

# Fountain Codes for Compression

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**(o) Definitions:**  
**The Burrows-Wheeler Transform (BWT)**  
**[M. Burrows and D.J. Wheeler, 1994]**

Operates on a sequence of size  $n$ .

Algorithm:

Do

Produces  $n$  cyclic shifts of the original sequence

Sorts these cyclic shifts lexicographically

End Do

Output: The result is the last column of the sorted table and the index position of the original sequence in the sorted table.

Complexity:  $O(n)$  using the prefix tree constructions

## (o) Definitions: The BWT

(o) example:  $S = \text{'aLgOLabO'}$ ,  $X = \{\text{a, b, g, L, O}\}$ ,  
SBWT =  $\text{'LOaLOabg'}$

	Step1
1	aLgOLabO
2	OaLgOLab
3	bOaLgOLa
4	abOaLgOL
5	LabOaLgO
6	OLabOaLg
7	gOLabOaL
8	LgOLabOa

	Step2
1	abOaLgOL
2	aLgOLabO
3	bOaLgOLa
4	gOLabOaL
5	LabOaLgO
6	LgOLabOa
7	OaLgOLab
8	OLabOaLg

	Step3
1	L
2	O
3	a
4	L
5	O
6	a
7	b
8	g

## (o) Definitions: BWT

(1) example:  $S = 1010$ ,  $X = \{0, 1\}$

SBWT = 1001

	Step1
1	2
2	21
3	210
4	2101
5	21010

	Step2
1	21010
2	210
3	2101
4	21
5	2

	Step3
1	NULL
2	1
3	0
4	0
5	1

## (o) Some properties: BWT

Definition : Given a random vector  $G^n = (G_1, \dots, G_n)$  and any integer  $1 \leq D \leq n$ , we call  $G^n$  D-piecewise independent and identically distributed (D-p.i.i.d.) if there exists some collection  $\{q_1, \dots, q_n\}$  of distributions on an alphabet  $A$  such that for any  $x^n \in A^n$  there exists an integer transition pattern  $(T_1, \dots, T_{D+1})$ ,  $1 = T_1 < T_2 < \dots < T_{D+1} = n+1$ , such that  $\Pr(G^n = x^n) = \prod_{j=1, \dots, D} \prod_{i=T_j, \dots, T_{j+1}-1} p_j(x_i)$

Theorem: The output distribution of the BWT is approximately memoryless and piecewise stationary, in the sense that the normalized divergence between the ourput distribution and a memoryless and piecewise stationary distribution is small

[Karthik Visweswariah et al., 2000]

Generalization of the previous theorem: For mememory sources

[Michelle Effors et al, 2002]

# (1) Definitions: The Move To Front transformation (MTF)

It operates on a sequence  $S$  of size  $n$ .

Algorithm:

Do

Initialize  $Y$  a list that contains all the symbol in the alphabet

For  $j = 0, \dots, n-1$

$S_{MTF}[j] = \#$  symbols preceding symbol  $S[j]$  in  $Y$

Move symbol  $S[j]$  to the front of  $Y$

End For

End Do

The output is a vector of  $n$  integers  $S_{MTF}$ .

Complexity:  $O(n*k)$ , where  $k$  is the alphabet size

# (1) Definitions: The MTF

(0) example:  $S = \text{'LOaLOagb'}$ ,  $X = \{a, b, g, L, O\}$

$S_{\text{MTF}} = \text{'3 4 2 2 2 2 4 4'}$

Y (List to update)	$S_{\text{MTF}}$ (Output)
[a b g L O]	'3'
[L a b g O]	'3 4'
[O L a b g]	'3 4 2 '
[a O L b g]	'3 4 2 2'
[L a O b g]	'3 4 2 2 2 '
[O L a b g]	'3 4 2 2 2 2'
[a O L b g]	'3 4 2 2 2 2 4'
[g a O L b]	'3 4 2 2 2 2 4 4'

## (2) Definitions: Tree sources

Consider:

- ❖ A finite ordered alphabet  $C$  of size  $|C|$
- ❖ Length- $N$  input sequences  $x = x_1, \dots, x_N$
- ❖  $X^*$  the set of finite-length sequences over  $X$
  
- A tree source is a finite set of sequences called states  $S \subset X^*$  that is complete and proper and a set of conditional probabilities  $p(\alpha/S)$  for each state  $s \in S$  and each symbol  $\alpha \in X$
- A sequence of symbols  $x_{i-1}, \dots, x_{i-L}$  that uniquely determine the current state  $s$  are called the context and  $L$  is the context depth for state  $s$ .

Let  $D = \max_{s \in S} |S|$ ,  $D$  is the maximum context depth.

(Example on the blackboard)



# (o) Universal source coding

## (o) Model estimation

Goal: Find a most efficient piecewise i.i.d. to attain the Merhav bound.

Idea: Model the source tree structure and estimate its state probability by processing the BWT output sequence. [Dror B., Yoram B., 2004]

The cost model: The source statistics model  $M$  is given by the number of segments  $S'$ , the distinct transition points and the model segment distributions  $\{Q_j(a) : j = 1, \dots, S', a \in A\}$ . The cost of a model  $M$  to represent  $X_{\text{BWT}}$ :

$$C(X_{\text{BWT}}, M) = S' \cdot (\log k + (q-1) \cdot b) + \sum_j \sum_a (N_j(a) \log(1/Q_j(a))),$$

Where  $j = 1, \dots, S'$  and  $a \in A$

# (o) Universal source coding

## (1) Model estimation

### Algorithm:

Depth- $d_{\max}$  segments are arranged as leaves of a  $q$ -ary tree where the root is the whole sequence (segment at depth 0), and for  $0 < d < d_{\max}$ , the segment with Context  $S_{d_{\max}} = (S_d, \dots, S_1)$  has at most  $q$  children segments with contexts  $(a, S_d)$

Input: The output of the BWT transform  $X_{\text{BWT}}$

Output. Estimation of piecewise i.i.d. (segmentation)

Do

Associate to each depth  $d_{\max}$  segment its cost

Partition  $X_{\text{BWT}}$  into segments of symbols with common context for a certain maximum depth  $d_{\max}$

For  $d = d_{\max} - 1$  to  $d = 0$ ,

Compute the cost associate to the segment  $S_d$  by taking the minimum of the cost of representing its children segments and the cost of representing him directly

End For

End Do

## (o) Linear channel codes in data compression

The Shannon-MacMillan theorem: For memoryless sources, there exist fixed length n-to-m compression codes of any rate  $m/n$  exceeding the entropy rate  $(H(S) + d)$  with vanishing block error probability as the blocklength goes to infinity  
[Shannon, 1948]

Fact: Generalization of the theorem for general sources.

Problems of almost-noiseless fixed-length data compression and almost noiseless coding of an additive-noise discrete channel whose noise has the same statistics as the source are identical.

[G. Caire et al., 2004]

# (o) Fountain codes: LT codes

[M. Luby, 2002]

Definition: Fountain code ensemble with parameters  $(l, \Omega)$  is a map  $F_2(k) \rightarrow F_2(N)$  represented by an  $\infty * l$  matrix where rows are chosen independently with identical distribution  $\Omega$ . The symbols produced by a Fountain code are called output symbols, and the  $l$  symbols from which these output symbols are calculated are called input symbols

Encoding process: To generate an encoding symbol, randomly choose a degree  $v$  from distribution  $\Omega$ . Choose uniformly at random  $v$  input symbols as neighbors of the encoding symbol. The value of the encoding symbol is the exclusive-or of the  $v$  neighbors.

Decoding process: Belief propagation algorithm

Extension: Raptor code [A. Shokrollahi, 2003]

# (o) Belief propagation(BP) algorithm

With  $m_{o,i}$  and  $m_{i,o}$  messages sent from output symbols to their adjacent input symbols and the message sent from input symbols to their adjacent output symbols. At round 0 of the BP algorithm, the input nodes send to all their adjacent output nodes the value 0.

