# Mathematical Preliminaries 

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## Ito's Lemma

Suppose a random variable $x$ follows the dynamics

$$
d x=a(x, t) d t+b(x, t) d z
$$

Here, $d z$ follows a Wiener process.
And $a(x, t)$ and $b(x, t)$ are functions of $x, t$.
A Wiener process is a Markov stochastic process with these two properties.
I. $\delta z=\varepsilon \sqrt{\delta t}$ The variable $\varepsilon$ is a $N(0,1) \mathrm{RV}$
2. The increments to $Z$ are independent

## Ito's Lemma (contd.)

The mean of $\delta z=0$ and its Variance $=\delta t$

Ito's lemma shows that if $G$ is a function of $x$ and $t$, then

$$
d G=\left(\frac{\partial g}{\partial x} a+\frac{\partial g}{\partial t}+\frac{1}{2} \frac{\partial^{2} G}{\partial x^{2}} b^{2}\right) d t+\frac{\partial G}{\partial x} b d z
$$

If $x$ follows an Ito process, so will $G$

## Markov Chains and Pushkin's Poetry

- The Russian mathematician Andrey Markov was trying to analyze whether to guess if in a document, the $k-t b$ letter would be a vowel or a constant.
- Markov analysed 20 thousand letters from Pushkin's poem Eugene Origin.
- Vowels occur $43 \%$ of the time; so always guessing consonant is right $57 \%$ of the time.
- But a vowel is followed by a consonant $87 \%$ of the time. A consonant is followed by a vowel $66 \%$ of the time. Therefore, knowledge of the preceding letter is very helpful! Reversal at work!
- But he found that knowledge of the preceding two letters did not confer any additional advantage.
- This leads to the central idea of a Markov Chain- while successive outcomes may not be independent, only the most recent outcome is helpful in predicting the next outcome


## Simple Way to Think About Ito's Lemma

Consider $G$, a continuous function of $x$ and $\delta x$ is a small change in $x$ and $\delta G$ is the resulting small change in $G$.

$$
\delta G \approx \frac{d G}{d x} \delta x
$$

This ignores all terms of order $\delta x^{2}$ and higher.
Applying Taylor's Theorem,

$$
\delta G=\frac{d G}{d x} \delta x+\frac{1}{2} \frac{d^{2} G}{d x^{2}} \delta x^{2}+\frac{1}{3!} \frac{d^{3} G}{d x^{3}} \delta x^{3}+\ldots \ldots \ldots
$$

## Simple Way ... (contd.)

Applying Taylor series expansion to the
$\delta G=\frac{\partial G}{\partial x} \delta x+\frac{\partial G}{\partial y} \delta y+\frac{1}{2} \frac{\partial^{2} G}{\partial x^{2}} \delta x^{2}+\frac{\partial^{2} G}{\partial x \partial y} \delta x \delta y+\frac{1}{2} \frac{\partial^{2} G}{\partial y^{2}} \delta y^{2}+$
As $\delta x$ and $\delta y$ tend to zero, this becomes

$$
d G=\frac{\partial G}{\partial x} d x+\frac{\partial G}{\partial y} d y
$$

Now we move to the case where variable $x$ follows an Ito's process

$$
\delta x=a \delta t+b \varepsilon \sqrt{\delta t}
$$

$$
\delta x^{2}=b^{2} \varepsilon^{2} \delta t+\text { terms of order }>2(\text { in } \delta t)
$$

## Simple Way ... (contd. 2)

Therefore........
$\delta G=\frac{\partial G}{\partial x} \delta x+\frac{\partial G}{\partial t} d t+\frac{1}{2} \frac{\partial^{2} G}{\partial x^{2}}\left(b^{2} \varepsilon^{2} \delta t\right)+\ldots \ldots$.
$d G=\frac{\partial G}{\partial x} d x+\left(\frac{\partial G}{\partial t} d t+\frac{1}{2} \frac{\partial^{2} G}{\partial x^{2}} b^{2}\right) d t$
we use the fact that for a random variable $\omega-N(0,1)$
$E\left(\omega^{2}\right)-[E(\omega)]^{2}=1$
$E(\omega)=0$, and $E\left(\omega^{2}\right)=1$, and
$\varepsilon^{2} \delta t$ can be thought of as a non-stochastic variable, equal to its expected value which is $\delta t$
So, we get the two forms of Ito's Lemma
$d G=\frac{\partial G}{\partial x} d x+\left(\frac{\partial G}{\partial t} d t+\frac{1}{2} \frac{\partial^{2} G}{\partial x^{2}} b^{2}\right) d t$
$d G=\left(\frac{\partial G}{\partial x} a+\frac{\partial G}{\partial t}+\frac{1}{2} \frac{\partial^{2} G}{\partial x^{2}} b^{2}\right) d t+\frac{\partial G}{\partial x} b d z$

## A Tragic Tale!

- Wolfgang Doeblin was a German-French Jewish Mathematician. He studied Probability Theory under Frechet, and gained a strong reputation.
- In World War II, he joined the army and volunteered to fight at the front where his company surrendered
- Rather than be captured, he burned his notes and took his life - however most of his work had been sent to the Academie des Sciences de Paris and his notebook lay in a safe - secure but forgotten.
- This was opened in 2000 and it was realized that Doeblin had been 25 years ahead of everyone else in the theory of Markov Processes.
- The Ito-lemma is now called Ito-Doeblin to recognize his achievement.


