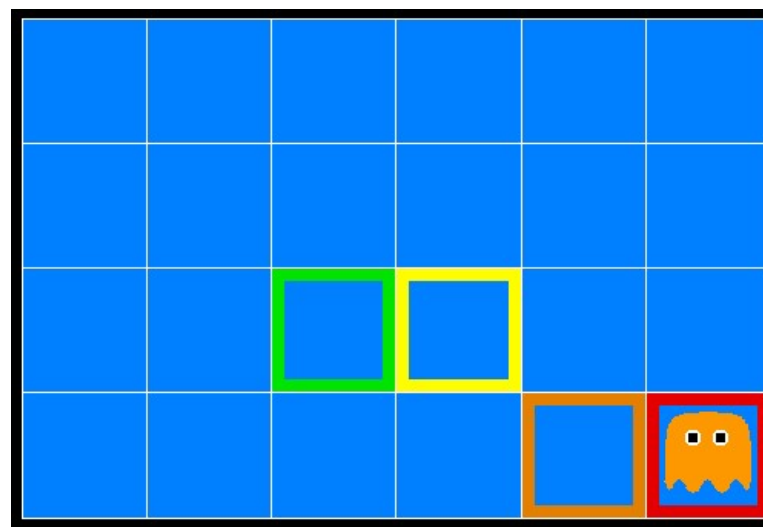


Quantifying Uncertainty

CHAPTER 13 IN THE TEXTBOOK

Inference in Ghostbusters

- A ghost is in the grid somewhere
- Sensor readings tell how close a square is to the ghost
 - On the ghost: red
 - 1 or 2 away: orange
 - 3 or 4 away: yellow
 - 5+ away: green



- Sensors are noisy, but we know $P(\text{Color} \mid \text{Distance})$

$P(\text{red} \mid 3)$	$P(\text{orange} \mid 3)$	$P(\text{yellow} \mid 3)$	$P(\text{green} \mid 3)$
0.05	0.15	0.5	0.3

Video of Demo Ghostbuster – No probability



Uncertainty

- General situation:
 - **Observed variables (evidence):**
Agent knows certain things about the state of the world (e.g., sensor readings or symptoms)
 - **Unobserved variables:**
Agent needs to reason about other aspects (e.g. where an object is or what disease is present)
 - **Model:** Agent knows something about how the known variables relate to the unknown variables
- **Probabilistic reasoning** gives us a framework for managing our beliefs and knowledge

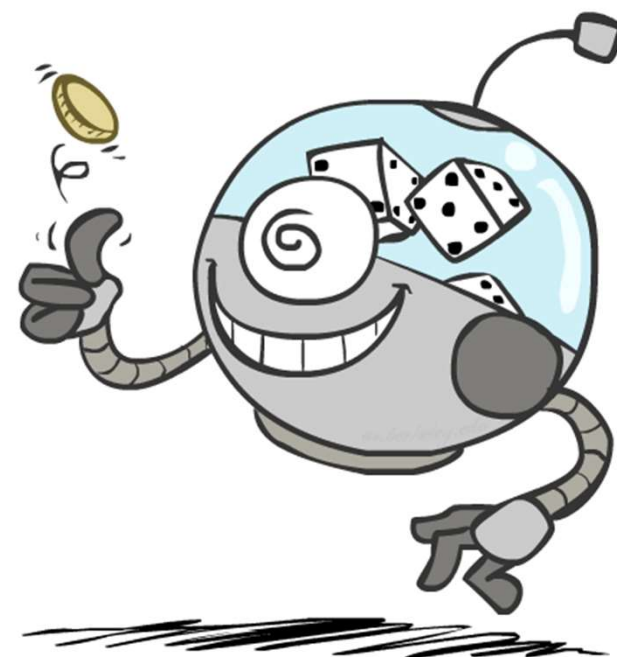
0.11	0.11	0.11
0.11	0.11	0.11
0.11	0.11	0.11

