



# Big Picture

Machine Learning – 10701/15781

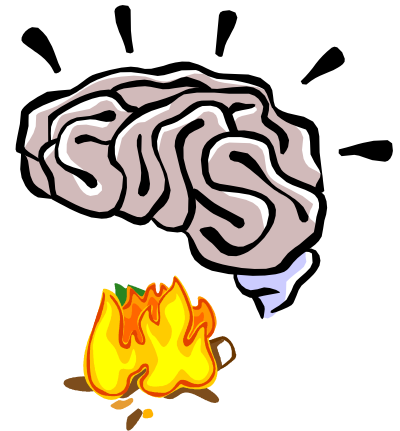
Carlos Guestrin

Carnegie Mellon University

March 2<sup>nd</sup>, 2005

# What you have learned thus far

- Learning is function approximation
- Point estimation
- Regression
- Naïve Bayes
- Logistic regression
- Bias-Variance tradeoff
- Neural nets
- Decision trees
- Cross validation
- Boosting
- Instance-based learning
- SVMs
- Kernel trick
- PAC learning
- VC dimension
- Margin bounds
- Mistake bounds



# Review material in terms of...



- Types of learning problems
- Hypothesis spaces
- Loss functions
- Optimization algorithms

# Text Classification

text  $\rightarrow \{C, P, U, \dots\}$



→ Company home page

VS

Personal home page

VS

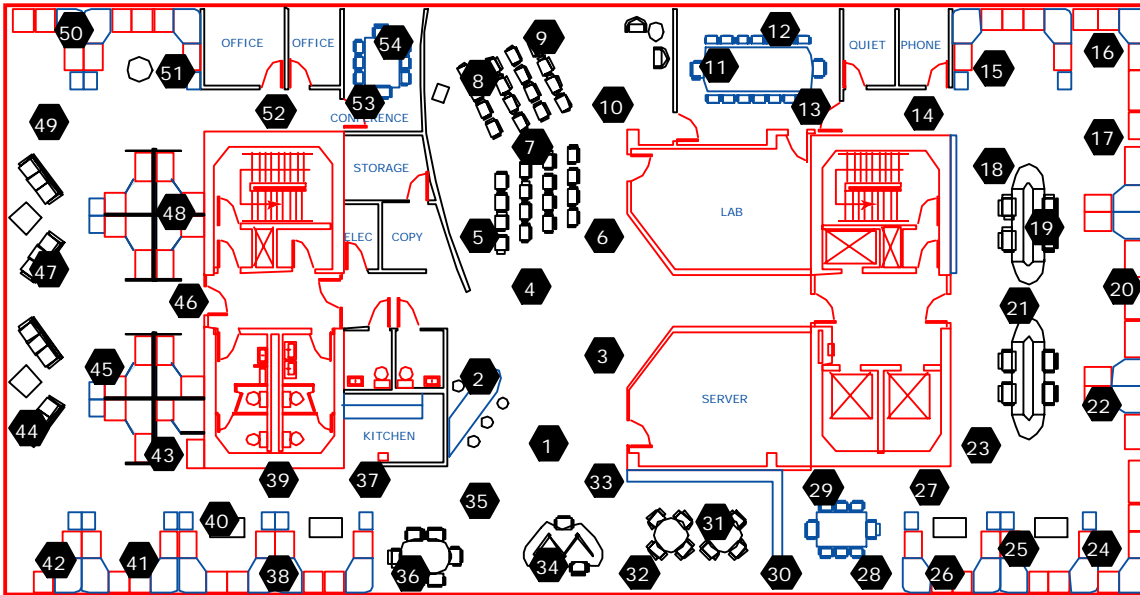
Univeristy home page

VS

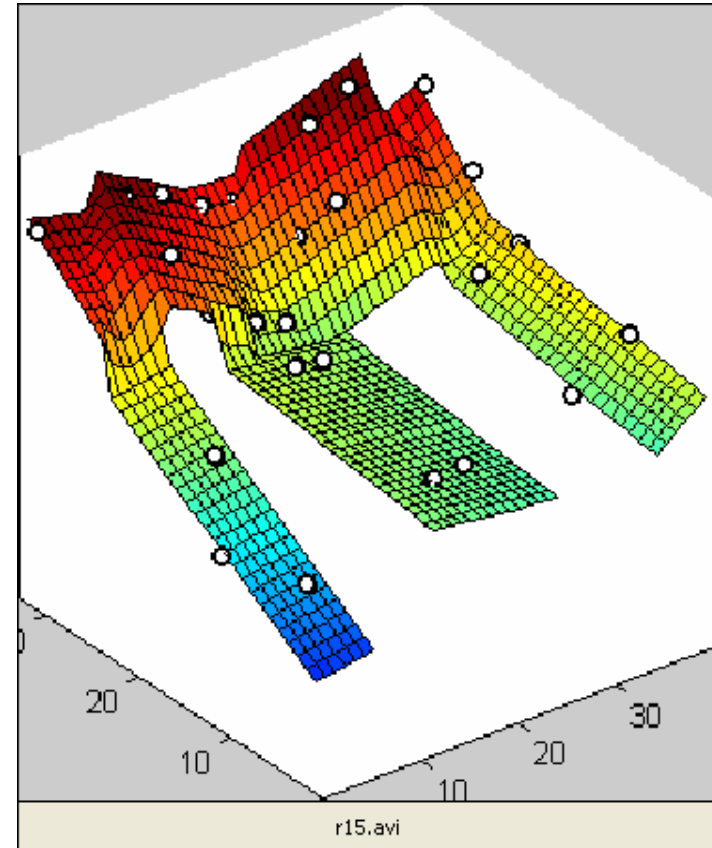
...

# Function fitting

$x, y, t \rightarrow \text{temps}$

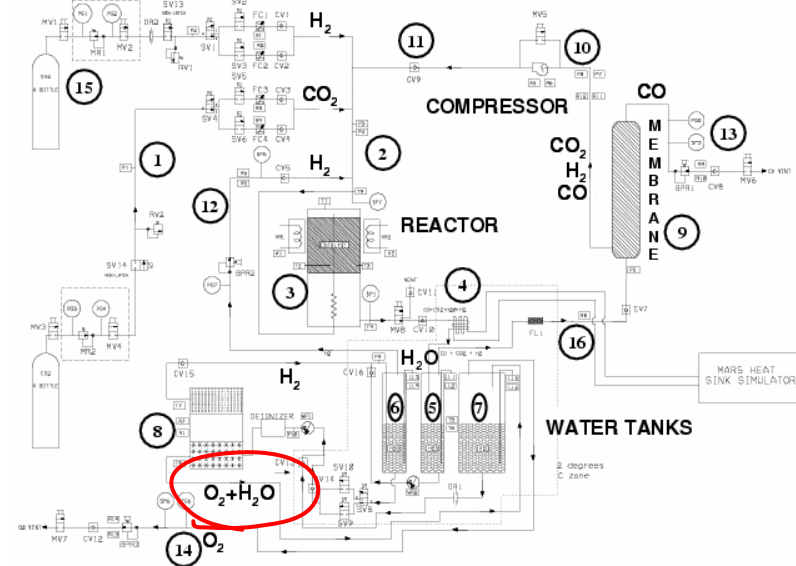


Temperature data



Sensors → probabilities

# Monitoring a complex system



- Reverse water gas shift system (RWGS)
- Learn model of system from data
- Use model to predict behavior and detect faults

