

# Machine Learning

## *An Overview*

Konstantin Todorov

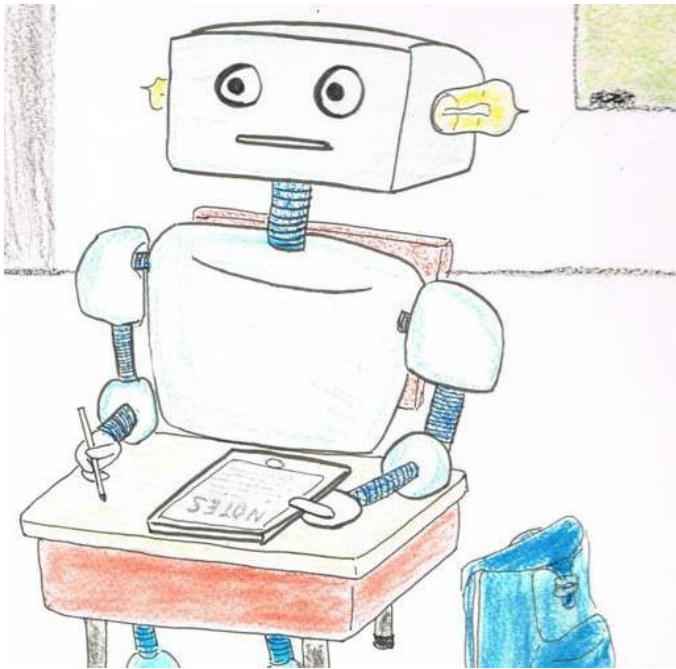


*Machine Learning Seminar*  
*February 2019*



# Machine Learning?

Could computers be made to *learn* and to *improve* automatically with experience?



Can we develop algorithms that can *learn from* and *make predictions* on *data*?

(Almost) like we humans do...

# *Defining the Machine Learning Problem*

# The Defining Question of ML

**How can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes?**



**Computer Science**

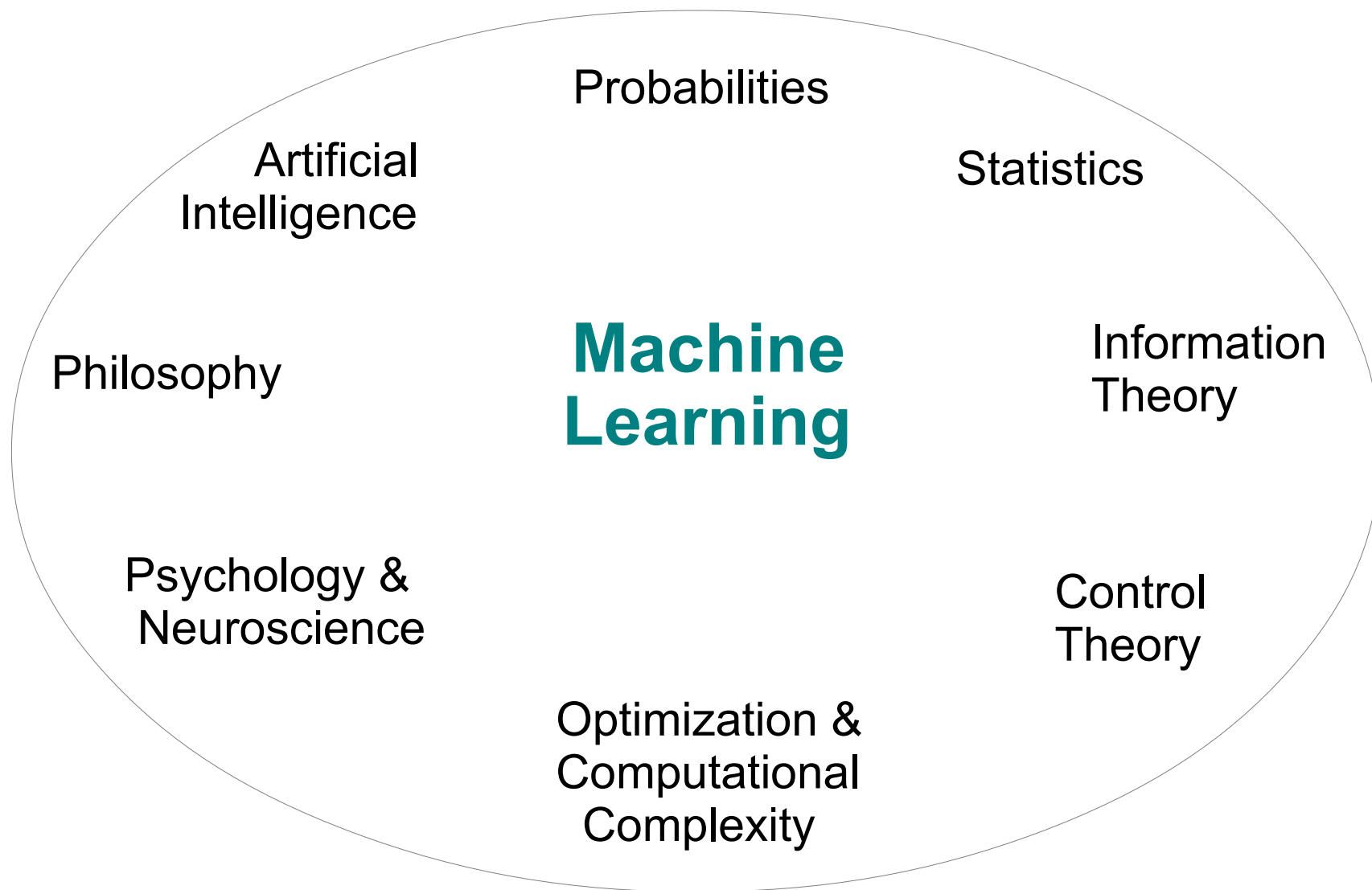
**How can we build machines that solve problems, and which problems are inherently tractable?**



