

AI Research – Criteo AI Lab

# An Introduction to Machine Learning

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**CRITEO**

## Outline

Exordium -- captatio benevolentiae

AI, Machine Learning, Deep Learning

Machine Learning in our everyday life

Core goal in supervised learning: generalization

Pivotal Advances (non Deep things)

Positioning

Warm-up: a first handcrafted classifier

Kernel methods: graceful methods

Adaboost: combining weak learners

Bandits: exploration vs. exploitation dilemma

Pivotal advances (deep stuff)

Perceptron: travelling in time (1958--)

Multilayer Perceptron, Feedforward Neural Networks: longstanding models

Unsupervised / Generative models

Two success stories

AlphaGo (Silver et al. 2016)

AlphaFold (Jumper et al, Nature 2021)

Conclusion

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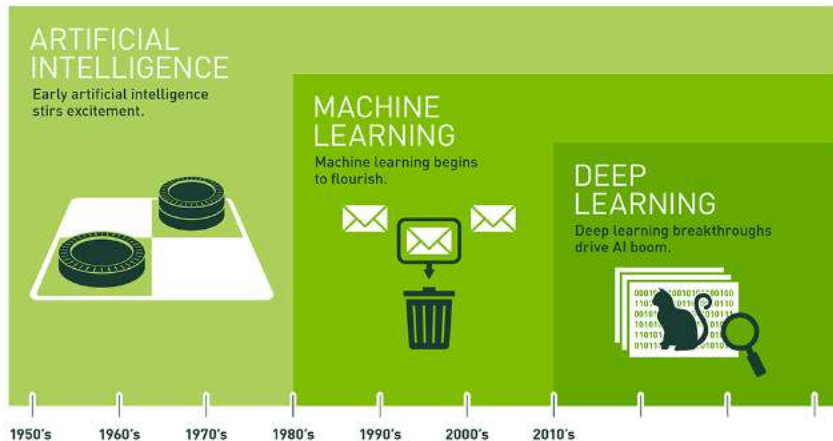
AlphaGo (Silver et al. 2016)

AlphaFold (Jumper et al, Nature 2021)

Conclusion

# AI, Machine Learning, Deep Learning

Today: data, software, computing power



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

# In the news... as of Oct. 10th, 2021

The screenshot shows a search engine interface with the following elements:

- Search bar: "Artificial Intelligence"
- Navigation: "Tous", "Actualités", "Vidéos", "Images", "Shopping", "Plus", "Outils"
- Filters: "Collections", "SafeSearch"
- Channel/Source filters: "ian bremer", "plato", "twitter", "intelligence market", "symphony", "nih", "gzero", "robots", "tenth symphony", "mo gawdat"
- Search Results (Grid):
  - Global Mobile Artificial Intelligence Market** (17 minutes) - Source: [marketsandmarkets.com](https://www.marketsandmarkets.com)
  - Podcast: The future of artificial intelligence with le...** (1 year) - Source: [genmeda.com](https://www.genmeda.com)
  - Trending news: Researchers m...** (42 minutes) - Source: [mahab.com](https://www.mahab.com)
  - Why Intel is (losing) Everyone in Artificial Intelligen...** (15 hours) - Source: [youtube.com](https://www.youtube.com)
  - Digital Medicine Association: LEADERS A...** (1 year) - Source: [digitalemedicine.org](https://www.digitalemedicine.org)
  - Precision Medicine: It's Time to Help Artificial Intellig...** (22 minutes) - Source: [linkedin.com](https://www.linkedin.com)
  - Why Social Networking Algorithms Are Becom...** (5 hours) - Source: [playcrazygames.com](https://www.playcrazygames.com)
  - Artificial Intelligence (AI) in Medicine and Fin...** (1 year) - Source: [todayzoo.com](https://www.todayzoo.com)
  - Whose House proposes each bill of n...** (22 hours) - Source: [wtbt.com](https://www.wtbt.com)
  - Top Machine Learning Project Ideas for Fresh...** (1 year) - Source: [analyticsig.com](https://www.analyticsig.com)

# Annotation/Image decoding



(from Farabet et al, 2013)

# P300 Speller

Vintage P300 Speller

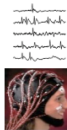


(from Breaking bad)

Modern P300 Speller (pictures from A. Rakotomamonjy, video from Robo Doc)



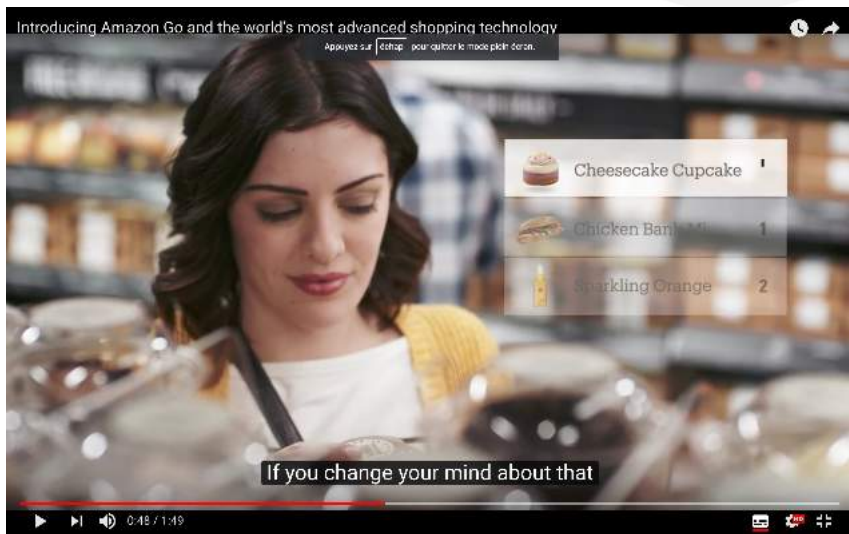
EEG Signals



BCI



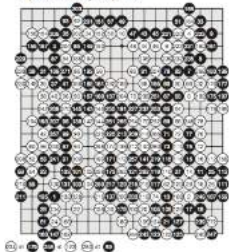
## ML-cashing Amazon shops



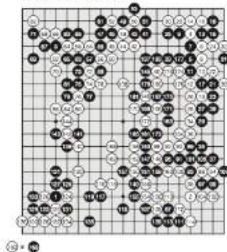


# AlphaGo (Silver et al. 2016)

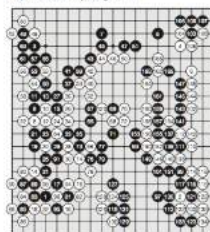
Game 1  
Fan Hui (Black), AlphaGo (White)  
AlphaGo wins by 2.5 points



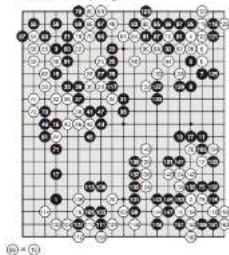
Game 2  
AlphaGo (Black), Fan Hui (White)  
AlphaGo wins by resignation



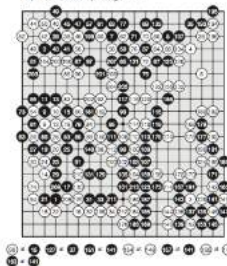
Game 3  
Fan Hui (Black), AlphaGo (White)  
AlphaGo wins by resignation



