

# Harvard · CS50-AI | Introduction to Artificial Intelligence with Python (2020)

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自然语言处理

RNN

tensorflow  
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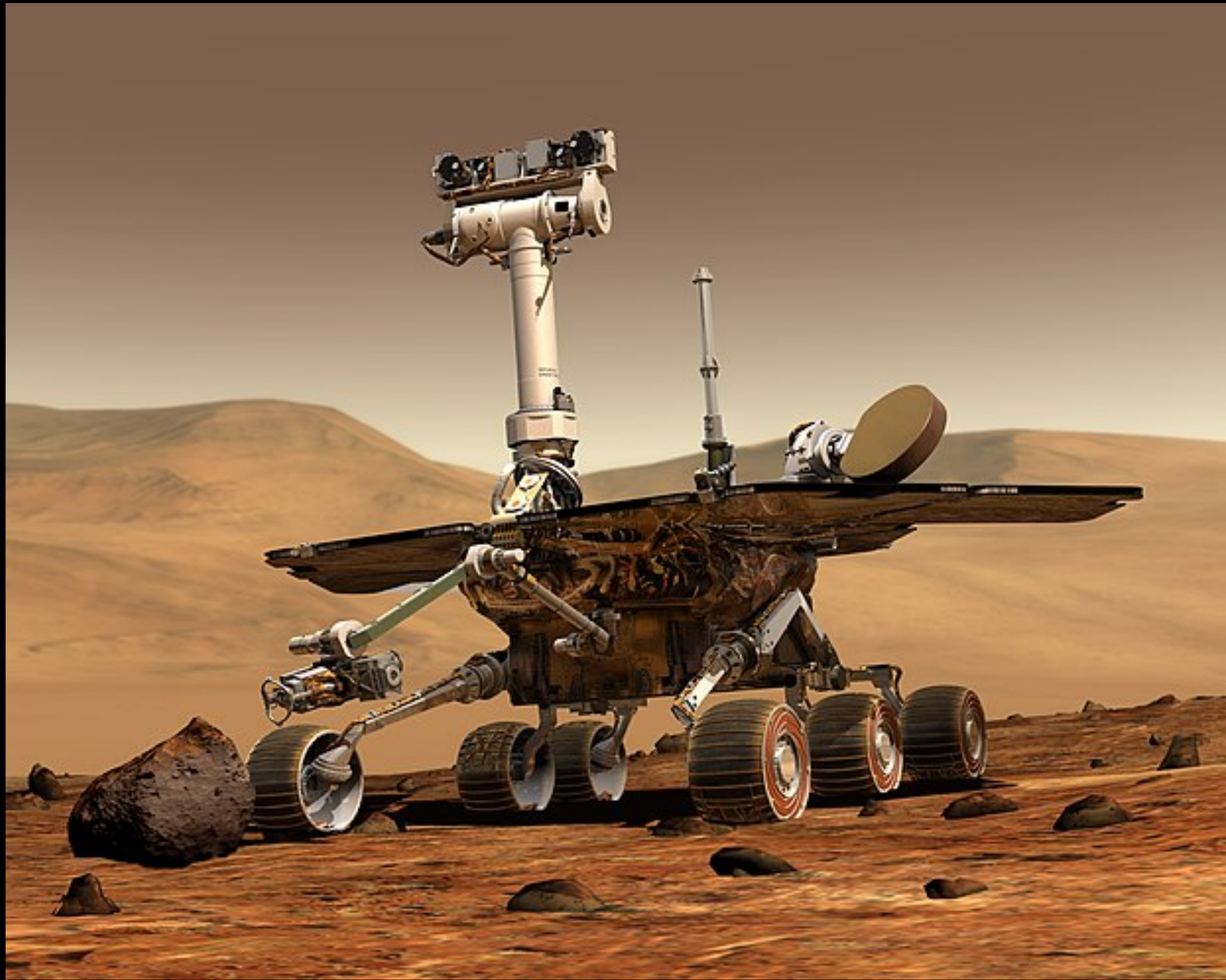
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Introduction to  
**Artificial Intelligence**  
with Python

# Uncertainty





## NEXT 36 HOURS

[HOURLY →](#) | [10 DAYS →](#)

TONIGHT  
CLEAR



LOW  
**20°**

0%

THU



HIGH  
**36°**

0%

THU NIGHT



LOW  
**25°**

0%

FRI



HIGH  
**46°**

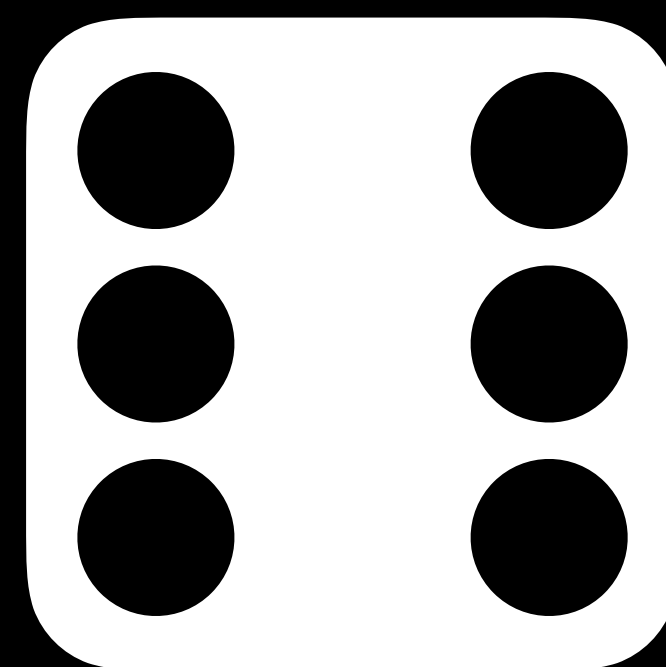
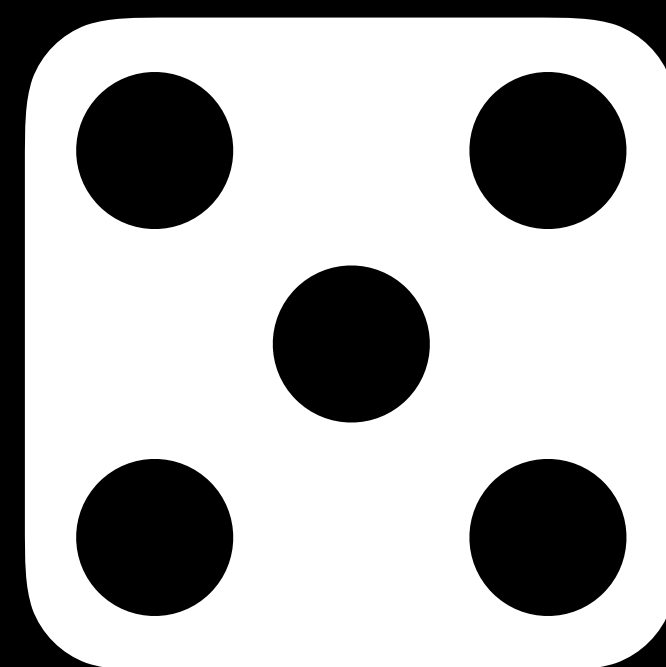
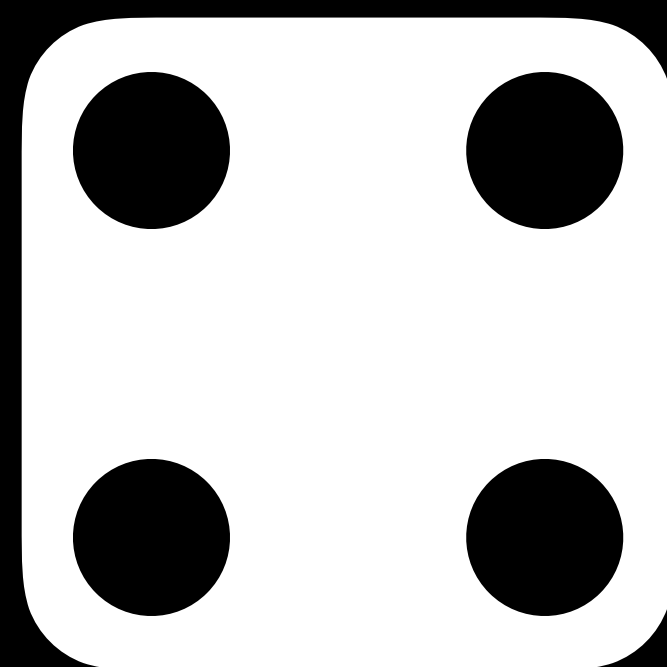
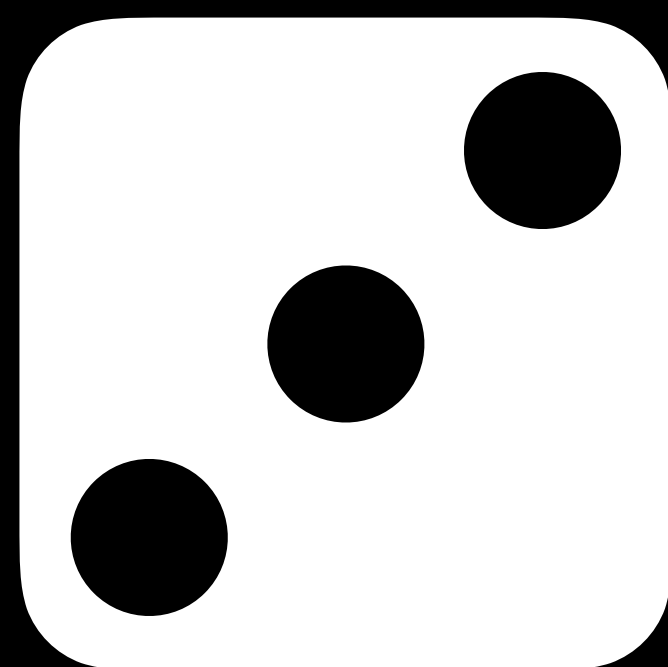
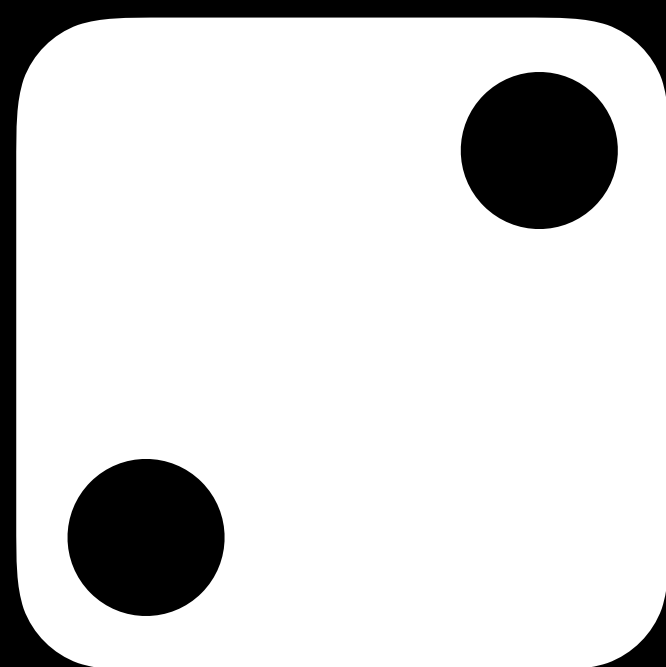
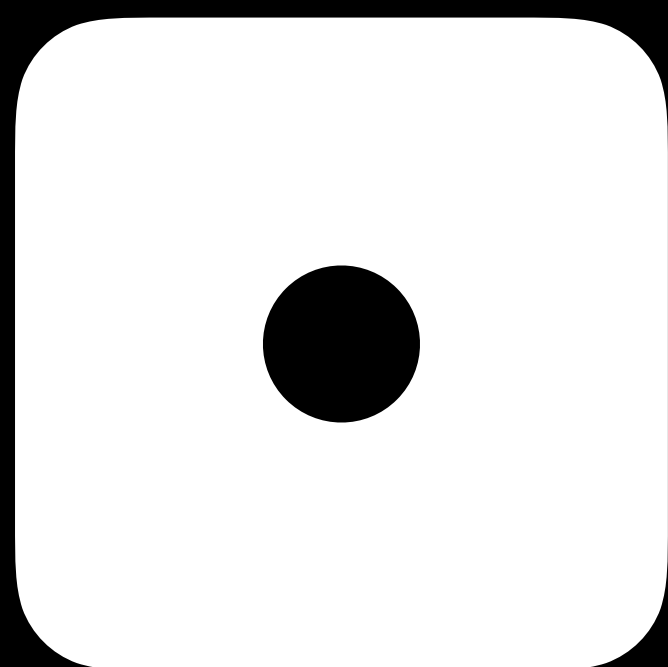
0%

