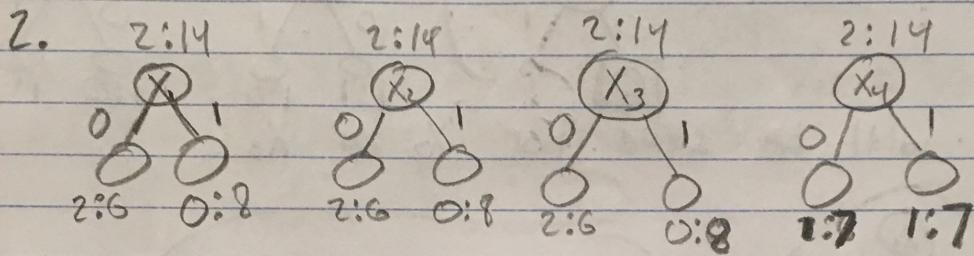


## Homework 2

Decision Trees

1. with  $d$  attributes and 2 possible inputs per attribute, there are  $2^d$  total unique inputs. Every input has two possible unique functions that return 0 or 1. So there are  $2^{2^d}$  unique functions.



$$\text{Error: } 2/16 = 1/8 \quad \leftarrow \quad \leftarrow \quad \leftarrow$$

$$\hookrightarrow (1/4)/2 + 0/2 = 1/8 \quad \leftarrow \quad \leftarrow \quad (1/8)/2 + (1/8)/2 = 1/8$$

$$\text{Entropy: } -1/8 \log_2(1/8) - 7/8 \log_2(1/8) = 0.544$$

$$\hookrightarrow -1/4 \log_2(1/4) + 3/4 \log_2(3/4) = 0.811 \quad \leftarrow 0.544$$

$$\hookrightarrow 0.811/2 = 0.406 \quad ((0.544)/2) \cdot 2 = 0.544$$

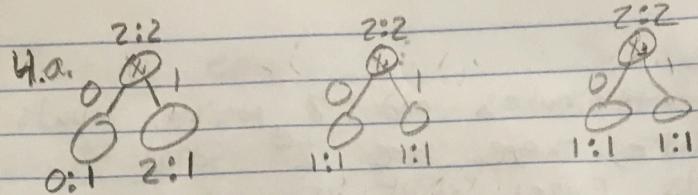
Gain: 0.138

According to training error all nodes are equally good to be the root because none of them reduce error. By looking at entropy you actually can see that  $X_1$ ,  $X_2$ , and  $X_3$  all are good picks for the root, while there is still no gain from  $X_4$ .

3.a. The tree would have to be full, so every output would have to be explored. For this you would need  $2^d$  inputs

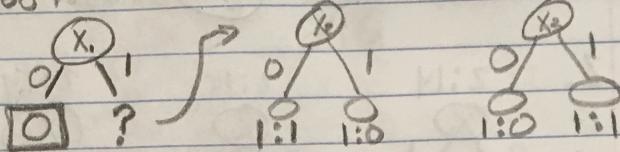
b. you would miss out on  $2^{d! / k!}$  results, so error would be  $2^{d! / k!} / 2^d = \boxed{2^{(d! / k!) - d}}$

This is because each level you remove is  $2^h$ , and that adds error that wasn't there before.

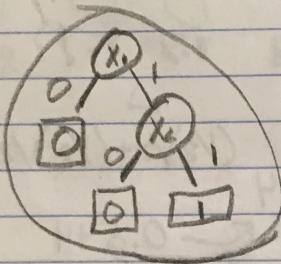


Gain: 0.082

$x_1$  is the root

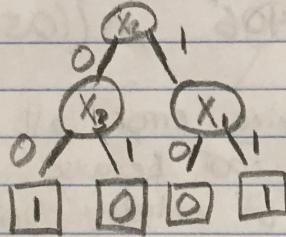


Gain will be same for  $X_2$  or  $X_3$



1/4 training error

b.



0 training error

### More Probability

$$1. E[X] = \sum x \cdot P(X=x) = (0) \cdot P(X=0) + (1) \cdot P(X=1) \\ = P(X=1) = P(A)$$

$$2. a. P(X \cap Y) \stackrel{?}{=} P(X) \cdot P(Y)$$

$$P(X \cap Y) = \frac{1}{10} + \frac{4}{45} = 0.1889 \quad P(X) = 0.3889 \quad P(Y) = 0.4667 \\ P(X) \cdot P(Y) = 0.1815 \neq 0.1889 \quad \text{They are not independent}$$

$$b. P((X \cap Y) | Z) \stackrel{?}{=} P(X | Z) \cdot P(Y | Z)$$

$$\frac{P(X \cap Y \cap Z)}{P(Z)} \stackrel{?}{=} \frac{P(X \cap Z)}{P(Z)} \cdot \frac{P(Y \cap Z)}{P(Z)}$$

$$P(X \cap Y \cap Z) = \frac{4}{45} \quad P(X \cap Z) = \frac{2}{9} \quad P(Y \cap Z) = \frac{4}{15}$$

$$P(Z) = \frac{2}{3}$$

$$\frac{\frac{4}{45}}{\frac{2}{3}} = 0.1333 \quad \frac{\frac{2}{9}}{\frac{2}{3}} = 0.1333$$

