Compression: Basic Algorithms

Recap: The Need for Compression

Raw Video, Image and Audio files can very large:

Uncompressed Audio

1 minute of Audio:

Audio Type	44.1 KHz	22.05 KHz	11.025 KHz
16 Bit Stereo	10.1 Mb	5.05 Mb	2.52 Mb
16 Bit Mono	5.05 Mb	2.52 Mb	1.26 Mb
8 Bit Mono	2.52 Mb	1.26 Mb	630 Kb

Uncompressed Images:

Image Type	File Size
512 x 512 Monochrome	0.25 Mb
512 x 512 8-bit colour image	0.25 Mb
512 x 512 24-bit colour image	0.75 Mb

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Video

Can also involve: Stream of audio **plus** video imagery.

Raw Video – Uncompressed Image Frames, 512x512 True Color PAL 1125 Mb Per Min

DV Video — 200-300 Mb per Min (Approx) Compressed

HDTV — **Gigabytes** per second Compressed.

- Relying on higher bandwidths is not a good option — M25 Syndrome.
- Compression **HAS TO BE** part of the representation of audio, image and video formats.

Classifying Compression Algorithms

What is Compression?

E.g.: Compression ASCII Characters `EIEIO`

$$\overbrace{01000101}^{\texttt{E(69)}}\overbrace{01001001}^{\texttt{I(73)}}\overbrace{01000101}^{\texttt{E(69)}}\overbrace{01001001}^{\texttt{I(73)}}\overbrace{01001111}^{\texttt{O(79)}} = 5 \times 8 = 40 \text{ bits}$$

The **Main aim** of Data Compression is find a way to use **less bits** per character, E.g.:

$$\overbrace{xx}^{\texttt{E(2bits)}}\ \overbrace{yy}^{\texttt{I(2bits)}}\ \overbrace{xx}^{\texttt{E(2bits)}}\ \overbrace{yy}^{\texttt{I(3bits)}}\ \overbrace{zzz}^{\texttt{O(3bits)}} = \overbrace{(2 \times 2)}^{2\times\texttt{E}} + \overbrace{(2 \times 2)}^{2\times\texttt{I}} + \overbrace{3}^{O} = 11$$

bits

Note: We usually consider character sequences here for simplicity. Other token streams can be used — e.g. Vectorised Image Blocks, Binary Streams.

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Compression in Multimedia Data

Compression basically employs redundancy in the data:

- Temporal — in 1D data, 1D signals, Audio etc.
- Spatial — correlation between neighbouring pixels or data items
- Spectral — correlation between colour or luminescence components.
  This uses the frequency domain to exploit relationships between frequency of change in data.
- Psycho-visual — exploit perceptual properties of the human visual system.

Lossless v Lossy Compression

Compression can be categorised in two broad ways:

Lossless Compression — after decompression gives an exact copy of the original data

Examples: Entropy Encoding Schemes (Shannon-Fano, Huffman coding), arithmetic coding,LZW algorithm used in GIF image file format.

Lossy Compression — after decompression gives ideally a 'close' approximation of the original data, in many cases perceptually lossless but a byte-by-byte comparision of files shows differences.

Examples: Transform Coding —
FFT/DCT based quantisation used in JPEG/MPEG differential encoding, vector quantisation

Why do we need Lossy Compression?

- Lossy methods for **typically** applied to high resoultion audio, image compression
- **Have to be employed** in video compression (apart from special cases).

Basic reason:

- *Compression ratio* of lossless methods (e.g., Huffman coding, arithmetic coding, LZW) is not high enough.

Lossless Compression Algorithms: Repetitive Sequence Suppression

- Fairly straight forward to understand and implement.
- Simplicity is their downfall: **NOT best compression ratios**.
- Some methods have their applications, *e.g. Component of JPEG, Silence Suppression*.

Simple Repetition Suppression

If a sequence a series on n successive tokens appears

- Replace series with a token and a count number of occurrences.
- Usually need to have a special *flag* to denote when the repeated token appears

For Example:

```
89400000000000000000000000000000000
```

we can replace with:

```
894f32
```

where `f` is the flag for zero.

Simple Repetition Suppression: How Much Compression?

Compression savings depend on the content of the data.

Applications of this simple compression technique include:

- Suppression of zero's in a file (*Zero Length Suppression*)
  - Silence in audio data, Pauses in conversation *etc.*
  - Bitmaps
  - Blanks in text or program source files
  - Backgrounds in simple images
- Other regular image or data tokens

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Lossless Compression Algorithms: Run-length Encoding (RLE)

This encoding method is frequently applied to graphics-type images (or pixels in a scan line) — simple compression algorithm in its own right.

It is also a component used in **JPEG compression pipeline.**

Basic RLE Approach:

- Sequences of image elements $X_1, X_2, \ldots, X_n$ (Row by Row)
- Mapped to pairs $(c_1, l_1), (c_2, l_2), \ldots, (c_n, l_n)$

  where c_i represent image intensity or colour and l_i the length of the ith run of pixels
- (Not dissimilar to zero length suppression above).

Run-length Encoding Example

Original Sequence (1 Row):

```
111122233333311112222
```

can be encoded as:

```
(1,4),(2,3),(3,6),(1,4),(2,4)
```

How Much Compression?

