



University of
Sheffield

School of
Computer
Science

COM6115: Text Processing

Weeks 1-6 Revision

Varvara Papazoglou

Week 1

Intro to Text Processing

Wooclap – Text preprocessing tasks (Weeks 1 & 5)



- 1
- 2

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Weeks 2-3

Text Encoding &

Text Compression

Character Encoding

- American Standard Code for Information Interchange (ASCII)
 - 7-bit code
 - Introduced in 1963, finalised in 1968
 - Not sufficient for several Western European languages
 - Additional accents and symbols
- Unicode Transformation Format (UTF)
 - **UTF-32:** 32-bit (4-byte) code unit length
 - **UTF-16:** 16-bit (2-byte) code unit length
 - **UTF-8:** 1-4 bytes (variable code unit length)

Wooclap – Encodings



1
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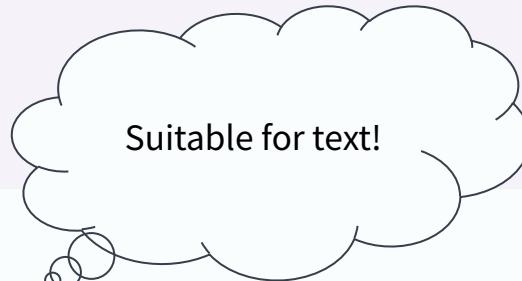
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Compression



- **Lossless** Compression:
 - class of algorithms allowing original data to be **perfectly reconstructed** from compressed data

- **Lossy** Compression:
 - achieve data reduction by **discarding** (i.e. losing) information
 - suitable for **certain media types**, esp.: image / video / audio data
 - widely used in data **streaming** contexts

ANNALS OF ARTIFICIAL INTELLIGENCE

CHATGPT IS A BLURRY JPEG OF THE WEB

OpenAI's chatbot offers paraphrases, whereas Google offers quotes. Which do we prefer?

By Ted Chiang

February 9, 2023

<https://www.newyorker.com/tech/annals-of-technology/chatgpt-is-a-blurry-jpeg-of-the-web>

Hidden Variables

Domenic's blog about coding and stuff

ChatGPT Is Not a Blurry JPEG of the Web. It's a Simulacrum.

February 19, 2023 | [Tweet](#) | posted in [ai](#)

<https://blog.domenic.me/chatgpt-simulacrum/>

Additional Resources

- Language Modelling is Compression (Delétang et al., 2024)
- LLMZip: Lossless Text Compression using Large Language Models (Valmeekam et al., 2023)
- Semantic and Generative Models for Lossy Text Compression (Witten et al., 1994)

Text compression techniques

- **symbolwise** vs. **dictionary** methods
 - **Symbolwise**: estimate the probabilities of symbols (characters/words); code one symbol at a time using shorter codewords for the more likely symbols
 - **Dictionary**: replace substrings in a text with codewords/indices that identify the substring in a dictionary
- **static** vs. **adaptive** methods
 - **Static**: pre-defined model/dictionary for all texts
 - **Semi-static**: derives model/dictionary for the file in a 1st pass; applies it in a 2nd pass
 - **Adaptive**: builds model/dictionary adaptively in 1 pass

