

Space for project label

CATAM: 19.2 Information content of natural language

1

Text A is chosen to answer the questions in this project. Refer to q1.m in Appendix (A) for the program for this question.

The source entropy found from q1.m is returned in $h = 4.0688$ (4 d.p.)

Huffman code returned from the program can be seen in figure (1)

0	11
1	100
2	11110
3	1101
4	101
5	0
6	11100
7	1100
8	1000
9	1001
10	11101100
11	11100
12	11
13	1111
14	1010
15	110
16	11111
17	111011011
18	10
19	1011
20	101
21	1000
22	111010
23	1001
24	1110111
25	11101
26	111011010

Figure 1: left column is the alphabet and right column is the corresponding huffman code

The expected codeword length is returned as $E = 4.1142$ (4 d.p.)

Shannon-fano code returned from the program can be seen in figure (2) Where in the program I have used the method of working out the lengths with $l_i = \lceil -\log_2(p_i) \rceil$, where l_i is the length and p_i is the probability of the letter represented by i. Then ordering the probabilities such that $p_1 \geq p_2 \geq \dots \geq p_{27}$, define cumulative probability $P_i = \sum_{j=1}^{i-1} p_j$. Then define the codeword for letter i as the first l_i digits of the binary representation of P_i after the decimal point.

This constructs a prefix-free code of the desired lengths:

From the definition of l_i , we know $\log_2(\frac{1}{p_i}) \leq l_i < \log_2(\frac{1}{p_i}) + 1 \Rightarrow \frac{1}{2^{l_i}} \leq p_i < \frac{1}{2^{l_i-1}}$. Therefore the code for P_i will differ from all succeeding codes in one or more of its l_i places, all the remaining P_i are at least $\frac{1}{2^{l_i}}$ larger, so their binary expansions will differ in the first l_i places. This means the code generated from this method is prefix free.

The expected codeword length is returned as $ESF = 4.6136$ (4 d.p.)

The expected codeword length for Huffman's code is less than for the Shannon-fano code, and both are greater than the source entropy, as expected from Shannon's noiseless encoding theorem.

0	000
1	0100
2	1111010
3	111000
4	11001
5	0011
6	111011
7	110111
8	01111
9	10001
10	11111111101
11	1111101
12	10111
13	111001
14	10011
15	01110
16	1111100
17	1111111111110
18	10110
19	10100
20	0101
21	110100
22	11111110
23	110110
24	1111111101
25	1111000
26	111111111101

Figure 2: left column is the alphabet and the right column is the corresponding Shannon-Fano code

How would segmentation improve expected length if source was assumed Bernoulli?

Previously we know by Shannon's noiseless encoding theorem that $h \leq \mathbb{E}(S) < h + 1$, where S is the length of optimal codewords and h is the source entropy.

With segmentation, let $S^{(n)}$ be the length of an optimal codeword for a segment of length n , and let h_n be the source entropy of the new code after segmentation. Then from the same way as before, with Shannon's noiseless encoding theorem, $\frac{h_n}{n} \leq \mathbb{E}(\frac{S^{(n)}}{n}) < \frac{h_n}{n} + \frac{1}{n}$. Where we look at $\frac{S^{(n)}}{n}$ instead as this represents the length of codeword per source letter, which is more comparable to the results before segmentation.[1]

By claim (1.1), we then know that $h \leq \mathbb{E}(S^{(n)}) < h + \frac{1}{n}$. Hence $\mathbb{E}(S^{(n)}) \rightarrow h$ as $n \rightarrow \infty$.

Thus there is advantage in segmented codes in terms of length of code. But this is ignoring the increased storage requirements need to store the new increased alphabet I_m^n and their respective codewords.

Claim 1.1. For a Bernoulli source, $h_n = n \times h$.

Proof. Since source is Bernoulli, the probability of a message of length n occurring is $p_{i_1}p_{i_2}\dots p_{i_n}$, where p_{i_j} is the probability of the letter corresponding with i_j occurring, where $i_1, i_2, \dots, i_n \in \{0, \dots, 26\}$.

$$\Rightarrow h_n = - \sum_{i_1, i_2, \dots, i_n} p_{i_1}p_{i_2}\dots p_{i_n} \log(p_{i_1}p_{i_2}\dots p_{i_n})$$

$$\Rightarrow h_n = - \sum_{i_1, i_2, \dots, i_n} p_{i_1}p_{i_2}\dots p_{i_n} \left(\sum_{j=1}^n \log(p_{i_j}) \right)$$

Rearranging the sum:

$$\Rightarrow h_n = n \times \sum_{j=1}^n \log(p_j)p_j \left(\sum_{i_1, i_2, \dots, i_{n-1} \neq j} p_{i_1}p_{i_2}\dots p_{i_{n-1}} \right) = nh$$

□

2

Refer to q2.m in Appendix (B) for the program for this question.