The savings are dependent on the data: In the **worst case** (**Random Noise**) encoding is more heavy than original file:

2*integer rather than 1* integer if original data is integer vector/array.

MATLAB example code:

runlengthencode.m , runlengthdecode.m

Lossless Compression Algorithms: Pattern Substitution

This is a simple form of statistical encoding.

Here we substitute a frequently repeating pattern(s) with a code.

The code is shorter than than pattern giving us compression.

A simple Pattern Substitution scheme could employ predefined codes

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Simple Pattern Substitution Example

For example replace all occurrences of pattern of characters ‘`and`’ with the predefined code ’&’.

So:

```
and you and I
```

Becomes:

```
& you & I
```

Similar for other codes — commonly used words

Token Assignment

More typically tokens are assigned to according to frequency of occurrence of patterns:

- Count occurrence of tokens
- Sort in Descending order
- Assign some symbols to highest count tokens

A predefined symbol table may be used *i.e.* assign code i to token T. (**E.g. Some dictionary of common words/tokens**)

However, it is more usual to dynamically assign codes to tokens.

The entropy encoding schemes **below** basically attempt to decide the optimum assignment of codes to achieve the best compression.

Lossless Compression Algorithms Entropy Encoding

- Lossless Compression frequently involves some form of **entropy encoding**
- Based on **information theoretic techniques**.

Basics of Information Theory

According to Shannon, the **entropy** of an information source S is defined as:

$$H(S) = \eta = \sum_i \; p_i \log_2 \frac{1}{p_i}$$

where p_i is the probability that symbol S_i in S will occur.

- $\log_2 \frac{1}{p_i}$ indicates the amount of information contained in S_i, i.e., the number of bits needed to code S_i.
- For example, in an image with uniform distribution of gray-level intensity, i.e. p_i = 1/256, then
  - The number of bits needed to code each gray level is 8 bits.
  - The entropy of this image is 8.

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The Shannon-Fano Algorithm — Learn by Example

This is a basic information theoretic algorithm.

A simple example will be used to illustrate the algorithm:

A finite token Stream:

```
ABBAAAACDEAAABBBDDEEAAA........
```

Count symbols in stream:

Symbol	A	B	C	D	E
Count	15	7	6	6	5

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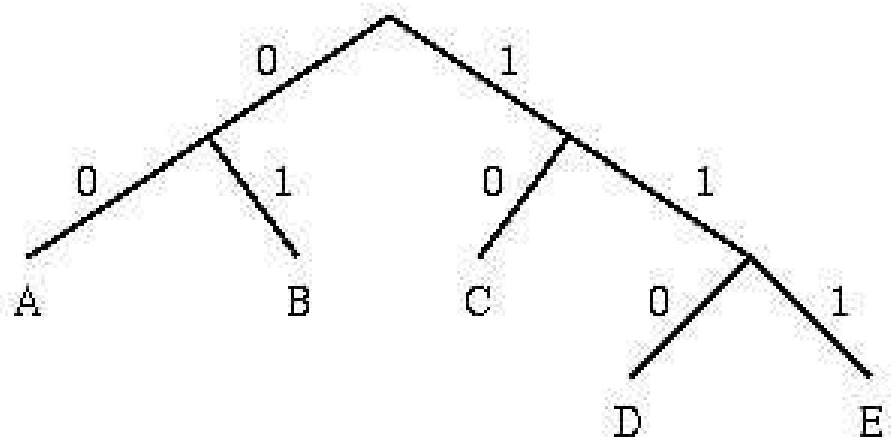
Encoding for the Shannon-Fano Algorithm:

- A top-down approach

1. Sort symbols (Tree Sort) according to their frequencies/probabilities, e.g., ABCDE.

2. Recursively divide into two parts, each with approx. same number of counts.



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3. Assemble code by depth first traversal of tree to symbol node

```
Symbol     Count     log(1/p)      Code        Subtotal (# of bits)
------     -----     --------    ---------     --------------------
  A         15        1.38          00             30
  B          7         2.48          01            14
  C          6         2.70          10            12
  D          6         2.70         110            18
  E          5         2.96         111            15
                            TOTAL (# of bits):     89
```

4. Transmit Codes instead of Tokens

- Raw token stream 8 bits per (39 chars) token = 312 bits
- Coded data stream = 89 bits

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Huffman Coding

- Based on the frequency of occurrence of a data item (pixels or small blocks of pixels in images).
- Use a lower number of bits to encode more frequent data
- Codes are stored in a **Code Book** — as for Shannon (previous slides)
- Code book constructed for each image or a set of images.
- Code book **plus** encoded data **must** be transmitted to enable decoding.

Encoding for Huffman Algorithm:

- A bottom-up approach

1. Initialization: Put all nodes in an OPEN list, keep it sorted at all times (e.g., ABCDE).

2. Repeat until the OPEN list has only one node left:

(a) From OPEN pick two nodes having the lowest frequencies/probabilities, create a parent node of them.