0.17	0.10	0.10
0.09	0.17	0.10
<0.01	0.09	0.17

<0.01	<0.01	0.03
<0.01	0.05	0.05
<0.01	0.05	0.81

Random Variables

- A random variable is some aspect of the world about which we (may) have uncertainty
 - R = Is it raining?
 - T = Is it hot or cold?
 - D = How long will it take to drive to work?
 - L = Where is the ghost?
- We denote random variables with capital letters
- Like variables in a CSP, random variables have domains
 - R in $\{\text{true}, \text{false}\}$ (often write as $\{+r, -r\}$)
 - T in $\{\text{hot}, \text{cold}\}$
 - D in $[0, \infty)$
 - L in possible locations, maybe $\{(0,0), (0,1), \dots\}$



Prior and posterior probability



- Rolling fair dice, we have

$$P(\text{Total} = 11) = P((5,6)) + P((6,5)) = 1/36 + 1/36 = 1/18$$

- Probability such as $P(\text{Total} = 11)$ is called **unconditional** or **prior probability**
- $P(a)$ is the degree of belief accorded to proposition a in the absence of any other information
- Once the agent has obtained some **evidence**, we have to switch to using **conditional (posterior) probabilities**

$$P(\text{doubles} \mid \text{Die}_1 = 5)$$

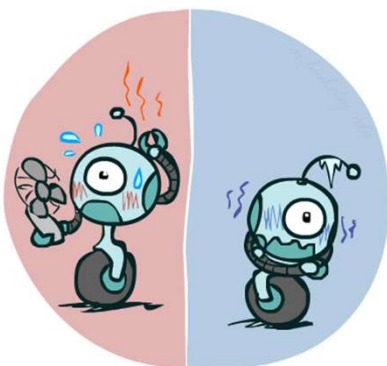
- $P(\text{cavity}) = 0.2$ is interesting when visiting a dentist for regular checkup, but $P(\text{cavity} \mid \text{toothache}) = 0.6$ matters when visiting the dentist because of a toothache

Probability Distributions

- Associate a probability with each value

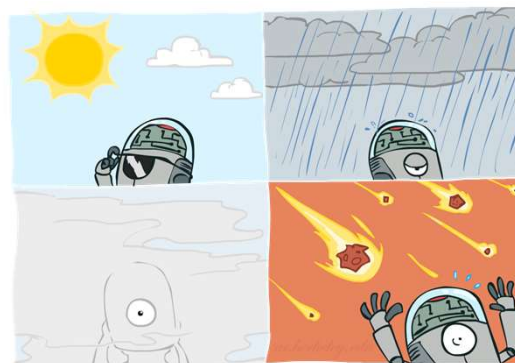
- Temperature:

- Weather:



$P(T)$

T	P
hot	0.5
cold	0.5



$P(W)$

W	P
sun	0.6
rain	0.1
fog	0.3
meteor	0.0

Probability Distributions

- Unobserved random variables have distributions

$P(T)$		$P(W)$	
T	P	W	P
hot	0.5	sun	0.6
cold	0.5	rain	0.1
		fog	0.3
		meteor	0.0

Shorthand notation:

$$\begin{aligned}
 P(\text{hot}) &= P(T = \text{hot}), \\
 P(\text{cold}) &= P(T = \text{cold}), \\
 P(\text{rain}) &= P(W = \text{rain}), \\
 &\dots
 \end{aligned}$$

OK if all domain entries are unique

- A distribution is a TABLE of probabilities of values
- A probability (lower case value) is a single number

$$P(W = \text{rain}) = 0.1$$

Must have: $\forall x \ P(X = x) \geq 0$ and $\sum_x P(X = x) = 1$

Joint Distributions

- A *joint distribution* over a set of random variables: X_1, X_2, \dots, X_n specifies a real number for each assignment (or *outcome*):

$$P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n)$$

$$P(x_1, x_2, \dots, x_n)$$

- Must obey:

$$P(x_1, x_2, \dots, x_n) \geq 0$$

$$\sum_{(x_1, x_2, \dots, x_n)} P(x_1, x_2, \dots, x_n) = 1$$

- Size of distribution if n variables with domain sizes d ?
 - For all but the smallest distributions, impractical to write out!

