TECHNISCHE UNIVERSITÄT
CHEMNITZ

Neurocomputing

Introduction

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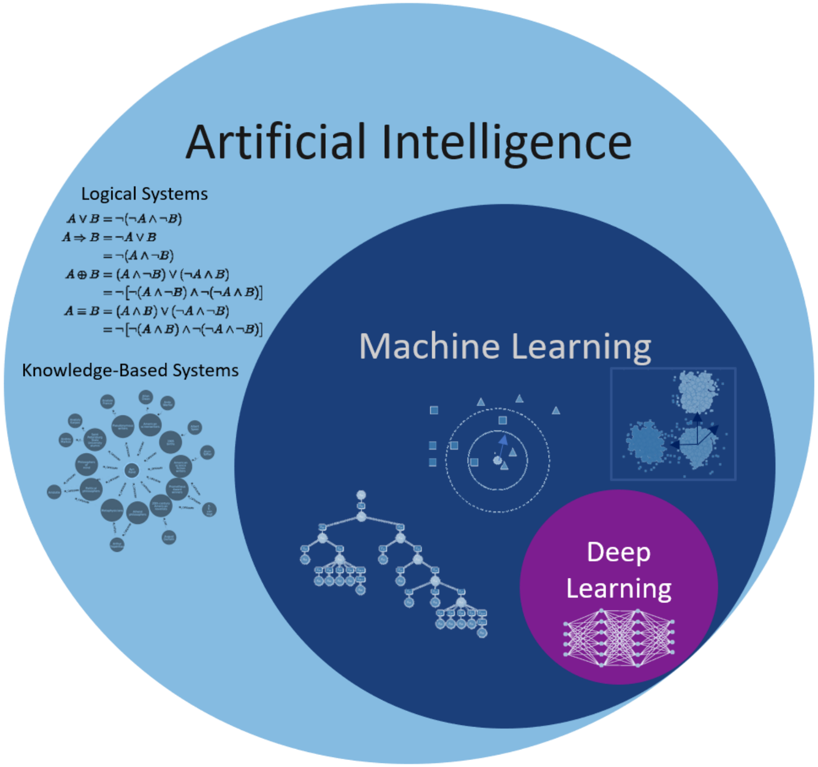
https://tu-chemnitz.de/informatik/KI/edu/neurocomputing

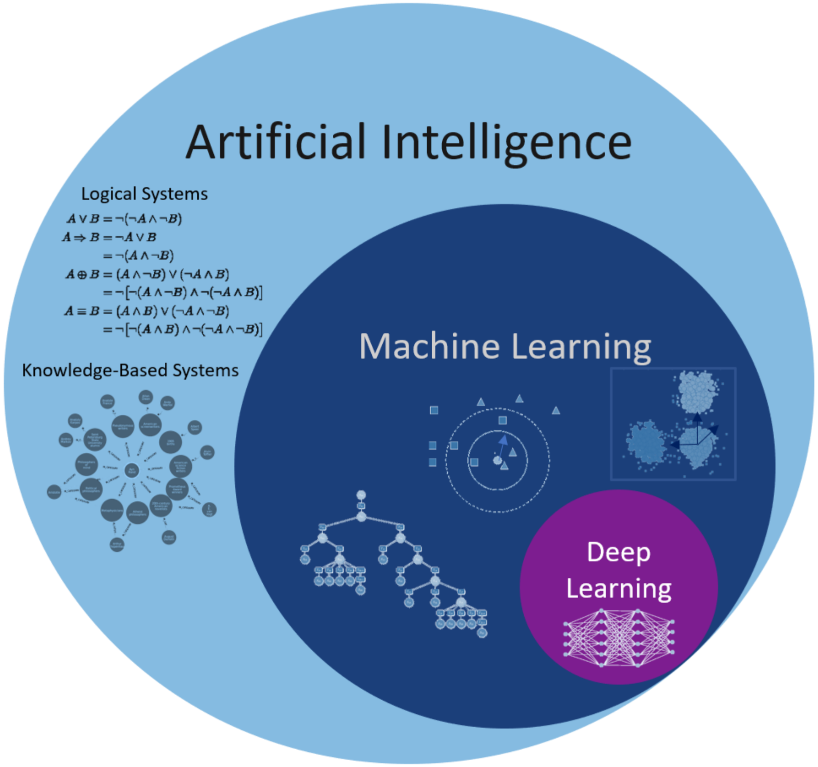
Artificial Intelligence, Machine Learning, Deep Learning, Neurocomputing



Source: https://data-science-blog.com/blog/2018/05/14/machine-learning-vs-deep-learning-wo-liegt-der-unterschied

- The term **Artificial Intelligence** was coined by John McCarthy at the Dartmouth Summer Research Project on Artificial Intelligence in **1956**.
- *“The study is 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.”*
- **Good old-fashion AI** approaches (GOFAI) were purely symbolic (logical systems, knowledge-based systems) or using linear neural networks.
- They were able to play checkers, prove mathematical theorems, make simple conversations (ELIZA), translate languages…

Artificial Intelligence, Machine Learning, Deep Learning, Neurocomputing



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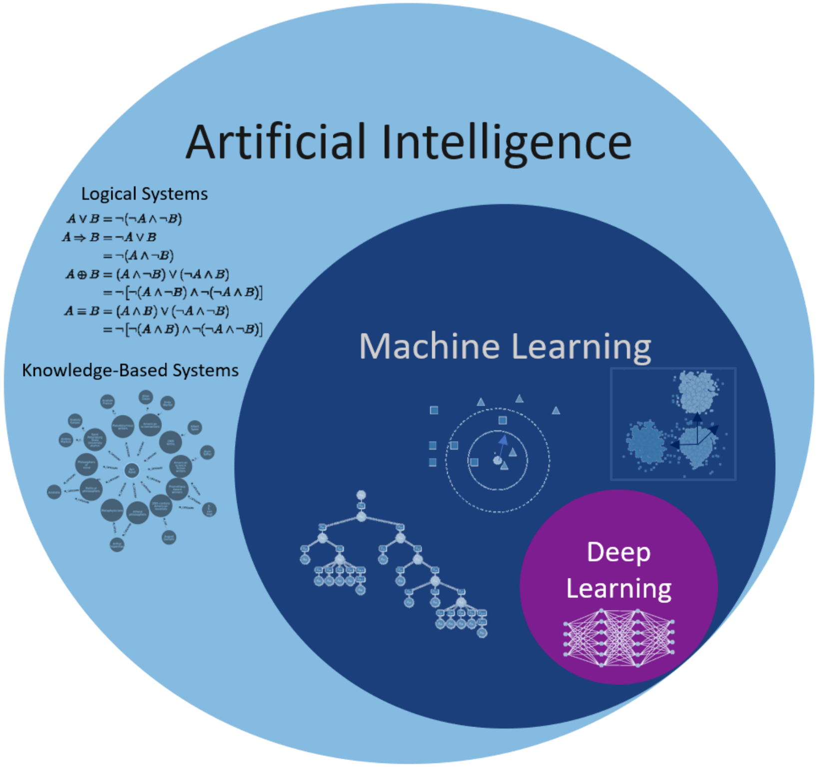
- **Machine learning** (ML) is a branch of AI that focuses on learning from examples (data-driven).
- ML algorithms include:
  - Neural Networks (multi-layer perceptrons)
  - Statistical analysis (Bayesian modeling, PCA)
  - Clustering algorithms (k-means, GMM, spectral clustering)
  - Support vector machines
  - Decision trees, random forests
- Other names: big data, data science, operational research, pattern recognition…

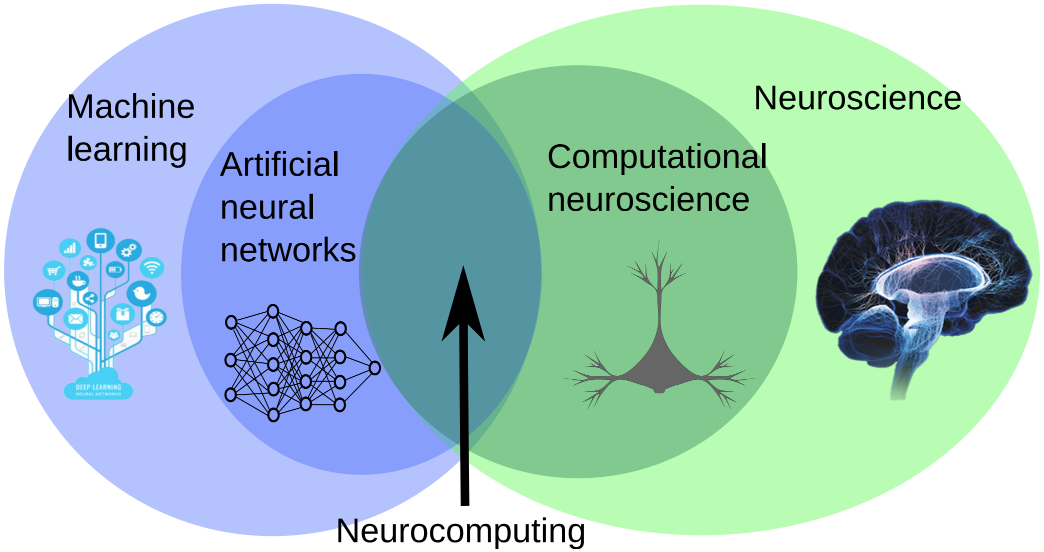
Artificial Intelligence, Machine Learning, Deep Learning, Neurocomputing



- **Deep Learning** is a recent re-branding of neural networks.
- Deep learning focuses on learning high-level representations of the data, using:
    - Deep neural networks (DNN)
    - Convolutional neural networks (CNN)
    - Recurrent neural networks (RNN)
    - Generative models (GAN, VAE)
    - Deep reinforcement learning (DQN, A3C, PPO)

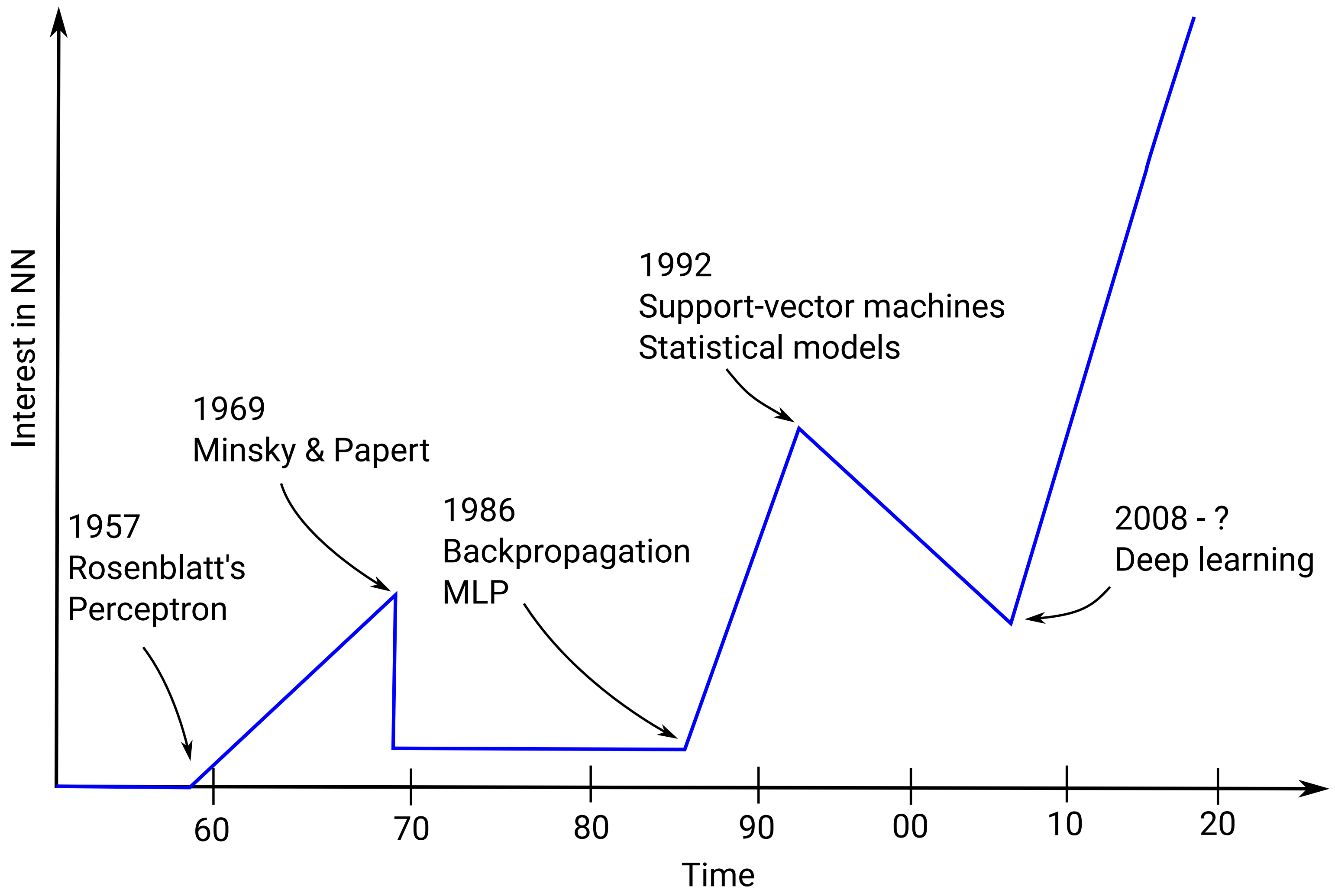
Source: https://data-science-blog.com/blog/2018/05/14/machine-learning-vs-deep-learning-wo-liegt-der-unterschied

Artificial Intelligence, Machine Learning, Deep Learning, Neurocomputing



- **Neurocomputing** is at the intersection between computational neuroscience and artificial neural networks (deep learning).
- Computational neuroscience studies the functioning of the brain through detailed models.
- Neurocomputing aims at bringing the mechanisms underlying human cognition into artificial intelligence.

AI hypes and AI winters

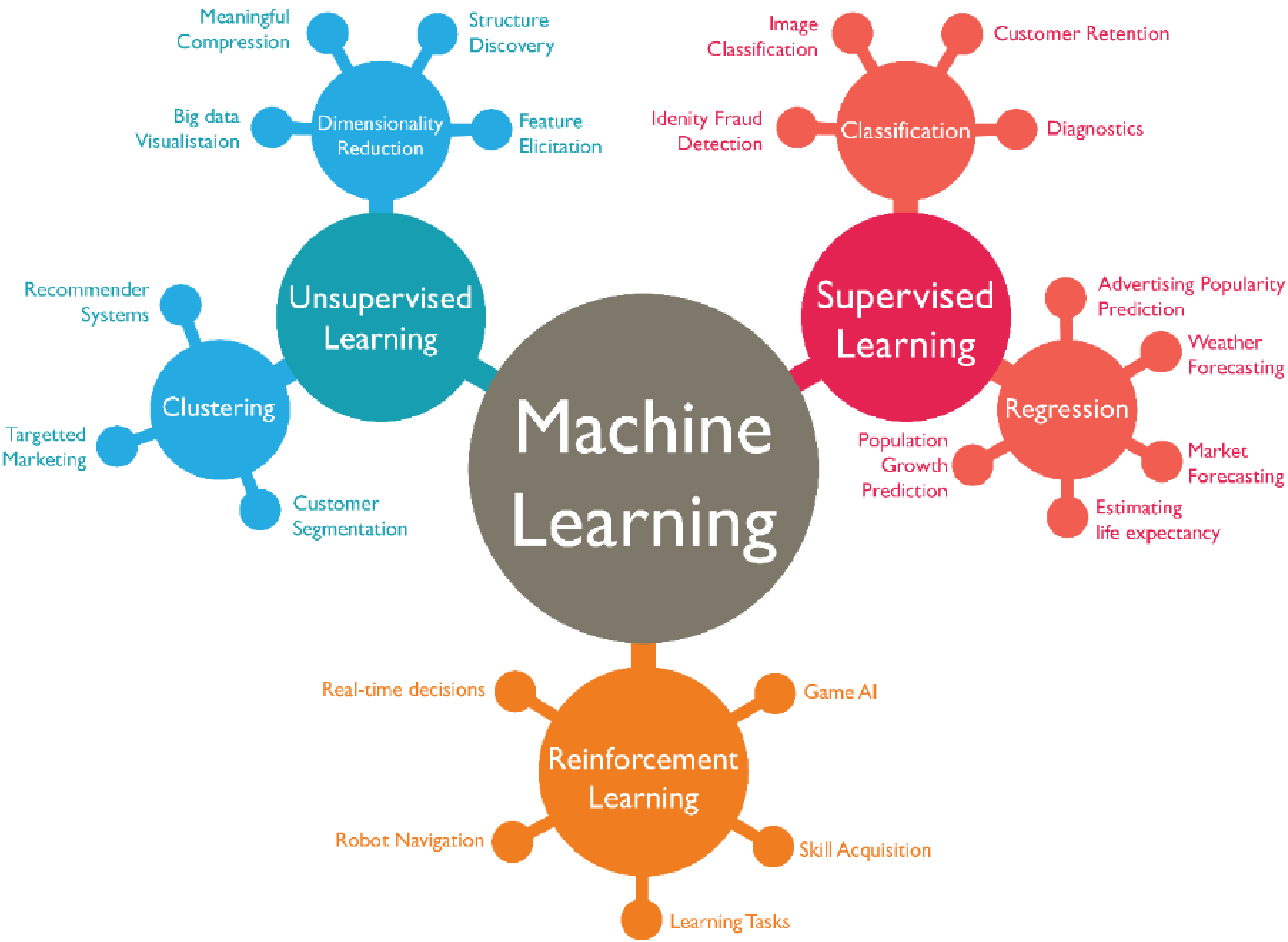


Classification of ML techniques:

- **Supervised learning**: The program is trained on a pre-defined set of training examples and used to make correct predictions when given new data.
- **Unsupervised learning**: The program is given a bunch of data and must find patterns and relationships therein.
- **Reinforcement learning**: The program explores its environment by producing actions and receiving rewards.

But also:

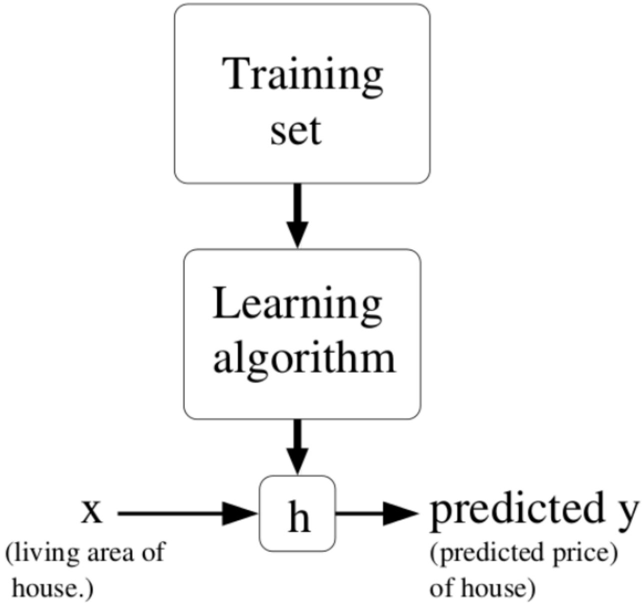
- Semi-supervised learning, self-taught learning, developmental learning…



Source http://www.isaziconsulting.co.za/machinelearning.html

1- Supervised learning

Supervised Learning



Source: Andrew Ng, Stanford CS229, https://see.stanford.edu/materials/aimlcs229/cs229-notes1.pdf

- **Supervised learning** consists in presenting a dataset of input and output **samples** (or examples) $(x_i, t_i)_{i=1}^N$ to a parameterized model.

$$y_i = f_\theta(x_i)$$

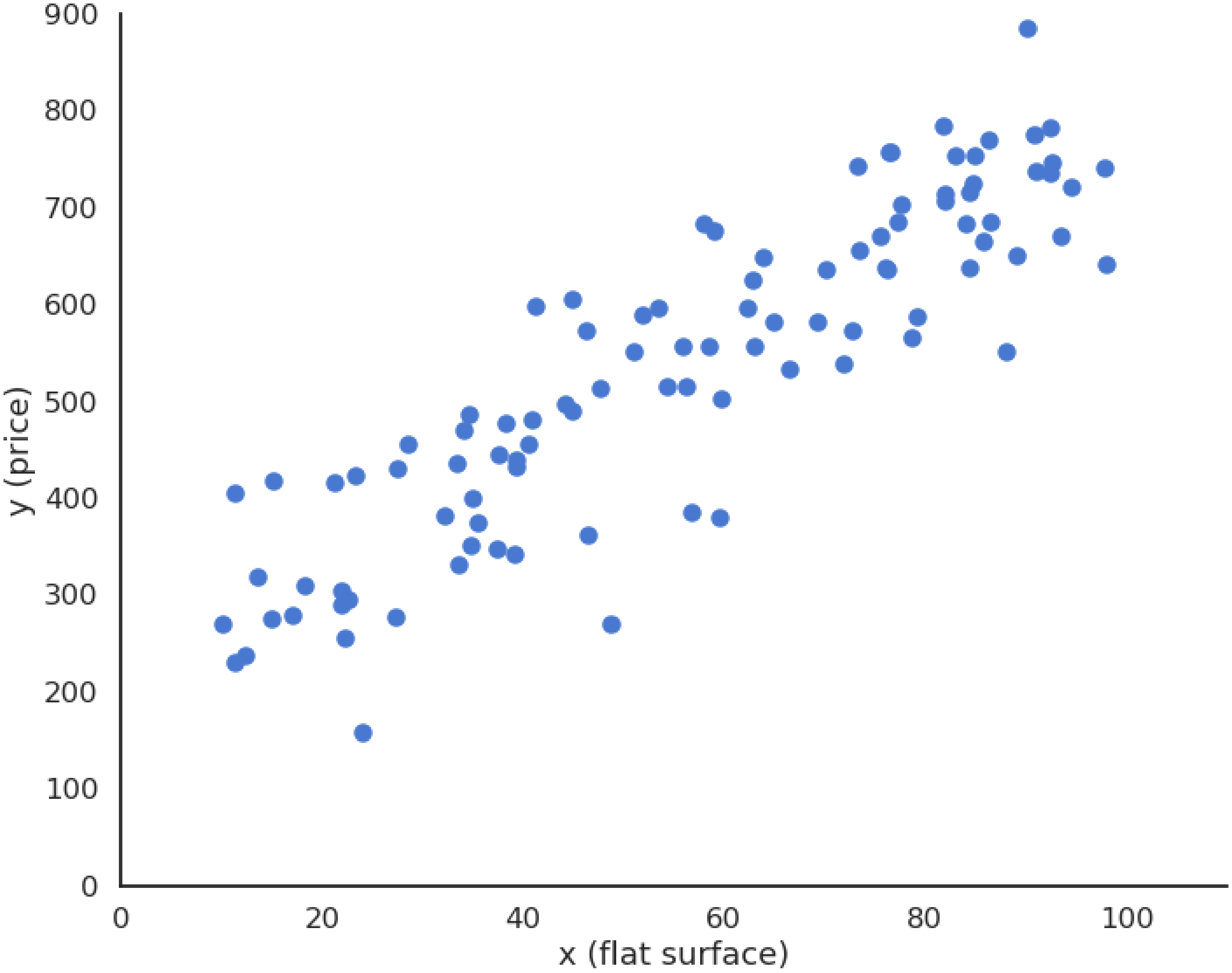
- The goal of learning is to adapt the parameters θ, so that the model reduces its **prediction error** on the training data.

