



Lecture 5, Part 1:

Stream Codes: Encoding Into Fractional Bits

Robert Bamler · Summer Term of 2023

These slides are part of the course “Data Compression With and Without Deep Probabilistic Models” taught at University of Tübingen. More course materials—including video recordings, lecture notes, and problem sets with solutions—are publicly available at <https://robamler.github.io/teaching/compress23/>.

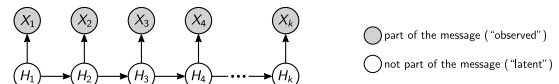
Recall: 4 Kinds of Scalable Probabilistic Models



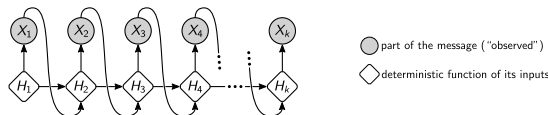
(1) Markov Process



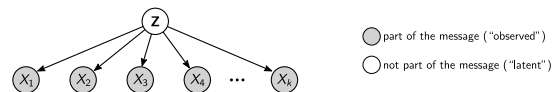
(2) Hidden Markov Model



(3) Autoregressive Model



(4) Latent Variable Model



Recall: Autoregressive Model + Huffman Coding



► **Problem 3.2:** (link to solutions in video description)

	msg. len (chars)	bits per character					
		Huffman	Shannon	inf. cont.	gzip	bzip2	bzip2'
validation set	106,864	2.38	2.72	2.12	3.43	2.82	2.40
test set	219,561	2.38	2.73	2.12	3.33	2.65	2.38
wikipedia-en	24,618	4.99	5.67	5.14	3.22	2.92	5.14
wikipedia-de	8,426	6.77	7.70	7.19	3.96	3.76	7.22

► **Observation:** Huffman coding has overhead over information content of up to 1 bit *per symbol*.

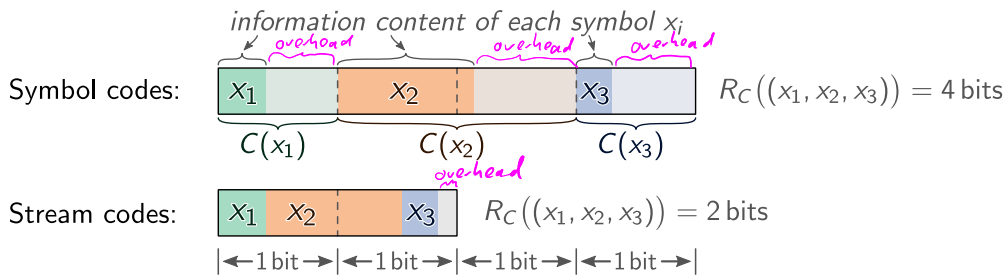
► Can be substantial in modern ML-based compression methods:

e.g., information content ≈ 0.3 bits per symbol; } \implies about 200% overhead. (\rightarrow useless)

but Huffman coding needs ≥ 1 bit per symbol.

► **Solution:** amortize compressed bits over symbols \rightarrow “stream code”

Stream Codes: Amortizing Bits Over Symbols



- ▶ **Intuitively:** stream codes “pack” information content as closely as possible.
 - ▶ We can no longer associate each bit in the compressed representation with any specific symbol.
- ▶ **2 important stream codes** with 2 different application domains:
 - ▶ **This lecture:** Arithmetic Coding & Range Coding [Pasco, 1976; Rissanen and Langdon, 1979]
 - ▶ **Next lecture:** Asymmetric Numeral Systems (ANS) [Duda et al., 2015]

Arithmetic Coding: Overview [Pasco, 1976]

- ▶ **Idea:** similar to Shannon coding, but on entire *message space* \mathfrak{X}^* instead of alphabet \mathfrak{X} .
 - ▶ **Thus:** overhead now only *per message*.
 - ▶ **Challenge:** computational efficiency

assume message of length k → we'd have to iterate over $O(|\mathfrak{X}|^k)$ messages (astronomically expensive)
- ▶ **2 variants:** Arithmetic Coding & Range Coding
 - ▶ very similar to each other (Range Coding is faster on real hardware);
 - ▶ both conceptually simple;
 - ▶ but a bit tricky in practice due to edge cases.

