

Harvard-MIT Division of Health Sciences and Technology

HST.951J: Medical Decision Support, Fall 2005

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Review of some concepts in predictive modeling



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Brigham and Women's Hospital

Topics

- Decision trees
- Linear regression
- Logistic regression
- Evaluation
- Classification trees
- Ensembles
- PCA
- Clustering
- MDS
- Neural nets

**2 x 2 table
(contingency table)**

	PPD+	PPD-	
TB	8	2	10
no TB	3	87	90
	11	89	100

Probability of TB given PPD- = 2/89

Bayes rule

- Definition of conditional probability:
- $P(A|B) = P(AB)/P(B)$

$$P(B|A) = P(BA)/P(A)$$

$$P(AB) = P(BA)$$

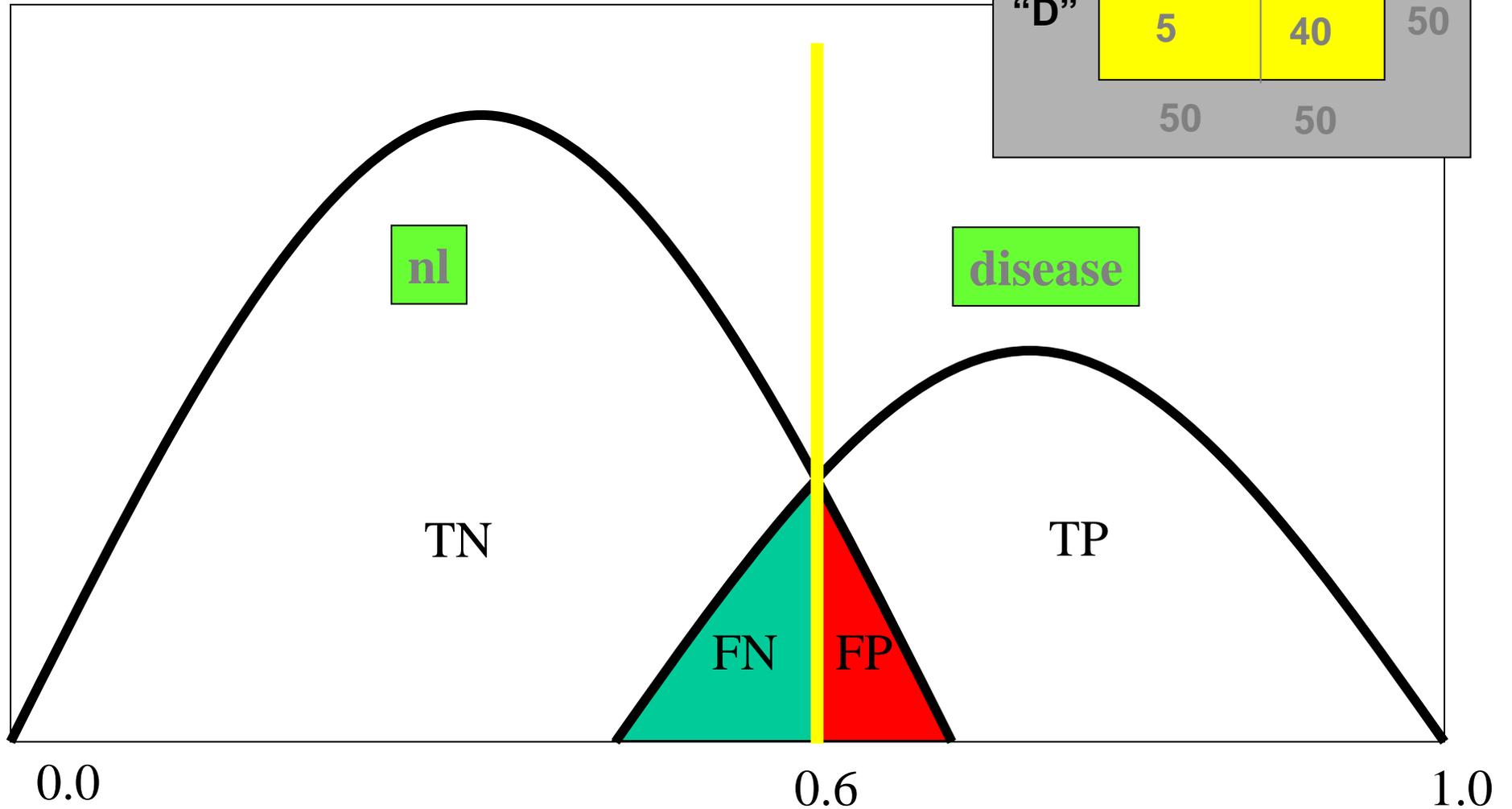
$$P(A|B)P(B) = P(B|A)P(A)$$

$$\mathbf{P(A|B) = P(B|A)P(A)/P(B)}$$

Sensitivity = $40/50 = .8$
Specificity = $45/50 = .9$

threshold

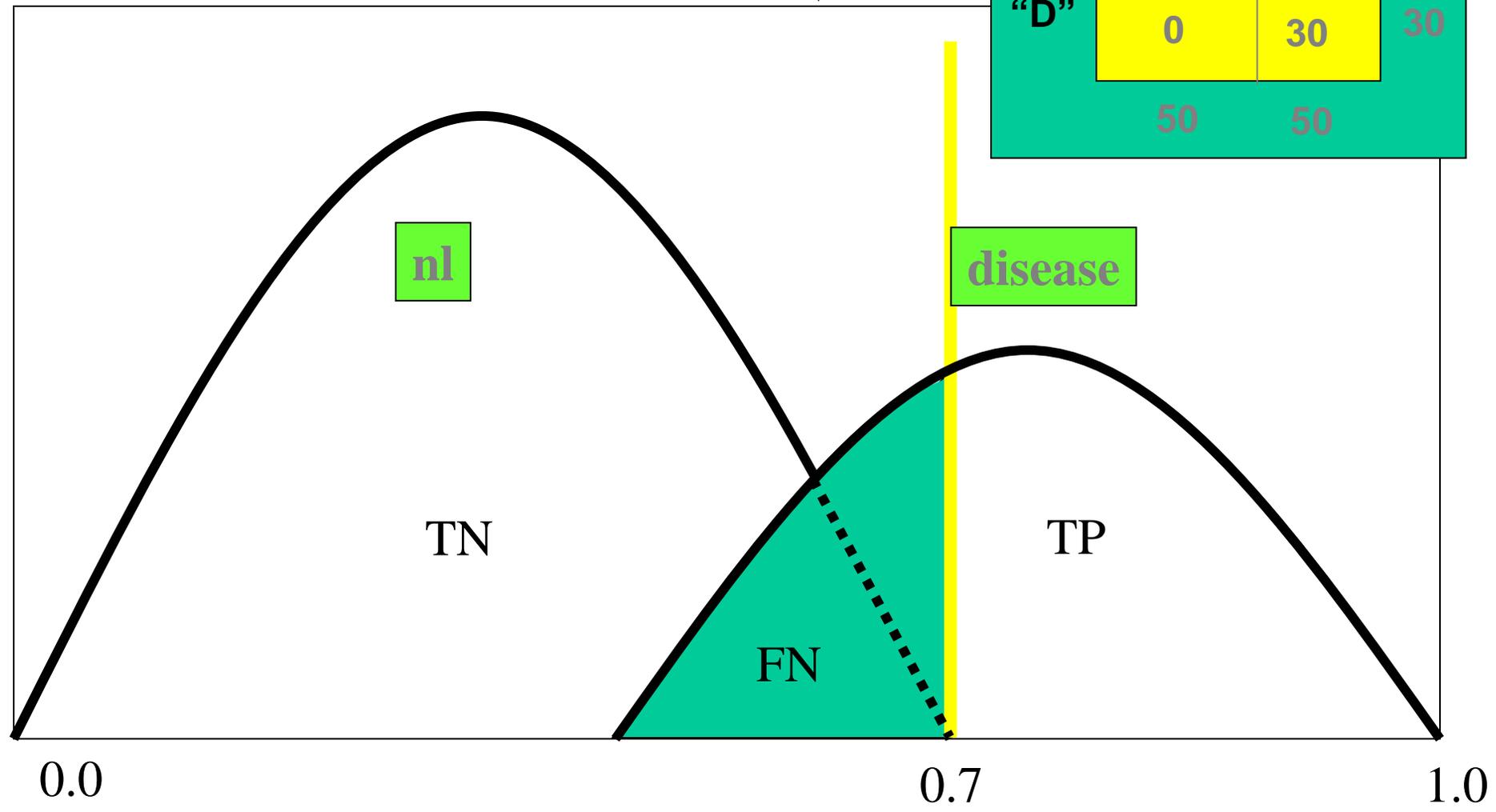
	nl	D	
"nl"	45	10	50
"D"	5	40	50