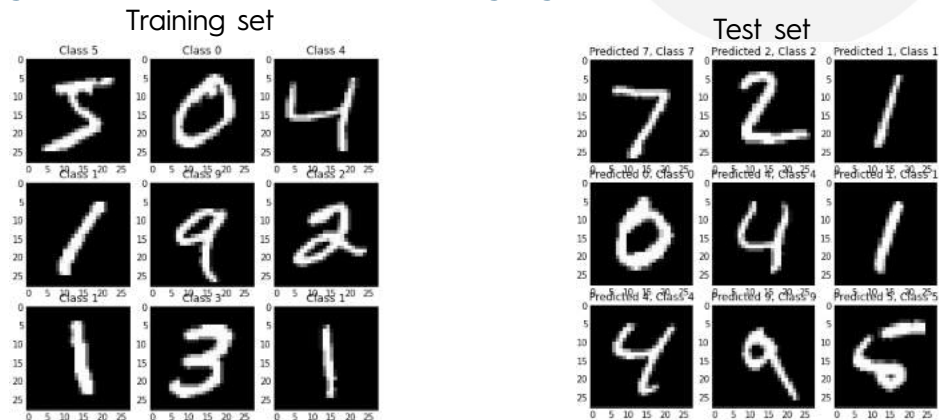
Game 4  
AlphaGo (Black), Fan Hui (White)  
AlphaGo wins by resignation



Game 5  
Fan Hui (Black), AlphaGo (White)  
AlphaGo wins by resignation



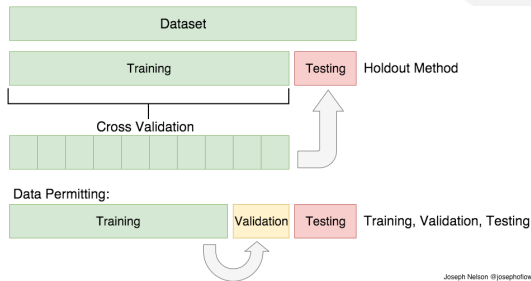
# Core goal in supervised learning: generalization



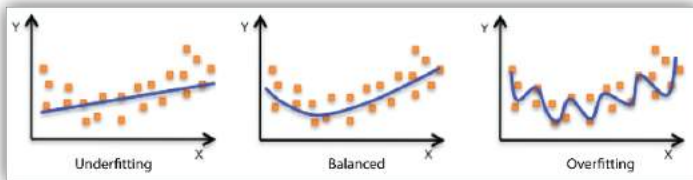
Generalization: from the training set to beyond

Design algorithms capable from pairs (measure, target), to create a predictors which, given a measure, estimates the corresponding target

# Core goal in supervised learning: generalization... in practice



(from [Train/Test Split and Cross Validation in Python](#))



(from [Amazon AWS](#))

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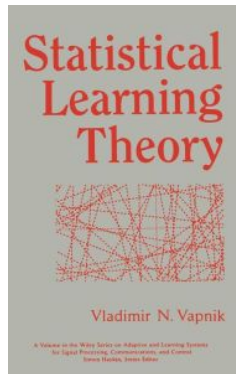
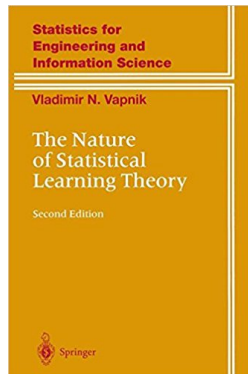
AlphaGo (Silver et al. 2016)

AlphaFold (Jumper et al, Nature 2021)

Conclusion

## Positioning

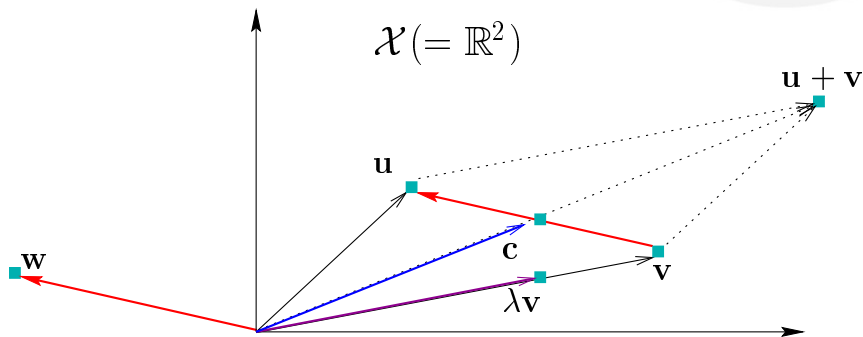
V. Vapnik sets, at the end of the 70's, the mathematical basis of **machine/statistical learning**, at the intersection of computer science, statistics, and optimization



*"ML is the study of computer algorithms that improve automatically through experience."*

T. Mitchell, 1997

## Warm-up: a first handcrafted classifier



- ▶  $\mathbf{u}, \mathbf{v}, \mathbf{w}, \mathbf{c}$  are vectors
- ▶  $\mathbf{w} = \mathbf{u} - \mathbf{v}$  (red arrows)
- ▶  $\mathbf{c} = \frac{1}{2}(\mathbf{u} + \mathbf{v})$
- ▶ Here:  $0 < \lambda < 1$

## Warm-up: a first handcrafted classifier

Inner product  $\langle \cdot, \cdot \rangle : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$

- ▶ symmetric:  $\langle \mathbf{u}, \mathbf{v} \rangle = \langle \mathbf{v}, \mathbf{u} \rangle$
- ▶ bilinear:  $\langle \lambda \mathbf{u}_1 + \gamma \mathbf{u}_2, \mathbf{v} \rangle = \lambda \langle \mathbf{u}_1, \mathbf{v} \rangle + \gamma \langle \mathbf{u}_2, \mathbf{v} \rangle$
- ▶ positive:  $\langle \mathbf{u}, \mathbf{u} \rangle \geq 0$
- ▶ definite:  $\langle \mathbf{u}, \mathbf{u} \rangle = 0 \Rightarrow \mathbf{u} = 0$

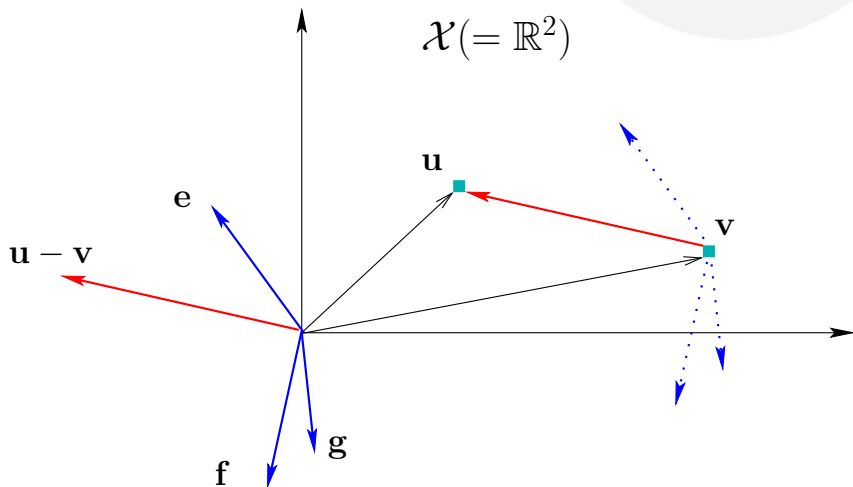
Inner product

- ▶ provides  $\mathcal{X}$  with a structure
- ▶ can be viewed as a 'similarity'
- ▶ defines a norm  $\| \cdot \|$  on  $\mathcal{X}$ :  $\| \mathbf{u} \| = \sqrt{\langle \mathbf{u}, \mathbf{u} \rangle}$

