

# Stochastic Processes

## Introduction to Probability

**Stochastic Processes for  
CS4070 multivariate data analysis**



↑  
**Dr. David Tax**

**Slides 'inspired' by:  
Prof.dr.ir. Inald Lagendijk**



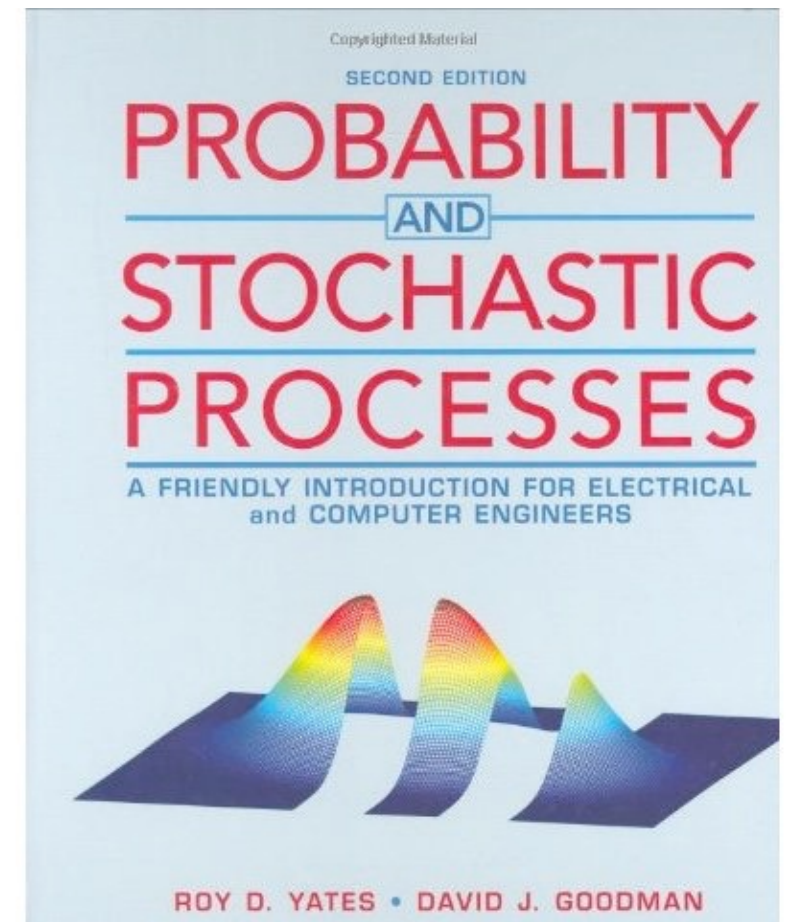
# Organisation CS4070

- Stochastic Processes is the first part of:
- **CS4070 Multivariate Data Analysis**
  - together with Jakob Söhl
- Part I: Stochastic Processes, by me: fundamentals of probability theory, extend to time series
- Part II: Statistical Learning, by Jakob: analysis of general data, frequentist- and Bayesian-approach



# Organisation Part I

- Plenary Lectures (HoorCollege): 7x
- Working Groups (WerkCollege): 7x
- Book: R.D. Yates and D.J. Goodman, Probability and Stochastic Processes: A Friendly Introduction for Electrical and Computer Engineers (Second Edition)
- UHM: (There is a **third** edition now, also fine)
- Sheets, exercises, etc: Brightspace



# More about Working Groups

- Plenary lectures:
  - Cover a lot of ground,
  - Don't necessarily stick to the subject order in book
  - Should give you overview, red line, main issues
- In preparation of working group:
  - Read entire chapter(s) at home: (topics in 'list.pdf' on Brightspace)
  - Study the examples, formulate questions to ask
  - Be ready to answer questions from lecturer
- Working groups:
  - Reflect on plenary lectures and discuss tough issues or problems
  - Solve selected exercises
- Problems solved: See Brightspace

# Final Computer Exercise

- At the end of the quarter on Stochastic Processes: a final computer exercise
- Pass or Fail
- You have to pass it before you can get the exam grade
- It will appear on Brightspace (Still constructing the exercise)

# Final exam

- Exam will be a physical written exam (but it depends on the Corona situation)
- I'll make a practice exam available.
- For the exam, you're allowed to bring one A4 paper with your own notes.

**Chapters 1, 2, and 3**

**Motivation**

**Probability Models**

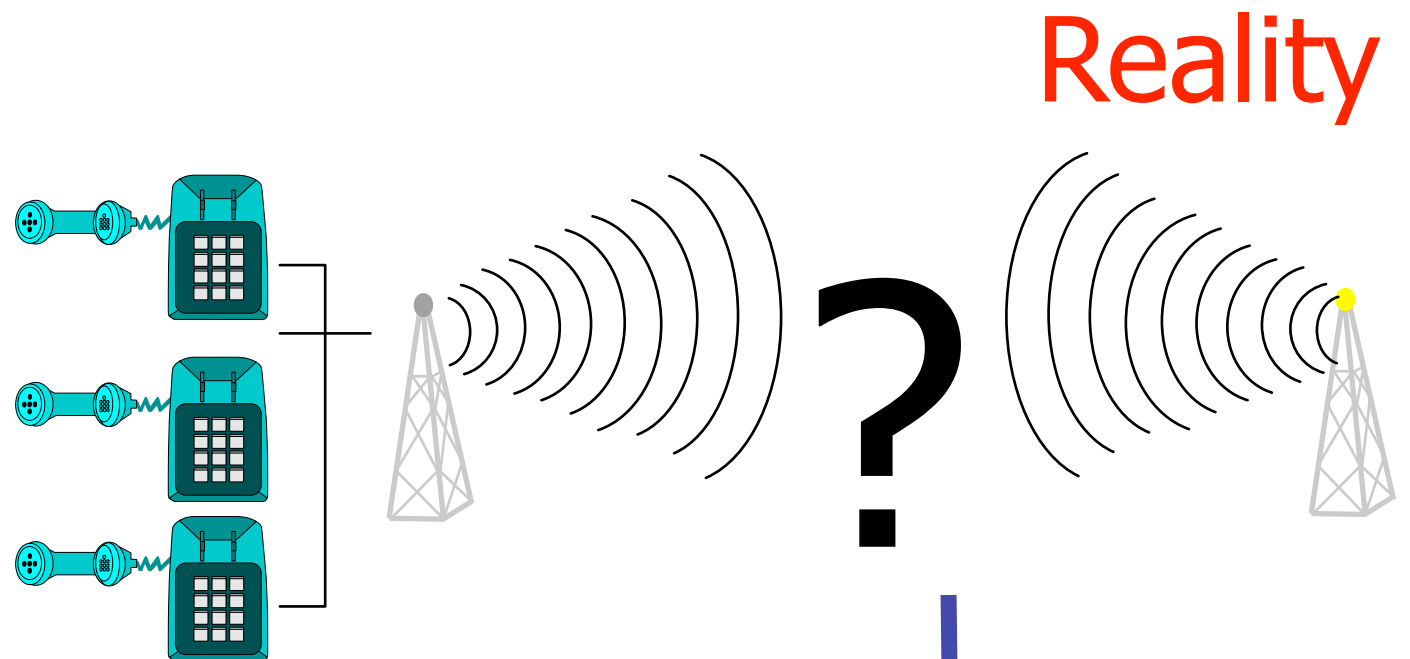
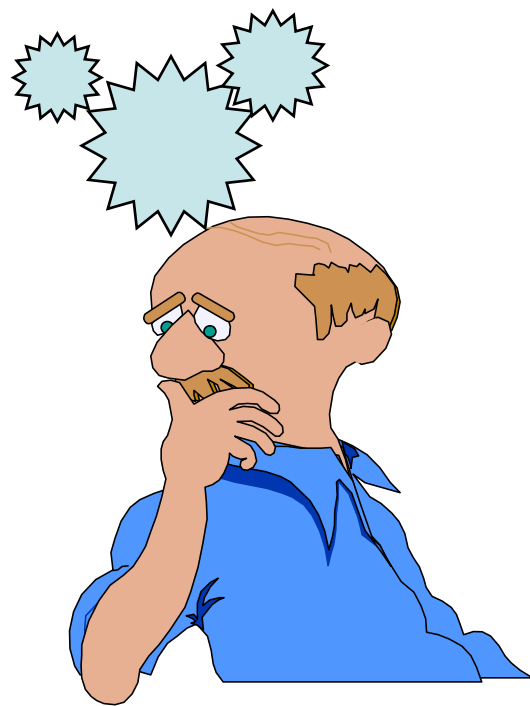
**Discrete and Continuous**

**Random Variables**

**PMF, PDF, expectation**



# The Engineer: Problem Solver



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## Tools:

