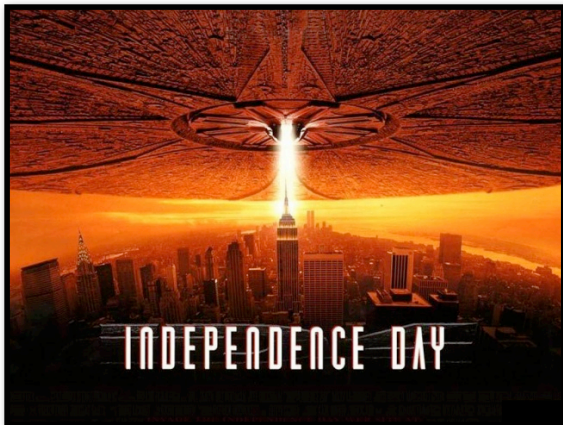


5. independence



Two events E and F are *independent* if

$$P(EF) = P(E) P(F)$$

equivalently: $P(E|F) = P(E)$

otherwise, they are called *dependent*

Roll two dice, yielding values D_1 and D_2

$$E = \{ D_1 = 1 \}$$

$$F = \{ D_2 = 1 \}$$

$$P(E) = 1/6, P(F) = 1/6, P(EF) = 1/36$$

$$P(EF) = P(E) \cdot P(F) \Rightarrow E \text{ and } F \text{ independent}$$

$$G = \{ D_1 + D_2 = 5 \} = \{(1,4), (2,3), (3,2), (4,1)\}$$

$$P(E) = 1/6, P(G) = 4/36 = 1/9, P(EG) = 1/36$$

not independent!

E, G dependent events



Two events E and F are *independent* if

$$P(EF) = P(E) P(F)$$

equivalently: $P(E|F) = P(E)$

otherwise, they are called *dependent*

Three events E, F, G are independent if

$$P(EF) = P(E)P(F), P(EG) = P(E)P(G), P(FG) = P(F)P(G)$$

and $P(EFG) = P(E) P(F) P(G)$

Example: Let X, Y be each $\{-1, 1\}$ with equal prob

$$E = \{X = 1\}, F = \{Y = 1\}, G = \{XY = 1\}$$

$$P(EF) = P(E)P(F), P(EG) = P(E)P(G), P(FG) = P(F)P(G)$$

but $P(EFG) = 1/4$!!! (because $P(G|EF) = 1$)

In general, events E_1, E_2, \dots, E_n are independent if for every subset S of $\{1, 2, \dots, n\}$, we have

$$P\left(\bigcap_{i \in S} E_i\right) = \prod_{i \in S} P(E_i)$$

(Sometimes this property holds only for small subsets S . E.g., E, F, G on the previous slide are *pairwise* independent, but not fully independent.)

Theorem: E, F independent $\Rightarrow E, F^c$ independent

Proof:
$$\begin{aligned} P(EF^c) &= P(E) - P(EF) \\ &= P(E) - P(E)P(F) \\ &= P(E)(1 - P(F)) \\ &= P(E)P(F^c) \end{aligned}$$

Theorem:

$$E, F \text{ independent} \Leftrightarrow P(E|F) = P(E) \Leftrightarrow P(F|E) = P(F)$$

Proof: Note $P(EF) = P(E|F)P(F)$, regardless of in/dep.
Assume independent. Then

$$P(E)P(F) = P(EF) = P(E|F)P(F) \Rightarrow P(E|F) = P(E) \quad (\div \text{ by } P(F))$$

$$\text{Conversely, } P(E|F) = P(E) \Rightarrow P(E)P(F) = P(EF) \quad (\times \text{ by } P(F))$$

Biased coin comes up heads with probability p .

P(heads on n flips)

$$= p^n$$



P(tails on n flips)

$$= (1-p)^n$$

P(exactly k heads in n flips)

$$= \binom{n}{k} p^k (1-p)^{n-k}$$

Aside: note that the probability of some number of heads $= \sum_k \binom{n}{k} p^k (1-p)^{n-k} = (p + (1-p))^n = 1$ as it should, by the binomial theorem.

m strings hashed (uniformly) into a table with n buckets

Each string hashed is an *independent* trial

E = at least one string hashed to first bucket

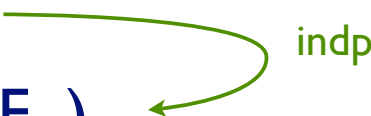
What is $P(E)$?

