Conditional Independence

CMPUT 261: Introduction to Artificial Intelligence

P&M §8.2

Assignment #1

- **Assignment #1** is due **TODAY** at 11:59pm
  - Hand in on eClass

Lecture Outline

1. Recap
2. Structure
3. Marginal Independence
4. Conditional Independence

After this lecture, you should be able to:

- Define marginal and conditional independence
- Compute joint probabilities by exploiting marginal and conditional independence
- Compute the minimal number of quantities needed to define a joint distribution given a particular structure / generating process
- Identify marginally or conditionally independent random variables

Recap: Probability

- **Probability** is a numerical measure of **uncertainty**
  - **Not** a measure of **truth**
- **Semantics:**
  - A **possible world** is a **complete assignment** of values to variables
  - Every possible world has a probability
  - Probability of a **proposition** is the sum of probabilities of **possible worlds** in which the statement is **true**

Recap:
Conditional Probability

- When we receive **evidence** in the form of a proposition e, it **rules out** all of the possible worlds in which e is **false**
    - We set those worlds' probability to **0**, and **rescale** remaining probabilities to sum to **1**
- Result is probabilities **conditional on e**: $P(h \mid e)$

Unstructured Joint Distributions

- Probabilities are not fully **arbitrary**
    - **Semantics** tell us probabilities given the joint distribution.
    - Semantics alone do not restrict probabilities **very much**
- In general, we might need to **explicitly** specify the entire **joint distribution**
    - **Question:** How many numbers do we need to assign to fully specify a joint distribution of k binary random variables?
- We call situations where we have to explicitly enumerate the entire joint distribution **unstructured**

Structure

- Unstructured domains are very hard to reason about
- Fortunately, most real problems are generated by some sort of **underlying process**
  - This gives us **structure** that we can exploit to represent and reason about probabilities in a more **compact** way
  - We can **compute** any required joint probabilities based on the process, instead of specifying every possible joint probability explicitly
- Simplest kind of structure is when random variables don't **interact**

Generating Process

Example: I keep flipping a fair coin until it come up Heads

- Let S be a random variable that counts how many times I flipped the coin
- Knowing the **process** that **generates** the probabilities gives us a way to **compute** the probabilities rather than explicitly specifying each one individually

Example 2: Same as example 1, except that the coin comes up heads with probability p

Questions:

1. What is $\Pr(S = 1)$?
2. What is $\Pr(S = k)$ (for integer $k > 0$?)
3. How many numbers would I have to assign to **explicitly** describe this distribution?
4. How many numbers would I need to assign to succinctly describe the distribution from Example 2?

Marginal Independence

When the value of one variable **never** gives you information about the value of the other, we say the two variables are **marginally independent.**

Definition:

Random variables X and Y are **marginally independent** iff

1. $P(X = x \mid Y = y) = P(X = x)$, and
2. $P(Y = y \mid X = x) = P(Y = y)$

for all values of $x \in dom(X)$ and $y \in dom(Y)$.

Marginal Independence Example

- I flip four **fair coins**, and get four results: C_1, C_2, C_3, C_4
- **Question:** What is the probability that C_1 is **heads**?
  - $P(C_1 = heads)$
- Suppose that C_2, C_3, and C_4 are **tails**
- **Question:** *Now* what is the probability that C_1 is **heads**?
  - $P(C_1 = heads \mid C_2 = tails, C_3 = tails, C_4 = tails)$
  - Why?

Properties of Marginal Independence

Proposition:

If X and Y are marginally independent, then

$$P(X = x, Y = y) = P(X = x)P(Y = y)$$

for all values of $x \in dom(X)$ and $y \in dom(Y)$.

Proof:

1. $P(X = x, Y = y) = P(X = x \mid Y = y)P(Y = y)$ Chain rule
2. $P(X = x, Y = y) = P(X = x)P(Y = y)$ Marginal independence

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Exploiting Marginal Independence