$$\theta^* = \text{argmin} \sum_{i=1}^N ||t_i - y_i||$$

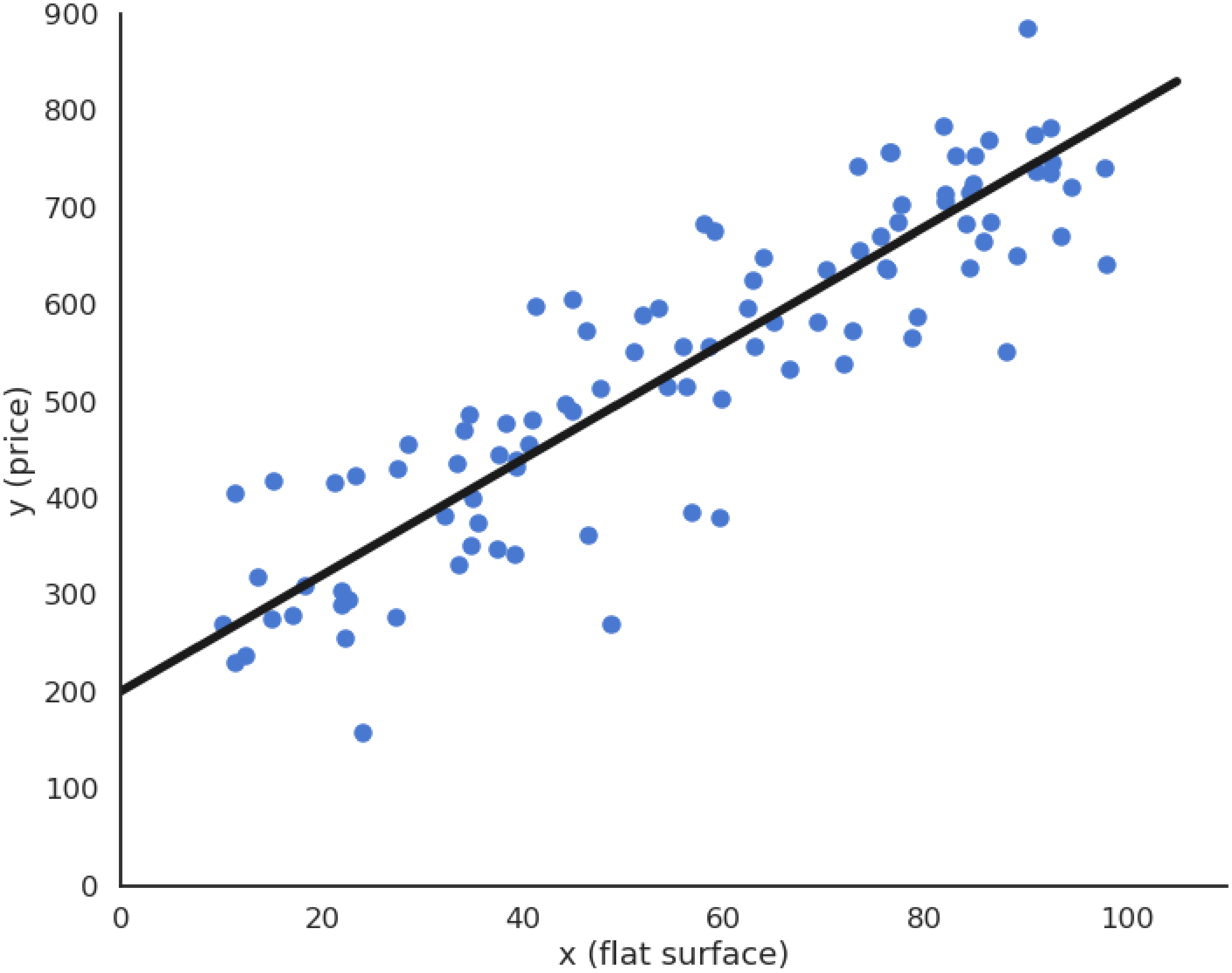
- When learning is successful, the model can be used on novel examples (**generalisation**).

- The modality of the inputs and outputs does not really matter:
  - Image $\rightarrow$ Label : **image classification**
  - Image $\rightarrow$ Image : **semantic segmentation**
  - Speech $\rightarrow$ Text : **speech recognition**
  - Text $\rightarrow$ Speech : **speech synthesis**

