Cognitive Modeling

Lecture 10: Basic Probability Theory

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Reading: Manning and Schütze (1999: Ch. 2).

Terminology

Terminology for probability theory:

- *experiment:* process of observation or measurement; e.g., coin flip;
- *outcome:* result obtained through an experiments; e.g., coin shows tail;
- *sample space:* set of all possible outcomes of an experiment; e.g., sample space for coin flip: $S = \{H, T\}$.

Sample spaces can be finite or infinite.

Terminology

Example: Finite Sample Space

Roll two dice, each with numbers 1–6. Sample space:

$$S_1 = \{(x, y) | x = 1, 2, \ldots, 6; y = 1, 2, \ldots, 6\}$$

Alternative sample space for this experiment: sum of the dice:

$$S_2 = \{x | x = 2, 3, \ldots, 12\}$$

Example: Infinite Sample Space

Flip a coin until head appears for the first time:

$$S_3 = \{H, TH, TTH, TTTH, TTTTH, \ldots\}$$

Events

Often we are not interested in individual outcomes, but in events. An *event* is a subset of a sample space.

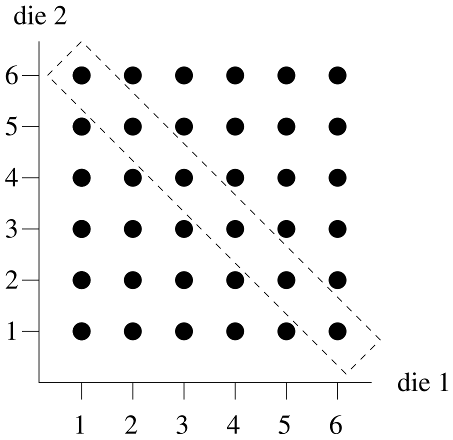
Example

With respect to S_1, describe the event B of rolling a total of 7 with the two dice.

$$B = \{(1,6),(2,5),(3,4),(4,3),(5,2),(6,1)\}$$

Events

The event B can be represented graphically:



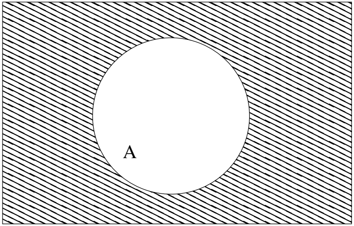
Events

Often we are interested in combinations of two or more events. This can be represented using set theoretic operations. Assume a sample space S and two events A and B:

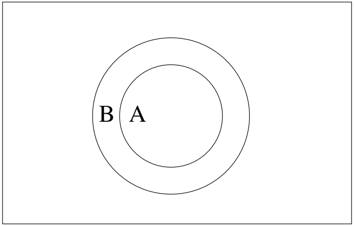
- *complement $\bar{A}$ (also A'):* all elements of S that are not in A;
- *subset $A \subset B$:* all elements of A are also elements of B;
- *union $A \cup B$:* all elements of S that are in A or B;
- *intersection $A \cap B$:* all elements of S that are in A and B.

These operations can be represented graphically using *Venn diagrams.*

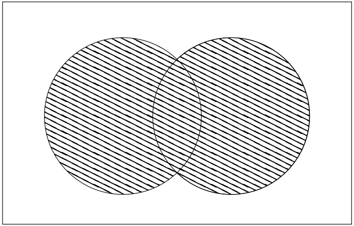
Venn Diagrams



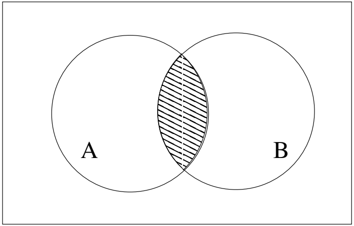
$\bar{A}$



$A \subset B$



$A \cup B$



$A \cap B$

Axioms of Probability

Events are denoted by capital letters A, B, C, etc. The *probability* of and event A is denoted by $P(A)$.

Axioms of Probability

1. The probability of an event is a nonnegative real number: $P(A) \geq 0$ for any $A \subset S$.
2. $P(S) = 1$.
3. If $A_1, A_2, A_3, \ldots,$ is a sequence of mutually exclusive events of S, then:

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

Probability of an Event

Theorem: Probability of an Event

If A is an event in a sample space S and $O_1, O_2, \ldots, O_n$, are the individual outcomes comprising A, then $P(A) = \sum_{i=1}^{n} P(O_i)$

Example

Assume all strings of three lowercase letters are equally probable. Then what's the probability of a string of three vowels?

There are 26 letters, of which 5 are vowels. So there are $N = 26^3$ three letter strings, and $n = 5^3$ consisting only of vowels. Each outcome (string) is equally likely, with probability $\frac{1}{N}$, so event A (a string of three vowels) has probability $P(A) = \frac{n}{N} = \frac{5^3}{26^3} = 0.00711$.

