## Basic Probability

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Some images and slides are used from:

1. AIMA
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## (Discrete) Random variables

## What is a random variable?

Suppose that the variable a denotes the outcome of a role of a single six-sided die:

a is a random variable
this is the domain of a

Another example:
Suppose $b$ denotes whether it is raining or clear outside:

$$
b \in\{\text { rain, clear }\}=B
$$

## Probability distribution

A probability distribution associates each with a probability of occurrence, represented by a probability mass function (pmf).
A probability table is one way to encode the distribution:

$$
a \in\{1,2,3,4,5,6\}=A \quad b \in\{\text { rain, clear }\}=B
$$

| a | $\mathrm{P}(\mathrm{a})$ |
| :---: | :---: |
| 1 | $1 / 6$ |
| 2 | $1 / 6$ |
| 3 | $1 / 6$ |
| 4 | $1 / 6$ |
| 5 | $1 / 6$ |
| 6 | $1 / 6$ |


| b | $\mathrm{P}(\mathrm{b})$ |
| :---: | :---: |
| rain | $1 / 4$ |
| clear | $3 / 4$ |

All probability distributions must satisfy the following:

1. $\forall a \in A, a \geq 0$
2. $\sum_{a \in A} a=1$

## Example pmfs



Two pmfs over a state space of $X=\{1,2,3,4\}$

## Writing probabilities

| a | $\mathrm{P}(\mathrm{a})$ |
| :---: | :---: |
| 1 | $1 / 6$ |
| 2 | $1 / 6$ |
| 3 | $1 / 6$ |
| 4 | $1 / 6$ |
| 5 | $1 / 6$ |
| 6 | $1 / 6$ |


| b | $\mathrm{P}(\mathrm{b})$ |
| :---: | :---: |
| rain | $1 / 4$ |
| clear | $3 / 4$ |

For example: $\quad p(a=2)=1 / 6$

$$
p(b=c l e a r)=3 / 4
$$

But, sometimes we will abbreviate this as: $\quad p(2)=1 / 6$

$$
p(\text { clear })=3 / 4
$$

## Types of random variables

Propositional or Boolean random variables

- e.g., Cavity (do I have a cavity?)
- Cavity = true is a proposition, also written cavity

Discrete random variables (finite or infinite)

- e.g., Weather is one of 〈sunny, rain, cloudy, snow)
- Weather = rain is a proposition
- Values must be exhaustive and mutually exclusive

Continuous random variables (bounded or unbounded)

- e.g., Temp < 22.0


## Continuous random variables

Cumulate distribution function (cdf), $F(q)=(X<q)$ with $P(a<X \leq b)=F(b)-F(a)$
Probability density function (pdf), $f(x)=\frac{d}{d x} F(x)$ with $P(a<X \leq b)=\int_{a}^{b} f(x)$

Express distribution as a parameterized function of value:

- e.g., $P(X=x)=U[18,26](x)=$ uniform density between 18 and 26


Here $P$ is a density; integrates to 1.
$P(X=20.5)=0.125$ really means $\lim _{d x \rightarrow 0} P(20.5 \leq X \leq 20.5+d x) / d x=0.125$

## Joint probability distributions

Given random variables: $X_{1}, X_{2}, \ldots, X_{n}$
The joint distribution is a probability
assignment to all combinations: $P\left(X_{1}=x_{1}, X_{2}=x_{2}, \ldots, X_{n}=x_{n}\right)$

$$
\text { or: } \quad P\left(x_{1}, x_{2}, \ldots, x_{n}\right)
$$

Sometimes written as: $P\left(X_{1}=X_{1} \wedge X_{2}=X_{2} \wedge \ldots \wedge X_{n}=X_{n}\right)$
As with single-variate distributions, joint distributions must satisfy:

$$
\begin{aligned}
& \text { 1. } P\left(x_{1}, x_{2}, \ldots, x_{n}\right) \geq 0 \\
& \text { 2. } \sum_{x_{1}, \ldots, x_{n}} P\left(x_{1}, x_{2}, \ldots, x_{n}\right)=1
\end{aligned}
$$

Prior or unconditional probabilities of propositions e.g., $\mathrm{P}($ Cavity $=$ true $)=0.1$ and $\mathrm{P}($ Weather $=$ sunny $)=0.72$ correspond to belief prior to arrival of any (new) evidence

## Joint probability distributions

Joint distributions are typically written in table form:

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.1 |
| Warm | hail | 0.3 |
| Cold | snow | 0.5 |
| Cold | hail | 0.1 |

## Marginalization

Given $P(T, W)$, calculate $P(T)$ or $P(W)$...


