

Information Theory

Lecture notes 2015-2016

Introduction

Organization

Professors:

- ▶ Lectures: Nicolae Cleju
- ▶ Laboratories: Daniel Matasaru

Grades

$$\text{Final grade} = 0.75 \text{ Exam} + 0.25 \text{ Lab}$$

Time schedule

- ▶ 14 weeks of lectures (3h each)
- ▶ 14 weeks of laboratories (2h each)
- ▶ Office hours: by appointment

Course structure

1. Chapter I: Discrete Information Sources
2. Chapter II: Discrete Transmission Channels
3. Chapter III: Source Coding
4. Chapter IV: Channel Coding

1. ***Elements of Information Theory*, Valeriu Munteanu, Daniela Tarniceriu, Ed. CERM I 2007**
2. *Elements of Information Theory*, Thomas M. Cover, Joy A. Thomas, 2nd Edition, Wiley 2006
3. *Information and Coding Theory*, Gareth A. Jones, J. Mary Jones, Springer 2000
4. *Transmisia si codarea informatiei*, lectures at ETTI (Romanian)

Introduction to probabilities

Basic notions of probability

- ▶ Random variable = the outcome of an experiment
- ▶ Distribution (probability mass function)
- ▶ Discrete distribution
- ▶ Alphabet
- ▶ Logarithm function
- ▶ Exponential function
- ▶ Average of some values

Basic properties

- ▶ Two independent events:

$$p(A \cap B) = p(A) \cdot p(B)$$

Chapter I: Discrete information sources

Block diagram of a communication system

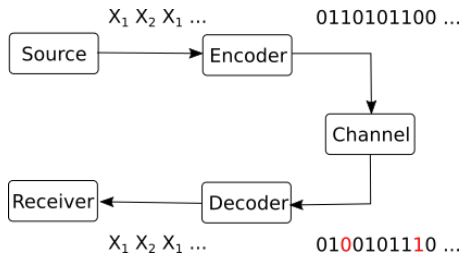


Figure 1: Block diagram of a communication system

What is information?

Example:

- ▶ I tell you the following sentence: “your favorite football team lost the last match”.
- ▶ Does this message carry information? How, why, how much?
- ▶ Consider the following facts:
 - ▶ the message carries information only because you didn't already know the result.
 - ▶ if you already known the result, the message is useless (brings no information)
 - ▶ since you didn't know the result, there were multiple results possible (win, equal or lose)
 - ▶ the actual information in the message is that *lost* happened, and not *win* or *equal*
 - ▶ if the result was to be expected, there is little information. If the result is highly unusual, there is more information in this message

Information source

- ▶ We will always consider information in a context similar to the above example.
- ▶ We will use terminology from probability theory to define information:
 - ▶ there is a *probabilistic source* that can produce a number of different *events*.
 - ▶ each event has a certain probability. We know all the probabilities beforehand.
 - ▶ at one time, an event is randomly selected according to its probability.
 - ▶ afterwards, a new message can be selected, and so on ==> a stream of messages is produced.
- ▶ The source is called an *information source* and the selected event is a *message*.
- ▶ A message carries the information that **it** happened, and not the other possible message events that could have been selected.
- ▶ The quantity of information is dependent in its probability.

Discrete memoryless source

- ▶ A discrete memoryless source (DMS) is an information source where the messages are **independent** , i.e. the choice of a message at one time does not depend on what were the previous messages
- ▶ Each message has a fixed probability. The set of probabilities is the *distribution* of the source.

$$S : \begin{pmatrix} s_1 & s_2 & s_3 \\ \frac{1}{2} & \frac{1}{4} & \frac{1}{4} \end{pmatrix}$$

- ▶ Properties:
 - ▶ Discrete: it can take a value from a discrete set (alphabet)
 - ▶ Complete: $\sum p(s_i) = 1$
 - ▶ Memoryless: successive values are independent of previous values (e.g. successive throws of a coin)
- ▶ A message from a DMS is also called a *random variable* in probabilistics.

Examples

- ▶ A coin is a discrete memoryless source (DMS) with two messages:

$$S : \begin{pmatrix} heads & tails \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix}$$

- ▶ A dice is a discrete memoryless source (DMS) with six messages:

$$S : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 & s_5 & s_6 \\ \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} \end{pmatrix}$$

- ▶ Playing the lottery can be modeled as DMS:

$$S : \begin{pmatrix} s_1 & s_2 \\ 0.9999 & 0.0001 \end{pmatrix}$$

Examples

- ▶ An extreme type of DMS containing the certain event:

$$S : \begin{pmatrix} s_1 & s_2 \\ 1 & 0 \end{pmatrix}$$

- ▶ Receiving an unknown *bit* (0 or 1) with equal probabilities:

$$S : \begin{pmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \end{pmatrix}$$

- ▶ When a DMS provides a new message, it gives out some new information, i.e. the information that a particular message took place.
- ▶ The information attached to a particular event (message) is rigorously defined as:

$$i(s_i) = -\log_2(p(s_i))$$

- ▶ Properties:
 - ▶ $i(s_i) \geq 0$
 - ▶ lower probability (rare events) means higher information
 - ▶ higher probability (frequent events) means lower information
 - ▶ a certain event brings no information: $-\log(1) = 0$
 - ▶ an event with probability 0 brings infinite information (but it never happens..)

Entropy of a DMS

- ▶ We usually don't care about a single message. We are interested in a large number of them (think millions of bits of data).
- ▶ We are interested in the *average* information of a message from a DMS.
- ▶ Definition: the entropy of a DMS source S is **the average information of a message**:

$$H(S) = \sum_k p_k i(s_k) = - \sum_k p_k \log_2(p_k)$$

where $p_k = p(s_k)$ is the probability of message k .

The choice of logarithm

- ▶ Any base of logarithm can be used in the definition.
- ▶ Usual convention: use binary logarithm $\log_2()$. $H(S)$ measured in *bits* (*bits / message*)
- ▶ If using natural logarithm $\ln()$, $H(S)$ is measured in *nats*.
- ▶ Logarithm bases can be converted to/from one another:

$$\log_b(x) = \frac{\log_a(x)}{\log_a(b)}$$

- ▶ Entropies using different logarithms differ only in scaling:

$$H_b(S) = \frac{H_a(S)}{\log_a(b)}$$

Examples

- ▶ Coin: $H(S) = 1 \text{ bit/message}$
- ▶ Dice: $H(S) = \log(6) \text{ bits/message}$
- ▶ Lottery: $H(S) = -0.9999 \log(0.9999) - 0.0001 \log(0.0001)$
- ▶ Receiving 1 bit: $H(S) = 1 \text{ bit/message}$ (hence the name!)

Interpretation of the entropy

All the following interpretations of entropy are true:

- ▶ $H(S)$ is the *average uncertainty* of the source S
- ▶ $H(S)$ is the *average information* of messages from source S
- ▶ A long sequence of N messages from S has total information $\approx N \cdot H(S)$
- ▶ $H(S)$ is the minimum number of bits (0,1) required to uniquely represent an average message from source S

Properties of entropy

We prove the following **properties of entropy**:

1. $H(S) \geq 0$ (non-negative)
2. $H(S)$ is maximum when all n messages have equal probability $\frac{1}{n}$. The maximum value is $\max H(S) = \log(n)$.
3. *Diversification* of the source always increases the entropy

The entropy of a binary source

- ▶ Consider a general DMS with two messages:

$$S : \begin{pmatrix} s_1 & s_2 \\ p & 1 - p \end{pmatrix}$$

- ▶ It's entropy is:

$$H(S) = -p \cdot \log(p) - (1 - p) \cdot \log(1 - p)$$

- ▶ Graphical plot. . .

Example - Game

Game: I think of a number between 1 and 8. You have to guess it by asking yes/no questions.

- ▶ How much uncertainty does the problem have?
- ▶ How is the best way to ask questions? Why?
- ▶ What if the questions are not asked in the best way?
- ▶ On average, what is the number of questions required to find the number?

