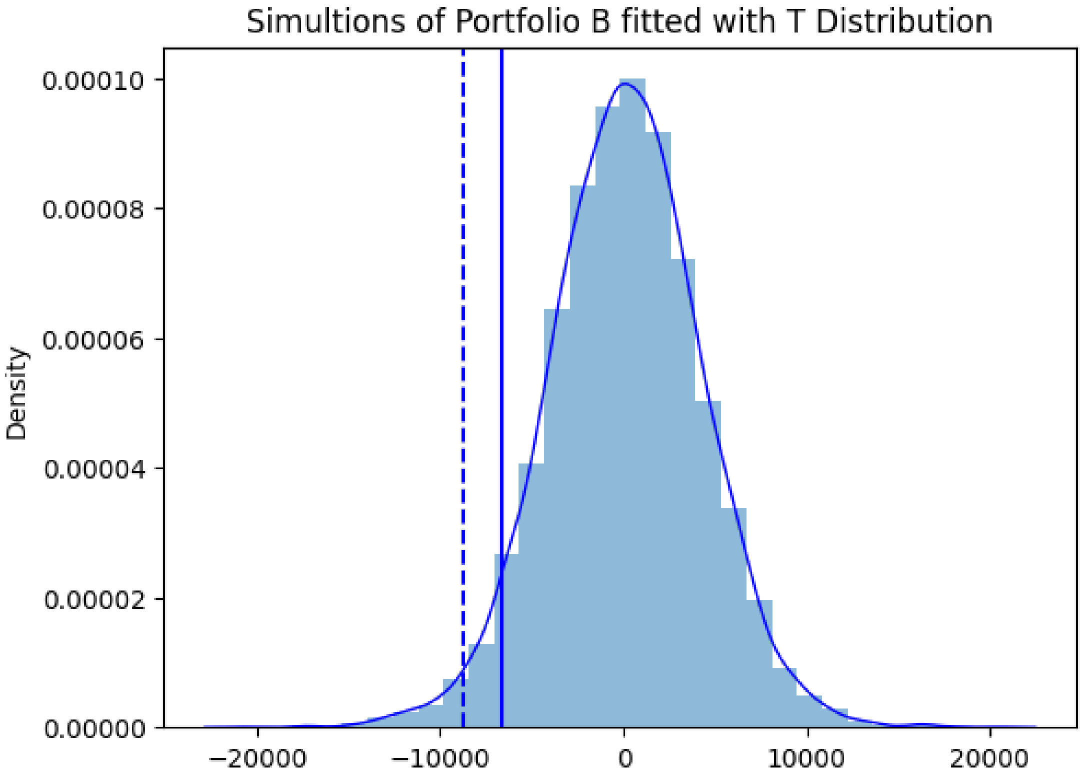
Fit a Generalized T model to each stock and calculate the VaR and ES of each portfolio as well as your total VaR and ES. Compare the results from this to your VaR form Problem 3 from Week 4.

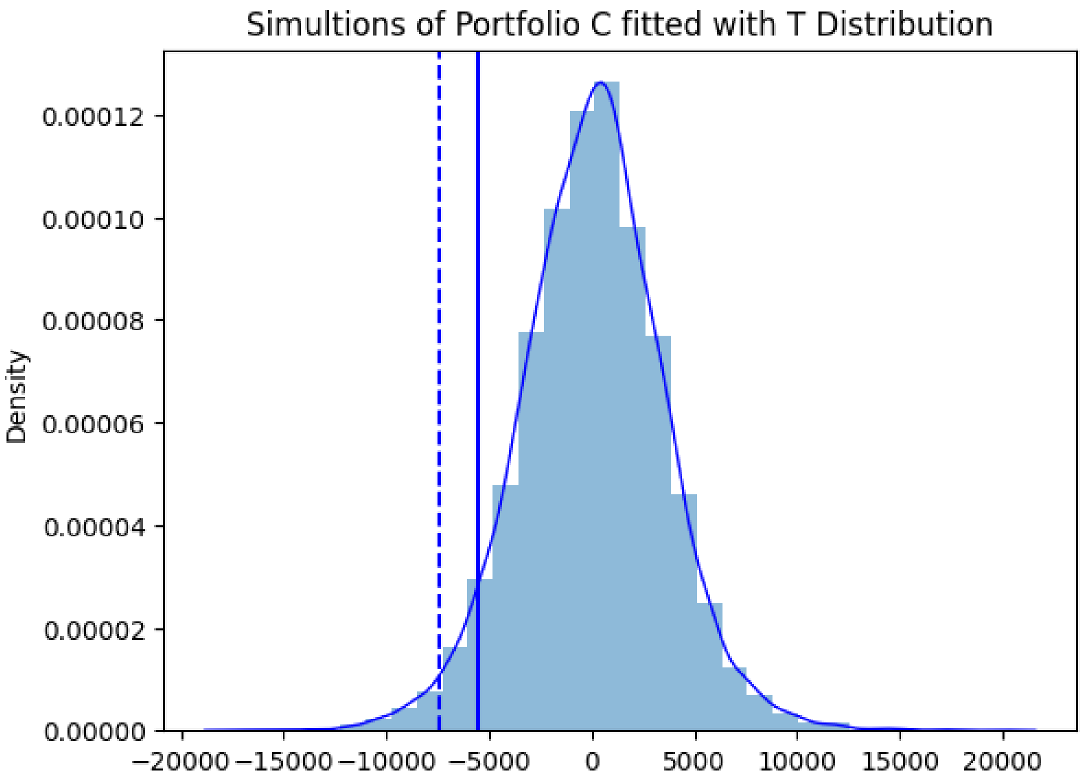
Analysis

Since each stock is fitted with Generalized T Distribution, I fitted the Gaussian Copula to simulate the returns. The results are as follows:

	A	B	C	TOTAL
VaR	8181.4243	6595.5644	5558.5206	20111.9146
ES	10848.3731	8754.0587	7393.3150	26427.1775




Simultions of Portfolio B fitted with T Distribution
Density
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
−20000
−10000
0
10000
20000


Simultions of Portfolio C fitted with T Distribution
Density
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
−20000
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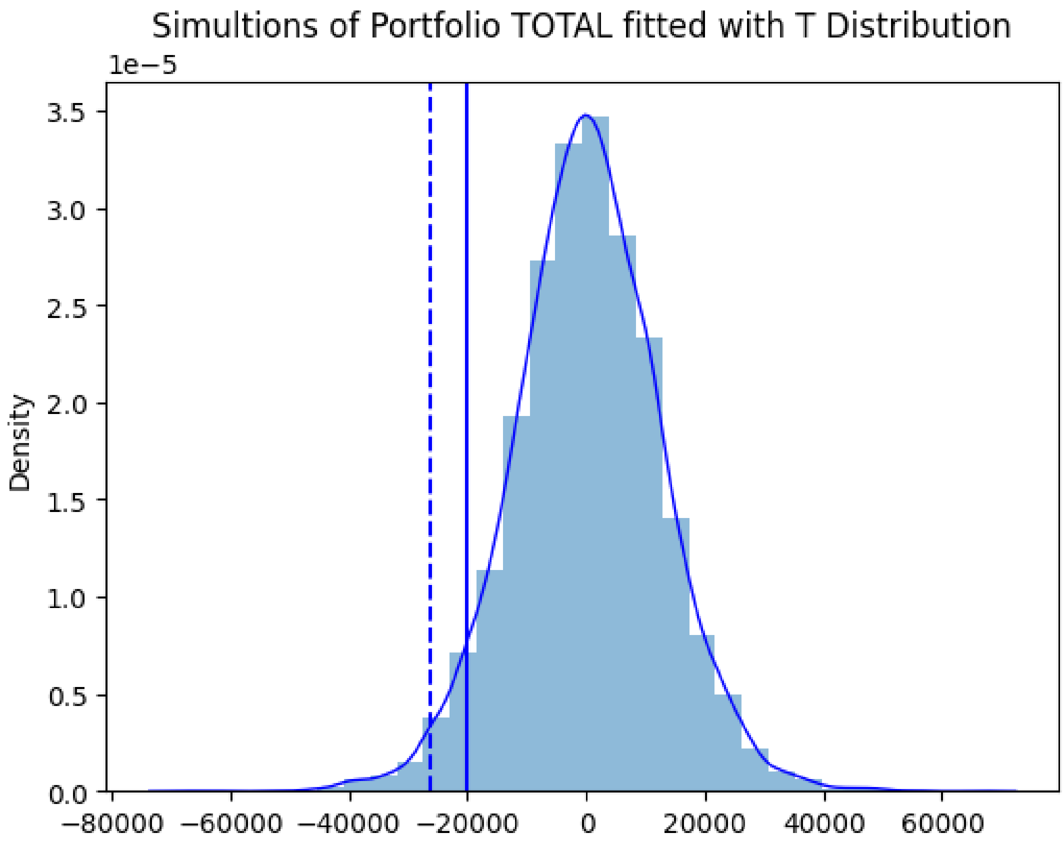
−10000
−5000
0
5000
10000
15000
20000



Then I compared the VaR with the results of Problem 3 from Week 4.

	PV ($)	Generalized T ($)	VaR_Delta ($)	VaR_MC ($)	His_VaR ($)
A	299950.0590	8181.4243	5670.2029	5567.8172	9005.0672
B	294385.5908	6595.5644	4494.5984	4404.5673	7001.1175
C	270042.8305	5558.5206	3786.589	3769.0776	5558.7244
Total	864378.4804	20111.9146	13577.0754	13244.1047	21103.398

It can be seen from the table that compared with Delta VaR and Monte Carlo VaR, VaRs calculated by fitted Generalized T distribution are similar to the VaRs calculated by Historical Simulation. This means Generalized T distribution can better explain real historical performances. This may because normal distribution assumption often underestimates the risk of extreme events while T distribution has fat tail effect, which means T distribution has taken those extreme values into consideration like the real cases. Besides, since historical data is limited, and the assumption of Generalized T distribution is still an assumption. There exists some differences between the VaRs of Generalized T assumptions and Historical VaRs.