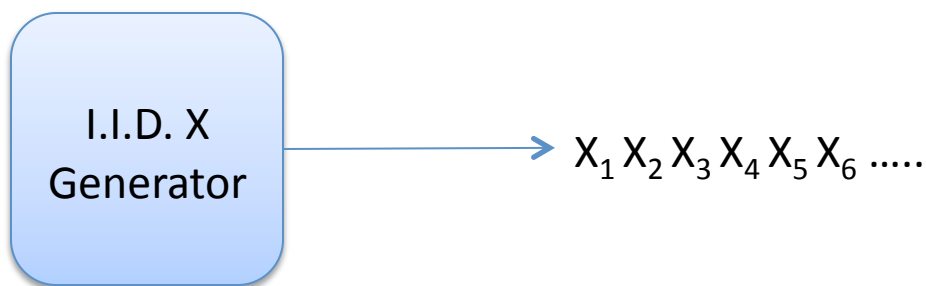


Information Theory and Decision Trees

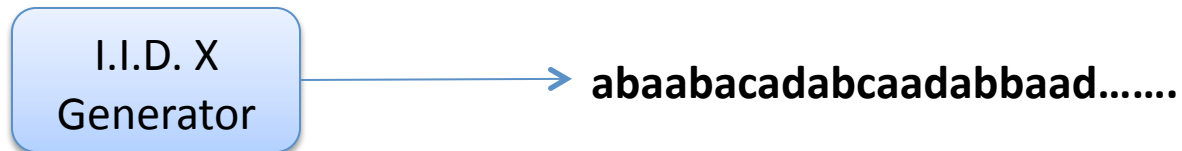
Entropy

- For a discrete random variable X
- Entropy: $H(X) = - \sum p(x) \log_2(p(x))$
- The “average number of bits needed each symbol of X ”

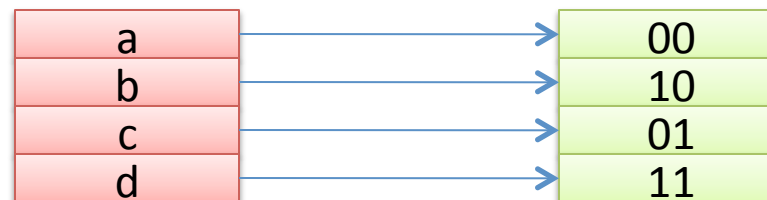


Example

- X generates 4 possible symbols {a,b,c,d}
 - $P(X = 'a') = 0.5$
 - $P(X = 'b') = 0.25$
 - $P(X = 'c') = 0.125$
 - $P(X = 'd') = 0.125$



Naïve Encoding:



Naïve Encoding

- X generates 4 possible symbols {a,b,c,d}
 - $P(X = 'a') = 0.5$
 - $P(X = 'b') = 0.25$
 - $P(X = 'c') = 0.125$
 - $P(X = 'd') = 0.125$

Naïve Encoding:

a	→	00
b	→	10
c	→	01
d	→	11

Average cost of encoding each symbol?

Length of Encoding symbol 'a' * Probability of symbol 'a'

Length of Encoding symbol 'b' * Probability of symbol 'b'

2 * 0.5	
2 * 0.25	+
2 * 0.125	+
2 * 0.125	+
= 2 bits	

We Can Do Better

- X generates 4 possible symbols {a,b,c,d}
 - $P(X = 'a') = 0.5$
 - $P(X = 'b') = 0.25$
 - $P(X = 'c') = 0.125$
 - $P(X = 'd') = 0.125$

Better Encoding:

a	→	0
b	→	10
c	→	110
d	→	111

Average cost of encoding each symbol?

Length of Encoding symbol 'a' * Probability of symbol 'a'

Length of Encoding symbol 'b' * Probability of symbol 'b'

1 * 0.5	
2 * 0.25	+
3 * 0.125	+
3 * 0.125	+

= 1.25 bits

This Encoding is Optimal

We Can Do Better

- X generates 4 possible symbols {a,b,c,d}
 - $P(X = 'a') = 0.5$
 - $P(X = 'b') = 0.25$
 - $P(X = 'c') = 0.125$
 - $P(X = 'd') = 0.125$

Better Encoding:



Average cost of encoding each symbol?

