CZ4041/CE4041: Machine Learning

Lesson 11: Density Estimation

Kelly KE

School of Computer Science and Engineering, NTU, Singapore

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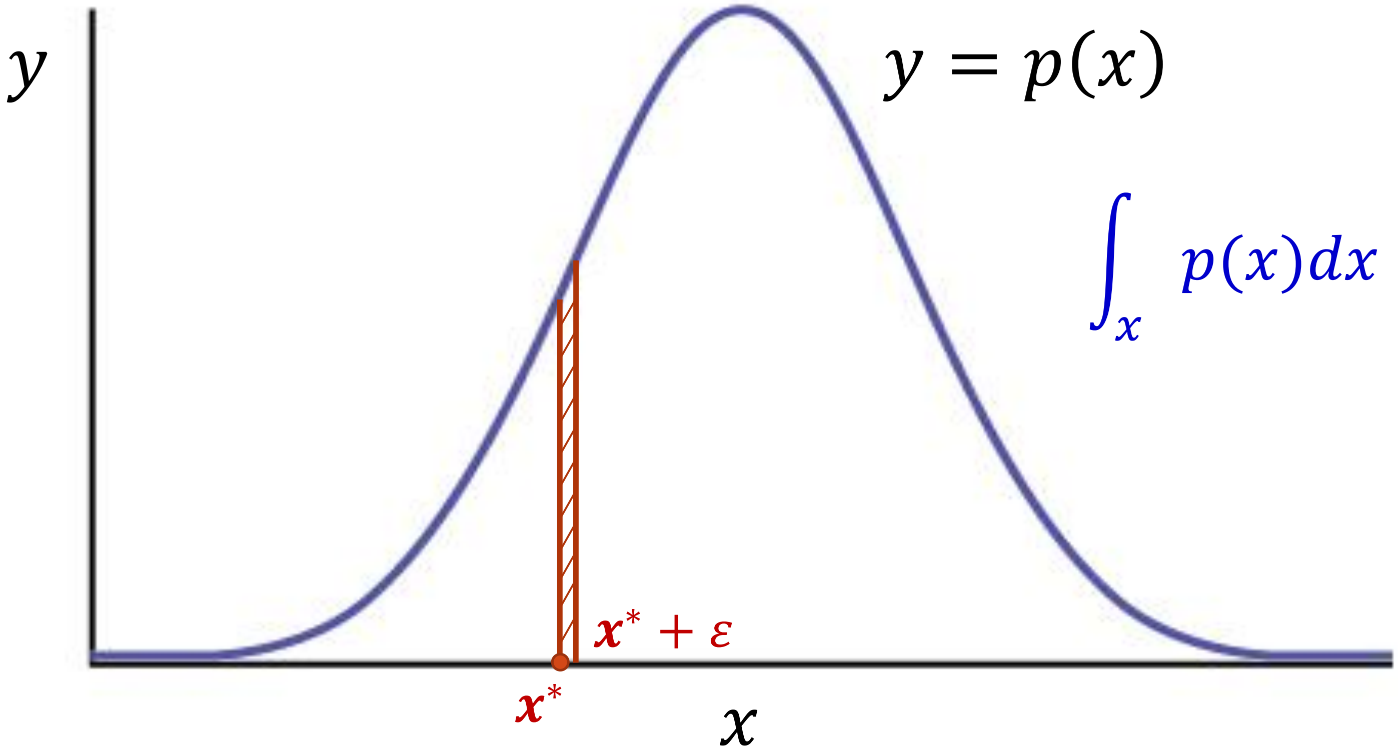
Density Estimation

- Density estimation aims to estimate an unobservable underlying probability density function based on observed data
- Denote by $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\}$ the set of observed data points, drawn from an unknown $p(\boldsymbol{x})$,

$$\boldsymbol{x}_i \sim p(\boldsymbol{x}), \text{for } i = 1, 2, \ldots, N$$

The goal is to estimate the probability density function $p(\boldsymbol{x})$

Probability Density Function



$$\int_x p(x)dx = 1$$

$$P(\boldsymbol{x}^*) = \int_{\boldsymbol{x}^*}^{\boldsymbol{x}^*+\varepsilon} p(x)dx \approx p(\boldsymbol{x}^*) \times \varepsilon$$

Why Density Estimation

- Recall Naïve Bayes Classifiers

$$y_i = \arg\max_c P(\boldsymbol{x}|y=c)P(y=c)$$

$$= \arg\max_c \prod_{i=1}^{d} P(x_i|y=c)\,P(y=c)$$

- Other advanced ML topics
  - One-class classification
  - Covariate shift, transfer learning, etc.

Density Estimation Approaches

- Parametric density estimation
  - Assume a form for $p(\boldsymbol{x};\boldsymbol{\theta})$, defined up to parameters, $\boldsymbol{\theta}$
    - E.g., Guassian distribution $\mathcal{N}(\mu,\sigma^2)$, $\boldsymbol{\theta}=\{\mu,\sigma^2\}$
  - Estimate $\boldsymbol{\theta}$ from the observed data points
    - Maximum Likelihood Estimation
- Nonparametric density estimation

The General Principle

- The observed data points $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$ are assumed to be a sample of N random variables independent and identically distributed (i.i.d.)
- Identically distributed: for any $\boldsymbol{x}_i \in \mathcal{D}$, it is sampled from the same probability distribution
- Independent: all the data points $\boldsymbol{x}_i \in \mathcal{D}$ are independent events

Parametric Density Estimation

- Assume that $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$ are drawn from some known probability density family, $p(\boldsymbol{x}; \boldsymbol{\theta})$, defined up to parameters, $\boldsymbol{\theta}$

$$\boldsymbol{x}_i \sim p(\boldsymbol{x}; \boldsymbol{\theta})$$

- To find $\boldsymbol{\theta}$ that makes sampling $\boldsymbol{x}_i$ from $p(\boldsymbol{x}; \boldsymbol{\theta})$ as likely as possible
- Approach: maximum likelihood estimation

Maximum Likelihood Estimation

- Likelihood of parameter $\boldsymbol{\theta}$ given sample $\mathcal{D}$:

$$l(\boldsymbol{\theta}|\mathcal{D}) \triangleq p(\mathcal{D}; \boldsymbol{\theta})$$

- As $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$ are i.i.d., the above likelihood is the product of the likelihoods of the individual data points

$$l(\boldsymbol{\theta}|\mathcal{D}) \triangleq p(\mathcal{D}; \boldsymbol{\theta}) = \prod_{i=1}^{N} p(\boldsymbol{x}_i; \boldsymbol{\theta})$$

- In MLE, we aim to find $\boldsymbol{\theta}$ that makes $\mathcal{D}$ the most likely to be drawn from. Mathematically, we aim to search for $\widehat{\boldsymbol{\theta}}$ such that

$$\widehat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} l(\boldsymbol{\theta}|\mathcal{D})$$

MLE (cont.)

- Typically, we maximize the log-likelihood:

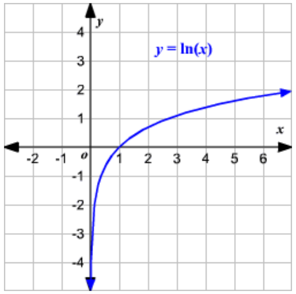
$$\mathcal{L}(\boldsymbol{\theta}|\mathcal{D}) \triangleq \ln l(\boldsymbol{\theta}|\mathcal{D})$$

- Why?

