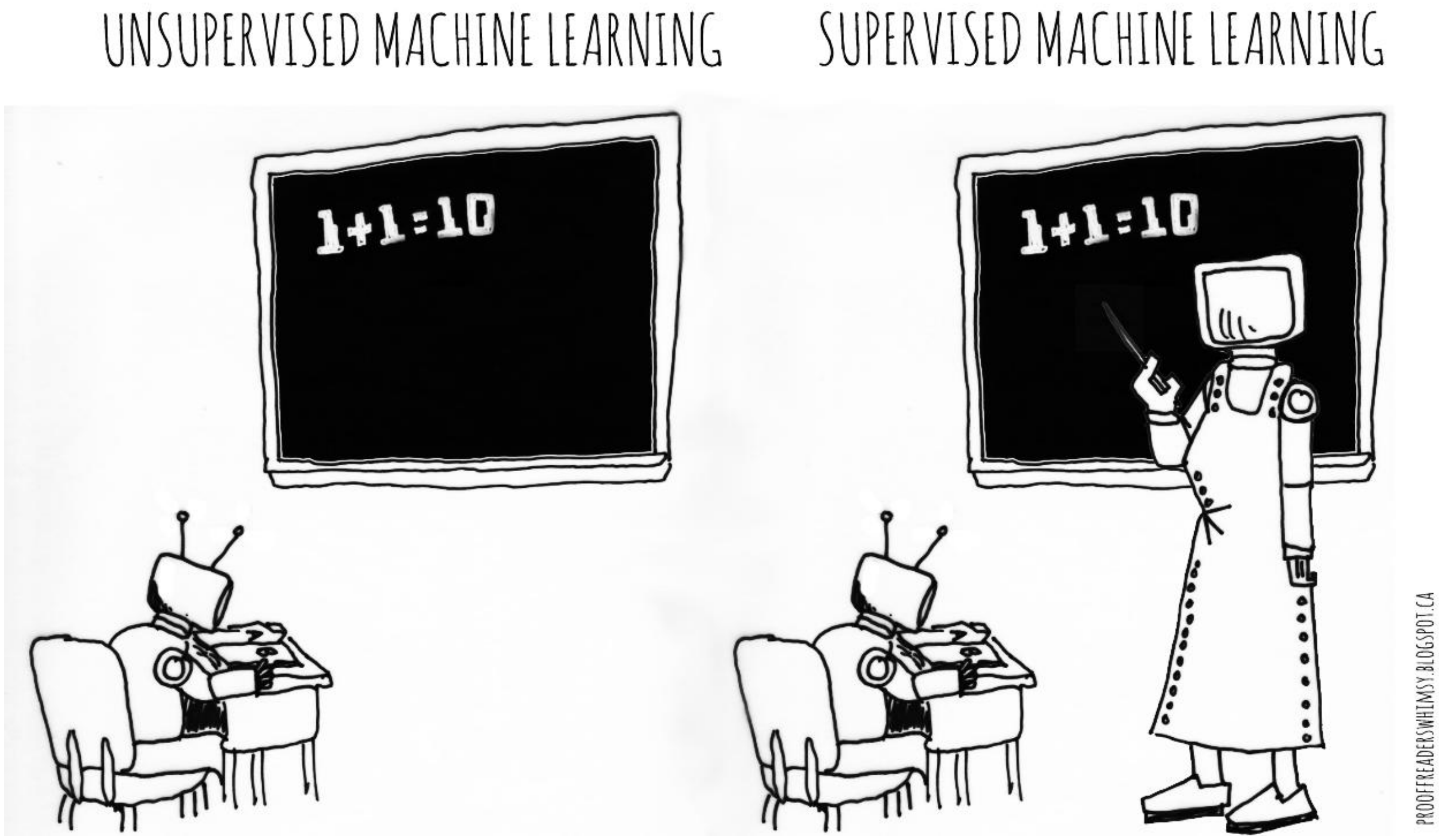
Artificial Intelligence (and Machine Learning)



Syllabus -- Broadly

- Problem solving by search
  - State space search
  - Game playing
- Planning
- Reasoning under Uncertainty
- Learning
  - Supervised , unsupervised, feature extraction.
- Additional Topics

Course Evaluation

- Assignments (Programming) – 25 Marks
- Quiz (best *n-1* out of *n* quizzes) – 20 Marks
- Mid1 – 15 Marks
- Mid2 – 25 Marks
- Endsem – 35 Marks
- Term Paper – 10 Marks

-- changes will be communicated, if any.

-- Makeup exams policy?

Books/Material

- 1. **Artificial Intelligence: A Modern Approach**
  -- Stuart J. Russell and Peter Norvig.
- 2. **Artificial Intelligence** – Deepak Khemani
- 3. **Pattern Classification**
  -- Duda, Hart & Stork
- 4. **Pattern Recognition and Machine Learning**
  --Christopher M. Bishop.

- Video Lectures – NPTEL – Available in YouTube. Prof Deepak Khemani (IITM) lectures are good for AI part.

AI?

- *Homo sapiens (human beings) are able to control (and exploit) other species and nature because of their thinking capability.*

We call programs intelligent if they exhibit behaviors that would be regarded intelligent if they were exhibited by human beings.

– Herbert Simon

Turing Test

http://en.wikipedia.org/wiki/Alan_Turing

Alan Turing's Imitation Game

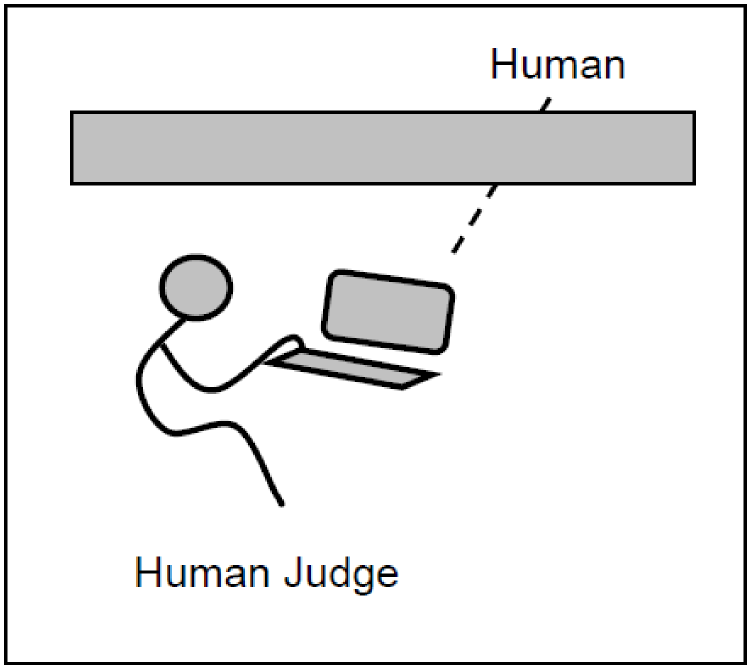
Alan Turing (1912 – 1954)

- The question whether machines can think itself "too meaningless"

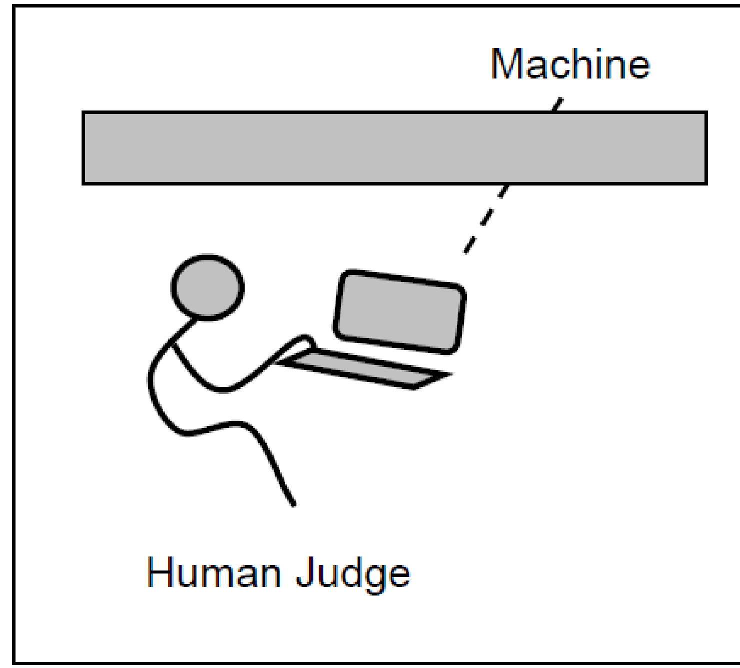
- Prescribed a test which he called the *Imitation Game* which is now known as *The Turing Test*

Human or Machine?

<u>The Turing Test</u>



or?



The Loebner Prize – an annual competition where chatbots are judged for human like response. The grand prize of USD 100,000 is still open.

"Reverse" Turing Test

Standard Turing Test: judge is human.