Example - Game v2

- ▶ Suppose I choose a number according to the following distribution:

$$S : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ \frac{1}{2} & \frac{1}{4} & \frac{1}{8} & \frac{1}{8} \end{pmatrix}$$

- ▶ On average, what is the number of questions required to find the number?
 - ▶ What questions would you ask?
- ▶ What if the distribution is:

$$S : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ 0.14 & 0.29 & 0.4 & 0.17 \end{pmatrix}$$

- ▶ In general:
 - ▶ What distribution makes guessing the number the most difficult?
 - ▶ What distribution makes guessing the number the easiest?

Information flow of a DMS

- ▶ Suppose that message s_i takes time t_i to be transmitted via some channel.
- ▶ Definition: the information flow of a DMS S is **the average information transmitted per unit of time**:

$$H_\tau(S) = \frac{H(S)}{\bar{t}}$$

where \bar{t} is the average duration of transmitting a message:

$$\bar{t} = \sum_i p_i t_i$$

Extended DMS

- ▶ Definition: the n -th order extension of a DMS S , S^n is the source with messages has as messages all the combinations of n messages of S :

$$\sigma_i = \underbrace{s_j s_k \dots s_l}_n$$

- ▶ If S has k messages, S^n has k^n messages
- ▶ Since S is DMS

$$p(\sigma_i) = p(s_j) \cdot p(s_k) \cdot \dots \cdot p(s_l)$$

Extended DMS - Example

► Examples:

$$S : \begin{pmatrix} s_1 & s_2 \\ \frac{1}{4} & \frac{3}{4} \end{pmatrix}$$

$$S^2 : \begin{pmatrix} \sigma_1 = s_1 s_1 & \sigma_2 = s_1 s_2 & \sigma_3 = s_2 s_1 & \sigma_4 = s_2 s_2 \\ \frac{1}{16} & \frac{3}{16} & \frac{3}{16} & \frac{9}{16} \end{pmatrix}$$

$$S^3 : \begin{pmatrix} s_1 s_1 s_1 & s_1 s_1 s_2 & s_1 s_2 s_1 & s_1 s_2 s_2 & s_2 s_1 s_1 & s_2 s_1 s_2 & s_2 s_2 s_1 & s_2 s_2 s_2 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{pmatrix}$$

Extended DMS - Another example

- ▶ Long sequence of binary messages:

010011001110010100...

- ▶ Can be grouped in bits, half-bytes, bytes, 16-bit words, 32-bit long words, and so on.

Property of DMS

- ▶ Theorem: The entropy of a n -th order extension is n times larger than the entropy of the original DMS

$$H(S^n) = nH(S)$$

- ▶ Interpretation: grouping messages from a long sequence in blocks of n does not change total information (e.g. groups of 8 bits = 1 byte)

An example [memoryless is not enough]

- The distribution (frequencies) of letters in English:

letter	probability	letter	probability
A	.082	N	.067
B	.015	O	.075
C	.028	P	.019
D	.043	Q	.001
E	.127	R	.060
F	.022	S	.063
G	.020	T	.091
H	.061	U	.028
I	.070	V	.010
J	.002	W	.023
K	.008	X	.001
L	.040	Y	.020
M	.024	Z	.001

- Text from a memoryless source with these probabilities:

OCRO HLI RGWR NMIELWIS EU LL NBNESEBYA TH EEI
ALHENHTTPA OOBTTVA NAH BRL

(taken from Elements of Information Theory, Cover, Thomas)

- What's wrong? **Memoryless**

Sources with memory

- ▶ **Definition:** A source has memory of order m if the probability of a message depends on the last m messages.
- ▶ The last m messages = the **state** of the source (S_i).
- ▶ A source with n messages and memory $m \Rightarrow n^m$ states in all.
- ▶ For every state, messages can have a different set of probabilities.
Notation: $p(s_i|S_k) = \text{"probability of } s_i \text{ in state } S_k \text{"}$.
- ▶ Also known as *Markov sources*.

Example

- ▶ A source with $n = 4$ messages and memory $m = 1$
 - ▶ if last message was s_1 , choose next message with distribution

$$S_1 : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ 0.4 & 0.3 & 0.2 & 0.1 \end{pmatrix}$$

- ▶ if last message was s_2 , choose next message with distribution

$$S_2 : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ 0.33 & 0.37 & 0.15 & 0.15 \end{pmatrix}$$

- ▶ if last message was s_3 , choose next message with distribution

$$S_3 : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ 0.2 & 0.35 & 0.41 & 0.04 \end{pmatrix}$$

- ▶ if last message was s_4 , choose next message with distribution

$$S_4 : \begin{pmatrix} s_1 & s_2 & s_3 & s_4 \\ 0.1 & 0.2 & 0.3 & 0.4 \end{pmatrix}$$

Transitions

- ▶ When a new message is provided, the source **transitions** to a new state:

$$s_i s_j s_k \quad s_l$$

old state

$$s_i \quad s_j s_k s_l$$

new state

- ▶ The message probabilities = the probabilities of transitions from some state S_u to another state S_v

Transition matrix

- ▶ The transition probabilities are organized in a **transition matrix** $[T]$

$$[T] = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1N} \\ p_{21} & p_{22} & \dots & p_{2N} \\ \dots & \dots & \dots & \dots \\ p_{N1} & p_{N2} & \dots & p_{NN} \end{bmatrix}$$

- ▶ p_{ij} is the transition probability from state S_i to state S_j
- ▶ N is the total number of states

Graphical representation

Example here

Entropy of sources with memory

- ▶ Each state S_k has a different distribution \rightarrow each state has a different entropy $H(S_k)$

$$H(S_k) = - \sum_i p(s_i|S_k) \cdot \log(p(s_i|S_k))$$

- ▶ Global entropy = average entropy

$$H(S) = \sum_k p_k H(S_k)$$

where p_k = probability that the source is in state S_i (i.e. after a very long sequence of messages, how many times the source was in state S_k)

Ergodic sources

- ▶ Let $p_i^{(t)}$ = the probability that source S is in state S_i at time t .
- ▶ In what state will it be at time $t + 1$? (after one more message) (probabilities)

$$[p_1^{(t)}, p_2^{(t)}, \dots, p_N^{(t)}] \cdot [T] = [p_1^{(t+1)}, p_2^{(t+1)}, \dots, p_N^{(t+1)}]$$

- ▶ After one more message:

$$[p_1^{(t)}, p_2^{(t)}, \dots, p_N^{(t)}] \cdot [T] \cdot [T] = [p_1^{(t+2)}, p_2^{(t+2)}, \dots, p_N^{(t+2)}]$$

- ▶ In general, after n messages the probabilities that the source is in a certain state are:

$$[p_1^{(0)}, p_2^{(0)}, \dots, p_N^{(0)}] \cdot [T]^n = [p_1^{(n)}, p_2^{(n)}, \dots, p_N^{(n)}]$$

- ▶ A source is called **ergodic** if every state can be reached from every state, in a finite number of steps.

Property of ergodic sources:

- ▶ After many messages, the probabilities of the states *become stationary* (converge to some fixed values), irrespective of the initial probabilities.

$$\lim_{n \rightarrow \infty} [p_1^{(n)}, p_2^{(n)}, \dots, p_N^{(n)}] = [p_1, p_2, \dots, p_N]$$

Finding the stationary probabilities

- ▶ After n messages and after $n + 1$ messages, the probabilities are the same:

$$[p_1, p_2, \dots, p_N] \cdot [T] = [p_1, p_2, \dots, p_N]$$

- ▶ Also $p_1 + p_2 + \dots + p_N = 1$.

\Rightarrow solve system of equations, find values.

