

# INFORMATION THEORY & CODING

## Week 5 : Source Coding 1

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## Theorem (AEP)

“Almost all events are almost equally surprising.” Specifically, if  $X_1, X_2, \dots$  are i.i.d.  $\sim p(x)$ , then

$$-\frac{1}{n} \log p(X_1, X_2, \dots, X_n) \rightarrow H(X) \text{ in probability.}$$

## Definition

The *typical set*  $A_\epsilon^{(n)}$  is the set of sequences  $x_1, x_2, \dots, x_n$  satisfying

$$2^{-n(H(X)+\epsilon)} \leq p(x_1, x_2, \dots, x_n) \leq 2^{-n(H(X)-\epsilon)}.$$

## Properties of the typical set

- ① If  $(x_1, x_2, \dots, x_n) \in A_\epsilon^{(n)}$ , then  
 $H(X) - \epsilon \leq -\frac{1}{n} \log p(x_1, x_2, \dots, x_n) \leq H(X) + \epsilon$ .
- ②  $\Pr[A_\epsilon^{(n)}] > 1 - \epsilon$  for  $n$  sufficiently large.
- ③  $|A_\epsilon^{(n)}| \leq 2^{n(H(X)+\epsilon)}$ , where  $|A|$  denotes the cardinality of the set  $A$ .
- ④  $|A_\epsilon^{(n)}| \geq (1 - \epsilon)2^{n(H(X)-\epsilon)}$  for  $n$  sufficiently large.

## Theorem

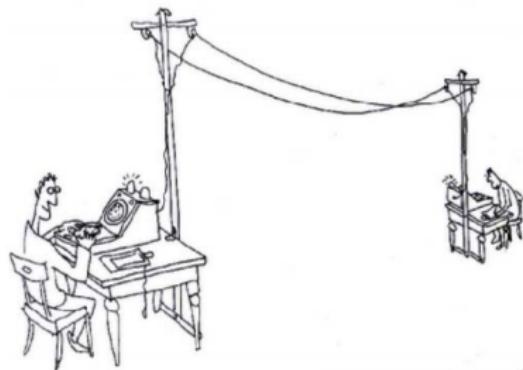
Let  $X^n$  be i.i.d.  $\sim p(x)$ . There exists a code that one-to-one maps sequences  $x^n$  of length  $n$  into binary strings with

$$E\left[\frac{1}{n}\ell(X^n)\right] \leq H(X) + \epsilon$$

for  $n$  sufficiently large.

# Source Coding

Which horse won in the horse racing?



ABC TELEGRAPH EXHIBIT FOR THE NATIONAL ARCHIVES  
INVENTIONS EXHIBITION TIM HUNKIN 7/10/85

Which horse won in the horse racing?

X	Pr	Code I	Code II
0	1/2	000	0
1	1/4	001	10
2	1/8	010	110
3	1/16	011	1110
4	1/64	100	111100
5	1/64	101	111101
6	1/64	110	111110
7	1/64	111	111111

$$H(X) = - \sum p_i \log p_i = 2\text{bits}$$

Which code is better?



# Source Coding (Data Compression)

- We interpret that  $H(X)$  is the best achievable data compression.
- We want to develop practical **lossless coding algorithms** that approach, or achieve the entropy limit  $H(X)$ .



# Terminology

X	Pr	Code I	Code II
0	1/2	000	0
1	1/4	001	10
2	1/8	010	110
3	1/16	011	1110
4	1/64	100	111100
5	1/64	101	111101
6	1/64	110	111110
7	1/64	111	111111

- Source alphabet  $\mathcal{X} = \{0, 1, 2, 3, 4, 5, 6, 7\}$ .
- Code alphabet  $\mathcal{D} = \{0, 1\}$ .
- Codeword, e.g., 010 for  $X = 2$  in Code 1.
- Codeword length, e.g., codeword length for Code 1 is 3.
- Codebook: all the codewords.



## Notation (Alphabet Extension)

The set of all possible sequences based on a finite alphabet  $\mathcal{D}$  is denoted by  $\mathcal{D}^*$ . E.g.,

$$\mathcal{D} = \{0, 1\} \rightarrow \mathcal{D}^* = \{0, 1, 00, 01, 10, 11, 000, \dots\}.$$

## Definition (Source Code)

Let  $\mathcal{X}$  be the alphabet of a random variable  $X$ , and  $\mathcal{D}$  be the alphabet of code. A *source code*  $C$  for the random variable  $X$  is a map

$$\begin{aligned} C : \quad & \mathcal{X} \rightarrow \mathcal{D}^* \\ & x \mapsto C(x) \end{aligned}$$

where  $C(x)$  is the codeword associated with  $x$ . Let  $\ell(x)$  denote the length of  $C(x)$ .

## Definition

The *expected length*  $L(X)$  of a source code  $C$  for a random variable  $X$  with probability mass function  $p(x)$  is

$$L(X) = E\ell(X) = \sum_{x \in \mathcal{X}} p(x)\ell(x).$$

$X$	$\text{Pr}$	Code I	Code II
0	$1/2$	000	0
1	$1/4$	001	10
2	$1/8$	010	110
3	$1/16$	011	1110
4	$1/64$	100	111100
5	$1/64$	101	111101
6	$1/64$	110	111110
7	$1/64$	111	111111

$$L_1(X) = 3$$

$$L_2(X) = 2$$



- Magnetic recording: cassette, hard drive ...
- Speech compression
- Compact disk (CD)
- Image compression: JPEG

# Source Coding: Set of codes

For  $\mathcal{X} = \{1, 2, 3, 4\}$  and  $\mathcal{D} = \{0, 1\}$ , consider

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

- Code efficiency =  $H(X)/E[\ell(X)]$
- Which code is **best**? Would we prefer  $C_I$  or  $C_{II}$ ?

Consider  $C_I$  and decode string: **00001**. It would come from 1, 2, 1, 2, 3 or 2, 1, 2, 1, 3 or 1, 1, 1, 1, 3, or etc.



# Source Coding: Set of codes

For  $\mathcal{X} = \{1, 2, 3, 4\}$  and  $\mathcal{D} = \{0, 1\}$ , consider

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

- Code efficiency =  $H(X)/E[\ell(X)]$
- Which code is **best**? Would we prefer  $C_I$  or  $C_{II}$ ?

