Essentials in Artificial Intelligence

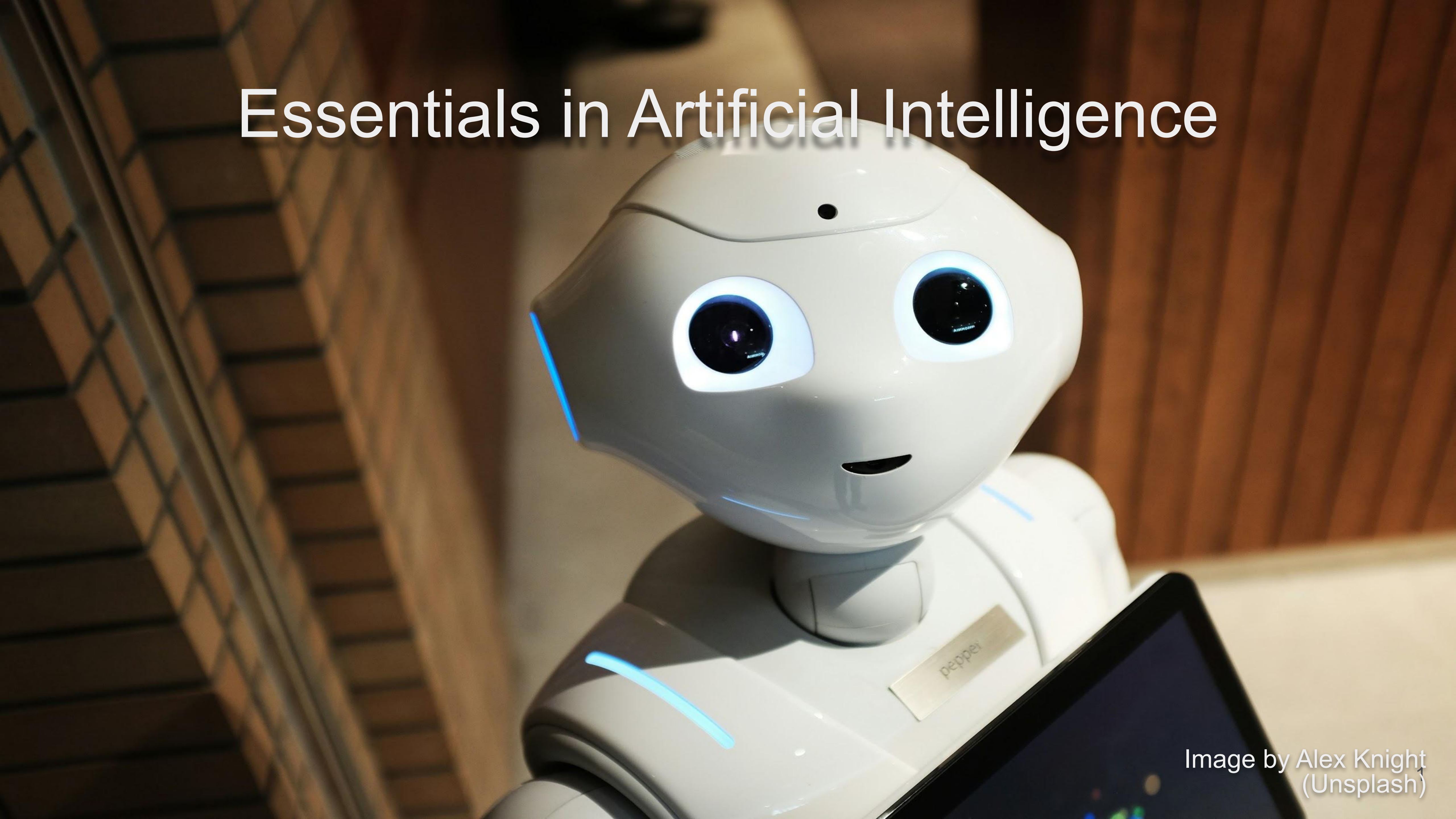

Image by Alex Knight
(Unsplash)

Course Introduction and Outline

Today's Plan

- Duration 09:00-17:00
- Morning coffee break & afternoon coffee break
- Slides will include reference material and practical exercises
- Discussion/questions are welcome!

Image by RosZie (Pixabay)

Nice to meet you!

- Teacher name
- Current role
- Relevant experience
- Anything else you want to share about yourself?
- My objectives:
    -

Image by RosZie (Pixabay)

Nice to meet you!

- Selina/Lina Blijleven
- Education Manager & Teacher
- M.Sc. Artificial Intelligence from University of Amsterdam
- Additional courses in Information Sciences (Data Science Track)
- My objectives:
  - Introducing you to the wonderful world of AI
  - Inspiring you!
  - … but also inform you of the pitfalls

Image by RosZie (Pixabay)

Nice to meet you!

- Tessel Haagen
- IT Teacher and AI engineer
- M.Sc. Artificial Intelligence from Utrecht University
- My objectives:
  - Introducing you to the wonderful world of AI
  - Inspiring you!
  - … but also inform you of the pitfalls

Image by RosZie (Pixabay)

What’s in it for me?

- Understanding (Artificial) Intelligence and its history
- Exploring the benefits, risks, and challenges of AI
- Preparing for a future where AI is everywhere

Image by RosZie (Pixabay)

Key Takeaways

- ❖ Artificial Intelligence is already all around us and will impact our life in many ways
- ❖ AI is developing rapidly and regulations are still in the works
- ❖ Machine learning, while powerful, comes with many challenges and requires good quality data and good quality algorithms
- ❖ Applying AI is not a catch-all solution

Image by Philippe Bout (Unsplash)

Artificial & Human Intelligence

Image by from Unsplash

Defining Intelligence

What is human intelligence?

- Hard to define, more than IQ/EQ?
- History of intelligence dating back to Aristotle (>300BC)
- Greatly impacted by the industrial revolutions
- Understanding our differences through Universal Design

Defining Intelligence

What is artificial intelligence?

- Definition
- History of artificial intelligence
    - Turing Machine, 1950s, AI Winters
    - Machine Learning from experience
- Digital Human – Cognitive simulation – Modelling the brain
- Deep Learning and Neural Networks

Defining Intelligence: comparing definitions

“Quickness of understanding; wisdom. The collection of information.”	*“The ability to understand and learn and make judgements or have opinions that are based on reason.”*	*“Problem-solving, reasoning, self awareness, creativity, emotional knowledge.”*
The Concise Oxford Dictionary	Cambridge International Dictionary of English	*Wikipedia*

Defining Intelligence: comparing definitions

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The Concise Oxford Dictionary	Cambridge International Dictionary of English	*Wikipedia*

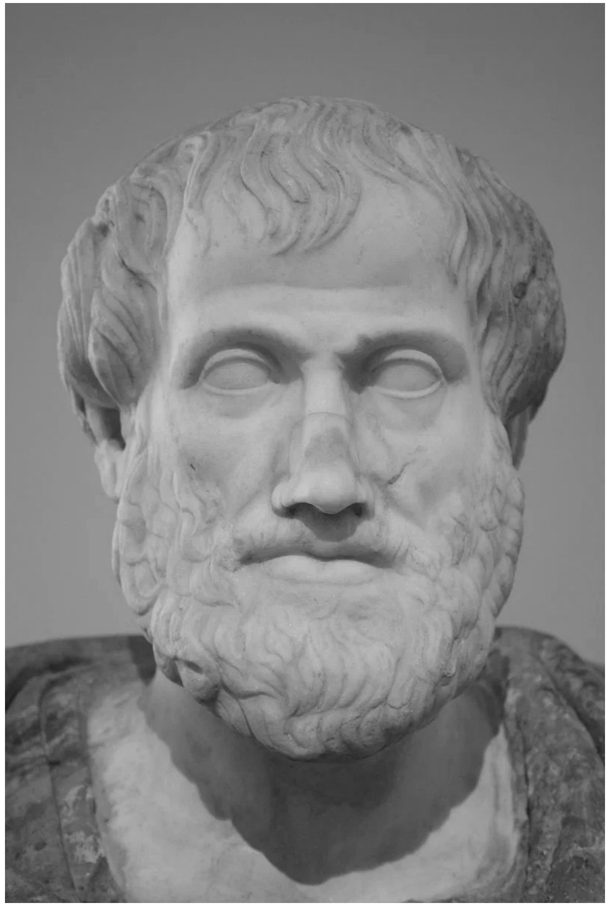
Common themes: learning, adaptation, understanding and handling abstract concepts, influencing our environment

Aristotle

364BC to 322BC – the father of western philosophy and an early expert in learning

He was the first to write about OBJECTS and laid the foundations of:

- Ontology – the natural of being, knowledge, engineering
- The Scientific Method



Aristotle Bust by Lisippo (photo by Mark Cartwright)

The scientific method – objective

- Empirical way we acquire knowledge:
  - Careful observation
  - Rigorous skepticism
  - Formulate a hypothesis
  - Test with experiments
  - Refine the hypothesis.
- Iterative and cyclical, we build on our results and we *learn from experience.*
- Useful in any academic research

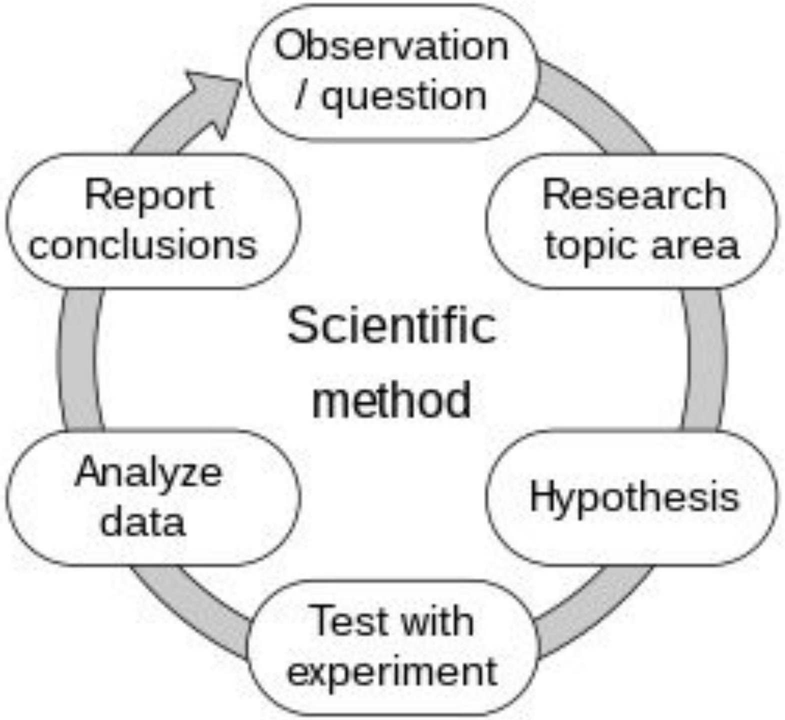
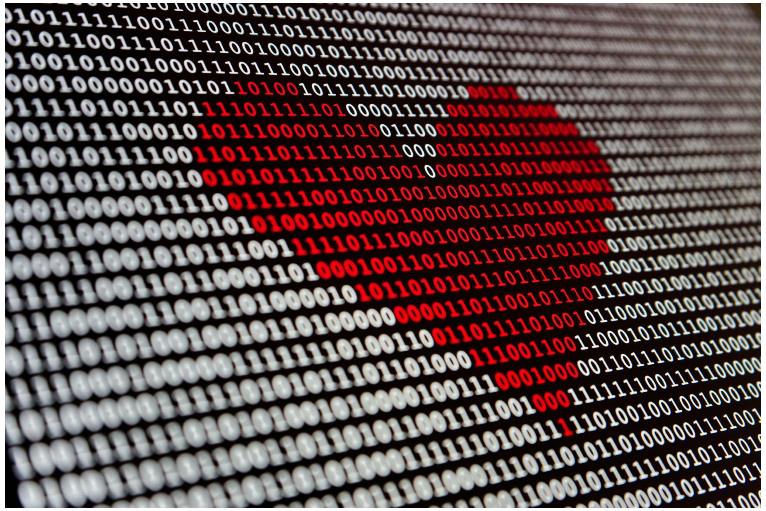


Image source: Wikipedia

Emotional Intelligence (EQ) – subjective

- The ability to understand one's own and others' emotions
- The ability to use this understanding to adapt to and change an environment
- The ability to empathise and make a judgement
- The hardest problem in AI is consciousness!
- Current scientific research is adding to our understanding



The industrial revolutions

- First, 18th & 19th centuries: Europe and USA – steam engine, rural societies became urban and industrial.
- Second, 1870–1914: electricity allowed mass production and technological advances such as the internal combustion engine, telephone and light bulb.
- Third, 1980s: digital, ICT (Information and Communications Technology), personal computer, internet and automation.
- Fourth – the present: exploits the digital revolution and is disruptive, driven by AI, robotics, IoT (Internet of Things), plastic printing, nano-technology, bio-engineering autonomy... Named by Klaus Schwab – founder of the World Economic Forum.

Reading tip: “The Fourth Industrial Revolution” by Klaus Schwab

Universal design – design for all

- We can now design for all people of whatever ability and age
  human plus machine (robot, computer, system…)
- It's about being more human, improving us as humans:
  - In performance
  - Socially

Further Reading:

- https://en.wikipedia.org/wiki/Universal_design

Image by RosZie (Pixabay)

Artificial Intelligence: what makes a machine intelligent?

Computer science view:

- *Intelligent agents* perceiving their environment and taking actions to achieve a goal.*
- Some traditional goals are sometimes called narrow or weak AI: reasoning, planning, learning, natural language processing, image recognition…

Objective / Depth	Human	Rational
Thinking	Cognitive modeling	Laws of thought
Acting	Turing Test	Rational agent *(Perspective of this work)*

Reading tip: “Artificial Intelligence: A Modern Approach” by Russell & Norvig

Artificial Intelligence: strong or narrow/weak?