Entropy of ergodic sources with memory

- ▶ The entropy of an ergodic source with memory is

$$H(S) = \sum_k p_k H(S_k) = - \sum_k p_k \sum_i p(s_i | S_k) \cdot \log(p(s_i | S_k))$$

Example English text as sources with memory

(taken from *Elements of Information Theory*, Cover, Thomas)

- ▶ Memoryless source, equal probabilities:

XFOML RXKHRJFFJUJ ZLPWCFWKCYJ
FFJEYVKCQSGXYD QPAAMKBZAACIBZLHJQD

- ▶ Memoryless source, probabilities of each letter as in English:

OCRO HLI RGWR NMIELWIS EU LL NBNSEBYA TH EEI
ALHENHTTPA OOBTTVA NAH BRL

- ▶ Source with memory $m = 1$, frequency of pairs as in English:

ON IE ANTSOUTINYS ARE T INCTORE ST BE S DEAMY
ACHIN D ILONASIVE TUCOOWE AT TEASONARE FUSO
TIZIN ANDY TOBE SEACE CTISBE

- ▶ Source with memory $m = 2$, frequency of triplets as in English:

IN NO IST LAT WHEY CRATICT FROURE BERS GROCID
PONDENOME OF DEMONSTURES OF THE REPTAGIN IS
REGOACTIONA OF CRE

- ▶ Source with memory $m = 3$, frequency of 4-plets as in English:

THE GENERATED JOB PROVIDUAL BETTER TRAND THE DISPLAYED
CODE, ABOVEY UPONDULTS WELL THE CODERST IN THESTICAL
IT DO HOCK BOTHE MERG. (INSTATES CONS ERATION. NEVER
ANY OF PUBLEAND TO THEORY. EVENTIAL CALLEGAND TO ELAST
BENERATED IN WITH PIES AS IS WITH THE)

Chapter summary

- ▶ Information of a message: $i(s_k) = -\log_2(p(s_k))$
- ▶ Entropy of a memoryless source:
 $H(S) = \sum_k p_k i(s_k) = -\sum_k p_k \log_2(p_k)$
- ▶ Properties of entropy:
 1. $H(S) \geq 0$
 2. Is maximum when all messages have equal probability
($H_{\max}(S) = \log(n)$)
 3. *Diversification* of the source always increases the entropy
- ▶ Sources with memory: definition, transitions
- ▶ Stationary probabilities of ergodic sources with memory:
 $[p_1, p_2, \dots, p_N] \cdot [T] = [p_1, p_2, \dots, p_N], \sum_i p_i = 1.$
- ▶ Entropy of sources with memory:

$$H(S) = \sum_k p_k H(S_k) = -\sum_k p_k \sum_i p(s_i|S_k) \cdot \log(p(s_i|S_k))$$

Chapter II: Discrete Transmission Channels

What are they?

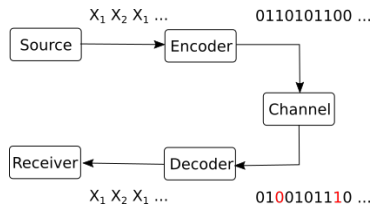


Figure 2: Communication system

- ▶ A system of two related random variables
- ▶ Input random variable $X = x_1, x_2, \dots$, output random variable $Y = y_1, y_2, \dots$
- ▶ X and Y are *related*, but still *random* (usually because of *noise*)

What do we want

- ▶ Successful communication: receive Y , deduce what was sent X
- ▶ We are interested in **deducing X when knowing Y**
- ▶ How much does knowing Y tell us about X ?
 - ▶ Depends on the relation between them
 - ▶ Is the same as how much X tells us about Y (symmetrical)

Nomenclature

- ▶ Discrete: the input alphabet and the output alphabet are finite
- ▶ Memoryless: the output symbol depends only on the current input symbol
- ▶ Stationary: the noise arising on the channel is time invariant (i.e. its statistics do not vary in time)

Systems of two random variables

- ▶ Two random variables: $X = x_1, x_2, \dots$, $Y = y_1, y_2, \dots$
- ▶ Example: throw a dice (X) and a coin (Y) simultaneously
- ▶ How to describe this system?

A single joint information source:

$$X \cap Y : \begin{pmatrix} x_1 \cap y_1 & x_1 \cap y_2 & \dots & x_i \cap y_j \\ p(x_1 \cap y_1) & p(x_1 \cap y_2) & \dots & p(x_i \cap y_j) \end{pmatrix}$$

Arrange in a nicer form (table):

	y_1	y_2	y_3
x_1
x_2
x_3

- ▶ Elements of the table: $p(x_i \cap y_j)$

Joint probability matrix

The table constitutes the **joint probability matrix**:

$$P(X, Y) = \begin{bmatrix} p(x_1 \cap y_1) & p(x_1 \cap y_2) & \cdots & p(x_1 \cap y_M) \\ p(x_2 \cap y_1) & p(x_2 \cap y_2) & \cdots & p(x_2 \cap y_M) \\ \vdots & \vdots & \cdots & \vdots \\ p(x_N \cap y_1) & p(x_N \cap y_2) & \cdots & p(x_N \cap y_M) \end{bmatrix}$$

$$\sum_i \sum_j p(x_i \cap y_j) = 1$$

- ▶ This matrix completely defines the two-variable system
- ▶ This matrix completely defines the communication process

Joint entropy

- ▶ The distribution $X \cap Y$ determines the **joint entropy**:

$$H(X, Y) = - \sum_i \sum_j p(x_i \cap y_j) \cdot \log(p(x_i \cap y_j))$$

- ▶ This is the global entropy of the system (knowing the input and the output)

Marginal distributions

- ▶ $p(x_i) = \sum_j p(x_i \cap y_j)$ = sum of row i from $P(X,Y)$
- ▶ $p(y_j) = \sum_i p(x_i \cap y_j)$ = sum of column j from $P(X,Y)$
- ▶ The distributions $p(x)$ and $p(y)$ are called **marginal distributions** (“summed along the margins”)

Examples [marginal distributions not enough]

- ▶ Example 1:

$$P(X, Y) = \begin{bmatrix} 0.3 & 0 \\ 0 & 0.7 \end{bmatrix}$$

- ▶ Example 2:

$$P(X, Y) = \begin{bmatrix} 0.15 & 15 \\ 0.15 & 0.55 \end{bmatrix}$$

- ▶ Both have identical $p(x)$ and $p(y)$, but are completely different
- ▶ Which one is better for a transmission?
- ▶ Marginal distribution are useful, but not enough. Essential is the *relation* between X and Y .

$$p(A \cap B) = p(A) \cdot p(B|A)$$

$$p(B|A) = \frac{p(A \cap B)}{p(A)}$$

- ▶ “The conditional probability of B **given A**” (i.e. given that event A happened)
- ▶ Examples. . .
- ▶ Independence:

$$p(A \cap B) = p(A)p(B)$$

$$p(B|A) = p(B)$$

Channel matrix

Noise (or channel) matrix:

$$P(Y|X) = \begin{bmatrix} p(y_1|x_1) & p(y_2|x_1) & \cdots & p(y_M|x_1) \\ p(y_1|x_2) & p(y_2|x_2) & \cdots & p(y_M|x_2) \\ \vdots & \vdots & \cdots & \vdots \\ p(y_1|x_N) & p(y_2|x_N) & \cdots & p(y_M|x_N) \end{bmatrix}$$

- ▶ Defines the probability of an output **given an input**
- ▶ Each row = a separate distribution that indicates the probability of the outputs **if the input is** x_i)
- ▶ The sum of each row is 1 (there must be some output if the input is x_i)

Relation of channel matrix and joint probability matrix

- ▶ $P(Y|X)$ is obtained from $P(X, Y)$ by dividing every row to its sum ($p(x_i)$)
- ▶ This is known as *normalization* of rows
- ▶ $P(X, Y)$ can be obtained back from $P(Y|X)$ by multiplying each row with $p(x_i)$
- ▶ $P(Y|X)$ contains less information than $P(X, Y)$

Definition of a discrete transmission channel

Definition: A discrete transmission channel is defined by three items:

1. The input alphabet $X = \{x_1, x_2, \dots\}$
2. The output alphabet $Y = \{y_1, y_2, \dots\}$
3. The noise (channel) matrix $P(Y|X)$ which defines the conditional probabilities of the outputs y_j for every possible input x_i

Graphical representation of a channel

- ▶ Nice picture with arrows :)

Three examples

Three examples to help you remember conditional probabilities

- ▶ Play and win the lottery
- ▶ Gambler's paradox
- ▶ CNN: Crippled cruise ship returns; passengers happy to be back

Conditional entropy $H(Y|X)$ (mean error)

- ▶ Since each row is a distribution, each row has an entropy
- ▶ Entropy of row x_i :

$$H(Y|x_i) = - \sum_j p(y_j|x_i) \log(p(y_j|x_i))$$

- ▶ *“The uncertainty of the output message when the input message is x_i ”*
- ▶ Example: lottery

Conditional entropy $H(Y|X)$ (mean error)

- ▶ A different $H(Y|x_i)$ for every x_i
- ▶ Compute the average over all x_i :

$$\begin{aligned} H(Y|X) &= \sum_i p(x_i) H(Y|x_i) \\ &= - \sum_i \sum_j p(x_i) p(y_j|x_i) \log(p(y_j|x_i)) \\ &= - \sum_i \sum_j p(x_i \cap y_j) \log(p(y_j|x_i)) \end{aligned}$$

- ▶ **“The uncertainty of the output message when we know the input message”** (any input, in general)

Equivocation matrix

Equivocation matrix:

$$P(X|Y) = \begin{bmatrix} p(x_1|y_1) & p(x_1|y_2) & \cdots & p(x_1|y_M) \\ p(x_2|y_1) & p(x_2|y_2) & \cdots & p(x_2|y_M) \\ \vdots & \vdots & \cdots & \vdots \\ p(x_N|y_1) & p(x_N|y_2) & \cdots & p(x_N|y_M) \end{bmatrix}$$

- ▶ Defines the probability of an input **given an output**
- ▶ Each column = a separate distribution that indicates the probability of the inputs **if the output is y_j**
- ▶ The sum of each column is 1 (there must be some input if the output is y_j)

Relation of equivocation matrix and joint probability matrix

- ▶ $P(X|Y)$ is obtained from $P(X, Y)$ by dividing every column to its sum ($p(y_j)$)
- ▶ This is known as *normalization* of columns
- ▶ $P(X, Y)$ can be obtained back from $P(X|Y)$ by multiplying each column with $p(y_j)$
- ▶ $P(X|Y)$ contains less information than $P(X, Y)$

Conditional entropy $H(X|Y)$ (equivocation)

- ▶ Since each column is a distribution, each column has an entropy
- ▶ Entropy of column y_j :

$$H(X|y_j) = - \sum_i p(x_i|y_j) \log(p(x_i|y_j))$$

- ▶ *“The uncertainty of the input message when the output message is y_j ”*
- ▶ Example: ...

Conditional entropy $H(X|Y)$ (equivocation)

- ▶ A different $H(X|y_j)$ for every y_j
- ▶ Compute the average over all y_j :

$$\begin{aligned}H(X|Y) &= \sum_j p(y_j) H(X|y_j) \\&= - \sum_i \sum_j p(y_j) p(x_i|y_j) \log(p(x_i|y_j)) \\&= - \sum_i \sum_j p(x_i \cap y_j) \log(p(x_i|y_j))\end{aligned}$$

- ▶ **“The uncertainty of the input message when we know the output message”** (any output, in general)
- ▶ Should be small for a good communication

Properties of conditional entropies

For a general system with two random variables X and Y :

- ▶ Conditioning always reduces entropy:

$$H(X|Y) \leq H(X)$$

$$H(Y|X) \leq H(Y)$$

(knowing something cannot harm)

- ▶ If the variables are independent:

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

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

(knowing the second variable does not help at all)

Mutual information $I(X,Y)$

- ▶ Mutual information $I(X,Y)$ = the average information that one variable has about the other
- ▶ Mutual information $I(X,Y)$ = the average information that is transmitted on the channel
- ▶ Consider a communication channel with X as input and Y as output:
 - ▶ We are the receiver and we want to find out the X
 - ▶ When we don't know the output: $H(X)$
 - ▶ When we know the output: $H(X|Y)$
- ▶ How much information was transmitted?
 - ▶ Reduction of uncertainty:

$$I(X, Y) = H(X) - H(X|Y)$$

Mutual information $I(X, Y)$

$$\begin{aligned} I(X, Y) &= H(X) - H(X|Y) \\ &= - \sum_i p(x_i) \log(p(x_i)) + \sum_i \sum_j p(x_i \cap y_j) \log(p(x_i|y_j)) \\ &= - \sum_i \sum_j p(x_i \cap y_j) \log(p(x_i)) + \sum_i \sum_j p(x_i \cap y_j) \log(p(x_i|y_j)) \\ &= \sum_i \sum_j p(x_i \cap y_j) \log\left(\frac{p(x_i|y_j)}{p(x_i)}\right) \\ &= \sum_i \sum_j p(x_i \cap y_j) \log\left(\frac{p(x_i \cap y_j)}{p(x_i)p(y_j)}\right) \end{aligned}$$

Properties of mutual information

Mutual information $I(X, Y)$ is:

- ▶ commutative: $I(X, Y) = I(Y, X)$
- ▶ non-negative: $I(X, Y) \geq 0$
- ▶ a special case of the Kullback–Leibler distance (relative entropy distance)

Definition: the Kullback–Leibler distance of two distributions is

$$D_{KL}(P, Q) = \sum_i P(i) \log\left(\frac{P(i)}{Q(i)}\right)$$

- ▶ In our case, the distributions are:
 - ▶ $P = p(x_i \cap y_j)$ (distribution of our system)
 - ▶ $Q = p(x_i) \cdot p(y_j)$ (distribution of two independent variables)

$$I(X, Y) = D(p(x_i \cap y_j), p(x_i) \cdot p(y_j))$$

Relations between the informational measures

- ▶ Nice picture with two circles :)
- ▶ All six: $H(X)$, $H(Y)$, $H(X, Y)$, $H(X|Y)$, $H(Y|X)$, $I(X, Y)$
- ▶ All relations on the picture are valid relations:

$$H(X, Y) = H(X) + H(Y) - I(X, Y)$$

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

$$I(X, Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$$

...

- ▶ If know three, can find the other three
- ▶ Simplest to find first $H(X)$, $H(Y)$, $H(X, Y)$ \longrightarrow then find others

Types of communication channels

1. Channels with zero equivocation

$$H(X|Y) = 0$$

- ▶ Each column of the noise (channel) matrix contains only one non-zero value
- ▶ No doubts on the input messages when the output messages are known
- ▶ All input information is transmitted

$$I(X, Y) = H(X)$$

- ▶ Example: codewords. . .

