

Probability and Statistics

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What's the point of data science/AI?

My feeling

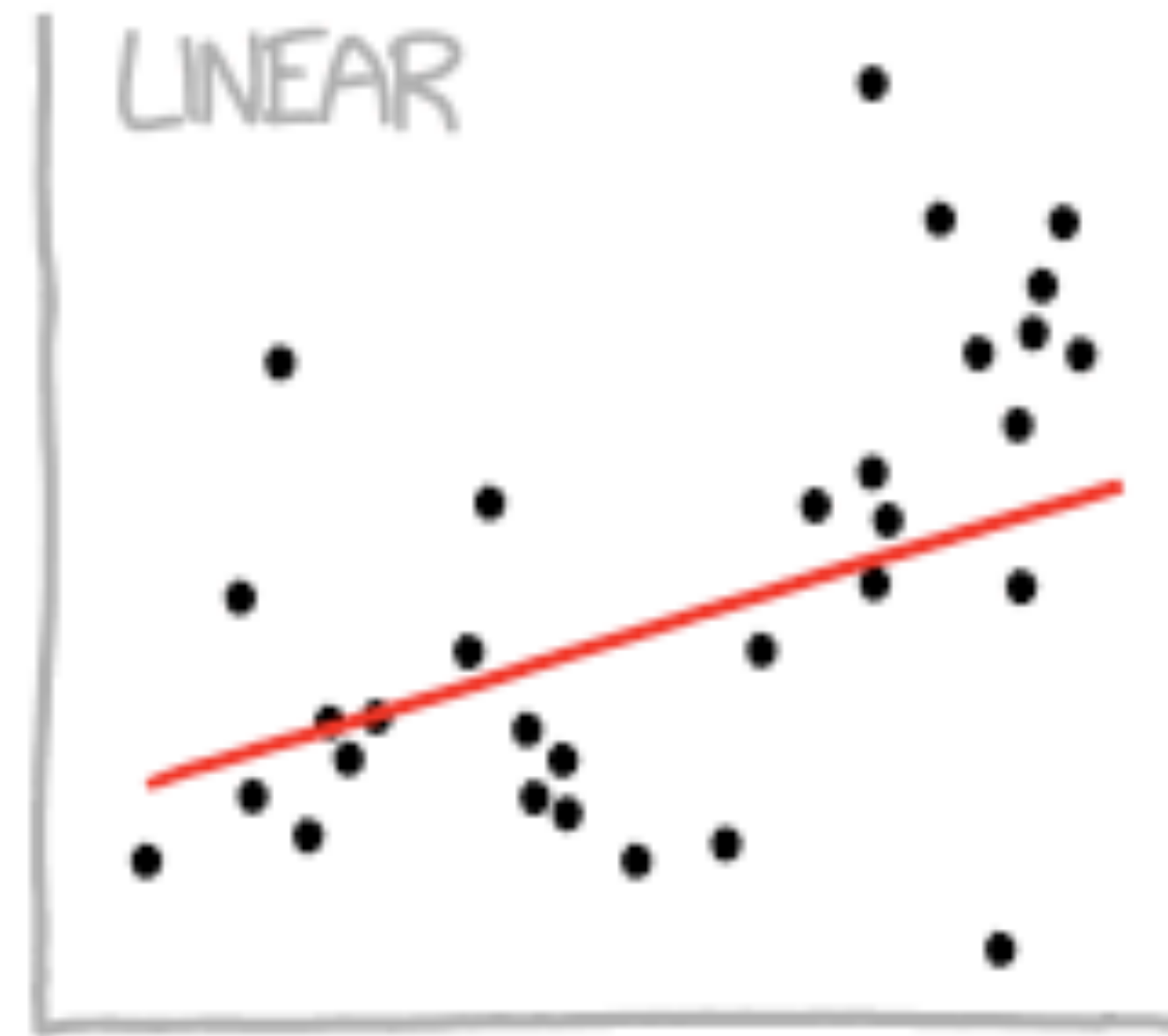
1. **Summarising** data in an understandable way



It's a feeling

Summarising data

EG rate of
heart attacks



"HEY, I DID A
REGRESSION."

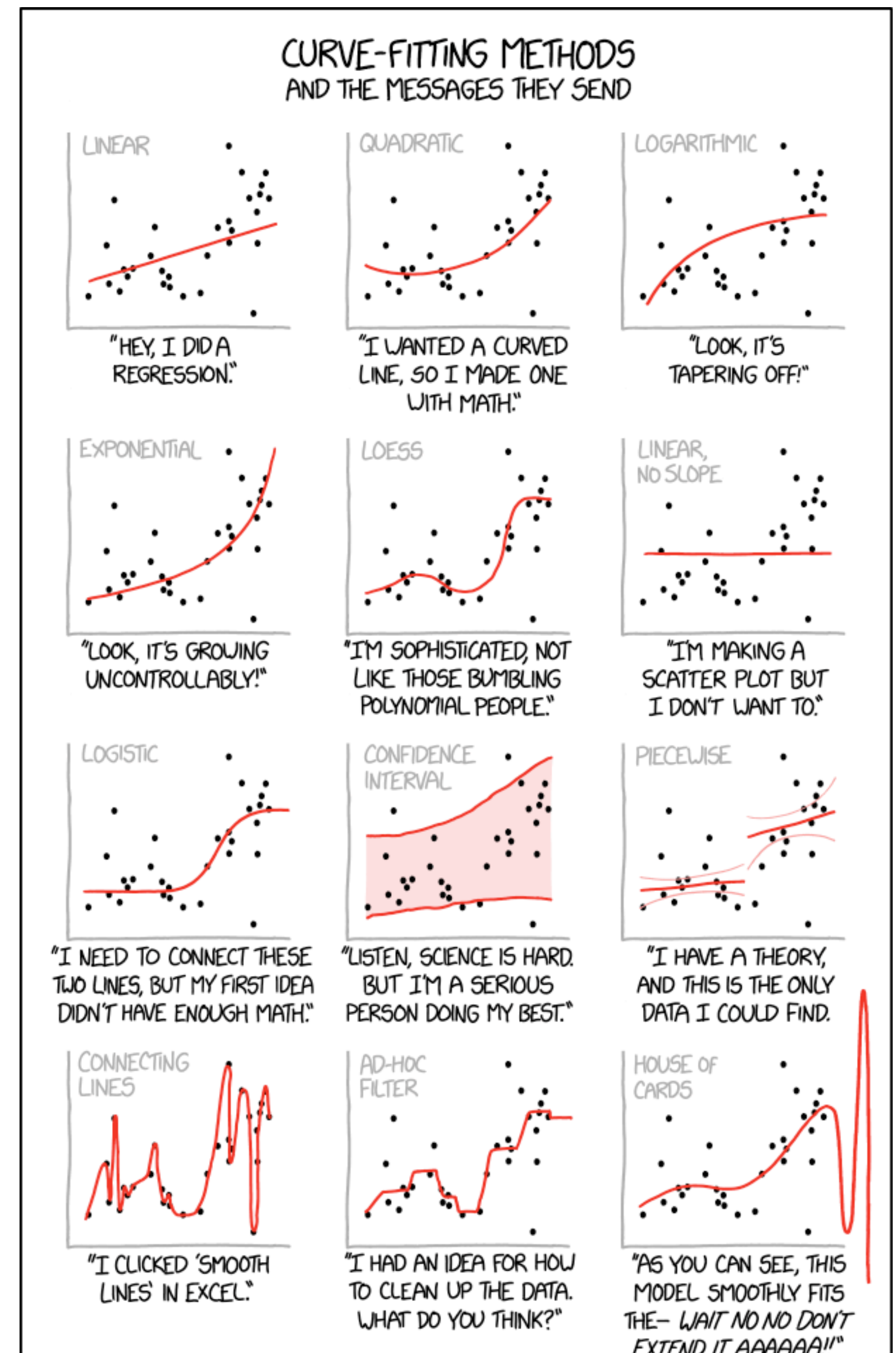
EG air pollution

EG dots are cities

Summarising data

Summaries can be wrong

Convoluted summaries
can be **useless**

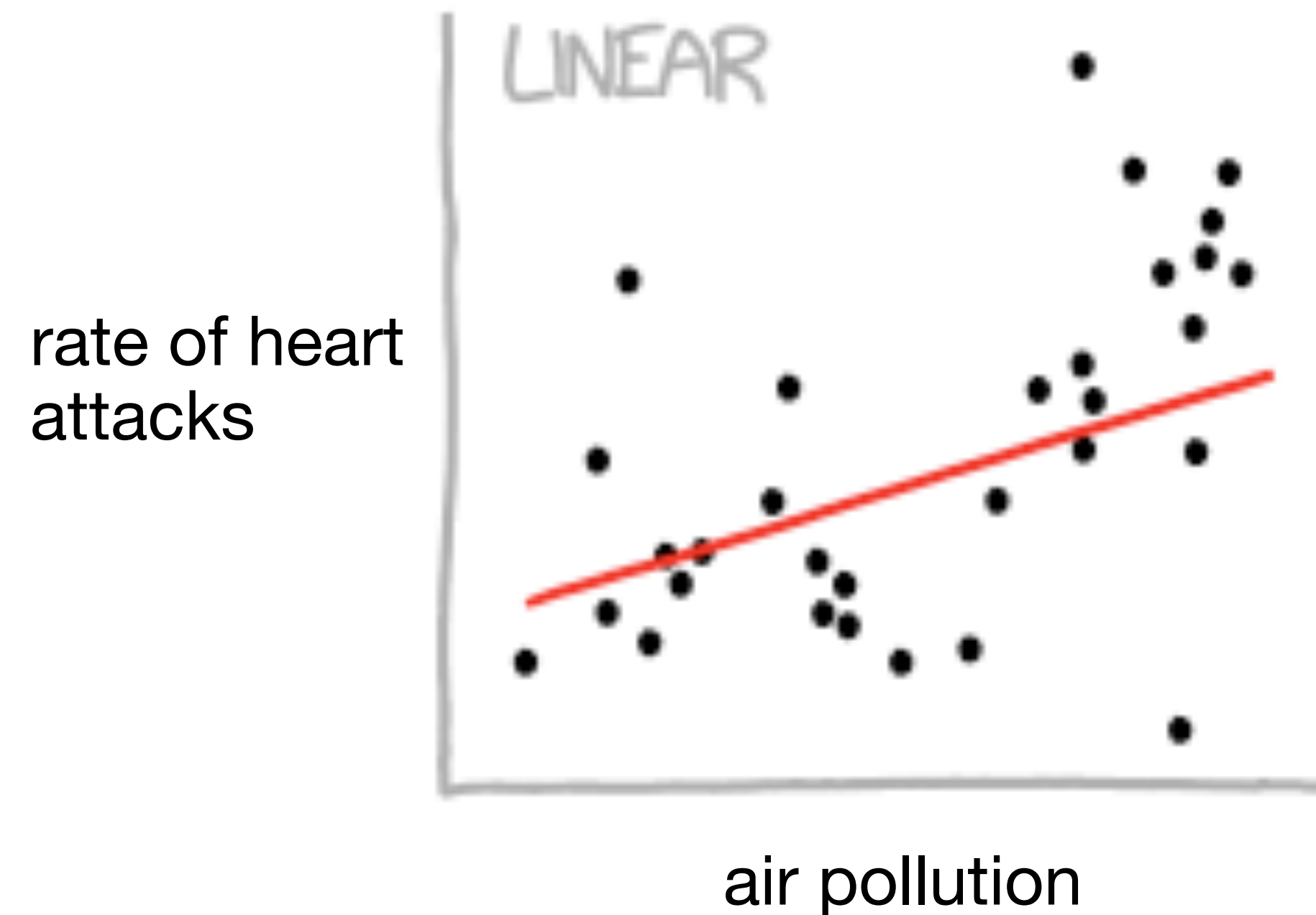


What's the point of data science/AI?

My feeling

1. **Summarising** data in a conceptually tractable way

2. Using these summaries to make (actionable) **predictions**



Congestion charge -> Less pollution
-> Save NHS £50 million

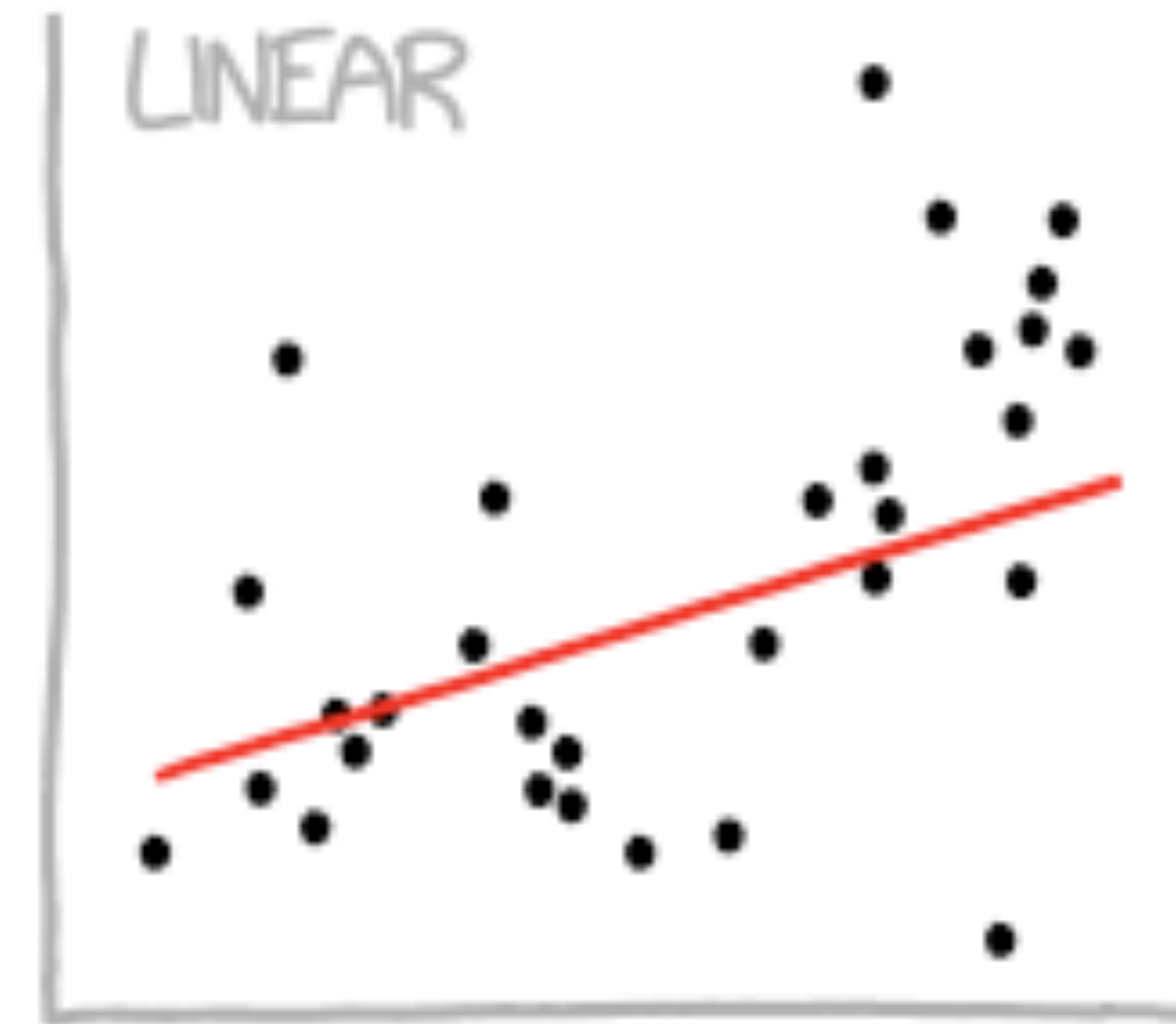
Key Question

How confident am I on my summaries/predictions?

1. Summarising data in a conceptually tractable way

2. Using these summaries to make (actionable) predictions

rate of heart attacks



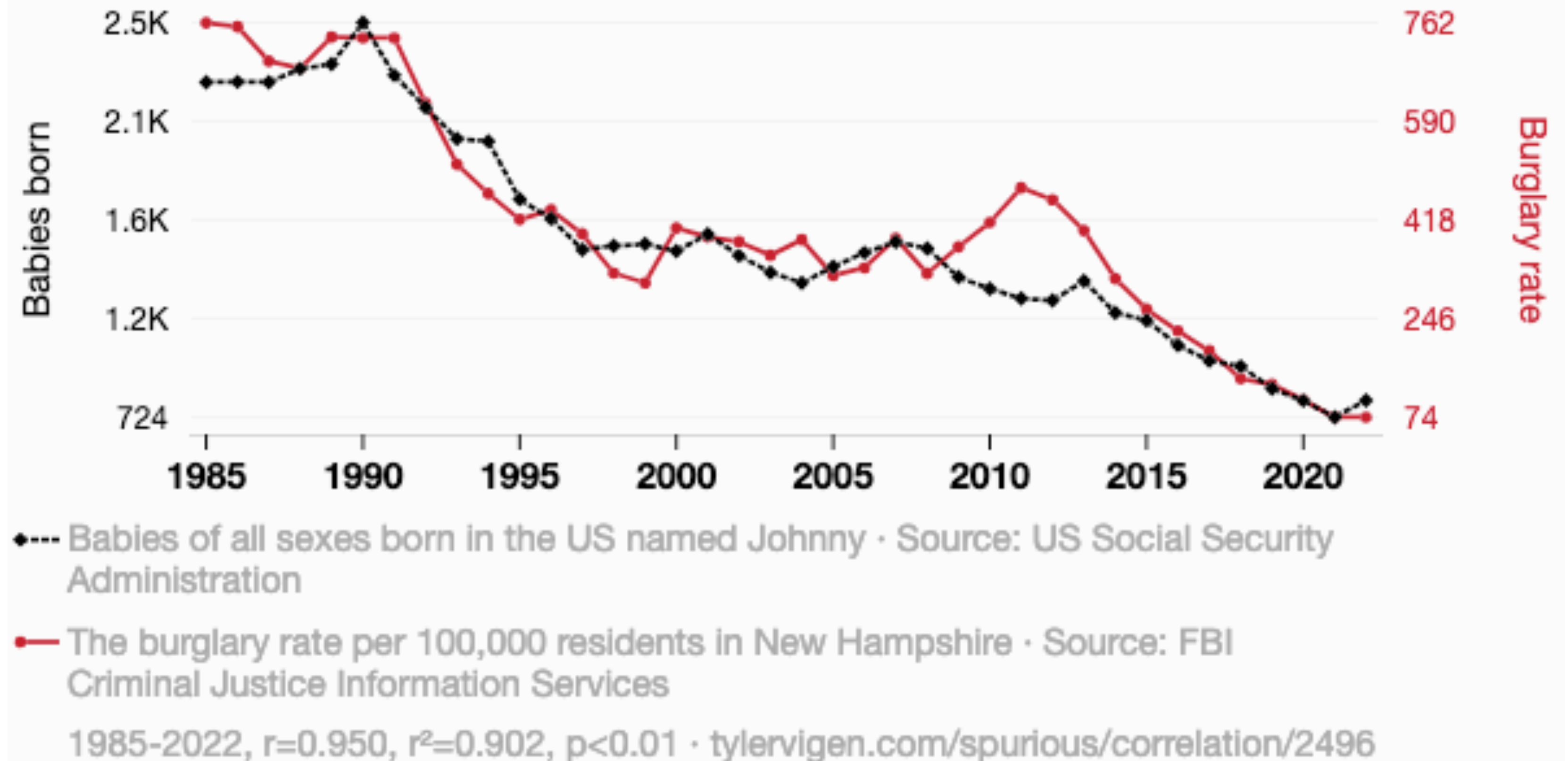
air pollution

Congestion charge -> Less pollution
-> Save NHS £50 million

Popularity of the first name Johnny

correlates with

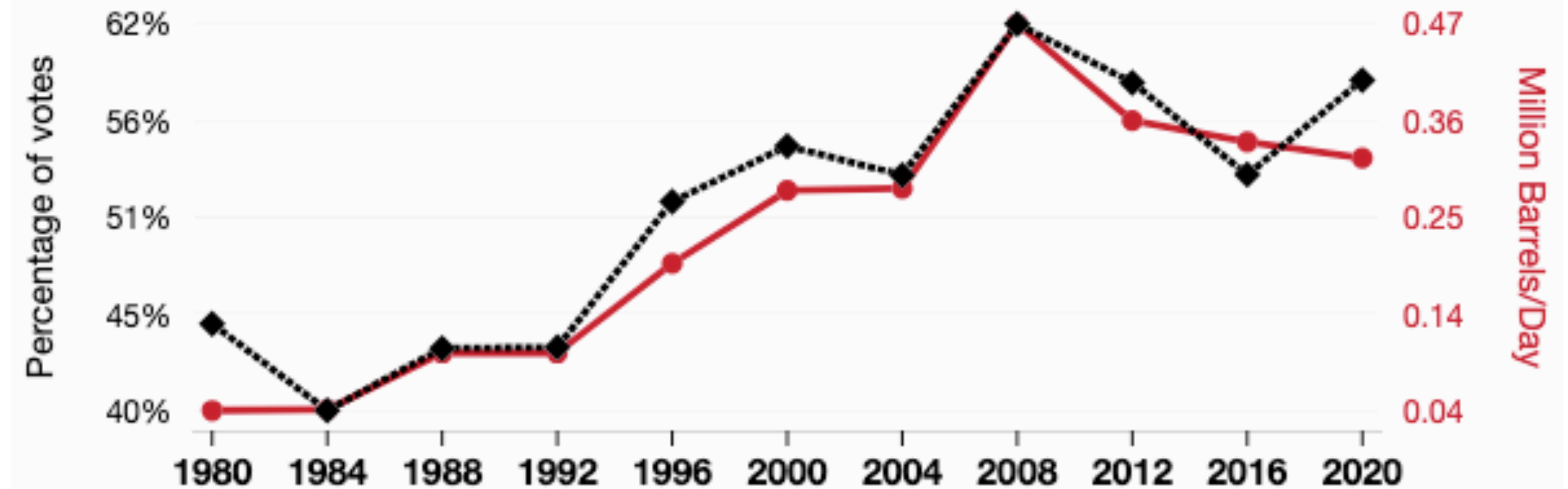
Burglaries in New Hampshire



Votes for the Democratic Presidential candidate in Delaware

correlates with

Jet fuel used in Greenland



◆ Percentage of all votes cast for the Democrat Presidential candidate in Delaware

· Source: MIT Election Data and Science Lab, Harvard Dataverse

● Volume of jet fuel used consumed in Greenland in millions of barrels per day

· Source: Energy Information Administration

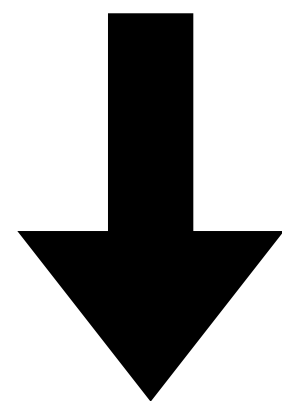
1980-2020, $r=0.958$, $r^2=0.917$, $p<0.01$ · tylervigen.com/spurious/correlation/4541

Data scientists are **not** domain experts

(Unfortunately)

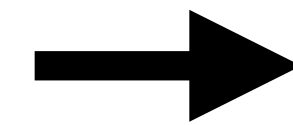
Meaningful relationship?

Is the correlation 'silly'? I don't know!

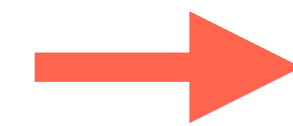


Statistics gives an answer

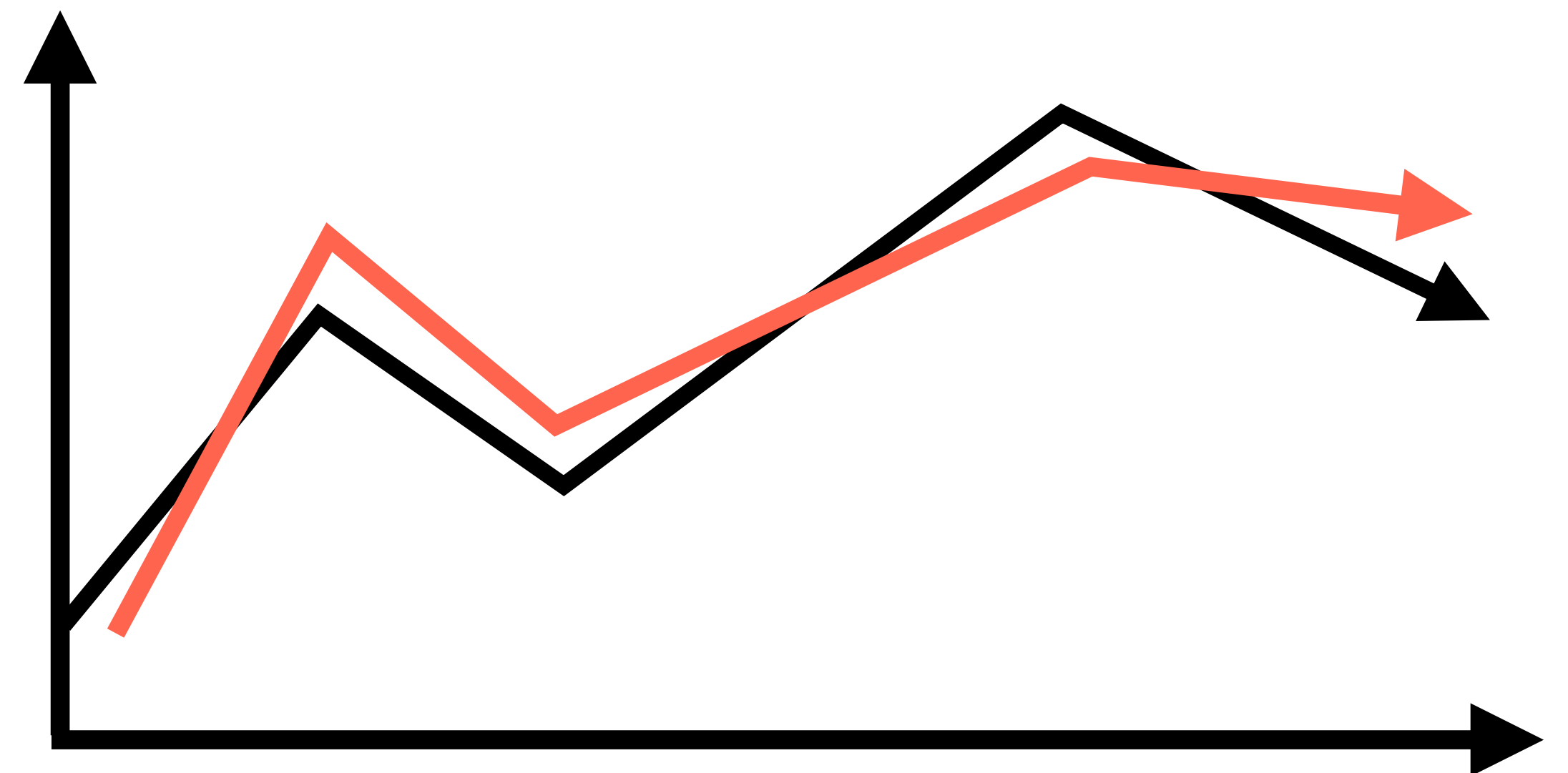
Sometimes it's even correct!



Something complicated
I don't really understand



Another complicated thing



Experiments

A process with
uncertain outcomes

Data scientist

Measure population's credit card scores

Climate scientist

Measure tomorrow's weather

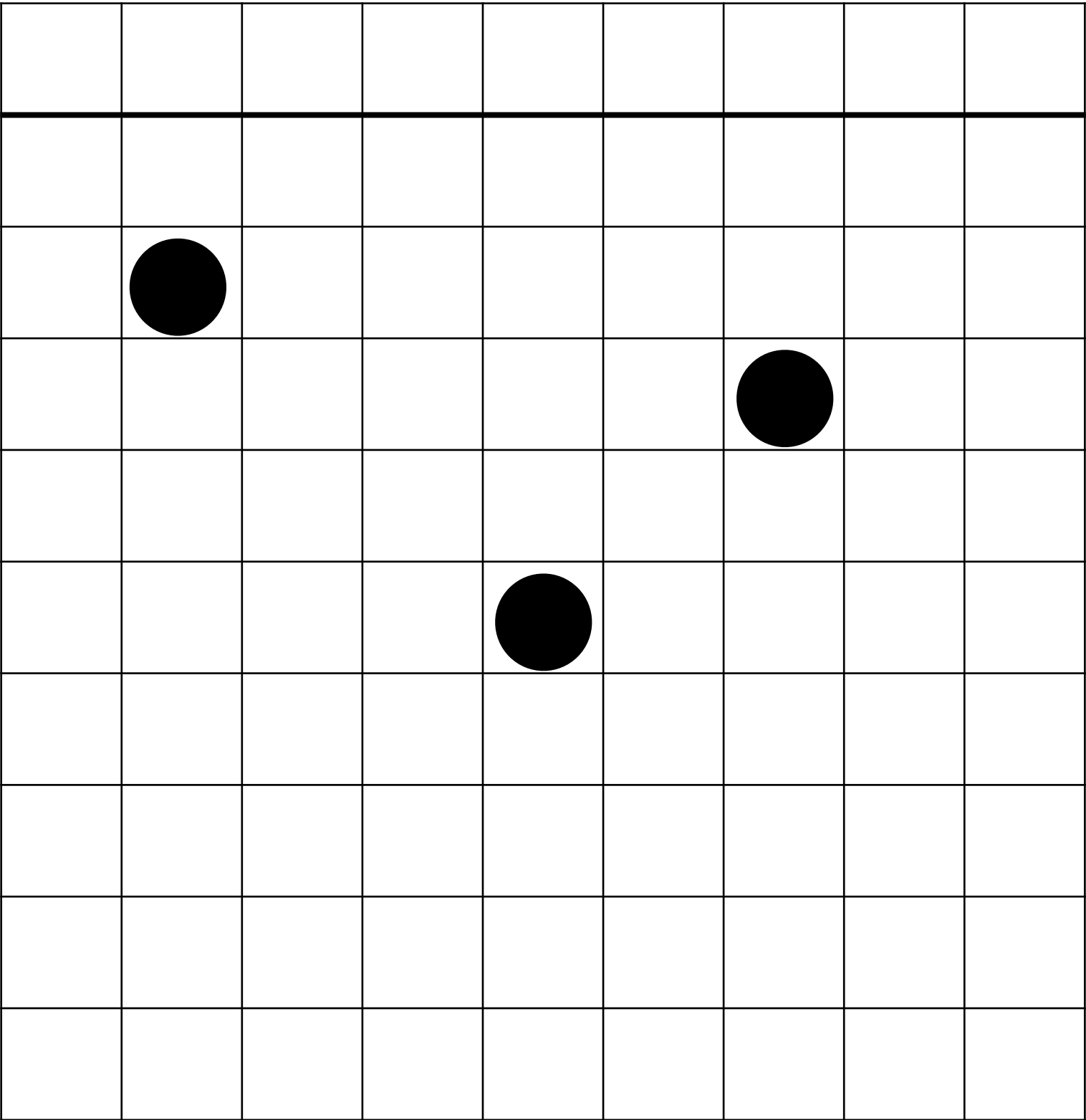
and they all need...

Mathematical framework to deal with
characterising and quantifying
uncertain events

(Probability theory)

Lecture theatre next week

● = Empty seat

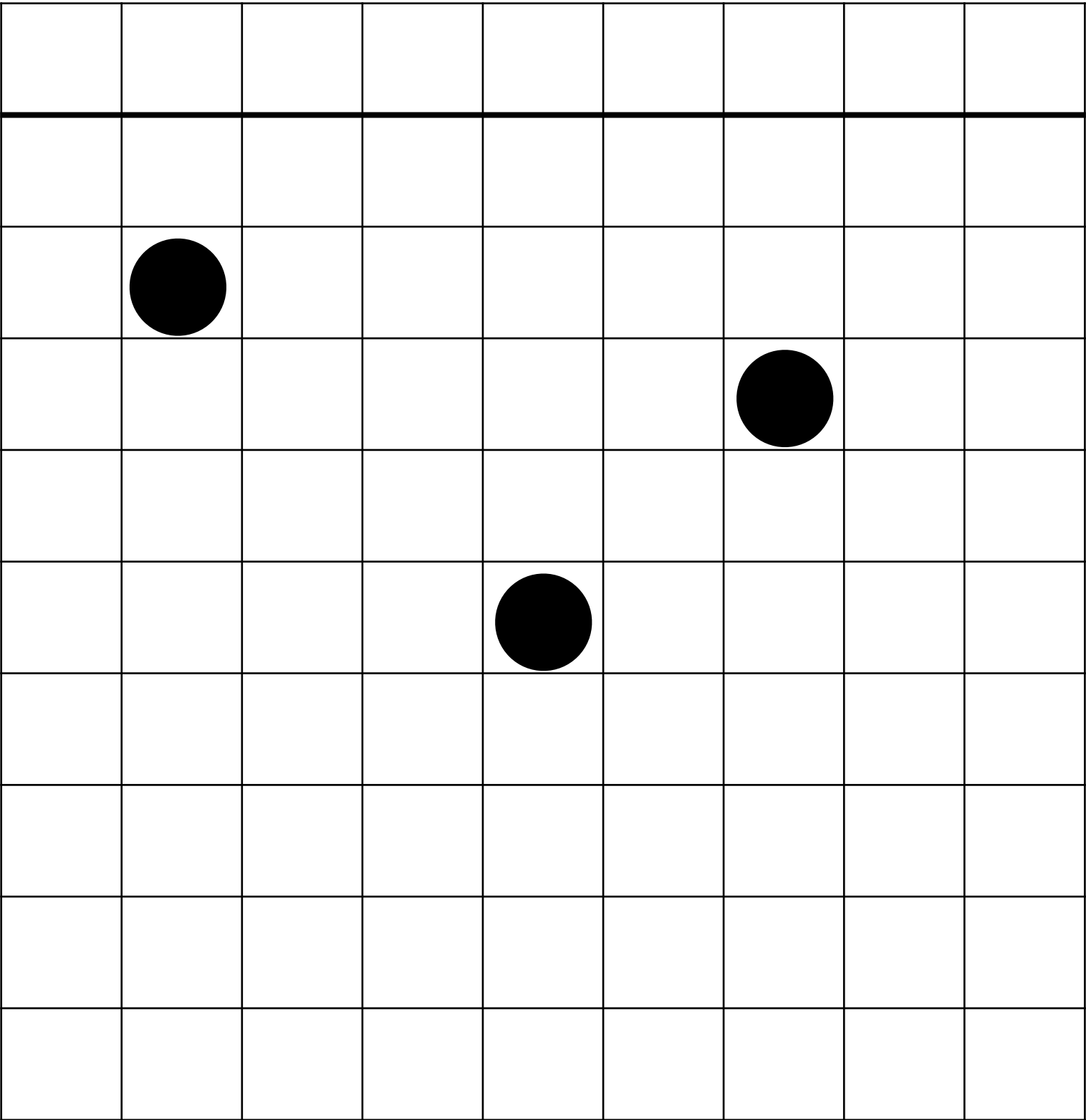
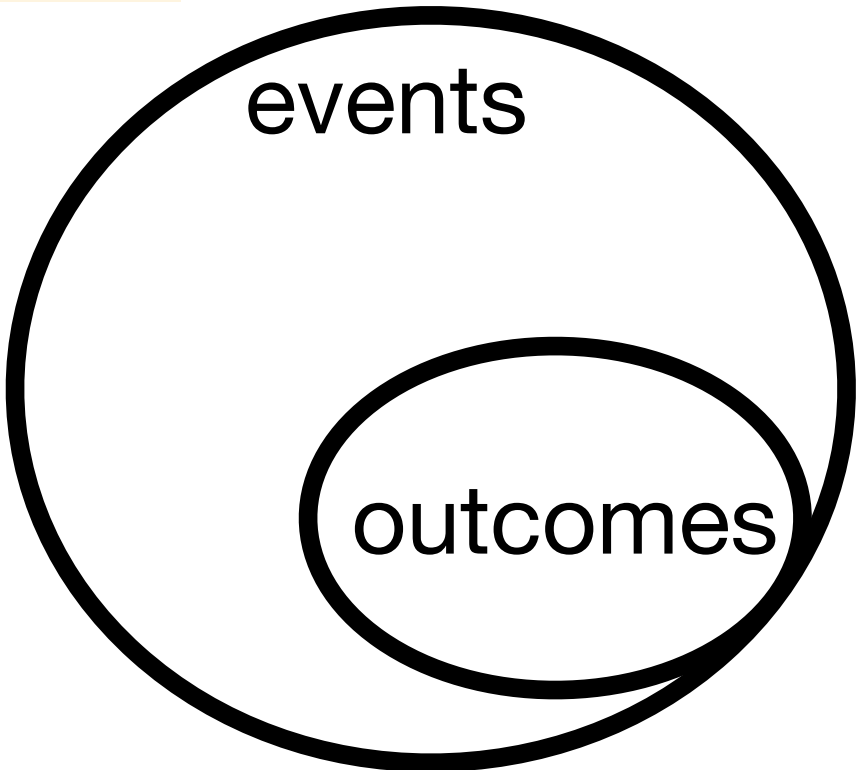


Lecture theatre next week

Formal terminology

Each seating combination
is an **outcome**

Combinations of
outcomes are
events



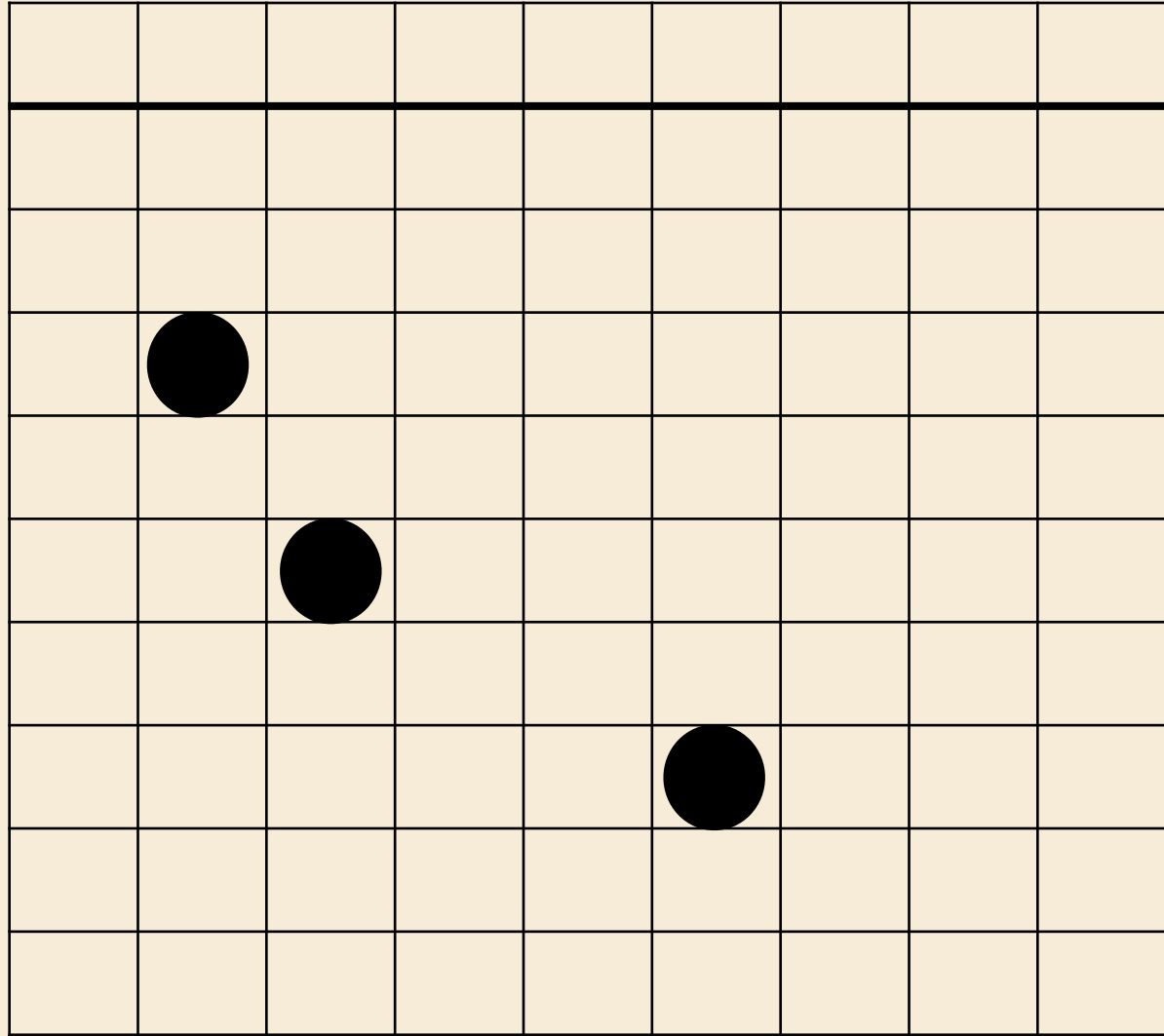
Events are sets of outcomes

↑
i.e. collections

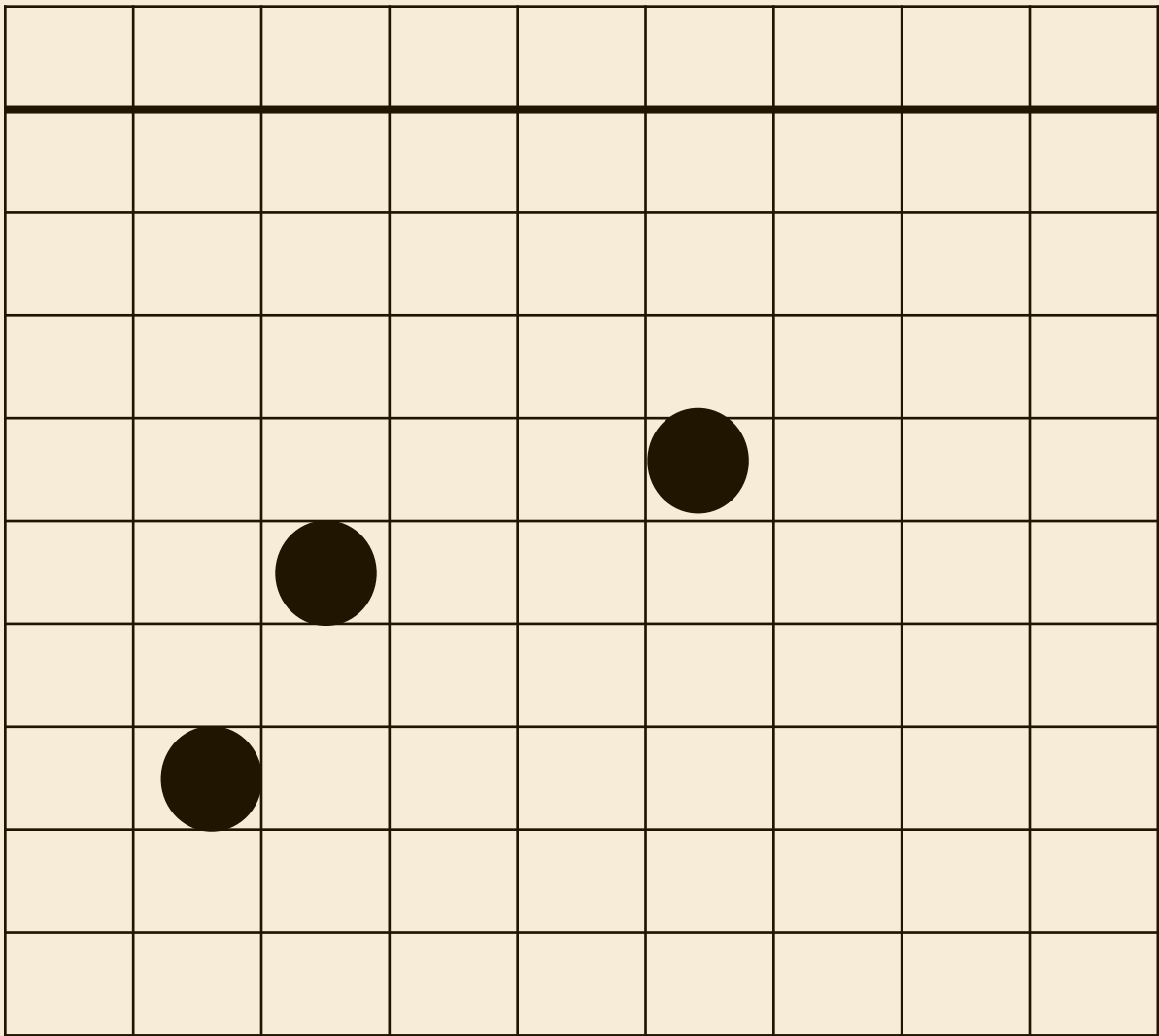
Curly braces denote
sets in maths notation

Event: the back row is completely filled

Outcome



Outcome



Events have a **set algebra**

Algebra

Rules for elements to
interact with each other

...and make babies!