1. The $\ln(\cdot)$ function converts the product into a sum

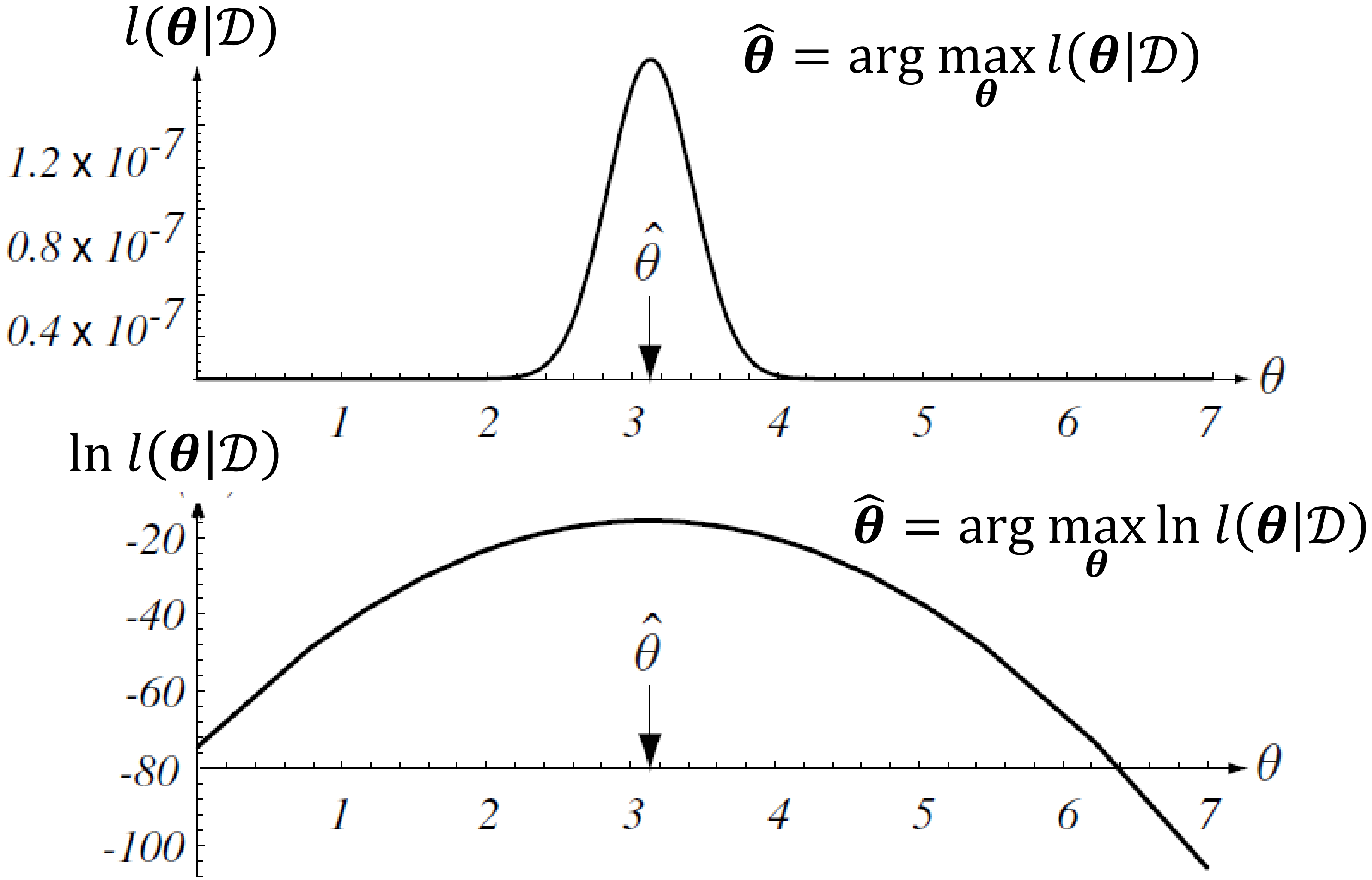
$$\ln l(\boldsymbol{\theta}|\mathcal{D}) = \ln p(\mathcal{D}; \boldsymbol{\theta}) = \ln\left(\prod_{i=1}^{N} p(\boldsymbol{x}_i; \boldsymbol{\theta})\right) = \sum_{i=1}^{N} \ln p(\boldsymbol{x}_i; \boldsymbol{\theta})$$

2. The $\ln(\cdot)$ function is a strictly increasing function, one can maximize the likelilood without changing the value where it takes its maximum



$$\widehat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} l(\boldsymbol{\theta}|\mathcal{D}) \Leftrightarrow \widehat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} \ln l(\boldsymbol{\theta}|\mathcal{D})$$

MLE Illustration



$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} l(\boldsymbol{\theta}|\mathcal{D})$$

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} \ln l(\boldsymbol{\theta}|\mathcal{D})$$

Solution of MLE

- Suppose $\boldsymbol{\theta}$ contains p parameters,

$$\boldsymbol{\theta} = [\theta_1\ \theta_2\ \ \dots\ \theta_p]^T$$

- As $\max_{\boldsymbol{\theta}} \ln l(\boldsymbol{\theta}|\mathcal{D})$ is an unconstrained optimization problem, to solve it, we first set to the derivative of $\ln l(\boldsymbol{\theta}|\mathcal{D})$ w.r.t. $\boldsymbol{\theta}$ to be zero

$$\boxed{\nabla_{\boldsymbol{\theta}}} \ln l(\boldsymbol{\theta}|\mathcal{D}) = \nabla_{\boldsymbol{\theta}} \left(\sum_{i=1}^{N} \ln p(\boldsymbol{x}_i|\boldsymbol{\theta}) \right) = \sum_{i=1}^{N} \nabla_{\boldsymbol{\theta}} \ln p(\boldsymbol{x}_i|\theta) = \mathbf{0},$$

Gradient operator

$$\nabla_{\boldsymbol{\theta}} = \left[\frac{\partial}{\partial\theta_1}\ \frac{\partial}{\partial\theta_2}\ \cdots\ \frac{\partial}{\partial\theta_p} \right]^T$$

- We then obtain a solution $\widehat{\boldsymbol{\theta}}$ by solving the above system of p equations

Univariate Gaussian

- Suppose $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$. Each data point $\boldsymbol{x}_i$ is of 1 dimension, and drawn from Guassian distribution with unknown μ and σ^2:

$$\boldsymbol{x}_i \sim p(\boldsymbol{x}; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(\boldsymbol{x}-\mu)^2}{2\sigma^2}\right)}$$

$$\mu = \boxed{\mathbb{E}}[\boldsymbol{x}] = \int p(\boldsymbol{x}; \mu, \sigma^2)\boldsymbol{x}d\boldsymbol{x}$$

$$\sigma^2 = \operatorname{cov}(\boldsymbol{x}) = \mathbb{E}[(\boldsymbol{x} - \mathbb{E}[\boldsymbol{x}])(\boldsymbol{x} - \mathbb{E}[\boldsymbol{x}])^T]$$

Expectation, considering all possible values (infinite)

Univariate Gaussian (cont.)

- The log-likelihood is

$$\ln l(\boldsymbol{\theta}|\mathcal{D}) = \sum_{i=1}^{N} \ln p(\boldsymbol{x}_i;\boldsymbol{\theta})$$

$$p(\boldsymbol{x};\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\left(-\frac{(\boldsymbol{x}-\mu)^2}{2\sigma^2}\right)}$$

$$= \sum_{i=1}^{N} \cancel{\ln} \Bigg(\cancel{\exp} \left(-\frac{(\boldsymbol{x}_i-\mu)^2}{2\sigma^2} \right) \Bigg) - \sum_{i=1}^{N} \ln(\sqrt{2\pi\sigma^2})$$

$$= -\frac{\sum_{i=1}^{N} (\boldsymbol{x}_i-\mu)^2}{2\sigma^2} - \frac{N}{2} \ln\left(2\pi\sigma^2\right)$$

$$= -\frac{\sum_{i=1}^{N} (\boldsymbol{x}_i-\mu)^2}{2\sigma^2} - \frac{N}{2} \ln(2\pi) - \frac{N}{2} \ln \sigma^2$$

Univariate Gaussian (cont.)

