



# Financial Systems Design Part II

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Finite Difference Method (FDM)

July 2020

# The Big Picture

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- Develop a mathematical model based on tradable assets in the market to calculate price of derivatives
- Model tells you how to value a derivative and hedge/replicate the derivative
- Clients of the bank will come with requests for certain type of new options or the bank will develop new options as investment products for clients
- Option payoff + Model = Option price / risk management

# Outline

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- Black Scholes PDE
- Explicit Finite Difference Method
- Implicit Finite Difference Method
- Crank Nicholson
- Richardson Extrapolation





# Black Scholes PDE

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# Quick Recap

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- Key step in the derivation by BSM is finding a self-financing portfolio growing at a deterministic rate
- This rate must equal the risk free rate in order not to allow arbitrage in the system
- Equating the portfolio growth rate to the risk free rate results in the famous PDE

$$f_t + rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf = 0$$

- This means the price function of the derivative must follow this PDE for the system to be arbitrage free

# Black-Scholes Equation

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- Black-Scholes PDE where  $f$  is price function of the option
- $f(x, t)$  = price at time  $t$  when underlying price is  $x$

$$f_t + rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf = 0$$

- We know the value of an option at maturity when  $t = T$  for all values of  $x$
- What we want to know is  $f(x, 0)$  i.e. the price at current time for all values of  $x$
- In other words, we need to move backwards in time

# Black-Scholes Equation

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- Alternatively, we can perform a change of variables where  $\tau = T - t$

- Then we get  $\frac{\partial f}{\partial t} = \frac{\partial f}{\partial \tau} \frac{\partial \tau}{\partial t} = -\frac{\partial f}{\partial \tau}$

- So we can rewrite the BS PDE as

$$f_{\tau} = rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf$$

- Transforms PDE to a forward equation which is how FDM is presented in most numerical analysis books

# Black-Scholes Equation

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- Taking a vanilla call option as an example

$$f(x, 0) = \max(x - K, 0) \text{ where } K \text{ is the strike}$$

- We already know  $f(x, \tau)$  for  $0 < \tau \leq T$  from your previous course
- However, there are options where we do not have the exact form of  $f(x, \tau)$ , e.g. American options
- Ultimately we want to price American options
- We will first spend time approximating European options since we have the exact solution which allows us to check for the error of the approximation



# Black-Scholes Equation

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- We are looking to use similar approximation methods as was used for ODEs to find  $f(x, \tau)$
- Since we are dealing with PDEs now, we need to extend the methodology to deal with partial derivatives



# Explicit Finite Difference Method

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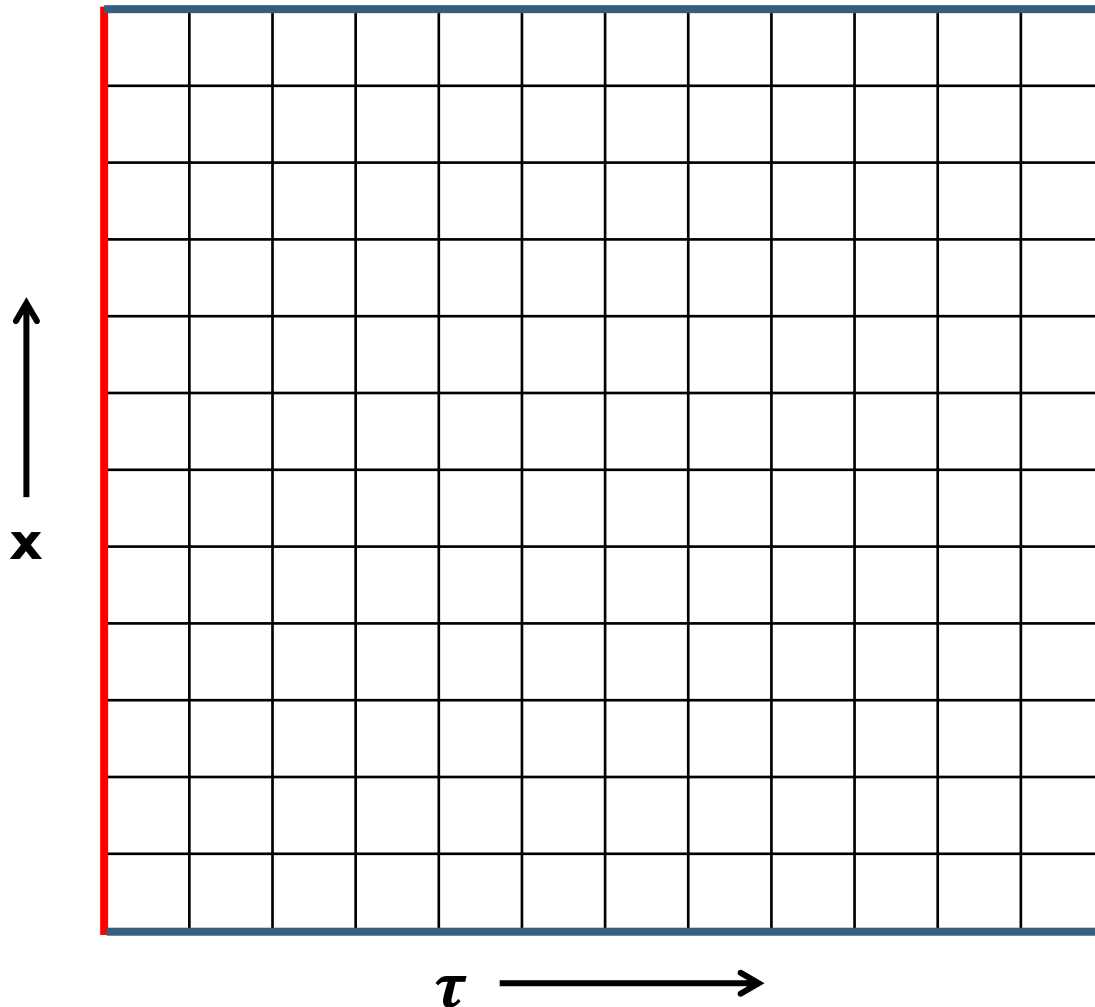
# Explicit Finite Difference Method

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- Moving from a one dimensional problem with ODEs to 2 dimensions now
- Discretize the domain into equally spaced 2D mesh and use the PDE to evolve the solution
- An initial condition is needed to start similar to the Euler method for ODEs
- We also need to know what happens on the boundaries of the mesh i.e. boundary conditions
- This is thus called an **Initial Boundary Problem**

# Explicit Finite Difference Method

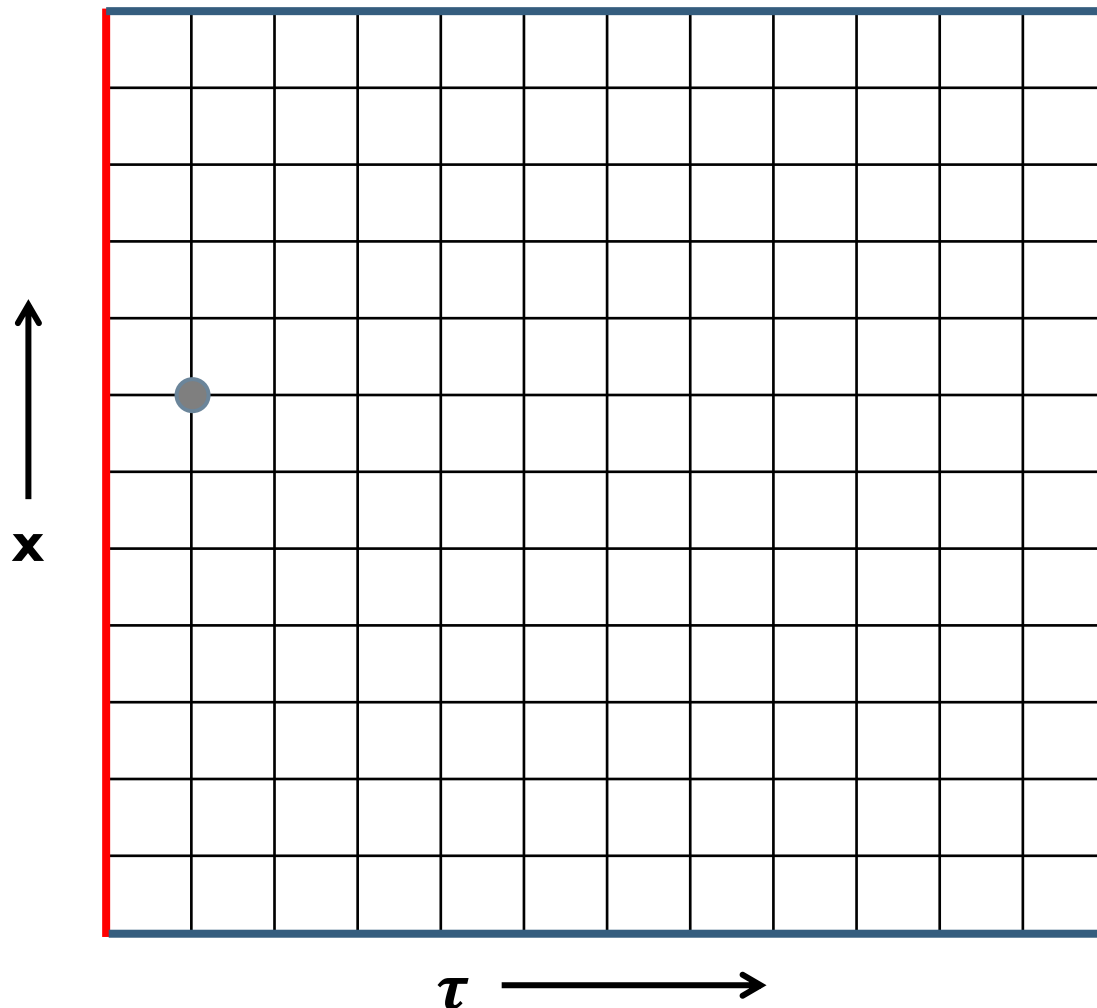
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- Create equally spaced grid/mesh
- Initial boundary condition is the starting line
- We need the solution at the end
- To evolve forward with the PDE, we also need to know what happens at the boundaries

