KPMG

Actuary vs Artificial Intelligence

Technology Advisory

—

August 24th 2018

KPMG

01

Story of AI

02

Models and applications

03

Actuary & AI

04

Q&A

KPMG

01 Story of AI


ALPHAGO
01:59:25
AlphaGo
Lee Sedol


IN THIS BUILDING DURING THE SUMMER OF 1956
JOHN McCARTHY (DARTMOUTH COLLEGE), MARVIN L. MINSKY (MIT),
NATHANIEL ROCHESTER (IBM), AND CLAUDE SHANNON (BELL LABORATORIES)
CONDUCTED
THE DARTMOUTH SUMMER RESEARCH PROJECT
ON ARTIFICIAL INTELLIGENCE
FIRST USE OF THE TERM "ARTIFICIAL INTELLIGENCE"
FOUNDING OF ARTIFICIAL INTELLIGENCE AS A RESEARCH DISCIPLINE
"To proceed on the basis of the conjecture
that every aspect of learning or any other feature of intelligence
can in principle be so precisely described that a machine can be made to simulate it."
IN COMMEMORATION OF THE PROJECT'S 50th ANNIVERSARY
JULY 13, 2006

1956

EARLY COMPUTER VISION & PERCEPTION SYSTEM

ONE OF THE
FIRST SELF
DRIVING ROBOTS

EARLY NATURAL LANGUAGE PROCESSING LAB

"The spirit is willing, but the flesh is weak. "

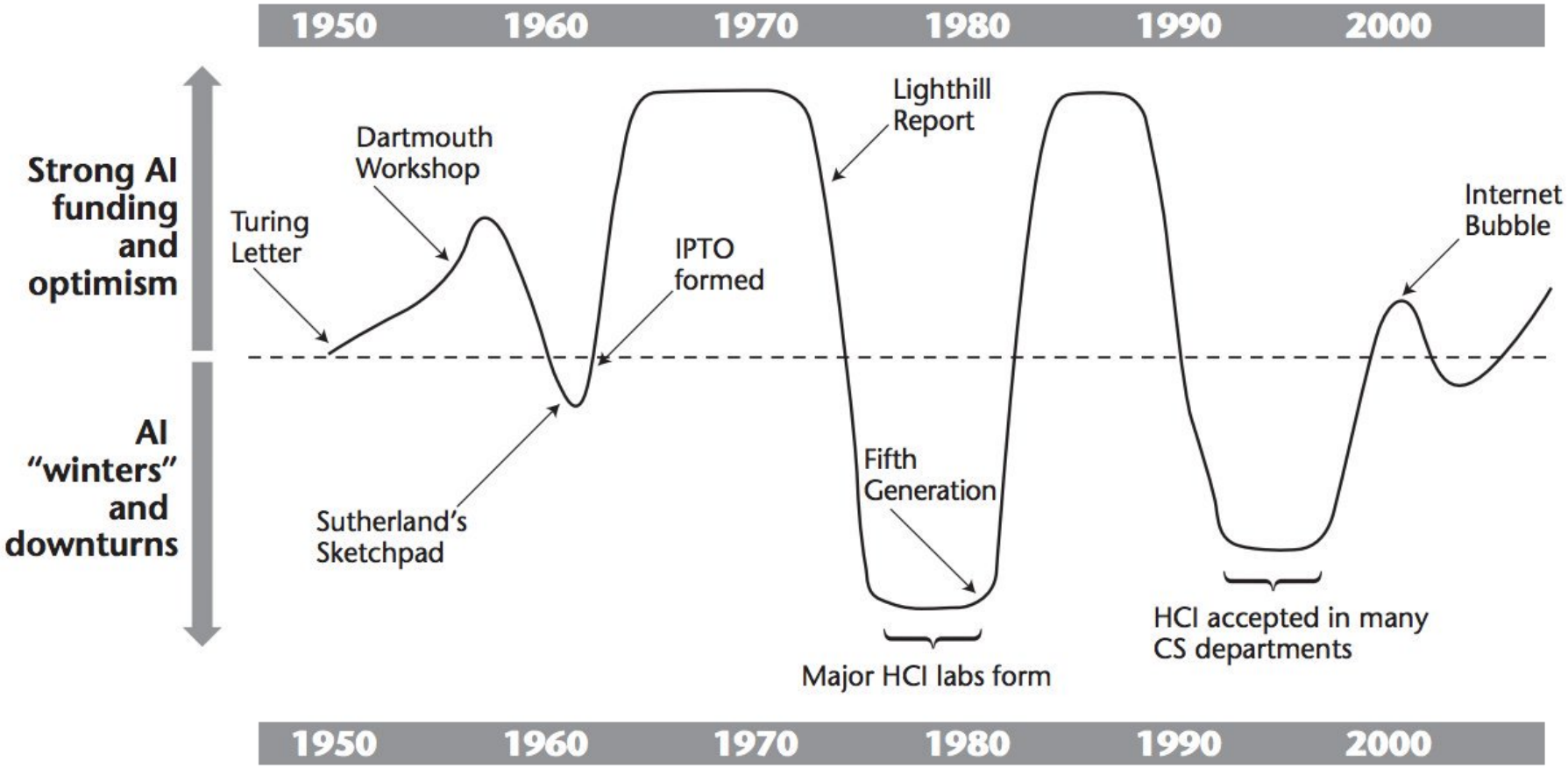
after

English - Russian - English

"The whisky is strong, but the meat is rotten."


2

Will it be THE NEXT BIG THING?



3 exponential laws

Moore's law

predicts the exponential increase of processing power of computers

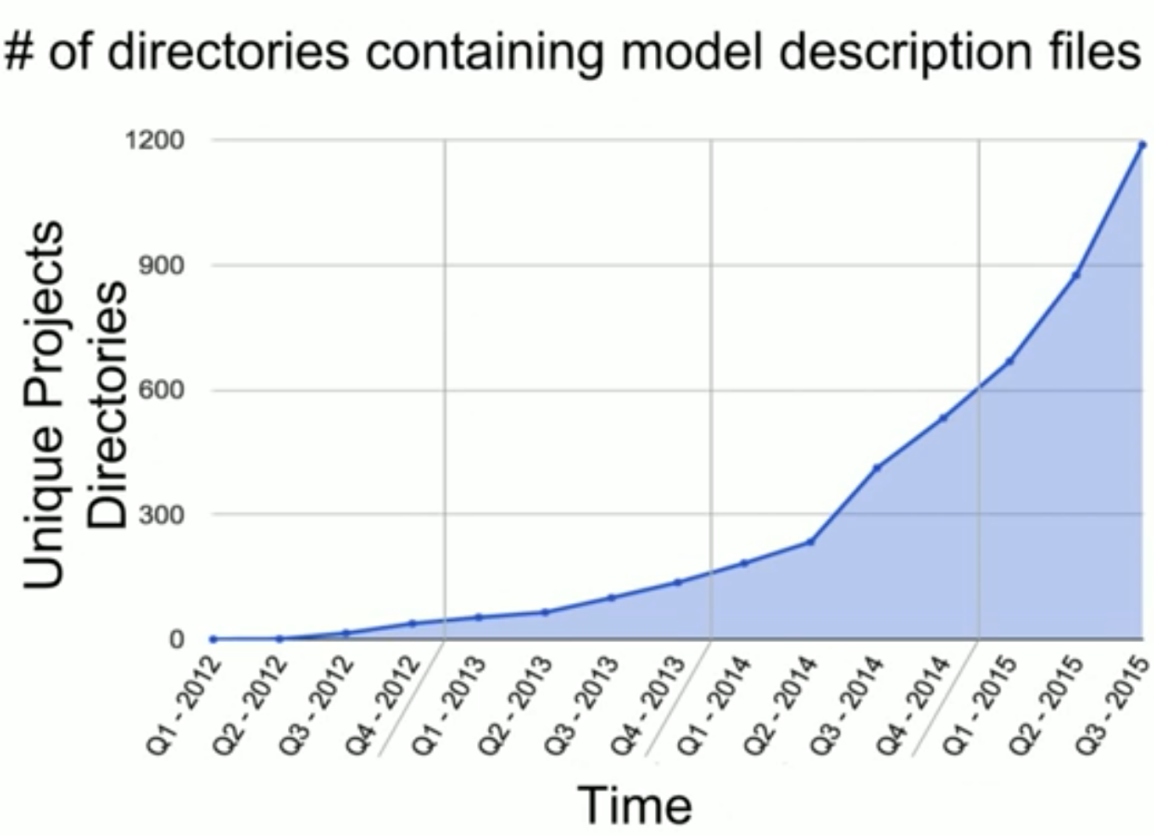
Metcalfe's law

talks about how the value of a network increases proportionally to the number of connected users to the system