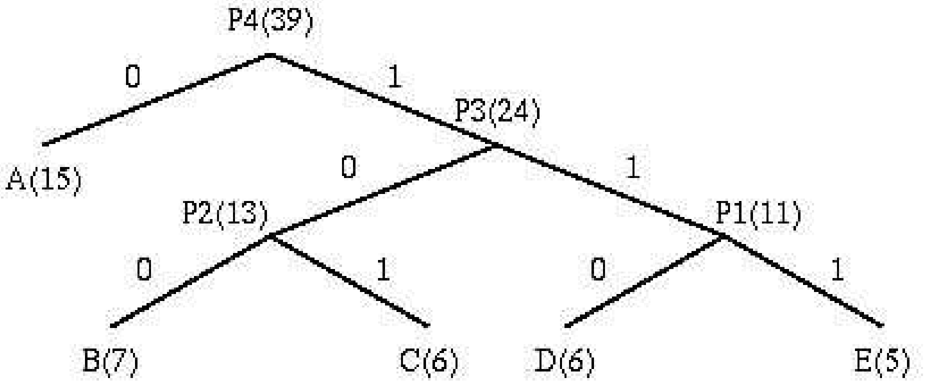
(b) Assign the sum of the children's frequencies/probabilities to the parent node and insert it into OPEN.

(c) Assign code 0, 1 to the two branches of the tree, and delete the children from OPEN.

3. Coding of each node is a top-down label of branch labels.

Huffman Encoding Example:

ABBAAAACDEAAABBBDDEEAAA........ (Same as Shannon-Fano E.g.)



Symbol	Count	log(1/p)	Code	Subtotal (# of bits)
A	15	1.38	0	15
B	7	2.48	100	21
C	6	2.70	101	18
D	6	2.70	110	18
E	5	2.96	111	15
		TOTAL	(# of bits):	87

Huffman Encoder Analysis

The following points are worth noting about the above algorithm:

- Decoding for the above two algorithms is trivial as long as the coding table/book is sent before the data.
  - There is a bit of an overhead for sending this.
  - But negligible if the data file is big.
- **Unique Prefix Property**: no code is a prefix to any other code (all symbols are at the leaf nodes) –> great for decoder, unambiguous.
- If prior statistics are available and accurate, then Huffman coding is very good.

Huffman Entropy

In the above example:

$$\begin{aligned}\mathrm{Idealentropy} &= (15 * 1.38 + 7 * 2.48 + 6 * 2.7 \\ &\quad +6 * 2.7 + 5 * 2.96)/39 \\ &= 85.26/39 \\ &= 2.19\end{aligned}$$

Number of bits needed for Huffman Coding is: $87/39 = 2.23$

Huffman Coding of Images

In order to encode images:

- Divide image up into (typically) 8x8 blocks
- Each block is a symbol to be coded
- Compute Huffman codes for set of block
- Encode blocks accordingly
- In **JPEG**: Blocks are DCT coded first before Huffman may be applied (More soon)

Coding image in blocks is common to all image coding methods

MATLAB Huffman coding example:
huffman.m (Used with JPEG code later),
huffman.zip (Alternative with tree plotting)

Arithmetic Coding

- A widely used entropy coder
- Also used in **JPEG — more soon**
- Only problem is it's speed due possibly complex computations due to large symbol tables,
- Good compression ratio (better than Huffman coding), entropy around the Shannon Ideal value.

Why better than Huffman?

- **Huffman coding etc.** use an integer number (k) of bits for each symbol,
  - hence k is never less than 1.
- Sometimes, e.g., when sending a 1-bit image, compression **becomes impossible**.

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Decimal Static Arithmetic Coding

- Here we describe basic approach of Arithmetic Coding
- Initially basic static coding mode of operation.
- Initial example **decimal coding**
- Extend to Binary and then machine word length later

Basic Idea

The idea behind arithmetic coding is

- To have a probability line, 0–1, and
- Assign to every symbol a range in this line based on its probability,
- The higher the probability, the higher range which assigns to it.

Once we have defined the ranges and the probability line,

- Start to encode symbols,
- Every symbol defines where the output floating point number lands within the range.

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Simple Basic Arithmetic Coding Example

Assume we have the following token symbol stream

`BACA`

Therefore

- A occurs with **probability 0.5**,
- B and C with **probabilities 0.25**.

Basic Arithmetic Coding Algorithm

Start by assigning each symbol to the probability range 0–1.

- Sort symbols highest probability first

Symbol	Range
A	[0.0, 0.5)
B	[0.5, 0.75)
C	[0.75, 1.0)

- The first symbol in our example stream is B

We now know that the code will be in the range 0.5 to $0.74999\ldots$.

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Range is not yet unique

- Need to narrow down the range to give us a unique code.

Basic arithmetic coding iteration

- Subdivide the range for the first token given the probabilities of the second token then the third etc.