In  $\mathbb{R}^2$

- ▶  $\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$ ,  $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$ :  $\langle \mathbf{u}, \mathbf{v} \rangle = u_1 v_1 + u_2 v_2$

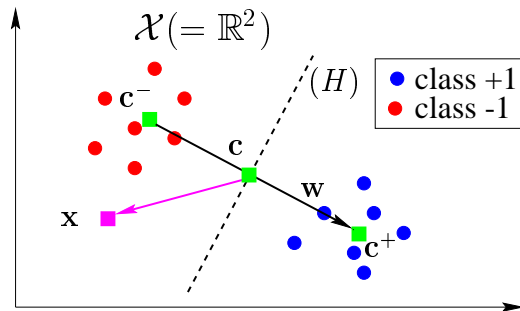
## Warm-up: a first handcrafted classifier



- ▶  $\langle \mathbf{u} - \mathbf{v}, \mathbf{e} \rangle > 0$ :  $\mathbf{u} - \mathbf{v}$  and  $\mathbf{e}$  point to the 'same direction'
- ▶  $\langle \mathbf{u} - \mathbf{v}, \mathbf{f} \rangle = 0$ :  $\mathbf{u} - \mathbf{v}$  and  $\mathbf{f}$  are orthogonal
- ▶  $\langle \mathbf{u} - \mathbf{v}, \mathbf{g} \rangle < 0$ :  $\mathbf{u} - \mathbf{v}$  and  $\mathbf{g}$  point to 'opposite directions'



## Warm-up: a first handcrafted classifier



$$\mathbf{c}^+ = \frac{1}{n^+} \sum_{\{i: y_i = +1\}} \mathbf{x}_i$$

$$\mathbf{c}^- = \frac{1}{n^-} \sum_{\{i: y_i = -1\}} \mathbf{x}_i$$

$$\mathbf{c} = \frac{1}{2}(\mathbf{c}^+ + \mathbf{c}^-)$$

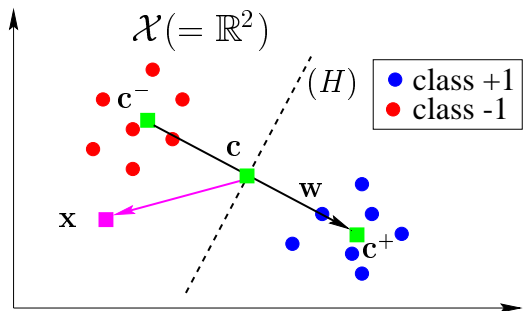
$$\mathbf{w} = \mathbf{c}^+ - \mathbf{c}^-$$

### Decision function

Classify points  $\mathbf{x}$  according to which of the two class means  $\mathbf{c}^+$  or  $\mathbf{c}^-$  is closer:

- ▶ for  $\mathbf{x} \in \mathcal{X}$ , it is sufficient to take the sign of the inner product between  $\mathbf{w}$  and  $\mathbf{x} - \mathbf{c}$
- ▶ if  $h(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} - \mathbf{c} \rangle$ , we have the classifier  $f(\mathbf{x}) = \text{sign}(h(\mathbf{x}))$
- ▶ the (dotted) hyperplane  $(H)$ , of normal vector  $\mathbf{w}$ , is the decision surface

## Warm-up: a first handcrafted classifier



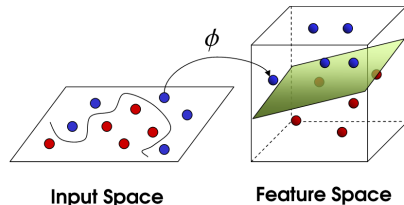
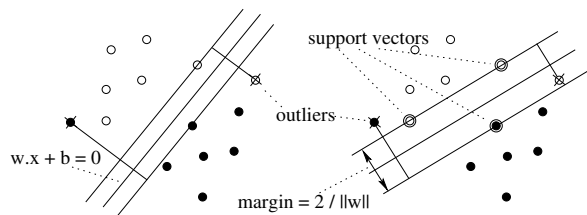
- ▶  $\mathbf{c}^+ = \frac{1}{n^+} \sum_{\{i: y_i = +1\}} \mathbf{x}_i$
- ▶  $\mathbf{c}^- = \frac{1}{n^-} \sum_{\{i: y_i = -1\}} \mathbf{x}_i$
- ▶  $\mathbf{c} = \frac{1}{2}(\mathbf{c}^+ + \mathbf{c}^-)$
- ▶  $\mathbf{w} = \mathbf{c}^+ - \mathbf{c}^-$

On evaluating  $h(\mathbf{x})$

$$\begin{aligned} h(\mathbf{x}) &= \langle \mathbf{w}, \mathbf{x} - \mathbf{c} \rangle = \langle \mathbf{w}, \mathbf{x} \rangle - \langle \mathbf{w}, \mathbf{c} \rangle = \dots \\ &= \sum_{i=1, \dots, m} \alpha_i \langle \mathbf{x}_i, \mathbf{x} \rangle + b, \quad \text{with } b \text{ a real constant} \end{aligned}$$

Inner products are sufficient (remember that)

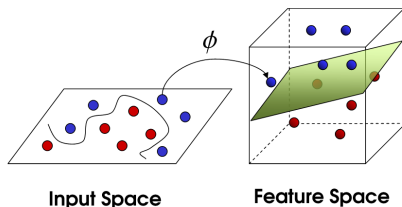
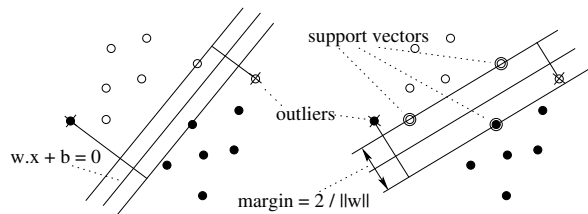
## Kernel methods: graceful methods



### Silk methods

- ▶ Theoretical guarantees
- ▶ Convex optimization
- ▶ Nonlinearity handled through the kernel trick
- ▶ Success stories: structured data classification, ranking, scoring, theory