Kryder's law

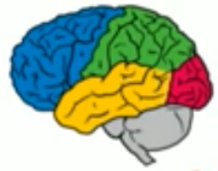
looks into storage expansion

Growing Use of Deep Learning at Google

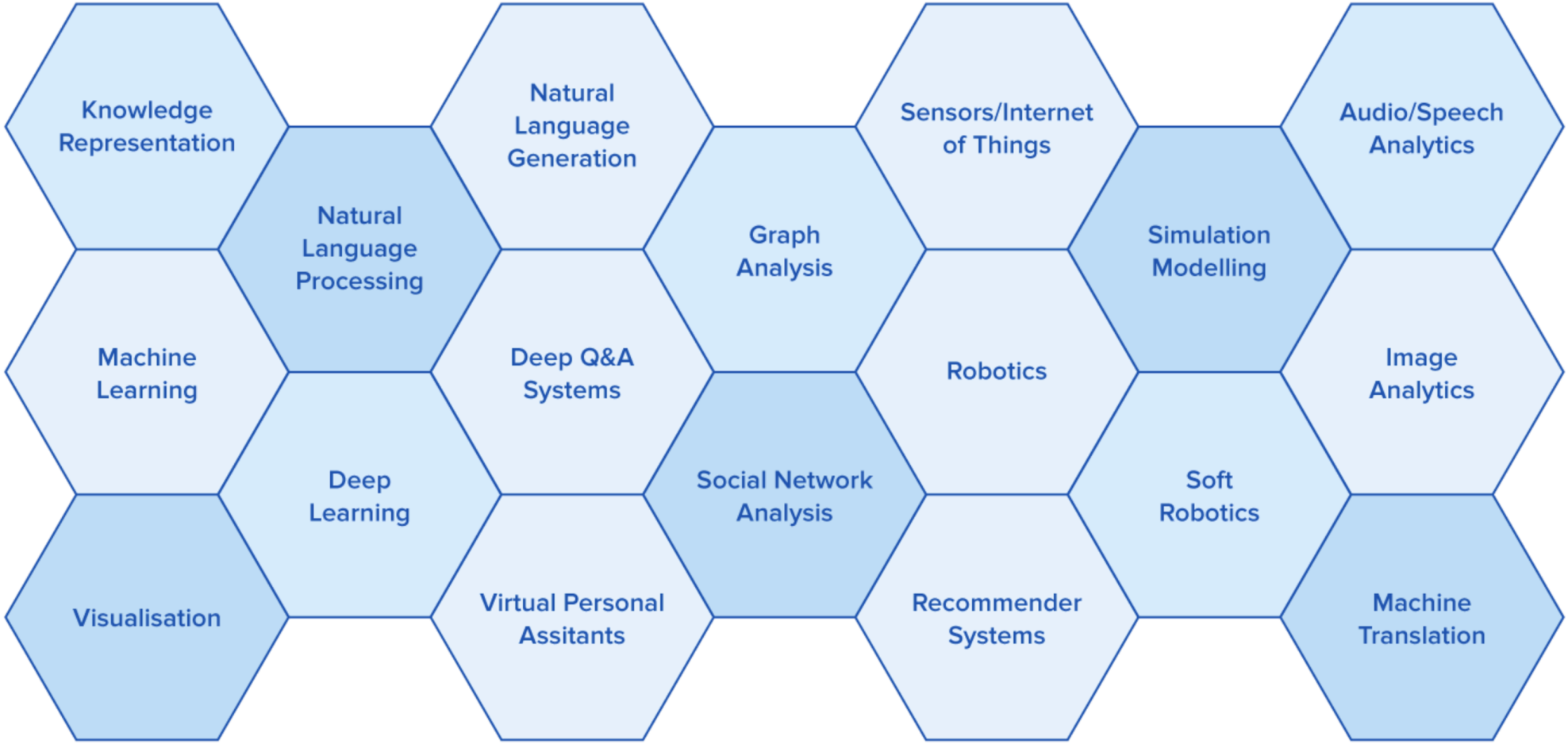


Across many products/areas:

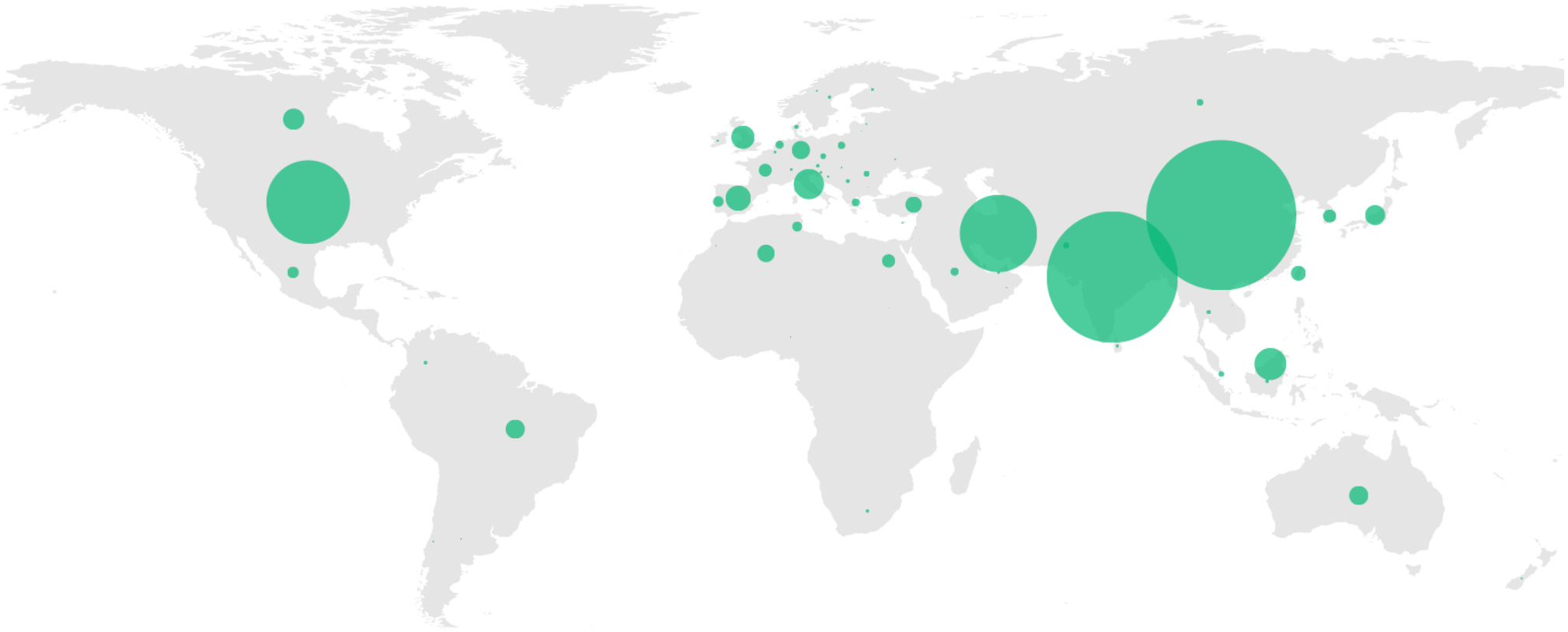
Android
Apps
GMail
Image Understanding
Maps
NLP
Photos
Speech
Translation
many research uses..
YouTube
… many others ...



