



Lecture 1: Introduction

DD2421 Machine Learning

Part II: Classification problems and Nearest Neighbor rule

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In this part we will visit:

- Some more examples of applications
- Concept of classification
 - Hand-written digit recognition
- Simple approaches for classification
 - **Nearest Neighbour** method

Where is machine learning useful?

- A pattern exists.
- Data available for training.
- Hard/impossible to define rules mathematically.

Related terms on data analysis

- Pattern Recognition
- Data Mining
- Statistics

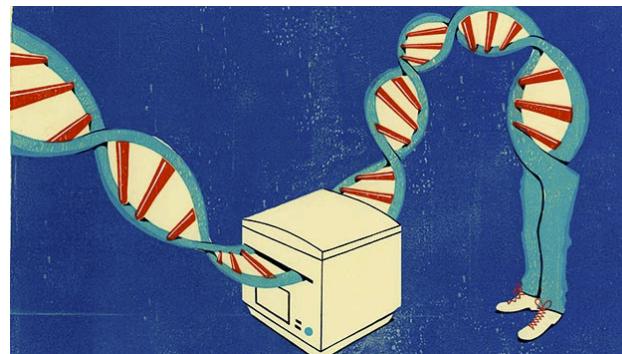
ML applications are pervasive

- Optic character recognition (OCR)

2|6|0|1|9|2|7|1|4|0
5|4|3|0|8|4|3|9|4|7

- Medical diagnosis

- DNA analysis

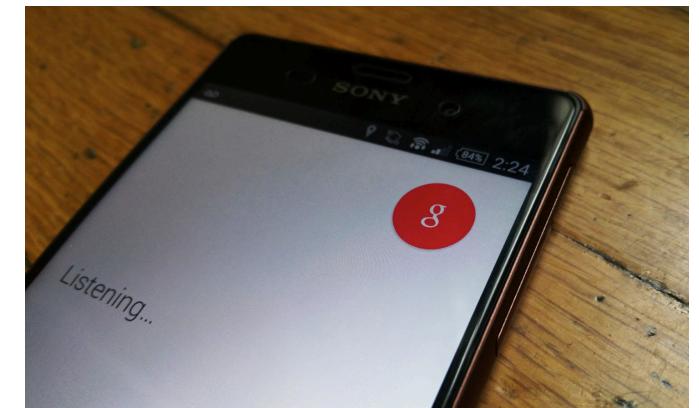


(by bejarprints)

- Remote sensing

- Speech technology

- NLP / automatic translation

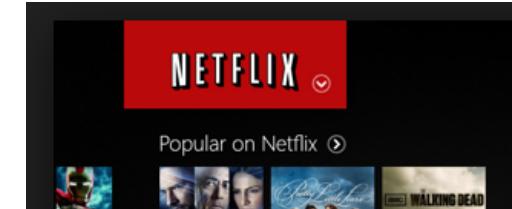


➤ Computer Vision



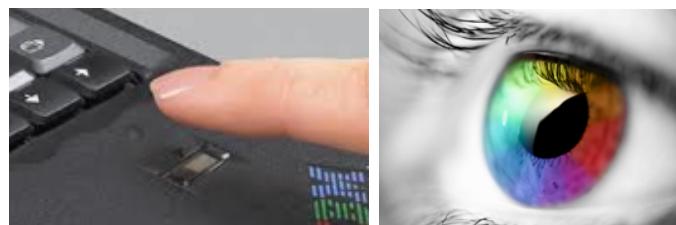
(The Cambridge-driving Labeled Video Database)

➤ Recommender systems: books, movies

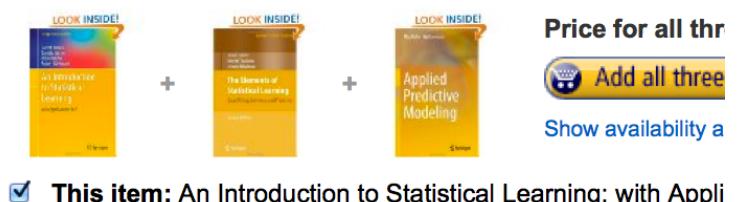


➤ Biometrics: fingerprint, iris, face

...