## Kernel methods: graceful methods



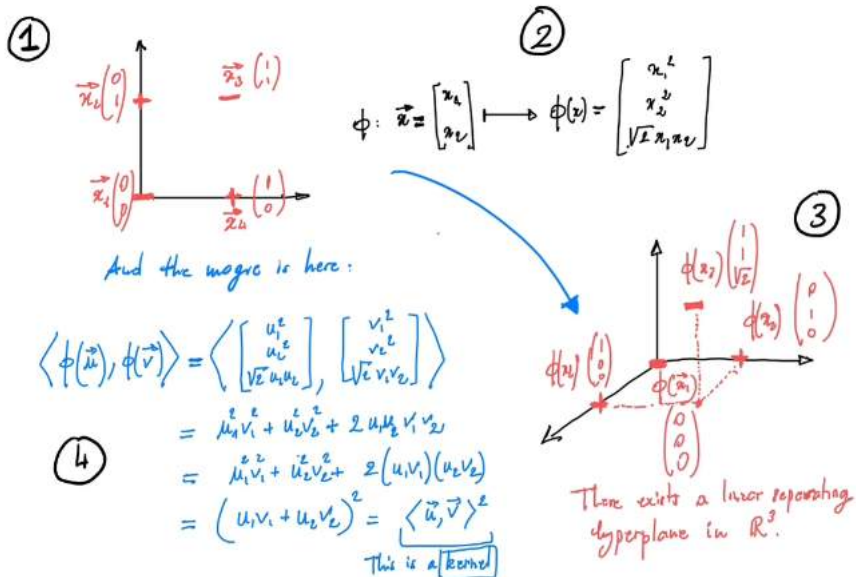
### Kernelizing the handcrafted classifier

$h(\cdot) = \sum_{i=1, \dots, m} \alpha_i \langle \mathbf{x}_i, \cdot \rangle + b$  simply turns into

$$h(\mathbf{x}) = \sum_{i=1, \dots, m} \alpha_i k(\mathbf{x}_i, \mathbf{x}) + b, \quad \text{with } b \text{ a real constant}$$

where  $k(\cdot, \cdot)$  has replaced  $\langle \cdot, \cdot \rangle$  and computes an inner product on the nonlinear embedding of its arguments

## Example: 2nd degree polynomial kernel



# Adaboost: combining weak learners

Given:  $(x_1, y_1), \dots, (x_m, y_m)$  where  $x_i \in \mathcal{X}, y_i \in \{-1, +1\}$ .

Initialize:  $D_1(i) = 1/m$  for  $i = 1, \dots, m$ .

For  $t = 1, \dots, T$ :

- Train weak learner using distribution  $D_t$ .
- Get weak hypothesis  $h_t: \mathcal{X} \rightarrow \{-1, +1\}$ .
- Aim: select  $h_t$  with low weighted error:

$$\epsilon_t = \Pr_{i \sim D_t} [h_t(x_i) \neq y_i].$$

- Choose  $\alpha_t = \frac{1}{2} \ln \left( \frac{1 - \epsilon_t}{\epsilon_t} \right)$ .
- Update, for  $i = 1, \dots, m$ :

$$D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

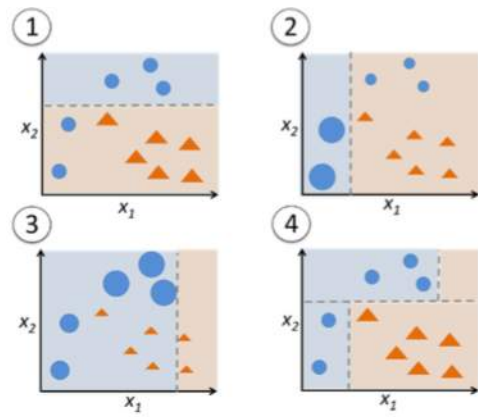
where  $Z_t$  is a normalization factor (chosen so that  $D_{t+1}$  will be a distribution).

Output the final hypothesis:

$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right).$$

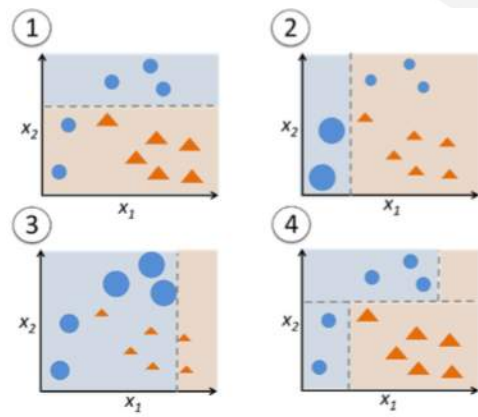
(from Freund and Schapire, 1997, 2012)

# Adaboost: combining weak learners



(from Raschka, <https://sebastianraschka.com/faq/docs/bagging-boosting-rf.html>)

# Adaboost: combining weak learners

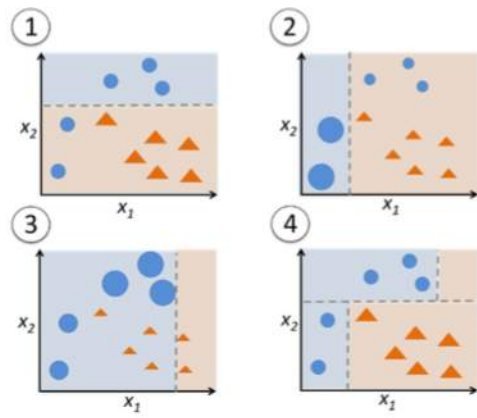


(from Raschka, <https://sebastianraschka.com/faq/docs/bagging-boosting-rf.html>)

- ▶ Algorithmic simplicity, effectiveness
- ▶ Theoretical results
- ▶ Gödel price 2003



# Adaboost: combining weak learners



(from Raschka, <https://sebastianraschka.com/faq/docs/bagging-boosting-rf.html>)

Find an illustrative example of Adaboost running

## Bandits: exploration vs. exploitation dilemma



How to make the best use of your budget and bet?

### Features

- ▶ Problem easy to pose, many variations
- ▶ Exploration/exploitation dilemma
- ▶ Success stories: ad placement, recommendation, Go

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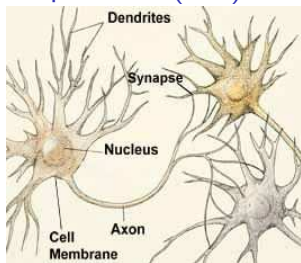
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AlphaFold (Jumper et al, Nature 2021)

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# Perceptron, binary case (Rosenblatt, 1958)

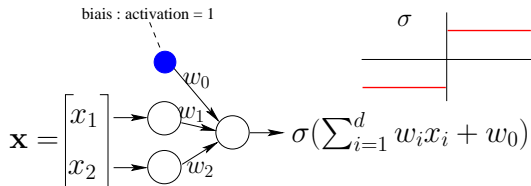
Inspiration: (real) neural networks



Biological motivations

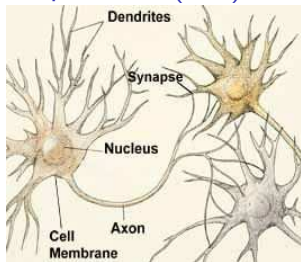
- ▶ Learning systems made of several simple computational units connected to each other
- ▶ Memory capacity / plasticity of these systems

Perceptron: a linear classifier,  $\mathcal{X} = \mathbb{R}^d$ ,  $\mathcal{Y} = \{-1, +1\}$



# Perceptron, binary case (Rosenblatt, 1958)

## Inspiration: (real) neural networks



## Biological motivations

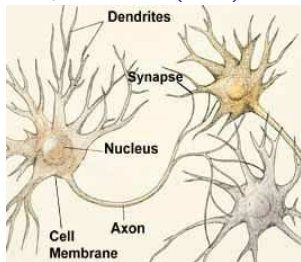
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## Perceptron: a linear classifier, $\mathcal{X} = \mathbb{R}^d$ , $\mathcal{Y} = \{-1, +1\}$

- ▶ Classifier parameters:  $\mathbf{w} \in \mathbb{R}^d$
- ▶ Prediction of the classifier:  $f(\mathbf{x}) = \text{sign}\langle \mathbf{w}, \mathbf{x} \rangle$
- ▶ Question: how to **learn**  $\mathbf{w}$  from observations?

