Deep Learning (CS324)

Introduction

Prof. Jianguo Zhang

Department of Computer Science and Engineering

SUSTech

Deep Learning

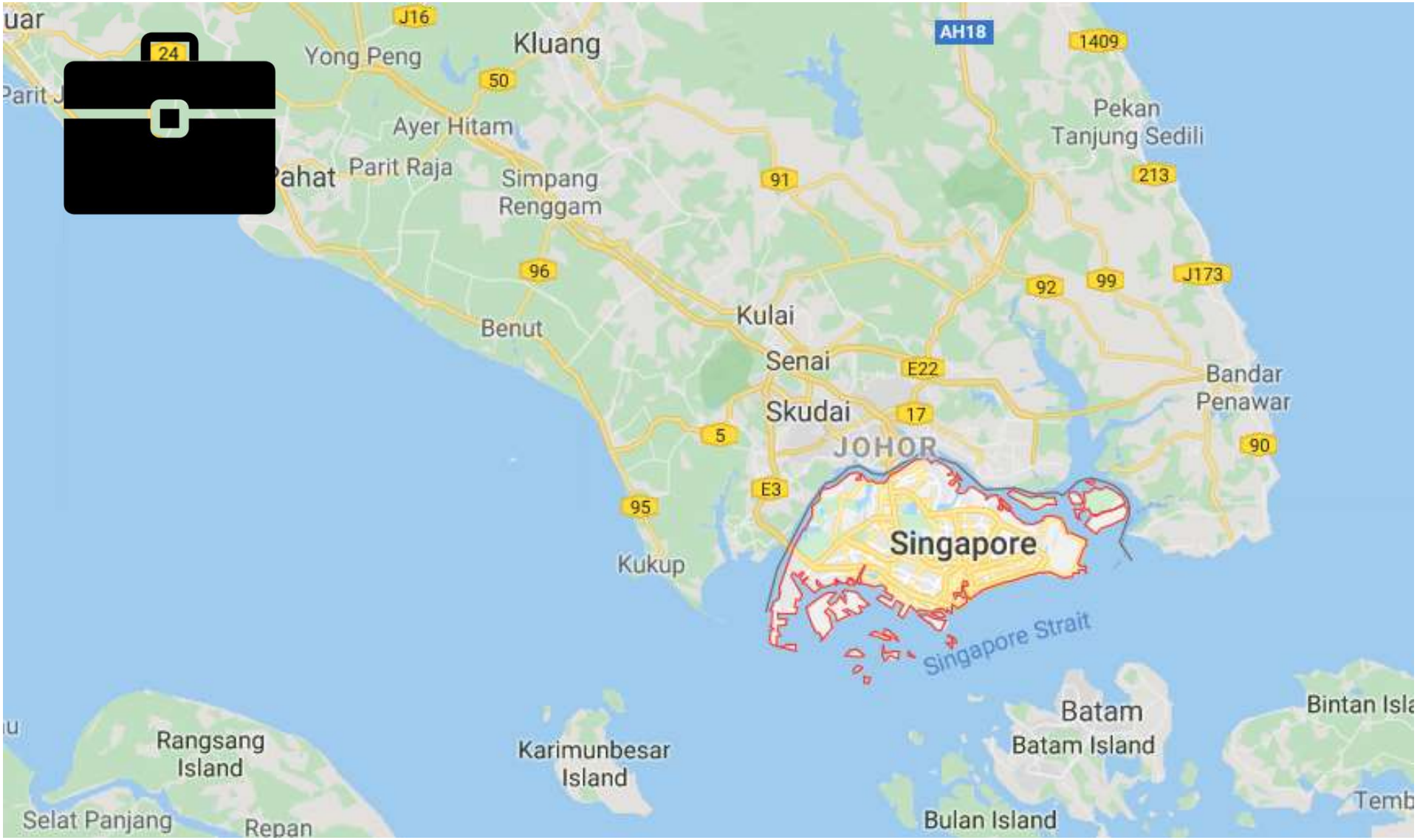
- This course (CS324) will provide an introduction to the field of deep learning, from both a theoretical and practical point of view
- Instructor: Prof. **Jianguo Zhang**, zhangjg@sustech.edu.cn
- Lab TA/SA:
  - Haoquan LI,
  - Hongru Wu
  - Jincan Lou
- **On line teaching:** Blackboard on the university website.

Who am I?

Who am I?


PhD, 2002
Beijing
北京市
Tianjin
天津市
HEBEI
Baoding
保定市
Cangzhou
沧州市
Xinzhou
忻州市
Shijiazhuang
石家庄市
Taiyuan
太原市
Lvliang
吕梁市
SHANXI
Jinan
济南市
Liaocheng
聊城市
Weifang
潍坊市
Yantai
烟台市
Dalian
大连市
Qinhuangdao
秦皇岛市
Huludao
葫芦岛市
Zhangjiakou
张家口市
锦州市

Who am I?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AH18
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Ayer Hitam
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Benut
Senai
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Bandar
Penawar
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Singapore
Kukup
Singapore Strait
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Rangsang
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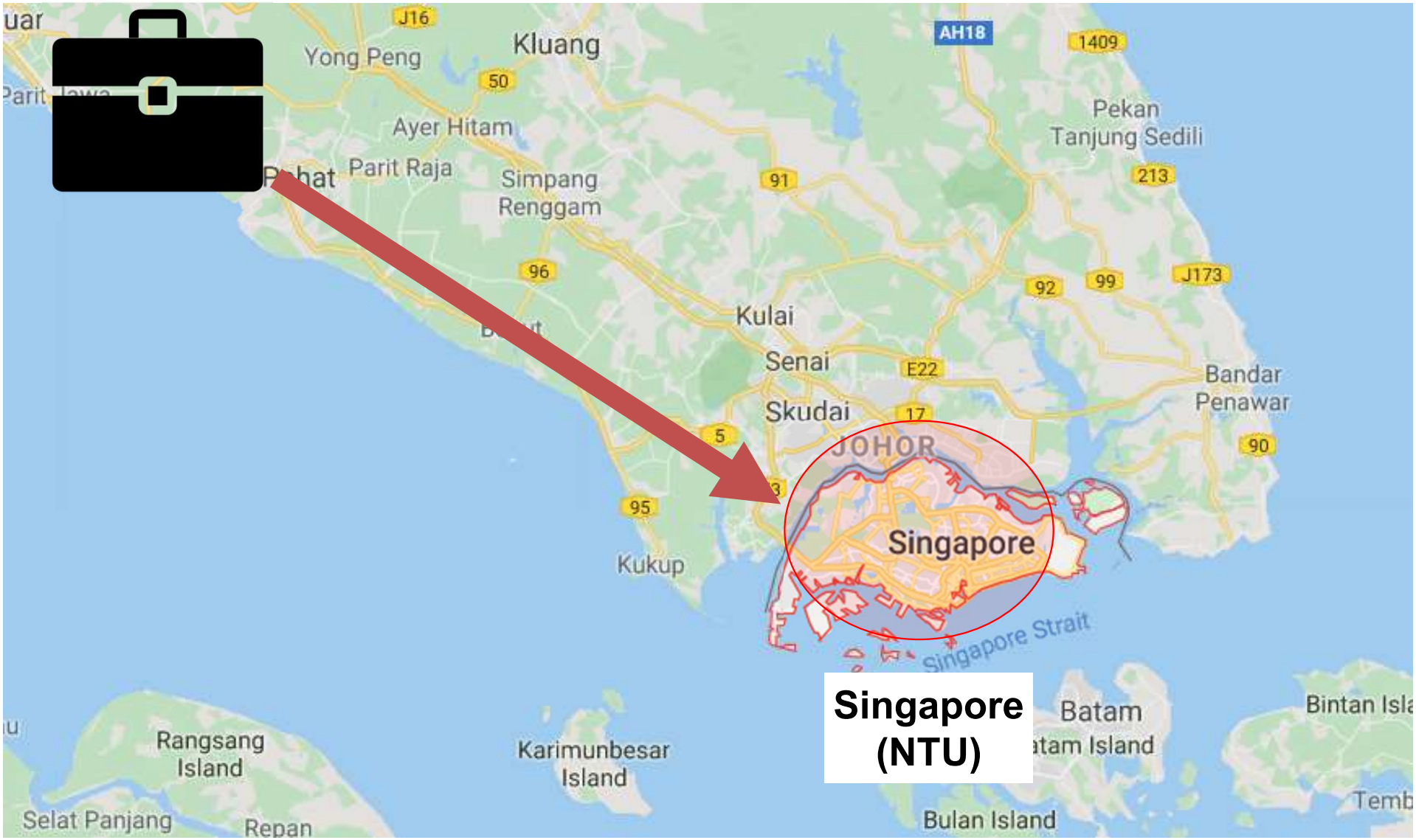
Karimunbesar
Island
Selat Panjang
Repan
Bulan Island

Who am I?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JOHOR
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Kukup
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Bandar Penawar
Batam
Bintan Isla
Rangsang Island
Karimunbesar Island
Selat Panjang
Repan
Bulan Island
Singapore (NTU)
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Who am I?


North Sea
Edinburgh
United Kingdom
Isle of Man
Dublin
Ireland
Liverpool
London
Denmark
Netherlands
Cologne
Brussels
Belgium
Luxembourg
Paris

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North Sea
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United Kingdom
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Dublin
Ireland
Netherlands
Cologne
London
Brussels
Belgium
Luxembourg
Paris
London (QMUL)

Who am I?


North Sea
Denmark
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Isle of Man
Dublin
Liverpool
Belfast (QUB)
London
Netherlands
Cologne
Brussels
Belgium
Luxembourg
Paris

Who am I?


Edinburgh
Dundee
(UoD)
Dublin
Ireland
Liverpool
London
North Sea
Denmark
Netherlands
Cologne
Brussels
Belgium
Luxembourg
Paris

Who am I?


Dongguan
东莞市
Huizhou
惠州市
Shizi Ocean
CHANGPINGZHEN
常平镇
HUIDONG
惠东县
HUMENZHEN
虎门镇
TANGXIAZHEN
塘厦镇
HUIYANG
惠阳区
LONGGANG
龙岗区
Baishouwan
白寿湾
Dawan Bay
大湾
New Port
新港
Daya Bay
大亚湾
Dongshan S
东山海
SHUNDE
顺德区
NANSHA
南沙区
交椅湾
Jiangmen
江门市
Zhongshan
中山市
BAO'AN
宝安区
Shenzhen
深圳市
YANTIAN
盐田区
Yangtaowan
洋涛湾
Chik Wan
赤湾
XINHUI
新会区
Heishawan
黑沙湾
Dawuwan
大坞湾
Xinyu River
Zhuhai
海市
Hong Kong
DOUMEN
斗门区
Macau
JINWAN
金湾区
Erwan
二湾
Xiaodongwan
小东湾
Huangmao
BOLUO
博罗县
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黄埔区
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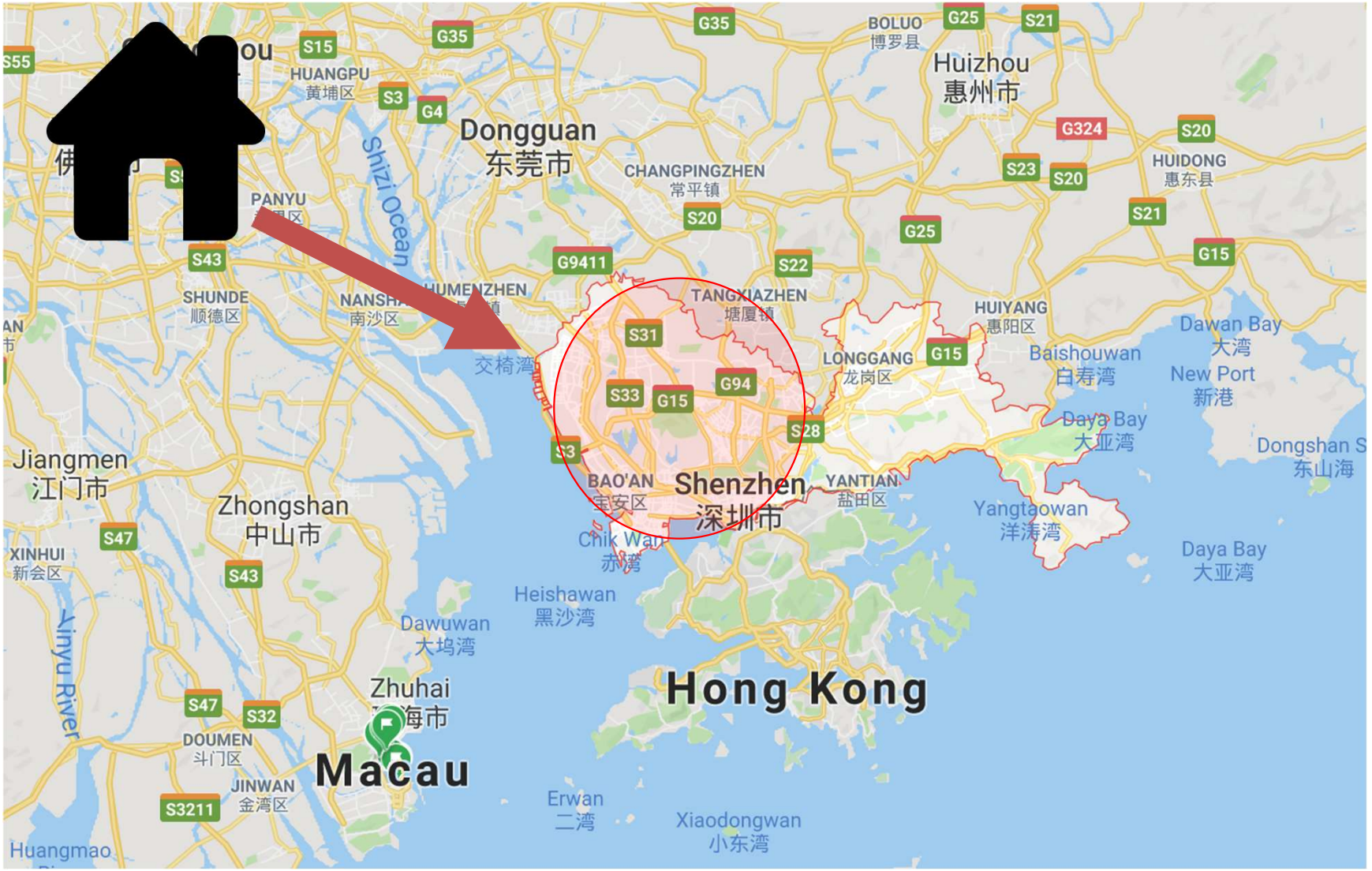
Who am I?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金湾区
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Chik Wan
赤湾
Yangtaowan
洋涛湾
Baishouwan
白寿湾
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New Port
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Daya Bay
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Dongshan S
东山海
Erwan
二湾
Xiaodongwan
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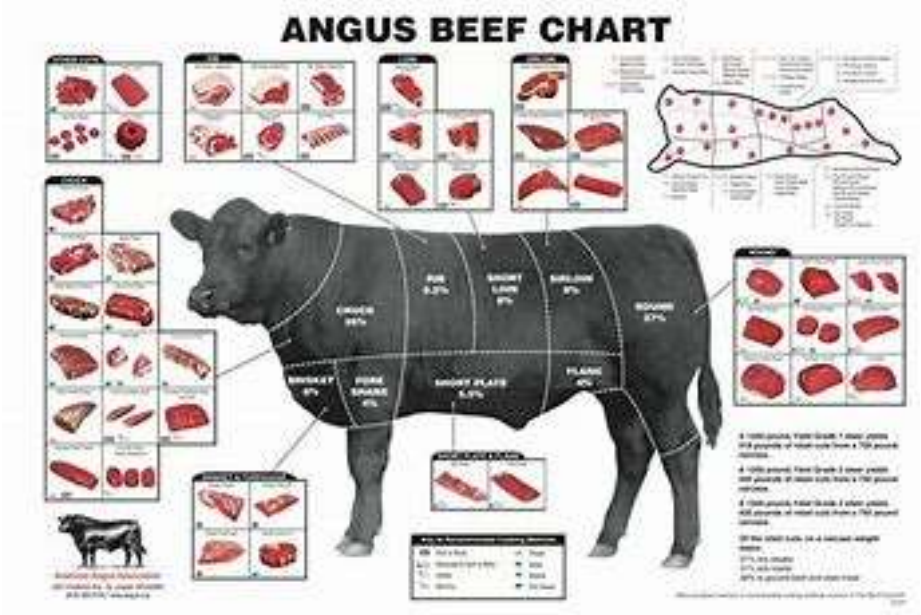
A bit introduction about myself

Jianguo Zhang
Former Affiliation
Computing,
School of Science and Engineering
University of Dundee

the best known in Scotland

School of Computing
UNIVERSITY OF DUNDEE



My working experience

School of Computing
UNIVERSITY OF DUNDEE

2002, PhD - CAS

2002-03, NTU, Singapore

2003-05: Lear group, France

2005-2007 - Queen Mary, University of London, UK

2007- 2010 – Queen's University, Belfast, UK

2010 – 2019 – University of Dundee, UK

2019 – present, SUSTech, China

OLD: Research directions: Medical image processing (retina, OPT, tracking 3D objects, etc) and surveillance, Biometrics, action recognition etc

- **Brain Tumour Segmentation (MR/Microscopy)**
- **OPT Colorectal Polyp Analysis**
- **Endoscopic Polyps in Colons**
- **Human Action/Activity Recognition (RGB-D)**
- **Robust Person Re-identification**

SUSTech: Research directions: Computer Vision and Medical Image Analysis

- **Multimodal Brain Lesion Segmentation (MR/CT)**
- **Semi- and Self-supervised Learning**
- **Attack and Defence in Deep Learning Models**
- **Human Action/Activity Recognition/Localisation**
- **Lifelong Learning for Person Re-identification**
- **Attention and Uncertainties**

My Publications

Journals:

IJCV

IEEE TPAMI

MIA

IEEE TMI

IEEE TIP

NeuroImage

Scientific report

Nature

Conferences:

ICCV

CVPR

ECCV

BMVC

MICCAI

AAAI

NeuRIPS

DUNDEE

School of Computing
UNIVERSITY OF DUNDEE

If you are interested in doing a PhD, please come to see me at some stage.

Communications and Feedback

1. Via Email, zhangjg@sustech.edu.cn
2. Pop into my office: RM313, Southern Block, College of Engineering, based on appointment
3. Time: In class and labs

Who am I?

- My research interests in AI:
  - Computer Vision
  - Pattern Recognition and multimodal analysis
    - Object recognition
    - Image segmentation
  - Medical Image Analysis
    - Multimodal Brain lesion (tumour) segmentation
  - Machine Learning
    - OOD, Calibration, Uncertainty

Module content

- Topics we will cover in this module:

Module content

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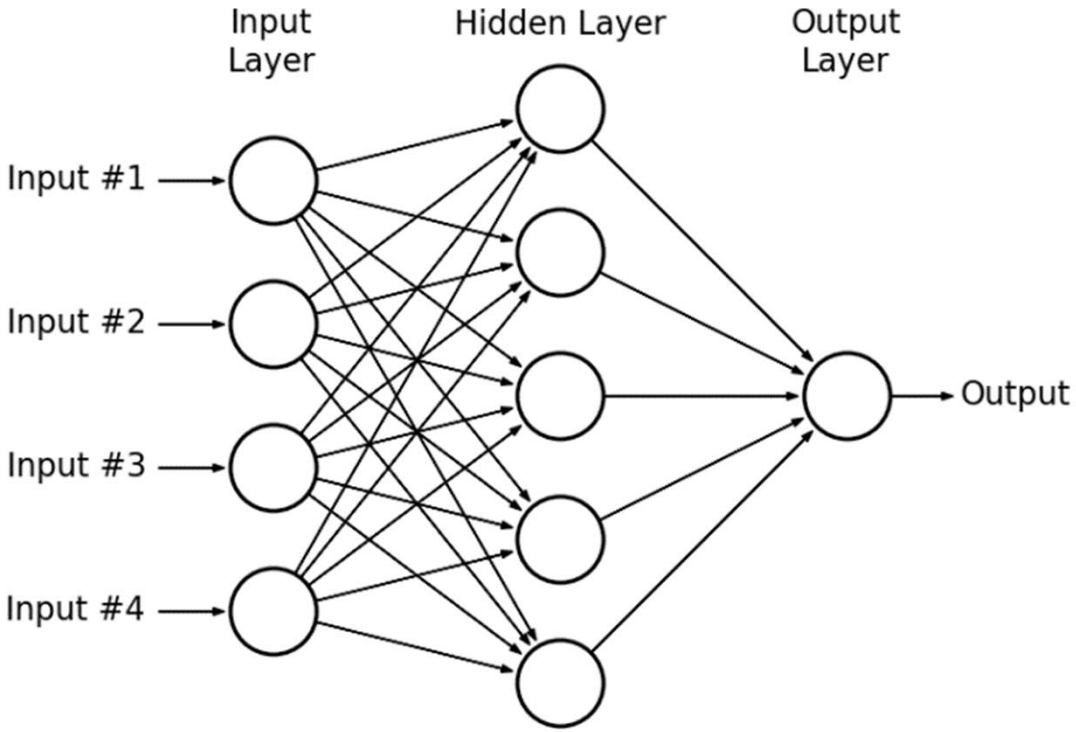
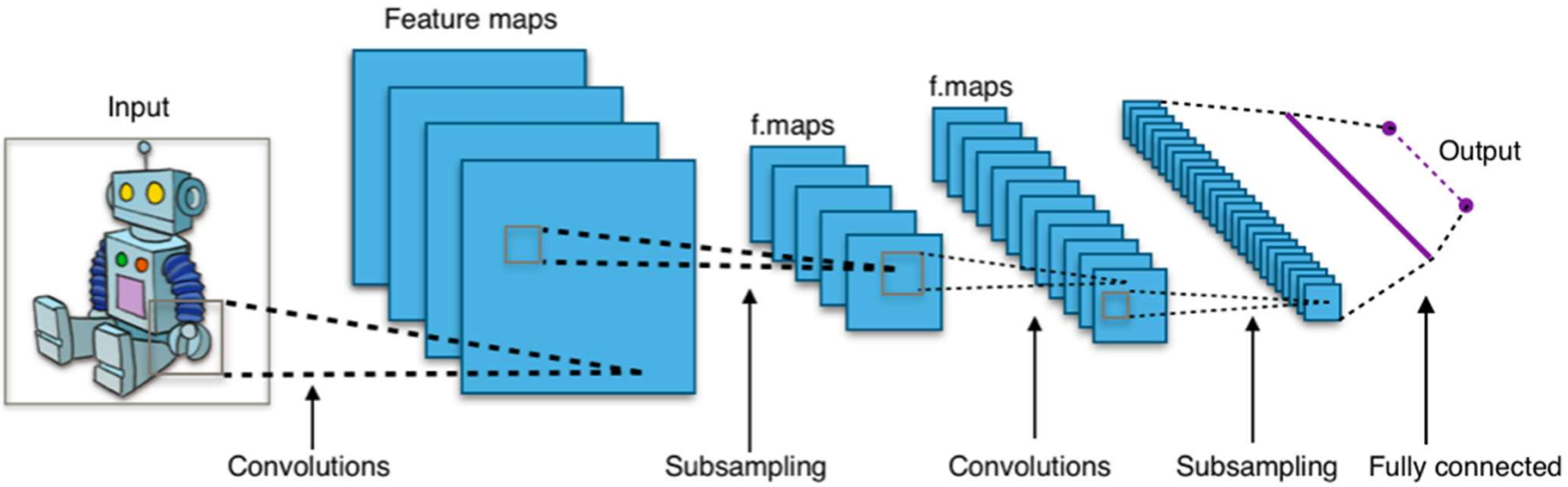