Numbers

$$x + y = z \leftarrow \text{Also a number!}$$

$$x - y = z$$

$$x * y = z$$

“plus, minus, times”

Events have a **set algebra**

Algebra

Rules for elements to
interact with each other

...and make babies!

Events

$$X \cup Y = Z$$

Union (or)

$$X \cap Y = Z$$

Intersection (and)

$$X \setminus Y = Z$$

Complement (not/without)

Questions for the audience

Event X: the back row is completely filled

Event Y1: the front row is completely filled

Event Y2: the back row is partially filled

Express (+ simplify) as English sentences:

$$X \cap Y_1$$

$$X \cap Y_2$$

$$X \cup Y_1$$

$$X \cup Y_2$$

$$X \setminus Y_1$$

$$X \setminus Y_2$$

\cup = 'or'

\cap = 'and'

\setminus = 'without'

Questions for the audience

Event X: the back row is completely filled

Event Y1: the front row is completely filled

Event Y2: the back row is partially filled

Express (+ simplify) as English sentences:

$$X \cap Y_1$$

$$X \cap Y_2 = X$$

$$X \cup Y_1$$

$$X \cup Y_2 = X$$

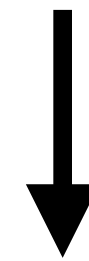
$$X \setminus Y_1$$

$$X \setminus Y_2 = \emptyset$$

————— The empty set. Learn this notation!

Each event has a **probability**

Event: the back row is completely filled



Probability 0.3

Probability function

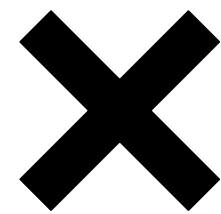
$\mathbb{P} : \text{events} \rightarrow [0,1]$

$0 \leq \mathbb{P}(x) \leq 1$

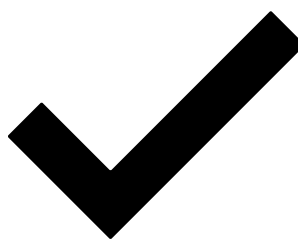
What does it mean to have a probability?

Probability is a way of expressing **partial** knowledge of an event

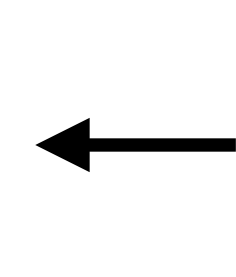
With enough knowledge and insight, could I predict tomorrow's weather without uncertainty?



Correct probability



Best probability given my knowledge of the world



Subjective!

Probability Space

is three things:

$$(\Omega, \mathcal{F}, \mathbb{P})$$


Sample space:
the set containing all
possible outcomes

Event space:
the set containing all possible
events (combinations of outcomes)

Probability function:
Assigns a probability to
every single event

Probability Space

for next week's lecture seating:

$$(\Omega, \mathcal{F}, \mathbb{P})$$

Sample space:

Every possible seating combination

Probability function:

Assigns a probability to every single event

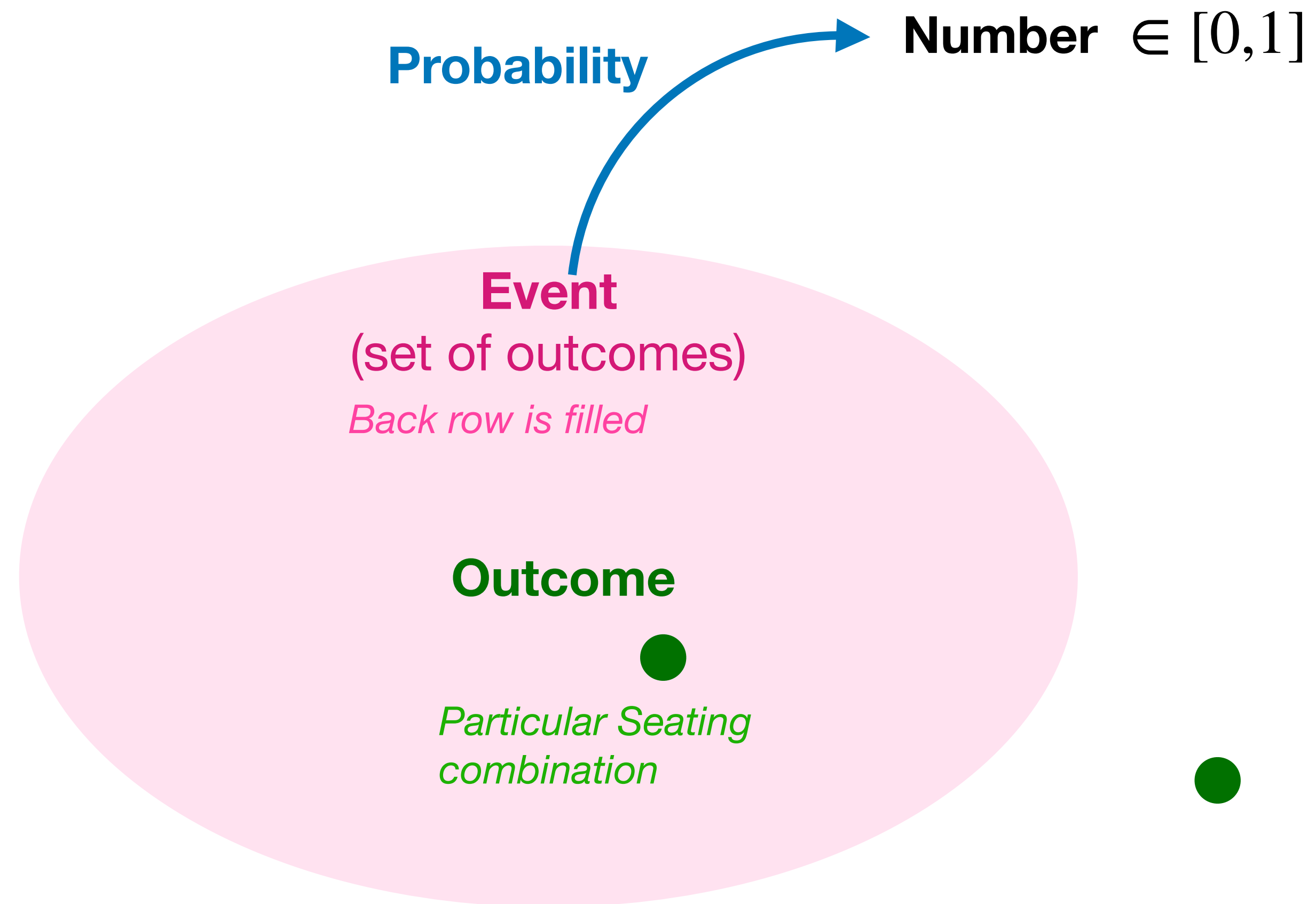
Event space:

Sets of seating combinations

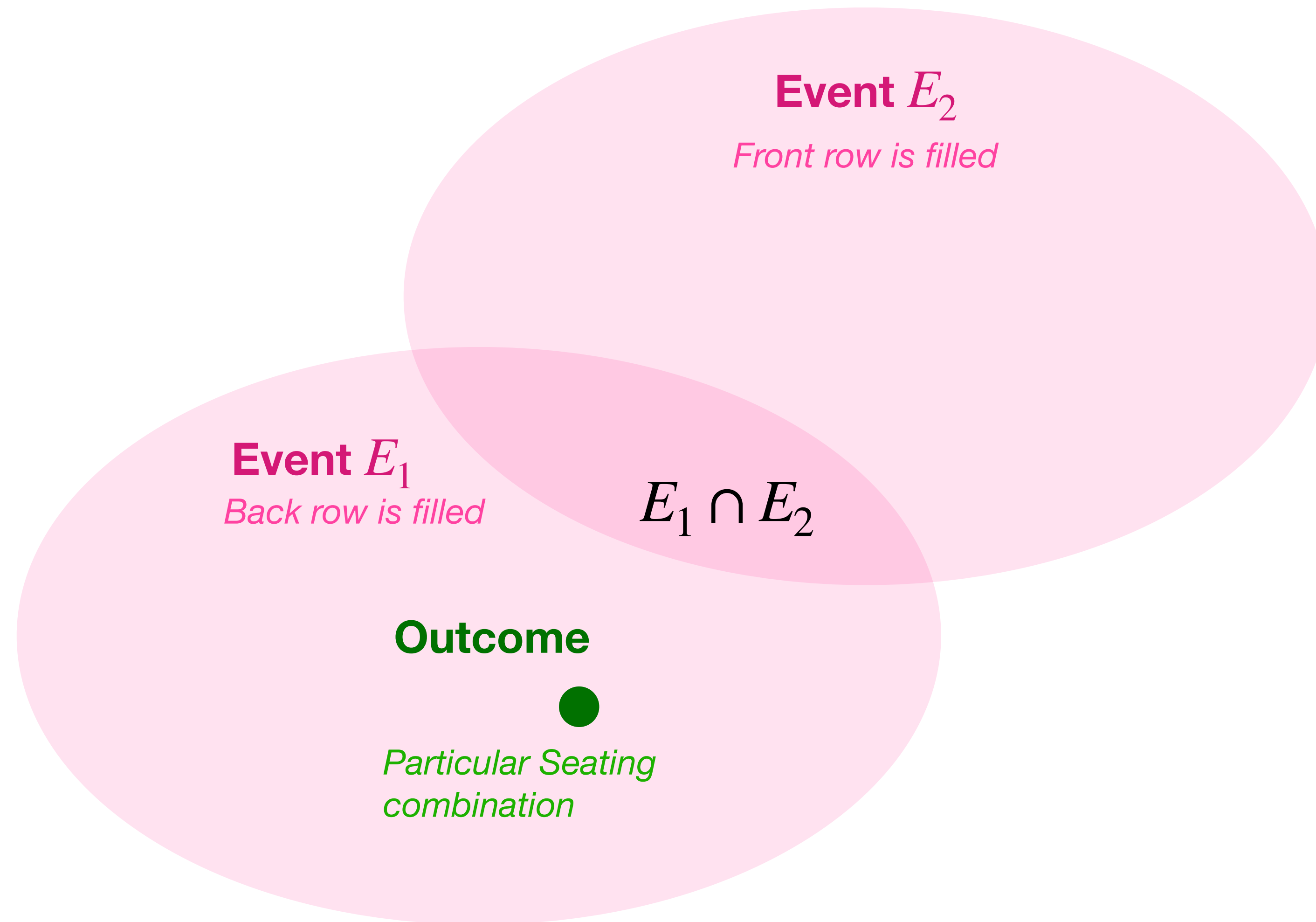
Example set:

All seating combinations where the back row is filled

Ω : event of all outcomes



Ω : event of all outcomes



\cap : and

\cup : or

Ω : event of all outcomes

Event E_2

Front row is filled

Event E_1

Back row is filled

$E_1 \cap E_2$

Outcome

●
*Particular Seating
combination*

$$\mathbb{P}[E_1 \cup E_2] =$$

$$\mathbb{P}[E_1] + \mathbb{P}[E_2] - \mathbb{P}[E_1 \cap E_2]$$

P(back OR front row filled)

=

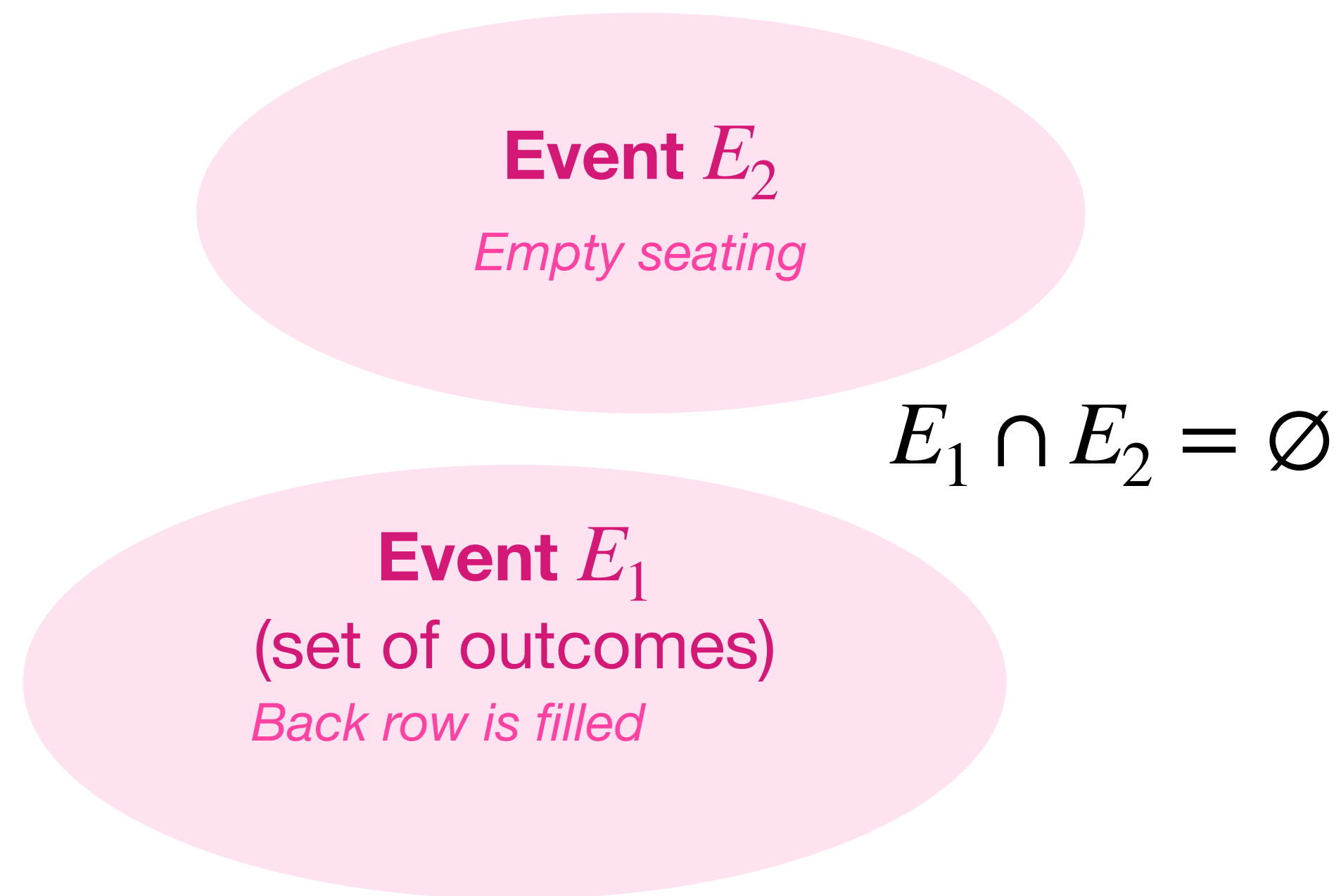
P(back row filled) +

P(front row filled) -

P(both filled)

Mutually exclusive events

Ω : event of all outcomes



$$\mathbb{P}[E_1 \cup E_2] =$$

$$\mathbb{P}[E_1] + \mathbb{P}[E_2] - \mathbb{P}[E_1 \cap E_2]$$

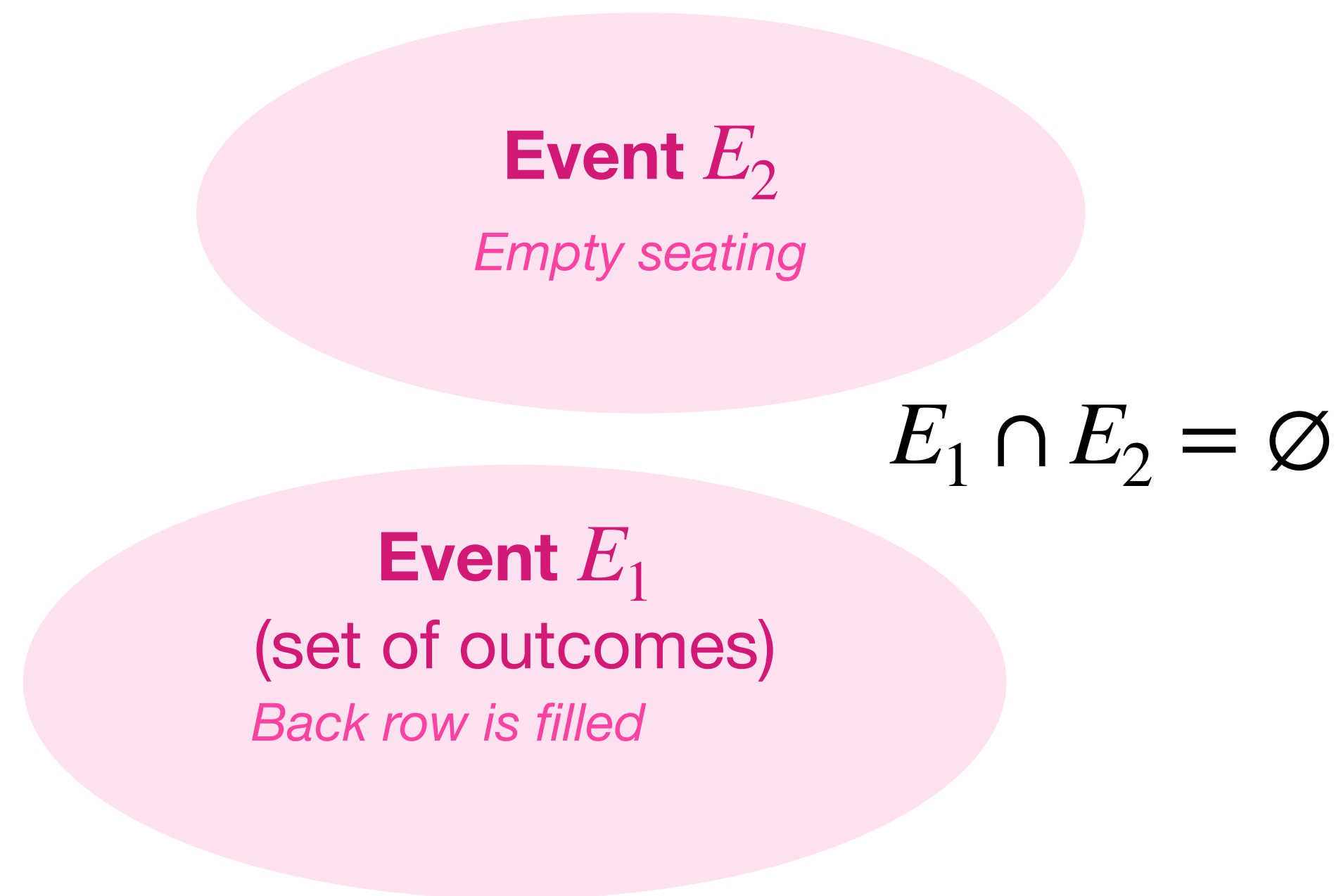
Condition for mutually exclusive events:

$$\mathbb{P}[E_1 \cap E_2] = 0$$

(They can't both happen at the same time)

Mutually exclusive events

Ω : event of all outcomes



$$\mathbb{P}[E_1 \cup E_2] =$$

$$\mathbb{P}[E_1] + \mathbb{P}[E_2] - \mathbb{P}[E_1 \cap E_2]$$

Equivalent condition for mutually exclusive events

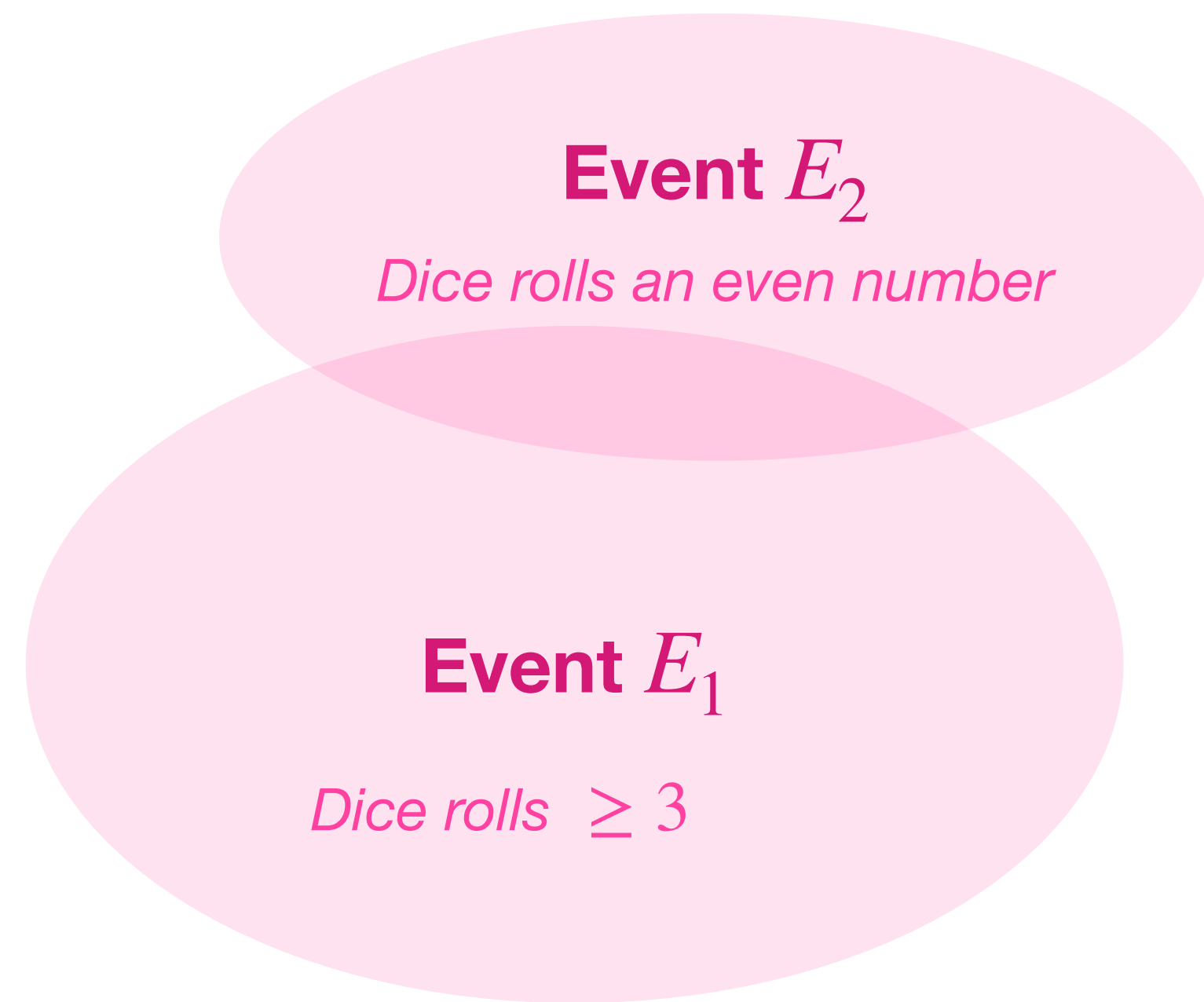
$$\mathbb{P}[E_2 | E_1] = \mathbb{P}[E_1 | E_2] = 0$$

“ E_2 given E_1 ”

“Conditional probability”

Independent events are **not** mutually exclusive

Ω : event of all outcomes



Independent?

Independent events definition:

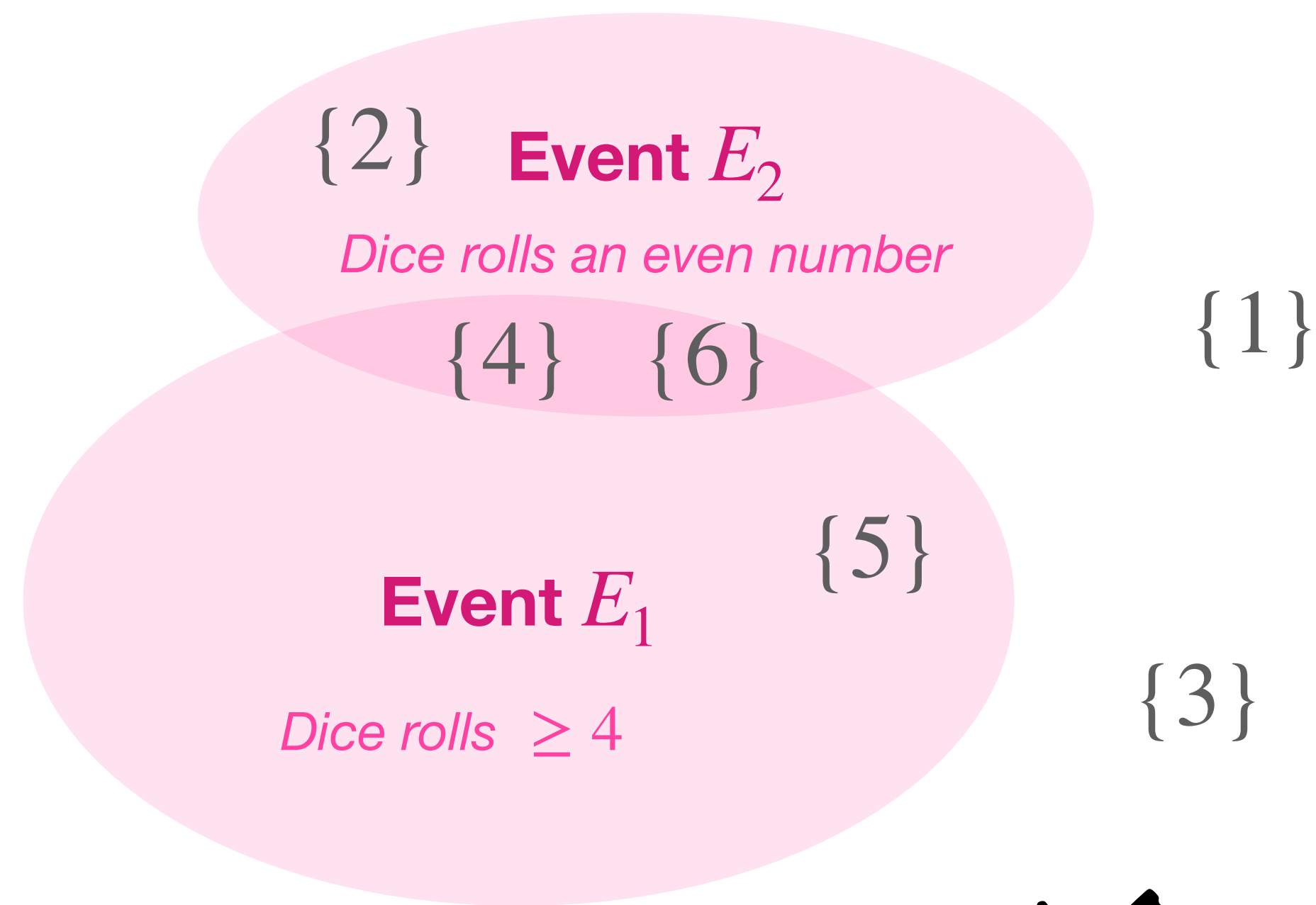
Knowledge of one outcome doesn't change probability of another

$$\mathbb{P}[E_2 | E_1] = \mathbb{P}[E_2]$$

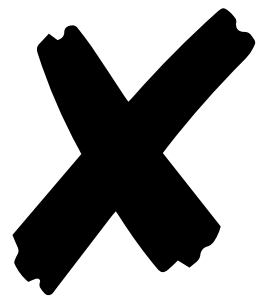
$$\mathbb{P}[E_1 | E_2] = \mathbb{P}[E_1]$$

Independent events are **not** mutually exclusive

Ω : event of all outcomes



Independent?



Independent events definition:

Knowledge of one outcome doesn't change probability of another

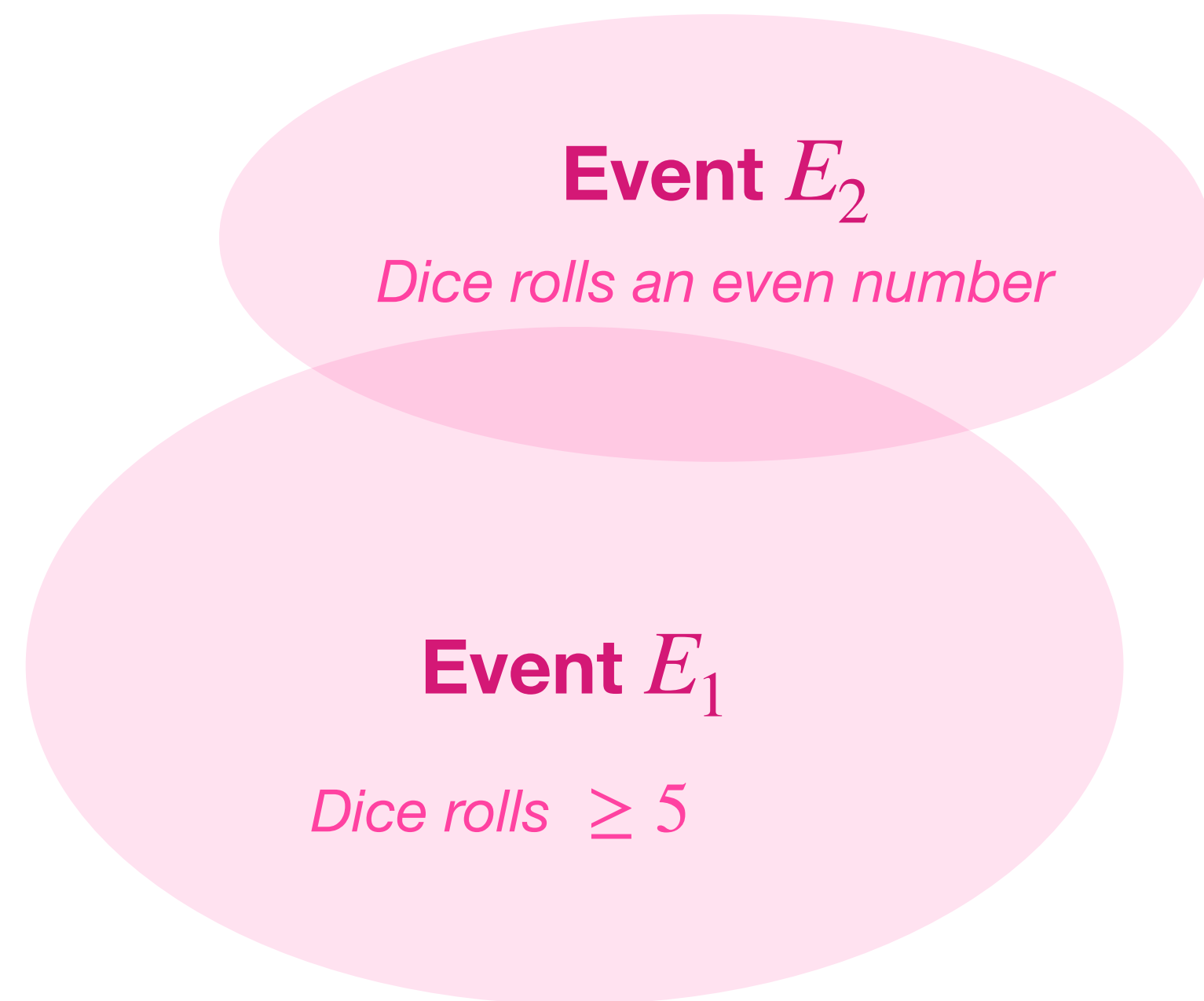
$$\mathbb{P}[E_2 | E_1] = \mathbb{P}[E_2] = 0.5$$

$$\mathbb{P}[E_1 | E_2] = \frac{2}{3}$$

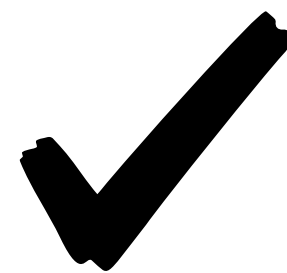
$$\neq \mathbb{P}[E_1] = 0.5$$

Independent events are **not** mutually exclusive

Ω : event of all outcomes



Independent?



Independent events definition:

Knowledge of one outcome doesn't change probability of another

$$\mathbb{P}[E_2 | E_1] = \mathbb{P}[E_2] = 0.5$$

$$\mathbb{P}[E_1 | E_2] = \mathbb{P}[E_1] = \frac{1}{3}$$

Independent? Mutually exclusive?



\subset = 'subset'

E^c = 'not (complement) E '

Experiment: take two balls from bag

E_1 : First ball is blue

E_2 : Second ball is green

E_3 : First ball is big

Questions:

$E_3 \subset E_1$?

$E_2 \subset E_1$?

$\mathbb{P}[E_2 | E_1] = ?$

$\mathbb{P}[E_3 | E_1] = ?$

$E_1^c \cap E_3$?

$\mathbb{P}[E_3 \cup E_1]$?

Independent? Mutually exclusive?



