

Parzen Windows and Real Distribution Estimation

Part 1: Classification Rule Derivation

Given:

$$\forall j \neq i : P(w_i | x) \geq P(w_j | x)$$

$$\text{Bayes rule: } P(w_i | x) = P(x | w_i) * P(w_i) / P(x)$$

We need to show that the classification rule can be reduced to:

$$\forall j \neq i \in \{1, \dots, C\} : \sum \phi((x_{ik} - x) / h) \geq \sum \phi((x_{jk} - x) / h)$$

Steps:

1. Start with Bayes Rule:

$$P(w_i | x) = P(x | w_i) * P(w_i) / P(x)$$

2. Using the given condition:

$$\forall j \neq i : P(w_i | x) \geq P(w_j | x)$$

3. Substitute Bayes rule:

$$\forall j \neq i : P(x | w_i) * P(w_i) / P(x) \geq P(x | w_j) * P(w_j) / P(x)$$

4. Simplify (since $P(x)$ is common in both):

$$\forall j \neq i : P(x | w_i) * P(w_i) \geq P(x | w_j) * P(w_j)$$

5. Assume uniform priors (i.e., $P(w_i) = P(w_j)$ for all i, j):

$$\forall j \neq i : P(x | w_i) \geq P(x | w_j)$$

6. Parzen Window Estimation for Likelihood:

$$P(x | w_i) \approx 1/(n_i h) \sum \phi((x_{ik} - x) / h)$$

Similarly,

$$P(x | w_j) \approx 1/(n_j h) \sum \phi((x_{jk} - x) / h)$$

7. Compare the likelihoods:

$$\forall j \neq i : 1/(n_i h) \sum \phi((x_{ik} - x) / h) \geq 1/(n_j h) \sum \phi((x_{jk} - x) / h)$$

8. Remove the common terms (assuming same h):

$$\forall j \neq i : \sum \phi((x_{ik} - x) / h) \geq \sum \phi((x_{jk} - x) / h)$$

This shows that the classification rule is indeed the majority vote of neighbors as given.

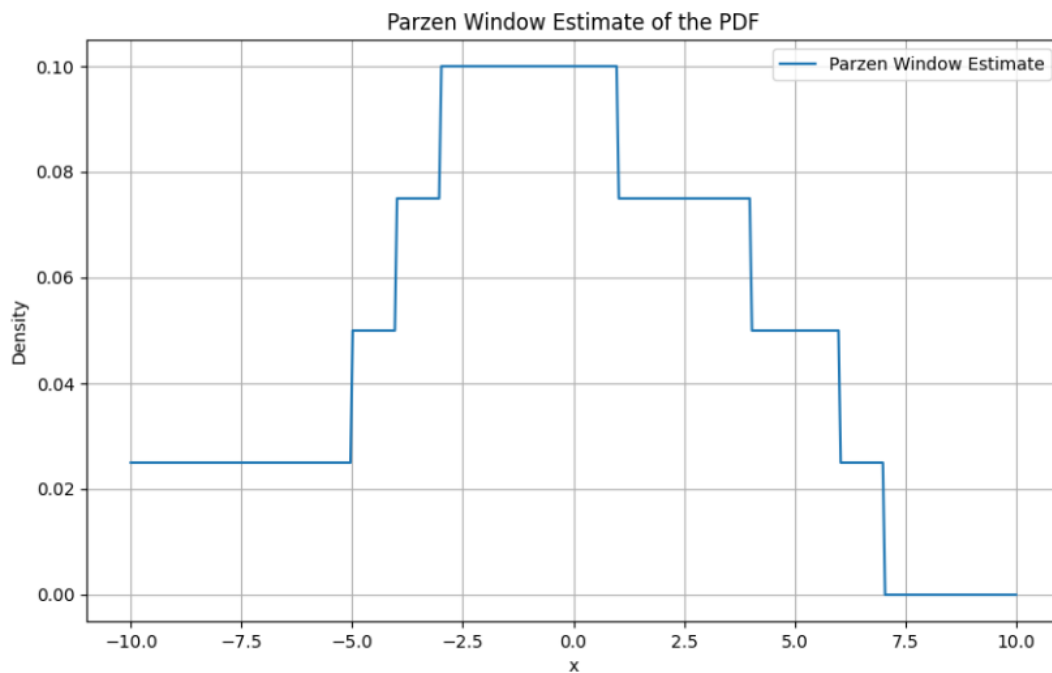
Part 2: Parzen Window Estimation and Real Distribution

Given the samples: $D = [1 -3 2 4 5 -8 0 -1 -2 -4]$

Using the 0-1 window function and $h = 4$, we estimated the Parzen window based PDF.

We can express the Parzen window estimation of the PDF as:

$$p(x) = \frac{1}{10 \cdot 4} \sum \varphi\left(\frac{x - x_i}{h}\right)$$



(a) According to the graph, the real distribution of the data appears to be a Normal distribution because of the bell shaped curve that it has around the mean.

(b) Using MLE to estimate the distribution parameters, we find:

mu = -0.60

sigma = 3.69

Explanation:

Step-by-Step Calculation of Mean (μ) and Standard Deviation (σ)

Data:

[1, -3, 2, 4, 5, -8, 0, -1, -2, -4]

Step-by-Step Calculation for Mean (μ):

1. Number of data points (n): 10

2. Sum of data points: $\sum x_i = -6$

3. Mean (μ) calculation:

$$\mu = \sum x_i / n$$

$$\mu = -6 / 10$$

$$\mu = -0.60$$

Step-by-Step Calculation for Standard Deviation (σ):

1. Mean (μ): -0.60

2. Calculate squared differences from the mean:

$$(x_1 - \mu)^2 = (1 - -0.60)^2 = 2.56$$

$$(x_2 - \mu)^2 = (-3 - -0.60)^2 = 5.76$$

$$(x_3 - \mu)^2 = (2 - -0.60)^2 = 6.76$$

$$(x_4 - \mu)^2 = (4 - -0.60)^2 = 21.16$$

$$(x_5 - \mu)^2 = (5 - -0.60)^2 = 31.36$$

$$(x_6 - \mu)^2 = (-8 - -0.60)^2 = 54.76$$

$$(x_7 - \mu)^2 = (0 - -0.60)^2 = 0.36$$

$$(x_8 - \mu)^2 = (-1 - -0.60)^2 = 0.16$$

$$(x_9 - \mu)^2 = (-2 - -0.60)^2 = 1.96$$

$$(x_{10} - \mu)^2 = (-4 - -0.60)^2 = 11.56$$

3. Sum of squared differences: $\Sigma(x_i - \mu)^2 = 136.40$

4. Variance (σ^2) calculation:

$$\sigma^2 = \Sigma(x_i - \mu)^2 / n$$

$$\sigma^2 = 136.40 / 10$$

$$\sigma^2 = 13.64$$

5. Standard Deviation (σ) calculation:

$$\sigma = \sqrt{\sigma^2}$$

$$\sigma = \sqrt{13.64}$$

$$\sigma = 3.69$$

The PDF of the normal distribution is calculated using these parameters.

Comparison between the 2 graphs:

