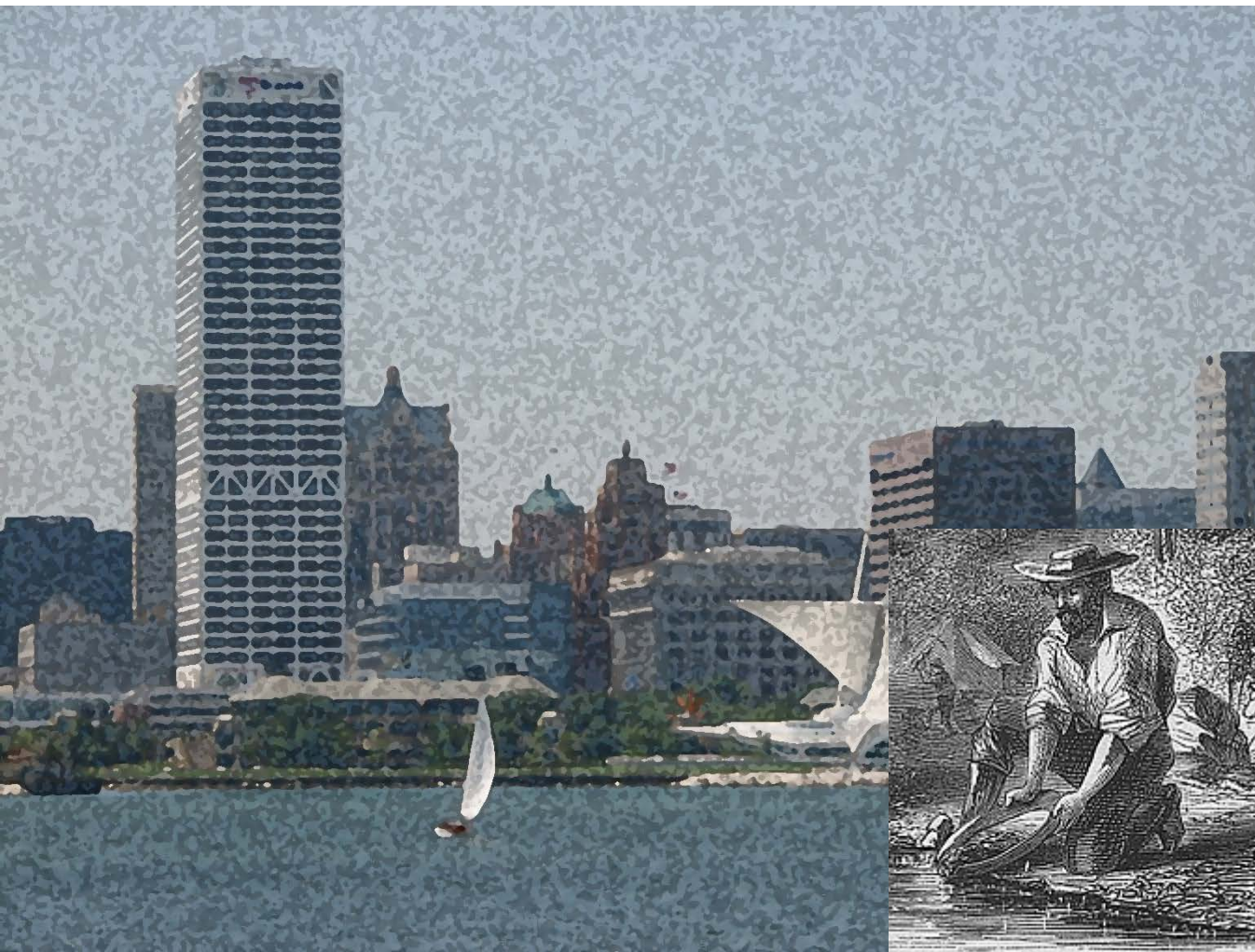


# Finding the Gold in Your Data

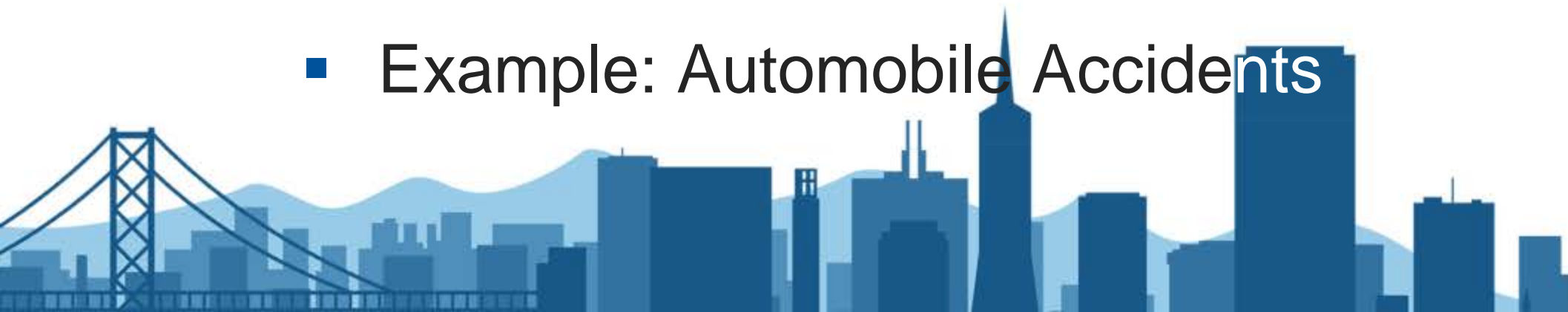
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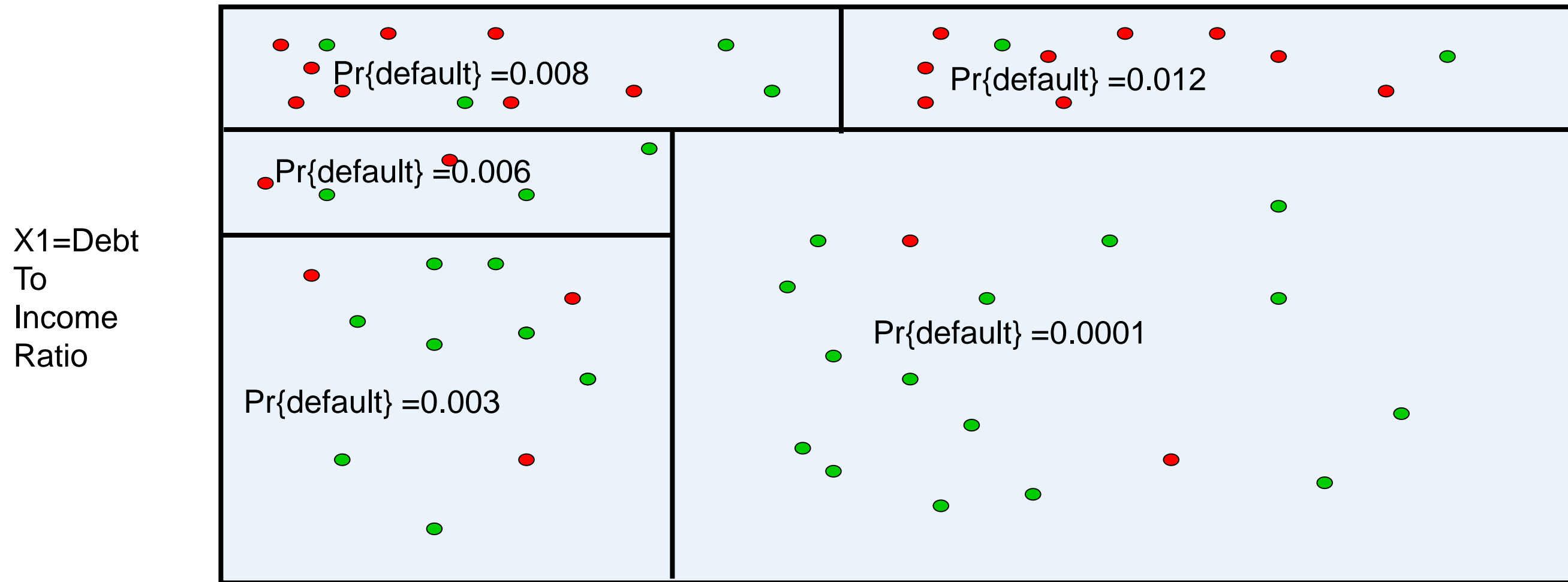
- An introduction to Data Mining
- Originally presented @ SAS Global Forum

# Decision Trees

- A “divisive” method (splits)
- Start with “root node” – all in one group
- Get splitting rules
- Response often binary
- Result is a “tree”
- Example: Loan Defaults
- Example: Framingham Heart Study
- Example: Automobile Accidents



# Recursive Splitting



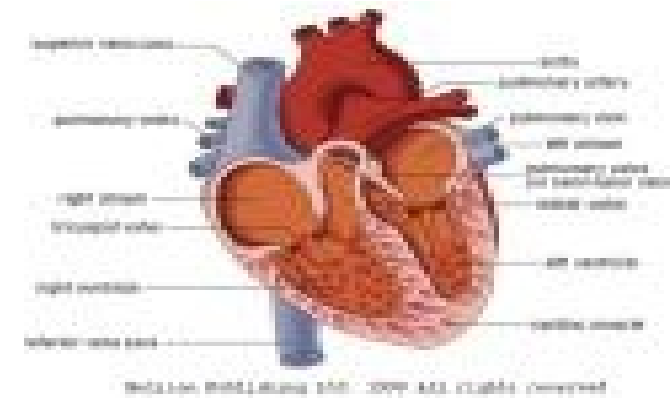
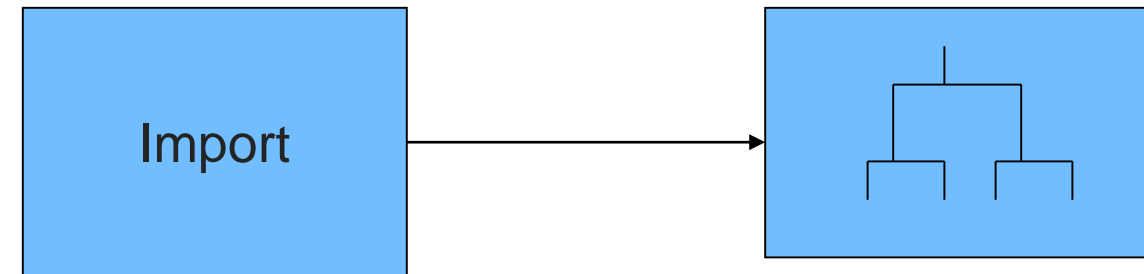
● No default  
● Default

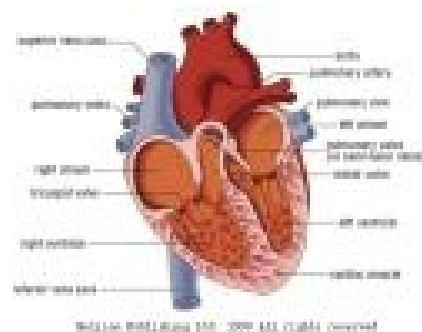
X2 = Age



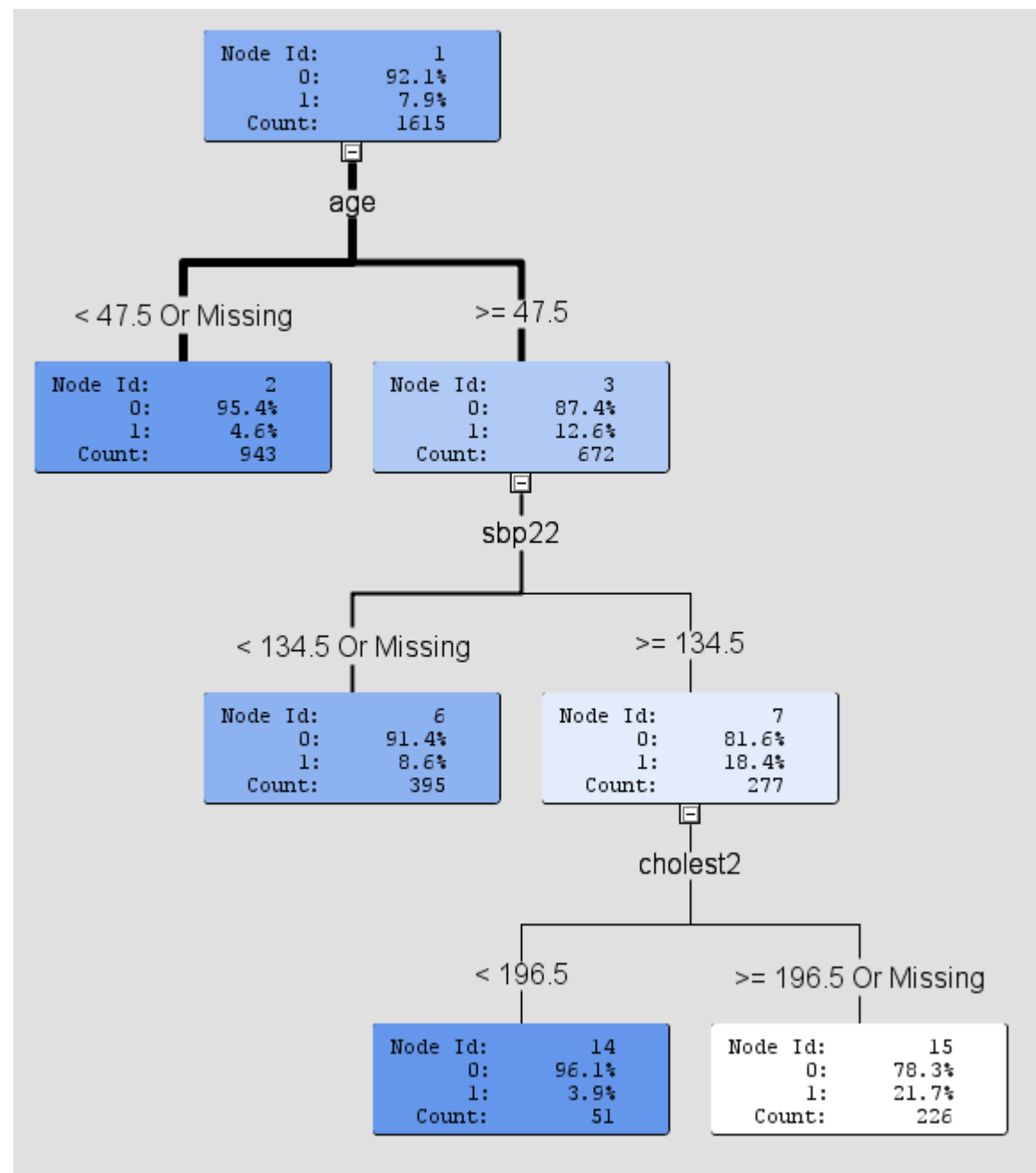
# Some Actual Data

- Framingham Heart Study
- First Stage Coronary Heart Disease
  - $P\{\text{CHD}\} = \text{Function of:}$ 
    - » Age - no drug yet! ☹️
    - » Cholesterol
    - » Systolic BP





Example of a “tree” →



# How to make splits?



- Contingency tables



180 ?  
240?

Low BP  
High BP

		Heart Disease		
		No	Yes	
	Low BP	95	5	100
	High BP	55	45	100
		150	50	

DEPENDENT (effect)

		Heart Disease		
		No	Yes	
	Low BP	75	25	100
	High BP	75	25	100
		150	50	

INDEPENDENT (no effect)



# How to make splits?



- Contingency tables





180 ?  
240?

