



# AI in Engineering

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**HTSC**

HIGH TECH  
SYSTEMS  
CENTER

**TU/e**

2 July 2020

# Artificial Intelligence is like a Swiss army knife ...



... as it can be applied to many different applications/areas, such as machine vision, logistics, planning, robotics, optimization, predictive maintenance, sales, ...

# High Tech prepares for AI

## Consumer 'database'-driven AI



### Google

Uses ML to predict traffic density based on anonymous mobile phone position data.

<https://ai.google/>



### Netflix

Uses ML as part of their movie recommender system.

<https://www.wired.co.uk/article/how-do-netflixs-algorithms-work-machine-learning-helps-to-predict-what-viewers-will-like>



### Facebook

Uses ML-based algorithms to detect and recognize faces in photo's.

<https://research.fb.com/category/machine-learning/>



### Spotify

Uses ML for recommending new music.

<https://www.oreilly.com/ideas/machine-learning-at-spotify-you-are-what-you-stream>



### Apple

Developed speech recognition service Siri with ML.

<https://machinelearning.apple.com/>



### Paypal

Uses ML to detect and combat fraud

<https://www.paypal-engineering.com/tag/machine-learning/>

2nd wave of AI applications

## Industrial 'sensor data'-driven AI



### General Electric

Uses ML develop Digital Twins to understand, predict and optimize performance of assets.

<https://www.ge.com/digital/predict/digital-twin>



### Tesla

Uses ML to develop autonomous driving cars.

<https://www.youtube.com/watch?v=2aVc84mGJfE>



### Siemens

Uses AI a.o. for Industry 4.0, medical and traffic optimization applications

<https://www.siemens.com/global/en/home/company/innovation/pictures-of-the-future/artificial-intelligence.html>



### PTC

Applies AR and ML for maintenance.

<https://www.ptc.com/en>



### SemioticsLab

Dutch startup using ML for predictive maintenance.

<https://www.semioticslabs.com/nl/>



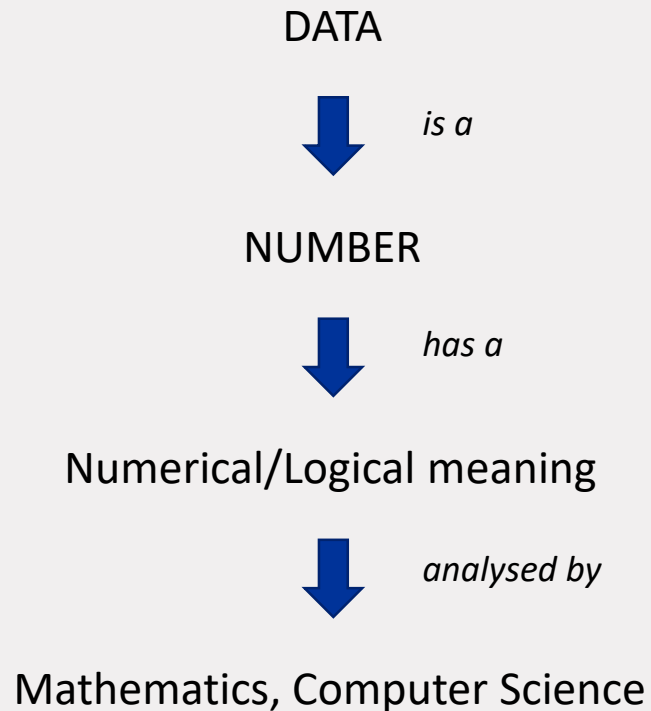
### Freenome

Startup using AI for early cancer detection.

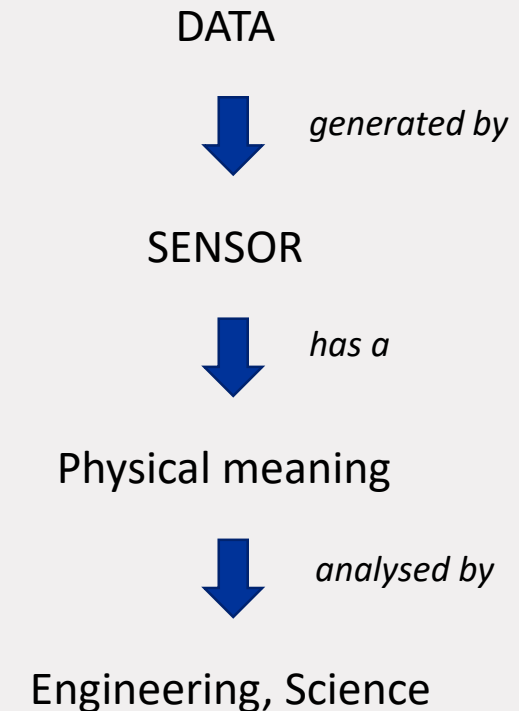
<https://www.freenome.com/>

# High Tech prepares for AI

## Data Science



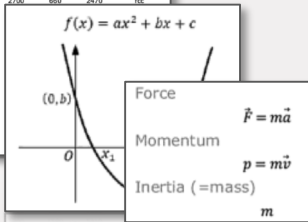
## AI (in) Engineering





# Designing high tech systems

Material	Atomic Number	Density [kg/m³]	Melting Point [°C]	Boiling Point [°C]	Crystal Structure
Actinium	89	10150	1050	3000	fcc
Aluminum	13	2700	660	2470	fcc
Americium	95				
Antimony	51				
Argon	18				
Arsenic	33				
Astatine	85				
Barium	56				
Berkelium	97				
Beryllium	4				
Bismuth	83				
Bohrium	107				
Boron	5				
Bromine	35				
Cadmium	48				

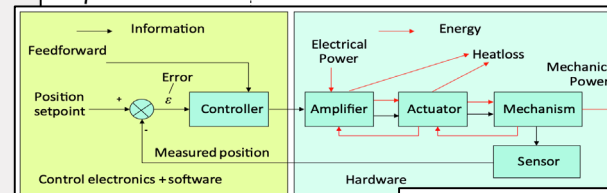
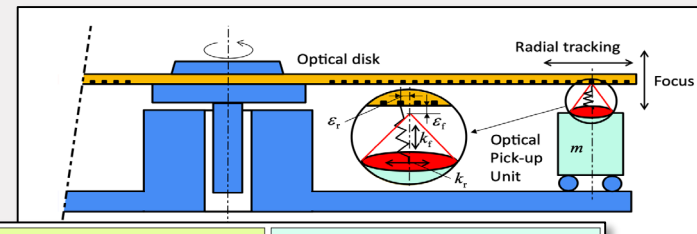


Engineer

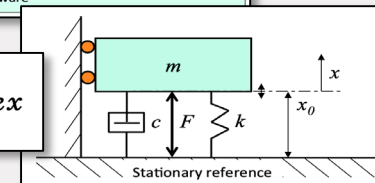
First principles



Data



$$F(t) = m \frac{d^2x}{dt^2} + c \frac{dx}{dt} + kx$$



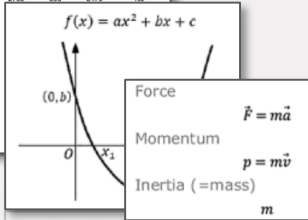
Optical disk system

SYSTEM

Source: 'The Design of High Performance Mechatronics', R.M. Schmidt et al, 2014

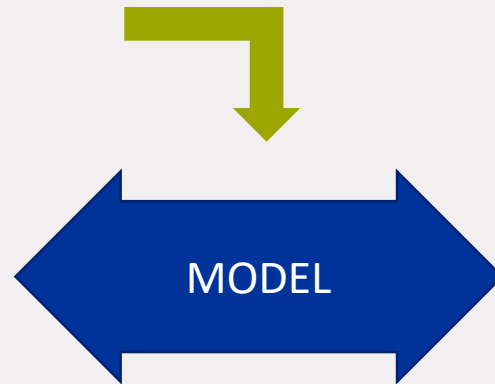
# Growing design challenges

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Bismuth	83				
Bohrium	107				
Boron	5				
Bromine	35				
Cadmium	48				
Calcium	20				
Californium	98				
Carbon	6				
Cerium	58				
Cesium	55				
Chlorine	17				