**Statistics**

**What can be inferred from data and a set of modelling assumptions, with what reliability?**

# A Multidisciplinary Field



# A Definition of Machine Learning

“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**.”

– *Tom M. Mitchell*

- An operational, not a cognitive or an etymological definition
- A. Turing: *Can machines **think**?* →  
*Can machines **do** what thinking beings can do?*

Depending on how we define **T**, **P**, and **E**, the learning task might also be called by names such as *data mining*, *classification*, *clustering*, *reinforcement learning*, etc...

# A Definition of Machine Learning

## **An example: filtering spam from emails**

**T** **task**: decide whether an email is spam or not

**P** **performance measure**: the percent of correctly filtered emails

**E** **training experience**: a dataset of emails with associated classes (spam / email)

## ***A long list of applications...***

web page ranking, recommendation, automatic translation, autonomous cars, diagnostics, face recognition...

# A Brief History Line

18 <sup>th</sup> – 20 <sup>th</sup>	Advances in probability theory (Bayes, Markov Chains,...)
1950	<b>Turing</b> : a learning machine that can become <b>artificially intelligent</b>
1951	<b>Minsky</b> : first <b>neural network</b> (NN) machine
1957	<b>Rosenblatt</b> : the <b>perceptron</b>
1967	Pattern recognition with <b>nearest neighbours</b>
1960s	The rise and fall of the perceptron
1970s	AI winter, due to unrealised promises of AI research
1982	Recurrent <b>neural networks</b>
1986	<b>LeCun</b> : <b>back-propagation</b> reinvented
1989	<b>Reinforcement</b> learning
1990s	<b>Vapnik</b> and <b>Cortes</b> : <b>Support Vector Machines</b> shadow NN
2000s	NN regaining popularity due to advanced computational powers
2010s	Rapid acceleration of <b>Deep Learning</b> research