Multi-layer perceptrons (MLPs)

Module content

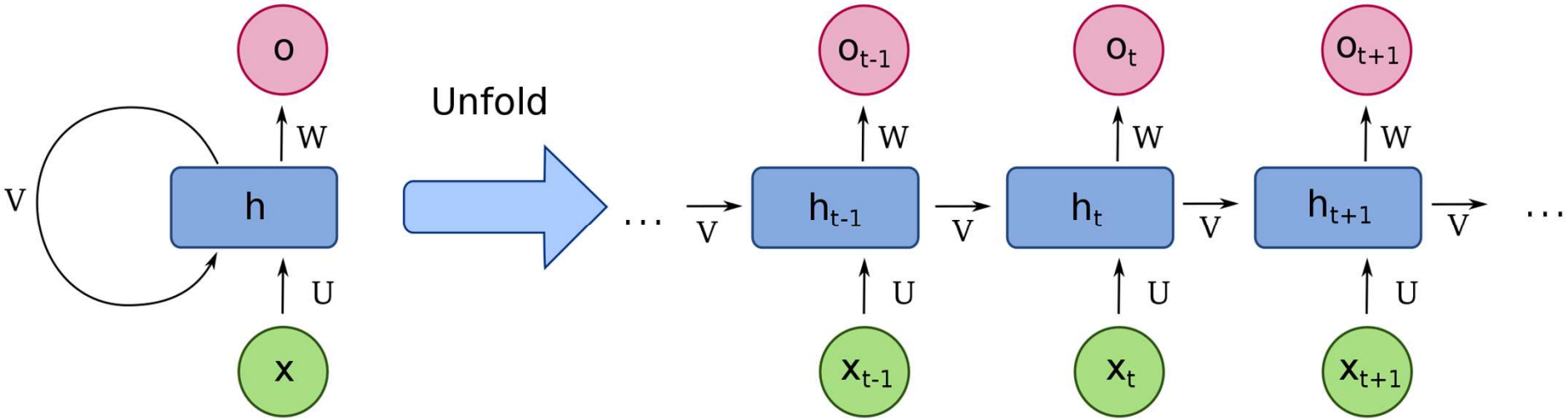
- Topics we will cover in this module:



Convolutional neural networks (CNNs)

Module content

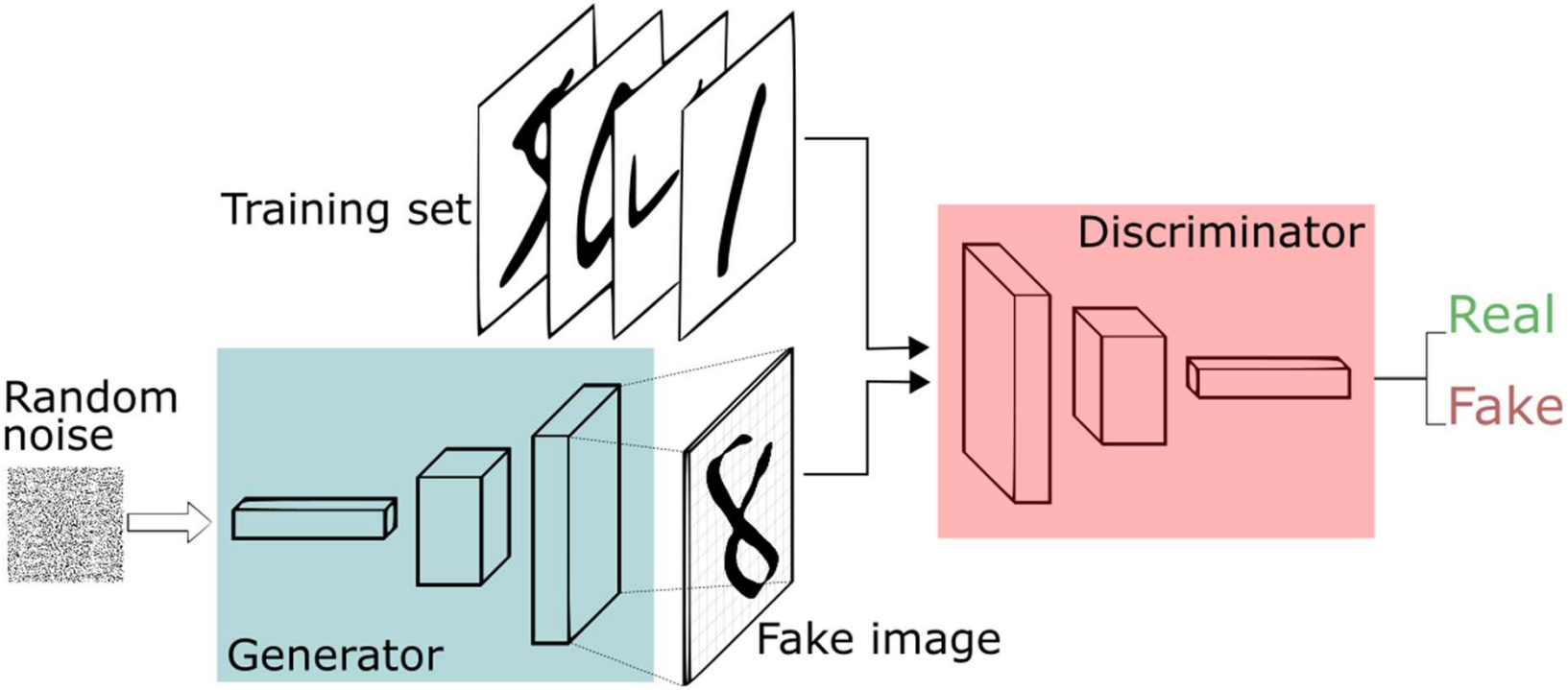
- Topics we will cover in this module:



Recurrent neural networks (RNNs)

Module content

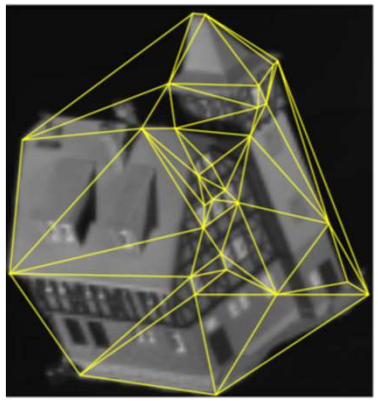
- Topics we will cover in this module:

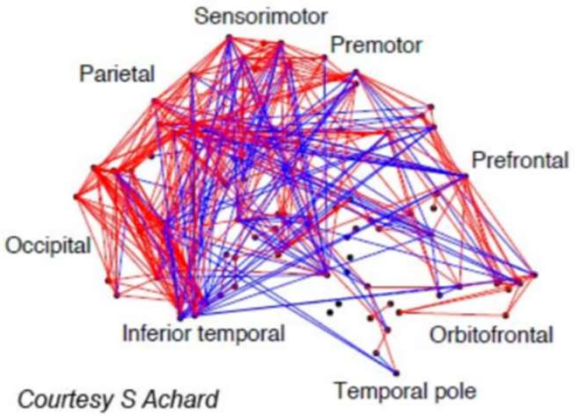


Generative adversarial networks (GANs)

Module content

- Topics we will cover in this module:

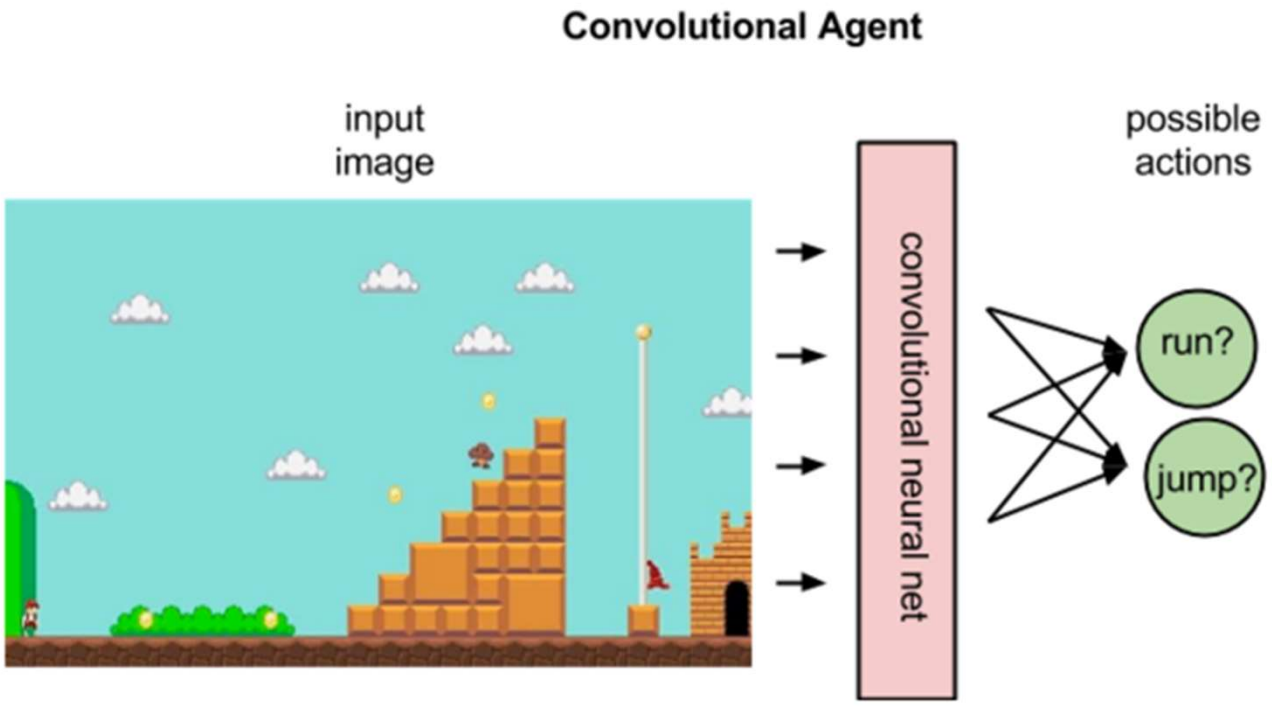




Deep learning on graphs

Module content

- Other Topics we will not cover in this module:



Deep reinforcement learning

Deep Learning Fall···

群号: 621659715

扫一扫二维码，加入群聊

QQ

Tentative Schedule: Week 1

- **Introduction**: course overview; information on lecture & labs schedule; assessments structure and rules; what is deep learning and why are you here?
- **[Lab 1]** Introduction to Pytorch and assignments overview

Tentative Schedule: Week 2

- **Where it all started**: brief recap of linear algebra; tensors; brief history of machine learning and recap of fundamental concepts; biological neurons; the perceptron
- **[Lab 2]** Assignment #1 is made available (MLP and back-propagation)

Tentative Schedule: Week 3

- **Going deep:** shallow networks and the hidden layer; multi-layer perceptron; gradient descent; back-propagation
- **[Lab 3]** Working on assignment #1

Tentative Schedule: Week 4

- **Optimisation**: batch gradient descent; stochastic gradient descent; challenges in optimisation; advanced techniques
- **[Lab 4]** Working on assignment #1

Tentative Schedule: Week 5

- **Regularisation and good practices:** input normalisation; l1 and l2 regularisation; dropout; learning rate; weight initialisation
- **[Lab 5]** Working on assignment #1

Tentative Schedule: Week 6

- **Convolutional neural networks, part one:** what are CNNs and what makes them special; their importance in computer vision; CNNs modules; how to train a CNN
- **[Lab 6]**: Assignment #2 is made available (CNNs and RNNs)

Tentative Schedule: Week 7

- **Convolutional neural networks, part two:** popular modern CNNs architectures; vanishing gradients; inception model
- **[Lab 7]:** Working on assignment #2

Tentative Schedule: Week 8

- **Recurrent neural networks: s**equential data; RNNs; back-propagation through time; exploding and vanishing gradients; LSTM architectures
- **[Lab 8]:** Working on assignment #2

Tentative Schedule: Week 9

- **Auto-encoders:** supervised versus unsupervised learning; manifold hypothesis; PCA; kernel PCA; auto-encoders
- **[Lab 9]:** Working on assignment #2

Tentative Schedule: Week 10

- **Generative adversarial networks:** generative vs discriminative models; generative adversarial networks; variants of GANs
- **[Lab 10]:** Assignment #3 is made available (GANs and VAEs)

Tentative Schedule: Week 11

- **Explicit generative models:** variational inference; variational auto-encoders; restricted Boltzmann machines (optional); deep Boltzmann machines (optional);
- **[Lab 11]:** Working on assignment #3

Tentative Schedule: Week 12

- **Adversarial learning – Attack and defense :** the safety issues of deep net; why deep net can be easily fooled; generating adversarial examples; different attack methods; defense;
- **[Lab 12]:** Working on assignment #3

Tentative Schedule: Week 13

- **Beyond vectors:** graph-based learning and neural networks, part one: graph-based vs vector-based learning, advantages and problems; deep learning on graph data; graph CNNs
- **[Lab 13]:** Working on assignment #3

Topics might not be covered in detail

- **Deep reinforcement learning:** what is reinforcement learning; Bellman equation; deep RL; Q-learning; stability problems; policy-based deep RL; model-based deep RL

Tentative Schedule: Week 14-15

- **Students presentations** on selected papers about state-of-the-art architecture. The format of the presentations will vary depending on the size of the cohort
- Revision, Q&A

Tentative Schedule: Week 14-15

- **Students presentations** on selected papers about state-of-the-art architecture. The format of the presentations will vary depending on the size of the cohort
- Revision, Q&A
- Flipped classroom activity: critical appraisal of deep learning, reflections and class discussion

Tentative Schedule: Week 14-15

- **Students presentations** on selected papers about state-of-the-art architecture. The format of the presentations will vary depending on the size of the cohort
- Revision, Q&A
- ~~Flipped classroom activity: critical appraisal of deep learning, reflections and class discussion~~ (?)

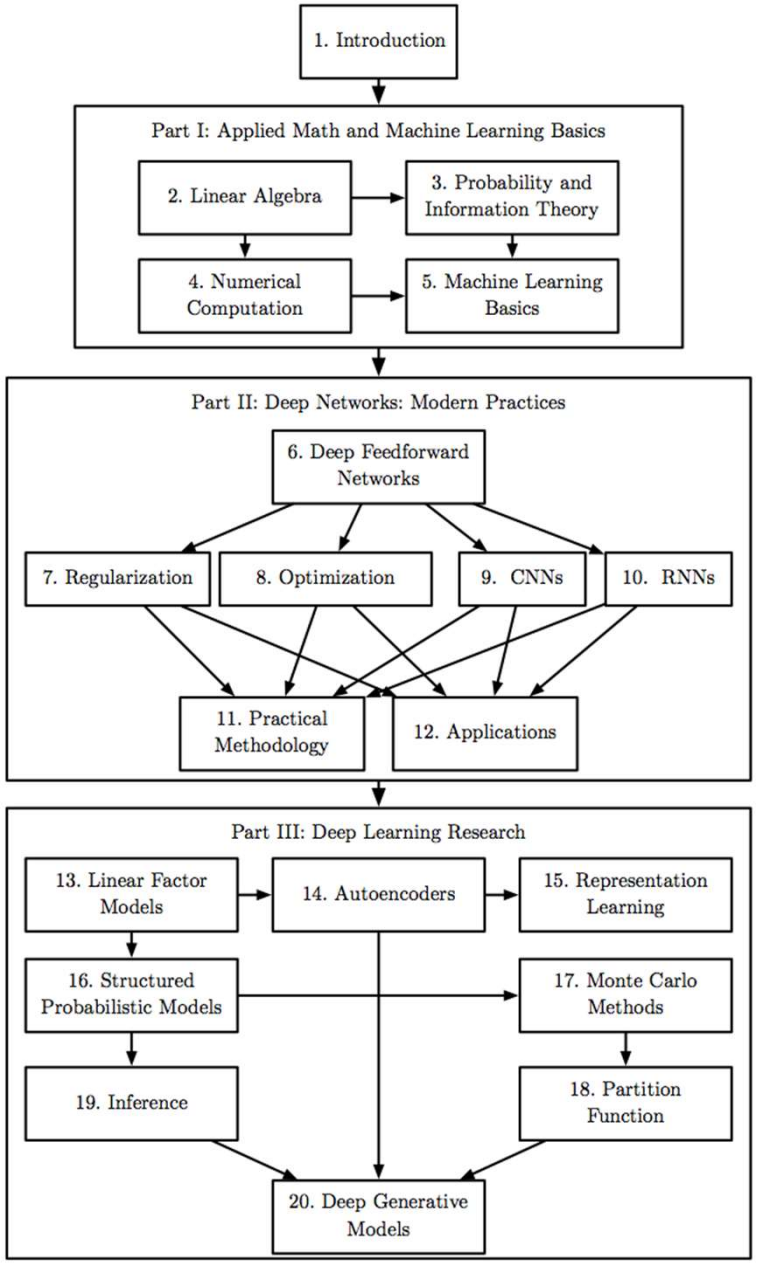
Assessment

- **Final exam** (40%)
- **practical assignments** worth 15%+15% +15% (45% total)
  - Plagiarism will not be tolerated (remember to always cite your sources)
- Student **presentation** (5%)
  - On an advanced topic (to be decided 2/3 into the course) or on (Demo on Chips)
- Demo AI on Chips (10%) --- Online real-time GAN-based face interpolation (demo) or other demo

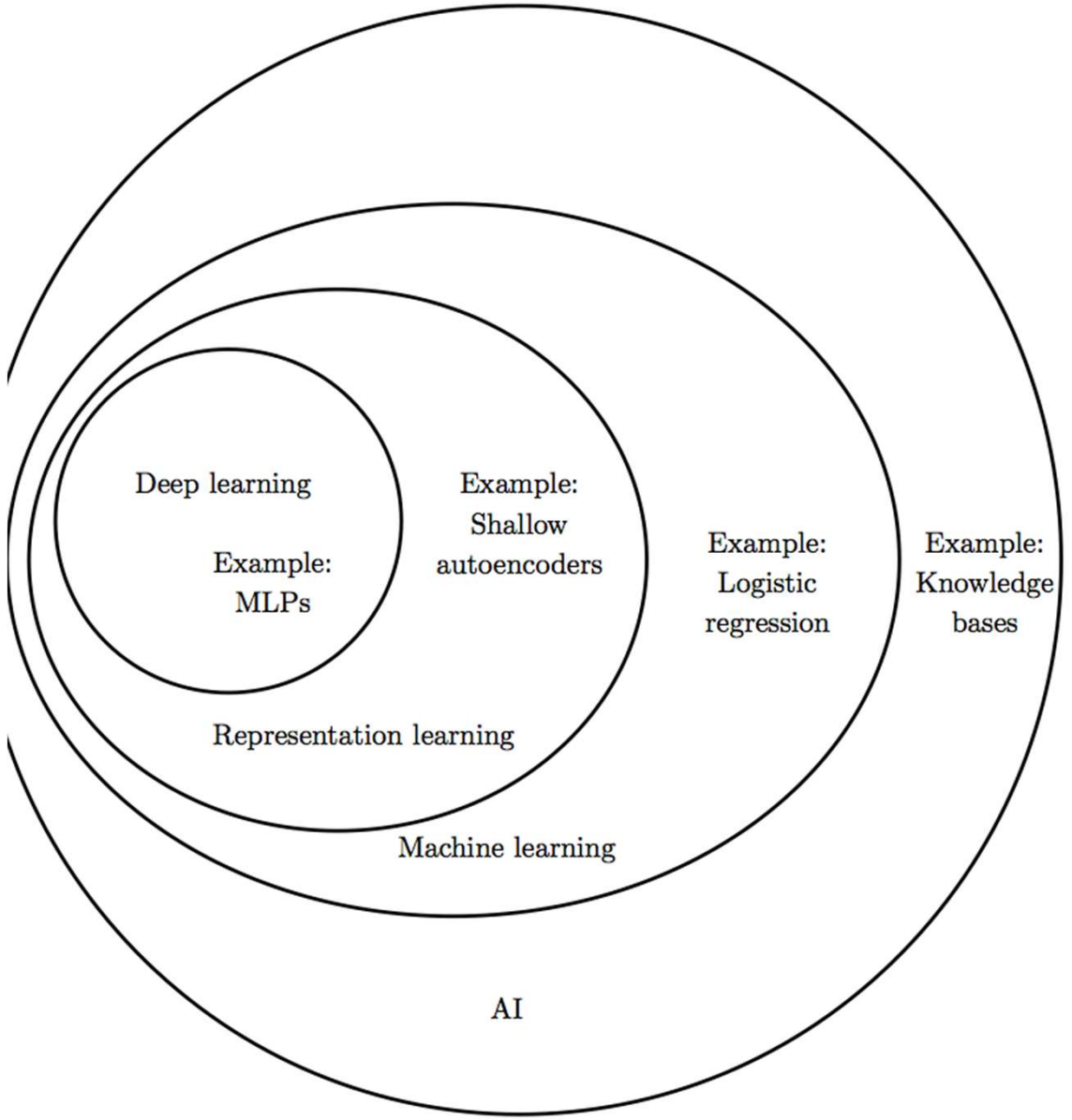
Reading List

- **Main textbook:**
  - Goodfellow, Ian, Yoshua Bengio, Aaron Courville. Deep learning. Vol. 1. Cambridge: MIT press, 2016. https://www.deeplearningbook.org/
- *Other recommended books:*
  - Chollet, Francois. Deep learning with python. Manning Publications Co., 2017.
  - Nielsen, Michael A. Neural networks and deep learning. Vol. 25. USA: Determination press, 2015.
- But, most importantly, come to the lectures and study what's in the slides!

