Foundations of Data Science, Fall 2020

1. Introduction: Machine Learning

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DaST Data•(Systems+Theory)

University of Zurich[UZH]

Sept 15, 2020

https://lms.uzh.ch/url/RepositoryEntry/16830890400

https://uzh.zoom.us/j/96690150974?pwd=cnZmMTduWUtCeWoxYW85Z3RMYnpTZz09

Machine Learning in Action

(Using https://www.betafaceapi.com/demo.html)

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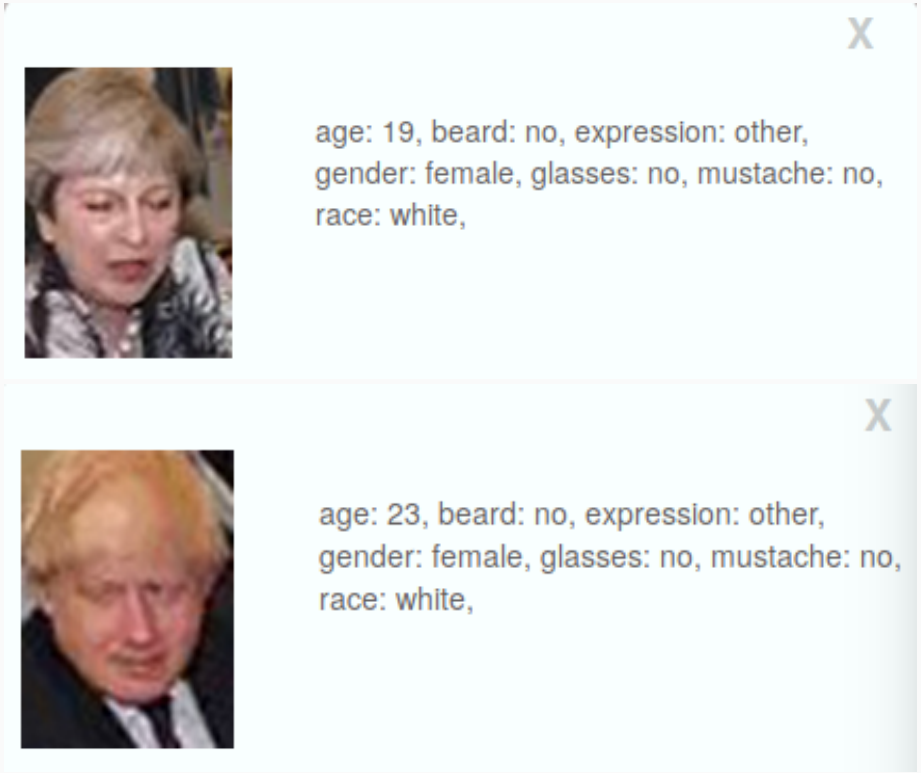

(Using https://www.betafaceapi.com/demo.html)

Is anything wrong?

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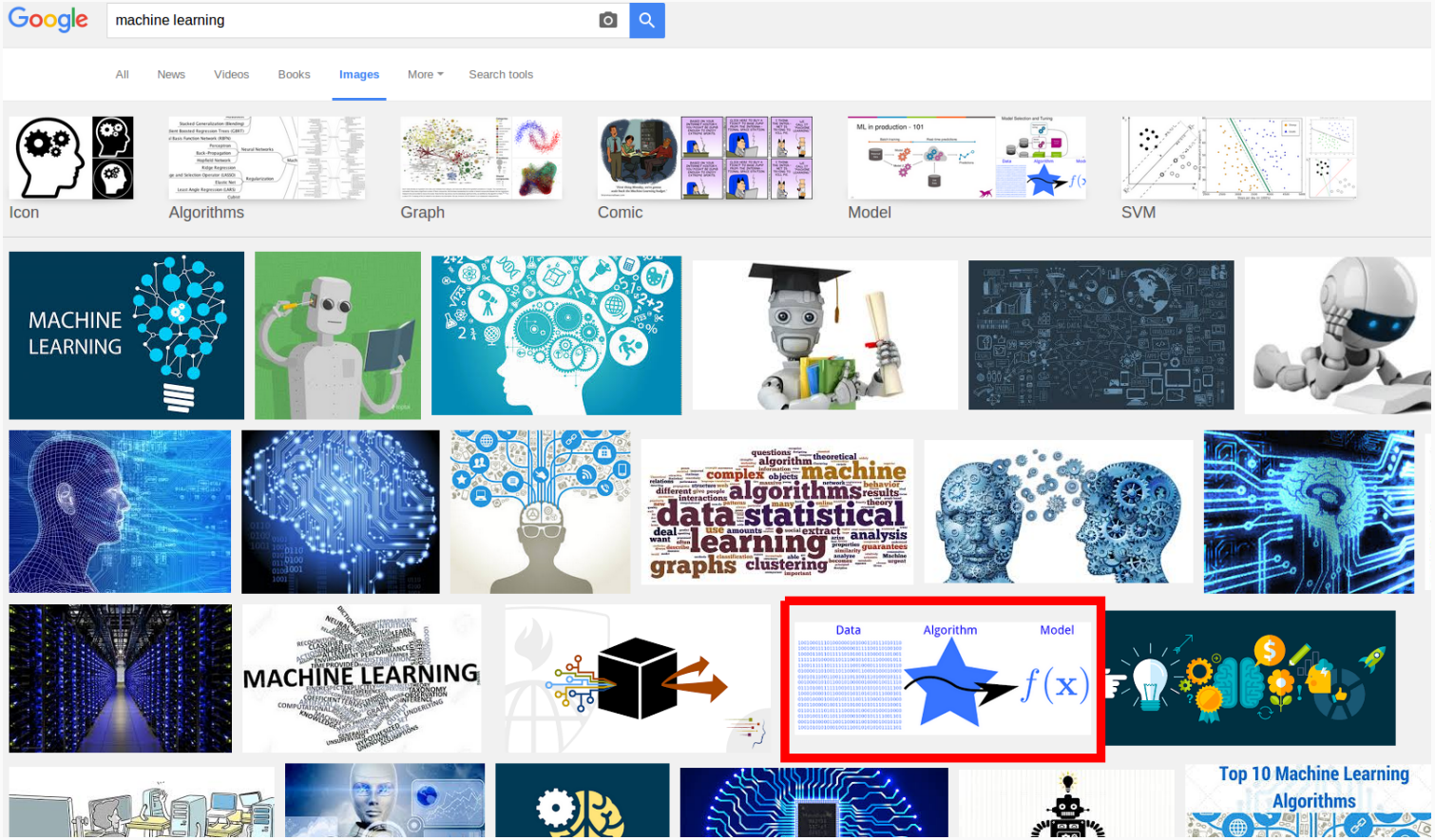
(See Guardian article)

What is machine learning?



circa October 2016

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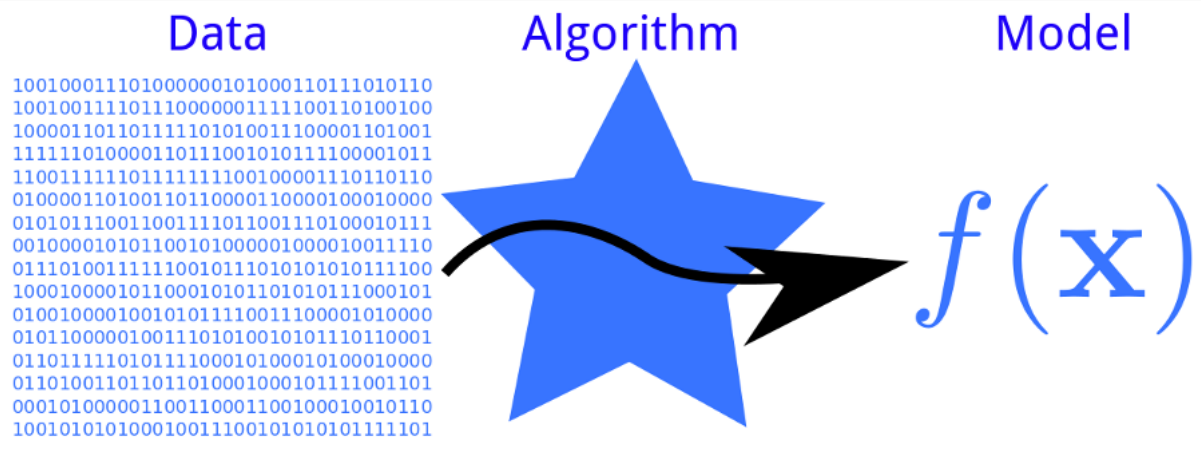

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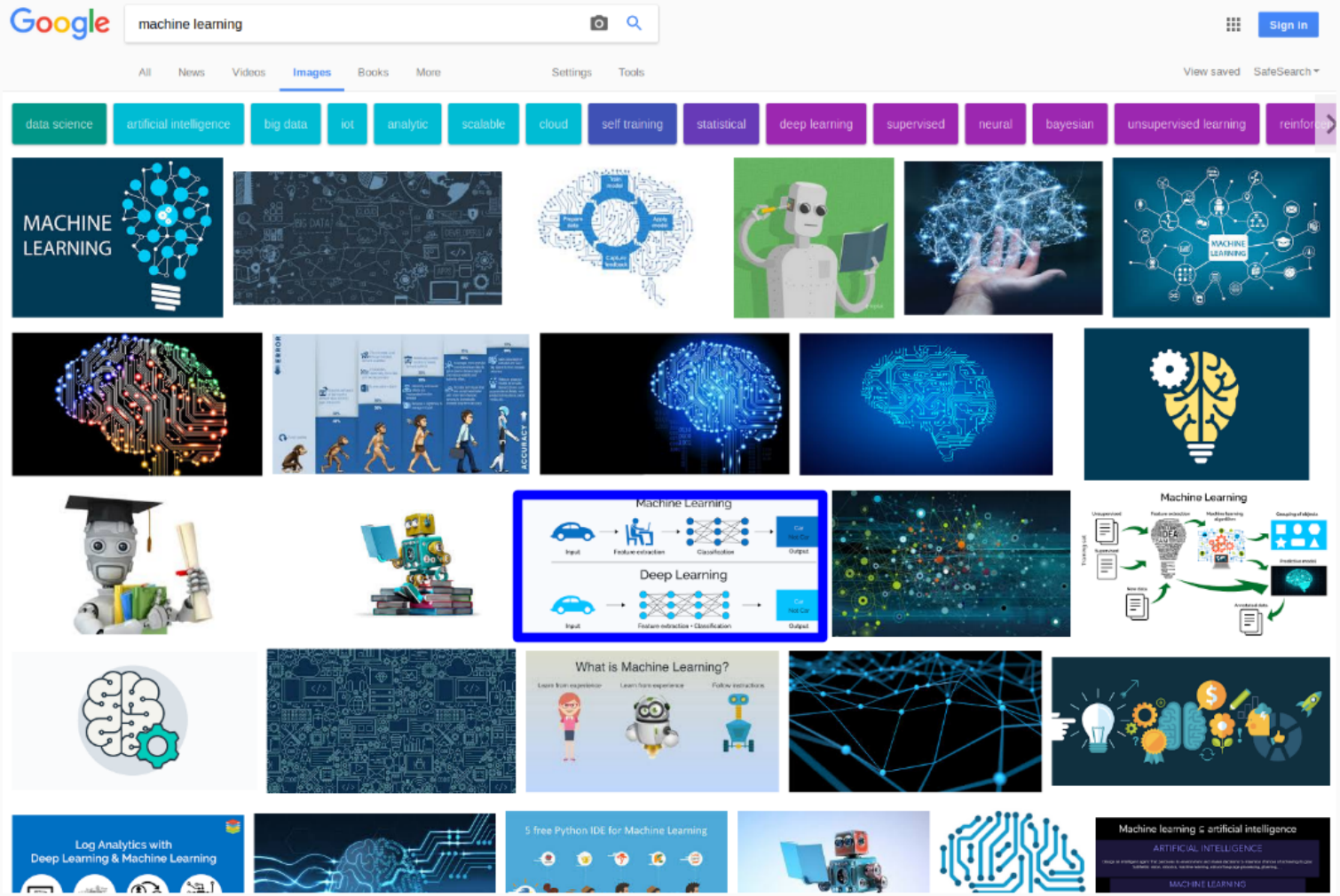

circa October 2017 (Le Cunn *et al.*, Deep Learning, Nature (2015))

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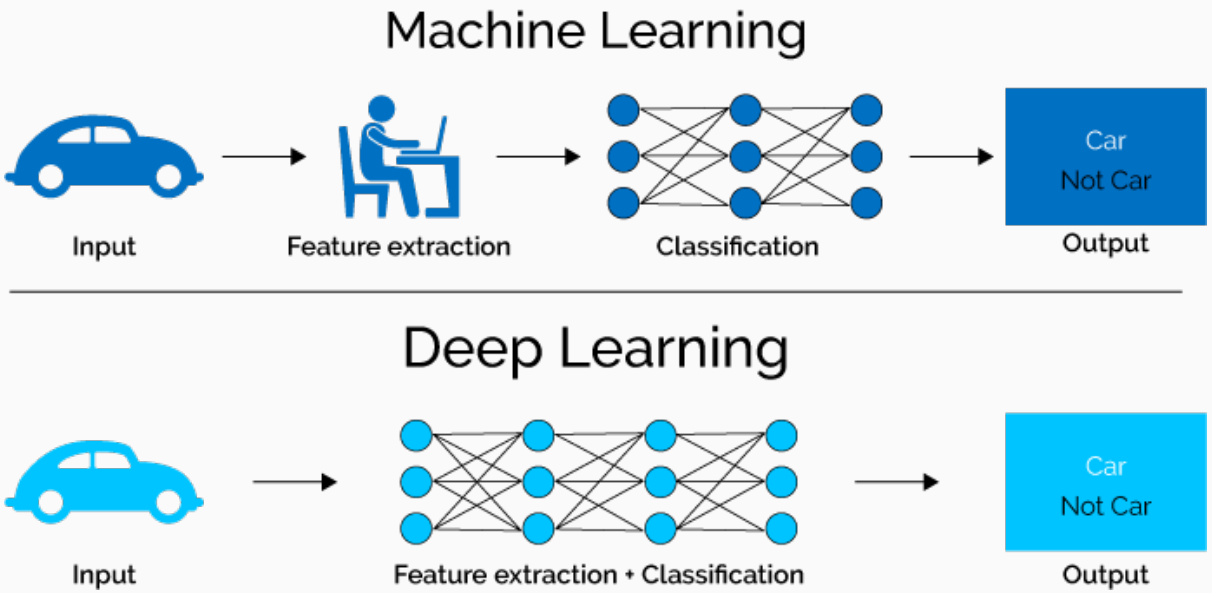

circa October 2017 (Le Cunn *et al.*, Deep Learning, Nature (2015))

What is artificial intelligence?