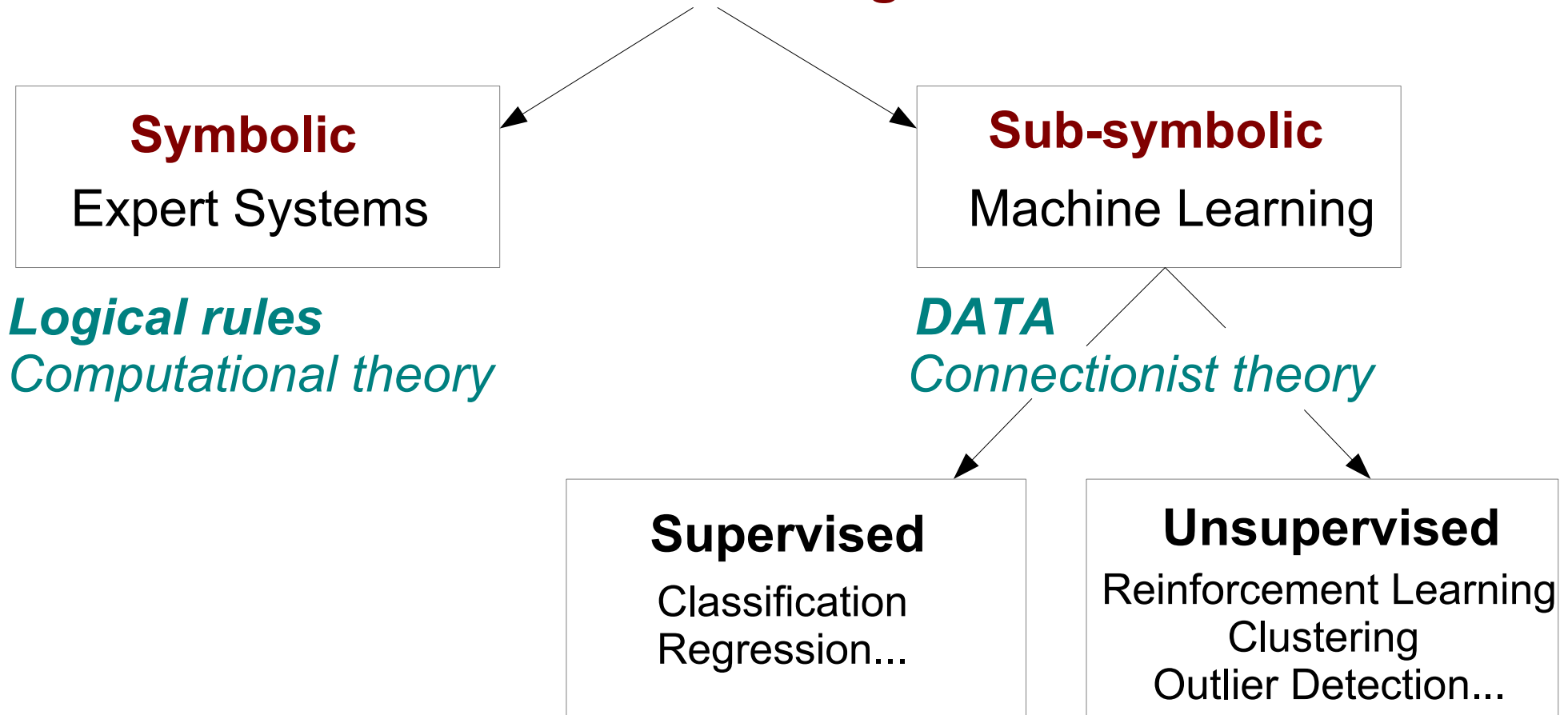


# *Kinds of Machine Learning*

# The Machine Learning Tasks

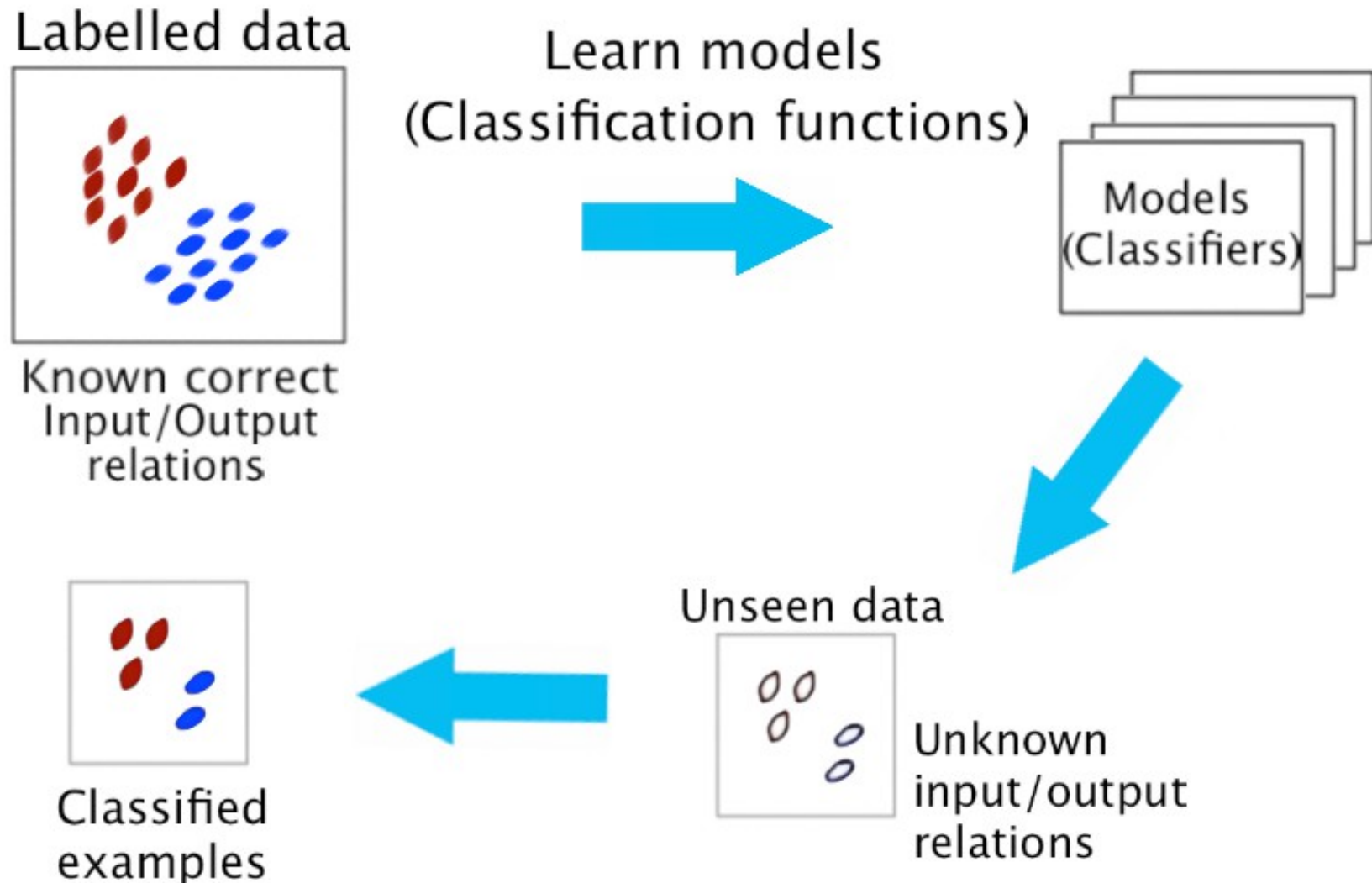
*(A vision of)*

## Artificial Intelligence



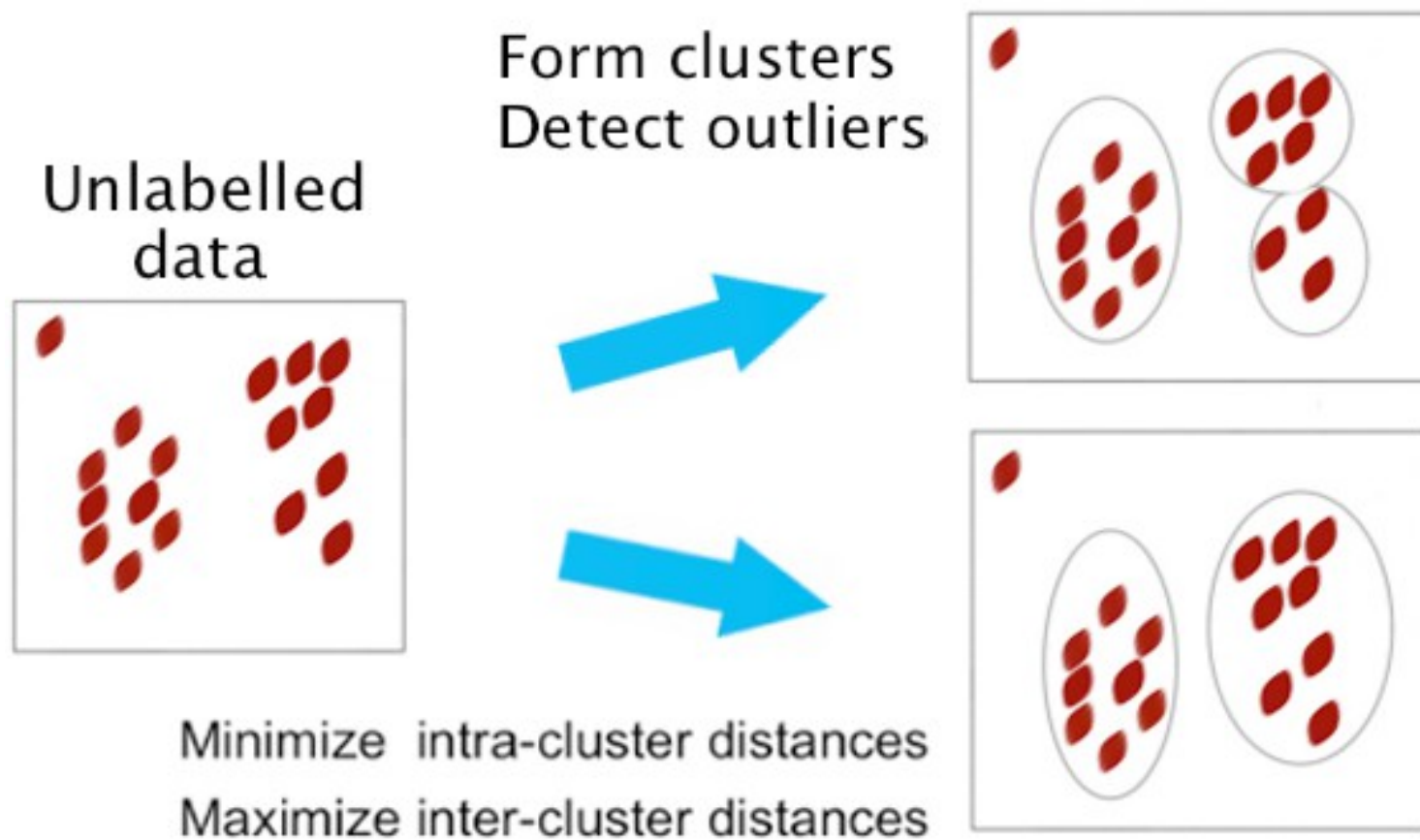
# Supervised Machine Learning

Infer input/output functions from *labelled* data.



# Unsupervised Machine Learning

Infer a latent structure from *unlabelled* data.

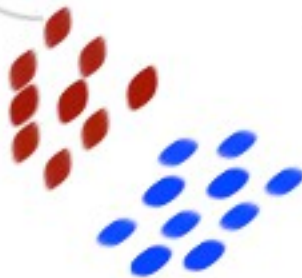


# Data Representation: Features

Remember our spam filtering example: data-points are emails.

term1	term2	...	termN	class
0.3	0.89	...	0.0	SPAM

term1	term2	...	termN	class
0.0	0.2	...	0.96	MAIL



Model instances as **vectors** described by a number of **features (variables, attributes)**.

