# Gaussian Random Variables 

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September 2, 2013

## Gaussian Random Variable

## Definition

A continuous random variable with pdf of the form

$$
p(x)=\frac{1}{\sqrt{2 \pi \sigma^{2}}} \exp \left(-\frac{(x-\mu)^{2}}{2 \sigma^{2}}\right), \quad-\infty<x<\infty,
$$

where $\mu$ is the mean and $\sigma^{2}$ is the variance.


## Notation

- $N\left(\mu, \sigma^{2}\right)$ denotes a Gaussian distribution with mean $\mu$ and variance $\sigma^{2}$
- $X \sim N\left(\mu, \sigma^{2}\right) \Rightarrow X$ is a Gaussian RV with mean $\mu$ and variance $\sigma^{2}$
- If $X \sim N(0,1)$, then $X$ is a standard Gaussian RV


## Affine Transformations Preserve Gaussianity

## Theorem

If $X$ is Gaussian, then $a X+b$ is Gaussian for $a, b \in \mathbb{R}, a \neq 0$.

## Remarks

- If $X \sim N\left(\mu, \sigma^{2}\right)$, then $a X+b \sim N\left(a \mu+b, a^{2} \sigma^{2}\right)$.
- If $X \sim N\left(\mu, \sigma^{2}\right)$, then $\frac{X-\mu}{\sigma} \sim N(0,1)$.


## CDF and CCDF of Standard Gaussian

- Cumulative distribution function of $X \sim N(0,1)$

$$
\Phi(x)=P[X \leq x]=\int_{-\infty}^{x} \frac{1}{\sqrt{2 \pi}} \exp \left(\frac{-t^{2}}{2}\right) d t
$$

- Complementary cumulative distribution function of $X \sim N(0,1)$

$$
Q(x)=P[X>x]=\int_{x}^{\infty} \frac{1}{\sqrt{2 \pi}} \exp \left(\frac{-t^{2}}{2}\right) d t
$$



## Properties of $Q(x)$

- $\Phi(x)+Q(x)=1$
- $Q(-x)=\Phi(x)=1-Q(x)$
- $Q(0)=\frac{1}{2}$
- $Q(\infty)=0$
- $Q(-\infty)=1$
- $X \sim N\left(\mu, \sigma^{2}\right)$

$$
\begin{aligned}
& P[X>\alpha]=Q\left(\frac{\alpha-\mu}{\sigma}\right) \\
& P[X<\alpha]=Q\left(\frac{\mu-\alpha}{\sigma}\right)
\end{aligned}
$$

## Jointly Gaussian Random Variables

## Definition (Jointly Gaussian RVs)

Random variables $X_{1}, X_{2}, \ldots, X_{n}$ are jointly Gaussian if any non-trivial linear combination is a Gaussian random variable.

$$
a_{1} X_{1}+\cdots+a_{n} X_{n} \text { is Gaussian for all }\left(a_{1}, \ldots, a_{n}\right) \in \mathbb{R}^{n} \backslash \mathbf{0}
$$

Example (Not Jointly Gaussian)
$X \sim N(0,1)$

$$
Y=\left\{\begin{array}{rr}
X, & \text { if }|X|>1 \\
-X, & \text { if }|X| \leq 1
\end{array}\right.
$$

$Y \sim N(0,1)$ and $X+Y$ is not Gaussian.

## Gaussian Random Vector

## Definition (Gaussian Random Vector)

A random vector $\mathbf{X}=\left(X_{1}, \ldots, X_{n}\right)^{T}$ whose components are jointly Gaussian.
Notation
$\mathbf{X} \sim N(\mathbf{m}, \mathbf{C})$ where

$$
\mathbf{m}=E[\mathbf{X}], \quad \mathbf{C}=E\left[(\mathbf{X}-\mathbf{m})(\mathbf{X}-\mathbf{m})^{T}\right]
$$

Definition (Joint Gaussian Density)
If $\mathbf{C}$ is invertible, the joint density is given by

$$
p(\mathbf{x})=\frac{1}{\sqrt{(2 \pi)^{m} \operatorname{det}(\mathbf{C})}} \exp \left(-\frac{1}{2}(\mathbf{x}-\mathbf{m})^{T} \mathbf{C}^{-1}(\mathbf{x}-\mathbf{m})\right)
$$

## Uncorrelated Random Variables

## Definition

$X_{1}$ and $X_{2}$ are uncorrelated if $\operatorname{cov}\left(X_{1}, X_{2}\right)=0$

## Remarks

For uncorrelated random variables $X_{1}, \ldots, X_{n}$,

$$
\operatorname{var}\left(X_{1}+\cdots+X_{n}\right)=\operatorname{var}\left(X_{1}\right)+\cdots+\operatorname{var}\left(X_{n}\right)
$$

If $X_{1}$ and $X_{2}$ are independent,

$$
\operatorname{cov}\left(X_{1}, X_{2}\right)=0
$$

Correlation coefficient is defined as

$$
\rho\left(X_{1}, X_{2}\right)=\frac{\operatorname{cov}\left(X_{1}, X_{2}\right)}{\sqrt{\operatorname{var}\left(X_{1}\right) \operatorname{var}\left(X_{2}\right)}} .
$$

## Uncorrelated Jointly Gaussian RVs are Independent

If $X_{1}, \ldots, X_{n}$ are jointly Gaussian and pairwise uncorrelated, then they are independent.

$$
\begin{aligned}
p(\mathbf{x}) & =\frac{1}{\sqrt{(2 \pi)^{m} \operatorname{det}(\mathbf{C})}} \exp \left(-\frac{1}{2}(\mathbf{x}-\mathbf{m})^{\top} \mathbf{C}^{-1}(\mathbf{x}-\mathbf{m})\right) \\
& =\prod_{i=1}^{n} \frac{1}{\sqrt{2 \pi \sigma_{i}^{2}}} \exp \left(-\frac{\left(x_{i}-m_{i}\right)^{2}}{2 \sigma_{i}^{2}}\right)
\end{aligned}
$$

where $m_{i}=E\left[X_{i}\right]$ and $\sigma_{i}^{2}=\operatorname{var}\left(X_{i}\right)$.

## Uncorrelated Gaussian RVs may not be Independent

## Example

- $X \sim N(0,1)$
- $W$ is equally likely to be +1 or -1
- $W$ is independent of $X$
- $Y=W X$
- $Y \sim N(0,1)$
- $X$ and $Y$ are uncorrelated
- $X$ and $Y$ are not independent

Thanks for your attention