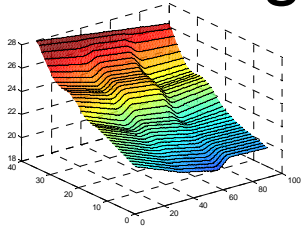
# Types of learning problems

## ■ Classification



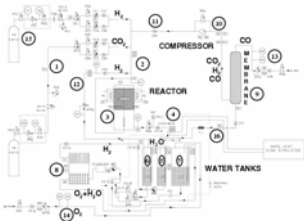
text  $\rightarrow \{C, P, U, \dots\}$

## ■ Regression



$x, y, t \rightarrow \mathbb{R}$

## ■ Density estimation



sensors  $\rightarrow [0, 1]$

**Input – Features**

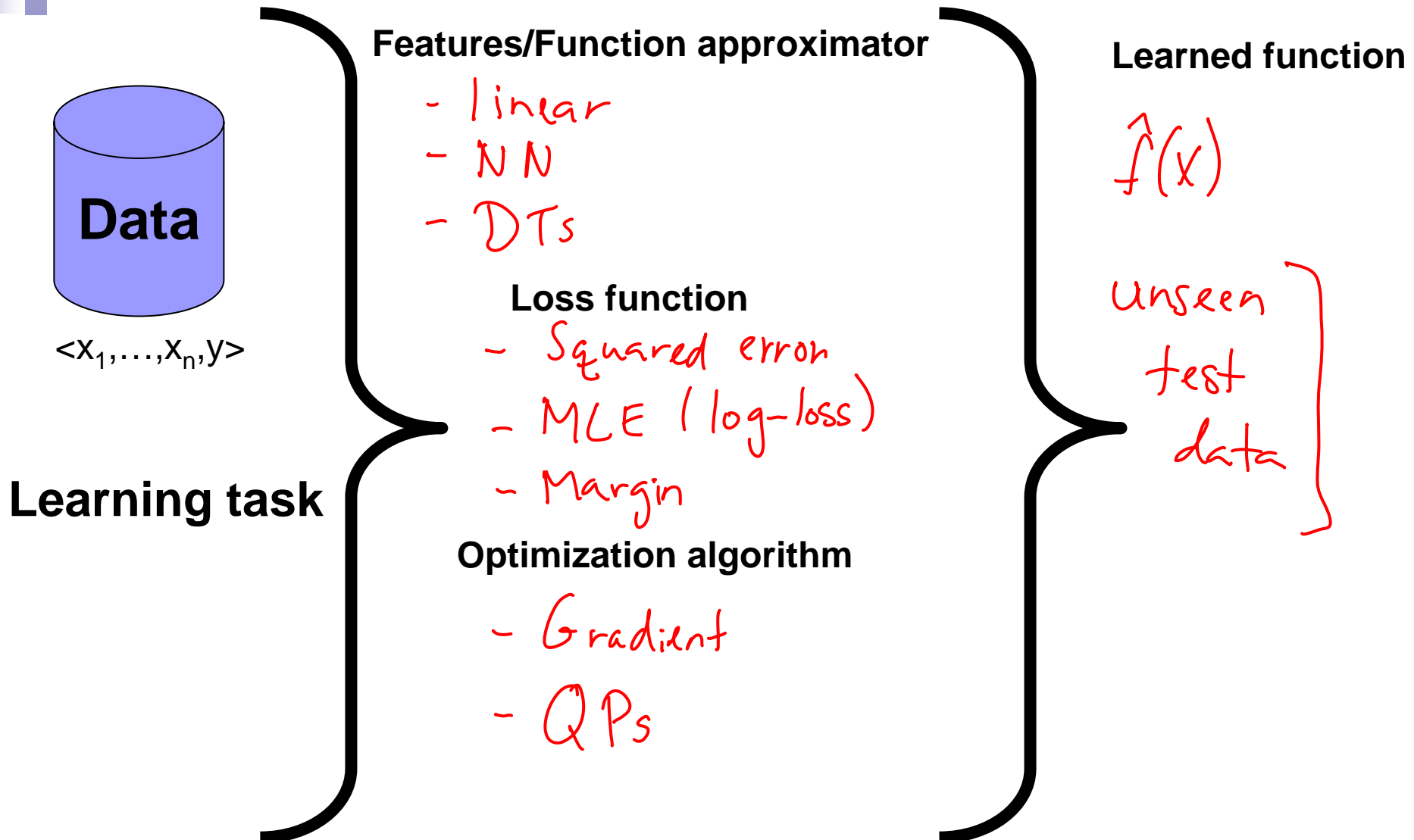
$X$   $\phi(x)$

**Output?**

$Y$ : classification; discrete  
Regression:  $\mathbb{R}$

Density Est. :  $[0, 1]$

# The learning problem





# Comparing learning algorithms



- Hypothesis space
- Loss function
- Optimization algorithm

# Naïve Bayes versus Logistic regression

Density estimation:  $P(Y|x)$

## Naïve Bayes

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$$

$$P(X|Y) = \prod_i P(X_i|Y)$$

strong indep. assumption

loss function:  
 $\max P(X, Y)$

MLE

## Logistic regression

$$P(Y = 1|x) = \frac{1}{1 + \exp(w_0 + \sum_i w_i x_i)}$$

weaker indep. assumptions

loss:  $\max P(Y|x)$

Gradient, MLE

← →  
equivalence  
indep. Gaussian features

# Naïve Bayes versus Logistic regression – Classification as density estimation

$$P(Y|X)$$

- Choose class with highest probability

$$\hat{y} = \underset{y}{\operatorname{argmax}} P(y|x)$$

- In addition to class, we get certainty measure
-

# Logistic regression versus Boosting

## Logistic regression

$$P(Y = y_i | \mathbf{x}) = \frac{1}{1 + \exp(-y_i(\mathbf{w} \cdot \mathbf{x} + b))}$$

