## 7 - Continuous random variables

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## Continuous random variables

A continuous random variable $x: \Omega \rightarrow \mathbb{R}$ is specified by its (induced) cumulative distribution function (cdf)

$$
F^{x}(z)=\operatorname{Prob}(x \leq z)
$$



Then we have

$$
\operatorname{Prob}(x \in[a, b])=F^{x}(b)-F^{x}\left(a^{-}\right)
$$

## Properties of the cumulative distribution function



- $F^{x}(a) \geq 0$ for all $a$
- $F^{x}$ is a non-decreasing function $F^{x}(a) \leq F^{x}(b)$ if $a \leq b$
- $F^{x}$ is right continuous, i.e,.

$$
\lim _{z \rightarrow a^{+}} F^{x}(z)=F^{x}(a)
$$

## Properties of the cumulative distribution function

If $F^{x}$ is differentiable, then the induced probability density function (pdf) is

$$
p^{x}(z)=\frac{d F^{x}(z)}{d z}
$$

then

$$
\operatorname{Prob}(x \in[a, b])=\int_{a}^{b} p^{x}(z) d z
$$

- Notice that $p^{x}(z)$ is not a probability; it may be greater than 1 .
- We use notation $x \sim p^{x}$ to mean $x$ is a random variable with pdf $p^{x}$


## Properties of the cumulative distribution function

If $x$ is a discrete random variable, then $F$ is just a staircase function


- The corresponding probability density function is a sum of $\delta$ functions.


## The uniform random variable

The uniform random variable $x \sim U[a, b]$ has pdf

$$
p^{x}(z)= \begin{cases}\frac{1}{b-a} & \text { if } a \leq z \leq b \\ 0 & \text { otherwise }\end{cases}
$$

## Gaussian random variables

The random variable $x$ is Gaussian if it has pdf

$$
p(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{-\frac{(x-\mu)^{2}}{2 \sigma^{2}}}
$$

write this as $x \sim \mathcal{N}\left(\mu, \sigma^{2}\right)$

- the mean or expected value of $x$ is $\quad \mathbf{E}(x)=\int_{-\infty}^{\infty} x p(x) d x=\mu$
- the variance of $x$ is $\quad \mathbf{E}\left((x-\mu)^{2}\right)=\int_{-\infty}^{\infty}(x-\mu)^{2} p(x) d x=\sigma^{2}$


## Gaussian random variables

pdf for $x \sim \mathcal{N}(0,1)$ is


- $p$ is symmetric about the mean
- decays very fast; but $p(x)>0$ for all $x$


## Computing probabilities for Gaussian random variables

The error function is

$$
\operatorname{erf}(x)=\frac{2}{\sqrt{\pi}} \int_{0}^{x} e^{-t^{2}} d t
$$

The Gaussian CDF is

$$
F_{\mathcal{N}}(a)=\frac{1}{2}+\frac{1}{2} \operatorname{erf}\left(\frac{a-\mu}{\sigma \sqrt{2}}\right)
$$

When $\mu=0$ and $\sigma=1$,


## Computing probabilities for Gaussian random variables

so for $x \sim \mathcal{N}\left(0, \sigma^{2}\right)$ we have for $a \geq 0$

$$
\operatorname{Prob}(x \in[-a, a])=\operatorname{erf}\left(\frac{a}{\sigma \sqrt{2}}\right)
$$

Some particular values:

$$
\begin{aligned}
\operatorname{Prob}(x \in[-\sigma, \sigma]) & \approx 0.68 \\
\operatorname{Prob}(x \in[-2 \sigma, 2 \sigma]) & \approx 0.9545 \\
\operatorname{Prob}(x \in[-3 \sigma, 3 \sigma]) & \approx 0.9973
\end{aligned}
$$

## Collecting data

- For discrete random variables, we can collect data and count the frequencies of outcomes
This converges to the true pmf.
- The analogous procedure for continuous random variables uses the cumulative distribution function.

Suppose $S=\left\{z_{1}, \ldots, z_{n}\right\}$ are $n$ samples of a real-valued random variable.
Let $F(a)$ be the fraction of samples less than or equal to $a$, given by

$$
F(a)=\frac{|\{z \in S \mid z \leq a\}|}{n}
$$

- $F$ is a piecewise constant function, called the empirical $c d f$


## Example: collecting data

Suppose $x \sim \mathcal{N}(0,1)$.
The plots below show 25 and 250 data points, respectively.



## Induced probability density

Suppose we have

- $x: \Omega \rightarrow \mathbb{R}$ is a random variable with induced pdf $p^{x}: \mathbb{R} \rightarrow \mathbb{R}$.
- $y$ is a function of $x$, given by $y=g(x)$

What is the induced pdf of $y$ ?

