UNIVERSITY OF SUSSEX | BUSINESS SCHOOL | SCIENCE POLICY RESEARCH UNIT

Textual data and text mining (1)

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Introductory Data Science for Innovation (995N1) – Week 8, 15 November 2021

Outline

Outline

- Defining text mining
- Text mining first steps
- Tokenisation
- Lemmatisation
- Stemming
- tf-idf

Defining text mining

What is text mining?

“[…] text mining seeks to extract useful information from data sources through the **identification and exploration of interesting patterns** *[…]“*

“[…] data sources are document collections, and interesting patterns are found not among **formalized database records but in the unstructured textual data** *in the documents in these collections”* (Feldman and Sanger 2006)

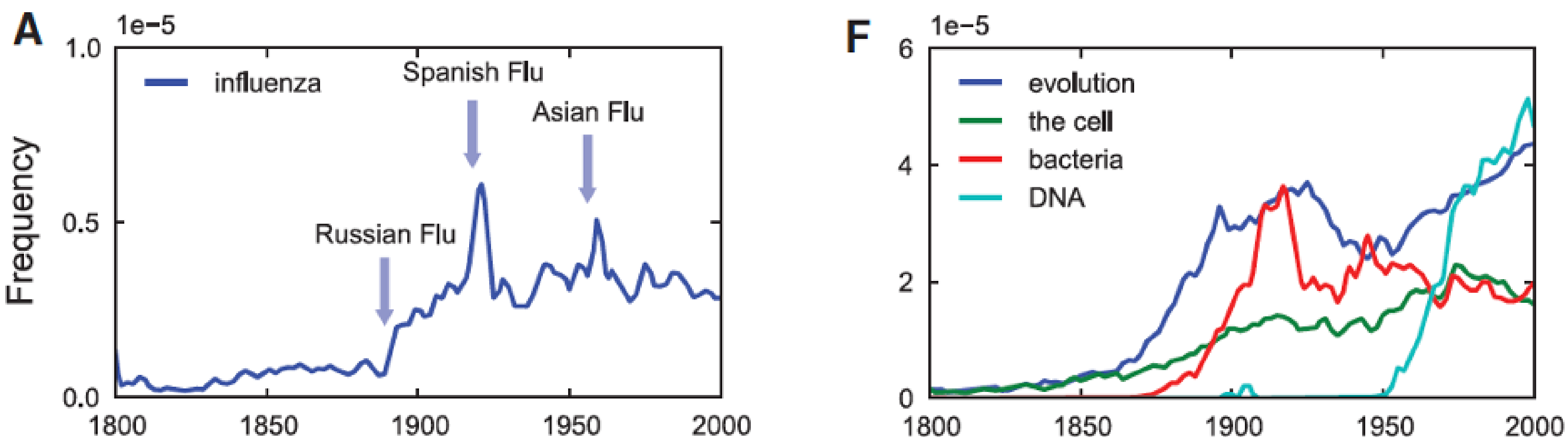
“Text mining represents the ability to take large amounts of **unstructured language** *and quickly extract useful and novel insights that can affect* **stakeholder decision-making**“ (Kwartler 2017)

Why text mining?

- **Increasing access** to data in the form of text
    - Newspapers
    - Bibliometric data (full text of publications and patents)
    - Social media (e.g. Twitter)
    - Parliamentary debates (e.g. https://hansard.parliament.uk)
    - …
- A phenomenon of considerable **magnitude** (https://www.webfx.com/internet-real-time/)
- Textual data are **unstructured**

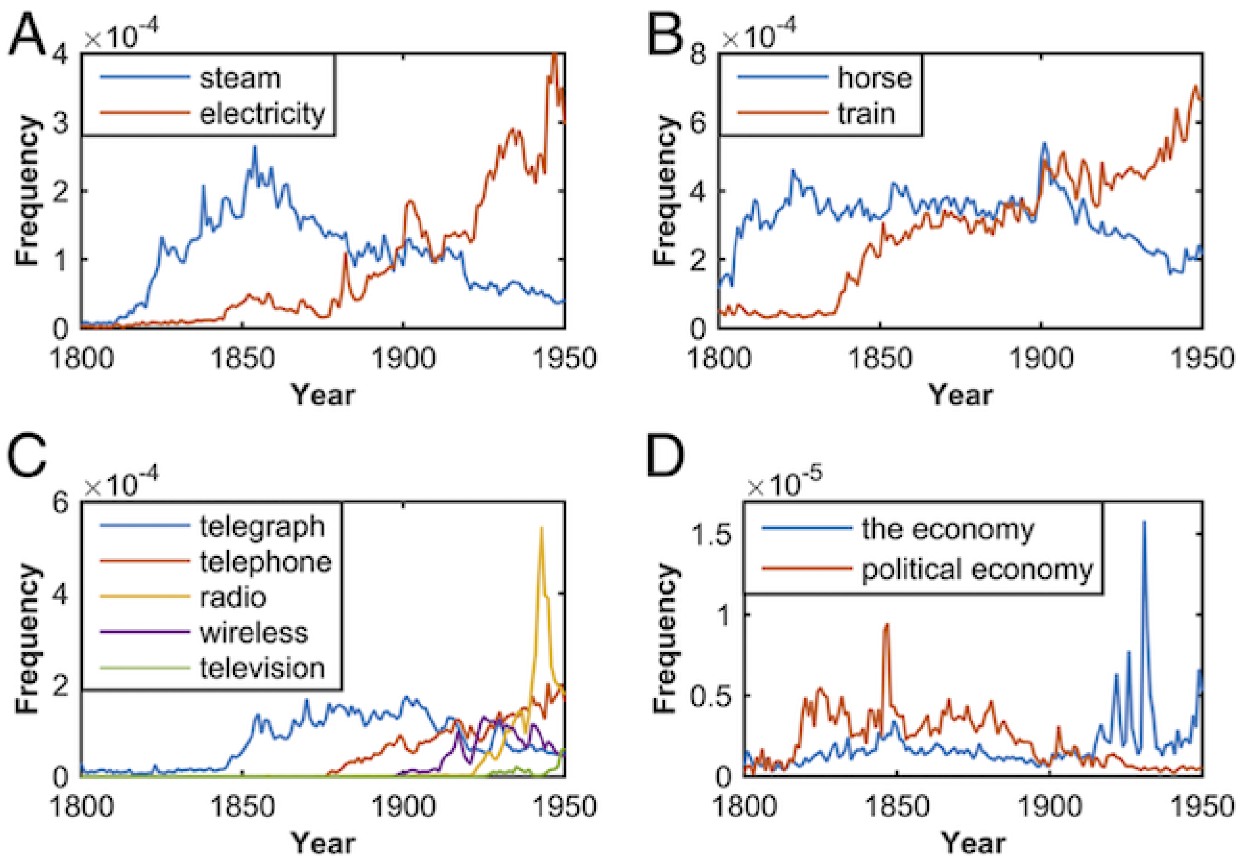
How can we identify patterns in these large amount of unstructured data?

Example 1



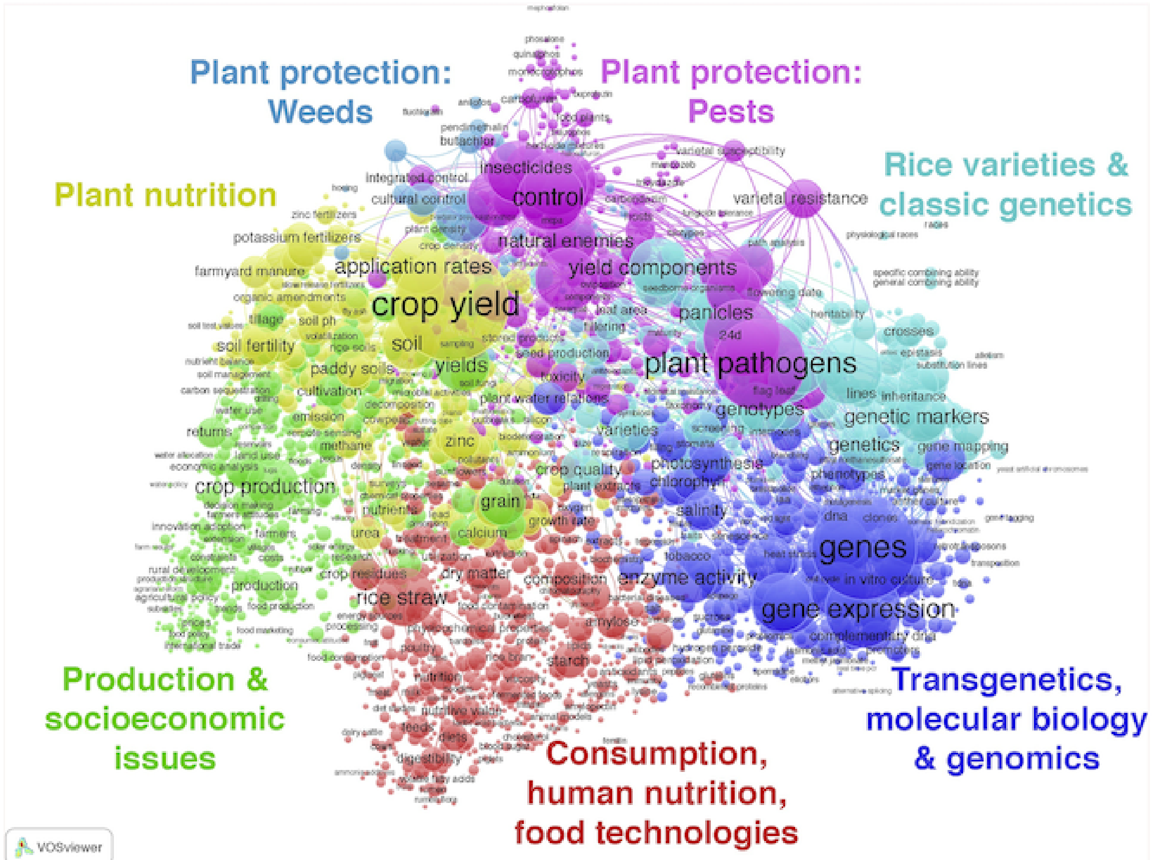
Source: Examining linguistic and cultural phenomena (1800-2000) - sample of 5 millions books (Michel et al. 2011)

Example 2



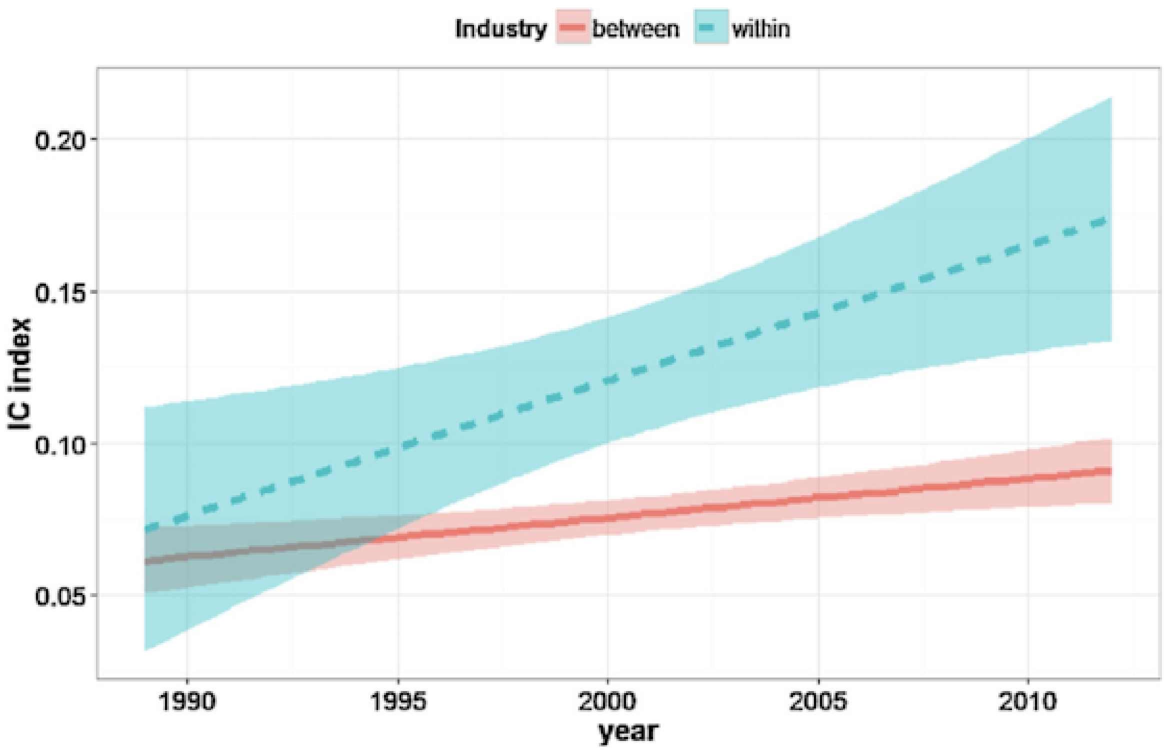
Source: A sample of 150 year of articles published in British periodicals (Lansdall-Welfare et al. 2017)

