

# Chapter 1

Eg 1.1  $N$  tosses, prob  $f$ . How many heads?

$$\Rightarrow \text{Bin}(r|f, N) = f^r (1-f)^{N-r} \binom{N}{r}$$

Stirling from Laplace:

$$\frac{x^x e^{-x}}{x!} \approx \frac{1}{\sqrt{2\pi x}} \Rightarrow x! \approx \left(\frac{x}{e}\right)^x \sqrt{2\pi x}$$

$$\Rightarrow \log_2 \binom{N}{r} \approx r \log_2 \frac{N}{r} + (N-r) \log_2 \frac{N}{N-r}$$

$$\approx N H_2\left(\frac{r}{N}\right) - \frac{1}{2} \log \left[ 2\pi N \frac{N-r}{N} \frac{r}{N} \right]$$

1.2

$s$	0	0	1	0	1
$t$	000	000	111	000	111
$n$	000	001	000	000	101
$r$	000	001	111	000	010

$$P(s|r) = \frac{P(r, r_2, r_3|s) P(s)}{P(r, r_2, r_3)}$$

Assume prior probabilities equal  
 $\Rightarrow$  ML yields  $s^*$

$$P(\vec{r}|s) = \prod p(r_n | t_n(s))$$

Assume BSC  $\begin{matrix} 0 \rightarrow 0 \\ 1 \rightarrow 1 \end{matrix}$

$$p(r_n | t_n) = \begin{cases} 1-f & r_n = t_n \\ f & r_n \neq t_n \end{cases}$$

$$\Rightarrow \text{likelihood ratio} = \frac{P(r|s=1)}{P(r|s=0)} = \prod_n \frac{p(r_n | t_n(1))}{p(r_n | t_n(0))}$$

$$= \begin{cases} \frac{1-f}{f} & r_n = 1 \\ \frac{f}{1-f} & r_n = 0 \end{cases} \quad \frac{1-f}{f} > 1 \text{ for } f < \frac{1}{2}$$

Ex 1.2  $p_b = p_B = 3f^2(1-f) + f^3 = 3f^2 - 2f^3 \ll f$

2 flips      3 flips

Ex 1.3 For  $R_N$  code

a)  $p_b = \sum_{n=\frac{N+1}{2}}^N \binom{N}{n} f^n (1-f)^{N-n}$

error probability       $P(n \text{ flips})$

b) leading term is largest  $\approx 2^{N/2} f^{N/2} (1-f)^{N/2}$

$$\approx 2^N [f(1-f)]^{N/2}$$

$$\approx [4f(1-f)]^{N/2} \approx p_b$$

Second term is  $\sim \frac{f}{1-f}$  times smaller

$\Rightarrow N = 2 \frac{\log 10^{-15}}{\log 4f(1-f)} \approx 68 \leftarrow \text{a bit too big}$

At next order  $\binom{N}{N/2} \approx \frac{2^N}{\sqrt{\pi N/4}}$  Bin( $k=1/2, N$ )

← can get this from norm:  $\sum_k \binom{N}{k} 2^{-N} = 1$

$\Rightarrow \frac{2}{\sqrt{\pi N/4}} f (4f(1-f))^{N/2} = 10^{-15}$

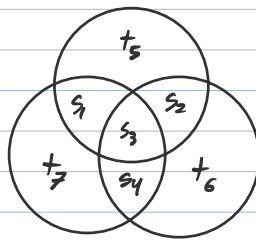
$\Rightarrow N \approx 60.9$

$= 2^{-N} \binom{N}{N/2} \int e^{-r^2/2\sigma^2}$

$= 2^{-N} \binom{N}{N/2} \sqrt{2\pi\sigma^2} \sigma^2 = \frac{N}{4}$

Block code: Add redundancy to blocks of data rather than one bit at a time

7,4 Hamming:



$s_1 \dots s_4$  are source

$t_1, t_2, t_3$  are parity

$\Rightarrow$  parity of each circle is even

eg  $0111 \rightarrow 0111010$

$$t = G^T s$$

$$G^T = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \end{pmatrix}$$

16 codewords lie in a 7-d space of  $2^7$  options

Decoding: Assume BSC

We could decode by finding message  $s$  whose encoding  $t(s)$  is closest to  $r$   
(16 choices)

Easier way: Find bit inside violated parity checks  
 $e_i$  outside unviolated ones

The violated circles give the syndrome

2-bit errors can't be fixed, and flipping them  
gives 3-bit errors

$$G^T = \begin{pmatrix} I \\ P \end{pmatrix} \Rightarrow H = \begin{pmatrix} P & I_3 \end{pmatrix} \quad z = H \cdot r$$

