



Clever Codes

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Learning Outcomes

Unit 8: *Clever Codes*

- 1. Know the principles and performance characteristics of *arithmetic coding*.
- **2.** Judge the use of arithmetic coding in applications.
- **3.** Understand the context of *error-prone communication*.
- **4.** Understand concepts of *error-detecting codes* and *error-correcting codes*.
- **5.** Know and understand *Hamming codes*, in particular (7,4) Hamming code.
- **6.** Reason about the *suitability of a code* for an application.

Outline

8 Clever Codes

- 8.1 Arithmetic Coding
- 8.2 Practical Arithmetic Coding
- 8.3 Error Correcting Codes
- 8.4 Coding Theory
- 8.5 Hamming Codes

8.1 Arithmetic Coding

Stream Codes

- ▶ **Recall:** (binary) character encoding $E: \Sigma \to \{0,1\}^*$
 - ► Huffman codes *optimal* for any given character frequencies
 - → encoding all characters with that code *minimizes* compressed size
 - ... *if we assume* that all characters must be encoded individually by a codeword!
- ► Stream codes instead compress entire **sequence** of characters
 - ▶ RLE and LZW are examples of stream codes → can sometimes do better
- Two indicative examples
 - **1.** "Low entropy bits:" $\Sigma = \{0, 1\}$, highly skewed: $p_0 = 0.99$
 - → entropy $\mathcal{H}(\frac{1}{100}, \frac{99}{100}) \approx 0.08$ bits per character, Huffman code must use 1 bit per character!
 - "optimal" Huffman code gives 12-fold space increase over entropy!
 - Can certainly do better here (RLE!)
 - **2.** "Trits": $\Sigma = \{0, 1, 2\}$, equally likely
 - \rightarrow entropy $\mathcal{H}(\frac{1}{3},\frac{1}{3},\frac{1}{3}) = \lg(3) \approx 1.58$ bits per character, Huffman code uses average of $\frac{1}{3} \cdot 1 + \frac{2}{3} \cdot 2 = \frac{5}{3} \approx 1.67$
- Can we do better?

A Decent Hack: Block Codes

- ► Huffman on trits wastes ≈ 0.0817 bits per character and over 5 % of space
- ► A simple trick can reduce this substantially!
 - ▶ treat 5 trits as one "supercharacter", e.g., 21101
 - \rightarrow 3⁵ = 243 possible combinations
 - \rightarrow encode these using 8 bits (with $2^8 = 256$ possible combinations)
 - entropy $lg(3^5) \approx 7.92$ bits, so less than 0.1 % wasted space!
- ▶ We can even use a Huffman code for the supercharacters to handle nonuniformity!
- ► For the low-entropy bits, could use 3 bits
 - → probabilities:

```
000: 0.97
```

001, 010, 100 : 0.0098 011, 101, 110 : 0.000099

111: 0.000001

- with Huffman code, 1.06 bits per superchar of 3 input bits
- → almost factor 3 better; can improve with larger blocks!

Block Codes - A Panacea?

Using supercharacters works well in our examples.



Hmmm . . . so why don't we treat the entire source text as one large block? Wouldn't that be even better!?

- \leadsto We can optimally compress any text, without doing anything intelligent!?
- **7** For general case, need to *communicate* the supercharacter encoding
 - ► Blocks of *k* characters need $Ω(σ^k)$ space for code
 - Huffman code has to be part of coded message
 - \leadsto Can only sensibly use block codes for small σ and k



There is no such thing as a free lunch . . .

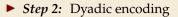
Arithmetic Coding

except in isolated lucky cases

- ▶ Also: Block codes still had $\Theta(n)$ wasted space for sequences of n symbols
- ► Arithmetic Coding:
 - **0.** Maintain $[\ell, \ell + p) \subseteq [0, 1)$; initially $\ell = 0, p = 1$
 - 1. Zoom into subinterval for each character
 - 2. Output dyadic encoding of final interval
- ► *Step 1:* "Zoom" for each character (trit) in S[0..n):
 - Of the current subinterval $[\ell, \ell + p)$, take first, second or last third depending whether S[i] = 0, 1, resp. 2: $\ell := \ell + S[i] \cdot \frac{1}{2} \cdot n$

$$\ell := \ell + S[i] \cdot \frac{1}{3} \cdot p$$

$$p := p \cdot \frac{1}{3}$$



- ► Find smallest m so that $\exists x \in \mathbb{N}_0$ with $\left[\frac{x}{2^m}, \frac{x+1}{2^m}\right] \subseteq [\ell, \ell+p)$
- ightharpoonup Output x in binary using m bits.
- \rightarrow Encode *n* trits in $n \lg(3) + 2 \text{ bits(!)}$ without cheating

