



COMPUTER ENGINEERING && IT DEPARTMENT  
AMIRKABIR UNIVERSITY OF TECHNOLOGY

---

# Statistical Pattern Recognition

---

*Submitted To:*  
Mohammad Rahmati  
Assoc. Professor  
Computer Engineering  
Department

*Submitted By :*  
Ahmad Asadi  
94131091  
Group-G1  
Fall-95

## Contents

1	Plotting conditional Parzen window based density estimates	2
2	Plotting Parzen window estimate using Gaussian window function	3

# 1 Plotting conditional Parzen window based density estimates

In the Parzen window formula, variable  $V$  denotes the hypercube volume which given  $h = 1$  is equal to 1. So the final formula is rewritten as (1) in which  $\omega_i$  denotes the  $i$ th class.

$$\hat{p}(x|\omega_i) = \frac{1}{n} \sum_{j=1}^{n_i} \phi(x - x_j) \quad (1)$$

According to (1), the first class conditional density estimate of first class based on Parzen window is expressed in (2).

$$\hat{p}(x|\omega_1) = \frac{1}{5}(\phi(x - x_1) + \phi(x - x_2) + \phi(x - x_3)) = \frac{1}{5}(\phi(x - 4) + \phi(x - 1) + \phi(x - 5)) \quad (2)$$

And that of the second class is expressed in (3).

$$\hat{p}(x|\omega_2) = \frac{1}{5}(\phi(x - x_4) + \phi(x - x_5)) = \frac{1}{5}(\phi(x - 3) + \phi(x - 2)) \quad (3)$$

Figure 1 displays both Parzen window estimated likelihood as a function of  $x$  for both classes.

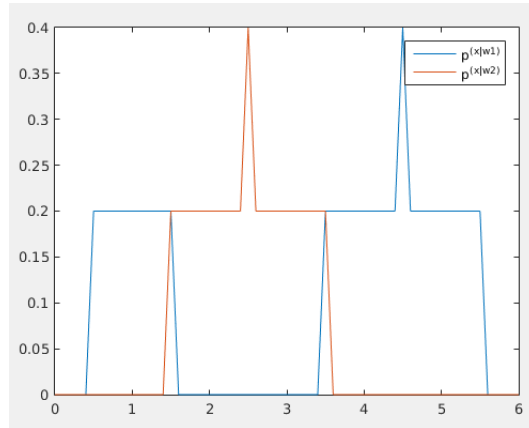


Figure 1: Estimated likelihood of class conditional densities using Parzen window.

## 2 Plotting Parzen window estimate using Gaussian window function

Equation (4) represents the normal kernel.

$$\frac{1}{h^2}\phi\left(\frac{X - X_i}{h}\right) = (2\pi)^{-\frac{n}{2}}h^{-n}|\Sigma|^{\frac{1}{2}}\exp\left[-\frac{1}{2}h^{-2}(X - X_i)^T\Sigma^{-1}(X - X_i)\right] \quad (4)$$

According to  $\phi \sim N(0, 1)$  the covariance matrix is  $\Sigma = I$  and the mean vector is  $\mu = 0$ . The variable  $n$  denoting the number of dimensions is equal to 2. So the normal kernel represented in (4) is rewritten as equation (5).

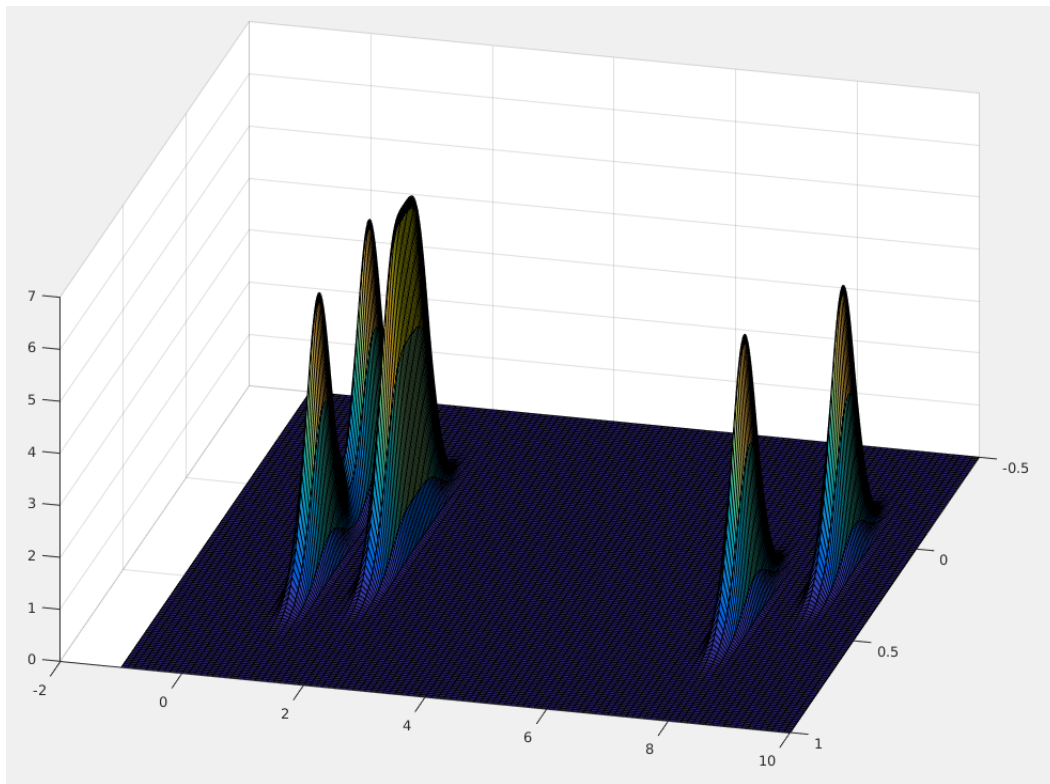
$$\frac{1}{h^2}\phi\left(\frac{X - X_i}{h}\right) = (2\pi)^{-1}h^{-2}\exp\left[-\frac{1}{2}h^{-2}(X - X_i)^T(X - X_i)\right] \quad (5)$$