# Explicit Finite Difference Method

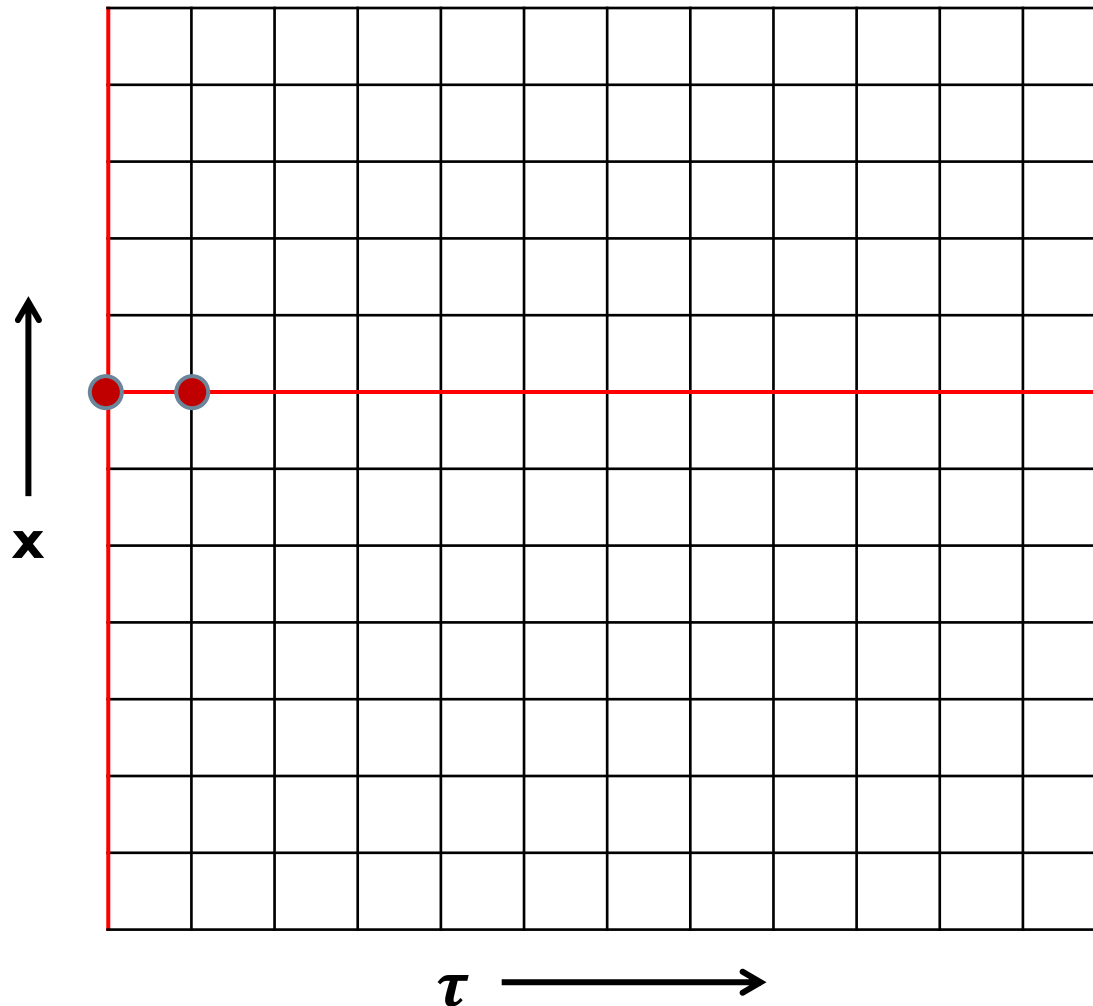
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- Start at  $\tau = 0$  (red line)
- Value of  $f(x, 0)$  which is the value of the option at maturity for all  $x$  is known
- Take a sample point where  $x = 100$  and say this is a call option with strike at 90 so  $f(100, 0) = 10$
- We ultimately want to know  $f(100, T)$  but we need to move in small steps to reduce the error so we start with  $f(100, \Delta\tau)$  which is represented by the grey dot

# Explicit Finite Difference Method

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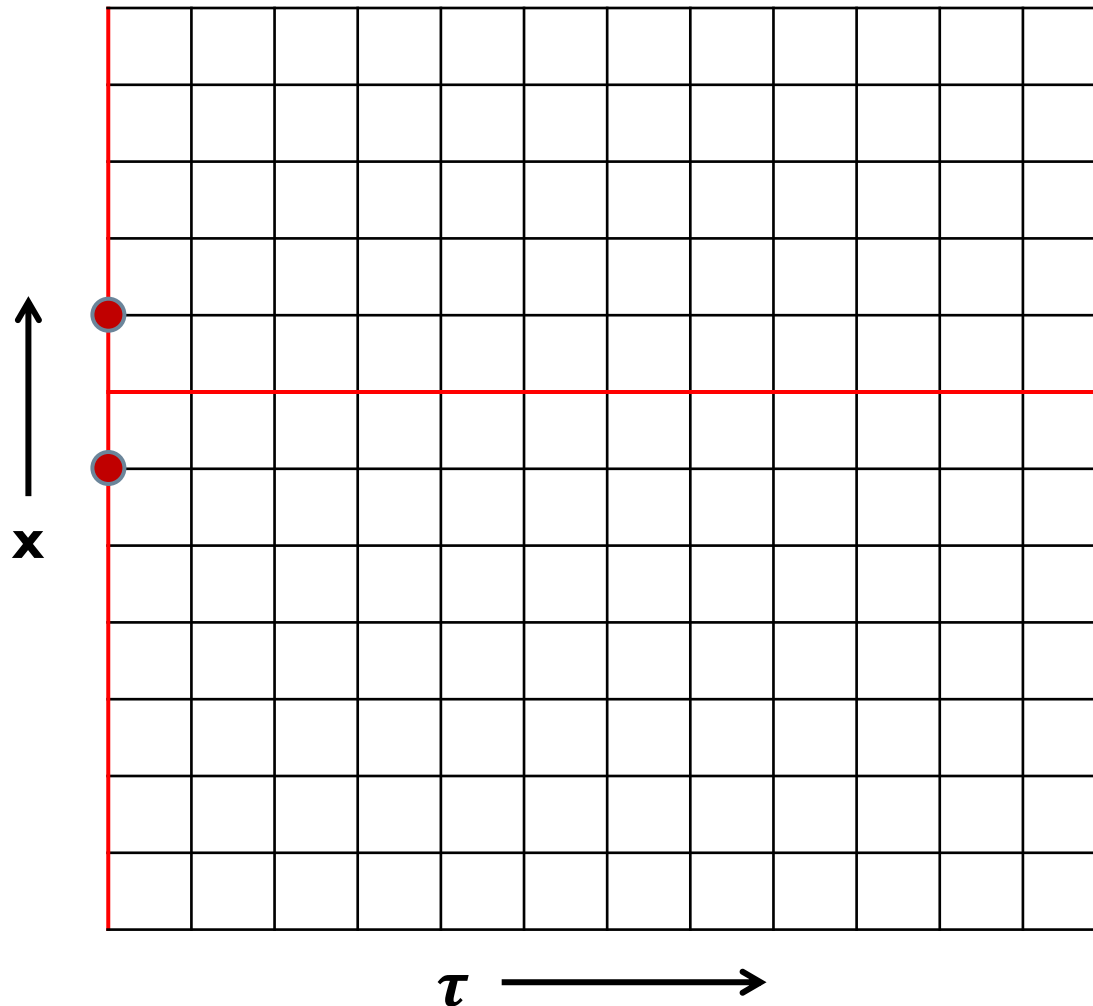
Two points to compute Theta with forward differencing:

$$f_{\tau} = \frac{f(x, \tau + \Delta\tau) - f(x, \tau)}{\Delta\tau}$$



# Explicit Finite Difference Method

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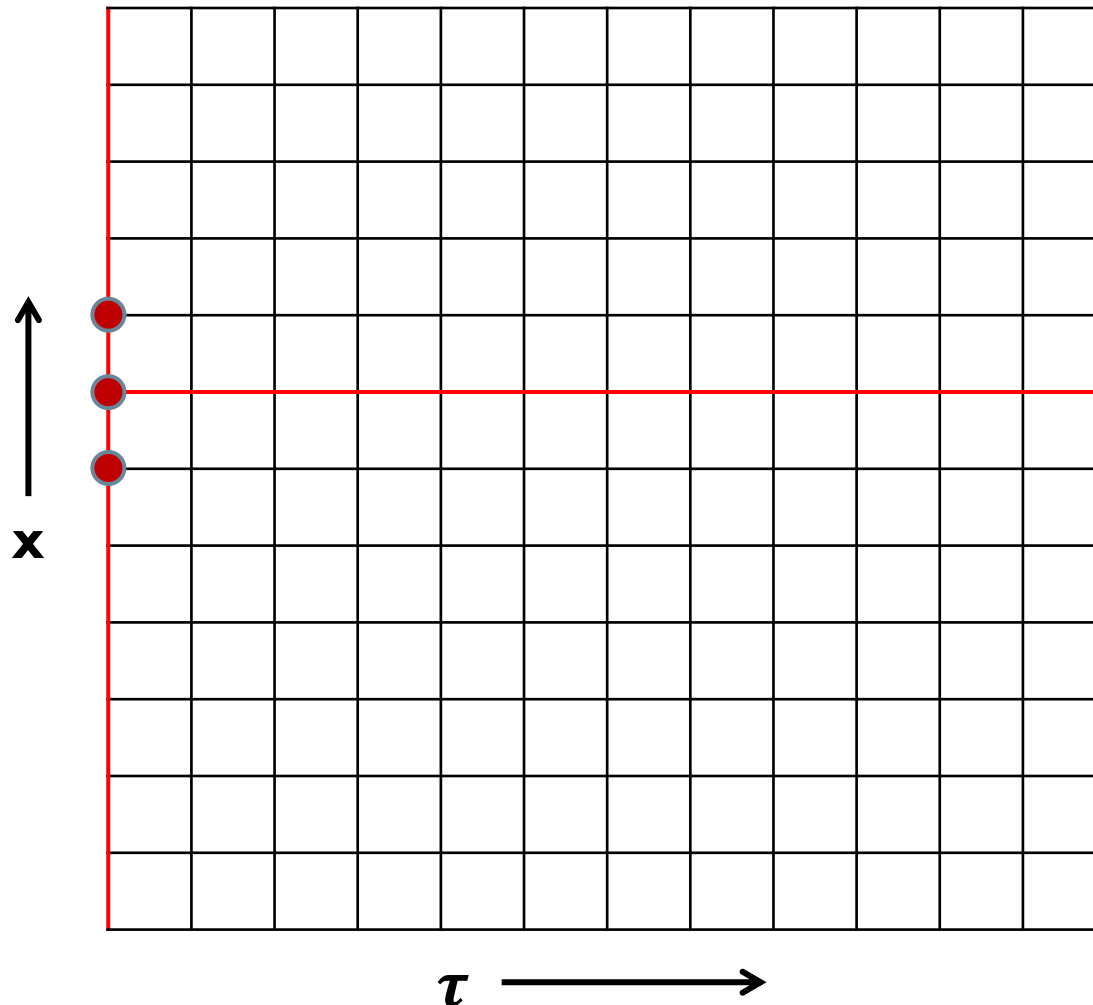


Two points to compute Delta with central differencing:

$$f_x = \frac{f(x+\Delta x, \tau) - f(x-\Delta x, \tau)}{2\Delta x}$$

# Explicit Finite Difference Method

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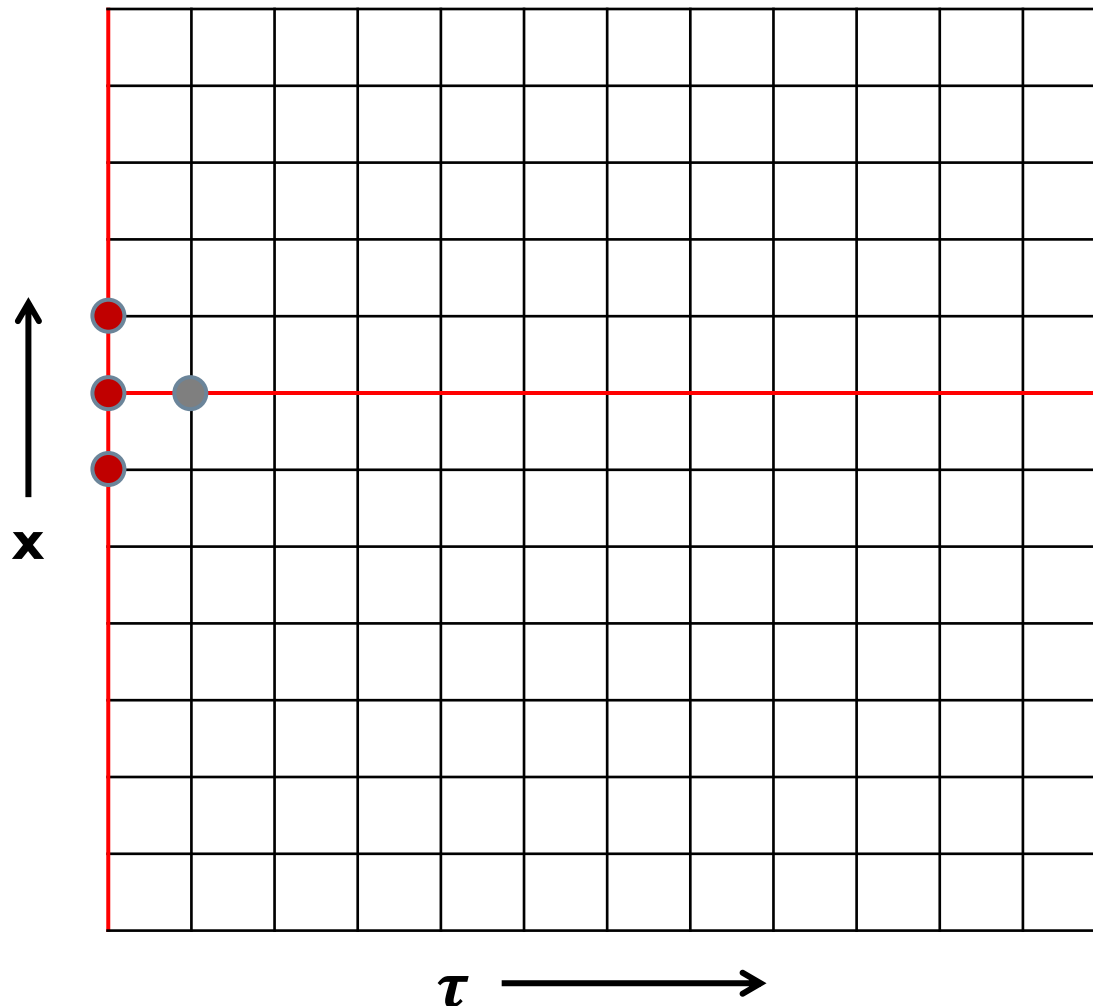


Three points to compute gamma with central differencing:

$$f_{xx} = \frac{f(x+\Delta x, \tau) - 2f(x, \tau) + f(x-\Delta x, \tau)}{\Delta x^2}$$

# Explicit Finite Difference Method

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Calculation of the point in grey only requires those points in red based on the Black Scholes PDE