	50	50	



Sensitivity = $30/50 = .6$
Specificity = 1

threshold

	nl	D	
"nl"	50	20	70
"D"	0	30	30
	50	50	



Threshold 0.4

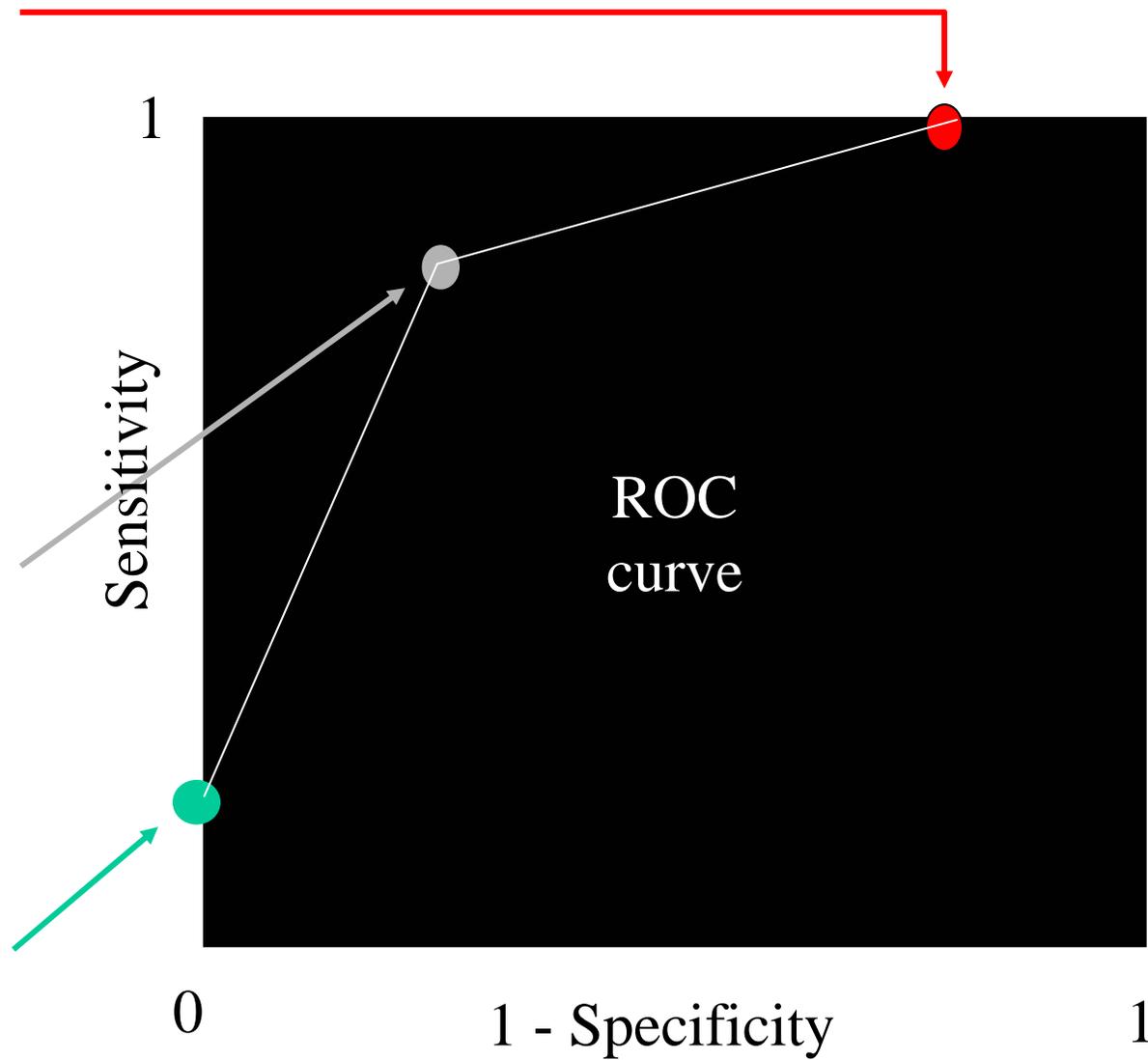
	nl	D	
"nl"	40	0	40
"D"	10	50	60
	50	50	

Threshold 0.6

	nl	D	
"nl"	45	10	50
"D"	5	40	50
	50	50	

Threshold 0.7

	nl	D	
"nl"	50	20	70
"D"	0	30	30
	50	50	



All possible pairs 0-1

- Healthy

0.3

0.2

0.5

0.1

0.7



- Sick

0.8

0.2

0.5

0.7

0.9

concordant

discordant

concordant

concordant

concordant

All possible pairs 0-1

Systems' estimates for

- Healthy

0.3

0.2

0.5

0.1

0.7

- Sick

0.8

0.2

0.5

0.7

0.9

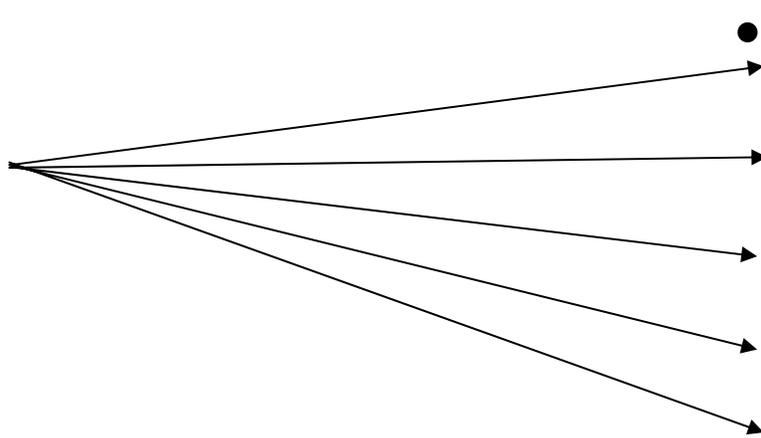
concordant

tie

concordant

concordant

concordant



C - index

- Concordant
18

- Discordant
4

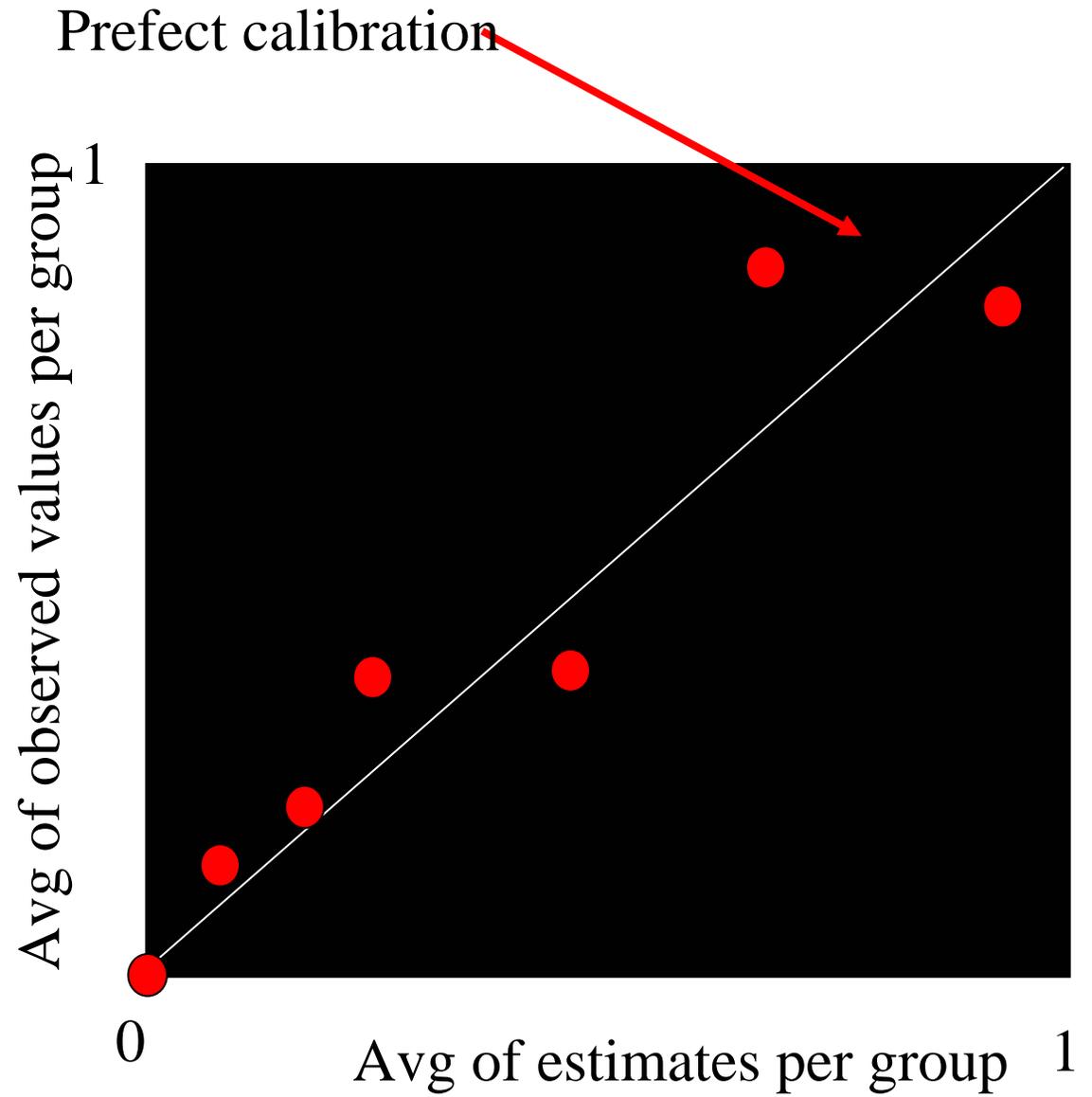
- Ties
3

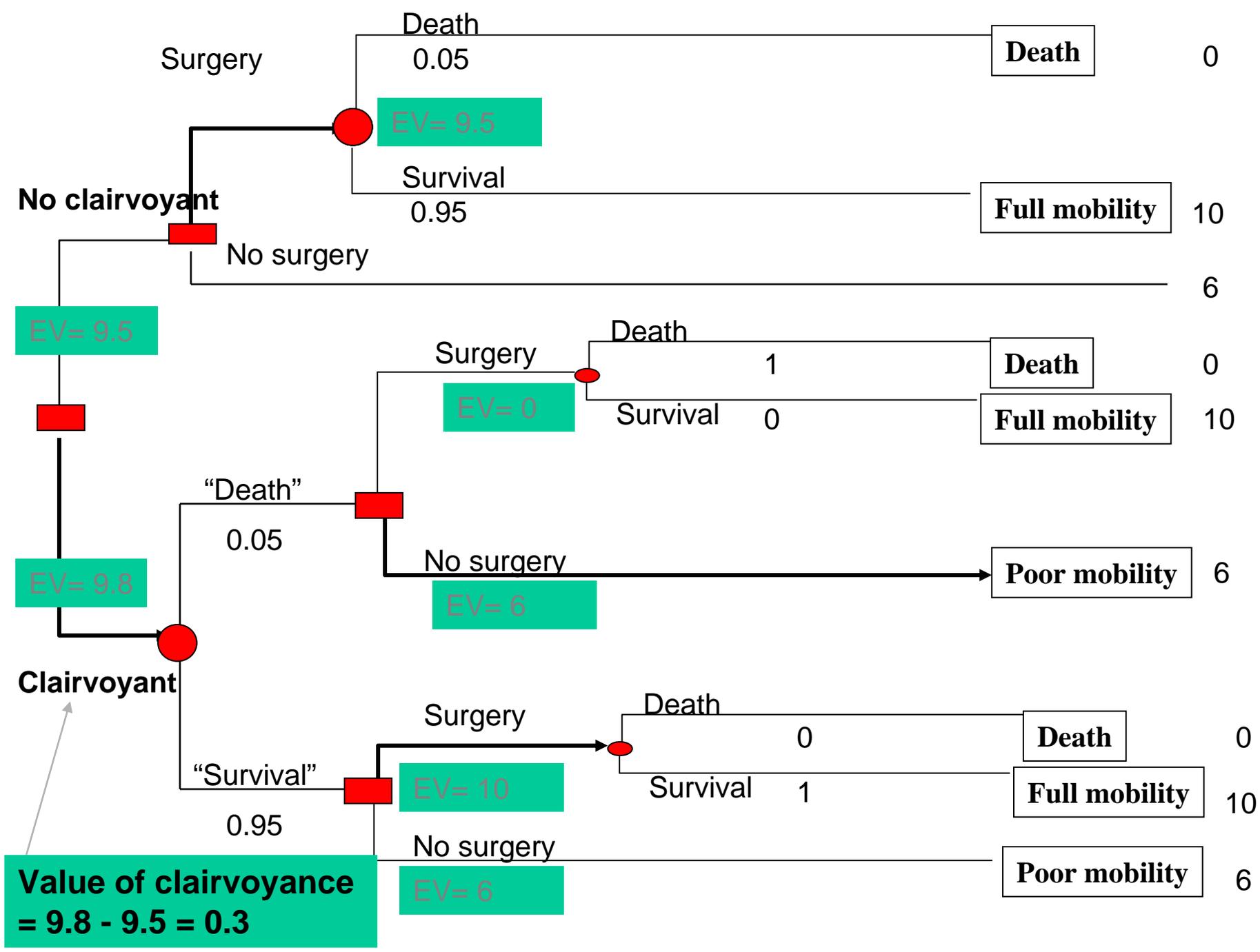
$$\text{C -index} = \frac{\text{Concordant} + 1/2 \text{ Ties}}{\text{All pairs}} = \frac{18 + 1.5}{25}$$