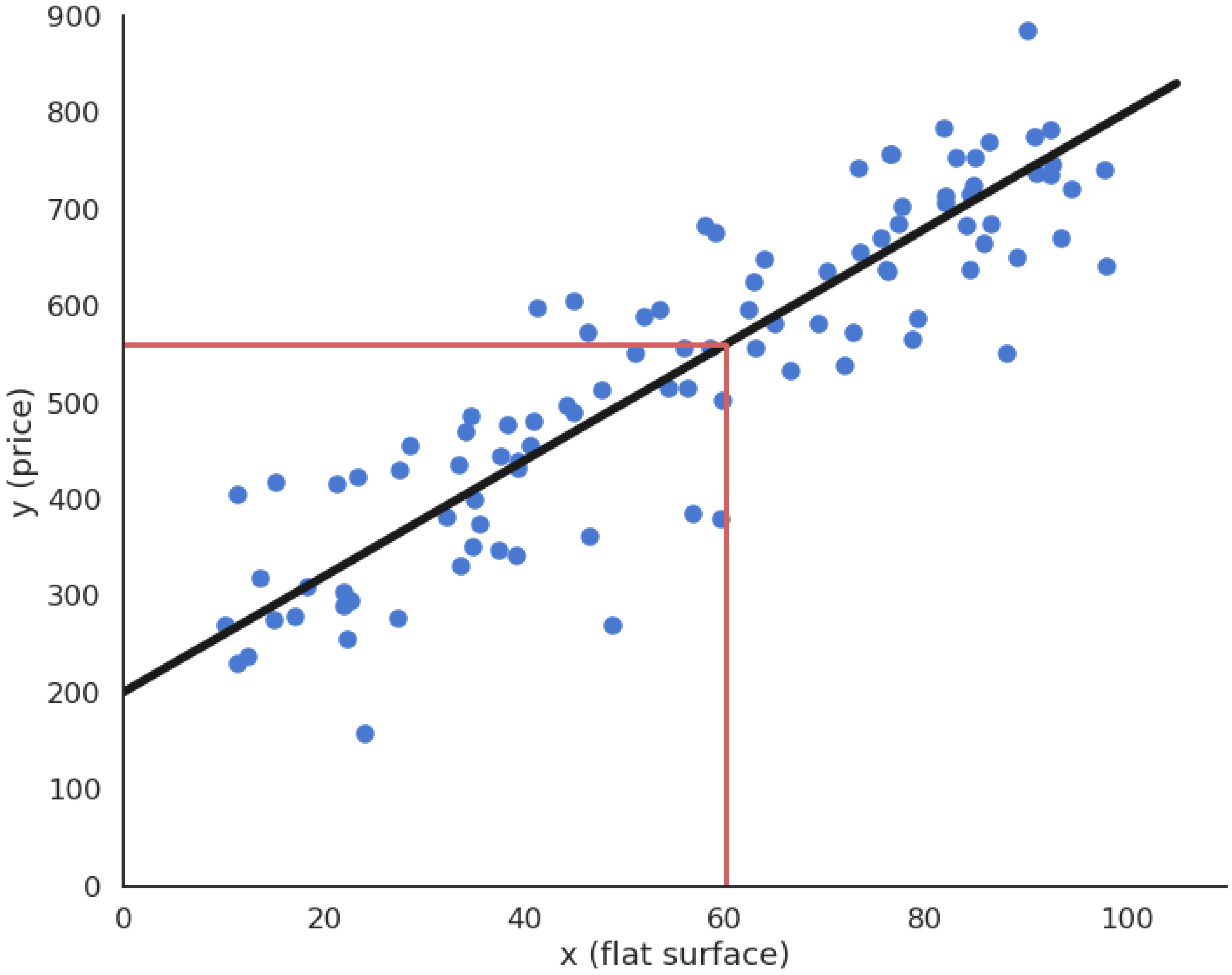
Supervised learning : regression



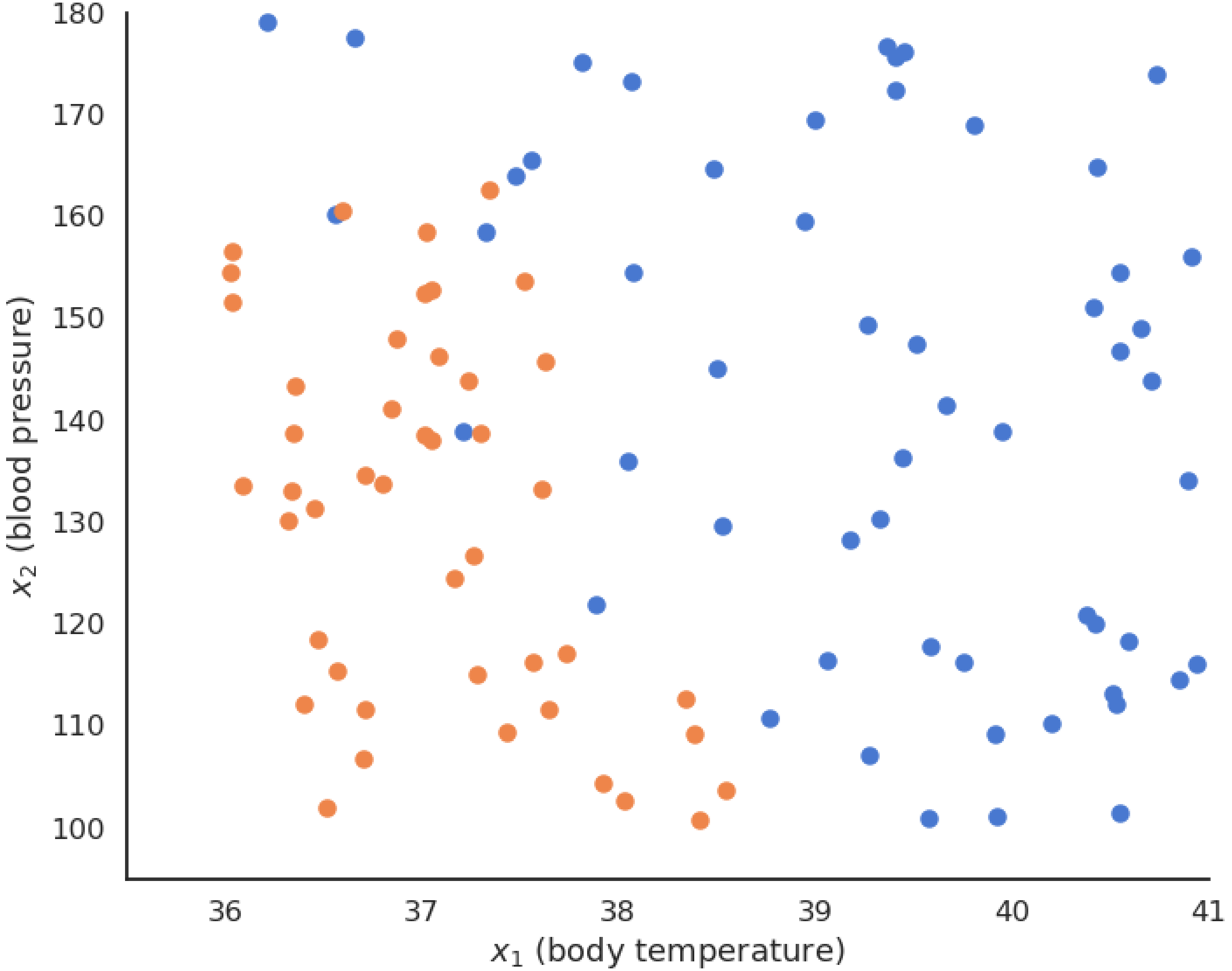
Supervised learning : regression



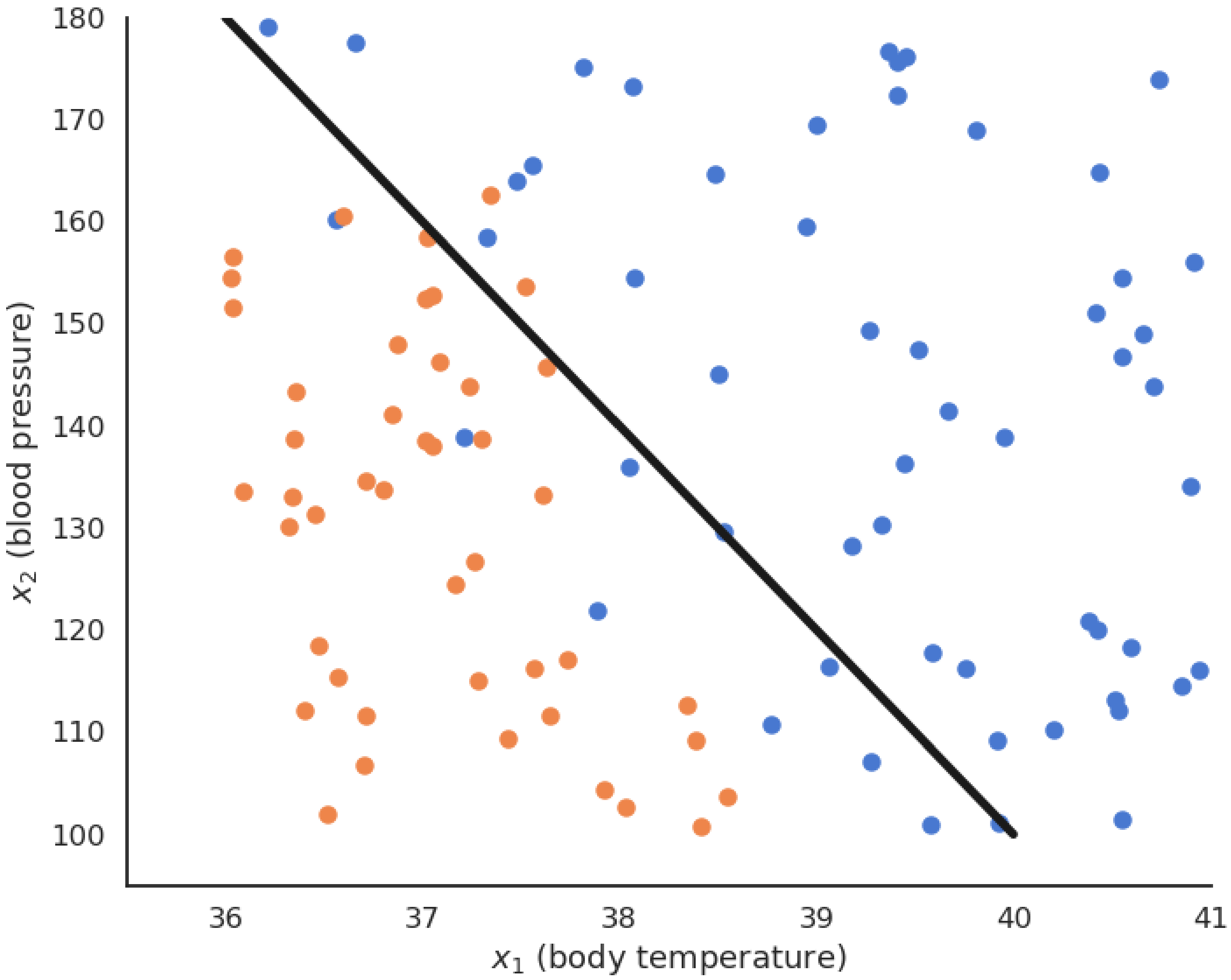
Supervised learning : regression



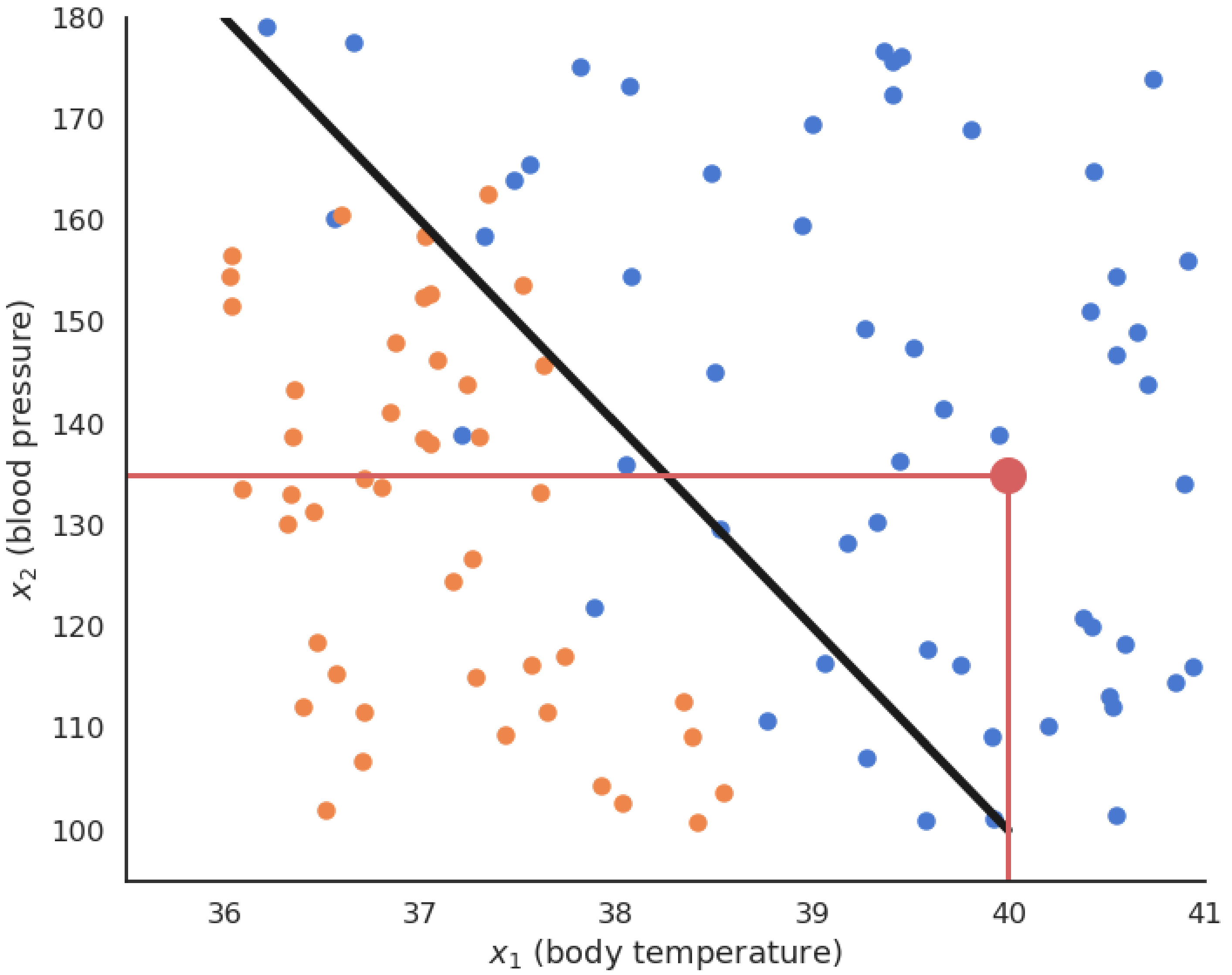
Supervised learning : classification



Supervised learning : classification

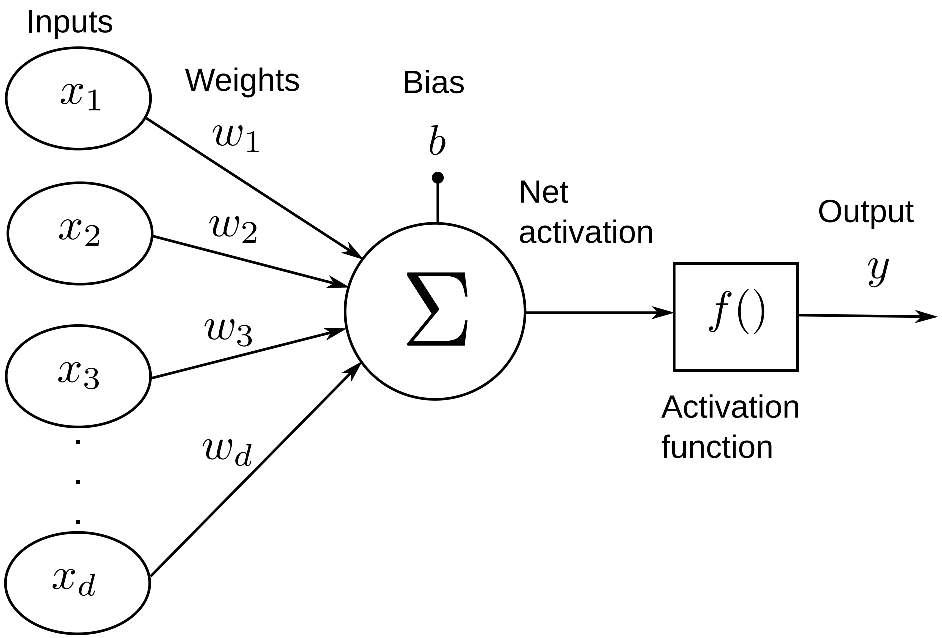


Supervised learning : classification



The artificial neuron

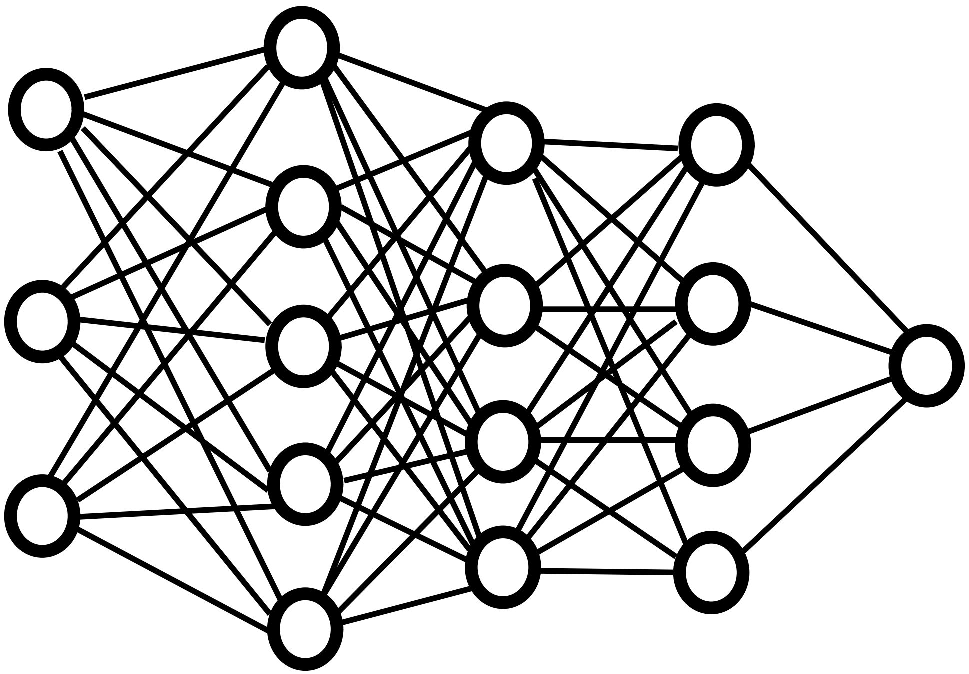
- A single artificial neuron is able to solve linear classification/regression problems:



$$y = f(\sum_{i=1}^{d} w_i \, x_i + b)$$

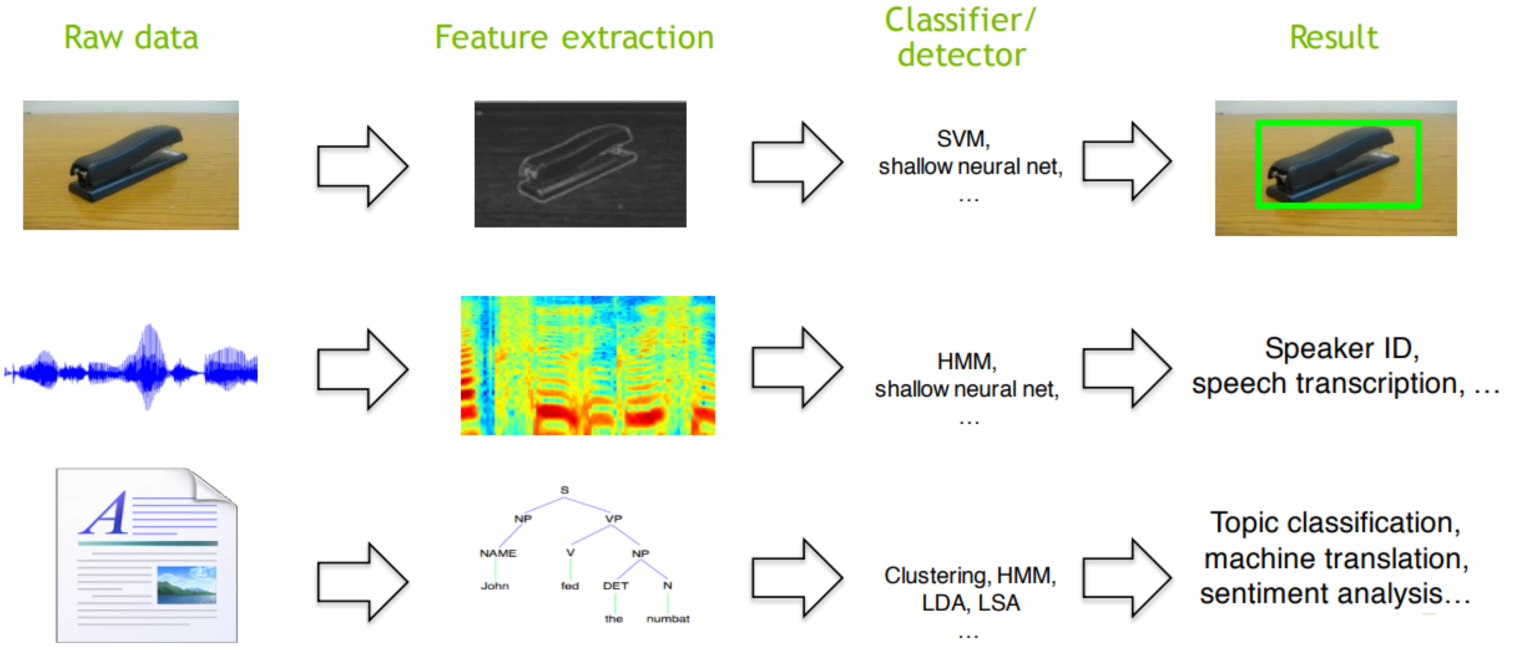
- A neuron integrates inputs x_i by multiplying them with weights w_i, adds a bias b and transforms the result into an output y using a transfer function (or activation function) f.

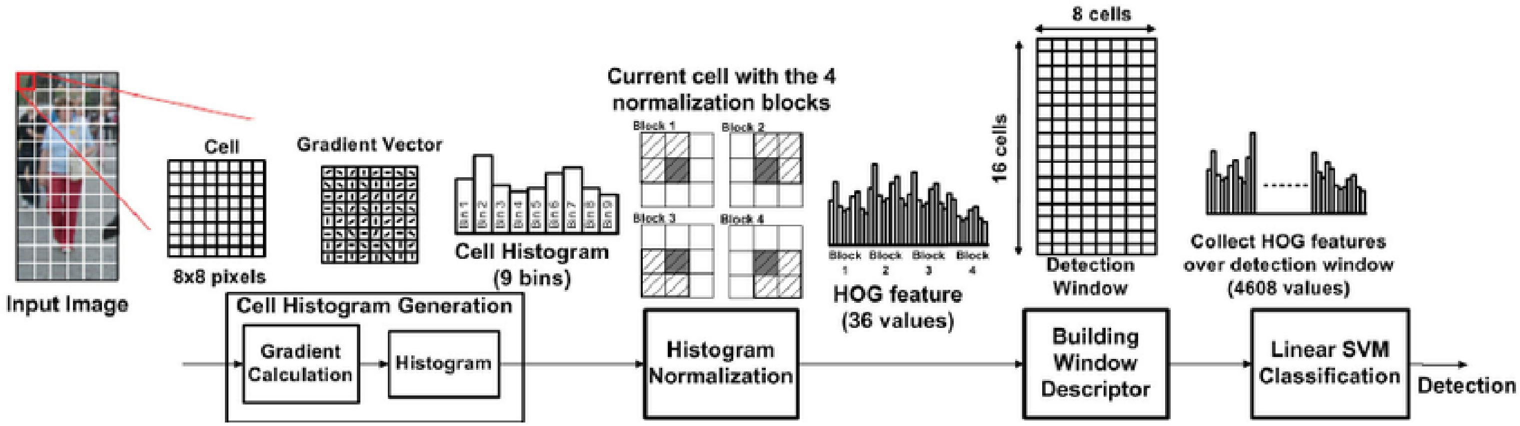
Artificial Neural Network



- A **neural network** (NN) is able to solve non-linear classification/regression problems by combining many artificial neurons.

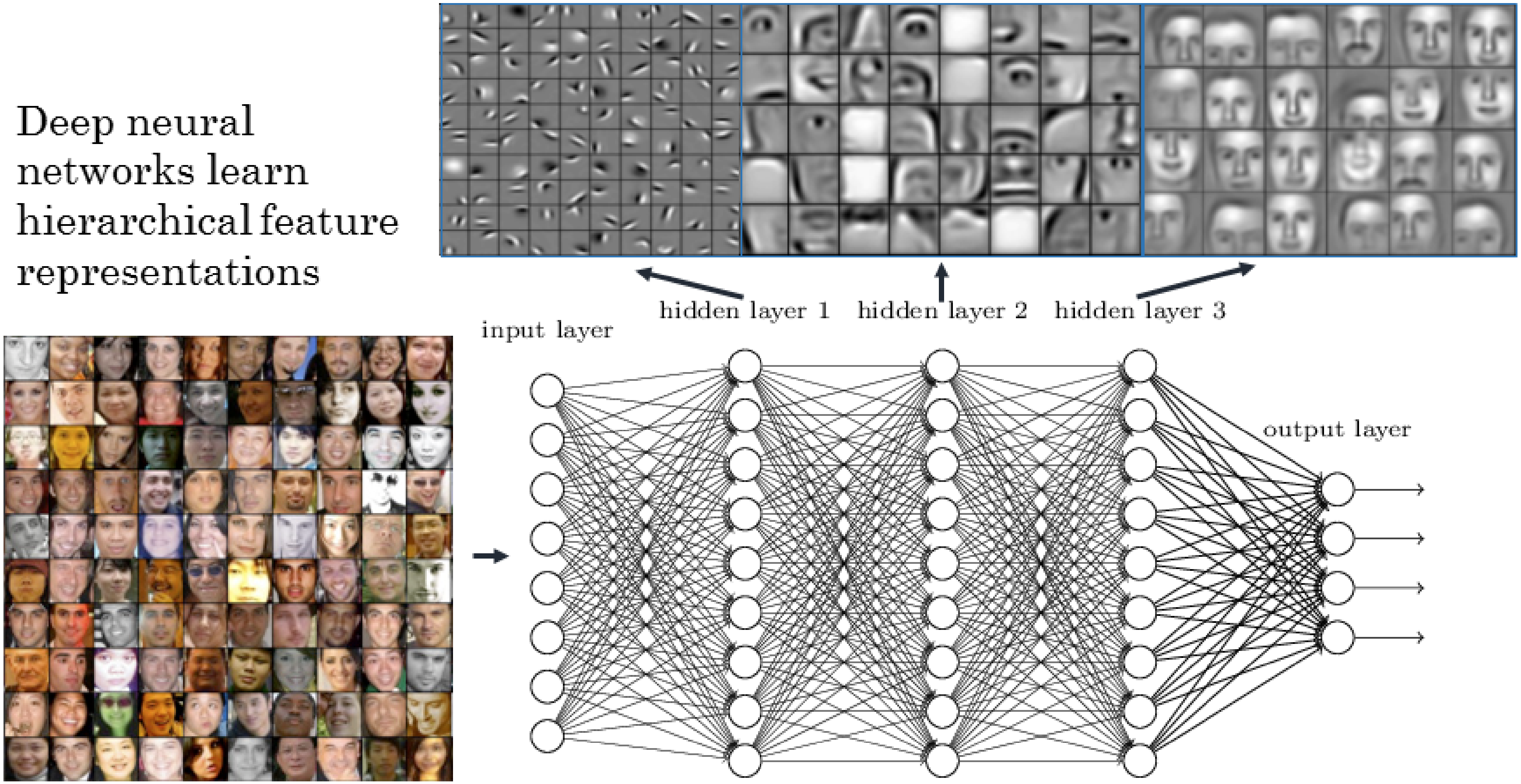
Classical approach to pattern recognition



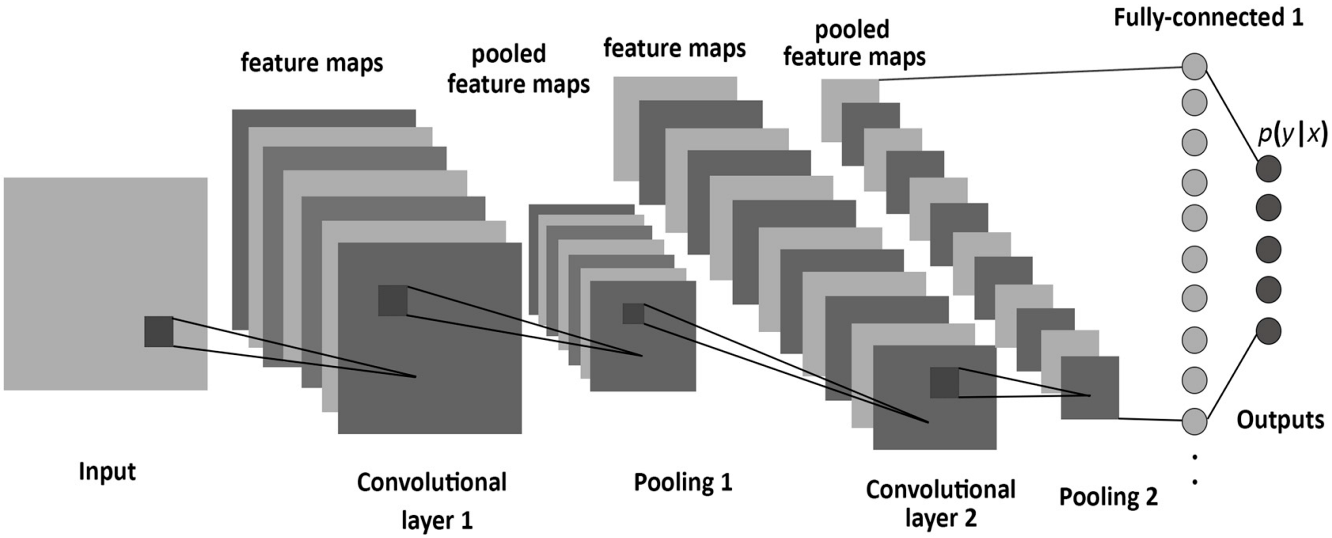


Deep Learning approach to pattern recognition

- **End-to-end** learning: the NN is trained directly on the raw data (pixels, sounds, text) and solves a non-linear classification/regression problem.



Convolutional neural networks



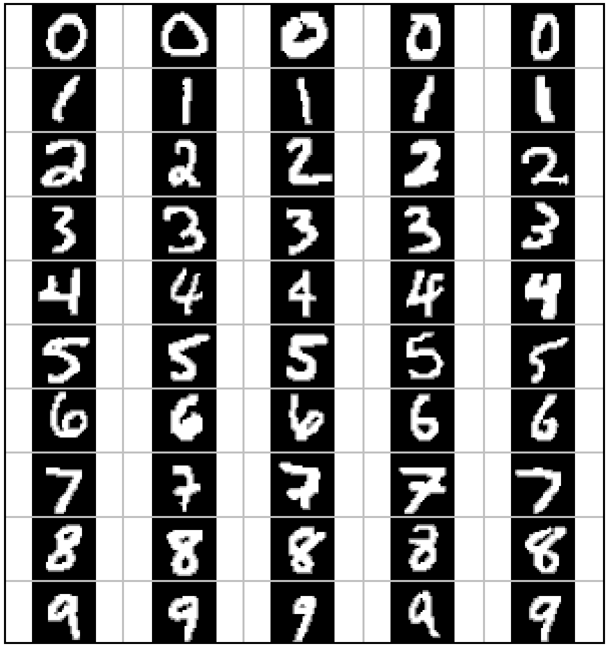
- A **convolutional neural network** (CNN) is a cascade of convolution and pooling operations, extracting layer by layer increasingly complex features.

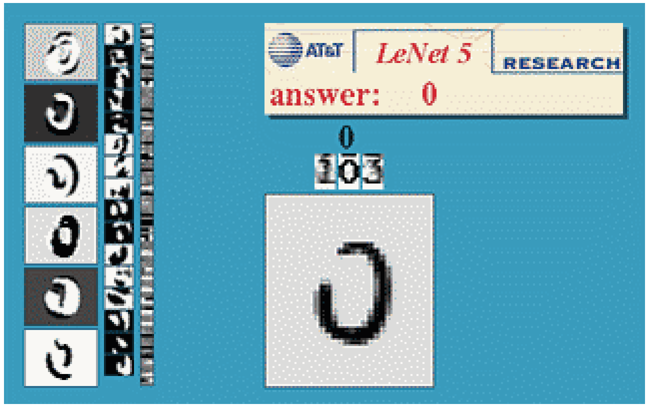
- It can be trained on huge datasets of annotated examples.

Albelwi S, Mahmood A. 2017. A Framework for Designing the Architectures of Deep Convolutional Neural Networks. Entropy 19:242. doi:10.3390/e19060242

Handwriting recognition

- The MNIST database is the simplest benchmark for object recognition (> 99.5 %).
- One of the early functional CNN was LeNet5, able to classify digits.



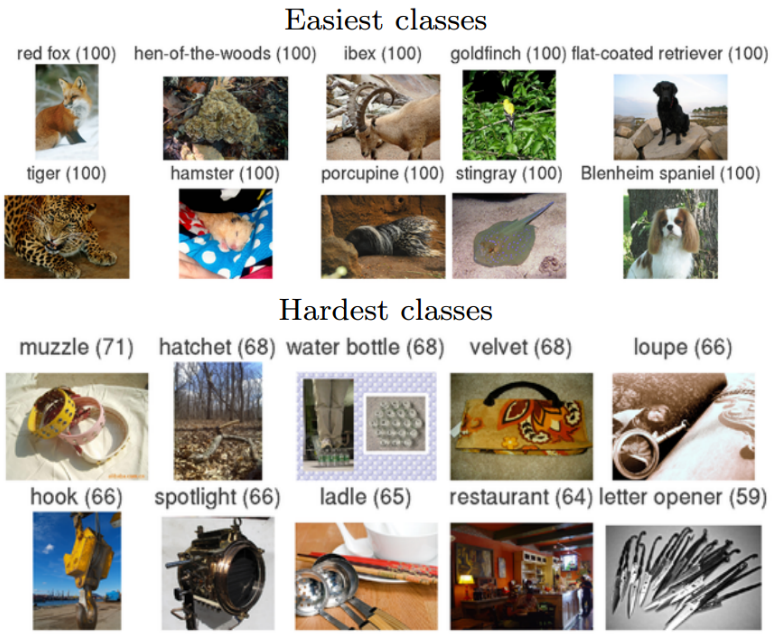


LeCun et al. (1998). Gradient-Based Learning Applied to Document Recognition (Proc. IEEE 1998)

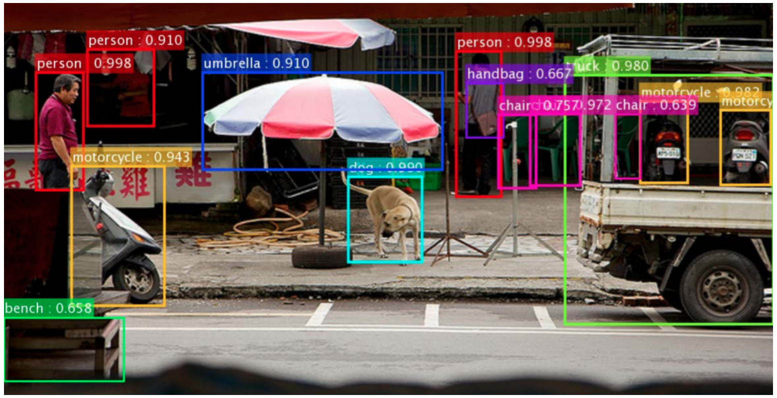
ImageNet recognition challenge (image-net.org)

- The ImageNet challenge was a benchmark for computer vision algorithms, providing millions of annotated images for object recognition, detection and segmentation.