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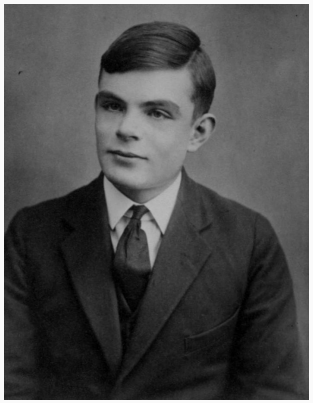
“Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child’s? If this were then subjected to an appropriate course of education one would obtain the adult brain.”



Turing, A.M. (1950). Computing machinery and intelligence. Mind, 59, 433-460.

Programming vs Learning

Programming, like all engineering, is a lot of work:

We have to build everything from scratch.

Learning is more like farming, which lets nature do most of the work. Farmers combine seeds with nutrients to grow crops.

Learners combine knowledge with data to grow programs.

What is machine learning?

Definition by Tom Mitchell (1997)

A computer program is said to **learn** from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

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Face Detection

- E : images (with bounding boxes) around faces

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Face Detection

- E : images (with bounding boxes) around faces
- T : given an image without boxes, put boxes around faces
- P : number of faces correctly identified

What is machine learning?

Learning = Representation + Evaluation + Optimisation

- Representation: Hypothesis space of the learner
  - Choose the set of classifiers that it can possibly learn
- Evaluation: Objective or scoring function
  - Distinguish good classifiers from bad ones
- Optimisation: Search method for the highest-scoring classifier
  - Key to the efficiency of the learner
  - Unlike in most optimisation problems, we do not have access to the function we want to optimise!
  - Use training error as a surrogate for test error :(
  - Objective function is only a proxy for the true goal $\Rightarrow$ no need to fully optimise it, local optimum may be OK

P. Domingos. A few useful Things to Know about Machine Learning. CACM, 2012.

An early (first?) example of automatic classification

Ronald Fisher: Iris Flowers (1936)

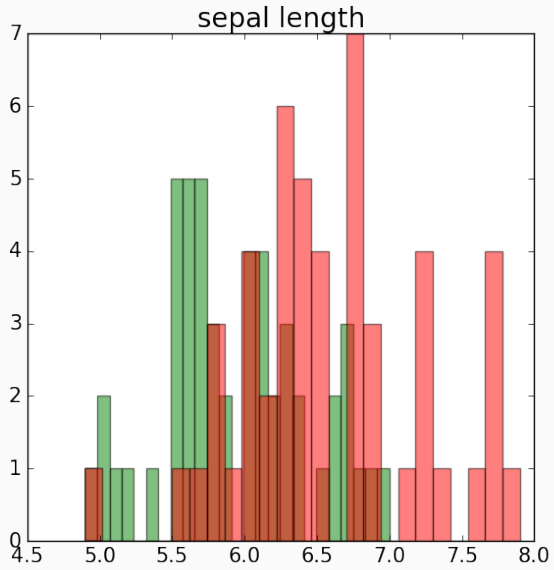
- Three types: setosa, versicolour, virginica
- Data: sepal width, sepal length, petal width, petal length

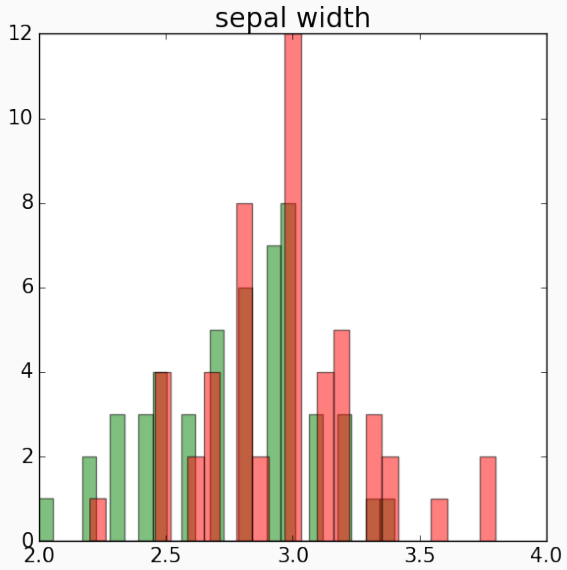
setosa

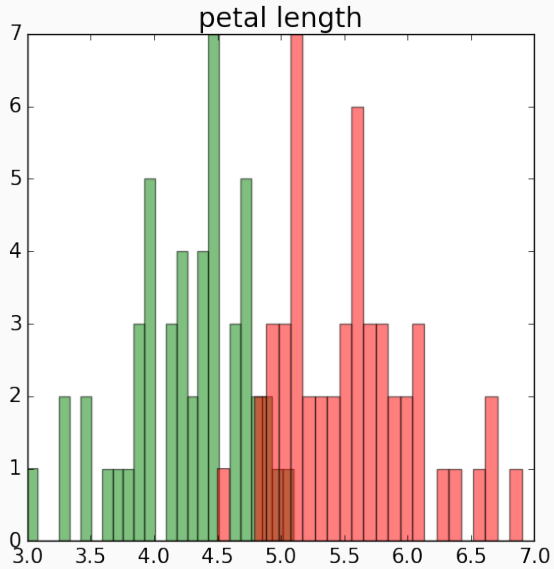
versicolour

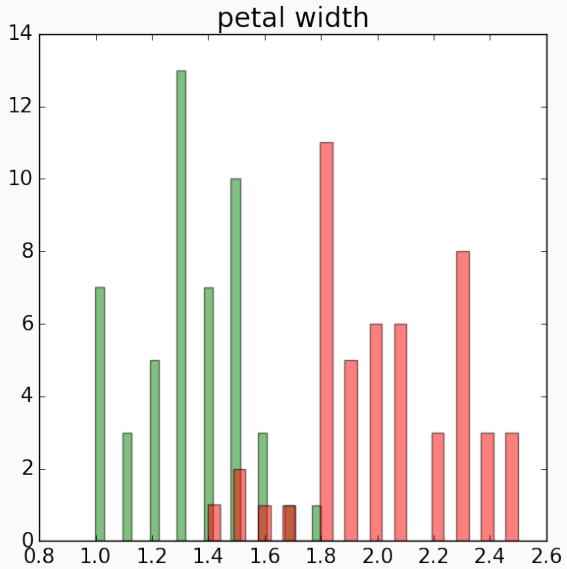
virginica

Histogram Plots for Different Measurements for Versicolour & Virginica

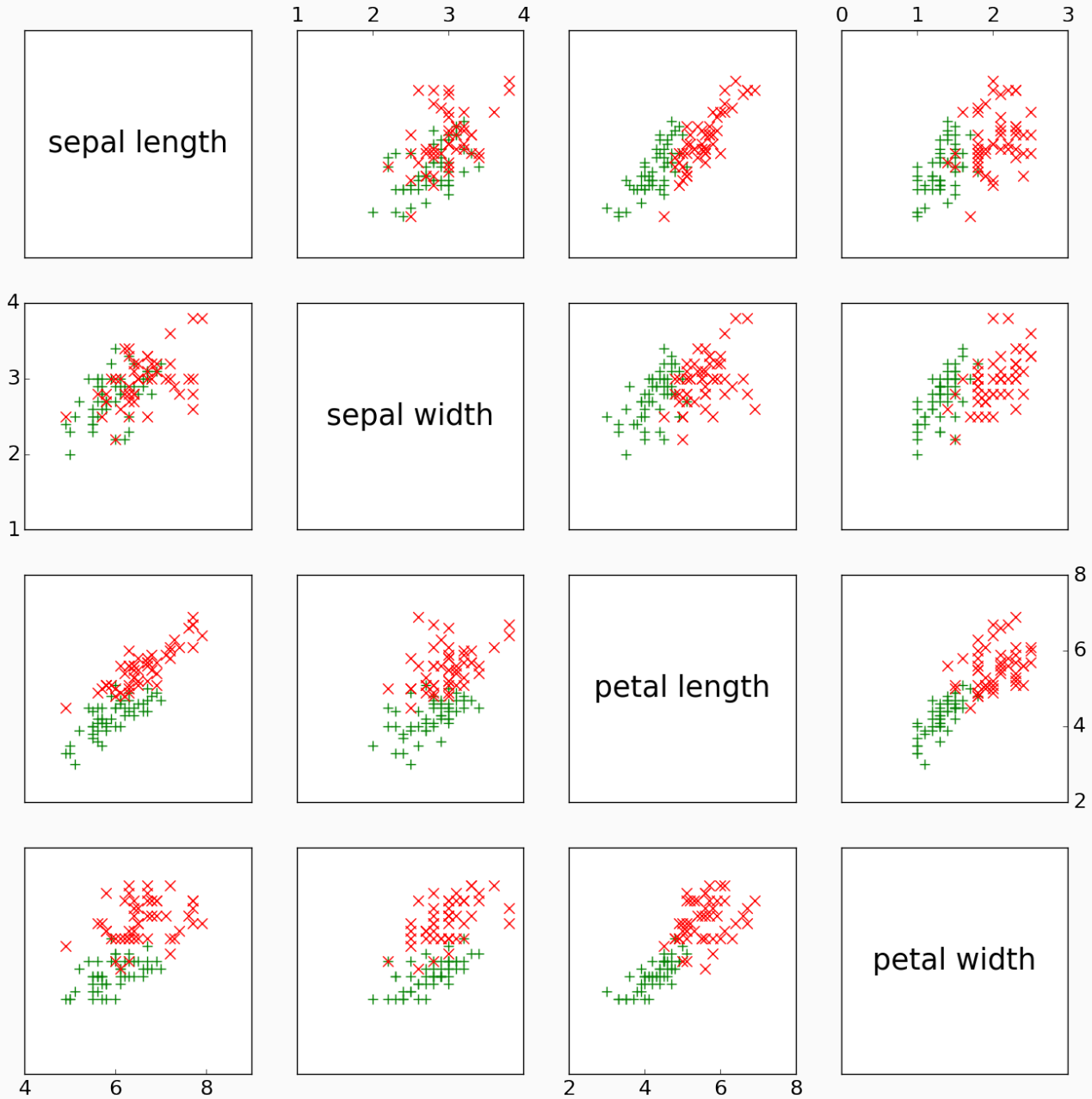








Scatter Plots of Pairwise Measurements for Versicolour & Virginica



An early (first?) example of automatic classification

Ronald Fisher: Iris Flowers (1936)

- Three types: setosa, versicolour, virginica
- Data: sepal width, sepal length, petal width, petal length
- Method: Find linear combinations of features that maximally differentiates the classes

