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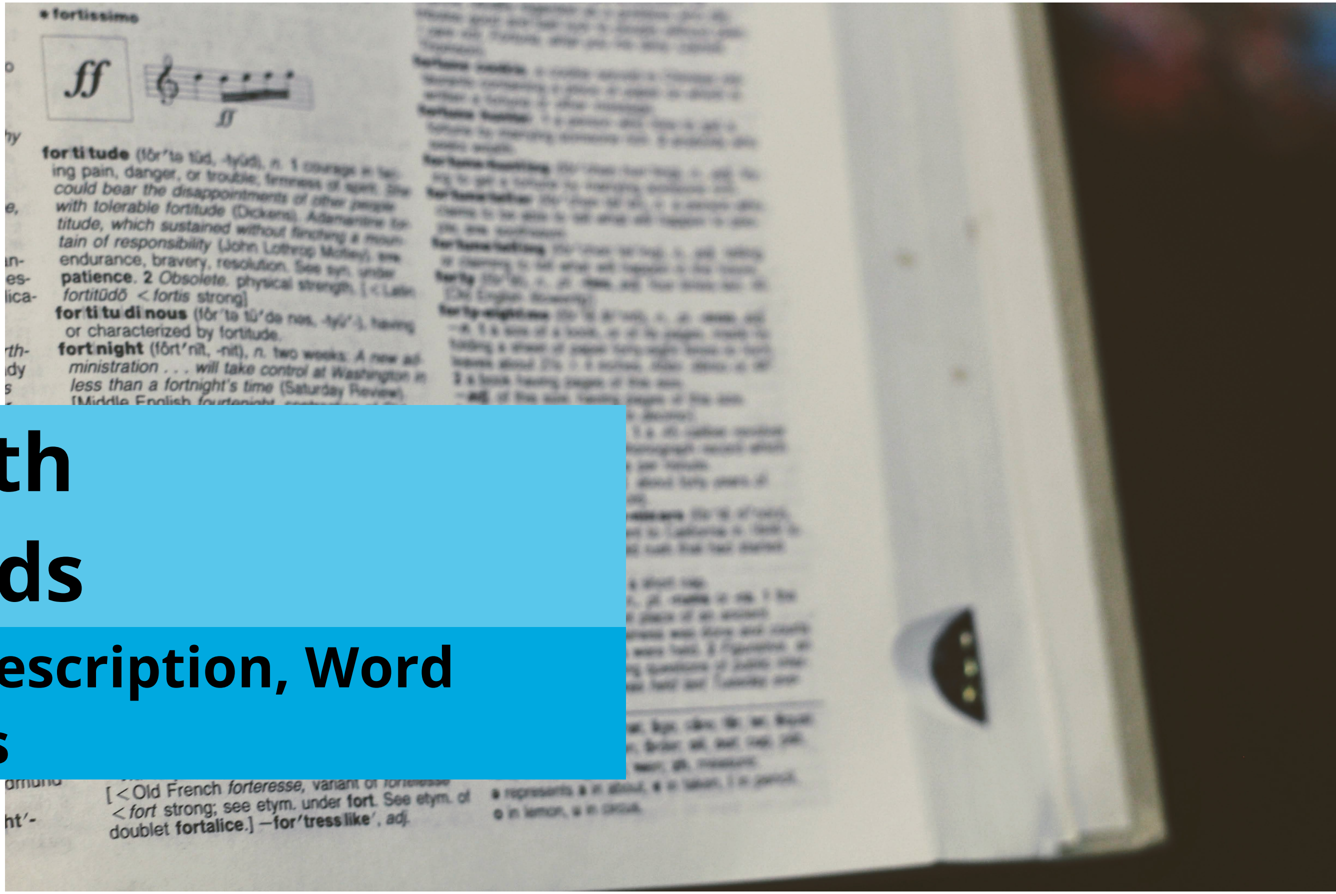

Studying News Use with Computational Methods

Text Analysis in R, Part I: Text Description, Word Metrics and Dictionary Methods

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Agenda

At it's most basic, automated content analysis is just counting stuff: most frequent words, co-occuring words, specific words, etc.

We can already learn a lot about a corpus of documents just by looking at word metrics and applying dictionaries. Even if they are not part of the main research interest, it still might prove useful to use the following methods to describe and familiarize yourself with a large text corpus.