- The log-likelihood:

$$\ln l(\boldsymbol{\theta}|\mathcal{D}) = -\frac{\sum_{i=1}^{N}(\boldsymbol{x}_i - \mu)^2}{2\sigma^2} - \frac{N}{2}\ln(2\pi) - \frac{N}{2}\ln\sigma^2$$

- The derivative of the log-likelihood:

$$\nabla_{\boldsymbol{\theta}}\ln l(\boldsymbol{\theta}|\mathcal{D}) = \sum_{i=1}^{N}\nabla_{\boldsymbol{\theta}}\ln p(\boldsymbol{x}_i;\theta) = \begin{bmatrix} \sum_{i=1}^{N}\nabla_{\mu}\ln p(\boldsymbol{x}_i;\theta) \\ \sum_{i=1}^{N}\nabla_{\sigma^2}\ln p(\boldsymbol{x}_i;\theta) \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sigma^2}\sum_{i=1}^{N}(\boldsymbol{x}_i - \mu) \\ \frac{\sum_{i=1}^{N}(\boldsymbol{x}_i - \mu)^2}{2(\sigma^2)^2} - \frac{N}{2\sigma^2} \end{bmatrix}$$

Univariate Gaussian (cont.)

- By setting the derivative to be zero:

$$\begin{cases} \dfrac{1}{\sigma^2}\displaystyle\sum_{i=1}^{N}(\boldsymbol{x}_i-\mu)=0 \\ \dfrac{\sum_{i=1}^{N}(\boldsymbol{x}_i-\mu)^2}{2(\sigma^2)^2}-\dfrac{N}{2\sigma^2}=0 \end{cases}$$

- We have

$$\begin{cases} \hat{\mu}=\dfrac{1}{N}\displaystyle\sum_{i=1}^{N}\boldsymbol{x}_i \\ \widehat{\sigma^2}=\dfrac{1}{N}\displaystyle\sum_{i=1}^{N}(\boldsymbol{x}_i-\hat{\mu})^2 \end{cases}$$

Unbiased estimation

$$\mathbb{E}[\hat{\mu}]=\boxed{\mu}$$

True

$$\mathbb{E}\left[\widehat{\sigma^2}\right]=\frac{N-1}{N}\boxed{\sigma^2}$$

Biased estimation

To correct bias

$$\widetilde{\sigma^2}=\frac{N}{N-1}\widehat{\sigma^2}$$

$$=\frac{1}{N-1}\sum_{i=1}^{N}(\boldsymbol{x}_i-\hat{\mu})^2$$

Multivariate Gaussian

- Suppose $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$, and each data point $\boldsymbol{x}_i$ is of d dimensions, and drawn from Guassian distribution with unknown $\boxed{\boldsymbol{\mu}}$ and $\boxed{\boldsymbol{\Sigma}}$:

d-dimensional mean vector

$d \times d$ covariance matrix

$$\boldsymbol{x}_i \sim p(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{d/2}} \frac{1}{|\boldsymbol{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{\mu})\right)$$

$|\boldsymbol{\Sigma}|$: the determinant of $\boldsymbol{\Sigma}$

$$\boldsymbol{\mu} = \mathbb{E}[\boldsymbol{x}] = \int p(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) \boldsymbol{x} d\boldsymbol{x}$$

$$\boldsymbol{\Sigma} = \mathrm{cov}(\boldsymbol{x}) = \mathbb{E}[(\boldsymbol{x} - \mathbb{E}[\boldsymbol{x}])(\boldsymbol{x} - \mathbb{E}[\boldsymbol{x}])^T]$$

Multivariate Gaussian (cont.)

- The log-likelihood of multivariate Gaussian is

$$\ln l(\boldsymbol{\theta}|\mathcal{D}) = \sum_{i=1}^{N} \ln p(\boldsymbol{x}_i; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = -\frac{Nd}{2}\ln(2\pi) - \frac{N}{2}\ln|\boldsymbol{\Sigma}| - \frac{1}{2}\sum_{i=1}^{N}(\boldsymbol{x}_i - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}_i - \boldsymbol{\mu})$$

- The derivative of the log-likelihood w.r.t. $\boldsymbol{\mu}$ is

$$\frac{\partial}{\partial \boldsymbol{\mu}} \ln l(\boldsymbol{\theta}|\mathcal{D}) = \sum_{i=1}^{N} \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}_i - \boldsymbol{\mu})$$

- By setting the derivative to zero, we have

$$\widehat{\boldsymbol{\mu}} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{x}_i$$

Unbiased estimation:

$$\mathbb{E}[\widehat{\boldsymbol{\mu}}] = \boldsymbol{\mu}$$

Multivariate Gaussian (cont.)

- By computing the derivative of the log-likelihood w.r.t.$\boldsymbol{\Sigma}$ (each Σ_{ij}, i.e., the entry of the i-th row and the j-th column), and setting to be zero, we have

$$\widehat{\boldsymbol{\Sigma}} = \frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{x}_i - \widehat{\boldsymbol{\mu}})(\boldsymbol{x}_i - \widehat{\boldsymbol{\mu}})^T$$

- The above estimation is biased!!!

$$\mathbb{E}[\widehat{\boldsymbol{\Sigma}}] = \frac{N-1}{N}\boldsymbol{\Sigma}$$

- We can correct the bias by timing $\widehat{\boldsymbol{\Sigma}}$ with $\frac{N}{N-1}$:

$$\widetilde{\boldsymbol{\Sigma}} = \frac{1}{N-1}\sum_{i=1}^{N}(\boldsymbol{x}_i - \widehat{\boldsymbol{\mu}})(\boldsymbol{x}_i - \widehat{\boldsymbol{\mu}})^T$$

Unbiased estimation

Summary: MLE for Multivariate Gaussian

- Suppose $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$. Each data point $\boldsymbol{x}_i$ is of d dimensions, and drawn from Guassian distribution with unknown $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$:

$$\boldsymbol{x}_i \sim p(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{d/2}} \frac{1}{|\boldsymbol{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{x}-\boldsymbol{\mu})\right)$$

- The unbiased MLE for $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are

$$\begin{cases} \widehat{\boldsymbol{\mu}} = \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{x}_i \\ \widetilde{\boldsymbol{\Sigma}} = \frac{1}{N-1} \sum_{i=1}^{N} (\boldsymbol{x}_i - \widehat{\boldsymbol{\mu}})(\boldsymbol{x}_i - \widehat{\boldsymbol{\mu}})^T \end{cases}$$

Note: in this module, when you are asked to estimate the mean vector and the covariate matrix of a sample, use the unbiased estimation

