# Notes of Stochastic Calculus, An introduction with Application 

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## 1 Probability space

We start by introducing the theoretical framework of probability theory. If this is too abstract for the reader, then he/she should directly jump to the next section. A probability space $(\Omega, \mathcal{F}, \mathbb{P})$ consists of three ingredients:

1. A sample space $\Omega$, which is the set of all possible outcomes.
2. An event space $\mathcal{F}$, which is a set of outcomes in the sample space. In particular, we have $\mathcal{F} \subset P(\Omega)$, where $P$ the set of all the subsets of $\Omega$.
3. A probability function $\mathbb{P}$, which assigns each event in the event space a probability, which is a number between 0 and 1.

In general, there is no specification on $\Omega$, so it is a "general" space, but it can happen that it corresponds to the six possible outcomes of a dice roll, etc.

## 2 Continuous random variable

A random variable is a function $X: \Omega \rightarrow \mathbb{R}$, where $\mathbb{R}:=(-\infty, \infty)$ is the space of real numbers. The probability that $X$ takes on a value in $S \subset \mathbb{R}$ is defined as

$$
\begin{equation*}
\mathbb{P}(X \in S)=\mathbb{P}(\{\omega \in \Omega \mid X(\omega) \in S\}) \tag{1}
\end{equation*}
$$

For example, $X$ can be equal to the current price of Mitsubishi asset, the current temperature in Tokyo, etc.
We say that $X$ has a related density $f_{X}$ if for any two real numbers $a \leq b$, we have:

$$
\begin{equation*}
\mathbb{P}(X \in[a, b])=\int_{a}^{b} f_{X}(s) d s \tag{2}
\end{equation*}
$$

The only density that we will be looking at in this class is the normal distribution, which we will be defining in a later section.
The definition can be generalized in the two-dimensional case, where we consider the joint density. More specifically, if $X$ and $Y$ are two random variables, then their joint density takes on the form $f_{X, Y}(s, t)$.

## 3 Independence

Two random variables are independent if the realization of one does not affect the probability distribution of the other. For example, if $X$ stands for the current temperature in Tokyo, and $Y$ corresponds to the number of students enrolled in this class, it would be reasonable to assume that $X$ and $Y$ are independent. If we add a third random variable $Z$, which is the current temperature in Yokohama, then it would be reasonable to assume $Y$ and $Z$ are independent, but it would be unreasonable to assume independence between $X$ and $Z$. Indeed, if it is cold in Tokyo, it will be most likely cold in Yokohama too, and vice versa.
Formally, two random variables $X$ and $Y$ are independent if their joint density and their own density satisfy

$$
\begin{equation*}
f_{X, Y}(s, t)=f_{X}(s) f_{Y}(t) \quad \text { for any }(s, t) \in \mathbb{R} \times \mathbb{R} \tag{3}
\end{equation*}
$$

## 4 Expectation

Now we define the expectation, which is a NUMBER and not a random variable, for a general function $h: \mathbb{R} \rightarrow \mathbb{R}$. Cases of interest for the reader are mean (i.e. when $h(s)=s$ ) and variance (i.e. when $\left.h(s)=(s-\mathbb{E}[X])^{2}\right)$, which will be specified after the
general definition. The formal definition of expectation is given as

$$
\begin{equation*}
\mathbb{E}[h(X)]=\int_{\mathbb{R}} h(s) f_{X}(s) d s \tag{4}
\end{equation*}
$$

In particular, the mean of $X$ is specified as

$$
\begin{equation*}
\mathbb{E}[X]=\int_{\mathbb{R}} s f_{X}(s) d s \tag{5}
\end{equation*}
$$

and the variance of $X$ as

$$
\begin{equation*}
\operatorname{Var}[X]=\mathbb{E}\left[(X-\mathbb{E}[X])^{2}\right]=\int_{\mathbb{R}}(s-\mathbb{E}[X])^{2} f_{X}(s) d s \tag{6}
\end{equation*}
$$

We also provide the definition of expectation, when there are two random variables $X$ and $Y$, and $h: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$. In that case, we have:

$$
\begin{equation*}
\mathbb{E}[h(X, Y)]=\int_{\mathbb{R} \times \mathbb{R}} h(s, t) f_{X, Y}(s, t) d s d t \tag{7}
\end{equation*}
$$

In particular, we have:

$$
\begin{equation*}
\mathbb{E}[X Y]=\int_{\mathbb{R} \times \mathbb{R}} s t f_{X, Y}(s, t) d s d t \tag{8}
\end{equation*}
$$

so that IN GENERAL $\mathbb{E}[X Y] \neq \mathbb{E}[X] \mathbb{E}[Y]$. We also give the definition of covariance:

$$
\begin{equation*}
\operatorname{Cov}[X, Y]=\mathbb{E}[(X-\mathbb{E}[X])(Y-\mathbb{E}[Y])]=\int_{\mathbb{R} \times \mathbb{R}}(s-\mathbb{E}[X])(t-\mathbb{E}[Y]) f_{X, Y}(s, t) d s d t \tag{9}
\end{equation*}
$$

We provide now some very useful properties about expectation and variance:

$$
\begin{align*}
\mathbb{E}[X+Y] & =\mathbb{E}[X]+\mathbb{E}[Y]  \tag{10}\\
\mathbb{E}[X Y] & =\mathbb{E}[X] \mathbb{E}[Y] \text { if XandYareINDEPENDENT }  \tag{11}\\
\operatorname{Var}[X] & =\mathbb{E}\left[X^{2}\right]-\mathbb{E}[X]^{2}  \tag{12}\\
\operatorname{Cov}[X, Y] & =\mathbb{E}[X Y]-\mathbb{E}[X] \mathbb{E}[Y]  \tag{13}\\
\operatorname{Var}[X+Y] & =\operatorname{Var}[X]+\operatorname{Var}[Y]+2 \operatorname{Cov}[X, Y] . \tag{14}
\end{align*}
$$

## 5 Normal distribution

In probability theory, a (one-dimensional) normal distribution is a continuous probability distribution. We say that a random variable $X$ is normally distributed if its related probability density function is

$$
f_{X}(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^{2}} f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^{2}}
$$

The parameter $\mu$ is the mean or expectation of the distribution, $\sigma$, and the variance is $\sigma^{2}$. If $\mu=0$ and $\sigma=1$, we say that it is a standard normal distribution.

