15-381: Artificial Intelligence

Decision trees

Bayes and Naïve Bayes Classifier

- Bayes classifiers find the label that maximizes:

$$\begin{aligned}\hat{y} &= \arg\max_v \, p(y = v \mid \Phi) \\ &= \arg\max_v \frac{p(\Phi \mid y = v)\, p(y = v)}{p(\Phi)} \\ &= \arg\max_v \, p(\Phi \mid y = v)\, p(y = v)\end{aligned}$$

- Naïve Bayes models assume independence of the features given the label leading to the following over documents and labels:

$$\hat{y} = \arg\max_v \, p(\Phi \mid y = v)\, p(y = v) = \left[\prod_i p(\phi_i \mid y = v, i)\right] p(y = v)$$

Here is a dataset

age	employment	education	edunu	marital	…	job	relation	race	gender	hours	country	wealth
					…							
39	State_gov	Bachelors	13	Never_marri	…	Adm_clerica	Not_in_famil	White	Male	40	United_Stat	poor
51	Self_emp_nc	Bachelors	13	Married	…	Exec_mana	Husband	White	Male	13	United_Stat	poor
39	Private	HS_grad	9	Divorced	…	Handlers_cle	Not_in_famil	White	Male	40	United_Stat	poor
54	Private	11th	7	Married	…	Handlers_cle	Husband	Black	Male	40	United_Stat	poor
28	Private	Bachelors	13	Married	…	Prof_specialt	Wife	Black	Female	40	Cuba	poor
38	Private	Masters	14	Married	…	Exec_mana	Wife	White	Female	40	United_Stat	poor
50	Private	9th	5	Married_spo	…	Other_servic	Not_in_famil	Black	Female	16	Jamaica	poor
52	Self_emp_nc	HS_grad	9	Married	…	Exec_mana	Husband	White	Male	45	United_Stat	rich
31	Private	Masters	14	Never_marri	…	Prof_specialt	Not_in_famil	White	Female	50	United_Stat	rich
42	Private	Bachelors	13	Married	…	Exec_mana	Husband	White	Male	40	United_Stat	rich
37	Private	Some_colleg	10	Married	…	Exec_mana	Husband	Black	Male	80	United_Stat	rich
30	State_gov	Bachelors	13	Married	…	Prof_specialt	Husband	Asian	Male	40	India	rich
24	Private	Bachelors	13	Never_marri	…	Adm_clerica	Own_child	White	Female	30	United_Stat	poor
33	Private	Assoc_acdm	12	Never_marri	…	Sales	Not_in_famil	Black	Male	50	United_Stat	poor
41	Private	Assoc_voc	11	Married	…	Craft_repair	Husband	Asian	Male	40	*MissingValu	rich
34	Private	7th_8th	4	Married	…	Transport_m	Husband	Amer_Indian	Male	45	Mexico	poor
26	Self_emp_nc	HS_grad	9	Never_marri	…	Farming_fish	Own_child	White	Male	35	United_Stat	poor
33	Private	HS_grad	9	Never_marri	…	Machine_op	Unmarried	White	Male	40	United_Stat	poor
38	Private	11th	7	Married	…	Sales	Husband	White	Male	50	United_Stat	poor
44	Self_emp_nc	Masters	14	Divorced	…	Exec_mana	Unmarried	White	Female	45	United_Stat	rich
41	Private	Doctorate	16	Married	…	Prof_specialt	Husband	White	Male	60	United_Stat	rich
:	:	:	:	:	:	:	:	:	:	:	:	:
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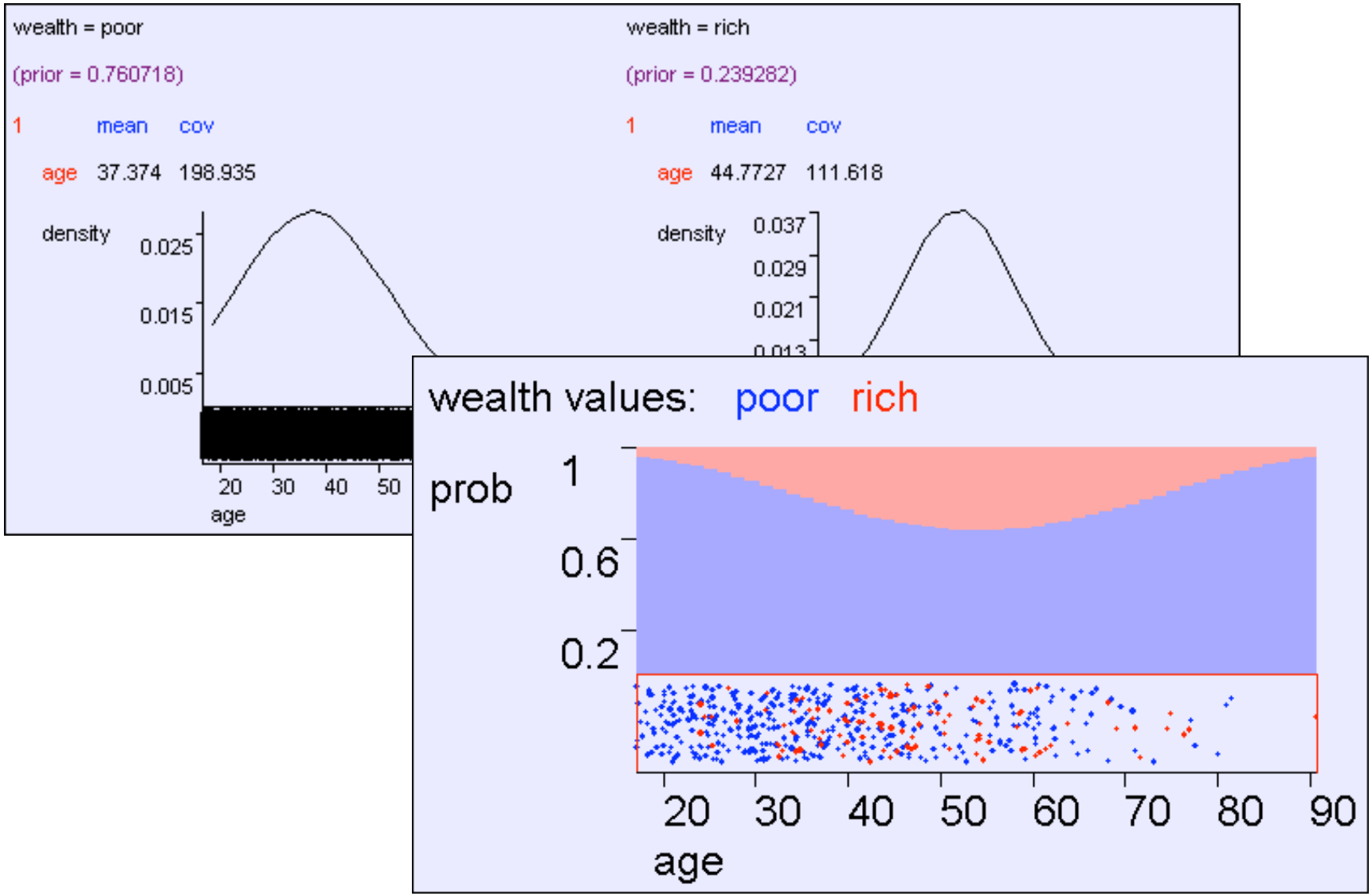
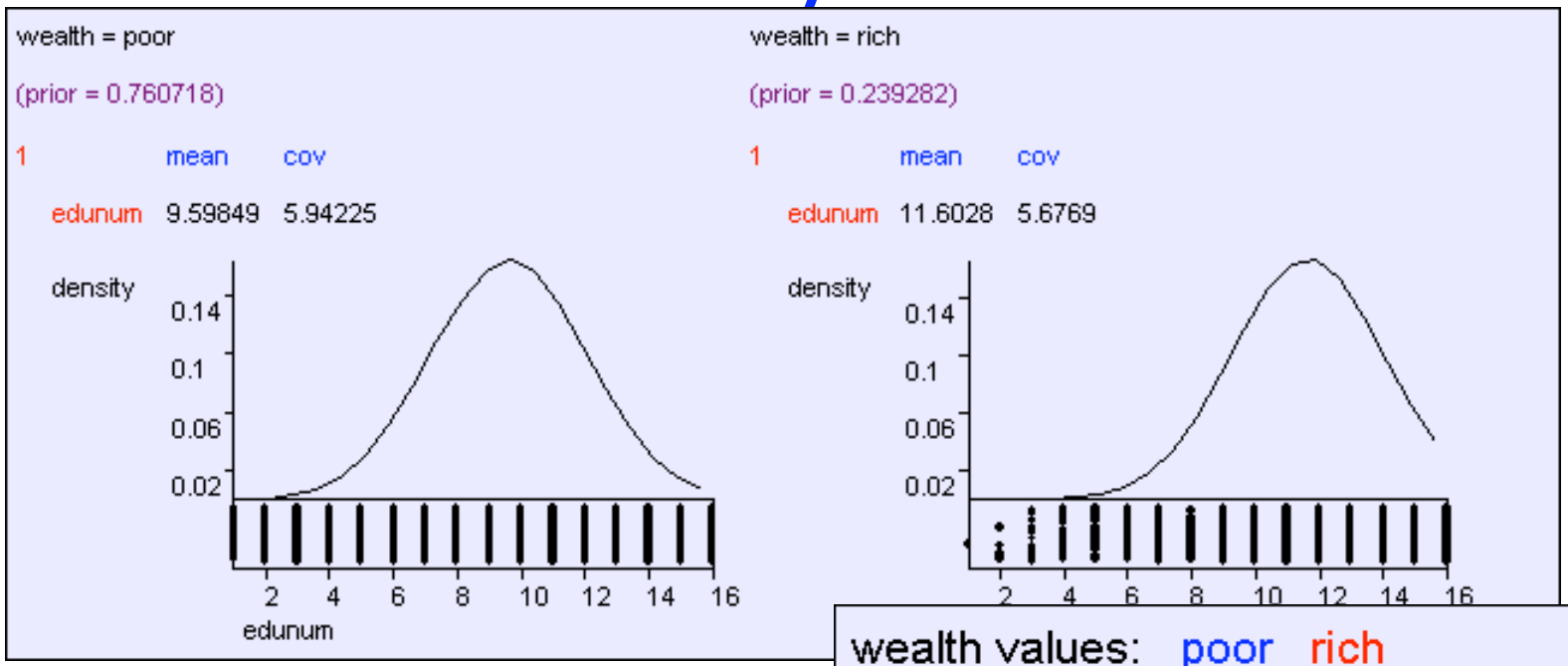
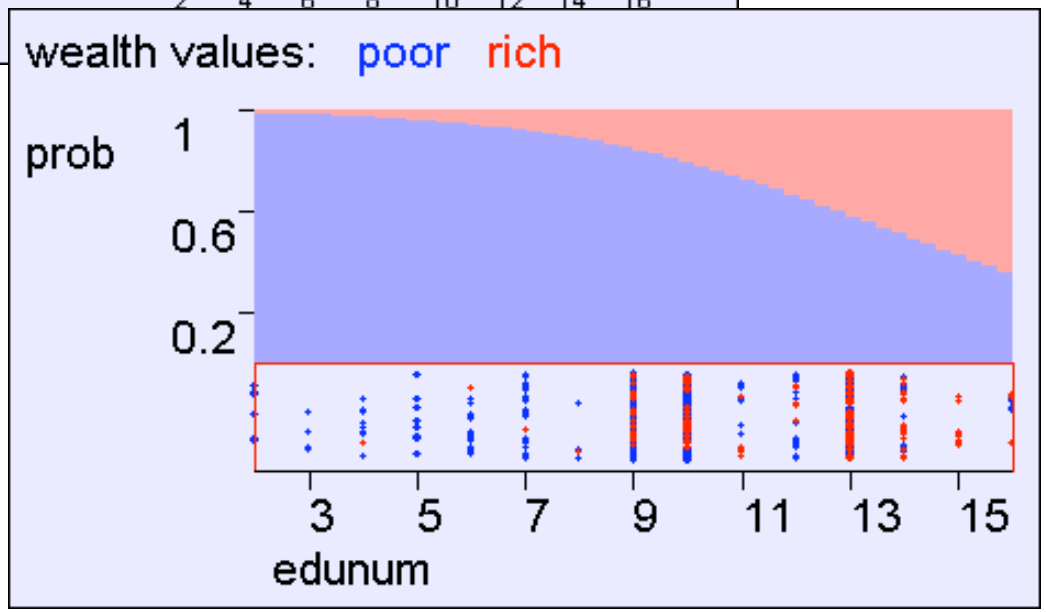
48,000 records, 16 attributes [Kohavi 1995]