Huffman coding

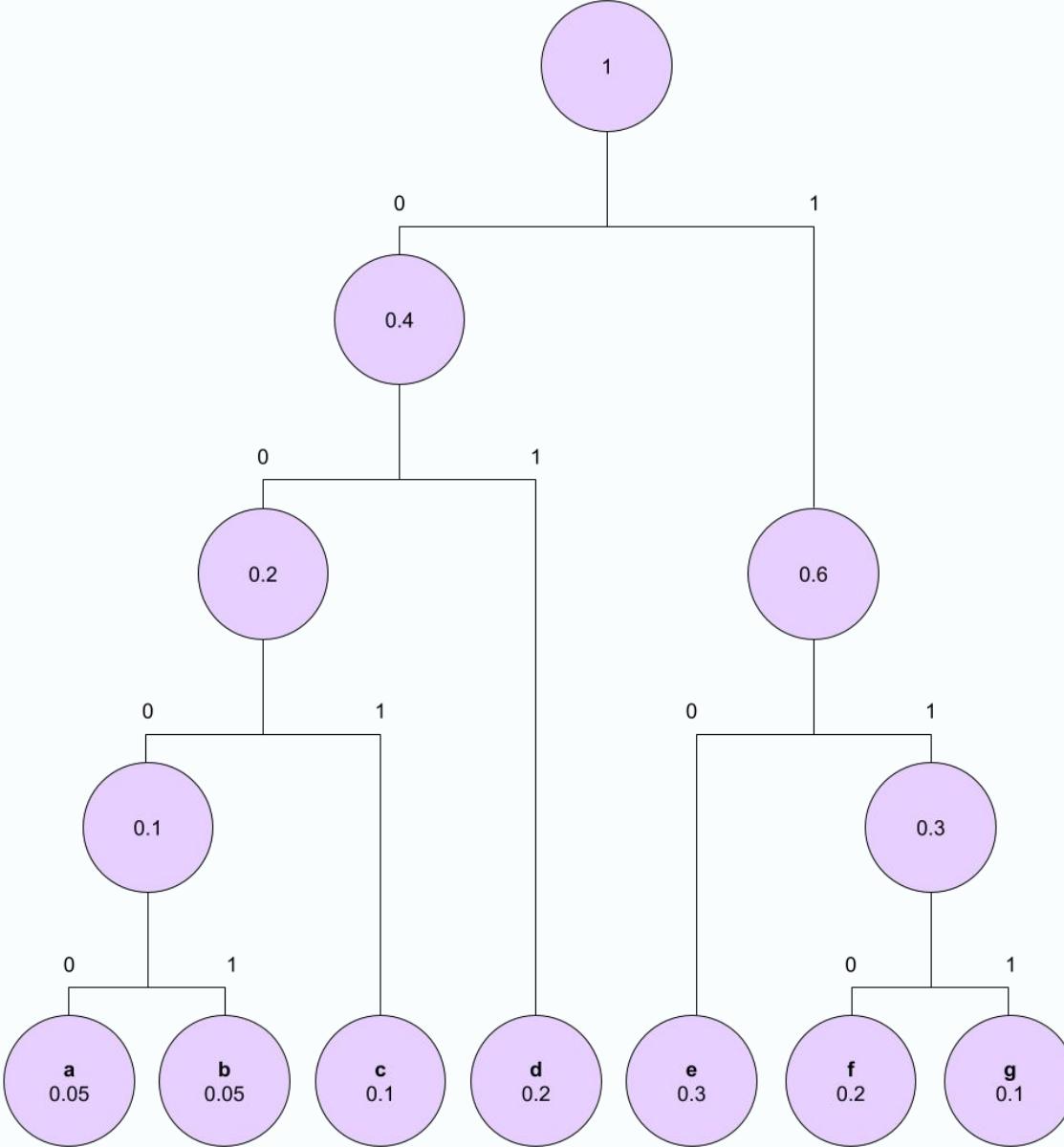
- Encoding:
 - Given the estimated probability of symbols, build the coding tree.
 - Start from the leave nodes.
- Decoding:
 - Given the coding tree (which is prefix-free), decode the sequence of integers into the corresponding symbols.
 - Start from the root to determine which codeword corresponds to each symbol.

