DCSP-1: Introduction

- Jianfeng Feng

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- http://www.dcs.warwick.ac.uk/~feng/dcsp.html

Time

- Thursday (L) 13.00 –- 14.00 R2 .41
- Friday (L) 12.00 -- 13.00 R0.14
- Monday (Workshop/L) 4.00 – 5.00 MB0.07
  (question time on line, team)
- Monday (S) 10.00-11.00 MB3.07

From week 2, seminar starts

My research: 冯建峰

- http://dcs.warwick.ac.uk/~feng

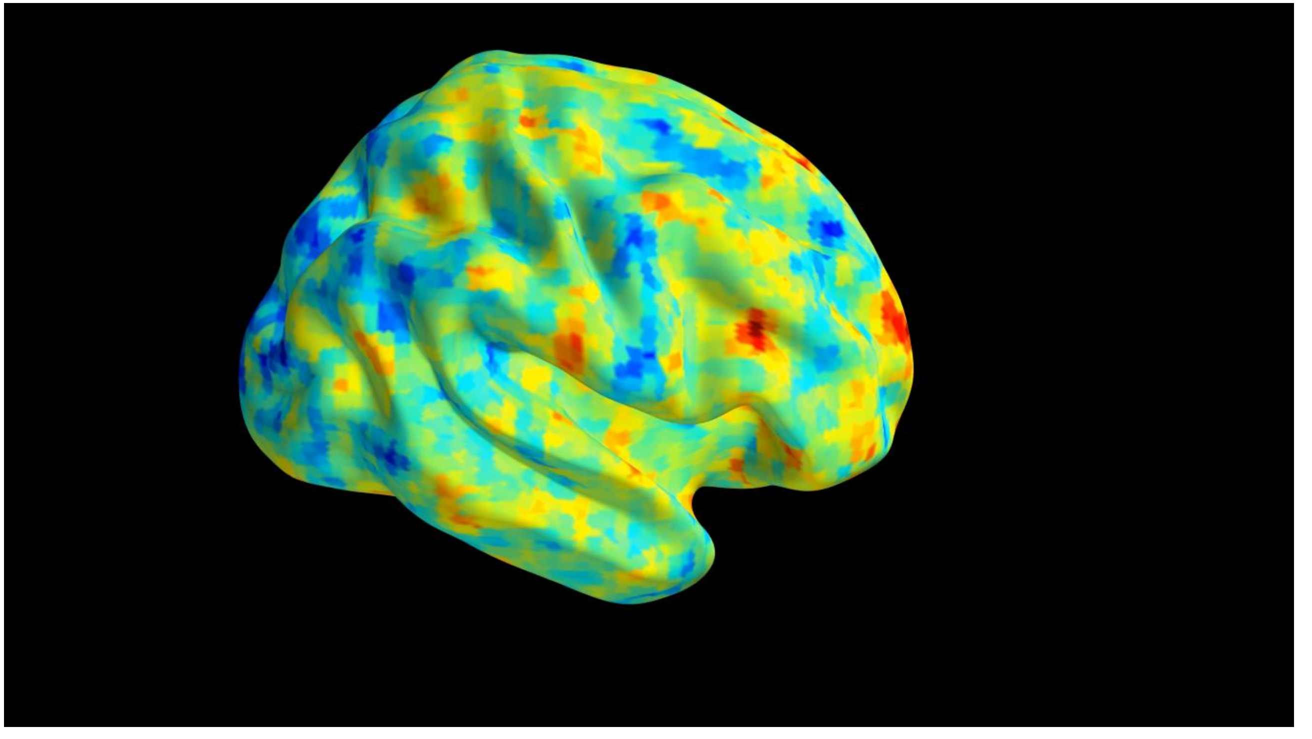
In general, our research is about

- **Dealing with big data**

- **Developing brain-inspired AI algorithms**

My research: an example of dealing with big data

My research: 冯建峰



(this is Feng's Brain)

Using MRI to peer into your brain

My research: 冯建峰

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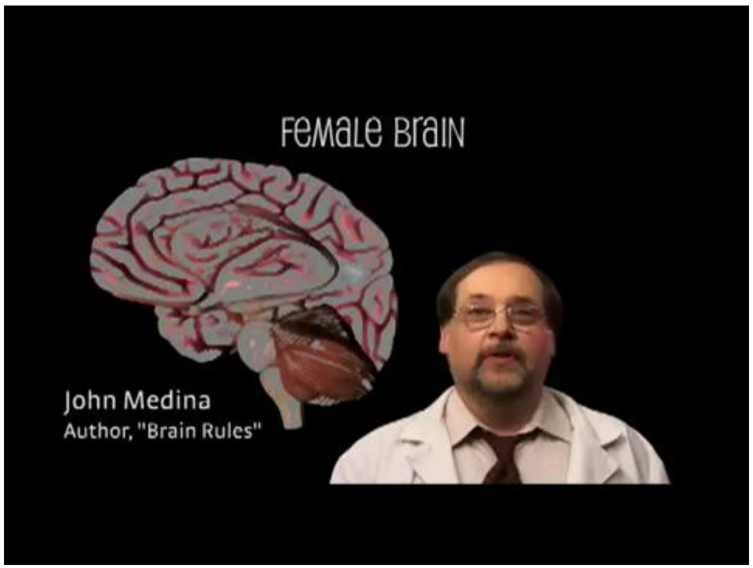
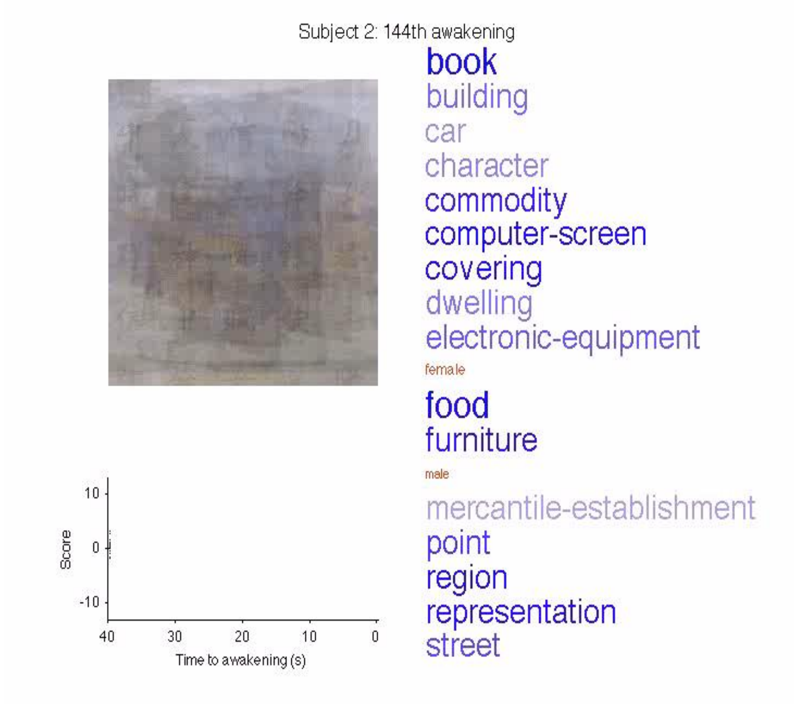
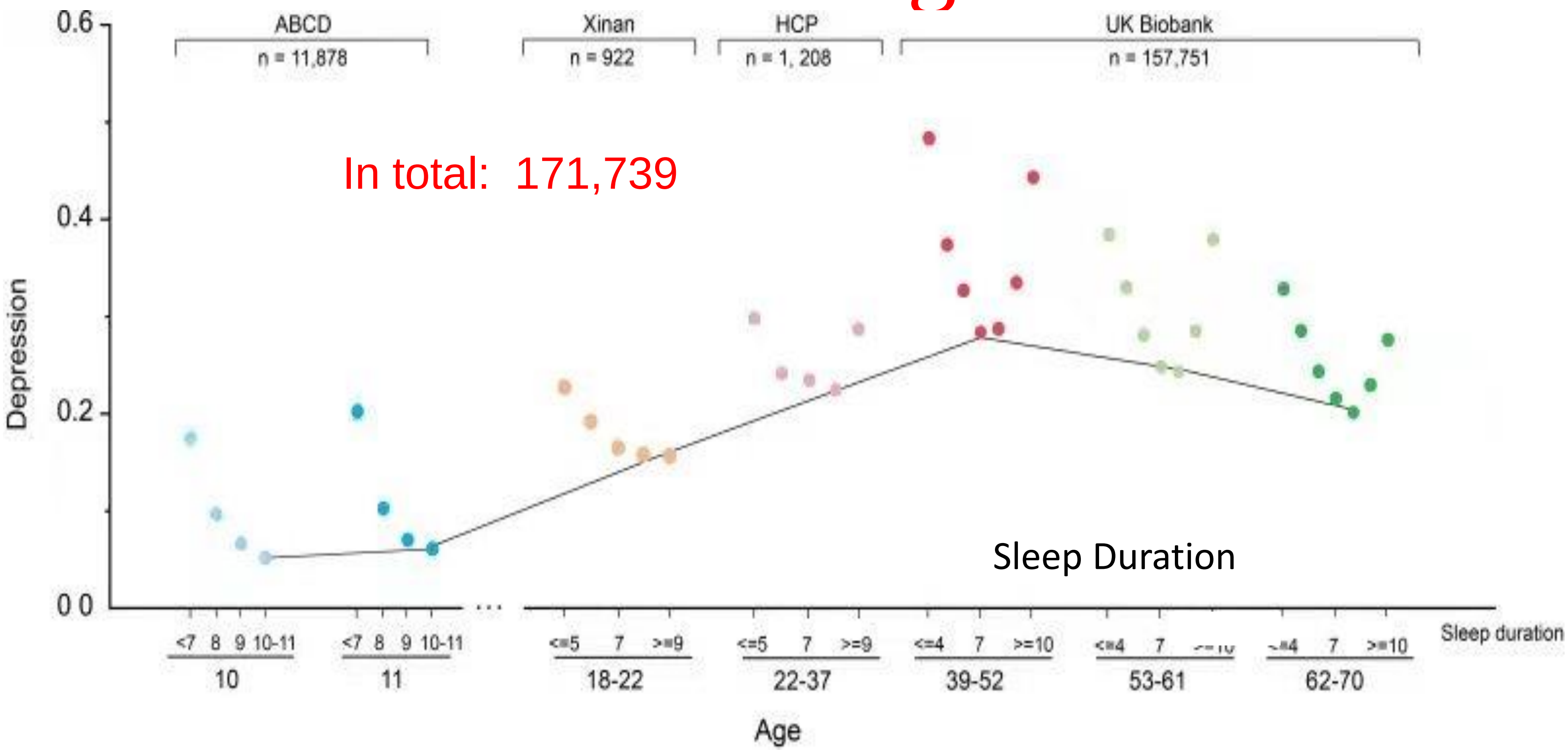




Mind Reading: Find out what is in your dream

My research: an example of dealing with big data

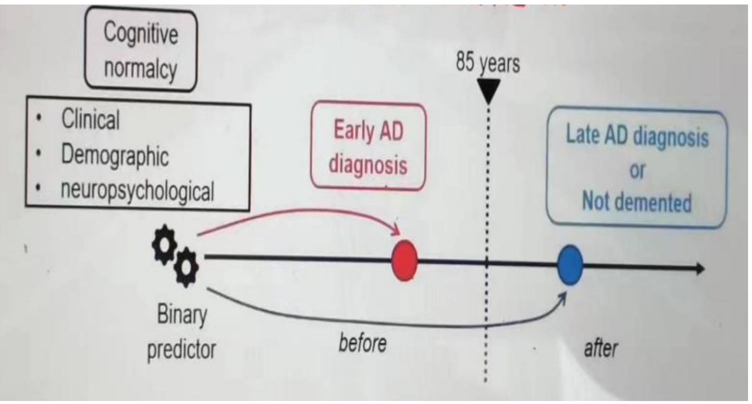


Cheng,W., Rolls, E. T., Gong,W., Du,J., Zhang,J., Zhang,X., Li,F. and Feng,J. (2020) Sleep duration, brain structure, and psychiatric and cognitive problems in children. Molecular Psychiatry doi: 10.1038/s41380-020-0663-2.

