## Tutorials 1 - Probability

## 1 Generate random numbers

We consider a (continuous) random variable $X$ with probability density function (PDF) $p(x)$ with support $[a, b]$.

1/ Given a monotonously increasing function $\Phi(x)$, what is the $\operatorname{PDF} q(y)$ of $Y=\Phi(X)$ ?
2/ $Y$ is generated by a computer with a box distribution, $q(y)=1$ on $[0,1]$ and 0 otherwise. How should you choose the function $y=\Phi(x)$ so that $X$ has distribution $p(x)$ ?
3/ Application $\mathrm{n}^{\circ} 1$ : power law distribution.
a) Give $\Phi(x)$ allowing to generate the distribution

$$
\begin{equation*}
p(x)=\mu x^{-1-\mu} \quad \text { for } x \geqslant 1 \tag{1}
\end{equation*}
$$

from the flat distribution.
b) Deduce how to generate the symmetric distribution $\mathcal{P}(x)=\frac{\mu}{2}(1+|x|)^{-1-\mu}$ defined on $\mathbb{R}$.

## 4/ Application n ${ }^{\circ} 2$ : Gaussian variable and the Box-Muller algorithm.

We consider two i.i.d. Gaussian random variables $X$ and $Y$ with zero mean and unit variance.
a) What is the distribution of the radius $R=\sqrt{X^{2}+Y^{2}}$ ? What is the distribution of the angle $\Theta$ ?
b) What is the distribution of $\xi=\frac{1}{2}\left(X^{2}+Y^{2}\right)$ ?
c) Deduce a method to generate a Gaussian random number from a box distribution.

## 2 Gaussian conditional probability

Consider two real random variables distributed according to the Gaussian distribution

$$
\begin{equation*}
P(x, y)=\mathcal{N} \exp \left[-\frac{1}{2} a x^{2}+b x y-\frac{1}{2} c y^{2}\right] . \tag{2}
\end{equation*}
$$

1/ Compute the normalisation constant $\mathcal{N}$. What is the condition on $a, b$ and $c$ ? Determine the conditional probability $P(x \mid y)$.

2/ Deduce $\langle X \mid Y=y\rangle$ the average of $X$ conditioned by $Y=y$.
3/ Application to the Brownian motion : We consider a mesoscopic particle at equilibrium in a fluid. We assume that the joint distribution $P\left(x_{t}, x_{0}\right)$ of its position at time $t=0$ and at time $t$ is Gaussian. We have $\left\langle x_{0}\right\rangle=\left\langle x_{t}\right\rangle=0$. Deduce the conditional probability $P\left(x_{t} \mid x_{0}\right)$ and the conditioned mean $\left\langle X_{t} \mid X_{0}=x_{0}\right\rangle$.
Hint : you can determine the coefficients $a, b$ and $c$ by noticing that $\left\langle\left(x_{t}-x_{0}\right)^{2}\right\rangle=2 D t$, where $D$ is the diffusion constant.

## 3 Multivariate Gaussian distribution

We consider $N$ Gaussian random variables $x_{1}, \cdots, x_{N}$. The most general Gaussian distribution has the form

$$
\begin{equation*}
P(\mathbf{x})=C_{N} \mathrm{e}^{-\frac{1}{2}\left(\mathbf{x}-\mathbf{x}_{0}\right)^{\mathrm{T}} A\left(\mathbf{x}-\mathbf{x}_{0}\right)} \tag{3}
\end{equation*}
$$

where $\mathbf{x}=\left(x_{1}, \cdots, x_{N}\right)^{\mathrm{T}}$ and $\mathbf{x}_{0}$ are column vectors $\in \mathbb{R}^{N}$ and $A$ is a real symmetric matrix. $C_{N}$ is a normalisation constant.
1/ Why $A$ is symmetric ? Give another property of the matrix required to define a good PDF.
2/ Compute the normalisation constant $C_{N}$.
Hint : any real symmetric matrix is diagonalisable with the help of an orthogonal matrix :
$A=\mathcal{O} \operatorname{diag}\left(\lambda_{1}, \cdots, \lambda_{N}\right) \mathcal{O}^{\mathrm{T}}$
$3 /$ We introduce the generating function