Reminder: Shannon Coding (for $B = 2$)

Input: alphabet \mathfrak{X} , probability measure P on \mathfrak{X}

output: prefix code $C_S : \mathfrak{X} \rightarrow \{0, 1\}^*$.

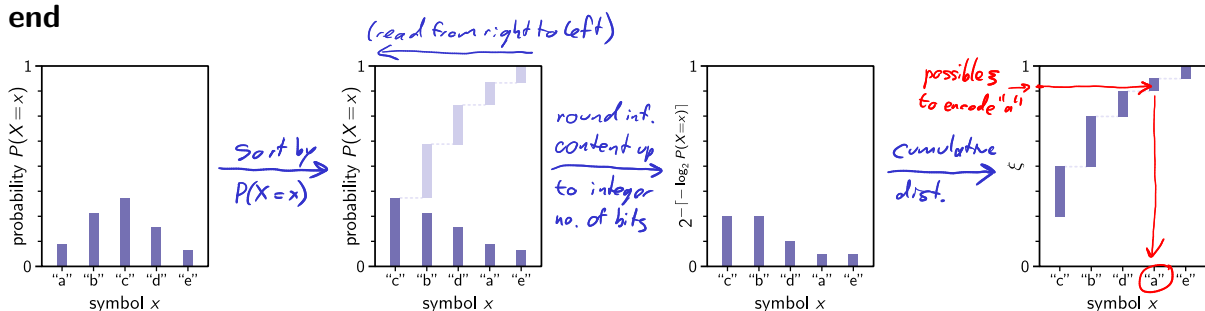
Initialize $\xi \leftarrow 1$

for $x \in \mathfrak{X}$ **in order of increasing** $P(X=x)$ **do**

 Update $\xi \leftarrow \xi - 2^{-\lceil -\log_2 P(X=x) \rceil}$

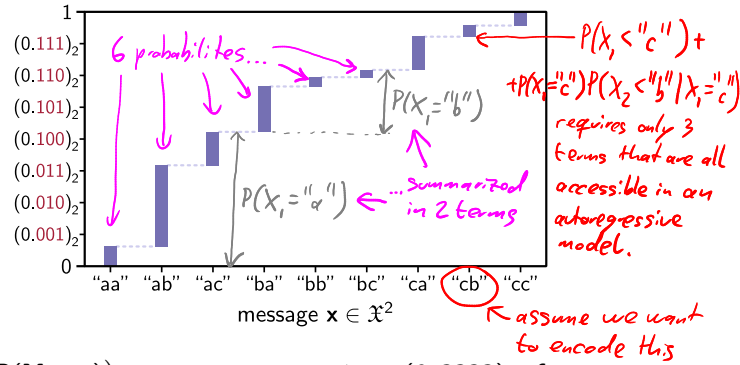
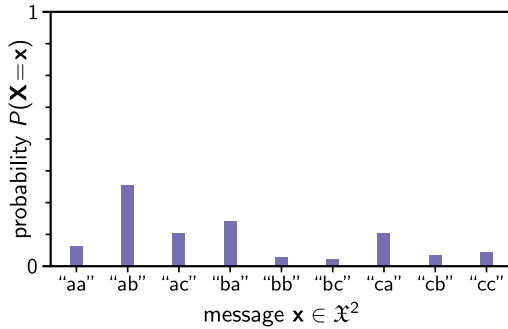
 Write out $\xi \in [0, 1)$ in binary: $\xi = (0.????\dots)_2$

end



Arithmetic Coding: General Idea

- ▶ Consider probability measure P on entire message space \mathcal{X}^k (with fixed length k , for now).