Length of Encoding symbol 'a' * Probability of symbol 'a'	1 * 0.5	
Length of Encoding symbol 'b' * Probability of symbol 'b'	2 * 0.25	+
...	3 * 0.125	+
...	3 * 0.125	+
		= 1.25 bits

But observe that:

$$-\log(0.5) = 1$$

$$-\log(0.25) = 2 \dots \text{etc}$$

$$\text{Length of Encoding of symbol } x = -\log(x)$$

$$\text{Average Cost of encoding a symbol} = - \sum p(x) \log_2(p(x)) = H(X)$$

More Generally

- X generates 4 possible symbols {a,b,c,d}
 - $P(X = 'a') = 0.21$
 - $P(X = 'b') = 0.14$
 - $P(X = 'c') = 0.52$
 - $P(X = 'd') = 0.13$

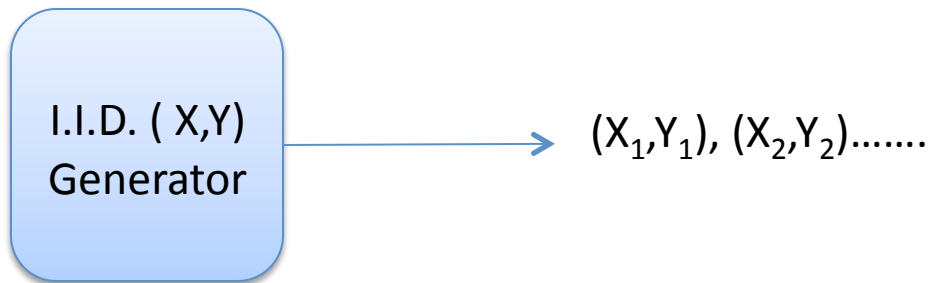
What is the optimal encoding for this?

It is possible to attain an average of $H(X)$ bits per symbol, but quite complicated: See **Arithmetic Compression**

Conditional Entropy

- $$H(X|Y) = \sum_y p(y) \sum_x H(X|Y = y)$$
$$= \sum_y p(y) \sum_x p(x|y) \log p(x|y)$$

Intuition: Average # bits needed to Encode Y, if X is already transmitted



Information Gain

- $H(X) = - \sum p(x) \log_2(p(x))$
- $H(X|Y) = \sum_y p(y) \sum H(X|Y = y)$
 $= \sum_y p(y) \sum_x p(x|y) \log p(x|y)$