Low BP  
High BP

Heart Disease		
No	Yes	
95	5	100
75	25	
55	45	100
75	25	
150	50	
DEPENDENT (effect)		

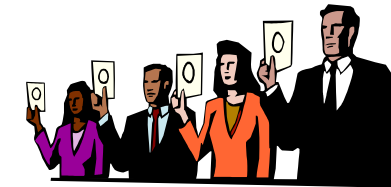
$$\chi^2 = \sum_{allcells} \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}} =$$
$$2(400/75) + 2(400/25) = 42.67$$

Compare to tables –  
Significant!  
(Why “Significant” ???)

$H_0$ :   
 $H_1$ : 



$H_0$ : Innocence  
 $H_1$ : Guilt



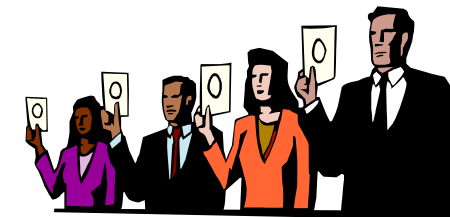
Beyond reasonable  
 doubt  
 $P < 0.05$



95 75	5 25
55 75	45 25

$H_0$ : No association  
 $H_1$ : BP and heart disease  
are associated

$P = 0.00000000064$



Framingham Conclusion: Sufficient evidence against the (null) hypothesis of no relationship.



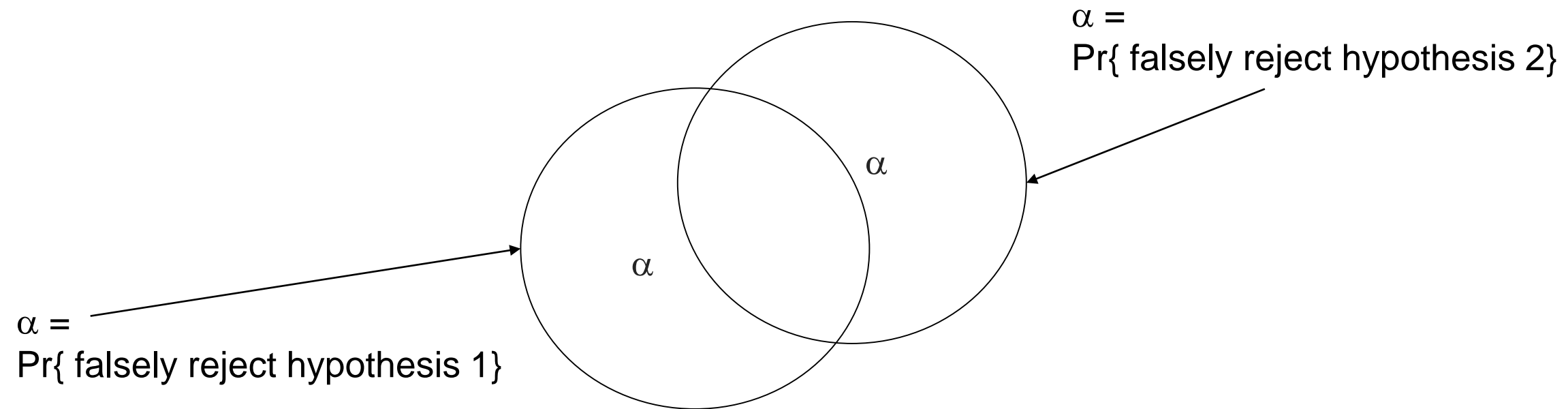
# How to make splits?



- Which variable to use?
- Where to split?
  - Cholesterol > \_\_\_\_\_
  - Systolic BP > \_\_\_\_\_
- Idea – Pick BP cutoff to minimize p-value for  $\chi^2$
- Split point data-derived!
- What does “significance” mean now?



# Multiple testing



$\text{Pr}\{\text{falsely reject one or the other}\} < 2\alpha$

Desired: 0.05 probability or less

Solution: Compare  $2(\text{p-value})$  to 0.05



# Other Sp



# lit Criteria

## ■ Gini Diversity Index

- (1) { A A A A B A B B C B }
- Pick 2,  $\Pr\{\text{different}\} = 1 - \Pr\{AA\} - \Pr\{BB\} - \Pr\{CC\}$ 
  - »  $1 - [10 + 6 + 0] / 45 = 29 / 45 = 0.64$
- (2) { A A B C B A A B C C }
- »  $1 - [6 + 3 + 3] / 45 = 33 / 45 = 0.73 \rightarrow (2) \text{ IS MORE DIVERSE, LESS PURE}$

## ■ Shannon Entropy

- Larger  $\rightarrow$  more diverse (less pure)
- $-\sum_i p_i \log_2(p_i)$

$\{0.5, 0.4, 0.1\} \rightarrow 1.36$   
 $\{0.4, 0.2, 0.3\} \rightarrow 1.51$  (more diverse)

# Validation

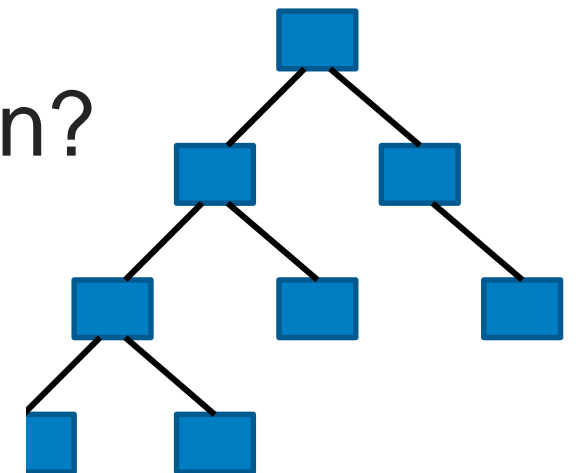


- Traditional stats – small dataset, need all observations to estimate parameters of interest.
- Data mining – loads of data, can afford “holdout sample”
- Variation: n-fold cross validation
  - Randomly divide data into  $n$  sets
  - Estimate on  $n-1$ , validate on 1
  - Repeat  $n$  times, using each set as holdout.



# Pruning

- Grow bushy tree on the “fit data”
- Classify validation (holdout) data
- Likely farthest out branches do not improve, possibly hurt fit on validation data
- Prune non-helpful branches.
- What is “helpful”? What is good discriminator criterion?



# Goals

- Split if diversity in parent “node” > summed diversities in child nodes
- Prune to optimize
  - Estimates
  - Decisions
  - Ranking
- in validation data



# Accounting for Costs

- Pardon me (sir, ma'am) can you spare some change?
- Say "sir" to male +\$2.00
- Say "ma'am" to female +\$5.00
- Say "sir" to female -\$1.00 (balm for slapped face)
- Say "ma'am" to male -\$10.00 (nose splint)



# Including Probabilities

Leaf has  $\Pr(\mathbf{M})=.7$ ,  $\Pr(\mathbf{F})=.3$

You say:

Sir

Ma'am

True  
Gender

**M**

**0.7** (2)

**0.7** (-10)

**F**

**0.3** (-1)

**0.3** (5)

+\$1.10

-\$5.50

Expected profit is  
 $2(0.7) - 1(0.3) = \$1.10$   
if I say "sir"

Expected profit is  
 $-7 + 1.5 = -\$5.50$  (a loss)  
if I say "Ma'am"

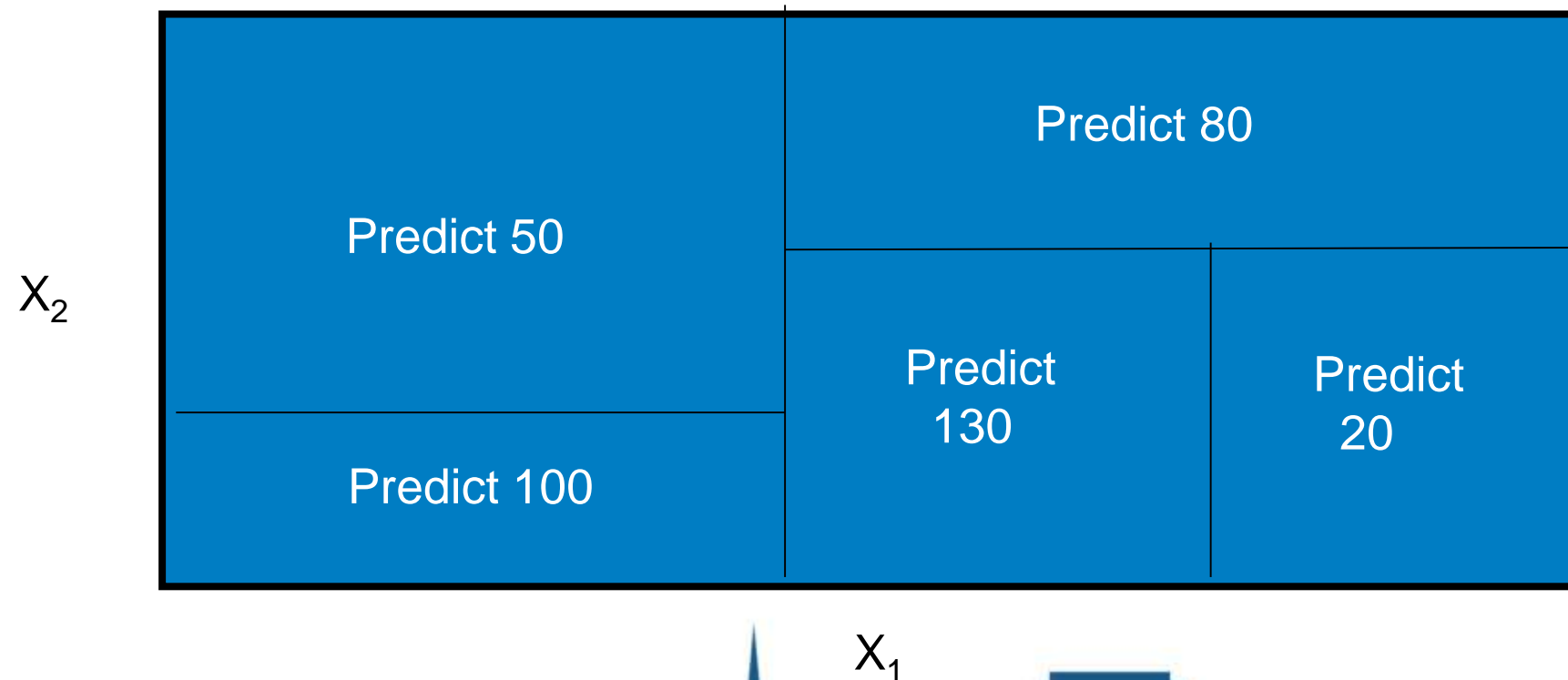
Weight leaf profits by leaf  
size (# obsns.) and sum.

Prune (and split) to  
maximize profits.



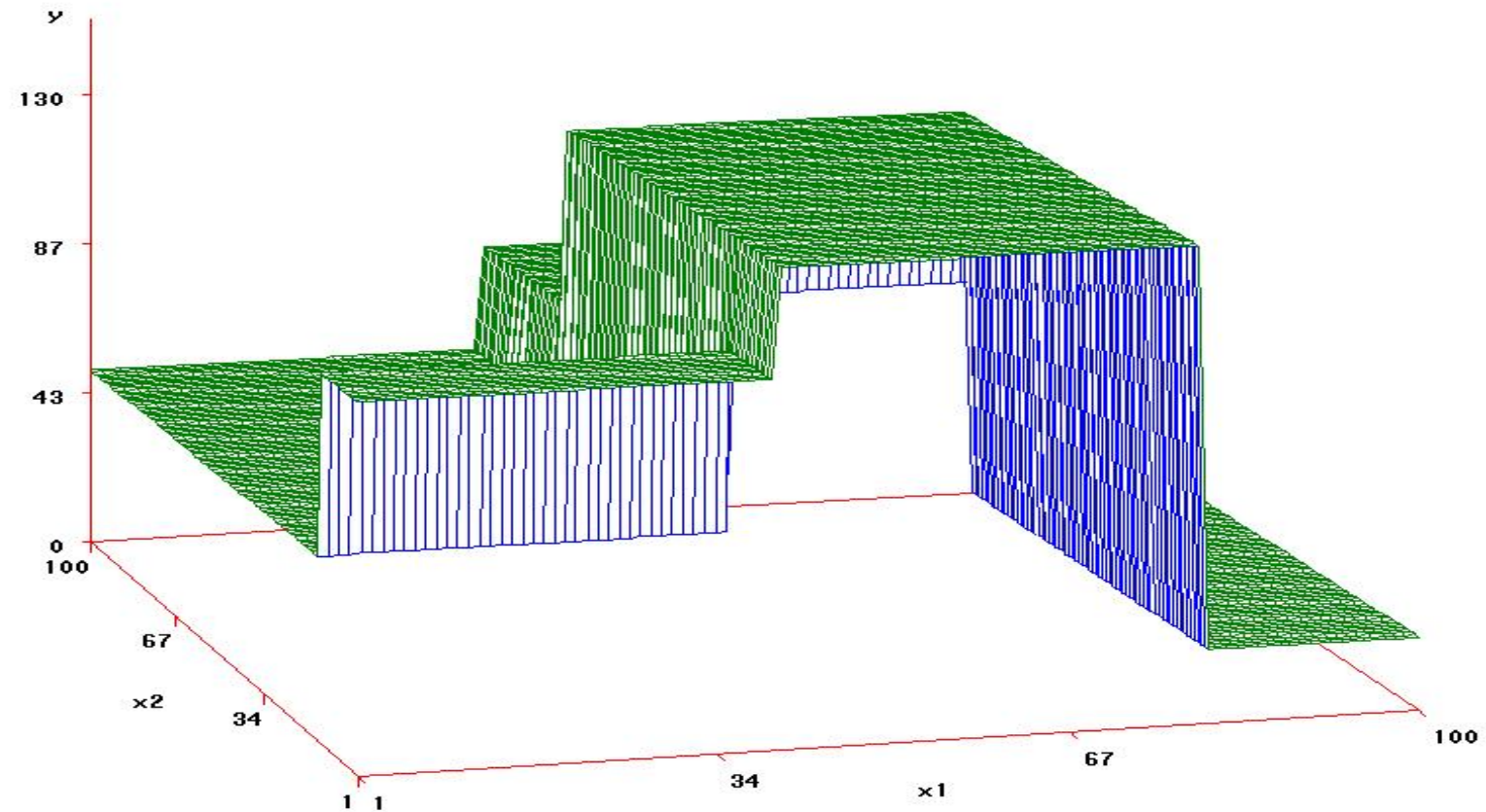
# Regression Trees

- Continuous response  $Y$
- Predicted response  $P_i$  constant in regions  $i=1, \dots, 5$