Consider  $C_{II}$  and decode string: **0011**. It could be either 1,1,2,2 or 3,4.



# Source Coding: Set of codes

For  $\mathcal{X} = \{1, 2, 3, 4\}$  and  $\mathcal{D} = \{0, 1\}$ , consider

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

- Consider  $C_{III}$ . Can we decode 1100000000?

Yes. But if we only see a prefix, such as 11, we don't know until we see more bits to the end.

$$1100000000 = 3, 2, 2, 2, 2$$

$$1100000000 = 4, 2, 2, 2, 2$$



# Source Coding: Set of codes

For  $\mathcal{X} = \{1, 2, 3, 4\}$  and  $\mathcal{D} = \{0, 1\}$ , consider

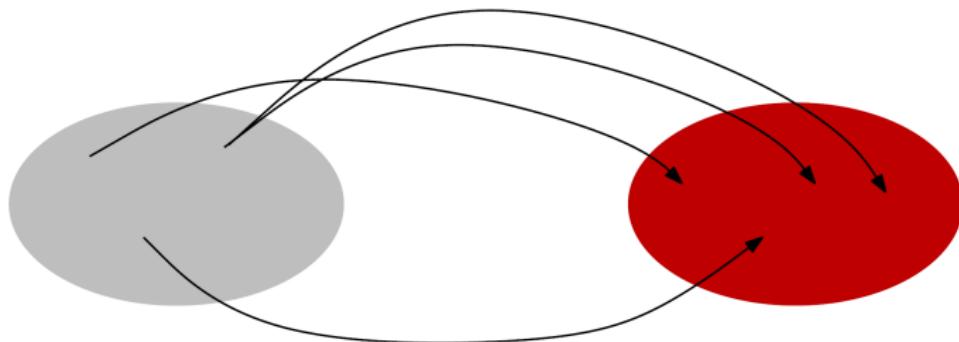
$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

- Consider  $C_{IV}$ . This code seems at least feasible (since  $E[\ell] \geq H$ ). Decoding seems **easy**: (e.g.,  $111110100 = 111, 110, 10, 0 = 4, 3, 2, 1$ ).

## Definition (Nonsingular Code)

A code  $C$  is called *nonsingular* if every realization of  $\mathcal{X}$  maps onto a difference codeword in  $\mathcal{D}^*$ , i.e.,

$$x \neq x' \Rightarrow C(x) \neq C(x').$$



## Definition (Nonsingular Code)

A code  $C$  is called *nonsingular* if every element of  $\mathcal{X}$  maps onto a difference string in  $\mathcal{D}^*$ , i.e.,

$$x \neq x' \Rightarrow C(x) \neq C(x').$$

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$	
1	1/2	0	0	10	0	$C_I$ is singular.
2	1/4	0	1	00	10	
3	1/8	1	00	11	110	
4	1/8	10	11	110	111	
$H(X)$	1.75	—	—	—	—	
$E\ell(X)$	—	1.125	1.25	2.125	1.75	



## Definition (Code Extension)

The *extension* of a code  $C: \mathcal{X} \rightarrow \mathcal{D}^*$  is defined by

$$C(x_1 x_2 \cdots x_n) = C(x_1)C(x_2) \cdots C(x_n).$$

## Definition (Unique Decodable Code)

A code is called *uniquely decodable* if its extension is nonsingular.

$$x_1 x_2 \dots x_m \neq x'_1 x'_2 \dots x'_n \Rightarrow C(x_1 x_2 \dots x_m) \neq C(x'_1 x'_2 \dots x'_n)$$

## Definition (Unique Decodable Code)

A code is called *uniquely decodable* if its extension is nonsingular.

$C_{II}^*$  is **singular**. ( $C(1, 1) = C(3) = 00$ )

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

$C_I$  is singular.  
 $C_{II}$  is NOT u.d..

## Definition (Unique Decodable Code)

A code is called *uniquely decodable* if its extension is nonsingular.

$C_{III}$  is **uniquely decodable**.

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

$C_I$  is singular.  
 $C_{II}$  is **NOT** u.d..

## Definition (Unique Decodable Code)

A code is called *uniquely decodable* if its extension is nonsingular.

$$1100000000 = 3, 2, 2, 2, 2$$

$$11000000000 = 4, 2, 2, 2, 2$$

To know the source, we have to **wait until the end!**

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

$C_I$  is singular.  
 $C_{II}$  is NOT u.d..



## Definition (Prefix Code)

A code  $C$  is called a *prefix code* (a.k.a. *instantaneous*) iff no codeword of  $C$  is a prefix of any other codeword of  $C$ .

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$	
1	1/2	0	0	10	0	$C_I$ is singular.
2	1/4	0	1	00	10	$C_{II}$ is NOT u.d..
3	1/8	1	00	11	110	$C_{III}$ is NOT prefix.
4	1/8	10	11	110	111	$C_{IV}$ is prefix.
$H(X)$	1.75	—	—	—	—	
$E\ell(X)$	—	1.125	1.25	2.125	1.75	

# Source Coding: Code types

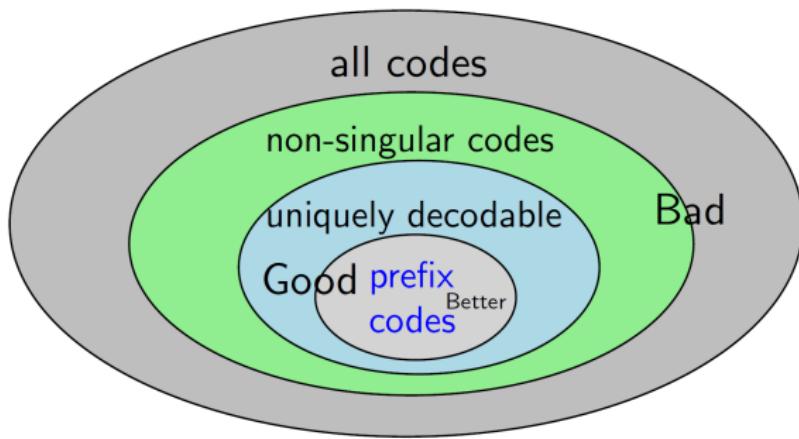
For  $\mathcal{X} = \{1, 2, 3, 4\}$  and binary code, consider

$x$	$p(x)$	$C_I$	$C_{II}$	$C_{III}$	$C_{IV}$
1	1/2	0	0	10	0
2	1/4	0	1	00	10
3	1/8	1	00	11	110
4	1/8	10	11	110	111
$H(X)$	1.75	—	—	—	—
$E\ell(X)$	—	1.125	1.25	2.125	1.75

- $C_I$  is singular.
- $C_{II}$  is non-singular, but not uniquely decodable.
- $C_{III}$  is non-singular, uniquely decodable, but NOT prefix.
- $C_{IV}$  is non-singular, uniquely decodable, and prefix.