- Weak/narrow AI: specialized tasks
- Artificial General AI, sometimes called strong AI:
  - Perform a full range of tasks
  - Predictions about reaching this milestone range from soon, to 50 years from now, to maybe never

DeepL

PIKTOCHART

grammarly

alexa

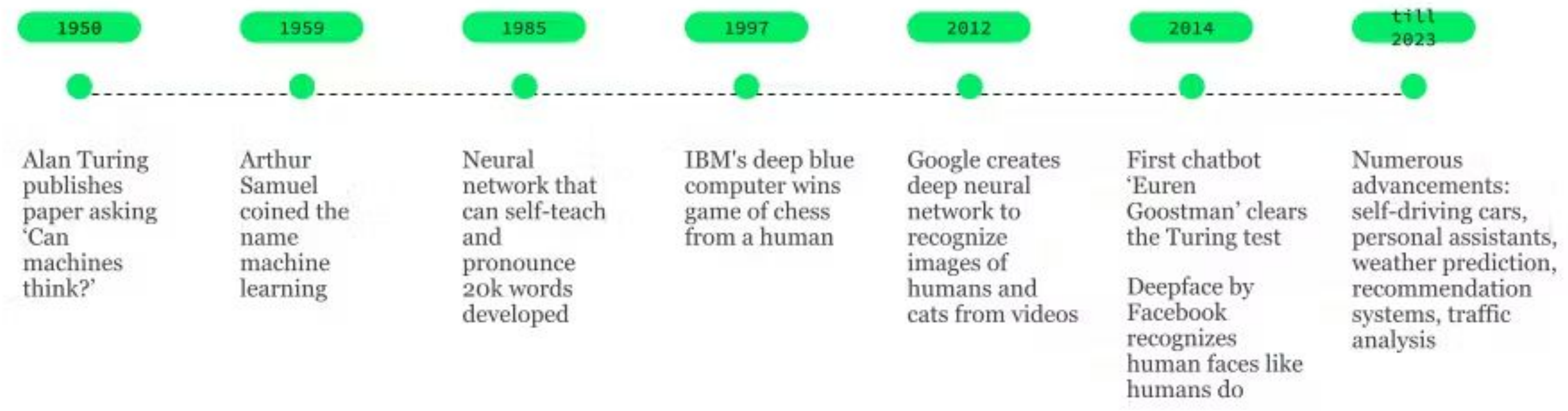
remove bg

Are these projects weak or strong AI?

Artificial Intelligence: strong or narrow/weak?

Is this project strong or weak AI?

The history of AI and Machine Learning



Source: https://www.mongodb.com/resources/basics/machine-learning

Machines learn from data

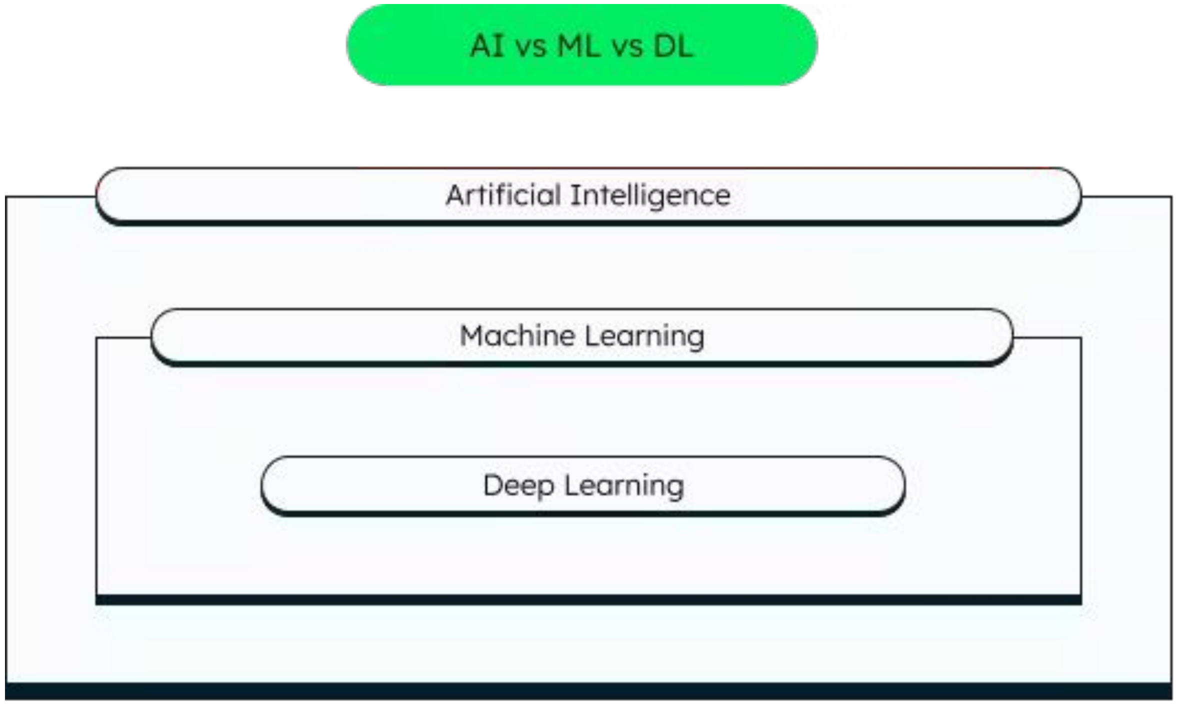
- Learning from experience often means learning from data
- Involves heavy data analysis – data scientist, data mining
- ML helps us detect patterns in data, giving us more capabilities
    - Fast internet search
    - Writing/coding assistance
    - Detection, planning, prediction etc…
- ML is improving accessibility – voice control, home automation, autonomous vacuum cleaners and lawn mowers, drone delivery…

  Everything in our lives is changing
- AI is all about displaying (human) intelligence, ML is about **learning from experience**.

So how do we define Machine Learning?

Samuel Arthur (IBM – 1959) first used the term ‘Machine Learning’.

‘The field of Machine Learning is concerned with the question of how to construct computer programs that automatically improve with experience.’ - Tom Mitchell



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Heuristic – sometimes works

‘**Heuristic** – a strategy derived from previous experiences with similar problems.’

In Machine Leaning, ‘Heuristic’ means a technique for solving a problem more quickly where classical techniques are too slow – a bit like a shortcut, rule of thumb, trade offs, developed using trial and error, discovery and experimentation…

…experts teach a ML algorithm how they do it, transform a problem into a simpler form which is easy to work with (e.g. reduction)

A human being is more than IQ and EQ

- We are still feeling, emotional and <u>conscious</u> beings…
- Our brain has a conscious and sub-conscious capability
  - Interacts with chemical and electrical signals from our physiology, our environment, our memory, other people
  - Has developed to prioritize sight, smell, hearing, taste and feeling as our data collectors
  - But we feel more; e.g. balance and acceleration (vestibular), pain, internal (hunger)
  - We experience intuition and so-called "gut feelings"

TACIT Knowledge: Knowledge that we pass on without begin able to write it down, without being explicit – example: we remember a face not its features, hard to put into words!

The digital human

Computer simulations are used to understand the whole human body.

- Ergonomics (reduce fatigue, improve well-being, improve performance, reduce errors…)
- Drug testing – modelling the physiological response to drugs
- Brain function – electrochemical, response to drugs, hormones, dehydration
- Sense function – how we see?
- Imagine if we could assess the evolutionary effect of food, exercise and medication on the human body.

Human brain inspired AI
– ‘Deep Learning’ (DL)

Deep Neural Networks (DNN) are used in:

- Speech recognition
- Image recognition
- Medical diagnosis
- Natural Language Processing (NLP) – Echo, Siri, Alexa, Cortana…

Inspired by the physiological construction of the human brain, DNN are widely thought to have revolutionised AI – WHY?

It closely matches the AI intelligent agent concept, since it **models a brain**.

What have we learned?

Artificial intelligence is a diverse, fascinating, complex and rich subject, and it is growing and learning.

The Fourth Industrial Revolution has the potential to change every aspect of our lives – make us more human.

‘Learning from experience’ can be enhanced by Machine Learning – a toolkit to re-imagine every area of our lives.

Machine Learning and AI are driven by the scientific method and need good quality data.

Test yourself!

What is an example of human intelligence?

(a) Running a marathon.

(b) Watching a movie.

(c) Tasting food.

(d) Identifying a horse in a misty field.

Answer: ?

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Test yourself!

What is NOT used to define Heuristic?

(a) Child’s play

(b) Discovery

(c) Trial and error

(d) Experimentation

Test yourself!

What is NOT used to define a heuristic?

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Answer: ?

💡 Exercise: Opportunities for an AI System

Objective: Think of an innovative AI application in a specific field.

What will the AI system do, and how does it align with our goals?

Examples:
Automotive: Develop driverless cars
Retail: Implement personalized shopping experiences
Farming: Monitor and analyse crop growth

What learning will the AI system perform, and what data will it use?

Examples:
Recognize products from images
Answer customer questions verbally
Identify the intent of emails
Detect customer clusters

What are the challenges, benefits, and risks of this project?

Examples:
Insufficient capability or functionality
Funding constraints
Cultural resistance

Who do we need in our project team?

Examples: Software Developer, Engineer, Scientist. Change Manager.

Reading tip: https://www.linkedin.com/advice/0/what-steps-define-ai-project-scope-deliverables

Applications of AI

Image by Possessed Photography (Unsplash)

The good, the bad and the challenging

- What do we need? – Functionality, software and hardware
- Smart applications are found in all fields and require us to **learn from experience**
- ML Enablers make it easier to apply ML than ever
- Social, societal, economic and environmental risks
- Machine Learning projects are challenging in many aspects
- Opportunities are everywhere
  - Robotics
  - NLP
  - Big Data & IoT
  - ML Frameworks & Software (usually open source!)

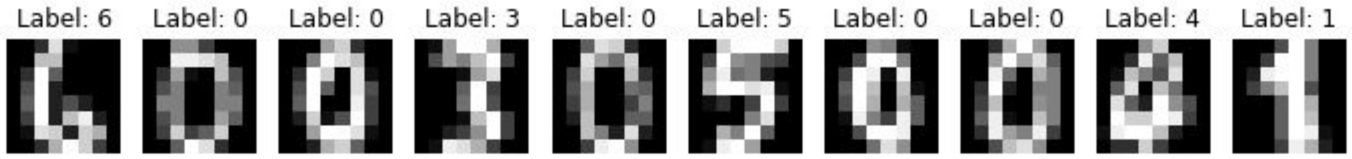
ML – what do we need?

- **Functionality**
  - Collecting, preparing & cleaning data
  - Algorithms
  - Data visualisations
  - Deployment functionality (product, service, publish)
- **Software**
  - Writing our own software with open-source frameworks
  - Open Source (e.g. Amazon, Google, IBM, Apple, Microsoft)
  - Commercial (e.g Microsoft Power BI, IBM Analytics, Google Analytics)
- **Hardware**
  - Desktop computer
  - A Computer Cluster
  - High Performance Computer – Cloud Service
  - Even your phone can run Python

Reading tip: click the icons to view some great open source initiatives!

The First Commercial AI Product

- Widely thought to be the first AI product,1974.
- Kurzweil Computer Products, Inc.
- Text-to-speech synthesiser
- Very normalised technology that uses ML
- Often the first ‘hello world’ ML project is OCR, but with handwritten text
- Natural Language Processing remains a very popular subfield of AI, with plenty of recent developments



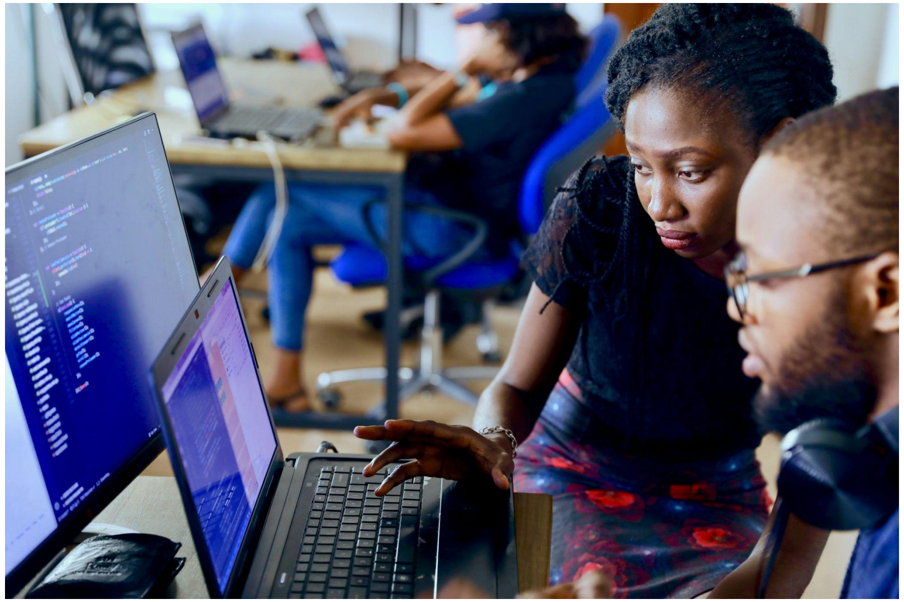
Tip: play around with a proof of concept on the MNIST Digit Playground

Kurzweil Reading Machine
(circa 1978)

source: Kurzweil Products

Applications: Research and development

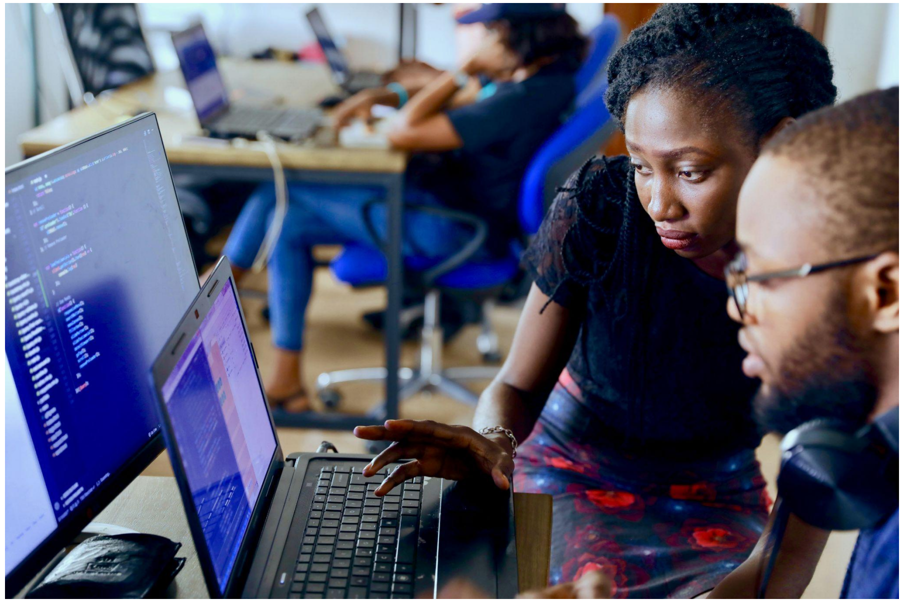
- R&D is the professional embodiment of learning from experience and the scientific method.
- AI and ML are part of its toolkit
- AI helps R&D through:
  - Great tools for data mining & analytics
  - Reducing R&D timescales.
  - Experimental selection
  - Exploring a wider range of design options
  - Exploring literature with the assistance of AI



Desola Lanre Ologun (Unsplash)

Example: Research and development

- Writing tool: https://jenni.ai/
- Search engine: https://consensus.app/



Desola Lanre Ologun (Unsplash)

Applications: Engineering

- Robotics
  - Extreme environments (e.g. sterile, vacuum, underwater, chemical hazards, radiological hazards, physical hazards)
  - Health and social care
  - Manufacturing (3D printing, smart supply chain and factories)
  - Autonomous vehicles (cars, aircraft, trams, trains, drones)
  - Swarms (multiple robotics working towards common goals)
- Design
  - Optimisation
  - Aesthetics
  - Virtual and augmented reality
  - Simulation
- Control and Automation (e.g. smart maintenance planning)
- AI hardware – (GPUs, OPUs, CPUs)
- Product nervous system – learning from the product (RR engines) in operation

Thibault Dandre (Unsplash)

Applications: Health & social care

- Health care
  - Diagnosis and treatment selection
  - Drug development
  - Smart hospitals and patient interaction
  - Patient monitoring (temperature, BP) 24/7 release nurse time
  - Robotic surgery (extending a surgeon's capability – nano-scale)
  - Image analysis
  - Genetic analysis (DNA)
- Social care
  - Monitoring and support at home (dementia help, drug administration)
  - Robotics (movement, bathing, food preparation, housework, toilet…)
  - Social interaction

Applications: Entertainment

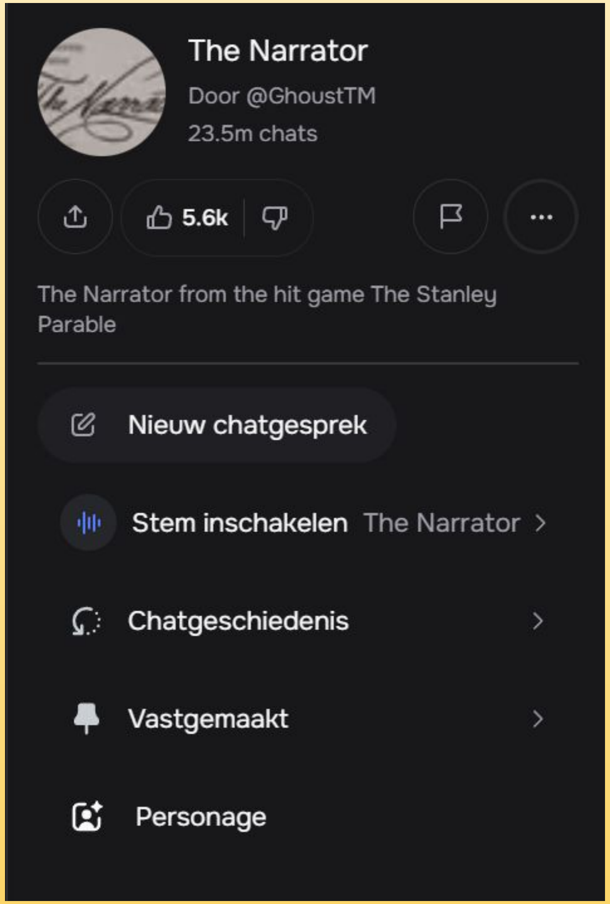
- Computer games: multi-player human and machine games
- Interactive media and news
- Immersive audience – Virtual Reality and Augmented Reality
- Personalised content selection (already here)
- CGI – AI-enhanced movies (colouring of B&W images)
- Personalised movie content – advertising in movies

XR Expo (Unsplash)

💡 Exercise: Build Your Personal Assistant!

https://character.ai/

- Decide what your assistant should do:
  - Help you with daily tasks?
  - Learning assistant?
  - City trip planner?
  - Text adventure narrator?
  - Endless possibilities
- Pick a picture or generate a person
  - Tip: https://thispersondoesnotexist.com/
- Write a little more in the description boxes, this will greatly influence how your character will speak!



Applications: Sales and marketing

- Chatbots (FAQ, advice line sales assistants, helplines)*
- Analytics (identifying customers, opportunities, demand, supply)
- Preventing fraud
- Streamlining marketing, marketing suggestion…
- Product pricing
- Market-size prediction
- Website design
- Social media analytics
- Search engine optimization

The Chatbot & the Turing Test

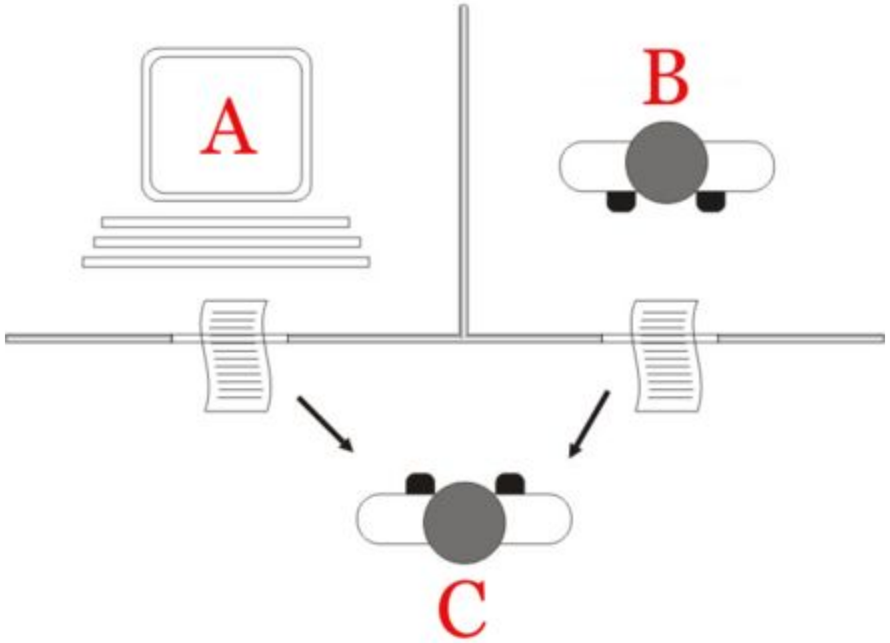
Alan Turing proposed a test where an observer is asked to determine if they are talking with a computer or a human based **only on text-based questions**:

https://en.wikipedia.org/wiki/Turing_test

Food for thought: is language what defines us as humans?

If you designed your own test for human intelligence,

what would it look like?



Source: Wikipedia (Turing Test)

Logistics – planning and organisation

- Data analytics are a VERY commercially successful business tool
- Re-humanising the workplace – removing monotonous task, improving accuracy, removing low value tasks
- Smart factories
- Smart integrated supply chain
- Smart integrated delivery
- Autonomous robotics
- Intelligent agent modelling – learning from simulated experience
- Knowledge engineering – learning from the experience of experts
- Human resources – search, selection and recruitment
- Agile projects – ML-driven projects
- Enhanced security
- Predictive maintenance
- Automated planning
- Internet of Things

ML enabler - the IoT and Big Data

The Internet of Things (IoT) is a large network of smart devices embedded with hardware, software, sensors, actuators, and connectivity

The estimated number of devices connected including mobile phones and tablets is 15-20 billion → lots of data!

Big data: high velocity, high volume and a wide variety.

Source: MIT News

ML enabler – cloud high performance computing

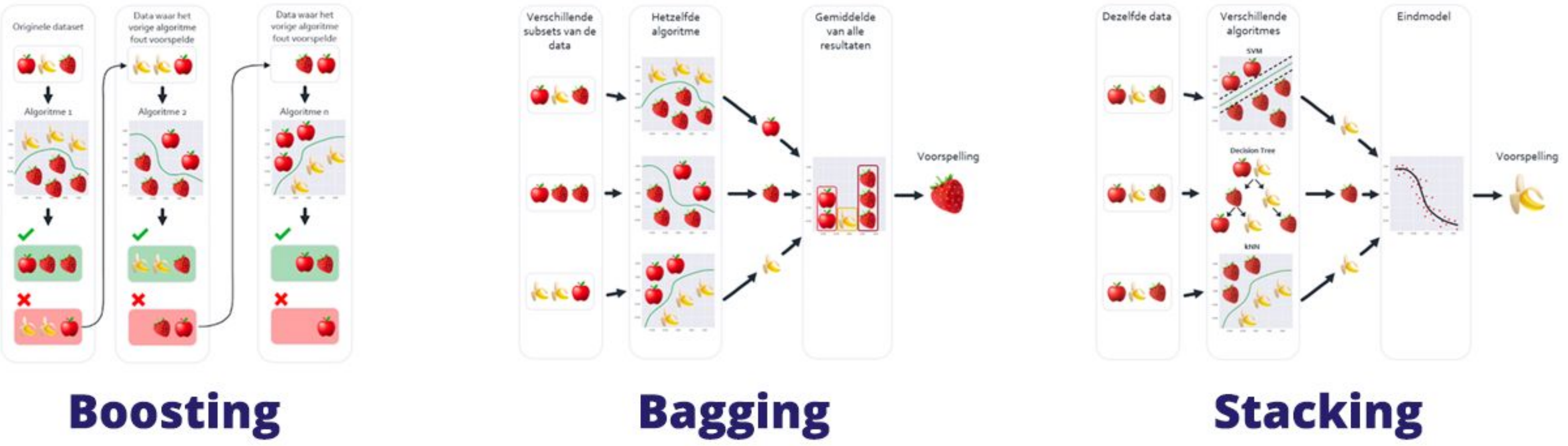
- Large data centres with parallel super computers
  - On-demand charge per hour
  - Handle Big Data
  - Develop product on the cloud served from HPC (AWS, IBM, Google, Microsoft)
  - 1 to 1000s processors
- Open Source software
- Specialized hardware, GPUs, CPUs, high bandwidth networks and internet
- Perfect for training and fine-tuning large scale models like LLM's

EU currently has plans for an Exa-scale HPC facility to model weather – 10 years to plan

ML tool: Ensemble Methods

- As humans, we are stronger together → <u>crowd labelling for large datasets</u>
- Generally speaking, more humans opinions combined → more reliable, closer to expert opinion

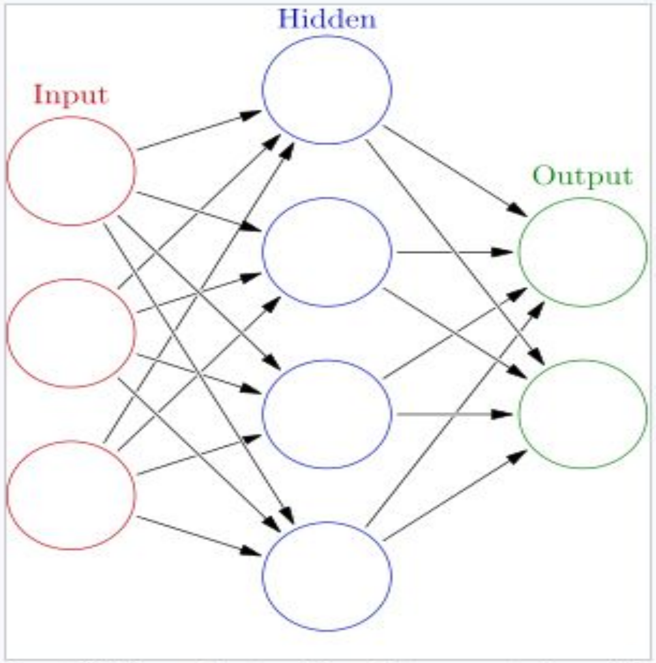
The same can be applied to ‘weak’ machine learning models (only slightly better than random).



Source: datasciencepartners.nl

ML enabler – Deep Learning artificial neural networks

- Based on the human brain
- Deep Learning = larger networks with more hidden layers
- Neural Networks have made significant progress in recent years
- **Big disadvantage: Require training and are black boxes – it is difficult to explain the results**
- Very promising results in Bioinformatics, Speech Recognition, Image Processing, Natural Language Processing
- Typically needs lots of computer resources
- Learns from structured and unstructured data



An artificial neural network is an interconnected group of nodes, similar to the vast network of neurons in a brain. Here, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another.

https://en.wikipedia.org/wiki/Artificial_neural_network

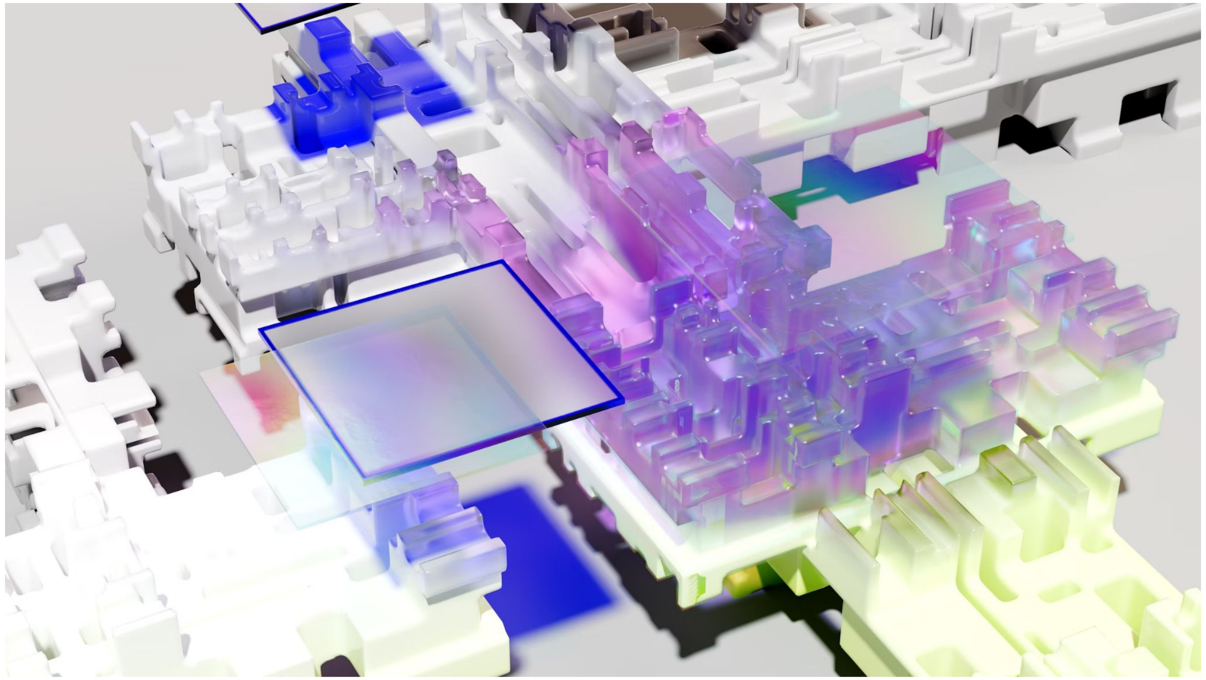
ML enabler
– Deep reinforcement learning

Google's Deep Mind AlphaGo beat World Go Champion Lee Sedol

Other examples include:

Swarm Intelligence – driven by the need to understand biological systems like bacteria, lots of autonomous robots…

Optimisation – making a system better by successively improving a metric or metrics



An artist's illustration of artificial intelligence (AI). This image visualises an artificial neural network as physical objects. The complex structure represents a network of information whilst colour represents data being fed through the system.

It was created by Rose Pilkington as part of the Visualising AI project launched by Google DeepMind. Source: Unsplash

Nasa’s TRL and Funding

Ethics & Accountability

- Leads to new questions – How? Who's responsible? Law? Human rights? Robotic rights?
- Artifical General Intelligence will have a strong connection to robotics:
  - Guidelines usually emphasize human autonomy and safety
- European Commission provides "Guidelines for Trustworthy AI"
- Possible consequences: inequality, discrimination, other bias, unemployment
  - Did we use biased data? – basis of a conviction
- Lethal Autonomous Weapons are considered a general red line
- Healthcare risks: genetic selection, social exclusion
- Ability to pay: AI charging more to vulnerable people

🕒Recent development: EU AI ACT, taking heavy inspiration from the GDPR.

