University of Information Technology

Multimedia project

Compression algorithms

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1 Introduction

Data compression is a set of steps for packing data into a smaller space, while allowing for the original data to be seen again. Compression is a two-way process: a compression algorithm can be used to make a data package smaller, but it can also be run the other way, to decompress the package into its original form. Data compression is useful in computing to save disk space, or to reduce the bandwidth used when sending data (e.g., over the Internet).

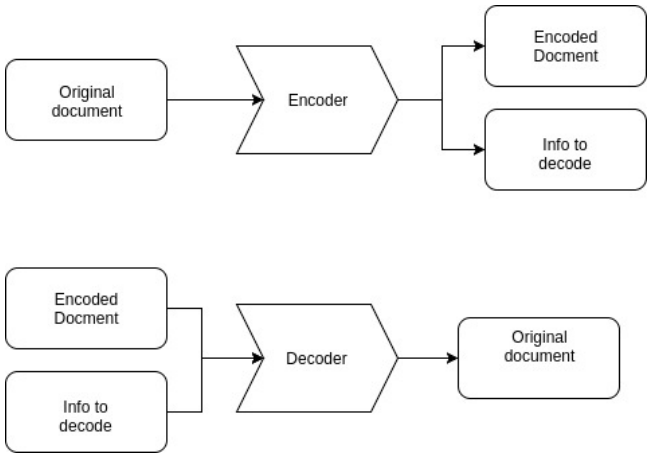

Figure 1: The flow chart show how data can be compressed and decompressed.

Compression can be either lossy or lossless. No information is lost in lossless compression. Lossy compression reduces bits by removing unnecessary or less important information.

Two main goals of this projects are:

1. Implements three lossless compression algorithms (run length, shannon-fano and jpeg) on real life data to see how it really works on different kinds of data.

2. Build a simple web application to work on the Internet environment for practice.

2 Dataset

Our dataset is collected from variety of sources such as Flicker, Google Images, news, html files from different sites, etc. We have 15 high quality images with smallest size is 1024x720 (formated as .jpg file) and 16 text file with different content includes some tutorial documents, news, source code (C++, Python),

Wikipedia documents, letters, mails, binary files and some manual written files.
For detail, you can check it out from *./data*

3 Methods

3.1 Run-length coding (RLC)

Input

The document need to compress.

Output

The compressed document.

Basic idea

Run-length encoding simple replaces sequences of the same data values within a file by a count number and a single value.

Example

Suppose the following string of data (17 bytes) has to be compressed: ABBBBBBBB-BCDEEEEF

Using RLE compression, the compressed file takes up 12 bytes and could look like this: 1A 8B 1C 1D 4E 1F

And for decompression, all we need is "write down" exactly "count number" times for each symbol. Finally, the result would be the same:
ABBBBBBBBBCDEEEEF

Pseudo-code

You can find pseudo-code (Python style) for Run-length encoding and decoding in *pseudo-code/run-length.py*

3.2 Shannon-Fano coding

Input

Set of symbol S.
The document need to compress.

Output

The compressed document.
The table of frequency (or number of times symbol appears in the document).

Basic idea

1. For a given list of symbols, calculate table of probabilities or frequency counts for the document
2. Sort the lists of symbols according to frequency (descending order)
3. Divide the list into two parts, with the total frequency counts of the left part being as close to the total of the right as possible.
4. The left part of the list is started with the code 0, and the right part is started with code 1.
5. Recursively apply the steps 3 and 4 to each of the two halves, subdividing groups and adding bits to the codes until each symbol has become a corresponding code leaf on the tree.

Example

The document need to compress: "ABBACAABCECAABADDDE".
Set of symbols S = A, B, C, D, E.
Encoded message: "000101001000000110111100000010011010110111".
Decoded message: "ABBACAABCECAABADDDE".

Symbol	*Count*	*Probability*
A	7	0.37
B	4	0.21
C	3	0.16
D	3	0.16
E	2	0.11

Table 1: Calculate the table of frequency (descending oder)

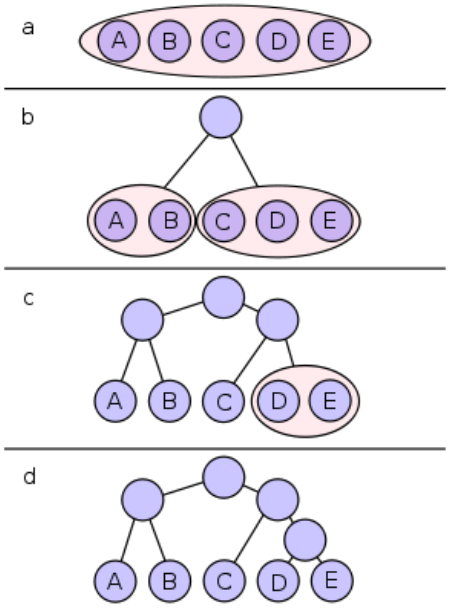

Figure 2: Divide the list of symbols and assign code

Symbol	*Code*
A	00
B	01
C	10
D	110
E	111

Table 2: The final code of symbols

Pseudo-code

You can find pseudo-code (Python style) for Shannon-Fano encoding and decoding in *pseudo-code/shannon-fano.py*

3.3 Lossless jpeg

Input

The input of jpeg usually is an image need to compress.