Types of communication channels

2. Channels with zero mean error

$$H(Y|X) = 0$$

- ▶ Each row of the noise (channel) matrix contains only one non-zero value
 - ▶ No doubts on the output messages when the input messages are known
 - ▶ *The converse is not necessary true!*
-
- ▶ Example: AND gate

Types of communication channels

3. Channels uniform with respect to the input

$$H(Y|x_i) = \textit{same}$$

- ▶ Each row of noise matrix contains the same values, possibly in different order
- ▶ $H(Y|x_i) = \textit{same} = H(Y|X)$
- ▶ $H(Y|X)$ does not depend on the actual probabilities $p(x_i)$

Types of communication channels

4. Channels uniform with respect to the output

- ▶ Each column of noise matrix contains the same values, possibly in different order
- ▶ If the input messages are equiprobable, the output messages are also equiprobable
- ▶ Attention:

$$H(X|y_j) \neq \text{same!}$$

Types of communication channels

5. Symmetric channels

- ▶ Uniform with respect to the input and to the output
- ▶ Example: binary symmetric channel

Channel capacity

- ▶ What is the maximum information we can transmit on a certain channel?
- ▶ **Definition:** the information capacity of a channel is the maximum value of the mutual information, where the maximization is done over the input probabilities $p(x_i)$

$$C = \max_{p(x_i)} I(X, Y)$$

- ▶ i.e. the maximum mutual information we can obtain if we are allowed to choose $p(x_i)$ as we want
- ▶ Use together with definition of $I(X, Y)$:

$$C = \max_{p(x_i)} (H(Y) - H(Y|X))$$

$$C = \max_{p(x_i)} (H(X) - H(X|Y))$$

What channel capacity means

- ▶ Channel capacity is the maximum information we can transmit on a channel, on average, with one message
- ▶ One of the most important notions in information theory
- ▶ Its importance comes from Shannon's second theorem (noisy channel theorem)

Preview of the channel coding theorem

- ▶ Even though some information $I(X, Y)$ is transmitted on the channel, there still is the $H(X|Y)$ uncertainty on the input
- ▶ We want error-free transmission, with no uncertainty
- ▶ Solution: use error coding (see chapter IV)
- ▶ How coding works:
 - ▶ coder receives k symbols (bits, usually) that we want to transmit
 - ▶ coder appends additional m symbols computed via some coding algorithm
 - ▶ the total $k + m$ bits are transmitted over a noisy channel
 - ▶ the decoding algorithm tries to detect and correct errors, based on the additional m bits that were appended
- ▶ Coding rate:

$$R = \frac{k}{k + m}$$

- ▶ stronger protection = bigger m = less efficient
- ▶ weaker protection = smaller m = more efficient

Preview of the channel coding theorem

- ▶ A rate is called **achievable** for a channel if, for that rate, there exists a coding and decoding algorithm guaranteed to correct all possible errors on the channel

Shannon's noisy channel coding theorem (second theorem)

For a given channel, all rates below capacity $R < C$ are achievable. All rates above capacity, $R > C$, are not achievable.

Channel coding theorem explained

In layman terms:

- ▶ For all coding rates $R < C$, there is a way to recover the transmitted data perfectly (de/coding algorithm will detect and correct all errors)
- ▶ For all coding rates $R > C$, there is no way to recover the transmitted data perfectly

Example:

- ▶ Send binary digits (0,1) on a channel with capacity 0.7 bits/message
- ▶ There exists coding schemes with $R < 0.7$ that allow perfect recovery
 - ▶ i.e. for every 7 bits of data coding adds 3 or more bits, on average \Rightarrow
$$R = \frac{7}{7+3}$$
- ▶ With less than 3 bits for every 7 bits of data \Rightarrow impossible to recover all the data

Efficiency and redundancy

- ▶ Efficiency of a channel:

$$\eta_C = \frac{I(X, Y)}{C}$$

- ▶ Absolute redundancy of a channel:

$$R_C = C - I(X, Y)$$

- ▶ Relative redundancy of a channel:

$$\rho_C = \frac{R_C}{C} = 1 - \frac{I(X, Y)}{C} = 1 - \eta_C$$

Computing the capacity

- ▶ Tricks for easier computation of the capacity
- ▶ Channel is uniform with respect to the input:
 - ▶ $H(Y|X)$ does not depend on the actual probabilities $p(x_i)$
 - ▶ $C = \max_{p(x_i)} I(X, Y) = \max_{p(x_i)} (H(Y) - H(Y|X)) = \max_{p(x_i)} (H(Y)) - H(Y|X)$
 - ▶ Should maximize $H(Y)$
- ▶ If channel is also uniform with respect to the output:
 - ▶ same values on columns of $P(Y|X)$
 - ▶ $p(y_j) = \sum_i p(y_j|x_i)p(x_i)$
 - ▶ if $p(x_i) = \text{uniform} = \frac{1}{n}$, then $p(y_j) = \frac{1}{n} \sum_i p(y_j|x_i) = \text{uniform}$
 - ▶ therefore $p(y_j)$ are constant = uniform = $H(Y)$ is maximized
 - ▶ $H(Y)$ is maximized when $H(X)$ is maximized (equiprobable messages)

Computing the capacity

- ▶ If channel is symmetric: use both tricks
 - ▶ $C = \max_{p(x_i)} (H(Y)) - H(Y|X)$
 - ▶ $H(Y)$ is maximized when $H(X)$ is maximized (equiprobable messages)

Examples of channels and their capacity

0 \longrightarrow 0

1 \longrightarrow 1

Figure 3: Noiseless binary channel

- Capacity = 1 bit/message, when $p(x_1) = p(x_2) = \frac{1}{2}$

Noisy binary non-overlapping channel

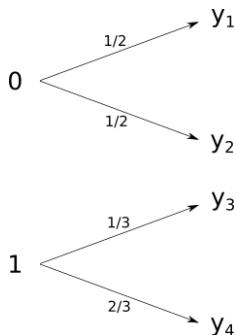


Figure 4: Noisy binary non-overlapping

- ▶ There is noise ($H(Y|X) > 0$), but can deduce the input ($H(X|Y) = 0$)
- ▶ Capacity = 1 bit/message, when $p(x_1) = p(x_2) = \frac{1}{2}$

Noisy typewriter

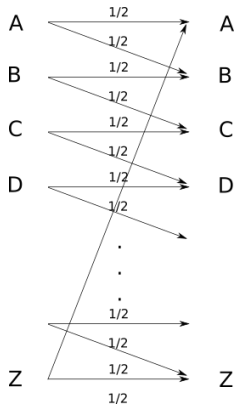


Figure 5: Noisy typewriter

$$\begin{aligned}\max I(X, Y) &= \max (H(Y) - H(Y|X)) = \max H(Y) - 1 \\ &= \log(26) - 1 = \log(13)\end{aligned}$$

Noisy typewriter

- ▶ Capacity = $\log(13)$ bit/message, when input probabilities are uniform
- ▶ Can transmit 13 letters with no errors (A, C, E, G, ...)

Binary symmetric channel

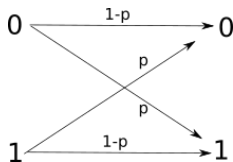


Figure 6: Binary symmetric channel (BSC)

- ▶ Capacity = $1 - H_p = 1 + p \log(p) + (1 - p) \log(1 - p)$
- ▶ Capacity is reached when input distribution is uniform

Binary erasure channel

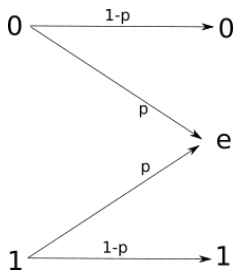


Figure 7: Binary erasure channel

- ▶ Different from BSC: here we know when errors happened
- ▶ Capacity = $1 - p$
- ▶ Intuitive meaning: lose p bits, remaining bits = capacity = $1 - p$

Symmetric channel of n -th order

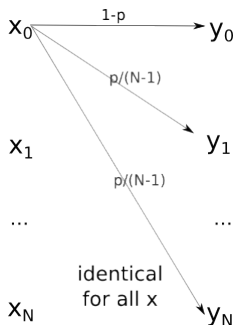


Figure 8: N -th order symmetric channel

- ▶ Extension of binary symmetric channel for n messages
- ▶ $1 - p$ chances that symbol has no error
- ▶ p chances that symbol is changed, uniformly to any other $(N-1)$ symbols ($\frac{p}{N-1}$ each)

Symmetric channel of n -th order

- ▶ Channel is symmetric \Rightarrow

$$C = \max_{p(x_i)} I(X, Y) = \max_{p(x_i)} (H(Y) - H(Y|X)) = \max_{p(x_i)} (H(Y)) - H(Y|X)$$

- ▶ $\max_{p(x_i)} (H(Y)) = \log(N)$
- ▶ $H(Y|X) = H(Y|x_i) = \text{entropy of any row (same values)}$

\Rightarrow

$$C = \log(N) + (1 - p) \log(1 - p) + p \log\left(\frac{p}{N - 1}\right)$$

- ▶ Capacity is reached when input probabilities are uniform

Chapter summary

- ▶ Channel = Probabilistic system with two random variables X and Y
- ▶ Characterization of transmission:
 - ▶ $P(X,Y) \Rightarrow H(X,Y)$ *joint entropy*
 - ▶ $p(x_i), p(y_j)$ *marginal distributions* $\Rightarrow H(X), H(Y)$
 - ▶ $P(Y|X)$ *channel matrix* $\Rightarrow H(Y|X)$ *average noise*
 - ▶ $P(X|Y) \Rightarrow H(X|Y)$ *equivocation*
 - ▶ $I(X,Y)$ *mutual information*
- ▶ Channel capacity: $C = \max_{p(x_i)} I(X, Y)$
- ▶ Examples:
 - ▶ Binary symmetric channel: $C = 1 - H_p$
 - ▶ Binary erasure channel: $C = 1 - p$
 - ▶ N -th symmetric channel: $C = \log(N) - H(\text{of a row of channel matrix})$



Figure 9: Claude Shannon (1916 - 2001)

- ▶ *A mathematical theory of communications*, 1948

Exercises and problems

- ▶ At blackboard only

Chapter III: Source coding

What does coding do?

