

# Machine Learning: Overview

September 25, 2017

# How (I guess) many people view Machine Learning



# Machine learning

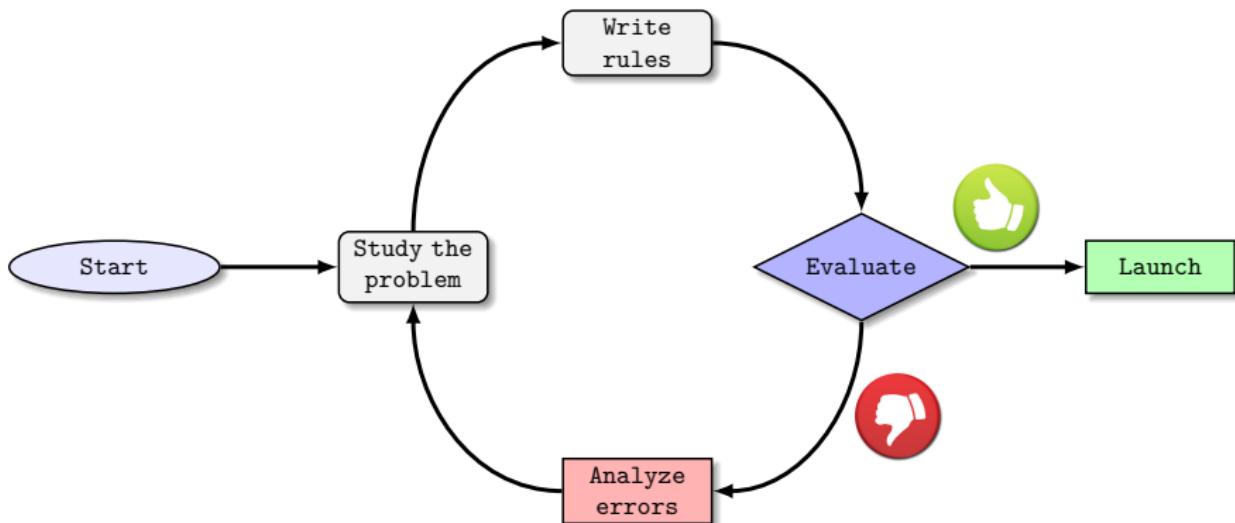
*[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed.*

- Arthur Lee Samuel, 1959

*A computer program is said to learn from experience  $E$  with respect to some task  $T$  and some performance  $P$ , if its performance on  $T$ , as measured by  $P$ , improves with experience  $E$ .*

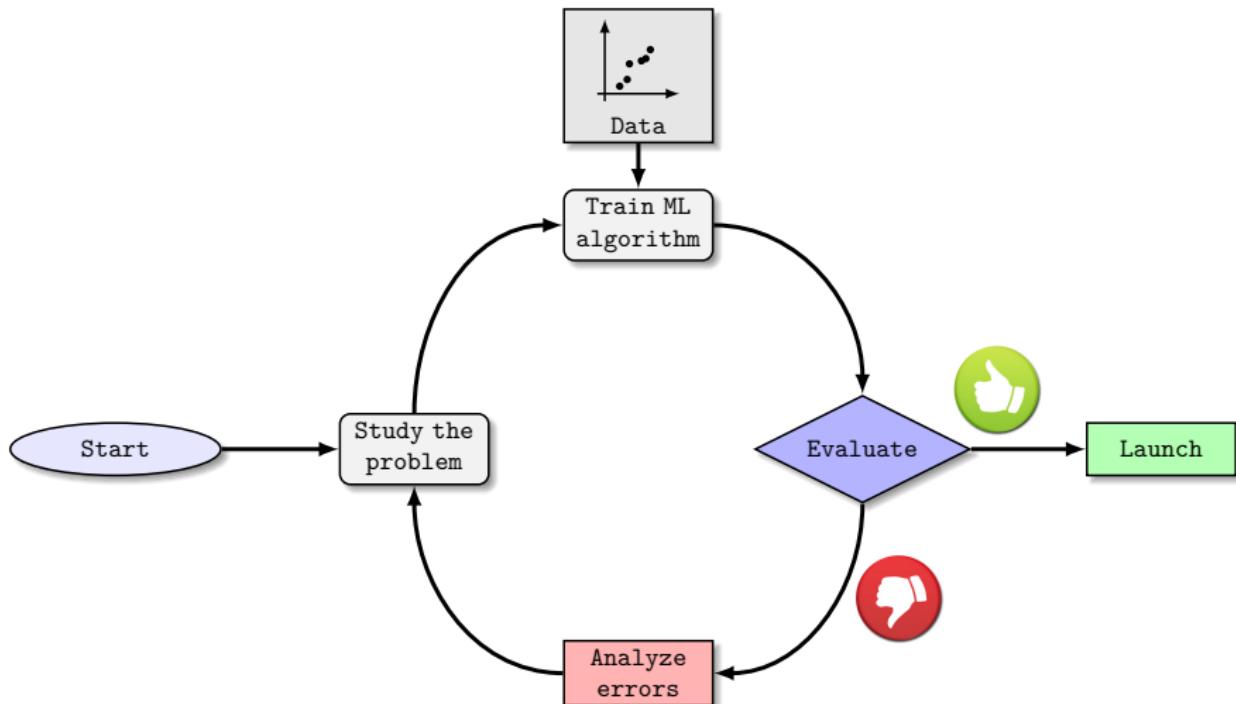
- Tom M. Mitchell, 1997

# Why do Machine Learning: Traditional approach



Writing general rules that cover every possibility can be hard!