Our agenda today:

- Text description and word metrics
  - Frequencies
  - Keywords in context
  - Collocations
  - Cooccurences
  - Lexical complexity
  - Keyness
- Dictionary-based methods
  - Basics
  - Applying categorical dictionaries
  - Applying weighted dictionaries
  - Validating dictionaries

Text description and word metrics

Setup

We will be mainly using the packages known from the last few sessions:

```
library(tidyverse)
library(tidytext)
library(quanteda)
```

```
## Package version: 3.0.0
## Unicode version: 13.0
## ICU version: 69.1

## Parallel computing: 16 of 16 threads used.

## See https://quanteda.io for tutorials and examples.
```

```
library(quanteda.textstats)
```

Setup

We will be working with a sample of 10,000 Guardian articles published in 2020:

```r
guardian_tibble <- readRDS("data/guardian_sample_2020.rds")
```

Setup

Before we start, let's add a column indicating the day the respective article was published in an extra column (you'll soon enough see why):

```
guardian_tibble <- guardian_tibble %>%
  mutate(day = lubridate::date(date))
```

```
guardian_tibble %>%
  select(date, day)
```

```
## # A tibble: 10,000 x 2
##    date                day
##    <dttm>              <date>
##  1 2020-01-01 00:09:23 2020-01-01
##  2 2020-01-01 00:34:18 2020-01-01
##  3 2020-01-01 02:59:09 2020-01-01
##  4 2020-01-01 06:20:56 2020-01-01
##  5 2020-01-01 07:00:58 2020-01-01
##  6 2020-01-01 08:00:01 2020-01-01
##  7 2020-01-01 08:50:00 2020-01-01
##  8 2020-01-01 09:01:00 2020-01-01
##  9 2020-01-01 10:00:02 2020-01-01
```

Preprocessing

Just like last time, we'll do some preprocessing of our data by creating a corpus object, tokenizing all documents and creating a DFM.

Keep all of these objects, as different methods require differently structured data.

```r
guardian_corpus <- corpus(guardian_tibble,
                          docid_field = "id", text_field = "body")

guardian_tokens <- guardian_corpus %>%
  tokens(remove_punct = TRUE, remove_symbols = TRUE, remove_numbers = TRUE,
         remove_url = TRUE, remove_separators = TRUE) %>%
  tokens_tolower()

guardian_dfm <- guardian_tokens %>%
  dfm()
```

Word frequencies

`featfreq()` counts all features. Not that the resulting list is not sorted:

```
featfreq(guardian_dfm)
```

```
##         there            is             a       message         woven 
##         18152         77962        187892           930            21 
##          into    everything           the         prime      minister 
##         11856          1856        453840          2482          3635 
##          says         about         these         fires     carefully 
##          9596         20189          6695           394           281 
##      threaded       through         every pronouncement          that 
##             9          6086          4226             5         86117 
##          they           are           not extraordinary unprecedented 
##         28376         39966         32524           476           526 
##          with         skill            of           man           who 
##         54959           141        205550          2789         24401 
##          made  pre-politics        career     messaging         scott 
##          6620             1          1314           155           517 
##    morrison's     narrative      disaster            in            no 
##            86           381           490        157939         12547 
##           way     different          from     disasters   australians 
##          6723          2873         37464           102           590 
```

Word frequencies

`topfeatures()` returns the *n* most common features (default: 10):

```
topfeatures(guardian_dfm)
```

```
##    the     to     of    and      a     in   that     is    for     on 
## 453840 225486 205550 197056 187892 157939  86117  77962  75739  66469
```

Word frequencies

Some more options, including grouping for docvars, are available with `textstat_frequency()`:

```
textstat_frequency(guardian_dfm, n = 5, groups = pillar)
```

```
##    feature frequency rank docfreq     group
## 1      the     73441    1    1713      Arts
## 2       of     38415    2    1708      Arts
## 3        a     37528    3    1711      Arts
## 4      and     37483    4    1711      Arts
## 5       to     33283    5    1708      Arts
## 6      the     31317    1     860 Lifestyle
## 7        a     18502    2     842 Lifestyle
## 8      and     18090    3     850 Lifestyle
## 9       to     17431    4     854 Lifestyle
## 10      of     15079    5     846 Lifestyle
## 11     the    253420    1    5325      News
## 12      to    127021    2    5321      News
## 13      of    110784    3    5319      News
## 14     and    100977    4    5317      News
## 15       a     91590    5    5301      News
## 16     the     42100    1     845   Opinion
## 17      to     21923    2     845   Opinion
```