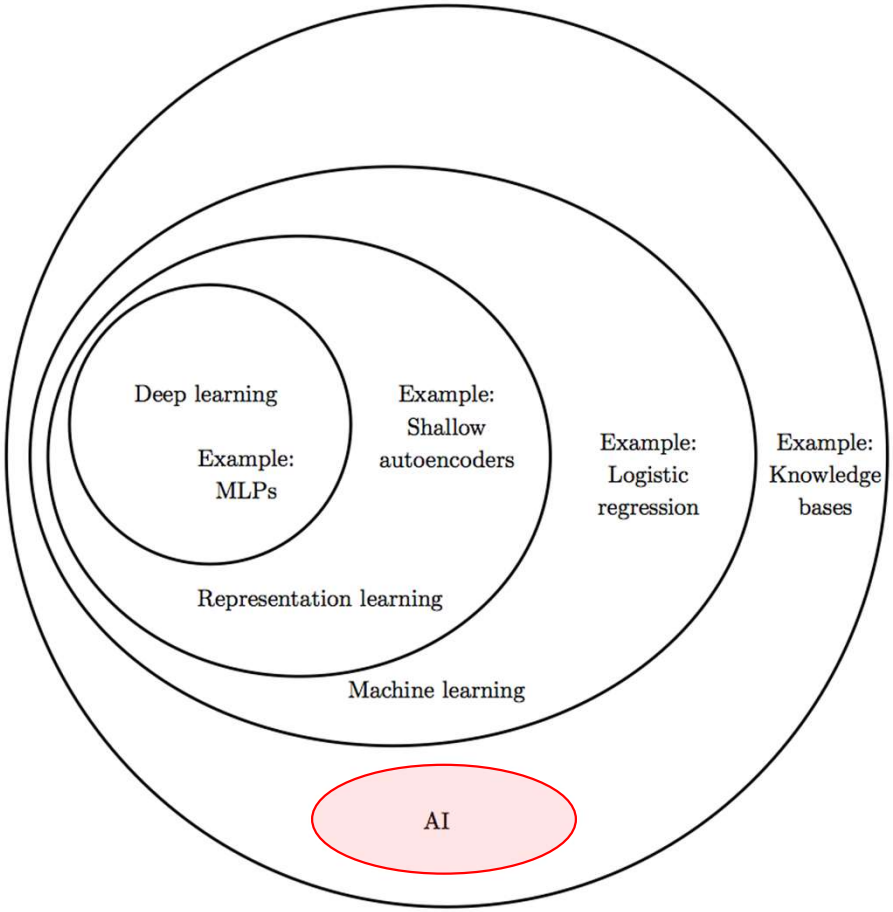
Textbook organisation



What is Deep Learning?

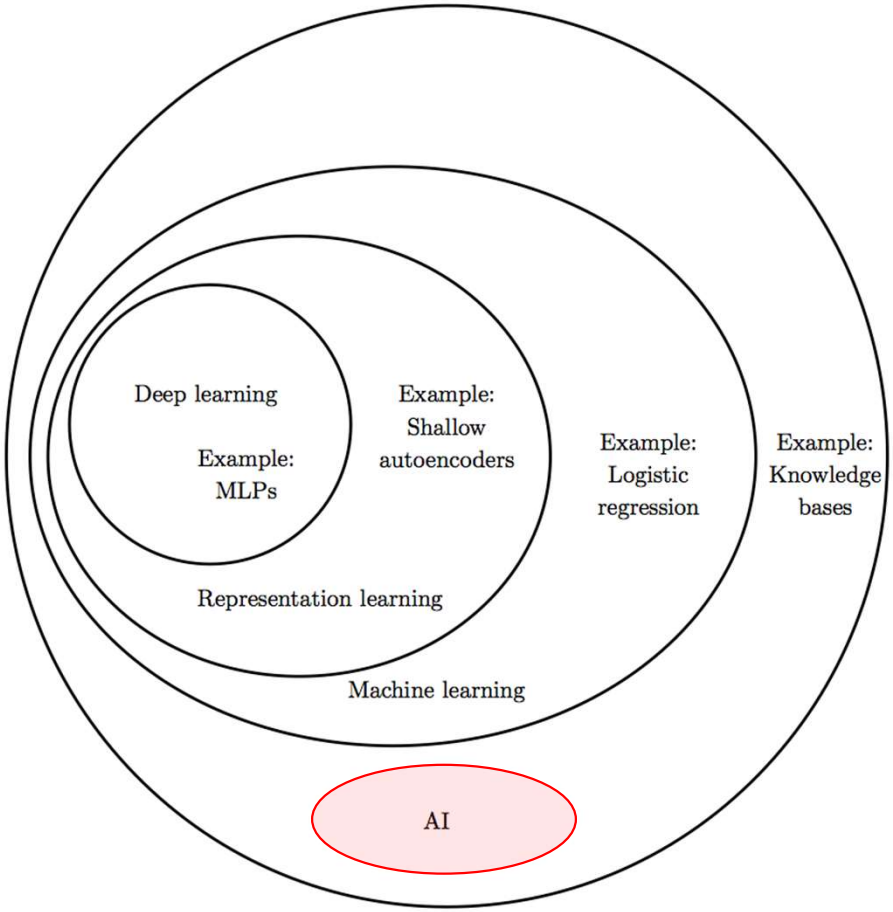


What is Deep Learning?



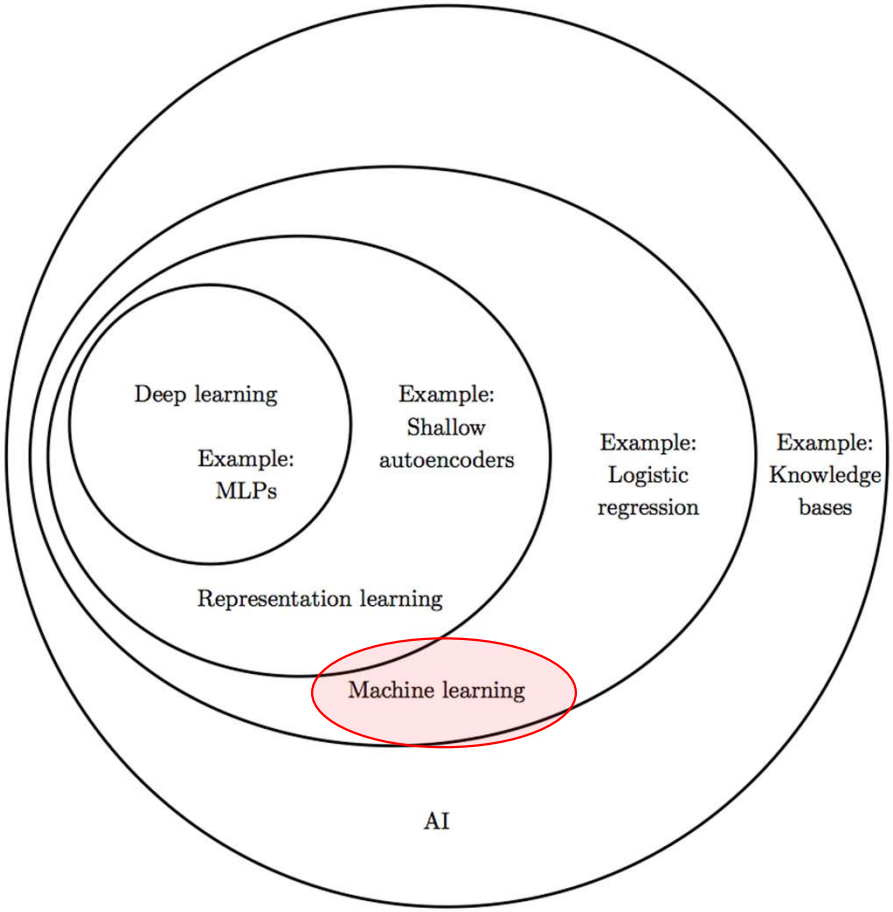
Can we make “intelligent” machines?
Automate labour, assist in diagnosis, understand speech…

What is Deep Learning?



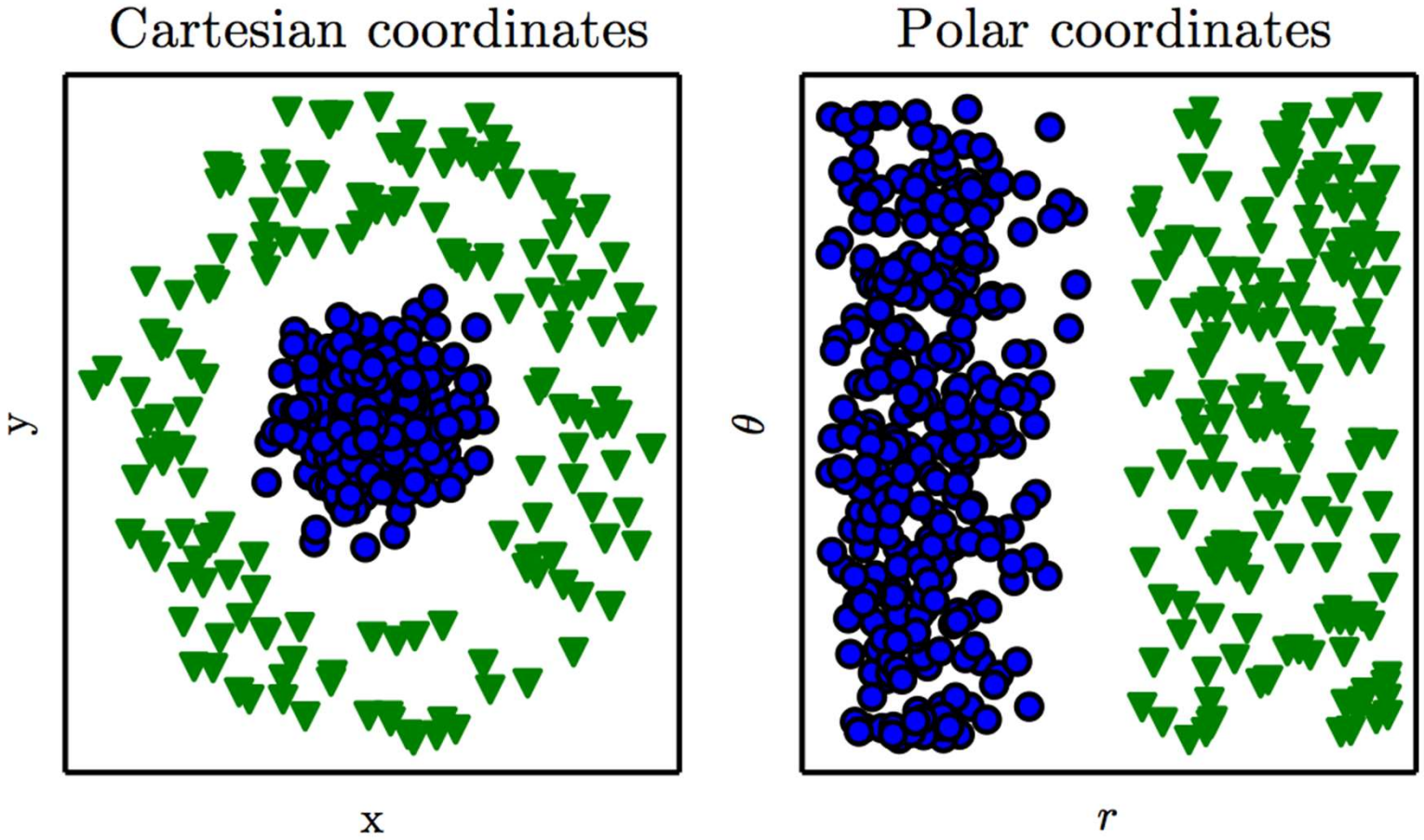
Knowledge bases use hardcoded inference rules to reason automatically about statements…

What is Deep Learning?



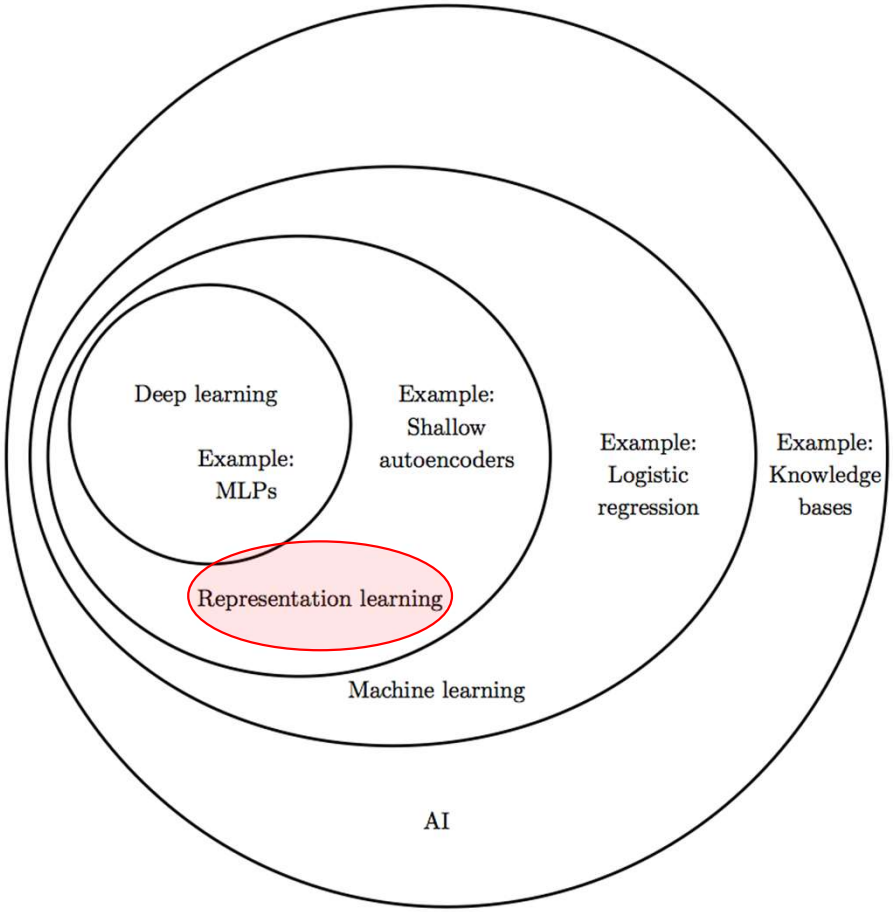
…but knowledge is difficult to hard-code, expensive and not flexible.
Machine learning comes to the rescue: machines acquire
their own knowledge by finding patterns in raw data!

Representation matters



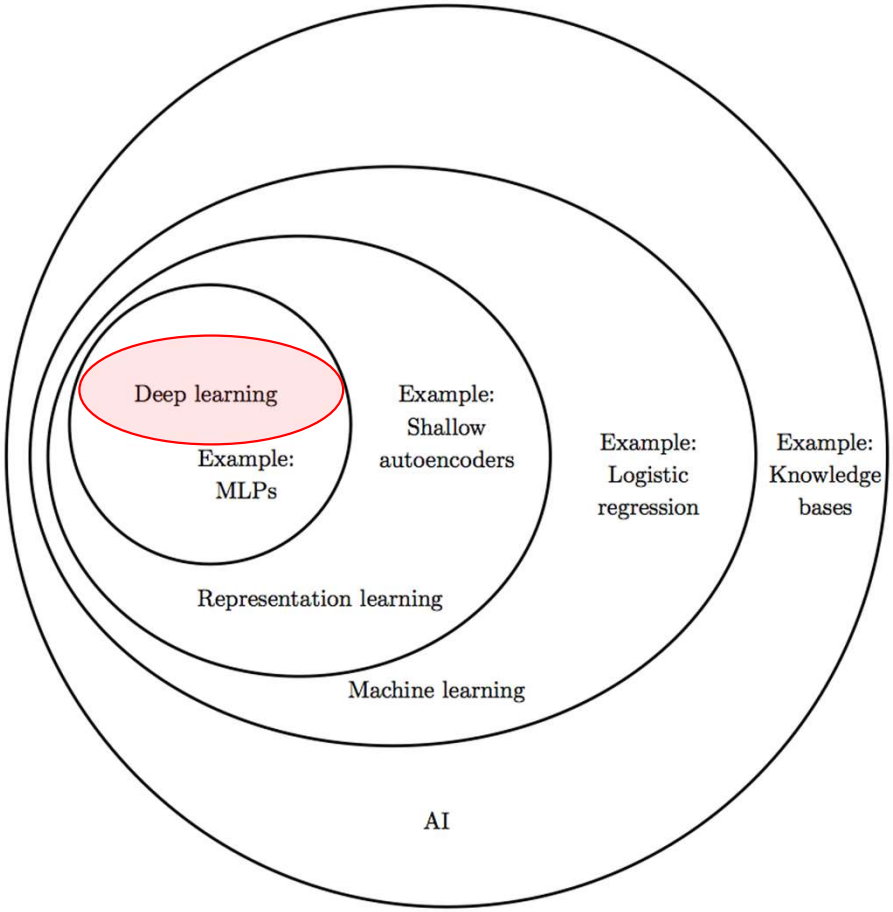
But we still need to feed the machines with a representation of the data…

What is Deep Learning?



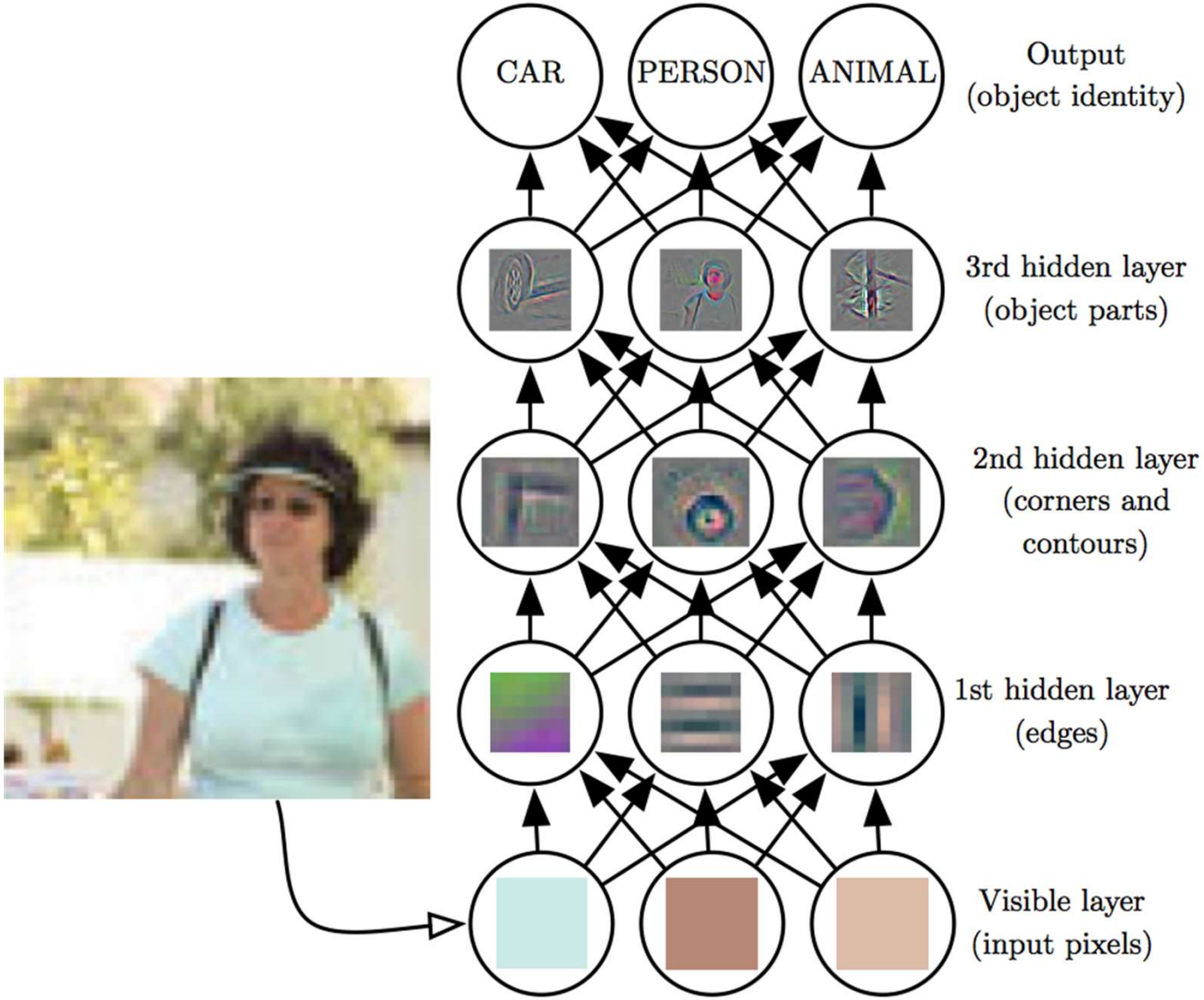
What about learning the representation instead? Representation learning comes to the rescue! Autoencoders learn to encode and decode data by preserving information but adding nice properties

What is Deep Learning?