Log-loss

$$\sum_{j=1}^m \log [1 + \exp(-y_j(\mathbf{w} \cdot \mathbf{x}_j + b))]$$

→  $\text{sign}(\mathbf{w} \cdot \mathbf{x} + b)$  classifier  
→ select features a priori

Global optima

## Boosting

Classifier

$$\text{sign} \left( \sum_{t=1}^T \alpha_t h_t(\mathbf{x}) \right)$$

*optimizing  $\alpha_t$*

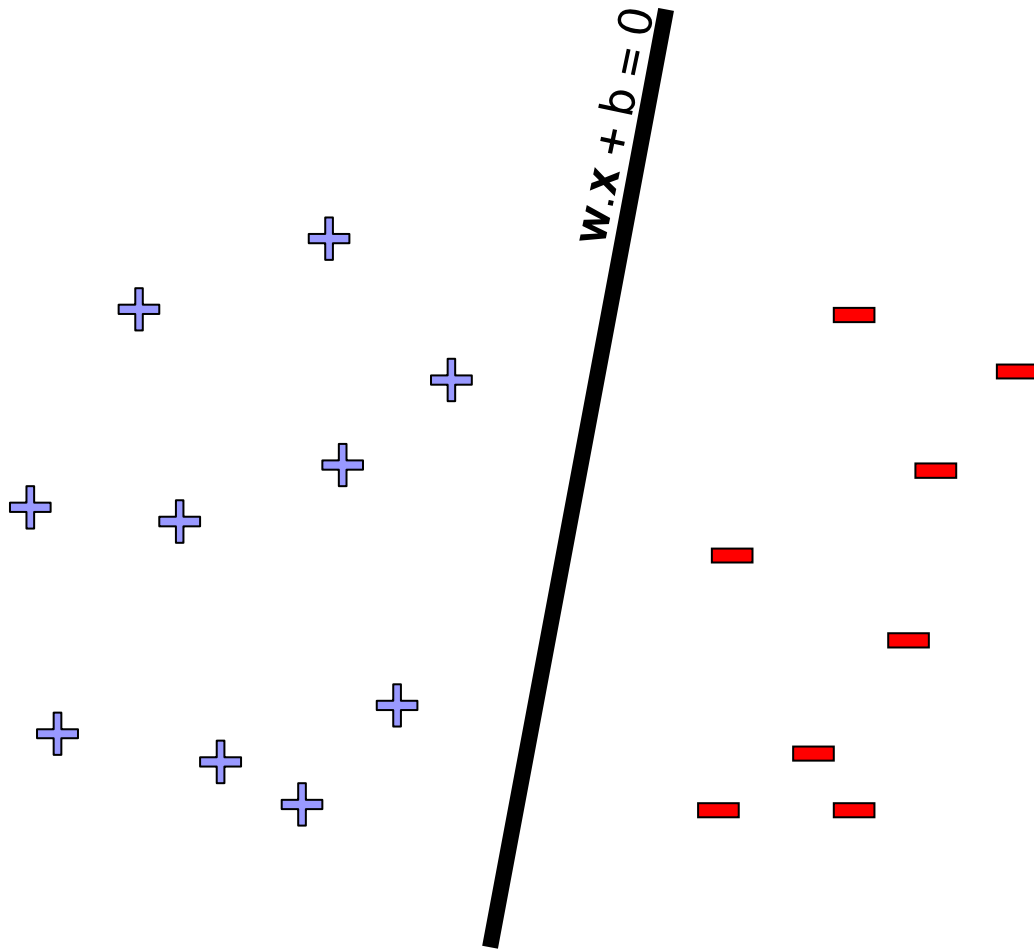
Exponential-loss

$$\frac{1}{m} \sum_{j=1}^m \exp \left( -y_j \sum_{t=1}^T \alpha_t h_t(\mathbf{x}_j) \right)$$