Solution:

F_i = string i *not* hashed into first bucket ($i=1,2,\dots,m$)

$P(F_i) = 1 - 1/n = (n-1)/n$ for all $i=1,2,\dots,m$

Event $(F_1 F_2 \dots F_m)$ = no strings hashed to first bucket

$$\begin{aligned} P(E) &= 1 - P(F_1 F_2 \dots F_m) \\ &= 1 - P(F_1) P(F_2) \dots P(F_m) \\ &= 1 - ((n-1)/n)^m \end{aligned}$$


m strings hashed (non-uniformly) to table w/ n buckets

Each string hashed is an *independent* trial, with probability p_i of getting hashed to bucket i

E = At least 1 of buckets 1 to k gets ≥ 1 string

What is $P(E)$?

Solution:

F_i = at least one string hashed into i-th bucket

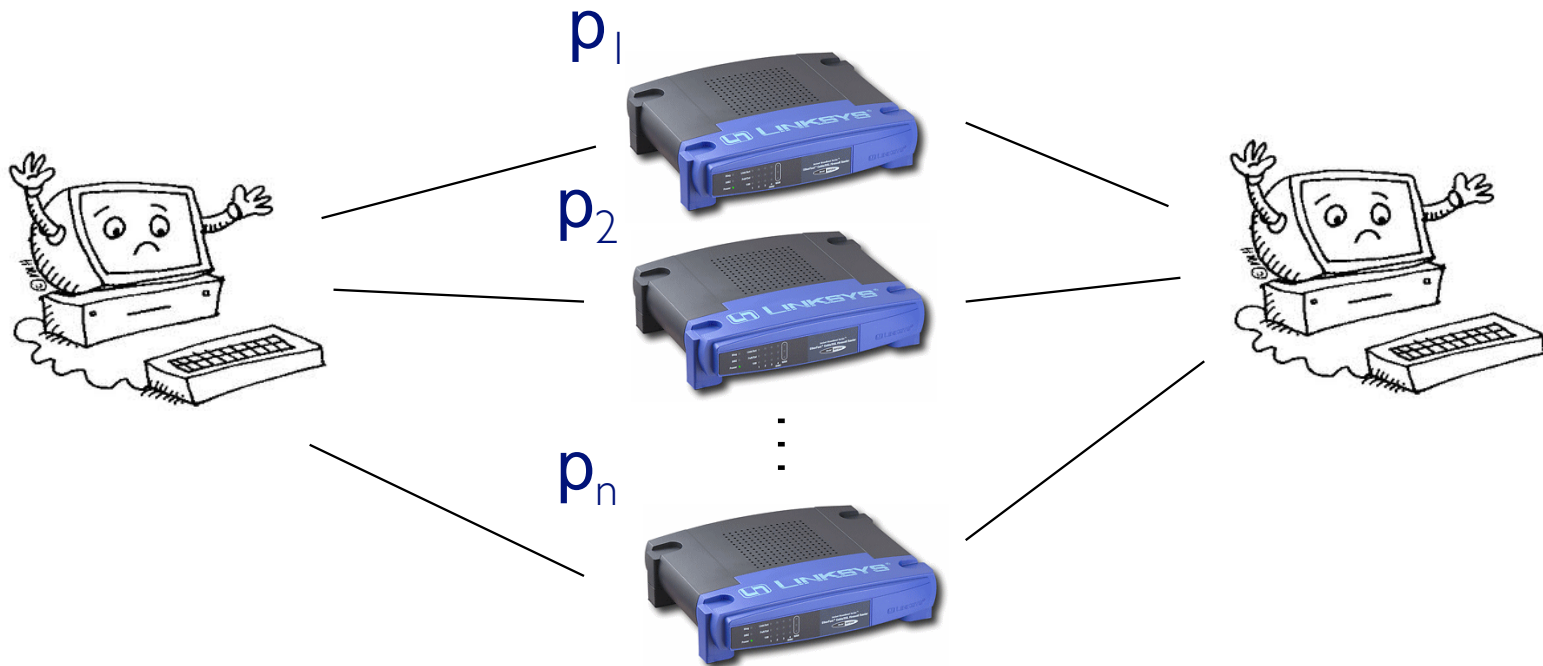
$$P(E) = P(F_1 \cup \dots \cup F_k) = 1 - P((F_1 \cup \dots \cup F_k)^c)$$