$$IG(X,Y) = H(X) - H(X|Y)$$

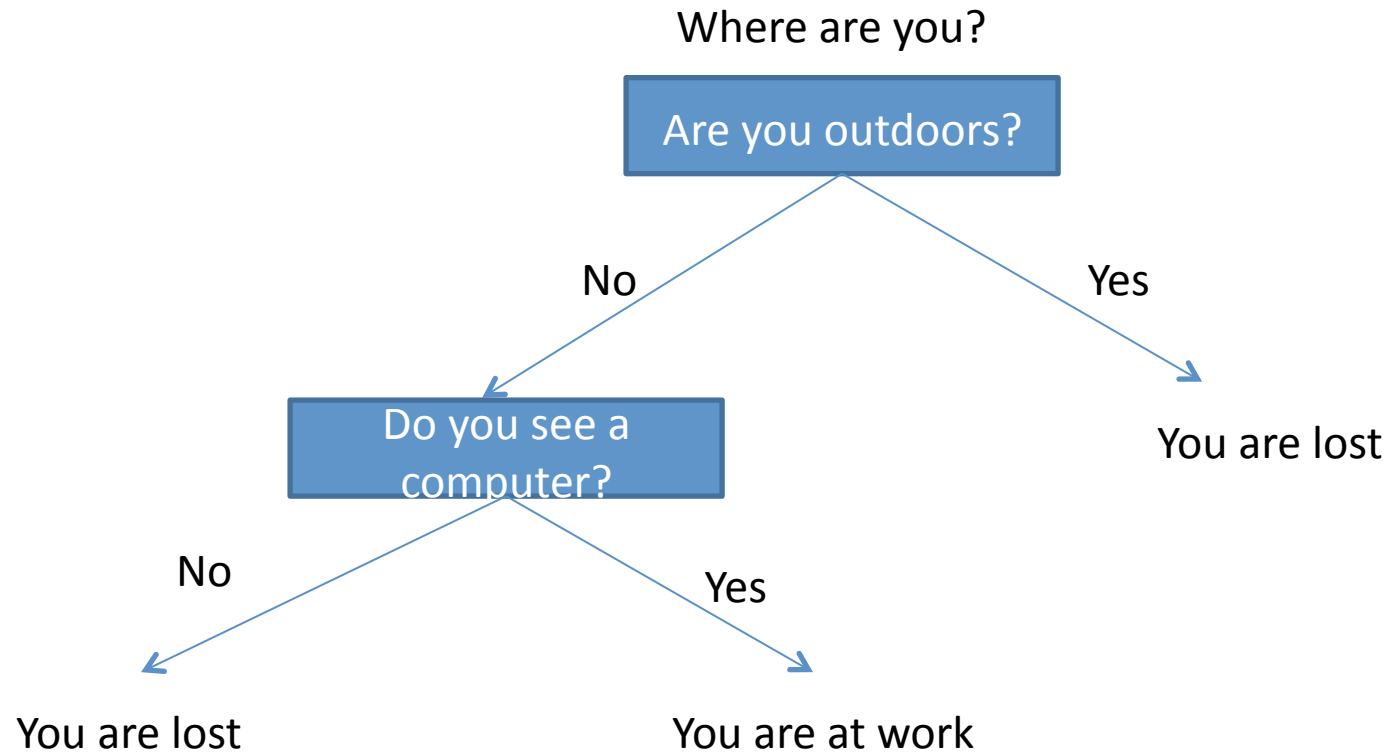
$H(X)$: # bits to encode X

$H(X|Y)$: # bits to encode X if Y is already transmitted

$IG(X,Y)$: The “number of bits of information” gained about X , by knowing Y

Counter Intuitive Property: $IG(X, Y) = IG(Y, X)$

Decision Tree



ID3

Heuristic: Pick the variable which provides the most Information Gain about Y

Outdoors	Computer	Lost	Count
T	T	T	2
T	F	T	2
F	T	F	5
F	F	T	1

ID3

Heuristic: Pick the variable which provides the most Information Gain about Y

X1	X2	Y	Count
T	T	T	2
T	F	T	2
F	T	F	5
F	F	T	1

$$IG(X1,Y) = H(Y) - H(Y | X1)$$

$$H(Y) = - (5/10) \log(5/10) - 5/10 \log(5/10) = 1$$

$$\begin{aligned} H(Y | X1) &= P(X1=T) H(Y | X1=T) + P(X1=F) H(Y | X1=F) \\ &= (4/10) * (1 \log(1) - 0 \log(0)) + (6/10) * (-(5/6) \log(5/6) - (1/6) \log(1/6)) \\ &= 0.3900 \end{aligned}$$

$$IG(X1, Y) = 0.6100$$

ID3

Heuristic: Pick the variable which provides the most Information Gain about Y

X1	X2	Y	Count
T	T	T	2
T	F	T	2
F	T	F	5
F	F	T	1

$$IG(X2, Y) = H(Y) - H(Y | X2)$$

$$H(Y) = - (5/10) \log(5/10) - 5/10 \log(5/10) = 1$$

$$\begin{aligned}
 H(Y | X2) &= P(X2=T) H(Y | X2=T) + P(X2=F) H(Y | X2=F) \\
 &= (7/10) * (-(2/7) \log(2/7) - (5/7) \log(5/7)) + (3/10) * (-(2/3) \log(2/3) - (1/3) \log(1/3)) \\
 &= 0.8797
 \end{aligned}$$