Analysis  
Algebra  
Physics  
Probability theory

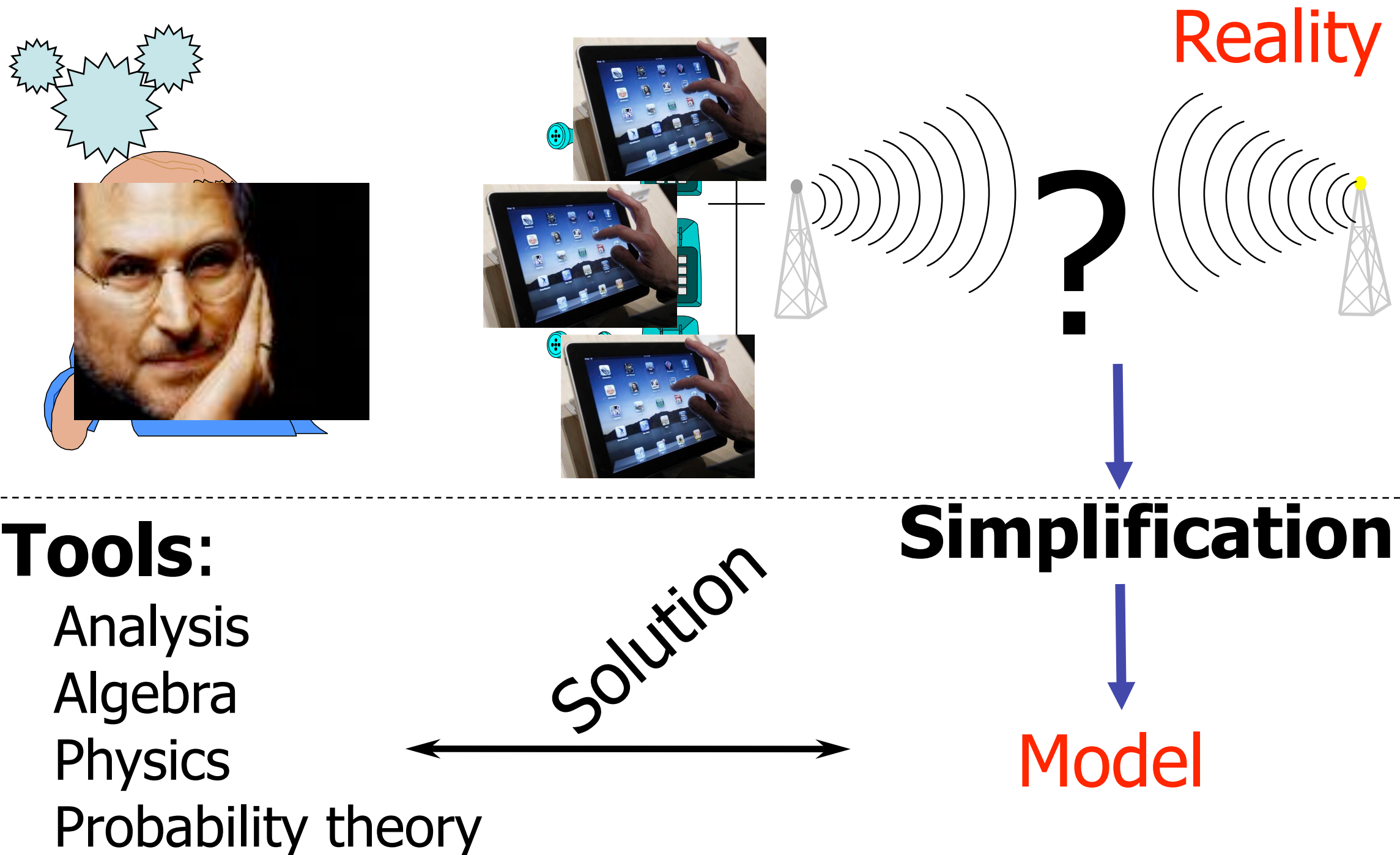
Solution

## Simplification:

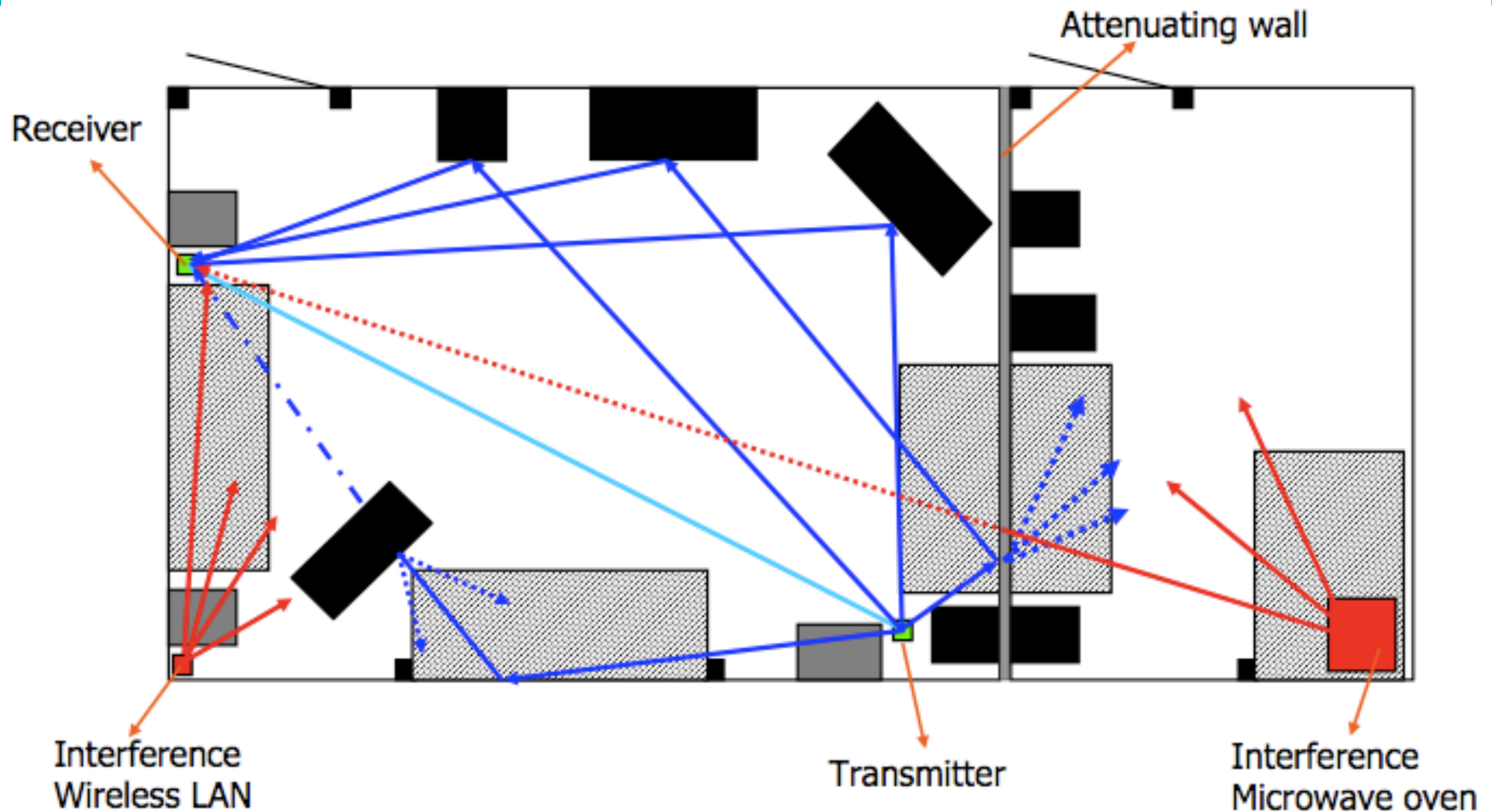
Model



# The Engineer: Problem Solver

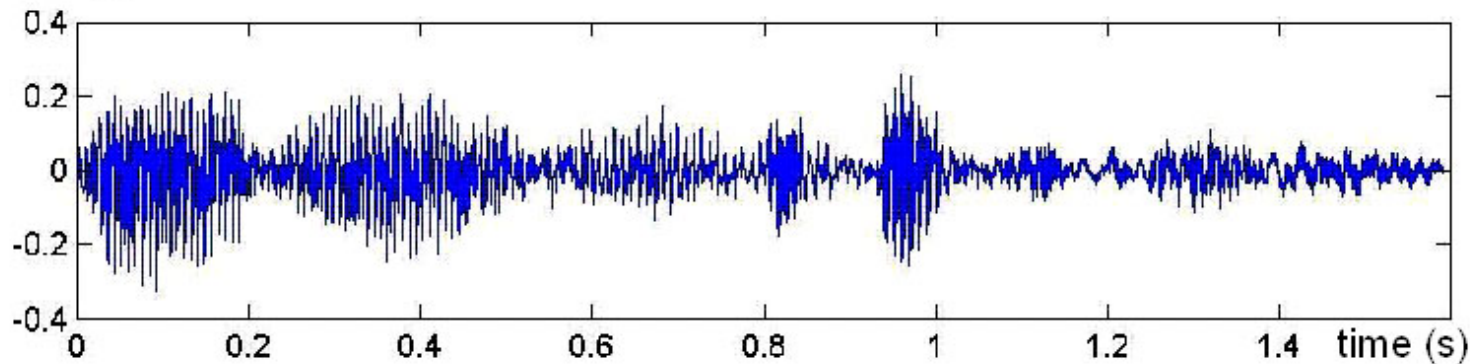


# Radio signals in an indoor environment

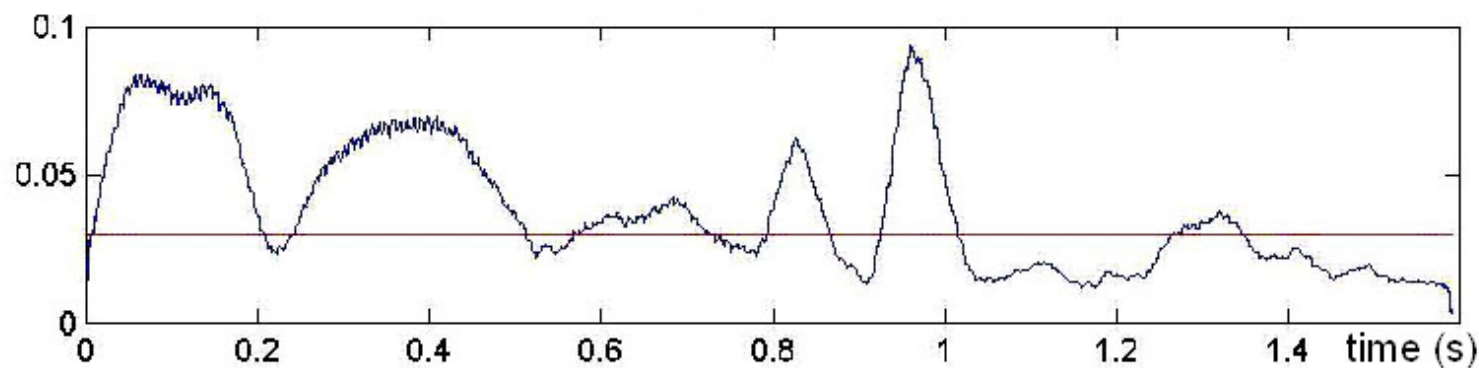


# Voice signal, weather, stock market

Signal

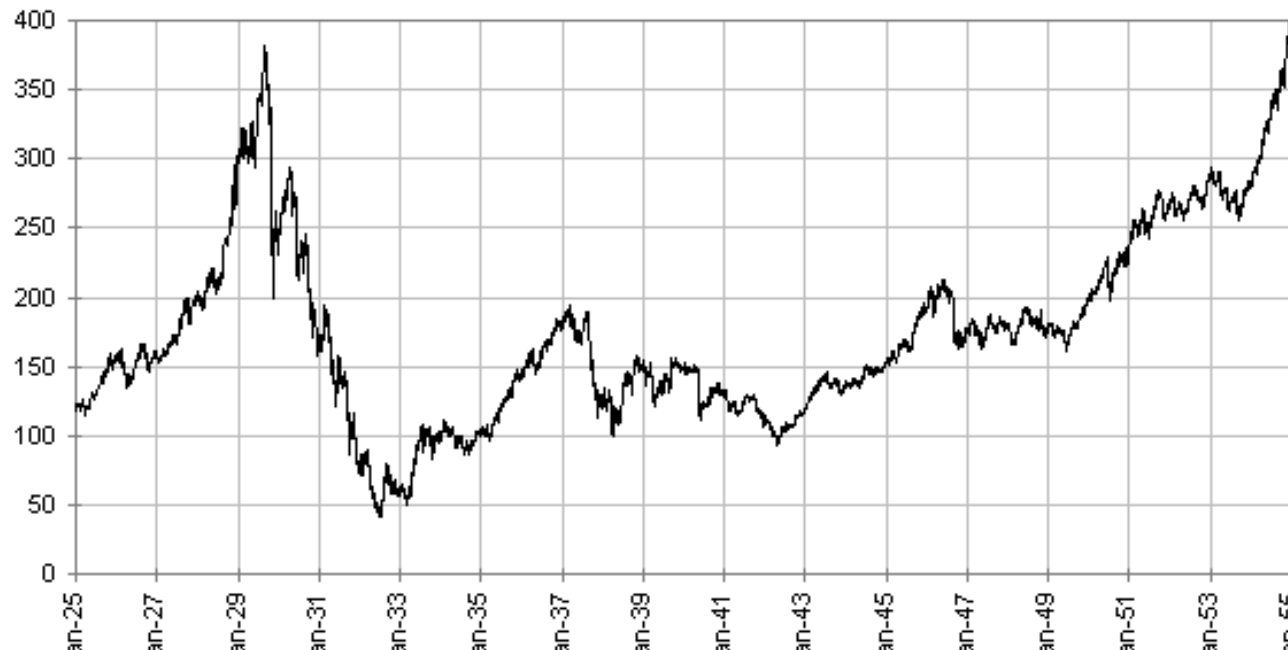


Signal Envelope



"I am am bi dex trous."

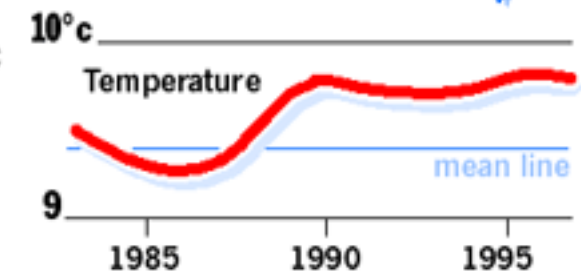
Dow Jones Industrial Average : 1925 - 1955



## Climate changes

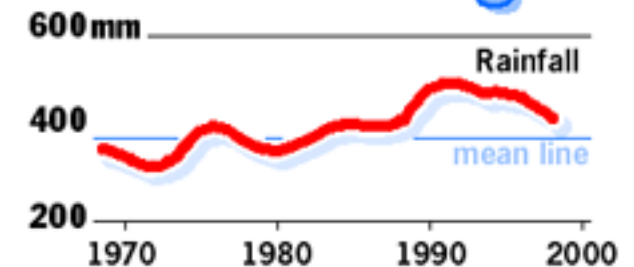
### Warm weather

Britain's average temperatures have risen by nearly 1°C in the last 100 years. Even small changes affect wildlife. The last decade was the hottest on record



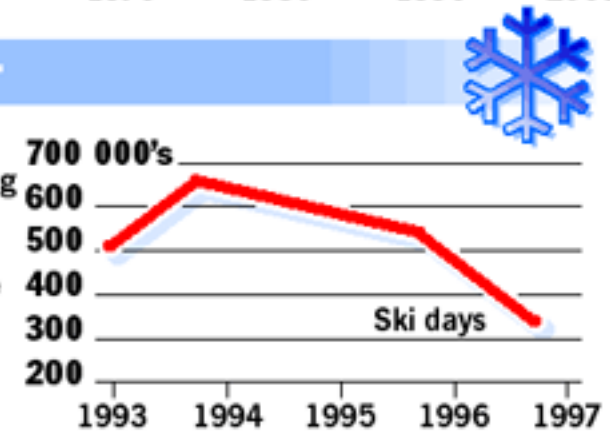
### Rainfall

Britain is getting wetter winters. Rainfall has been above average every year since 1990



### Cold weather

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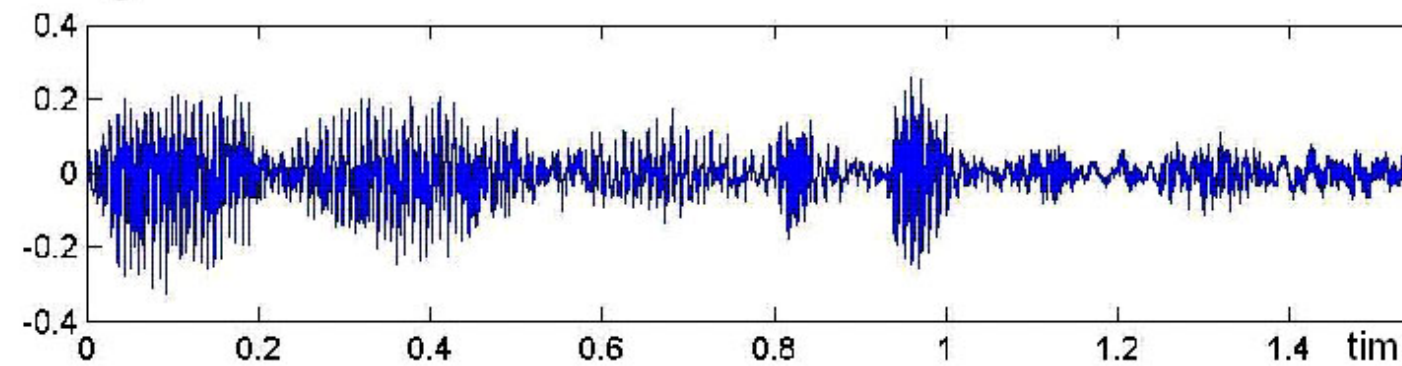


# Stochastic processes

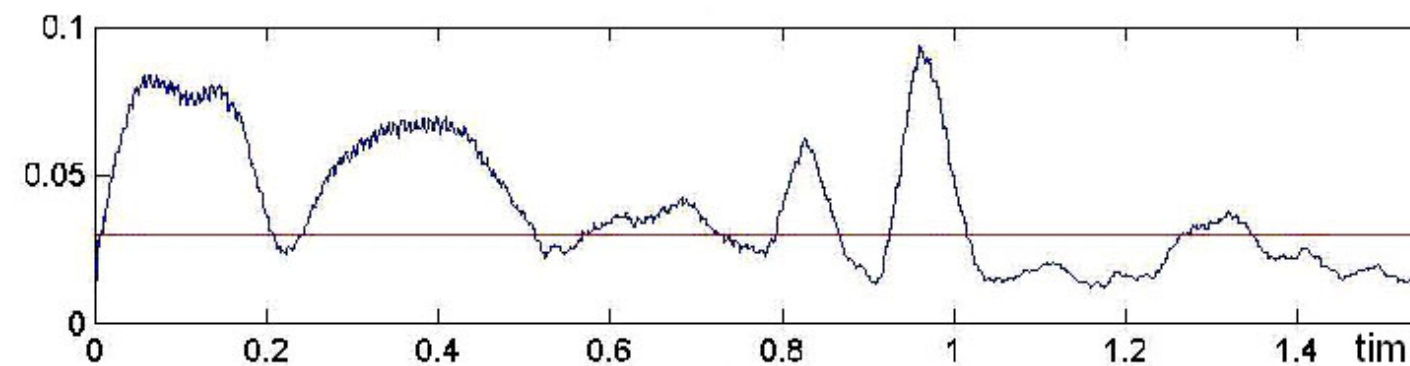
Dow Jones Industrial Average : 1925 - 1955



