### **CSC3022H:**

# Machine Learning: Introduction

Geoff Nitschke

Department of Computer Science University of Cape Town, South Africa

### Course Syllabus

#### Supervised Learning:

- ANNs: Back propagation.
- Generative Learning algorithms: Monte-Carlo.
- Concept Learning.

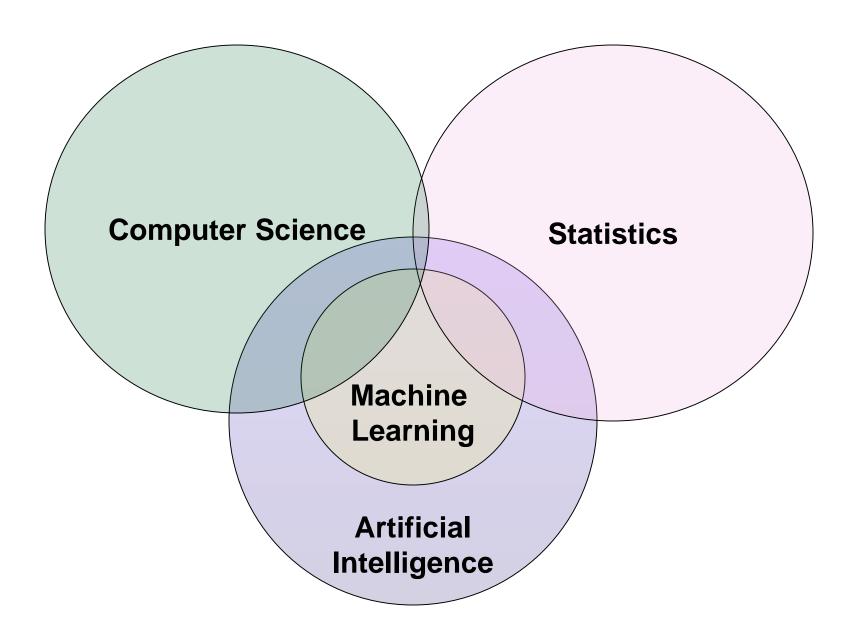
#### Unsupervised Learning:

- Clustering: Hierarchical clustering, K-means, EC, NE.
- PCA, ICA, SOM, ART.

#### Reinforcement Learning:

Q-learning. Policy and Value function approximation.

### Where Does ML Fit In?



## Approaches to AI

 GOFAI: Good Old Fashioned AI (McCarthy, 1955; Haugeland, 1985).

New (Biologically Inspired) AI (Brooks, 1989).

## **GOFAI:** Central Hypothesis

- Knowledge can be represented by symbols and intelligence is reducible to symbol manipulation (Allen and Simon, 1963).
- Al is achieved by manipulation of symbols.
- Dominated AI paradigm until the late 20th century.

#### Philosophical Roots:

- Gottfried Leibniz (1646 1716): Attempted to create a logical calculus of all human ideas.
- David Hume (1711 1776): Perception is reducible to "atomic impressions".
- Immanuel Kant (1724 1804): Experience is controlled by formal rules.

## **GOFAI** and Symbols

#### Formal Logic:

- Symbols: AND, OR, NOT, A, B...
- Expressions: TRUE or FALSE statements.
- Process: Rules of logical deduction.

#### Chess:

- Symbols: The pieces.
- Expressions: All possible board configurations.
- Processes: The legal chess moves.

## **GOFAI** and Symbols

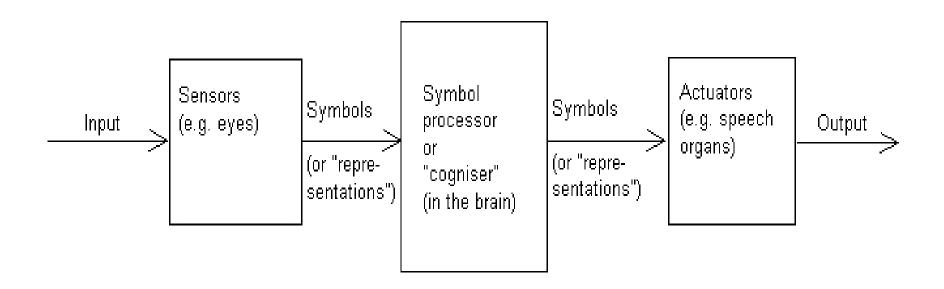
#### Human Thought:

- Symbols: Encoded in our brains.
- Expressions: Our thoughts.
- Processes: The mental operations of thinking.