Reverse Turing Test: judge is computer!

Why?

- Yahoo allows each user 15 Mbytes of Web storage.
  - You write a "bot" to to sign up 1 million users.
  - Congratulations. You now have 15 Terabytes of storage !
- PayPal once offered $5 for each user who opens a new account.
  - You write a bot to sign up 1 billion users.
  - Congratulations. You now have $5,000,000,000 !
- Both need to distinguish real humans from bots (programs).

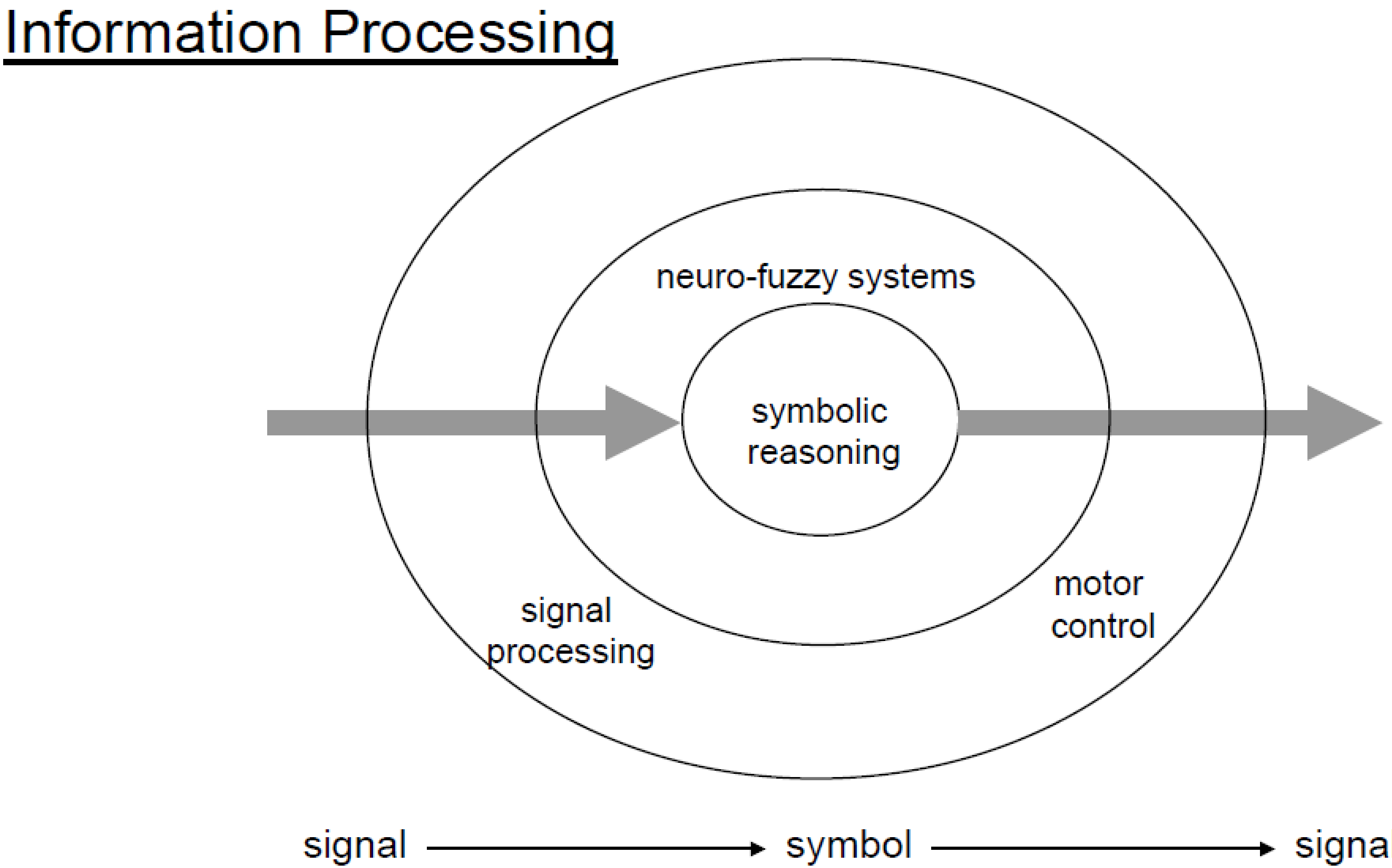
CAPTCHA.

- **C**ompletely **A**utomated **P**ublic **T**uring test to tell **C**omputers and **H**umans **A**part

The Chinese Room Argument

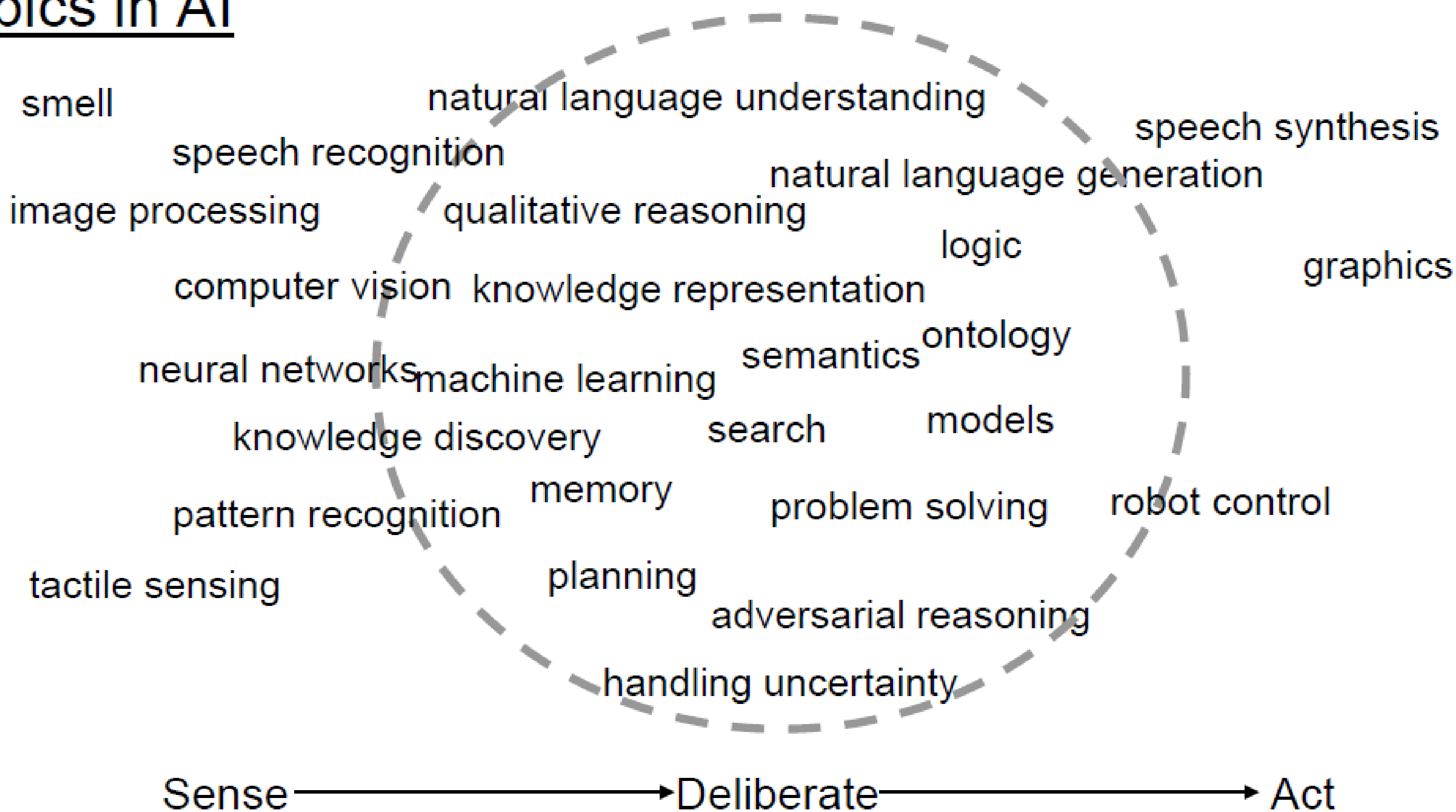
- John Searle: The Chinese Room argument – can an agent locked in a room processing questions in Chinese based on a set of syntactic rules be said to *understand* Chinese?
  - How many rules will the agent need to have for the thought experiment to be convincing?

Information Processing?