\subset = 'subset'

E^c = 'not (complement) E '

Experiment: take two balls from bag

E_1 : First ball is blue

E_2 : Second ball is green

E_3 : First ball is big

Questions:

$$E_3 \subset E_1$$

$$\mathbb{P}[E_2 | E_1] = 0.5$$

$$E_1^c \cap E_3 = \emptyset$$

$$E_2 \subset E_1$$

$$\mathbb{P}[E_3 | E_1] = \frac{1}{3}$$

$$\mathbb{P}[E_3 \cup E_1] = \frac{3}{5}$$

Random variables

are quantitative questions
about the experiment

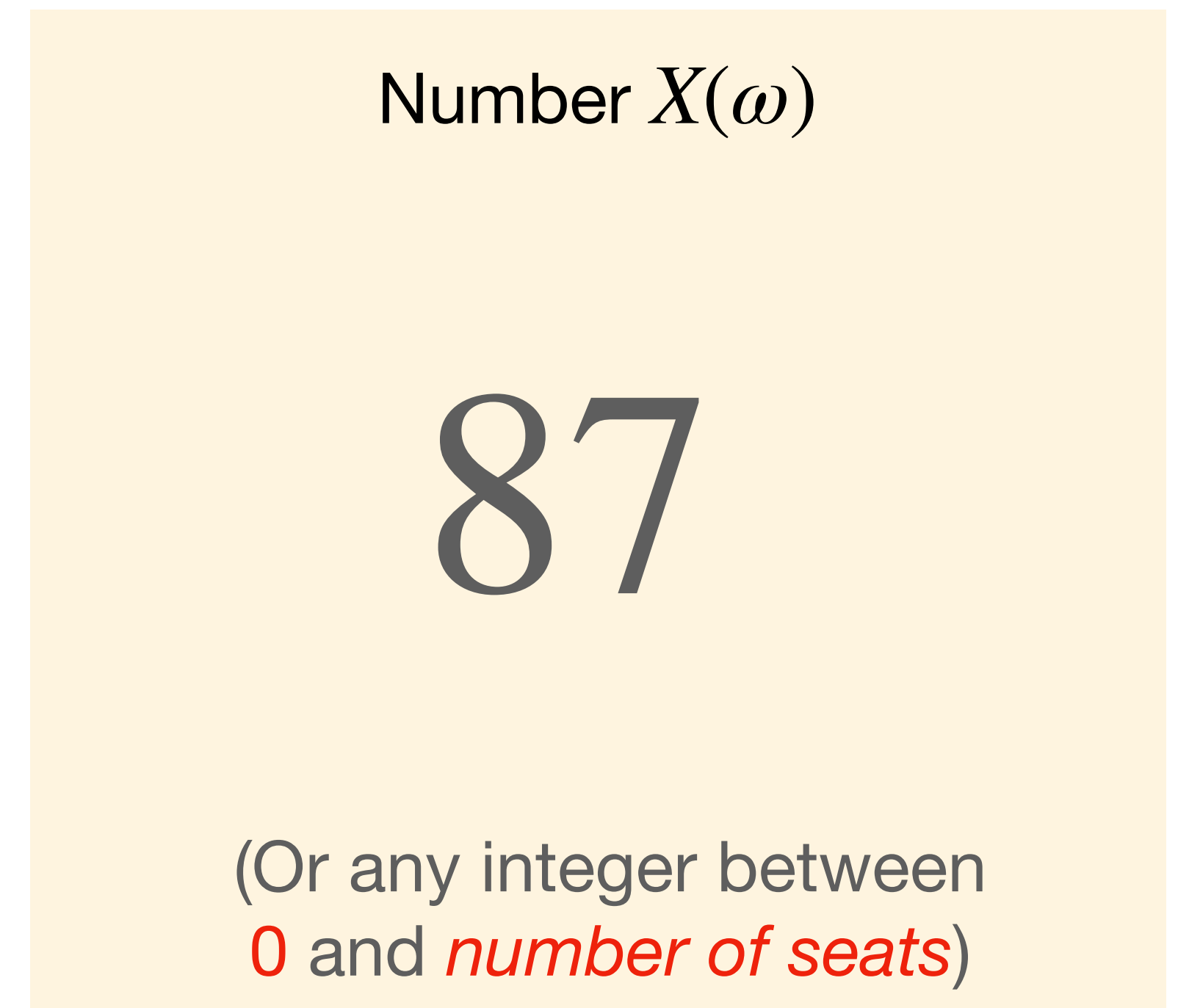
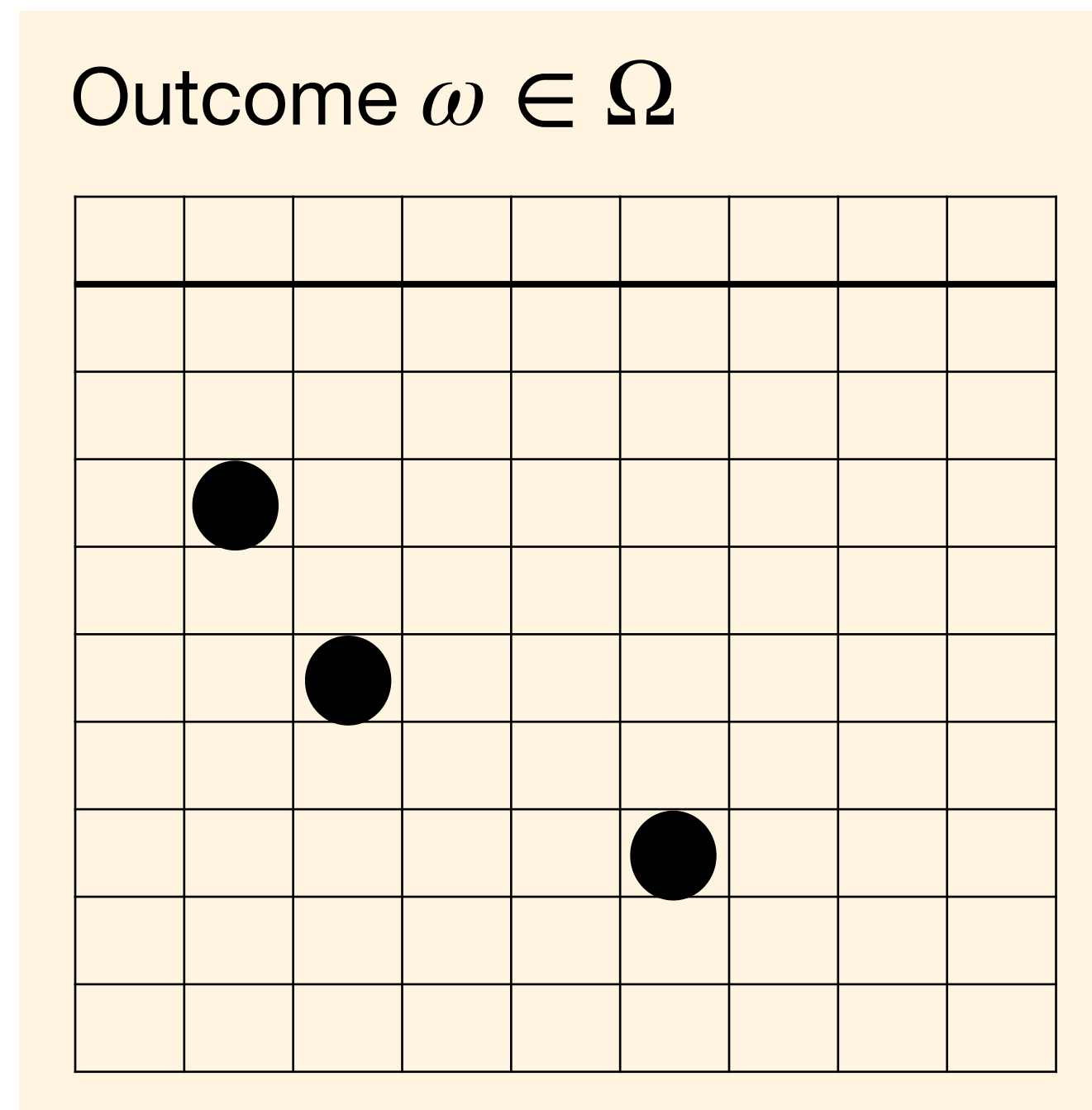
Random variables

are **quantitative questions**
about the experiment

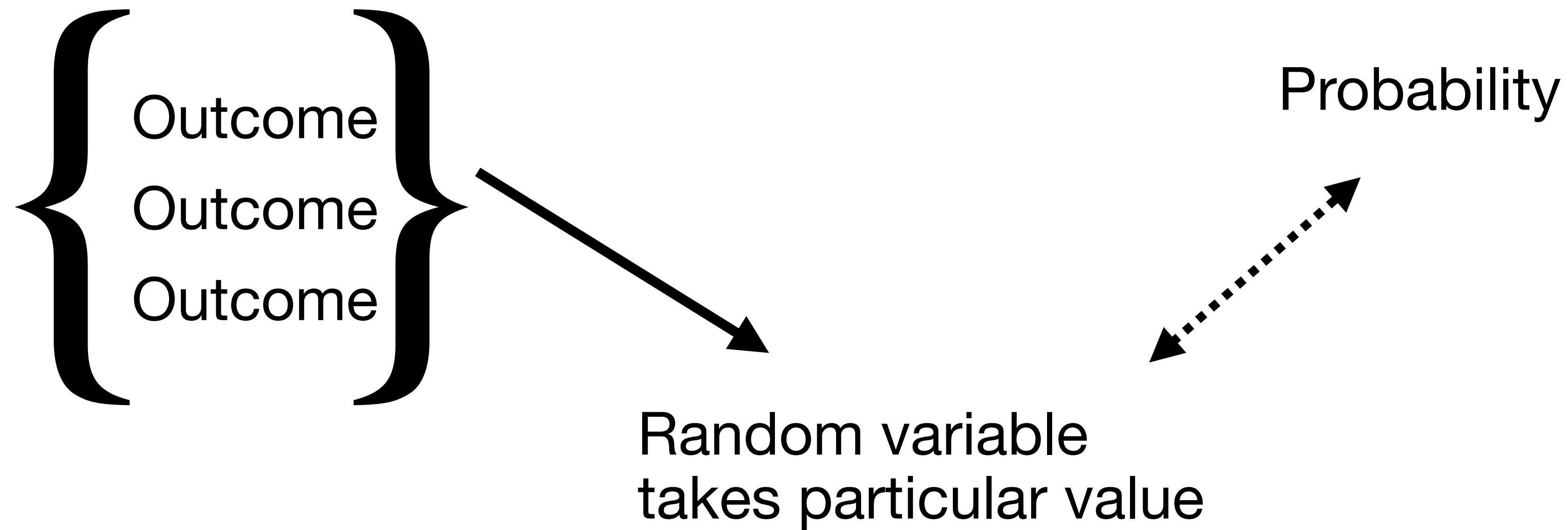
are functions that map from
outcomes to **numbers**

Random variables example

What was the number of unfilled seats? $X(\omega)$



Random variable taking value is an **event**

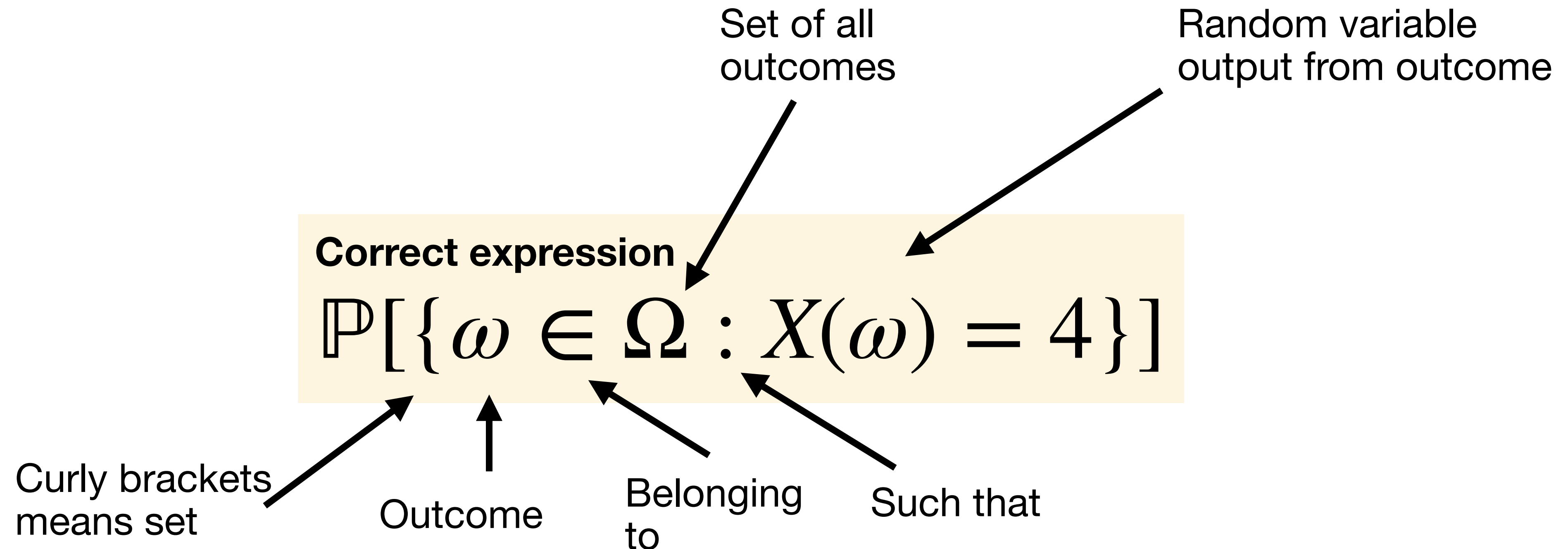


Eg { outcomes where number of unfilled seats = 87 }

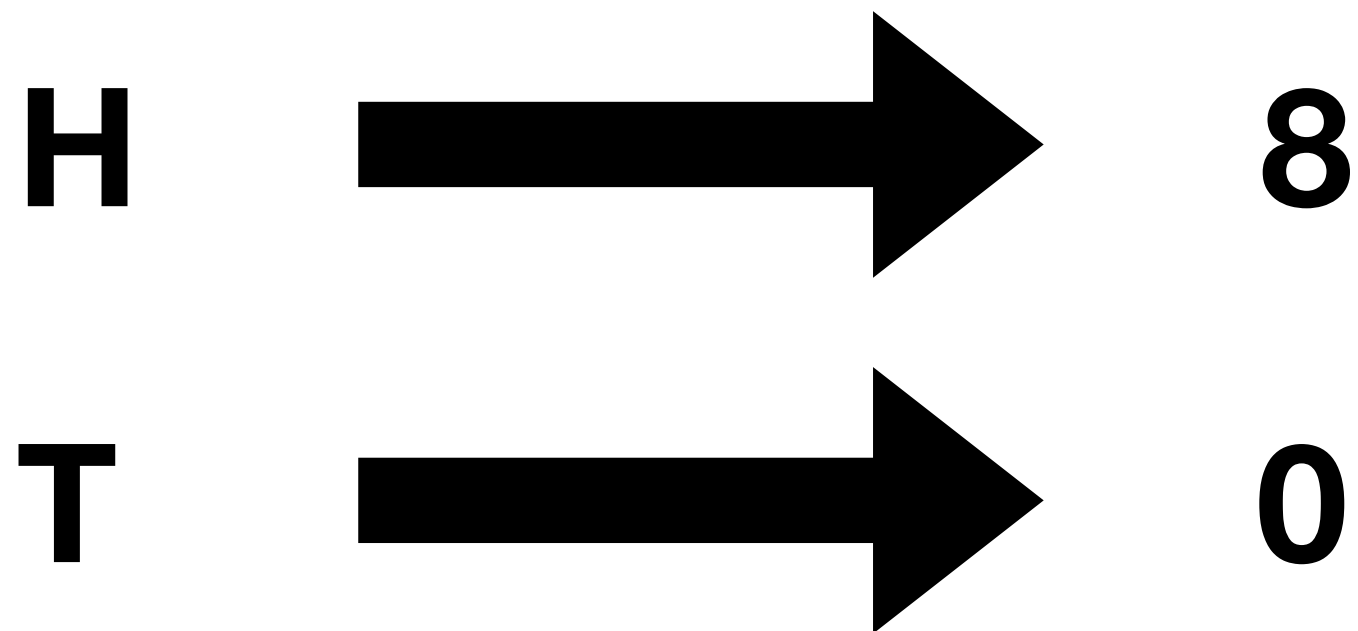
Notation

Probability of four unfilled seats?

... is an event!



Flipping a coin

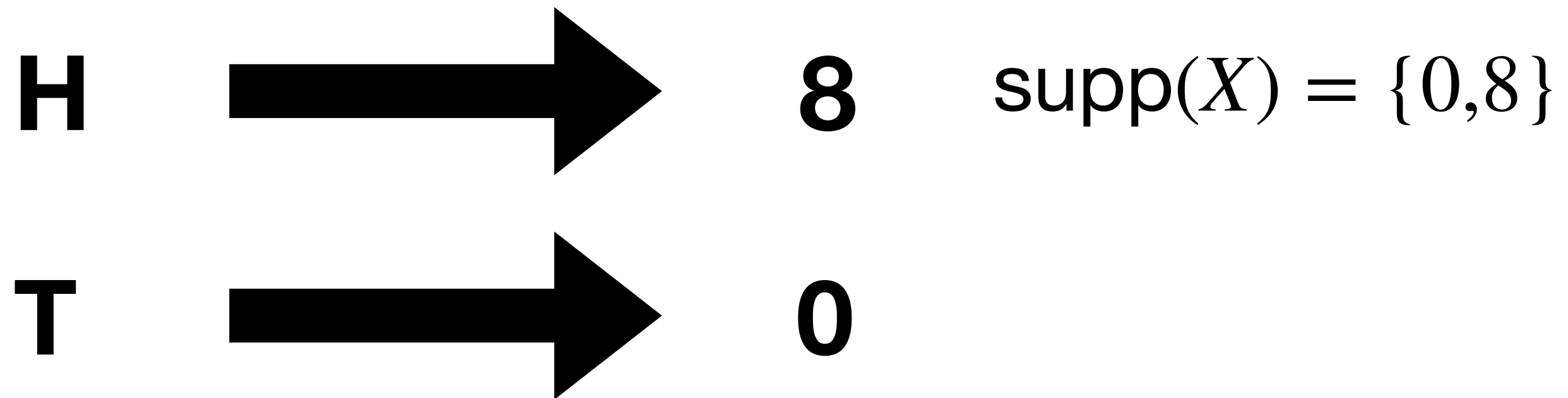


Random variable is **not**
'random'. The outcome is.

RV is the **deterministic** mapping
from 'random' outcomes to numbers

Support of a random variable

Set of **plausible** values a random variable can take



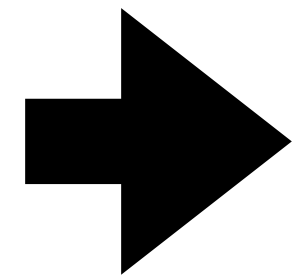
Support of a random variable

X is the number of unfilled seats

Smallest set S such that
 $\mathbb{P}[X \in S] = 1$

With probability one:

$$0 \leq X \leq \text{number of seats}$$
$$X \in \mathbb{Z}$$



$$\text{supp}(X) = \{0, 1, \dots, \text{number of seats}\}$$

Support of a random variable

Y is whether the back row is filled

What's the support of Y?

Support of a random variable

Z is height of 2nd person in 3rd row

What's the support of Z?

Support of a random variable

Z is height of 2nd person in 3rd row

What's the support of Z ?

$$\text{supp}(Z) = (l, u)$$

l : height of shortest person on course

h : height of tallest person on course

Two flavours of random variables

Support is **finite** set

—————

Discrete random variables

X is the number of unfilled seats

$$\text{supp}(X) = \{0, 1, 2, \dots, 200\}$$

Y is whether the back row is filled

$$\text{supp}(Y) = \{0, 1\}$$

Support is **infinite** set

—————

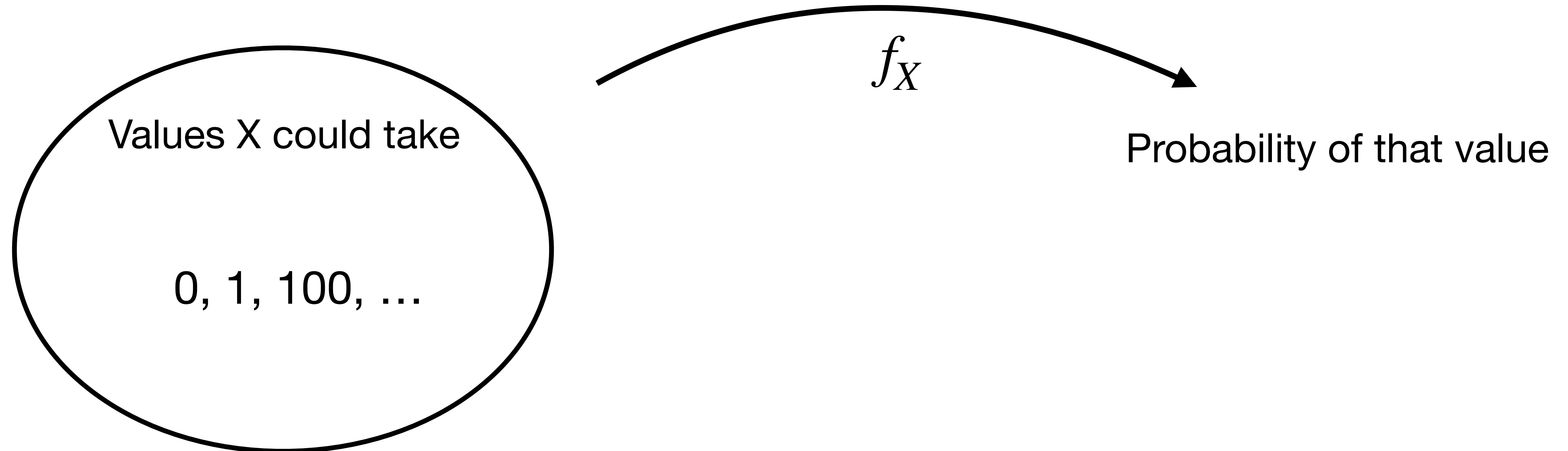
Continuous random variables

Z is height of 2nd person in 3rd row

$$\text{supp}(Z) = (l, u)$$

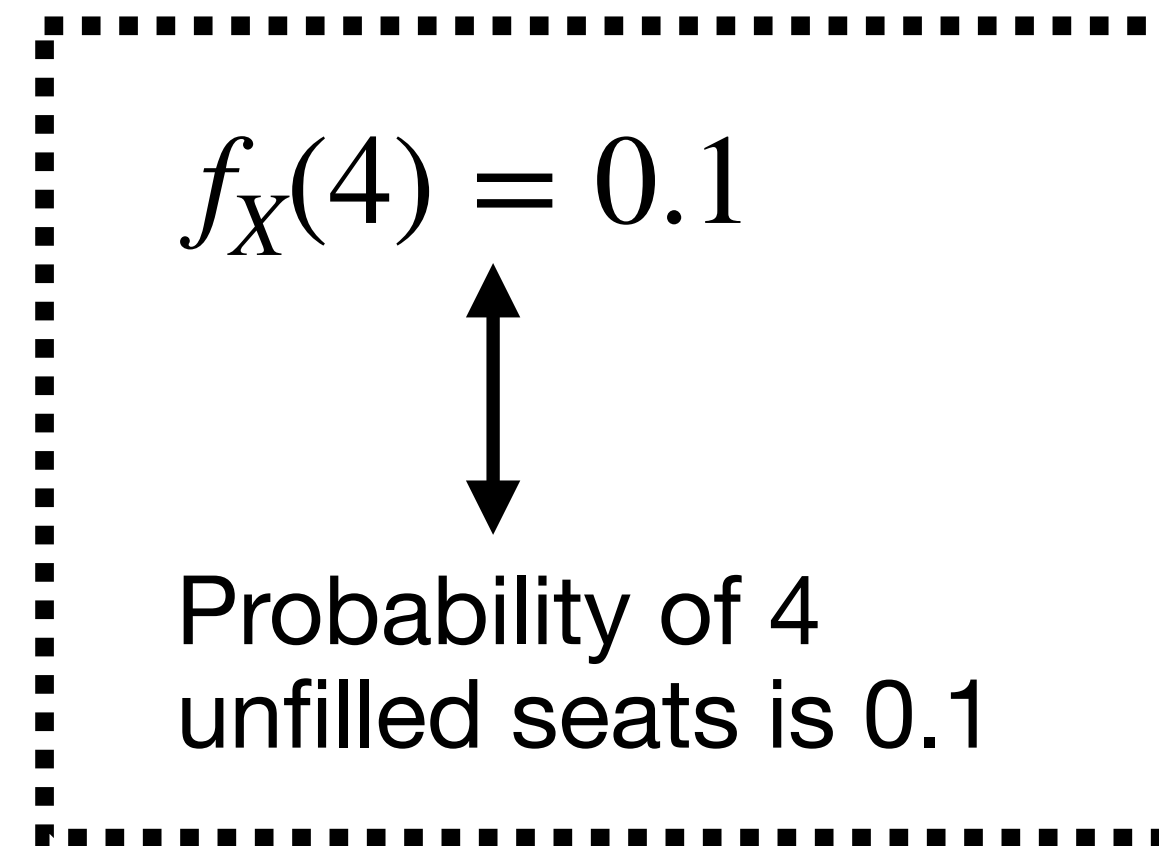
Probability mass function of a **discrete** random variable

$$f_X : \mathbb{R} \rightarrow [0,1]$$

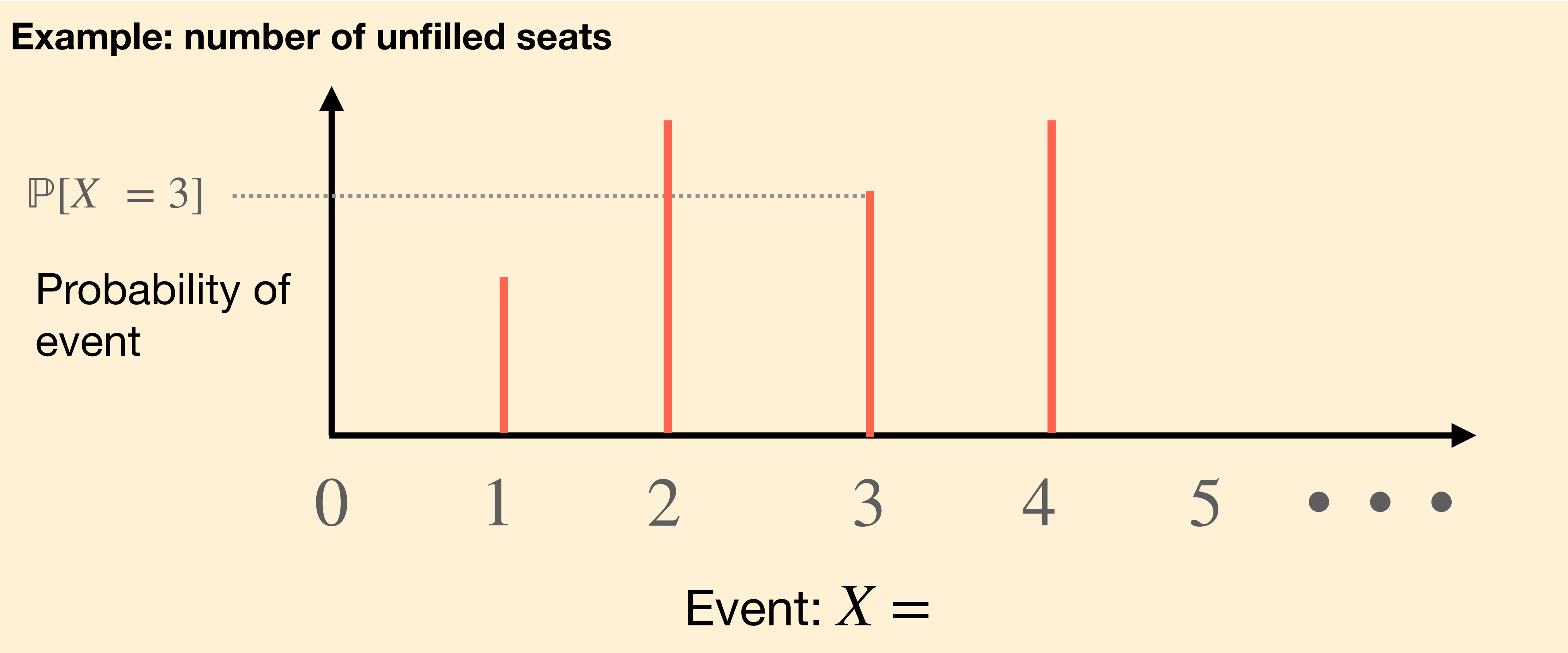


Probability mass function of a **discrete** random variable

X is the number of unfilled seats



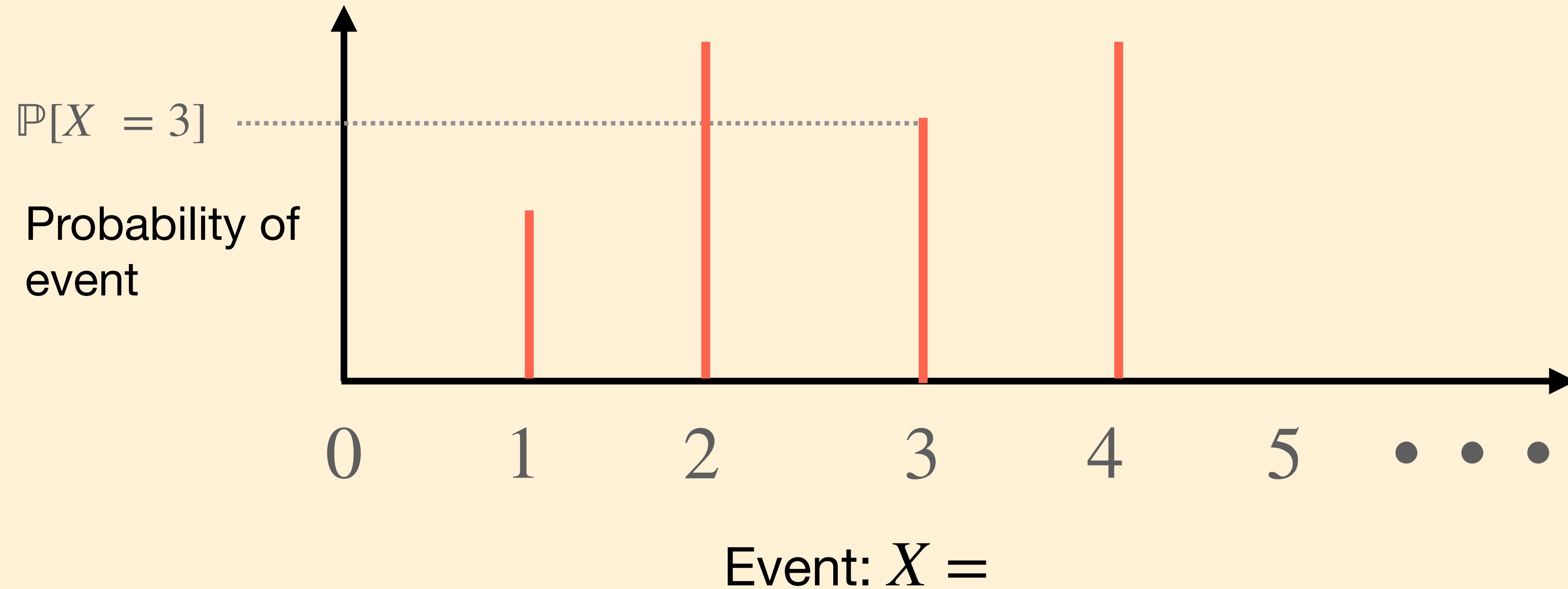
Graph of probability mass function f_X



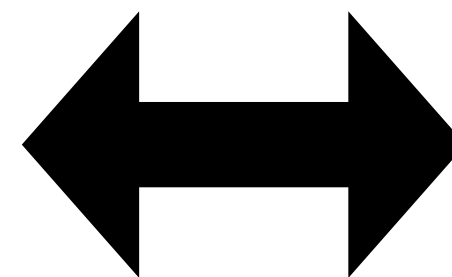
Total length of red lines?

Properties of Probability mass functions

Example: number of unfilled seats



Sum of red line lengths
adds to one



Probability of X taking
some value = 1

Random variables with particular PMFs pop up quite often, **across experiments**

We give them names

Bernoulli random variable

Random variables are
quantitative questions
about the experiment

Bernoulli random variables are
binary questions (yes/no)

*Y is whether the back row is filled
 f_Y ?*

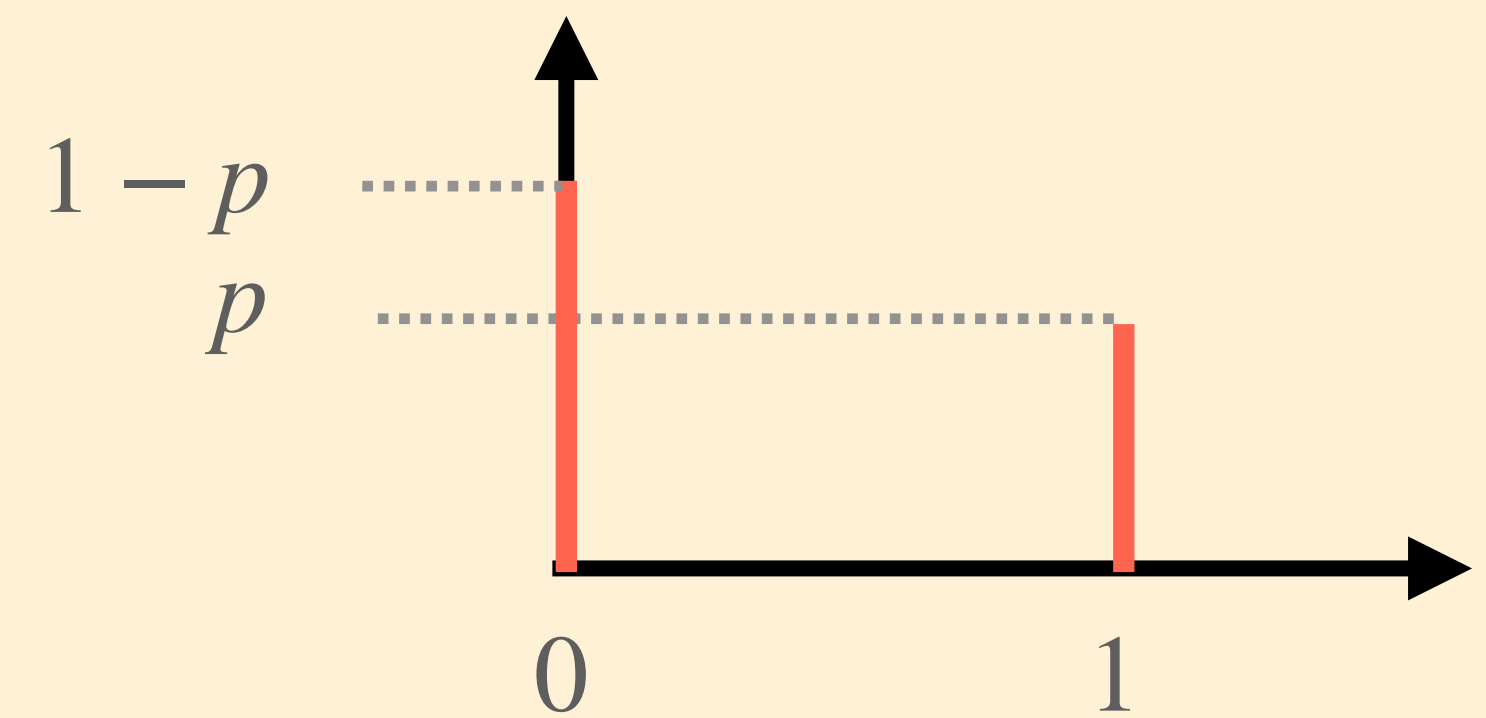
Bernoulli random variable

```
numpy.random.binomial(1,p)
```

$$Y \sim \text{Bern}(p)$$

Y is distributed as a Bernoulli random variable,
with probability p (of yes)

$$f_Y = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \end{cases}$$



Uniform random variables

`numpy.random.rand`

Probability of every outcome
in support is **equal**

*(Probably means we know very little
about experiment)*

NB: S is support

X is uniformly distributed
on the set S



$X \sim U(S)$

X is a discrete
random variable



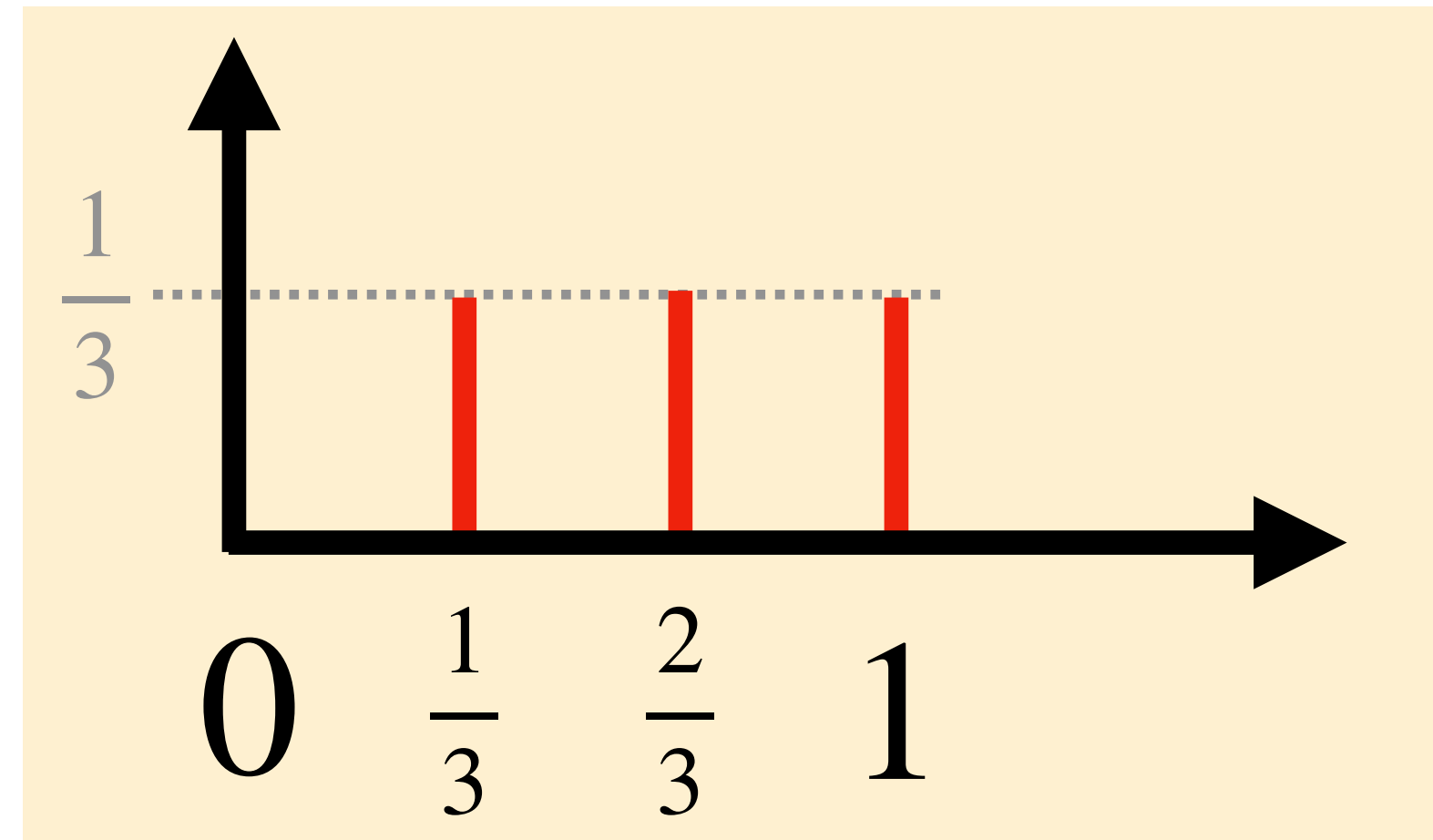
$|S| < \infty$ (Finite number of
elements in set)

Example of a Uniform random variable

$$X \sim U \left(\left\{ \frac{1}{3}, \frac{2}{3}, 1 \right\} \right)$$

NB: curly brackets
 $\{ \bullet \}$ means set

Probability
mass function



Random variable with **continuous** support

What's the probability a
human is 180cm tall?

Random variable with **continuous** support

What's the probability a
human is 180cm tall?

What's the probability a human is
180.00000000... cm tall?

