Black-Scholes Formula

We can calculate the price of the European put and call options explicitly using the Black–Scholes formula.

Call Option

The value of a call option for a non-dividend-paying underlying stock in terms of the Black–Scholes parameters is:

$$egin{align} C(S_t,t) &= N(d_1)S_t - N(d_2)PV(K) \ d_1 &= rac{1}{\sigma\sqrt{T-t}}\left[\ln\left(rac{S_t}{K}
ight) + \left(r + rac{\sigma^2}{2}
ight)(T-t)
ight] \ d_2 &= d_1 - \sigma\sqrt{T-t} \ PV(K) &= Ke^{-r(T-t)} \ \end{split}$$

Put Option

The price of a corresponding put option based on put-call parity is:

$$P(S_t, t) = Ke^{-r(T-t)} - S_t + C(S_t, t)$$

= $N(-d_2)PV(K) - N(-d_1)S_t$

Where in both cases the notion is the following:

- N(.) is the cumulative distribution function of the standard normal distribution
- **T-t** is the time to maturity (expressed in years)
- St is the spot price of the underlying asset
- K is the strike price
- r is the risk-free rate (annual rate, expressed in terms of continuous compounding)
- σ is the volatility of returns of the underlying asset.

Pricing of European Options with Black-Scholes formula

We can easily get the price of the European Options in R by applying the Black-Scholes formula.

Scenario. Let's assume that we want to calculate the price of the call and put option with:

- K: Strike price is equal to 100
- r: The risk-free annual rate is 2%
- sigma: The volatility σ is 20%
- T: time to maturity in years is 0.5
- S0: The current price is equal to 102

```
K = 100

r = 0.02

sigma = 0.2

T = 0.5
```

```
# call option

d1 <- (log(S0/K) + (r + sigma^2/2) * T)/(sigma * sqrt(T))
d2 <- d1 - sigma * sqrt(T)
phid1 <- pnorm(d1)
call_price <- S0 * phid1 - K * exp(-r * T) * pnorm(d2)

# put option
d1 <- (log(S0/K) + (r + sigma^2/2) * T)/(sigma * sqrt(T))
d2 <- d1 - sigma * sqrt(T)
phimd1 <- pnorm(-d1)
put_price <- -S0 * phimd1 + K * exp(-r * T) * pnorm(-d2)

c(call_price, put_price)

[1] 7.288151 4.293135</pre>
```

So the price of the call and put option is 7.288151 and 4.293135 respectively.

Pricing of European Options with Monte Carlo Simulation

Given the current asset price at time 0 is (S_0) , then the asset price at time T can be expressed as:

```
(S_T = S_0e^{(r- \frac{sigma^2}{2})T + sigma W_T})
```

where $\(W_T\)$ follows the normal distribution with mean $\mathbf{0}$ and variance \mathbf{T} . The pay-off of the call option is $\(\max(S_T-K,0)\)$ and for the put option is $\(\max(K-S_T)\)$.

Simple Monte Carlo

Let's apply a simple Monte Carlo Simulation with 1M runs, where we will get the price and the standard error of the call and put option. As parameters, we will use the same as the example above.

```
# call put option monte carlo
call_put_mc<-function(nSim=1000000, tau, r, sigma, S0, K) {
   Z <- rnorm(nSim, mean=0, sd=1)
   WT <- sqrt(tau) * Z
   ST = S0*exp((r - 0.5*sigma^2)*tau + sigma*WT)

# price and standard error of call option
   simulated_call_payoffs <- exp(-r*tau)*pmax(ST-K,0)
   price_call <- mean(simulated_call_payoffs)
   sterr_call <- sd(simulated_call_payoffs)/sqrt(nSim)

# price and standard error of put option
   simulated_put_payoffs <- exp(-r*tau)*pmax(K-ST,0)
   price put <- mean(simulated put payoffs)</pre>
```

And we get:

```
$price_call
[1] 7.290738

$sterr_call
[1] 0.01013476

$price_put
[1] 4.294683

$sterr_put
[1] 0.006700902
```

As we can see, the estimated prices from the Monte Carlo Simulation are very close to those obtained from the Black-Scholes formula (7.290738 vs 7.288151 and 4.294683 vs 4.293135)

Antithetic Variates Method

The method of antithetic variates attempts to **reduce variance** by introducing negative dependence between pairs of replications. In a simulation driven by independent standard normal random variables, antithetic variates can be implemented by pairing a sequence ZI, Z2, ... of standard normal variables with the sequence -ZI, -Z2, ... of standard normal variables. If the Zi are used to simulate the increments of a Brownian path, then the – Zi simulate the increments of the reflection of the path about the origin. This again suggests that running a pair of simulations using the original path and then its reflection **may result in lower variance**. Note that the antithetic variates estimator is simply the average of all 2n observations. Let's apply the "Antithetic Variates Method" and compare the results with the simple Monte Carlo.