Algorithm:

Do

$$T = \tanh(W/2) \prod_{i' \neq i} \tanh(m_{i'o} (r))$$

$$m_{o,i} (r) = \ln \left( \frac{1+T}{1-tT} \right)$$

$$m_{i,o} (r + 1) = \sum_{o' \neq o} m_{o',i} (r)$$

$$\text{Reliability of each input node: } R = \sum_o m_{oi} (r)$$

Take a decision to stop or to continue

While (error)

Where  $W$  is the initial log-likelihood ratio at output

# **(o) Closed loop iterative doping (CLID) algorithm [G. Caire et al., 2004]**

During the BP-algorithm, the input symbol with the smallest reliability is marked and its log-likelihood is set to  $+\infty$  or  $-\infty$  depending on whether its value is 0 or 1

Do

Every  $d$  iterations

Reliability sorting

Least-reliable symbol doping

End of Do

The BP will converge after  $d \cdot n$  iterations !

# (1) Closed loop iterative doping (CLID) algorithm

## Qualities properties:

- ❖ The position of doped symbols need not be explicitly communicated to the decoder
- ❖ The algorithm never dopes twice the same symbol
- ❖ The algorithm stops in at most  $d \cdot n$  iterations
- ❖ Good strategy to enforce the convergence of the BP

Bad encoding it self!: The longer the number of required doped bits, and the higher the resilience against channel error and /or erasures

# (o) Universal source coding

## (o) Coding

The first approach: LT

Compressor: LT encoder, LT-decoder (BP )

Decompressor: LT-decoder incorporating the statistics of the source (BP)

The second approach: LT-CLID

Compressor: LT-encoder, LT-decoder (BP and CLID algorithms).

Decompressor: LT-decoder incorporating the statistics of the source ( (BP and CLID algorithms)



# (1) Universal source coding: binary case

## (1) Coding

- ❑ The third approach: Two-stage LT-codes

Compressor: The input here is an original  $k$ -data vector  $X$

- Block sorting of sequence  $X$
- Move To Front transform to  $X$ :  $X_{\text{BWT}}$
- Modeling ( $X, X_{\text{BWT}}$ ): estimate marginal probabilities on each segment and empirical entropy  $H(S)$ . Output is  $X_M$
- An intermediate block  $Y$  of length  $k$  is calculated from  $X_M$
- A vector  $Z$  of  $m$  symbols is generated from  $Y$  through encoding with an LT code with parameters  $(k, W)$ . A bipartite graph is set up between  $X_M, Y$  and  $Z$
- The BP algorithm is applied to the graph created in the previous step
- The CLID algorithm is applied during the BP algorithm: A vector  $W$  of  $d$  symbols is generated