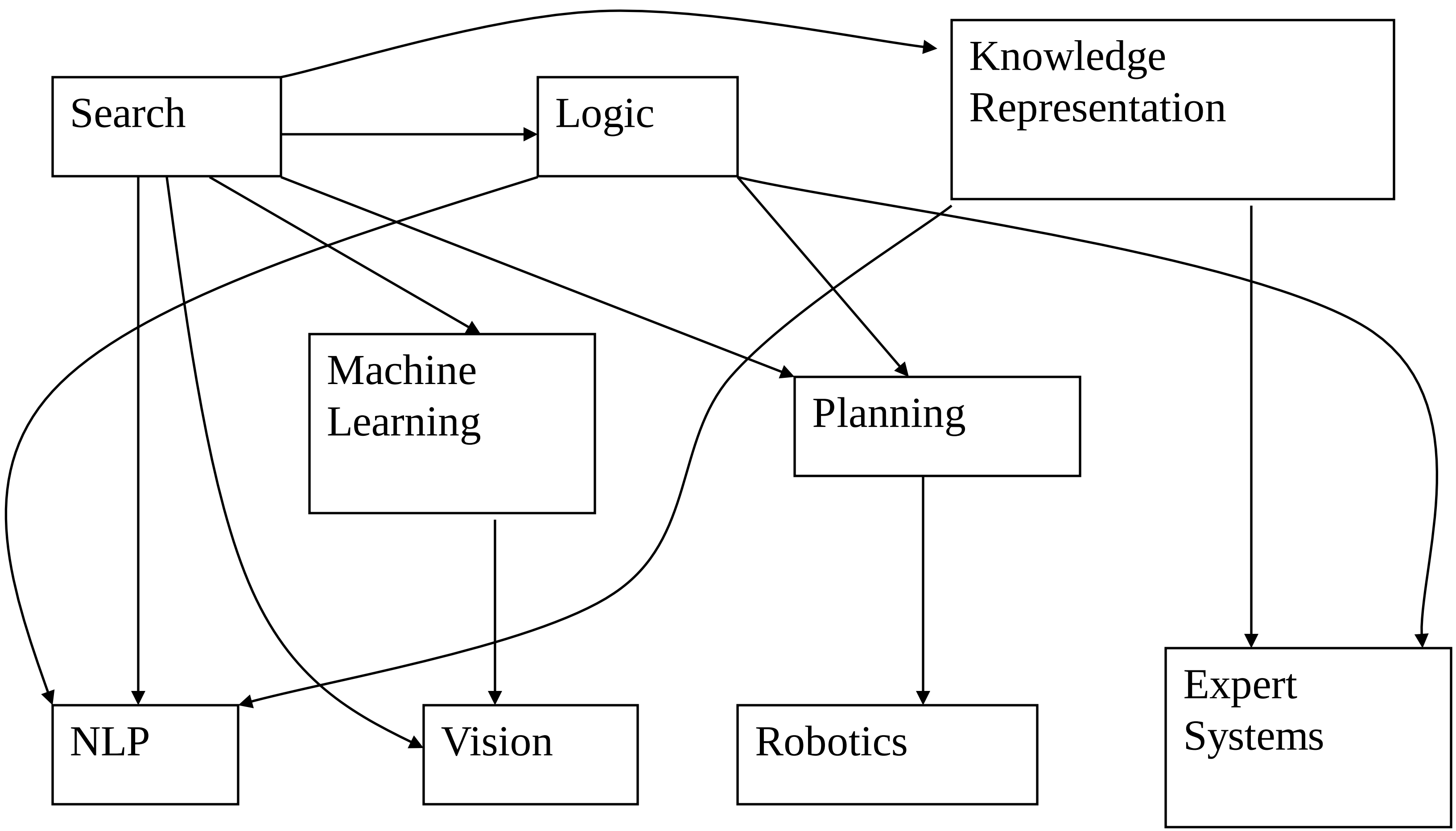
Topics in AI

Topics in AI



Source: Deepak Khemani, A First Course in Artificial Intelligence

Areas of AI and Some Dependencies

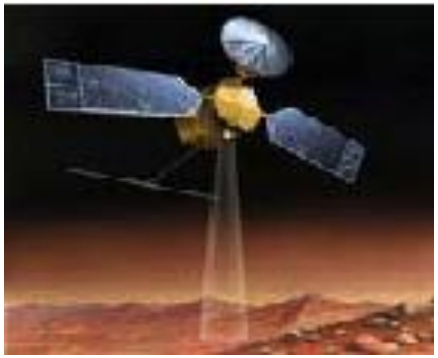


What we already achieved in AI?

- Board games – Chess, Checkers, Go, etc
- Solving Puzzles – Sudoku, etc
- Route finding in a map
- Image/speech enhancement
  - Creating high resolution images, noise suppression, …
-

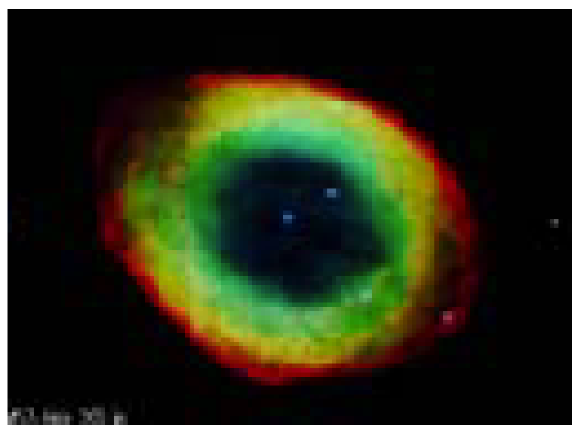
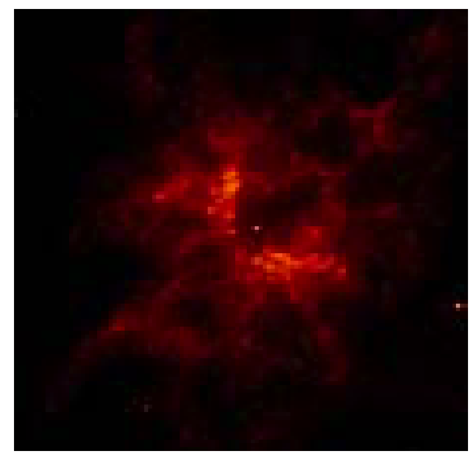
AI Applications

- Autonomous Planning & Scheduling:
  - Autonomous rovers.



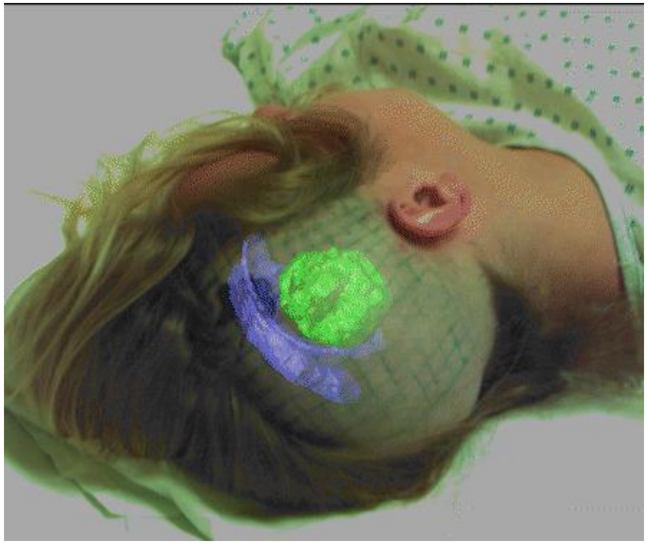
AI Applications

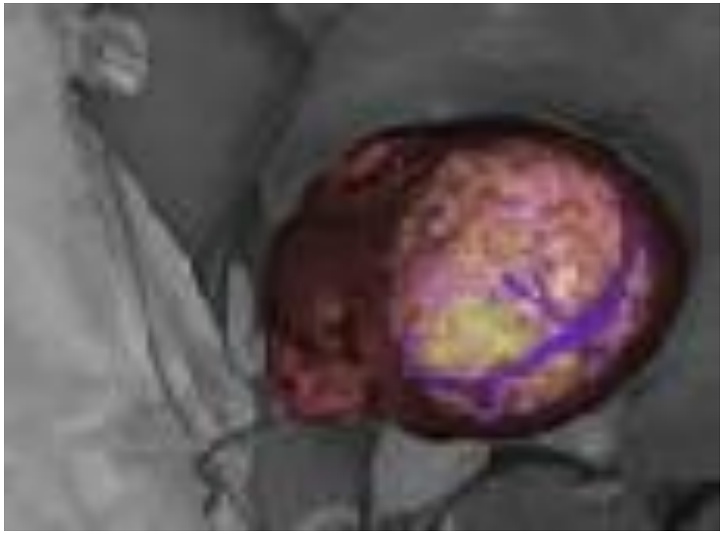
- Autonomous Planning & Scheduling:
  - Analysis of data:

AI Applications

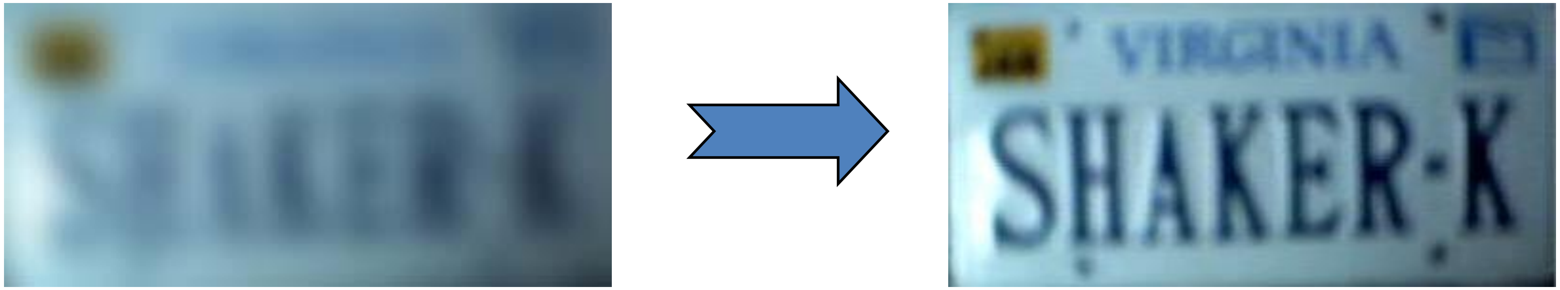
- **Medicine**:
  - Image guided surgery





AI Applications

- **Medicine**:
  - Image analysis and enhancement



AI Applications

- **Transportation**:
  - **Autonomous vehicle control:**

AI Applications

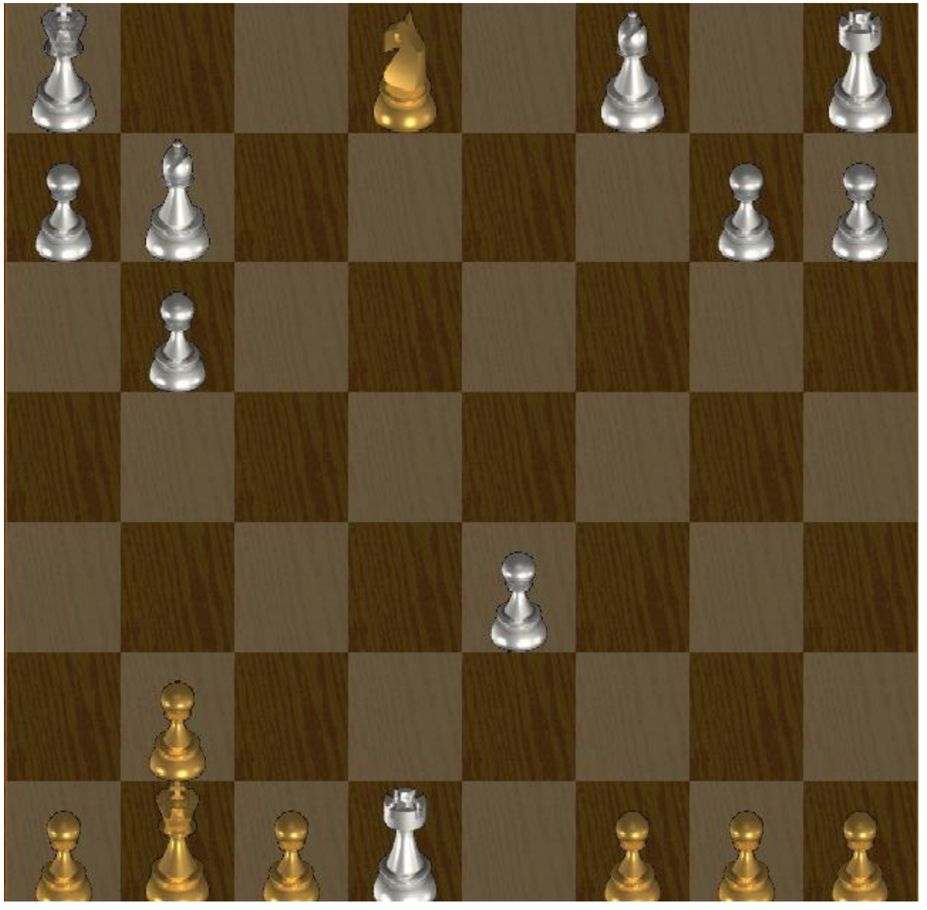
- **Transportation**:
  - **Pedestrian detection:**

AI Applications

Games:

AI Applications

- **Games**:



AI Applications

- **Robotic toys**:

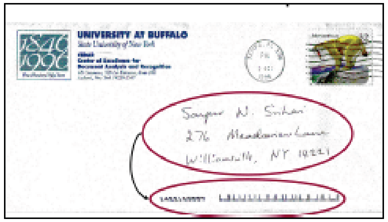
AI Applications

Other application areas:

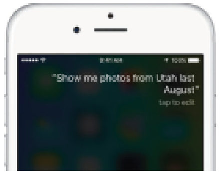
- **Bioinformatics:**
  - Gene expression data analysis
  - Prediction of protein structure
- **Text classification, document sortin**g:
  - Web pages, e-mails
  - Articles in the news
- **Video, image classification**
- **Music composition, picture drawing**
- **Natural Language Processing** .
- **Perception.**

Today's AI

- Today, AI is a thriving field
  – Many practical applications and active research
- We look to intelligent software to:
  – Automate routine labor
    - Handwritten address interpretation

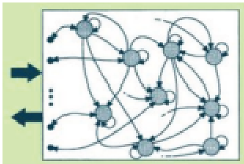


  – Understand speech or images
    - SIRI



  – Make diagnosis in medicine
    - Watson Health

  – Support basic science research
    - Computational chemistry



Future prospects of AI

Survey of AI researchers

- AI will outperform humans in:
  - Translating languages 2024
  - Writing high-school essays 2026
  - Driving a truck 2027
  - Working in retail 2031
  - Writing a best-selling book 2049
  - Working as a surgeon 2053
  - Outperform humans in all tasks: 50% chance in 45 years
  - Automating all human jobs 120 years
- Survey population: 2015 NIPS/ICML authors
  - Questions on AI capabilities (e.g. folding laundry, language translation), superiority at specific occupations (e.g. truck driver, surgeon), superiority over humans at all tasks.

TECHNIQUES

Search

- *Search* is <u>the fundamental</u> technique of AI.
  - Possible answers, decisions or courses of action are structured into an abstract space, which we then search.
- Search is either "blind" or “uninformed":
  - blind
    - we move through the space without worrying about what is coming next, but recognising the answer if we see it
  - informed
    - we guess what is ahead, and use that information to decide where to look next.
- We may want to search for the first answer that satisfies our goal, or we may want to keep searching until we find the best answer.

Knowledge Representation & Reasoning

- The <u>second</u> most important concept in AI
- If we are going to act rationally in our environment, then we must have some way of describing that environment and drawing inferences from that representation.
  - how do we describe what we know about the world ?
  - how do we describe it *concisely* ?
  - how do we describe it so that we can get hold of the right piece of knowledge when we need it ?
  - how do we generate new pieces of knowledge ?
  - how do we deal with *uncertain* knowledge ?

Symbolic and Sub-symbolic AI

- Symbolic AI is concerned with describing and manipulating our knowledge of the world as explicit symbols, where these symbols have clear relationships to entities in the real world.
- Sub-symbolic AI (e.g. neural-nets) is more concerned with obtaining the correct response to an input stimulus without ‘looking inside the box’ to see if parts of the mechanism can be associated with discrete real world objects.
- This course is concerned with symbolic AI.

Deductive Vs Inductive Learning

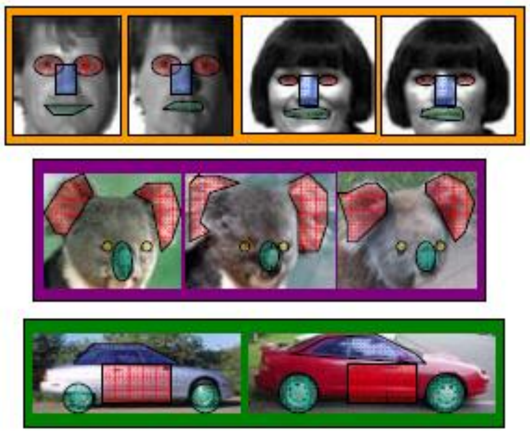
- Deductive
  - Rules of the game are (hard coded) given ahead.
  - Eg: An algorithm to do multiplication of numbers is given. Given any two numbers you can apply this and get the answer.
- Inductive
  - We are given with examples (not the concept). We need to learn the mapping from i/p to o/p.
    - Supervised learning problems in AI comes under this

Learning strategies

- Supervised
  - Classification, Regression, …
- Unsupervised
  - Clustering, density estimation, …
- Reinforced
  - A robot navigating through obstacles, …
- Learn the good features (attributes)
  - Feature extraction

Spectrum of supervision

Less **More**



Unsupervised

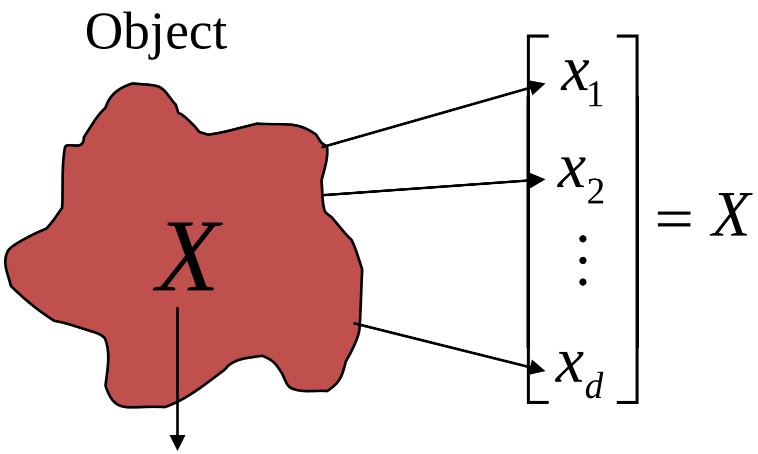
“Semi” supervised

Fully supervised

What is a classification problem?