→ weak learners are the features  $h_t(\mathbf{x})$

→ sequential optimization

# Linear classifiers – Logistic regression versus SVMs



# What's the difference between SVMs and Logistic Regression? (Revisited again)

	<b>SVMs</b>	<b>Logistic Regression</b>
<b>Loss function</b>	 Hinge loss	 Log-loss
<b>High dimensional features with kernels</b>	Yes!	Yes!
<b>Solution sparse</b>	Often yes!	Almost always no!
<div><div>Classification</div><div><math>P(Y x)</math> density estimation</div></div>		

# SVMs and instance-based learning

$$\mathbf{w} \cdot \Phi(\mathbf{x}) = \sum_i \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i)$$

$$b = y_k - \sum_i \alpha_i y_i K(\mathbf{x}_k, \mathbf{x}_i)$$

for any  $k$  where  $C > \alpha_k > 0$

**SVMs**

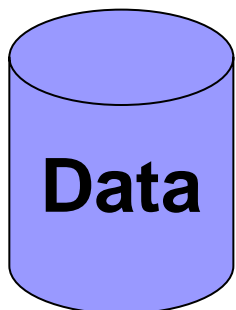
Classify as

$$\text{sign} \left( \sum_i \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) + b \right)$$

**Instance based learning**

*as density estimation*

$$P(y | \mathbf{x}) = \frac{\sum_i y_i K(\mathbf{x}, \mathbf{x}_i)}{\sum_i K(\mathbf{x}, \mathbf{x}_i)} > 0.5?$$



**Data**

Classify as

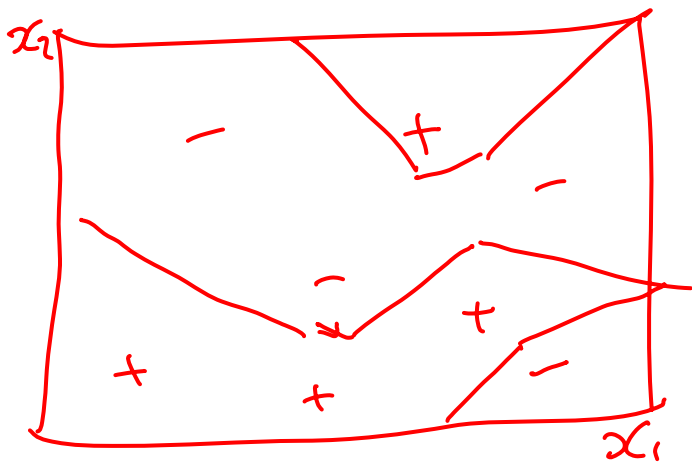
$$\text{sign} \left( \sum_i y_i K(\mathbf{x}, \mathbf{x}_i) - 0.5 \sum_i K(\mathbf{x}, \mathbf{x}_i) \right)$$

$\langle \mathbf{x}_1, \dots, \mathbf{x}_n, \mathbf{y} \rangle$

*optimize  $\alpha_i$*   
*" $\alpha_i$ " are fixed*

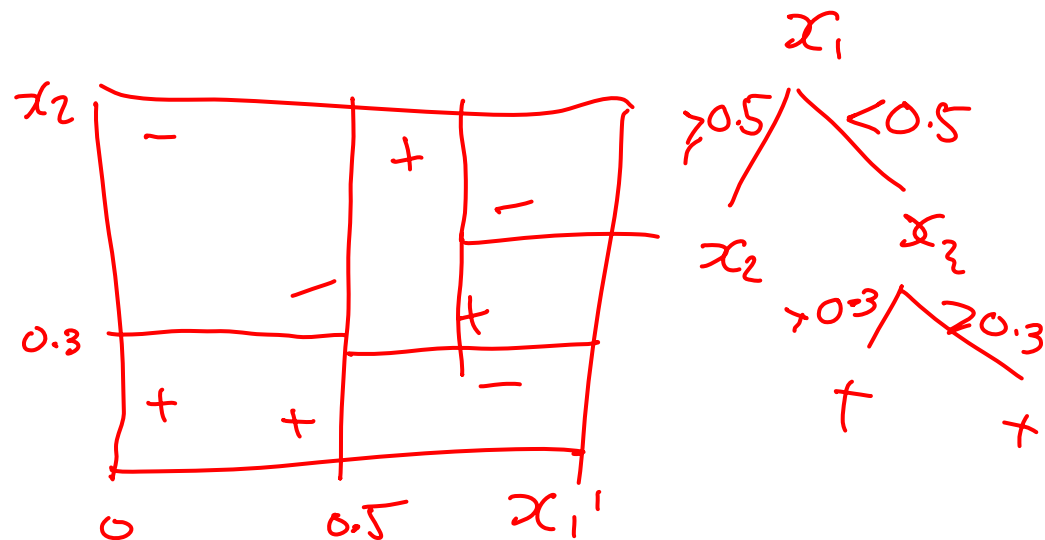
# Instance-based learning versus Decision trees