AI development topics



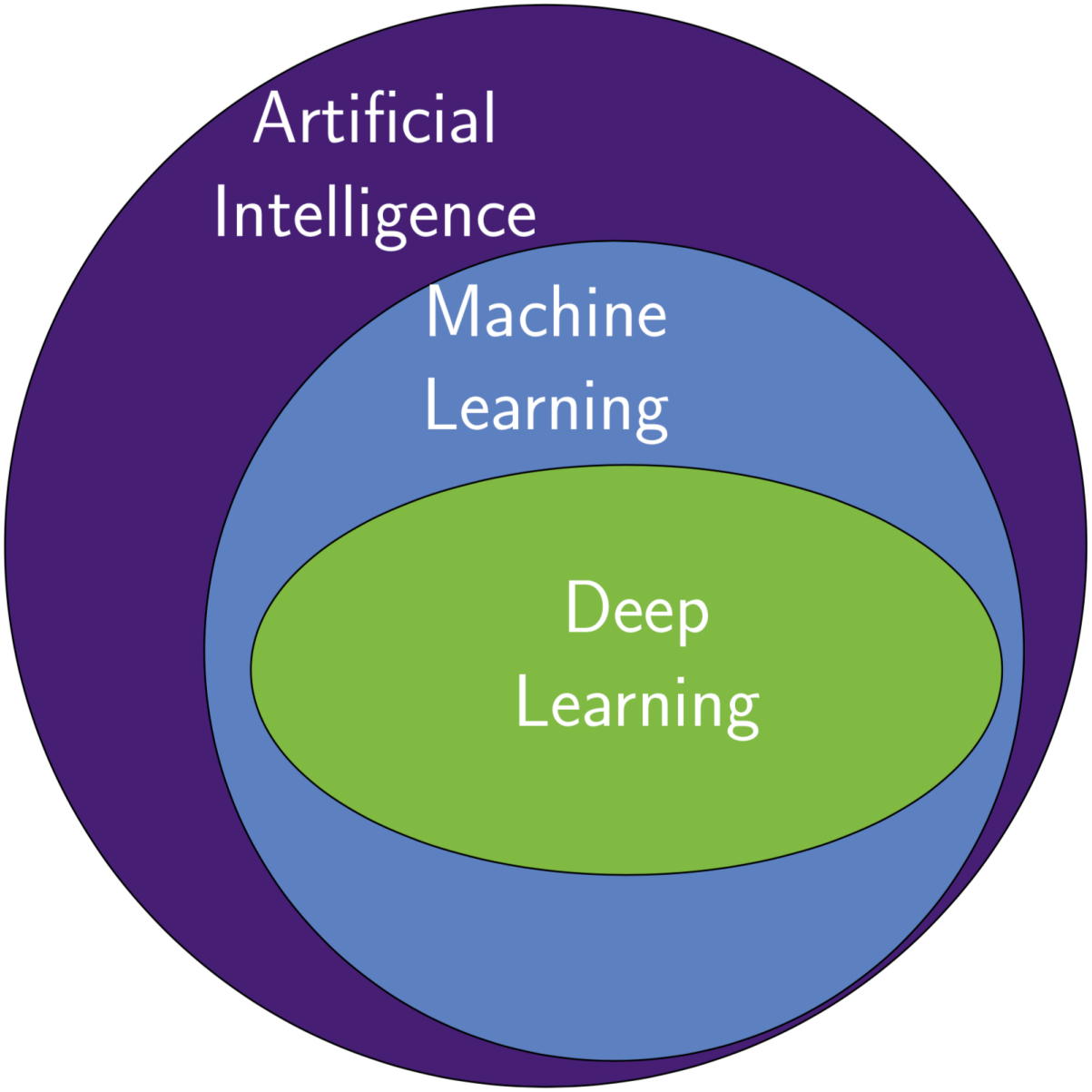
Countries by activity in AI research



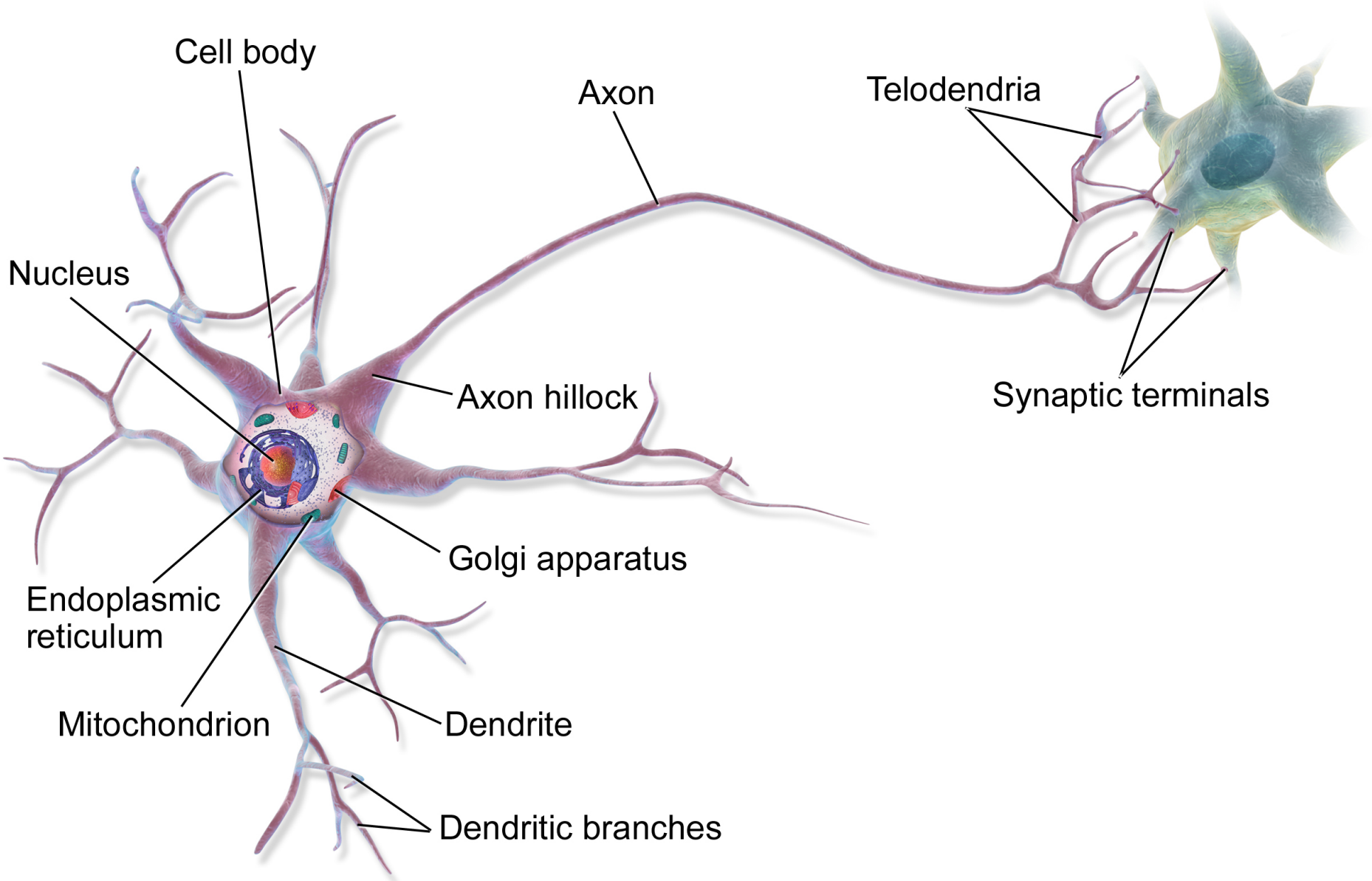
KPMG

02 Models and applications

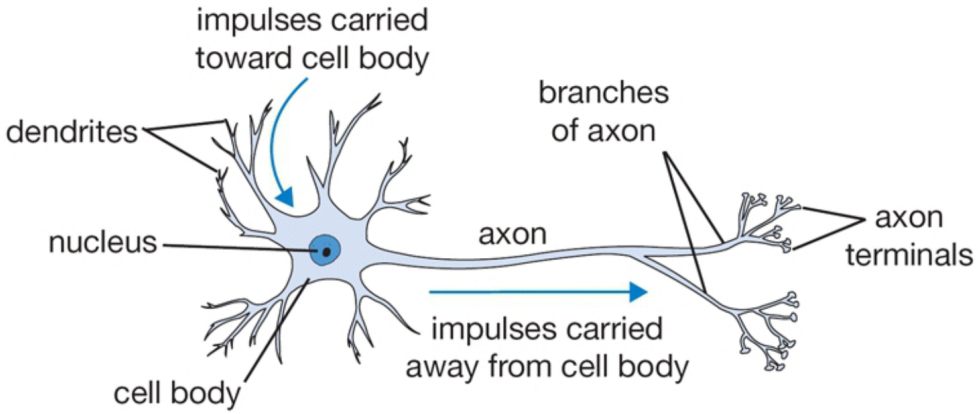
Definitions

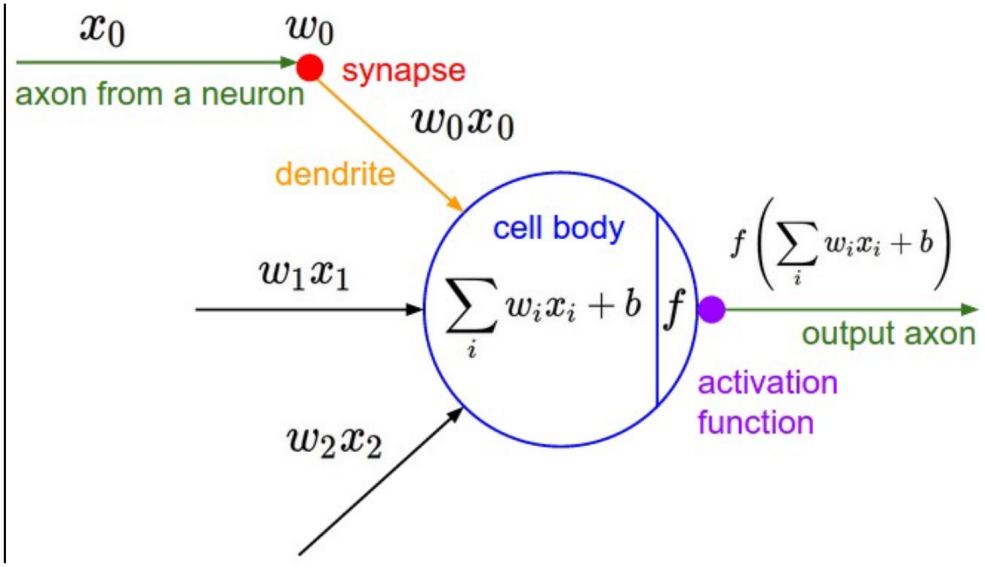


KPMG


Cell body
Axon
Telodendria
Nucleus
Axon hillock
Synaptic terminals
Golgi apparatus
Endoplasmic reticulum
Mitochondrion
Dendrite
Dendritic branches

