An Introduction to AI

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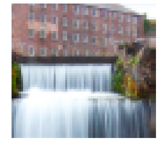
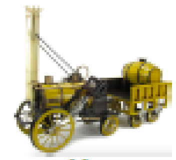
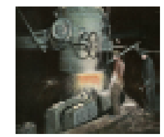
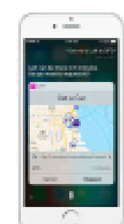
IIITS

Overview

- History of AI
  - past, present, future.
- Techniques
  - Supervised learning techniques
  - Feature extraction
- Some Challenges

History of Technology

- 1771 Industrial Revolution
  
  - Arkwright's mill in Cramford
- 1826 Age of Steam and Railways
  
  - "Rocket steam" engine for Manchester railway
- 1875 Age of Steel, Electricity & Heavy Eng.
  
  - Carnegie Bessemer steel plant in Pittsburgh
- 1908 Age of Oil, Automobile, Mass Production
  
  - First model T comes out in Detroit
- 1971 Age of Information & Telecommunications
  
  - Intel microprocessor announced in Santa Clara
- 2017 Age of Artificial Intelligence
  
  - Machines, data and people connected in new era

- The term **artificial intelligence** was first coined in 1956, at the Dartmouth conference.
- Artificial Intelligence is still a growing active field of science and technology.
  - Has the potential to affect our lives

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

Alan Turing's Imitation Game

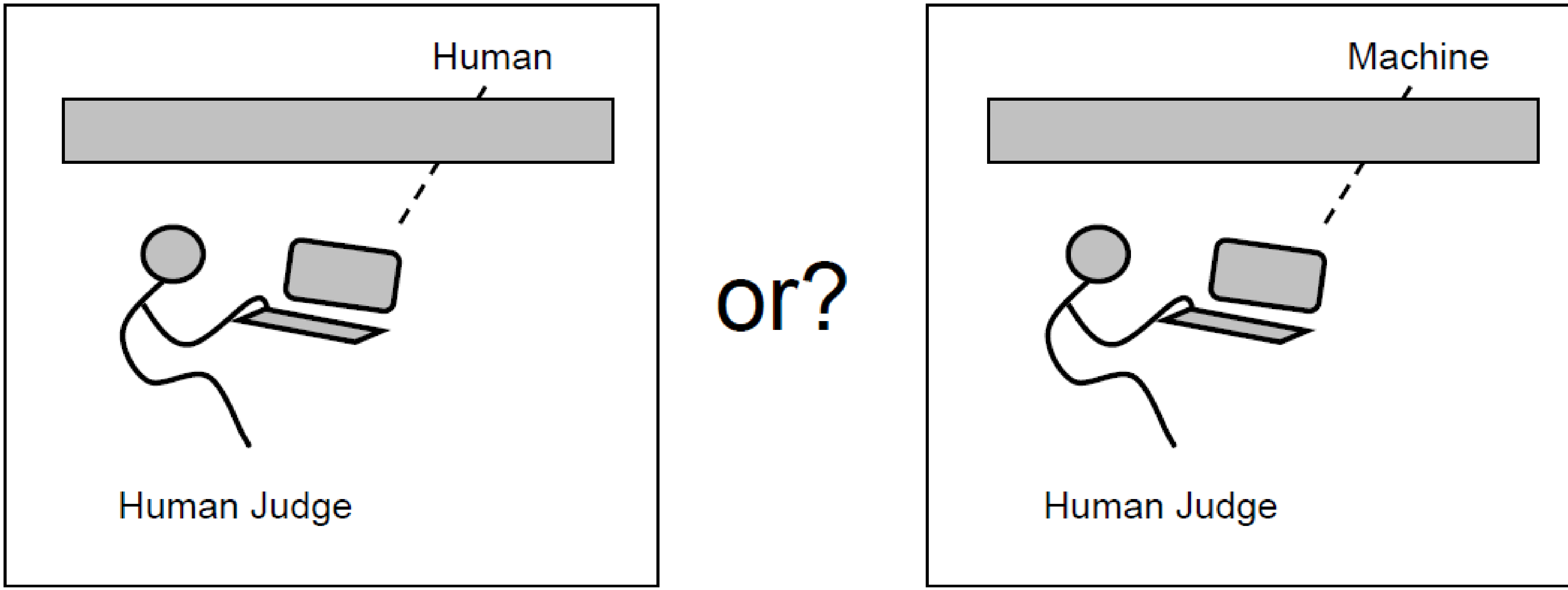
http://en.wikipedia.org/wiki/Alan_Turing

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>

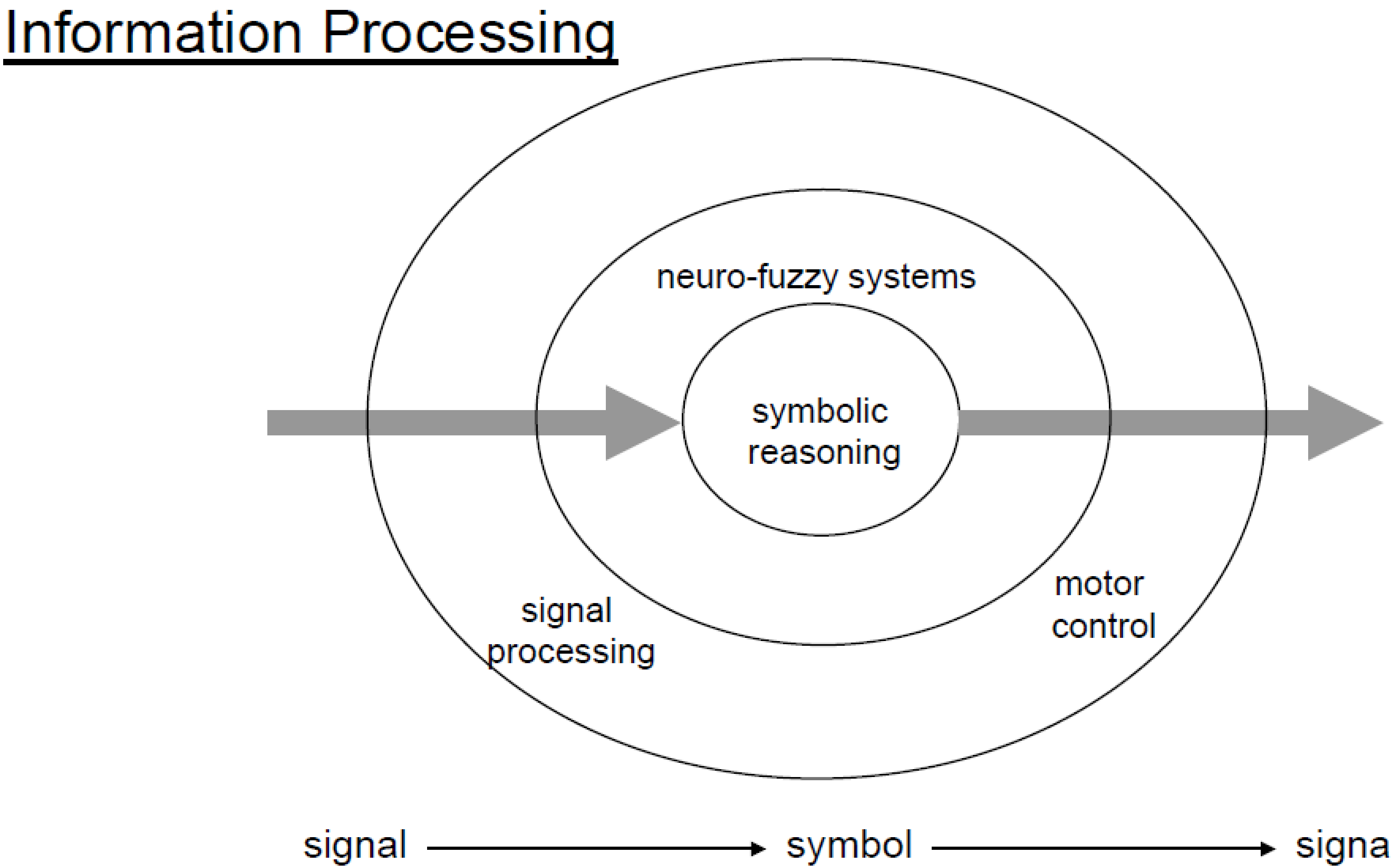


The Loebner Prize – an annual competition where chatbots are judged for human like response. The grand prize of USD 100,000 is still open.

