

LESSON 4

Probability : Sample Space,
Events, Classical And Axiomatic

Definitions of Probability,
Properties of Probability Measures

What is probability?

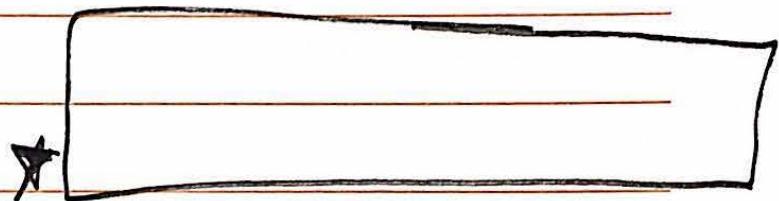
It is a mathematical theory of
"probabilistic" uncertainty.

Remark: There are other
types of uncertainty that

Cannot be modeled using
probability.

Example : Make a random
number generator select

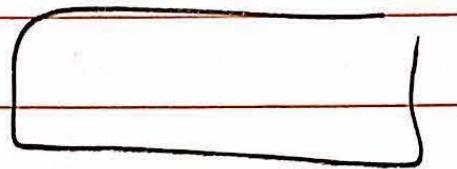
$$x \in [0, 1]:$$



what is the probability
of selecting $*$?

Is it probable to

select \star ?



Is it possible to select

\star ?

probable \rightarrow possible

possible $\cancel{\rightarrow}$ probable

Because $P(\text{Something}$

possible) may be 0.

Possibility is modified by []

It is NOT AN EASY
THEORY.

Example: You have three
decks of 52 cards

blue	blue	red
blue	red	red

You pick a card and observe
that one side of the card
is blue. What is the
probability that the other
side is also blue? $\frac{1}{2}$
 $\frac{1}{2}$

Classical Definition of

probability :

Ratio of favorable outcomes

and the total number of

possible outcomes, if all

outcomes are equally likely

$$P(A) = \frac{n_A}{N}$$

we have

Example: Five balls, one is red, the

rest are blue.

$$P(\text{blue}) = \underline{\hspace{2cm}}$$

Relative Frequency Definition:

$$P(A) = \lim_{N \rightarrow \infty} \frac{n_A}{N}$$

Example: We flip a coin

10,000,000 times.

$$P(\text{Heads}) = \underline{\quad}$$

Axiomatic Definition:

A countably additive function

defined on the set of events

with a range $[0, 1]$.

Sample Space:

Set of all possible outcomes

of an experiment is called

the sample Space, Ω

Example: Coin toss

(a) Interested in knowing

whether the toss produces a

head or a tail $\Omega =$

(b) Interested in the number

of tumbles before the coin hits

the ground $\Omega =$

— Interested in the speed with which the coin hits the ground $\Omega =$

Thus,
For the same experiment,
 Ω can be different,

depending on what the observer is interested in.

Example: (a) Roll of a die

$$\Omega =$$

(b) Tossing two coins

$$\Omega = \{ \text{ } \} \times \{ \text{ } \} =$$

Example: What is Ω when
a coin is tossed until
heads appear?

$$\Omega = \{$$

$$\}$$

Example: Life expectancy
of a random person

$$\Omega =$$

Def (Informal) : An event is a subset of the sample space, to which probabilities will be assigned

Def (Informal) : An event is

Said to have occurred if the outcome of the experiment (ω) belongs to it.

Example: Coin toss $\Omega = \{H, T\}$

$$E =$$

Roll of a die : $\Omega =$

$$E = \{2, 4, 6\} = \boxed{\quad}$$

Life expectancy $\Omega = [0, 120]$

$$E = [50, 120] = \boxed{\quad}$$

Assignment of probability to

events :

$$P(\emptyset) =$$

$$P(H) = P(T) =$$

$$P(\Omega) =$$

Roll of a die

$$P(A) =$$

$$\sqrt{A} \subseteq \Omega$$

Question: Can we always assign probabilities to all subsets of Ω ?

- Yes,

- No,

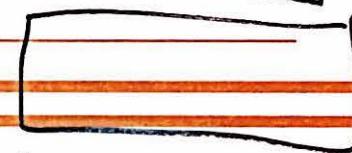
Relation between set theory and probability

We use the algebra of
sets to model events

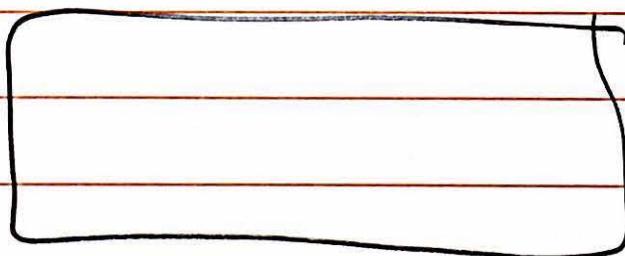
A or B occurred



A and B occurred



A occurred, but B didn't occur



To model events, we need

Some structure that
includes all possible events

σ -field of events

Def: A subset of 2^{ω} , $F \subseteq 2^{\omega}$

is called a σ -field (or σ -algebra)
iff

(1)

(2)

(3)

This structure allows us to
model events like

$$A^c \cup (B^c \cap C^c)$$

Example : The smallest σ -field for any Ω

$$\mathcal{F} =$$

Example : $A \subseteq \Omega$ $\mathcal{F} =$

Example : is 2^{Ω} a σ -field?

Probability Measure

(Kolmogorov)

Assume that Ω is

a Sample Space and

\mathcal{F} is a σ -field of subsets

of Ω , i.e. $\mathcal{F} \subseteq \mathcal{P}(\Omega)$.

A probability measure on

(Ω, \mathcal{F}) is a function

$$P: \mathcal{F} \rightarrow [0, 1]$$

s.t.

(1) Probability of Ω

(2) Probability of countable unions
of disjoint events

(Countable additivity property)

Alternatively $P: \mathcal{F} \rightarrow \mathbb{R}$

(1) Probability of \emptyset

(2) Probability of Ω

(3) Countable additivity

We call (Ω, \mathcal{F}, P)

a probability space or a probability model

Aside: P is a special case

of an additive measure:

$$\mu: \mathcal{F} \rightarrow [0, +\infty)$$

$$\mu(\emptyset) = 0$$

$$\mu\left(\bigcup_{i=1}^{\infty} A_i\right) = \boxed{\quad}$$

when A_i 's are mutually exclusive

Examples:

Coin toss: $\Omega =$

$\mathcal{F} =$

$P(\emptyset) =$

$P(\{H\}) =$

$P(\{T\}) =$

$P(\Omega) =$

Roll of a die

$\Omega =$

$\mathcal{F} =$

$$P(\{i\}) = p_i \quad , \quad \sum_{i=1}^6 p_i = 1$$

$P(A) =$

$\sqrt{A} \subseteq \Omega$

Lemmas

(1) Additivity for a finite number of events

$$A_1, \dots, A_n \in \mathcal{F}, A_i \cap A_j = \emptyset \quad \checkmark i \neq j$$

$$\Rightarrow P\left(\bigcup_{i=1}^n A_i\right) = \boxed{}$$

(2) Probability of complement

$$A \in \mathcal{F} \Rightarrow P(A^c) =$$

(3) Preservation of order

$$A \subseteq B \Rightarrow P(A) \leq P(B)$$

(4) Boole's Inequality (Union Bound)

