

Review of probability concepts

Random experiment / process : deterministic prediction is hard.

Example: coin toss with high initial velocity

Random experiments generate simple events

Example: coin tossing twice

events: HH, HT, TH, TT

$S = \{HH, HT, TH, TT\}$ - Sample space

An event is any subset space:

$A = \text{"at least one H"} = \{HH, HT, TH\}$

Def: If events do not overlap, they are called mutually exclusive (disjoint in terms of set theory)

Note: do not confuse mutually exclusive with independent events

Event arithmetic:

$A \overset{\text{or}}{\cup} B = \{ \text{simple events in } A \text{ or } B, \text{ or both} \}$

$A \overset{\text{and}}{\cap} B = \{ \text{simple events in } A \text{ and } B \}$

$\overset{\text{complement}}{A^c} = \{ \text{simple events not in } A \}$

$$A = \{HH, HT, TH\}$$

$$A \cup B = \{HH, HT, TH, TT\}$$

$$B = \{HT, TH, TT\}$$

$$A \cap B = \{HT, TH\}$$

$$A^c = \{TT\}$$

Probability is a function that maps events (subsets of the sample space) into $[0, 1]$.

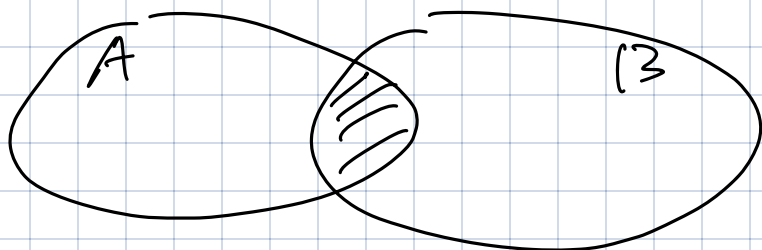
$$1) \text{ For any } A \subset S, \quad 0 \leq P(A) \leq 1$$

$$2) \quad P(S) = 1$$

$$3) \quad A \cap B = \emptyset \Rightarrow P(A \cup B) = P(A) + P(B)$$

\uparrow
 empty set

$$\text{Addition rule: } P(A \cup B) = P(A) + P(B) - P(A \cap B)$$



Where do probabilities come from?

$$1) \text{ long term frequencies } P(A) = \frac{\# \text{ of times } A \text{ occurs}}{\# \text{ of r.e. repetitions}}$$

2) $P(A)$ - come from some assumed prob mass function or density

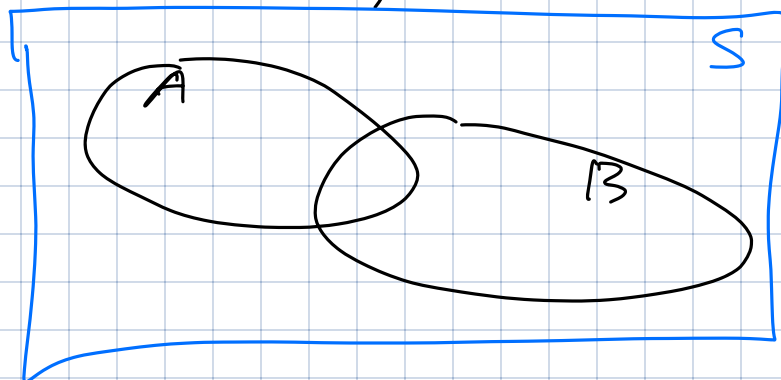
3) $P(A)$ - subjective probabilities

Conditional probability

Sometimes we want to think about of A and how it depends on whether or not event B had occurred

$\Pr(\text{"being struck by lightning"}) < \Pr(\text{"being struck by lightning"} \mid \text{"caught in a storm"})$

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}, \text{ where } P(B) > 0$$



Example (medical testing)

Suppose we are evaluating results of a medical diagnostic test for a disease D. No test is perfect. This particular test has false negative rate/prob of 1% and false positive rate/prob of 2%.

$T^+ = \text{"test is positive"} \quad D^+ = \text{"disease is present"}$

$T^- = \text{"test is negative"} \quad D^- = \text{"disease is absent"}$

$$P(T+ | D+) = 0.09$$

$$P(T+ | D-) = 0.02$$

$$P(T- | D+) = 0.01$$

$$P(T- | D-) = 0.98$$

We also assume that $P(D+) = 0.001$ - frequency of the disease in the population (prevalence)

In practice, every patient should be interested in:

$$P(D+ | T+) = \frac{P(D+ \cap T+)}{P(T+)}$$

$$P(T+ | D+) = \frac{P(T+ \cap D+)}{P(D+)} \Rightarrow$$

$$P(T+ \cap D+) = P(T+ | D+) \cdot P(D+)$$

$$P(T+) = P((T+ \cap D+) \cup (T+ \cap D-)) =$$

mutually exclusive

$$= P(T+ \cap D+) + P(T+ \cap D-) =$$

$$= \underbrace{P(T+ | D+)}_{\text{conditional on}} \cdot P(D+) + P(T+ | D-) \cdot P(D-) =$$

$$= 0.99 \cdot 0.001 + 0.02 \cdot (1 - 0.001) = 0.02097$$

$$P(D+ | T+) = \frac{\underbrace{P(T+ | D+)}_{\text{conditional on}} \cdot P(D+)}{P(T+)} = \frac{0.99 \cdot 0.001}{0.02097} \approx 0.047$$