# Perceptron, binary case (Rosenblatt, 1958)

Inspiration: (real) neural networks



Biological motivations

- ▶ Learning systems made of several simple computational units connected to each other
- ▶ Memory capacity / plasticity of these systems

Algorithm:  $\mathcal{D} = \{(X_n, Y_n)\}_{n=1}^N$

$\mathbf{w} \leftarrow \mathbf{0}$

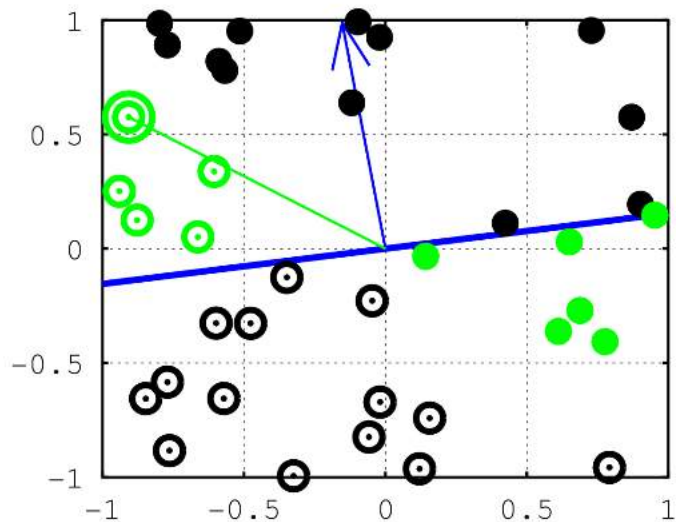
**while** there exists  $(X_n, Y_n): Y_n \langle \mathbf{w}, X_n \rangle \leq 0$  **do**

$\mathbf{w} \leftarrow \mathbf{w} + Y_n X_n$

**end while**

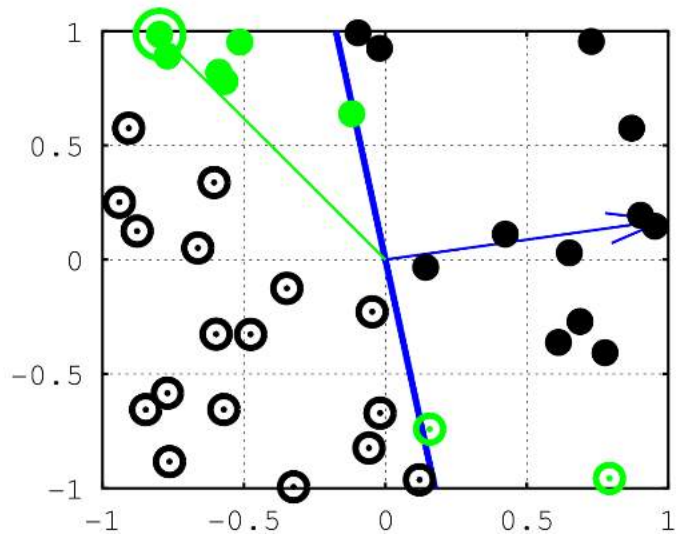


## Perceptron learning in action

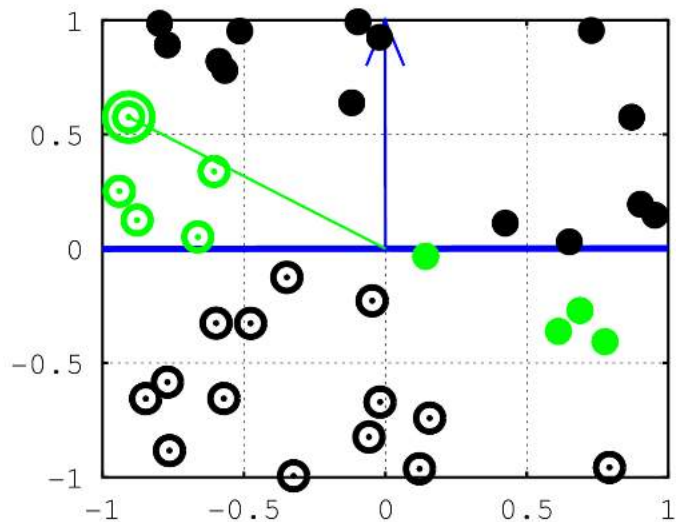




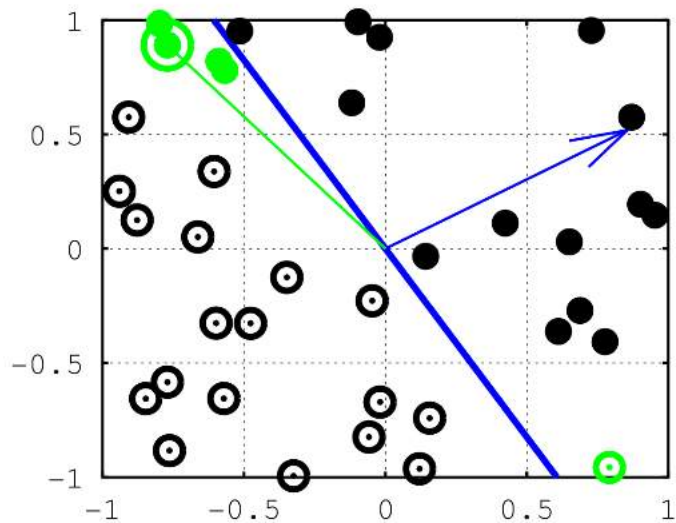
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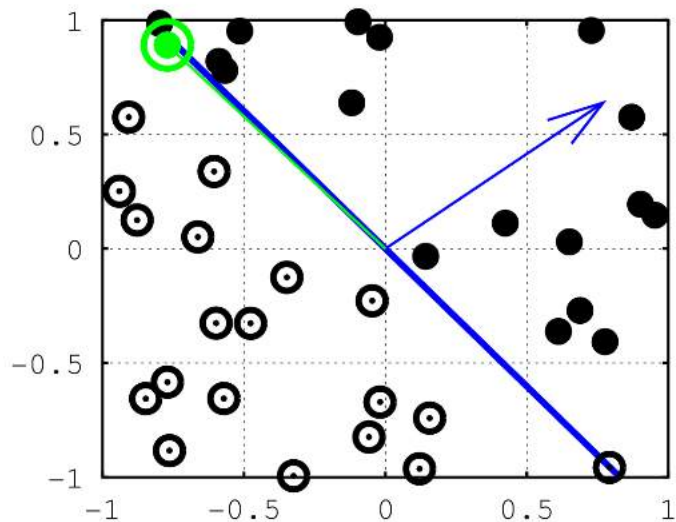