EU AI ACT

The AI Act is broad in scope:

(1) having a **potential global reach** [...];

(2) **using a (very) broad definition of AI system**. The latest and expected definition is: “An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment.”

(3) **introducing requirements and obligations for stakeholders** through the supply chain [...]

The AI Act uses a risk-based approach [...]:

(1) **Unacceptable risk**: e.g. social scoring and biometric categorization

(2) **High-risk**: e.g. AI systems that include safety components of products covered by sectorial Union legislation, AI systems that are described in specific use cases as in the sphere of employment or education;

(3) **Specific transparency risk**: for chatbots and deep fakes; and

(4) **Minimal risk**: for which providers of such systems may choose to adhere to voluntary codes of conduct.

[...] Some of the key obligations for high-risk AI systems include **conformity assessments, quality and risk management systems, registration in a public EU database, and information access by authorities**. In addition, high-risk systems **must be technically robust and must minimize the risk of unfair biases**.

https://www2.deloitte.com/nl/nl/pages/legal/articles/political-agreement-on-the-EU-AI-act.html

EU AI ACT

As for g**eneral-purpose AI models (including generative AI)**, the AI Act requires providers of such models to d**isclose information to downstream system providers**, and to have policies in place to ensure that they **respect copyright** when training their models. In addition, for general purpose AI models that were trained using a total **computing power of more than 10^25 FLOPs are considered to carry 'systemic risks'** [...]

Deployers that are **bodies governed by public law or private operators providing public services, and operators providing high-risk systems shall perform a fundamental rights impact assessment ('FRIA')**. [...]

The AI Act provides for huge fines, almost two times higher than under the GDPR. For the most severe violations of the prohibited applications, fines can go up to 7% of the global turnover or €35 million (GDPR: 4%/ €20 million), and up to 1.5% for failing to cooperate with authorities and/or to provide accurate information. The AI Act will be supervised by national authorities, but there will also be a European AI Board and a European AI Office (within the European Commission) that will supervise general-purpose AI models, cooperate with the European Artificial Intelligence Board and be supported by a scientific panel of independent experts.

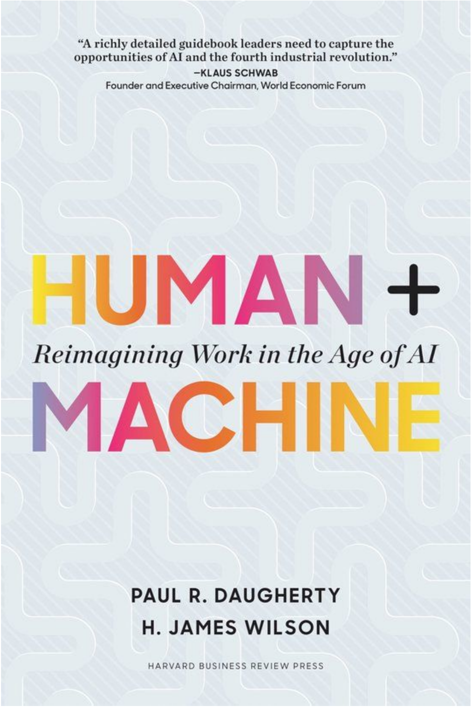
Complex systems → complex laws

https://www2.deloitte.com/nl/nl/pages/legal/articles/political-agreement-on-the-EU-AI-act.html

Humans and machines working together

Paul Daugherty and James Wilson: *the missing middle*

What do you think are good examples of humans and machines working together?



Human vs. Machine Capabilities

- Provide leadership – set the goals
- Are creative
- Can empathise (humans, groups, animals, nature, ideas, ethics)
- Can judge (law, ambiguity, 50/50)

What machines do well:

- Transactions – monotonous tasks
- Prediction
- Iteration
- Adaption
- Weak AI

Andy Kelly (Unsplash)

Reading tip: Human + Machine by Paul Daugherty and James Wilson

AI vs. Automation

‘Automatically controlled operation of an apparatus, process, or system by mechanical or electronic devices that take the place of human labour.’ (*Merriam-Webster dictionary*)

- No learning from experience
    - → not intelligent
    - → not AI
- No human involvement

In Machine Learning, we never program explicit knowledge, but we **learn from experience**.

ML challenges and risks

Data

- Obtaining data
- Legal (GDPR, IP, copyright) General Data Protection Regulation
- Preparing it for ML – <u>STRUCTURED OR UNSTRUCTURED</u>, encoding, cleaning, missing data

ML algorithms

- Selecting the right one
- Understanding the results (bias, variance, overfitting, underfitting)
- Understanding the differences from a group of ML algorithms
- Combining results of different ML algorithms

Data visualization

- Large amounts of data to visualise

ML results deployment

- Launching and maintaining the system

ML challenges and risks (1/2)

Mathematical and Scientific

- May not be solvable – combinatorial explosion, non-linear…
- Statistical – probability, random numbers
- Linear Algebra – properties of matrices
- Computer and Data Science – data structures, algorithms, graphs
- Vector Calculus – differentiation, integration
- Operational Research
- Control Theory

Hardware Required

- Parallel Computation
- GPU, CPU and OPU (Optical Processing Units)
- Quantum

ML challenges and risks (2/2)

Data visualization and presentation

- Large amounts of data to visualise

Culture

- Fear of AI – society and organisational
- Organisational – fear of failure and experimentation (Victorian values, patronage, … leadership)

Skills

- Individual – education and experience
- Team – style of project delivery (Waterfall compared to Agile)

Test yourself!

What part of the human body is the Artificial Neural Network based on?

(a) Nervous system.

(b) Brain.

(c) Hand.

(d) Senses.

Answer: ?

Test yourself!

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Test yourself!

What is a form of Artificial Intelligence?

(a) Deep Learning.

(b) Statistics.

(c) Linear Algebra.

(d) Graph Theory.

Answer: ?

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(c) Linear Algebra.

(d) Graph Theory.

Answer: ?

Test yourself!

Automation is a system that does not require…

(a) Software.

(b) Power supply.

(c) Human Intervention.

(d) Hardware.

Answer: ?

Test yourself!

Automation is a system that does not require…

(a) Software.

(b) Power supply.

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(d) Hardware.

Test yourself!

What disadvantage does AI have when compared to a human?

(a) Little empathic ability.

(b) Accurate calculations.

(c) Deal with monotonous tasks.

(d) Repeatability.

Answer: ?

Test yourself!

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Test yourself!

An artificial Neural Network is a form of…

(a) Machine Learning that learns from structured and unstructured data.

(b) Automation that learns from sensors and the Internet of Things.

(c) Scripting that learns from unstructured data randomly.

(d) Biological computing that learns from human emotions.

Answer: ?

Test yourself!

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Test yourself!

Alan Turing's test inspired what type of conversational commerce program for ecommerce?

(a) Chatbot.

(b) Intelligent credit cards.

(c) Talking money.

(d) Talking piggy banks.

Answer: ?

Test yourself!

Alan Turing’s test inspired what type of conversational commerce program for ecommerce?

(a) Chatbot.

(b) Intelligent credit cards.

(c) Talking money.

(d) Talking piggy banks.

💡 Exercise: Maturity and funding of an AI system

Objective: try to determine what should be developed at each Technological Readiness Level for your system from Exercise 1.

Artificial Intelligent System Project					
	Technology Readiness Level (NASA / EARTO) 'How mature is it?'	Functionality 'What do we want it to do?'	Software 'Can the software do what we need it to do?'	Hardware 'Is the hardware capable of delivering the functionality using the software?'	Funding 'Who is going to pay for it?'
Invention	1				
	2				
Concept validation	3				
	4				
Prototyping	5				
Pilot production and demonstration	6				
	7				
Initial market introduction	8				
Market expansion	9				

An introduction to Machine Learning

Machine Learning – part one

What is Machine Learning? AI to ML

- AI agent and environment
  - Agents types
  - Agent world
  - Typical AI learning tools for agents
- Machine Learning is part of the AI toolkit
- Machine Learning is multi-disciplinary
- Types of Machine Learning

Formal Tom Mitchell definition of ML

Samuel Arthur (IBM,1959) first used the term ‘Machine Learning’.

The Tom Mitchell definition is more widely quoted:

“The field of Machine Learning is concerned with the question of how to construct computer programs that automatically improve with experience”

“A computer program is said to learn from experience, *E*, with respect to some class of tasks, *T*, and performance measure, *P*, if its performance at tasks, *T*, as measured by *P*, improves with experience, *E.”*

Tom Mitchell definition example

Task: Chess

Performance: Number of wins

Experience: Practice games

LEARNING FROM DATA – ENGINEERS NEED MORE THAN DATA IF WE ARE GOING TO BUILDING INTELLIGENT ENTITIES

Engineers build models every day

Top university engineering departments build models EVERY DAY

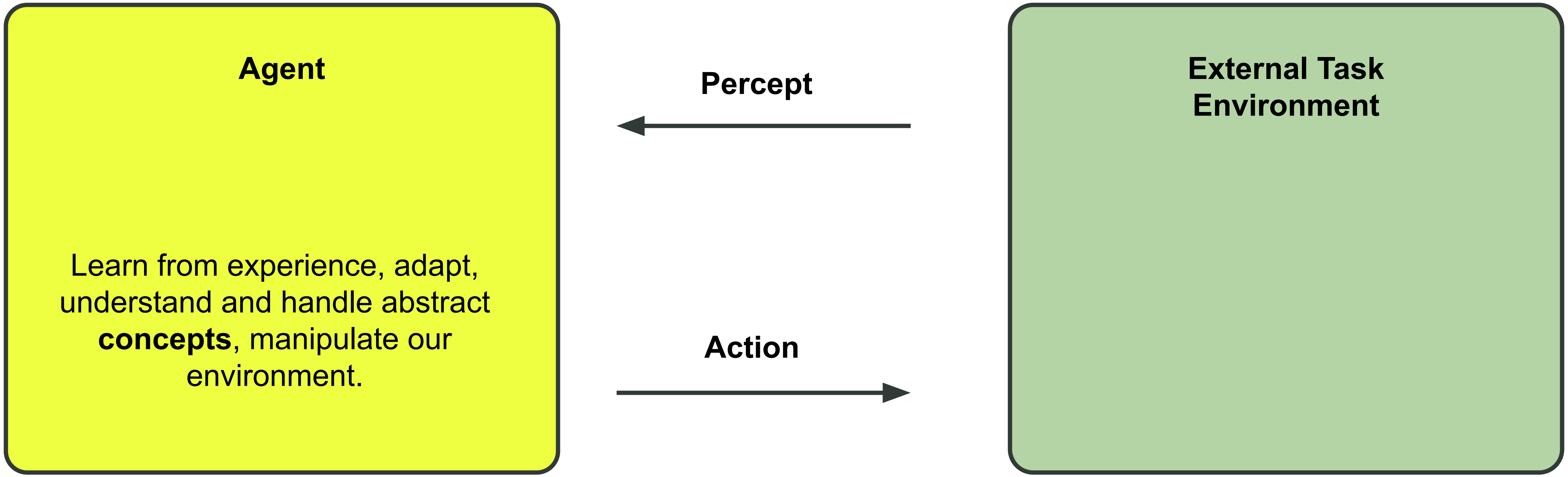
AI can help engineers build better models which means:

better engineering – better products – better society

Engineers use partial differential equations, experiments, computational physics and simulations, statistics… Models, models, models

Patrick Winston, MIT – AI is the modelling of representations that support models targeted at thinking, perception and actions.

Schematic of an artificial intelligence agent



The term ‘Percept’ is the collective term for all the agents’ perceptual inputs at any given time.

We assume agents have the following

We expect them to be rational and this depends on four things:

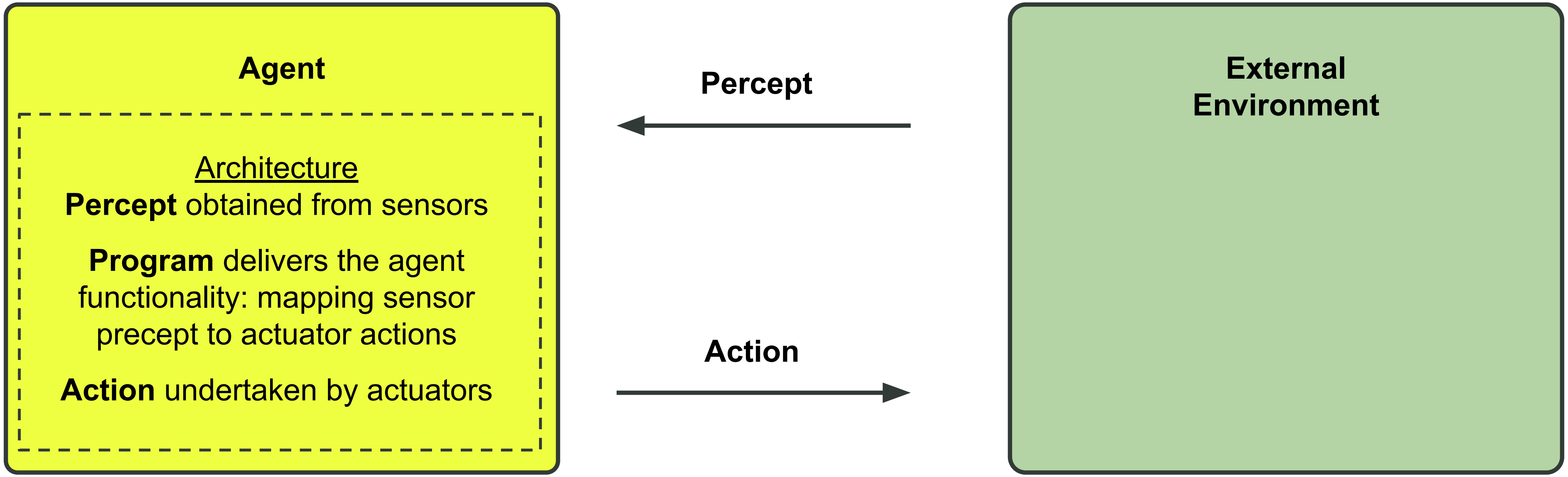
1. The performance measure that defines the criterion of success.
2. The agent's prior knowledge of the environment.
3. The actions that the agent can perform.
4. The agent’s percept sequence to date.

We assume agents have the following

Stuart Russell and Peter Norvig's *Artificial Intelligence – A Modern Approach,* 3rd edition defines a rational agent as:

'For each possible percept sequence, a rational agent should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has.'

Agent structure



The program will run on a computing device improving its performance through learning.

Agent examples

Agent Description	Performance Measure	Environment	Actuators	Sensors
Central heating thermostat	Temperature, heating cost	Building, inhabitants, heating system	Inhabitant display, boiler, power	Temperature, keypad, phone, computer
Interactive sales chatbot	Number of sales	Customers, sale environment (internet, store, phone)	Robot, display, speaker	Keyboard, microphone, camera, kinesthetic sensors

Types of agent – what's missing?

