

# Nonparametric, Nearest Neighbors

CSci 5525: Machine Learning

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October 8, 2020

# Announcements

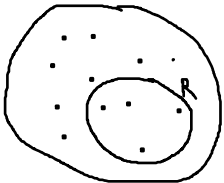
- HW2 is posted (due Oct 15)
- Exam 1 will be posted on Oct 20 (due 48 hours later)
- Course feedback form

# Parametric vs Nonparametric

- Parametric models
  - Set of parameters with fixed size
  - Independent of the number of training points
  - Example: Linear regression, Linear classification
  - Great for small amounts of data
  - May miss subtleties if huge amounts of data is available
- Nonparametric models
  - *Not* “Do not use any parameters”
  - Number of ‘parameters’ grow with data
  - Example:  $k$ -nearest neighbor classifier
  - Good for large datasets with ‘subtleties’
  - Care is needed to avoid under- or over-fitting

# Density estimation

- True density  $p(\mathbf{x})$ ,  $\mathbf{x} \in \mathbb{R}^p$ , we draw  $N$  samples
- Density at a local region  $R$ :  $P = \int_R p(\mathbf{x}) d\mathbf{x}$ 
  - Number of samples in the region  $K \approx NP$
  - For small region of volume  $V$ , density is uniform,  $P \approx p(\mathbf{x})V$
- Estimate of density:

$$p(\mathbf{x}) \approx \frac{K}{NV}$$


- Two approaches to estimation
  - Kernel density estimate: Keep  $V$  fixed, estimate  $K$  from data
  - Nearest neighbor estimate: Keep  $K$  fixed, estimate  $V$  from data

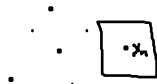
# Kernel Density Estimation

$$k(u) = \begin{cases} 1 & \text{if } |u_i| \leq \frac{1}{2}, \\ 0 & \text{o/w} \end{cases}$$

- Consider a kernel  $k : \mathbb{R}^p \mapsto \mathbb{R}_+$ 
  - Need  $k(\mathbf{u}) \geq 0$ ,  $\int k(\mathbf{u}) d\mathbf{u} = 1$
  - Bounded support, e.g.,  $k(\mathbf{u}) = 1, |\mathbf{u}_i| \leq 1/2, 0$  otherwise
- Total number of points inside cube of size  $h$  is

$$p(\mathbf{x}) \approx \frac{K}{N V} \quad K = \sum_{n=1}^N k\left(\frac{\mathbf{x} - \mathbf{x}_n}{h}\right)$$

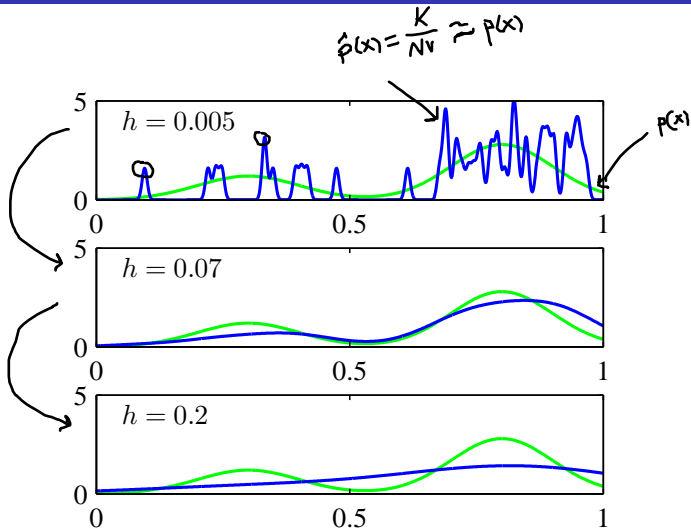
$V = h^p$



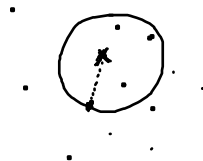
- Since volume is  $h^p$ , the density estimate is

$$p(\mathbf{x}) \approx \frac{1}{N} \sum_{n=1}^N \frac{1}{h^p} k\left(\frac{\mathbf{x} - \mathbf{x}_n}{h}\right)$$

# Kernel Density Estimation

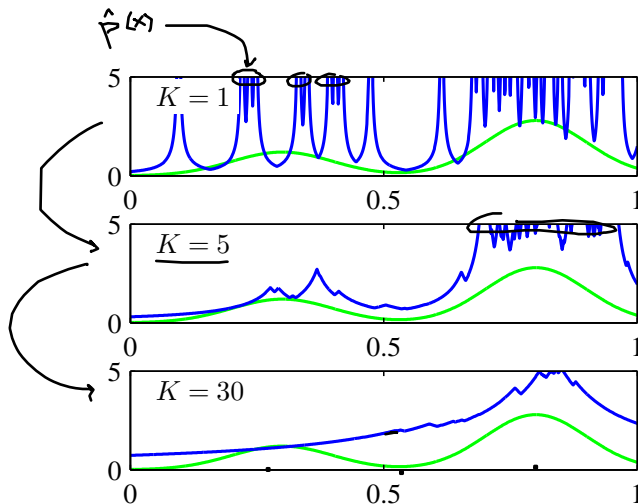


# Nearest Neighbor Density Estimation



- Main idea: Fix  $K$ , estimate  $V$  from data
- Estimating density  $p(\mathbf{x})$  around  $\mathbf{x}$ 
  - Fix  $K$ , number of neighbors
  - Grow a sphere around  $\mathbf{x}$ , till it includes  $K$  points
  - Volume of the sphere is  $V$
- Radius of sphere is distance to the  $K^{th}$  nearest neighbor
- Estimate density as:  $p(\mathbf{x}) = \frac{K}{NV}$