bio / ML neuron





1 + 6 = 7

3 * 13 = 39

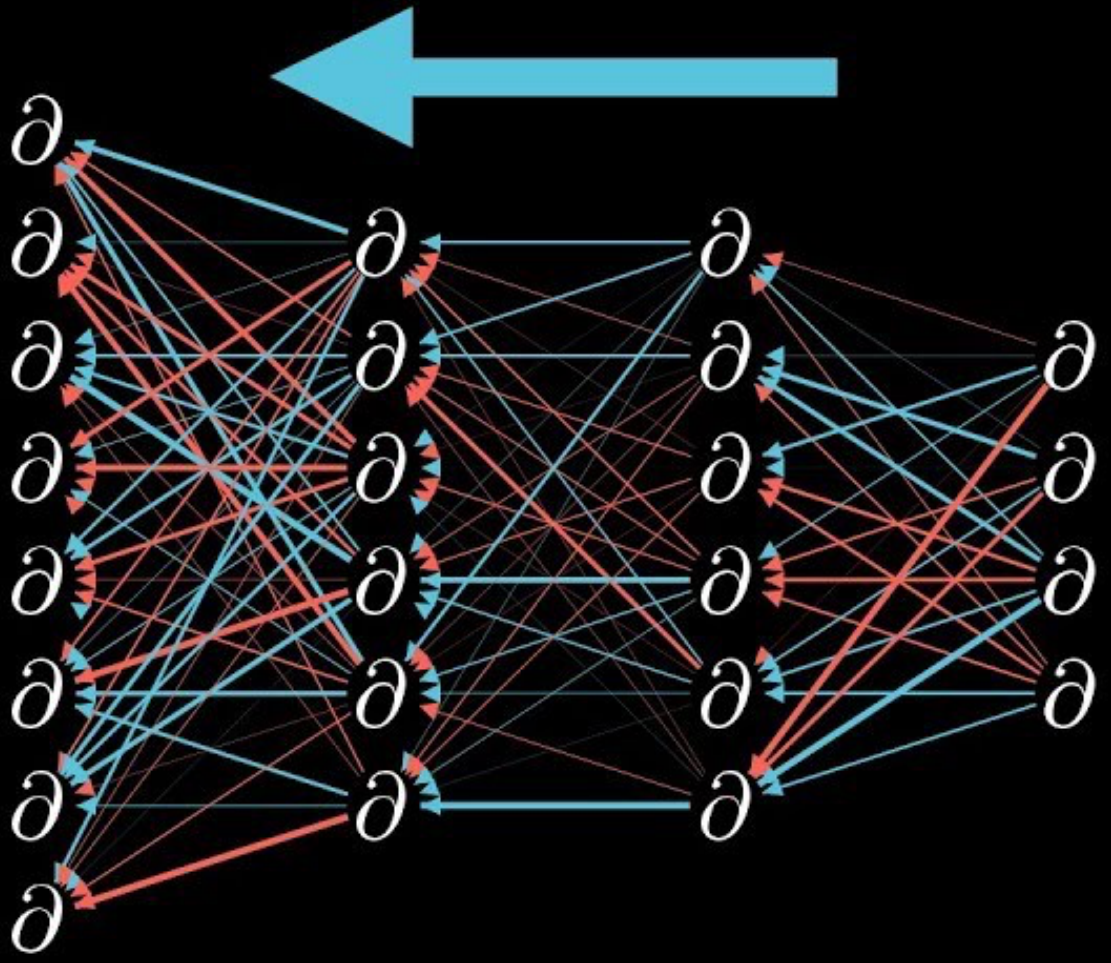
9 / 9 = 1

1 6 = 7

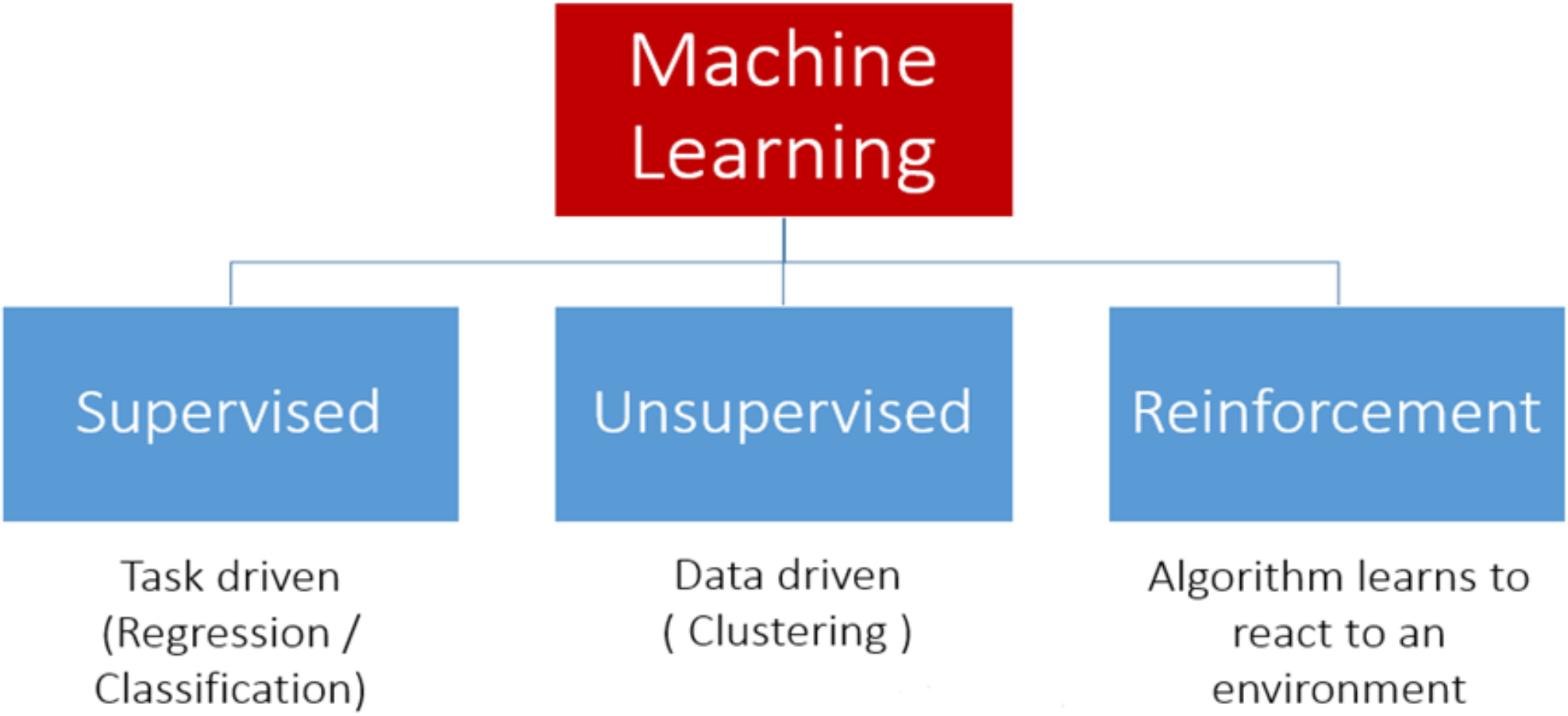
3 13 = 39

9 9 = 1

Backpropagation calculus



Types of Machine Learning



ML algorithms

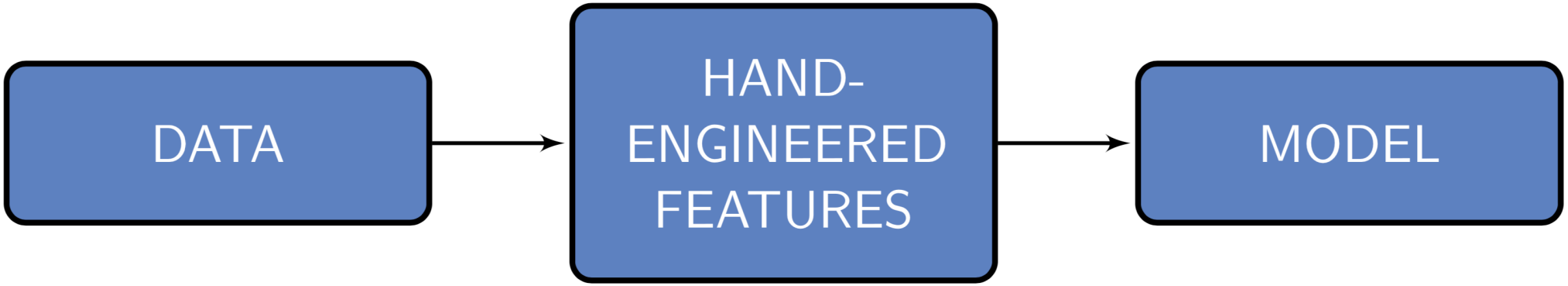
Supervised learning

- Decision trees;
- Random forests;