Ex 1.4

Codewords (in  $G$ ) has

$$H G^T = \begin{pmatrix} P & I_3 \end{pmatrix} \begin{pmatrix} I \\ P \end{pmatrix}$$

$$= \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

$$\Rightarrow r = G^T s + \eta$$

⇒ find most probable  $n$  s.t.  $Hn = z$

"Maximum Likelihood Decoder"

Every vector in  $\mathbb{F}_2^7$  is either a codeword or 1 Flip away from one

**Block error:**

One or more bits fails to match the source:

$$P_B := P[s \neq \hat{s}]$$

**Bit error:**

Average probability that a decoded bit doesn't match its source bit:

$$P_b := \frac{1}{K} \sum_{k=1}^K P(s_k \neq \hat{s}_k)$$

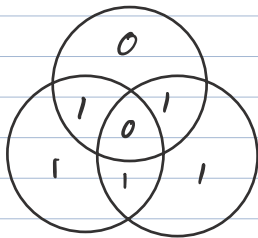
$P_B \propto P[2 \text{ or more flipped}]$  for Hamming  $\neq 4$

$O(f^2)$

But rate is  $\frac{4}{7} > \frac{1}{3}$  from before

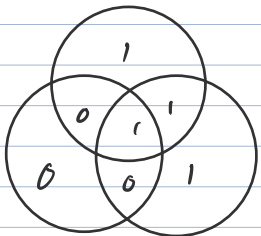
Ex 1.5 Decode

a) 1101011



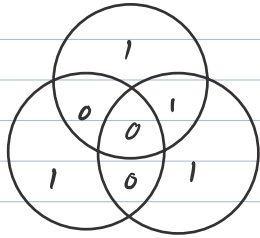
⇒  $z = 011$  ⇒ 1100011

b) 0110110



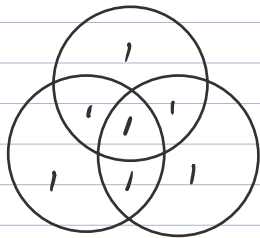
⇒  $z = 111$  ⇒ 0100110

c) 0100111



$$\Rightarrow z = 001 \quad 0100110$$

d) 1111111



$$\Rightarrow z = 000 \quad 1111111$$

1.6 a)  $P_B$  for Hamming is  $\binom{7}{2} f^2 (1-f)^{7-2} + O(f^3)$   
 $\approx 21 f^2$

b)  $P_B$  for 2 flips is  $\propto f^2$  since we need 2 bits to flip

$$21 f^2 \cdot \frac{3}{7} = 9 f^2 + O(f^3)$$

$\uparrow$  (2 flip)       $\leftarrow$  # of wrong bits in that case

because the Hamming code is symmetric any bit (including the source bits) has an equal  $\frac{3}{7}$  chance of flipping.

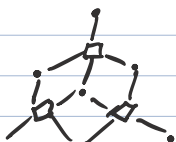
1.7 How many  $n$  give the zero syndrome?

The  $n$  w/ zero syndrome are exactly the 16 codewords by linearity

1.8 Can't have all 3 incorrectly flipped bits be parity, since flipping any 2 would never lead to the "corrected" 3rd one being the 3rd parity

$\Rightarrow$  2 noise flips implies block error

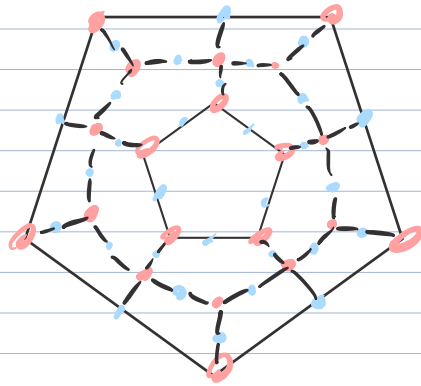
1.9



$\Rightarrow$  4 Hamming

Bipartite graph  $\Rightarrow$   $3 \times 7$  matrix w/ ones whenever there's an edge  
 Bipartite graph  $\Rightarrow$  error correcting code

30,11 Dodecahedron code



Any bit flip on pentagonal side still gives 0 syndrome  
 $\Rightarrow$  lowest weight codewords have weight 5

Distance 5  $\Rightarrow$  can correct 2x bit flip errors

$\Rightarrow$  block error probability goes as  $12 \cdot \binom{5}{3} \cdot f^3(1-f)^{17}$