Random variable with **continuous** support

Every possible (single) outcome is *impossible*

Only reasonable quantity: **ranges** of outcomes

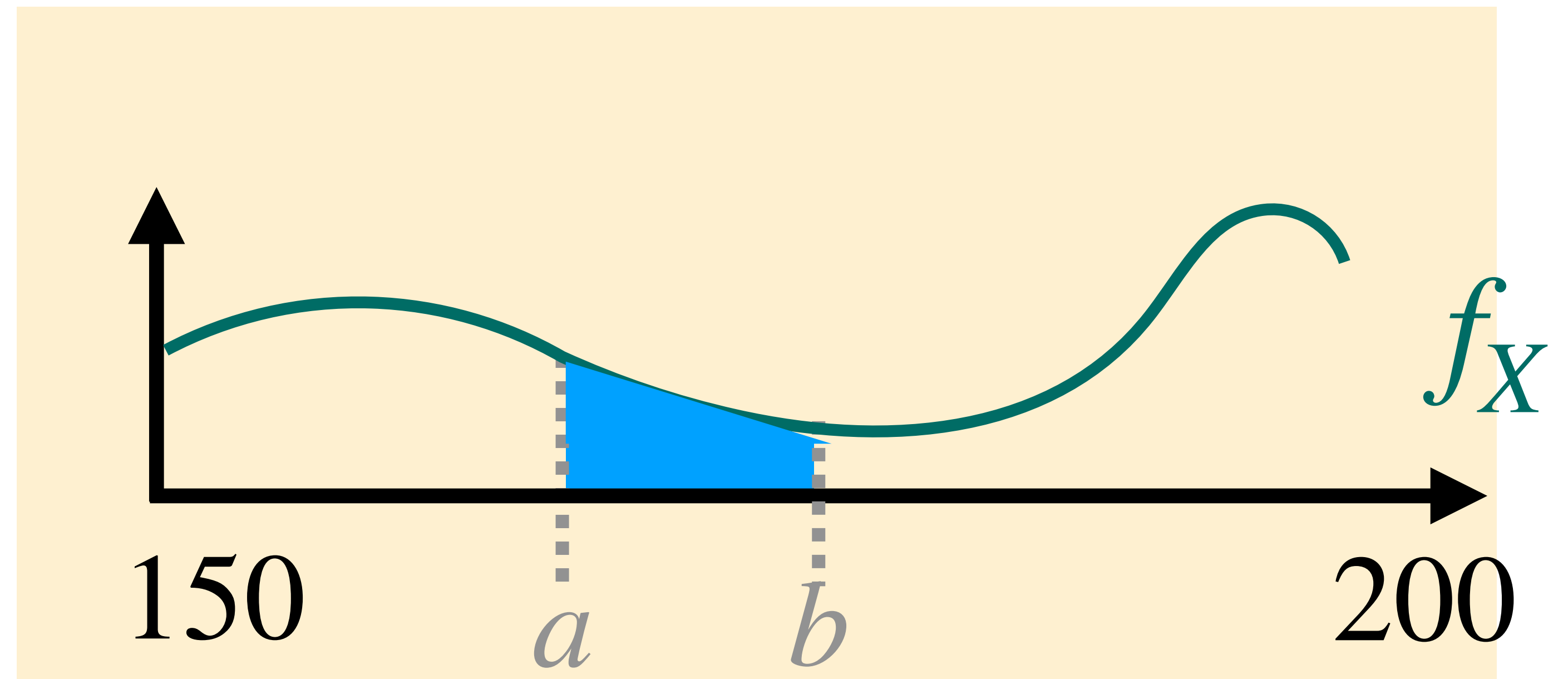
Probability density functions

Continuous random variables only

$$\mathbb{P}[X = \text{anything}] = 0$$

Instead, look for probability
 X is **between** values:

$$\mathbb{P}[a \leq X \leq b] = ?$$

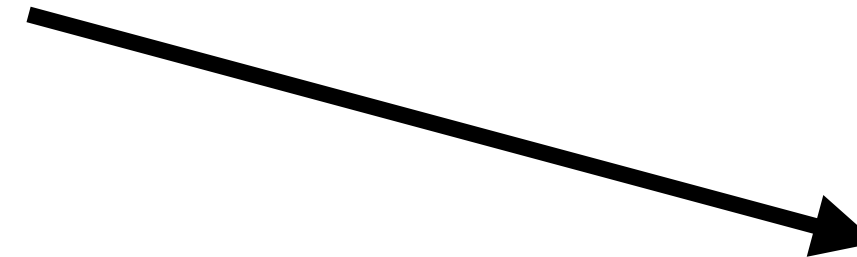


$$\mathbb{P}[x \in (a, b)] = \int_a^b f_X(x) dx$$

Catching breath

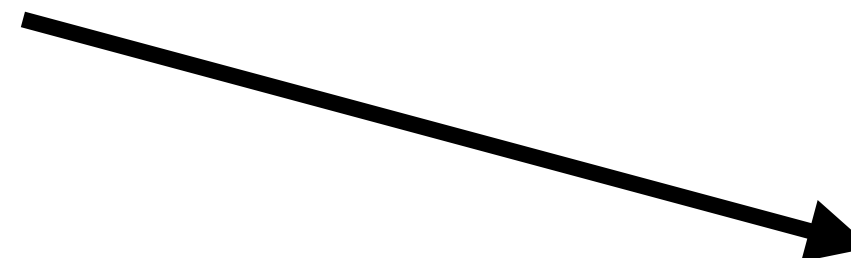
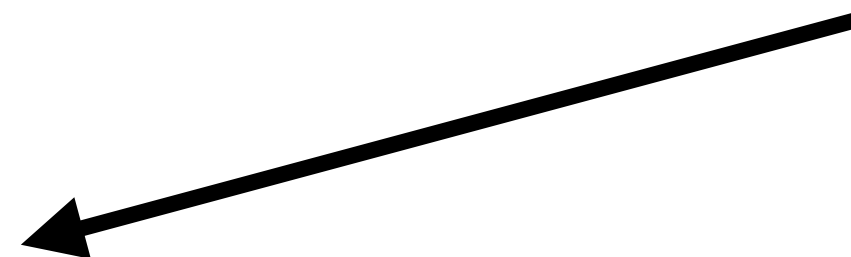
<https://www.youtube.com/watch?v=8idr1WZ1A7Q>

Experiments have
outcomes with probabilities



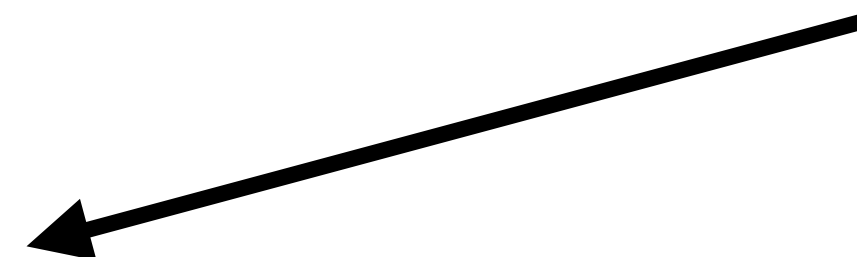
Sets of outcomes
are events

Random variables map
outcomes to values



Random variable taking
particular values is an event

PMFs/PDFS give
probabilities of such events



Next up

Statistics of random variables

Expected value

Functions of RVs

Variance

Central limit theorem

Conditional probability

Independent events

Bayes' law

Recap: probability space

Can only talk about probabilities
when you have an **experiment**

Experiments have
outcomes

Sets of outcomes
are **events**

All events have
probabilities

Experiment: tomorrow's midday temperature

Number
 $\in [0,1]$

Ω : All possible outcomes
(is event)

Probability

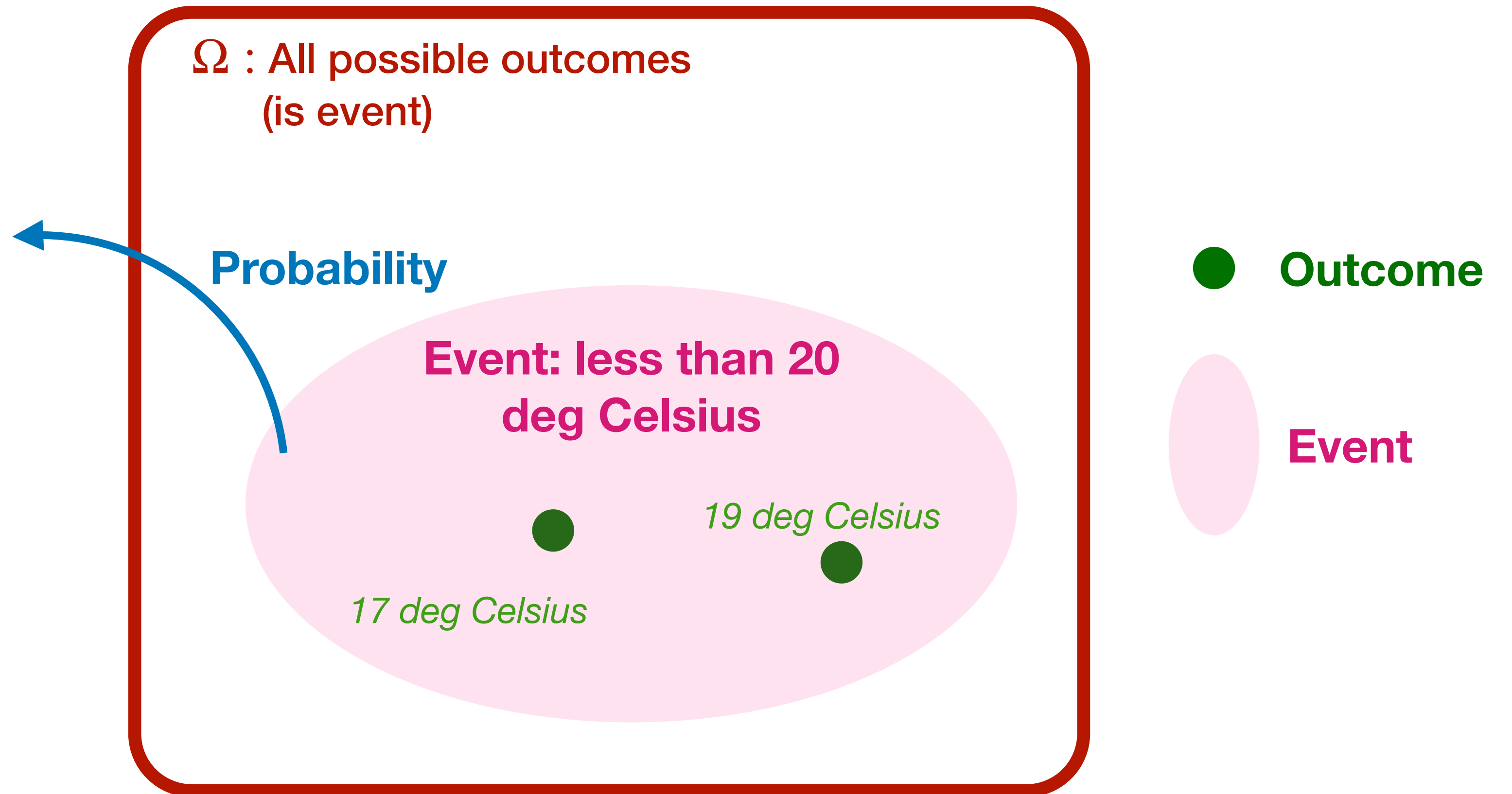
**Event: less than 20
deg Celsius**

17 deg Celsius

19 deg Celsius

● **Outcome**

Event



Random variables

Recap

are **quantitative questions**
about the experiment

are functions that map from
outcomes to **numbers**

(or to any “measurable space”)

Purpose

Say **something quantitative** about
a situation we can't model fully
(e.g. lecture seating next week)

Practice

$$\begin{bmatrix} \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \end{bmatrix}$$

Outcome space?

What type of RV is:
“Is the matrix invertible?”

$$\bullet \sim U[-1, 1]$$

is distributed as

Uniform RV

On set of numbers between
-1 and 1

Probability of event?
“Matrix is invertible”

Hint: invertible \leftrightarrow nonzero eigenvalues

Terminology

Experimental trial

Run the experiment once:
 $(\Omega, \mathcal{F}, \mathbb{P})$

$\omega_i = \text{outcome on trial } i$

$X_i = \text{Value of RV } X \text{ on trial } i$

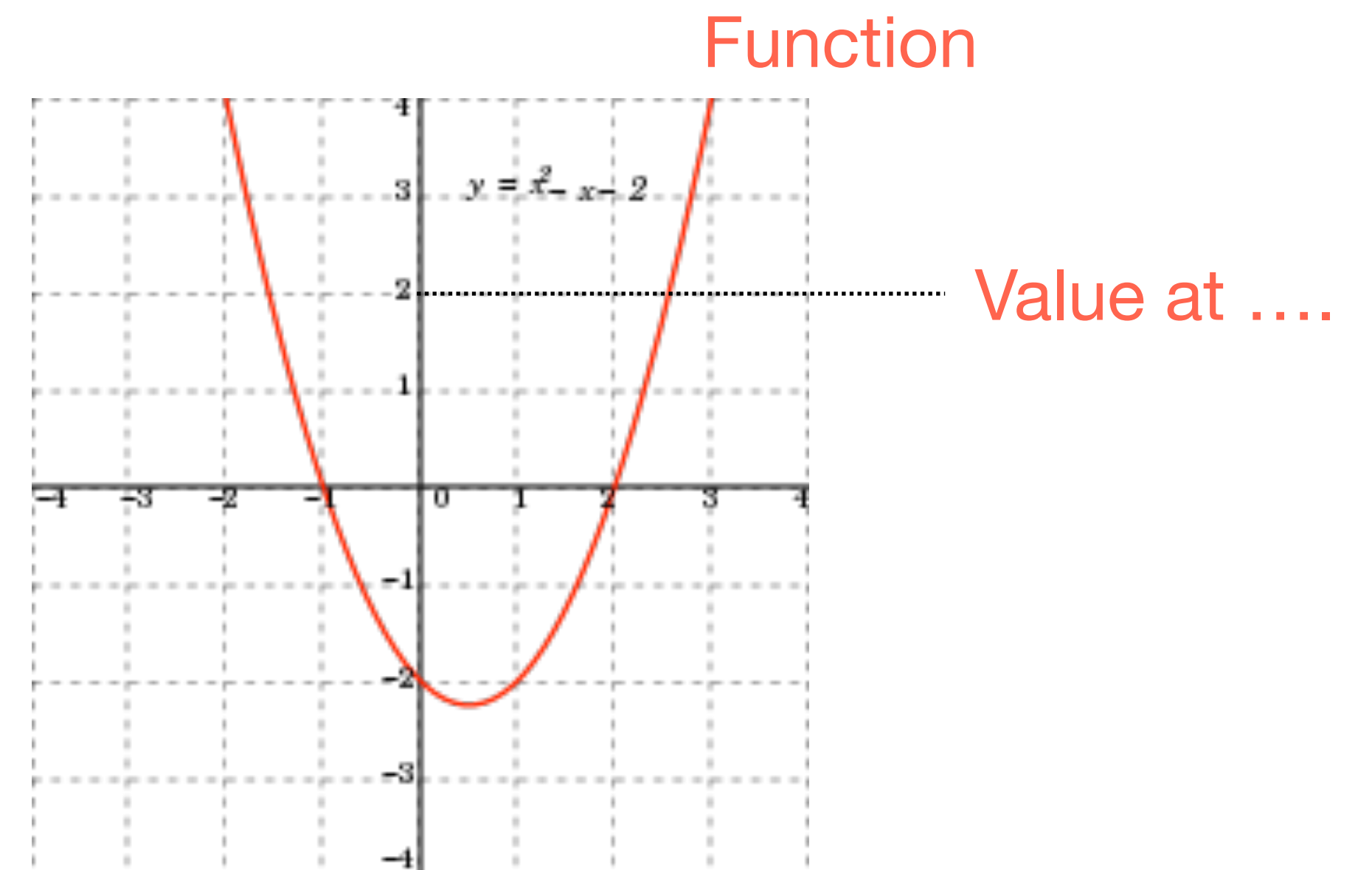
EG $X_i = \text{Filled seats on week } i$

Spot the difference

$X(\omega)$: RV is a **function**

X_i : is a **value** for the
function on trial i

Just like....

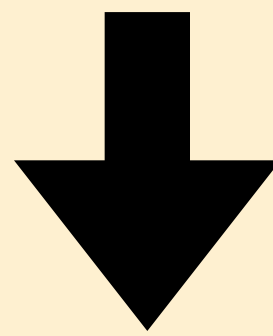


Statistics

Summaries of a random variable

Statistical
function:

Random variable



Number

Expectation

“On average, there are 23 unfilled seats”

Variance

“Number of empty seats typically varies this much across samples”

Sacrifice information for interpretability

Population vs sample statistics

Experiment

Pick somebody at
Sussex uni

Outcome

$\omega \in \Omega$

Person

RV $X(\omega)$

Height

Statistic

Average
height?

Population statistic

Statistic over **all**
outcomes (people)

Sample statistic

Statistic over **limited**
outcomes (some people)

Event $f \in \mathcal{F}$

Sets of people

Population vs sample statistics

Population statistic

Statistic over **all** outcomes (people)

Sample statistic

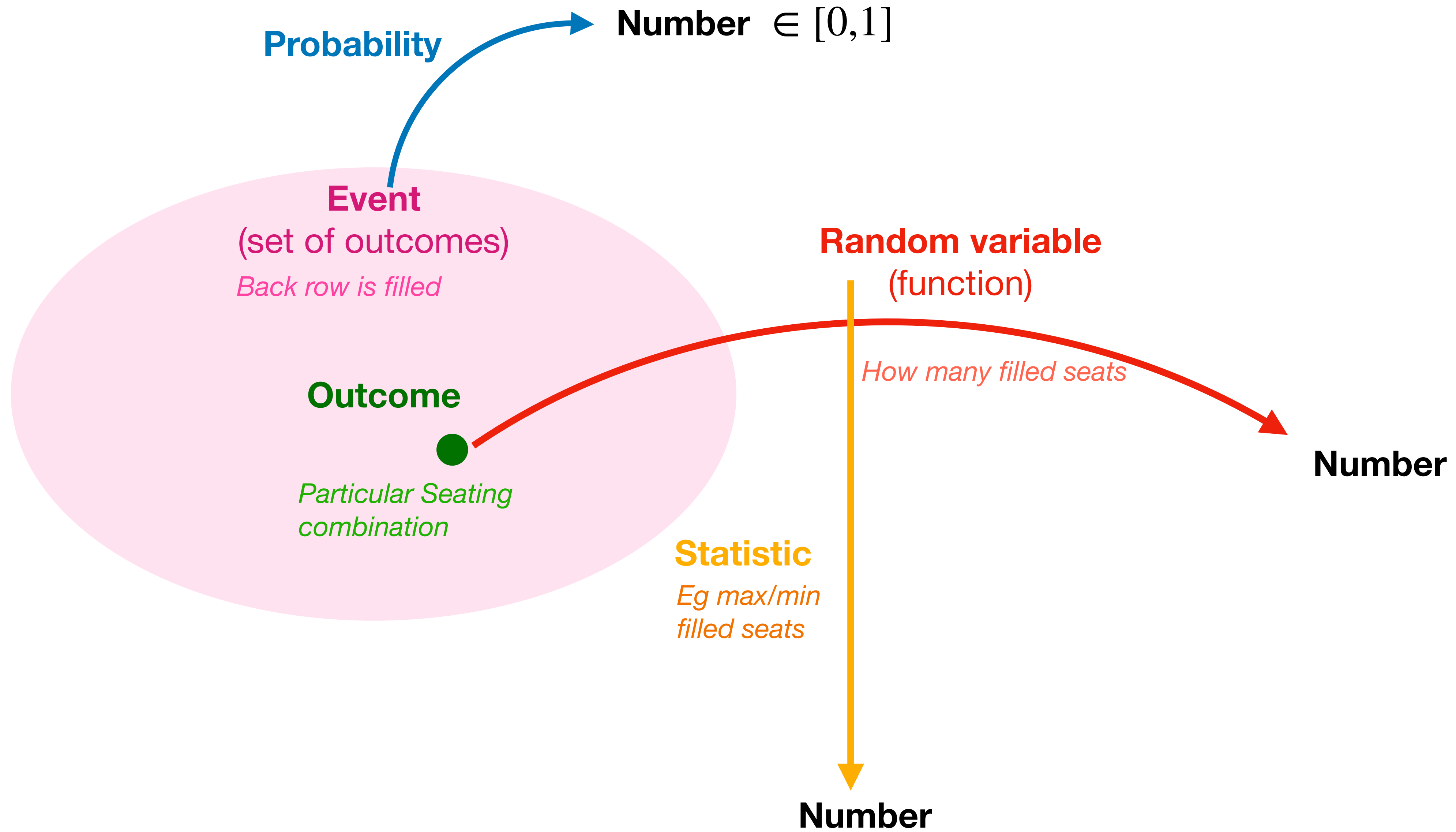
Statistic over **limited** outcomes (some people)

Hard to measure

Easier to measure

Sample statistic called **estimator**

Use sample statistic to estimate?



Statistic 1: expectation by example

(Mean/average)

Ω : **all** outcomes

All possible seating combinations

$S \subset \Omega$: **subset** of outcomes

Seating combinations **sampled** during course

$X : \Omega \rightarrow \mathbb{Z}$

RV from outcomes to number of filled seats

Samples:

$$S = \{\omega_1, \omega_2, \dots, \omega_5\}$$

$$S = \{\omega_i\}_{i=1}^5$$

Samples of RV:

$$\{X(\omega_1), X(\omega_2), \dots\} = \{90, 90, 110, 80, 130\}$$

Sample expectation

$$\bar{\mu}(X) = \sum_{\omega \in S} X(\omega) \mathbb{P}(\omega)$$

$$= 90 \times \frac{1}{5} + 90 \times \frac{1}{5} + 80 \times \frac{1}{5} + \dots$$

$$= 100$$

Statistic 1: expectation

(Mean/average)

Ω : **all** outcomes

All possible seating combinations

$S \subset \Omega$: **subset** of outcomes

Seating combinations **sampled** during course

$X : \Omega \rightarrow \mathbb{Z}$

RV from outcomes to number of filled seats

Sample expectation

$$\bar{\mu}(X) = \sum_{\omega \in S} X(\omega) \mathbb{P}(\omega)$$

Population expectation

$$\mu(X) = \sum_{\omega \in \Omega} X(\omega) \mathbb{P}(\omega)$$

Average over *all* possible outcomes

Law of large numbers

“As you take **more** samples, the sample expectation **converges** to the population expectation”

Statistic 1: expectation

Alternative (better)
formula

Sample
expectation

$$\bar{\mu}(X) = \sum_{\omega \in S} X(\omega) \mathbb{P}(\omega)$$

Population
expectation

$$\mu(X) = \sum_{\omega \in \Omega} X(\omega) \mathbb{P}(\omega)$$

Average over *all*
possible outcomes

Samples of RV:

$$\{X(\omega_1), X(\omega_2), \dots\} = \{90, 90, 110, 80, 130\}$$

5 outcomes

4 values

Sum over probability of **values**
of RV. Instead of outcomes

$$\mu(X) = \sum_{x \in \text{supp}(X)} x \times \mathbb{P}[X(\omega) = x]$$

$$= 90 \times \frac{2}{5} + 80 \times \frac{1}{5} + \dots$$

Statistic 1: expectation

Alternative (better)
formula

Sample
expectation

$$\bar{\mu}(X) = \sum_{\omega \in \mathcal{S}} X(\omega) \mathbb{P}(\omega)$$

Population
expectation

$$\mu(X) = \sum_{\omega \in \Omega} X(\omega) \mathbb{P}(\omega)$$

Average over *all*
possible outcomes

$$\bar{\mu}(X) = \sum_{x \in \text{supp}(X)} x \times \mathbb{P}_{\omega \in \mathcal{S}}[X(\omega) = x]$$

$$\mu(X) = \sum_{x \in \text{supp}(X)} x \times \mathbb{P}[X(\omega) = x]$$

↑
This is probability
mass function!

Statistic 1: expectation

Alternative (better)
formula

<https://www.youtube.com/watch?v=OvTEhNL96v0>

Sample
expectation

$$\bar{\mu}(X) = \sum_{\omega \in \mathcal{S}} X(\omega) \mathbb{P}(\omega)$$

$$\bar{\mu}(X) = \sum_{x \in \text{supp}(X)} x \times \mathbb{P}_{\omega \in \mathcal{S}}[X(\omega) = x]$$

Population
expectation

$$\mu(X) = \sum_{\omega \in \Omega} X(\omega) \mathbb{P}(\omega)$$

Average over *all*
possible outcomes

$$\mu(X) = \sum_{x \in \text{supp}(X)} x \times f_X(x)$$

↑
This is probability
mass function!

Lévy distribution

How big will it be?

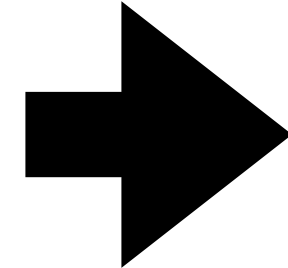
$$\mathbb{E}[X] = \infty$$

Google if interested

Usual terminology

Functions:

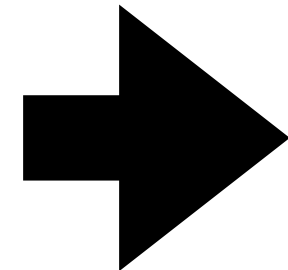
Inputs



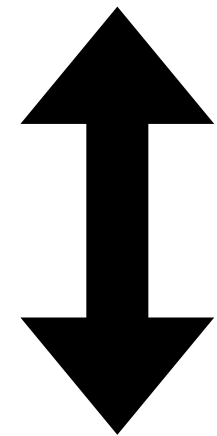
Outputs

Functionals:

Functions



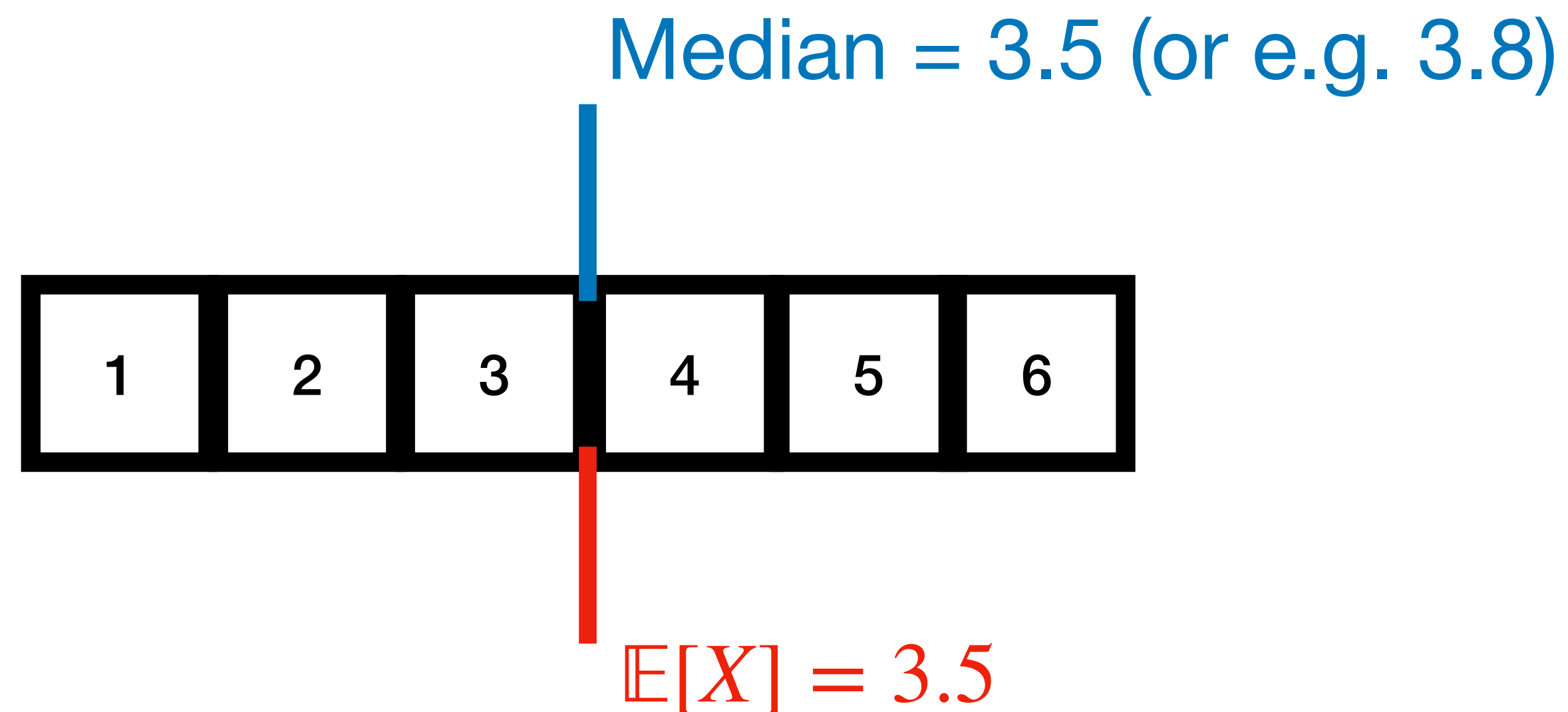
Outputs



**Higher-order function
in programming**

Think of a statistic as a
functional

Expected value is sensitive to outliers

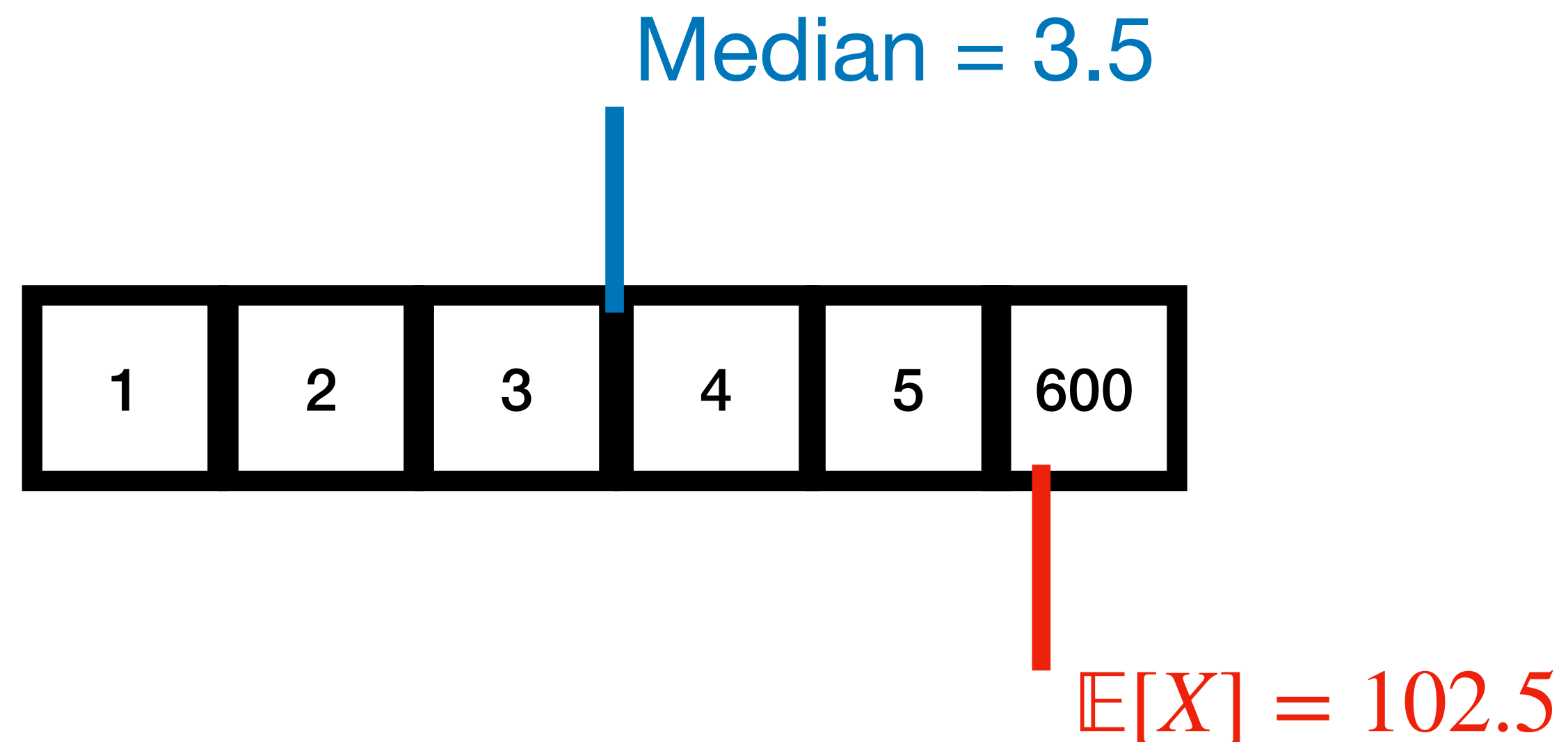


$$\frac{1}{6} \times 1 + \frac{1}{6} \times 2 + \dots \frac{1}{6} \times 6 = 3.5$$

Experiment: roll dice

Random variable:
outcome \rightarrow number on die

Expected value is sensitive to **outliers**



$$\frac{1}{6} \times 1 + \frac{1}{6} \times 2 + \dots + \frac{1}{6} \times 600 = 102.5$$

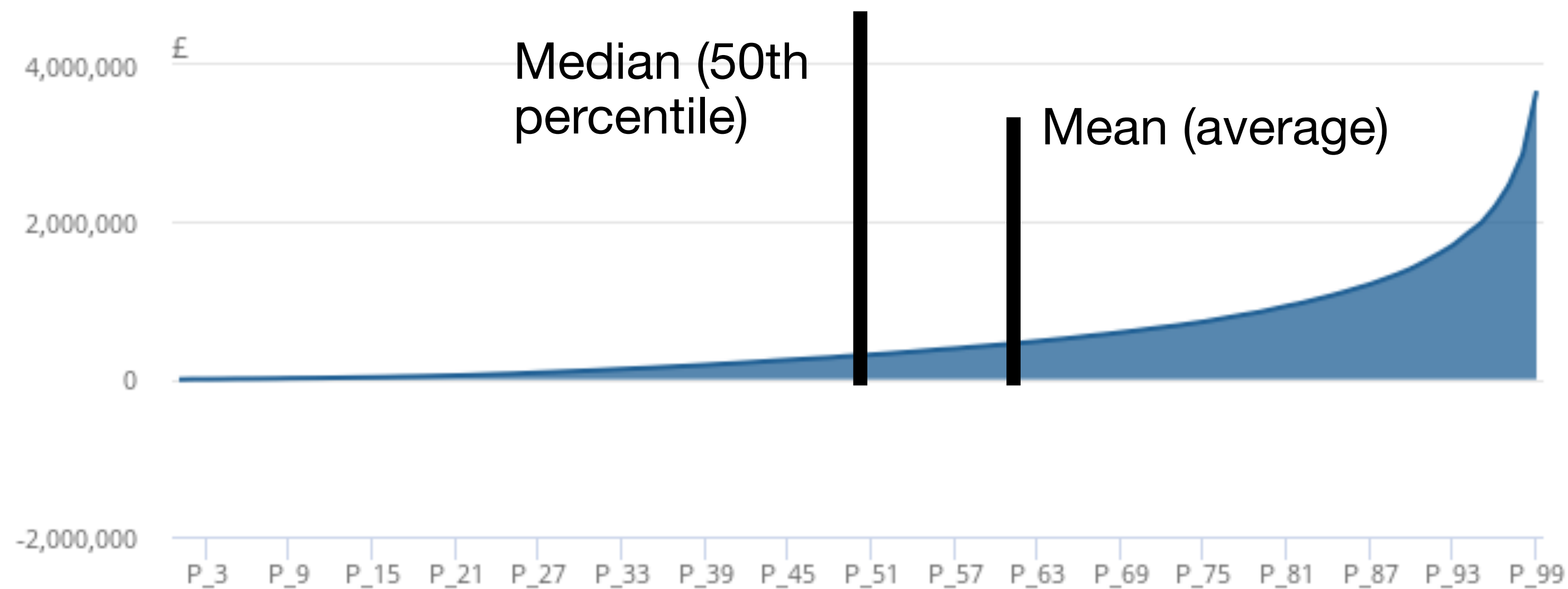
Experiment: roll dice

Random variable:
outcome \rightarrow number on die

Expectation of a random variable

Figure 2: The richest 1% of households had wealth of more than £3.6 million, least wealthy 10% had £15,400 or less

Household total wealth by percentiles, Great Britain, April 2018 to March 2020



Experiment: pick random UK household

Random variable: household \rightarrow net wealth

Source: Office for National Statistics

Expectation of **function** of random variable

What's the mean of $h(X)$ over many trials?

Example

Mean of $h(X) = X^2$ where X
is outcome of dice roll

$$\frac{1}{6} \times 1^2 + \frac{1}{6} \times 2^2 + \dots \frac{1}{6} \times 6^2 = 15\frac{1}{6}$$

$h(1)$

$h(2)$

\dots

Experiment: roll dice

Random variable:
outcome \rightarrow number on die

Expectation of **function** of random variable

What's the mean of $h(X)$ over many trials?

$$\mathbb{E}[h(X)] = \sum_{x \in \text{supp}(X)} h(x) f_X(x)$$

Value of $h(x)$

Probability of $X = x$

Expectation of **function** of random variable

Do it yourself! (At home)

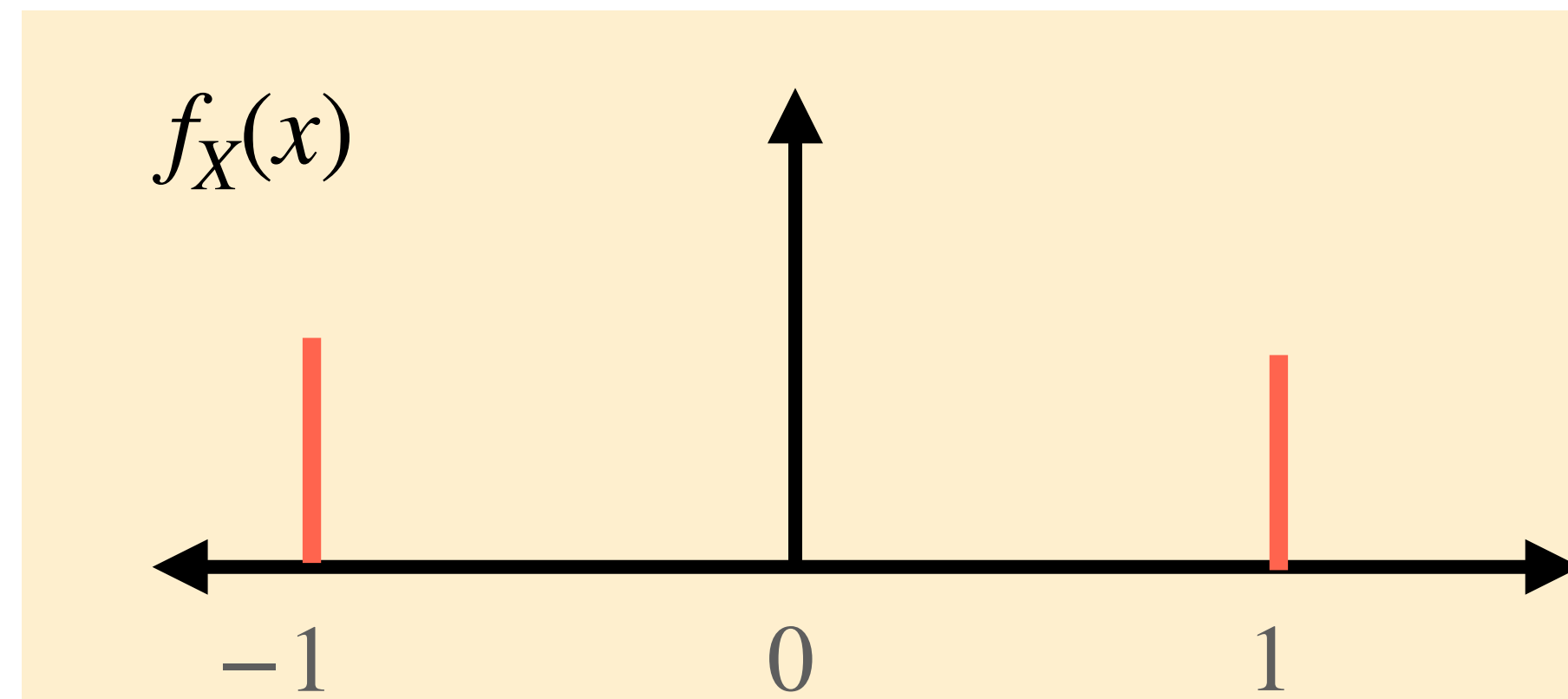
1. New random variable $Y = h(X)$

$$2. \mathbb{E}[Y] = \sum_{\text{supp}(Y)} y \mathbb{P}[Y = y]$$

3. Rewrite RHS in terms of X (i.e. get rid of Y)

Getting intuition on expectations

Let's consider $X \sim U(\{-1, 1\})$



$\mathbb{E}[X]$?