FRI NIGHT



LOW  
**32°**

20%



# Probability

# Possible Worlds

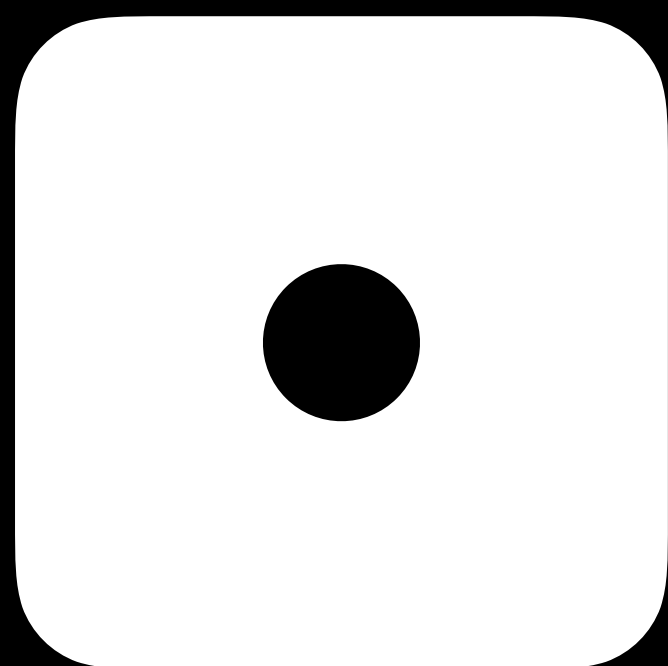
*$\omega$*



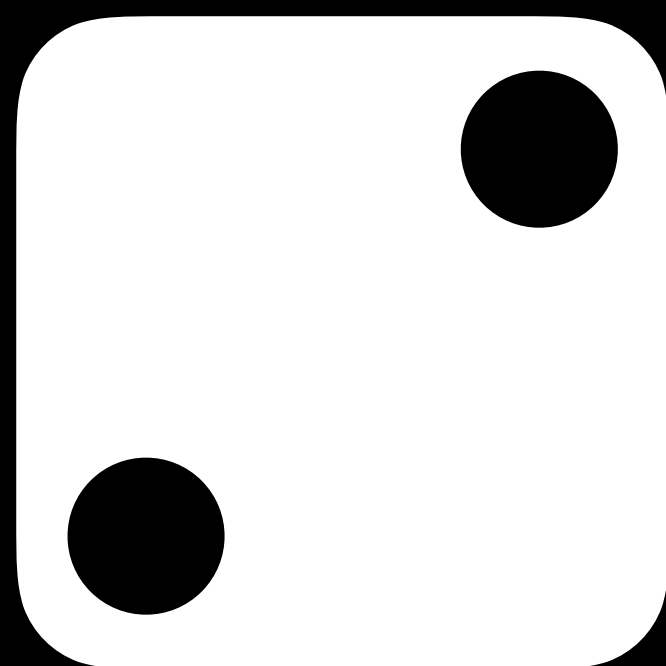
$$P(\omega)$$

$$0 \leq P(\omega) \leq 1$$

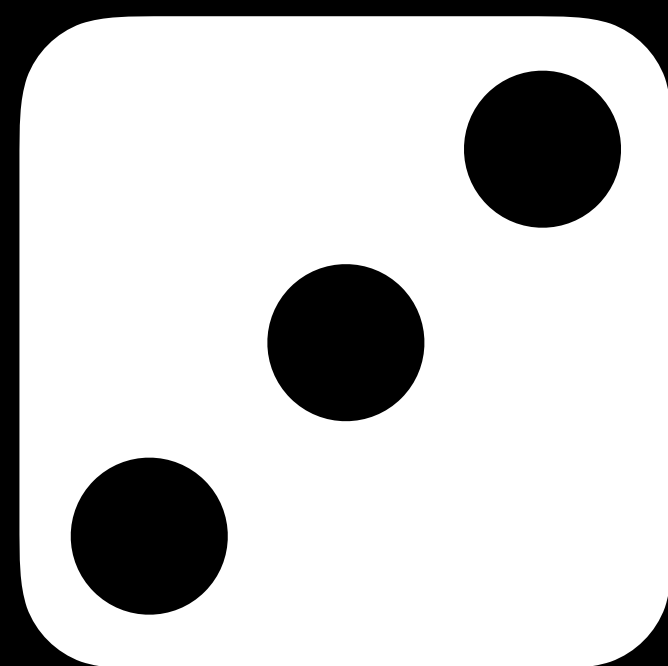
$$\sum_{\omega \in \Omega} P(\omega) = 1$$



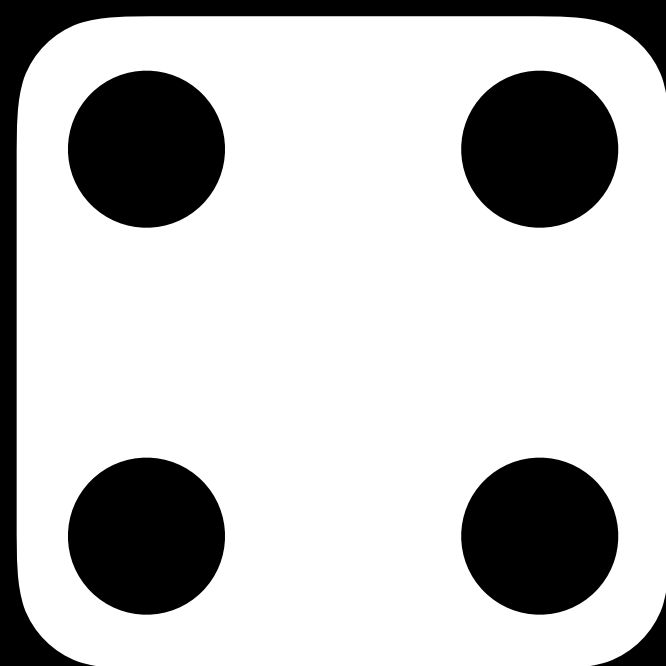
$$\frac{1}{6}$$



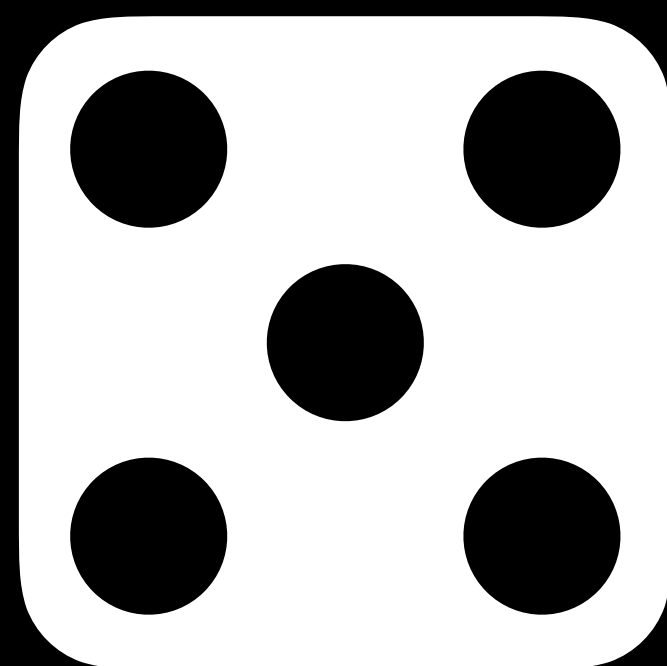
$$\frac{1}{6}$$



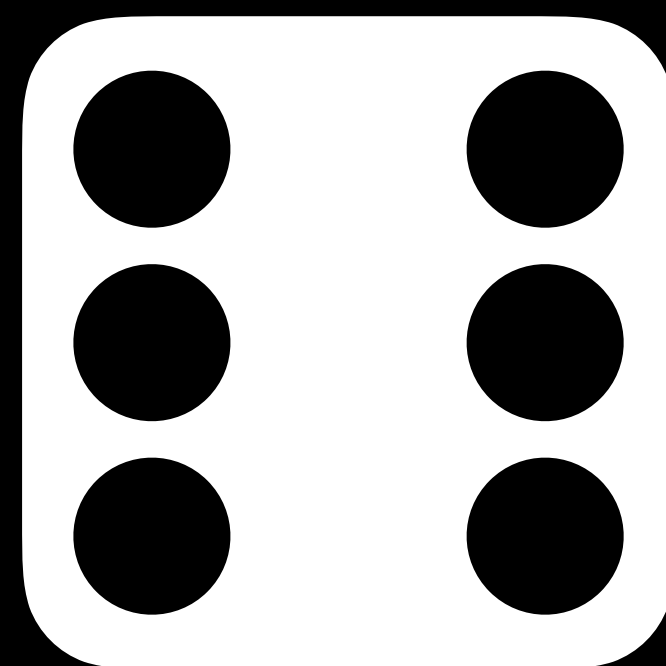
$$\frac{1}{6}$$



$$\frac{1}{6}$$



$$\frac{1}{6}$$

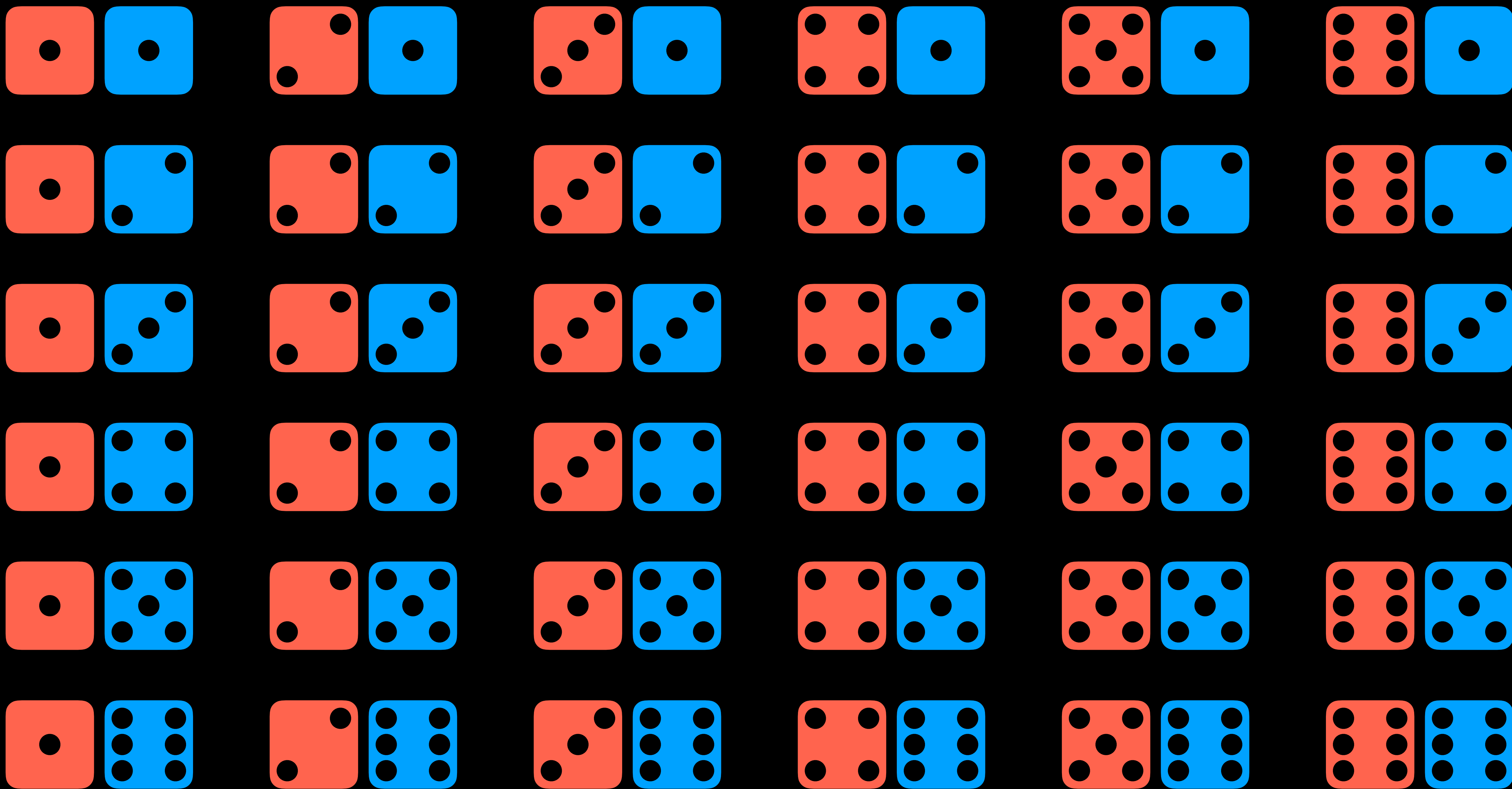


$$\frac{1}{6}$$

$$P(\text{🎲}) = \frac{1}{6}$$







2	3	4	5	6	7
3	4	5	6	7	8
4	5	6	7	8	9
5	6	7	8	9	10
6	7	8	9	10	11
7	8	9	10	11	12

2	3	4	5	6	7
3	4	5	6	7	8
4	5	6	7	8	9
5	6	7	8	9	10
6	7	8	9	10	11
7	8	9	10	11	12

2	3	4	5	6	7
3	4	5	6	7	8
4	5	6	7	8	9
5	6	7	8	9	10
6	7	8	9	10	11
7	8	9	10	11	12

$$P(\textit{sum to } 12) = \frac{1}{36}$$

$$P(\textit{sum to } 7) = \frac{6}{36} = \frac{1}{6}$$

# unconditional probability

degree of belief in a proposition  
in the absence of any other evidence



# conditional probability

degree of belief in a proposition  
given some evidence that has already  
been revealed