C_1	P
H	0.5

C_2	P
H	0.5

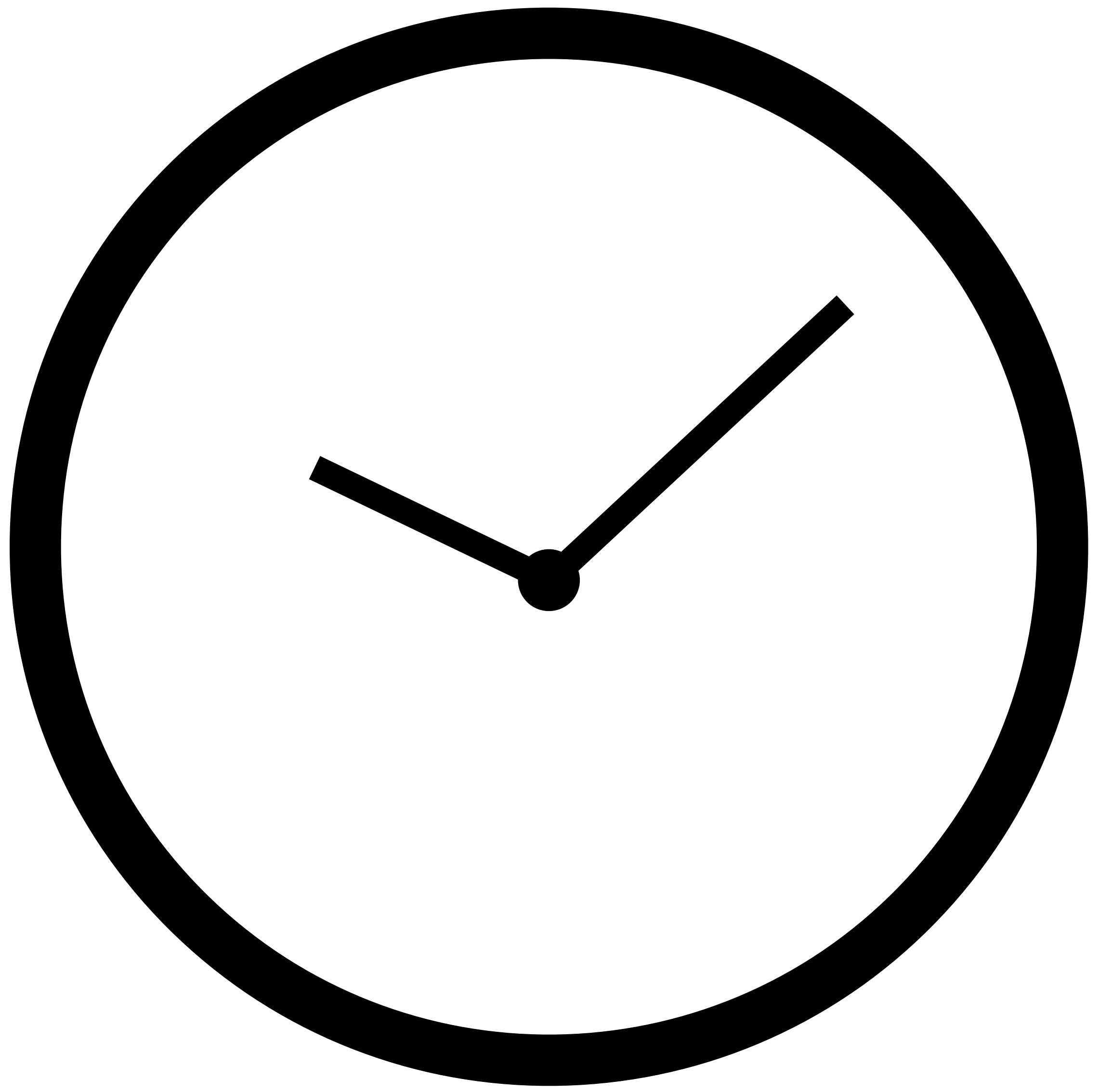
C_3	P
H	0.5

C_4	P
H	0.5

- Instead of storing the **entire joint distribution**, we can store 4 **marginal distributions**, and use them to recover joint probabilities
  - **Question:** How many numbers do we need to assign to fully specify the marginal distribution for a **single** binary variable?
- If **everything** is independent, learning from observations is hopeless (**why?**)
  - But also if **nothing** is independent
  - The **intermediate** case, where many variables are independent, is ideal

C_1	C_2	C_3	C_4	P
H	H	H	H	0.0625
H	H	H	T	0.0625
H	H	T	H	0.0625
H	H	T	T	0.0625
H	T	H	H	0.0625
H	T	H	T	0.0625
H	T	T	H	0.0625
H	T	T	T	0.0625
T	H	H	H	0.0625
T	H	H	T	0.0625
T	H	T	H	0.0625
T	H	T	T	0.0625
T	T	H	H	0.0625
T	T	H	T	0.0625
T	T	T	H	0.0625

Clock Scenario



Example:

- I have a stylish but impractical clock with no number markings
- Two students, Alice and Bob, both look at the clock at the same time, and form opinions about what time it is
  - Their opinion of the time is **directly affected** by the actual time
  - They don't talk to each other, so Alice's opinion of the time is not directly affected by Bob's opinion of the time (& vice versa)
- **Question:** Are A and B **marginally independent**?

$$P(A \mid B) \neq P(A)$$

- **Question:** If we know it is 10:09. Are A and B **independent**?

$$P(A \mid B, T = 10{:}09) = P(A \mid T = 10{:}09)$$

Random variables:

A - Time Alice thinks it is

B - Time Bob thinks it is

T - Actual time

Conditional Independence

When knowing the value of a **third** variable Z **makes** two variables A, B independent, we say that they are **conditionally independent given** Z (or **independent conditional on** Z).