Predicting wealth from age



Wealth from years of education





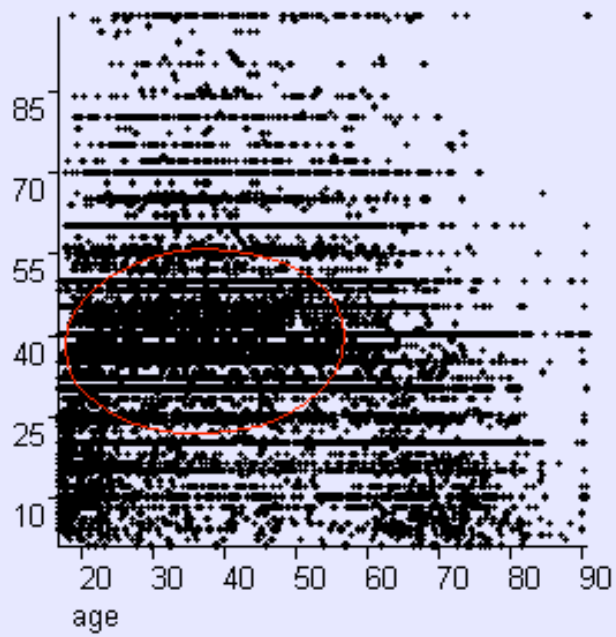
age, hours → wealth

wealth = poor

(prior = 0.760718)

1	mean	cov	
age	37.374	198.935	8.70283
hours_worked	38.84	8.70283	152.692

hours_worked

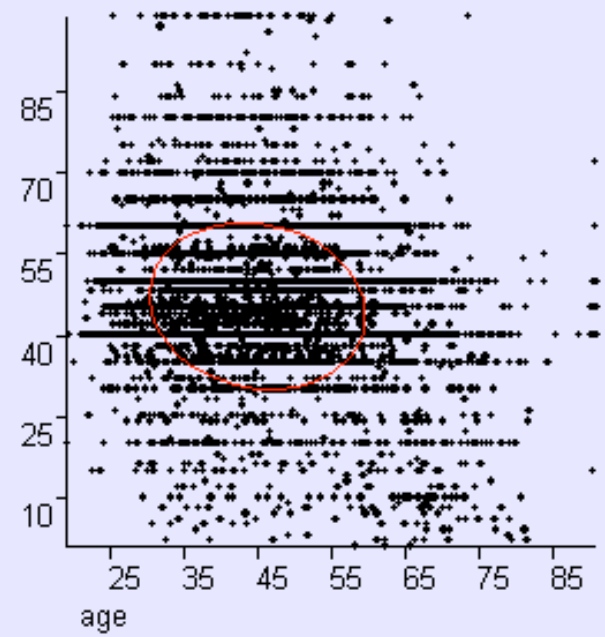


wealth = rich

(prior = 0.239282)

