W05 Notes

Discrete families: summary

01 Theory

Bernoulli: $X \sim \mathrm{Ber}(p)$

- Indicates a win.
- $P_X(1) = p,\ P_X(0) = q$
- $E[X] = p$
- $\mathrm{Var}[X] = pq$

Binomial: $X \sim \mathrm{Bin}(n, p)$

- Counts number of wins.
- $P_X(k) = \binom{n}{k} p^k q^{n-k}$
- $E[X] = np$
- $\mathrm{Var}[X] = npq$
- These are n times the Bernoulli numbers.

Geometric: $X \sim \mathrm{Geom}(p)$

- Counts discrete wait time until first win.
- $P_X(k) = q^{k-1}p$
- $E[X] = \dfrac{1}{p}$
- $\mathrm{Var}[X] = \dfrac{q}{p^2}$

Pascal: $X \sim \mathrm{Pasc}(\ell, p)$

- Counts discrete wait time until ℓ^{th} win.
- $P_X(k) = \binom{k-1}{\ell-1} q^{k-\ell} p^\ell$
- $E[X] = \dfrac{\ell}{p}$
- $\mathrm{Var}[X] = \dfrac{\ell q}{p^2}$
- These are ℓ times the Geometric numbers.

Poisson: $X \sim \mathrm{Pois}(\lambda)$

- Counts “arrivals” during time interval.
- $P_X(k) = e^{-\lambda} \dfrac{\lambda^k}{k!}$
- $E[X] = \lambda$

- $\text{Var}[X] = \lambda$

Function on a random variable

02 Theory

By composing any function $g : \mathbb{R} \to \mathbb{R}$ with a random variable $X : S \to \mathbb{R}$ we obtain a new random variable $g \circ X$. The new one is called a **derived** random variable.

Notation

The derived random variable $g \circ X$ may be written "$g(X)$".

Expectation of derived variables

Discrete case:

$$E\big[g(X)\big] \;=\; \sum_k g(k) \cdot P_X(k)$$

(Here the sum is over all *possible values* k of X, i.e. where $P_X(k) \neq 0$.)

Continuous case:

$$E\big[g(X)\big] \;=\; \int_{-\infty}^{+\infty} g(x) \cdot f_X(x)\, dx$$

Notice: when applied to outcome $s \in S$:

- k is the output of X
- $g(k)$ is the output of $g \circ X$

The proofs of these formulas are tricky because we must relate the PDF or PMF of X to that of $g(X)$
.

Proof - Discrete case - Expectation of derived variable

$$\begin{aligned} E[g(X)] &= \sum_y y \cdot P_{g(X)}(y) \\ &= \sum_y y \cdot \sum_{k \in g^{-1}(y)} P_X(k) \\ &= \sum_y \sum_{k \in g^{-1}(y)} g(k) \cdot P_X(k) \\ &= \sum_k g(k) \cdot P_X(k) \end{aligned}$$

Linearity of expectation

For constants a and b:

$g(X) = aX + b$

$$E[aX+b] \;=\; aE[X]+b$$

For any X and Y on the same probability model:

$$E[X+Y] \;=\; E[X]+E[Y]$$

Exercise - Linearity of expectation

Using the definition of expectation, verify both linearity formulas for the discrete case.

⚠ Be careful!

Usually $E\big[g(X)\big] \neq g(E[X])$.

For example, usually $E[X \cdot X] \neq E[X] \cdot E[X]$.

We distribute E over *sums* but *not products* (unless the factors are independent).

Variance squares the scale factor

For constants a and b:

$\mathrm{Var}[X] = E[(X-\mu)^2]$

$$\mathrm{Var}[aX+b] \;=\; a^2\,\mathrm{Var}[X]$$

Thus variance *ignores the offset* and *squares the scale factor*. It is not linear!