## Source Coding: Classes of codes



- Goal: to find a **prefix code** with **minimum expected length**.



## Theorem 5.2.1 (Kraft Inequality)

*For any prefix code over an alphabet of size  $D$ , the codeword lengths  $\ell_1, \ell_2, \dots, \ell_m$  must satisfy the inequality*

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

*Conversely, given a set of codeword lengths that satisfy this inequality, there exists a prefix code with these codeword lengths.*

# Kraft Inequality

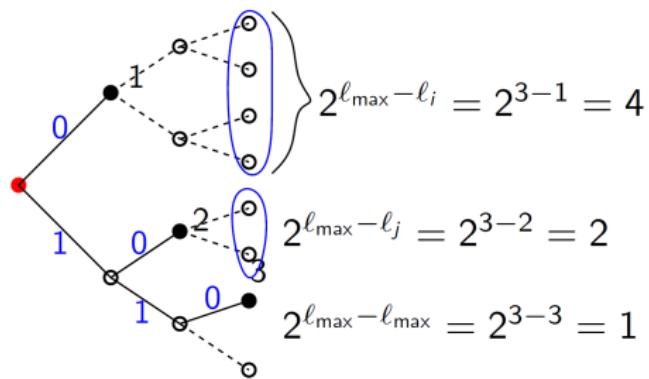
**Proof Idea.** (A small example) To prove: A prefix code with lengths  $\ell_1, \ell_2, \dots, \ell_m$ , the inequality

$$\sum_i D^{-\ell_i} \leq 1 \quad \text{holds.}$$

Depth: 0 1 2 3

$x$	$c(x)$
1	0
2	10
3	110

$$\ell_{\max} = 3$$

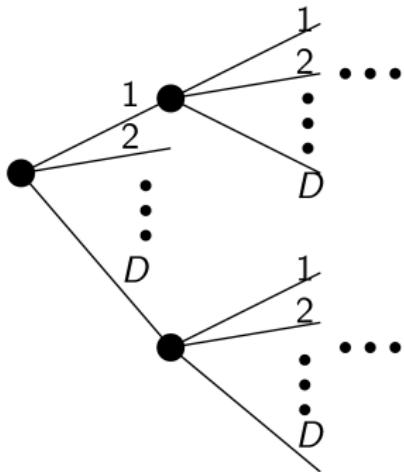


$$\sum_i 2^{-\ell_i} \leq 1 \Leftarrow \sum_i 2^{\ell_{\max}-\ell_i} \leq 2^{\ell_{\max}}$$



## Proof. (in general)

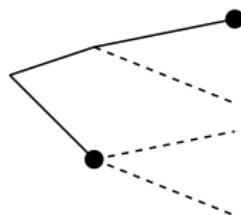
- Represent the set of prefix codes on a  $D$ -ary tree:



- Codewords correspond to leaves
- Path from root to each leaf determines a codeword
- Prefix condition:** won't get to a codeword until we get to a leaf (no descendants of codewords are codewords)

## Proof. (in general)

- $\ell_{\max} = \max_i(\ell_i)$  is the length of the longest codeword.
- We can expand the full-tree down to depth  $\ell_{\max}$ :



The nodes at the level  $\ell_{\max}$  are either

- ① codewords
- ② descendants of codewords
- ③ neither

- Consider a codeword  $i$  at depth  $\ell_i$  in tree
- There are  $D^{\ell_{\max}-\ell_i}$  descendants in the tree at depth  $\ell_{\max}$
- Descendants of code  $i$  are **disjoint** from decedents of code  $j$  (prefix free condition)

## Proof. (in general)

- All the above implies:

$$\sum_i D^{\ell_{\max} - \ell_i} \leq D^{\ell_{\max}} \Rightarrow \sum_i D^{-\ell_i} \leq 1$$

- **Conversely:** given codewords lengths  $\ell_1, \ell_2, \dots, \ell_m$  satisfying Kraft inequality, try to construct a **prefix code**.

# Kraft Inequality

## Proof. (in general)

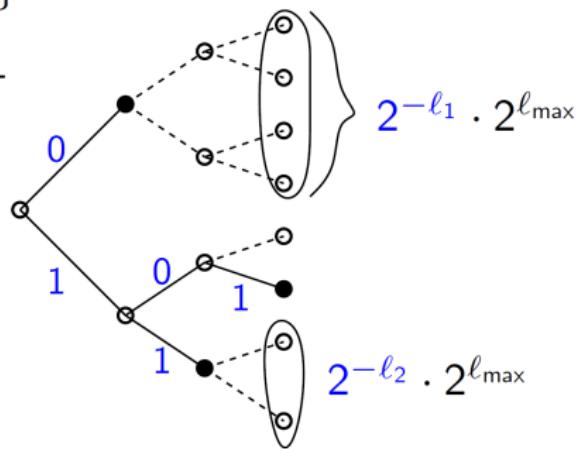
- Conversely: given codewords lengths  $\ell_1, \ell_2, \dots, \ell_m$  satisfying Kraft inequality, try to construct a **prefix code**.

$$\{\ell_1, \ell_2, \ell_3\} = \{1, 2, 3\}$$

$$2^{-1} + 2^{-2} + 2^{-3} \leq 1$$

$x$	$c(x)$
1	0
2	11
3	101

$C$  is prefix.



## Proof. (in general)

- Conversely: given codewords lengths  $\ell_1, \ell_2, \dots, \ell_m$  satisfying Kraft inequality, try to construct a prefix code.

Left as an Exercise.