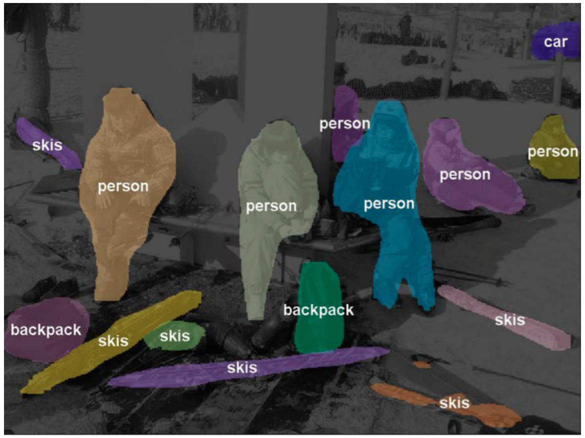
Object recognition



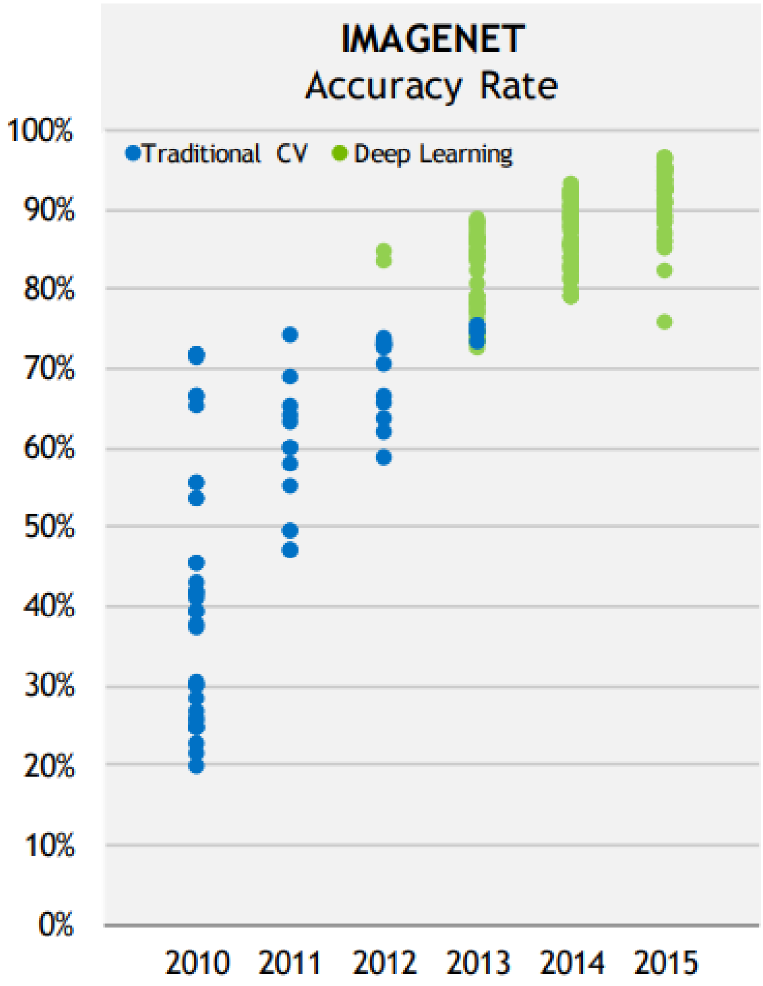
Object detection



Object segmentation



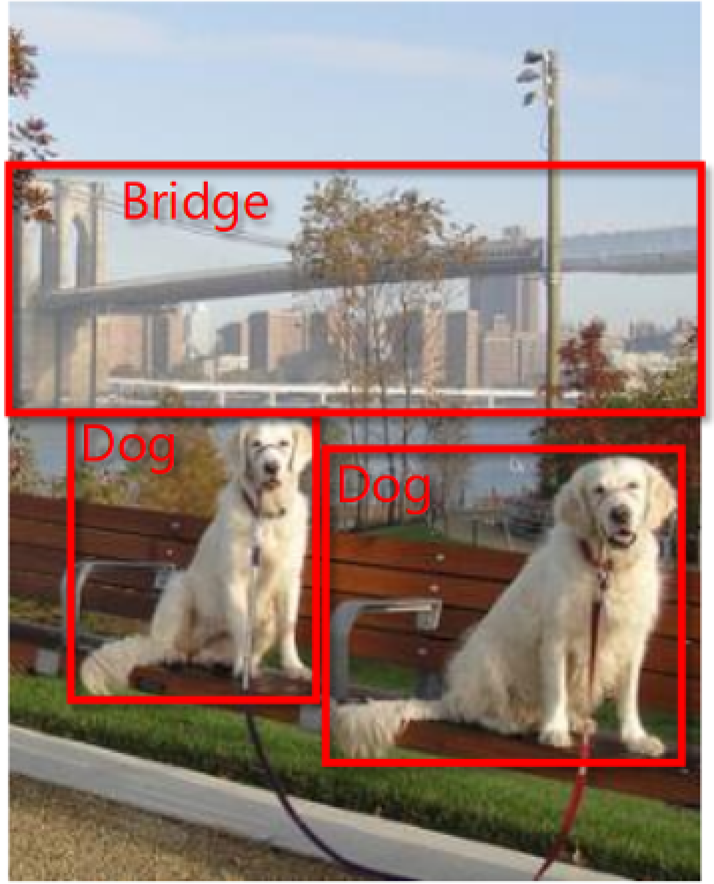
ImageNet recognition challenge (image-net.org)



- Classical computer vision methods obtained moderate results, with error rates around 30%.
- In 2012, Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton (Uni Toronto) used a CNN (**AlexNet**) without any preprocessing, using directly images as inputs.
- To the big surprise of everybody, they won with an error rate of 15%, half of what other methods could achieve.
- Since then, everybody uses deep neural networks for object recognition.
- The deep learning hype had just begun…
  - Computer vision
  - Natural language processing
  - Speech processing
  - Robotics, control

Object detection

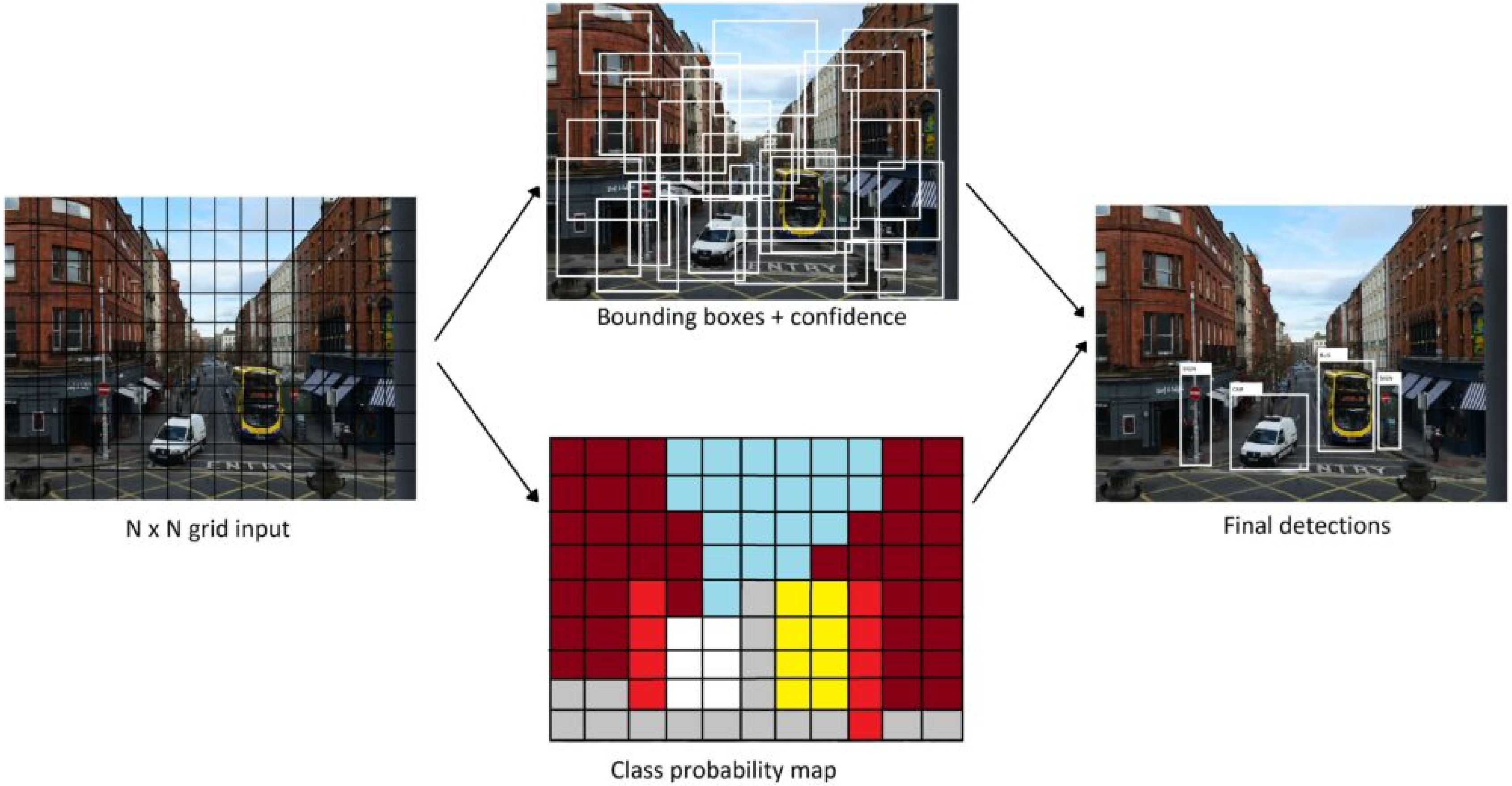
Classification, easy these days



Object detection, still a lot harder

Object detection

- It turns out object detection is both a classification (what) and regression (where) problem.
- Neural networks can be trained to do it given enough annotated data.



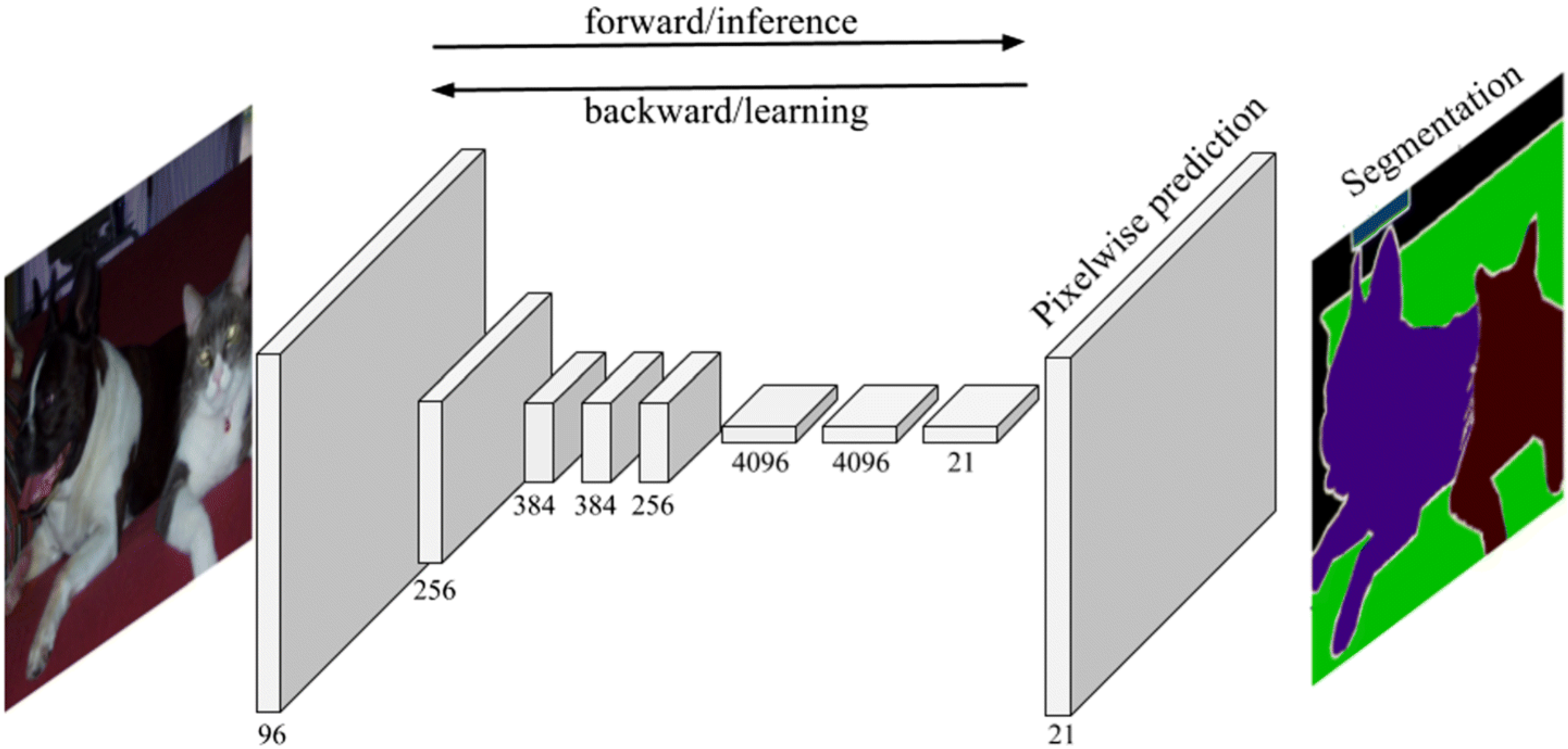
http://datahacker.rs/od1-yolo-object-detection/

Object detection

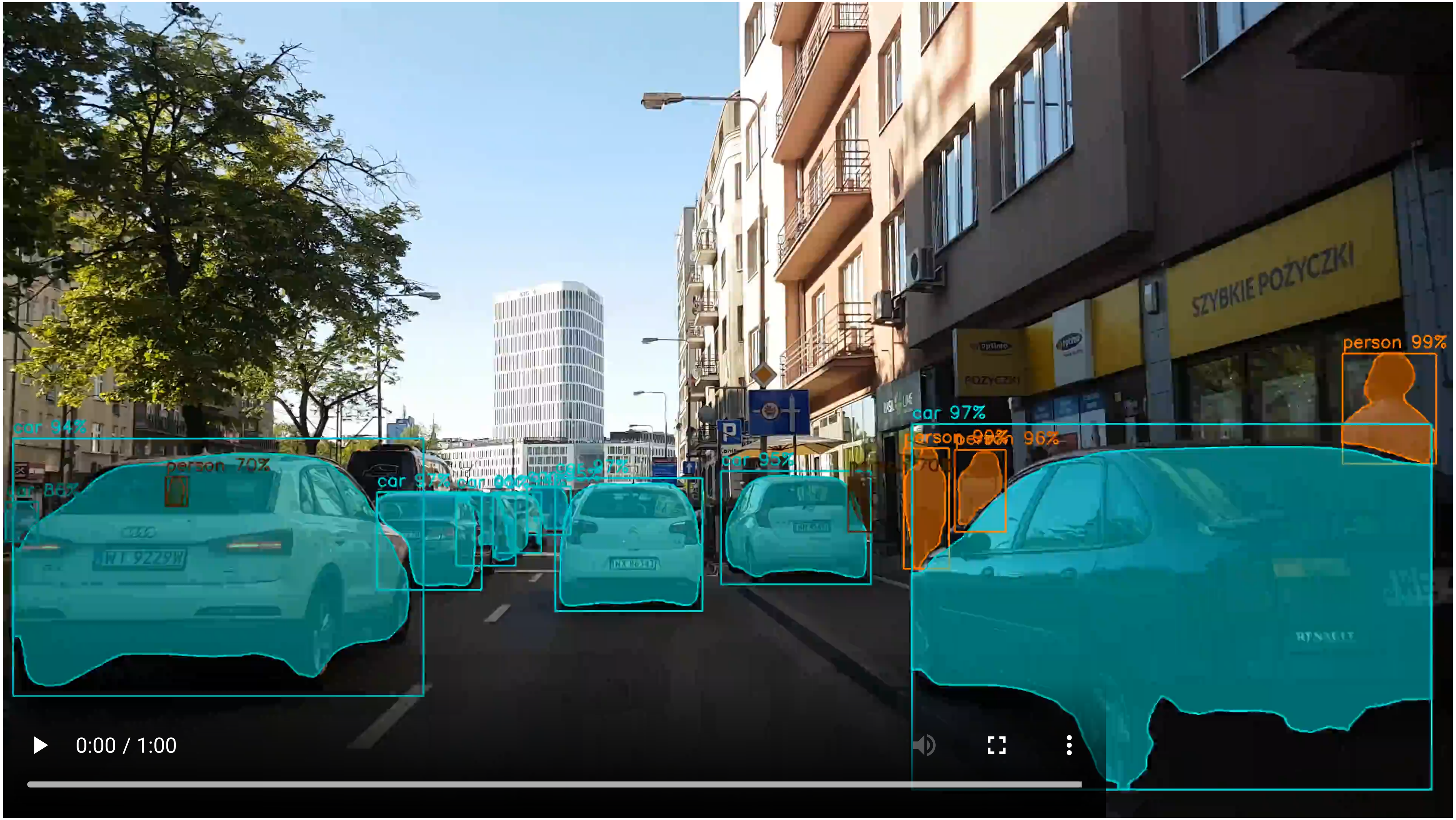
https://pjreddie.com/darknet/yolo/ https://www.youtube.com/watch?v=MPU2HistivI

Semantic segmentation

- Classes can be predicted at the pixel level, allowing **semantic segmentation**.

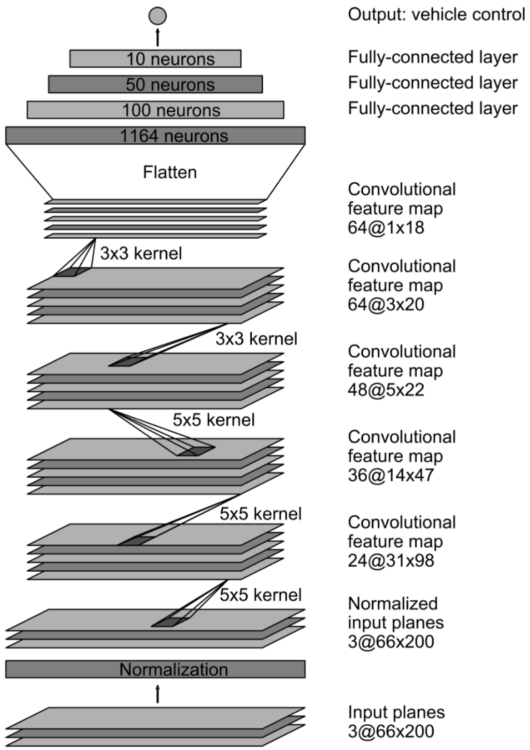


Semantic segmentation

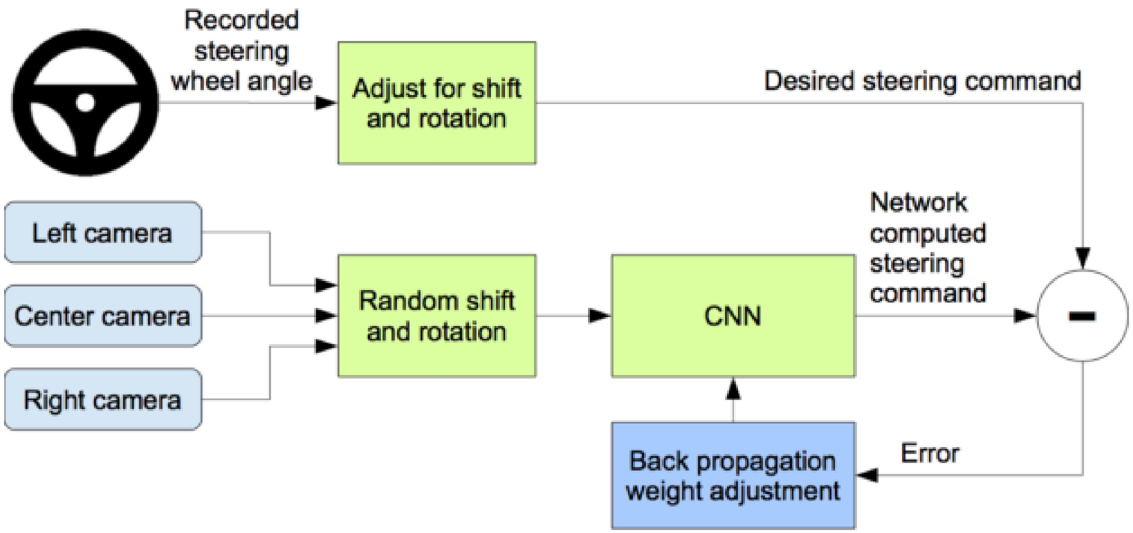


https://www.youtube.com/watch?v=OOT3UIXZztE

Dave2 : NVIDIA's self-driving car



- NVIDIA trained a CNN to reproduce wheel steerings from experienced drivers using only a front camera.
- After training, the CNN took control of the car.