#### Al "Thought":

- Symbols: Data structures.
- Expressions: Sets of data structures.
- Processes: Programs that manipulate the data structures.

# GOFAI → Thinking Machine?



## **GOFAI** Approaches

Top-Down Approach: Hierarchical symbolic based algorithm.



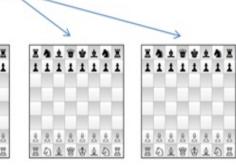
ComputerMove

ComputerMove2

11111111

GOFAI algorithms?

ComputerMove3

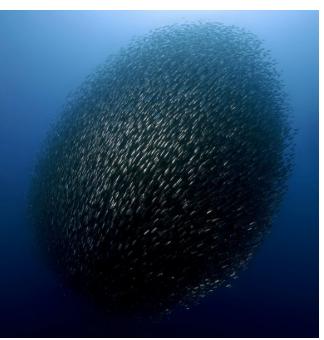


## Some GOFAI Algorithms

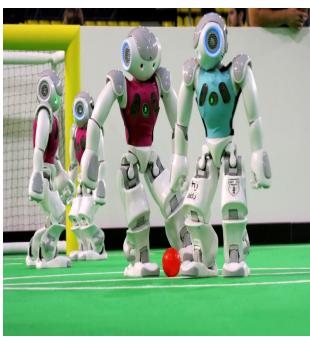
- Finite State Machines (FSMs).
- MINIMAX, Alpha-Beta Pruning.
- Monte-Carlo Search.
- Rule (Knowledge) Based Systems / Bayesian inference (Expert Systems).
- Concept Learning.

## New (Biologically Inspired) AI

- Bottom-Up (Synthetic) Approach: Individual components interact (self-organise) to produce global (system-level) behaviour.
- New Al methods: How should simple components interact to produce "intelligent" behaviour?







### Some New AI Methods

- Evolutionary Algorithms (EAs).
- Artificial Neural Networks (ANNs)
- Reinforcement Learning (RL)
- Particle Swarm Optimisation (PSO).

### "Weak" AI?

- We can build machines that act as if they were intelligent.
- Most AI research is in this area (and successful for many applications).
- Constrained problem sets / domains.
- Specific techniques to "simulate" intelligent decisions/actions.
- Does not try to solve the problem of general intelligence.
- All Al applications today are "weak" Al.



## "Strong" AI?

The goal is to build machines that are actually thinking "like people" (as opposed to just simulating thinking)

The Chinese room.

Examples ... ?

## Chinese Room Argument (Searle, 1980)

- Person in room speaks English but not Mandarin.
- Receives notes in Mandarin.
- Has English *rule-book* for how to write new Chinese
   characters given input Chinese
   characters returns notes.



- Person = CPU, Rule-book = Al Program, Notes = Data
- From outside observer's point of view, the room appears to speak perfect Mandarin!

## The Learning Problem

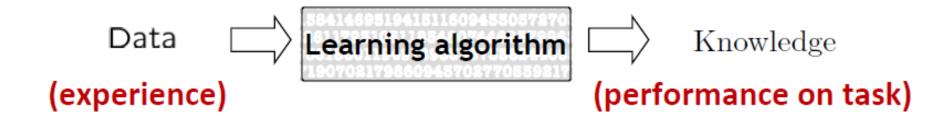
- Machine Learning (ML) is programming computers to optimise a performance criterion using example data or past experience.
- Learning is used when:
  - Human expertise does not exist (e.g.: Robots navigating on Mars).
  - Humans are unable to explain their expertise (e.g.: Speech and facial recognition).
  - Solution changes in time (e.g.: Routing on a computer network).
  - Solution needs to be adapted to particular cases (e.g.: Biometrics).