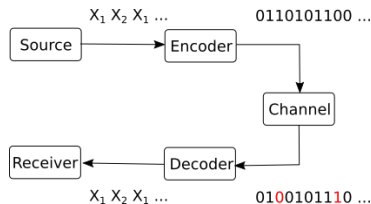


Figure 10: Communication system

► Why coding?

1. Source coding:

- Convert source messages to channel symbols (for example 0,1)
- Minimize number of symbols needed
- Adapt probabilities of symbols to maximize mutual information

2. Error control

- Protection against channel errors

Source-channel separation theorem

Source-channel separation theorem (informal):

- ▶ It is possible to obtain the best reliable communication by performing the two tasks separately:
 1. Source coding: to minimize number of symbols needed
 2. Error control coding (channel coding): to provide protection against noise

Source coding

- ▶ Assume we code for transmission over ideal channels with no noise
- ▶ Transmitted symbols are perfectly recovered at the receiver
- ▶ Main concerns:
 - ▶ minimize the number of symbols needed to represent the messages
 - ▶ make sure we can decode the messages
- ▶ Advantages:
 - ▶ Efficiency
 - ▶ Short communication times
 - ▶ Can decode easily

Definitions

- ▶ Let $S = \{s_1, s_2, \dots, s_N\}$ = an input discrete memoryless source
- ▶ Let $X = \{x_1, x_2, \dots, x_M\}$ = the alphabet of the code
 - ▶ Example: binary: $\{0,1\}$
- ▶ A **code** is a mapping from S to the set of all codewords:

$$C = \{c_1, c_2, \dots, c_N\}$$

Message	Codeword
s_1	$c_1 = x_1 x_2 x_1 \dots$
s_2	$c_2 = x_1 x_2 x_2 \dots$
\dots	\dots
s_N	$c_3 = x_2 x_2 x_2 \dots$

- ▶ Decoding: given a sequence of symbols, deduce the original sequence of messages
- ▶ Codeword length l_i = the number of symbols in c_i

Example: ASCII code

Letter	ASCII Code	Binary	Letter	ASCII Code	Binary
a	097	01100001	A	065	01000001
b	098	01100010	B	066	01000010
c	099	01100011	C	067	01000011
d	100	01100100	D	068	01000100
e	101	01100101	E	069	01000101
f	102	01100110	F	070	01000110
g	103	01100111	G	071	01000111
h	104	01101000	H	072	01001000
i	105	01101001	I	073	01001001
j	106	01101010	J	074	01001010
k	107	01101011	K	075	01001011
l	108	01101100	L	076	01001100
m	109	01101101	M	077	01001101
n	110	01101110	N	078	01001110
o	111	01101111	O	079	01001111
p	112	01110000	P	080	01010000
q	113	01110001	Q	081	01010001
r	114	01110010	R	082	01010010
s	115	01110011	S	083	01010011
t	116	01110100	T	084	01010100
u	117	01110101	U	085	01010101
v	118	01110110	V	086	01010110
w	119	01110111	W	087	01010111
x	120	01111000	X	088	01011000
y	121	01111001	Y	089	01011001
z	122	01111010	Z	090	01011010

Figure 11: ASCII code (partial)

Average code length

- ▶ How to measure representation efficiency of a code?
- ▶ **Average code length** = average of the codeword lengths:

$$\bar{l} = \sum_i p(s_i) l_i$$

- ▶ The probability of a codeword = the probability of the corresponding message
- ▶ Smaller average length: code more efficient (better)
- ▶ How small can the average length be?

Definitions

A code can be:

- ▶ **non-singular**: all codewords are different
- ▶ **uniquely decodable**: for any received sequence of symbols, there is only one corresponding sequence of messages
 - ▶ i.e. no sequence of messages produces the same sequence of symbols
 - ▶ i.e. there is never a confusion at decoding
- ▶ **instantaneous** (also known as **prefix-free**): no codeword is prefix to another code
 - ▶ A *prefix* = a codeword which is the beginning of another codeword

Examples: at the blackboard

The graph of a code

Example at blackboard

Instantaneous codes are uniquely decodable

Theorem

- ▶ An instantaneous code is uniquely decodable
- ▶ (The converse is not necessary true; there exist uniquely decodable codes which are not instantaneous)

Proof

- ▶ blackboard

Comments:

- ▶ How to decode an instantaneous code: graph-based decoding
- ▶ Advantage on instantaneous code over uniquely decodable: simple decoding

Existence of instantaneous codes

- ▶ When can there an instantaneous code exist?

Kraft inequality theorem:

- ▶ There exists an instantaneous code with D symbols and codeword lengths l_1, l_2, \dots, l_n if and only if the lengths satisfy the following inequality:

$$\sum_i D^{-l_i} \leq 1.$$

Proof:

- ▶ At blackboard

Comments:

- ▶ If lengths do not satisfy this, no instantaneous code exists
- ▶ If the lengths of a code satisfy this, that code can be instantaneous or not (there exists an instantaneous code, but not necessarily that one)
- ▶ Kraft inequality means that the codewords lengths cannot be all very small

Instantaneous codes with equality in Kraft

- ▶ From the proof \Rightarrow we have equality in the relation

$$\sum_i D^{-l_i} = 1$$

only if the lowest level is fully covered \Leftrightarrow no unused branches

- ▶ For an instantaneous code which satisfies Kraft with equality, all the graph branches terminate with codewords (there are no unused branches)

Kraft inequality for uniquely decodable codes

- ▶ Instantaneous codes must obey Kraft inequality
- ▶ How about uniquely decodable codes?

McMillan theorem:

- ▶ An uniquely decodable code satisfies the Kraft inequality:

$$\sum_i D^{-l_i} \leq 1.$$

Consequence:

- ▶ For every uniquely decodable code, there exists an instantaneous code with the same lengths.
- ▶ Even though the class of uniquely decodable codes is larger than that of instantaneous codes, we have no benefit.
- ▶ We can always use just instantaneous codes.