Calibration

Sorted pairs by systems' estimates		Real outcomes
0.1		0
0.2		0
<u>0.2</u>	<u>sum of group = 0.5</u>	<u>sum = 1</u>
0.3		0
0.5		0
<u>0.5</u>	<u>sum of group = 1.3</u>	<u>sum = 1</u>
0.7		0
0.7		1
0.8		1
<u>0.9</u>	<u>sum of group = 3.1</u>	<u>sum = 3</u>

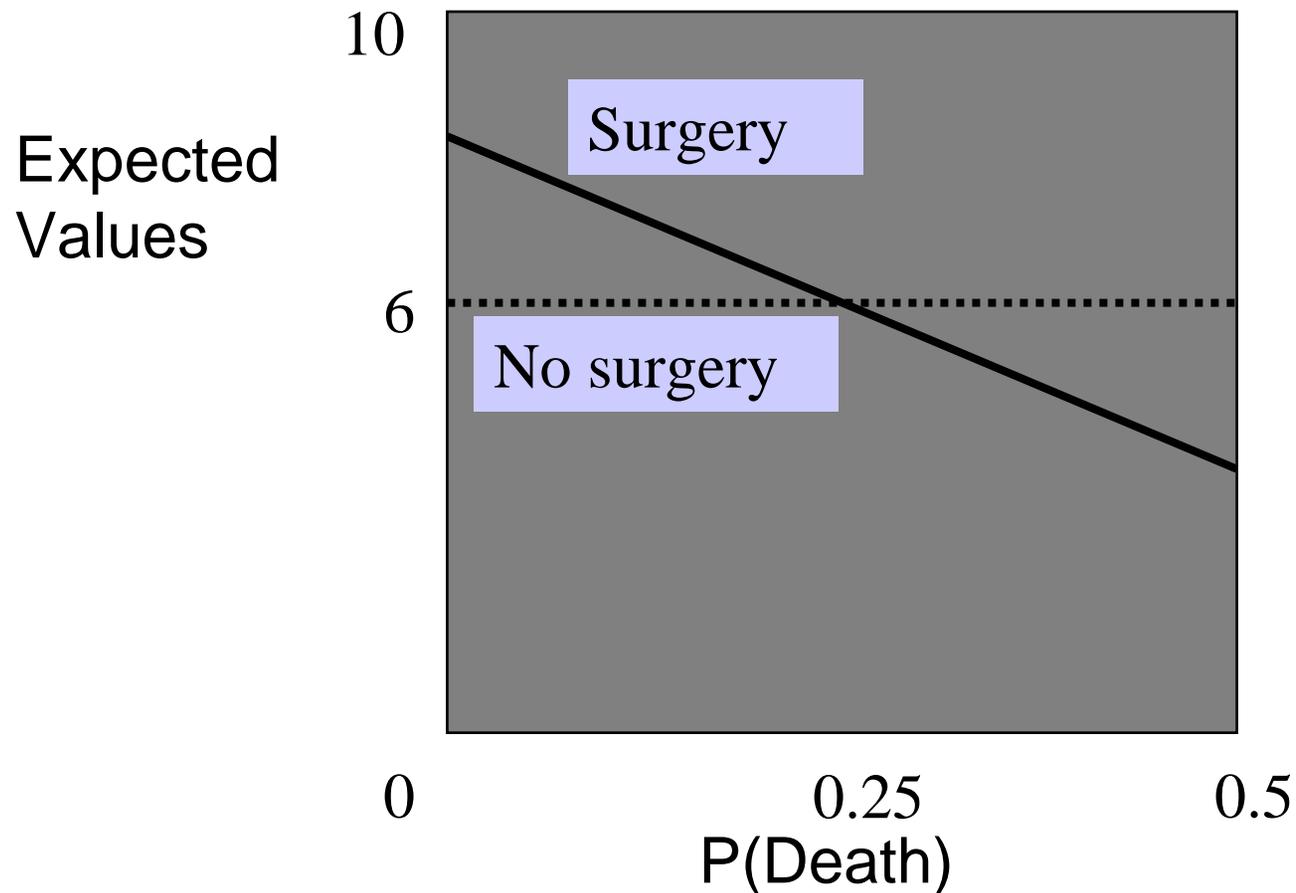
Calibration plot





Sensitivity Analysis

- Effect of probabilities in the decision



What predictive models do

Predict this

Case 1	0.7	-0.2	0.8
Case 2	0.6	0.5	-0.4
	-0.6	0.1	0.2
	0	-0.9	0.3
	-0.4	0.4	0.2
	-0.8	0.6	0.3
	0.5	-0.7	-0.4

and evaluate
performance on
new cases

0.6	-0.1	?
0.4	0.6	?
-0.1	0.2	?
0	-0.5	?
-0.3	0.4	?
-0.8	0.7	?
0.3	-0.7	?

Using these

Predictive Model Considerations

- Select a model
 - Linear, Nonlinear
 - Parametric, non-parametric
 - Data separability
 - Continuous versus discrete (categorical) outcome
 - Continuous versus discrete variables
 - One class, multiple classes
- Estimate the parameters (i.e., “learn from data”)
- Evaluate

Predictive Modeling Tenets

- Evaluate performance on a set of new cases
- Test set should not be used in any step of building the predictive modeling (model selection, parameter estimation)
- Avoid overfitting
 - “Rule of thumb”: 2-10 times more cases than attributes
 - Use a portion of the training set for model selection or parameter tuning
- Start with simpler models as benchmarks

Desirable properties of models

- Good predictive performance (even for non-linearly separable data)
- Robustness (outliers are ignored)
- Ability to be interpreted
 - Indicate which variables contribute more for the predictions
 - Indicate the nature of variable interactions
 - Allow visualization
- Be easily applied, be generalizable to other measurement instruments, and easily communicated

correlation_coefficient

$$r = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} = \rho$$

VARIANCE

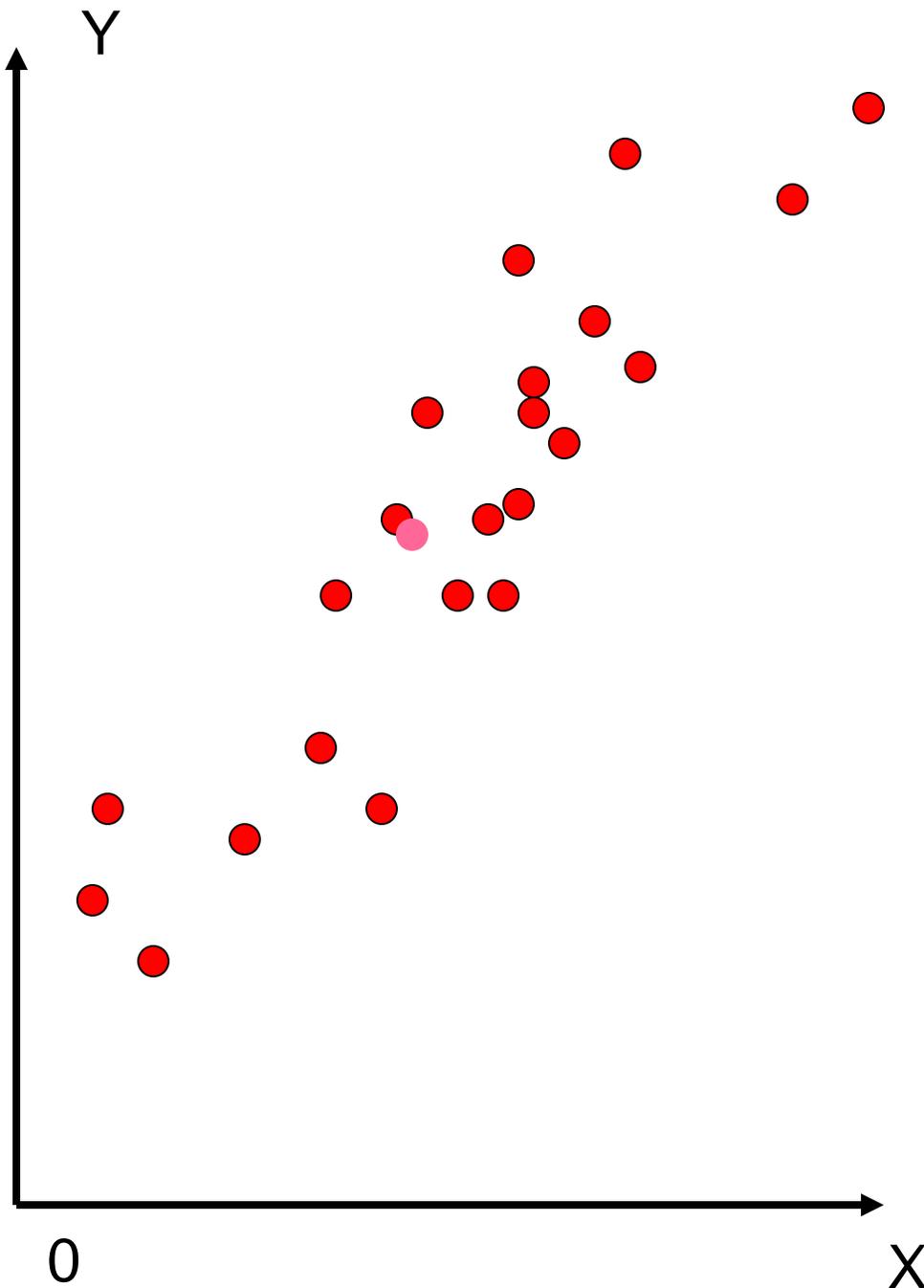
$$\sigma_{XX} = \frac{\sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{X})}{n-1}$$

st_deviation

$$\sigma_X = \sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{X})}{n-1}}$$

COVARIANCE

$$\sigma_{XY} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{n-1}$$



Covariance and Correlation Matrices

$$\text{COV} = \begin{bmatrix} \sigma_{XX} & \sigma_{XY} \\ \sigma_{YX} & \sigma_{YY} \end{bmatrix}$$

$$\text{corr} = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

$$\sigma_{XY} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{n-1}$$

$$\sigma_{XX} = \frac{\sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{X})}{n-1}$$