**conditional probability**

$$P(a \mid b)$$

$P(\textit{rain today} \mid \textit{rain yesterday})$

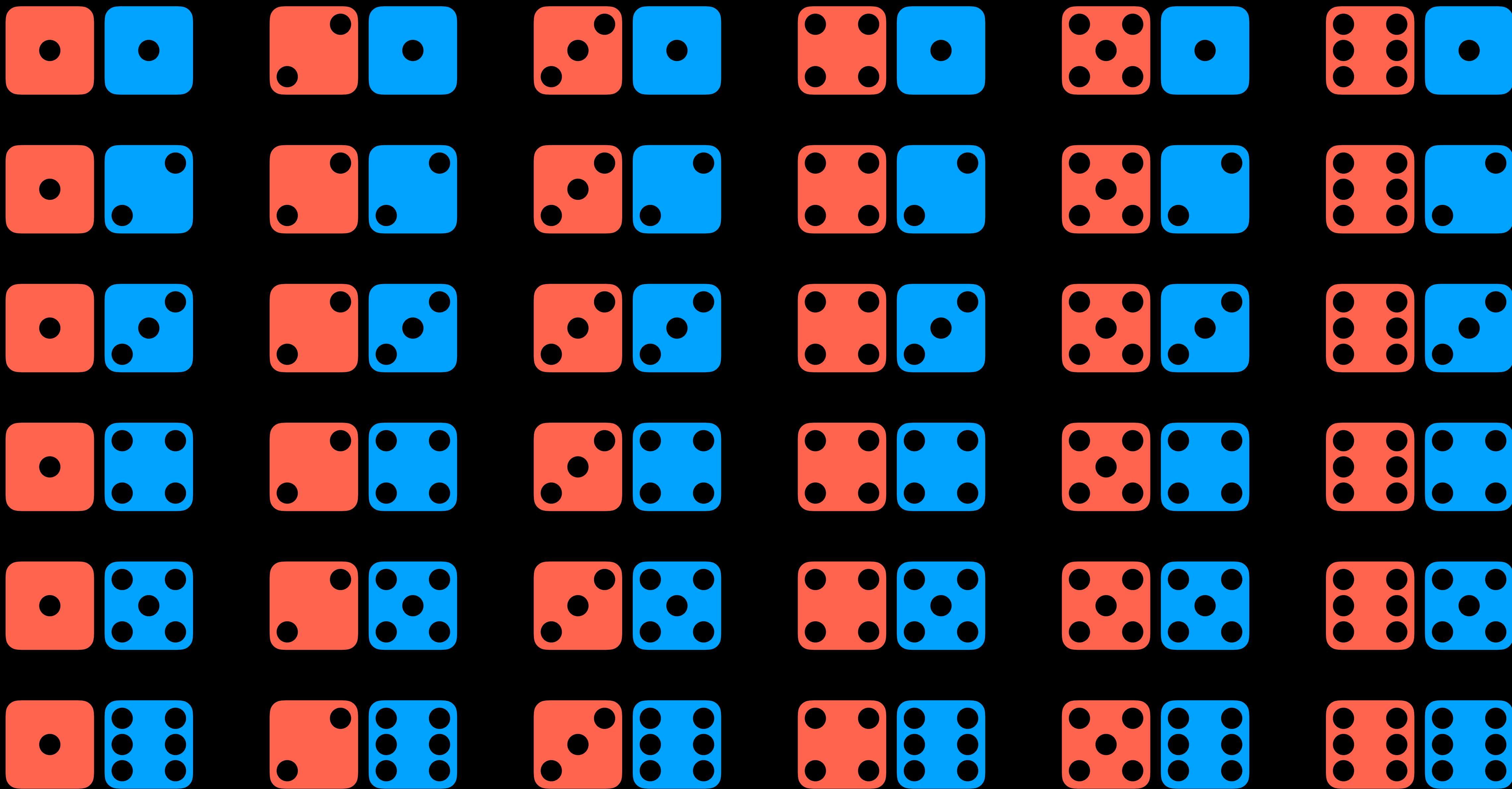
*$P(\text{route change} \mid \text{traffic conditions})$*