$\mathbb{E}[X^2]$?

Getting intuition on expectations

Expectations **don't** play nicely with nonlinearities!

$$\mathbb{E}[X] = 0$$

$$\mathbb{E}[X^2] = 1$$

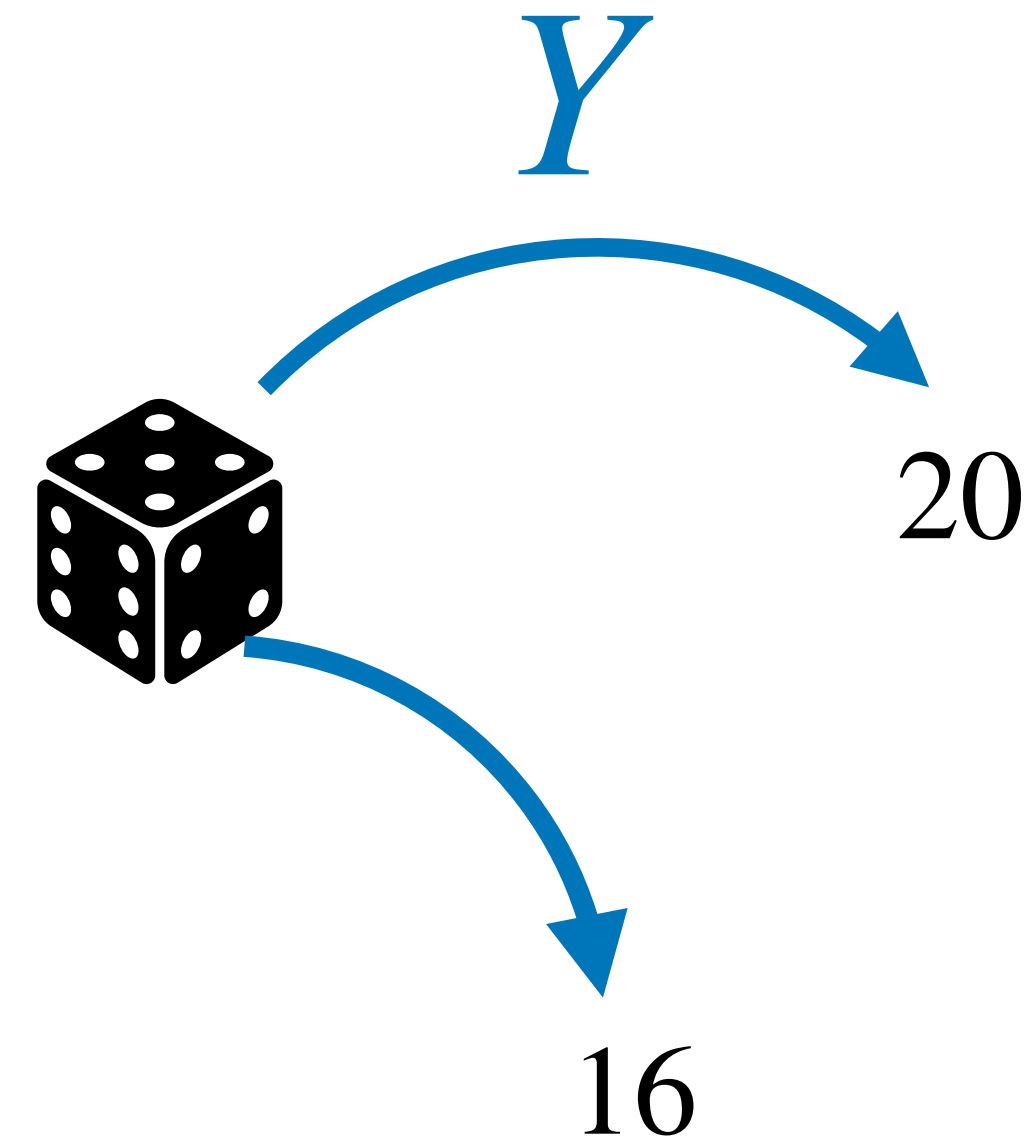
Expectation **satisfies** linearity

$X =$ Dice number

$$Y = 4X$$

$$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

Linearity means I can separate out the expectations under addition!



$$\mathbb{E}[Y] = \mathbb{E}[4X] = 4\mathbb{E}[X]$$

Linearity means I can take the scalar out of the expectation!

Expectation **satisfies** linearity

$$\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y] \quad \forall a, b \in \mathbb{R}$$

(For any real numbers
 a and b)

...for any random variables X, Y

Examples

$$\mathbb{E}\left[\sum_i a_i X_i\right] = \sum_i a_i \mathbb{E}[X_i] \quad \forall a_i \in \mathbb{R}$$

Expectation **satisfies** linearity

$$\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y] \quad \forall a, b \in \mathbb{R}$$

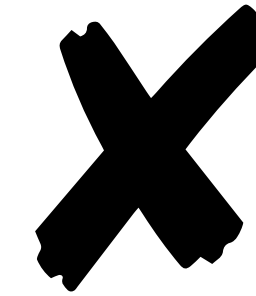
(For any real numbers
 a and b)

...for any random variables X, Y

“If you’re adding random variables or multiplying them by a constant number, you can do the same to their expectations”

Expectation preserved under multiplication?

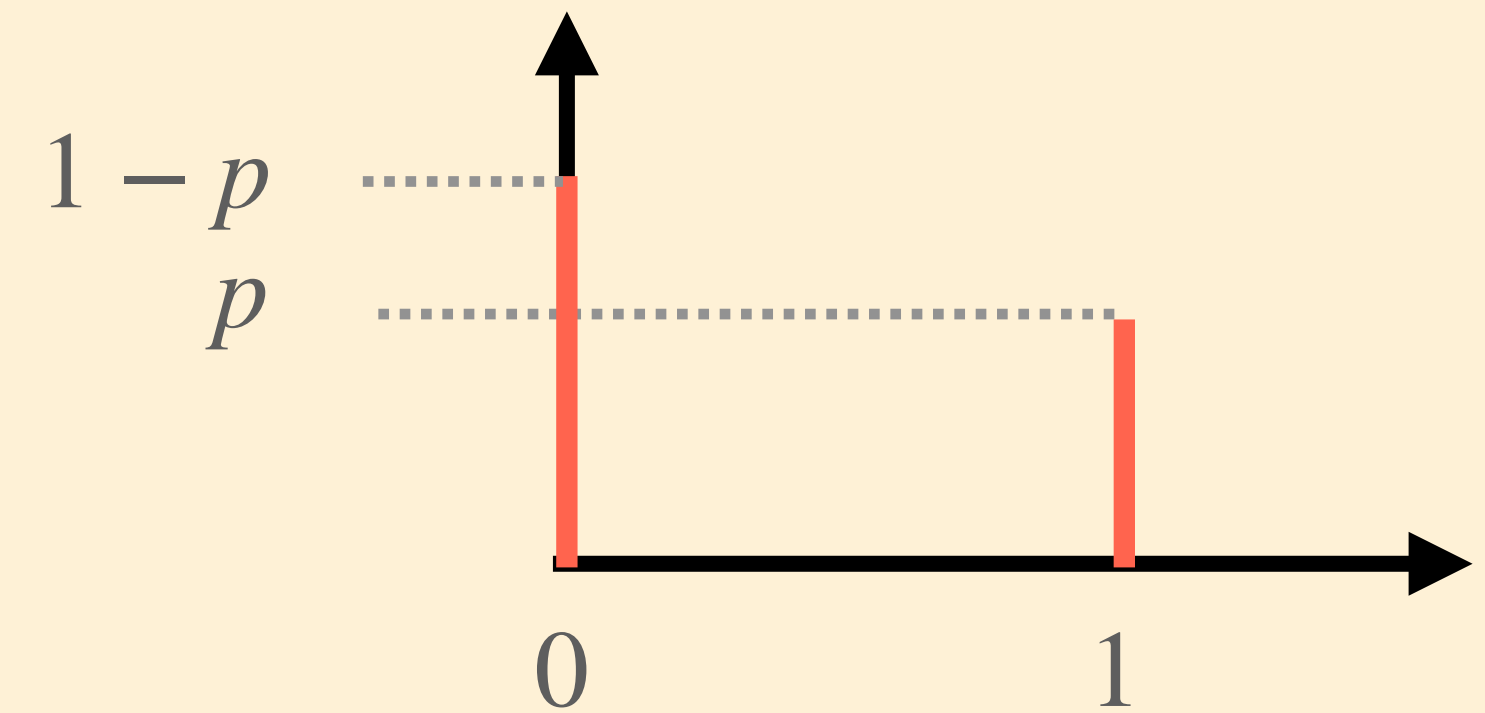
$$\mathbb{E}[XY] \underset{p}{=} \mathbb{E}[X] \underset{p}{\mathbb{E}[Y]}?$$



EG X is Bernoulli:

$$f_X(x) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \end{cases}$$

EG $Y = X$, so $XY = X^2$



Summarising random variables

How **big** is a random variable (on average)

Expected value: $\mathbb{E}[X]$ or $\mu(X)$



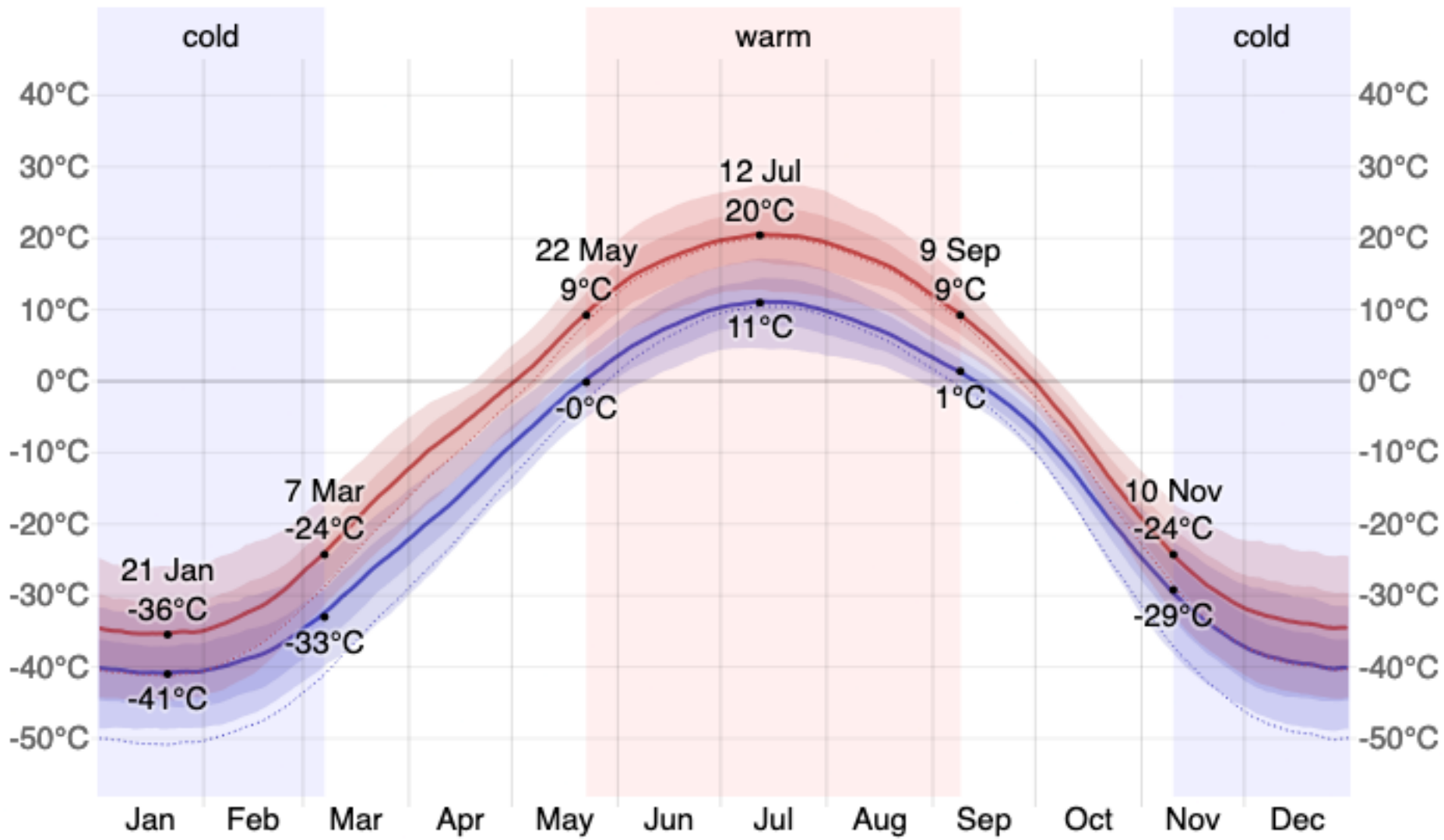
How **variable** is a random variable (on average)

Variance: $\text{Var}[X]$ or $\sigma^2(X)$

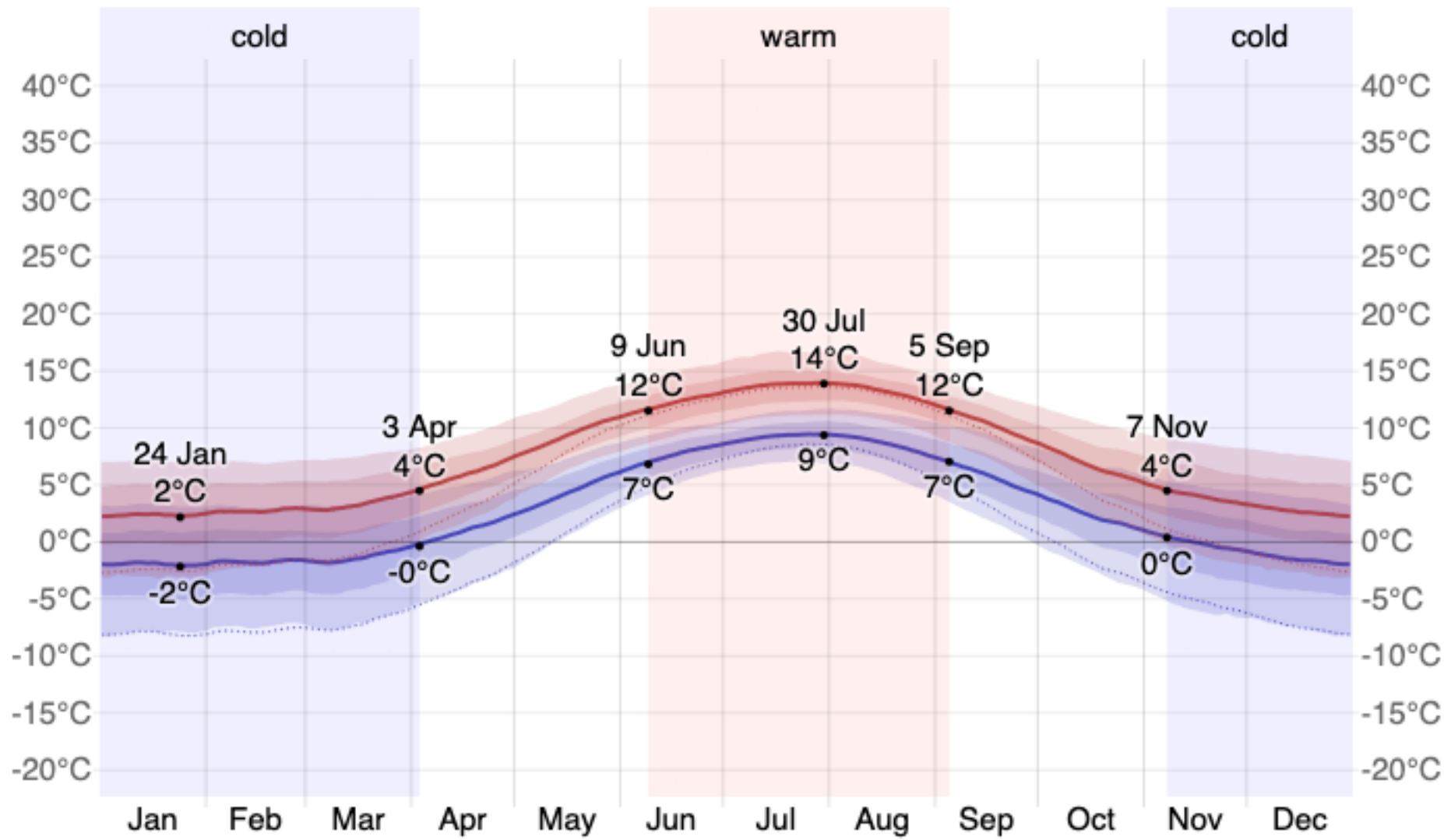
Temperature

Experiment: take temperature on a random day in...

Verkhoyansk



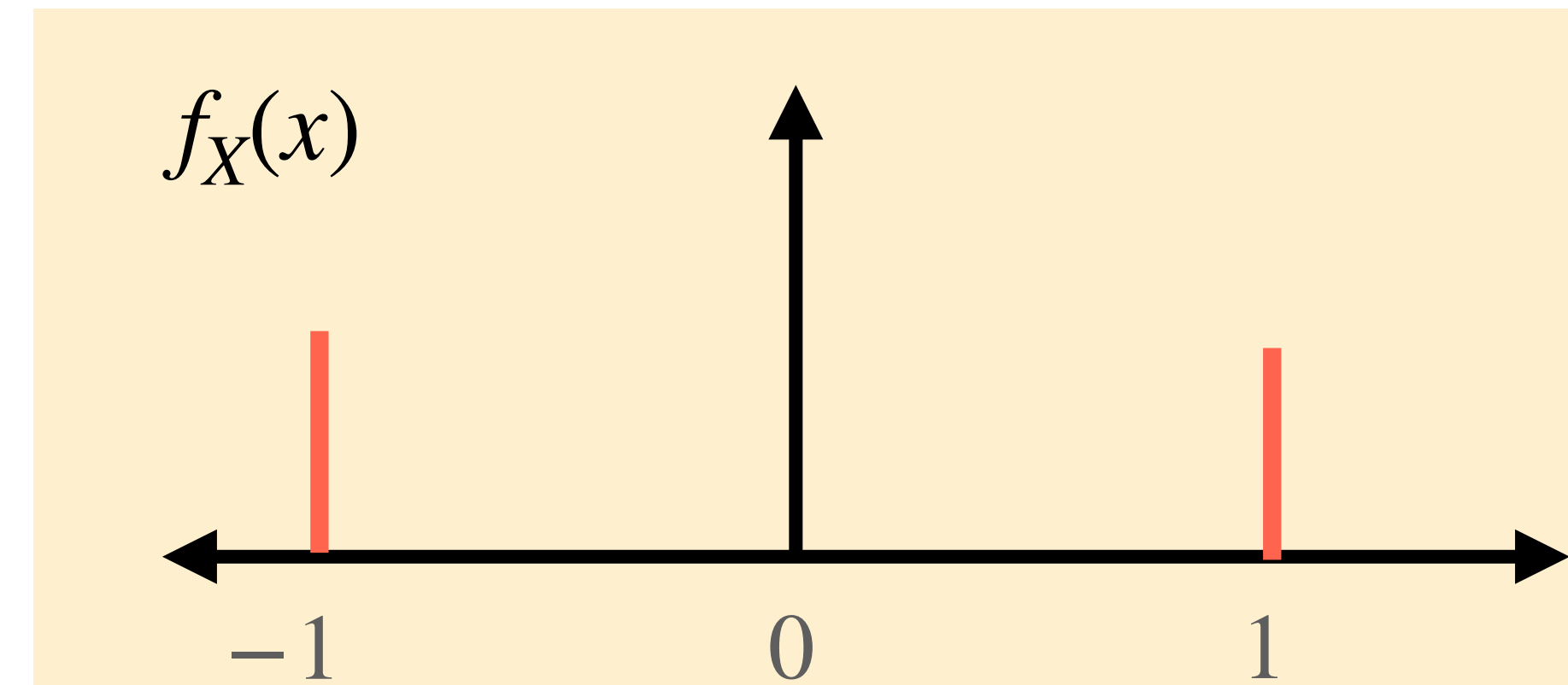
Reykjavik



Variance of an example random variable

Let's consider $X \sim U(\{-1, 1\})$ again

How far from mean
do we expect?



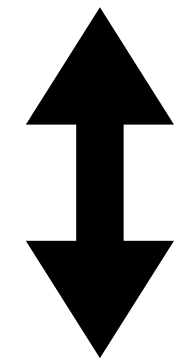
Expectation of:

$$(X - \mathbb{E}[X])^2? \quad 1$$

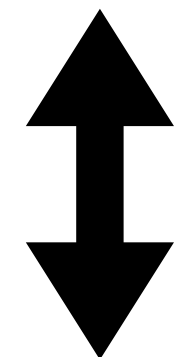
Why not $X - \mathbb{E}[X]$?

Conceptualising variance

How far does a random variable usually fall from its expected value?



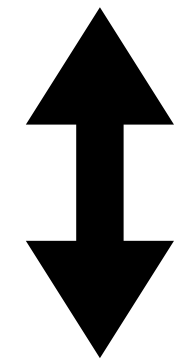
How much uncertainty in the random variable?



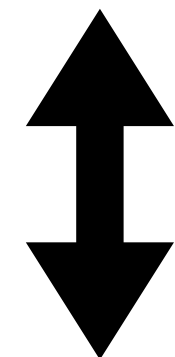
$$\mathbb{E}[(X - \mathbb{E}[X])^2]$$

Conceptualising variance

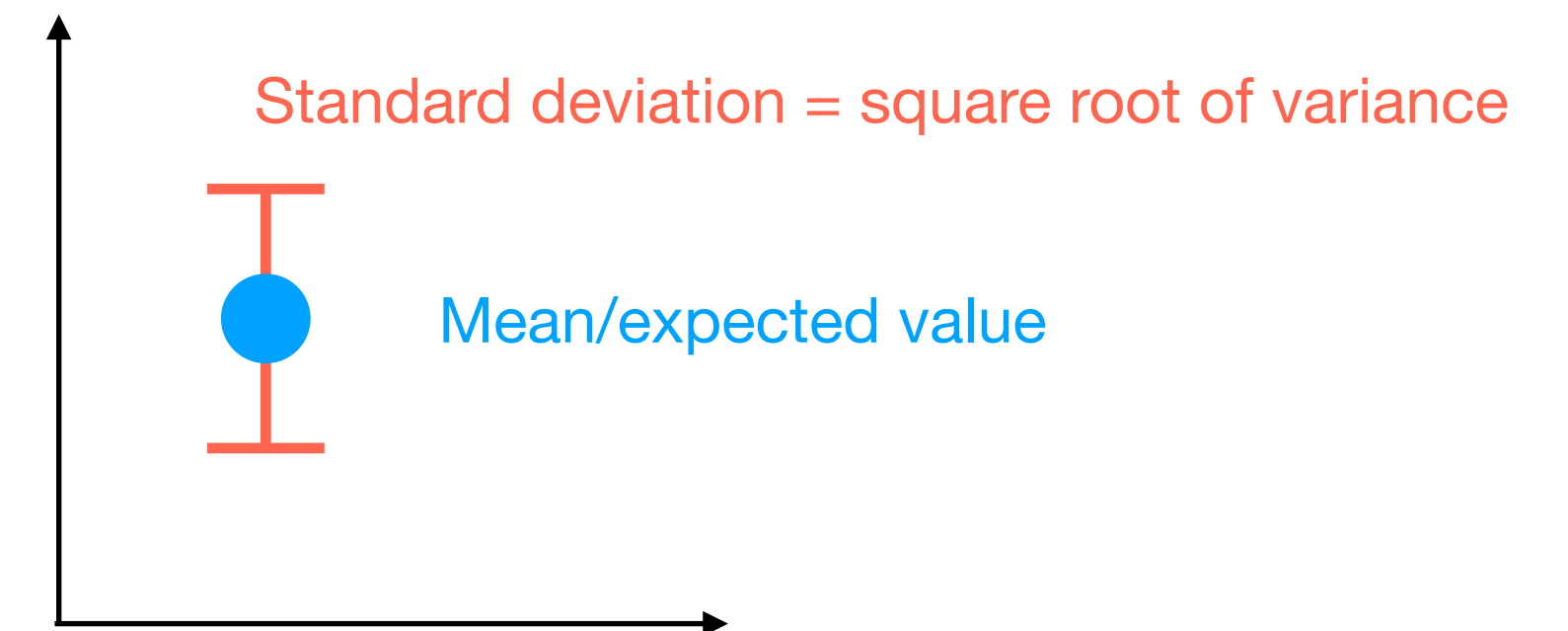
How far does a random variable usually fall from its expected value?



How much uncertainty in the random variable?

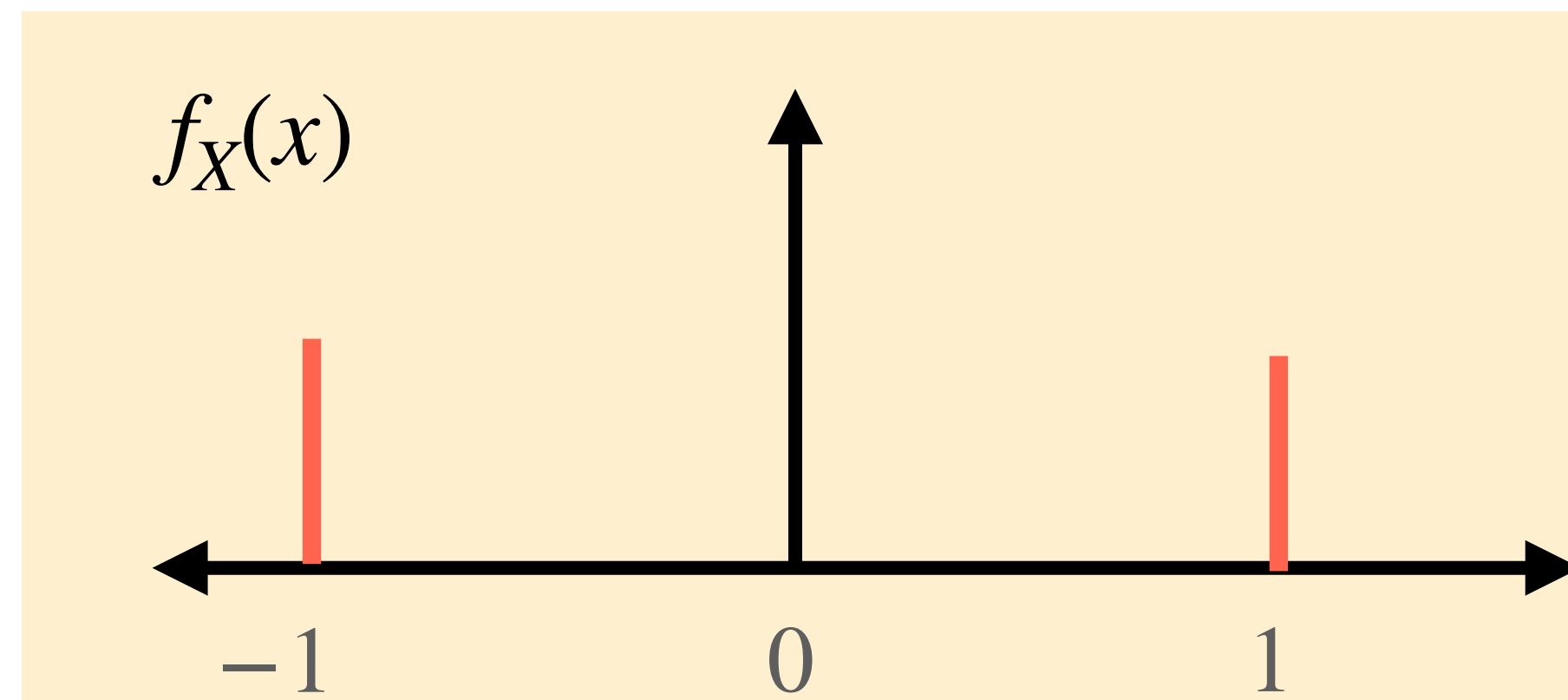


$$\mathbb{E}[(X - \mathbb{E}[X])^2]$$



Variance of an example random variable

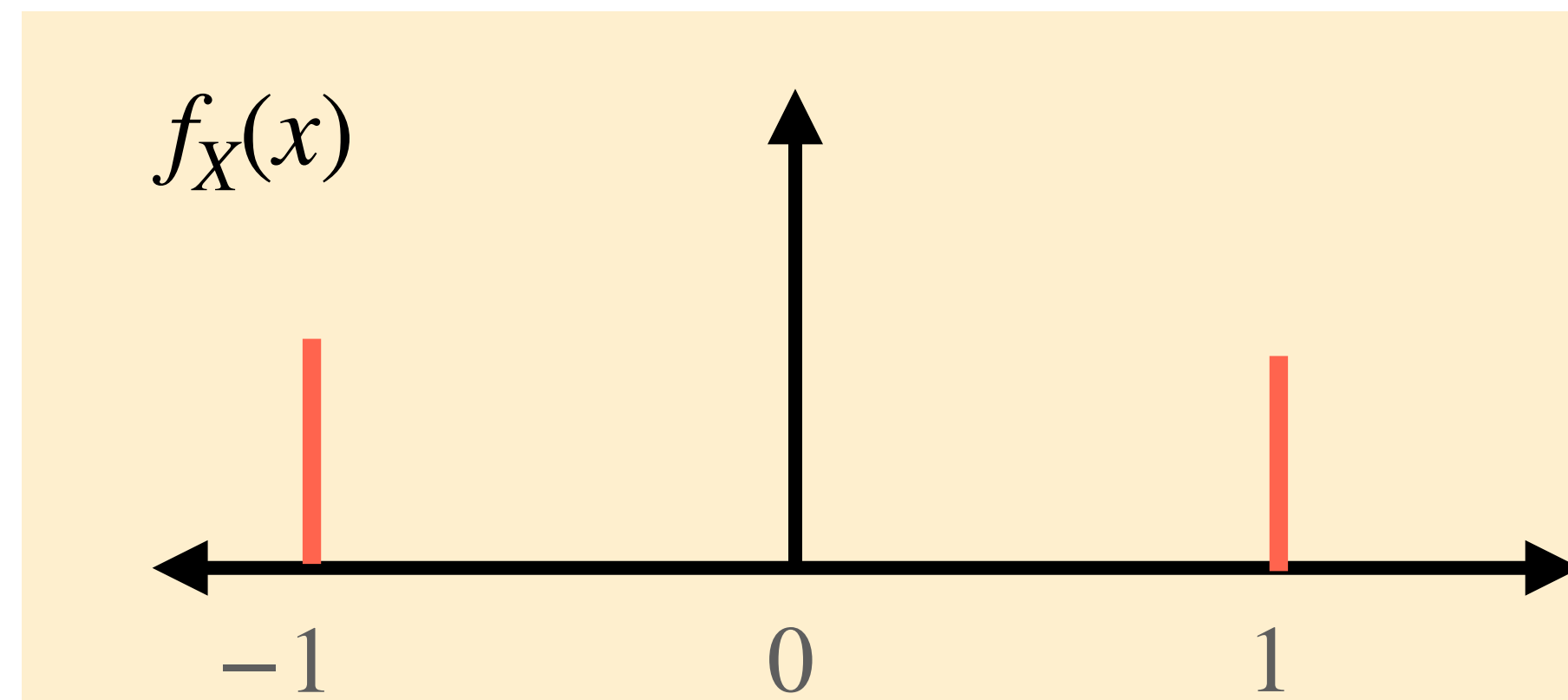
Let's consider $X \sim U(\{-1, 1\})$ again



$$\mathbb{E}[(X - \mathbb{E}[X])^2]?$$

Variance of an example random variable

Let's consider $X \sim U(\{-1, 1\})$ again



$$\mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] = 1$$

Algebra on the expected value

$$\mathbb{E}[(X - \mathbb{E}[X])^2]$$

$$= \mathbb{E}\left[X^2 - 2X\mathbb{E}[X] + \mathbb{E}[X]^2\right]$$

$$= \mathbb{E}[X^2] - 2\mathbb{E}[X\mathbb{E}[X]] + \mathbb{E}[\mathbb{E}[X]^2]$$

(Linearity of expectation)

Algebra on the expected value

How to simplify $\mathbb{E}[\mathbb{E}[X]]$ and similar?

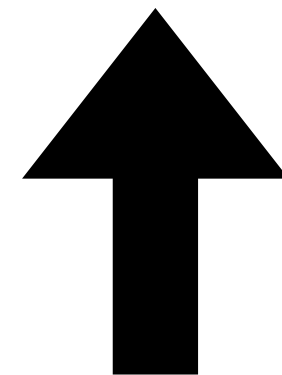
Well $\mathbb{E}[X]$ is a **number**, not a random variable! Apply linearity

$$= \mathbb{E}[X^2] - 2\mathbb{E}[X\mathbb{E}[X]] + \mathbb{E}[\mathbb{E}[X]^2]$$

$$= \mathbb{E}[X^2] - 2\mathbb{E}[X]^2 + \mathbb{E}[X]^2$$

Two **equivalent** expressions for the variance

$$\mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

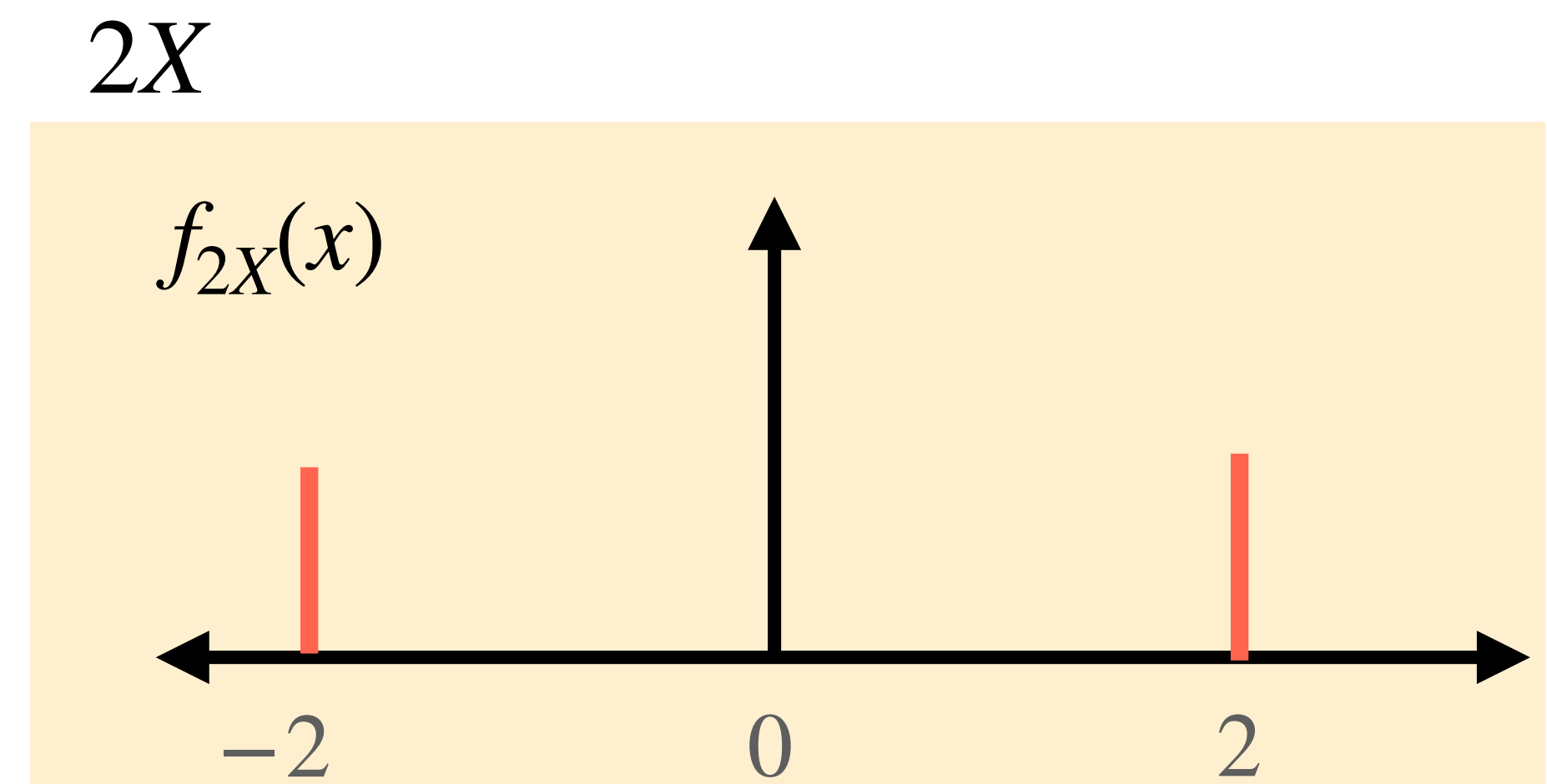
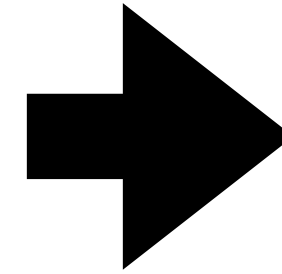
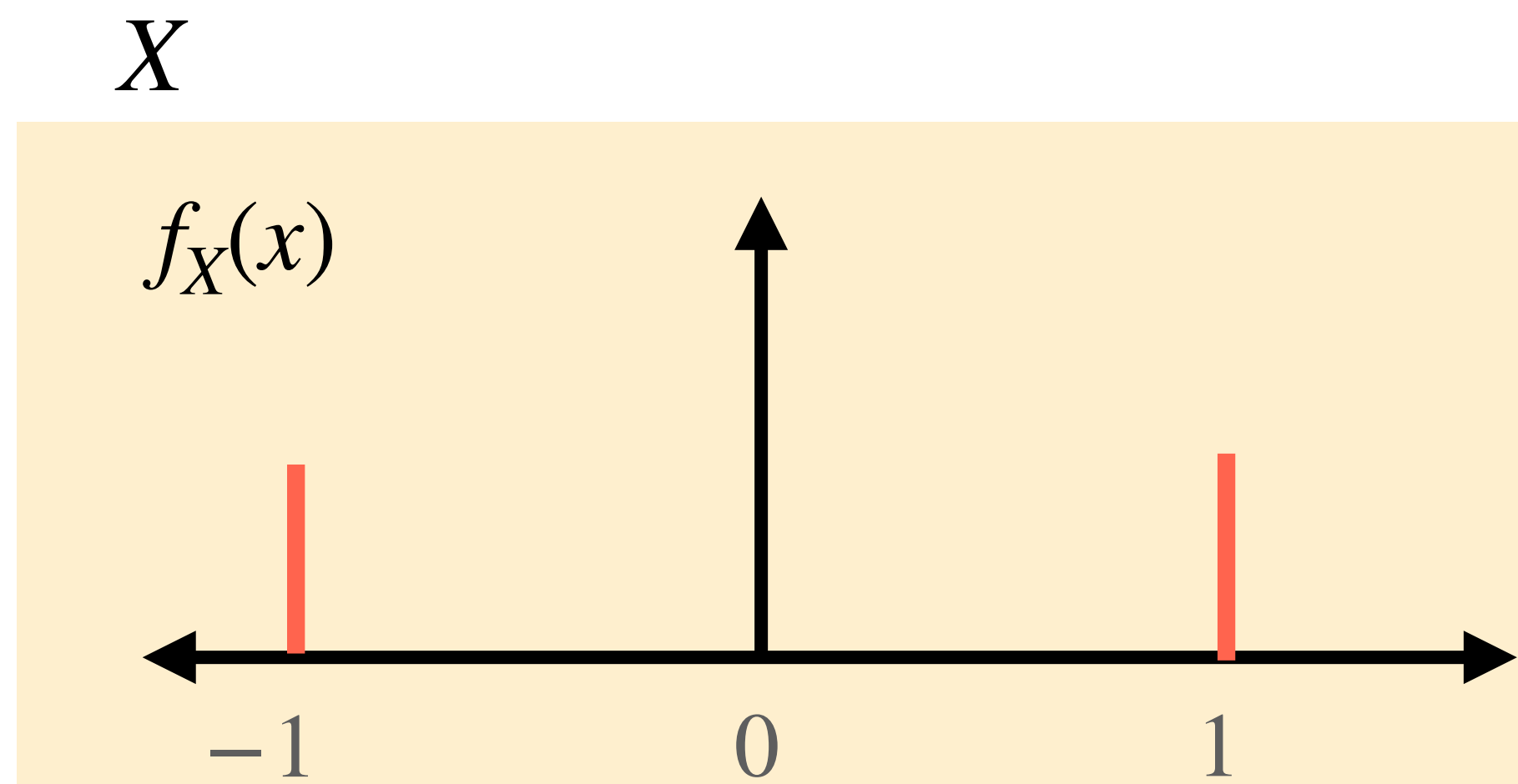


$$= \mathbb{E}[X^2] - 2\mathbb{E}[X\mathbb{E}[X]] + \mathbb{E}[\mathbb{E}[X]^2]$$

$$= \mathbb{E}[X^2] - 2\mathbb{E}[X]^2 + \mathbb{E}[X]^2$$

How does the variance scale?