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Given $P(T, W)$, calculate $P(T)$ or $P(W)$...


## Conditional Probabilities

Conditional or posterior probabilities

- e.g., $P$ (cavity|toothache) $=0.8$
- i.e., given that toothache is all I know

If we know more, e.g., cavity is also given, then we have $P$ (cavity|toothache, cavity) $=1$

- Note: the less specific belief remains valid after more evidence arrives, but is not always useful

New evidence may be irrelevant, allowing simplification

- e.g., $P$ (cavity|toothache, redsoxwin) $=P$ (cavity|toothache) $=0.8$

This kind of inference, sanctioned by domain knowledge, is crucial

## Conditional Probabilities

Conditional or posterior probabilities

- e.g., $P$ (cavity|toothache) $=0.8$
- i.e., given that toothache is all I know

If we know more, e.g., cavity is also give

- Note: the less specific belief rema always useful

Often written as a conditional probability table:

| cavity | P(cavity\|toothache) |
| :---: | :---: |
| true | 0.8 |
| false | 0.2 |

New evidence may be irrelevant, allowing sitm

- e.g., $P$ (cavity|toothache, redsoxwin) $=P$ (cavity|toothache) $=0.8$

This kind of inference, sanctioned by domain knowledge, is crucial

## Conditional Probabilities

Conditional probability: $P(A \mid B)=\frac{P(A, B)}{P(B)} \quad$ (if $\mathrm{P}(\mathrm{B})>0$ )
Example: Medical diagnosis
Product rule: $\mathrm{P}(\mathrm{A}, \mathrm{B})=\mathrm{P}(\mathrm{A} \wedge \mathrm{B})=\mathrm{P}(\mathrm{A} \mid \mathrm{B}) \mathrm{P}(\mathrm{B})$
Marginalization with conditional probabilities:

$$
P(A)=\sum_{b \in B} P(A \mid B=b) P(B=b)
$$

This formula/rule is called the law of of total probability
Chain rule is derived by successive application of product rule:
$P\left(X_{1}, \ldots, X_{n}\right)=P\left(X_{1}, \ldots, X_{n-1}\right) P\left(X_{n} \mid X_{1}, \ldots, X_{n-1}\right)$
$=P\left(X_{1}, \ldots, X_{n-2}\right) P\left(X_{n-1} \mid X_{1}, \ldots, X_{n-2}\right) P\left(X_{n} \mid X_{1}, \ldots, X_{n-1}\right)=\ldots$
$=\Pi_{i=1}^{n} P\left(X_{i} \mid X_{1}, \ldots, X_{i-1}\right)$

## Conditional Probabilities

$\mathrm{P}($ snow|warm $)=$ Probability that it will snow given that it is warm

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
| Warm | hail | 0.2 |
| Cold | snow | 0.2 |
| Cold | hail | 0.3 |

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t}) \ldots$

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
| Warm | hail | 0.2 |
| Cold | snow | 0.2 |
| Cold | hail | 0.3 |

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

|  |  |  | $\checkmark$ | W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | snow | ? |
| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |  | hail | ? |
| Warm | snow | 0.3 |  | hail | ? |
| Warm | hail | 0.2 | $P(W, t)$ |  |  |
| Cold | snow | 0.2 | $P(W \mid t)=\frac{P}{P(t)}$ |  |  |
| Cold | hail | 0.3 | $P(t)$ |  |  |

Where did this formula come from?

