Fintech 545 Project Week04

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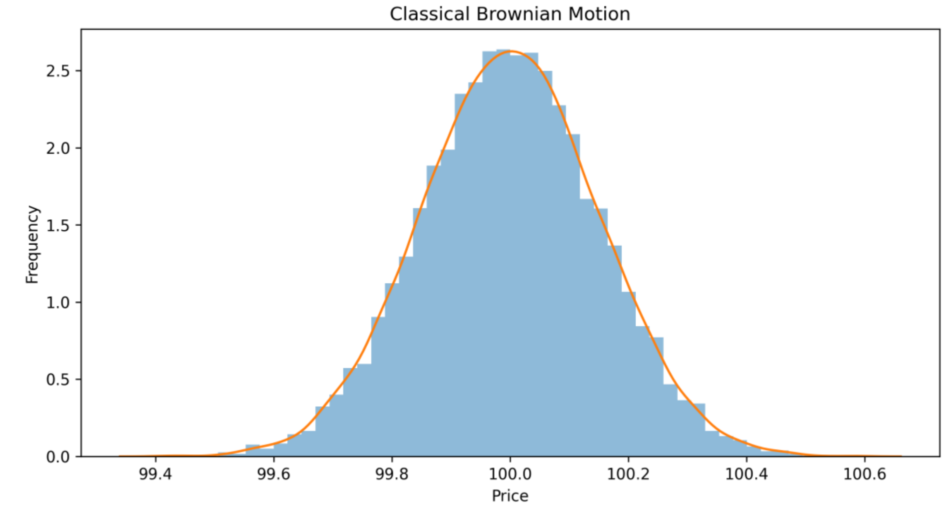
Problem 1

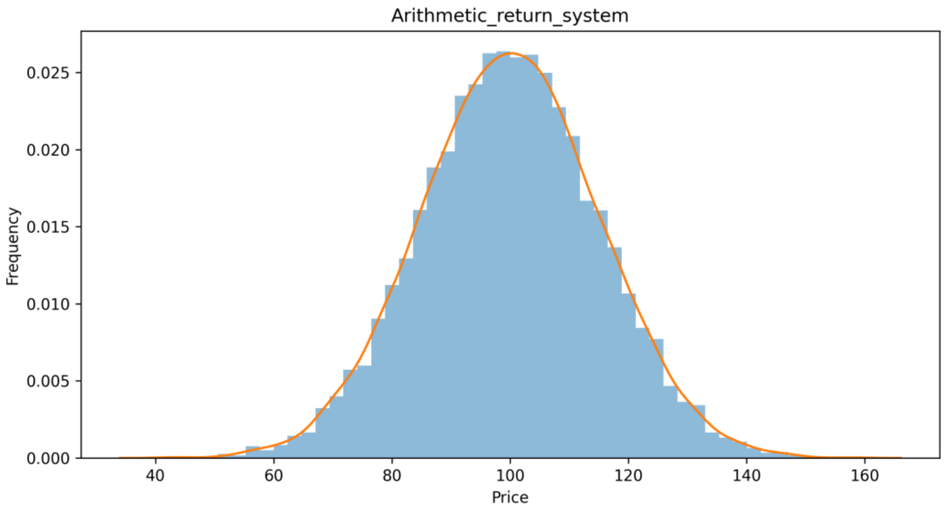
Given to the 3 types of price returns and $r_t \sim N(0, \sigma^2)$, we know that the mean and standard deviation as following ($\sigma = 0.15, P_t = 100$):

