



Announcements

- Collaboration session on A2
 - Tuesday, 23 March 2021, 7pm AEDT
- Weekly forum
- Quiz 1 due 22/03/2021 12:59 am



Agenda

- SLP Week 1
- Week 2 Topics
- Week 2 SLPs



SLP Week 1

- MA5851 Week 1 SLP 2
- MA5851 Week 1 SLP 3

44 submissions; total students 82

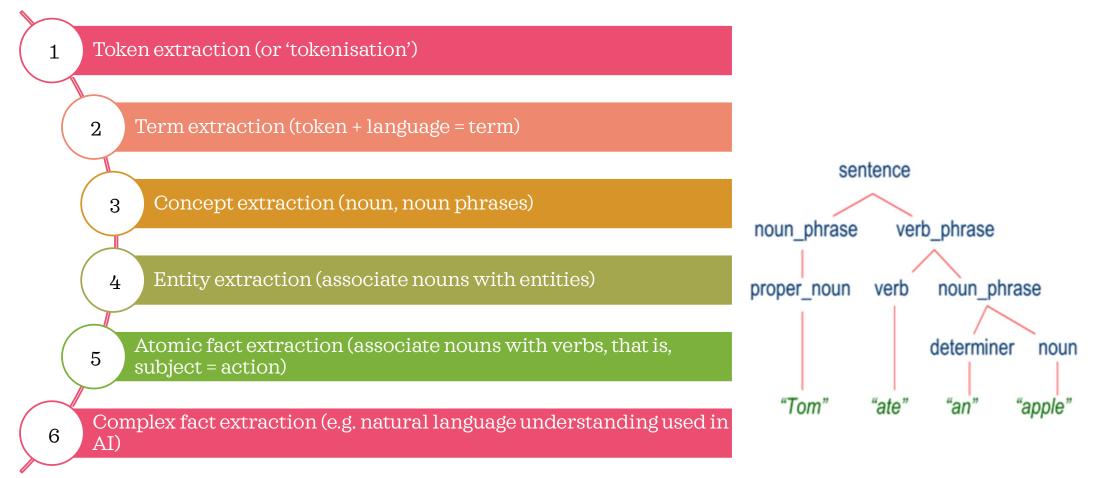


Week 2 – Extracting and Quantifying Informative Text

- Language Parsing
- Document metrics
- Zipf's law
- Concept linking
- Quantifying text (Vectorisation, TF-IDF)
- Metadata and Search Engine
- Semantic web

Language Parsing





"i am so disappointed that i am paying thousands of dollars for a course that has been prepared in a way where it will be largely useless in my professional career."

Parsing output:

['(NX i/NN NX) (VX am/VBP so/RB disappointed/VBN VX) that/IN (NX I/PRP NX) (VX am/VBP paying/VBG VX) (NX thousands/NNS NX) of/IN (NX dollars/NNS NX) for/IN (NX a/DT course/NN NX) (NX that/WDT NX) (VX has/VBZ been/VBN prepared/VBN VX) in/IN (NX a/DT way/NN NX) where/WRB (NX it/PRP NX) (VX will/MD be/VB largely/RB VX) (AX useless/JJ AX) in/IN (NX my/PRP\$ professional/JJ career/NN NX) ./.']

Document metrics



```
"content_metrics": {
    "number_of_sentences": 120,
    "number_of_paragraphs":19,
    "number_of_characters": 5447,
    "number_of_words": 2379,
    "number_of_characters_without_whitespaces": 5170,
    "number_of_noun_phrases":520,
    "number_of_verb_phrases":618,
    "list_of_np":[.....],
    "list_of_treq_words":[.....],
.....
}
```

Metric	Train	Validation	Test
No. of documents	238	10	10
No. of entries	8387	485	376
No. of phrases	21497	1329	973
No. of tokens	347 18	2169	1571
Mean entries per document	35.2	48.5	37.6
Mean phrases per document	90.3	132.9	97.3
Mean tokens per document	145.9	216.9	157.1
Mean phrases per entry	2.6	2.7	2.6
Mean tokens per entry	4.1	4.5	4.2
Mean tokens per phrase	1.6	1.6	1.6
Vocabulary of target tokens	2267	442	4372
Out of vocabulary tokens	N/A	48	52

- Pattern matching: pattern of words, sentences, paragraph, punctuation, structural items etc. → document similarity
 - Plagiarism checker, stylometry, forensic legal work
- Content extraction: NP, VP, entities → summarisation

Zipf's Law



If r be the rank of word, Prob(r) be the probability of a word at rank r, Prob(r) = freq(r) / N freq(r) = the number of times the word at rank r appears in the collection $N = total \ number \ of \ words \ in \ the \ collection \ (not \ number \ of \ unique \ words).$

Zipf's law states that: r * Prob(r) = A; In most cases, A = 0.1 Prob(r) = freq(r) / N we can rewrite Zipf's law as r * freq(r) = A * N Freq(r) = (A * N)/rthe frequency of any word is inversely proportional to its rank in the frequency table