- Let there are two classes of objects.
  - Class 1: Set of dog pictures
  - Class 2: Set of cat pictures
- Problem is –
  - Given a picture, you should say whether it is cat or dog.
  - For a human being it is easy..., but for a machine it is a non-trivial problem.

Basic concepts



<u>Feature vector</u> $X \in \chi$

- A vector of observations (measurements).

- X is a point in feature space χ .

<u>Class to which *X* belongs is</u> $y \in Y$

-Needs to be estimated, based on training set.

<u>Task</u>

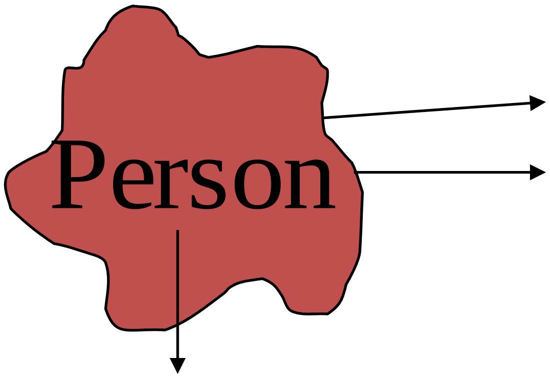
- To design a classifer (decision rule) $f : \chi \to Y$

which decides about the class label based on *X*.

An example

χ is a set of persons

Object



$$\begin{bmatrix} h \\ w \end{bmatrix}$$

<u>Feature vector</u>

- A vector of observations (height, weight).

<u>Class to which *X* belongs is</u>

$$y \in \{\text{overweight}, \text{normal}\}$$

-Needs to be estimated, based on training set.

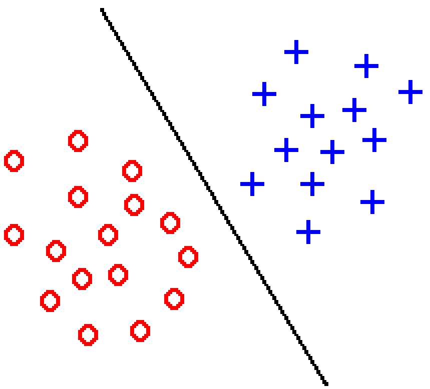
<u>Task</u>

- To design a classifer (decision rule) $f : \chi \to Y$
- given height and weight of a person, classify him/her.

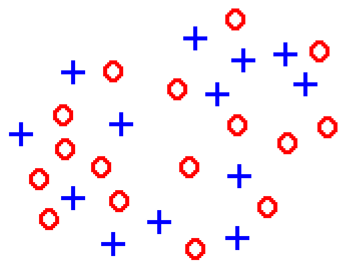
Feature extraction

Task: to extract features which are good for classification.

Good features:
- Objects from the same class have similar feature values.
- Objects from different classes have different values.



“Good” features



“Bad” features

An easy, but bad classifier

- Remember the training set.
- See whether the given feature vector to be classified is available in the training set.
- If yes, then return the label of that training example.
- Else return a random class label.

- ***This is called Rote learning***

Classifiers

- There are many classification methods.
  - Baye’s classifier, Naïve Bayes classifier
  - HMM (graphical model)
  - Artificial Neural Networks
  - Decision Trees
  - SVMs
  - ….

Generative vs. Discriminative Classifiers

Generative Models

- Represent both the data and the labels
- Often, makes use of conditional independence and priors
- Examples
  - Naïve Bayes classifier
  - Bayesian network

- Models of data may apply to future prediction problems

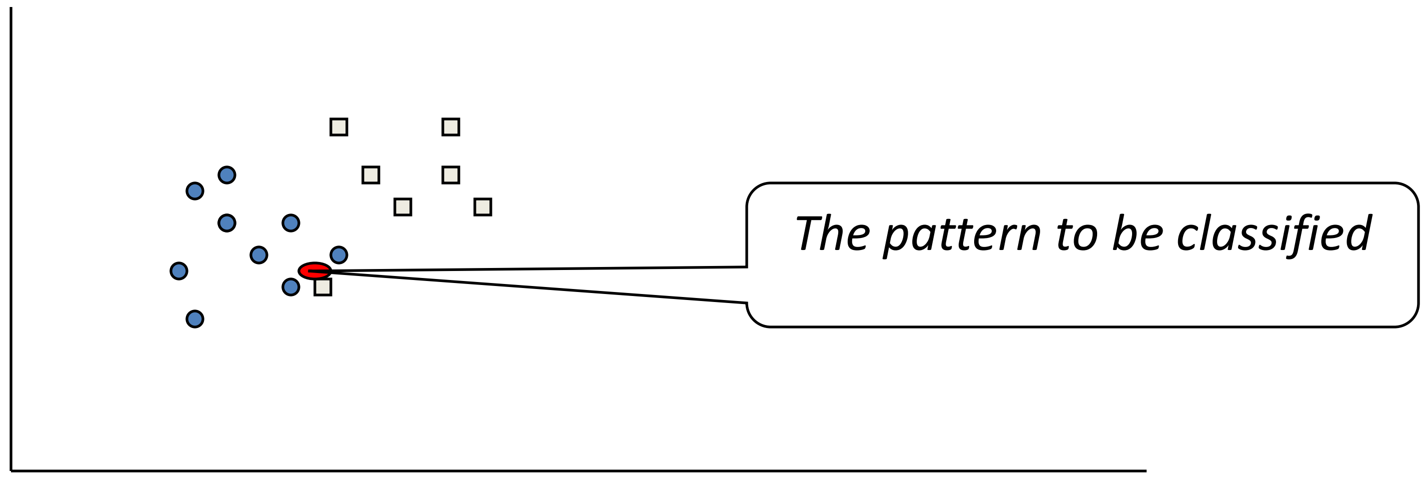
Discriminative Models

- Learn to directly predict the labels from the data
- Often, assume a simple boundary (e.g., linear)
- Examples
  - Logistic regression
  - SVM
  - Boosted decision trees