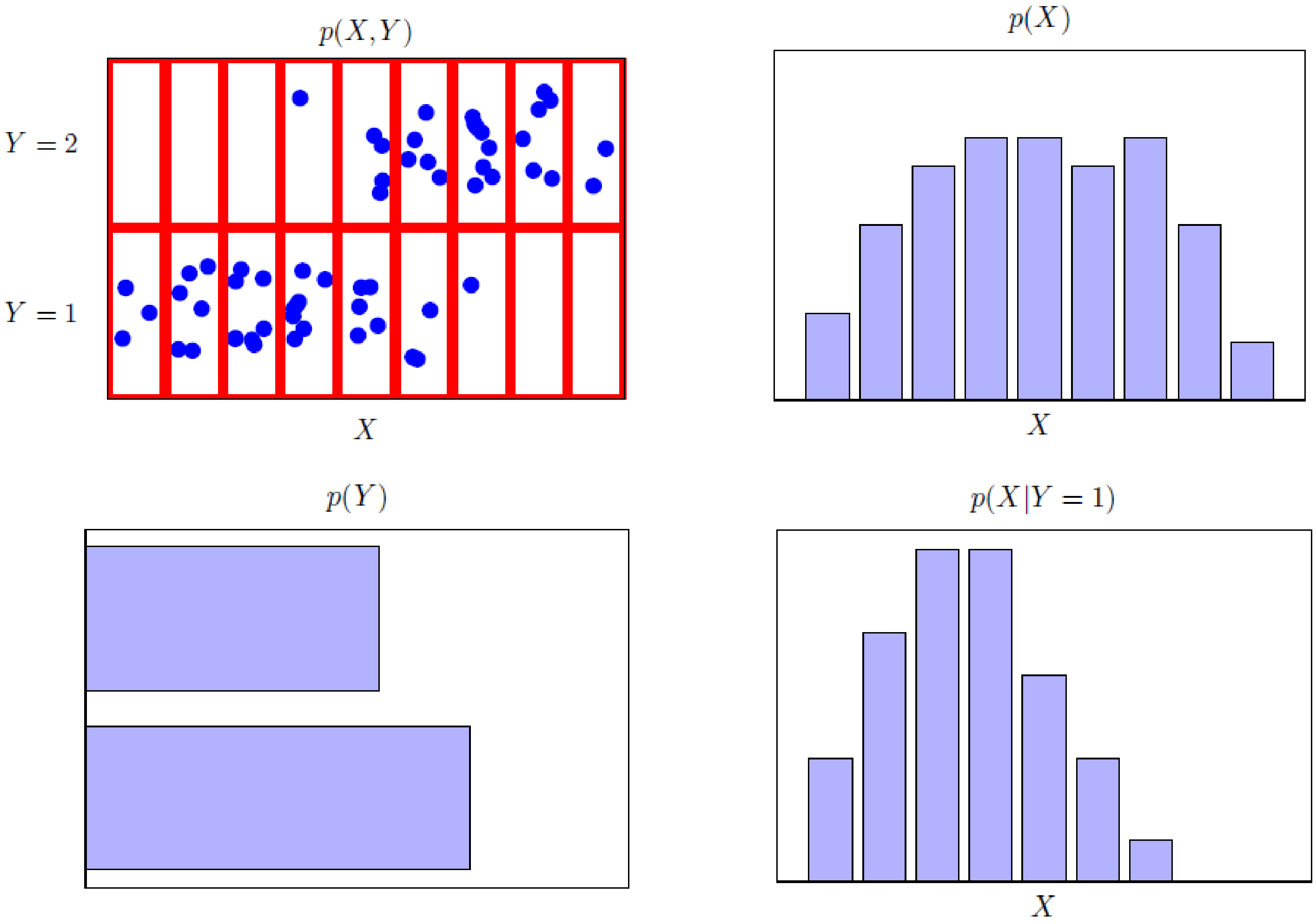
Density Estimation Approaches

- Parametric density estimation
- Nonparametric density estimation
  - Without assuming any forms for the underlying density
  - Assume that similar inputs have similar outputs: if $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are similar, then $p(\boldsymbol{x}_i)$ and $p(\boldsymbol{x}_j)$ are similar
  - Approaches
    - Histogram Estimator
    - Naïve Estimator / Parzen Windows / Kernel Estimator
    - *K*-NN Estimator

Non-Parametric Density Estimation

- Assume that $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$ are drawn from some unknown probability density $p(\boldsymbol{x})$
- To learn the estimator $\hat{p}(\boldsymbol{x})$ for $p(\boldsymbol{x})$
- We first focus on the univariate case, i.e., $\boldsymbol{x}_i$ is 1-dimensional
- Note that the introduced approaches can be generalized to multivariate case easily

Histogram Estimator



Histogram Estimator (cont.)

- Simply partition $\boldsymbol{x}$ into distinct bins of a fixed width Δ
- Count the number N_t of data points falling into bin t
- Turn this count into a normalized probability density via dividing by the total number of observed data points N and by the width Δ of the bins:

$$p_t = \frac{N_t}{N\boxed{\Delta}}$$

Why divided by Δ?

- The model for the density $p(\boldsymbol{x})$ is constant over the width of each bin: find the bin where $\boldsymbol{x}$ is in (e.g., bin t), then

$$\hat{p}(\boldsymbol{x}) = \frac{\#\{\boldsymbol{x}_i \mid \boldsymbol{x}_i \text{ in the same bin as } \boldsymbol{x}\}}{N\Delta} = p_t$$

Histogram Estimator (cont.)

- For a bin t, given a density function, the probability that a data instance falling into the bin t is

$$P_t = \int_{\Delta} p(\boldsymbol{x})d\boldsymbol{x} \;\; = p_t(\boldsymbol{x})\Delta$$

- On the other hand,

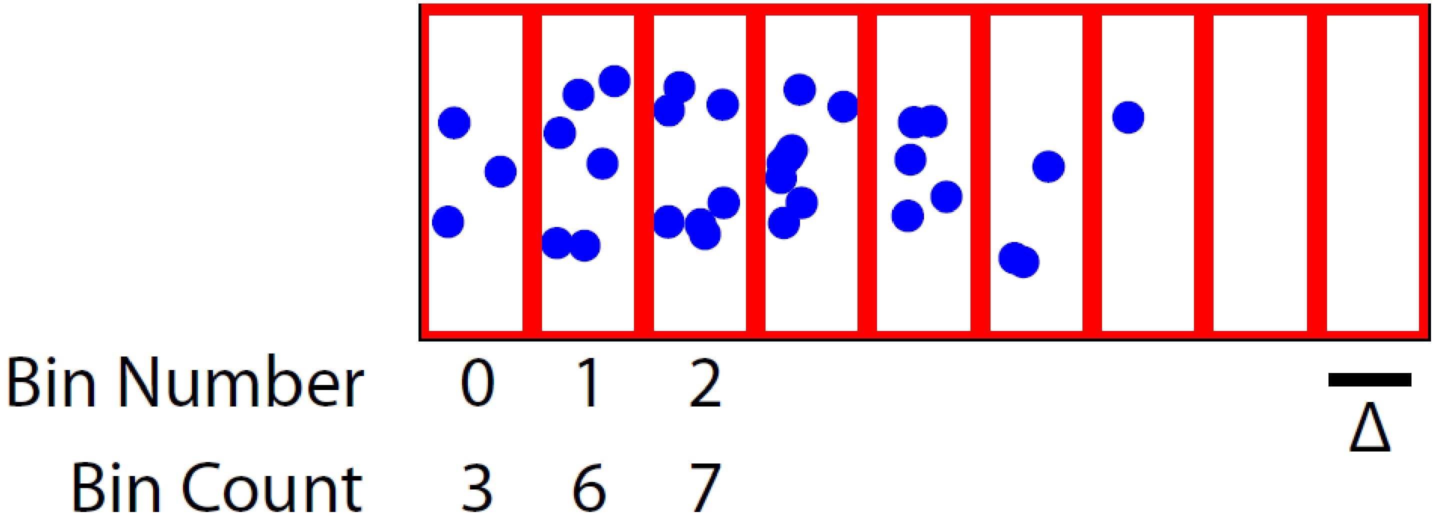
$$P_t = \frac{\#\{\boldsymbol{x}_i \mid \boldsymbol{x}_i \text{ in bin } t\}}{N} = \frac{N_t}{N}$$

- Therefore:

$$p_t(\boldsymbol{x})\Delta = \frac{N_t}{N} \quad \Longrightarrow \quad p_t(\boldsymbol{x}) = \frac{N_t}{N\Delta}$$

Histogram Estimator (cont.)

- Note: different bins may have different widths Δ_t in general, but in practice, we use the same width Δ

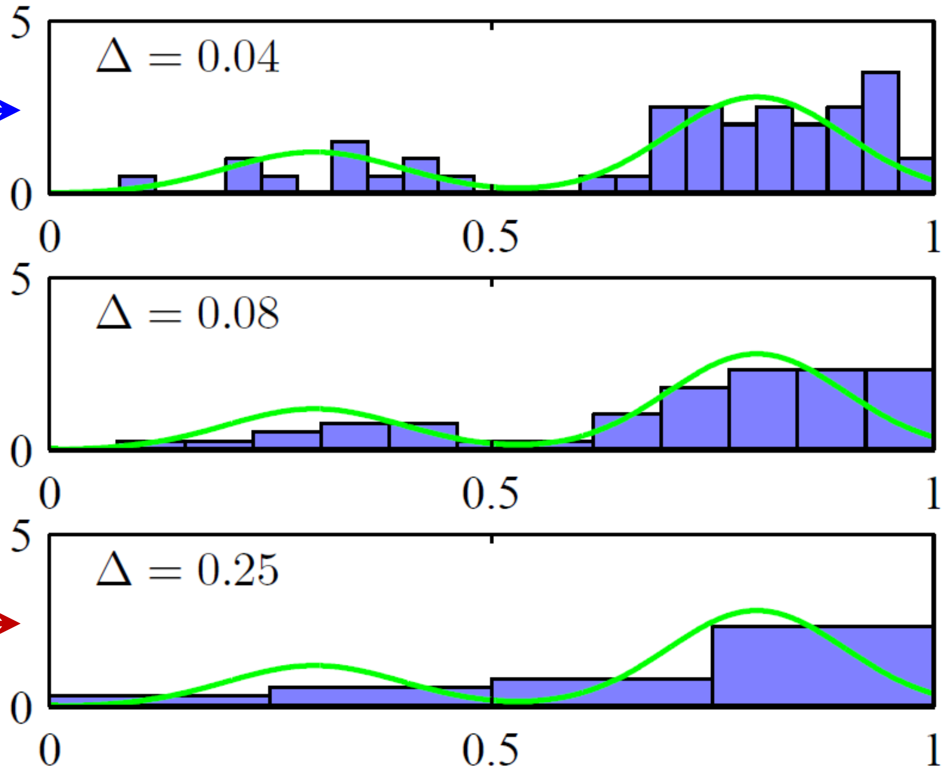


Histogram Estimator (cont.)