1	mean	cov	
age	44.7727	111.618	-14.1565
hours_worked	45.4529	-14.1565	123.014

hours_worked



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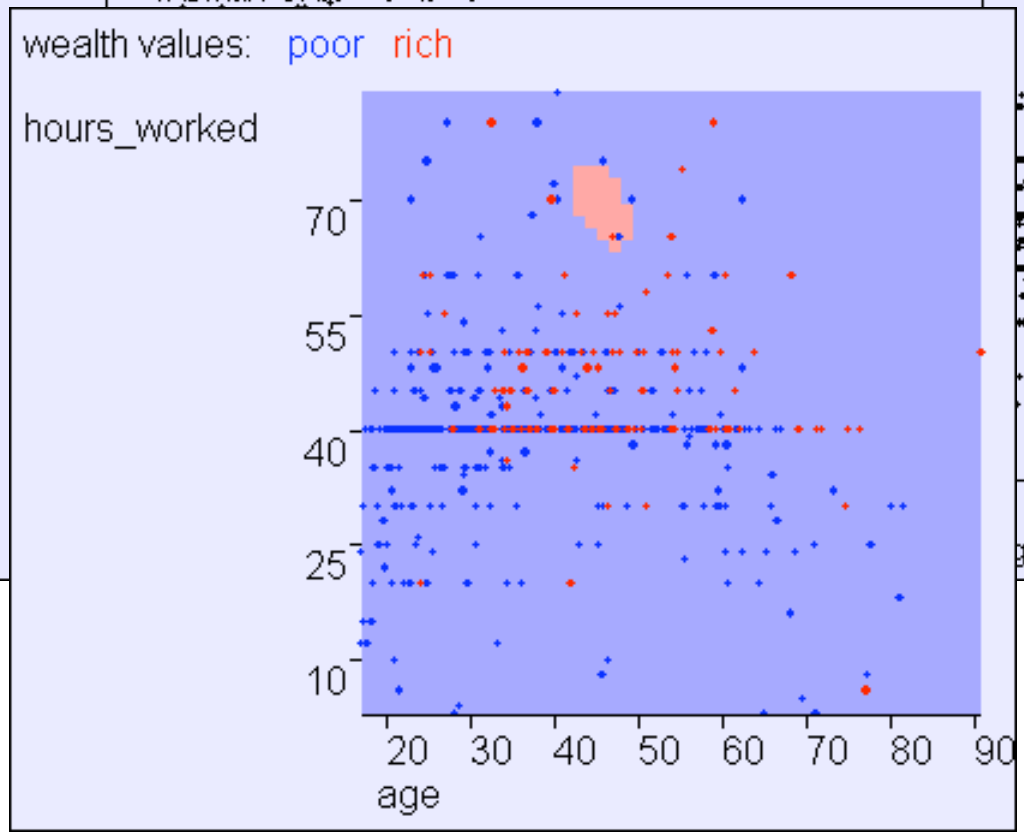


Having 2 inputs instead of one helps in two ways:

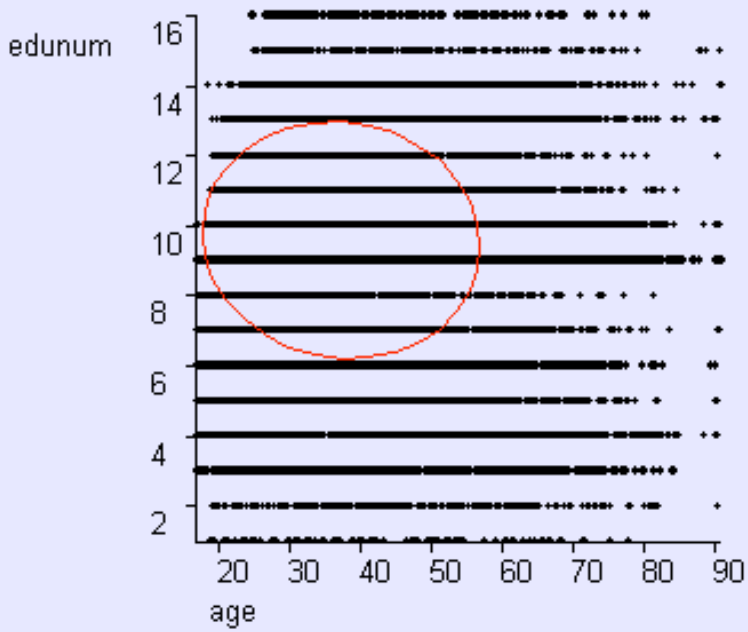
1. Combining evidence from two 1d Gaussians
2. Off-diagonal covariance distinguishes class "shape"

age, edunum → wealth

wealth = poor

(prior = 0.760718)

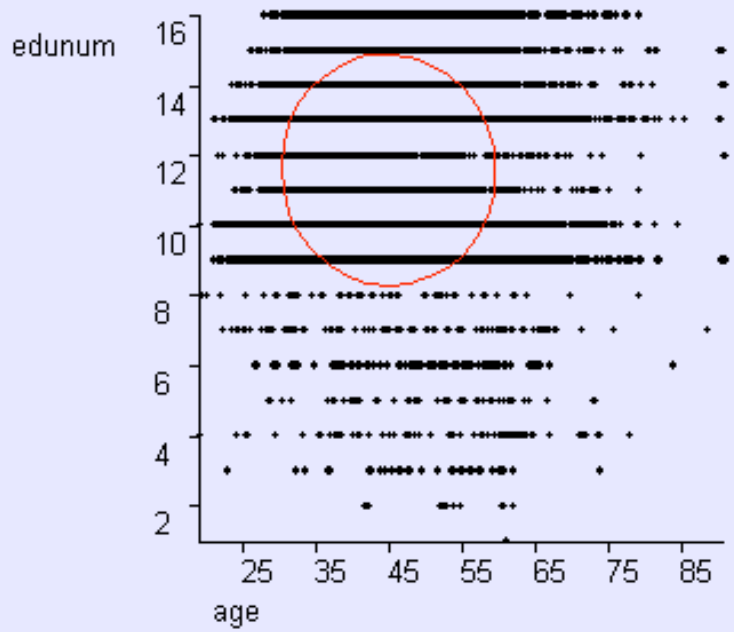
1	mean	cov	
age	37.374	198.935	-1.94765
edunum	9.59849	-1.94765	5.94225



wealth = rich

(prior = 0.239282)

1	mean	cov	
age	44.7727	111.618	-0.557852
edunum	11.6028	-0.557852	5.6769



age, edunum → wealth

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age	37.374	198.935	-1.94765
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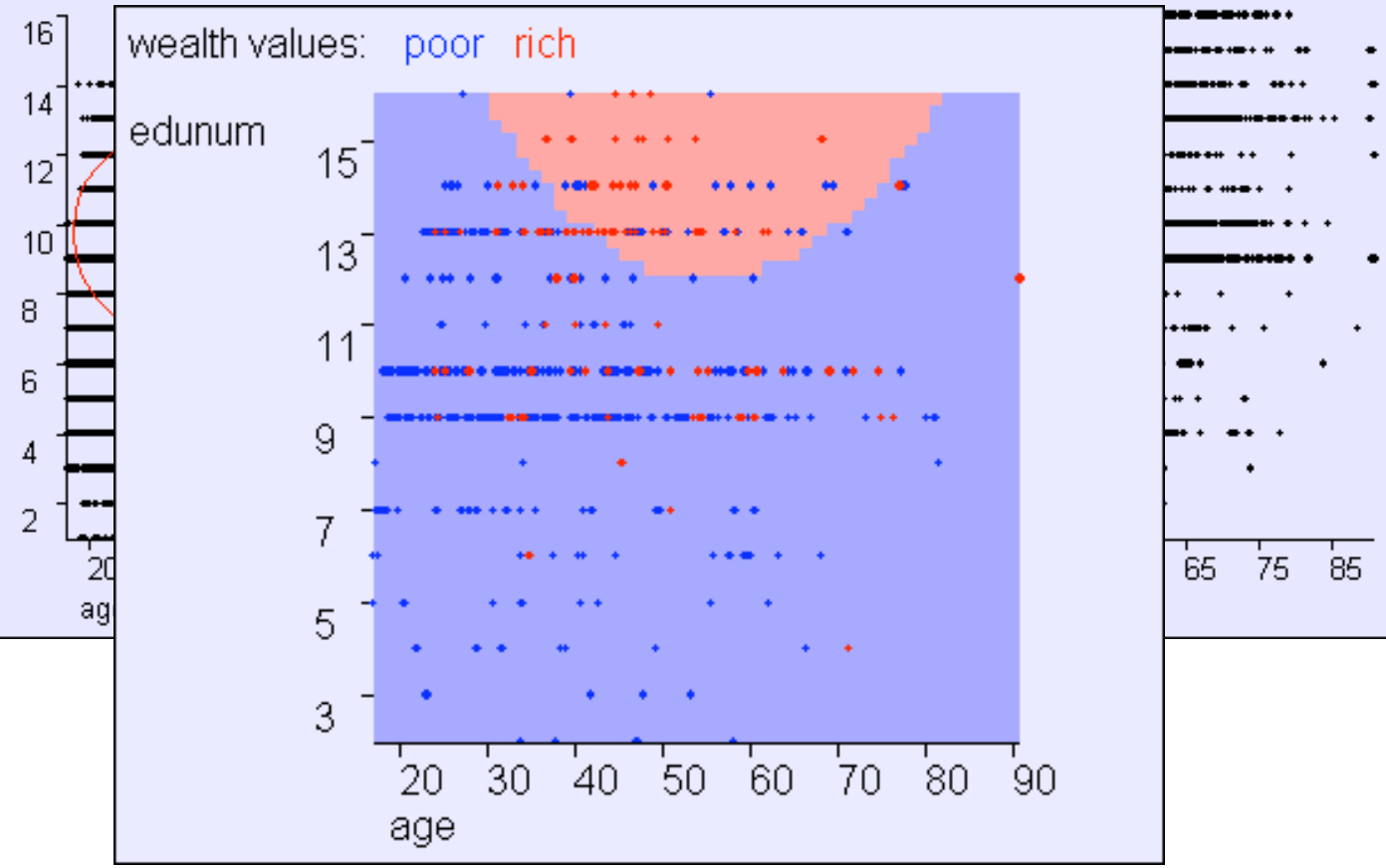
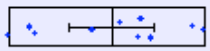
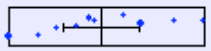
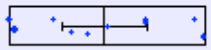
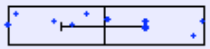


