

Inference

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Outline

Logical inference

- Set theory and logic

- Logical inference

Probability background

- Probability facts

- Conditional probability and independence

- Posterior distributions and model estimation

Graphical models

- Graphical model

- Exercises

Statistical Decision Theory

- Elementary Decision Theory

- Random variables, expectation and variance

- Statistical Decision Theory

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Set theory

- ▶ First, consider some universal set Ω .
- ▶ A set A is a collection of points x in Ω .
- ▶ $\{x \in \Omega : f(x)\}$: the set of points in Ω with the property that $f(x)$ is true.

Unary operators

- ▶ $\neg A = \{x \in \Omega : x \notin A\}$.

Binary operators

- ▶ $A \cup B$ if $\{x \in \Omega : x \in A \vee x \in B\}$ - (c.f. $A \vee B$)
- ▶ $A \cap B$ if $\{x \in \Omega : x \in A \wedge x \in B\}$ - (c.f. $A \wedge B$)

Binary relations

- ▶ $A \subset B$ if $x \in A \Rightarrow x \in B$ - (c.f. $A \Rightarrow B$)
- ▶ $A = B$ if $x \in A \Leftrightarrow x \in B$ - (c.f. $A \Leftrightarrow B$)

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The inference problem

- ▶ Given statements A_1, \dots, A_n we know to be true (i.e. a knowledge base), is another statement B true?

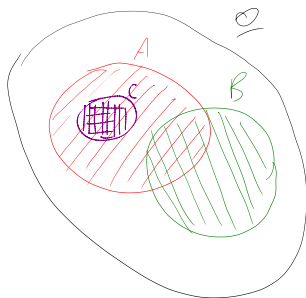
The following statements are equivalent:

- ▶ $A \implies B$ iff $(A \cap \neg B) = \emptyset$.
- ▶ $A \implies B$ iff $A \subset B$.

In addition

- ▶ If $(A \implies B) \wedge A$ then B .
- ▶ If $(A \wedge B)$ then A .

Illustration



$$(A|C) =$$

inferred known

$$(B|C) =$$

$$(C|A) =$$

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

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Events as sets

The universe and random outcomes

- ▶ The Ω contains all events that can happen.
- ▶ When something happens, we observe an element $\omega \in \Omega$.

Events in the universe

- ▶ An event is true if $\omega \in A$, and false if $\omega \notin A$.
- ▶ The negative event $\neg A = \Omega \setminus A$ is the set
- ▶ The possible events are a collection of subsets Σ of Ω so that

(i) $\Omega \in \Sigma$, (ii) $A, B \in \Sigma \Rightarrow A \cup B \in \Sigma$ (iii) $A \in \Sigma \Rightarrow \neg A \in \Sigma$

Example: Traffic violation

- ▶ A car is moving with speed $\omega \in [0, \infty)$ in front of the speed camera.
- ▶ $A_0 = [0, 50]$: below the speed limit
- ▶ $A_1 = (50, 60]$: low fine
- ▶ $A_2 = (60, \infty]$: high fine
- ▶ $A_3 = (100, \infty)$: Suspension of license
- ▶ All combinations of the above events are interesting.

Probability fundamentals

Probability measure P

Probability can be seen as an area-like function assigning a likelihood to sets.

- ▶ $P : \Sigma \rightarrow [0, 1]$ gives the likelihood $P(A)$ of an event $A \in \Sigma$.
- ▶ $P(\Omega) = 1$
- ▶ For $A, B \subset \Omega$, if $A \cap B = \emptyset$ then $P(A \cup B) = P(A) + P(B)$.

Marginalisation

Partition

If A_1, \dots, A_n are a partition of B then:

- ▶ $A_j \cap A_i = \emptyset$ for $i \neq j$
- ▶ $\bigcup_{i=1}^n A_i = B$.

Marginalisation

If $A_1, \dots, A_n \subset \Omega$ are a partition of Ω

$$P(B) = \sum_{i=1}^n P(B \cap A_i).$$

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Conditional probability

Definition (Conditional probability)

The conditional probability of an event A given an event B is defined as

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

The above definition requires $P(B)$ to exist and be positive.