$$IG(X2, Y) = 0.1203$$

ID3

Heuristic: Pick the variable which provides the most Information Gain about Y

Outdoors	Computer	Lost	Count
T	T	T	2
T	F	T	2
F	T	F	5
F	F	T	1

$$IG(X1, Y) = 0.6100$$

$$IG(X2, Y) = 0.1203$$

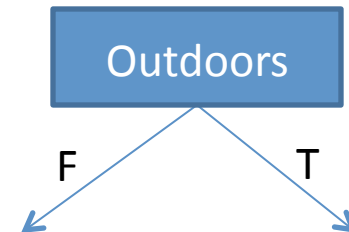
ID3

Heuristic: Pick the variable which provides the most Information Gain about Y

Outdoors	Computer	Lost	Count
T	T	T	2
T	F	T	2
F	T	F	5
F	F	T	1

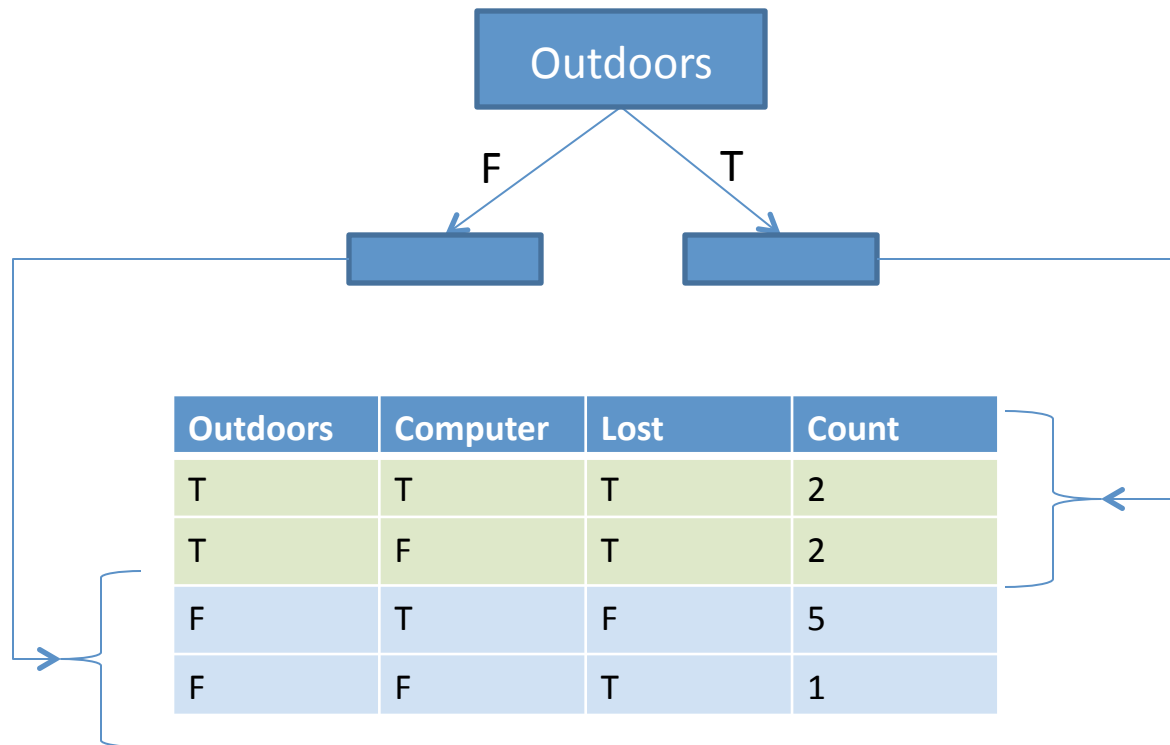
$$\text{IG}(\text{Lost}, \text{Outdoors}) = 0.6100$$

