

Reasoning under uncertainty

- In incomplete or imperfect settings. Not enough information.
- Why reasoning under uncertainty:
 - Modeling every detail of a complex system is difficult.
 - Not enough information to understand the system.

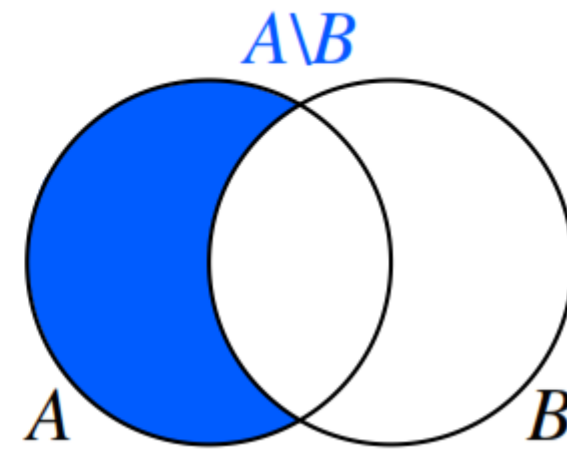
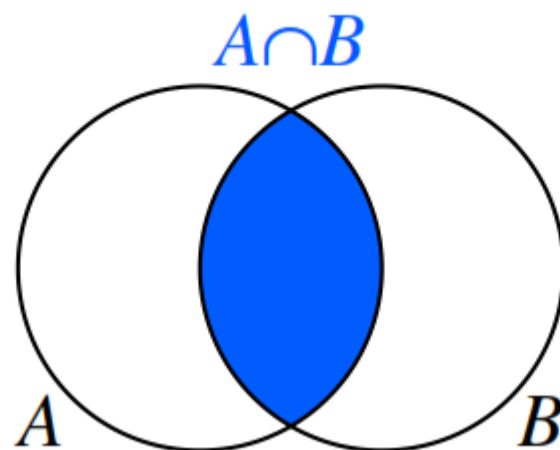
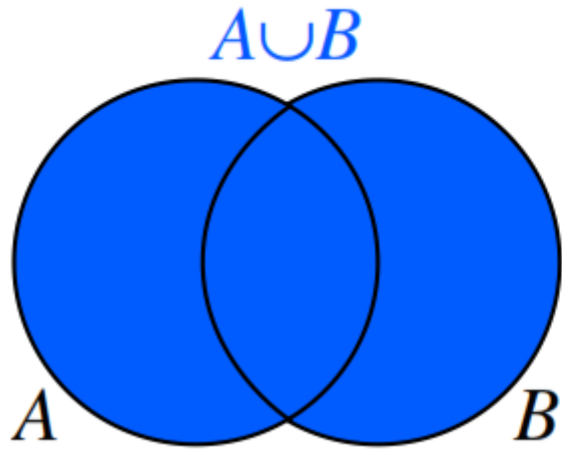
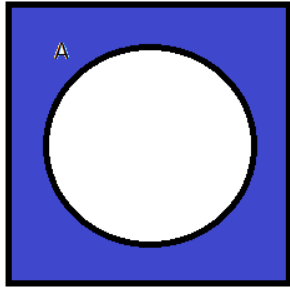
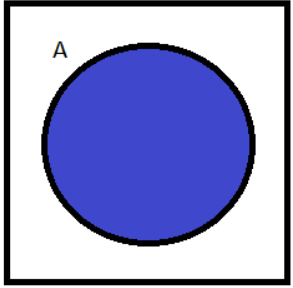
What is Probability?

Different conditions:

- All outcomes have equal probability.
- Randomness (such as weather)
- Frequency approach, that is probability is based on history.

Probabilities quantify uncertainty regarding the occurrence of events.

Set Theory

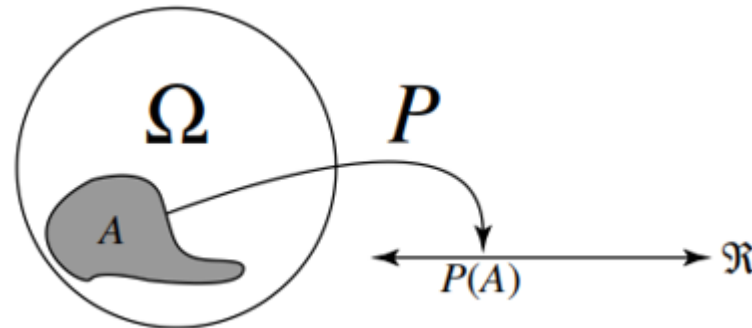


Showing all possible logical relations between a finite collection of sets.

