Artificiële Intelligentie

RCA AIG 04Q6 03 JUNI 2021

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Computational Foundations of Machine Learning [ML] with Python

The Good
The Bad
& the UGLY

DataLab

Rob van der Willigen

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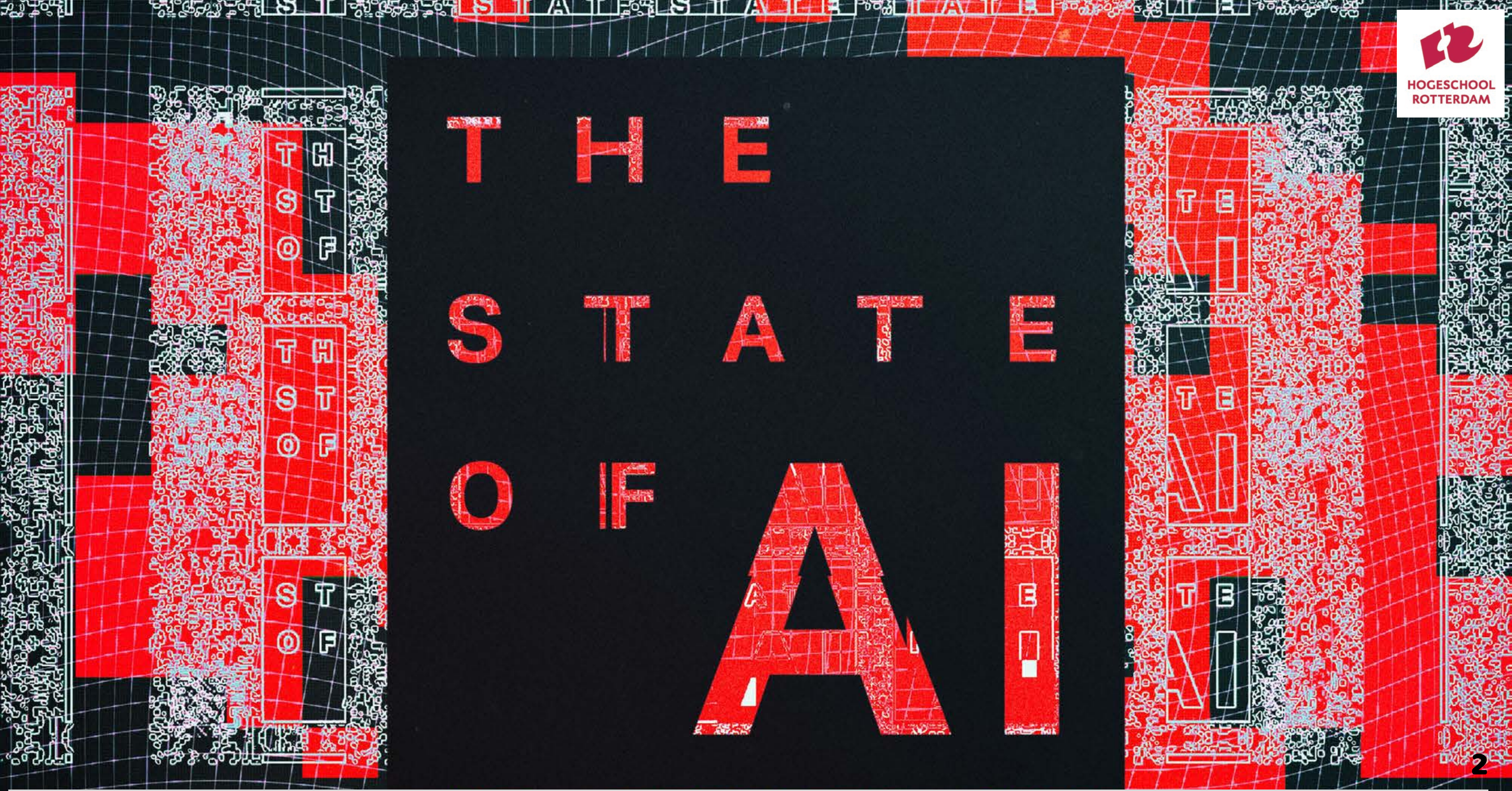


https://www.theverge.com/2019/1/28/18197520/ai-artificial-intelligence-machine-learning-

What did we learn about AI

Data [Science] vs AI

Lecture 09

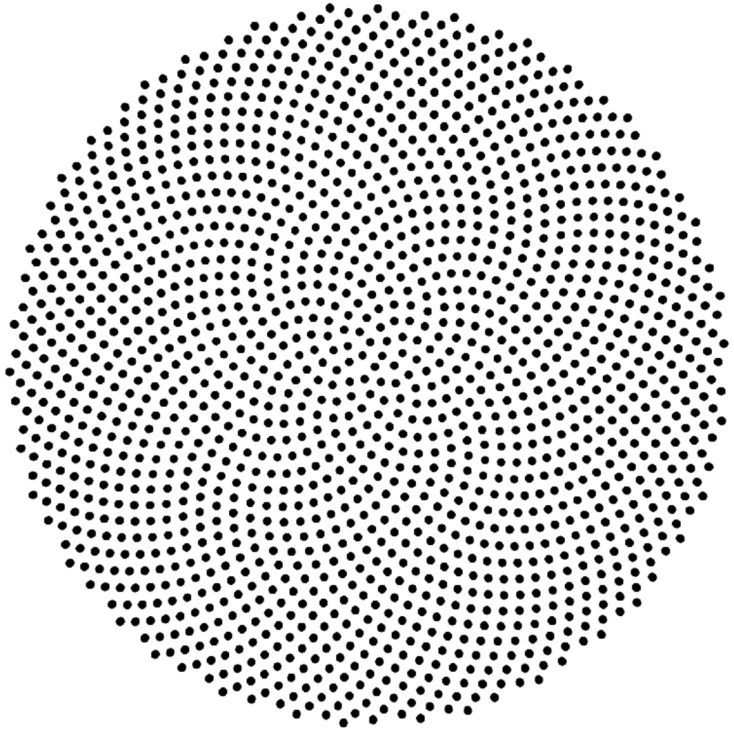
- **Basic definitions and concepts of Machine Learning (ML):**

  What did we learn about AI: Top-Down vs Bottom-Up

- **➔ SYSTEMS & COMPLEXITY THINKING⇐**

{02}

What did we learn about AI



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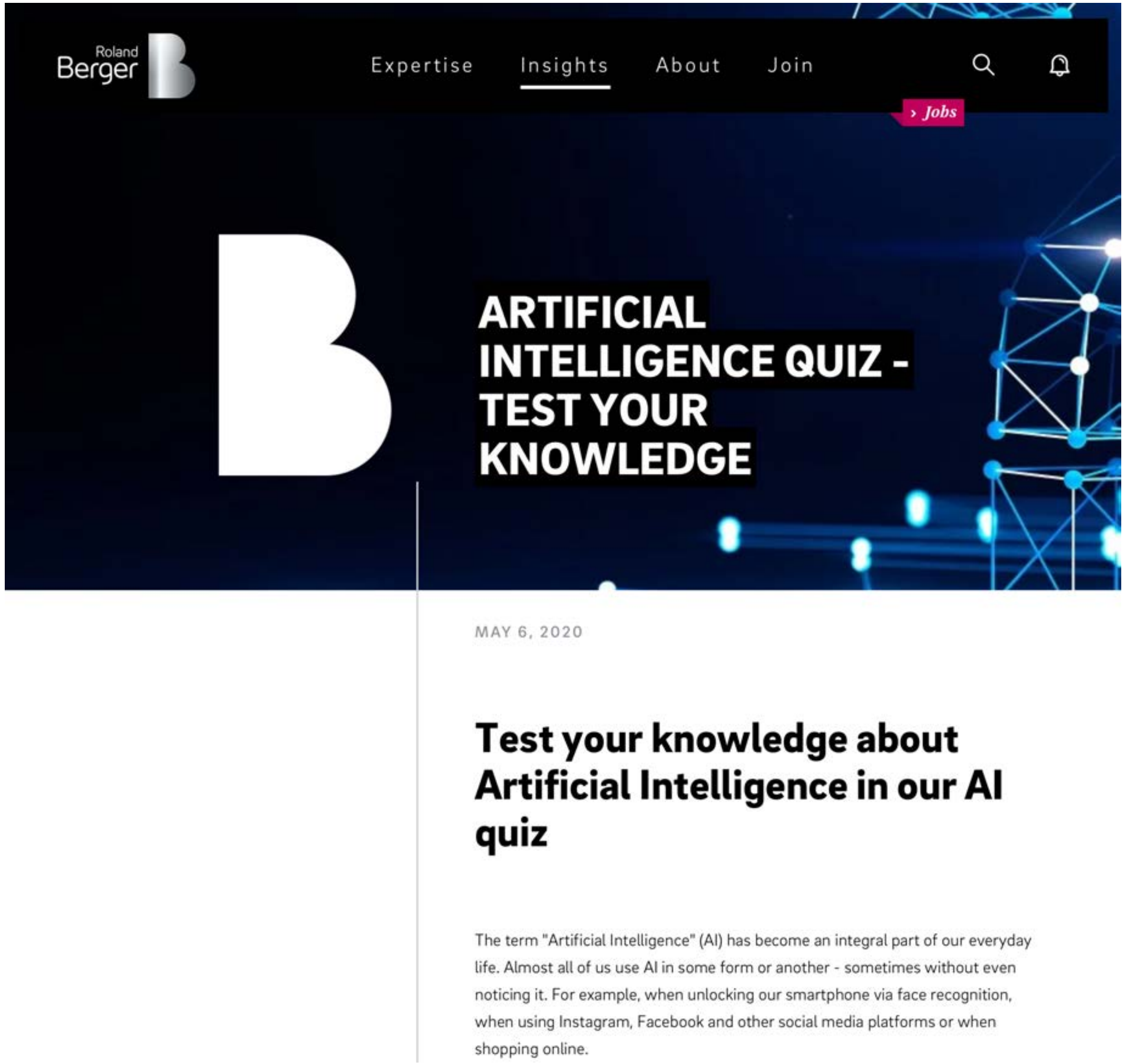
Roland Berger

Expertise Insights About Join

› Jobs

ARTIFICIAL INTELLIGENCE QUIZ - TEST YOUR KNOWLEDGE

MAY 6, 2020

Test your knowledge about Artificial Intelligence in our AI quiz

The term "Artificial Intelligence" (AI) has become an integral part of our everyday life. Almost all of us use AI in some form or another - sometimes without even noticing it. For example, when unlocking our smartphone via face recognition, when using Instagram, Facebook and other social media platforms or when shopping online.

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GO TO QUIZ

https://www.rolandberger.com/en/Insights/Publications/The-Artificial-Intelligence-Quiz-Test-Your-Knowledge.html#quiz

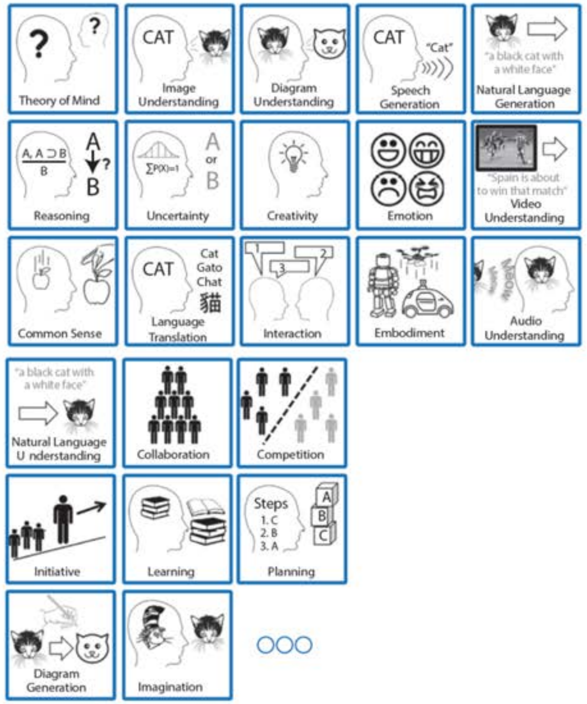
Serengeti Plains. By Kristin Moger

The World-Wide-Web AI-Safari

Artificial Intelligence: a Human Centred View

RobFvdW Nov 12, 2020 · 6 min read

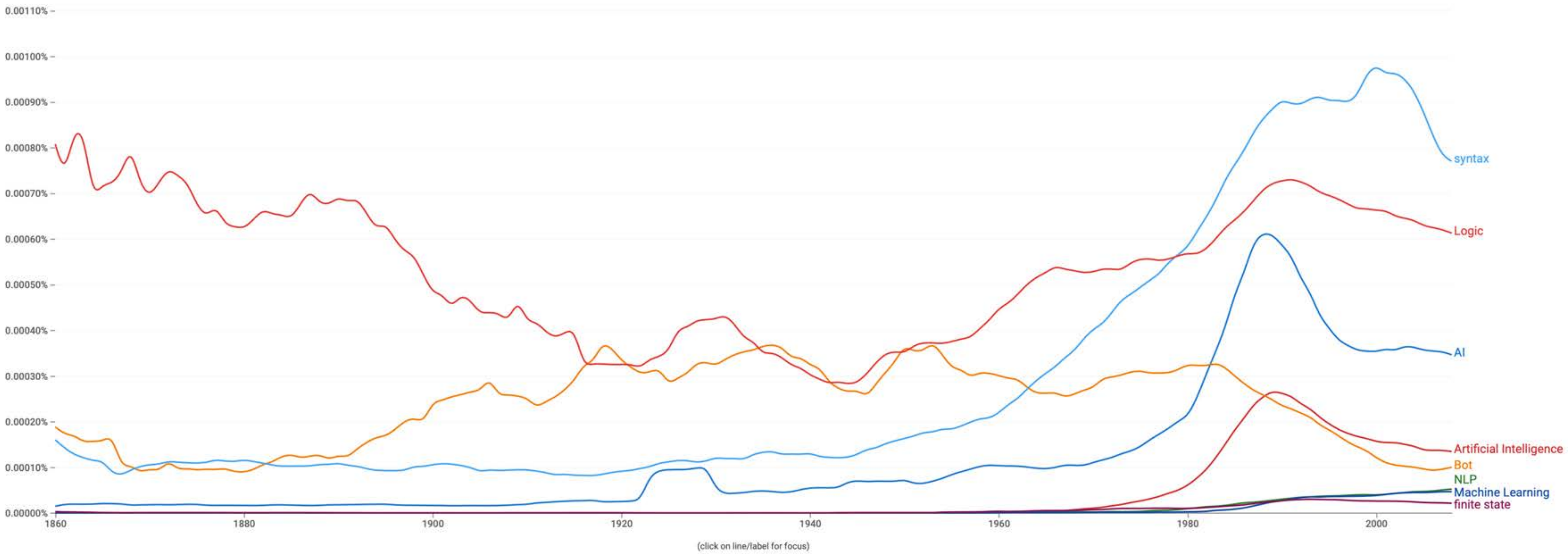
AI aims to **mimic & automatise** tasks which otherwise require human **perception, cognition** and/or **motor skills** — e.g. pattern recognition, learning, logical reasoning & planning, decision making, problem solving, designing, creativity, likelihood estimation, language acquisition, multi-sensory interfacing, actuated body movement control, locomotion & manipulation, sentiment analysis, and generalisation *(see refs [1]…[3])*.



