

16 Sep 2025

Tuesday, September 16, 2025

2:01 PM

Mutual Independence (review):

Box of tickets:

111	111
010	010
100	100
001	001

A1 = First digit is a 1

A2 = Second digit is a 1

A3 = Third digit is a 1

$$P(A1) = 4/8$$

$$P(A2) = 4/8$$

$$P(A3) = 4/8$$

$$P(A_1 \cap A_2) = \frac{2}{8} = \frac{1}{4} = \frac{1}{2} \cdot \frac{1}{2}$$

$$P(A_1 \cap A_3) = \dots$$

$$P(A_2 \cap A_3) = \dots$$

$$P(A_1 \cap A_2 \cap A_3) = \frac{2}{8} \neq \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2}$$

So, these events are all pairwise independent but not mutually independent

Conditional Independence

Two events A and B are conditionally independent given C if:

$$P(A \cap B | C) = P(A | C) P(B | C)$$

If A, B are conditionally independent, does that mean A, B are independent. Not necessarily (A and B given C is a subset of A and B, what applies for the smaller space might not apply for the whole)

Ex: (standard Bayes' stuff to start)

- 1% of women aged 40-50 have breast cancer.
- Women with breast cancer have 90% chance of testing positive from mammogram
- Women without breast cancer have 10% chance of testing positive from mammogram (false positive)
- B = Has Breast Cancer, T = Positive Test

$$\text{WANT: } P(B | T)$$

$$P(B) = 1/100$$

$$P(T | B) = \frac{9}{10}$$

$$P(T | B^c) = \frac{1}{10}$$

$$P(B | T) = \frac{P(T | B) P(B)}{P(T | B) P(B) + P(T | B^c) P(B^c)}$$
$$= \frac{.9(.01)}{.9(.01) + .1(.99)} = \frac{9}{108}$$

Now we have a second test.

... INDEPENDENCE

T1 = positive first test, T2 = positive second test

$$P(B | T_1, T_2) = \frac{P(T_1, T_2 | B) P(B)}{P(T_1, T_2)}$$

IF WE ASSUME CONDITIONAL INDEPENDENCE

$$= \frac{P(T_1 | B) P(T_2 | B) P(B)}{P(T_1 | B) P(T_2 | B) P(B) + P(T_1 | B^c) P(T_2 | B^c) P(B^c)}$$

$$= \frac{9}{20}$$

- OR -

$$P(B | T_1, T_2) = \frac{P(T_2 | B) P(B | T_1)}{P(T_2 | B) P(B | T_1) + P(T_2 | B^c) P(B^c | T_1)}$$

Basically, use the probability from test 1 in the calculation for test 2

Ex: Flip two fair coins. Flip each once

A = first coin is heads. B = second coin is heads. C = Both coins are same

A & B are independent: $P(A \cap B) = P(A)P(B) = \frac{1}{4}$

$$P(A \cap B | C) = \frac{1}{2} \text{ (COUNT OUT ALL SAMPLES)}$$

$$P(A | C) = \frac{1}{2} \quad P(B | C) = \frac{1}{2}$$

Therefore, not conditionally independent, but are marginally independent (independent from each other on some level)

Random Variable

Random variable: function, mapping. Mapping from sample space into new 'image'

Def: a random variable (vector) is a function from the sample space to the real numbers

Formally: $X: S \Rightarrow \mathbb{R}$ $\tilde{X}: S \Rightarrow \mathbb{R}$

Example:

Experiment	Sample Space	Random Variable
Toss two dice	$\{(1, 1), (1, 2) \dots (6, 6)\}$	$X = \text{Sum}, Y = \text{Max}$
Toss coin 25 times	$\{H, T\}^{25}$	$X = \# \text{ heads}$

$$\boxed{S} \xrightarrow{X} \boxed{x}$$

Ex: Let $S = \{s_1, \dots, s_n\}$ with probability function $P(\cdot)$. Let new subspace $X_{\text{fancy}} = \{x_1, \dots, x_n\}$.

Since $X = x_i$ iff s_j in S maps to x_i (ie. $X(s_j) = x_i$) then the new probability (induced probability) function on X_{fancy} is:

$$P(X = x_i) = P(\{s_j \in S : X(s_j) = x_i\})$$

Ex. Toss 3 fair coins, consider the r.v. $X = \#$ of heads

- $X(\text{hhh}) = 3, X(\text{hht}) = 2, \dots, X(\text{ttt}) = 0$

X	0	1	2	3
---	---	---	---	---

P(X)	1/8	3/8	3/8	1/8
------	-----	-----	-----	-----

- This is the induced Probability Mass Function

Cumulative Distribution Function

The Cumulative Distribution Function (CDF) of a r.v. is denoted

$F_X(x)$

And is defined by

$P(X \leq x)$ For all $x \in \mathbb{R}$

Ex. Tossing 3 fair coins

$$F_X(x) = \begin{cases} 0 & -\infty < x < 0 \\ 1/8 & 0 \leq x < 1 \\ 4/8 & 1 \leq x < 2 \\ 7/8 & 2 \leq x < 3 \\ 1 & x \geq 3 \end{cases}$$

$$1. \lim_{x \rightarrow -\infty} F_X(x) = 0 \quad \lim_{x \rightarrow \infty} F_X(x) = 1$$

$$2. F_X(x) \text{ IS NON-DECREASING i.e. for } x_1 \leq x_2 \quad F_X(x_1) \leq F_X(x_2)$$

$$3. F_X(x) \text{ IS RIGHT CONTINUOUS } \lim_{x \downarrow x_0} F_X(x) = F_X(x_0)$$