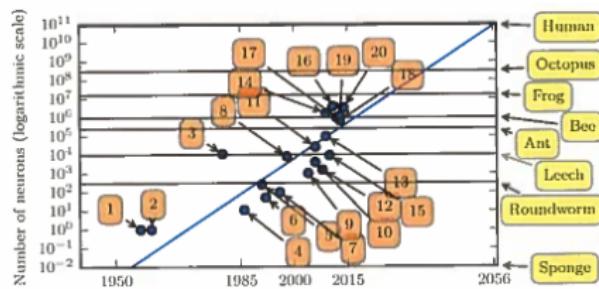
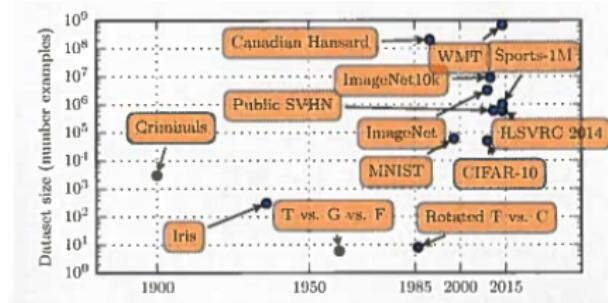
# Why do Machine Learning: Machine Learning approach



Do not write rules, instead let the machine figure it out!

# I've heard about ML since the 50's. Why now?

The **most** significant factor is increase in computing power!



*Rule of thumb:* A Machine Learning algorithm will achieve **acceptable performance** at 5000 examples, and **super-human performance** with at least 10 million examples.

# Big Data

The amount of data generated in the world increases each year.

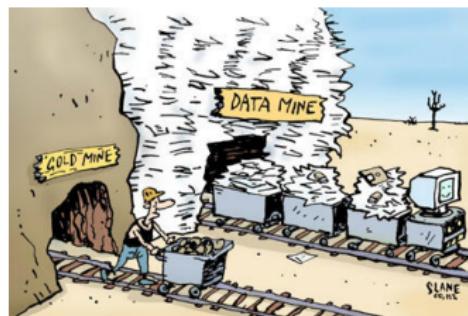
"90% of the worlds data has been generated in the last two years." (2013)

Data mining (Facebook, Google, etc.).

Machine learning is ideal for exploiting opportunities hidden in big data.

*We are drowning in information and starving for knowledge.*

- Rutherford D. Rogers



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"According to all the big data we've gathered,  
our discussions about big data are up 72%  
this year alone."

# Types of Machine Learning problems

## Unsupervised Learning

Learning from *unlabeled* data.

## Supervised Learning

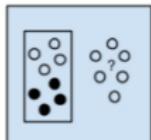
Learning from *labeled* data (examples).

## Semi-supervised Learning

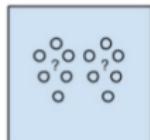
Combination of unsupervised and supervised learning.

## Reinforcement Learning

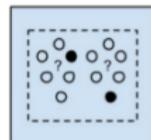
Learning from experience.



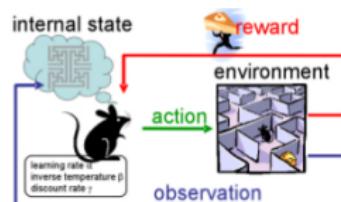
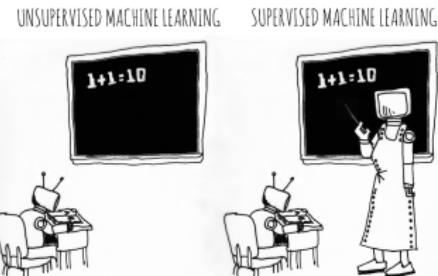
Supervised  
Learning



Unsupervised  
Learning



Semi-Supervised  
Learning



Reinforcement  
Learning

# Small Machine Learning (ML) dictionary

**Attribute:** A data type. For car data it might be, e.g. "Mileage".

**Feature:** Depends somewhat on context, but usually means *attribute plus value*, e.g. "Mileage = 15.000".

**Instance:** A collection of all *features* for a single data point.

**Predictors:** *Features* that you want use for predictions on new *instances*.

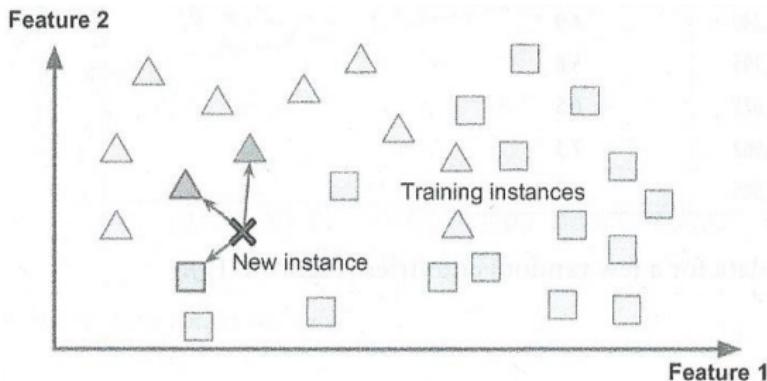
**Label:** Desired output given input.



# Instance-based learning

**Instance- or memory** based learning compares new problem instances with instances seen in training.

Learning by heart.

