The Derivation: From SDE to Python Code

Objective: Solve the Ornstein-Uhlenbeck Stochastic Differential Equation (SDE) to find the formula for $X_{t+\Delta t}$ given X_t.

1. The Continuous "Physics" (The SDE)

We start with the Ornstein-Uhlenbeck equation, which models a mean-reverting process (like a rubber band pulling the price back to a center).

$$dX_t = \theta(\mu - X_t)dt + \sigma dW_t$$

- dX_t: The tiny change in the spread over a tiny time dt.
- θ: The Mean Reversion Rate. How strong is the rubber band? (High θ = snaps back fast).
- μ: The Long-Term Mean. Where is the rubber band anchored?
- X_t: The current value of the spread.
- σdW_t: The Noise. dW_t is a random shock (Brownian Motion).

The "chemistry intuition"

- $\theta(\mu - X_t)dt$ (The Drift Term): This is exactly like a first-order rate law. If X_t is the concentration of a reactant, θ is the "rate constant" that pulls the concentration back toward the equilibrium value μ. The further you are from μ, the stronger the "pull.
- σdW_t (The Diffusion Term): This represents "white noise" or thermal fluctuations. σ is the volatility (strength of the noise), and dW_t is the increment of a Wiener process (Brownian motion).

2. Rearranging for Solution

We want to solve for X_t. First, let's rearrange the terms to look like a standard linear Ordinary Differential Equation (ODE). Move the X_t term to the left:

$$dX_t + \theta X_t dt = \theta\mu dt + \sigma dW_t$$

3. The "Integrating Factor" Trick

This is a standard ODE technique. We want to collapse the left side ($dX_t + \theta X_t dt$) into a single derivative. We do this by multiplying the entire equation by the Integrating Factor $e^{\theta t}$.

Multiply both sides by $e^{\theta t}$:

$$e^{\theta t} dX_t + e^{\theta t} \theta X_t dt = e^{\theta t} \theta \mu dt + e^{\theta t} \sigma dW_t$$

Key Observation (The Product Rule):

In standard calculus, the derivative of a product $d(X_t e^{\theta t})$ is:

$$d(X_t e^{\theta t}) = e^{\theta t} dX_t + X_t(\theta e^{\theta t} dt)$$

Notice that the right side of this Product Rule matches the left side of our equation exactly! So, we can rewrite the left side as a single derivative:

$$d(X_t e^{\theta t}) = \theta \mu e^{\theta t} dt + \sigma e^{\theta t} dW_t$$

4. Integration

Now we integrate both sides from the current time s to a future time t:

$$\int_s^t d(X_u e^{\theta u}) = \int_s^t \theta \mu e^{\theta u} du + \int_s^t \sigma e^{\theta u} dW_u$$

The left side simplifies instantly (fundamental theorem of calculus):

$$X_t e^{\theta t} - X_s e^{\theta s} = \int_s^t \theta \mu e^{\theta u}\, du + \int_s^t \sigma e^{\theta u} dW_u$$

Solve the first integral on the right (it's just a standard exponential integral):

$$\int_s^t \theta \mu e^{\theta u}\, du = \theta \mu \left[\frac{e^{\theta u}}{\theta}\right]_s^t = \mu(e^{\theta t} - e^{\theta s})$$

Now the equation is:

$$X_t e^{\theta t} - X_s e^{\theta s} = \mu(e^{\theta t} - e^{\theta s}) + \sigma \int_s^t e^{\theta u} dW_u$$

5. Solving for X_t

To isolate X_t, multiply the entire equation by $e^{-\theta t}$:

$$X_t = X_s e^{\theta(s-t)} + \mu(1 - e^{\theta(s-t)}) + \sigma e^{-\theta t} \int_s^t e^{\theta u} dW_u$$

6. Discretization (The Step Required for Python)

In your code, you are stepping from today (t) to tomorrow ($t + \Delta t$).

Let's set:

- Current time $s = t$
- Future time $t = t + \Delta t$
- Therefore, $s - t = -\Delta t$

Substitute these into our solution:

$$X_{t+\Delta t} = X_t e^{-\theta \Delta t} + \mu\left(1 - e^{-\theta \Delta t}\right) + \text{Noise Term}$$

The Noise Term:

The messy integral term $\sigma e^{-\theta(t+\Delta t)} \int_t^{t+\Delta t} e^{\theta u} dW_u$ looks scary, but for a computer, it is just a random number!

It is a Gaussian Random Variable (Normal Distribution) with mean 0 and variance:

$$\text{Variance} = \frac{\sigma^2}{2\theta}\left(1 - e^{-2\theta \Delta t}\right)$$

7. The Final Formula (Your "F" and "Q" Matrices)

The State Transition:

$$X_{next} = A \cdot X_{current} + B$$

Where:

- $A = e^{-\theta \Delta t}$ (The decay factor)
- $B = \mu\left(1 - e^{-\theta \Delta t}\right)$ (The drift towards the mean)

The Process Noise (Q):

In your Kalman Filter, the noise matrix Q is not just "a guess." It is strictly derived from this variance:

$$Q = \frac{\sigma^2}{2\theta}\left(1 - e^{-2\theta \Delta t}\right)$$