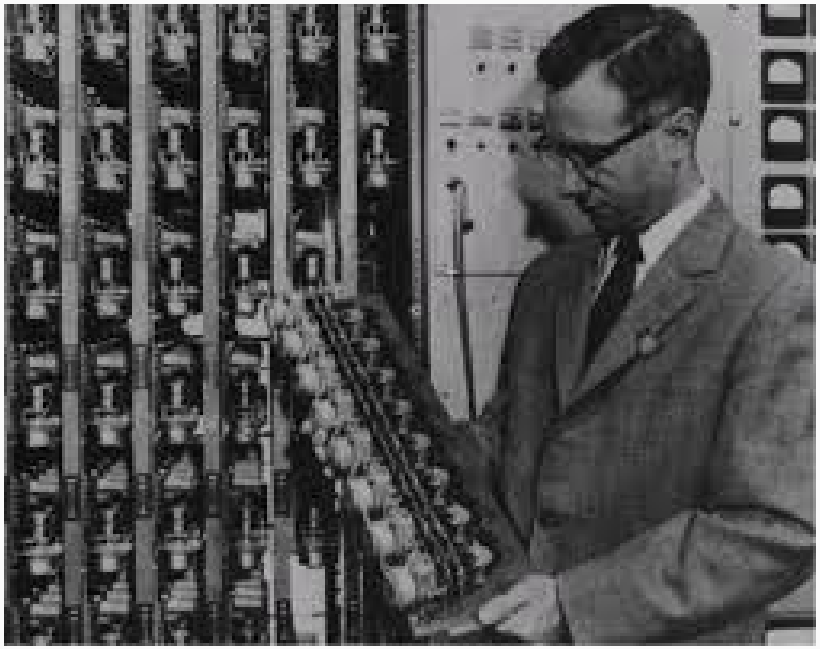
setosa

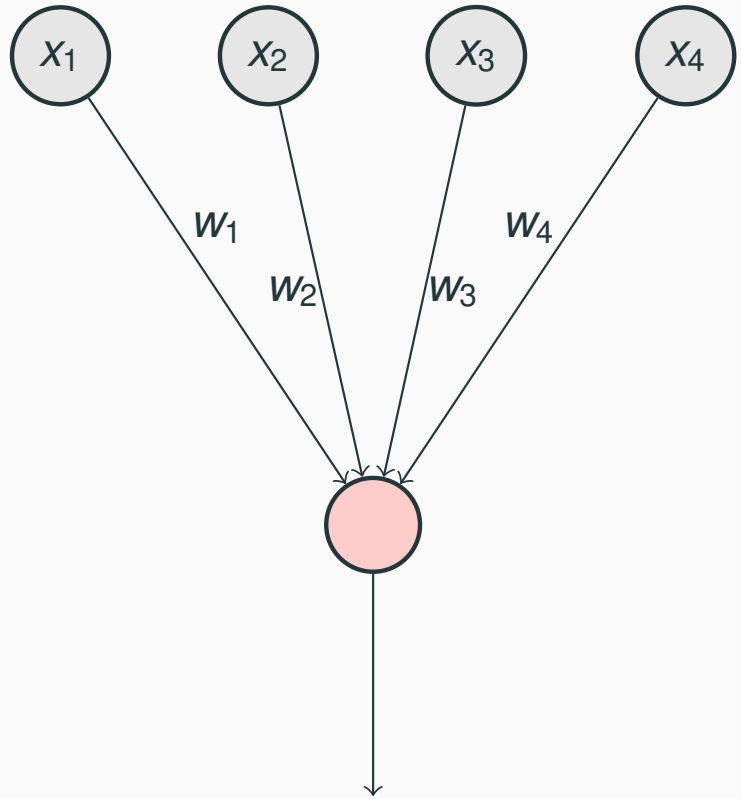
versicolour

virginica

Frank Rosenblatt and the Perceptron

- Perceptron (1957) - inspired by neurons
- Simple learning algorithm: Adjust the weights if incorrect prediction on new input
- Built using specialised hardware

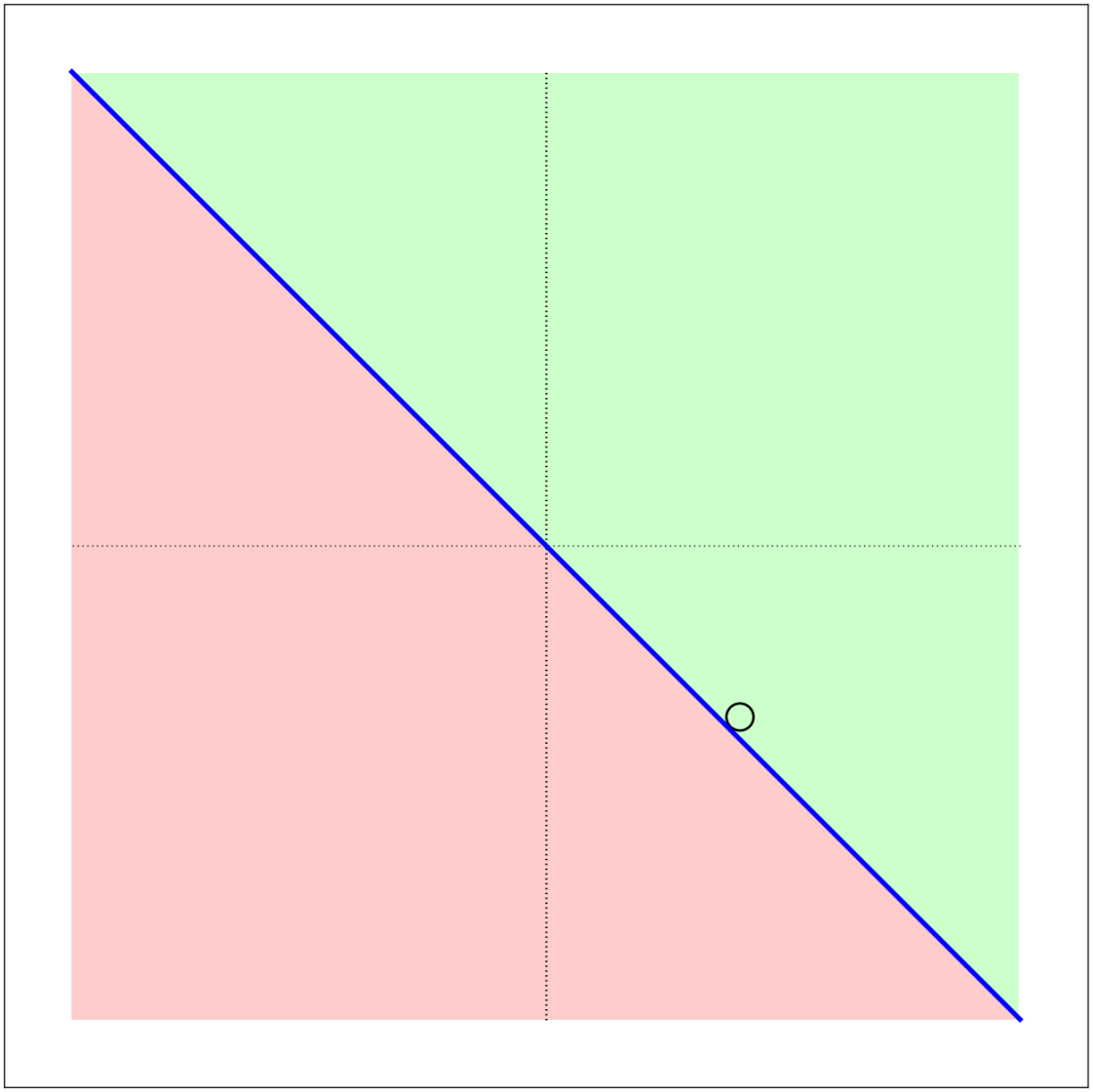




$$\text{sign}(w_0 + w_1 x_1 + \cdots + w_4 x_4)$$

$$= \text{sign}(\boldsymbol{w} \cdot \mathbf{x}) = \begin{cases} +1 & \text{if } \boldsymbol{w} \cdot \mathbf{x} \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

Perceptron Training Algorithm



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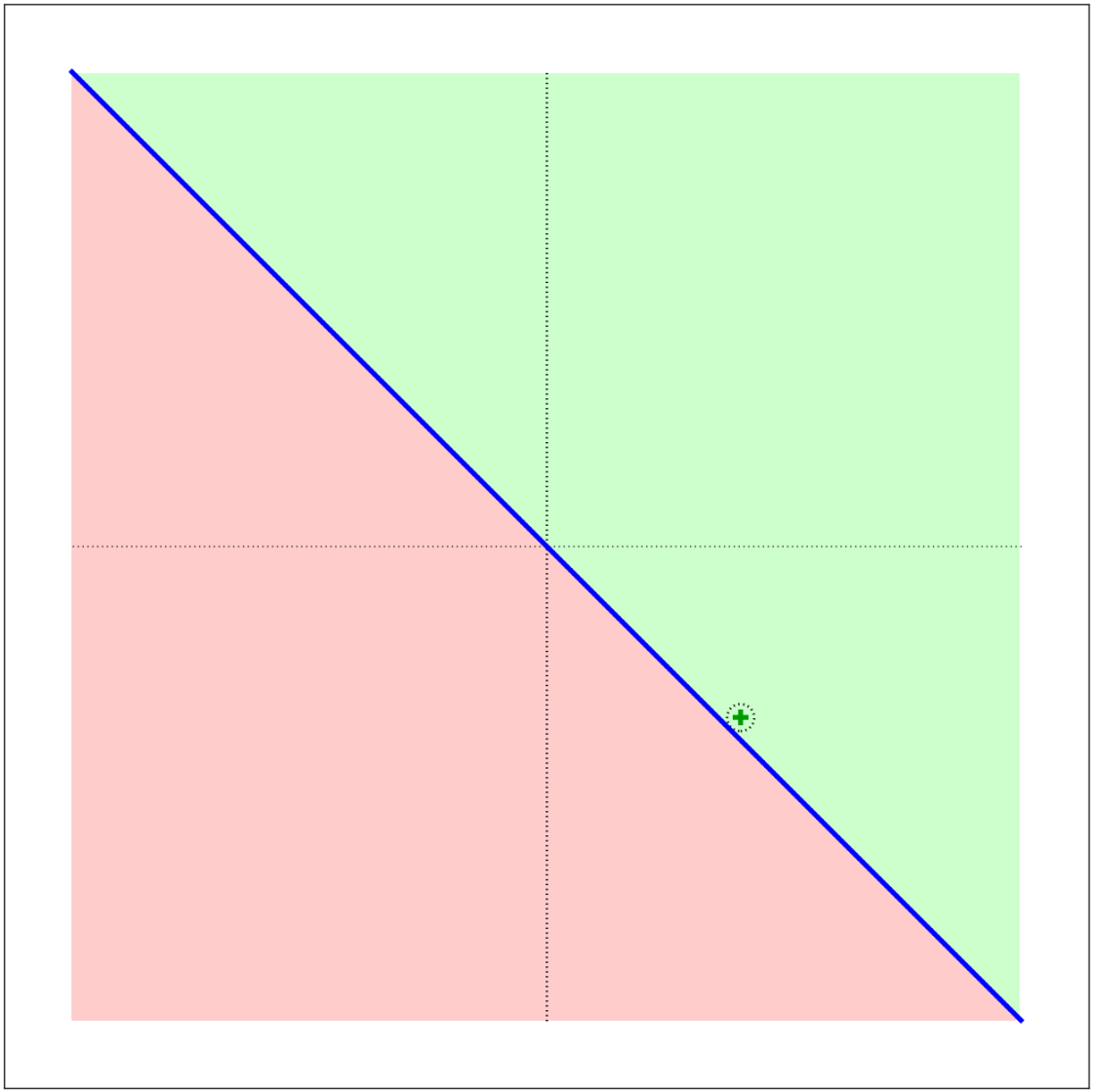

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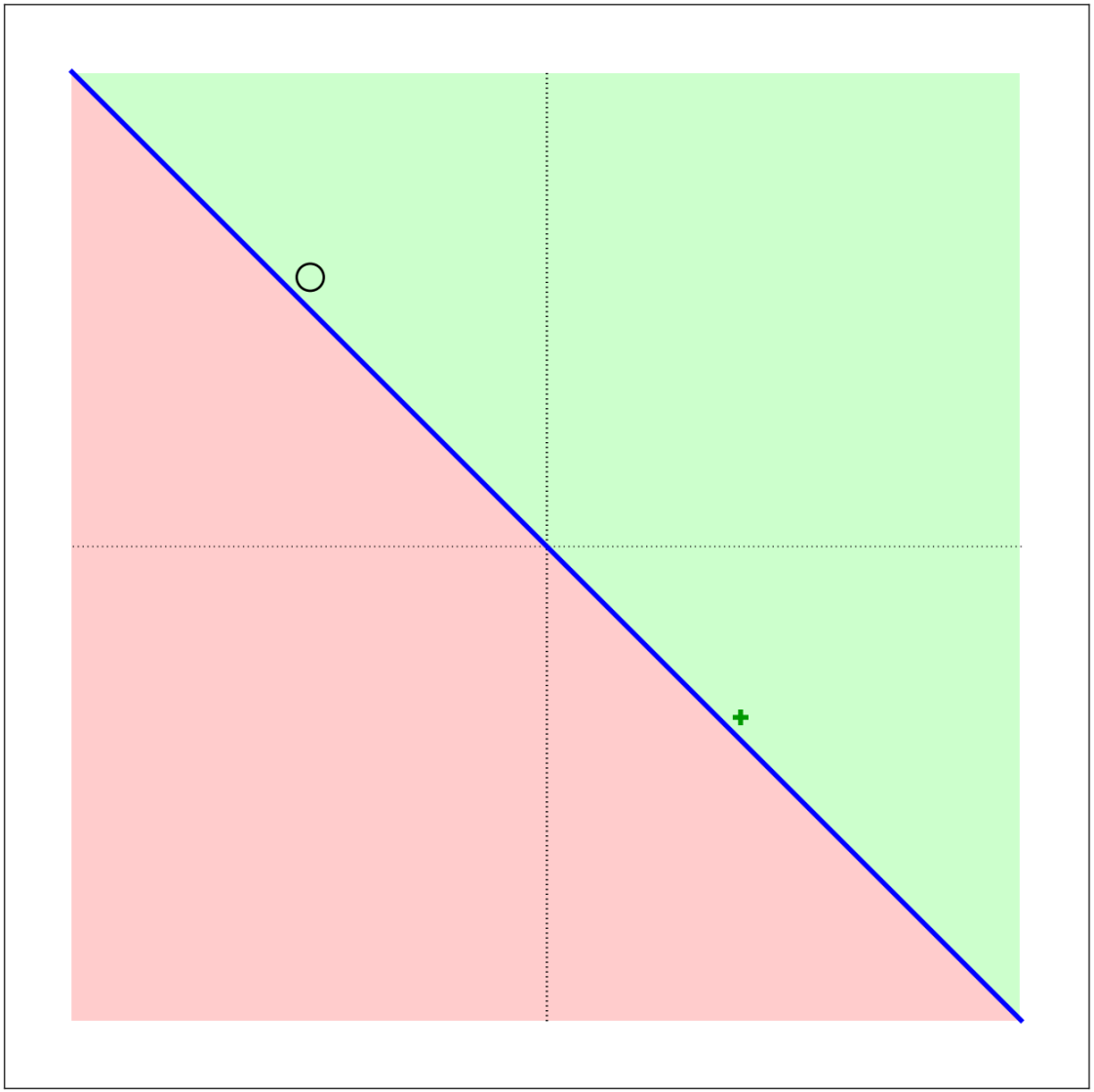