$A_1, A_2, \dots \in \mathcal{F}$

$$\Rightarrow P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$$

(5) Inclusion-Exclusion

$A_1, A_2 \in \mathcal{F}$

$$P(A_1 \cup A_2) =$$

(6) Inclusion-Exclusion

(General form)

$A_1, A_2, \dots, A_n \in \mathcal{F}$

$$P\left(\bigcup_{i=1}^n A_i\right) =$$

for $n=3$

$$P(A_1 \cup A_2 \cup A_3) =$$

for $n=4$

$$P(A_1 \cup A_2 \cup A_3 \cup A_4) =$$

(1) Finite sequence of disjoint

events $A_1, \dots, A_n \in \mathcal{F}$

To use axioms of probability.

we create an infinite sequence
of disjoint events

$$(2) \quad P(A) = 1 - P(A^c)$$

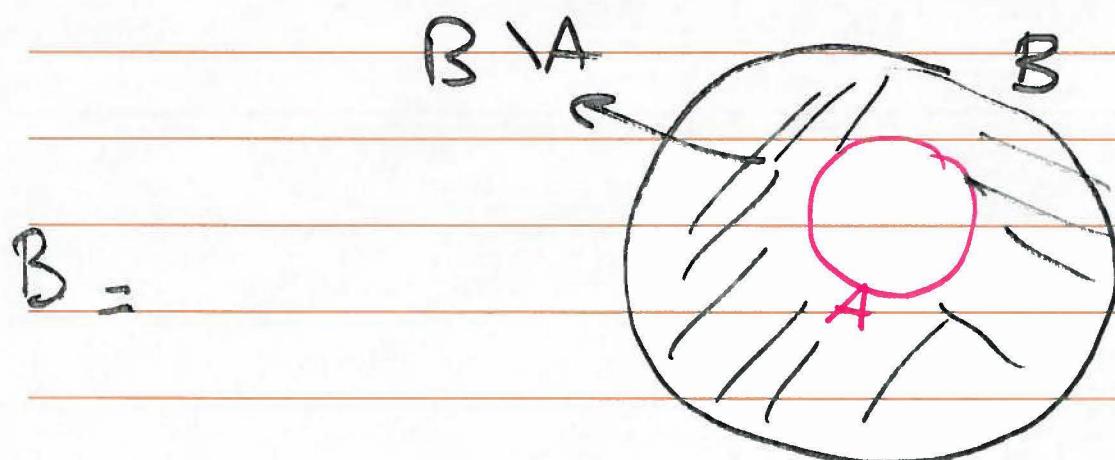
Note that

$$A \cup A^c =$$

$$A \cap A^c =$$

$$P(A \cup A^c) =$$

$$(3) \quad A \subset B \quad P(A) < P(B)$$



Important Corollary:

$$A \subseteq B \Rightarrow P(B \setminus A) = P(B) - P(A)$$

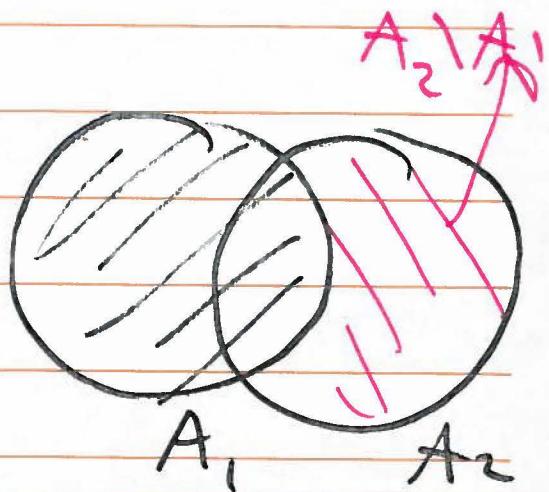
(A) Boole's Inequality

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) \leq \sum_{i=1}^{\infty} P(A_i)$$

(5) Inclusion Exclusion

$$\begin{aligned} P(A_1 \cup A_2) &= P(A_1) + P(A_2) \\ &\quad - P(A_1 \cap A_2) \end{aligned}$$

$$A_1 \cup A_2 = \cup$$



How can we prove
the general case?

By mathematical induction

Let us review the

concept of mathematical
induction

Principle of Mathematical Induction

Theorem: Let $p(n)$ be a

predicate, $n \in \mathbb{N}$. Assume

that:

(a) $p(m_0)$ is true " for some
 $m_0 \in \mathbb{N}$

(b) If $p(k)$ is true for some $k \geq m_0$, then $p(k+1)$ is also true

Then $p(n)$ is true for all $n \geq m_0, n \in \mathbb{N}$

Example: Prove that

$$S(n) : 1 + 3 + 5 + \dots + (2n-1) = n^2 \quad \forall n \in \mathbb{N}$$

Induction on n

$$n=1 \Rightarrow 1=1 \text{ true. } \checkmark$$

Assume for $n=k$

$S(k): 1 + 3 + 5 + \dots + (2k-1) = k^3$. is true

To use induction, we must

Show that $S(k+1)$ is also true, i.e.

$S(k+1)$:

Back to proving inclusion-exclusion

$$\begin{aligned} n=2 \quad P(A_1 \cup A_2) &= P(A_1) + P(A_2) \\ &\quad - P(A_1 \cap A_2) \end{aligned}$$

Assume that

$$n=k: \quad P(A_1 \cup A_2 \cup \dots \cup A_k)$$

$$= \sum_{i=1}^k P(A_i) - \sum_{i < j} P(A_i \cap A_j)$$

$$+ \sum_{i < j < k} P(A_i \cap A_j \cap A_k) - \dots$$

$$+ (-1)^{k+1} P(A_1 \cap A_2 \cap \dots \cap A_k)$$

We must prove that for

$$n = k+1 : \quad ?$$

$$\text{Ans} \quad P\left(\bigcup_{i=1}^{l+1} A_i\right) =$$

(It is a good exercise in applying probability properties to solving problems)

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A large rectangular frame with a red border, containing ten horizontal blue lines for handwriting practice.

Continuity of Probability Measure

Lemma: Assume that

$\forall i \in \mathbb{N}, A_i \in \mathcal{F}$ (A_i is an

event, or is \mathcal{F} -measurable) then

$$P\left(\bigcup_{i \in \mathbb{N}} A_i\right) = \lim_{n \rightarrow \infty} P\left(\bigcup_{i=1}^n A_i\right)$$

P_n

This lemma defines a sequence

$$\text{of numbers } P_n = P\left(\bigcup_{i=1}^n A_i\right)$$

and states that the limit of

the sequence P_n is equivalent

to the probability $P\left(\bigcup_{i \in \mathbb{N}} A_i\right)$.

