

Fast Fourier Transform

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad \left[\text{P.D.F of Normal Dist.} \right]$$

where μ = mean & σ^2 = variance, x = variable

PDF is the Fourier transform of characteristic function.

Characteristic function of normal distribution:

$$\hat{f}(t) = e^{i\mu t} \cdot e^{-\frac{1}{2}\sigma^2 t^2}$$

characteristic function can be used to recover PDF, which can then be used to price options

$$V = \int_R e^{-\delta T} \cdot \pi(T) \cdot f(x) dx$$

$\downarrow \quad \quad \downarrow \quad \quad \downarrow$
Discounting Payoff PDF

Inversion Lemma

random variable

$$F(x) = \frac{1}{\pi} R \left(\int_0^{\infty} e^{-iux} \phi(u) du \right)$$

\downarrow PDF of x Parameter Characteristic function of u .

Proof of Inversion Lemma

$$F(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-iux} \phi(u) du$$

$$= \frac{1}{2\pi} \left[\int_{-\infty}^0 e^{-iux} \phi(u) du + \int_0^{\infty} e^{-iux} \phi(u) du \right]$$

Now, taking $u = -v$, left side integral becomes

$$\int_{-\infty}^0 e^{-iux} \phi(u) du = \int_0^{\infty} e^{ivx} \phi(-v) dv$$

$$\int_0^{\infty} e^{ivx} \phi(-v) dv = \int_0^{\infty} e^{-iux} \phi(u) du$$

(Taking conjugate of 1st integral)

Plugging the Conjugate in first integral

$$F(x) = \frac{1}{2\pi} \left[\int_{-\infty}^0 e^{-iux} \phi(u) du + \int_0^{\infty} e^{-iux} \phi(u) du \right]$$

$$\Rightarrow \frac{1}{2\pi} \left[\int_0^{\infty} e^{-iux} \phi(u) du + \int_0^{\infty} e^{-iux} \phi(u) du \right]$$

For any $z \in \mathbb{C}$ we have $z + \bar{z} = 2R(z)$. Therefore the equation becomes:-

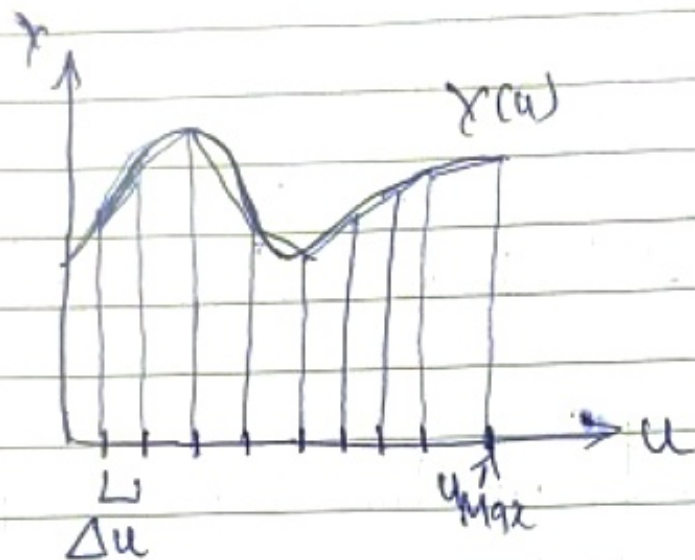
$$F(x) = \frac{1}{\pi} R \left(\int_0^{\infty} e^{-iux} \phi(u) du \right)$$

↓
Inversion lemma.

In the inversion lemma, replace $e^{-iux} \phi(u)$ with $\gamma(u)$.

$$\int_0^{\infty} e^{-iux} \phi(u) du = \int_0^{\infty} \gamma(u) du$$

We will ~~can~~ evaluate this integral using Trapezoidal integration (Numerically).



$$\int_0^{u_{Max}} \gamma(u) du = \frac{\gamma(u_1) + \gamma(u_2)}{2} \cdot \Delta u + \frac{\gamma(u_2) + \gamma(u_3)}{2} \cdot \Delta u$$

$$\dots \dots \dots \frac{\gamma(u_{n-1}) + \gamma(u_n)}{2} \cdot \Delta u$$

Taking $\frac{\Delta u}{2}$ Common and summing the like terms

$$\int_0^{u_{Max}} \gamma(u) du = \frac{\Delta u}{2} \left[2 \sum_{k=2}^{n-1} \gamma(u_k) + \gamma(u_1) + \gamma(u_n) \right]$$

$$\approx \Delta u \left[\sum_{k=2}^{N-1} \gamma(u_k) + \frac{1}{2} (\gamma(u_1) + \gamma(u_N)) \right]$$

Set the following:

$$u_{\max} = N \Delta u \rightarrow \text{Terminal point}$$

$$u_m = (m-1) \Delta u \rightarrow \text{Starting points of Trapezoids}$$

$$x_k = -b + \Delta x (k-1)$$

minimum point on x grid, $k = 1, 2, 3, \dots, N$

Replacing $\gamma(u)$ with $e^{-iux} \phi(u)$ in our discrete version of integral.

$$\int_0^{u_{\max}} \gamma(u) du = \Delta u \sum_{m=1}^N e^{-i[(m-1)\Delta u] [-b + \Delta x (k-1)]} \phi(u_m) \\ - \frac{1}{2} \left[e^{-ix u_1} \phi(u_1) + e^{ix u_N} \phi(u_N) \right]$$

We are summing from 1 to N , hence subtracting the last term. Note the last term has no negative sign. x domain ranges from $-x$ to $+x$.

We'll now rearrange the above summation to that 'fast Fourier transform' in python is possible.

$$\int_0^{u_{max}} Y(u) du \approx \Delta_u \sum_{m=1}^N e^{-i \Delta_x \Delta_u (m-1)(k-1)} e^{i(m-1)b \Delta_u} \phi(u_m)$$

$$= \frac{1}{2} \left[e^{-ixu_1} \phi(u_1) + e^{ixu_N} \phi(u_N) \right]$$

Setting $\Delta_x \Delta_u = \frac{2\pi}{N}$ and $u_m = (m-1)\Delta_u$

We have the following:

$$\int_0^{u_{max}} Y(u) du \approx \frac{\Delta_u}{\pi} \sum_{m=1}^N e^{-i \frac{2\pi}{N} (m-1)(k-1)} e^{ib u_m} \phi(u_m) \xrightarrow{\text{FFT}}$$

$$= \frac{1}{2} \left[e^{-ixu_1} \phi(u_1) + e^{ixu_N} \phi(u_N) \right]$$

FFT reduces the number of multiplications required for a matrix $M \in \mathbb{C}^{N \times N}$ the number of multiplications required are $O(N^2)$ but with FFT you only do $O(N \log N)$ multiplications. This is because the matrix written in FFT form is identical about its diagonal.