Information Theory. 2nd Chapter Slides

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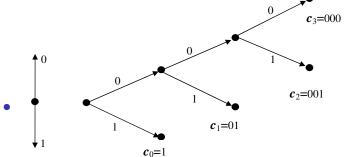
Agenda

- Uneven letter-by-letter coding
- 2 Kraft inequality
- 3 Letter-by-letter coding theorems
- 4 Huffman code
- 6 Huffman code redundancy
- 6 Shannon code
- Gilbert-Moore code
- 8 Stationary source coding

Letter-by-letter coding

Example: $X = \{0, 1, 2, 3\}$

- $C_1 = \{00, 01, 10, 11\};$
- $C_2 = \{1, 01, 001, 000\};$
- $C_3 = \{1, 10, 100, 000\}$;
- $C_4 = \{0, 1, 10, 01\};$



Letter-by-letter coding

- Consider $X = \{1, ..., M\}$, $\{p_1, ..., p_M\}$. $C = \{c_1, ..., c_M\}$, codewords $I_1, ..., I_M$.
- Average codeword length

$$ar{I} = \mathbf{M}[I_i] = \sum_{i=1}^M p_i I_i$$

Theorem

Kraft inequality Prefix code of size M with codewords of length $I_1, ..., I_M$ exists iff Kraft inequality holds:

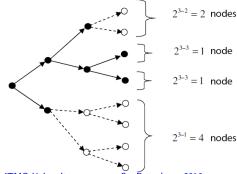
$$\sum_{i=1}^{M} 2^{-l_i} \le 1. \tag{1}$$

Proof of theorem

• Consider L, such that $L \ge \max_i I_i$.

$$\sum_{i=1}^{M} 2^{L-l_i} \leq 2^L.$$

Consider:



Proof of theorem

•

$$2^{l_2} - 2^{l_2 - l_1} \ge 1$$

•

$$2^{l_3} - 2^{l_3 - l_2} - 2^{l_3 - l_1} \ge 1$$

•

$$2^{l_M} - 2^{l_M - l_{M-1}} - 2^{l_M - l_{M-2}} - \dots - 2^{l_M - l_1}$$

• $l_1 = 1$, $l_2 = 2$, $l_3 = l_4 = 3$.

 $l_1=1$. ${\bf n}=2^{l_1}=2$. From n nodes choose one node for word of length $l_1=1$.

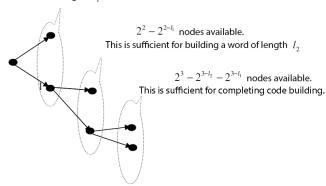


Figure: Binary code tree construction.

Theorem

For any uniquely decoded binary code of size M with codeword length $I_1, ..., I_M$ holds

$$\sum_{i=1}^{M} 2^{-l_i} \le 1. \tag{2}$$

Proof of Theorem

• Consider $N \in \mathbb{N}$

$$\left(\sum_{i=1}^{M} 2^{-l_i}\right)^{N} = \underbrace{\left(\sum_{i_1=1}^{M} 2^{-l_{i_1}}\right) ... \left(\sum_{i_N=1}^{M} 2^{-l_{i_N}}\right)}_{\text{N factors}} = \underbrace{\sum_{i_1=1}^{M} ... \sum_{i_N=1}^{M} 2^{-(l_{i_1} + ... + l_{i_N})}}_{\text{N factors}}.$$

•

$$\left(\sum_{i=1}^{M} 2^{-l_i}\right)^N = \sum_{l=1}^{Nl_M} A_l 2^{-l}.$$

$$\left(\sum_{i=1}^{M} 2^{-l_i}\right)^N \leq \sum_{l=1}^{Nl_M} 2^{L} 2^{-L} = Nl_M.$$

N-th root:

$$\sum_{i=1}^{M} 2^{-l_i} \le (N l_M)^{1/N} = 2^{\frac{\log(N l_M)}{M}}.$$

Theorem

Achievability Theorem. For ensemble $X = \{x, p(x)\}$ with entropy H there exists letter-by-letter uneven prefix code with average codeword length $\overline{l} < H + 1$.