Conditional probabilities as a collection of probabilities

More generally, we can define conditional probabilities as simply a collection of probability distributions:

$$\{P_\theta : \theta \in \Theta\},$$

where Θ is indexing possible values of θ .

- θ is sometimes called the **model** or **parameter**

The theorem of Bayes

Theorem (Bayes's theorem)

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

The theorem of Bayes

Theorem (Bayes's theorem)

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

The general case

If A_1, \dots, A_n are a partition of Ω , meaning that they are mutually exclusive events (i.e. $A_i \cap A_j = \emptyset$ for $i \neq j$) such that one of them must be true (i.e. $\bigcup_{i=1}^n A_i = \Omega$), then

$$P(B) = \sum_{i=1}^n P(B|A_i)P(A_i)$$

and

$$P(A_j|B) = \frac{P(B|A_j)}{\sum_{i=1}^n P(B|A_i)P(A_i)}$$

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Bayes's theorem

As a conditional measure

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

Bayes's theorem

As a conditional measure

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

As a causal explanation

$$\mathbb{P}(\text{cause} | \text{effect}) = \frac{\mathbb{P}(\text{effect} | \text{cause}) \mathbb{P}(\text{cause})}{\mathbb{P}(\text{effect})}$$

Bayes's theorem

As a conditional measure

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

As a causal explanation

$$\mathbb{P}(\text{cause} | \text{effect}) = \frac{\mathbb{P}(\text{effect} | \text{cause}) \mathbb{P}(\text{cause})}{\mathbb{P}(\text{effect})}$$

As model inference

- ▶ Prior $\beta(\theta)$
- ▶ Model class $\{P_{\theta}(\beta) : \theta \in \Theta\}$
- ▶ Data x

$$\beta(\theta | x) = \frac{P_{\theta}(x)\beta(\theta)}{\mathbb{P}_{\beta}(x)} = \frac{P_{\theta}(x)\beta(\theta)}{\sum_{\theta' \in \Theta} P_{\theta'}(x)\beta(\theta')}$$

Example: COVID symptoms

Activity (with playing cards or dice)

- ▶ Pick two (x, y) from 1 to 10.
- ▶ If $(x = 1 \text{ and } y < 9)$, **or** $(x \text{ is even and } y \geq 9)$, you have **symptoms**.
- ▶ Do you have COVID?

Example: COVID symptoms

Activity (with playing cards or dice)

- ▶ Pick two (x, y) from 1 to 10.
- ▶ If $(x = 1 \text{ and } y < 9)$, **or** $(x \text{ is even and } y \geq 9)$, you have **symptoms**.
- ▶ Do you have COVID?

Information

- ▶ 20% of people have COVID
- ▶ 50% of people **with** COVID have symptoms.
- ▶ 10% of people with **no** COVID have symptoms.
- ▶ If you **do** have symptoms, what are the chances you have COVID?

Example: COVID symptoms

Activity (with playing cards or dice)

- ▶ Pick two (x, y) from 1 to 10.
- ▶ If $(x = 1 \text{ and } y < 9)$, **or** $(x \text{ is even and } y \geq 9)$, you have **symptoms**.
- ▶ Do you have COVID?

Information

- ▶ 20% of people have COVID
- ▶ 50% of people **with** COVID have symptoms.
- ▶ 10% of people with **no** COVID have symptoms.
- ▶ If you **do** have symptoms, what are the chances you have COVID?