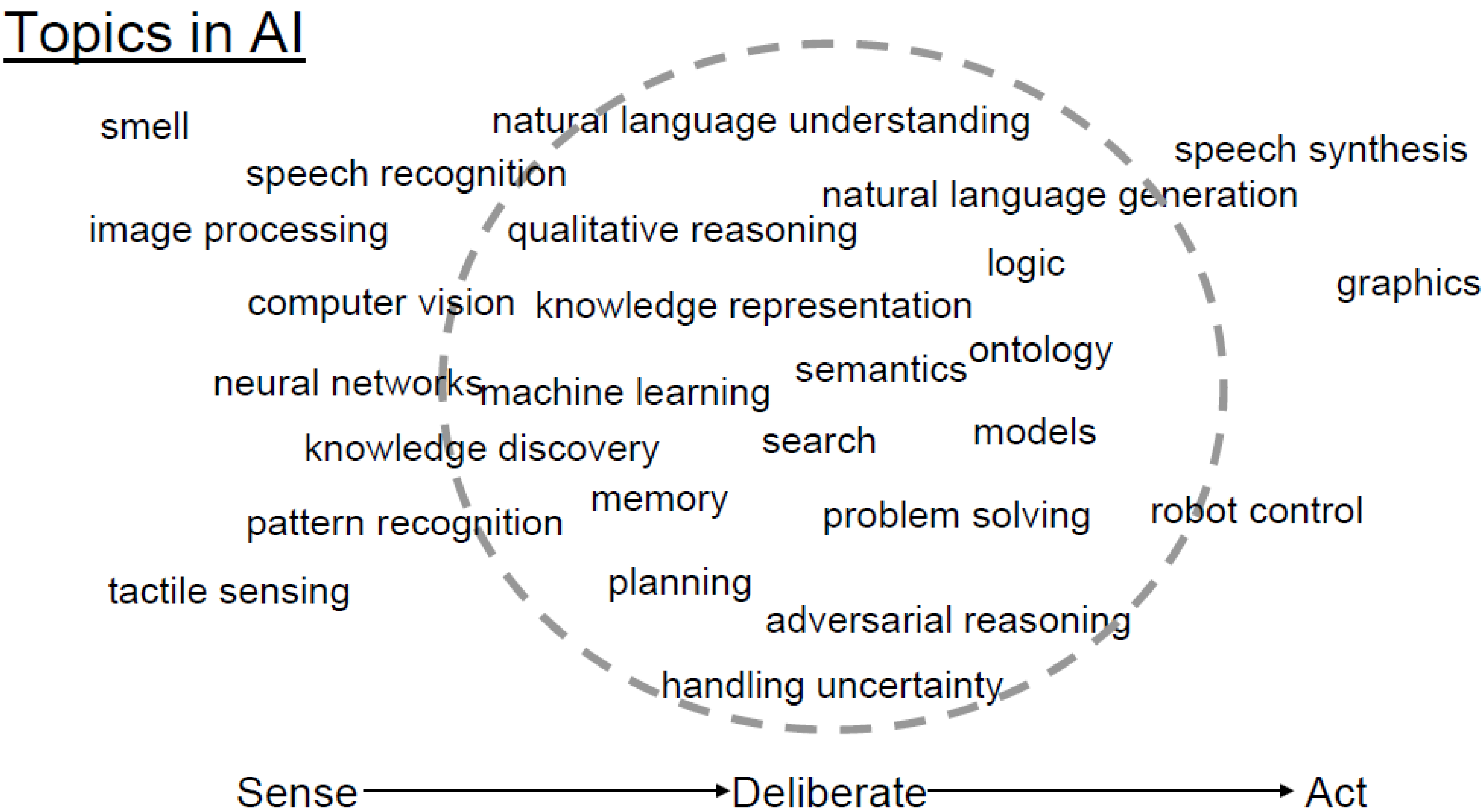
The Chinese Room Argument

- 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



Source: Deepak Khemani, A First Course in Artificial Intelligence

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, …
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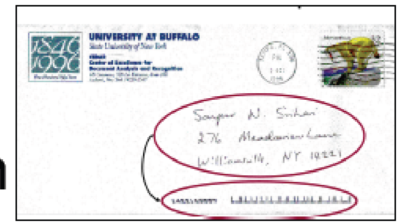
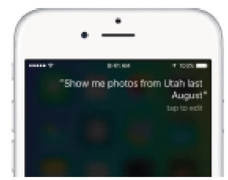
Today's AI

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

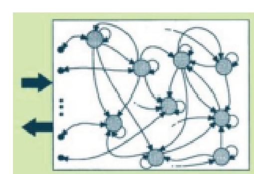


  - Understand speech or images
    - SIRI



  - 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

Deductive Vs Inductive Learning

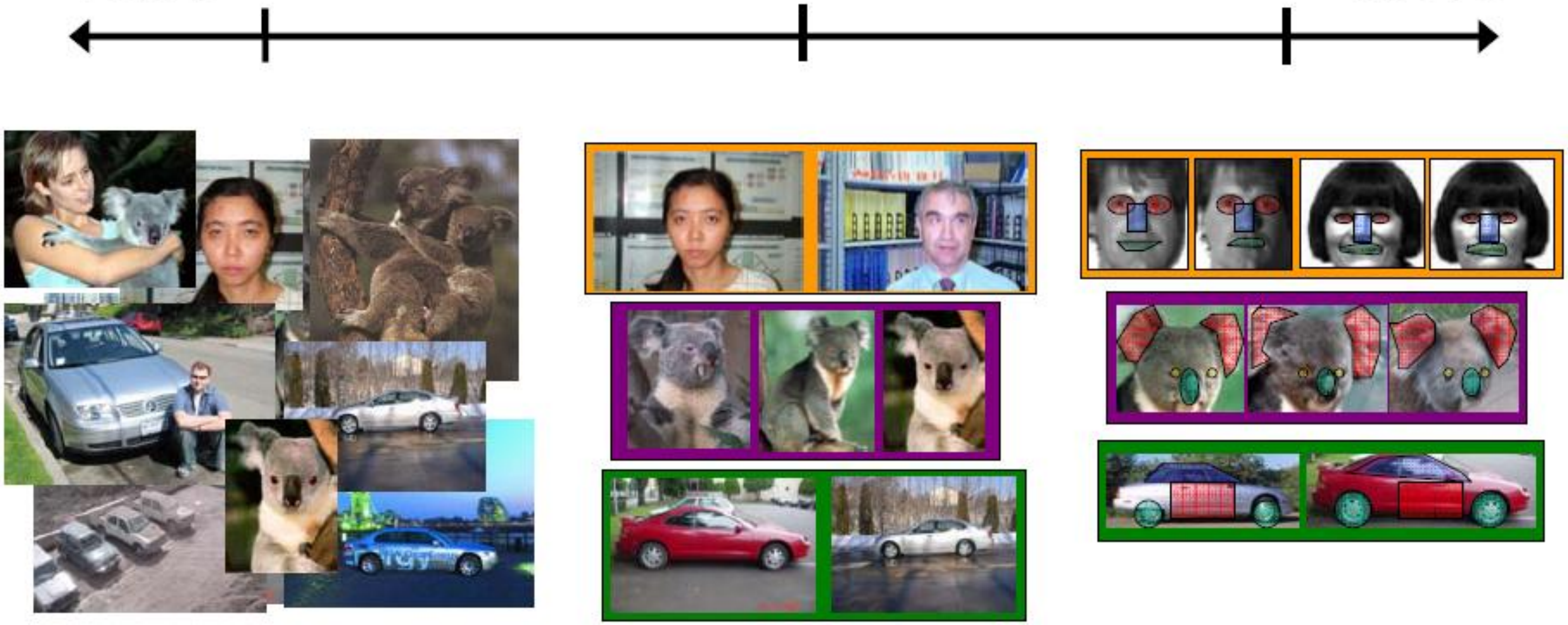
- Deductive
  - Rules of the game are (hard coded) given ahead.
  - Eg: An algorithm to do multiplication of numbers is given. Given any two numbers you can apply this and get the answer.
- Inductive
  - We are given with examples (not the concept). We need to learn the mapping from i/p to o/p.
    -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

