Lecture 3: Information and quantification

Lecture Outlines :

- Random Variables
- Discrete Probability Distribution
- Distribution Functions for Random Variables
- Expectation of a Discrete Random Variables
- Variance of a Discrete Random Variable
- Continuous Random Variables
- Distribution Functions for Continuous Random Variables
- Variance of a Discrete Random Variable
- The Binomial Distribution
- Normal distribution (Gaussian)
- Poisson Distributions

Random Variables: Suppose that to each point of a sample space we assign a number. We then have a function defined on the sample space. This function is called a random variable (or stochastic variable). It is usually denoted by a capital letter such as X or Y.

Example 1: X is the variable for the number of heads for a coin tossed three times Solution: X = 0, 1, 2, 3

Discrete random variable has accountable number of possible values
Number of sales, Number of calls, People in line, Mistakes per page, dice.



A continuous random variable takes all values in an interval of numbers
 ➢ electrical current, pressure, temperature, time, voltage, blood pressure, the speed of a car,
 the real numbers from 1 to 6.



The probability distribution of a discrete random variable is a graph, table or formula that specifies the probability associated with each possible outcome the random variable can assume.

- $f(\mathbf{x} \ge \mathbf{00}$ for all values of \mathbf{x}
- $\sum_{\mathbf{x}} f(\mathbf{x}) = 11$

f(x) is the probability function

Example 2: Suppose that a fair coin is tossed twice. Let *X* represent the number of heads that can come up. Find the probability function corresponding to the random variable X. **Solution:** For each sample point we can associate a number for X as follows:

Sample Point	HH	HT	TH	TT
X	2	1	1	0

P(HH) = 1/4, P(HT) = 1/4, P(TH) = 1/4, P(TT) = 1/4 P(X=0) = P(TT) = 1/4 $P(X=1) = P(HT \cup TH) = P(HT) + P(TH) = 1/4 + 1/4 = 1/2$ P(X=2) = P(HH) = 1/4The probability function is given by

<u>Cumulative Distribution Function (CDF) F(x)</u> - is a function that returns the probability that a random variable X is less than or equal to a value. The CDF is also sometimes called the distribution function (DF).

$$F(x) = P(X \le x)$$

Requirements for CDFs

(1) F (x) ≥ 0 everywhere the distribution is defined
(2) F (x) non-decreasing everywhere the distribution is defined.
(3) F (x) → 1 as x → ∞

x	f(x)	F(x)
0	0.05	0.05
1	0.15	0.20
2	0.20	0.40
3	0.60	1.00

Expectation : The expected value, or mean, of a random variable is a measure of central location.

$$E(XX) = \Upsilon = \sum x. f(x)$$

Example 4: Suppose that a game is to be played with a single die assumed fair. In this game a player wins 20\$ if a 2 turns up; 40\$ if a 4 turns up; loses 30\$ if a 6 turns up; while the player neither wins nor loses if any other face turns up. Find the expected sum of money to be won. **Solution:**

$$f(x_1) = f(x_2) = f(x_3) = f(x_4) = f(x_5) = f(x_6) = 1/6$$

x	0	+20	0	+40	0	-30
f(x)	1/6	1/6	1/6	1/6	1/6	1/6

The expected value, or expectation, is

$$E(XX) = (09)\binom{11}{66} + (2209)\binom{11}{66} + (09)\binom{11}{66} + (4409)\binom{11}{66} + (09)\binom{11}{66} + (-3309)\binom{11}{66} = 55$$

The player should expect to pay 5 \$ in order to play the game.



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Lecture 2: Distribution function

Variance of a Discrete Random Variable

Variance : A positive quantity that measures the spread of the distribution of the random variable about its mean value. Larger values of the variance indicate that the distribution is more spread out. $\Re^{22} = \frac{1}{2} (XX - \mu)^{\frac{3}{2}} = \exp(-\mu)^{22} f(\mathbf{x}_{||}) = \exp(-\mu)^{22} f(\mathbf{x})$

The standard deviation is the positive square root of the variance

$$\sigma^{22} = \sqrt{E[(XX - \mu)^{22}]} = \sqrt{\sum(x - \mu)^{22}f(x)}$$

Example 5: Find the variance and standard deviation for the game played in previous Example



Some properties of Expectation and Variance

Some properties of expected values :

• $E(a \cdot x) = a \cdot E(x) = a \cdot \mu$

where *a* is a constant

- $E(a \cdot x + b) = a \cdot E(x) + b = a \cdot \mu + b$
- E(x+y) = E(x) + E(y)

Some properties of variance :

•
$$\sigma^2 = E[(X - \mu)^2] = E(X^2) - \mu^2 = E(X^2) - [E(X)]^2$$

• $Var(cX) = c^2 Var(X)$

- where $\mu = E(X)$
- where c is any constant

where a and b are constants

- The quantity $E[(X-a)^2]$ is a minimum when $a = \mu = E(X)$
- If X and Y are independent random variables,

 $Var(X+Y) = Var(X) + Var(Y) \text{ or } \sigma_{XX+Y}^{22} = \sigma_{XX}^{22} + \sigma_{Y}^{22}$

Var(X - Y) = Var(X) - Var(Y) or $\sigma_{XX-Y}^{22} = \sigma_{XX}^{22} - \sigma_{Y}^{22}$

Expectation of a Discrete Random Variables

Exercise 1: compute the expected value and variance of the number of rewards in Example 3 in this Lecture. E(x) = 0*.05+1*0.15+2*0.20+3*0.60 = 2.35 $Var(x) = (0-2.35)^2*0.05+(1-2.35)^{2*}0.15+(2-2.35)^{2*}0.20+(3-2.35)^{2*}0.60 = 0.8275$

Homework 1: Let X and Y be the random independent events of rolling a fair die. Compute the expected value of X + Y, and the variance of X + Y.

Homework 2: The number of e-mail messages received per hour has the following distribution. compute the expected value and variance.

x = number of message	10	11	12	13	14	15
f(x)	0.08	0.15	0.30	0.20	0.20	0.07



Lecture 2: Distribution function

Continuous Random Variables

Continuous Random Variables :

A nondiscrete random variable *X* is said to be *absolutely continuous*, or simply *continuous*, if its distribution function may be represented as

$$F(\mathbf{x}) = P\left(\mathbf{X}\mathbf{X} \le \mathbf{x}\right) = \bigotimes_{-\infty}^{\infty} f\left(u\right) du$$

where the function f(x) has the properties

1. $f(\mathbf{x}) \ge 00$ 2. $\int_{-\infty}^{\infty} f(\mathbf{x}) = 11$ The function $f(\mathbf{x})$ is called the probability density function (n

The function f(x) is called the probability density function (p.d.f.).

Example 6: Find the constant c such that the function

$$f(\mathbf{x}) = \begin{cases} cx^2 & 0 < \mathbf{x} < 3 \\ 0 & otheroomse \end{cases}$$

is a density function, and then find P(1 < X < 2).

Solution:

Notice that if $c \ge 0$, then Property 1 is satisfied. So f(x) must satisfy Property 2 in order for it to be a density function.

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Lecture 2: Distribution function

Continuous Random Variables





Distribution Functions for Continuous Random Variables

Cumulative Distribution Function (c.d.f.)

The c.d.f. of a continuous random variables is defined exactly the same as for discrete random variables

 $F(\mathbf{x}) = P(\mathbf{X} \leq \mathbf{x})$ where x is any real number, i.e., $-\infty \leq x \leq \infty$. So, ×

$$F(x) = \oint f(x) dx$$

 $-\infty$

Example 7: Find the distribution function for example 6.

$$F(x) = \int_{-\infty}^{x} f(x) dx = \int_{-\infty}^{x} \frac{1}{99} x^2 dx = \frac{x^3}{2222} \qquad \text{where } x \le 3.$$



Expectation of a Discrete Random Variables

<u>Expectation :</u>

If X is a continuous random variable having probability density function f(x), then it can be shown

that

$$\mu_{\mathsf{x}} = E[g(\mathsf{x})] = \int_{-\infty}^{\infty} g(\mathsf{x}) f(\mathsf{x}) d\mathsf{x}$$





Variance :

If *X* is a continuous random variable having probability density function f(x), then the variance is given by

$$\sigma_{XX}^{22} = E\left[(XX - \mu)^{22}\right] = \bigcirc_{-\infty}^{\infty} (\mathbf{x} - \mu)^{22} f(\mathbf{x}) d\mathbf{x}$$

Example 9: Find the variance and standard deviation of the random variable from Example 8, using the fact that the mean was found

To be
$$\mu_{x} = \mathbf{E} (\mathbf{X}) = \frac{44}{33}$$

 $\sigma^{22} = E \left[(XX - \frac{44}{33})^{22} \right] = \bigoplus_{-\infty}^{\infty} \left(x - \frac{44}{33} \right)^{22} f(x) dx = \bigoplus_{-\infty}^{\infty} \left(x - \frac{4}{33} \right)^{22} \left(\frac{11}{22} \right) dx = \frac{Z}{99}$
And so the standard deviation is $\sigma = \sqrt{\frac{22}{99}} = \frac{\sqrt{22}}{33}$.



Binomial: An experiment for which the following four conditions are satisfied is called a *binomial experiment*.

- **1.** The experiment consists of a sequence of n trials, where n is fixed in advance of the experiment.
- 2. The trials are identical, and each trial can result in one of the same two possible outcomes, which are denoted by success (S) or failure (F).
- 3. The trials are independent.
- 4. The probability of success is constant from trial to trial: denoted by p.

The probability mass function (PMF) of X is

for x = 0; 1; 2; ...; n p = probability of success q = (1 - p) probability of failure n = number of trials

x = number of successes

$$f(x) = P(X = x) = \binom{n}{x} p^{x} q^{n-x}$$

Example 10: In a digital communication system, the number of bits in error in a packet depicts a Binomial discrete random variable



The Binomial Distribution

Lecture 2: Distribution function

Example 11:The probability of getting exactly 2 heads in 6 tosses of a fair coin is **Solution:**

$$P(XX = 22) = {\binom{60}{22}} \left(\frac{11}{22}\right)^{22} \left(\frac{11}{22}\right)^{66-22} = \frac{66!}{22! \ 44!} \left(\frac{11}{22}\right)^{22} \left(\frac{11}{22}\right)^{44} = \frac{1155}{6644}$$

Exercise 2: If I toss a coin 20 times, what's the probability of getting 2 or fewer heads? **Solution:** $\begin{pmatrix} 20 \\ 0 \end{pmatrix} = 20 = 20 = 20$

$$\binom{20}{0}(.5)^{0}(.5)^{20} = \frac{20!}{20!0!}(.5)^{20} = 9.5x10^{-7} + \binom{20}{1}(.5)^{1}(.5)^{19} = \frac{20!}{19!1!}(.5)^{20} = 20x9.5x10^{-7} = 1.9x10^{-5} + \binom{20}{2}(.5)^{2}(.5)^{18} = \frac{20!}{18!2!}(.5)^{20} = 190x9.5x10^{-7} = 1.8x10^{-4} = 1.8x10^{-4}$$



Properties of Binomial Distributions

Lecture 2: Distribution function

(Mean and Variance for Binomial Distribution) :

If X is a binomial random variable with parameters p and n, then Mean $\mu = np$

Variance

Standard Deviation $\sigma = \sqrt{npq}$

 $\sigma^2 = npq$

Exercise 3: Digital Channel the chance that a bit transmitted through a digital transmission channel is received in error is 0.1. Also, assume that the transmission trials are independent. Let X = the number of bits in error in the next four bits transmitted. Determine P(X = 2), the mean, variance, and standard deviation of this experiment.