$\uparrow$                      $\uparrow$                      $\uparrow$   
 Faces                3 bits                adds  
                          from 5                on face

Generically no need to be planar

1.10 For  $N$  transmitted bits with  $\leq 2$  flips

$$\binom{N}{2} + \binom{N}{1} + \binom{N}{0} \text{ patterns}$$

14, 8 code  
 $\Rightarrow$  6 syndrome bits

$$N = 14 \Rightarrow 91 + 14 + 1 = 106$$

$$M = 6 \Rightarrow 2^6 = 64$$

$$K = N - M$$

$$8 = 14 - 6$$

$106 > 64 \Rightarrow$  can't be 2-error correcting

Source = tot - syndrome

Linear or nonlinear  $2^K \cdot \left[ \binom{N}{2} + \binom{N}{1} + \binom{N}{0} \right] \leq 2^N$

necessary for error correction

$$S_t \cdot S_n \leq 2^N$$

1.11 see (30,11) code before

1.12  $P_b[R_3^2] \approx p[R_3] \cdot (3 p[R_3] + \dots)$

↑  
same message  
as  $R_9$  but  
different decoder

$$\approx 3(3f^2)^2 = 27f^4$$

$$P_b[R_9] \approx \binom{4}{5} f^5 \sim 125f^5$$

↑  
better

## Chapter 2

Eg 2.1 Joint ensemble of bigrams

$$P(x,y)$$

Marginalizing over either var gives same dist

Ex 2.2  $X, Y$  not indep in  $P(x,y)$

Eg 2.3  $a = \begin{cases} 1 & \text{Jo has disease} \\ 0 & \text{Jo doesn't} \end{cases}$

$b = \begin{cases} 1 & \text{pos} \\ 0 & \text{neg} \end{cases}$

$$p(a=1) = 0.01$$

$$p(b=1|a=1) = .95$$

$$p(b=0|a=0) = .95$$

$$\begin{aligned} \Rightarrow P(a=1|b=1) &= \frac{P(b=1|a=1) P(a=1)}{P(b=1|a=1) P(a=1) + P(b=1|a=0) P(a=0)} \\ &= \frac{.95 \cdot .01}{.95 \cdot .01 + .05 \cdot .99} \end{aligned}$$

$$= \frac{95}{95 + 99.5} \approx 0.16$$

You cannot do inference w/o making assumptions

### 2.3 Forward & inverse probability

Find:

Ex 2.4  $K$  balls  $B$  black  $W=K-B$  white  
draw w/ replacement  $N$  times

a)  $\pi_B = \text{Bin}(f_B, N)$   $f_B = \frac{B}{K}$

b)  $E[\pi_B] = \frac{B}{K} \cdot N$

$$\text{Var}[\pi_B] = N \frac{B}{K} \left(1 - \frac{B}{K}\right)$$

$B=2$   $\left\{ \begin{array}{l} N=5: 1, \frac{4}{5} \Rightarrow \sigma = \frac{2}{\sqrt{5}} \\ N=100: 80, \frac{64}{100} \Rightarrow \sigma = 8 \end{array} \right.$

Find:

Ex 2.5  $z = \frac{(\pi_B - f_B N)^2}{N f_B (1 - f_B)} \sim \chi^2$  (approx)

$$E[z] = 1$$

$N=5$   $f_B = \frac{1}{5} \Rightarrow \text{Var} = \frac{4}{5}$   $\mu = 1$

only  $\pi_B = 1$  gives  $z < 1$

$$P[\pi_B = 1] = \binom{5}{1} \frac{1}{5} \cdot \left(\frac{4}{5}\right)^4 \sim \frac{256}{625} \approx 0.41$$

Inv:

Ex 2.6 11 urns  
Urn  $u$  has  $u$  black,  $10-u$  white

$\pi_B$  blacks  $N - \pi_B$  whites

$N=10$

$\pi_B = 3$

$$P(u, \pi_B | N) = P(\pi_B | N, u) P(u)$$

$$P(u | \pi_B, N) = \frac{P(\pi_B | u, N) P(u)}{\dots}$$



$$P(\pi_B | N) \propto \binom{N}{\pi_B} \pi_B^{\pi_B} (1 - \pi_B)^{N - \pi_B}$$

$$\rightarrow P(u | \pi_B, N) = \frac{1}{P(\pi_B | N)} \frac{1}{11} \binom{N}{\pi_B} \left(\frac{\pi_B}{10}\right)^{\pi_B} \left(\frac{10 - \pi_B}{10}\right)^{N - \pi_B}$$

can eval & see it peaks near  $u=3$

Assuming now a new ball is drawn

$$P(N+1 \text{ is black} | \pi_B, N) = \sum_u \underbrace{P(N+1 \text{ is black} | \pi_B, u, N)}_{\frac{u}{10}} P(u | \pi_B, N)$$

$$\approx 0.333$$

MAP would just give  $3/10$

Eq 2.7 Observe  $\pi_H$  in  $N$  tosses

$$P(N+1 \text{ is H} | \pi_H, N)$$

$\rightarrow$  Need assumption (prior)

