

Lecture Schedule:						
	Week	Date	Lecture Title			
	TTEER	29-Feb	Introduction			
	1	3-Mar	Systems Overview			
	2	7-Mar	Systems as Maps & Signals as Vectors			
	2	10-Mar	Data Acquisition & Sampling			
	3	14-Mar	Sampling Theory			
		17-Mar	Antialiasing Filters			
	4	21-Mar	Discrete System Analysis			
	4	24-Mar	Convolution Review			
		28-Mar	Holiday			
		31-Mar	Holiday			
	5	4-Apr	Frequency Response & Filter Analysis			
	3	7-Apr	Filters			
	6	11-Apr	Digital Filters			
	0	14-Apr	Digital Filters			
	7	18-Apr	Digital Windows			
	,	21-Apr	FFT			
	8	25-Apr	Holiday			
		28-Apr	Introduction to Feedback Control			
		3-May	Holiday			
		5-May	Feedback Control & Regulation			
	10	9-May	Servoregulation/PID			
	-	12-May	Introduction to (Digital) Control			
	11	16-May	Digital Control Design & State-Space			
		19-Mav	Observability, Controllability & Stability of Digital Systems			
	12	23-May	Digital Control Systems: Shaping the Dynamic Response & Estimation			
		26-May	Applications in Industry			
	12	30-May	System Identification & Information Theory			
	13	2-Jun	Summary and Course Review			
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#### Entropy

### • Entropy: Probability in Disguise!

The entropy of a random variable X with a probability mass function p(x) is defined by

$$H(X) = -\sum_{x} p(x) \log_2 p(x).$$
 (1.1)

**Example 1.1.2** Suppose that we have a horse race with eight horses taking part. Assume that the probabilities of winning for the eight horses are  $(\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \frac{1}{64}, \frac{1}{64}, \frac{1}{64}, \frac{1}{64})$ . We can calculate the entropy of the horse race as

$$H(X) = -\frac{1}{2}\log\frac{1}{2} - \frac{1}{4}\log\frac{1}{4} - \frac{1}{8}\log\frac{1}{8} - \frac{1}{16}\log\frac{1}{16} - 4\frac{1}{64}\log\frac{1}{64}$$
  
= 2 bits. (1.3)

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#### Entropy

• A message  $X_1 \dots X_n$  has length

$$\sum_{i} -\log_2 p(X=X_i)$$

• A long message, has an average length per codeword of:

$$H(X) = E(-\log_2 p(X)) = \sum_X -p(X)\log_2 p(X)$$

Entropy is always positive, since  $p(X) \ge 0$ .

## **Connection to Physics**

- A macrostate is a description of a system by large-scale quantities such as pressure, temperature, volume.
- A macrostate could correspond to many different microstates i, with probability  $p_i$ .
- Entropy of a macrostate is
- $S = -k_B \sum_i p_i \ln p_i$
- Hydrolysis of 1 ATP molecule at body temperature: ~ 20 bits

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Entropy: So why does this work? Example 2.1.1 Let  $X = \begin{cases} 1 & \text{with probability } p, \\ 0 & \text{with probability } 1 - p. \end{cases} (2.4)$ Then  $H(X) = -p \log p - (1 - p) \log(1 - p) \stackrel{\text{def}}{=} H(p). \quad (2.5)$ Plot a graph of H(p) against p.



## Maximum entropy distributions

- Entropy measures uncertainty in a variable.
- If all we know about a variable is some statistics, we can find a distribution matching them that has maximum entropy.
- For constraints  $E(S_i) = s_i$ ,  $i = 1 \dots n$ , usually of form

$$p(X) = e^{-\sum_i \lambda_i S_i}$$

- Relationship between  $\lambda_i$  and  $s_i$  not always simple
- For continuous distributions there is a (usually ignored) dependence on a reference density depends on coordinate system

oles of maximum entropy distributions					
Data type	Statistic	Distribution			
Continuous	Mean and variance	Gaussian			
Non-negative continuous	Mean	Exponential			
Continuous	Mean	Undefined			
Angular	Circular mean and vector strength	Von Mises			
Non-negative Integer	Mean	Geometric			
Continuous stationary process	Autocovariance function	Gaussian process			
Point process	Firing rate	Poisson process			

# Conditional Entropy

- Suppose Alice wants to tell Bob the value of X
   And they both know the value of a second variable Y.
- Now the optimal code depends on the conditional distribution p(X|Y)
- Code length for X = i has length  $-\log_2 p(X = i|Y)$
- Conditional entropy measures average code length when they know Y

$$H(X|Y) = -\sum_{X,Y} p(X,Y) \log_2 p(X|Y)$$

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## Mutual information

• How many bits do Alice and Bob save when they both know Y?

$$I(X;Y) = H(X) - H(X|Y)$$
$$= \sum_{X,Y} p(X,Y)(-\log_2 p(X) + \log_2 p(X|Y))$$
$$= \sum_{X,Y} p(X,Y) \log_2 \left(\frac{p(X,Y)}{p(X)p(Y)}\right)$$

- Symmetrical in X and Y!
- Amount saved in transmitting X if you know Y equals amount saved transmitting Y if you know X.