	Outcome	х	Outcome	х
Solution:	0000	0	EOOO	1
	OOOE	1	EOOE	DOO 1 DOE 2 DEO 2 DEE 3 EOO 2 EOE 3 EEO 3
	OOEO	1	EOEO	2
	OOEE	2	EOEE	3
$P(XX = 22) = () (00 \ 11)^{22} (00 \ 99)^{44-22}$	OEOO	1	EEOO	2
	OEOE	2	EEOE	3
	OEEO	2	EEEO	3
$\mathbf{E}(\mathbf{X}) = \mu_{\mathbf{X}} = 44(00.11) = 00.44$ $\sigma^{22} = 44(00.11)(00.99) = 00.3366$	0000	3	EEEE	4

Homework 3: Suppose that three telephone users use the same number and that we are interested in estimating the probability that more than one will use it at the same time. If independence of telephone habit is assumed, the probability of exactly k persons requiring use of the telephone at the same time is given by the mass function $p_X(k)$ associated with the binomial distribution. Let it be given that, on average, a telephone user is on the phone 5 minutes per hour.

Homework 4: In a digital communication channel, assume that the number of bits received in error can be modeled by a binomial random variable. The probability that a bit is received in error is 10^{-5} . If 16 million bits are transmitted, what is the probability that 150 or fewer errors occur? Let X denote the number of errors.

Note : Clearly, this probability is difficult to compute. Fortunately, the normal distribution can be used to provide an excellent approximation in this example.

Homework 5: Consider the problem of missile firing. Enumerate the possible outcomes of trail firing of missiles. Lets S denote the success of each trail with probability p and F denote the failure with probability q=1-p, then there are, 2^4 possible outcomes s listed below as set U, the complete sample space.

Lecture 2: Distribution function

- One of the most important examples of a continuous probability distribution is the <u>normal</u> <u>distribution</u>, sometimes called the <u>Gaussian distribution</u>. most popular to communication engineers is ... AWGN Channels.
- Random variation of many physical measurements are normally distributed.
- The location and spread of the normal are independently determined by mean (μ) and standard deviation (σ). $f^{(x)}$



The density function for this distribution is given by

$$f(\mathbf{x}) = \frac{11}{\sqrt{22\pi\sigma}} e^{\frac{-(\mathbf{x}-\boldsymbol{\mu})^{22}}{22\sigma^{22}}} \qquad -\infty < \mathbf{x} < \infty$$

where μ and σ are the mean and standard deviation, respectively. The corresponding distribution function is given by $F(\mathbf{x}) = P(\mathbf{X}\mathbf{X} \le \mathbf{x}) = \frac{11}{\sigma\sqrt{22\pi}} \int_{-\infty}^{\infty} e^{-(\nu-\mu)^{2}/22\sigma^{2}} d\nu$

Normal distribution (Gaussian)

Example 12: Assume that the current measurements in a strip of wire follows a normal distribution with a mean of 10 mA & a variance of 4 mA2. Let X denote the current in mA. What is the probability that a measurement exceeds 13 mA? $f(x) \neq f(x)$







Lecture 2: Distribution function

Standard Normal Distribution







Exercise 4: $P(Z \le 1.53)$.	Answer: 0.93699	
Exercise 5: $P(Z \le 0.01)$.	Answer: 0.50398	

Example 14:

1. P(Z > 1.26) = 0.1038

Lecture 2: Distribution function

- 2. P(Z < -0.86) = 0.195
- 3. P(Z > -1.37) = 0.915
- 4. P(-1.25 < 0.37) = 0.5387
- 5. $P(Z \leq -4.6) \approx 0$
- 6. Find z for $P(Z \le z) = 0.05, z = -1.65$
- 7. Find z for (-z < Z < z) = 0.99, z = 2.58





Standard Normal Distribution

Example 15: From a previous example with $\mu = 10$ and $\sigma = 2$ mA, what is the probability that the current measurement is between 9 and 11 mA? $P(9 < X < 11) = P\left(\frac{9-10}{2} < \frac{x-10}{2} < \frac{11-10}{2}\right)$ **Answer:** = P(-0.5 < z < 0.5)= P(z < 0.5) - P(z < -0.5)= 0.69146 - 0.30854 = 0.38292Distribution of $Z = \frac{X - \mu}{\sigma}$ 0 1.5 Distribution of X9 1011 13 16 x -1.5 -0.5 0 0.5 1.5 3 z10 13 х



Lecture 2: Distribution function

Standard Normal Distribution

Example 16: Determine the value for which the probability that a current measurement is below this value is 0.98. Answer: $P(X < x) = P\left(\frac{X-10}{2} < \frac{x-10}{2}\right)$ $= P\left(Z < \frac{x-10}{2}\right) = 0.98$ z = 2.05 is the closest value.

$$z = 2(2.05) + 10 = 14.1$$
 mA.

Determining the value of x to meet a specified probability.

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Homework 6: Assume that in the detection of a digital signal, the background noise follows a normal distribution with $\mu = 0$ volt and $\sigma = 0.45$ volt. The system assumes a digital 1 has been transmitted when the voltage exceeds 0.9.

- 1. What is the probability of detecting a digital 1 when none was sent? Let the random variable N denote the voltage of noise.
- 2. Determine the symmetric bounds about 0 that include 99% of all noise readings.
- 3. Suppose that when a digital 1 signal is transmitted, the mean of the noise distribution shifts to 1.8 volts. What is the probability that a digital 1 is not detected? Let S denote the voltage when a digital 1 is transmitted.



Homework 7: Repeat solve Homework 4 by using Gaussian distribution.

Homework 8: Atelevision cable company receives numerous phone calls throughout the day from customers reporting service troubles and from would-be subscribers to the cable network. Most of these callers are put "on hold" until a company operator is free to help them. The company has determined that the length of time a caller is on hold is normally distributed with a mean of 3.1 minutes and a standard deviation 0.9 minutes. Company experts have decided that if as many as 5% of the callers are put on hold for 4.8 minutes or longer, more operators should be hired.

- a) What proportion of the company'scallers are put on hold formore than 4.8 minutes? Should the company hire more operators?
- b) At another cable company (length of time a caller is on hold follows the same distribution as before), 2.5% of the callers are put on hold for longer than x minutes. Find the value of x

Homework 9: Suppose that a binary message either 0 or 1 must be transmitted by wire from location *A* to location *B*. However, the data sent over the wire are subject to a channel noise disturbance, so to reduce the possibility of error, the value 2 is sent over the wire when the message is 1 and the value - 2 is sent when the message is 0. If $x, x = \pm 2$, is the value sent from location *A*, then *R*, the value received at location *B*, is given by R = x + N, where *N* is the channel noise disturbance. When the message is received at location B the receiver decodes it according to the following rule: If $R \ge 0.5$, then 1 is concluded If R < 0.5, then 0 is concluded

If the channel noise follows the standard normal distribution compute the probability that the message will be wrong when decoded.

Let X be a discrete random variable that can take on the values 0, 1, 2,... such that the probability function of X is given by

$$f(\mathbf{x}) = P(\mathbf{X}\mathbf{X} = \mathbf{x}) = \frac{\lambda^{\mathbf{x}\mathbf{x}}\mathbf{e}^{-\lambda}}{\mathbf{x}!} \qquad \mathbf{x} = 00, 11, 22, \dots \qquad \lambda = np$$

where λ is a given positive constant. This distribution is called the Poisson distribution

Example 17: If the probability that an individual will suffer a bad reaction from injection of a given serum is 0.001, determine the probability that out of 2000 individuals, (a) exactly 3, (b) more than 2, individuals.

Solution:

X is Bernoulli distributed, but since bad reactions are assumed to be rare events, we can suppose that X is Poisson distributed

a)
$$P(XX = x) = \frac{\lambda^{xx}e^{-\lambda}}{\frac{x!}{33}e^{-2}}$$
 $\lambda = np = (2000)(0.001) = 2$
 $P(XX = 33) = \frac{\lambda^{33}e^{-2}}{\frac{33!}{33}} = 0.18$



Poisson Distributions

b)
$$P(X>2) = 1 - [P(X=0) + P(X=1) + P(X=2)]$$

= $11 - [\frac{2^{00}e^{-2}}{00!} + \frac{2^{11}e^{-2}}{11!} + \frac{2^{22}e^{-2}}{22!} + 1 - 5e^{-2} = 0.323$

Exercise 6: Let's say you want to send a bit string of length $n = 10^{44}$ where each bit is independently corrupted with $p = 10^{-66}$. What is the probability that the message will arrive uncorrupted? **Solution:**

$$\lambda = np = 10^{44} 10^{-66} = 0.01.$$

$$P(X = 00) = \frac{0.01^{00} e^{-0.01}}{00!} = 00.9999$$

Homework 10: Are we could have modelled X as a binomial distribution. That would have been computationally harder to compute but would have resulted in the same number (up to the millionth decimal)



Poisson Distributions

Example 18: The number of visitors to a webserver per minute follows a Poisson distribution. If the average number of visitors per minute is 4, what is the probability that:

- a) There are two or fewer visitors in one minute?
- b) There are exactly two visitors in 30 seconds?

Solution:

a) The average number of visitors in a minute. In this case the parameter $\lambda = 4$. So the probability of two or fewer visitors in a minute is

$$P(X = 0) + P(X = 1) + P(X = 2)$$

$$P(XX = 00) = \frac{e^{-44}44^{00}}{00!} = e^{-44}$$

$$P(XX = 11) = \frac{e^{-44}44^{11}}{11!} = 44e^{-44}$$

$$P(XX = 22) = \frac{e^{-44}44^{22}}{22!} = 88e^{-44}$$

The probability of two or fewer visitors in a minute is $e^{-44} + 44e^{-44} + 88e^{-44} = 0.238$ b) If the average number of visitors in 1 minute is 4, the average in 30 seconds is 2.

$$P(X=2) = \frac{e^{-2}2^2}{2!} = 2e^{-2} = 0.271$$

Poisson Distributions

Homework 12: Consider a computer system with Poisson job-arrival stream at an average of 2 per minute. Determine the probability that in any one-minute interval there will be

- a) 0 jobs;
- b) exactly 2 jobs;
- c) at most 3 arrivals.