$$\text{IG}(\text{Lost}, \text{Computer}) = 0.1203$$



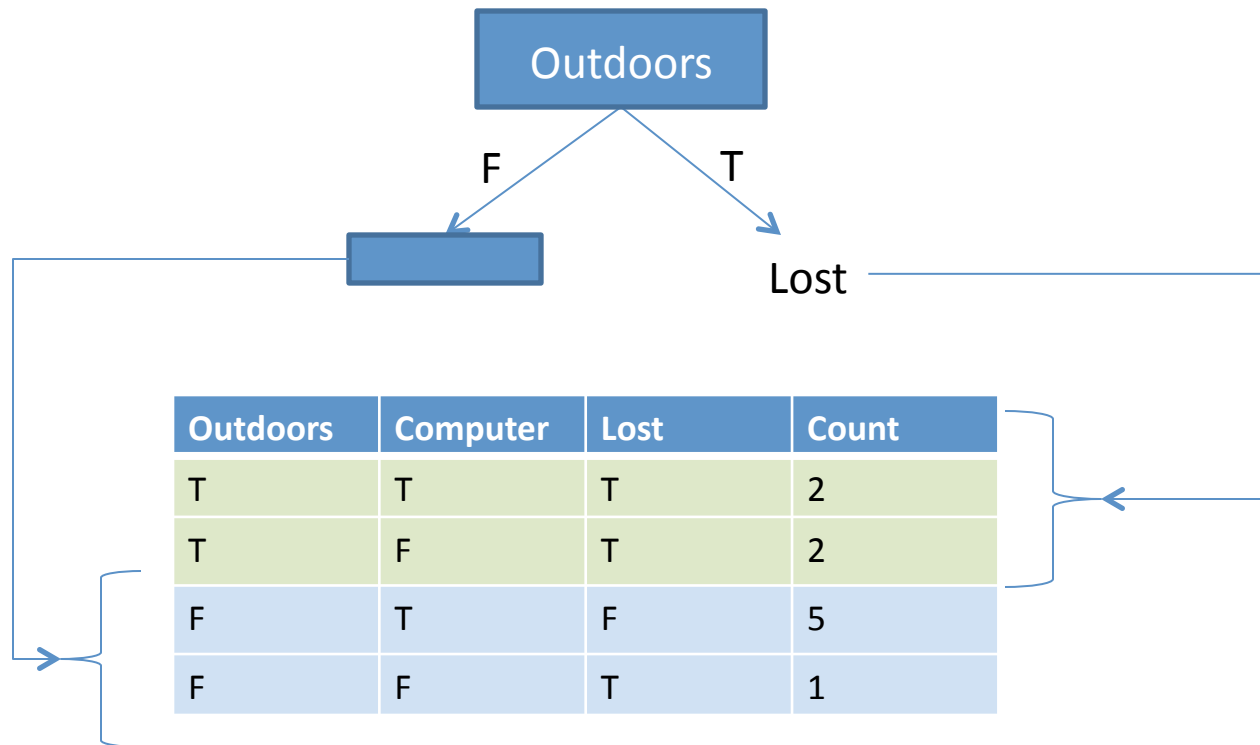
ID3

Heuristic: Pick the variable which provides the most Information Gain about Y
Recurse on the branches



ID3

Heuristic: Pick the variable which provides the most Information Gain about Y
Recurse on the branches



Chi Square Pruning

- Decision Trees tend to overfit
- Pruning Necessary
- Bottom Up Pruning

Chi Square Pruning

1. Build Complete Tree
2. Consider each “leaf” decision and perform the chi-square test (label vs split variable)

Chi Square Pruning

of instances entering this decision: s

of + instances entering this decision: p

of - instances entering this decision: n



...

F

T

instances here: s_f

of + instances here: p_f

of - instances here: n_f

instances here: s_t

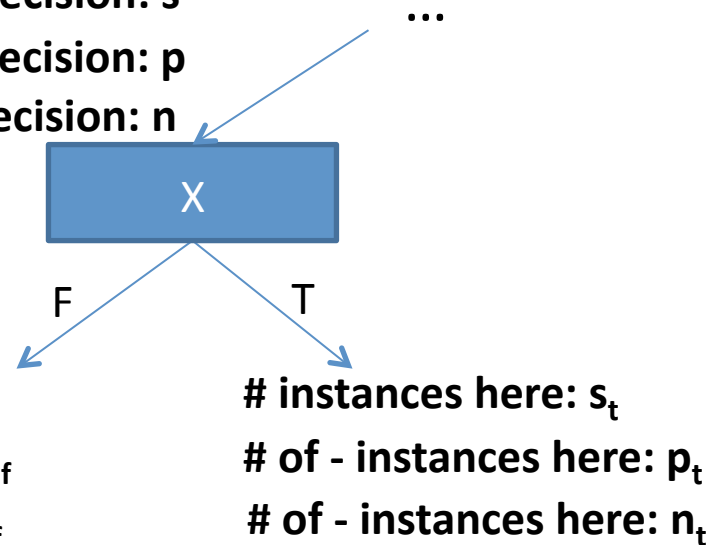
of + instances here: p_t

of - instances here: n_t

Hypothesis: X is uncorrelated with the decision

Chi Square Pruning

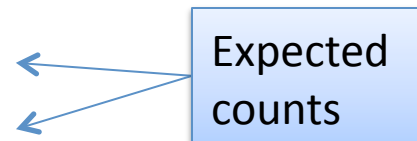
of instances entering this decision: s
of + instances entering this decision: p
of - instances entering this decision: n



