Text as data

DSTA

0.1 Big picture

- [verbal] language is the main vehicle of human comunication
- until short ago, the main encoding of data/knowledge

. . .

- languages represent what we value and [seems to] determine what we **can** think.
- universal grammars are studied.

- complex grammars: a sign of affectation?
- terms are ambiguos **by design**

. . .

- the polar opposite of what data analytics needs!

From the British Medical Journal:

Organ specific immune-related adverse events are uncommon with anti-PD-1 drugs but the risk is increased compared with control treatments. General adverse events related to immune activation are largely similar. Adverse events consistent with musculoskeletal problems are inconsistently reported but adverse events may be common.

From Men’s Health:

The stats don’t lie... here’s how to get the looks of her dreams

Love is in the eye of the beholder.

But good looks are down to science... sort of.

Ah, the chest. The part of the body most men would like to grow. Luckily, you have come to the right place. We really do know a thing or two about building muscle. Take your pick from the workouts below to stretch your chest.

1 From Text to numerical methods

1.1 The occurrence matrix

Often text (document) analysis begins with word occurrence analysis: we record word usage irrespective of the position in text.

. . .

Let a document be a bag of words. Let a corpus be a collection of documents.

. . .

The occurence matrix A:

$a_{ij} = k$

means that word i appears k times in document j.

Word i is represented by the i-th row of A (also A_i^T)

. . .

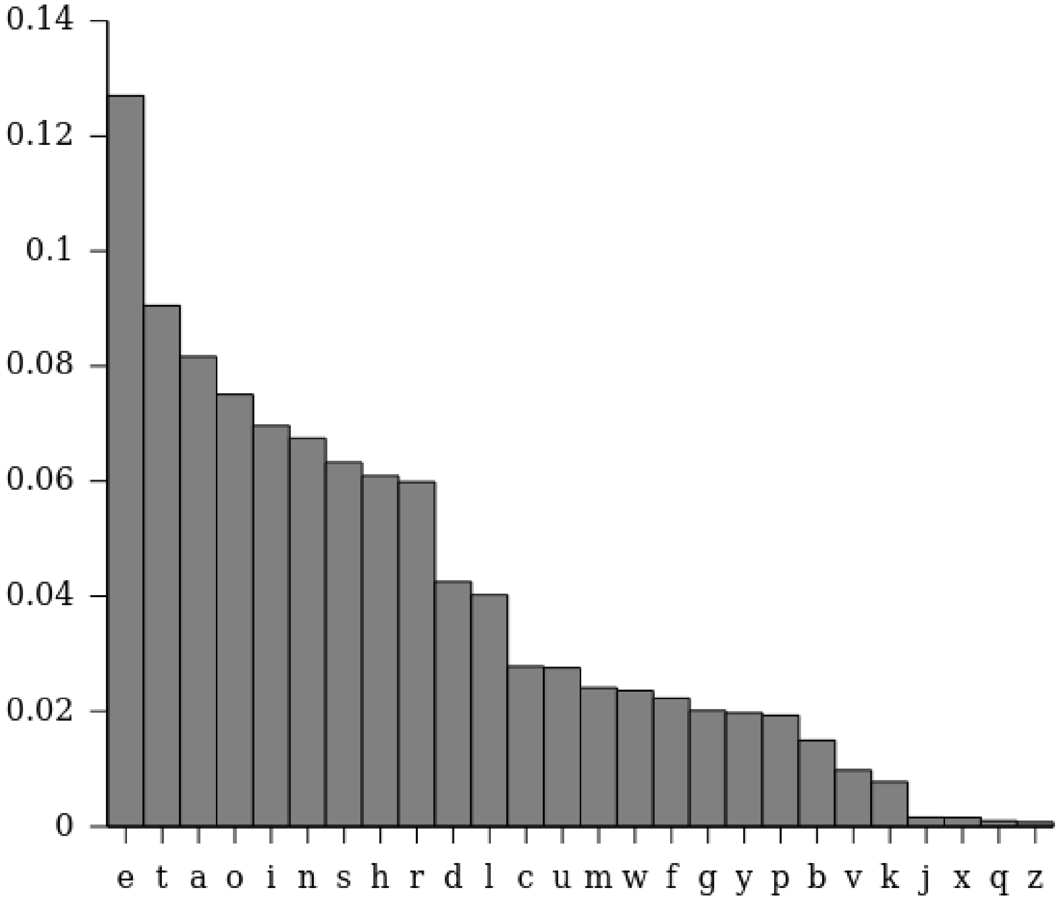
With row normalisation, word usage becomes a prob. distribution to which Entropy analysis can be applied.