Ex 2.8 uniform prior

$$P(\pi_H | \pi_H, N) = \frac{P(\pi_H | \pi_H, N) P[\pi_H]}{P(\pi_H | N)}$$

$$= \pi_H^{\pi_H} (1 - \pi_H)^{N - \pi_H} \frac{(N+1)!}{\pi_H! (N - \pi_H)!}$$

*prior = 1*

$$P(N+1 \text{ is heads} | \pi_H, N) = \int_0^1 d\pi_H \underbrace{P(N+1 \text{ is heads} | \pi_H, \pi_H, N)}_{\pi_H} P[\pi_H | \pi_H, N]$$

$$= \frac{(N+1)!}{\pi_H! (N - \pi_H)!} \int_0^1 d\pi_H \pi_H^{\pi_H + 1} (1 - \pi_H)^{N - \pi_H}$$

$$= \frac{(N+1)! (n_H+1)! (N-n_H)!}{(N+2)! n_H! (N-n_H)!}$$

$$= \frac{n_H+1}{N+2}$$

$$N=3 \quad n_H=0 \rightarrow \frac{1}{5}$$

$$N=3 \quad n_H=2 \rightarrow \frac{3}{5}$$

$$N=10 \quad n_H=3 \rightarrow \frac{4}{12} = \frac{1}{3}$$

$$N=300 \quad n_H=29 \rightarrow \frac{30}{302}$$

2.9 Compress binary files  $\rightarrow$  Chapter 6  
 $\rightarrow$  estimate  $p(i)$  empirically

$$2.10 \quad \left| \begin{array}{c} A \\ \hline \cdot \cdot \cdot \end{array} \right| \quad \left| \begin{array}{c} B \\ \hline \cdot \cdot \cdot \end{array} \right|$$

$$P(A | \text{black}) = \frac{P(\text{black} | A) P(A)}{P(\text{black})} = \frac{\frac{1}{3} \cdot \frac{1}{2}}{\frac{1}{2}} = \frac{1}{3}$$

likelihood principle:

$\theta \rightarrow D$  generative

$$p(D|\theta)$$

After observing a particular  $D$ , all inferences and predictions should depend only on  $p(D|\theta)$

2.4 Entropy  $\mathcal{E}$  Related

$$H(X) < \log |A_X|$$

$$\text{redundancy} : 1 - \frac{H(X)}{\log |A_X|}$$

## 2.5 Decomposability of entropy

$$H(\vec{p}) = H_2(p_1) + (1-p_1) H\left(\frac{p_2}{1-p_1}, \frac{p_3}{1-p_1}, \dots\right)$$

keep  
flipping

Generally

$$H(\vec{p}) = H_2(p_1 + \dots + p_m, p_{m+1} + \dots + p_k) \\ + (p_1 + \dots + p_m) H\left(\frac{p_1}{p_1 + \dots + p_m}, \dots, \frac{p_m}{p_1 + \dots + p_m}\right) \\ + (p_{m+1} + \dots + p_k) H\left(\frac{p_{m+1}}{p_{m+1} + \dots + p_k}, \dots, \frac{p_k}{p_{m+1} + \dots + p_k}\right)$$

Ex 2.13:  $\log 3 + \frac{1}{3} [\log 10 + \log 5 + \log 21]$   
 $\sim \log 30$  bits

## 2.6 Gibbs' inequality:

$$D_{KL}(p||q) \geq 0$$

## 2.7 Jensen's inequality:

$f$  convex

$$f(\lambda x_1 + (1-\lambda)x_2) \leq \lambda f(x_1) + (1-\lambda)f(x_2)$$

$$\Rightarrow \mathbb{E}[f] \leq f(\mathbb{E}[x])$$

Ex 2.14: Prove by induction

$$f\left(\sum p_i x_i\right) \leq p_1 f(x_1) + \sum_{i=2}^n p_i f\left(\frac{\sum_{i=2}^n p_i x_i}{\sum_{i=2}^n p_i}\right)$$