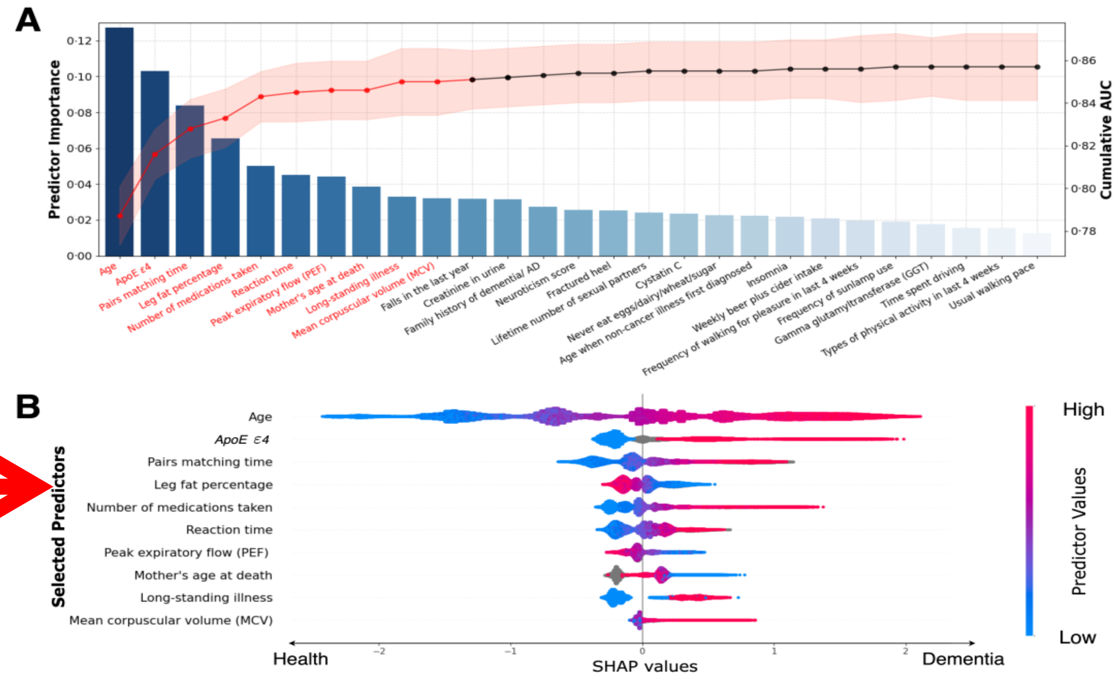
Li YZ et al. (2022) Nature Aging


GMA MORNING RUNDOWN
THE NEW "MAGIC NUMB
STUDY: MIDDLE-TO-OLDER AGE ADU
abc
NEWS

Dementia **Prediction: ten years before**

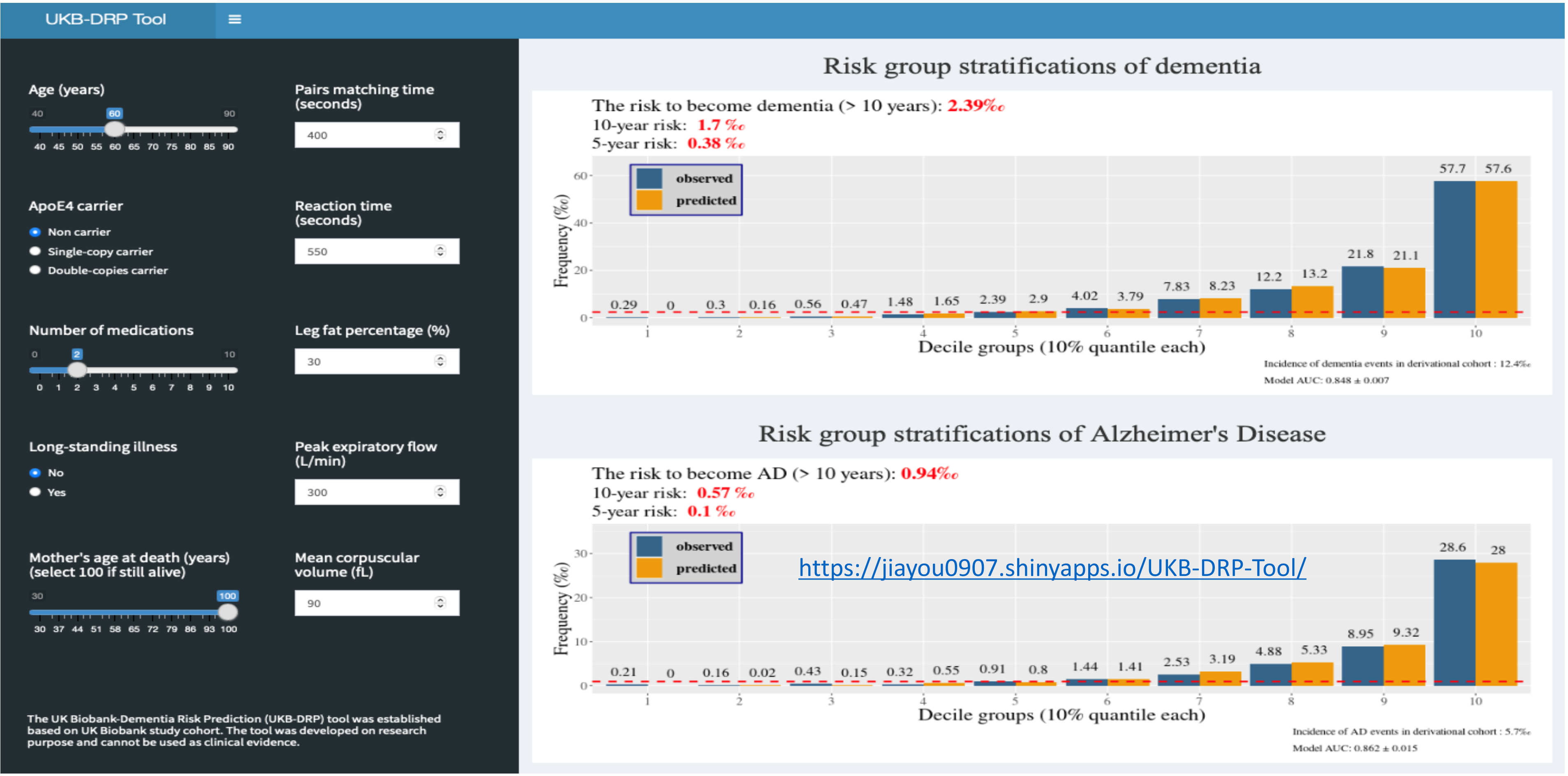


IBM and Pfeizer: **AI model can predict the onset of dementia 7 years ago, with an accuracy of 71%** (eClinicalMedicine, 2020)



We developed UKB-DRP. We can do it ten years ago with an accuracy of **85%** (eClinicalMedicine，2022)

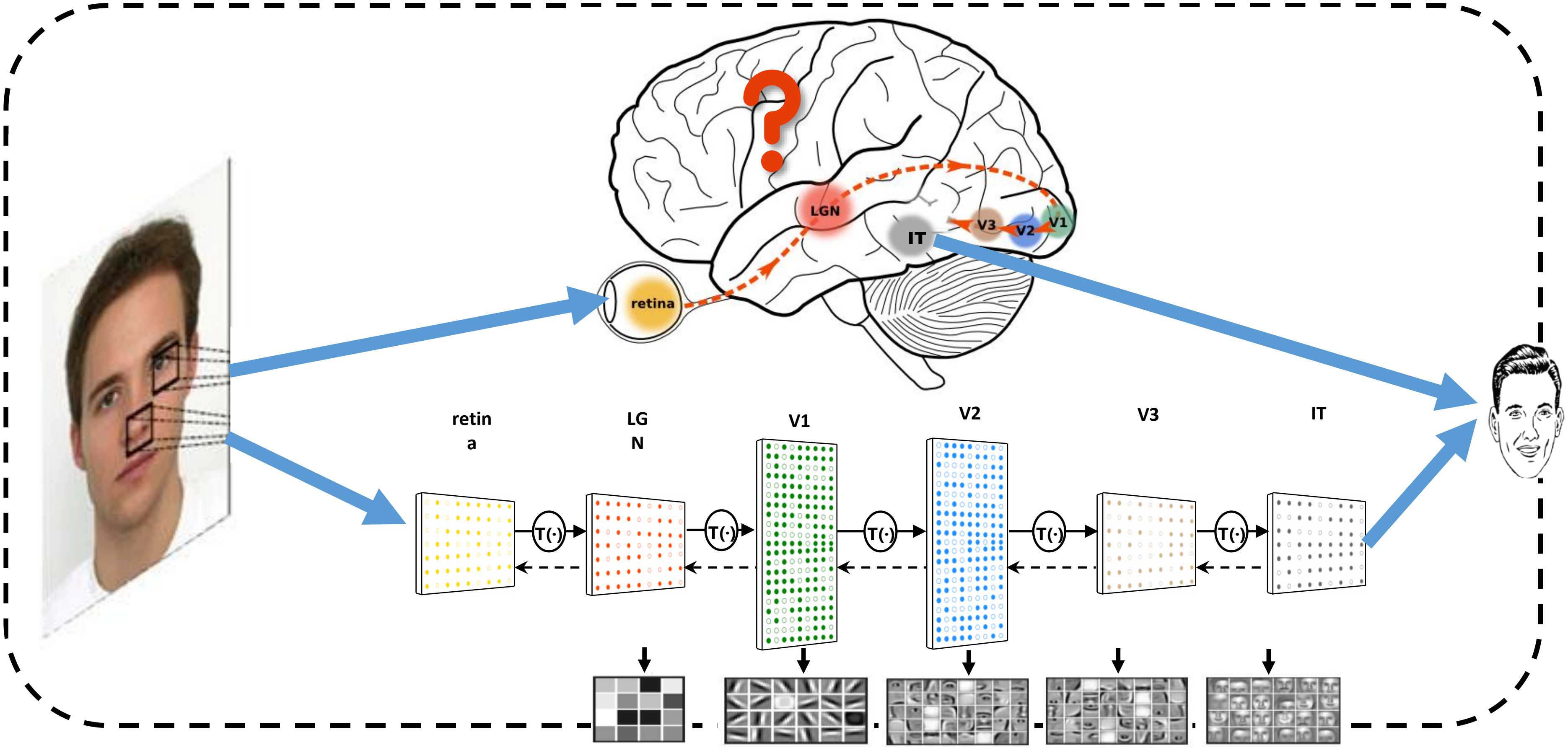
Dementia **Prediction: ten years before**