Uniform Distribution

Lecture 2: Distribution function

Uniform Distribution A random variable X is said to be uniformly distributed in $a \le x \le b$ if its density function is flat over a region.

$$f(\mathbf{x}) = \frac{11}{b-a}, \quad for a \le \mathbf{x} \le b$$

The distribution function is given by

$$F(\mathbf{x}) = P(\mathbf{X} \le \mathbf{x}) = \begin{cases} 00 & \mathbf{xx} < a \\ (x-a)/(b-a), & \mathbf{a} \le x \le b \\ 11 & \mathbf{xx} \ge b \end{cases}$$

The mean and variance are, respectively

$$\mu_{x} = \frac{11}{22}(a+b), \qquad \sigma^{22} = \frac{11}{1122}(b-a)^{22}$$





Example 19: The figure below depicts the probability distribution for temperatures in a manufacturing process. The temperatures are controlled so that they range between 0 and 5 degrees Celsius, and every possible temperature is equally likely.







Uniform Distribution





Homework 13: The current (in mA) measured in a piece of copper wire is known to follow a uniform distribution over the interval [0, 25]. Write down the formula for the probability density function f(x) of the random variable X representing the current. Calculate the mean and variance of the distribution and find the cumulative distribution function F(x).



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Lecture Outlines :

- Introduction
- General model of communication system
- Information Source
- Self Information
- Entropy
- Information Rate
- Joint Entropy
- Conditional Entropy
- Mutual Information

2/24/2019

Lecture 3: Information and quantification

"The fundamental problem of communication is that of reproducing at one point either

exactly or approximately a message selected at another point."

(Claude Shannon 1948)

Information Theory is concerned with the theoretical limitations and potentials of systems that communicate. *E.g.*, \What is the best compression or communications rate we can achieve''

Communication is sending information from one place and/or time to another place and/or time over a medium that might have errors.







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Information Theory



2/24/2019
Lecture 3: Information and quantification



- First stage: data reduction (keep only important bits or remove source redundancy),
- Followed by redundancy insertion catered to channel.
- A code = a mechanism for representation of information of one signal by another.
- An *encoding* = representation of information in another form.

Decoder

Encoder

- exploit and then remove redundancy
- remove and fix any transmission errors
- restore the information in original form

Consider Discrete Information Source

Assuming:

- Information source generates a group of symbols from a given alphabet $S = \{s_o, s_1, ..., s_{K-1}\}$

- Each symbol has a probability P_k
- Symbols are independent

Lecture 3: Information and quantification

Information
Source
$$S = \{s_o, s_1, ..., s_{K-1}\}$$

 $P(s_k) = P_k, \ k = 0, 1, ..., K-1$, $\sum_{k=0}^{K-1} P_k = 1$

The amount of information gained from knowing that the source produces the symbols is s_{k} is related with as p_k follows :

- *If* $P_k = 1$

Then there is no uncertainty of occurrence of the event ; no gain of information i.e., there is no need for communications because the receiver knows everything.

- As_{P_k} decreases

Then the uncertainty increases; the reception of s_k corresponds to some gain of information

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But How Much?

<u>Self Information</u>: Is a function which measures the amount of information after observing the symbol s_k





The unit of information depends on the base of the log

The amount of information in bits about a symbol is closely related to its probability of occurrence

A low probability event contains a lot of information and vice versa

Properties of Self Information $I(s_k) = 0$, a real nonnegative measure 0, $I(S_i) \ge 0$, a real nonnegative measure $I(S_i)$ is a continuous function of p $I(s_k) > I(s_i)$ if $P_k < P_i$



Information Source / Self Information

-The information obtained from the occurrence of two independent events is the sum of the information obtained from the occurrence of the individual events

$$I(AB) = \log_b \frac{1}{P(AB)}$$
$$= \log_b \frac{1}{P(A)P(B)}$$
$$= \log_b \frac{1}{P(A)} + \log_b \frac{1}{P(B)}$$
$$= I(A) + I(B)$$
$$\therefore I(AB) = I(A) + I(B)$$

Example 1: Let H and T are the outcomes of a flipping coin, calculate the self information for the following cases:

(a) Fair coin with P(H) = P(T) = 0.5(a) I(H) = I(T) = 1 bit(b) Unfair coin with P(H) = 1/8, P(T) = 7/8(b) I(H) = 3 bits I(T) = 0.193 bits

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Lecture 3: Information and quantification

Information Source / Self Information

Example 2: A source puts out one of five possible messages during each message interval. The probability of these messages are $\{m_1, \dots, m_5\}$: P1 = 1/2, P2 = 1/4, P3 = 1/8, P4 = 1/16 and P5 = 1/16 What is the information content of these messages in bit?

$$I(m_1) = \log_2 \frac{1}{P(m_1)} = -\log_2 P(m_1) = -\log_2 \left(\frac{1}{2}\right) = 1bit$$
$$I(m_2) = \log_2 \frac{1}{P(m_2)} = -\log_2 P(m_2) = -\log_2 \left(\frac{1}{4}\right) = 2bits$$

$$I(m_3) = \log_2 \frac{1}{P(m_3)} = -\log_2 P(m_3) = -\log_2 \frac{1}{(\frac{1}{8})} = 3bits$$

$$I(m_{4}) = \log_{2} \frac{1}{P(m_{4})} = -\log_{2} P(m_{4}) = -\log_{2} (\frac{1}{16}) = 4bits$$

$$I(m_{5}) = \log_{2} \frac{1}{P(m_{5})} = -\log_{2} P(m_{5}) = -\log_{2} (\frac{1}{16}) = 4bits$$



Exercise 1: For 128 equally likely and independents messages find the information content (in bits) in each of the messages. **Solution:**

$$I(m) = \log_2 \frac{1}{P(m)} = -\log_2 P(m) = \log_2(128) = 7bits$$

Homework 1: Suppose in sizing up the data storage requirements for a word processing system to be used in production of a book, it is required to calculate the information capacity. The book consist of 450 pages, 500 words per page, each containing 5 symbols are chosen at random from a 37- ary alphabet (26 letters, 10 numerical digits and one blank space). Calculate the information capacity of the book.



Information Source / Entropy

Entropy: It is the average number of bits per symbol required to describe a source

For a source containing N independent symbols, its entropy is defined as

$$H = \sum_{i=1}^{N} P_i I(s_i)$$

$$H = \sum_{i=1}^{N} P_i \log_b \frac{1}{P(s_i)}$$

Example 3: Calculate the entropy of the outcomes of a fair flipping coin

$$H = P(H)\log_2 \frac{1}{P(H)} + P(T)\log_2 \frac{1}{P(T)}$$
$$H = 0.5\log_2 \frac{1}{0.5} + 0.5\log_2 \frac{1}{0.5} = 0.5 + 0.5 = 1bit / symbol$$



Properties of Entropy

H is a positive quantity $H \ge 0$

If all a priori probabilities are equally likely $(P_i = 1 / N \text{ for all } N \text{ symbols})$ then <u>the entropy is maximum</u> and given by:

$$H = \log_b N$$

The proof:

If all a priori probabilities are equally likely $(P_i = 1/N \text{ for all } N \text{ symbols})$ $H = -\sum_{i=1}^{N} P_i \log_2 (P_i) = -(1/N) \sum_{i=1}^{N} \log_2 (1/N)$ $= -(1/N) [N \log_b (1/N)]$ $= -\log_2 (1/N) = \log_2 N$ $\therefore 0 \le H \le \log_b N$



i.e., you need log₂N bits to represent a variable that can take one of N values if N is a power of 2 If these values are equally probable, the entropy is equal to certain number of bits

If one of the events is more probable than others, observation of that event is less informative

Conversely, rarer events provide more information when observed. Since observation of less probable events occurs more rarely, the net effect is that the entropy received from non uniformly distributed data is less than log_2N

Entropy is zero when one outcome is certain, so entropy refers to disorder or uncertainty of a <u>message</u>

<u>According to Shannon</u>, the entropy is the average of the information contained in each message of the source, irrespective the meaning of the message



Lecture 3: Information and quantification

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Information Source / Entropy

Example 4: Find and plot the entropy of the binary code in which the probability of occurrence for the symbol 1 is P and for the symbol 0 is 1-P

Example 5: Calculate the average information in bits/character in English assuming each letter is equally likely

$$H = \sum_{i=1}^{26} \log_2 N = \log_2 26 = 4.7$$
 bits/character



Exercise 2: For Uniform distribution P(xi)= 1/N find the average information				
Solutions:	H(X) X	$=_{ii=11\frac{N}{N}} I(xii) = \frac{11}{N} \sum_{ii=11}^{N} -\log_{22} \frac{11}{N} I(xii) = \frac{11}{N} * N * \log_{22} N$		
		$= log_{22}N$		

Homework 2: Consider source transmitting six symbols with probability as given :

 A
 (1/2)
 D
 (1/16)

 B
 (1/32)
 E
 (1/4)

 C
 (1/8)
 F
 (1/32)

Find the average information or entropy.

Homework 3: A source sending 2 symbols. A and B if the $(H \times_{ii}) = 00.66$ and self information is 0.3 find the probability of A and B.

The information rate is represented by R and it is represented in average number of bits of information per second. And is given as,

Information Rate : R = rH

Information rate R it is calculated as follows:

 $R = \left(r \, iin \frac{symbol}{second}\right) * \left(H \, iin \frac{biits}{symbol}\right) = \frac{biits}{second}$

Example 6: A PCM source transmits four samples (messages) with a rate 2 samples / second. The probabilities of occurrence of these 4 samples (messages) are p1 = p4 = 1/8 and p2 = p3 = 3/8. Find out the information rate of the source. Solution: $H = p \log_{10} (11) + p \log_{10} (11) + p \log_{10} (11)$

$$H = \frac{p \log_{11} p \log_{11}}{11 \log_{12} \left(\frac{11}{p_{11}}\right)} + \frac{p \log_{10} p \log_{11}}{11 \log_{12} \left(\frac{11}{p_{22}}\right)} + \frac{p \log_{10} p \log_{11} \left(\frac{11}{p_{33}}\right)}{33 \log_{11} \left(\frac{11}{p_{33}}\right)} + \frac{p \log_{12} \left(\frac{11}{p_{44}}\right)}{11 \log_{12} \left(\frac{11}{p_{44}}\right)}$$

$$H = \frac{11}{88} \log_{12} \left(\frac{33}{88}\right) + \frac{33}{88} \log_{12} \left(\frac{33}{88}\right) + \frac{11}{88} \log_{12} \left(\frac{33}{88}\right) + \frac{11}{88} \log_{12} \left(\frac{33}{88}\right) = 11.88 \frac{biits}{message}$$

$$R = rH = 22B \frac{message}{second} + 11.88 \frac{biits}{message} = 33.66 \frac{biits}{second}$$

In the example we discussed above, there are four samples (levels). Those four levels can be coded using binary PCM as shown down in the table:



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Lecture 3: Information and quantification

Information Rate

Message or level	Probability	Binary digits
Q1	1/8	00
Q2	3/8	01
Q3	3/8	10
Q4	1/8	11

Since one bit is capable of conveying 1 bit of information, the above coding scheme is capable of conveying 4 bits of information per second. But in example, we have obtained that we are transmitting 3.6 bits of information per second. This shows that the information carrying ability of binary PCM is not completely utilized by the transmission scheme discussed in example.