$\leftarrow$  in  $f(x_1)$  ...  $\leftarrow$  in  $f(\dots)$

$\leftarrow$  in  $f(\dots)$

$$-p_1 J(x_1) + p_2 J(x_2) + \sum_{i=2}^n p_i J(x_i) \leq \sum_{i=2}^n p_i J(x_i)$$

$$\leq \sum_{i=2}^n p_i J(x_i)$$

Ex 2.15: 3 squares w/  $\bar{A} = 100$   
 $\bar{L} = 10$

$(\bar{L})^2 = \bar{A} \Rightarrow$  all squares the same

Ex 2.16: a)  $2, 3, 4, 5 \dots 10, 11, 12$  } sum of 2 dice  
 $\frac{1}{36} \frac{2}{36} \frac{3}{36} \frac{4}{36} \dots \frac{3}{36} \frac{2}{36} \frac{1}{36}$

0	1	2	3	4	5
$\frac{1}{6}$	$\frac{4}{6} \cdot \frac{1}{3} + \frac{1}{3} \cdot \frac{1}{6}$			$\frac{4}{36}$	$\frac{2}{36}$
$\frac{6}{36}$	$\frac{10}{36}$	$\frac{8}{36}$	$\frac{6}{36}$		

b) mean  $3.5 \cdot 100 = 350$   
var  $\frac{35}{12} \cdot 100 \sim 292 \in \text{Gaussian}$

$$\frac{1}{3} \cdot \left( \frac{1}{4} + \frac{9}{4} + \frac{25}{4} \right) = \frac{35}{12}$$

c) One ordinary 1 2 3 4 5 6  
One spiky 666 000

~~AA~~  
return

d) Label  $r$ th dice by  $\{0, 1, 2, 3, 4, 5\} \cdot 6^r$

2.17  $\frac{p}{1-p} = \exp(a) \Rightarrow 1-p = p \exp(-a)$   
 $1 = p(1 + \exp(-a))$   
 $\Rightarrow p = \frac{1}{1 + e^{-a}}$

$\frac{1 + \tanh(a/2)}{2}$

$$2.18 \quad \log \frac{P(x=1|y)}{P(x=0|y)} = \log \frac{P(y|x=1) p(x=1)}{P(y|x=0) p(x=0)} \quad \square$$

$$2.19 \quad d_1 \perp d_2 \mid x$$

$$\frac{P(x=1|\{d_i\})}{P(x=0|\{d_i\})} = \frac{P(d_1|x=1) P(d_2|x=1) P(x=1)}{P(d_1|x=0) P(d_2|x=0) P(x=0)}$$

$$2.20 \quad \frac{\sum_N \int_{r-e}^r dr r^{N-1}}{\sum_N \int_0^r dr r^{N-1}} = \frac{\sum_N [r^N - (r-e)^N]}{\sum_N r^N} = 1 - \left(1 - \frac{e}{r}\right)^N$$

as  $N \rightarrow \infty$   
this fraction  $\rightarrow 1$

$$2.21 \quad E f(x) = 0.1 \cdot 10 + 0.2 \cdot 5 + 0.7 \cdot \frac{10}{7} = 3$$

$$E \frac{1}{f} = 3$$

$$2.22 \quad E \left[ \frac{1}{f} \right] = |A| \text{ always}$$

$$2.23 \quad 0.2$$

$$2.24 \quad P[P(x) \in [0.15, 0.5]] = 0.2$$

$$P \left[ \left| \log \frac{P(x)}{0.2} \right| > 0.05 \right] = P_a + P_c = 0.8$$

$$2.25 \quad H(x) = E \log \frac{1}{p} = \log E \frac{1}{p} = \log |A_x|$$

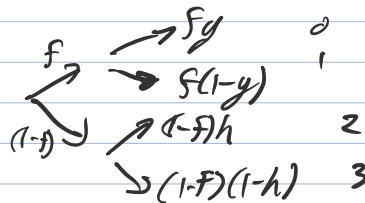
$$2.26 \quad D_{KL}(P||Q) = -\mathbb{E}_P\left(\log \frac{q}{p}\right) \geq -\log \mathbb{E} 1 = 0$$

$$2.27 \quad -\sum_{\underline{x}} p(\underline{x}) \log p(\underline{x}) = -\sum_{x_1} p(x_1) \sum_{x_2 \dots | x_1} p(x_2 \dots | x_1) \log p(x_1) p(x_2 \dots | x_1)$$

$$= -\sum_{x_1} p(x_1) \log p(x_1) - \sum_{x_1} \sum_{x_2 \dots} p(x_2 \dots | x_1) \log p(x_2 \dots | x_1)$$

