Meaning from measurement: how Metrology and Machine Learning could co-produce knowledge

Measurement and models: from ancient philosophy to public health
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The usual framing

The relation between Artificial Intelligence (AI) and Measurement Science (MS) is usually meant as

either

- **AI for MS**: how can AI help improving MS?
  (“smart” meters, automated test generation and evaluation, …)

or

- **MS for AI**: how can MS help improving AI?

An example

The New York Times

A.I. Has a Measurement Problem

Which A.I. system writes the best computer code or generates the most realistic image? Right now, there's no easy way to answer those questions.

(15 April 2024, https://www.nytimes.com/2024/04/15/technology/ai-models-measurement.html)

My subject today

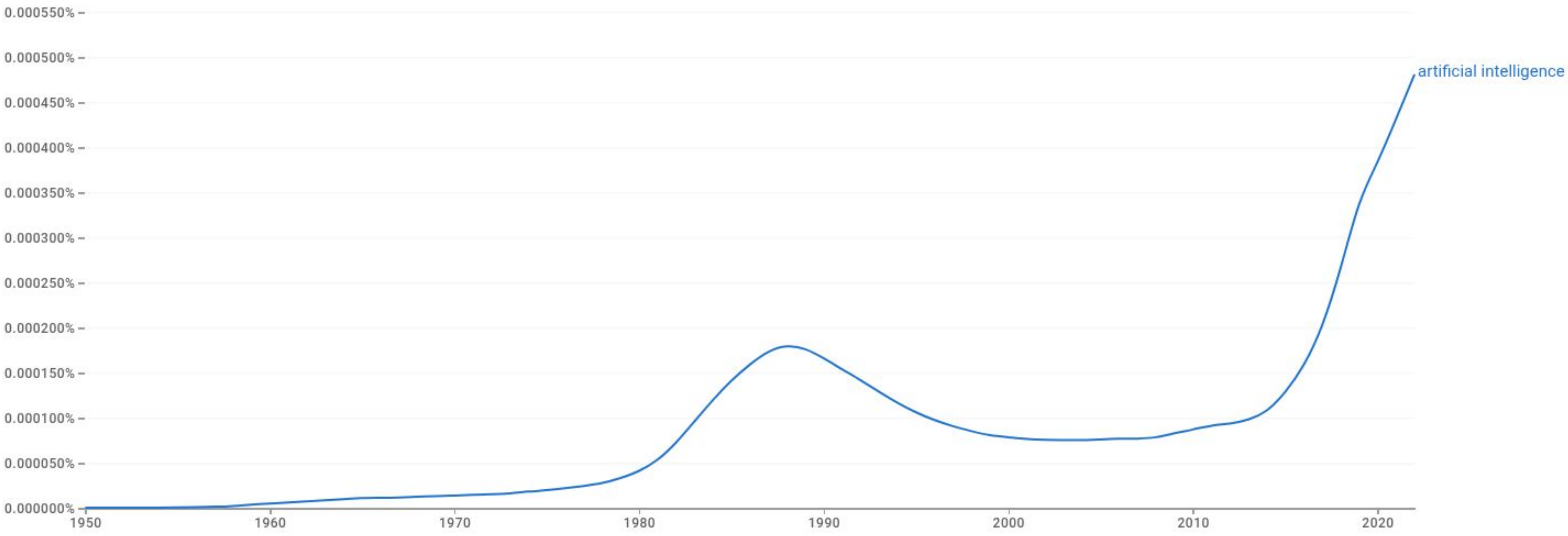
Both measuring systems and AI systems
may be specializations of a broader class:

adaptive model-based information systems

This perspective reveals
hidden epistemological assumptions and structures

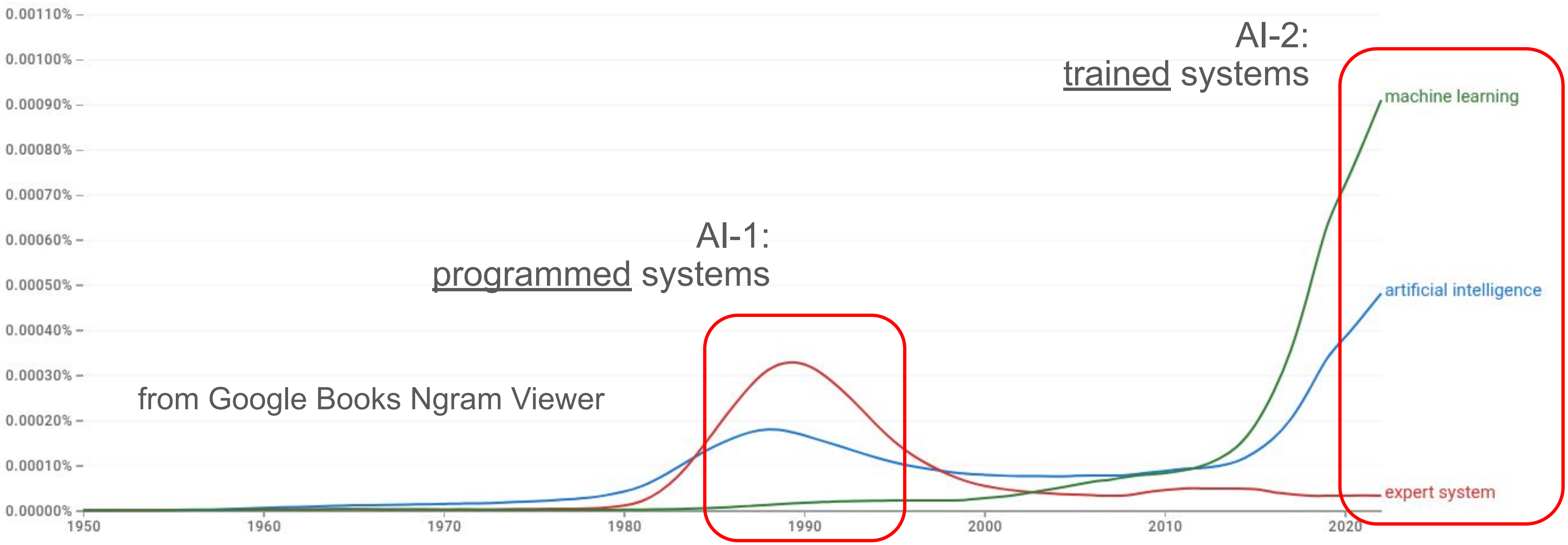
Each helps us understand the other

Artificial Intelligence?



https://books.google.com/ngrams/graph?content=artificial+intelligence&year_start=1950&year_end=2022&corpus=en&smoothing=3

Artificial Intelligence $\cong_{\text{today}}$ Machine Learning



https://books.google.com/ngrams/graph?content=artificial+intelligence%2Cexpert+system%2Cmachine+learning&year_start=1950&year_end=2022&corpus=en&smoothing=3&case_insensitive=false

