

Stochastic Calculus Problem Set I: Question 1

In [1]:

```
import numpy as np
import pandas as pd
from itertools import product
```

In [2]:

```
# As specified in question setup and part (e)
u = 1.005
d = 1.002
r = 0.003
p_1 = 0.4
p_2 = 0.6
N = 100
L = 1000
S_0 = 1

# Assert that model is arbitrage-free
assert d < 1+r, 'd >= 1+r. This model is not arbitrage-free.'
assert 1+r < u, '1+r >= u. This model is not arbitrage-free.'
```

Part (a)

For the binomial asset pricing model, $S_n = (\prod_{i=1}^N y_i) S_0$

where $y_i = u$ if the result of the i th coin toss is heads or $y_i = d$ if the result of the i th coin toss is tails.

Let $R_n = \log(\frac{S_n}{S_0})$

Then,

$$R_n = \sum_{i=1}^N \log y_i$$

$$\implies R_n = (\log u - \log d) \sum_{i=1}^N Y_n + n \log d$$

where $Y_n \sim B(n, p)$.

Thus,

$$E(R_n) = (\log u - \log d)(np) + n \log d = n(p \log u + (1-p) \log d)$$

and

$$\text{Var}(R_n) = (\log u - \log d)^2 np(1-p)$$

Part (b)

In [3]:

```
def risk_neutral_probabilities(u, d, r):
    """
    Computes risk neutral probabilities from binomial
    model parameters (u and d) and risk-free rate (r).
    """
    p_tilde = ((1+r) - d) / (u - d)
    q_tilde = (u - (1+r)) / (u - d)
    return p_tilde, q_tilde

p_tilde, q_tilde = risk_neutral_probabilities(u, d, r)
```

Part (c)

Part (c)

Modified in email. This question now contains code to compute Δ_n and X_n given a path ω_n .

In [4]:

```
def stock_value(path):  
    '''  
    Computes the value of a stock given some path  
    (a NumPy array of 0s and 1s).  
    Returns the value of the stock at time N.  
    '''  
    return S_0 * np.prod((u - d)*path + d)
```

```
path = np.random.randint(low=0, high=2, size=N)
```

In [5]:

```
def portfolio_from_path(omega_n, derivative_value, stock_value):  
    '''  
    Given a path omega_n, computes the delta_n and X_n.  
    '''  
    heads_case = np.append(omega_n, 1)  
    tails_case = np.append(omega_n, 0)  
    numerator = derivative_value(heads_case) - derivative_value(tails_case)  
    denominator = stock_value(heads_case) - stock_value(tails_case)  
    delta_n = numerator / denominator  
    X_n = derivative_value(omega_n) # X_n = V_n almost surely  
    return delta_n, X_n
```

Part (d)

In [6]:

```
def exotic_derivative(path):  
    return max(S_0 * np.cumprod((u-d)*path + d))
```

In [7]:

```
def european_call(paths, strike_price):  
    # If there is only one path, coerce to 2D  
    if len(paths.shape) == 1:  
        paths = np.atleast_2d(paths)  
    S_N = (S_0 * np.cumprod((u-d)*paths + d, axis=-1))[:, -1]  
    out = S_N.copy()  
    out[S_N - strike_price <= 0] = 0  
    return out
```

In [8]:

```
def european_put(paths, strike_price):  
    # If there is only one path, coerce to 2D  
    if len(paths.shape) == 1:  
        paths = np.atleast_2d(paths)  
    S_N = (S_0 * np.cumprod((u-d)*paths + d, axis=-1))[:, -1]  
    out = S_N.copy()  
    out[strike_price - S_N <= 0] = 0  
    return out
```

In [9]:

```
# Check that the functions work  
path = np.random.binomial(n=1, p=p_tilde, size=[100])  
_ = exotic_derivative(path)  
_ = european_call(path, 1)  
_ = european_put(path, 1)
```

Part (a)

Part (e)

In [10]:

```
probabilities = [p_tilde, p_1, p_2]
strike_prices = [S_0 * np.exp(N*(p*np.log(u) + (1-p)*np.log(d)))
                 for p in probabilities]
```

In [11]:

```
# Bernoulli(p) = B(1, p)
paths_1 = np.random.binomial(n=1, p=p_1, size=[L, N])
E1_discounted_VN_call = [np.mean(european_call(paths_1, K) / (1+r)**N) for K in strike_prices]
E1_discounted_VN_put = [np.mean(european_put(paths_1, K) / (1+r)**N) for K in strike_prices]

paths_2 = np.random.binomial(n=1, p=p_2, size=[L, N])
E2_discounted_VN_call = [np.mean(european_call(paths_2, K) / (1+r)**N) for K in strike_prices]
E2_discounted_VN_put = [np.mean(european_put(paths_2, K) / (1+r)**N) for K in strike_prices]
```

Part (f)

By the martingale property, $V_0 = \tilde{E}\left(\frac{V_N}{(1+r)^N}\right)$. But we compute \tilde{E} using a Monte Carlo approach, so we need only average.

In [12]:

```
paths_tilde = np.random.binomial(n=1, p=p_tilde, size=[L, N])
Etilde_V0_call = [np.mean(european_call(paths_tilde, K) / (1+r)**N) for K in strike_prices]
Etilde_V0_put = [np.mean(european_put(paths_tilde, K) / (1+r)**N) for K in strike_prices]
```

Part (g)

Modified in email. I still don't think I really understand this...

In [13]:

```
for _ in range(3):
    path = np.random.binomial(n=1, p=1/2, size=N-3)
    extensions = np.array(list(product([0, 1], repeat=3)))
    extended_paths = [np.append(path, extension) for extension in extensions]

    portfolio_from_path(path,
                        lambda x: european_call(x, strike_prices[0]).item(),
                        stock_value)
```

Part (h)

In [14]:

```
results = np.vstack([
    E1_discounted_VN_call,
    E1_discounted_VN_put,
    E2_discounted_VN_call,
    E2_discounted_VN_put,
    Etilde_V0_call,
    Etilde_V0_put
])

names = [
    'E1_discounted_VN_call',
    'E1_discounted_VN_put',
    'E2_discounted_VN_call',
    'E2_discounted_VN_put',
    'Etilde_V0_call',
    'Etilde_V0_put'
]

strikes = ['K_tilde', 'K_1', 'K_2']
```

```
pd.DataFrame(data=results,  
             index=names,  
             columns=strikes)
```

Out[14]:

	K_tilde	K_1	K_2
E1_discounted_VN_call	0.916551	0.488635	0.000000
E1_discounted_VN_put	0.103287	0.518963	1.019838
E2_discounted_VN_call	1.083276	1.083276	0.567470
E2_discounted_VN_put	0.000000	0.000000	0.502812
Etilde_V0_call	0.519402	0.090388	0.000000
Etilde_V0_put	0.481843	0.904737	1.001246