# Reading & Homework

Reading : 5.1, 5.2

Homework : Problems 5.1, 5.3



# INFORMATION THEORY & CODING

## Week 6 : Source Coding 2

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- **Classes of codes**

Prefix codes  $\Rightarrow$  Uniquely decodable codes  $\Rightarrow$  Nonsingular codes

- **Kraft inequality**

Prefix codes  $\Leftrightarrow \sum D^{-\ell_i} \leq 1.$

- Extended Kraft inequality for prefix code
- Kraft inequality for uniquely decodable code

Uniquely decodable code does NOT provide more choices than prefix code

- Bounds on optimal expected length

Entropy length is achievable when jointly encoding a random sequence.

## Theorem 5.5.1 (Extended Kraft Inequality)

*Kraft inequality holds also for all countably infinite set of codewords, i.e., the codeword lengths satisfy the extended Kraft inequality,*

$$\sum_{i=1}^{\infty} D^{-\ell_i} \leq 1$$

*Conversely, given any  $\ell_1, \ell_2, \dots$  satisfying the extended Kraft inequality, we can construct a prefix code with these codeword lengths.*

# Extended Kraft Inequality

## Theorem 5.2.2 (Extended Kraft Inequality)

*Kraft inequality holds also for all countably infinite set of codewords.*

### Proof.

Consider the  $i$ th codeword  $y_1y_2 \cdots y_{\ell_i}$ . Let  $0.y_1y_2 \cdots y_{\ell_i}$  be the real number given by the  $D$ -ary expansion

$$0.y_1y_2 \cdots y_{\ell_i} = \sum_{j=1}^{\ell_i} y_j D^{-j},$$

which corresponds to the interval

$$\left[0.y_1y_2 \cdots y_{\ell_i}, 0.y_1y_2 \cdots y_{\ell_i} + \frac{1}{D^{\ell_i}}\right).$$



# Extended Kraft Inequality

Theorem 5.2.2 (Extended Kraft Inequality)

*Kraft inequality holds also for all countably infinite set of codewords.*

Proof. (cont.)

By the **prefix condition**, these intervals are disjoint in the **unit interval**  $[0, 1]$ . Thus, the sum of their lengths is  $\leq 1$ . This proves that

$$\sum_{i=1}^{\infty} D^{-\ell_i} \leq 1.$$

For **converse**, **reorder indices in increasing order and assign intervals as we walk along the unit interval.**



# Kraft Inequality for Uniquely Decodable Codes

## Theorem 5.2.3 (McMillan)

*The codeword lengths of any uniquely decodable  $D$ -ary code must satisfy the Kraft inequality*

$$\sum D^{-\ell_i} \leq 1.$$

*Conversely, given a set of codeword lengths that satisfy this inequality, it is possible to construct a uniquely decodable code with these codeword lengths.*

## Proof.

Consider  $C^k$ , the  $k$ -th extension of the code by  $k$  repetitions. Let the codeword lengths of the symbols  $x \in \mathcal{X}$  be  $\ell(x)$ . For the  $k$ -th extension code, we have

$$\ell(x_1, x_2, \dots, x_k) = \sum_i^k \ell(x_i).$$



# Kraft Inequality for Uniquely Decodable Codes

## Theorem 5.5.1 (McMillan)

*The codeword lengths of any uniquely decodable D-ary code must satisfy the Kraft inequality*

$$\sum D^{-\ell_i} \leq 1.$$

## Proof. (cont.)

Consider

$$\begin{aligned} \left( \sum_{x \in \mathcal{X}} D^{-\ell(x)} \right)^k &= \sum_{x_1 \in \mathcal{X}} \sum_{x_2 \in \mathcal{X}} \dots \sum_{x_k \in \mathcal{X}} D^{-\ell(x_1)} D^{-\ell(x_2)} \dots D^{-\ell(x_k)} \\ &= \sum_{x_1, x_2, \dots, x_k \in \mathcal{X}^k} D^{-\ell(x_1)} D^{-\ell(x_2)} \dots D^{-\ell(x_k)} \\ &= \sum_{x^k \in \mathcal{X}^k} D^{-\ell(x^k)} \end{aligned}$$

# Kraft Inequality for Uniquely Decodable Codes

## Theorem 5.5.1 (McMillan)

*The codeword lengths of any uniquely decodable  $D$ -ary code must satisfy the Kraft inequality*

$$\sum D^{-\ell_i} \leq 1.$$

## Proof. (cont.)

Let  $\ell_{\max}$  be the maximum codeword length and  $a(m)$  is the number of source sequences  $x^k$  mapping into codewords of length  $m$ . Unique decodability implies that  $a(m) \leq D^m$ . We have

$$\begin{aligned} \left( \sum_{x \in \mathcal{X}} D^{-\ell(x)} \right)^k &= \sum_{x^k \in \mathcal{X}^k} D^{-\ell(x^k)} = \sum_{m=1}^{k\ell_{\max}} a(m) D^{-m} \\ &\leq \sum_{m=1}^{k\ell_{\max}} D^m D^{-m} \\ &= k\ell_{\max} \end{aligned}$$

# Kraft Inequality for Uniquely Decodable Codes

## Theorem 5.5.1 (McMillan)

*The codeword lengths of any uniquely decodable  $D$ -ary code must satisfy the Kraft inequality*

$$\sum D^{-\ell_i} \leq 1.$$

## Proof. (cont.)

$$\left( \sum_{x \in \mathcal{X}} D^{-\ell(x)} \right)^k \leq k \ell_{\max}.$$

Hence,

$$\sum_j D^{-\ell_j} \leq (k \ell_{\max})^{1/k}$$

holds for all  $k$ . Since the RHS  $\rightarrow 1$  as  $k \rightarrow \infty$ , we prove the Kraft inequality. For the converse part, we can construct a prefix code as in **Theorem 5.2.1**, which is also uniquely decodable. □

**Problem** To find the set of lengths  $\ell_1, \ell_2, \dots, \ell_m$  satisfying the Kraft inequality and whose expected length  $L = \sum p_i \ell_i$  is minimized.

## Optimization:

minimize  $L = \sum p_i \ell_i$

subject to  $\sum D^{-\ell_i} \leq 1$  and  $\ell_i$ 's are integers.

## Theorem 5.3.1

The *expected length*  $L$  of any prefix  $D$ -ary code for a random variable  $X$  is no less than  $H_D(X)$ , i.e.,

$$L \geq H_D(X),$$

with equality iff  $D^{-\ell_i} = p_i$ .