- Histogram density as a function of bin width Δ

The green curve is the underlying true density from which the data points were drawn

When Δ is very small, the resulting density is quite spiky and hallucinates a lot of structure not present in the true density →



When Δ is very big, the resulting density is quite smooth and consequently fails to capture the bimodality of the true density →

Analysis on Histogram Estimator

- Advantages:
  - Simple to evaluate and simple to use
  - One can throw away $\mathcal{D}$ once the histogram is computed
  - Can be updated incrementally
- Disadvantages:
  - The estimated density has discontinuities due to the bin edges rather than any property of the underlying density
  - Scales poorly to multivariate cases: we would have m^d *bins* (hypercubes) if we divided each feature (dimension) in a d-dimensional space into m bins

Naïve Estimator: An Alterative

- In Histogram Estimator, besides Δ, we have to choose an origin x_0 as well, the bins are the intervals defined as

$$[\boldsymbol{x}_0 + \boxed{m}\Delta, \boldsymbol{x}_0 + (m+1)\Delta)$$

0, positive or negative integers

- The Naïve Estimator does not need to set an origin

$$\hat{p}(\boldsymbol{x}) = \frac{\#\{\boldsymbol{x}_i \mid \boldsymbol{x}_i \text{ in the same bin as } \boldsymbol{x}\}}{N\Delta}$$

Given $\boldsymbol{x}$, use $\boldsymbol{x}$ as a center to create a bin with a length of Δ

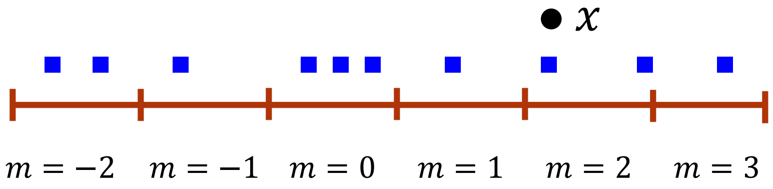
$$[\xleftrightarrow{\frac{\Delta}{2}} \boldsymbol{x} \xleftrightarrow{\frac{\Delta}{2}}]$$

$$\hat{p}(\boldsymbol{x}) = \frac{\#\{\boldsymbol{x}_i \mid \boxed{\boldsymbol{x} - \frac{\Delta}{2} \le \boldsymbol{x}_i < \boldsymbol{x} + \frac{\Delta}{2}}\}}{N\Delta}$$

Histogram v.s. Naïve Estimator

Histogram Estimator

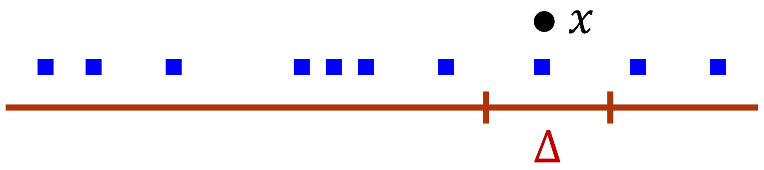
$$p(x) = \frac{2}{10 \times \Delta}$$



Count: 2 1 3 1 2 1

Naïve Estimator

$$p(x) = \frac{1}{10 \times \Delta}$$



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Naïve Estimator: An Alterative (cont.)

$$\hat{p}(\boldsymbol{x}) = \frac{\#\{\boldsymbol{x}_i \mid \boldsymbol{x} - \frac{\Delta}{2} \leq \boldsymbol{x}_i < \boldsymbol{x} + \frac{\Delta}{2}\}}{N\Delta}$$

The Naïve Estimator can also be written as

$$\hat{p}(\boldsymbol{x}) = \frac{1}{N\Delta}\sum_{i=1}^{N} \boxed{w}\left(\frac{\boldsymbol{x} - \boldsymbol{x}_i}{\Delta}\right)$$

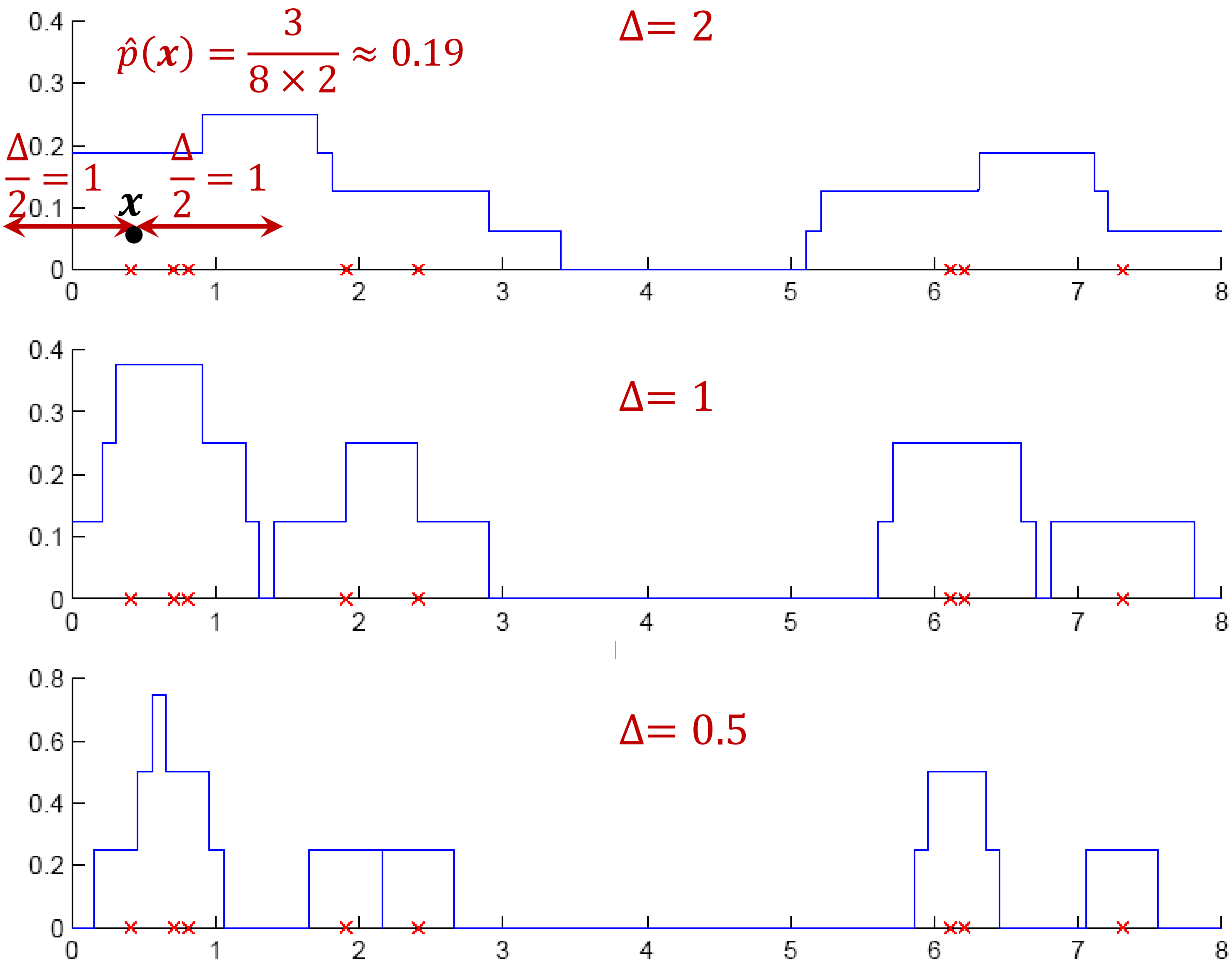
If x_i is in the bin with width Δ centered at x, then the count is increased by 1

$$u = \frac{\boldsymbol{x} - \boldsymbol{x}_i}{\Delta}$$

Windowing function $w(u) = \begin{cases} 1 & \text{if } -\frac{1}{2} \leq \boxed{u} < \frac{1}{2} \\ 0 & \text{otherwise} \end{cases}$