Reflex agent

- The program selects actions based on the current precept
- Simple to understand and program

E.g. central heating overheats, program selects the action to switch off the power

Model-based reflex agent

The agent has a model of the world:

- Can make up for a lack of sensor (virtual world that doesn't need sensor data)
- Program now looks at the percept and updates its own internal world (**state**)
- Program can assess the possible actions and future states and uses reflex agent approach to determine what actions to take

E.g. underwater vehicle loses visual sensors (silt – not enough light), continues using 3D-mapped geometrical model

Types of agent – what's missing?

Goal-based agent

- The program needs more than just sensors and an internal world to implement the agent's functionality – it needs a goal
- These programs are more versatile and flexible – can adapt to changes

E.g. autonomous vehicle can chose one of five exits from a motorway – the goal:
safest, quickest, most scenic, cheapest, shortest

Utility-based reflex agent

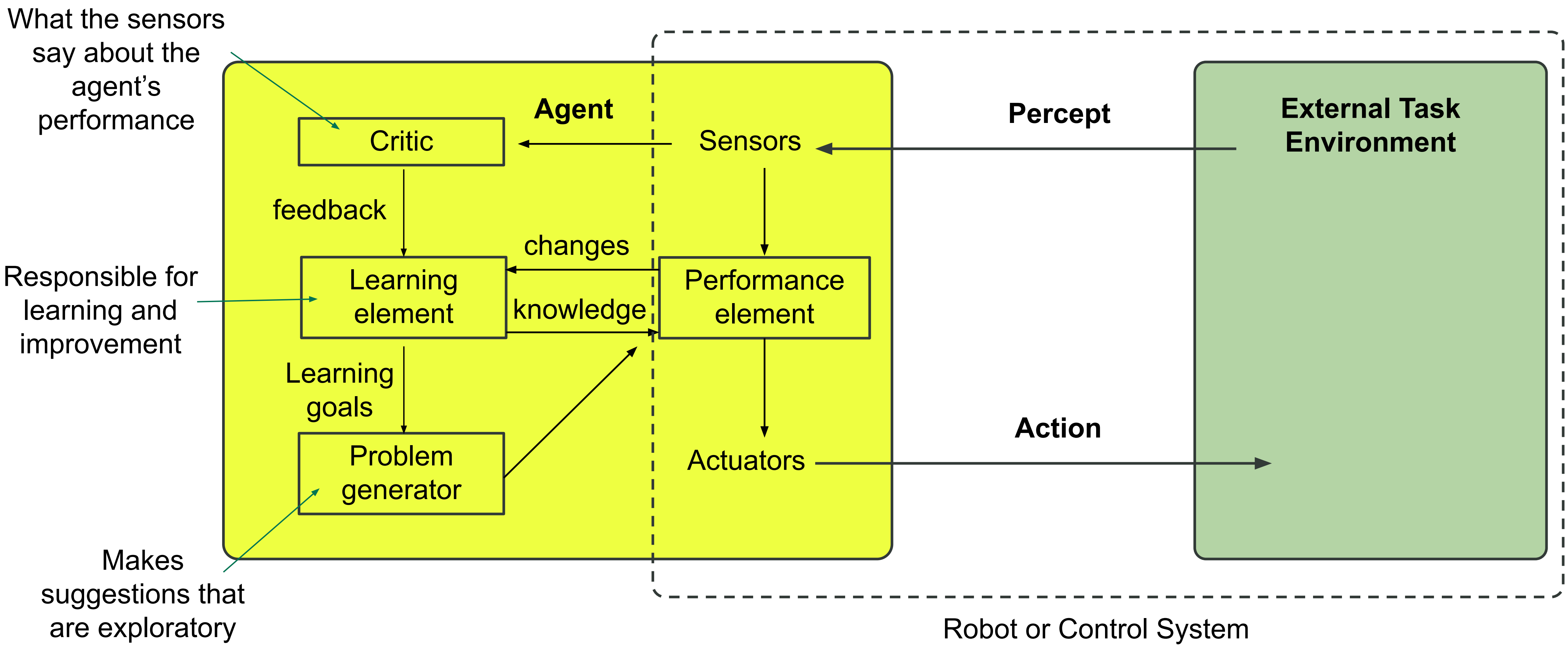
Utility is the scientific way economists measure an agent's happiness. It's more versatile than a yes/no, happy or unhappy – it measures how useful it is.

e.g. Chatbot doctor assesses the efficacy of a treatment based on patients' needs

What was missing?

Learning from experience

Russell and Norvig
– a general learning agent



State of the agent world

How can we represent the world that supports the making of models?

Increasing Fidelity

- Atomic state which is a black box and has no internal structure
- Factored state which is vector (list) of attributes made up of Booleans, real-valued or one of a fixed set of states
- Structured state which is made up of objects (could have its own attributes) as well as relationships with other objects

Scientific way of describing objects

Typical agent functionality

Given an inner agent representation of the world what types of functionality would an agent need?

Planning

Searching (multi-agent games, games of chance (rolling dice), route finding, robot navigation…)

Natural language processing

Representing knowledge

Making decisions

Learning from examples

Perception

…

Machine Learning
– part of the AI toolkit

Machine Learning is the theory and practice of how computers learn from data without being programmed explicitly – REMEMBER Tom Mitchell's definition!

It's useful on its own in understanding data – Big Data, Internet of Things, Spam Filtering, Image analysis, research, engineering, medicine…

Defined by the type of learning it undertakes on data – learning from example.

There are free, open source and transparent systems (functionality, software and hardware) we can start using today!

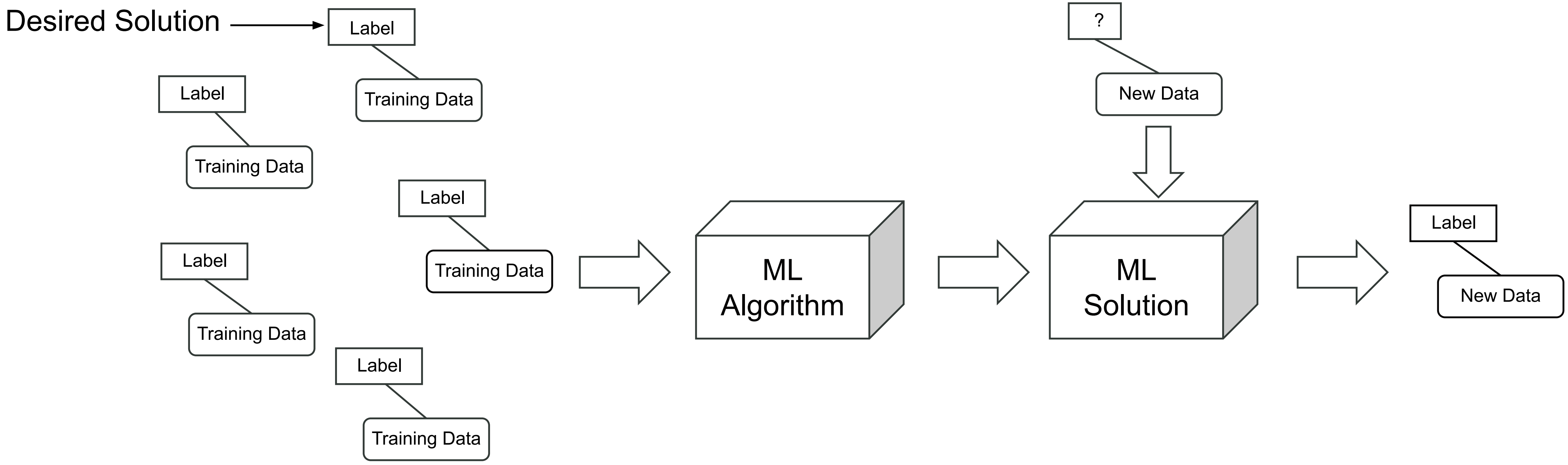
It is popular for analyzing large data sets (e.g. business analytics).

Contrast this with AI examples – home automation, ROBOTS, home assistants, chatbots, smart phones and smart watches.

The types of Machine Learning

Supervised Learning – ML learns from the training data that includes the desired solutions.

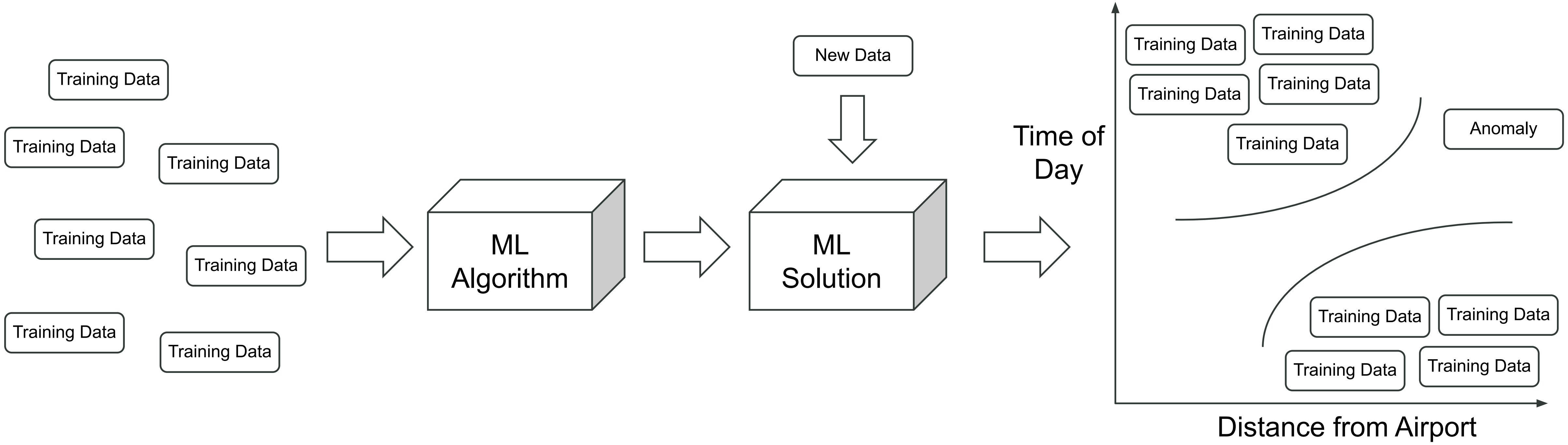
- The Desired Solution is called a label.
- The ML has a stage where (lots of) training data is used to train the algorithm.
- Once trained the ML system can then tell us something about new data.
- The algorithm maps the input to the output (e.g. classification, curve fitting).



The types of Machine Learning

Unsupervised Learning – ML learns from the training data that does not include the desired solutions.

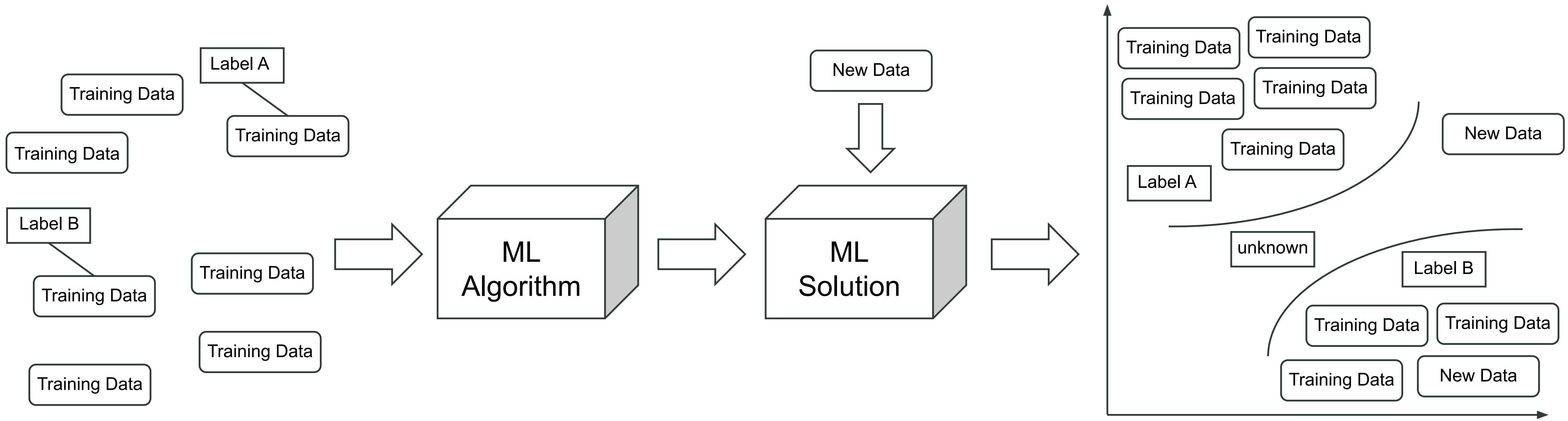
- It finds trends, patterns, groups.
- The ML has a stage where (lots of) training data is used to train the algorithm.
- Once trained, the ML system can then tell us something about new data.
- Example: fraud detection.



The types of Machine Learning

Semi-supervised Learning – ML learns from the training data that does includes some labelled data.