Word frequencies

Let's get some more useful results by removing stopwords:

```
dfm_remove(guardian_dfm, stopwords("english")) %>%
  textstat_frequency(n = 5, groups = pillar)
```

```
##       feature frequency rank docfreq     group
## 1         one      3929    1    1330      Arts
## 2        like      3124    2    1096      Arts
## 3      people      2883    3     909      Arts
## 4        just      2389    4     993      Arts
## 5        says      2376    5     504      Arts
## 6         one      1807    1     647 Lifestyle
## 7         can      1787    2     592 Lifestyle
## 8        says      1551    3     263 Lifestyle
## 9        like      1499    4     566 Lifestyle
## 10     people      1298    5     433 Lifestyle
## 11       said     28843    1    4490      News
## 12     people     13557    2    3579      News
## 13        one      8569    3    3514      News
## 14 government      8521    4    2841      News
## 15        new      8351    5    3095      News
## 16     people      2404    1     650   Opinion
```

Word frequencies

More relevant features emerge after some strong trimming of the DFM:

```
dfm_trim(guardian_dfm, max_docfreq = .20, docfreq_type = "prop") %>%
  textstat_frequency(n = 3, groups = pillar)
```

```
##      feature frequency rank docfreq     group
## 1       film      1686    1     558      Arts
## 2       show      1480    2     612      Arts
## 3      music      1358    3     440      Arts
## 4    fashion       508    1      99 Lifestyle
## 5       food       498    2     194 Lifestyle
## 6        add       430    3     139 Lifestyle
## 7      trump      4029    1     826      News
## 8     police      3621    2     926      News
## 9      cases      3443    3    1249      News
## 10     trump       808    1     184   Opinion
## 11 political       660    2     291   Opinion
## 12     black       632    3     150   Opinion
## 13    league      2266    1     684     Sport
## 14   players      1962    2     669     Sport
## 15    season      1824    3     688     Sport
```

Keywords in context

Use kwic() to get a view of up to 1000 occurences of a keyword in a given context window (default: 5 words before/after):

```
kwic(guardian_tokens, "belarus") %>%
  as_tibble()
```

```
## # A tibble: 66 x 7
##    docname  from    to pre                  keyword post                 pattern
##    <chr>   <int> <int> <chr>                <chr>   <chr>                <fct>
##   1 959      609   609 and europe we went ~ belarus she said it was rea~ belarus
##   2 1633     445   445 jack on a stick as   belarus gives the uk a desu~ belarus
##   3 2033     321   321 that were stuck in ~ belarus and they were after~ belarus
##   4 2637     112   112 wants noah explaine~ belarus president alexander~ belarus
##   5 2945      62    62 the authoritarian p~ belarus and turkmenistan ov~ belarus
##   6 2978     196   196 countries president~ belarus has made the claim ~ belarus
##   7 3656      54    54 sporting plans alth~ belarus burundi tajikistan ~ belarus
##   8 3692      14    14 include thousands t~ belarus for ve day parade d~ belarus
##   9 3694     133   133 looked very differe~ belarus where elderly veter~ belarus
## 10 3901      350   350 action beyond the b~ belarus haaland's desire to~ belarus
## # ... with 56 more rows
```

Keywords in context

Use phrase() for multi-word keywords and set window size with window:

```
kwic(guardian_tokens, phrase("champions league"),
     window = 3) %>%
  as_tibble()
```

```
## # A tibble: 321 x 7
##    docname  from    to pre             keyword      post             pattern
##    <chr>   <int> <int> <chr>           <chr>        <chr>            <fct>
##  1 20         126   127 restart of the  champions l~ all competition~ champions ~
##  2 29         171   172 to swap probab~ champions l~ qualification a~ champions ~
##  3 42        1331  1332 performance in~ champions l~ fixture suggest~ champions ~
##  4 96         419   420 the league and  champions l~ and his selecti~ champions ~
##  5 113         45    46 scored in genk~ champions l~ defeat by liver~ champions ~
##  6 138        148   149 qualify for the champions l~ victory against~ champions ~
##  7 138        396   397 rather than the champions l~ however there w~ champions ~
##  8 155        202   203 scored in barc~ champions l~ final defeat to  champions ~
##  9 155        312   313 victory in the  champions l~ final in june    champions ~
## 10 223        480   481 bus carrying l~ champions l~ winners drive p~ champions ~
## # ... with 311 more rows
```