Note: if we redo these calculations

with $P(D+) = 0.01$ we get $P(D+|T+) \approx 0.33$

Note: if the patient takes the test twice

$$P(D+ | T+ \cap T+)$$

Note: More practically, this patient would be interested in

$$P(D+ | T+ \cap \text{symptoms})$$

Random variables

A random variable is a function mapping sample space $S \rightarrow \mathbb{R}^n$ - n -dimensional space of real numbers

Example: coin flipping

Random variable: # of heads ($g: S \rightarrow \mathbb{R}$)

Simple events	g (simple event)
HH	2
HT	1
TH	1
TT	0

In practice, we start with a distributional assumption, which defines a sample space and probabilities for all events

Example: X is a discrete random variable with values $S = \{1, 2, 3\}$ with prob mass function :

$$p(1) = 0.1$$

$$p(2) = 0.4$$

$$p(3) = 0.5$$

Bernoulli random variable :

$$X = \begin{cases} 1 & \text{if heads} \\ 0 & \text{if tails} \end{cases}$$

$$P(X=1) = p, \quad P(X=0) = 1-p$$

Binomial random variable

X_1, X_2, \dots, X_n - independent and identically distributed Bernoulli random variables (so p is the same for all X_s)

$$Y = \sum_{i=1}^n X_i \sim \text{Binomial}(n, p)$$

↑
of successes in n Bernoulli (coin toss) experiments

prob mass function: $p(k) = \binom{n}{k} p^k (1-p)^{n-k}$

$$k = 0, 1, \dots, n$$

0 1 0 1 0 0 \rightarrow 2 successes

1 1 0 0 0 0 \rightarrow 2 successes

$$\sum_{k=0}^n p(k) = 1$$

Def $F(x) = P(X \leq x)$ — cumulative distribution function (cdf) of X

\uparrow random variable \nwarrow fixed scalar

ve distribution function (cdf) of X

Properties:

- 1) $0 \leq F(x) \leq 1$
- 2) $F(x) \leq F(y)$ for $x \leq y$

Discrete uniform random variable over

$$\{1, \dots, n\} \quad p(k) = \frac{1}{n}, k=1, \dots, n$$

$$F(x) = P(U \leq x)$$

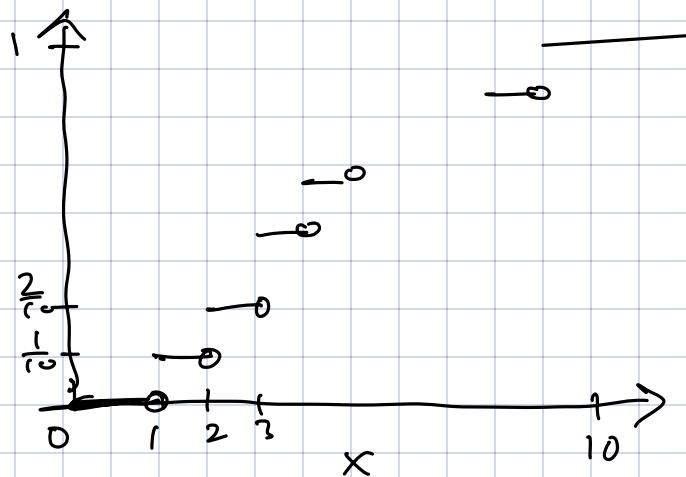
$$\text{if } x < 1 : P(U \leq x) = 0$$

$$\text{if } 1 \leq x < 2 \quad P(U \leq x) = P(U=1) = \frac{1}{n}$$

$$2 \leq x < 3 \quad P(U \leq x) = P(U=1) +$$

$$P(U=2) = \frac{1}{n} + \frac{1}{n}$$

$$F(x) = \begin{cases} 0, & \text{if } x < 1 \\ \frac{1}{n}, & \text{if } 1 \leq x < 2 \\ \frac{2}{n}, & \text{if } 2 \leq x < 3 \\ \vdots & \\ \frac{n-1}{n}, & \text{if } n-1 \leq x < n \\ 1, & \text{if } x \geq n \end{cases}$$