My research: an example of developing novel AI algorithms

2019 Turing Award for Deep Learning

(Yoshua Bengio)
(Yann LeCun)
(Geoffrey Hinton)

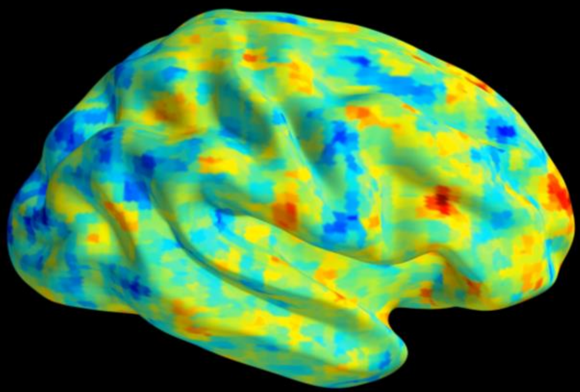


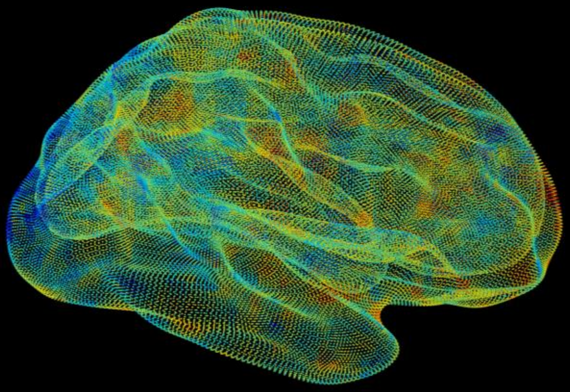
A neuronal network inspired by brain vision systems

Simulation of 86 B spiking neuron network

BB: (Biological Brain)

DTB:(Digital Twin Brain)



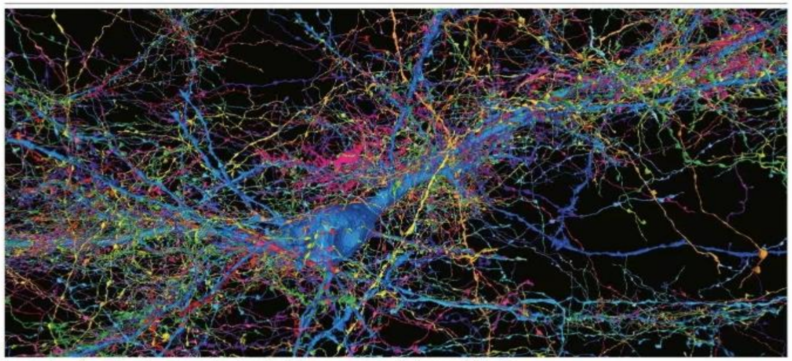


Similarity between BB and DTB: 90%

NSR, 2024, in press

Setting the agenda in research

Comment



A. SHAPSON-COE, M. JANUSZEWSKI, D. BERGER, A. POPE, V. JAIN & J. LICHTMAN/GOOGLE RESEARCH/HARVARD UNIV.

A reconstruction of incoming connections to a single human neuron, called a pyramidal cell.

How AI could lead to a better understanding of the brain

Viren Jain

Early machine-learning systems were inspired by neural networks — now AI might allow neuroscientists to get to grips with the brain's unique complexities.

Can a computer be programmed to simulate a brain? It's a question mathematicians, theoreticians and experimentalists have long been asking — whether spurred by a desire to create artificial intelligence (AI) or by the idea that a complex system such as the brain can be understood only when mathematics or a computer can reproduce its behaviour. To try ing simplified models of brain neural networks since the 1940s[1]. In fact, today's explosion in machine learning can be traced back to early work inspired by biological systems.

However, the fruits of these efforts are now enabling investigators to ask a slightly different question: could machine learning be used to build computational models that simulate the activity of brains?

At the heart of these developments is a growing body of data on brains. Starting in the 1970s, but more intensively since the mid-2000s, neuroscientists have been producing connectomes — maps of the connectivity and morphology of neurons that capture a static representation of a brain at a particular moment. Alongside such advances have been improvements in researchers' abilities to make functional recordings, which measure neural activity over time at the resolution of a single cell. Meanwhile the field of transcriptomics is enabling investigators to measure the gene activity in a tissue sample, and even to map when and where that activity is occurring.

So far, few efforts have been made to connect these different data sources or collect them simultaneously from the whole brain of the same specimen. But as the level of detail,

DOI: 10.1002/qub2.6

COMMENTARY

Quantitative Biology
Open Access

Simulating the whole brain as an alternative way to achieve AGI

Jianfeng Feng

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Funding information
Shanghai Municipal Science and Technology Major Project, Grant/Award Number: 2018SHZDZX01; ZJ Lab; Shanghai Center for Brain Science and Brain-Inspired Technology; 111 Project, Grant/Award Number: B18015

We have all seen the current attention, and even hype, on big models and artificial general intelligence (AGI). Indeed, many colleagues are arguing that we have achieved AGI with the current version of ChatGPT. Really? Looking back, it is not surprising to have a machine, even a normal calculator, which can outperform us. For example, a calculator can easily beat most of us on the multiplication of two large numbers with its speed, while a basic laptop can store many books, but humans have far weaker means of recall. So it is something that we have already got used to, that man-made machines can perform *certain* tasks far better than us.

This general issue leads us back to the big original question: how to define intelligence? People have come up with many different definitions which could serve this purpose. For example, Stephen Hawking said "intelligence is the ability to adapt to change." Along a similar line one of my close colleagues, the most cited psychologist, Trevor Robbins, who also won the Brain prize, has defined intelligence as "flexibility." Others might argue that complex language might be the carrier of "intelligence," which we, as human beings, own uniquely. I am more in favor of the latter: a chameleon can adapt to its environment, but does it have intelli-

that this is an over claim. Another, more mechanical way, to define/test intelligence is the Turing test, which has its pros and cons and has been both criticized and applied widely (Figure 1A).

Hence we have no criterion to really assess intelligence, at least, one which I am happy with. We can make a direct comparison between the human brain, the one which we all agree has the intelligence, and ChatGPT. First let us have a look of what ChatGPT has achieved. It can (amazingly) generate comprehensive answers, some of which are completely wrong! It can, sometimes, outperform an individual human. As we all know, the mechanism for ChatGPT, or all current machine learning, is to establish a correlation between different objects, and with ChatGPT the object is the word. With such a large model, with more than 100B parameters, a reasonable argument is that it obeys the Hegel's law [2]: quantitative changes give rise to qualitative differences. It might be a good idea to carry out a similar analysis in, for example, the Ising model: when the size increases in ChatGPT, the correlation coefficient between nodes in the model diverges: a typical phase transition, which confirms the Hegel's law.

Now let us look at our brain. Massachusetts Institute of Technology (MIT) neurobiologist Robert Desimone

Algorithms

- Data, computational power and algorithm are three key elements for AI
- This module is all about

algorithm algorithm Algorithm

- This module will enable you to equip with new skills to deal with data

Algorithms

- Very successful with deep learning
- But it deals with only static data such as faces
- We will deal with dynamic data (language, video etc.)
- ‘Most practical module in our two years’ – comments from students of previous years

Announcement for Seminars

- DCSP seminars (to cover DCSP tutorial problems) start in Week 2.

Assignment

- Assignment will be issued in Week 4
- Worth 20% of the module assessment
- Submission deadline is 12 noon on
  Thursday Week 10 -- 14th March 2024
  (The winner will be awarded 100 Pounds)

References

- Any good book about digital communications and digital signal processing
- Wikipedia, the free encyclopedia or public lectures
- Lecture notes is available at

  http://www.dcs.warwick.ac.uk/~feng/dcsp.html

- Public lectures
- Update my lecture notes every week

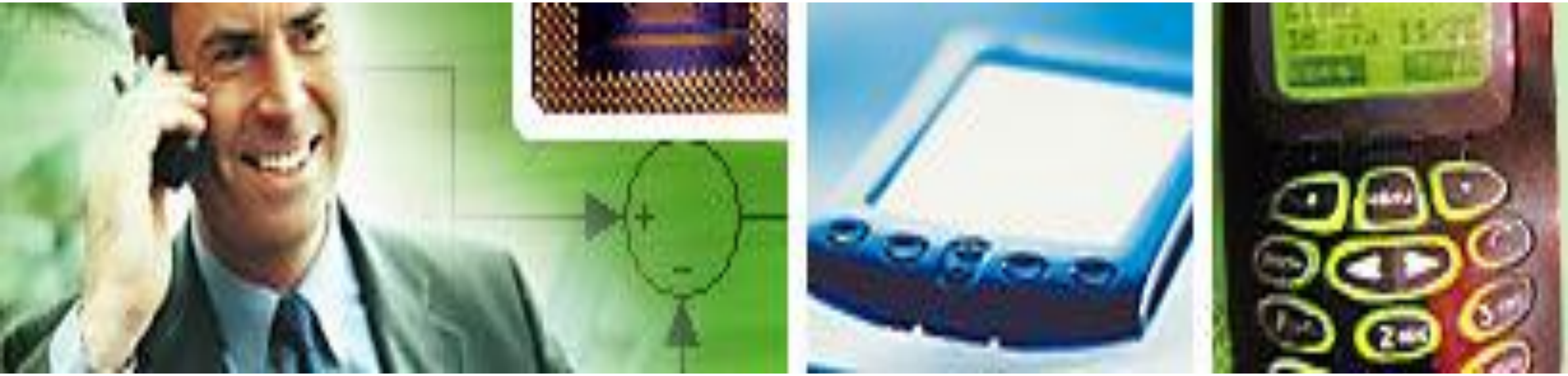
Outline of today's lecture

- Digital vs. analog

- Module outline

- Data transmission (sampling)