What features best describe instances and allow to separate classes or form clusters? → **Feature (variable) selection**

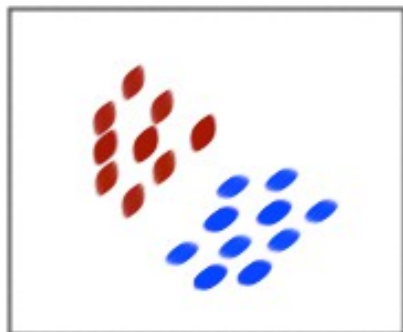
- remove **noisy** features
- analyse their **explanatory** strength
- reduce **dimensionality**

# Model Selection and Assessment

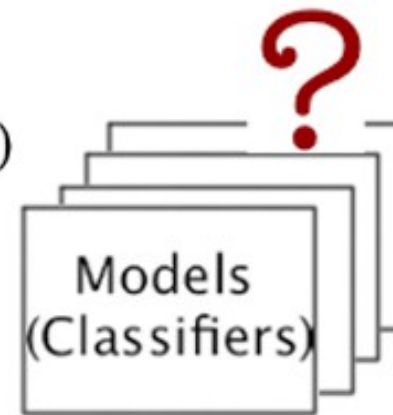
## Overfitting vs. Generalisation

- how well the learned function performs on *unseen* data?
- select a model (a set of parameters) that *generalises* well
- *evaluate* and avoid overfitting

Labeled Data



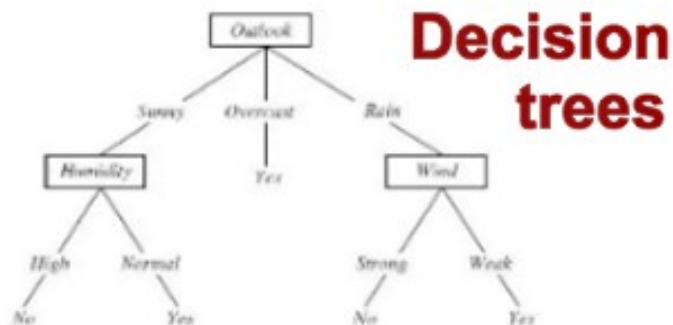
Learn Model  
(Classification Function)