Example 3



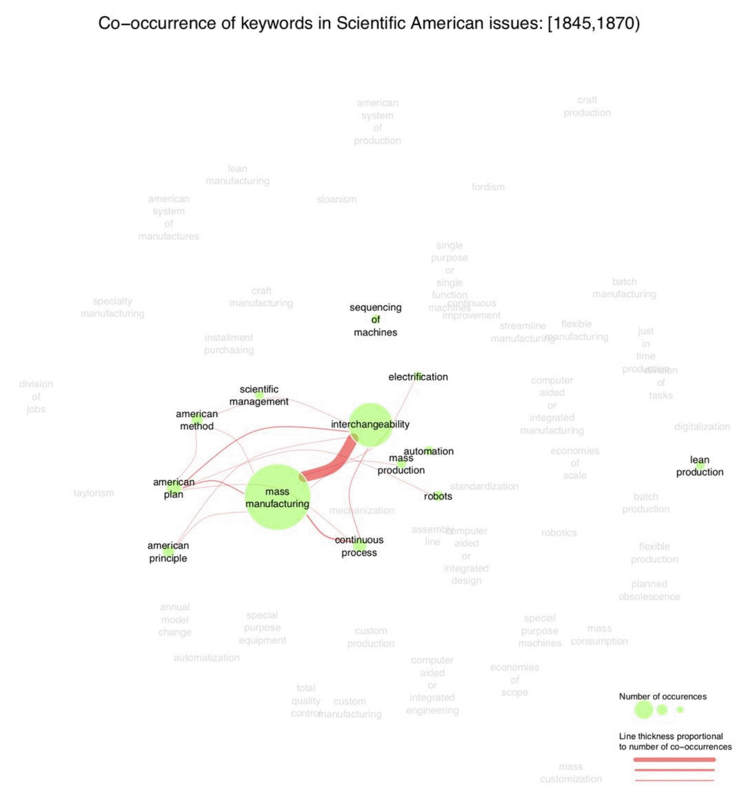
Source: Research priorities and societal demand(Ciarli and Ràfols 2019)

Example 4



Source: Convergence of industries using 2 million newspaper articles from 1989 to 2012 (IC = Industry convergence index, which is based on co-occurrence of industry in a sentence) (Kim et al. 2015)

Example 5



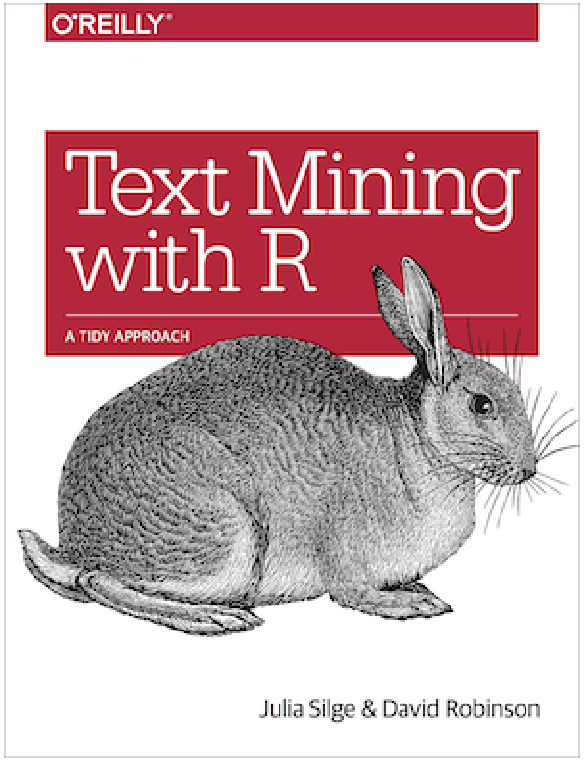
Source: Emergence of mass production in the text of Scientific American (1845-1995) (Bone and Rotolo 2020)

Types of text mining

- **Bag of words**
  - Words or groups of words are considered to be a feature of documents
  - The order of words and the grammar are not considered
  - Computationally inexpensive and data ready for machine learning (Document-Term Matrices)
- **Syntactic parsing**
  - Syntactic rules used to build the sentence are defined
  - Words or groups of words are tagged (e.g. adjectives, nouns, verbs)
  - Computationally expensive and complex language-dependent models
  - In-depth analysis of the relationships between the elements of a corpus

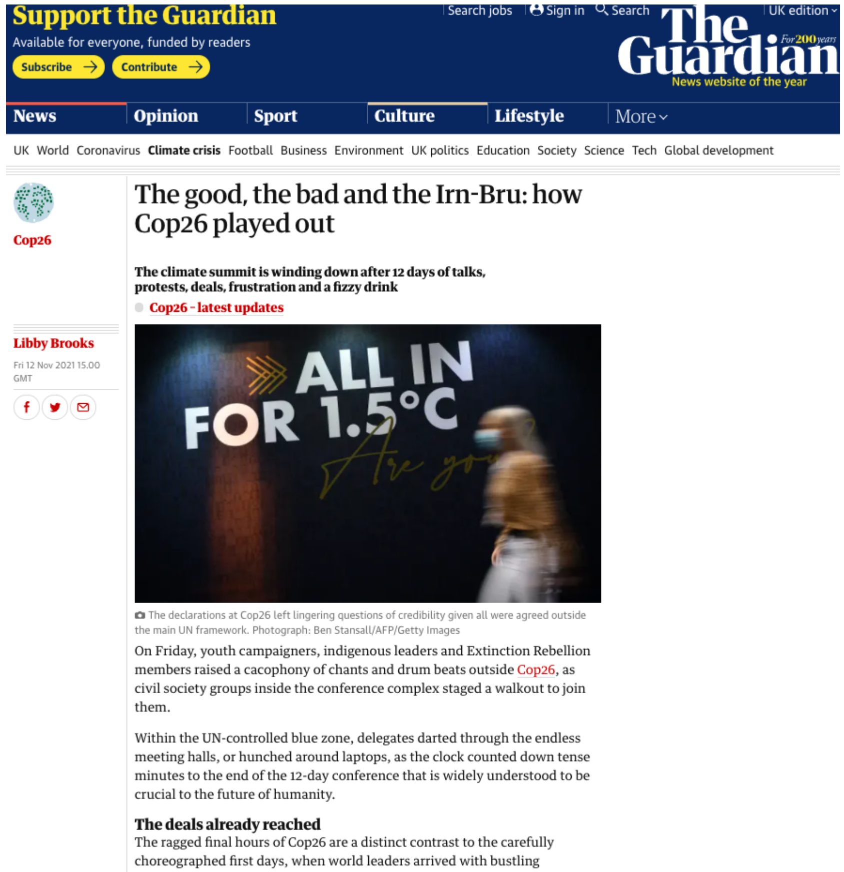
Text mining first steps

The `tidytext` package in R



Source: https://www.tidytextmining.com

How can we “tidy” unstructured data?



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Cop26

The good, the bad and the Irn-Bru: how Cop26 played out

The climate summit is winding down after 12 days of talks, protests, deals, frustration and a fizzy drink

Cop26 - latest updates

Libby Brooks

Fri 12 Nov 2021 15.00 GMT

The declarations at Cop26 left lingering questions of credibility given all were agreed outside the main UN framework. Photograph: Ben Stansall/AFP/Getty Images

On Friday, youth campaigners, indigenous leaders and Extinction Rebellion members raised a cacophony of chants and drum beats outside Cop26, as civil society groups inside the conference complex staged a walkout to join them.

Within the UN-controlled blue zone, delegates darted through the endless meeting halls, or hunched around laptops, as the clock counted down tense minutes to the end of the 12-day conference that is widely understood to be crucial to the future of humanity.

The deals already reached

The ragged final hours of Cop26 are a distinct contrast to the carefully choreographed first days, when world leaders arrived with bustling

Source: The Guardian, 12 November 2021

How can we “tidy” unstructured data?

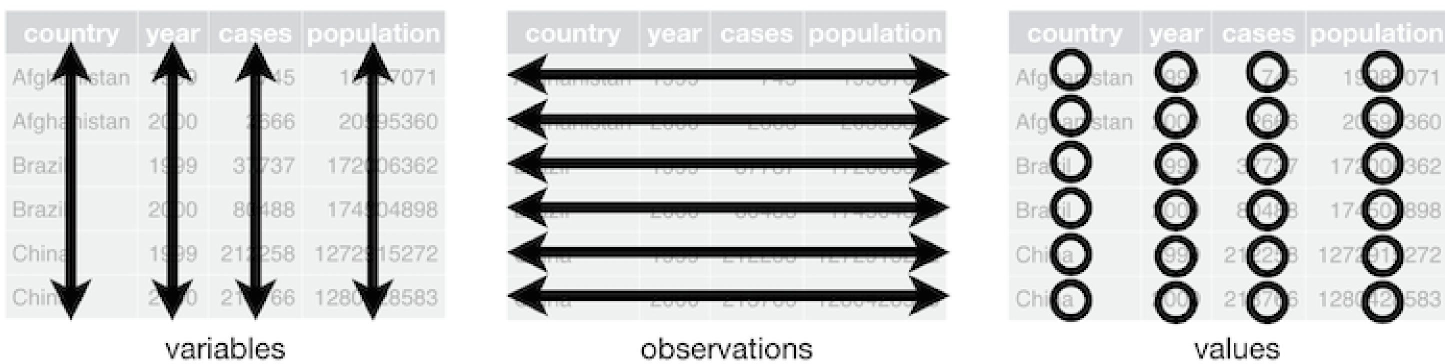
“On Friday, youth campaigners, indigenous leaders and Extinction Rebellion members raised a cacophony of chants and drum beats outside Cop26, as civil society groups inside the conference complex staged a walkout to join them. Within the UN-controlled blue zone, delegates darted through the endless meeting halls, or hunched around laptops, as the clock counted down tense minutes to the end of the 12-day conference that is widely understood to be crucial to the future of humanity. The deals already reached The ragged final hours of Cop26 are a distinct contrast to the carefully choreographed first days, when world leaders arrived with bustling entourages to deliver a flourish of eye-catching pledges and, in the case of Boris Johnson, eye-watering metaphors, as the host nation’s prime minster proffered a string of clumsy analogies, likening the climate crisis to a football game and then a James Bond movie in his welcome address….”

Source: The Guardian, 12 November 2021

Tidy data

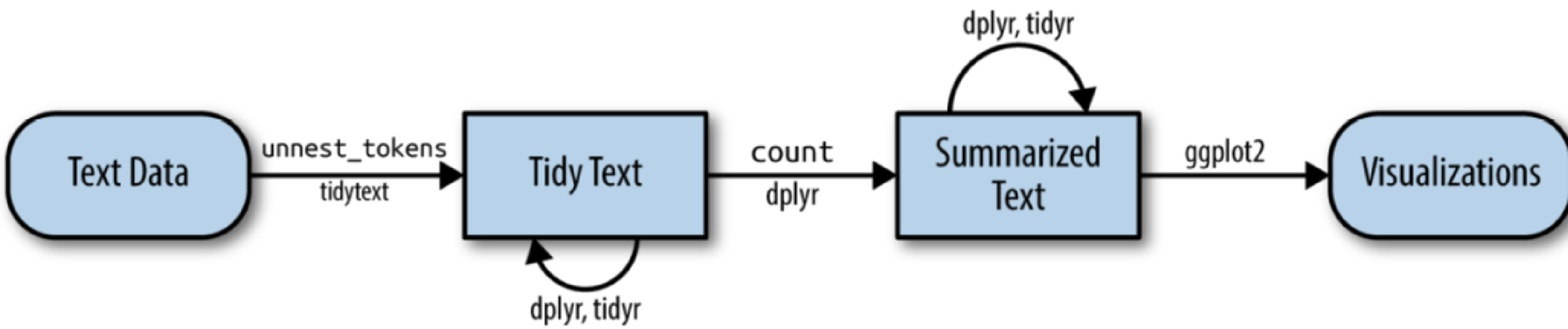
Wickham and Grolemund (2017) describe tidy data as data were

- **Observations** are in rows
- **Variables** are in columns
- Each **value** is in a cell