$$P(T, W)$$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Probabilistic Models

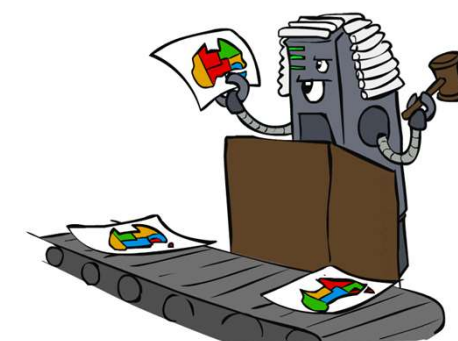
- A probabilistic model is a joint distribution over a set of random variables
- Probabilistic models:
 - (Random) variables with domains
 - Assignments are called *outcomes*
 - Joint distributions: say whether assignments (outcomes) are likely
 - *Normalized*: sum to 1.0
 - Ideally: only certain variables directly interact
- Constraint satisfaction problems:
 - Variables with domains
 - Constraints: state whether assignments are possible
 - Ideally: only certain variables directly interact

Distribution over T, W

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Constraint over T, W

T	W	P
hot	sun	T
hot	rain	F
cold	sun	F
cold	rain	T



Events

- An *event* is a set E of outcomes

$$P(E) = \sum_{(x_1 \dots x_n) \in E} P(x_1 \dots x_n)$$

- From a joint distribution, we can calculate the probability of any event

- Probability that it's hot AND sunny?
- Probability that it's hot?
- Probability that it's hot OR sunny?

- Typically, the events we care about are *partial assignments*, like $P(T = \text{hot})$

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Quiz: Events

- $P(+x, +y)$?
- $P(+x)$?
- $P(-y \text{ OR } +x)$?

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

Marginal Distributions

- Marginal distributions are sub-tables which eliminate variables
- Marginalization (summing out): Combine collapsed rows by adding