M Bojarski, D Del Testa, D Dworakowski, B Firner (2016). End to end learning for self-driving cars. arXiv:1604.07316, 2016

Dave2 : NVIDIA's self-driving car

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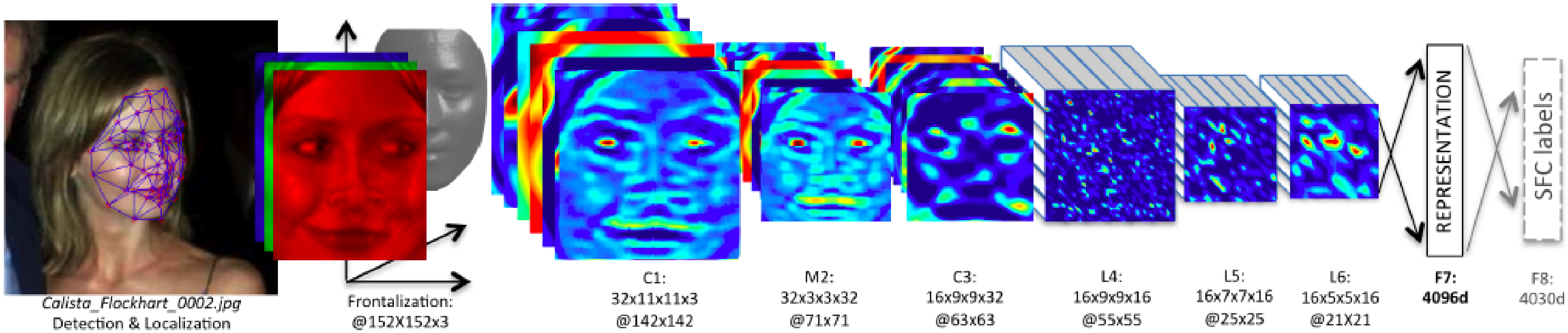
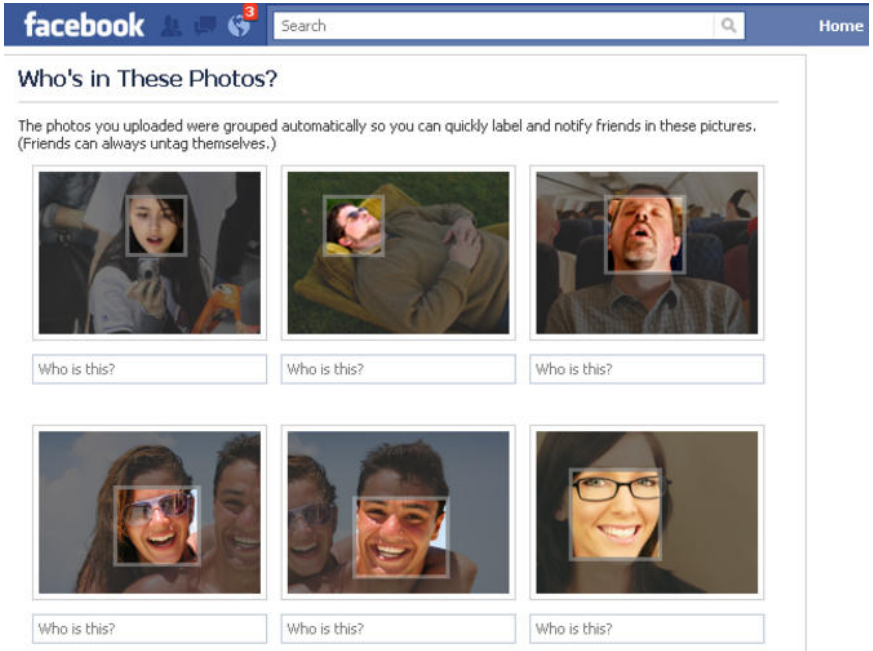
Facial recognition

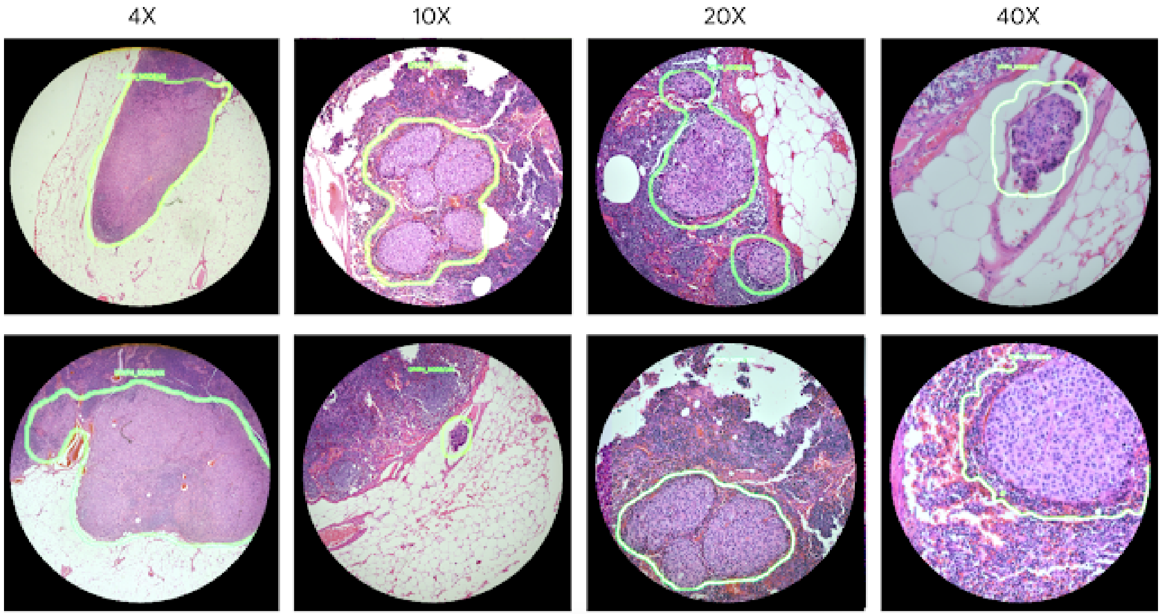


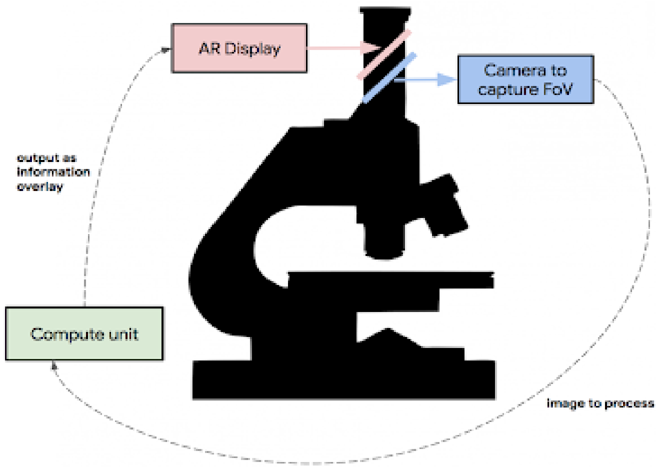


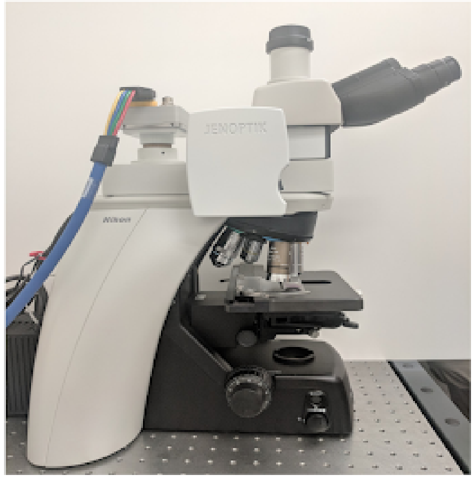
- Facebook used 4.4 million annotated faces from 4030 users to train **DeepFace**.
- Accuracy of 97.35% for recognizing faces, on par with humans.
- Used now to recognize new faces from single examples (transfer learning, one-shot learning).

Yaniv Taigman; Ming Yang; Marc'Aurelio Ranzato; Lior Wolf (2014), DeepFace: Closing the Gap to Human-Level Performance in Face Verification, Conference on Computer Vision and Pattern Recognition (CVPR)

Augmented Reality Microscope for Real-time Automated Detection of Cancer

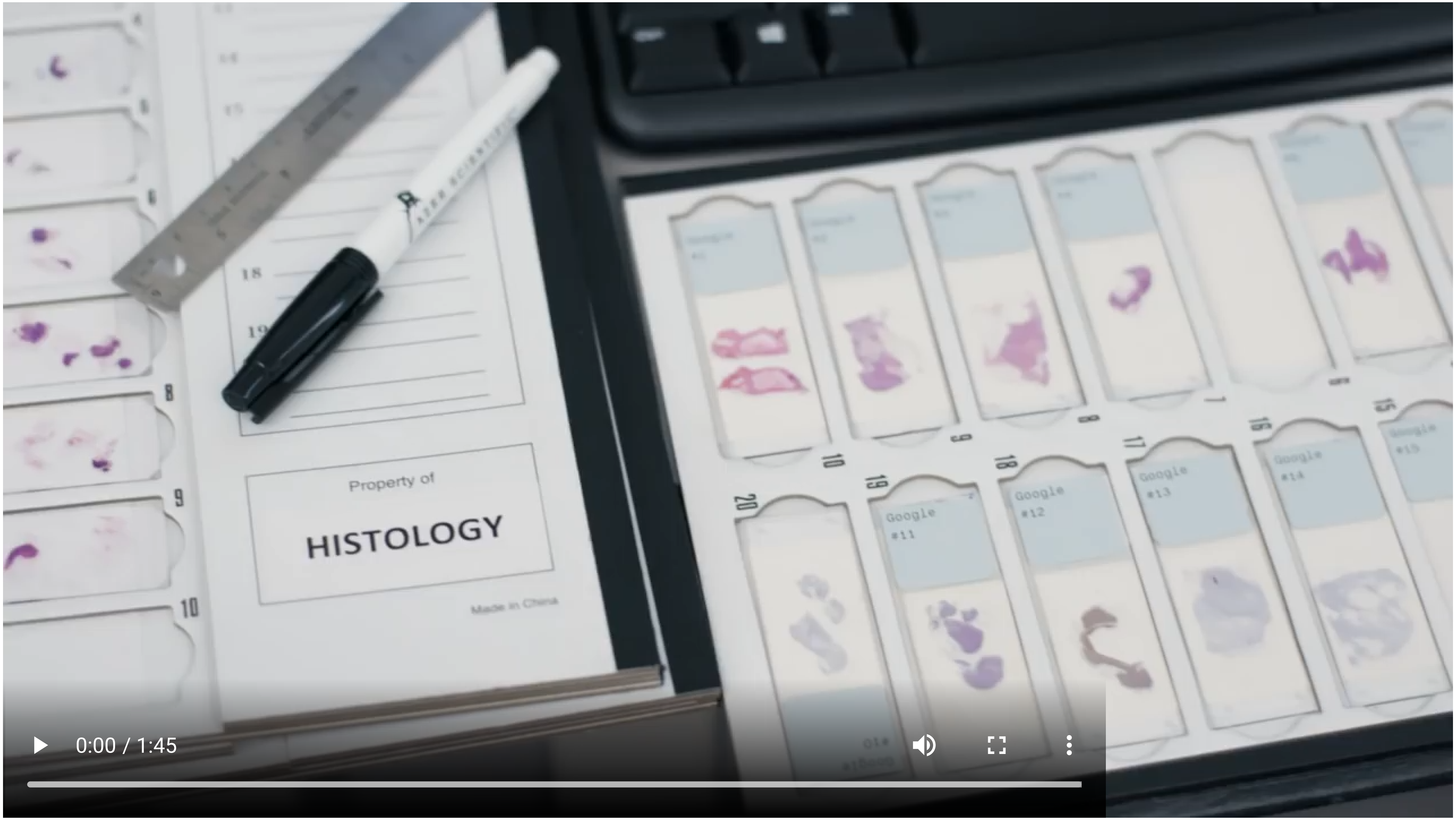






Google AI Research http://ai.googleblog.com/2018/04/an-augmented-reality-microscope.html

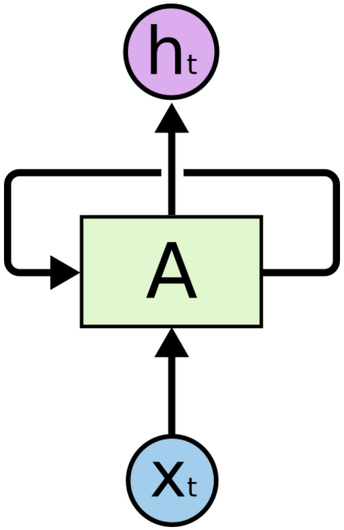
Augmented Reality Microscope for Real-time Automated Detection of Cancer

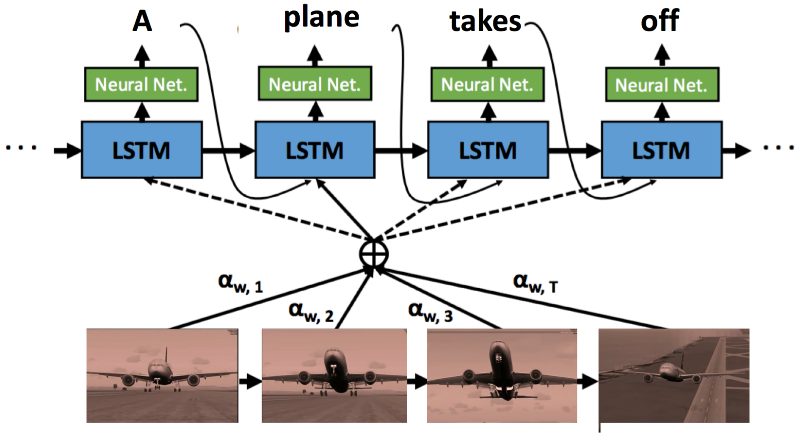


https://www.youtube.com/watch?v=9Mz84cwVmS0

Recurrent neural networks

Recurrent neural networks

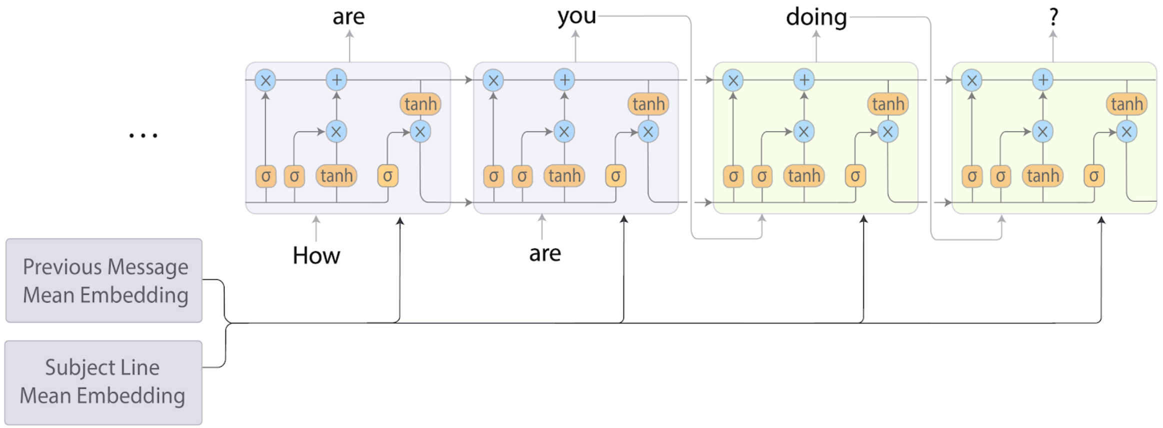


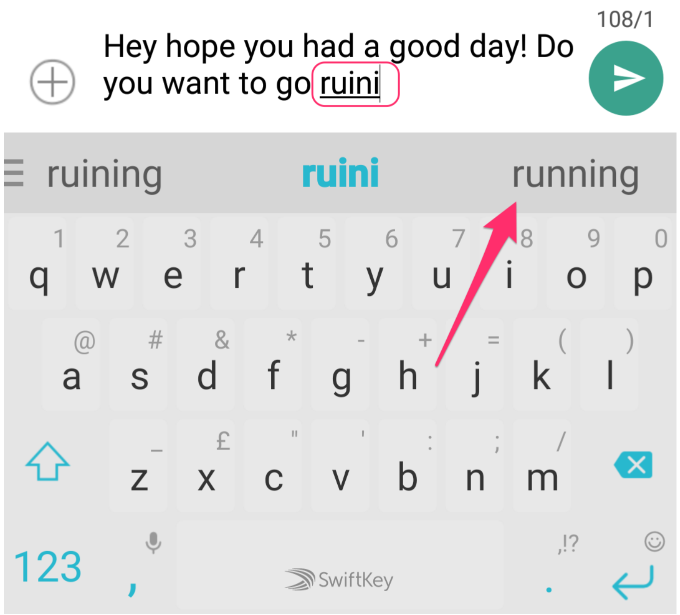


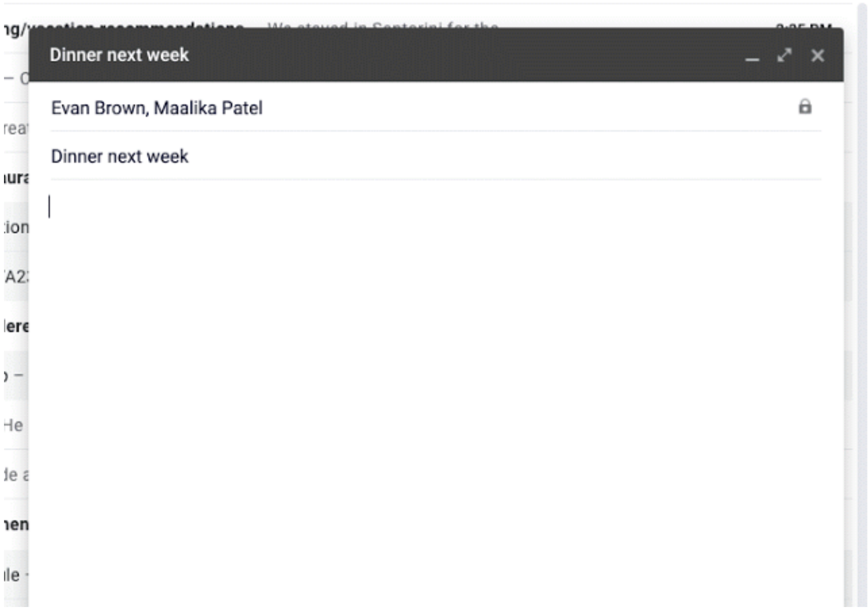
- A **recurrent neural network** (RNN) uses it previous output as an additional input (*context*).
- The inputs are integrated over time to deliver a response at the correct moment.
- This allows to deal with time series (texts, videos) without increasing the input dimensions.
- The input to the RNN can even be the output of a pre-trained CNN.
- The most efficient RNN is called **LSTM** (Long short-term memory networks) (Hochreiter and Schmidhuber, 1997).

Source: C. Olah

Natural Language Processing : Automatic word/sentence completion







Google AI reserach http://ai.googleblog.com/2018/05/smart-compose-using-neural-networks-to.html

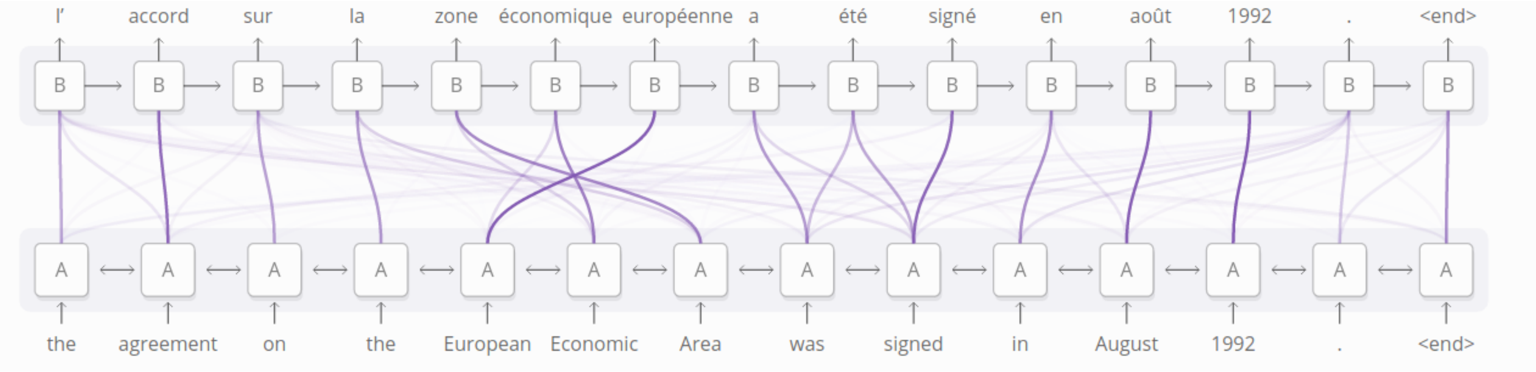
Natural Language Processing : Text Generation

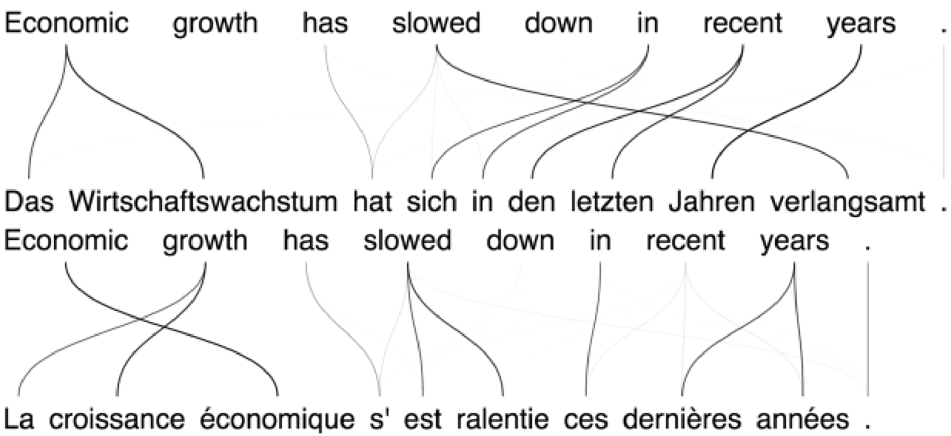
```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never
fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.
```

- Characters or words are fed one by one into a LSTM.
- The desired output is the next character or word in the text.
- Example:
  - Inputs: **To, be, or, not, to**
  - Output: **be**
- The text on the left was generated by a LSTM having read the entire writings of William Shakespeare.
- Each generated word is used as the next input.