Engineer

First principles



Data



## Complexer models and bigger data needed to deal with challenges

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$f(x) = ax^2 + bx + c$   
 Force  
 $\vec{F} = m\vec{a}$   
 Momentum  
 $p = m\vec{v}$   
 Inertia (=mass)  
 $m$

# First principles



## COMPLEXER MODEL



## BIGGER Data

# Engineer



## MORE COMPLEXITY



## MORE PERFORMANCE



## MORE INTELLIGENCE



## MORE INTEROPERABILITY

Artificial Intelligence is a technology platform to deal with bigger datasets and complexer models

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$f(x) = ax^2 + bx + c$

Force

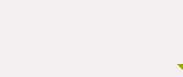
$$\vec{F} = m\vec{a}$$

Momentum

$$\vec{p} = m\vec{v}$$

Inertia (=mass)

$$m$$



**COMPLEXER  
MODEL**

# BIGGER Data

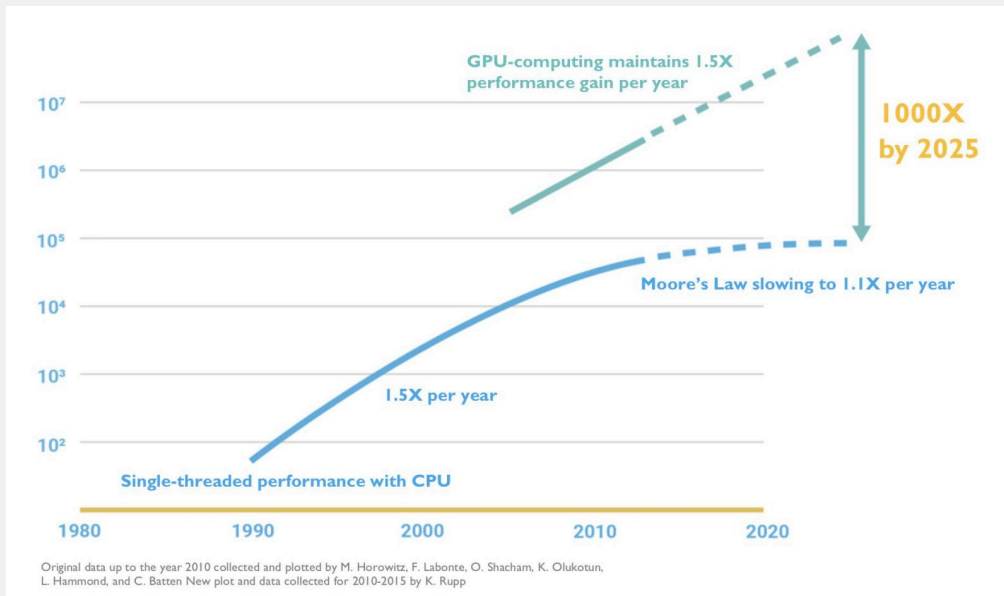




# Bigger compute

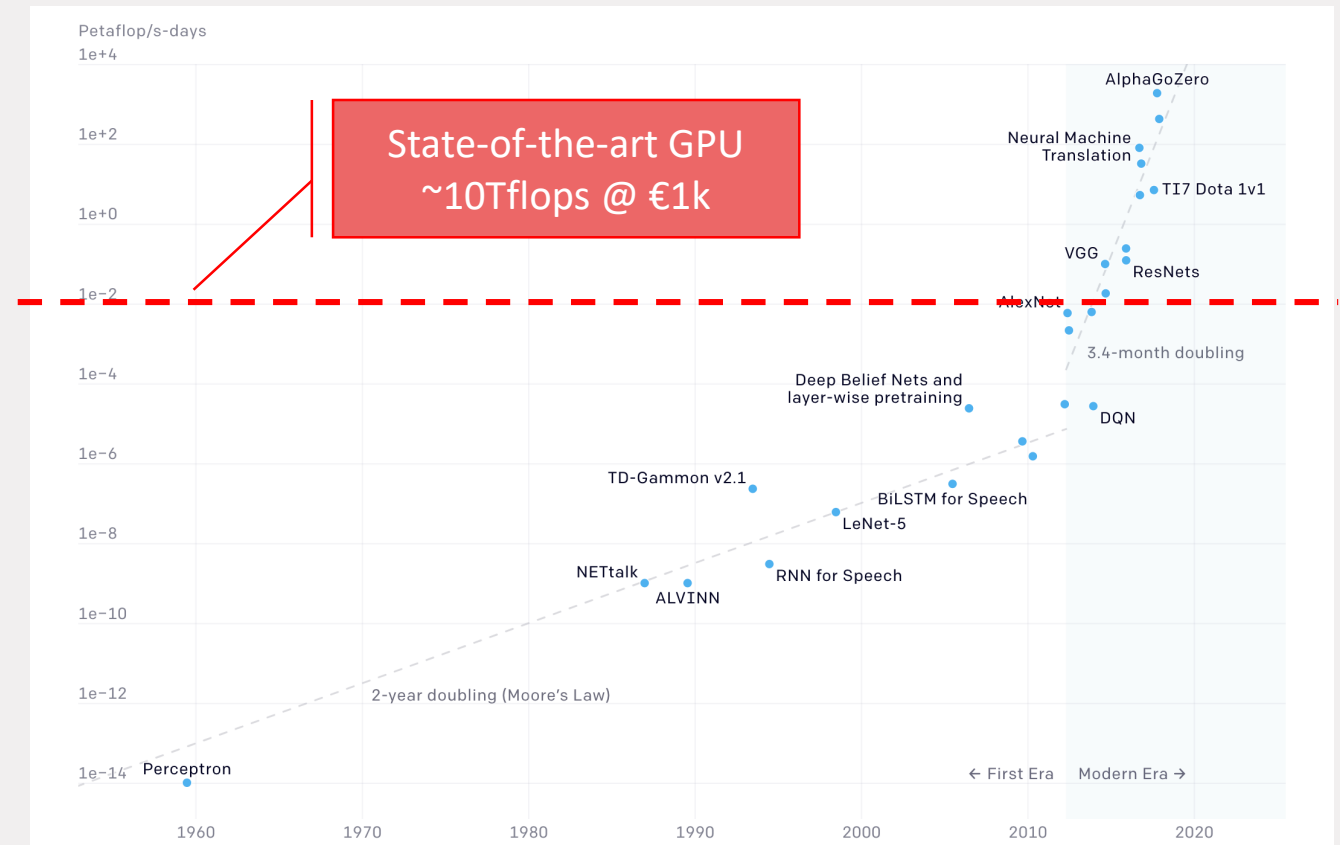
GPU computing drives AI

## GPU COMPUTING ROADMAP



Source: Nvidia, 2018

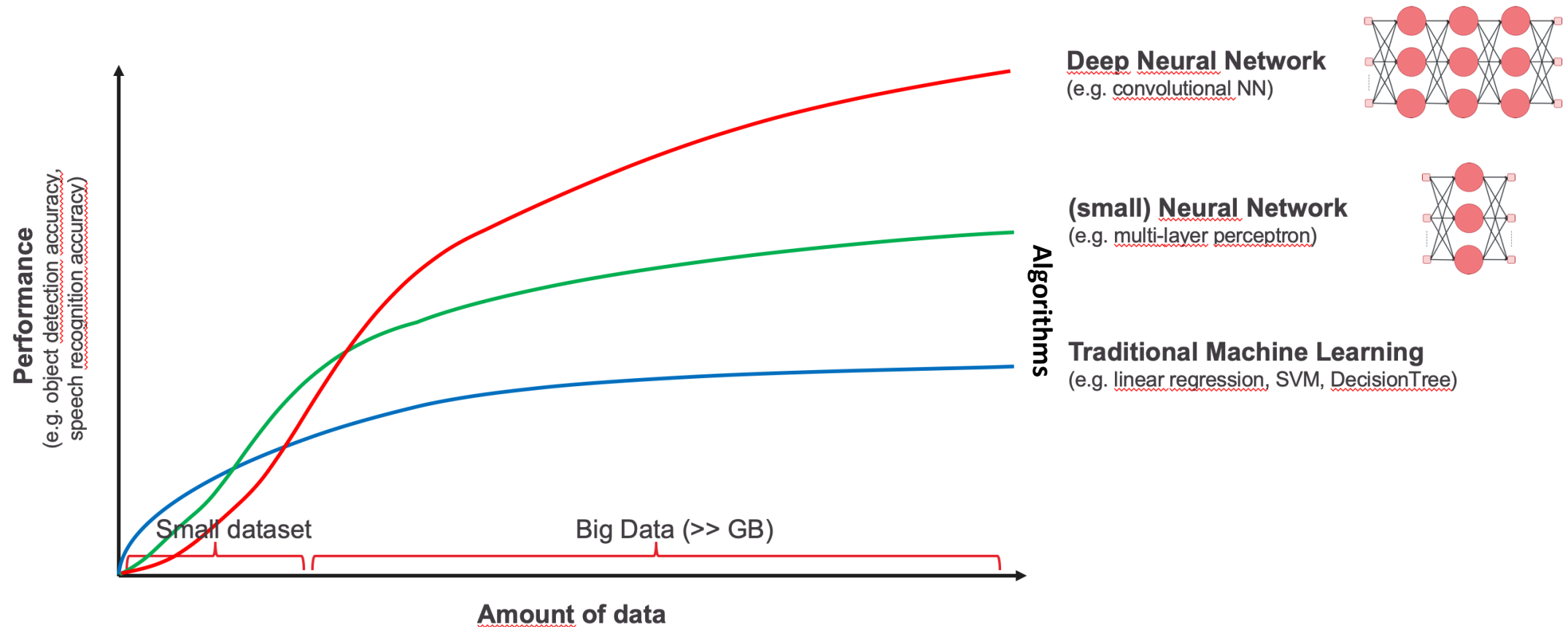
## AI COMPUTE USAGE FOR VISION, PLANNING, SPEECH



Source: <https://openai.com/blog/ai-and-compute/>

# Smarter algorithms

Scale drives performance



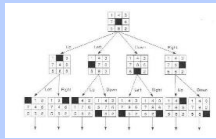
Source: 'Masterclass Deep Learning', VBTI 2018

# Artificial Intelligence

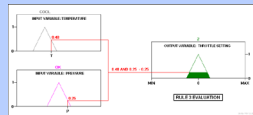
Artificial Intelligence (AI) is a multidisciplinary field of science whose goal is to create intelligent machines.

AI Technology

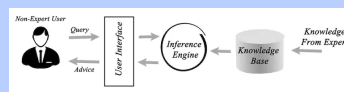
## Knowledge/Logic



tree search

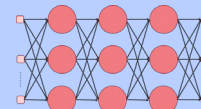


fuzzy logic



expert system

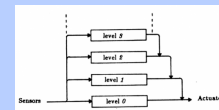
## Machine Learning



neural networks