Event A: A student has selected the statistics course.
Event B: A student has selected the language course.
Explain set of events using the van diagrams.

Probability Space

- A *probability space* represents our uncertainty regarding an experiment
- Three parts:
 - The *sample space* Ω , which is a set of *outcomes*
 - A set \mathcal{l} of subsets of Ω , called *events*
 - The *probability measure* $P: \mathcal{l} \rightarrow \mathbb{R}^+$



- $A \in \mathcal{l}$ is a set of outcomes, an event. $P(A)$ represents the probability that the experiment's actual outcome will be a member of A .

σ – algebra

- Let Ω be an arbitrary set. A non-empty collection \mathcal{l} subsets of Ω satisfying the following conditions called σ – algebra:
 - $\emptyset \in \mathcal{l}$
 - If $D \in \mathcal{l}$ then its complement is also in \mathcal{l} , that is $\Omega \setminus D \in \mathcal{l}$
 - If D_1, D_2, \dots , is a countable collection of sets in \mathcal{l} then their union implies $\bigcup_{i=1}^{\infty} D_i \in \mathcal{l}$

Example of a probability space

- Example 1: Throwing a dice.
 - Sample Space: $\{1,2,3,4,5,6\}$
 - Event (Dice number ≤ 3) : $\{1,2,3\}$

Repeating the experiment for large number of times, the fraction of times that an event A occurs is called the Probability of A.

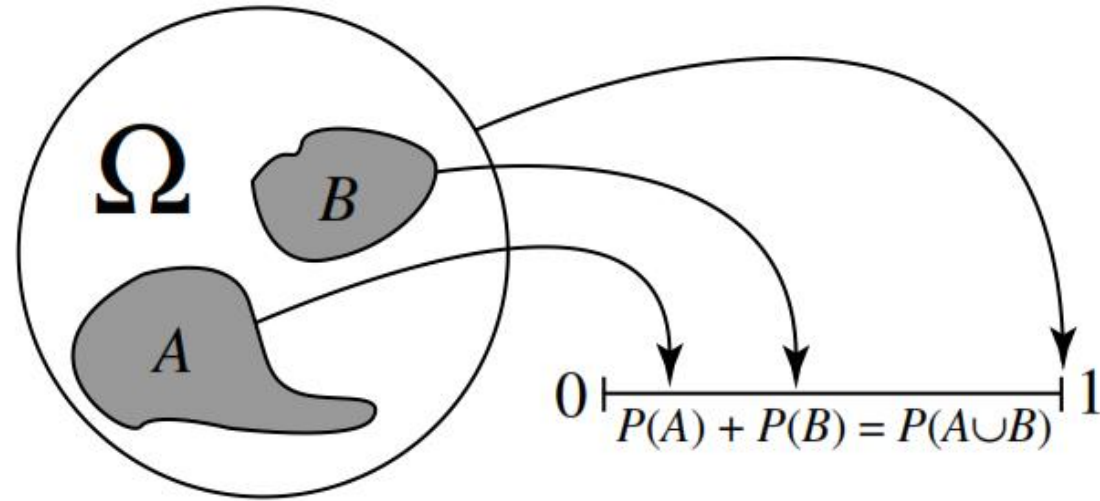
$$\text{That is } P(A) = \frac{n}{N}$$

Discrete sample space

- Example 2: t is the lifespan of an electrical device and shown as $S = \{t | t \geq 0\}$.
- Event: A device lasts less than 5 years shown as $A = \{t | 0 \leq t < 5\}$.

Three axioms of probability space

1. $P(A) \geq 0$ for all events A
2. $P(\Omega) = 1$
3. $P(A \cup B) = P(A) + P(B)$ for disjoint events A and B



Events – [Mutually Exclusive]

- Two events are mutually exclusive if they cannot occur at the same time. Another word that means mutually exclusive is disjoint.

- Let \mathcal{l} be a σ – algebra on the universe Ω .

for sets $D_1, D_2, \dots, D_n \in \mathcal{l}$, that are mutually disjoint, we have

$$D_i \cap D_j = \emptyset, \text{ if } i \neq j.$$

$$P(\cup_{i=1}^n D_i) = \sum_{i=1}^n P(D_i)$$

- $P(A) = 0.2$, $P(B) = 0.7$, A and B are disjoint.