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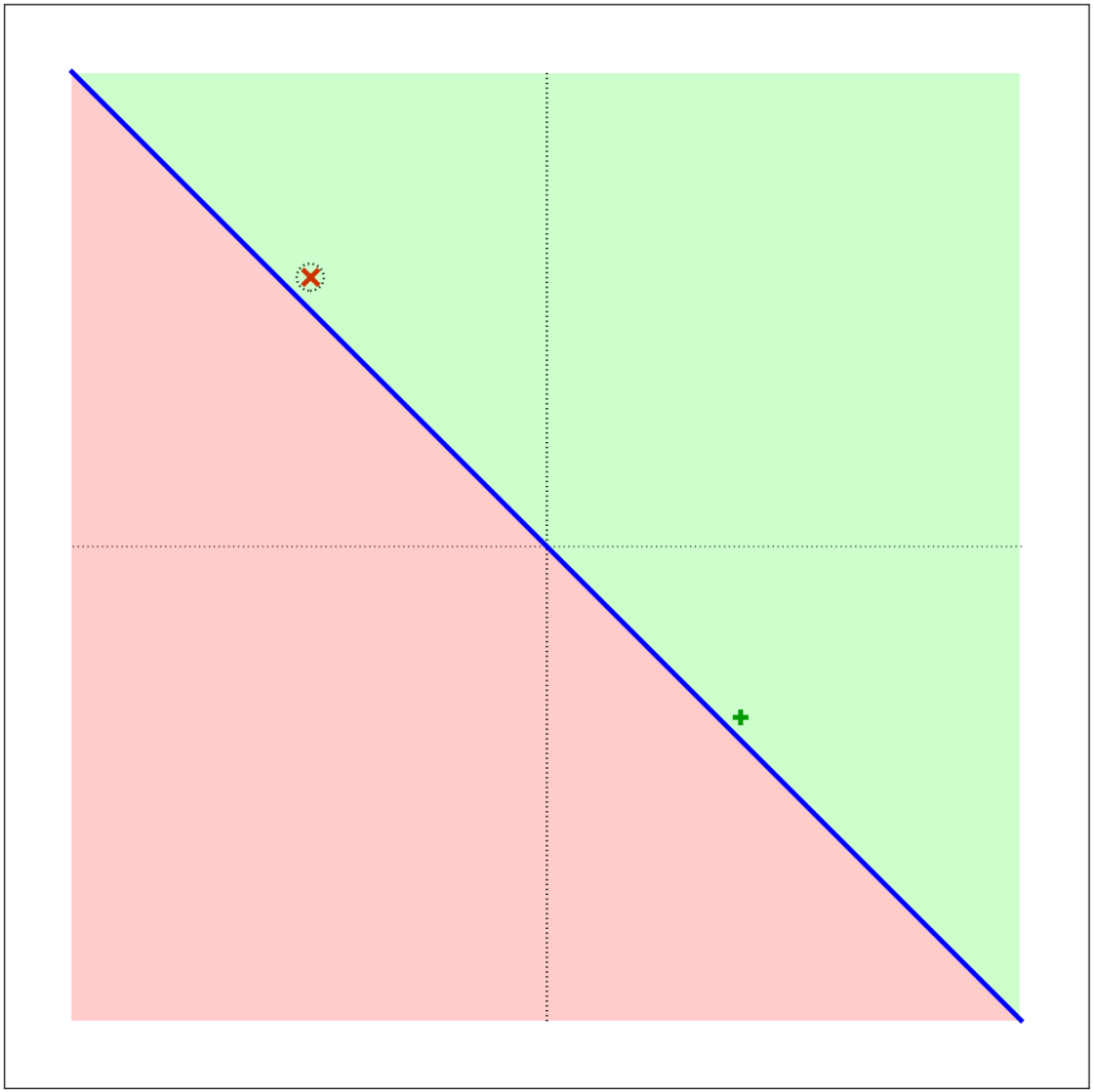

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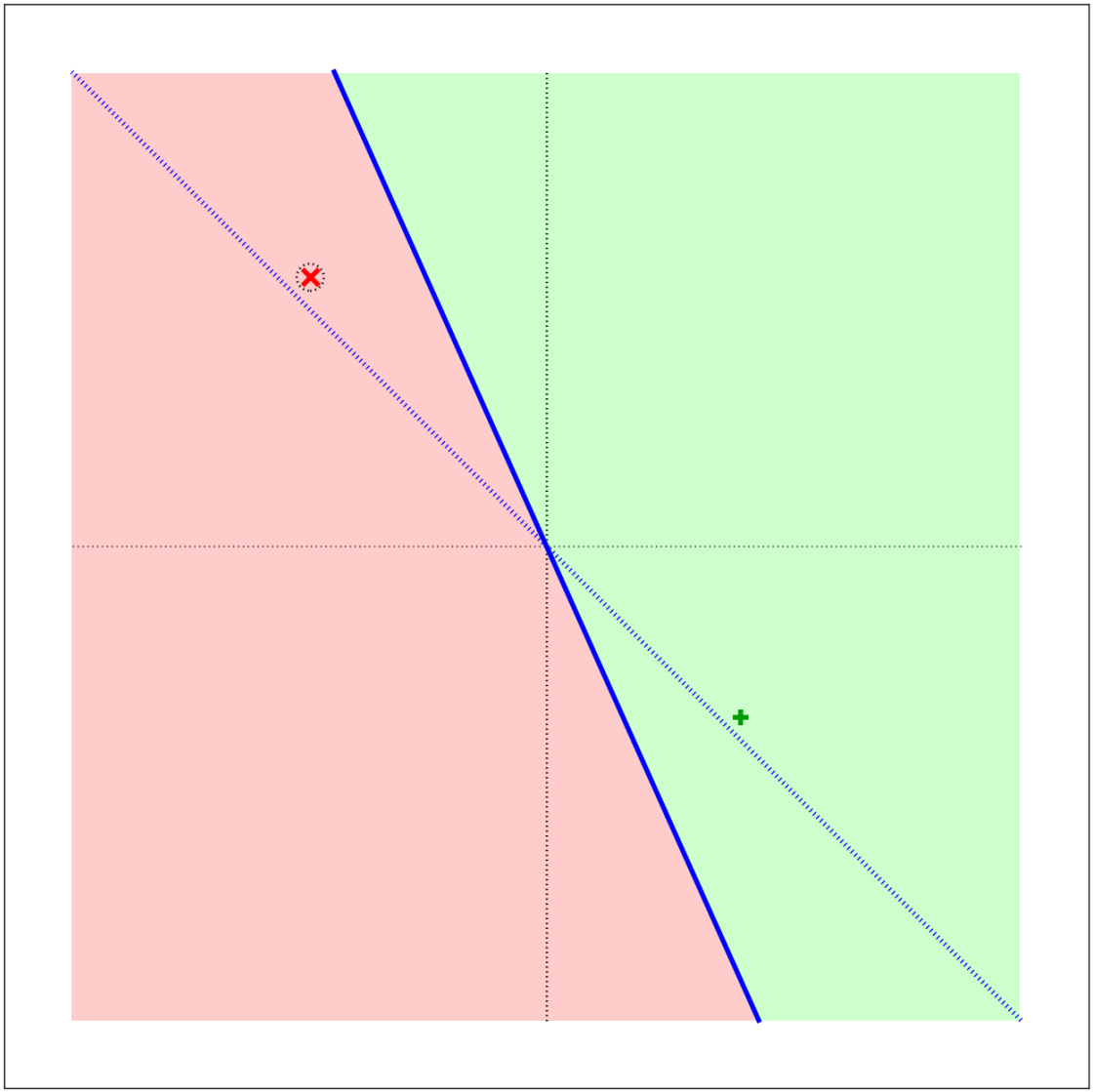

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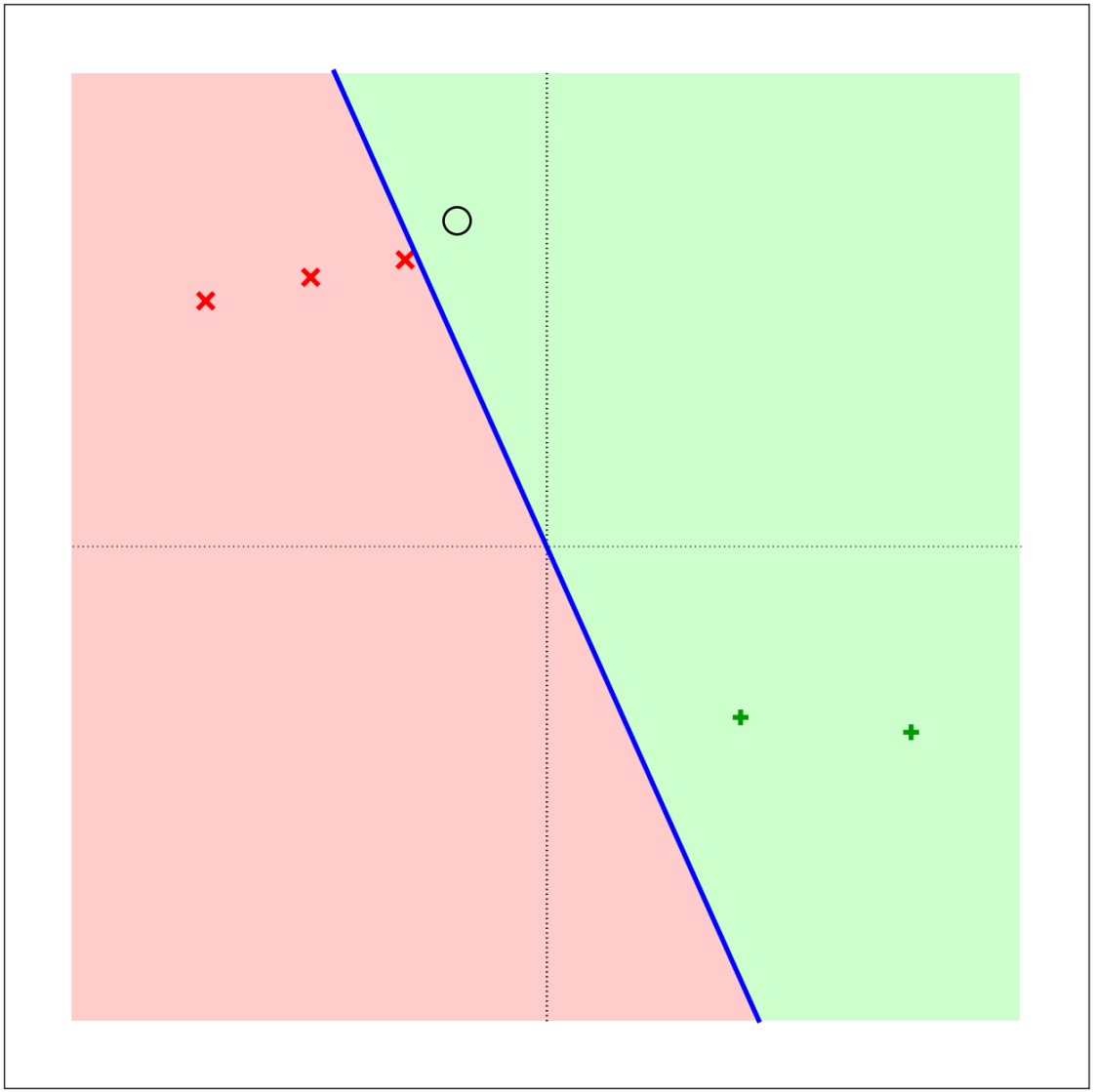