Test your understanding:

1. Encode

a. “ddef”

b. “cab”



Test your understanding:

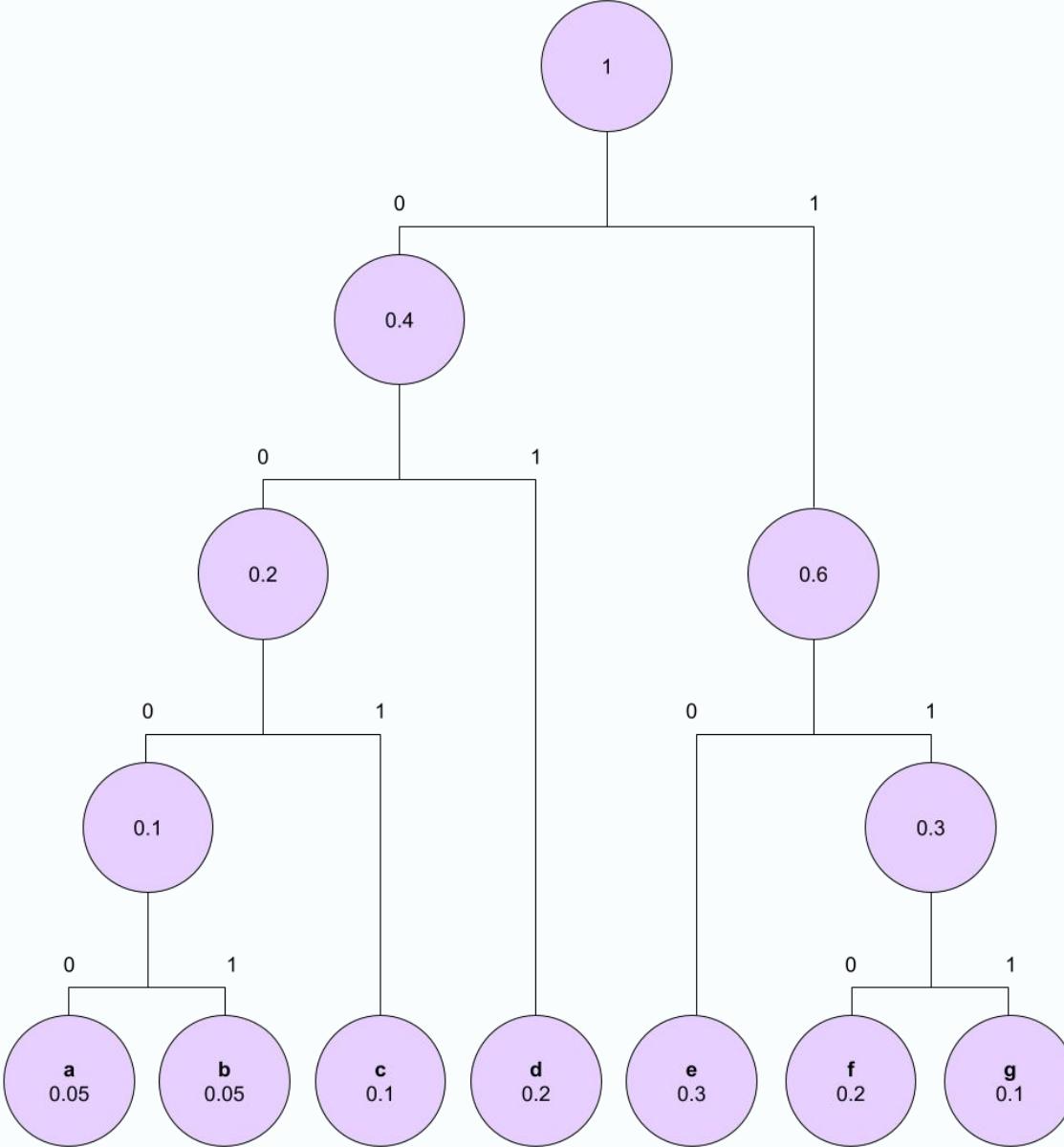
1. Encode

a. “ddef”

010110110

b. “cab”

0010000001

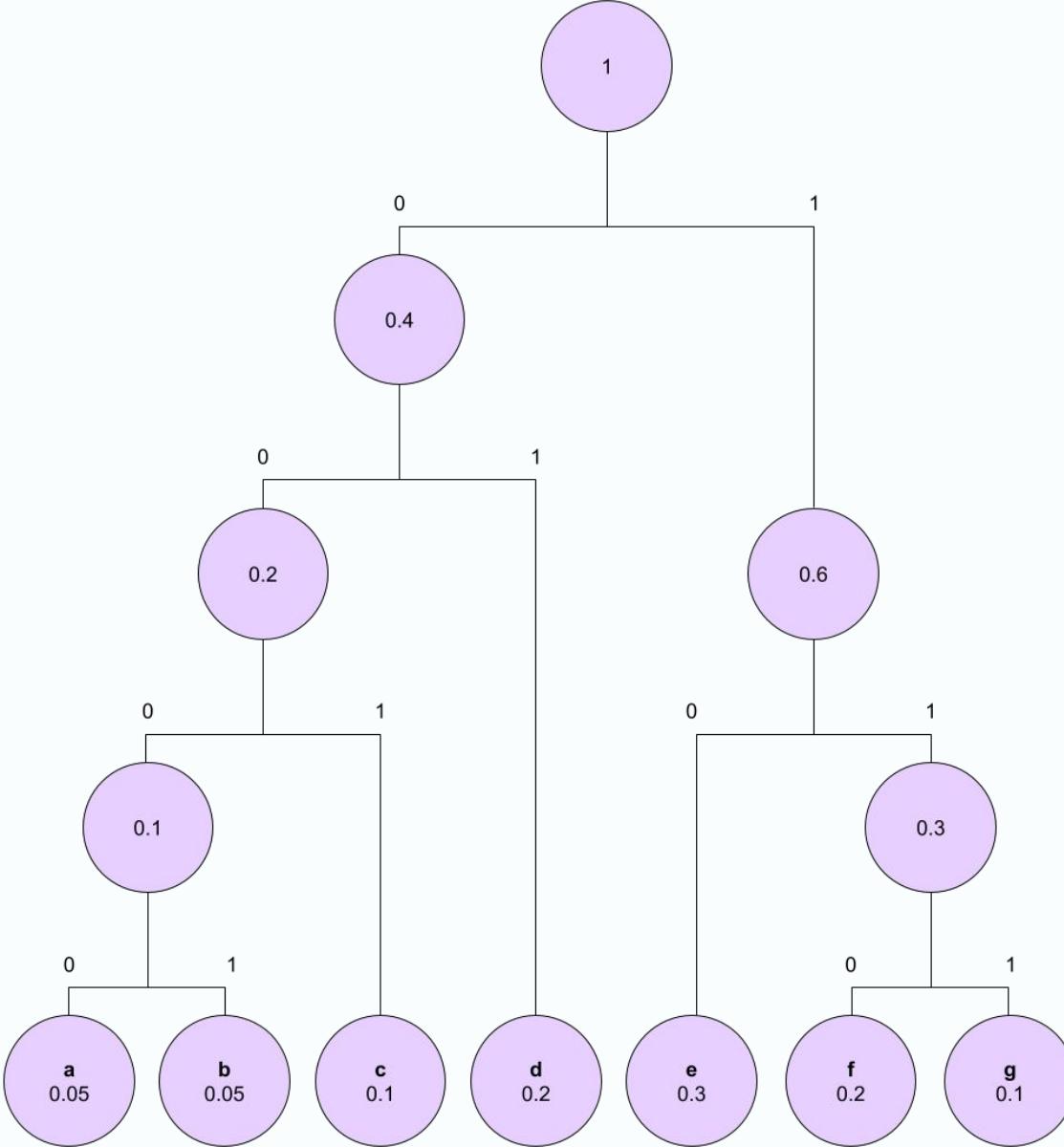


Test your understanding:

2. Decode

a. 0001000001

b. 1111101001

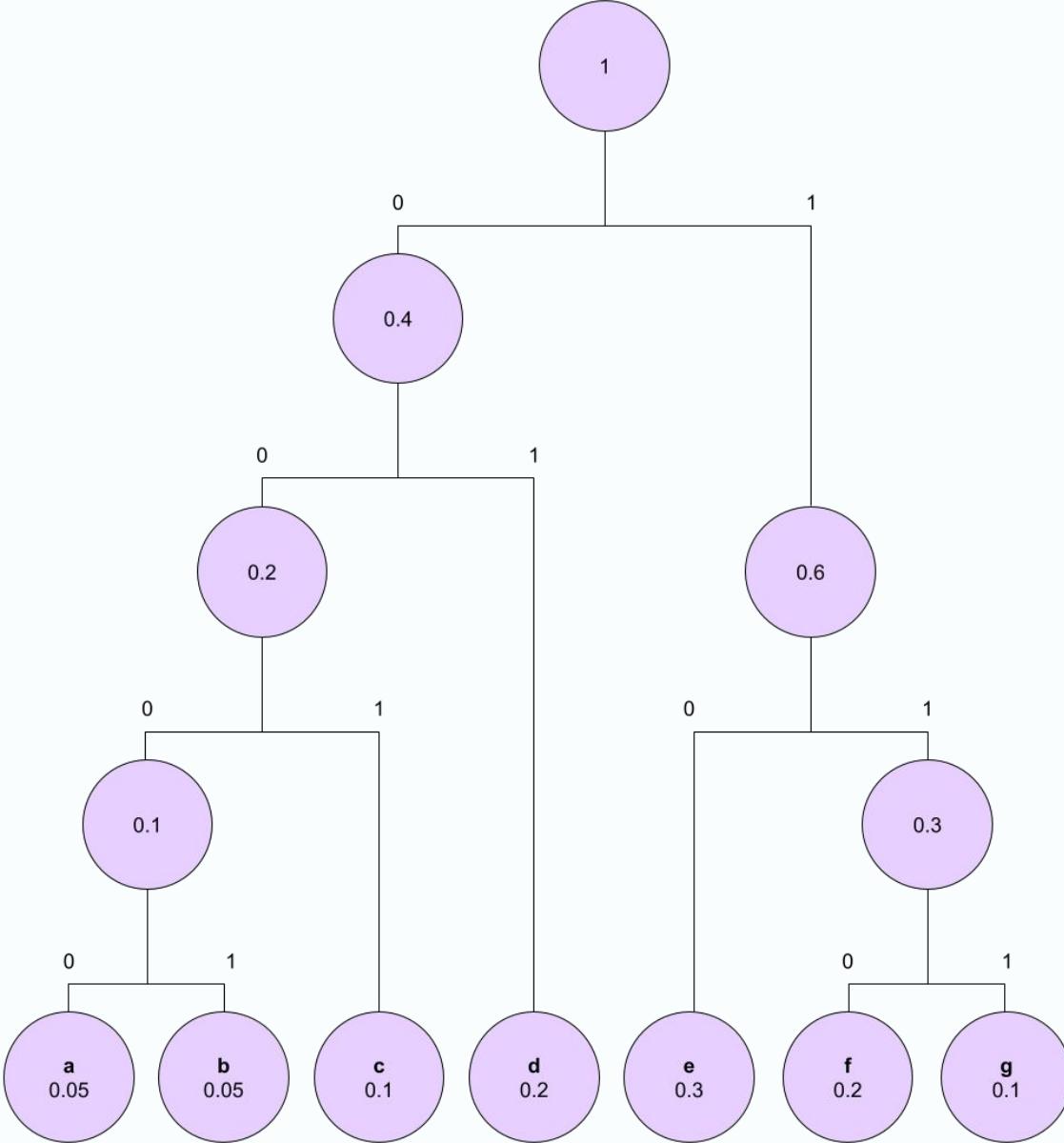


Test your understanding:

2. Decode

a. 0001000001
“bad”

b. 1111101001
“gfed”