Signal



Signal Envelope

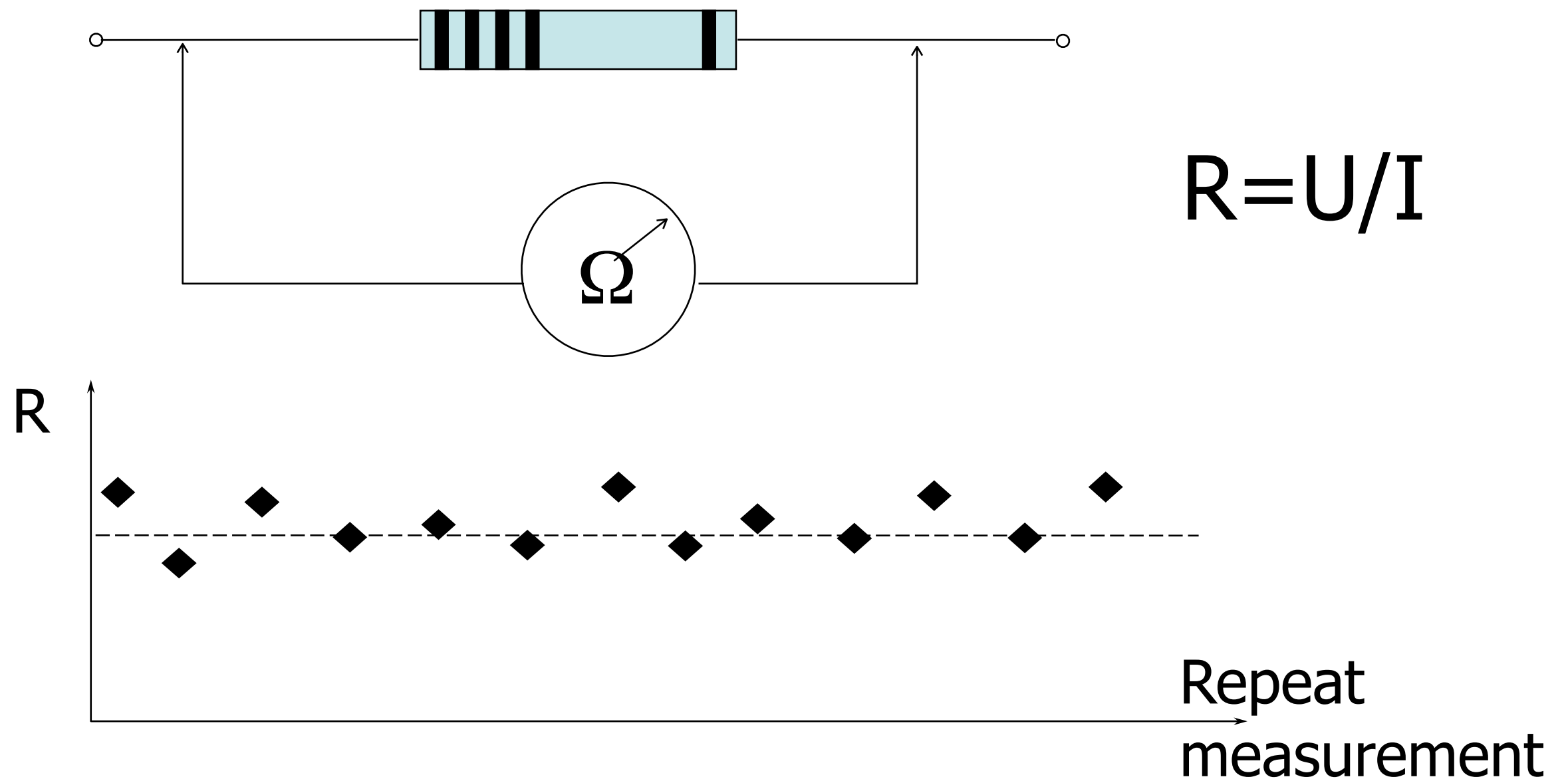


“I am am bi dex trous.”

- The goal of this course:  
**describe** these types of signal (and get rich?!?)

# Model: Abstraction of Reality

## The Resistor



# Models

- **Deterministic** model
  - $R = U / I$
  - $R = U / I + f(T)$
  - $R = U / I + f(T) + g(\text{measuring equipment})$
  - ...
  - increasing complexity to describe behaviour
- **Stochastic** (=probability) model
  - $R = U / I + N$
  - N is unpredictable (random, stochastic) component  
~ Obtain a different value when measurement is repeated

# Model: Abstraction of Reality

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- Sometimes a stochastic (probability) model leads to a **simpler** description, analysis, and design of a problem or solution than a deterministic model
- Stochastic models enhance the toolkit of the modern engineer
- Skilful usage of probability theory can greatly reduce complexity in some case
- ... but don't use a saw if you need a screwdriver



# Applications in CS

*But applicability is  
much much broader*

- Computer and network performance analysis
- Prediction of internet traffic
- Security and reliability analysis
  
- Prediction of energy consumption
- Decision support systems
  
- Design of digital filters for speech, audio, images, communication signal processing
- Multimedia processing
- Data analysis, data mining
- Character and pattern recognition

# Question

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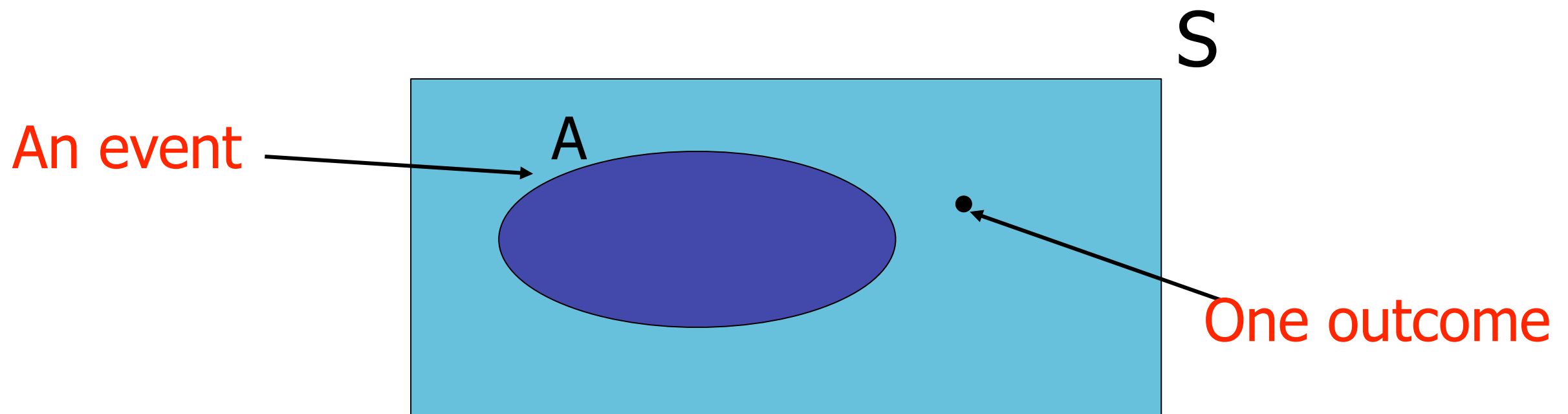
- Can you come up with something that is **not** a stochastic process?

# Probability Model

- **What does a model describe?**
- **What do we actually mean by “probability”?**

# Probability (Stochastic) Model

- Describe the situation (reality, experiment)
- Identify the values that can be observed
  - Outcomes
  - Events (sets of outcomes)



- Assign probabilities to events  $P(A)$ ,  $P(S)$

# Notion of Probability

- How to assign probabilities to outcomes or events in a stochastic model?
- Intuitively: How frequent does an outcome/event occur when the experiment is repeated many times?

$$P_k = \lim_{n \rightarrow \infty} f_k(n) = \lim_{n \rightarrow \infty} \frac{N_k(n)}{n}$$

Number of times  
↓  
Outcome number

# Axiomatic Approach to Probability

- Axiomatic: Pose (three) basic assumptions (axioms) and build the theory on top of that.

1. A probability is never negative

$$P(A) \geq 0 \text{ for any } A$$

2. The probability of the sample space is 1

$$P(S) = 1$$

3. The probability of events  $A$  and  $B$  that are mutually exclusive (disjoint) can be added:

$$P(A \cup B) = P(A \text{ or } B) = P(A) + P(B)$$

# Mutually exclusive/disjoint

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- Take the standard, silly, example: throwing with a dice
- (1) what are the possible outcomes?



# Mutually exclusive/disjoint

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- Take the standard, silly, example: throwing with a dice
- (1) what are the possible outcomes?
- (2) are the outcomes disjoint?

# Mutually exclusive/disjoint

- Take the standard, silly, example: throwing with a dice
- (1) what are the possible outcomes?
- (2) are the outcomes disjoint?
- (3) are events  $A=\{1,3,5\}$  and  $B=\{3,4,5\}$  disjoint?

# Examples of Probability Models

- Bernoulli probability model
  - Probability of success in binary situation
- Geometric probability model
  - Probability of  $n$  repeats of Bernoulli experiment needed before success
- Binomial probability model
  - Probability of  $k$  successes in  $n$  repeats of Bernoulli experiment
- Poisson probability model
  - Probability of  $k$  events in certain period of time

Have a look  
in the book!

# Conditional Probability

- Notation  $P(A / B)$  or  $P(A | B)$
- Interpretation: The probability of A, given that we know that the outcome is in event B
- Probability of A "given B"

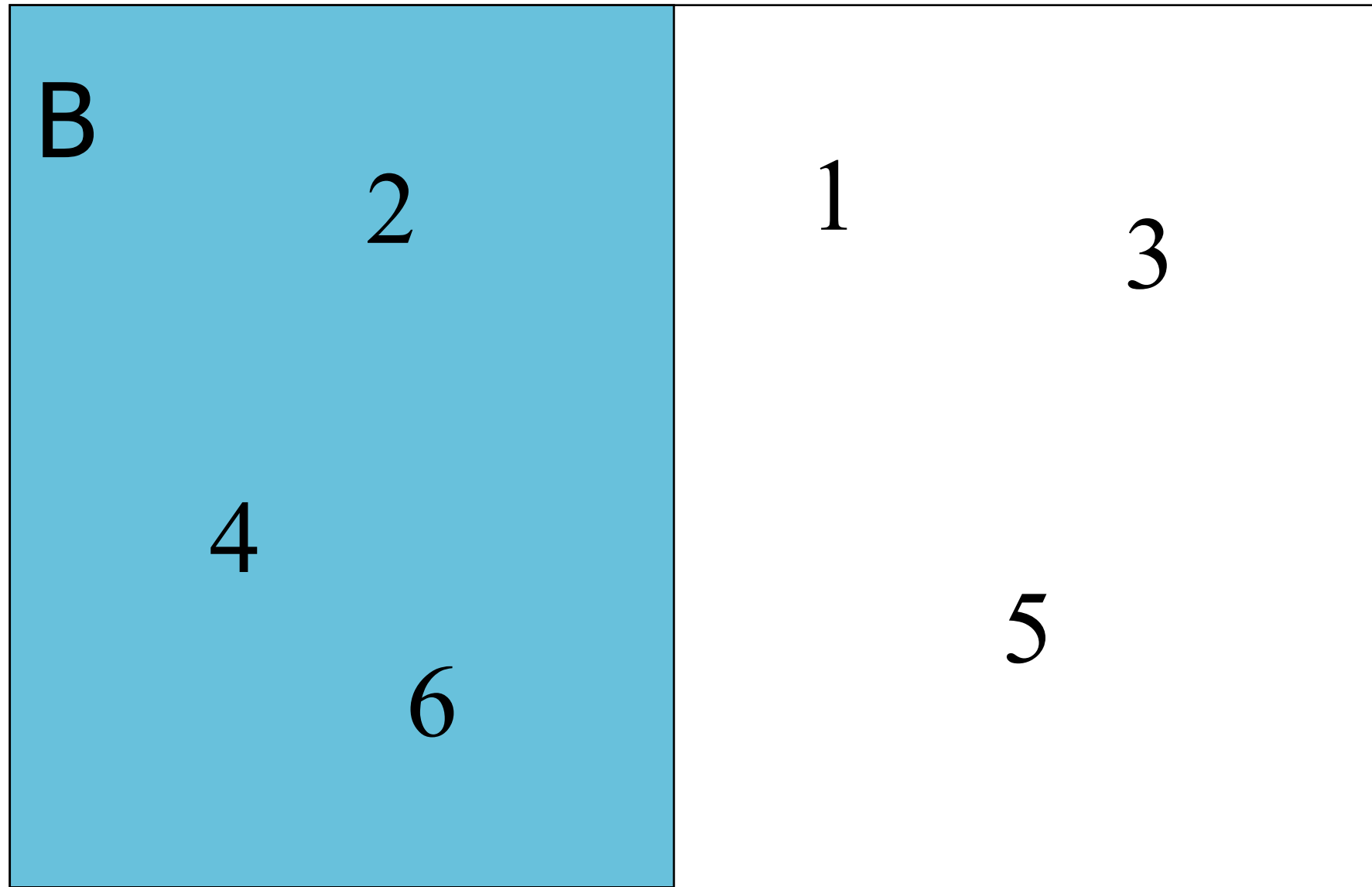
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$$P(A|B) \stackrel{?}{<}{=} P(A)$$