## Proof.

$$\begin{aligned} L - H_D(X) &= \sum p_i \ell_i - \sum p_i \log_D \frac{1}{p_i} \\ &= - \sum p_i \log_D D^{-\ell_i} + \sum p_i \log_D p_i \\ &= \sum p_i \log_D \frac{p_i}{r_i} - \log_D c \\ \text{"=" holds if } c &= 1 \quad \text{and } r_i = p_i. \end{aligned}$$
$$= D(\mathbf{p} \| \mathbf{r}) + \log_D \frac{1}{c} \geq 0$$

where  $r_i = D^{-\ell_i} / \sum_j D^{\ell_j}$  and  $c = \sum D^{-\ell_i} \leq 1$ . □

## Theorem 5.3.1

The *expected length*  $L$  of any prefix  $D$ -ary code for a random variable  $X$  is no less than  $H_D(X)$ , i.e.,

$$L \geq H_D(X),$$

with equality iff  $D^{-\ell_i} = p_i$ .

## Definition

A probability distribution is called  $D$ -adic if each of the probabilities is equal to  $D^{-n}$  for some  $n$ . Thus, we have **equality** in the theorem iff the distribution of  $X$  is  $D$ -adic.

## Remark

$H_D(X)$  is a *lower bound* on the optimal code length. The equality holds iff  $p$  is  $D$ -adic.

# Bound on the Optimal Code Length

## Theorem 5.4.1 (Shannon Codes)

Let  $\ell_1^*, \ell_2^*, \dots, \ell_m^*$  be optimal codeword lengths for a source distribution  $\mathbf{p}$  and a  $D$ -ary alphabet, and let  $L^*$  be the associated expected length of an optimal code ( $L^* = \sum p_i \ell_i^*$ ). Then

$$H_D(X) \leq L^* < H_D(X) + 1.$$

## Proof.

Take  $\ell_i = \lceil -\log_D p_i \rceil$ . Since

$$\sum_{i \in \mathcal{X}} D^{-\ell_i} \leq \sum_{i \in \mathcal{X}} p_i = 1,$$

these lengths satisfy Kraft inequality and we can create a prefix code. Thus,

$$\begin{aligned} L^* &\leq \sum p_i \lceil -\log_D p_i \rceil \\ &< \sum p_i (-\log_D p_i + 1) \\ &= H_D(X) + 1. \end{aligned}$$

# Bound on the Optimal Code Length

## Theorem 5.4.2

Consider a system in which we send a sequence of  $n$  symbols from  $X$ . The symbols are assumed to be i.i.d. according to  $p(x)$ . The minimum expected codeword length per symbol satisfies

$$\frac{H(X_1, X_2, \dots, X_n)}{n} \leq L_n^* < \frac{H(X_1, X_2, \dots, X_n)}{n} + \frac{1}{n}.$$

## Proof.

First,

$$L_n = \frac{1}{n} \sum p(x_1, x_2, \dots, x_n) \ell(x_1, x_2, \dots, x_n) = \frac{1}{n} E[\ell(X_1, X_2, \dots, X_n)]$$

We also have

$$H(X_1, X_2, \dots, X_n) \leq E[\ell(X_1, X_2, \dots, X_n)] < H(X_1, X_2, \dots, X_n) + 1.$$

Since  $X_1, X_2, \dots, X_n$  are i.i.d.,  $H(X_1, X_2, \dots, X_n) = nH(X)$ . □

Related Sections : 5.3 - 5.5

# INFORMATION THEORY & CODING

## Part 7 : Source Coding 3 - Huffman Code

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October 31, 2023



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## Problem 5.1

Given source symbols and their probabilities of occurrence, how to design an optimal source code (**prefix code** and **the shortest on average**)?

## Huffman Codes

- ① Merge the  $D$  symbols with the smallest probabilities, and generate one new symbol whose probability is the summation of the  $D$  smallest probabilities.
- ② Assign the  $D$  corresponding symbols with digits  $0, 1, \dots, D - 1$ , then go back to Step 1.

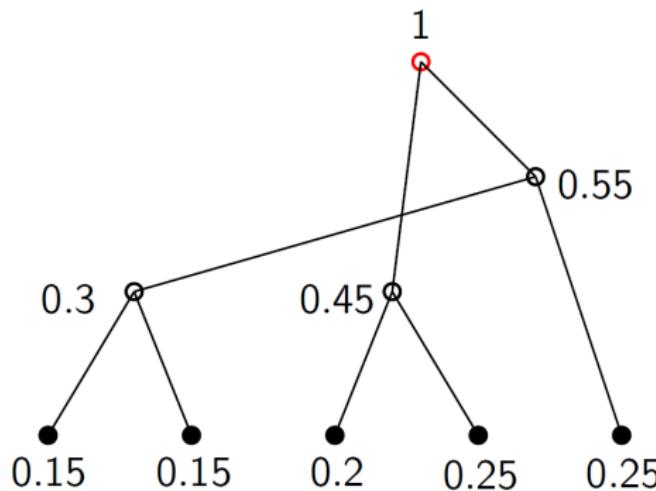
Repeat the above process until  $D$  probabilities are merged into probability 1.



# Huffman Codes: A few examples

## Example 1

$x$	$p(x)$
1	0.25
2	0.25
3	0.2
4	0.15
5	0.15



Reconstruct the tree



# Huffman Codes: A few examples

## Example 1

$x$	$p(x)$	$C(x)$
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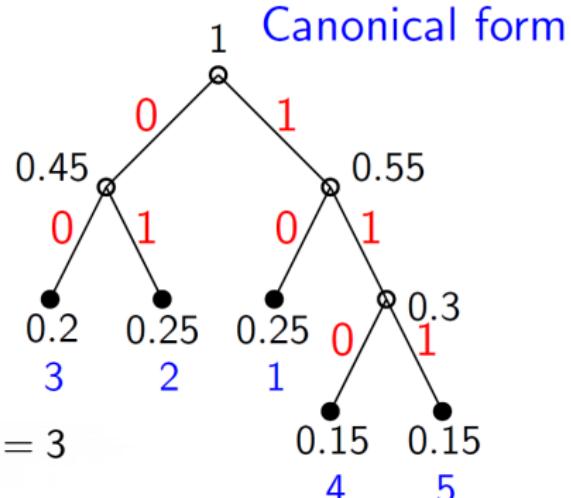
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$$\ell(1) = \ell(2) = \ell(3) = 2, \ell(4) = \ell(5) = 3$$

$$L = \sum \ell(x)p(x) = 2.3 \text{ bits}$$

$$H_2(X) = - \sum p(x) \log_2 p(x) = 2.29 \text{ bits}$$

$$L \geq H_2(X)$$



# Huffman Codes: A few examples

## Example 2

$x$	$p(x)$
1	0.25
2	0.25
3	0.2
4	0.1
5	0.1
6	0.1
Dummy	0

At one time, we merge  $D$  symbols, and at each stage of the reduction, the number of symbols is reduced by  $D - 1$ . We want the total # of symbols to be  $1 + k(D - 1)$ . If not, we add dummy symbols with probability 0.