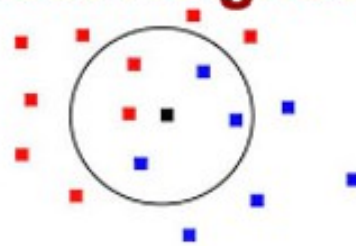
**Model Selection, Model Validation**

# *Methods, Tools and Applications (Examples)*

# Methods and Applications



## K Nearest Neighbours



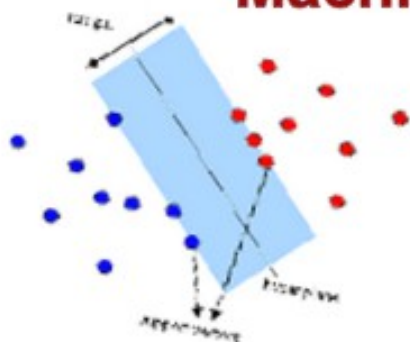
## Reinforcement Learning



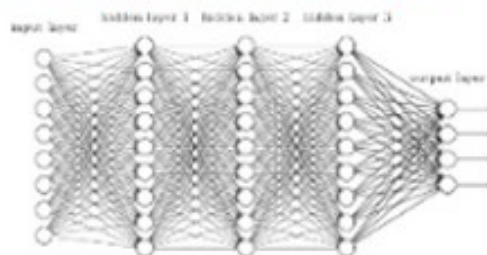
## Bayesian Classifiers

$$P(C | A) = \frac{P(A | C)P(C)}{P(A)}$$

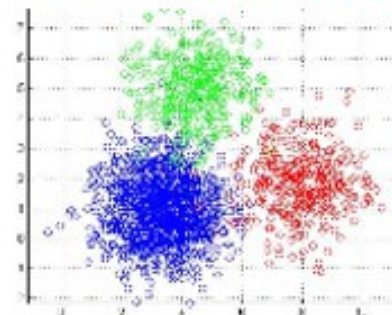
## Support Vector Machines



## Neural Networks / Deep Learning



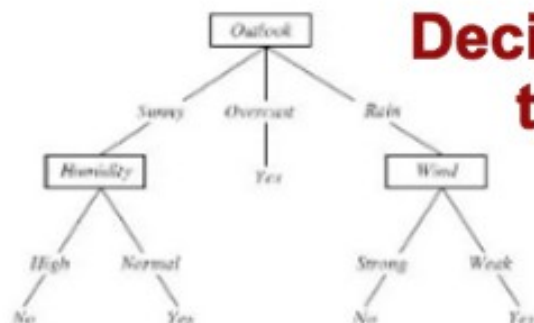
## Cluster Analysis





# Methods and Applications

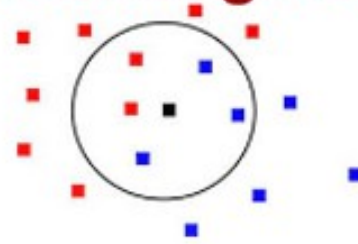
## Decision trees



Financial  
distress prediction  
Process control

Fraud detection  
Medical diagnosis

## K Nearest Neighbours



Robotics

Driving  
autonomous cars

Playing games

Trading strategies

Gene clustering

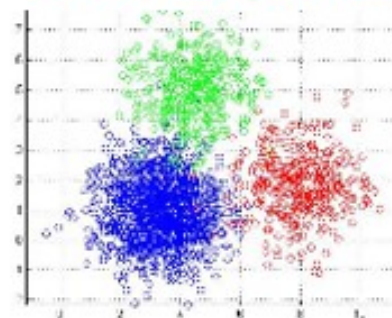
Topic discovery

Market segmentation

## Reinforcement Learning



## Cluster Analysis



## Bayesian Classifiers

$$P(C | A) = \frac{P(A | C)P(C)}{P(A)}$$

Text Categorization

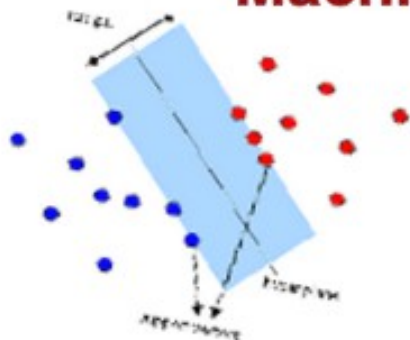
Automatic translation

Web search

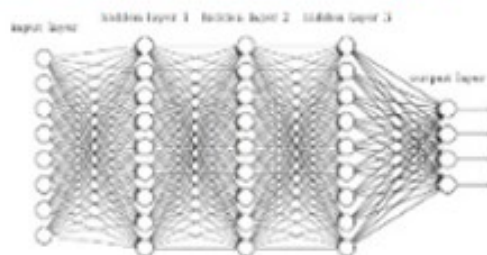
Computer vision

Image retrieval

## Support Vector Machines



## Neural Networks / Deep Learning



# Tools and Their Usefulness

A long list of open source tools...

**Weka, ELKI, R, Mahout, RapidMiner\*,...**

Often balckboxes for users.

- How to implement a given ML solution (which API)?  
*Algorithms don't change from one API to another...*
- What and how much data is needed? How to select a model?  
Which method for what problem?  
*An empirical science... with some heuristics.*
- How deep an understanding of the algorithms is required?  
*Investing in statistical inference:*
  - *hiring a statistician / data scientist, training engineers*

# Sources & Reading

Mitchell, T. M. (1997). *Machine learning*. WCB.

Mitchell, T. M. (2006). *The discipline of machine learning* (Vol. 9). Carnegie Mellon University, School of Computer Science, Machine Learning Department.

Alpaydin, E. (2014). *Introduction to machine learning*. MIT press.

Langley, P. (2011). The changing science of machine learning. *Machine Learning*, 82(3), 275-279.

Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1). Springer, Berlin: Springer series in statistics.

Joachims, T. (1998). Text categorization with support vector machines: Learning with many relevant features. In *European conference on machine learning* (pp. 137-142). Springer Berlin Heidelberg.

*Thank you for listening.*

# ML Methods and Applications

## Decision trees

### *Supervised / Classification*

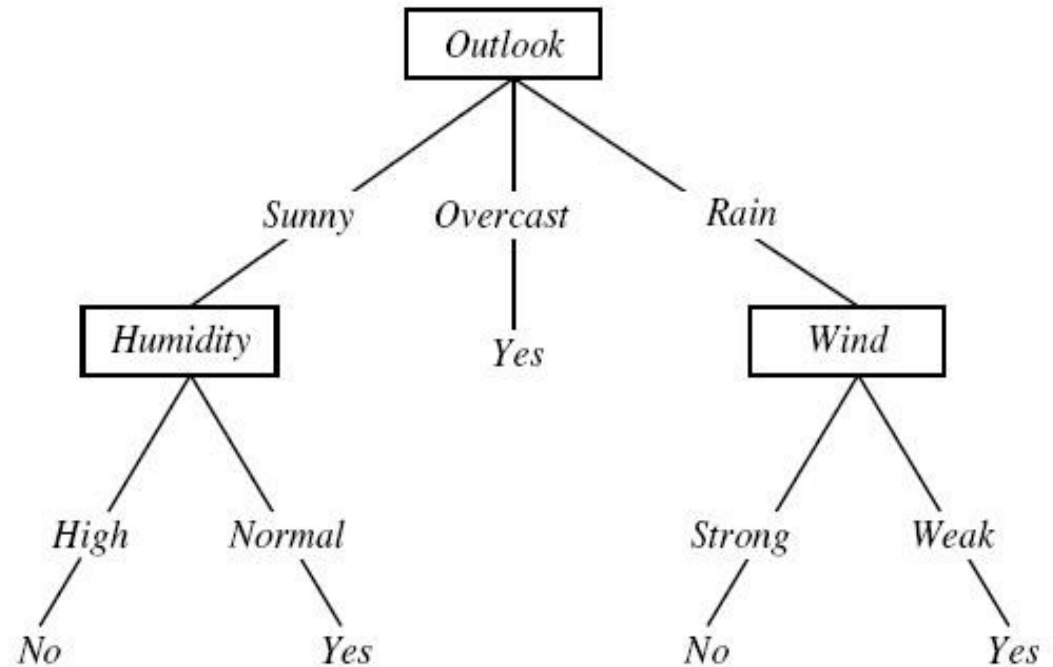
Fits data into a tree

Attributes → nodes

Values → branches

Easy to interpret

Overfitting occurs often



*From T. Mitchell's "Machine Learning"*

## Applications

Biomedical engineering: selecting features for implantable devices

Manufacturing, production: process control

Molecular biology: analyzing amino acid sequences

Fraud detection

# ML Methods and Applications

## Bayesian Classifiers

### *Supervised / Classification*

Creates a model per class, using probability theory.