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
|  | $P(W \mid t)=\frac{P(W, t)}{P(t)}$ | $?$ |
|  |  | 0.2 |
|  |  | 0.2 |
|  |  | 0.3 |

$$
P(\text { snow } \mid \text { warm })=\frac{P(\text { warm, snow })}{P(\text { warm })}=\frac{P(\text { warm }, \text { snow })}{P(\text { warm }, \text { hail })+P(\text { warm }, \text { snow })}
$$

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
|  |  |  |
| Warm | snow | 0.3 |
| Warm | hail | 0.2 |
| Cold | snow | 0.2 |
| Cold | hail | 0.3 |$\quad \bullet$| W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: | :---: |
| snow | 0.6 |
| hail | $?$ |

$$
\begin{aligned}
P(\text { snow } \mid \text { warm })=\frac{P(\text { warm }, \text { snow })}{P(\text { warm })} & =\frac{P(\text { warm }, \text { snow })}{P(\text { warm }, \text { hail })+P(\text { warm }, \text { snow })} \\
& =\frac{0.3}{0.2+0.3}
\end{aligned}
$$

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ | - | snow | --- $-0_{0}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Warm | snow | 0.3 | $P(W \mid t)=\frac{P(W, t)}{P(t)}$ | hail | ? |
| Warm | hail | 0.2 |  |  | - |
| Cold | snow | 0.2 |  | How do we solve for this? |  |
| Cold | hail | 0.3 |  |  |  |

$$
\begin{aligned}
P(\text { snow } \mid \text { warm })=\frac{P(\text { warm }, \text { snow })}{P(w a r m)} & =\frac{P(\text { warm }, \text { snow })}{P(\text { warm }, \text { hail })+P(\text { warm }, \text { snow })} \\
& =\frac{0.3}{0.2+0.3}
\end{aligned}
$$

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
|  |  |  |
| Warm | snow | 0.3 |
| Warm | hail | 0.2 |
| Cold | snow | 0.2 |
| Cold | hail | 0.3 |$\quad \bullet$| W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: | :---: |
| snow | 0.6 |
| hail | 0.4 |

$$
\begin{aligned}
P(\text { snow } \mid \text { warm })=\frac{P(\text { warm }, \text { snow })}{P(\text { warm })} & =\frac{P(\text { warm }, \text { snow })}{P(\text { warm }, \text { hail })+P(\text { warm }, \text { snow })} \\
& =\frac{0.3}{0.2+0.3}
\end{aligned}
$$

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

|  |  |  | $P(W \mid t)=\frac{P(W, t)}{P(t)}$ | W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | snow | 0.6 |
| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |  | hail | 0.4 |
| Warm | snow | 0.3 |  |  |  |
| Warm | hail | 0.2 |  |  |  |
| Cold | snow | 0.2 |  |  |  |
| Cold | hail | 0.3 |  |  |  |
|  |  |  | - | W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ cold $)$ |
|  |  |  |  | snow | ? |
|  |  |  |  | hail | ? |

## Conditional distribution

Given $\mathrm{P}(\mathrm{T}, \mathrm{W})$, calculate $\mathrm{P}(\mathrm{T} \mid \mathrm{w})$ or $\mathrm{P}(\mathrm{W} \mid \mathrm{t})$...

|  |  |  | $P(W \mid t)=\frac{P(W, t)}{P(t)}$ | W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | snow | 0.6 |
| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |  | hail | 0.4 |
| Warm | snow | 0.3 |  |  |  |
| Warm | hail | 0.2 |  |  |  |
| Cold | snow | 0.2 |  |  |  |
| Cold | hail | 0.3 |  |  |  |
|  |  |  | - | W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ cold $)$ |
|  |  |  |  | snow | 0.4 |
|  |  |  |  | hail | 0.6 |

## Normalization

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
| Warm | hail | 0.2 |
| Cold | snow | 0.2 |
| Cold | hail | 0.3 |


$P(W \mid t)=\underset{\sim}{P(W, t)} \quad$| W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: |
| snow | 0.6 |
| hail | 0.4 |

Can we avoid explicitly computing this denominator?

$$
P(\text { snow } \mid \text { warm })=\frac{1 \text { P(warm, snow })}{P(\text { warm, hail })+\text { P(warm, snow })}
$$

Any ideas?