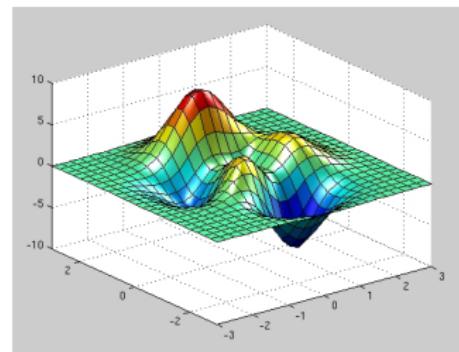
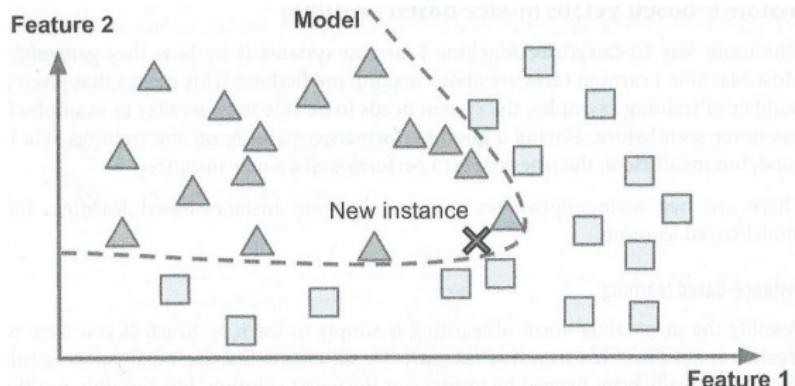


# Model based learning

Build a model from examples, and use the model to make predictions.

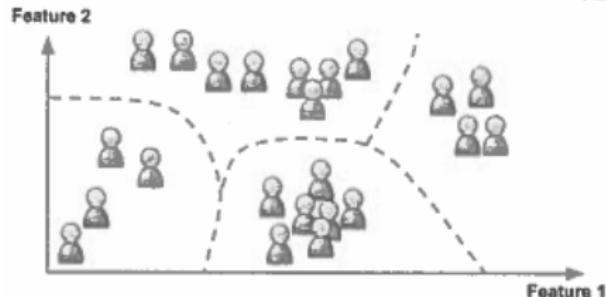
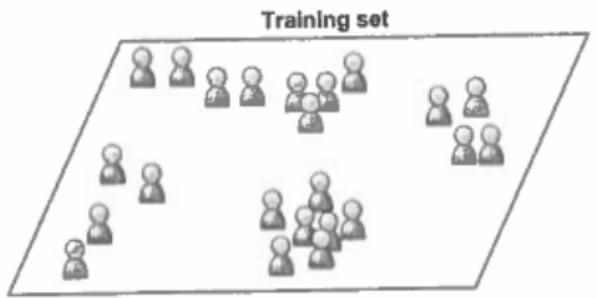
Specific instances in the training are not used to compare against!

Depending on the model training might be a multidimensional  
**optimization** problem!



# Unsupervised learning

Unsupervised learning works with **unlabeled data**.

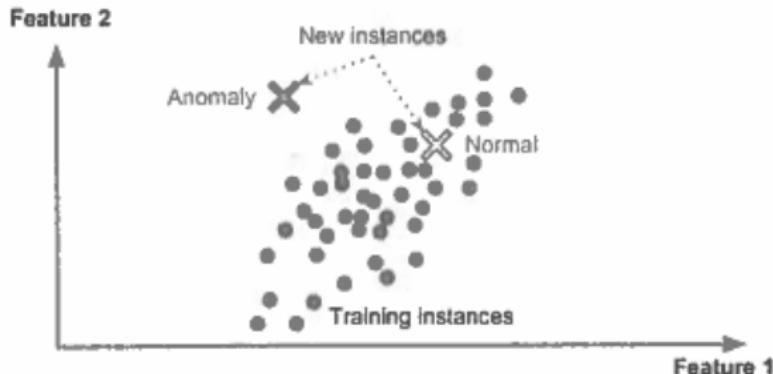


Typical use is **Clustering**.

Example: Users of a homepage, who is visiting?

# Unsupervised learning: Continued

Also used for **Anomaly detection**.



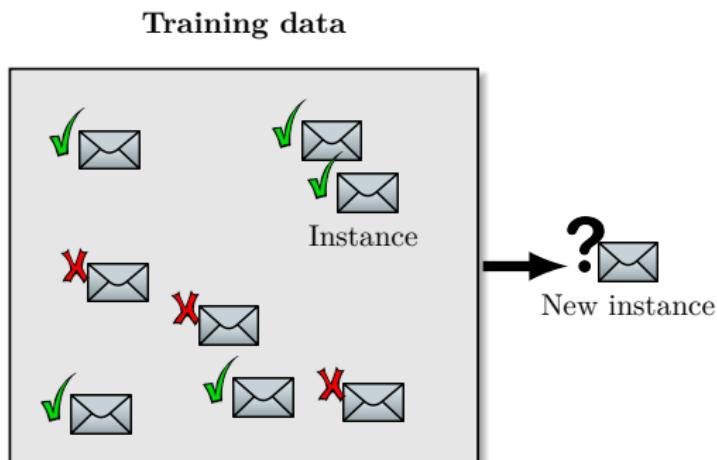
Some unsupervised learning methods:

k-Means (Clustering)

Principal Component Analysis (Visualization, Dimensionality reduction, Feature extraction)

# Supervised learning

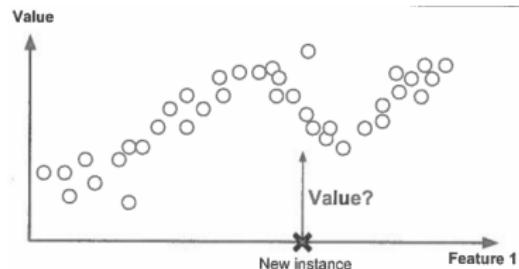
Supervised learning works with **labeled data**, i.e. some input accompanied by desired output.



Typical task is **classification**, e.g. classify an email as spam or ham.

Predict a **target** numeric value, given a set of **features** called **predictors** (Regression).