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3



$$P(t) = \sum_s P(t, s)$$

$P(T)$

T	P
hot	0.5
cold	0.5

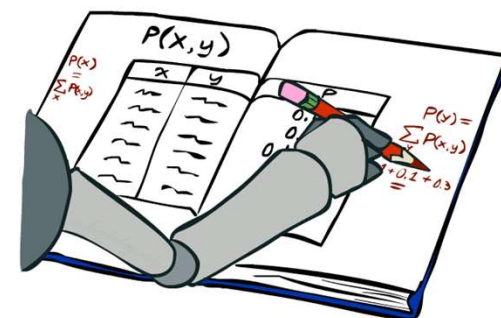


$$P(s) = \sum_t P(t, s)$$

$P(W)$

W	P
sun	0.6
rain	0.4

$$P(X_1 = x_1) = \sum_{x_2} P(X_1 = x_1, X_2 = x_2)$$



Quiz: Marginal Distributions

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1



$$P(x) = \sum_y P(x, y)$$

$P(X)$

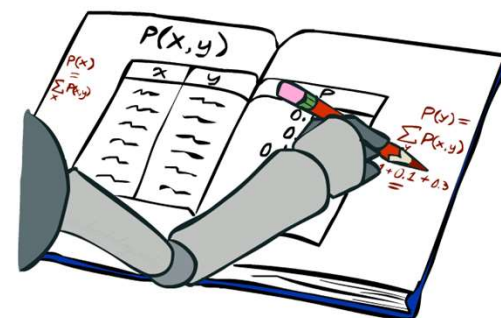
X	P
+x	
-x	



$$P(y) = \sum_x P(x, y)$$

$P(Y)$

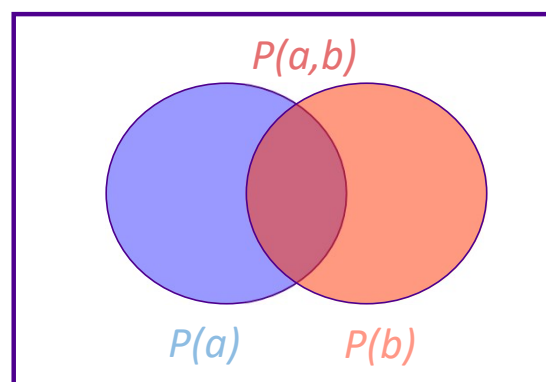
Y	P
+y	
-y	



Conditional Probabilities

- A simple relation between joint and conditional probabilities
 - In fact, this is taken as the *definition* of a conditional probability

$$P(a|b) = \frac{P(a, b)}{P(b)}$$



$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

$$P(W = s|T = c) = \frac{P(W = s, T = c)}{P(T = c)} = \frac{0.2}{0.5} = 0.4$$

$$\begin{aligned}
 &= P(W = s, T = c) + P(W = r, T = c) \\
 &= 0.2 + 0.3 = 0.5
 \end{aligned}$$

Quiz: Conditional Probabilities

• $P(+x \mid +y)$?

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

• $P(-x \mid +y)$?

• $P(-y \mid +x)$?

Conditional Distributions

- Conditional distributions are probability distributions over some variables given fixed values of others

Conditional Distributions

$$P(W|T)$$

$P(W T = \text{hot})$	
W	P
sun	0.8
rain	0.2

$P(W T = \text{cold})$	
W	P
sun	0.4
rain	0.6

Joint Distribution

$$P(T, W)$$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Normalization Trick

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

$$\begin{aligned}
 P(W = s|T = c) &= \frac{P(W = s, T = c)}{P(T = c)} \\
 &= \frac{P(W = s, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.2}{0.2 + 0.3} = 0.4
 \end{aligned}$$



$P(W|T = c)$

W	P
sun	0.4
rain	0.6

$$\begin{aligned}
 P(W = r|T = c) &= \frac{P(W = r, T = c)}{P(T = c)} \\
 &= \frac{P(W = r, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.3}{0.2 + 0.3} = 0.6
 \end{aligned}$$

Normalization Trick

$$\begin{aligned}
 P(W = s|T = c) &= \frac{P(W = s, T = c)}{P(T = c)} \\
 &= \frac{P(W = s, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.2}{0.2 + 0.3} = 0.4
 \end{aligned}$$

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

SELECT the joint probabilities matching the evidence



$P(c, W)$

T	W	P
cold	sun	0.2
cold	rain	0.3

NORMALIZE the selection (make it sum to one)



$P(W|T = c)$

W	P
sun	0.4
rain	0.6

$$\begin{aligned}
 P(W = r|T = c) &= \frac{P(W = r, T = c)}{P(T = c)} \\
 &= \frac{P(W = r, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.3}{0.2 + 0.3} = 0.6
 \end{aligned}$$

Normalization Trick

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

SELECT the joint probabilities matching the evidence



$P(c, W)$

T	W	P
cold	sun	0.2
cold	rain	0.3

NORMALIZE the selection
(make it sum to one)



$P(W|T = c)$

W	P
sun	0.4
rain	0.6

- Why does this work? Sum of selection is $P(\text{evidence})!$ ($P(T = c)$, here)

$$P(x_1|x_2) = \frac{P(x_1, x_2)}{P(x_2)} = \frac{P(x_1, x_2)}{\sum_{x_1} P(x_1, x_2)}$$

Quiz: Normalization Trick

- $P(X | Y=-y)$?