## Types of Data

- Discrete: One of a finite number of values (e.g.: Address).
- Continuous: Within a range (e.g.: Salary).
- Ordinal: Ranking for numerical value (e.g.: Age).
- Relational (e.g.: Employee records).
- Independent identical distributed vectors (e.g. Employee X record).
- Time series dependent vectors (e.g. Financial indicators for time t, related to t-1).
- Images ( Matrices ).
- Variable-size non-vector data (e.g. Strings, trees, graphs, text).
- Objects (e.g. Within a relational schema).

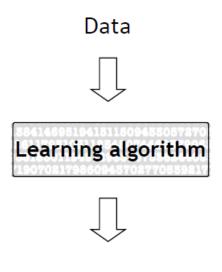
## What is Machine Learning (ML)?

- Data is cheap and abundant Knowledge is expensive and scarce.
- Build model that is a good and useful approximation to the data:
  - Learn general models from data of particular examples.
- ML: Design and Analysis of algorithms that improve their performance at some task with experience (Mitchell, 1997).



### What is ML?

- Optimise performance criteria using example data (past experience).
- Statistics: Inference from a sample.



Main Goal of Learning: Prediction

Knowledge

- Obtain a model of some training data, through a learning process.
- Use that model to predict something about data not seen before.
- Learn the same distribution as training data using test data.

### **Inferential Statistics**

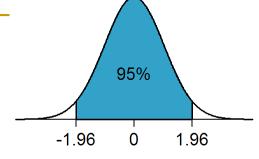
We have to get information about this large group of Work with a small group of people randomly selected people Random selection

### What is ML?

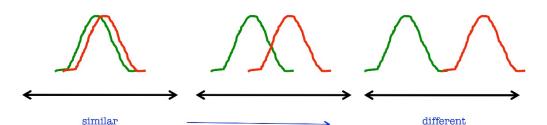
- ML ≈ Inferential + Multivariate + Computational statistics:
  - □ Inferential statistics ≈ Inference from data sample.
  - Multivariate statistics ≈ Prediction of values of a function assumed to describe a multivariate dataset.

 Computational statistics ≈ Computational methods for statistical problems.

### What is ML?



- Main types of inference problems:
  - Point estimation.
  - Confidence sets.
  - Hypothesis testing.



- ML is mostly about point estimation:
  - A statistic (best guess) derived from sample data.

Data mining: "Knowledge extraction"!

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# Types of Learning

### Supervised Learning:

Classification / Regression.

#### Unsupervised Learning:

Clustering / Dimensionality reduction.

#### Reinforcement Learning:

Value and policy iteration / Q Learning.

## Supervised Learning

- Predicting a target variable for which we get to see examples.
  - Classification: Predict a discrete target variable.
  - Regression: Predict a continuous target variable.

#### Prediction of future cases:

Find a rule that predicts output for future inputs.

#### Knowledge extraction:

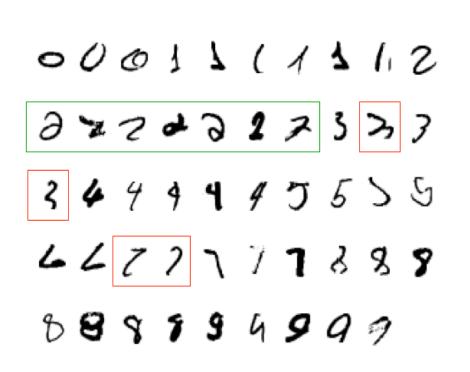
Finding a rule that is easy to understand.

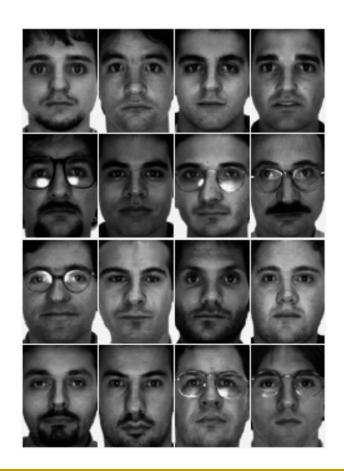
#### Compression:

Finding rule that is simpler than the data it explains.

# Supervised Learning

Useful when humans cannot define a decision rule, but can perform the classification task – for example:





# Supervised Learning: Classification

- Given: Set of labeled examples (training data), each described by a set of attributes, and labeled with a class:
  - Find a model for the class attribute as a function of the values of other attributes.
- Goal: Classify previously unseen examples (test data) accurately.