Subdivide the range as follows

For all the symbols:

```
range = high - low;
high = low + range * high_range of the symbol being coded;
low = low + range * low_range of the symbol being coded;
```

Where:

- `range`, keeps track of where the next range should be.
- `high` and `low`, specify the output number.
- Initially `high = 1.0`, `low = 0.0`

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Back to our example

The second symbols we have
(now `range` = 0.25, `low` = 0.5, `high` = 0.75):

Symbol	Range
B**A**	[0.5, 0.625)
BB	[0.625, 0.6875)
BC	[0.6875, 0.75)

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Third Iteration

We now reapply the subdivision of our scale again to get for our third symbol

(range = 0.125, low = 0.5, high = 0.625):

Symbol	Range
BAA	[0.5, 0.5625)
BAB	[0.5625, 0.59375)
BA**C**	[0.59375, 0.625)

Fourth Iteration

Subdivide again
(`range` = 0.03125, `low` = 0.59375, `high` = 0.625):

Symbol	Range
BAC**A**	[0.59375, 0.60937)
BACB	[0.609375, 0.6171875)
BACC	[0.6171875, 0.625)

So the (Unique) output code for BACA is any number in the range:

[0.59375, 0.60937).

Decoding

To **decode** is essentially the opposite

- We compile the table for the sequence given probabilities.
- Find the range of number within which the code number lies and carry on

Binary static algorithmic coding

This is very similar to above:

- **Except** we us **binary fractions**.

Binary fractions are simply an extension of the binary systems into fractions much like decimal fractions.

Binary Fractions — Quick Guide

Fractions in **decimal**:

0.1 decimal = $\frac{1}{10^1} = 1/10$
0.01 decimal = $\frac{1}{10^2} = 1/100$
0.11 decimal = $\frac{1}{10^1} + \frac{1}{10^2} = 11/100$

So in **binary** we get

0.1 binary = $\frac{1}{2^1} = 1/2$ decimal
0.01 binary = $\frac{1}{2^2} = 1/4$ decimal
0.11 binary = $\frac{1}{2^1} + \frac{1}{2^2}$ = 3/4 decimal

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Binary Arithmetic Coding Example

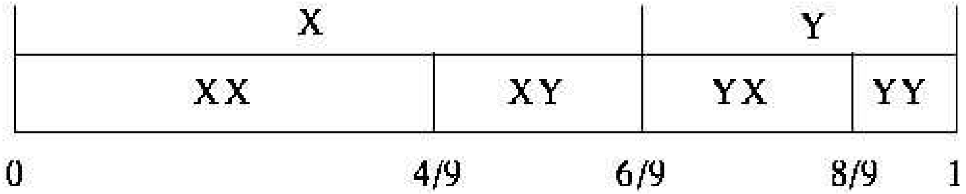
- Idea: Suppose alphabet was `X, Y` and token stream:

  `XXY`

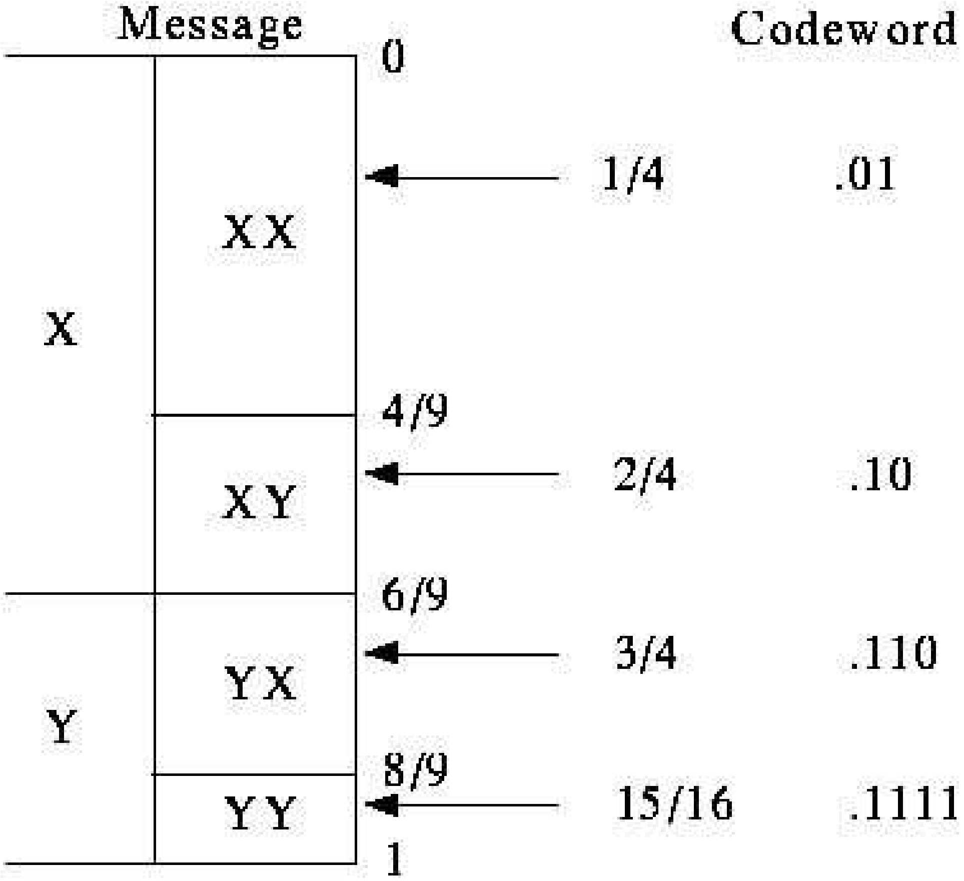
  Therefore:

  ```
  prob(X) = 2/3
  prob(Y) = 1/3
  ```