- ▶ **Observation:** $\forall x \in \mathcal{X}^k$: interval $[P(\mathbf{X} < x), P(\mathbf{X} \leq x)]$ contains a point $\xi_x = (0.????)_2$ if:

size of interval \leq spacing between numbers of form $(0.????)_2$ $\mathcal{R}(x)$ bits

$$P(\mathbf{X} \leq x) - P(\mathbf{X} < x) = P(\mathbf{X} = x) \leq (0.0001)_2 = 2^{-\mathcal{R}(x)}$$

$\mathcal{R}(x)$ bits

$$P(\mathbf{X} = x) \leq 2^{-\mathcal{R}(x)}$$

$\Leftrightarrow \mathcal{R}(x) \geq -\log_2 P(\mathbf{X} = x)$

Sufficient Condition

Arithmetic Coding: Super Naive Algorithm

- ▶ **Encoder:**

Initialize $c \leftarrow 0$ and $p \leftarrow 1$.

for i from 1 to k do

Update $c \leftarrow c + pP(X_i < x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1})$.

Update $p \leftarrow pP(X_i = x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1})$.

▶ **Claim:** at this point, we have $c = P(\mathbf{X}_{1:i} < \mathbf{x}_{1:i})$ and $p = P(\mathbf{X}_{1:i} = \mathbf{x}_{1:i})$

\Rightarrow invariant: $[c, c + p) = [P(\mathbf{X}_{1:i} < \mathbf{x}_{1:i}), P(\mathbf{X}_{1:i} \leq \mathbf{x}_{1:i})) \subseteq [0, 1)$

end

Encode some $\xi \in [c, c + p)$ in binary: $\xi = (0.?????)_2$
 $[-\log_2 p]$ bits

extra step in decoder:
 identify symbol $x_i \in \mathcal{X}$ for which
 $\xi \in [c + pP(X_i < x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1}), c + pP(X_i \leq x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1}))$

- ▶ **Decoder:** Analogous to encoder, but introduce an extra step

Caveats

- ▶ **Unique Decodability:**

- ▶ not such a big deal as it was with symbol codes

(it's unusual to concatenate entire compressed messages without delimiters);

- ▶ can be solved with 1 extra bit: guarantee that $[\xi, \xi + 2^{-\mathcal{R}(x)}) \subseteq [c, c + p)$ (rather than just $\xi \in [c, c + p)$)

- ▶ **Variable message length:**

- ▶ end of bit string $\not\leftrightarrow$ end of message (since symbols can have information content < 1 bit)

- ▶ for variable-length messages, the message length is fundamentally a part of the message

- ▶ simple solution: introduce EOF symbol (\rightarrow Problem Set 7)

- ▶ **Numerical precision:**

- ▶ e.g, if bit rate = 1 Mbit then c and p on last slide are 1-million-bit numbers

- ▶ Run-time complexity for encoding k symbols: $\Theta(k^2)$

Arithmetic Coding: Naive Algorithm

► **Encoder:**

Initialize $c \leftarrow 0$ and $p \leftarrow 1$ (fixed point numbers $\in [0, 1]$ with precision bits);

for i **from** 1 **to** k **do**

Update $c \leftarrow c + pP(X_i < x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1});$ (rounding to fixed point precision)

Update $p \leftarrow pP(X_i = x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1});$ (rounding to fixed point precision)

while $p < \frac{1}{2}$ **do**

Emit first bit of $c = (0.????)_2;$

Update $p \leftarrow 2p;$

Update $c \leftarrow$ fractional part of $2c;$

end

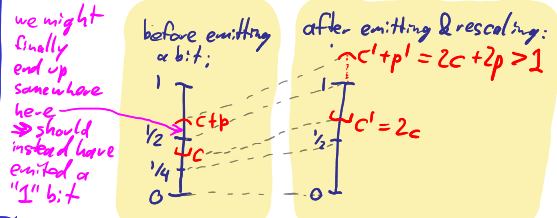
end

Emit first bit of $c = (0.????)_2;$

► **Decoder:** exercise

"rescaling"