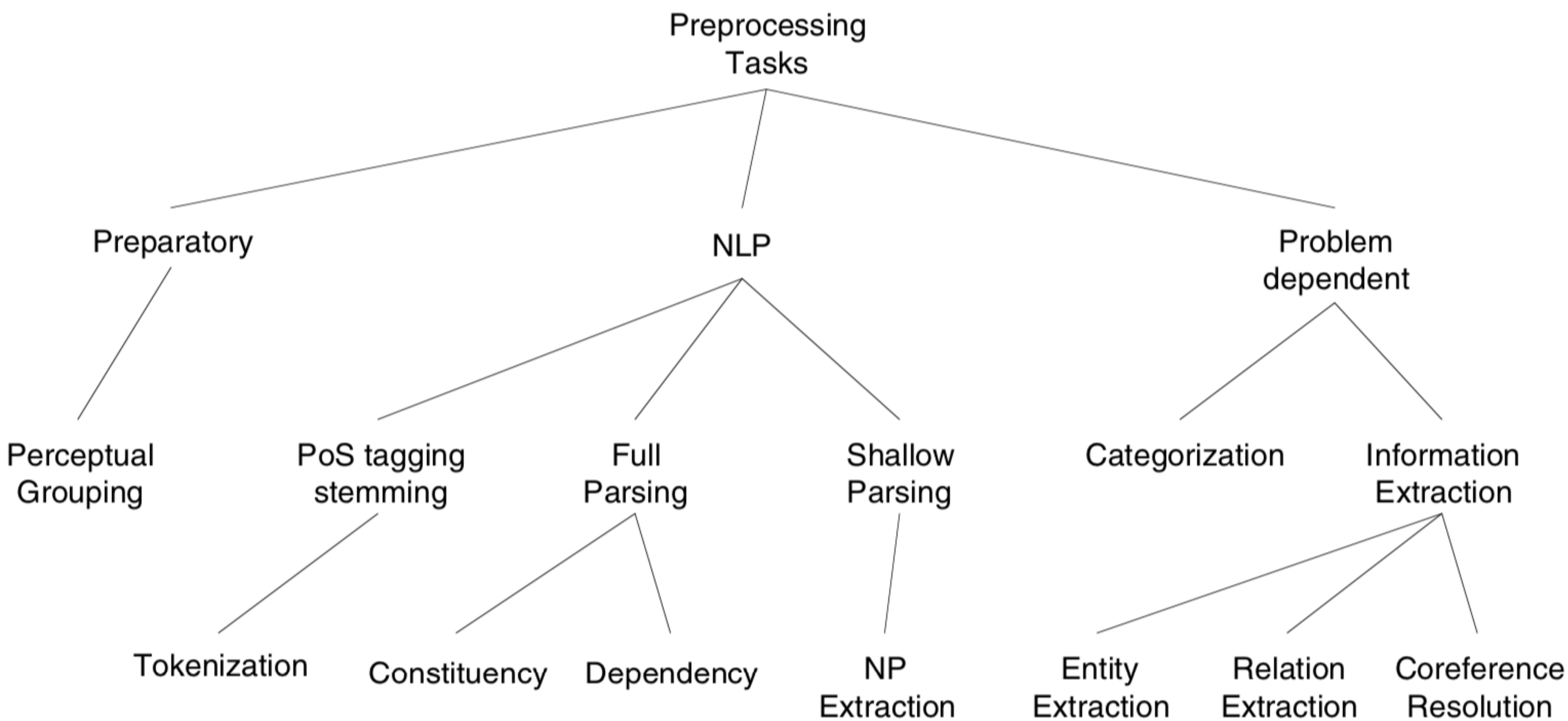
Source: Wickham and Grolemund (2017)

An overview of the process



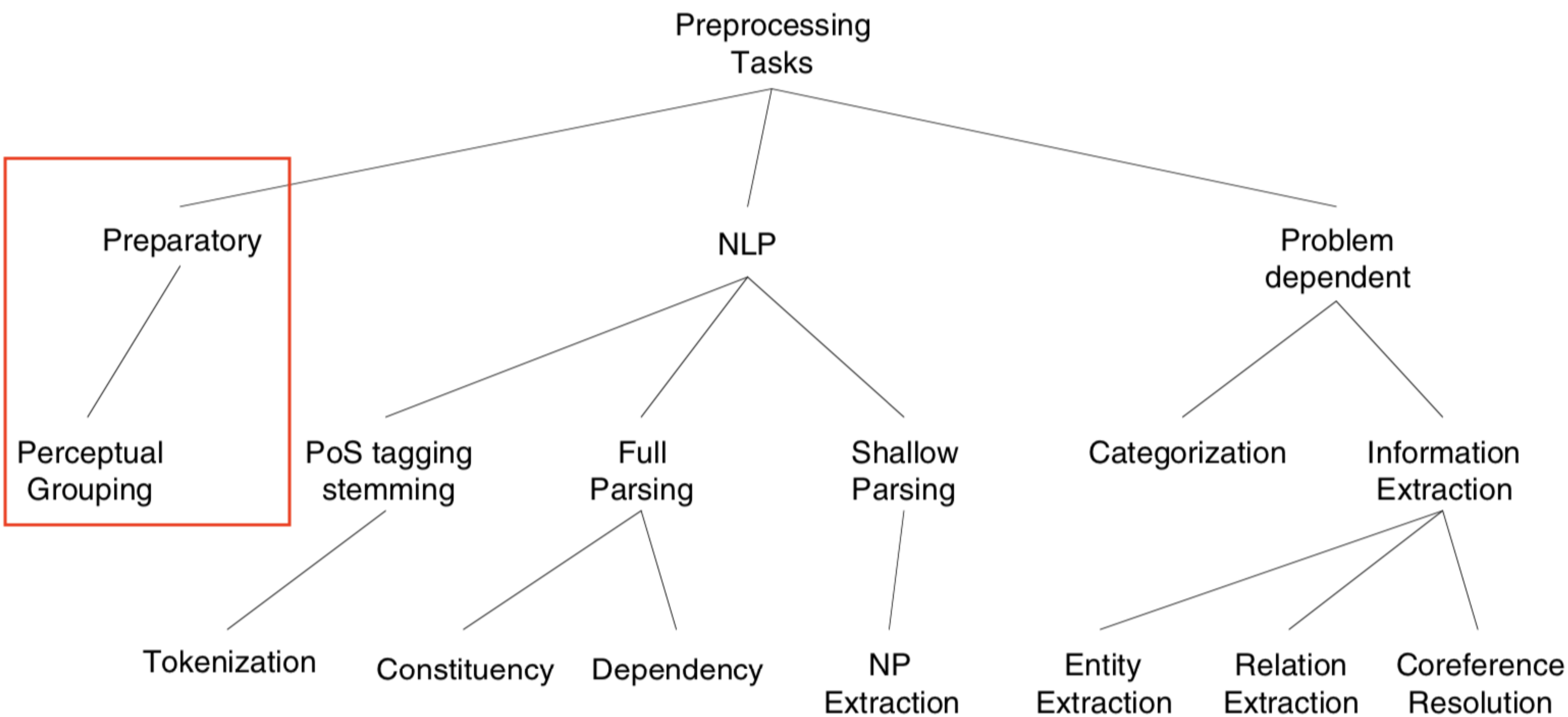
Source: Silge and Robinson (2017)

Preprocessing tasks



Source: Feldman and Sanger (2006)

Preparatory processing

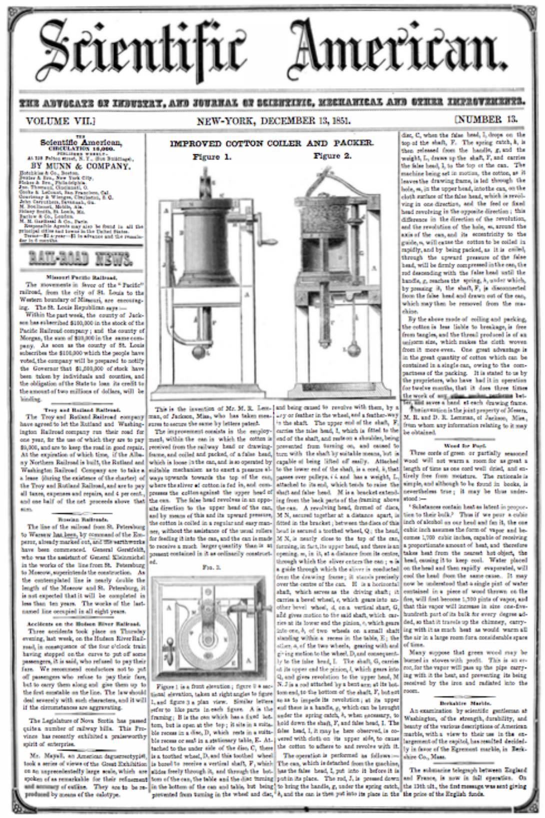


Source: Feldman and Sanger (2006)

Preparatory processing

- Text data may be in formats that are not ready for text mining
- These include:
  - PDF files
  - XML files
  - scanned images
  - recorded audio (e.g. speeches)
  - www
  - handwritten text
  - …

Preparatory processing


Scientific American.

THE ADVOCATE OF INDUSTRY, AND JOURNAL OF SCIENTIFIC, MECHANICAL AND OTHER IMPROVEMENTS.

VOLUME VII.] NEW-YORK, DECEMBER 13, 1851. [NUMBER 13.

BY MUNN & COMPANY.

RAIL-ROAD NEWS.

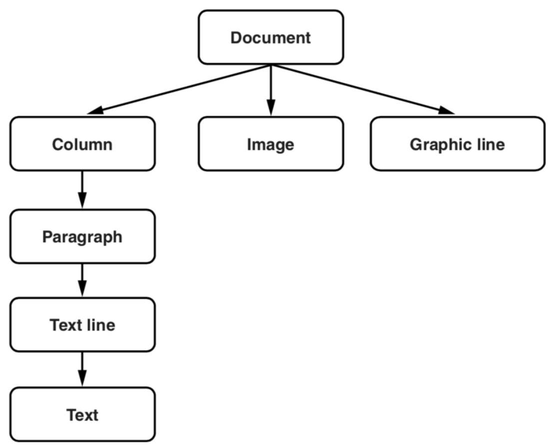
IMPROVED COTTON COILER AND PACKER.

Figure 1. Figure 2.

Source: Scientific American, December 1851

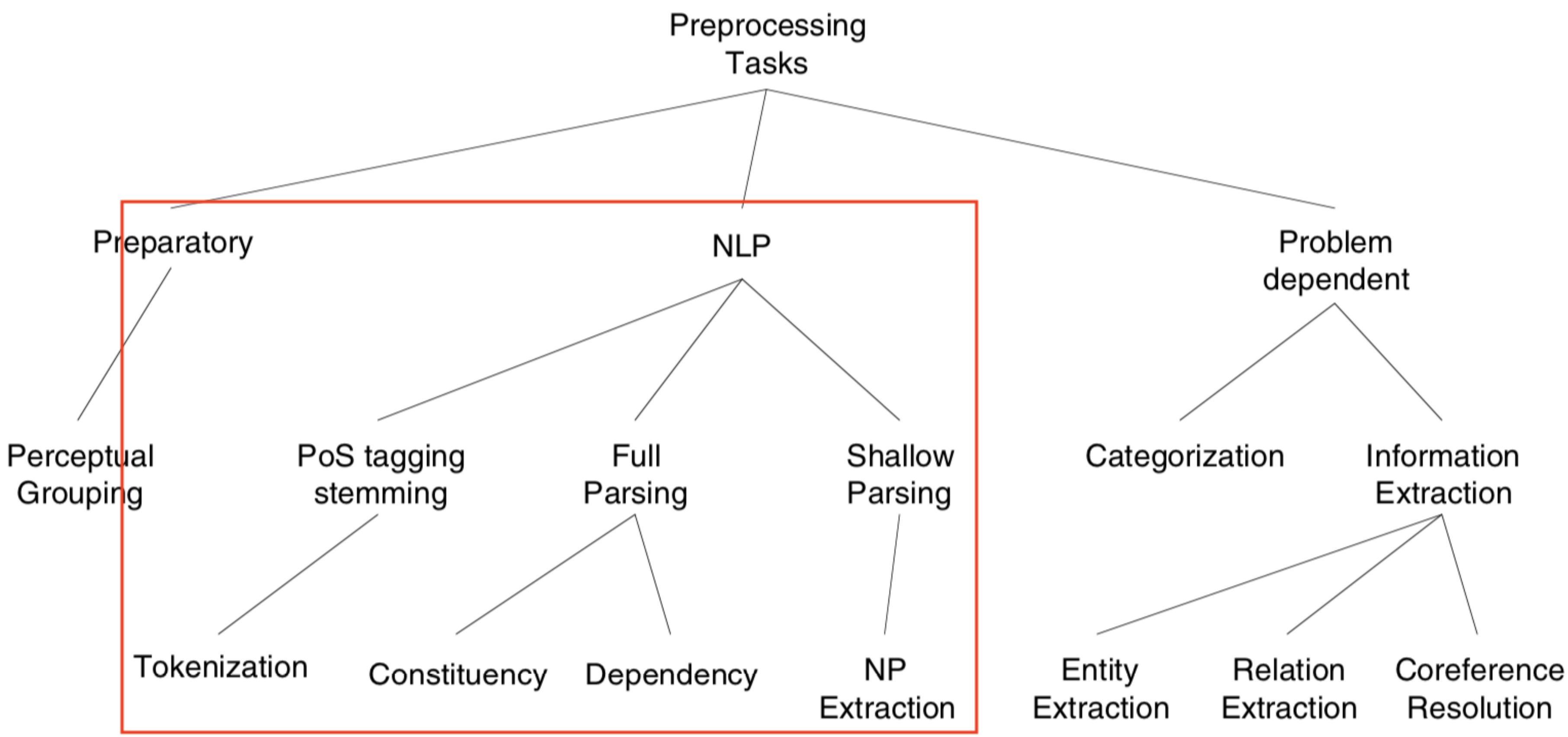
Preparatory processing

- A key preparatory task is **perceptual grouping**
- The aim is to group the primitive elements of the documents into objects of higher levels, i.e. to generate an **O-Tree**
- For example, some OCR software packages can recognise objects such as columns from scanned images



Source: O-Tree (Feldman and Sanger 2006)

Natural Language Processing (NLP)



Source: Feldman and Sanger (2006)

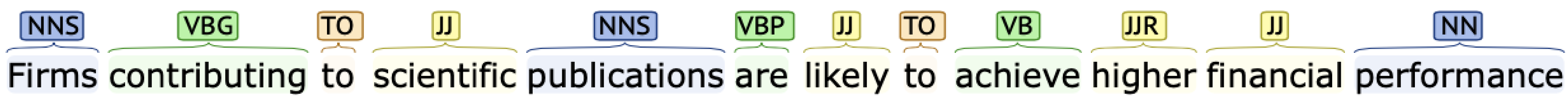
Natural Language Processing (NLP)

- Natural Language Processing (NLP) is an important area of an interdisciplinary research domain called **computational linguistic**
- NLP provides techniques to **transform and process text data**, so to identify patterns in these data
- NLP is particulalrly important for **“syntactic parsing”** than for “bag of words” text mining
- Three main approaches:
  1. Part-of-Speech (POS) tagging
  2. Full parsing
  3. Shallow parsing

Natural Language Processing (NLP)

Part-of-Speech (POS) tagging

- Words are categorised according to the role they play in the sentence: article, noun, verb, adjective, preposition, number, proper noun, etc.
- List of POS tags
- The tokenisation of text into words or groups of words (*we will see this in practice later*)



Source: https://corenlp.run

Natural Language Processing (NLP)

Full parsing

- The objective is to perform a full syntactical analysis of sentence identifying two elements
  - **Constituency grammars**: short phases that convey a meaning
    - **Noun phrase (NP)**: subjects or objects to a verb
    - **Verb phrase (VP)**: verbs
    - **Adjective phrase (ADJP)**: adjectives to qualify nouns and pronouns
    - **Adverb phrase (ADVP)**: adverbs to modify nouns, verbs, or adverbs
    - **Prepositional phrase (PP)**: prepositions to describe words or phrases
  - **Dependency grammars**: relationships between words (e.g. a subject and an object depend on a verb)

Natural Language Processing (NLP)

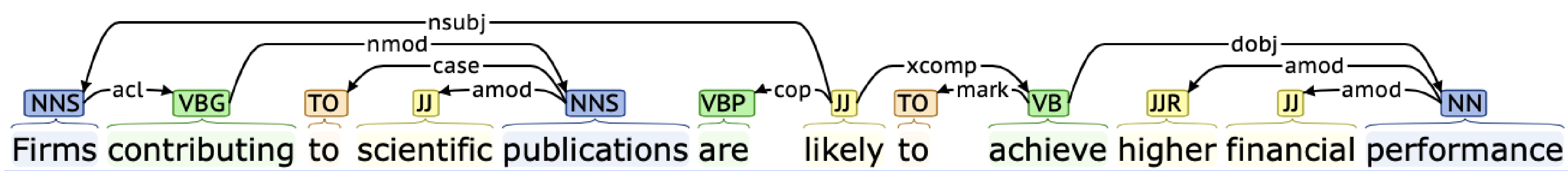
Constituency grammars

```
(ROOT
  (S
    (NP
      (NP (NNS Firms))
      (VP (VBG contributing)
        (PP (TO to)
          (NP (JJ scientific) (NNS publications)))))
    (VP (VBP are)
      (ADJP (JJ likely)
        (S
          (VP (TO to)
            (VP (VB achieve)
              (NP (JJR higher) (JJ financial) (NN performance))))))))
```

Source: https://corenlp.run

Natural Language Processing (NLP)

Dependency grammars



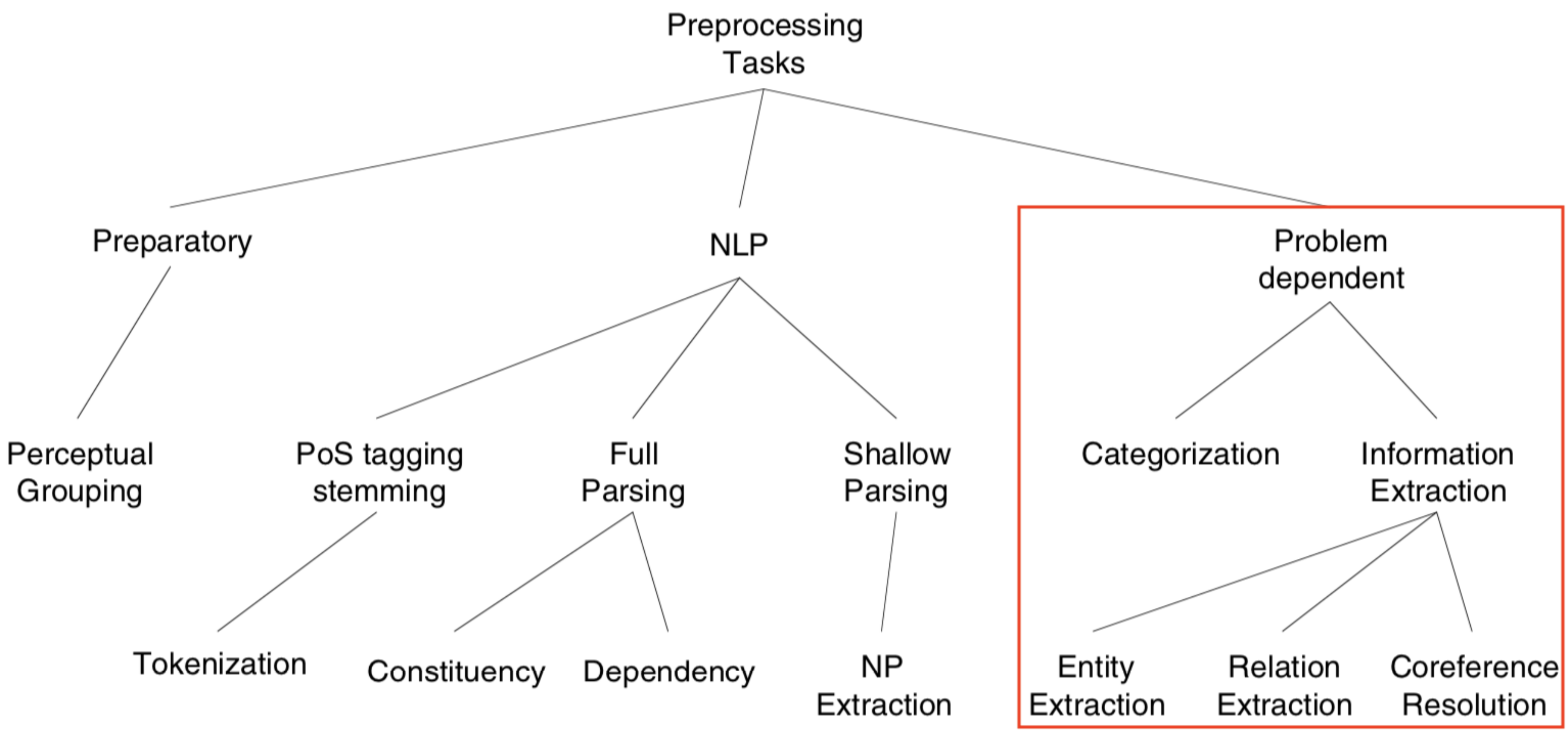
Source: https://corenlp.run

Natural Language Processing (NLP)

Shallow parsing

- Performing a full parsing for large text corpora could be **computationally expensive**
- Shallow parsing reduces the **depth** of the parsing analysis for the sake of **speed**
    - **Simple and short phrases are** identified
    - **Unclear and ambiguous dependency** are left unresolved
- The results of the shallow parsing are sufficient to characterise a corpus

Problem dependent processing



Source: Feldman and Sanger (2006)

Problem dependent processing

- **Text categorization or classification**
  - Assigning **tags** representing concepts or keywords to documents
  - Tags may have a **hierarchical structure**
  - Examples: Medical Subject Headings, JEL Classification System
- **Information extraction**
  - Extracting information and presenting this in a **structured format** (e.g. tables, charts), beyond the simple information retrieval (e.g. identification of keywords in text)
  - **Entity extraction**: entities in the text (e.g. individuals)
  - **Relation extraction**: relationships between entities as in the text
  - **Coreference resolution**: expressions referring to the same entity (e.g. Daniel, him, his)

Our focus

- We will focus on text mining based on **bags of words**
- Techniques to **process** and **analyse** the text
    - Tokenisation
    - Lemmatisation
    - Stemming
    - tf-idf
    - Visualisation
    - Sentiment analysis
    - Topic modelling

Tokenisation

What is tokenisation?

- The objective is to break text into **meaningful elements**
- For example, we can break a document into
  - chapters
  - sections
  - paragraphs
  - sentences
  - words
  - syllables

What is tokenisation?

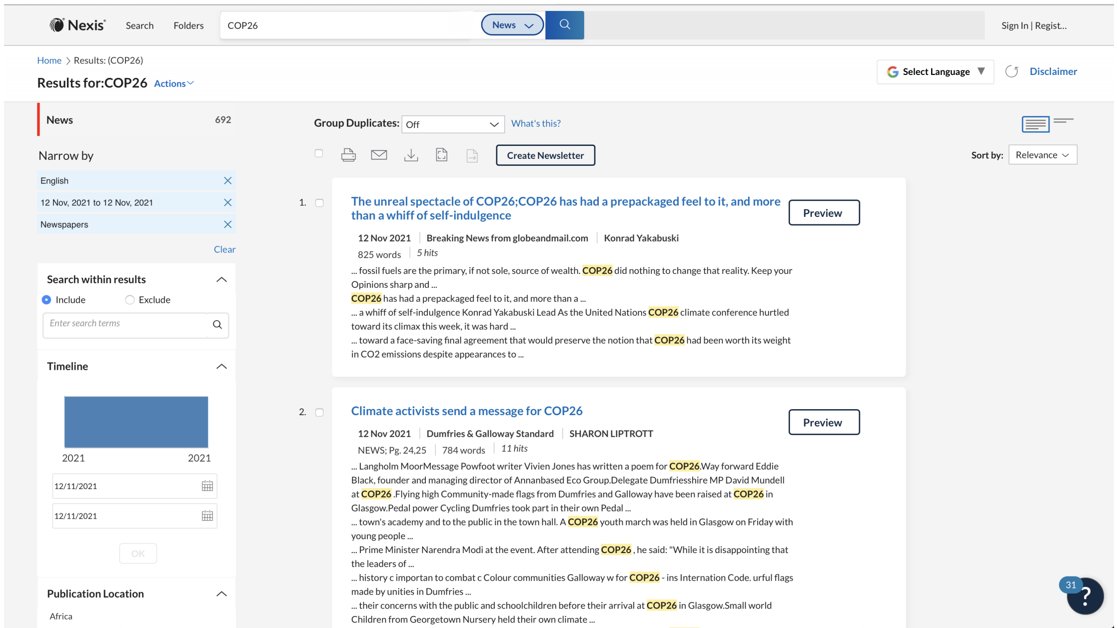
- A commonly used approach is to break the text into words, i.e. **tokens**
- A token could be
  - a single word (unigram)
  - two subsequent words (i.e. bigram)
  - …
  - n subsequent words (n-gram)
- We can use token to build a **tidy dataset**, where each row reports a **token**

Tokenisation in `tidytext`

- In `tidytext`, the function `unnest_tokens` enables us to tokenise the text
- This function
  - removes punctuation
  - converts tokens into lower case
- For more options see `??unnest_tokens`

Example: (1) Data on news articles

- Text from 692 news English articles on COP26 published by newspapers on 12 November 2021



Source: Nexis database (available at the University of Sussex Library)

Example: (2) Data on news articles

- Each news article has a numeric id
- Text is include in the fields
  - “Title”
  - “Headline”
  - “Hlead”

Example: (3) Reading the data

- We load the **`readr`**, **`tidyverse`**, **`tidytext`**, and **`ggplot`** packages
- We store our data into R as a dataframe/tibble
- We focus on the text reported in the field “Title”

```
library(readr)
library(ggplot2)
library(tidyverse)
library(tidytext)

my_text <- read_csv("news_articles_example.csv") %>%
  select(id, Title)
```

Example: (3) Reading the data

```
print(my_text, n = 6)
```

```
## # A tibble: 692 × 2
##      id Title
##   <dbl> <chr>
## 1     1 The unreal spectacle of COP26;COP26 has had a prepackaged feel to it, a…
## 2     2 Climate activists send a message for COP26
## 3     3 COP26: Nicola Sturgeon urges Boris Johnson to return and use position t…
## 4     4 COP26: Nicola Sturgeon urges Boris Johnson to return and use position t…
## 5     5 COP26: Police Scotland arrested eight people on penultimate day of Glas…
## 6     6 COP26: Top 10 bizzare moments of the Glasgow climate talks ranked
## # … with 686 more rows
```

Example: (4) Tokenisation (unigrams)

We tokenise each sentence into unigrams

```
my_text_uni <- my_text %>%
  unnest_tokens(output = word, input = Title)

print(my_text_uni, n = 6)
```

```
## # A tibble: 7,925 × 2
##      id word
##   <dbl> <chr>
## 1     1 the
## 2     1 unreal
## 3     1 spectacle
## 4     1 of
## 5     1 cop26
## 6     1 cop26
## # … with 7,919 more rows
```

Example: (4) Tokenisation (bigrams)

We could also tokenise into n-grams, for example bigrams

```
my_text_bi <- my_text %>%
  unnest_tokens(output = bigram, input = Title,
                token = "ngrams", n = 2)

print(my_text_bi, n = 6)
```

```
## # A tibble: 7,238 × 2
##        id bigram
##     <dbl> <chr>
## 1       1 the unreal
## 2       1 unreal spectacle
## 3       1 spectacle of
## 4       1 of cop26
## 5       1 cop26 cop26
## 6       1 cop26 has
## # … with 7,232 more rows
```

Example: (4) Tokenisation (trigrams)