Let's consider $X \sim U(\{-1, 1\})$ again



$$\text{Var}[X] = \mathbb{E}[(X - \mathbb{E}[X])^2] = 1$$

$$\text{Var}[2X] = ?$$

4!

Algebra on the variance

Homework

Use linearity of expectation to convince yourself that:

$$\text{Var}(cX) = c^2 \text{Var}(X)$$

$$c \in \mathbb{R}$$

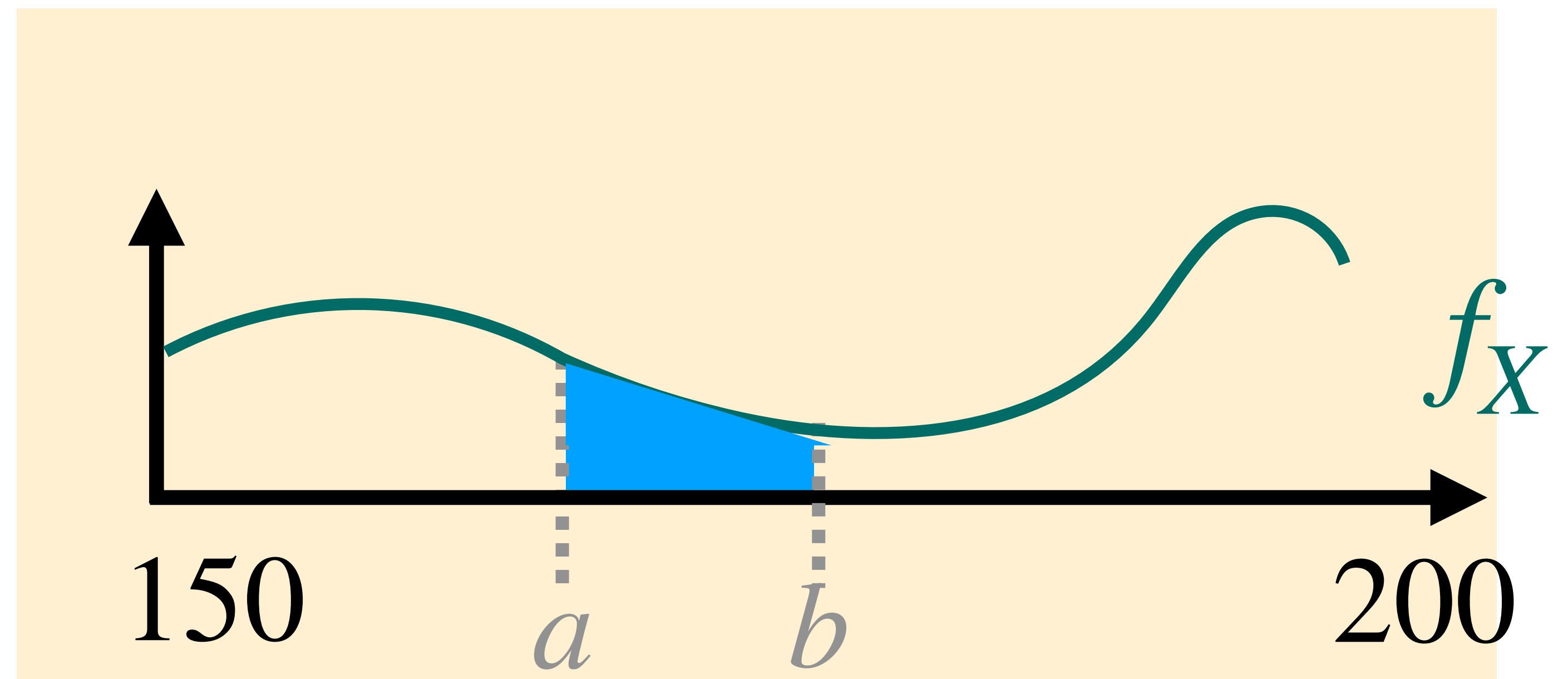
Recap: Probability density functions

Continuous random variables only

$$\mathbb{P}[X = \text{anything}] = 0$$

Instead, look for probability
 X is **between** values:

$$\mathbb{P}[a \leq X \leq b] = ?$$

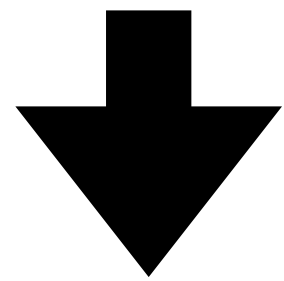


$$\mathbb{P}[x \in (a, b)] = \int_a^b f_X(x) \, dx$$

Expectation of a **continuous** random variable

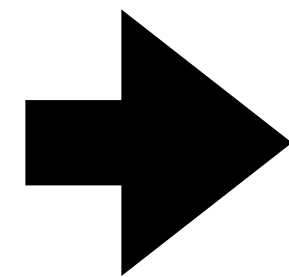
Discrete:

$$\mathbb{E}[X] = \sum_{x \in \text{supp}(X)} x \times \mathbb{P}[X = x]$$



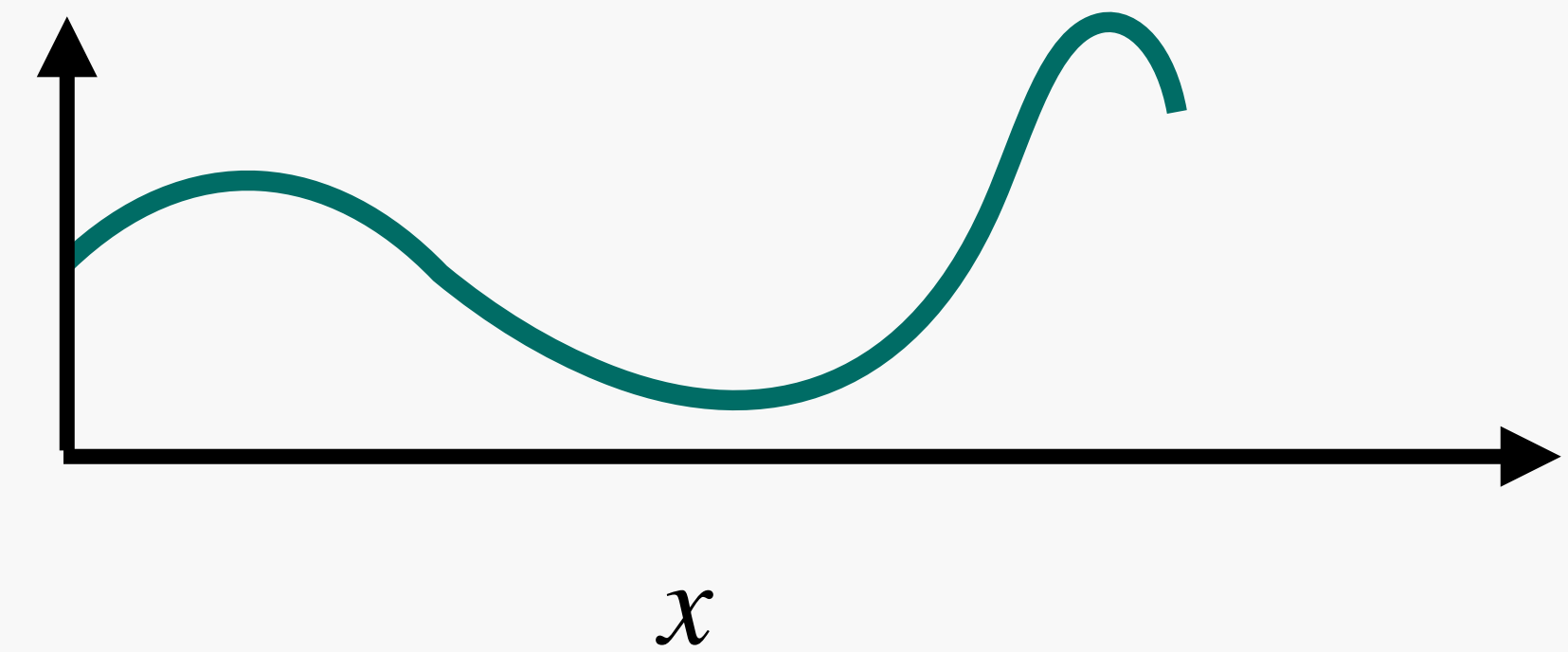
Continuous:

$$\mathbb{E}[X] = \int_{x \in \text{supp}(X)} x \times f_X(x) \, dx$$

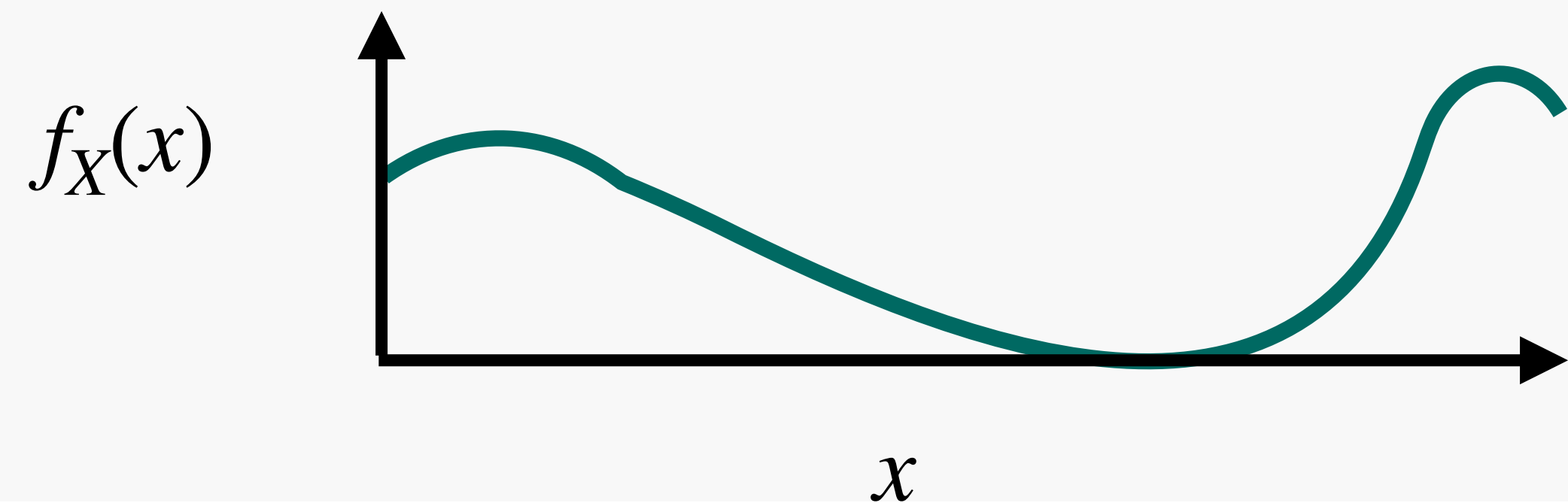


$f_X(x)$
(Prob density
function)

Smaller expected value

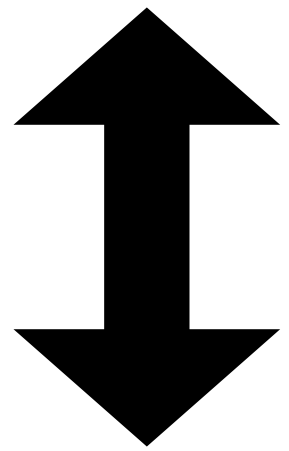


Larger expected value



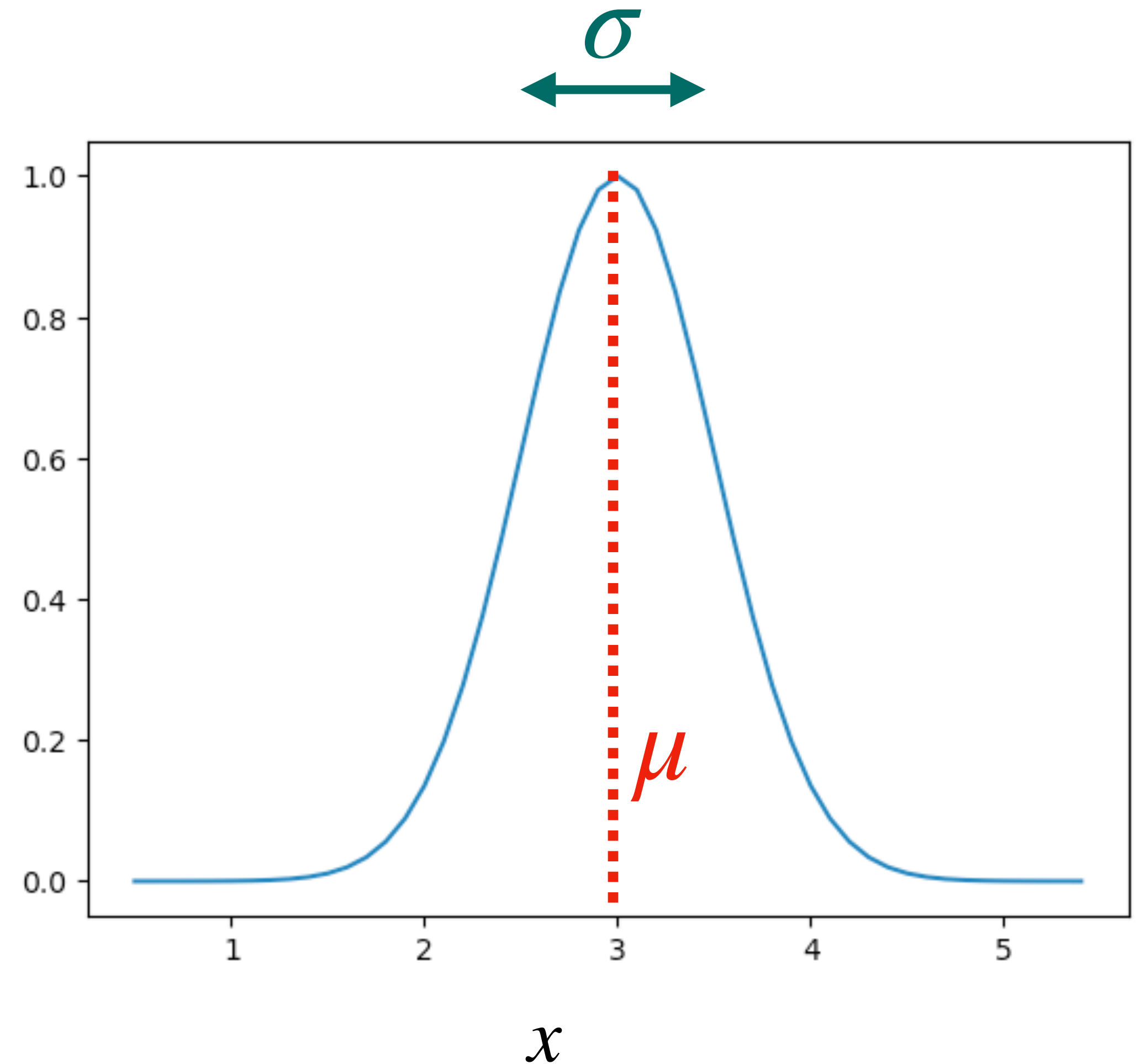
Gaussian random variable are **special**

$$X \sim \mathcal{N}(\mu, \sigma^2)$$



“ X is a Gaussian with mean μ and variance σ^2 ”

$f_X(x)$



Also known as: bell curve, Normal distribution

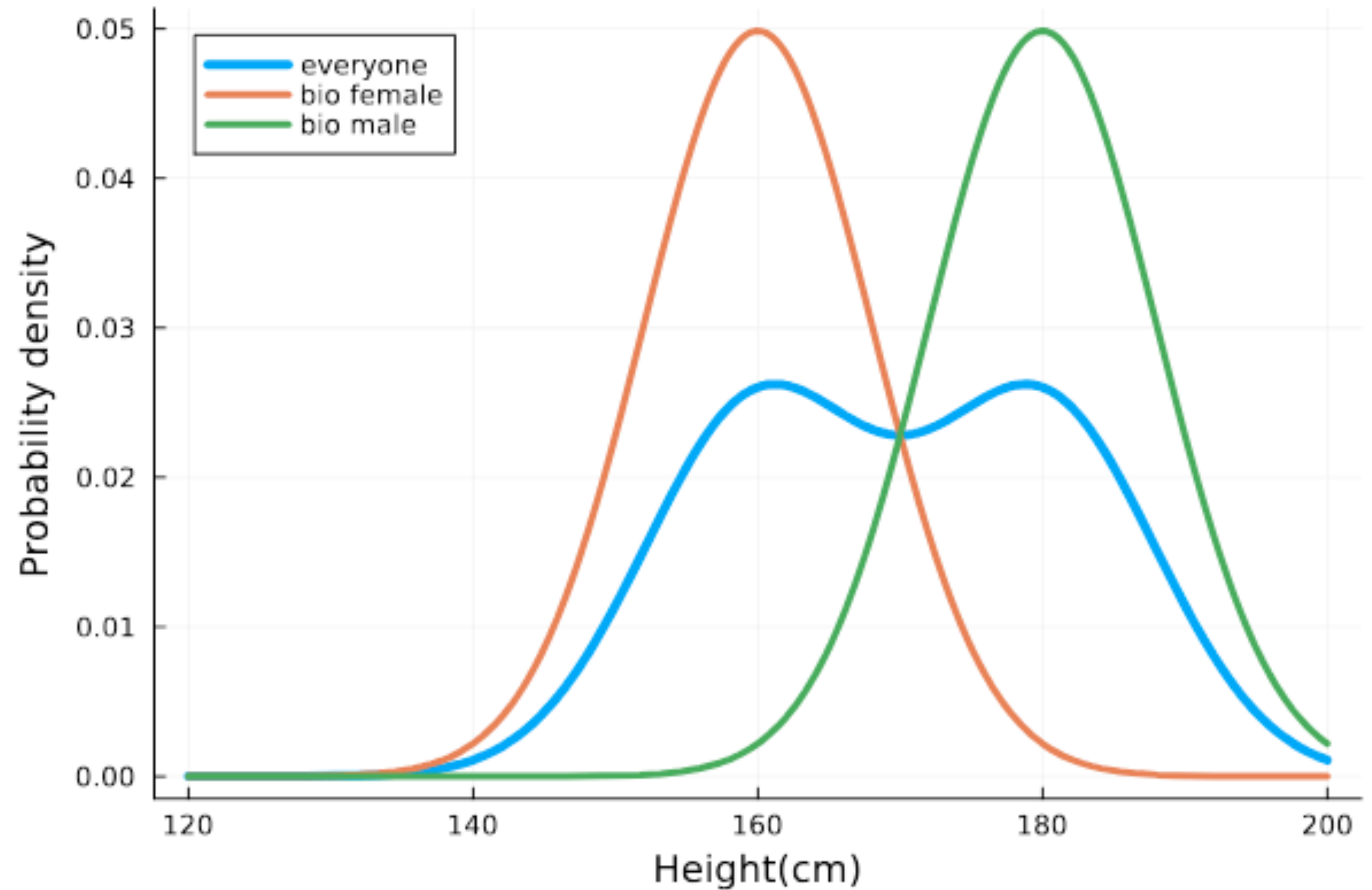
Gaussian random variable are **special:** **Central Limit Theorem**

Is height approximately
normally (gaussian) distributed?

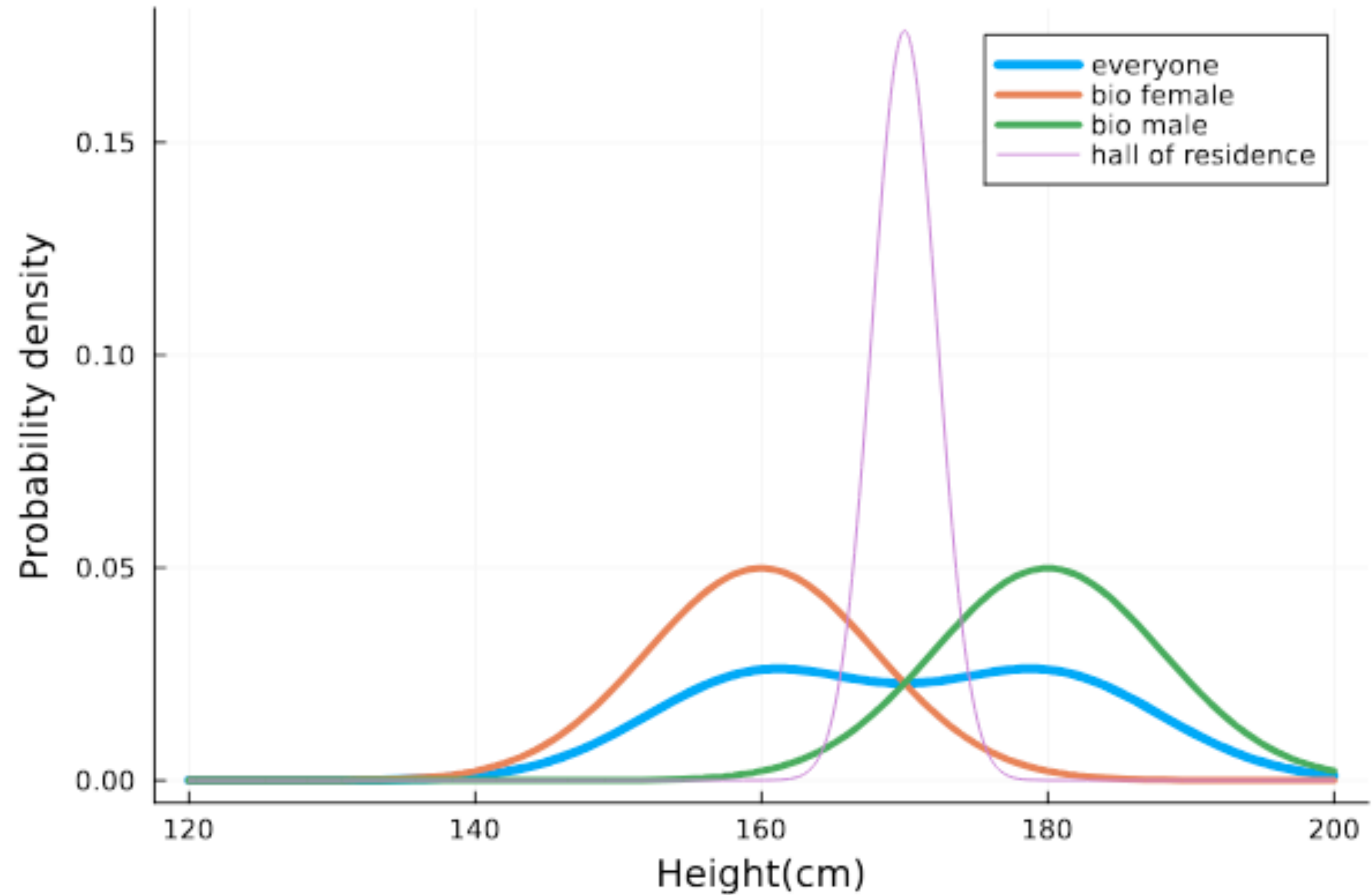
Is the average height of groups of 100
people normally distributed?

(e.g. hall of residence)

Height probably isn't Gaussian



Halls of residences might be



Why lower variance?

Central limit theorem

Random variables depend on **single** experiments

$$X_i = i^{th} \text{ height}$$

CLT is about **groups** of *independent, identically distributed (i.i.d)* experiments

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i = \text{mean height}$$

$n = \text{group size}$

Experiment E1: pick random person

Outcome: a person

Random var: person -> height

Experiment: run E1 100 times

Outcome: 100 people

Random var: people -> mean height

Central limit theorem

Sample mean on (large enough) groups of i.i.d experiments has a Gaussian distribution

CLT is about **groups** of *independent, identically distributed (i.i.d)* experiments

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i = \text{mean height}$$

$n = \text{group size}$

Experiment: run E1 100 times

Outcome: 100 people

Random var: people -> mean height

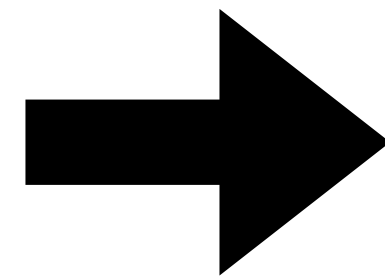
Central limit theorem

“Independent, identically distributed”
(remember abbreviation)

$\{X_1 \dots X_n\}$ are **i.i.d.**

$$\mathbb{E}[X_i] = \mu$$

$$\text{Var}[X_i] = \sigma^2$$



Converges in distribution

$$\bar{X}_n \rightarrow^d \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$$

regardless of X_i distribution

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

Average outcome over
groups of n experiments

Central limit theorem

Caveat

How large should n be for the Central Limit Approximation to be reasonable?

Pragmatic: $n=30$

Theoretical: arbitrarily large! (depends on how 'non-Gaussian' X is)

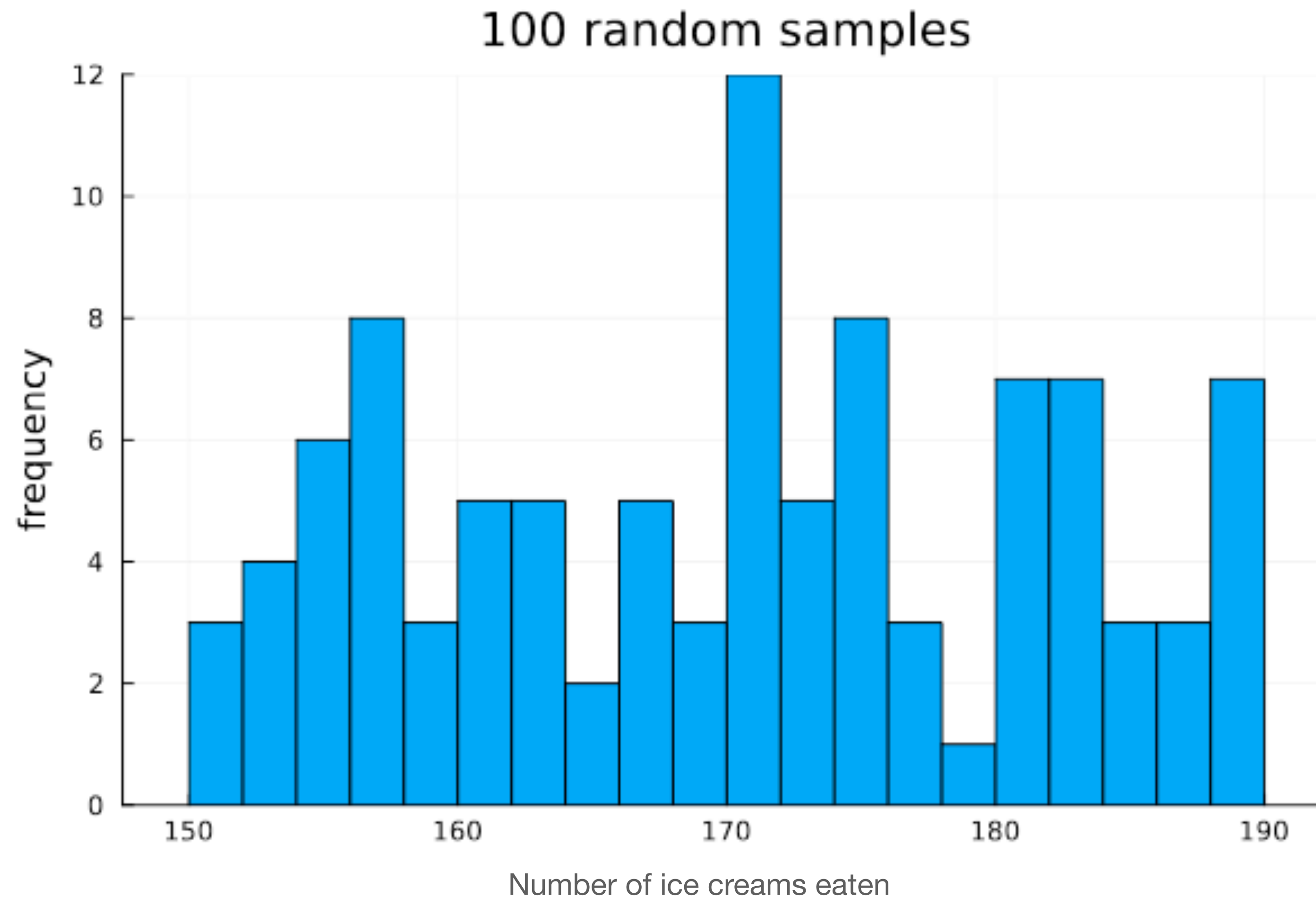
Central Limit Theorem

$$\bar{X}_n \xrightarrow{d} \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right) \text{ regardless of } X_i \text{ distribution}$$

Converges in distribution

Central limit theorem

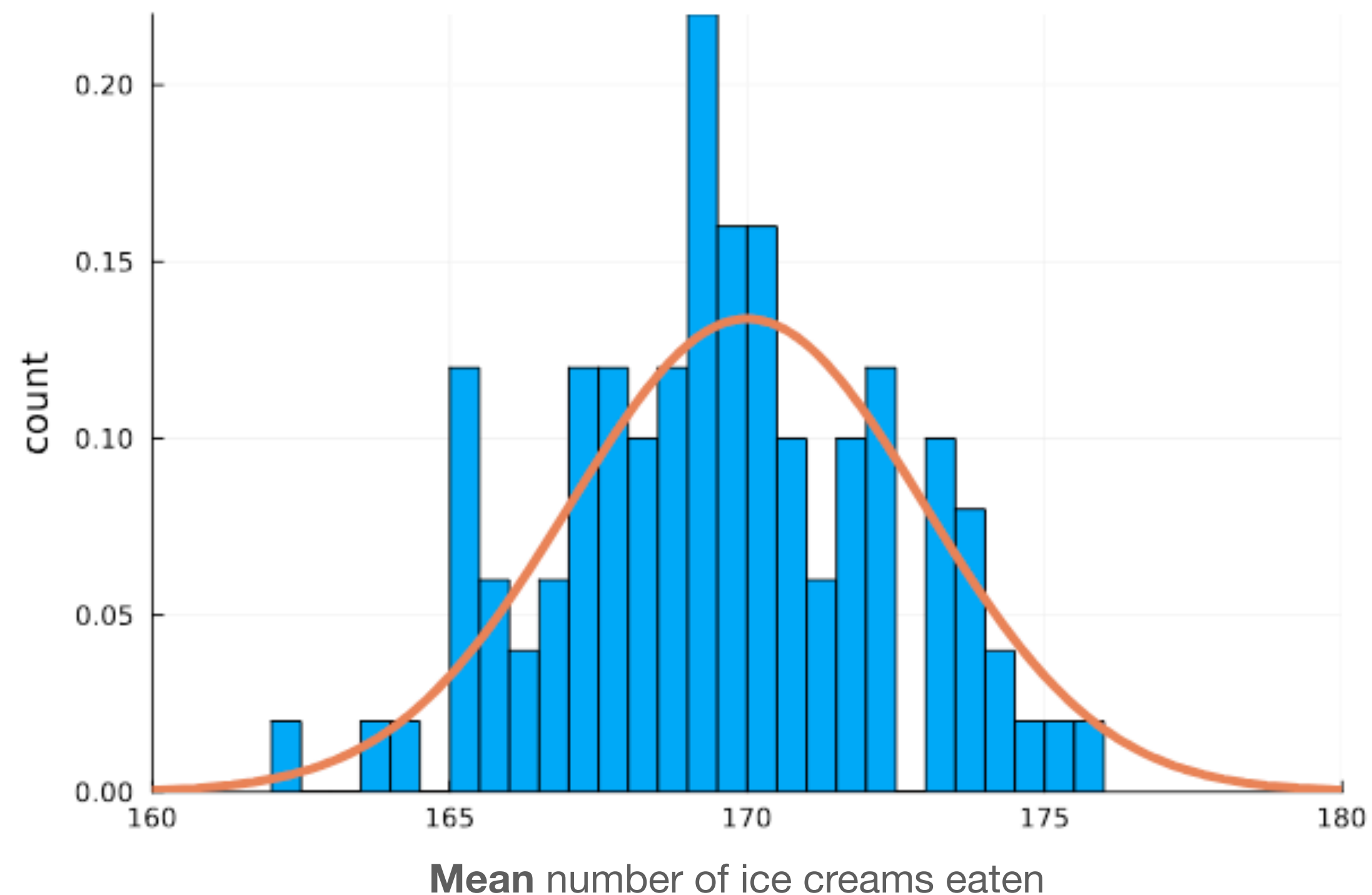
Toy assumption: Ice creams per year $\sim U(150,190)$



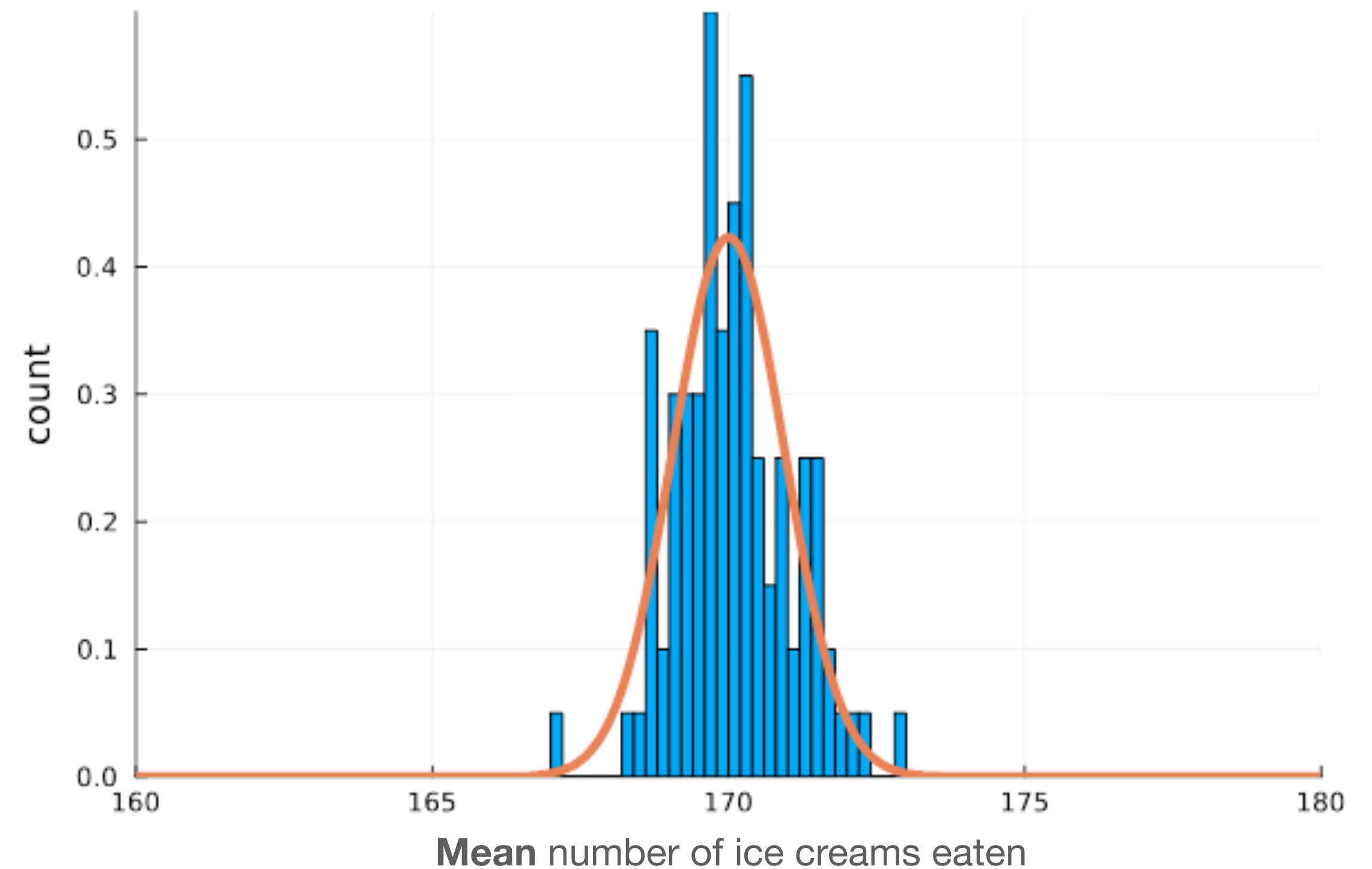
Central limit theorem

Toy assumption: Ice creams per year $\sim U(160, 180)$

Groups of 15 people



Groups of 150 people



**Why do we care about the probability
density of experimental outcomes?**

(Optional interlude)

Why do we care about the probability density of experimental outcomes?

Quantify and weight **confidence** in summaries/predictions/decisions

Can I really cluster this population into three groups?