All red points are known values as it is values of  $f(x, 0)$

# Explicit Finite Difference Method

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- Using central differencing for Delta and Gamma
- Using forward differencing for Theta
- $V_i^k = f(\tau = \tau_0 + k\Delta\tau, x = x_0 + i\Delta x)$  i.e. price at discretized time k & asset price i
- Similarly,  $x_i = x_0 + i\Delta x$
- $f_\tau = rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf$
- $\frac{V_i^{k+1} - V_i^k}{\Delta\tau} = rx_i \frac{V_{i+1}^k - V_{i-1}^k}{2\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{V_{i+1}^k - 2V_i^k + V_{i-1}^k}{\Delta x^2} - rV_i^k$

# Explicit Finite Difference Method

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- Rearrange the equation so that all the derivative prices at the next time step is on the LHS and those in the current time step is on the RHS
- $$V_i^{k+1} = \left( \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} - \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} \right) V_{i-1}^k + \left( 1 - \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} - r \Delta \tau \right) V_i^k + \left( \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_{i+1}^k$$

# Initial Condition

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□ For vanilla options:

□ Call:  $v_0 = f(\tau = 0) = \max(x - K, 0)$

□ Put:  $v_0 = f(\tau = 0) = \max(K - x, 0)$



# Boundary Conditions

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- We also need boundary conditions in  $x$  for similar reasons as we did for 2<sup>nd</sup> order ODEs
- Our boundaries are  $x = 0$  and  $x = \infty$  (large values)
- Plug in  $x = 0$  to the Black Scholes PDE

$$f_{\tau} = rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf$$

- The  $x$  derivatives go to zero:  $f_{\tau} = -rf$ 
  - ▣ This is called a **natural boundary condition**
- At  $x = \infty$  we usually just assume  $f_{xx} = 0$

# Loops or Matrices

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- Can be programmed using loops or matrices
- Built in packages with Python or Matlab makes programming with matrices much easier than loops
- Let's try both and see which is easier to programme

# In-Class Exercise

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- Let's price a vanilla call option using loops
- Assume  $r = 3\%$ ,  $\sigma = 30\%$ ,  $K = \$100$ ,  $T = 1$
- Let's use 2 times of the strike as the upper bound for the mesh
- Try  $\Delta x = 1$  i.e. 200 steps
- And  $\Delta \tau = 0.00025$  i.e. 4,000 steps
- Plot the option price  $v$  vs  $x$

# In-Class Exercise

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- Remember that

$$f_\tau = rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf$$

$$f_\tau \approx \frac{V^{k+1} - V^k}{\Delta\tau}$$

So

$$V^{k+1} \approx V^k + \Delta\tau f_\tau$$

- At  $x = 0$ , we have  $V_0^{k+1} = (1 - r\Delta t)V_0^k$
- At large  $x$ , we have  $V_N^{k+1} = 2V_{N-1}^{k+1} - V_{N-2}^{k+1}$

# In-Class Exercise

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- Now we try with matrices

$$\begin{aligned} V_i^{k+1} &= \left( \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} - \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} \right) V_{i-1}^k + \left( 1 - \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} - r \Delta \tau \right) V_i^k \\ &+ \left( \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_{i+1}^k \end{aligned}$$

- These equations naturally form a tri-diagonal matrix
- At  $x = 0$ , we have  $V_0^{k+1} = (1 - r \Delta t) V_0^k$
- At large  $x$ , we have  $V_N^{k+1} = 2V_{N-1}^{k+1} - V_{N-2}^{k+1}$

# In-Class Exercise

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$$\begin{pmatrix} V_0^{k+1} \\ V_1^{k+1} \\ \vdots \\ V_{n-1}^{k+1} \\ V_n^{k+1} \end{pmatrix} = A \begin{pmatrix} V_0^k \\ V_1^k \\ \vdots \\ V_{n-1}^k \\ V_n^k \end{pmatrix}$$

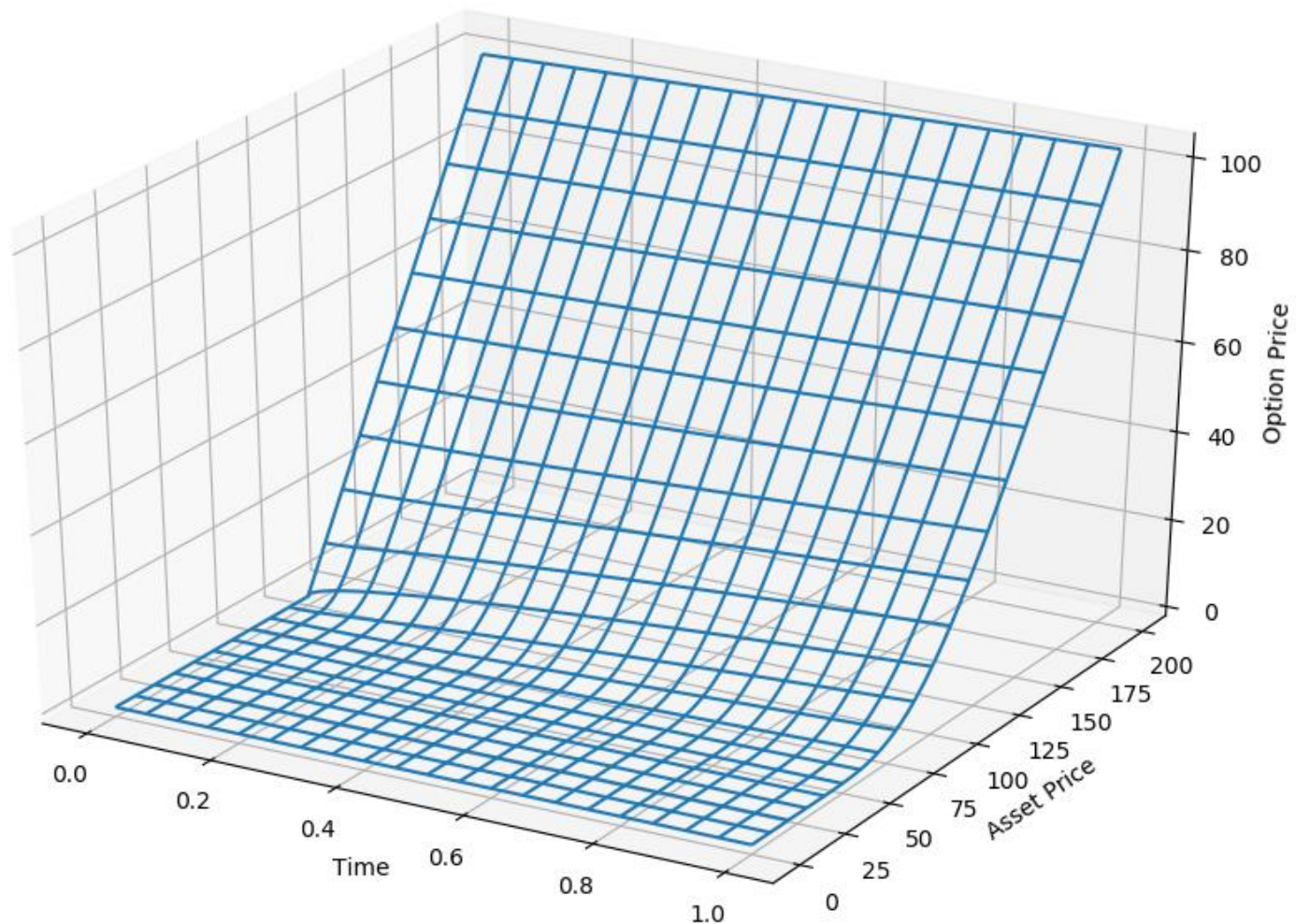
$A =$

$$\begin{bmatrix} (1 - r\Delta t) & 0 & 0 & \dots & 0 \\ \left(\frac{1}{2}\sigma^2 x_1^2 \frac{\Delta\tau}{\Delta x^2} - \frac{1}{2}rx_1 \frac{\Delta\tau}{\Delta x}\right) & \left(1 - \sigma^2 x_1^2 \frac{\Delta\tau}{\Delta x^2} - r\Delta\tau\right) & \left(\frac{1}{2}rx_1 \frac{\Delta\tau}{\Delta x} + \frac{1}{2}\sigma^2 x_1^2 \frac{\Delta\tau}{\Delta x^2}\right) & \dots & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \left(\frac{1}{2}\sigma^2 x_{n-1}^2 \frac{\Delta\tau}{\Delta x^2} - \frac{1}{2}rx_{n-1} \frac{\Delta\tau}{\Delta x}\right) & \left(1 - \sigma^2 x_{n-1}^2 \frac{\Delta\tau}{\Delta x^2} - r\Delta\tau\right) & \left(\frac{1}{2}rx_1 \frac{\Delta\tau}{\Delta x} + \frac{1}{2}\sigma^2 x_{n-1}^2 \frac{\Delta\tau}{\Delta x^2}\right) \\ 0 & 0 & \dots & ? & ? \end{bmatrix}$$



