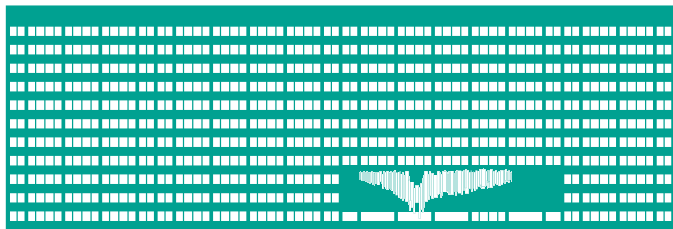


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Statistical Compression

Part II - Arithmetic coding

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- Encoding messages.
- Arithmetic Coding.
- Adaptive coding.
- Higher-order coding.
- Prediction by Partial Matching.



- Consider following simple example: let length of the message be $|m| = 3$, $\Sigma = \{a, b, c\}$ and $f(a) = f(b) = f(c) = 1$.
- How many messages with frequency distribution f exists?
- There are 6 different messages: $M = \{abc, acb, bac, bca, cab, cba\}$.
- To distinguish between 6 objects we need $\log 6 = 2.58$ bits.
- To obtain number of bits per symbol \Rightarrow divide by the message length: $\frac{1}{3} \log 6 = 0.86$ bits.
- Empirical entropy in per symbol interpretation:
 $H(X) = -3 \frac{1}{3} \log \frac{1}{3} = 1.58$ bits.

Question

Does it mean that we can compress below entropy if we encode messages instead of symbols?



Question

Does it mean that we can compress below entropy if we encode messages instead of symbols?

- No, we cannot.
- Entropy is based on probabilities, so there are non-zero probabilities for messages: aaa, aab, aac, \dots . $p(X_1X_2X_3) = p(x_1)p(x_2)p(x_3)$.
- Knowledge of frequencies means, that once we encode one symbol, the rest is encoded by adjusted frequencies:
 - 1 Start with $f_0(a) = f_0(b) = f_0(c) = 1$. Say the first symbol was a . Encode it by $\log 3$ bits.
 - 2 Adjust frequencies $f_1(a) = 0$ and $f_1(b) = f_1(c) = 1$. Encode the next symbol, say b , by $\log 2$ bits.
 - 3 Adjust frequencies $f_2(a) = f_2(b) = 0$ and $f_2(c) = 1$. Only one symbol left, encode using $\log 1 = 0$ bits.
 - 4 Together: $\log 2 + \log 3 = \log 6$ bits.



Entropy - Definition

Number of bits needed to distinguish one message from other messages having the knowledge of symbol frequencies.

- We have a very long message of N symbols over alphabet $\Sigma = \{0, 1\}$.
- It is simple task to compute frequencies $f(0)$ and $f(1)$.

Question

How many distinct messages can we create using $f(0)$ zeros and $f(1)$ ones?



Question

How many distinct messages can we create using $f(0)$ zeros and $f(1)$ ones?

Permutation with repetition:

$$\frac{N!}{f(0)!f(1)!}$$

To describe uniquely k different objects we need $\log k$ bits. The same for messages.

$$\log \frac{N!}{f(0)!f(1)!} = \log N! - \log f(0)! - \log f(1)!$$



Problem

How to handle logarithm of factorial?

Answer: Use Stirling approximation.

$$\log k! = k \log k - k$$

Task

Use Stirling formula to simplify the expression:

$$\log \frac{N!}{f(0)!f(1)!} = \log N! - \log f(0)! - \log f(1)!$$



- $N = f(0) + f(1)$
- $p(x) = \frac{f(x)}{N} \Rightarrow f(x) = p(x)N$

$$\begin{aligned}\log \frac{N!}{f(0)!f(1)!} &= \log N! - \log f(0)! - \log f(1)! \\ &= N \log N - N - f(0) \log f(0) + f(0) \\ &\quad - f(1) \log f(1) + f(1) \\ &= N \log N - f(0) \log f(0) - f(1) \log f(1) \\ &= N \log N - Np(0) \log p(0)N - Np(1) \log p(1)N \\ &= N(\log N - p(0) \log p(0)N - p(1) \log p(1)N)\end{aligned}$$



$$p(x) \log Np(x) = p(x) \log p(x) + p(x) \log N$$

$$-p(0) \log N - p(1) \log N = -(p(0) + p(1)) \log N = -\log N$$

Taking it together:

$$\begin{aligned} &= N(\log N - p(0) \log p(0)N - p(1) \log p(1)N) \\ &= N(-p(0) \log p(0) - p(1) \log p(1)) \\ &= NH(X) \end{aligned}$$

Since there are N symbols in the message dividing by N gives the entropy related to one symbol, i.e. Shannon's entropy.