Aside: Real Sequences and

their limits

A sequence $\{a_n\}_{n=1}^{\infty}$ is

a function from \mathbb{N} to another set,

therefore a real sequence

is

$$a_n : \mathbb{N} \rightarrow \mathbb{R}$$

Def: limit of a sequence

We say a_n converges to L as

$n \rightarrow \infty$ and write

$$\lim_{n \rightarrow \infty} a_n = L$$

iff:

$$\text{Example: } \lim_{n \rightarrow \infty} \frac{1}{n} = 0$$

Back To Continuity of Probability.

$$P\left(\bigcup_{i \in \mathbb{N}} A_i\right) = \lim_{n \rightarrow \infty} P\left(\bigcup_{i=1}^n A_i\right)$$

Proof:

Corollary :

$$\bigcap_{i \in \mathbb{N}} A_i$$

If A_i is a sequence of nested

events:

(a) If A_i is increasing, i.e.

$$A_i \subseteq A_{i+1} \quad \forall i \in \mathbb{N}, \text{ then}$$

$\underbrace{\phantom{A_i \subseteq A_{i+1}}}_{\text{increasing}}$

$$P\left(\bigcup_{i \in \mathbb{N}} A_i\right) = \lim_{n \rightarrow \infty} P(A_n)$$

(b) If A_i is decreasing, i.e.

$$A_i \supseteq A_{i+1} \quad \forall i \in \mathbb{N}, \text{ then}$$

$$P\left(\bigcap_{i \in \mathbb{N}} A_i\right) = \lim_{n \rightarrow \infty} P(A_n)$$

Proof

(a) From continuity of probability

$$P\left(\bigcup_{i \in N} A_i\right) = \lim_{n \rightarrow \infty} P\left(\bigcup_{i=1}^n A_i\right)$$

$$A_i \subseteq A_{i+1} \quad \bigcup_{i=1}^n A_i = A_n$$

$$\Rightarrow P\left(\bigcup_{i \in N} A_i\right), \lim_{\substack{i \in N \\ i \rightarrow \infty}} P(A_n)$$

$$\lim_{i \rightarrow \infty} A_i$$

$$P\left(\lim_{i \rightarrow \infty} A_i\right) = \lim_{i \rightarrow \infty} P(A_i)$$

$$\lim_{x \rightarrow a} f(x) = f\left(\lim_{x \rightarrow a} x\right)$$

continuous function

(b) We use (a)

$$A_i \supseteq A_{i+1} \Rightarrow A_i^c \subseteq A_{i+1}^c$$

by (a)

$$\begin{aligned} P\left(\bigcup_{i \in \mathbb{N}} A_i^c\right) &= \lim_{n \rightarrow \infty} P(A_n^c) \\ &= P\left(\left[\bigcap_{i \in \mathbb{N}} A_i\right]^c\right) = \lim_{n \rightarrow \infty} \left\{1 - P(A_n)\right\} \end{aligned}$$

$$2) 1 - P\left(\bigcap_{i \in \mathbb{N}} A_i\right) \geq 1 - \lim_{n \rightarrow \infty} P(A_n)$$

$$2) P\left(\bigcap_{i \in \mathbb{N}} A_i\right) = \lim_{n \rightarrow \infty} P(A_n)$$

Why is it called continuity?

$$\lim_{i \rightarrow \infty} P(A_i) = P\left(\lim_{i \rightarrow \infty} A_i\right)$$

The \lim operator passes probability.

like continuous Functions:

$$\lim_{x \rightarrow x_0} f(x) = f\left(\lim_{x \rightarrow x_0} x\right) = f(x_0)$$

Remark(Zero Probability and

Almost Sure Events)

(Ω, \mathcal{F}, P) : Probability Space

If $A \in \mathcal{F}$, $\underline{P(A) = 0}$,

\Leftrightarrow

Can we conclude that $A = \emptyset$?

No. Example. Selecting $\{\frac{1}{2}\}$ from $[0, 1]$.

A is called a zero probability event

If $\cancel{A} \in \mathcal{F}$, $\underline{P(A) = 1}$,

Can we conclude that

$A = \Omega$? No, Example $[0, 1] \setminus \{\frac{1}{2}\}$

A is called an event that

occurs almost surely (a.s.)

Almost sure event

$[0, 1] \setminus \{x \in \mathbb{Q} \mid x \in [0, 1]\}$

Conditional Probability

Def : Let (Ω, \mathcal{F}, P) be

a probability space and the event $B \in \mathcal{F}$ be such that

$P(B) > 0$. For any event

$A \in \mathcal{F}$, the conditional probability that A occurs given B is denoted as $P(A|B)$ and is defined by :

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

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

Example: Two fair dice are thrown. Given that the first die shows 3, what is the probability that the sum exceeds 6?

Intuition: The second die must be

4, 5, 6

. Answer: 3/6

Principled answer:

$$\Omega_1 = \{1, 2, -6\} \times \{1, 4, -6\}$$

$$F = 2$$

$$|F| = |2^{\omega_1}| \cdot 2^{\omega_2}$$

$$P(A) = \frac{|A|}{|\Omega|} \quad \forall A \in \mathcal{F}$$

So we defined the probability space (Ω, \mathcal{F}, P)

Assume

A = the event that the

total number exceeds 6

$$A = \{(a,b) \mid a, b \in \{1, 2, \dots, 6\}, a+b > 6\}$$

B = the event that the first die

shows 3

$$B = \{(3,1), (3,2), (3,3), \dots, (3,6)\}$$

$$\text{Find } P(A|B) : \frac{P(A \cap B)}{P(B)}$$

$$A \cap B = \{(3,4), (3,5), (3,6)\}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{\cancel{3/36}}{\cancel{6/36}} = \frac{1}{2}$$

Remark: $P(A|B)$ is left

undefined when $\underline{P(B)=0}$, i.e.

when B is a zero probability event. In other words, we

cannot condition on zero probability events.

Theorem (Conditional Probability

is a Probability Measure Itself)

Assume that (Ω, \mathcal{F}, P) is

a probability space and $B \in \mathcal{F}$

and $P(B) > 0$.



$$\forall A \in \mathcal{F} : P_B(A) = P(A|B)$$

is a probability measure, i.e. it satisfies Kolmogorov's axioms.

Proof:

$$(1) 0 \leq P_B(A) \leq 1 \quad A \cap B \subseteq B$$

$$0 \leq P(A \cap B) \leq P(B) \Rightarrow 0 \leq \frac{P(A \cap B)}{P(B)} \leq 1$$

$$\Rightarrow 0 \leq P_B(A) \leq 1$$

$$(2) P_B(\Omega) = 1$$

$$P_B(\Omega) = \frac{P(\Omega \cap B)}{P(B)} = \frac{P(B)}{P(B)} = 1$$

(3) Countable Additivity

For disjoint events A_1, A_2, \dots

$$P_B\left(\bigcup_{i \in \mathbb{N}} A_i\right) = \sum_{i=1}^{\infty} P_B(A_i)$$

$$\frac{P_B\left(\bigcup_{i \in \mathbb{N}} A_i\right)}{P(B)} = \frac{P\left(\left(\bigcup_{i \in \mathbb{N}} A_i\right) \cap B\right)}{P(B)}$$

$$= \frac{P\left(\bigcup_{i \in \mathbb{N}} (A_i \cap B)\right)}{P(B)} +$$

C_i G

Claim: $i \neq j \Rightarrow (A_i \cap B) \cap (A_j \cap B) = \emptyset$

Because

$$(A_i \cap B) \cap (A_j \cap B) = (A_i \cap A_j) \cap B = \emptyset$$

C_i 's = $A_i \cap B$ are also disjoint

$$P_2 = \frac{\sum_{i=1}^{\infty} P(A_i \cap B)}{P(B)}$$

$$P_2 = \frac{\sum_{i=1}^{\infty} P(A_i \cap B)}{P(B)} = \sum_{i=1}^{\infty} \cancel{\frac{P(A_i)}{P(B)}}$$

Exercise : Assume that (Ω, \mathcal{F}, P)

is a probability space and

$B \in \mathcal{F}$, $P(B) > 0$.

(a) Show that the "reduced

σ -field"

$$\mathcal{F} \cap \mathcal{B} = \{B \cap A \mid A \in \mathcal{F}\}$$

is a σ -field itself.