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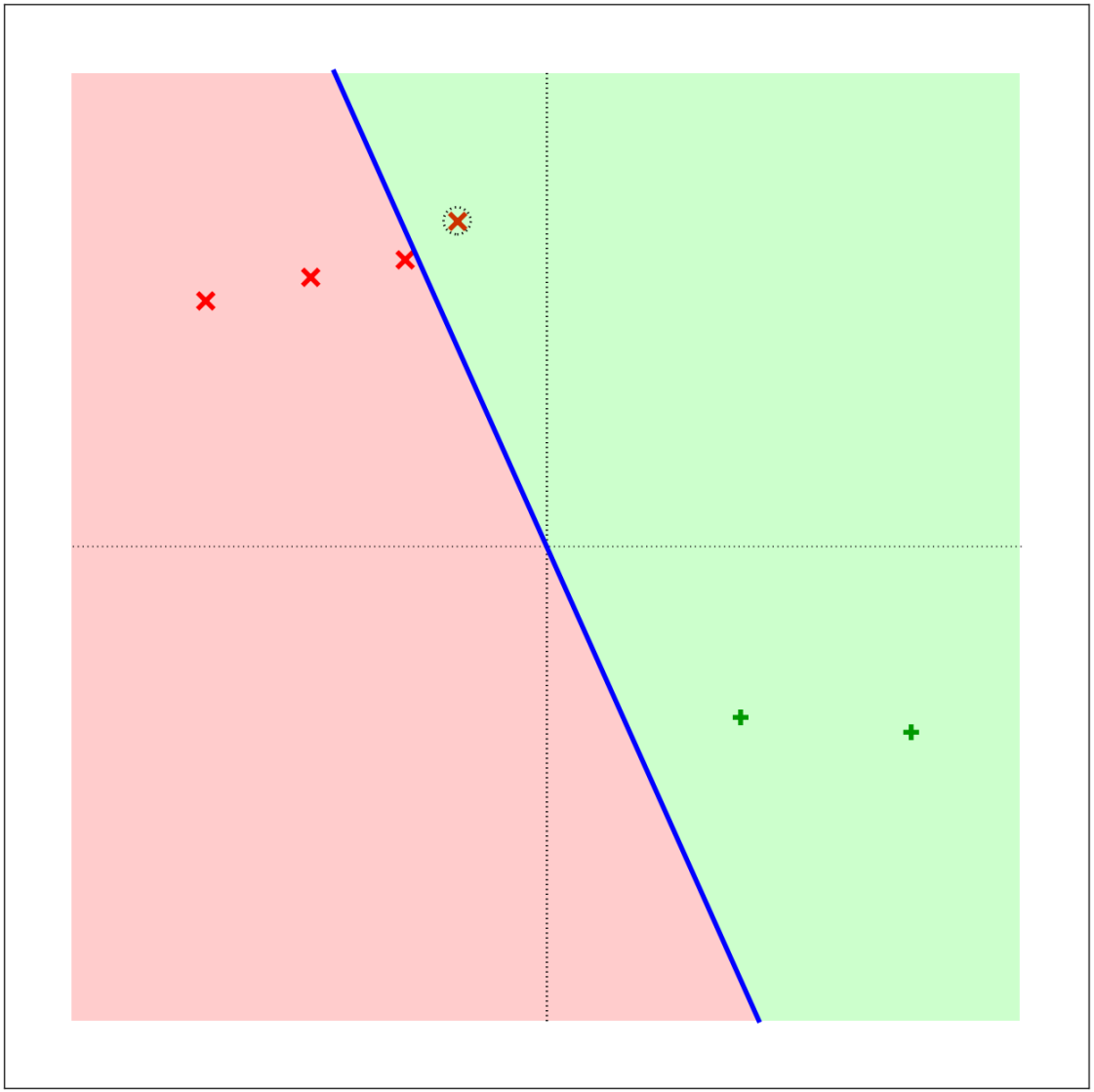

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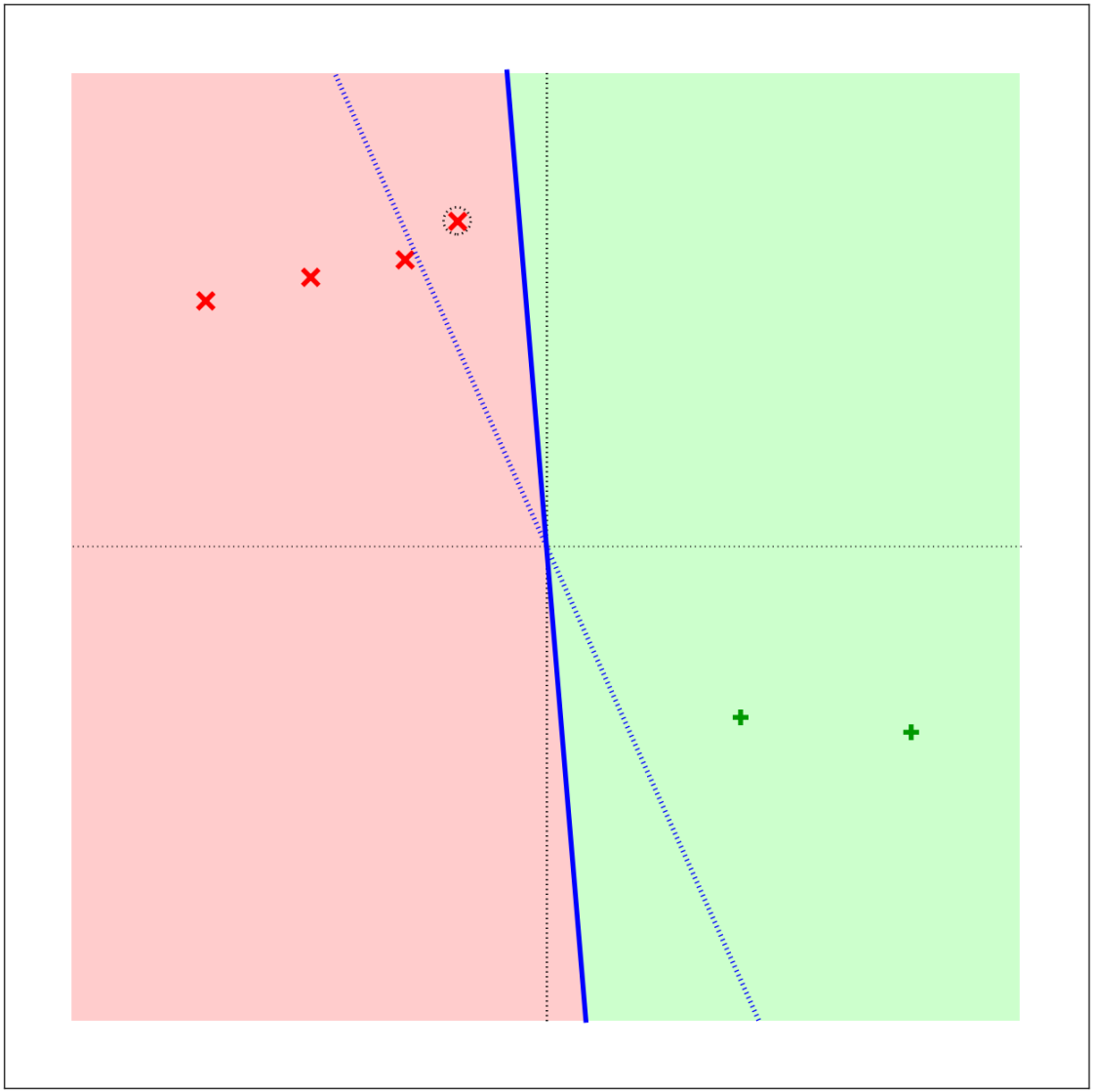

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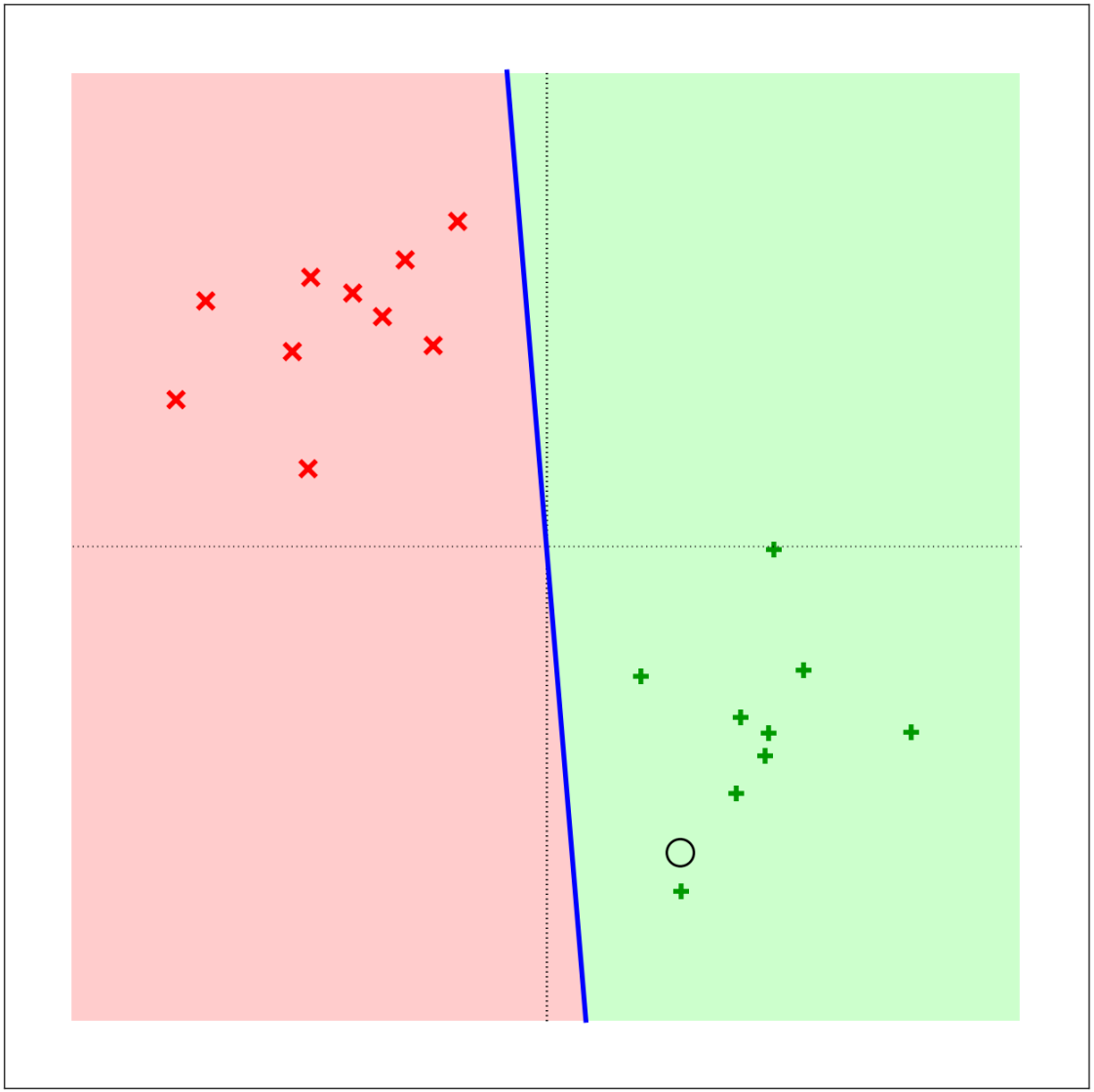