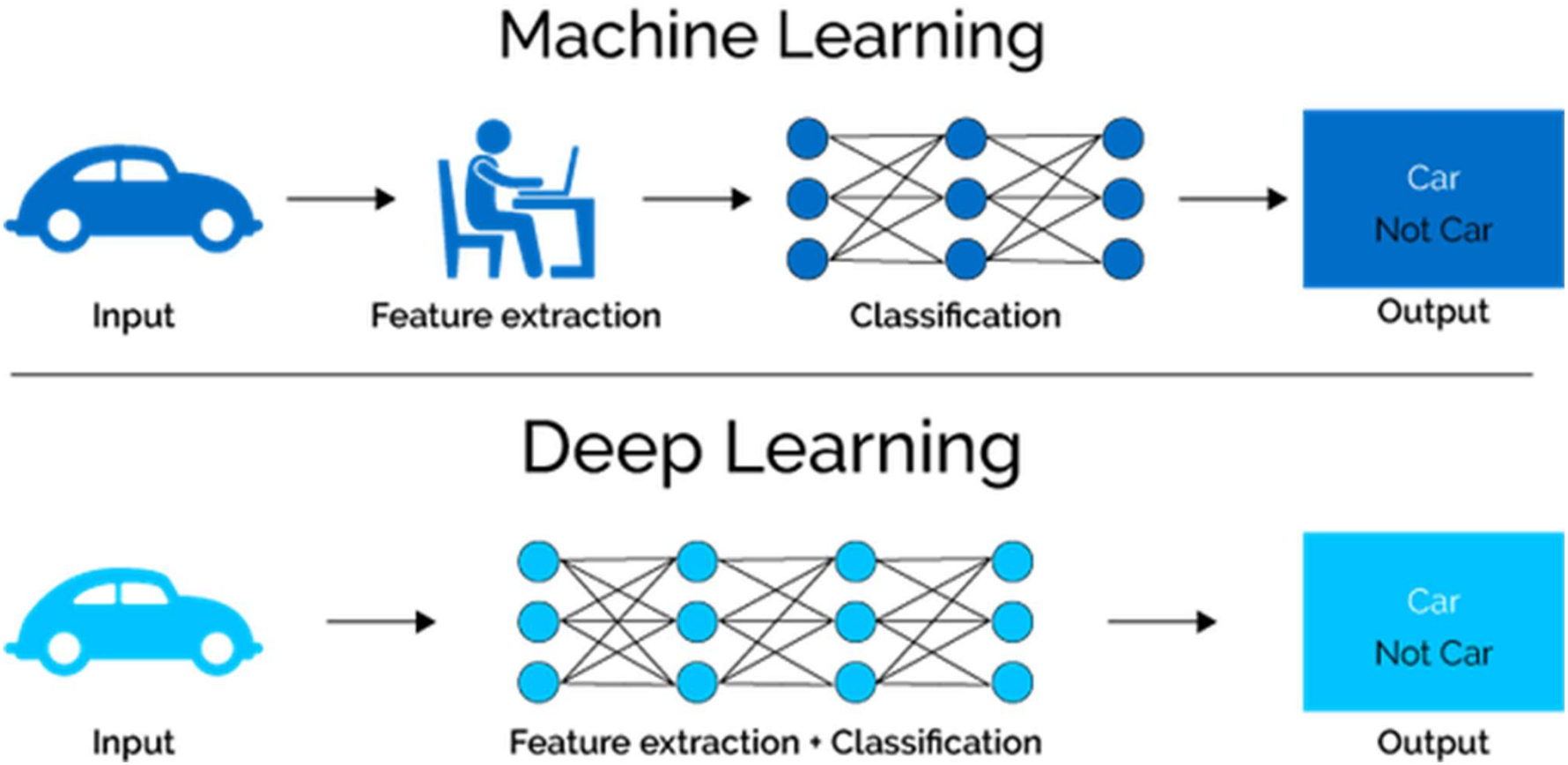


But sometimes the features are too complex to be automatically extracted from raw data in this way. They need to be represented in terms of hierarchy of more and more complex concepts: from shallow to deep learners!

Complexity through composition



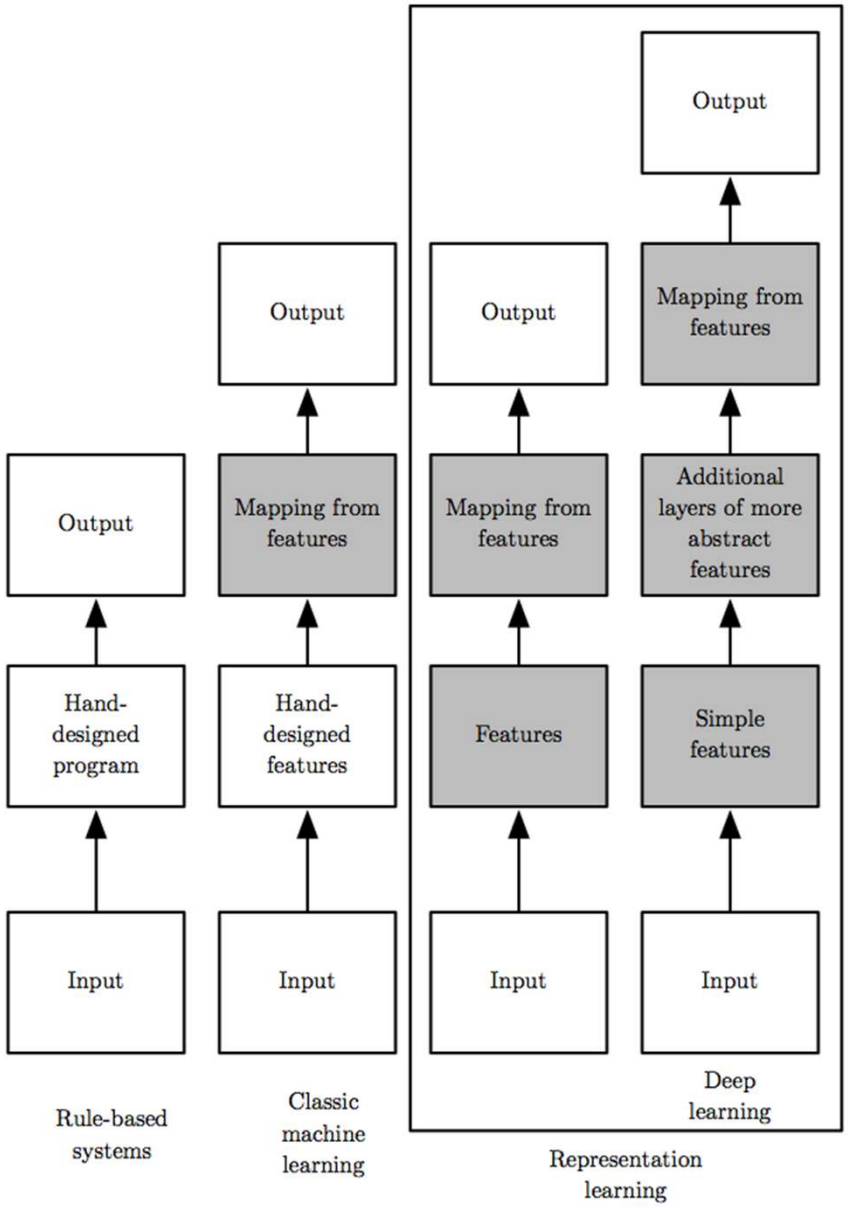
Machine Learning vs Deep Learning



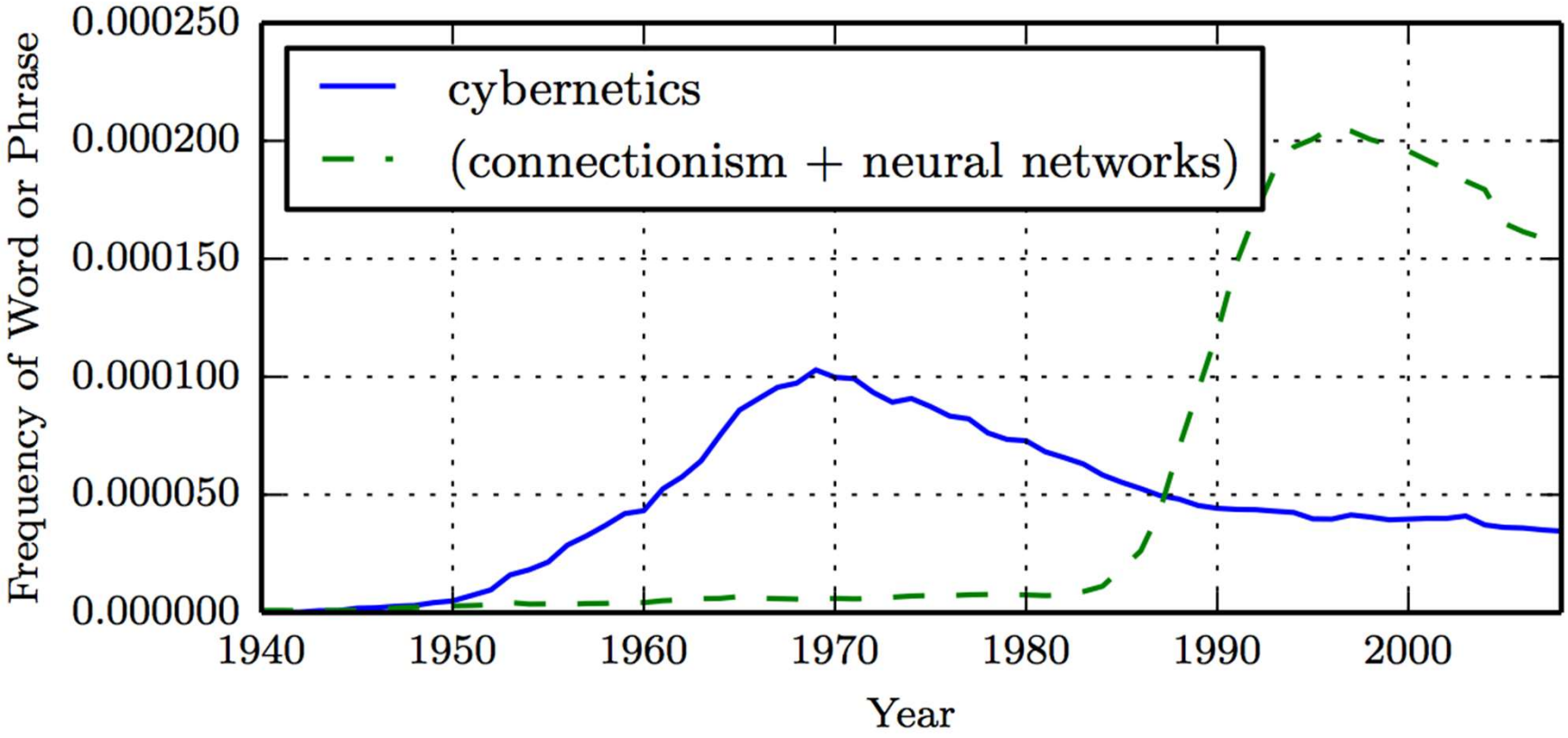
Source https://codeutsava.in/blog/40

Another way of seeing this: deep learning learns not only the classification but also the representation

Yet another perspective

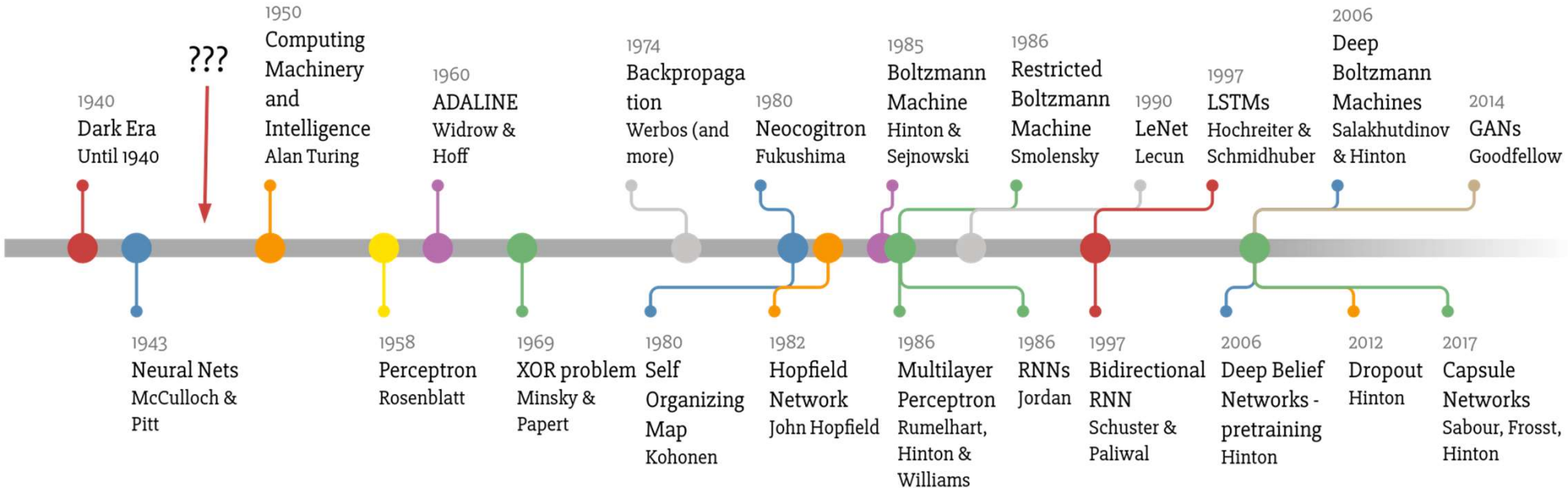


The many names of deep learning



Deep learning has been around for a loooong time…

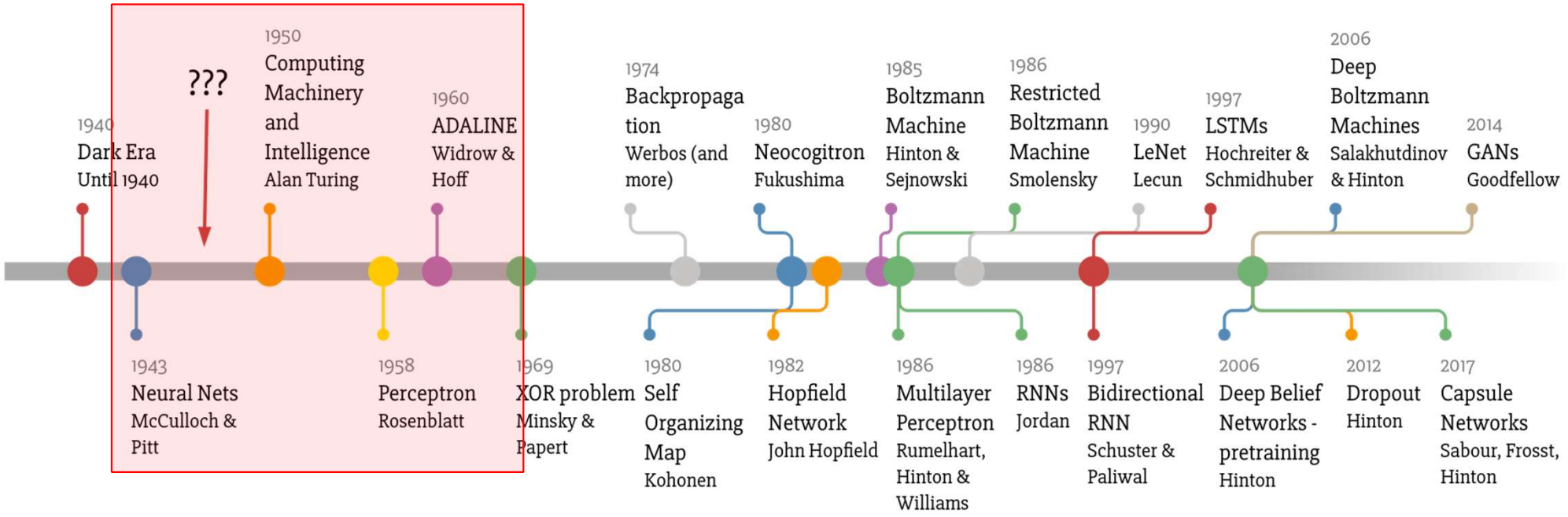
The many names of deep learning



source: https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0

The many names of deep learning

First wave: cybernetics



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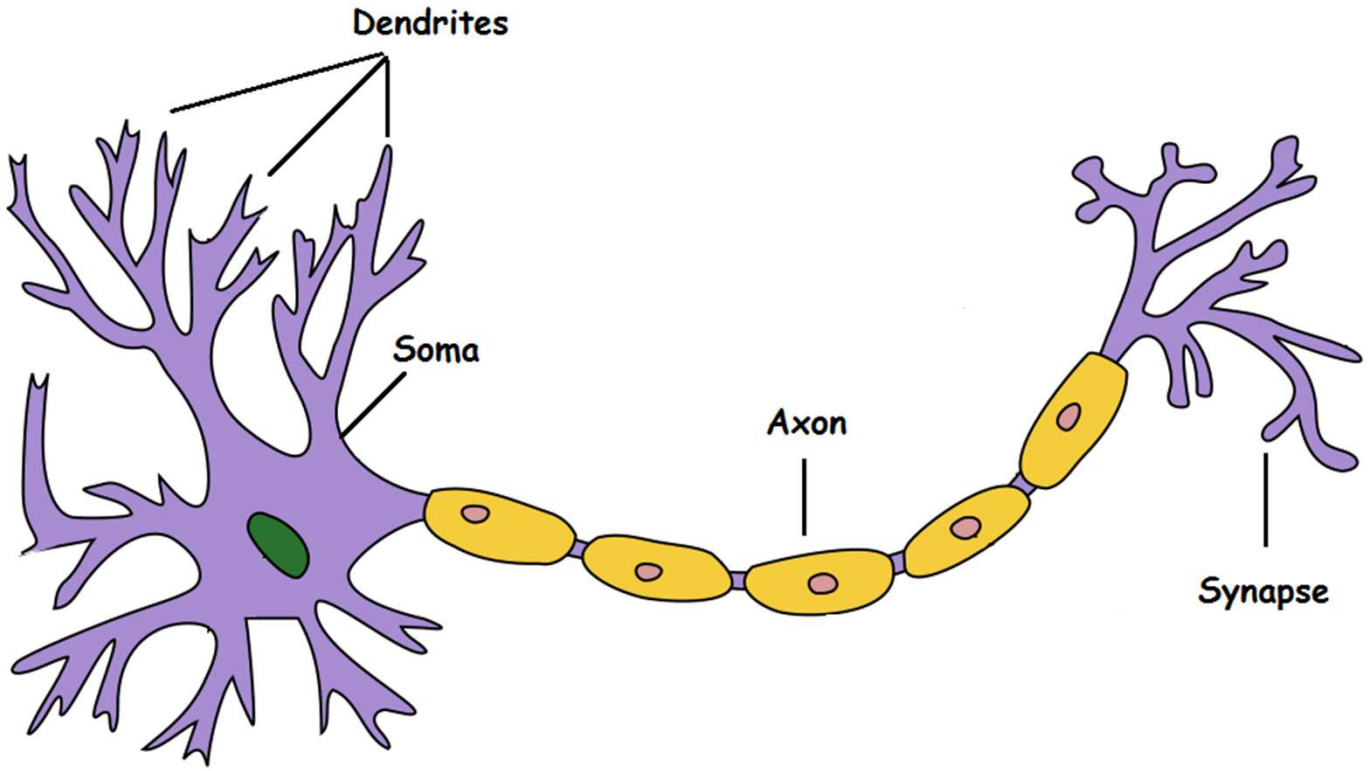
Biological neurons



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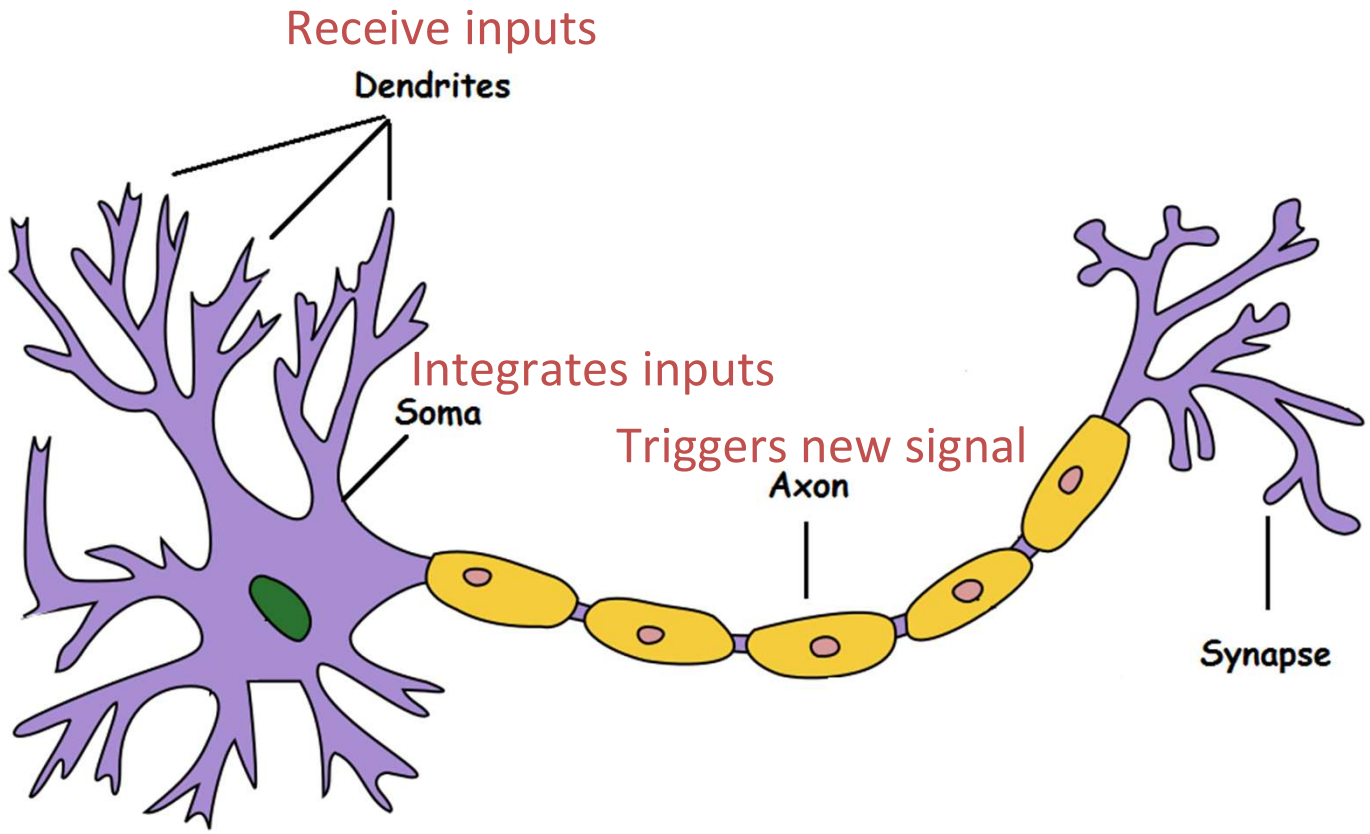
Biological neurons