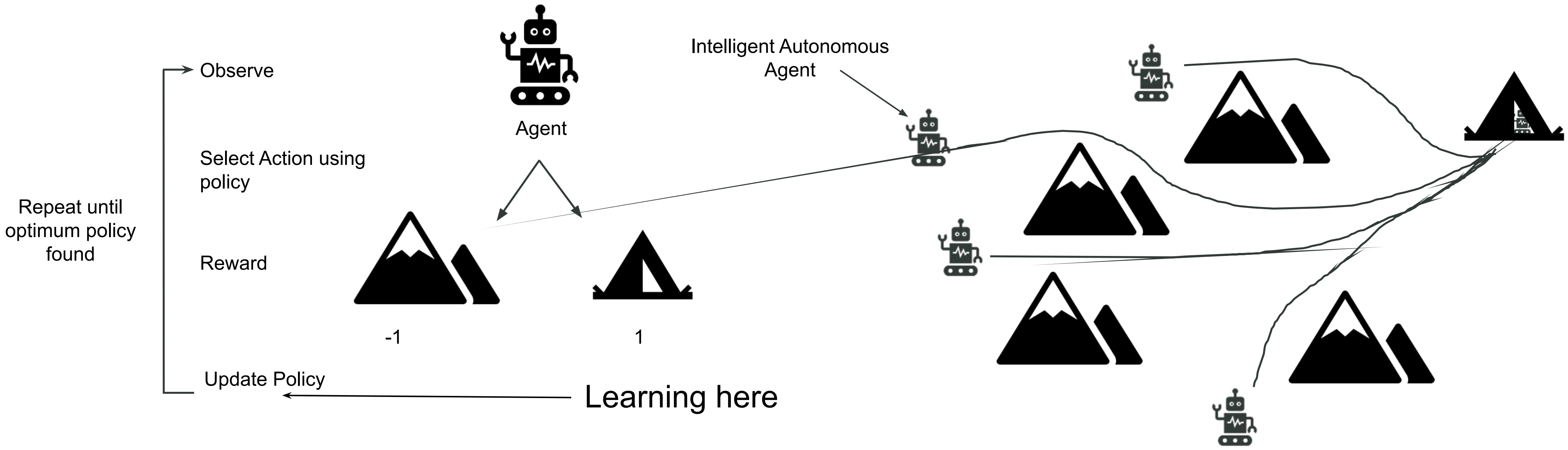
- It finds trends, patterns, groups and tries to label them.
- Once trained the ML system can then tell us something about new data.
- Example: photo labelling



The types of Machine Learning

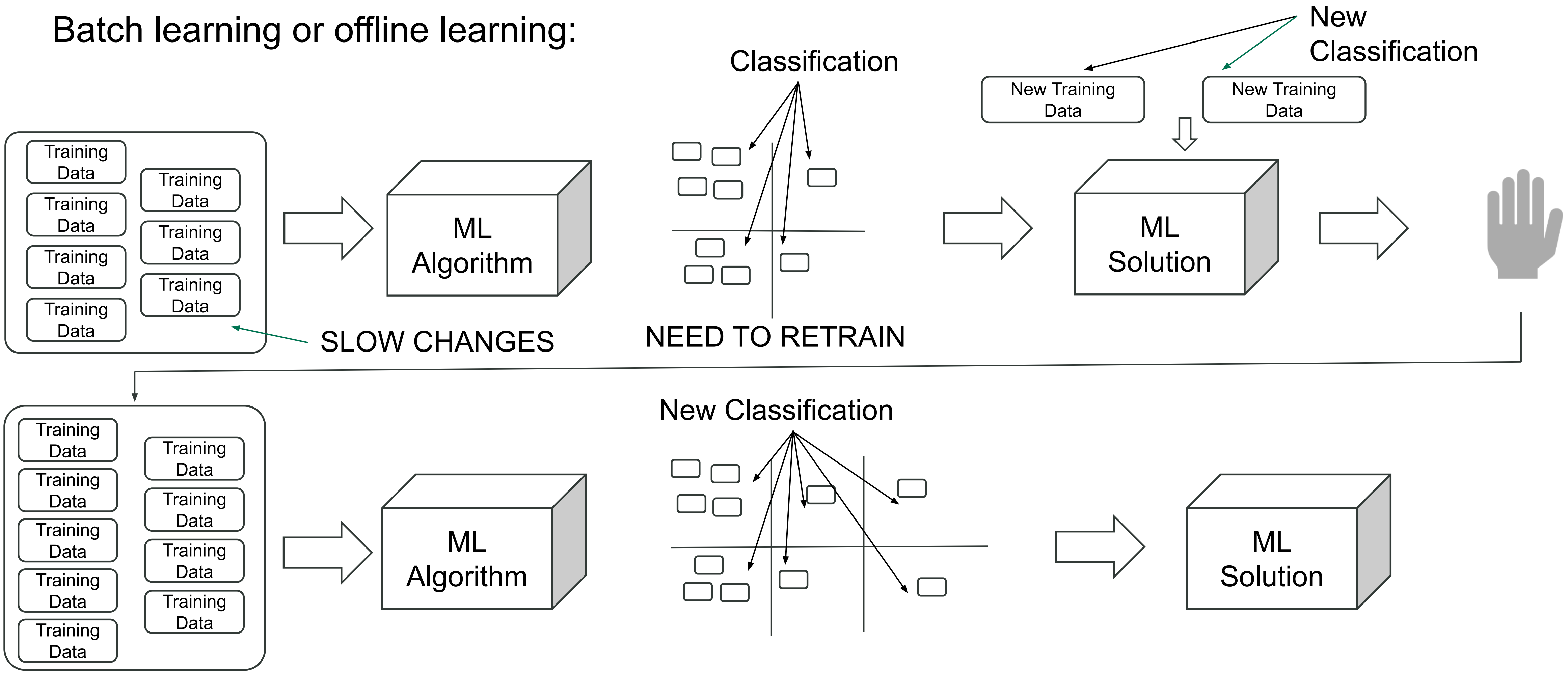
Reinforcement Learning – an agent can observe an environment, select and perform actions which in return are rewarded or penalised.

- The learning finds its own strategy, called a policy, to get the most reward over time.
- Once trained the ML system can then use that policy to achieve goals.
- Example: robot control, factory automation, scheduling, planning



The types of Machine Learning

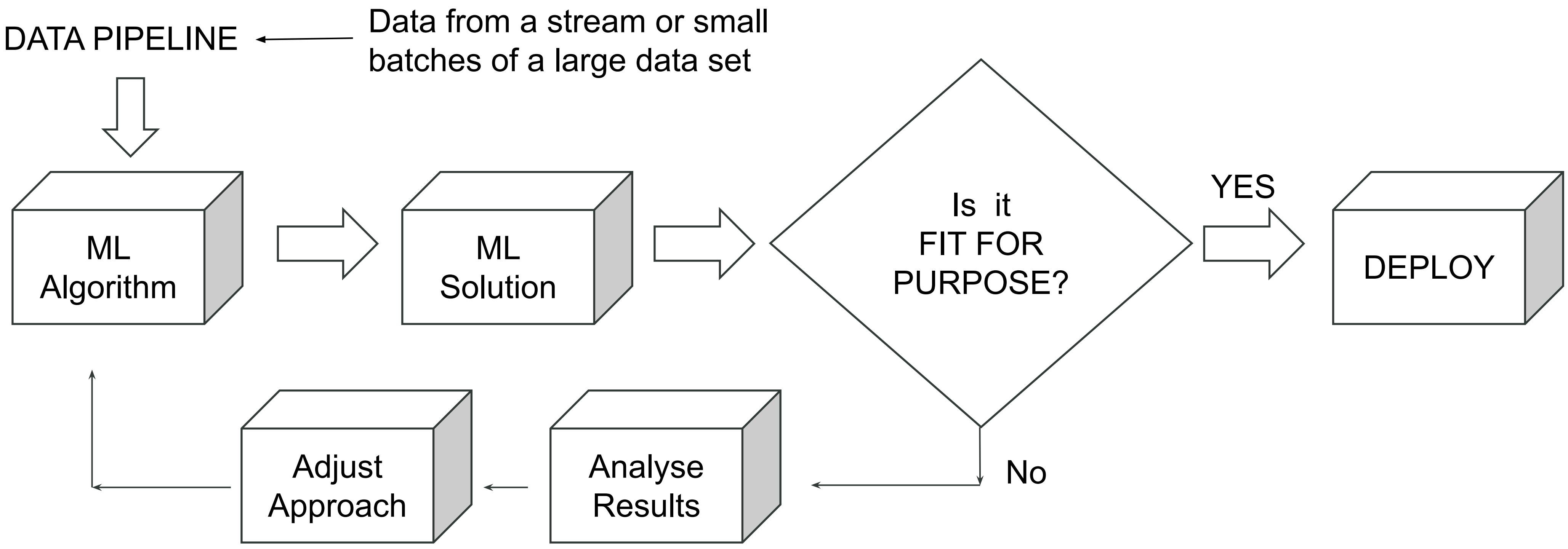
Batch learning or offline learning:



The types of Machine Learning

Online learning

- System learns in incremental steps with single, groups or small batches of data
- Useful for quickly changing data where the ML solution needs to adapt
- Useful for large datasets and where there are limited hardware resource



The types of Machine Learning

Instance-based learning

- Is the simplest form of learning, often called learning by heart - example: times tables, spelling
- Can be made more general by building a similarity measure, unknown data can then be assessed to known measures - example: spam filter

Model-based learning

- Here, we build a model of the data (we choose the type of model)
- The model is used to make predictions
- Example: fit a straight line through experiment data and use the formula to make predictions

Machine Learning is multi-disciplinary

Machine Learning is taught in computer science at all levels of education. It involves:

- Artificial Intelligence – Building Intelligent Entities (more than just working on data)
- Mathematics – statistics and probability, operational research, numerical analysis (numerical solutions rather than symbolic manipulation)
- Engineering
- Information theory – data and computer scientists
- Philosophy
- Control theory
- Psychology
- Neurobiology
- Business and management science
- Economics

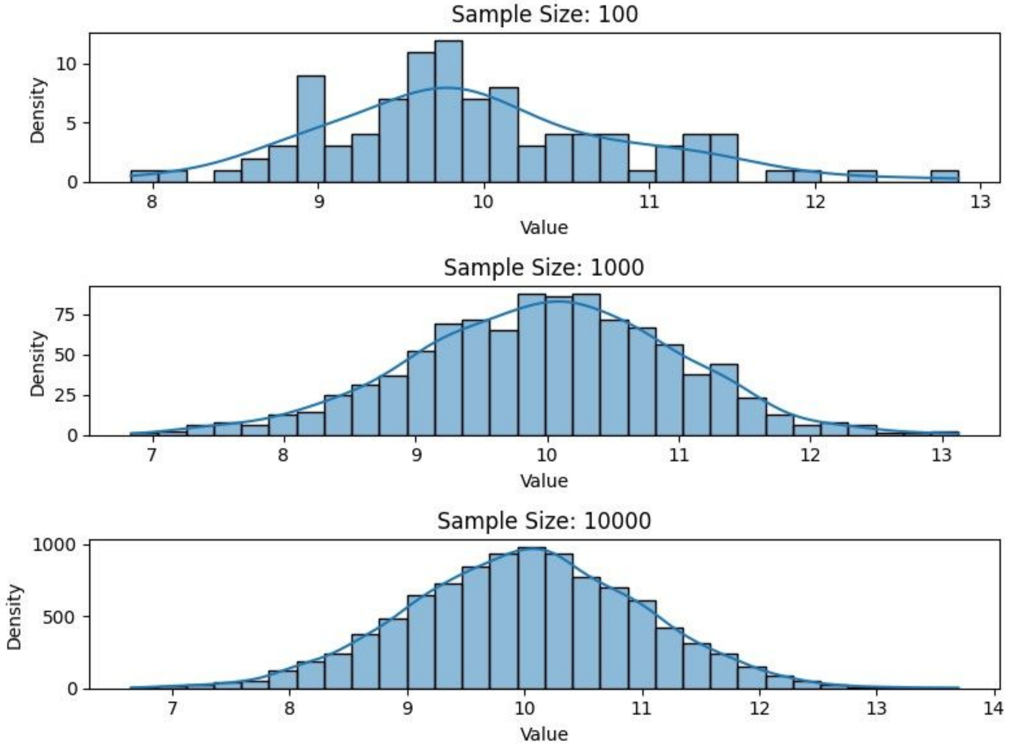
Stuart Russell & Peter Norvig – ‘AI is relevant to any intellectual task: it is truly a universal field.’

Machine Learning
– good data and algorithms

ML data:

Insufficient quantity of data (e.g. a child can recognise vegetables with a few prompts and then identify variations almost effortlessly)

- ML needs lots of data, not a few examples but 1,000,000s and 1,000,000s!
- Algorithms tend to perform better with the more data you have – Peter Norvig et al., 2009.
- Algorithms tend to converge on the right answer with enough data, provided they are fit for purpose.



If we don’t have enough data, we are missing part of the picture!

Machine Learning - **We Need Good Data**

ML data:

The wrong data set (e.g. teach a child about sponges and expect them to identify a face cloth)

- ML needs data that is representative of the problem you are learning about
- ML can suffer from BIAS (sample data from the wrong group)

We need to <u>mitigate the risks and detect biases</u>.

Column name	Description
CRIM	per capita crime rate by town
ZN	proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS	proportion of non-retail business acres per town
CHAS	Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
NOX	nitric oxides concentration (parts per 10 million)
RM	average number of rooms per dwelling
AGE	proportion of owner-occupied units built prior to 1940
DIS	weighted distances to five Boston employment centers
RAD	index of accessibility to radial highways
TAX	full-value property-tax rate per $10,000
PTRATIO	pupil-teacher ratio by town
B	1000(Bk - 0.63)^2 where Bk is the proportion of Black people by town
LSTAT	% lower status of the population
MEDV	Median value of owner-occupied homes in $1000's

The Boston Housing dataset: a case study on racism (source: Fairlearn)

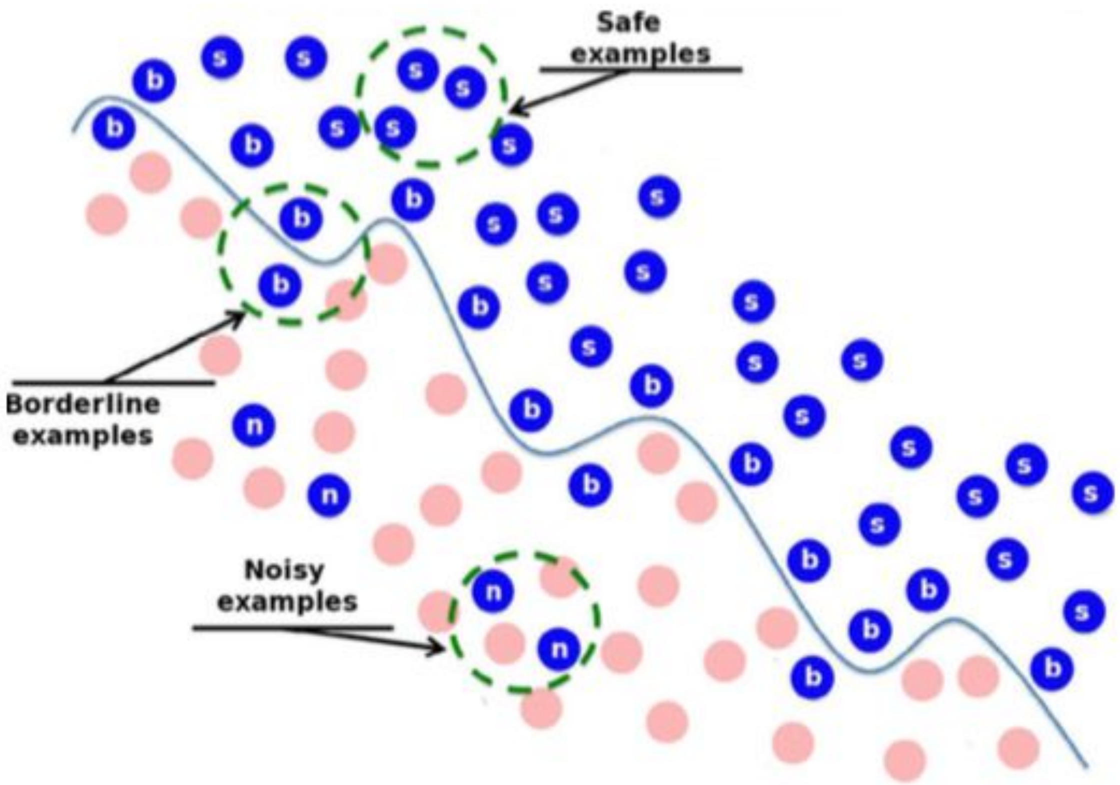
Machine Learning – Poor Data

ML data:

A poor data set (e.g. teach a child (partially) wrong answers to times tables)

- Might contain errors, randomness and/or noise, extremes
- Might contain irrelevant features
- Might contain different units for the same measurement