Note that the pair for the call will be the:

```
Z <- rnorm(nSim, mean=0, sd=1)</pre>
  WT <- sqrt(tau) * Z
  # ST1 and ST2 and the antithetic variates
  ST1 = (S0*exp((r - 0.5*sigma^2)*tau + sigma*WT))
  ST2 = (S0*exp((r - 0.5*sigma^2)*tau + sigma*(-WT)))
  # call option price and standard error
  simulated call payoffs1 <- exp(-r*tau)*pmax(ST1-K,0)</pre>
  simulated call payoffs2 <- exp(-r*tau)*pmax(ST2-K,0)</pre>
  # get the average
  simulated call payoffs <- ( simulated call payoffs1 +</pre>
simulated call payoffs2)/2
  price call <- mean(simulated call payoffs)</pre>
  sterr call <- sd(simulated call payoffs)/sqrt(nSim)</pre>
  # put option price and standard error
  simulated_put_payoffs1 <- exp(-r*tau)*pmax(K-ST1,0)</pre>
  simulated put payoffs2 <- exp(-r*tau)*pmax(K-ST2,0)</pre>
  # get the average
  simulated put payoffs <- (simulated put payoffs1+</pre>
simulated put payoffs2)/2
  price put <- mean(simulated put payoffs)</pre>
  sterr put <- sd(simulated put payoffs)/sqrt(nSim)</pre>
  output<-list(price_call=price_call, sterr_call=sterr_call,</pre>
                price put=price put, sterr put=sterr put )
  return (output)
}
set.seed(1)
results<-antithetic call put mc(n=1000000, tau=0.5, r=0.02, sigma=0.2,
S0=102, K=100)
results
And we get:
$price call
[1] 7.290193
$sterr call
[1] 0.004993403
$price put
[1] 4.294812
$sterr put
[1] 0.003636479
```

We see that the estimated prices are again very close but the standard error is much much lower with the antithetic variates method compared to the simple Monte Carlo (0.004993403 vs 0.01013476 and 0.003636479 vs 0.006700902). Someone can argue that this variance reduction is due to the fact that by generating 1M pairs was like generating 2M simulations. We have to mention that computationally was not expensive to get the pairs because again we generated from the standard normal and the pair was consisting of the original value and of the original value with a different sign. However, we can run the simulation again half times, just for comparison.

```
set.seed(1)
results<-antithetic_call_put_mc(n=1000000/2, tau=0.5, r=0.02,
sigma=0.2, S0=102, K=100)
results

$price_call
[1] 7.28989

$sterr_call
[1] 0.007057805

$price_put
[1] 4.294863

$sterr_put
[1] 0.005140888</pre>
```

As we can see, even if we run the half simulations, the standard error is lower than that of the simple Monte Carlo.

Importance Sampling Method

This is the idea of the importance sampling, is to try to give more weight to the "important" so that to increase sampling efficiency and as a result to reduce the standard error of the simulation. We will change the measure by considering the identical function I[ST>K] for the call options and I[ST

```
importance_call_put_mc<-function(nSim, tau, r, sigma, S0, K) {
   Z <- rnorm(nSim, mean=0, sd=1)
   WT <- sqrt(tau) * Z
   ST = S0*exp((r - 0.5*sigma^2)*tau + sigma*WT)

# call option price and standard error
   simulated_call_payoffs <- (exp(-r*tau)*pmax(ST-K,0))[ST>K]
   price_call <- mean(simulated_call_payoffs*mean(ST>K))
   sterr_call <- sd(simulated_call_payoffs*mean(ST>K))/sqrt(nSim)

# put option price and standard error
   simulated put payoffs <- (exp(-r*tau)*pmax(K-ST,0))[ST</pre>
```

And we get:

```
$price_call
[1] 7.28989

$sterr_call
[1] 0.007057805

$price_put
[1] 4.294863

$sterr_put
[1] 0.005140888
```

Again, we see that by applying the importance sampling technique, we got a very close estimation of the price and much lower standard error compared to the simple Monte Carlo Method.

Discussion

We showed how we can calculate the price of the European options explicitly by applying the Black-Scholes formula and we showed how we can estimate the prices by applying Monte Carlo simulation. Finally, we provided examples of advanced Monte Carlo techniques such as the antithetic variates and the importance sampling which have as a result a more effective simulation with lower standard error.