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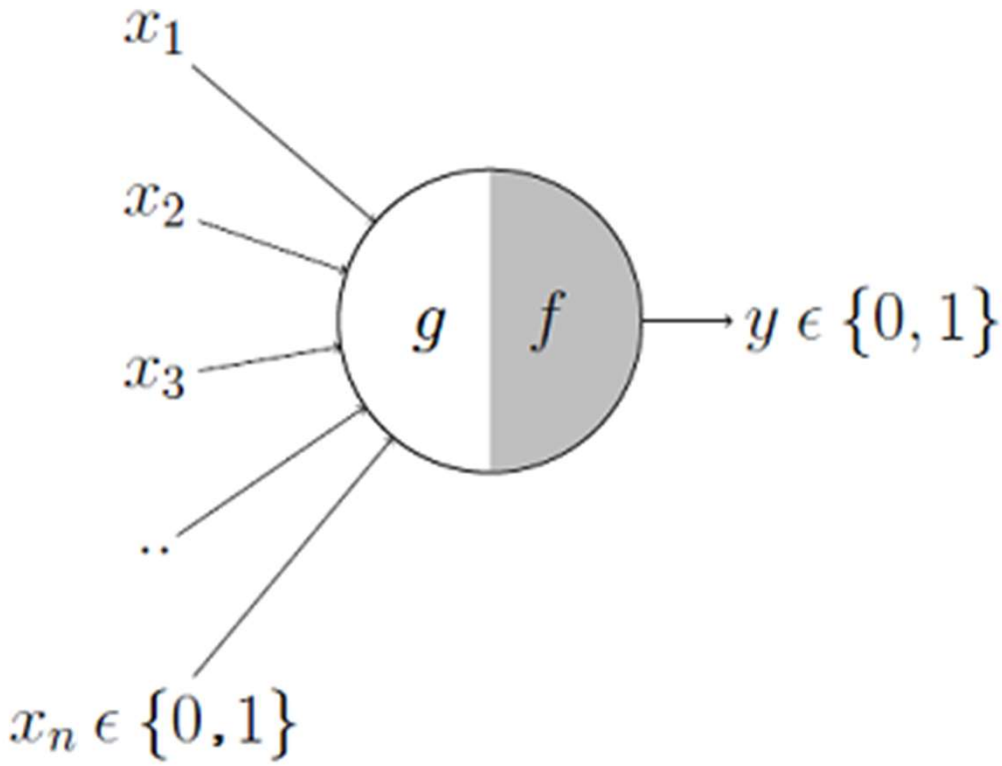
Artificial neurons

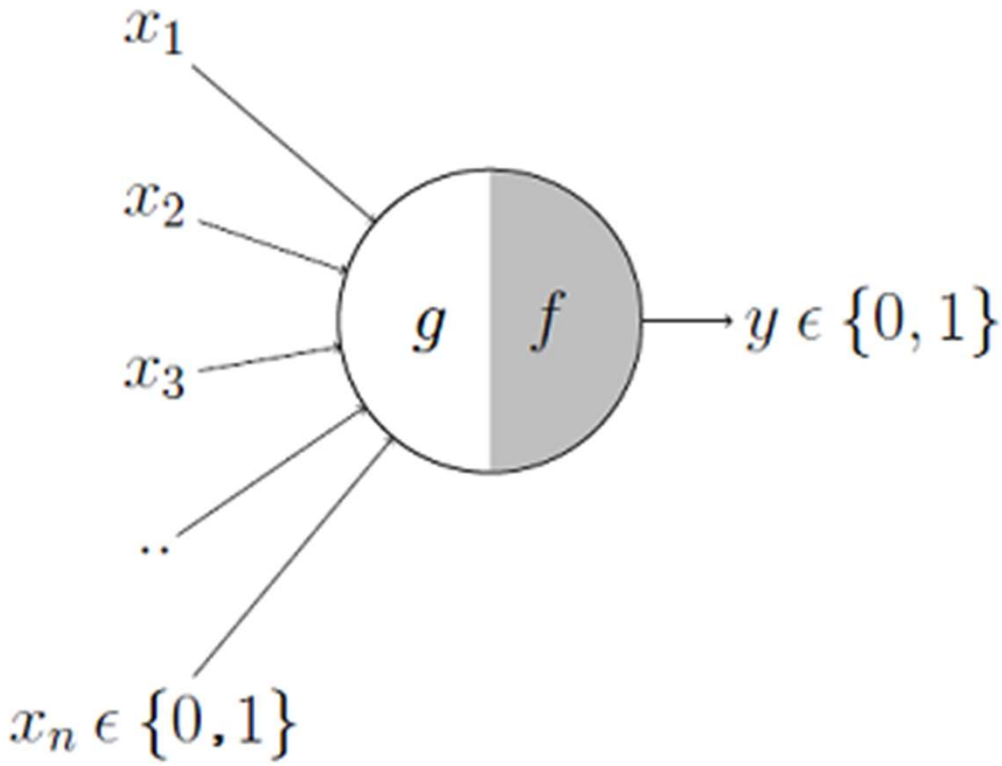
McCulloch-Pitts neuron



source: https://towardsdatascience.com/mcculloch-pitts-model-5fdf65ac5dd1

Artificial neurons

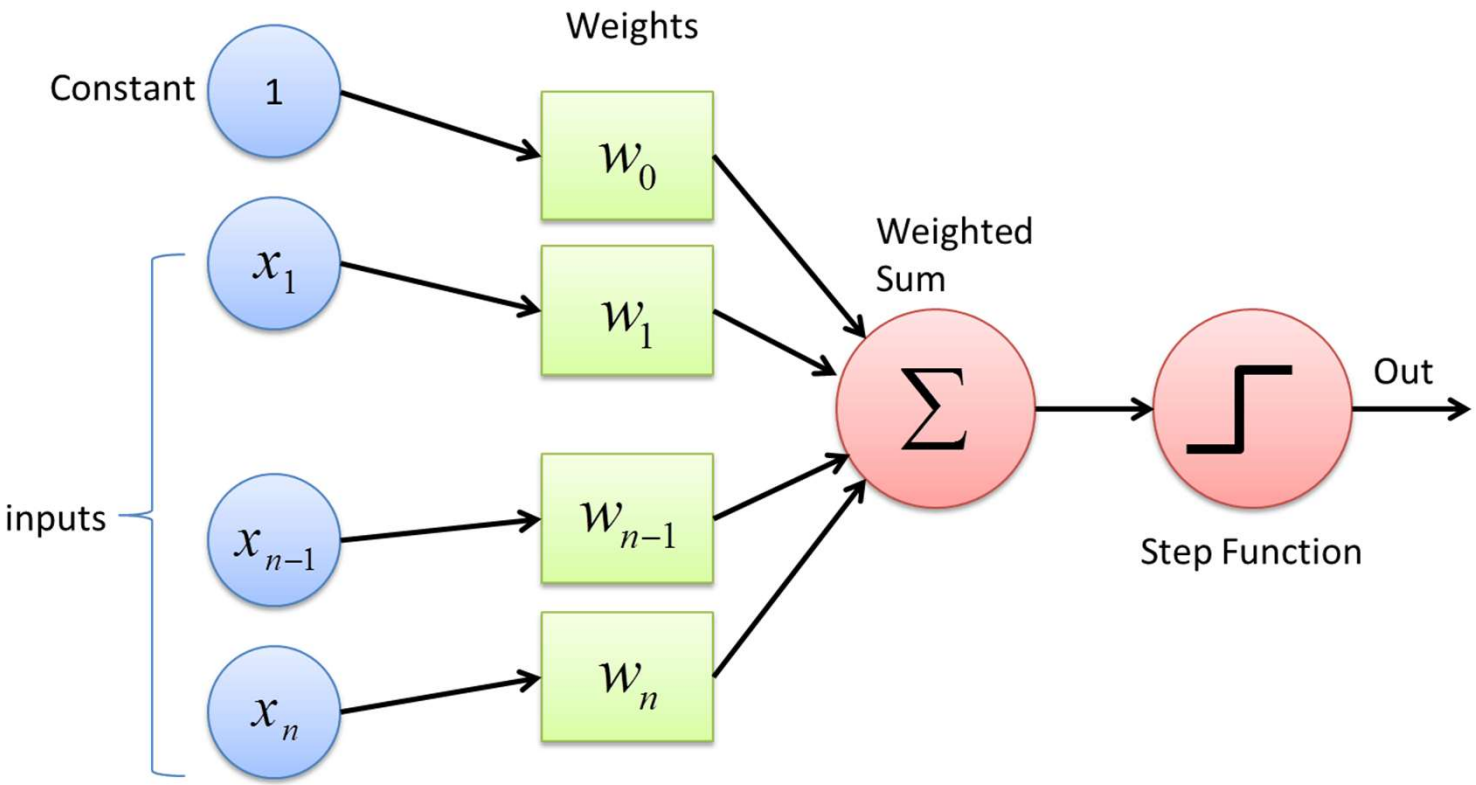
Can implement AND, OR, NOT, etc., but



source: https://towardsdatascience.com/mcculloch-pitts-model-5fdf65ac5dd1

Artificial neurons

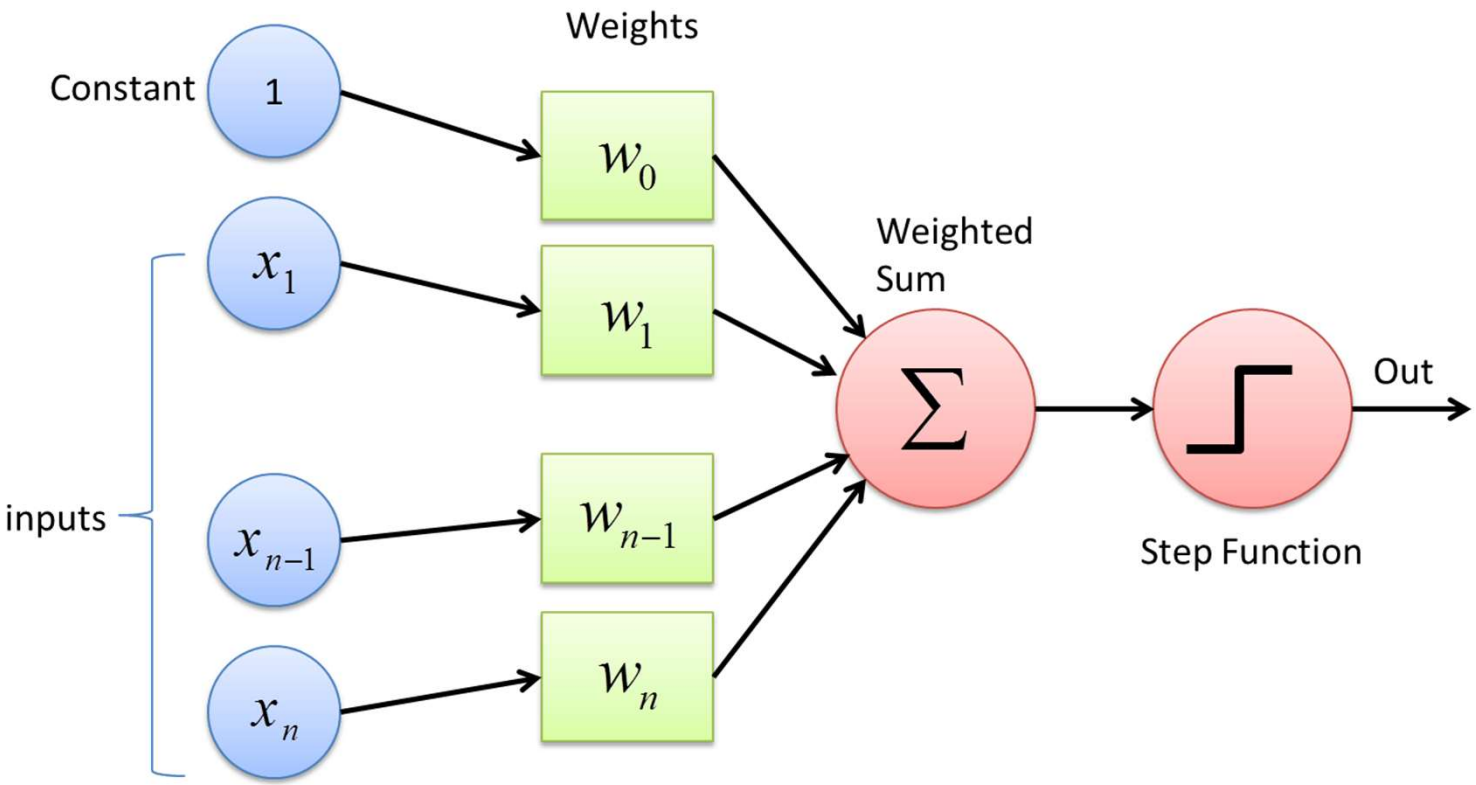
Perceptron by Rosenblatt - same as MP neuron but weighted sum



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

Artificial neurons

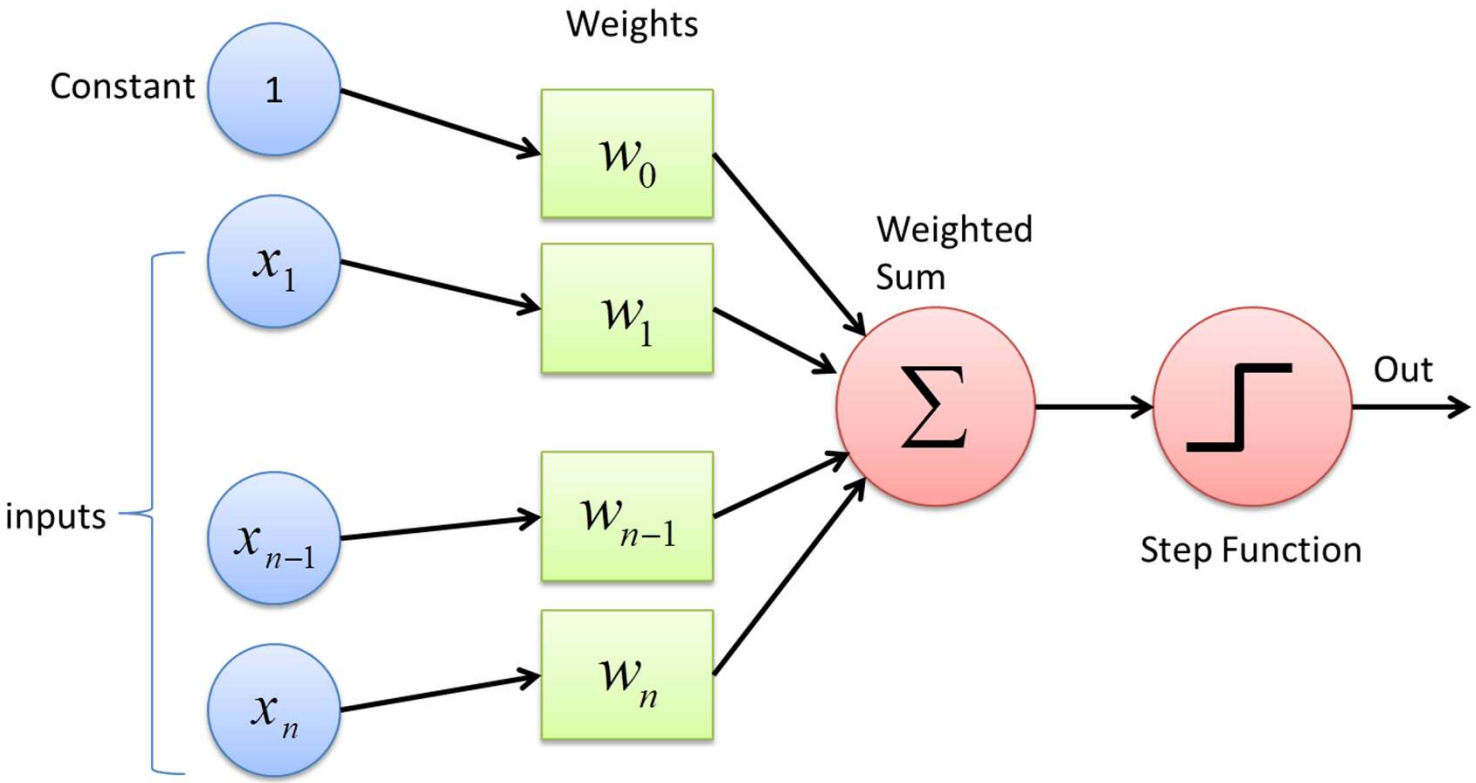
Main innovation is the learning algorithm



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

Artificial neurons

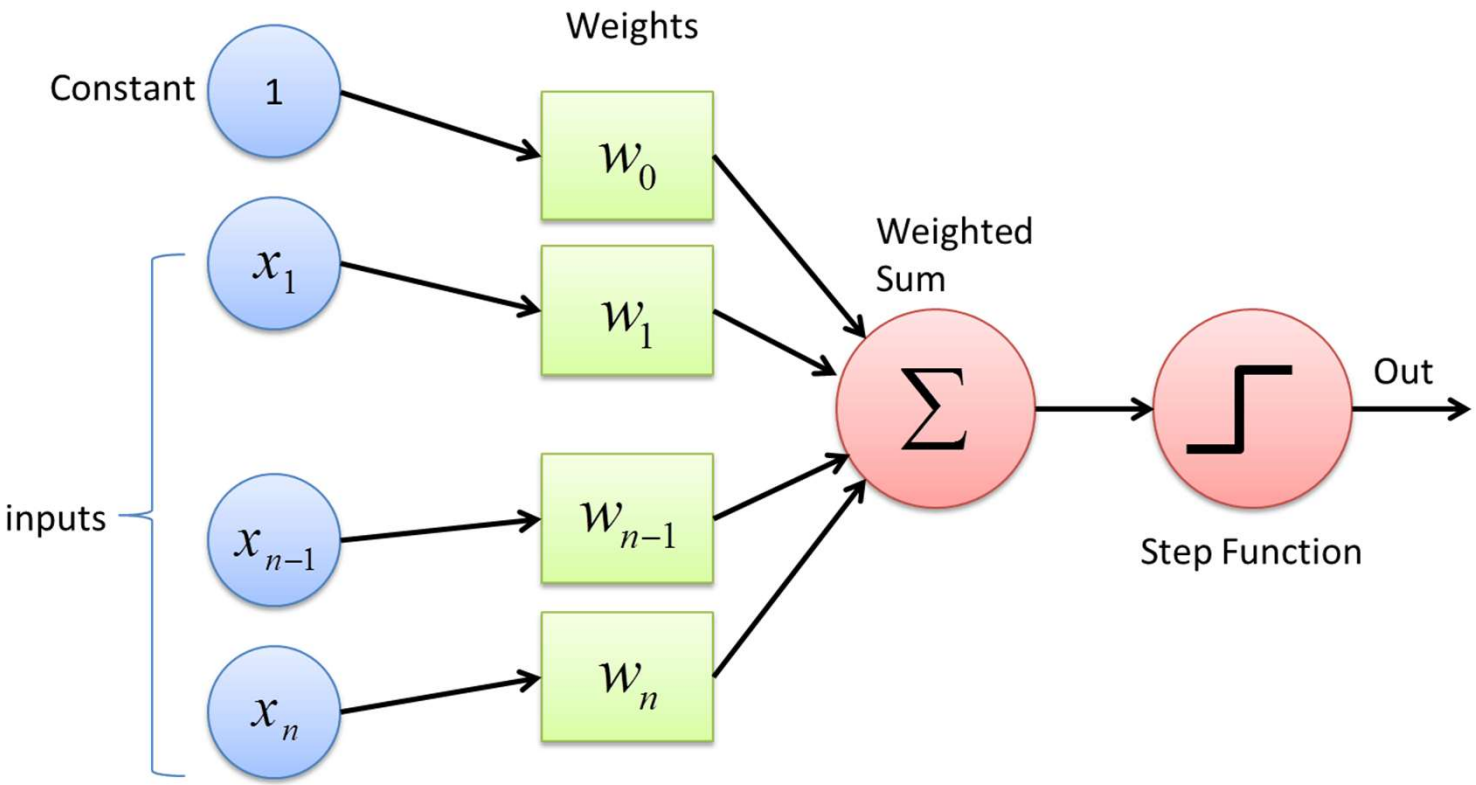
1. Start with random weights



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

Artificial neurons

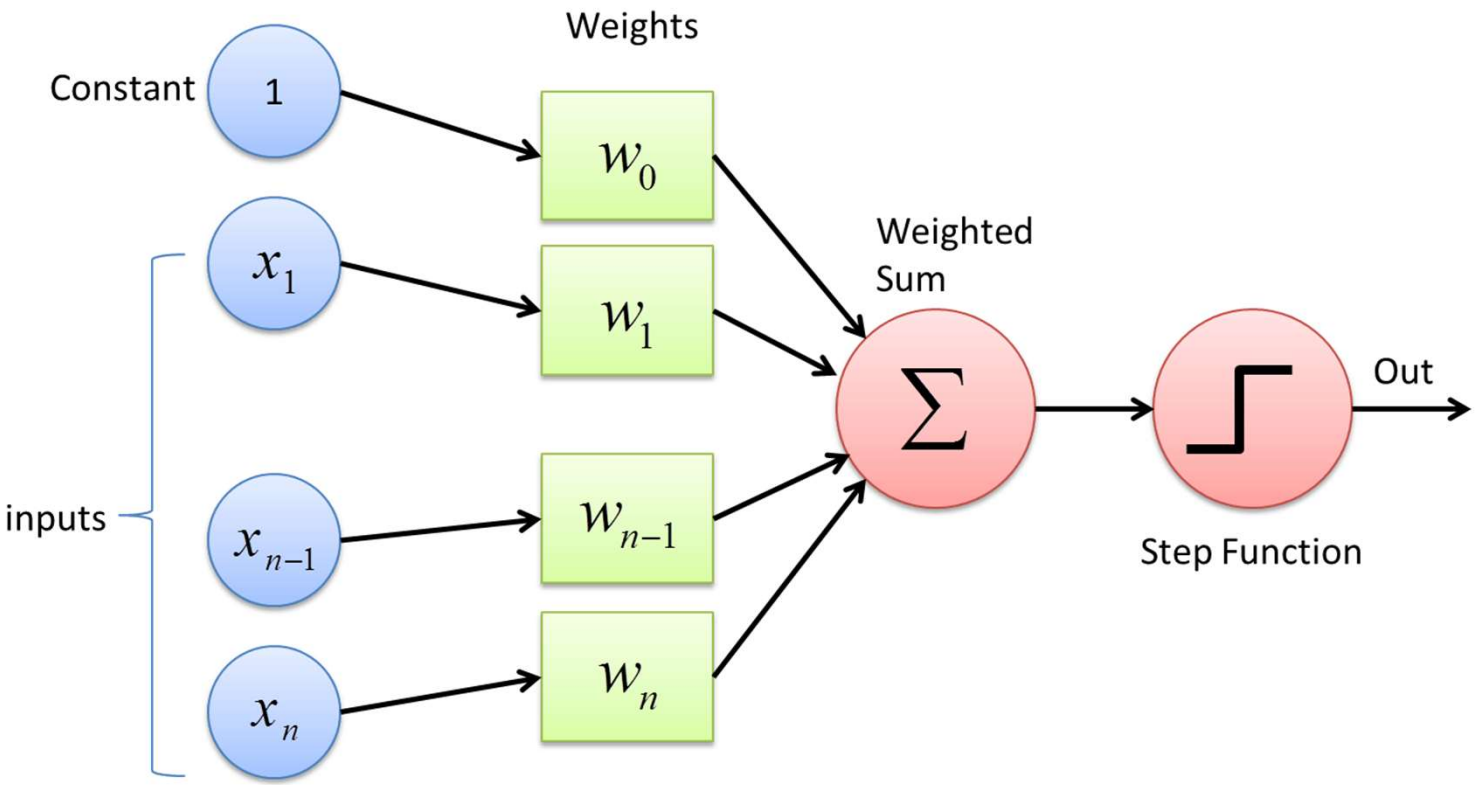
2. Take one sample $\mathbf{x}_j = [x_1, \ldots, x_n]$ and predict $\mathbb{y}_j$