Collocations

Collocations define words directly appearing after each other and can be computed with `textstat_collocations()`. The output is sorted by the λ parameter, which increases if *exactly* this combination of words is more common than the same words appearing in other collocations. Note that this can be very computationally expensive, so adjust the `min_count()` parameter accordingly:

```
guardian_tokens %>%
  tokens_remove(stopwords("english")) %>%
  textstat_collocations(min_count = 100) %>%
  as_tibble()
```

```
## # A tibble: 615 x 6
##    collocation     count count_nested length lambda     z
##    <chr>           <int>        <int>  <dbl>  <dbl> <dbl>
##  1 prime minister   1880            0      2   8.92  169.
##  2 last week        1567            0      2   5.33  168.
##  3 last year        1694            0      2   4.95  167.
##  4 social media     1074            0      2   6.67  157.
##  5 public health    1196            0      2   5.17  149.
##  6 chief executive   986            0      2   8.39  149.
##  7 white house       871            0      2   6.45  145.
##  8 years ago        1081            0      2   6.22  142.
```

Collocations

We can look for multi-word collocations of any size by adjusting the `size` parameter:

```r
guardian_tokens %>%
  tokens_remove(stopwords("english")) %>%
  textstat_collocations(min_count = 10, size = 4) %>%
  as_tibble()
```

```
## # A tibble: 653 x 6
##    collocation                            count count_nested length lambda     z
##    <chr>                                  <int>        <int>  <dbl>  <dbl> <dbl>
##  1 andrés manuel lópez obrador               18            0      4  12.9   2.96
##  2 new york los angeles                      10            0      4  10.9   2.93
##  3 prime minister narendra modi              19            0      4  11.0   2.82
##  4 crown prince mohammed bin                 16            0      4   9.91  2.81
##  5 kenan malik observer columnist            12            0      4  10.0   2.55
##  6 prime minister boris johnson              52            0      4   6.42  2.39
##  7 department education spokesperson said    13            0      4   4.41  2.26
##  8 prime minister viktor orbán               20            0      4   8.51  2.20
##  9 thousands inboxes every weekday           20            0      4   7.51  2.06
## 10 ruby princess cruise ship                 13            0      4   5.81  2.04
## # ... with 643 more rows
```

Cooccurences

Cooccurences look for words appearing in the same document (and not just directly after each other).

Cooccurences are best represented as a *feature cooccurence matrix* of size `n_features * n_features`. Create one with `fcm()`. Again, to decrease computational load, some trimming of the DFM may be useful:

```r
guardian_fcm <- guardian_dfm %>%
  dfm_remove(stopwords("english")) %>%
  dfm_trim(min_termfreq = 100, max_docfreq = .25, docfreq_type = "prop") %>%
  fcm()
```

Cooccurences

```
guardian_fcm
```

```
## Feature co-occurrence matrix of: 6,009 by 6,009 features.
##                 features
## features        message everything prime minister  says fires carefully
##   message           293        237   436      567  1206    81        34
##   everything          0        590   468      616  4777   128        77
##   prime               0          0  2576     7549  2154   119       104
##   minister            0          0     0     4361  2928   197       156
##   says                0          0     0        0 42752   430       493
##   fires               0          0     0        0     0  1414         7
##   carefully           0          0     0        0     0     0        21
##   extraordinary       0          0     0        0     0     0         0
##   unprecedented       0          0     0        0     0     0         0
##   skill               0          0     0        0     0     0         0
##                 features
## features        extraordinary unprecedented skill
##   message                  76            69    17
##   everything              156            98    51
##   prime                   151           226    21
##   minister                193           271    21
##   says                    696           652   243
```