- For sufficiently long messages, there is no difference between encoding per symbol or per message.
- To encode one message we have to establish mapping between messages and binary code of $c = NH(X)$ bits.

$$m_0 \rightarrow 0^c$$

$$m_1 \rightarrow 0^{c-1}1$$

$$\dots \rightarrow \dots$$

- The instance of such mapping: let M and B be two alphabetically ordered set of messages, where M is a set of possible input messages (knowing frequency distribution) and B is a set of output binary messages. The size of both sets is $NH(X)$. i -th message $M[i]$ is then assigned a $B[i]$ binary code.



- Principle proposed by Peter Elias in early 60s.
- Encodes message instead of symbols.
- Represents a message as a real number in $[0; 1)$ interval.
- Achieves bits per symbol very close to entropy.



Let $m = abac$ then $p(a) = 0.5$ and $p(b) = p(c) = 0.25$.

L	$L = 0$	$L = 0$	$L = 0.25$
H	$H = 1$	$H = 0.5$	$H = 0.375$
Symbol	a	b	a
a	[0;0.5)	[0;0.25)	[0.25;0.3125)
b	[0.5;0.75)	[0.25;0.375)	[0.3125;0.34375)
c	[0.75;1)	[0.375;0.5)	[0.34375;0.375)
L	$L = 0.25$	$L = 0.296875$	
H	$H = 0.3125$	$H = 0.3125$	
Symbol	c		
a	[0.25;0.28125)		
b	[0.28125;0.296875)		
c	[0.296875;0.3125)		

Any number from interval $[0.296875;0.3125)$ can be used for representation of m .



Task

Decode binary number 0.101 into decimals.

Task

Encode decimal number 0.375 into binary representation.



Task

Decode binary number 0.101 into decimals.

$$2^{-1} + 2^{-3} = 0.625$$

Task

Encode decimal number 0.375 into binary representation.

$$0.011 = (0)2^{-1} + (1)2^{-2} + (1)2^{-3}$$



Objective

We want to find a shortest binary number within interval [L;H).

- The interval be [0.296875;0.3125).
- Representation:

$$b = b_02^{-1} + b_12^{-2} + b_22^{-3} \dots$$

binary	interval	decimal
.0...	[0;0.5)	0
.01...	[0.25;0.5)	0.25
.010...	[0.25;0.375]	0.25
.0100...	[0.25;0.3125]	0.25
.01001...	[0.28125;0.3125)	0.28125
.010011...	[0.296875;0.3125)	0.296875



- Message $m = abac$ will be encoded by binary code $b = 010011$.
- $H(X) = 1.5$ bits per symbol, message will be encoded optimally by $mH(X) = 6$ bits.
- We have an optimal coding of m !



Assume message m , alphabet $\Sigma = \{x_1, x_2, \dots, x_\sigma\}$ with frequency distribution F and let $Pr[X < x]$ be a cumulative probability.

- 1 Count probabilities of symbols in m . Set $L = 0$, $H = 1$ and $i = 0$.
- 2 Divide interval $[L; H)$ proportionally to probabilities. To encode symbol $x = m[i]$: set

$$L_1 = L_0 + (H_0 - L_0)Pr[X < x]$$

and

$$H_1 = L_0 + (H_0 - L_0)Pr[X \leq x]$$

- 3 Increment i , if there are no more symbols output number from interval $[L; H)$ so that its binary representation is the shortest one, otherwise continue with Step 2.



Decoding 010011:

decoding interval output	0 [0;0.5) a	1 [0.25;0.5)	0 [0.25;0.375] b
a	[0;0.5)	[0;0.25)	[0;0.25)
b	[0.5;0.75)	[0.25;0.375)	[0.25;0.375)
c	[0.75;1)	[0.375;0.5)	[0.375;0.5)
decoded interval output	0 [0.25;0.3125] a	1 [0.28125;0.3125)	1 [0.296875;0.3125) c
a	[0.25;0.3125)	[0.25;0.28125)	[0.25;0.28125)
b	[0.3125;0.34375)	[0.28125;0.296875)	[0.28125;0.296875)
c	[0.34375;0.375)	[0.296875;0.3125)	[0.296875;0.3125)



- 1 Reconstruct the initial intervals using probabilities.
- 2 Read bit and adjust $[L; H)$ interval.
- 3 If the interval is a subinterval of some initial interval then output corresponding symbol and adjust intervals for symbols.
- 4 Repeat step 2



- Achieves better compression rate than Huffman coding.
- Generally slower compression and decompression $O(n \log \sigma)$.
- Historically restricted by patents, even though almost all expired, not used in many commercial applications.
- JPEG supports arithmetic coding from 1990, but very few manufactures used ac coding as Huffman based one was free.
- Used in the state of the art compressors like PPMd and PAQ family as entropy coders.



- The procedure we have described so far is impractical \Rightarrow using standard **double** data type we can represent precisely only 14(15) decimal places.
- Any practical implementation of arithmetic coding should use integers.
- Low and High are integers, but we still don't want to let them grow too much.

