

## Worksheet 3 #1

# The landscape of machine learning

DSE 220

# Three learning modalities

## ① Supervised learning

For solving prediction problems

## ② Unsupervised learning

For finding good representations

## ③ Learning through interaction

E.g., reinforcement learning

# Machine learning versus Algorithms

A central goal of both fields:

*develop procedures that exhibit a desired input-output behavior.*

- **Algorithms:** the input-output mapping can be precisely defined.

Input: Graph  $G$ , two nodes  $u, v$  in the graph.

Output: Shortest path from  $u$  to  $v$  in  $G$ .

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Instead, we simply provide examples of (input,output) pairs and ask the machine to *learn* a suitable mapping itself.

# Inputs and outputs

Basic terminology:

- The input space,  $\mathcal{X}$ .  
E.g.  $32 \times 32$  RGB images of animals.
- The output space,  $\mathcal{Y}$ .  
E.g. Names of 100 animals.

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**Prediction problems** can be categorized by the type of **output space**:  
(1) discrete, (2) continuous, or (3) probability values.

# Discrete output space: classification

## Binary classification

E.g., Spam detection

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## Structured outputs

E.g., Parsing

$\mathcal{X} = \{\text{sentences}\}$

$\mathcal{Y} = \{\text{parse trees}\}$

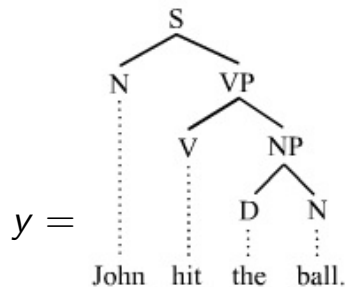
## Multiclass

E.g., News article classification

$\mathcal{X} = \{\text{news articles}\}$

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$x = \text{"John hit the ball"}$



# Continuous output space: regression

- **Pollution level prediction**

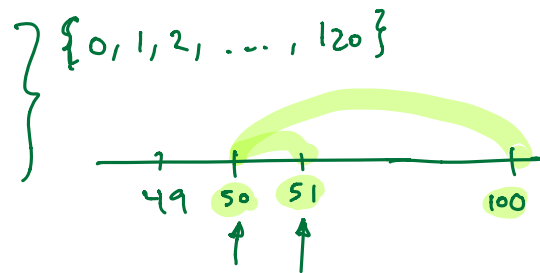
Predict tomorrow's air quality index in my neighborhood

$\mathcal{Y} = [0, \infty)$  ( $< 100$ : okay,  $> 200$ : dangerous)

- **Insurance company calculations**

What is the expected life expectancy of this person?

$\mathcal{Y} = [0, 120]$



What are suitable predictor variables ( $\mathcal{X}$ ) in each case?

# Probability estimation

$\mathcal{Y} = [0, 1]$  represents **probabilities**

Example: Credit card transactions

- $x$  = details of a transaction
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Why not just treat this as a binary classification problem?

# Three learning modalities

## ① Supervised learning

### Methods:

nearest neighbor, generative models for prediction, linear regression, logistic regression, perceptron, support vector machines, kernel methods, decision trees, boosting, random forests, neural nets

### Underlying math:

linear algebra, optimization, probability

### Formal models:

statistical learning framework, online learning

## ② Unsupervised learning

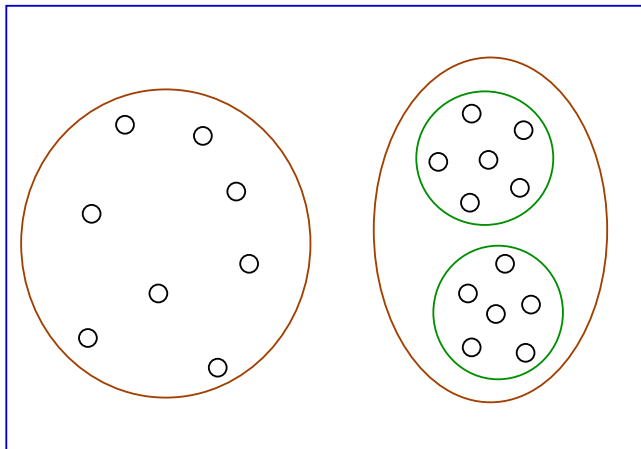
## ③ Learning through interaction

# Unsupervised learning

Find **structure** in data: underlying **degrees of freedom**.

# Unsupervised learning

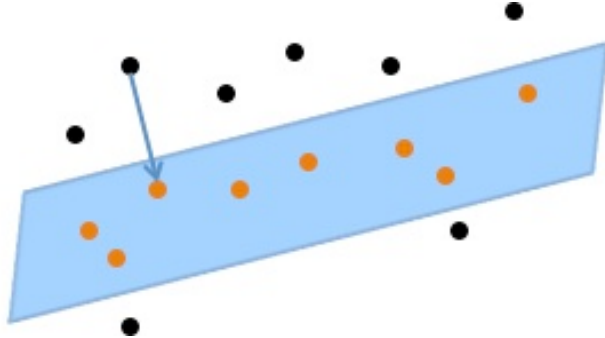
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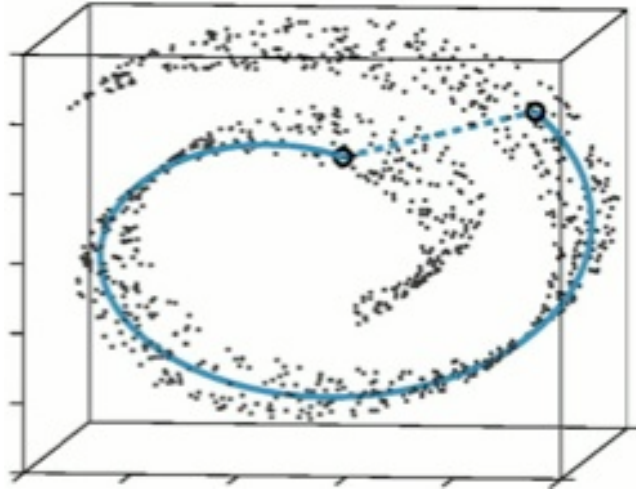
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# Three learning modalities

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### Types of structure:

clusters; low-dimensional subspaces; manifolds; dictionaries; independent components; topics

### Algorithmic foundations:

local search; linear algebra

## ③ Learning through interaction