Definition:
Random variables X and Y are **conditionally independent given *Z*** iff

$$P(X = x \mid Y = y, Z = z) = P(X = x \mid Z = z)$$

for all values of $x \in dom(X)$, $y \in dom(Y)$, and $z \in dom(Z)$.
We write this using the notation $X \perp\!\!\!\perp Y \mid Z$.

Clock example: A and B are conditionally independent given T.

Properties of Conditional Independence

Proposition:

If X and Y are conditionally independent given Z, then

$$P(X = x, Y = y \mid Z) = P(X = x \mid Z)P(Y = y \mid Z)$$

for all values of $x \in dom(X)$, $y \in dom(Y)$, and $z \in dom(Z)$.

Proof:

1. $P(X = x, Y = y \mid Z) = \boxed{P(X = x \mid Y = y, Z = z)}P(Y = y \mid Z)$ Chain rule
2. $P(X = x, Y = y \mid Z) = P(X = x \mid Z)P(Y = y \mid Z)$ Conditional independence

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Properties of Conditional Independence

Question: Is conditional independence **commutative**?

- i.e., If $X \perp\!\!\!\perp Y \mid Z$, is it also true that $Y \perp\!\!\!\perp X \mid Z$?

Proof:

$$X \perp\!\!\!\perp Y \mid Z \iff P(X, Y \mid Z) = P(X \mid Z)P(Y \mid Z)$$ previous result

$$\iff P(Y, X \mid Z) = P(Y \mid Z)P(X \mid Z)$$ commutativity of multiplication

$$\iff Y \perp\!\!\!\perp X \mid Z \qquad \blacksquare$$

Exploiting Conditional Independence

If X and Y are marginally independent given Z, then we can again just store **smaller tables** and recover joint distributions by **multiplication.**

- **Question:** How many **tables** do we need to store in order to be able to compute the joint distribution of X, Y, Z when X and Y are independent given Z?
  - i.e., how many table to be able to compute $P(X = x, Y = y, Z = z)$ for every combination of x, y, z?

Preview: In the upcoming lectures, we will see how to efficiently exploit **complex structures** of conditional independence

Simplified Clock Example

A	*T*	P(A | T)
12	1	0.25
1	1	0.50
2	1	0.25
1	2	0.25
2	2	0.50
3	2	0.25
2	3	0.25
3	3	0.50
4	3	0.25
⋮		

B	*T*	P(B | T)
12	1	0.25
1	1	0.5
2	1	0.25
1	2	0.25
2	2	0.5
3	2	0.25
2	3	0.25
3	3	0.5
4	3	0.25
⋮		

T	P(T)
1	0
2	1/10
3	1/10
4	1/10
5	1/10
6	1/10
7	1/10
8	1/10
9	1/10
10	1/10
11	1/10
12	0

$$
\begin{aligned}
&P(A=1, B=2, T=2) \\
&= P(A=1 \mid T=2)P(B=2 \mid T=2)P(T=2) \\
&= 0.25 \times 0.5 \times 0.10 \\
&= 0.0125
\end{aligned}
$$

$$
\begin{aligned}
&P(A=1, B=2, T=1) \\
&= P(A=1 \mid T=1)P(B=2 \mid T=1)P(T=1) \\
&= 0.5 \times 0.25 \times 0.0 \\
&= 0
\end{aligned}
$$

Warnings

- Often, when two variables are **marginally** independent, they are also **conditionally** independent given a third variable
  - E.g., coins C_1, and C_2 are marginally independent, **and also** conditionally independent given C_3: Learning the value of C_3 does not make C_2 any more informative about C_1.
- This is **not always true**
  - Consider another random variable: B is true if both C_1 and C_2 are the **same** value
  - C_1 and C_2 are **marginally independent**: $P(C_1 = heads \mid C_2 = heads) = P(C_1 = heads)$
    - In fact, C_1 and C_2 are also both **marginally independent of *B***: $P(C_1 \mid B = true) = P(C_1)$
  - But if I know the value of B, then knowing the value of C_1 tells me **exactly** what the value of C_2 must be: $P(C_1 = heads \mid B = true, C_2 = heads) \neq P(C_1 = heads \mid B = true)$
    - C_1 and C_2 are **not conditionally independent given *B***

Summary

- **Unstructured** joint distributions are **exponentially** expensive to represent (and operate on)
- **Marginal and conditional independence** are especially important forms of **structure** that a distribution can have
  - Vastly **reduces the cost** of representation and computation
  - **Beware:** The **relationship** between marginal and conditional independence is not fixed
- Joint probabilities of (conditionally or marginally) **independent** random variables can be computed by **multiplication**