- Gradient boosted machines;
- Generalised linear models;
- Support vector machines;
- K-nearest neighbour;
- Neural networks.

Unsupervised learning

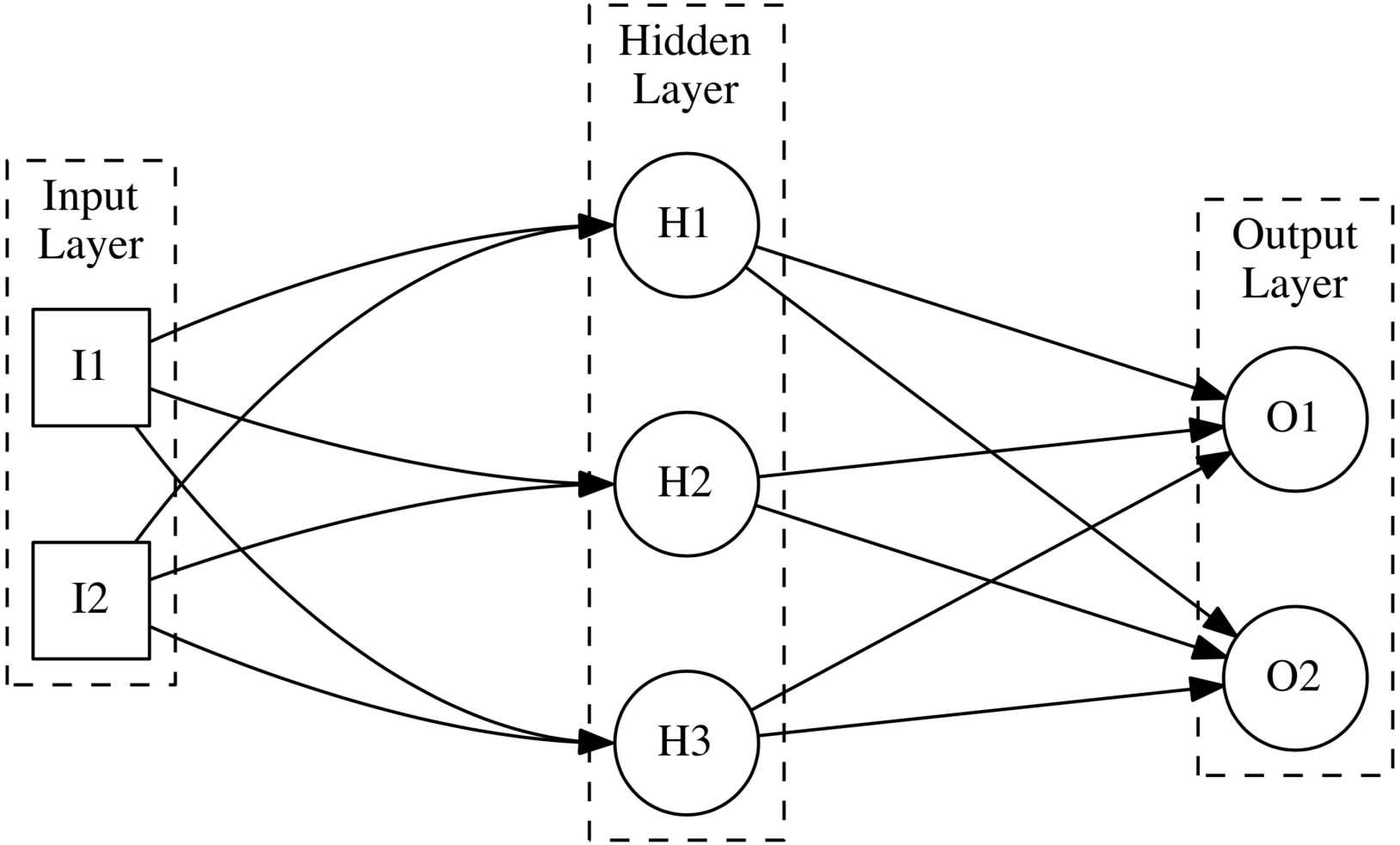
- K-means clustering;
- K-nearest neighbour;
- Hierarchical clustering;
- Principal component analysis;
- Support vector machines;
- Neural networks.