The Parzen estimate is represented in (6) in normal kernel case.

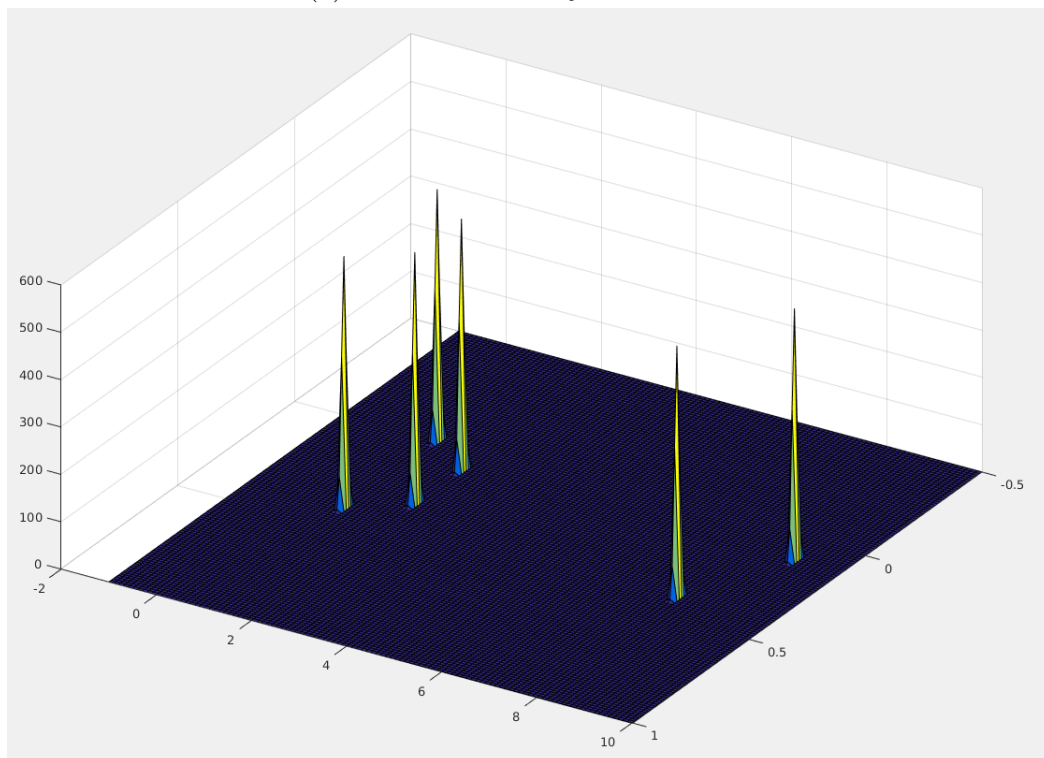
$$\hat{P} = \frac{1}{N}\sum_{i=1}^N \frac{1}{h^2}\phi\left(\frac{X - X_i}{h}\right) = \frac{1}{2N\pi h^2}\sum_{i=1}^N \exp\left[-\frac{1}{2}h^{-2}(X - X_i)^T(X - X_i)\right] \quad (6)$$

Using given dataset  $x = \{< 0.0, 1 >; < 0.1, 2 >; < 0.1, 9 >; < 0.3, 2 >; < 0.4, 1 >; < 0.4, 8 >\}$  the Parzen estimate is computable. Figure 2a displays the estimated density using  $h = 0.1$  and figure 2b displays estimated density in case of  $h = 0.01$ .

As it is clearly obvious, decreasing  $h$  strongly makes model finer. The estimated density function is coarser when  $h = 0.1$  rather than when  $h = 0.01$ .



(a) Estimated density with  $h = 0.1$



(b) Estimated density with  $h = 0.01$

Figure 2: Estimated density functions using Parzen Gaussian window