Frequently Bought Together



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This item: An Introduction to Statistical Learning: with Appli

Concept of classification

- We would like to enable a computer to learn from **data** to answer a question - “What is it?”
You’re given sample data (for finding patterns).

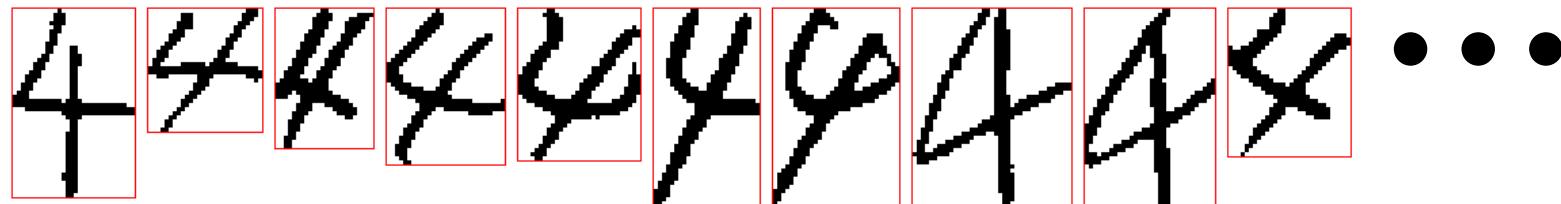
The framework of classification

1. **Training phase:** to give the concept of classes to a machine using **labeled data**
2. **Testing phase:** to determine the class of new unseen (**unlabeled**) data

Example: Hand-written digits

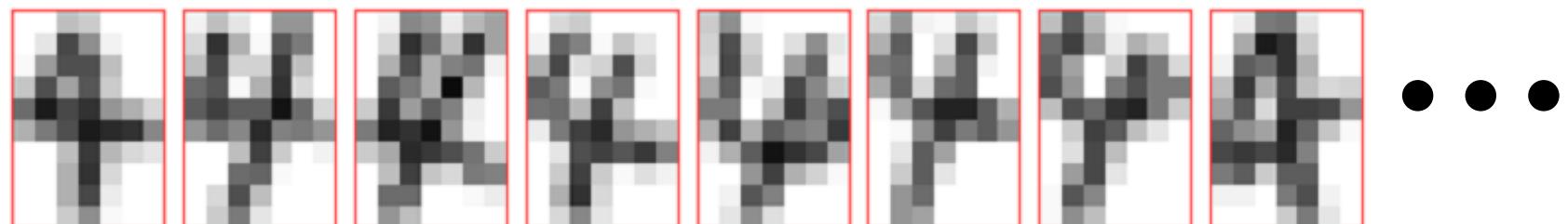
One of the first commercial system with ML, used for zip codes

Training samples:



Feature extraction

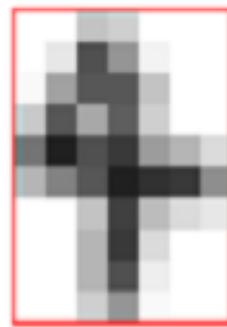
Pattern vectors: normalized & blurred patterns



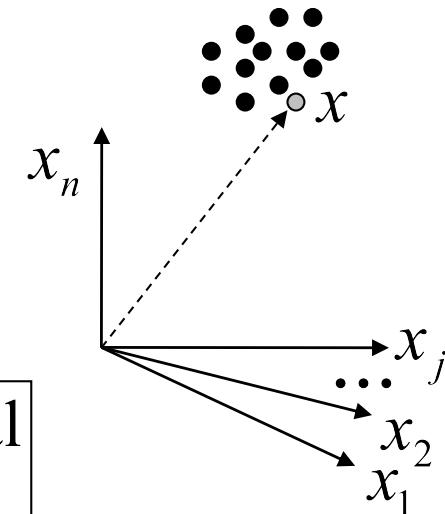
Feature extraction for digit recognition

- Represent an image by a **feature vector**

- Sampling: $n = 7 \times 10$ pixels



n -dimensional
feature space



- A set of n gray values: $\mathbf{x} = (x_1, \dots, x_n)$
i.e. corresponding to a point in feature space

More training samples of “4” and others

<http://yann.lecun.com/exdb/mnist/>

OCR system (a historical example)



ASPET/71 (ETL, Toshiba; 1971)

Recognition of letters; 2000 alphanumeric chars/sec.,
200 sheets/min. Analog circuit for similarity calculation.

<http://museum.ipsj.or.jp/en/heritage/ASPET/71.html>

Example: Face images

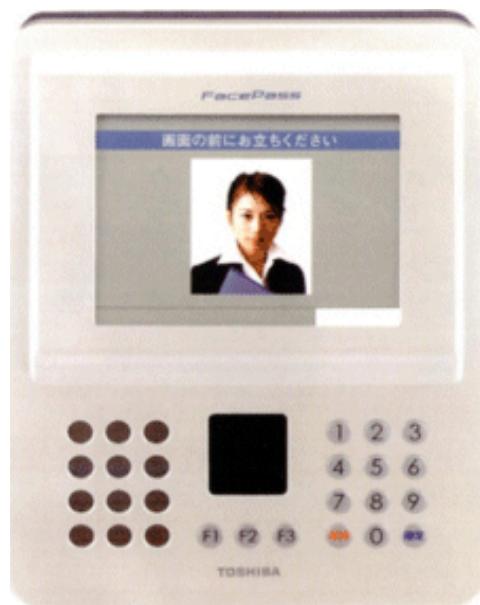
Training samples of frontal faces



(Face image database, CMU)

Face Recognition (a biometric example)

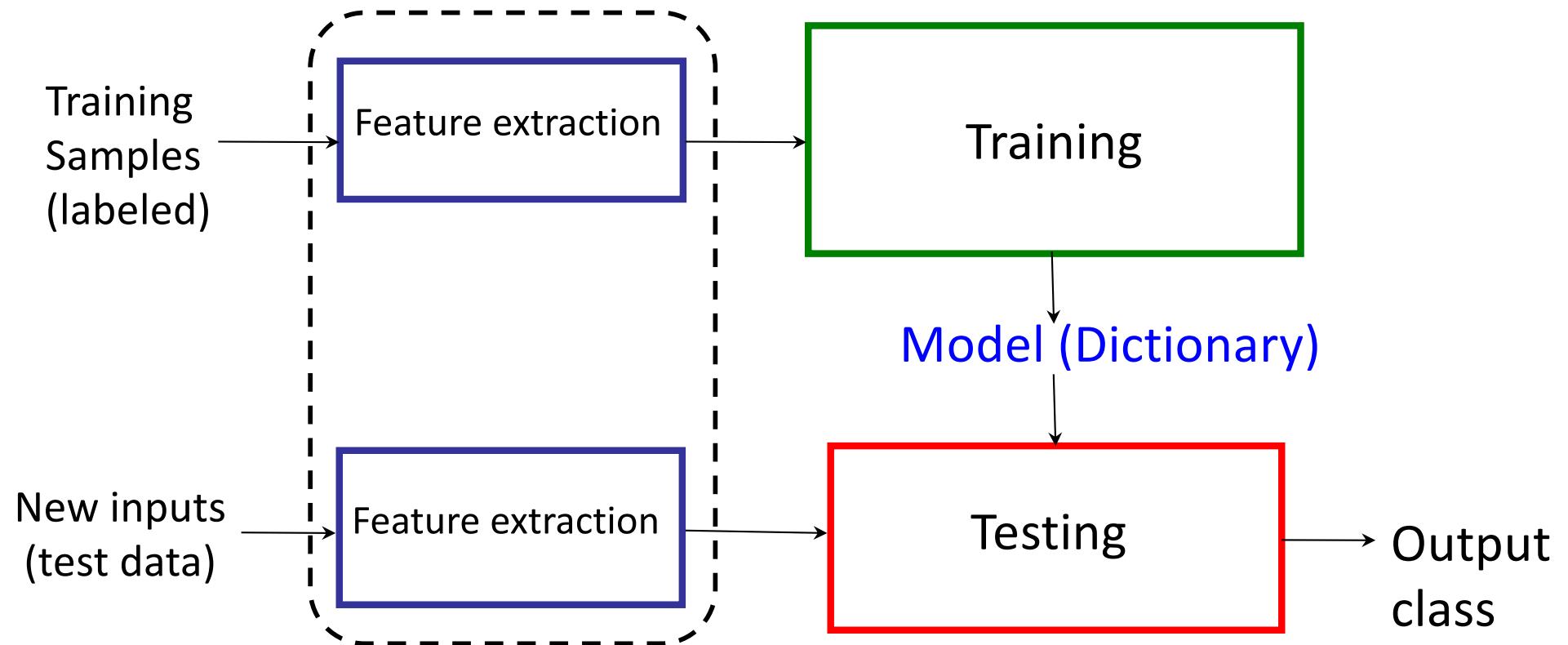
Security system
FacePass(R)