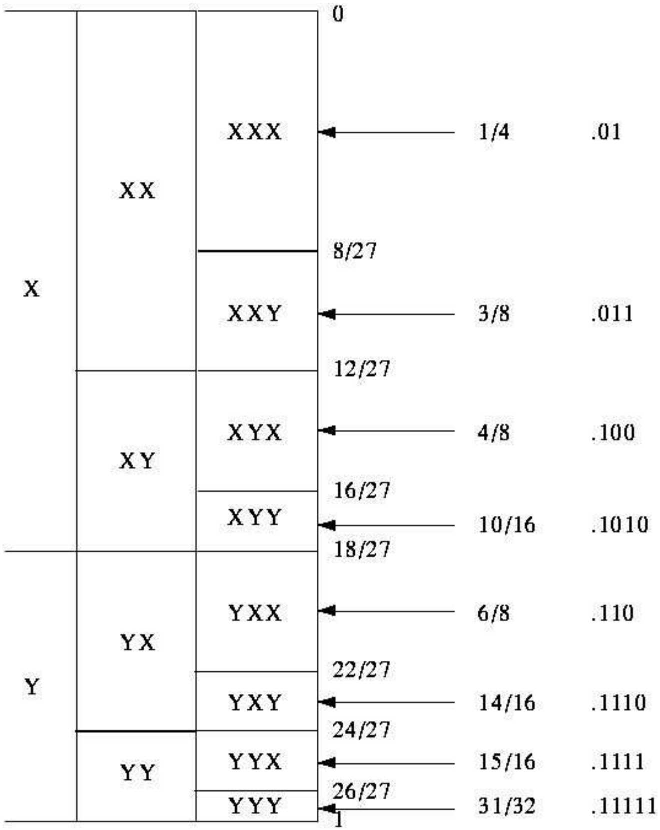
- If we are only concerned with encoding length 2 messages, then we can map all possible messages to intervals in the range [0..1]:



- To encode message, just send enough bits of a binary fraction that uniquely specifies the interval.



- Similarly, we can map all possible length 3 messages to intervals in the range [0..1]:



Implementation Issues

FPU Precision

- Resolution of the of the number we represent is limited by FPU precision
- Binary coding extreme example of rounding
- Decimal coding is the other extreme — theoretically no rounding.
- Some FPUs may us up to 80 bits
- As an example let us consider working with 16 bit resolution.

16-bit arithmetic coding

We now encode the range 0–1 into 65535 segments:

0.000	0.250	0.500	0,750	1.000
0000h	4000h	8000h	C000h	FFFFh

If we take a number and divide it by the maximum (FFFFh) we will clearly see this:

```
0000h: 0/65535 = 0.0
4000h: 16384/65535 = 0.25
8000h: 32768/65535 = 0.5
C000h: 49152/65535 = 0.75
FFFFh: 65535/65535 = 1.0
```

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The operation of coding is similar to what we have seen with the binary coding:

- Adjust the probabilities so the bits needed for operating with the number aren't above 16 bits.
- Define a new interval
- The way to deal with the infinite number is
  - to have only loaded the 16 first bits, and when needed shift more onto it:

    ```
    1100 0110 0001 000 0011 0100 0100 ...
    ```
  - work only with those bytes
  - as new bits are needed they'll be shifted.

Memory Intensive

What about an alphabet with 26 symbols, or 256 symbols, ...?

- In general, number of bits is determined by the size of the interval.
- In general, (from entropy) need $-\log p$ bits to represent interval of size p.
- Can be memory and CPU intensive

MATLAB Arithmetic coding examples:
Arith06.m (Version 1),
Arith07.m (Version 2)

Lempel-Ziv-Welch (LZW) Algorithm

- A very common compression technique.
- Used in GIF files (LZW), Adobe PDF file (LZW), UNIX `compress` (LZ Only)
- Patented — LZW not LZ.

Basic idea/Example by Analogy:

Suppose we want to encode the Oxford Concise English dictionary which contains about 159,000 entries.

Why not just transmit each word as an 18 bit number?

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LZW Constructs Its Own Dictionary

Problems:

- Too many bits per word,
- Everyone needs a dictionary,
- Only works for English text.

Solution:

- Find a way to build the dictionary adaptively.
- Original methods (LZ) due to Lempel and Ziv in 1977/8.
- Quite a few variations on LZ.
- Terry Welch improvement (1984), **Patented LZW Algorithm**
  - LZW introduced the idea that only the **initial dictionary** needs to be transmitted to enable **decoding**:
    The decoder is able to **build** the **rest** of the table from the **encoded sequence**.

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LZW Compression Algorithm

The LZW Compression Algorithm can summarised as follows:

```
w = NIL;
while ( read a character k )
  {    if wk exists in the dictionary
            w = wk;
         else
            { add wk to the dictionary;
               output the code for w;
                w = k;
             }
   }
```

- Original LZW used dictionary with 4K entries, first 256 (0-255) are ASCII codes.