## Lognormal Distribution

Lognormal distribution :
A random variable X is said to follow a Lognormal distribution if its Logarithm is Normally distributed
pdf of X: $\frac{1}{(\sqrt{2} \pi) \sigma x} e^{-\frac{\left\{(\log x-\mu)^{2}\right\}}{2 \sigma^{2}}} \quad, \mathrm{x}>0$
$\mu=$ mean of $\log \mathrm{X}, \sigma=$ std dev of $\log \mathrm{X}$
Mean of $X=e^{\left[\mu+\frac{1}{2} \sigma^{2}\right]}$ (note the + symbol)
Variance of $\mathrm{X}=e^{\left(2 \mu+\sigma^{2}\right)} \cdot\left(e^{\sigma^{2}}-1\right)$
Normal distribution
pdf: $\frac{1}{(\sqrt{2} \pi) \sigma} e^{-\frac{(x-\mu)^{2}}{2 \sigma^{2}}}$

## Applying Ito's Lemma to Log S

If $d S=S(\mu d t+\sigma d z)$ and $G=\ln S$
$d G=\left(\mu-\frac{\sigma^{2}}{2}\right) d t+\sigma d z$
changes in $\ln S$ are normally distributed; the drift is $\left(\mu-\frac{\sigma^{2}}{2}\right)$ and the variance is $\sigma^{2}$
If you observe the change in $\log (\mathrm{S})$ from 0 to $T$ its mean is $\left(\mu-\frac{\sigma^{2}}{2}\right) T$ \& variance is $\sigma^{2} T$

This is used in Monte Carlo simulation of Geometric Brownian Motion

$$
\begin{aligned}
& d \ln S=\left(\mu-\frac{\sigma^{2}}{2}\right) d t+\sigma d z \quad \text { (note the -symbol) } \\
& s(t+\Delta t)=s(t) \cdot e^{\left[\left(\mu-\frac{1}{2} \sigma^{2}\right) \Delta t+\sigma \varepsilon \sqrt{\Delta t}\right]}
\end{aligned}
$$

## Monte Carlo and Stanislaw Ulam

- Stanislaw Ulam was a Jewish mathematician from Poland who fled to the US on the eve of the World War.
- John von Neuman invited him to join a secret war project in New Mexico; he borrowed a book on New Mexico, looked at check out card and saw all the names of people who had left University of Wisconsin-Madison.
- Invented the monte Carlo technique while at Los Alamos for evaluating integrals. (Enrico Fermi had used this earlier).
- Worked on Hydrogen Bomb with Edward Teller.Improved on Teller's design; fission-fusion. Computer calculation...


## Derivation of Black-Scholes-Merton Equation

We can apply Ito's Lemma to a derivative security $V$
$d V=\left(\frac{\partial V}{\partial S} \mu S+\frac{\partial V}{\partial t}+\frac{1}{2} \frac{\partial^{2} V}{\partial S^{2}} \sigma^{2} S^{2}\right)+\frac{\partial V}{\partial S} \sigma S d z$
Now, if we are short 1 unit of $V$ and long $\frac{\partial V}{\partial x}$ shares of $S$ then this portfolio is $\Pi=-V+\frac{\partial V}{\partial S} S$
$\delta \Pi=-\delta V+\frac{\partial V}{\partial S} \cdot \delta S$ But recall $\delta S=S(\mu d t+\sigma \delta z)$
and therefore $\delta \Pi=\left(-\frac{\partial V}{\partial t}-\frac{1}{2} \frac{\partial^{2} V}{\partial S^{2}} \sigma^{2} S^{2}\right) \delta t$
This does not involve the Wiener process term. Therefore it grows at the risk less rate: $\delta \Pi=r \Pi \delta t$
and substitute (a) and (b) into (c)

$$
\left(-\frac{\partial V}{\partial t}-\frac{1}{2} \frac{\partial^{2} V}{\partial S^{2}} \sigma^{2} S^{2}\right) \delta t=r\left(-V+\frac{\partial V}{\partial S} S\right) \delta t
$$

or $\left(\frac{\partial V}{\partial t}+\frac{1}{2} \frac{\partial^{2} V}{\partial S^{2}} \sigma^{2} S^{2}\right)=r\left(V-\frac{\partial V}{\partial S} S\right)$
or

$$
\left(\frac{\partial V}{\partial t}+\frac{\partial V}{\partial S} r S+\frac{1}{2} \frac{\partial^{2} V}{\partial S^{2}} \sigma^{2} S^{2}\right)=r V
$$

This is Black-Scholes-Merton equation

## Black - Scholes-Merton Formula

$$
\begin{array}{ll}
\text { BSM Call } & e^{-q \tau} S \Phi\left(d_{1}\right)-e^{-r \tau} K \Phi\left(d_{2}\right) \\
\text { BSM Put } & e^{-r \tau} K \Phi\left(-d_{2}\right)-e^{-q \tau} S \Phi\left(-d_{1}\right)
\end{array}
$$

$$
\begin{aligned}
& d_{1}=\frac{\ln (S / X)+\left(r-\sigma^{2} / 2\right) t}{\sigma \sqrt{t}} \\
& d_{2}=d_{1}-\sigma \sqrt{t}
\end{aligned}
$$

Where $S$ is the stock price, $X$ is the strike price, $r$ is the risk free rate and $t$ is the time to maturity and the volatility of the underlying is represented by $\sigma$