$$H(X, Y) = H(X) + H(Y|X)$$

$$2.28 \quad H(X) = H_2(F) + F H_2(g) + (1-F) H_2(h)$$



$$\frac{\partial H(X)}{\partial F} = \log \frac{1-F}{F} + H_2(g) - H_2(h)$$

$$2.29 \quad \text{Directly: } \begin{array}{l} p(1) = 1 - \frac{1}{2} \\ p(2) = \frac{1}{2} (1 - \frac{1}{2}) \\ \vdots \end{array} \quad \begin{array}{l} \frac{1}{2} \\ \frac{1}{4} \\ \frac{1}{8} \end{array} \Rightarrow H(X) = \sum_{n=0}^{\infty} 2^{-n} \cdot n$$

$$= \frac{\partial}{\partial a} \frac{1}{1-a} \Big|_{a=\frac{1}{2}}$$

$$H(X) = H(1) + \frac{1}{2} H(2) + \dots + \frac{1}{2} H(3)$$

$$= 2$$

$$= \frac{1}{1-\frac{1}{2}} = 2$$

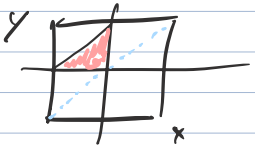
$$2.30 \quad P[B_2=W] = P[B_1=W] \cdot P[B_2=W|B_1=W]$$

$$= P[B_1 = D] \cdot P[P_2 = W | B_1 = D]$$

$$= \frac{W}{N} \frac{W-1}{N-1} + \frac{N-W}{N} \frac{W}{N-1} = \frac{W(N-1)}{N(N-1)} = \frac{W}{N}$$

2.31  $\frac{a}{b}$  chance of intersecting a line horizontally or vertically  
 $\Rightarrow (1 - \frac{a}{b})^2$  chance of being in a square

$$2.32 \int_0^{2\pi} \frac{d\theta}{2\pi} \frac{a \cos \theta}{b} = \frac{a}{b} \int_{-\pi/2}^{\pi/2} \frac{d\theta}{\pi} \cos \theta = \frac{2a}{b\pi}$$

2.33   $x, y-x, 1-y$

$$x + y - x > 1 - y \Rightarrow y > 1 - y$$

$$x < 1 - y > y - x \Rightarrow 1 - y + x > y - x$$

$$1 - y + y - x > x \Rightarrow 1 - x > x$$

$$y < x + 1/2$$

$$y - x < 1/2$$

$$x < 1/2$$

$$y > 1/2$$



$$P = 1/4$$

$$2.34 \mathbb{E} x = \sum_{n=0}^{\infty} n 2^{-n} = 2$$

$$\langle f \rangle = \left\langle \frac{h}{h+t} \right\rangle = \left\langle \frac{1}{h+t} \right\rangle \Rightarrow \mathbb{E} \frac{1}{n} = \sum_{n=1}^{\infty} \frac{f(n)^{n-1}}{n} = \frac{f \log f}{f-1}$$

2.35 a) Exponential dist

$$P(r) = \left(\frac{5}{6}\right)^{r-1} \frac{1}{6}$$

} memoryless

$$\mathbb{E}[r] = 6$$

$$e^{-\alpha r} \quad \alpha = \log \frac{6}{5}$$

z

b) still 6 (memoryless)

c) still 6

d)  $6 + 6 - 1 = 11$

e) Yes. More likely to arrive in bigger open spot

2.36 a)  $\frac{1}{2}$

b)  $\frac{2}{3}$

FAB  
 FBA  
 AFB  
 BFA  
 ABF  
 BAF

$$2.37 \quad P(1_T | 2_T) = \frac{P(2_T | 1_T) P(1_T)}{P(2_T | 1_T) P(1_T) + P(2_T | 1_F) P(1_F)}$$

$$= \frac{\frac{1}{3} \cdot \frac{1}{3}}{\frac{1}{3} \cdot \frac{1}{3} + \frac{2}{3} \cdot \frac{2}{3}} = \frac{1}{5}$$

2.38 1)  $P_B = 3f^2(1-f) + f^3$

2)  $P(r=000) = \frac{1}{2} (1-f)^3 + \frac{1}{2} f^3$

$P(r=001) = \frac{1}{2} f(1-f)^2 + \frac{1}{2} f^2(1-f) = \frac{1}{2} f(1-f)$

$p(\text{error} | \dots) \left\{ \begin{array}{l} P(s=1 | 000) = \frac{f^3 \cdot \frac{1}{2}}{\frac{1}{2} [(1-f)^3 + f^3]} = \frac{f^3}{(1-f)^3 + f^3} \end{array} \right.$