## 1-Nearest neighbor



Voronoi split

## Decision trees



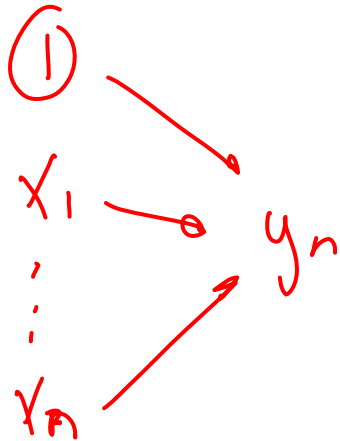
axis aligned split



# Logistic regression versus Neural nets

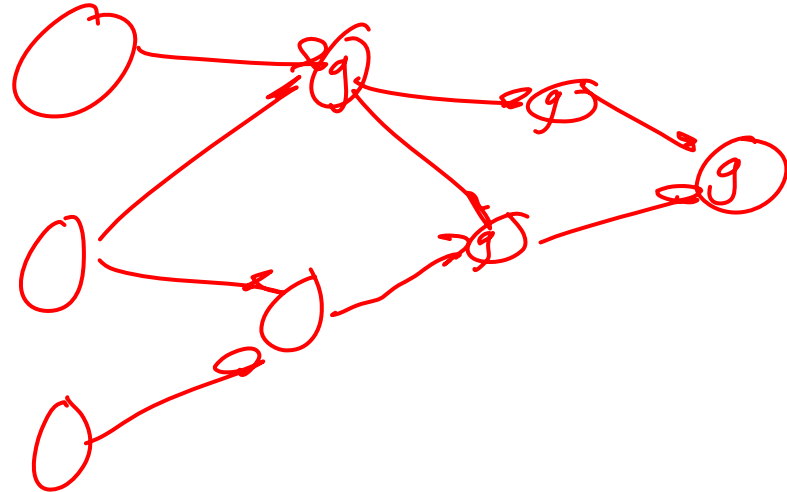
$$g(w_0 + \sum_i w_i x_i) = \frac{1}{1 + e^{-(w_0 + \sum_i w_i x_i)}}$$