… or trigrams

```
my_text_tri <- my_text %>%
  unnest_tokens(output = trigram, input = Title,
                token = "ngrams", n = 3)

print(my_text_tri, n = 6)
```

```
## # A tibble: 6,557 × 2
##      id trigram
##   <dbl> <chr>
## 1     1 the unreal spectacle
## 2     1 unreal spectacle of
## 3     1 spectacle of cop26
## 4     1 of cop26 cop26
## 5     1 cop26 cop26 has
## 6     1 cop26 has had
## # … with 6,551 more rows
```

Example: (4) Tokenisation (characters)

… or sequences of characters (five in the case below)

```
my_text_char <- my_text %>%
  unnest_tokens(output = character_shingles, input = Title,
                token = "character_shingles", n = 5)

print(my_text_char, n = 6)
```

```
## # A tibble: 36,769 × 2
##      id character_shingles
##   <dbl> <chr>
## 1     1 theun
## 2     1 heunr
## 3     1 eunre
## 4     1 unrea
## 5     1 nreal
## 6     1 reals
## # … with 36,763 more rows
```

Example: (5) POS tagging

```r
my_text_uni_pos <- my_text_uni %>%
  left_join(parts_of_speech, by  = "word")

print(my_text_uni_pos, n = 6)
```

```
## # A tibble: 15,047 × 3
##      id word      pos
##   <dbl> <chr>     <chr>
## 1     1 the       Definite Article
## 2     1 the       Adverb
## 3     1 unreal    Adjective
## 4     1 spectacle Noun
## 5     1 of        Noun
## 6     1 of        Preposition
## # … with 15,041 more rows
```

Example: (5) POS tagging

```
my_text_uni_pos <- my_text_uni_pos %>%
  group_by(pos) %>%
  count(pos, sort = T)

print(my_text_uni_pos, n = 6)
```

```
## # A tibble: 13 × 2
## # Groups:   pos [13]
##   pos                          n
##   <chr>                    <int>
## 1 Noun                      4953
## 2 <NA>                      1521
## 3 Adverb                    1456
## 4 Verb (usu participle)     1449
## 5 Preposition               1395
## 6 Adjective                 1175
## # … with 7 more rows
```

Example: (5) POS tagging

Show 5 entries

Search:

pos	n
All	All
Noun	4953
	1521
Adverb	1456
Verb (usu participle)	1449
Preposition	1395

Showing 1 to 5 of 13 entries

Previous 1 2 3 Next

Example: (6) Counting words

Let’s focus on unigrams and count the number of words

```
my_text_uni_count <- my_text_uni %>%
  count(word, sort = T)

print(my_text_uni_count, n = 6)
```

```
## # A tibble: 2,436 × 2
##   word        n
##   <chr>   <int>
## 1 to        300
## 2 the       188
## 3 of        161
## 4 cop26     160
## 5 on        148
## 6 climate   135
## # … with 2,430 more rows
```

Example: (6) Counting words

Show 5 entries Search:

word	n
All	All
to	300
the	188
of	161
cop26	160
on	148

Showing 1 to 5 of 2,436 entries

Previous 1 2 3 4 5 … 488 Next

Example: (6) Counting words

Basic descriptive statistics

```
summarise(my_text_uni_count,
          num_words = n(),
          mean = mean(n),
          sd   = sd(n),
          min  = min(n),
          max  = max(n))
```

```
## # A tibble: 1 × 5
##   num_words  mean    sd   min   max
##       <int> <dbl> <dbl> <int> <int>
## 1      2436  3.25  11.1     1   300
```

Example: (6) Counting words

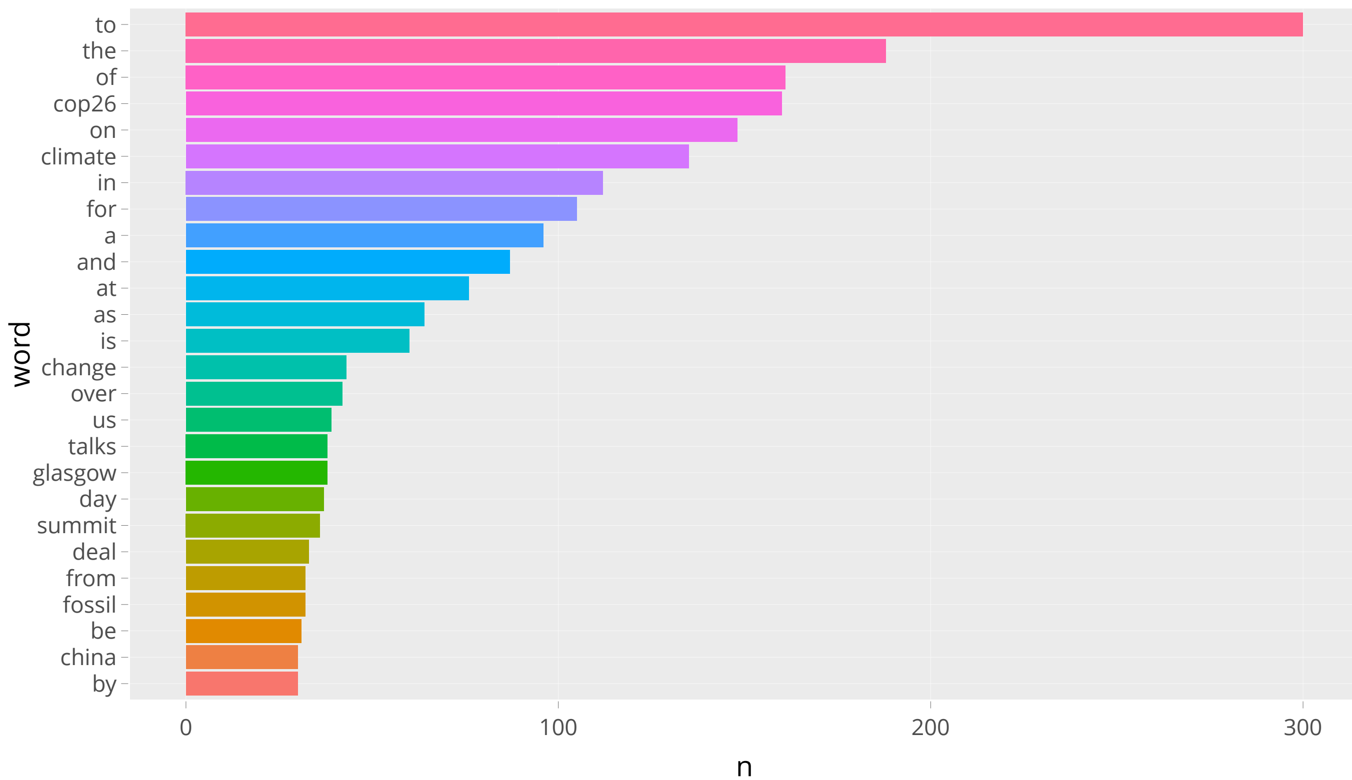
We can plot the most frequent words representing the 1% of the total sample

```
min_occur <- quantile(my_text_uni_count$n, 0.99)

g <- my_text_uni_count %>%
  filter(n >= min_occur) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(x = word, y = n, fill = word)) +
  geom_col() +
  theme(legend.position = "none") +
  coord_flip()
```

Example: (6) Counting words

- Many words are not particularly relevant (e.g. to, the, in)
- These terms are called stopwords



Example: (7) Removing stopwords

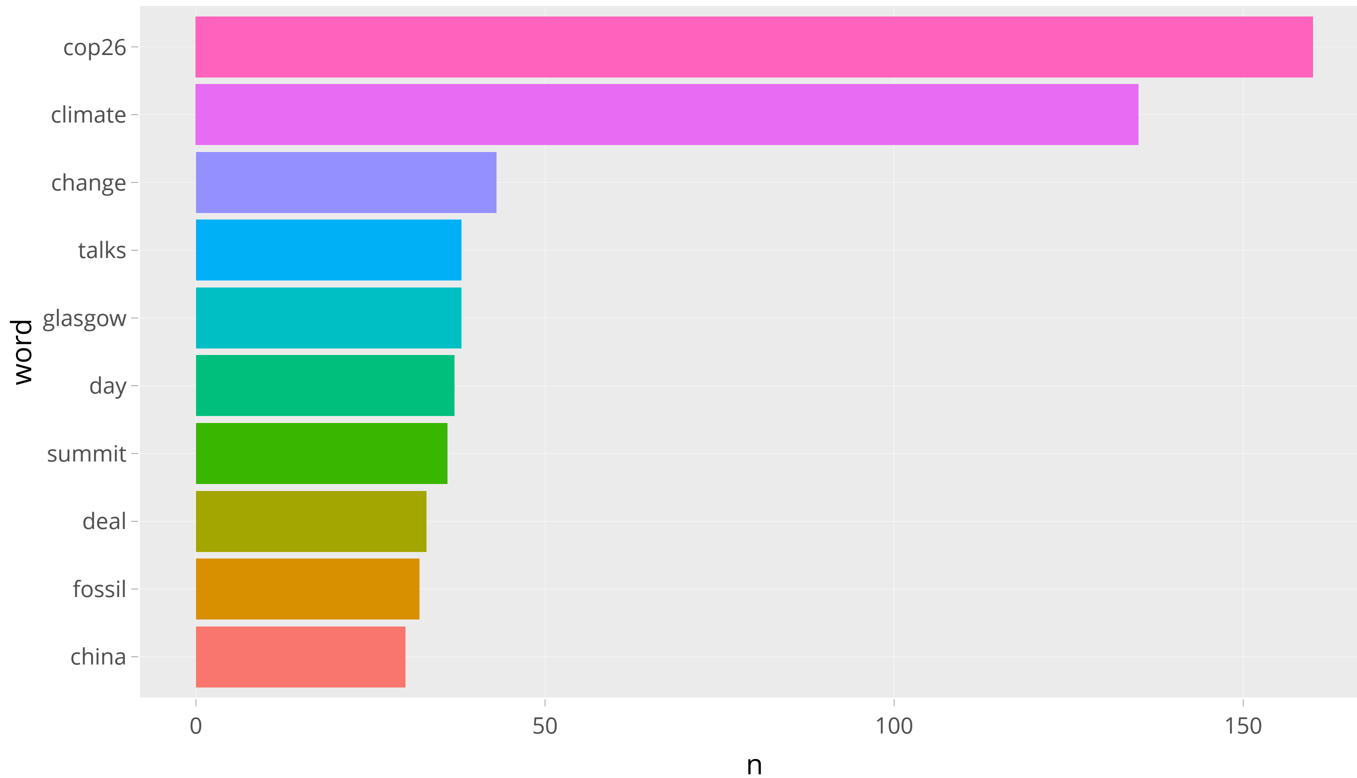
```
data(stop_words)

my_text_uni <- my_text_uni %>%
      anti_join(stop_words)

my_text_uni_count <- my_text_uni %>%
  count(word, sort = T)

g <- my_text_uni_count %>%
  filter(n >= min_occur) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(x = word, y = n, fill = word)) +
  geom_col() +
  theme(legend.position = "none") +
  coord_flip()
```

Example: (7) Removing stopwords



Example: (8) Removing numbers

- Numbers my not be meaningful for your analysis
- We can remove numbers converting text into numeric format

```
my_text_uni <- my_text_uni %>%
    mutate(word_numeric = as.numeric(word))
```

```
## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion
```

Example: (8) Removing numbers

Show 5 entries

Search:

id	word	word_numeric
All	All	All
1	unreal	
1	spectacle	
1	cop26	
1	cop26	
1	prepackaged	

Showing 1 to 5 of 4,985 entries

Previous 1 2 3 4 5 … 997 Next

Example: (8) Removing numbers

- `NAs` in the table are word, so we can filter those only
- We can reduce the threshold to the most frequnet words representing the 2% of the total sample so to explore more words