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

SELECT the joint probabilities matching the evidence



NORMALIZE the selection
(make it sum to one)



To Normalize

- (Dictionary) To bring or restore to a normal condition

All entries sum to ONE

- Procedure:

- Step 1: Compute $Z = \text{sum over all entries}$
- Step 2: Divide every entry by Z

- Example 1

W	P
sun	0.2
rain	0.3

Normalize
 $Z = 0.5$

W	P
sun	0.4
rain	0.6

- Example 2

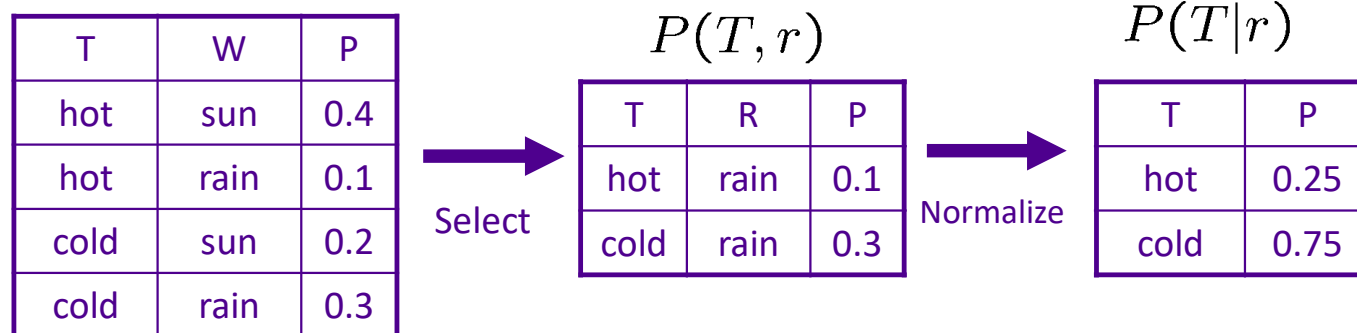
T	W	P
hot	sun	20
hot	rain	5
cold	sun	10
cold	rain	15

Normalize
 $Z = 50$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Normalization Trick

- A trick to get a whole conditional distribution at once:
 - Select the joint probabilities matching the evidence
 - Normalize the selection (make it sum to one)
 - Why does this work? Sum of selection is $P(\text{evidence})$! ($P(r)$, here)
- $P(T, W)$



$$P(x_1|x_2) = \frac{P(x_1, x_2)}{P(x_2)} = \frac{P(x_1, x_2)}{\sum_{x_1} P(x_1, x_2)}$$

Conditional Distributions

- Conditional distributions are probability distributions over some variables given fixed values of others

Conditional Distributions

Joint Distribution

$P(W|T)$

$P(W T = \text{hot})$	
W	P
sun	0.8
rain	0.2

$P(W T = \text{cold})$	
W	P
sun	0.4
rain	0.6

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Probabilistic Inference

- Probabilistic inference: compute a desired probability from other known probabilities (e.g. conditional from joint)
- We generally compute conditional probabilities
 - $P(\text{on time} \mid \text{no reported accidents}) = 0.90$
 - These represent the agent's *beliefs* given the evidence
- Probabilities change with new evidence:
 - $P(\text{on time} \mid \text{no accidents, 5 a.m.}) = 0.95$
 - $P(\text{on time} \mid \text{no accidents, 5 a.m., raining}) = 0.80$
 - Observing new evidence causes *beliefs to be updated*



Inference by Enumeration

- General case:

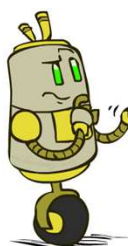
- Evidence variables: $E_1 \dots E_k = e_1 \dots e_k$
 - Query* variable: Q
 - Hidden variables: $H_1 \dots H_r$
- X_1, X_2, \dots, X_n
All variables

- We want:

* Works fine with multiple query variables, too

$$P(Q|e_1 \dots e_k)$$

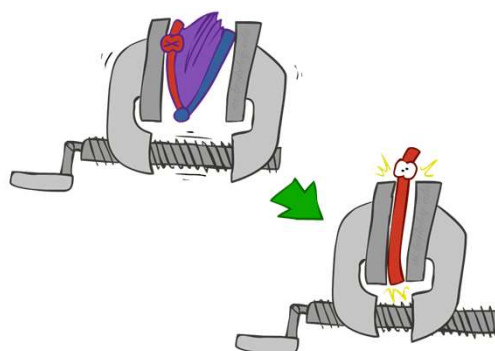
- Step 1: Select the entries consistent with the evidence



x	P(x)
-3	0.05
-1	0.25
0	0.07
1	0.2
5	0.01

2 0.15

- Step 2: Sum out H to get joint of Query and evidence



$$P(Q, e_1 \dots e_k) = \sum_{h_1 \dots h_r} P(Q, \underbrace{h_1 \dots h_r}_{X_1, X_2, \dots, X_n}, e_1 \dots e_k)$$

- Step 3: Normalize

$$\times \frac{1}{Z}$$

$$Z = \sum P(Q, e_1 \dots e_k)$$

$$P(Q|e_1 \dots e_k) = \frac{1}{Z} P(Q, e_1 \dots e_k)$$

Inference by Enumeration

- $P(W)$?
- $P(W \mid \text{winter})$?
- $P(W \mid \text{winter, hot})$?

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

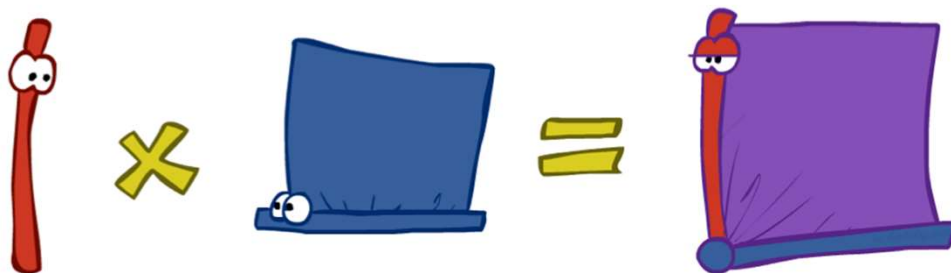
Inference by Enumeration

- Obvious problems:
 - Worst-case time complexity $O(d^n)$
 - Space complexity $O(d^n)$ to store the joint distribution

The Product Rule

- Sometimes have conditional distributions but want the joint

$$P(y)P(x|y) = P(x, y) \quad \longleftrightarrow \quad P(x|y) = \frac{P(x, y)}{P(y)}$$



The Product Rule

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

- Example:

$P(W)$		$P(D W)$			$P(D, W)$		
R	P	D	W	P	D	W	P
sun	0.8	wet	sun	0.1	wet	sun	
rain	0.2	dry	sun	0.9	dry	sun	
		wet	rain	0.7	wet	rain	
		dry	rain	0.3	dry	rain	

The Chain Rule

- More generally, can always write any joint distribution as an incremental product of conditional distributions

$$P(x_1, x_2, x_3) = P(x_1)P(x_2|x_1)P(x_3|x_1, x_2)$$

$$P(x_1, x_2, \dots, x_n) = \prod_i P(x_i|x_1 \dots x_{i-1})$$

- Why is this always true?

Probability Recap

- Conditional probability

$$P(x|y) = \frac{P(x, y)}{P(y)}$$

- Product rule

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

- Chain rule

$$\begin{aligned} P(X_1, X_2, \dots, X_n) &= P(X_1)P(X_2|X_1)P(X_3|X_1, X_2) \dots \\ &= \prod_{i=1}^n P(X_i|X_1, \dots, X_{i-1}) \end{aligned}$$

- X, Y independent if and only if: $\forall x, y : P(x, y) = P(x)P(y)$

- X and Y are conditionally independent given Z if and only if: $X \perp\!\!\!\perp Y | Z$

$$\forall x, y, z : P(x, y|z) = P(x|z)P(y|z)$$