Machine Learning and Artificial Intelligence

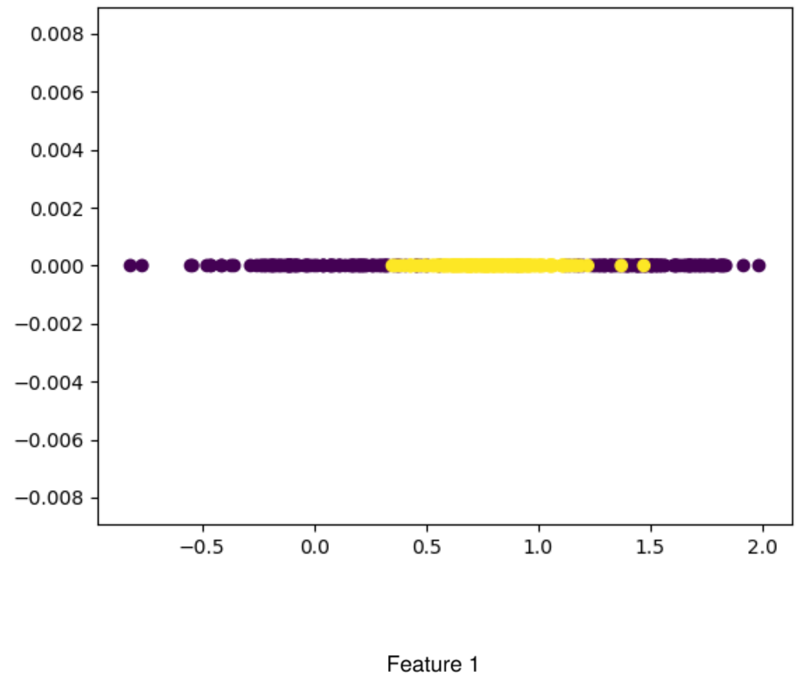
Lab 03 – K-Nearest Neighbours & Parzen Windows

23/03/2021

The problem

Starting point:

- Train data set (400 objects, 1 feature)
- Test data set (100 objects, 1 feature)
- Train data labels
- Test data labels (will never be considered except in final validation)



Non-parametric methods

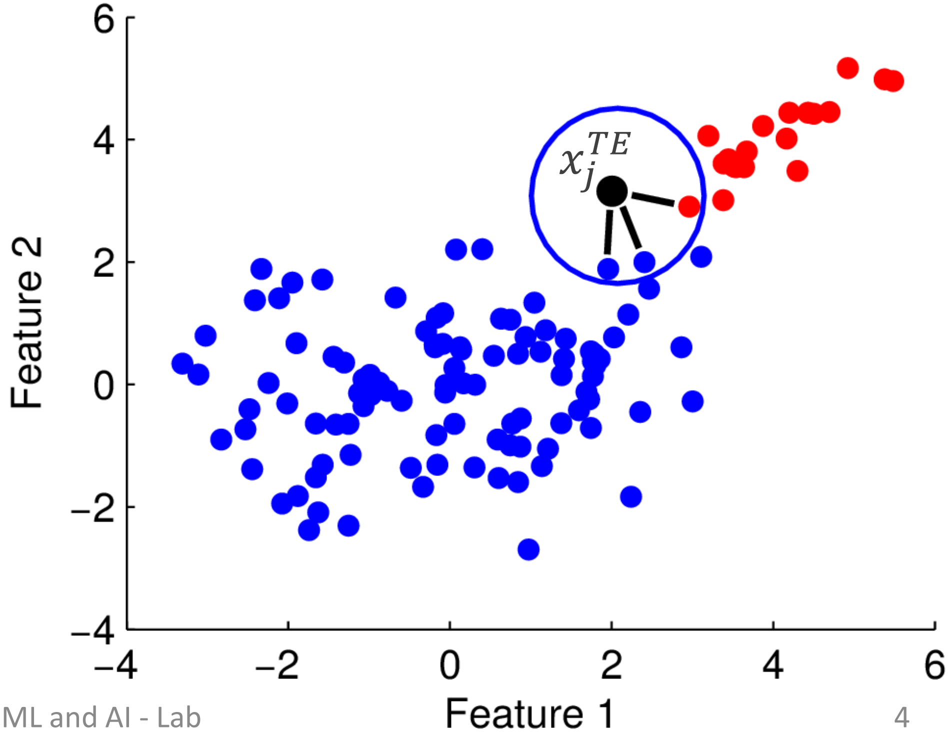
- Parametric methods make a *strong* assumption, which is that the shape of the probability densities is known. This assumption cannot be made in many problems.

- Idea of non-parametric methods: estimate the probability density function from the samples directly:
  1. K-Nearest Neighbors
  2. Parzen Windows

K-Nearest Neighbours

- Idea: given a test point x_j^{TE} to be classified, I consider the K train points closest to it, according to a certain metric.

- I assign to x_j^{TE} the most frequent class among these K points.