LZW Compression Algorithm Example:

Input string is "^WED^WE^WEE^WEB^WET".

w	k	output	index	symbol
NIL	^			
^	W	^	256	^W
W	E	W	257	WE
E	D	E	258	ED
D	^	D	259	D^
^	W			
^W	E	256	260	^WE
E	^	E	261	E^
^	W			
^W	E			
^WE	E	260	262	^WEE
E	^			
E^	W	261	263	E^W
W	E			
WE	B	257	264	WEB
B	^	B	265	B^
^	W			
^W	E			
^WE	T	260	266	^WET
T	EOF	T		

- A 19-symbol input has been reduced to 7-symbol plus 5-code output. Each code/symbol will need more than 8 bits, say 9 bits.
- Usually, compression doesn't start until a large number of bytes (e.g., $>$ 100) are read in.

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LZW Decompression Algorithm

The LZW Decompression Algorithm is as follows:

```
read a character k;
output k;
w = k;
while ( read a character k )
/* k could be a character or a code. */
  {
          entry = dictionary entry for k;
          output entry;
          add w + entry[0] to dictionary;
          w = entry;
  }
```

Note (Recall):

LZW decoder only needs the **initial dictionary**:

The decoder is able to **build** the **rest** of the table from the **encoded sequence**.

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LZW Decompression Algorithm Example:

Input string is

"^WED<256>E<260><261><257>B<260>T"

w	k	output	index	symbol
^	^			
^	W	W	256	^W
W	E	E	257	WE
E	D	D	258	ED
D	<256>	^W	259	D^
<256>	E	E	260	^WE
E	<260>	^WE	261	E^
<260>	<261>	E^	262	^WEE
<261>	<257>	WE	263	E^W
<257>	B	B	264	WEB
B	<260>	^WE	265	B^
<260>	T	T	266	^WET

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MATLAB LZW Code

norm2lzw.m: LZW Encoder

lzw2norm.m: LZW Decoder

lzw_demo1.m: Full MATLAB demo

More Info on MATLAB LZW code

Lossy Compression: Source Coding Techniques

Source coding is based changing on the content of the original signal.

Also called *semantic-based coding*

High compression rates may be high but a price of loss of information. Good compression rates make be achieved with source encoding with (occasionally) **lossless** or (mostly) little **perceivable** loss of information.

There are three broad methods that exist:

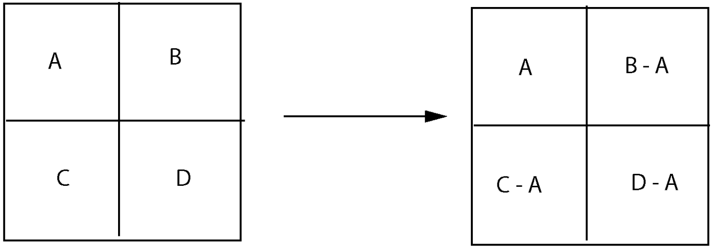
- Transform Coding
- Differential Encoding
- Vector Quantisation

Transform Coding

A simple transform coding example

A Simple Transform Encoding procedure maybe described by the following steps for a 2x2 block of monochrome pixels:

1. Take top left pixel as the base value for the block, pixel A.
2. Calculate three other transformed values by taking the difference between these (respective) pixels and pixel A, **Ii.e. B-A, C-A, D-A.**
3. Store the base pixel and the differences as the values of the transform.



A	B
C	D

A	B - A
C - A	D - A

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Simple Transforms

Given the above we can easily form the forward transform:

$$
\begin{aligned}
X_0 &= A \\
X_1 &= B - A \\
X_2 &= C - A \\
X_3 &= D - A
\end{aligned}
$$

and the inverse transform is:

$$
\begin{aligned}
A_n &= X_0 \\
B_n &= X_1 + X_0 \\
C_n &= X_2 + X_0 \\
D_n &= X_3 + X_0
\end{aligned}
$$

Compressing data with this Transform?

Exploit redundancy in the data:

- Redundancy transformed to values, X_i.
- Compress the data by using fewer bits to represent the differences — *Quantisation*.
  - I.e if we use 8 bits per pixel then the 2x2 block uses 32 bits
  - If we keep 8 bits for the base pixel, X0,
  - Assign 4 bits for each difference then we only use 20 bits.
  - Better than an average 5 bits/pixel

Example

Consider the following 4x4 image block:

120	130
125	120

then we get:

$$
\begin{aligned}
X_0 &= 120 \\
X_1 &= 10 \\
X_2 &= 5 \\
X_3 &= 0
\end{aligned}
$$

We can then compress these values by taking less bits to represent the data.

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Inadequacies of Simple Scheme

- It is **Too Simple**
- Needs to operate on larger blocks (typically 8x8 min)
- Simple encoding of differences for large values will result in loss of information
  - V. poor losses possible here 4 bits per pixel = values 0-15 unsigned,
  - Signed value range: $-7 - 7$ so either quantise in multiples of 255/max value or massive overflow!!

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Differential Transform Coding Schemes

- **Differencing** is used in some compression algorithms:
  - Later part of JPEG compression
  - Exploit static parts (*e.g.* background) in MPEG video
  - Some speech coding and other simple signals
  - **Good** on repetitive sequences
- **Poor** on highly varying data sequences
  - *e.g* interesting audio/video signals

MATLAB Simple Vector Differential Example

diffencodevec.m: Differential Encoder
diffdecodevec.m: Differential Decoder
diffencodevecTest.m: Differential Test Example

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Differential Encoding

Simple example of transform coding mentioned earlier and instance of this approach.