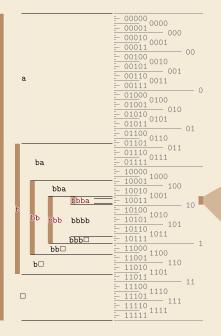
Arithmetic Coding – Encode Trits Example

- \triangleright S[0..n) = 21101 (n = 5)
- ► **Step 1:** Zoom into subintervals

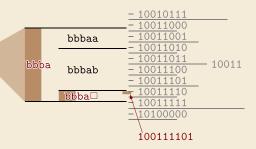
Iteration	ℓ	p	Interval (rounded)	
0	0	1	[0.00000, 1.00000)	
1	$\frac{2}{3}$	$\frac{1}{3}$	[0.66667, 1.00000)	
2	<u>7</u>	$\frac{1}{9}$	[0.77778, 0.88889)	⊢
3	<u>22</u> 27	$\frac{1}{27}$	[0.81482, 0.85185)	Н
4	66 81	$\frac{1}{81}$	[0.81482, 0.82716)	Н
5	199 243	$\frac{1}{243}$	[0.81893, 0.82305)	

- ► **Step 2:** Dyadic encoding for interval $[\ell, \ell + p) = \left[\frac{199}{243}, \frac{200}{243}\right]$
 - ► Must have $m \ge \lg(1/p) > 7$
 - ► m = 8: smallest $x/2^m \ge \frac{199}{243}$ is x = 210, but $[210/256, 211/256) \approx [0.82031, 0.82422)$ \checkmark $[\ell, \ell + p)$
 - ► m = 9: smallest $x/2^m \ge \frac{199}{243}$ is x = 420 and $[420/512, 421/512) \approx [0.82031, 0.82227) \subset [\ell, \ell + p)$
 - \rightarrow Output x = 420 in binary with m = 9 digits: 110100100

Versatility of Arithmetic Coding – Adaptive Model



Context (sequence thus far)	Probability of next symbol				
	P(a) = 0.425	P(b) = 0.425	$P(\Box) = 0.15$		
b	P(a b) = 0.28	P(b b) = 0.57	$P(\Box \mathbf{b}) = 0.15$		
bb	P(a bb) = 0.21	P(b bb) = 0.64	$P(\Box \mathrm{bb}){=}0.15$		
bbb	$P(\mathtt{a} \mathtt{bbb}){=}0.17$	$P(\mathbf{b} \mathbf{bbb}){=}0.68$	$P(\Box \mathtt{bbb}){=}0.15$		
bbba	$P(\mathtt{a} \mathtt{bbba}){=}0.28$	$P(\mathbf{b} \mathbf{bbba}){=}0.57$	$P(\Box \mathtt{bbba}){=}0.15$		



adapted from Figure 6.4 of MacKay: Information Theory, Inference, and Learning Algorithms 2003

Arithmetic Coding – General framework

- ▶ Note: Arithmetic coder *doesn't care* if probabilities or even σ change all the time!
 - As long as encoder and decoder know from context what they are!

General stochastic sequence:

Sequence of random variables X_0, X_1, X_2, \dots such that

- 1. $X_i \in [0..U_i) \cup \{\$\}$ (We use \$ to signal "end of text")
- **2.** $\mathbb{P}[X_i = j] = P_{ij}$
- **3.** both U_i and P_{ij} are random variables as they *depend* on X_0, \ldots, X_{i-1} , but conditioned on X_0, \ldots, X_{i-1} , they are fixed and known: $P_{ij} = P_{ij}(X_0, \ldots, X_{i-1}) = \mathbb{P}[X_i = j \mid X_0, \ldots, X_{i-1}]$

$$P_{ij} = P_{ij}(X_0, ..., X_{i-1}) = \mathbb{P}[X_i = j \mid X_0, ..., X_{i-1}]$$

 $U_i = U_i(X_0, ..., X_{i-1}) = \max\{j : P_{ij}(X_0, ..., X_{i-1}) > 0\}$

- ► Can model arbitrary dependencies on previous outcomes
- Assume here that random process is known by both encoder and decoder (fixed coding) otherwise extra space needed to encode model!