Rules of Probability

Theorems: Rules of Probability

1. If A and $\bar{A}$ are complementary events in the sample space S, then $P(\bar{A}) = 1 - P(A)$.
2. $P(\emptyset) = 0$ for any sample space S.
3. If A and B are events in a sample space S and $A \subset B$, then $P(A) \leq P(B)$.
4. $0 \leq P(A) \leq 1$ for any event A.

Addition Rule

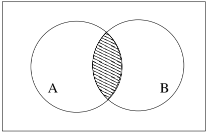
Axiom 3 allows us to add the probabilities of mutually exclusive events. What about events that are not mutually exclusive?

Theorem: General Addition Rule

If A and B are two events in a sample space S, then:

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

Ex: $A =$ "has glasses", $B =$ "is blond". $P(A) + P(B)$ counts blondes with glasses twice, need to subtract once.



Conditional Probability

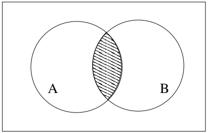
Definition: Conditional Probability, Joint Probability

If A and B are two events in a sample space S, and $P(A) \neq 0$ then the *conditional probability* of B given A is:

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

$P(A \cap B)$ is the *joint probability* of A and B, also written $P(A, B)$.

Intuitively, $P(B|A)$ is the probability that B will occur given that A has occurred.
Ex: The probability of being blond given that one wears glasses: $P(\text{blond}|\text{glasses})$.



Conditional Probability

Example

Consider sampling an adjacent pair of words (bigram) from a large text. Let A = (first word is *run*), B = (second word is *amok*).

If $P(A) = 10^{-3.5}$, $P(B) = 10^{-5.6}$, and $P(A, B) = 10^{-6.5}$, what is the probability of seeing *amok* following *run*? *Run* preceding *amok*?

$$P(\text{run before amok}) = P(A|B) = \frac{P(A, B)}{P(B)} = \frac{10^{-6.5}}{10^{-5.6}} = .126$$

$$P(\text{amok after run}) = P(B|A) = \frac{P(A, B)}{P(A)} = \frac{10^{-6.5}}{10^{-3.5}} = .001$$

To consider: how do we determine $P(A)$, $P(B)$, $P(A, B)$ in the first place?

Conditional Probability

From the definition of conditional probability, we obtain:

Theorem: Multiplication Rule

If A and B are two events in a sample space S, and $P(A) \neq 0$ then:

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

As $A \cap B = B \cap A$, it follows also that:

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

Independence

Definition: Independent Events

Two events A and B are independent if and only if:

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

Intuition: two events are independent if knowing whether one event occurred does not change the probability of the other.

Note that the following are equivalent:

$$\begin{aligned} P(A, B) &= P(A)P(B) && (1) \\ P(A|B) &= P(A) && (2) \\ P(B|A) &= P(B) && (3) \end{aligned}$$

Independence

Example

A coin is flipped three times. Each of the eight outcomes is equally likely. A: head occurs on each of the first two flips, B: tail occurs on the third flip, C: exactly two tails occur in the three flips. Show that A and B are independent, B and C dependent.

$$\begin{array}{ll}
A = \{HHH, HHT\} & P(A) = \frac{1}{4} \\
B = \{HHT, HTT, THT, TTT\} & P(A) = \frac{1}{2} \\
C = \{HTT, THT, TTH\} & P(C) = \frac{3}{8} \\
A \cap B = \{HHT\} & P(A \cap B) = \frac{1}{8} \\
B \cap C = \{HTT, THT\} & P(B \cap C) = \frac{1}{4}
\end{array}$$

$P(A)P(B) = \frac{1}{4} \cdot \frac{1}{2} = \frac{1}{8} = P(A \cap B)$, hence A and B are independent.
$P(B)P(C) = \frac{1}{2} \cdot \frac{3}{8} = \frac{3}{16} \neq P(B \cap C)$, hence B and C are dependent.

Conditional Independence

Definition: Conditionally Independent Events

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

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

Intuition: Once we know whether C occurred, knowing about A or B doesn't change the probability of the other.

Example: $A =$ "vomiting", $B =$ "fever", $C =$ "food poisoning".

Exercise

Show that the following are equivalent:

$$P(A, B|C) = P(A|C)P(B|C) \tag{4}$$

$$P(A|B, C) = P(A|C) \tag{5}$$

$$P(B|A, C) = P(B|C) \tag{6}$$

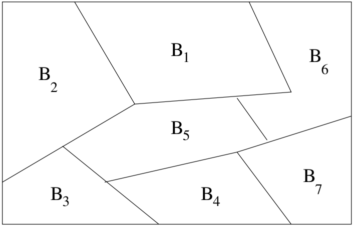
Total Probability

Theorem: Rule of Total Probability

If events $B_1, B_2, \ldots, B_k$ constitute a partition of the sample space S and $P(B_i) \neq 0$ for $i = 1, 2, \ldots, k$, then for any event A in S:

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

$B_1, B_2, \ldots, B_k$ form a *partition* of S if they are pairwise mutually exclusive and if $B_1 \cup B_2 \cup \ldots \cup B_k = S$.