Example 7: In the transmission scheme of example 6, calculate the information rate if all messages are equally likely. Solution: Since they are equally likely, their probabilities p1 = p2 = p3 = p4 = 1/4 $H = log_{22}(44) = 22$ bits/message

$$R = rH = 22 \frac{message}{second} * 22 \frac{biits}{message} = 44 \frac{biits}{second}$$

Just before this example we have seen that a binary coded PCM with 2 bits per message is capable of conveying 4 bits of information per second. This has been made possible since all the messages are equally likely. Thus with binary PCM coding the maximum information rate is achieved if all messages are equally likely.



Joint Entropy

The joint entropy represents the amount of information needed on average to specify the value of two discrete random variables The entropy of the pairing (X,Y)

 $H(XX, Y) = \sum_{i=11}^{n} \sum_{i=11}^{n} p(\mathbf{x}_{ii}, y_{ij}) \log_{22} p(\mathbf{x}_{ii}, y_{ij})$

Example 8: Let X represent whether it is sunny or rainy in a particular town on a given day. Let Y represent whether it is above 70 degrees or below seventy degrees. Compute the entropy of the joint distribution P(X, Y) given by P(sunny, hot) = 1/2P(sunny, cool) = 1/4P(rainy, hot) = 1/4P(rainy, cool) = 0**Answer:** $H(X, Y) = - [1/2 \log 1/2 + 1/4 \log 1/4 + 1/4 \log 1/4 + 0 \log 0]$ $= - [-1/2 + -1/2 + -1/2] = \frac{33}{2}$ bits/symbol



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Joint Entropy

Lecture 3: Information and quantification

Homework 4 xxxx For discrete memory channel the joint probability is tabulated as :.

$$P(x,y) = \begin{bmatrix} 0.22 & 0.11 & 0.33 \\ 0.0011 & 0.0033 & 0.0000 \end{bmatrix}$$

Find H(X), H(Y), and H(X,Y)

Homework 5: Two random variables have joint probability distribution p(x, y) given



Find E(X), E(Y), H(X), H(Y), and H(X,Y)



Conditional Entropy

Lecture 3: Information and quantification

Given a pair of random variables (X, Y), the conditional entropy H(X/Y) is defined as

- $= H(XX/Y) = \sum_{ij=11}^{n} \sum_{ii=11}^{n} p(\mathbf{x}_{ii}, y_{ij}) \log_{22} p(\mathbf{x}_{ii}/y_{ij})$
- $= H(Y/XX) = \sum_{j=11}^{n} \sum_{i=11}^{n} p(\mathbf{x}_{ii}, y_{ji}) \log_{22} p(y_{ji}/\mathbf{x}_{ii})$

Example 9: For discrete memory channel the joint probability is tabulated as:.

p(x, y)	y=0	y=1
<i>x=0</i>	1/2	1/4
<i>x=1</i>	0	1/4

Find joint and conditional entropy H(Y | X)

Answer:

H(X,Y) = -1/2log(1/2) - 1/4log(1/4) - 0log(0) - 1/4log(1/4) = 1.5 bits/symbol H(Y/X) = -1/2log2/3 - 1/4log1/3 - 0log0 - 1/4log1 = 0.689 bits/symbol



Chain Rule:

Lecture 3: Information and quantification

H(X,Y) =	H(Y/X)	+H(X)
----------	--------	-------

H(Y|X) is the average additional information in Y when you know X

Example 10: Find joint and conditional entropy	p(x, y)	y=0	y=1
	<i>x=0</i>	1/2	1/4
Answer: $H(X,X) = H(X,X) = H($	<i>x=1</i>	0	1/4
H(X/Y) = H(X,Y) - H(X) = H(1/2,1/4,0,1/4) - H(3/4,1/4) = 0.6989			

Ή(**y**)

 $H(\mathbf{y}|\mathbf{x})$

Conditional Entropy

H(X, y)

(H(X | y))

 $H(\mathbf{X})$

Homework 6: A transmitter produces three symbols A, B, C which are related with joint probabilities as shown in the table below.



P(j	j/k)	J				
		Α	В	С		
1.	Α	0	4/5	1/5		
K	B	1/2	1/2	0		
	С	1/2	2/5	1/10		

Calculated the joint probabilities, the average entropy of a given symbols..

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Lecture 3: Information and quantification

Mutual Information

Mutual Information I(X; Y): consider the set of symbols $x_{11}, x_{22}, ..., x_n$. The source may produce $y_{11}, y_{22}, ..., y_n$. Theoretically, if the noise and jamming is zero then the set x = set y and n = m. however, due to noise and jamming there will be a conditional probability of $p(y_{jj}/x_{jj})$.

This the statistical average of all the pairs $I(x_{ii}, y_{jj})$, i = 1, 2, ..., n, j = 1, 2, ..., m.





Homework 7: Prove that 1. H(X, Y) = H(X) + H(Y|X). 2. I(X; Y) = H(X) - H(X|Y).



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Mutual Information

<u>Mutual Information I(X; Y)</u>: It is a measure of mutual dependence between variables; it quantifies the amount of information obtain about random variable from the other.



I(X; Y) = H(X) - H(X|Y) = H(X) + H(Y) - H(X, Y)

Lecture 3: Information and quantification **Mutual Information Example 12:** of joint entropy. Let p(x, y) be given by Y_{11} Y_{22} Find Х₁₁ Г 00. 00 00. 2200 (a) The marginal entropies [H(X), H(Y)]. \mathbf{X}_{22} 00 00. 112200 (b) The system entropy H(X, Y). X₃₃ L00. 00662200 00.00662200 (c) The noise and losses entropies H(Y | X). (d) The mutually information between $(x_{11}andy_{22})$. (e) The transformation. (f) Draw a channel model. Solution: a. From p(X, Y) $P(x) = [0.75 \quad 0.125]$ 0.125] P(y) = [0.5625]0.4375] Ν М $H(X) = - \bigoplus_{(X_{ij})} \log_{22} p(X_{(j)}) , \quad H(Y) = - \bigoplus_{(Y_{ij})} \log_{22} p(Y_{(jj)})$ *ii*=11 *ii*=11 $H(X) = -[0.75 \log_{22} 0.75 + 0.125 \log_{22} 0.125 + 0.125 \log_{22} 0.125] = 1.06127$ bits/ symbol $H(Y) = -[0.5662200 \log_{22} 0.5662200 + 0.44334400 \log_{22} 0.44334400] = 0.9887 \text{ bits/ symbol}$

Lecture 3: Information and quantification

Mutual Information

$$b. H(X, Y) = -\sum_{jj=11}^{m} \sum_{ii=11}^{n} p(X_{ii}, Y_{jj}) log_{2}p(X_{ii}, Y_{jj}) H(X,Y) = 1.875 bits/symbolc. H(Y/X) = H & Y ext{} H(X) = 1.875 - 1.06127 = 0.81373 bits/symbolH(X/Y) = H & Y ext{} H(Y) = 1.875 - 0.9887 = 0.8863d. I(X_{11}, Y_2) = lg_{22} \frac{p(X_{ii}, Y_{jj})}{p(X_{11})}, I(X_{11}, Y_2) = lg_{22} \frac{p(X_{11}/Y_{22})}{p(X_{13})} but p(X_{11}/Y_2) = \frac{p(X_{11}, Y_{22})}{p(Y_{22})} Then I(X_{11}, Y_{22}) = lg_{22} \frac{p(X_{11}, Y_{22})}{n \frac{p(X_{11}, Y_{22})}{p(X_{11})}} = lg_{220.75 * 0.4375} = -0.3923 bits, that means Y _{22} gives ambiiguilty about X _{11} = I.06127 - 0.8863 = 0.1749 bits/ symbolf. To draw channel model we must find p(y/x) matrix from p(x, y) _{p(Y/X)} = -\sum_{ij=11}^{N} (X_{ii}, Y) / p(X_{ii})$$

Lecture 3: Information and quantification

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Mutual Information







Mutual Information



(f) Venn diagram to illustrate the relationships of entropy and relative entropy

Ministry of Higher Education and Scientific Research Al-Furat Al- Awsat Technical University **Engineering** Technical college / Najaf **Communication Engineering Department Information Technology (CE231)** 2nd Class 2018/2019 Lecturer Ali M. Alsahlany

Lecture Outlines :

- Introduction
- Source coding of discrete sources
- Fixed Length Code
- Variable Length Code
- Minimum Code Length
- Code Efficiency
- Average Code Length
- Requirements for a useful symbol code



Lecture 5: Source Coding

Introduction

Introduction: A general block diagram of a point-to-point digital communication system given in Figure below. The source encoder converts the sequence of symbols from the source to a sequence of binary digits, preferably using as few binary digits per symbol as possible. The source decoder performs the inverse operation.



• Discrete sources

The output of a discrete source is a sequence of symbols from a known discrete alphabet X. This alphabet could be the alphanumeric characters, the characters on a computer keyboard, English letters, Chinese characters, the symbols in sheet music (arranged in some systematic fashion), binary digits, etc.

• Analog waveform sources

The output of an analog source, in the simplest case, is an analog real waveform, representing, for example, a speech waveform. The word analog is used to emphasize that the waveform can be arbitrary and is not restricted to taking on amplitudes from some discrete set of values.