Training (Learning phase)

We have shown a set of dog pictures and a set of cat pictures to a child.

Testing phase

→

→ DOG

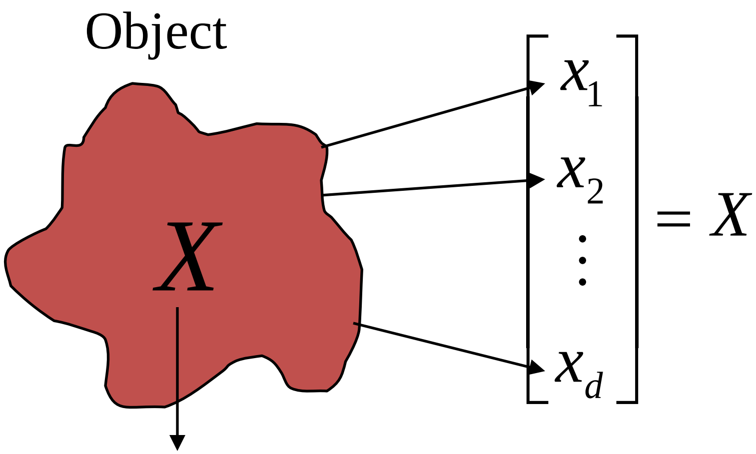
This picture as it is may not be in the training set

Child has done more than just remembering

What is learning (pattern recognition)?

- Child has learnt what is it that is common among dogs … and, what is it that is common among cats… also, what are the distinguishing features/attributes.
- Child has learnt the pattern (regularity) behind all dogs and the pattern behind all cats.
- Child then recognized a test image as having a particular pattern that is unique to dogs.

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>

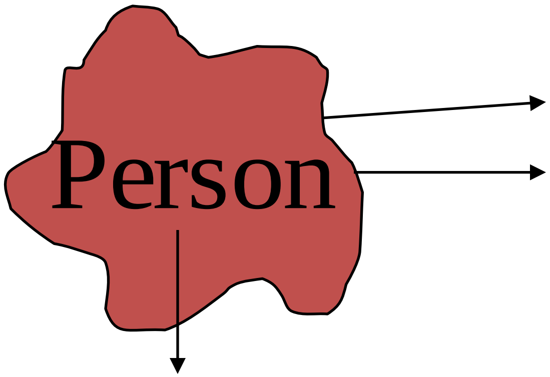
- To design a classifer (decision rule) $f : \chi \to Y$

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

An example

χ is a set of persons

Object



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

Feature vector

- A vector of observations (height, weight).

Class to which X belongs is $\quad y \in \{\text{overweight}, \text{normal}\}$

-Needs to be estimated, based on training set.

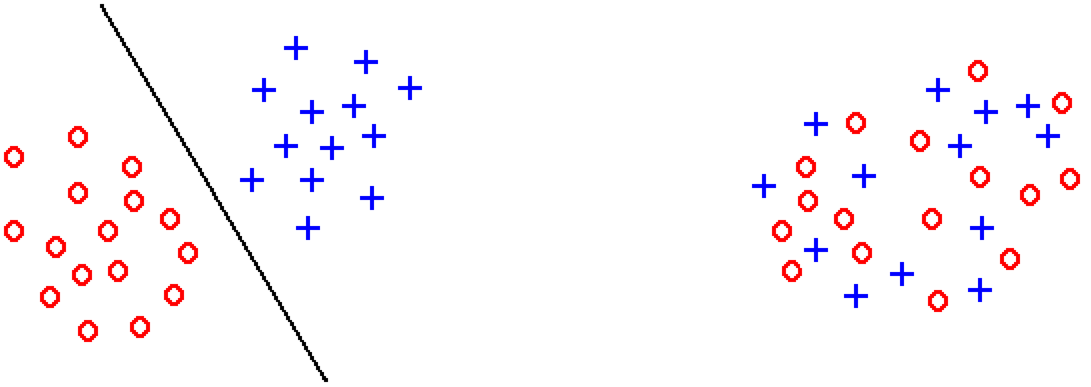
Task

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

Feature extraction

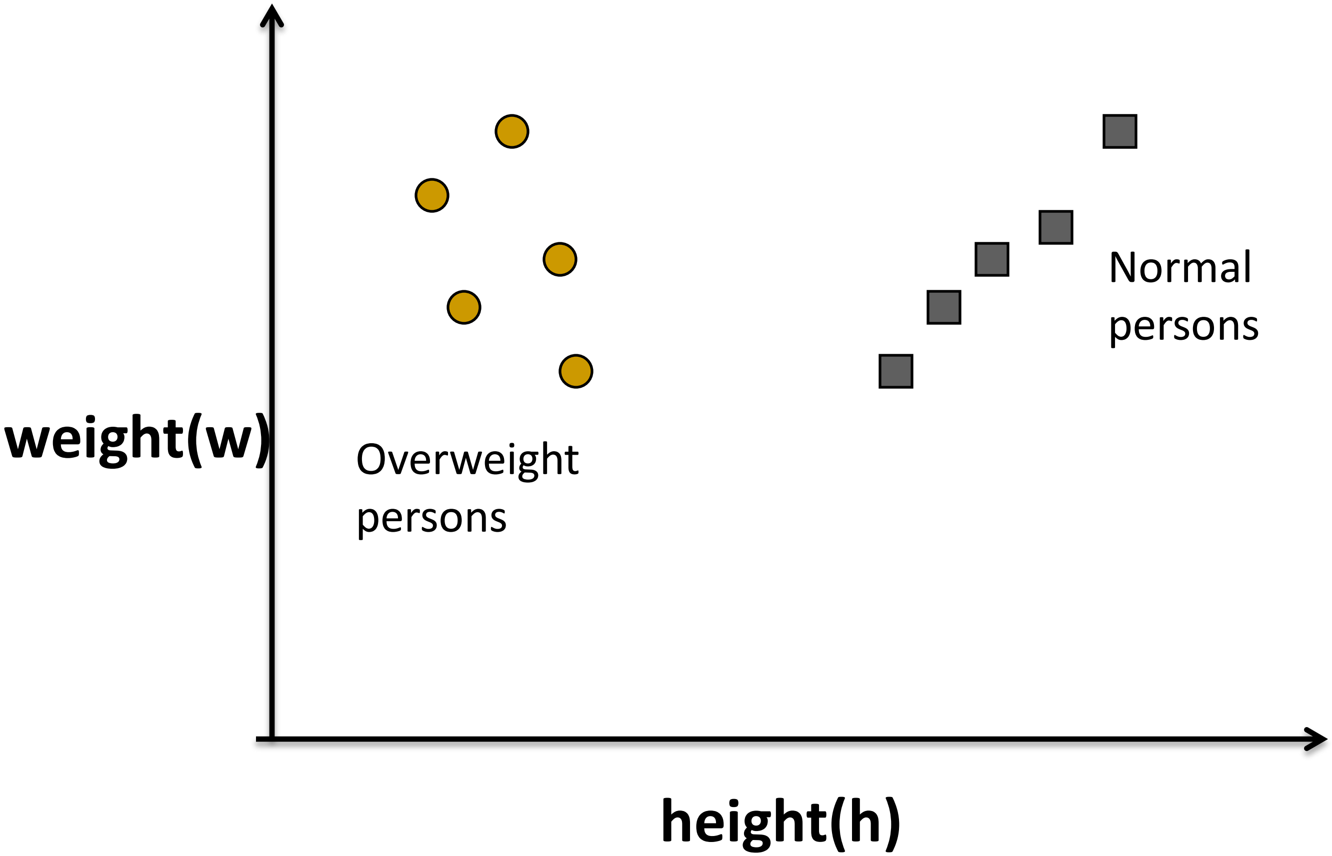
Task: to extract features which are good for classification.