Canonical Huffman Codes

- Encoding:
 - Given the length of the codewords, group symbols by their code-length
 - Assign codes

Example:

[2]	d	e	[3]	c	f	g	[4]	a	b
	00	01		100	101	110		1110	1111

Canonical Huffman Codes

- Decoding:
 - Given the sequence of symbols & number of symbols at each code-length, form the symbol groups

Example:

d e c f g a b, (0, 2, 3, 2)

Canonical Huffman Codes

- Decoding:
 - Given the sequence of symbols & number of symbols at each code-length, form the symbol groups

Example:

d e c f g a b, (0, 2, 3, 2)

[1] - [2] d e [3] c f g [4] a b

Canonical Huffman Codes

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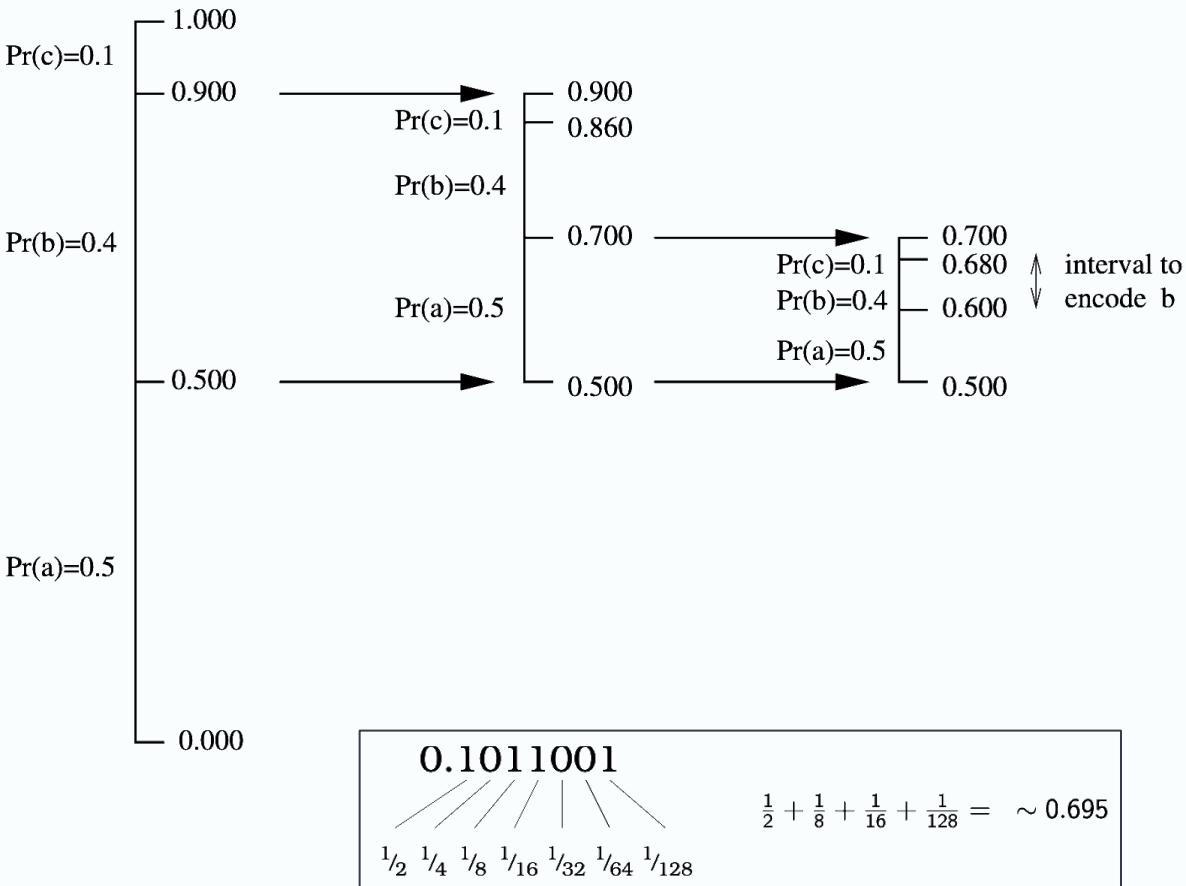
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[2]	d	e	[3]	c	f	g	[4]	a	b
	00	01		100	101	110		1110	1111