Human capabilities (adapted from AI Magazine)

What kind(s) of AI are you Going to use?

https://robfvdw.medium.com/the-world-wide-web-ai-safari-b2e4f7f90647



https://books.google.com/ngrams/graph?content=AI%2CArtificial+Intelligence%2CNLP%2CBot%2CMachine+Learning%2Cfinite+state%2Csyntax%2CLogic&year_start=1860&year_end=2008&corpus=15&smoothing=3&share=&direct_url=t1%3B%2CAI%3B%2Cc0%3B.t1%3B%2CArtificial%20Intelligence%3B%2Cc0%3B.t1%3B%2CNLP%3B%2Cc0%3B.t1%3B%2CBot%3B%2Cc0%3B.t1%3B%2CMachine%20Learning%3B%2Cc0%3B.t1%3B%2Cfinite%20state%3B%2Cc0%3B.t1%3B%2Csyntax%3B%2Cc0%3B.t1%3B%2CLogic%3B%2Cc0

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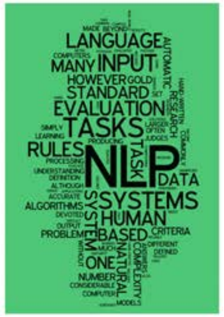
There is no such things as LowCode or NoCode - Or: How to turn your grandmother into a software developer

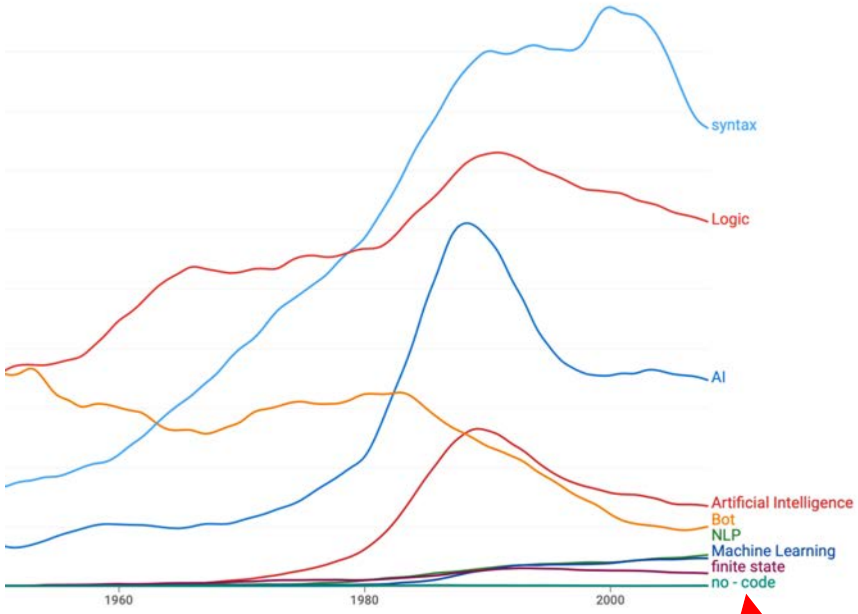
July 1, 2017 | Written by Markus Henschel | Leave a Comment

LowCode and NoCode are misleading terms, as neither of them are true or make sense. Wheather the code gets generated out of a visual model or a nocode model is being interpreted at runtime in a proprietary runtime engine – in the end there is always code – no matter how high the level of abstraction is – everything end up being instructions to a machine that get executed. With a number of layers on top that add their bits until there is assembler and 0s and 1s – everything else is fake news. If we manage to distance ourselves from those terms – as in fact they are not too different from each other – we can talk about what they really are: They talk about a creation process. What these terms describe is the process of the creation of an application or enterprise software but in the end there is always code and software which solves problems.

So if the space we really need to talk about is problem solving then what those technologies fundamentally have managed to address, is the skillset problem, which is the real problem to solve and the reason why humanity creates tools. Software tools are equally just tools for a specialised worker to use. Abstraction and simplifications widens the audience that has access to these tools and mass productions makes them affordable. If we are able to make the process of building applications even simpler, then we can enable more people – less skilled people – to produce what previously only experts were able to archieve. Experts are expensive though and my grandmother is bored. So how can we turn her into a software developer ?



With the rise of Artificial Intelligence and especially Natural Language Processing (NLP) into consumer electronics such as Alexa, Cortana and the likes, the next step of evolutions is just that. Talk to a machine. No ? Well, what Integrated Development Environments (IDEs) such as eclipse, android or visual studio and all their friends do, is to enable people experienced in those tools and with software development to build and release applications. They are assistive technologies that have improved the efficiency of software development, but they are fundamentally on the same evolutionary ladder as notepad… just better. Low/No Code Platforms/IDEs sit a little bit higher on that ladder, but the fundamental difference is that they are a next generation tool. The problem – whilst partially lowering the skillset entry level into software development is that it's still too complicated for most people – but hey, it's a starting point. Evolution took for ever to get us where



What is no-code AI and why should you care?

By Anshul Pandey December 18, 2020

The rise of no-code has enabled businesses to re-evaluate their technical processes and needs

https://www.techradar.com/news/what-is-no-code-ai-and-why-should-you-care

https://www.jade-eli.com/2017/07/01/there-is-no-such-things-as-lowcode-or-nocode-or-how-to-turn-your-grandmother-into-a-software-developer/

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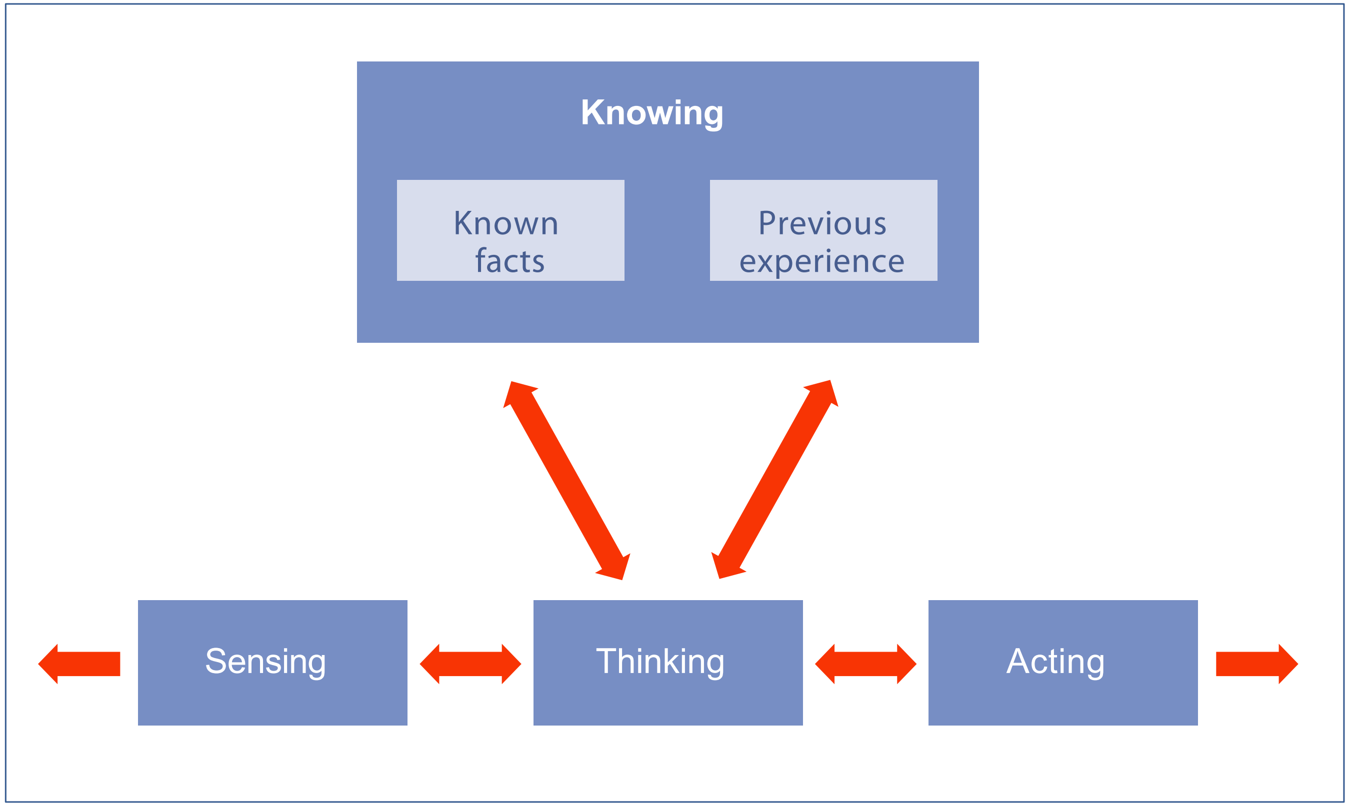


Figure 1: The model of mind

Informatieverwerking Fysieke Stimuli In Ons Brein

Sensation: [Sensibilisatie]

'…immediate and basic experiences generated as stimuli fall on our sensory systems'

➔ *Verwerken van ruwe data (prikkels of Fysieke stimuli) volgens een vast patroon*

Perception: [Perceptie]

'…interpretation of those sensations, giving them meaning and organization'

➔ *Gestuurd door "ingebouwde" informatie (niet lerend),*

Cognition: [Cognitie]

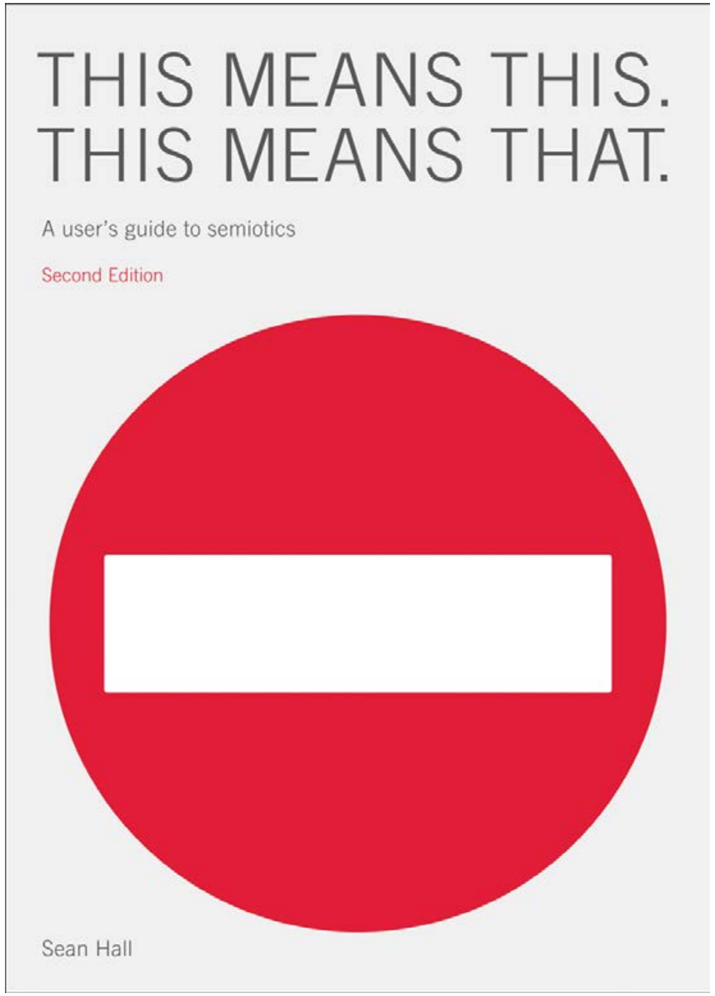
'…acquisition, storage, retrieval, and use of information'

➔ *Gestuurd door "verworven" informatie (zelf-lerend)*

M.W. Matlin & H.J. Foley, 1992

GEWAARWORDING & PERCEPTIE

"De menselijke maat"
wordt voor een groot deel bepaald door
selecteren, organiseren en interpreteren *van*
zintuigelijke prikkels


THIS MEANS THIS.
THIS MEANS THAT.
A user's guide to semiotics
Second Edition
Sean Hall

COGNITIE & SEMIOTHIEK

“De menselijke maat”
wordt voor een groot deel bepaald door
denken en waarnemen, dus gedragingen die
ofwel tot
kennisverwerving leiden of voor het gebruik van
kennis nodig zijn.


UNITED COLORS
OF BENETTON.

Intermenselijke communicatie

moet worden geïnterpreteerd als:
"de manier waarop mensen de wereld proberen te begrijpen door te streven naar emotionele verbondenheid"

Emotionele verbondenheid met de wereld wordt versterkt door fenomenen zoals:

- Beelden & Objecten
- Symbolen
- Concepten
- Modellen
- Gebaren
- Taal

representatie van de wereld

TURING-TEST versus CHINESE-ROOM

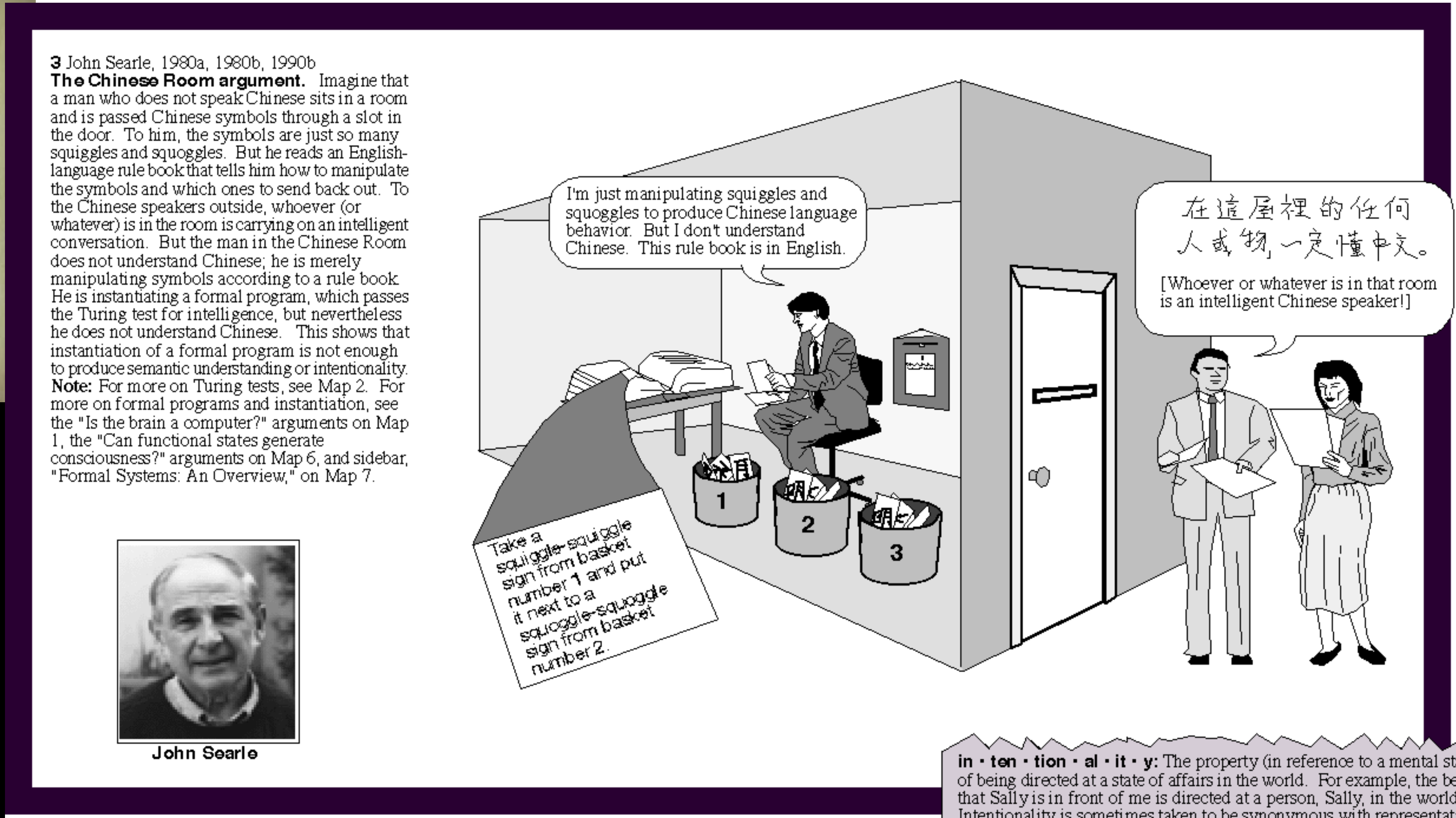
The Turing test is one of the simplest and perhaps best-known proposals for determining a computer's capability to display intelligence. It was proposed by the father of artificial intelligence, Alan Turing, in 1950.