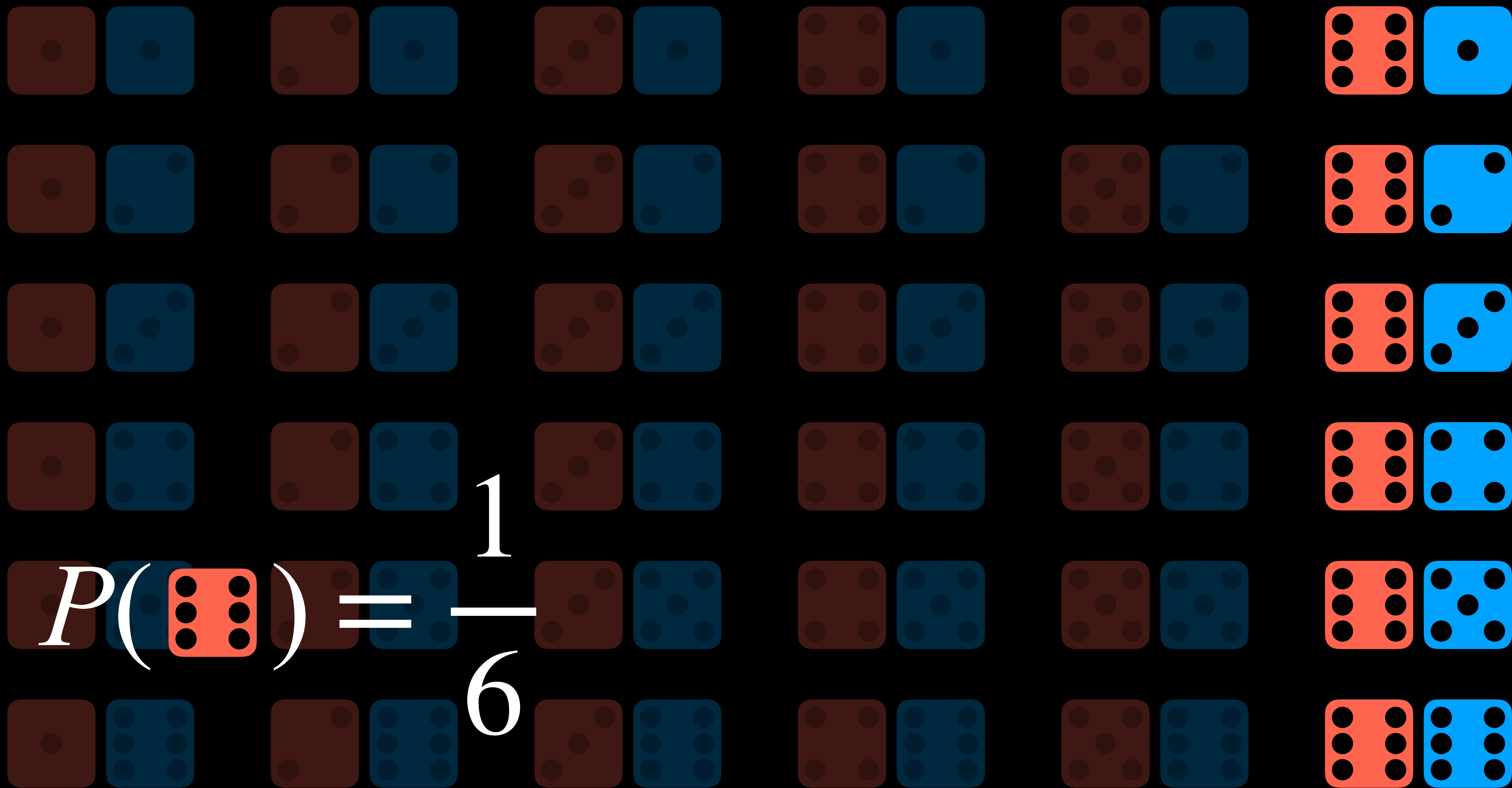
*P(disease | test results)*

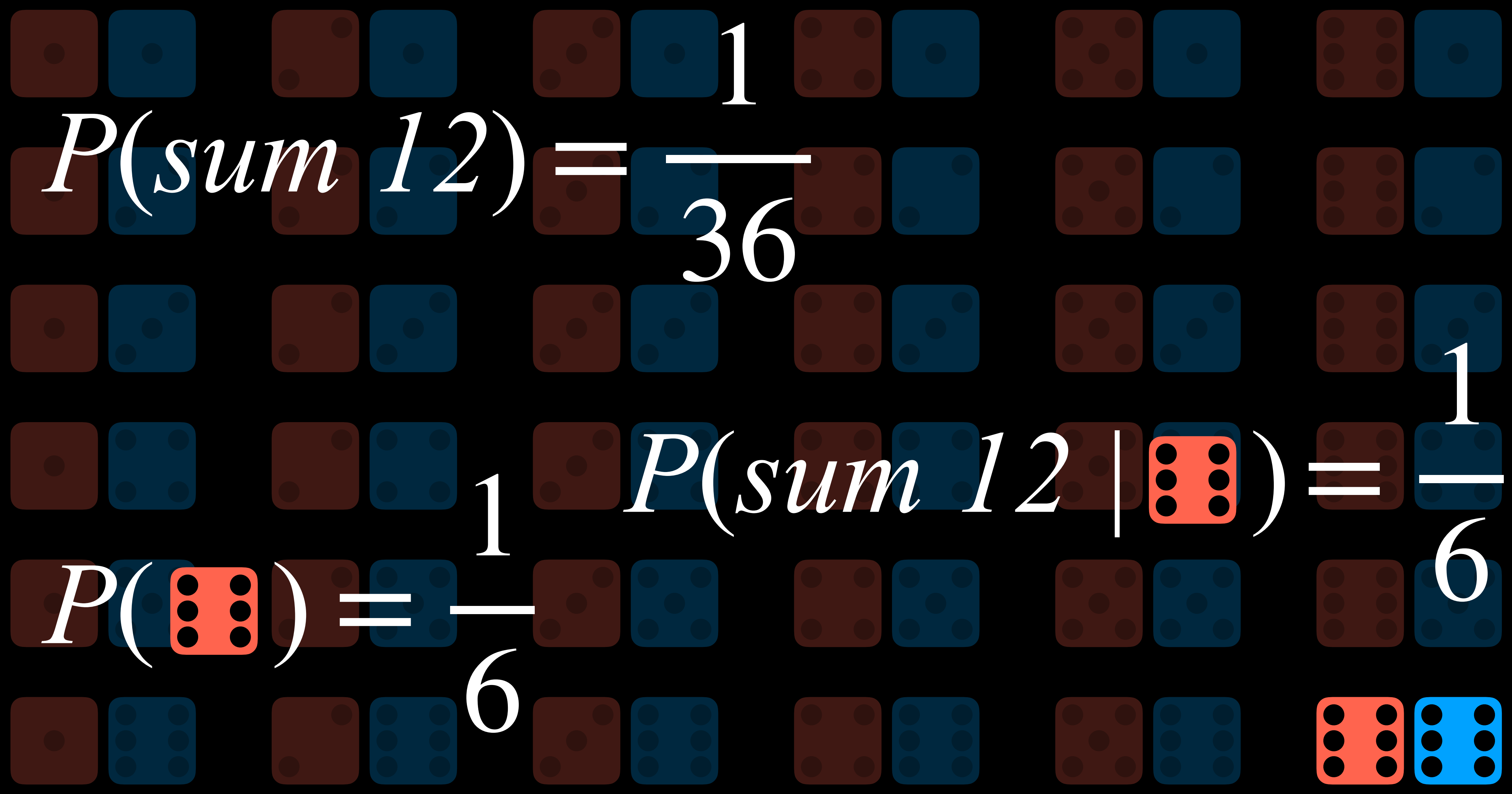
$$P(a|b) = \frac{P(a \wedge b)}{P(b)}$$



$$P(\textit{sum } 12 \mid \text{🎲})$$







$$P(\text{sum } 12) = \frac{1}{36}$$

$$P(\text{sum } 12 \mid \text{red die}) = \frac{1}{6}$$

$$P(\text{red die}) = \frac{1}{6}$$

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

$$P(a \wedge b) = P(b)P(a|b)$$

$$P(a \wedge b) = P(a)P(b|a)$$

# random variable

a variable in probability theory with a domain of possible values it can take on



random variable

*Roll*

$\{1, 2, 3, 4, 5, 6\}$

random variable

*Weather*

$\{sun, cloud, rain, wind, snow\}$

random variable

*Traffic*

$\{none, light, heavy\}$

random variable

*Flight*

*{on time, delayed, cancelled}*

# probability distribution

$$P(\textit{Flight} = \textit{on time}) = 0.6$$

$$P(\textit{Flight} = \textit{delayed}) = 0.3$$

$$P(\textit{Flight} = \textit{cancelled}) = 0.1$$

probability distribution

$$\mathbf{P}(\textit{Flight}) = \langle 0.6, 0.3, 0.1 \rangle$$

# independence

the knowledge that one event occurs does not affect the probability of the other event

independence

$$P(a \wedge b) = P(a)P(b | a)$$



independence

$$P(a \wedge b) = P(a)P(b)$$

independence

$$P(\text{red die} \text{ blue die}) = P(\text{red die})P(\text{blue die})$$

$$= \frac{1}{6} \cdot \frac{1}{6} = \frac{1}{36}$$

independence

$$P(\text{🎲 🎲}) \neq P(\text{🎲})P(\text{🎲})$$

$$= \frac{1}{6} \cdot \frac{1}{6} = \frac{1}{36}$$

independence

$$P(\text{🎲} \text{🎲}) \neq P(\text{🎲})P(\text{🎲} \mid \text{🎲})$$

$$= \frac{1}{6} \cdot 0 = 0$$

# Bayes' Rule

$$P(a \wedge b) = P(b) P(a | b)$$

$$P(a \wedge b) = P(a) P(b | a)$$

$$P(a) P(b | a) = P(b) P(a | b)$$

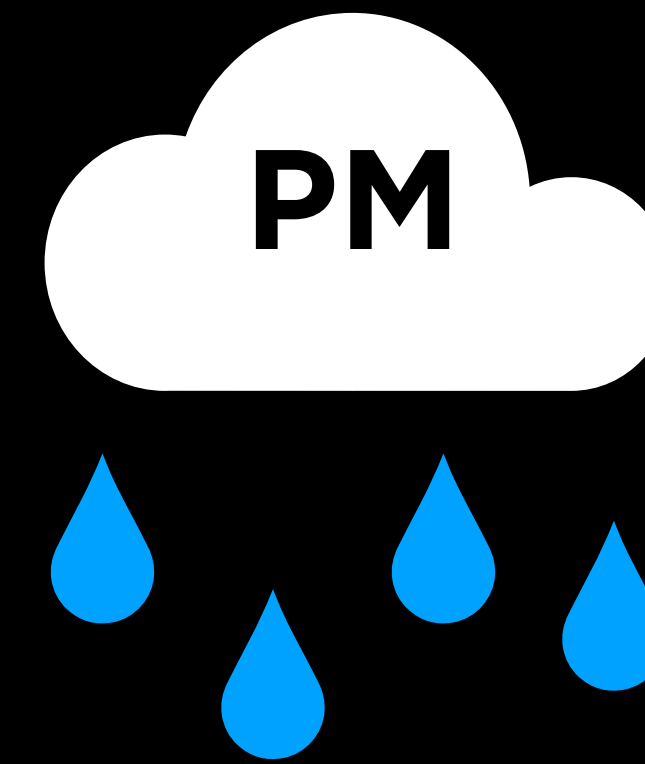
# Bayes' Rule

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



# Bayes' Rule

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



Given clouds in the morning,  
what's the probability of rain in the afternoon?

- 80% of rainy afternoons start with cloudy mornings.
- 40% of days have cloudy mornings.
- 10% of days have rainy afternoons.

$$P(\textit{rain} \mid \textit{clouds}) = \frac{P(\textit{clouds} \mid \textit{rain})P(\textit{rain})}{P(\textit{clouds})}$$

$$= \frac{(.8)(.1)}{.4}$$

$$= 0.2$$

Knowing

$$P(\textit{cloudy morning} \mid \textit{rainy afternoon})$$

we can calculate

$$P(\textit{rainy afternoon} \mid \textit{cloudy morning})$$

Knowing

$$P(\textit{visible effect} \mid \textit{unknown cause})$$

we can calculate

$$P(\textit{unknown cause} \mid \textit{visible effect})$$

Knowing

$$P(\textit{medical test result} \mid \textit{disease})$$

we can calculate

$$P(\textit{disease} \mid \textit{medical test result})$$

Knowing

$$P(\textit{blurry text} \mid \textit{counterfeit bill})$$

we can calculate

$$P(\textit{counterfeit bill} \mid \textit{blurry text})$$

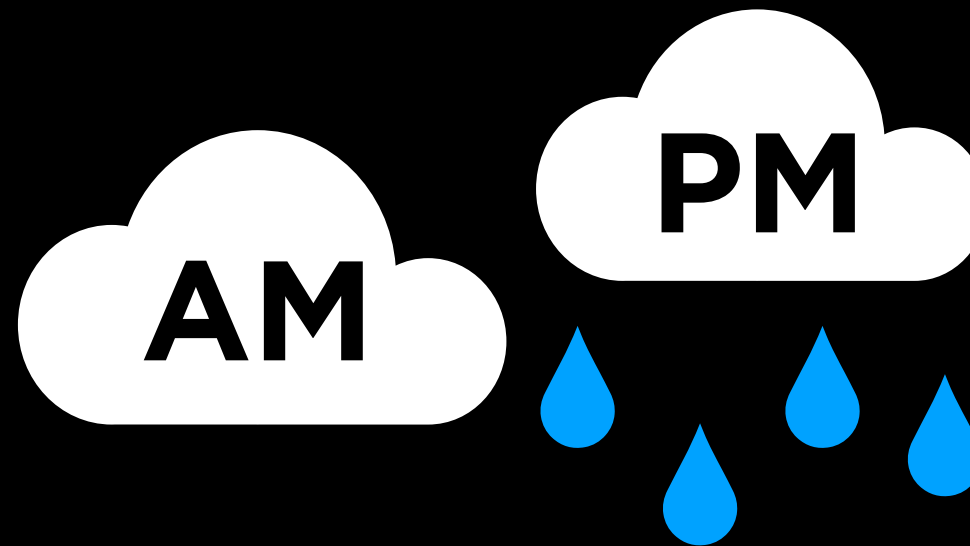
# Joint Probability





$C = \textit{cloud}$	$C = \neg \textit{cloud}$
0.4	0.6

$R = \textit{rain}$	$R = \neg \textit{rain}$
0.1	0.9



	$R = \textit{rain}$	$R = \neg \textit{rain}$
$C = \textit{cloud}$	0.08	0.32
$C = \neg \textit{cloud}$	0.02	0.58

$\mathbf{P(C \mid rain)}$

$$\mathbf{P(C \mid rain)} = \frac{\mathbf{P(C, rain)}}{\mathbf{P(rain)}} = \alpha \mathbf{P(C, rain)}$$

$$= \alpha \langle 0.08, 0.02 \rangle = \langle 0.8, 0.2 \rangle$$

	R = <i>rain</i>	R = $\neg$ <i>rain</i>
C = <i>cloud</i>	0.08	0.32
C = $\neg$ <i>cloud</i>	0.02	0.58

# Probability Rules

# Negation

$$P(\neg a) = 1 - P(a)$$

# Inclusion-Exclusion

$$P(a \vee b) = P(a) + P(b) - P(a \wedge b)$$

# Marginalization

$$P(a) = P(a, b) + P(a, \neg b)$$

# Marginalization

$$P(X = x_i) = \sum_j P(X = x_i, Y = y_j)$$

# Marginalization

	$R = \textit{rain}$	$R = \neg \textit{rain}$
$C = \textit{cloud}$	0.08	0.32
$C = \neg \textit{cloud}$	0.02	0.58

$$P(C = \textit{cloud})$$

$$= P(C = \textit{cloud}, R = \textit{rain}) + P(C = \textit{cloud}, R = \neg \textit{rain})$$

$$= 0.08 + 0.32$$

$$= 0.40$$



# Conditioning

$$P(a) = P(a \mid b)P(b) + P(a \mid \neg b)P(\neg b)$$

# Conditioning

$$P(X = x_i) = \sum_j P(X = x_i | Y = y_j) P(Y = y_j)$$

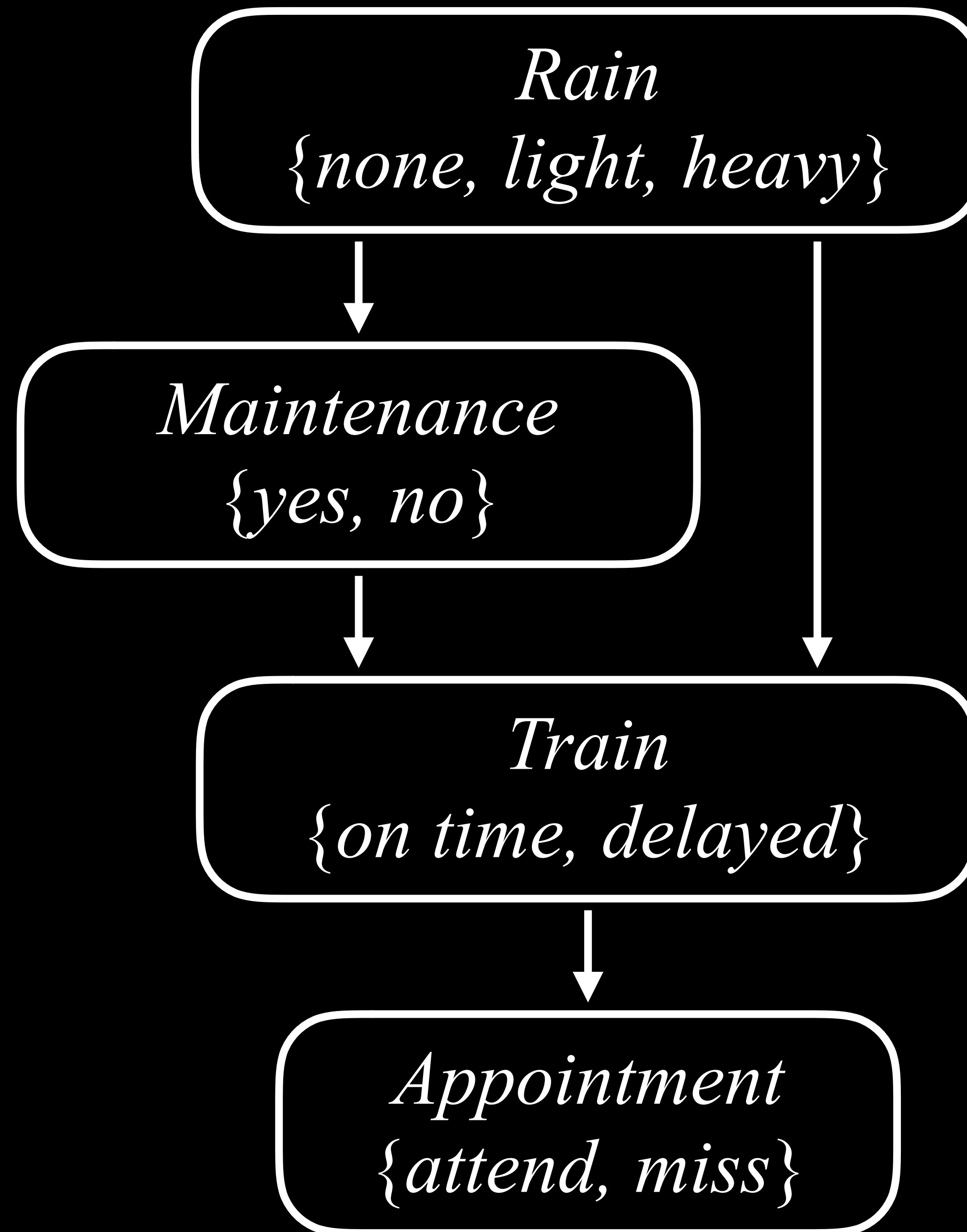
# Bayesian Networks

# Bayesian network

data structure that represents the dependencies among random variables

# Bayesian network

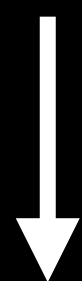
- directed graph
- each node represents a random variable
- arrow from  $X$  to  $Y$  means  $X$  is a parent of  $Y$
- each node  $X$  has probability distribution  $\mathbf{P}(X \mid \textit{Parents}(X))$