Finding an instantaneous code for given lengths

- ▶ How to find an instantaneous code with code lengths $\{l_i\}$
 1. Check that lengths satisfy Kraft relation
 2. Draw graph
 3. Assign nodes in a certain order (e.g. descending probability)
- ▶ Easy, standard procedure
- ▶ Example: blackboard

Optimal codes

- ▶ We want to minimize the **average length** of a code:

$$\bar{l} = \sum_i p(s_i) l_i$$

- ▶ But the lengths must obey the Kraft inequality (for uniquely decodable)

$$\begin{array}{ll} \text{minimize} & \sum_i p(s_i) l_i \\ \text{subject to} & \sum_i D^{-l_i} \leq 1 \end{array}$$

- ▶ The optimal values are:

$$l_i = -\log(p(s_i))$$

- ▶ Rigorous proof: at blackboard (method of Lagrange multiplier)
- ▶ Intuition: using $l_i = -\log(p(s_i))$ satisfies Kraft with equality, so the lengths cannot be any shorter, in general

Entropy = minimal codeword lengths

- If the optimal values are:

$$l_i = -\log(p(s_i))$$

- Then the minimal average length is:

$$\min \bar{l} = \sum_i p(s_i) l_i = - \sum_i p(s_i) \log(p(s_i)) = H(S)$$

Average length \geq entropy

The average length of an uniquely decodable code cannot be smaller than the source entropy

$$H(S) \leq \bar{l}$$

Non-optimal codes

- ▶ Problem: $-\log(p(s_i))$ might not be an integer number
- ▶ $l_i = -\log(p(s_i))$ only when probabilities are power of 2 (*dyadic distribution*)
- ▶ Shannon's solution: round to bigger integer

$$l_i = \lceil -\log(p(s_i)) \rceil$$

Shannon coding

- ▶ Shannon coding:
 1. Arrange probabilities in descending order
 2. Use codeword lengths $l_i = \lceil -\log(p(s_i)) \rceil$
 3. Find an instantaneous code for these lengths
- ▶ Simple scheme, better algorithms are available
 - ▶ Example: compute lengths for $S : (0.9, 0.1)$
- ▶ But still enough to prove fundamental results

Average length of Shannon code

- ▶ The average length of a Shannon code satisfies

$$H(S) \leq \bar{l} < H(S) + 1$$

- ▶ Proof:

1. The first inequality is because $H(S)$ is minimum length
2. The second inequality:

2.1 Use Shannon code:

$$l_i = \lceil -\log(p(s_i)) \rceil = -\log(p(s_i)) + \epsilon_i$$

where $0 \leq \epsilon_i < 1$

2.2 Compute average length:

$$\bar{l} = \sum_i p(s_i) l_i = H(S) + \sum_i p(s_i) \epsilon_i$$

2.3 Since $\epsilon_i < 1 \Rightarrow \sum_i p(s_i) \epsilon_i < \sum_i p(s_i) = 1$

Average length of Shannon code

- ▶ Shannon code approaches minimum possible lengths up to at most 1 extra bit
 - ▶ That's not bad at all
 - ▶ There exist even better codes, in general
- ▶ Can we get even closer to the minimum length?
- ▶ Yes, as close as we want! See next slide.

Shannon's first theorem

Shannon's first theorem (coding theorem for noiseless channels):

- ▶ One can always compress messages from a source S with an average length as close as desired to $H(S)$, but never below $H(S)$ (for infinitely long sequences of messages)

Proof:

- ▶ Average length can never go below $H(S)$ because this is minimum
- ▶ How can it get very close to $H(S)$ (from above)?
 1. Use n -th order extension S^n of S
 2. Use Shannon coding for S^n , so it satisfies

$$H(S^n) \leq \overline{l_{S^n}} < H(S^n) + 1$$

3. But $H(S^n) = nH(S)$, and **average length per message of S is**

$$\overline{l_S} = \frac{\overline{l_{S^n}}}{n}$$

because messages of S^n are just n messages of S glued together

Shannon's first theorem

- ▶ Continuing:

- 4. So, dividing by n :

$$H(S) \leq \overline{l}_S < H(S) + \frac{1}{n}$$

- 5. If extension order $n \rightarrow \infty$, then

$$\overline{l}_S \rightarrow H(S)$$

Comments:

- ▶ Shannon's first theorem says what entropy $H(S)$ means:
- ▶ The entropy $H(S)$ means the minimum number of bits required to describe a message from S , in general
- ▶ For any distribution we can approach $H(S)$ to any desired accuracy using extensions of large order
 - ▶ The complexity is too large for large n , so in practice we settle with a close enough value
- ▶ Other codes are even better the Shannon coding

Efficiency and redundancy of a code

- ▶ **Efficiency** of a code (M = size of code alphabet):

$$\eta = \frac{H(S)}{\bar{l} \log M}$$

- ▶ **Redundancy** of a code:

$$\rho = 1 - \eta$$

- ▶ These measures indicate how close is the average length to the optimal value
- ▶ When $\eta = 1$: **optimal code**
 - ▶ for example when $l_i = -\log(p(s_i))$

Coding with the wrong code

- ▶ Consider a source with probabilities $p(s_i)$
 - ▶ We use a code designed for a different source: $l_i = -\log(q(s_i))$
 - ▶ The message probabilities are $p(s_i)$ but the code is designed for $q(s_i)$
 - ▶ How much do we lose?
 - ▶ Example: different languages
-
- ▶ Codeword lengths are not optimal for this source \Rightarrow increased \bar{l}
 - ▶ If code were optimal, best average length = entropy $H(S)$:

$$\overline{l_{optimal}} = -\sum p(s_i) \log p(s_i)$$

- ▶ The actual average length:

$$\overline{l_{actual}} = \sum p(s_i) l_i = -\sum p(s_i) \log q(s_i)$$

The Kullback–Leibler distance

- ▶ Difference is:

$$\overline{l_{actual}} - \overline{l_{optimal}} = \sum_i p(s_i) \log\left(\frac{p(s_i)}{q(s_i)}\right) = D_{KL}(p, q)$$

Definition: the Kullback–Leibler distance of two distributions is

$$D_{KL}(p, q) = \sum_i p(i) \log\left(\frac{p(i)}{q(i)}\right)$$

Properties:

- ▶ Always positive:

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

- ▶ Equals 0 only when the two distributions are identical

$$D_{KL}(p, q) = 0 \iff p(s_i) = q(s_i), \forall i$$

The Kullback–Leibler distance

Where is the Kullback–Leibler distance used:

- ▶ Using a code for a different distribution:
 - ▶ Average length is increased with $D_{KL}(p, q)$
- ▶ Definition of mutual information:
 - ▶ Distance between $p(x_i \cap y_j)$ and the distribution of two independent variables $p(x_i) \cdot p(y_j)$

$$I(X, Y) = \sum_{i,j} p(x_i \cap y_j) \log\left(\frac{p(x_i \cap y_j)}{p(x_i)p(y_j)}\right)$$

Shannon-Fano coding (binary)

Shannon-Fano (binary) coding procedure:

1. Sort the message probabilities in descending order
2. Split into two subgroups as nearly equal as possible
3. Assign first bit 0 to first group, first bit 1 to second group
4. Repeat on each subgroup
5. When reaching one single message \Rightarrow that is the codeword

Example: blackboard

Comments:

- ▶ Shannon-Fano coding does not always produce the shortest code lengths
- ▶ Connection: yes-no answers (see example from source chapter)

Huffman coding (binary)

Huffman coding procedure (binary):

1. Sort the message probabilities in descending order
2. Join the last two probabilities, insert result into existing list, preserve descending order
3. Repeat until only two messages are remaining
4. Assign first bit 0 and 1 to the final two messages
5. Go back step by step: every time we had a sum, append 0 and 1 to the end of existing codeword

Example: blackboard

Properties of Huffman coding

Properties of Huffman coding:

- ▶ Produces a code with the **smallest average length** (better than Shannon-Fano)
- ▶ Assigning 0 and 1 can be done in any order => different codes, same lengths
- ▶ When inserting a sum into existing list, may be equal to another value => options
 - ▶ we can insert above, below or in-between equal values
 - ▶ leads to codes with different *individual* lengths, but same *average* length
- ▶ Some better algorithms exist which do not assign a codeword to every single message (they code a while sequence at once, not every message)

Huffman coding (M symbols)

General Huffman coding procedure for codes with M symbols:

- ▶ Have M symbols $\{x_1, x_2, \dots, x_M\}$
- ▶ Add together the last M symbols
- ▶ When assigning symbols, assign all M symbols
- ▶ **Important:** at the final step must have M remaining values
 - ▶ May be necessary to add *virtual* messages with probability 0 at the end of the initial list, to end up with exactly M messages in the end
- ▶ Example : blackboard

Comparison of Huffman and Shannon-Fano coding

Comparison of binary Huffman and Shannon-Fano example:

$$p(s_i) = \{0.35, 0.17, 0.17, 0.16, 0.15\}$$

Chapter IV: Error control coding

What is error control coding?