Cooccurences

A simple way to get at the most common cooccurences is by transforming the FCM into a Tibble with the `tidy()` function:

```
guardian_fcm %>%
  tidy() %>%
  filter(document != term) %>%
  arrange(desc(count))
```

```
## # A tibble: 16,598,119 x 3
##    document  term      count
##    <chr>     <chr>     <dbl>
##  1 died      hospital 25139
##  2 died      family   16223
##  3 president trump    15829
##  4 trump     biden    14949
##  5 hospital  family   14809
##  6 trump     trump's  13384
##  7 hospital  covid-19 12021
##  8 died      worked   12013
##  9 trump     election 11424
## 10 died      covid-19 11209
## # ... with 16,598,109 more rows
```

Lexical complexity

Lexical complexity may be indicated through a document's readability and lexical diversity. `textstat_readability()` offers several readability measures, by default the `Flesch Reading Ease` which is based on the average sentence length and average syllable count per word (note that we need to use the corpus object in this case, as sentences are preserved here). Lower values indicate a lower readability:

```
textstat_readability(guardian_corpus) %>%
  as_tibble()
```

```
## # A tibble: 10,000 x 2
##    document Flesch
##    <chr>     <dbl>
##  1 1          39.6
##  2 2          60.7
##  3 3          48.7
##  4 4          52.5
##  5 5          42.0
##  6 6          46.9
##  7 7          45.8
##  8 8          55.2
##  9 9          59.9
## 10 10         47.6
```

Lexical complexity

Accordingly, `textstat_lexdiv()` offers several measures to quantify the lexical diversity of documents. By default, the *Type-Token-Ratio* (unique tokens divided by number of tokens per document) is computed. Note that the *TTR* is heavily influenced by document length:

```
textstat_lexdiv(guardian_dfm) %>%
  as_tibble()
```

```
## # A tibble: 10,000 x 2
##    document   TTR
##    <chr>    <dbl>
##  1 1        0.453
##  2 2        0.634
##  3 3        0.438
##  4 4        0.669
##  5 5        0.429
##  6 6        0.427
##  7 7        0.657
##  8 8        0.509
##  9 9        0.508
## 10 10       0.491
## # ... with 9,990 more rows
```

Keyness

Finally, *keyness* (and accordingly `textstat_keyness()`) presents a measure of the distinctivness of words for a certain (group of) documents as compared to other documents. For example, we can group our corpus by the `pillar` (Arts, Lifestyle, News, Opinion, or Sport) and get to the most distinctive terms for Sport documents by:

```
guardian_dfm %>%
  dfm_group(pillar) %>%
  textstat_keyness(target = "Sport") %>%
  as_tibble()
```

```
## # A tibble: 135,480 x 5
##    feature    chi2     p n_target n_reference
##    <chr>     <dbl> <dbl>    <dbl>       <dbl>
##  1 league   14537.     0     2266         298
##  2 players  12498.     0     1962         270
##  3 game      8593.     0     1813         754
##  4 season    8592.     0     1824         770
##  5 football  6760.     0     1299         420
##  6 team      6221.     0     1770        1309
##  7 cup       6182.     0     1019         184
##  8 club      6046.     0     1292         554
##  9 player    4816.     0      828         181
## 10 ball      4537.     0      803         197
```

Text description and word metrics

Exercise 1: Text description

`btw_tweets.csv` (on ILIAS) contains 1377 tweets by the three German chancellor candidates Annalena Baerbock, Armin Laschet & Olaf Scholz made in 2021, as obtained by Twitter's Academic API.

- Load the tweets into R and do the necessary preprocessing
- Investigate the tweets using the text and word metrics you just learned
- What are the most common words?
- What are the most common collocations?
- What are the most distinct words per account?

Dictionary-based methods

Basics

Dictionaries contain a list of predefined words (or other features) that should represent a latent construct. This is probably the simplest way to automatically anaylze texts for the presence of latent constructs.

At their core, dictionary-based methods are just counting the presence of the dictionary words in the documents. Usually, this is based on two (implicit) assumptions:

- **Bag-of-words**: Just like with many other automated text analysis methods, word order and thus semantical and syntactical relationships are ignored.
- **Additivity**: The more words from the dictionary are found in a document, the more pronounced the latent construct.