Slope from linear regression is asymmetric,
covariance and ρ are symmetric

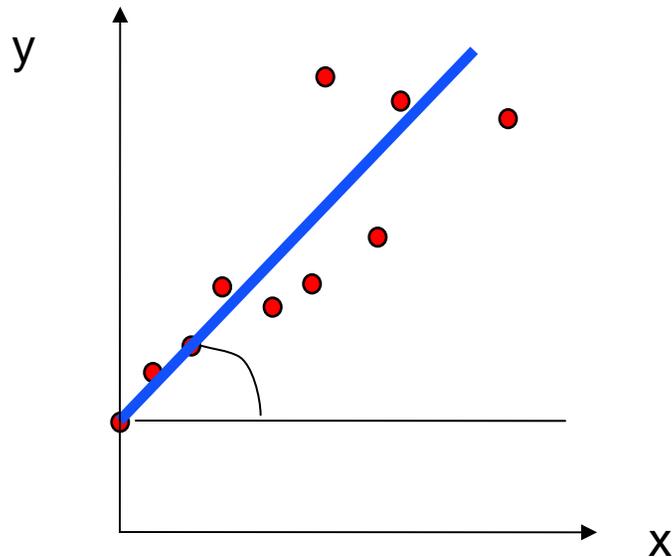
$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

$$y = \beta_0 + \beta_1 x$$

$$\beta_1 = \frac{\Sigma(x - \bar{x})(y - \bar{y})}{\Sigma(x - \bar{x})^2}$$

$$y = 2 + 4x$$

$$x = y/4 - 2$$



$$\text{cov} = \begin{bmatrix} 0.86 & 0.35 \\ 0.35 & 15.69 \end{bmatrix} = \Sigma$$

$$\text{corr} = \begin{bmatrix} 1 & 0.96 \\ 0.96 & 1 \end{bmatrix}$$

Solve system of normal equations

$$\beta_0 n + \beta_1 \sum x = \sum y$$

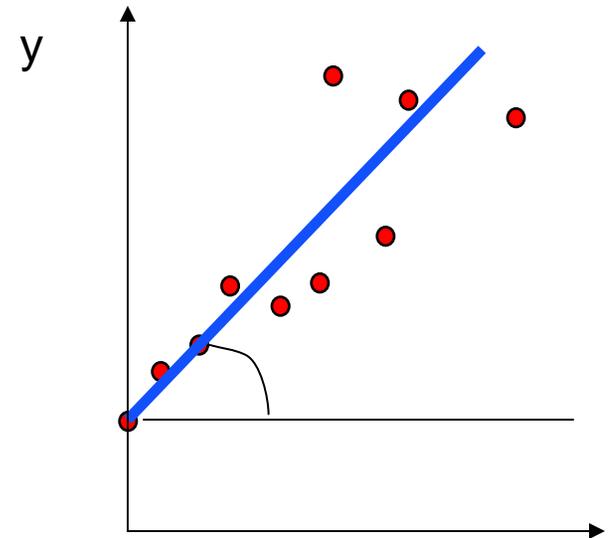
Normal equation 1

$$\beta_0 \sum x + \beta_1 \sum x^2 = \sum yx$$

Normal equation 2

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

$$\beta_1 = \frac{\Sigma(x - \bar{x})(y - \bar{y})}{\Sigma(x - \bar{x})^2}$$



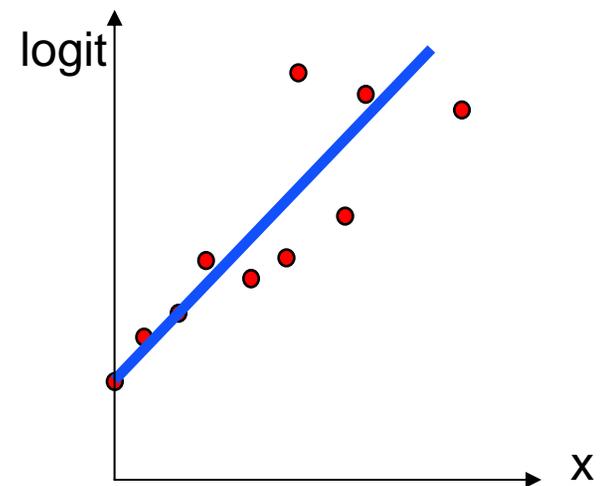
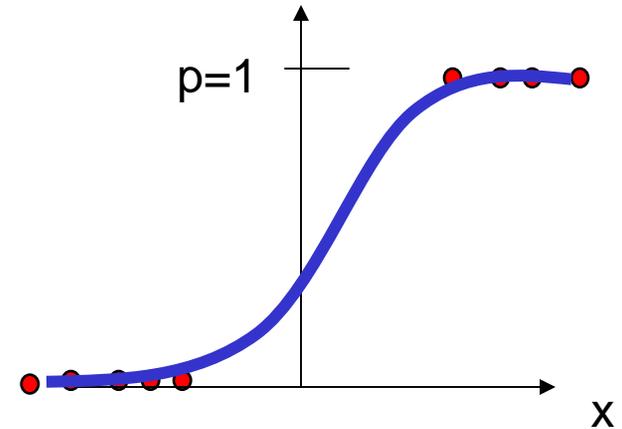
Logit Model

$$p_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_i)}}$$

$$p_i = \frac{e^{\beta_0 + \beta_1 x_i}}{e^{\beta_0 + \beta_1 x_i} + 1}$$

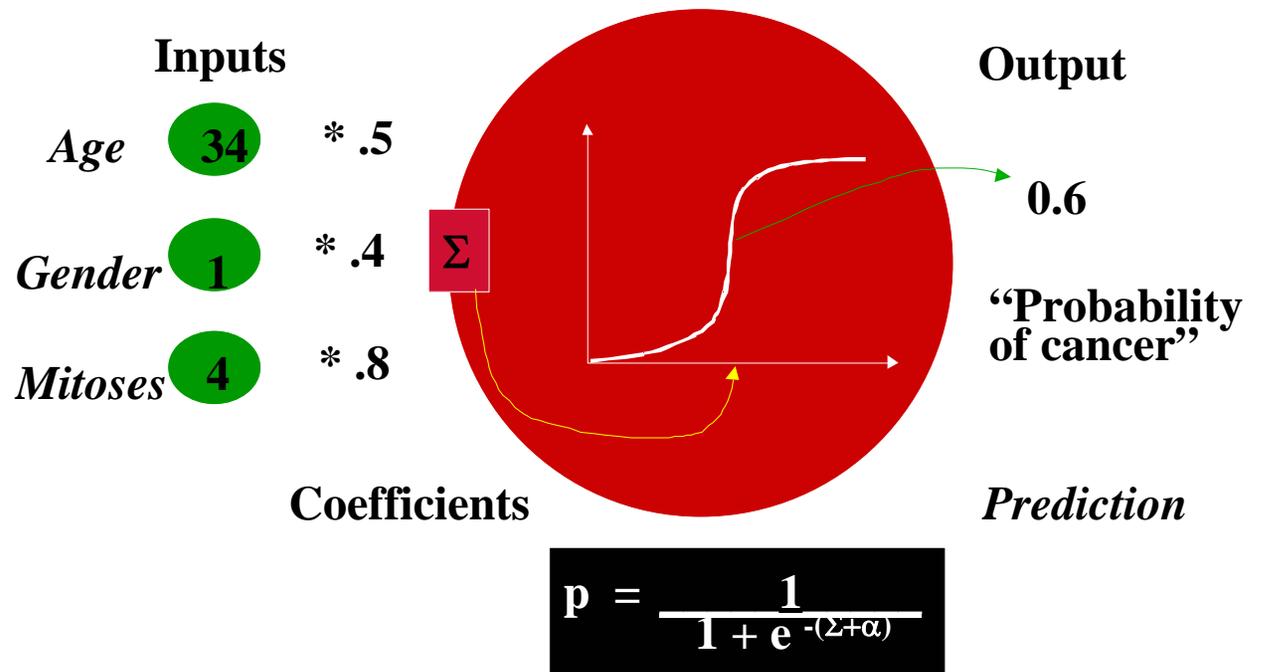
$$\log \left[\frac{p_i}{1 - p_i} \right] = \beta_0 + \beta_1 x_i$$

$$\log \left[\frac{p_i}{1 - p_i} \right] = \sum_i \beta x_i$$



Logistic Regression

- Good for interpretation
- Works well only if data are linearly separable
- Interactions need to be entered manually
- Not likely to overfit if # variables is low



What do coefficients mean?

$$e^{\beta_{\text{age}}} = \text{OR}_{\text{age}}$$

	Age49	Age50	
Death	28	22	50
Life	45	52	97
Total	73	74	147

$$OR = \frac{\frac{p_{\text{death}|age=50}}{1 - p_{\text{death}|age=50}}}{\frac{p_{\text{death}|age=49}}{1 - p_{\text{death}|age=49}}}$$

What do coefficients mean?

$$e^{\beta_{\text{color}}} = \text{OR}_{\text{color}}$$

	Blue	Green	
Death	28	22	50
Life	45	52	97
Total	73	74	147

$$OR = \frac{28 / 45}{22 / 52} = 1.47$$

$$e^{\beta_{\text{color}}} = 1.47$$

$$\beta_{\text{color}} = 0.385$$

$$p_{\text{blue}} = \frac{1}{1 + e^{-(-0.8616 + 0.385)}} = 0.383$$

$$p_{\text{green}} = \frac{1}{1 + e^{0.8616}} = 0.297$$

Maximum Likelihood Estimation

- Steps:
 - Define expression for the probability of data as a function of the parameters
 - Find the values of the parameters that maximize this expression

Likelihood Function

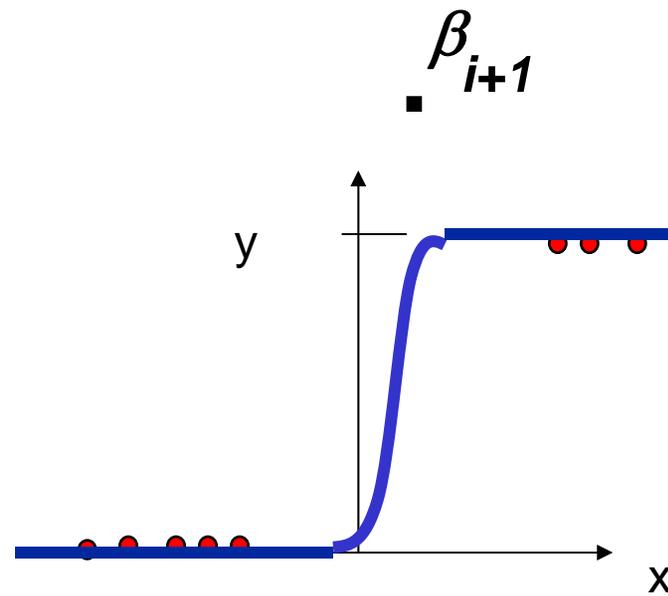
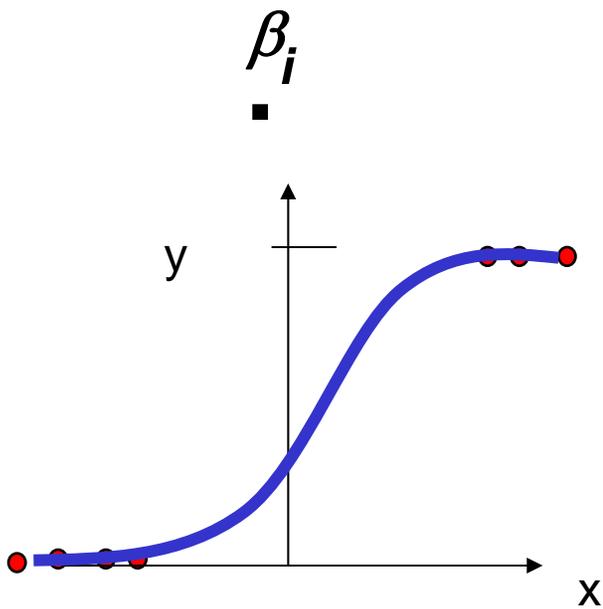
$$L = \Pr(Y)$$

$$L = \Pr(y_1, y_2, \dots, y_n)$$

$$L = \Pr(y_1) \Pr(y_2) \dots \Pr(y_n) = \prod_{i=1}^n \Pr(y_i)$$

Complete separation

MLE does not exist (ie, it is infinite)