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

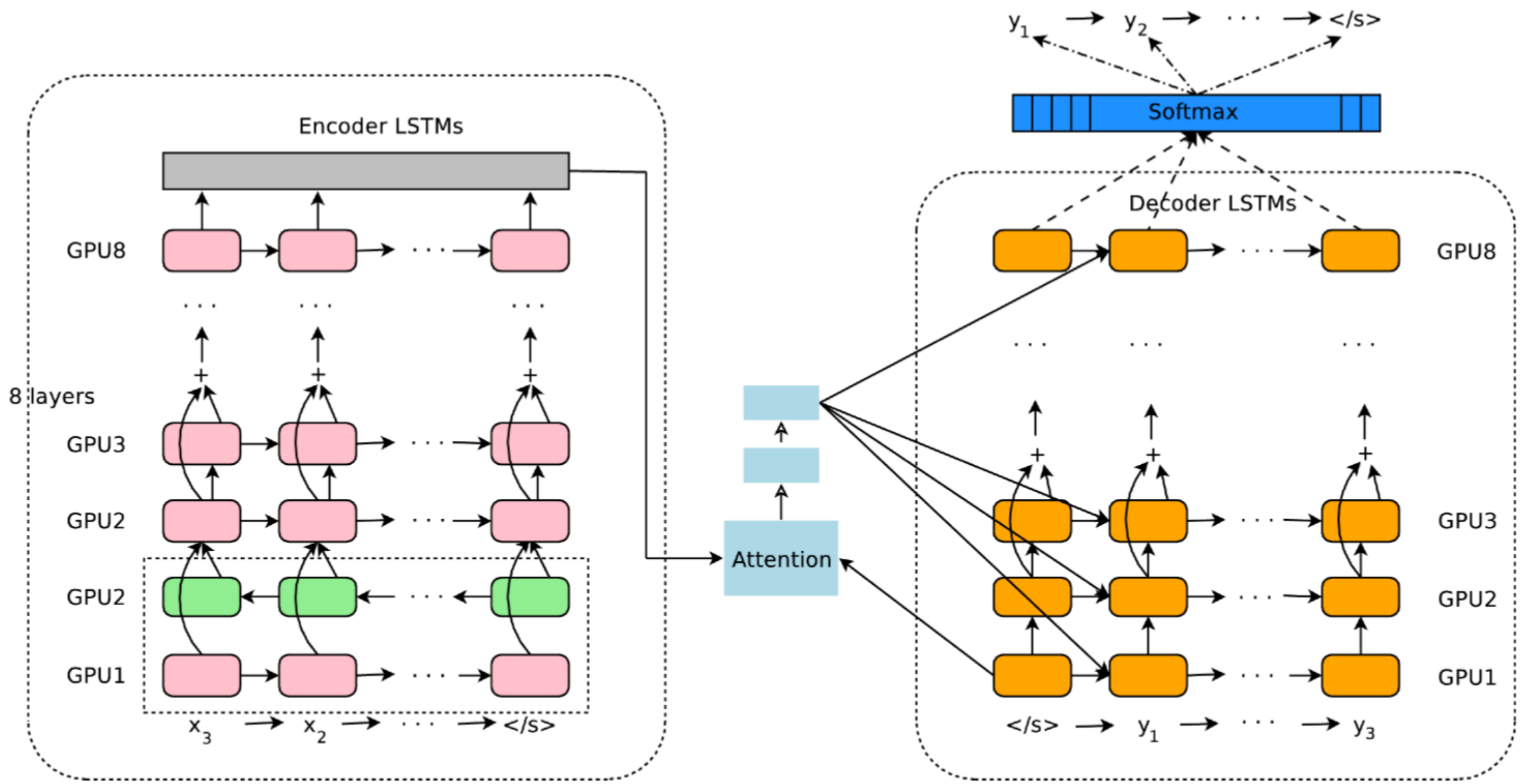
Natural Language Processing : text translation





- Two LSTM can be stacked to perform sequence-to-sequence translation (**seq2seq**).
- One is the encoder, the other the decoder.

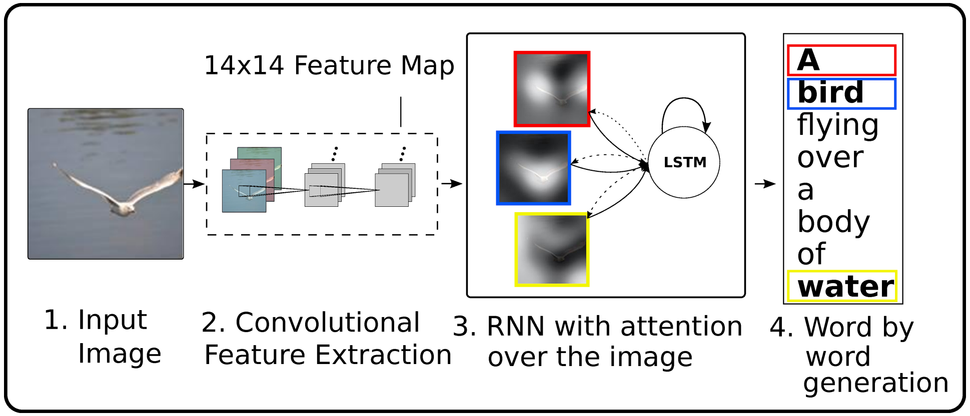
Natural Language Processing : Google Neural Machine Translation

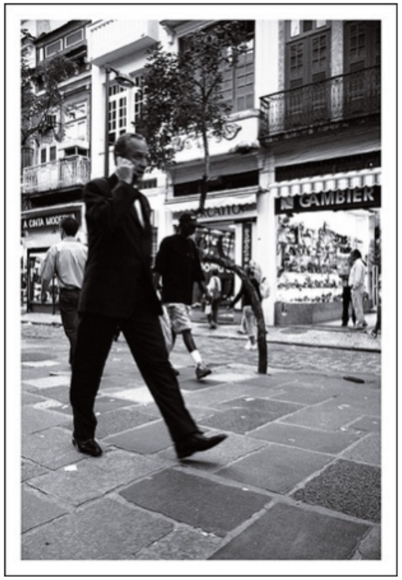


- Same idea, but with much more layers…
- Can translate any pair of languages!

https://ai.google/research/pubs/pub45610

Caption Generation





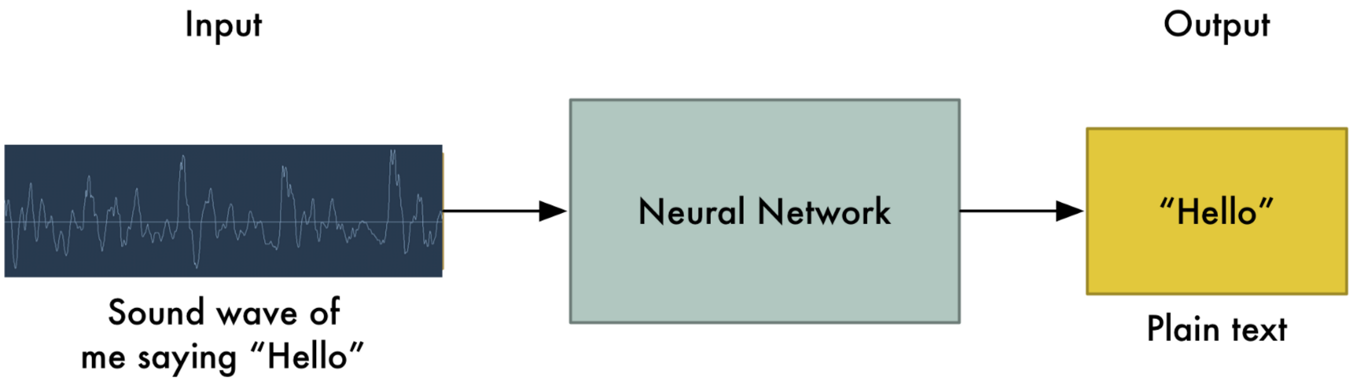
↑ a living room with a couch and a television

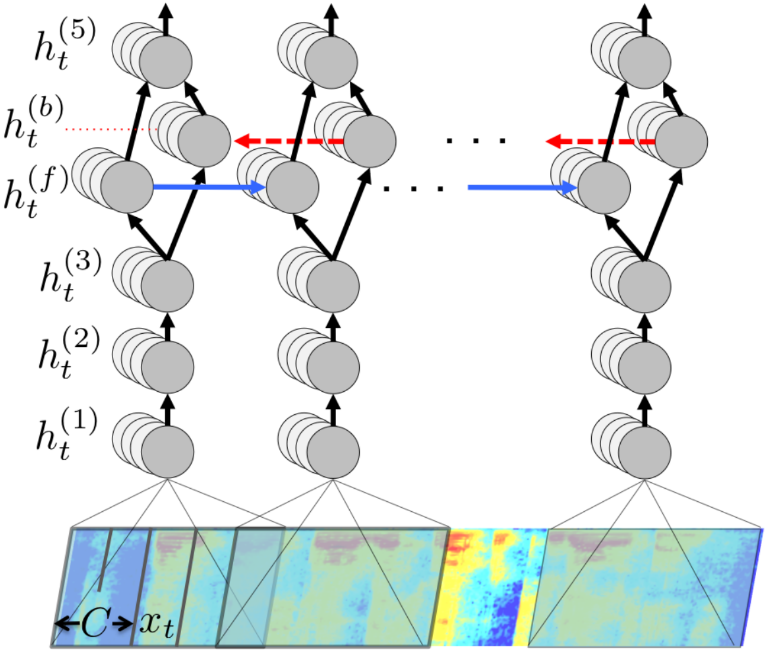
↑ a man riding a bike on a beach

a man is walking down the street with a suitcase ↗

Xu et al. (2015). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. NIPS.

Voice recognition





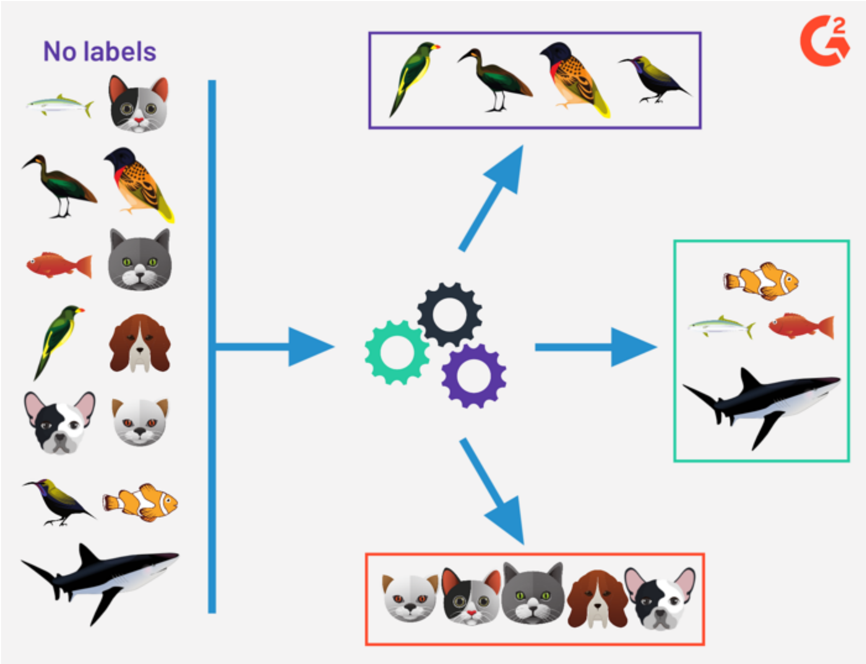
- CNNs are not limited to images, voice signals can also be recognized using their mel-spectrum.
- Siri, Alexa, Google now, etc. use recurrent CNNs to recognize vocal commands and respond.
- **DeepSpeech** from Baidu is one of the state-of-the-art approach.

Hannun et al (2014). Deep Speech: Scaling up end-to-end speech recognition. arXiv:1412.5567

2 - Unsupervised learning

Unsupervised learning

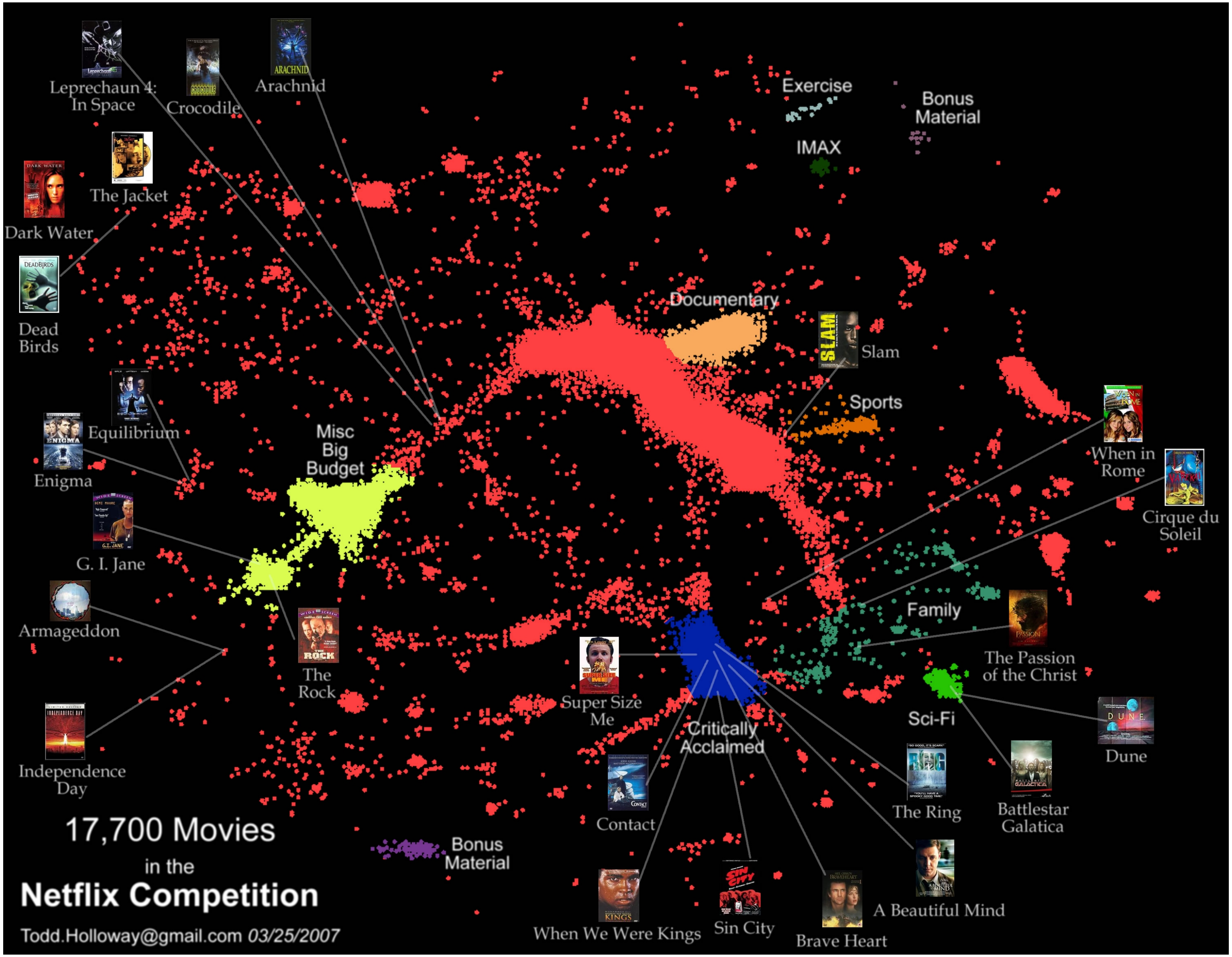
- In unsupervised learning, only raw input data is provided to the algorithm, which has to analyze the statistical properties of the data.



https://learn.g2.com/supervised-vs-unsupervised-learning

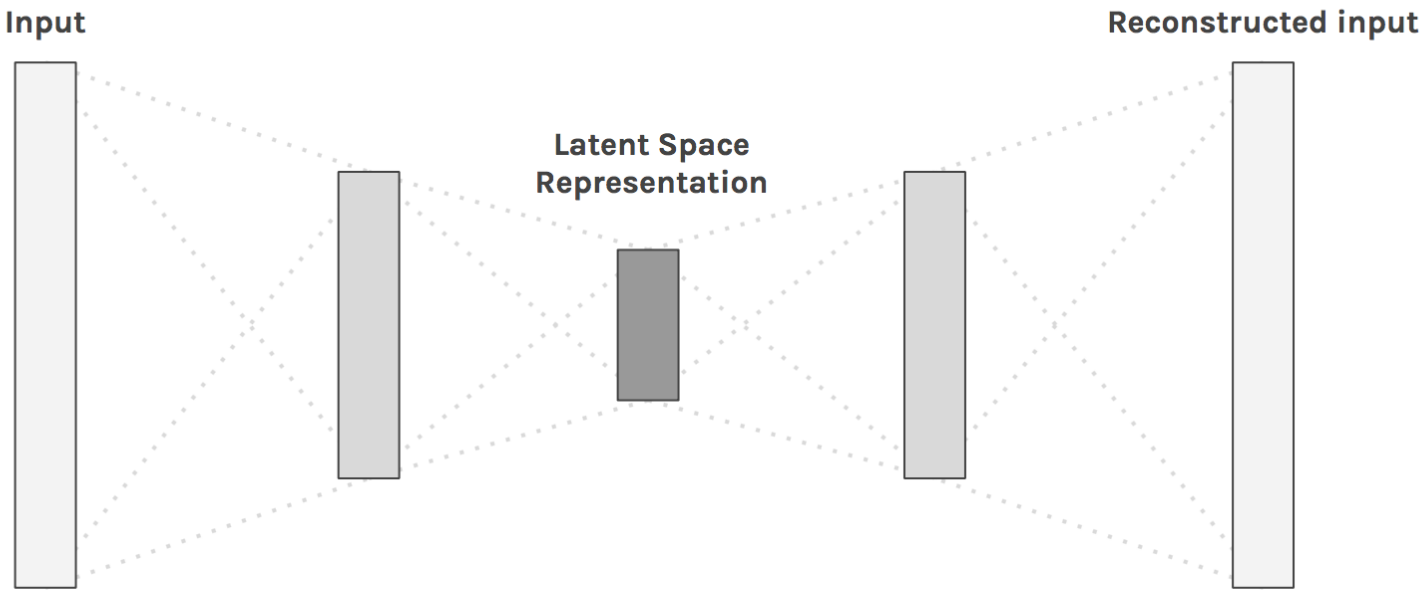
- The goal of **unsupervised learning** is to build a model or find useful representations of the data, for example:
  - finding groups of similar data and model their density (**clustering**).
  - reduce the redundancy of the input dimensions (**dimensionality reduction**).
  - finding good explanations / representations of the data (**latent data modeling**).
  - generate new data (**generative models**).

Clustering: learning topologies in film preferences



Dimensionality reduction: finding the right latent space

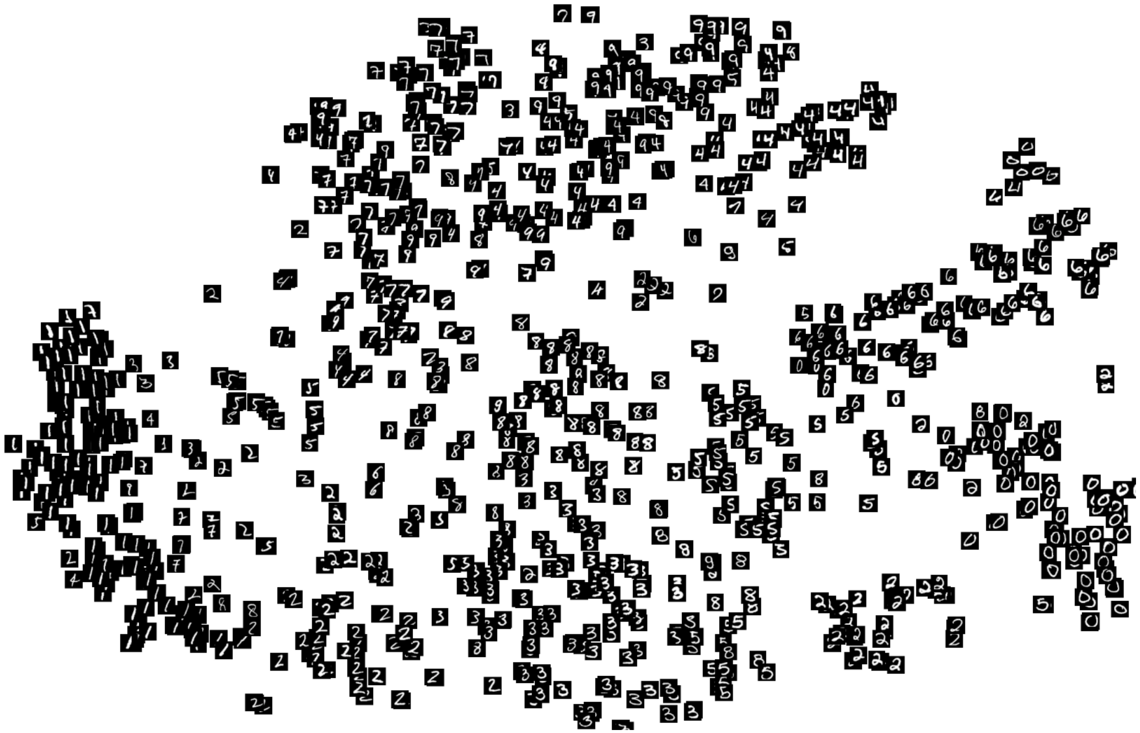
- Images have a lot of dimensions (pixels), most of which are redundant.
- Dimensionality reduction techniques allow to reduce this number of dimensions by projecting the data into a **latent space**.
- **Autoencoders** are NN that learn to reproduce their inputs by compressing information through a bottleneck.



https://hackernoon.com/autoencoders-deep-learning-bits-1-11731e200694

Dimensionality reduction: visualization

- If the latent space has two or three dimensions, you can use dimensionality reduction to **visualize** your data.