Signal: video, audio, etc. -- Data



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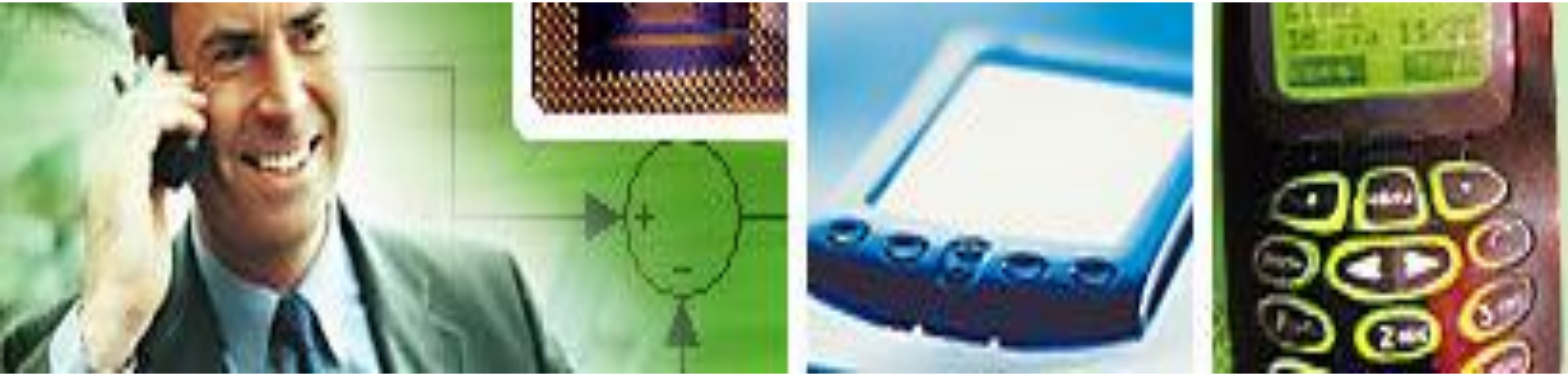
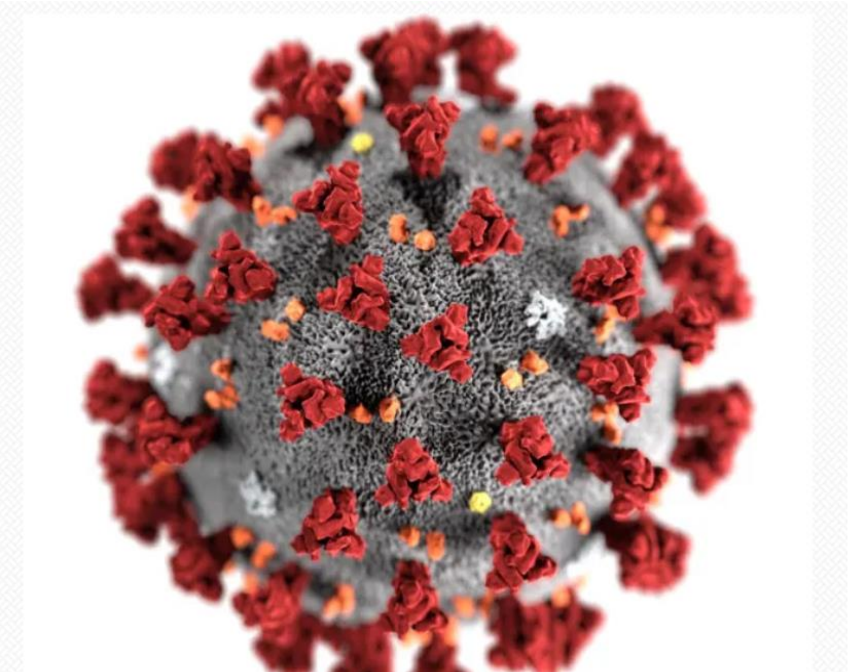
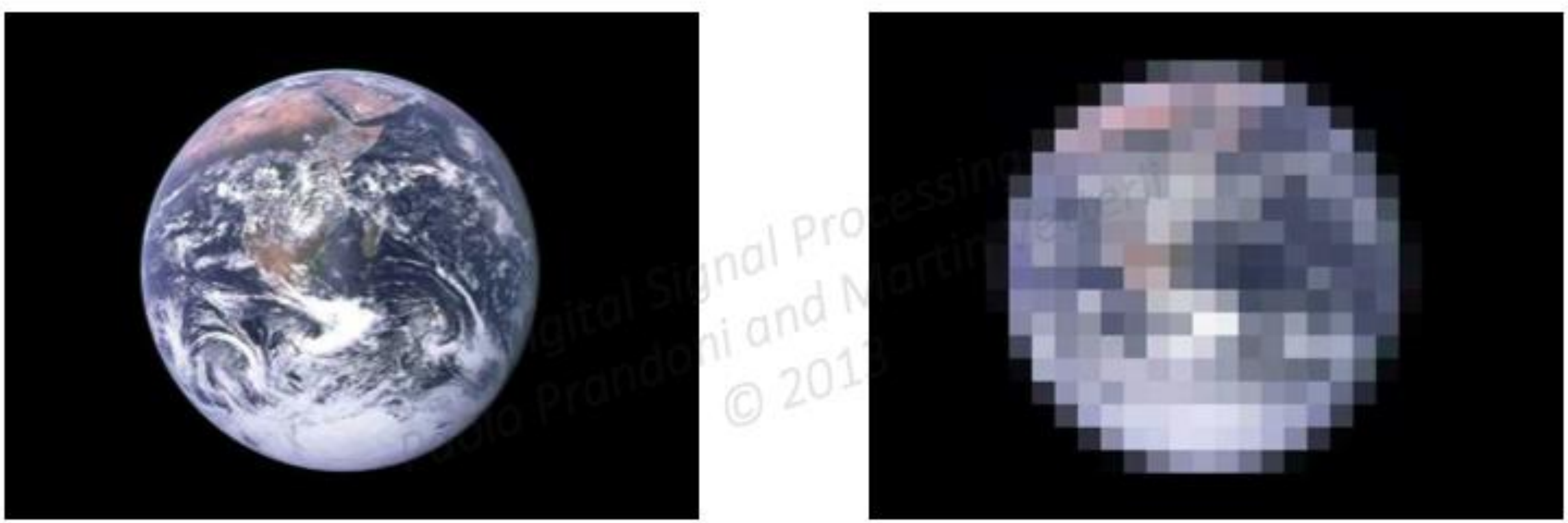




Two types of signal

information carrying signals are divided into two broad classes

Continuous $x(t)$ *vs .* *Digital* $x[n]$



Analog/continuous versus discrete/digital

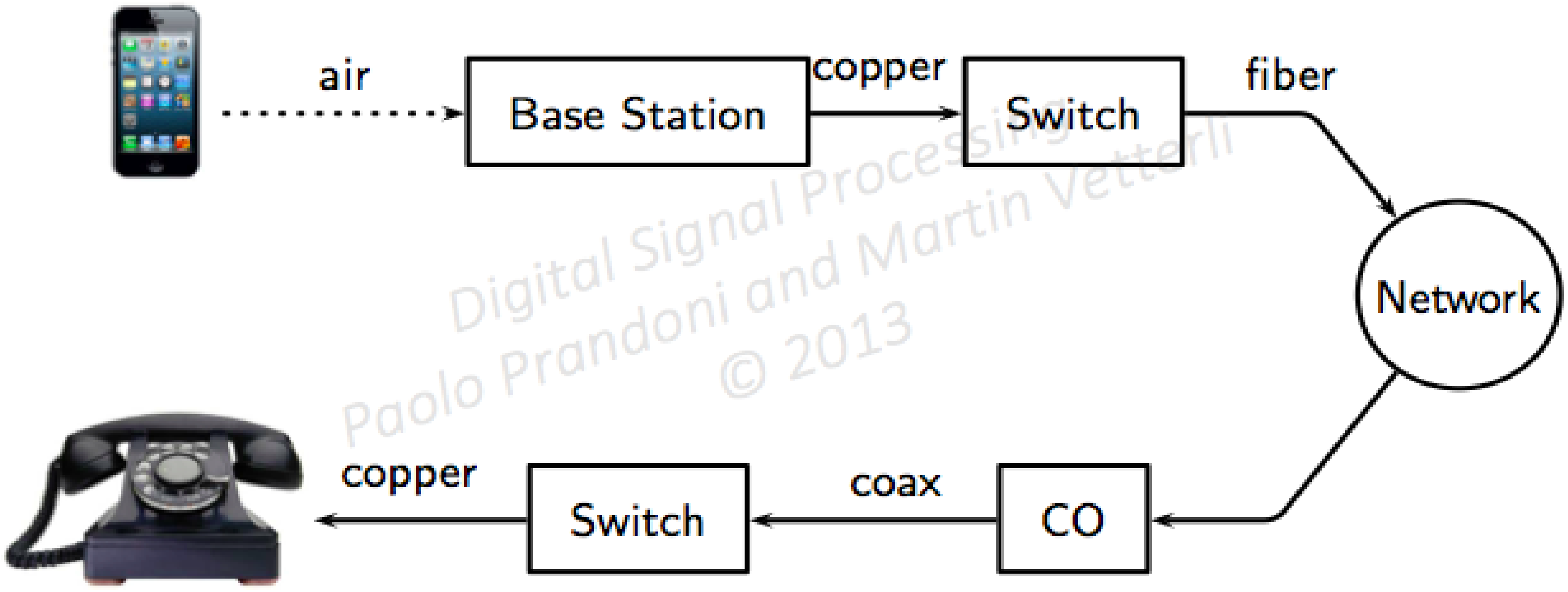
Continuous (Analog) Signals

- Analog signals: continuous (electrical) signals that vary in time
- Most of the time, the variations follow that of the non-electric (original) signal.
- The two are analogous hence the name *analog*.

Example I

Telephone voice signal is analog.

- The intensity of the voice causes electric current variations.
- At the receiving end, the signal is reproduced in the same proportion.