ML vs Deep Learning

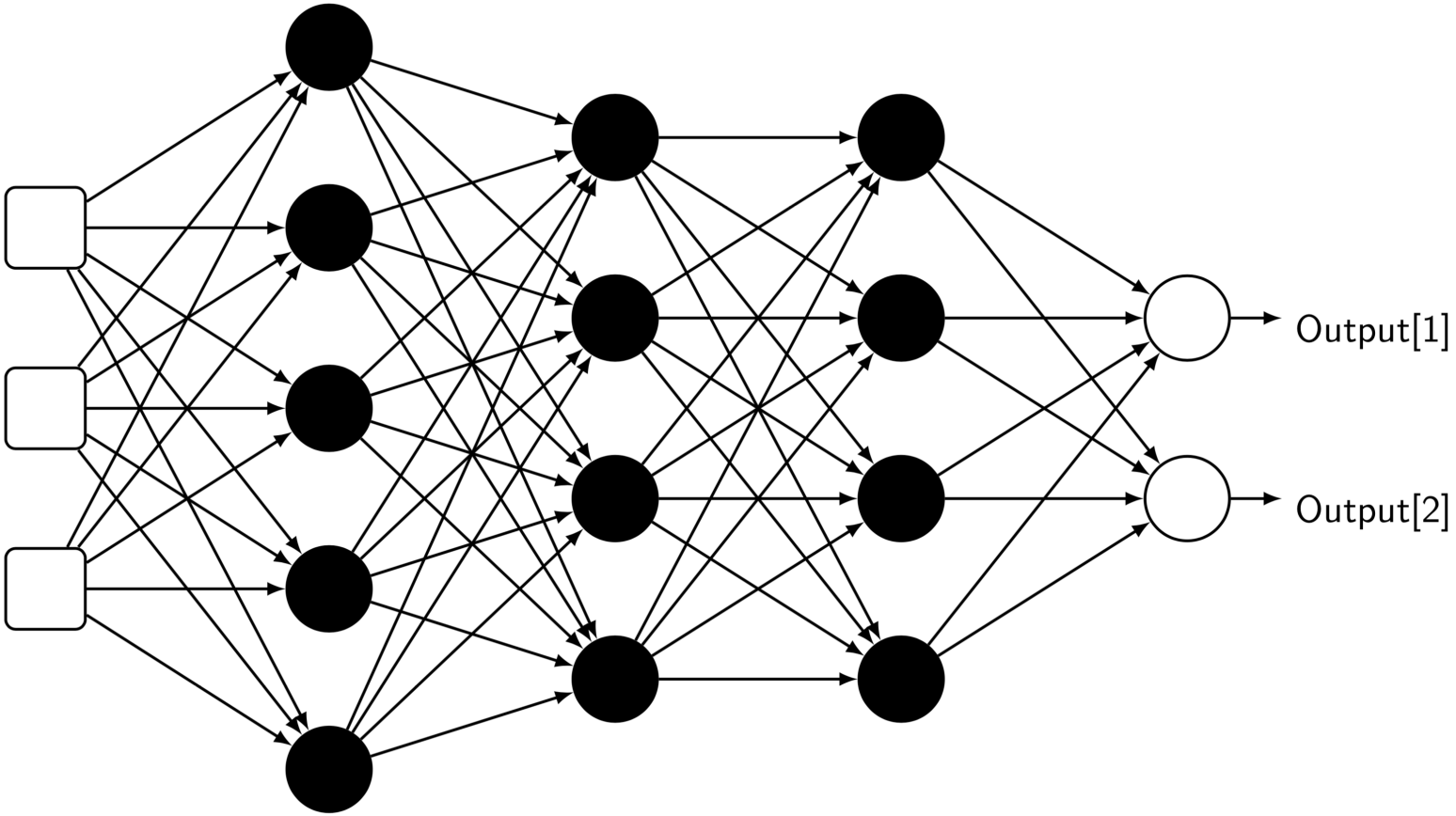


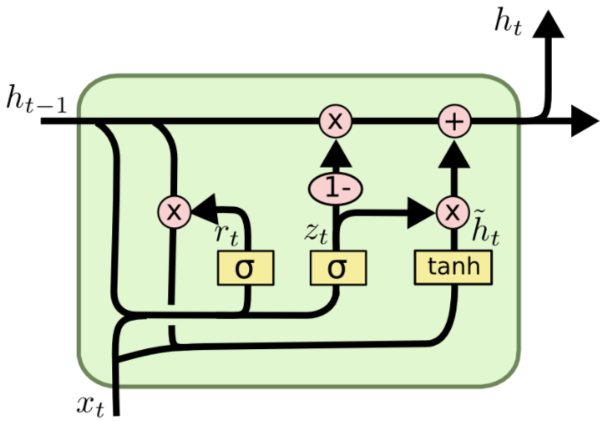
ML vs DL

Neural Network

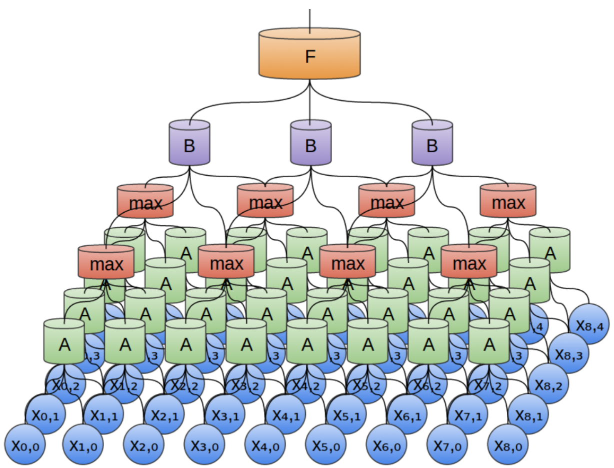


Deep Neural Network

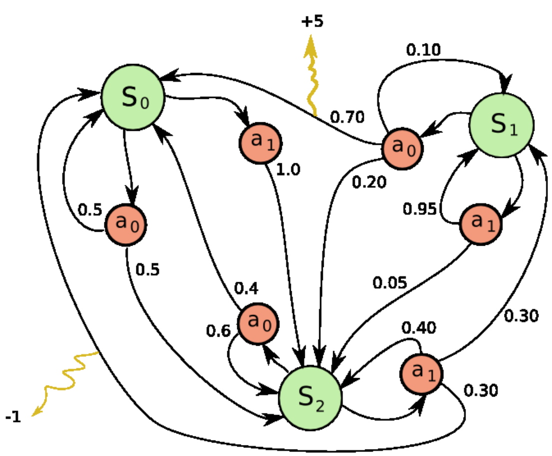




Recurrent Neural Network (LSTM RNN)



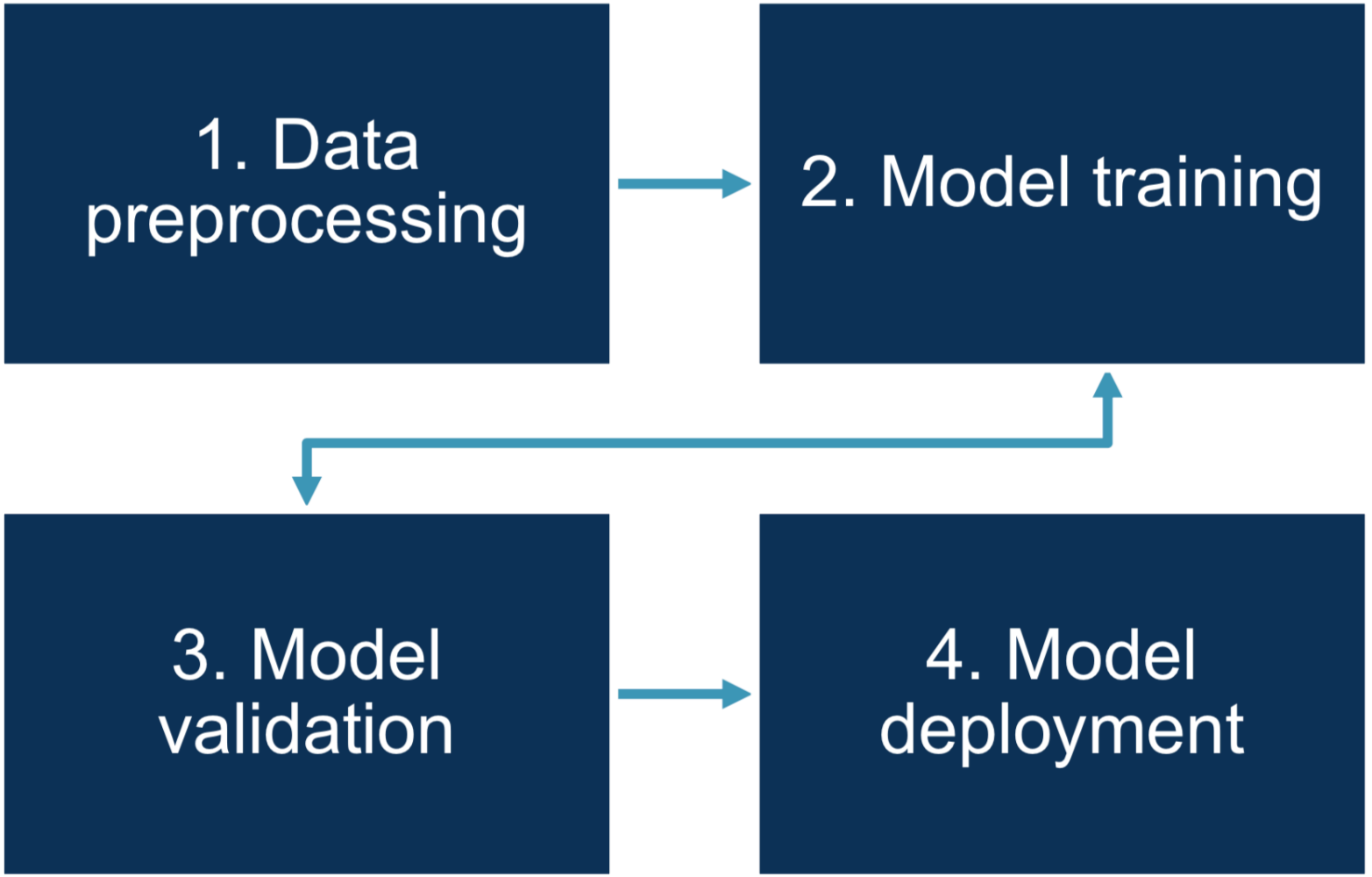
Convolutional Neural Network (CNN)

