Machine Learning & Applications

IT3011

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Where Does Knowledge Come From?

Evolution

Culture

Experience

Computers

NUS National University of Singapore

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"Most of the knowledge in the world in the future is going to be extracted by machines and will reside in machines."

Yann LeCun, Director of AI Research, Facebook

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Knowledge Discovery by Computers

- Fill in gaps in existing knowledge
- Emulate the brain
- Simulate evolution
- Systematically reduce uncertainty
- Notice similarities between old and new

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5 Tribes of ML

5 Tribes of Machine Learning

Tribe	Origins	Algorithm
Symbolists	Logic, Philosophy	Inverse deduction
Connectionists	Neuroscience	Backpropagation
Evolutionaries	Evolutionary biology	Genetic programming
Bayesians	Statistics	Probabilistic inference
Analogizers	Psychology	Support vector machines

Symbolists

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Inverse Deduction

Addition	Subtraction
1	1
+ 1	+ ?
= ?	= 2

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Inverse Deduction (Induction)

Deduction	Induction
Socrates is human	Socrates is human
+ Humans are mortal	+ ?
= ?	= Socrates is mortal

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Robot Scientist (Drug Discovery)

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Connectionists

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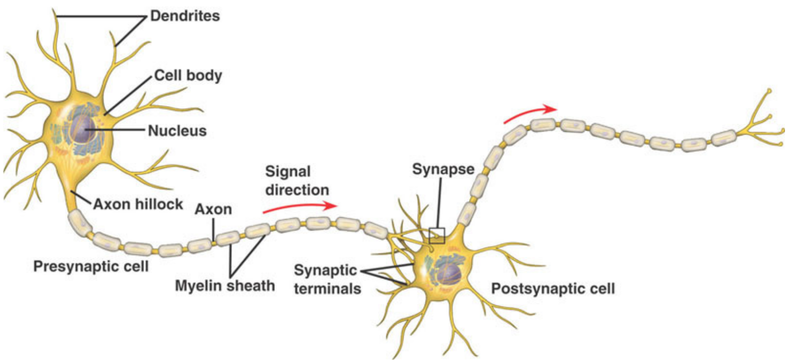
Neuron



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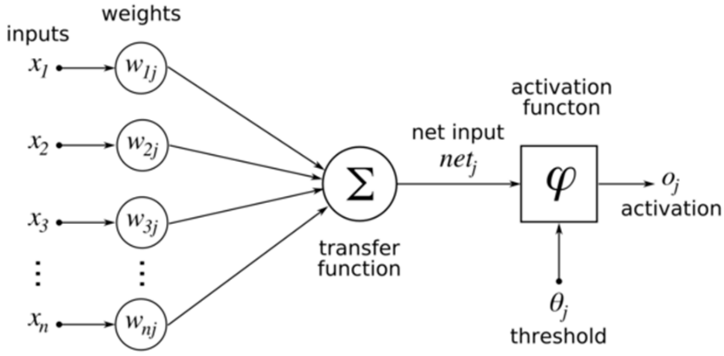
Artificial Neuron



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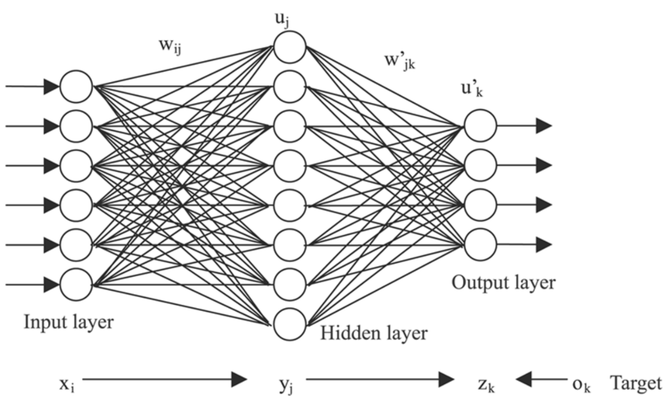
Artificial Neural Network



Determine weights via Backpropagation

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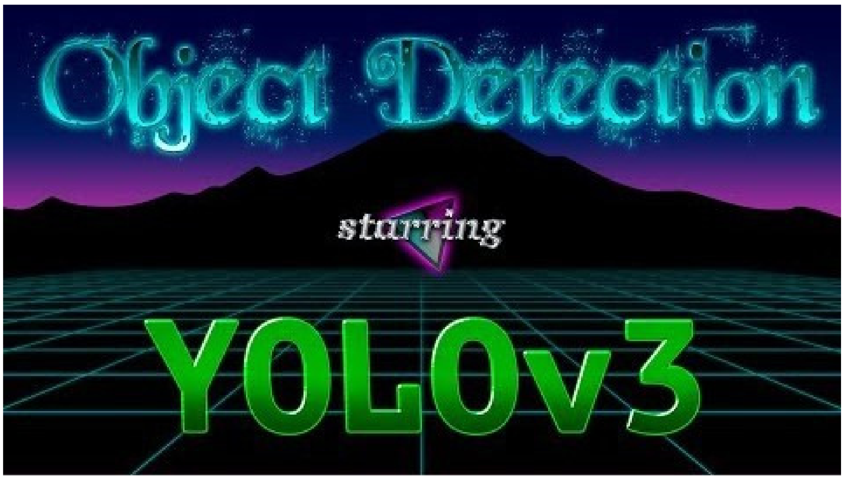
Object Detection