In the Turing test, an impartial (human) judge converses with two parties: a human and a computer (or, in Turing's language, a "machine") that has been programmed to attempt to appear human. If the judge is not able to determine which party is human and which is the computer, then the computer is said to pass the Turing test.

Note that it is not actually required that the computer mimic human speech, only that its responses be indistinguishable from those a human might make. For this reason, the communication is commonly restricted to take place via teletype, instant messaging, etc.

Searle's CHINESE ROOM ARGUMENT

https://www.youtube.com/watch?v=TryOC83PH1g



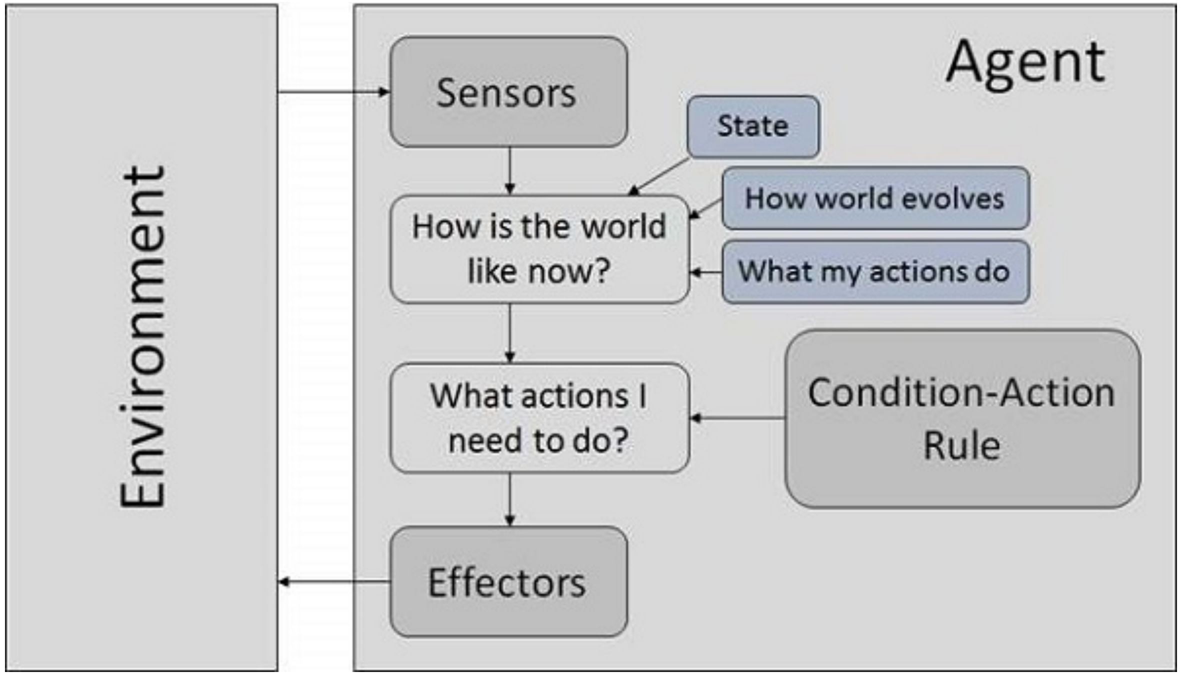
3 John Searle, 1980a, 1980b, 1990b
The Chinese Room argument. Imagine that a man who does not speak Chinese sits in a room and is passed Chinese symbols through a slot in the door. To him, the symbols are just so many squiggles and squoggles. But he reads an English-language rule book that tells him how to manipulate the symbols and which ones to send back out. To the Chinese speakers outside, whoever (or whatever) is in the room is carrying on an intelligent conversation. But the man in the Chinese Room does not understand Chinese; he is merely manipulating symbols according to a rule book. He is instantiating a formal program, which passes the Turing test for intelligence, but nevertheless he does not understand Chinese. This shows that instantiation of a formal program is not enough to produce semantic understanding or intentionality.
Note: For more on Turing tests, see Map 2. For more on formal programs and instantiation, see the "Is the brain a computer?" arguments on Map 1, the "Can functional states generate consciousness?" arguments on Map 6, and sidebar, "Formal Systems: An Overview," on Map 7.

John Searle

in · ten · tion · al · it · y: The property (in reference to a mental state) of being directed at a state of affairs in the world. For example, the belief that Sally is in front of me is directed at a person, Sally, in the world. Intentionality is sometimes taken to be synonymous with representation, understanding, consciousness, meaning, and semantics. Although there are important and subtle distinctions in the definitions of "intentionality," "understanding," "semantics," and "meaning," in this debate they are sometimes used synonymously.

http://www.cogsci.rpi.edu/~heuveb/Teaching/CogSci/Web/Presentations/ChineseRoom.pdf

Goal based Robotic Agents need AI (human cognition)



Stanford Encyclopedia of Philosophy

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QUIZ omg

Buzz • Posted on Feb 12, 2021

Create Your Perfect Boyfriend (or Girlfriend) Using AI Technology

Take this quiz and imagine a better future with no dating apps.

by BuzzFeed Labs
BuzzFeed Staff

View 657 comments

Sick of dating annoying, needy humans? Wish you could just design your perfect lover already? Now you can, with BuzzFeed Labs' extremely scientific BF-GAN-69 Artificial Intelligence. Just answer a few simple questions, and we'll help you generate the partner of your dreams.

https://www.buzzfeed.com/buzzfeedlabs/create-your-perfect-ai-soulmate

We guarantee your new AI partner Patricia is way less annoying than dating an actual human!

BuzzFeed AI-Generated Lover

Retake

Patricia X.

59 • Libra • Originally from Kinshasa, Dem. Rep. of Congo

How are you?

I'm a big Herbalife ambassador and I can't live without coffee roasting

I have 7 million dollars in liquid assets

I've always wanted to rescue dogs with someone ;)

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Full-body High-resolution Anime Generation with Progressive Structure-conditional Generative Adversarial Networks

Koichi Hamada, Kentaro Tachibana, Tianqi Li, Hiroto Honda, and Yusuke Uchida
DeNA Co., Ltd., Tokyo, Japan

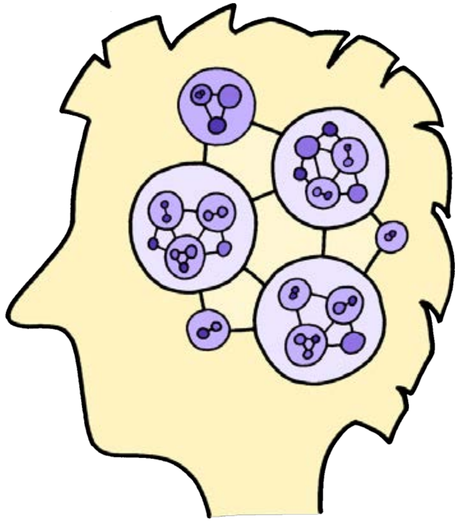
[Paper][ArXiv][Generated Anime 1][Generated Anime 2]

Artwork and paper have been accepted to
the ECCV Workshop on Computer Vision for Fashion, Art and Design, 2018.

- May 11, 2018: Project page launched.
- September 6, 2018: Submitted to arXiv.
- September 6, 2018: Generated animes updated to 1024x1024 res.
- September 14, 2018: Plan to present at the ECCV Workshop on Computer Vision for Fashion, Art and Design, 2018.

https://dena.com/intl/anime-generation/

Complexity Thinking
or Systems Thinking ++ ?



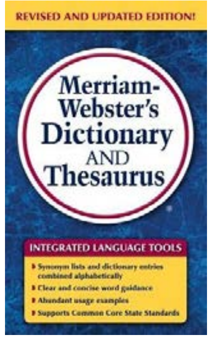
"The search for simple –if not simpleminded– solutions to complex problems is a consequence of the inability to deal effectively with complexity."

– Russell L. Ackoff

Model <> System

def·i·ni·tion
\ˌde-fə-ˈni-shən\

mod·el ***noun*** \ˈ*mä-dᵊl*\

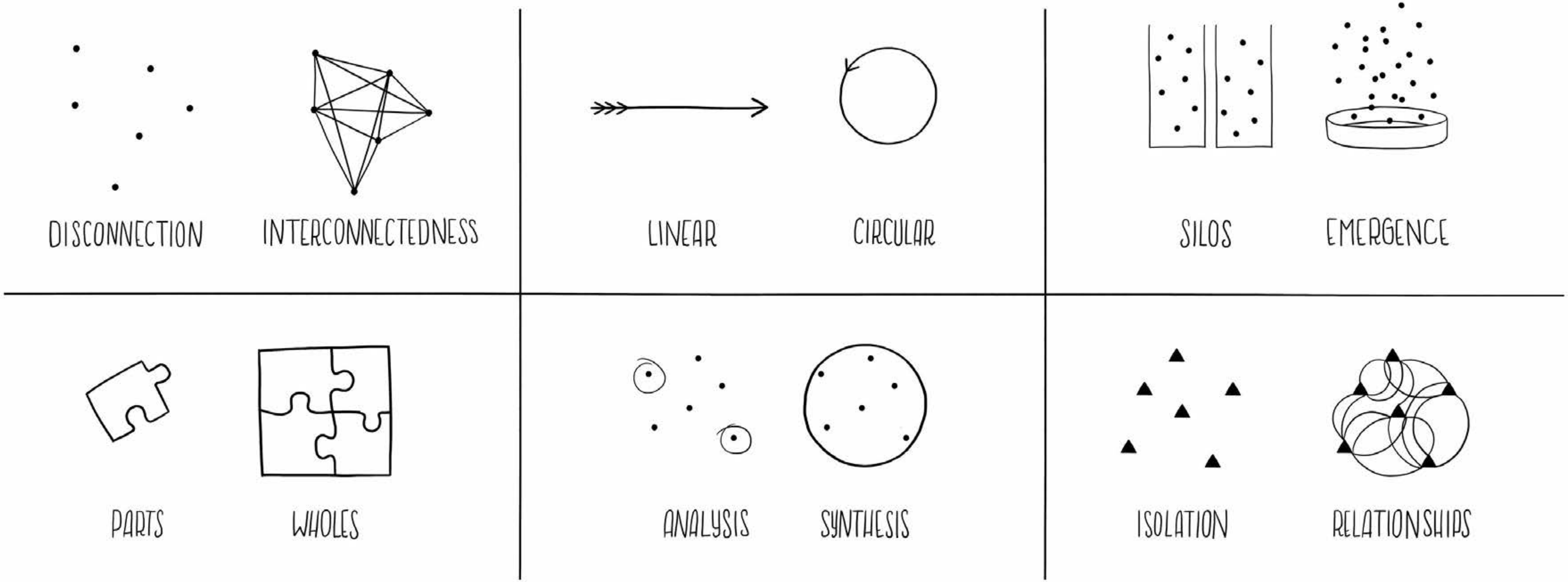


a usually miniature **representation of something**

a **description or analogy** used to help visualize something (as an atom) that cannot be directly observed

a system of postulates, data, and inferences presented as a mathematical **description of an entity** or state of affairs

TOOLS OF A SYSTEM THINKER



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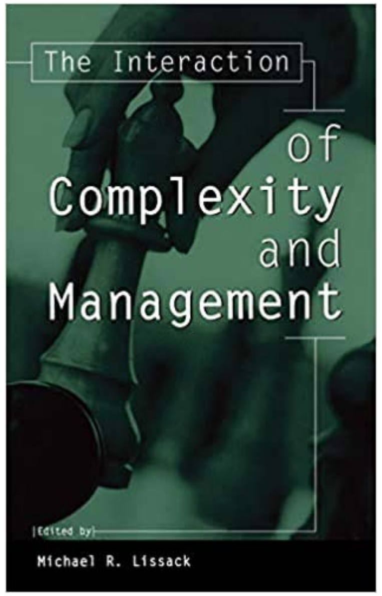
DISRUPT DESIGN

Models are often applied to:

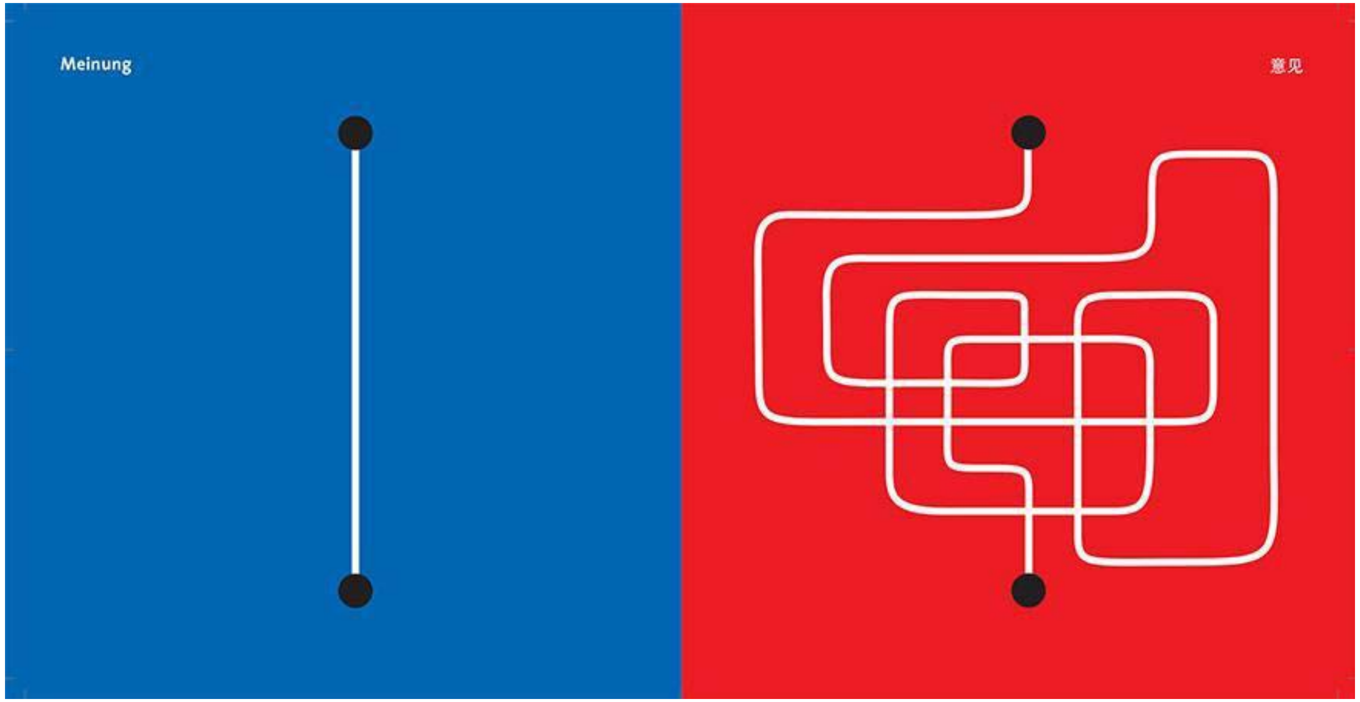
Confirme: prediction & control

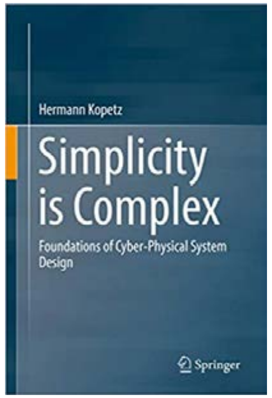
Explore: insight & understanding

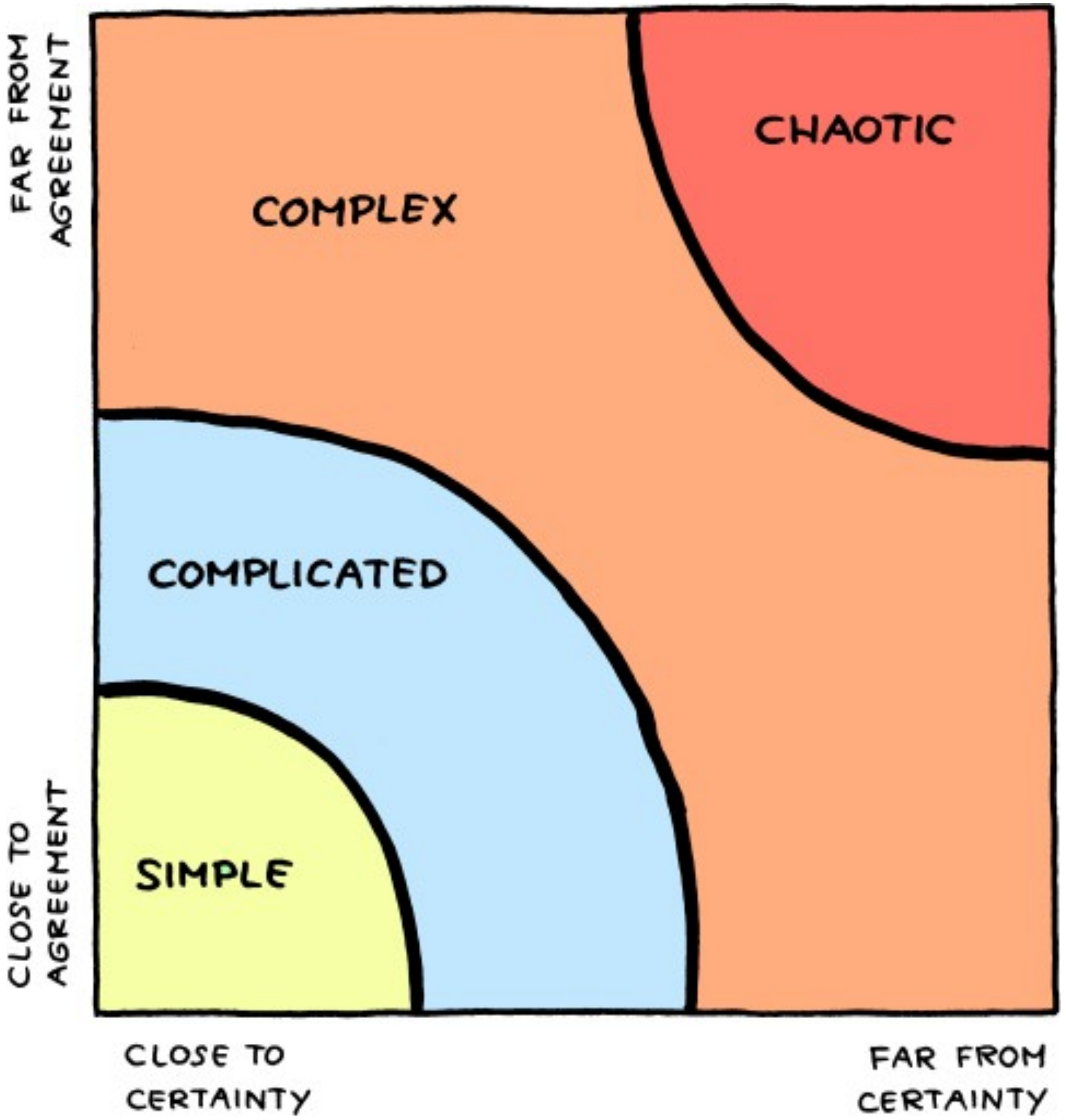
– Steve Phelan

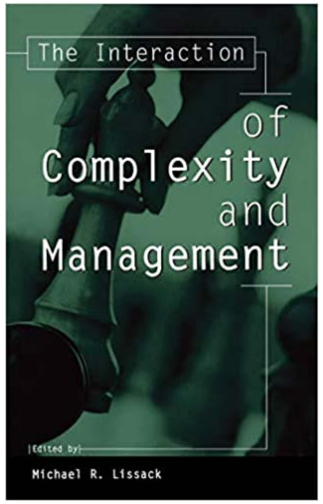


simple versus complex

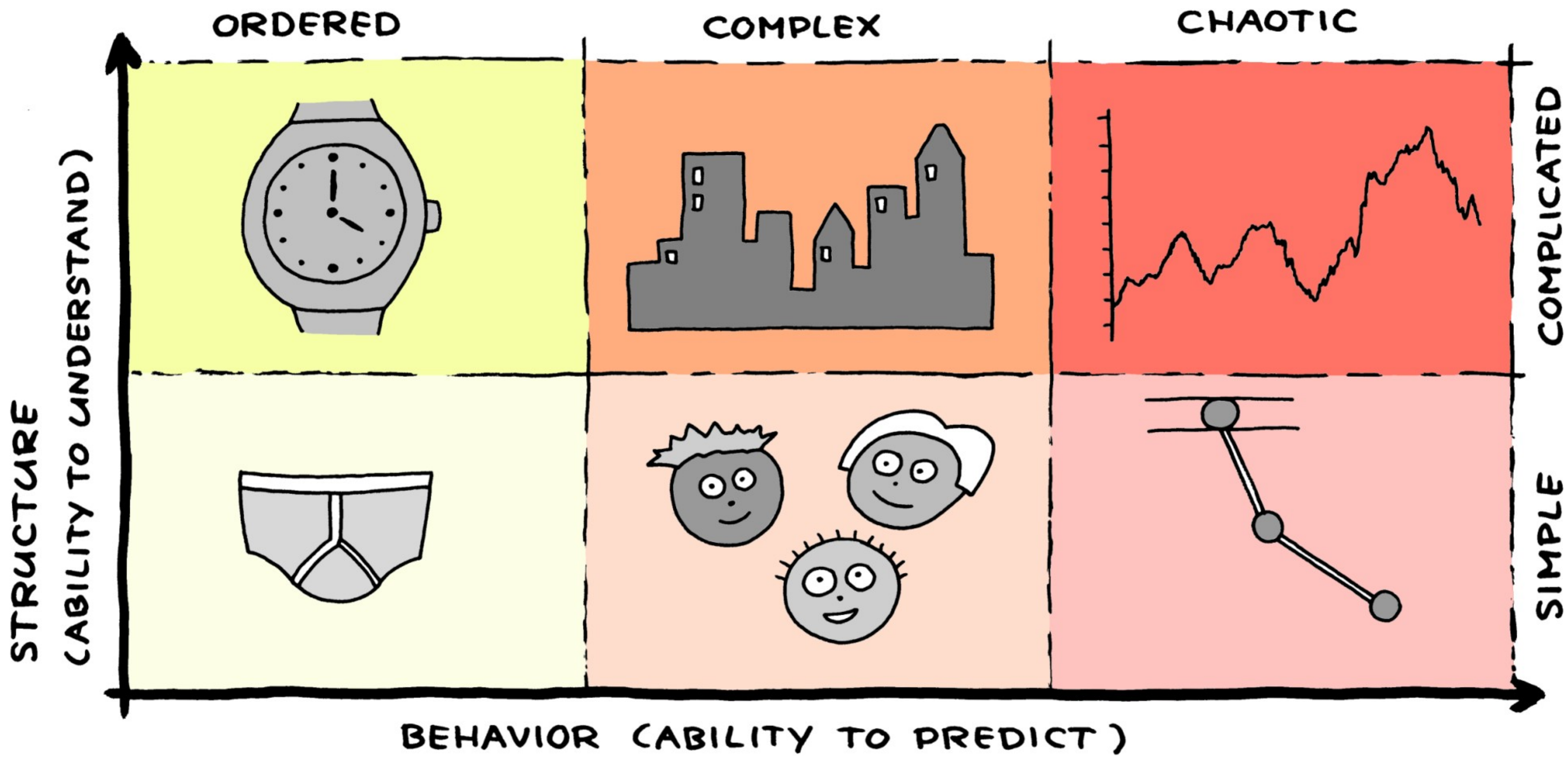








Ralph Stacey



You can try to **simplify** a system to make it **understandable**
But you cannot **linearize** the system to make it **predictable**

WHAT IS MACHINE LEARNING?

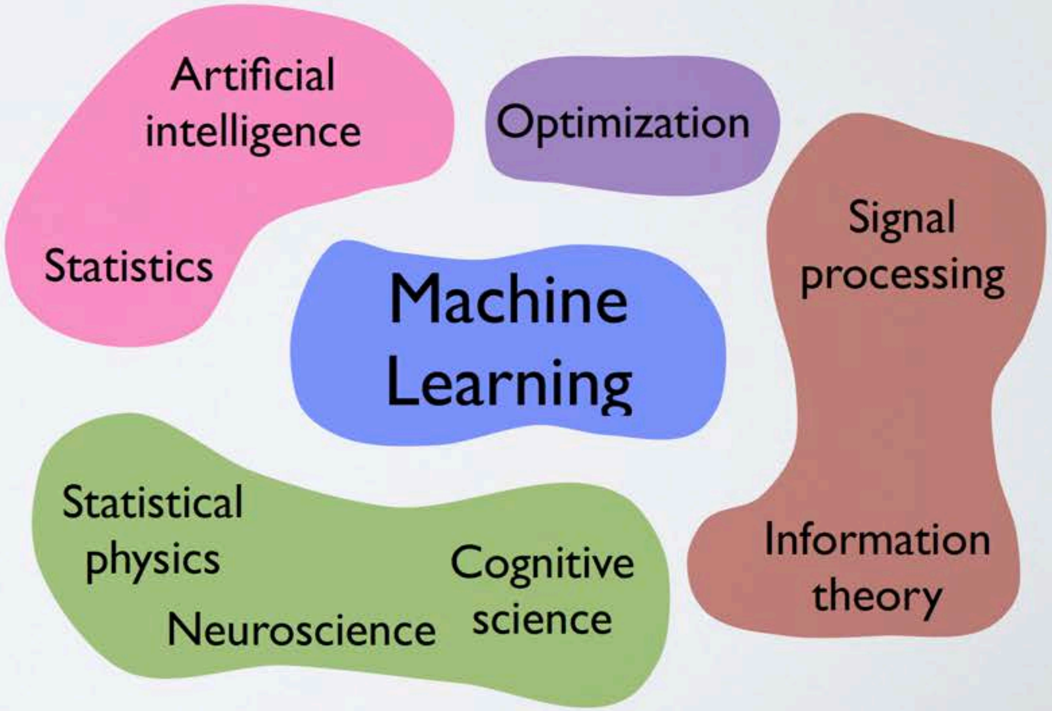
part of standard computer science curriculum since the 90s

inferring knowledge from data

generalizing to unseen data

usually no parametric model assumptions

emphasizing the computational challenges



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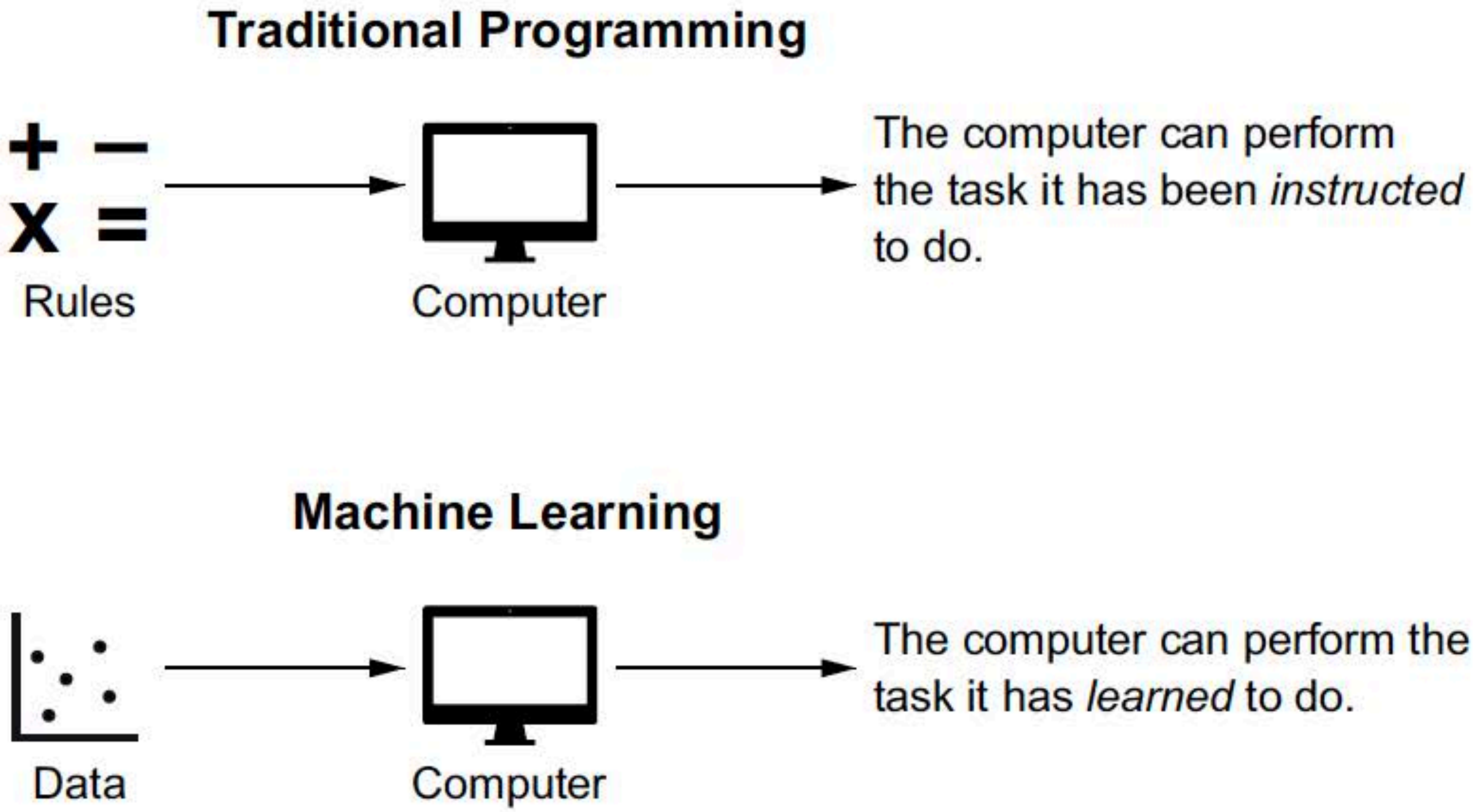
WHAT IS MACHINE LEARNING?