Problem: invariant $[c, c+p) \subseteq [0, 1)$ can be violated here:



called "inverted" situation on next slide

Arithmetic Coding: Actual Algorithm

Initialize $c \leftarrow 0$ and $p \leftarrow 1$ (fixed point numbers $\in [0, 1]$ with precision bits);

Initialize $inverted \leftarrow 0$ (nonnegative integer);

for i **from** 1 **to** k **do**

Update $c \leftarrow c + pP(X_i < x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1});$

Update $p \leftarrow pP(X_i = x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1});$

while $p < \frac{1}{2}$ **do**

Emit first bit of $c = (0.????)_2;$

Update $p \leftarrow 2p;$

Set $c' \leftarrow$ fractional part of $2c;$

Update $c \leftarrow c';$

end

end

if $inverted \neq 0$:
flush (exercise)

Emit first bit of $c = (0.????)_2;$

"rescaling"

if $inverted \neq 0$ and $[c, c+p) \subseteq [0, 1)$:

► transitioning from inverted to normal situation:
emit a single "0" bit followed by $(inverted-1)$ "1" bits
update $inverted \leftarrow 0$

if $inverted \neq 0$ and $[c, c+p) \subseteq [1, 2)$

► transitioning from inverted to normal situation:
update $c \leftarrow c-1$ ($\in [0, 1)$)
emit a single "1" bit followed by $(inverted-1)$ "0" bits
update $inverted \leftarrow 0$

if $inverted \neq 0$:

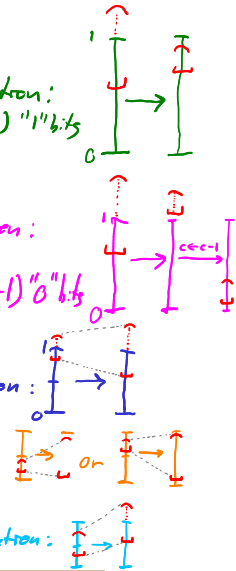
► rescaling from inverted to inverted situation:
update $inverted \leftarrow inverted+1$

if $inverted = 0$ and $[c, c+p) \subseteq [0, 1)$:

► rescaling from normal to normal situation:
emit first bit of $c = (0.????)_2$

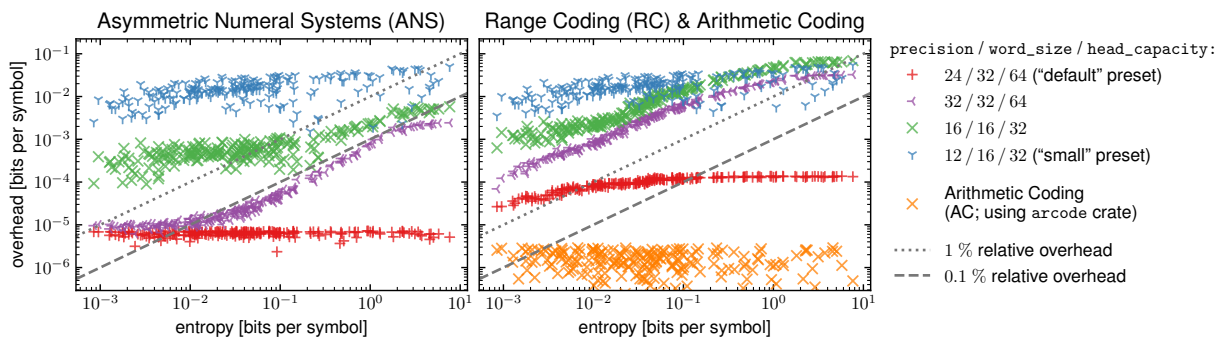
if $inverted = 0$ and $[c, c+p) \subseteq [1, 2)$:

► rescaling from normal to inverted situation:
update $inverted \leftarrow 1$

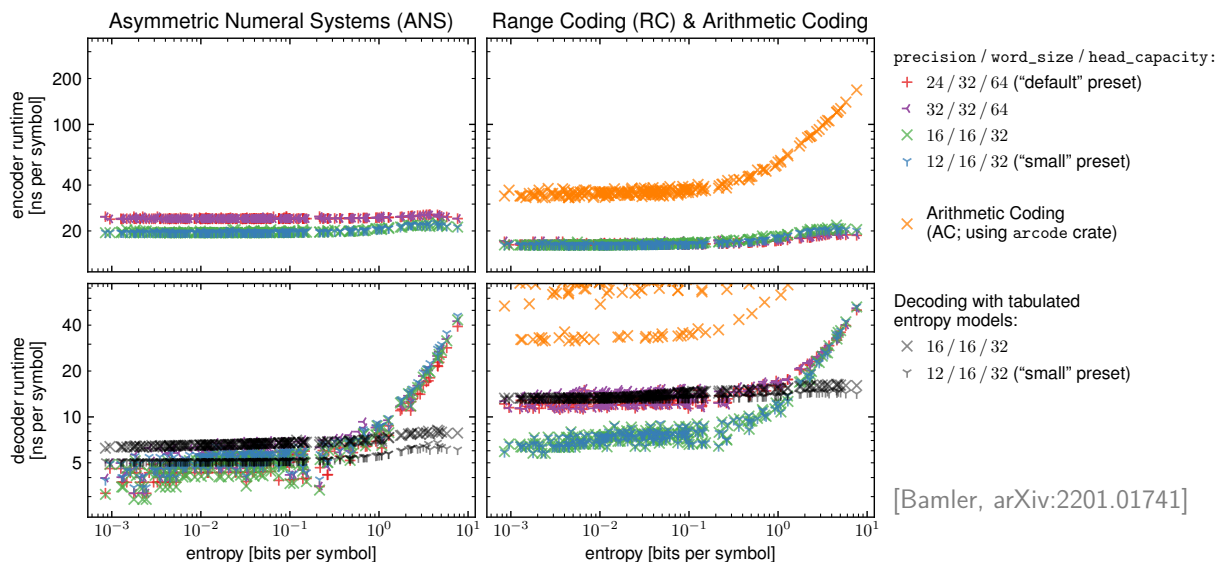


Real Hardware: Range Coding

- CPUs are not optimized to operate on single bits
- *mechanical sympathy*: to best exploit the capabilities of a tool (e.g., a computer), one has to understand how the tool works.
- **Range Coding**: like arithmetic coding, but operating on precision bits at a time
 - accumulators c and p become numbers with $2 \times$ precision bits
 - individual symbol probabilities $P(X_i = x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1}) \in (0, 1)$ are precision-bit numbers
 $\implies P(X_i = x_i | \mathbf{X}_{1:i-1} = \mathbf{x}_{1:i-1}) \geq 2^{-\text{precision}}$ (smallest representable nonzero number)
 - Emit precision bits at once when $p < 2^{-\text{precision}}$
 \implies always restores $p \geq 2^{-\text{precision}}$, thus at most 1 emission per symbol is necessary.
 - inverted keeps track of how many "00000000" or "11111111" blocks have accumulated.
 (instead of how many "0" or "1" bits have accumulated, as in our implementation of arithmetic coding on the last slide)



[Bamler, arXiv:2201.01741 (2022)]



Outlook

- ▶ **Next week (Lecture 6): Asymmetric Numeral Systems**
 - ▶ modern stream code that operates as a *stack* ("last-in-first-out")
 - ▶ conceptionally more difficult but easier to implement in real code → (which we will actually do for ANS)
 - ▶ uses "bits-back trick"
 - ▶ enables "bits-back trick" for latent variable models (→ Lecture 7)
- ▶ **Problem Set 7: use range coding** (from a library) for our autoregressive model of natural language from Problem Set 3.
 - removes overhead of symbol codes and achieves bit rates very close to the information content (less than 0.1% overhead)