Formalisation

- ▶ Prior $P(C) = 0.1$:
- ▶ Likelihood: $P(S|C) = 0.5$, $P(S|\neg C) = 0.1$
- ▶ Posterior:

$$P(C|S) = \frac{P(S|C)P(C)}{P(S|C)P(C) + P(S|\neg C)P(\neg C)}$$

Example: The k-meteorologists problem (set notation)

- ▶ R_t : The **event** that it rains at time t .
- ▶ A set of stations Θ , with $\theta \in \Theta$ making weather predictions:

$$P(R_{t+1} \mid R_1, \dots, R_t, \theta),$$

- ▶ A **prior probability** $P(\theta)$ on the stations.
- ▶ The **marginal** probability

$$P(R_1, \dots, R_t) = \sum_{\theta \in \Theta} P(R_1, \dots, R_t \mid \theta) P(\theta)$$

- ▶ The **posterior** probability

$$\begin{aligned} P(\theta \mid R_1, \dots, R_t) &= \frac{P(R_1, \dots, R_t \mid \theta) P(\theta)}{P(R_1, \dots, R_t)} = \frac{\prod_{i=1}^t P(R_i \mid R_1, \dots, R_{i-1}, \theta) P(\theta)}{P(R_1, \dots, R_t)} \\ &= \frac{P(R_t \mid R_1, \dots, R_{t-1} \mid \theta) P(\theta \mid R_1, \dots, R_{t-1})}{P(R_t \mid R_1, \dots, R_{t-1})} \end{aligned}$$

- ▶ The **marginal posterior** probability

$$P(R_{t+1} \mid R_1, \dots, R_t) = \sum_{\theta \in \Theta} P(R_{t+1} \mid R_1, \dots, R_t, \theta) P(\theta \mid R_1, \dots, R_t)$$

Example: The k-meteorologists problem (stat notation)

- ▶ $x_t \in \{0, 1\}$: A **random variable**, telling us whether it rains at time t .
- ▶ A set of stations Θ , with $\theta \in \Theta$ making weather predictions:

$$P_{\theta}(x_{t+1} \mid x_1, \dots, x_t)$$

- ▶ A **prior probability** $\beta(\theta)$ on the stations.
- ▶ The **marginal** probability

$$\mathbb{P}_{\beta}(x_1, \dots, x_t) = \sum_{\theta \in \Theta} P_{\theta}(x_1, \dots, x_t) \beta(\theta)$$

- ▶ The **posterior** probability

$$\begin{aligned} \beta(\theta \mid x_1, \dots, x_t) &= \frac{P_{\theta}(x_1, \dots, x_t) \beta(\theta)}{\mathbb{P}_{\beta}(x_1, \dots, x_t)} = \frac{\prod_{i=1}^t P_{\theta}(x_i \mid x_1, \dots, x_{i-1}) \beta(\theta)}{\mathbb{P}_{\beta}(x_1, \dots, x_t)} \\ &= \frac{P_{\theta}(x_t \mid x_1, \dots, x_{t-1}) \beta(\theta \mid x_1, \dots, x_{t-1})}{\mathbb{P}_{\beta}(x_t \mid x_1, \dots, x_{t-1})} \end{aligned}$$

- ▶ The **marginal posterior** probability

$$\mathbb{P}_{\beta}(x_{t+1} \mid x_1, \dots, x_t) = \sum_{\theta \in \Theta} P_{\theta}(x_{t+1} \mid x_1, \dots, x_t) \beta(\theta \mid x_1, \dots, x_t)$$

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Independence

Independent events $A \perp\!\!\!\perp B$

- ▶ A, B are **independent** iff $P(A \cap B) = P(A)P(B)$.
- ▶ Knowing if A happened, does not tell us anything about whether B happened

Conditional independence $A \perp\!\!\!\perp B \mid C$

- ▶ A, B are **conditionally independent** given C iff $P(A \cap B \mid C) = P(A \mid C)P(B \mid C)$.
- ▶ Knowing if C happened tells us all we need to know about A and B .

For random variables

- ▶ Independence: $P(x, y) = P(x)P(y)$.
- ▶ Conditional independence: $P(x, y \mid z) = P(x \mid z)P(y \mid z)$.