Arithmetic Coding

- Given: the static model of probabilities and the string to be encoded
- Divide the intervals between 0-1
- Represent the codewords as a stream of bits, which is actually expressed as a fractional binary number between 0 and 1

Arithmetic Coding



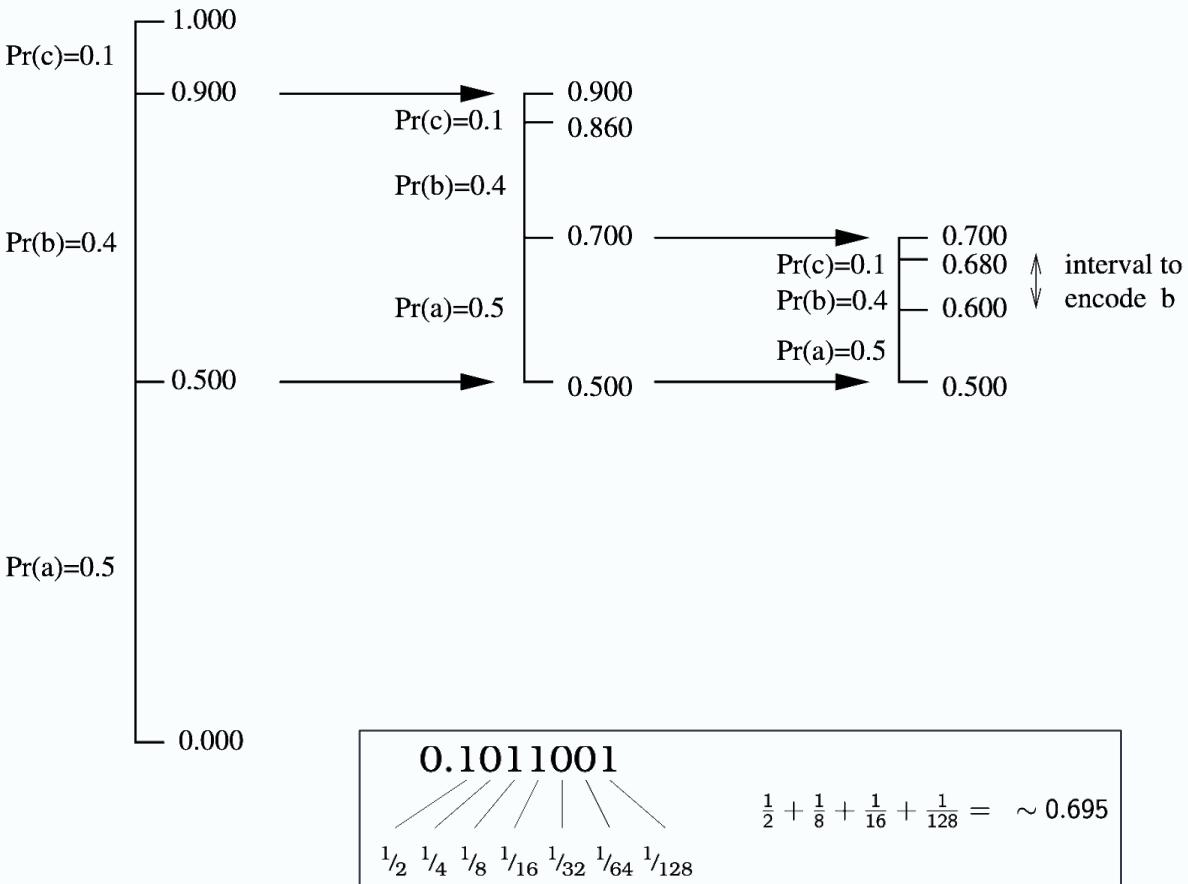
Test your understanding:

This is how you can encode "bab" → 101 (0.625), given
 $\Pr(a) = 0.5 \quad \Pr(b) = 0.4 \quad \Pr(c) = 0.1$

1. Why is "bb" → 11 ?

2. Why is 1011 → "bac" ?

Arithmetic Coding

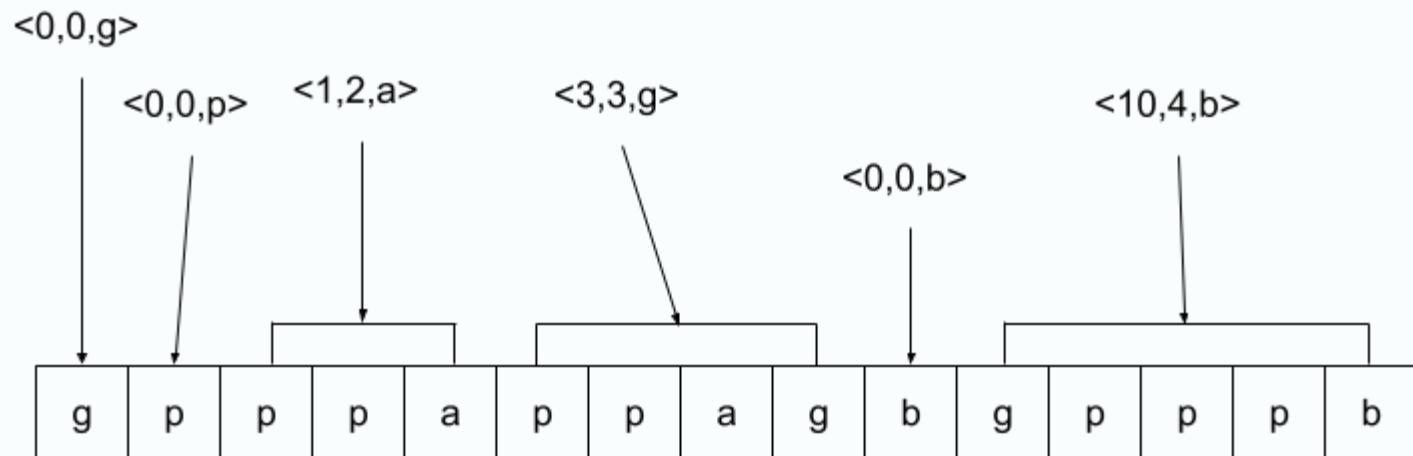


Test your understanding:

This is how you can encode "bab" → 101 (0.625), given
 $\Pr(a) = 0.5 \quad \Pr(b) = 0.4 \quad \Pr(c) = 0.1$

1. Why is "bb" → 11 ?
 $11 \rightarrow 0.11 \rightarrow \frac{1}{2} + \frac{1}{4} = 0.75$
2. Why is 1011 → "bac" ?
 $\frac{1}{2} + \frac{1}{8} + \frac{1}{16} = 0.688$

LZ77



Weeks 4-5

Information Retrieval

Retrieval Models

- the **Boolean Model**
 - each document in a collection is either relevant to a given query or not relevant to that query
 - queries are formulated using boolean operators (AND, OR, NOT) between terms
- the **Vector Space Model**
 - each document in a collection has some degree of relevance to query
 - documents and queries are both represented as vectors of the terms occurring within them
 - degree of similarity computed as cosine of angle between document and query vectors
- the **Probabilistic Model**
 - ranked retrieval model like the vector space model
 - relatedness of document to query measured as the probability that a document is relevant to a given query

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Term weighting

- Binary weighting
- tf
- tf.idf

→ Why is each of the above increasingly ‘better’ for IR?

Wooclap – IR



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