Total Probability

Example

In an experiment on human memory, participants have to memorize a set of words (B_1), numbers (B_2), and pictures (B_3). These occur in the experiment with the probabilities $P(B_1) = 0.5$, $P(B_2) = 0.4$, $P(B_3) = 0.1$.

Then participants have to recall the items (where A is the recall event). The results show that $P(A|B_1) = 0.4$, $P(A|B_2) = 0.2$, $P(A|B_3) = 0.1$. Compute $P(A)$, the probability of recalling an item.

By the theorem of total probability:

$$
\begin{aligned}
P(A) &= \textstyle\sum_{i=1}^{k} P(B_i)P(A|B_i) \\
&= P(B_1)P(A|B_1) + P(B_2)P(A|B_2) + P(B_3)P(A|B_3) \\
&= 0.5 \cdot 0.4 + 0.4 \cdot 0.2 + 0.1 \cdot 0.1 = 0.29
\end{aligned}
$$

Bayes' Theorem

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

(Derived using mult. rule: $P(A,B) = P(A|B)P(B) = P(B|A)P(A)$)

- Denominator can be computed using theorem of total probability: $P(A) = \sum_{i=1}^{k} P(B_i)P(A|B_i)$.
- Denominator is a normalizing constant (ensures $P(B|A)$ sums to one). If we only care about relative sizes of probabilities, we can ignore it: $P(B|A) \propto P(A|B)P(B)$.

Bayes' Theorem

Example

Reconsider the memory example. What is the probability that an item that is correctly recalled (A) is a picture (B_3)?

By Bayes' theorem:

$$P(B_3|A) = \frac{P(B_3)P(A|B_3)}{\sum_{i=1}^{k} P(B_i)P(A|B_i)} = \frac{0.1 \cdot 0.1}{0.29} = 0.0345$$

The process of computing $P(B|A)$ from $P(A|B)$ is sometimes called *Bayesian inversion.*

Manipulating Probabilities

In Anderson's (1990) memory model, A is the event that some item is needed from memory. Assumes A depends on contextual cues Q and usage history H_A, but Q is independent of H_A given A.

Show that $P(A|H_A, Q) \propto P(A|H_A)P(Q|A)$.

Solution:

$$\begin{aligned} P(A|H_A, Q) &= \frac{P(A, H_A, Q)}{P(H_A, Q)} \\ &= \frac{P(Q|A, H_A)P(A|H_A)P(H_A)}{P(Q|H_A)P(H_A)} \\ &= \frac{P(Q|A, H_A)P(A|H_A)}{P(Q|H_A)} \\ &= \frac{P(Q|A)P(A|H_A)}{P(Q|H_A)} \\ &\propto P(Q|A)P(A|H_A) \end{aligned}$$

Random Variables

Definition: Random Variable

If S is a sample space with a probability measure and X is a real-valued function defined over the elements of S, then X is called a random variable.

We will denote random variable by capital letters (e.g., X), and their values by lower-case letters (e.g., x).

Example

Given an experiment in which we roll a pair of dice, let the random variable X be the total number of points rolled with the two dice.

For example $X = 7$ picks out the set $\{(1,6),(2,5),(3,4),(4,3),(5,2),(6,1)\}$.

Random Variables

Example

Assume a balanced coin is flipped three times. Let X be the random variable denoting the total number of heads obtained.

Outcome	Probability	x
HHH	$\frac{1}{8}$	3
HHT	$\frac{1}{8}$	2
HTH	$\frac{1}{8}$	2
THH	$\frac{1}{8}$	2

Outcome	Probability	x
TTH	$\frac{1}{8}$	1
THT	$\frac{1}{8}$	1
HTT	$\frac{1}{8}$	1
TTT	$\frac{1}{8}$	0

Hence, $P(X = 0) = \frac{1}{8}$, $P(X = 1) = P(X = 2) = \frac{3}{8}$, $P(X = 3) = \frac{1}{8}$.

Probability Distributions

Definition: Probability Distribution

If X is a random variable, the function $f(x)$ whose value is $P(X = x)$ for each x within the range of X is called the probability distribution of X.