Conditional probability

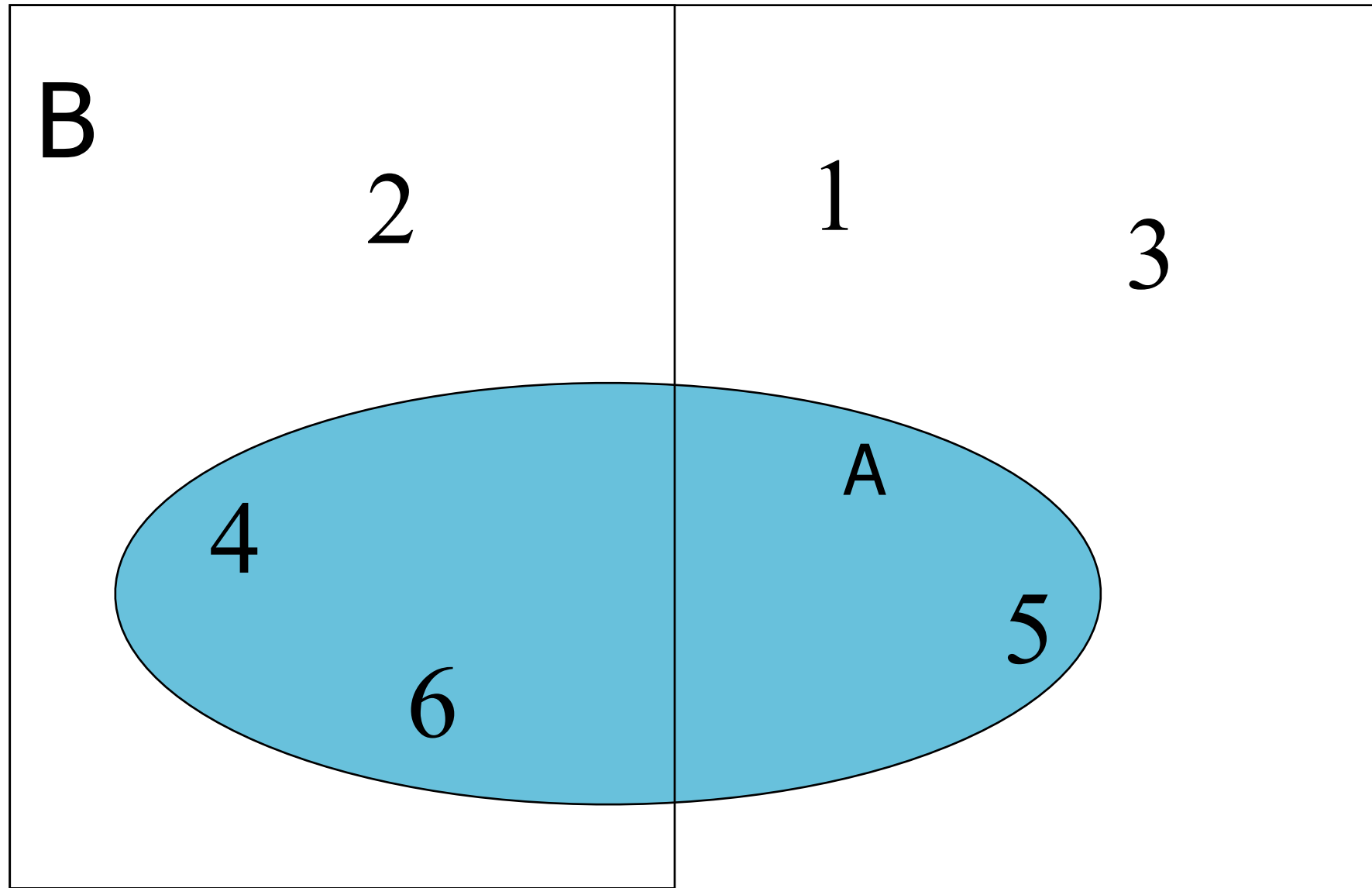
A priori probability

# Example (1)



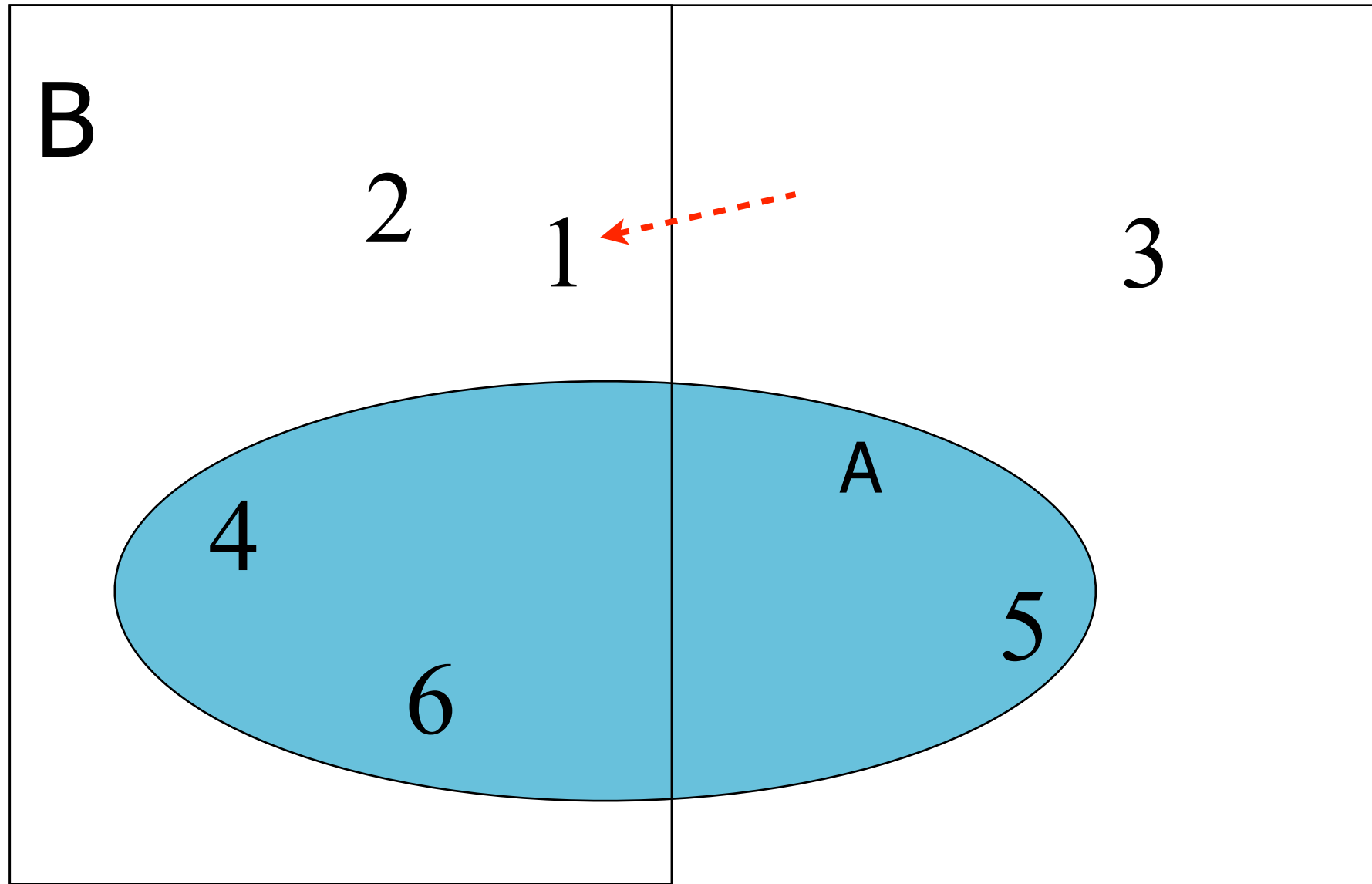
- B: "Even outcome" when rolling the dice

# Example (2)



- A: "4 or more" when rolling the dice: what is  $P(A)$ ?
- How large is  $P(A|B)$ ?

# Example (3)



- Different B! How large is  $P(A|B)$  now?



# Definition Conditional Probability

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad P(B) > 0$$

Notation:

$$P(A \text{ and } B) = P(A, B) = P(A \cap B) = P(AB)$$

Alternative formulation

$$P(A \cap B) = P(A|B)P(B)$$

# Bayes' theorem

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- A consequence of the definition of conditional probabilities: Bayes' theorem
- Due to time limitations: study it **yourself**, section 1.5 pg.16-21

# Independent Events

- If  $P(A|B) = P(A)$  then A and B are independent events

- Hence if A and B are independent events, then

$$P(A, B) = P(A|B)P(B) = P(A)P(B)$$

- Independence is a **special case** and can never be assumed to be true by default
- Be careful: Independence and mutually exclusive are different concepts
- Example:  $A=\{2,4,6\}$     $B=\{1,3,5\}$ .

# Random Variables

**Outcomes, events**

**Probability mass functions**

**Probability density functions**

**Cumulative distribution functions**

**Expected value**

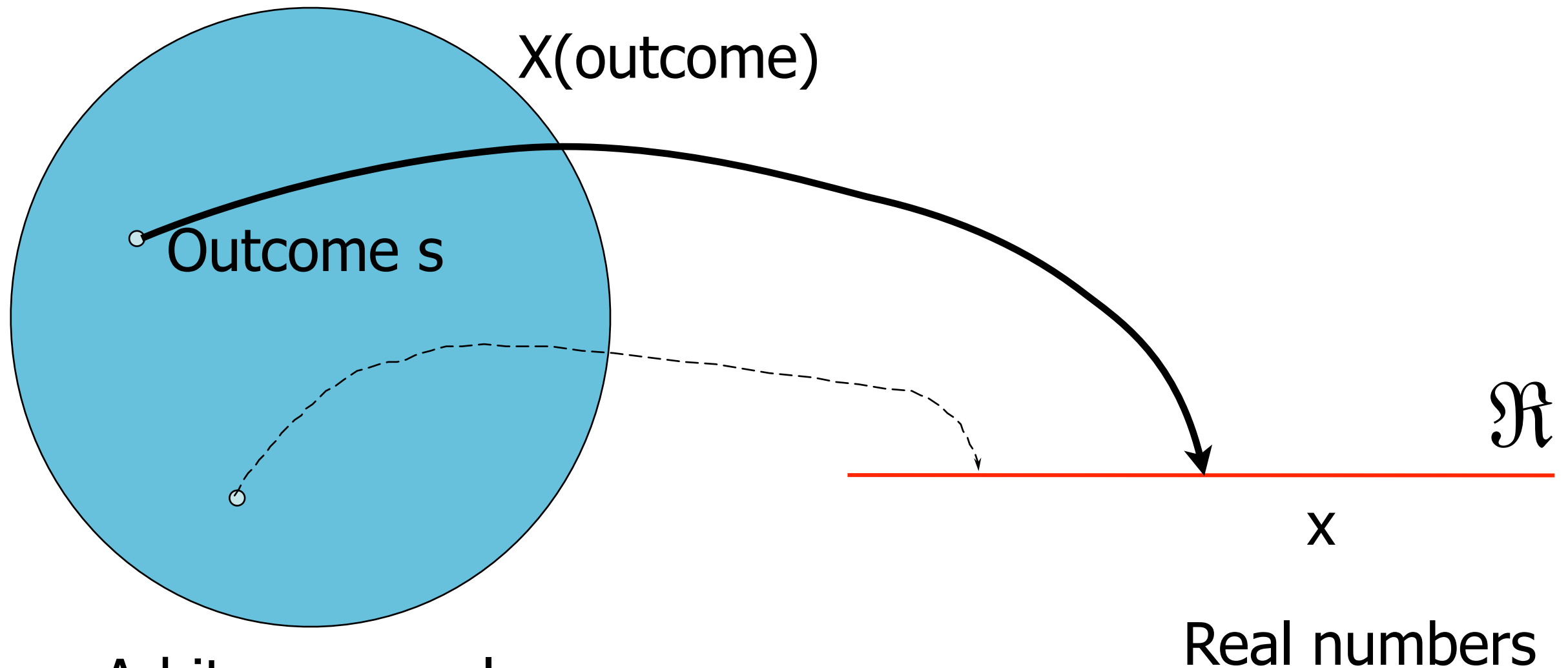
**Variance**

# Definition of Random Variable (1)

- Experiments often take place in a physical world
  - We observe physical quantities
- Probability theory works in a mathematical world, with mathematical tools.
- How to map “physical observations” to numbers we can do mathematics on?
  - E.g. Flip a coin: Outcomes are head/tail
  - E.g. Observe flooding because of frequent rainfall. Outcomes are yes/no

