COMP90042 Web Search & Text Analysis

Workshop Week 2

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March 12, 2019

University of Melbourne

Timetable

Mon	13:15	207-221-Bouverie-St-B113	Andrei
Mon	17:15	207-221-Bouverie-St-B116	Andrei
Thu	14:15	Alice-Hoy-211	Ekaterina
Thu	15:15	Alice-Hoy-211	Ekaterina
Mon	18:15	Old-Engineering-EDS4	Navnita
Wed	11:00	Elec.-Engineering-121	Navnita
Fri	10:00	221-Bouverie-St-B117	Nitika
Thu	17:15	221-Bouverie-St-B132	Nitika
Fri	15:15	Alice-Hoy-210	Shivashankar
Tue	18:15	Old-Engineering-EDS4	Shivashankar
Mon	11:00	Elec.-Engineering-121	Winn
Mon	9:00	Doug-McDonell-502	Xudong
Mon	17:15	221-Bouverie-St-B132	Xudong
Tue	16:15	221-Bouverie-St-B113	Zenan
Tue	17:15	221-Bouverie-St-B132	Zenan

Contact

- LMS - Discussion Board

- Subject Coordinator
  - A/Prof. Trevor Cohn
  - `t.cohn@unimelb.edu.au`
  - `https://trevorcohn.github.io/comp90042/`

- Me
  - Zenan Zhai
  - `zenan.zhai@unimelb.edu.au`

Programming

- Python 3
  - Virtualenv
  - Anaconda3
- Canopy EPD
  - License available when register with Unimelb Email.
- Packages
  - NLTK, gensim
  - Matplotlib, Numpy, Scipy
  - Scikit-learn

Outline

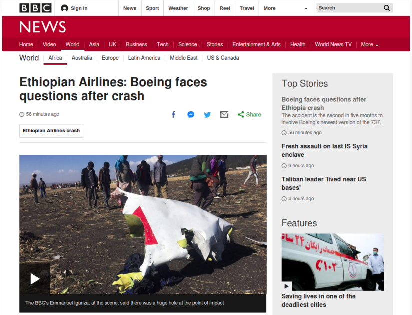
- Pre-processing
  - Pipeline
  - Lemmatisation/Stemming
- Vector Space Model
  - Document-Term Matrix/Inverted Index
  - TF-IDF/BM25
  - Exercise

Pre-processing

Pre-processing Pipeline

- Formatting
- Sentence Segmentation
- Tokenisation
- Normalisation
  - Lemmatisation
  - Stemming
- Remove Stopwords
  - May varies in different toolkit

Formatting



```
        <div id="page" class="configurable story " data-story-id="world-africa-47519467">      <div role="main"> <div
class="container-width-only">       <span class="index-title index-title--redundant " id="comp-index-title" data-index-title-
meta="{&quot;id&quot;:&quot;comp-index-title&quot;,&quot;type&quot;:&quot;index-
title&quot;,&quot;handler&quot;:&quot;indexTitle&quot;,&quot;deviceGroups&quot;:null,&quot;opts&quot;:
{&quot;alwaysVisible&quot;:false,&quot;onFrontPage&quot;:false},&quot;template&quot;:&quot;index-title&quot;}">
        <span class="index-title__container">
            <a href="/news/world/africa">Africa</a>
        </span>
    </span>
    </div>     <div class="container">      <div class="container--primary-and-secondary-columns column-clearfix">
<div class="column--primary">

<div class="story-body">
    <h1 class="story-body__h1">Ethiopian Airlines: Boeing faces questions after crash</h1>

        <div class="with-extracted-share-icons">
        <div class="story-body__mini-info-list-and-share">
            <div class="story-body__mini-info-list-and-share-row">
                <div class="mini-info-list-wrap">
                                            <ul class="mini-info-list">
    <li class="mini-info-list__item"><div class="date date--v2" data-seconds="1552267449" data-datetime="11 March 2019">11 March
2019</div></li>
</ul>
                                    </div>
                                    <div class="share-tools--event-tag">


    <div id="comp-pattern-library-5" class="distinct-component-group container-twite">

            <ul class="sharetools">
        <li class="twite__channel-out twite__channel-out--desktop twite__channel-out--facebook twite__channel-click-extracted--
facebook twite__list-elements" aria-hidden="true">
            <a class="extracted__channel-link extracted__channel-link--
facebook"onclick="window.open('http://www.facebook.com/dialog/feed?
app_id=58567469885&amp;redirect_uri=http%3A%2F%2Fwww.bbc.co.uk%2Fnews%2Fspecial%2Fshared%2Fvj_sharetools%2Ffb_red_uri.html&amp;lin
k=https%3A%2F%2Fwww.bbc.com%2Fnews%2Fworld-africa-47519467%3FSThisFB&amp;display=popup', '_blank',
'toolbar=no,scrollbars=yes,resizable=no,fullscreen=no,top=50,left=50,width=555,height=615').opener = null" href='#'
tabindex="-1">
```