# Regression Trees

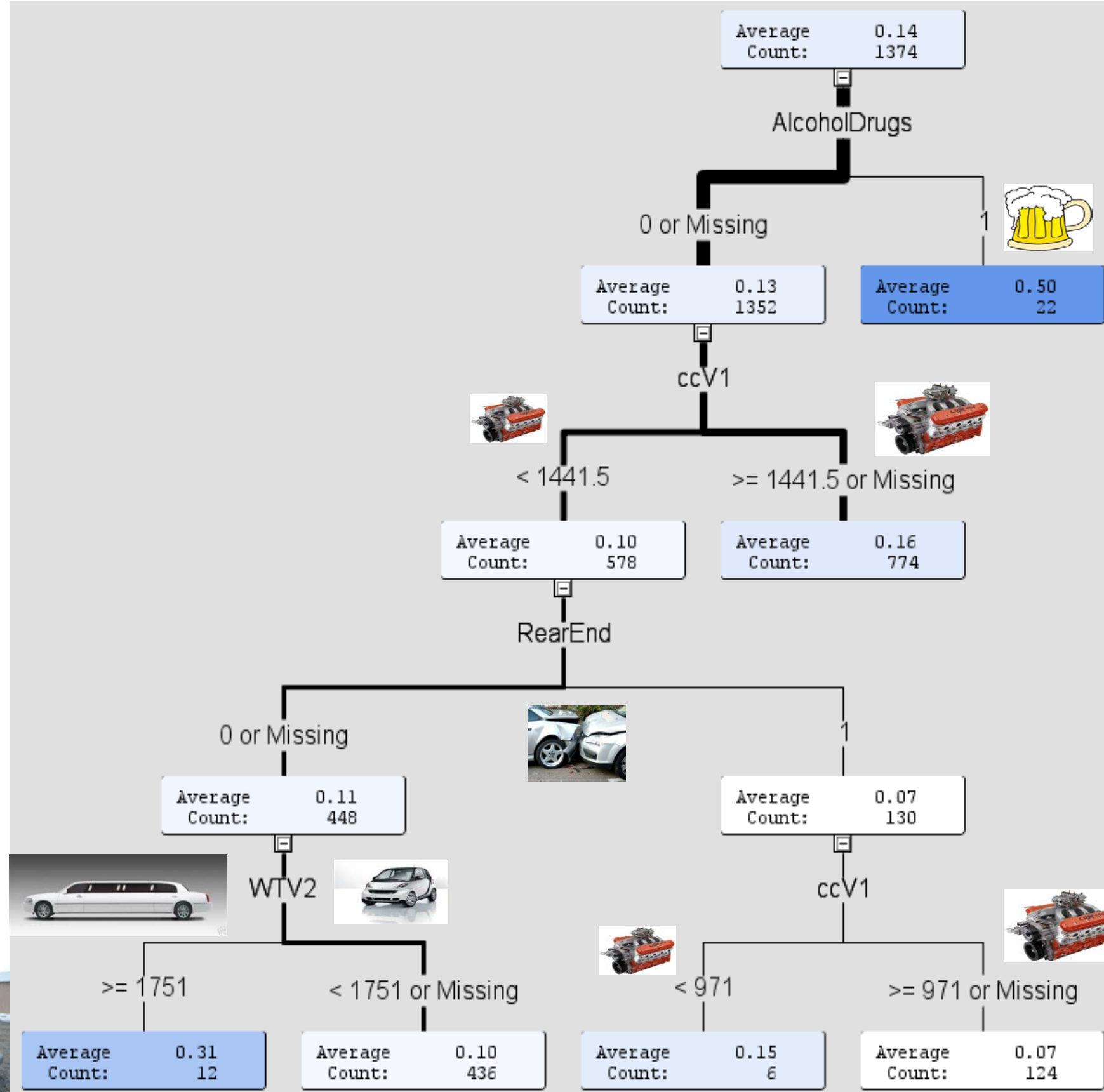
- Predict  $P_i$  in cell  $i$ .
- $Y_{ij}$   $j^{\text{th}}$  response in cell  $i$ .
- Split to minimize  $\sum_i \sum_j (Y_{ij} - P_i)^2$



Real data  
example:  
Traffic accidents  
in Portugal\*

Y = injury  
induced “cost to  
society”

Help - I ran  
Into a “tree”



\* Tree developed by  
Guilhermina Torrao, (used  
with permission)  
NCSU Institute for  
Transportation Research &  
Education

Help - I ran  
Into a “tree”



# Logistic Regression

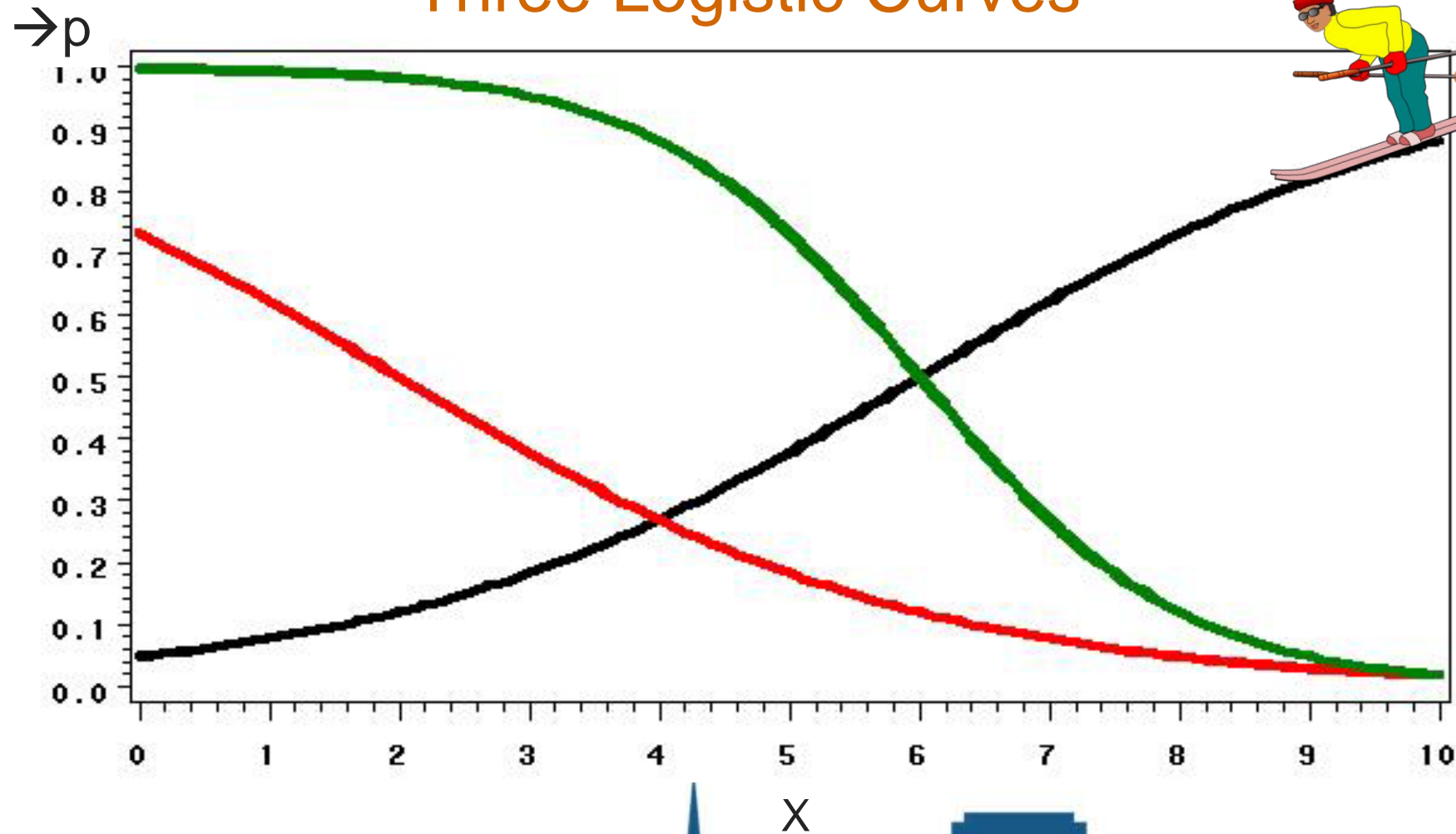
- Logistic – another classifier
- Older – “tried & true” method
- Predict **probability** of response from input variables (“Features”)
- **Linear regression** gives infinite range of predictions
- $0 < \text{probability} < 1$  so not linear regression.



# Logistic Regression

Three Logistic Curves

$$\frac{e^{a+bX}}{(1+e^{a+bX})} \rightarrow p$$

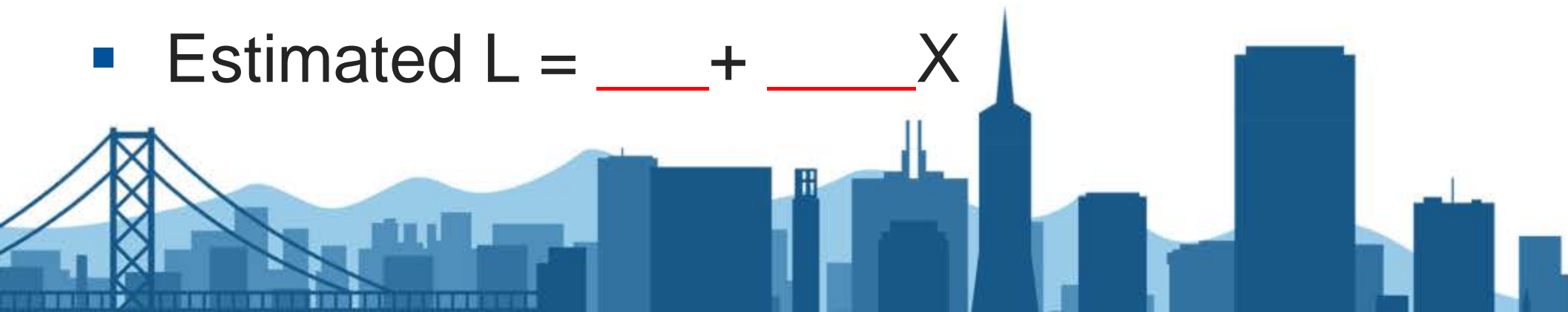
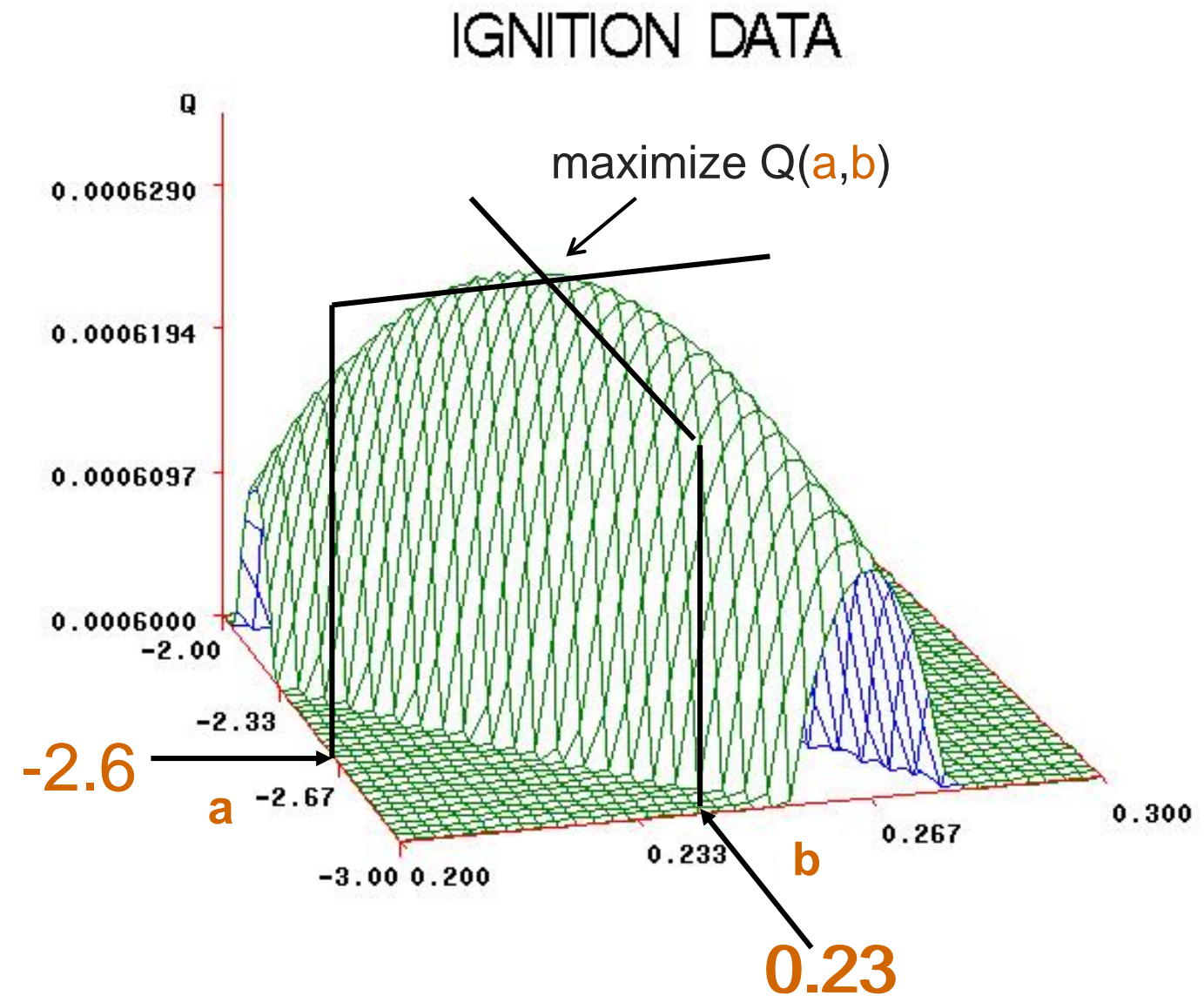


# Example: Seat Fabric Ignition

- Flame exposure time =  $X$
- $Y=1 \rightarrow$  ignited,  $Y=0 \rightarrow$  did not ignite
  - $Y=0$ ,  $X = 3, 5, 9, 10, 13, 16$
  - $Y=1$ ,  $X = 11, 12, 14, 15, 17, 25, 30$
- $Q = (1-p_1)(1-p_2)(1-p_3)(1-p_4)p_5p_6(1-p_7)p_8p_9(1-p_{10})p_{11}p_{12}p_{13}$
- $p$ 's all different  $p_i = f(a+bX_i) = e^{a+bX_i} / (1+e^{a+bX_i})$
- Find  $a, b$  to maximize  $Q(a, b)$



- Logistic idea:
- Given temperature  $X$ , compute  $L(x)=a+bX$  then  $p = e^L/(1+e^L)$
- $p(i) = e^{a+bX_i}/(1+e^{a+bX_i})$
- Write  $p(i)$  if response,  $1-p(i)$  if not
- Multiply all  $n$  of these together, find  $a, b$  to maximize this “likelihood”
- Estimated  $L = \underline{\hspace{1cm}} + \underline{\hspace{1cm}} X$