🗑️data → 🗑️model



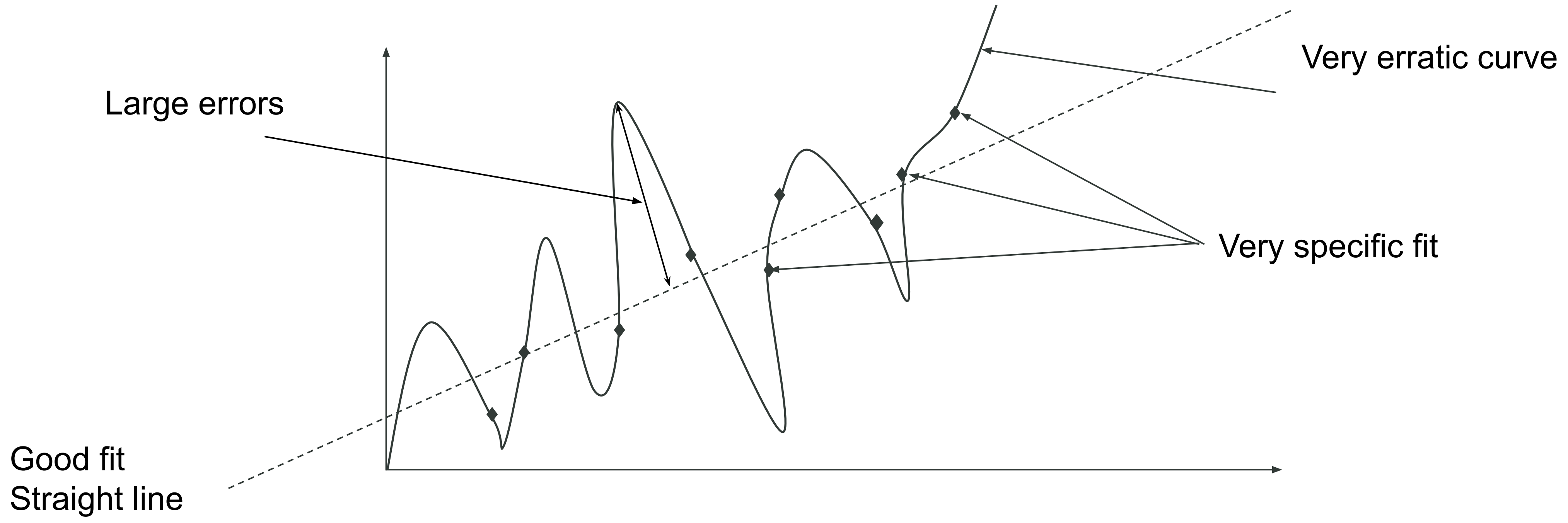
Source (interesting article): https://sci2s.ugr.es/noisydata

Machine Learning
– good data and algorithms

ML algorithms – we need good algorithms that don't suffer from:

Overfitting (e.g. a child is knocked over by a small cat and thinks all animals are clumsy.)

- It works well on the training data but not so well on general data.



Machine Learning
– good data and algorithms

ML algorithms – we need good algorithms that don’t suffer from:

Overfitting – (e.g. a child is knocked over by a small cat and thinks all animals are clumsy)

Cause: complexity too high

Potential solutions:

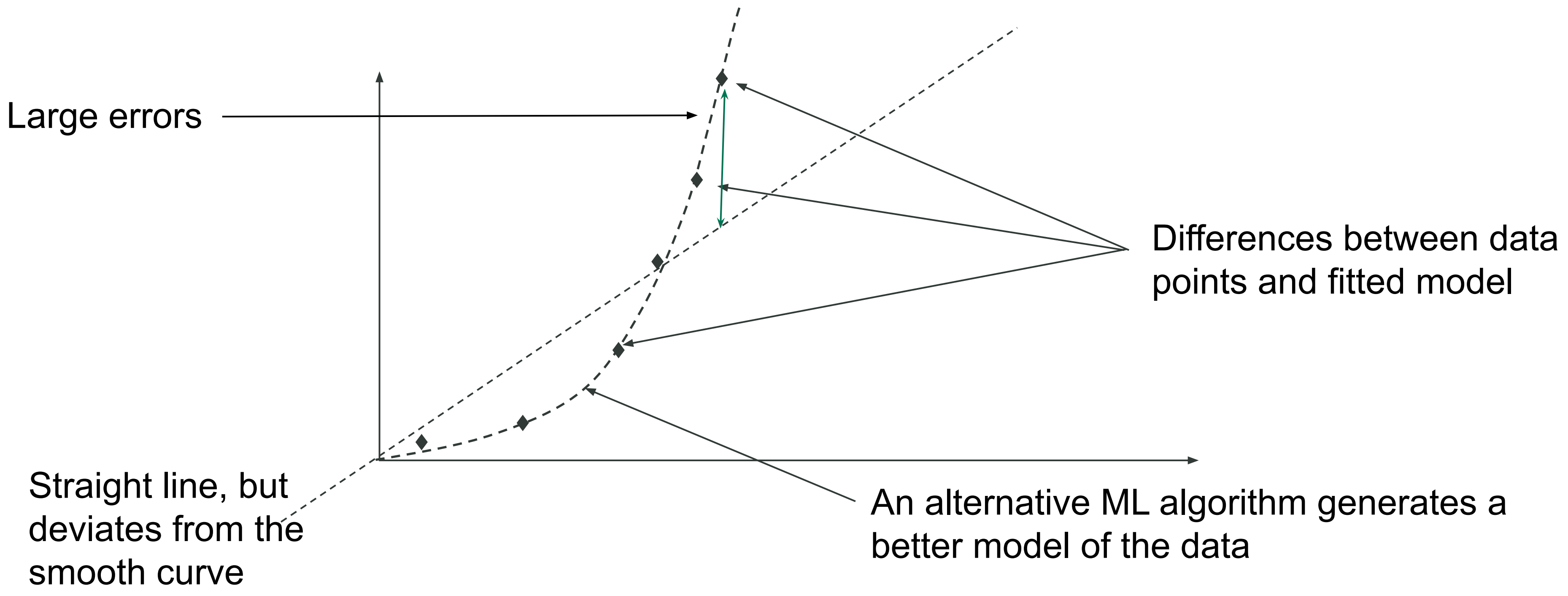
- Reduce the complexity of the algorithm.
- Reduce the number of attributes in the training data.
- Use more training data.
- Reduce the noise in the data (remove outliers that can distort the result).
- Constrain the model, make it simpler and limit the amount of overfitting.

Machine Learning
– good data and algorithms

ML algorithms – we need good algorithms that don’t suffer from:

Underfitting (e.g. a child is taught what food is then asked to pick out a red apple)

- Model is too simple/limited



Machine Learning
– good data and algorithms

ML algorithms – we need good algorithms with the best hyperparameters:

Hyperparameters are high-level descriptions of the ML and model we are training with the data:

- Fixed at the start of the training of the ML algorithm
- Cannot be determined from the dataset
- Need to be systematically tuned to obtain the best learning results

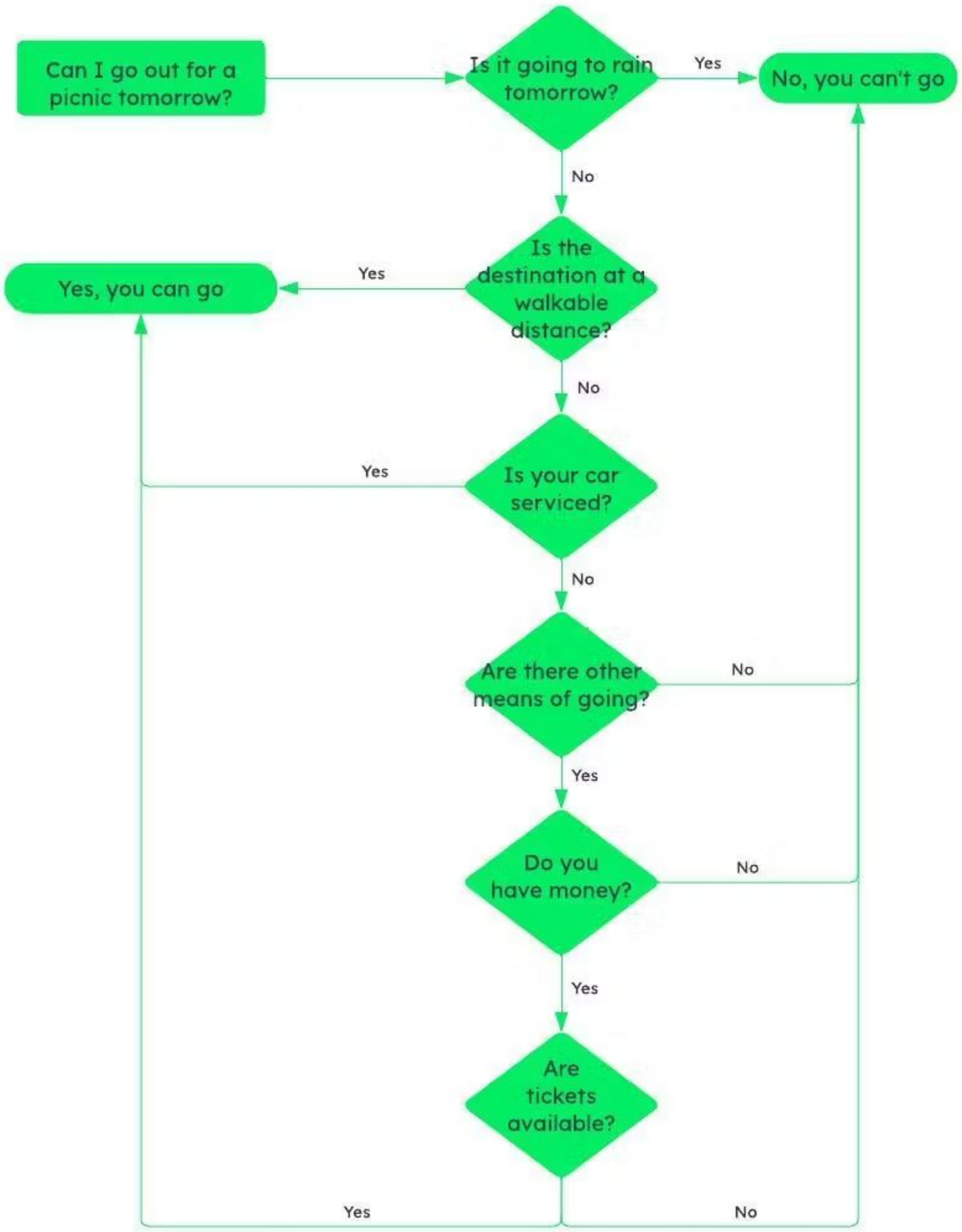
Examples are:

- Number of layers in a neural net
- Size of the dataset to train on

Hyperparameter Example

Decision trees are very similar to flowcharts

What is missing from a real world situation?



Source: https://www.mongodb.com/resources/basics/machine-learning

Hyperparameter Example

Decision trees are very similar to flowcharts

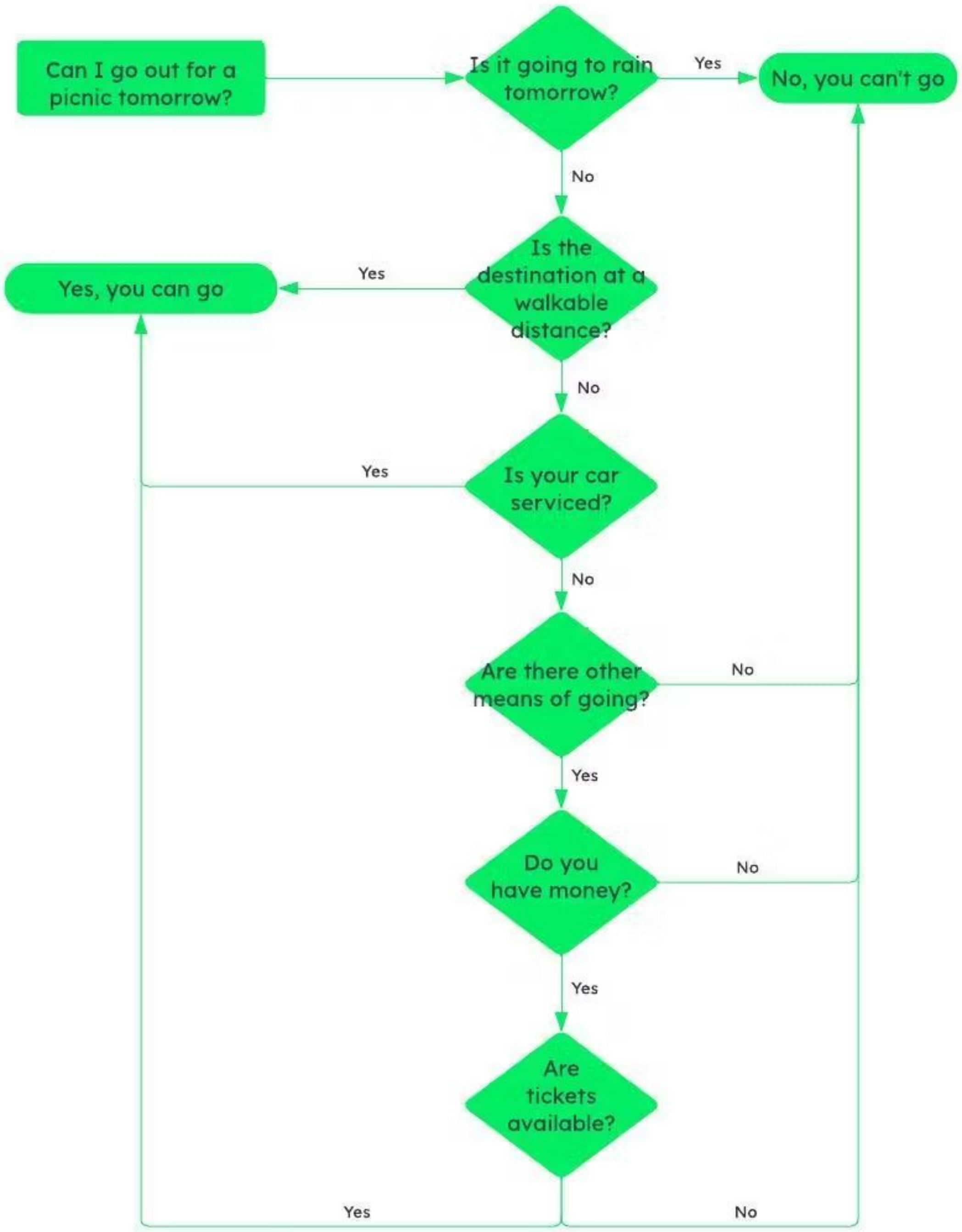
What is missing from a real world situation?

- "Do I know the route?"
- "Am I alone?"
- "Are there any taxis available?"
- etc.