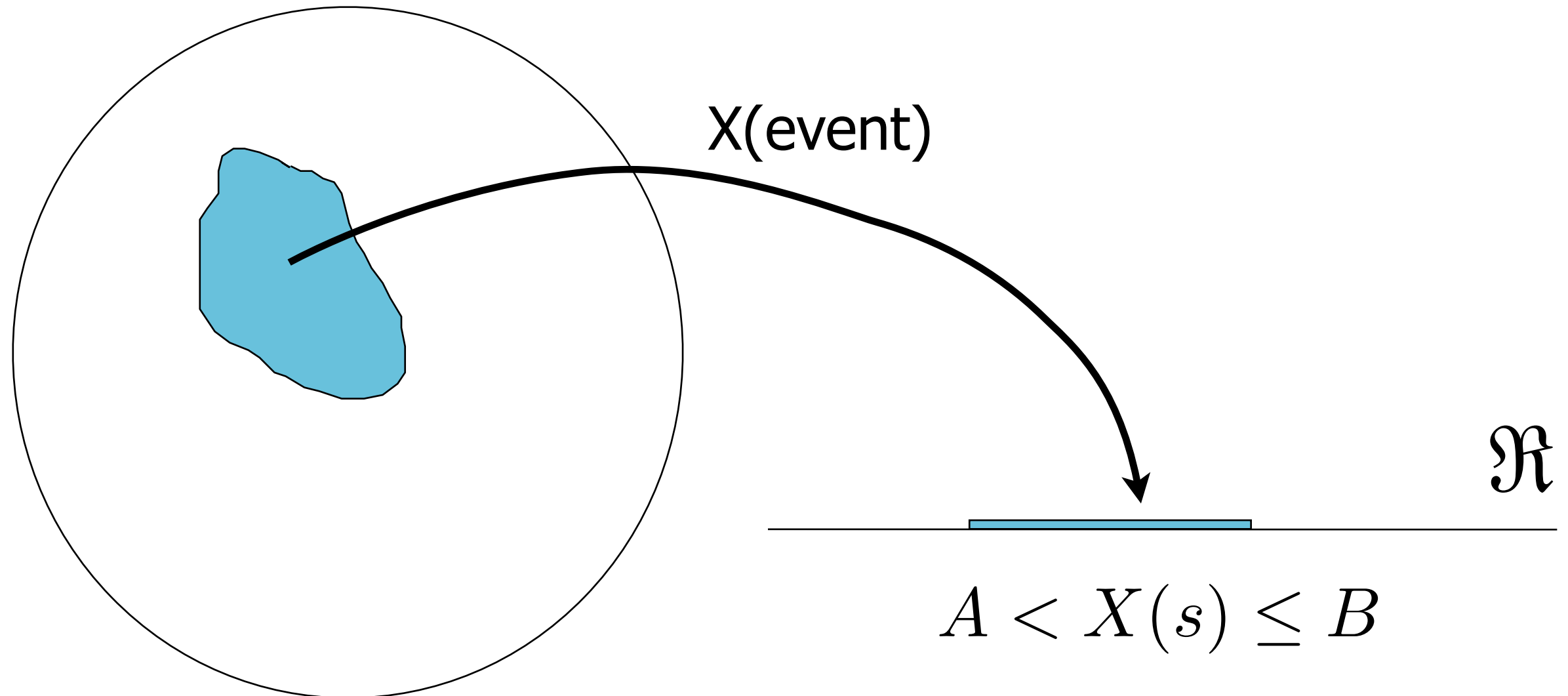
# Definition of Random Variable (2)

$$x = X(\text{outcome}) = X(s)$$



Arbitrary sample space  
Often related to physical world

# Definition of Random Variable (3)



- draw red ball;    roll even;    grown up
- $\{1\}$          $\{2, 4, 6\}$          $[18, \infty)$



# Notational Convention

$$a < X(s) < b$$

- is the same as

$$a < X < b$$

- But with  $X$  (upper case) we mean a function of the outcomes of the experiment
- The outcomes themselves are denoted by  $x$  (lower case), so we get:

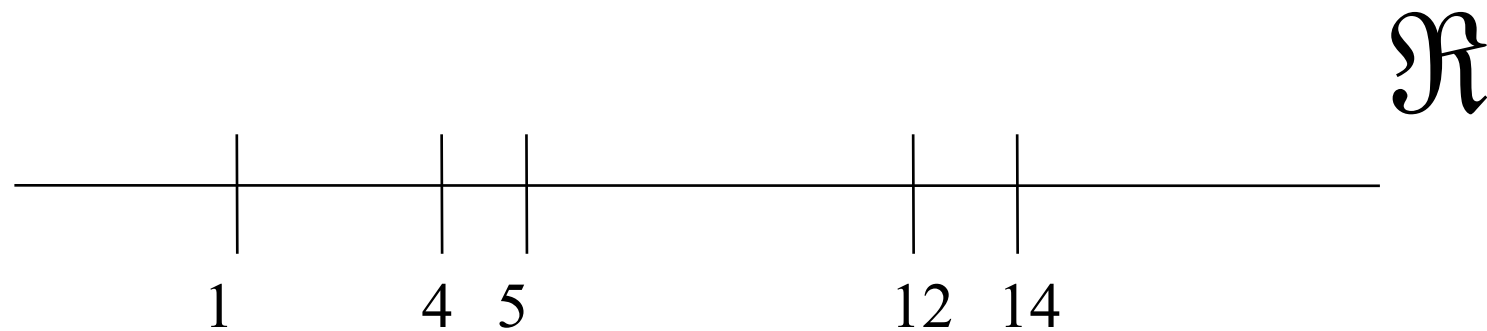
$$X = x$$

# Why Numerical Function $X$ ?

- Many engineering problems consider numerical problems
- Numbers in  $\Re$  can be ranked
- With numerical functions one can carry out calculations, such as “averages”
- Model behaviour of the abstract random variables, not of particular experiments
- Consequence: the values that  $X$  takes on, are now random

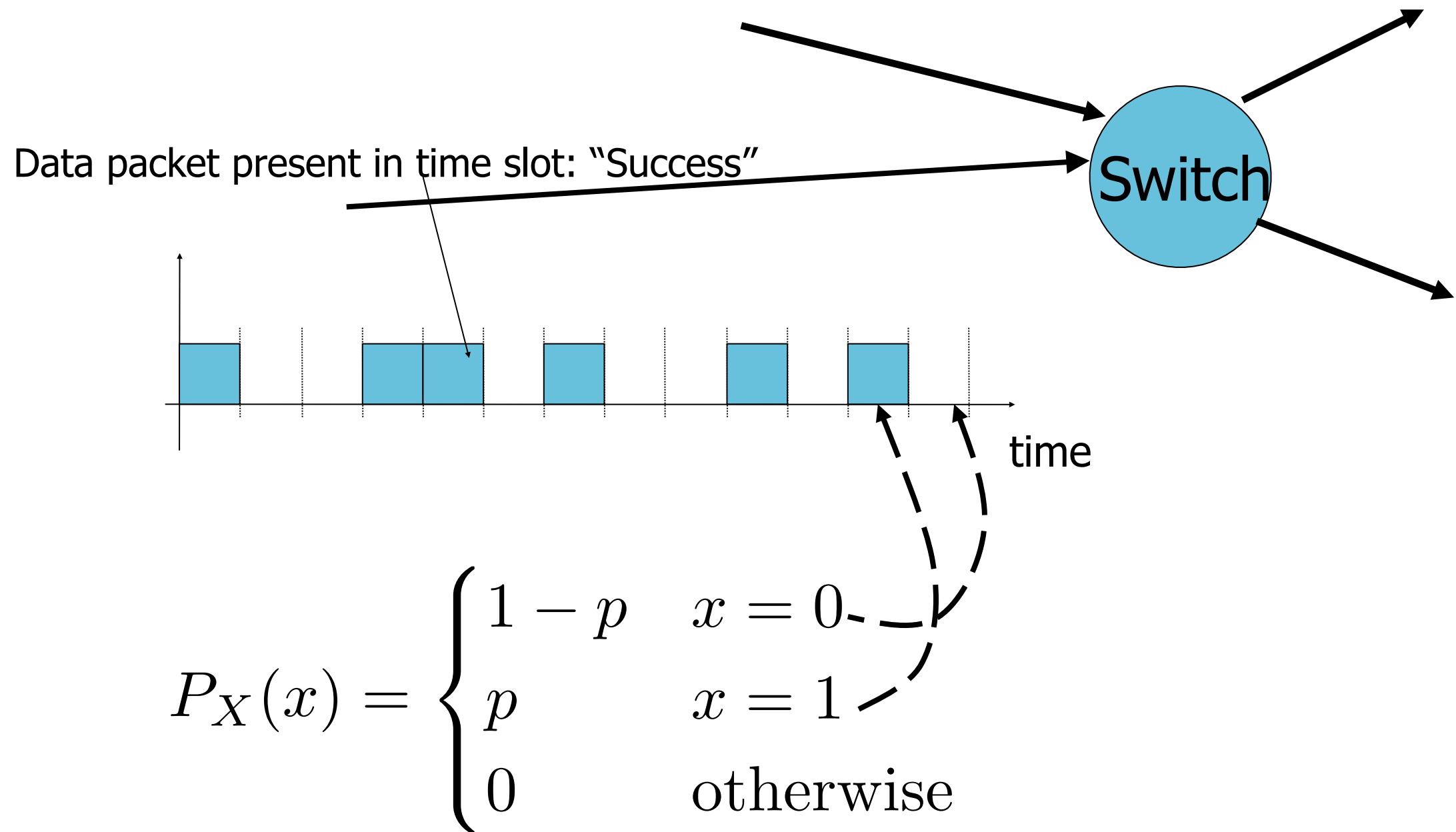
# Definition Discrete RV

- If an experiment has a countable number of outcomes, the random variable is discrete
- Example:



- Other example:
  - Number of active speakers  $X$
  - $X \in \{0, 1, 2, 3, 4, 5\}$

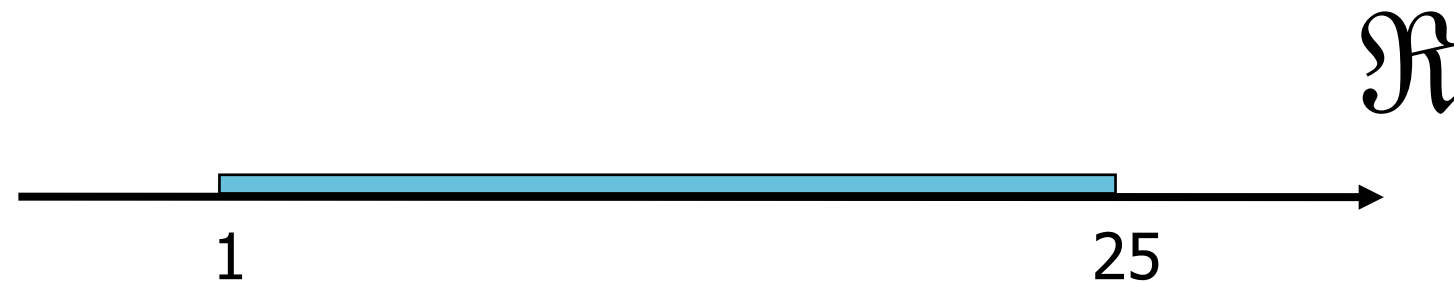
# Probability Mass Function



- $P_X(x)$  is called the **Probability Mass Function (PMF)**

# Continuous Random Variables

- Have as range the entire Real Axis
- Events are always intervals on the real axis
  - $A = \{x | 1 < X < 25\}$



- Theory is comparable to discrete random variables, with one additional concept namely **PDF** (probability density function)
- Problems with discrete RV's are more insightful
- ... but calculations with continuous RV's are usually a little easier in practical cases of interest.

# What is Different ...

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- Discrete sample space
  - Countable number of outcomes
  - Each outcome has a non-zero probability of occurrence
- But now ... continuous sample space
  - Have an infinite number of outcomes
  - Example: Pick a real-valued number between 3 and 5.
    - How many outcomes?
    - What is probability of each outcome?

# Two Consequences

- For continuous RV's it is meaningless to describe its behaviour in terms of the probability of an outcome
  - Probability mass function (PMF) is not a useful way of describing continuous random variables
  - $P[X=x] = 0$
  - We will consider events instead
- The probability "0" apparently does not mean that an outcome can not occur ...
  - It occurs statistically too infrequent to yield a non-zero relative frequency.

# Cumulative Distribution Function

- We consider a particular event in  $\mathfrak{R}$  namely

- event  $X \leq x$

upper value of  $X$

name of random variable

- $F_X(x) = P[X \leq x]$  for **ALL**  $x$

is called the **cumulative distribution function** (CDF)

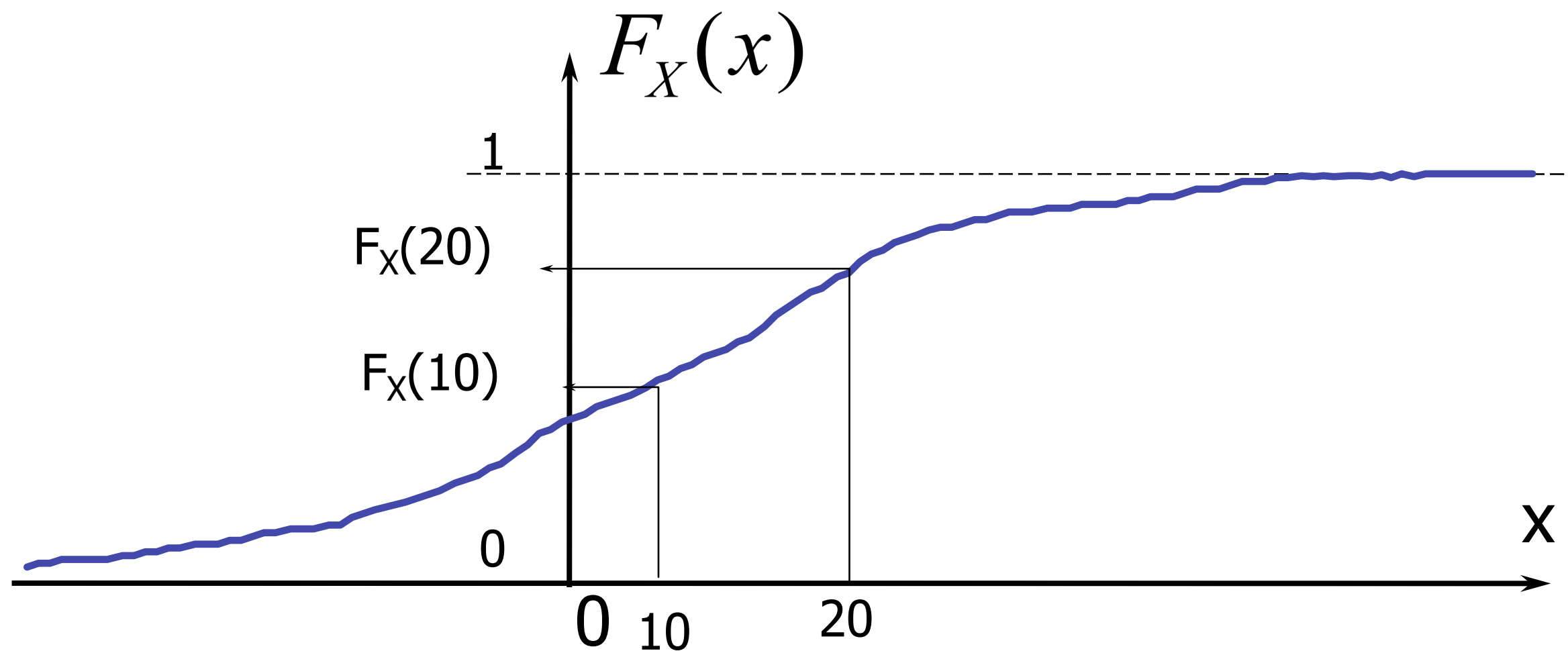
- No problem! Easy to define for continuous random variables