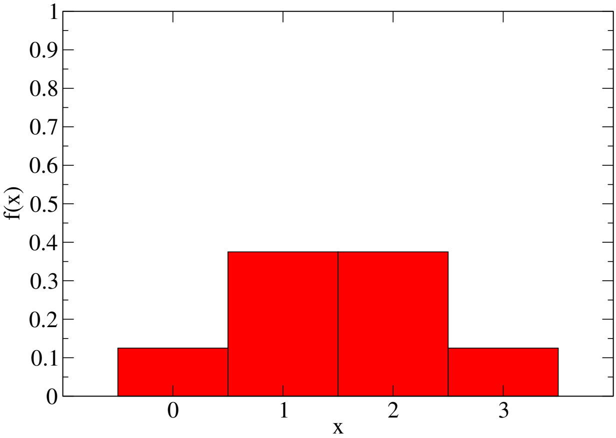
Example

For the probability function defined in the previous example:

x	$f(x)$
0	$\frac{1}{8}$
1	$\frac{3}{8}$
2	$\frac{3}{8}$
3	$\frac{1}{8}$

Probability Distributions

A probability distribution is often represented as a *probability histogram*. For the previous example:



Distributions over Infinite Sets

Example: geometric distribution

Let X be the number of coin flips needed before getting heads, where p_h is the probability of heads on a single flip. What is the distribution of X?

Assume flips are independent, so $P(T^{n-1}H) = P(T)^{n-1}P(H)$. Therefore, $P(X = n) = (1 - p_h)^{n-1}p_h$.

Expectation

The notion of mathematical expectation derives from games of chance. It's the product of the amount a player can win and the probability of wining.

Example

In a raffle, there are 10,000 tickets. The probability of winning is therefore $\frac{1}{10{,}000}$ for each ticket. The prize is worth \$4,800. Hence the expectation per ticket is $\frac{\$4{,}800}{10{,}000} = \$0.48$.

In this example, the expectation can be thought of as the average win per ticket.

Expectation

This intuition can be formalized as the *expected value* (or *mean*) of a random variable:

Definition: Expected Value

If X is a random variable and $f(x)$ is the value of its probability distribution at x, then the expected value of X is:

$$E(X) = \sum_x x \cdot f(x)$$

Expectation

Example

A balanced coin is flipped three times. Let X be the number of heads. Then the probability distribution of X is:

$$f(x) = \begin{cases} \frac{1}{8} & \text{for } x = 0 \\ \frac{3}{8} & \text{for } x = 1 \\ \frac{3}{8} & \text{for } x = 2 \\ \frac{1}{8} & \text{for } x = 3 \end{cases}$$

The expected value of X is:

$$E(X) = \sum_x x \cdot f(x) = 0 \cdot \frac{1}{8} + 1 \cdot \frac{3}{8} + 2 \cdot \frac{3}{8} + 3 \cdot \frac{1}{8} = \frac{3}{2}$$

Expectation

The notion of expectation can be generalized to cases in which a function $g(X)$ is applied to a random variable X.

Theorem: Expected Value of a Function

If X is a random variable and $f(x)$ is the value of its probability distribution at x, then the expected value of $g(X)$ is:

$$E[g(X)] = \sum_x g(x)f(x)$$

Expectation

Example

Let X be the number of points rolled with a balanced die. Find the expected value of X and of $g(X) = 2X^2 + 1$.

The probability distribution for X is $f(x) = \frac{1}{6}$. Therefore:

$$E(X) = \sum_x x \cdot f(x) = \sum_{x=1}^{6} x \cdot \frac{1}{6} = \frac{21}{6}$$

$$E[g(X)] = \sum_x g(x) f(x) = \sum_{x=1}^{6} (2x^2 + 1) \frac{1}{6} = \frac{94}{6}$$

Summary

- Sample space S contains all possible outcomes of an experiment; events A and B are subsets of S.
- rules of probability: $P(\bar{A}) = 1 - P(A)$.
  if $A \subset B$, then $P(A) \leq P(B)$.
  $0 \leq P(B) \leq 1$.
- addition rule: $P(A \cup B) = P(A) + P(B) - P(A, B)$.
- conditional probability: $P(B|A) = \frac{P(A,B)}{P(A)}$.
- independence: $P(B, A) = P(A)P(B)$.
- total probability: $P(A) = \sum_{B_i} P(B_i)P(A|B_i)$.
- Bayes' theorem: $P(B|A) = \frac{P(B)P(A|B)}{P(A)}$.
- a random variable picks out a subset of the sample space.
- a distribution returns a probability for each value of a RV.
- the expected value of a RV is its average value over a distribution.

References

Anderson, John R. 1990. *The Adaptive Character of Thought*. Lawrence Erlbaum Associates, Hillsdale, NJ.

Manning, Christopher D. and Hinrich Schütze. 1999. *Foundations of Statistical Natural Language Processing*. MIT Press, Cambridge, MA.