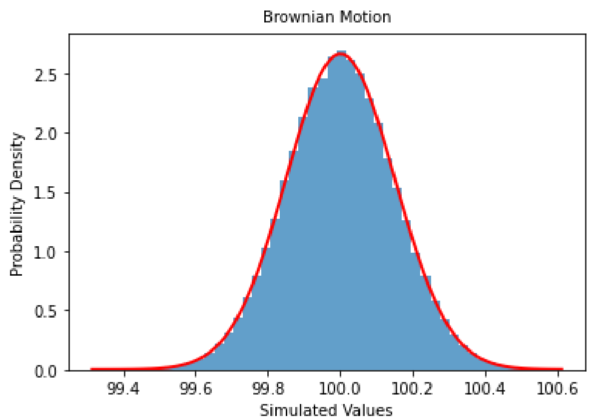
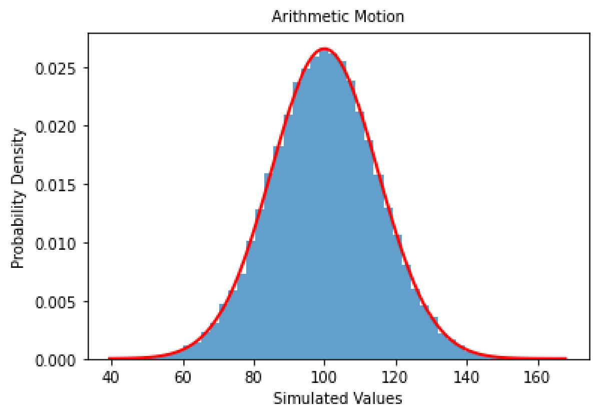
For problem 1 I assumed to use 100 for the price, 0.15 for sigma, skew = 0 and kurtosis = 0. After running 100,000 simulations on Arithmetic, geometric, and Brownian I got the following results:

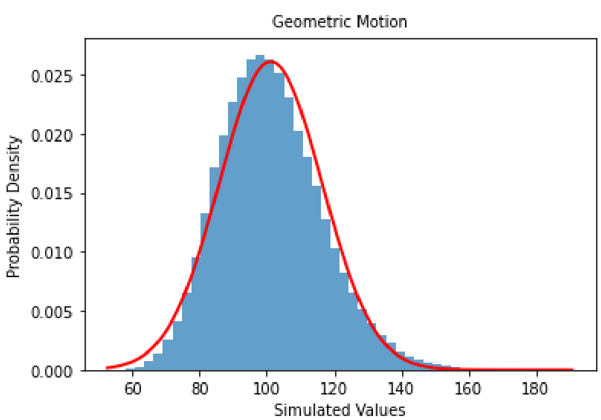
Simulation Type	Mean	Sigma	Skew	Kurtosis
Arithmetic	100.00458	14.9815	0.000195	0.0033
Brownian	100.0003	15.029	-0.00898	-0.0207
Geometric	101.1399	15.21	0.4525	0.3896

While Arithmetic and Brownian both have around the same price near 100 and appear to be follow a normal distribution given the graphs below this is expected given the 100,000 simulations where after a high enough number of sims, the values should normalize:





Because they normalized, this can explain why the Skew and Kurtosis are near or almost near zero. When Comparing Arithmetic and Brownian to Geometric, Geometric is the simulation with noticeable difference. The mean value of   101.13 and sigma of 15.21 is noticeable difference compared to the values that we get from Arithmetic and Brownian. Looking further at both the Skew and kurtosis values of .4525 and .3896 respectively, we can then see that geometric simulation produces right tails, which can then be seen and explained by the graph below:

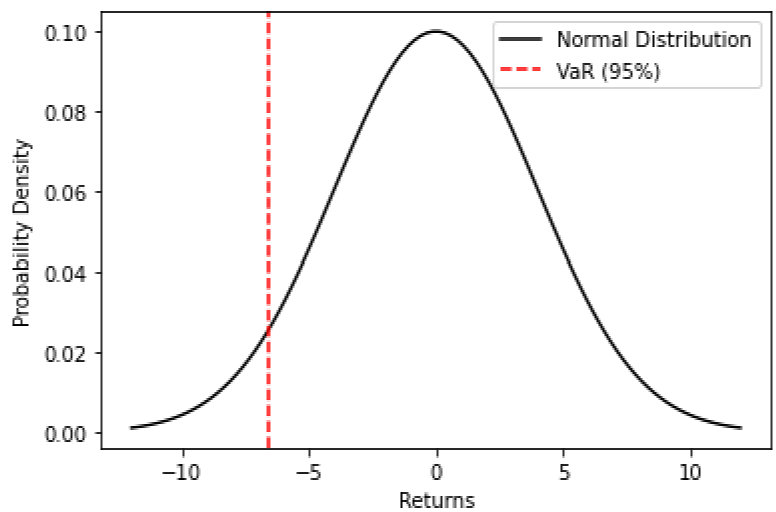


We can see geometric sim follows a log distribution over a normal distribution. This helps us understand why market returns are said to be geometric and the meaning of Fat tailed distributions.

Problem 2

For problem 2, the following var values are the results of their respective calculations. The output for calculating along with the calculations include graphs for VaR. When calculating VaR, I'm multiplied by 100 as professor did during class.

1. For Normal Distribution, distribution the original bar value I got was 6.54. Below is the graph for the Normal Distribution.



2. When calculating the normalized exponentially weighted variance with a lambda of .94, it produces an array of values. Becauae VaR is a minimum loss on a normal bad day, I decided to find the minimum value which was 2.88. This was most logically sound approach because the output coincides with the idea of being exponentially weighted which in turn could reduce possibility of more volatile data to come into play since the calculation front weights data which seem to have little movement
3. For MLE I got a very small number of .22 which seems very stragely low. But also at the same time it makes sense because the model is utilizing t distribution which will diminish the effects of outliers.
4. The ARIMA model produced a value of 6.544 very close to number 1 answer since being autoregressive will be dependent on previous iterations of itself giving a value close to answer 1.
5. The Result of 5.59 is close to the answer of 6.54 from number 1 but its lower than number 1 since historical VaR suffers from recency bias. And as of recent META's Stock has not been that volatile.

Problem 3

For number 3 when calculating the $VaR for the three portfolios:

Portfolio A VaR$: $5670.20

Portfolio B VaR$: $4494.60

Portfolio C VaR$: $3786.59

While at first these seem high, when you look deeper at the assets in for instance Portfolio A, it has very high Beta names that are volatile such as AMD,GOOGL and other tech stocks. So this is generally within reason. Below are the VaRret that was produced from my model.

Portfolio A VaRret: 205.54

Portfolio B VaRret: 14.90

Portfolio C VaRret: 413.43

When I decided to rerun the simulation I went with the Monte Carlo VaR since it is truly random and should eliminate most biases. as you can see the dollar var is significantly more pronounce and can be argued to be more realistic then delta var since delta var is linear. Monte Carlo being truly random w we'll bring in some of those extremes to make the picture for VaR much more realistic.

Portfolio Portfolio A VaR ($): 44929.54

Portfolio Portfolio A VaR (return): -0.1498

Portfolio Portfolio B VaR ($): 21550.09

Portfolio Portfolio B VaR (return): -0.0732

Portfolio Portfolio C VaR ($): 39058.04

Portfolio Portfolio C VaR (return): -0.1446