Model specification: Independent

x_1

x_2

$f = \text{Bernoulli}(1/2)$

$g = \text{Bernoulli}(0.8)$

$x_1 \sim f$

$x_2 \sim g$

```
def f():
```

```
    return np.random.choice(2)
```

```
def g:
```

```
    return np.random.choice(2, [0.2, 0.8])
```

```
x1 = f()
```

```
x2 = g()
```

Model specification: Gaussian Dependent variables



$f = \text{Normal}(0, 1)$

$g(a) = \text{Normal}(a, 1)$

$x_1 \sim f$

$x_2 | x_1 = a \sim g(a)$

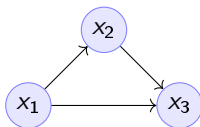
```
def f():  
    return np.random.normal(0, 1)  
def g(a):  
    return np.random.normal(a)  
x1 = f()  
x2 = g(x1)
```

Model specification: Bernoulli Dependent variables



$f = \text{Bernoulli}(1/2)$	<code>def f():</code>
$g(a) = \text{Bernoulli}(\theta_a)$	<code> return np.random.choice(2)</code>
$x_1 \sim f$	<code>def g(a):</code>
$x_2 x_1 = a \sim g(a)$	<code> theta = [0.6, 0.5]</code>
$\theta = (0.6, 0.5)$	<code> return np.random.choice(theta[a])</code>
	<code>x1 = f()</code>
	<code>x2 = g(x1)</code>

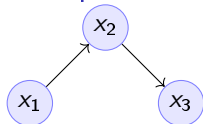
Graphical models



- ▶ Variables: x_1, x_2, x_3
- ▶ Arrows denote dependencies between variables.

Conditional independence

Example



Graphical model for the factorisation

$$\mathbb{P}(x_3 \mid x_2) \mathbb{P}(x_2 \mid x_1) \mathbb{P}(x_1).$$

Definition

- ▶ Consider variables x_1, \dots, x_n .
- ▶ Let B, D be subsets of $[n]$.

We say x_i is **conditionally independent** of x_B given x_D and write

$$x_i \perp\!\!\!\perp x_B \mid x_D$$

if and only if:

$$\mathbb{P}(x_i, x_B \mid x_D) = \mathbb{P}(x_i \mid x_D) \mathbb{P}(x_B \mid x_D).$$

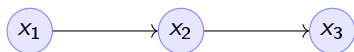
Directed graphical model

A collection of n random variables $x_i : \Omega \rightarrow X_i$, and let $X \triangleq \prod_i X_i$, with underlying probability measure P on Ω . Let $\mathbf{x} = (x_i)_{i=1}^n$ and for any subset $B \subset [n]$ let

$$\mathbf{x}_B \triangleq (x_i)_{i \in B} \tag{1}$$

$$\mathbf{x}_{-j} \triangleq (x_i)_{i \neq j} \tag{2}$$

Model specification: Chain



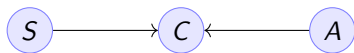
$$x_1 \sim f \quad (3)$$

$$x_2 \mid x_1 = a \sim g(a) \quad (4)$$

$$x_3 \mid x_2 = b \sim h(b), \quad (5)$$

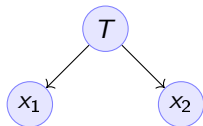
```
def f():  
    return np.random.uniform()  
def g(a):  
    return np.random.uniform() + a  
def h(b):  
    return np.random.uniform * b  
x1 = f()  
x2 = g(x1)  
x3 = h(x2)
```

Smoking and lung cancer



Smoking and lung cancer graphical model, where S : Smoking, C : cancer, A : asbestos exposure.

Time of arrival at work



Time of arrival at work graphical model where T is a traffic jam and x_1 is the time John arrives at the office and x_2 is the time Jane arrives at the office.

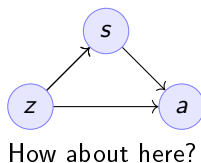
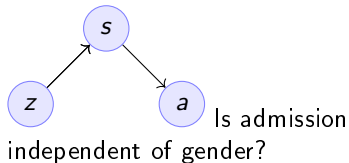
*Conditional independence:

- ▶ Even though x_1, x_2 are **not independent**, they become independent once you know T .