Achievability Theorem Proof

- Consider $X = \{1, ..., M\}, p_1, ..., p_M$.
- $x_m < > I_m = [-\log p_m], m = 1, ..., M.$
- Codeword length satisfies Kraft inequality:

$$\sum_{m=1}^{M} 2^{-l_m} = \sum_{m=1}^{M} 2^{-\lceil -\log p_m \rceil} \le$$

$$\leq \sum_{m=1}^{M} 2^{\log p_m} = \sum_{m=1}^{M} p_m = 1.$$

Achievability Theorem Proof

Average codeword length:

$$ar{I} = \sum_{m=1}^{M} p_m I_m = \ = \sum_{m=1}^{M} p_m \lceil -\log p_m \rceil < \ < \sum_{m=1}^{M} p_m (-\log p_m + 1) = \ = H + \sum_{m=1}^{M} p_m = \ = H + 1,$$

Theorem

Inverse Theorem. For any uniquely decoded code of discrete source $X = \{x, p(x)\}$ with entropy H, average codeword length \bar{I} satisfies:

$$\bar{l} \ge H.$$
 (3)

Proof Inverse Theorem

Let I(x) be the codeword length for message x.

$$H - \bar{l} = -\sum_{x \in X} p(x) \log p(x) - \sum_{x \in X} p(x) l(x) = \sum_{x \in X} p(x) \log \frac{2^{-l(x)}}{p(x)}.$$

Use Kraft inequality:

$$\log x \le (x-1)\log e,$$

We get

$$H - \bar{l} \leq \log e \sum_{x \in X} p(x) \left(\frac{2^{-l(x)}}{p(x)} - 1 \right) =$$

$$= \log e \left(\sum_{x \in X} 2^{-l(x)} - \sum_{x \in X} p(x) \right) \leq$$

$$\leq \log e \left(1 - \sum_{x \in X} p(x) \right) = 0. \tag{4}$$

Properties of Huffman code

- 1 If $p_i < p_j$, the $l_i \ge l_j$.
- 2 At least two codewords have the same langth $I_M = \max_m I_m$.
- 3 There are two codewords of length $I_M = \max_m I_m$ which differ only in the last character.
- 4 If code C' for X' is optimal, then, code C is optimal for X.

Proof of property 4

$$I_{m} = \begin{cases} I'_{m} & \text{при } m \leq M - 2, \\ I'_{M-1} + 1 & \text{при } m = M - 1, M. \end{cases}$$

$$\bar{I} = \sum_{m=1}^{M} p_{m}I_{m} = \sum_{m=1}^{M-2} p_{m}I_{m} + p_{M-1}I_{M-1} + p_{M}I_{M} = \sum_{m=1}^{M-2} p_{m}I_{m} + (p_{M-1} + p_{M})(I'_{M-1} + 1) = \sum_{m=1}^{M-2} p'_{m}I'_{m} + p'_{M-1}I'_{M-1} + p_{M-1} + p_{M} = \sum_{m=1}^{M-1} p'_{m}I'_{m} + p'_{M-1}I'_{M-1} + p_{M-1} + p_{M} = \sum_{m=1}^{M-1} p'_{m}I'_{m} + p_{M-1} + p_{M} = \bar{I}' + p_{M-1} + p_{M}.$$

```
Input: Alphabet size M, probabilities of characters
Output: Bitary tree of Huffman code
Init: number of unprocessed nodes M_0 = M while
 M_0 > 1 \, do
   Find two unprocessed nodes with min
    probabilities. Exclude these nodes from the list
    of unprocessed. Introduce new node, attribute
    to him the total probability of two excluded
    nodes. Bind new node with edges to two
    excluded node. M_0 \leftarrow M_0 - 1.
end
```