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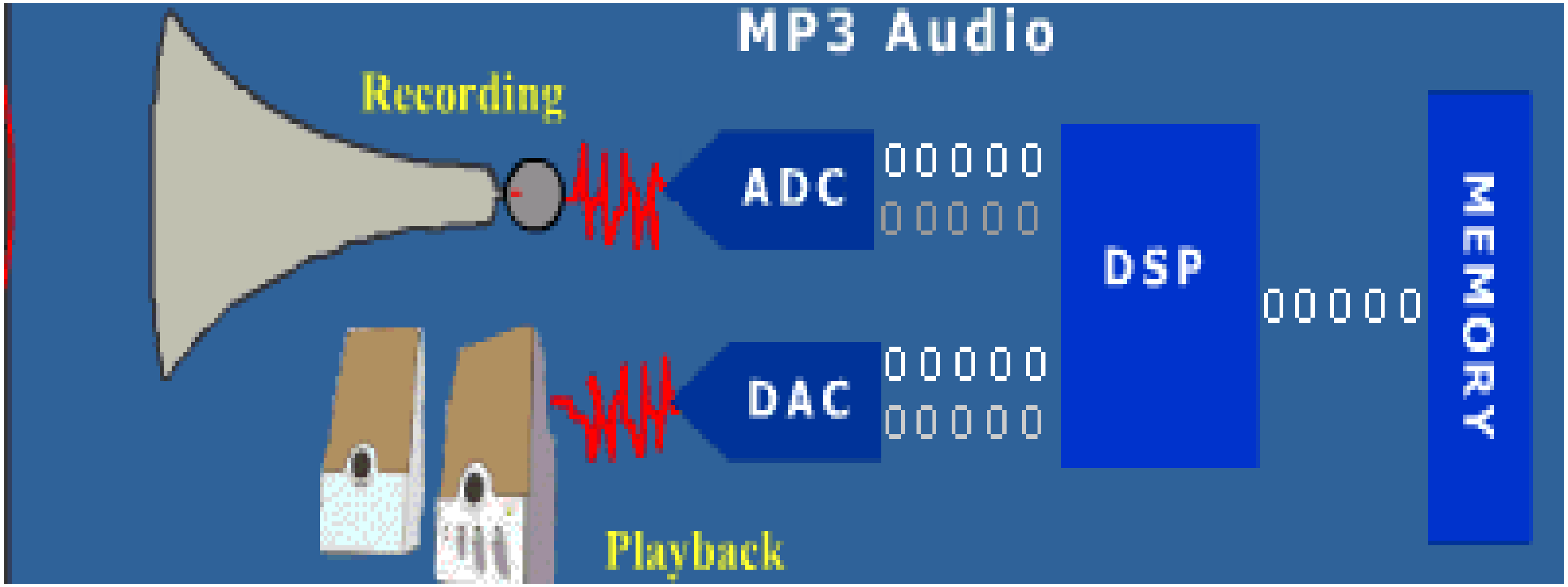

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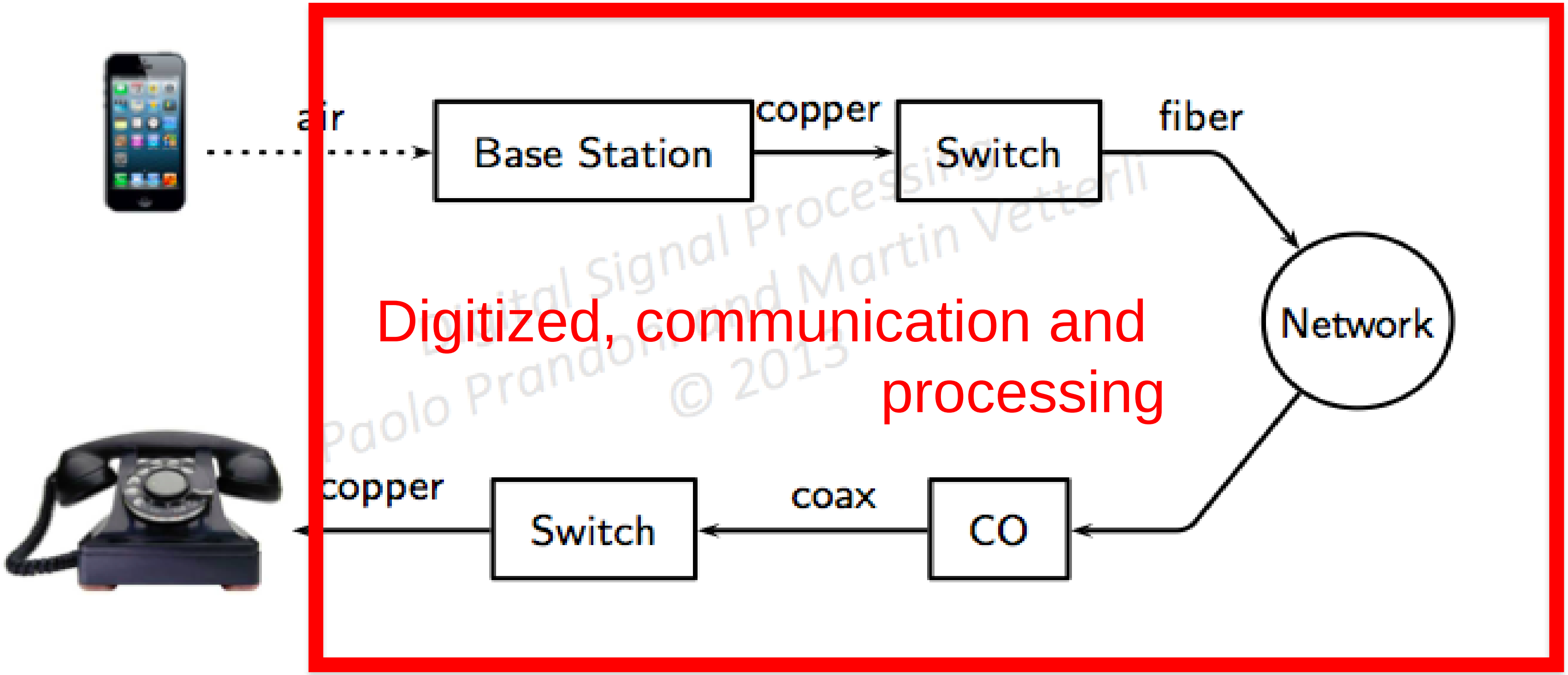
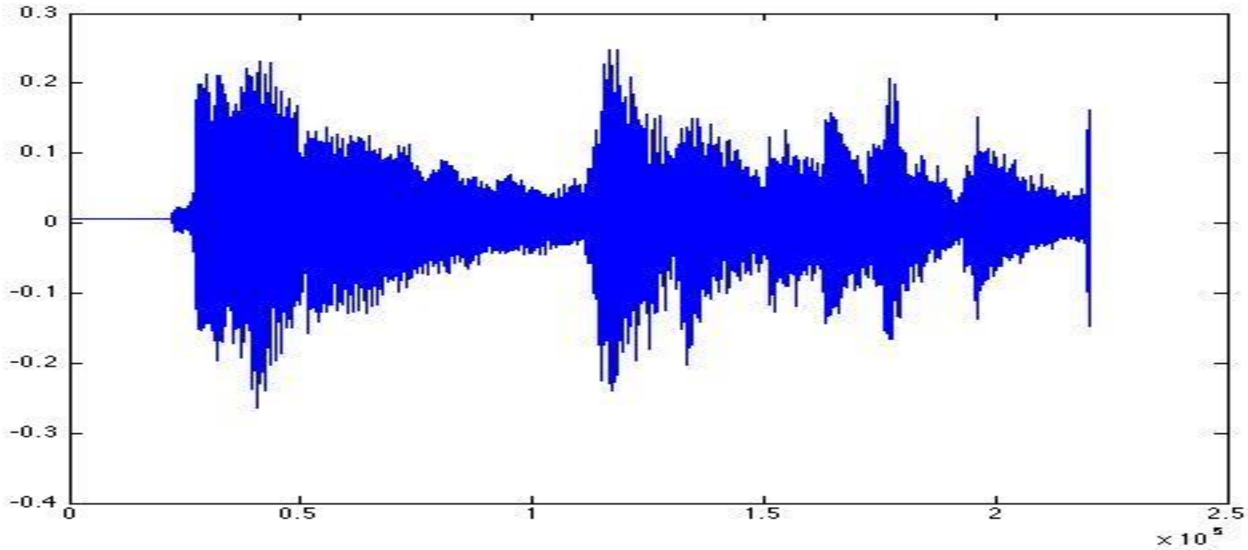


Example II



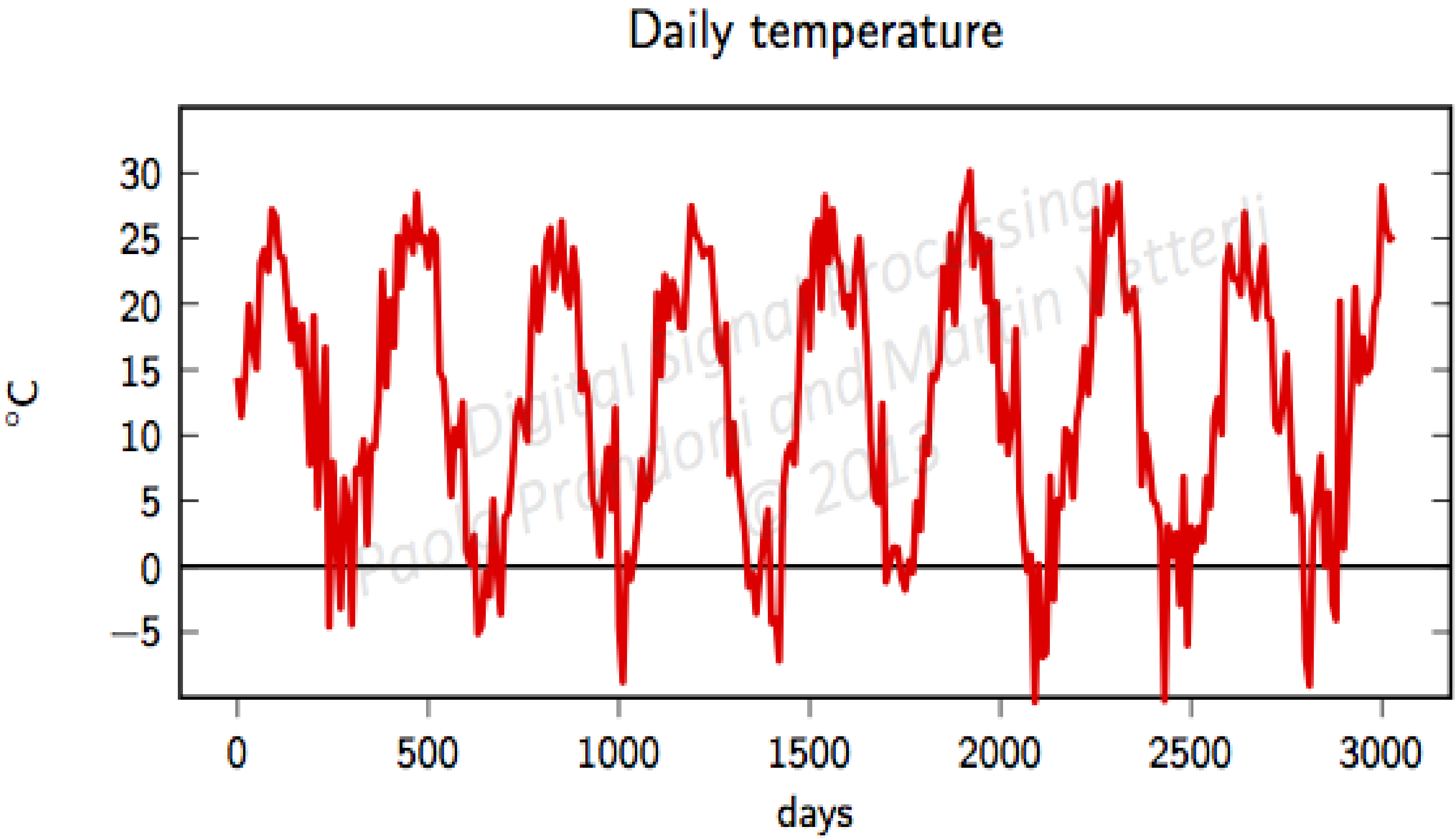
Digital Signals

Non-continuous, they change in individual steps.