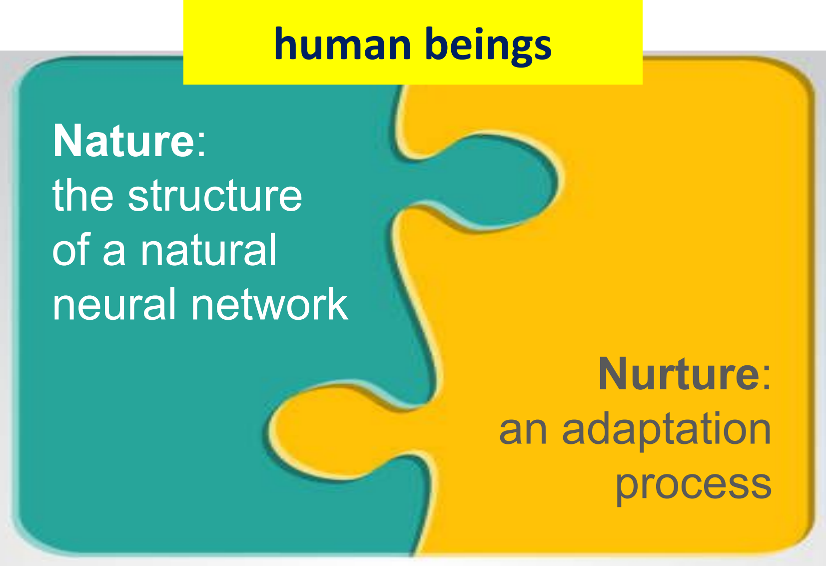
Machine Learning

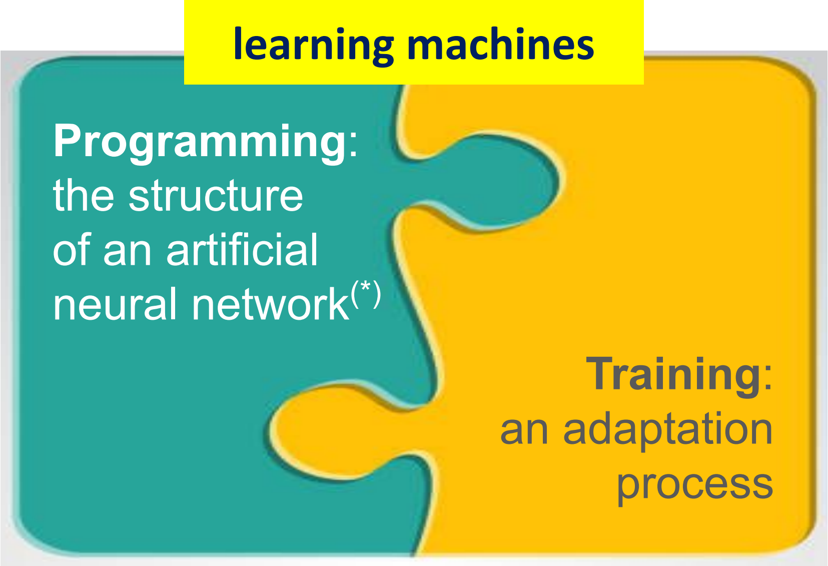
“Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed”

A. Samuel, 1959

Learning Machines: a tentative interpretation

“**Nature versus nurture** is a long-standing debate in biology and society about the relative influence on human beings of their genetic inheritance (nature) and the environmental conditions of their development (nurture).”
https://en.wikipedia.org/wiki/Nature_versus_nurture

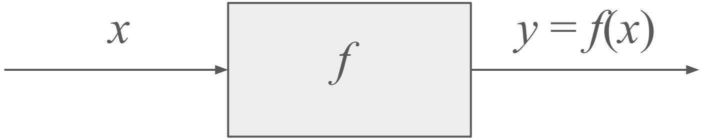




(*) Or some other adaptive software system

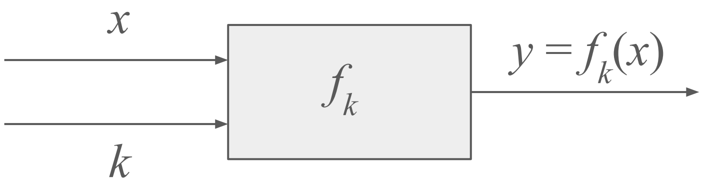
A simple mathematical model

1. analytically fixed behavior



the behavior is fully set according to the knowledge formalized in f

2. adaptive behavior

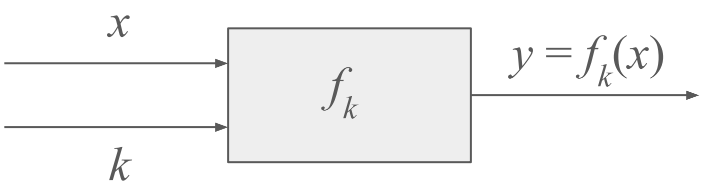


the behavior depends on both the knowledge formalized in f and the values of k

A simple mathematical model /2

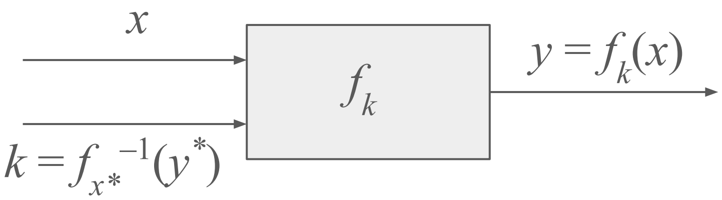
2.1 knowledge-driven adaptation

the values of k are set
according to explicit knowledge



2.2 data-driven adaptation

the values of k result from
a data-driven optimization
based on (x^*, y^*) references



In this case the adaptation can be described as "training the function"