Figure: Building Huffman code tree

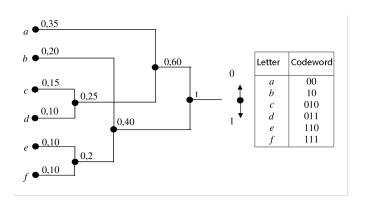


Figure: Huffman code example

Huffman code redundancy

Theorem

Let p_1 be maximal probability of message. Then redundancy of Huffman code for this ensemble satisfies:

$$r \leq \begin{cases} p_1 + \sigma, & \text{for } p_1 < 1/2, \\ 2 - \eta(p_1) - p_1 & \text{for } p_1 \geq 1/2, \end{cases}$$
 (5)

where $\eta(x) = -x \log x - (1-x) \log(1-x)$ is binary ensemble entropy, and

$$\sigma = 1 - \log e - \log \log e \approx 0,08607. \tag{6}$$

Huffman code redundancy

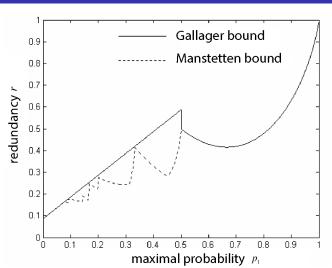


Figure: Huffman code redundancy

```
Input: Alphabet size M, character probabilities
         p_i, i = 1, ..., M
Output: List of Shannon codewords
Sorting: for i = 1 to M do
   j(i) \leftarrow \text{index of } i\text{-th descending character}
     probability
end
Cumulative probabilities: q_{i(1)} = 0; for i = 2
 to M do
    q_{i(i)} = q_{i(i-1)} + p_{i(i-1)};
end
Codewords: for i = 1 to M do
    c_i \leftarrow \text{first } [-\log p_i] \text{ bits after comma in a binary}
     number q_i.
end
```

Figure: Shannon code construction algorithm

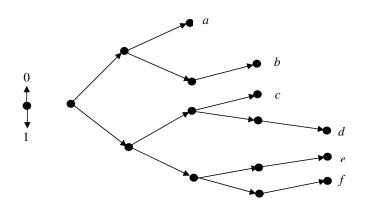


Figure: Shannon codetree for $X = \{a, b, c, d, e, f\}$, $\{0, 35, 0, 2, 0, 15, 0, 1, 0, 1, 0, 1\}$

Table: Shannon codetree building for $X = \{a, b, c, d, e, f\}, \{0, 35, 0, 2, 0, 15, 0, 1, 0, 1, 0, 1\}$

X	p _m	q_m	I _m	Binary notation q_m	Codeword c_m
а	0,35	0,00	2	0,00	00
Ь	0,20	0,35	3	0,0101	010
С	0,15	0,55	3	0,10001	100
d	0,10	0,70	4	0,10110	1011
е	0,10	0,80	4	0,11001	1100
f	0,10	0,90	4	0,11100	1110

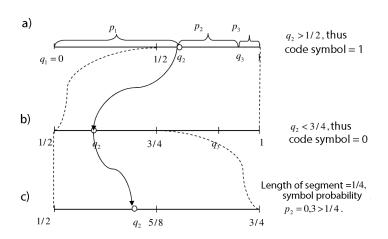


Figure: Graphical interpretation of Shannon code

```
Input: Alphabet size M, character probabilities
        p_i, i = 1, ..., M
Output: List of Gilbert-Moore code
Auxiliary probabilities: q_1 = 0; for i = 2 to
 M do
   q_i = q_{i-1} + p_{i-1}; \ \sigma_i = q_i + p_i/2;
end
Codewords: for i = 1 to M do
   c_i \leftarrow первые [-\log p_i] + 1 bits after comma in
     a binary number \sigma_i.
end
```

Figure: Gilbert-Moore code constriction algorithm

Table: Gilbert-Moore code eample

X _m	p _m	q_m	σ_{m}	I _m	c _m a	$\tilde{\boldsymbol{c}}_m^{\ b}$
1	0,1	0,0=[0,00000]	0,05=[0,00001]	5	00001	0000
2	0,6	0,1=[0,00011]	0,40=[0,01100]	2	01	0
3	0,3	0,7=[0,10110]	0,85=[0,11011]	3	110	10