Proof - Variance squares the scale factor

$$\begin{aligned}
\mathrm{Var}[aX+b] \;&=\; E[(aX+b-E[aX+b])^2] \\
&=\; E[(aX+b-a\mu_X-b)^2] \\
&=\; E[(aX-a\mu_X)^2] \\
&=\; E[a^2(X-\mu_X)^2] \\
&=\; a^2\,E[(X-\mu_X)^2] \\
&=\; a^2\,\mathrm{Var}[X]
\end{aligned}$$

Extra - Moments

The n^{th} **moment** of X is defined as the expectation of X^n:

Discrete case:

$$E[X^n] = \sum_k k^n \cdot p(k)$$

Continuous case:

$$E[X^n] = \int_{-\infty}^{+\infty} x^n \cdot f(x)\, dx$$

A **central moment of X** is a moment of the variable $X - E[X]$:

$$E\big[(X - E[X])^n\big]$$

The data of all the moments collectively determines the probability distribution. This fact can be very useful! In this way moments give an analogue of a series representation, and are sometimes more useful than the PDF or CDF for encoding the distribution.

03 Illustration

Example - Function given by chart

Suppose that $g : \mathbb{R} \to \mathbb{R}$ in such a way that $g : 1 \mapsto 4$ and $g : 2 \mapsto 1$ and $g : 3 \mapsto 87$ and *no other values* are mapped to 4, 1, 87.

$Y = g(X)$

X :	1	2	3
$P_X(k)$:	1/7	2/7	4/7
Y :	4	1	87

Then:

$$E[X] = 1 \cdot \frac{1}{7} + 2 \cdot \frac{2}{7} + 3 \cdot \frac{4}{7} \quad \gg\gg \quad \frac{17}{7}$$

And: $E[g(X)] = \sum_{k \text{ pos. of } X} g(k) P_X(k) = g(1)P_X(1) + g(2)P_X(2) + g(3)P_X(3)$

$$E[Y] = 4 \cdot \frac{1}{7} + 1 \cdot \frac{2}{7} + 87 \cdot \frac{4}{7} \quad \gg\gg \quad \frac{354}{7}$$

Therefore:

$$E[5X + 2Y + 3] \quad \gg\gg \quad 5 \cdot \frac{17}{7} + 2 \cdot \frac{354}{7} + 3 \quad \gg\gg \quad \frac{814}{7}$$

$= 5E[X] + 2E[Y] + 3$

Variance of uniform random variable

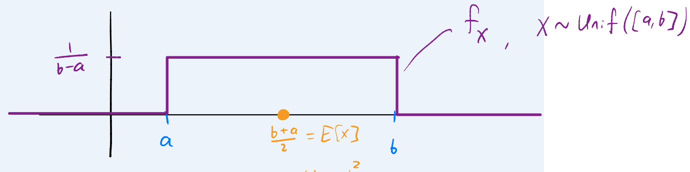
The uniform random variable X on $[a,b]$ has distribution given by $P\big[c \le X \le d\big] = \dfrac{d-c}{b-a}$ when $a \le c \le d \le b$.

(a) Find $\mathrm{Var}[X]$ using the shorter formula.

(b) Find $\mathrm{Var}[3X]$ using "squaring the scale factor."

(c) Find $\mathrm{Var}[3X]$ directly.

$h \cdot (b-a) = 1$
$\Rightarrow h = \frac{1}{b-a}$



$Var[X] = \frac{(b-a)^2}{12}$

Solution

(a)

(1) Compute density.

The density for X is:

$$f_X(x) \;=\; \begin{cases} \dfrac{1}{b-a} & \text{for } x \in [a,b] \\ 0 & \text{otherwise} \end{cases}$$

Shorter Variance:
$Var[X] = E[X^2] - E[X]^2$

(2) Compute $E[X]$ and $E[X^2]$ directly using integral formulas.

Compute $E[X]$:

$$E[X] \;=\; \int_a^b \frac{x}{b-a}\,dx \quad \gg\!\gg \quad \frac{b+a}{2}$$

$E[X] = \int_{-\infty}^{\infty} x f_X \, dx$

Now compute $E[X^2]$:

$$E[X^2] = \int_a^b \frac{x^2}{b-a}\,dx \quad \gg\!\gg \quad \frac{1}{3}(b^2 + ba + a^2)$$

$\frac{1}{b-a}\left(\frac{b^3-a^3}{3}\right)$

a. Find f_{X^2}, then $\int x f_{X^2} dx$

b. Faster: $\int g(x) f_X \, dx$

$\gg\!> \int_a^b x^2 \frac{1}{b-a} dx$

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(3) Find variance using short formula.