Accuracy

Name	Model	Parameters	FracRight			
age+hours	bayesclass	density=joint submodel=gauss gausstype=general	0.760452	+/-	0.00319521	

Name	Model	Parameters	FracRight			
age+hours+edunum	bayesclass	density=joint submodel=gauss gausstype=general	0.798513	+/-	0.00542432	

Name	Model	Parameters	FracRight			
a+h+e+capgain	bayesclass	density=joint submodel=gauss gausstype=general	0.793518	+/-	0.00319241	

Name	Model	Parameters	FracRight			
a+h+e+c+taxweight	bayesclass	density=joint submodel=gauss gausstype=general	0.793477	+/-	0.00321524	

Generative classification models

- So far we discussed models that capture joint probability distributions
- These have many uses, and as we discussed they can be used to determine binary values for variables
- However, they also rely on specific assumptions and require the estimation of many parameters:
  - model structure
  - probability model
  - model parameters

Generative vs. discriminative models

- Graphical models can be used for classification

  - They represent a subset of classifiers known as ‘generative models’
- But we can also design classifiers that are more specific to a given task and do not require an estimation of joint probabilities

  - These are often referred to as discriminative models
- Examples:

  - Support vector machines (SVM)

  - Decision trees

Decision trees

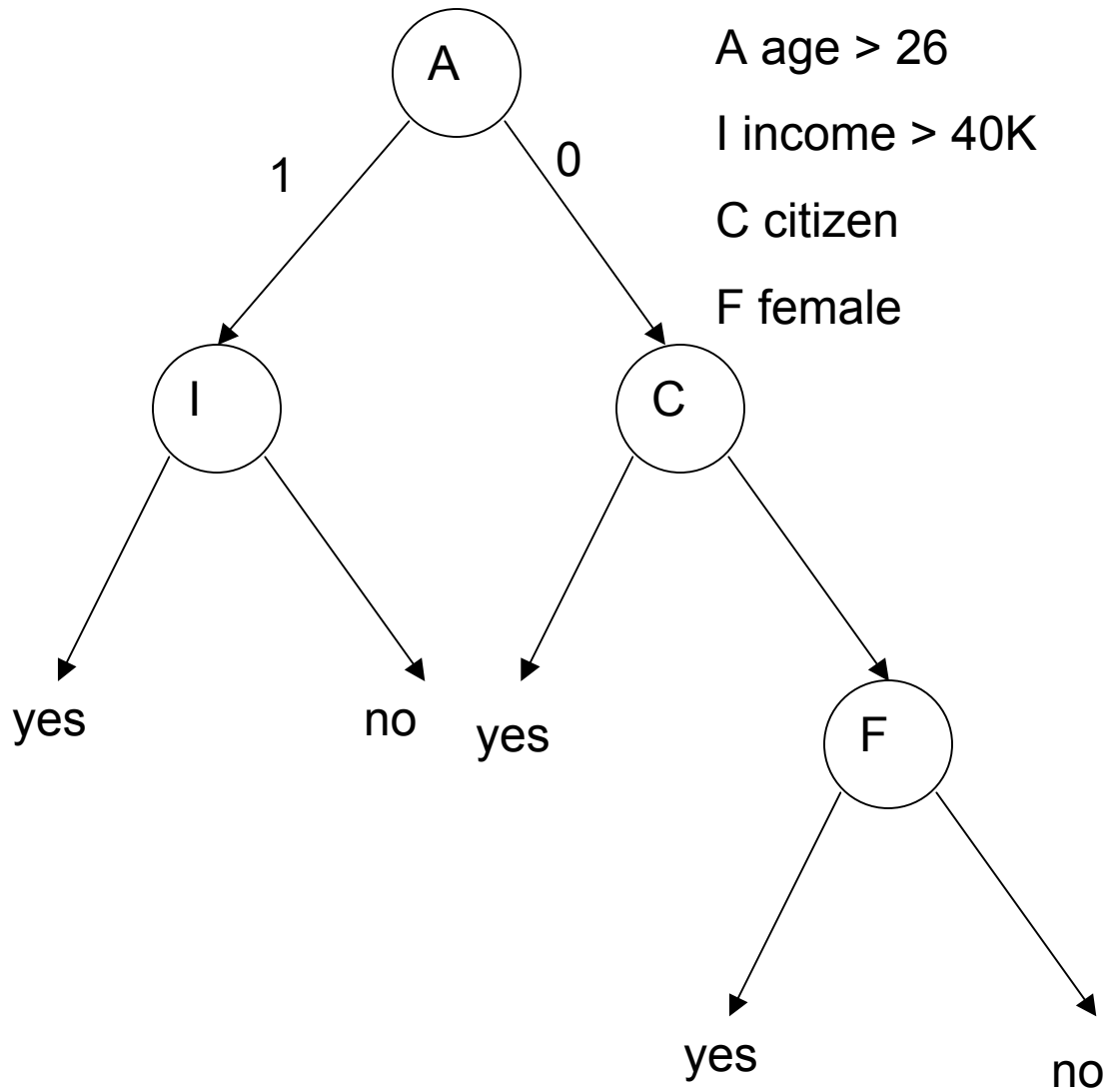
- One of the most intuitive classifiers
- Easy to understand and construct
- Surprisingly, also works very (very) well*

Lets build a decision tree!