Recognition while walking
SmartConcierge(R), 2007

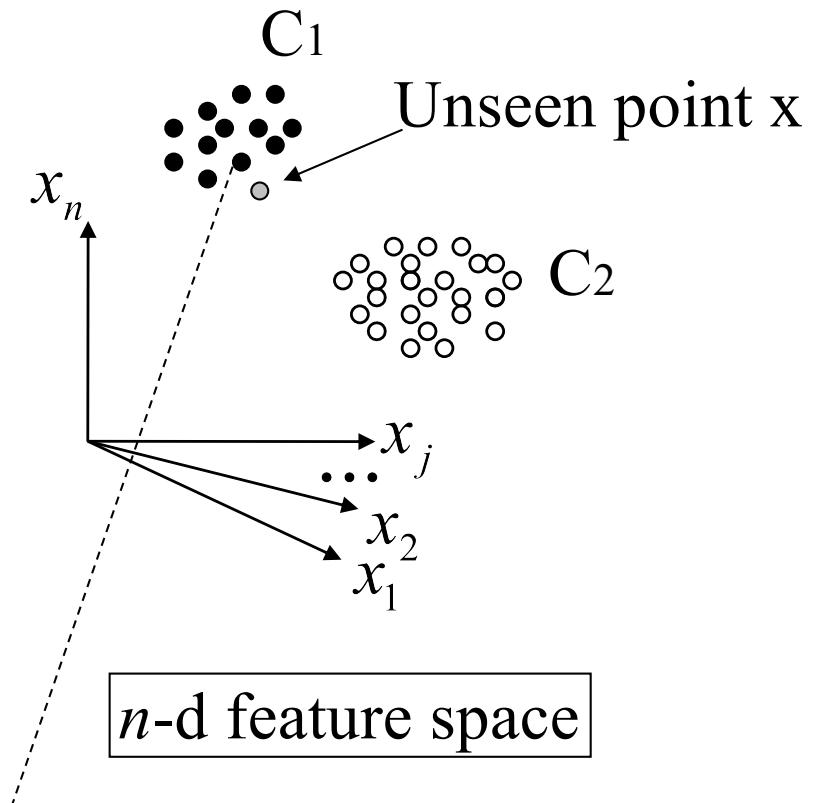


Schematic of classification



Nearest Neighbour methods

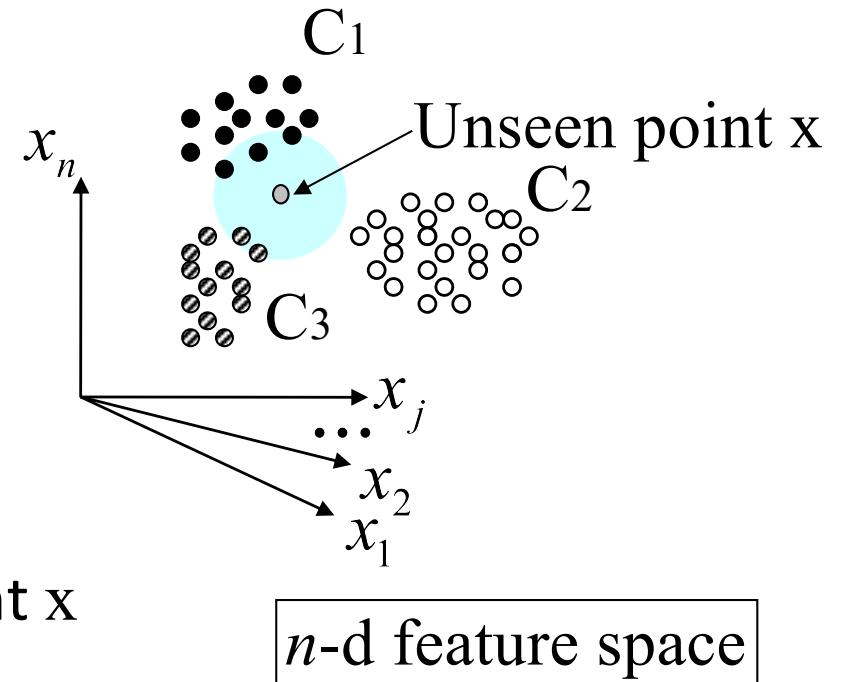
- Binary classification
 - N_1 samples of class C_1
 - N_2 samples of class C_2
 - Unseen data x
→ Compute distances to all the $N_1 + N_2$ samples