- Often easier to predict a label from the data than to model the data

Slide credit: D. Hoiem

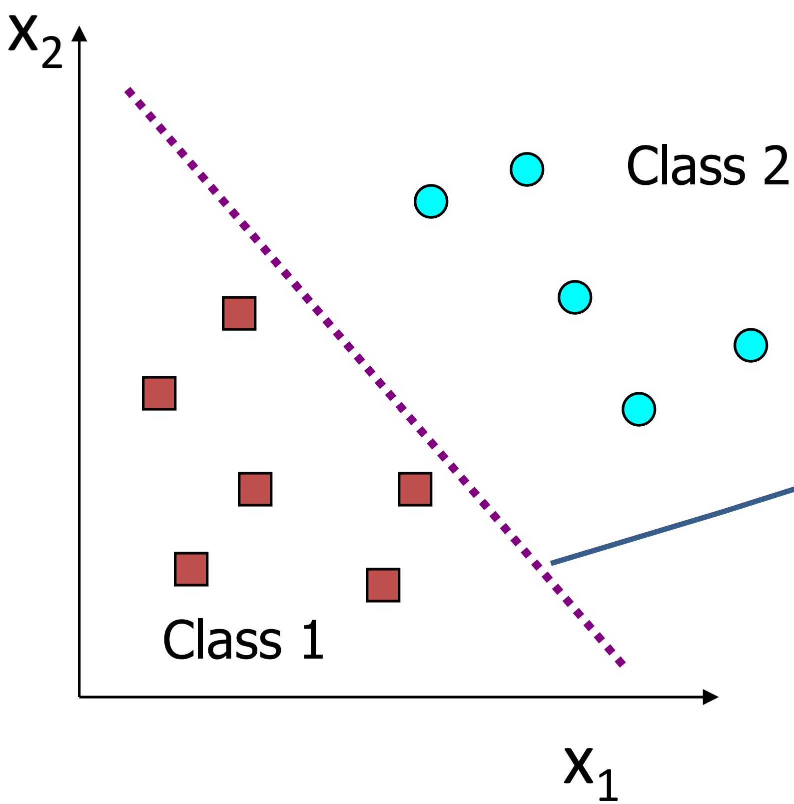
k-Nearest Neighbor Classifier



If k = 1 then the class assigned is □

If k = 3 then the class assigned is ●

Linear Classifier



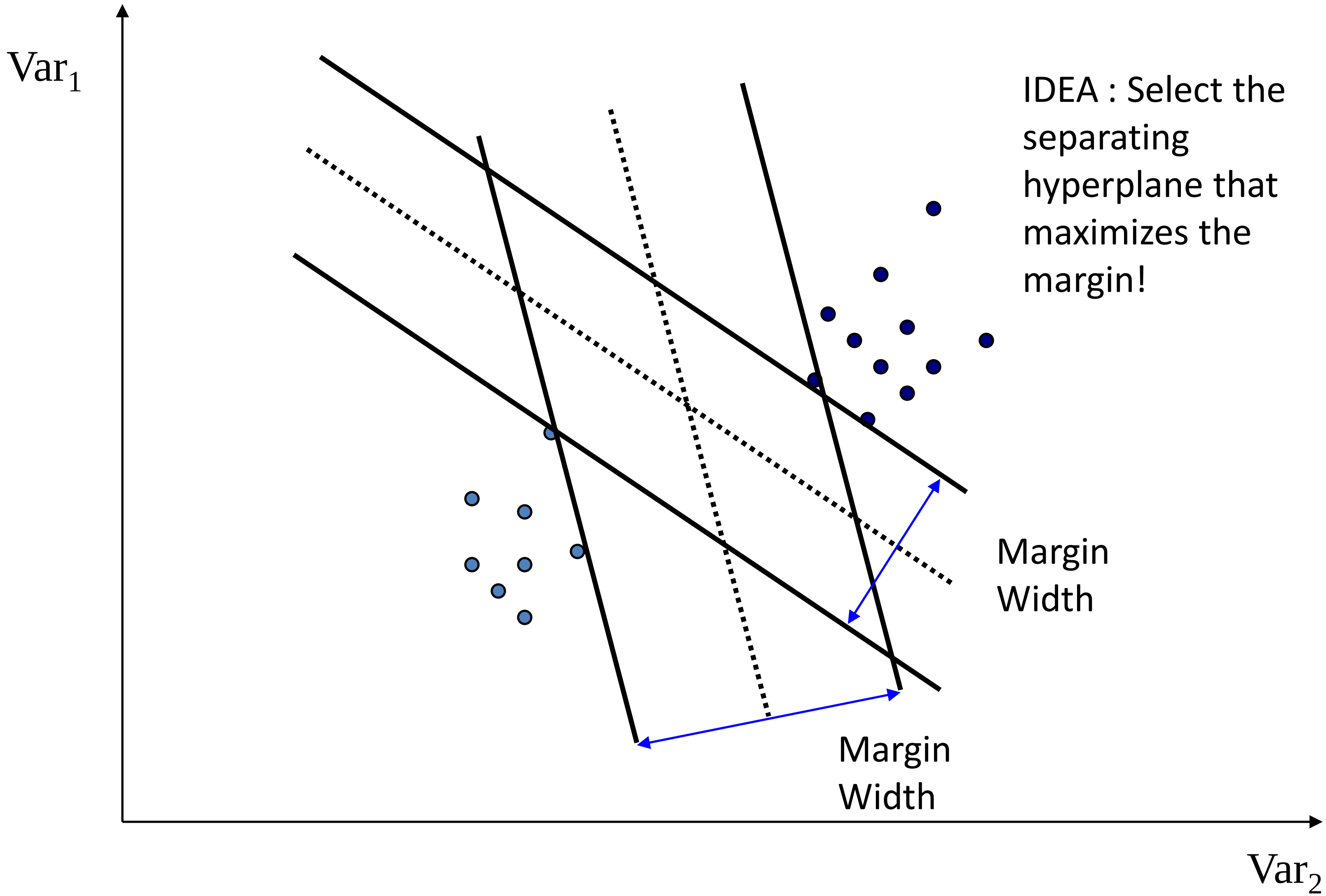
Classifier:

If $f(x_1,x_2) < 0$ assign Class 1;

If $f(x_1,x_2) > 0$ assign Class 2;

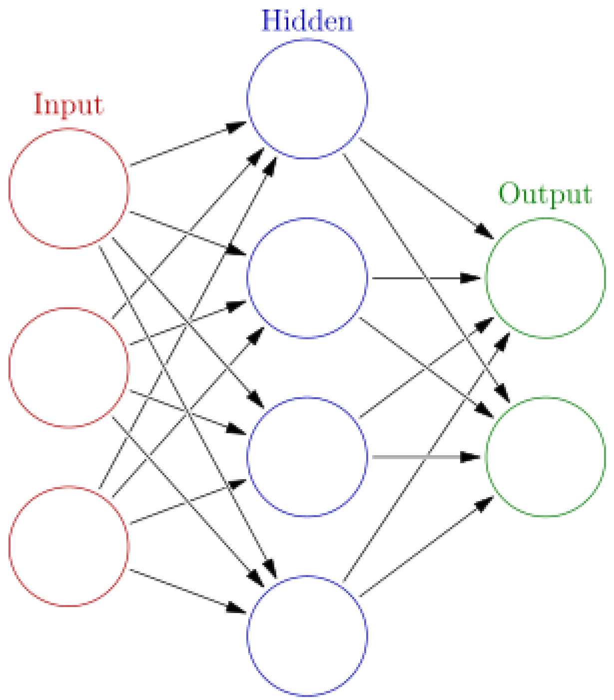
$$\boxed{f(x_1,x_2) = w_1x_1+w_2x_2+b = 0}$$

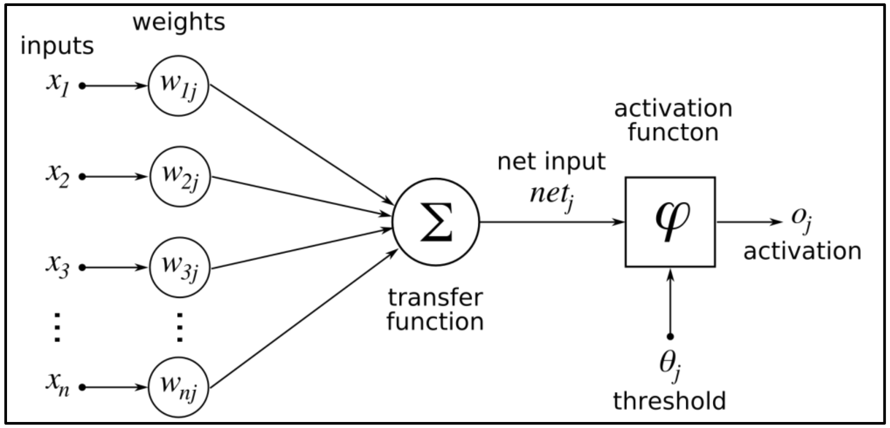
Maximizing the Margin➔ SVM



IDEA : Select the separating hyperplane that maximizes the margin!

Artificial Neural Networks





Remember…

- No classifier is inherently better than any other: you need to make assumptions to generalize

- Two components of the error
  – Bias: due to over-simplifications
  – Variance: due to inability to perfectly estimate parameters from limited data

Slide credit: D. Hoiem
Slide credit: D. Hoiem

Generalization

Training set (labels known)

Test set (labels unknown)

- How well does a learned model generalize from the data it was trained on to a new test set?