## Logistic regression



loss: log loss

## Neural Nets

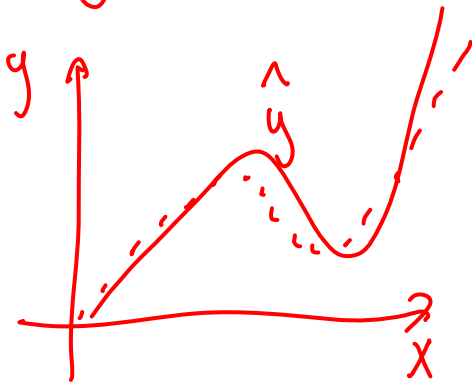


loss: Sum-squared error

# Linear regression versus Kernel regression

## Linear Regression

$$\hat{y} = w_0 + \sum_i w_i f_i(x)$$



## Kernel regression

$$\hat{y} = \frac{\sum_j w_j y_j}{\sum_j w_j}$$

$$w_j = K(x, x_j)$$

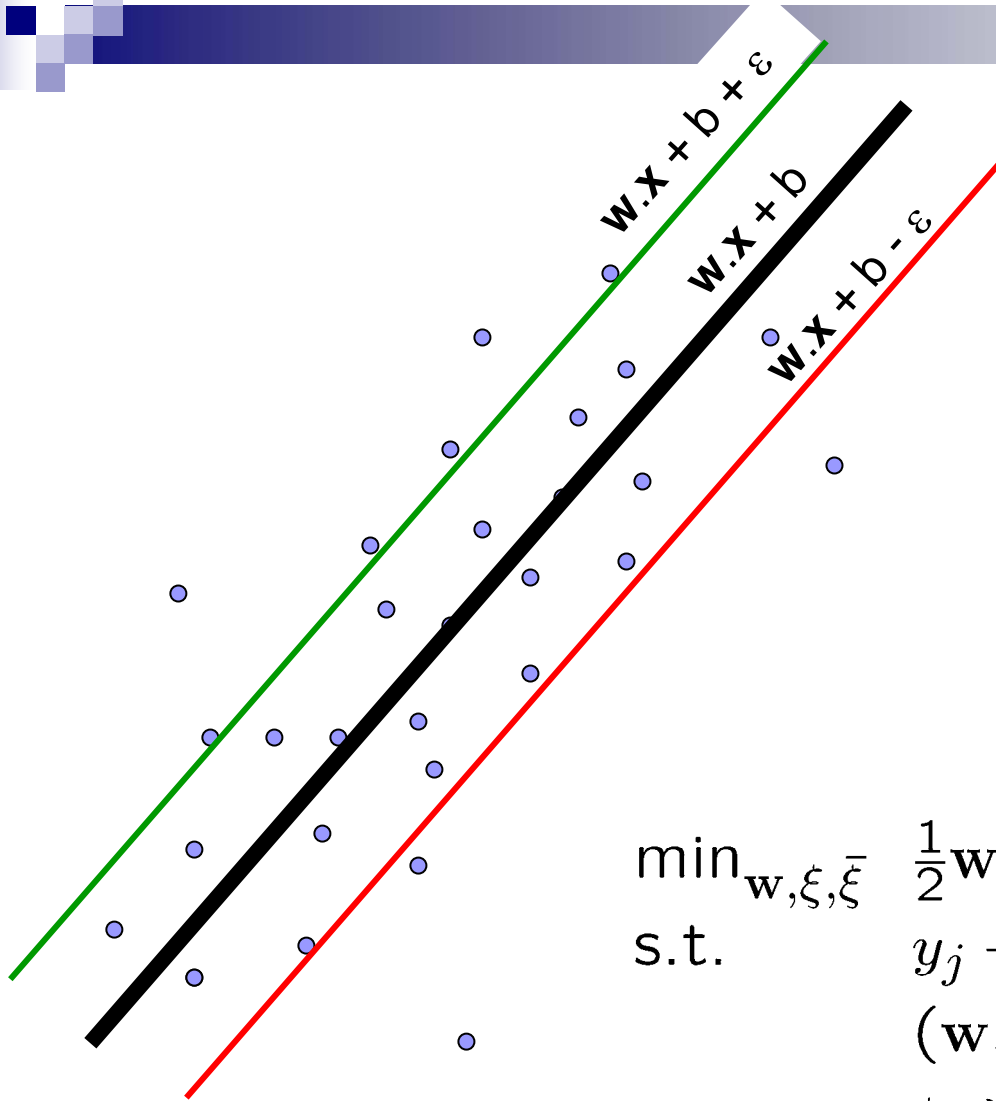
$K(\cdot, \cdot)$  has some parameters,  
gradient descent

## Kernel-weighted linear regression

Combine:  
linear regression  
with kernels



# SVM regression



$$\begin{aligned} \min_{w, \xi, \bar{\xi}} \quad & \frac{1}{2} w \cdot w + C \sum_{j=1}^m (\xi_j + \bar{\xi}_j) \\ \text{s.t.} \quad & y_j - (w \cdot x_j + b) \leq \epsilon + \xi_j \\ & (w \cdot x_j + b) - y_j \leq \epsilon + \bar{\xi}_j \\ & \xi_j \geq 0, \quad \bar{\xi}_j \geq 0, \quad \forall j \end{aligned}$$

# BIG PICTURE

(a few points of comparison)

learning  
task

loss  
function

DE	density estimation
CI	Classification
Reg	Regression
LL	Log-loss/MLE
Mrg	Margin-based
RMS	Squared error

Naïve  
Bayes  
DE, LL

*ind  
Gaussian  
features*

Boosting  
CI, exp-loss

*same H  
diff. loss*

Logistic  
regression  
DE, LL

SVMs  
CI, Mrg

SVM  
regression  
Reg, Mrg

kernel  
regression  
Reg, RMS

Instance-based  
Learning  
DE, CI, Reg

Neural  
Nets  
DE, CI, Reg, RMS

Decision  
trees  
DE, CI, Reg

linear  
regression  
Reg, RMS

This is a very incomplete view!!!