$p(s=1 | 001) = \frac{(1-f)f^2 \cdot \frac{1}{2}}{\frac{1}{2} f(1-f)} = f$

$\Rightarrow p(\text{error}) = \sum_r p(r) p(\text{error} | r) = 2 \cdot \frac{1}{2} [(1-f)^3 + f^3] P(\text{err} | 000) + 6 \cdot \frac{1}{2} f(1-f) P(\text{err} | 001)$   
 $= f^3 + 3f^2(1-f)$

2.39  $-\sum \frac{0!}{n} \log_2 \frac{0!}{n} \sim 9.72 \text{ bits/word}$



## Chapter 3

$$\text{Ex 3.1} \quad \frac{P(A|D)}{P(B|D)} = \frac{1}{2} \frac{3}{2} \frac{1}{1} \frac{3}{2} \frac{1}{2} \frac{2}{2} \frac{1}{2} = \frac{9}{32} \Rightarrow B$$

$$P(A|D) = \frac{9}{9+32} = \frac{9}{41}$$

$$\begin{aligned} \text{Ex 3.2} \quad 20^7 P(A|D) &= 3 \cdot 1 \cdot 2 \cdot 1 \cdot 3 \cdot 1 \cdot 1 = 18 \\ 20^7 P(B|D) &= 2 \cdot 2 \cdot 2 \cdot 2 \cdot 2 \cdot 1 \cdot 2 = 2^6 = 64 \\ 20^7 P(C|D) &= 1 = 1 \end{aligned}$$

$$\frac{18}{83} \quad \frac{64}{83} \quad \frac{1}{83}$$

Ex 3.3

$$P(x|\lambda) = \begin{cases} \frac{1}{\lambda} e^{-x/\lambda} & 1 < x < 20 \\ 0 & \text{else} \end{cases}$$

$$P(\lambda | \{x_i\}) = \frac{1}{(\lambda Z(\lambda))^N} \exp\left[-\sum_n x_n / \lambda\right] P(\lambda)$$

$$Z(\lambda) = \int_1^{20} dx \frac{e^{-x/\lambda}}{\lambda} = e^{-1/\lambda} - e^{-20/\lambda}$$

What you know about  $\lambda$  after the data is what you know before  $P(\lambda)$  & what the data told you  $P(\{x_i\}|\lambda)$

$\lambda$  is not stochastic. Rather we have a degree of belief

$$\text{Ex 3.4} \quad \begin{aligned} P(O) &= .6 \\ P(AB) &= .01 \end{aligned}$$

$$P(\text{crime} | O) = \frac{P(O | \text{crime}) P(\text{crime})}{P(O)}$$

$$P(D|S) = P_{AB} \quad \left\{ \begin{array}{l} P(D|S) = \frac{1}{2p_0} \\ P(D|S) = \frac{1}{2p_0} \end{array} \right. = \frac{1/2}{p_0} P(\text{crime}) \leq P(\text{crime})$$

$$P(D|S) = 2p_0 P_{AB}$$

Ex 3.5  $P(p_a | aba) = p_a^2 (1-p_a)^1$

$$P(p_a | bbb) = (1-p_a)^3$$



$$P(a|s, F) = \frac{\Gamma_a + 1}{\Gamma_a + \Gamma_b + 2} \quad \left\{ \begin{array}{l} \text{Laplace} \end{array} \right.$$

\*  
Ex 3.6  $H_1$  is uniform  
 $H_0$  is  $p = 1/6$

$$\frac{P(H_1 | \mathcal{E}, F)}{P(H_0 | \mathcal{E}, F)} = \frac{\Gamma_a! \Gamma_b!}{(\Gamma_a + \Gamma_b + 1)!} \frac{1}{p_0^{\Gamma_a} (1-p_0)^{\Gamma_b}}$$

$$\rightarrow \log \frac{P(H_1 | \mathcal{E})}{P(H_0 | \mathcal{E})} = -\log \binom{F}{\Gamma_a} - \log(F+1) - \log p_0^{\Gamma_a} (1-p_0)^{\Gamma_b}$$

$$= \Gamma_a \log p_a + \Gamma_b \log p_b - F \log F + \frac{1}{2} \log \frac{2\pi \Gamma_a \Gamma_b}{F} - \Gamma_a \log p_0 - \Gamma_b \log (1-p_0) - \log(F+1)$$

$$= F(p_a \log p_a + p_b \log p_b) + \frac{1}{2} \log(2\pi p_a p_b F)$$

$$= F \left( p_a \log \frac{p_a}{p_0} + \log \frac{p_b}{1-p_0} \right) + \frac{1}{2} \log(2\pi p_a p_b F)$$

$$= F D_{KL}(P_a || P_0) - \frac{1}{2} \log \left( \sqrt{F} + \frac{1}{\sqrt{F}} \right)$$