# Supervised Learning: Continued



Some supervised learning algorithms:

k-Nearest Neighbours

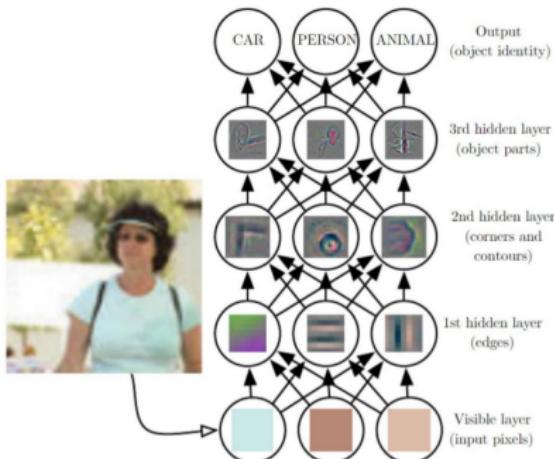
Linear Regression

Support Vector Machines (SVMs)

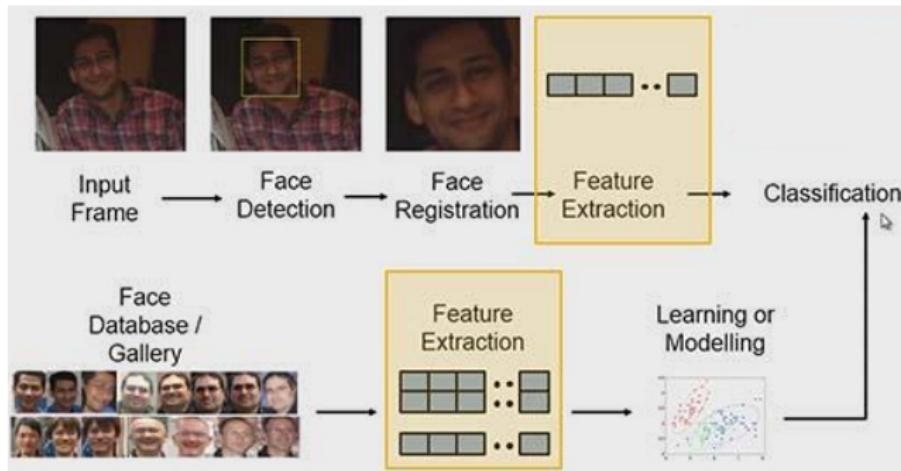
GPR

Neural Networks

Etc., etc., etc, ...



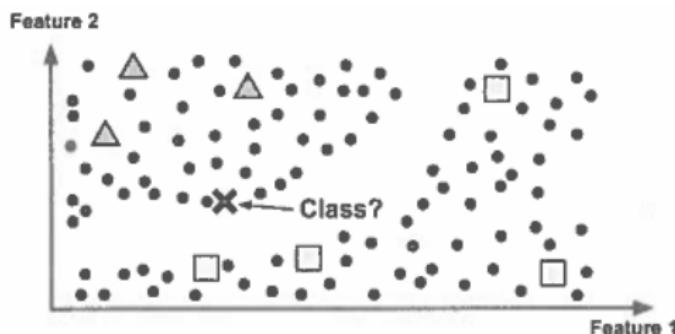
# Example: Facial recognition



# Semi-supervised learning

Semi-supervised learning deals with labeled and unlabeled data.

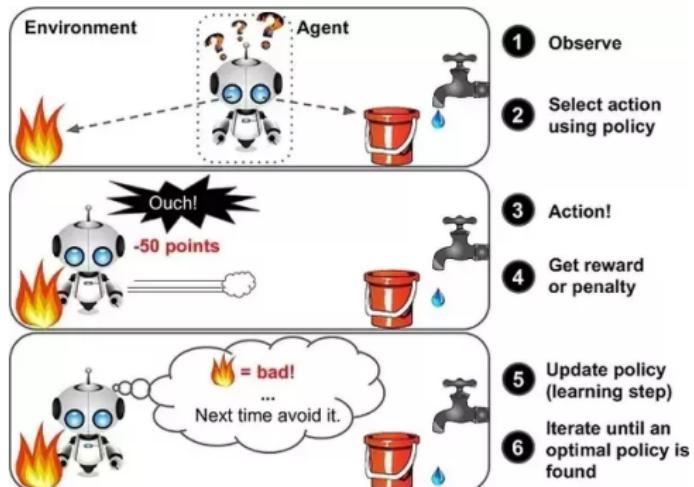
Most algorithms are combinations of supervised and unsupervised learning algorithms.



A semi-supervised algorithm could be a *Deep belief network*.

# Reinforcement learning

Reinforcement learning is learning by **experience**.