The output of the compressor is the sequence  $ZW$

The choice of  $\Omega$  is crucial;  $m = k (H(S) + \Delta)$

# (2) Universal source coding

## (2) Coding

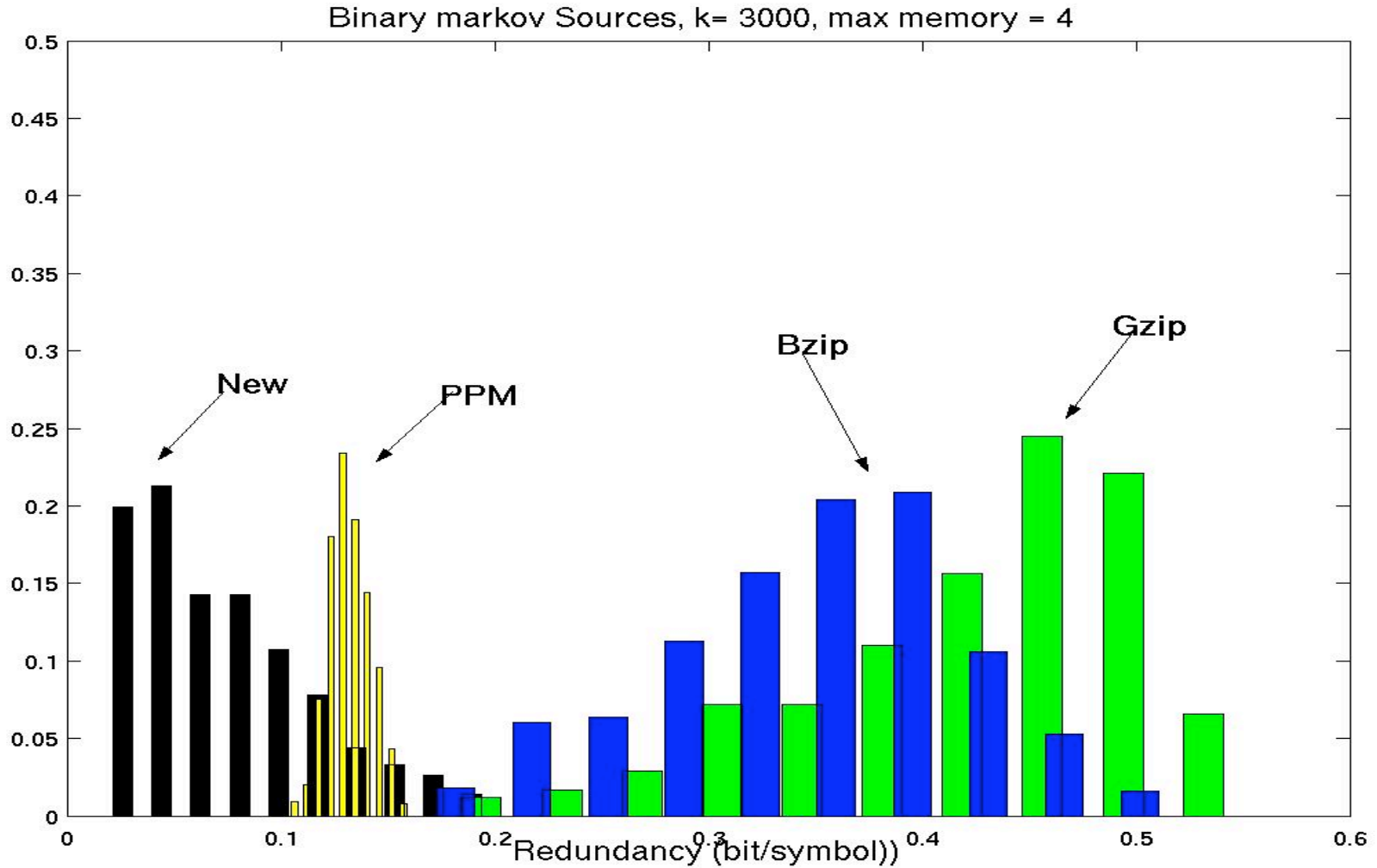
- ❑ The third approach: Two-stage LT-codes

Decompressor: The input here is the compressed sequence  $C = ZW$ , the seed for generating the transformation from  $X_M$   $Y$ , the seed for LT-encoder from  $Y$  to  $Z$ , the segmentation transitions points, the segments distribution, a flag to indicate if the MTF has been done after BWT

- From  $Z$  and  $W$ , the sequence of intermediate bits  $Y$  is reconstructed using a mirror image of the BP and CLID used at the compressor
- Applying the transformation inverse of generating intermediate symbols used at the compressor
- An inverse block sorting followed or not by the MTF transform recover the original data sequence