Terminology

Dictionaries are commonly differentiated along two dimensions, the first being the source of the dictionary:

- **Organic** dictionaries are created for the specific research task from scratch, for example by theoretical assumptions about the latent construct(s), investigating the most common features, etc.
- **Off-the-shelf** dictionaries are pre-made, (hopefully) pre-validadated dictionaries used for specific purposes, for example sentiment analysis.

Second, dictionaries may be either categorical or weighted:

- In **categorical** dictionaries, every word is valued the same.
- In **weighted** dictionaries, weights are assigned to words. For example, in a positivity dictionary, "love" may have a higher weight than "like".

Applying categorical dictionaries

We start by applying categorical dictionaries to texts. In quanteda, dictionaries are simply created by passing a named list of constructs represented in the dictionary, with each construct represent by a character vector of words.

For demonstration purposes, we create our own dictionary from the populism dictionary by Rooduijn & Pauwels (2011). Note that dictionary terms may include asterisks for placeholders:

```
pop_words <- list(populism = c(
  "elit*", "consensus*", "undemocratic*", "referend*", "corrupt*",
  "propagand*", "politici*", "*deceit*", "*deceiv*", "shame*", "scandal*",
  "truth*", "dishonest*", "establishm*", "ruling*")
  )
```

Applying categorical dictionaries

We create the actual dictionary by using `quanteda`'s `dictionary()` function.

```
pop_dictionary <- dictionary(pop_words)
pop_dictionary
```

```
## Dictionary object with 1 key entry.
## - [populism]:
##   - elit*, consensus*, undemocratic*, referend*, corrupt*, propagand*, politici*, *deceit*, *deceiv*,
```

Applying categorical dictionaries

Applying the dictionary to our corpus is simple as well: We use the function `dfm_lookup()` on our DFM (remember, word order doesn't matter). This counts out all features in the dictionary and reduces the dimensionality of the DFM to `n_documents * n_dictionary_constructs`:

```
guardian_pop <- dfm(guardian_dfm) %>%
  dfm_lookup(pop_dictionary)

guardian_pop
```

```
## Document-feature matrix of: 10,000 documents, 1 feature (74.61% sparse) and 5 docvars.
##     features
## docs populism
##    1        0
##    2        0
##    3        0
##    4        0
##    5        0
##    6        0
## [ reached max_ndoc ... 9,994 more documents ]
```

Applying categorical dictionaries

`tidytext`'s `tidy()` function is again helpful in transforming and analyizing the results. For example, we can sort by count to get the document ids of the documents with the highest count of dictionary words:

```
guardian_pop %>%
  tidy() %>%
  arrange(desc(count))
```

```
## # A tibble: 2,539 x 3
##    document term     count
##    <chr>    <chr>    <dbl>
##  1 526      populism    16
##  2 4257     populism    16
##  3 5610     populism    14
##  4 4799     populism    13
##  5 8717     populism    13
##  6 2727     populism    12
##  7 9436     populism    12
##  8 5169     populism    11
##  9 5761     populism    11
## 10 6214     populism    11
## # ... with 2,529 more rows
```

Applying categorical dictionaries

Let's take a look at the article with highest count of populism terms (i.e., the *most populist* article in our corpus):

```
guardian_tibble %>%
  filter(id == 526)
```

```
## # A tibble: 1 x 7
##      id title       body        url        date                pillar day
##   <int> <chr>       <chr>       <chr>      <dttm>              <chr>  <date>
## 1   526 ‘Middle Cl~ Democrats ~ https://w~ 2020-01-20 11:00:24 Opini~ 2020-01-20
```

It's the article ‘Middle Class’ Joe Biden has a corruption problem – it makes him a weak candidate | Zephyr Teachout, an opinion piece about Joe Biden and the US election.