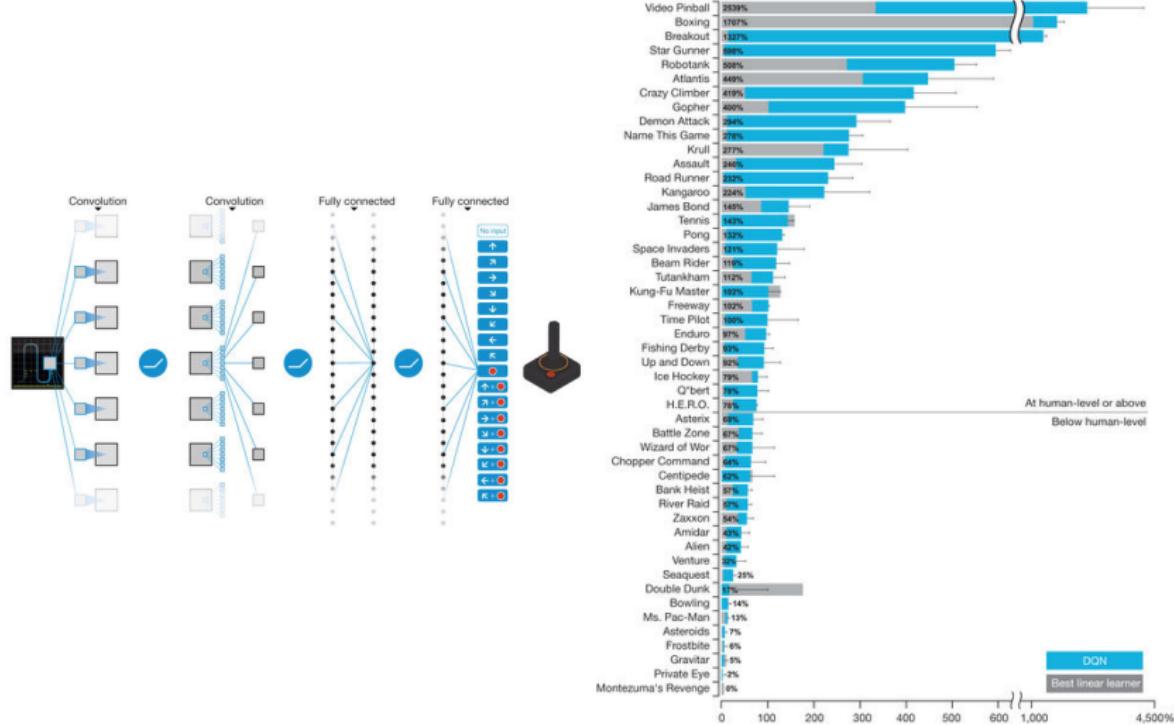
Some reinforcement learning algorithms:

Q-learning (Q-networks)

Genetic algorithms

# Yo dawg, I heard you like computers...

... so I taught your computer to use the computer! (Q-Learning)



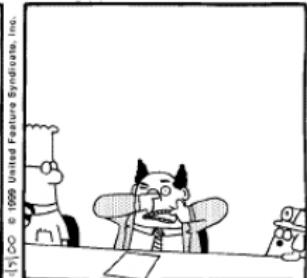
Lets have a look:

[Link](#)

## Example: Self-driving cars



# Correlation doesn't mean causation!



"The machine learning algorithm wants to know if we'd like a dozen wireless mice to feed the Python book we just bought."

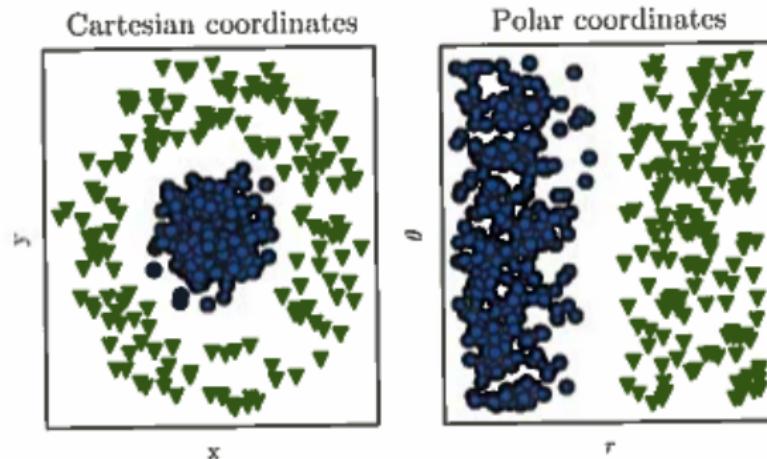


"You can't keep adjusting the data to prove that you would be the best Valentine's date for Scarlett Johansson."

# Representation of Data

Tasks may be **impossible** in one representation, but **easy** in another.

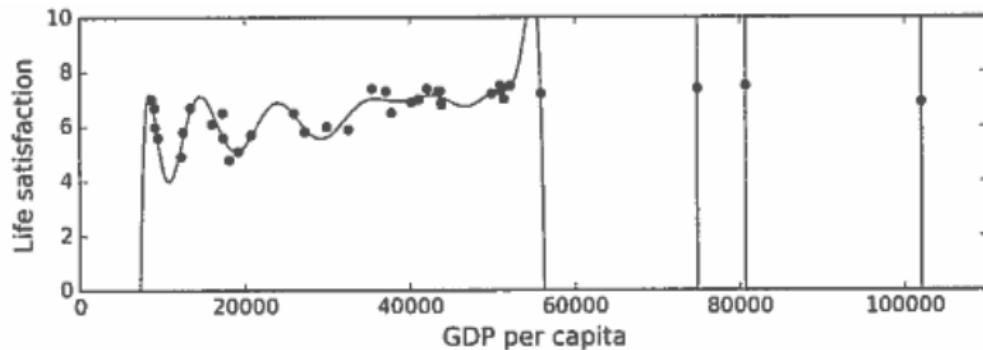
Can you draw a straight line separating the two categories?



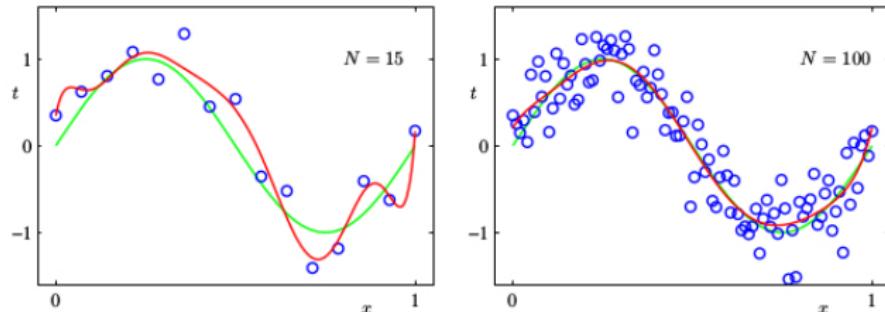
It is crucially important which **features** to use in the model.