## Perceptron learning in action

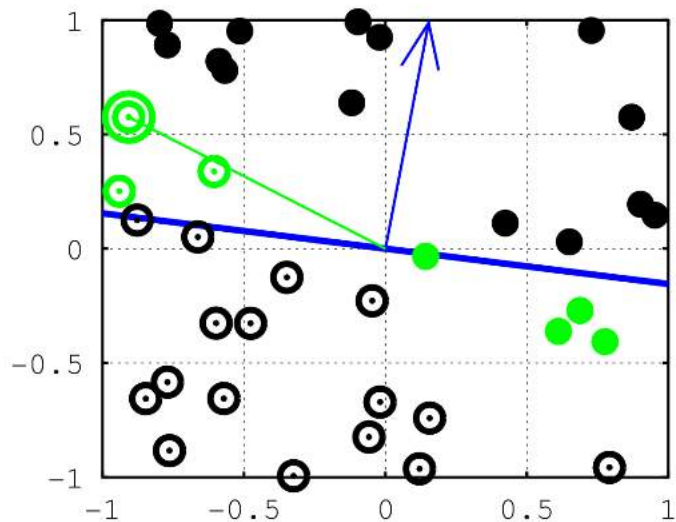




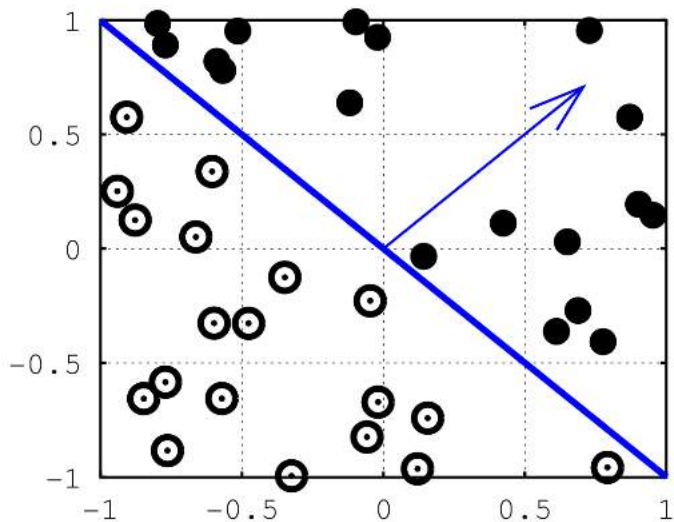
## Perceptron learning in action



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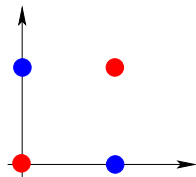
## Perceptron: a few results

Theorem (Bound on the number of updates, Novikoff, 1962)

If there exist  $\gamma > 0$ ,  $\mathbf{w}^*$ ,  $\|\mathbf{w}^*\| = 1$ ,  $\|X_n\| \leq R$ ,  $\forall n = 1, \dots, N$ , et  $Y_n \langle \mathbf{w}^*, X_n \rangle \geq \gamma$  then the Perceptron algorithm converges in less than  $R^2/\gamma^2$  updates

Theorem (XOR, Minsky, Papert, 1969)

The Perceptron (algorithm) cannot solve the XOR problem



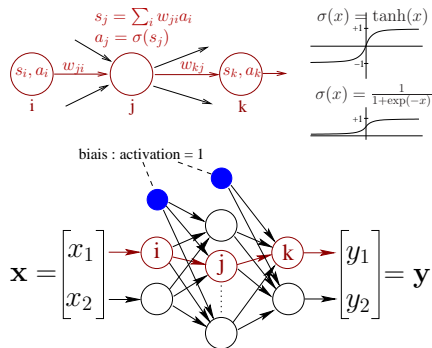
Theorem (Generalization error, Vapnik et Chevonenkis, 1979)

$\forall \mathbf{w} \in \mathbb{R}^d$ : with high probability

$$R(\mathbf{w}) \leq \hat{R}(\mathbf{w}, \mathcal{D}) + \tilde{O}\left(\sqrt{\frac{d}{n}}\right)$$



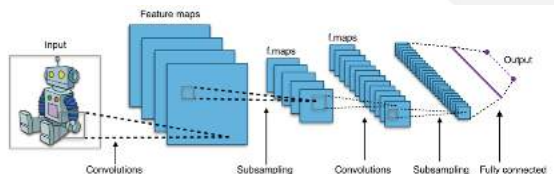
# Multilayer Perceptron, Convolutional Networks



Up until the 90's

- ▶ Feedforward networks
- ▶ Gradient backpropagation (Rumelhart et al. 86)
- ▶ Preferred task: multiclass classification

# Multilayer Perceptron, Convolutional Networks



(By Aphex34 - Own work, CC BY-SA 4.0, [Wikimedia CNN](#))

## Since 2005

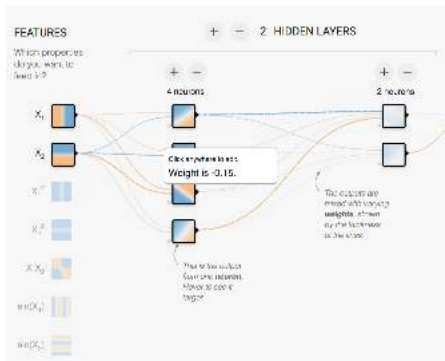
- ▶ Feedforward networks, recurrent networks
- ▶ Backpropagation (and autodiff), layerwise learning, computational power
- ▶ Tasks: almost everything (provided there is data)

## But, more importantly

- ▶ Libraries: Tensorflow, Theano, Keras, Torch, Caffe (see [là](#))
- ▶ Hardware: GPU, TPU (Tensor Processing Units)
- ▶ Data...

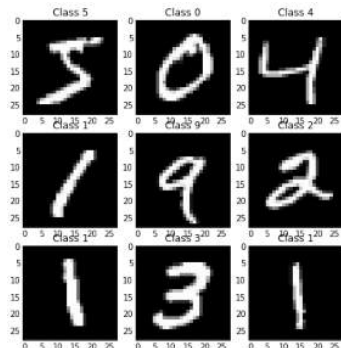
# Deep Learning: Hands-on

## Visualization



<https://tinyurl.com/ydclvgas>

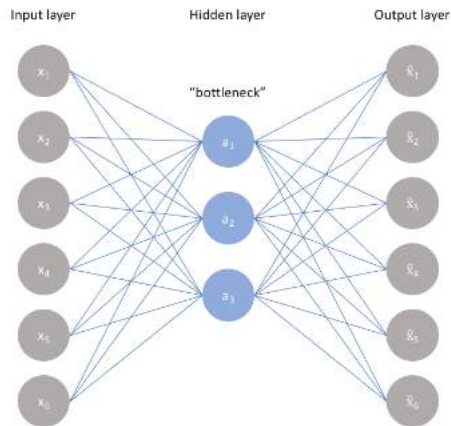
## Keras Mnist Tutorial



<https://tinyurl.com/ydzypus4>

Dozens of examples can be found on [Keras code examples page](#)