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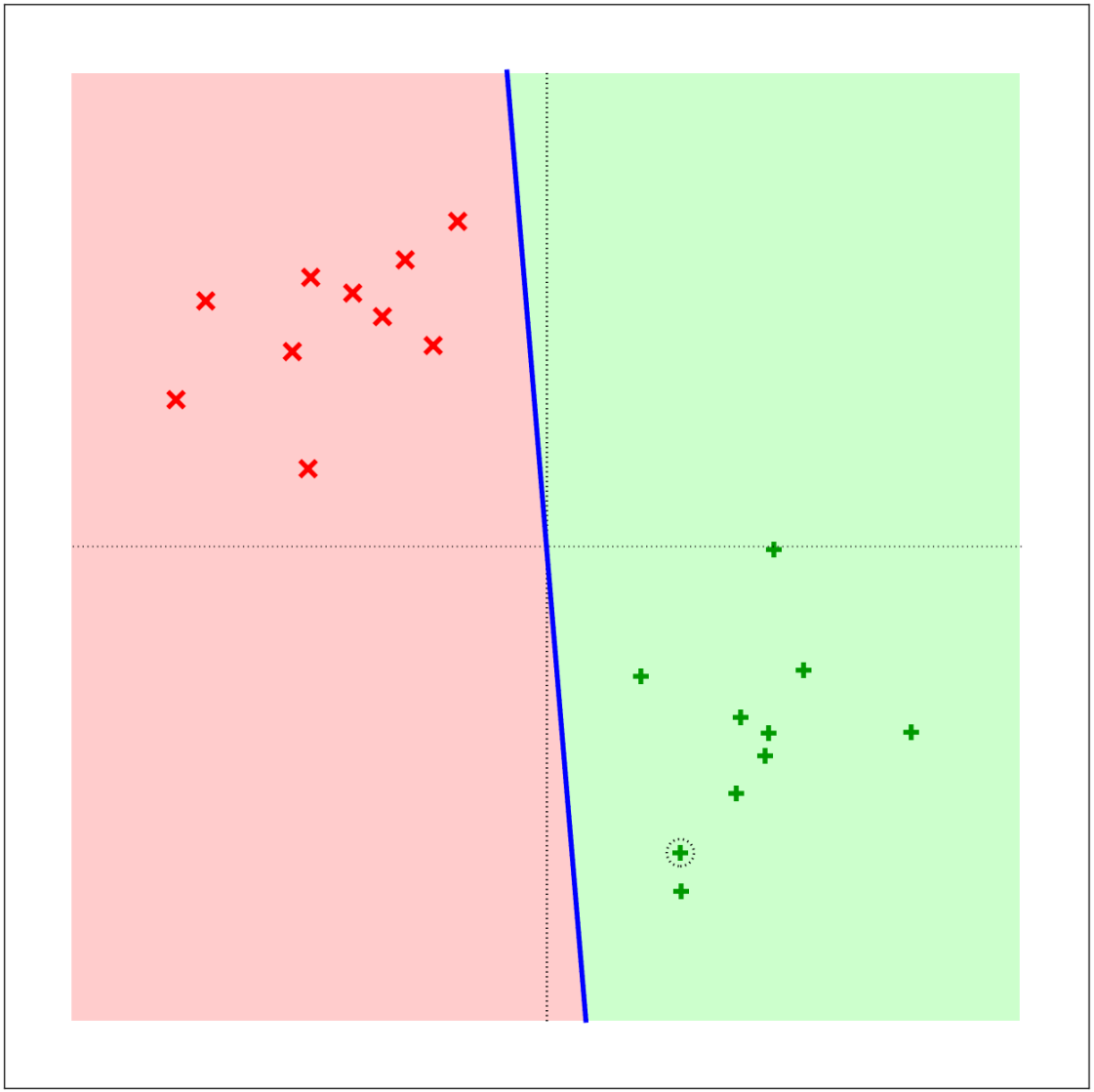

The Perceptron Algorithm

Initialisation $\boldsymbol{w} = \mathbf{0}$ -- all params set to 0

Repeat Until Convergence:

For $t = 1 \ldots n$ -- go over all examples

1. $y' = \text{sign}(\mathbf{x}_t \cdot \boldsymbol{w})$ -- compute the prediction
2. If $y' \neq y_t$ then $\boldsymbol{w} := \boldsymbol{w} + y_t \mathbf{x}_t$ -- update the params

else leave $\boldsymbol{w}$ unchanged

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Convergence: **w** remains unchanged for an entire pass over the training set.
Then, all training examples are classified correctly.

The Perceptron Convergence Theorem

Assume:

- $\exists\, \mathbf{w}', \gamma > 0$ such that $\forall t = 1 \ldots n$: $y_t(\mathbf{x}_t \cdot \mathbf{w}) \geq \gamma$
- $\forall t = 1 \ldots n : \|\mathbf{x}_t\| \leq R$ `-- ‖·‖ is the Euclidean norm`

Then the perceptron algorithm makes at most $\frac{R^2}{\gamma^2}$ updates.

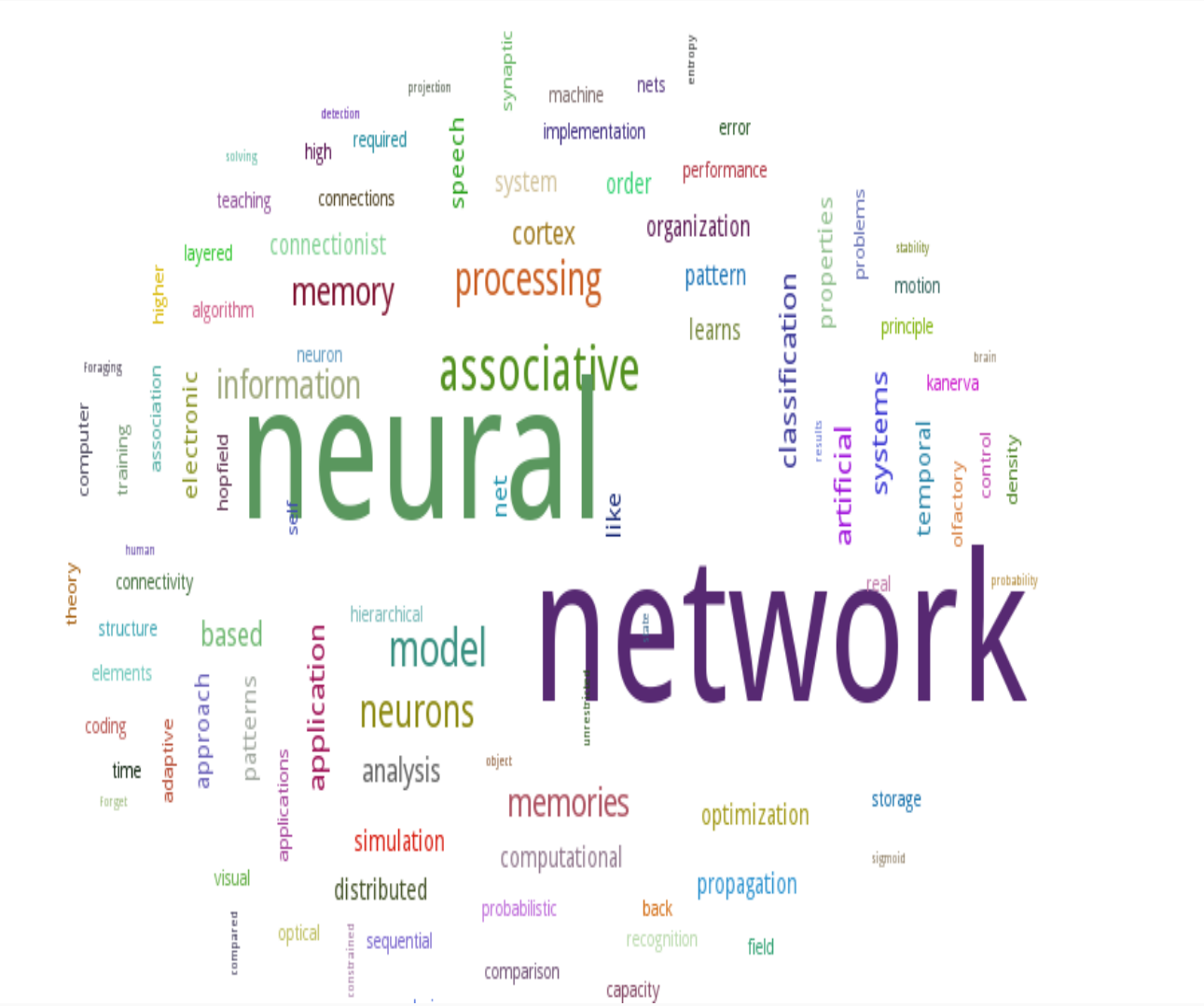
Simple proof by Michael Collins available online.

Machine Learning Models and Methods

k-Nearest Neighbours
Linear Regression
Logistic Regression
Ridge Regression
Hidden Markov Models
Mixtures of Gaussian
Principle Component Analysis
Independent Component Analysis
Kernel Methods
Decision Trees
Boosting and Bagging
Belief Propagation
Variational Inference
EM Algorithm
Monte Carlo Methods
Spectral Clustering
Hierarchical Clustering
Recurrent Neural Networks

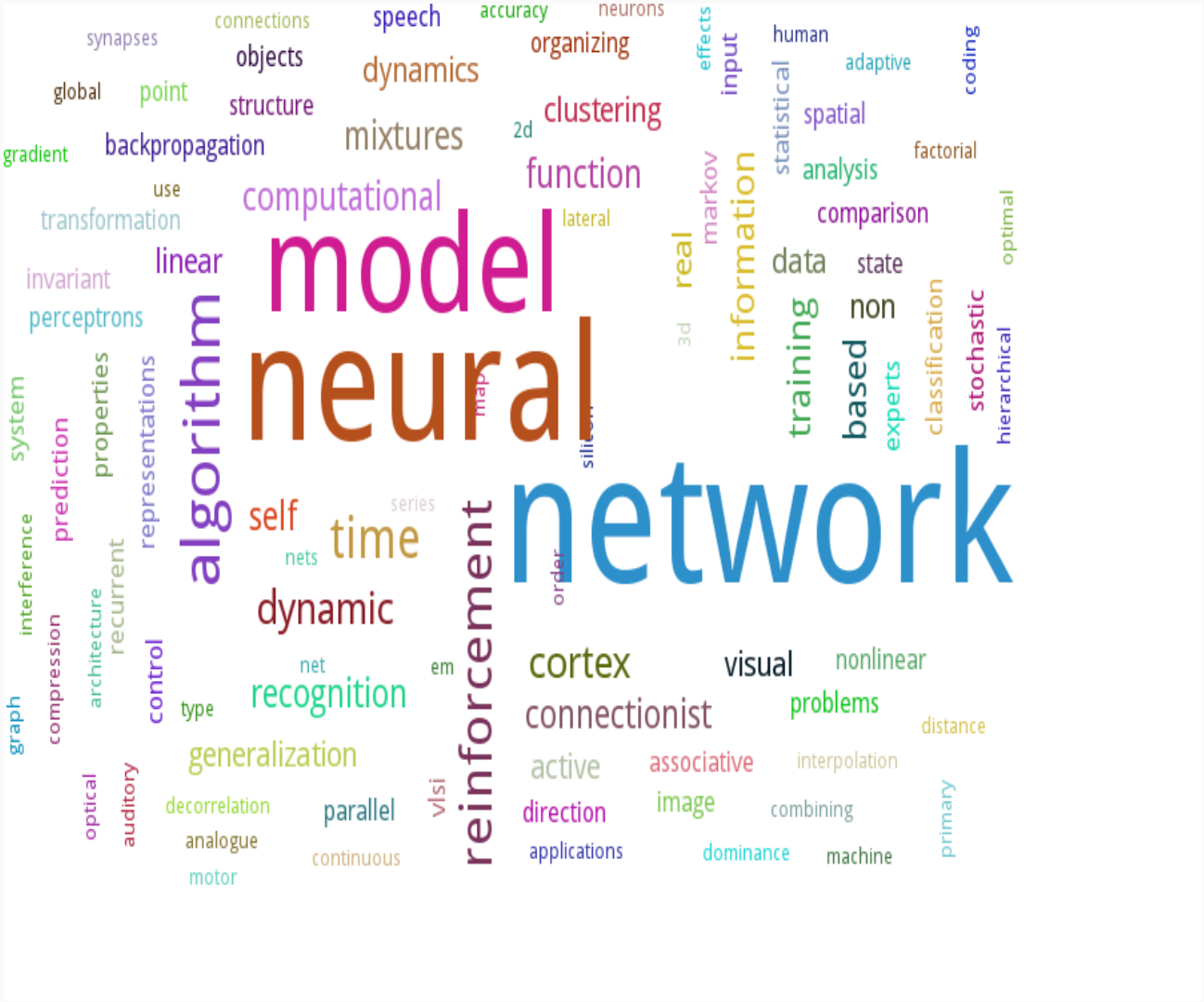
Linear Discriminant Analysis
Quadratic Discriminant Analysis
Perceptron Algorithm
Naïve Bayes Classifier
Hierarchical Bayes
k-means Clustering
Support Vector Machines
Gaussian Processes
Deep Neural Networks
Convolutional Neural Networks
Markov Random Fields
Structural SVMs
Conditional Random Fields
Structure Learning
Restricted Boltzmann Machines
Multi-dimensional Scaling
Reinforcement Learning
...

NIPS Papers!