Consist of pulses with discrete levels or values.

Each pulse is constant, but there is an abrupt change from one digit to the next.

Example I

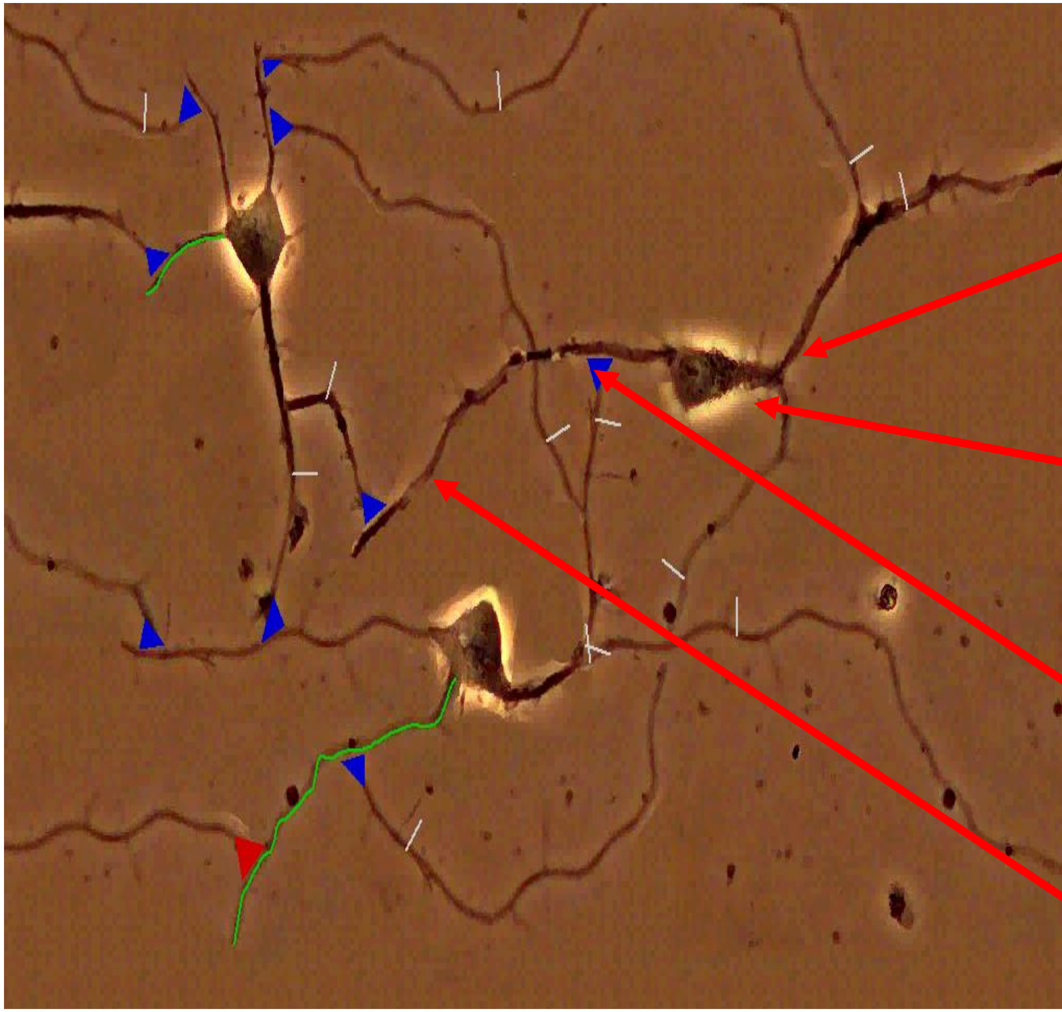


Daily temperature
°C
30
25
20
15
10
5
0
−5
0
500
1000
1500
2000
2500
3000
days
Digital Signal Processing
Paolo Prandoni and Martin Vetterli
© 2013

Example II: please meet

- Two-dimensional signal $x[n_1,n_2]$, $n_1,n_2 \in Z$
- A point on a grid $\rightarrow$ pixel
- Grid is usually regularly spaced
- Values $x[n_1,n_2]$ refer to the pixel's appearance

Example III: Our brain, Neuronal Activities



Vertical white bar: spik

axon

soma

synapse

Dendrite

Advantages I

a. The ability to process a digital signal means that errors caused by random processes can be detected and corrected.

b. Digital signals can also be sampled instead of continuously monitored and multiple signals can be multiplexed together to form one signal.

Advantages II

c. Advances in wideband communication channels and solid-state electronics have allowed scientists to fully realize a and b digital communications has grown quickly.

d. Digital communications is quickly edging out analog communication because of the vast demand to transmit computer data and the ability of digital communications to do so.

Module Summary I

- One sentence: **Deal with digital signals**

Module Summary II

- *Data transmission*: Channel characteristics, signalling methods, interference and noise,

  data compression and encryption;

- *Information Sources and Coding:* Information theory, coding of information for efficiency and error protection;

Module Summary III

- *Data transmission:* Channel characteristics, signalling methods, interference and noise, synchronisation, data compression and encryption;

- *Information Sources and Coding:* Information theory, coding of information for efficiency and error protection;

- *Signal Representation*: Representation of discrete time signals in time and frequency; z transform and Fourier representations; discrete approximation of continuous signals; sampling and quantisation; stochastic signals and noise processes;

Module Summary IV

- *Data transmission:* Channel characteristics, signalling methods, interference and noise, synchronisation, data compression and encryption;
- *Information Sources and Coding:* Information theory, coding of information for efficiency and error protection;
- *Signal Representation:* Representation of discrete time signals in time and frequency; z transform and Fourier representations; discrete approximation of continuous signals; sampling and quantisation; stochastic signals and noise processes;
- *Filtering:* Analysis and synthesis of discrete time filters; finite impulse response and infinite impulse response filters; frequency response of digital filters; poles and zeros; filters for correlation and detection; matched filters;

Module Summary V

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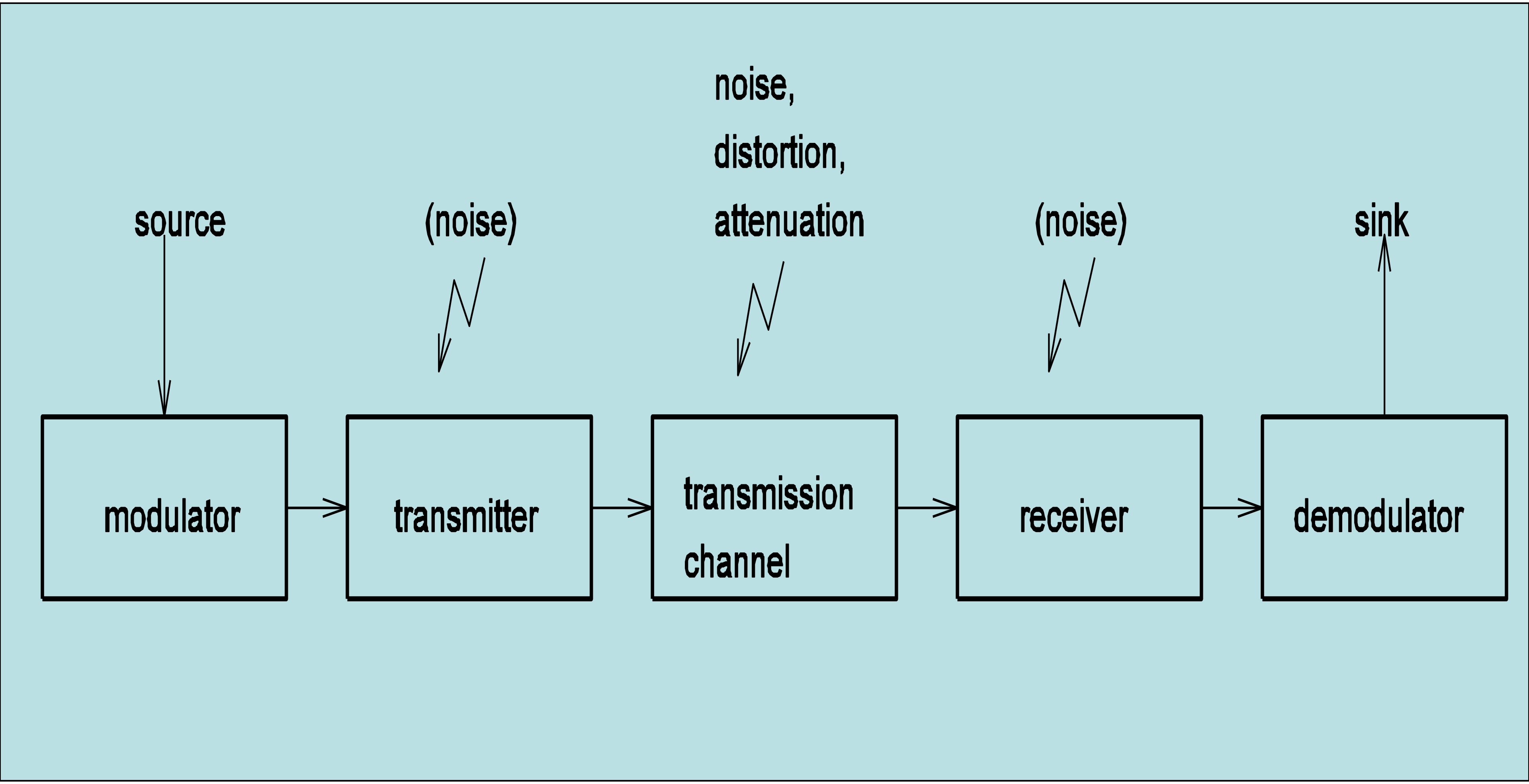
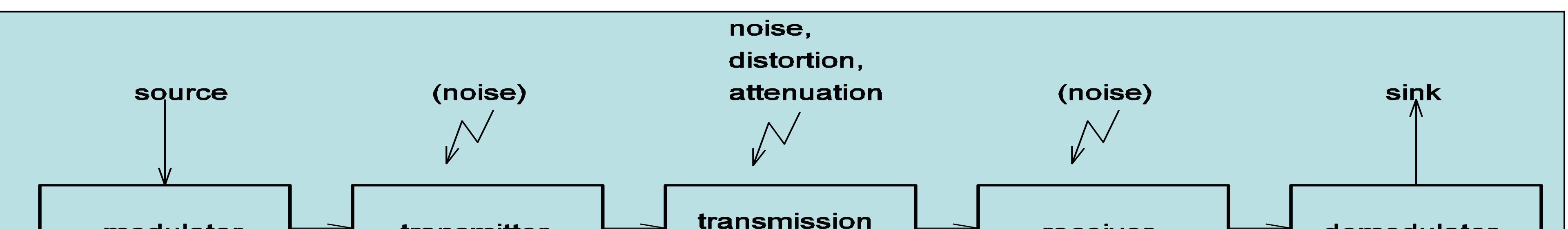
- *Filtering:* Analysis and synthesis of discrete time filters; finite impulse response and infinite impulse response filters; frequency response of digital filters; poles and zeros; filters for correlation and detection; matched filters;
- *Digital Signal Processing applications:* Processing of images and sound using digital techniques.