The English text is definitely not Bernoulli, for example if the previous letter is space, the probability of the following letter being space is 0.

Looking at the probabilities of pairs occurring deduced from the source text in the program, from the 729 possible combinations, only 334 are non-zero. If source was Bernoulli, then all the probabilities would be non-zero because the probabilities for the original alphabet is all non-zero.

Certain pairs of letters that do not appear in the text are assumed to have probability 0, so will be ignored and not assigned any codeword. See figure (3) for Huffman code assigned to pairs of letters for the pairs that appear in the text. In this table the numbers associated with the alphabet has been shifted by 1, ie. 1 - space, 2 - A, 3 - B, etc.

The expected length is then also calculated from this with the result of $\mathbb{E}(S^{(n)}/n) = 3.6572$ (4 d.p.).

This is an improvement on expected word length per source letter compared to the Huffman code in question 1 with $E = 4.1142$ before segmentation. Hence segmentation reduces the expected length of codewords.

If the source was Bernoulli, the expected codeword length per source letter would be at least the source entropy from question 1 ($h = 4.0688$). So English text has shorter expected length. This confirms that English text is not Bernoulli, as the result does not match what we proved in question 1 for Bernoulli sources. In fact segmentation improves the expected word length more than expected of a bernoulli source, this is because segmentation helps include some of the relations of the letters to each other.

References

- [1] Goldie CM, Pinch RGE. Communication Theory; 1991.