If we keep adding more, the model will be very specific and prone to overfitting

Decision tree solution: maximum depth as a hyperparameter, random forests

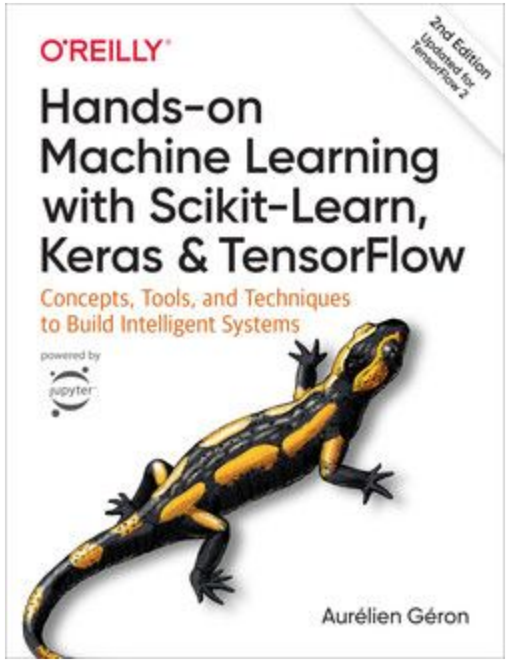
But maybe consider a different algorithm…



Source: https://www.mongodb.com/resources/basics/machine-learning

The Machine Learning Process

1. Look at the big picture
2. Get the data
3. Discover and visualize the data to gain insights
4. Prepare the data for machine learning algorithms
5. Select and train a model
6. Fine-tune your model
7. Launch, monitor and maintain your system



Source: Aurélien Geron, Hands-on Machine Learning

Test yourself!

What is hard to transform into value, requires specialist technology to learn from because it has large amounts of high volume, high velocity and variety of data?

(a) Weather simulations.

(b) Tax returns.

(c) World economy.

(d) Big Data.

Answer: ?

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Test yourself!

Optical Character Recognition (OCR) uses Machine Learning to interpret…

(a) Images of handwriting and text.

(b) Images.

(c) Technical drawings.

(d) Road signs.

Answer: ?

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Test yourself!

What does NLP stand for?

(a) National Language Process.

(b) Natural Language Processing.

(c) Natural Linear Processing.

(d) Non-Linear Programming.

Answer: ?

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Test yourself!

What type of data does Semi-supervised Machine Learning use?

(a) No data

(b) Random

(c) Labelled and unlabelled

(d) Expert System Data

Answer: ?

Test yourself!

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(a) No data

(b) Random

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(d) Expert System Data

Answer: ?

Test yourself!

Swarm Intelligence and optimisation are used in what type of Machine Learning?

(a) Revision Learning

(b) Repeat Learning

(c) Reinforcement Learning

(d) Reflective Practice Learning

Answer: ?

Test yourself!

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Answer: ?

Test yourself!

Who is not part of a Machine Learning project team?

(a) Data scientist

(b) Computer scientist

(c) Questionnaire specialist

(d) Statistician

Answer: ?

Test yourself!

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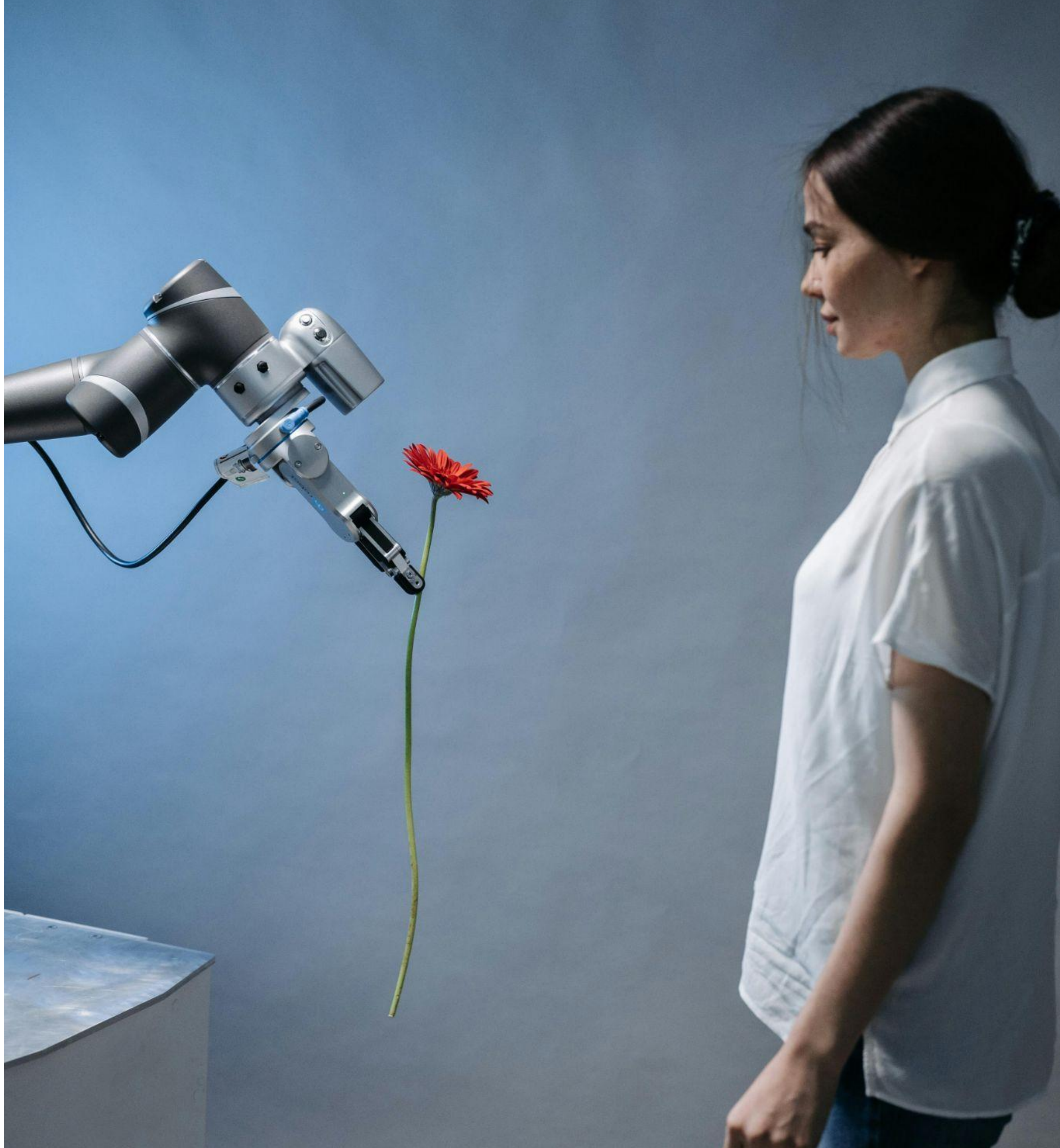
Answer: ?

💡 Exercise: The Early Concept

Ask yourself some questions about your own AI/ML concept:

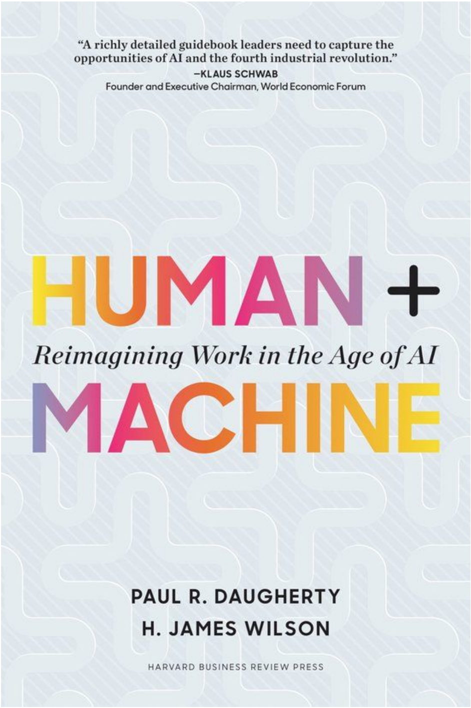
- Where do you think you can obtain data?
- Would the data contain a lot of numerical data? Would the data contain a lot of text?
- Does your data contain any labels?
- What kind of ML algorithm do you think is best suited for your task?
- What are some of the ethical challenges in using this data?

Human
+
Machine



Ethics

- Humans have their own strengths and weaknesses
- So do computers
- Daugherty and Wilson propose the missing middle in their book



Robotics guidelines EPSRC (UK)

5 principles and 7 high-level messages to encourage responsibility

- Broken down into a legal, general audience and commentary

General audience principles

1. ‘Robots should not be designed as weapons, except for national security reasons.’
2. ‘Robots should be designed and operated to comply with existing law, including privacy.’
3. ‘Robots are products: as with other products, they should be designed to be safe and secure.’
4. ‘Robots are manufactured artefacts: the illusion of emotions and intent should not be used to exploit vulnerable users.’
5. ‘It should be possible to find out who is responsible for any robot.’

Ethics in AI

General background:

https://en.wikipedia.org/wiki/Ethics_of_artificial_intelligence#Machine_ethics

Common theme:

Open and transparent Open Source Code.

Do no harm.

The culture in AI research and AI community is now developing AI for good:

- Just like chemists make medicine not poison.
- Engineers continually make cars safer, less polluting…

BUT: What happens if Super AI develops consciousness – <u>WE DO NOT KNOW</u>

Human consciousness

Philosophical subject – studied for centuries (René Descartes (1596–1650): ‘I think therefore I am.’)

It is subjective and depends on the individual.

Professor David Chalmers has broken this down into Easy and Hard Questions of Consciousness.

Easy Consciousness Question: Explaining the ability to discriminate, integrate information, report mental states, focus our attention, etc …

Hard Consciousness Question: The hard problem of consciousness is the problem of experience. https://en.wikipedia.org/wiki/Hard_problem_of_consciousness

Synthetic consciousness, Artificial General AI and Robotics are NOT going to help us with the hard problem any time soon and even if we did solve it, David Chalmers thinks it might be confusing, a bit like quantum theory!

Humans provide the subjective

René Descartes (1596–1650): ‘An optimist may see a light where there is none, but why must the pessimist always run to blow it out?’

Benjamin Franklin (1706–1790): ‘Tell me and I forget. Teach me and I remember. Involve me and I learn.’

Daugherty and Wilson (*Human Plus Machine*):

- Human roles
- Hybrid human plus machine roles
- Machine roles

Max Tegmark (*Life 3.0*):

- Humans ensure AI is aligned with human goals.

‘Humans only’ roles

From Daugherty and Wilson:

- Leadership
- Ethics
- Judgement
- Creativity

Humans complement machine by …

Training – e.g. teaching AI systems to adapt to us, how to do a task, both individuals and groups teaching AI

Explaining – e.g. explaining why a black box AI system is acting the way it is especially when it goes against conventional wisdom

Sustaining – e.g. limiting the application of AI (including robotics) based on legal, sustainability or ethical compliance. IT’S NOT JUST A BUSINESS CASE.

From Daugherty and Wilson

AI enhances humans by …

Amplifying – Extraordinary data insight, searches the web in seconds, optimises engineering design, fast diagnosis of medical issues for doctors

Interacting – personal assistant roles in customer service, FAQs on helplines – LEAVES humans to deal with awkward ambiguous problems

Embodying – works in physical spaces via sensors, motors, actuators, robots for collaborative work with humans

From Daugherty and Wilson

Humans drive the change

Humans are a fundamental and integral part of re-imagining our life with AI, they:

- Set the goals.
- Set the ethics.

Deep Neural Networks have boosted Machine Learning capability.

General AI, Consciousness AI, Subjective AI are unknowns – we are not sure what the future holds.

In the short to medium term – we can become more human as we embrace AI and the Fourth Industrial Revolution.

Asilomar principles

‘Our Call to Action – Re-imagining every aspect of our lives with AI’

The Beneficial AI Conference 2017 developed the Asilomar principles for AI. There are 23 principles relating to:

Research

Goals, funding, policy, cultures, race avoidance (speed of progress)

Ethics and values

Safety, failure transparency, judicial transparency, responsibility, value alignment, human values, personal privacy, liberty and privacy, shared benefit, shared prosperity, human control, non-subversion, AI arms race

Longer term issues

Capability caution, importance, risks, recursive self-improvement, common good

Get the KASH

‘Our Call to Action – Re-imagining every aspect of our lives with AI’

Knowledge Start ‘learning from experience’, with some AI ML help.

Attitude The right attitude determines the outcome.

Skills Develop the skills (e.g. Agile Project Management – ‘learning from experience’ at its heart).

Habits Make these habits.

Test Yourself!

Artificial Intelligence, machines and humans will develop a new, exciting future by…

(a) Learning to complement each other.

(b) Specialising in one focused task.

(c) Building a new society, one for machines and one for humans.

(d) Allowing machine ethics to drive human ethics.

Answer: ?

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💡Exercise Three: Re-imagining the future opportunities for AI and human systems

Objective: Explore some key questions of what the future holds for human and machine augmented systems

1. Give three examples of where a human is the best at undertaking an activity
2. Give three examples of where a machine is the best at undertaking an activity
3. Give three examples of where a machine augments a human
4. Give three examples where a human augments a machine
5. Name three examples of jobs you think will not be replaced by machines in the next 50 years.

Conclusion and reading list

What have we learned ?

- The history of AI
- The definition of AI
- The focus on Machine Learning
- ML project basics
- Benefits, challenges, risks
- The future of human + machine

What’s in it for me?

- Understanding (Artificial) Intelligence and its history
- Exploring the benefits, risks, and challenges of AI
- Preparing for a future where AI is everywhere

Image by RosZie (Pixabay)

Key Takeaways

- ❖ Artificial Intelligence is already all around us and will impact our life in many ways
- ❖ AI is developing rapidly and regulations are still in the works
- ❖ Machine learning, while powerful, comes with many challenges and requires good quality data and good quality algorithms
- ❖ Applying AI is not a catch-all solution

Reading list

Artificial Intelligence and Consciousness

Artificial Intelligence, A Modern Approach, Third Edition, Stuart Russell and Peter Norvig, 2016, ISBN-10: 1292153962

The Conscious Mind, David Chalmers, 1996, ISBN: 9780195117899

Life 3.0, Max Tegmark, Penguin Books, 2017, ISBN: 9780141981802

High-Level Management Consultants' View

The Fourth Industrial Revolution, Klaus Schwab, Penguin Random House, 2016, ISBN: 9780241300756

Human + Machine – Re-imagining Work in the Age of AI, Paul R. Daugherty and H. James Wilson, Harvard Business Review Press, 2018, ISBN-10: 1633693869.

Reading list

Get Started on Machine Learning

Machine Learning For Absolute Beginners: A Plain English Introduction (Second Edition), Oliver Theobald, 2017, ISBN-10: 1549617214.

High Level Research and Political View of Machine Learning

https://royalsociety.org/topics-policy/projects/machine-learning/

Professional Development of Machine Learning Algorithms and Planning

Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, Aurélien Géron, O’Reilly, 2017, ISBN-10: 1491962291.

Machine Learning – A Probabilistic Perspective, Kevin P. Murphy, MIT, 2012, ISBN-10: 0262018020

The End

Thank you for your participation!