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



“Good” features　　　　　　　　“Bad” features

Feature Space



Training set is shown in the feature space

Learning Steps

- Feature extraction: This is an important step. Good features are needed.
  - This is a lower level step. Normally done by techniques like image processing, speech processing, video processing, etc.
- Training set: Set of feature vectors along with their class labels.
  - An expert can see a few examples and give labels to them based on his experience.
- Build the classifier by using the training set.

Classification Problem

- Given a training set, build the classifier.

- One has to evaluate, how good is the built classifier.
  - Of course, it has to agree with the training set
    - Is this 100% true?
  - But, it should do more than this.
  - The behavior of the classifier when it is asked to classify some thing which is not in the training set determines the quality.

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

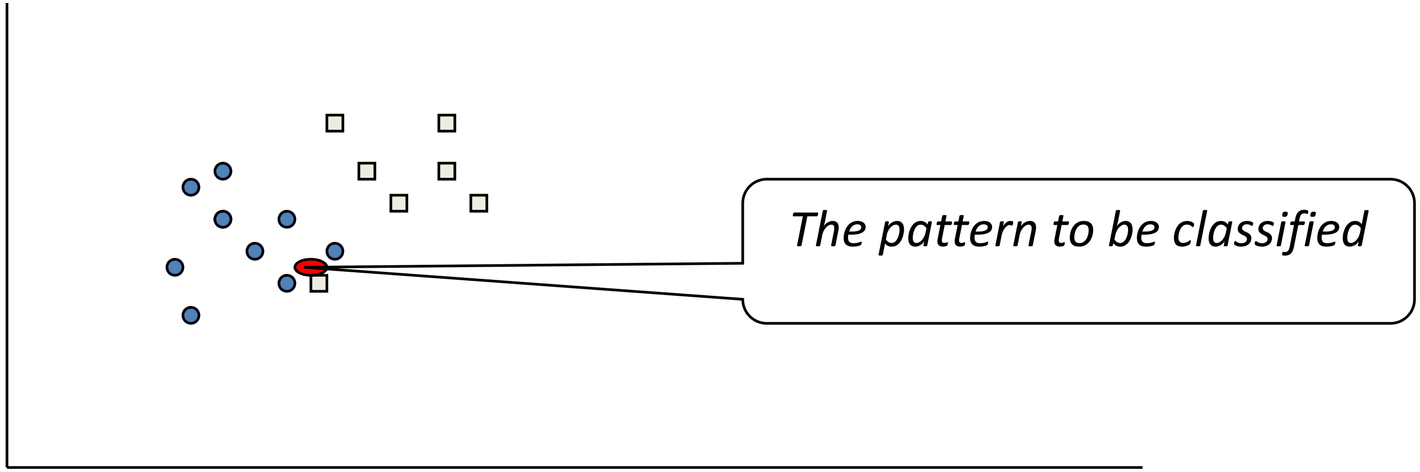
- Represent both the data and the labels
- Often, makes use of conditional independence and priors
- Examples
  - Naïve Bayes classifier
  - Bayesian network
- Models of data may apply to future prediction problems

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

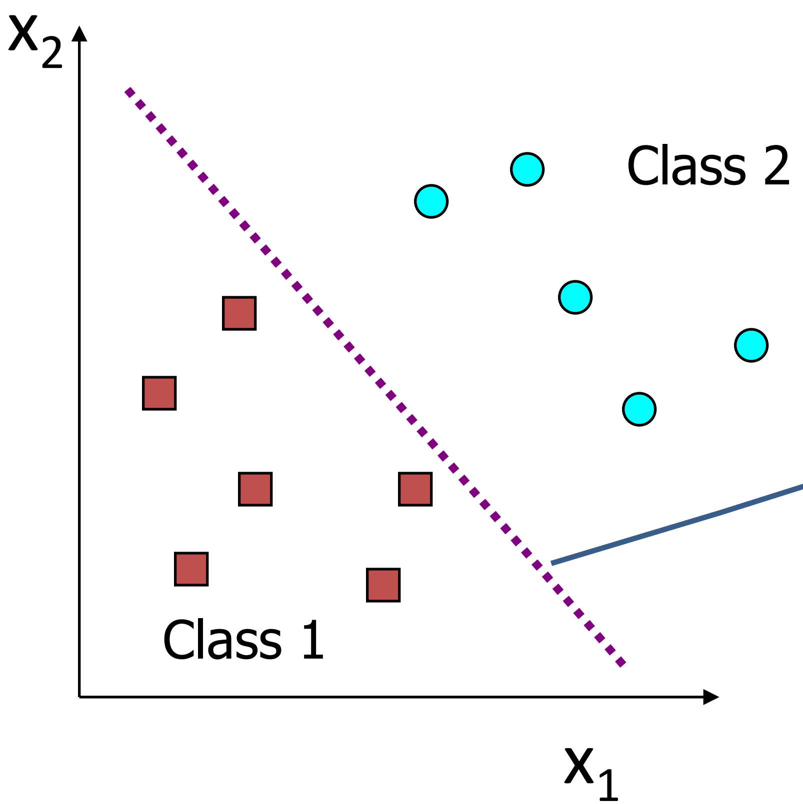
k-Nearest Neighbor Classifier



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;