The key idea is that we need to change variables for integration of probabilities. Recall the following.

If $f$ and $h^{\prime}$ are continuous, then

$$
\int_{h(a)}^{h(b)} f(x) d x=\int_{a}^{b} f(h(y)) h^{\prime}(y) d y
$$

## Induced probability density

Assume $g^{\prime}$ is continuous, and $g$ is strictly increasing, i.e.,

$$
\text { if } a<b \text { then } g(a)<g(b)
$$

This implies that $g$ is invertible, i.e., for every $y$ there is a unique $x$ such that $y=g(x)$.

We would like to find the pdf of $y$ is $p^{y}$, which satisfies for $a \leq b$,

$$
\operatorname{Prob}(y \in[a, b])=\int_{a}^{b} p^{y}(y) d y
$$

We also know that this probability is

$$
\begin{aligned}
\operatorname{Prob}(y \in[a, b]) & =\operatorname{Prob}(g(x) \in[a, b]) \\
& =\operatorname{Prob}\left(x \in\left[g^{-1}(a), g^{-1}(b)\right]\right) \text { since } g \text { is increasing } \\
& =\int_{g^{-1}(a)}^{g^{-1}(b)} p^{x}(x) d x
\end{aligned}
$$

## Induced probability density

We have

$$
\int_{a}^{b} p^{y}(y) d y=\int_{g^{-1}(a)}^{g^{-1}(b)} p^{x}(x) d x
$$

Now we can apply the change of variables $x=h(y)$ to the integral on the right hand side, where $h=g^{-1}$. We have

$$
h^{\prime}(y)=\frac{1}{g^{\prime}\left(g^{-1}(y)\right)}
$$

because $g(h(y))=y$, so $\frac{d}{d y} g(h(y))=1$, i.e., $g^{\prime}(h(y)) h^{\prime}(y)=1$

Therefore, by the change of variables formula

$$
\int_{a}^{b} p^{y}(y) d y=\int_{a}^{b} \frac{p^{x}\left(g^{-1}(y)\right)}{g^{\prime}\left(g^{-1}(y)\right)} d y
$$

## Induced probability density

Since this holds for all $a$ and $b$, we have the following.
If $y=g(x)$, and $g$ is strictly increasing with $g^{\prime}$ continuous, then the pdf of $y$ is

$$
p^{y}(y)=\frac{p^{x}\left(g^{-1}(y)\right)}{g^{\prime}\left(g^{-1}(y)\right)}
$$

More generally, if $g^{\prime}(x) \neq 0$ for all $x$, then

$$
p^{y}(y)=\frac{p^{x}\left(g^{-1}(y)\right)}{\left|g^{\prime}\left(g^{-1}(y)\right)\right|}
$$

## Example: linear transformations

Suppose $x: \Omega \rightarrow \mathbb{R}$, and $y=\alpha x+\beta$


We have

$$
p^{y}(y)=\frac{1}{|\alpha|} p^{x}\left(\frac{y-\beta}{\alpha}\right)
$$

## Non-invertible transformations

What happens when $g$ is not invertible? e.g., when $y=x^{2}$


$$
\begin{aligned}
\operatorname{Prob}(y \in[a, b]) & =\operatorname{Prob}\left(x^{2} \in[a, b]\right) \\
& =\operatorname{Prob}(x \in[-\sqrt{b},-\sqrt{a}])+\operatorname{Prob}(x \in[\sqrt{a}, \sqrt{b}]) \\
& =\int_{-\sqrt{b}}^{-\sqrt{a}} p^{x}(x) d x+\int_{\sqrt{a}}^{\sqrt{b}} p^{x}(x) d x \\
& =\int_{a}^{b} \frac{p^{x}(-\sqrt{y})}{2 \sqrt{y}} d y+\int_{a}^{b} \frac{p^{x}(\sqrt{y})}{2 \sqrt{y}} d y
\end{aligned}
$$

$$
y=x^{2} \quad \Longrightarrow \quad p^{y}(y)=\frac{1}{2 \sqrt{y}}\left(p^{x}(-\sqrt{y})+p^{x}(\sqrt{y})\right)
$$

## Simulation of random variables

We are given $F: \mathbb{R} \rightarrow[0,1]$

- We would like to simulate a random variable $y$ so that it has cumulative distribution function $F$
- We have a source of uniform random variables $x \sim U[0,1]$

To construct $y$, set

$$
y=F^{-1}(x)
$$

Because

$$
\begin{aligned}
\operatorname{Prob}(y \leq a) & =\operatorname{Prob}\left(F^{-1}(x) \leq a\right) \\
& =\operatorname{Prob}(x \leq F(a)) \\
& =F(a)
\end{aligned}
$$

- This works when $F$ is invertible and continuous