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Source coding of discrete sources

- Lecture 5: Source Coding
 - Simple Model of a source (Called a DISCRETE MEMORYLESS SOURCE OR DMS)





Basic idea is to use as few binary digits as possible and still be able to recover the information exactly

Lecture 5: Source Coding

2/24/2019

Fixed Length Code

- Sometimes the output of the source decoder must be an exact {replica of the information (e.g. computer data) called NOISELESS CODING
- Other times the output of the source decoder can be approximately equal to the information (e.g. music, tv, speech) called CODING WITH DISTORTION



Assume N is the number of symbols> If N is a power of 2, the fixed codeword length $R = l = \log_2 N$ > If N is not a power of 2, the fixed codeword length $R = l = \log_2 N$ $H \le \log_{22}N$, $l \ge H$ l = H (If the symbols have the same probability)



Lecture 5: Source Coding

Variable Length Code

- When the source symbols are not equally probable, a more efficient encoding method is to use variable length code words
- A significant amount of data compression can be realized when there is a wide differences in probabilities of the symbols. To achieve this compression, there must also be a sufficiently large number of symbols

Ex: Morse Code

The codewords of letters that occur more frequently are shorter than those for letters that occur less frequently

Α	•-	M	1.000	Y		6	
В		Ν		Z		7	
С		0		Ä	•-•-	8	
D		P		Ö	·	9	8
E		Q	·•	Ü			
F		R		Ch		,	
G		S		0		?	
Η		Τ		1	•	!	•••

• The variable length codewords should depend on the probability



Minimum Code Length



To be efficient one using knowledge of the statistics of the source such that:

Frequent source symbols should be assigned SHORT code words

Rare source symbols should be assigned LONGER code words

Average Code Length

• Consider a source has K symbols, each symbol s_k has probability P_k, and represented by a code word C_kof length l_k bits, then

Average code word length $k = \bigotimes_{k=11}^{K} l_{k}$ VarWan

Variance of the code word length

$$VarWance = \bigotimes_{k=11}^{K} (l_k - k)^{22}$$



Example 1: Simple discrete source, Alphabet size of 4 (A,B,C,D), $P(A) = p_{11} = P(B) = p_{22} = P(C) = p_{33} = P(D) = p_{44}$, Calculate the average and variance of the code Solution:

 $\mathbf{P} = \mathbf{2}(p_{11} + p_{22} + p_{33} + p_{44}) = \mathbf{2}$



Lecture 5: Source Coding

Average Code Length



average the length of the code is 2.27 bits



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Average Code Length





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Lecture 5: Source Coding

Code Efficiency

Example 3: Source has an alphabet of 26 letters (English Alphabet) with independent and identically distributed random variables: { Xi , i=1,...,26} each occurring with the same probability. Evaluate the efficiency of a fixed length binary code in which:

- a. Each letter is encoded separately into a binary sequence
- b. Two letters at a time are encoded into a binary sequence
- a. Each letter is encoded separately into a binary sequence

$$H = \bigoplus_{\substack{V = 11 \\ V = 11}} g_{22}N = \bigoplus_{\substack{V = 11 \\ 2222}} g_{22}2222 = 44.77 \frac{bVVts}{symbol}$$
$$R = L = \bigoplus_{\substack{V = 11 \\ V = 11}} g_{22}N t = 55 \frac{bVVts}{symbole}$$
$$\eta = \frac{H(S)}{L^{-}} = 9944.00000077\%$$

b. Two letters at a time are encoded into a binary sequence

N=26*26=676 possible sequences $R = log_{22}^{227722} t = 10bits/2 \text{ symbol} = 5bits/symbol$ $\eta = \frac{H(S)}{L^{-}} = 9944.00000077$



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Lecture 5: Source Coding

Code Efficiency

Example 4: Calculate the entropy, minimum length, average code word length, and the compression ratio for the flowing source and the given two different codes for the following symbols

Source	Symbol Probability P _{kk}	Co	de I	Code II	
Symbol SS _{kk}		Symbol Code Word cc _{kk}	Code Word Length l_{kk}	Symbol Code Word cc _{kk}	Code Word Length l_{kk}
SS ₀₀	1/2	00	2	0	1
SS ₁₁	1/4	01	2	10	2
SS ₂₂	1/8	10	2	110	3
SS ₃₃	1/8	11	2	1111	4

 $H(s) = \sum_{k=11}^{K} P \log_{22} \left(\frac{11}{P_{W}}\right) = \frac{12\log_{22} (2) + 1/4\log_{22} (4) + 18\log_{22} (8) + 1/8\log_{22} (8) = 1.75 \text{ bits/symbol} = L_{mW_{W}}$

$$\begin{aligned}
\hat{\mathbf{k}} &= \sum_{k=11}^{K} P l \\
\eta &= \frac{H(S)}{L} \\
\hat{\mathbf{k}} &= 2\mathbf{x}(1/2+1/4+1/8+1/8) = 2 \\
\hat{\mathbf{k}} &= 2\mathbf{x}(1/2+1/4+1/8+1/8) = 2 \\
\hat{\mathbf{k}} &= \left(11 \times \frac{11}{22} + 22 \times \frac{11}{44} + 33 \times \frac{11}{00} + 44 \times \frac{11}{00}\right) = 11.007755 \\
\eta &= ---= 00.99333333 \\
\hat{\mathbf{k}} &= 22 \\
\hat{\mathbf{k}} &= \left(11 \times \frac{11}{22} + 22 \times \frac{11}{44} + 33 \times \frac{11}{00} + 44 \times \frac{11}{00}\right) = 11.007755 \\
\hat{\mathbf{k}} &= 22 \times \frac{11.007755}{11.7755} = 00.007755 \\
\hat{\mathbf{k}} &= 2/2 = 1 \\
\hat{\mathbf{k}} &= \left(11 \times \frac{11}{22} + 22 \times \frac{11}{44} + 33 \times \frac{11}{00} + 44 \times \frac{11}{00}\right) = 11.007755 \\
\hat{\mathbf{k}} &= 22 \times \frac{11.007755}{11.007755} \\
\hat{\mathbf{k}} &= 2/2 = 1 \\
\hat{\mathbf{k}} &= 2/2 \\$$

2/24/2019
Requirements for a useful symbol code /Uniquely Decodable

Uniquely Decodable

A code is <u>not uniquely decodable if</u> two symbols have <u>the same codeword</u>, i.e., if $Cs_{(II)} = Cs_{(II)}$ for any $i \neq j$ <u>or the</u> <u>combination of two codewords gives a third one</u>

It allows the user to invert mapping to the original sequence of elements of the source to (decoding)

Example 5:	Source symbol	Code 1	Code 2
	·	Symbol Codeword	Symbol Codeword
	Α	00	0
	В	1	1
	С	00	00
	D	11	11

CODE1, the symbols A &C are assigned to the same codeword. Thus, <u>the first requirement of a useful code is</u> <u>that each symbol be assigned to a unique binary sequence IS NOT VALID.</u>

CODE2, It is confusing to detect the code, Why? C is decoded as combination of (A, A), also D (B,B).



Requirements for a useful symbol code /Uniquely Decodable

womple 6					
xample o:	${\mathcal S}_{(\mathbb{T})}$	Р	Code 1	Code 2	Code 3
	S ₍₁₁₎	0.5	0	0	0
	$S_{(22)}$	0.25	0	10	01
	$S_{(33)}$	0.125	1	110	011
	S ₍₄₄₎	0.125	10	111	0111
	٨	1	1.125	1.75	1.875

<u>CODE1</u>, the symbols $S_1 \& S_2$ are assigned to the same codeword. S_4 is a combination of (S_3, S_1) or (S_3, S_2) . It is non uniquely detectable code

<u>CODE2</u>, all code words end with 0 except the last one is three 1s. The <u>decoding rule</u> is simple, accumulate bits until you get 0 or until you have three 1s. There is no ambiguity in this rule.

<u>CODE3</u>, each codeword starts with 0, and the only time we see a 0 is in the beginning of a codeword. Therefore, the decoding rule is accumulate bits until you see 0. The bit before the 0 is the last bit of the previous codeword.

Based on the average length, code 1 appears to be the best code However, it is not useful because it is non detectable



Requirements for a useful symbol code /Uniquely Decodable

Example 6:	$S_{(II)}$	Р	Code 1	Code 2	Code 3
	S ₍₁₁₎	0.5	0	0	0
	$S_{(22)}$	0.25	0	10	01
	$S_{(33)}$	0.125	1	110	011
	S ₍₄₄₎	0.125	10	111	0111
	٨	1	1.125	1.75	1.875

<u>CODE2</u>, is called <u>INSTANTENOUS CODE</u> because the decoder knows the moment a codeword is complete.

<u>CODE3</u>, is called <u>NOT INSTANTENOUS CODE</u> because we have to wait till the beginning of the next codeword before we know that the current codeword is complete

This property (Instantaneous) is not a requirement for unique decodability, because it depends

How does the channel terminate the transmission? -e.g. it could explicitly mark the end -it could send only 0s after the end -it could send random garbage after the end,... How soon do we require a decoded symbol to be known? e.g. "instantaneously" as soon as the codeword for the symbol is received.

-within a fixed delay of when its codeword is received -not until the entire message has been received



Lecture 5: Source Coding

Requirements for a useful symbol code /Uniquely Decodable

Example 7: Decode the string 01111111111111111 by code1 01010101010101010 by code2

Si	Code 1	Code 2
S_1	0	0
S_2	01	01
S 3	11	10

Using code1

Using code2



Requirements for a useful symbol code /Uniquely Decodable

Test for Unique Decodability

Suppose we have two binary codewords a and b, where, a is k bits long, b is n bits long, and k < n If the first k bits of b are identical to a, then a is called <u>a prefix of b</u>. The <u>last n-k</u> bits of b are called the <u>dangling suffix</u>

Example 8: if a = 010 and b = 01011, then a is a prefix of b and the dangling suffix is 11

Steps of Unique Decodability

1-Construct a list of all the codewords.

2-Examine all pairs of codewords to see if any codeword is a prefix of another codeword.

3-Whenever you find such a pair, add the dangling suffix to the list unless you have added the same dangling suffix to the list in a previous iteration.

4-Now repeat the procedure using this larger list.