Pairs of letters	codewords	Pairs of letters	codewords	Pairs of letters	codewords	Pairs of letters	codewords
1 2	10111	6 26	001010110	15 12	11001101000	22 15	000110010
1 3	0001011	7 1	1011000	15 15	11001101001	22 17	0110010111
1 4	0101010	7 2	0010001000	15 16	010000001	22 19	000001001
1 5	0111110	7 6	0010001001	15 20	0010011111	22 20	001001010
1 6	000110011	7 7	011001101	15 21	01100010	22 21	01110110
1 7	0111000	7 10	0010001110	15 23	110010010101	22 27	110011100000
1 8	10010110	7 13	11000010010	15 24	110011101010	23 2	11001111011
1 9	011011	7 16	100110011	15 26	0010001101	23 6	01100000
1 10	101001	7 13	1011010001	16 1	00011100	23 10	110011100001
1 11	100101011	7 21	00100100110	16 2	1100110110	24 1	0010000111
1 12	00100101110	7 22	00100100111	16 3	1100101001	24 2	1110110
1 13	0110100	8 1	1111110	16 4	0110010010	24 3	110011100110
1 14	0100010	8 2	0000011011	16 5	000010101	24 5	110011100111
1 15	011101000	8 6	11110010	16 7	1010110	24 6	01110111
1 16	111010	8 8	1011010110	16 8	1100101110	24 7	110011100100
1 17	00101100	8 3	011010100	16 10	1100101111	24 8	110011100101
1 19	01010011	8 10	0110011000	16 12	0000011110	24 9	011001010
1 20	010111	8 13	0110011001	16 13	001010100	24 10	01010111
1 21	10000	8 15	11000010011	16 14	010000110	24 13	001000001011
1 22	1111101	8 16	1011010111	16 15	1111100	24 15	1001010110
1 23	11110101	8 19	001010100100	16 16	00110101	24 16	100101010
1 24	101010	8 20	1011010100	16 17	1100101100	24 19	110011110000
1 26	001100100	8 21	110010000100	16 19	1110011	24 20	11001111010
2 1	0010111	9 1	0100111	16 20	0010000010	25 10	11001111001
2 3	101000100	9 2	1010000	16 21	000001010	25 21	11001111011
2 4	1110111	9 6	10001	16 23	1001000	25 26	11001111000
2 5	000110000	9 10	1110010	16 23	0010000011	26 1	0010100
2 7	11000011010	9 13	110010000101	16 24	001010101	26 6	00100001000
2 8	0001110110	9 16	11110011	16 26	110011101011	26 10	1100111110
2 10	00001110	9 19	1011010101	17 1	000001011	26 16	1100111011
2 12	00100101111	9 21	0100000010	17 2	000101011	26 20	110011111001
2 13	00000010	9 22	1100101010	17 6	100110000	26 21	00100001001
2 14	110001110	9 26	110010011010	17 10	110011101000	26 24	110011111110
2 15	011110	10 1	11110000	17 12	110011101001	27 13	110011111111
2 17	11000011011	10 2	11000010000	17 13	01110101	6 12	110010000110
2 18	110010001110	10 3	110010011011	17 16	00100000000	6 13	11010111
2 19	0111001	10 4	110000010	17 17	0110010011	6 14	0110000101
2 20	0100011	10 5	00110011	17 19	1100110111	6 15	1001001
2 21	0101101	10 6	110000011	17 20	11001101100	6 17	001001000000
2 22	000111011	10 7	1100101011	17 22	00100111100	6 19	100111
2 23	0001110100	10 8	000010100	19 1	111101	6 20	1010111
2 24	111101000	10 12	010000011	19 2	01010110	6 21	000010111
2 26	0110000110	10 13	11110001	19 3	11001110110	6 22	110010000111
3 1	110010100111	10 14	0010101111	19 4	00101011101	6 23	011001011010
3 2	1111101001	10 15	0000110	19 5	00100110010	6 24	00100100001
3 3	110010001101	10 16	110010011000	19 6	0011000	6 25	1011010000
3 6	110001111	10 17	11000010001	19 8	00100110011	14 19	11001101010
3 10	11000011000	10 19	10010100	19 10	100110001	14 20	00100111110
3 13	010100100	10 20	00101101	19 12	00100110000	14 22	11001101011
3 16	101000101	10 21	00000011	19 13	00100110001	14 26	00100011100
3 19	110001100	10 22	110010011001	19 15	0110010000	15 1	111000
3 22	011101001	10 23	00100100101	19 16	00110110	15 2	0000011000
3 23	110010001101	10 25	11000010110	19 17	110011101111	15 4	0110011101
3 26	11000011001	10 27	110010011110	19 19	1100101101	15 5	0000100
4 2	011010110	11 22	1100101000	19 20	1100000000	15 6	001010100
4 6	010100101	12 1	00110111	19 21	100110110	15 8	1011001
4 9	000110001	12 2	110010011111	19 22	00100110110	15 9	110010010100
4 10	11000011110	12 6	01110101	19 23	11001101101	15 10	0000011001
4 12	10110110	12 10	00100111010	19 26	0000011111	21 24	00100110101
4 13	100110010	12 15	00100111011	20 1	010010	21 26	11001100111
4 16	000010110	12 20	0110011110	20 2	010000111	22 1	0010000110
4 18	11001000001	13 1	000000000	20 4	11001100010	22 2	11001100100
4 19	001000101100	13 2	00011110	20 6	01100011	22 4	11001100101
4 22	0001110101	13 3	110010011100	20 9	000001111	22 5	110011101101
5 1	11010	13 5	0100000000	20 10	0110010001	22 6	00100001010
5 2	1011010010	13 6	0111111	20 12	00100110111	22 7	110011100010
5 5	11000011111	13 7	110010011101	20 13	110000001	22 8	000001000
5 6	000101010	13 8	110010010010	20 14	0000011100	22 10	11001111010
5 8	11000011100	13 10	00110100	20 15	11001100011	22 13	010011010
5 10	110001101	13 12	11000010111	20 16	0010000001	22 14	110011100011
5 12	11000011101	13 13	01011001	20 17	1100100010		
5 13	00100101101	13 14	110010010011	20 20	010000100		
5 15	0010001010	13 16	00000001	20 21	1100010		
5 16	001100101	13 17	110010010000	20 22	11001100000		
5 19	11001000001	13 19	110010010001	20 24	11001100001		
5 20	00100001011	13 20	00100111000	21 1	000100		
5 21	11001000000	13 21	11000010100	21 2	10011011		
5 22	00100100010	13 22	0110011111	21 4	110011101100		
5 26	0000011010	13 23	110010010110	21 6	01001100		
6 1	00111	13 26	00011111	21 9	11011		
6 2	01011000	14 1	10100011	21 10	100110100		
6 4	0110000111	14 2	00100001111	21 13	100110101		
6 5	0001101	14 3	11000010101	21 15	11001100110		
6 6	011010111	14 6	1111111	21 16	0101000		
6 7	0110000100	14 7	110010010111	21 19	010000101		
6 8	1011010011	14 10	0110011100	21 20	0000011101		
6 9	11001000000	14 16	10110111	21 21	0110010110		
6 10	00100100011	14 17	00100111001	21 22	00100110100		