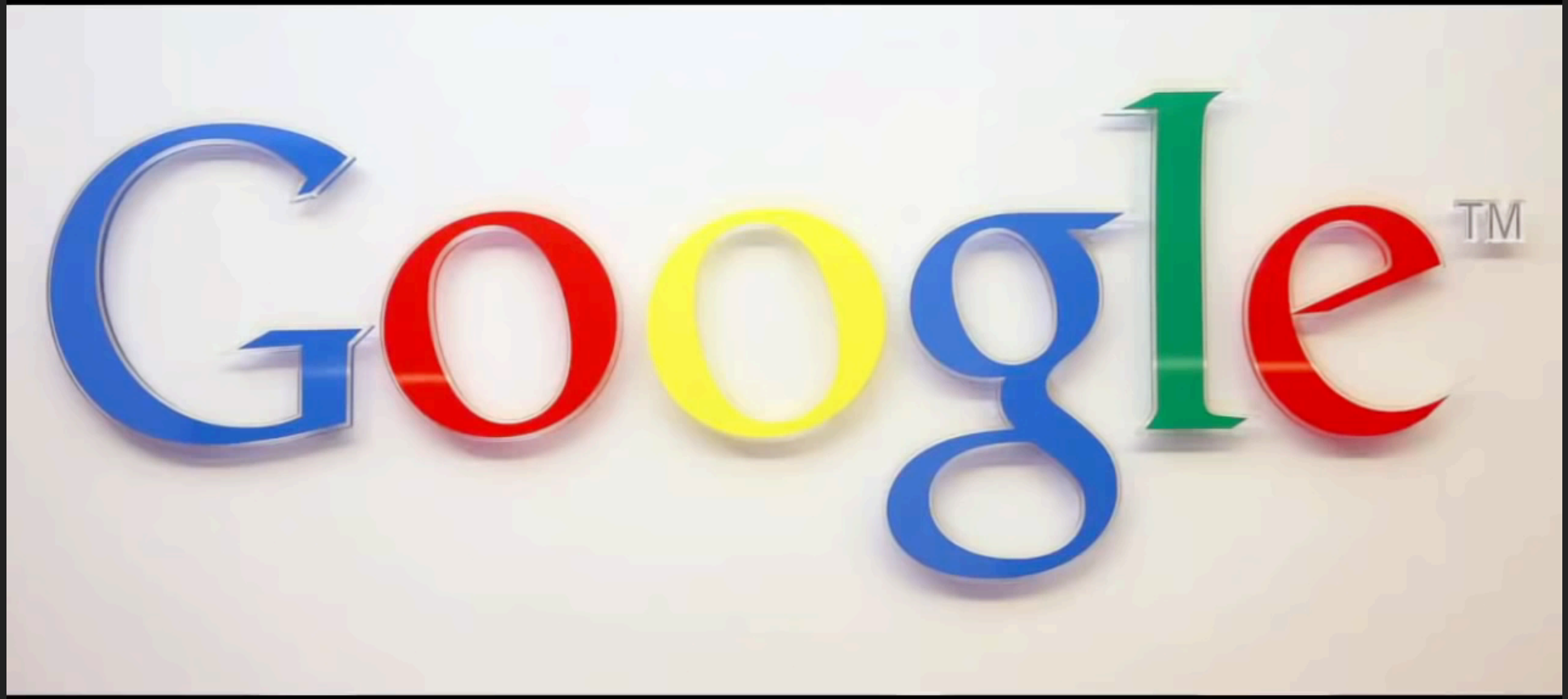


Reinforcement Learning Neural Network

...

DP path


1. Data preprocessing
2. Model training
3. Model validation
4. Model deployment

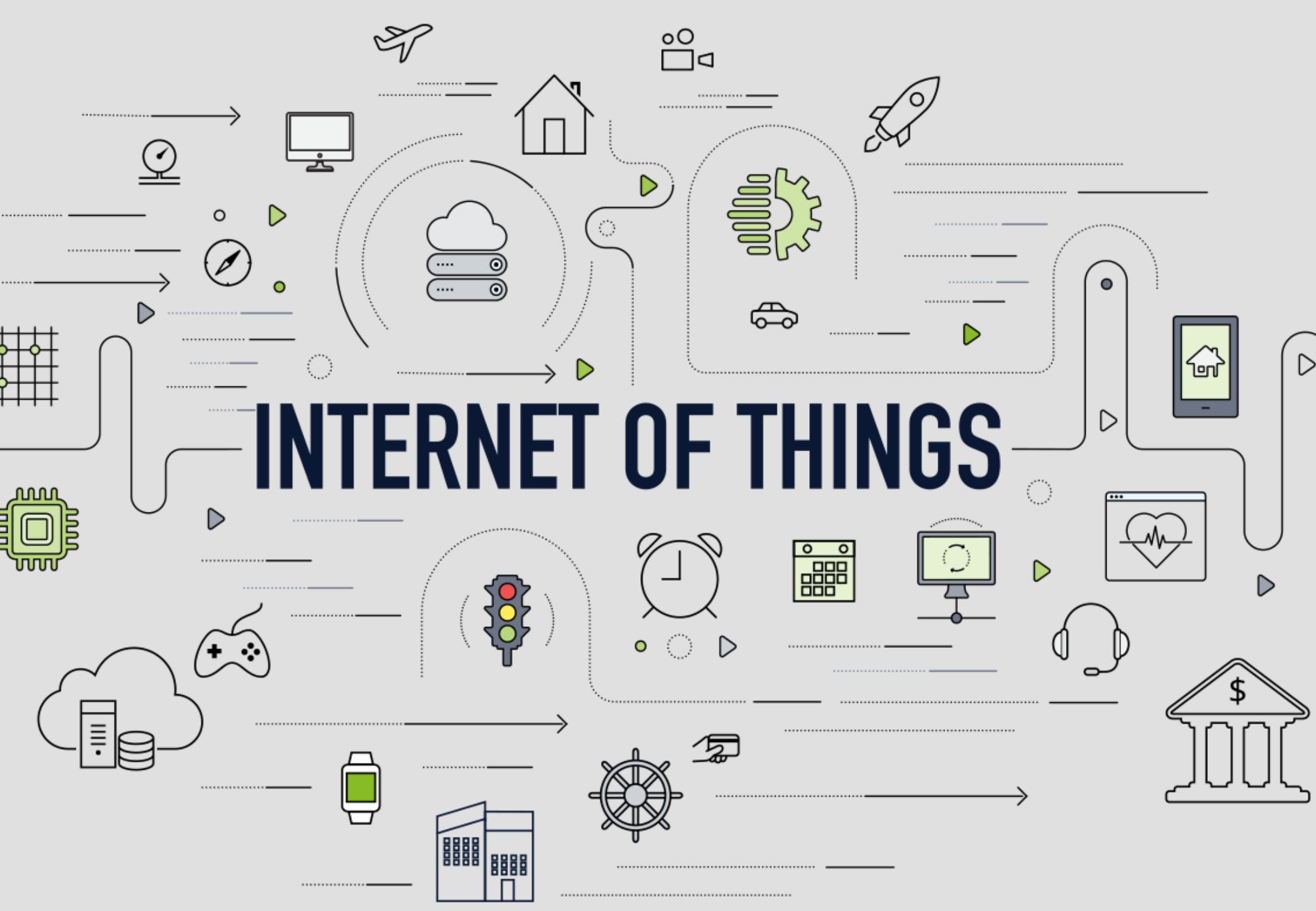

Google™

KPMG

03 Actuary & AI

Will AI make actuary profession obsolete?

NO


INTERNET OF THINGS

Why AI/ML should matter to you?

Improved Data Quality

Opportunity to improve the quality of data which businesses are using.

As competitors start utilising better data, businesses not attempting to do the same may become left behind.