School admission

School	Male	Female
A	62	82
B	63	68
C	37	34
D	33	35
E	28	24
F	6	7

- ▶ z : gender
- ▶ s : school applied to
- ▶ a : admission



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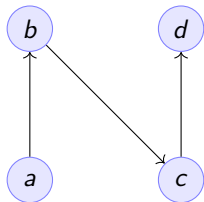
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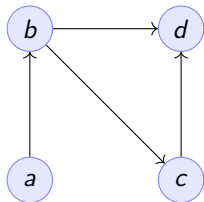
Statistical Decision Theory

What is the model for this graph?



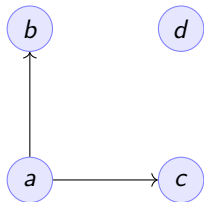
$$P(a, b, c, d) = \dots$$

What is the model for this graph?



$$P(a, b, c, d) =$$

What is the model for this graph?



$$P(a, b, c, d) =$$

Draw the graph for this model

b

d

a

c

$$P(a, b, c, d) = P(a)P(b|a)P(c|b)P(d|b)$$

Draw the graph for this model

b

d

a

c

$$P(a, b, c, d) = P(a)P(b|a)P(d|c)P(c)$$

Draw the graph for this model

b

d

a

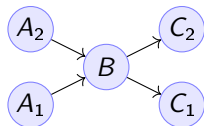
c

$$P(a, b, c, d) = P(a)P(b|a)P(c|a)P(d|b, c)$$

Conditional independence

For any set of events A_1, A_2, A_3, \dots , we can write their co-occurrence probability as $\prod_i P(A_i | \cap A_1 \cap A_2 \cap \dots \cap A_{i-1})$. However, we can use a **Bayesian network** to define conditional independence structures.

If A is a parent of B and C is a child of B , and there are **no other paths** from A to C then the following conditional independence holds:



$$P(C | B, A) = P(C | B)$$

i.e. C is conditionally independent of A given B .

Conditional probability tables

We can now write the distribution of the above example as

$$P(B, C_1, C_2) = P(A_1)P(A_2)P(B|A_1 \cap A_2)P(C_1|B)P(C_2|B).$$

Example: COVID test

Information

- ▶ 10% of people have COVID
- ▶ 50% of people with COVID have a positive **test**
- ▶ 50% of people with COVID have **symptoms**
- ▶ 10% of people without COVID have a positive **test**
- ▶ 20% of people without COVID have **symptoms**

Example: COVID test

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- ▶ 20% of people without COVID have **symptoms**

Formalisation

- ▶ Prior: $P(C = 1) = 0.1$
- ▶ Likelihood: $P(T, S|C) = P(T|C)P(S|C)$, $P(T, S|\neg C)$ for all values of T, S, C .
- ▶ Posterior:

$$P(C|T, S) = \frac{P(S|C)P(T|C)P(C)}{\sum_{i=0}^1 P(S|C=i)P(T|C=i)P(C=i)}$$

Example: Naive Bayes models

Sometimes we observe multiple effects that have a common cause, but which are otherwise independent:

$$\mathbb{P}(\text{effect}_1, \dots, \text{effect}_n \mid \text{cause}) = \prod_{i=1}^n \mathbb{P}(\text{effect}_i \mid \text{cause})$$

Naive Bayes model

- ▶ Observations $(\mathbf{x}_t, y_t)_{t=1}^T$ with $\mathbf{x}_t = (x_{t,1}, \dots, x_{t,n})$.
- ▶ Probability **models** $P_\theta(y \mid \mathbf{x}) = \prod_{i=1}^n P_\theta(y \mid x_i)$.

Example: Wumpus world

	⦿	

	O	
	⦿	

	⦿	O

	O	
	⦿	O

Details

- ▶ Probability of each world A_i being true: $1/4$
- ▶ Probability of each hole generating a breeze:
 $P(B_1|A_2 \cup A_4) = P(B_2|A_3 \cup A_4)$ with B_1, B_2 conditionally independent given A .

Questions

- ▶ What is the probability of feeling a breeze $B = B_1 \cup B_2$ in each world?
- ▶ What is the probability of a hole above if you **feel** a breeze?
- ▶ What is the probability of a hole above if you **don't** feel a breeze?