*Rain*  
*{none, light, heavy}*

<i>none</i>	<i>light</i>	<i>heavy</i>
0.7	0.2	0.1

*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*

<i>R</i>	<i>yes</i>	<i>no</i>
<i>none</i>	0.4	0.6
<i>light</i>	0.2	0.8
<i>heavy</i>	0.1	0.9



*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*

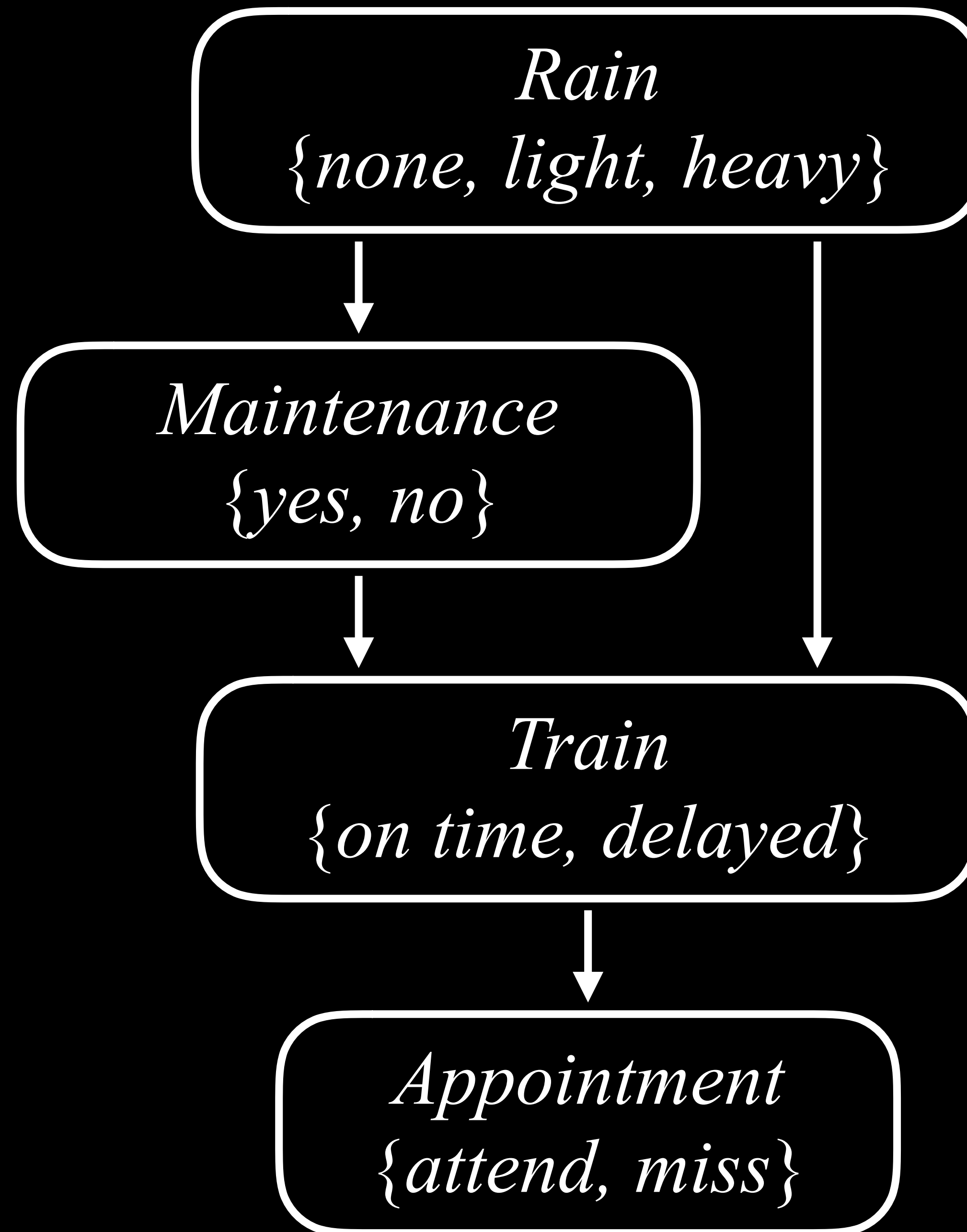
<i>R</i>	<i>M</i>	<i>on time</i>	<i>delayed</i>
<i>none</i>	<i>yes</i>	0.8	0.2
<i>none</i>	<i>no</i>	0.9	0.1
<i>light</i>	<i>yes</i>	0.6	0.4
<i>light</i>	<i>no</i>	0.7	0.3
<i>heavy</i>	<i>yes</i>	0.4	0.6
<i>heavy</i>	<i>no</i>	0.5	0.5