Attributes are assumed independent.

Probabilities are estimated from data.

$$P(C | A) = \frac{P(A | C)P(C)}{P(A)}$$

## Applications

Text categorisation

Speech recognition

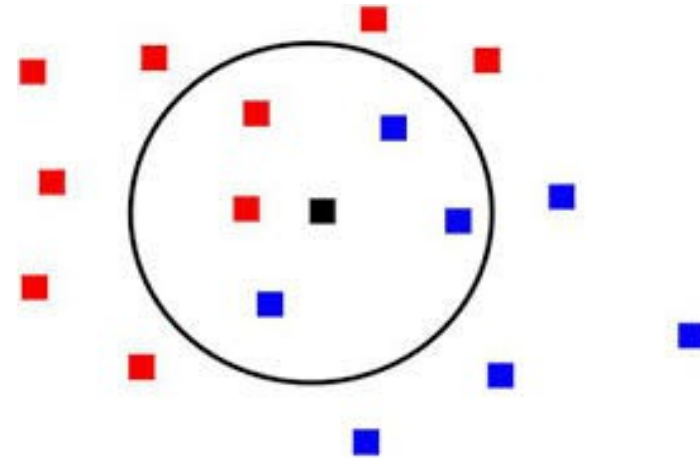
Automatic medical diagnosis

# ML Methods and Applications

## K Nearest Neighbours

### *Supervised / Classification*

Lazy instance-based learners.  
Uses distance calculation over  
all instance pairs.



## Applications

Cancer diagnosis  
Financial distress prediction  
Computer vision

# ML Methods and Applications

## Support Vector Machines

### *Supervised / Classification*

Learns a maximum margin separation hyperplan.