^aGilbert-Moore codewords

^bShannon codewords whithout character probability ordering

Consider

$$\begin{split} \sigma_{j} + \frac{p_{j}}{2} - \sigma_{i} &= \sum_{h=1}^{j-1} p_{h} - \sum_{h=1}^{i-1} p_{h} - \frac{p_{i}}{2} = \\ &= \sum_{h=i}^{j-1} p_{h} + \frac{p_{j} - p_{i}}{2} \geq \\ &\geq p_{i} + \frac{p_{j} - p_{i}}{2} = \\ &= \frac{p_{j} + p_{i}}{2} \geq \frac{\max\{p_{i}, p_{j}\}}{2}. \end{split}$$

For codeword length and its probability holds:

$$I_m = \left[-\log \frac{p_m}{2} \right] \ge -\log \frac{p_m}{2}.$$

• Thus,

$$\sigma_j - \sigma_i \ge \frac{\max\{p_i, p_j\}}{2} \ge 2^{-\min\{l_i, l_j\}},$$

Average codeword length estimation

$$\bar{I} < H + 2$$
.

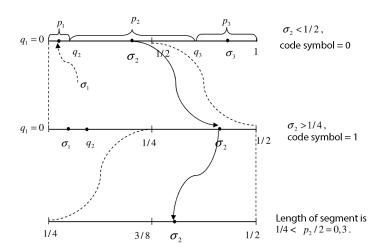


Figure: Graphical interpretation of Gilbert-Moore code.

Theorem

Inverse Theorem For DSS with entropy H for any FV-coding holds:

$$\bar{R} \geq H$$
.

Proof.

consider Xⁿ.

$$M[I(x)] \ge H(X^n) = nH_n(X) \ge nH_\infty(X) = nH.$$

• $H_n(X)$ does not increase with increasing n. Thus, $\forall n$

$$\bar{R}_n \geq H$$

•

$$\bar{R} = \inf_{n} R_n \ge H.$$

Theorem

Achievability theorem For DSS with entropy H and $\forall \delta > 0$ there exists FV-coding such that

$$\bar{R} \leq H + \delta$$
.

Proof.

$$M[I(x)] \le H(X^n) + 1 = nH_n(X) + 1.$$
 (7)

$$|H_n(X)-H|\leq \frac{\delta}{2},$$

$$H_n(X) \leq H + \frac{\delta}{2}, \quad n > n_1.$$
 (8)

Proof.

$$\frac{1}{n} \le \frac{\delta}{2}.\tag{9}$$

For $n \ge \max\{n_1, n_2\}$, we get

$$\bar{R} = \inf_{m} \bar{R}_{m} \leq
\leq \bar{R}_{n} =
= \frac{M [I(x)]}{n} \leq
\leq H_{n}(X) + \frac{1}{n} \leq
\leq H + \frac{\delta}{2} + \frac{\delta}{2} =
= H + \delta.$$

- For sequences $\mathbf{x} = (x_1, ..., x_n)$, $\mathbf{y} = (y_1, ..., y_n)$ denote i to be the least index such that $x_i \neq y_i$.
- Then $\mathbf{y} \prec \mathbf{x}$, if $y_i \prec x_i$.
- Cumulative probability

$$q(x) = \sum_{\mathbf{y} \prec x} p(\mathbf{y}), \tag{10}$$

For memoryless source

$$p(x) = \prod_{i=1}^{n} p(x_i).$$

• For calculating q(x).