*Maintenance*  
*{yes, no}*

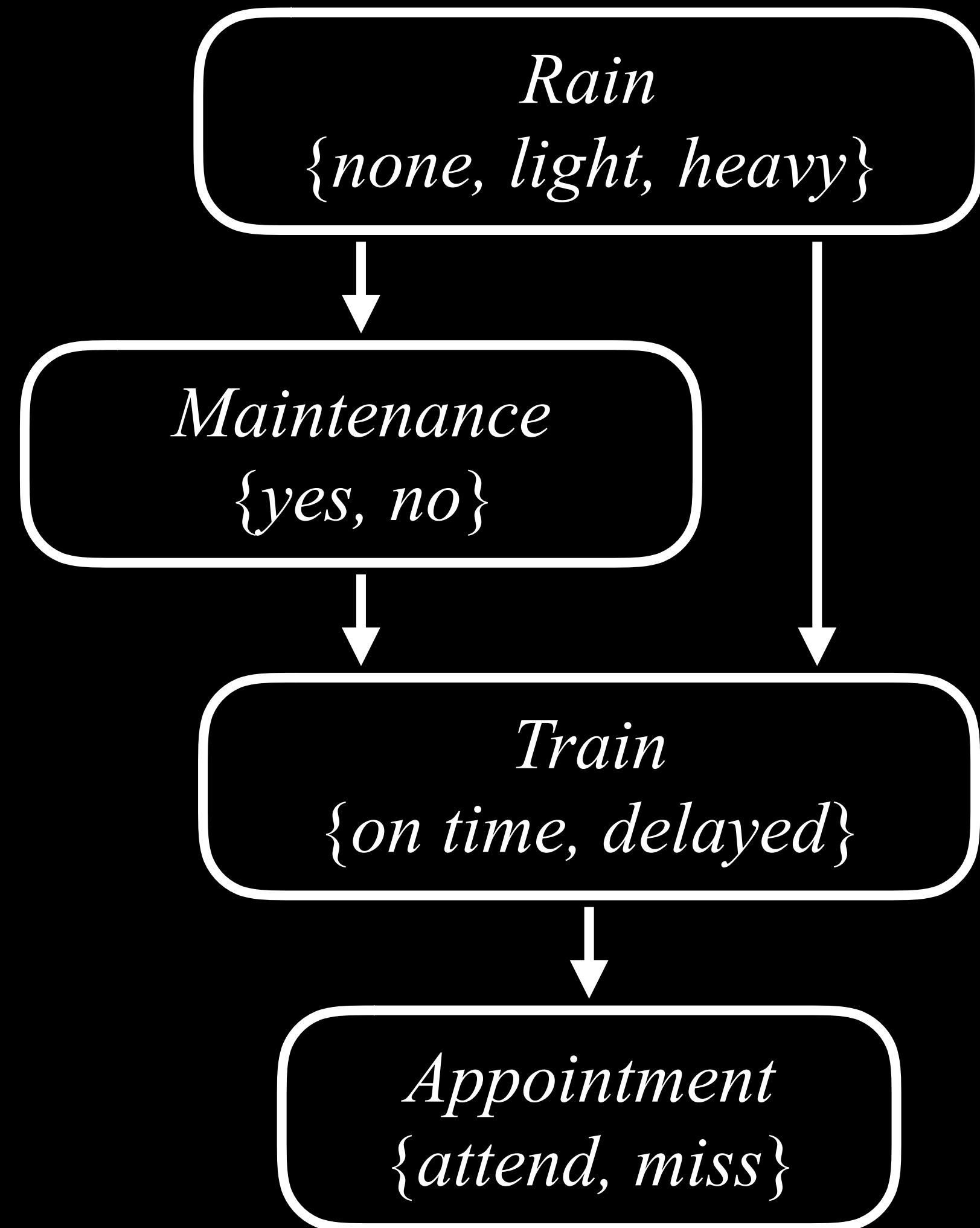
*Train*  
*{on time, delayed}*

*Appointment*  
*{attend, miss}*

<i>T</i>	<i>attend</i>	<i>miss</i>
<i>on time</i>	0.9	0.1
<i>delayed</i>	0.6	0.4



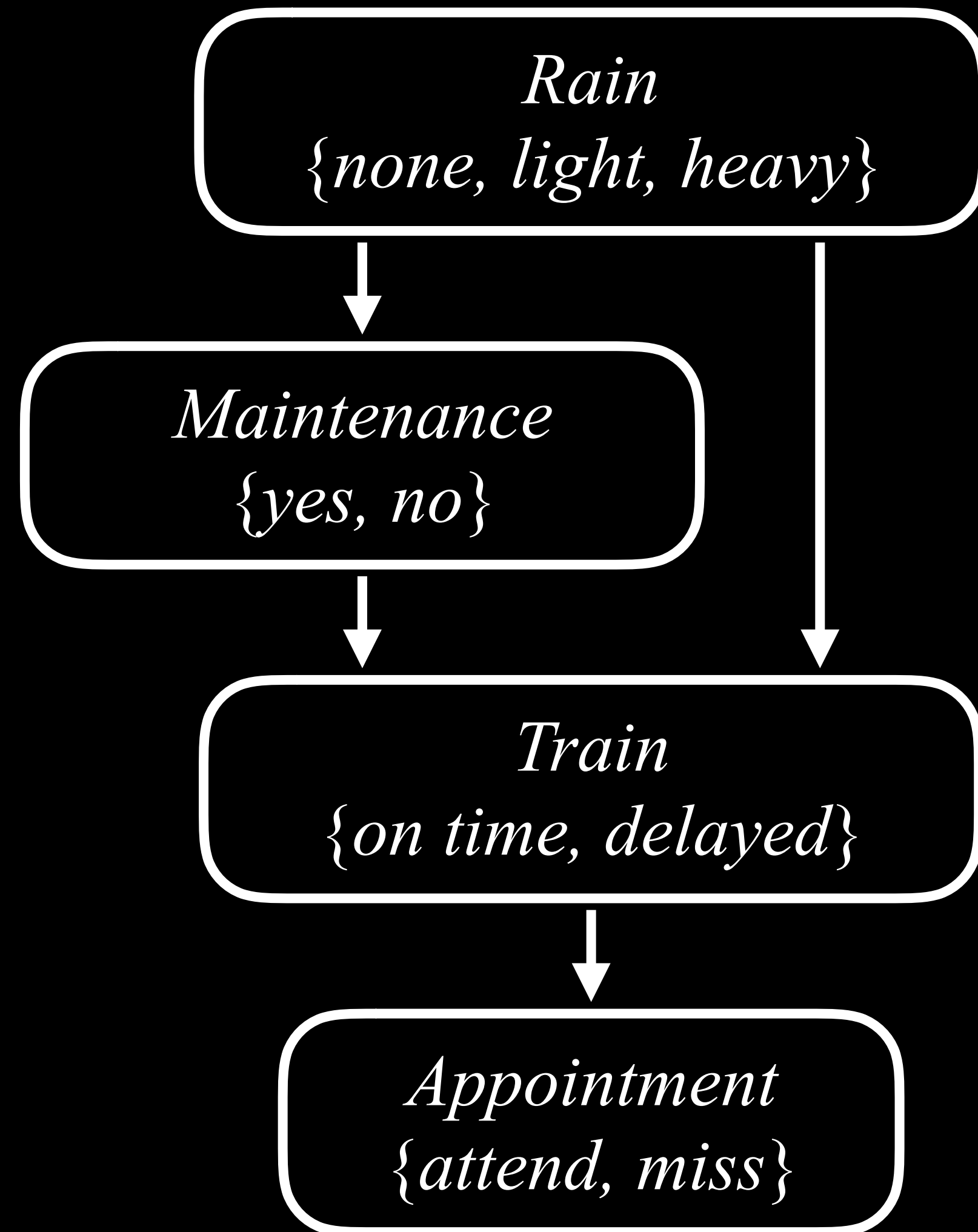
# Computing Joint Probabilities



$P(\textit{light})$

$P(\textit{light})$

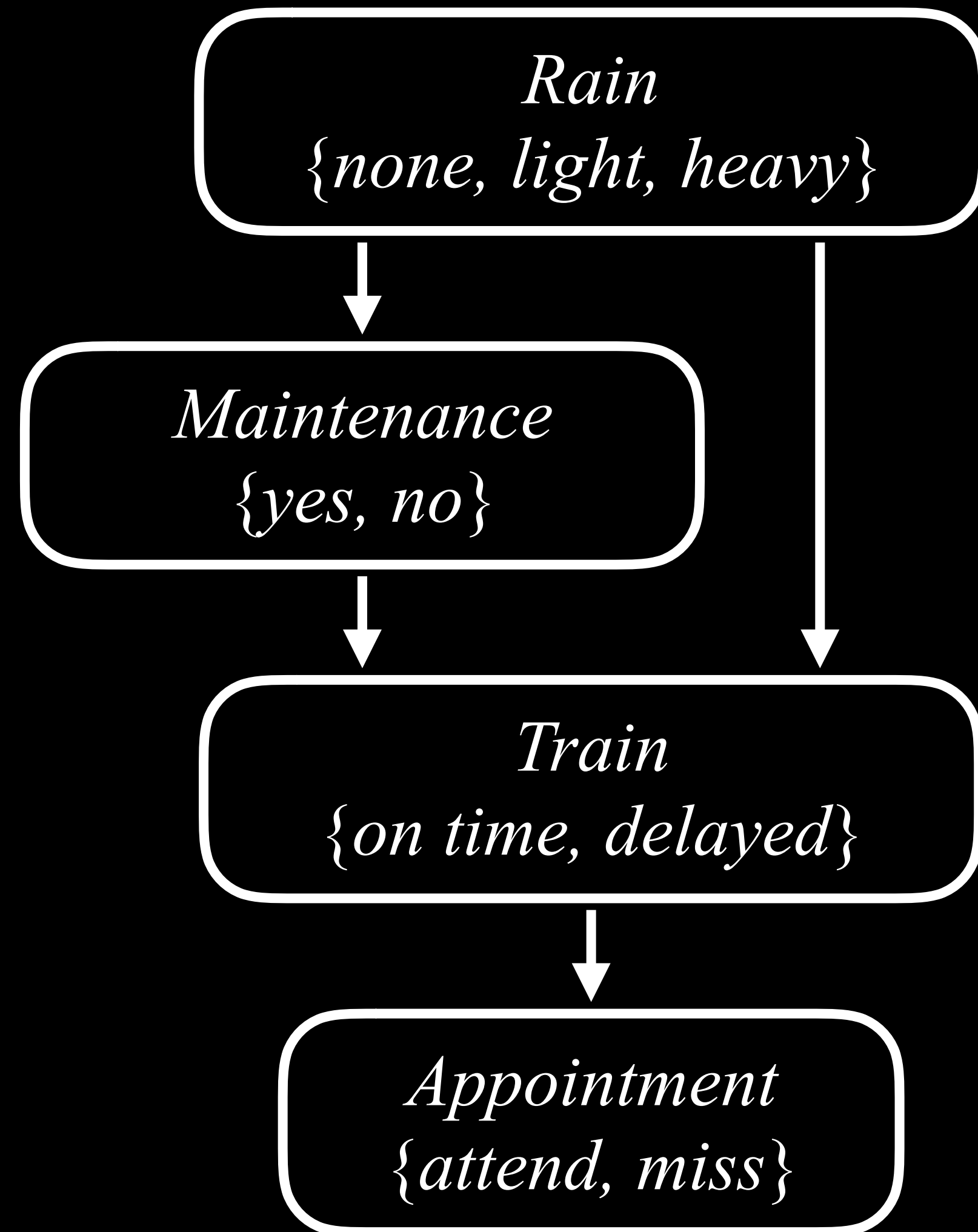
# Computing Joint Probabilities



$$P(light, no)$$

$$P(light) P(no \mid light)$$

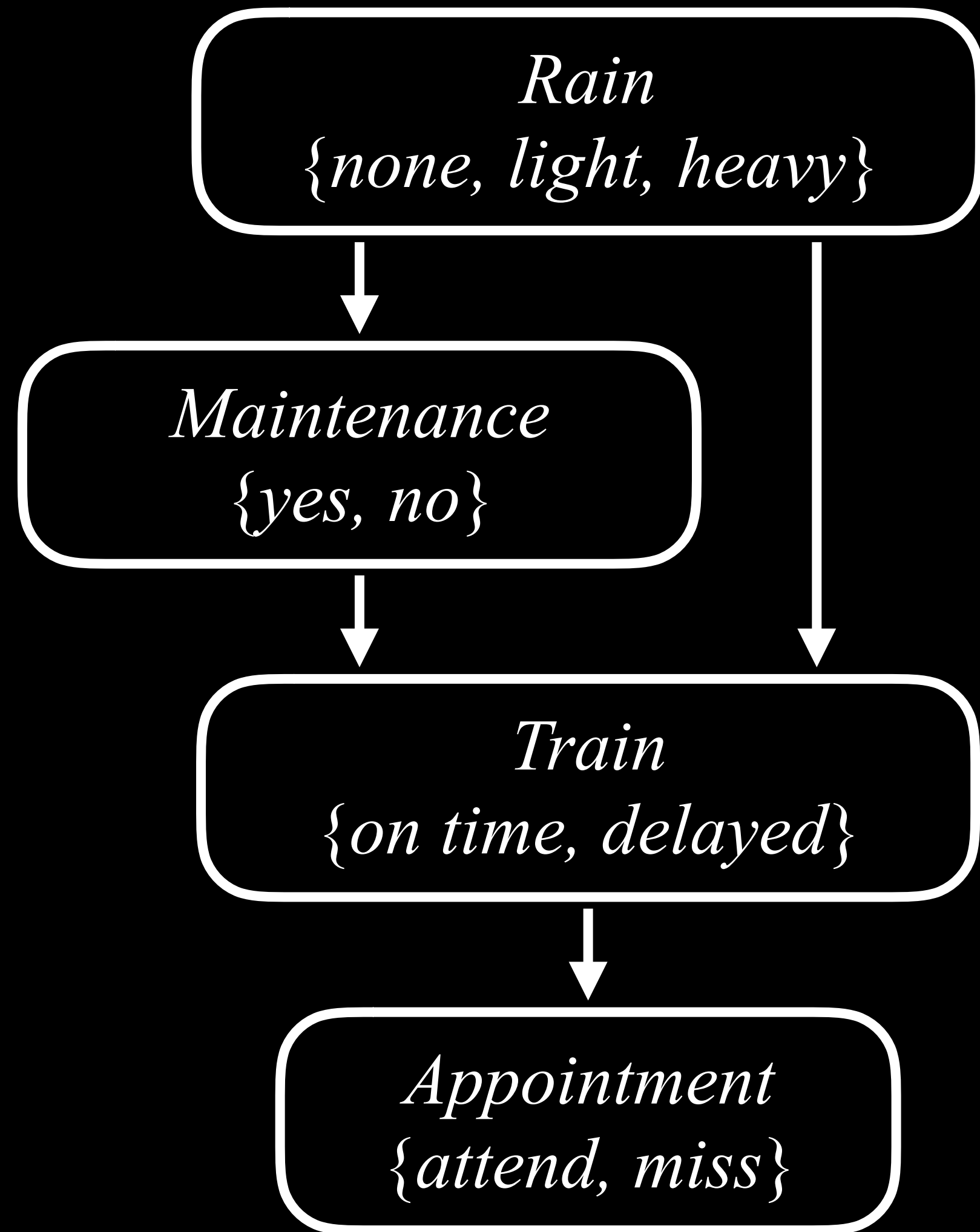
# Computing Joint Probabilities



$P(\text{light}, \text{no}, \text{delayed})$

$P(\text{light}) P(\text{no} \mid \text{light}) P(\text{delayed} \mid \text{light}, \text{no})$

# Computing Joint Probabilities



$P(\text{light}, \text{no}, \text{delayed}, \text{miss})$

$P(\text{light}) P(\text{no} \mid \text{light}) P(\text{delayed} \mid \text{light}, \text{no}) P(\text{miss} \mid \text{delayed})$

# Inference



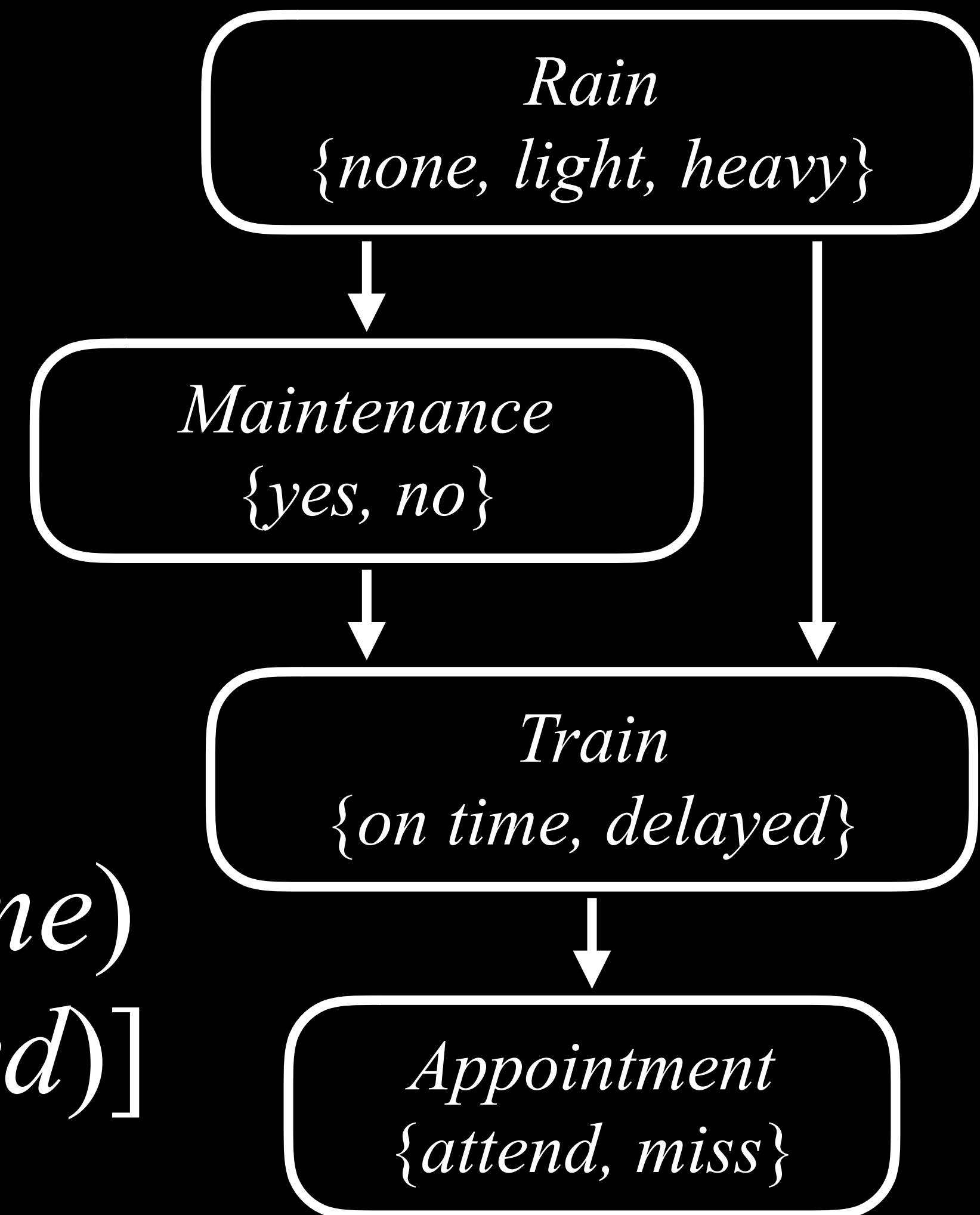
# Inference

- Query  $X$ : variable for which to compute distribution
- Evidence variables  $\mathbf{E}$ : observed variables for event  $\mathbf{e}$
- Hidden variables  $\mathbf{Y}$ : non-evidence, non-query variable.
- Goal: Calculate  $\mathbf{P}(X \mid \mathbf{e})$