https://youtu.be/MPU2HistivI

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Evolutionaries

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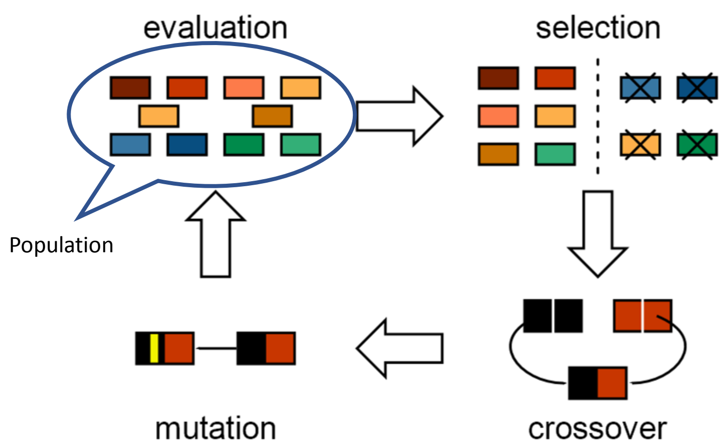
Genetic Algorithms



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Learning to Walk

https://vimeo.com/80822626

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Bayesians

Probabilistic Inference

Likelihood: How probable is the data given that our hypothesis is true?

Prior: How probable was the hypothesis before observing the data?

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$$

Posterior: How probable is our hypothesis given the observed evidence?

Marginal: How probable is the evidence under all possible hypotheses?

Spam Filtering

"Wow! I've got one from someone I know!"

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Analogizers

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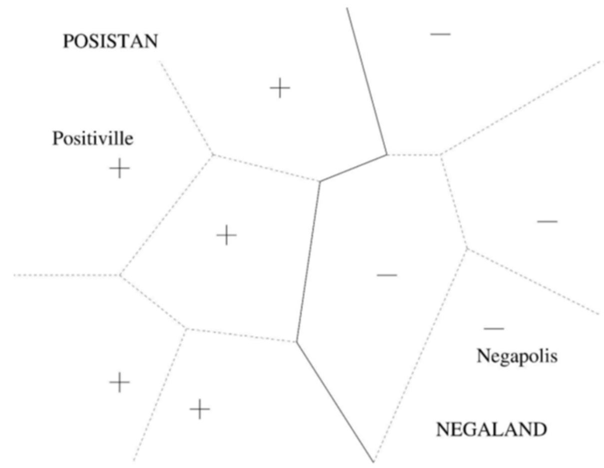
Nearest Neighbors



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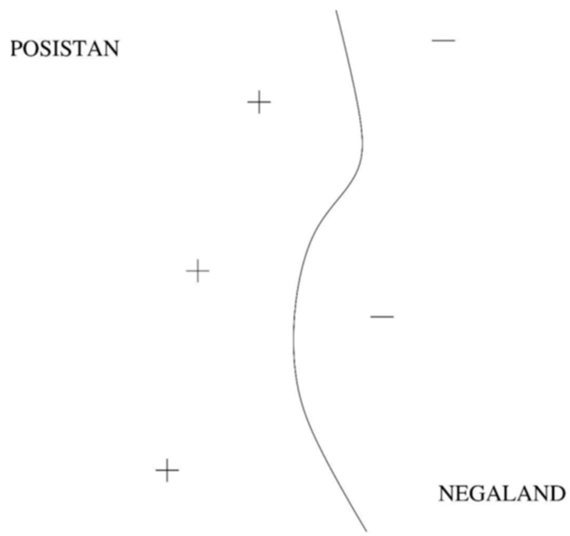
Support Vector Machines