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

Artificial neurons

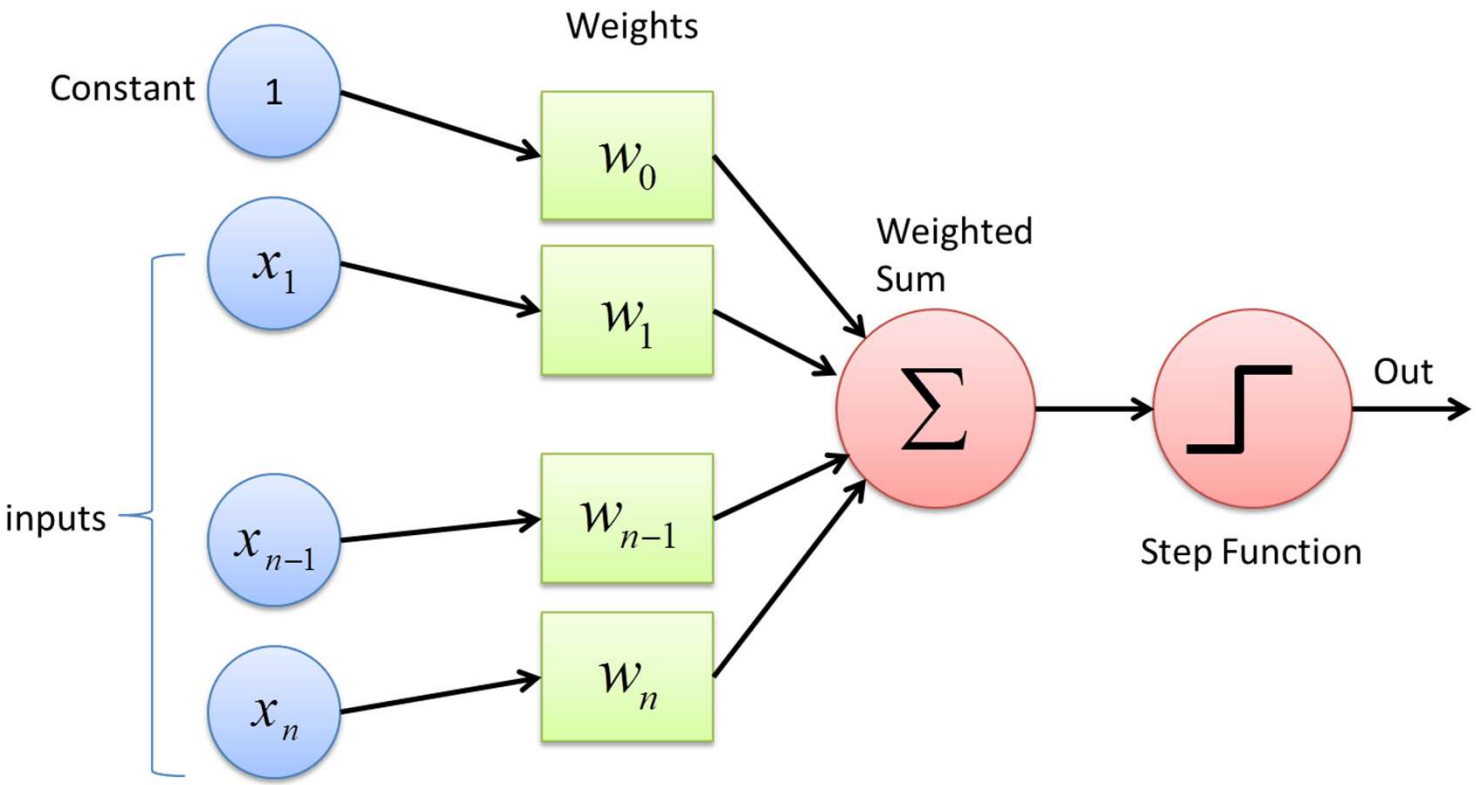
3. If $y_j = 0$ but $\mathbb{y}_j = 1$ then decrease weights



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

Artificial neurons

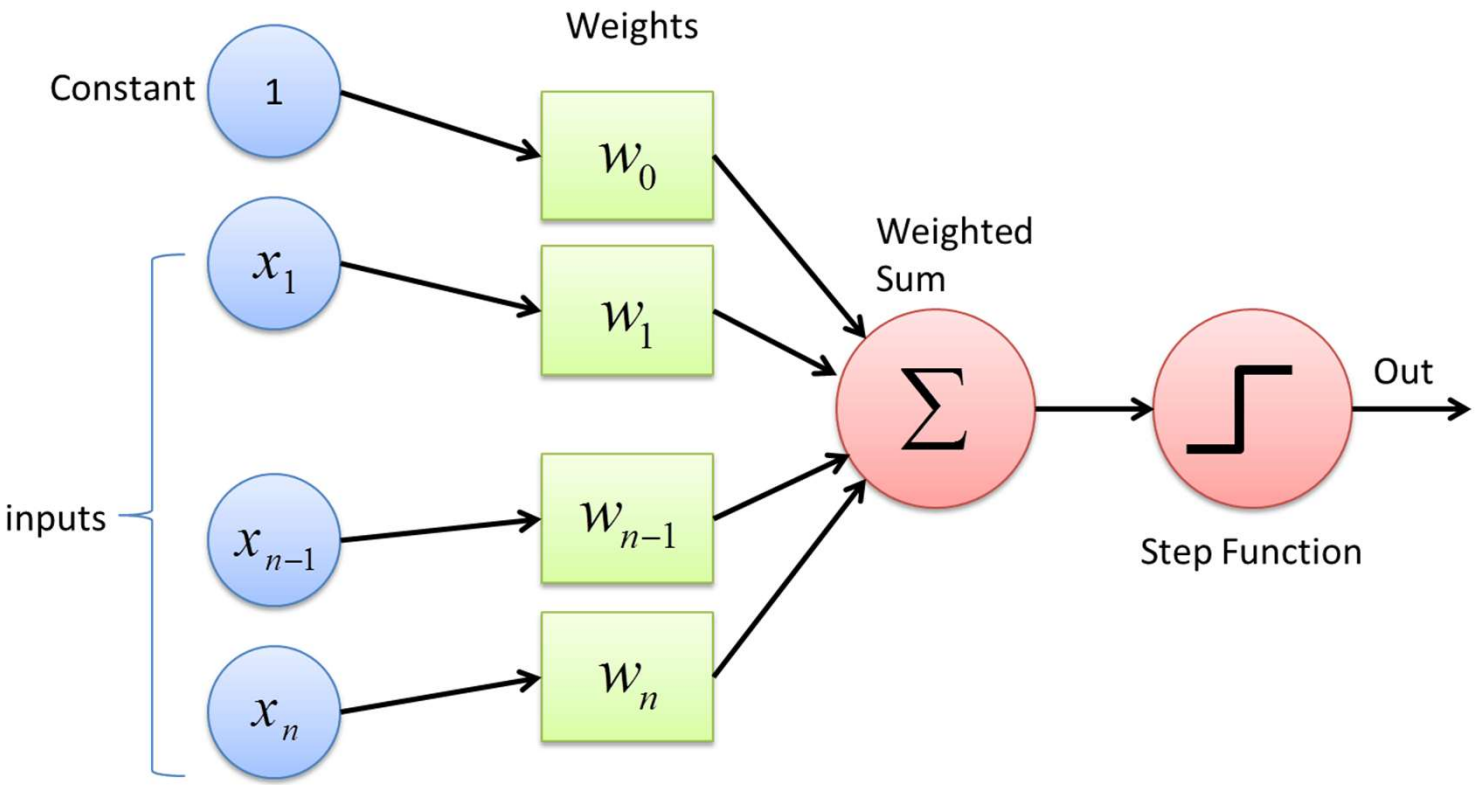
3. If $y_j = 1$ but $\mathbb{y}_j = 0$ then increase weights



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

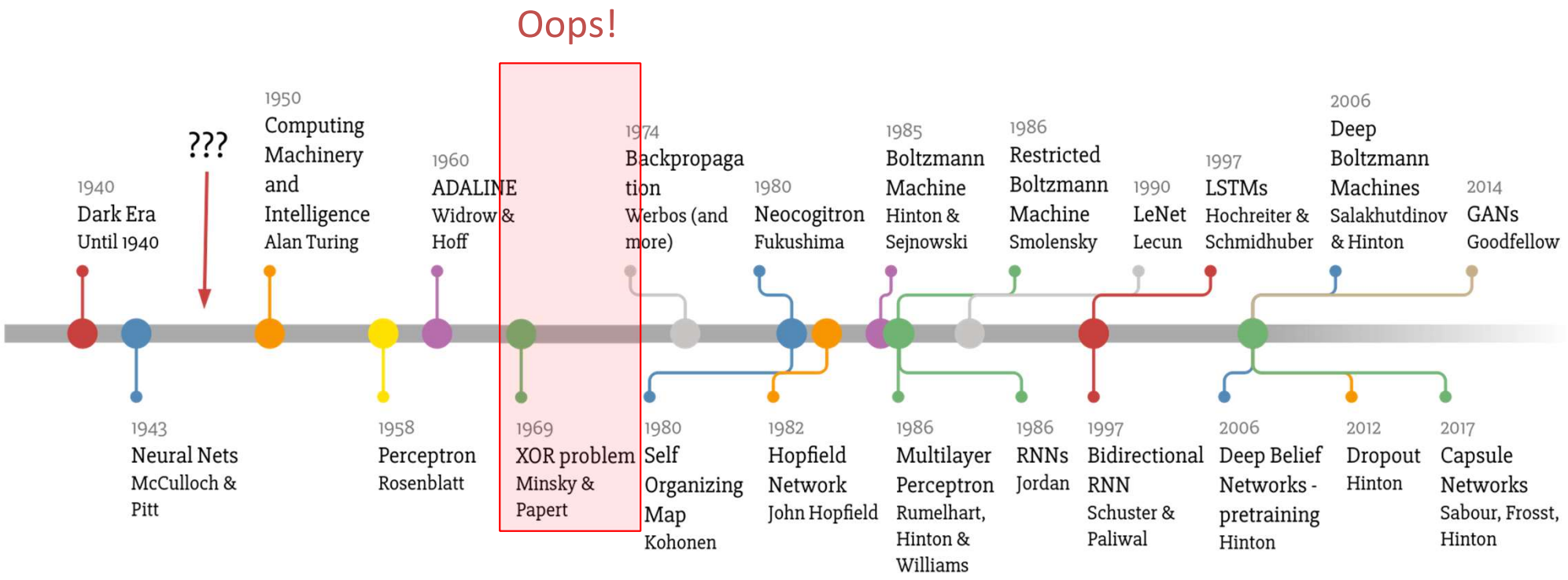
Artificial neurons

Repeat until convergence



source: https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53

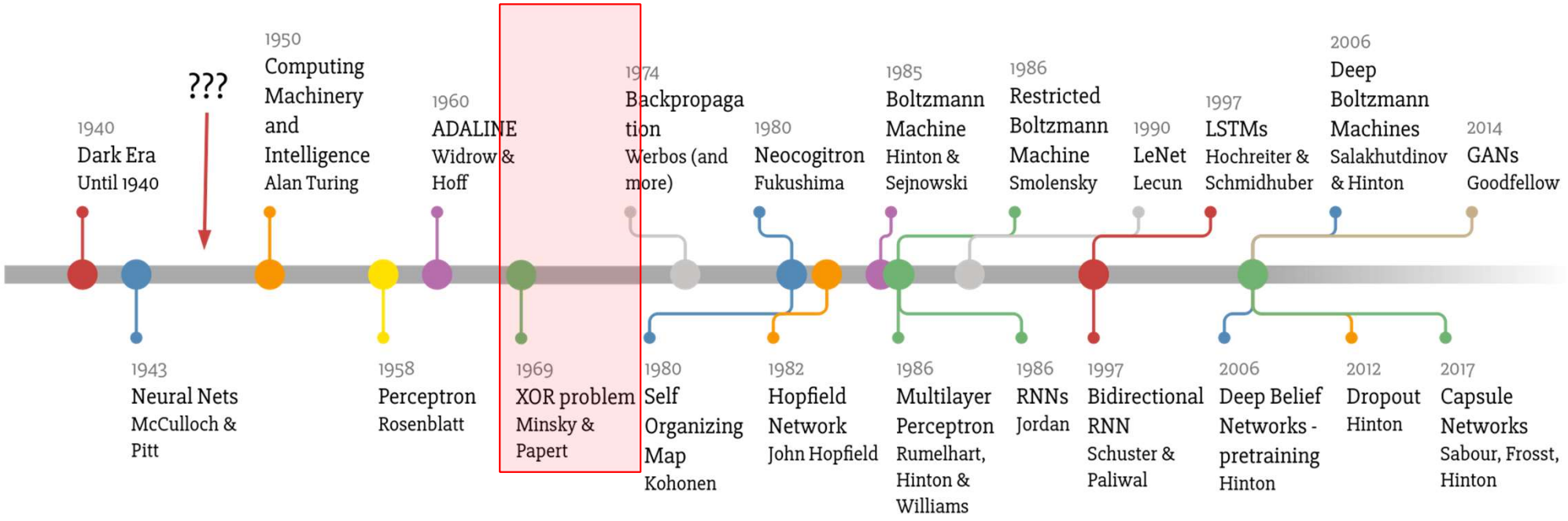
The many names of deep learning



source: https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0

The many names of deep learning

MP neurons can't solve simple XOR problems! (non linearly separable)



source: https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0

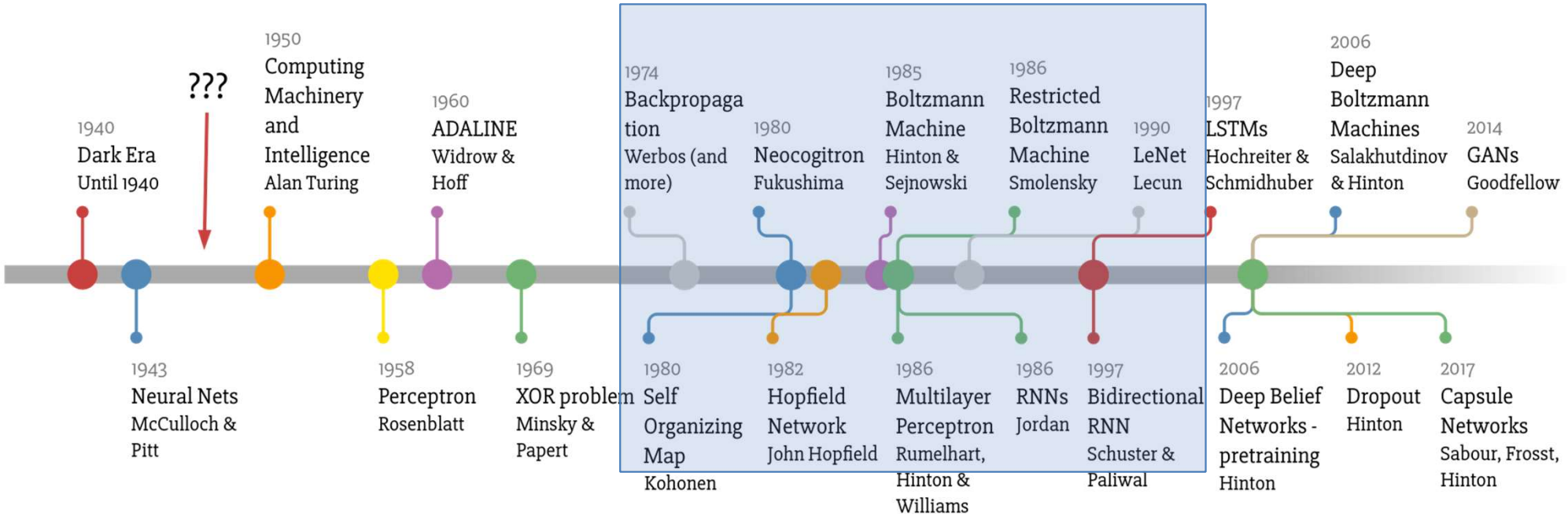
The many names of deep learning

source: https://towardsdata...ce.com/a-weird-introduction-to-deep-learning-7828803693b0

Brace yourself….

The many names of deep learning

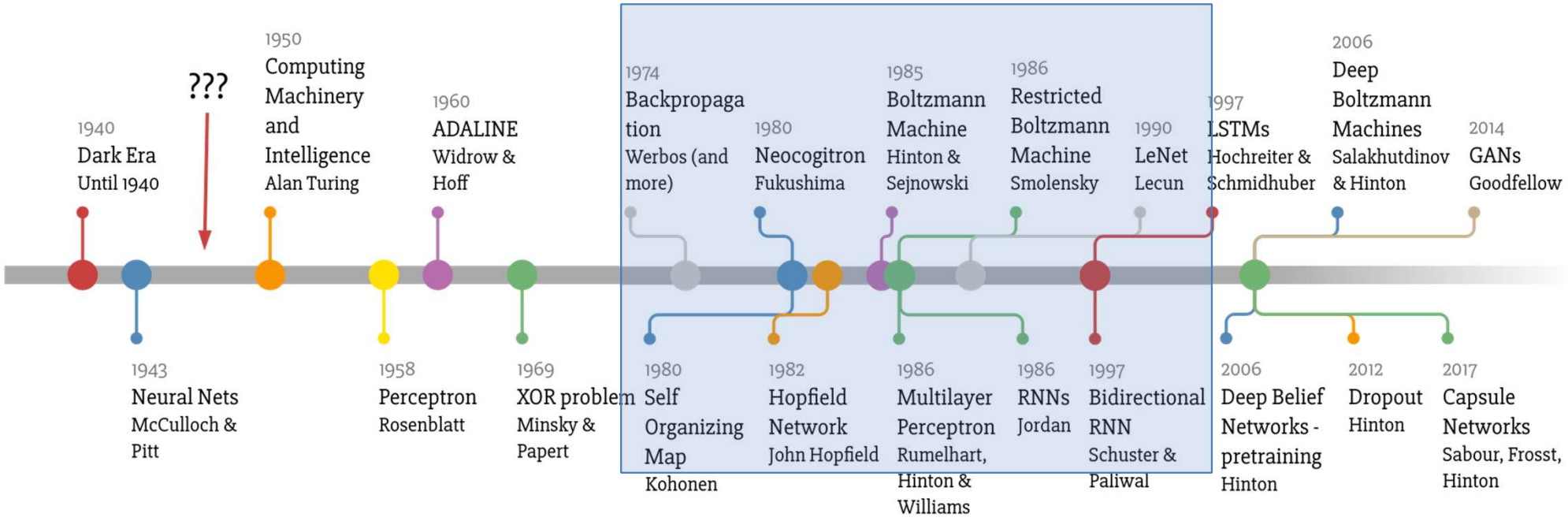
Second wave: back propagation, MLP, lots of cool ideas…