Sentence Segmentation & Tokenisation

'Ethiopian Airlines: Boeing faces questions after crash.'

$\Downarrow$

['Ethiopian', 'Airlines', ':', 'Boeing', 'faces', 'questions', 'after', 'crash', '.']

- Sentence Segmentation / Tokenisation
  - Rule-based / Machine Learning
  - Varies in different languages/domains (e.g. Medicine Chemistry)
- Off-the-shelf implementations
  - NLTK
    `https://www.nltk.org/`
  - OpenNLP
    `https://opennlp.apache.org/`
  - StanfordNLP
    `https://stanfordnlp.github.io/stanfordnlp/`

- Inflectional Morphology
  - Grammatical variants
- Derivational morphology
  - Another word with different meaning

Inflectional Morphology

airline → airlines

face → faces

question → questions

Derivational morphology

Ethiopia → Ethiopian

Lemmatisation & Stemming

Lemmatisation

Remove all inflections

Matches with lexicons

Product: Lemma

Stemming

Remove all suffixes

No matching required

Product: Stem

```
import nltk
nltk.download('wordnet')

sentence = ['Ethiopian', 'Airlines', ':', 'Boeing', 'faces', 'questions', 'after', 'crash', '.']
lemmatiser = nltk.stem.wordnet.WordNetLemmatizer()
stemmer = nltk.stem.porter.PorterStemmer()

# Code below from ...
def lemmatise(word):
    lemma = lemmatiser.lemmatize(word, 'v')
    if lemma == word:
        lemma = lemmatiser.lemmatize(word, 'n')
    return lemma
# End of copied code

lemmatised_sent = [lemmatise(word) for word in sentence ]
stemmed_sent = [stemmer.stem(word) for word in sentence ]

print('Sentence after lemmatisation: 'lemmatised_sent)
print('Sentence after stemming: ', stemmed_sent)
```

```
['Ethiopian', 'Airlines', ':', 'Boeing', 'face', 'question', 'after', 'crash', '.']
['ethiopian', 'airlin', ':', 'boe', 'face', 'question', 'after', 'crash', '.']
```

Sparsity

More word types ⇒ Larger sparsity

- { 'apple': 1, 'apples':1, 'Apple': 1 }
- { 'apple': 3 }

- Stemming creates less sparsity than lemmatisation.
- When do we prefer smaller sparsity?
- Can we increse sparsity?

Removing unwanted tokens

- Stopword
  - Examples (NLTK): me, what, by, with, into, above ...
- Punctuation
  - Examples: , . : ! ’ ” ...