Applying categorical dictionaries

Relying on counts does ignore document lenght, though, so longer documents have a per se higher chance of including dictionary terms. It is thus a good idea to weight the DFM beforehand to get the share of dictionary terms among the full document:

```
guardian_pop_prop <- guardian_dfm %>%
  dfm_weight(scheme = "prop") %>%
  dfm_lookup(pop_dictionary)

guardian_pop_prop
```

```
## Document-feature matrix of: 10,000 documents, 1 feature (74.61% sparse) and 5 docvars.
##       features
## docs populism
##    1        0
##    2        0
##    3        0
##    4        0
##    5        0
##    6        0
## [ reached max_ndoc ... 9,994 more documents ]
```

Applying categorical dictionaries

Let's check again the documents with the highest share of populist terms:

```
guardian_pop_prop %>%
  tidy() %>%
  arrange(desc(count))
```

```
## # A tibble: 2,539 x 3
##    document term      count
##    <chr>    <chr>     <dbl>
##  1 4799     populism 0.0216
##  2 526      populism 0.0171
##  3 5141     populism 0.0163
##  4 5761     populism 0.0146
##  5 4257     populism 0.0143
##  6 6259     populism 0.0139
##  7 188      populism 0.0136
##  8 5169     populism 0.0130
##  9 4817     populism 0.0126
## 10 6597     populism 0.0124
## # ... with 2,529 more rows
```

Applying categorical dictionaries

One handy tool in applying dictionaries is `dfm_group()`. For example, we can group the DFM by day before applying the dictionary to get the share of populism in Guardian articles on each day:

```
guardian_pop_by_day <- guardian_dfm %>%
  dfm_group(day) %>%
  dfm_weight(scheme = "prop") %>%
  dfm_lookup(pop_dictionary)

guardian_pop_by_day
```

```
## Document-feature matrix of: 366 documents, 1 feature (0.00% sparse) and 1 docvar.
##              features
## docs             populism
##   2020-01-01 0.0006833869
##   2020-01-02 0.0004933129
##   2020-01-03 0.0007507508
##   2020-01-04 0.0004430268
##   2020-01-05 0.0002653576
##   2020-01-06 0.0012358648
## [ reached max_ndoc ... 360 more documents ]
```