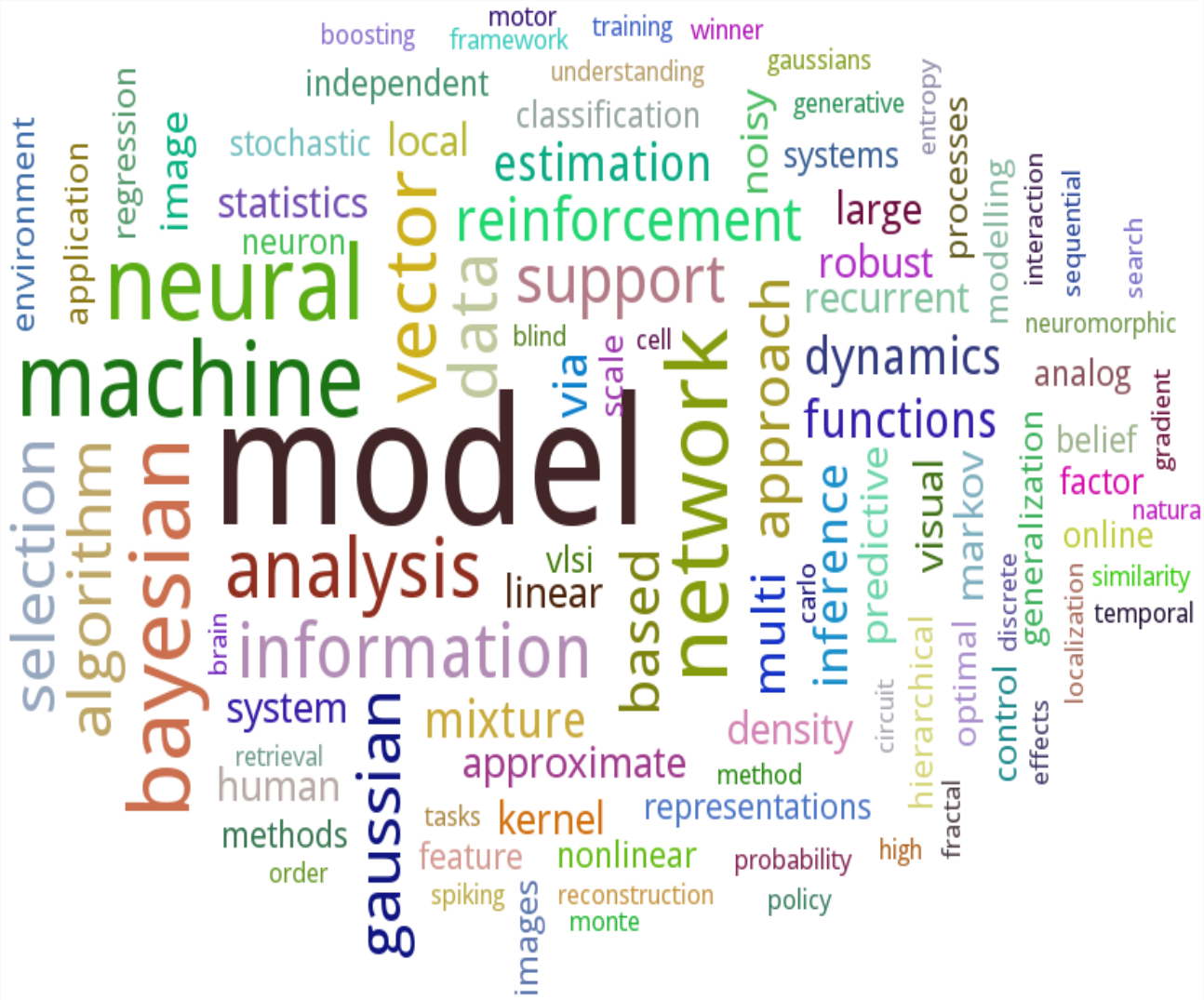
Advances in Neural Information Processing Systems 1988

NIPS Papers!



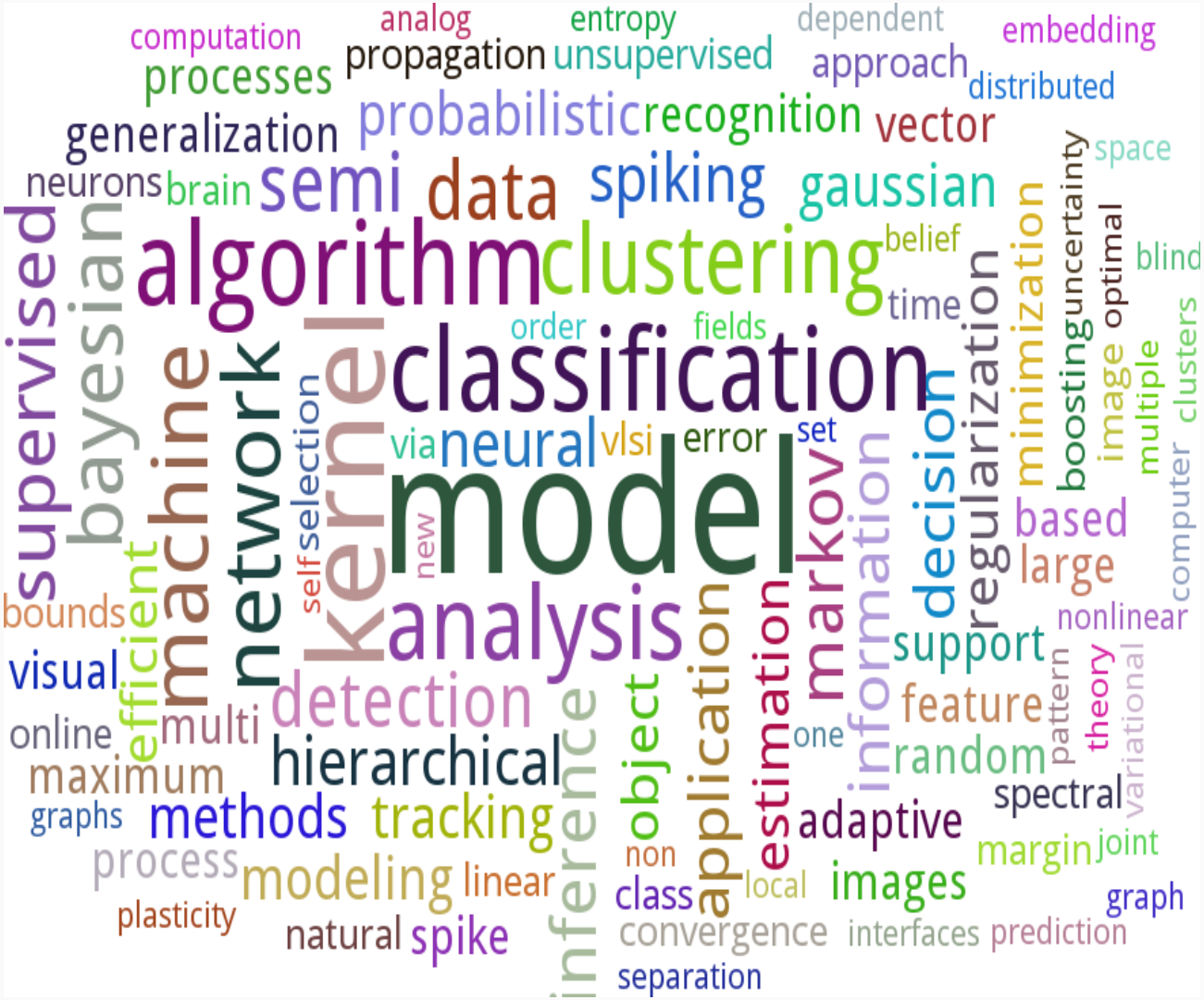
Advances in Neural Information Processing Systems 1995

NIPS Papers!



Advances in Neural Information Processing Systems 2000

NIPS Papers!

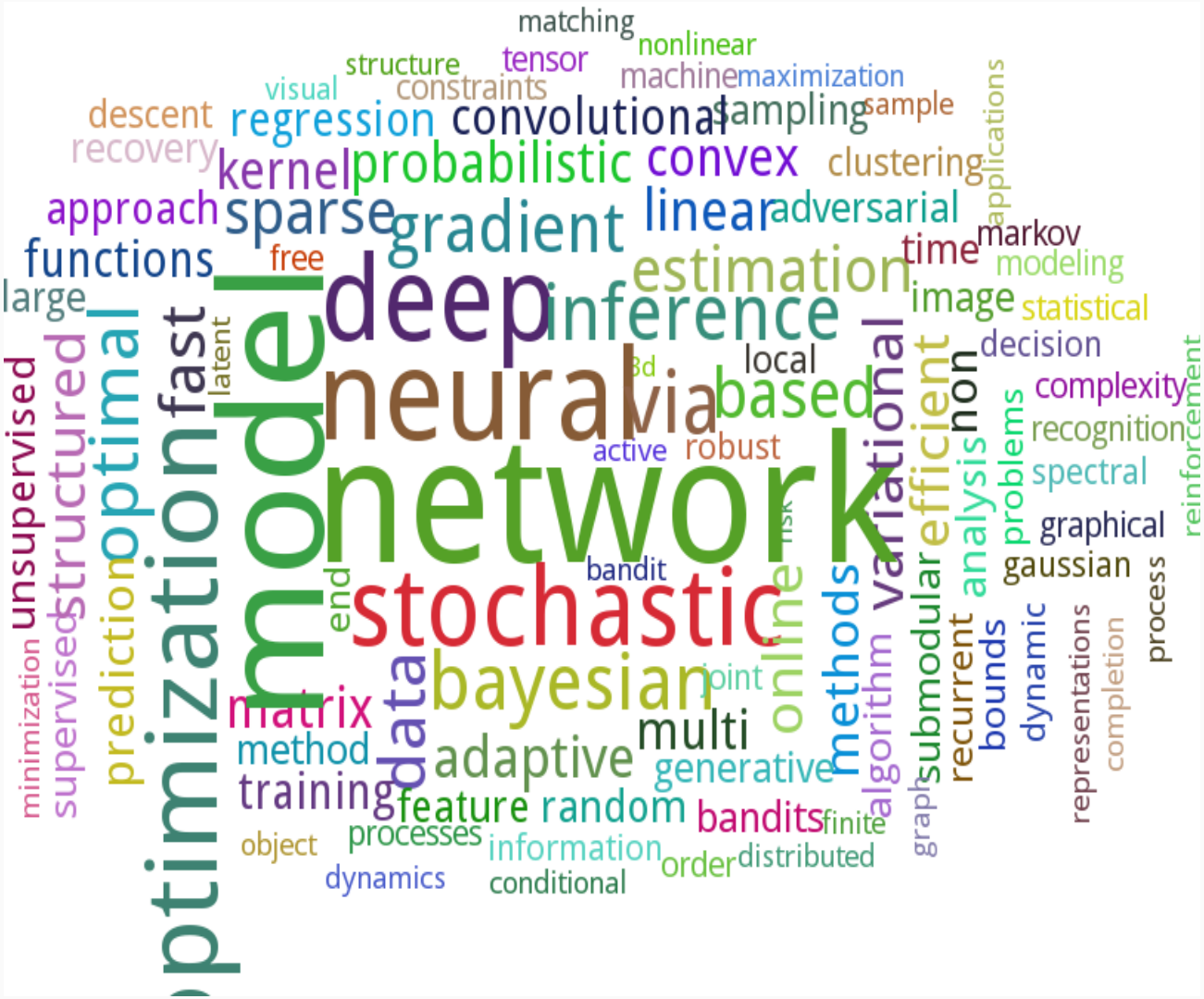


Advances in Neural Information Processing Systems 2005

NIPS Papers!

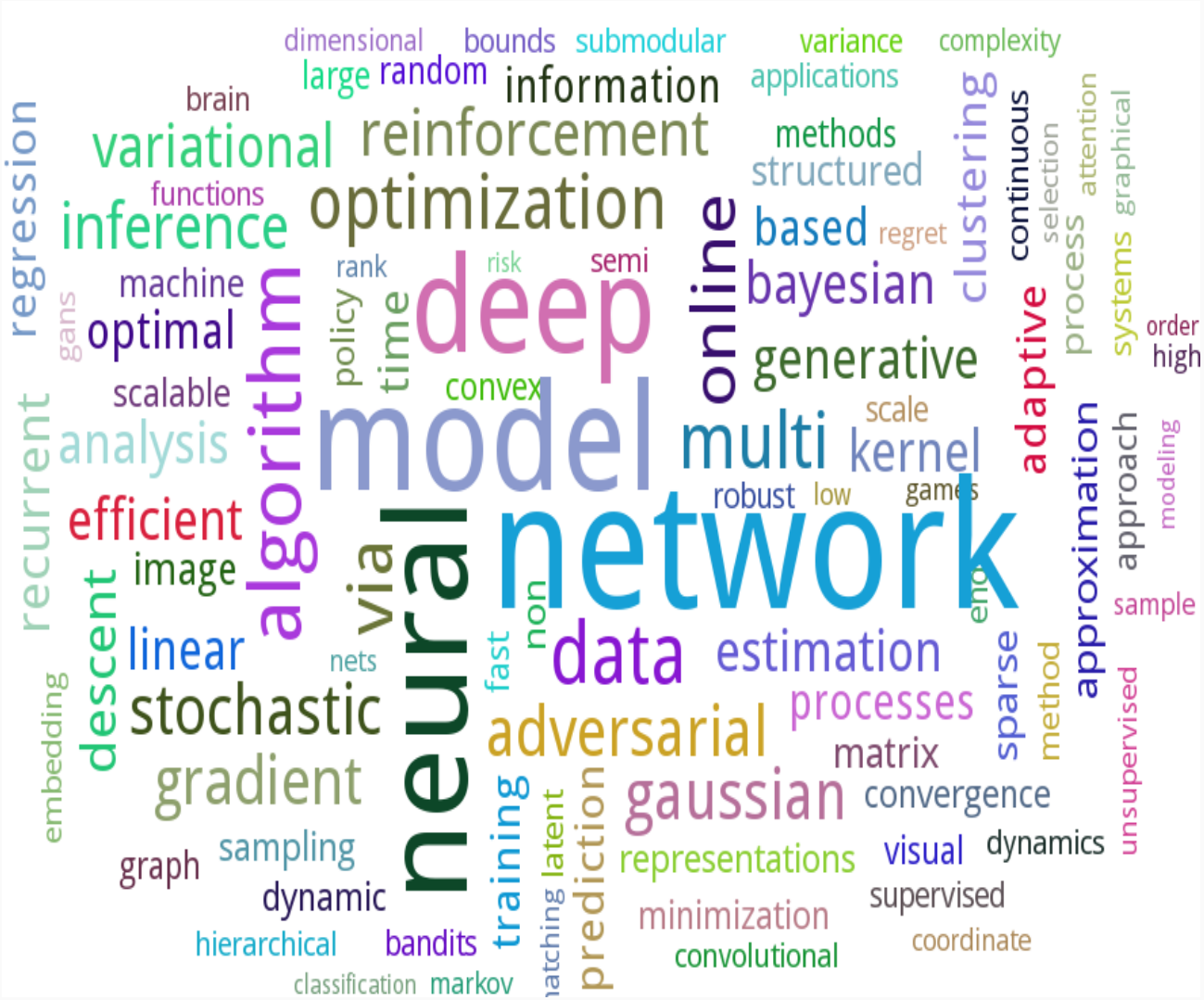
Advances in Neural Information Processing Systems 2009

NIPS Papers!