Words in a document



"Sports" "News"

"Science"

Discrete Labels Classification

### Supervised Learning: Classification

Facial Recognition: Predicting a discrete target variable:

### Training examples

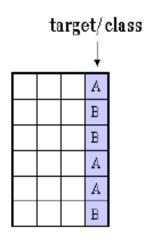


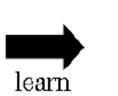






training dataset





model

#### Test images

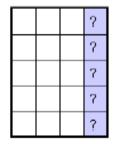








test dataset





	В
	В
	В
	A
	A

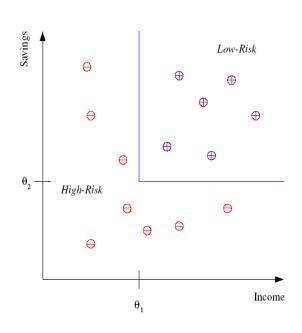
# Classification Examples

#### Fraud Detection:

- Predict fraudulent cases in credit card transactions.
- Training data: Previous transactions of given account holder.
- Attributes: Time of purchase, product type, cost, location,...
- Class: Label transactions as fraudulent or fair.

#### Credit Scoring:

- Differentiate between low-risk and high-risk credit applications.
- Training data: Incoming and savings
- Attributes: Income, expenses, debts,...
- Class: Label application as good or bad.



# Supervised Learning: Regression

- Predict a continuous valued variable based on attribute values.
  - e.g.: Stock price prediction
  - Predict the value based on a combination of the last k values
    (linear regression):

#### **Feature** Space ${\mathcal X}$

**Label** Space  ${\mathcal Y}$ 



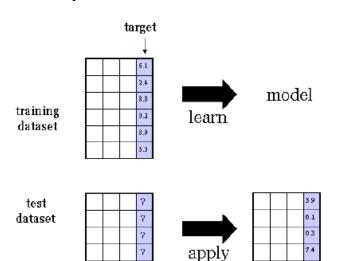
Share Price "\$ 24.50"

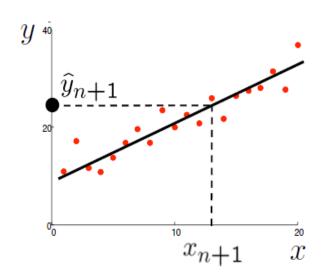
Continuous Labels Regression

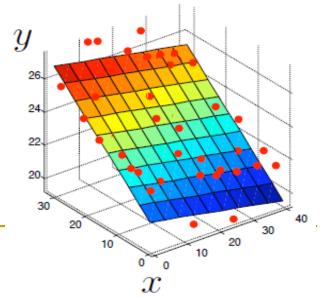
**Task:** Given  $X \in \mathcal{X}$ , predict  $Y \in \mathcal{Y}$ .

# Regression Example

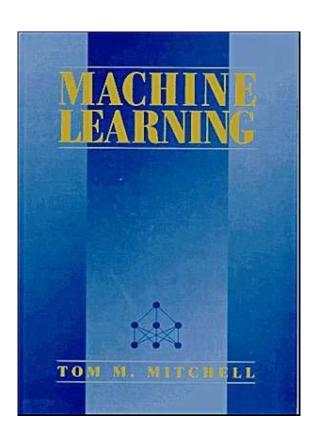
- Predicting a continuous target variable: Price of a car:
  - x: car attributes.
  - □ y: price.
  - $y = g(x \mid \theta)$ .
  - □ *g()* model.
  - $\Box$   $\theta$  parameters.



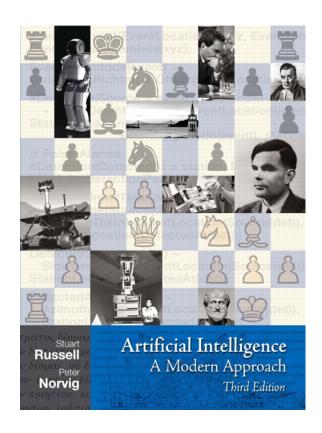




# Reading



**Chapter 14** – Key Ideas in Machine Learning



**Chapter 1** – Introduction