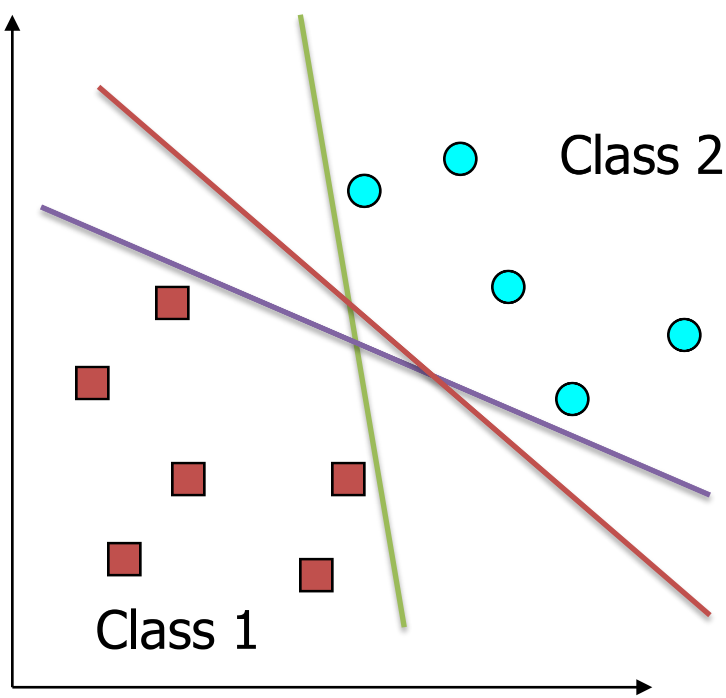
$$f(x_1,x_2) = w_1x_1+w_2x_2+b = 0$$

Perceptron

- Perceptron is the name given to the linear classifier.
- If there exists a Perceptron that correctly classifies all training examples, then we say that the training set is linearly separable.
- In 1960s Rosenblatt gave an algorithm for Perceptron learning for linearly separable data.

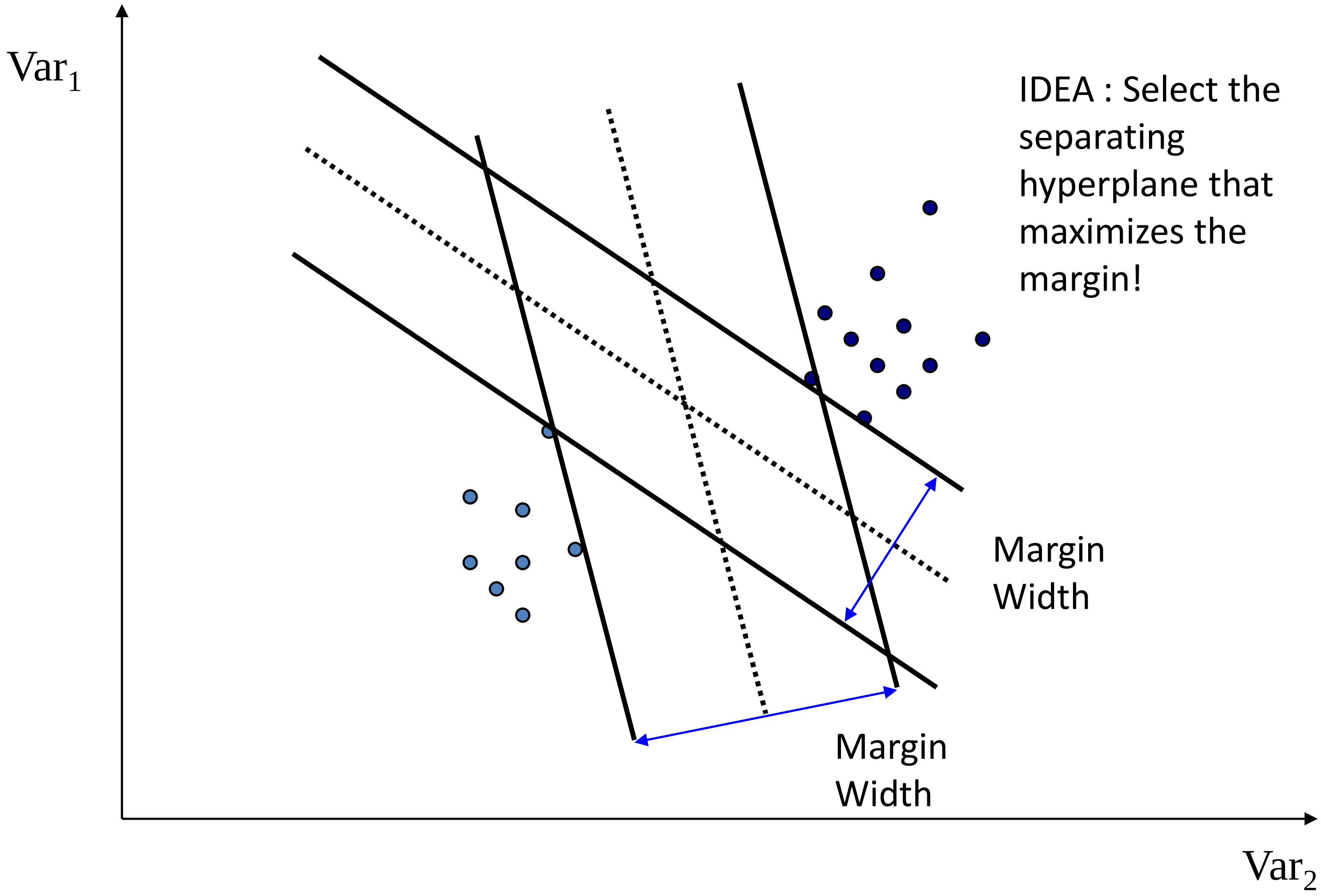
Perceptron

- For linearly separable data many classifiers are possible.



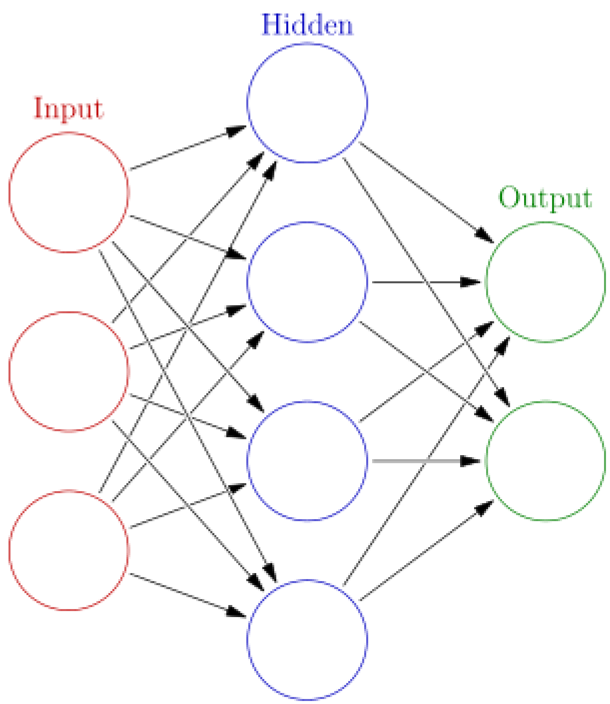
All being doing equally good on training set, which one is good on the unseen test set?

Maximizing the Margin➔ SVM



IDEA : Select the separating hyperplane that maximizes the margin!