* More on this towards the end of this lecture

Structure of a decision tree

- Internal nodes correspond to attributes (features)
- Leafs correspond to classification outcome
- edges denote assignment



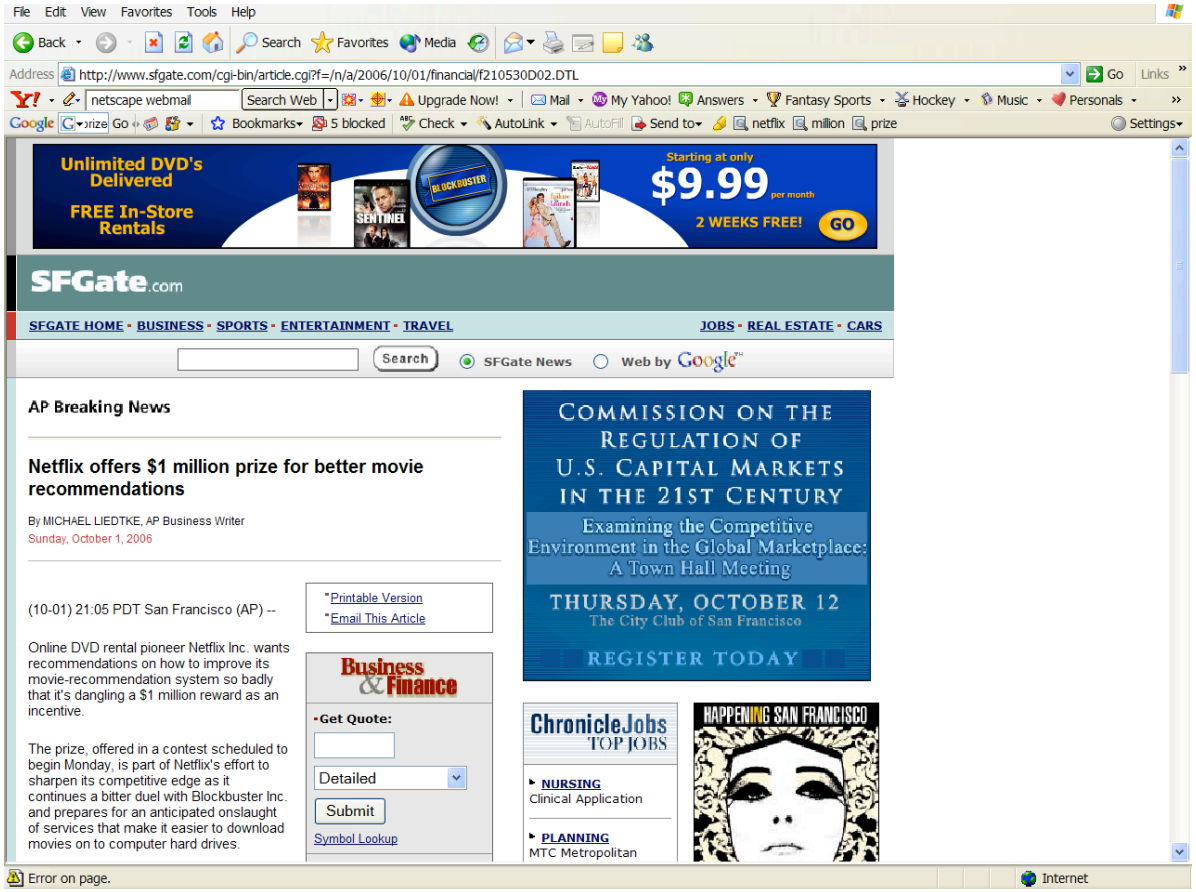
A age > 26

I income > 40K

C citizen

F female

Netflix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Netflix offers $1 million prize for better movie recommendations
By MICHAEL LIEDTKE, AP Business Writer
Sunday, October 1, 2006
(10-01) 21:05 PDT San Francisco (AP) --
Printable Version
Email This Article
Online DVD rental pioneer Netflix Inc. wants recommendations on how to improve its movie-recommendation system so badly that it's dangling a $1 million reward as an incentive.
The prize, offered in a contest scheduled to begin Monday, is part of Netflix's effort to sharpen its competitive edge as it continues a bitter duel with Blockbuster Inc. and prepares for an anticipated onslaught of services that make it easier to download movies on to computer hard drives.
Business & Finance
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Detailed
Submit
Symbol Lookup
COMMISSION ON THE REGULATION OF U.S. CAPITAL MARKETS IN THE 21ST CENTURY
Examining the Competitive Environment in the Global Marketplace: A Town Hall Meeting
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Dataset

Attributes (features)

Label

Movie	Type	Length	Director	Famous actors	Liked?
m1	Comedy	Short	Adamson	No	Yes
m2	Animated	Short	Lasseter	No	No
m3	Drama	Medium	Adamson	No	Yes
m4	animated	long	Lasseter	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m6	Drama	Medium	Singer	Yes	Yes
m7	animated	Short	Singer	No	Yes
m8	Comedy	Long	Adamson	Yes	Yes
m9	Drama	Medium	Lasseter	No	Yes

Building a decision tree

```
Function BuildTree(n,A)    // n: samples (rows), A: attributes
  If empty(A) or all n(L) are the same
      status = leaf
      class = most common class in n(L)
  else
      status = internal
      a ⇐ bestAttribute(n,A)
      LeftNode = BuildTree(n(a=1), A \ {a})
      RightNode = BuildTree(n(a=0), A \ {a})
   end
end
```

Building a decision tree

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Function BuildTree(n,A)    // n: samples (rows), A: attributes
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      RightNode = BuildTree(n(a=0), A \ {a})
   end
end
```

n(L): Labels for samples in this set

We will discuss this function next

Recursive calls to create left and right subtrees, n(a=1) is the set of samples in n for which the attribute a is 1

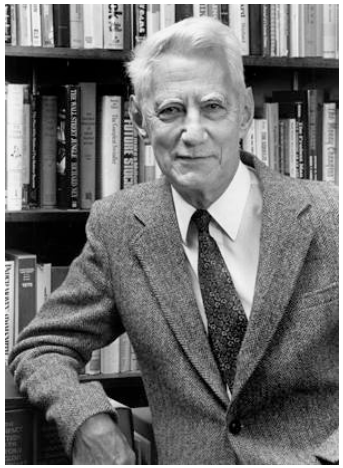
Identifying ‘bestAttribute’

- There are many possible ways to select the best attribute for a given set.
- We will discuss one possible way which is based on information theory and generalizes well to non binary variables

Entropy

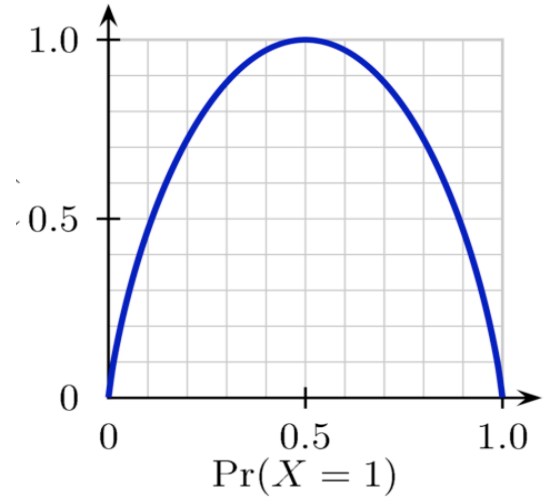
- Quantifies the amount of uncertainty associated with a specific probability distribution
- The higher the entropy, the less confident we are in the outcome
- Definition

$$H(X) = \sum_{c} - p(X = c) \log_2 p(X = c)$$



Claude Shannon (1916 – 2001), most of the work was done in Bell labs

Entropy



- Definition

$$H(X) = \sum_i - p(X = i) \log_2 p(X = i)$$

- So, if P(X=1) = 1 then

$$H(X) = -p(x = 1) \log_2 p(X = 1) - p(x = 0) \log_2 p(X = 0)$$
$$= -1 \log 1 - 0 \log 0 = 0$$

- If P(X=1) = .5 then

$$H(X) = -p(x = 1) \log_2 p(X = 1) - p(x = 0) \log_2 p(X = 0)$$
$$= -.5 \log_2 .5 - .5 \log_2 .5 = -\log_2 .5 = 1$$

Interpreting entropy

- Entropy can be interpreted from an information standpoint
- Assume both sender and receiver know the distribution. How many bits, on average, would it take to transmit one value?
- If $P(X=1) = 1$ then the answer is 0 (we don't need to transmit anything)
- If $P(X=1) = .5$ then the answer is 1 (either values is equally likely)
- If $0<P(X=1)<.5$ or $0.5<P(X=1)<1$ then the answer is between 0 and 1

  - Why?

Expected bits per symbol

- Assume P(X=1) = 0.8
- Then P(11) = 0.64, P(10)=P(01)=.16 and P(00)=.04
- Lets define the following code
  - For 11 we send 0
  - For 10 we send 10
  - For 01 we send 110
  - For 00 we send 1110

Expected bits per symbol

- Assume P(X=1) = 0.8
- Then P(11) = 0.64, P(10)=P(01)=.16 and P(00)=.04
- Lets define the following code
  - For 11 we send 0
  - For 10 we send 10
  - For 01 we send 110
  - For 00 we send 1110

so: 0100110111000110111 0

can be broken to: 0 10 0 110 1110 0 0 110 1110

which is: 11 10 11 01 00 11 11 01 00

- What is the expected bits / symbol?
  (.64*1+.16*2+.16*3+.04*4)/2 = 0.8
- Entropy (lower bound) H(X)=0.7219

Conditional entropy

Movie length	Liked?
Short	Yes
Short	No
Medium	Yes
long	No
Long	No
Medium	Yes
Short	Yes
Long	Yes
Medium	Yes

- Entropy measures the uncertainty in a specific distribution
- What if both sender and receiver know something about the transmission?
- For example, say I want to send the label (liked) when the length is known
- This becomes a conditional entropy problem: $H(Li \mid Le=v)$

Is the entropy of Liked among movies with length v

Conditional entropy: Examples for specific values

Movie length	Liked?
Short	Yes
Short	No
Medium	Yes
long	No
Long	No
Medium	Yes
Short	Yes
Long	Yes
Medium	Yes

Lets compute H(Li | Le=v)

1. H(Li | Le = S) = .92

Conditional entropy: Examples for specific values

Movie length	Liked?
Short	Yes
Short	No
Medium	Yes
long	No
Long	No
Medium	Yes
Short	Yes
Long	Yes
Medium	Yes

Lets compute H(Li | Le=v)

1. H(Li | Le = S) = .92
2. H(Li | Le = M) = 0
3. H(Li | Le = L) = .92

Conditional entropy

Movie length	Liked?
Short	Yes
Short	No
Medium	Yes
long	No
Long	No
Medium	Yes
Short	Yes
Long	Yes
Medium	Yes

- We can generalize the conditional entropy idea to determine H(Li | Le)
- That is, what is the expected number of bits we need to transmit if both sides know the value of Le for each of the records (samples)
- Definition: $$H(X \mid Y) = \sum_i P(Y = i) H(X \mid Y = i)$$

We explained how to compute this in the previous slides

Conditional entropy: Example

$$H(X \mid Y) = \sum_i P(Y = i) H(X \mid Y = i)$$

Movie length	Liked?
Short	Yes
Short	No
Medium	Yes
long	No
Long	No
Medium	Yes
Short	Yes
Long	Yes
Medium	Yes

- Lets compute H(Li | Le)

H(Li | Le) = P(Le = S) H(Li | Le=S)+

P(Le = M) H(Li | Le=M)+

P(Le = L) H(Li | Le=L) =

1/3*.92+1/3*0+1/3*.92 =

0.61

we already computed:

H(Li | Le = S) = .92

H(Li | Le = M) = 0

H(Li | Le = L) = .92

Information gain

- How much do we gain (in terms of reduction in entropy) from knowing one of the attributes
- In other words, what is the reduction in entropy from this knowledge
- Definition: $IG(X|Y)^* = H(X)-H(X|Y)$

*$IG(X|Y)$ is always ≥ 0

Proof: Jensen inequality

Where we are

- We were looking for a good criteria for selecting the best attribute for a node split
- We defined the entropy, conditional entropy and information gain
- We will now use information gain as our criteria for a good split
- That is, BestAttribute will return the attribute that maximizes the information gain at each node

Building a decision tree