"The science of getting computers to act without being explicitly programmed" - Andrew Ng (Stanford/Coursera)


Traditional Programming
Rules
Computer
The computer can perform the task it has been *instructed* to do.
Machine Learning
Data
Computer
The computer can perform the task it has *learned* to do.

An Problem Solving Algorithm is a

step by step **process or recipe** that **describes how to solve a problem** and/or **complete a task**, which will **always give** the **correct result**

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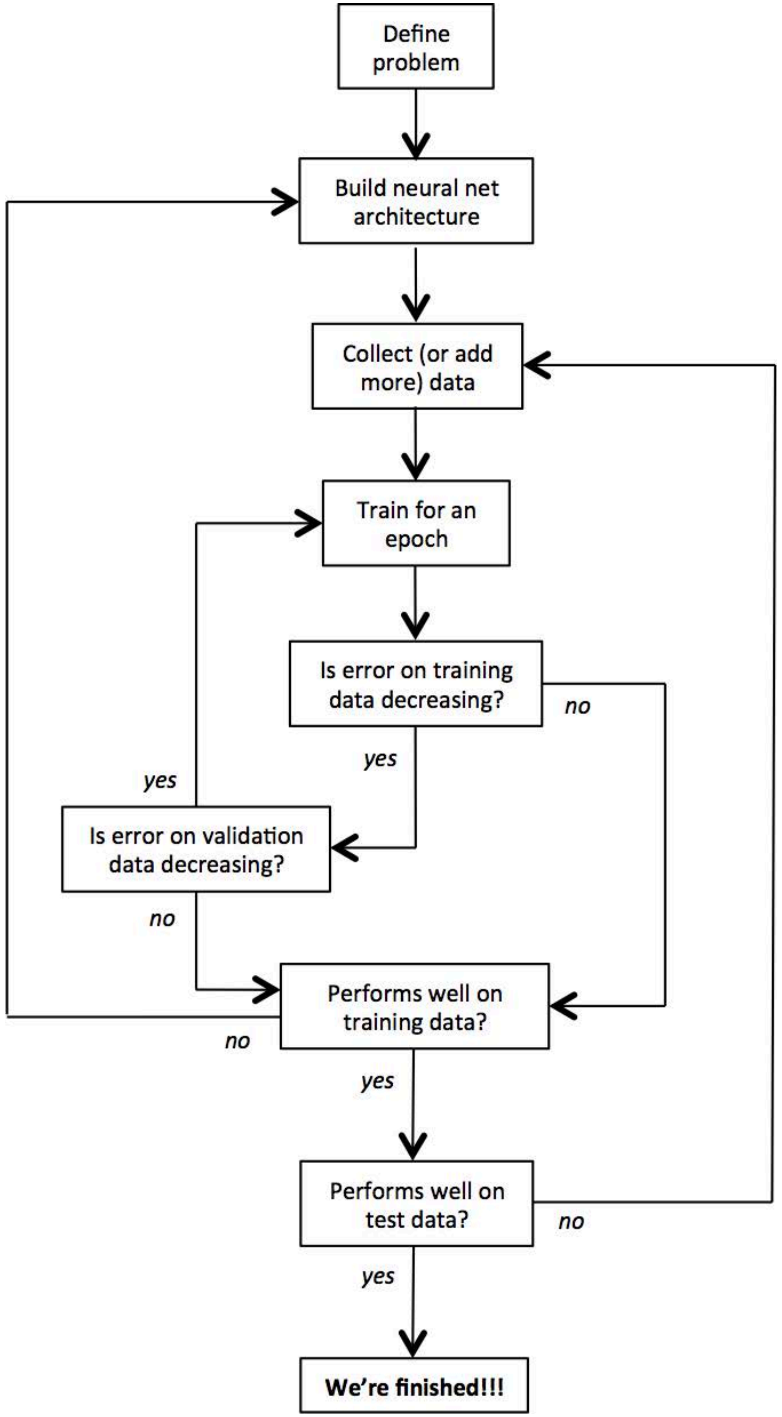
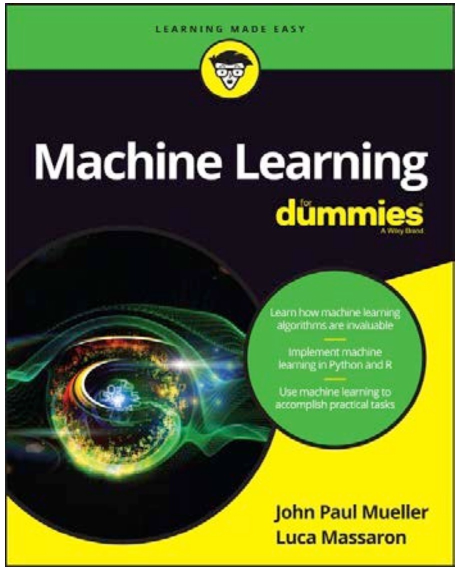
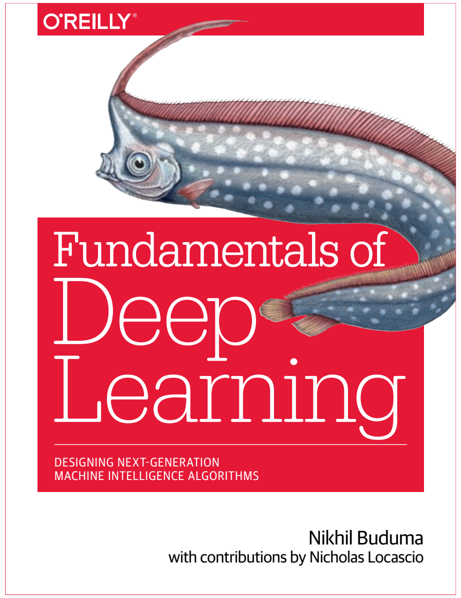
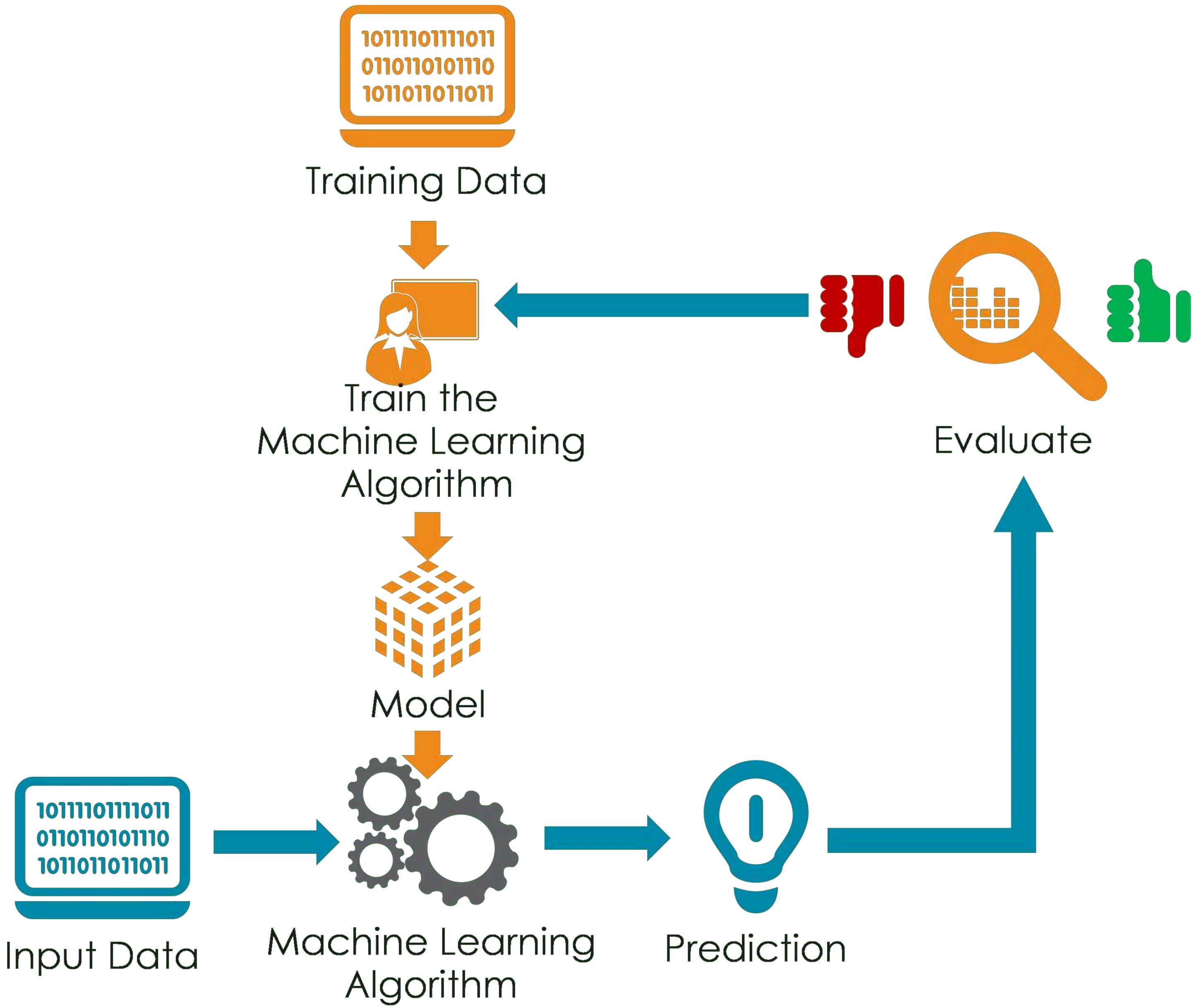
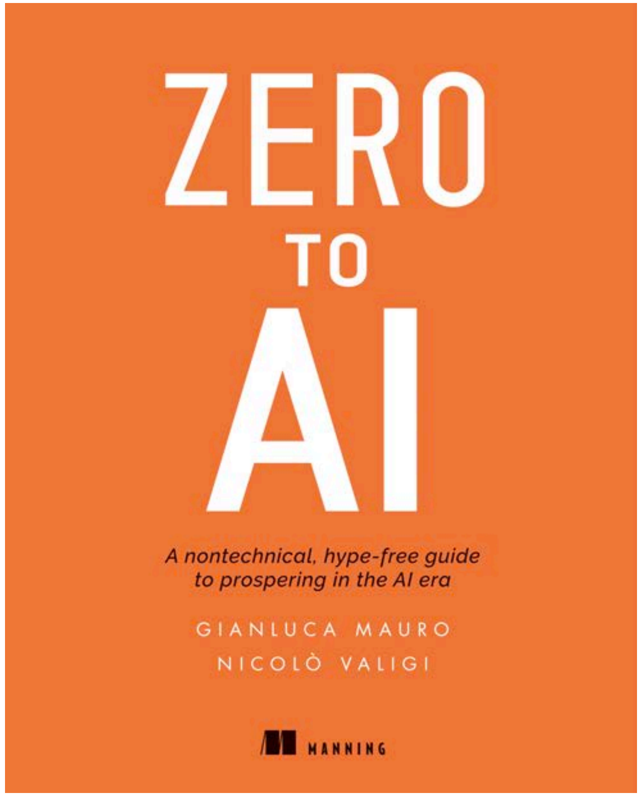

Define problem
Build neural net architecture
Collect (or add more) data
Train for an epoch
Is error on training data decreasing?
no
yes
yes
Is error on validation data decreasing?
no
Performs well on training data?
no
yes
Performs well on test data?
no
yes
We're finished!!!


LEARNING MADE EASY
Machine Learning
for dummies
A Wiley Brand
Learn how machine learning algorithms are invaluable
Implement machine learning in Python and R
Use machine learning to accomplish practical tasks
John Paul Mueller
Luca Massaron


O'REILLY
Fundamentals of
Deep
Learning
DESIGNING NEXT-GENERATION
MACHINE INTELLIGENCE ALGORITHMS
Nikhil Buduma
with contributions by Nicholas Locascio


1011110111011
0110110101110
1011011011011
Training Data
Train the
Machine Learning
Algorithm
Evaluate
Model
1011110111011
0110110101110
1011011011011
Input Data
Machine Learning
Algorithm
Prediction



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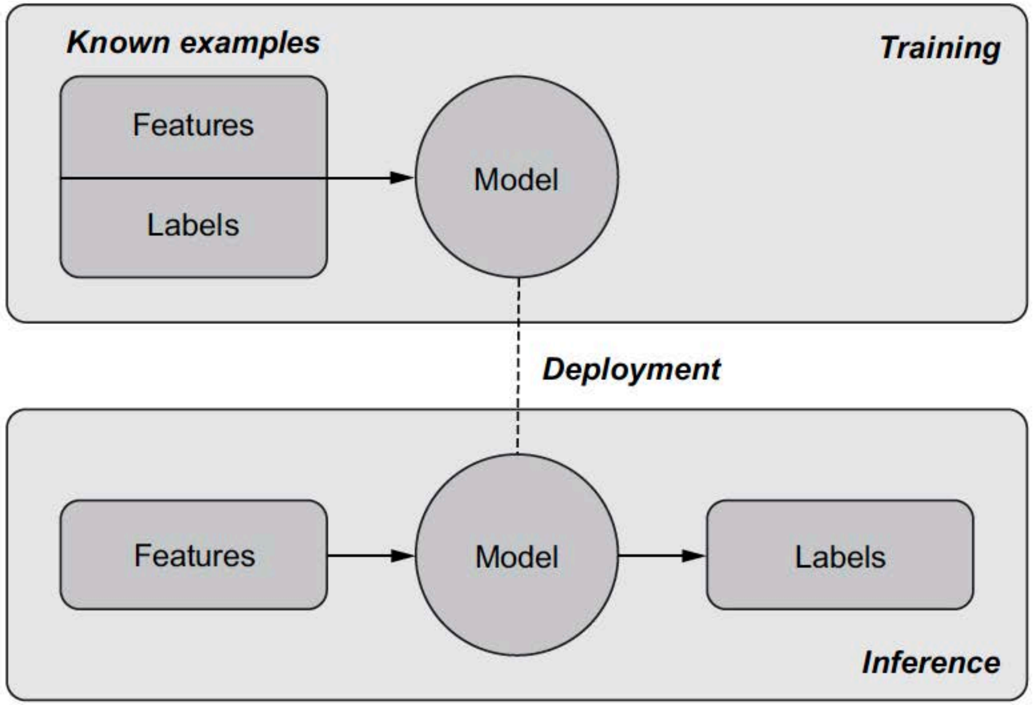