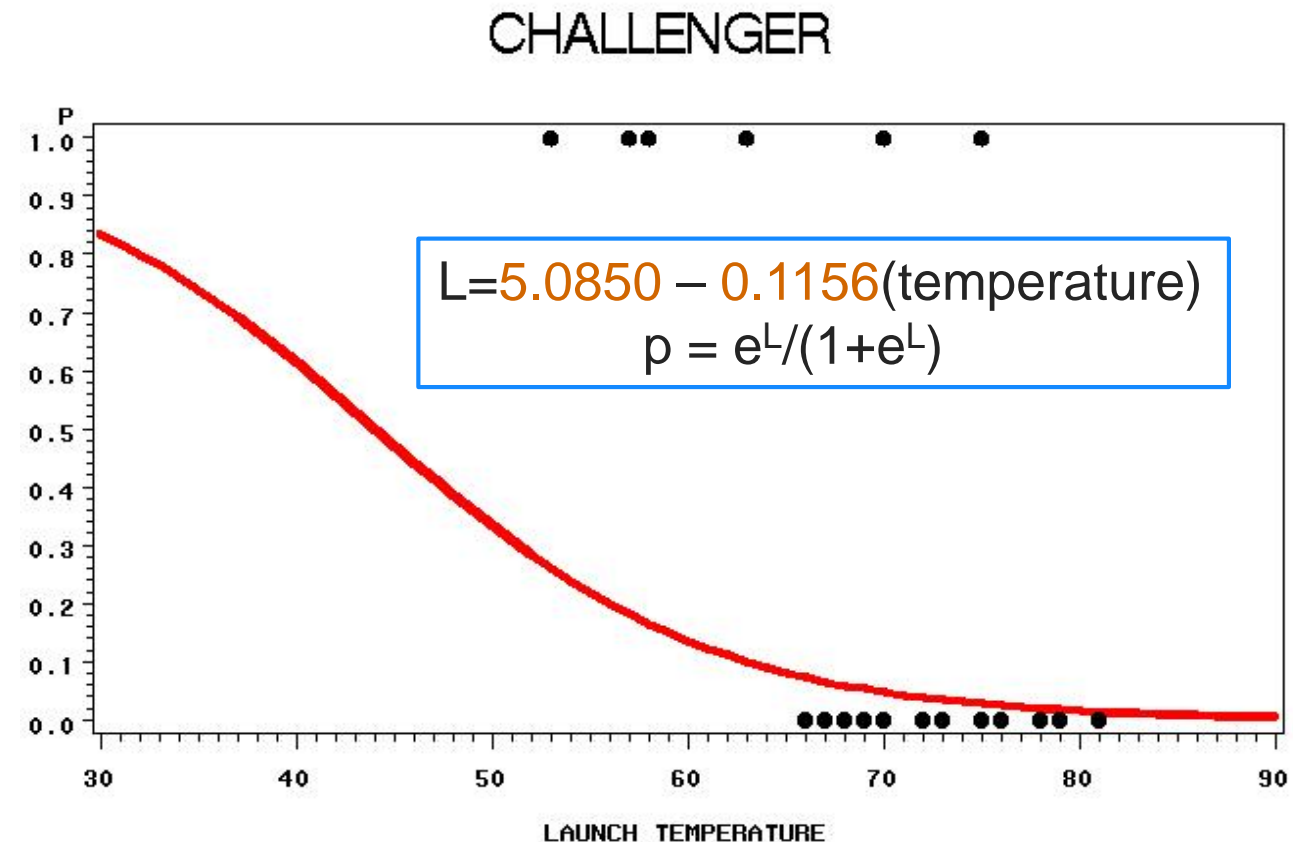




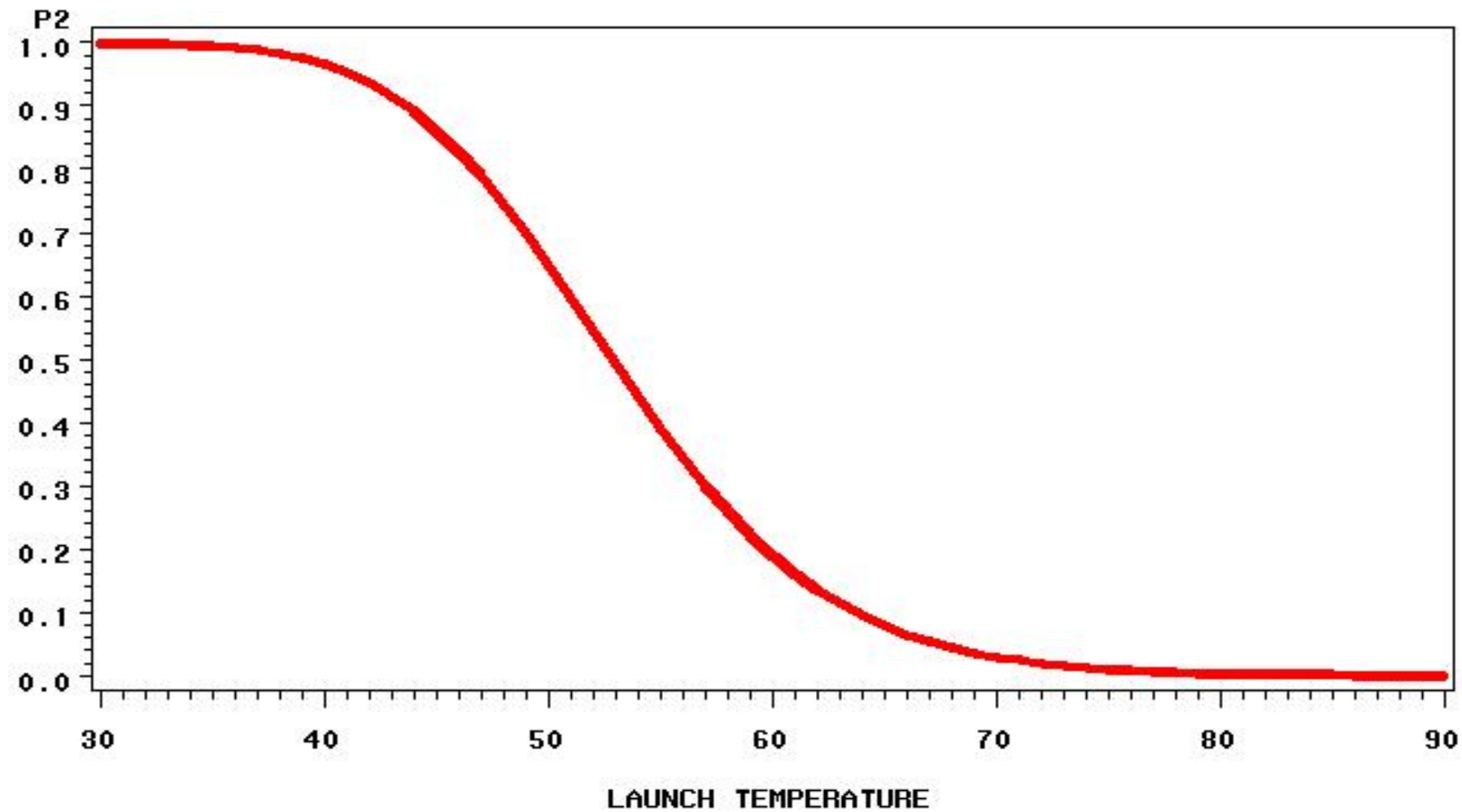
## Example: Shuttle Missions



- O-rings failed in Challenger disaster
- Prior flights “erosion” and “blowby” in O-rings (6 per mission)
- Feature: Temperature at liftoff
- Target: (1) - erosion or blowby vs. no problem (0)



## $\Pr\{2 \text{ OR MORE FAILURES}\}$

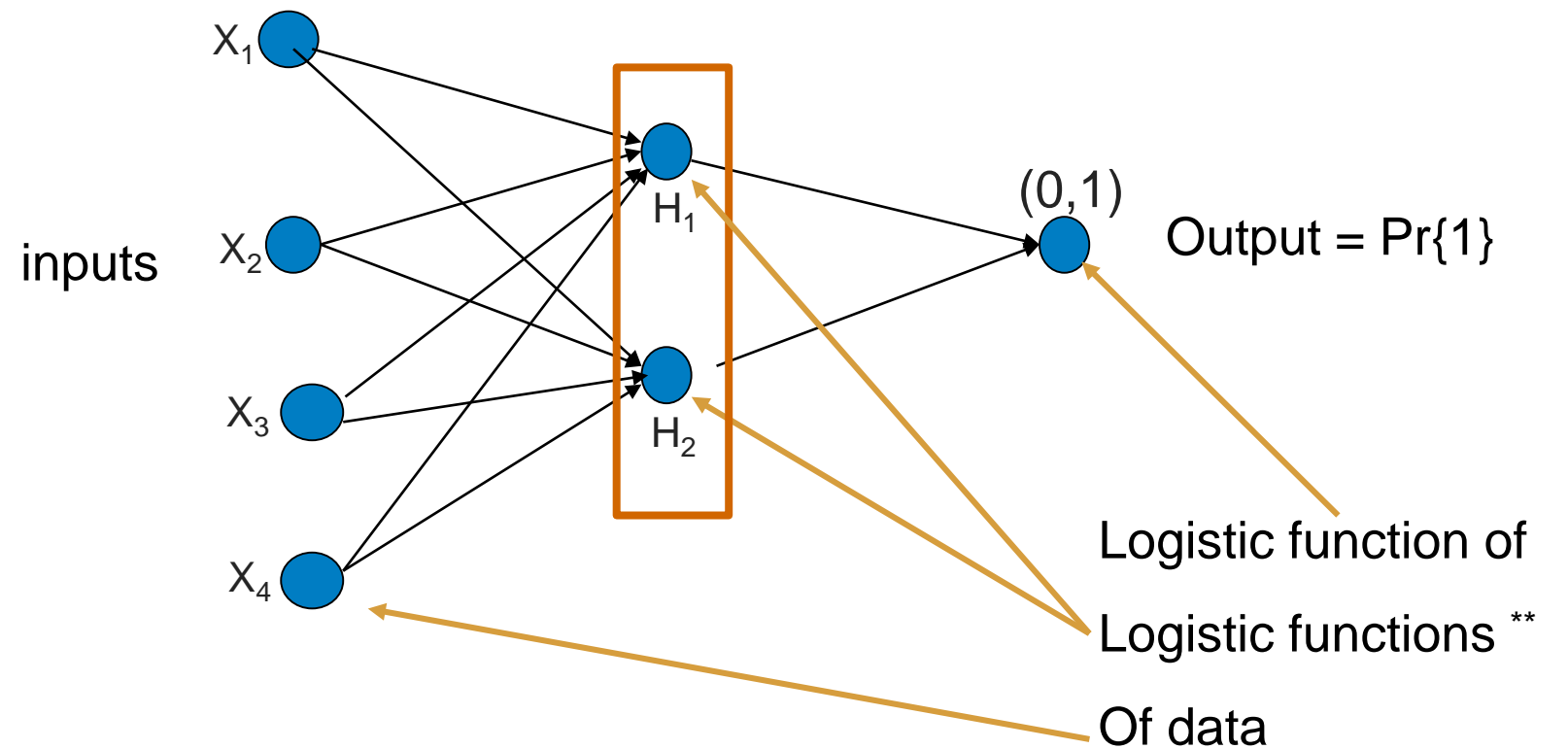


$$\Pr\{2 \text{ or more}\} = 1 - p_x^0 (1 - p_x)^6 - 6 p_x (1 - p_x)^5$$



# Neural Networks

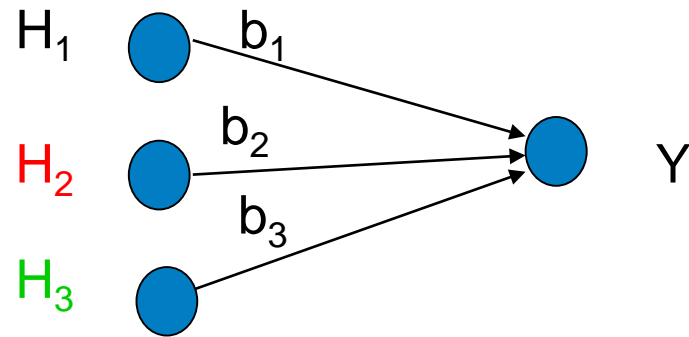
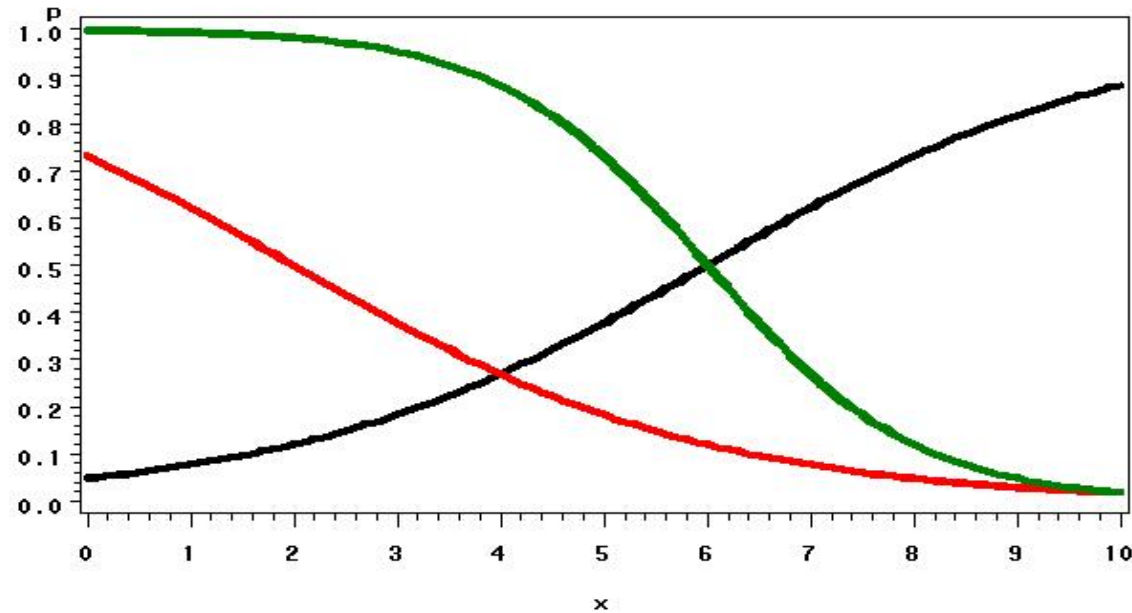
- Very flexible functions
- “Hidden Layers”
- “Multilayer Perceptron”



\*\* (note: Hyperbolic tangent functions are just reparameterized logistic functions)

## Three Logistic Curves

$p(i) = \exp(L(i)) / (1 + \exp(L(i)))$  where  $L(1) = -3 + .5X$ ,  
 $L(2) = 1 - 0.5X$ , and  $L(3) = 6 - X$



Arrows represent linear combinations of “basis functions,” e.g. logistic curves (hyperbolic tangents)

Example:

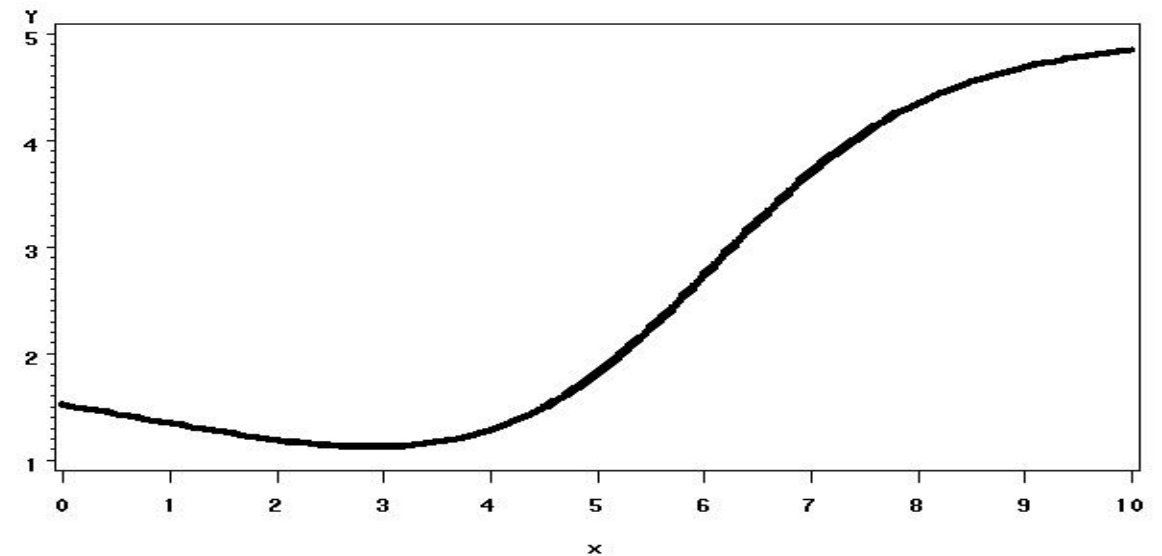
$$Y = a + b_1 H_1 + b_2 H_2 + b_3 H_3$$

$$Y = 4 + 1 H_1 + 2 H_2 - 4 H_3$$

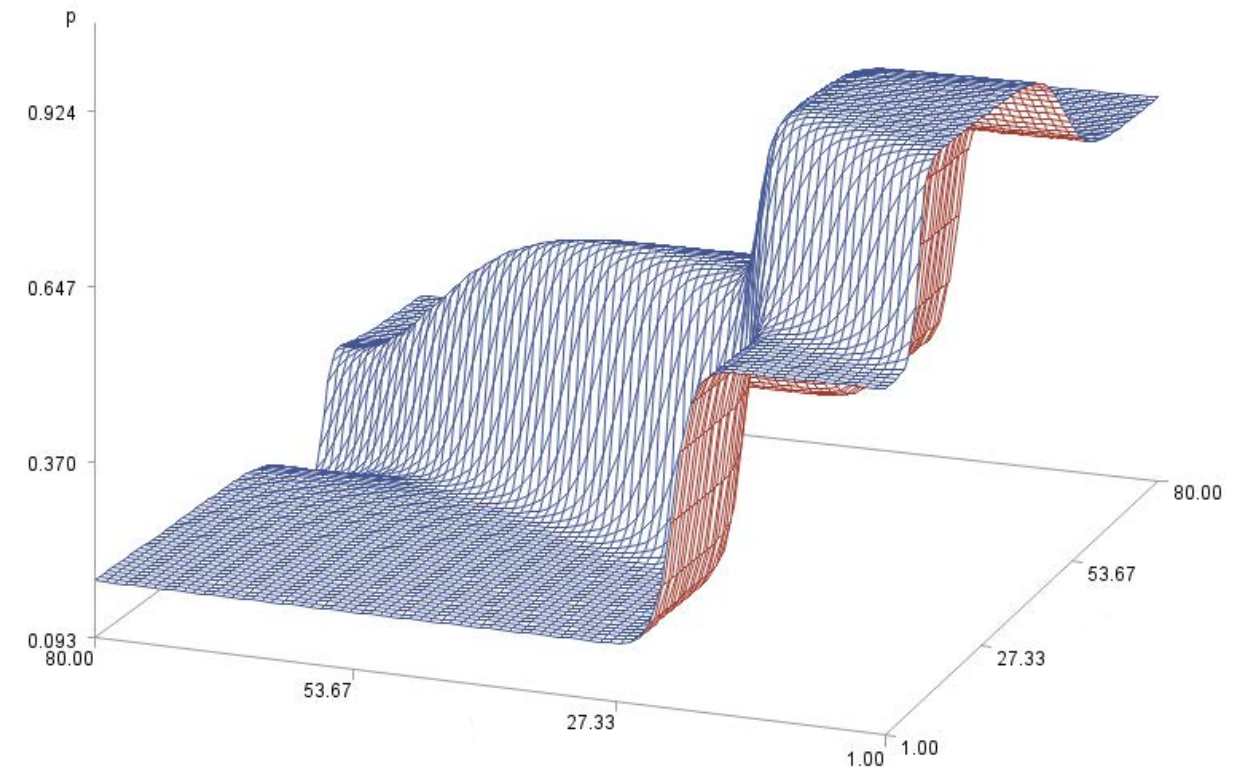
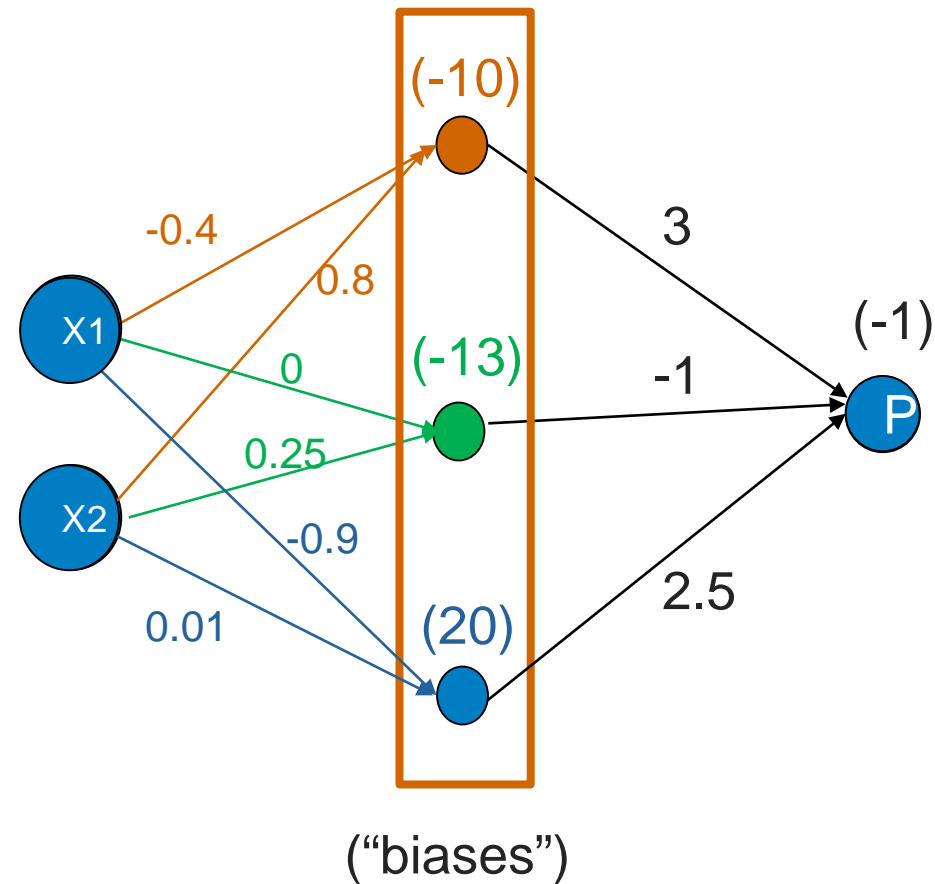
“bias”  $\swarrow$   $\nwarrow$   $\nearrow$   $\nwarrow$   $\nearrow$   
 “weights”

Combining for Neural Network

$$4 + p(1) + 2 p(2) - 4 p(3)$$



# A Complex Neural Network Surface



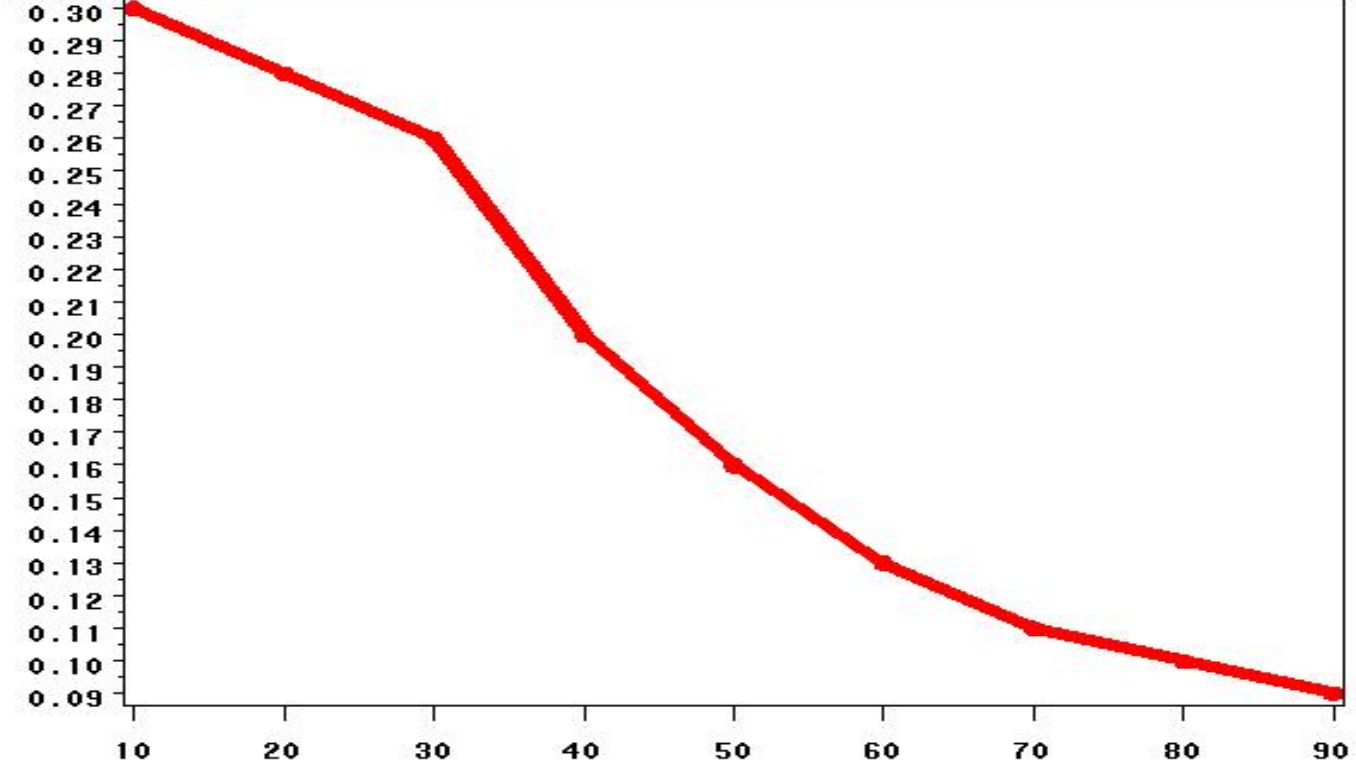


Lift Chart

Lift

3.3 →

response



1 →

Predicted pct response

high ← ----- → low

## \* Cumulative Lift Chart

- Go from leaf of most to least predicted response.
- **Lift** is proportion responding in first p% overall population response rate



# A Combined Example

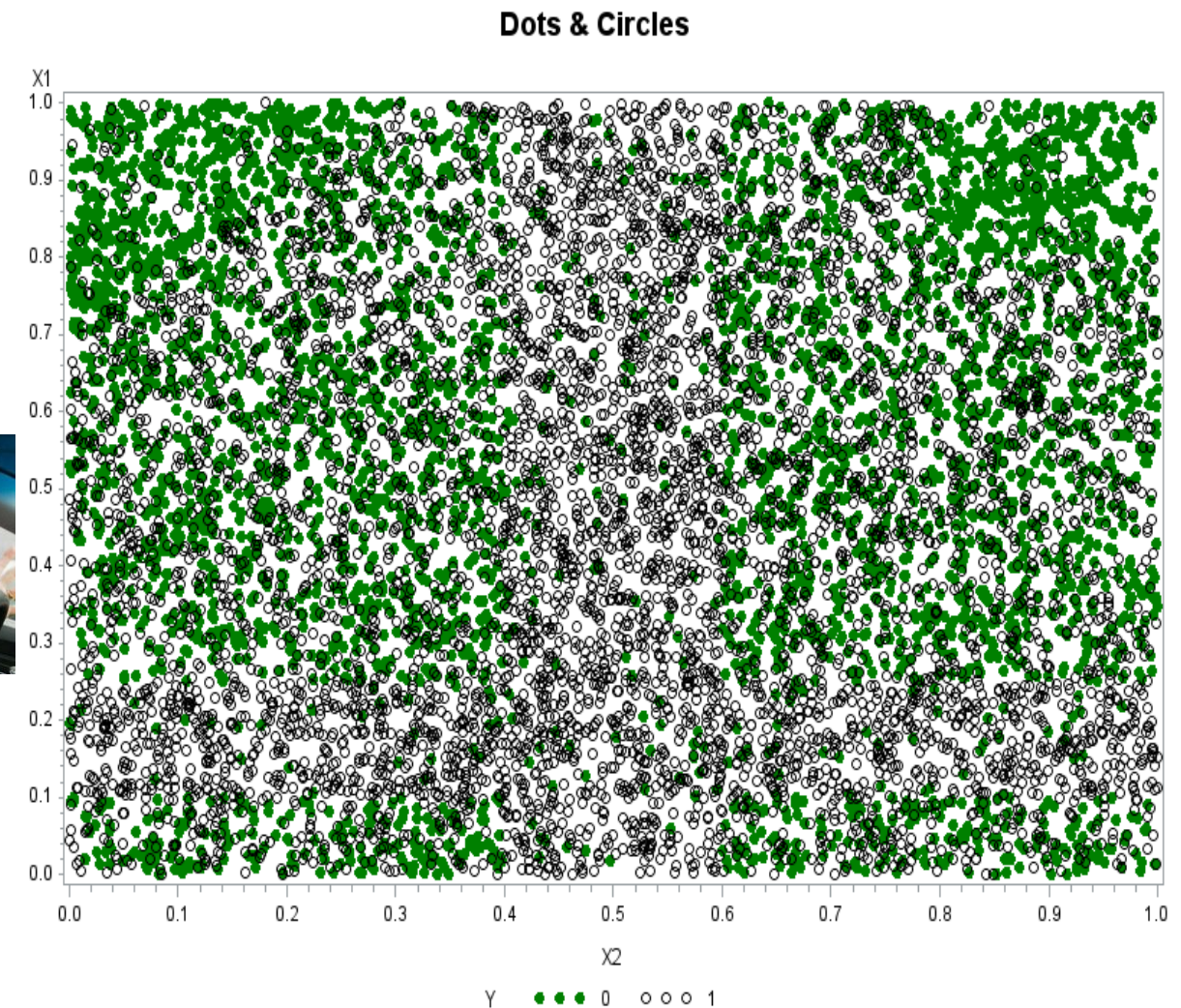
## Cell Phone Texting Locations

Black circle: ○

Phone moved > 50 feet in first two minutes of texting.

Green dot: ●

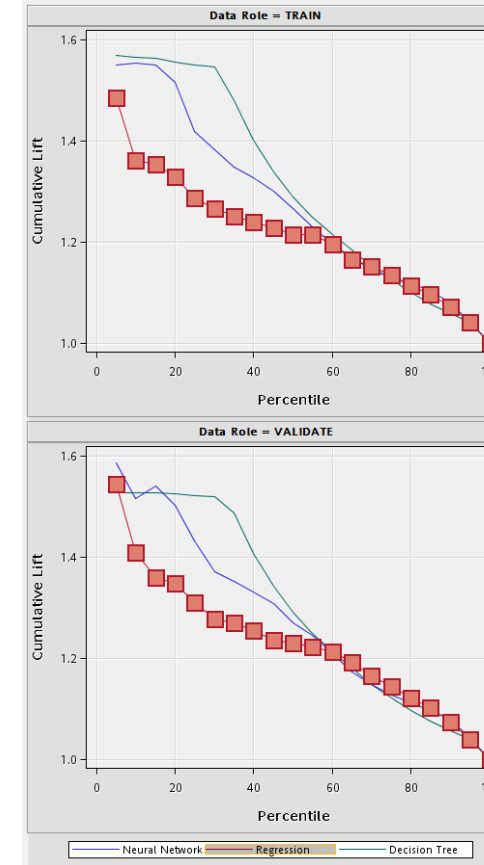
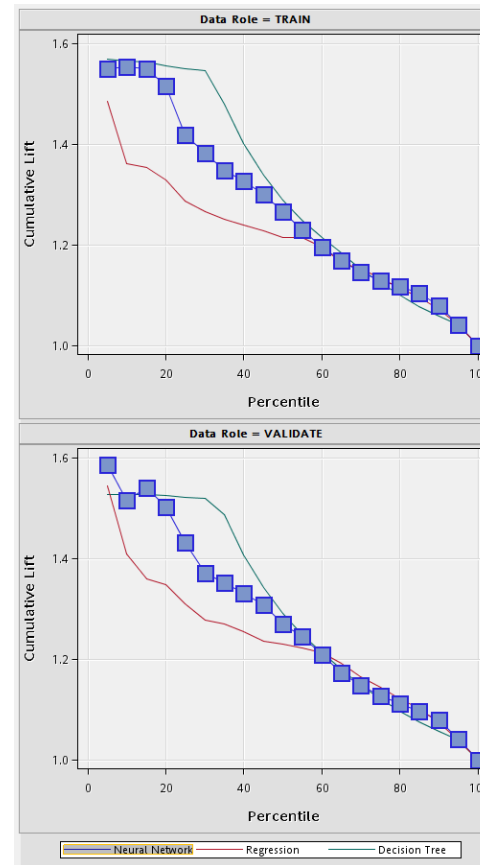
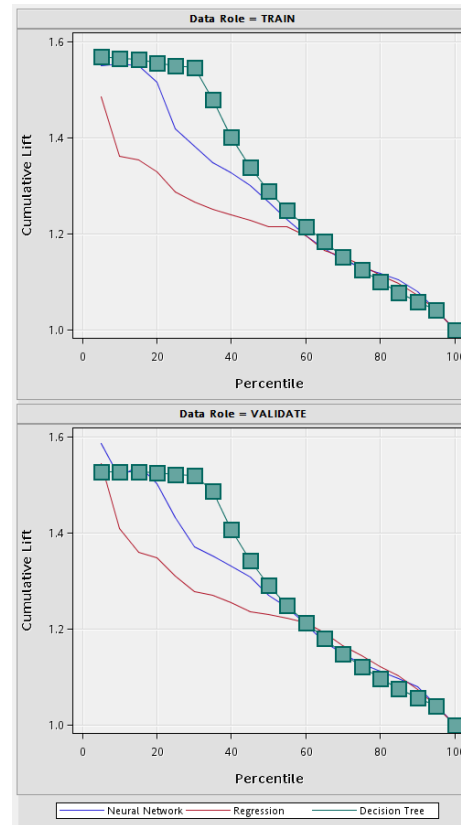
Phone moved < 50 feet. .