# Evolution of Option Price Curve

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# In-Class Exercise

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- Notice we are using much more steps for the time variable than the asset price variable
- What if we try a more balanced ratio?
- Try  $\Delta x = 1$  i.e. 200 steps
- And  $\Delta \tau = 0.0025$  i.e. 400 steps

# Stability of Explicit Method

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- There are stability issues with the explicit method where a small error can get magnified with each time step
- The behavior of the error can be analyzed by Von Neumann stability analysis which works for linear PDEs
- We will not go into the mathematics which is quite involved and simply state the condition that provides stability
- The condition is  $\Delta\tau < \frac{1}{N_x^2 \sigma^2}$  where  $N_x$  is number of steps for  $x$
- With  $N_x = 200$ ,  $\sigma = 30\%$ , it means we need  $\Delta\tau < \frac{1}{3600}$

# Stability of Explicit Method

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- The stability condition violation produces negative probabilities
- Notice that the condition imposes high computational cost
- If we need to improve accuracy by doubling the number of asset steps then the number of time times must increase by 4 times
- This causes total computational time to increase 8 folds

# In-Class Exercise

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- Add the appropriate modification to the Explicit FDM from the last exercise to determine a suitable  $\Delta\tau$  to use which ensures the stability condition is not violated

# Other Boundary Conditions

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- The boundary conditions in the preceding example is generic to most derivatives
- There are also other ways to write simpler boundary conditions specific for vanilla call and put options
- For call options, we can also use  $V = 0$  when  $x = 0$  and  $V = S - Ke^{-rt}$  for large  $x$
- Similarly, we can also use  $V = 0$  for large  $x$  when it comes to put options and  $V = Ke^{-rt}$  when  $x = 0$





# Implicit Finite Difference Method

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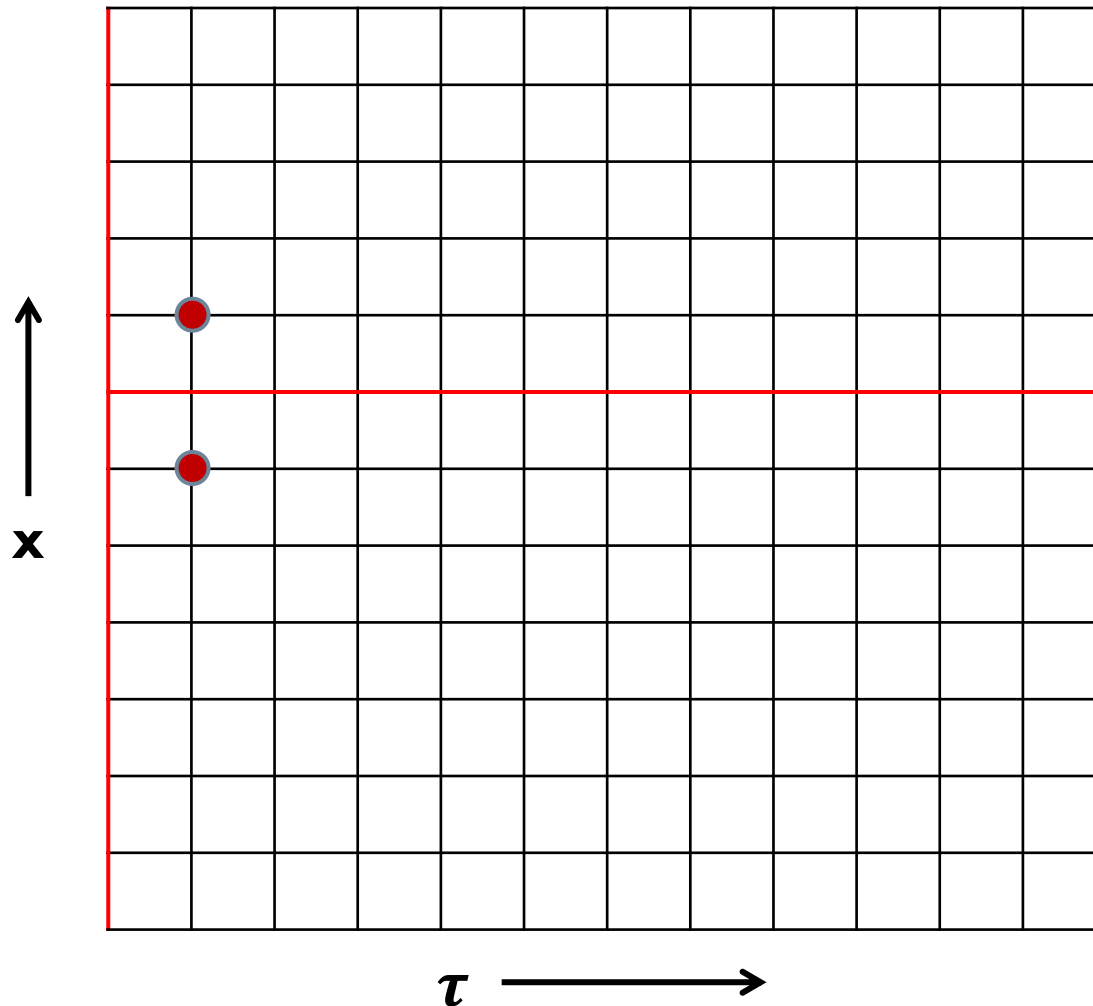
# Explicit vs. Implicit

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- For even a simple problem we need a huge number of time steps with the **EXPLICIT** method
- We can achieve unconditional stability if we choose to approximate the x derivatives at a forward time step
  - ▣ Similar to the homework problem for Euler method where we used  $\hat{y}_{i+1}$  instead
- This is called the **IMPLICIT** method

# Implicit Finite Difference Method

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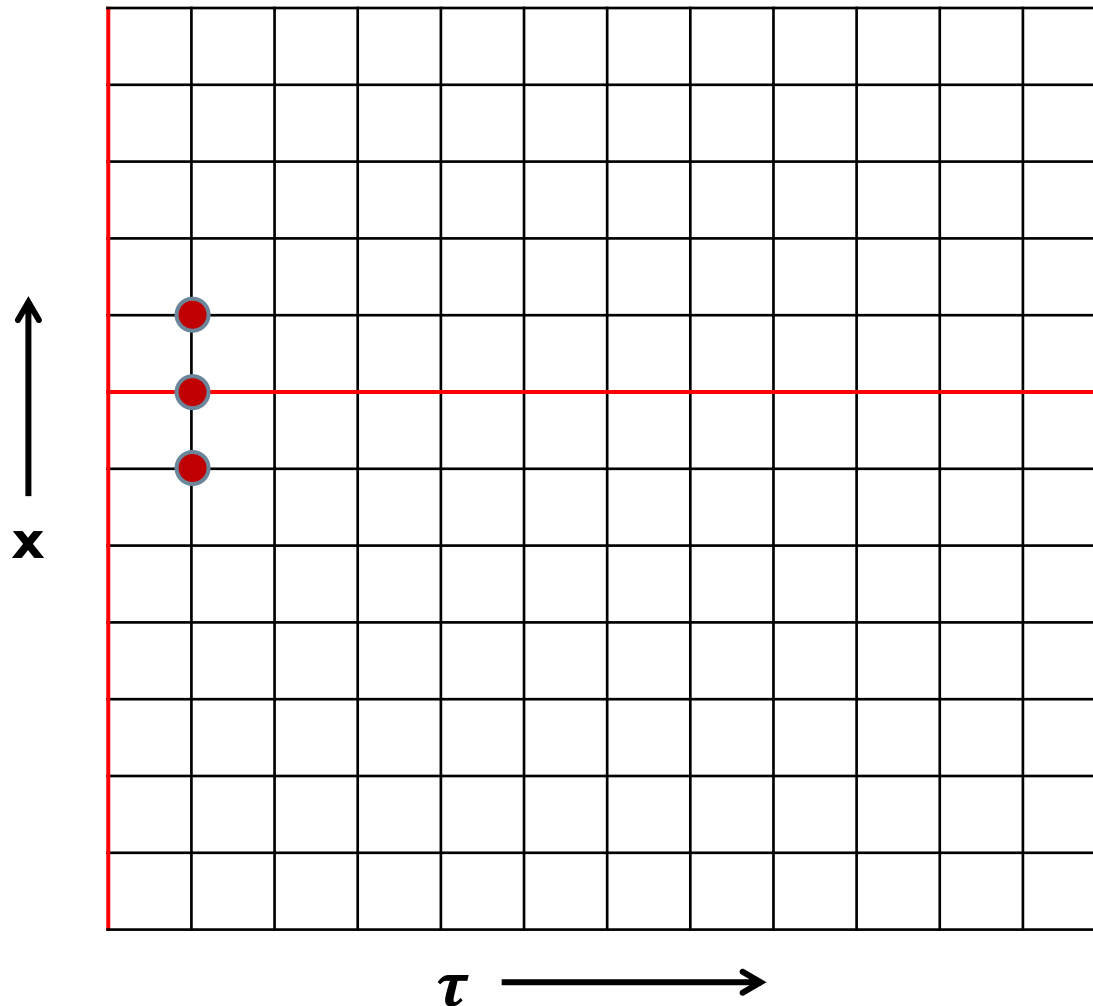