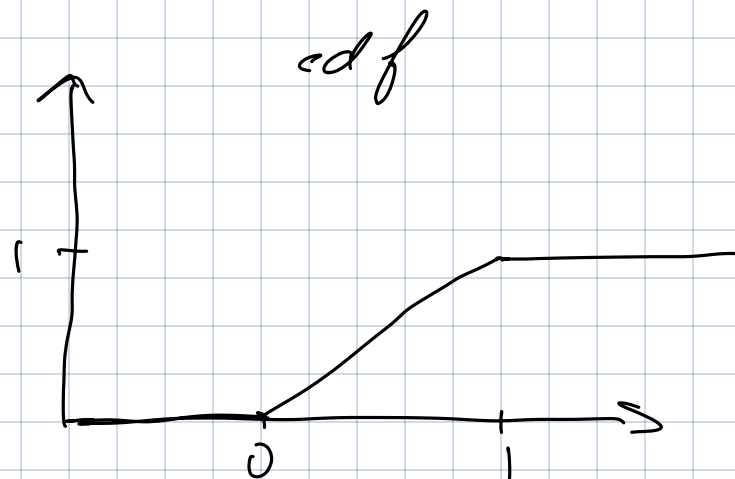
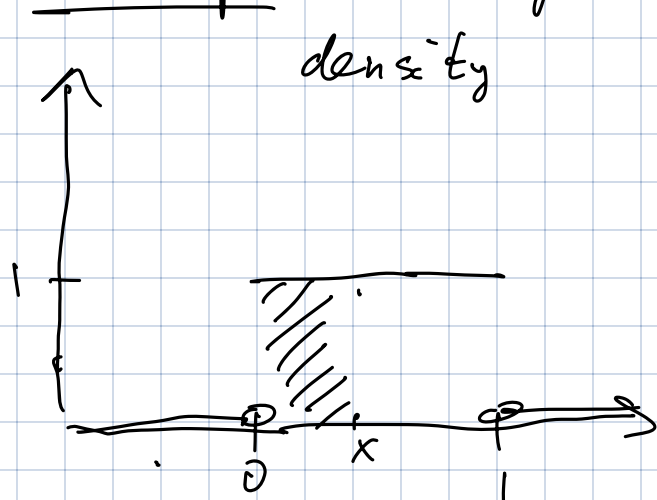


Def If $F(x) = \int_{-\infty}^x f(y) dy$ for some $f(x) \geq 0$
 then $f(x)$ — density

Note: $\int_a^b f(x) dx = F(b) - F(a) = P(a \leq X < b)$

$$\frac{dF(x)}{dx} = f(x)$$

Example: Uniform random variable on $[0, 1]$



$$f(x) = \begin{cases} 1 & \text{if } x \in [0, 1] \\ 0 & \text{otherwise} \end{cases}$$

The cdf of U

$$F(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } 0 \leq x < 1 \\ 1 & \text{if } x \geq 1 \end{cases}$$

Inverse CDF method for generating realizations of random variables

Suppose we have a random variable with cdf $F(x)$. We would like to generate realizations of this random variable, but we only have access to a stream of independent $\text{Unif}[0, 1]$ random varia-

bles.

Theorem Let X be a continuous random variable with cdf $F(x)$ such that $F^{-1}(u)$ exists for all $u \in (0,1)$.

If $U \sim \text{Unif}[0,1]$, then random variable $F^{-1}(U)$ has the same distribution as X

Proof: since cdf uniquely characterizes the distribution of a random variable, it is enough to show the cdf of $F^{-1}(U)$ is $F(x)$

recall: $x \leq y \Rightarrow F(x) \leq F(y)$

$$\begin{aligned} P(F^{-1}(U) \leq x) &= P(\cancel{F(F^{-1}(U))} \leq F(x)) = \\ &= P(U \leq \overset{\in [0,1]}{F(x)}) = F(x) \quad \checkmark \end{aligned}$$

Example: simulating exponential random variable

Suppose $X \sim \text{Exp}(\lambda)$ with density

$$f(x) = \lambda e^{-\lambda x} \quad \text{if } x \geq 0$$

$$\text{cdf of } X \text{ is } \int_{-\infty}^x f(x) dx = \int_0^x \lambda e^{-\lambda x} dx = 1 - e^{-\lambda x}$$

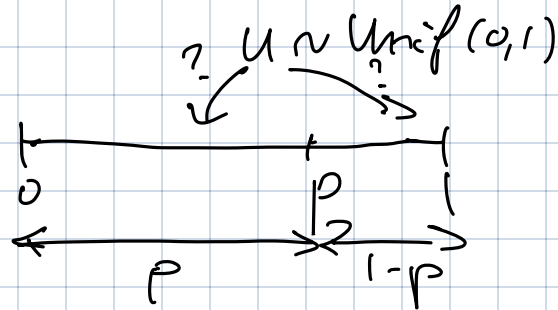
Let $U \sim \text{Unif}[0, 1]$. Let's invert the cdf:

$$F(x) = U \Leftrightarrow 1 - e^{-\lambda x} = U \Leftrightarrow 1 - U = e^{-\lambda x} \Leftrightarrow$$

$$\Leftrightarrow \ln(1 - U) = -\lambda x \Leftrightarrow x = -\frac{1}{\lambda} \ln(1 - U) > 0$$

Inverse CDF for Discrete Random Variables

Bernoulli(p)



$X \sim \text{Discrete}(p_1, \dots, p_m)$ $\sum_{i=1}^m p_i = 1$