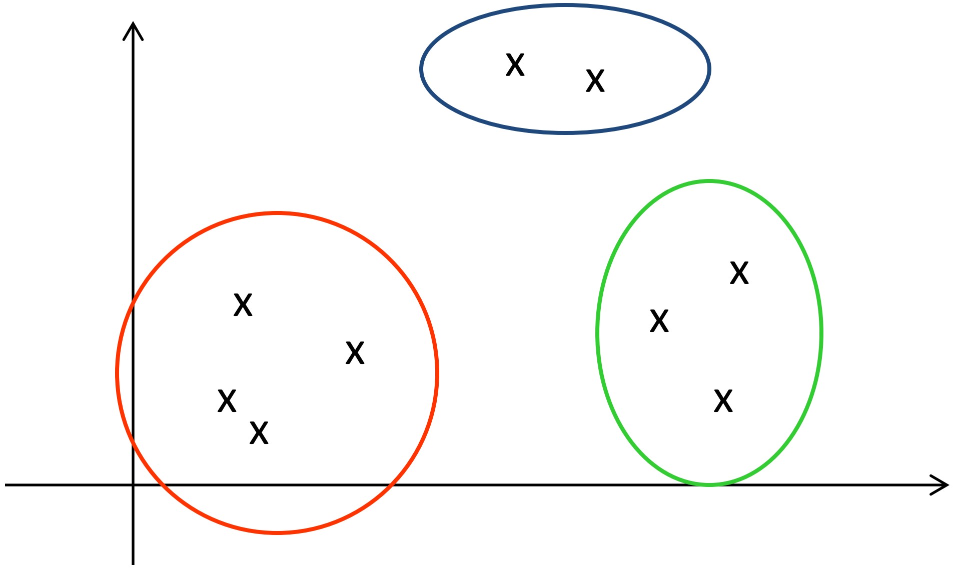
Generalization

- Components of generalization error
  - **Bias:** how much the average model over all training sets differ from the true model?
    - Error due to inaccurate assumptions/simplifications made by the model
  - **Variance:** how much models estimated from different training sets differ from each other
- **Underfitting:** model is too “simple” to represent all the relevant class characteristics
  - High bias and low variance
  - High training error and high test error
- **Overfitting:** model is too “complex” and fits irrelevant characteristics (noise) in the data
  - Low bias and high variance
  - Low training error and high test error

Slide credit: L. Lazebnik

Clustering

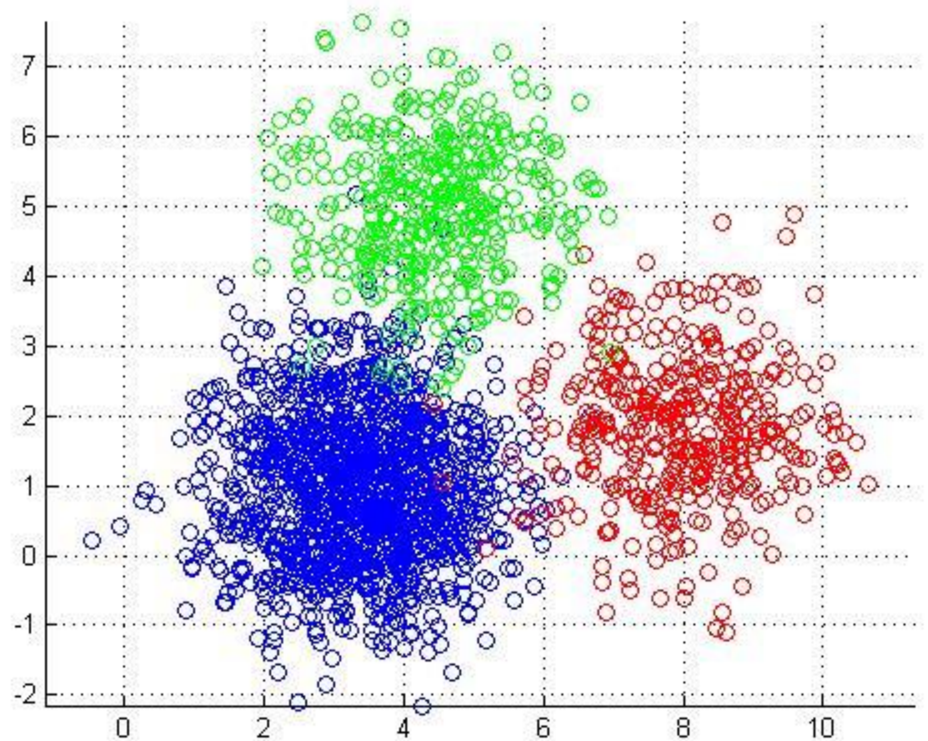
- The goal of clustering is to
  - group data points that are close (or **similar**) to each other
  - identify such groupings (or clusters) in an **unsupervised** manner
    - Unsupervised: no information is provided to the algorithm on which data points belong to which clusters
- Example



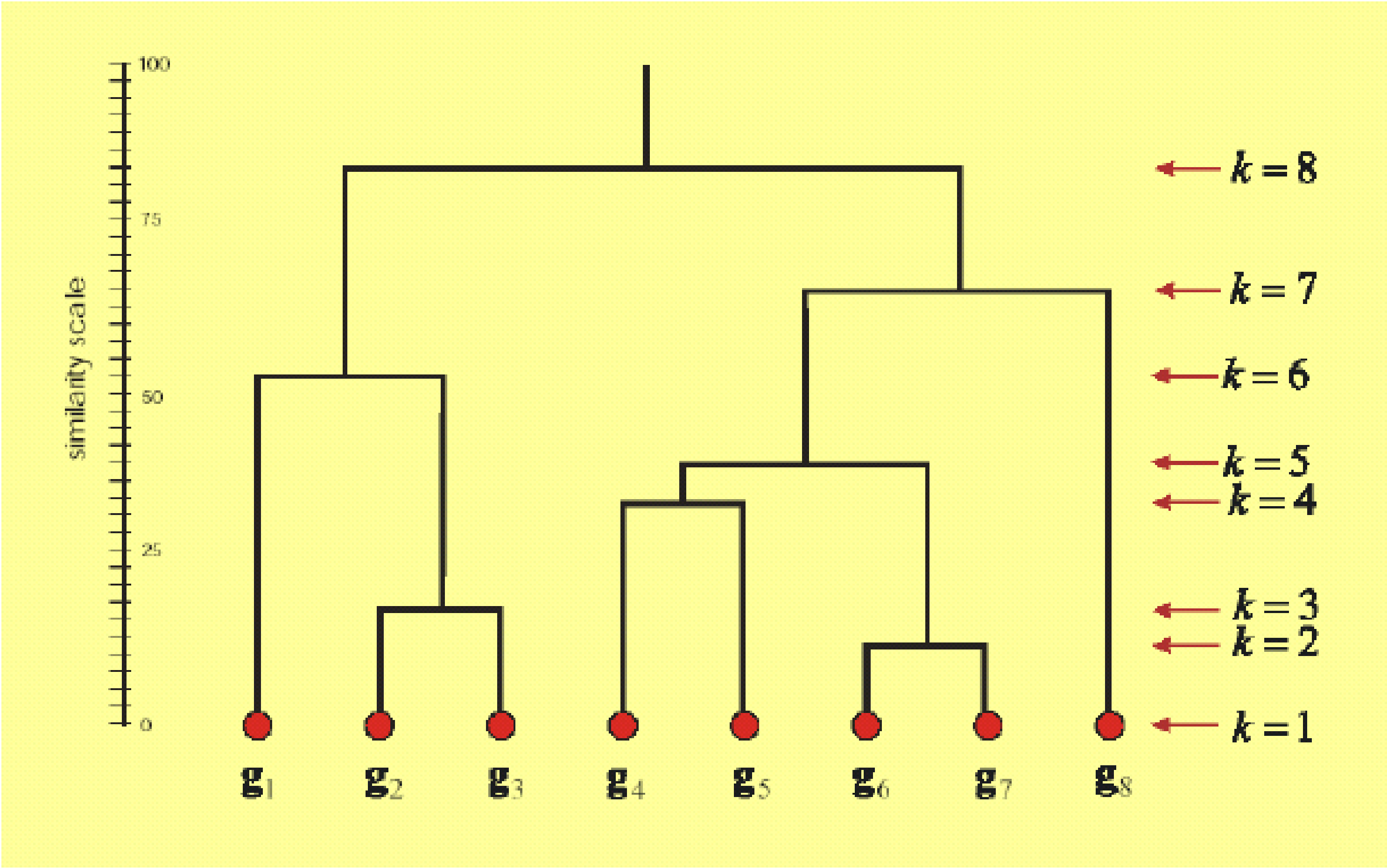
Clustering Strategies

- K-means
  - Iteratively re-assign points to the nearest cluster center
- Hierarchical
  - Agglomerative clustering
  - Start with each point as its own cluster and iteratively merge the closest clusters
- Spectral clustering
  - Split the nodes in a graph based on assigned links with similarity weights

K-means is good at spherical clusters



Hierarchical clustering

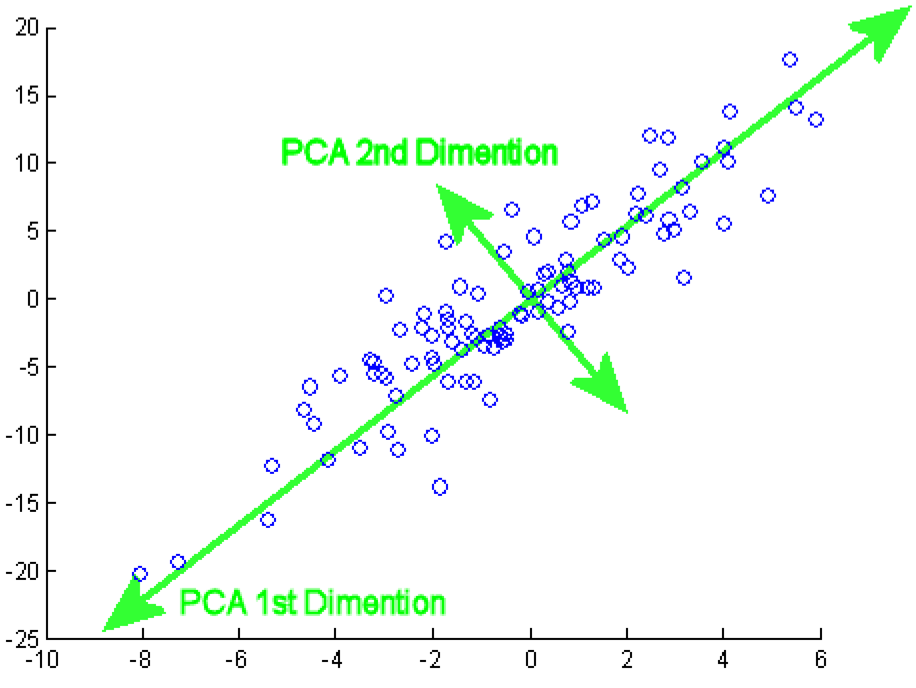


Can find non-spherical clusters

Clusters of arbitrary shape.