Two points to  
compute Delta with  
central differencing:

$$f_x = \frac{f(x+\Delta x, \tau+\Delta \tau) - f(x-\Delta x, \tau+\Delta \tau)}{2\Delta x}$$

# Implicit Finite Difference Method

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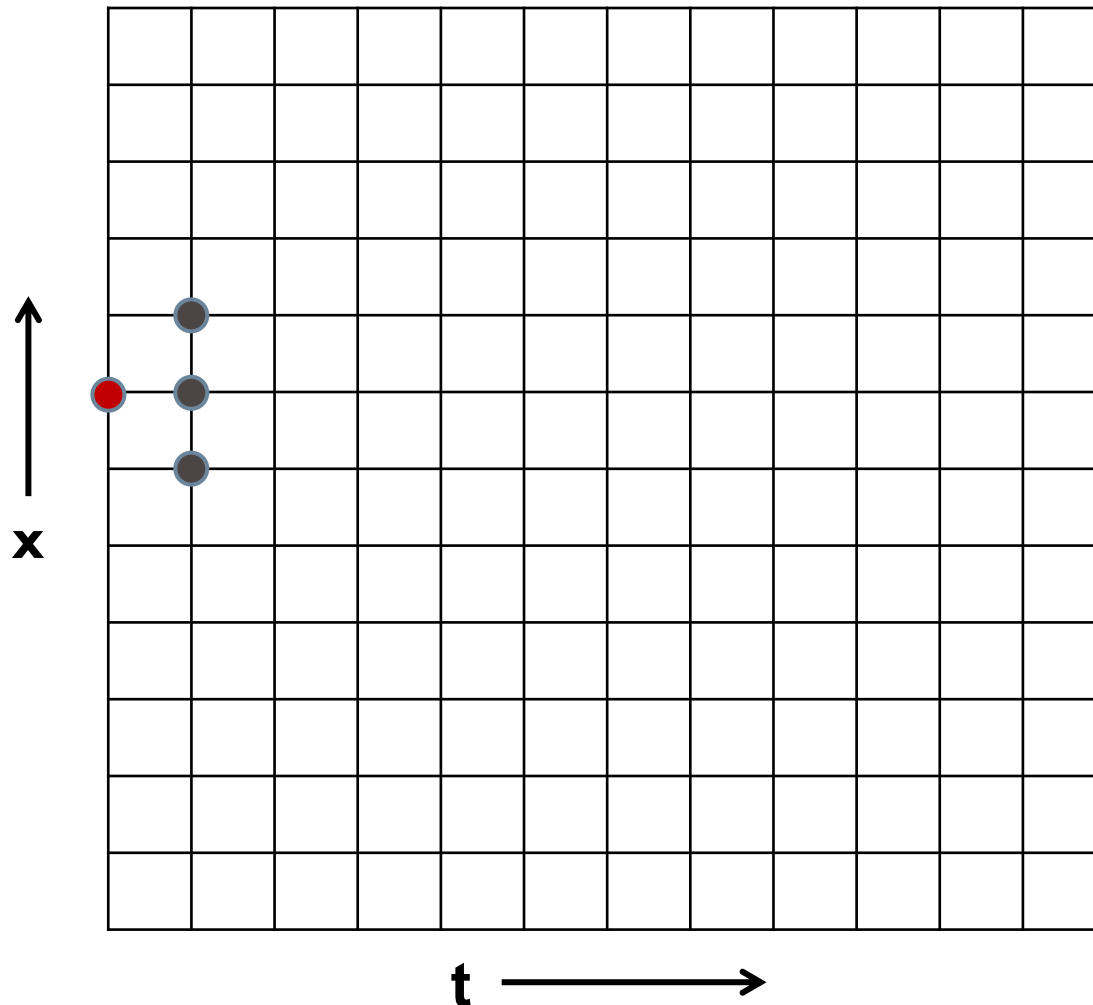


Three points to compute gamma with central differencing:

$$f_{xx} = \frac{f(x+\Delta x, \tau+\Delta \tau) - 2f(x, \tau+\Delta \tau) + f(x-\Delta x, \tau+\Delta \tau)}{\Delta x^2}$$

# Implicit Finite Difference Method

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- Form an equation of 3 unknown points in grey using the known point in red
- Boundary conditions supply missing equations for system to have a solution (recall linear algebra)
- Solve system of linear equations
- Recall 2<sup>nd</sup> Order ODE

# Implicit Finite Difference Method

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- The main difference is using the values of  $V$  at the next time step  $i+1$  to compute the  $x$  derivatives

$$\begin{aligned} f_\tau &= rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf \\ \frac{V_i^{k+1} - V_i^k}{\Delta\tau} &= rx_i \frac{V_{i+1}^{k+1} - V_{i-1}^{k+1}}{2\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{V_{i+1}^{k+1} - 2V_i^{k+1} + V_{i-1}^{k+1}}{\Delta x^2} - rV_i^{k+1} \\ &\left( \frac{1}{2} rx_i \frac{\Delta\tau}{\Delta x} - \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) V_{i-1}^{k+1} + \left( 1 + r\Delta\tau + \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) V_i^{k+1} \\ &+ \left( -\frac{1}{2} rx_i \frac{\Delta\tau}{\Delta x} - \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) V_{i+1}^{k+1} = V_i^k \end{aligned}$$

# Implicit FDM

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- Same conditions at the boundaries of  $x$
- At  $x = 0$ , we have  $V_0^{k+1} = (1 - r\Delta t)V_0^k$
- At large  $x$ , we have  $V_N^{k+1} = 2V_{N-1}^{k+1} - V_{N-2}^{k+1}$
- These equations naturally form a matrix equation

$$A\vec{v}_{k+1} = \vec{v}_k$$

- Both conditions can be build into the matrix e.g.

$$\begin{pmatrix} 1 & & & & \\ \frac{1}{1-r\Delta t} & \cdots & & & 0 \\ \vdots & \ddots & & & \vdots \\ 0 & \cdots & 1 & -2 & 1 \end{pmatrix} \vec{v}_{k+1} = \begin{pmatrix} v_0^k \\ \vdots \\ v_{N-1}^k \\ 0 \end{pmatrix}$$

# Stability of Implicit Method

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- The implicit method provides unconditional stability
- Computational cost comes in the form of solving the system of linear equations



# In-Class Exercise

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- Same example to implement with the implicit method
- Assume  $r = 3\%$ ,  $\sigma = 30\%$ ,  $K = \$100$ ,  $T = 1$
- Let's use 2 times of the strike as the upper bound for the mesh
- Try  $\Delta x = 1$  i.e. 200 steps
- And  $\Delta \tau = 0.0025$  i.e. 400 steps
- Plot the option price  $v$  vs  $x$