# Overfitting

If the model has too much freedom, overfitting can occur.



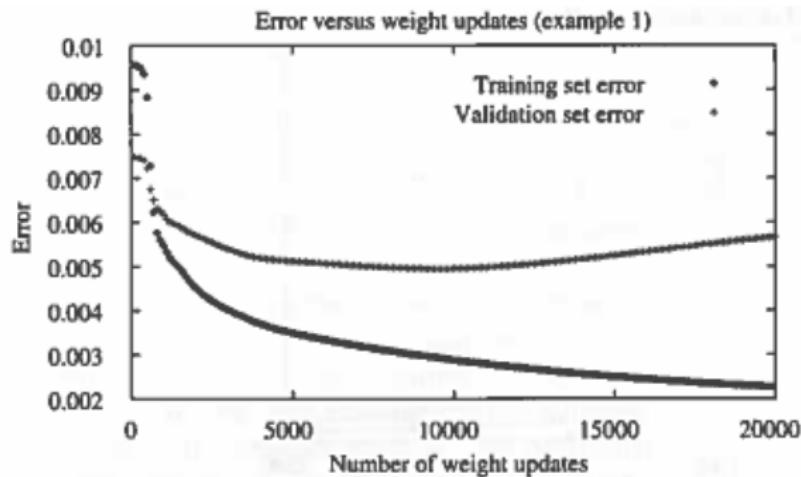
This can be mitigated somewhat by large data sets.



## Bias towards training data

Be careful to have a broad spectrum of training data.

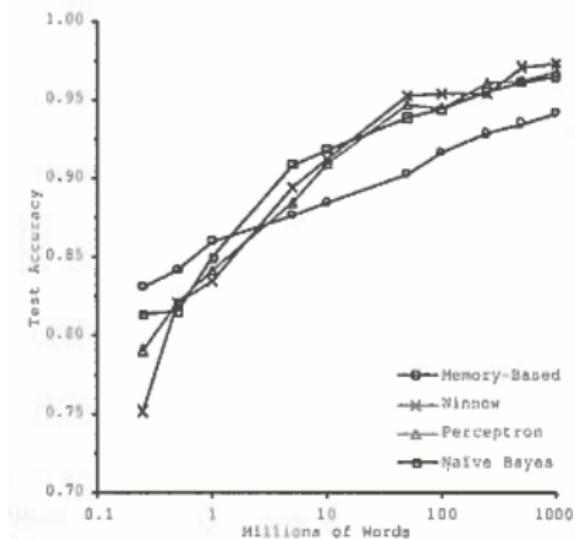
Some algorithms can be overtrained to idiosyncrasies of the training data.



Be sure to validate your model!

## Needs lots of data

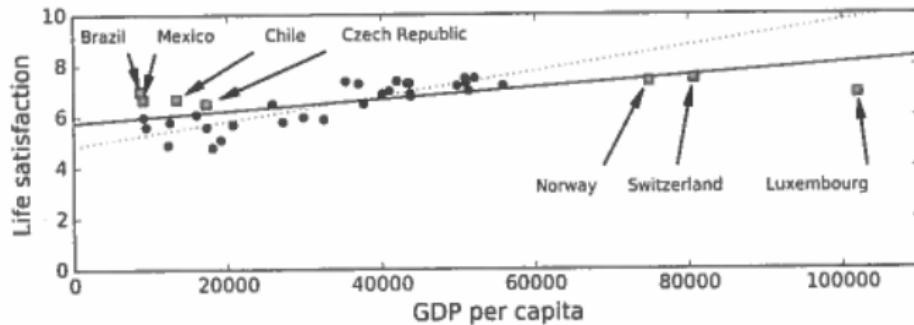
Actually, having the right (amount of) data is often more important than having the right model.



*"Data is ten times more powerful than algorithms"*  
- Peter Norvig

# Quality of data

Use data that is **representative** of the problem you want to model.



Poor data quality: clean out **noise** and **outliers**.

Apply **feature engineering**:

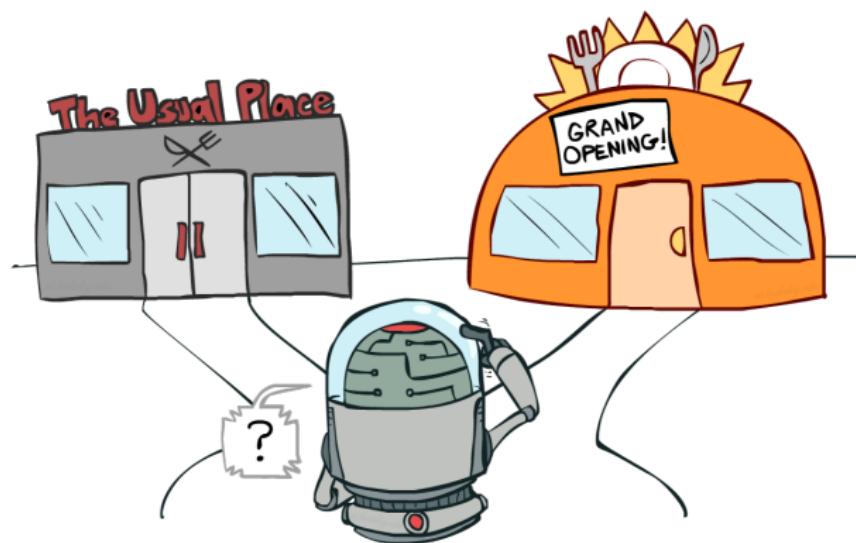
*Feature selection:* Select the most important features.