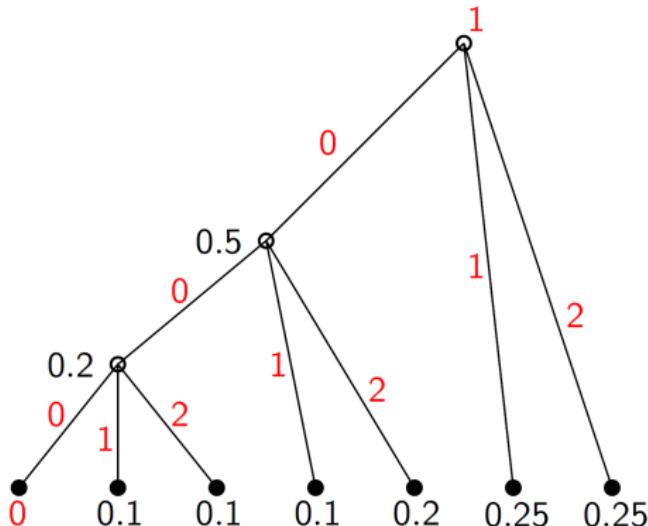
$$\mathcal{D} = \{0, 1, 2\}$$



# Huffman Codes: A few examples

**Example 2** ( $D \geq 3$ )

$x$	$p(x)$	$C(x)$
1	0.25	1
2	0.25	2
3	0.2	02
4	0.1	01
5	0.1	002
6	0.1	001
Dummy	0	000



## Validations:

$$L = \sum \ell(x)p(x) = 1.7 \text{ ternary digits}$$

$$H_3(X) = -\sum p(x) \log_3 p(x) \approx 1.55 \text{ ternary digits}$$

## Lemma 5.8.1

For any distribution, the optimal prefix codes (with minimum expected length) should satisfy the following properties:

- ① If  $p_j > p_k$ , then  $\ell_j \leq \ell_k$ .
- ② The two longest codewords have the same length.
- ③ There exists an optimal prefix code, such that two of the longest codewords differ only in the last bit and correspond to the two least likely symbols.

# Optimality of Huffman Codes

- 1. If  $p_j > p_k$ , then  $\ell_j \leq \ell_k$ .

Proof.

Suppose that  $C_m$  is an optimal code. Consider  $C'_m$ , with the codewords  $j$  and  $k$  of  $C_m$  interchanged. Then

$$\begin{aligned}\underbrace{L(C'_m) - L(C_m)}_{\geq 0} &= \sum p_i \ell'_i - \sum p_i \ell_i \\ &= p_j \ell_k + p_k \ell_j - p_j \ell_j - p_k \ell_k \\ &= \underbrace{(p_j - p_k)}_{>0} (\ell_k - \ell_j)\end{aligned}$$

Thus, we must have  $\ell_k \geq \ell_j$ . □

# Optimality of Huffman Codes

- 2. The **two longest** codewords have the **same** length.



- 3. There exists an optimal prefix code, such that two of the longest codewords differ **only in the last bit** and correspond to the two least likely symbols.

## Proof.

If there is a maximal-length codeword **without a sibling**, we can delete the last bit of the codeword and still **preserve** the prefix property. This **reduces** the average codeword length and **contradicts** the optimality of the code. Hence, **every** maximum-length codeword in any optimal code has a **sibling**. Now we can exchange the longest codewords s.t. **the two lowest-probability source symbols are associated with two siblings on the tree, without changing the expected length.** □

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For any distribution, the optimal prefix codes (with minimum expected length) should satisfy the following properties:

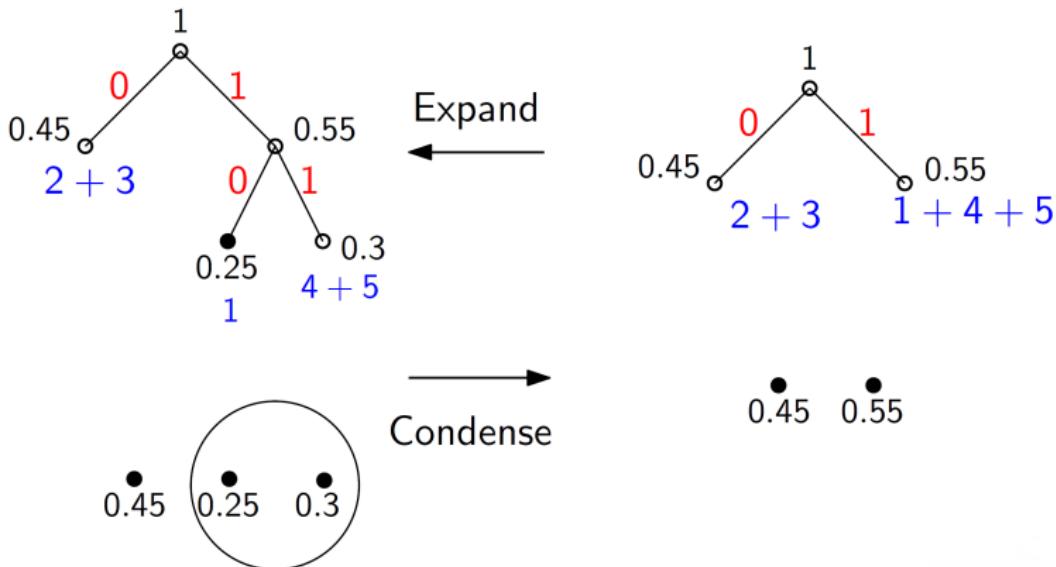
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- ③ There exists an optimal prefix code, such that two of the longest codewords differ only in the last bit and correspond to the two least likely symbols.