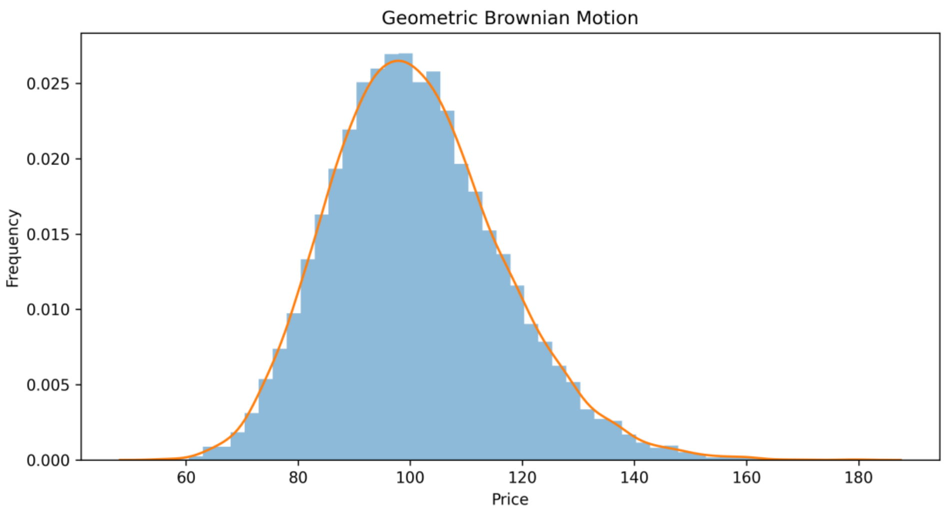
Method	Model	Formula	Mean	Std
Classical Brownian Motion	$P_t = P_{t-1} + r_t$	$P_t \sim N(P_{t-1}, \sigma^2)$	P_{t-1}	σ
Arithmetic Return System	$P_t = P_{t-1}(1 + r_t)$	$P_t \sim N(P_{t-1}, {P_{t-1}}^2 \sigma^2)$	P_{t-1}	$P_{t-1}\sigma$
Geometric Brownian Motion	$P_t = P_{t-1} e^{r_t}$	$P_t \sim LN(\ln(P_{t-1}), \sigma^2)$	$P_{t-1} * e^{\frac{\sigma^2}{2}}$	$P_{t-1} * e^{\frac{\sigma^2}{2}} * \sqrt{e^{\sigma^2} - 1}$

Using python to calculate, we can see the tiny difference between estimated one and expected one as following:

Method	Estimated Mean	Expected Meam	Estimated Std	Expected Std
Classical Brownian Motion	99.999679	100	0.150511	0.15
Arithmetic Return System	99.96796	100	15.05118	15.0
Geometric Brownian Motion	101.10689	101.13135	15.30925	15.25543


Classical Brownian Motion
Frequency
Price
0.0
0.5
1.0
1.5
2.0
2.5
99.4
99.6
99.8
100.0
100.2
100.4
100.6


Arithmetic_return_system
Frequency
Price
0.000
0.005
0.010
0.015
0.020
0.025
40
60
80
100
120
140
160

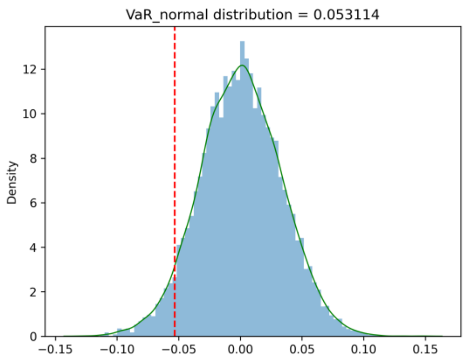

Geometric Brownian Motion
Frequency
Price
0.000
0.005
0.010
0.015
0.020
0.025
60
80
100
120
140
160
180

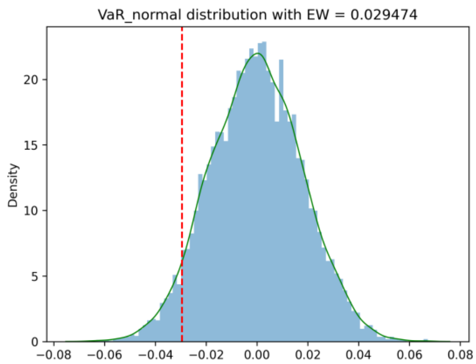
Problem 2:

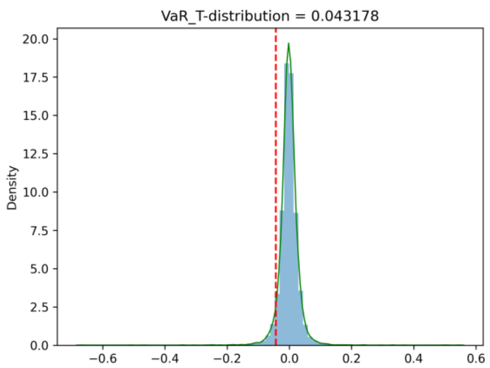
Using the stock prices of META and 5 methods to calculate VaR, the results of VaR are as following:

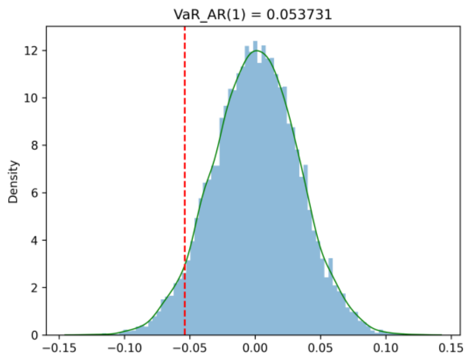
simulation	VaR
Normal Distribution	0.0531
Normal Distribution with EW	0.0295
T-distribution	0.0432
AR(1)	0.0537
Historic Simulation	0.0395

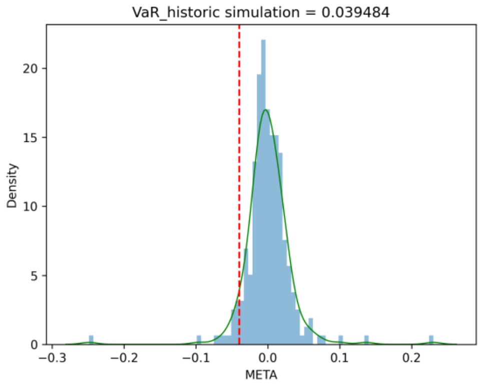
The simulation results of return are distributed as following:











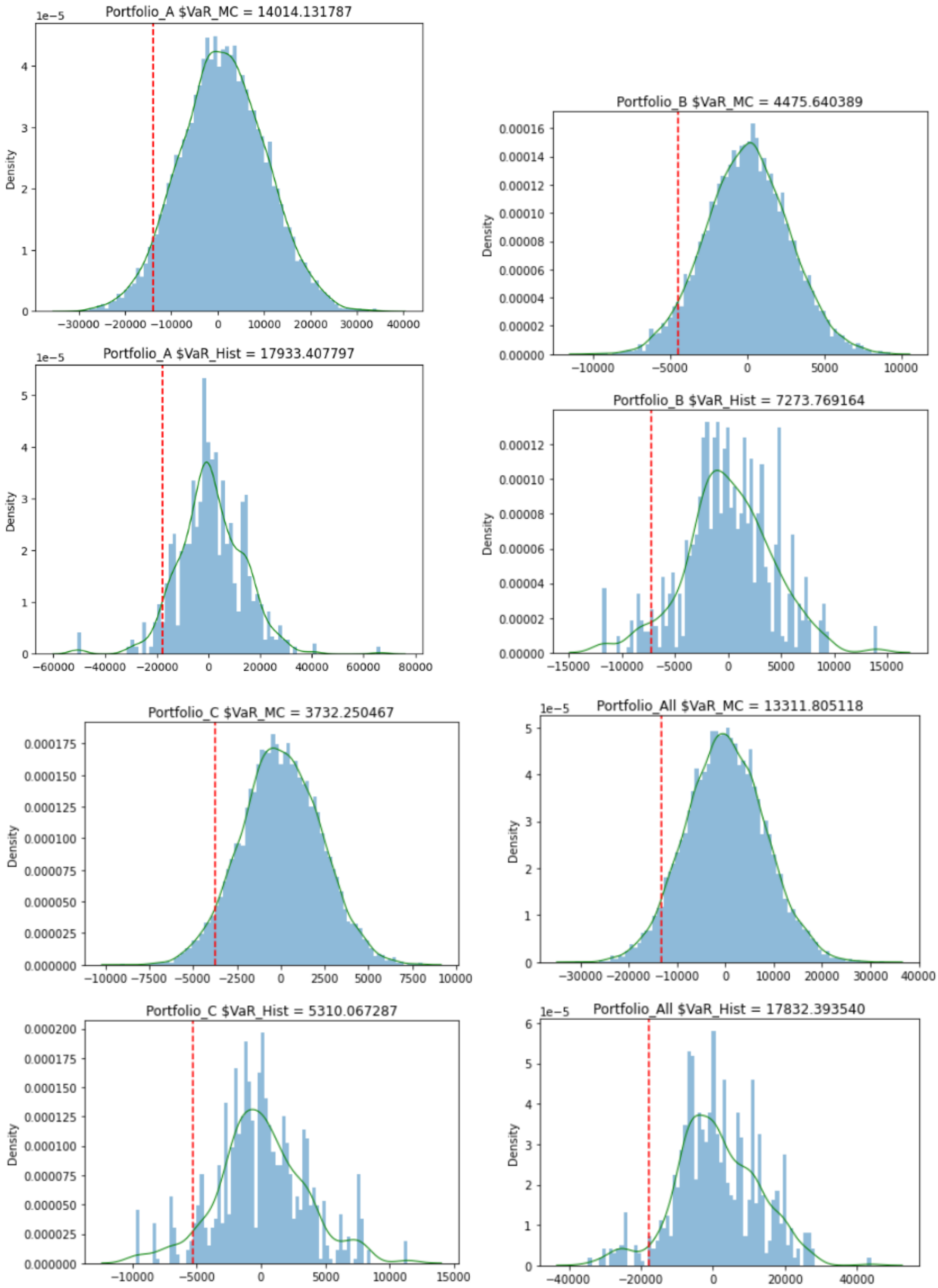
In comparing different Value at Risk (VaR) calculation methods, we found that the results from the T-distribution closely match those from historical simulation. This suggests both methods similarly account for extreme market movements. On the other hand, VaR values from the normal distribution method are quite similar to those from the AR(1) model, indicating these approaches may align when assessing risks in markets with more predictable behaviors. These findings highlight that despite different theoretical foundations, some risk assessment methods can offer comparable insights into financial risks.

Problem 3

I employed three distinct models for calculating the Value at Risk (VaR) for portfolios A, B, and C: Delta Normal, Monte Carlo, and Historical.

Portfolio	Current Value	Delta Normal	Monte Carlo	Historic
A	1089316.16	15426.97	14014.13	17933.41
B	574542.41	8082.57	7474.11	10983.46
C	1387409.51	18163.29	16285.41	21409.75
Total	3051268.07	38941.38	35642.05	49544.19

The returns of portfolios from Monte Carlo and historic are distributed as following:



From the VaR and graphs, we can see:

1. Delta Normal VaR assumes that returns are normally distributed. This method is computationally efficient and straightforward but may not accurately capture tail risks or non-linear exposures in portfolios. The results indicated that portfolio A has the highest VaR, followed by B and C, suggesting a higher risk or volatility in portfolio A.

2. Monte Carlo VaR utilizes simulated price paths to estimate potential losses, which allows for the incorporation of non-linearities and the modeling of complex dependencies between assets. The VaR values calculated using this method were slightly lower than those from the Delta Normal approach, which suggests that the simulated scenarios might have captured some diversification effects not fully accounted for in the simpler Delta Normal model.

3. Historical VaR directly uses historical price changes to estimate potential future losses, without assuming any specific distribution of returns. This method produced the highest VaR estimates across all portfolios, likely reflecting the impact of extreme market movements captured in the historical data.