With column norm., we analyse a document by its entropy.

2 Text Compression

2.1 Example application: text compression

In languages, the occurrence of symbols is statistically imbalanced:



Zipf's law: if the most frequent word appears k times, then the i-th word by freq. appears $\frac{k}{i}$ times.

- low-frequency characters have high information entropy
- similarly, low-frequency words have high information entropy: **they tell more about the underlying topic of the document**
- A simpler application of Entropy is text compression

2.2 Encoding compression

1. collect the frequencies of characters in a relevant **corpus**

A collection of documents taken to be representative of the target language

. . .

1. sort letters by their **increasing** freq., e.g., for English

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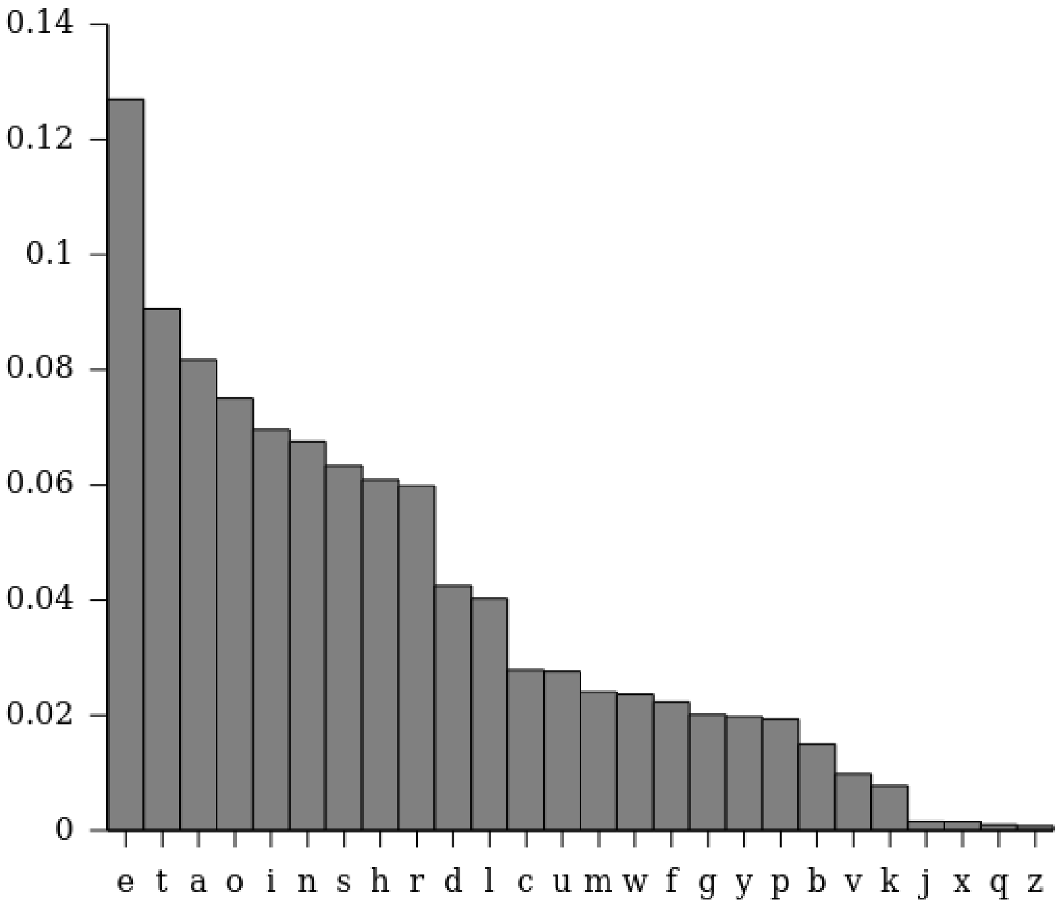

Encoding compressed from $\log_2 27 \approx 4.75$ to $H[Pr[l_i]] \approx 4.22$

Further comp. by taking 2- and 3-grams: sequences of 2 or 3 characters.