Plug in:

$$\mathrm{Var}[X] \;=\; E[X^2] - E[X]^2$$

$$\gg\!\gg \quad \frac{1}{3}(b^2 + ab + a^2) - \left(\frac{b+a}{2}\right)^2$$

$$\gg\!\gg \quad \frac{(b-a)^2}{12}$$

(b)

(1) "Squaring the scale factor" formula:

$$\mathrm{Var}[aX + b] \;=\; a^2 \mathrm{Var}[X]$$

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(2) Plugging in:

$$\operatorname{Var}[3X] \quad \ggg \quad 9\operatorname{Var}[X] \quad \ggg \quad \frac{9}{12}(b-a)^2$$

(c)

(1) Density.

The variable $3X$ will have $1/3$ the density spread over the interval $[3a, 3b]$.

Density is then:

$$f_{3X}(x) \;=\; \begin{cases} \dfrac{1}{3b-3a} & \text{on } [3a, 3b] \\ 0 & \text{otherwise} \end{cases}$$

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(2) Plug into prior variance formula.

Use $a \rightsquigarrow 3a$ and $b \rightsquigarrow 3b$.

Get variance:

$$\operatorname{Var}[3X] \;=\; \frac{(3b-3a)^2}{12}$$

Simplify:

$$\ggg \quad \frac{(3(b-a))^2}{12} \quad \ggg \quad \frac{9}{12}(b-a)^2$$

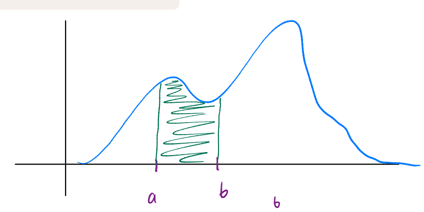
Exercise - Probabilities via CDF

Suppose the CDF of X is given by $F_X(x) = \dfrac{1}{1+e^{-x}}$. Compute:

(a) $P[X \le 1]$ (b) $P[X < 1]$ (c) $P[-0.5 \le X \le 0.2]$ (d) $P[-2 \le X]$

Solution

04 Theory



Suppose we are given the PDF $f_X(x)$ of X, a continuous RV.

What is the PDF $f_{g(X)}$, the derived variable given by composing X with $g : \mathbb{R} \to \mathbb{R}$?

$P[a \le X \le b] = \int_a^b f_X \, dx$

$F_X(x) = P[X \le x] = \int_{-\infty}^{x} f_X(t)\, dt$

Thus: $f_X(x) = \frac{d}{dx} F_X(x)$

⚠ PDF of derived

The PDF of $g(X)$ is *not* (usually) equal to $g \circ f_X(x)$.

Relating PDF and CDF

When the CDF of X is differentiable, we have:

$$F_X(x) = \int_{-\infty}^{x} f_X(t)\,dt \quad \Longleftrightarrow \quad f_X(x) = \frac{d}{dx} F_X(x)$$

$$F_{g(X)}(x) = \int_{-\infty}^{x} f_{g(X)}(t)\,dt \quad \Longleftrightarrow \quad f_{g(X)}(x) = \frac{d}{dx} F_{g(X)}(x)$$

Therefore, if we know $f_X(x)$, we can find $f_{g(X)}(x)$ using a 3-step process:

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(1) Find $F_X(x)$, the CDF of X, by integration:

Compute $F_X(x) = \int_{-\infty}^{x} f_X(t)\,dt$.

Now remember that $F_X(x) = P[X \leq x]$.