Learning Machines and Measuring Systems

Both LMs and MSs can be relatively simple
(e.g., logistic regression, spring dynamometer)
or complex

Simple examples are sufficient for most of our purposes today

Learning Machines and Measuring Systems

The basic analogy:

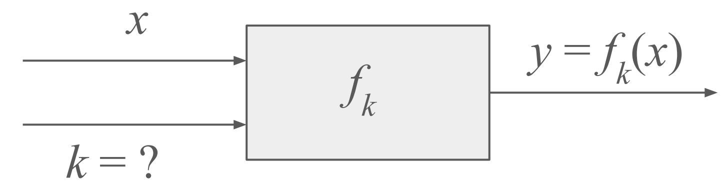
- both LMs and MSs are input-output, information-producing systems
- LMs perform inference (*forward mode,* f)
  after having been trained (*backward mode,* f^{-1})
- MSs perform measurement (*forward mode,* f)
  after having been calibrated (*backward mode,* f^{-1})

Training	**Calibration**
training set	calibrated measurement standards
labels in training set	reference values of quantities of measurement standards

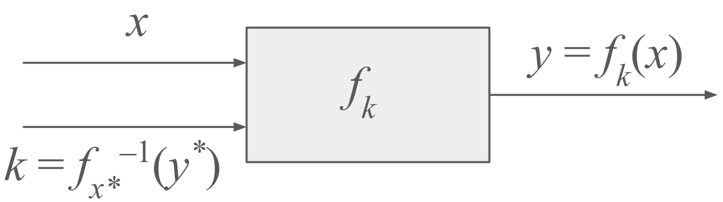
Inference	**Measurement**
input data	measurand
prediction	measurement result

Learning Machines and Measuring Systems

Structural knowledge → Prior parameter-free model



Exemplary references → Posterior parameter-bound model



Learning Machines and Measuring Systems

A fundamental analogy:

- both LMs and MSs are information-producing systems,
- designed as input-output entities
- which implement a model of the input-output relation,
- acknowledged to be too complex to be fully identified in analytical way,
- and therefore first built as an adaptive, parametric structure
- then specified by setting the values of the parameters
- through a matching with some exemplary references
- with the purpose that the produced output is reliably informative on the fed input

These could be considered cases of "epistemic engineering"

Some (important…) differences

Input

MSs: empirical world → information

LMs: information → new information

Ground truth

MSs: in principle unique reference values (with uncertainty)

LMs: sometimes multiple acceptable outputs; preferences may replace truth

Structure

MSs: usually custom because grounded in physical laws and quite simple

LMs: usually based on “standard” algorithms and possibly very complex

Context

MSs: in principle the aim is to remove the effects of influence quantities

LMs: sometimes the context is exploited as further information

Evaluating the quality of behavior of adaptive systems

The analogy with measuring systems is suggestive

The quality of the behavior of

a LM depends on

– the quality of its structure

– the quality of its training

which is about

– the training set (correctly sampled and unbiased)

– the training process

a MS depends on

– the quality of its structure

– the quality of its calibration

which is about

– measurement standards (correctly sampled and unbiased)

– the calibration process

A philosophical wrap up

Machines with

(1) analytically fixed behavior or

(2.1) adaptive behavior through knowledge-driven adaptation

are embodiments of external explicit knowledge:
either they only handle data
or the information they handle is only a mirror of such external knowledge

Machines, like LMs and MSs, with

(2.2) adaptive behavior through data-driven adaptation

have a behavior which is partly obtained by information-related optimization:
they can be interpreted as handling information in some specific and original way

Why does this matter? Back to the title

Measurement is not only about numbers:
it is a way to produce trustworthy knowledge about the world

Machine learning is not only about prediction:
it is a way to produce models transforming data in reliable information

Measurement and Machine Learning
are complementary forms of epistemic engineering:
technologies for producing meaningful knowledge
through adaptive models constrained by empirical references

A different way of looking at measurement

For centuries, we assumed that only humans could acquire behaviour from experience

Machine Learning has revealed another possibility:
artefacts that acquire behaviour from empirical references

This provides us with a new perspective on measurement:
measuring systems are not merely instruments implementing physical laws
After calibration, they also become experience-shaped artefacts

Perhaps **we have been building learning machines for centuries**:
we simply never thought of measuring systems that way

Thank you for your attention

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