Here:

- The difference between the actual value of a sample and a prediction of that values is encoded.
- Also known as **predictive encoding**.
- Example of technique include: differential pulse code modulation, delta modulation and adaptive pulse code modulation — differ in prediction part.
- Suitable where successive signal samples do not differ much, but are not zero. E.g. Video — difference between frames, some audio signals.

Differential Encoding Methods

- **Differential pulse code modulation** (DPCM)

Simple prediction (also used in JPEG):

$$f_{predict}(t_i) = f_{actual}(t_{i-1})$$

I.e. a simple Markov model where current value is the predict next value.

So we simply need to encode:

$$\Delta f(t_i) = f_{actual}(t_i) - f_{actual}(t_{i-1})$$

If successive sample are close to each other we only need to encode first sample with a large number of bits:

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Simple Differential Pulse Code Modulation Example

Actual Data: 9 10 7 6

Predicted Data: 0 9 10 7

$\Delta f(t)$: +9, +1, -3, -1.

MATLAB Complete (with quantisation) DPCM Example

dpcm_demo.m.m: DPCM Complete Example
dpcm.zip.m: DPCM Support FIles

Differential Encoding Methods (Cont.)

- **Delta modulation** is a special case of DPCM:
  - Same predictor function,
  - Coding error is a **single bit or digit** that indicates the current sample should be increased or decreased by a step.
  - Not Suitable for rapidly changing signals.
- **Adaptive pulse code modulation**

Fuller Temporal/Markov model:

- Data is extracted from a function of a series of previous values
- **E.g.** Average of last n samples.
- Characteristics of sample better preserved.

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Frequency Domain Methods

Another form of Transform Coding

Transformation from one domain —time (*e.g.* 1D audio, video:2D imagery over time) or Spatial (*e.g.* 2D imagery) domain to the **frequency** domain via

- **Discrete Cosine Transform (DCT)**— Heart of **JPEG** and **MPEG Video**, (alt.) MPEG Audio.
- **Fourier Transform (FT)** — **MPEG Audio**

Theory already studied earlier

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RECAP — Compression In Frequency Space

How do we achieve compression?

- Low pass filter — ignore high frequency noise components
- Only store lower frequency components
- High Pass Filter — Spot Gradual Changes
- If changes to low Eye does not respond so ignore?

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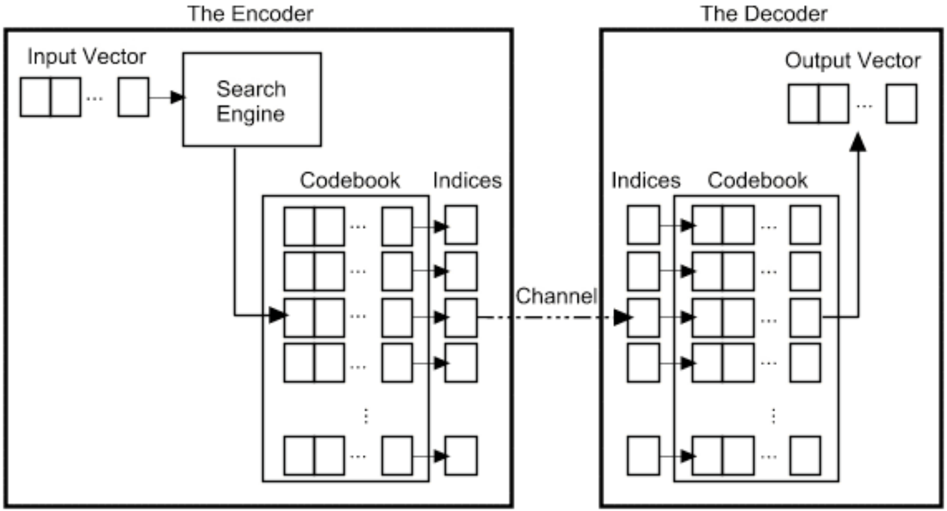
Vector Quantisation

The basic outline of this approach is:

- Data stream divided into (1D or 2D square) blocks — **vectors**
- A table or **code book** is used to find a pattern for each block.
- Code book can be dynamically constructed or predefined.
- Each pattern for block encoded as a look value in table
- Compression achieved as data is effectively subsampled and coded at this level.
- Used in MPEG4, Video Codecs (Cinepak, Sorenson), Speech coding, Ogg Vorbis.