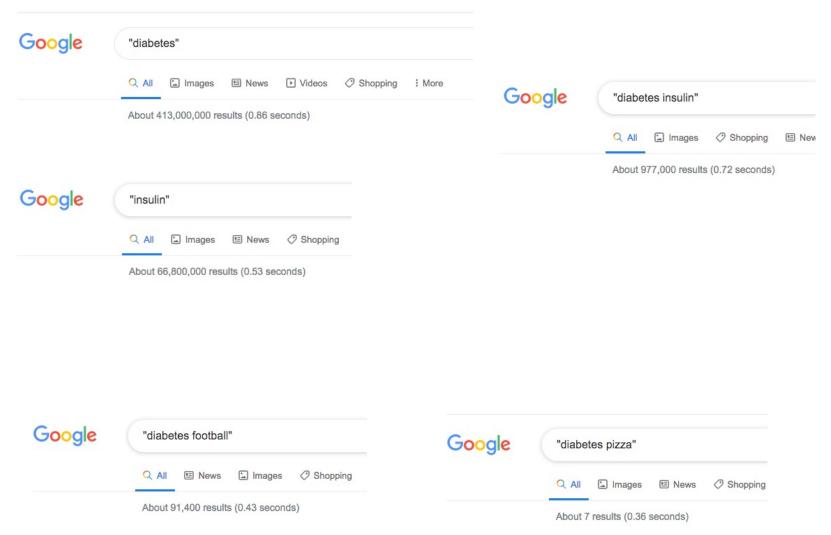
the frequency of the nth most common word is about 1/n times the frequency of the most common word

The same relationship occurs in many other rankings, unrelated to language, such as the population ranks of cities in various countries, corporation sizes, income rankings, etc.

http://norvig.com/mayzner.html

Concept linking (co-occurance)





Textual Similarity Metrics



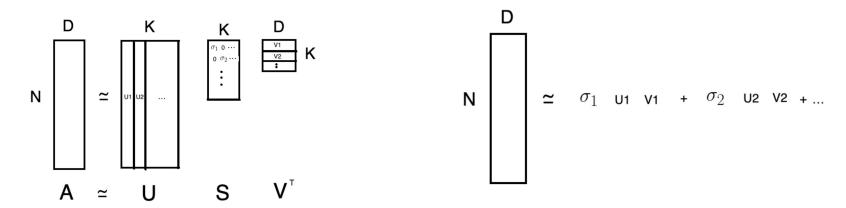
- Measuring similarity of two texts is a well-studied problem.
- Standard metrics are based on a "bag of words" model of a document that ignores word order and syntactic structure.
- May involve removing common "stop words" and stemming to reduce words to their root form.
- Vector-space model from Information Retrieval (IR) is the standard approach.
- Other metrics (e.g., Levenshtein-distance) are also used.
- Levenshtein distance: text similarity measure that compares two words and returns a numeric value representing the distance between them.
- Word Embedding: neural network based; learnt representation word (of a given corpus)

Quantifying Text



Quantifying Steps:

- 1. Text Corpus as input: pre-processing like tokenisation, stemming, synonyms, filtering etc.
- 2. Form a weighted matrix: document by term matrix
- Apply Singular Value Decomposition (SVD): reduce sparsity
- 4. Apply Clustering: topic generation, summarisation, information extraction from lower-dimensional vector space



N: Number of rows, D: Number of dimensions;

SVD reduces dimensionality by selecting only the t largest singular values, and only keeping the first t columns of U and V

Document Collection



A collection of *n* documents can be represented in the vector space model by a term-document matrix.

An entry in the matrix corresponds to the "weight" of a term in the document; zero means the term has no significance in the document or it simply doesn't exist in the document.

The Vector-Space Model



Assume *t* distinct terms remain after preprocessing; call them index terms or the vocabulary.

These "orthogonal" terms form a vector space.

Dimension = t = |vocabulary|

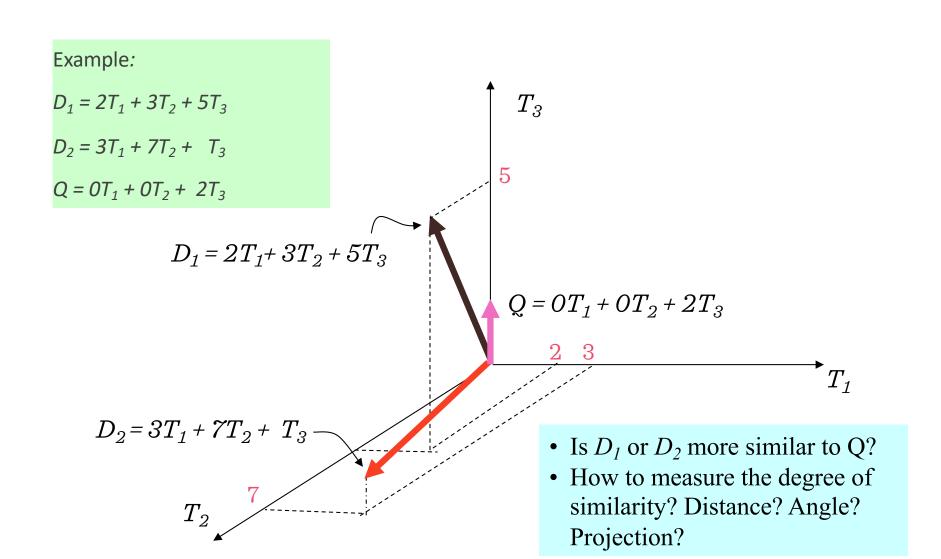
Each term, i, in a document or query, j, is given a real-valued weight, w_{ij} .