$$
\begin{equation*}
G(\mathbf{k}) \stackrel{\text { def }}{=}\left\langle\mathrm{e}^{\mathbf{k}^{\mathrm{T}} \mathbf{x}}\right\rangle \tag{4}
\end{equation*}
$$

where $\mathbf{k}$ is the conjugated vector. Assuming $G(\mathbf{k})$ known, how can you deduce $\left\langle x_{i}\right\rangle,\left\langle x_{i} x_{j}\right\rangle$, $\left\langle x_{i} x_{j} x_{k}\right\rangle$, etc ?
4/ a) Compute $G(\mathbf{k})$ for the Gaussian distribution.
b) We consider the correlator $\left\langle x_{i} x_{j}\right\rangle_{c}=\left\langle x_{i} x_{j}\right\rangle-\left\langle x_{i}\right\rangle\left\langle x_{j}\right\rangle$. Show that

$$
\begin{equation*}
\left\langle x_{i} x_{j}\right\rangle_{c}=\left(A^{-1}\right)_{i j} \tag{5}
\end{equation*}
$$

The result is remarkable : it is sufficient to identify the matrix $A$ in the Gaussian measure (and inverse it) to get the correlation function (no need to compute a multiple integral), and any correlation function, as we show below.
5/ "Discrete Furutsu-Novikov theorem" : We consider $f(\mathbf{x})$, a function in $\mathbb{R}^{N}$. Show that for Gaussian random variables such that $\left\langle x_{i}\right\rangle=0$ one has

$$
\begin{equation*}
\left\langle x_{i} f(\mathbf{x})\right\rangle=\sum_{j}\left\langle x_{i} x_{j}\right\rangle\left\langle\frac{\partial f}{\partial x_{j}}\right\rangle . \tag{6}
\end{equation*}
$$

6/ Wick theorem : We consider $N$ Gaussian random variables with distribution $P(\mathbf{x}) \propto$ $\mathrm{e}^{-\frac{1}{2} \mathbf{x}^{\mathrm{T}} A \mathbf{x}}$.
a) Compute the four point correlation function $\left\langle x_{i} x_{j} x_{k} x_{l}\right\rangle$.
b) Generalize to the $2 n$-point correlation function $\left\langle x_{1} x_{2} \cdots x_{2 n}\right\rangle$.

7/ Discrete Ornstein-Uhlenbeck process : We consider random Gaussian variables ( $\cdots, \phi_{n}, \cdots$ ) with probability weight $P(\phi) \propto \exp [-S]$ where the action is

$$
\begin{equation*}
S=\frac{1}{2} \sum_{n \in \mathbb{Z}}\left[\left(\phi_{n+1}-\phi_{n}\right)^{2}+\mu^{2} \phi_{n}^{2}\right] \tag{7}
\end{equation*}
$$

a) Write the action as $S=\frac{1}{2} \phi^{\mathrm{T}} A \phi$ and show that the matrix $A$ involves the discrete Laplace operator $\Delta_{n, m}=\delta_{n, m+1}-2 \delta_{n, m}+\delta_{n, m-1}$.
b) Give the eigenvalues and the (normalised) eigenvectors of $\Delta$ on the infinite line ( $n \in \mathbb{Z}$ ). Deduce the correlation function $\left\langle\phi_{n} \phi_{m}\right\rangle$.
c) Discuss the limit $\mu \rightarrow 0$.

Hint : we give the integral $\int_{0}^{2 \pi} \frac{\mathrm{~d} \theta}{2 \pi} \frac{\sinh \lambda}{\cosh \lambda+\cos \theta} \mathrm{e}^{\mathrm{i} n \theta}=\mathrm{e}^{-\lambda|n|}$.