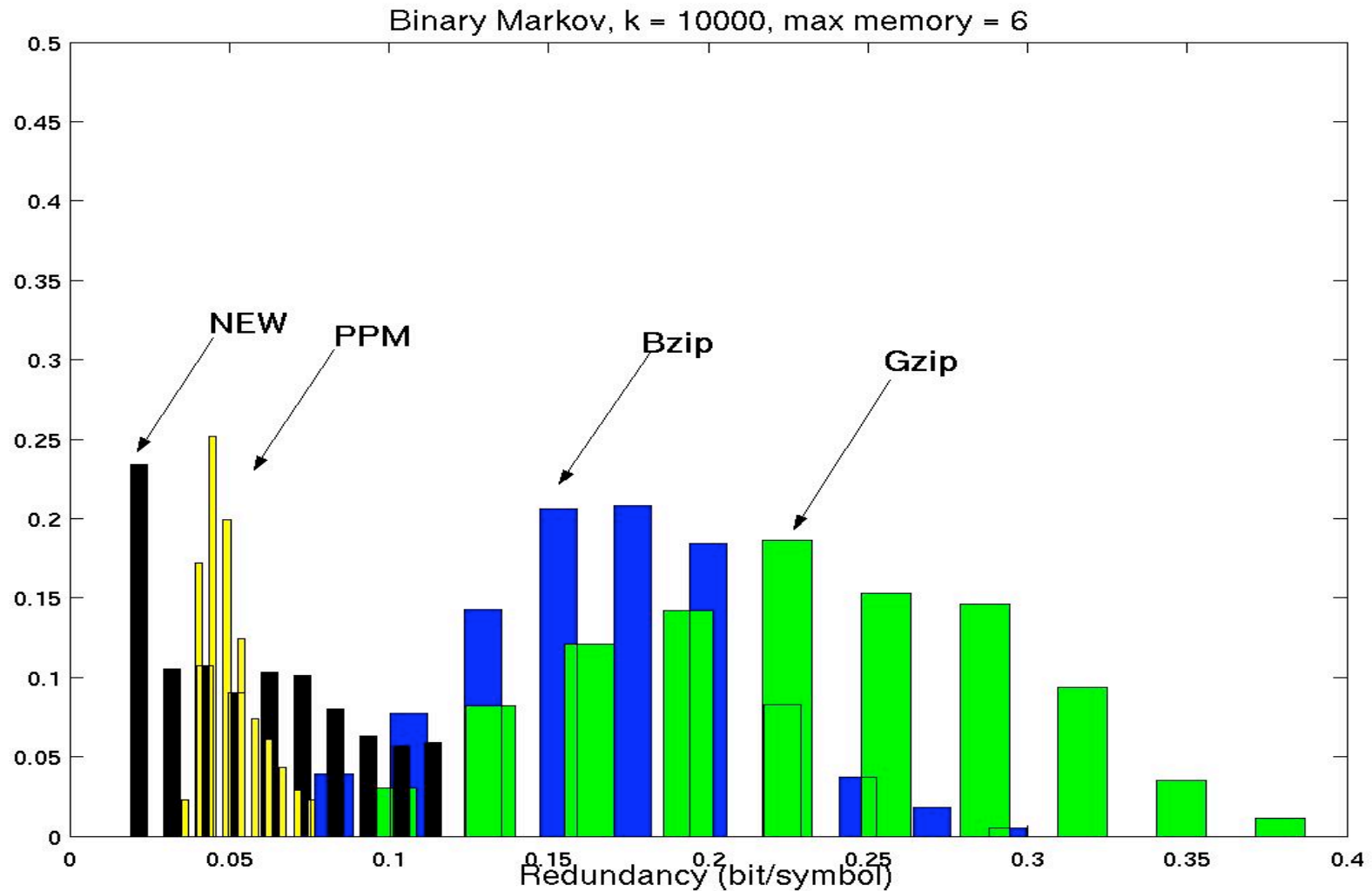
# (3) Universal source coding: binary case

## (o) Experiments



# (4) Universal source coding: binary case

## (1) Experiments



# (5) Universal source coding

## (o) Model estimation

[H. cai et al., 2004]

□ Approaches: Uniform segmentation and adaptive segmentation

➤ Uniform segmentation: Partition the BWT output so that each segment contains an equal number of symbols  $w(n)$  from the sequence according to which we are segmenting. Taking  $w(n)$  to grow as  $\sqrt{n}$  is a balanced choice.

