

## Decision Tree.

Entropy of a loaded coin with probability  $p$  of heads:

$$-P \log_2 P - (1-P) \log_2 (1-P)$$

Case 1.  $P(\text{tail}) = 8/9$ ,  $P(\text{head}) = 1/9$

$$\begin{aligned} \Rightarrow & -1/9 \log_2 1/9 - (1-1/9) \log_2 (1-1/9) = -1/9 \log_2 1/9 - 8/9 \log_2 8/9 \\ \Rightarrow & -8/9 \log_2 8/9 - (1-8/9) \log_2 (1-8/9) = -8/9 \log_2 8/9 - 1/9 \log_2 1/9 \\ \Rightarrow & 0.5 \end{aligned} \quad \left. \begin{array}{l} \leftarrow \\ \leftarrow \end{array} \right\} \text{Same}$$

Case 2  $P(\text{tail}) = 4/9$ ,  $P(\text{head}) = 5/9$

$$\Rightarrow -5/9 \log_2 5/9 - 4/9 \log_2 4/9 = 0.99.$$

Remark: based on Case 1 & 2,  
the more "impure", "uncertain",  
"chaotic", the bigger the entropy

For more than binary outcomes:

$$H(Y) = - \sum_{y \in Y} P(y) \log_2 P(y)$$

Joint entropy

$$H(X, Y) = - \sum_x \sum_y P(x, y) \log_2 P(x, y).$$

$X \backslash Y$	cloudy	not cloudy
Rain	24/100	1/100
Not Raining	25/100	50/100

observe: the probabilities add up to 1

$$\begin{aligned} H(X, Y) &= - \sum_x P(x, \text{cloudy}) \log_2 P(x, \text{cloudy}) + P(x, \text{not cloudy}) \log_2 P(x, \text{not cloudy}) \\ &= - P(\text{rain, cloudy}) \log_2 P(\text{rain, cloudy}) - P(\text{rain, } \neg \text{cloudy}) \log_2 P(\text{rain, } \neg \text{cloudy}) \\ &\quad - P(\neg \text{rain, cloudy}) \log_2 P(\neg \text{rain, cloudy}) \\ &\quad - P(\neg \text{rain, } \neg \text{cloudy}) \log_2 P(\neg \text{rain, } \neg \text{cloudy}) \\ &= - 24/100 \log_2 24/100 - 1/100 \log_2 1/100 - 25/100 \log_2 25/100 - 50/100 \log_2 50/100 \\ &= 1.56 \text{ bits} \end{aligned}$$

Specific Conditional Entropy  $H(Y|X=x) = - \sum_y P(y|x) \log_2 P(y|x)$

$$P(y|x) = \frac{P(x,y)}{P(x)}$$

$$P(x) = \sum_y P(x,y)$$

$$\Rightarrow P(\text{rain}) = P(\text{rain, cloudy}) + P(\text{rain, } \neg \text{cloudy})$$

$$H(Y|X=\text{rain}) = - \sum_y P(y|\text{rain}) \log_2 P(y|\text{rain})$$

$$= - P(\text{cloudy}|\text{rain}) \log_2 P(\text{cloudy}|\text{rain})$$

$$- P(\neg \text{cloudy}|\text{rain}) \log_2 P(\neg \text{cloudy}|\text{rain})$$

$$P(\text{cloudy}|\text{rain}) = \frac{P(\text{cloudy, rain})}{P(\text{rain})} = \frac{24}{100} / \frac{24+1}{100} = \frac{24}{25}$$

$$P(\neg \text{cloudy}|\text{rain}) = \frac{P(\neg \text{cloudy, rain})}{P(\text{rain})} = \frac{1}{100} / \frac{24+1}{100} = \frac{1}{25}$$

$$H(Y|X=\text{rain}) = - \frac{24}{25} \log_2 \frac{24}{25} - \frac{1}{25} \log_2 \frac{1}{25} \approx 0.24 \text{ bits}$$

Conditional Entropy

$$H(Y|X) = \sum_x P(x) H(Y|X=x) = - \sum_x \sum_y P(x,y) \log_2 P(x,y)$$

$$\Rightarrow - \sum_x \sum_y \underbrace{P(x) P(y|x)}_{P(x,y)} \log_2 P(y|x)$$

What is the entropy of cloudiness  $Y$ , given the variable  $X$ ?

$$H(Y|X) = \sum_x P(x) H(Y|X=x) = P(\text{rain}) H(Y|X=\text{rain}) + P(\neg \text{rain}) H(Y|\neg \text{rain})$$

$$= \left( \frac{24}{100} + \frac{1}{100} \right) H(Y|X=\text{rain}) + \left( \frac{25}{100} + \frac{50}{100} \right) H(Y|\neg \text{rain})$$

$$= \frac{1}{4} H(Y|\text{rain}) + \frac{3}{4} H(Y|\neg \text{rain}) \approx 0.75 \text{ bits}$$

Information Gain  $IG(Y|X) = H(X) - H(Y|X)$

$\Rightarrow$  the information we gained on the observation of  $y$  after observing how  $y$  "fare" when we have knowledge about  $x$ .

Picture at slides 29.

$$H(X) = -\frac{2}{7} \log_2 \frac{2}{7} - \frac{5}{7} \log_2 \frac{5}{7}$$

$$H(Y|\text{left}) = 0.81, H(Y|\text{right}) = 0.92$$

$$IG(\text{split}) = 0.86 - (\frac{4}{7} \cdot 0.81 + \frac{3}{7} \cdot 0.92) = 0.006$$

Picture at slides 30

$$H(Y|\text{left}) = 0, H(Y|\text{right}) = 0.97$$

$$IG(\text{split}) = 0.86 - (\frac{2}{7} \cdot 0 + \frac{5}{7} \cdot 0.97) = 0.71$$

$\Rightarrow$  the split at 30 is better than the split at 29 because a better information gain.