Output

The compressed "image"

Basic idea

For Compression:

1. Choose a predictor P.
2. Apply the predictor P on the input image I to get I_p (the first pixel [0, 0] mustn't change).
3. Calculate the different image $I_d = I - I_p$.
4. Run a lossless compression algorithm on I_d and get the compressed image.

For decompression:

1. Run the lossless decompression (same with the 4th step above) we get I_d
2. Apply the predictor P fro each pixel p_i from the first pixel [0, 0] of I_d
3. Then sum up the value from step 2 with the value of p_i in I_d and we will pixel value of the original image.

Examples

Suppose we have a gray-scale image (4x4) I like this:

$$\begin{matrix} 90 & 92 & 89 & 70 \\ 75 & 65 & 67 & 69 \\ 90 & 92 & 89 & 70 \\ 90 & 92 & 89 & 70 \end{matrix}$$

Now, we apply the predictor $X = A + B - C$ to compute I_p:

$$\begin{matrix} 90 & 90 & 92 & 89 \\ 90 & 77 & 62 & 48 \\ 75 & 65 & 82 & 83 \\ 75 & 75 & 89 & 93 \end{matrix}$$

Then, we have the different image I_d:

$$\begin{matrix} 90 & 2 & -3 & -19 \\ -15 & -12 & 5 & 21 \\ 0 & 15 & -1 & 4 \\ -5 & 10 & 1 & -13 \end{matrix}$$

Finally, we can choose another lossless compressor to compress I_d.

Pseudo-code

You can find pseudo-code (Python style) for Lossless jpeg encoding and decoding in *pseudo-code/lossless-jpeg.py*

4 Experiments

Notice that the implementation for compression algorithms was written as readable as possible so the performance may not good.

Testing process For each algorithm we run the encoder, saved the encoded files and calculate the compression ratio as a table. Then, we run the decoder on encoded files to check whether it right or wrong (the same as the original file or not). Some special parameters values would be shown in tables below. RLC and Shannon-Fano Coding were perform on text data and JPEG-Lossless on images data.

As a simplest compression algorithms, RLC works extremely bad on real life document (news, article, mail, etc).Table 3 shows that RLC even expends data instead of reduce it(!). The only time RLC really works is the text file that we manually create just for seeing RLC works.

input file	bits before encode	bits after encode	ratio
../data/text/0.txt	1517	2978	0.51
../data/text/1.txt	2619	5144	0.51
../data/text/2.txt	1903	2732	0.70
../data/text/3.txt	3004	5862	0.51
../data/text/4.txt	3573	7030	0.51
../data/text/5.txt	28077	54814	0.51
../data/text/6.txt	5752	11252	0.51
../data/text/7.txt	27304	53548	0.51
../data/text/8.txt	3389	6523	0.52
../data/text/9.txt	13261	20869	0.64
../data/text/10.txt	4649	9130	0.51
../data/text/11.txt	4850	9388	0.52
../data/text/12.txt	8816	17290	0.51
../data/text/13.txt	7374	14402	0.51
../data/text/14.txt	16000	31148	0.51
../data/text/15.txt	101	30	3.37

Table 3: Run-length coding result on text data

input file	bits before encode	bits after encode	ratio
../data/text/0.txt	1517	8742	1.39
../data/text/1.txt	2619	14089	1.49
../data/text/2.txt	1903	9791	1.55
../data/text/3.txt	3004	16701	1.44
../data/text/4.txt	3573	21824	1.31
../data/text/5.txt	28077	158819	1.41
../data/text/6.txt	5752	31292	1.47
../data/text/7.txt	27304	163974	1.33
../data/text/8.txt	3389	21897	1.24
../data/text/9.txt	13261	81003	1.31
../data/text/10.txt	4649	27224	1.37
../data/text/11.txt	4850	27650	1.40
../data/text/12.txt	8816	52135	1.35
../data/text/13.txt	7374	44004	1.34
../data/text/14.txt	16000	101360	1.26
../data/text/15.txt	101	334	2.42

Table 4: Shannon Fano coding result on text data

The Shannon-fano coding is much more better RLC. At least, it really reduce the size of data. The table 4 shows that compression ratio is between 1.3 and

2.4, it seems Shannon-fano works but it's not good enough for what we expected.

Web Application

5 Conclusions

6 References

7 Appendices