Both documents and queries are expressed as t-dimensional vectors:

$$d_i = (w_{1i}, w_{2i}, ..., w_{ti})$$

Graphic Representation





Term Weights: Term Frequency



More frequent terms in a document are more important, i.e. more indicative of the topic.

 f_{ij} = frequency of term i in document j

May want to normalize *term frequency* (*tf*) by dividing by the frequency of the most common term in the document:

$$tf_{ij} = f_{ij} / max_i \{f_{ij}\}$$

Term Weights: Inverse Document Frequency



Terms that appear in many different documents are less indicative of overall topic.

```
df_i = document frequency of term i

= number of documents containing term i

idf_i = inverse document frequency of term i,

= \log_2 (N/df_i)

(N: total number of documents)
```

An indication of a term's discrimination power.

Log used to dampen the effect relative to tf.

TF-IDF Weighting



A typical combined term importance indicator is *tf-idf* weighting:

$$w_{ij} = tf_{ij} idf_i = tf_{ij} \log_2 (N/df_i)$$

A term occurring frequently in the document but rarely in the rest of the collection is given high weight.

Many other ways of determining term weights have been proposed.

Experimentally, tf-idf has been found to work well.

Cosine Similarity Measure



Cosine similarity measures the cosine of the angle between two vectors.

Inner product normalized by the vector lengths.

$$\operatorname{CosSim}(\boldsymbol{d}_{j},\boldsymbol{q}) = \frac{\vec{d}_{j} \cdot \vec{q}}{\left|\vec{d}_{j}\right| \cdot \left|\vec{q}\right|} = \frac{\sum_{i=1}^{t} (w_{ij} \cdot w_{iq})}{\sqrt{\sum_{i=1}^{t} w_{ij}^{2} \cdot \sum_{i=1}^{t} w_{iq}^{2}}} D_{1}$$

$$t_{1}$$

$$t_{2}$$

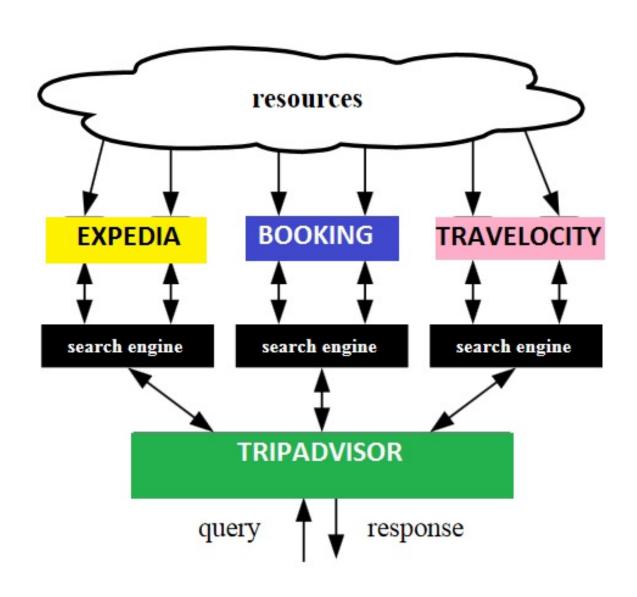
$$D_{2}$$

$$D_1 = 2T_1 + 3T_2 + 5T_3$$
 CosSim $(D_1, Q) = 10 / \sqrt{(4+9+25)(0+0+4)} = 0.81$
 $D_2 = 3T_1 + 7T_2 + 1T_3$ CosSim $(D_2, Q) = 2 / \sqrt{(9+49+1)(0+0+4)} = 0.13$
 $Q = 0T_1 + 0T_2 + 2T_3$

 D_1 is 6 times better than D_2 using cosine similarity but only 5 times better using inner product.

Metadata and Search





Semantic Web



Web of linked data.

It enables people to create data stores on the Web, build vocabularies, and write rules for handling data.

Linked data are empowered by technologies such as RDF, SPARQL, OWL, and SKOS

RDF: Resource Description Framework (https://www.w3.org/RDF/)

SPARQL: Query language to query RDF data

OWL: Web Ontology Language (https://www.w3.org/OWL/)

SKOS: Simple Knowledge Organization System

HL7: For Health Data, Fast Health Interop Resources (FHIR)

https://search.carrot2.org