Logistic Regression and non-linearly-separable problems

- Simple form below cannot deal with it
- $Y = 1/(1+\exp-(ax_1+bx_2))$
- Adding interaction terms transforms the space such that problem may become linearly separable
- $Y = 1/(1+\exp-(ax_1 + bx_2 + cx_1x_2))$

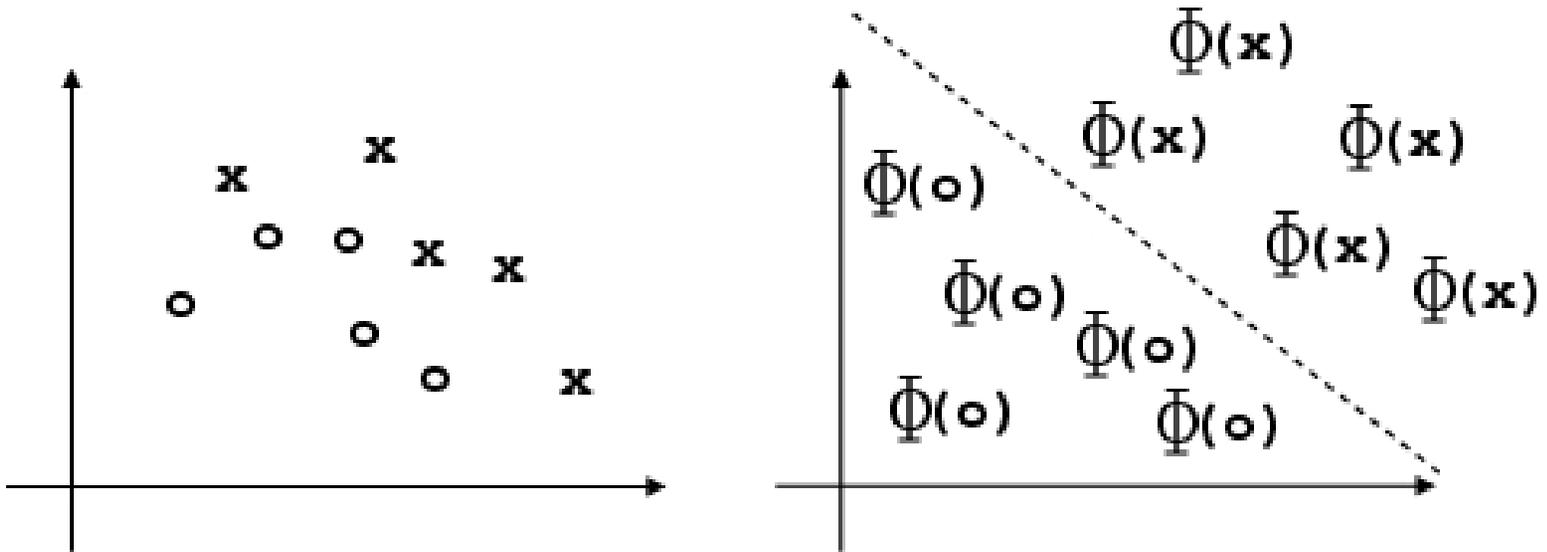
Figures removed due to copyright reasons.

Please see:

Khan, J., et. al. "Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks." *Nat Med* 7, no. 6 (June 2001): 673-9.

Kernel trick

- Idea: Nonlinearly project data into higher dimensional space with $\Phi: \mathbb{R}^m \rightarrow H$
- Apply linear algorithm in H