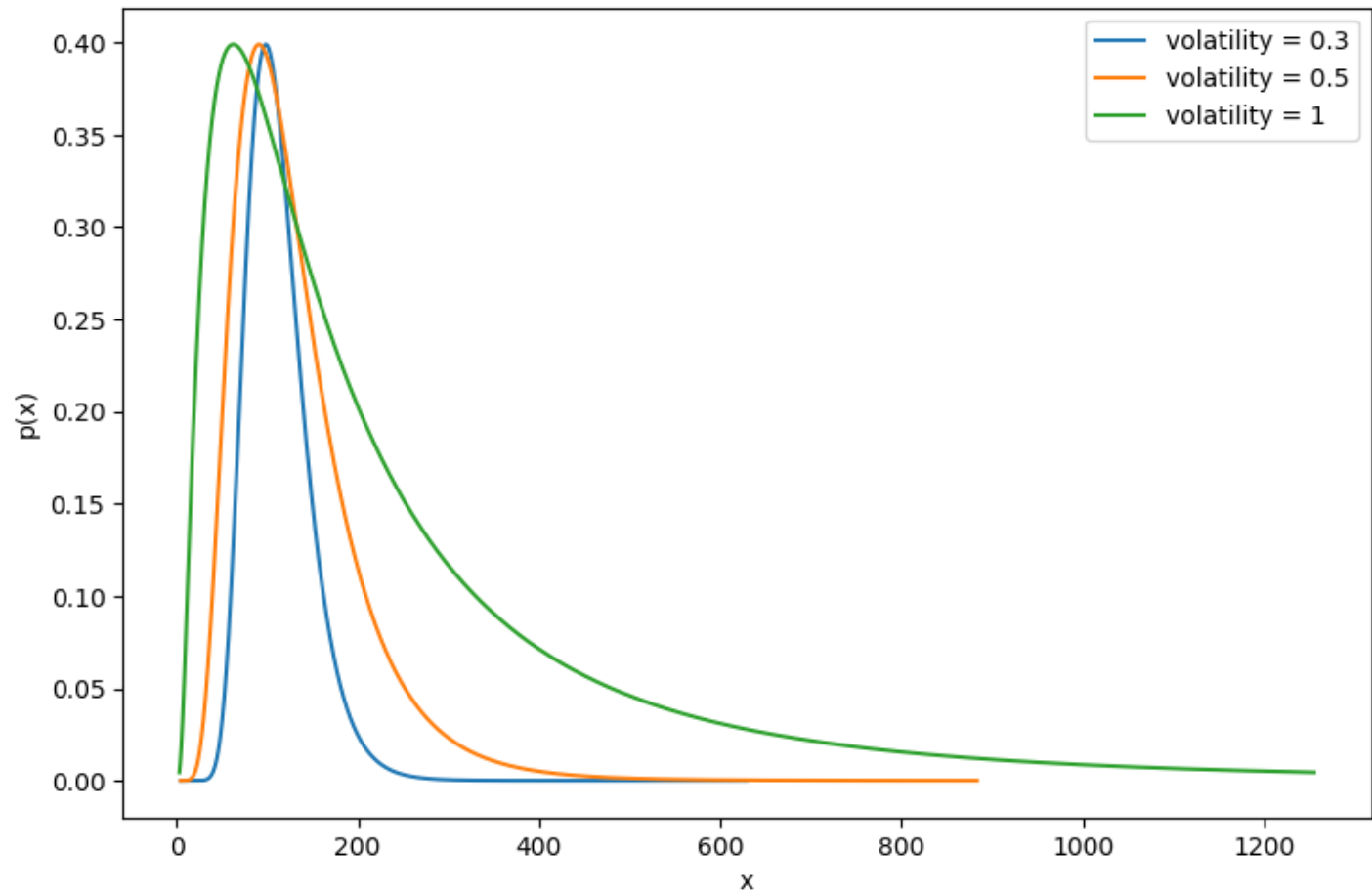
# In-Class Exercise

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- Back to the same example
- Try increasing volatility to 70%
- What happens to the error?
- Does the error reduce if we reduce the size of the steps?
- What is wrong?

# Lognormal Distribution

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# Upper Bound for $x$

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- One way to automate the solution is to use the inverse CDF to solve for a suitable upper bound
- E.g. Solve for the  $x$  value that would cover 99% of the distribution
- In the example with 70% volatility, the  $x$  value will be  $\sim 400$



# Crank Nicolson

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# Order of Error

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- Both the Explicit and Implicit method have local truncation error of  $O(\Delta t^2, \Delta t \Delta x^2)$  and global error of  $O(\Delta t, \Delta x^2)$
- The stability requirement for Explicit method requires large number of time steps
- The form of the Implicit method requires solving a linear system of equations
- In other words, both have its costs
- Can we improve the error without much added cost?

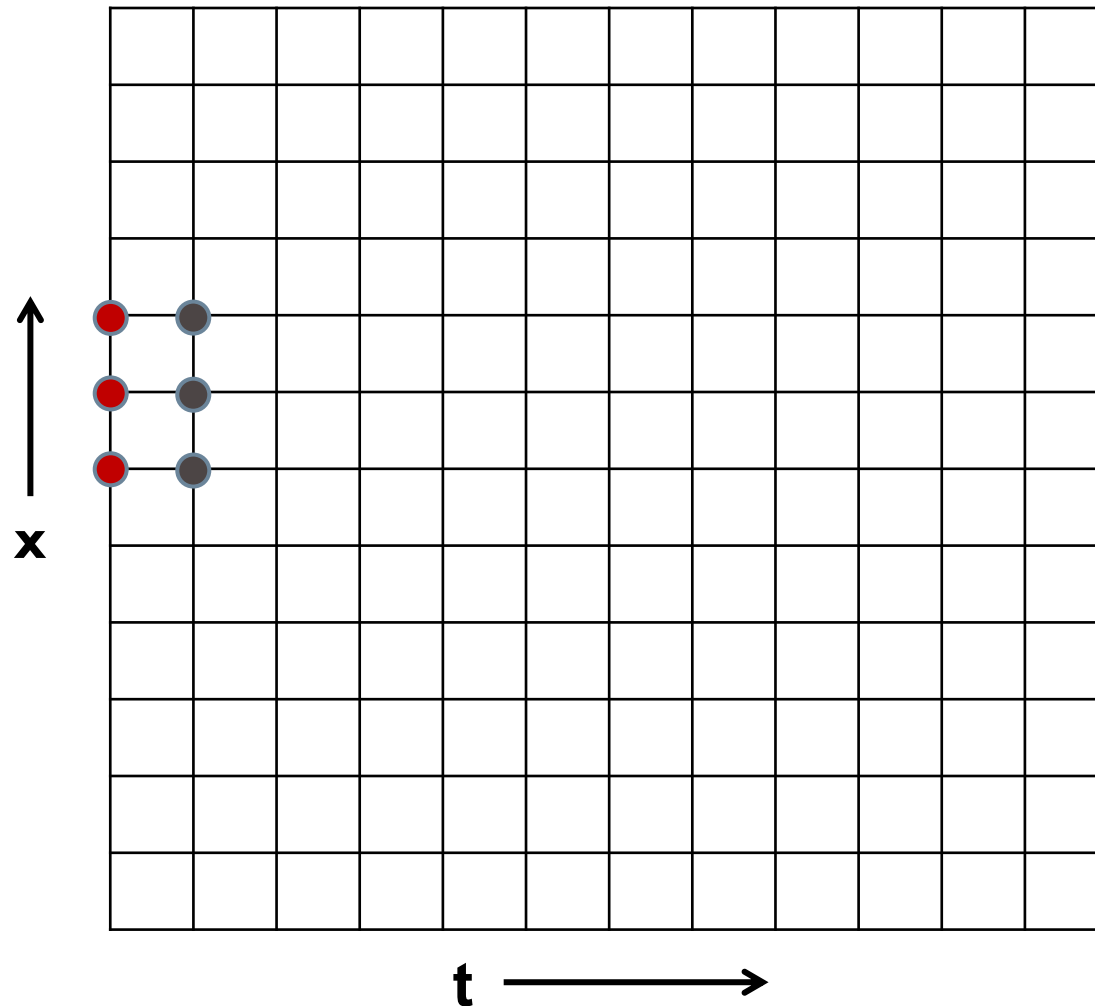
# Crank Nicholson

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- Can be written as a 2<sup>nd</sup> Order Runge Kutta method
- An average of the implicit and explicit method
- It also provides unconditional stability
- The key benefit is that the error is  $O(\Delta t^2, \Delta x^2)$
- Computational cost is only marginally higher than the Implicit method

# Crank Nicolson

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- We use all 6 points with the Crank Nicolson method



# Crank Nicolson

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- $f_\tau = rx f_x + \frac{1}{2} \sigma^2 x^2 f_{xx} - rf$
- $\frac{V_i^{k+1} - V_i^k}{\Delta \tau} = rx_i \frac{V_{i+1}^k - V_{i-1}^k}{2\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{V_{i+1}^k - 2V_i^k + V_{i-1}^k}{\Delta x^2} - rV_i^k$
- In matrix form, we write Explicit FDM as  $f_\tau = A \overrightarrow{v_\tau}$  which is rearranged to  $\overrightarrow{v_{\tau+1}} = (I + \Delta \tau A) \overrightarrow{v_\tau}$  since  $f_\tau = \frac{\overrightarrow{v_{\tau+1}} - \overrightarrow{v_\tau}}{\Delta \tau}$  where  $I$  is the identity matrix
- For Implicit method, it will be  $f_\tau = A \overrightarrow{v_{\tau+1}}$  which is rearranged to  $(I - \Delta \tau A) \overrightarrow{v_{\tau+1}} = \overrightarrow{v_\tau}$