Advances in Neural Information Processing Systems 2016

NIPS Papers!



Advances in Neural Information Processing Systems 2017

`https://www.youtube.com/watch?v=mlXzufEk-2E`

Application: Boston Housing Dataset

Numerical attributes

- Crime rate per capita
- Non-retail business fraction
- Nitric Oxide concentration
- Age of house
- Floor area
- Distance to city centre
- Number of rooms

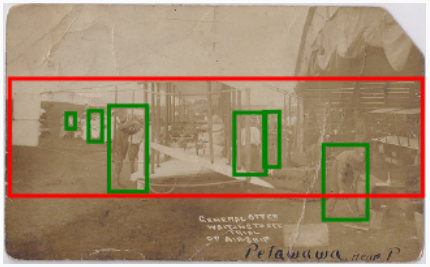
Categorical attributes

- On the Charles river?
- Index of highway access (1-5)

Source: UCI repository

Predict house cost

Application: Object Detection and Localisation






- 200-basic level categories
- Here: Six pictures containing airplanes and people
- Dataset contains over 400,000 images
- Imagenet competition (2010-)
- All recent successes through very deep neural networks!

Supervised Learning

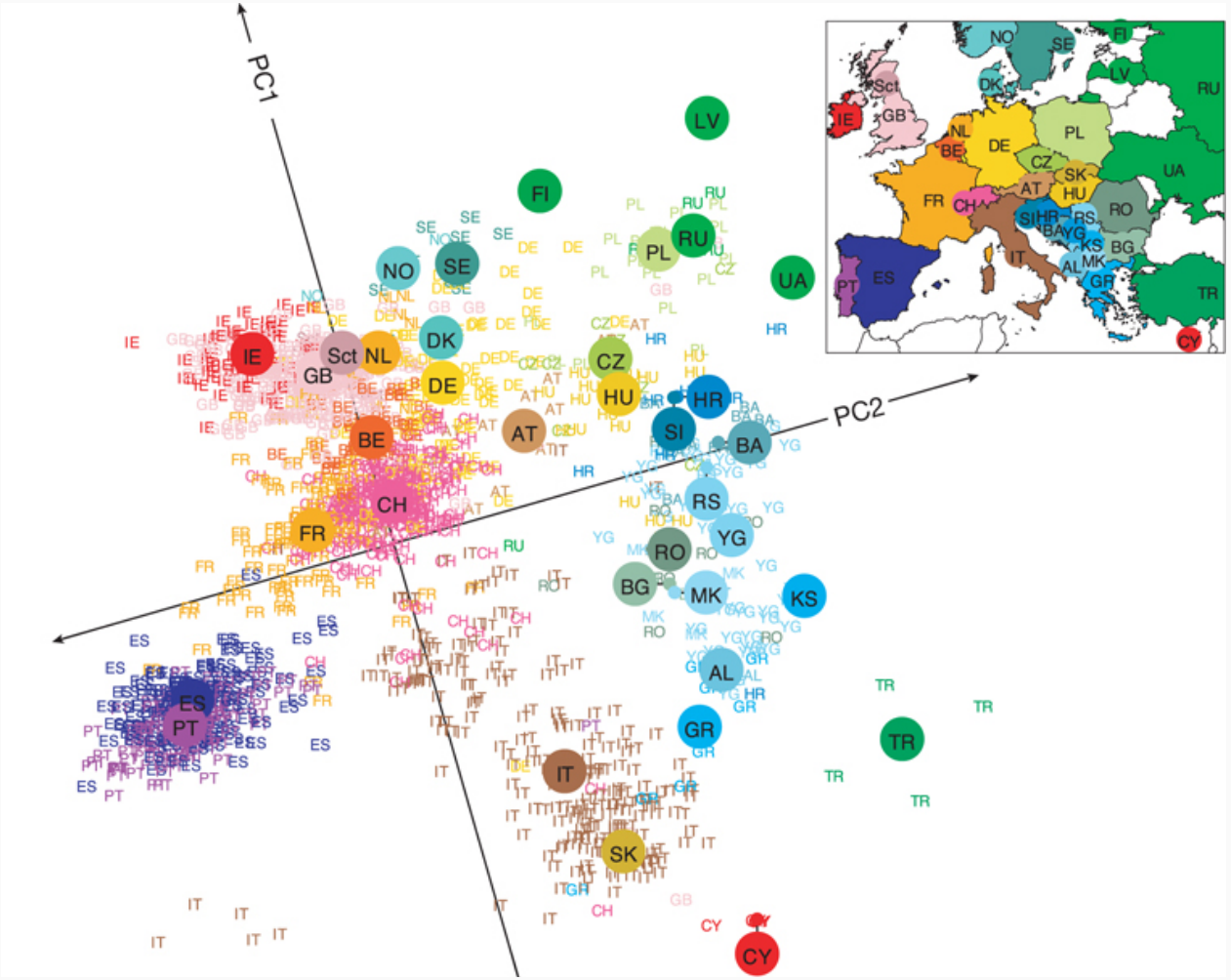
Training data has inputs $\mathbf{x}$ (numerical, categorical) as well as outputs y (target)

Regression: When the output is real-valued, *e.g.,* housing price

Classification: Output is a category

- Binary classification: only two classes *e.g.,* spam
- Multi-class classification: several classes *e.g.,* object detection

Unsupervised Learning : Genetic Data of European Populations

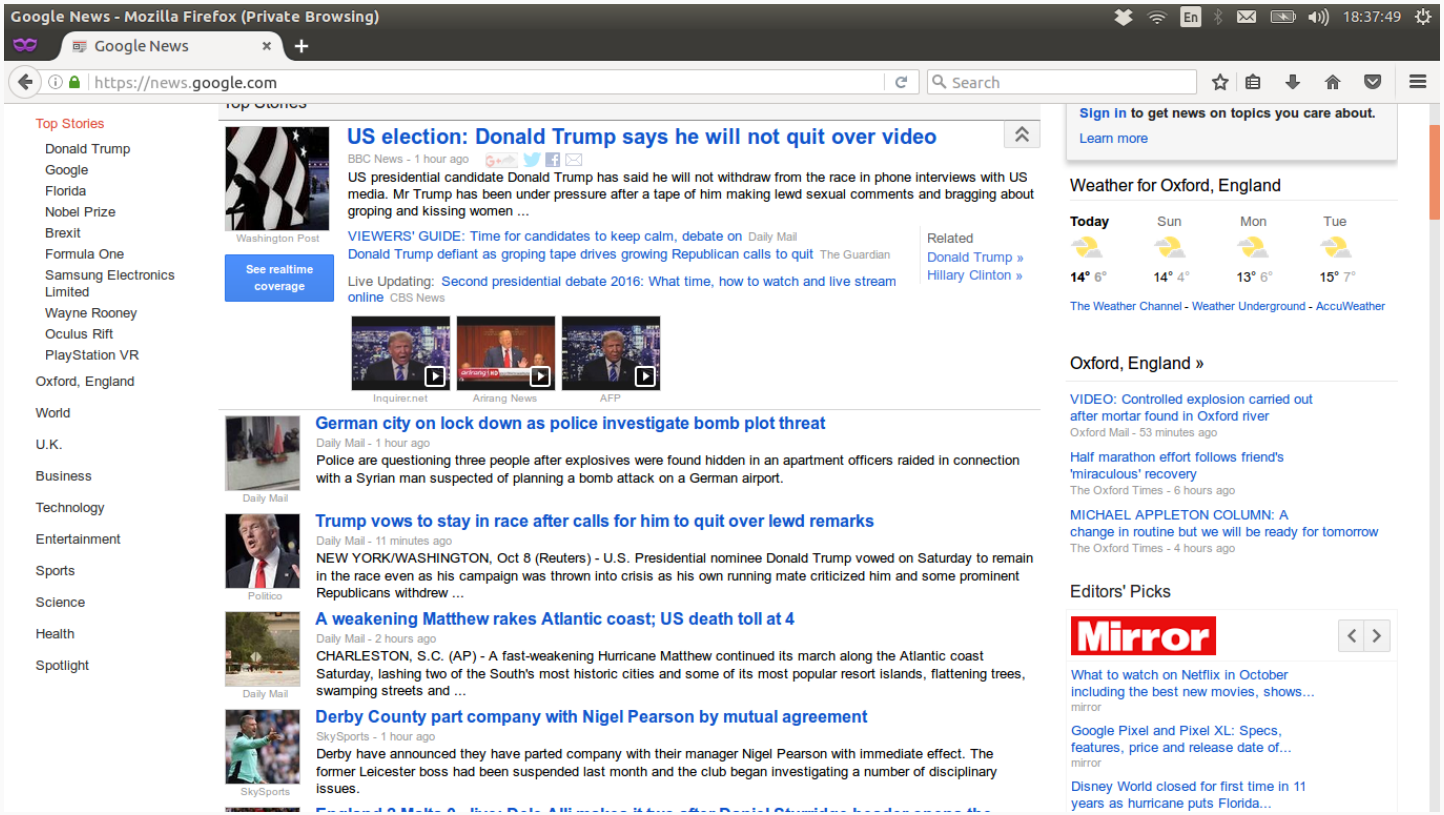


Source: Novembre *et al.*, Nature (2008)

Dimensionality reduction - Map high-dimensional data to low dimensions

Clustering - group together individuals with similar genomes

Unsupervised Learning : Group Similar News Articles



Group similar articles into categories such as politics, music, sport, *etc.*

In the dataset, there are no labels for the articles

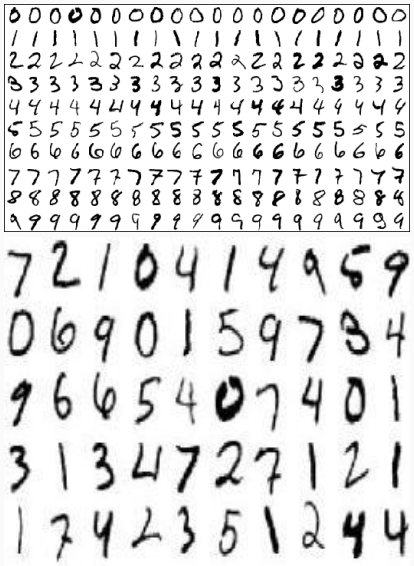
Active and Semi-Supervised Learning

Active Learning

- Initially all data is unlabelled
- Learning algorithm can ask a human to label some data

Semi-supervised Learning

- Limited labelled data, lots of unlabelled data
- How to use the two together to improve learning?



Collaborative Filtering : Recommender Systems

Movie / User	Alice	Bob	Charlie	Dean	Eve
The Shawshank Redemption	7	9	9	5	2
The Godfather	3	?	10	4	3
The Dark Knight	5	9	?	6	?
Pulp Fiction	?	5	?	?	10
Schindler's List	?	6	?	9	?

Netflix competition to predict user-ratings (2008-09)

Any individual user will not have used most products

Most products will have been use by some individual

Reinforcement Learning

- Automatic flying helicopter; self-driving cars
- Cannot conceivably program by hand
- Uncertain (stochastic) environment
- Must take sequential decisions
- Can define reward functions
- Fun: Playing Atari breakout!

  `https://www.youtube.com/watch?v=V1eYniJ0Rnk`

Cleaning up data

Spam Classification

- Look for words such as Nigeria, millions, Viagra, *etc.*
- Features such as the IP, other metadata
- If email addressed by to user personally

Getting Features

- Often hand-crafted features by domain experts
- In this course, we mainly assume that we already have features
- Feature learning using deep networks

Some pitfalls

Sample Email

"To build a spam classifier, we check if at least two words such as Nigeria, millions, *etc.* appear in the message. If that is the case, we mark the email as spam."

Training vs Test Data

- Future data should look like past data
- Not true for spam classification. Spammers will try adversarially to break the learning algorithm.

Cats vs Dogs