Hypothesis: **X is uncorrelated with the decision**

Then p_f should be “close” to $(s_f * p/s)$

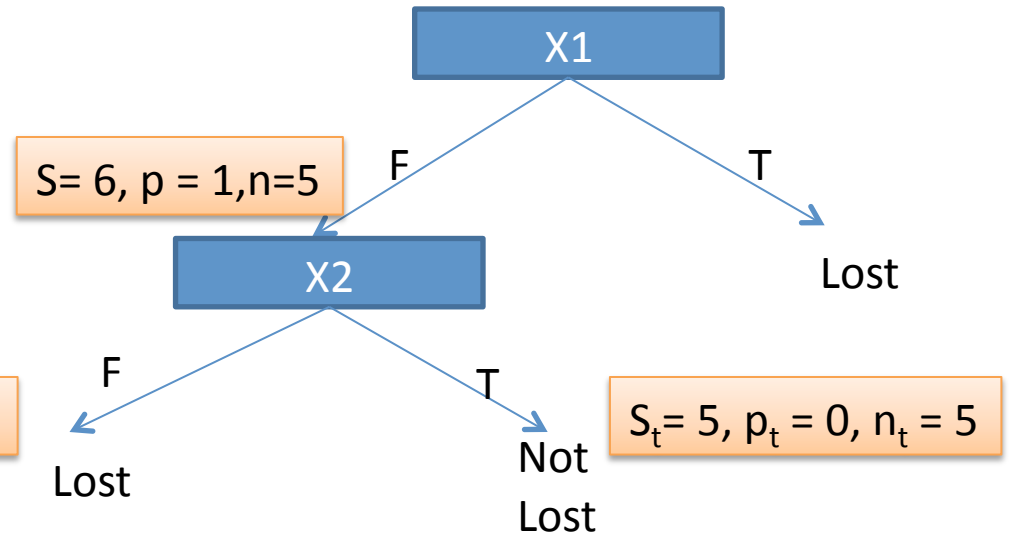
And p_t should be “close” to $(s_t * p/s)$



Similarly for n_f and n_t

Chi Square Pruning

X1	X2	Y	Count
T	T	Lost	2
T	F	Lost	2
F	T	Not Lost	5
F	F	Lost	1



Consider the X2 split

Y = Lost

Variable Assignment	Real Counts	Expected Counts ($S_{x2} * p / S$)
X2 = F	1	1/6
X2 = T	0	5/6

Y = Not Lost

Variable Assignment	Real Counts	Expected Counts ($S_{x2} * n / S$)
X2 = F	0	5/6
X2 = T	5	25/6

Chi Square Pruning

Y = Lost

Variable Assignment	Real Counts	Expected Counts ($S_{x2} * p / S$)
X2 = F	1	1/6
X2 = T	0	5/6

Y = Not Lost

Variable Assignment	Real Counts	Expected Counts ($S_{x2} * n / S$)
X2 = F	0	5/6
X2 = T	5	25/6

If uncorrelated, I expect the Real Counts to be close to Expected Counts
Need some kind of measure of “deviation”

$$C = \sum_{X_2} \frac{(\text{Real Count}_{\text{lost}} - \text{Expected Count}_{\text{lost}})^2}{\text{Expected Count}_{\text{lost}}} + \frac{(\text{Real Count}_{\text{notlost}} - \text{Expected Count}_{\text{notlost}})^2}{\text{Expected Count}_{\text{notlost}}}$$