Parzen windows

Naïve Estimator



$$\hat{p}(\boldsymbol{x}) = \frac{3}{8 \times 2} \approx 0.19$$

$\Delta = 2$

$\frac{\Delta}{2} = 1$ $\boldsymbol{x}$ $\frac{\Delta}{2} = 1$

$\Delta = 1$

$\Delta = 0.5$

Generalization to Multivariate

- Suppose the observed data points $\mathcal{D} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_N\}$ are d-dimensional
- In a d-dimensional space, we define $\mathcal{R}$ is a d-dimensional hypercube with h being the length of each edge. Then the volume of the hypercube is given by

$$V = h^d$$

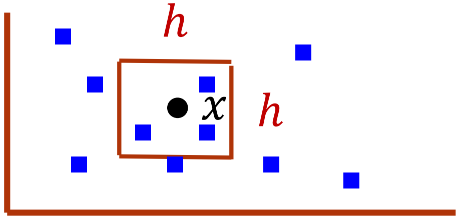
- The windowing function can be defined as

$$\boldsymbol{u} = \frac{\boldsymbol{x} - \boldsymbol{x}_i}{h}$$

$$w(\boxed{\boldsymbol{u}}) = \begin{cases} 1 \quad \text{if } -\frac{1}{2} \le u_j < \frac{1}{2} \text{ for all } j \in \{1,2,\dots,d\} \\ 0 \quad \text{otherwise} \end{cases}$$

Defines a hypercube of length h centered at $\boldsymbol{x}$, if $\boldsymbol{x}_i$ falls in the cube, then the count is increased by 1

E.g., $d = 2$



Generalization to Multivariate (cont.)

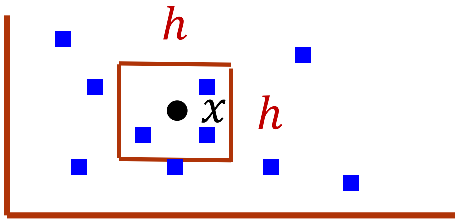
- Hence, $w\left(\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right)$ is equal to unity if $\boldsymbol{x}_i$ falls within the hypercube of volume V centered at $\boldsymbol{x}$, and is zero otherwise
- The density estimator can be written as

$$\hat{p}(\boldsymbol{x}) = \frac{\#\{\boldsymbol{x}_i \mid \boldsymbol{x}_i \text{ in the same hypercube as } \boldsymbol{x}\}}{NV}$$

⬇

$$\hat{p}(\boldsymbol{x}) = \frac{1}{NV}\sum_{i=1}^{N} w\left(\frac{\boldsymbol{x}-\boldsymbol{x}_i}{h}\right)$$

Parzen window function can be a kernel function – Kernel estimator (Appendix, optional)



$$\hat{p}(\boldsymbol{x}) = \frac{3}{10\boxed{h^2}}$$

K-Nearest Neighbor Estimator

- Recall

$$p(\boldsymbol{x}) = \frac{\overset{K_{\boldsymbol{x}}}{\boxed{\#\{\boldsymbol{x}_i \mid \boldsymbol{x}_i \text{ in the same hypercube as } \boldsymbol{x}\}}}}{VN}$$

- In the previous approaches, V (or Δ for univariate) is fixed for different queries $\boldsymbol{x}$'s
- The K-NN Estimator *adapts* the amount of smoothing to the *local* density of data, and the degree of smoothing is controlled by K, the number of neighbors

Consider K nearest neighbors of $\boldsymbol{x}$

$$p(\boldsymbol{x}) = \frac{\boxed{K}}{N\boxed{V_{\boldsymbol{x}}}}$$

The volume of the space centered at $\boldsymbol{x}$ that exactly contains K nearest neighbors of $\boldsymbol{x}$

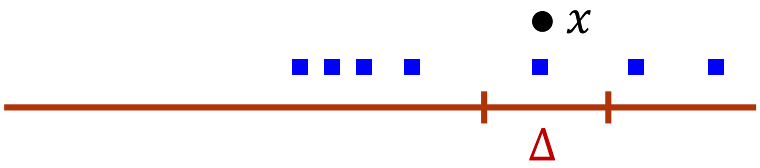
- Note that the number of nearest neighbors is typically much smaller than the number of training data points, i.e., $K \ll N$

Naïve Estimator v.s. *K*-NN Estimator

Univariate Case

Naïve Estimator

$$\hat{p}(\boldsymbol{x}) = \frac{\#\{\boldsymbol{x}_i \mid \boldsymbol{x} - \frac{\Delta}{2} \leq \boldsymbol{x}_i < \boldsymbol{x} + \frac{\Delta}{2}\}}{N\Delta}$$

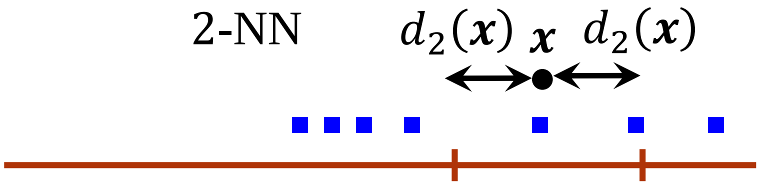


$$\mathrm{p}(\boldsymbol{x}) = \frac{1}{7 \times \Delta}$$

- Fix Δ, and check how many data points fall in the bin

K-NN Estimator

$$\hat{p}(\boldsymbol{x}) = \frac{K}{N\left(2d_K(\boldsymbol{x})\right)}$$



$$\mathrm{p}(\boldsymbol{x}) = \frac{2}{7 \times (2 \times d_2(\boldsymbol{x}))}$$

- Fix *K*, the number of observed data points to fall in the bin, and compute the bin size

K-Nearest Neighbor Estimator (cont.)

- With a predefined K, for a particular data point $\boldsymbol{x}$,

1. Compute distance between $\boldsymbol{x}$ and all the observed data, e.g., Euclidean distance $\|\boldsymbol{x}-\boldsymbol{x}_i\|_2$
2. Sort the observed data points based on the distances in ascending order:

$$\boxed{d_1(\boldsymbol{x})} \leq d_2(\boldsymbol{x}) \leq \cdots \boxed{d_j(\boldsymbol{x})} \leq \cdots \leq d_N(\boldsymbol{x})$$

$d_1(\boldsymbol{x})$ is the distance of $\boldsymbol{x}$ to the nearest observed instance

$d_j(\boldsymbol{x})$ is the distance of $\boldsymbol{x}$ to the j-th nearest observed instance