(b) Show that

$$(B \cap \Omega, B \cap \mathcal{F}, P(A))$$

is also a probability space.

Remark: This exercise presents

the "reduced sample space"

view of conditional probability.

In this viewpoint, conditioning on

B is equivalent to selecting

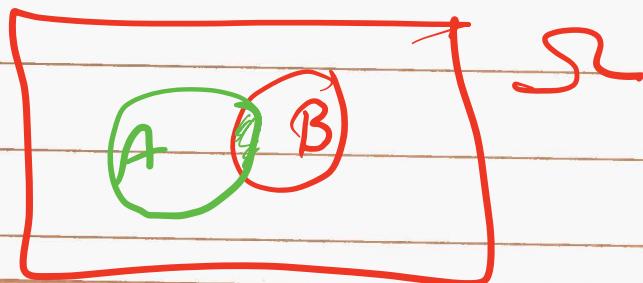
B as the new sample space.

Exercise: Make sure you

knew how to do this.

Hint: $F \cap B$ is a sigma field

$C \in F \cap B$ we want to show
 ~~$A \cap B$~~ \cup ~~$A \cap F$~~
 that $C^c \in F \cap B$.

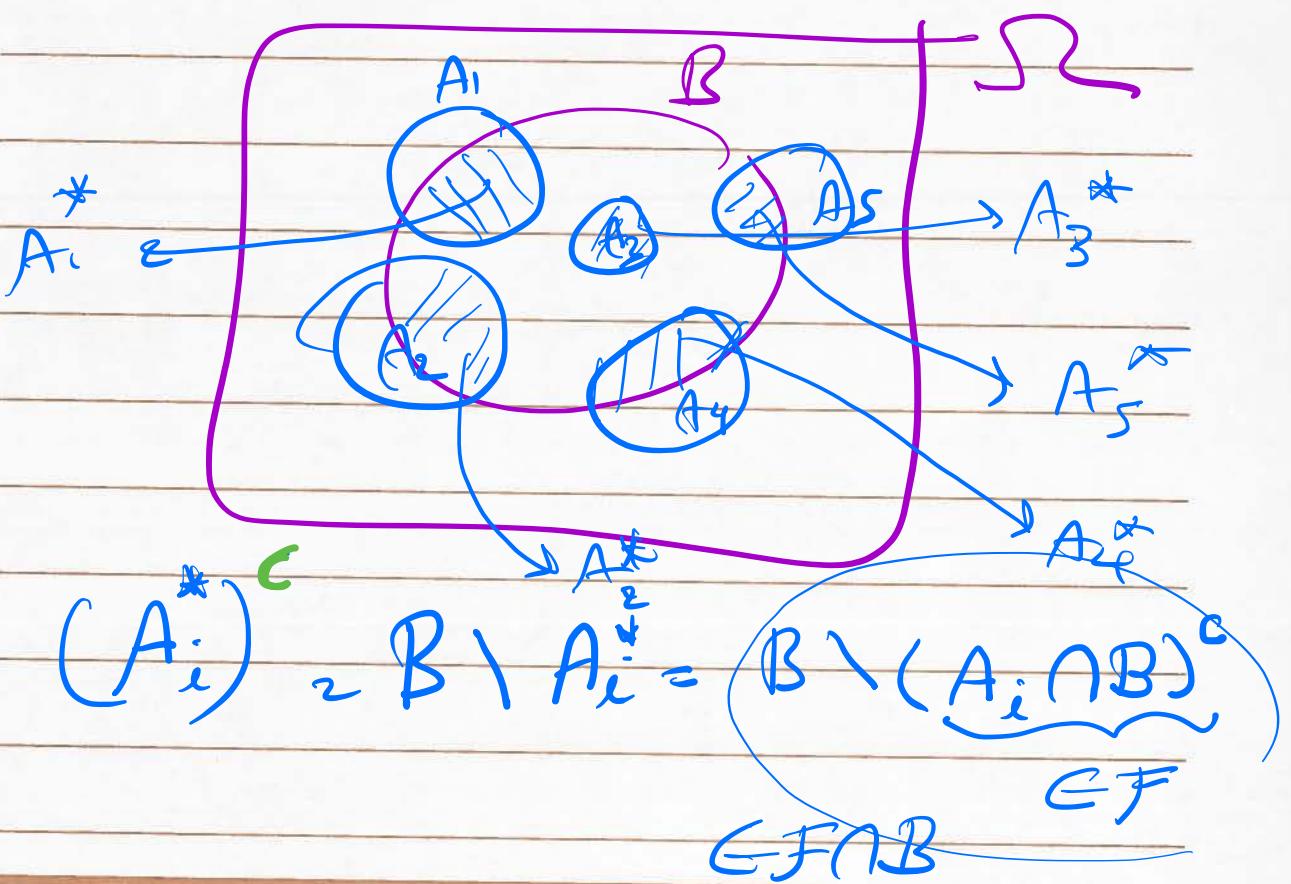


Complement of C with respect

to the new sample space is

$$B \setminus C = B \cap (A \cap B)^c$$

↓ EF ↓ EF ↓ EF
 $E \neq A \cap B$



($\mathcal{F} \cap \mathcal{B}$, \cap , \cup , e)

Theorem (The Law of Total

Probability) :

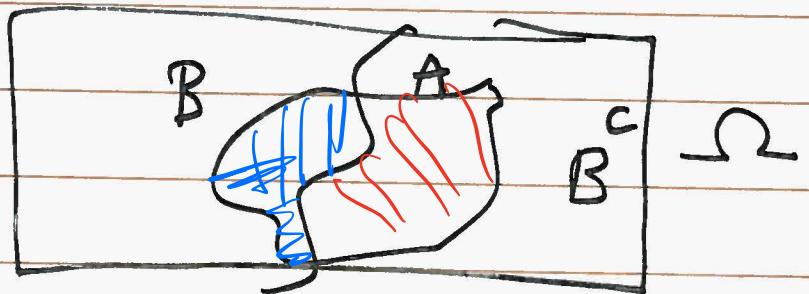
Assume that (Ω, \mathcal{F}, P)

is a probability space and

$\exists A, B \in \mathcal{F}$ s.t. $0 < P(B) < 1$.

$$\text{Then : } P(A) = P(A|B)P(B)$$

$$+ P(A|B^c)P(B^c)$$



Proof:

$$A_2 A \cap S_2 = A \cap (B \cup B^c)$$

$$= (A \cap B) \cup (A \cap B^c)$$

↗ mutually exclusive
 $(A \cap B) \cap (A \cap B^c) = \emptyset$

$$P(A) = P(A \cap B) + P(A \cap B^c)$$

$$= P(A|B)P(B) + P(A|B^c)P(B^c)$$

Note that we conditioned on B and

B^c and because $P(B) < 1$,

$P(B) \neq 0$ and $P(B^c) \neq 0$

Theorem (General Total Probability)

Assume that (Ω, \mathcal{F}, P) is a probability space and

B_1, B_2, \dots is a partition of Ω such that $P(B_i) > 0$, then:

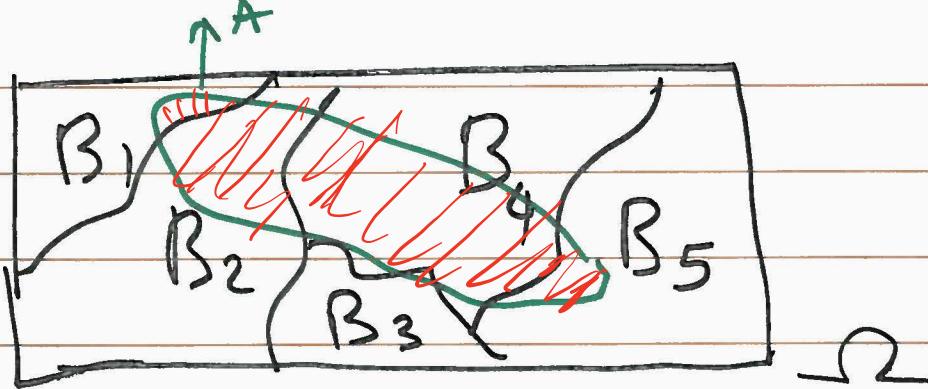
$$P(A) = \sum_{i=1}^{\infty} P(A|B_i) P(B_i)$$

Remark: For a finite partition

B_1, B_2, \dots, B_n the theorem is

still true, i.e.

$$P(A) = \sum_{i=1}^n P(A|B_i) P(B_i)$$



$$\text{Proof: } A = A \cap \Omega = A \cap (\bigcup_{i=1}^n B_i)$$

$$= \bigcup_{i=1}^n (A \cap B_i)$$

$$(A \cap B_i) \cap (A \cap B_j) = \emptyset$$

$$P(A) = P\left(\bigcup_{i=1}^n (A \cap B_i)\right)$$

$$= \sum_{i=1}^n P(A \cap B_i) = \sum_{i=1}^n P(A | B_i) P(B_i)$$

Infinite Case

$$A = A \cap \Sigma_n A \cap \left(\bigcup_{i \in N} B_i \right)$$

$$= \bigcup_{i \in N} (A \cap B_i)$$

Mutually
exclusive

$$P(A) = P\left(\bigcup_{i \in N} (A \cap B_i)\right) \text{ By continuity of prob}$$

$$= \lim_{n \rightarrow \infty} \sum_{i=1}^n P(A \cap B_i)$$

$$= \lim_{n \rightarrow \infty} \sum_{i=1}^n P(A|B_i) P(B_i)$$

$$= \sum_{i=1}^{\infty} P(A|B_i) P(B_i)$$

Example: A USC student is participating in a charity fundraiser event. CEO's of small sized, medium sized, and large companies are participating

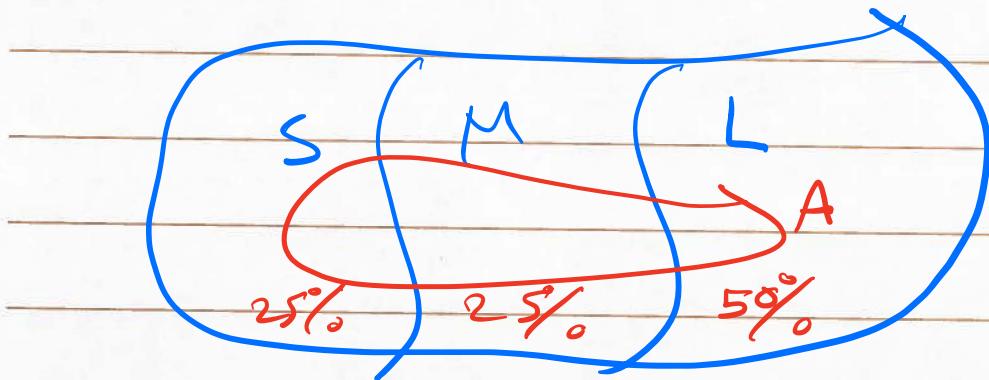
in the event as well. 50% of the CEO's are from large companies, 25% are from medium companies, and 25% are from small companies.

Probability of raising funds from
the
~~the~~ CEO of a large company
is 2%, while it is 7% for
the CEO of a medium company
and 30% for the CEO of

a small company.

What is the probability of
raising funds from a randomly
selected CEO?

Solution:



B_1 : small sized

B_2 : Medium sized

B_3 : Large companies

A = raising funds

$$P(A) = P(A|B_1) \underbrace{P(B_1)}_{= 25} + P(A|B_2) \underbrace{P(B_2)}_{= 25}$$

$$+ P(A|B_3) \underbrace{P(B_3)}_{= 5} =$$

Theorem (The Baye's Rule)

Assume that (Ω, \mathcal{F}, P) is a probability space and $A, B \in \mathcal{F}$ and $P(A) > 0$ and $P(B) > 0$.

Then :

$$P(B|A) = \frac{P(B) P(A|B)}{P(A)}$$

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

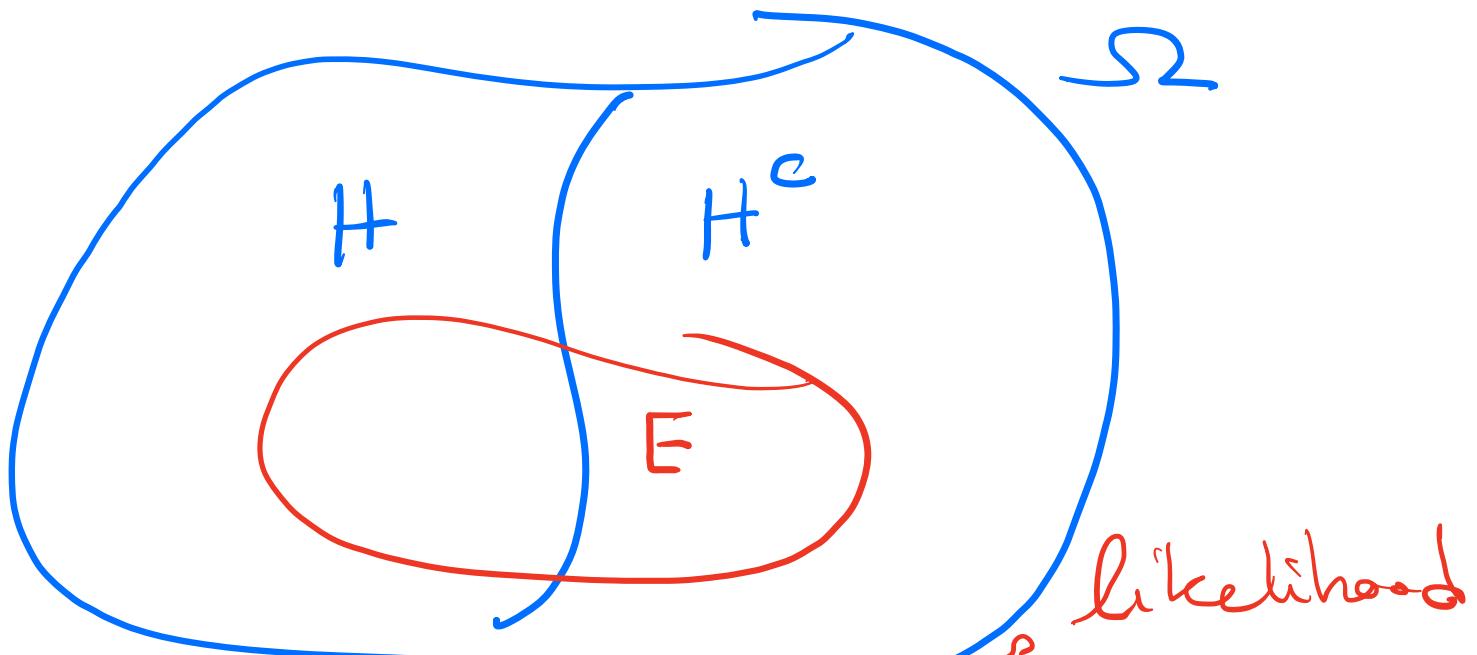
$$\text{Total prob.}$$

Proof:

$$P(B|A) = \frac{P(B \cap A)}{P(A)} = \frac{P(A|B)P(B)}{P(B)}$$

Total
Prob

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



$$P(H|E) = \frac{P(E|H) P(H)}{P(E)}$$

Posterior

likelihood

prior

$$P(H^c|E) = \frac{P(E|H^c) P(H^c)}{P(E|H^c) P(H^c) + P(E|H) P(H)}$$

$$P(H|E) \propto P(E|H) P(H)$$

$$P(H^c|E) \propto P(E|H^c) P(H^c)$$

Theorem (General Baye's Rule)