source: https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0

The many names of deep learning

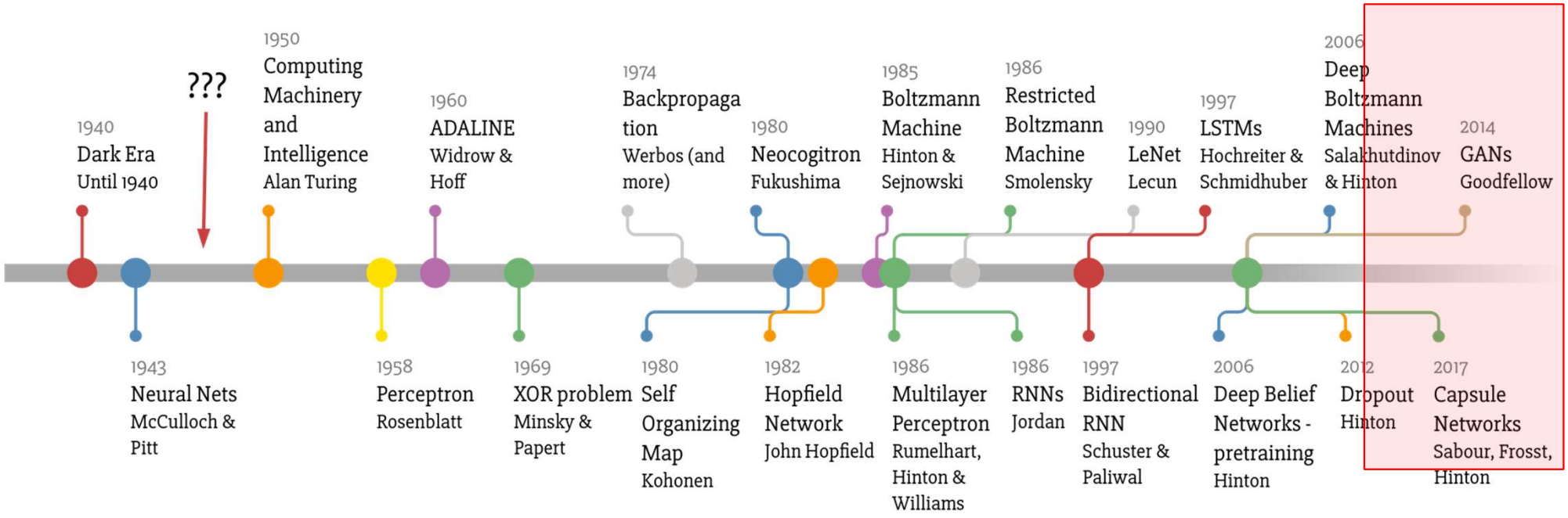
…but too much hype. Until…



source: https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0

The many names of deep learning

…NN blooming again



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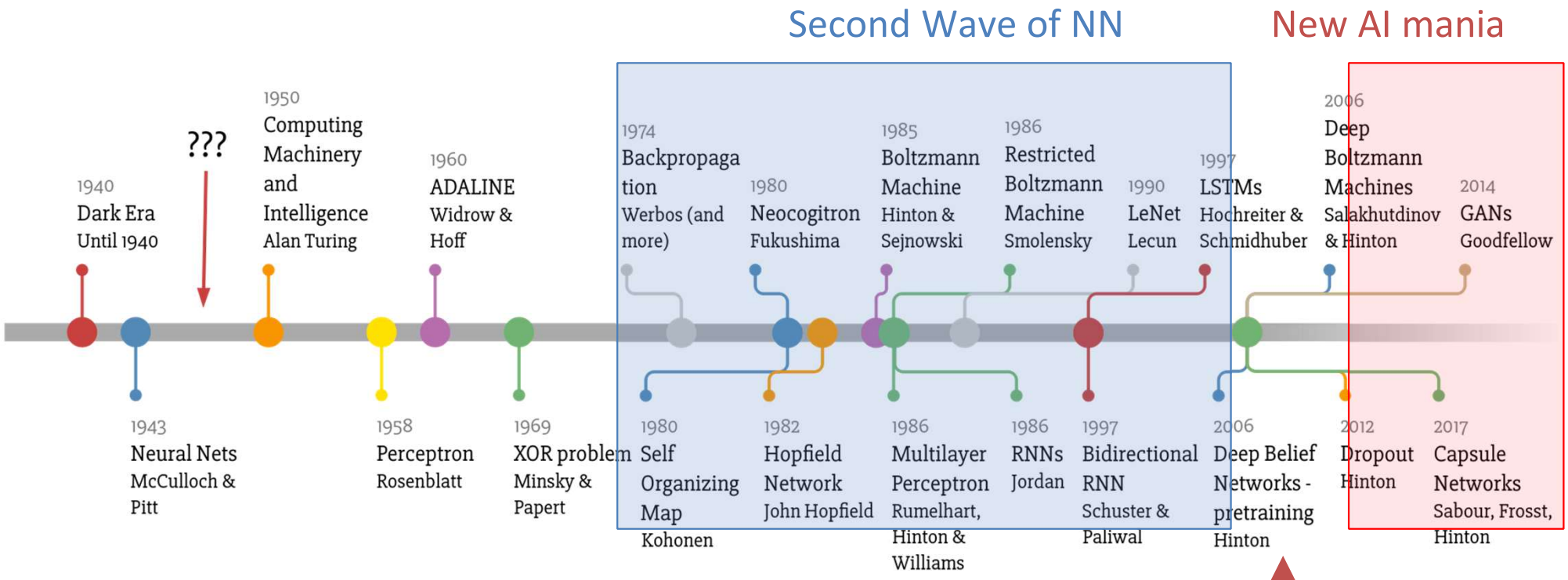
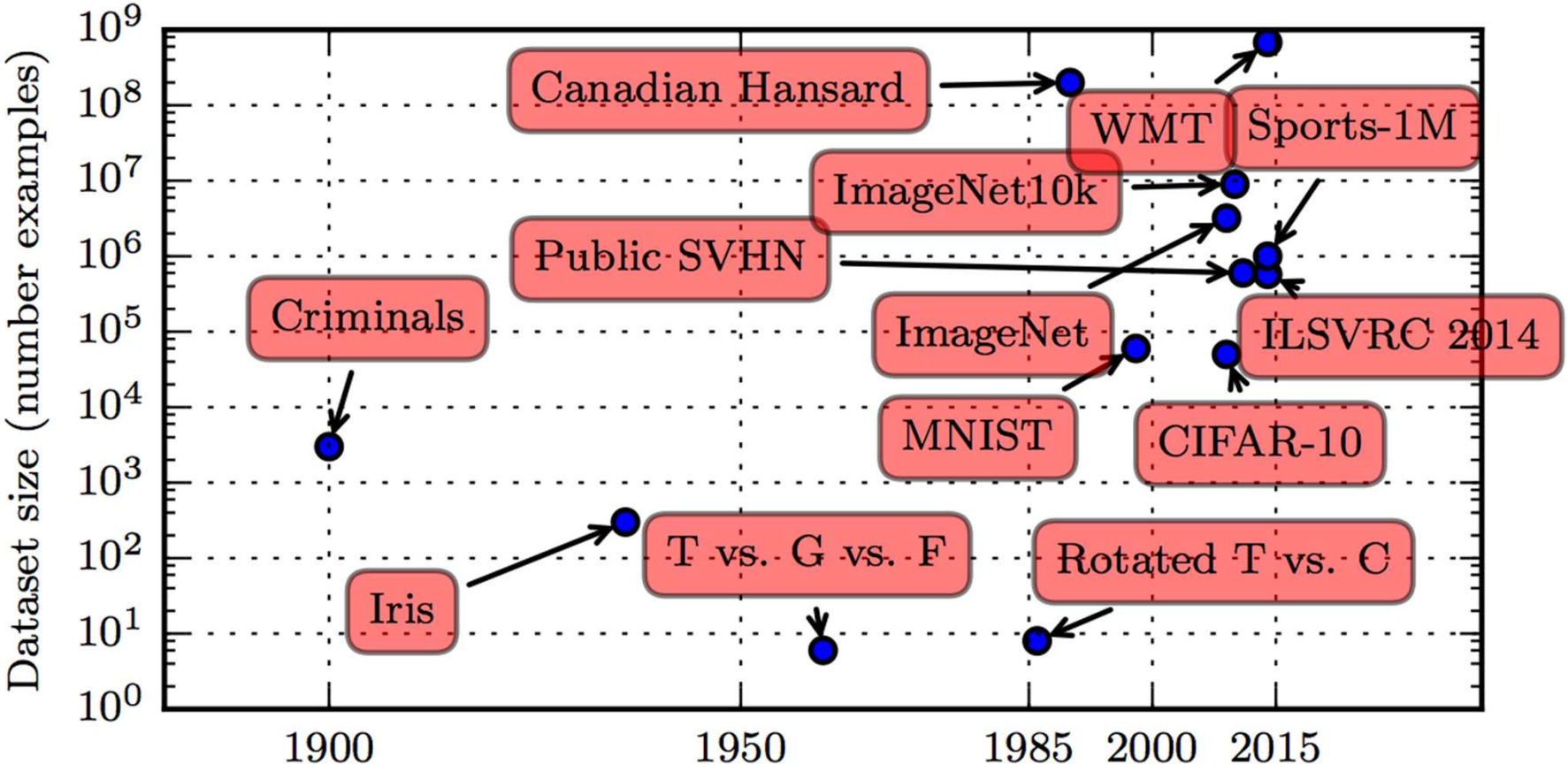
The many names of deep learning



source: https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b

What happened here??

Hungry learners



Deep learning is Big Data Hungry! More data, better performing models

Hungry learners

deep learning hungry for:
- data: need to collect data
- computing resources: GPU,
- money: spend on cpu, gpu...

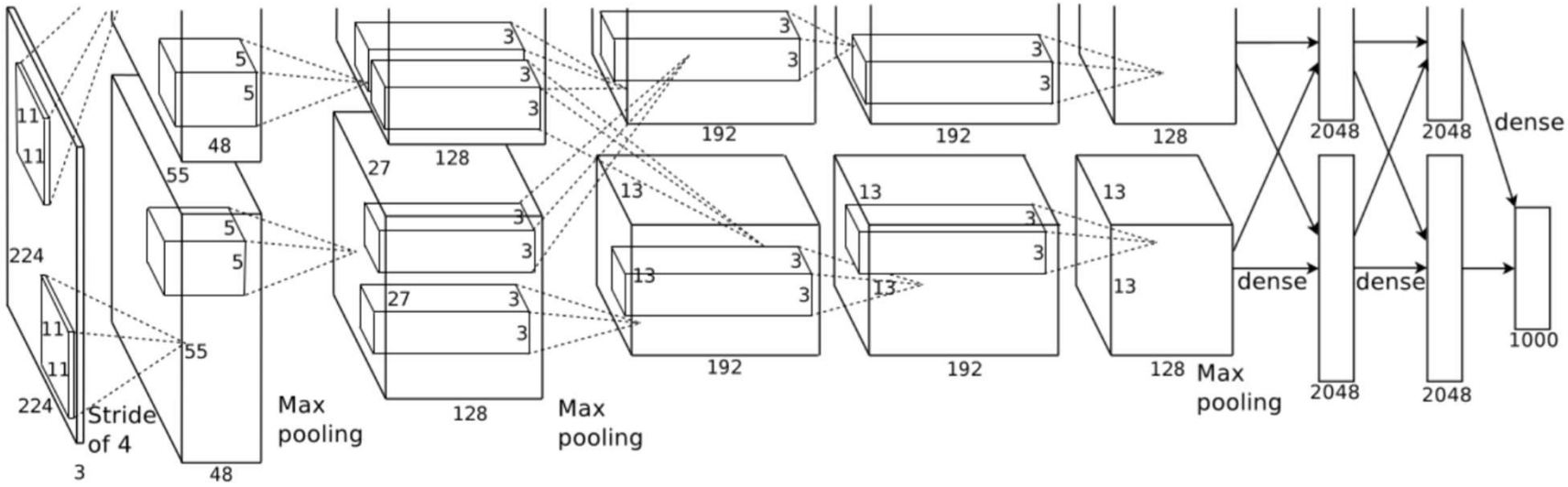
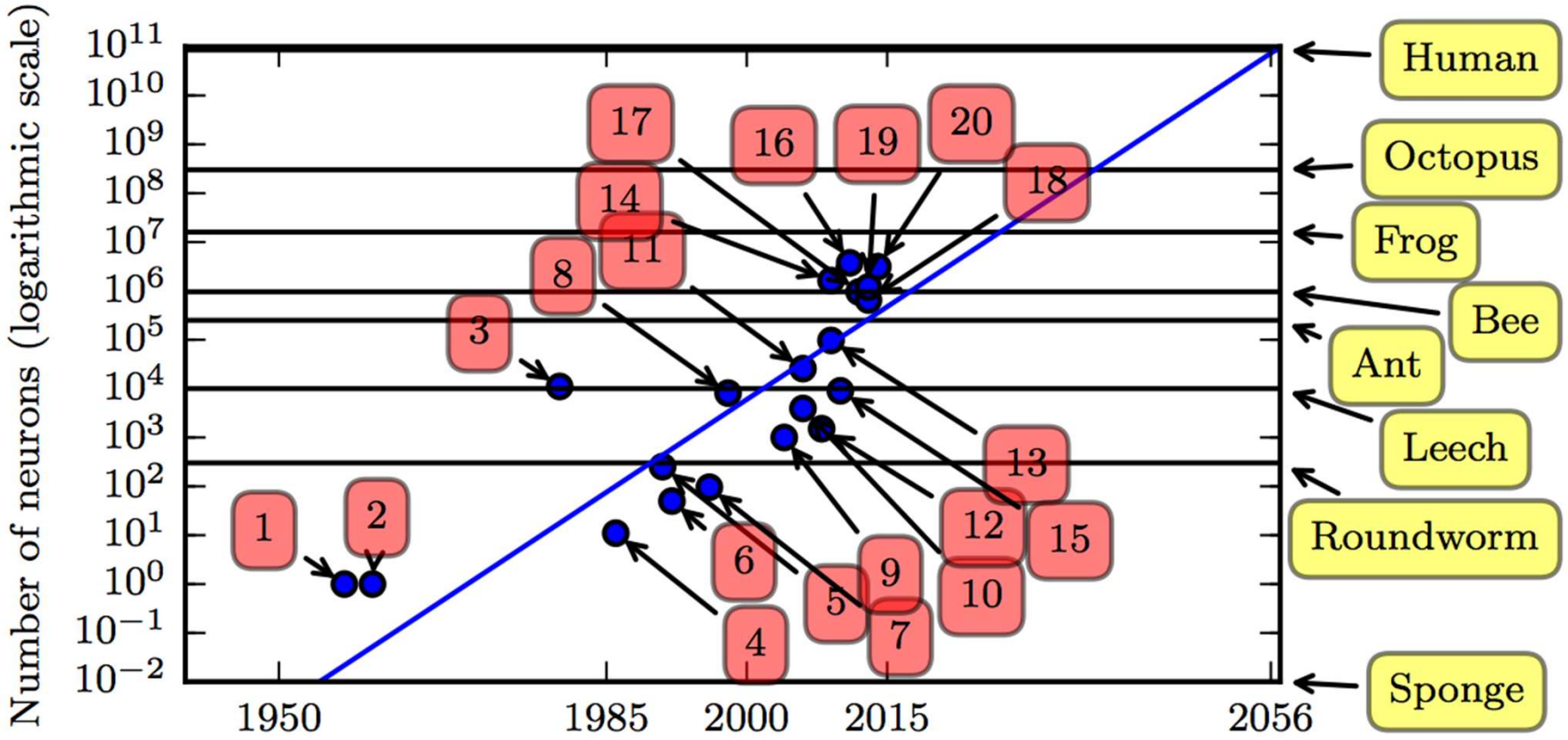


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

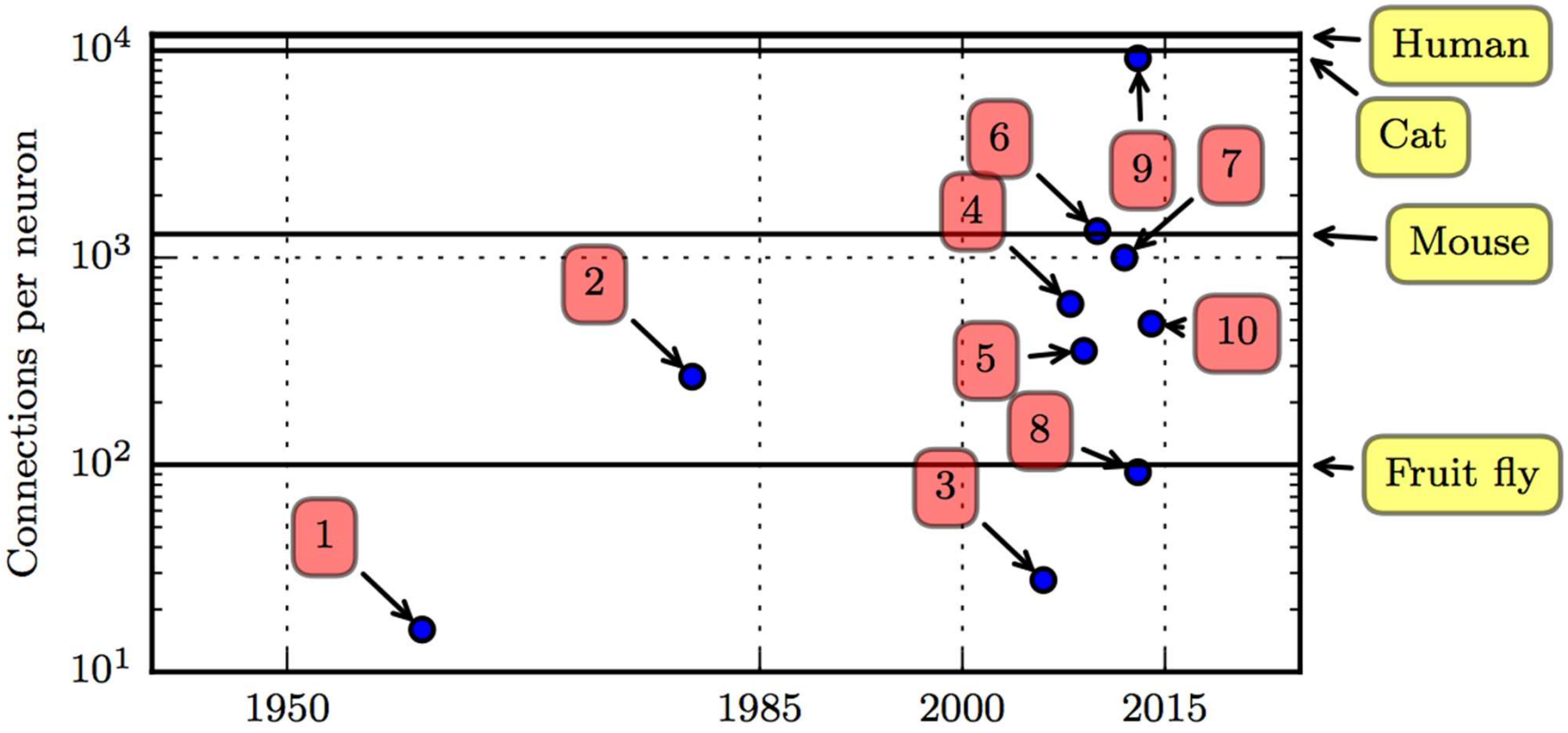
Deep learning is Resources Hungry!
Advent of general purpose GPUs made the difference

Hungry learners



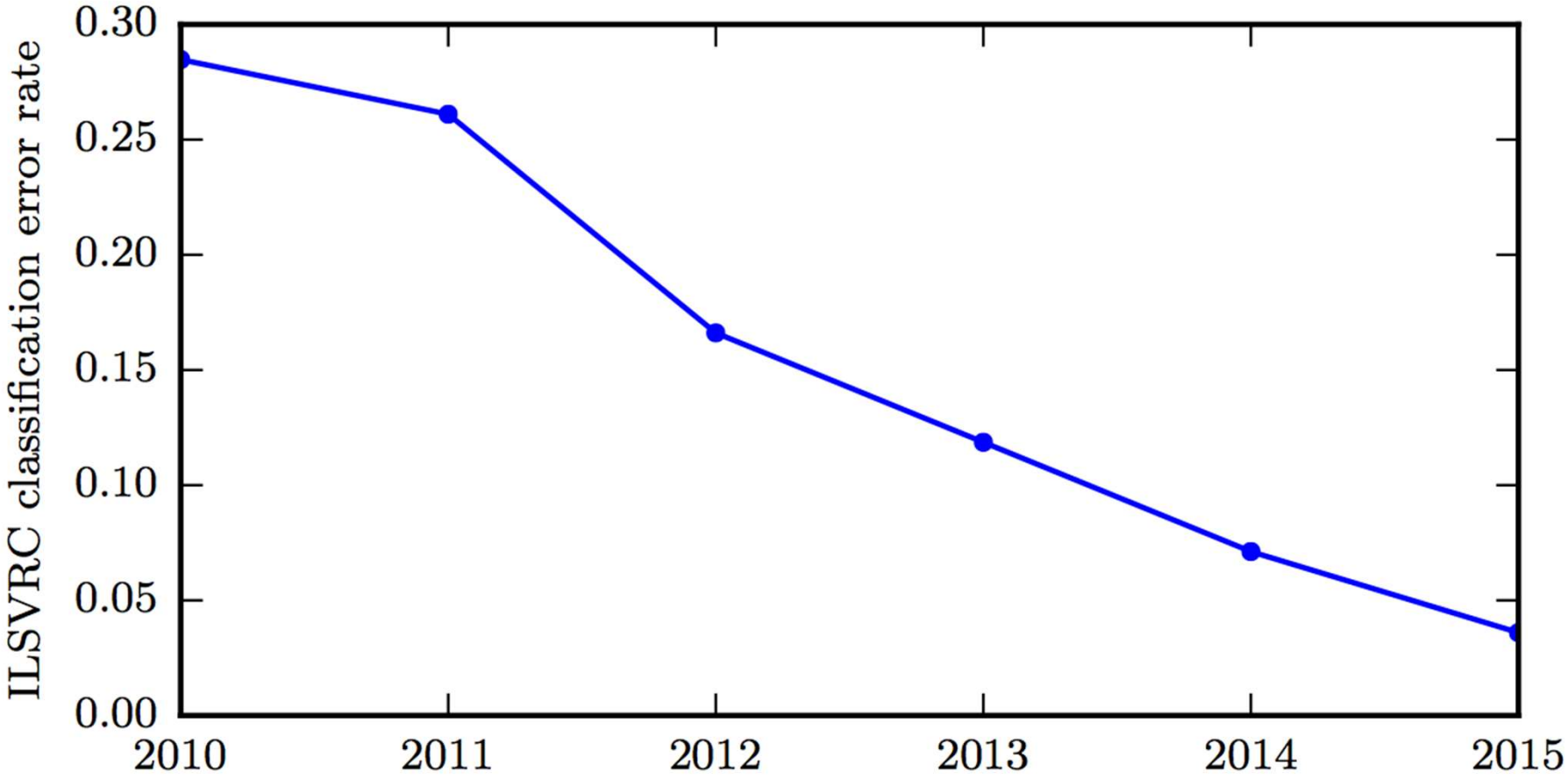
More computational resources means more neutrons and thus better models

Hungry learners



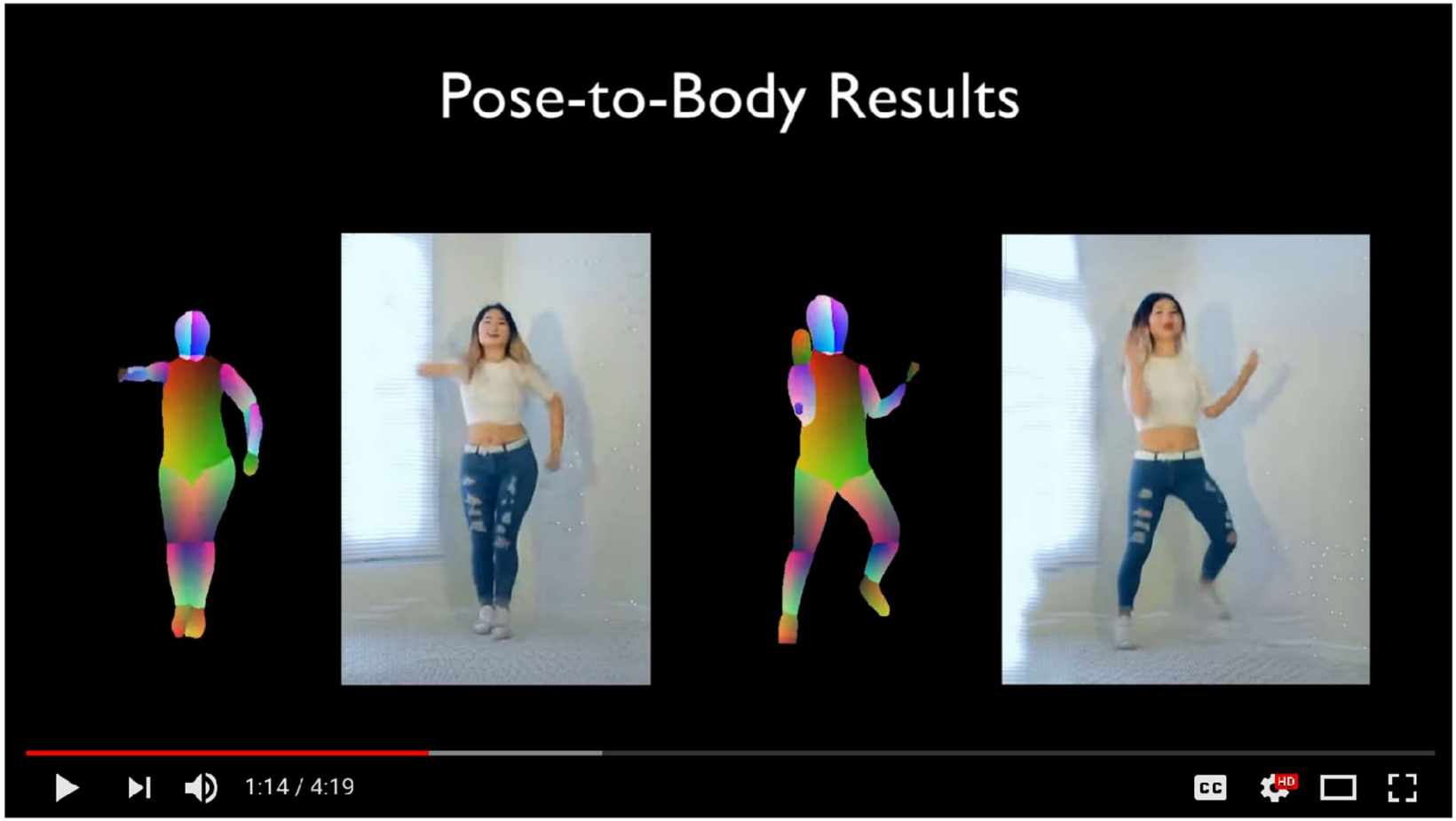
But note: biological neural networks are not very dense, compared to deep networks