3. The K-NN density estimate is

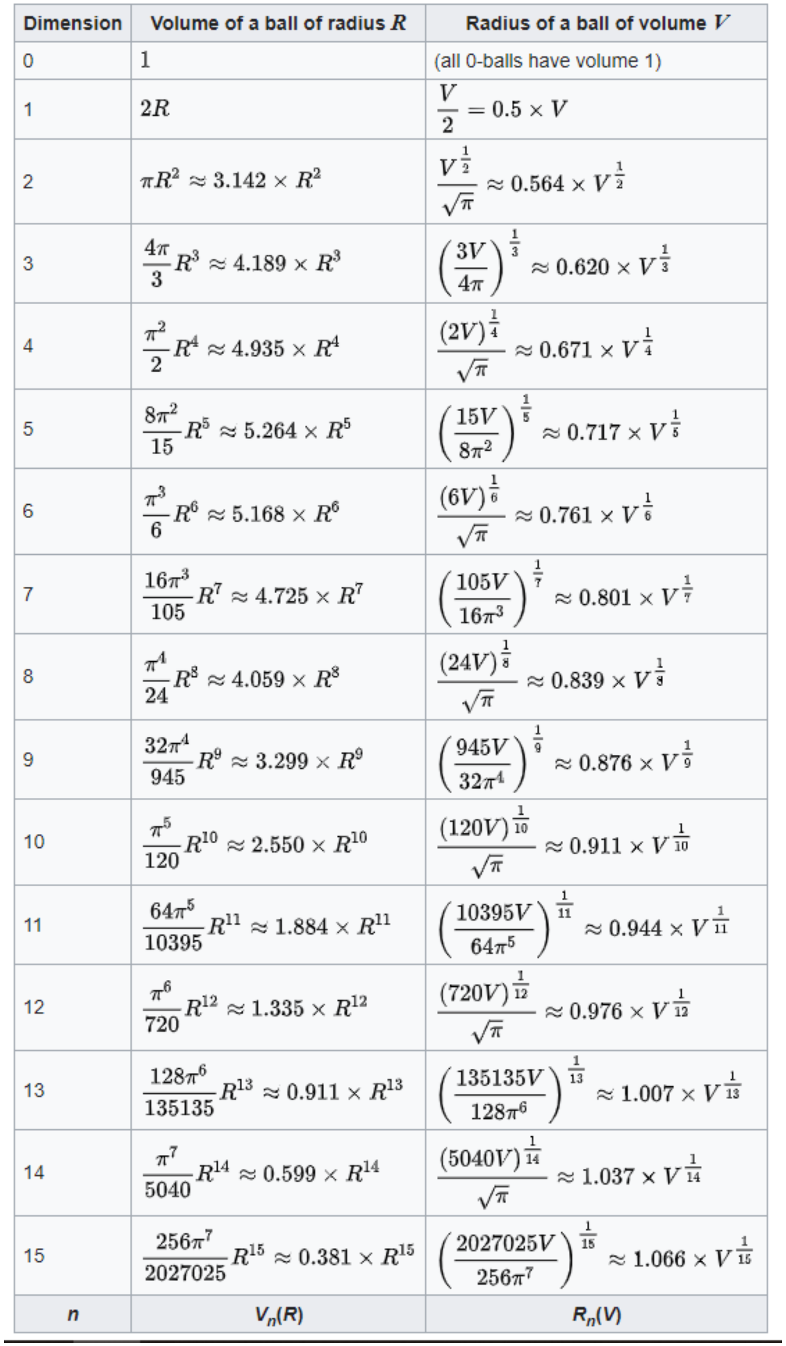
$$\hat{p}(\boldsymbol{x}) = \frac{K}{N\boxed{V_{d_K(\boldsymbol{x})}}}$$

A ball in d-dimensional Euclidean space

The volume of the d-ball of the radius $d_K(\boldsymbol{x})$ centered at $\boldsymbol{x}$. And $d_K(\boldsymbol{x})$ is the distance of $\boldsymbol{x}$ to the K-th nearest observed instance