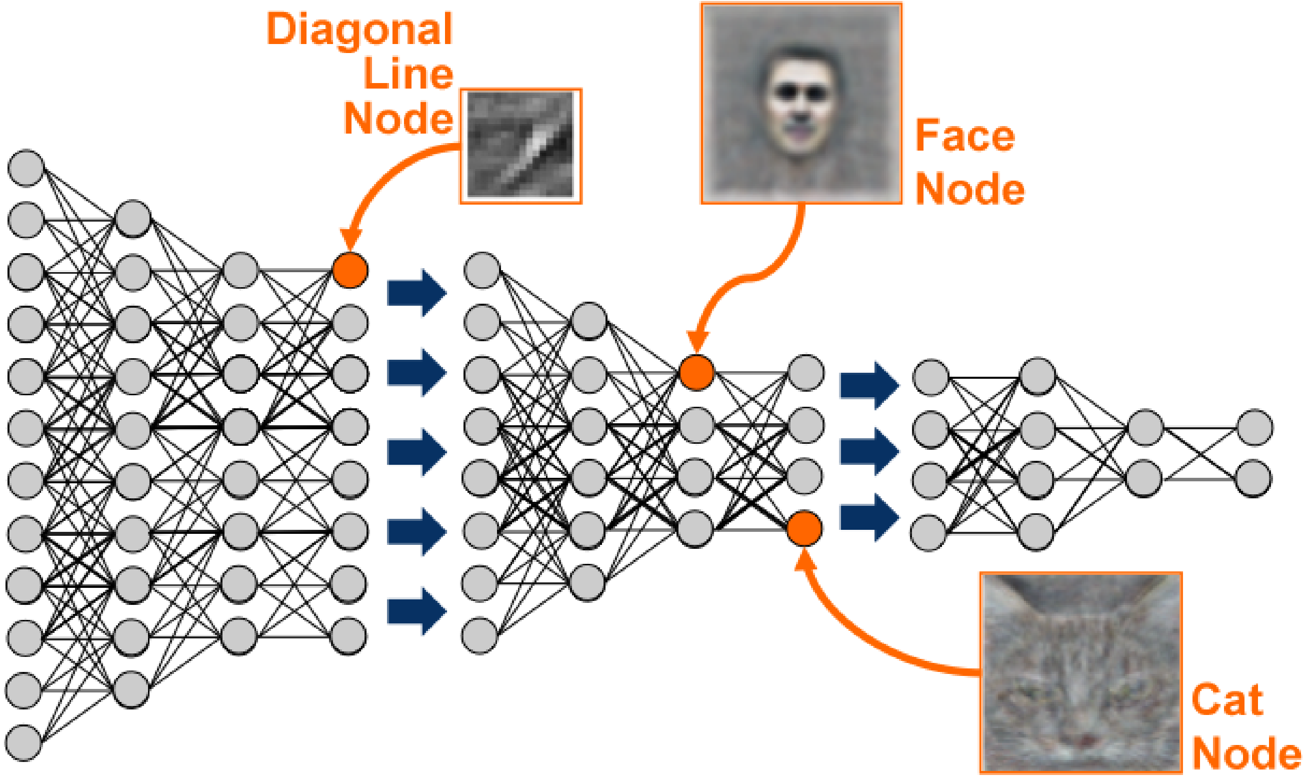


- Classical machine learning algorithms include PCA (principal component analysis) or t-SNE.
- NN autoencoders can also be used for visualization, e.g. UMAP.

McInnes L, Healy J, Melville J. 2020. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. arXiv:180203426.
https://hackernoon.com/latent-space-visualization-deep-learning-bits-2-bd09a46920df

Feature extraction: self-taught learning

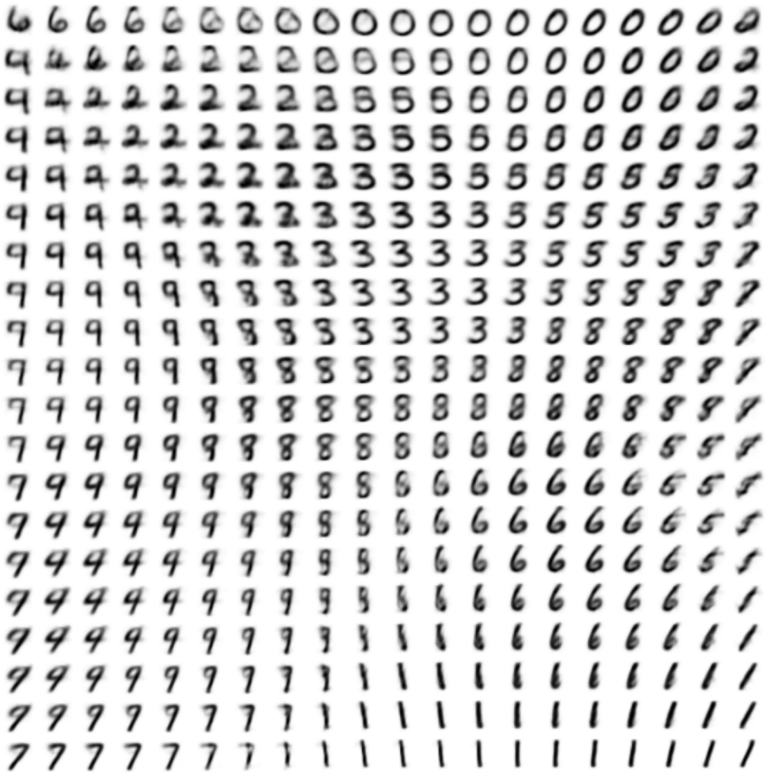
- **Pretrain** a neural network on huge unlabeled datasets (e.g. Youtube videos) before applying it to small-data supervised problems.

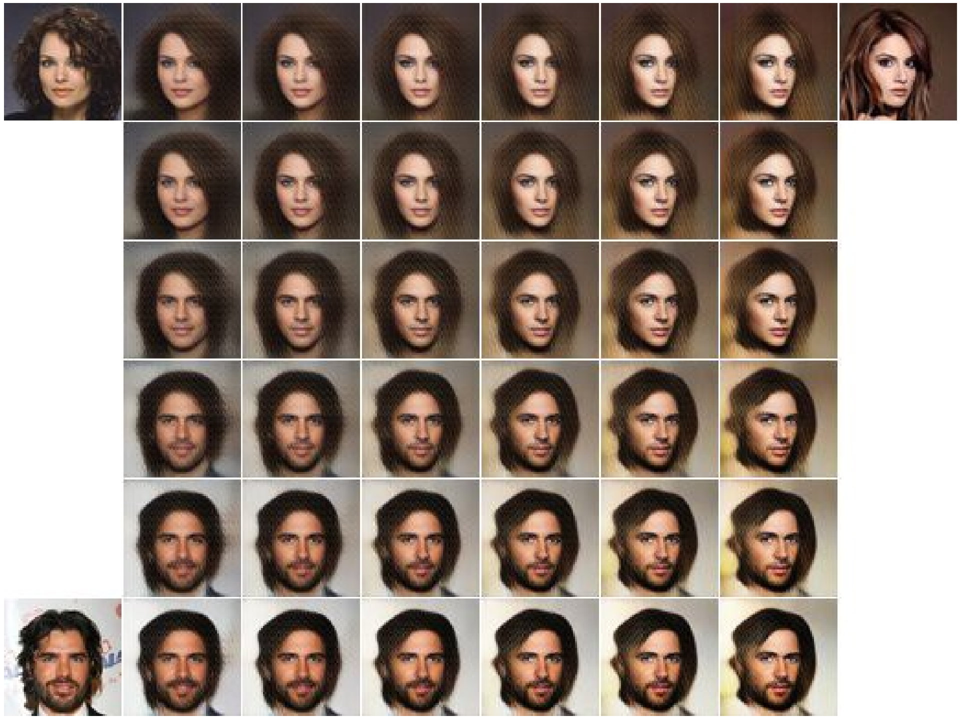


Quoc et al. (2012). Building high-level features using large scale unsupervised learning. ICML12

Generative models

- If the latent space is well organized, you can even sample from it to generate new images using **variational autoencoders** (VAE).





https://hackernoon.com/latent-space-visualization-deep-learning-bits-2-bd09a46920df

DeepFake

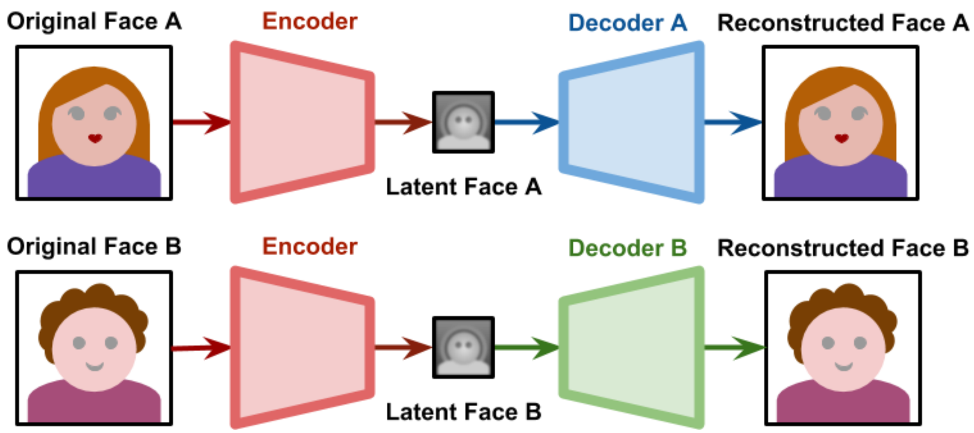
- Try it:

https://github.com/iperov/DeepFaceLab

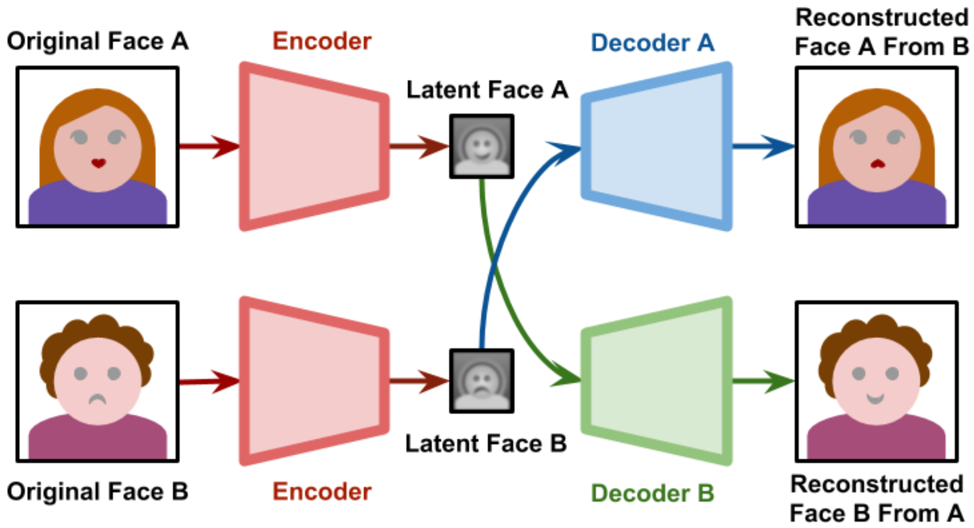
https://www.youtube.com/watch?v=JbzVhzNaTdI

DeepFake

- During training, each autoencoder learns to reproduce the face of one person.

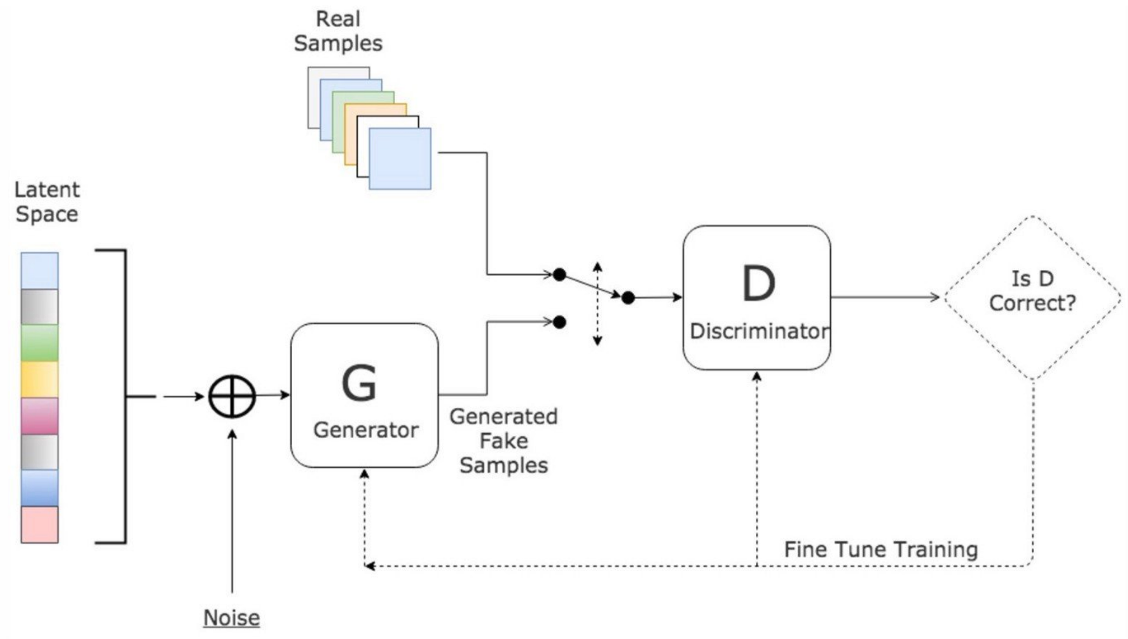


- When generating the deepfake, the decoder of person B is used on the encoder of person A.



https://www.alanzucconi.com/2018/03/14/understanding-the-technology-behind-deepfakes/

Generative Adversarial Networks

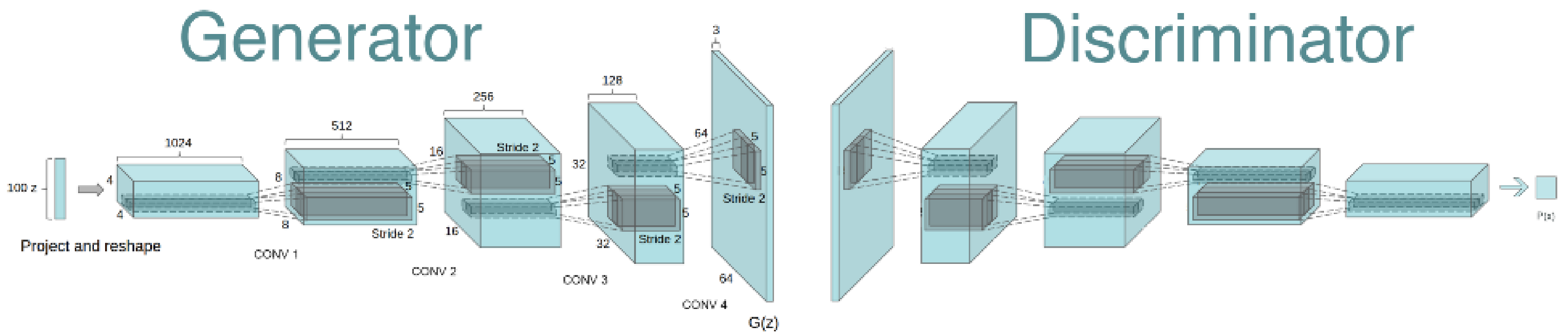


- A **Generative Adversarial Network** (GAN) is composed of two networks:
  - The **generator** learns to produce realistic images.
  - The **discriminator** learn to differentiate real data from generated data.
- Both compete to reach a Nash equilibrium:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim P_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z \sim P_z(z)}[\log(1 - D(G(z)))]$$

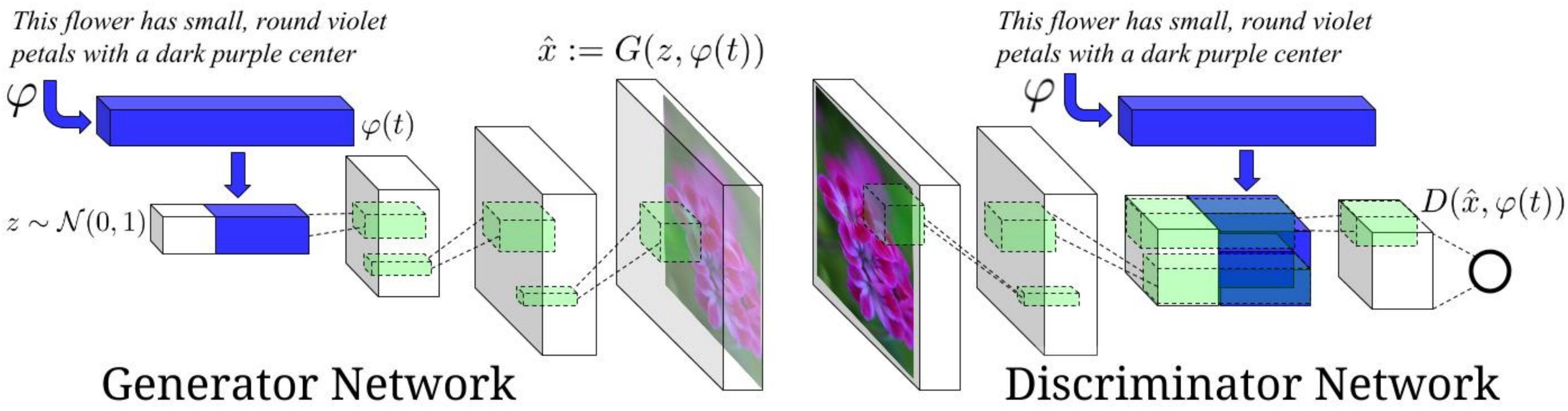
Goodfellow IJ, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A, Bengio Y. 2014. Generative Adversarial Networks. arXiv:1406.2661.

DCGAN : Deep convolutional GAN



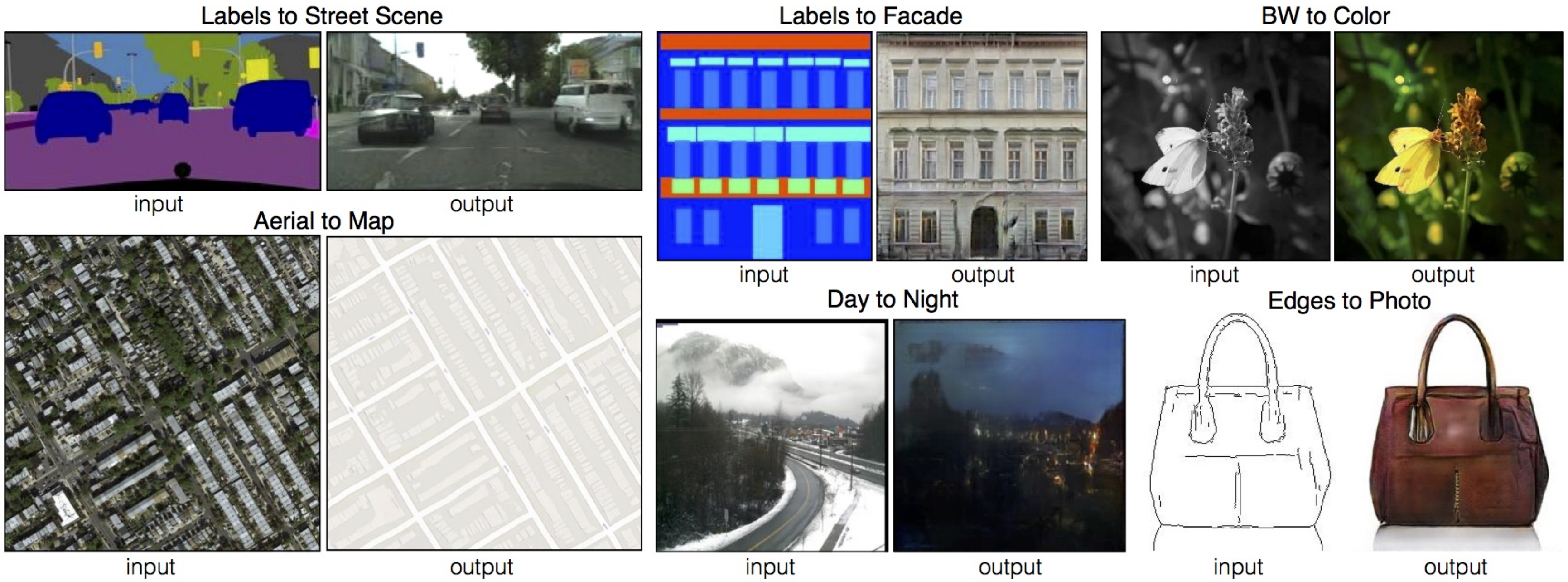
Radford, Metz and Chintala (2015). Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. arXiv:1511.06434

cGAN : conditional GAN for image synthesis



Reed S, Akata Z, Yan X, Logeswaran L, Schiele B, Lee H. 2016. Generative Adversarial Text to Image Synthesis. arXiv:160505396.

