

02. Multivariate Monte Carlo

August 2, 2021

```
[1]: import pandas as pd
import numpy as np

[2]: close_price_df = pd.read_csv("./sample_stock_close_price.csv", index_col=0,
    ↪parse_dates=True)
close_price_df.columns = ['Samsung Electronics', 'SK Hynix', 'KAKAO', 'NAVER',
    ↪'KODEX Inverse']
close_price_df.tail(3)
```

```
[2]:
```

| | Samsung Electronics | SK Hynix | KAKAO | NAVER | KODEX Inverse |
|------------|---------------------|----------|----------|----------|---------------|
| date | | | | | |
| 2021-07-28 | 79200.0 | 114000.0 | 148000.0 | 442000.0 | 3765.0 |
| 2021-07-29 | 79000.0 | 114000.0 | 148500.0 | 439500.0 | 3755.0 |
| 2021-07-30 | 78500.0 | 112500.0 | 147000.0 | 433500.0 | 3805.0 |

0.0.1 Multivariate

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix} \sim N \left(\begin{bmatrix} \mu_1 \\ \vdots \\ \mu_n \end{bmatrix}, \begin{bmatrix} \sigma_{1,1} & \dots & \sigma_{1,n} \\ \vdots & \ddots & \vdots \\ \sigma_{n,1} & \dots & \sigma_{n,n} \end{bmatrix} \right) \quad (1)$$

$$X \sim N(\mu, K) \quad (2)$$

$$K = L \cdot L^T \quad (3)$$

$$Z_{cor} = L \cdot \epsilon \quad (4)$$

$$\epsilon = Z_{ind} \times \sigma \quad (5)$$

$$Z_{ind} \sim N(0, 1) \quad (6)$$

$$Z_{cor} = L \cdot (Z_{ind} \times \sigma) \quad (7)$$

$$X \sim N(\mu, L \cdot (Z_{ind} \times \sigma)) \quad (8)$$

```
[3]: returns_means = close_price_df.pct_change().mean()
      returns_means
```

```
[3]: Samsung Electronics    0.000700
      SK Hynix              0.000828
      KAKAO                 0.001075
      NAVER                 0.000939
      KODEX Inverse         -0.000254
      dtype: float64
```

```
[4]: returns_std = close_price_df.pct_change().std()
      returns_std
```

```
[4]: Samsung Electronics    0.017170
      SK Hynix              0.024069
      KAKAO                 0.023309
      NAVER                 0.022415
      KODEX Inverse         0.011115
      dtype: float64
```

```
[5]: rho_matrix = close_price_df.pct_change().corr()
      rho_matrix
```

```
[5]:          Samsung Electronics  SK Hynix    KAKAO    NAVER  \
Samsung Electronics          1.000000  0.507238  0.149265  0.212039
SK Hynix                     0.507238  1.000000  0.177784  0.162638
KAKAO                        0.149265  0.177784  1.000000  0.319981
NAVER                        0.212039  0.162638  0.319981  1.000000
KODEX Inverse                -0.732306 -0.571248 -0.294286 -0.338091

          KODEX Inverse
Samsung Electronics   -0.732306
SK Hynix              -0.571248
KAKAO                 -0.294286
NAVER                 -0.338091
KODEX Inverse         1.000000
```

```
[6]: L = np.linalg.cholesky(rho_matrix)
      pd.DataFrame(L, columns=close_price_df.columns)
```

```
[6]:          Samsung Electronics  SK Hynix    KAKAO    NAVER  KODEX Inverse
0          1.000000  0.000000  0.000000  0.000000  0.000000
1          0.507238  0.861806  0.000000  0.000000  0.000000
2          0.149265  0.118439  0.981678  0.000000  0.000000
3          0.212039  0.063917  0.286000  0.932286  0.000000
```

4 -0.732306 -0.231832 -0.160461 -0.130973 0.605872

```
[7]: z_ind = np.random.normal(size=(100, len(close_price_df.columns)))
pd.DataFrame(z_ind, columns=close_price_df.columns)
```

```
[7]:      Samsung Electronics  SK Hynix      KAKAO      NAVER  KODEX Inverse
0          -0.010418 -2.091732 -1.593299 -0.718171          0.458936
1           0.484347  0.444071 -0.009666 -1.077548          0.272307
2           0.224473  0.962848  0.303770  0.091169          0.321802
3           0.585634  3.560049 -0.417033 -0.818109          1.659349
4          -0.670369  0.026291 -1.262533  0.161998         -0.216747
..          ...          ...          ...          ...          ...
95          0.262134  0.514455  0.343532  0.356085          1.357451
96         -1.751437  0.798450 -0.390593 -0.762740          0.820272
97         -0.828632 -0.393085 -0.322816  0.456986          0.010230
98         -0.042782  0.055115  1.421120  0.567286          0.426348
99         -0.119502 -1.585516  2.390145 -1.110405         -0.229470
```