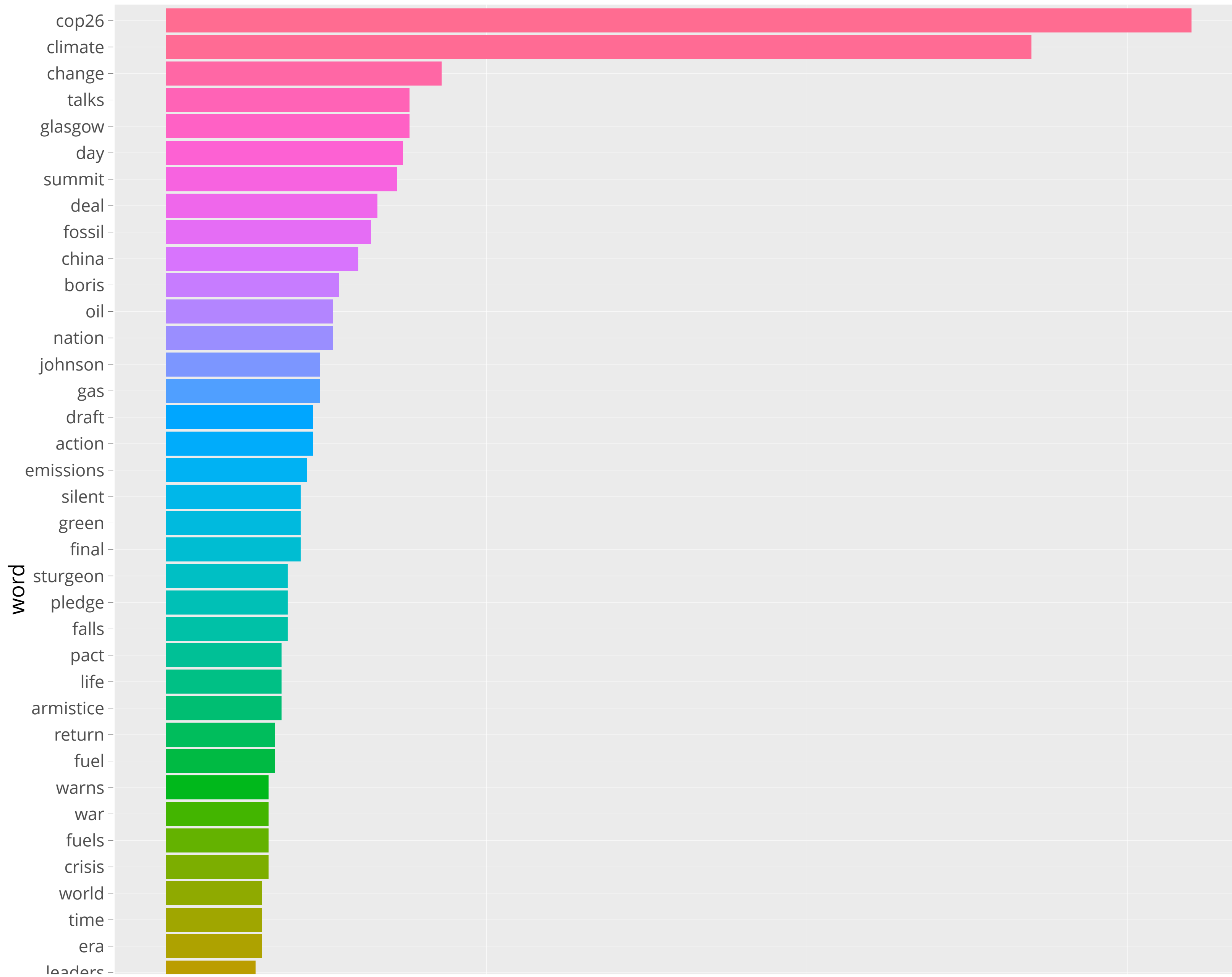
```
my_text_uni <- my_text_uni %>%
  filter(is.na(word_numeric))

my_text_uni_count <- my_text_uni %>%
  count(word, sort = T)

min_occur <- quantile(my_text_uni_count$n, 0.98)

g <- my_text_uni_count %>%
  filter(n >= min_occur) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(x = word, y = n, fill = word)) +
  geom_col() +
  theme(legend.position = "none") +
  coord_flip()
```

Example: (8) Removing numbers



Example: (9) Additional stopwords

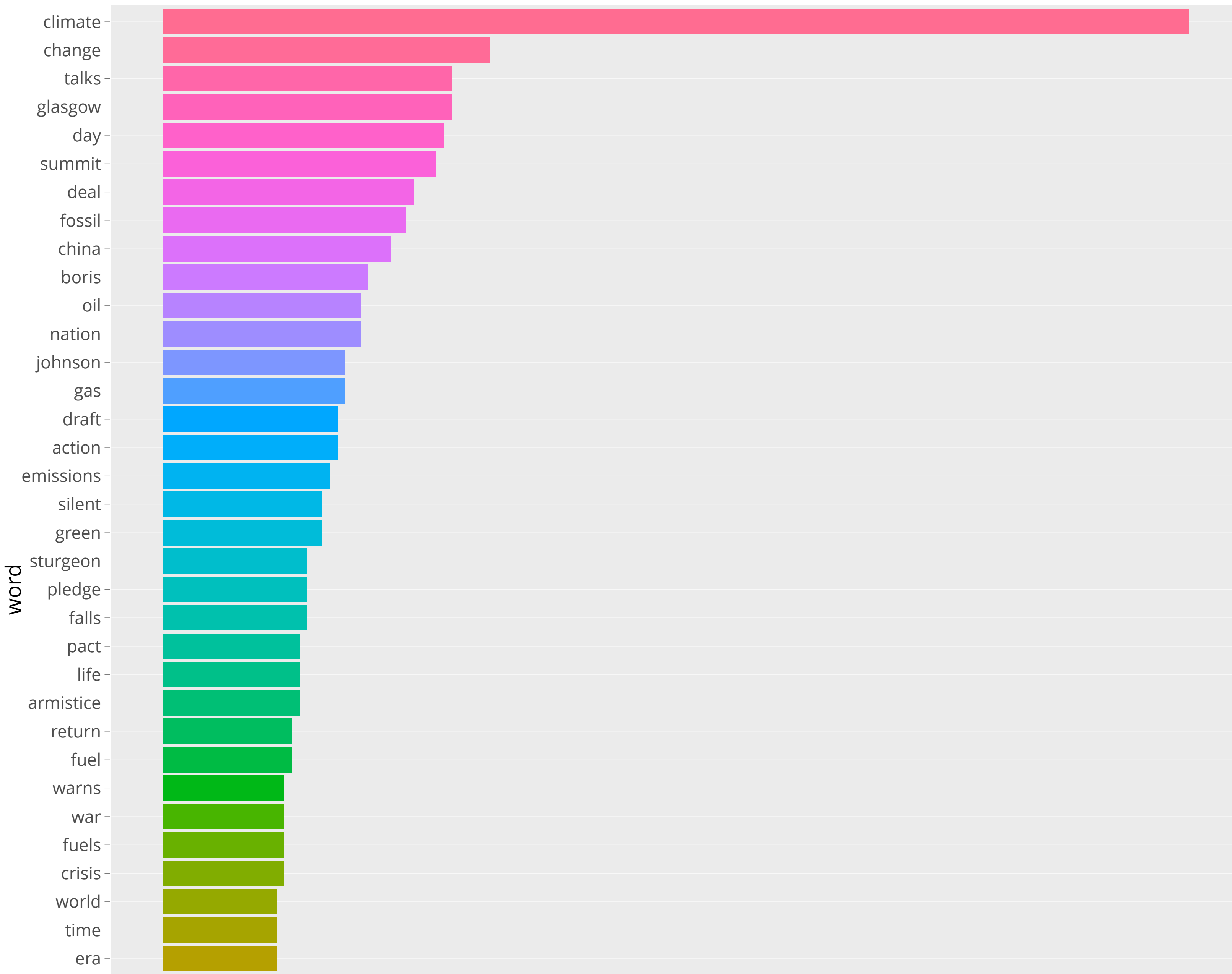
- In some case, you may want to remove words that are not particularly relevant

```
my_stop_words <- tibble(word = c("cop26", "final", "news"),
                        lexicon = "mywords")

my_text_uni<- my_text_uni %>%
      anti_join(my_stop_words)

g <- my_text_uni %>%
  count(word, sort = T) %>%
  filter(n >= min_occur) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(x = word, y = n, fill = word)) +
  geom_col() +
  theme(legend.position = "none") +
  coord_flip()
```

Example: (9) Additional stopwords



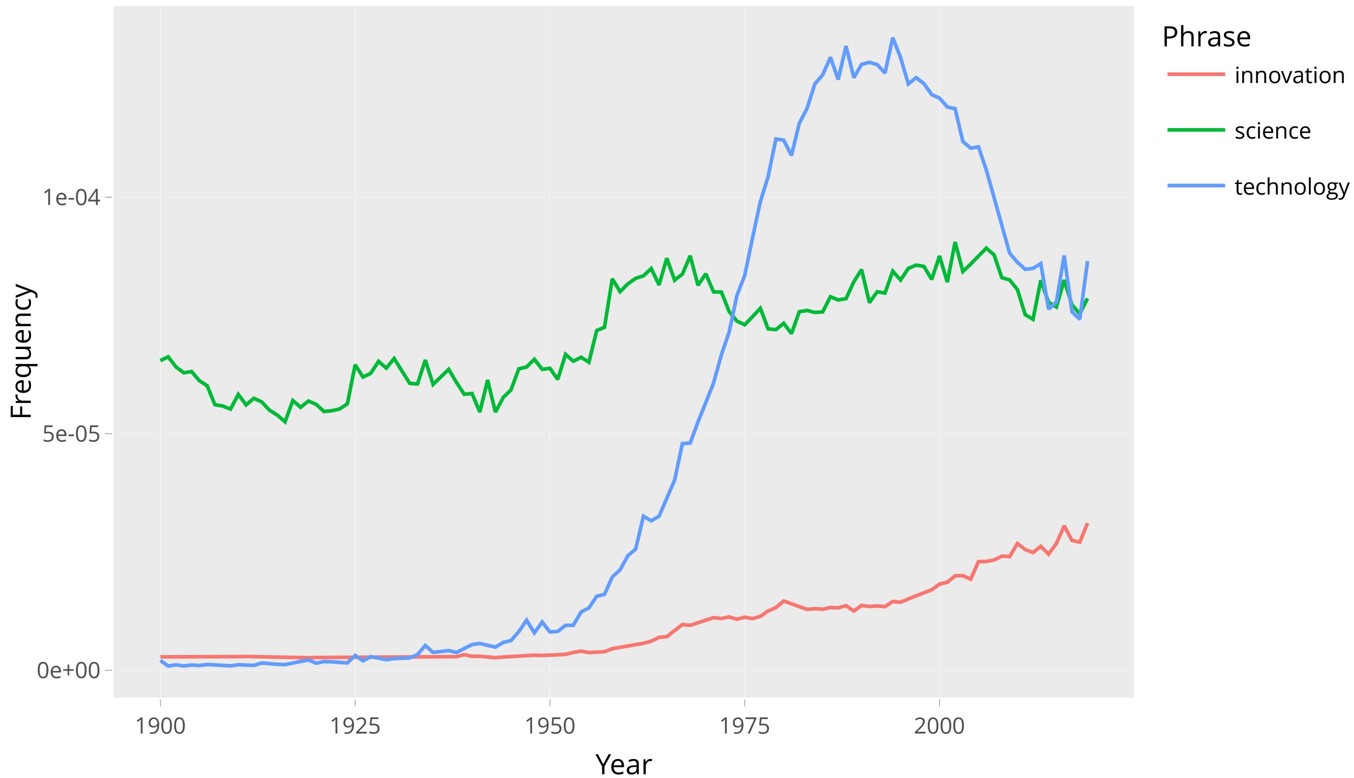
Tokenised data

- Google Books provides access to tokenised data for several millions of books
- Data structure
  - token (n-gram)
  - number of occurrences (match_count)
  - number of occurrences in distinct books (volume_count)
- **Warning:** The database includes a large amount of data (several gigabytes)
- Google Books query interface
- We can use the `ngramr` package to gather data

Example: (10) Google Books

```
library(ngramr)
library(ggplot2)
googlebook_data  <- ngram(c("science", "technology", "innovation"),
             smoothing = 0, year_start = 1900)
g <- ggplot(googlebook_data,
       aes(x = Year, y = Frequency, colour=  Phrase)) +
  geom_line()
```

Example: (10) Google Books



Lemmatisation

What is lemmatisation?

- Individual tokens are reduced to their base form, called “lemma”
  - “am,” “are,” “is” –> “be”
  - “cars” –> “car”
  - “arrived” –> “arrive”
  - …
- **Lemmatisation** normalise text (e.g. counting)
- This processing is useful for **sentiment analysis**

Example: (1) Unigrams lemmatisation

- We can use the package `textstem`
- We have already remove stopwords, numbers, and additional stopwords from the list of unigrams

```
library(textstem)
my_text_uni <- my_text_uni %>%
  mutate(word_lemma = textstem::lemmatize_words(word))
```

Example: (1) Unigrams lemmatisation

Show 5 entries

Search:

id	word	word_numeric	word_lemma
All	All	All	All
1	unreal		unreal
1	spectacle		spectacle
1	prepackaged		prepackaged
1	feel		feel
1	whiff		whiff