# Example

$$F_X(x) = P[X \leq x]$$



$$P(10 < X \leq 20) = F_X(20) - F_X(10)$$

# Probability Density Function

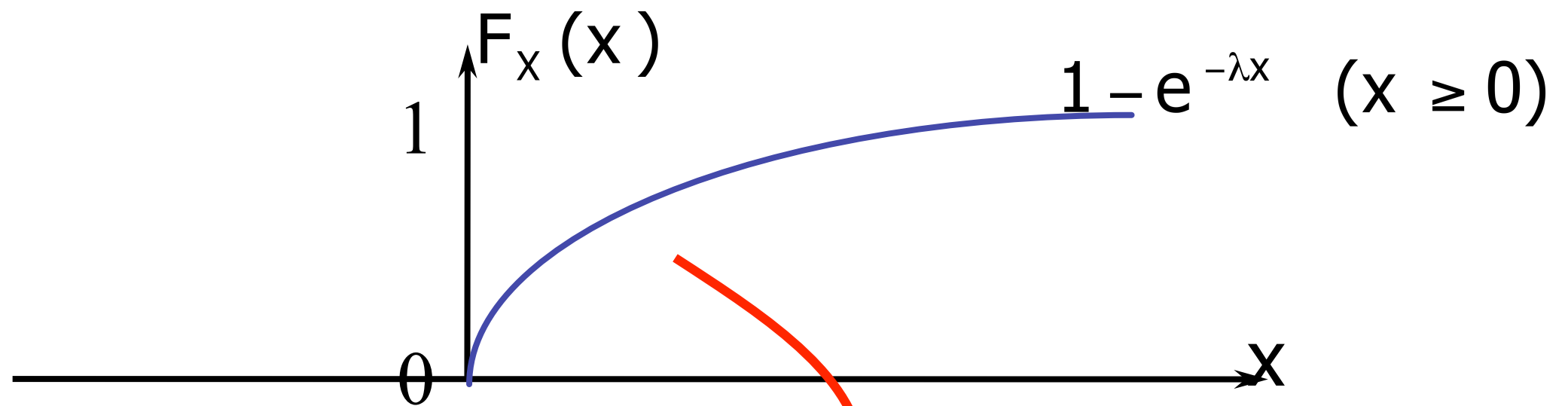
- Instead of a PMF (for discrete RVs), we have a probability density function, or pdf, for continuous RVs

$$f_X(x) = \frac{dF_X(x)}{dx}$$

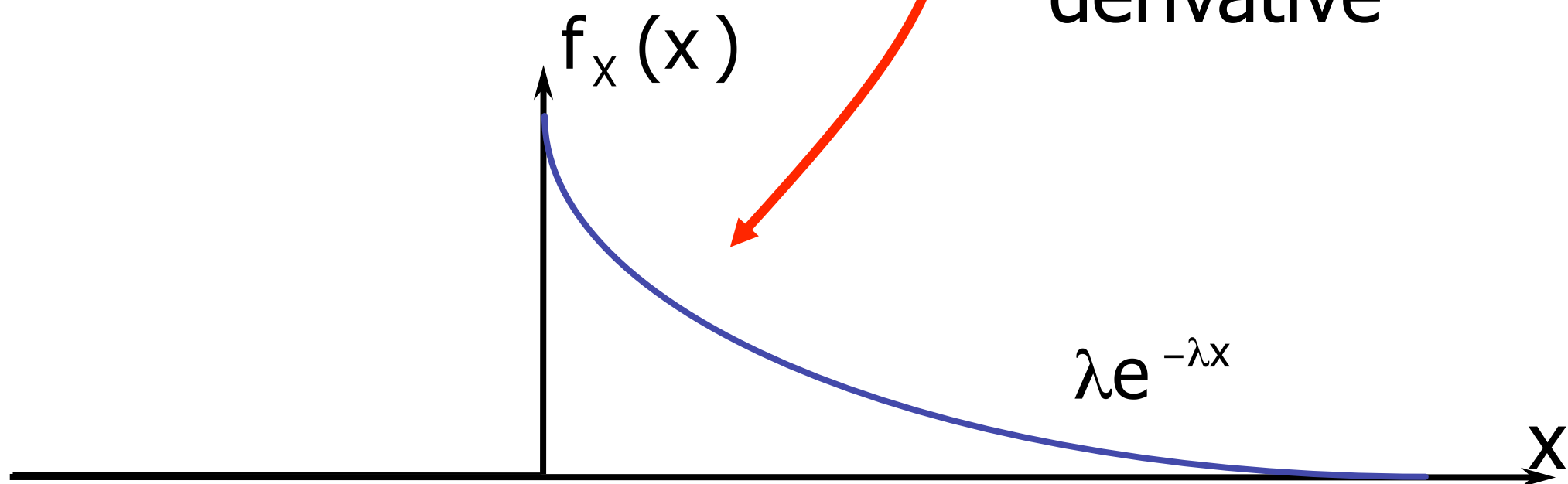
- A probability density is NOT a probability  
It can even be larger than one!

# Example

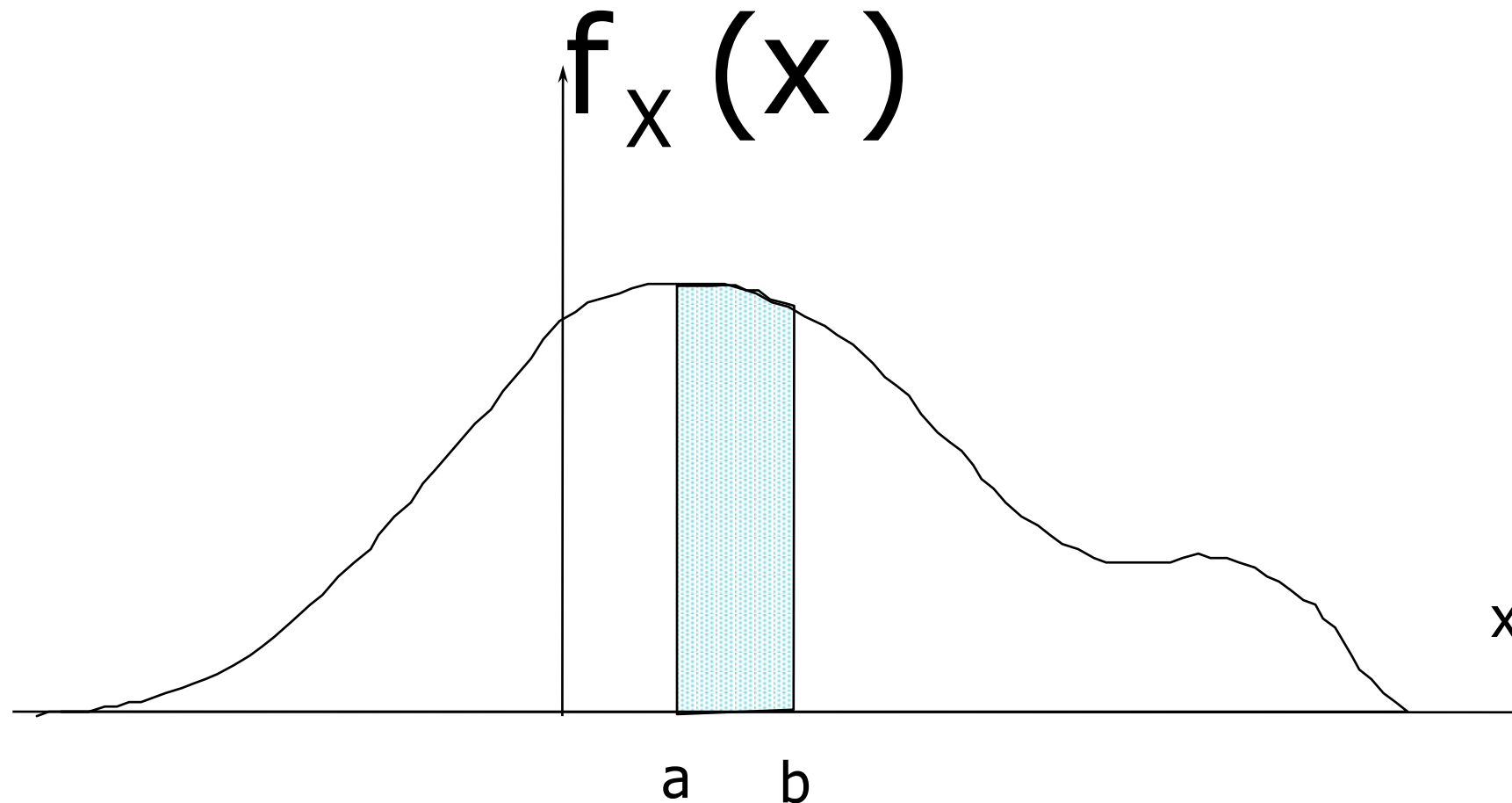
CDF



PDF



# To get a probability...



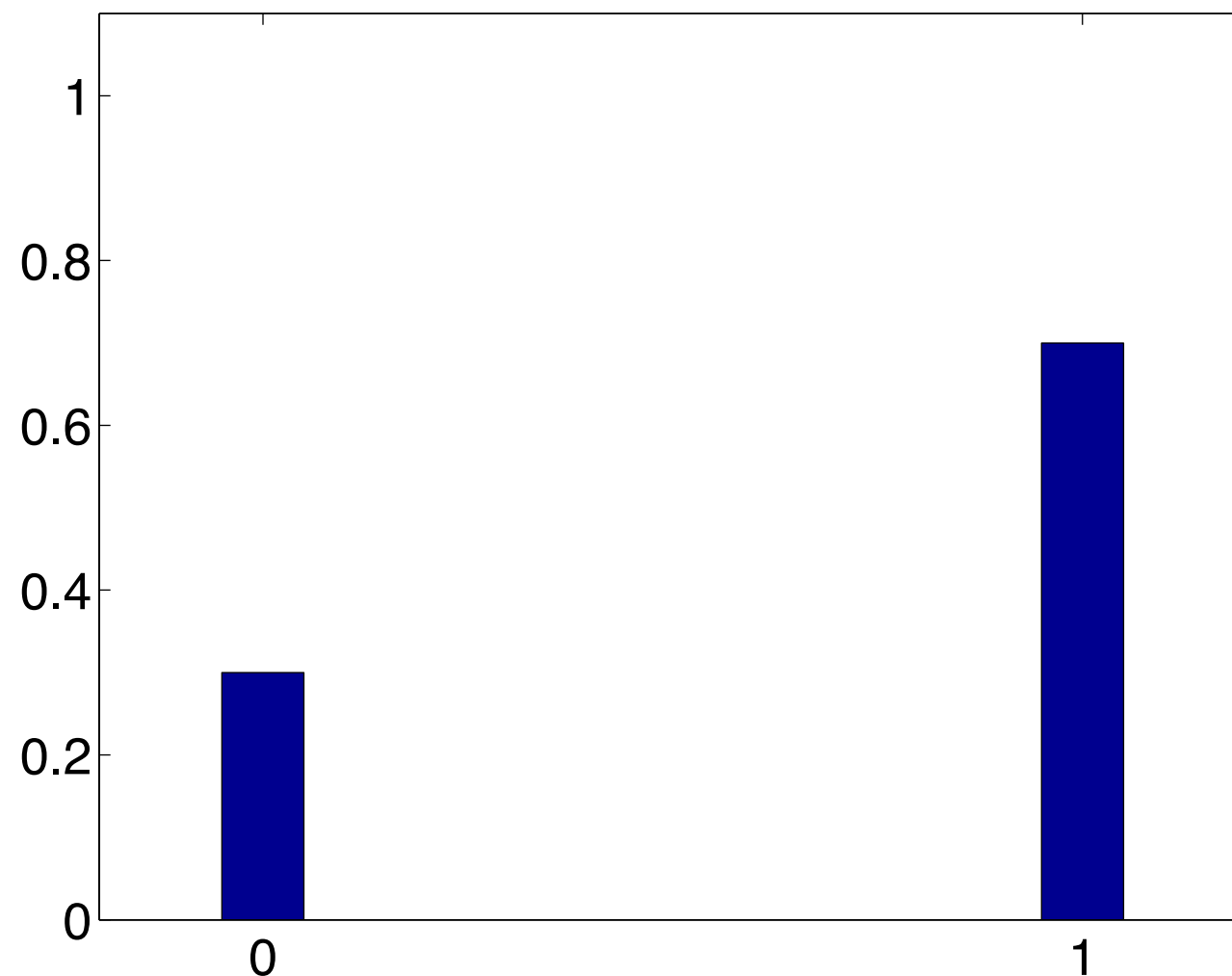
$$P[a < X < b] = \int_a^b f_X(x) dx$$

- You need to integrate the pdf to get to the probability

# The Bernoulli distribution

- The Bernoulli RV is a discrete RV:

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

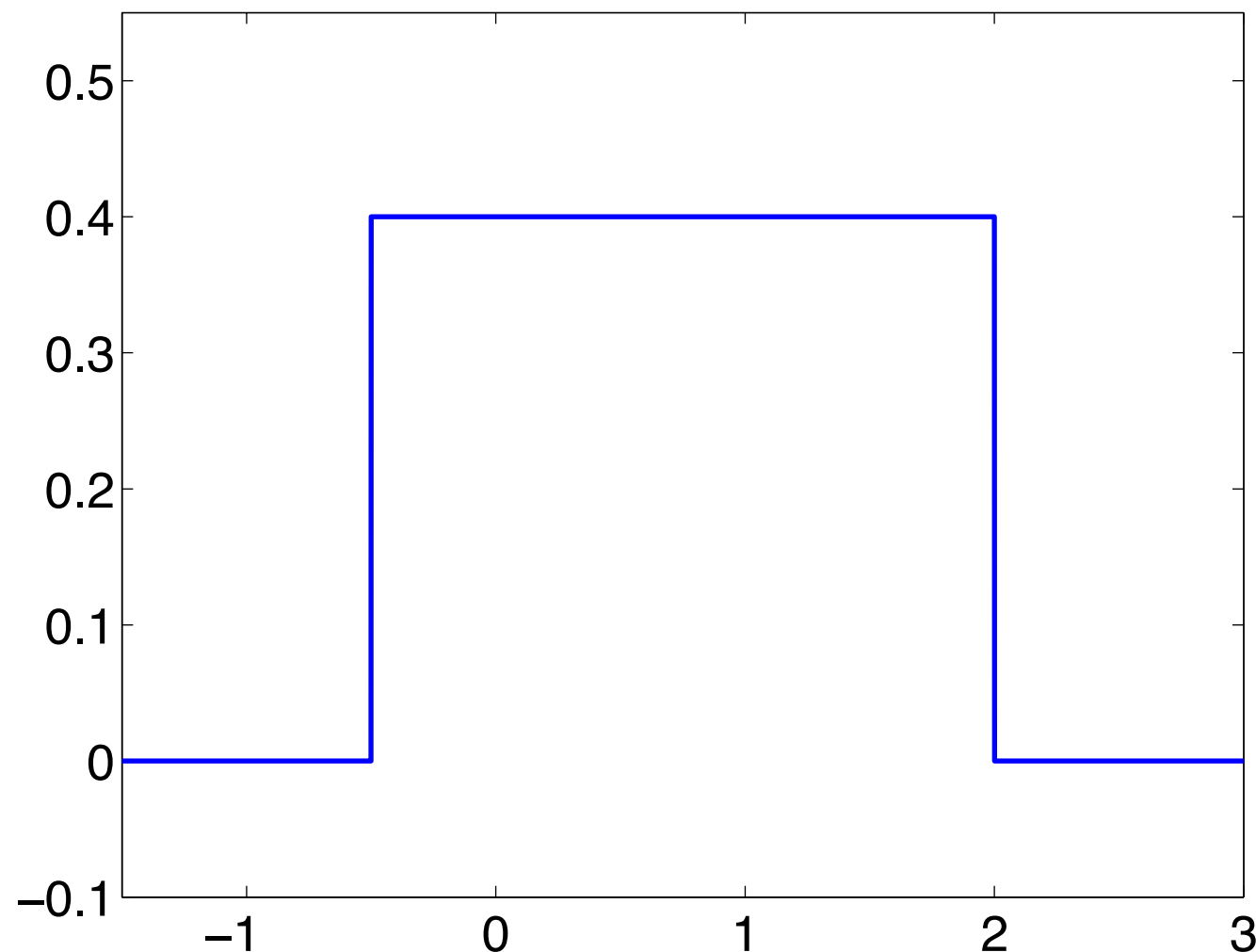


$p = ?$

# The Uniform Distribution

- Uniform distribution is (almost) always **continuous**!

$$f_X(x) = \begin{cases} 1/(b-a) & a \leq x < b \\ 0 & \text{otherwise} \end{cases}$$



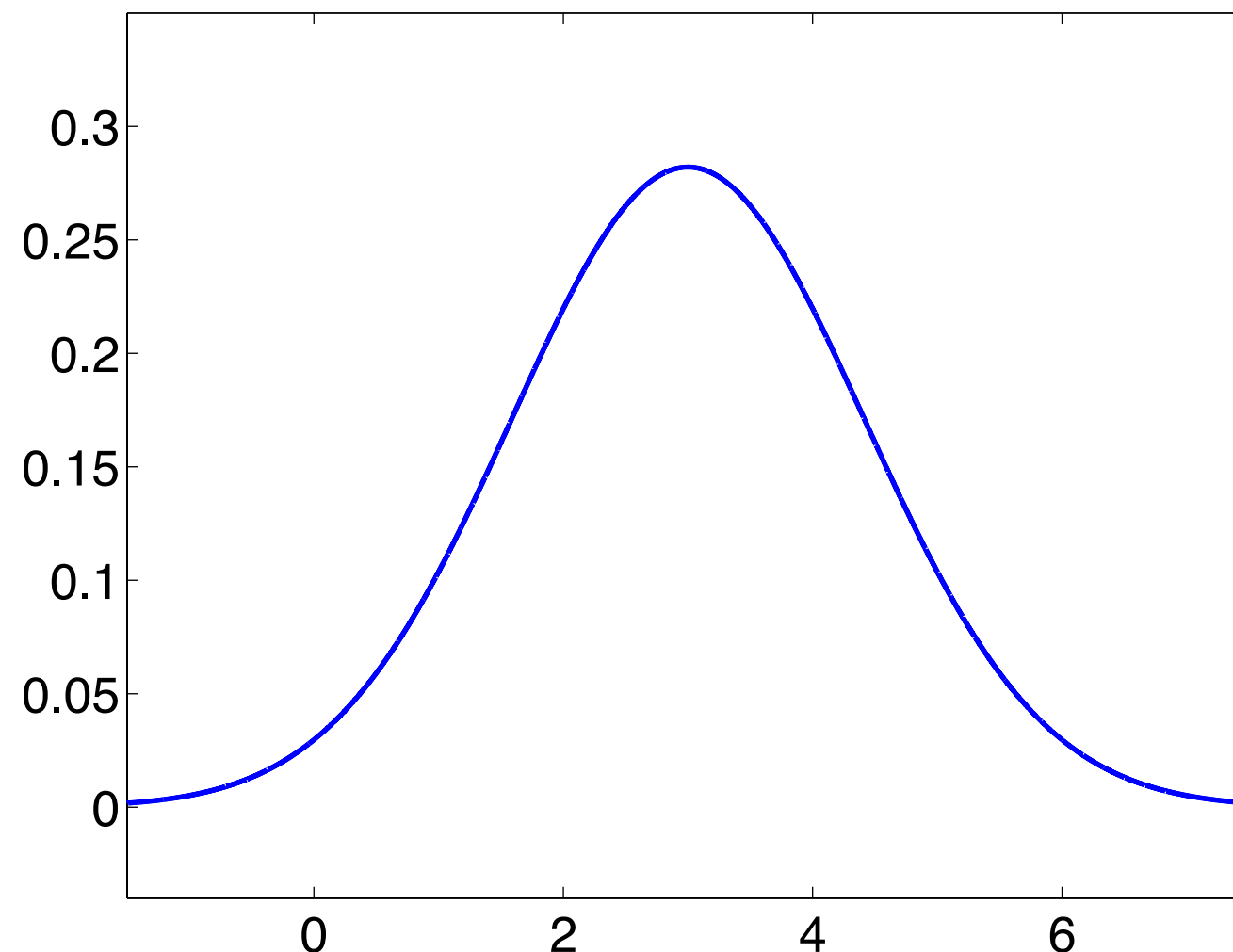
$a = ?$

$b = ?$

# The Gaussian distribution

- The Gaussian distribution is the same as the normal distribution

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$



$\mu = ?$

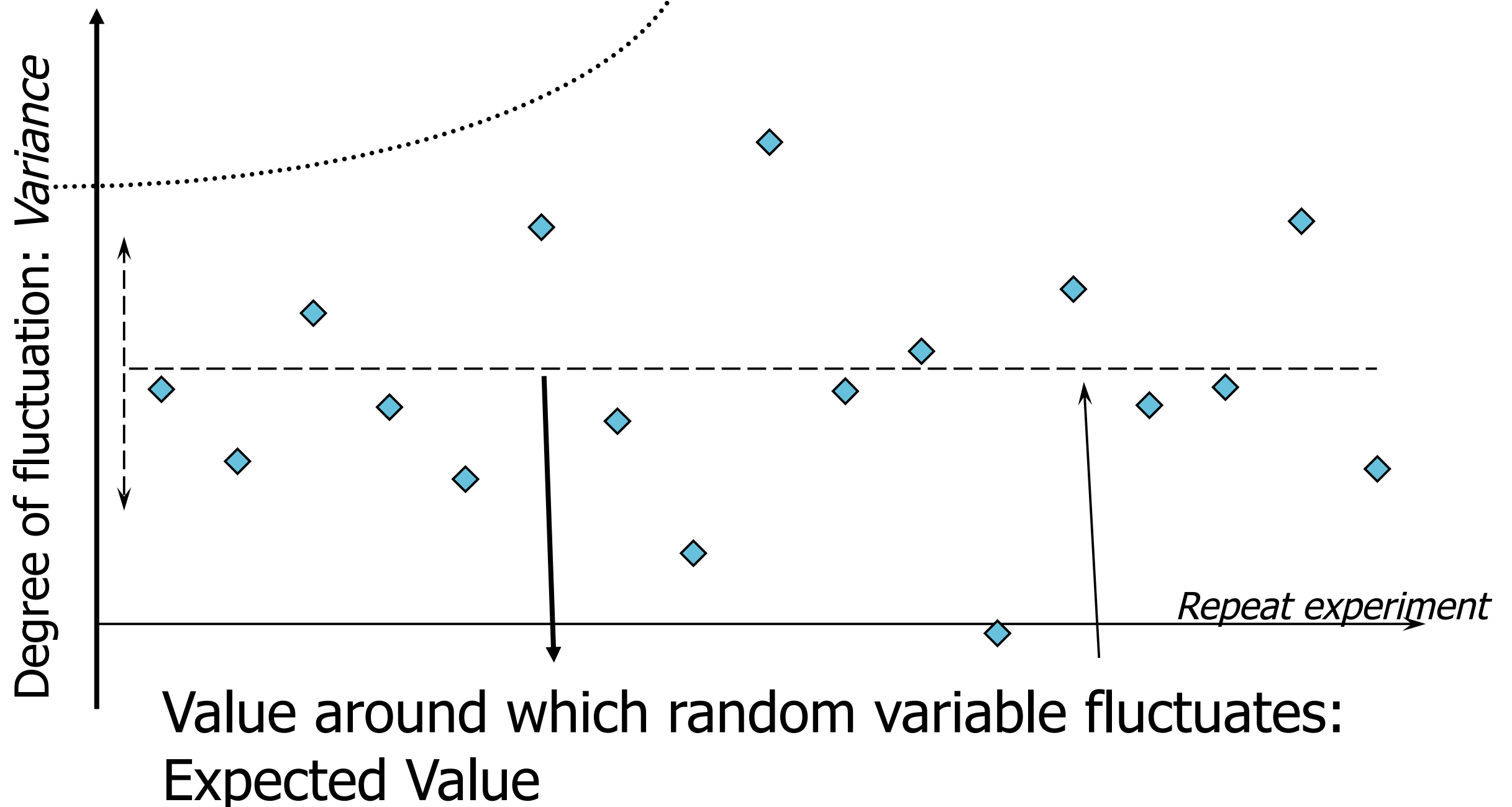
# Expected value

- The precise and total behaviour of a random variable is described by the PMF or CDF
- Sometimes we use an approximating description of its behavior because
  - this is sufficient for the application studied
  - this is the only information we can obtain in a practical application
- Two measures for average behavior:
  - expected value (expectation, mean)
  - variance (standard deviation)



# Characterisation of a RV

**Not:** the interval (range) of the fluctuations

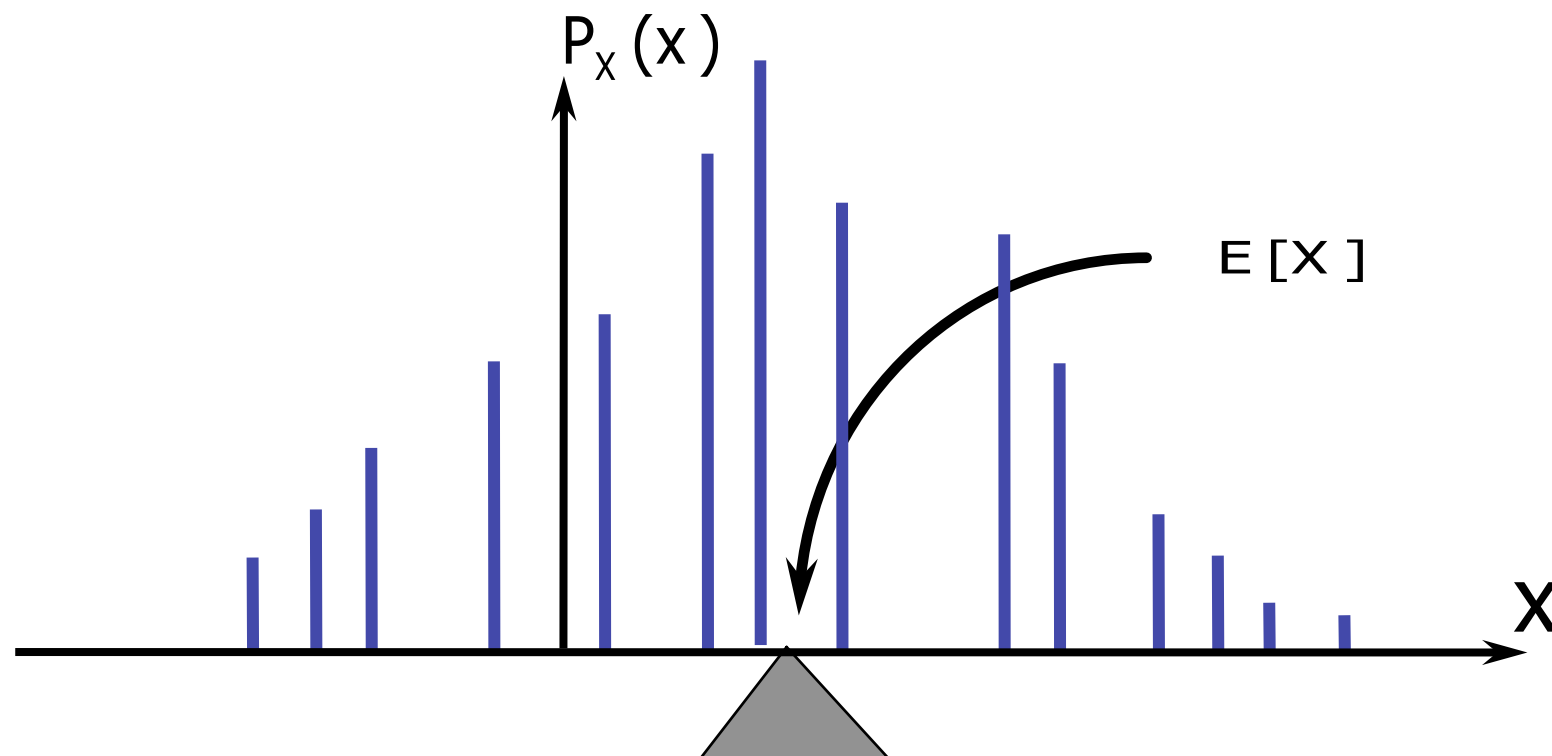


# Definition of Expected Value

- Expected value is one number that characterises the PMF (and CDF)