*Feature extraction:* Combine features to produce more useful ones.

# Reinforcement learning: Exploration VS Exploitation

**Exploitation:** Make *best decision* given current information.

**Exploration:** gather *more information*.



# No Free Lunch

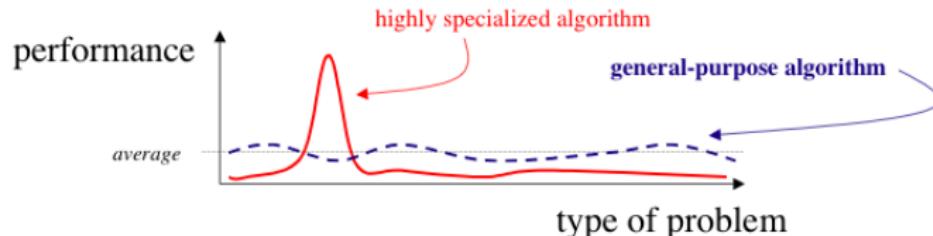
*"No Free Lunch"*

- David H. Wolpert

A model is a simplification of reality.

Simplification is based on assumption.

Assumptions **always** fail in certain situations.



**No one model works best in all possible situations.**

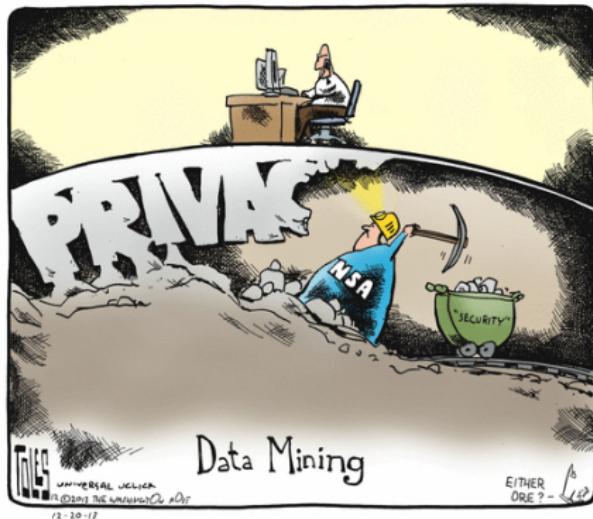
# Social and ethical aspects

## Cathy O'Neil: The era of blind faith in big data must end



Algorithms decide who gets a loan, who gets a job interview, who gets insurance and much more -- but they don't automatically make things fair. Mathematician and data scientist Cathy O'Neil coined a term for algorithms that are secret, important and harmful: "weapons of math destruction." Learn more about the hidden agendas behind the formulas.

[http://www.ted.com/talks/cathy\\_o\\_neil\\_the\\_era\\_of\\_blind\\_faith\\_in\\_big\\_data\\_must\\_end](http://www.ted.com/talks/cathy_o_neil_the_era_of_blind_faith_in_big_data_must_end)



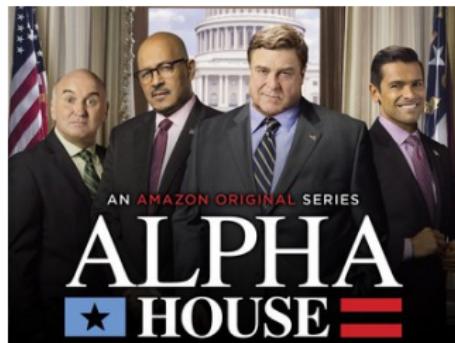
# MAGIC?!

Just feed in the data and watch the computer magically figure out the equation that fits the data!

**But**, it's important to remember that machine learning only works if the problem is actually solvable with **the data that you have**.

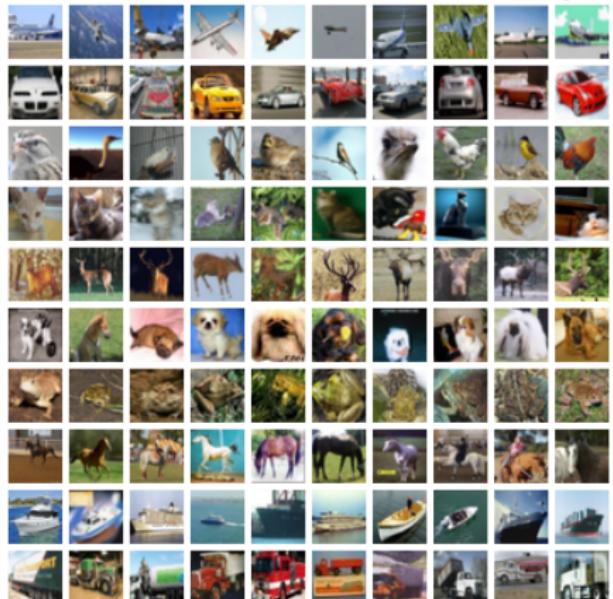
**Remember**, if a human expert couldn't use the data to solve the problem manually, a computer probably won't be able to either.

**Focus** on problems where a human could solve the problem, but where it would be great if a computer could solve it much more quickly.