5-Continue in this fashion until one of the following two things happens:

You get a dangling suffix that is a codeword, not uniquely decodable There are no more unique dangling , uniquely decodable



Lecture 5: Source Coding

Requirements for a useful symbol code /Uniquely Decodable

Example 9:	Si	Code 1	Code 2
	<i>S1</i>	0	0
	<i>S2</i>	01	01
	<i>S3</i>	11	10

<u>Code1:</u> S_1 is a prefix of $S_2 \longrightarrow$ code 1 will be [0,01,11,1] 1 is a prefix of 11 but it is already added then the last version is [0,01,11,1] the codeword 1 is not a codeword. <u>IT IS UNIQUELY DECODABLE</u>

<u>Code2</u>: S_1 is a prefix of $S_2 \longrightarrow$ code 2 will be [0,01,10, 1] In new list, 1 is a prefix for 10, the dangling suffix 0, which is the codeword. then the last version is [0,01,10,1] IT IS <u>NOT UNIQUELY</u> DECODABLE

> The variable length codewords should DEPEND ON PROBABILITY

Code should be UNIQUELY DECODABLE



Requirements for a useful symbol code /Prefix Code

Prefix Code

Is a code in which no codeword is the beginning of another codeword
Is a code in which no codeword is a prefix to another codeword

Since no codeword is a prefix of the other, we will never face the possibility of a dangling suffix being a codeword. In this case, the set of dangling suffixes is the null set, and we do not have to worry about finding a dangling suffix that is identical to a codeword

A prefix code is uniquely decodable but the converse is not true

Example 10:				
	${\mathcal S}_{(\mathbb{T})}$	Code 1	Code 2	Code 3
	S ₍₁₁₎	0	0	0
	$S_{(22)}$	1	10	01
	S ₍₃₃₎	00	110	011
	S ₍₄₄₎	11	111	0111
		Not Uniquely Decodable Nor Prefix Code	Uniquely De	codable Codes



Requirements for a useful symbol code /Prefix Code

Homework 1: Determine the prefix codes and the uniquely decodable codes of the following codes Symbol Prob. Code 1 Code 2 Code 3 Code 4 P[A]=1/2 1 00 A 1 0 *P[B]=1/4* В 01 10 10 01 С *P[C]=1/8* 001 100 110 10 D P[D]=1/16 0001 1000 1110 11 P[E]=1/16 Ε 00001 10000 1111 110 Average 31/16 31/16 30/16 33/16 Length



Requirements for a useful symbol code /Prefix Code

Test for Prefix Code

- 1. Draw the <u>rooted binary tree</u> corresponding to the code (<u>Decoding Tree</u>) Starts from a single node (the root node) and has a maximum of two possible branches at each node. One of these <u>branches corresponds to a 1</u> and the other branch corresponds to a 0
- 2. The code for any symbol can be obtained by traversing the tree from the root to the external node corresponding to that symbol.





S_1 0 0 0 S_2 1 10 01 S_3 00 110 011	S _i	Code 1	Code 2	Code 3
S2 1 10 01 S3 00 110 011	S_{I}	0	0	0
S ₃ 00 110 011	S_2	1	10	01
	S_3	00	110	011
δ_4 11 111 0111	S_4	11	111	0111





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Lecture 5: Source Coding

Requirements for a useful symbol code /Prefix Code



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Lecture 5: Source Coding

Requirements for a useful symbol code /Kraft-McMillan Inequality



A prefix code must satisfy the Kraft McMillan's inequality But a code satisfies Kraft McMillan's inequality is not necessarily be a prefix code

Example 12:



For this code $2^{-1} + 2^{-2} + 2^{-3} + 2^{-2} = 9/8$ which means that the code IS NOT A PREFIX CODE

i.e., Kraft-McMillan Inequality can determine that a given code IS NOT A PREFIX CODE

Requirements for a useful symbol code /Kraft-McMillan Inequality

Example 13: For this code	s _k	Co	de
		c _k	l
$2^{-1} + 2^{-2} + 2^{-3} + 2^{-3} = 1$	s ₀	0	1
Is the code a PREFIX code?	<i>s</i> ₁	100	Ĵ
NO WHY?	<i>s</i> ₂	110	3
s3 is a beginning of s2	S 3	11	2

Hence, if we have a uniquely decodable code that its codeword lengths satisfy the Kraft- McMillan inequality, then we can always find a prefix code with those codeword lengths

Thus, by restricting ourselves to prefix codes, no need for nonprefix uniquely decodable codes that have a shorter average length

Code Redundancy

Is the difference between the average length and the entropy

$$\rho = \overline{L} - H = \sum_{k=1}^{K} P_k \left(l_k - \log P_k(s_k) \right)$$



Example 6: The code $C_{11} = \{0; 101\}$ is a prefix code because 0 is not a prefix of 101, nor is 101 a prefix of 0.

Exercise 1: Is the code $C_{22} = \{0; 10; 110; 111\}$ prefix or not?

Exercise 2: Is the code C₃₃ = {00; 01; 10; 11} prefix or not?

Exercise 3: Is the code $C_{44} = \{1; 101\}$ prefix or not?

Homework 2: : Calculate the entropy, minimum length, average code word length, and the compression ratio for the flowing

source





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Lecture Outlines :

- Shannon-Fano code
- Huffman Code
- Huffman vs. Shannon

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Lecture 6: Source Coding

Shannon-Fano code

It is a technique for constructing a prefix code based on a set of symbols and their probabilities (estimated or measured)

It is <u>suboptimal</u> in <u>the sense that</u> it <u>does not achieve the lowest possible expected code word length</u> Algorithm

- 1. Source symbols are listed in order of decreasing probability from left to right.
- 2. Divide the list into two parts, with the total probability (or frequency of occurrence) of the left part being as close to the total of the right as possible.
- 3. The left part of the list is assigned the binary digit 0, and the right part is assigned the digit 1. This means that the codes for the symbols in the first part will all start with 0, and the codes in the second part will all start with 1.
- 4. Recursively apply the steps 2 and 3 to each of the two halves, subdividing groups and adding bits to the codes until each symbol has become a corresponding code leaf on the tree.



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Shannon-Fano code

Example 1: Assume a sequence of alphabet S={ A, B, C, D, E, F } with the following occurrence weights, {9, 8, 6, 5, 4, 2} respectively. Apply Shannon Fano coding and discuss the suboptimality.

Solution:



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Lecture 6: Source Coding

Shannon-Fano code



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Shannon-Fano code



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Shannon-Fano code

Symbol	Frequency	Р	CODE
Α	9	0.265	00
В	8	0.235	01
С	6	0.176	100
D	5	0.147	101
E	4	0.118	110
F	2	0.059	111

 $\mathbf{R} = \mathbf{R}_k l_k$ k=11

x = 2x(0.235+0.265)+3x(0.176+0.147+0.118+0.058)=2.5 bits/symbol



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Shannon-Fano code

Exercise 1	: C	onstr	uct t	the S	Shann	:0 n- .	Fano	cod	e and	the cor	resj	ponding	efficien	cy for DA	AS with th	e followi	ing
probability	V• [r	c	x	1)	x ₂	х	¢3	x_4		<i>x</i> ₅	<i>x</i> ₆	<i>x</i> ₇	<i>x</i> ₈		
		P(x	c _{ii})	0	.5	0	.15	0.	.15	0.08		0.08	0.02	0.01	0.01		
Solution:	Solution:																
	•	x	P(x)	(ii)											Final	length	
	x	1	0.	.5	0										0	1	
	x	2	0.	15	1		0		0						100	3	
	x	3	0.	15	1		0		1						101	3	
	x	4	0.	08	1		1			0					110	3	
	x	5	0.0	08	1		1			1		0			1110	4	
	x	6	0.0	02	1		1			1		1	0		11110	5	
	x	7	0.	01	1		1			1		1	1	0	111110	6	
	x	8	0.	01	1		1			1		1	1	1	111111	6	



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Lecture 6: Source Coding

Shannon-Fano code

$$H(X) = - \bigoplus_{\substack{i=11\\i=11}}^{N} \chi_{i} \ log_{22}p \ (\chi_{i}) = H = \sum_{i=1}^{N} P_i I(s_i)$$

$$H(X) = 00.55 \times -log_{22}(00.55) + 22 \times (00.1155) \times -log_{22}(00.1155) + 22 \times 00.0000 \times -log_{22}(00.000) + 00.0022 \times -log_{22} (00.0022) + 22 \times 00.0011 \times log_{22}(00.0011) = 2.149 \approx 2.15 \ bit/symbol$$

$$\mathbf{\hat{P}} = 00.55 \times 11 + 00.1155 \times 33 + 00.1155 \times 33 + 00.0000 \times 33 + 00.0000 \times 44 + 00.0022 \times 55 + 00.0011 \times 66 + 00.0011 \times 66 = 22.1100 \ bitit/symbol$$

$$\eta = \frac{L_miin}{L_m} = \frac{H(S)}{L_m} = \frac{22.1155}{22.1100} = 9900 \ \%$$



Shannon-Fano code

<u>Homework 1</u>: Apply the Shannon-Fano code procedure for DMS with the following probability. Find the corresponding efficiency and <u>redundancy</u>.

x	x_1	<i>x</i> ₂	<i>x</i> ₃	x_4	x_5	<i>x</i> ₆
$P(x_{ii})$	0.3	0.25	0.15	0.12	0.08	0.1

<u>Homework 2:</u> Apply the Shannon-Fano code procedure for DMS with the following probability. Find the corresponding efficiency and <u>redundancy.</u>

x	x_1	<i>x</i> ₂	<i>x</i> ₃	x_4	<i>x</i> ₅	<i>x</i> ₆	<i>x</i> ₇	<i>x</i> ₈
$P(x_{ii})$	1/4	1/8	1/16	1/16	1/16	1/4	1/16	1/8

<u>Homework 3:</u> The text [AAAABBBCDC]

1. Find min code word used <u>Shaanon-Fano</u>.



Huffman procedure is based on two observations regarding optimum prefix codes:

1- Symbols that occur more frequently (have a higher probability of occurrence) will have shorter codewords than symbols that occur less frequently

2- The two symbols that occur least frequently will have the same length. It is commonly used for lossless compressions

- <u>Huffman code</u> is a prefix, variable length code that can achieve the shortest average code length for a given input alphabet with probability mass function (pmf).
- In general, Huffman coding is a form of statistical coding as not all characters occur with the same frequency (Probability).
- The process of <u>finding the optimal code</u> was algorithmized by Huffman.
- A code is an optimal prefix code if it has the same average codeword length as a Huffman code for the given pmf.

<u>Huffman Algorithm</u>

- 1. Source symbols are listed in order of decreasing probability (frequency).
- 2. The two source symbols of lowest probability are assigned a 0 and 1(<u>splitting stage</u>).
- 3. These two source symbols are combined into a new source symbol with probability equal to the sum of the two original probabilities (*The list of source symbols and therefore source statistics is thereby reduced in size by one*).
- 4. The probability of the new symbol is placed in the list in accordance with its value

The steps are repeated until we are left with a final list of source statistics of only two for which a 0 and a 1 are assigned



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Lecture 6: Source Coding

Huffman Code



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Lecture 6: Source Coding

Huffman Code





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Huffman Code

<u>Homework 4</u>: Consider the following short text

Eerie eyes seen near lake Build the Huffman code to encode the text

<u>Homework 5:</u> Source transmitted symbols with probability as shown in table below. Find corresponding efficiency.