[100 rows x 5 columns]

```
[8]: epsilon = pd.DataFrame(z_ind, columns=close_price_df.columns) * returns_std
epsilon
```

```
[8]:      Samsung Electronics  SK Hynix      KAKAO      NAVER  KODEX Inverse
0          -0.000179 -0.050345 -0.037137 -0.016098          0.005101
1           0.008316  0.010688 -0.000225 -0.024153          0.003027
2           0.003854  0.023175  0.007080  0.002044          0.003577
3           0.010056  0.085686 -0.009720 -0.018338          0.018444
4          -0.011510  0.000633 -0.029428  0.003631         -0.002409
..          ...          ...          ...          ...          ...
95          0.004501  0.012382  0.008007  0.007982          0.015089
96         -0.030073  0.019218 -0.009104 -0.017097          0.009118
97         -0.014228 -0.009461 -0.007524  0.010243          0.000114
98         -0.000735  0.001327  0.033124  0.012716          0.004739
99         -0.002052 -0.038161  0.055711 -0.024890         -0.002551
```

[100 rows x 5 columns]

```
[9]: z_cor = L.dot(epsilon.T).T
pd.DataFrame(z_cor, columns=close_price_df.columns)
```

```
[9]:      Samsung Electronics  SK Hynix      KAKAO      NAVER  KODEX Inverse
0          -0.000179 -0.043479 -0.042447 -0.028885          0.022961
1           0.008316  0.013430  0.002286 -0.020136         -0.003535
2           0.003854  0.021927  0.010271  0.006229         -0.007432
3           0.010056  0.078945  0.002107 -0.012267         -0.012092
4          -0.011510 -0.005293 -0.030532 -0.007431          0.011069
```

```

..          ...          ...          ...          ...
95          0.004501  0.012954  0.009999  0.011477          0.000645
96         -0.030073  0.001308 -0.011150 -0.023691          0.026791
97         -0.014228 -0.015371 -0.010631  0.003776          0.012547
98         -0.000735  0.000771  0.032565  0.021257         -0.003879
99         -0.002052 -0.033929  0.049864 -0.010145          0.003125

```

[100 rows x 5 columns]

```

[10]: generated_X = returns_means + pd.DataFrame(z_cor, columns=close_price_df.
      ↪ columns)
      generated_X

```

```

[10]:      Samsung Electronics  SK Hynix      KAKAO      NAVER  KODEX Inverse
0          0.000521 -0.042651 -0.041372 -0.027946          0.022707
1          0.009016  0.014258  0.003361 -0.019196         -0.003789
2          0.004554  0.022755  0.011346  0.007168         -0.007686
3          0.010755  0.079773  0.003182 -0.011328         -0.012346
4         -0.010811 -0.004465 -0.029457 -0.006492          0.010815
..          ...          ...          ...          ...
95          0.005201  0.013782  0.011074  0.012416          0.000391
96         -0.029373  0.002136 -0.010075 -0.022752          0.026537
97         -0.013528 -0.014542 -0.009556  0.004716          0.012293
98         -0.000035  0.001599  0.033640  0.022197         -0.004133
99         -0.001352 -0.033100  0.050939 -0.009206          0.002871

```

[100 rows x 5 columns]

```

[11]: generated_X.corr()

```

```

[11]:      Samsung Electronics  SK Hynix      KAKAO      NAVER  \
Samsung Electronics          1.000000  0.378364  0.222631  0.306941
SK Hynix                    0.378364  1.000000  0.099157  0.239514
KAKAO                      0.222631  0.099157  1.000000  0.499104
NAVER                     0.306941  0.239514  0.499104  1.000000
KODEX Inverse             -0.790731 -0.620474 -0.475547 -0.601092

      KODEX Inverse
Samsung Electronics    -0.790731
SK Hynix              -0.620474
KAKAO                 -0.475547
NAVER                 -0.601092
KODEX Inverse         1.000000

```