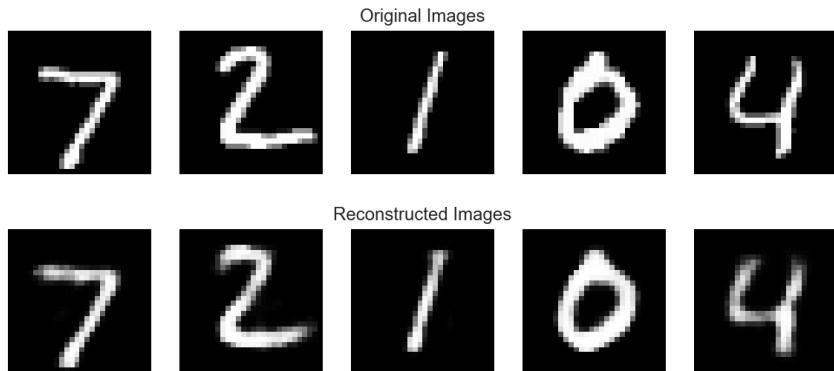
# Unsupervised Deep Learning: auto-encoders



(From [An introduction to Autoencoders](#))

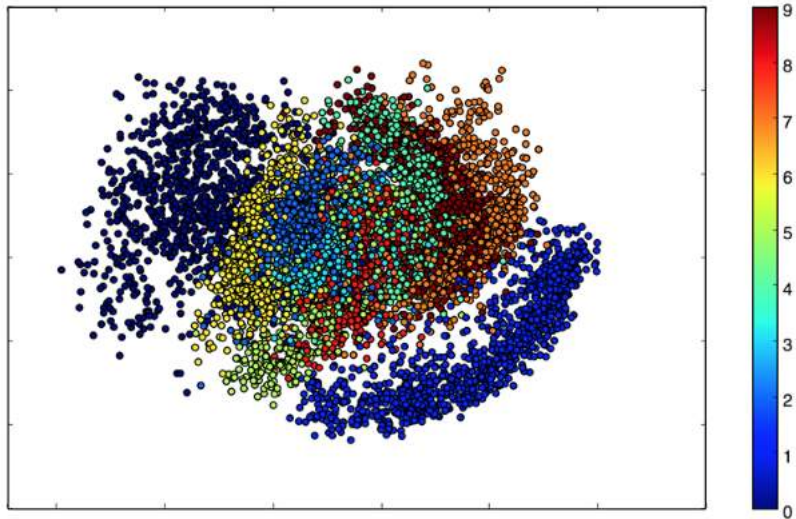
Code: <https://www.tensorflow.org/tutorials/generative/autoencoder>

# Unsupervised Deep Learning: auto-encoders



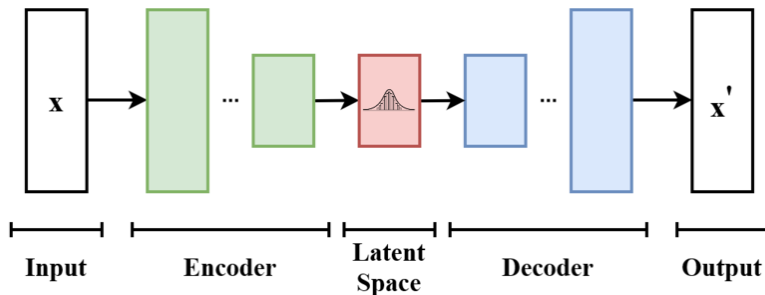
(From [Applied Deep Learning - Part 3: Autoencoders](#))

# Unsupervised Deep Learning: auto-encoders



(From [Building Autoencoders in Keras](#))

# Unsupervised/Generative Deep Learning: Variational Auto-Encoders (Kingma and Welling, 2014)

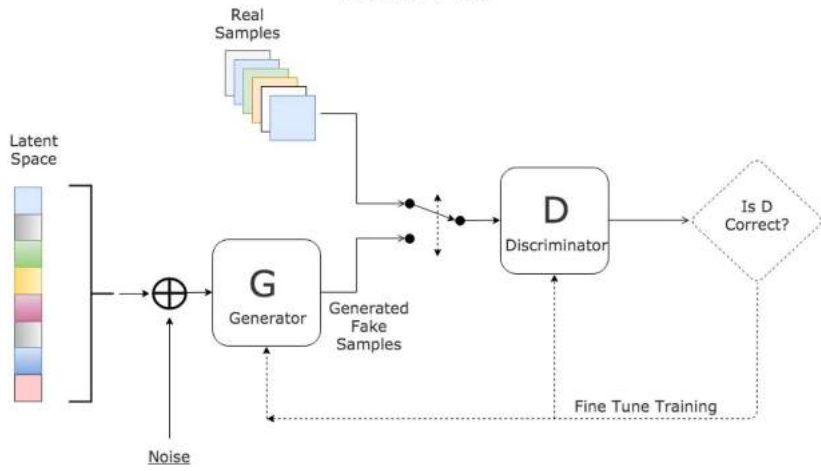


(From [Wikipedia VAE page](#))

Code: [https://deeplearning.neuromatch.io/tutorials/W2D5\\_GenerativeModels/student/W2D5\\_Tutorial1.html](https://deeplearning.neuromatch.io/tutorials/W2D5_GenerativeModels/student/W2D5_Tutorial1.html)

# Generative Deep Learning: GANs, (Goodfellow and al, 2014)

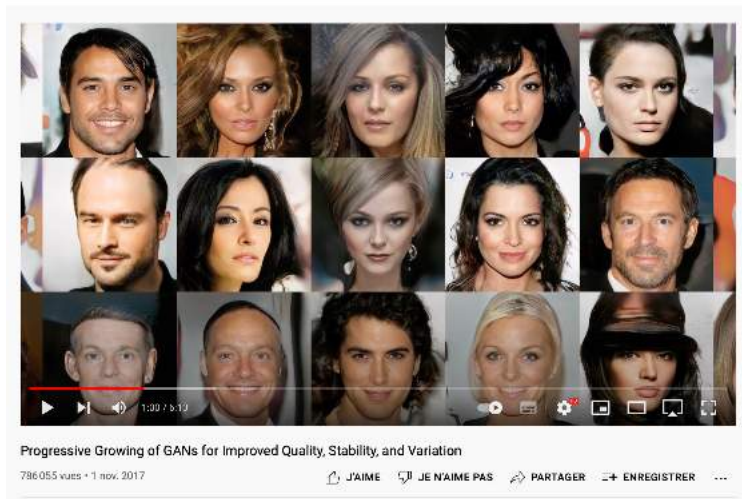
## Generative Adversarial Network



(From [GANs from Scratch](#))



# Generative Deep Learning: GANs, (Goodfellow and al, 2014)



(From **NVidia Video**)

# Models Zoo

**Model Zoo**  
Discover open source deep learning code and pretrained models.

[Browse Frameworks](#) [Browse Categories](#)

Filter models...

### OpenPose

★ 14800

OpenPose represents the first real-time multi-person system to jointly detect human body, hand, and facial keypoints (in total 130 keypoints) on single images.

[Caffe](#)

[CV](#)

### Mask R-CNN

★ 14504

This is an implementation of Mask R-CNN on Python 3, Keras, and TensorFlow. The model generates bounding boxes and segmentation masks for each instance of an object in the image. It's based on Feature Pyramid Network (FPN) and a ResNet101 backbone.

[Keras](#)

[CV](#)

### pytorch-CycleGAN-and-pix2pix

★ 9980

PyTorch implementation for both unpaired and paired image-to-image translation.