S	$P(x_{ii})$
<i>S</i> ₁	0.3
<i>S</i> ₂	0.25
<i>S</i> ₃	0.2
S_4	0.12
<i>S</i> ₅	0.08
S_5	0.05



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Lecture 6: Source Coding

Huffman vs. Shannon



 $\mathbf{P} = \sum_{k=11}^{K} P_k l_k , \mathbf{P} = 2x(0.235 + 0.265 + 0.176) + 3x(0.147) + 4x(0.118 + 0.058) = 2.47 \text{ bits/symbol}$

The average code length is less than that of Shannon Fano code, Hence Huffman is optimum, but Shannon is suboptimal



Extended Huffman Code

In applications where the alphabet size is large; P_{max} is generally quite small, and the amount of deviation of the entropy from the average code length (or in terms of a percentage of the rate) is quite small. However, in cases where the alphabet is small and the probability of occurrence of the different letters is skewed, the value of P_{max} can be quite large and the Huffman code can become rather inefficient when compared to the entropy.

Ex: Find the Huffman code for the following source given the corresponding probabilities

$$S_o$$
 0.8
 0.8
 0.8
 0
 S_1
 0.02
 S_2
 0.18
 0
 0.2
 0.2
 10
 S_2
 0.18
 S_1
 0.02
 1
 11

 $H(S) = (00.00) \times log_{22}(11/00.00) + (00.0022) log_{22}(11/00.0022) + (00.1100) log_{22}(11/00.1100) = 00.001166 \ biits/symbol$ $P = 00.00 \times 11 + 00.0022 \times 22 + 00.1100 \times 22 = 11.22 \ biits/symbol$ There is a big difference between the average code length and the entropy (Code Redundancy), $\rho = P - H(S) = 0.384 \ bits/symbol$



We can reduce the rate (average length) by grouping (blocking)symbols together which is called Extended (Block) Huffman Code -Consider a source S that emits a sequence of letters $[s_1, s_2, s_3, ..., s_m]$ -Each element of the sequence is generated independently -The entropy for this source is given by $H(S) = \sum_{ii=11}^{N} p_{(s_{ii})} log_{2i} \frac{11}{p_{(s_{ii})}}$ -One can generate a Huffman code for this source with rate R (In data compression it is bits per symbol like the average length not bits per second as in communication) Such that $H(S) \le R \le H(S) + 11$ -Encode the sequence by generating one codeword for every n symbols, hence there are m_n combinations of n symbols

-Denote the rate for the new source as $R^{(n)}$, hence $H(S^{(n)}) \leq R^{(n)} \leq H(S^{(n)}) + 1$

 $R^{(n)}$ is the number of bits required to code *n* symbols together. Therefore, the number of bits required per symbol, *R*, is given by

$$R \le R^{(n)}/n$$
 $\frac{H(S^{(n)})}{n} \le \frac{R(n)}{n} \le \frac{H(S^{(n)})}{n} + \frac{1}{n}$



Extended Huffman Code

Lecture 6: Source Coding

<u>Example 4:</u>	Find the	extended	Huffman	code fo	r the f	ollowing	source	given th	ne corresp	onding

SI

Sa

S.

0.8

0.02

0.18

probabilities by blocking every two symbols.

Sol	ution:

-m=3, n=2, the number of possible symbol pairs or the extended symbols are $33^{22}=9$

-The probability of each extended symbol is calculated by multiplying the probabilities of the original single items together -Follow the steps of getting Huffman code, you get the code in that table

Extended Symbol	Probability Model	Huffman Code
<i>S</i> ₁ <i>S</i> ₁	0.64	0
<i>S</i> ₁ <i>S</i> ₂	0.016	10101
<i>S</i> ₁ <i>S</i> ₃	0.144	11
<i>S</i> ₂ <i>S</i> ₁	0.016	101000
<i>S</i> ₂ <i>S</i> ₂	0.0004	10100101
<i>S</i> ₂ <i>S</i> ₃	0.0036	1010011
<i>S</i> ₃ <i>S</i> ₁	0.144	100
S_3S_2	0.0036	10100100
<i>S</i> ₃ <i>S</i> ₃	0.0324	1011

 $H(S) = (00.00) \times log_{22}(11/00.00) + (00.0022) log_{22}(11/00.0022) + (00.1100) log_{22}(11/00.1100) = 00.001166 \ biits/symbol$ $L_{e\times t} = 11.77222200 \ biits/symbol$



Extended Huffman Code

Each symbol in the extended alphabet corresponds to two symbols from the original alphabet

 $L_{e\times t} = \frac{11.77222200}{22} = 00.006611 \ biits/symbol$

Redundancy = 0.0045 *bits/symbol*

There is no big difference between the average code length and the entropy,

Hence, one can see that by encoding the output of the source in longer blocks of symbols can guarantee a closer rate to the entropy

But as we block more and more symbols together, the size of the alphabet grows exponentially, and the Huffman coding scheme becomes impractical



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Lecture Outlines :

- Introduction
- Error detection codes
 - Error detection codes / parity codes
- Error correction codes
 - Error correction codes / Basic definitions
 - Error Correction Codes / Hamming Codes
 - Error Correction Codes / Cyclic Codes

Lecture 6: Channel Coding

Introduction

<u>Channel Coding:</u> To ensure reliable communications, techniques have been developed that allow bit errors to be detected and corrected. The process of error detection and correction involves adding extra redundant bits to the data to be transmitted. This process is generally referred to as channel coding.

Channel coding methods fall into to two separate categories:

- <u>Error detection codes</u>: only have the ability to confirm that bit error(s) has occurred, however they cannot tell you which bit was in error. To fix the error, the receiver must request a retransmission.
- <u>Error correcting codes or forward error correction (FEC) codes:</u> have the ability to detect some bit errors and fix them without requiring a retransmission.




Lecture 6: Channel Coding

Introduction

Example 1 : Linear block code (7,4) with $k = 4$ and $k + r = 7$		N
	((\mathbf{C})

Message	Code words
$(0\ 0\ 0\ 0)$	$(0\ 0\ 0\ 0\ 0\ 0\ 0)$
(0001)	$(1\ 0\ 1\ 0\ 0\ 0\ 1)$
(0 0 1 0)	$(1\ 1\ 1\ 0\ 0\ 1\ 0)$

A key point about channel coding is that there is a cost to be paid of increasing reliability. The extra n bits added by encoding result in:

Larger file sizes for storage.
Higher required transmission data rates.

This cost is represented by the code rate. The code rate R_c is the ratio of the number of information bits k to the number of bits in the codeword k + r.

n = k + r

 $R_c = k/n$

r bits (add redundancy)	k bits (information or message bit)
-------------------------	-------------------------------------

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Error detection codes

Example 2: code (8,7) **That is mean n = 8bit, k = 7bit, and r = 8 - 7 = 1bit** $<math>R_c = k/n = 77/88$

Simple Error Detection Codes:

Parity check code (n, k)

 $R_c = k/(k + 11)$

<u>**Parity codes**</u> The simplest kind of error-detection code is the *parity code*. To construct an even-parity code, add a parity bit such that the total number of 1's is even.

Information bits	Even parity code	Odd parity code
000	000 0	000 1
001	001 1	001 0
010	010 1	010 0
011	011 0	011 1

<u>1-bit parity codes</u> can detect single bit errors, but they do not detect <u>2 bit errors</u>. Probability (detecting errors)= Probability (odd number of errors) and Probability (undetecting errors)= Probability (even number of errors).



Example 3: Parity check code of k=7 bit. Calculate P (undetected error) and P (detected error) Solution: P (undetect error) = $\sum_{k} C_{k}^{n} p^{k} (11 - p^{k}) = C_{22}^{88} p^{22} (11 - p)^{66} + C_{44}^{88} p^{44} (11 - p)^{44} + C_{66}^{88} p^{66} (11 - p)^{22} + C_{88}^{88} p^{88} \approx$ 28x1111⁻⁴⁴ The probability of detected errors will be: P (detect error) = $\sum_{k} C_{n}^{n} p^{k} (11 - p^{k}) = C_{11}^{88} p^{11} (11 - p)^{77} + C_{33}^{88} p^{33} (11 - p)^{55} + C_{55}^{88} p^{55} (11 - p)^{33} + C_{77}^{88} p^{77} (11 - p) \approx$ 8×1111⁻³³

<u>Homework1</u>: assume there are n=12 bits in a codeword (packet). Probability of error in a single bit transmission $p_b=1111^{-33}$. Find the probability of error-detection failure.



Lecture 6: Channel Coding

Error detection codes / parity codes

To implement these parity generators, simple Ex-OR gates are used at TX and RX as shown below If the 7-bit ASCII character contains: 7-bit ASCII character - an even # of 1s, this output will be a 0 stored in - an odd # of 1s, this output will be a 1 Exclusive OR a register (XOR) circuit $C = A \bigoplus B$ XOR circuits Even parity Truth Table AB C **Information** Even 0 0 0 0 1 bits parity code 1 0 1 Odd 1 1 0 parity 1010111 1 Start bit 7-bit ASCII code Stop bit Mark 0110101 0 0 0 0 0 Space Parity bit (even)



Lecture 6: Channel Coding

Example 4: *Parity cheak code* (8,7) *find code word if data* $I_{11} = [11111111111], I_{22} = [11111111111], and I_{33} = [11111111111]$ Solution: $C_{bb} = [I_{bb}: parbbty bbbt]$

 $C_{11} = [1111111111111111]$

Excersise 1: detect error in the received code word (use parity check code (8,7) then find data words. $C_{22} = [111111111111111111]$ $C_{11} = [1111111111111111]$ $C_{33} = [11111111111111111]$

Solution:

- In code C₁₁ number of ones is even there is no error, data is 0101010
- In code C₂₂ number of ones is odd there is error
- In code C_{33} number of ones is even there is no error, data is 1111011

Error correction codes / Basic definitions

<u>Systematic and nonsystematic codes:</u> If information bits (a 's) are unchanged in their values and position at the transmitted codeword, then this code is said to be systematic.

Input data [D]= $[a_{11} a_{22} a_{33} \dots \dots a_k]$,

Output systematic (n,k) codeword is $[C] = [a_{11} a_{22} a_{33} \dots a_k c_{11} c_{22} c_{33} \dots c_r]$

However if data bits are spread or changed at the output codeword then, the code is said to be nonsystematic:

Output nonsystematic (7,4) codeword is $[C] = [c_{22} a_{11} c_{33} a_{22} c_{11} a_{44} a_{33}]$

<u>Hamming distance</u>: The ability of error detection and correction codes depends on this parameter. The Hamming distance between two codewords c_{bb} and c_{jj} is denoted by d_{bbj} which is the number of bits that differ. For a binary (n,k) code with 22^k possible codeword then the minimum Hamming distance (HD) is the min) (d_{bbj}) of course $n \ge d_{bbj} \ge 11$

Example 5: Find the Hamming distance between the two codewords: $C_{11} = [11111111111]$ and $C_{22} = [11111111111]$. **Solution:** Here, the number of bits that differ is 2, hence $d_{1122} = 22$



Error correction codes / Basic definitions

<u>Homework 2:</u> Find the minimum Hamming distance for the 3 codewords. $C_{11} = [111111111111]$, $C_{22} = [111111111111]$, $C_{22} = [1111111111111]$

<u>Hamming weight</u>: This is the number of 1's in the non zero codeword c_{\parallel} . It is denoted by cc_{\parallel} . As will be shown later, and for linear codes, $cc_{m\parallel n} = HD = mbn(d_{\parallel n})$. This simplifies the calculation of HD. As an example 5, <u>Example 6</u>: If $C_{11} = [111111111111]$, then $cc_{\parallel} = 3$, for $C_{22} = [111111111111111111111]$, then $cc_{\parallel} = 2$ and so on.