$$= 1 - P(F_1^c \cap F_2^c \cap \dots \cap F_k^c)$$

$$= 1 - P(\text{no strings hashed to buckets 1 to k})$$

$$= 1 - (1 - p_1 - p_2 - \dots - p_k)^m$$

Consider the following parallel network

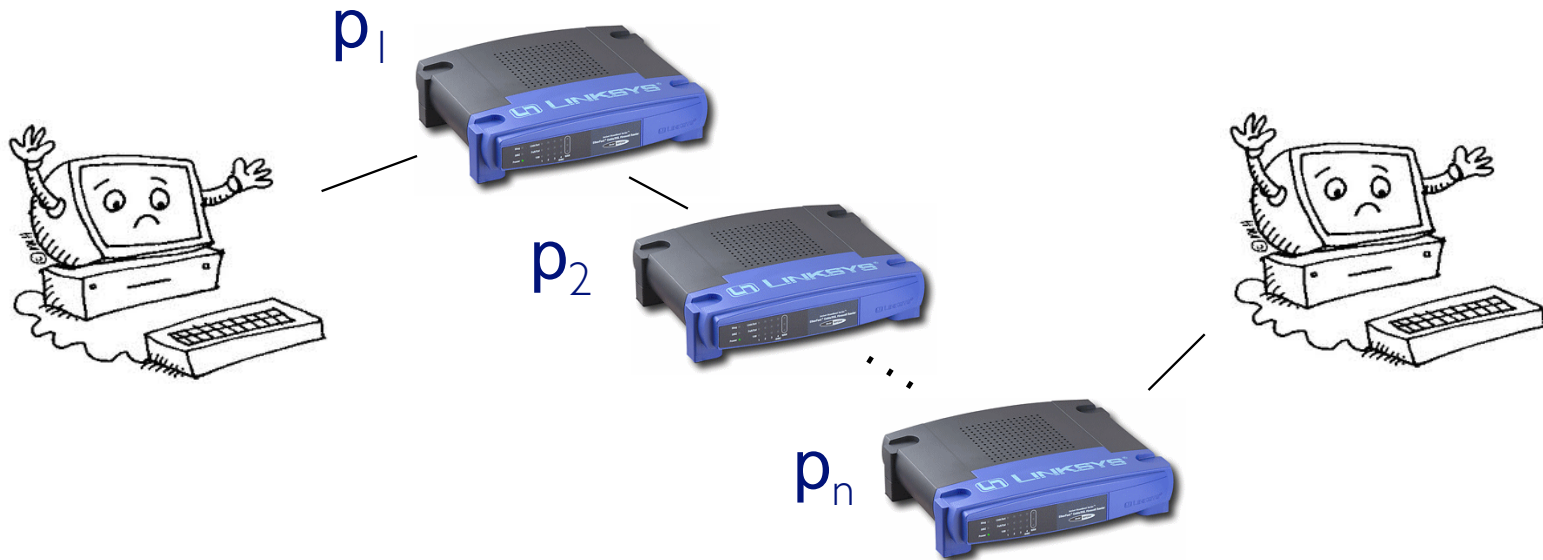


n routers, i^{th} has probability p_i of failing, independently

$P(\text{there is functional path}) = 1 - P(\text{all routers fail})$

$$= 1 - p_1 p_2 \cdots p_n$$

Contrast: a series network



n routers, i^{th} has probability p_i of failing, independently

$P(\text{there is functional path}) =$

$$P(\text{no routers fail}) = (1 - p_1)(1 - p_2) \cdots (1 - p_n)$$

Recall: Two events E and F are independent if

$$P(EF) = P(E) P(F)$$

If E & F are independent, does that tell us anything about

$$P(EF|G), P(E|G), P(F|G),$$

when G is an arbitrary event? In particular, is

$$P(EF|G) = P(E|G) P(F|G) ?$$

In general, *no*.

deeper into independence

Roll two 6-sided dice, yielding values D_1 and D_2

$$E = \{ D_1 = 1 \}$$

$$F = \{ D_2 = 6 \}$$

$$G = \{ D_1 + D_2 = 7 \}$$

E and F are independent

$$P(E|G) = 1/6$$

$$P(F|G) = 1/6, \text{ but}$$

$$P(EF|G) = 1/6, \text{ not } 1/36$$

so $E|G$ and $F|G$ are not independent!

conditional independence

Two events E and F are called *conditionally independent given G* , if

$$P(EF|G) = P(E|G) P(F|G)$$

Or, equivalently,

$$P(E|FG) = P(E|G)$$

do CSE majors get fewer A's?

Say you are in a dorm with 100 students

10 are CS majors: $P(\text{CS}) = 0.1$

30 get straight A's: $P(\text{A}) = 0.3$

3 are CS majors who get straight A's

$P(\text{CS}, \text{A}) = 0.03$

$P(\text{CS}, \text{A}) = P(\text{CS}) P(\text{A})$, so CS and A *independent*

At faculty night, only CS majors and A students show up

So 37 students arrive

Of 37 students, 10 are CS \Rightarrow

$P(\text{CS} \mid \text{CS or A}) = 10/37 = 0.27 < .3 = P(\text{A})$

Seems CS major *lowers* your chance of straight A's ☹️

Weren't they supposed to be independent?

In fact, CS and A are *conditionally dependent* at fac night

Say you have a lawn

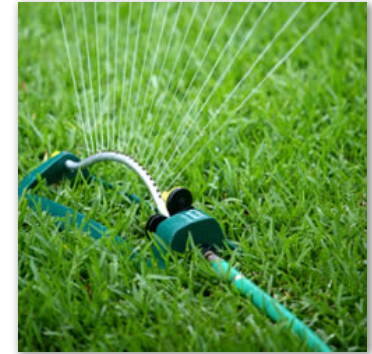
It gets watered by rain or sprinklers

These two events are independent

You come outside and the grass is wet.