Arithmetic Coding – Encoding

```
procedure arithmeticEncode(X_0, \ldots, X_n):
        // Assume model U_i and P_{ij} are fixed.
       // Assume X_i \in [0..U_i) for i < n and X_n = $
3
      // Step 1: Interval zooming
   \ell := 0; \ p := 1
     for i := 0, ..., n-1 do
            q := \sum_{i=0}^{K_l} P_{ij};
             \ell := \ell + q \cdot p; \quad p := p \cdot P_{i,X_i}
        end for
        q := 1 - P_{n,\$} // encode $ as last character
10
       \ell := \ell + q \cdot p; \quad p := p \cdot P_{n,\$}
11
       // Step 2: Dyadic encoding
12
        m := \lceil \lg(1/p) \rceil - 1
13
        do
14
             m := m + 1; \quad x := \lceil \ell \cdot 2^m \rceil
15
        while (x + 1)/2^m > \ell + p
16
        return x in binary using m bits
17
```

Arithmetic Coding – Decoding

```
1 procedure arithmeticDecode(C[0..m)):
       // Assume model U_i and P_{ij} are fixed.
       //C[0..m) bit string produced by arithmeticEncode
       x = \sum_{i=0}^{m-1} C[i] \cdot 2^{m-1-i} // final interval [x/2^m, (x+1)/2^m)
      \ell := 0; p := 1; i := 0
       while true
            c := 0; q := 0 // Decode next character c
7
            while \ell + q \cdot p < x/2^m // Iterate through characters until final interval
                 if c == U_i + 1 // reached $
                     X[i] := $
10
                      return X[0..i]
11
                 else
12
                      q := q + P_{i,c}; c := c + 1
13
            end while
14
            c := c - 1; q := q - P_{i,c} // we overshot by 1
15
           X[i] := c
16
            \ell := \ell + q \cdot p; \quad p := p \cdot P_{i,c}
17
            i := i + 1
18
       end for
19
```

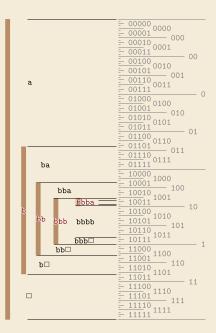
8.2 Practical Arithmetic Coding

Arithmetic Coding – Numerics

- ► As implemented above, *p* usually gets smaller by a constant factor with *each character*
 - \rightarrow *p* gets exponentially small in *n*!
 - ▶ ℓ does not get smaller in absolute terms, but we need it to ever higher accuracy
- \rightsquigarrow requires $\Omega(n)$ bit precision and exact arithmetic!
- ▶ With a clever trick, this can be avoided!
 - ▶ If $[\ell, \ell + p) \subseteq [0, \frac{1}{2})$, we know:
 - ▶ Our final x with $\left[\frac{x}{2^m}, \frac{x+1}{2^m}\right] \subseteq [\ell, \ell+p)$ must start with a 0-bit!
 - Output a 0 and renormalize interval: $\ell := 2\ell$; p := 2p
 - ► If $[\ell, \ell + p) \subseteq [\frac{1}{2}, 1)$, similarly:
 - ▶ Output 1 and renormalize:

$$\ell := \ell - \frac{1}{2}$$

$$\ell := 2\ell; \ p := 2p$$



Arithmetic Coding – Renormalization

Does this guarantee ℓ and p stay in a reasonable range?

► No! Consider (uniform) trits in {0, 1, 2} again and encode 11111111111111111...

$$\Rightarrow p = (\frac{1}{3})^n, \quad \ell = \frac{1}{3} + \frac{1}{9} + \frac{1}{27} + \dots = \sum_{i=1}^n 3^{-i} = \frac{1}{2} - \frac{3^{-n}}{2}$$

 $\Rightarrow \ell < \frac{1}{2} \text{ and } \ell + p > \frac{1}{2} \Rightarrow \text{ next bit unknown as of yet}$

But: If $[\ell, \ell + p) \subseteq [\frac{1}{4}, \frac{3}{4})$, next **two** bits are either 01 or 10

- ► Remember an "outstanding opposite bit" (increment counter)
- ► Renormalize:

$$\begin{array}{l} \ell := \ell - \frac{1}{4} \\ \ell := 2\ell; \ p := 2p \end{array}$$

- \rightsquigarrow ℓ and p remain in range of P_{ij}
- \rightarrow round P_{ij} to integer multiple of 2^{-F} \rightarrow fixed-precision arithmetic