Deals with non-lineary separable data

Uses kernels

## Applications

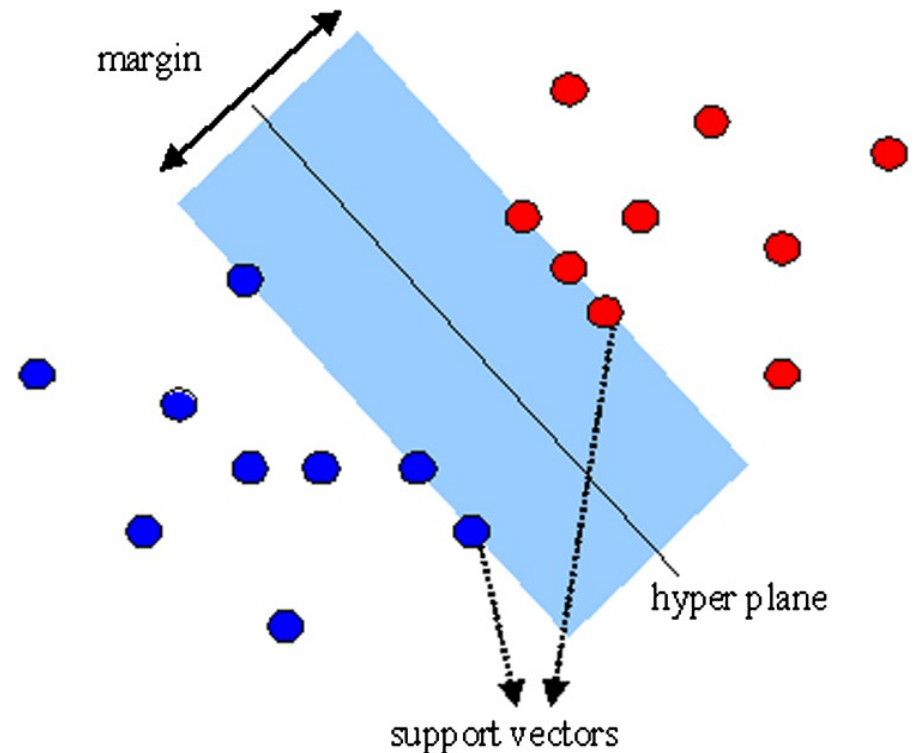
Text categorisation

Automatic translation

Computer vision

Handwriting / face / facial expression recognition

Content-based image retrieval



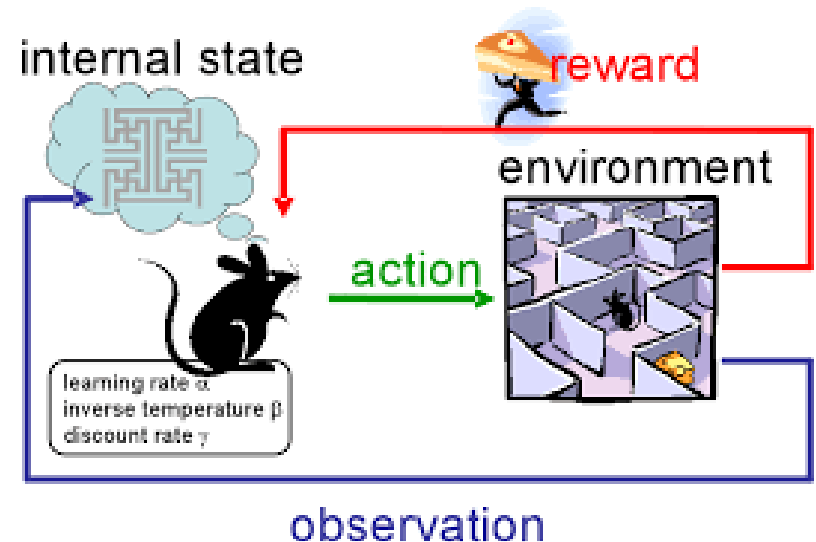


# ML Methods and Applications

## Reinforcement Learning

### *Unsupervised or Semi-supervised*

Take actions according to rewards.  
Behaviour optimisation with respect to the environment.



## Applications

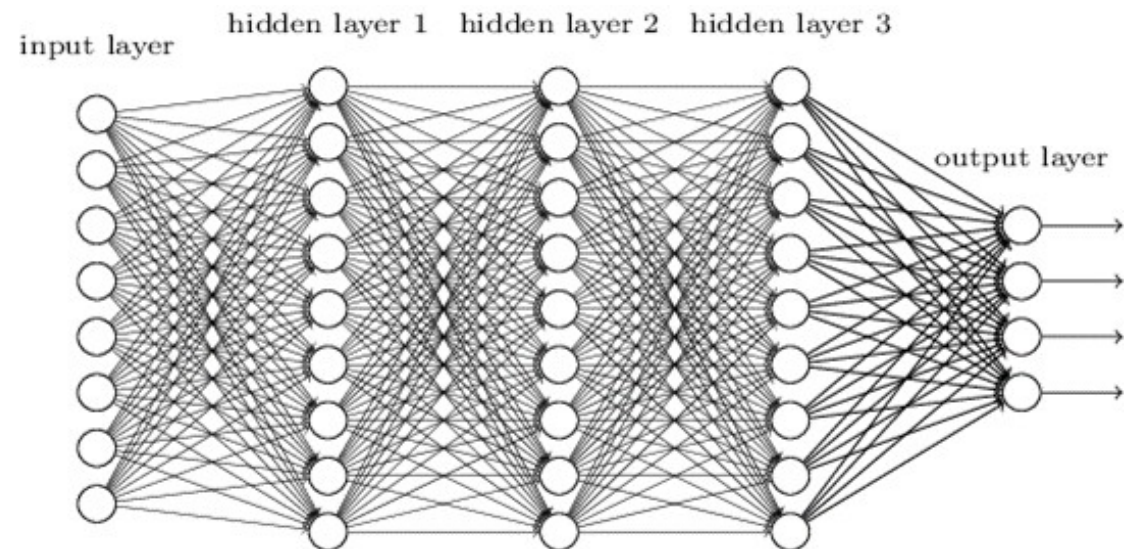
Driving autonomous vehicles  
Robot vision  
Playing games

# ML Methods and Applications

## Neural Networks / Deep Learning

### *Supervised and Unsupervised*

Bio-inspired: a complex net of interconnected neurones



## Applications

- Driving autonomous vehicles
- Computer vision
- Speech / face / handwriting recognition
- Sensor data interpretation
- Image retrieval

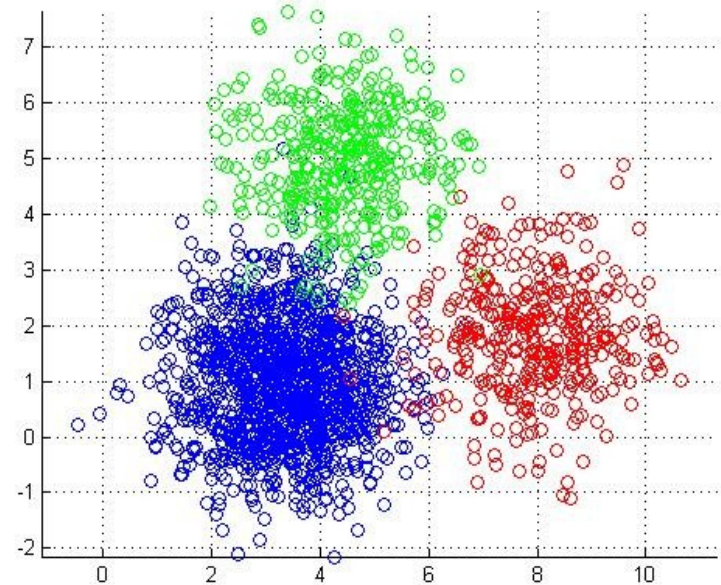
# ML Methods and Applications

## Cluster Analysis

### *Unsupervised / Clustering*

Group together instances into subsets  
Maximise intra-cluster instance  
similarities and inter-cluster distances.

K-means, DBSCAN,  
Descriptive Statistics, ...



## Applications

Market segmentation  
Gene clustering  
News summarisation  
Topic discovery