## Normalization

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
| Warm | hail | 0.2 |
| Cold | snow | 0.2 |
| Cold | hail | 0.3 |


$P(W \mid t)=\frac{P(W, t)}{P(t)} \bullet$| W | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: |
| snow | 0.6 |
| hail | 0.4 |

Two steps:

1. Copy entries

| W | $\mathrm{P}(\mathrm{W}, \mathrm{T}=$ warn $)$ |
| :---: | :---: |
| snow | 0.3 |
| hail | 0.2 |


|  |
| :--- |
| 2. Scale them up so <br> that entries sum to 1 |$\qquad$| Snow | $\mathrm{P}(\mathrm{W} \mid \mathrm{T}=$ warm $)$ |
| :---: | :---: |
| hail | 0.6 |

## Normalization

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Warm | snow | 0.3 |  |  |  |
| Warm | hail | 0.4 |  |  |  |
| Cold | snow | 0.2 |  |  |  |
| Cold | hail | 0.1 | Two steps: |  |  |
|  | T | $\mathrm{P}(\mathrm{T}, \mathrm{W}=$ hail $)$ |  | T | $P(T \mid W=$ hail $)$ |
|  | warm | ? |  | warm | ? |
|  | cold | ? | that entries sum to 1 | cold | ? |

## Normalization

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Warm | snow | 0.3 |  |  |  |
| Warm | hail | 0.4 |  |  |  |
| Cold | snow | 0.2 |  |  |  |
| Cold | hail | 0.1 | Two steps: |  |  |
|  | T | $\mathrm{P}(\mathrm{T}, \mathrm{W}=$ hail $)$ |  | T | $P(T \mid W=$ hail $)$ |
|  | warm | 0.4 |  | warm | ? |
|  | cold | 0.1 | that entries sum to 1 | cold | ? |

## Normalization

| T | W | $\mathrm{P}(\mathrm{T}, \mathrm{W})$ |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Warm | snow | 0.3 |  |  |  |
| Warm | hail | 0.4 |  |  |  |
| Cold | snow | 0.2 |  |  |  |
| Cold | hail | 0.1 | Two steps: |  |  |
|  | T | $\mathrm{P}(\mathrm{T}, \mathrm{W}=$ hail $)$ |  | T | $\mathrm{P}(\mathrm{T} \mid \mathrm{W}=$ hail $)$ |
|  | warm | 0.4 | $\rightarrow$ | warm | 0.8 |
|  | cold | 0.1 | that entries sum to 1 | cold | 0.2 |

$$
P(W \mid t)=\frac{P(W, t)}{P(t)}
$$

The only purpose of this denominator is to make the distribution sum to one.

- we achieve the same thing by scaling.


## Bayes Rule

$$
P(a \mid b)=\frac{P(b \mid a) P(a)}{P(b)}
$$



Thomas Bayes (1701-1761):

- English statistician, philosopher and Presbyterian minister
- formulated a specific case of the formula above
- his work later published/generalized by Richard Price


## Bayes Rule

$$
P(a \mid b)=\frac{P(b \mid a) P(a)}{P(b)}
$$

It's easy to derive from the product rule:

$$
\begin{gathered}
P(a, b)=P(b \mid a) P(a)=\underbrace{P(a \mid b) P(b)}_{\Uparrow} \\
\Uparrow
\end{gathered}
$$

Solve for this

## Using Bayes Rule

$$
P(a \mid b)=\frac{P(b \mid a) P(a)}{P(b)}
$$

$$
P(\text { cause } \mid e f f e c t)=\frac{P(e f f e c t \mid \text { cause }) P(\text { cause })}{P(e f f e c t)}
$$

## Using Bayes Rule

$$
\begin{aligned}
& P(a \mid b)=\frac{P(b \mid a) P(a)}{P(b)} \\
& P(\text { cause } \mid \text { effect })=\frac{P(e f f e c t \mid \text { cause }) P(c a u s e)}{P(e f f e c t)}
\end{aligned}
$$

It's often easier to estimate this

## Bayes Rule Example

$$
P(\text { cause } \mid \text { effect })=\frac{P(\text { effect } \mid \text { cause }) P(\text { cause })}{P(e f f e c t)}
$$

Suppose you have a stiff neck...
Suppose there is a $70 \%$ chance of meningitis if you have a stiff neck:

$$
\text { stiff neck } \quad \text { meningitis }
$$

What are the chances that you have meningitis?