Assume that (Ω, \mathcal{F}, P) , and

$A, B_i \in \mathcal{F} \forall i \in N$. Furthermore,

B_i 's form a partition and

$\forall i \in N, P(B_i) > 0$. Then:

$$P(B_i | A) = \frac{P(A | B_i) P(B_i)}{P(A)}$$

$$\underbrace{P(A | B_i) P(B_i)}_{\text{in}}$$

$$\sum_{i=1}^{\infty} P(A | B_i) P(B_i)$$

Prof-Exercise. Write the definition
of conditional prob and use
the law of total prob in the
denom.

$$P(H_i | E) \xrightarrow{\text{Posterior}} \frac{P(E | H_i) P(H_i)}{\sum_{j=1}^n P(E | H_j) P(H_j)} \xrightarrow{\text{prior}} \text{prior}$$

$\xrightarrow{\text{Posterior}}$

$\xrightarrow{\text{prior}}$

$\xrightarrow{\text{likelihood}}$

Example : (Charity Fundraiser)

Assume that the USC student
from a CEO
raised some funds in the event.

What is the probability that
it was from the CEO of

a large company? $P(B_3) \sim .5$

$$P(B_3|A) = \frac{P(A|B_3) P(B_3)}{P(A|B_1) P(B_1) + P(A|B_2) P(B_2)}$$

$$= \frac{P(A|B_3) P(B_3)}{P(A|B_3) P(B_3)}$$

Plug in probabilities

Remark: Total probability and Baye's Rule deal with conditional probabilities of events given partitions of a sample Space:

Unconditional
When The Probability of An Event Is Needed.—USE TOTAL PROB

(Conditional)
When The Probability of One of The Partitions Is Needed—

USE BAYE'S
(you need evidence)

Remark: In Baye's Rule, A \underline{E}

is an event that we observe,
 H_i

while B_i 's are events that we

do not observe, but would like

to make some inference about

Before any observation we

know the prior probabilities

$P(B_i)$

and also know the $P(E|H_i)$
 $P(H_i)$

conditional probabilities $P(A|B_i)$.

After observing A, we compute
 E

the Posterior probabilities

$P(B_i | A)$. We actually

$P(H_i | E)$

"update our belief" about

H_i

occurrence of B_i , given that A

was observed.

Theorem: (The Multiplication Rule)

Let (Ω, \mathcal{F}, P) be a probability space and A_1, A_2, \dots, A_n be events, i.e. $A_i \in \mathcal{F}$ $\forall i \in \{1, 2, \dots, n\}$.

Then:

$$P\left(\bigcap_{i=1}^n A_i\right) = P(A_1)P(A_2|A_1) \cdots P(A_n|A_1 \cap A_2 \cdots A_{n-1})$$

$$\cap A_3 \cdots \cap A_{n-1}) = \boxed{P(A_1) \prod_{i=2}^n P(A_i | A_1 \cap A_2 \cdots \cap A_{i-1})}$$

Provided that the conditional probabilities are defined, i.e. $\forall i \in \{1, 2, \dots, n\}$

$$P\left(\bigcap_{j=1}^i A_j\right) \neq 0.$$

(First order) Markovian Property

$$\frac{P(A_i | A_1 \cap A_2 \cap \dots \cap A_{i-1})}{= P(\underbrace{A_i | A_{i-1}}_{\text{↑}})}$$

Proof (by induction)

$$n=1 : P(A_1) = P(A_1)$$

$$n=2 : P(A_1 \cap A_2) = P(A_1) P(A_2 | A_1)$$

Next, assume $P(\bigcap_{i=1}^k A_i) = P(A_1) \times$

$$\times P(A_2 | A_1) \dots P(A_k | A_1 \cap A_2 \cap \dots \cap A_{k-1}).$$

One must show that

$$P\left(\bigcap_{i=1}^{k+1} A_i\right) = P(A_1) \prod_{i=2}^{k+1} P(A_i | A_1 \cap A_2 \cap \dots \cap A_{i-1})$$

$$P\left(\bigcap_{i=1}^{k+1} A_i\right) = P\left(\bigcap_{i=1}^k A_i \cap A_{k+1}\right)$$

$$= \underbrace{P\left(\bigcap_{i=1}^k A_i\right)}_{\sim} \underbrace{P(A_{k+1} | \bigcap_{i=1}^k A_i)}_{\sim}$$

$$= P(A_1) P(A_2 | A_1) \cdots P(A_k | A_1 \cap A_2 \cap \cdots \cap A_{k-1})$$

$$\times P(A_{k+1} | \bigcap_{i=1}^k A_i)$$

$$= P(A_1) \prod_{i=2}^{k+1} P(A_i | A_1 \cap A_2 \cap \cdots \cap A_{i-1})$$

Theorem: (General Multiplication Rule):

The multiplication rule holds for an infinite number of events

A_1, A_2, \dots , where $A_i \in \mathcal{F} \forall i \in \mathbb{N}$

i.e.

$$\bigcap_{i \in \mathbb{N}} A_i$$

$$P\left(\bigcap_{i=1}^{\infty} A_i\right) = P(A_1) \prod_{i=2}^{\infty} P(A_i | A_1 \cap \dots \cap A_{i-1})$$

Provided that all conditional probabilities are defined, i.e.

$$P\left(\bigcap_{j=1}^l A_j\right) \neq 0 \quad \forall l \in \mathbb{N}$$

Proof: Take a limit from the $n \rightarrow \infty$

multiplication rule and use

Continuity of probability.

$$P\left(\bigcap_{i=1}^n A_i\right) = P(A_1) \prod_{i=2}^n P(A_i | A_1 \cap A_2 \cap \dots \cap A_{i-1})$$

$$\lim_{n \rightarrow \infty} P\left(\bigcap_{i=1}^n A_i\right) = P(A) \cdot \lim_{n \rightarrow \infty} \prod_{i=2}^n P(A_i | A_1 \cap A_2 \cap \dots \cap A_{i-1})$$

By Continuity of prob:

$$P\left(\lim_{n \rightarrow \infty} \bigcap_{i=1}^n A_i\right) = P(A) \prod_{i=2}^{\infty} P(A_i | A_1 \cap A_2 \cap \dots \cap A_{i-1})$$

$$P\left(\bigcap_{i=1}^{\infty} A_i\right)$$

- Independence

Assume that (Ω, \mathcal{F}, P) is

a probability space and

$A, B \in \mathcal{F}$. A, B are

called independent iff

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

and if $P(B) > 0$, it means:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(A)P(B)}{\cancel{P(B)}} = \cancel{P(A)}$$

Question: Can an event be independent from itself?

$$P(A \cap A) = P(A) P(A)$$

$$\Rightarrow P(A) = [P(A)]^2$$

$$P(A) \geq 0 \quad P(A) \leq 1$$

Almost sure and zero prob. events

Example: (Ω, \mathcal{F}, P) is a probability

space, $A, B \in \mathcal{F}$, and $0 < P(B) < 1$.