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Preferences

Types of rewards

- ▶ For e.g. a student: Tickets to concerts.
- ▶ For e.g. an investor: A basket of stocks, bonds and currency.
- ▶ For everybody: Money.

Preferences among rewards

For any rewards $x, y \in R$, we either

- ▶ (a) Prefer x at least as much as y and write $x \succeq^* y$.
- ▶ (b) Prefer x not more than y and write $x \preceq^* y$.
- ▶ (c) Prefer x about the same as y and write $x \sim^* y$.
- ▶ (d) Similarly define \succ^* and \prec^*

Utility and Cost

Utility function

To make it easy, assign a utility $U(x)$ to every reward through a utility function $U : R \rightarrow \mathbb{R}$.

Utility-derived preferences

We prefer items with higher utility, i.e.

- ▶ (a) $U(x) \geq U(y) \Leftrightarrow x \succeq^* y$
- ▶ (b) $U(x) \leq U(y) \Leftrightarrow y \succeq^* x$

Cost

It is sometimes more convenient to define a cost function $C : R \rightarrow \mathbb{R}$ so that we prefer items with lower cost, i.e.

- ▶ $C(x) \geq C(y) \Leftrightarrow y \succeq^* x$

Random outcomes

Choosing among rewards

-[A] Bet 10 CHF on black -[B] Bet 10 CHF on 0 -[C] Bet nothing What is the reward here?

Choosing among trips

-[A] Taking the car to Zurich (50' without delays, 80' with delays) -[B] Taking the train to Zurich (60' without delays) What is the reward here?

Random rewards

- ▶ Each gamble gives us different rewards with different probabilities.
- ▶ These rewards are then **random**
- ▶ For simplicity, we assign a real-valued **utility** to outcomes. This is a **random variable**

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Random variables

A random variable $f : \Omega \rightarrow \mathbb{R}$ is a real-valued **function**, with $\omega \sim P$.

The distribution of f

The probability that f lies in some subset $A \subset \mathbb{R}$ is

$$P_f(A) \triangleq P(\{\omega \in \Omega : f(\omega) \in A\}),$$

and we write $f \sim P_f$.

Shorthands for RV

- ▶ For RVs $f : \Omega \rightarrow \mathbb{R}$, we write $P(f \in A)$ to mean $P_f(A)$.
- ▶ For RVs $f : \Omega \rightarrow X$, where X is a finite set e.g. $\{1, 2, \dots, n\}$, we write $P(f = x) = P_f(\{x\})$ for any $x \in X$.

Independence of random variables

Two RVs f, g are independent in the same way that events are independent.

$$P(f \in A \wedge g \in B) = P(f \in A)P(g \in B) = P_f(A)P_g(B).$$

In that sense, $f \sim P_f$ and $g \sim P_g$.

Formal definition

More specifically, we are measuring the set of ω values for which $f(\omega) \in A$ and $g(\omega) \in B$:

$$P(\{\omega : f(\omega) \in A, g(\omega) \in B\}) = P_f(A)P_g(B).$$

Shorthand notation

Since the above is very cumbersome, we usually just write that

$$P(f, g) = P(f)P(g)$$

for any two independent random variables f, g .

Expectation

For any real-valued random variable $f : \Omega \rightarrow \mathbb{R}$, the expectation with respect to a probability measure P is

$$\mathbb{E}_P(f) = \sum_{\omega \in \Omega} f(\omega)P(\omega).$$

When Ω is continuous, we can use a density p

$$\mathbb{E}_P(f) = \int_{\Omega} f(\omega)p(\omega)d\omega.$$

Linearity of expectations

For any RVs x, y :

$$\mathbb{E}_P(x + y) = \mathbb{E}_P(x) + \mathbb{E}_P(y)$$

Multiple variables

The joint distribution $P(x, y)$

For two (or more) RVs $x : \Omega \rightarrow \mathbb{R}$, and $y : \Omega \rightarrow \mathbb{R}$, this is a **shorthand** for the distribution of $(x(\omega), y(\omega))$ when $\omega \sim P$. We can also use $P(x = i, y = j)$ for the probability that the two variables assume the values i, j respectively.