		_
- 00000 - 00001		
- 00001		
= 00000 = 00001 = 00010		
- 00001 000 - 00010 0001	~ ~	
= 00100	00	
= 00101 0010		
00110 001		
= 00111 0011		_
- 01000		O
- 00011 0001 - 00100 0010 - 00110 0011 - 00111 0011 - 01000 - 01001 0100 - 01010 0100		
01010 0101		
= 01011		
= 01100	01	
= 01100 0110		
= 01101 = 01110 011		
01111 0111		
= 10000		_
= 10001 1000		
10010		
= 10011 1001		
= 10101	10	
10101 1010		
10110		
- 01100 0110 - 01101 0111 - 01110 0111 - 01111 0111 - 10001 1000 - 10001 1000 - 10010 1001 - 10100 1010 - 10100 1010 - 10110 1010 - 10110 1011		
= 11000		1
= 11000 = 11001 1100		
= 11010		
= 11010 = 11011 1101		
	11	
= 11100 1110		
111111 11111		

Fixed Precision Arithmetic Encode

Detailed code from Moffat, Neal, Witten, Arithmetic Coding Revisited, ACM Trans. Inf. Sys. 1998

Note: *L* is our ℓ , *R* is our p, $b \le w$ is #bits for variables

$arithmetic_encode(l, h, t)$

/* Arithmetically encode the range [l/t,h/t) using low-precision arithmetic. The state variables R and L are modified to reflect the new range, and then renormalized to restore the initial and final invariants $2^{b-2} < R \le 2^{b-1}$, $0 < L < 2^b - 2^{b-2}$, and $L + R < 2^b$ */

- (1) Set $r \leftarrow R \text{ div } t$
- (2) Set $L \leftarrow L + r$ times l
- (3) If h < t then set $R \leftarrow r$ times (h l) else

set
$$R \leftarrow R - r$$
 times l

(4) While $R < 2^{b-2}$ do

Use Algorithm ENCODER RENORMALIZATION (Figure 7) to renormalize R, adjust L, and output one bit

Fixed Precision Renormalize

In arithmetic_encode()

```
/* Reestablish the invariant on R, namely that 2^{b-2} < R < 2^{b-1}. Each doubling
    of R corresponds to the output of one bit, either of known value, or of value
    opposite to the value of the next bit actually output */
(4) While R < 2^{b-2} do
         If L+R < 2^{b-1} then
              bit_plus_follow(0)
         else if 2^{b-1} < L then
              bit_plus_follow(1)
              Set L \leftarrow L - 2^{b-1}
         else
              Set bits_outstanding \leftarrow bits_outstanding + 1 and L \leftarrow L - 2^{b-2}
         Set L \leftarrow 2L and R \leftarrow 2R
bit_plus_follow(x)
    /* Write the bit x (value 0 or 1) to the output bit stream, plus any outstanding
    following bits, which are known to be of opposite polarity */
(1) write\_one\_bit(x).
(2) While bits\_outstanding > 0 do
         write\_one\_bit(1-x)
         Set bits\_outstanding \leftarrow bits\_outstanding - 1
```

Fixed Precision Arithmetic Decode

Functions *decode_target* and *arithmetic_decode* to be called alternatingly.

$decode_target(t)$

/* Returns an integer target, $0 \le target < t$ that is guaranteed to lie in the range [l,h) that was used at the corresponding call to $arithmetic_encode()$ */

- (1) Set $r \leftarrow R$ div t
- (2) Return $(\min\{t-1, D \text{ div } r\})$

$arithmetic_decode(l, h, t)$

/* Adjusts the decoder's state variables R and D to reflect the changes made in the encoder during the corresponding call to $arithmetic_encode()$. Note that, compared with Algorithm CACM CODER (Figure 6), the transformation D = V - L is used. It is also assumed that r has been set by a prior call to $decode_target()$ */

- (1) Set $D \leftarrow D r$ times l
- (2) If h < t then

set
$$R \leftarrow r$$
 times $(h - l)$

else

set
$$R \leftarrow R - r$$
 times l

(3) While $R \le 2^{b-2}$ do Set $R \leftarrow 2R$ and $D \leftarrow 2D + read_one_bit()$

Arithmetic Coding Discussion

- Subtle code (→ libraries!)
- Typically slower to encode/decode than Huffman codes
- Encoded bits can be produced/consumed in bursts
- Extremely versatile w. r. t. random process
- Almost optimal space usage / compression
- Widely used (instead of Huffman) in JPEG, zip variants, ...