Linear and non Linear codes: when the parity bits are obtained from a linear function of the k information bits then the code is said to be linear, otherwise it is a nonlinear code.



Lecture 6: Channel Coding

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Error correction codes / Basic definitions

Hamming Bound: The purpose of Hamming bound is either 1) to choose the number of parity bits (r) so that a certain error correction capability is obtained. Or

2) to find the error correction capability (t) if the number of parity bits (r) is known for binary codes, this is given by:

$$22^{n-k} = 22^r \ge \sum_{jj=11}^t C_{jj}^n$$

where t is the number of corrected bits.

$$t = bbnt[\frac{HD - 11}{22}]$$
no. of detected error bbbt = HD - 11

Example 7: for a single correction code with k=4 find the no. of parity bits that should be added. **Solution:**

$$22^{r} \geq \sum_{ii=11}^{11} C_{ii}^{44+r} = C_{11}^{44+r} + C_{11}^{44+r}$$
 This gives $2^{r} \geq 1 + (4+r)$ and the minimum r is r=3

(take minimum r to have max code efficiency). This is the (7,4) code. the code is said to be perfect code.

Homework 3: if k=5 and up to 3 errors are to be corrected, find the no. of check bits that should be added.



Lecture 6: Channel Coding

Error correction codes / Basic definitions

<u>Note:</u> If the (n,k) codewords are trans. through a channel having error $prob=p_e$, then prob. of decoding a correct word at the Rx for t-error correcting code will be: P(correct words)=p(no error)+p(1 error)+.....p(t errors) and prob(erroneous word)=1-P(correct word).



Lecture 6: Channel Coding

Error correction codes / Basic definitions

Example 8: Block code (7, 4) calculate no. detect and correct bit Hamming Distance (HD) and P(correct error). **Solution:** n = 77 k = 44 r = 77 - 44 = 33 bbbt $22^r \ge \sum^t C^n$ $22^{33} \ge \frac{C^{77}}{11} + \frac{11}{C^{77}} + \frac{11}{66} \times \frac{77}{77} + \frac{11}{66} \times \frac{77}{77}$ $\mathbf{88} \geq \mathbf{11} + \mathbf{77} + \underline{}_{\mathbf{22}} \cdots \cdots$ Taken two element that mean t = 11 $t = bbnt \left[\frac{HD - 11}{22}\right] \Rightarrow \Rightarrow HD = 33$ No. of detected error = (HD - 11) = 22 $P(\text{ correct error}) = \bigoplus_{i=1}^{n} P^{ii} (1-P)^{n-ii}$ $P_{\text{(correct error)}} = C_{11}^{77} P_{11}^{11} (\overline{\mathbf{1}} - P_{11}^{77} + C_{11}^{77} P_{11}^{11} (\mathbf{1} - P_{11}^{66}))$ $= 11 * 1(11 - P)^{77} + 7P(11 - P)^{6}$ Code rate = $\frac{k}{-} = \frac{44}{-}$



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Lecture 6: Channel Coding

Error Correction Codes / Hamming Codes

One way to detect and correct errors is to add parity checks to the codewords:

- If we add a parity check bit at the end of each codeword we can detect one (but not more) error per codeword.
- By clever use of more than one parity bits, we can actually identify where the error occurred and thus also correct errors.
- Designing ways to add as few parity bits as possible to correct and detect errors is a really hard problem.



Richard W. Hamming (11.2.1915-7.1.1998)



Lecture 6: Channel Coding

Error Correction Codes / Hamming Codes

Linear Block Codes:

Only systematic binary codes will be described. The r parity bits are obtained using a linear function of the a's data. Mathematically, this can be described by the set of equations:

 $\begin{array}{l} C_1 = h_{11}a_1 + h_{12}a_2 + h_{13}a_3 + \dots + h_{1k}a_k \\ C_2 = h_{21}a_1 + h_{22}a_2 + h_{23}a_3 + \dots + h_{2k}a_k \\ \dots \\ C_r = h_{r1}a_1 + h_{r2}a_2 + h_{r3}a_3 + \dots + h_{rk}a_k \end{array}$ (1)

Where + is mod-2 addition (EX-OR), product is the AND multiplication and h_{ij} coefficients are binary variables for a binary coding. The complete output codeword can be written in matrix form as:

 $[C] = [D][G] \dots (1)$, where: $[G] = \begin{bmatrix} G \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

$$[G] = \begin{bmatrix} 1 & 0 & 0 & 0 & h_{11} & h_{21} & h_{31} & . & h_{r1} \\ 0 & 1 & 0 & 0 & h_{12} & h_{22} & h_{32} & . & h_{r2} \\ 0 & 0 & 1 & 0 & . & . & . & . \\ 0 & 0 & 0 & 1 & h_{1k} & h_{2k} & h_{3k} & . & h_{rk} \end{bmatrix}$$

 $G = [I_k : P_{kxr}]$ which is kxn matrix.

This matrix is called the generator matrix of the linear block code (LBC). Equation(1) can also be written in matrix form as:



Error Correction Codes / Hamming Codes

$$[H] [C]^{T} = [0]$$
....(2)

where: $[C]=[a_1 a_2 a_3 \dots a_k c_1 c_2 c_3 \dots c_r]$ and [H] matrix is in fact related with [G] matrix by:

 $[H]=[-P^T: I_r]$, and for binary coding this – sign drops out. This rxn [H] matrix is called the parity check matrix. As will be shown, encoding can be done either using eq(1) ([G] matrix) or eq(2) ([H] matrix), but decoding is done using [H] matrix only.

Example 9: a given binary (7,4) Hamming code with a parity check matrix:

$$G = \begin{bmatrix} 1000011\\0100101\\0010110\\0001111 \end{bmatrix}$$

$$G = [I_{kxk}: P_{kxr}]$$

Find: 1) no. of error correction and detect capability 2) Code rate 3) encoder circuit 4) if data [1011] find codewords.



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 $C_{11}=I_{22} \bigoplus I_{33} \bigoplus I_{44}$ $C_{22}=I_{11} \bigoplus I_{33} \bigoplus I_{44}$ $C_{33}=I_{11} \bigoplus I_{22} \bigoplus I_{44}$

Codeword Truth Table:

Data 4 bits	Codeword 7 bits
0000	0000000
0001	0001111
0010	0010
0011	0011
1111	1111





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Homework 4: The generator matrix of a LBC is given by:

 $[G] = \begin{bmatrix} 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 1 \end{bmatrix}$

a-Use Hamming bound to find error correction capability. b-Find the parity check matrix. c-find the code table, Hamming weight and the error correction capability then compare with part(a). d-If the received word is [R]=[1011110011], find the corrected word at the Rx.



Cyclic Codes

These are subclass from the linear block codes. The name cyclic comes from the fact that any cyclic shift of a codeword is another codeword. i.e, if [C1]=[0011010] is a codeword then [C2]=[0001101] is another codeword obtained from [C1] by a right circular shift.

Cyclic codes can be classified into two types:

Nonsystematic
cyclic codesSystematic cyclic
codes

Generation of cyclic codes: A) nonsystematic Cyclic Codes: (Multiplicative):



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Error Correction Codes / Cyclic Codes

Procedure:

(1) For [D]=[a₁ a₂ a_k] data word, write the data word in terms of a power of a dummy variable x with a₁ weighted as MSB (Most Significant Bit) and a_k as LSB(Least Significant Bit).

$$\mathbf{x}^{k-11}\mathbf{x}^{k-2}$$
 \mathbf{x}^{22} \mathbf{x}^{11} \mathbf{x}^{11}
 \mathbf{a}_{1} \mathbf{a}_{2} \mathbf{a}_{k-2} \mathbf{a}_{k-1} \mathbf{a}_{k}

MSB LSB $D(x)=a_k+a_{k-1} x+a_{k-2} x^2+...+a_2 x^{k-2}+a_1 x^{k-1}$ where "+" sign is mod-2 addition(Ex-OR) <u>For example if [D]=[1 1 1 0 1]</u>,

then $D(x)=1+x^2+x^3+x^4$

<u>and if D(x)= x⁶+x²+1 then [D]=[1000101]</u>

2) Multiply D(x) by what is called generator polynomial g(x) of order r=n-k.
(3) The output codeword polynomial will be:
C(x)=D(x) g(x) from which we can find the output codeword [C]

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Lecture 6: Channel Coding		Error Correction Codes / Cyclic Code
Example: $g(x) = x^{33} + x + 11$		
A.		
1. $xx^{rr} = xx^{33}$		
2. have x^r , 1		
D		
$D_{-}[1011]$		
	$D(x) = 11 \pm 11x \pm 11x^{22} \pm 11x^{33}$	
	$D(\mathbf{x}) = 11 + 11\mathbf{x} + 11\mathbf{x}^{3}$ $D(\mathbf{x}) = 11 + 11\mathbf{x} + 11\mathbf{x}^{3}$	
	$D(X) = \Pi + \Pi X + \Pi X$	
D = [1 0 0 0]		
	$D(\mathbf{x}) = \mathbf{x}^{33}$	



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Error Correction Codes / Cyclic Codes

Example 10: Find codeword using nonsystematic cyclic code, if $g(x) = x^{33} + x + 11$ and $D = [11 \ 11 \ 11 \ 11]$ Solution: 1. $G(\mathbf{x}) = \mathbf{x}^{33} + \mathbf{x} + 11$ **2.** $D = [11 \ 11 \ 11 \ 11]$ $D(\mathbf{x}\mathbf{x}) = \mathbf{1}\mathbf{1} + \mathbf{x} = \mathbf{z} \mathbf{k} \mathbf{z}$ r=3 N = k + r = 44 + 33 = 77Code (7,4) , code rate = 4/7 $C(\mathbf{x}) = G(\mathbf{x})D(\mathbf{x})$ $= (x + 11)(x^{33} + x + 11)$ $= [x^{44} + x^{22} + x + x^{33} + x + 11]$

<u>Homework 5</u>: Find codeword using nonsystematic cyclic code, if $g(x) = x^{44} + x^{22} + 11$ and D = [1111111]