Data Transmission I: General Form



Data Transmission II:

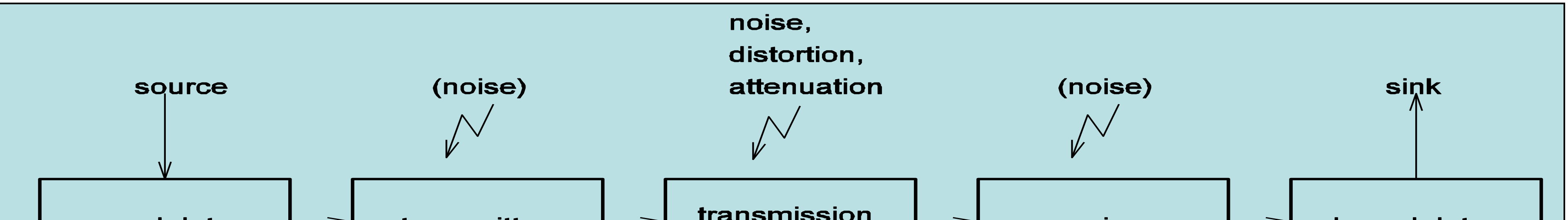
- A modulator that takes the source signal and transforms it so that it is physically suitable for the transmission channel



Data Transmission II:

- A modulator that takes the source signal and transforms it so that it is physically suitable for the transmission channel

- A transmitter that actually introduces the modulated signal into the channel, usually amplifying the signal as it does so



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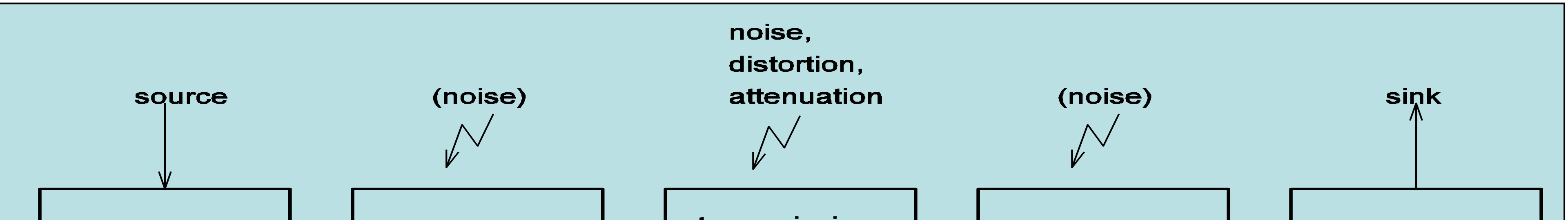
- A transmission channel that is the physical link between the communicating parties



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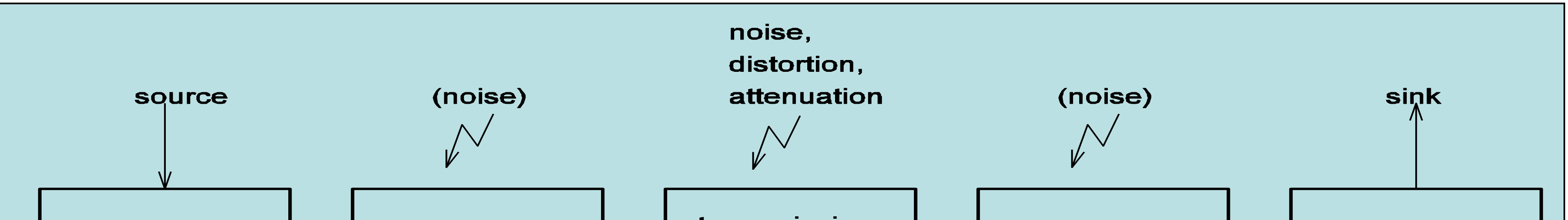

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- A demodulator that receives the original source signal from the received signal and passes it to the sink

Data Transmission III:

Digital data is universally represented by strings of 1s or 0s.

Each one or zero is referred to as a bit.

Often, but not always, these bit strings are interpreted as numbers in a binary number system.

Thus $101001_2=41_{10}$.

The information content of a digital signal is equal to the number of bits required to represent it.

Thus a signal that may vary between 0 and 7 has an information content of 3 bits.

Data Transmission IV

Written as an equation this relationship is

$$I = log_2(n) \qquad \text{bits}$$

where n is the number of levels a signal may take.

It is important to appreciate that information is a measure of the number of different outcomes a value may take.

The information rate is a measure of the speed with which information is transferred. It is measured in bits/second or b/s.

Bandwidth

Signal is bandlimited if it contains no energy
at frequencies higher than some bandlimit
or bandwidth B

Examples

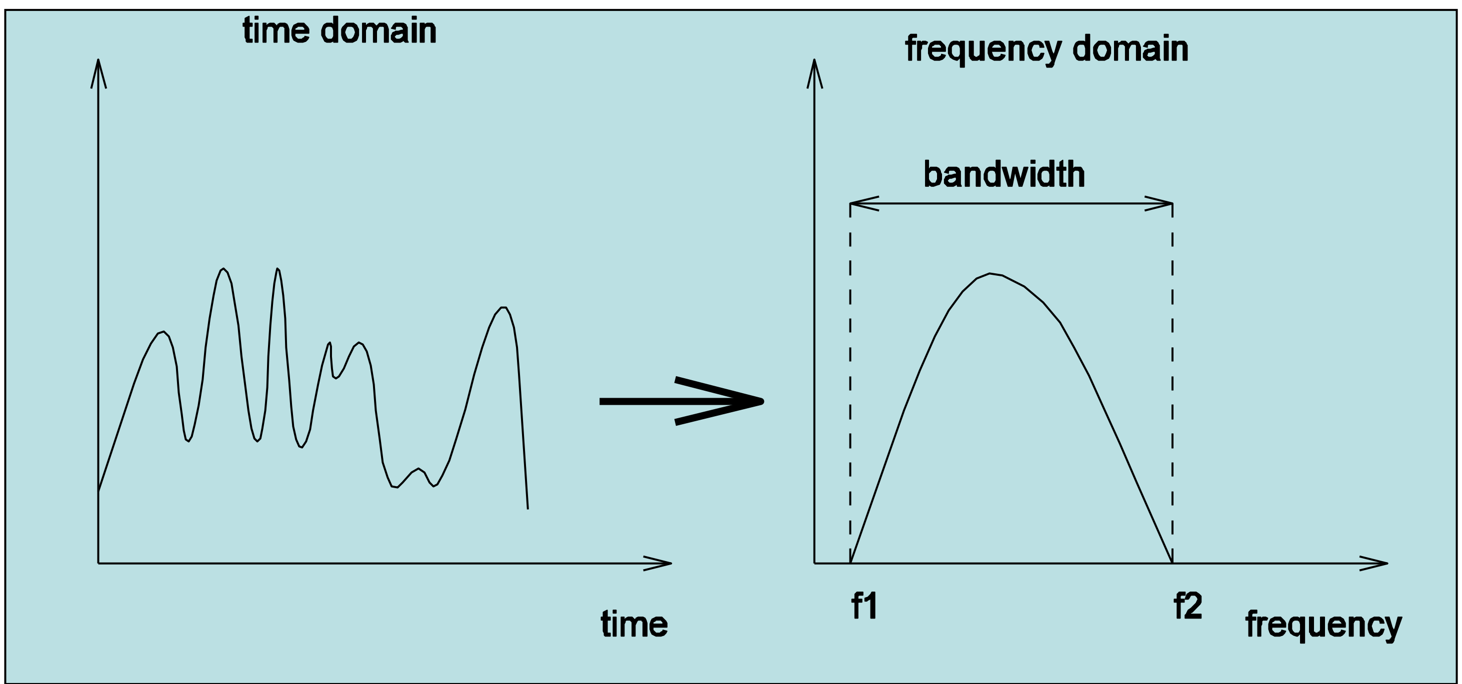
Audio signals. An audio signal is an example of an analogue signal.

It occupies a frequency range from about 200 Hz to about 15KHz.

Speech signals occupy a smaller range of frequencies, and telephone speech typically occupies the range 300 Hz to 3300 Hz..

The range of frequencies occupied by the signal is called its

bandwidth (B = f2 – f1 ~ f2)



Examples

Television. A television signal is an analogue signal created by linearly scanning a two dimensional image.

Typically the signal occupies a bandwidth of about 6 MHz.

Teletext is written (or drawn) communications that are interpreted visually.