The party crasher



Deep learning achieved astounding performance on many tasks

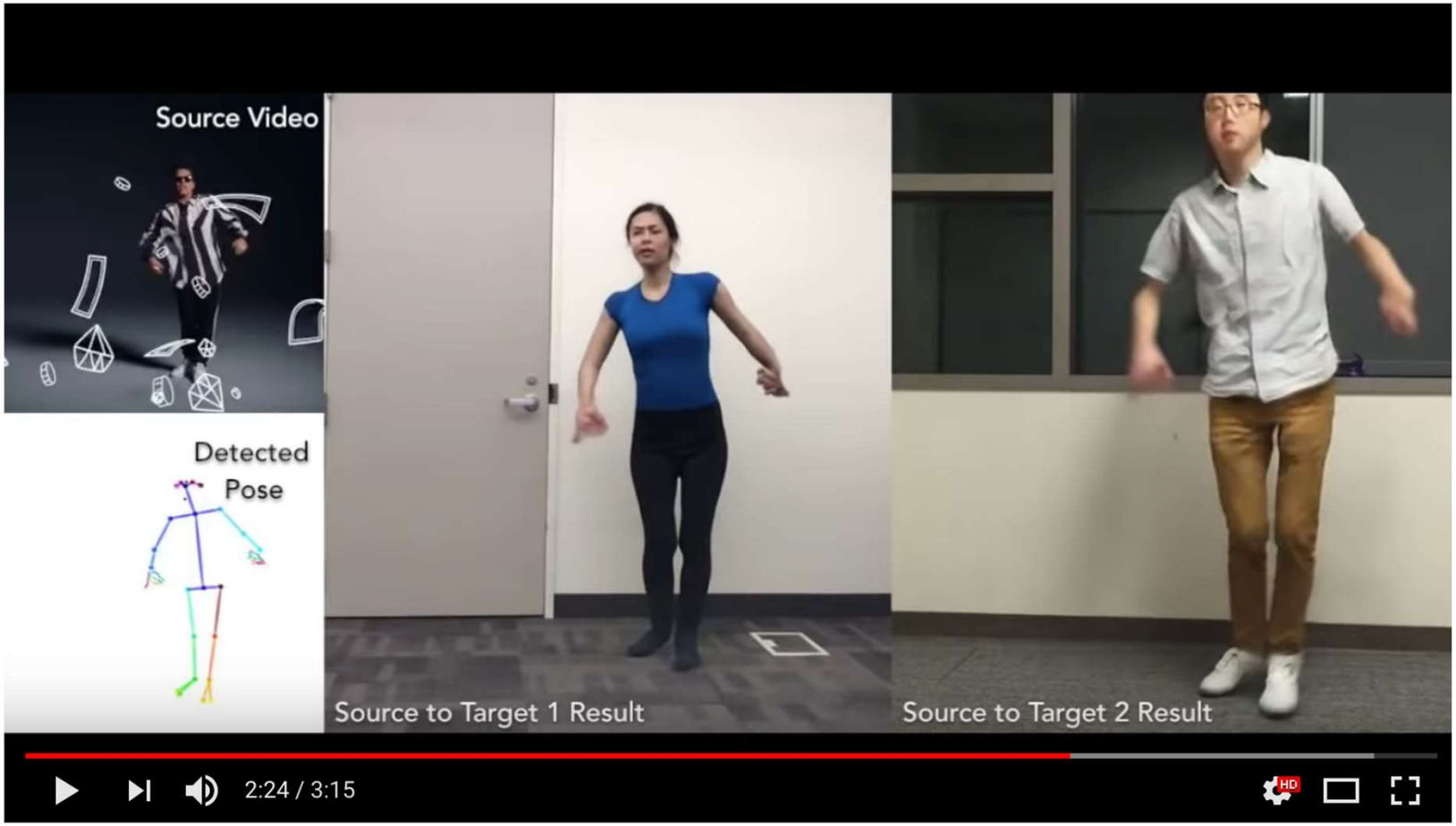
Some cool applications of DL



(Wang et al, 2018)

https://www.bilibili.com/video/BV1vE411B7LS?from=search&seid=14546211848937884840

Some cool applications of DL



(Chan et al 2018)

Some cool applications of DL

Figure 3: The leftmost plot shows the predicted value function for a 30 frame segment of the game Seaquest. The three screenshots correspond to the frames labeled by A, B, and C respectively.

(Mnih et al 2013)

Demo 1 Demo 2

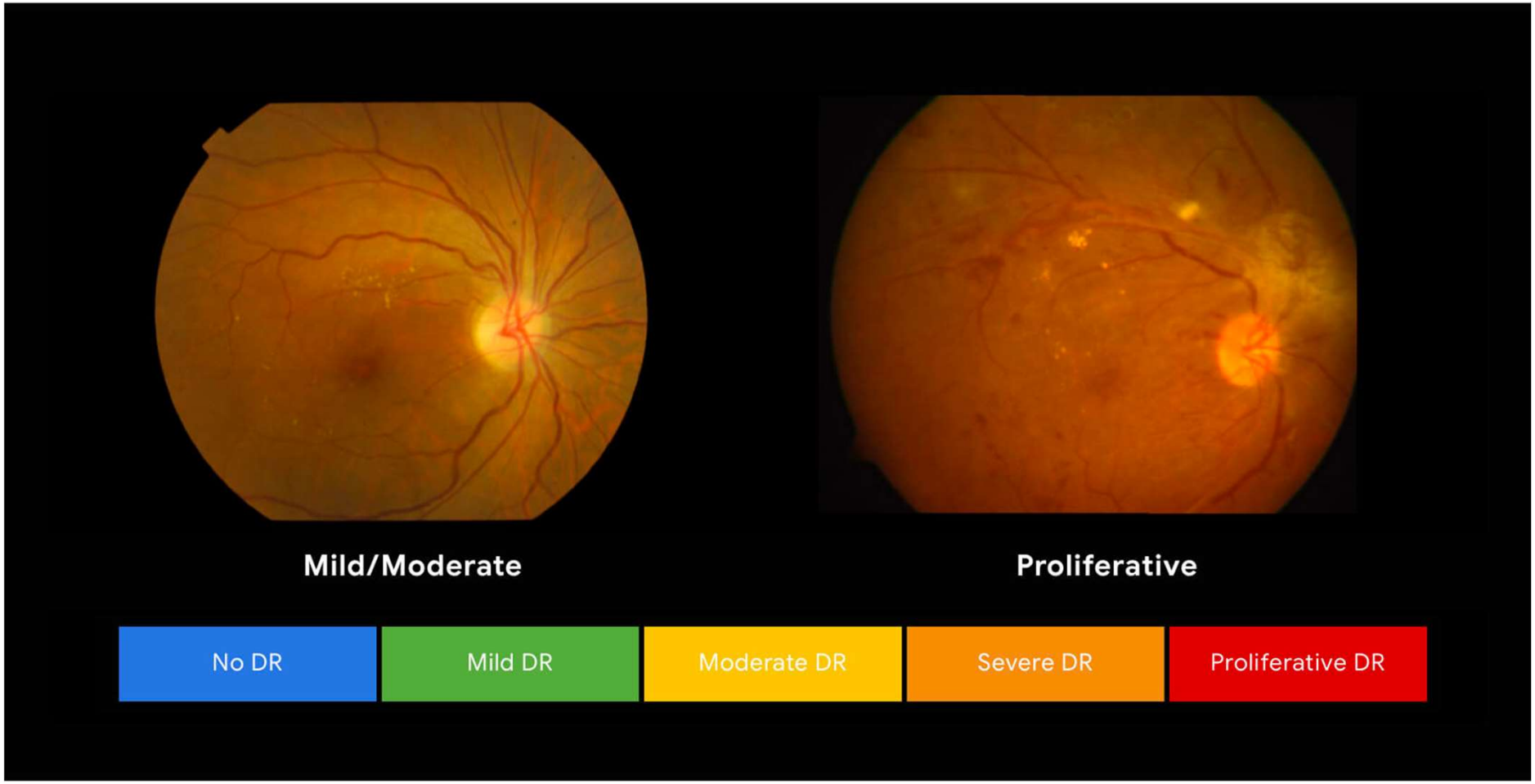
Some cool applications of DL

https://www.youtube.com/watch?v=S1OwOd-war8

https://www.youtube.com/watch?v=S1OwOd-war8

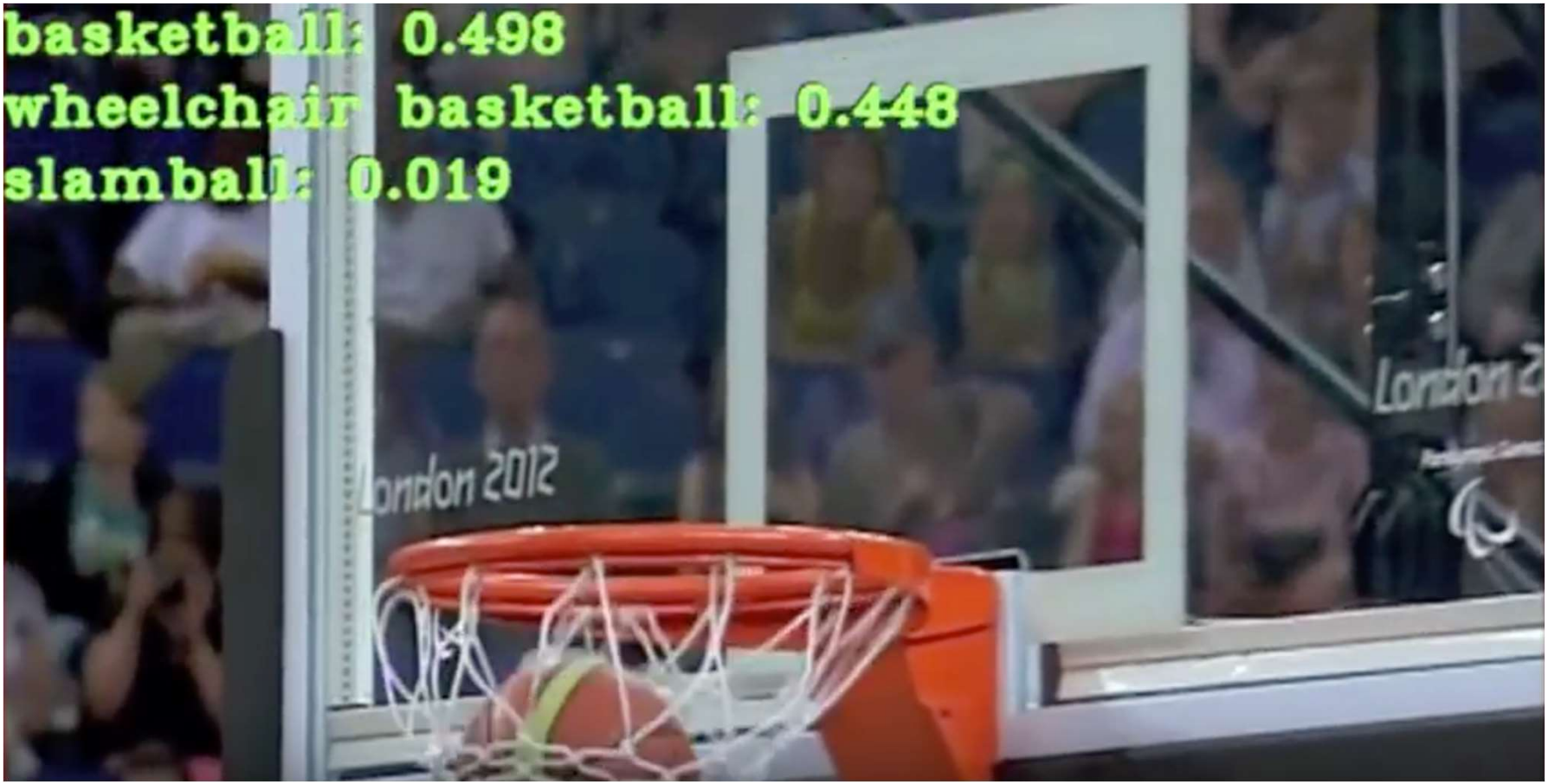
(WayMo)

Some cool applications of DL



(Google Brain)

Some cool applications of DL



(Video classification)

Some cool applications of DL

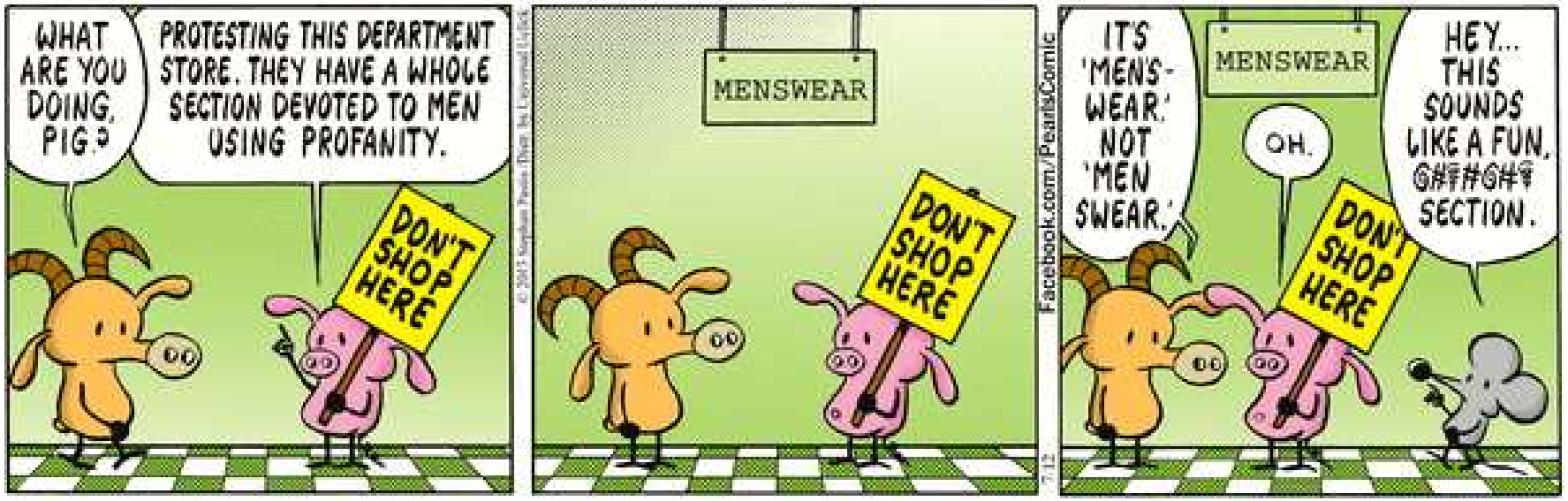
("deep" art))

Are you trying to impress me?

- Well, these are all **very complex problems**:
  - Lots of different game states in Game AI, e.g., ((10)^10^)48 possible GO games!

Are you trying to impress me?

- Well, these are all **very complex problems**:
  - Natural language processing is very high dimensional and vague



Are you trying to impress me?

- Well, these are all **very complex problems**:
  - Computer vision is really challenging:
    - For 256x256 resolution, 2^{524288} possible images!! That's a lot, btw
    - Massive visual and semantic variation



OpenAI -- SORA

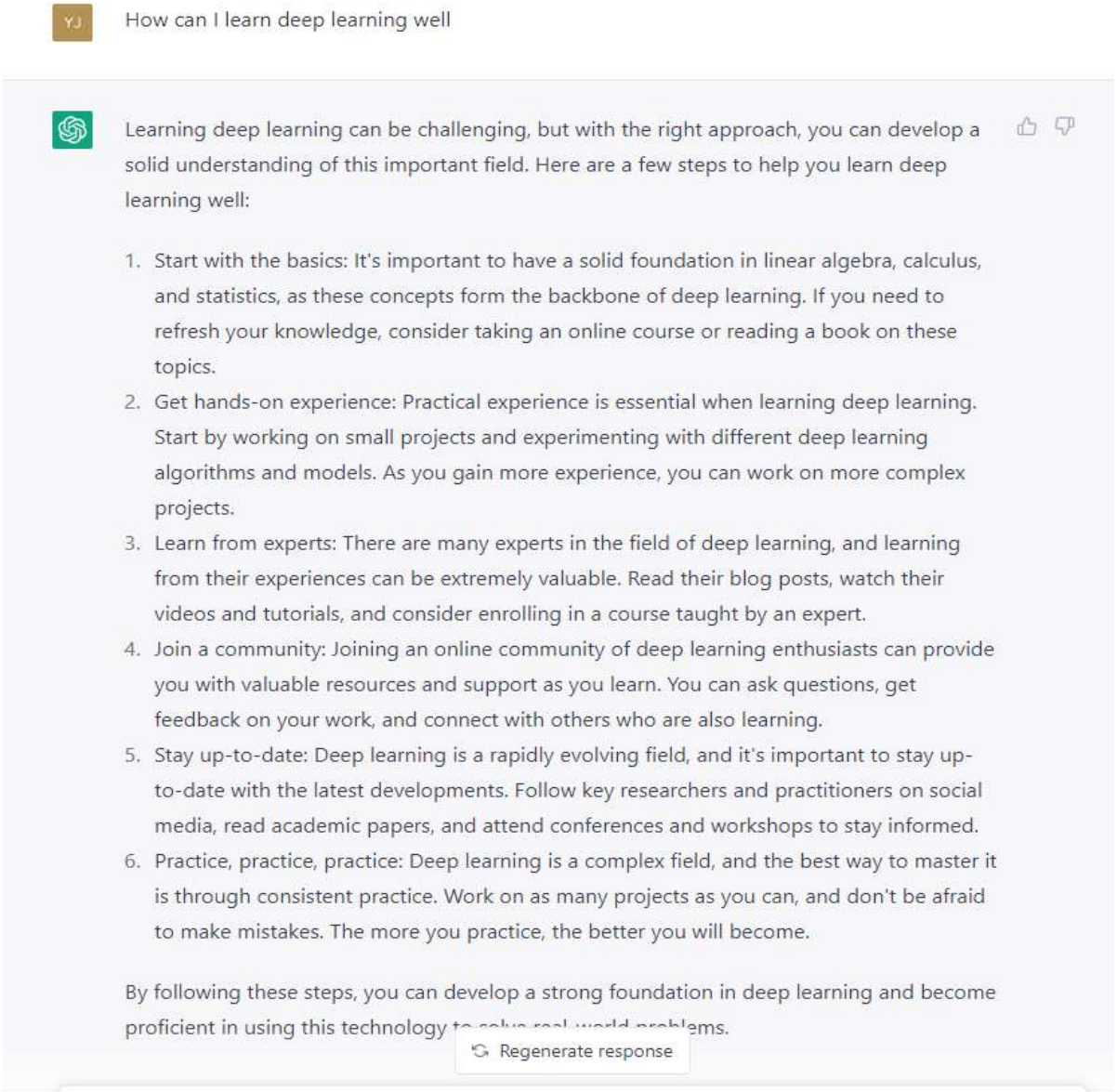
- Prompt: A stylish woman walks down a Tokyo street filled with warm glowing neon and animated city signage. She wears a black leather jacket, a long red dress, and black boots, and carries a black purse. She wears sunglasses and red lipstick. She walks confidently and casually. The street is damp and reflective, creating a mirror effect of the colorful lights. Many pedestrians walk about.

SORA

- We have watched the video at the beginning of this class.

How Can I learn deep learning well? By ChatGPT

ATTENDING MY LECTURES



YJ

How can I learn deep learning well

Learning deep learning can be challenging, but with the right approach, you can develop a solid understanding of this important field. Here are a few steps to help you learn deep learning well:

1. Start with the basics: It's important to have a solid foundation in linear algebra, calculus, and statistics, as these concepts form the backbone of deep learning. If you need to refresh your knowledge, consider taking an online course or reading a book on these topics.
2. Get hands-on experience: Practical experience is essential when learning deep learning. Start by working on small projects and experimenting with different deep learning algorithms and models. As you gain more experience, you can work on more complex projects.
3. Learn from experts: There are many experts in the field of deep learning, and learning from their experiences can be extremely valuable. Read their blog posts, watch their videos and tutorials, and consider enrolling in a course taught by an expert.
4. Join a community: Joining an online community of deep learning enthusiasts can provide you with valuable resources and support as you learn. You can ask questions, get feedback on your work, and connect with others who are also learning.
5. Stay up-to-date: Deep learning is a rapidly evolving field, and it's important to stay up-to-date with the latest developments. Follow key researchers and practitioners on social media, read academic papers, and attend conferences and workshops to stay informed.
6. Practice, practice, practice: Deep learning is a complex field, and the best way to master it is through consistent practice. Work on as many projects as you can, and don't be afraid to make mistakes. The more you practice, the better you will become.

By following these steps, you can develop a strong foundation in deep learning and become proficient in using this technology to solve real-world problems.

Regenerate response