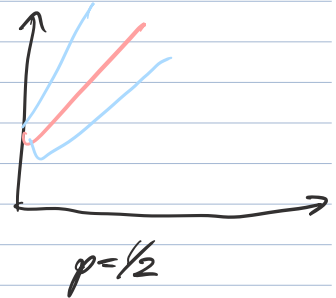
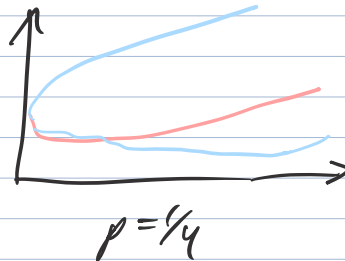
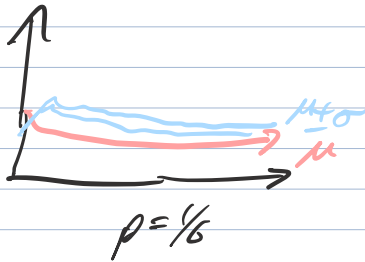
increases linearly unless

increases logarithmically

$p_a \rightarrow p_0$  in KL

3.7  $F_a = p_a F \pm \sqrt{F p_a (1-p_a)}$

→ Make plots of evidence



3.8 Monty Hall: switch

3.9 Earthquake MH: no need

3.10  $l, m, n$  are the sexes

$$l=1 \Rightarrow \begin{cases} m=0 & n=0 \\ m=1 & n=0 \\ m=0 & n=1 \end{cases}$$

→  $\frac{2}{3}$  chance of 2 girls 1 boy  
 $\frac{1}{3}$  chance of 1 girl 2 boys

3.11

$$P(h|m=1) = 0.28$$

↑  
husband  
did it

$$P(b|h=0) = 0.02$$

↑  
murdered

$$P(b|h=1) = 0.9$$

$$\begin{aligned} P(h|b=1, m=1) &= \frac{P(b=1|h=1) \cdot P(h=1|m=1)}{P(b=1|h=1)P(h=1|m=1) + P(b=1|h=0)P(h=0|m=1)} \\ &= \frac{0.9 \cdot 0.28}{\dots} \approx 95\% \end{aligned}$$

$$0.9 \cdot 0.28 + 0.02 \cdot 0.72$$

3.12  $P(D | H=0) = 1$        $P(D | H=1) = 1/2$   
*draw*      *original was white*

$$\Rightarrow P(H=0 | D) = \frac{1 \cdot 1/2}{3/4} = 2/3$$

$$P(H=1 | D) = 1/3$$

3.13  $P(D | \mathcal{H}_0) = 1$

$$P(D | \mathcal{H}_1) = \alpha \cdot \beta$$

*P(valid)*      *P(busy / valid)*

$$\approx \frac{75000}{10^6} \cdot 0.01 \quad (\text{Sever is YAM})$$

$$\approx 0.1 \cdot 190$$

$$\Rightarrow \frac{P(D | \mathcal{H}_0)}{P(D | \mathcal{H}_1)} \approx 10^3$$

if prior was 50/50 then

$$P(\mathcal{H}_0 | D) = \frac{1}{1 + \frac{P(D | \mathcal{H}_1)}{P(D | \mathcal{H}_0)}} \approx 0.99$$

3.14  $1/3$  prob

3.15  $\mathcal{H}_0 \Rightarrow p_0 = 1/2$

$\mathcal{H}_1 \Rightarrow$  biased, w uniform prior on bias

$$\frac{P(D | \mathcal{H}_1)}{P(D | \mathcal{H}_0)} = \frac{\frac{140! 110!}{251!}}{\left(\frac{1}{2}\right)^{250}} \approx 0.48$$

Tweaking to Beta prior:

$$\frac{P(D|H_1)}{P(D|H_0)} = 2^{250} \frac{\Gamma(140+\alpha)\Gamma(110+\alpha)}{\Gamma(250+2\alpha)} \frac{\Gamma(\alpha)}{\Gamma(\alpha)^2}$$

ratio is  $\leq 1$  for  $\alpha < 3$   
and never  $> 2$

IF 141, 109, get p-val of 0.05  
but  $H_1$  is even less likely  
under uniform prior

⇒ Don't be a frequentist!