```
Function BuildTree(n,A)    // n: samples (rows), A: attributes
  If empty(A) or all n(L) are the same
      status = leaf
      class = most common class in n(L)
  else
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      a ⇐ bestAttribute(n,A)
      LeftNode = BuildTree(n(a=1), A \ {a})
      RightNode = BuildTree(n(a=0), A \ {a})
   end
end
```

Based on information gain

Example: Root attribute

P(Li=yes) = 2/3

H(Li) = .91

H(Li | T) =

H(Li | Le) =

H(Li | D) =

H(Li | F) =

Movie	Type	Length	Director	Famous actors	Liked ?
m1	Comedy	Short	Adamson	No	Yes
m2	Animated	Short	Lasseter	No	No
m3	Drama	Medium	Reiner	No	Yes
m4	animated	long	Adamson	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m6	Thriller	Medium	Singer	Yes	Yes
M7	animated	Short	Singer	No	Yes
m8	Comedy	Long	Marshall	Yes	Yes
m9	Drama	Medium	Linklater	No	Yes

Example: Root attribute

P(Li=yes) = 2/3

H(Li) = .91

H(Li | T) = 0.61

H(Li | Le) = 0.61

H(Li | D) = 0.36

H(Li | F) = 0.85

Movie	Type	Length	Director	Famous actors	Liked ?
m1	Comedy	Short	Adamson	No	Yes
m2	Animated	Short	Lasseter	No	No
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Example: Root attribute

P(Li=yes) = 2/3

H(Li) = .91

H(Li | T) = 0.61

H(Li | Le) = 0.61

H(Li | D) = 0.36

H(Li | F) = 0.85

IG(Li | T) = .91-.61 = 0.3

IG(Li | Le) = .91-.61 = 0.3

IG(Li | D) = .91-.36 = 0.55

IG(Li | Le) = .91-.85 = 0.06

Movie	Type	Length	Director	Famous actors	Liked ?
m1	Comedy	Short	Adamson	No	Yes
m2	Animated	Short	Lasseter	No	No
m3	Drama	Medium	Adamson	No	Yes
m4	animated	long	Lasseter	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m6	Drama	Medium	Singer	Yes	Yes
M7	animated	Short	Singer	No	Yes
m8	Comedy	Long	Adamson	Yes	Yes
m9	Drama	Medium	Lasseter	No	Yes

Example: Root attribute

P(Li=yes) = 2/3

H(Li) = .91

H(Li | T) = 0.61

H(Li | Le) = 0.61

H(Li | D) = 0.36

H(Li | F) = 0.85

IG(Li | T) = .91-.61 = 0.3

IG(Li | Le) = .91-.61 = 0.3

IG(Li | D) = .91-.36 = 0.55

IG(Li | Le) = .91-.85 = 0.06

Movie	Type	Length	Director	Famous actors	Liked ?
m1	Comedy	Short	Adamson	No	Yes
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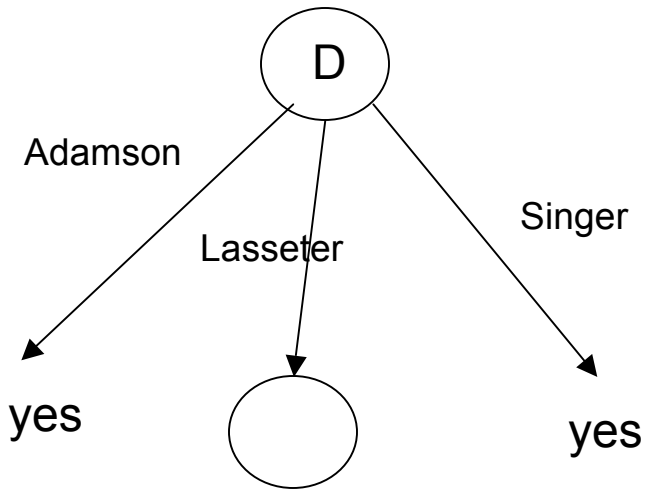
m4	animated	long	Lasseter	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m6	Drama	Medium	Singer	Yes	Yes
M7	animated	Short	Singer	No	Yes
m8	Comedy	Long	Adamson	Yes	Yes
m9	Drama	Medium	Lasseter	No	Yes

Building a tree



Movie	Type	Length	Director	Famous actors	Liked ?
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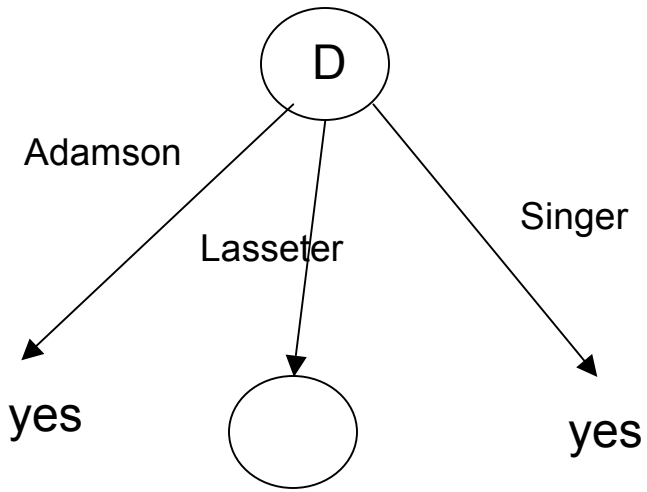
m6	Drama	Medium	Singer	Yes	Yes
