# Ito's Lemma 

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This short note summarizes the sketch of derivation of Ito's lemma presented in Chapter 1 of Dixit (1993)

## 1 Random walk representation

Consider time periods of length $\Delta t$ and steps of length $\Delta h$. The random walk variable $\Delta x$ can take values $\pm \Delta h$ with probability $p$ and $q=1-p$ (up and down, respectively). Then, the first moments are:

$$
\begin{aligned}
\mathbb{E}(\Delta x) & =p(\Delta h)+q(-\Delta h)=(p-q) \Delta h \\
\mathbb{E}\left[(\Delta x)^{2}\right] & =p(\Delta h)^{2}+q(-\Delta h)^{2}=(p+q)(\Delta h)^{2}=(\Delta h)^{2} \\
\mathbb{V}(\Delta x) & =\mathbb{E}\left[(\Delta x)^{2}\right]-[\mathbb{E}(\Delta x)]^{2}=(\Delta h)^{2}-(p-q)^{2}(\Delta h)^{2}=4 p q(\Delta h)^{2}
\end{aligned}
$$

The time interval of length $t$ has $n=t / \Delta t$ discrete steps. Since each step is independent of the previous one, the cumulative change $x_{t}-x_{0}$ has a binominal distribution with mean $n(p-q) \Delta h=t(p-q) / \Delta t$ and variance $4 n p q(\Delta h)^{2}=4 t p q(\Delta h)^{2} / \Delta t$. This is, the same expectation and variance of the random walk but multiplied by the number of steps between the origina and the current realization.
Now consider $\Delta h=\sigma \sqrt{t}, p=\frac{1}{2}\left[1+\frac{\mu}{\sigma} \sqrt{\Delta t}\right]=\frac{1}{2}\left[1+\frac{\mu}{\sigma^{2}} \Delta h\right]$ and $q=\frac{1}{2}\left[1-\frac{\mu}{\sigma} \sqrt{\Delta t}\right]=\frac{1}{2}\left[1-\frac{\mu}{\sigma^{2}} \Delta h\right]$, where $\mu$ and $\sigma$ are the mean and standard deviation of $x$, which is normally distributed. With this parametrization we have the following mean and variance for the cumulative change:

$$
\begin{gathered}
\text { Mean : } t(p-q) \frac{\Delta h}{\Delta t}=t(2 p-1) \frac{\Delta h}{\Delta t}=t\left[2 \frac{1}{2}\left[1+\frac{\mu}{\sigma^{2}} \Delta h\right]-1\right] \frac{\Delta h}{\Delta t}=t \frac{\mu}{\sigma^{2}} \sigma^{2} \frac{\Delta t}{\Delta t}=\mu t \\
4 p q=\left[1+\frac{\mu}{\sigma^{2}} \Delta h\right]\left[1-\frac{\mu}{\sigma^{2}} \Delta h\right]=1-\left(\frac{\mu}{\sigma}\right)^{2} \Delta t \\
\text { Var : } 4 t p q \frac{(\Delta h)^{2}}{\Delta t}=t\left[1-\left(\frac{\mu}{\sigma}\right)^{2} \Delta t\right] \frac{(\Delta h)^{2}}{\Delta t}=t\left[1-\left(\frac{\mu}{\sigma}\right)^{2} \Delta t\right] \sigma^{2} \rightarrow \sigma^{2} t
\end{gathered}
$$

Therefore, the limit of the random walk, when both time length and step goes to zero, is a Brownian motion. The key element is to preserve the relation $\Delta h=\sigma \sqrt{\Delta t}$.

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## 2 Ito's lemma

Assume $x_{t}$ follows a Brownian motion with parameters $(\mu, \sigma)$ and the following relation $y_{t}=f\left(x_{t}\right)$, where $f$ is a given non-random twice.continuous differentiable function. Consider a Taylor expansion at the point $y_{0}=f\left(x_{0}\right)$ :

$$
y_{t}-y_{0}=f^{\prime}\left(x_{0}\right)\left(x_{t}-x_{0}\right)+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right)\left(x_{t}-x_{0}\right)^{2}+\ldots
$$

Now, consider the expectation of this expression:

$$
\begin{aligned}
\mathbb{E}\left(y_{t}-y_{0}\right) & =f^{\prime}\left(x_{0}\right) \mathbb{E}\left(x_{t}-x_{0}\right)+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right) \mathbb{E}\left[\left(x_{t}-x_{0}\right)^{2}\right]+\ldots \\
& =f^{\prime}\left(x_{0}\right) \mu t+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right)\left[\sigma^{2} t+\mu^{2} t^{2}\right]+\ldots \\
& =\left[f^{\prime}\left(x_{0}\right) \mu+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right) \sigma^{2}\right] t
\end{aligned}
$$

where in the second line we use $\mathbb{E}\left[\left(x_{t}-x_{0}\right)^{2}\right]=\mathbb{V}\left(x_{t}-x_{0}\right)+\left[\mathbb{E}\left(x_{t}-x_{0}\right)\right]^{2}=\sigma^{2} t+\mu^{2} t^{2}$ and in the third line the fact that $t$ is small, so only first order terms are relevant.
The variance is:

$$
\begin{aligned}
\mathbb{V}\left(y_{t}-y_{0}\right) & =\mathbb{V}\left\{f^{\prime}\left(x_{0}\right)\left(x_{t}-x_{0}\right)+\frac{1}{2} f^{\prime \prime}\left(x_{0}\right)\left(x_{t}-x_{0}\right)^{2}+\ldots\right\} \\
& =\left[f^{\prime}\left(x_{0}\right)\right]^{2} \mathbb{V}\left(x_{t}-x_{0}\right)=\left[f^{\prime}\left(x_{0}\right)\right]^{2} \sigma^{2} t
\end{aligned}
$$

We want to apply the same idea to any infinitesimal increment $d y$ in $y=f(x)$ in the interval $d t$. Therefore:

$$
\begin{aligned}
\mathbb{E}(d y) & =\left[f^{\prime}(x) \mu+\frac{1}{2} f^{\prime \prime}(x) \sigma^{2}\right] d t \\
\mathbb{V}(d y) & =\left[f^{\prime}(x)\right]^{2} \sigma^{2} d t
\end{aligned}
$$

which is the same as before but for any $x_{t}$ and using the right time interval $d t$.
Finally we say that the process of $y$ is a general diffusion process of the form:

$$
\begin{equation*}
d y=\left[f^{\prime}(x) \mu+\frac{1}{2} f^{\prime \prime}(x) \sigma^{2}\right] d t+f^{\prime}(x) \sigma d \omega \tag{1}
\end{equation*}
$$

The, equation (1) corresponds to the Ito's lemma.

## References

Dixit, A. (1993). The Art of Smooth Pasting, Princeton University Press.


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