Feature Extraction

- Principal Component Analysis
- Fisher Discriminant Analysis
-



Representing Face Images: Eigenfaces

Q: How do we pick the set of basis faces?

A: We take a set of real training faces

…

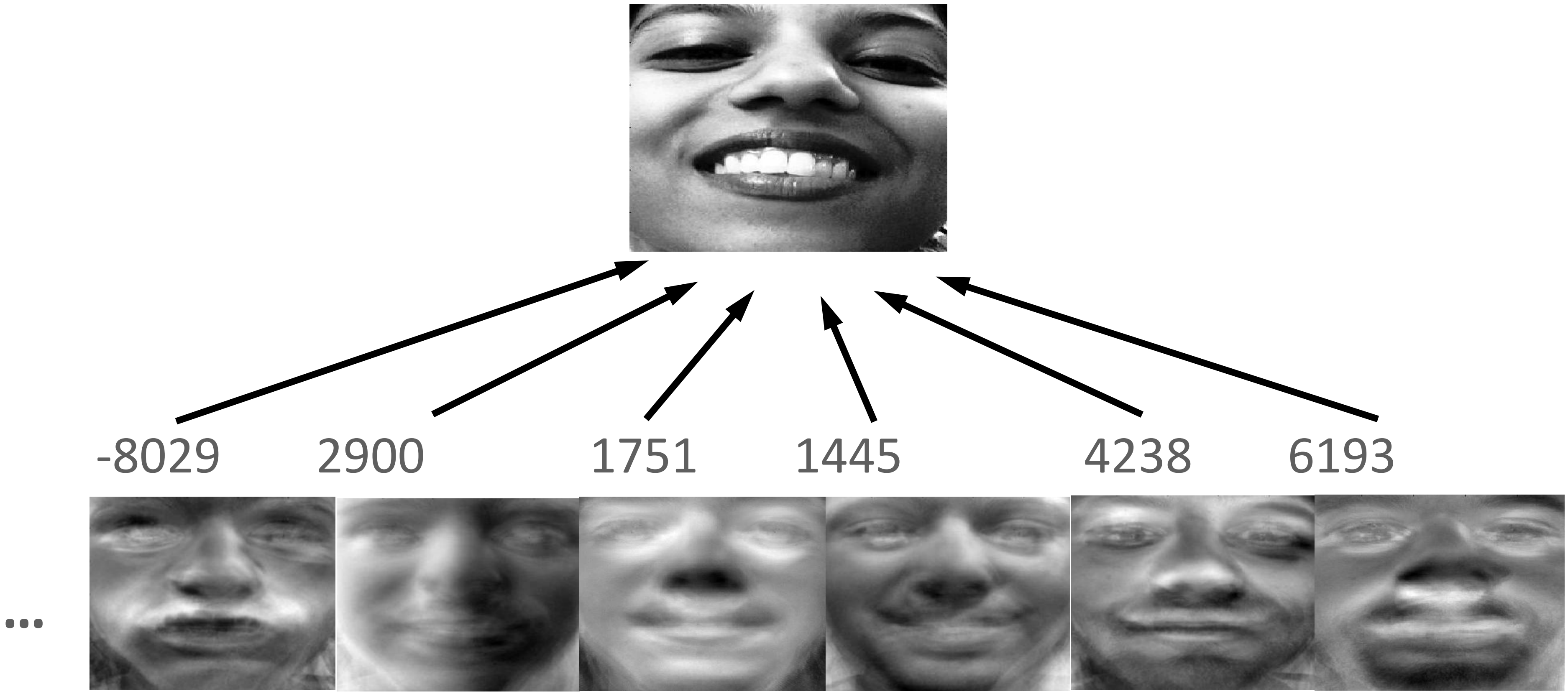
Then we find (learn) a set of basis faces which best represent the differences between them

That is, apply PCA and choose top Eigen vectors (Eigen faces)

We can then store each face as a set of weights for those basis faces

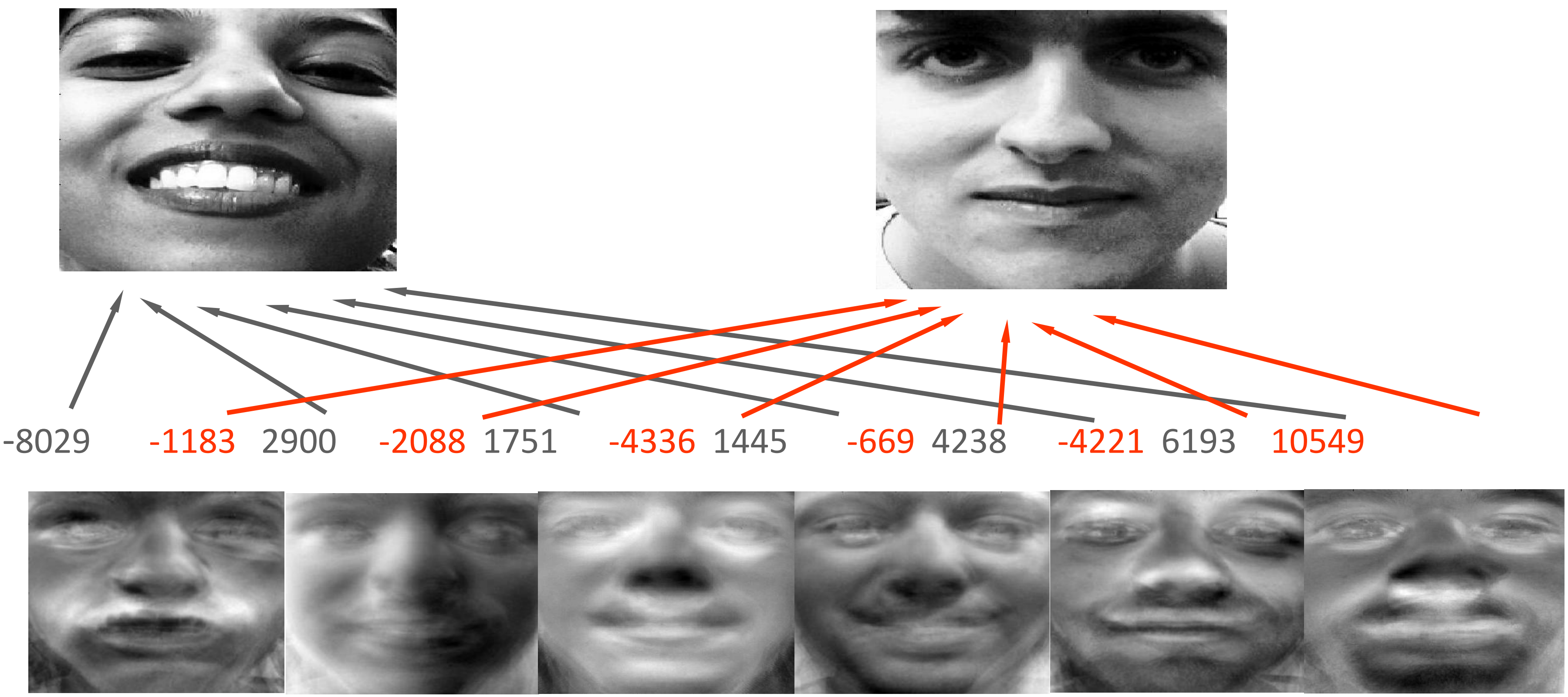
Eigenfaces: the idea

- **Think of a face as being a weighted combination of some "component" or "basis" faces**
- **These basis faces are called eigenfaces**



Eigenfaces: representing faces

- **These basis faces can be differently weighted to represent any face**
- **So we can use different vectors of weights to represent different faces**



Next Class

- Problem Solving by Search
  - Puzzles
  - Games
  -