Showing 1 to 5 of 4,730 entries

Previous 1 2 3 4 5 … 946 Next

Example: (2) Counting lemmas

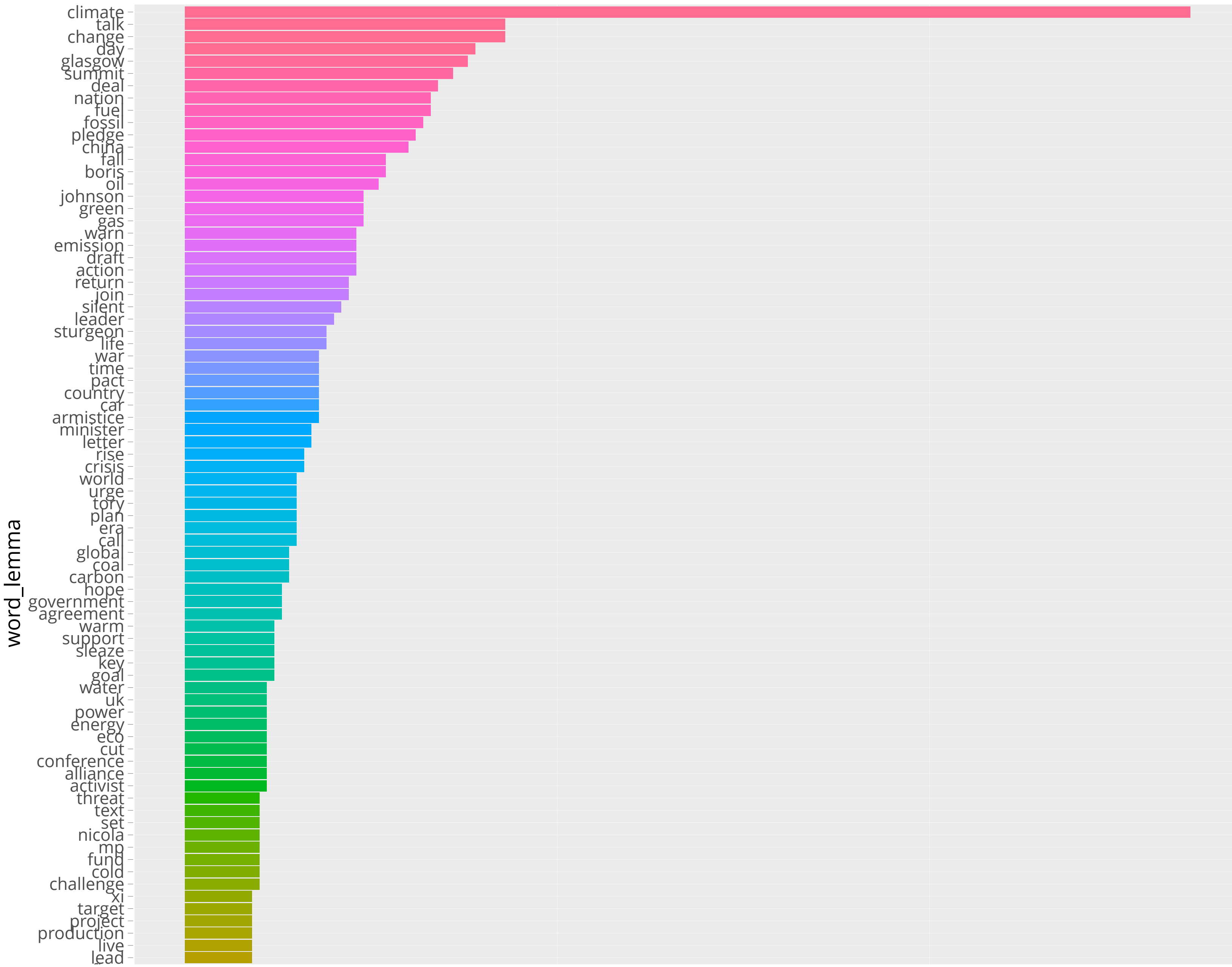
- We can now count lemmas and plot the results

```
my_text_uni_count <- my_text_uni %>%
  count(word_lemma, sort = T)

min_occur <- quantile(my_text_uni_count$n, 0.95)

g <- my_text_uni_count %>%
  filter(n >= min_occur) %>%
  mutate(word_lemma = reorder(word_lemma, n)) %>%
  ggplot(aes(x = word_lemma, y = n, fill = word_lemma)) +
  geom_col() +
  theme(legend.position = "none") +
  coord_flip()
```

Example: (2) Counting lemmas



Stemming

What is stemming?

- Stemming is similar to the lemmatisations
- It removes the suffix of a word
    - “playing” –> “play”
    - “consultant” –> “consult”
    - “magically” –> “magic”
    - …

Example: (1) Stemming unigrams

- We can use the package `SnowballC`
- We have already removed stopwords, numbers, and additional stopwords from the list of unigrams

```
library(SnowballC)
my_text_uni <- my_text_uni %>%
  mutate(word_stem = wordStem(word))
```

Example: (1) Stemming unigrams

Show 5 entries

Search:

id	word	word_numeric	word_lemma	word_stem
All	All	All	All	All
1	unreal		unreal	unreal
1	spectacle		spectacle	spectacl
1	prepackaged		prepackaged	prepackag
1	feel		feel	feel
1	whiff		whiff	whiff

Showing 1 to 5 of 4,730 entries

Previous 1 2 3 4 5 … 946 Next

Example: (2) Counting stems

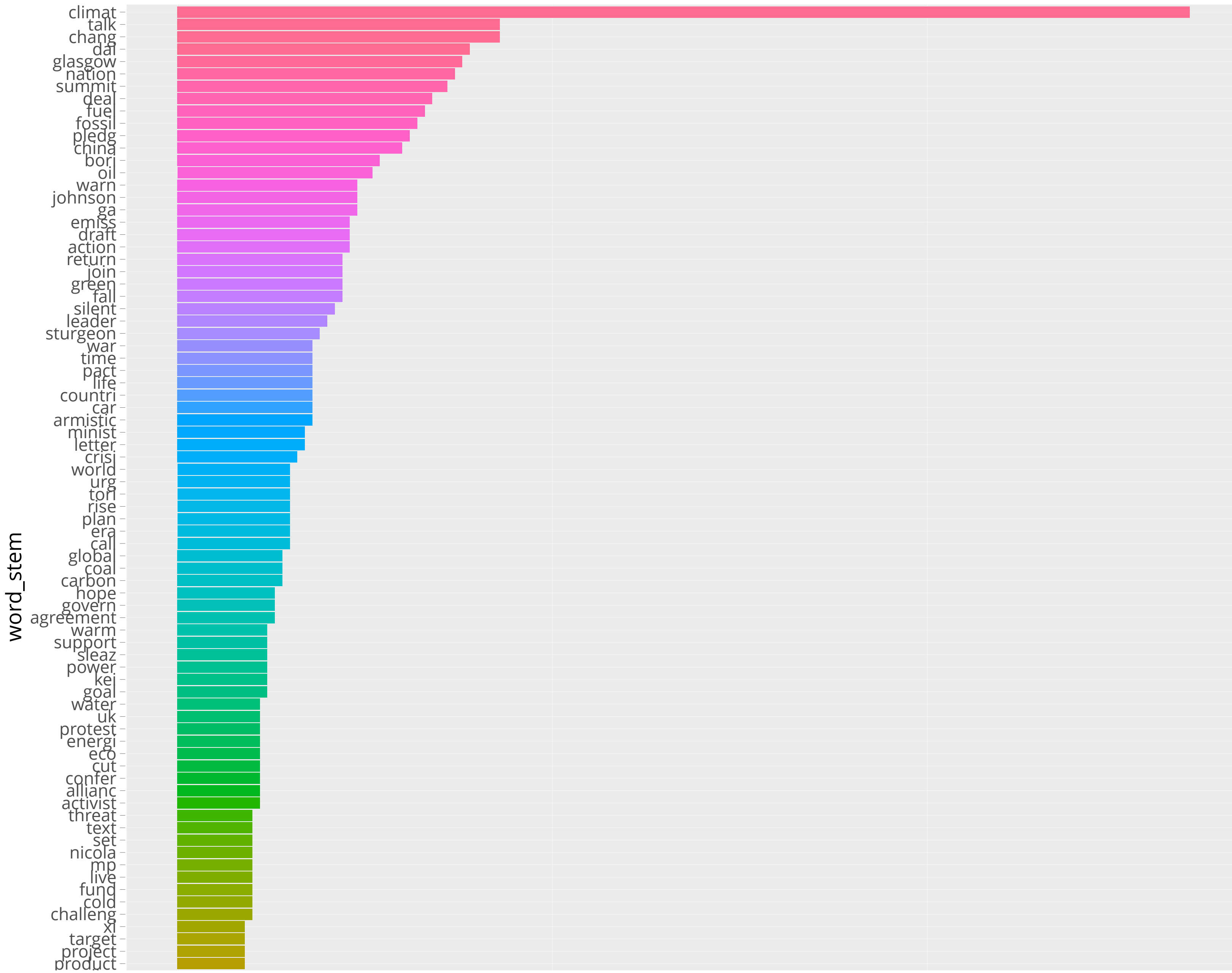
- We can now count words/stems and plot the results

```
my_text_uni_count <- my_text_uni %>%
  count(word_stem, sort = T)

min_occur <- quantile(my_text_uni_count$n, 0.95)

g <- my_text_uni_count %>%
  filter(n >= min_occur) %>%
  mutate(word_stem = reorder(word_stem, n)) %>%
  ggplot(aes(x = word_stem, y = n, fill = word_stem)) +
  geom_col() +
  theme(legend.position = "none") +
  coord_flip()
```

Example: (2) Counting stems



tf-idf

tf-idf

- Term frequency provides an indication of the most frequent words in a corpus
- Some words may be not very frequent in a corpus, but they may be particular for some documents in the corpus
- We can identify these words using the **term frequency-inverse document frequency** indicator

$$\text{tf-idf}_{i,d} = \text{tf}_{i,d} * \text{idf}_i$$

$$\text{tf-idf}_{i,d} = \frac{\text{n of times term } i \text{ appears in document } d}{\text{n of terms in the document } d} * ln\left(\frac{\text{n of documents}}{\text{n of documents containing the term } i}\right)$$

Example: (1) Tokenisation, stopwords, numbers

- We use the lead paragraph (“Hlead”), we tokenize data into unigram, we remove stopwords and numbers
- Our corpus include 242,831 id-unigram pairs

```
my_text_uni<- read_csv("news_articles_example.csv") %>%
  select(id, Hlead) %>%
  unnest_tokens(output = word, input = Hlead) %>%
  anti_join(stop_words) %>%
  mutate(word_numeric = as.numeric(word)) %>%
  filter(is.na(word_numeric)) %>%
  select(-word_numeric)
```

```
## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion
```

Example: (2) term frequency (tf)

We can calculate the tf (term frequency by document)

```
article_words <- my_text_uni %>%
  count(id, word, sort = T) %>%
  ungroup()

head(article_words)
```

```
## # A tibble: 6 × 3
##      id word        n
##   <dbl> <chr>   <int>
## 1   659 pwa        84
## 2   659 editor     70
## 3   659 bar        66
## 4   170 water      57
## 5   124 parties    52
## 6   124 paris      50
```

Example: (3) term frequency (tf)

```
total_words <- article_words %>%
      group_by(id) %>%
      summarize(total = sum(n))

print(total_words, n = 6)
```

```
## # A tibble: 692 × 2
##      id total
##   <dbl> <int>
## 1     1   381
## 2     2   378
## 3     3   558
## 4     4   558
## 5     5   346
## 6     6   722
## # … with 686 more rows
```

Example: (4) term frequency (tf)

We remove document with only a single word

```
article_words <- left_join(article_words, total_words) %>%
  filter(total > 1) %>%
  mutate(word_freq = n/total)

print(article_words, n = 6)
```

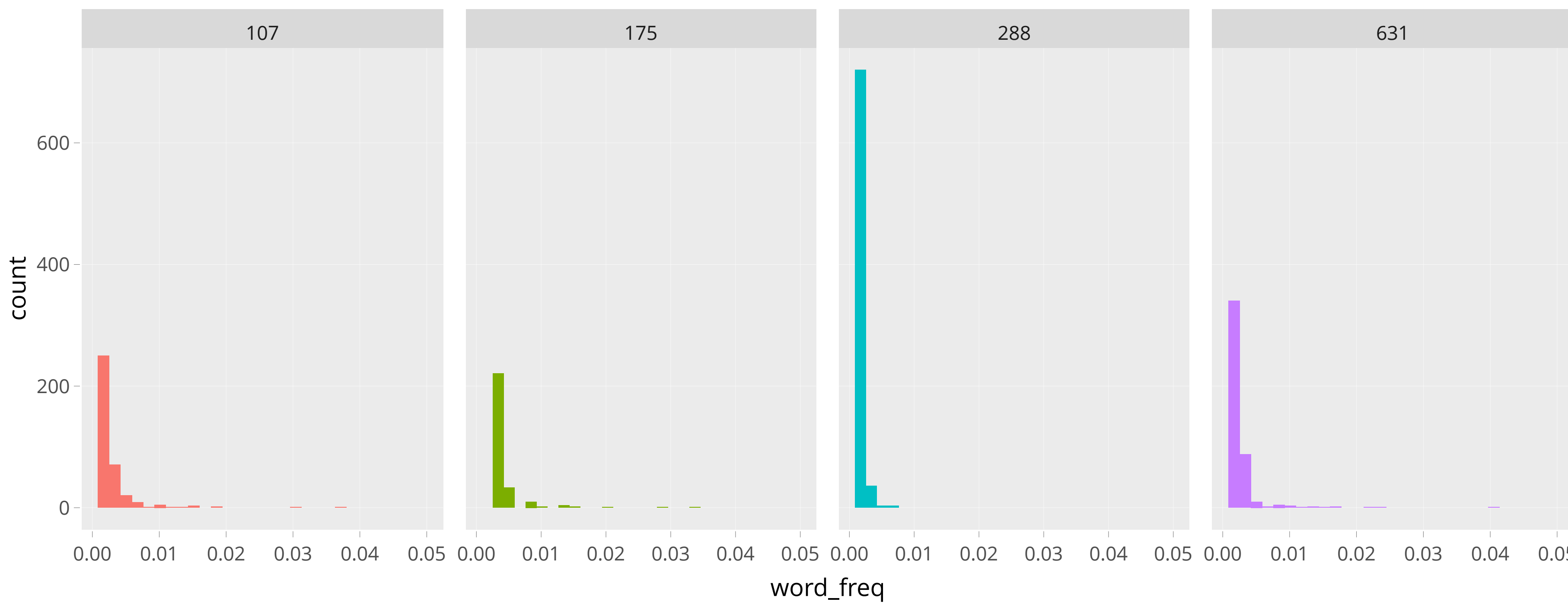
```
## # A tibble: 131,673 × 5
##      id word         n total word_freq
##   <dbl> <chr>    <int> <int>     <dbl>
## 1   659 pwa         84  1168    0.0719
## 2   659 editor      70  1168    0.0599
## 3   659 bar         66  1168    0.0565
## 4   170 water       57  1053    0.0541
## 5   124 parties     52  2040    0.0255
## 6   124 paris       50  2040    0.0245
## # … with 131,667 more rows
```