Higher quality data will produce better models regardless of the techniques being employed.

New Data Sources

ML potentially opens up opportunities to explore alternative data sources, i.e., text fields could be explored to understand key themes and images could potentially be incorporated into predictive models.

Speed of Analysis

Much time taken to produce a model is used to gather, clean and manipulate data. These tasks will largely be similar, regardless of the methods used. Once a modelling data set has been produced, machine learning can be beneficial. Models can generally be fitted and validated in a short space of time, allowing tasks to be completed quickly.

Why AI/ML should matter to you?

New Modelling Techniques

Utilising alternative approaches, such as unsupervised learning, allows different perspectives to be gained on data. Techniques such as anomaly detection or time series modelling can potentially produce a stronger predictive power for certain problems, improving the performance of actuarial models.

New Approaches to Problems

Actuaries typically use relatively standard modelling approaches. However, in all cases, models will suffer from model error and therefore being able to produce a wider variety of models in a short space of time will allow actuaries to better select the appropriate modelling approach for a given problem.

Improved Data Visualisations

With new modelling techniques and new software for machine learning, users have an increasing power to produce stunning visualisations of data which can itself provide new perspectives on a task.

TRADITIONAL ACTUARIAL PRACTICE AREAS	General Insurance	Pensions	Life, Health & Care	Investment
Pricing	√		√	
Product Design / Propensity Customer Behaviour	√		√	
Reserving	√			
Capital Modelling	√		√	
Exposure Management	√			
Scheme Valuation		√		
Surplus Distribution			√	
Strategic / Tactical Asset Allocation				√
Asset & Liability Management / Hedging				√
Claims Management	√	√	√	√
Data Cleansing (Table 5)	√	√	√	√
External Data Sources (Table 5)	√	√	√	√

Actuary or Data Scientist

Data scientists tend to tackle a wide variety of modelling tasks (financial and non-financial) and therefore are often more reliant on gaining an understanding of the domain specific elements of a task from other domain specialists.

- The statistical techniques used by actuaries and data scientists often differ;
- The approaches taken to validate assumptions may differ;
- The approaches used for variable selection may differ;
- The approaches used to assess the performance of a model may differ;
- Good data scientists need subject expertise

Despite these differences, what should be clear is that data science and actuarial modelling approaches have much in common. This leaves the actuarial profession well placed to utilise these new techniques within the scope of their existing work.

Domains to explore

General insurance

Pricing	- Supervised Learning: decision tree, forests and penalised regression - Unsupervised Learning: using a non-linear approach - Deep Learning and high level decision making - Experience monitoring with a larger dataset
Product Design / Propensity Customer Behaviour	- Big Data on consumer information - Sentiment Analysis using external sources and social media
Reserving	- Making projections more predictive; claim predicting pattern could vary - Explore supervised learning (penalised regression) - Experience monitoring with a larger database
Capital Modelling	- Network / Graph Modelling - looking at driving dependencies rather than correlation assumptions - Strategically flexible, more decision aid based model on environment - Portfolio / Reinsurance optimisation – genetic algorithms
Exposure Management	Build predictive models based on weather patterns

Pensions & Investment

Scheme Valuation	- More granular individual information from alternative data sources e.g. social media - More sophisticated longevity model - Tailoring investment strategy to individual circumstances
Asset & Liability Management / Hedging	- More granular data for asset/liability modelling - Enhanced market risk monitoring
Capital Modelling	- Network / Graph Modelling- looking at driving dependencies rather than correlation assumptions - Strategically flexible, more decision aid based model on environment - Portfolio / Reinsurance optimisation – genetic algorithms

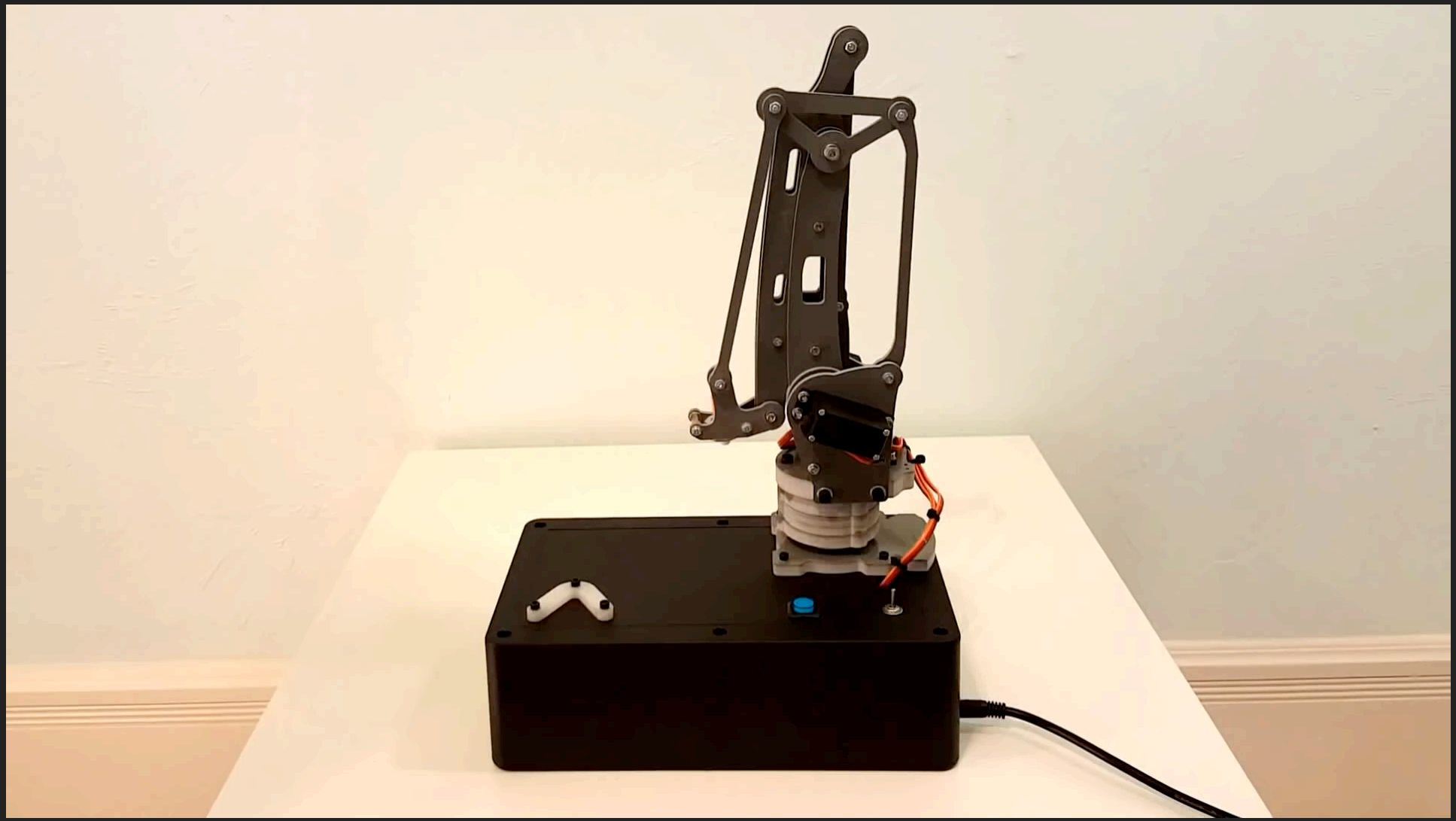
Life, health, care

Pricing	- Supervised Learning: decision tree, forests and penalised regression - Unsupervised Learning: using a non-linear approach - Deep Learning and high level decision making - Experience Monitoring with a larger database
Capital Modelling	- Network / Graph Modelling looking at driving dependencies rather than correlation assumptions - Strategically flexible, more decision aid based model on environment - Portfolio / Reinsurance optimisation – genetic algorithms
Surplus Distribution	- More granular individual information from social media sites - More sophisticated longevity model

All practice areas

Data Cleansing	- Reducing errors i.e. data validation - Filling in gaps i.e. missing latitude and longitudes - Increasing sample size using Machine Learning extrapolation - Web scraping, word search / natural language analysis
External Data Sources	- Quandl / Dun and Brad Street / Bloomberg / social media feeds / credit agencies / telemetry / images / etc.
Feedback Loop / Actuarial Control Cycle	- Year on year to keep track of outputs


can AI hurt us?



KPMG

04 Q&A

Thank you