Vector Quantisation Encoding/Decoding

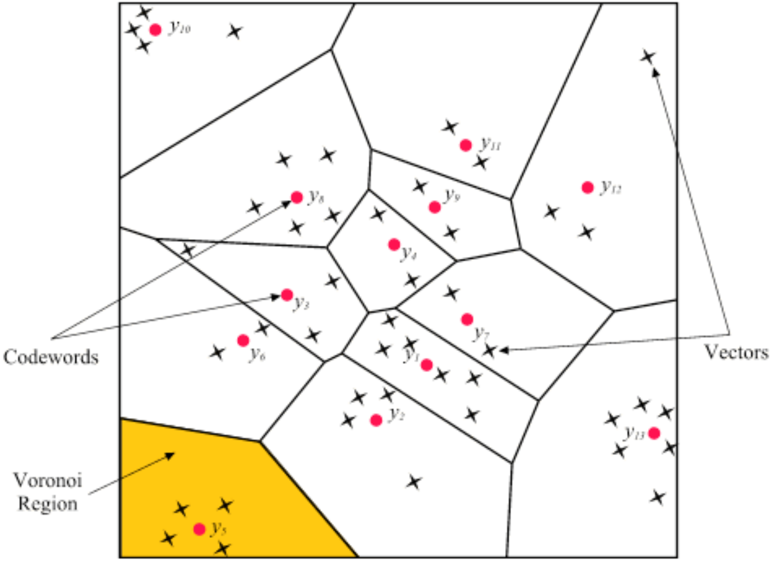


- **Search Engine**:
  - Group (Cluster) data into vectors
  - Find closest code vectors
- On decode output need to *unblock* (smooth) data

Vector Quantisation Code Book Construction

How to cluster data?

- Use some clustering technique,
  e.g. K-means, Voronoi decomposition
  Essentially cluster on some closeness measure, minimise inter-sample variance or distance.



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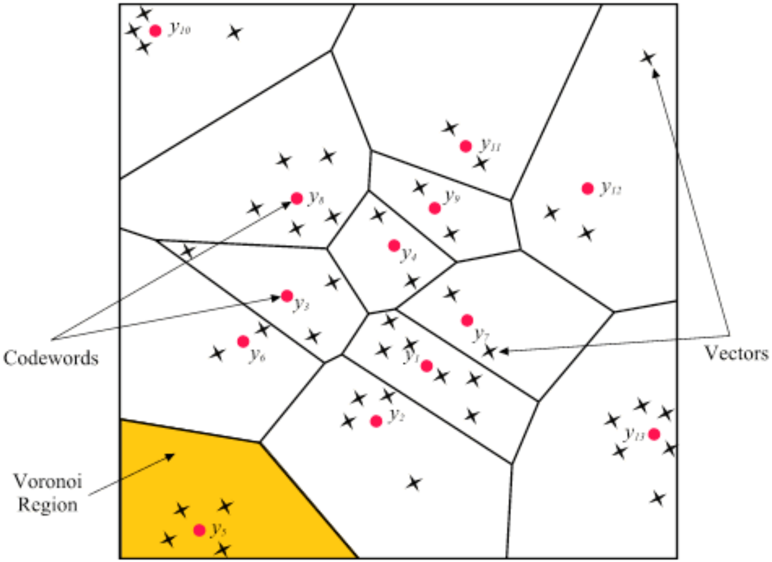
Vector Quantisation Code Book Construction

How to code?

- For each cluster choose a mean (median) point as representative code for all points in cluster.



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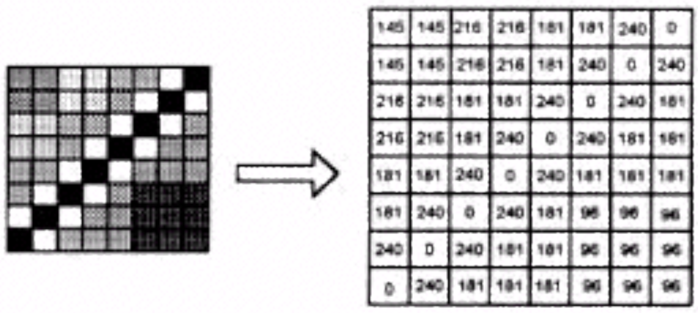
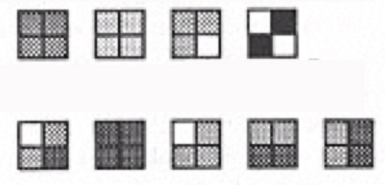
Vector Quantisation Image Coding Example

- A small block of images and intensity values



145	145	216	216	181	181	240	0
145	145	216	216	181	240	0	240
216	216	181	181	240	0	240	181
216	216	181	240	0	240	181	181
181	181	240	0	240	181	181	181
181	240	0	240	181	96	96	96
240	0	240	181	181	96	96	96
0	240	181	181	181	96	96	96

- Consider Vectors of 2x2 blocks, and only allow 8 codes in table.
- 9 vector blocks present in above:



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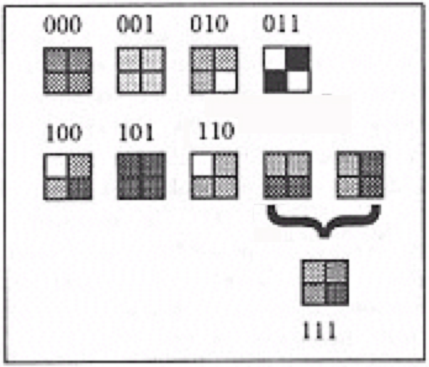
Vector Quantisation Image Coding Example (Cont.)

- 9 vector blocks, so **only one** has to be **vector quantised** here.
- Resulting code book for above image



MATLAB EXAMPLE: vectorquantise.m