8.3 Error Correcting Codes

Noisy Communication

- most forms of communication are "noisy"
 - humans: acoustic noise, unclear pronunciation, misunderstanding, foreign languages
- ► How do humans cope with that?
 - ▶ slow down and/or speak up
 - ask to repeat if necessary



► But how is it possible (for us) to decode a message in the presence of noise & errors?

Because it semes taht nearrul lanaguge has a lots fo **redundancy** bilt itno it!

- → We can
- **1. detect errors** "This sentence has aao pi dgsdho gioasghds."
- **2. correct** (some) **errors** "Tiny errs ar corrrected automaticly." (sometimes too eagerly as in the Chinese Whispers / Telephone)



Noisy Channels

- computers: copper cables & electromagnetic interference
- transmit a binary string
- ▶ but occasionally bits can "flip"
- → want a robust code



- ▶ We can aim at
 - 1. error detection
- → can request a re-transmit
- 2. error correction
- → avoid re-transmit for common types of errors
- ▶ This will require *redundancy*: sending *more* bits than plain message
 - → goal: robust code with lowest redundancy

that's the opposite of compression!

8.4 Coding Theory

Block codes

- ▶ model:
 - ▶ want to send message $S \in \{0, 1\}^*$ (bitstream) across a (communication) channel
 - ▶ any bit transmitted through the channel might *flip* $(0 \rightarrow 1 \text{ resp. } 1 \rightarrow 0)$ **no other errors** occur (no bits lost, duplicated, inserted, etc.)
 - ▶ instead of *S*, we send *encoded bitstream* $C \in \{0, 1\}^*$ sender *encodes S* to *C*, receiver *decodes C* to *S* (hopefully)
 - → what errors can be detected and/or corrected?
- ▶ all codes discussed here are *block codes*
 - ▶ divide *S* into *messages* $m \in \{0, 1\}^k$ of *k* bits each $(k = message \ length)$
 - ▶ encode each message (separately) as $C(m) \in \{0,1\}^n$ $(n = block \ length, \ n \ge k)$
 - → can analyze everything block-wise
- ▶ between 0 and n bits might be flipped invalid code
 - how many flipped bits can we definitely detect?
 - how many flipped bits can we correct without retransmit?

i. e. decoding *m* still possible

Code distance

$$m \neq m' \implies C(m) \neq C(m')$$

- each block code is an *injective* function $C: \{0,1\}^k \to \{0,1\}^n$
- ▶ define $C = \text{set of all codewords} = C(\{0, 1\}^k)$
- $\hookrightarrow \mathcal{C} \subseteq \{0,1\}^n$ $|\mathcal{C}| = 2^k \text{ out of } 2^n \text{ } n\text{-bit strings are valid codewords}$
- decoding = finding closest valid codeword
- ▶ distance of code:

 $d = \text{minimal Hamming distance of any two codewords} = \min_{x,y \in \mathcal{C}} d_H(x,y)$

Implications for codes

- **1.** Need distance d to **detect** all errors flipping up to d-1 bits.
- **2.** Need distance *d* to **correct** all errors flipping up to $\lfloor \frac{d-1}{2} \rfloor$ bits.

Lower Bounds

► Main advantage of concept of code distance: can *prove* lower bounds on block length

otherwise no such code exists

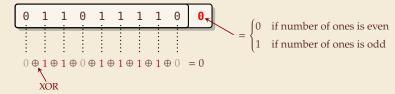
Given block length n, message length k, code distance d, we must have:

- ► Singleton bound: $2^k \le 2^{n-(d-1)} \rightsquigarrow n \ge k+d-1$
 - ▶ *proof sketch:* We have 2^k codeswords with distance d after deleting the first d-1 bits, all are still distinct but there are only $2^{n-(d-1)}$ such shorter bitstrings.
- ► Hamming bound: $2^k \le \frac{2^n}{\sum_{f=0}^{\lfloor (d-1)/2 \rfloor} \binom{n}{f}}$
 - ▶ proof idea: consider "balls" of bitstrings around codewords count bitstrings with Hamming-distance $\leq t = \lfloor (d-1)/2 \rfloor$ correcting t errors means all these balls are disjoint so 2^k · ball size $\leq 2^n$
- → We will come back to these.

8.5 Hamming Codes

Parity Bit

▶ simplest possible error-detecting code: add a parity bit



- ► can detect any single-bit error (actually, any odd number of flipped bits)
- ▶ used in many hardware (communication) protocols
 - PCI buses, serial buses
 - caches
 - early forms of main memory
- very simple and cheap
- cannot correct any errors

Error-correcting codes

any downtime is expensive!