⇒ If  $p_1 \geq p_2 \geq \dots \geq p_m$ , then there exists an optimal code with  $\ell_1 \leq \ell_2 \leq \dots \leq \ell_{m-1} = \ell_m$ , and codewords  $C(x_{m-1})$  and  $C(x_m)$  differ only in the last bit.  
(canonical codes)



# Optimality of Huffman Codes

- We prove the **optimality** of Huffman codes by **induction**.  
Assume binary code in the proof.



## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

## Key idea.

expand  $C_{m-1}^*$  to  $C_m(\mathbf{p}) \Rightarrow L(C_m) = L(C_m^*)$

# Optimality of Huffman Codes

Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

	$C_{m-1}^*(\mathbf{p}')$		$C_m(\mathbf{p})$	
$p_1$	$w'_1$	$l'_1$	$w_1 = w'_1$	$l_1 = l'_1$
$p_2$	$w'_2$	$l'_2$	$w_2 = w'_2$	$l_2 = l'_2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$p_{m-2}$	$w'_{m-2}$	$l'_{m-2}$	$w_{m-2} = w'_{m-2}$	$l_{m-2} = l'_{m-2}$
$p_{m-1} + p_m$	$w'_{m-1}$	$l'_{m-1}$	$w_{m-1} = w'_{m-1}0$ $w_m = w'_{m-1}1$	$l_{m-1} = l'_{m-1} + 1$ $l_m = l'_{m-1} + 1$



# Optimality of Huffman Codes

Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

$C_{m-1}(\mathbf{p}')$	$C_m^*(\mathbf{p})$
$p_1$	$w'_1$
$p_2$	$w'_2$
$\vdots$	$\vdots$
$p_{m-2}$	$w'_{m-2}$
$p_{m-1} + p_m$	$w'_{m-1}$
	$l'_1$
	$l'_2$
	$\vdots$
	$l'_{m-2}$
	$l'_{m-1}$
	$w_1 = w'_1$
	$w_2 = w'_2$
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## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

expand  $C_{m-1}^*(\mathbf{p}')$  to  $C_m(\mathbf{p})$

$$L(\mathbf{p}) = L^*(\mathbf{p}') + p_{m-1} + p_m$$

condense  $C_m^*(\mathbf{p})$  to  $C_{m-1}^*(\mathbf{p}')$

$$L^*(\mathbf{p}) = L(\mathbf{p}') + p_{m-1} + p_m$$

## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

$$L(\mathbf{p}) = L^*(\mathbf{p}') + p_{m-1} + p_m$$

$$L^*(\mathbf{p}) = L(\mathbf{p}') + p_{m-1} + p_m$$

$$\underbrace{(L(\mathbf{p}') - L^*(\mathbf{p}'))}_{\geq 0} + \underbrace{(L(\mathbf{p}) - L^*(\mathbf{p}))}_{\geq 0} = 0$$

## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

Thus,  $L(\mathbf{p}) = L^*(\mathbf{p})$ . Minimizing the expected length  $L(C_m)$  is equivalent to minimizing  $L(C_{m-1})$ . The problem is reduced to one with  $m - 1$  symbols and probability masses  $(p_1, p_2, \dots, p_{m-1} + p_m)$ . Proceeding this way, we finally reduce the problem to two symbols, in which case the optimal code is obvious.

## Theorem 5.8.1

Huffman coding is *optimal*, that is, if  $C^*$  is a Huffman code and  $C'$  is any other uniquely decodable code,  $L(C^*) \leq L(C')$ .

## Remark

Huffman coding is a *greedy algorithm* in which it merges the two **least likely** symbols at each step.

LOCAL OPT → GLOBAL OPT

Related Sections : 5.6 - 5.8

# INFORMATION THEORY & CODING

## Part 7 : Source Coding 3 - Huffman Code

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November 7, 2023



## Problem 5.1

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- ① Merge the  $D$  symbols with the smallest probabilities, and generate one new symbol whose probability is the summation of the  $D$  smallest probabilities.
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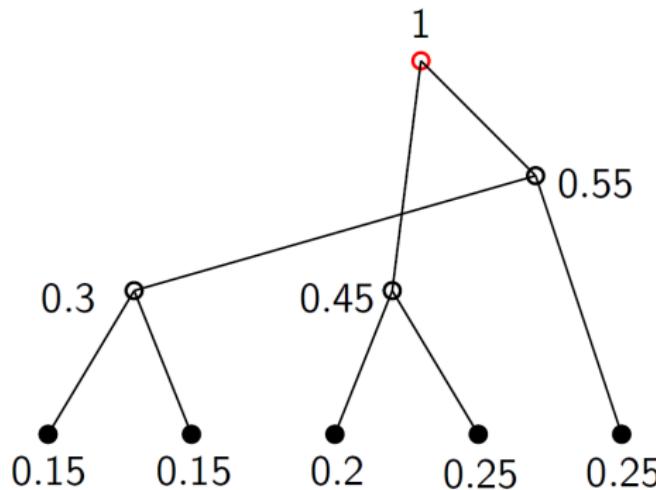
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## Example 1

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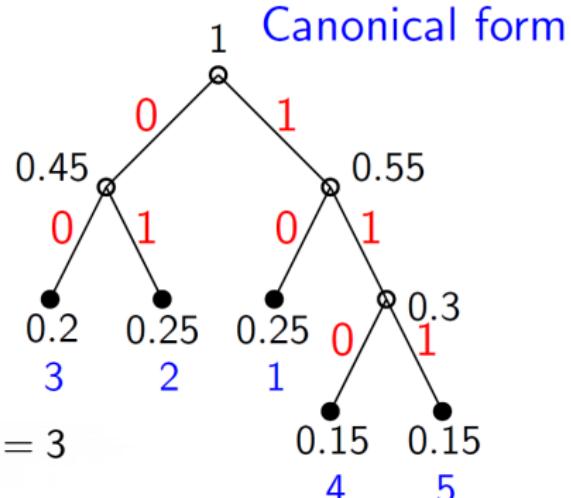
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$x$	$p(x)$
1	0.25
2	0.25
3	0.2
4	0.1
5	0.1
6	0.1
Dummy	0