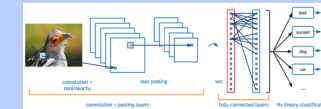


genetic algorithms

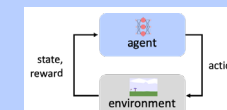


subsumption

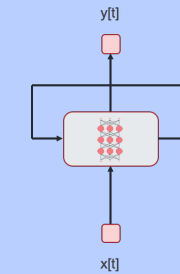
## Deep Learning



convolutional nn



reinforcement learning

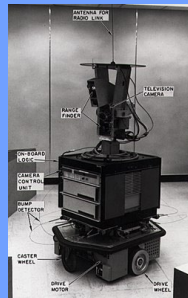


recurrent nn

AI Application

```

• list - cons list data structure (list gets its name from List Processing)
length list: 0
  => (2 2 3 4)
  (list 2 2 3 4)
  => (cons 1 empty)
  => (cons 1 (cons 2 empty))
  => (list 1 2 3 4 5)
  (list 1 2 3 4 5)
  => A list can contain any data type
  => (define list (list 1 2 3 4 "hello" 5 6 "bangalore"))
  => list:
  (list 1 2 3 4 "hello" 5 6 "bangalore")
  => (cons 1 (cons 2 (cons 3 (cons "hello" (cons "bangalore" (cons 4 empty)))))
  (1 2 3 "hello" "bangalore")
  
```



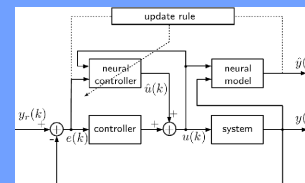
Shakey robot

Lisp, Prolog STRIPS planning system

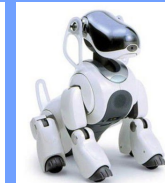


Fuzzy Logic

Rice Cooker



neural control



(consumer) robotics



self-driving car



HomePods

1950's

1960's

1970's

1980's

1990's

2000's

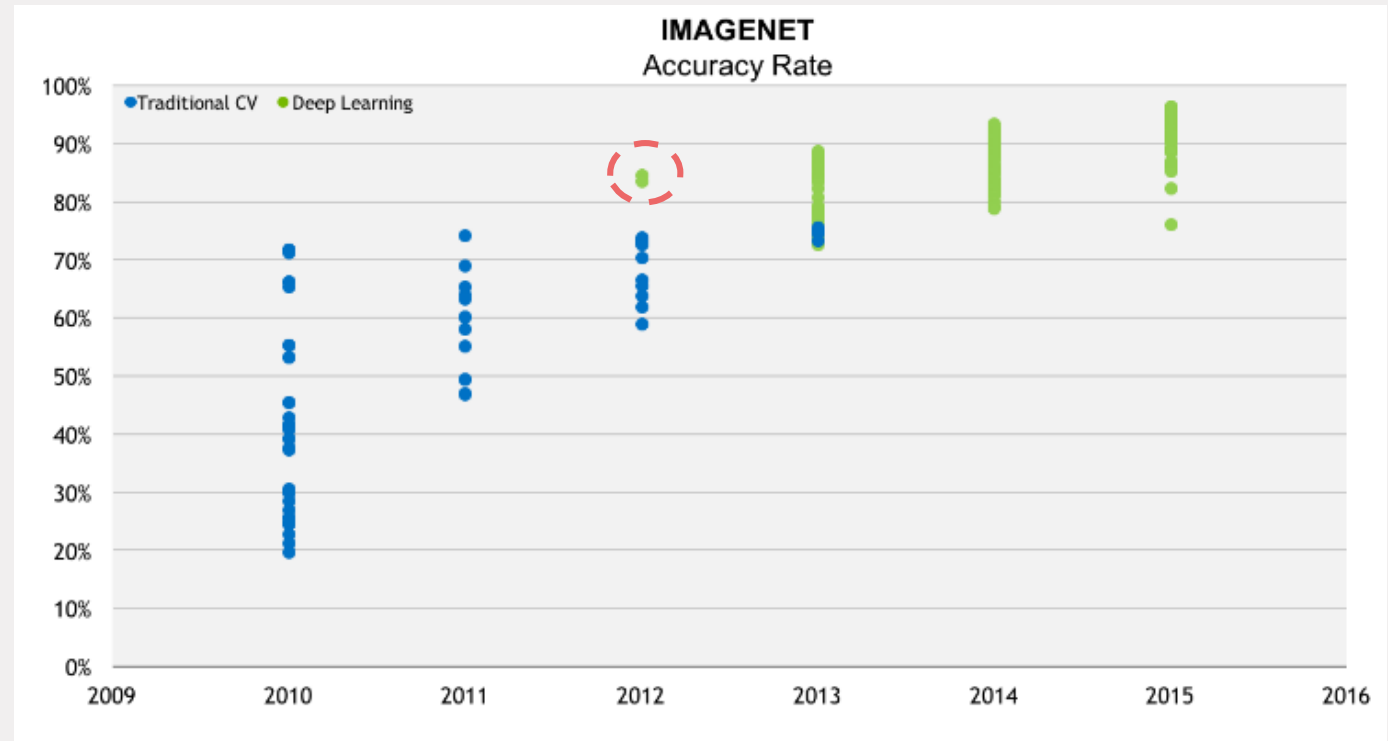
2010's

2020's

# Deep learning: Convolutional Neural Networks (CNNs)

- A CNN is a deep neural network optimized for processing image data
- CNNs became popular in 2012 when 'AlexNet' won the ImageNet competition
  - **13 layers** deep, **± 62mln parameters** to train
  - Trained the network on **15 mln annotated images (22,000 categories)**
  - **1.4 ExaFLOP** (= 1.4e6 TFLOP) needed for training
  - 7.8 GFLOP per forward pass per image
  - Trained **on two GTX 580 GPUs for 5 to 6 days**
  - 1500 GFLOPS / GPU, 3000 GFLOPS total
- CNNs are outperforming traditional CV systems in many visual domains