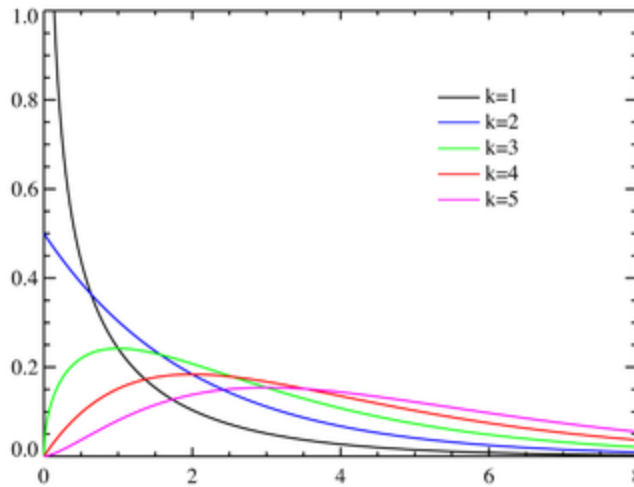
$$C \sim \chi^2((\text{num Y labels} - 1) \times (\text{num X2 labels} - 1))$$

$$C \sim \chi^2(1)$$

Chi Square Pruning

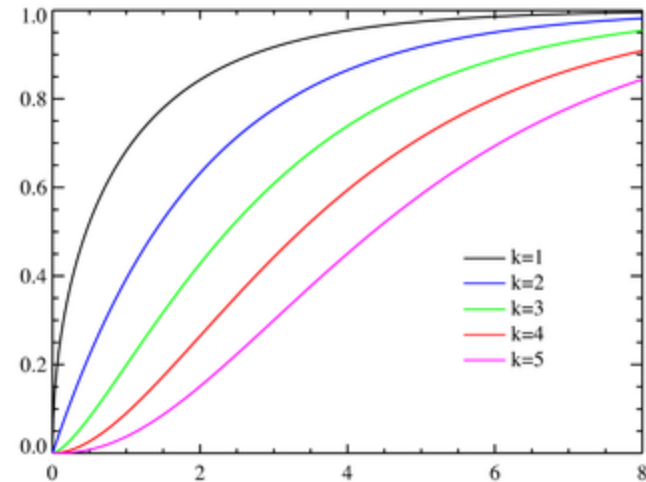
$$c = \sum_{X_2} \frac{(\text{Real Count}_{\text{lost}} - \text{Expected Count}_{\text{lost}})^2}{\text{Expected Count}_{\text{lost}}} + \frac{(\text{Real Count}_{\text{notlost}} - \text{Expected Count}_{\text{notlost}})^2}{\text{Expected Count}_{\text{notlost}}}$$

Intuitively, the smaller C is, the more likely they are uncorrelated.



$$c = 6$$

$$c \sim \chi^2(1)$$



If X_2 and Y are uncorrelated,

$P(C \geq c)$ is the “probability” that we see such large deviations “by chance”.

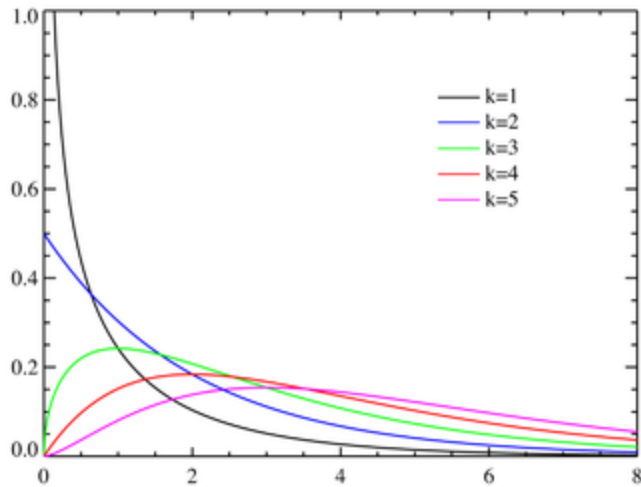
We define “maxPChance” as the “worst chance we are willing to accept”

**(Coin Flip Example: we believe coin is unbiased. Then out of 1000 flips,
How many “heads” do you want to see before you stop believing coin is unbiased?)**