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(2) Find $F_{g(X)}$, the CDF of $g(X)$, by *comparing conditions*:

When g is monotone increasing, we have equivalent conditions:

$$g(X) \leq x \quad \Longleftrightarrow \quad X \leq g^{-1}(x)$$

$$\ggg \quad P[\,g(X) \leq x\,] \quad = \quad P[\,X \leq g^{-1}(x)\,]$$

$$\ggg \quad F_{g(X)}(x) \quad = \quad F_X(g^{-1}(x))$$

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(3) Find $f_{g(X)}$ by differentiating $F_{g(X)}$:

$$f_{g(X)}(x) \;=\; \frac{d}{dx} F_{g(X)}(x) \;=\; \frac{d}{dx} F_X(g^{-1}(x))$$

05 Illustration

Example - PDF of derived from CDF

Suppose that $F_X(x) = \dfrac{1}{1+e^{-x}}$.

(a) Find the PDF of X. (b) Find the PDF of e^X. I.e. $g(x) = e^x$

Solution

(a)

Formula:

$$F_X(x) = \int_{-\infty}^{x} f_X(t)\,dt \qquad \Longrightarrow \qquad f_X(x) = \frac{d}{dx} F_X(x)$$

Plug in:

$$f_X(x) = \frac{d}{dx}\left(1 + e^{-x}\right)^{-1} \quad \gg\gg \quad -(1+e^{-x})^{-2} \cdot (-e^{-x})$$

$$\gg\gg \quad \frac{e^{-x}}{\left(1+e^{-x}\right)^2}$$

(b)

By definition:

$$F_{e^X}(x) = P[e^X \leq x]$$

Since e^X is increasing, we know:

$$e^X \leq a \qquad \Longleftrightarrow \qquad X \leq \ln a$$

Therefore:

$$F_{e^X}(x) = F_X(\ln x)$$

$$\gg\gg \quad \frac{1}{1+e^{-\ln x}} \quad \gg\gg \quad \frac{1}{1+x^{-1}}$$

Then using differentiation:

$$f_{e^X}(x) = \frac{d}{dx}\left(\frac{1}{1+x^{-1}}\right)$$

$$\gg\gg \quad -(1+x^{-1})^{-2} \cdot (-x^{-2}) \quad \gg\gg \quad \frac{1}{(x+1)^2}$$

Continuous wait times

06 Theory

Exponential variable

A random variable X is **exponential**, written $X \sim \mathrm{Exp}(\lambda)$, when X measures the *wait time until first arrival* in a Poisson process with rate λ.

Exponential PDF:

$$f_X(t) \;=\; \begin{cases} \lambda e^{-\lambda t} & t \geq 0 \\ 0 & t < 0 \end{cases}$$

- Poisson is continuous analog of binomial
- Exponential is continuous analog of geometric

Notice the coefficient λ in f_X. This ensures $P[-\infty \leq X \leq \infty] = 1$:

$$\int_0^\infty e^{-\lambda t}\,dt \quad \ggg \quad -\lambda^{-1}(e^{-\lambda \cdot \infty} - 1) \quad \ggg \quad \lambda^{-1}$$

Notice the "tail probability" is a simple exponential decay:

$$P[X > t] \;=\; e^{-\lambda t}$$

(Compute an improper integral to verify this.)

Erlang variable

A random variable X is **Erlang**, written $X \sim \text{Erlang}(\ell, \lambda)$, when X measures the *wait time until ℓ^{th} arrival* in a Poisson process with rate λ.

Erlang PDF:

$$f_X(t) \;=\; \frac{\lambda^\ell}{(\ell-1)!} t^{\ell-1} e^{-\lambda t}$$

- Erlang is continuous analog of Pascal

07 Illustration

Example - Earthquake wait time

Suppose the San Andreas fault produces major earthquakes modeled by a Poisson process, with an average of 1 major earthquake every 100 years.

(a) What is the probability that there will *not* be a major earthquake in the next 20 years?

(b) What is the probability that *three* earthquakes will strike within the next 20 years?