<https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>

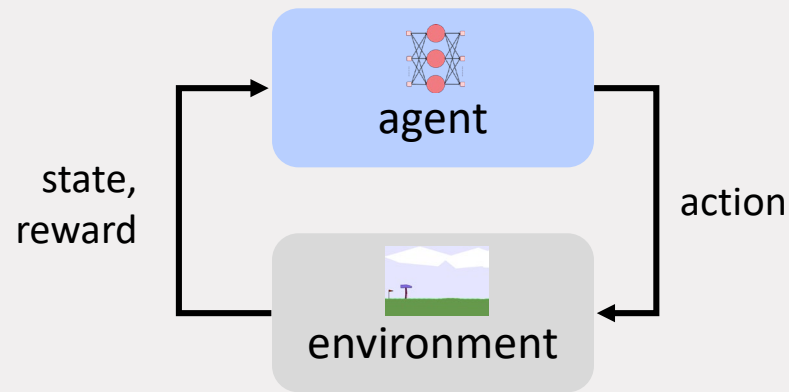


feature map

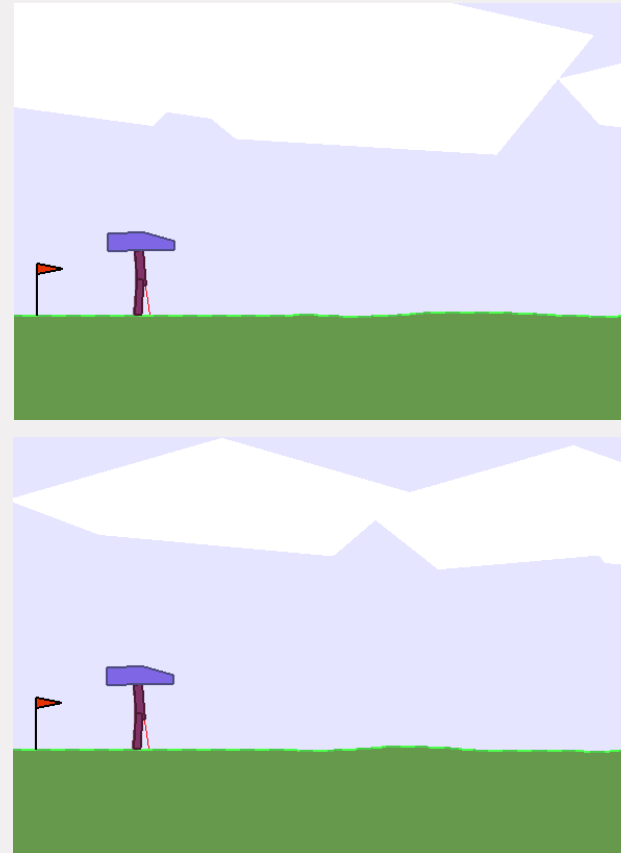
Source: 'Masterclass Deep Learning', <https://vbt.nl/masterclasses/>, VBTI 2018

# Deep learning: Deep Reinforcement Learning (DRL)

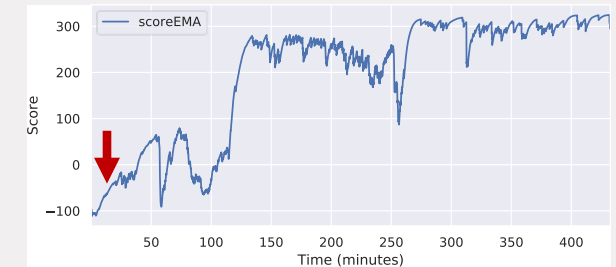
- RL is a machine learning technique that learns to optimize a reward by interacting with (virtual/real) environments.
- Performance of recent RL algorithms on games surpass human-performance on many games, including Atari games, Dota 2, poker, chess, Shogi, checkers, and Go.



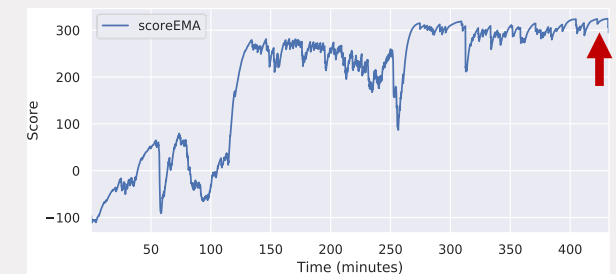
OpenAI gym benchmark environment



Agent not trained



Agent trained after 8 hours



Source: 'Masterclass Deep Learning', <https://vbt.nl/masterclasses/>, VBTI 2018



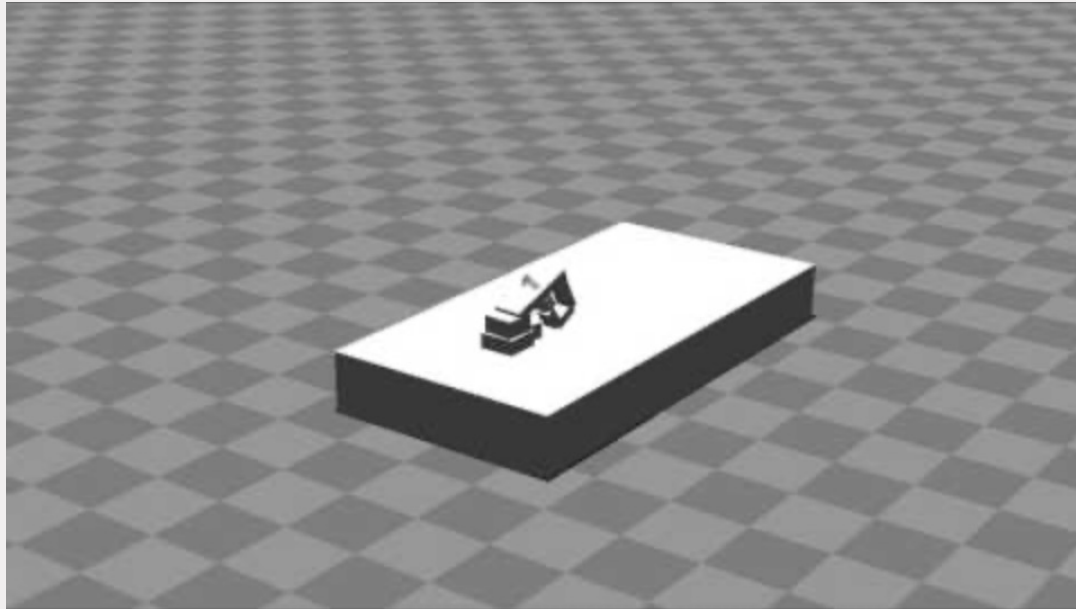
# AI research & trends

- **Computer vision:** Deep Learning outperform human-expert based algorithms and are the 'low hanging fruit' for industry, for a.o. robotics, inspection and monitoring applications.
- **Natural language processing:** Deep Learning enabled mature level of speech recognition and text processing. Could be applied for developing machine interface (e.g. in combination with Augmented Reality) or for processing engineering documents.
- **Planning & Problem Solving:** By combining different Deep Learning techniques such as convolutional neural networks and reinforcement learning, new systems are build that ourperform humans in solving specific tasks (and games).
- **Robotics & Control:** Training AI algorithms on (virtual) Digital Twins of systems results in robust control solutions to problems virtually impossible to humanly solve.