Figure 3: pairs of letters and their corresponding huffman codewords

Appendix

A q1.m

```
function [h, codewords, codewordsSF] = q1()
%h stores source entropy
%codewords contains codewords after hamming's code
%codewordsSF contains codewords after shannon-fano code
clear
format long
A = readmatrix("https://www.maths.cam.ac.uk/undergrad/catam/data/II-19-2-dataA.txt");
A(end, :) = [];
A = A + 1;%add one to every letter, so we work in 1= space, 2 = A, 3 = B, ... to fit matlab
    ↪ better
%disp(A)
%first need to create list of probabilities for alphabet in this text.
n = 400*25; %is the number of characters in the text
p = zeros(27, 1);
for i = 1:n
    for j = 1:27
        if A(i) == (j)
            p(j) = p(j) + 1;
        end
    end
end
%now divide all entries of p by n so that it is a probability
p = p./n;

%with this we can work out source entropy
h = 0;
for i = 1:27
    h = h - p(i) * log2(p(i));
end

letters = [1:1:27]';

p = [letters p];

psorted = sortrows(p, 2, {'descend'});%sorted by probabilities

codewords = strings(27, 1);%This will store the code words corresponding to the alphabet
%where position 1 stores cw for space, position 2 stores cw for A, etc.

I = num2cell(psorted); %first create copy of p as cell

for i = 1:26
    last1 = cell2mat(I(end, 1));
    last2 = cell2mat(I(end-1, 1));

    for k = 1:size(last1, 2)
        codewords(last1(k)) = '1' + codewords(last1(k));
    end
    for l = 1 : size(last2, 2)
        codewords(last2(l)) = '0' + codewords(last2(l));
    end

    I(end-1, 1) = {[last2, last1]};
    I{end-1, 2} = I{end-1, 2} + I{end, 2};
    I(end, :) = [];
end
```

```

    I = sortrows(I, 2, 'descend');
end

%now with codewords we can work out expected word length, E
E = 0;
for i = 1:27
    E = E + p(i, 2) * strlen(codewords(i));
end

%Now that's done do the same for Shannon-fano

lengths = ceil(-log2(p(:, 2)));
%lengths = [letters lengths];
%lengths = sortrows(lengths, 2);

cumulativep = zeros(27, 1);%will store the cumulative probabilities of the sorted p

for i = 2:27
    cumulativep(i) = cumulativep(i-1) + psorted(i-1, 2);
end

cumulativep = [psorted(:, 1) cumulativep];
cumulativep = sortrows(cumulativep, 1, 'ascend');

%Now workout codewords. again pos1 stores space, pos2 stores A etc
codewordsSF = strings(27, 1);

for i = 1:27
    for j = 1:lengths(i)
        temp = cumulativep(i, 2)*2;
        if temp >= 1
            codewordsSF(i) = codewordsSF(i) + '1';
            cumulativep(i, 2) = cumulativep(i, 2)*2 - 1;
        else
            codewordsSF(i) = codewordsSF(i) + '0';
            cumulativep(i, 2) = cumulativep(i, 2)*2;
        end
    end
end

%now work out corresponding expected length
ESF = 0;

for i = 1:27
    ESF = ESF + p(i, 2)*strlen(codewordsSF(i));
end

end

```

B q2.m

```

function [] = q2()

clear
format long
A = readmatrix("https://www.maths.cam.ac.uk/undergrad/catam/data/II-19-2-dataA.txt");
A(end, :) = [];
A = A + 1;%add one to every letter, so we work in 1= space, 2 = A, 3 = B, ... to fit matlab
    ↪ better

```

```

%disp(A)
%first need to create list of probabilities for alphabet in this text.
n = 400*25; %is the number of characters in the text

%now create a new alphabet consisting of any combination of pairs of
%letters
alphabet = zeros(27*27, 2);
m = 27*27; %size of alphabet

for i = 1:27
    for j = 1:27
        alphabet((i-1)*27 + j, :) = [i, j];
    end
end

A = A'; %take A transposed so we go through entries row by row of original A
p = zeros(m, 1);
for i = 1:2:n-1
    for j = 1:m
        if A(i) == alphabet(j, 1) && A(i+1) == alphabet(j, 2)
            p(j) = p(j) + 1;
        end
    end
end

%A contains n/2 pairs
p = p./(n/2);

%rename alphabet for easier process
L = [1:1:27*27]';
p = [L p];

psorted = sortrows(p, 2, 'descend');

%we can delete rows where probability is 0, as we assume those cannot
%occur.
for i = m:-1:1
    if psorted(i, 2) == 0
        psorted(i, :) = [];
    end
end

% %with this we can work out source entropy(Actually not needed)
% h = 0;
% for i = 1:size(psorted, 1)
% h = h - psorted(i, 2) * log2(psorted(i, 2));
% end

%Now do Huffman again
codewords = strings(m, 1);

I = num2cell(psorted); %first create copy of p as cell

for i = 1:size(psorted, 1)-1
    last1 = cell2mat(I(end, 1));
    last2 = cell2mat(I(end-1, 1));

    for k = 1:size(last1, 2)
        codewords(last1(k)) = '1' + codewords(last1(k));
    end
end

```

```

end
for l = 1 : size(last2, 2)
    codewords(last2(l)) = '0' + codewords(last2(l));
end

I(end-1, 1) = {[last2, last1]};
I{end-1, 2} = I{end-1, 2} + I{end, 2};
I(end, :) = [];
I = sortrows(I, 2, 'descend');
end

%Now find expected length
E = 0;
for i = 1:m
    E = E + p(i, 2) * strlen(codewords(i))/2;
end

end

```