- typical application: heavy-duty server RAM
 - bits can randomly flip (e.g., by cosmic rays)
 - individually very unlikely, but in always-on server with lots of RAM, it happens!

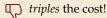
https://blogs.oracle.com/linux/attack-of-the-cosmic-rays-v2





Can we correct a bit error without knowing where it occurred? How?

- ► Yes! store every bit *three times!*
 - ▶ upon read, do majority vote
 - ▶ if only one bit flipped, the other two (correct) will still win





You want WHAT!?!

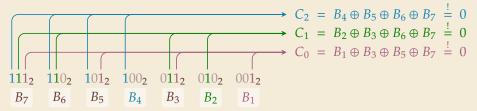


instead of 200% (!)

Can do it with 11% extra memory!

How to locate errors?

- ► **Idea**: Use several parity bits
 - each covers a subset of bits
 - ▶ clever subsets → violated/valid parity bit pattern narrows down error
 - flipped bit can be one of the parity bits!
- ▶ Consider n = 7 bits $B_1, ..., B_7$ with the following constraints:



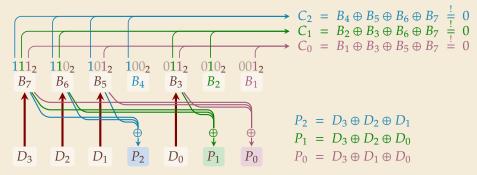
Observe:

- No error (all 7 bits correct) \rightarrow $C = C_2C_1C_0 = 000_2 = 0$
- ▶ What happens if (exactly) 1 bit, say B_i flips?

 $C_j = 1$ iff *j*th bit in binary representation of *i* is $1 \rightarrow C$ encodes **position of error!**

(7, 4) Hamming Code

► How can we turn this into a code?



- ▶ B_4 , B_2 and B_1 occur only in one constraint each \leadsto **define** them based on rest!
- ► (7,4) *Hamming Code* Encoding
 - **1. Given:** message $D_3D_2D_1D_0$ of length k=4
 - **2.** copy $D_3D_2D_1D_0$ to $B_7B_6B_5B_3$
 - **3.** compute $P_2P_1P_0 = B_4B_2B_1$ so that C = 0
 - **4.** send $D_3D_2D_1P_2D_0P_1P_0$

(7, 4) Hamming Code – Decoding

- ► (7,4) *Hamming Code* Decoding
 - **1. Given:** block $B_7B_6B_5B_4B_3B_2B_1$ of length n = 7
 - **2.** compute *C* (as above)
 - 3. if C = 0 no (detectable) error occurred otherwise, flip B_C (the Cth bit was twisted)
 - **4.** return 4-bit message $B_7B_6B_5B_3$

(7, 4) Hamming Code – Properties

- ► Hamming bound:
 - ▶ 2⁴ valid 7-bit codewords (on per message)
 - ▶ any of the 7 single-bit errors corrected towards valid codeword
 - → each codeword covers 8 of all possible 7-bit strings
- ightharpoonup distance d = 3
- ► can *correct* any 1-bit error
- ► How about 2-bit errors?
 - We can detect that something went wrong.
 - ▶ **But:** above decoder mistakes it for a (different!) 1-bit error and "corrects" that
 - ► Variant: store one additional parity bit for entire block
 - → Can *detect* any 2-bit error, but *not correct* it.

Hamming Codes – General recipe

- construction can be generalized:
 - Start with $n = 2^{\ell} 1$ bits for $\ell \in \mathbb{N}$ (we had $\ell = 3$)
 - use the ℓ bits whose index is a power of 2 as parity bits
 - ▶ the other $n \ell$ are data bits
- ► Choosing $\ell = 7$ we can encode entire word of memory (64 bit) with 11% overhead (using only 64 out of the 120 possible data bits)
- simple and efficient coding / decoding
- fairly space-efficient

Outlook

- ▶ Indeed: $(2^{\ell}-1, 2^{\ell}-\ell-1)$ Hamming Code is "perfect" code

- = matches Hamming lower bound
- ▶ if message length is $2^{\ell} \ell 1$ for $\ell \in \mathbb{N}_{\geq 2}$ i. e., one of 1, 4, 11, 26, 57, 120, 247, 502, 1013, . . .
- ▶ and we want to correct 1-bit errors
- ▶ For other scenarios, finding good codes is an active research area
 - ▶ information theory predicts that *almost all* randomly chosen codes are good(!)
 - but these are inefficient to decode
 - clever tricks and constructions needede. g. low density parity check codes