pix2pix : Image translation



https://phillipi.github.io/pix2pix/

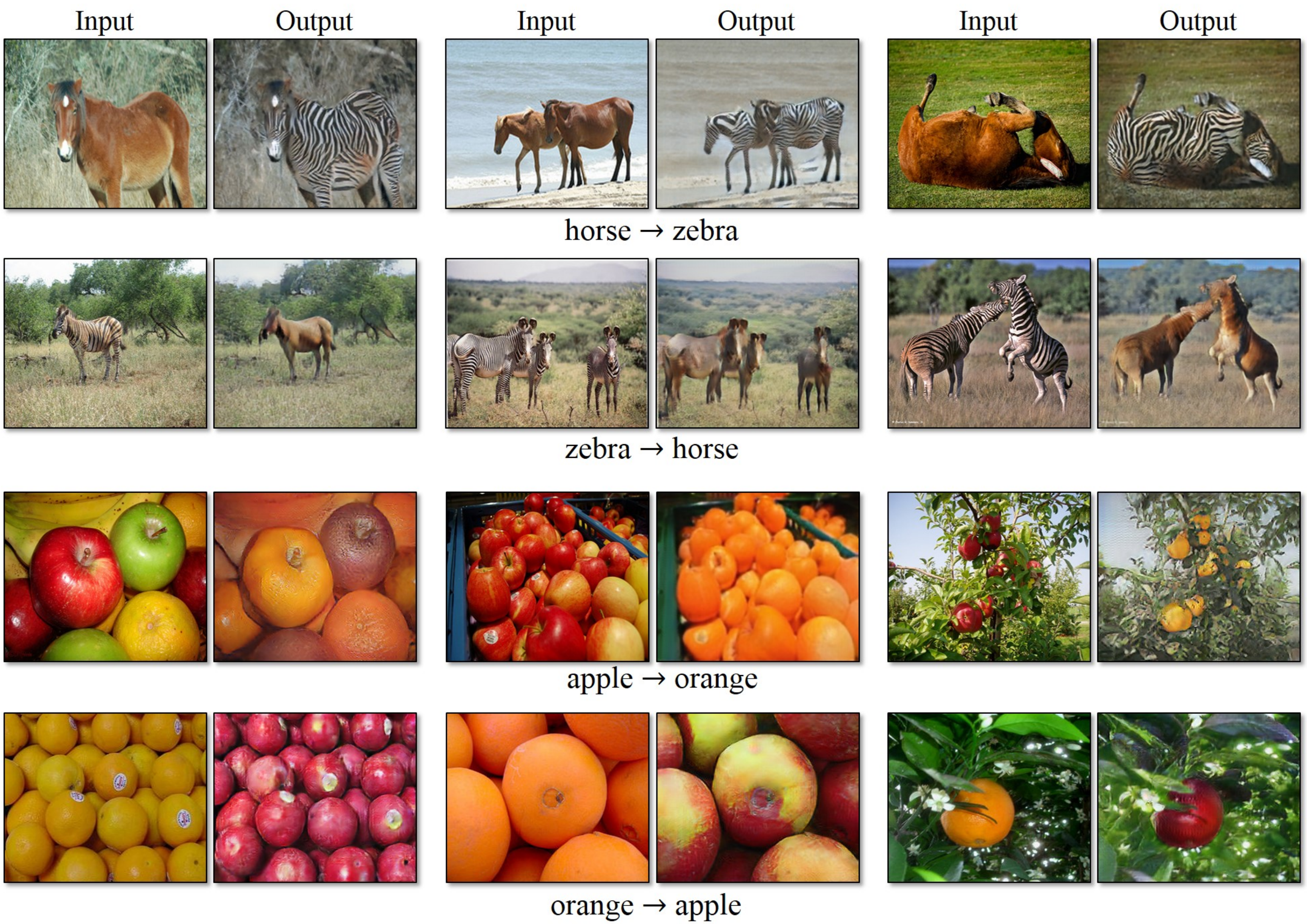
CycleGAN : Monet Paintings to Photo

https://github.com/junyanz/CycleGAN

CycleGAN : Neural Style Transfer

https://github.com/junyanz/CycleGAN

CycleGAN : Object Transfiguration



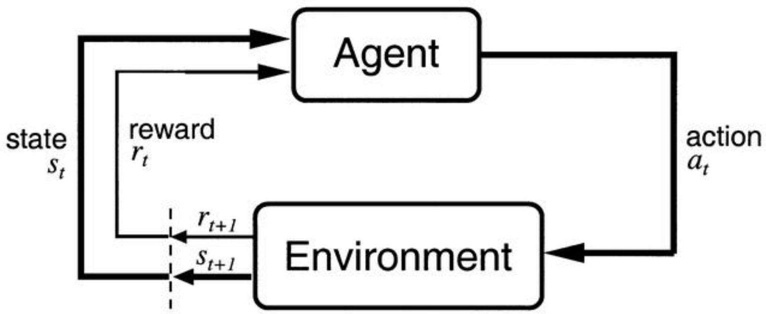
https://github.com/junyanz/CycleGAN

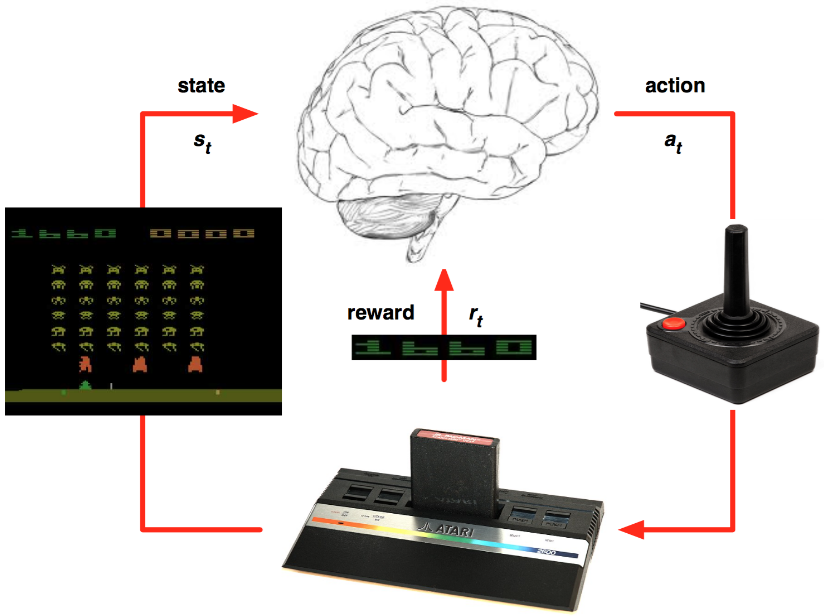
3 - Deep Reinforcement Learning

See the deep reinforcement learning course:

https://www.tu-chemnitz.de/informatik/KI/edu/deeprl/

Reinforcement learning



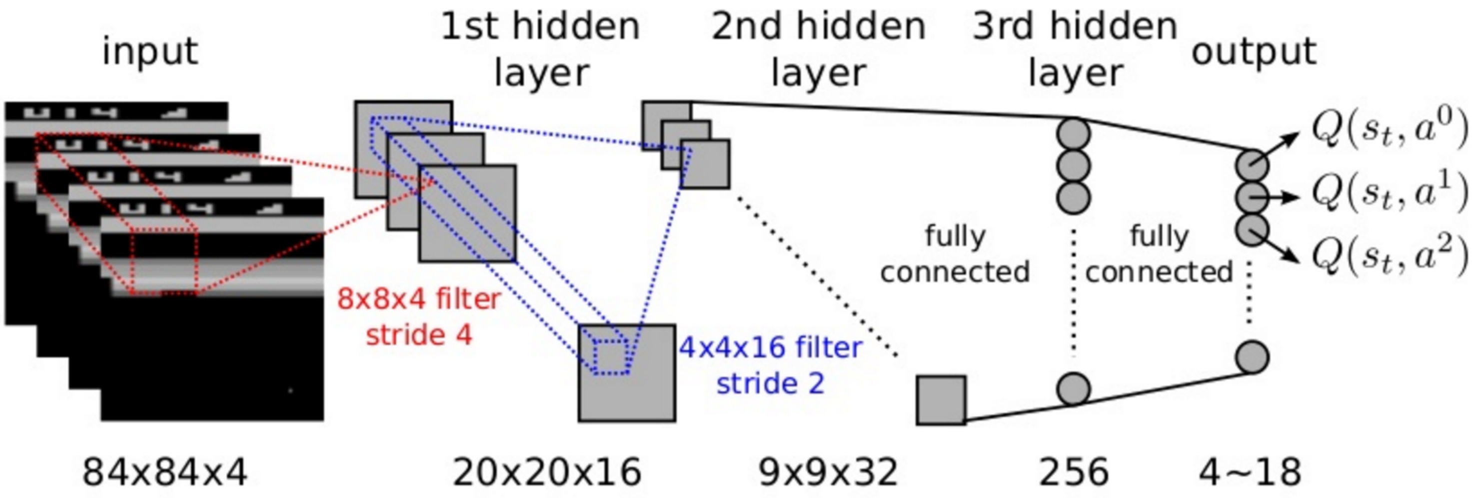


- **Supervised learning** allows to learn complex input/output mappings, given there is enough data.
- Sometimes we do not know the correct output, only whether the proposed output is correct or not (*partial feedback*).
- **Reinforcement Learning** (RL) can be used to learn by **trial and error** an optimal policy $\pi(s, a)$.
- Each action (=output) is associated to a **reward**.
- The goal of the system is to find a policy that maximizes the sum of the rewards on the **long-term** (return).

$$R(s_t, a_t) = \sum_{k=0}^{\infty} \gamma^k \, r_{t+k+1}$$

Sutton and Barto (1998). Reinforcement Learning: An Introduction. MIT Press. http://incompleteideas.net/sutton/book/the-book.html

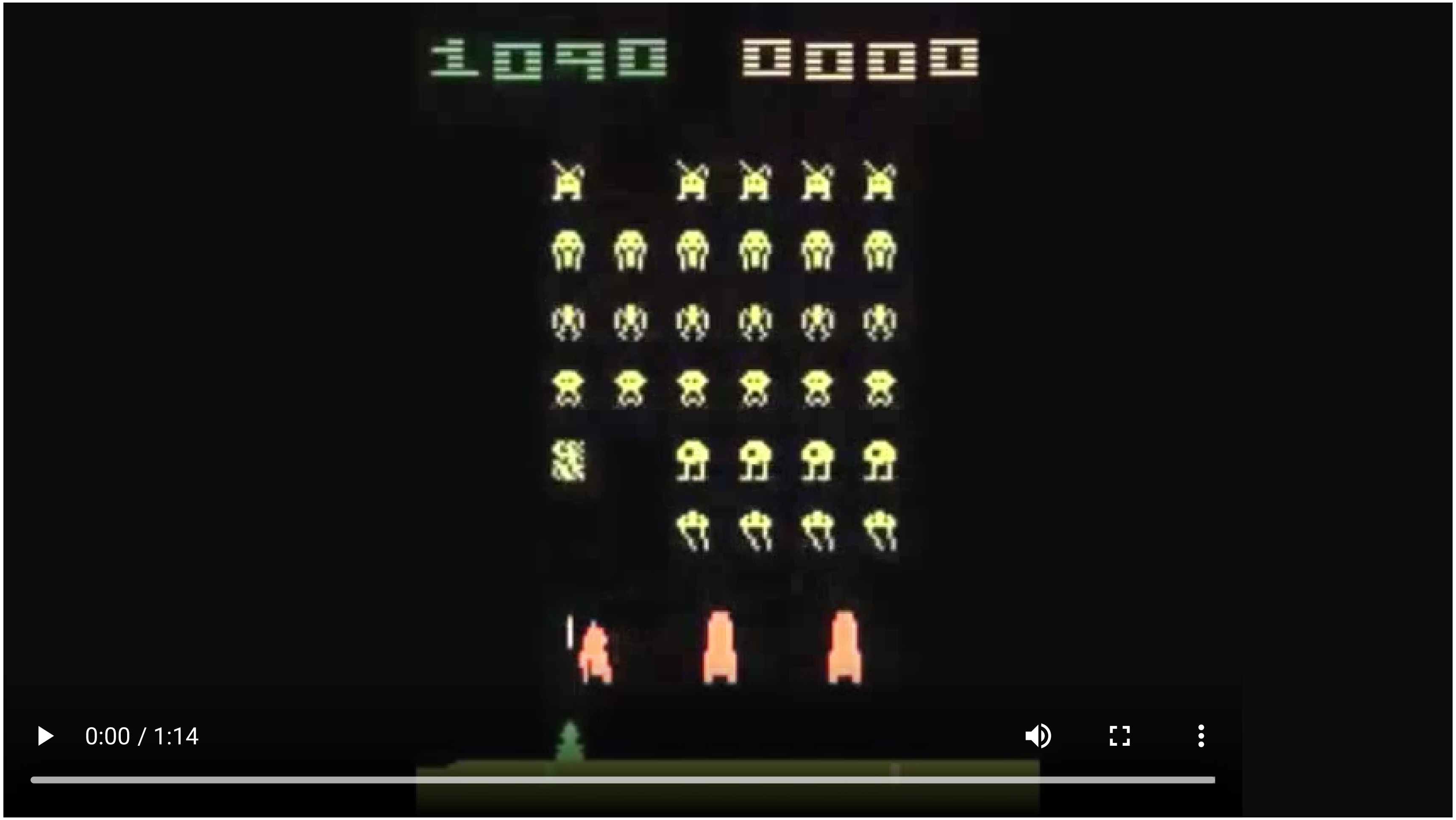
DQN : learning to play Atari games



- A CNN takes raw images as inputs and outputs the probabilities of taking particular actions.
- Learning is only based on **trial and error**: what happens if I do that?
- The goal is simply to maximize the final score.

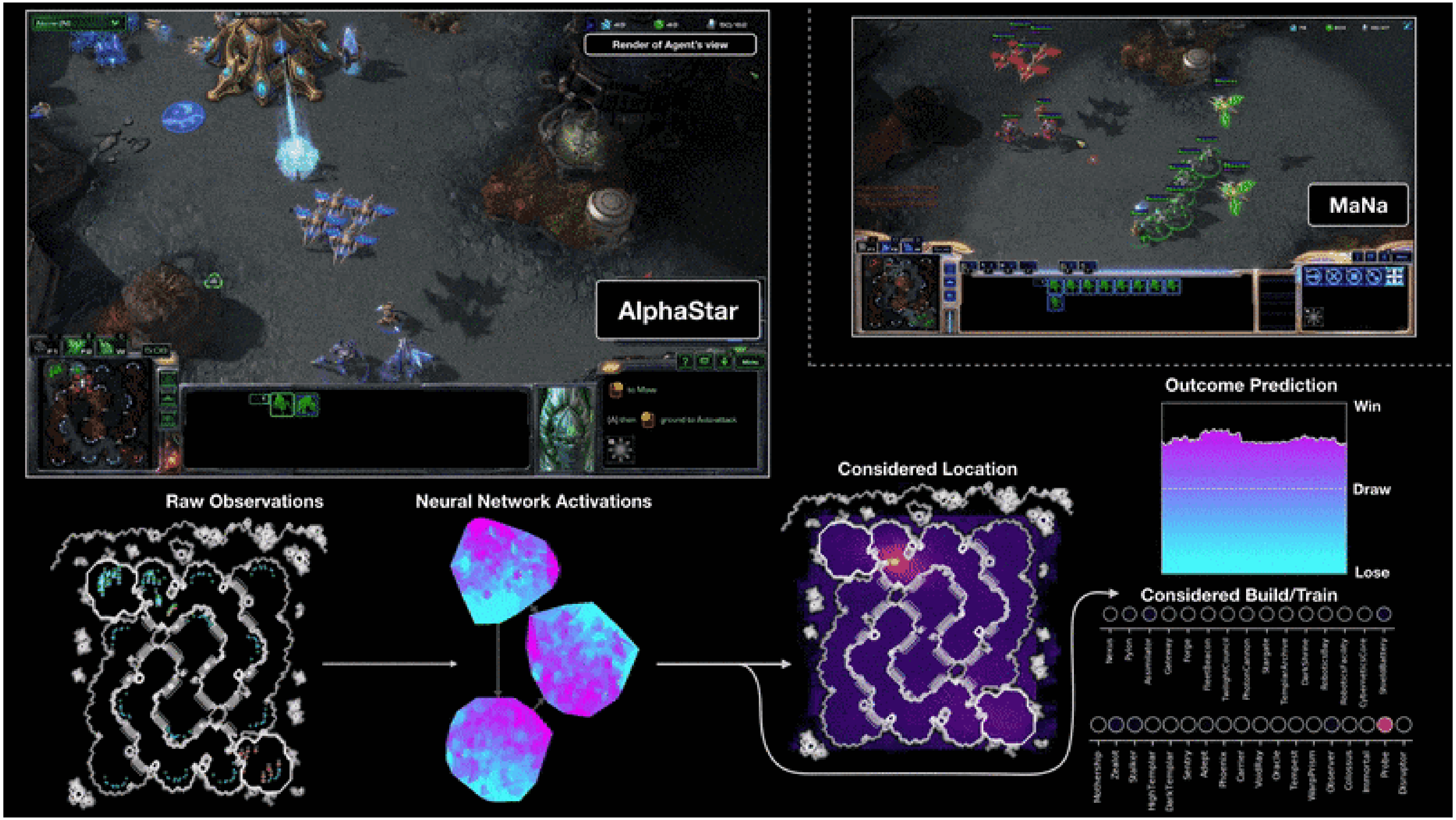
Mnih et al. (2015). Playing Atari with Deep Reinforcement Learning. NIPS.

DQN : learning to play Atari games



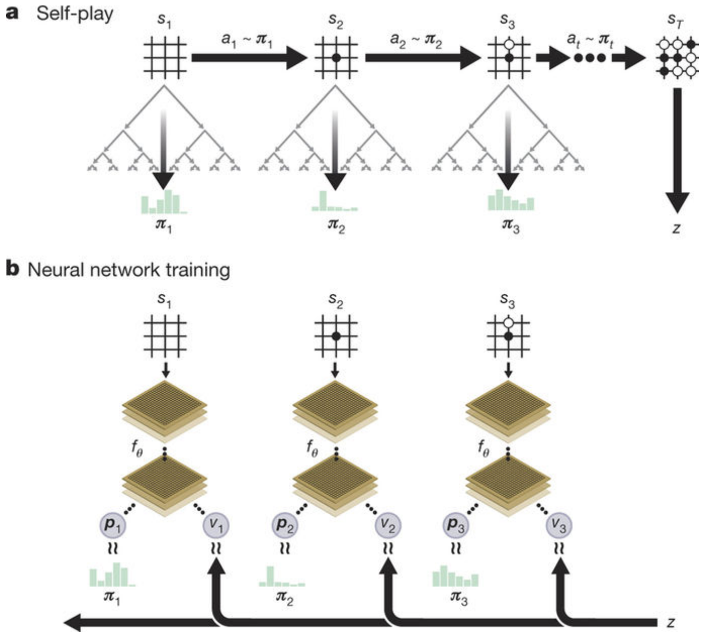
Mnih et al. (2015). Playing Atari with Deep Reinforcement Learning. NIPS. https://www.youtube.com/iqXKQf2BOSE

AlphaStar : learning to play Starcraft II



https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/

Google Deepmind - AlphaGo



- In 2015, Google Deepmind surprised everyone by publishing **AlphaGo**, a Go AI able to beat the world's best players, including **Lee Sedol** in 2016, 19 times world champion.
- The RL agent discovers new strategies by using self-play: during the games against Lee Sedol, it was able to use **novel** moves which were never played before and surprised its opponent.
- The new version **AlphaZero** also plays chess and sokoban at the master level.

David Silver et al. (2016). Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587):484–489, arXiv:1712.01815.

Parkour

Source: https://www.youtube.com/watch?v=faDKMMwOS2Q

Dexterity

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

Autonomous driving

Source : https://wayve.ai/blog/learning-to-drive-in-a-day-with-reinforcement-learning

Neurocomputing syllabus

1. **Linear learning machines**
    - Optimization, Gradient Descent
    - Linear regression and classification
    - Multi-class classification
    - Learning theory, Cross-validation
2. **Neural networks**
    - Multi-layer perceptron
    - Backpropagation algorithm
    - Regularization, Batch Normalization
3. **Convolutional neural networks**
    - Convolutional layer, pooling
    - Transfer learning
    - Adversarial attacks
    - Object detection (Fast-RCNN, YOLO)
    - Semantic segmentation
4. **Autoencoders and generative models**
    - Auto-encoders
    - Variational autoencoders
    - Restricted Boltzmann machines
    - Generative adversarial networks
5. **Recurrent Neural Networks**
    - RNN
    - LSTM / GRU
    - Attention-gated networks
6. **Attractor networks**
    - Hopfield networks
    - Associative memory
    - Neural fields
7. **Reservoir computing**
    - Echo-state networks, Liquid state machines
    - SORN
    - Reward-modulated RC networks
8. **Unsupervised Hebbian learning**
    - Hebb, Oja, BCM
    - Models of visual cortex
9. **Spiking neural networks**.
    - Spiking Neurons, STDP
    - Deep spiking networks
    - Neuromorphic hardware

Literature

- **Deep Learning**. *Ian Goodfellow, Yoshua Bengio & Aaron Courville*, MIT press.

http://www.deeplearningbook.org

- **Neural Networks and Learning Machines**. *Simon Haykin*, Pearson International Edition.

http://www.pearsonhighered.com/haykin

- **Deep Learning with Python**. *Francois Chollet*, Manning.

https://www.manning.com/books/deep-learning-with-python

- **Neuronal Dynamics - a Neuroscience Textbook.**, *Wulfram Gerstner, Werner Kistler, Richard Naud, and Liam Paninski*, Cambridge University Press.

https://neuronaldynamics.epfl.ch/index.html

- **The Elements of Statistical Learning: Data Mining, Inference, and Prediction**, *Trevor Hastie, Robert Tibshirani & Jerome Friedman*, Springer.

https://web.stanford.edu/~hastie/ElemStatLearn/printings/ESLII_print12.pdf

But also

- The machine learning course of Andrew Ng (Stanford at the time) hosted on Coursera is great for beginners:

https://www.coursera.org/learn/machine-learning

- His advanced course on deep learning allows to go further:

https://www.coursera.org/specializations/deep-learning

- The machine learning course on EdX focuses on classical ML methods and is a good complement to this course:

https://www.edx.org/course/machine-learning

- https://medium.com has a lot of excellent blog posts explaining AI-related topics, especially:

https://towardsdatascience.com/