Example: (5) term frequency (tf)

Let's look at the term frequency distribution of three random articles

```
g <-  article_words %>%
  filter(id == 107 | id == 175 | id == 288 | id == 631)  %>%
  ggplot(aes(word_freq, fill = as.character(id))) +
  geom_histogram() +
  xlim(NA, 0.05) +
  theme(legend.position = "none") +
  facet_wrap(~id, ncol = 4)
```

Example: (6) term frequency (tf)



Example: (7) tf-idf

- Some words are very frequent in a number of documents (articles in this case)
- tf-idf helps us to identify words that are able to characterize documents
- In `tidytext` the function `bind_tf_idf` calculate the tf-idf scores starting from a tidy text dataset: one row per token per document including the information about term frequency
- Check the help guide `??bind_tf_idf`

Example: (8) tf-idf

Let's start from reading the data again

```
article_words_tfidf <- read_csv("news_articles_example.csv") %>%
  select(id, Hlead) %>%
  unnest_tokens(output = word, input = Hlead) %>%
  anti_join(stop_words) %>%
  mutate(word_numeric = as.numeric(word)) %>%
  filter(is.na(word_numeric)) %>%
  select(-word_numeric) %>%
  count(id, word, sort = T) %>%
  ungroup() %>%
  bind_tf_idf(word, id, n)
```

```
## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion
```

Example: (9) tf-idf

```
print(article_words_tfidf, n = 6)
```

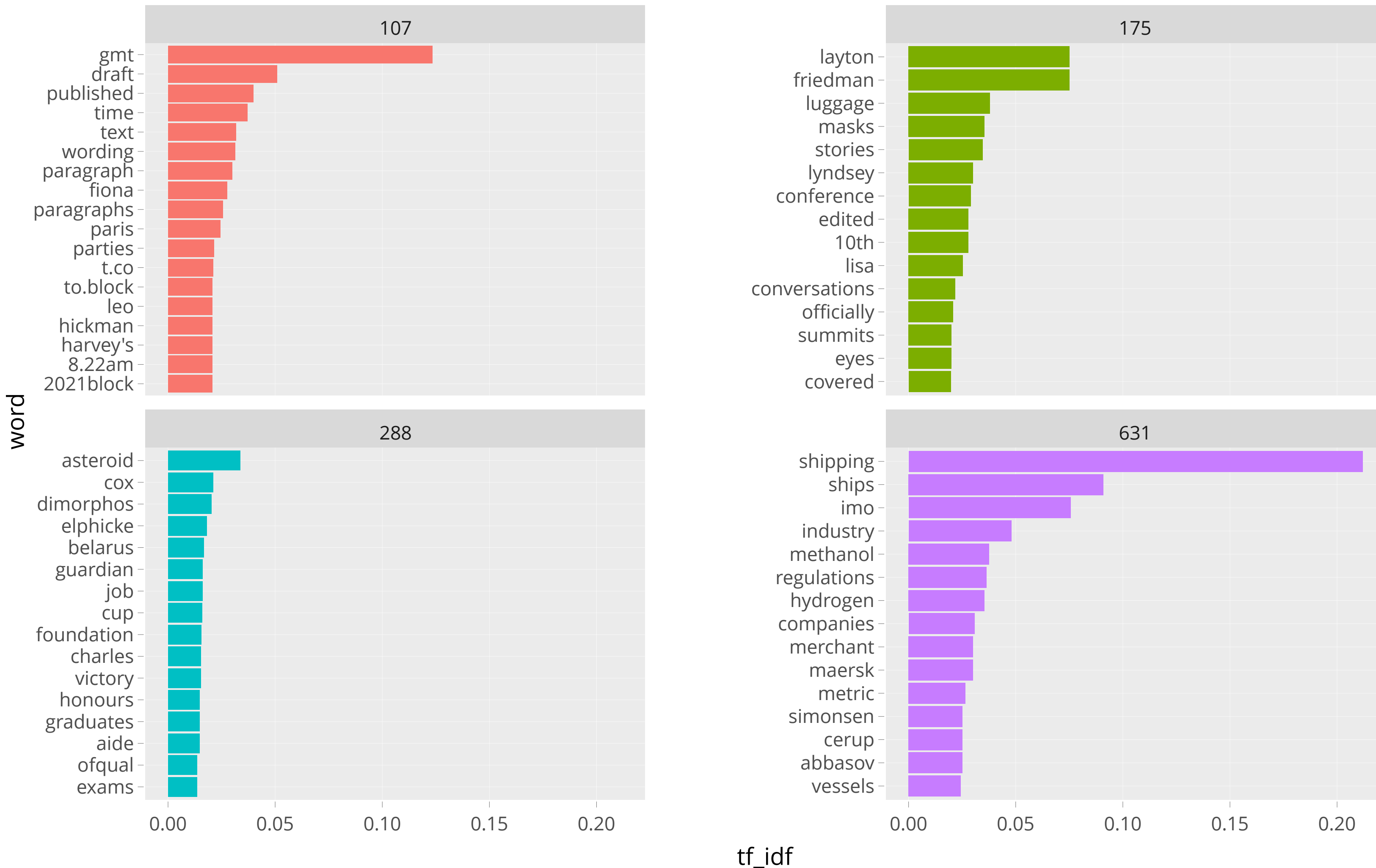
```
## # A tibble: 131,673 × 6
##      id word        n     tf   idf tf_idf
##   <dbl> <chr>   <int>  <dbl> <dbl>  <dbl>
## 1   659 pwa        84 0.0719  6.54 0.470
## 2   659 editor     70 0.0599  2.93 0.176
## 3   659 bar        66 0.0565  4.14 0.234
## 4   170 water      57 0.0541  2.29 0.124
## 5   124 parties    52 0.0255  2.26 0.0577
## 6   124 paris      50 0.0245  1.56 0.0381
## # … with 131,667 more rows
```

Example: (10) tf-idf

Let's look at top 15 words by tf-idf in the case of four random articles

```
g <- article_words_tfidf %>%
  filter(id == 107 | id == 175 | id == 288 | id == 631)  %>%
  group_by(id) %>%
  top_n(15, tf_idf) %>%
  ungroup %>%
  mutate(id = as.factor(id),
         word = reorder_within(word, tf_idf, id)) %>%
  ggplot(aes(word, tf_idf, fill = id)) +
  geom_col() +
  facet_wrap(~id,  nrow = 2, scales = "free_y") +
  coord_flip() +
  theme(legend.position = "none") +
  scale_x_reordered()
```

Example: (11) tf-idf



Example: (12) tf-idf (bigrams)

- In the case of bigrams, to remove stopwords you need first to `separate()`, filter stop words, and then `unite()` bigrams again
- Similarly in the case of n-grams

```
article_words_tfidf <- read_csv("news_articles_example.csv") %>%
  select(id, Hlead) %>%
  unnest_tokens(output = bigram, input = Hlead,
                token = "ngrams", n = 2) %>%
  separate(bigram, c("word_1", "word_2"), sep = " ") %>%
  filter(!word_1 %in% stop_words$word) %>%
  filter(!word_2 %in% stop_words$word) %>%
  unite(bigram, word_1, word_2, sep = " ") %>%
  count(id, bigram, sort = T) %>%
  bind_tf_idf(bigram, id, n)
```

Example: (13) tf-idf (bigrams)

```
print(article_words_tfidf, n = 6)
```

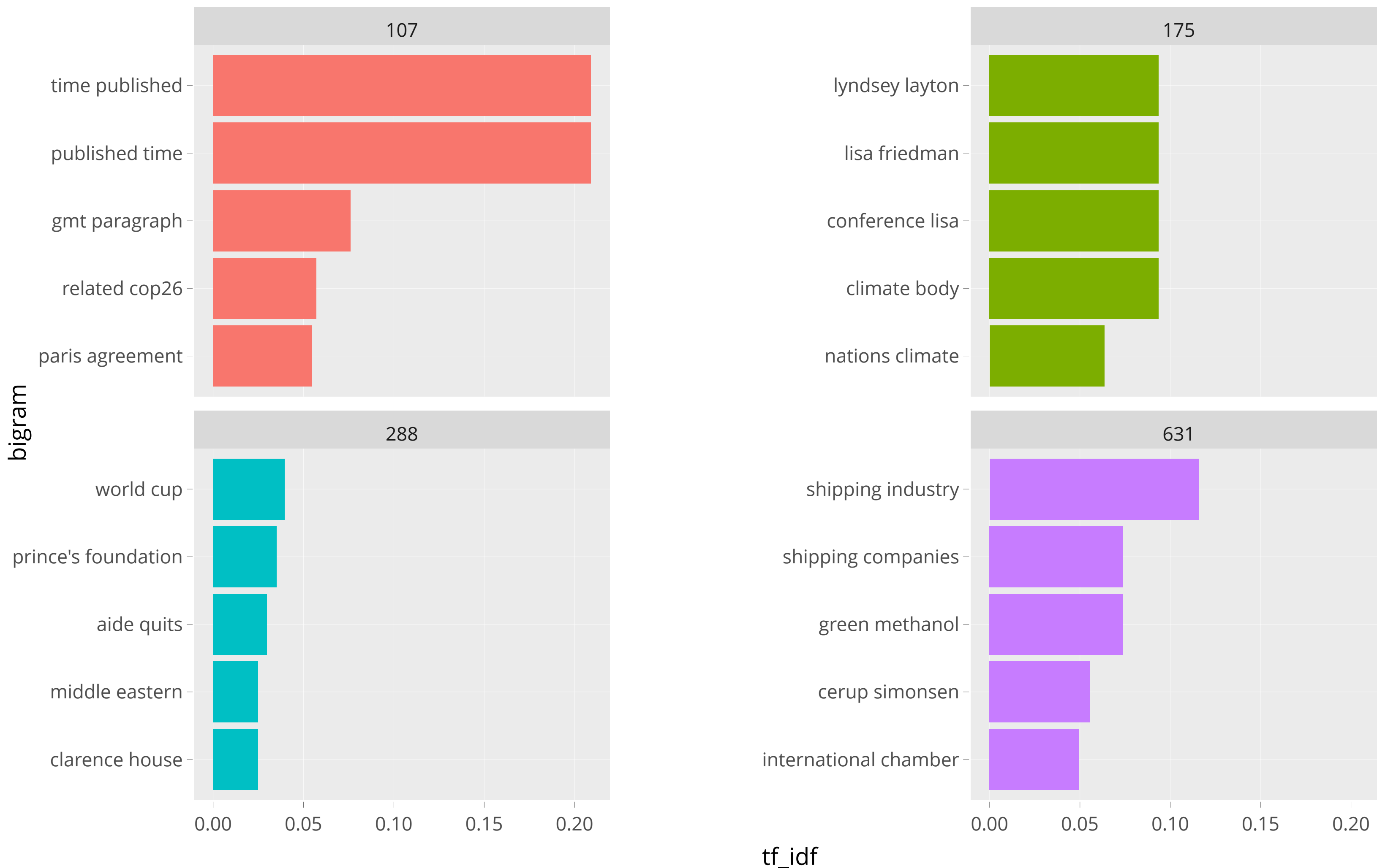
```
## # A tibble: 73,776 × 6
##       id bigram                n     tf   idf tf_idf
##    <dbl> <chr>             <int>  <dbl> <dbl>  <dbl>
## 1    659 editor bar           64 0.0706  6.54 0.461
## 2    124 paris agreement      44 0.0486  1.89 0.0917
## 3    659 pwa editor           34 0.0375  6.54 0.245
## 4    659 data pwa             32 0.0353  6.54 0.231
## 5    659 bar panel            30 0.0331  6.54 0.216
## 6    248 words photos         20 0.0430  6.54 0.281
## # … with 73,770 more rows
```

Example: (14) tf-idf (bigrams)

Let's look at top 15 bigrams by tf-idf in the case of four random articles

```
g <- article_words_tfidf %>%
  filter(id == 107 | id == 175 | id == 288 | id == 631) %>%
  group_by(id) %>%
  top_n(5, tf_idf) %>%
  ungroup %>%
  mutate(id = as.factor(id),
         bigram = reorder_within(bigram, tf_idf, id)) %>%
  ggplot(aes(bigram, tf_idf, fill = id)) +
  geom_col() +
  facet_wrap(~id,  nrow = 2, scales = "free_y") +
  coord_flip() +
  theme(legend.position = "none") +
  scale_x_reordered()
```

Example: (15) tf-idf (bigrams)



Questions

Computer session

Plan

1. Students are grouped in randomly generated groups
2. Groups will select at least one **text corpus** and develop a script in R that undertake a text mining analysis (data are available on Canvas)
3. Groups will upload the R script and the main findings in Padlet by the end of Week 9 workshop

Groups

Group 1
Adebisi, Jongho, Maria, Keiho

Group 2
Charunan, Poojani, Abdul, Satoshi

Group 3
Oscar, Tsukumo, Jiyoung, Nicholas

Group 4
Alessandro, Shaunna, Jonathan, Rachel

Next time

Next time

- Visualising text data
- Sentiment analysis
- Regular expressions
- Introduction to topic modelling

References

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