Tree

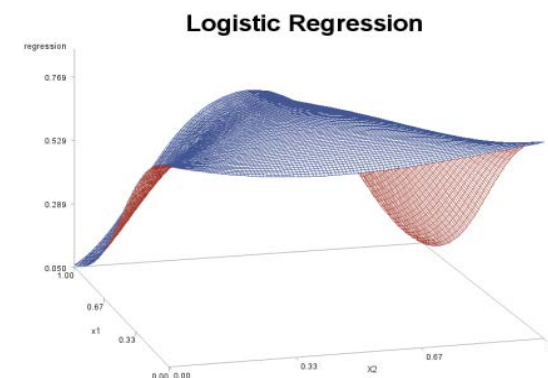
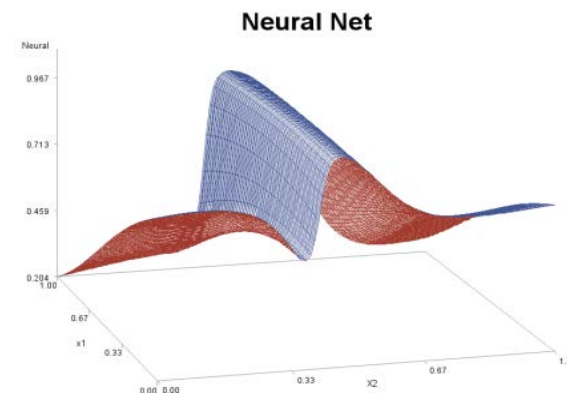
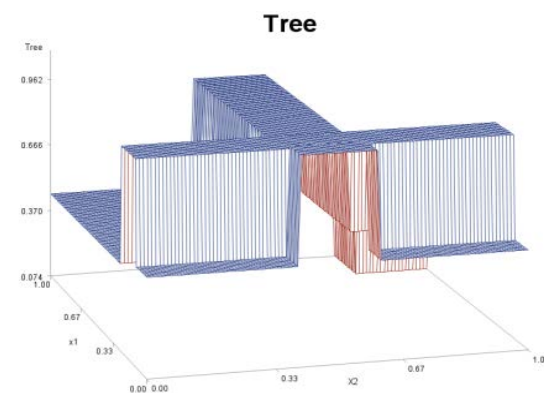
Neural Net

Logistic Regression ← Three Models

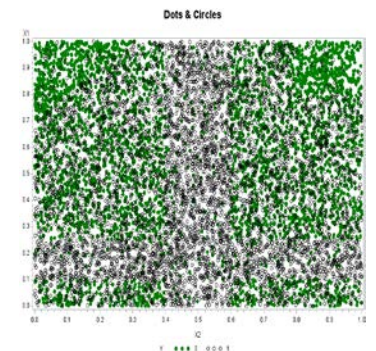


Training Data  
← Lift Charts

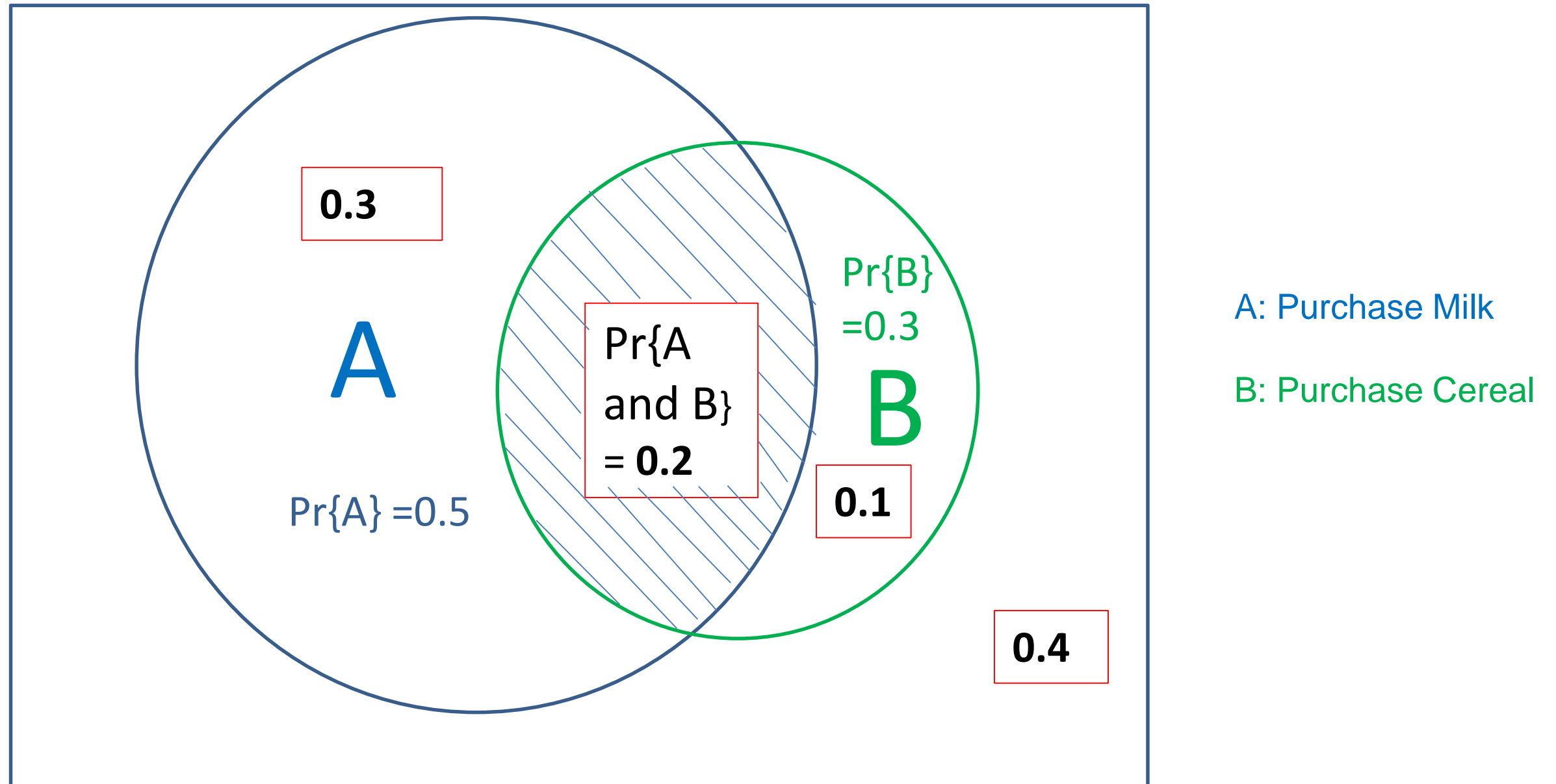
Validation Data  
← Lift Charts



Resulting  
Surfaces  
←



# Association Analysis is just elementary probability with new names



$$0.3 + 0.2 + 0.1 + 0.4 = 1.0$$

Cereal=> Milk

**Rule**  $B \Rightarrow A$  “people who buy B will buy A”

**Support:**

Support=  $\Pr\{A \text{ and } B\} = 0.2$

Independence means that  $\Pr\{A|B\} = \Pr\{A\} = 0.5$   
 $\Pr\{A\} = 0.5 = \text{Expected confidence}$  if there is no relation to B..

**Confidence:**

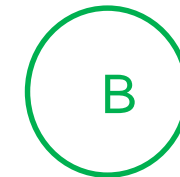
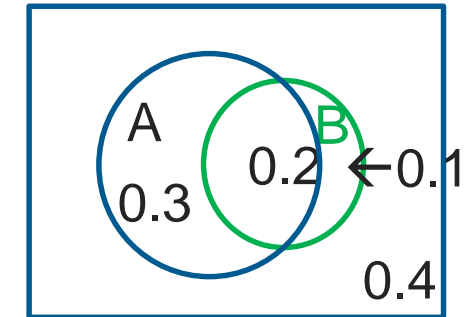
Confidence =  $\Pr\{A|B\} = \Pr\{A \text{ and } B\} / \Pr\{B\} = 2/3$

??- Is the confidence in  $B \Rightarrow A$  the same as the confidence in  $A \Rightarrow B$ ? (yes, no)

**Lift:**

Lift = confidence / E{confidence} =  $(2/3) / (1/2) = 1.33$

Gain = 33%



Marketing A to the 30% of people who buy B will result in 33% better sales than marketing to a random 30% of the people.

# Unsupervised Learning

- We have the “features” (predictors)
- We do NOT have the response even on a training data set (UNsupervised)
- Another name for clustering
- EM
  - Large number of clusters with k-means (k clusters)
  - Ward’s method to combine (less clusters)
  - One more k means



# Text Mining

Hypothetical collection of news releases (“corpus”) :

release 1: Did the **NCAA** investigate the **basketball scores** and **vote** for sanctions?

release 2: **Republicans** **voted** for and **Democrats** **voted** against it for the **win**.

(etc.)

Compute word counts:

	<b>NCAA</b>	<b>basketball</b>	<b>score</b>	<b>vote</b>	<b>Republican</b>	<b>Democrat</b>	<b>win</b>
Release 1	1	1	1	1	0	0	0
Release 2	0	0	0	2	1	1	1



Text Mining Mini-Example: Word counts in 16 e-mails

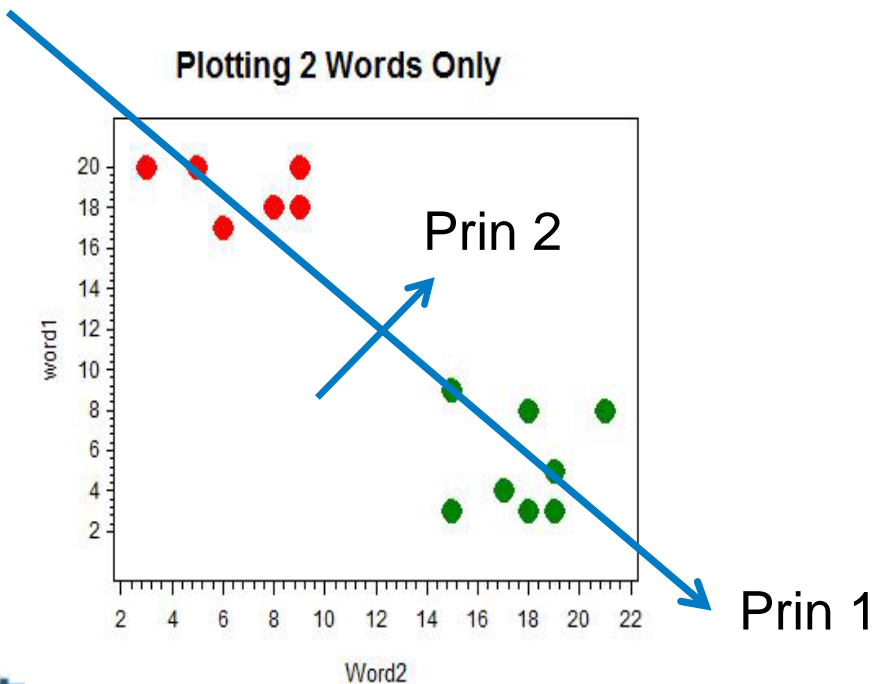
←-----words-----→

d o c u m e n t	E l e c t i o n	P r e s i d e n t	R e p u b l i c a n	B a s k e t b a l l	D e m o c r a t	V o t e r s	N C A A	L i a r	T o u r n a m e n t	S p e e c h	W i n s	S c o r e  V	S c o r e  N
1	20	8	10	12	6	0	1	5	3	8	18	15	21
2	5	6	9	5	4	2	0	9	0	12	12	9	0
3	0	2	0	14	0	2	12	0	16	4	24	19	30
4	8	9	7	0	12	14	2	12	3	15	22	8	2
5	0	0	4	16	0	0	15	2	17	3	9	0	1
6	10	6	9	5	5	19	5	20	0	18	13	9	14
7	2	3	1	13	0	1	12	13	20	0	0	1	6
8	4	1	4	16	2	4	9	0	12	9	3	0	0
9	26	13	9	2	16	20	6	24	4	30	9	10	14
10	19	22	10	11	9	12	0	14	10	22	3	1	0
11	2	0	0	14	1	3	12	0	16	12	17	23	8
12	16	19	21	0	13	9	0	16	4	12	0	0	2
13	14	17	12	0	20	19	0	12	5	9	6	1	4
14	1	0	4	21	3	6	9	3	8	0	3	10	20



## Eigenvalues of the Correlation Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	7.10954264	4.80499109	0.5469	<b>0.5469</b>
2	2.30455155	1.30162837	0.1773	<b>0.7242</b>
3	1.00292318	0.23404351	0.0771	<b>0.8013</b>
4	0.76887967	0.21070080	0.0591	<b>0.8605</b>
5	0.55817886	0.10084923	0.0429	<b>0.9034</b>
		(more)		
13	0.0008758		0.0001	1.0000

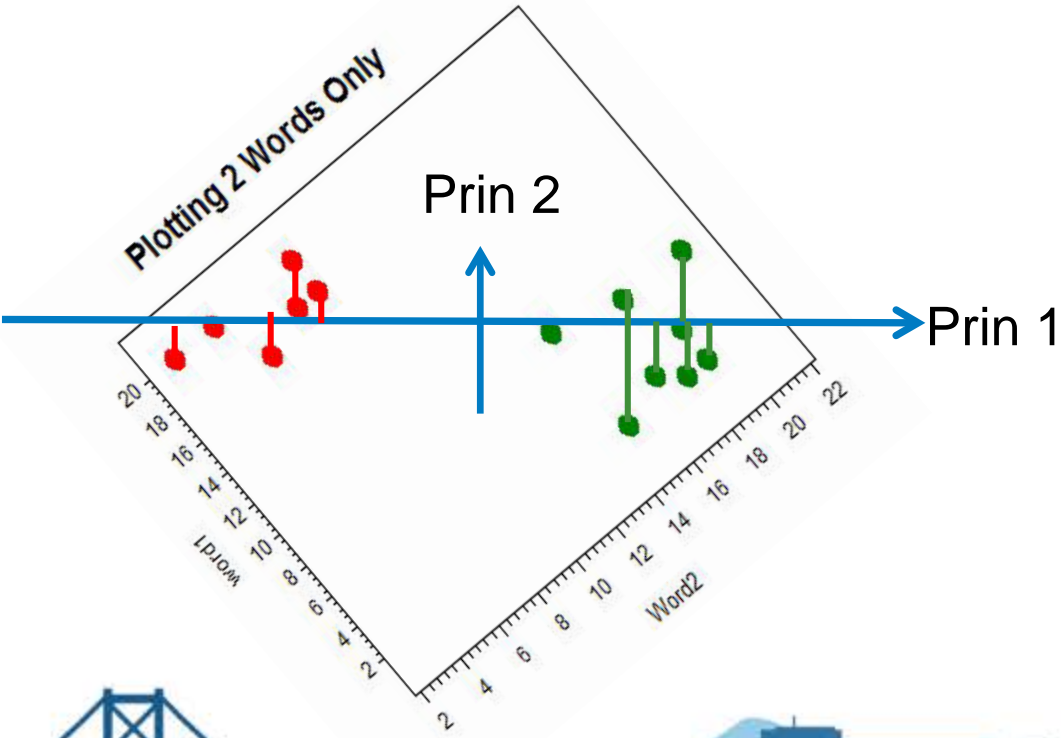


**55%** of the variation in these 13-dimensional vectors occurs in **one** dimension.

Variable	Prin1
Basketball	- .320074
NCAA	- .314093
Tournament	- .277484
Score_V	- .134625
Score_N	- .120083
Wins	- .080110
Speech	0.273525
Voters	0.294129
Liar	0.309145
Election	0.315647
Republican	0.318973
President	0.333439
Democrat	0.336873