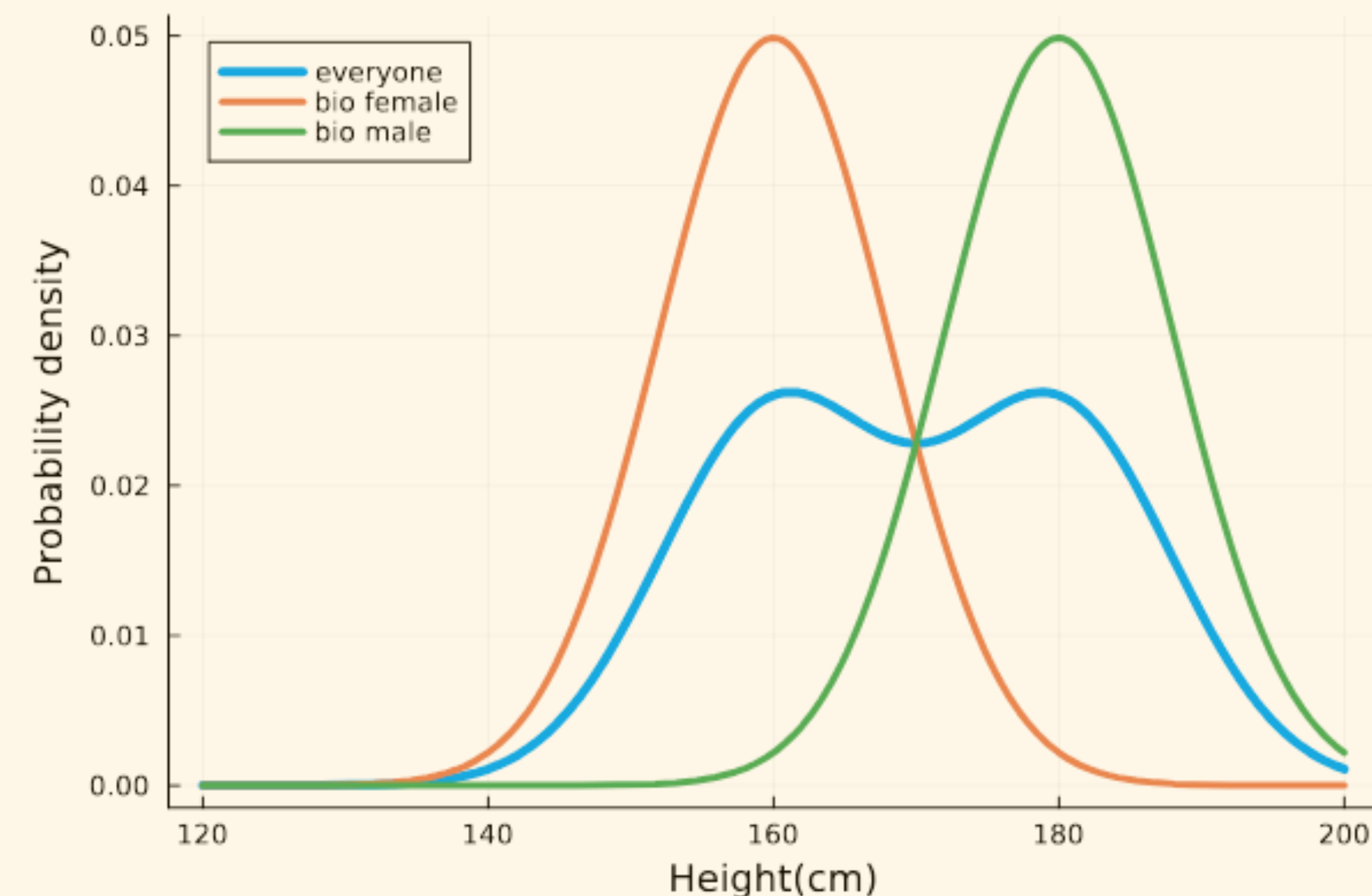
What's their **probability** of paying back the loan?

Low risk/reward or high risk/reward action?

Problem: **don't know** distribution of real random variables

What's the **actual** probability distribution of height?

This is just a guess!



Solution:
learn from data!

Option 1 for learning distributions

Parametric estimation

1. **Assume** data comes from distribution (e.g. Gaussian)
2. Estimate necessary **statistics** of distribution (e.g. mean, variance)

Example:

Data $\{X_i\}_{i=1}^N$ on N people's heights

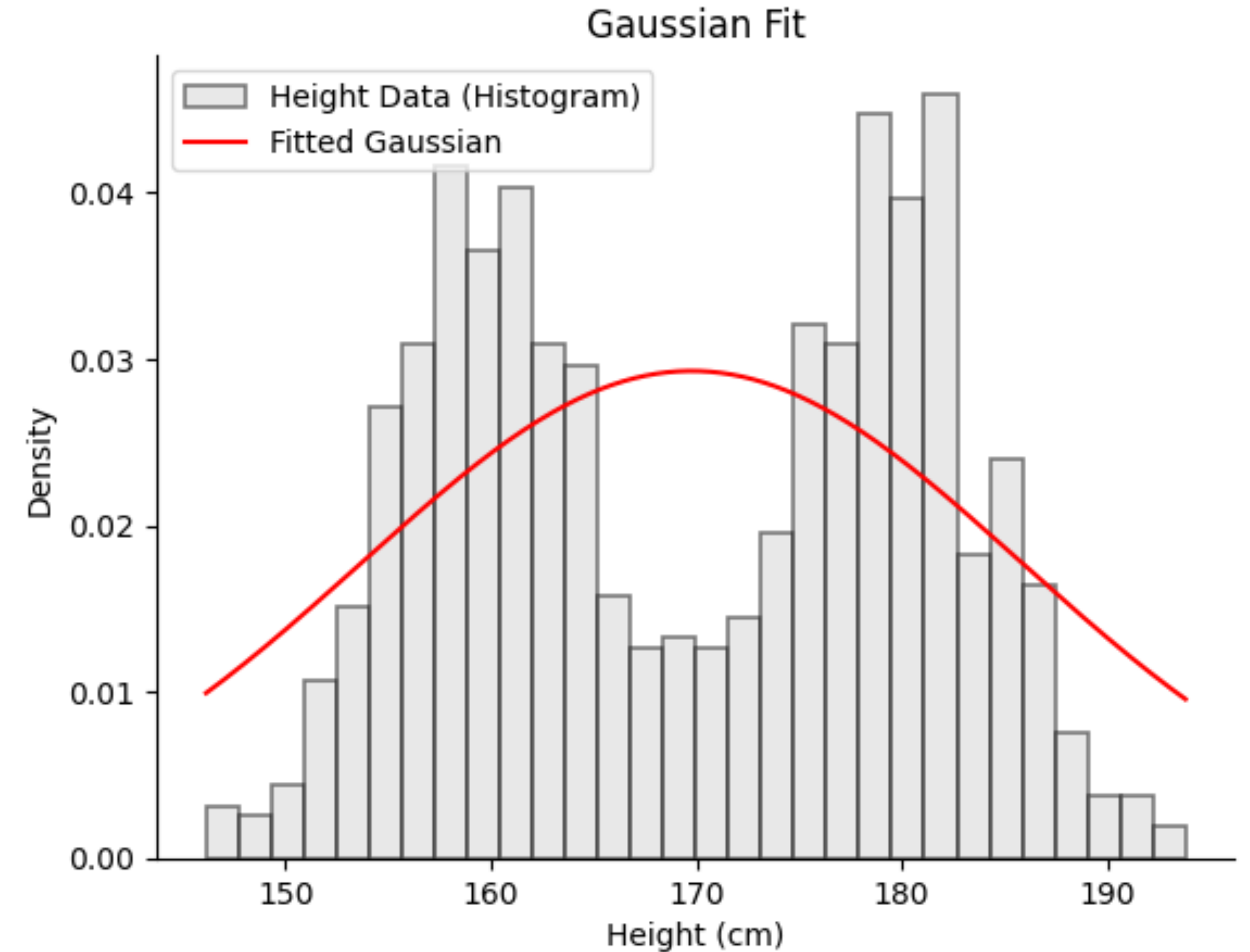
```
1 from scipy.optimize import curve_fit
2 curve_fit(gaussian, ...)
```

=> Answer questions like
"what's the probability of >190cm"

Option 1 for learning distributions

Parametric estimation

1. **Assume** data comes from distribution (e.g. Gaussian)
2. Estimate necessary **statistics** of distribution (e.g. mean, variance)



What's the problem?

Learning distributions

Parametric estimation

1. **Assume** data comes from distribution (e.g. Gaussian)
2. Estimate necessary **statistics** of distribution (e.g. mean, variance)

Vs

Nonparametric estimation

1. **Don't assume** predefined distribution
2. **Jointly** estimate statistics **and** distribution

Nonparametric estimation

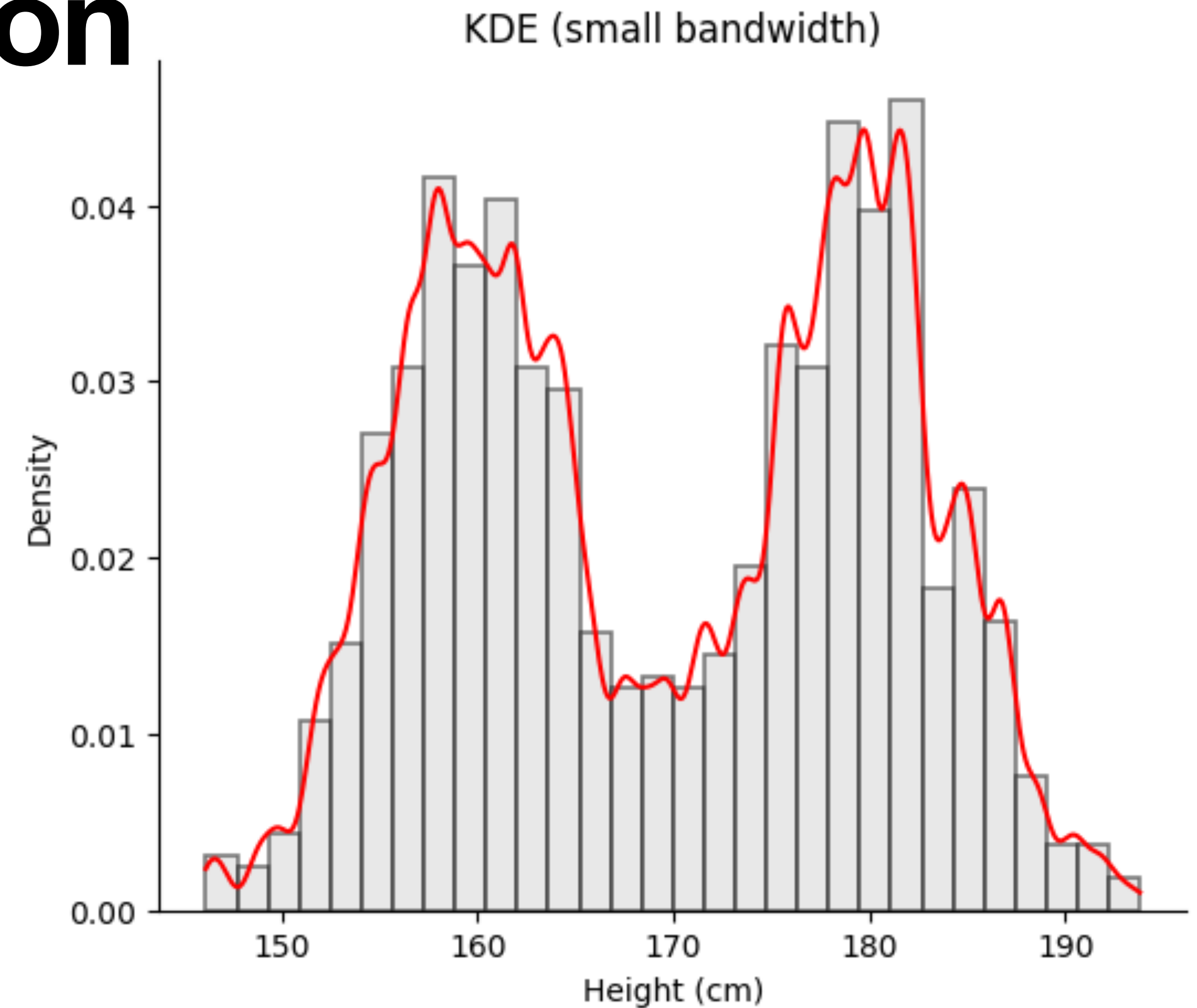
One solution

Kernel density estimation (KDE)

“Draw a line over the histogram”

What’s bad about this?

Models noisy fluctuations



```
1  
2 from scipy.stats import gaussian_kde  
3 gaussian_kde(heights, bw_method=0.05)  
4
```

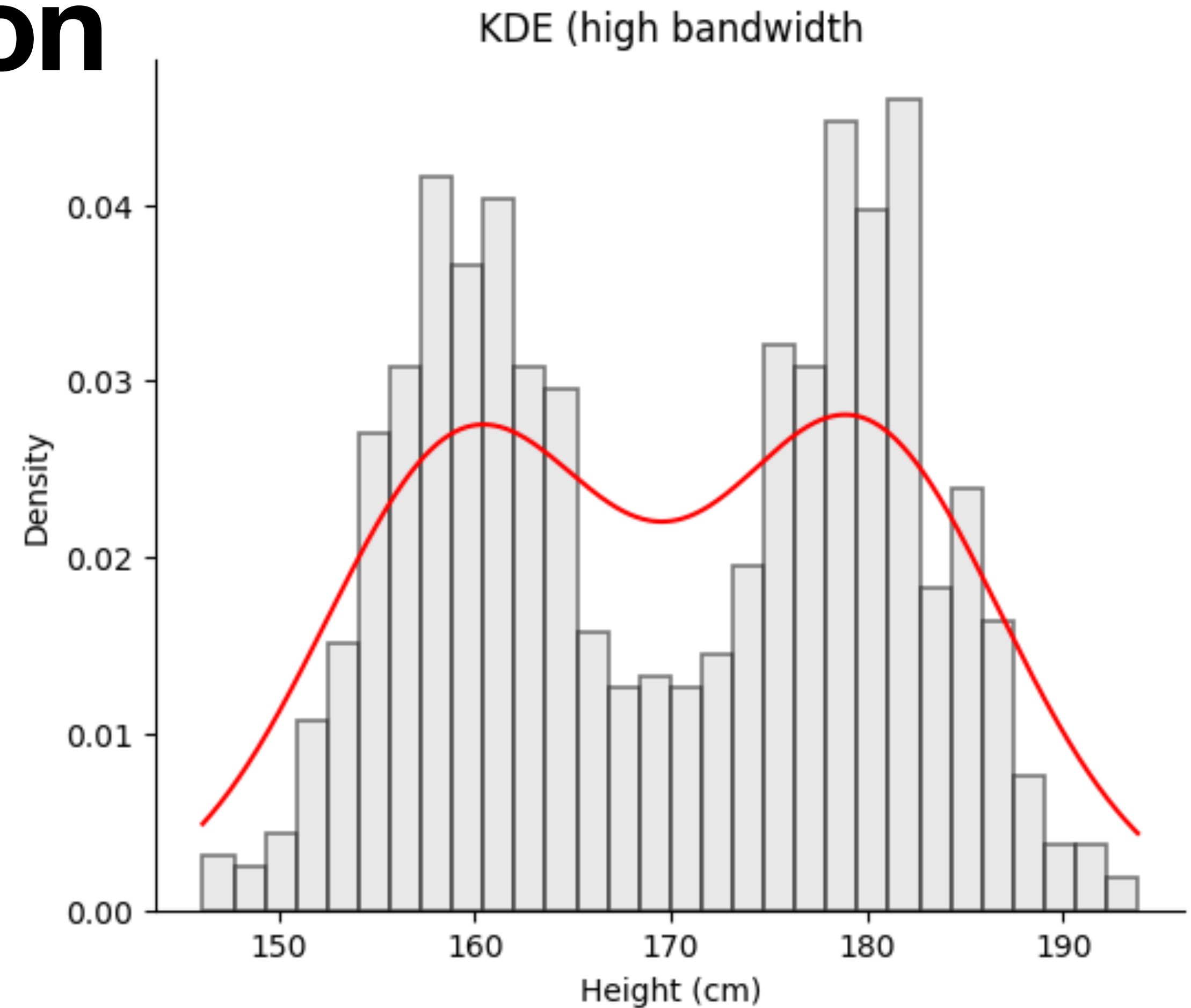
Nonparametric estimation

Better?

Not if they are meaningful
fluctuations!

How can we decide?

More data!



+

```
1 from scipy.stats import gaussian_kde
```

+

```
2 gaussian_kde(heights, bw_method=0.5)
```

Fundamental tradeoff in **all of
applied maths**

Techniques with **fewer
assumptions need **more** data**

Learning distributions

Parametric estimation

1. **Assume** data comes from distribution (e.g. Gaussian)
2. Estimate necessary **statistics** of distribution (e.g. mean, variance)

Vs

Nonparametric estimation

1. **Don't assume** predefined distribution
2. **Jointly** estimate statistics **and** distribution

More assumptions

More data

Which to use? Subjective!

Multivariate distributions

Random variable

Quantitative question about
outcome of experiment

What if we have two
related questions?

Experiment

Choose random person

Random variables

Height, foot size

Multivariate distributions

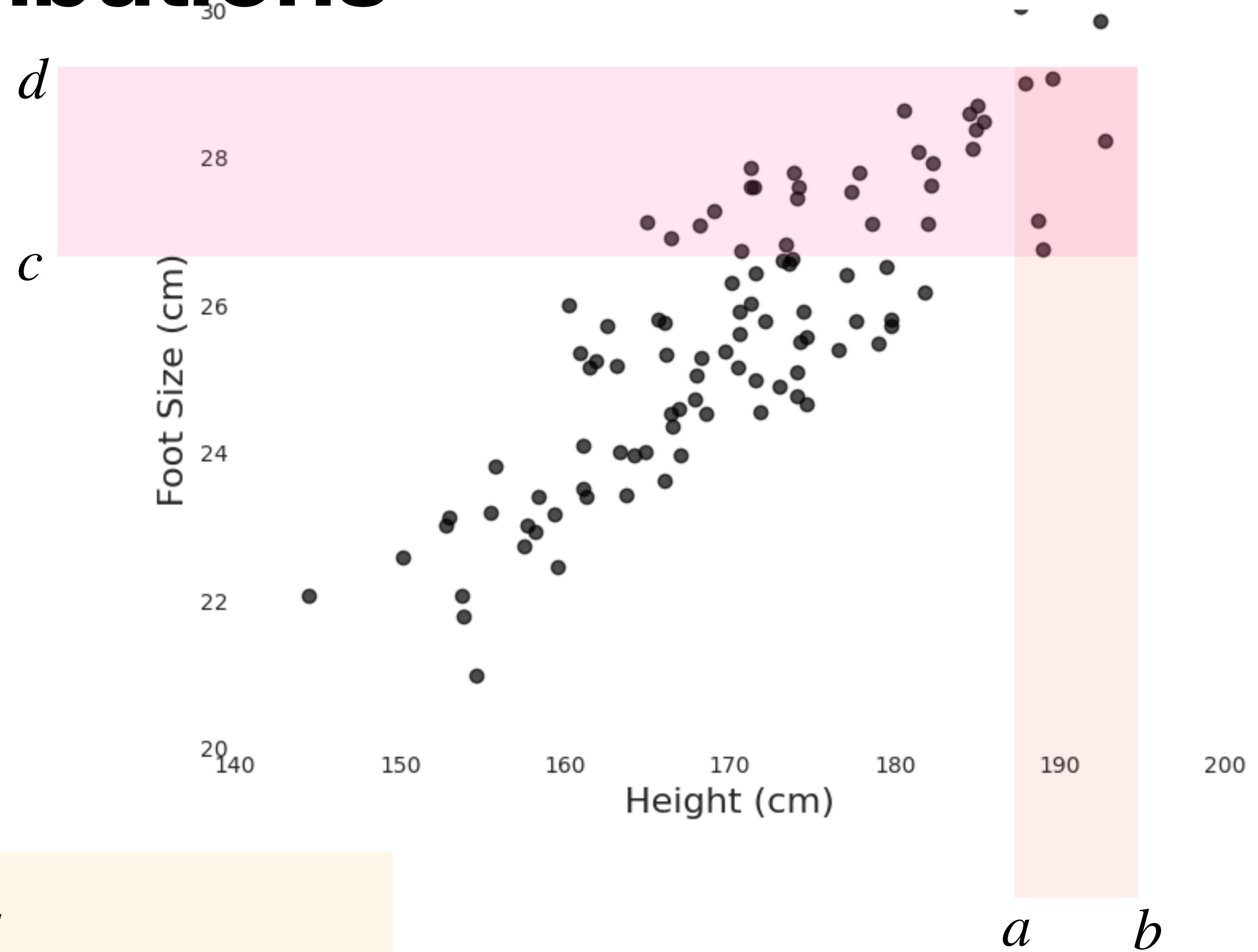
Probability of one is influenced by the other

Joint PMF (discrete)

$$\mathbb{P}[X = x, Y = y] = f_{XY}(x, y)$$

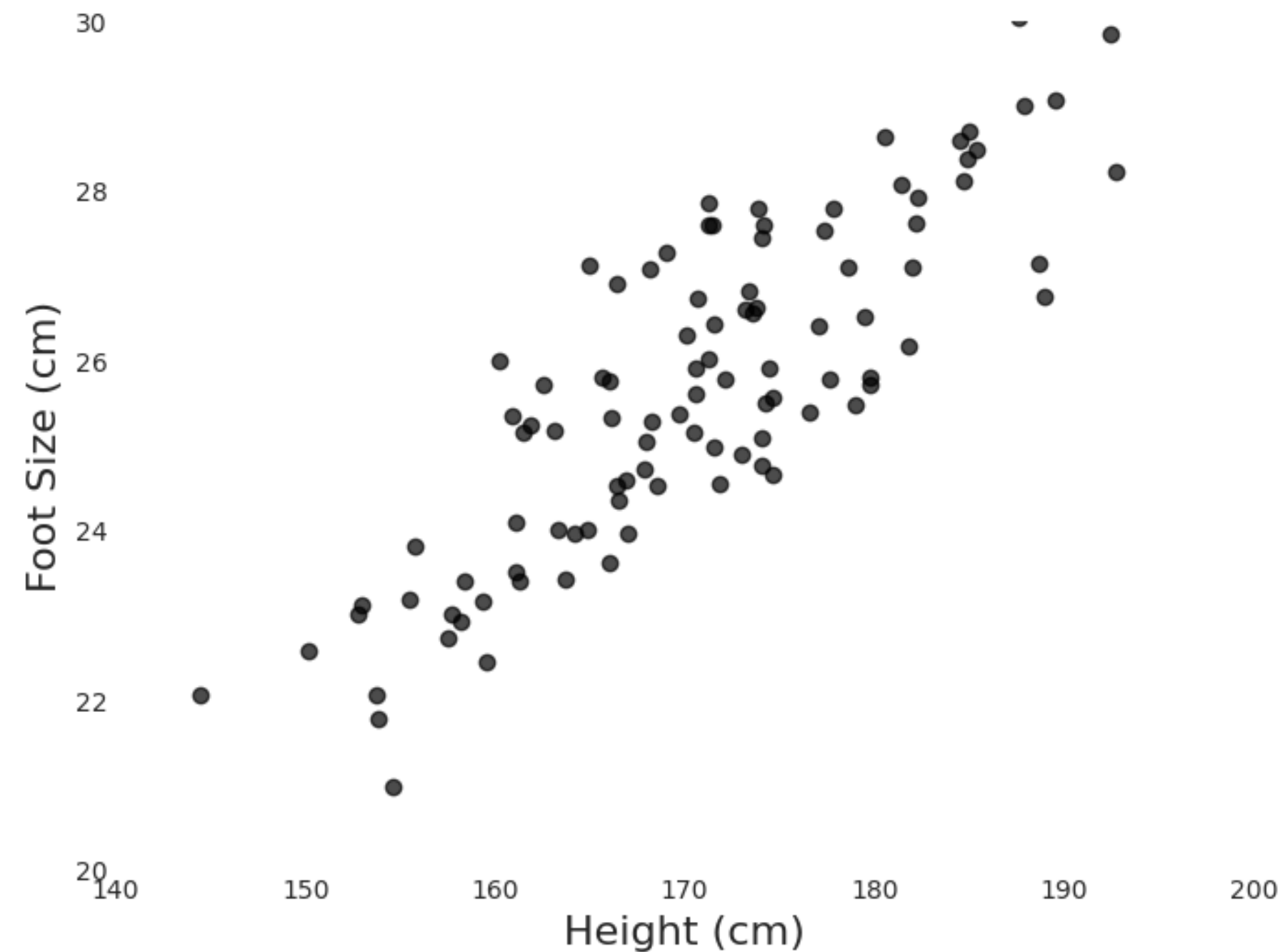
Joint PDF (continuous)

$$\mathbb{P}[X \in [a, b], Y \in [c, d]] = \int_a^b \int_c^d f_{XY}(x, y) \, dx \, dy$$



Marginalising

Scatter of X and Y



Joint pdf: $f_{XY}(x, y)$

Squeeze X axis to scatter of Y

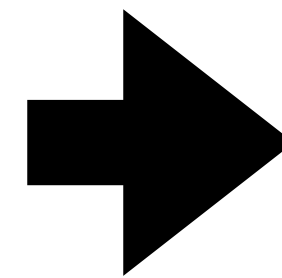


Marginalised pdf: $f_Y(y)$

Marginalising

PDF if we **didn't** have any
information on X (height)

*(Squeeze Y axis to marginalise
the other way)*



Squeeze X axis to scatter of Y



Marginalised pdf: $f_Y(y)$

Covariance of variables X and Y

Meaning:

Quantitative measure of how much they influence each other

$$\text{cov}(X, Y)$$

Positive covariance

“Knowing that X is big **increases** how big we expect Y to be”

Negative covariance

“Knowing that X is big **decreases** how big we expect Y to be”

Zero covariance

“Knowing that X is big **doesn't affect** how big we expect Y to be”

Covariance of variables X and Y

Meaning:

Quantitative measure of how much they influence each other

Formula:

$$\mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

Or equivalently:

$$\mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$$

...why?

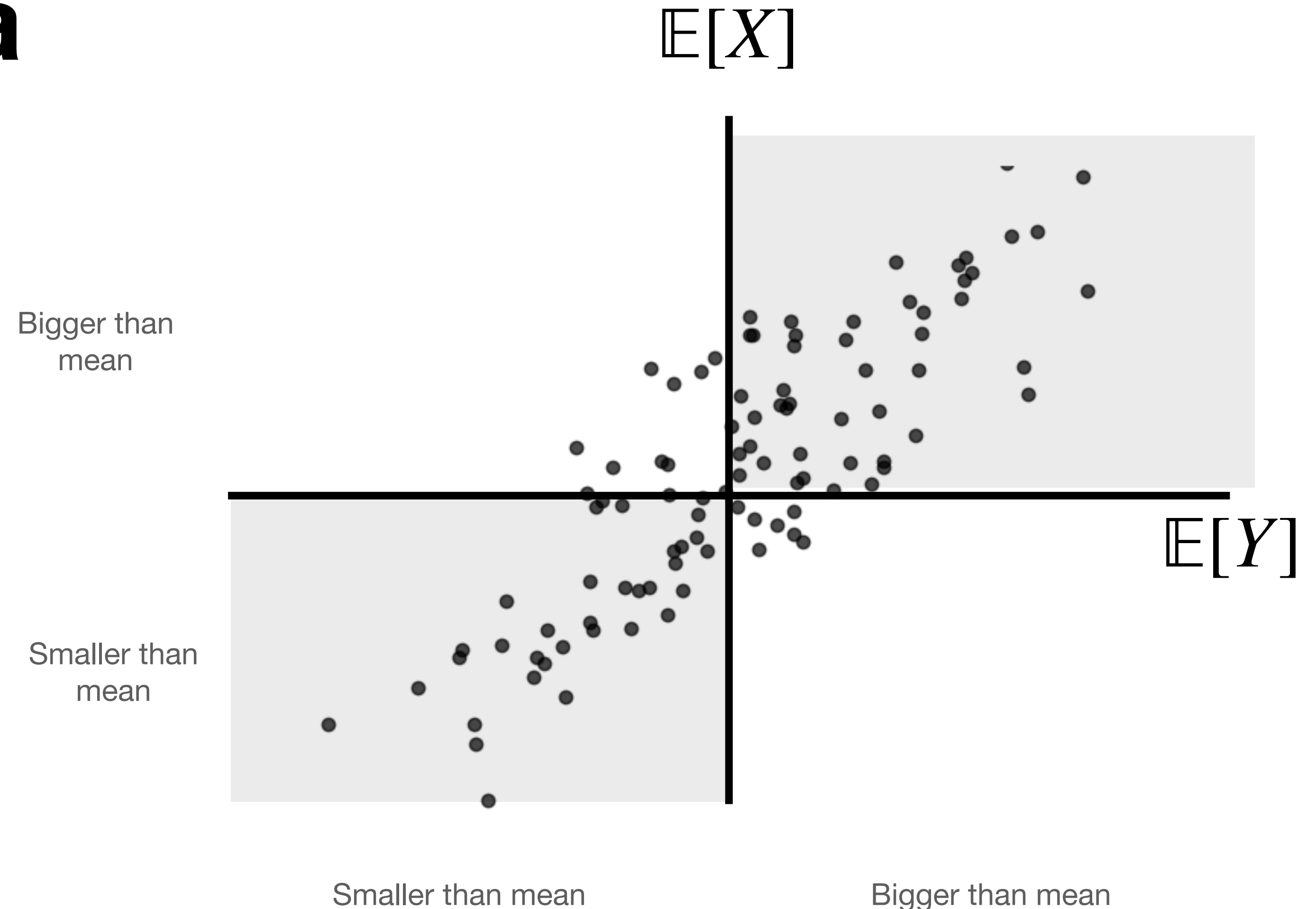
Understanding covariance formula

$$\mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

$(X - \mathbb{E}[X])(Y - \mathbb{E}[Y]) > 0$
when...

X and Y are bigger than their means:

X and Y are smaller than their means:



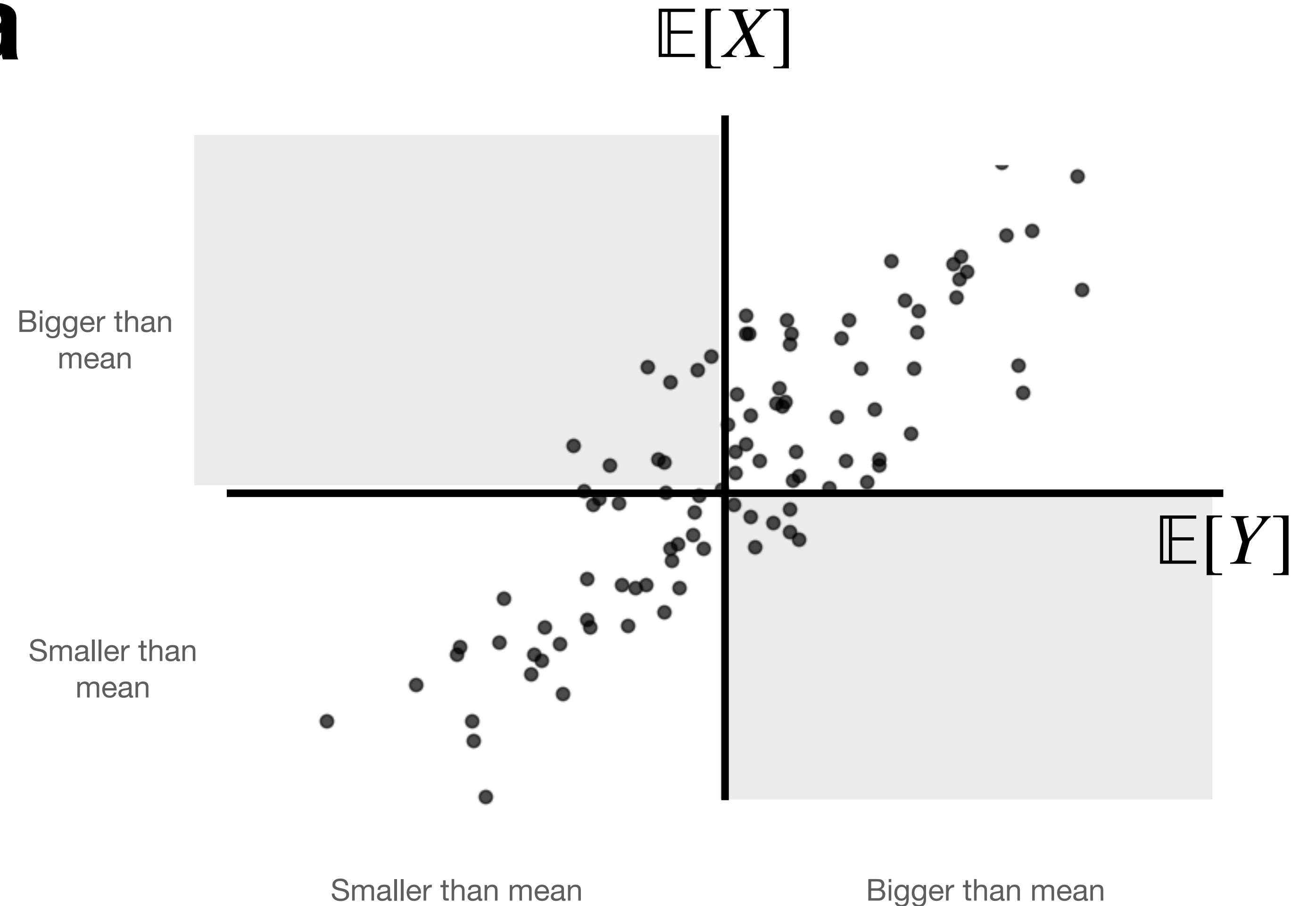
Understanding covariance formula

$$\mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$$

$(X - \mathbb{E}[X])(Y - \mathbb{E}[Y]) < 0$
when...

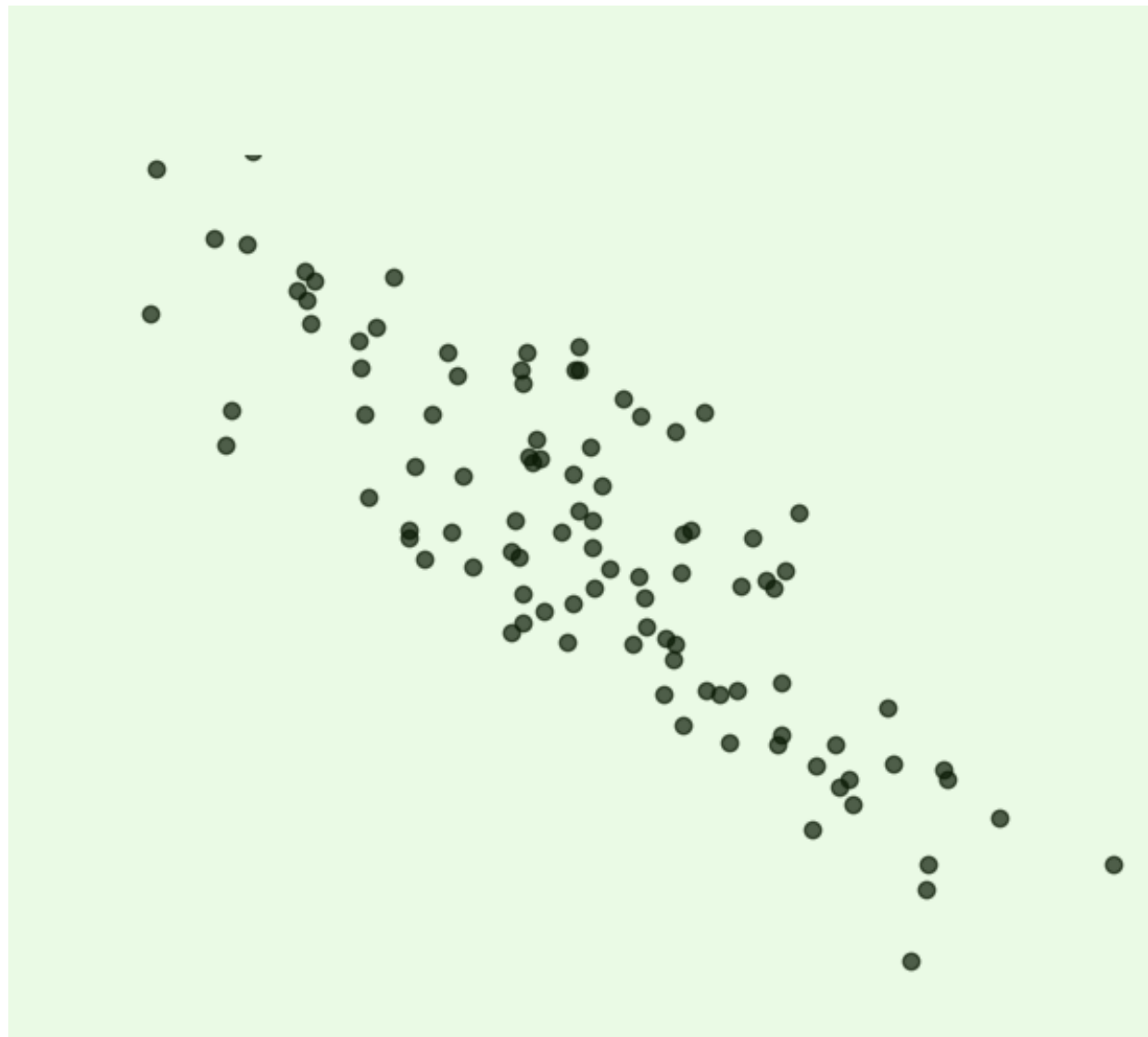
One is bigger than mean

One is smaller than mean

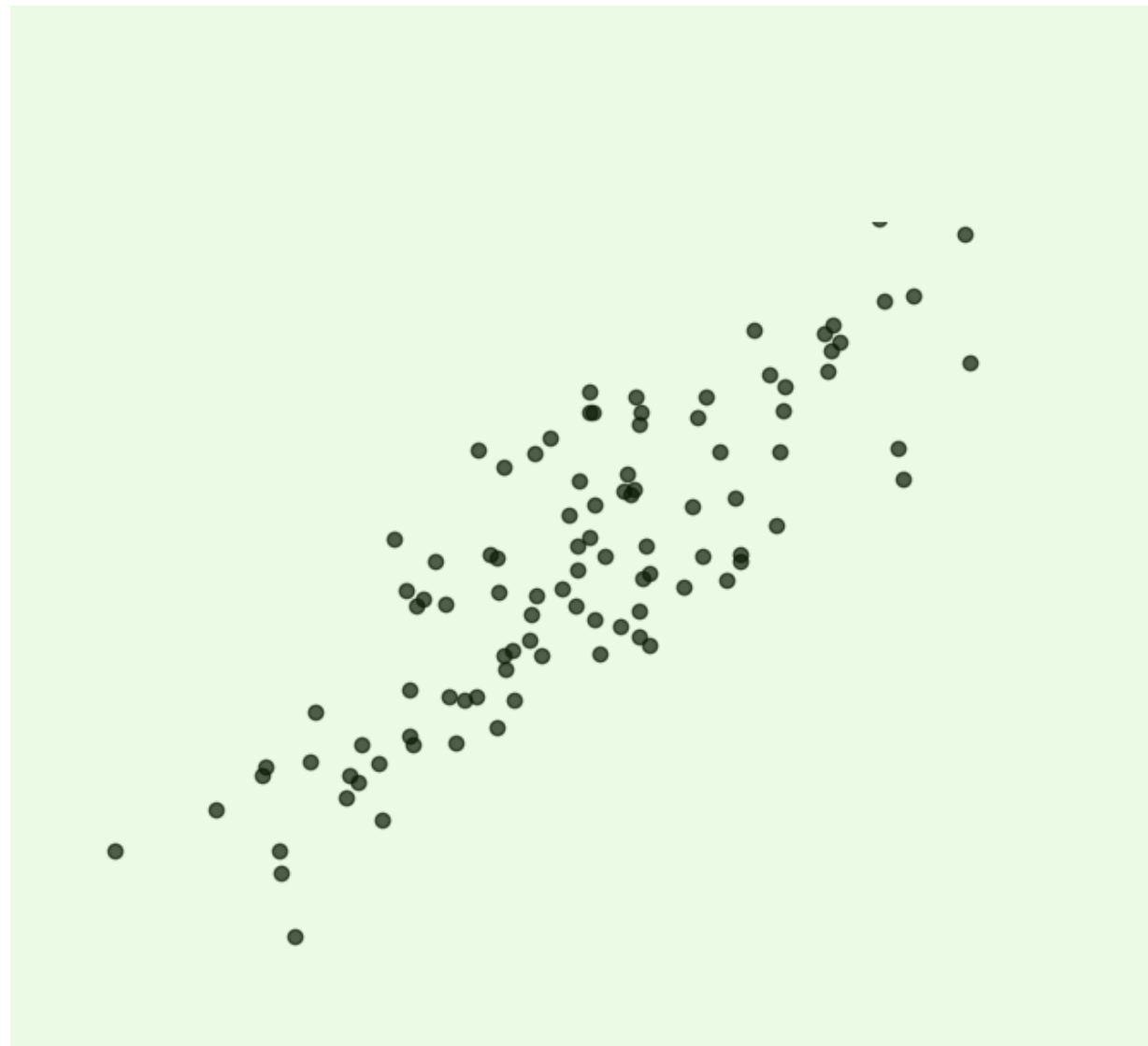


What's the sign of the covariance?