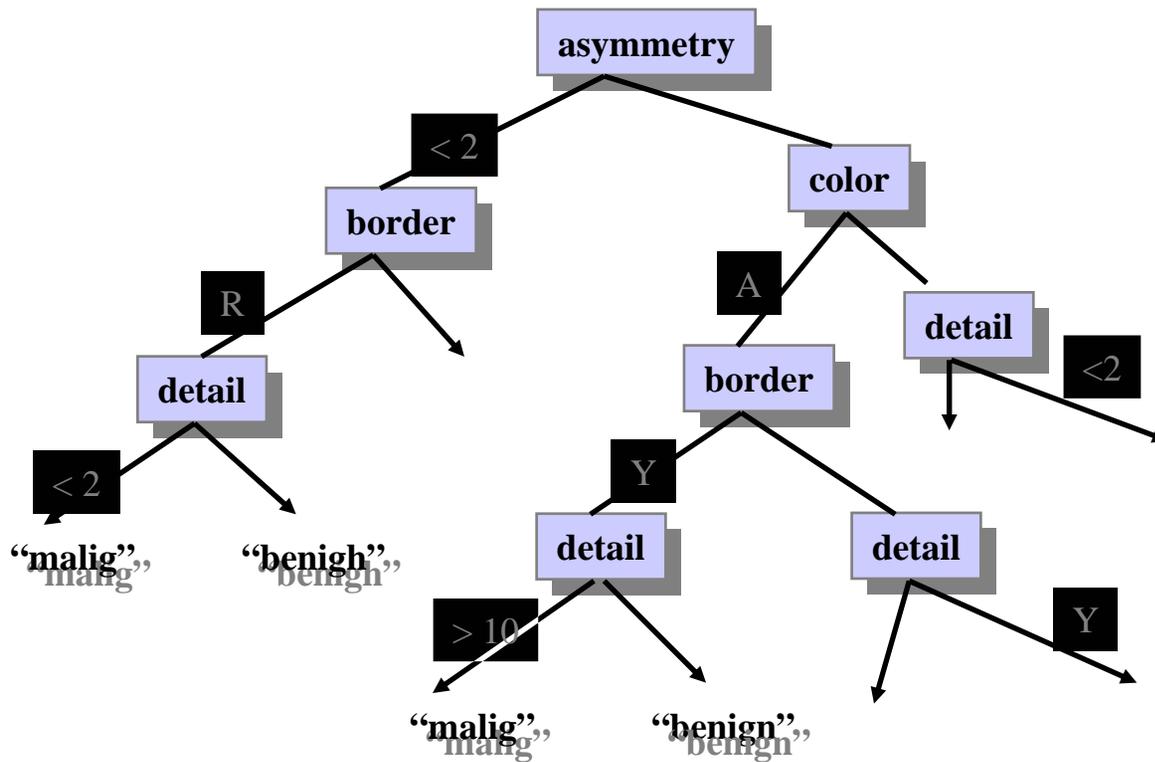


Classification Trees

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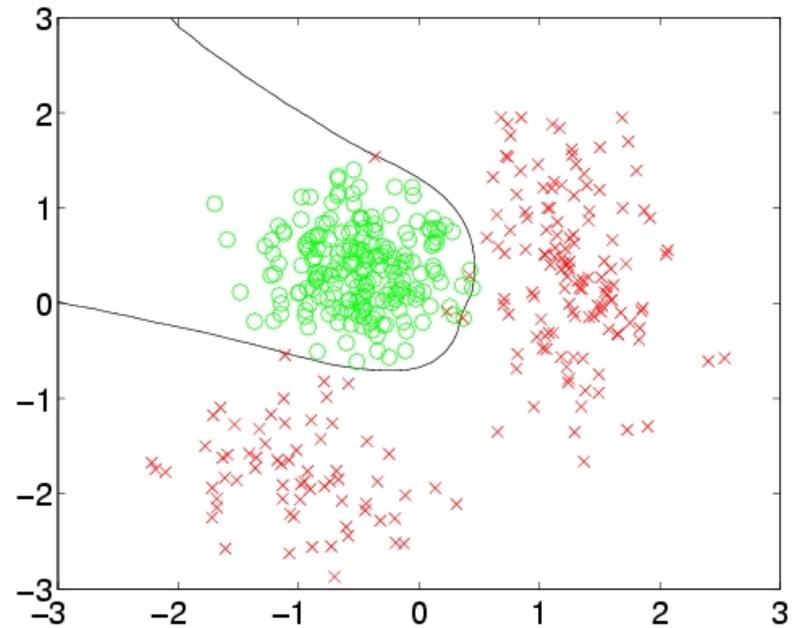
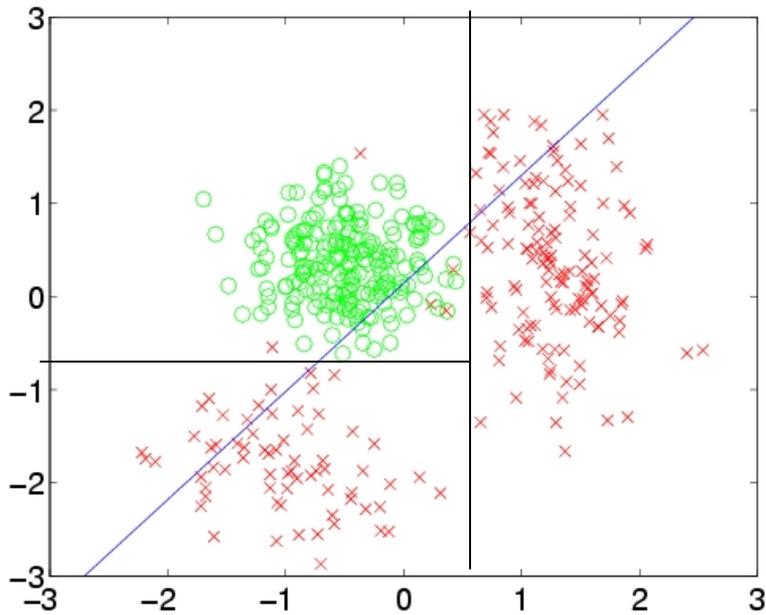
0-TEST: null VALUE: null Num Cases: 700.0 Num Dord: 241.0
2-TEST: breath VALUE: 1 Num Cases: 75.0 Num Dord: 1.0
*****PRUNED!!!
*****PRUNED!!!
1-TEST: breath VALUE: 0 Num Cases: 625.0 Num Dord: 240.0
4-TEST: CWender VALUE: 1 Num Cases: 11.0 Num Dord: 0
3-TEST: CWender VALUE: 0 Num Cases: 614.0 Num Dord: 240.0
8-TEST: age VALUE: >32 Num Cases: 611.0 Num Dord: 240.0
10-TEST: Duration VALUE: >72 Num Cases: 3.0 Num Dord: 0
9-TEST: Duration VALUE: <=72 Num Cases: 608.0 Num Dord: 240.0
12-TEST: Duration VALUE: >48 Num Cases: 2.0 Num Dord: 2.0
11-TEST: Duration VALUE: <=48 Num Cases: 606.0 Num Dord: 238.0
14-TEST: prevang VALUE: 1 Num Cases: 340.0 Num Dord: 92.0
18-TEST: Eps: VALUE: 1 Num Cases: 8.0 Num Dord: 0
17-TEST: Eps: VALUE: 0 Num Cases: 332.0 Num Dord: 92.0
22-TEST: Worsening VALUE: >72 Num Cases: 6.0 Num Dord: 0
21-TEST: Worsening VALUE: <=72 Num Cases: 326.0 Num Dord: 92.0
28-TEST: Duration VALUE: <=36 Num Cases: 3.0 Num Dord: 0
27-TEST: Duration VALUE: <=36 Num Cases: 323.0 Num Dord: 92.0
36-TEST: Worsening VALUE: >28 Num Cases: 3.0 Num Dord: 2.0
35-TEST: Worsening VALUE: <=28 Num Cases: 320.0 Num Dord: 90.0
44-TEST: age VALUE: >55 Num Cases: 240.0 Num Dord: 81.0
52-TEST: Worsening VALUE: >0 Num Cases: 238.0 Num Dord: 81.0
64-TEST: OMMI VALUE: 1 Num Cases: 49.0 Num Dord: 9.0
74-TEST: Smokes VALUE: 0 Num Cases: 37.0 Num Dord: 9.0
86-TEST: age VALUE: >65 Num Cases: 30.0 Num Dord: 5.0
*****PRUNED!!!
85-TEST: age VALUE: <=65 Num Cases: 7.0 Num Dord: 4.0
98-TEST: Worsening VALUE: >2 Num Cases: 5.0 Num Dord: 2.0
97-TEST: Worsening VALUE: <=2 Num Cases: 2.0 Num Dord: 2.0
75-TEST: Smokes VALUE: 1 Num Cases: 12.0 Num Dord: 0
63-TEST: OMMI VALUE: 0 Num Cases: 189.0 Num Dord: 72.0
72-TEST: Nausea VALUE: 0 Num Cases: 165.0 Num Dord: 57.0
84-TEST: Duration VALUE: >16 Num Cases: 3.0 Num Dord: 2.0
83-TEST: Duration VALUE: <=16 Num Cases: 162.0 Num Dord: 55.0
*****PRUNED!!!
71-TEST: Nausea VALUE: 1 Num Cases: 24.0 Num Dord: 15.0
82-TEST: Back VALUE: 0 Num Cases: 21.0 Num Dord: 15.0
94-TEST: post VALUE: 1 Num Cases: 1.0 Num Dord: 0
93-TEST: post VALUE: 0 Num Cases: 20.0 Num Dord: 15.0
81-TEST: Back VALUE: 1 Num Cases: 3.0 Num Dord: 0
51-TEST: Worsening VALUE: <=0 Num Cases: 2.0 Num Dord: 0
43-TEST: age VALUE: <=5 Num Cases: 80.0 Num Dord: 9.0
50-TEST: Worsening VALUE: >1 Num Cases: 68.0 Num Dord: 5.0
*****PRUNED!!!
*****PRUNED!!!
*****PRUNED!!!
*****PRUNED!!!
*****PRUNED!!!
49-TEST: Worsening VALUE: <=1 Num Cases: 12.0 Num Dord: 4.0
60-TEST: age VALUE: >47 Num Cases: 10.0 Num Dord: 2.0
68-TEST: OMMI VALUE: 1 Num Cases: 1.0 Num Dord: 1.0
67-TEST: OMMI VALUE: 0 Num Cases: 9.0 Num Dord: 1.0
*****PRUNED!!!
59-TEST: age VALUE: <=47 Num Cases: 2.0 Num Dord: 2.0
13-TEST: prevang VALUE: 0 Num Cases: 266.0 Num Dord: 146.0
16-TEST: Duration VALUE: >0 Num Cases: 259.0 Num Dord: 146.0
20-TEST: post VALUE: 1 Num Cases: 13.0 Num Dord: 2.0
26-TEST: Diabetes VALUE: 1 Num Cases: 1.0 Num Dord: 1.0
25-TEST: Diabetes VALUE: 0 Num Cases: 12.0 Num Dord: 1.0
*****PRUNED!!!
19-TEST: post VALUE: 0 Num Cases: 246.0 Num Dord: 144.0
24-TEST: Nausea VALUE: 0 Num Cases: 202.0 Num Dord: 105.0
32-TEST: OMMI VALUE: 1 Num Cases: 13.0 Num Dord: 1.0
42-TEST: BP VALUE: 1 Num Cases: 1.0 Num Dord: 1.0
41-TEST: BP VALUE: 0 Num Cases: 12.0 Num Dord: 0
31-TEST: OMMI VALUE: 0 Num Cases: 189.0 Num Dord: 104.0
40-TEST: age VALUE: >37 Num Cases: 184.0 Num Dord: 103.0
48-TEST: Eps: VALUE: 1 Num Cases: 8.0 Num Dord: 2.0
58-TEST: Duration VALUE: >8 Num Cases: 2.0 Num Dord: 2.0
57-TEST: Duration VALUE: <=8 Num Cases: 6.0 Num Dord: 0
47-TEST: Eps: VALUE: 0 Num Cases: 176.0 Num Dord: 101.0
56-TEST: Duration VALUE: >15 Num Cases: 2.0 Num Dord: 0
55-TEST: Duration VALUE: <=15 Num Cases: 173.0 Num Dord: 101.0