Figure 2.3 The two phases of machine learning: training and inference

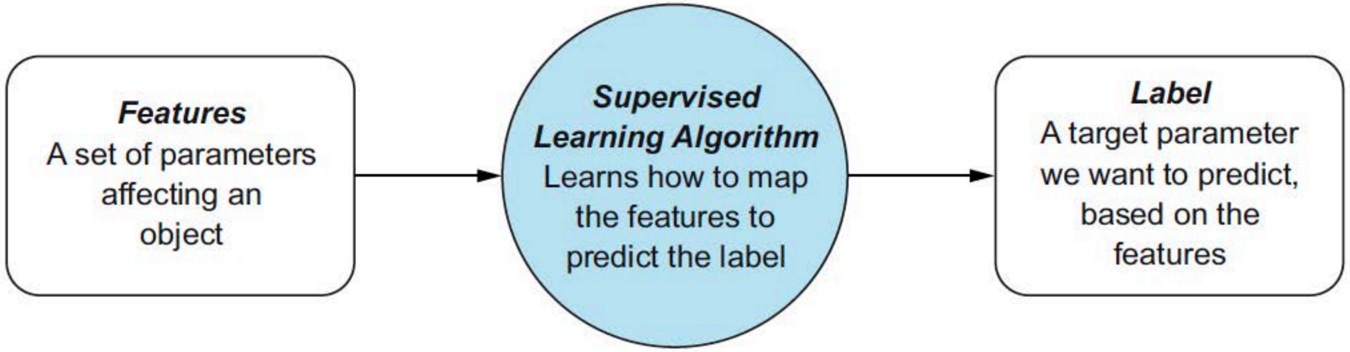
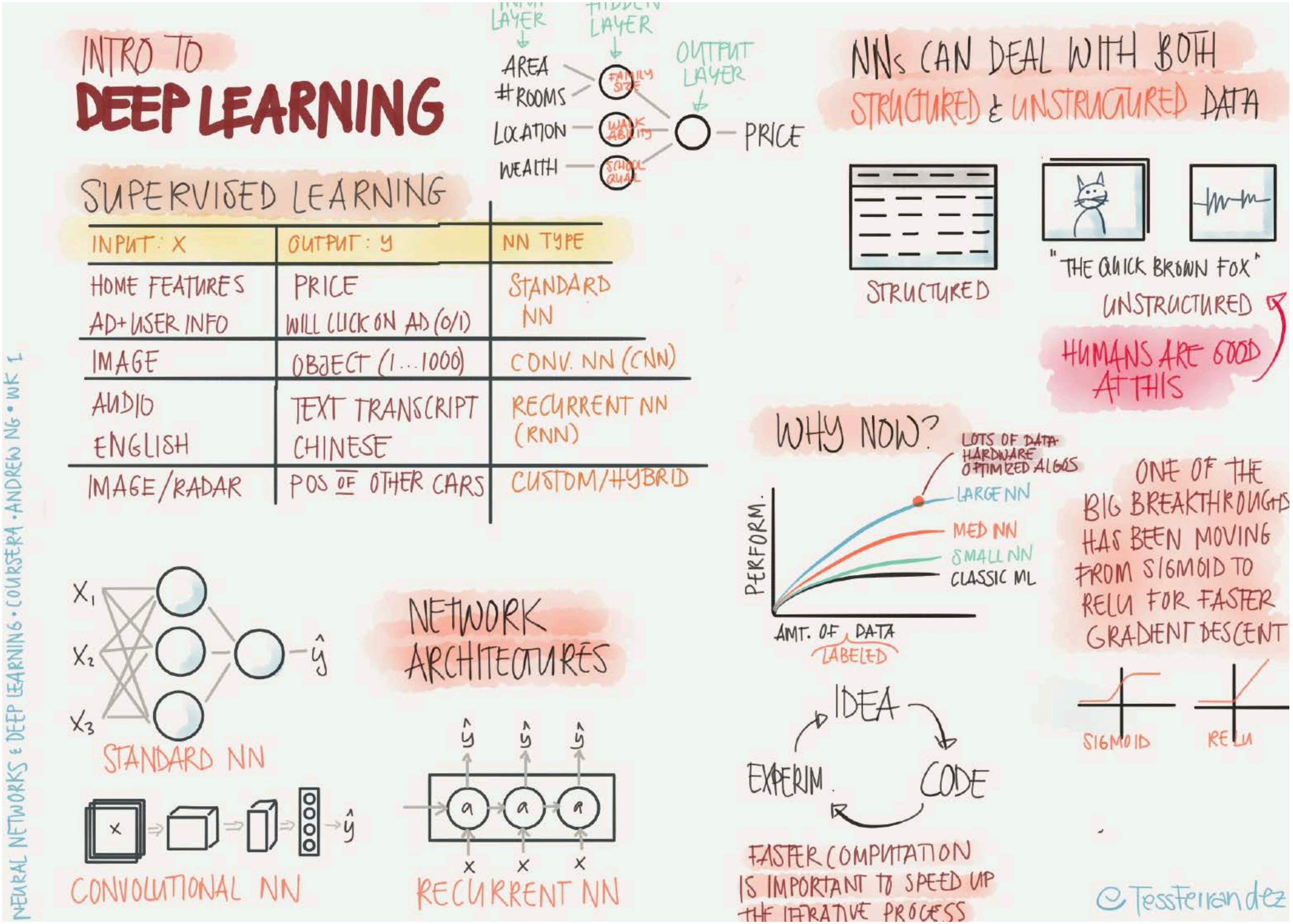


Figure 2.4 The core concept of supervised learning: finding a mapping between a set of features and a label



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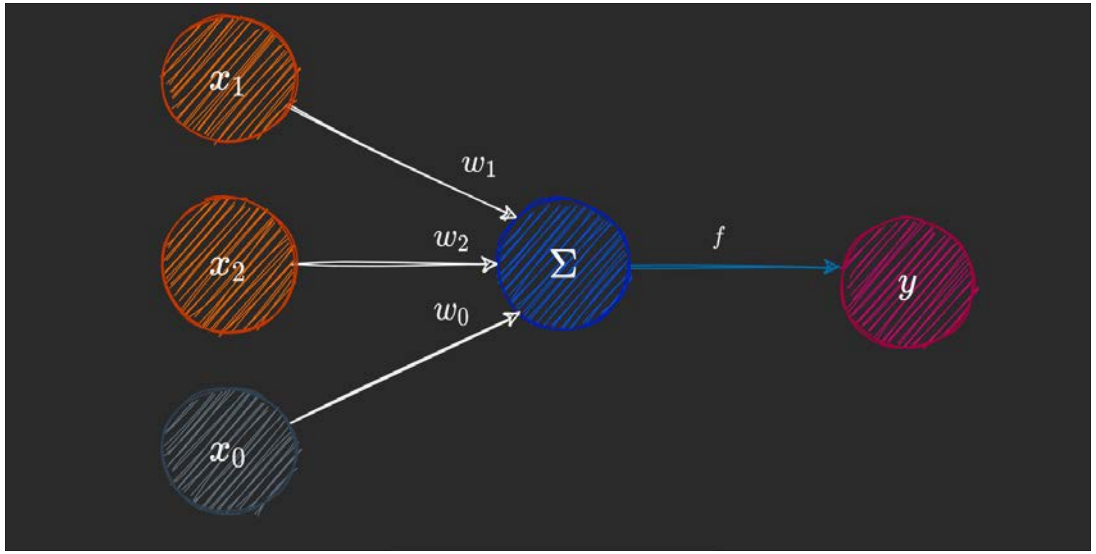
Artificial Neuron Model: PERCEPTRON structure

Perceptron Components :

- Input nodes   x0 … Xn
- Output node y
- An activation function
- Weights and biases
- Summation
- Activation Function f



Artificial Neuron Model:
PERCEPTRON maths

FEED FORWARD
CACULATION:

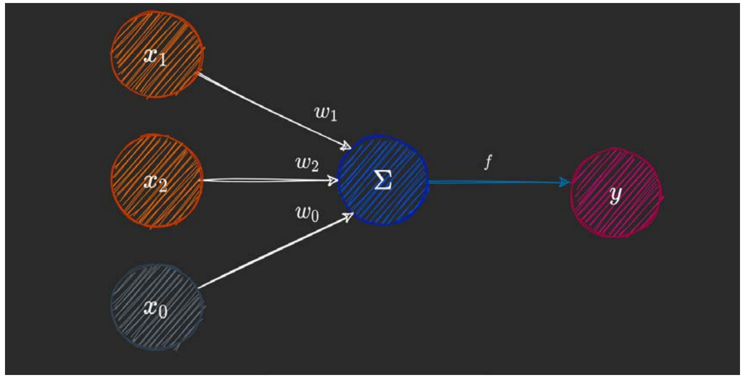
The output calculation is straightforward.

Compute the
DOT PRODUCT
of the input
[x1 x2]
and weight vector
[w1 w2]

The bias b equals w0

Apply the activation function.

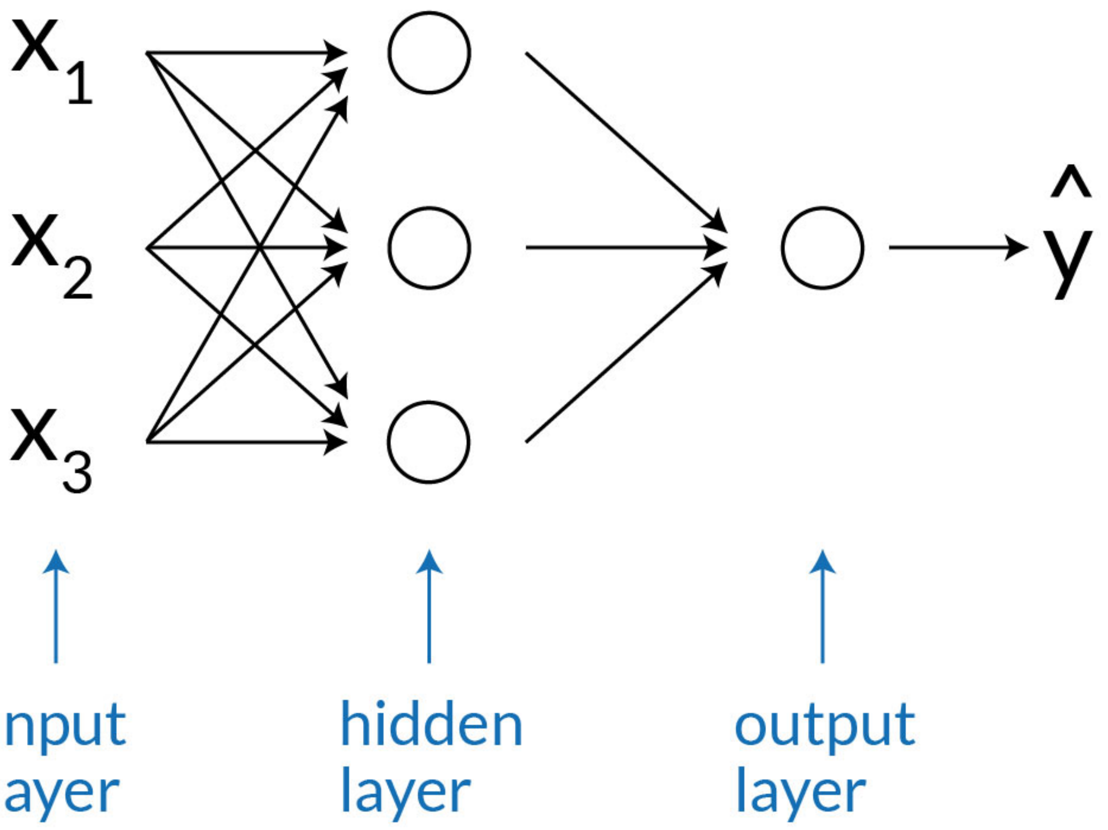
$$y = f(w \cdot X + b)$$



Feedforward computation:
(DOT PRODUCT is a form of mathematical summation)

$$y = f(x_1 \cdot w_1 + x_2 \cdot w_2 + b)$$

Code Python Perceptron class object
for XOR PROBLEM requires hidden layer



Example Python Code
Perceptron class object for XOR PROBLEM

```
import numpy as np
#np.random.seed(0)

def sigmoid (x):
    return 1/(1 + np.exp(-x))

def sigmoid_derivative(x):
    return x * (1 - x)

#Input datasets
inputs = np.array([[0,0],[0,1],[1,0],[1,1]])
expected_output = np.array([[0],[1],[1],[0]])

epochs = 10000
lr = 0.1
inputLayerNeurons, hiddenLayerNeurons, outputLayerNeurons = 2,2,1

#Random weights and bias initialization
hidden_weights = np.random.uniform(size=(inputLayerNeurons,hiddenLayerNeurons))
hidden_bias =np.random.uniform(size=(1,hiddenLayerNeurons))
output_weights = np.random.uniform(size=(hiddenLayerNeurons,outputLayerNeurons))
output_bias = np.random.uniform(size=(1,outputLayerNeurons))

print("Initial hidden weights: ",end='')
print(*hidden_weights)
print("Initial hidden biases: ",end='')
print(*hidden_bias)
print("Initial output weights: ",end='')
print(*output_weights)
print("Initial output biases: ",end='')
print(*output_bias)
```

```
#Training algorithm
for _ in range(epochs):
    #Forward Propagation
    hidden_layer_activation = np.dot(inputs,hidden_weights)
    hidden_layer_activation += hidden_bias
    hidden_layer_output = sigmoid(hidden_layer_activation)

    output_layer_activation = np.dot(hidden_layer_output,output_weights)
    output_layer_activation += output_bias
    predicted_output = sigmoid(output_layer_activation)

    #Backpropagation
    error = expected_output - predicted_output
    d_predicted_output = error * sigmoid_derivative(predicted_output)

    error_hidden_layer = d_predicted_output.dot(output_weights.T)
    d_hidden_layer = error_hidden_layer * sigmoid_derivative(hidden_layer_output)

    #Updating Weights and Biases
    output_weights += hidden_layer_output.T.dot(d_predicted_output) * lr
    output_bias += np.sum(d_predicted_output,axis=0,keepdims=True) * lr
    hidden_weights += inputs.T.dot(d_hidden_layer) * lr
    hidden_bias += np.sum(d_hidden_layer,axis=0,keepdims=True) * lr

print("Final hidden weights: ",end='')
print(*hidden_weights)
print("Final hidden bias: ",end='')
print(*hidden_bias)
print("Final output weights: ",end='')
print(*output_weights)
print("Final output bias: ",end='')
print(*output_bias)

print("\nOutput from neural network after 10,000 epochs: ",end='')
print(*predicted_output)
```

{02}
Data Science

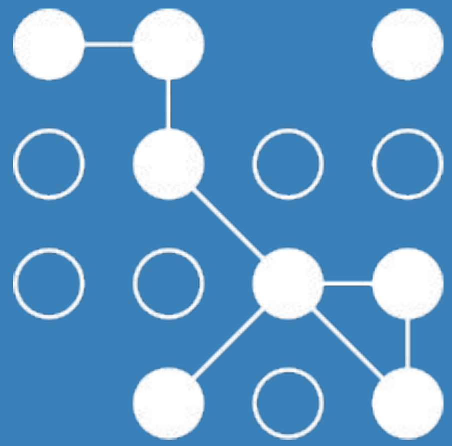
DATA SCIENCE

+

HUMAN
FACTORS

=

DATA PRODUCT



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DATA SCIENCE (ANALYTICS) VERSUS DATA ENGINEERING (PROBLEM SOLVING)