Solution

(a)

Since the average wait time is 100 years, we set $\lambda = 0.01$ earthquakes per year. Set $X \sim \text{Exp}(0.01)$ and compute:

$$P[X > 20] = e^{-\lambda \cdot 20} \quad \ggg \quad e^{-0.01 \cdot 20} \quad \ggg \quad \approx 0.82$$

(b)

The same Poisson process has the same $\lambda = 0.01$ earthquakes per year. Set $X \sim \text{Erlang}(3, 0.01)$, so:

$$f_X(t) = \frac{\lambda^\ell}{(\ell - 1)!} t^{\ell - 1} e^{-\lambda t}$$

$$\ggg \quad \frac{(0.01)^3}{(3-1)!} t^{3-1} e^{-0.01 \cdot t} \quad \ggg \quad \frac{10^{-6}}{2} t^2 e^{-0.01 \cdot t}$$

and compute:

$$P[X \leq 20] = \int_0^{20} f_X(x)\, dx$$

$$\ggg \quad \int_0^{20} \frac{10^{-6}}{2} t^2 e^{-0.01 \cdot t}\, dt \quad \ggg \quad \approx 0.00115$$

08 Theory

The memoryless distribution is exponential

The exponential distribution is memoryless.
This means that knowledge that an event has not yet occurred does not affect the probability of its occurring in future time intervals:

$$P[X > t + s \mid X > t] \; = \; P[X > s].$$

This is easily checked using the PDF:

$$e^{-\lambda(t+s)} \big/ e^{-\lambda t} = e^{-\lambda s}$$

No other continuous distribution is memoryless.
This means any other (continuous) memoryless distribution agrees in probability with the exponential distribution. The reason is that the memoryless property can be rewritten as $P[X > t + s] = P[X > t]P[X > s]$. Consider $P[X > x]$ as a function of x, and notice that this function *converts sums into products*. Only the exponential function can do this.

The geometric distribution is the *discrete* memoryless distribution.

$$P[X > n] \quad \ggg \quad \sum_{k=n+1}^{\infty} q^{k-1} p \quad \ggg \quad q^n p(1 + q + q^2 + \ldots)$$

$$\ggg \quad q^n \frac{p}{1-q} \quad \ggg \quad q^n$$

and by substituting $n + k$, we also know $P[X > n + k] = q^{n+k}$.

Then:

$$P[X = n + k \mid X > n] \quad \ggg \quad \frac{P[X = n+k]}{P[X > n]} \quad \ggg \quad \frac{q^{n+k-1}p}{q^n}$$

$$\ggg \quad q^{k-1}p \quad \ggg \quad P[X = k]$$

Extra - Inversion of decay rate factor in exponential

For constants a and λ:

$$\text{Exp}(a\lambda) \;\sim\; \tfrac{1}{a}\text{Exp}(\lambda)$$

Derivation:
Let $X \sim \text{Exp}(\lambda)$ and observe that $P[X > t] = e^{-\lambda t}$ (the "tail probability").

Now observe that:

$$P[a^{-1}X > t] \;=\; P[X > at] \quad \ggg \quad e^{-\lambda at}$$

Let $Y \sim \text{Exp}(a\lambda)$. So we see that:

$$P[a^{-1}X > t] \;=\; P[Y > t]$$

Since the tail event is complementary to the cumulative event, these two distributions have the same CDF, and therefore they are equal.

Extra - Geometric limit to exponential

Divide the waiting time into small intervals. Let $p = \frac{\lambda}{n}$ be the probability of at least one success in the time interval $[a, a + \frac{1}{n}]$ for any a. Assume these events are independent.

A random variable T_n measuring the end time of the first interval $[\frac{k-1}{n}, \frac{k}{n}]$ containing a success would have a geometric distribution with $\frac{k}{n}$ in place of k:

$$P\left[T_n = \frac{k}{n}\right] \;=\; \left(1 - \frac{\lambda}{n}\right)^{k-1} \frac{\lambda}{n}$$

By taking the sum of a geometric series, one finds:

$$P[T_n > x] \;=\; \left(1 - \frac{\lambda}{n}\right)^{\lfloor nx \rfloor}$$

Thus $P[T_n > x] \to e^{-\lambda x}$ as $n \to \infty$.