# Nearest Neighbor Density Estimation





# Nearest Neighbors: Classification, Regression

$$k=3$$



- Find  $NN_K(\mathbf{x})$ , the  $k$  nearest neighbors of  $\mathbf{x}$
- Classification: Majority class in  $NN_K(\mathbf{x})$
- Regression: Solve linear regression using  $NN_K(\mathbf{x})$
- Choice of distance metric

$$\hat{y}(x) = \frac{2+3+4}{3} = \frac{9}{3} = 3$$

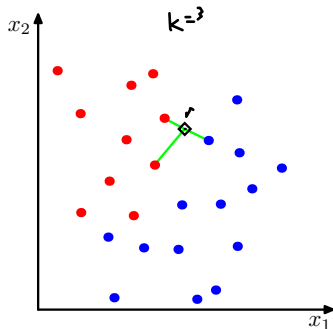
- Suitable  $L_p$  norm
- z-scored metrics, Mahalanobis distance
- Metrics defined by nonlinear 'kernels'
- Application domain dependent metrics

$$\hat{y}(x) = w^T x$$

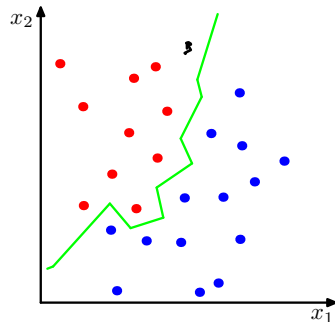
$$\underset{w}{\operatorname{argmax}} \frac{1}{n} \sum_{i \in n_k} (y_i - w^T x_i)^2$$

$$n_k = \text{KNN to point } x$$

# Nearest Neighbor Classification

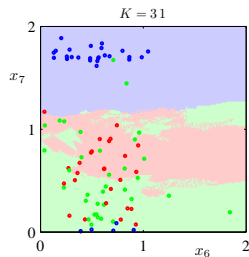
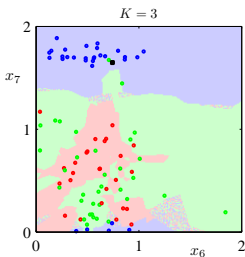
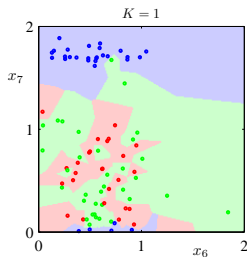


(a)

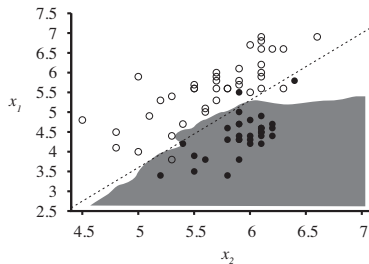
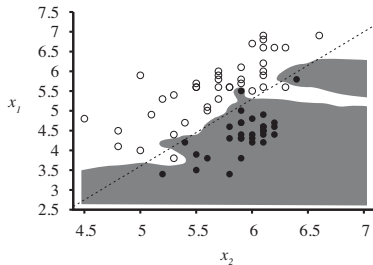


(b)

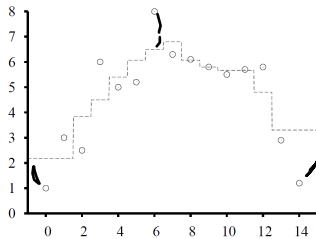
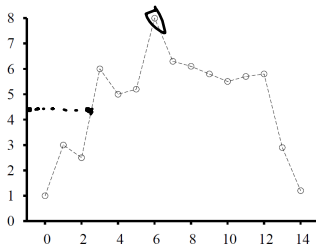
# Nearest Neighbor Classification



# Over-fitting, Under-fitting

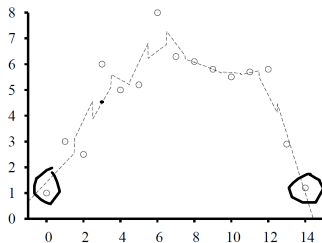


# Nonparametric Regression

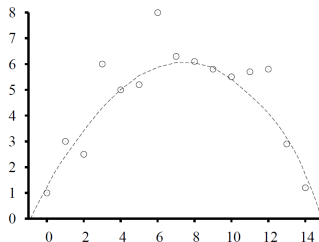


- 'Connect-the-dots' regression can be 'spiky'
- $K$ -nearest neighbor regression: mean of  $K$  points

# Nonparametric Regression (Contd.)



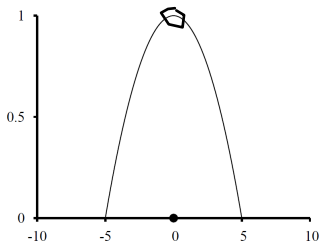
(j)



(k)

- $k$ -nearest neighbor linear regression: best line
- Locally weighted regression: Weighting is done using a kernel

# Locally Weighted Regression



- Kernel  $k(\cdot)$  is symmetric around 0 and maximum at 0
- The area under the kernel should remain bounded
- Bandwidth of the kernel: Underfitting vs Overfitting
- Locally weighted regression:

$$\mathbf{w}^*(\mathbf{x}) = \operatorname{argmin}_{\mathbf{w}} \sum_{n=1}^N k\left(\frac{\mathbf{x} - \mathbf{x}_n}{h}\right) (y_n - \mathbf{w}^\top \mathbf{x}_n)^2$$

$\Rightarrow \quad y(\mathbf{x}) = (\mathbf{w}^*(\mathbf{x}))^\top \mathbf{x}$

$\uparrow$