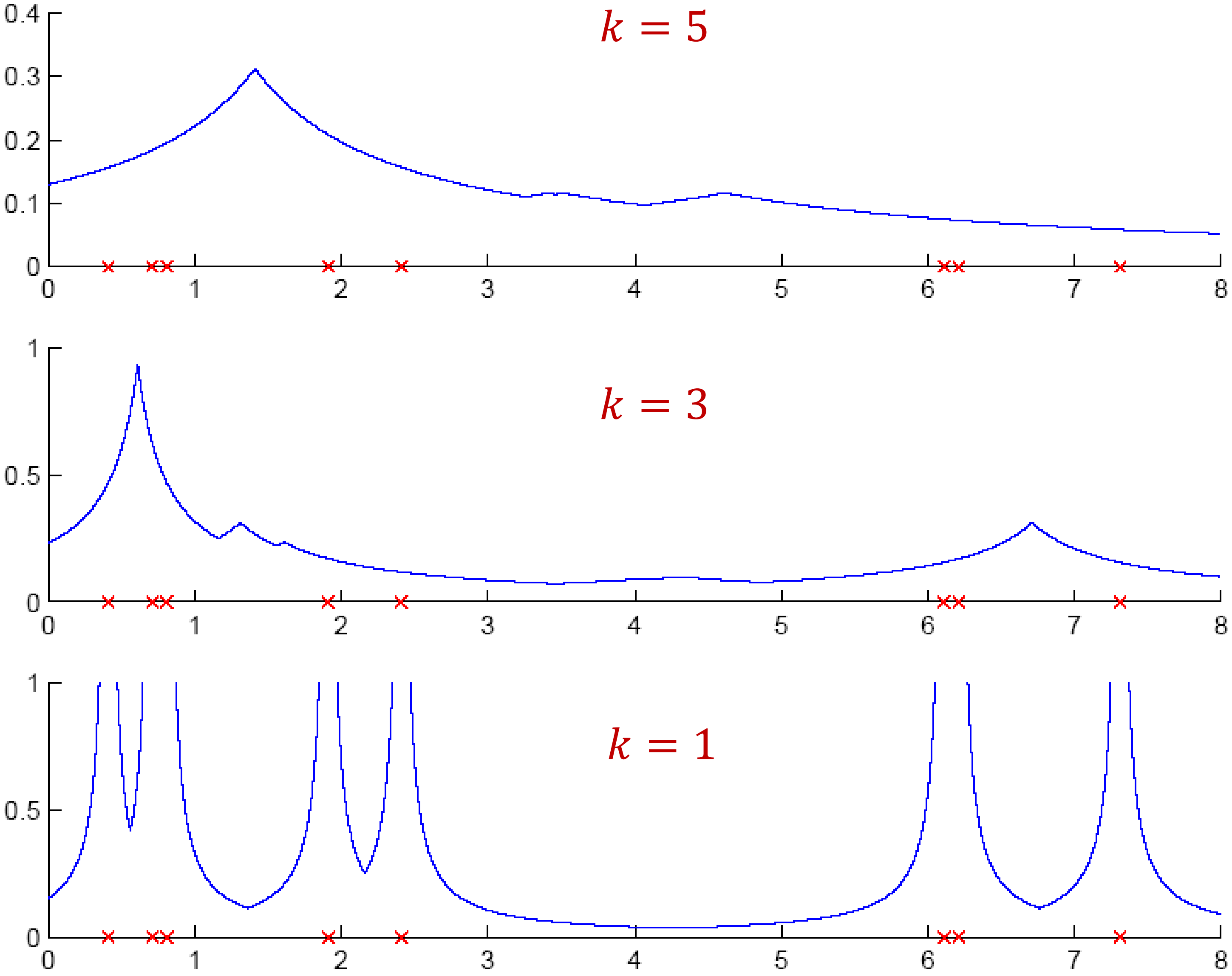
Look-up table for Volume of an n-ball

https://en.wikipedia.org/wiki/Volume_of_an_n-ball



Dimension	Volume of a ball of radius R	Radius of a ball of volume V
0	1	(all 0-balls have volume 1)
1	$2R$	$\frac{V}{2} = 0.5 \times V$
2	$\pi R^2 \approx 3.142 \times R^2$	$\frac{V^{\frac{1}{2}}}{\sqrt{\pi}} \approx 0.564 \times V^{\frac{1}{2}}$
3	$\frac{4\pi}{3}R^3 \approx 4.189 \times R^3$	$\left(\frac{3V}{4\pi}\right)^{\frac{1}{3}} \approx 0.620 \times V^{\frac{1}{3}}$
4	$\frac{\pi^2}{2}R^4 \approx 4.935 \times R^4$	$\frac{(2V)^{\frac{1}{4}}}{\sqrt{\pi}} \approx 0.671 \times V^{\frac{1}{4}}$
5	$\frac{8\pi^2}{15}R^5 \approx 5.264 \times R^5$	$\left(\frac{15V}{8\pi^2}\right)^{\frac{1}{5}} \approx 0.717 \times V^{\frac{1}{5}}$
6	$\frac{\pi^3}{6}R^6 \approx 5.168 \times R^6$	$\frac{(6V)^{\frac{1}{6}}}{\sqrt{\pi}} \approx 0.761 \times V^{\frac{1}{6}}$
7	$\frac{16\pi^3}{105}R^7 \approx 4.725 \times R^7$	$\left(\frac{105V}{16\pi^3}\right)^{\frac{1}{7}} \approx 0.801 \times V^{\frac{1}{7}}$
8	$\frac{\pi^4}{24}R^8 \approx 4.059 \times R^8$	$\frac{(24V)^{\frac{1}{8}}}{\sqrt{\pi}} \approx 0.839 \times V^{\frac{1}{8}}$
9	$\frac{32\pi^4}{945}R^9 \approx 3.299 \times R^9$	$\left(\frac{945V}{32\pi^4}\right)^{\frac{1}{9}} \approx 0.876 \times V^{\frac{1}{9}}$
10	$\frac{\pi^5}{120}R^{10} \approx 2.550 \times R^{10}$	$\frac{(120V)^{\frac{1}{10}}}{\sqrt{\pi}} \approx 0.911 \times V^{\frac{1}{10}}$
11	$\frac{64\pi^5}{10395}R^{11} \approx 1.884 \times R^{11}$	$\left(\frac{10395V}{64\pi^5}\right)^{\frac{1}{11}} \approx 0.944 \times V^{\frac{1}{11}}$
12	$\frac{\pi^6}{720}R^{12} \approx 1.335 \times R^{12}$	$\frac{(720V)^{\frac{1}{12}}}{\sqrt{\pi}} \approx 0.976 \times V^{\frac{1}{12}}$
13	$\frac{128\pi^6}{135135}R^{13} \approx 0.911 \times R^{13}$	$\left(\frac{135135V}{128\pi^6}\right)^{\frac{1}{13}} \approx 1.007 \times V^{\frac{1}{13}}$
14	$\frac{\pi^7}{5040}R^{14} \approx 0.599 \times R^{14}$	$\frac{(5040V)^{\frac{1}{14}}}{\sqrt{\pi}} \approx 1.037 \times V^{\frac{1}{14}}$
15	$\frac{256\pi^7}{2027025}R^{15} \approx 0.381 \times R^{15}$	$\left(\frac{2027025V}{256\pi^7}\right)^{\frac{1}{15}} \approx 1.066 \times V^{\frac{1}{15}}$
n	$V_n(R)$	$R_n(V)$

K-NN Estimator



$k = 5$

$k = 3$

$k = 1$

Thank you!

Optional

Appendix: Kernel Estimator

- To get a smooth estimate, we use a smooth weight function, *kernel function*, e.g., the Gaussian kernel
- For the univariate case, i.e., each data point is 1-dimensional, the Gaussian kernel is defined as

$$k(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right)$$

- The Kernel Estimator is computed via

$$\hat{p}(x) = \frac{1}{N\Delta} \sum_{i=1}^{N} k\left(\frac{x - x_i}{\Delta}\right)$$

Optional

Kernel Estimator (cont.)

- For the multivariate case, i.e., each data point is d-dimensional, the Gaussian kernel is defined as

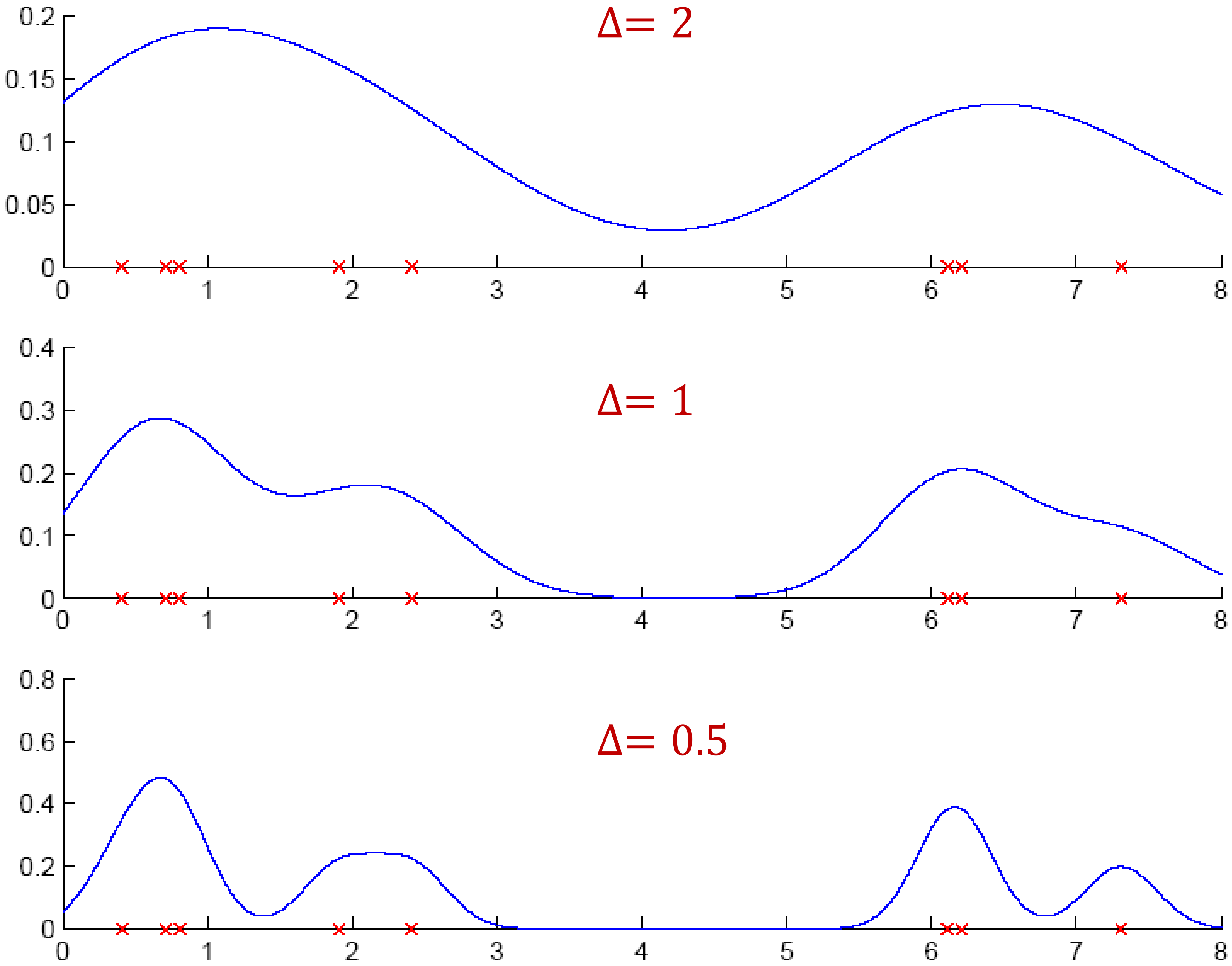
$$k(\boldsymbol{u}) = \frac{1}{(2\pi)^{d/2}} \exp\left(-\frac{\|\boldsymbol{u}\|_2^2}{2}\right)$$

- The Kernel Estimator is computed via

$$\hat{p}(\boldsymbol{x}) = \frac{1}{NV} \sum_{i=1}^{N} k\left(\frac{\boldsymbol{x} - \boldsymbol{x}_i}{h}\right)$$

Kernel Estimator

Optional



$\Delta = 2$

$\Delta = 1$

$\Delta = 0.5$