



University of Pittsburgh

# ECE 2195: Special Topics – Computers Machine Learning

## Support Vector Regression

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# Recall Linear Regression with Regularization

- Objective function of linear regression:

$$\underbrace{\frac{1}{2} \sum_{i=1}^n (y_i - \hat{y}_i)^2}_{\text{Error RSS}} + \frac{\lambda}{2} ||w||^2 \text{ Ridge regularization}$$

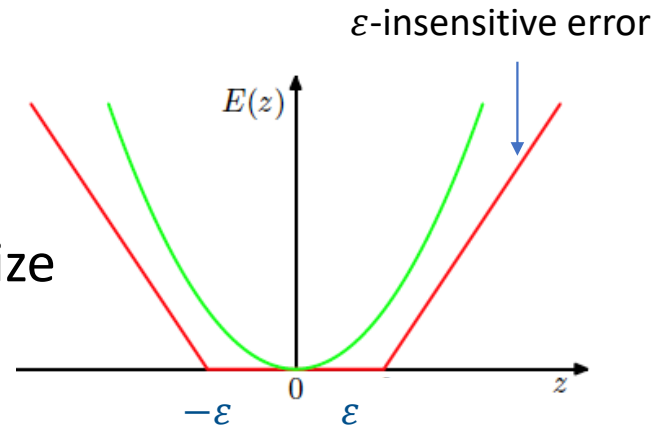
- Let's replace the loss  $\frac{1}{2} \sum_{i=1}^n (y_i - \hat{y}_i)^2$  with  $\epsilon$ -insensitive error function  $E(z)$

- Consider error only if they are more than  $\epsilon$

- The objective now becomes to minimize

$$C \sum_{i=1}^n E(y_i - \hat{y}_i) + \frac{1}{2} ||w||^2$$

$C$  is the inverse regularization parameter



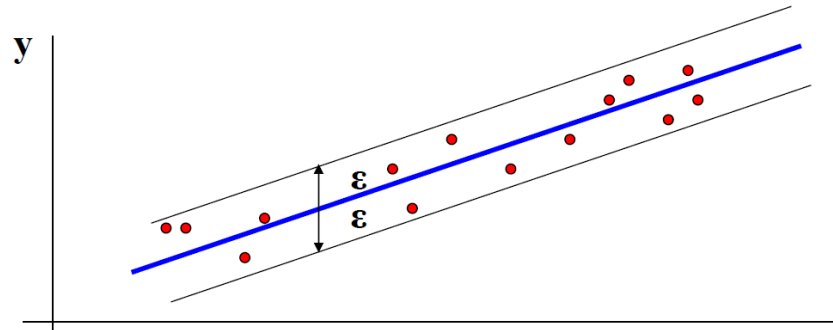
# Regression using SVC

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = \langle \mathbf{w}, \mathbf{x} \rangle + b$$

- Linear function for regression
- If all points assumed to be with  $\varepsilon$  neighborhood
  - With  $\varepsilon$ -insensitive error function
- The objective will be

minimize  $\frac{1}{2} \|\mathbf{w}\|^2$

subject to 
$$\begin{cases} y_i - \langle \mathbf{w}_i, \mathbf{x}_i \rangle - b \leq \varepsilon \\ \langle \mathbf{w}_i, \mathbf{x}_i \rangle + b - y_i \leq \varepsilon \end{cases}$$



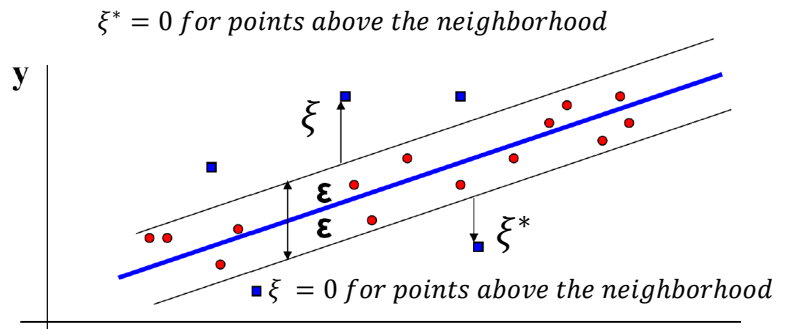
# Get it more general

- Not all data could satisfy neighborhood
- Allow some errors but add constraint to limit the error
- Objective function

(some have more error)

$$\begin{aligned} &\text{minimize} && \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*) \\ &\text{subject to} && \begin{cases} y_i - \langle w_i, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle w_i, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \end{aligned}$$

$$\langle w, x \rangle = w^T x$$



- Solve using Lagrange as before

# Solution

- Use Lagrange, we get

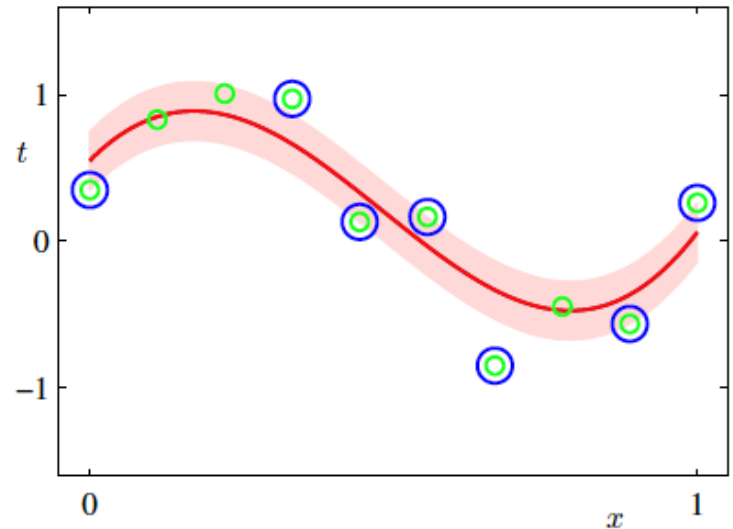
$$f(x) = \sum_{i=1}^n (C_i) \langle x_i, x \rangle + b$$

Dot product  
↓

- where  $C_i$  depends on Lagrange multipliers

- We can apply Kernel as before
  - Replace dot product with kernel to get Get non linear function

$$f(x) = \sum_{i=1}^n (C_i) K(x_i, x) + b$$



example with Radial Basis Kernel