The 3-gram **ent** appears more often than **uzb.**

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1. encode the least frequent two as 0 and 1.

Char.

Freq.

Encoding

z

.007

0

q

.009

1

. . .

4. Prefix “1” to the existing codes; encode the third-least freq. letter as 0:

Char.

Freq.

Encoding

z

.007

10

q

.009

11

x

.15

0

---

5. Prefix “1” to all; encode the fourth-least frequent letter as 0 again:

Char.

Freq.

Encoding

z

.007

110

q

.009

111

x

.15

10

j

.153

0

---

5. finally…

Char.

Freq.

Encoding

z

.007

1…10

…

…

…

t

9.05

10

e

12.72

0

2.3 Application: text compression

Huffmann algorithm: frequency-based letter encoding

- Optimal wrt. the theoretical lower-bound H.
- coding is **prefix-free:** no code is the prefix of another
- **greedy** algorithm: cost grows with $n \log n$

3 Information Retrieval

3.1 Definition

Instance:

- a collection of N documents
- a query ([set of]keyword[s])

. . .

Solution:

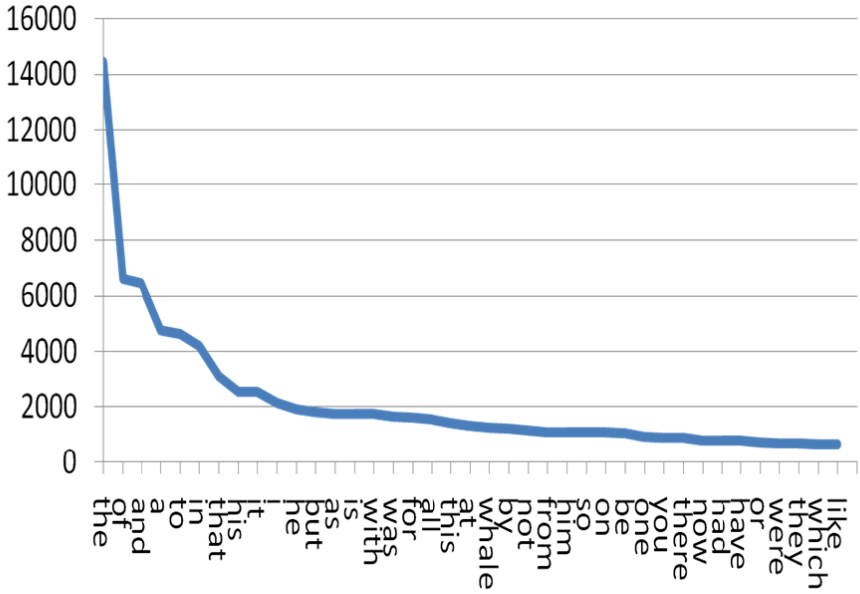
- a selection of the documents ranked by their importance wrt. the keyword[s]

. . .

text documents

keyword-based ranking (doc. is a **bag of words)**

3.2 Stopwords



3.3 Term frequency (TF)

Rank documents on the basis of the frequence of the keyword in each

. . .

Euristics: At same frequency, choose those where the keyword appears **earlier**

. . .

For low-frequency (high-Entropy) terms simple relative frequencies work: eliminate **stop-words**

$TF(q_i, d_j) = \frac{|q_i \in d_j|}{MAX|q_x \in d_j|}$

3.4 Inverted Doc. Freq. (IDF)

A query term q_i is **specific** in inverse relation to the number of documents in which it occurs

. . .

N documents, $n(q_i)$ of which contain q_i.

. . .

$$IDF(q_i) = \log \frac{N}{n(q_i)}$$

3.5 TF-IDF

The standard **empirical** measure for IR ranking

$$TFIDF(q_i, d_j, C) = TF(q_i, d_j) \cdot IDF(q_i, C)$$

. . .

For frequent terms (after stopwords) we can *smooth* $IDF(q_i, C)$ to $\log(1 + \frac{N}{n(q_i)})$

3.6 Advanced tools

- Part-of-speech recognition (POS)

the context and its frequency guides the labelling of **words**.

. . .

- Named-Entity recognition (NER)
- follows POS
- A group of words are recognized as **naming** a worldy object or a stand-alone concept.