Independence

If x, y are independent RVs then $P(x, y) = P_x(x)P_y(y)$.

Correlation

If x, y are **not** correlated then $\mathbb{E}_P(xy) = \mathbb{E}(x) \mathbb{E}(y)$.

IID (Independent and Identically Distributed) random variables

A sequence x_t of r.v.s is IID if $x_t \sim P$ so that

$$(x_1, \dots, x_t, \dots, x_T) \sim P^T$$

i.e. a T -length sample is drawn from the product distribution
 $P^T = P \times P \times \dots \times P$.

Conditional expectation

The conditional expectation of a random variable $f : \Omega \rightarrow \mathbb{R}$, with respect to a probability measure P conditioned on some event B is simply

$$\mathbb{E}_P(f|B) = \sum_{\omega \in \Omega} f(\omega)P(\omega|B).$$

Conditional expectations are similar to conditional probabilities.

Conditional probabilities of RVs

Similarly to the notation over sets,

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

when dealing with RVs, it is common to use the notation

$$P(x, y) = P(x|y)P(y)$$

This equation works for all possible values of x, y e.g.

$$P(x = 1, y = 0) = P(x = 1|y = 0)P(y = 0)$$

which then denotes the probability masses of each

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Expected utility

Actions, outcomes and utility

In this setting, we obtain random outcomes that depend on our actions.

- ▶ Actions $a \in A$
- ▶ Outcomes $\omega \in \Omega$.
- ▶ Probability of outcomes $P(\omega \mid a)$
- ▶ Utility $U : \Omega \rightarrow \mathbb{R}$

Expected utility

The expected utility of an action is:

$$\mathbb{E}_P[U \mid a] = \sum_{\omega \in \Omega} U(\omega)P(\omega \mid a).$$

The expected utility hypothesis

We prefer a to a' if and only if

$$\mathbb{E}_P[U \mid a] \geq \mathbb{E}_P[U \mid a']$$

The St-Petersburg Paradox

The game

If you give me x CHF, then I promise to (a) Throw a fair coin until it comes heads. (b) If it does so after T throws, then I will give you 2^T CHF.

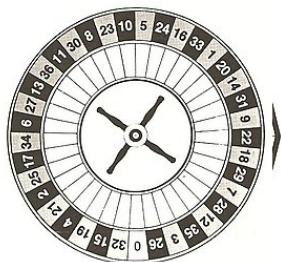
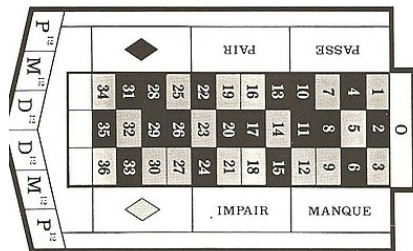
The question

- ▶ How much x are you willing to pay to play?
- ▶ Given that the expected amount of money is infinite, why are you only willing to pay a small x ?

Example: Betting

In this example, probabilities reflect actual randomness

Choice	Win Probability p	Payout w	Expected gain
Don't play	0	0	0
Black	18/37	2	
Red	18/37	2	
0	1/37	36	
1	1/37	36	



What are the expected gains for these bets?

Example: Route selection

- ▶ In this example, probabilities reflect subjective beliefs

Choice	Best time	Chance of delay	Delay amount	Expected time
Train	80	5%	5	
Car, route A	60	50%	30	
Car, route B	70	10%	10	

Example: Estimation

- In this example, probabilities are calculated starting from subjective beliefs

Mean-Square Estimation

If we want to guess $\hat{\theta}$, and we knew that $\theta \sim P$, then the guess

$$\hat{\theta} = \mathbb{E}_P(\theta) = \arg \min_{\hat{\theta}} \mathbb{E}_P[(\theta - \hat{\theta})^2]$$

Example: Noisy optimisation

We wish to find the maximum of a function

$$f(x) \triangleq \mathbb{E}[g|x], \quad \mathbb{E}[g|x] = \int_{-\infty}^{\infty} g(\omega, x) p(\omega) d\omega \quad (6)$$