If A and B are independent,

Show that the probability of A

given B is equal to the probability
of A given B^c .

In other words, the probability
of A doesn't change whether or
not B occurs.

$$P(A|B) = P(A|B^c)$$

$$A = \underbrace{(A \cap B)}_{\text{A and } B} \cup \underbrace{(A \cap B^c)}_{\text{A and } B^c}$$

$$P(A) = P(A \cap B) + P(A \cap B^c)$$

$$= \underbrace{P(A|B) P(B)}_{P(A)} + P(A|B^c) \underbrace{P(B^c)}_{1 - P(B)}$$

$$P(A) = P(A) P(B) + P(A|B^c) (1 - P(B))$$

$$P(A) - P(A) P(B) = P(A|B^c) (1 - P(B))$$

~~$$P(A) (1 - P(B)) = P(A|B^c) (1 - P(B))$$~~

$$\frac{P(A|B)}{P(A)} = P(A|B^c)$$

Exercise =

Also show that A^c is indep
from both B & B^c .

More rigorously, we say the
 σ -field generated by A is

independent from the σ -field
generated by B .

$$\mathcal{F}_A = \{A, A^c, \emptyset, \Omega\}$$

$$\mathcal{F}_B = \{B, B^c, \emptyset, \Omega\}$$

Because every member of \mathcal{F}_A
is indep from every member of
 \mathcal{F}_B .

Remark: The concept of mutually exclusive events should not be confused with that of independent events.

Mutually exclusive sets (events)

are sets whose overlap is

empty. We do not need a

probability measure to assess

whether they are mutually

exclusive or not. On the

other hand, independent

events are meaningful within

the concept of probability.

Without having a probability

space equipped with a

probability measure, one cannot

define independence.

Is there an event that

is mutually exclusive with
itself

$$A \cap A = \emptyset \Rightarrow A \neq \emptyset$$

When are two mutually
exclusive events indep?

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

$$\Rightarrow P(A) P(B) = 0$$

only if at least one of them
is zero probability

Conditional Independence

Assume that (Ω, \mathcal{F}, P) is a

probability space and C is

\mathcal{F} -measurable, i.e. $C \in \mathcal{F}$. Also

assume that $P(C) > 0$.

$A, B \in \mathcal{F}$ are called conditionally

independent given C iff:

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

Use: Bayesian Networks / Graphical Models / Naïve Bayes classifier

Example: Assume that A, B are independent events. Are they conditionally independent given any C ∈ F, for which $P(C) > 0$?

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

we would like to know if

$$P(A \cap B | C) \stackrel{?}{=} P(A | C) P(B | C)$$

$$\frac{P(A \cap B \cap C)}{P(C)} \stackrel{?}{=} \frac{P(A \cap C)}{P(C)} \frac{P(B \cap C)}{P(C)}$$

Does not hold for all C

(Provide a counterexample)

Counter-example (\Rightarrow disprove):

Roll of a die:

$$A = \{1, 2\} \quad B = \{3, 4\}, \quad C = \{2, 5\}$$

$$P(A) = \frac{2}{6} = \frac{1}{3} \quad P(B) = \frac{3}{6} = \frac{1}{2}$$

$$P(A \cap B) = P(\{2\}) = \frac{1}{6} = P(A)P(B)$$

A, B are indep (but not

mutually exclusive)

$$P(A|C) = \frac{P(A \cap C)}{P(C)} = \frac{\frac{1}{6}}{\frac{4}{6}} = \frac{1}{2}$$

$$P(B|C) = \frac{P(B \cap C)}{P(C)} = \frac{\frac{1}{6}}{\frac{4}{6}} = \frac{1}{2}$$

$$P(A \cap B|C) = \frac{P(A \cap B \cap C)}{P(C)} = \frac{\frac{1}{6}}{\frac{4}{6}} = \frac{1}{2}$$

$$\neq P(A|C)P(B|C)$$

Independence for More

Than Two Events

For an indexed family of events

$\{A_i \in \mathcal{F} \mid i \in I\}$, A_i 's are independent

if for all J , finite subsets of I ,

$$P(\bigcap_{i \in J} A_i) = \prod_{i \in J} P(A_i) \quad \forall J \subseteq I, \\ |J| < \infty$$

Therefore, if A, B, C are independent

then: $P(A \cap B \cap C) = \underline{P(A)P(B)P(C)}$

$$\overbrace{P(A \cap B)} = \underline{P(A)P(B)}$$

$$\overbrace{P(B \cap C)} = \underline{P(B)P(C)}$$

$$\overbrace{P(A \cap C)} = \underline{P(A)P(C)}$$

Note: I can be infinite

Example: We have a pack of well-shuffled.

52 playing cards. Is the

suit of a card independent

from its rank?

$$\text{Suit} = \{\heartsuit, \clubsuit, \spadesuit, \diamondsuit\}$$

$$\text{Rank} = \{2, 3, 4, \dots, 10, J, Q, K, A\}$$

WLOG

Assume

$$\text{Suit} = \heartsuit$$

$$\text{rank} = Q$$

$$P(\text{Suit} = \heartsuit) = \frac{13}{52} = \frac{1}{4}$$

$$P(\text{rank} = Q) = \frac{4}{52} = \frac{1}{13}$$

$$P(\text{rank} = Q, \text{Suit} = \heartsuit) = \frac{1}{52}$$

$$= \underbrace{P(\text{rank} = Q)}_{1/13} \underbrace{P(\text{Suite} = \heartsuit)}_{1/4}$$

The above calculation would
be true for any rank &
Suite.

Pairwise Independence :

$\{A_i \in \mathcal{F} | i \in I\}$ is called pairwise independent if

$$P(A_i \cap A_j) = P(A_i) P(A_j) \text{ if } i \neq j$$

Question: Which of the following

implications is true?

Not true

pairwise independence $\not\Rightarrow$ Independence

Independence \Rightarrow Pairwise
Independence

This is because if $\{A_i | i \in I\}$ are independent, $\{A_i, A_j | i \neq j\}$, etc must be independent but the reverse is not true.

Exercise: Consider mutually exclusive events B_1, B_2, B_3 , and C on the probability space (Ω, \mathcal{F}, P) , with $P(B_1) = P(B_2) = p$, $P(B_3) = q$, and $P(C) = r$.

where $3p+q \leq 1$. Assume that

$p = -q + \sqrt{q}$, and show that

the events $B_1 \cup C$, $B_2 \cup C$, and

$B_3 \cup C$ are pairwise independent.

Also, is there any $p > 0$ and $q > 0$

such that these three events are

independent.