Eigenvalues of the Correlation Matrix

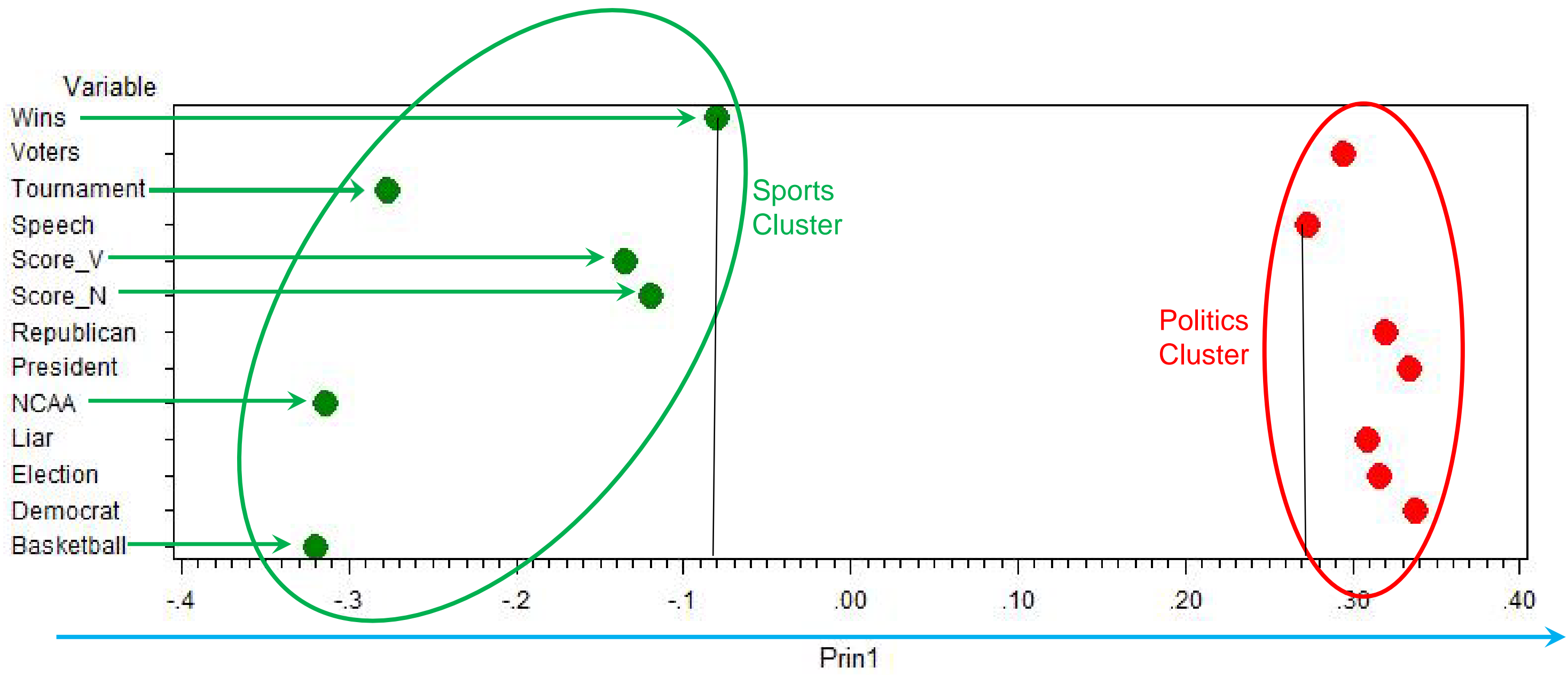
	Eigenvalue	Difference	Proportion	Cumulative
1	7.10954264	4.80499109	0.5469	0.5469
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4	0.76887967	0.21070080	0.0591	0.8605
5	0.55817886	0.10084923	0.0429	0.9034
		(more)		
13	0.000875		0.0001	1.0000



55% of the variation in these 13-dimensional vectors occurs in **one** dimension.

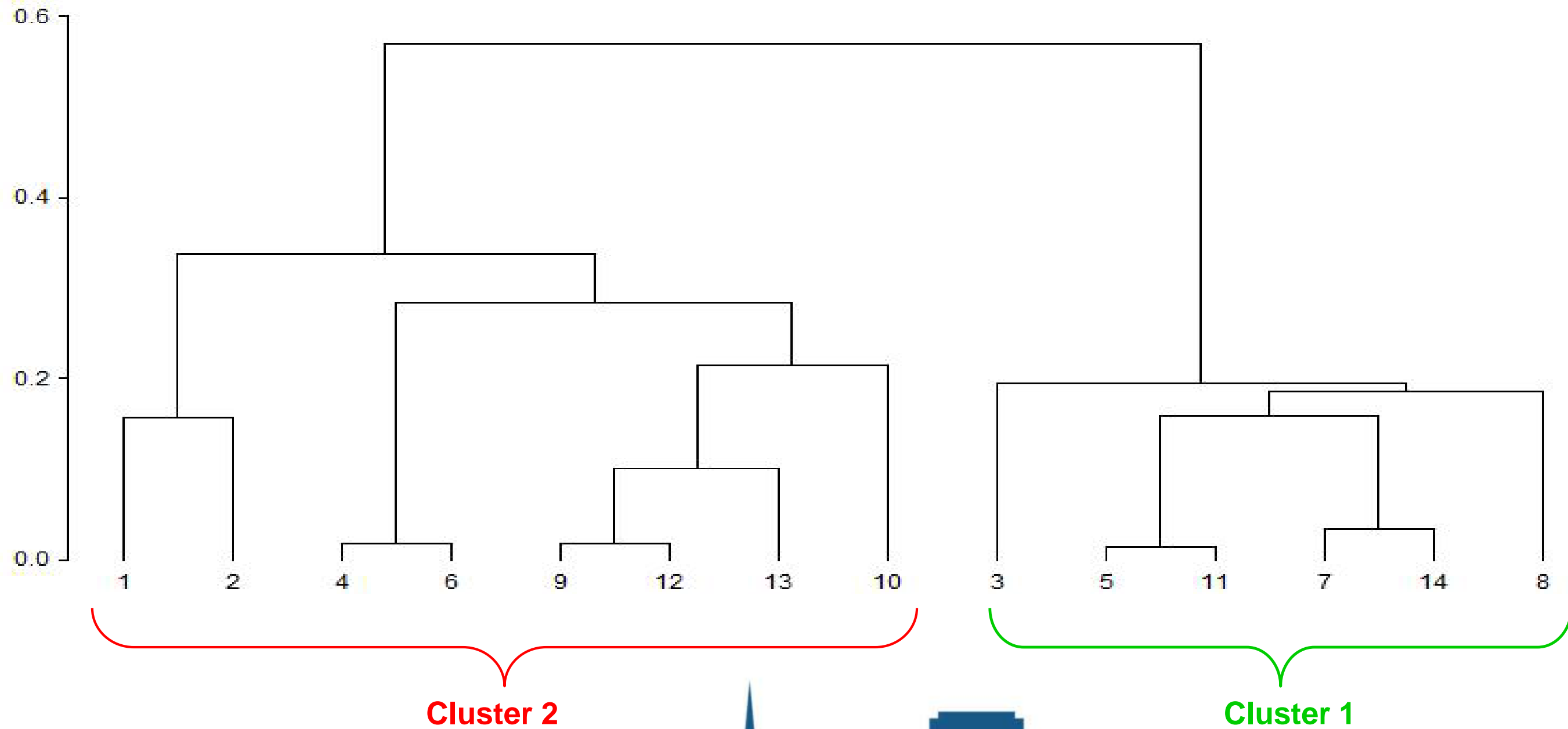
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President	0.333439
Democrat	0.336873





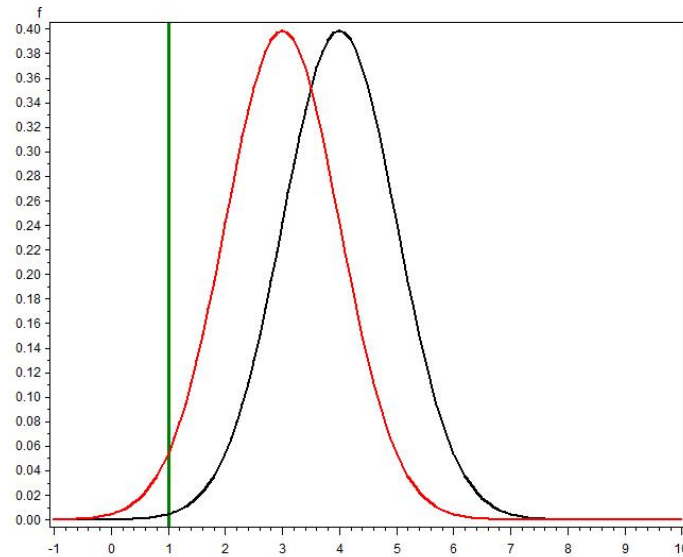
	document	CLUSTER	Prin1	Electi on	Pre sident	Re pub lican	Ba sk et bal l	Dem oc rat	V ot ers	N C A A	L i a r	T ou r na ment	S p ee ch	W i n s	S c o r e ̄V	S c o r e ̄N
Sports Documents	3	1	-3.63815	0	2	0	14	0	2	12	0	16	4	24	19	30
	11	1	-3.02803	2	0	0	14	1	3	12	0	16	12	17	23	8
	5	1	-2.98347	0	0	4	16	0	0	15	2	17	3	9	0	1
	14	1	-2.48381	1	0	4	21	3	6	9	3	8	0	3	10	20
	7	1	-2.37638	2	3	1	13	0	1	12	13	20	0	0	1	6
	8	1	-1.79370	4	1	4	16	2	4	9	0	12	9	3	0	0
(biggest gap)																
Politics Documents	1	2	-0.00738	20	8	10	12	6	0	1	5	3	8	18	15	21
	2	2	0.48514	5	6	9	5	4	2	0	9	0	12	12	9	0
	6	2	1.54559	10	6	9	5	5	19	5	20	0	18	13	9	14
	4	2	1.59833	8	9	7	0	12	14	2	12	3	15	22	8	2
	10	2	2.49069	19	22	10	11	9	12	0	14	10	22	3	1	0
	13	2	3.16620	14	17	12	0	20	19	0	12	5	9	6	1	4
	12	2	3.48420	16	19	21	0	13	9	0	16	4	12	0	0	2
	9	2	3.54077	26	13	9	2	16	20	6	24	4	30	9	10	14

## PROC CLUSTER (single linkage) agrees !



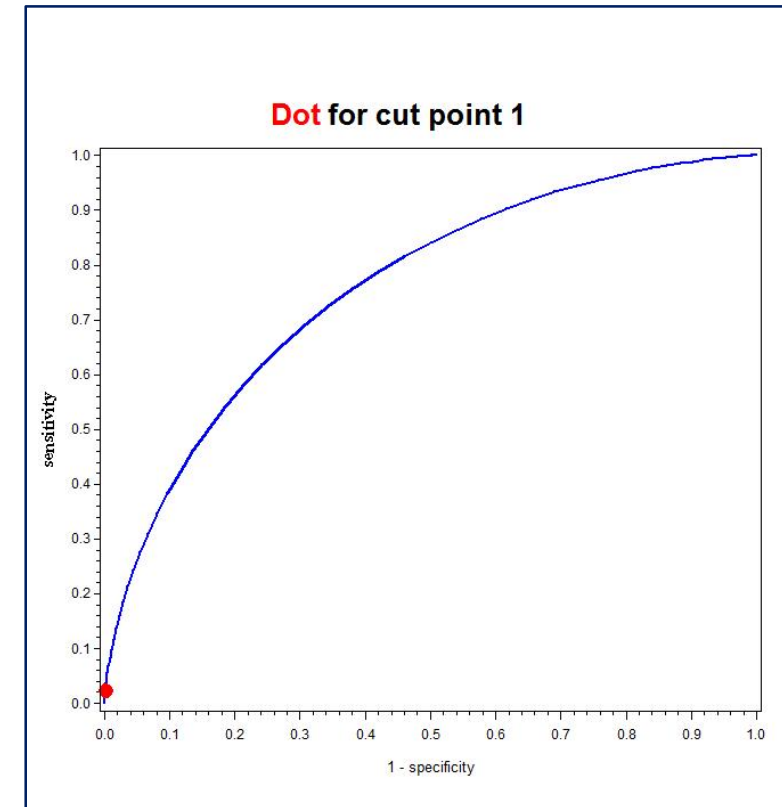
# Receiver Operating Characteristic Curve

Cut point 1



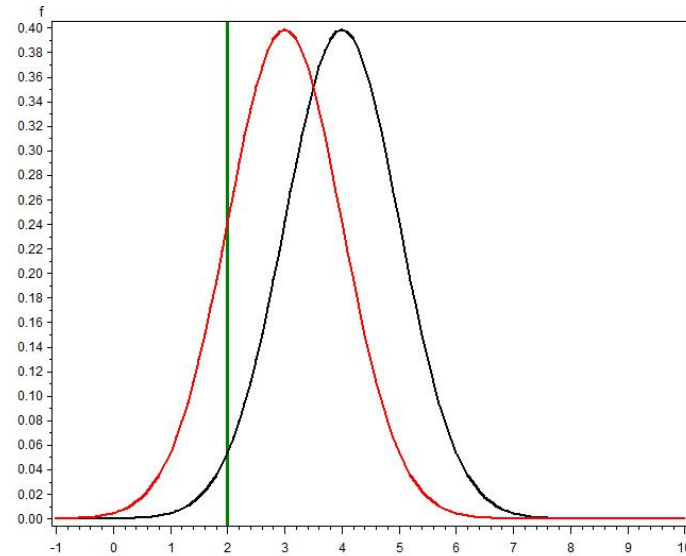
Logits of 1s  
red

Logits of 0s  
black



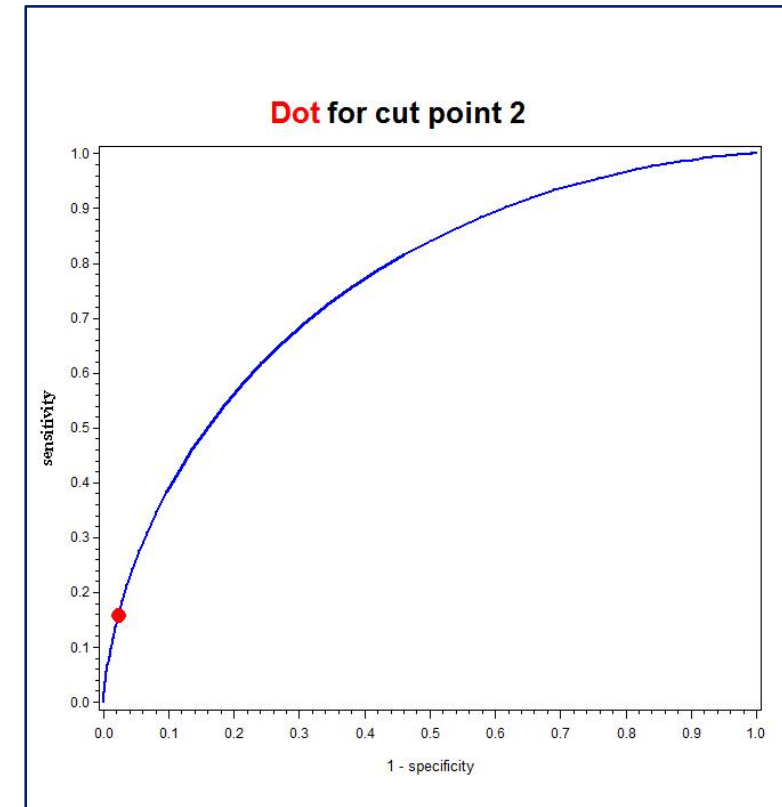
# Receiver Operating Characteristic Curve