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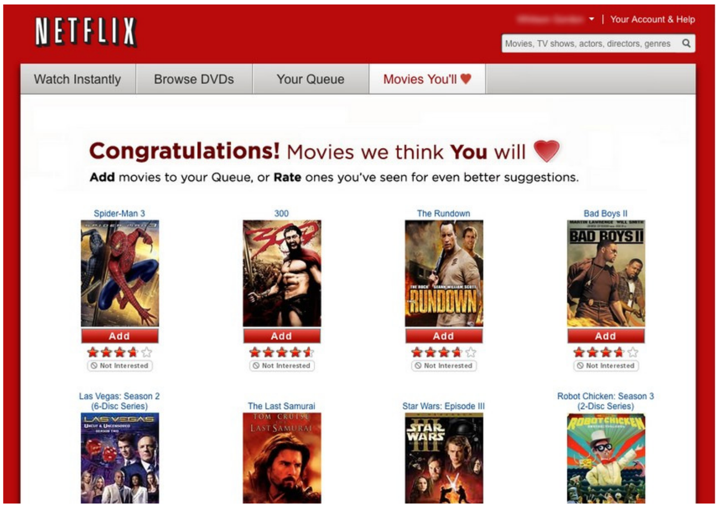
Recommender Systems



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5 Tribes of Machine Learning

Tribe	Problem	Algorithm
Symbolists	Knowledge Composition	Inverse deduction
Connectionists	Credit assignment	Backpropagation
Evolutionaries	Structure discovery	Genetic programming
Bayesians	Uncertainty	Probabilistic inference
Analogizers	Similarity	Support vector machines

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Back to Basics

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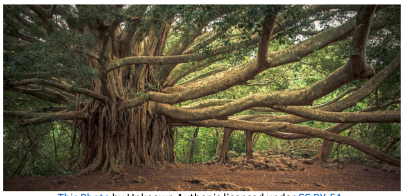
What is a Tree?



- Toddlers can identify trees
- Defining a tree is not obvious

- 3 criteria that define ML well:
  - A pattern exists;
  - It's difficult to pin down formally (mathematically);
  - We have data for it.

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Example: Credit Approval

- Banks need know to which loan applicants should be approved for their loan application.
  - If the bank approves an applicant that eventually defaults on their loan, this is a loss for the bank.
  - Conversely, if they reject an applicant that could actually pay back the loan with the compounded interest, they have missed an opportunity to make money.
- Input: Application
- Output: Decision

  - A pattern exists;
  - It's difficult to pin down formally (mathematically);
  - We have data for it.

Example: Credit Approval

- Inputs (observations, variables, features):

Variable / Feature	Value
Age	26
Gender	Female
Salary	$50k
Debt	$250k
Credit score	643

  - *n*-dimensional vector $\boldsymbol{x}$

- Outputs (labels, ground truth, targets):
  - Binary variable *y = {approve, reject}*
- <Input, output> pair = instance

Notation

Notation	Meaning
$\mathbf{x}$	an input example (vector)
$\mathbf{X}$	a stacked set of inputs of form $\mathbf{x}$
$\mathbf{y}$	set of (aligned) outputs
n	number of features
m	number of instances
$\mathbf{x}_i$	i^{th} feature of input $\mathbf{x}$
$\mathbf{x}^{(j)}$	j^{th} input or instance

- Data matrix **X**: Collection of all input vectors (rows of **X**)

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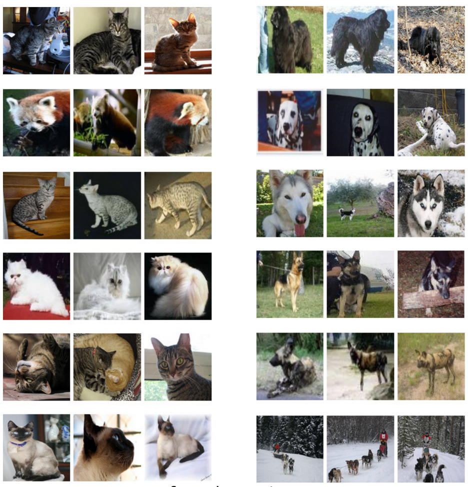
Supervised ML



Source: image-net.org

cat dog

- Function *f(**x**)* ⟶ *y*
- *Learn best possible approximation*, $h_\theta(\mathbf{x})$
- Classification vs. regression
  - A pattern exists;
  - It's difficult to pin down formally (mathematically);
  - We have data for it.
- *What else?*

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Python example: sklearn (scikit-learn)

- Using colab
- https://www.comp.nus.edu.sg/~winkler/IT3011/01b.colab

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Unsupervised ML

Source: image-net.org

- *How/what can you learn without labels?*
- Clustering
  - Grouping the data such that data points in the same group are **similar** to other data points in the same group and dissimilar to data points in other groups

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Where is Machine Learning Useful?

- Automatic pattern discovery in large datasets
- Domains where humans lack knowledge to define effective features/algorithms
- Dynamically adapting to changing conditions

Issues in Machine Learning

- What algorithms exist for learning from training examples?
- In what settings will particular algorithms converge?
- Which algorithms performs best?
- How much training data is necessary/sufficient?
- What bounds on accuracy/confidence can be determined?
- How to best choose the next data point for training?
- When/how can prior knowledge guide the process?
- What specific function should the system learn?