1.



2.



3.



Conditional probability

Partial knowledge of an outcome



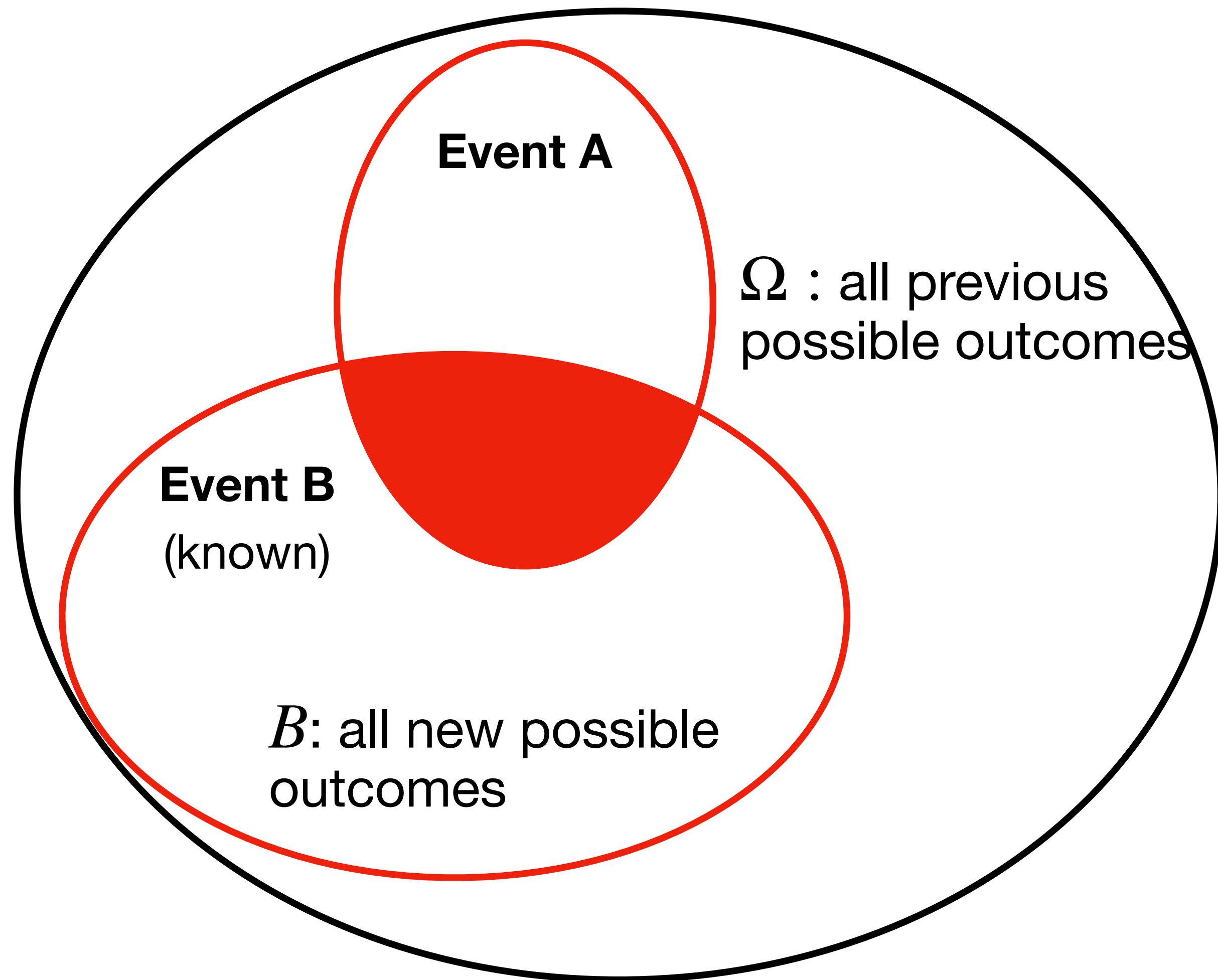
Other events are still uncertain, but their probability has **changed**

Y : first seat in back row filled?

Z : all seats unfilled?

(Draw on Venn diagram)

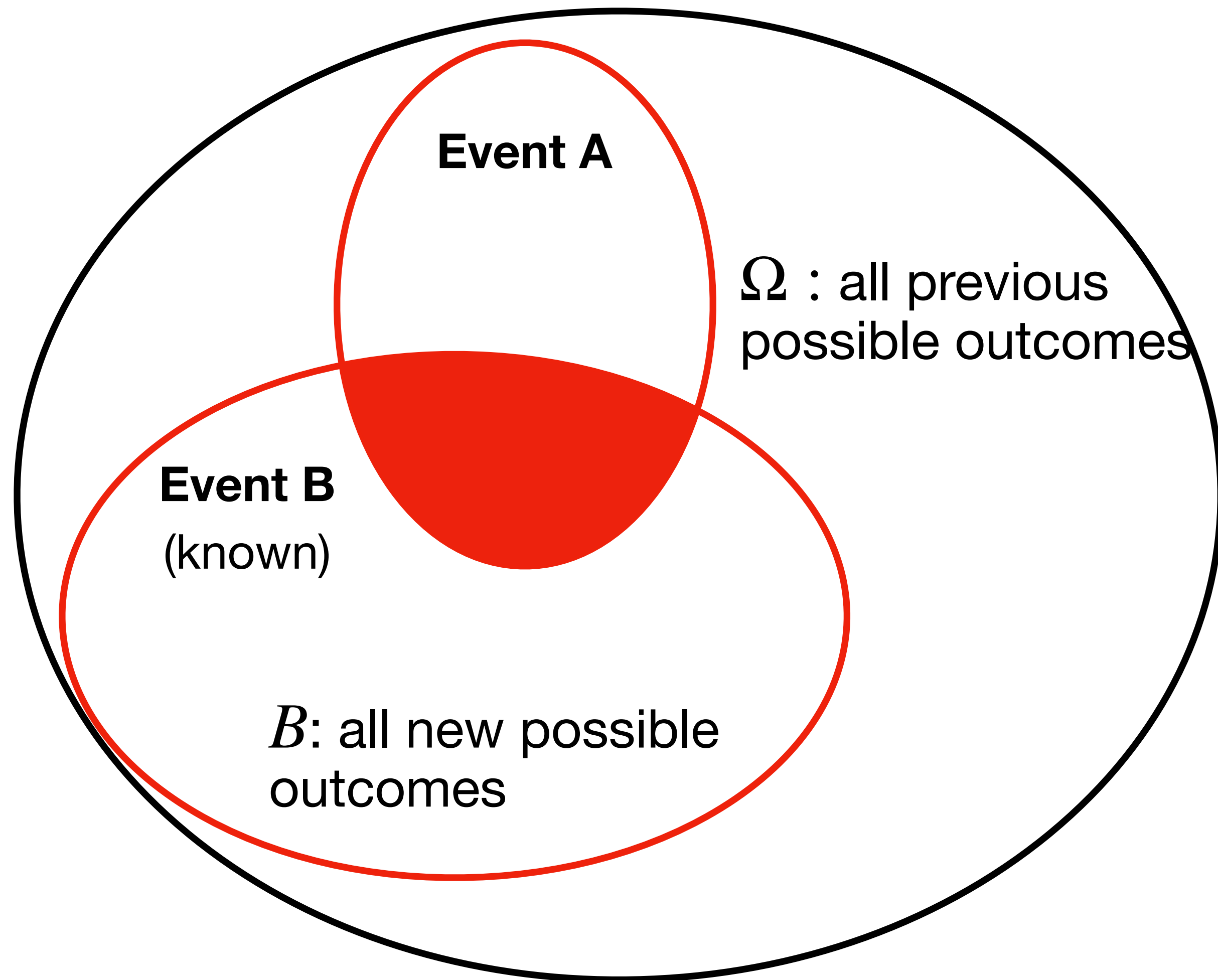
New Probability Space when Event B occurred



New set of outcomes in which event A happens: $A \cap B$

New set of all possible outcomes: B

New Probability Space when Event B occurred

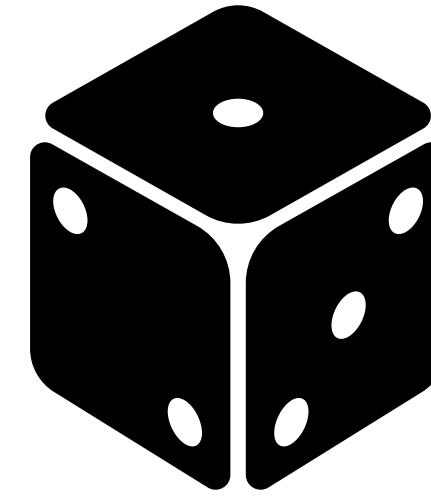
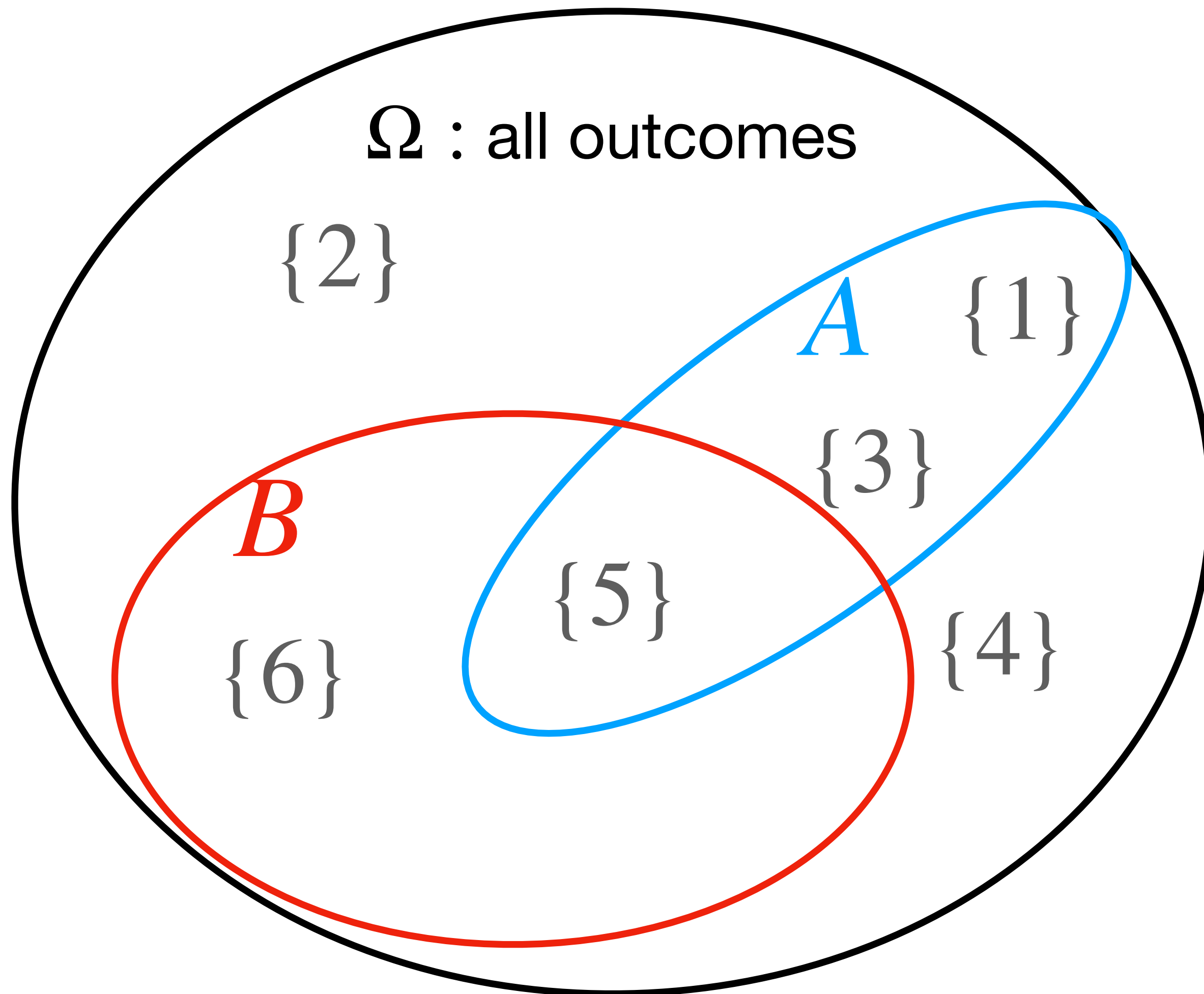


New set of outcomes in which event A happens: $A \cap B$

New set of all possible outcomes: B

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

Partial knowledge of an outcome



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

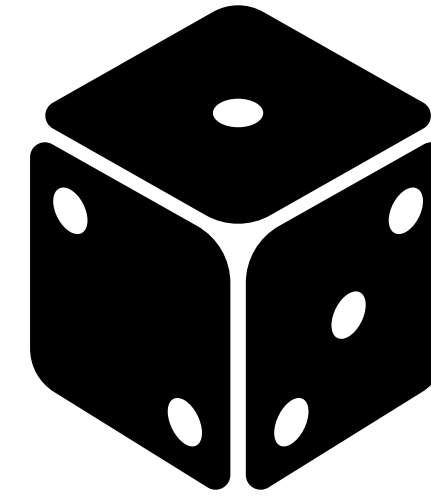
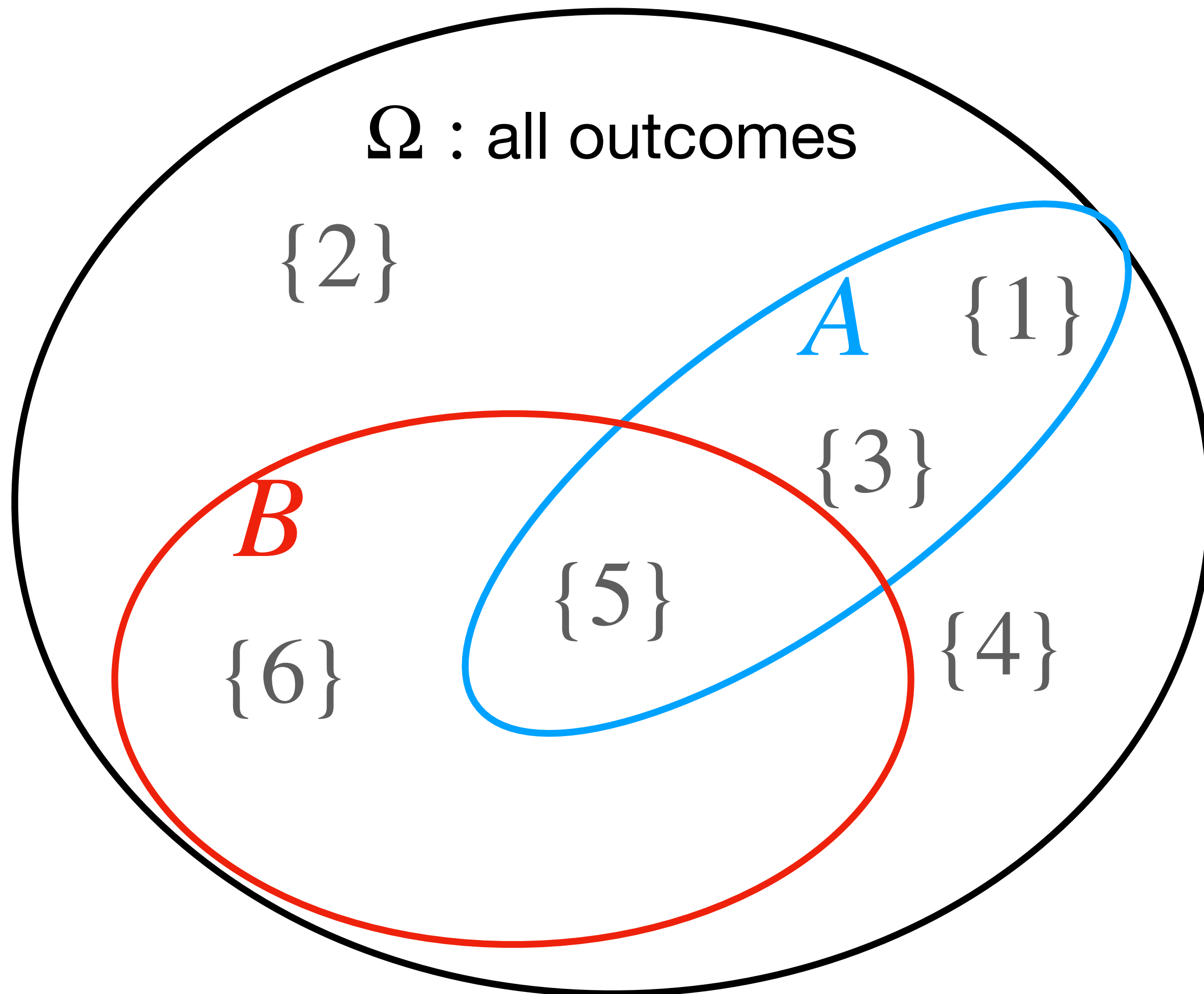
Law of conditional probability

$$\mathbb{P}[A \mid B] = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}$$

Independent events

$$\begin{aligned} \mathbb{P}[A \mid B] &= \mathbb{P}[A] \\ \Rightarrow \mathbb{P}[A \cap B] &= \mathbb{P}[A]\mathbb{P}[B] \end{aligned}$$

Independent events?



$$\frac{1}{6} = \frac{1}{3} \times \frac{1}{2} \quad \checkmark$$

$$\begin{aligned} \mathbb{P}[A | B] &= \mathbb{P}[A] \\ \Rightarrow \mathbb{P}[A \cap B] &= \mathbb{P}[A]\mathbb{P}[B] \end{aligned}$$

Independent events?

Can exclusive events ever be independent?

Independent

$$\mathbb{P}[A | B] = \mathbb{P}[A]$$

$$\mathbb{P}[B | A] = \mathbb{P}[B]$$

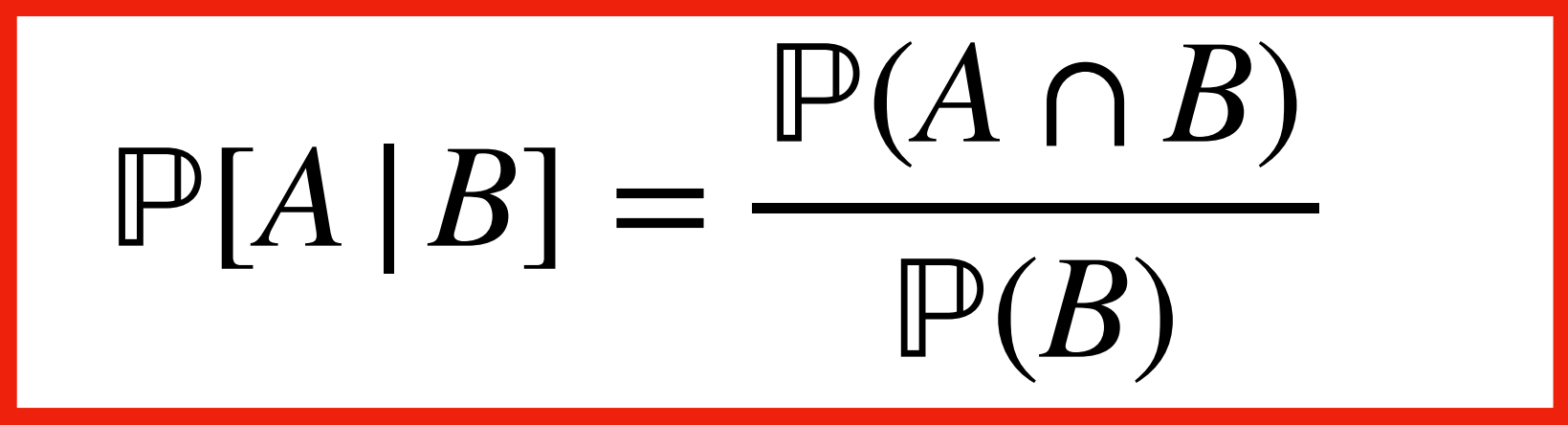
Exclusive

$$\mathbb{P}[A | B] = 0$$

$$\mathbb{P}[B | A] = 0$$

Exclusive events:

0


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

...only if one of their initial probabilities are zero

Bayes' Theorem

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

Aim is to understand and apply

Bayes' Theorem is **useful**

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

A

B

Probability of COVID | sore throat?

$$= \frac{0.3 \times 0.01}{0.05}$$

$$= 6 \%$$

Probability of COVID = 1%

Probability of sore throat = 5%

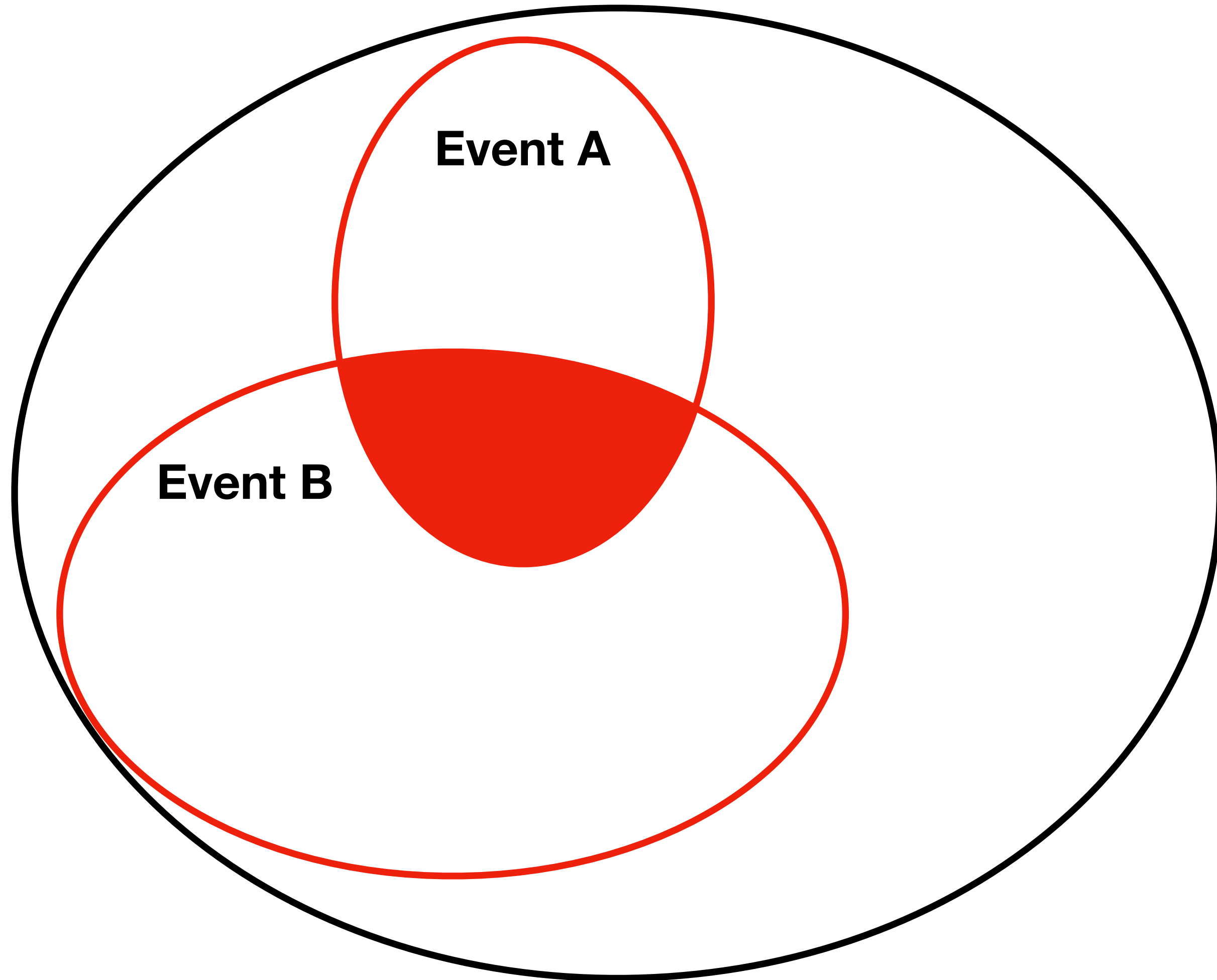
Percentage of Covid patients with sore throat
= 30%

$\mathbb{P}[A]$

$\mathbb{P}[B]$

$\mathbb{P}[B | A]$

Understanding Bayes' Theorem

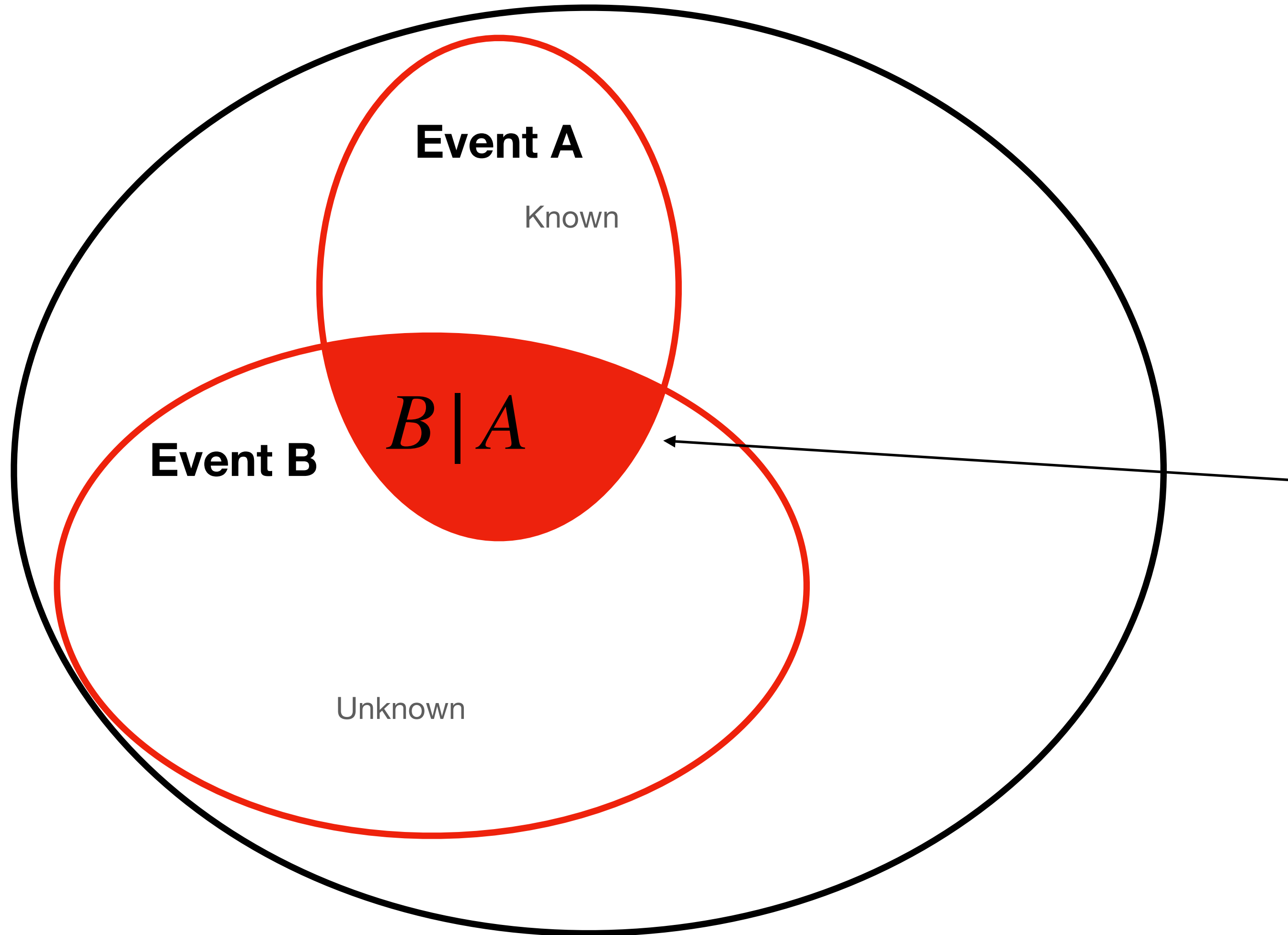


$$\mathbb{P}[A | B] = \frac{\mathbb{P}(B | A)\mathbb{P}[A]}{\mathbb{P}(B)}$$

Going to think about the intersection in two different ways...

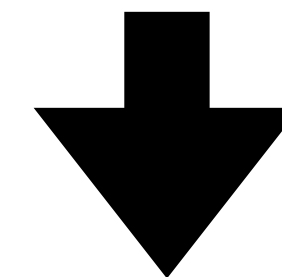
Bayes' Theorem

$B | A :$



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

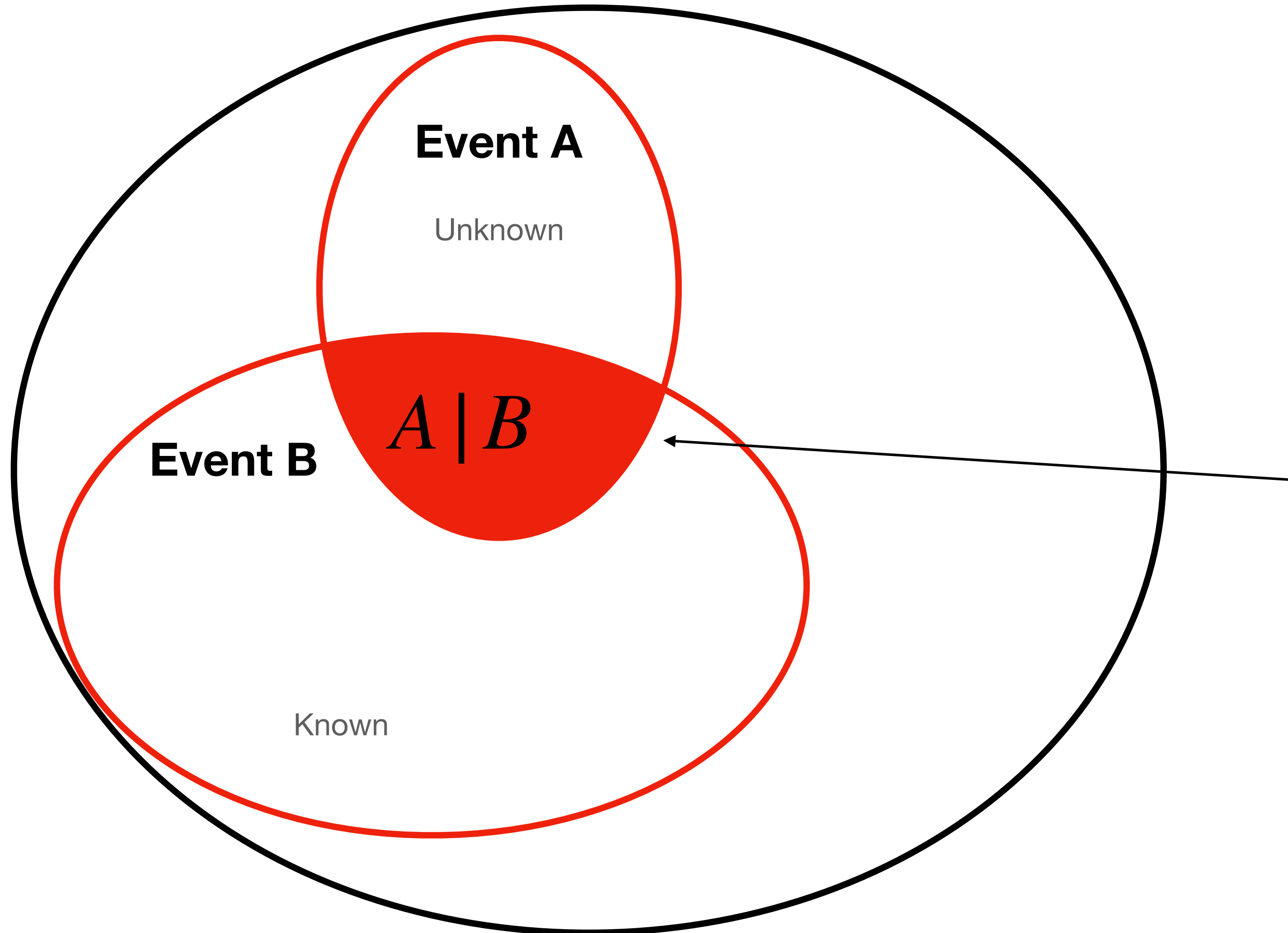
$$\mathbb{P}[B | A] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[A]}$$



$$\mathbb{P}[A \cap B] = \mathbb{P}[B | A]\mathbb{P}[A]$$

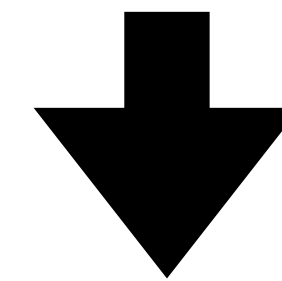
Bayes' Theorem

$A | B :$



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

$$\mathbb{P}[A | B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}$$



$$\mathbb{P}[A \cap B] = \mathbb{P}[A | B]\mathbb{P}[B]$$

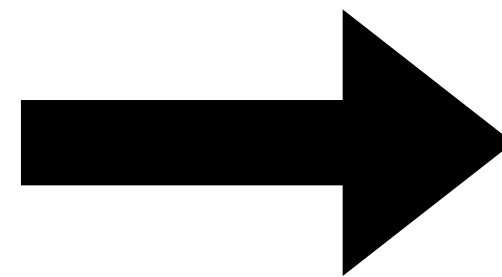
Altogether...

$A | B :$

$$\mathbb{P}[A \cap B] = \mathbb{P}[A | B] \mathbb{P}[B]$$

$B | A :$

$$\mathbb{P}[A \cap B] = \mathbb{P}[B | A] \mathbb{P}[A]$$



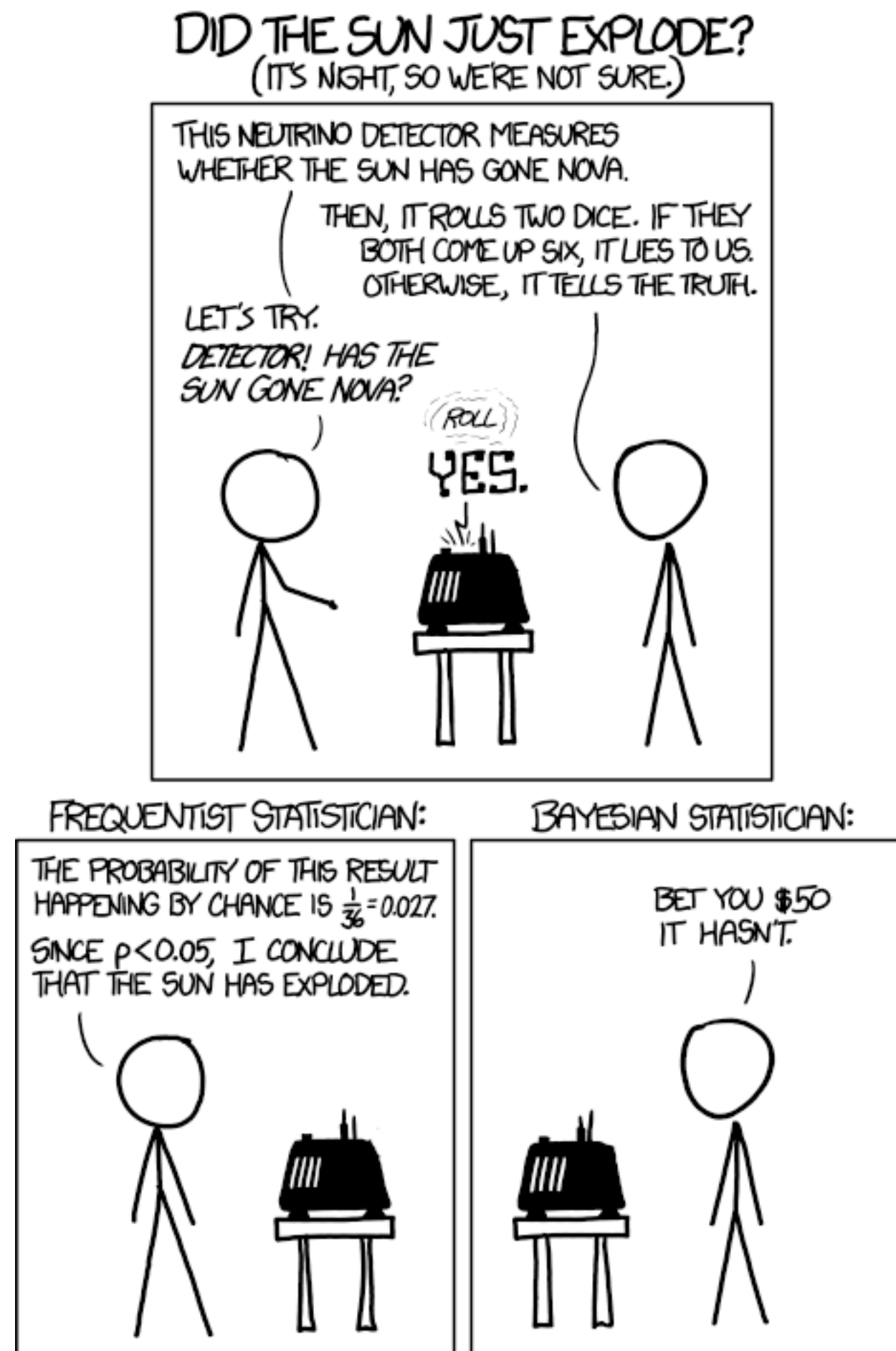
$$\mathbb{P}[A | B] = \frac{\mathbb{P}(B | A) \mathbb{P}[A]}{\mathbb{P}(B)}$$

$$\mathbb{P}[A | B] \mathbb{P}[B]$$

$=$

$$\mathbb{P}[B | A] \mathbb{P}[A]$$

Homework: tell me why this joke is funny



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