$$q(\mathbf{x}_{1}^{n}) = \sum_{\mathbf{y}_{1}^{n} \prec \mathbf{x}_{1}^{n}} p(\mathbf{y}_{1}^{n}) =$$

$$= \sum_{\mathbf{y}_{1}^{n-1} \prec \mathbf{x}_{1}^{n-1}} \sum_{y_{n}} p(\mathbf{y}_{1}^{n-1}y_{n}) + \sum_{\mathbf{y}_{1}^{n-1} = \mathbf{x}_{1}^{n-1}} \sum_{y_{n} \prec \mathbf{x}_{n}} p(\mathbf{y}_{1}^{n-1}y_{n}) =$$

$$= \sum_{\mathbf{y}_{1}^{n-1} \prec \mathbf{x}_{1}^{n-1}} p(\mathbf{y}_{1}^{n-1}) + \sum_{\mathbf{y}_{1}^{n-1} = \mathbf{x}_{1}^{n-1}} p(\mathbf{y}_{1}^{n-1}) \sum_{y_{n} \prec \mathbf{x}_{n}} p(y_{n}) =$$

$$= q(\mathbf{x}_{1}^{n-1}) + p(\mathbf{x}_{1}^{n-1})q(\mathbf{x}_{n}),$$

where $q(x_n)$ is cumulative probability of x_n .

$$q(\mathbf{x}_1^n) = q(\mathbf{x}_1^{n-1}) + p(\mathbf{x}_1^{n-1})q(\mathbf{x}_n);$$
 (11)

$$p(x_1^n) = p(x_1^{n-1})p(x_n). (12)$$

```
Input: Alphabet size M character probabilities
         p_i, i = 1, ..., M length n sequence at output
         (x_1, ..., x_n).
Output: Arithmetic codeword
Cumulative probabilities: q_1 = 0; for i = 2
 to M do
    q_i = q_{i-1} + p_{i-1};
end
Coding: for i = 1 to n do
    F \leftarrow F + q(x_i)G; G \leftarrow p(x_i)G;.
end
Codeword creation: \boldsymbol{c} \leftarrow \text{first } [-\log G] + 1 \text{ bits }
 after comma in a binary number F + G/2.
```

Figure: Arithmetic coding algorithm

Table: Arithmetic coding of sequence

Step i	Xi	$p(x_i)$	$q(x_i)$	F	G		
0	-	-	-	0,0000	1,0000		
1	b	0,6	0,1	0,1000	0,6000		
2	С	0,3	0,7	0,5200	0,1800		
3	b	0,6	0,1	0,5380	0,1080		
4	а	0,1	0,0	0,5380	0,0108		
5	b	0,6	0,1	0,5391	0,0065		
6	Codeword length $\left[-\log G + 1\right] = 9$						
U	Со	deword	5423 →				
	$ ightarrow \hat{F} = 0,541 ightarrow 100010101$						

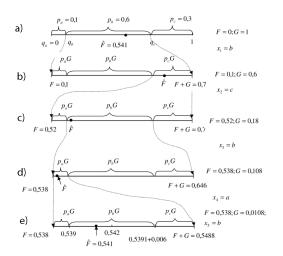


Figure: Graphical interpretation of arithmetic coding

```
Input: Alphabet size M cumulative probabilities q_i, i=1,...,M; decode input \hat{\sigma}.

Output: Decoded character x

Init: q_{M+1}=1; \ m=1.; character search: while q_{m+1}<\hat{\sigma} do
```

end

Result: $x = x_m$

 $m \leftarrow m + 1$.

Figure: Gilbert-Moore decoding algorithm

```
Input: Alphabet size M;
character probabilities \{p_1, ..., p_M\} cumulative
probabilities q_i, i = 1, ..., M decoded sequence length
n, codeword as a number \hat{F}.
Output: Decoded character sequence (x_1, ..., x_n)
Init: q_{M+1} = 1; S = 0; G = 1.;
Decoding: ;
for i = 1 to n do
   i = 1:
   while S + q_{i+1}G < \hat{F} do
     i \leftarrow i + 1.
   end
   S \leftarrow S + q_i G;
   G \leftarrow p_i G;
   x_i = i:
end
Result: sequence (x_1, ..., x_n);
```