Cut point 2



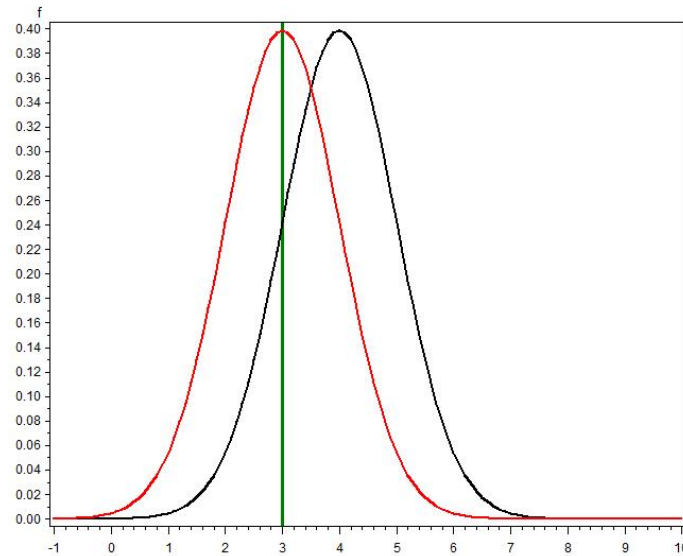
Logits of 1s  
red

Logits of 0s  
black



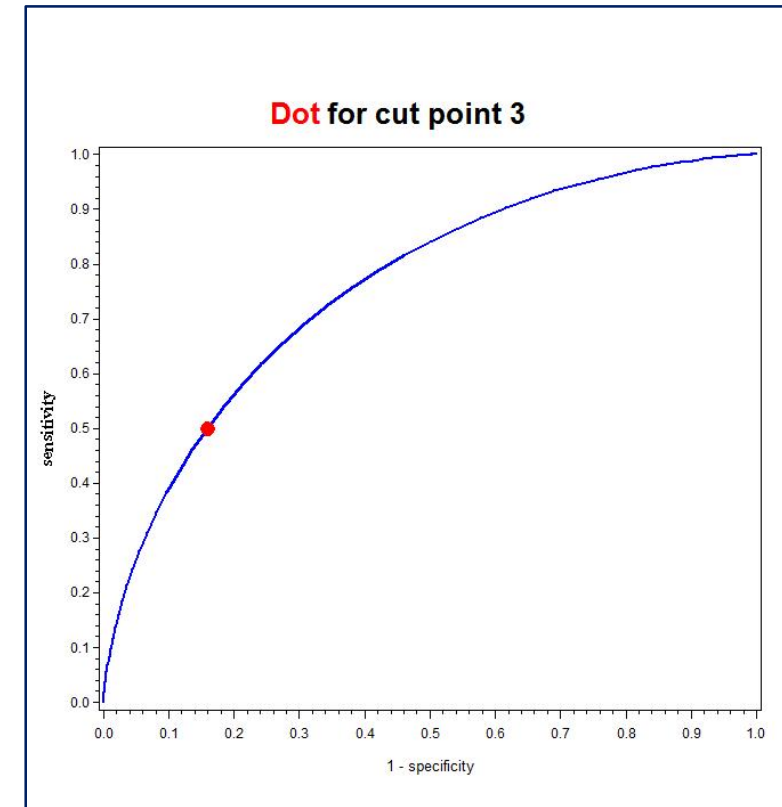
# Receiver Operating Characteristic Curve

Cut point 3



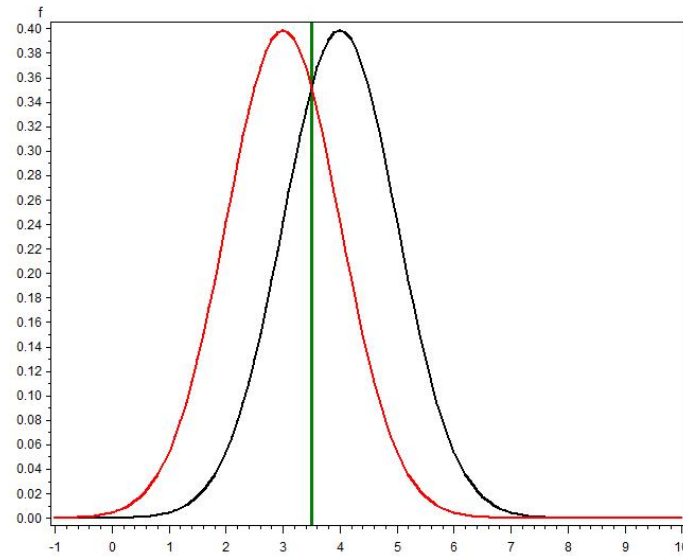
Logits of 1s  
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Logits of 0s  
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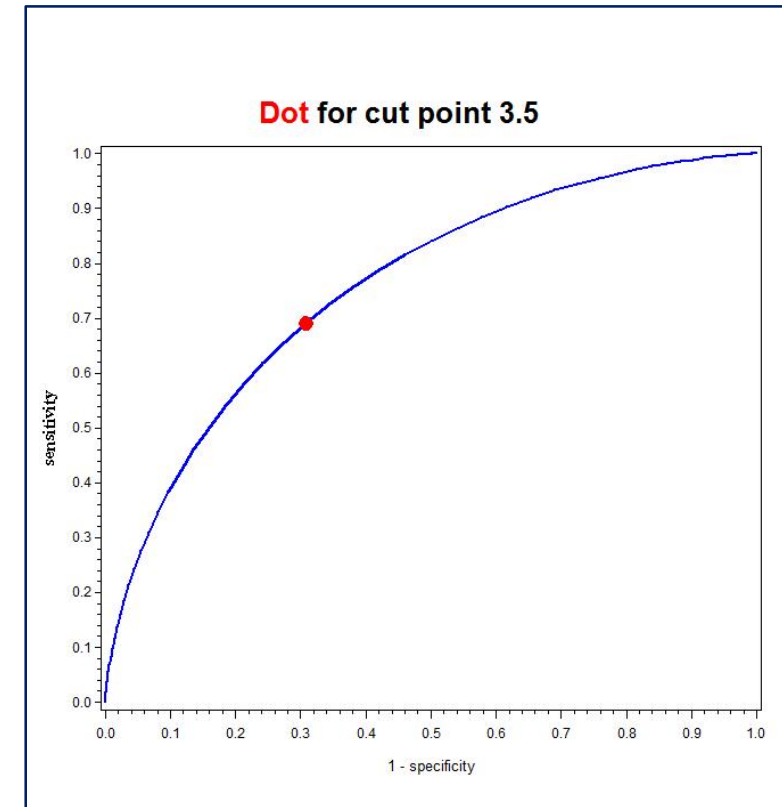
# Receiver Operating Characteristic Curve

Cut point 3.5



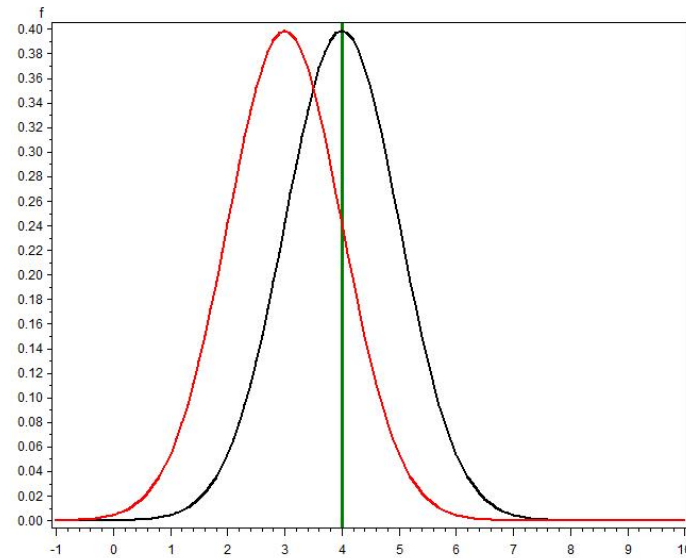
Logits of 1s  
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Logits of 0s  
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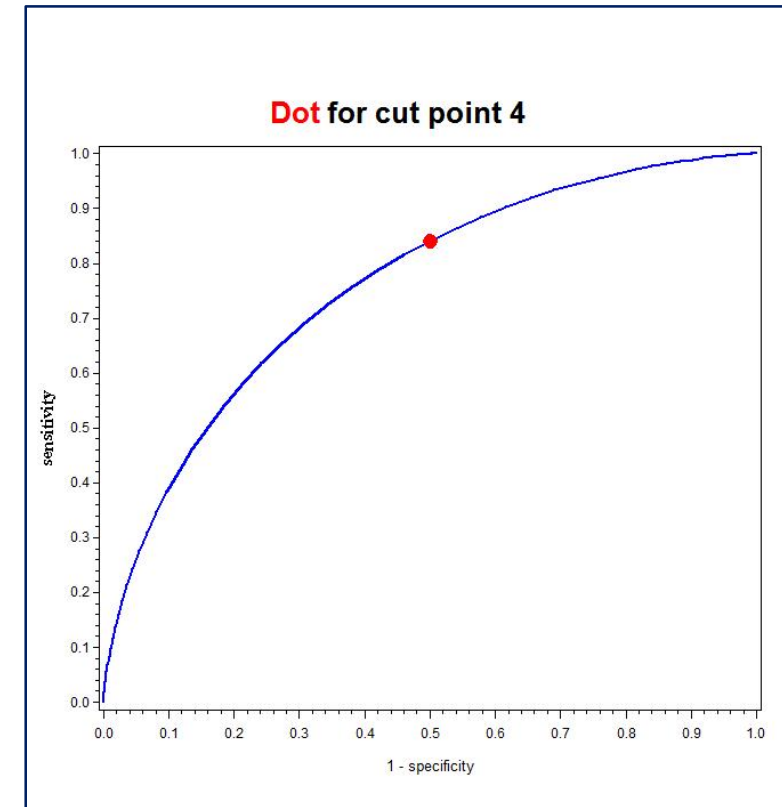
# Receiver Operating Characteristic Curve

Cut point 4



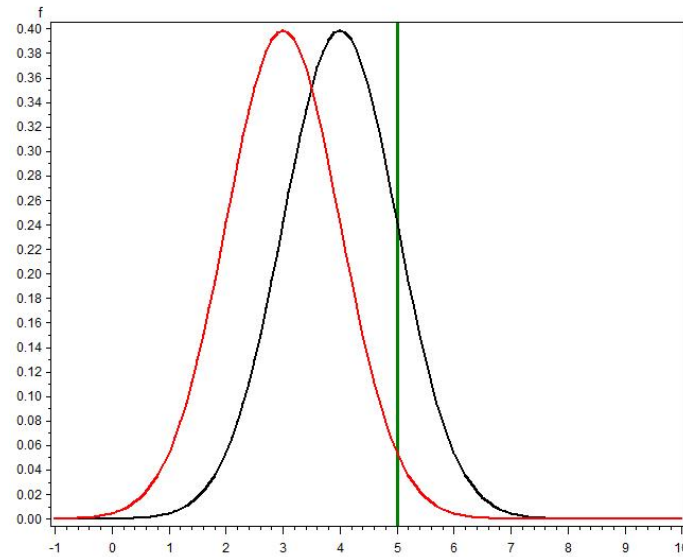
Logits of 1s  
red

Logits of 0s  
black



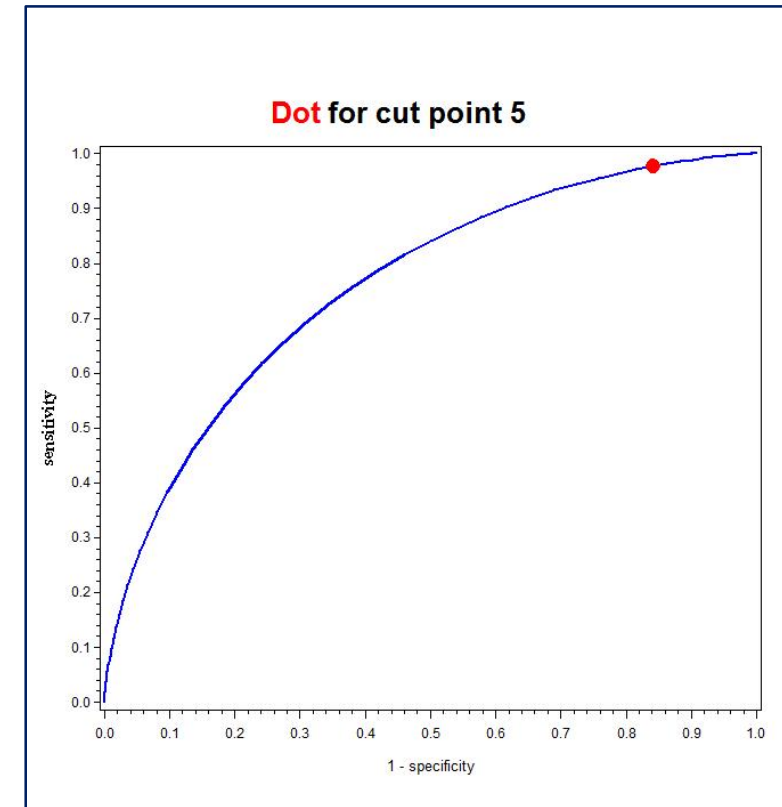
# Receiver Operating Characteristic Curve

Cut point 5



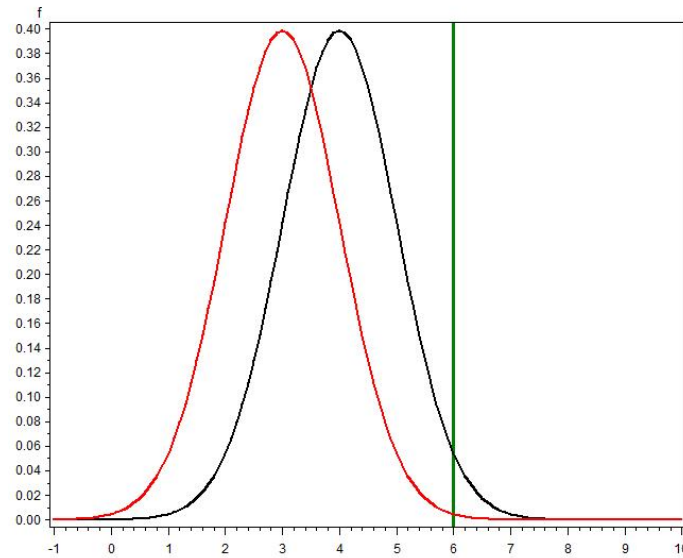
Logits of 1s  
red

Logits of 0s  
black



# Receiver Operating Characteristic Curve

Cut point 6



Logits of 1s  
red

Logits of 0s  
black