$P(\text{Appointment} \mid \text{light}, \text{no})$

$= \alpha P(\text{Appointment}, \text{light}, \text{no})$

$= \alpha [P(\text{Appointment}, \text{light}, \text{no}, \text{on time})$   
 $+ P(\text{Appointment}, \text{light}, \text{no}, \text{delayed})]$



# Inference by Enumeration

$$P(X \mid \mathbf{e}) = \alpha P(X, \mathbf{e}) = \alpha \sum_{\mathbf{y}} P(X, \mathbf{e}, \mathbf{y})$$

$X$  is the query variable.

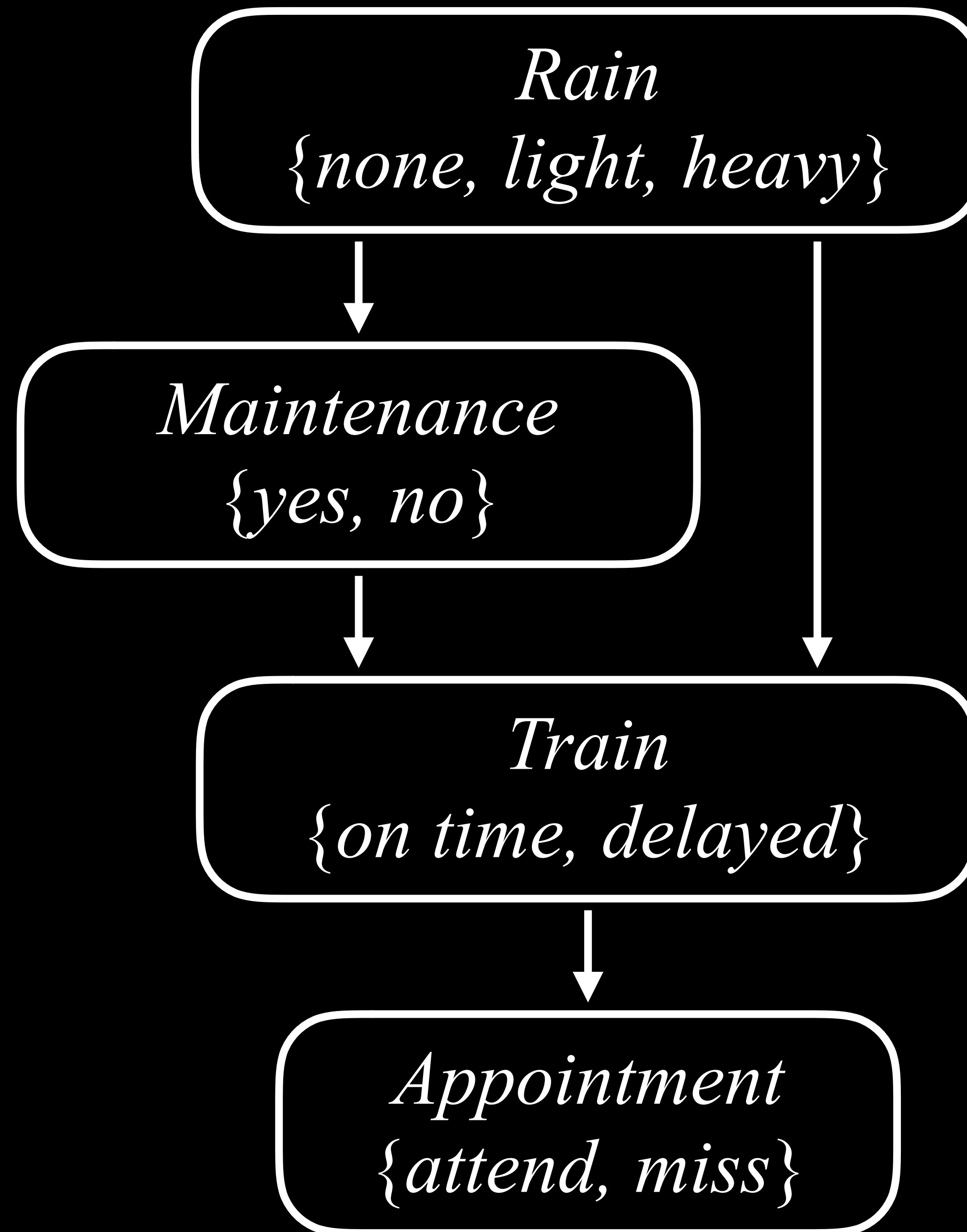
$\mathbf{e}$  is the evidence.

$\mathbf{y}$  ranges over values of hidden variables.

$\alpha$  normalizes the result.

# Approximate Inference

# Sampling



*Rain*  
*{none, light, heavy}*

$R = \textit{none}$

<i>none</i>	<i>light</i>	<i>heavy</i>
0.7	0.2	0.1

*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



$R = none$
$M = yes$

$R$	$yes$	$no$
$none$	0.4	0.6
$light$	0.2	0.8
$heavy$	0.1	0.9



*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*



$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$

$R$	$M$	<i>on time</i>	<i>delayed</i>
<i>none</i>	<i>yes</i>	0.8	0.2
<i>none</i>	<i>no</i>	0.9	0.1
<i>light</i>	<i>yes</i>	0.6	0.4
<i>light</i>	<i>no</i>	0.7	0.3
<i>heavy</i>	<i>yes</i>	0.4	0.6
<i>heavy</i>	<i>no</i>	0.5	0.5

*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*



*Appointment*  
*{attend, miss}*

$R = none$

$M = yes$

$T = on\ time$

$A = attend$

<i>T</i>	<i>attend</i>	<i>miss</i>
<i>on time</i>	0.9	0.1
<i>delayed</i>	0.6	0.4

$R = \textit{none}$

$M = \textit{yes}$

$T = \textit{on time}$

$A = \textit{attend}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{delayed}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{heavy}$
$M = \textit{no}$
$T = \textit{delayed}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$P(\textit{Train} = \textit{on time}) ?$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{delayed}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{heavy}$
$M = \textit{no}$
$T = \textit{delayed}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{delayed}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{heavy}$
$M = \textit{no}$
$T = \textit{delayed}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$P(\text{Rain} = \textit{light} \mid \text{Train} = \textit{on time}) ?$



$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{delayed}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{heavy}$
$M = \textit{no}$
$T = \textit{delayed}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{delayed}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{heavy}$
$M = \textit{no}$
$T = \textit{delayed}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{delayed}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{none}$
$M = \textit{yes}$
$T = \textit{on time}$
$A = \textit{attend}$

$R = \textit{heavy}$
$M = \textit{no}$
$T = \textit{delayed}$
$A = \textit{miss}$

$R = \textit{light}$
$M = \textit{no}$
$T = \textit{on time}$
$A = \textit{attend}$

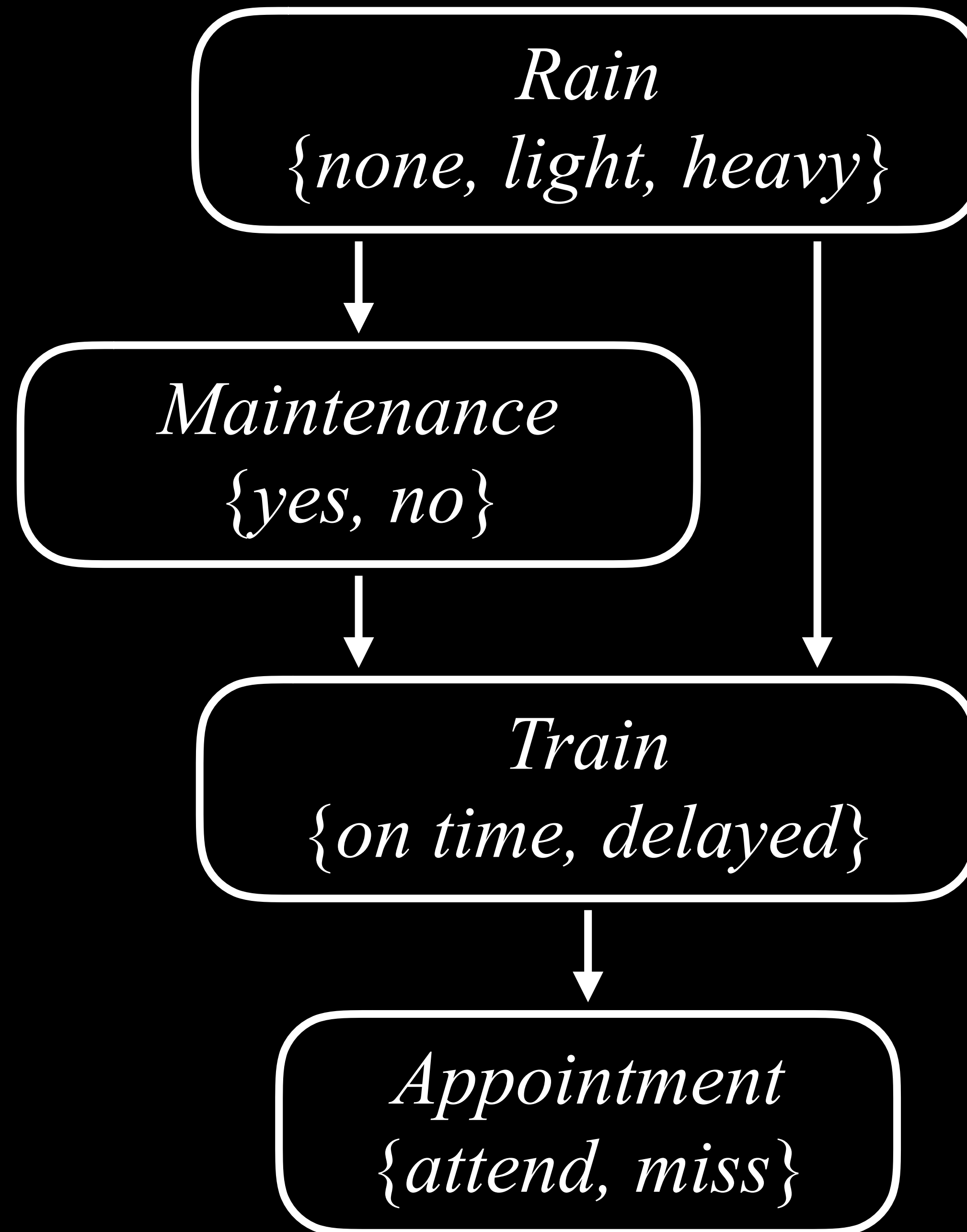
# Rejection Sampling

# Likelihood Weighting

# Likelihood Weighting

- Start by fixing the values for evidence variables.
- Sample the non-evidence variables using conditional probabilities in the Bayesian Network.
- Weight each sample by its **likelihood**: the probability of all of the evidence.