Figure: Arithmetic code decoding algorithm

Table: $X = \{a, b, c\}$. $p_a = 0, 1$, $p_b = 0, 6$, $p_c = 0, 3$. 0100010101

Step	S	G	Hypotesis	q(x)	S + qG	Decision	p(x)	
			X	`` /	-	x _i	, ,	
0	$100010101 ightarrow \hat{F} = 0,541$							
			а	0,0	$0,0000 < \hat{F}$			
1	0,0000	1,0000	Ь	0,1	$0,1000 < \hat{F}$	Ь	0,6	
			С	0,7	$0,7000 > \hat{F}$			
	0,1000	0,6000	а	0,0	$0,1000 < \hat{F}$	С	0,3	
2			Ь	0,1	$0,1600 < \hat{F}$			
			С	0,7	$0,5200 < \hat{F}$			
	0,5200	0,1800	а	0,0	$0,5200 < \hat{F}$	ь	0,6	
3			Ь	0,1	$0,5380 < \hat{F}$			
			С	0,7	$0,6460 > \hat{F}$			
4	0,5380	0,1080	а	0,0	$0,5380 < \hat{F}$	а	0,1	
			Ь	0,1	$0,5488 > \hat{F}$			
	0,5380	0,0108	а	0,0	$0,5380 < \hat{F}$	Ь		
5			Ь	0,1	$0,5391 < \hat{F}$		0,6	
			С	0,7	$0,5456 > \hat{F}$			



```
function y=int arithm encoder(x,q);
% x is input data sequence.
% q is cumulative distribution (model)
% v is binary output sequence
% Constants
k=16:
R4=2^(k-2); R2=R4*2; R34=R2+R4;% half.quarter.ei
                                  % Precision
% Initialization
Low-0:
             96 1 nw
High=R-1: % High
             % Bits to Follow
btf=0:
y=[ ];
             % code sequence
% Encoding
for i=1:length(x):
  Range=High-Low+1;
  High=Low+fix(Range*g(x(i)+1)/g(m))-1:
  Low=Low+fix(Range*q(x(i))/q(m));
  % Normalization
  while 1
    if High<R2
       y=[y 0 ones(1,btf)]; btf=0;
       High=High*2+1: Low=Low*2:
       if I ows-R2
         v=[v 1 zeros(1 btf)]: btf=0:
          High=High*2-R+1: Low=Low*2-R:
         if Low>=R4 & High<R34
            High=2*High-R2+1; Low=2*Low-R2;
            btf=btf+1:
            break:
         end:
       end:
    end:
  end: % while
end: % for
% Completing
if Low<R4
  y=[y \ 0 \ ones(1,btf+1)];
else
  y=[y 1 zeros(1,btf+1)];
end:
```

```
function x=int arithm decoder(v.g.n):
% v is binary encoded data sequence
% q is cumulative distribution (model)
% x is output sequence
% n is number of messages to decode
% Constants
k=16: R4=2^(k-2): R2=R4*2: R34=R2+R4: R=2*R2:
m=length(q);
% Start decoding. Reading first k bits
Value=0: v=fv zeros(1.k)1:
for ib=1 k
  Value=2*Value+v(ib):
end:
% Initialization
Low=0: High=R-1:
% Decodina
for i=1:n
  Range=High-Low+1:
  aux=fix(( (Value-Low+1)*q(m)-1)/Range);
  i=1: % message index
  while q(i+1)<=aux, i=i+1; end;
  High=Low+fix(Range*q(i+1)/q(m))-1;
  Low=Low+fix(Range*q(i)/q(m)):
  % Normalization
  while 1
    if High<R2
      High+2+1; Low=Low+2;
      ib=ib+1:
      Value = 2*Value+y(ib);
      if I ow>=R2
        High=High*2-R+1: Low=Low*2-R:
        Value = 2*Value-R+v(ib):
        if Low>=R4 & High<R34
           High=2*High-R2+1; Low=2*Low-R2;
           ib=ib+1:
           Value = 2*Value-R2+y(ib);
        else
           break;
        end:
      end;
    end
  end: % while
                       4 교 》 4 교 》 4 교 》 
end: % for
```