66-TEST: Lipids VALUE: 1 Num Cases: 1.0 Num Dord: 1.0
65-TEST: Lipids VALUE: 0 Num Cases: 173.0 Num Dord: 100.0
76-TEST: Sweating VALUE: 0 Num Cases: 73.0 Num Dord: 32.0
*****PRUNED!!!
*****PRUNED!!!
75-TEST: Sweating VALUE: 1 Num Cases: 100.0 Num Dord: 68.0
88-TEST: Duration VALUE: >8 Num Cases: 7.0 Num Dord: 2.0
104-TEST: Rarm VALUE: 0 Num Cases: 5.0 Num Dord: 0
103-TEST: Rarm VALUE: 1 Num Cases: 2.0 Num Dord: 2.0
87-TEST: Duration VALUE: <=8 Num Cases: 93.0 Num Dord: 66.0
*****PRUNED!!!
*****PRUNED!!!
39-TEST: age VALUE: <=37 Num Cases: 5.0 Num Dord: 1.0
23-TEST: Nausea VALUE: 1 Num Cases: 44.0 Num Dord: 39.0
30-TEST: age VALUE: >47 Num Cases: 41.0 Num Dord: 39.0
38-TEST: Duration VALUE: >7 Num Cases: 7.0 Num Dord: 5.0
46-TEST: Larm VALUE: 0 Num Cases: 1.0 Num Dord: 0
45-TEST: Larm VALUE: 1 Num Cases: 6.0 Num Dord: 5.0
54-TEST: Rarm VALUE: 0 Num Cases: 5.0 Num Dord: 5.0
53-TEST: Rarm VALUE: 1 Num Cases: 1.0 Num Dord: 0
37-TEST: Duration VALUE: <=7 Num Cases: 34.0 Num Dord: 34.0
29-TEST: age VALUE: <=47 Num Cases: 3.0 Num Dord: 0
15-TEST: Duration VALUE: <=0 Num Cases: 7.0 Num Dord: 0
7-TEST: age VALUE: <=32 Num Cases: 3.0 Num Dord: 0

```



From perceptrons to CART, to multilayer perceptrons

Why?



“LARGE” data sets

- In predictive modeling, large data sets have several cases (with few attributes or variables for each case)
- In some domains, “large” data sets with several attributes and few cases are subject to analysis (predictive modeling)
- The main tenets of predictive modeling should be always used

“Large m small n ” problem

- m variables, n cases
- Underdetermined systems
- Simple memorization even with simple models
- Poor generalization to new data
- Overfitting

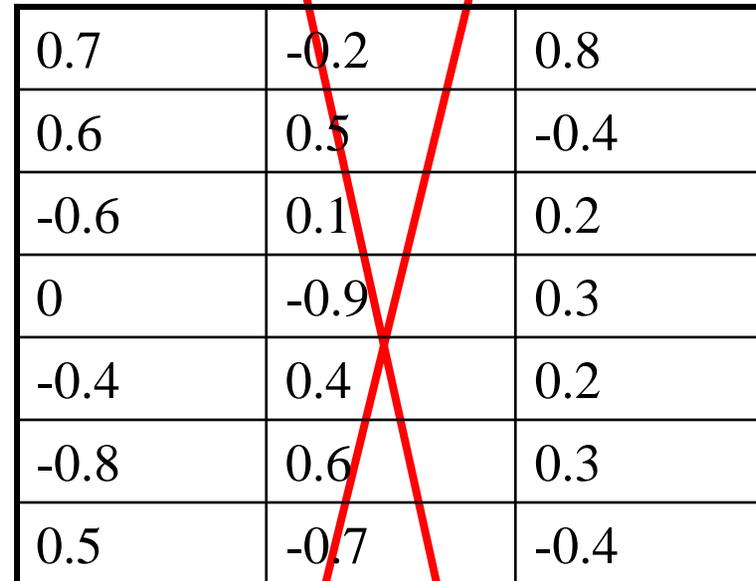
Reducing Columns

Some approaches:

- Principal Components Analysis

(a component is a linear combination of variables with specific coefficients)

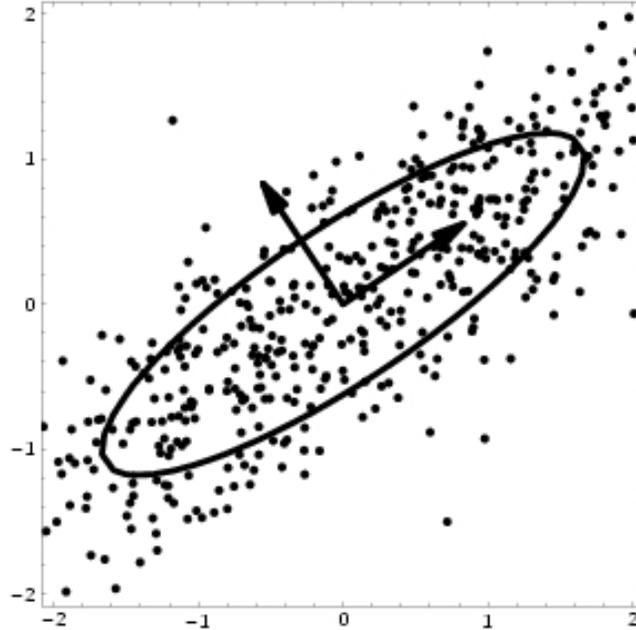
- Variable selection



0.7	-0.2	0.8
0.6	0.5	-0.4
-0.6	0.1	0.2
0	-0.9	0.3
-0.4	0.4	0.2
-0.8	0.6	0.3
0.5	-0.7	-0.4

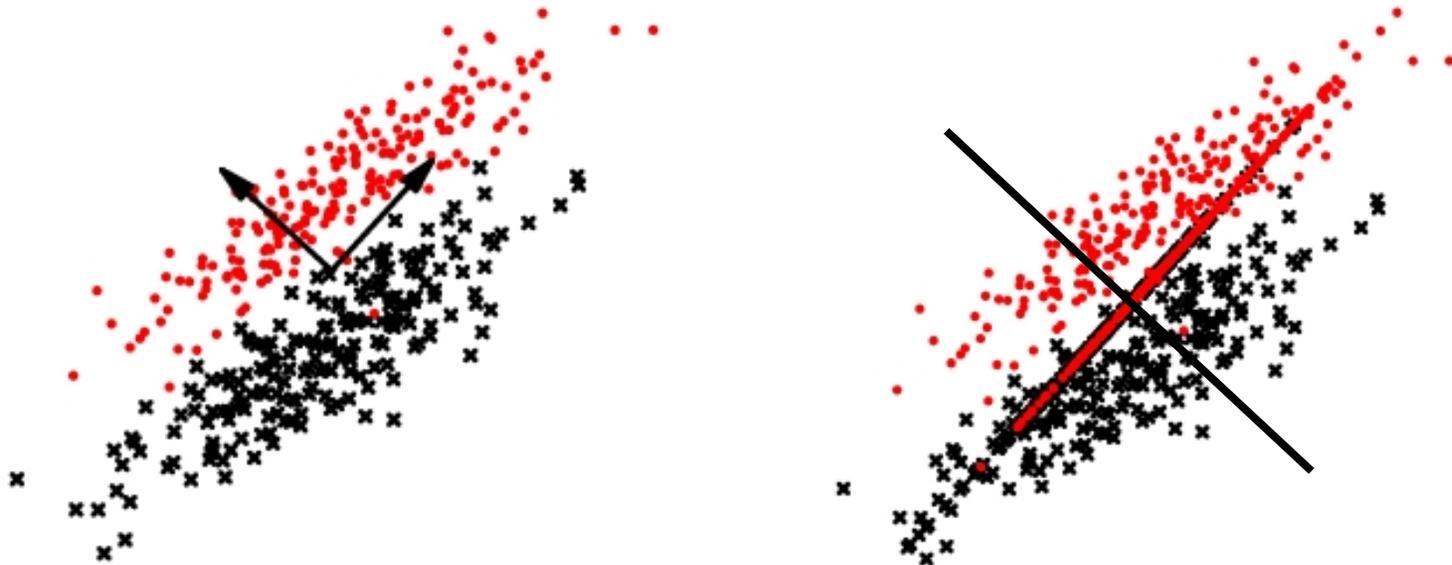
Principal Component Analysis

- Identify direction with greatest variation (combination of variables with different weights)
- Identify next direction conditioned on the first one, and so on until the variance accounted for is acceptable



PCA disadvantage

- No class information used in PCA
- Projected coordinates may be bad for classification



Related technique

- Partial Least Squares
 - PCA uses X to calculate directions of greater variation
 - PLS uses X and Y to calculate these directions
 - It is a variation of multiple linear regression

PCA maximizes

$\text{Var}(X\alpha),$

PLS maximizes

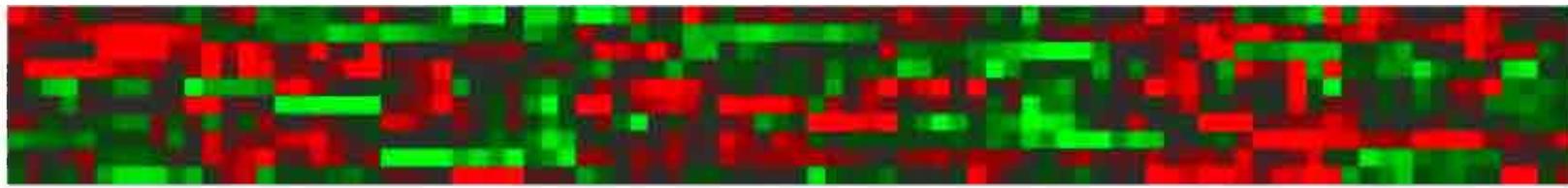
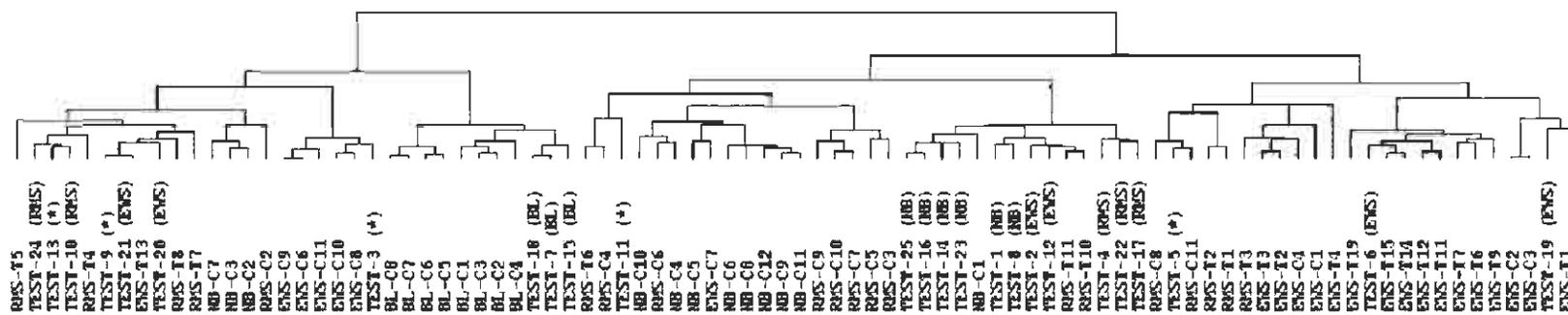
$\text{Corr}^2(y, X\alpha)\text{Var}(X\alpha)$

Variable Selection

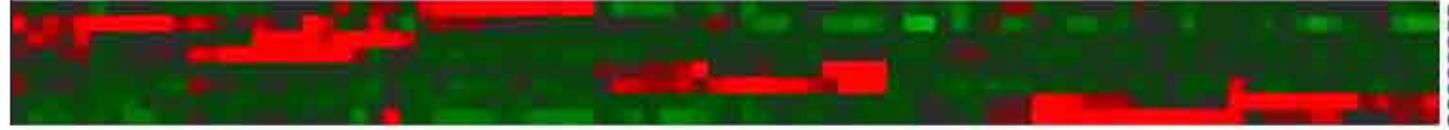
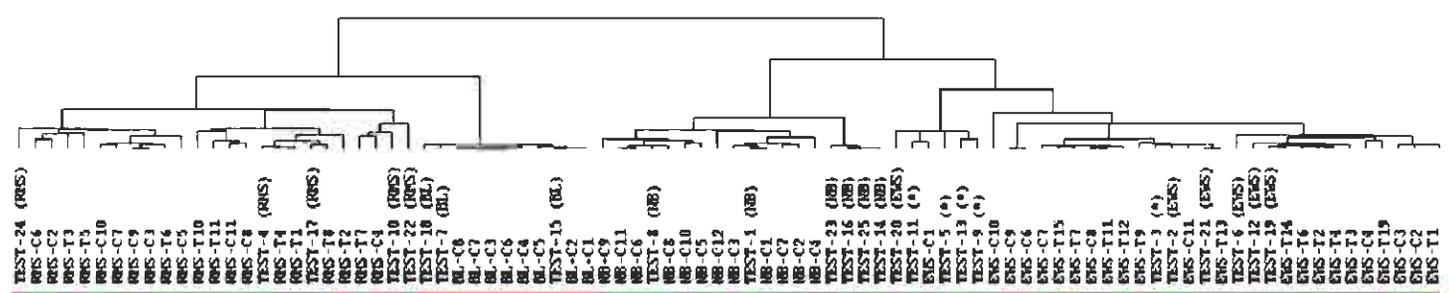
- Ideal: consider all variable combinations
 - Not feasible: 2^n
 - Greedy Backward: may not work if more variables than cases
- Greedy Forward:
 - Select most important variable as the “first component”
 - Select other variables conditioned on the previous ones
 - Stepwise: consider backtracking
- Other search methods: genetic algorithms that optimize classification performance and # variables

Simple Forward Variable Selection

- Conditional ranking of most important variables is possible
- Easy interpretation of resulting LR model
 - No artificial axis that is a combination of variables as in PCA
- No need to deal with too many columns
- Selection based on outcome variable
 - uses classification problem at hand



PC6
PC1
PC10
PC9
PC7
PC3
PC8
PC5
PC4
PC2



DL-H62098
RMS-Y54213
RMS-AA705225
RMS-R36960
NB-H06992
NB-W49619
EWS-AA459208
EWS-AA937095

Cross-validation

- Several training and test set pairs are created
- Results are pooled from all test sets