Artificial Neural Networks



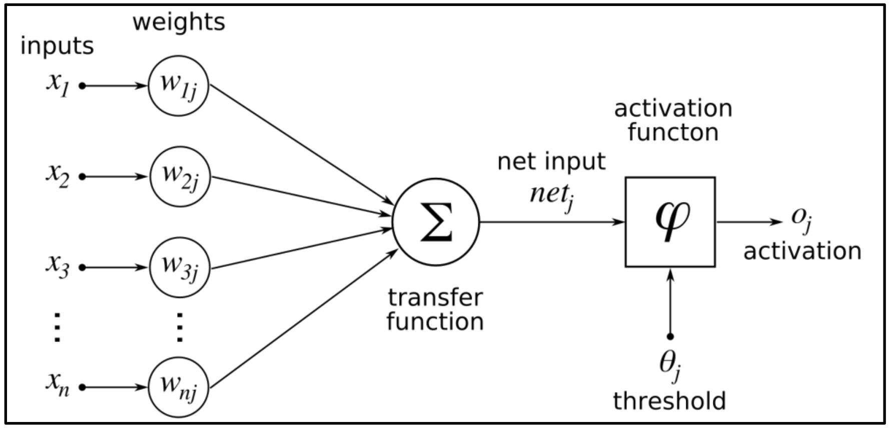
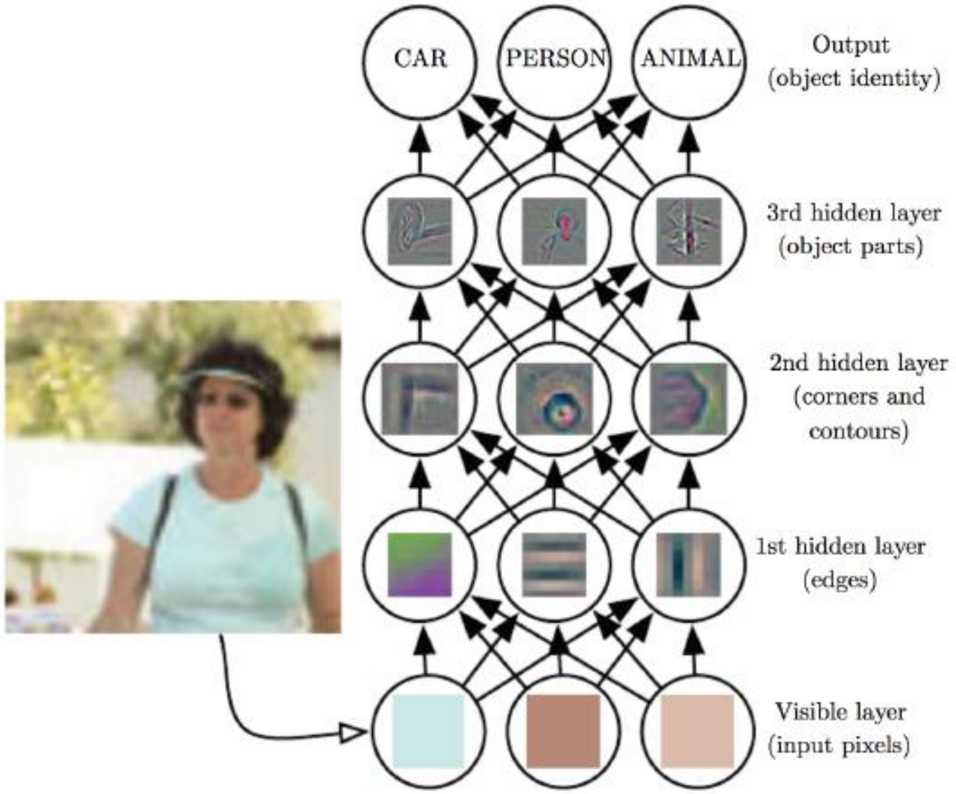


Illustration of Deep Learning

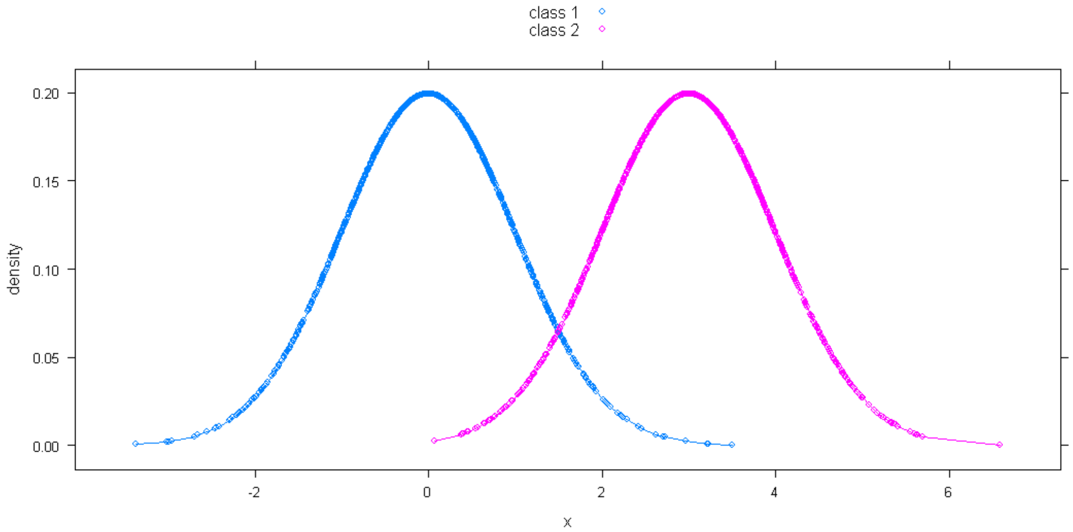
- Function mapping from pixels to object identity is complicated
- Series of hidden layers extract increasingly abstract features



Zeiler and Fergus 2014

Generative Models

- Bayes
  - Naïve Bayes
- Graphical models
  - Belief 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