K-NN: In practice

Starting point:

- Train data set
- Train data labels
- Test data set
- Test data labels (will never be considered until final validation)

K-NN: In practice

- A priori, I decide how many nearest neighbours K to consider.
- Given a test point x_j^{TE}:
  - I calculate the (Euclidean) distance between x_j^{TE} and all train points x_j^{TR}.
  - I order the distances (ascending) and find the indices of the neighbouring K train points.
  - I check the labels of these K points: I have to find the most frequent class label.

K-NN: In practice

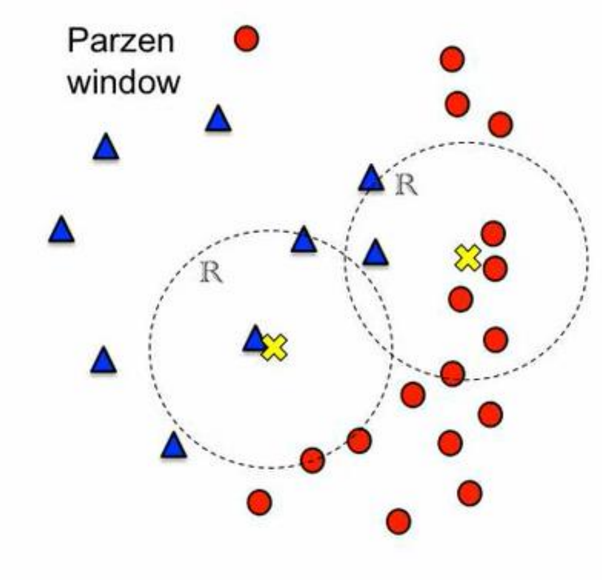
- To assign a class to the test instance, we use the statistical concept of *mode:* the value that appears most often in a set of data values.

- Given the vector of labels of K neighbouring points (the vector will be K long), we find the mode and assign the it as the class of x_j^{TE}.

Exercises

Parzen Windows

- Idea: estimate the pdf (underlying probability distribution) by looking at individual regions in space.
- If you need to estimate p(x=x0), you look at the region in a window centred on x0 and estimate from that region.
- This can be repeated for all the points to be classified.



Parzen Windows: In practice

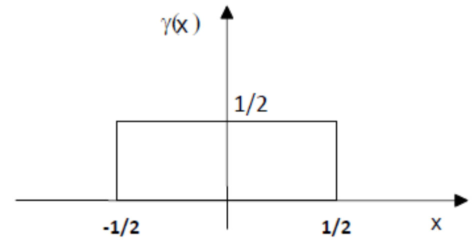
- A priori, I decide the width of the window h (e.g., h=0.2)

- I divide the training dataset in two, based on the classes (the labels of the test are unknown)

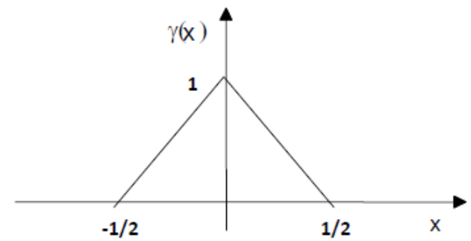
- Given a test point x_j^{TE}:
    - For every train point x_i^{TR} <u>of class c</u>:
        - Calculate the function $\gamma\left(\frac{x_j^{TE} - x_i^{TR}}{h}\right)$
    - The likelihood $p\left(x_j^{TE}|\omega_c\right) = \frac{1}{N_c}\sum_{i=1}^{N_c} \frac{1}{h}\gamma\left(\frac{x_j^{TE} - x_i^{TR}}{h}\right)$
        - N_c : Number of points belonging to class c
    - Assign x_j^{TE} to the class with max. likelihood

Viable functions for γ

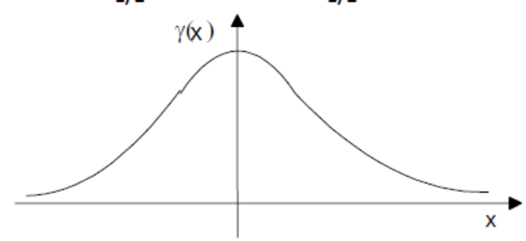
1) $$\gamma(\mathbf{x}) = \begin{cases} 0{,}5 & |\mathbf{x}| \le 1 \\ 0 & |\mathbf{x}| > 1 \end{cases}$$ Rectangle



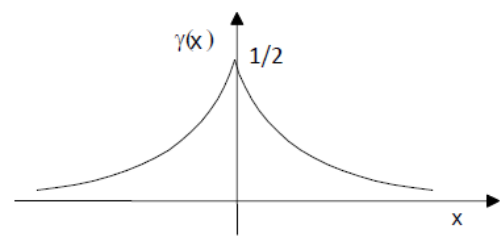
2) $$\gamma(\mathbf{x}) = \begin{cases} 1 - |\mathbf{x}| & |\mathbf{x}| \le 1 \\ 0 & |\mathbf{x}| > 1 \end{cases}$$ Triangle



3) $$\gamma(\mathbf{x}) = (2\pi)^{-\frac{1}{2}} e^{-\left(\frac{\mathbf{x}^2}{2}\right)}$$ Gaussian



4) $$\gamma(\mathbf{x}) = \frac{1}{2} e^{-|\mathbf{x}|}$$ Exponential (decreasing)



Exercises