They are equal, so Yes X is conditionally dependant on Y Given Z.

c.  $P(X=0 | X+Y>0) = \frac{P(X=0 \cap X+Y>0)}{P(X+Y>0)}$

$$P(X+Y>0) = \frac{1}{10} + \frac{1}{10} + \frac{1}{15} + \frac{2}{15} + \frac{8}{45} + \frac{4}{45} = \frac{2}{3}$$

$$P(X=0 \cap X+Y>0) = \frac{1}{10} + \frac{8}{45} = \frac{5}{18}$$

$$\frac{\frac{5}{18}}{\frac{2}{3}} = \frac{5}{12} = 0.4167$$

MLE and MAP of Gaussians

1.  $M_{ML} = \frac{1}{n} \sum_{i=1}^n x_i = \frac{1}{n} \sum_{i=1}^n x_i$

$$MLE = \frac{1}{n-1} \sum_{i=1}^n (x_i - M_{ML})^2$$

2.

$$N(\mu; \mu_0, \sigma_0) \times N(x; \mu, \sigma) \quad N = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(x-\mu)^2/\sigma^2}$$

$$\left( \frac{1}{\sqrt{2\pi}\sigma_0} e^{-\frac{1}{2}(\mu-\mu_0)^2/\sigma_0^2} \right) \times \left( \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(x-\mu)^2/\sigma^2} \right)$$

$$= \frac{1}{\sqrt{2\pi}\sigma} e^{\left\{ -\frac{1}{2}(\mu-\mu_0)^2/\sigma_0^2 - \frac{1}{2}(x-\mu)^2/\sigma^2 \right\}}$$

$$\exp \rightarrow -\frac{1}{2\sigma^2} (\mu^2 - 2\mu\mu_0 + \mu_0^2) - \frac{1}{2\sigma^2} (\mu^2 - 2x\mu + x^2)$$

$$\exp \rightarrow -\frac{1}{2\sigma^2} (2\mu^2 - 2\mu\mu_0 - 2x\mu + x^2 + \mu_0^2)$$

$$2\mu(\mu - \mu_0 - x) + x^2 + \mu_0^2 - 2x\mu_0 + 2x\mu_0$$

$$2\mu^2 - 2\mu\mu_0 - 2x\mu + (x - \mu_0)^2 + 2x\mu_0$$

$$2(\mu^2 - \mu\mu_0 - x\mu + x\mu_0) + (x - \mu_0)^2$$

$$2(\mu(\mu - \mu_0) - x(\mu - \mu_0)) + (x - \mu_0)^2$$

$$2(\mu - \mu_0)(\mu - x) + (x - \mu_0)^2$$

$$= \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2} \left( 2(\mu - \mu_0)(\mu - x) + (x - \mu_0)^2 \right) / \sigma^2 \right\}$$

3. MAP =  $N(\mu; \mu_N, \sigma_N^2)$

$$\mu_N = \frac{\sigma^2}{n\sigma_0^2 + \sigma^2} \mu_0 + \frac{n\sigma_0^2}{n\sigma_0^2 + \sigma^2} \mu_{ML} \quad \leftarrow \mu_{ML} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\frac{1}{\sigma_N^2} = \frac{1}{\sigma_0^2} + \frac{n}{\sigma^2}$$

$$\frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2} (\mu - \mu_N) / \sigma_N^2 \right\} = N(\mu; \mu_N, \sigma_N^2) = MAP$$

MLE and MAP of Multinomial

1.  $\mu_{ML} = \frac{1}{n} \sum_i a_{ik}$

$$PML = \frac{1}{n-1} \sum_{i=1}^n (a_{ii} - \mu_{ML})^2$$

2.  $Dir(\theta | a+m) = \text{posterior}$

$$\frac{\Gamma(a_0+n)}{\Gamma(a_1+m_1) \cdots \Gamma(a_K+m_K)} \cdot \prod_{k=1}^K \theta_k^{a_k+m_k-1}$$

where  $\Gamma(x)$  is defined as here  $a_0 = \sum_{k=1}^K a_k$

$Dir(\mu | a+m) = MAP$

$$\frac{\Gamma(a_0+n)}{\Gamma(a_1+m_1) \cdots \Gamma(a_K+m_K)} \cdot \prod_{k=1}^K \mu_k^{a_k+m_k-1}$$

$$\Gamma(x) = \int_0^\infty u^{x-1} e^{-u} du$$