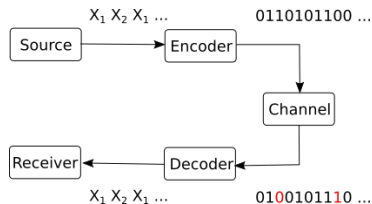


Figure 12: Communication system

- ▶ The second main task of coding: error control
- ▶ Protect information against channel errors

Mutual information and error control

- ▶ Mutual information $I(X, Y)$ = the information transmitted on the channel
- ▶ Why do we still need error control?

Example: consider the following BSC channel ($p = 0.01$, $p(x_1) = 0.5$, $p(x_2) = 0.5$):

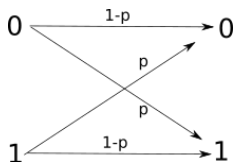


Figure 13: Binary symmetric channel (BSC)

- ▶ The receiver would like to know the source messages
 - ▶ In absence of communication, the uncertainty is $H(X) = 1$ bit/msg
 - ▶ With communication, the uncertainty is $H(X|Y) \approx 0.081$ bit/msg

Mutual information and error control

- ▶ The reduction in uncertainty due to communication = mutual information
 - ▶ $I(X, Y) = H(X) - H(X|Y) \approx 0.919$ bit/msg
- ▶ Even though we have large $I(X, Y)$, about 1% of all bits are erroneous
 - ▶ Imagine downloading a file, but having 1% wrong bits

Why is error control needed?

- ▶ In most communications it is required that *all* bits are received correctly
 - ▶ Not 1% errors, not 0.1%, not 0.0001%. **None!**
- ▶ But that is not possible unless the channel is ideal.
- ▶ So what do to? Error control coding

Modelling the errors on the channel

- ▶ We consider only binary channels (symbols = $\{0, 1\}$)
- ▶ An error = a bit is changed from 0 to 1 or viceversa
- ▶ Errors can appear:
 - ▶ **independently**: each bit on its own
 - ▶ in **packets of errors**: groups of errors

Modelling the errors on the channel

- ▶ Changing the value of a bit = modulo-2 sum with 1
- ▶ Value of a bit remains the same = modulo-2 sum with 0

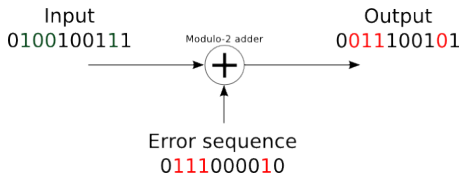


Figure 14: Channel error model

- ▶ Channel model we use (simple):
 - ▶ The transmitted sequence is summed modulo-2 with an **error sequence**
 - ▶ Where the error sequence is 1, there is a bit error
 - ▶ Where the error sequence is 0, there is no error

Error detection and error correction

Binary error correction:

- ▶ For binary channels, know the location of error \Rightarrow fix error by inverting bit
- ▶ Locating error = correcting error

Two possibilities in practice:

- ▶ **Error detection:** find out if there is any error in the received sequence
 - ▶ don't know exactly where, so cannot correct the bits, but can discard whole sequence
 - ▶ perhaps ask the sender to retransmit (examples: TCP/IP, internet communication etc)
 - ▶ easier to do
- ▶ **Error correction:** find out exactly which bits have errors, if any
 - ▶ can correct all errored bits by inverting them
 - ▶ useful when can't retransmit (data is stored: on HDD, AudioCD etc.)
 - ▶ harder to do than mere detection

What is error control coding?

The process of error control:

1. Want to send a sequence of k bits = **information word**

$$\mathbf{i} = i_1 i_2 \dots i_k$$

2. For each possible information word, the coder assigns a **codeword** of length $n > k$:

$$\mathbf{c} = c_1 c_2 \dots c_n$$

3. The codeword is sent on the channel instead of the original information word
4. The receiver receives a sequence $\hat{\mathbf{c}} \approx \mathbf{c}$, with possible errors:

$$\hat{\mathbf{c}} = \hat{c}_1 \hat{c}_2 \dots \hat{c}_n$$

5. The decoding algorithm detects/corrects the errors in $\hat{\mathbf{c}}$

Definitions

- ▶ An **error correcting code** is an association between the set of all possible information words to a set of codewords
 - ▶ Each possible information word \mathbf{i} has a certain codeword \mathbf{c}
- ▶ The association can be done:
 - ▶ randomly: codewords are selected and associated randomly to the information words
 - ▶ based on a certain rule: the codeword is computed with some algorithm from the information word
- ▶ A code is a **block code** if it operates with words of *fixed size*
 - ▶ Size of information word $\mathbf{i} = k$, size of codeword $\mathbf{c} = n$, $n > k$
 - ▶ Otherwise it is a *non-block code*
- ▶ A code is **linear** if any linear combination of codewords is also a codeword
- ▶ The **coding rate** of a code is:

$$R = k/n$$

- ▶ Examples: at blackboard (random code, parity bit)

Shannon's noisy channel theorem (second theorem, channel coding theorem)

- ▶ A coding rate is called **achievable** for a channel if, for that rate, there exists a coding and decoding algorithm guaranteed to correct all possible errors on the channel

Shannon's noisy channel coding theorem (second theorem)

For a given channel, all rates below capacity $R < C$ are achievable. All rates above capacity, $R > C$, are not achievable.

Channel coding theorem explained

In layman terms:

- ▶ For all coding rates $R < C$, there is a way to recover the transmitted data perfectly (decoding algorithm will detect and correct all errors)
- ▶ For all coding rates $R > C$, there is no way to recover the transmitted data perfectly

Example:

- ▶ Send binary digits (0,1) on a BSC channel with capacity 0.7 bits/message
- ▶ For any coding rate $R < 0.7$ there exist error correction codes that allow perfect recovery
 - ▶ i.e. for every 7 bits of data coding adds slightly more than 3 bits, on average $\Rightarrow R < \frac{7}{7+3}$
- ▶ With less than 3 bits for every 7 bits of data \Rightarrow impossible to recover all the data

Ideas behind channel coding theorem

- ▶ The rigorous proof of the theorem is too complex to present
- ▶ Key ideas of the proof:
 - ▶ Use very long information words, $k \rightarrow \infty$
 - ▶ Use random codes, compute the probability of having error after decoding
 - ▶ If $R < C$, *in average for all possible codes*, the probability of error after decoding goes to 0
 - ▶ If the average for all codes goes to 0, there exists at least one code better than the average
 - ▶ That is the code we should use
- ▶ **!! The theorem does not tell what code to use**, only that some code exists
- ▶ There is no hint of how to actually find the code
- ▶ Except general principles:
 - ▶ using longer information words is better
 - ▶ random codewords are generally good
- ▶ In practice, cannot use infinitely long codewords, so will only get a *good enough* code

Practical scenario

Practical ideas for error correcting codes:

- * If a codeword \mathbf{c}_1 is received with errors and becomes identical to another codeword $\mathbf{c}_2 \implies$ cannot detect any errors
- * Receiver will think it received a correct codeword c_2 and the information word was \mathbf{i}_2 , but actually it was \mathbf{i}_1
- * We want codewords as different as possible from each other
- * How to measure this difference? Hamming distance
- * The **Hamming distance** of two binary sequences a , b of length n = the total number of bit differences between them

$$d(a, b) = \sum_{i=1}^N a_i \oplus b_i$$

► It satisfies the 3 properties of a metric function:

1. $d(a, b) \geq 0 \forall a, b$, with $d(a, b) = 0 \Leftrightarrow a = b$
2. $d(a, b) = d(b, a), \forall a, b$
3. $d(a, c) = d(a, b) + d(b, c), \forall a, b, c$