TF-IDF V.S. BM25

TF-IDF

$$W_{d,t} = tf_{d,t} \times \log \frac{N}{df_t}$$

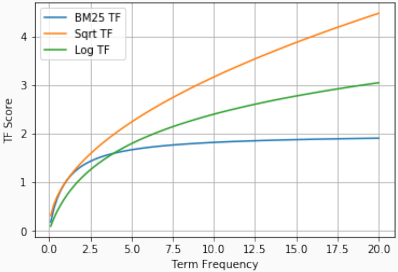
(TF) (IDF)

Okapi BM25

$$W_{d,t} = \frac{(k_1 + 1)tf_{d,t}}{k_1((1-b) + b(\frac{L}{L_{avg}})) + tf_{d,t}} \times \log \frac{N - df_t + 0.5}{df_t + 0.5} \times \frac{(k_3 + 1)tf_{q,t}}{k_3 + tf_{q,t}}$$

(Document TF, document length) (IDF) (Query TF)

TF smoothing

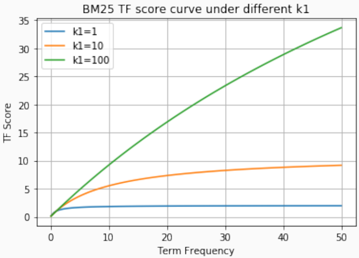


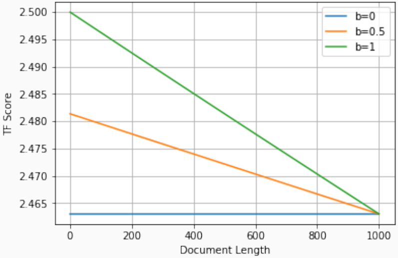
Raw TF	$TF_{score} = tf_{d,t}$
Square Root TF	$TF_{score} = \sqrt{tf_{d,t}}$
Log TF	$TF_{score} = \log(tf_{d,t})$

BM25 $\qquad TF_{score} = \frac{(k+1)tf_{d,t}}{k + tf_{d,t}}$

$$\lim_{tf_{d,t} \to \infty} \frac{(k+1)tf_{d,t}}{k + tf_{d,t}} = k + 1$$

Document TF and Document length





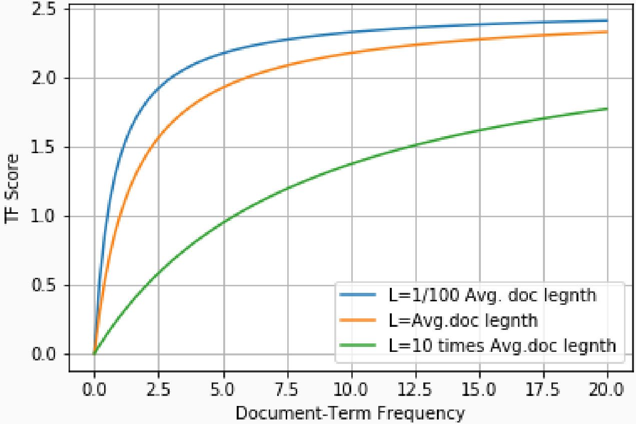
$$TF_{score} = f(tf_{d,t})$$

$$TF_{score} = f(L)$$

$$\frac{(k_1 + 1)tf_{d,t}}{k_1((1 - b) + b(\frac{L}{L_{avg}})) + tf_{d,t}}$$

- What does k_1 controls?
- What happens when $b = 0$?

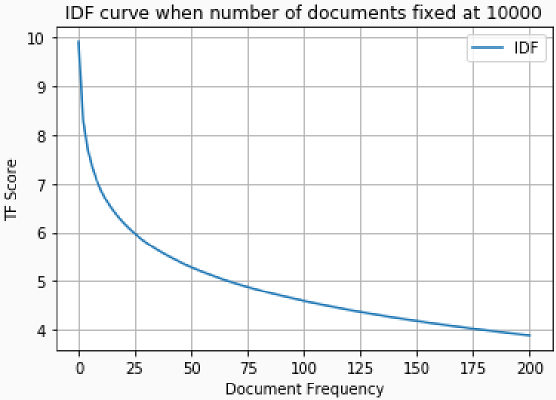
Document length and growth of TF



$$\frac{(k_1+1)tf_{d,t}}{k_1((1-b)+b(\frac{L}{L_{avg}}))+tf_{d,t}}$$

TF score grows faster when document length is short. Why?

Inverted Document Frequency



$$IDF_{score} = \log \frac{N - df_t + 0.5}{df_t + 0.5}$$

What are “stop-words” and why are they often discarded in information retrieval? (Final exam, 2015)