- Find the nearest neighbour
→ classify x to the same class



- k -nearest neighbour rule

- Compute the distances to all the samples from new data x
- Pick k neighbours that are nearest to x

→ Majority vote to classify point x
(Nearest Neighbour is 1-NN)



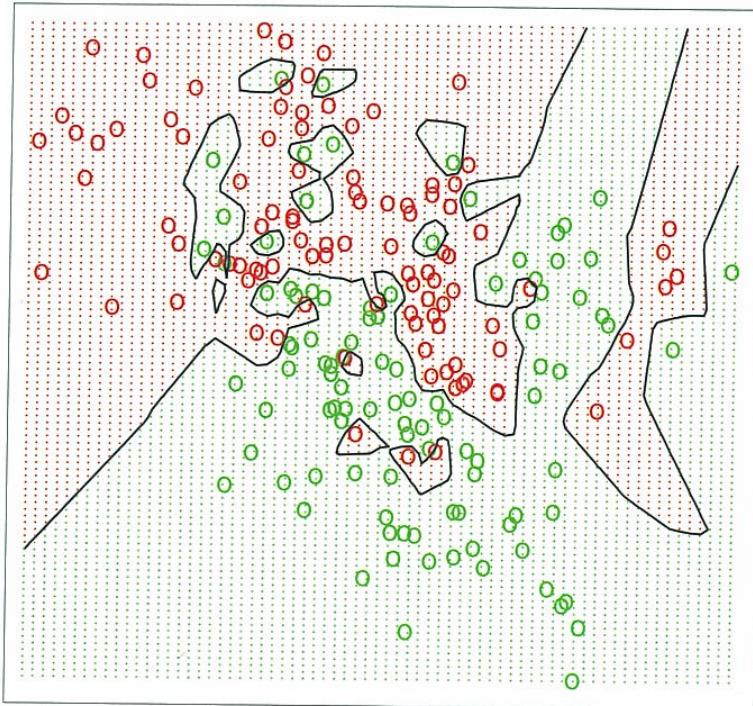
- How does k -NN compare to 1-NN ?

What is the influence of k ?