$P(\text{Rain} = \textit{light} \mid \text{Train} = \textit{on time}) ?$





$R = \textit{light}$

$T = \textit{on time}$

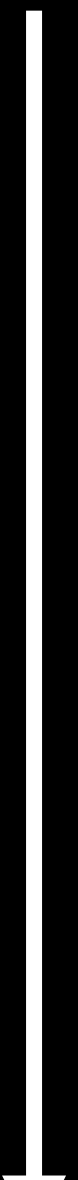
*Rain*  
 $\{\textit{none}, \textit{light}, \textit{heavy}\}$

<i>none</i>	<i>light</i>	<i>heavy</i>
0.7	0.2	0.1

*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{on time}$

$R$	$yes$	$no$
$none$	0.4	0.6
$light$	0.2	0.8
$heavy$	0.1	0.9

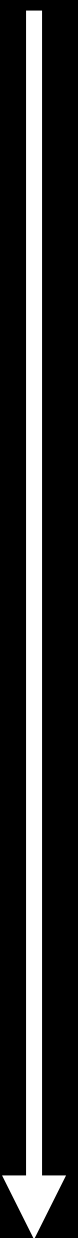
*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*



$R = \textit{light}$
$M = \textit{yes}$
$T = \textit{on time}$

<i>R</i>	<i>M</i>	<i>on time</i>	<i>delayed</i>
<i>none</i>	<i>yes</i>	0.8	0.2
<i>none</i>	<i>no</i>	0.9	0.1
<i>light</i>	<i>yes</i>	0.6	0.4
<i>light</i>	<i>no</i>	0.7	0.3
<i>heavy</i>	<i>yes</i>	0.4	0.6
<i>heavy</i>	<i>no</i>	0.5	0.5

*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*



*Appointment*  
*{attend, miss}*

$R = \textit{light}$

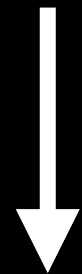
$M = \textit{yes}$

$T = \textit{on time}$

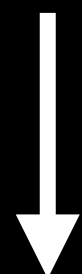
$A = \textit{attend}$

<i>T</i>	<i>attend</i>	<i>miss</i>
<i>on time</i>	0.9	0.1
<i>delayed</i>	0.6	0.4

*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*



$R = \textit{light}$

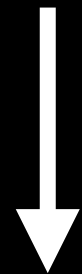
$M = \textit{yes}$

$T = \textit{on time}$

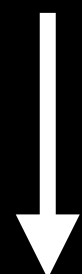
$A = \textit{attend}$

<i>R</i>	<i>M</i>	<i>on time</i>	<i>delayed</i>
<i>none</i>	<i>yes</i>	0.8	0.2
<i>none</i>	<i>no</i>	0.9	0.1
<i>light</i>	<i>yes</i>	0.6	0.4
<i>light</i>	<i>no</i>	0.7	0.3
<i>heavy</i>	<i>yes</i>	0.4	0.6
<i>heavy</i>	<i>no</i>	0.5	0.5

*Rain*  
*{none, light, heavy}*



*Maintenance*  
*{yes, no}*



*Train*  
*{on time, delayed}*



$R = \textit{light}$

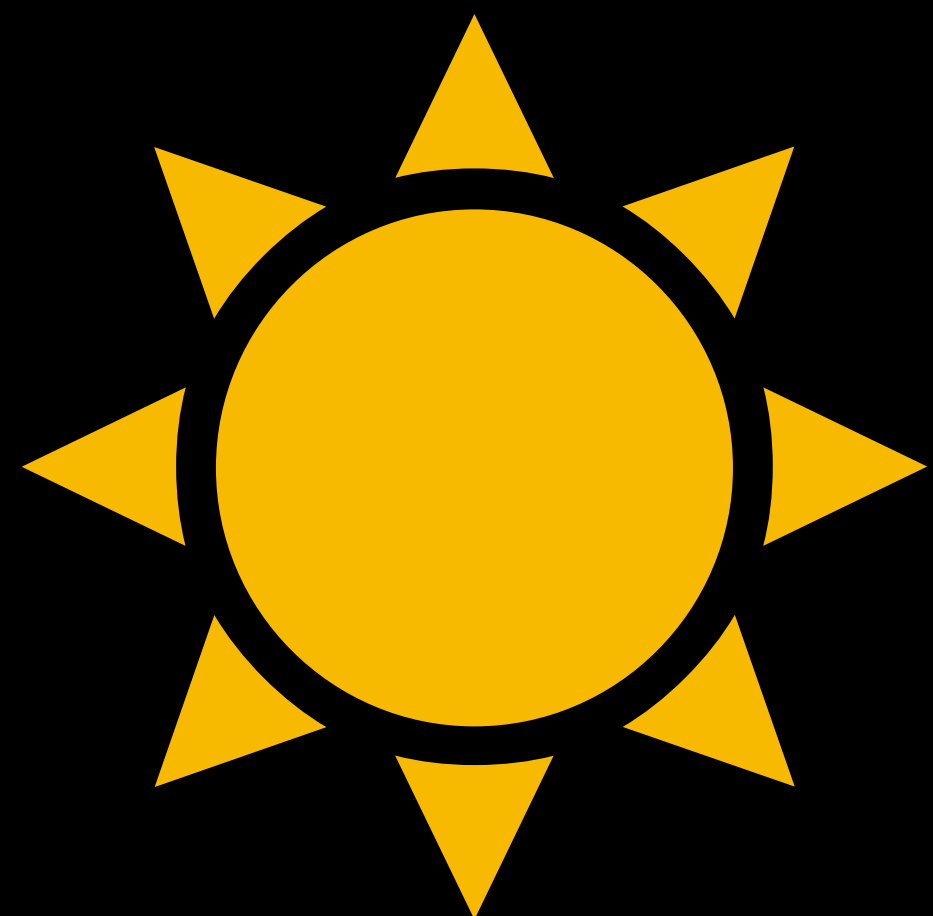
$M = \textit{yes}$

$T = \textit{on time}$

$A = \textit{attend}$

<i>R</i>	<i>M</i>	<i>on time</i>	<i>delayed</i>
<i>none</i>	<i>yes</i>	0.8	0.2
<i>none</i>	<i>no</i>	0.9	0.1
<i>light</i>	<i>yes</i>	0.6	0.4
<i>light</i>	<i>no</i>	0.7	0.3
<i>heavy</i>	<i>yes</i>	0.4	0.6
<i>heavy</i>	<i>no</i>	0.5	0.5

# Uncertainty over Time



$X_t$ : Weather at time  $t$



# Markov assumption

the assumption that the current state depends on only a finite fixed number of previous states

# Markov Chain





# Markov chain

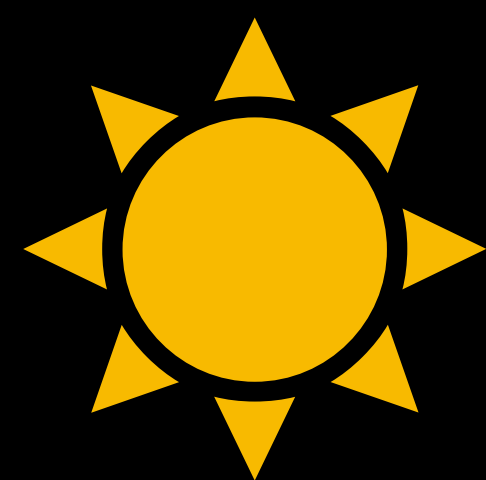
a sequence of random variables where the distribution of each variable follows the Markov assumption

# Transition Model

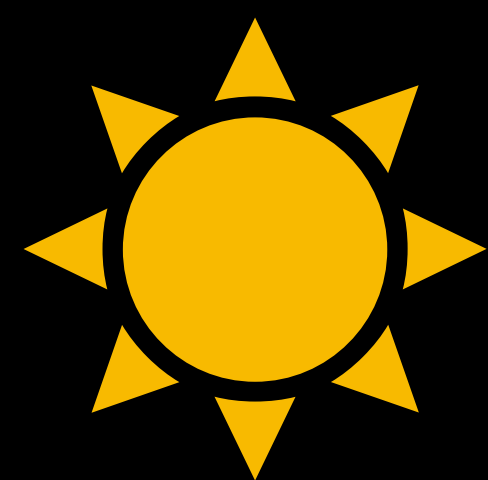
Tomorrow ( $X_{t+1}$ )

Today ( $X_t$ )

		
	0.8	0.2
	0.3	0.7



$X_0$



$X_1$



$X_2$



$X_3$



$X_4$



# Sensor Models

Hidden State	Observation
robot's position	robot's sensor data
words spoken	audio waveforms
user engagement	website or app analytics
weather	umbrella

# Hidden Markov Models







# Hidden Markov Model

a Markov model for a system with hidden states that generate some observed event

# Sensor Model

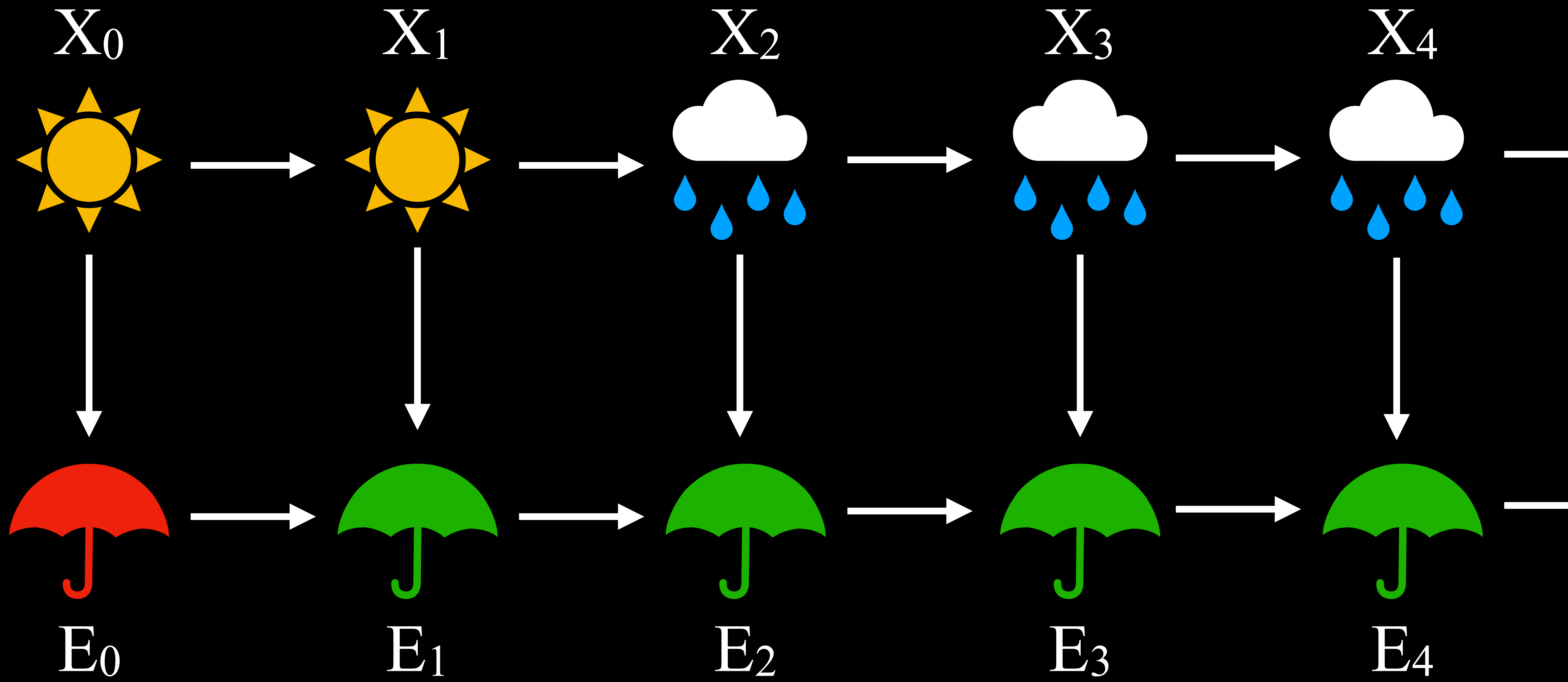
Observation ( $E_t$ )

State ( $X_t$ )

		
	0.2	0.8
	0.9	0.1

# sensor Markov assumption

the assumption that the evidence variable depends only the corresponding state



Task	Definition
filtering	given observations from start until now, calculate distribution for <b>current</b> state
prediction	given observations from start until now, calculate distribution for a <b>future</b> state
smoothing	given observations from start until now, calculate distribution for <b>past</b> state
most likely explanation	given observations from start until now, calculate most likely <b>sequence</b> of states

# Uncertainty

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