M7	animated	Short	Singer	No	Yes
m8	Comedy	Long	Adamson	Yes	Yes
m9	Drama	Medium	Lasseter	No	Yes

Building a tree

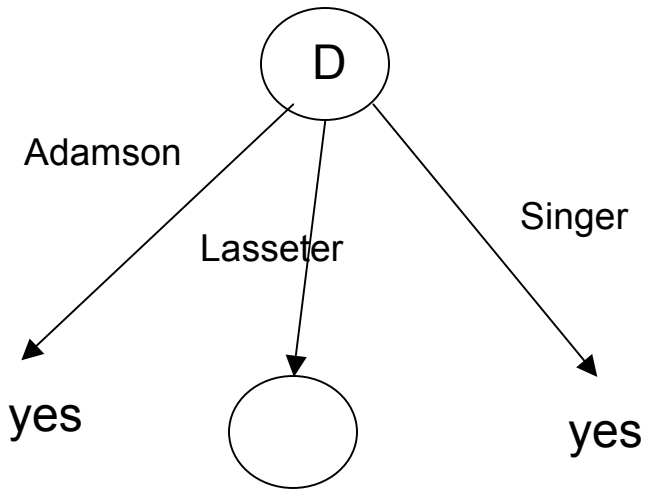


Movie	Type	Length	Director	Famous actors	Liked ?
m2	Animated	Short	Lasseter	No	No
m4	animated	long	Lasseter	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m9	Drama	Medium	Lasseter	No	Yes

We only need to focus on the records (samples) associated with this node

Building a tree

We eliminated the 'director' attribute. All samples have the same director



Movie	Type	Length	Famous actors	Liked ?
m2	Animated	Short	No	No
m4	animated	long	Yes	No
m5	Comedy	Long	Yes	No
m9	Drama	Medium	No	Yes

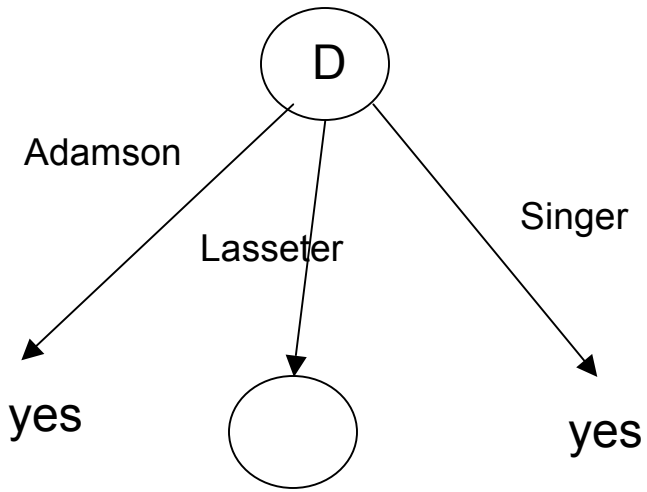
P(Li=yes) = 1/4 H(Li) = .81

H(Li | T) = 0

H(Li | Le) = 0

H(Li | F) = 0.5

Building a tree



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m4	animated	long	Yes	No
m5	Comedy	Long	Yes	No
m9	Drama	Medium	No	Yes

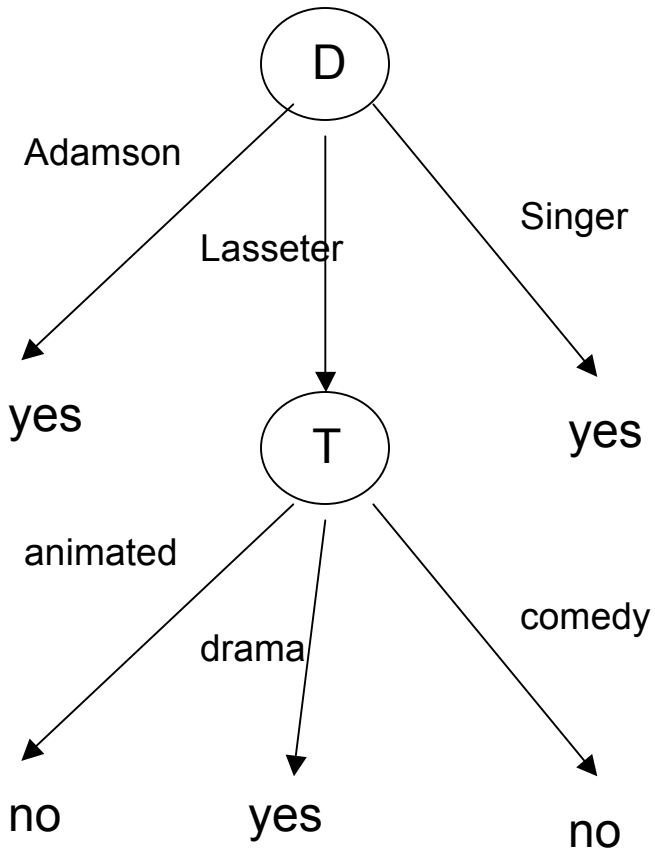
P(Li=yes) = 1/4 H(Li) = .81

H(Li | T) = 0 IG(Li | T) = 0.81

H(Li | Le) = 0 IG(Li | Le) = 0.81

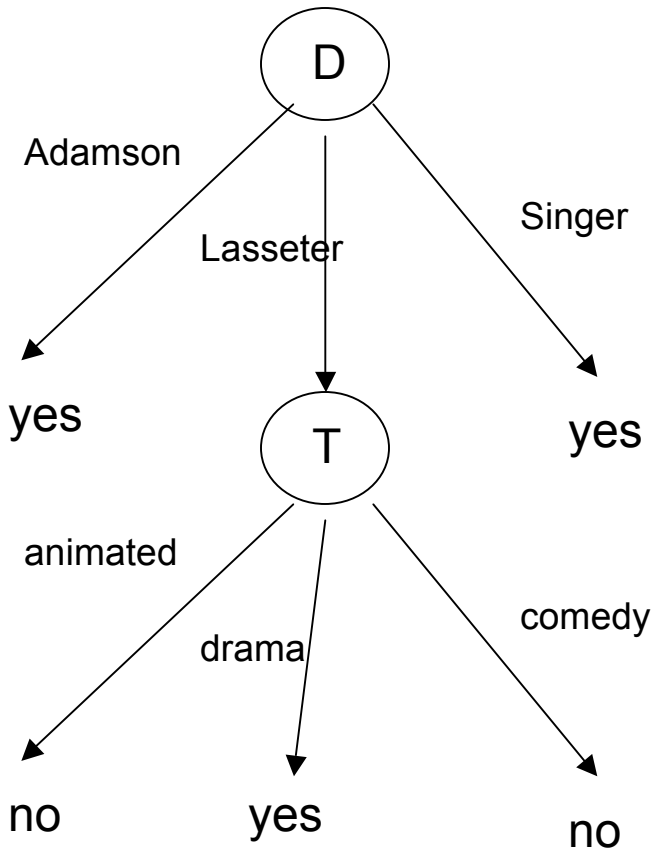
H(Li | F) = 0.5 IG(Li | F) = .31

Building a tree



Movie	Type	Length	Famous actors	Liked ?
m2	Animated	Short	No	No
m4	animated	long	Yes	No
m5	Comedy	Long	Yes	No
m9	Drama	Medium	No	Yes

Final tree



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m4	animated	long	Lasseter	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m6	Drama	Medium	Singer	Yes	Yes
M7	animated	Short	Singer	No	Yes
m8	Comedy	Long	Adamson	Yes	Yes
m9	Drama	Medium	Lasseter	No	Yes

Additional points

- The algorithm we gave reaches homogonous nodes (or runs out of attributes)
- This is dangerous: For datasets with many (non relevant) attributes the algorithm will continue to split nodes
- This will lead to overfitting!

Avoiding overfitting: Tree pruning

- Split data into train and test set
- Build tree using training set

  - For all internal nodes (starting at the root)
    - remove sub tree rooted at node
    - assign class to be the most common among training set
    - check test data error
      - if error is lower, keep change
      - otherwise restore subtree, repeat for all nodes in subtree

Continuous values

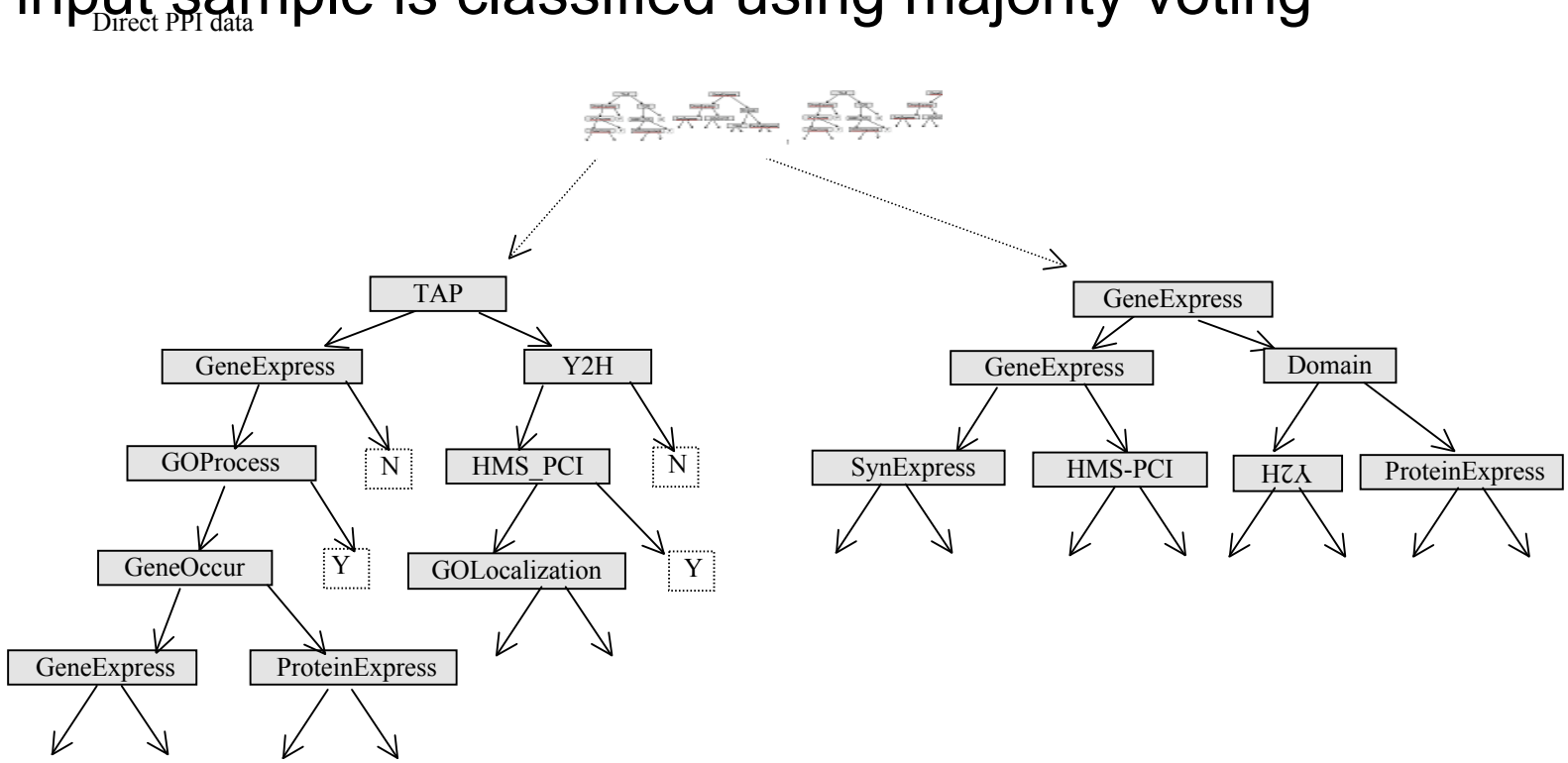
- Either use threshold to turn into binary or discretize
- Its possible to compute information gain for all possible tresholds (there are a finite number of training samples)
- Harder if we wish to assign more than two values (can be done recursively)

The ‘best’ classifier