Chi Square Pruning

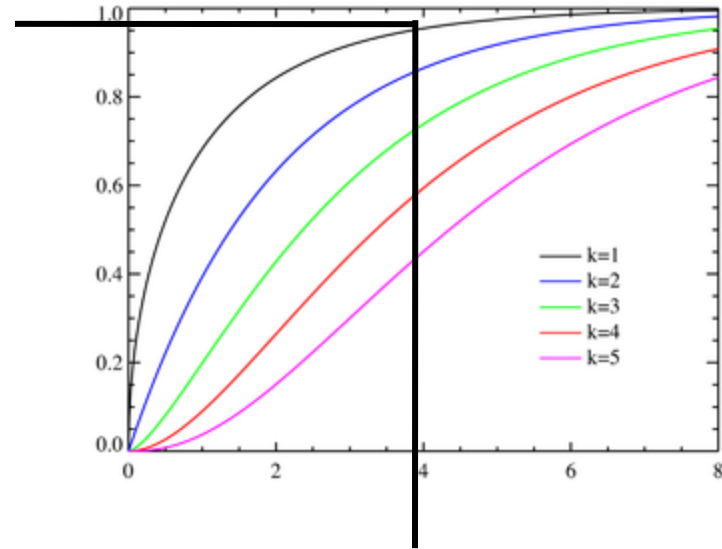
$$c = \sum_{X_2} \frac{(\text{Real Count}_{\text{lost}} - \text{Expected Count}_{\text{lost}})^2}{\text{Expected Count}_{\text{lost}}} + \frac{(\text{Real Count}_{\text{notlost}} - \text{Expected Count}_{\text{notlost}})^2}{\text{Expected Count}_{\text{notlost}}}$$

Intuitively, the smaller C is, the more likely they are uncorrelated.



$$c = 6$$

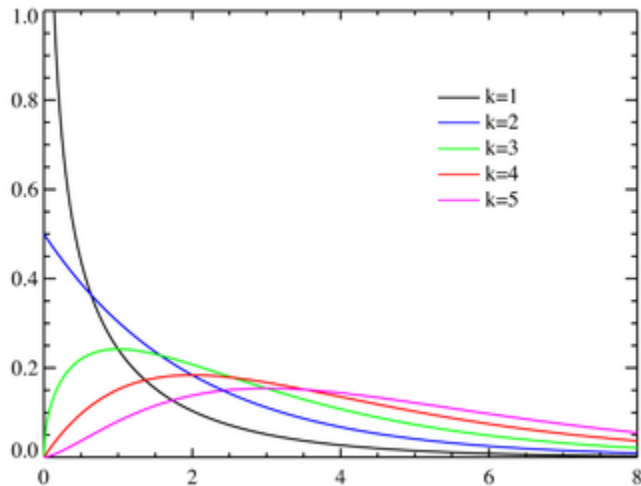
$$c \sim \chi^2(1)$$



Let maxPchance = 0.05

We only stop believing that the splits are “by chance” if the probability of getting a deviation larger than c is < 0.05.

Chi Square Pruning



Let maxPchance = 0.05

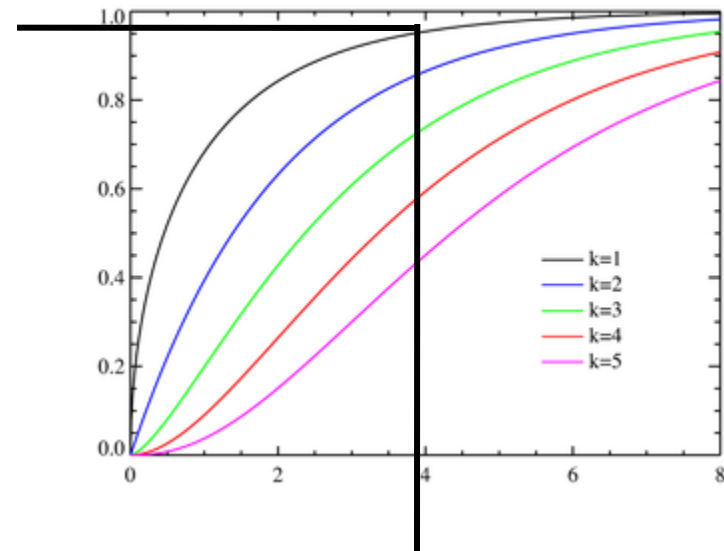
We only stop believing that the splits are “by chance” if the probability of getting a deviation larger than c is < 0.05 .

Look at cdf. $P(C \leq 3.8415) = 0.95$
 $P(C > 3.8415) = 0.05$

If $c \leq 3.8415$ we believe the split is “by chance” and prune the decision
 If $c > 3.8415$ we do not believe the split is “by chance”

$$c = 6$$

$$c \sim \chi^2(1)$$



Applet

Play With Applet