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Exa	ample: Mystery Text					
I.	Emma Woodh*use, hands*me, clever* and rich,*with a comiortab*e home an* happy di*position,*seemed to*unite som* of the b*st bless*ngs of e*istence;*and had *ived nea*ly twenty *ne year* in the*world w*th very*little *0 distr*ss or vex*her. *he was*the yo*ngest *f the *wo dau*hters *f a most *ffect*onate* indu*gent *ather* and *ad, i* cons*quenc* of h*r si*ter'* mar*iage* bee* mis*ress*of h*s ho*se f*om a ver* ea*ly *eri*d. *er *oth*r h*d d*ed *00 *ong*ago*for*her to*ha*e *or* t*an*an*in*is*in*t *em*mb*an*e *f *er*ca*es*es* a*d*h*r*p*a*e*h*d*b*e* *u*p*i*d*b* *n*e*c*l*e*t*w*m*n*a* g**e**e**,**h**h** **l**n**i**l**s**r*o**a**o**e**i* a**cc**n**S**e**y**s***d***s**a***r**e***n*** W****o****s***i**i***l*****g***n***t***a****e******					
11.	Emma Woodhouse, handsome, clever, and rich, with a comfortable home and happy disposition, seemed to unite some of the best blessings of existence; and had lived nearly twenty one years in the world with very little to distress or Vex her. She was the youngest of the two daughters of a most affectionate, indolent father; and had , in consequence of her sister's marriage , been mistress of his house from a very early period. Her mother had died too lone ago for her to have more than an indistinct remembrance of her caresses; and her place had been supplied by an excellent woman as governess, who had fallen little short of a mother in affection. Sixteen years had Miss Taylor been in Mr Woodhouse's family , less as a eoverness than a friend , very					
Source: MacKay VideoLectures 02, Slide 5						
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## Ben/Unfair Coin

- Outcome:  $x \in \{Tails, Heads\}$
- Probabilities {0.9, 0.1}

$$P(x = Tails) = 0.9$$

Such that:

•  $P(x = a_i) = p_i$ 

$$\sum_{i} p_i = 1$$

Source: MacKay VideoLectures 02, Slide 10















## Continuous variables

- *X* uniformly distributed between 0 and 1.
- How many bits required to encode X to given accuracy?

1	3.3219
2	6.6439
3	9.9658
4	13.2877
5	16.6096
Infinity	Infinity

• Can we make any use of information theory for continuous variables?

# K-L divergence for continuous variables

- Even though entropy is infinite, K-L divergence is usually finite.
- Message lengths using optimal and non-optimal codes both tend to infinity as you have more accuracy. But their difference converges to a fixed number.

$$\sum_{x} p(x) \log_2 \frac{p(x)}{q(x)} \to \int p(x) \log_2 \frac{p(x)}{q(x)} dx$$

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But this is not very good	
<ul> <li>Why?</li> <li>Entropy is not the minimum average codeword length for source with memory</li> <li>If the other pixel values are known we can predict the un pixel with much greater certainty and hence the effective conditional) entropy is much less.</li> </ul>	or a 1known e (ie.
<ul> <li>Entropy Rate</li> <li>The minimum average codeword length for any source.</li> <li>It is defined as</li> </ul>	
$H(\chi) = \lim_{n \to \infty} \frac{1}{N} H(X_1, X_2, \dots, X_n)$	
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- It is very difficult to achieve codeword lengths close to the entropy rate
  - In fact it is difficult to calculate the entropy rate itself
- We looked at LZW as a practical coding algorithm
  - Average codeword length tends to the entropy rate if the file is large enough
  - Efficiency is improved if we use Huffman to encode the output of LZW
  - LZ algorithms used in lossless compression formats (eg. .tiff, .png, .gif, .zip, .gz, .rar...)

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## Lossy Compression

- But this is still not enough compression
  - Trick is to throw away data that has the least perceptual significance



Effective bit rate = 8 bits/pixel



Effective bit rate = 1 bit/pixel (approx)