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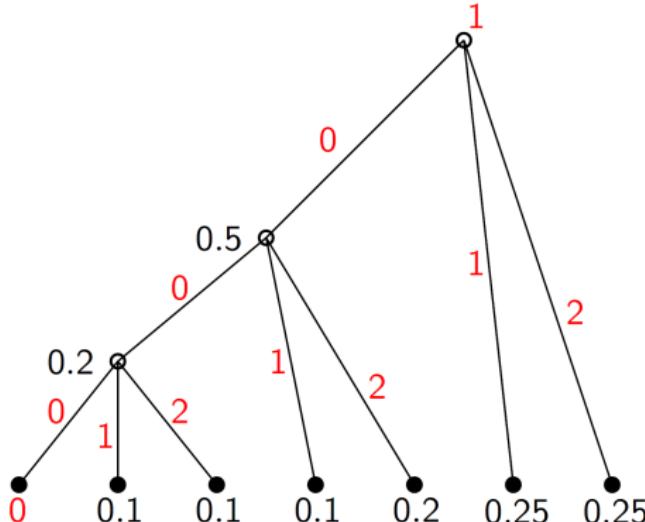
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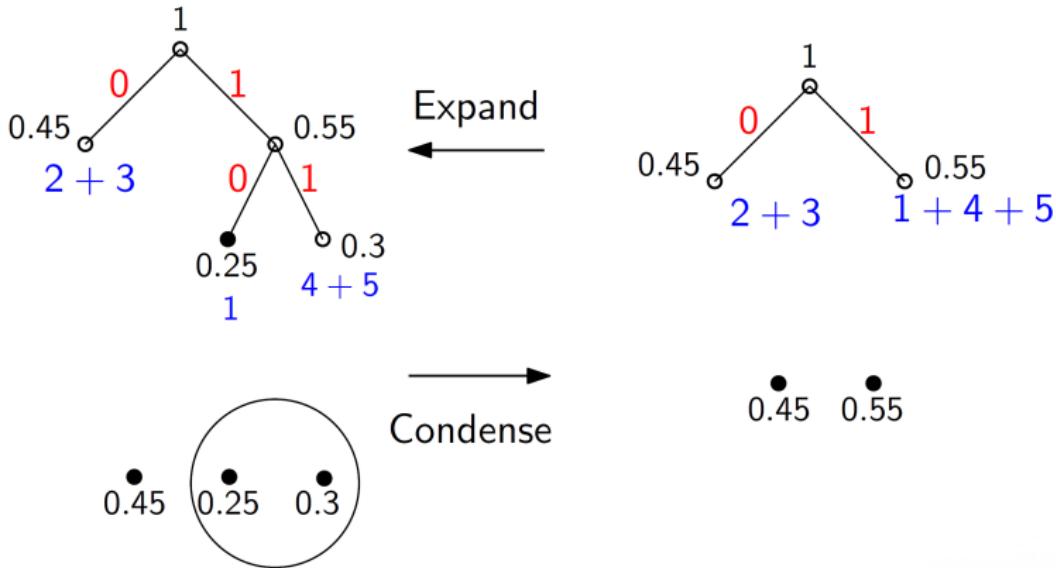
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- We prove the **optimality** of Huffman codes by **induction**.  
Assume binary code in the proof.



## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

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$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$p_{m-2}$	$w'_{m-2}$	$l'_{m-2}$	$w_{m-2} = w'_{m-2}$	$l_{m-2} = l'_{m-2}$
$p_{m-1} + p_m$	$w'_{m-1}$	$l'_{m-1}$	$w_{m-1} = w'_{m-1}0$ $w_m = w'_{m-1}1$	$l_{m-1} = l'_{m-1} + 1$ $l_m = l'_{m-1} + 1$



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$p_{m-2}$	$w'_{m-2}$
$p_{m-1} + p_m$	$w'_{m-1}$
	$l'_1$
	$l'_2$
	$\vdots$
	$l'_{m-2}$
	$l'_{m-1}$
	$w_1 = w'_1$
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	$\vdots$
	$w_{m-2} = w'_{m-2}$
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	$l_1 = l'_1$
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	$\vdots$
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## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

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$$L(\mathbf{p}) = L^*(\mathbf{p}') + p_{m-1} + p_m$$

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For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

$$L(\mathbf{p}) = L^*(\mathbf{p}') + p_{m-1} + p_m$$

$$L^*(\mathbf{p}) = L(\mathbf{p}') + p_{m-1} + p_m$$

$$\underbrace{(L(\mathbf{p}') - L^*(\mathbf{p}'))}_{\geq 0} + \underbrace{(L(\mathbf{p}) - L^*(\mathbf{p}))}_{\geq 0} = 0$$

## Proof.

For  $\mathbf{p} = (p_1, p_2, \dots, p_m)$  with  $p_1 \geq p_2 \geq \dots \geq p_m$ , we define the Huffman reduction  $\mathbf{p}' = (p_1, p_2, \dots, p_{m-1} + p_m)$  over an alphabet size of  $m - 1$ . Let  $C_{m-1}^*(\mathbf{P}')$  be an optimal Huffman code for  $\mathbf{p}'$ , and let  $C_m^*(\mathbf{p})$  be the canonical optimal code for  $\mathbf{p}$ . □

Thus,  $L(\mathbf{p}) = L^*(\mathbf{p})$ . Minimizing the expected length  $L(C_m)$  is equivalent to minimizing  $L(C_{m-1})$ . The problem is reduced to one with  $m - 1$  symbols and probability masses  $(p_1, p_2, \dots, p_{m-1} + p_m)$ . Proceeding this way, we finally reduce the problem to two symbols, in which case the optimal code is obvious.

## Theorem 5.8.1

Huffman coding is *optimal*, that is, if  $C^*$  is a Huffman code and  $C'$  is any other uniquely decodable code,  $L(C^*) \leq L(C')$ .

## Remark

Huffman coding is a *greedy algorithm* in which it merges the two **least likely** symbols at each step.

LOCAL OPT → GLOBAL OPT

Related Sections : 5.6 - 5.8