Reproducing cells, in which the daughter cells's DNA contains information from the parent cells;

A disk drive

Our brain

ADC and DAC

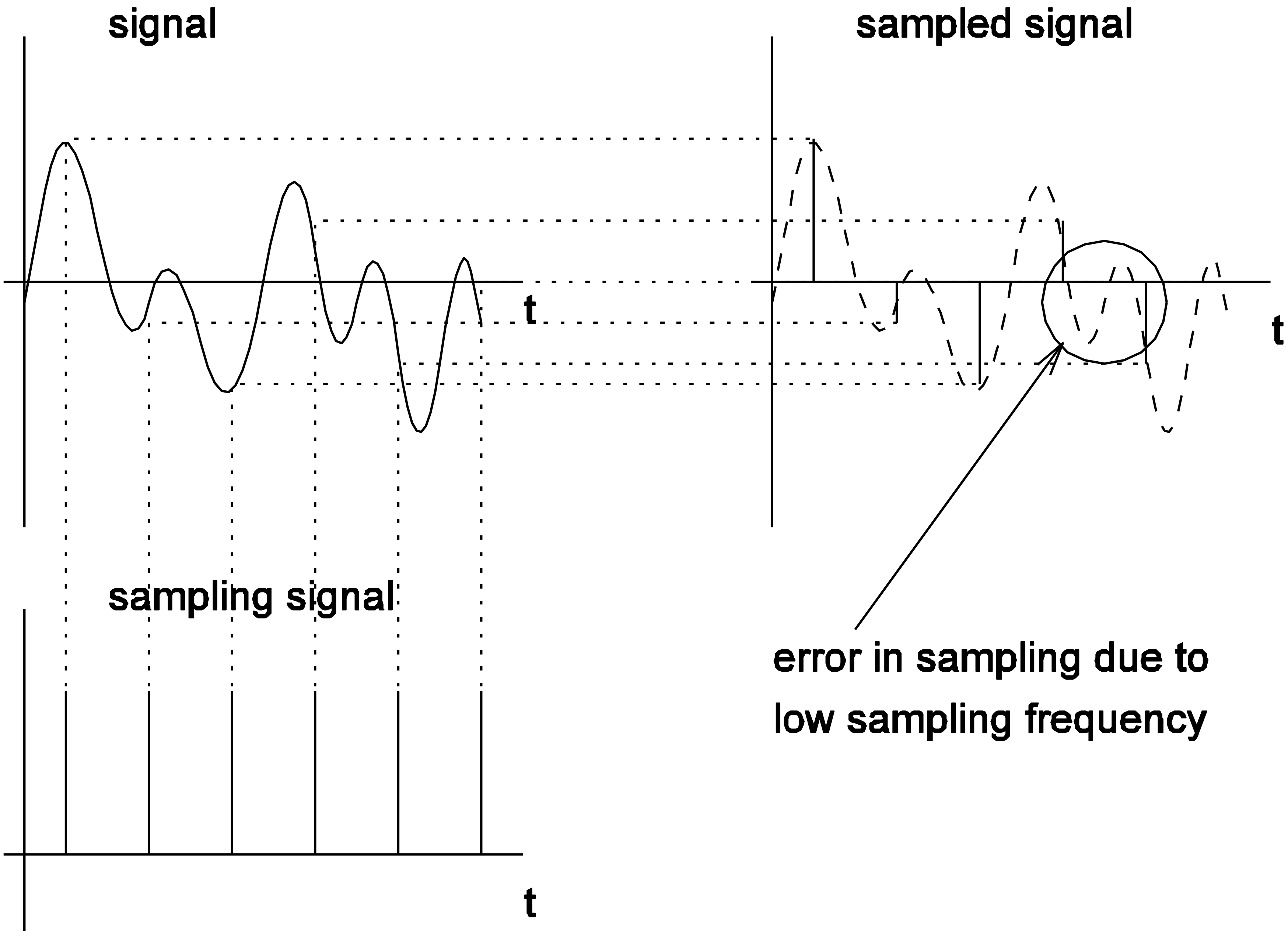
send analogue signals over a digital communication system, or process them on a digital computer, to convert analogue signals to digital ones.

preformed by an analogue-to-digital converter (ADC).

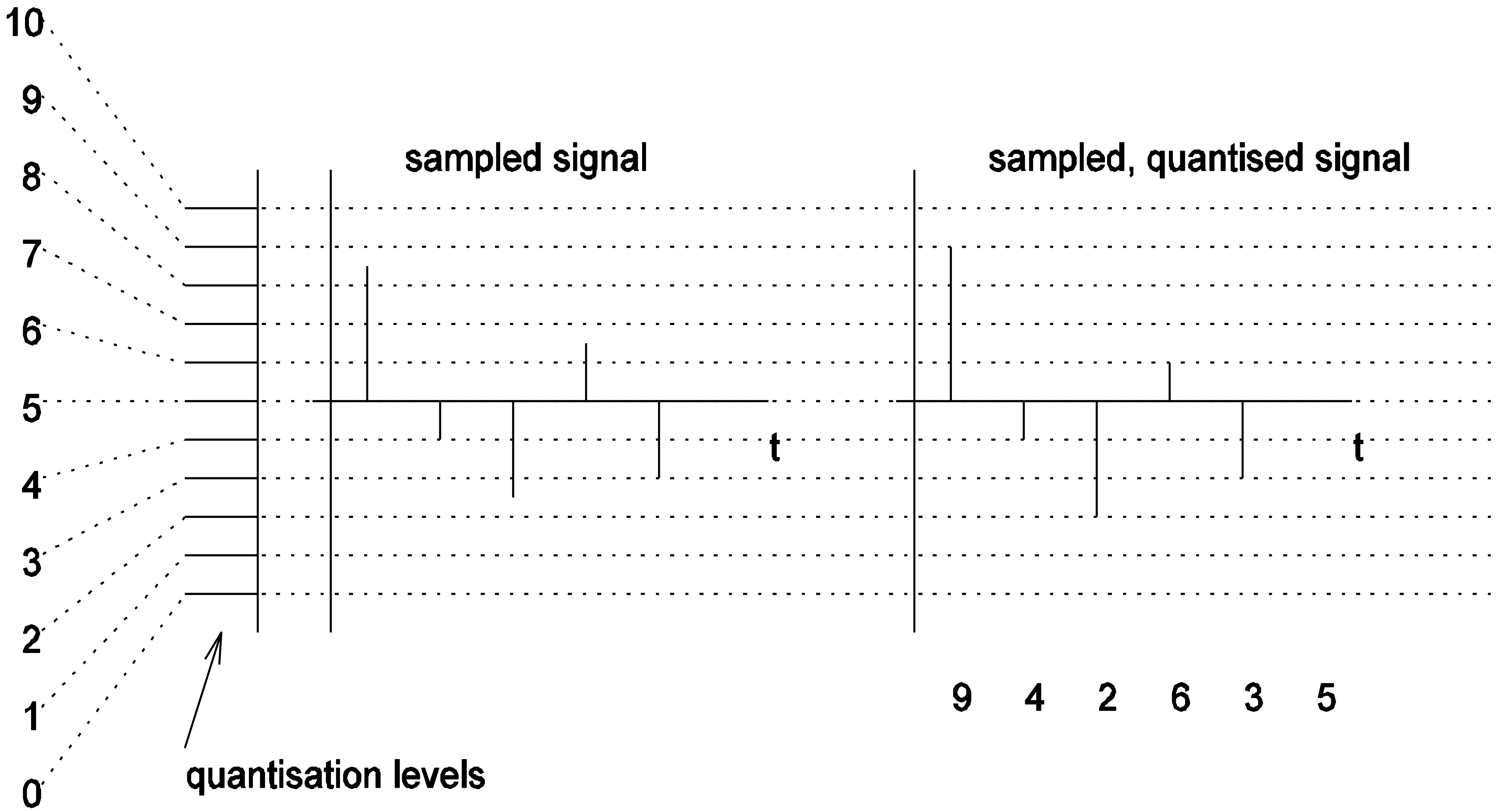
The analogue signal is sampled (i.e. measured at regularly spaced instant)

The converse operation to the ADC is performed by a digital-to-analogue converter (DAC).

Example

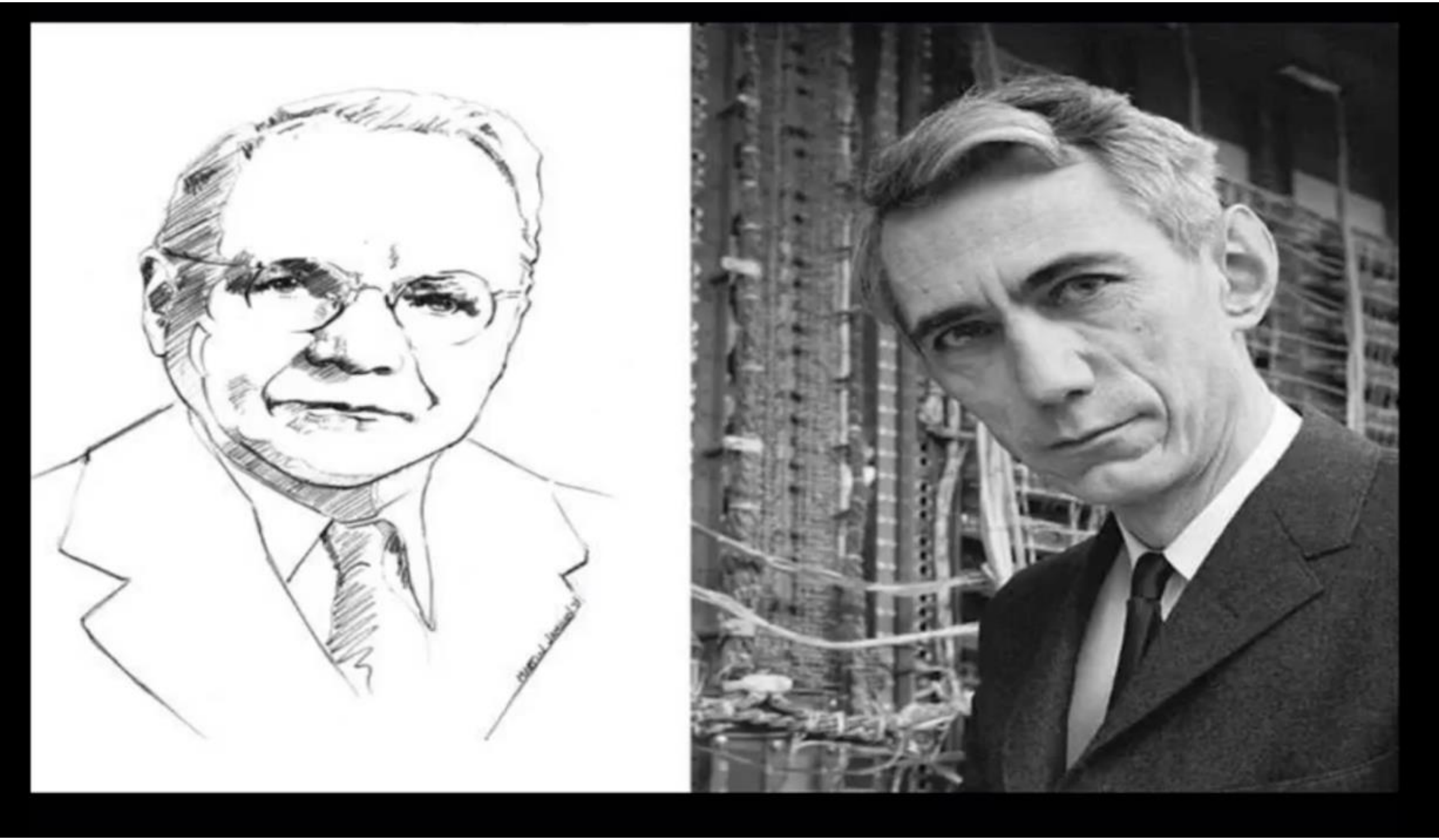

signal
sampled signal
t
t
sampling signal
1
t
error in sampling due to
low sampling frequency

Example



How can we get the original signal back?

How fast we have to sample to recover the original signal?



Nyquist-ShannonThm

(will be discussed in Chapter 3)

An analogue signal of bandwidth B can be

completely recreated from its sampled from

provided its sampled at a rate equal to at

least twice it bandwidth

$$\boxed{S > 2B}$$

Boston Dynamics (find out yourself on what they have evolved)