# Crank Nicolson

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- Crank Nicolson is  $f_\tau = \frac{1}{2} A \overrightarrow{v_{t+1}} + \frac{1}{2} A \overrightarrow{v_t}$  which rearranges to  $(I - \frac{1}{2} \Delta\tau A) \overrightarrow{v_{t+1}} = (I + \frac{1}{2} \Delta\tau A) \overrightarrow{v_t}$

# Crank Nicolson

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## □ Explicit FDM

$$\begin{aligned} & V_i^{k+1} \\ &= \left( \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} - \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} \right) V_{i-1}^k + \left( 1 - r \Delta \tau - \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_i^k \\ &+ \left( \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_{i+1}^k \end{aligned}$$

## □ Implicit FDM

$$\begin{aligned} & \left( \frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} - \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_{i-1}^{k+1} + \left( 1 + r \Delta \tau + \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_i^{k+1} \\ &+ \left( -\frac{1}{2} r x_i \frac{\Delta \tau}{\Delta x} - \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta \tau}{\Delta x^2} \right) V_{i+1}^{k+1} = V_i^k \end{aligned}$$

# Crank Nicolson

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$$\begin{aligned} \frac{V_i^{k+1} - V_i^k}{\Delta\tau} = & \frac{1}{2} \left[ r x_i \frac{V_{i+1}^k - V_{i-1}^k}{2\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{V_{i+1}^k - 2V_i^k + V_{i-1}^k}{\Delta x^2} - r V_i^k \right] + \\ & \frac{1}{2} \left[ r x_i \frac{V_{i+1}^{k+1} - V_{i-1}^{k+1}}{2\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{V_{i+1}^{k+1} - 2V_i^{k+1} + V_{i-1}^{k+1}}{\Delta x^2} - r V_i^{k+1} \right] \end{aligned}$$

Rearranges to

$$\begin{aligned} \frac{1}{2} \left( \frac{1}{2} r x_i \frac{\Delta\tau}{\Delta x} - \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) V_{i-1}^{k+1} + \left( 1 + \frac{1}{2} \left( r \Delta\tau + \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) \right) V_i^{k+1} + \\ \frac{1}{2} \left( -\frac{1}{2} r x_i \frac{\Delta\tau}{\Delta x} - \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) V_{i+1}^{k+1} = \frac{1}{2} \left( \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} - \frac{1}{2} r x_i \frac{\Delta\tau}{\Delta x} \right) V_{i-1}^k + \\ \left( 1 - \frac{1}{2} \left( \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} + r \Delta\tau \right) \right) V_i^k + \frac{1}{2} \left( \frac{1}{2} r x_i \frac{\Delta\tau}{\Delta x} + \frac{1}{2} \sigma^2 x_i^2 \frac{\Delta\tau}{\Delta x^2} \right) V_{i+1}^k \end{aligned}$$

# In-Class Exercise

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- Same example to implement with the implicit method
- Assume  $r = 3\%$ ,  $\sigma = 30\%$ ,  $K = \$100$ ,  $T = 1$
- Let's use 2 times of the strike as the upper bound for the mesh
- Try  $\Delta x = 1$  i.e. 200 steps
- And  $\Delta \tau = 0.0025$  i.e. 400 steps
- Plot the option price  $v$  vs  $x$

# Choice of FDM Type

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- Order of the error
- Stability restrictions
- Ease of programming
- Flexibility to boundary conditions and decision points

# In-Class Exercise

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- Use the Crank Nicolson Method to price the put option
- Assume  $r = 3\%$ ,  $\sigma = 40\%$ ,  $K = \$90$ ,  $T = 2$ ,
- Create a function to compute the actual put price using the Black Scholes formula to check on the error
- Previously it was an At-The-Money (ATM) option that was being priced i.e. strike price = spot price
- Now assume  $x_0 = 100$
- Experiment with the step sizes and boundaries for  $x$



# Richardson Extrapolation

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# Richardson Extrapolation

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- Recall Richardson Extrapolation with 1 dimension
- Suppose we are using an expression  $g(h)$  with error  $ch^n$  to estimate a quantity  $G$
- We know  $g(\cdot)$  at two different step sizes  $h_1$  and  $h_2$ :

$$g(h_1) = G + ch_1^n + O(h_1^{n+1})$$

$$g(h_2) = G + ch_2^n + O(h_2^{n+1})$$

- We combine these two equations to eliminate the error term, obtaining:

$$\hat{G} = \frac{\left(\frac{h_1}{h_2}\right)^n g(h_2) - g(h_1)}{\left(\frac{h_1}{h_2}\right)^n - 1}$$

# Richardson Extrapolation

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- Applying Richardson Extrapolation to the Explicit FDM

$$\hat{V}_1 = V + c_1 \Delta t_1 + c_2 \Delta x_1^2 + O(\Delta t^2, \Delta x^3)$$

$$= V + \Delta x_1^2 \left( c_1 \frac{\Delta t_1}{\Delta x_1^2} + c_2 \right) + O(\Delta t^2, \Delta x^3)$$

$$\hat{V}_2 = V + c_1 \Delta t_2 + c_2 \Delta x_2^2 + O(\Delta t^2, \Delta x^3)$$

$$= V + \Delta x_2^2 \left( c_1 \frac{\Delta t_2}{\Delta x_2^2} + c_2 \right) + O(\Delta t^2, \Delta x^3)$$

- Choosing  $\frac{\Delta t_1}{\Delta x_1^2} = \frac{\Delta t_2}{\Delta x_2^2}$  we get a better solution with the

$$\text{estimate } \hat{V}_R = \frac{\Delta x_2^2 \hat{V}_1 - \Delta x_1^2 \hat{V}_2}{\Delta x_2^2 - \Delta x_1^2} + O(\Delta t^2, \Delta x^3)$$



# The Greeks

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# Calculating Greeks with FDM

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- The Greeks are essential information in risk management of derivative portfolios
- The Greeks of a portfolio is a linear combination of the Greeks of the individual positions
- Delta:  $\frac{\partial C}{\partial x} = N(d_1)$  and  $\frac{\partial P}{\partial x} = N(d_1) - 1$
- Gamma:  $\frac{\partial^2 C}{\partial x^2} = \frac{\partial^2 P}{\partial x^2} = \frac{N'(d_1)}{x\sigma\sqrt{\tau}}$
- Theta:  $\frac{\partial C}{\partial t} = -\frac{xN'(d_1)\sigma}{2\sqrt{\tau}} - rKe^{-r\tau}N(+d_2)$

# Delta hedging

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- Imagine you are a trader who sold a call option to a client and now you need to hedge the risk exposure
- Ignoring bid/ask spreads, on day 1 you receive the option premium equal to the value of the option
- If the underlying price moves up, the value of the option moves up and your liability goes up
- How do you hedge this risk?

# Delta hedging

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- If the underlying price moves up 1 unit, the option price should go up by  $\frac{\partial C}{\partial x}$
- If you buy  $\frac{\partial C}{\partial x}$  units of shares then the value of the shares you own will move up in the same amount as the option
- This is essentially Delta hedging where you try to adjust the portfolio to be Delta neutral
- But there are some things to note

# Delta hedging

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- Buying the shares will require financing which generates additional cost and that cost is factored into the option premium that you receive
- The Delta does not stay constant so similar to the problem you encounter with Euler method, there will be errors
- For example, as the underlying price moves up, the Delta moves up which requires you to buy more shares to keep up

# Delta hedging

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- Not a problem in the Black Scholes world but a problem in the real world
- In the case, where you are short the call, you are “chasing” the market by having to buy more shares as prices move up which means the “errors” cost you PnL
- This happens when you are essentially short Gamma and the “errors” that build up must be factored into the option price and is linked to the volatility of the underlying



# Delta hedging

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- In the reverse case where the client sells you the call then you are selling the shares into rising prices which earns you PnL
- The question is whether the profits that accumulate is enough to offset the decay in option value as Theta is negative (remember you paid for the option)
- This is sometimes called Gamma Scalping as you are long Gamma in this case

# In Class Exercise

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- FDM provides an easy way to calculate the Greeks with a grid of option prices for differencing technique
- Modify the Crank Nicolson cell to compute the Delta, Gamma and Theta for the same call option
- 1-year call option with strike at 100
- Volatility of the underlying is 30%, interest rates are 3% and current price of the underlying is 100 i.e.  $x_0 = 100$

# In Class Exercise

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- Delta:  $f_x = \frac{f(x_0 + \Delta x, T) - f(x_0 - \Delta x, T)}{2\Delta x}$
- Gamma:  $f_{xx} = \frac{f(x_0 + \Delta x, T) - 2f(x_0, T) + f(x_0 - \Delta x, T)}{\Delta x^2}$
- Theta:  $f_\tau = \frac{f(x_0, T) - f(x_0, T - \Delta \tau)}{\Delta \tau}$