[0] Collection	Big Data (Acuisition/Aggregation) Empirical(Sensor/IoT Measuring/Sampling)	Gathering
[1] Access + Retrieval	Ownership (Open/Closed) Storage (Cloud/Database)	Ingesting
[2] Preparation + Wrangling (Munging)	Loading Feature Extraction/Reduction Normalization Transformation Conversion	Processing
[3] Exploration	Graphical (spatial) Ontological (Language) Semantic (text) Rule-based/Algorithmic Quantitative/Qualitative Numerical/Categorical/Symbolic	Discovering
[4] Analysis + Machine-Learning	Mining (Heuristics/Statistics/Descriptive/Prescriptive) Construct Useful Insights/Trends/Patterns/Diagnosis(Information)	Conceptualizing
[5] Abstraction	Parameter Selection + Representation Summarization Problem Solving Diagnostic Prediction Encription	Modelling
[6] Organization + Managing	Visualization Virtualization	Presenting
[7] Automation + Reporting	Performance (Measure/Monitor) Evaluation & Review Decision & Advise or Prescription (Interactive/Passive) Story Telling Prototyping	Applying

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DATA SCIENCE
focuses on **Analytics**

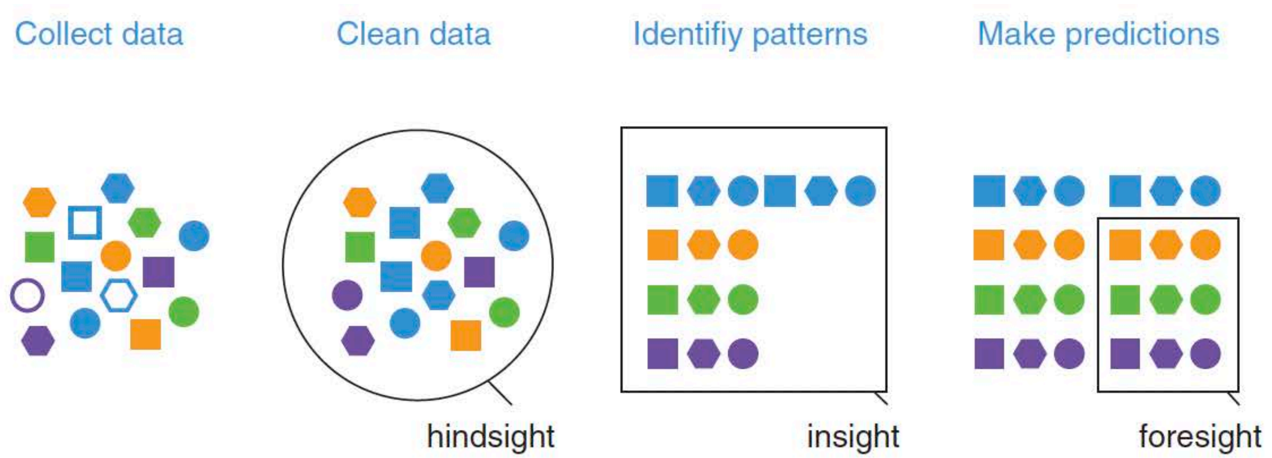
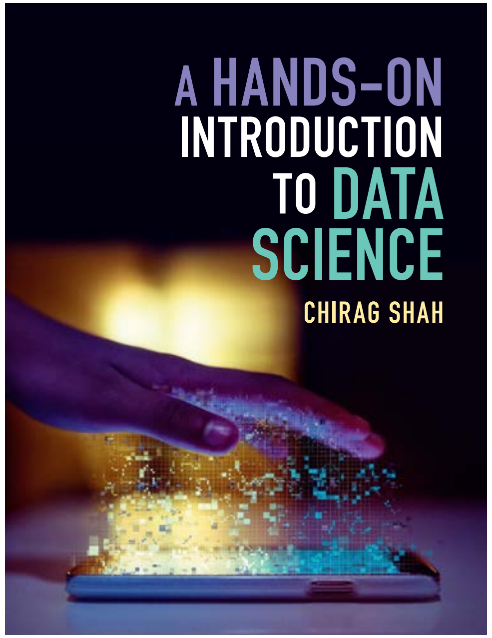


Figure 3.11 Process of predictive analytics.[7]

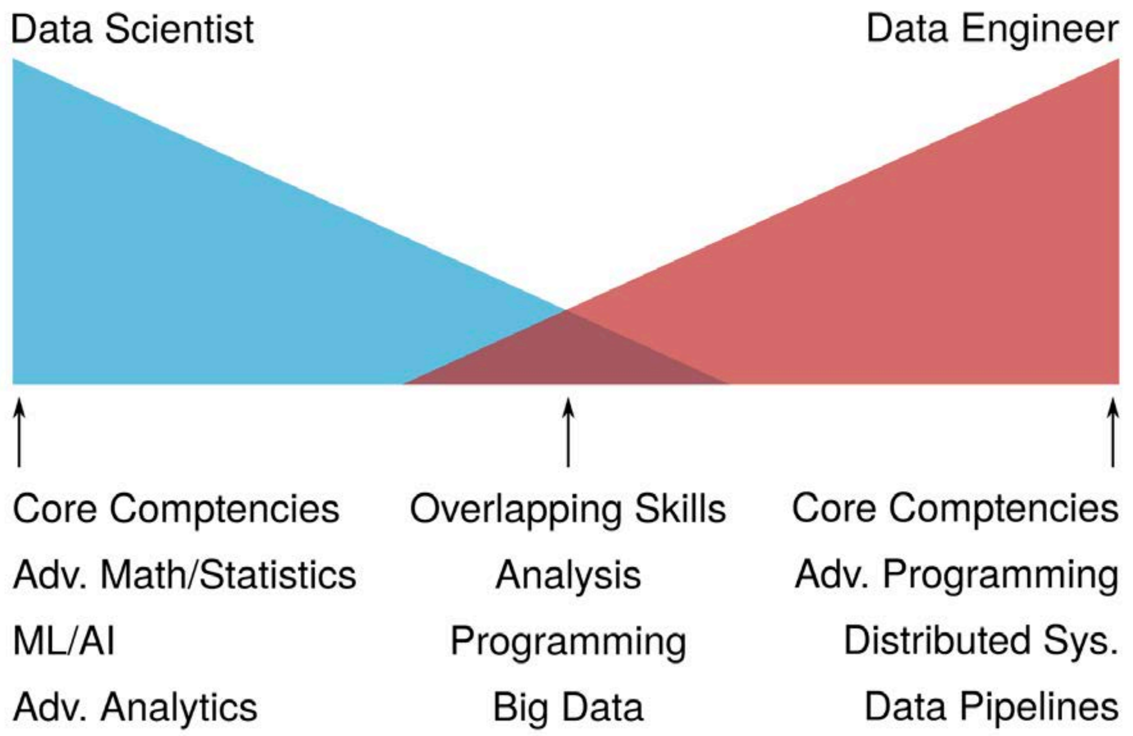


DATA ENGINEERING focuses on Problem Solving

Data engineers build and maintain data pipelines

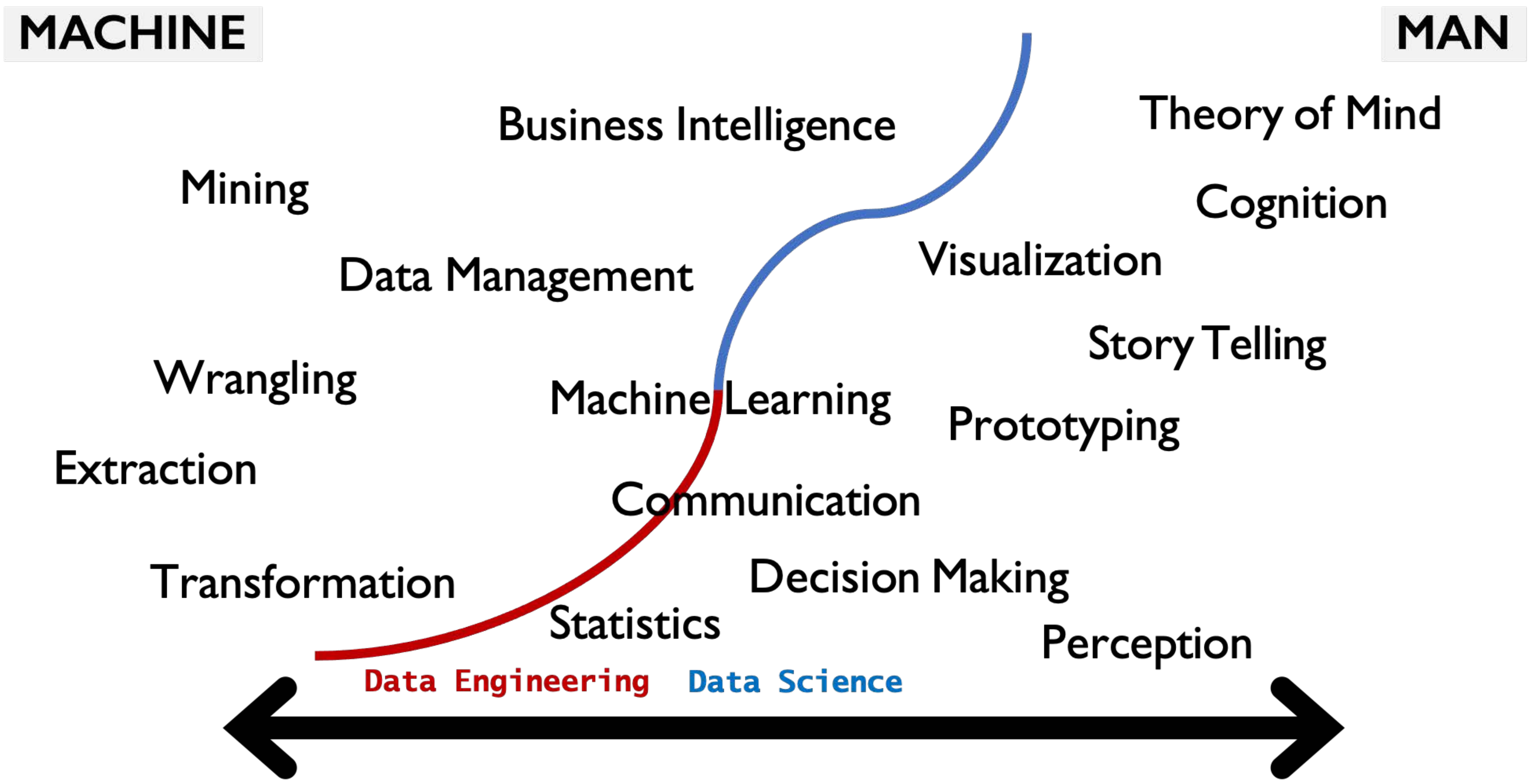
Data pipelines encompass the journey and processes that data undergoes within a company.

Data engineers are responsible for creating those pipelines.



{02}

Data Science



Inspired by Daniel Keim, "Visual Analytics: Definition, Process, and Challenges"

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To make sense of the world

“ Sense-making is the way that humans **choose between multiple possible explanations** of sensory input. ”

– Dave Snowden

https://doi.org/10.14236/JHI.V13I1.578

Informatics in Primary Care 2005;13:45–53

Conference papers

Multi-ontology sense making: a new simplicity in decision making

David J Snowden
Founder, Cynefin Centre for Organizational Complexity, UK

Imagine organising a birthday party for a group of young children. Would you agree a set of learning objectives with their parents in advance of the party? Would those objectives be aligned with the mission statement for education in the society to which you belong? Would you create a project plan for the party with clear milestones associated with empirical measures of achievement? Would you start the party with a motivational video so that the children did not waste time in play not aligned with the learning objectives? Would you use PowerPoint to demonstrate to the children that their pocket money is linked to achievement of the empirical measures at each milestone? Would you conduct an after-action review at the end of the party, update your best practice database and revise standard operating procedures for party management?

No! Instead, like most parents, you would create barriers to prevent certain types of behaviour, you would use attractors (party games, a football, a videotape) to encourage the formation of beneficial largely self-organising identities; you would disrupt negative patterns early, to prevent the party becoming chaotic, or necessitating the draconian imposition of authority. At the end of the party you would know whether it had been a success, but you could not have defined (in other than the most general terms) what that success would look like in advance.

From The Cynefin Manifesto, www.cynefin.net

Introduction

The purpose of this article is to introduce a new simplicity into acts of decision making and intervention design in organisations. That may seem ironic given the title, with its use of the terms 'ontology' and 'sense making' which may be unfamiliar to readers; but new ideas often need new or at least unfamiliar language and I make no apology for that (although some readers may wish to skip the remainder of this introduction which may only be relevant to academics wishing to situate my language). New language aside, the basic principles that underlie this paper are very easy to understand and are illustrated by the inset example of the children's party. Multi-ontology sense making is about understanding when to use both methods of management outlined in the story, both the structured and ordered approach based on planned outcomes and the un-ordered, emergent approach focused on starting conditions expressed as barriers, attractors and identities.

Ontology[a] is derived from the Greek word for being, and it is the branch of metaphysics that concerns itself with the nature of things. In this article I am using it to identify different types of system defined by the relationship, if any, between cause and effect. I will later discuss two contrasting types of ontology (order and un-order), each of which requires a different approach to both diagnosis and intervention. In practice, we need to consider three physical and five human ontologies. The three physical ontologies are order, complexity and chaos; in human systems order divides into visible and hidden forms and we add a fifth state of disorder. These are more fully described elsewhere.[1] Here I will combine complex and chaotic into a single category of un-order and ignore disorder.

[a] Ontology is commonly misused in the IT profession as an elevated version of taxonomy and is in fact closer to onomastics than it is to ontology.

What do these people have in common?

Alphabet

amazon

PayPal

TESLA

{02}
Data Science

Big-Tech is build upon data [products]

Alphabet

amazon

PayPal

TESLA

FOURSQUARE

Data Product a definition:

Products fueled by data and machine learning can be a powerful way to solve users' needs.

Prime examples include:

- Google-search
- Amazon product recommendation
- Tesla?
- Facebook?

