# Implied Volatility using Newton's Method

#### Introduction

Implied volatility (IV) is a key metric in options pricing, representing the market's expectation of future volatility. Newton's method, a numerical root-finding algorithm, can be used to calculate the implied volatility of European options.

### **Objectives:**

- 1. Implement Newton's Method to compute implied volatility.
- 2. Use the Black-Scholes model for theoretical option pricing.
- 3. Visualize the progression of Newton's method using Python.

#### Libraries Used:

- py\_vollib : For Black-Scholes pricing and Greeks computation.
- matplotlib: For plotting and visualization.
- **numpy**: For numerical operations.

# Importing Libraries

We use the following libraries:

- 1. **py\_vollib.black\_scholes**: To compute option prices using the Black-Scholes model.
- 2. **py\_vollib.black\_scholes.greeks.analytical**: To calculate the vega (rate of change of option price w.r.t. volatility).
- 3. **matplotlib**: For plotting and creating animations.
- 4. **numpy**: For numerical operations.
- 5. **IPython.display**: To render animations directly in the notebook.

```
In [1]: from py_vollib.black_scholes import black_scholes as bs
    from py_vollib.black_scholes.greeks.analytical import vega
    import matplotlib.pyplot as plt
    import matplotlib.animation as animation
    import numpy as np
    from IPython.display import HTML
    from matplotlib import rc

# Configure matplotlib for animations
    rc('animation', html='jshtml')
    plt.style.use('ggplot')
```

# Implementing Newton-Raphson Method

The Newton-Raphson method is an iterative numerical technique used to find roots of a real-valued function. In this context, it is used to find the implied volatility of a European option by solving the equation:

$$f(\sigma) = C_{\rm BS}(\sigma) - C_{\rm market} = 0$$

Where:

- $C_{\mathrm{BS}}(\sigma)$ : Black-Scholes price with volatility  $\sigma$ .
- $C_{\mathrm{market}}$ : Observed market price.

The iteration follows the formula:

$$\sigma_{
m new} = \sigma_{
m old} - rac{f(\sigma)}{f'(\sigma)}$$

Here,  $f'(\sigma)$  is the vega of the option.

```
In [2]: def implied vol(S0, K, T, r, market price, flag='c', tol=0.00001):
            Compute the implied volatility of a European Option.
            Parameters:
            S0 : float : Initial stock price
            K : float : Strike price
            T : float : Time to maturity (in years)
            r : float : Risk-free interest rate
            market price : float : Observed market price of the option
            flag : str : Option type ('c' for call, 'p' for put)
            tol : float : Tolerance for convergence
            Returns:
            float : Implied volatility
            max iter = 200 # Maximum number of iterations
            vol_old = 0.30 # Initial guess for implied volatility
            for k in range(max_iter):
                # Black-Scholes price and vega
                bs_price = bs(flag, S0, K, T, r, vol_old)
                Cprime = vega(flag, S0, K, T, r, vol old) * 100
                # Function value and update
                C = bs_price - market_price
                vol_new = vol_old - C / Cprime
                # Convergence check
                if abs(vol old - vol new) < tol:</pre>
                    break
                vol_old = vol_new
            return vol old
```

We calculate the implied volatility of a European call option with the following parameters:

- Initial stock price  $(S_0)$ : \$30
- Strike price (*K*): \$28
- Time to maturity (T): 0.2 years
- Risk-free rate (r): 2.5%
- Market price: \$3.97

```
In [3]: # Example parameters
S0, K, T, r = 30, 28, 0.2, 0.025
market_price = 3.97

# Calculate implied volatility
implied_vol_est = implied_vol(S0, K, T, r, market_price, flag='c')
print("Implied Volatility is:", round(implied_vol_est * 100, 2), "%")
```

Implied Volatility is: 53.81 %

# Visualizing Newton's Method for Implied Volatility

To better understand how Newton's Method converges to the implied volatility, we plot the intermediate steps of the calculation. The plot shows:

- 1. The relationship between implied volatility and option price (Black-Scholes curve).
- 2. Iterative adjustments made by Newton's Method to reach the implied volatility.