Pairwise indep if for $B_i \cup C$ and

$B_j \cup C$

(i) $i \neq j$

$$P((B_i \cup C) \cap (B_j \cup C)) = P(B_i \cup C)P(B_j \cup C)$$

$$P(B_i \cup C) \cap (B_j \cup C) = P(\underbrace{B_i \cap B_j}_{\emptyset}) \cup C$$

$$= P(C) = q$$

$$P(B_i \cup C) = P(B_i) + P(C) = p + q$$

~~$$= -q + \sqrt{q} + q = \sqrt{q}$$~~

$B_i \cup C$ and $B_j \cup C$ are pairwise indep

because

$$P((B_i \cup C) \cap (B_j \cup C)) = q$$

$$= P(B_i \cup C) P(B_j \cup C)$$

For independence

$$P([B_1 \cup C] \cap [B_2 \cup C] \cap [B_3 \cup C])$$

$$= P(B_1 \cup C) P(B_2 \cup C) P(B_3 \cup C)$$

$$\underbrace{\sqrt{q}}_{\sqrt{q}} \quad \underbrace{\sqrt{q}}_{\sqrt{q}} \quad \underbrace{\sqrt{q}}_{\sqrt{q}}$$

$$\Rightarrow P((\overbrace{B_1 \cap B_2 \cap B_3}^{\emptyset}) \cup C) \\ = (\sqrt{q})^3$$

$$\Leftrightarrow P(C) \geq (\sqrt{q})^3$$

\sqrt{q}

$$\Leftrightarrow \begin{cases} q = 0 & \rightarrow \text{not acceptable} \\ q = 1 \end{cases}$$

$$P = -q + \sqrt{q} \Rightarrow P \geq 0 \quad \text{not acceptable}$$

This serves as a general counterexample
for events that are pairwise indep,
but not indep.

The Borel - Cantelli Lemmas

An event that occurs infinitely often :

Assume that (Ω, \mathcal{F}, P) is

a probability space and $A_i \in \mathcal{F}$

$\forall i \in \mathbb{N}$.

Define :



$$B_1 = \bigcup_{i=1}^{\infty} A_i$$

$$B_2 = \bigcup_{i=2}^{\infty} A_i$$

$$\vdots$$

$$B_n = \bigcup_{i=n}^{\infty} A_i$$

If $A_{i.o.}$ is an event that occurs

infinitely often, then :

$x \in A_{i.o.}$ must be in all B_n 's,

i.e. $\forall n, x \in B_n \Rightarrow x \in \bigcap_{n=1}^{\infty} B_n$

$$\Rightarrow A_{i.o.} \subseteq \bigcap_{n=1}^{\infty} B_n$$

$$\bigcap_{n=1}^{\infty} \bigcup_{i=n}^{\infty} A_i$$

On the other hand, if

$x \in B_K \vee \forall k \in \mathbb{N}, x \notin B_k$, we can

show that x is a member of
an infinite number of A_i 's, i.e.

$x \in A_{i.o.} :$

$x \in B_1 \Rightarrow x \in \bigcup_{i=1}^{\infty} A_i \Rightarrow \exists i > 0$
 s.t. $x \in A_i$

$x \in B_2 \Rightarrow x \in \bigcup_{i=2}^{\infty} A_i \Rightarrow \exists i > 1$
 s.t. $x \in A_i$

$x \in B_{l+1} \Rightarrow x \in \bigcup_{i=l+1}^{\infty} A_i \Rightarrow \exists i > l$
 s.t. $x \in A_i$

$\forall k \ x \in B_k \Rightarrow x \in \bigcap_{k=1}^{\infty} B_k$

Therefore, there is an infinite

Sequence of integers $\{j_l\}$ s.t.

$x \in A_{j_l} \quad \forall l \in \mathbb{N} \Rightarrow$

$x \in A_{j_{l+1}} \Rightarrow$

$$\bigcap_{n=1}^{\infty} \bigcup_{i=n}^{\infty} A_i \subseteq A_{j_{l+1}}$$

$$A_{j_{l+1}} = \bigcap_{n=1}^{\infty} \bigcup_{i=n}^{\infty} A_i$$

Lemma (Borel-Cantelli):

Assume that (Ω, \mathcal{F}, P) is a probability space, A_1, A_2, \dots

are events, i.e. $A_i \in \mathcal{F} \forall i \in \mathbb{N}$.

Define $A_{i.o.} = \bigcap_{n=1}^{\infty} \bigcup_{i=n}^{\infty} A_i$. Then:

$$(1) \sum_{i=1}^{\infty} P(A_i) < \infty \Rightarrow P(A_{i.o.}) = 0$$

$$(2) \sum_{i=1}^{\infty} P(A_i) = \infty \text{ and } A_i's$$

are independent $\Rightarrow P(A_{i.o.}) = 1$.

Proof: $A_{i.o.} = \bigcap_{n=1}^{\infty} \bigcup_{i \geq n} A_i$

$$A_{i.o.} \subseteq B_n \Rightarrow P(A_{i.o.}) \leq P(B_n)$$

$$P(B_n) = P\left(\bigcup_{i \geq n} A_i\right) \leq \sum_{i \geq n} P(A_i)$$

$$\Rightarrow P(A_{i.o.}) \leq \sum_{i \geq n}^{\infty} P(A_i)$$

$$\lim_{n \rightarrow \infty} P(A_{i.o.}) \leq \lim_{n \rightarrow \infty} \sum_{i \geq n}^{\infty} P(A_i)$$

$\overbrace{P(A)}$

\circ

Show that

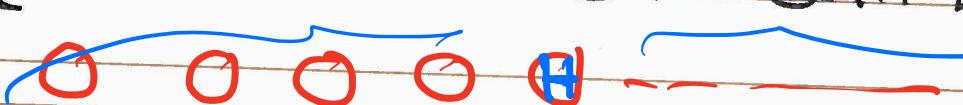
Take $\sum_{i \geq n}^{\infty} P(A_i) = \lim_{m \rightarrow \infty} S_m$

$$S_m = \sum_{i \geq n}^m P(A_i)$$

Example (Erdős–Rényi):

Consider an experiment in which a coin is tossed independently an infinite number of times. Let

$$A_i = \{H \text{ occurs in the } i^{\text{th}} \text{ coin toss}\}$$

As 

(1) Assume that $P(A_i) = \frac{1}{2}$.

$$\text{Then } \sum_{i=1}^{\infty} P(A_i) = \sum_{i=1}^{\infty} \frac{1}{2} = \infty$$

By the second Borel-Cantelli

lemma, it follows that infinitely many heads will occur with probability 1 (almost surely)

(2) Next assume that $P(A_i) = \left(\frac{1}{2}\right)^i$.

$$\text{Then } \sum_{i=1}^{\infty} P(A_i) = \sum_{i=1}^{\infty} \left(\frac{1}{2}\right)^i \cdot \frac{\frac{1}{2}}{1-\frac{1}{2}} = 1 < \infty$$

Hence, by the first Borel-Cantelli Lemma, the probability that infinitely many heads occurs is 0.

In other words, almost surely, only finitely many heads will occur!

It might appear surprising that in the first example, where probability of getting heads is γ_i , for any i we select (no matter how large), there occurs a heads

beyond i almost surely.

The reason is that the decay

rate γ_i of the probability of

observing heads is not

"adequately fast."

On the other hand, in

the second example, the rate of decay $(\gamma_2)^i$ is adequately fast that after a finite i , there will almost surely be no heads.

Exercise: (Infinite Monkey):

A monkey sits in front of a computer and starts pressing keys randomly on the keyboard.

Using the Borel-Cantelli Lemmas,

Show that the monkey will

type any text of your choice

(e.g. ABRACADABRA or the whole

declaration of independence), with

probability 1.

You can assume that the

monkey selects the keys

uniformly at random, and that

it selects the successive keys

independently.