# AI solving challenges

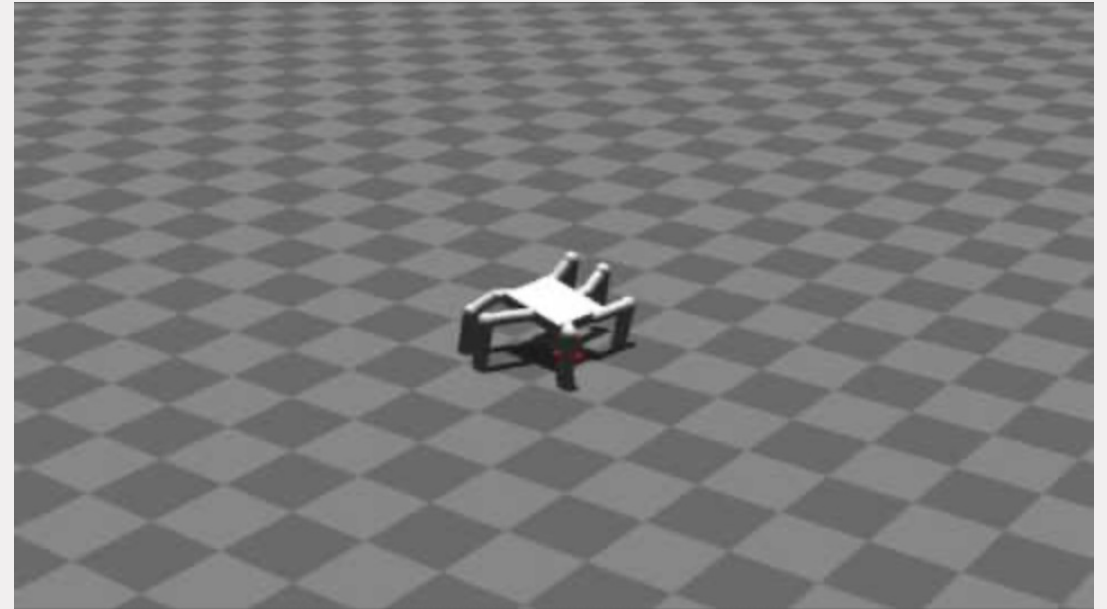
## CHALLENGE 1

Fingers of gripper are glued together and robot needs to pickup part.



## CHALLENGE 2

Robot need to walk around while minimizing ground-feet contact.

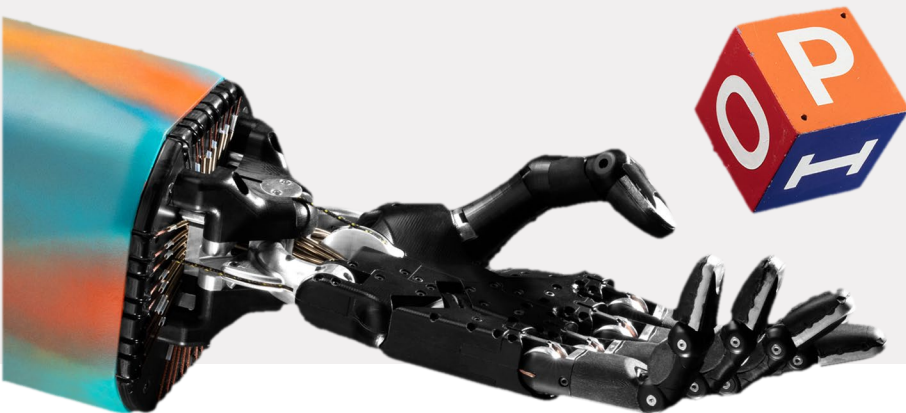


# Robotics example: learning dexterity

## Problem

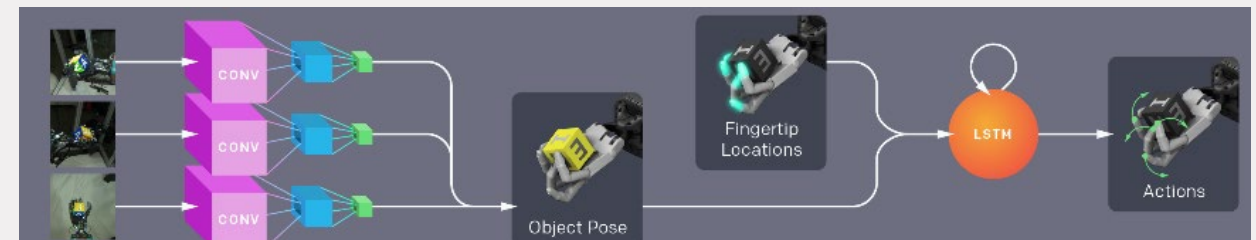
- Robot hand should reposition an object
- High-dimensional control (24 DoF)
- Noisy and partial observations (friction, slippage)
- Manipulating more than one object

Source: <https://arxiv.org/abs/1808.00177>



## Solution

- Train in simulation
- CNN to estimate object pose from 3 camera's
- RL + RNN (LSTM) to determine fingertip actions
- Transfer to real world
- OpenAI's Rapid platform is used with 6144 CPU cores and 8 GPUs, collecting about one hundred years of experience in 50 hours.

