# Pattern Recognition

Lecture 10. Generative Methods II: non-Parametric methods:
Kernel Density Estimation

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# Agenda

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- Non-Parametric Modeling

# Parametric Modeling

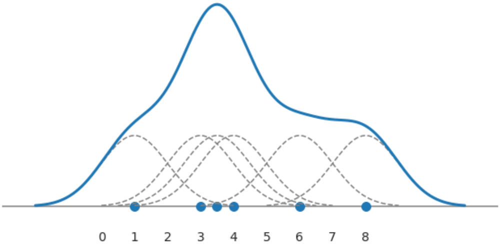
- Data availability in a Bayesian framework
  - We could design an optimal classifier if we knew $P(\omega_i)$ and $P(x|\omega_i)$
  - Unfortunately, we rarely have that much information available.
- Assumption
  - A prior information about the problem
  - The form of underlying density
    - Example: Normal density $P(x|\omega_i)$ : decided by 2 parameters.
- Estimation techniques
  - Maximum-Likelihood(ML) and Maximum A Posteriori (MAP)
- Other techniques
  - Gaussian Mixture Model (GMM) and Hidden Markov Model (HMM)
  - *You might touch these topics in your Master or PhD.*

# Non-Parametric Modeling

This part is taught on white board, the content of which is provided in LMO.

# Play around

KDEplot.ipynb

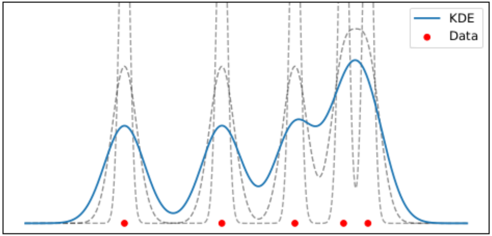


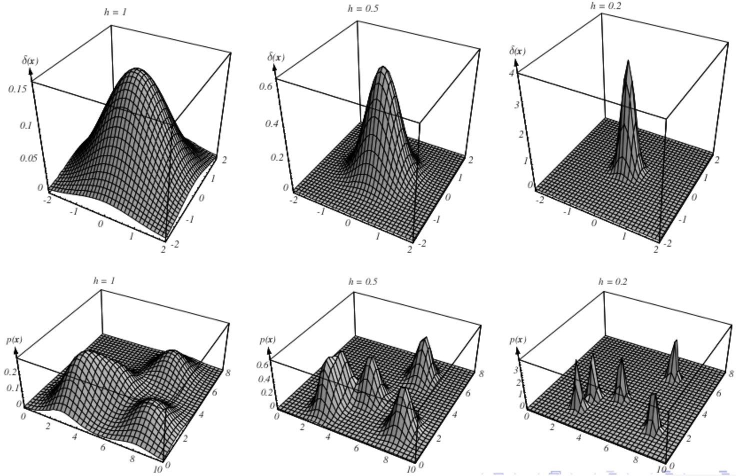
# TASK

- Show that whether the choice of kernel matters much.
- Show that whether the bandwidth of kernel matters much.

We use $h$ to control for the *bandwidth* of $\hat{f}(x)$ by writing

$$\hat{f}(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x-x_i}{h}\right).$$




h = 1
h = 0.5
h = 0.2
δ(x)
p(x)

# TASK 2

Try the code with other dataset, e.g., iris
`https://archive.ics.uci.edu/ml/datasets/iris`

# Reference I

# Thank You !

$\mathcal{Q}$ & $\mathcal{A}$