# Test data bases: MNIST and CIFAR-10

|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 8 | 9 | 0 | 1 | 2 | 3 | 4 | 7 | 8 | 9 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 6 |
| 4 | 2 | 6 | 4 | 7 | 5 | 5 | 4 | 7 | 8 | 9 | 2 | 4 | 3 | 9 | 3 | 8 | 2 | 0 | 5 |
| 0 | 7 | 6 | 4 | 2 | 6 | 5 | 3 | 5 | 3 | 8 | 0 | 0 | 3 | 4 | 1 | 5 | 3 | 0 | 8 |
| 3 | 0 | 6 | 2 | 7 | 1 | 1 | 8 | 1 | 7 | 1 | 3 | 8 | 9 | 7 | 6 | 7 | 4 | 1 | 6 |
| 7 | 5 | 1 | 7 | 1 | 9 | 8 | 0 | 6 | 9 | 4 | 9 | 9 | 3 | 7 | 1 | 9 | 2 | 2 | 5 |
| 3 | 7 | 8 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 0 |
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| 3 | 8 | 4 | 7 | 7 | 8 | 5 | 0 | 6 | 5 | 5 | 3 | 3 | 3 | 9 | 8 | 1 | 4 | 0 | 6 |
| 1 | 0 | 0 | 6 | 2 | 1 | 1 | 3 | 2 | 8 | 8 | 7 | 8 | 4 | 6 | 0 | 2 | 0 | 3 | 6 |
| 8 | 7 | 1 | 5 | 9 | 9 | 3 | 2 | 4 | 9 | 4 | 6 | 5 | 3 | 2 | 4 | 5 | 9 | 4 | 1 |
| 6 | 5 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 8 | 9 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 6 | 4 | 2 | 6 | 4 | 7 | 5 | 5 |
| 4 | 7 | 8 | 9 | 2 | 9 | 3 | 9 | 3 | 8 | 2 | 0 | 9 | 8 | 0 | 5 | 6 | 0 | 1 | 0 |
| 4 | 4 | 2 | 6 | 5 | 5 | 5 | 4 | 3 | 4 | 1 | 5 | 3 | 0 | 8 | 3 | 0 | 6 | 2 | 7 |
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| 7 | 7 | 5 | 1 | 2 | 6 | 7 | 1 | 9 | 8 | 0 | 6 | 9 | 4 | 9 | 9 | 6 | 2 | 3 | 7 |
| 9 | 9 | 2 | 2 | 5 | 3 | 7 | 8 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 0 | 1 | 2 |
| 4 | 4 | 5 | 6 | 7 | 8 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 0 | 1 | 2 | 1 |
| 9 | 9 | 8 | 5 | 3 | 7 | 0 | 7 | 7 | 5 | 7 | 9 | 9 | 4 | 7 | 0 | 3 | 4 | 1 | 4 |
| 4 | 4 | 7 | 5 | 8 | 1 | 4 | 8 | 4 | 1 | 8 | 6 | 6 | 4 | 6 | 3 | 5 | 7 | 2 | 5 |
| 9 | 9 | 8 | 5 | 3 | 7 | 0 | 7 | 7 | 5 | 7 | 9 | 9 | 4 | 7 | 0 | 3 | 4 | 1 | 4 |



# Other resources: TED

Screenshot of a web browser showing the TED website search results for "machine learning".

The search bar contains "machine learning". Below it, the results are displayed under the heading "All results". There are 1 - 12 of 89 results.

**Playlist: What are we really teaching AI? (6 talks)**

A thumbnail image shows a blue and white abstract graphic. Description: "A glimpse inside what we're teaching artificially intelligent machines and a cautionary tale of what could happen if we get it wrong." Curated by TED. [http://www.ted.com/playlists/what\\_are\\_we\\_really\\_teaching\\_ai](http://www.ted.com/playlists/what_are_we_really_teaching_ai)

**Jeremy Howard: The wonderful and terrifying implications of computers that can learn**

A thumbnail image shows a man speaking at a podium. Description: "What happens when we teach a computer how to learn? Technologist Jeremy Howard shares some surprising new developments in the fast-moving field of deep learning, a technique that can give computers the ability to learn Chinese, or to recognize objects in photos, or to help think through a medical diagnosis. (One deep learning tool, after watchin..." [http://www.ted.com/talks/jeremy\\_howard\\_the\\_wonderful\\_and\\_terrifying\\_implications\\_of\\_computers\\_that\\_can\\_learn](http://www.ted.com/talks/jeremy_howard_the_wonderful_and_terrifying_implications_of_computers_that_can_learn)

**Nick Bostrom: What happens when our computers get smarter than we are?**

A thumbnail image shows a man speaking at a podium. Description: "Artificial intelligence is getting smarter by leaps and bounds – within this century, research suggests, a computer AI could be as "smart" as a human being. And then, says Nick Bostrom, it will overtake us: "Machine intelligence is the last invention that humanity will ever need to make." A philosopher and technologist, Bostrom asks us to think..." [http://www.ted.com/talks/nick\\_bostrom\\_what\\_happens\\_when\\_our\\_computers\\_get\\_smarter\\_than\\_we\\_are](http://www.ted.com/talks/nick_bostrom_what_happens_when_our_computers_get_smarter_than_we_are)

**Shyam Sankar: The rise of human-computer cooperation**

A thumbnail image shows a man speaking. Description: "Brute computing force alone can't solve the world's problems. Data mining innovator Shyam Sankar explains why solving big problems (like catching terrorists or identifying huge hidden trends) is not a question of finding the right algorithm, but rather the right symbiotic relationship between computation and human creativity." [http://www.ted.com/talks/shyam\\_sankar\\_the\\_rise\\_of\\_human\\_computer\\_cooperation](http://www.ted.com/talks/shyam_sankar_the_rise_of_human_computer_cooperation)

**Mehdi Ordikhani-Seyedlar: What happens in your brain when you pay attention?**

A thumbnail image shows a person's face. Description: "Attention isn't just about what we focus on -- it's also about what our brains filter out. By investigating..." [http://www.ted.com/talks/mehdi\\_ordikhani-seyedlar\\_what\\_happens\\_in\\_your\\_brain\\_when\\_you\\_pay\\_attention](#)

## Final note

*"I propose to consider the question 'Can machines think?'".*  
- Alan Turing, 1950