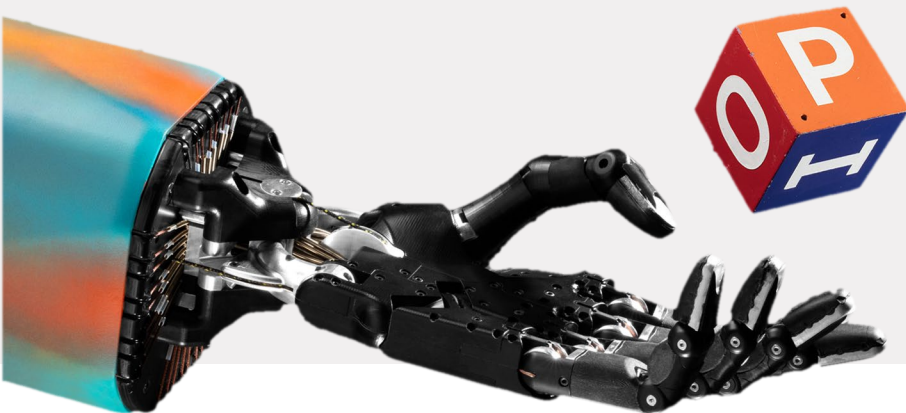


# Robotics example: learning dexterity

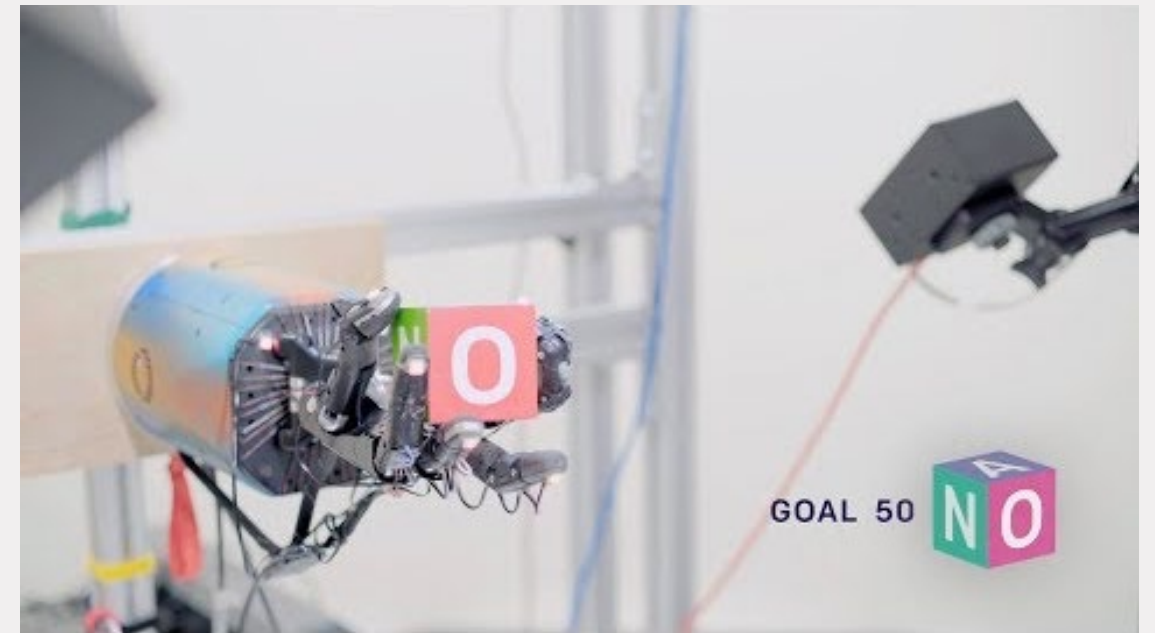
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Source: <https://arxiv.org/abs/1808.00177>



## Result



<https://www.youtube.com/watch?feature=oembed&v=DKe8FumoD4E>

# Summary

- Artificial Intelligence technology is **maturing rapidly** the last few years and **outperforms human (solutions)** in various areas.
- There is a **gap** between the world of **engineering** and **data science** that can be bridged by:
  - **Combining** first principle techniques with machine learning
  - Making Deep Learning algorithms **explainable**
- AI performance is driven by **compute power**, **big data** and **algorithms**
- Still **many barriers** need to be taking by industry to adopt AI, a.o.
  - Complex AI technology stack
  - Many number of different AI algorithms (which to use when?)
  - Transfer results from virtual to real world

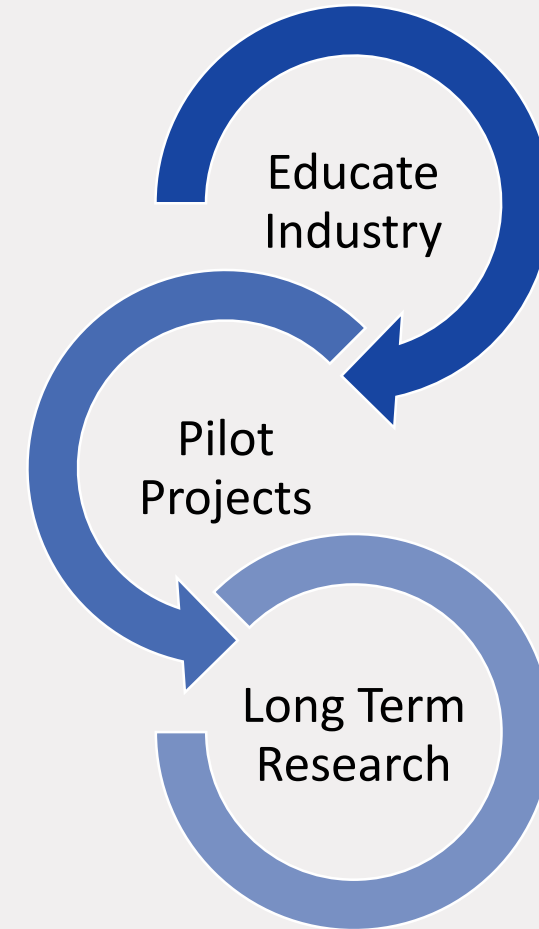


# AI Engineering Lab

*Support industry with adopting AI technology  
and create research consortia*

- Part of the Eindhoven AI Systems Institute (EAI SI)
- Multidisciplinary
  - Brings together researchers across the areas of mechatronics, data science, mathematics, computer science, computer vision, embedded systems, robotics, control engineering and more.
    - Partners include FME

**aie-lab@tue.nl**

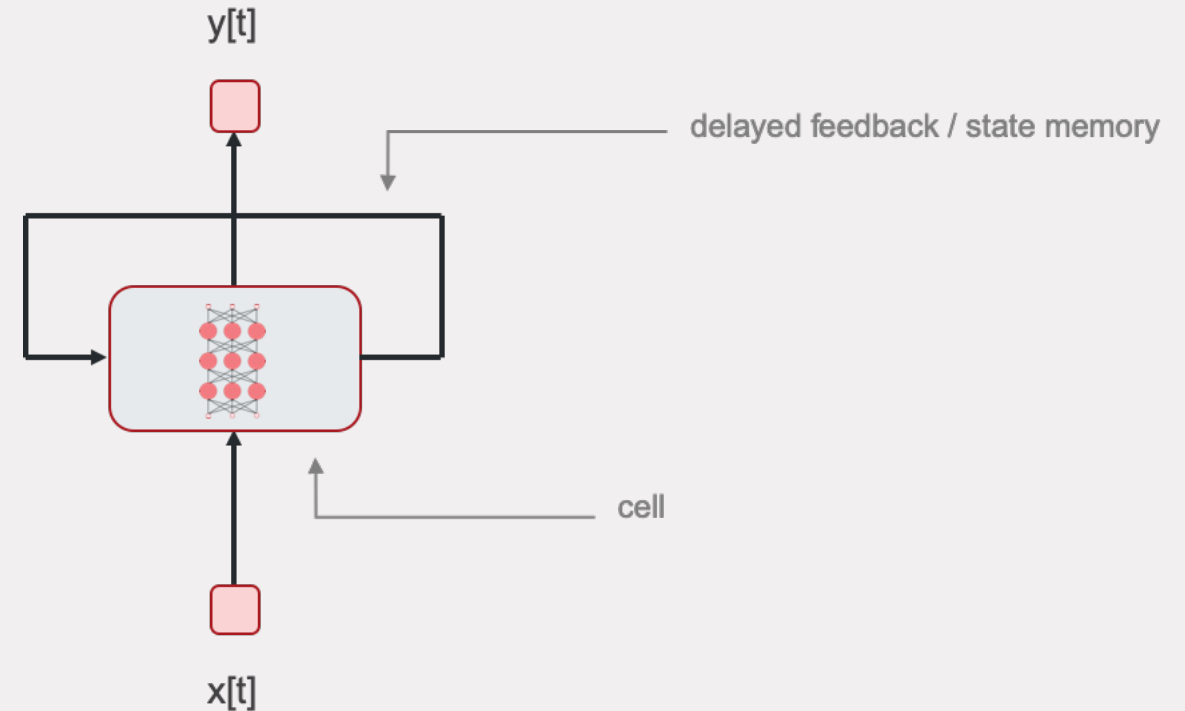


An abstract graphic featuring a network of interconnected nodes and lines, overlaid with several interlocking gears. The background is a light blue grid with faint binary code (0s and 1s) and numbers. A bright yellow and green light source is visible on the right side, casting a glow. The text "The end" is centered in a large, white, sans-serif font.

The end

# Deep learning: Recurrent Neural Networks (RNNs)

- RNN uses feedback loops from the output of a layer to the input of a previous layer
- RNN have a memory for past events
- RNN can learn correlations between signals at different time moments
- A special type of cell structure, called Long Short Term Memory, enabled learning
- RNN's are success behind many speech recognition and natural language processing systems.