Important note

Once the leftmost digits of Low and High become identical, they never change.

The leftmost identical digits of Low and High are sent to output and bit-wise shifted. Using this procedure we adjust intervals corresponding to symbols and they never grow above certain predefined level.



symbol	$p(x)$	interval
a	0.5	$[0,0.5)$
b	0.25	$[0.5,0.75)$
c	0.25	$[0.75,1)$

- Encoded using 4-bit buffer.
- Value range: $< 0, 16)$.
- Encode 'abac'.

$L = 0$	0000
$H = 15$	1111
read 'a'	
$L = 0$	0000
$H = 7$	0111
write 0, shift 1 bit	
$L = 0$	0000
$H = 15$	1111
read 'b'	
$L = 8$	1000
$H = 11$	1011
write 10, shift 2 bits	



symbol	$p(x)$	interval
a	0.5	$[0,0.5)$
b	0.25	$[0.5,0.75)$
c	0.25	$[0.75,1)$

- Encoded using 4-bit buffer.
- Value range: $< 0, 16)$.
- Encode 'abac'.
- Encoded to: 010011.

$L = 0$	0000
$H = 15$	1111
read 'a'	
$L = 0$	0000
$H = 7$	0111
write 0, shift 1 bit	

$L = 0$	0000
$H = 15$	1111
read 'c'	
$L = 12$	1100
$H = 15$	1111
write 11, shift 2 bits	



symbol	$p(x)$	interval
a	0.5	[0,8)
b	0.25	[8,12)
c	0.25	[12,15)

- Encoded using 4-bit buffer.
- Value range: $< 0, 16$).
- Encode 'abac'.
- Encoded to: 010011.

$L = 0$	0000
$H = 15$	1111
read (0100)11	C=4
write 'a'	
$L = 0$	0000
$H = 7$	0111
shift 1 bit	

read 0(1001)1	C=9
write 'b'	
$L = 8$	1000
$H = 11$	1011
shit 2 bits	
$L = 0$	0000
$H = 15$	1111



symbol	$p(x)$	interval
a	0.5	$[0,8)$
b	0.25	$[8,12)$
c	0.25	$[12,15)$

- Encoded using 4-bit buffer.
- Value range: $< 0, 16$).
- Encode 'abac'.
- Encoded to: 010011.

$L = 0$	0000
$H = 15$	1111
read 010(0110)	C=6
write 'a'	
$L = 0$	0000
$H = 7$	0111
shift 1 bit	
read 0100(1100)	C=12
write 'c'	



- For more discussion see Arithmetic Coding chapter in Solomon, Data Compression Handbook.
- Further implementation details: Witten, Neal, Cleary(89)
<https://dl.acm.org/doi/pdf/10.1145/214762.214771>
- Real implementation of arithmetic coding based on Witten:
<http://home1.vsb.cz/~vas218/source/acs/Arithmetic.h>



- We don't have to use the first pass through message to count symbols.
- We can read symbol after symbol and adjust frequencies \Rightarrow adapt the model to the current data.
 - The model is based on all preceding symbols.
 - The model is based on k preceding symbols.
- Initialization
 - We know the alphabet \Rightarrow set the initial frequency of each symbol to 1.
 - We don't know the alphabet \Rightarrow define a special escape symbol η , once we process yet unseen symbol we escape it by η and encode in binary.
- No need to store the frequency model \Rightarrow zero order-model are usually small but higher order...



- We can use any estimate of probabilities (k -th order context or neural network) to adjust intervals and L and H .
- We only have to ensure that compressor and decompressor are synchronized, i.e. they deduce the same probability when adjusting the model.
- We can easily build k -th order adaptive arithmetic model. <http://home1.vsb.cz/~vas218/source/acs/AdaptiveArithmetic.h>
- There is no problem if k is fixed, but what if we let the k to vary?



- Prediction by partial matching, in short PPM.
- Uses context-based (N preceding symbols) estimate of probability which is feeded to arithmetic coder.
- PPM encoder is usually adaptive.
- PPM can switch to a shorter context when a longer one has resulted in 0 probability.
- PPM searches for symbol S in the context C , if it finds no occurrence C , it switches to $N - 1$ length context and so on.



- Suppose the current order-3 context is the string "the".
- Its current frequency is 27 and it was followed by r(11 times), s(9 times), n (6 times), m (once).
- The encoder assigns these cases probabilities $11/27$, $9/27$, $6/27$ and $1/27$.
- If the next symbol is "r", then we sent "r" to adaptive arithmetic coder with probability $11/27$.
- If the next symbol is "a", then PPM switches to order-2 context and try it again.
- Each context switch is represented by special escape symbol.
- If we encounter symbol for the first time, we switch context till we reach context = -1 and we will encode the symbol with probability $1/\text{size of the alphabet}$.

Thank you for your attention

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