	B	$\Omega \setminus B$
A	0.00	0.20
$\Omega \setminus A$	0.70	0.10

Events – [Independent Events]

- Two events are independent if the occurrence of one does not change the probability of the other occurring.
- If events are independent, then the probability of them both occurring is the product of the probabilities of each occurring.
- $P(A \cap B) = P(A) * P(B)$
- A and B are independent events
 - $P(A \text{ and } B) = P(A) * P(B)$
 - $P(A|B) = P(A)$
 - $P(B|A) = P(B)$

$P(A) = 0.20, P(B) = 0.70. \Rightarrow P(\Omega \setminus A) = 0.80, P(\Omega \setminus B) = 0.30$

	B	$\Omega \setminus B$
A	0.14	0.06
$\Omega \setminus A$	0.56	0.24

Independent and identically distributed data

- Pick multiple random samples $s_1, s_2, \dots, s_n \in \Omega$
- Probability that $s \in \Omega$ is picked: $P(s)$
- The sampling is independent and identically distributed iff
 - All samples are picked from the same probability space (Ω, l, P) (= identically distributed)
 - Samples are mutually independently picked, i.e.
$$P(s_1, s_2) = P(s_1)P(s_2)$$
- The overall probability then can be written as
$$P(s_1, s_2, \dots, s_n) = \prod_{i=1}^n P(s_i)$$

Dependent Events

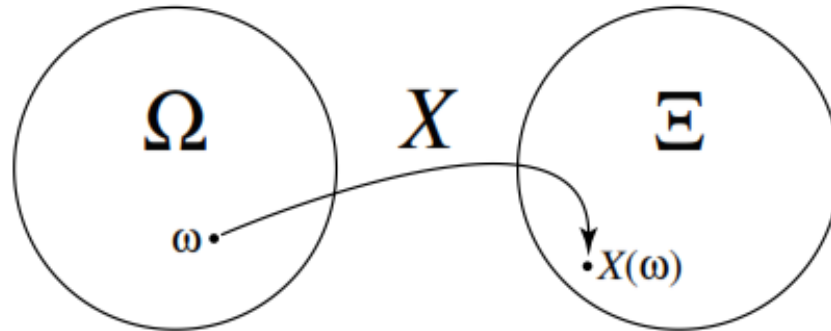
If the occurrence of one event does affect the probability of the other occurring, then the events are dependent.

- Conditional probability allows us to reason with *partial information*.
- When $P(B) > 0$, the *conditional probability of A given B* is defined as

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

Random variables

- It is often useful to “pick out” aspects of the experiment’s outcomes.
- A *random variable* X is a function from the sample space Ω .

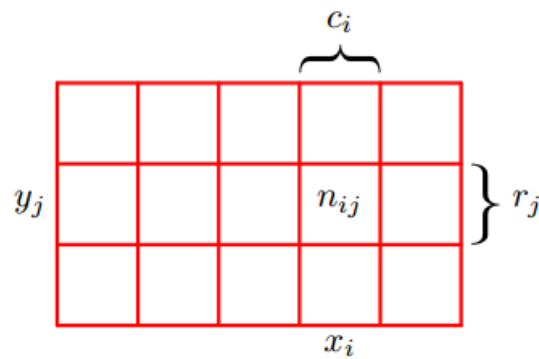


- Random variables can define events, e.g., $\{\omega \in \Omega : X(\omega) = \text{true}\}$.
- One will often see expressions like $P\{X = 1, Y = 2\}$ or $P(X = 1, Y = 2)$.
These both mean $P(\{\omega \in \Omega : X(\omega) = 1, Y(\omega) = 2\})$.