Source: 'Masterclass Deep Learning', <https://vbt.nl/masterclasses/>, VBTI 2018

# Drone example: learning to fly

## Problem

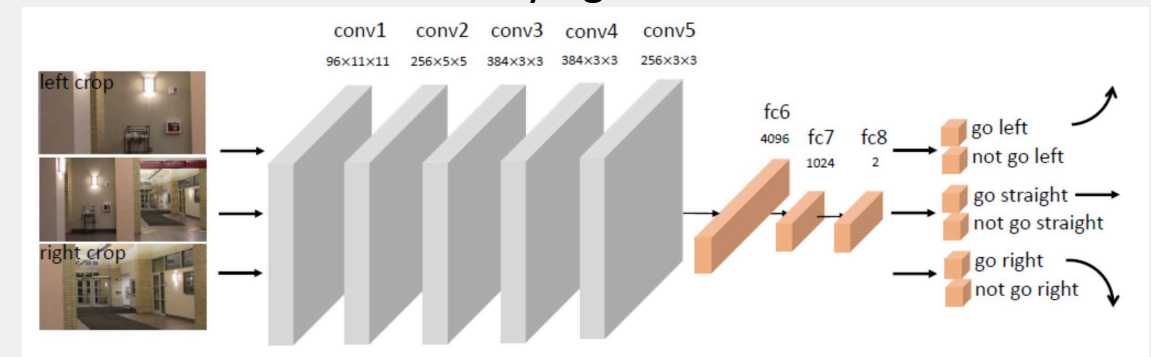
- Learn a drone to navigate indoor and avoid objects
- Reduce gap between simulated and real-world training

Source: <https://arxiv.org/pdf/1704.05588.pdf>



## Solution

- Make robust drone to collect real-world data to learn from
- Use pre-trained CNN (AlexNet, transfer learning) to map camera input to actions
- AR Drone 2.0 flew in 20 different indoor environments, racking up 11,500 collisions over the course of 40 hours of flying time.





# Drone example: learning to fly

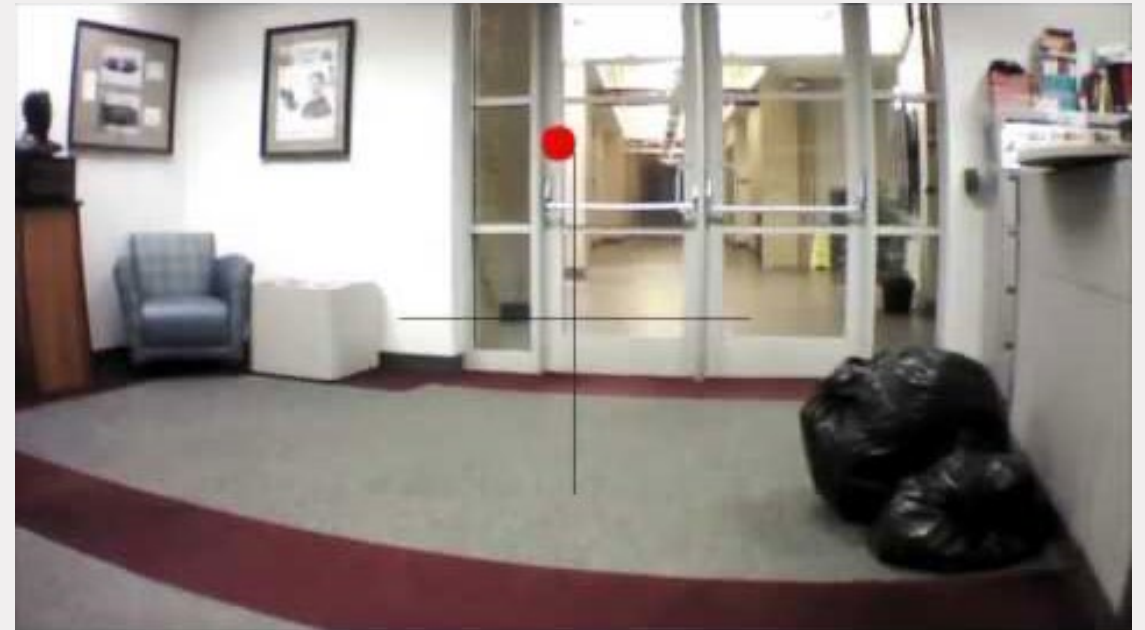
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Source: <https://arxiv.org/pdf/1704.05588.pdf>



## Result



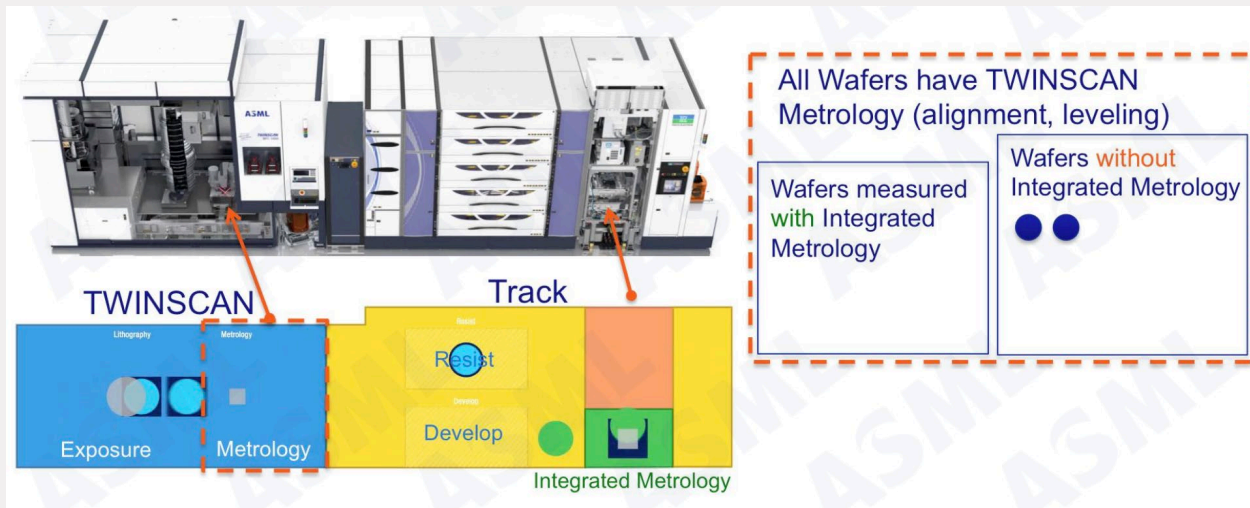
<https://www.youtube.com/watch?feature=oembed&v=HbHqC8Himol>



# Metrology example: improve semicon production yield

## Problem

- Reducing the influence known contributors have toward the on product overlay budget when moving semicon manufacturing toward 7nm node for logic and 15nm node for memory (2015!)
- Inline metrology is costly (duration)



## Solution

- Use **TWINSKAN metrology** to measure all wafers and use **inline metrology** to measure overlay for some wafers
- Train a model to approximate overlay vector maps for the entire lot of wafers.
- With the approximated overlay vector maps for all wafers coming off the track, a process engineer can redirect wafers or lots with overlay signatures outside the standard population to offline metrology for excursion validation.

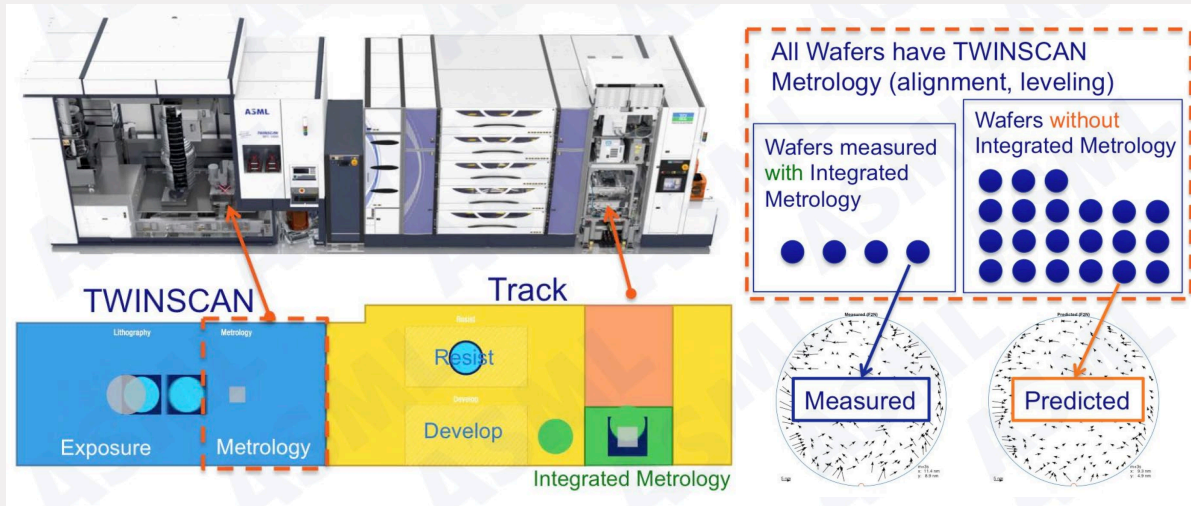
"Virtual overlay metrology for fault detection supported with integrated metrology and machine learning", Emil Schmitt-Weaver, MATLAB Expo 2016 Benelux – June 28th