[PyTorch](#)

[CV](#) [NLP](#) [Generative](#)

<https://modelzoo.co>

# Outline

Exordium -- captatio benevolentiae

AI, Machine Learning, Deep Learning

Machine Learning in our everyday life

Core goal in supervised learning: generalization

Pivotal Advances (non Deep things)

Positioning

Warm-up: a first handcrafted classifier

Kernel methods: graceful methods

Adaboost: combining weak learners

Bandits: exploration vs. exploitation dilemma

Pivotal advances (deep stuff)

Perceptron: travelling in time (1958--)

Multilayer Perceptron, Feedforward Neural Networks: longstanding models

Unsupervised / Generative models

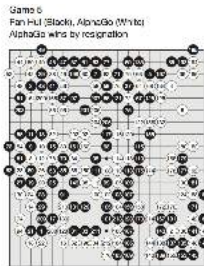
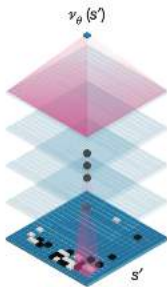
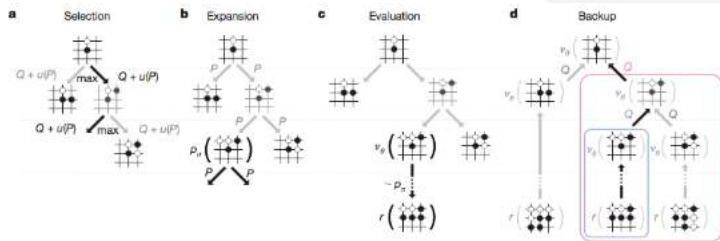
Two success stories

AlphaGo (Silver et al. 2016)

AlphaFold (Jumper et al, Nature 2021)

Conclusion

# AlphaGo (Silver et al. 2016)



<https://deepmind.com/blog/alphago-zero-learning-scratch/>

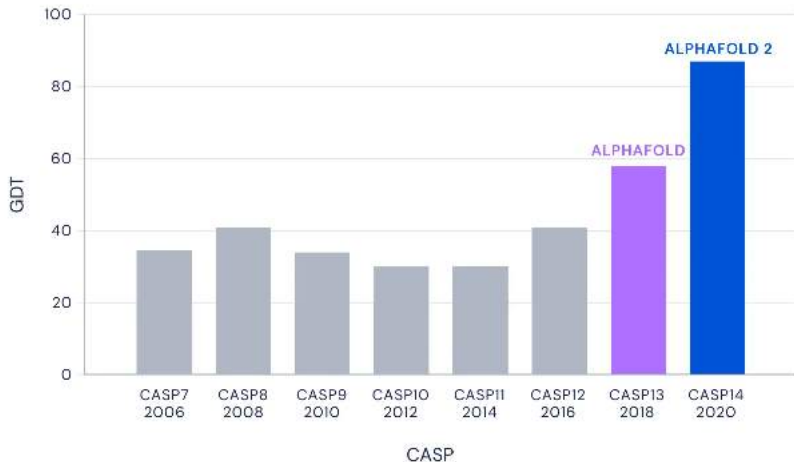
## AlphaGo (Silver et al. 2016)



(From [AlphaGo Netflix \(Deepmind youtube\)](#))

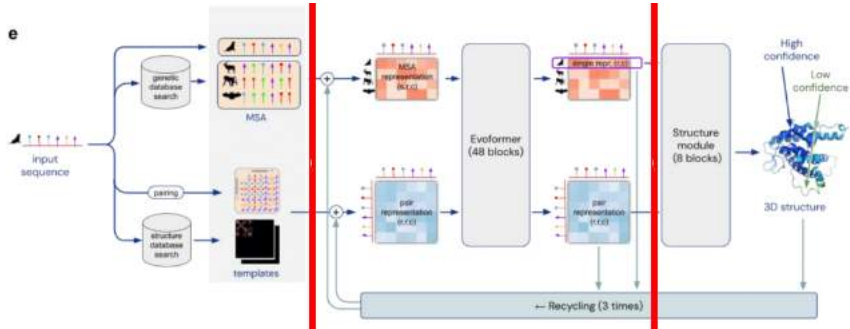
# AlphaFold (Jumper et al, Nature 2021)

Median Free-Modelling Accuracy



(From [AlphaFold: a solution to a 50-year-old grand challenge in biology](#))

# AlphaFold (Jumper et al, Nature 2021)



(From Jumper et al, Nature, 2021)

# AlphaFold (Jumper et al, Nature 2021)

A notebook to play around



AlphaFold2.ipynb

ColabFold: AlphaFold2 using MMseqs2

Easy to use protein structure and complex prediction using [AlphaFold2](#) and [alphafold2-multimer](#). Sequence alignments/templates are generated through [MMseqs2](#) and [HHsearch](#). For more details, see [bottom](#) of the notebook, check out the [ColabFold GitHub](#) and read our [manuscript](#).

[Mirna M. Schwach, K. Morzek, Y. Heo, J. Cochinnico, S. Steinberger, M. Casbick, M. Steiner, protein folding accessible in \*nl\*, \*Nature\*, 2021](#)

Old versions: [v1.0](#), [v1.1](#), [v1.2](#)

Input protein sequence(s), then hit Run time -> Run all

```
query_sequence: PIAQHILLEGSDCKCTLRVSEAVSRGLDAPLTSYRWITEMAKGI FQIGGLASK
```

- Use : to specify inter-protein chains for **modeling complexes** (supports homo- and hetero-oligomers). For example **P1...SKP1...SK** for a mono-cloner.

jobname: test

use\_templates:

save\_to\_google\_drive:

If the `save_to_google_drive` option was selected, the result zip will be uploaded to your Google Drive

Advanced settings

(From [AlphaFold Notebook](#))



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# Machine Learning: a Variety of Problems/Mixes

## Many application fields

- ▶ Computer vision
- ▶ NLP
- ▶ Robotics
- ▶ Advertising, recommendation systems
- ▶ Games (Go, chess, poker)
- ▶ Biology
- ▶ ...

## Many problems

- ▶ Algorithmics
- ▶ Statistics
- ▶ Modelling
- ▶ ... and beyond

# Conclusion

## Machine Learning: a field in itself

- ▶ A vivid branch of AI
- ▶ At the crossroads of computer science and mathematics
- ▶ Ever-growing community (from applied research to more fundamental one)

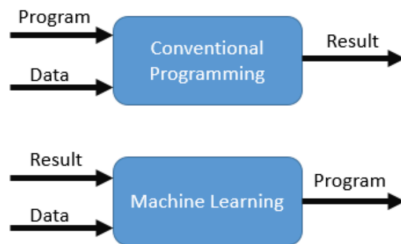
## Machine Learning is ubiquitous

- ▶ At the heart of data science
- ▶ In many real-world applications
- ▶ ML at the time of revisiting other well-established fields of research

## Example of future problems

- ▶ ML and small datasets: prior knowledge, active learning, feature selection
- ▶ ML & other fields: game theory, cryptography, biology, physics, law...

## Hot AI topics (personal take)



### Revisit classical fields from the Machine Learning perspective

- ▶ Privacy-Preserving ML: MLize encryption mechanisms, distributed computing
- ▶ Repeated Mechanism Design: MLize game theory, deal with cooperative and competitive agents
- ▶ Green ML: hardware-aware methods, communication-sensitive methods...