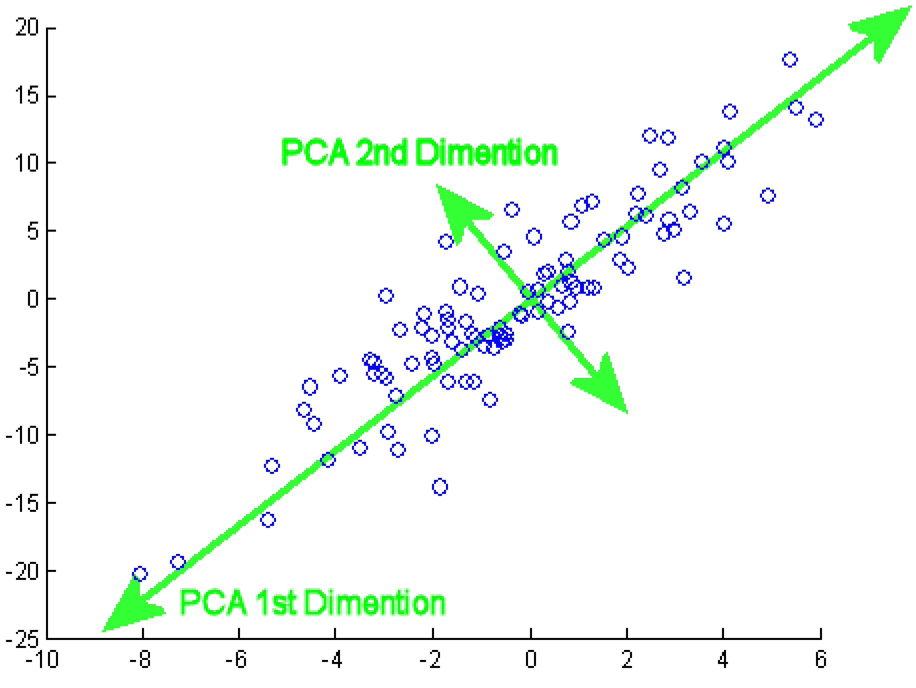
Slide credit: L. Lazebnik

Clustering Strategies

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

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

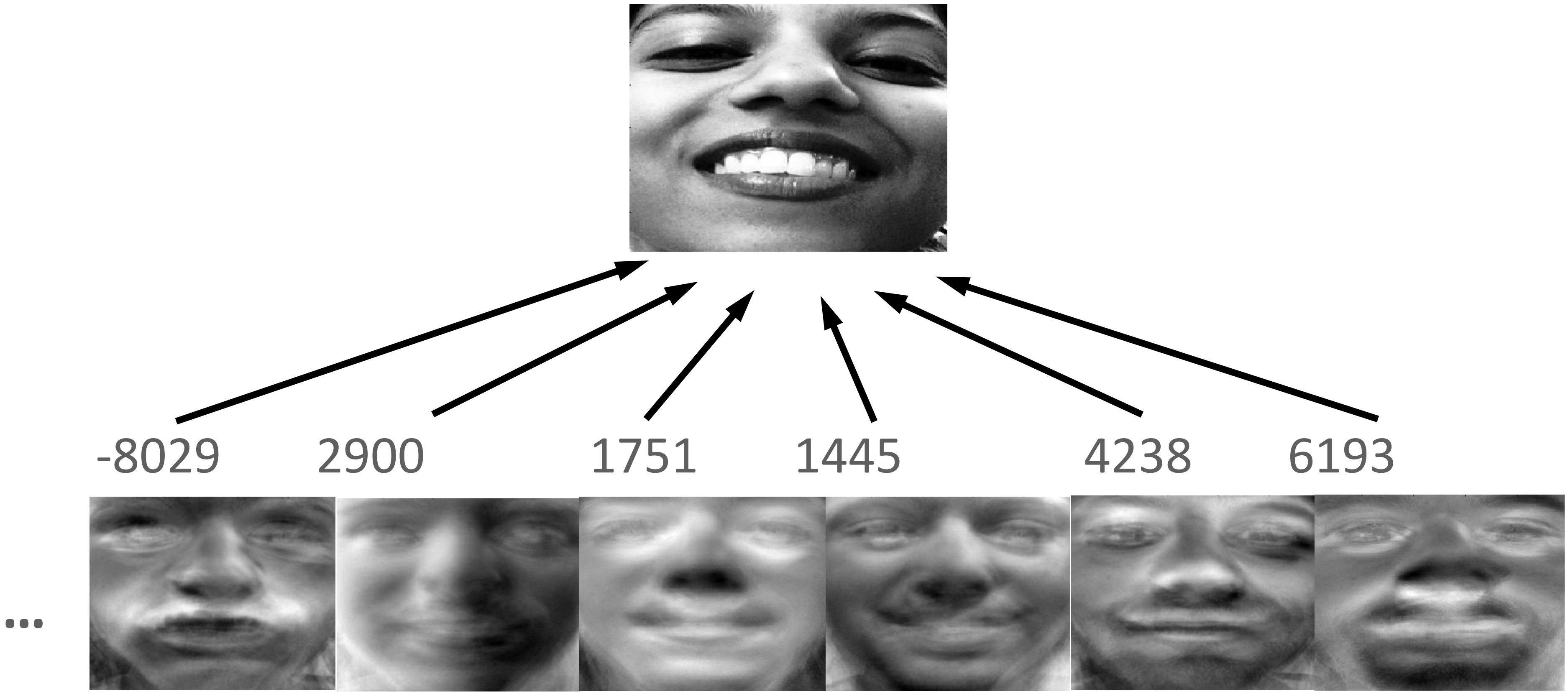
That is, apply PCA and choose top Eigen vectors (Eigen faces)

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

Eigenfaces: the idea

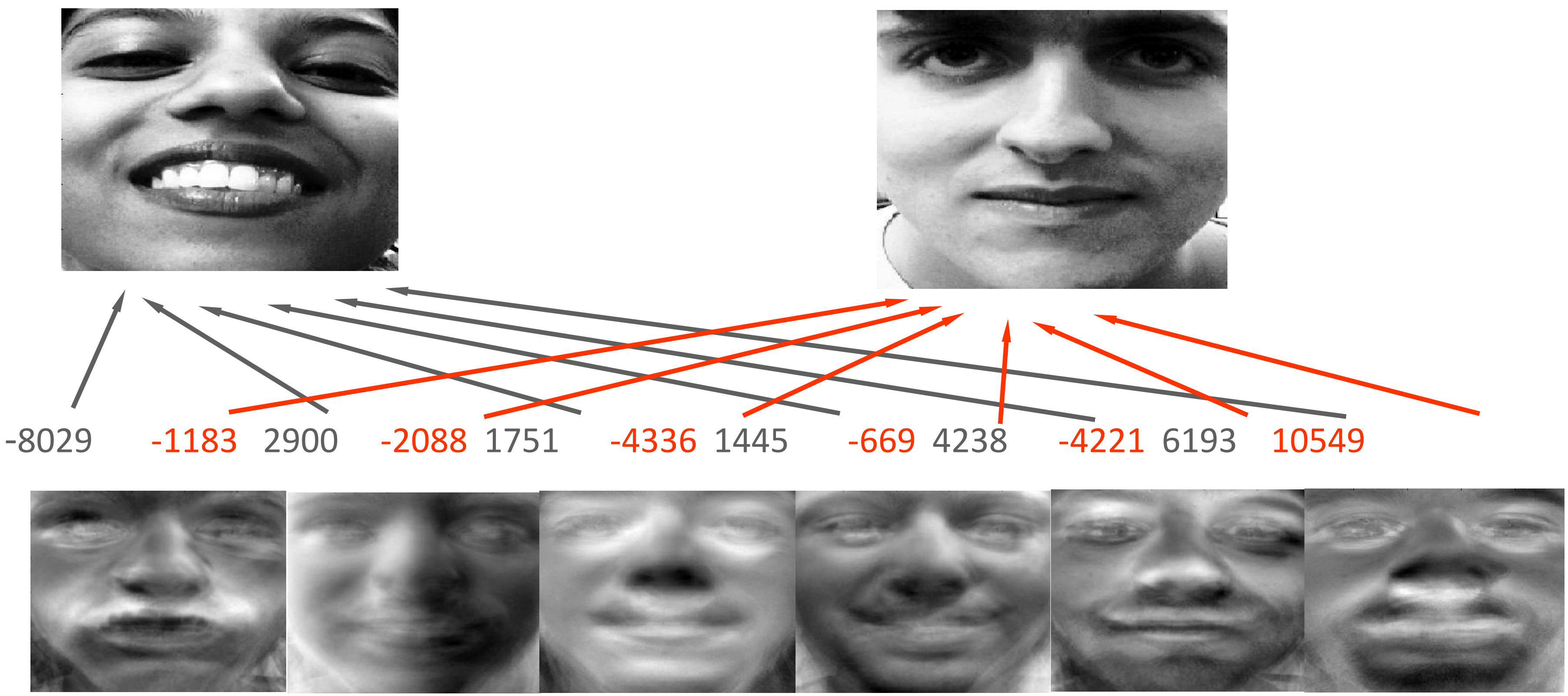
- **Think of a face as being a weighted combination of some “component” or “basis” faces**