## Bayes Rule Example

$$
P(\text { cause } \mid e f f e c t)=\frac{P(\text { effect } \mid \text { cause }) P(\text { cause })}{P(\text { effect })}
$$

Suppose you have a stiff neck...
Suppose there is a $70 \%$ chance of meningitis if you have a stiff neck:

$$
\text { stiff neck } \quad P(s \mid m)=0.7
$$

What are the chances that you have meningitis?

We need a little more information...

## Bayes Rule Example

$$
\begin{aligned}
& P(\text { cause } \mid e f f e c t)=\frac{P(e f f e c t \mid c a u s e) P(c a u s e)}{P(e f f e c t)} \\
& P(s \mid m)=0.7 \\
& P(s)=0.01 \\
& P(m)=\frac{1}{50000} \quad \text { Prior probability of stiff neck } \\
& P(m \mid s)=\frac{P(s \mid m) P(m)}{P(s)}=\frac{0.7 \times \frac{1}{50000}}{0.01}=0.0014
\end{aligned}
$$

## Bayes Rule Example

Given:

| W | $\mathrm{P}(\mathrm{W})$ |
| :---: | :---: |
| snow | 0.8 |
| hail | 0.2 |


| T | W | $\mathrm{P}(\mathrm{T} \mid \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
| Warm | hail | 0.4 |
| Cold | snow | 0.7 |
| Cold | hail | 0.6 |

Calculate $\mathrm{P}(\mathrm{W} \mid$ warm $)$ :
$P(W \mid w a r m)=\frac{P(w a r m \mid W) P(W)}{P(w a r m)}$

## Bayes Rule Example

## Given:

| $W$ | $\mathrm{P}(\mathrm{W})$ |
| :---: | :---: |
| snow | 0.8 |
| hail | 0.2 |


| T | W | $\mathrm{P}(\mathrm{T} \mid \mathrm{W})$ |
| :---: | :---: | :---: |
| Warm | snow | 0.3 |
| Warm | hail | 0.4 |
| Cold | snow | 0.7 |
| Cold | hail | 0.6 |

Calculate $\mathrm{P}(\mathrm{W} \mid$ warm $)$ :

$$
\begin{aligned}
P(W \mid \text { warm }) & =\frac{P(w a r m \mid W) P(W)}{P(w a r m)} \\
P(\text { hail } \mid \text { warm }) & =\frac{0.4 \times 0.2}{P(w a r m)}=\frac{0.08}{P(\text { warm })}=0.25 \\
P(\text { snow } \mid \text { warm }) & =\frac{0.3 \times 0.8}{P(\text { warm })}=\frac{0.24}{P(\text { warm })}
\end{aligned}
$$

## Independence

If two variables are independent, then: $\quad P(a, b)=P(a) P(b)$

$$
\begin{gathered}
\stackrel{\text { or }}{P(a)}=P(a \mid b) \\
\text { or } \\
P(b)=P(b \mid a)
\end{gathered}
$$

## Independence

If two variables are independent, then: $\quad P(a, b)=P(a) P(b)$

$$
\begin{gathered}
\text { or } \\
P(a)^{\text {or }}=P(a \mid b) \\
P(b)=P(b \mid a)
\end{gathered}
$$

independent


## Independence

If two variables are independent, then: $\quad P(a, b)=P(a) P(b)$

$$
\begin{gathered}
\text { or } \\
P(a)^{\text {or }}=P(a \mid b) \\
P(b)=P(b \mid a)
\end{gathered}
$$

Not independent


## Conditional Independence

If two variables $a, b$ are conditionally independent given $c$, then:

$$
P(a, b \mid c)=P(a \mid c) P(b \mid c)
$$



Without conditioning on $\mathrm{c}, \mathrm{a}$ and b are not independent!!!