$$E[X] = \mu_X = \sum_{\text{all } x} x P_X(x)$$

- Comparable to “Center of Mass” in physics



# Properties of $E[X]$

- We introduce the following shorthand notation

$$E[.] = \sum_{\text{all } x} \{.\} P_X(x)$$

- Work as much as possible with  $E[.]$
- $E[.]$  is a linear operator:

$$E[Z] = E[X + Y] = E[X] + E[Y]$$

$$E[aX] = aE[X]$$

- Expected value scales linearly

# Variance: $\text{Var}[X]$

- Variance is (again) one number to characterise the behaviour of the PMF

$$\text{Var}[X] = \sigma_X^2 = E \left[ \underline{(X - E[X])^2} \right]$$

$$= \sum_{\text{all } x} \underline{(x - E[X])^2} P_X(x)$$

- Measure for “width”, or “dispersion” of  $X$  around expected value of PMF

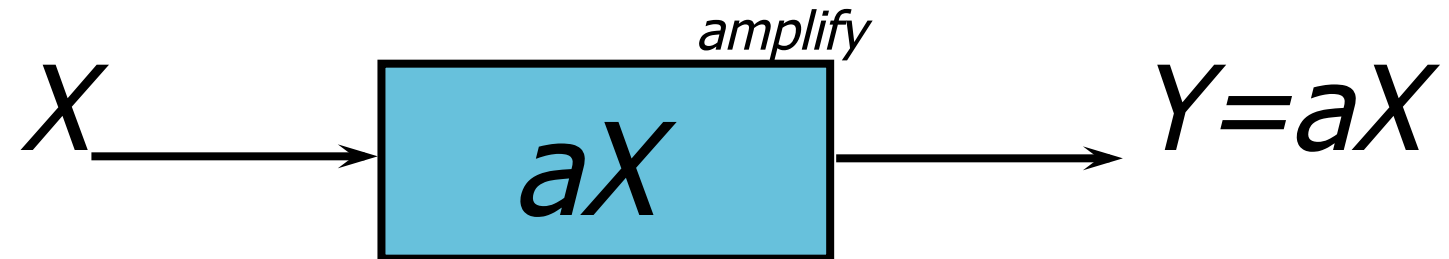
# Usual Way to Calculate Var[X]

- Because  $E[.]$  is a linear operator, we get:

$$\begin{aligned} \text{Var}[X] &= E[(X - E[X])^2] \\ &= E[X^2] - E[X]^2 \end{aligned}$$

- Use this form for calculations (when possible)
- Square root of  $\text{Var}[X]$  is called standard deviation  $\sigma_X$

# Example



$$\begin{aligned} \text{Var}[aX] &= E[(aX)^2] - E[aX]^2 \\ &= E[a^2 X^2] - (aE[X])^2 \\ &= a^2 E[X^2] - a^2 E[X]^2 \\ &= a^2 (E[X^2] - E[X]^2) = a^2 \text{Var}(X) \end{aligned}$$

- Variance scales quadratically

# Expected Value Continuous RV

- Same concept as for discrete RV
  - “Replace” summation by integration
  - “Replace” PMF by PDF

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx$$

$$Var[X] = \int_{-\infty}^{\infty} (x - E[X])^2 f_X(x) dx$$

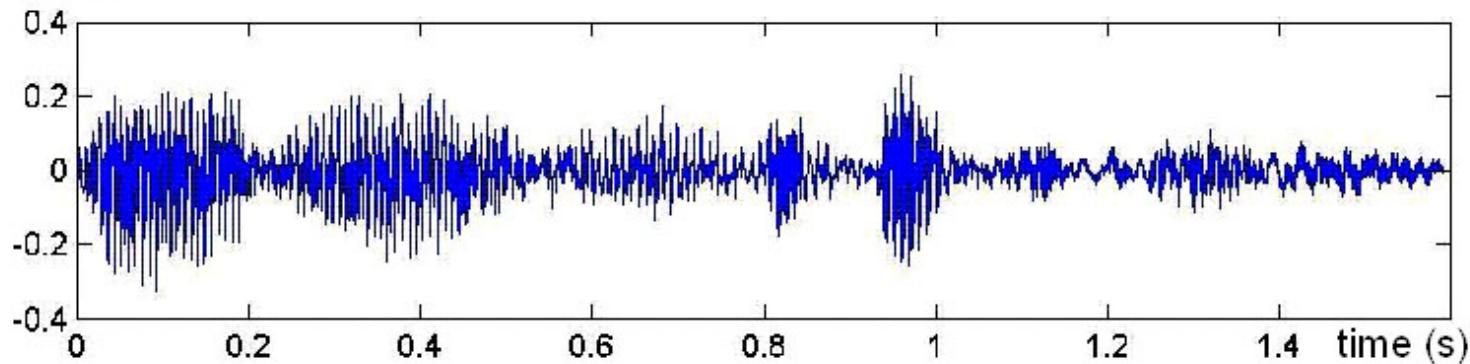
# Moments

- We have seen
  - $E[X]$  Expected value or first moment
  - $E[X^2]$  Second moment
  - $E[(X-E[X])^2]$  Second central moment
- Generalising
  - $E[X^n]$   $n^{\text{th}}$  moment
  - $E[(X-E[X])^n]$   $n^{\text{th}}$  central moment
- First and second moment are used a lot. Other moments can be useful in certain applications to characterize the PMF

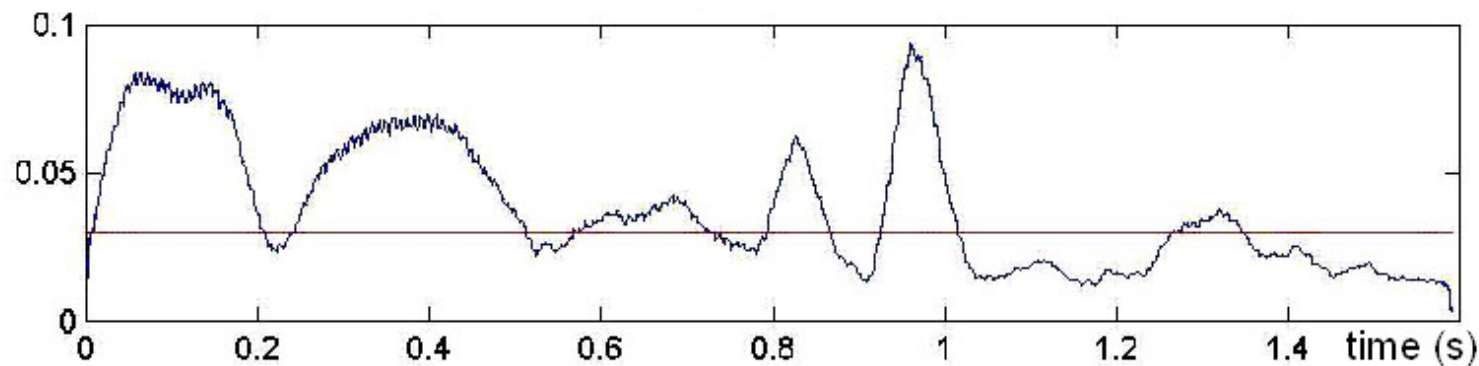


# Still a long way to go...

Signal

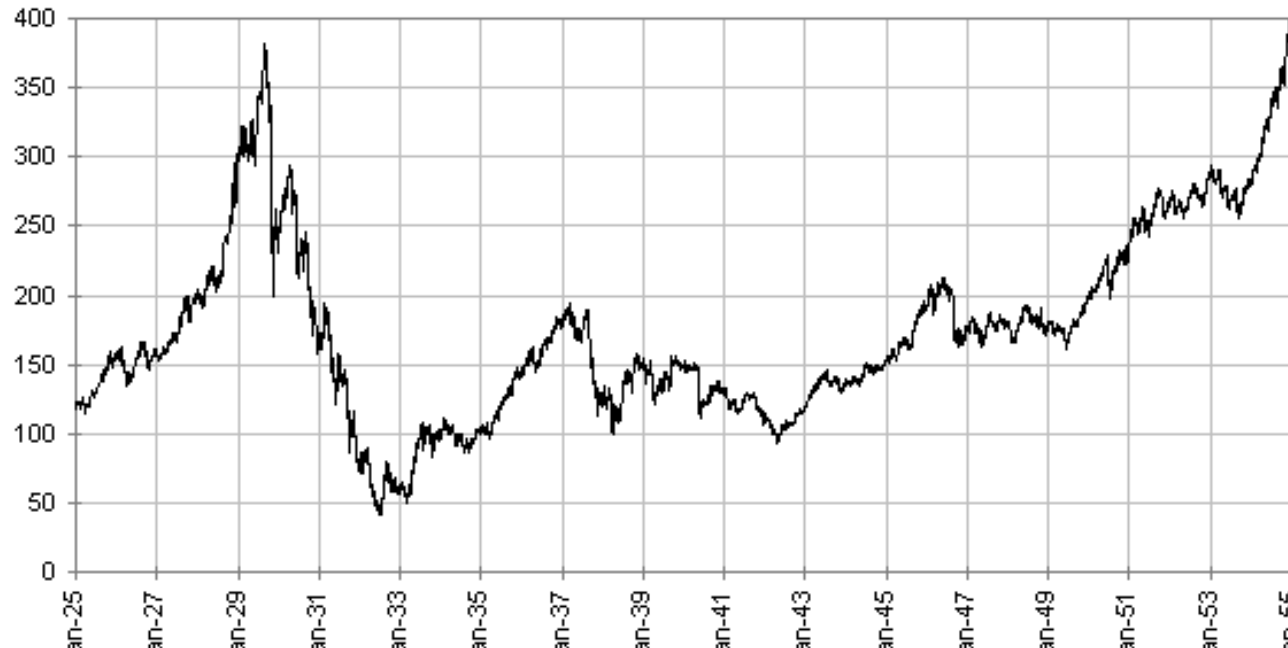


Signal Envelope



"I am am bi dex trous."

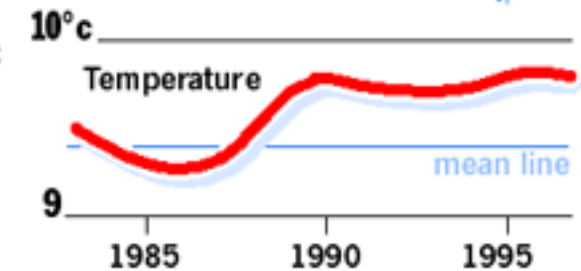
Dow Jones Industrial Average : 1925 - 1955



## Climate changes

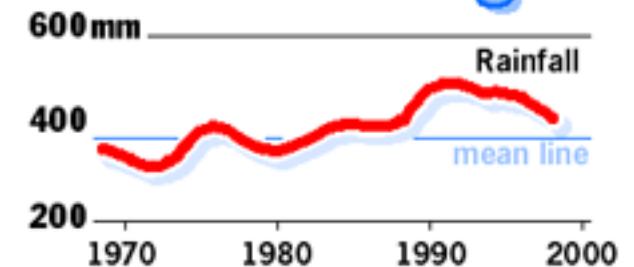
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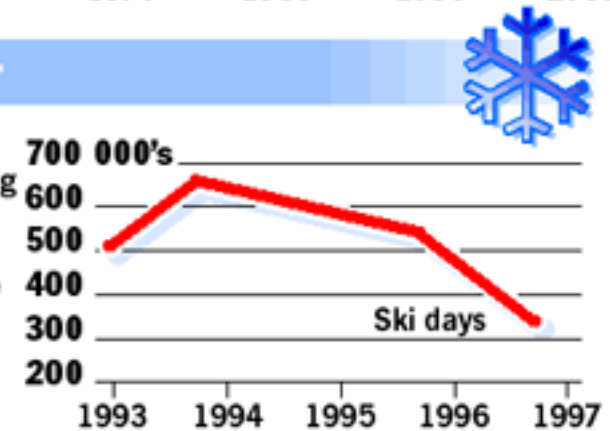
### Rainfall

Britain is getting wetter winters. Rainfall has been above average every year since 1990



### Cold weather

Scotland's ski slopes are opening later and closing earlier. The number of people who spent a day skiing has fallen from 650,000 to 350,000



# Covered Today

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- Chapter 1, 3, and 4
- Key terms
  - Stochastic (probability) model
  - Outcome, event
  - Axioms of probability
  - Conditional probability
  - Independence of events
  - Discrete and continuous random variables
  - Bernoulli, Uniform, Gaussian
  - Expectation, variance
  - Moments