$k = 1$

$k = ?$

1-Nearest Neighbor Classifier

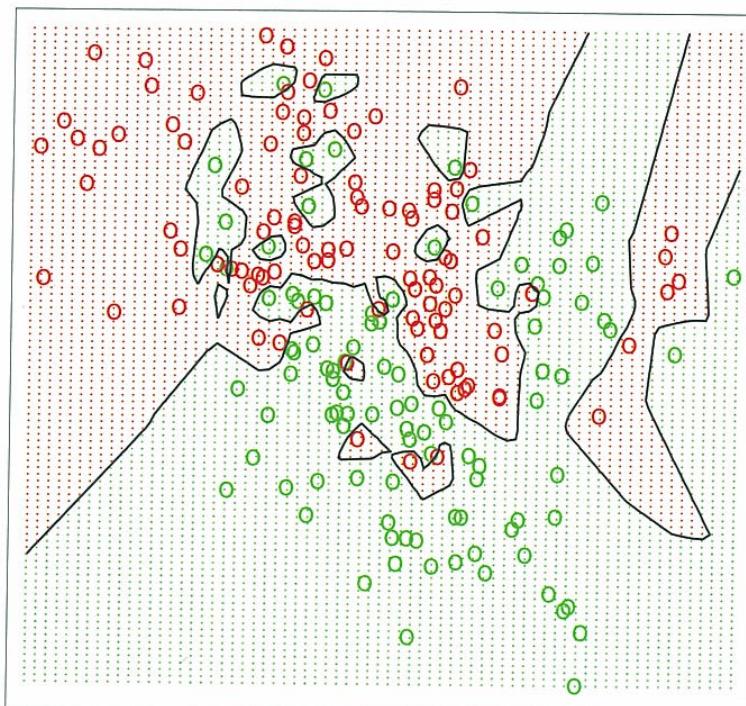


?

Decision boundaries with different k

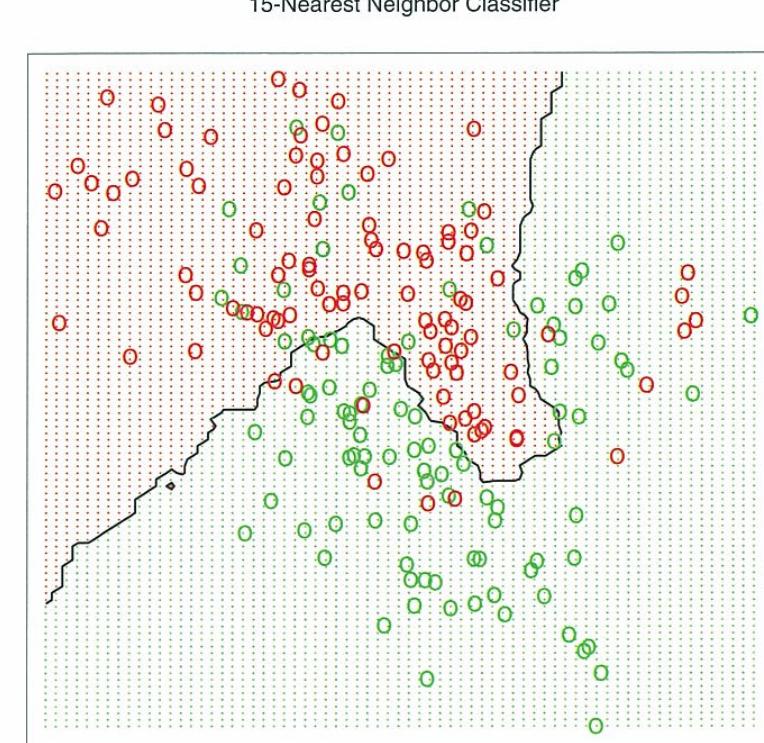
$k = 1$

No misclassifications on training data



$k = 15$

More generalized



(T. Hastie et al, The Elements of Statistical Learning)

Pros and cons of k -NN

- k -NN / 1-NN comparison summary
 - the boundary becomes smoother as k increases
 - lower computational cost for lower k
 - k -NN better **generalizes** given many samples
- Pros:
 - simple; only with a single parameter k
 - applicable to multi-class problems
 - good performance, effective in **low dimension data**
- Cons:
 - costly to compute distances to search for the nearest
 - memory requirement: must store all the training set

Notes on “generalization”

- Our goal is to determine the class of **unseen data**.
- Strategies/parameters that achieve minimum loss on training samples is **not** necessarily best for test data.
- We want the machine to learn the **true pattern** (and not noise) that resides in the sample data for **generalization**.

Keywords to remember

- Classification
 - Feature extraction
 - Training/Testing
 - Generalization
- Classification methods
 - Nearest Neighbour rule
- Decision trees (to come)