- “Leave- n -out”
- Jackknife (“Leave-1-out”)

Leave-N/3-out

1	23	54	0	1	1
2	43	23	1	0	1
3	34	35	0	0	0
4	20	21	1	1	1
5	19	03	1	1	0
6	78	04	0	1	0
7	98	03	0	1	1
8	35	05	1	1	1
9	99	23	0	0	1
10	23	34	0	0	0

→ Training Set

Model Building

→ Test Set

Evaluation

Bootstrap

- Efron (Stanford biostats) late 80's
 - “Pulling oneself up by one’s bootstraps”
- Nonparametric approach to statistical inference
- Uses *computation* instead of traditional distributional assumptions and asymptotic results
- Can be used for non-linear statistics without known standard error formulas

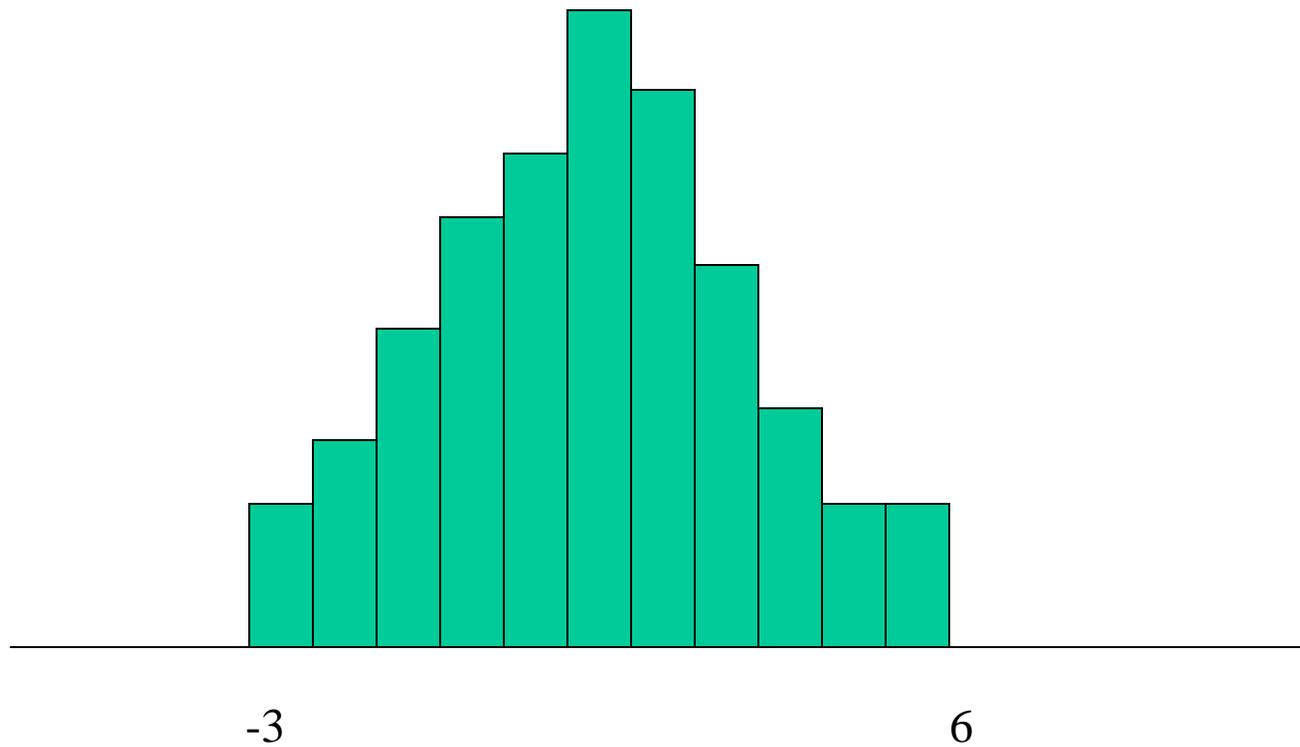
Sample with Replacement

Sample	Y_1^*	Y_2^*	Y_3^*	Y_4^*	\bar{Y}^*
1	6	6	6	6	6.00
2	6	6	6	-3	3.75
3	6	6	6	5	5.75
..					
100	-3	5	6	3	2.75
101	-3	5	-3	6	1.25
...					
255	-3	3	3	5	3.5
256	3	3	3	3	3.00

**The population is to the sample
as
the sample is to the bootstrap samples**

In practice (as opposed to previous example),
not all bootstrap samples are selected

Empirical distribution of Y



Bootstrap Confidence Intervals

- Percentile Intervals

Example

- 95% CI is calculated by taking
- Lower = 0.025 x bootstrap replicates
- Upper = 0.975 x bootstrap replicates

Bagging

- Breiman, 1996
- Derived from bootstrap (Efron, 1993)
- Create classifiers using training sets that are bootstrapped (drawn with replacement)
- Average results for each case

Boosting

- A family of methods
- Sequential production of classifiers
- Each classifier is dependent on the previous one, and focuses on the previous one's errors
- Examples that are incorrectly predicted in previous classifiers are chosen more often or weighted more heavily

Visualization

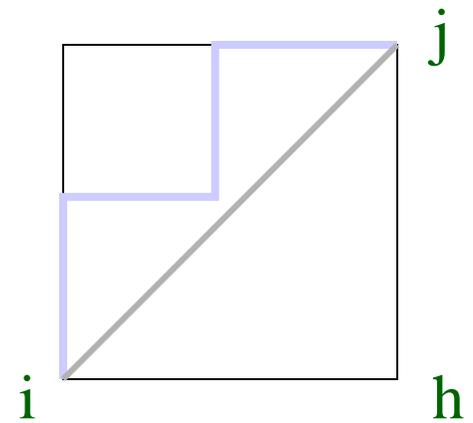
- Capabilities of predictive models in this area are limited
- Clustering is often good for visualization, but it is generally not very useful to separate data into pre-defined categories
 - Hierarchical trees
 - 2-D or 3-D multidimensional scaling plots
 - Self-organizing maps

Visualizing the classification potential of selected inputs

- Clustering visualization that uses classification information may help display the separation of the cases in a limited number of dimensions
- Clustering without selection of dimensions important for classification is less expected to display this separation

Metric spaces

- Positivity Reflexivity $d_{ij} > d_{ii} = 0$
- Symmetry $d_{ij} = d_{ji}$
- Triangle inequality $d_{ij} \leq d_{ih} + d_{hj}$



Figures removed due to copyright reasons.

Please see:

Khan, J., et. al. "Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks." *Nat Med* 7, no. 6 (June 2001): 673-9.

k -means clustering (Lloyd's algorithm)

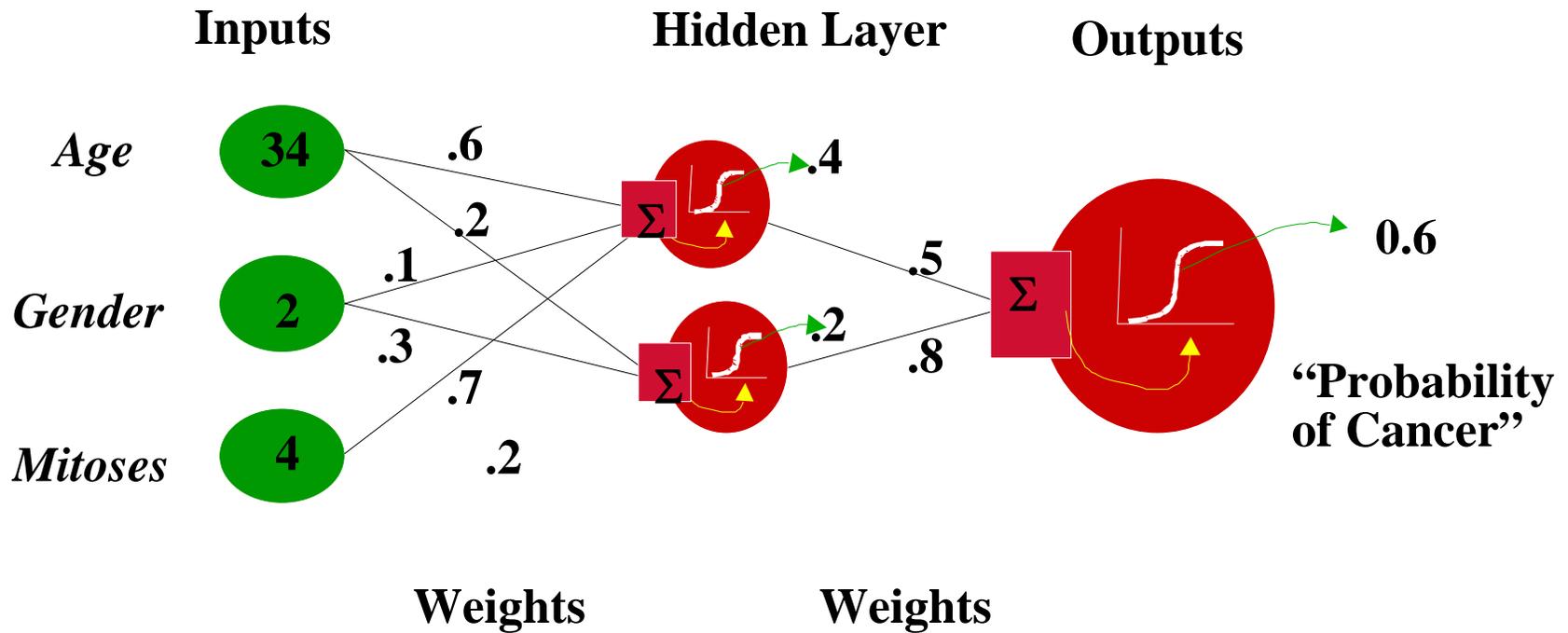
1. Select k (number of clusters)
2. Select k initial cluster centers c_1, \dots, c_k
3. Iterate until convergence: For each i ,
 1. Determine data vectors v_{i1}, \dots, v_{in} closest to c_i (i.e., partition space)
 2. Update c_i as $c_i = 1/n (v_{i1} + \dots + v_{in})$

Figures removed due to copyright reasons.

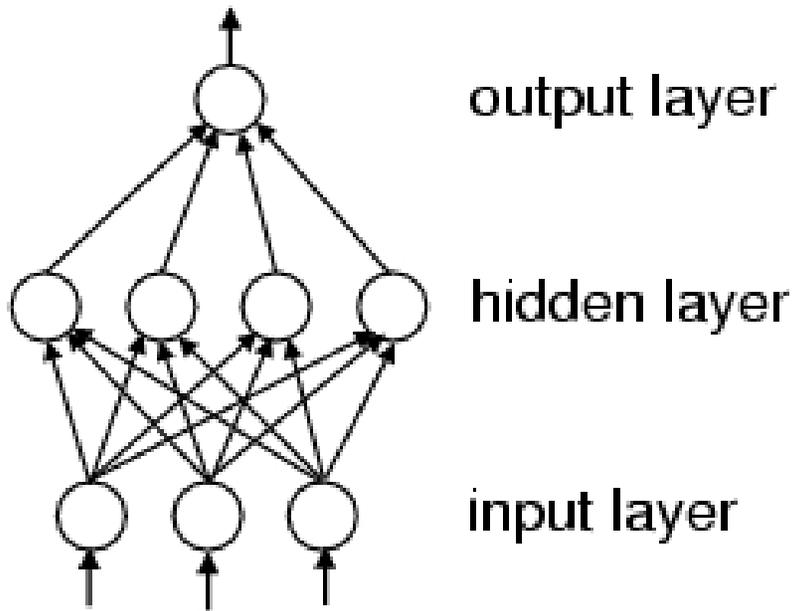
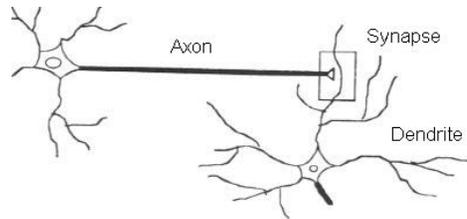
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Neural Networks



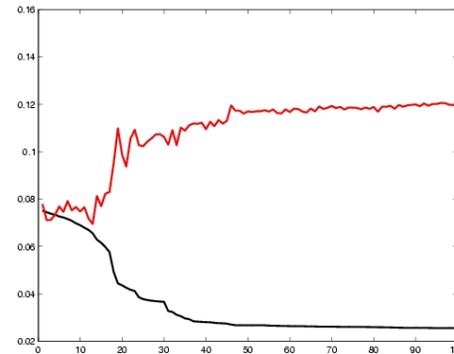
Neural Networks



Work well even with non-linearly separable data

Overfitting control:

- Few weights
- Little training
- Penalty for large weights



Backpropagation algorithm

Classification

cross-entropy

sigmoidal neuron

sigmoidal neurons

linear neurons

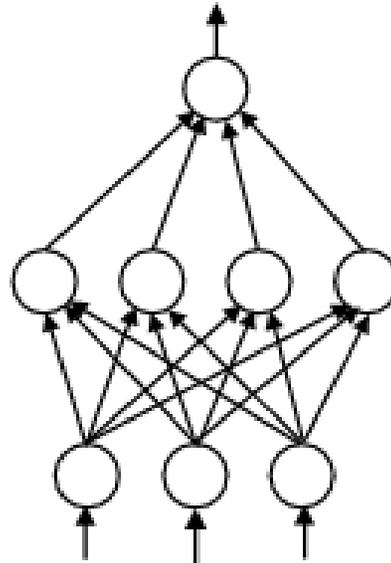
Regression

sum-of-squares

linear neuron

sigmoidal neurons

linear neurons



Some reminders

- Simple models may perform at the same level of complex ones for certain data sets
- A benchmark can be established with these models, which can be easily accessed
- Simple rules may have a role in generalizing results to other platforms
- No model can be proved to be best, need to try all