- **These basis faces are called eigenfaces**



Eigenfaces: representing faces

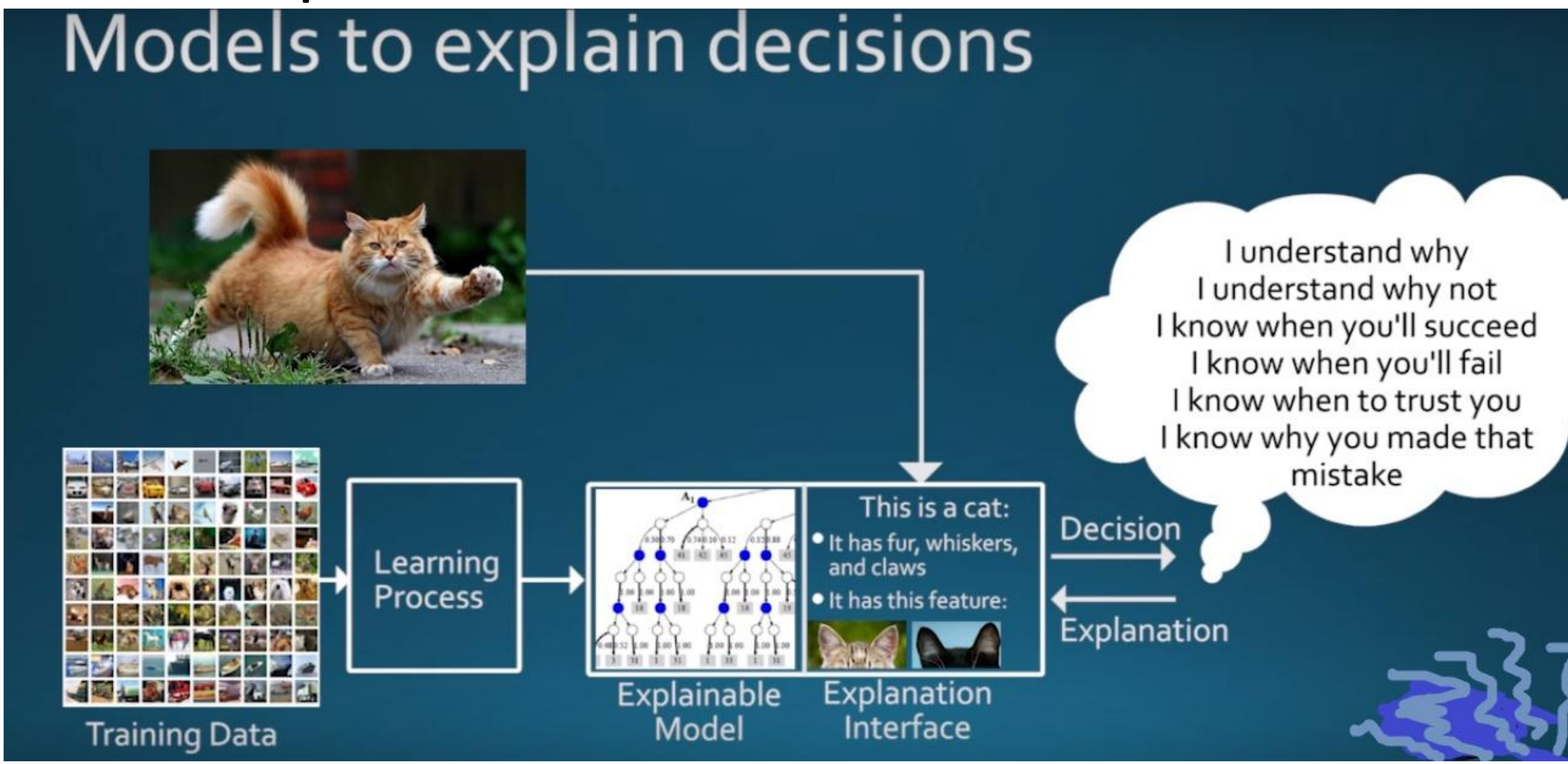
- **These basis faces can be differently weighted to represent any face**
- **So we can use different vectors of weights to represent different faces**

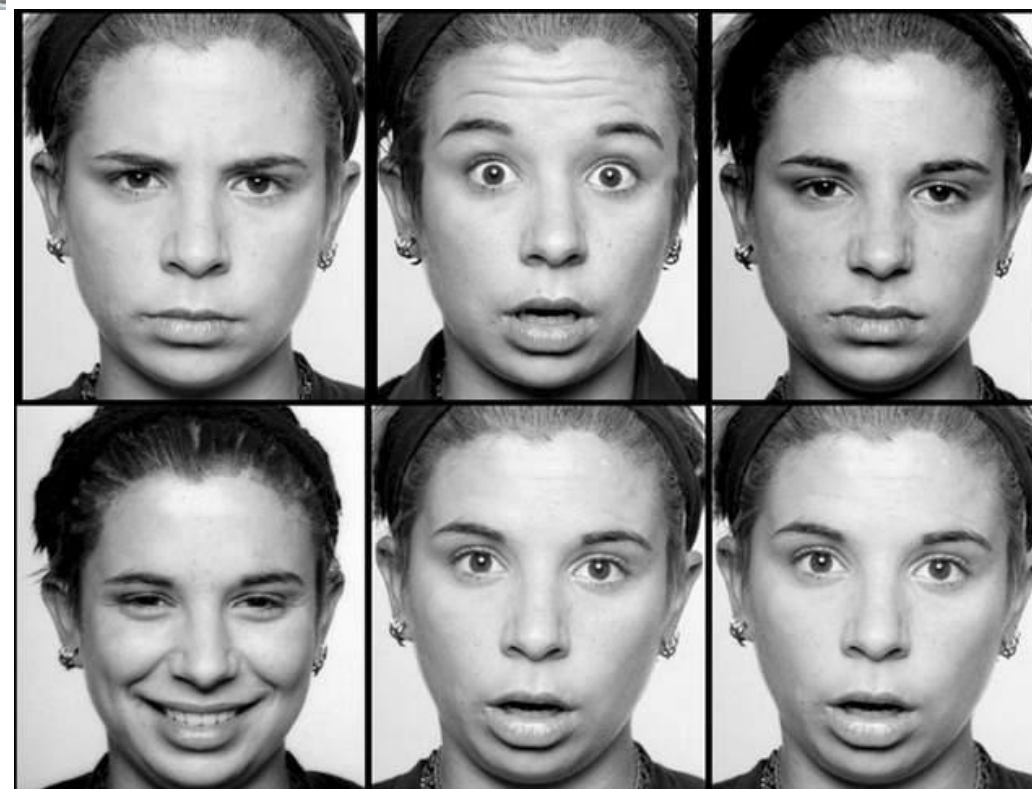


CHALLENGES

- King – man + woman = Queen
- Face – emotion + surprise = Surprised face

- Interpretable models.

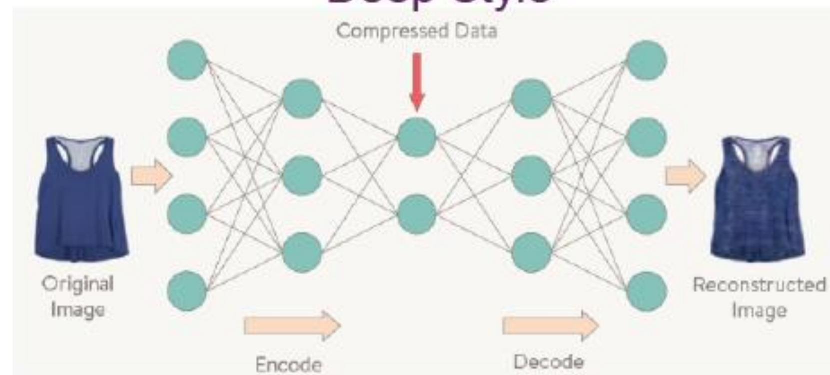




Example of Representation Learning

- Autoencoder:
  - Quintessential example of representation learning
  - Encoder:
    - Converts input into a representation with nice properties
  - Decoder:
    - Converts the representation back to input

Deep Style



New designs from representation

THANK YOU