Theorem: For a sequence of length  $n$  generated from a stationary ergodic source, the entropy estimator using uniform segmentation with segment length  $W(n) = c \cdot n^x$  ( $0 < x < 1$ ) converges to the entropy rate with probability one.

➤ Adaptive segmentation: uses a two-level hierarchical scheme to first obtain rough estimates for transition locations, followed by a second pass that refines the locations of the estimates

## (6) Universal source coding (non Binary alphabets)

### (O) Multilevel coding

[G. Caire et al. , 2004]

We suppose that an alphabet  $A$  is of cardinality  $2^L$  and  $X$  a i.i.d. source with distribution  $P_X$

Let  $f: A \rightarrow GF(2)^L$  such that  $f(x) = (b_1, \dots, b_L)$  is the binary label corresponding to  $x$ .

The mapping  $f$  and the source probability  $P_X$  induce a probability assignment

$P_{B_1, \dots, B_L}(f(x)) = P_X(x)$ , where without loss of generality,  $B_1, \dots, B_L$  are random variables in the natural order  $l = 1, \dots, L$

The conditional probability of  $B_l = 1$  given  $(B_1, \dots, B_L) = (b_1, \dots, b_L)$  is given by

$$P_l(b_1, \dots, b_{l-1}) = P(b_l(X) = 1 / b_1(X) = b_1, \dots, b_{l-1}(X) = b_{l-1}) \\ = (\sum_{x \in R} P_X(x)) / (\sum_{x \in S} P_X(x))$$

with  $R = \{x \in A : b_1(x) = b_1, \dots, b_{l-1}(x) = b_{l-1}, b_l(x) = 1\}$ , and

$S = \{x \in A : b_1(x) = b_1, \dots, b_{l-1}(x) = b_{l-1}\}$ ,

The entropy is  $H(X) = \sum_{l=1, \dots, l=L} H(b_l(X) / b_1(X), \dots, b_{l-1}(X))$

$$= \sum_{l=1, \dots, l=L} \sum_{x \in S} P_X(x) h(P_l(b_1, \dots, b_{l-1}))$$

With  $h(p) = -p \log(p) - (1-p) \log(1-p)$

# (7) Universal source coding (non Binary alphabets)

## (1) Multilevel coding

### Examples:

➤  $L = 1, A = \{0, 1\}, X = "01101011011", P_X(0) = 4/11, P_X(1) = 7/11$

$$P_1(b_0) = P(b_1(X) = 1) = 7/11$$

$$H(X) = P_X(0) h(P_1(b_0)) + P_X(1) h(P_1(b_0)) = h(P_1(b_0)) = h(7/11)$$

➤  $L = 2, A = \{0, 1, 2, 3\}, X = "3102230121", f(X):$   $b_0 = 1100010100$

$$b_1 = 1001110011$$

$$P_X(0) = 0.2, P_X(1) = 0.3, P_X(2) = 0.3, P_X(3) = 0.2$$

$$P_1(b_0) = P(b_1(X) = 1) = 0.4,$$

$$P(b_2(X) = 1 / b_1(X) = 0) = 4/6, P(b_2(X) = 1 / b_1(X) = 1) = 2/4$$

$$H(X) = H(b_0(x)) + H(b_1(x) / b_0(x))$$

$$= h(P_1(b_0)) + P_X(0) h(P(b_2(X) = 1 / b_1(X) = 0)) + P_X(1) h(P(b_2(X) = 1 / b_1(X) = 1))$$

$$+ P_X(2) h(P(b_2(X) = 1 / b_1(X) = 0)) + P_X(3) h(P(b_2(X) = 1 / b_1(X) = 1))$$

$$= h(0.4) + 0.5 h(4/6) + 0.5 h(2/4)$$

# Further work

- Optimization of the decoding part of fountain codes to improve the compression and decompression time
- Slepian-Wolf problem with Fountain codes
- Fountain codes for lossy compression



## (o) References

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