#### Steps:

- 1. Track intermediate implied volatility and option price values during the iterations.
- 2. Plot these steps on a graph for visualization.
- 3. Highlight the market price and the calculated implied volatility.

```
In [4]: def implied_vol(S0, K, T, r, market_price, flag='c', tol=0.000001):
    """
    Compute the implied volatility of a European Option with intermediate

    Parameters:
    S0 : float : Initial stock price
    K : float : Strike price
    T : float : Time to maturity (in years)
    r : float : Risk-free interest rate
    market_price : float : Observed market price of the option
    flag : str : Option type ('c' for call, 'p' for put)
    tol : float : Tolerance for convergence

Returns:
    float : Implied volatility
    list : x_vals : Intermediate implied volatility values for plotting
    list : y_vals : Corresponding option price values for plotting
    """
    max_iter = 200 # Maximum number of iterations
```

```
vol old = 0.11 # Initial guess for implied volatility
x vals, y vals = [], [] # Lists to store values for visualization
for k in range(max iter):
    # Black-Scholes price and vega
    bs price = bs(flag, S0, K, T, r, vol old)
    Cprime = vega(flag, S0, K, T, r, vol old) * 100
    # Function value and update
    C = bs_price - market_price
    vol new = vol old - C / Cprime
    # Track iteration values
    x_vals.append([vol_old * 100, vol_old * 100]) # Vertical movemen
    y vals.append([0, bs price]) # Horizontal movement
    # Track the next step
    x vals.append([vol old * 100, vol new * 100]) # Step to new poin
    y vals.append([bs price, 0])
    # Convergence check
    if abs(vol_old - vol_new) < tol:</pre>
    vol old = vol new
return vol_old, x_vals, y_vals
```

#### Generate Black-Scholes Prices for Visualization

We compute the Black-Scholes prices for a range of implied volatilities to create a reference curve. This curve represents the theoretical relationship between implied volatility and option price.

```
In [5]: # Parameters
S0, K, T, r, sigma = 30, 28, 0.2, 0.025, 0.3

# Generate Black-Scholes prices
prices, vols = [], []
for sigma in range(1, 125): # Volatility from 1% to 125%
    prices.append(bs('c', S0, K, T, r, sigma / 100))
    vols.append(sigma)

# Market price
market_price = 3.9790765403377035

# Calculate implied volatility and intermediate values
implied vol, x vals, y vals = implied vol(S0, K, T, r, market price, flag
```

## Plotting Newton's Method Progression

We visualize the convergence process of Newton's Method:

1. The Black-Scholes price curve represents the theoretical option prices for different implied volatilities.

2. Intermediate points and steps taken by Newton's Method are plotted to show the adjustment process.

```
In [6]: # Plot setup
        fig, ax = plt.subplots()
        plt.title('Newton-Raphson Method for Option Implied Volatility')
        plt.ylabel('Call Price ($)')
        plt.xlabel('Implied Volatility (%)')
        # Plot Black-Scholes curve and market price
        y1, = ax.plot(vols, prices, label='Black-Scholes Price')
        y3, = ax.plot([54], [market_price], 'bo', label='Market Price') # Market
        y2, = ax.plot([], [], 'r--') # Red dashed line for steps
        y4, = ax.plot([], [], 'ro', label='Calculated Price') # Red points
        y5, = ax.plot([], [], 'go', label='Calculated Implied Volatility') # Gre
y6, = ax.plot([], [], 'g--') # Green dashed line for convergence
        # Animation functions
        def init():
             ax.set xlim(0, 125)
             ax.set_ylim(0, max(prices))
             return y2, y4
        def update(frame):
             # Update intermediate points
             xdata, ydata = x_vals[frame], y_vals[frame]
             if frame % 2 == 0: # Step to new point
                 y2.set data([xdata], [ydata])
                 y4.set data([xdata[1]], [ydata[1]])
                 return y2, y4
             else: # Convergence
                 y6.set data([xdata], [ydata])
                 y5.set data([xdata[1]], [ydata[1]])
                 return y2, y4
        # Create animation
        anim = animation.FuncAnimation(fig, update, frames=len(x_vals),
                                           init func=init, interval=750, repeat=True
        ax.legend(loc='upper left')
        # Render animation
        HTML(anim.to_html5_video())
```