- There has been a lot of interest lately in decision trees.
- They are quite robust, intuitive and, surprisingly, very accurate

Random forest

- A collection of decision trees
- For each tree we select a subset of the attributes (recommended square root of |A|) and build tree using just these attributes
- An input sample is classified using majority voting



Ranking classifiers

Table 2. Normalized scores for each learning algorithm by metric (average over eleven problems)

MODEL	CAL	ACC	FSC	LFT	ROC	APR	BEP	RMS	MXE	MEAN	OPT-SEL
BST-DT	PLT	.843*	.779	**.939**	**.963**	**.938**	.929*	**.880**	**.896**	**.896**	**.917**
RF	PLT	.872*	.805	.934*	.957	.931	**.930**	.851	.858	.892	.898
BAG-DT	–	.846	.781	.938*	.962*	.937*	.918	.845	.872	.887*	.899
BST-DT	ISO	.826*	.860*	.929*	.952	.921	.925*	.854	.815	.885	.917*
RF	–	**.872**	.790	.934*	.957	.931	**.930**	.829	.830	.884	.890
BAG-DT	PLT	.841	.774	.938*	.962*	.937*	.918	.836	.852	.882	.895
RF	ISO	.861*	**.861**	.923	.946	.910	.925	.836	.776	.880	.895
BAG-DT	ISO	.826	.843*	.933*	.954	.921	.915	.832	.791	.877	.894
SVM	PLT	.824	.760	.895	.938	.898	.913	.831	.836	.862	.880
ANN	–	.803	.762	.910	.936	.892	.899	.811	.821	.854	.885
SVM	ISO	.813	.836*	.892	.925	.882	.911	.814	.744	.852	.882
ANN	PLT	.815	.748	.910	.936	.892	.899	.783	.785	.846	.875
ANN	ISO	.803	.836	.908	.924	.876	.891	.777	.718	.842	.884
BST-DT	–	.834*	.816	**.939**	**.963**	**.938**	.929*	.598	.605	.828	.851
KNN	PLT	.757	.707	.889	.918	.872	.872	.742	.764	.815	.837
KNN	–	.756	.728	.889	.918	.872	.872	.729	.718	.810	.830
KNN	ISO	.755	.758	.882	.907	.854	.869	.738	.706	.809	.844
BST-STMP	PLT	.724	.651	.876	.908	.853	.845	.716	.754	.791	.808
SVM	–	.817	.804	.895	.938	.899	.913	.514	.467	.781	.810
BST-STMP	ISO	.709	.744	.873	.899	.835	.840	.695	.646	.780	.810
BST-STMP	–	.741	.684	.876	.908	.853	.845	.394	.382	.710	.726
DT	ISO	.648	.654	.818	.838	.756	.778	.590	.589	.709	.774
DT	–	.647	.639	.824	.843	.762	.777	.562	.607	.708	.763
DT	PLT	.651	.618	.824	.843	.762	.777	.575	.594	.706	.761
LR	–	.636	.545	.823	.852	.743	.734	.620	.645	.700	.710
LR	ISO	.627	.567	.818	.847	.735	.742	.608	.589	.692	.703
LR	PLT	.630	.500	.823	.852	.743	.734	.593	.604	.685	.695
NB	ISO	.579	.468	.779	.820	.727	.733	.572	.555	.654	.661
NB	PLT	.576	.448	.780	.824	.738	.735	.537	.559	.650	.654
NB	–	.496	.562	.781	.825	.738	.735	.347	-.633	.481	.489

Rich Caruana & Alexandru Niculescu-Mizil, An Empirical Comparison of Supervised Learning Algorithms, ICML 2006

Important points

- Classifiers vs. graphical models
- Entropy
- Information gain
- Building decision trees