Random variables - Example

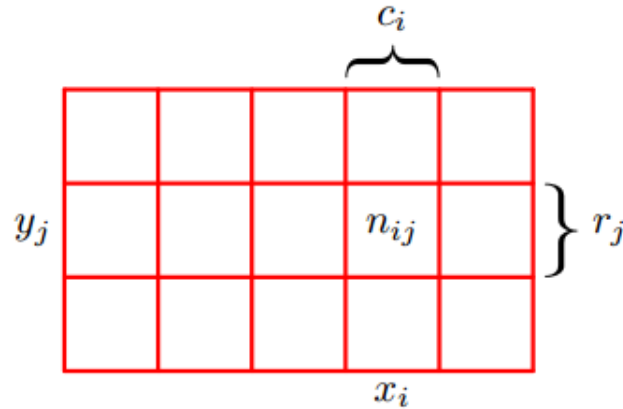
- Toss a coin 10 times.
- Sample Space (S)= {HTHT ...}, all different configurations of H & T.
- Random variable X = number of heads. $X: S \rightarrow R$
- $X: S \rightarrow \{0, 1, \dots, 10\}$.

Product and Sum rule



- Random variable X can take values $\{x_i\}, i = 1, 2, \dots, M$ ($M = 5$), Y can take values $\{y_j\}, j = 1, 2, \dots, L$ ($L = 3$).
- Consider a total number N of instances of these variables, and denote the number of instances where $X = x_i$ and $Y = y_i$ by n_{ij} (number of points in the corresponding cell of the array).

Product and Sum rule



- Number of points in column i , corresponding to $X = x_i$, is denoted by c_i .
- Number of points in row j , corresponding to $Y = y_i$, is denoted by r_j .

Sum Rule

Number of instances in column i is just the sum of the number of instances in each cell of that column, we have $c_i = \sum_j n_{ij}$ and hence

$$\begin{aligned} p(X = x_i) &= \frac{c_i}{N} \\ &= \frac{\sum_{j=1}^L n_{ij}}{N} \\ &= \sum_{j=1}^L p(X = x_i, Y = y_j). \end{aligned}$$

Sometimes also called *marginal* probability, because it is obtained by marginalizing, or summing out, the other variables (here Y).

Product Rule

Now we are interested in finding the fraction of those points in column i that fall in cell i, j , that is

$$p(Y = y_j | X = x_i) = \frac{n_{ij}}{c_i}.$$

By means of this *conditional* probability, we can derive the following relationship

$$\begin{aligned} p(X = x_i, Y = y_j) &= \frac{n_{ij}}{N} = \frac{n_{ij}}{c_i} \cdot \frac{c_i}{N} \\ &= p(Y = y_j | X = x_i) p(X = x_i) \end{aligned}$$

which is the product rule of probabilities.

Two Important Rule in Probability Theory

- The product Rule
 - The probability that A and B both happens is given as the probability that A happens times the probability that B happens, given A has occurred.

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

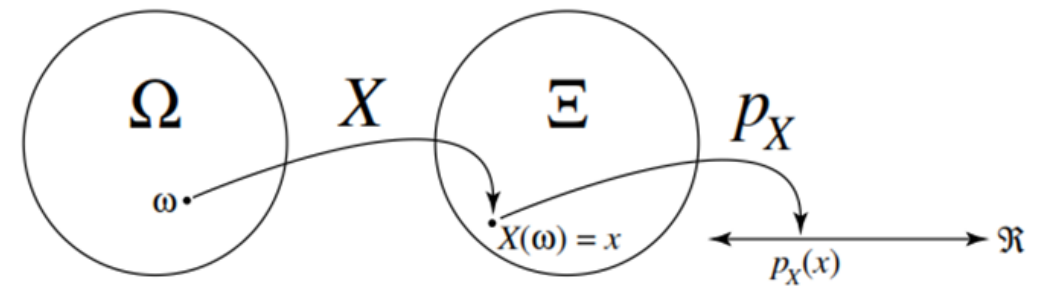
Densities

- We considered probabilities defined over discrete sets of events.
- Consider now probabilities with respect to *continuous* variables.

If the probability of a real-valued variable x falling in the interval $(x, x + \delta x)$ is given by $p(x)\delta x$ for $\delta x \rightarrow 0$, then $p(x)$ is called the *probability density* over x .

- The *probability* that x will lie in an interval (a, b) is given by

$$p(x \in (a, b)) = \int_a^b p(x)dx.$$



Expected Value

Let X be a numerically-valued discrete random variable with sample space of Ω and the distribution function $m(x)$. The expected value is given as:

$$E(X) = \sum_{x \in \Omega} xm(x)$$

Let an experiment consist of tossing a fair coin three times. Let X denote the number of heads which appear. Then the possible values of X are 0, 1, 2 and 3. The corresponding probabilities are $1/8, 3/8, 3/8$, and $1/8$. Thus, the expected value of X equals