Data products types

Type I

Data as a Service

› Weather data

Type II

Data-enhanced Products

› Autonomous driving

Type III

Data as Insights

› Marketing planning

Data Product (top- down)taxonomy:

automated decision-making

decision support

algorithms-as-a-service

derived structured data

raw unstructured data

TYPES of DATA PRODUCTS

Sort items into predefined classes

Estimate a numeric value at a specific time

Predict the behaviour of a value in the future

Sort items into similar groups

Recommend items to users

Generate artificial text

Choose from alternative strategies, acting on feedback

Choose from alternative strategies, acting on existing data

Outlier detection

Estimate the probability of an event happening

Rank items to prioritize human action

https://queirozf.com/entries/11-types-of-data-products-with-examples#1-sort-items-into-predefined-classes

DATA: LEVELS OF MEASUREMENTS versus OBSERVATION SCALES

Meetniveaus [level] /Meetschalen [scale]:

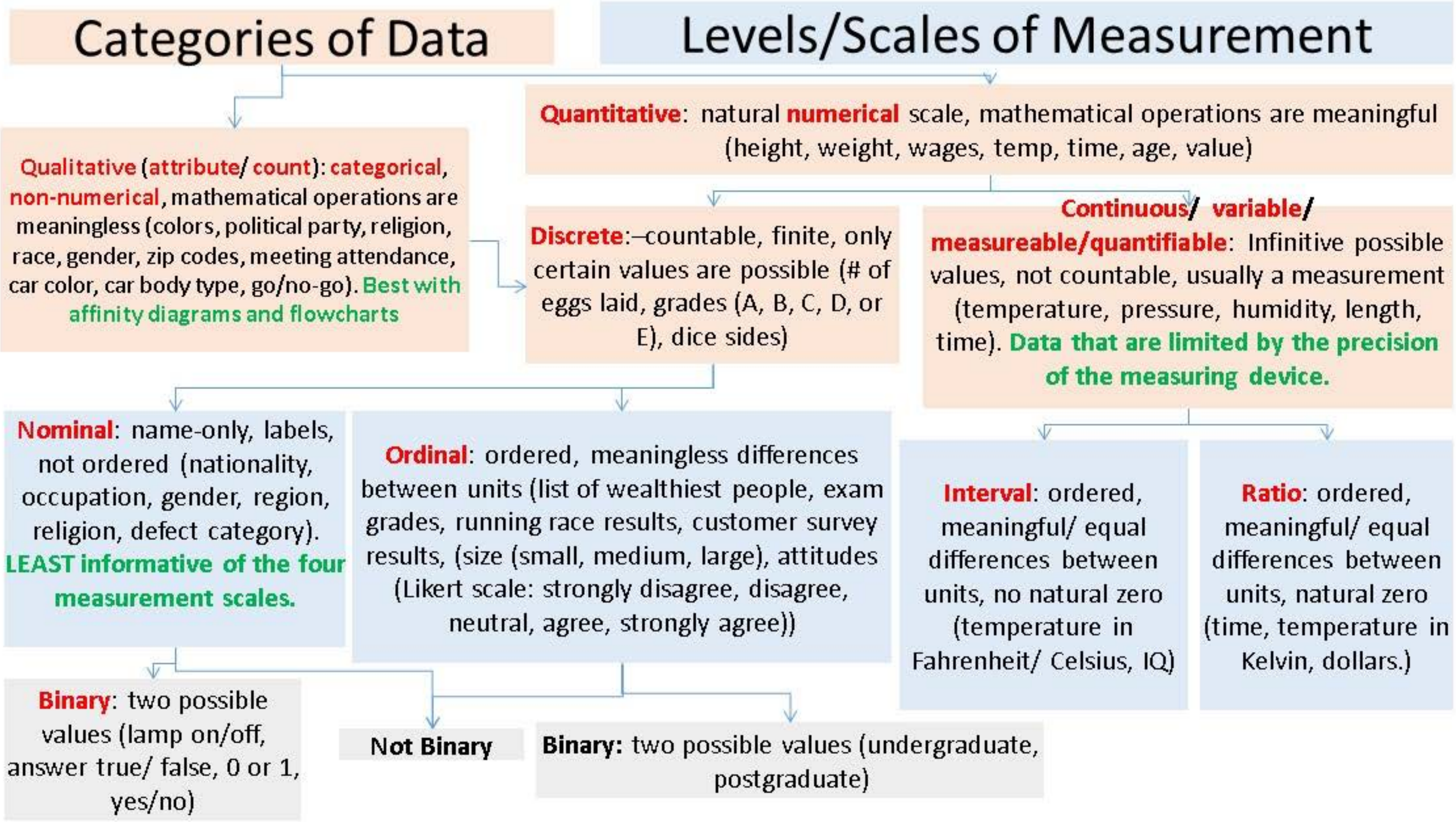
De hoogte van het meetniveau is bepalend voor:

Statische-analyse / Grafische weergave

Meetniveaus & hun kenmerken

		Scale	**Rationiveau**
		Intervalniveau	Verhouding blijven gelijk
	Ordinaal niveau	Gelijke verschillen	Gelijke verschillen
Nominale niveau	Ordening	Ordening	Ordening
Onderscheid	Onderscheid	Onderscheid	Onderscheid
Geslacht	*Opleidingsniveau*	*Intelligentie*	*Leeftijd*

Data Typen versus Meetschalen



A modern more holistic view of data {types}

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In "What are algorithms dreaming of ?"
Cardon proposes a framework based on four types of web measurements, each resting on a specified data type:

1st type of filter bubble: the one created by audience measurement

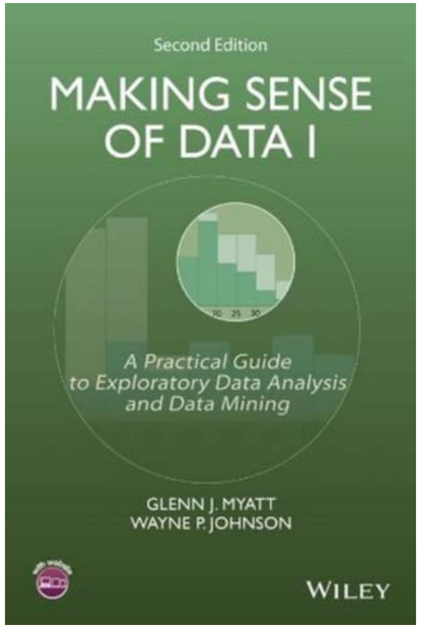
2nd type of filter bubble: the one created by hyperlinks

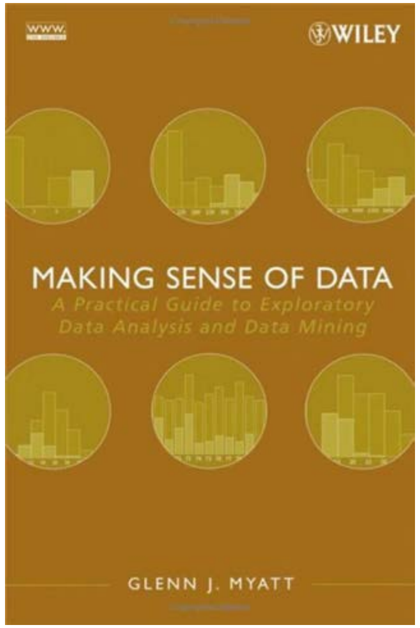
3rd type of filter bubble: the one created by social influencers

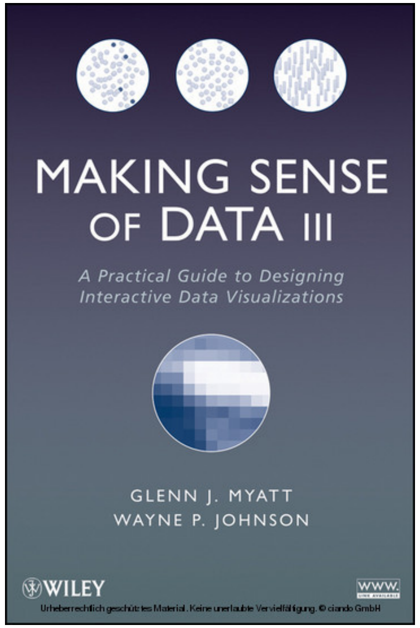
4th type of filter bubble: one created by our own behavior

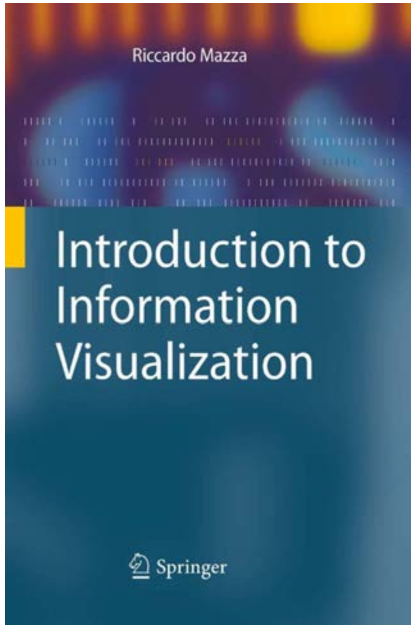
A modern more holistic view of data {types}

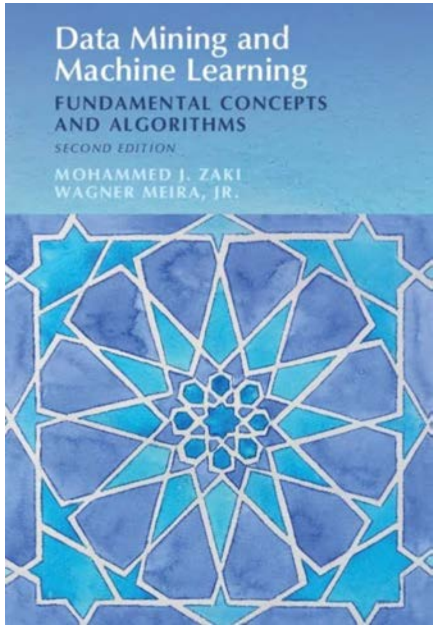
	On the side	Above	In	Below
Examples	Médiamétrie, Google Analytics, advertising	Google Page Rank, Digg, Wikipedia	Number of Facebook friends, Retweets on Twitter, ratings	Amazon Recommendation, Targeted advertising
Data	Views	Links	Likes	Tracks
Population	Representative sample	Selective vote, communities	Social network, affinities, declarative data	implicit feedback and behaviors
Type of computation	Vote	Meritocratic rankings	Benchmark	Machine Learning
Principle	Popularity	Authority	Reputation	Prediction

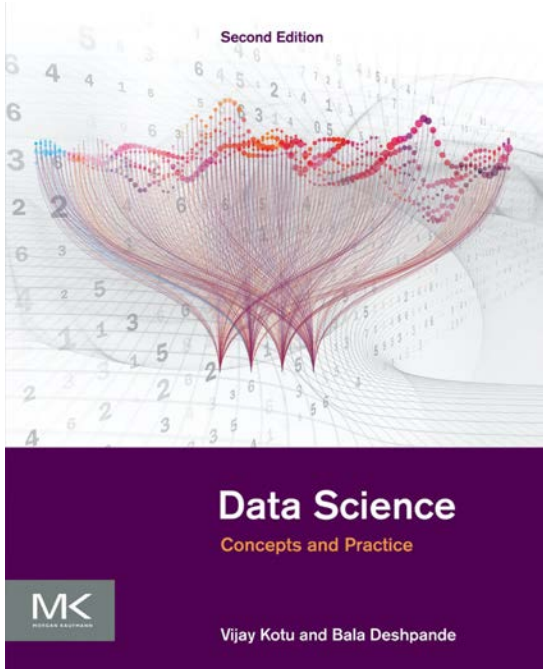


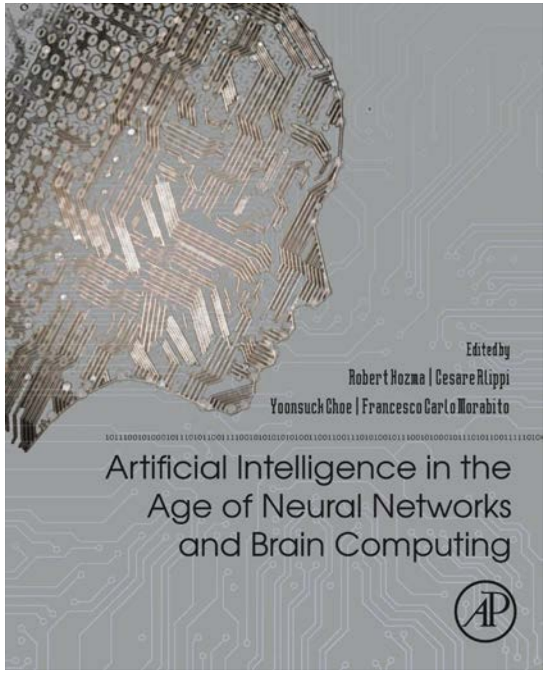


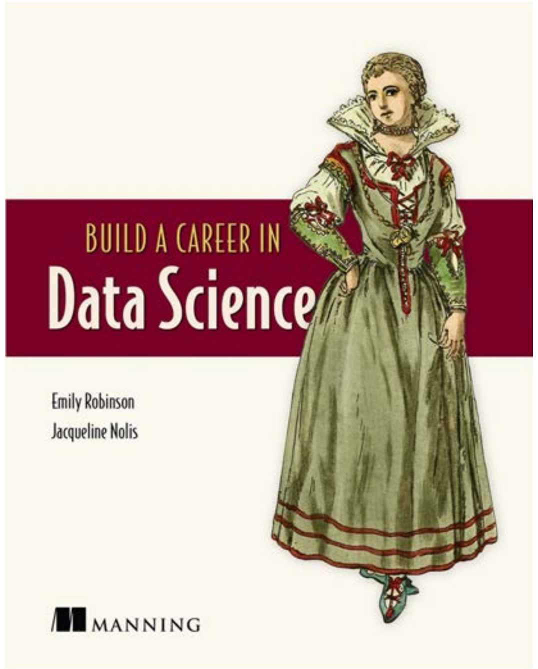


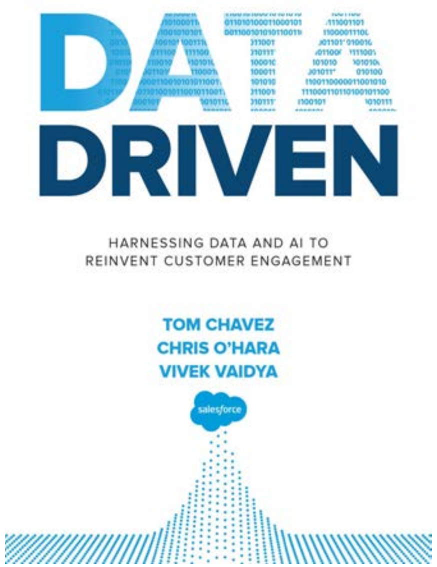












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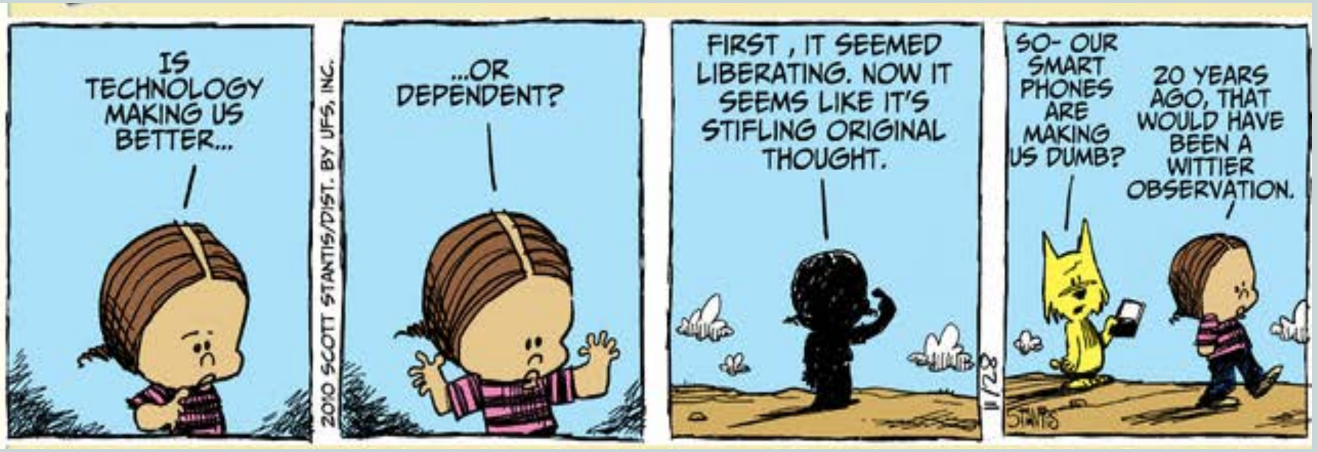

This lesson was developed by:

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OKT 2020

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