You know that the sprinklers were on

Does that lower the probability that it rained?



This is a phenomenon is called “explaining away” –

One cause of an observation makes another
cause less likely

Only CS majors and A students come to faculty night

Knowing you came because you’re a CS major makes it
less likely you came because you get straight A’s

conditioning can also break **DEPENDENCE**

Randomly choose a day of the week

$A = \{ \text{It is not a Monday} \}$

$B = \{ \text{It is a Saturday} \}$

$C = \{ \text{It is the weekend} \}$

A and B are dependent events

$P(A) = 6/7, P(B) = 1/7, P(AB) = 1/7.$

Now condition both A and B on C:

$P(A|C) = 1, P(B|C) = 1/2, P(AB|C) = 1/2$

$P(AB|C) = P(A|C) P(B|C) \Rightarrow A|C \text{ and } B|C \text{ independent}$



Dependent events can become independent by conditioning on additional information!

gamblers ruin

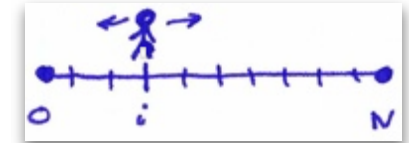
Ross 3.4, ex 41

2 Gamblers: Alice & Bob.

A has i dollars; B has $(N-i)$

Flip a coin. Heads – A wins \$1; Tails – B wins \$1

Repeat until A or B has all N dollars



aka "Drunkard's Walk"

What is $P(A \text{ wins})$?

Let E_i = event that A wins starting with \$ i

Approach: Condition on outcome of 1st flip; H = heads

$$P_i = P(E_i) = P(E_i | H) P(H) + P(E_i | \bar{H}) P(\bar{H})$$

$$P_i = \frac{1}{2}(P_{i+1} + P_{i-1})$$

$$2P_i = P_{i+1} + P_{i-1}$$

$$P_{i+1} - P_i = P_i - P_{i-1}$$

$$P_2 - P_1 = P_1 - P_0 = P_1 \quad \text{since } P_0 = 0$$

$$\text{so } P_2 = 2P_1$$

$$\dots$$
$$P_i = i P_1$$

nice example of the utility of conditioning: future decomposed into two crisp cases instead of being a blurred superposition thereof

$$P_N = N P_1 = 1$$

$$\text{so } P_i = i/N$$

See book for more

$P(\cdot | F)$ is a probability

Ross 3.5

Theorem

Let S be any sample space and F be any event in S with $P(F) \neq 0$. Then " $P(\cdot | F)$ ", conditional

probabilities given F , satisfy the axioms of probability

(a) $0 \leq P(E | F) \leq 1$

(b) $P(S | F) = 1$

(c) If E_i are mutually exclusive, then

$$P(\cup_i E_i | F) = \sum_i P(E_i | F)$$

Proof: See book (some algebra + some set theory)

but the idea is very simple: Every event of interest is " $\cdot \cap F$ ", so just as if S shrinks to F .

DNA paternity testing

Ross 3.5, ex 5b

Child is born with (A,a) gene pair (event $B_{A,a}$)

Mother has (A,A) gene pair

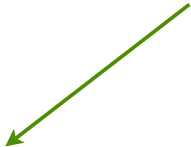
Two possible fathers: $M_1 = (a,a)$, $M_2 = (a,A)$

$P(M_1) = p$, $P(M_2) = 1-p$

What is $P(M_1 | B_{A,a})$?

Solution:

All terms implicitly
conditioned on the
observed genotypes
AA, Aa, ...



$$\begin{aligned} & P(M_1 | B_{Aa}) \\ &= \frac{P(B_{Aa} | M_1)P(M_1)}{P(B_{Aa} | M_1)P(M_1) + P(B_{Aa} | M_2)P(M_2)} \\ &= \frac{1 \cdot p}{1 \cdot p + 0.5(1 - p)} = \frac{2p}{1 + p} > \frac{2p}{1 + 1} = p \end{aligned}$$

independence: summary

Events E & F are *independent* if

$$P(EF) = P(E) P(F), \text{ or, equivalently } P(E|F) = P(E)$$

More than 2 events are indep if, for *all subsets*, joint probability = product of separate event probabilities

Independence can greatly simplify calculations

For fixed G, conditioning on G gives a probability measure, $P(E|G)$

But “conditioning” and “independence” are orthogonal:

Events E & F that are (unconditionally) independent may become dependent when conditioned on G

Events that are (unconditionally) dependent may become independent when conditioned on G