"Virtual overlay metrology for fault detection supported with integrated metrology and machine learning", Hong-Goo Lee et al., SPIE, 19 March 2015

# Metrology example: improve semicon production yield

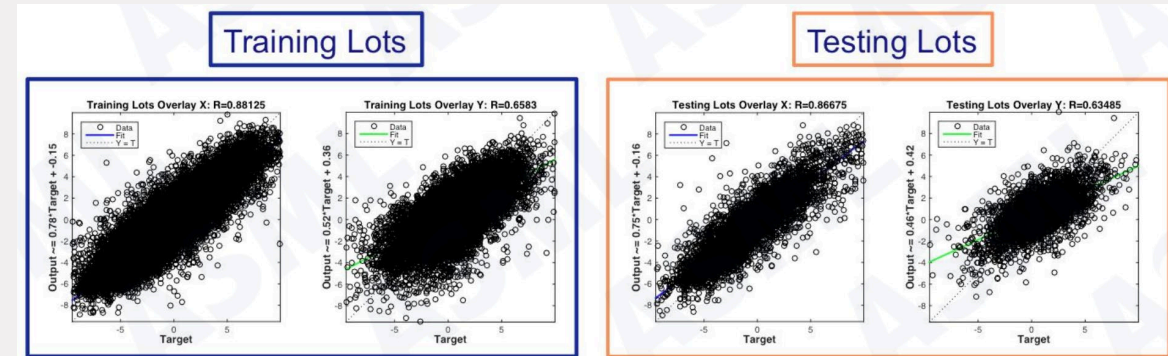
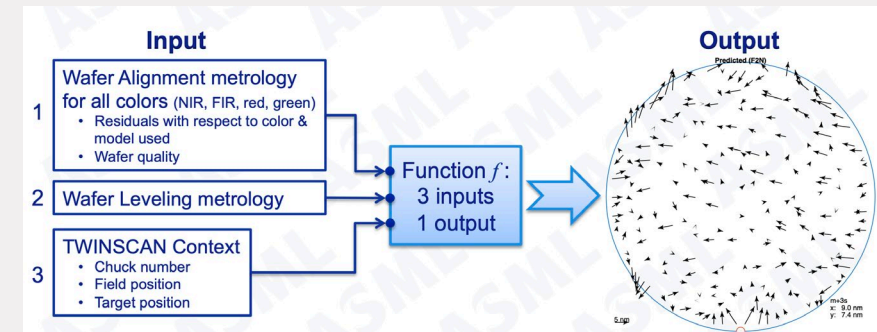
## Problem

- Reducing the influence known contributors have toward the on product overlay budget when moving semicon manufacturing toward 7nm node for logic and 15nm node for memory (2015!)
- Inline metrology is costly (duration)



## Result

- The model identifies systematic and random overlay errors, improving overlay performance.



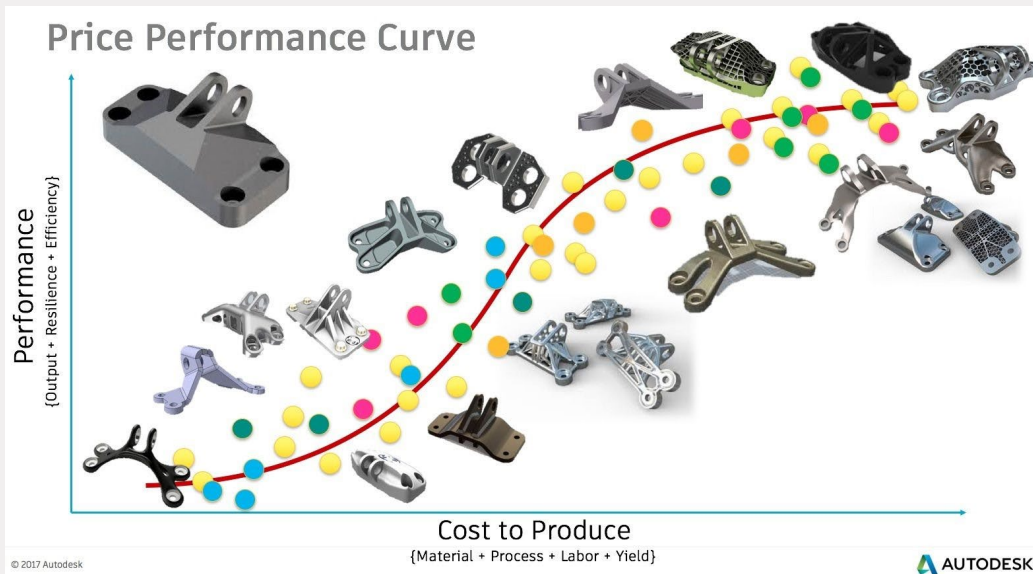
# Problem solving example: generative design

## Problem

- Optimizing products by taking design and manufacturing constraints simultaneously into account.

## Solution

- Use AI as a tool during the engineering design process
- Autonomously creates optimal designs from a set of system design requirements.
- Engineers can interactively specify their requirements and goals, including preferred materials and manufacturing processes—and a **generative engine** will automatically produce a manufacture-ready design as a starting point or as a final solution.



Source: <https://www.autodesk.com/solutions/generative-design/manufacturing>

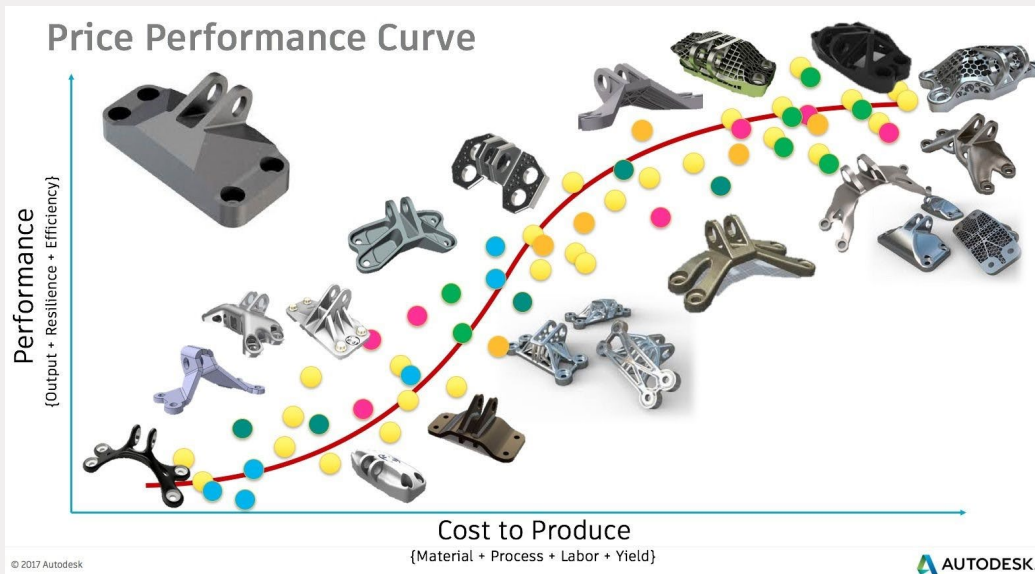


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<https://www.youtube.com/watch?feature=oembed&v=vtfNIWEJxw4>