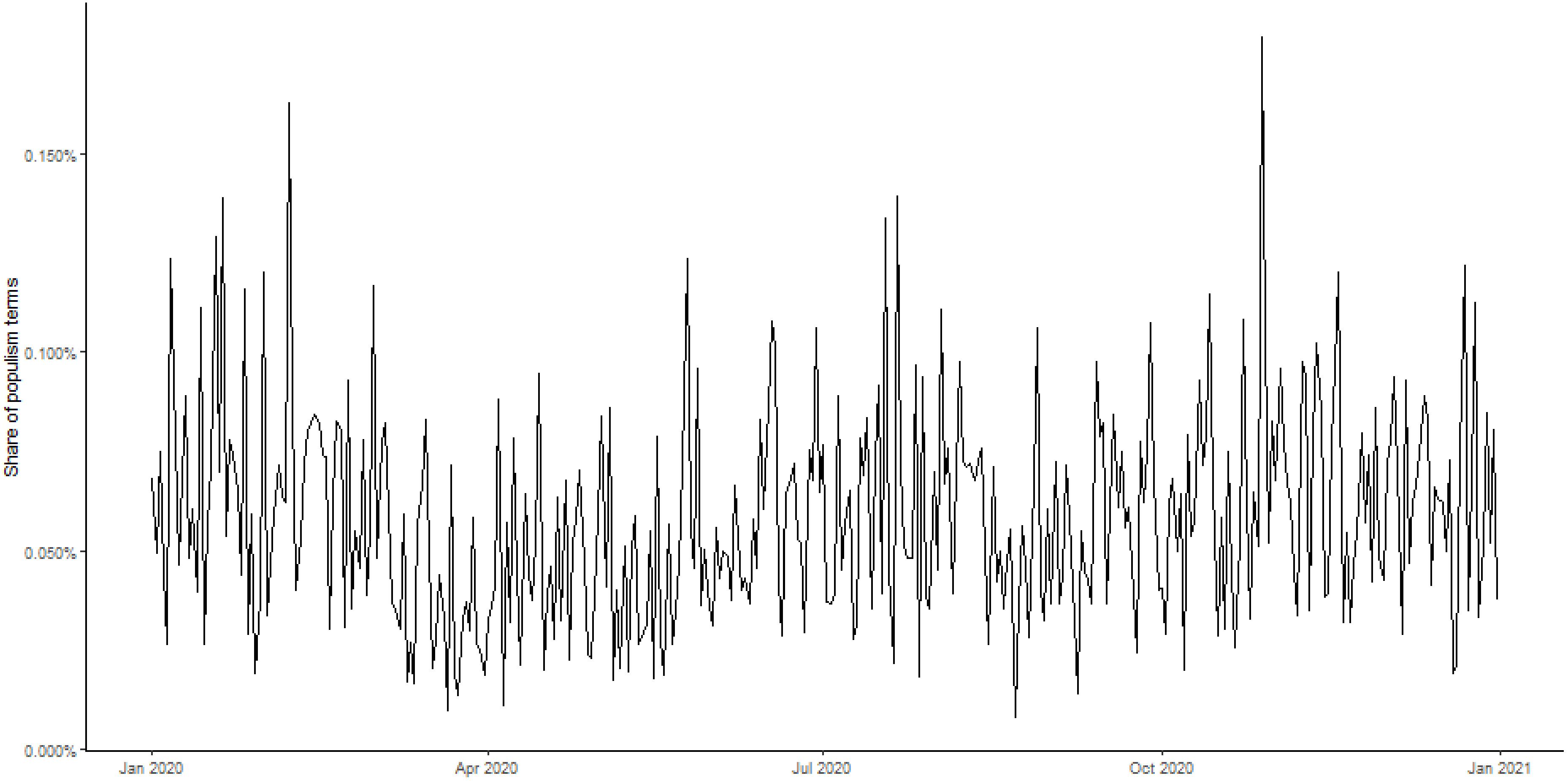
Applying categorical dictionaries

Let's plot this. When would we expect the highest share of populist terms?

```
p_pop_guardian_by_day <- guardian_pop_by_day %>%
  tidy() %>%
  mutate(day = as.Date(document)) %>%
  ggplot(aes(x = day, y = count)) +
  geom_line() +
  theme_classic() +
  scale_y_continuous(labels = scales::percent) +
  labs(x = NULL, y = "Share of populism terms")
```

Applying categorical dictionaries

```
p_pop_guardian_by_day
```



Applying categorical dictionaries

Exercise 2: Applying categorical dictionaries

The Bing Liu opinion lexicon is a widely used, multi-categorical dictionary for sentiment analysis, including ~6000 terms indicating positive and negative sentiment. The word lists are stored in separate files (`positive-words.txt` and `negative-words.txt`) on ILIAS.

Load them into R with `scan()`:

```r
positive_words <- scan("data/positive-words.txt", what = character(), skip = 30)
negative_words <- scan("data/negative-words.txt", what = character(), skip = 31)
```

Applying categorical dictionaries

Exercise 2: Applying categorical dictionaries

Then:

- create a `quanteda` dictionary with the two categories "positive" and "negative"
- apply the dictionary to the Guardian corpus
- investigate the difference between weighting the DFM proportionally before and after applying the dictionary
- plot the sentiment by day

Applying weighted dictionaries

Applying weighted dictionaries is simple as well, but relies on `tidytext` again. `tidytext()` also provides a function `get_sentiments()` to access common sentiment dictionaries. The AFINN dictionary is one widely used weighted dictionary:

```r
get_sentiments("afinn")
```

```
## # A tibble: 2,477 x 2
##    word       value
##    <chr>      <dbl>
##  1 abandon       -2
##  2 abandoned     -2
##  3 abandons      -2
##  4 abducted      -2
##  5 abduction     -2
##  6 abductions    -2
##  7 abhor         -3
##  8 abhorred      -3
##  9 abhorrent     -3
## 10 abhors        -3
## # ... with 2,467 more rows
```

Applying weighted dictionaries

In the tidytext style, applying dictionaries is just joining them with an unnested text corpus. Note that using inner_join() throws out all terms not found in the dictionary - if you want to preserve those terms, use left_join() instead:

```r
guardian_afinn_sentiments <- guardian_tibble %>%
  unnest_tokens(word, body) %>%
  select(id, day, word) %>%
  inner_join(get_sentiments("afinn"))
```

```
## Joining, by = "word"
```

```r
guardian_afinn_sentiments
```

```
## # A tibble: 421,362 x 4
##        id day        word      value
##     <int> <date>     <chr>     <dbl>
##  1      1 2020-01-01 carefully     2
##  2      1 2020-01-01 disaster     -2
##  3      1 2020-01-01 no           -1
##  4      1 2020-01-01 disasters    -2
##  5      1 2020-01-01 terrible     -3
```

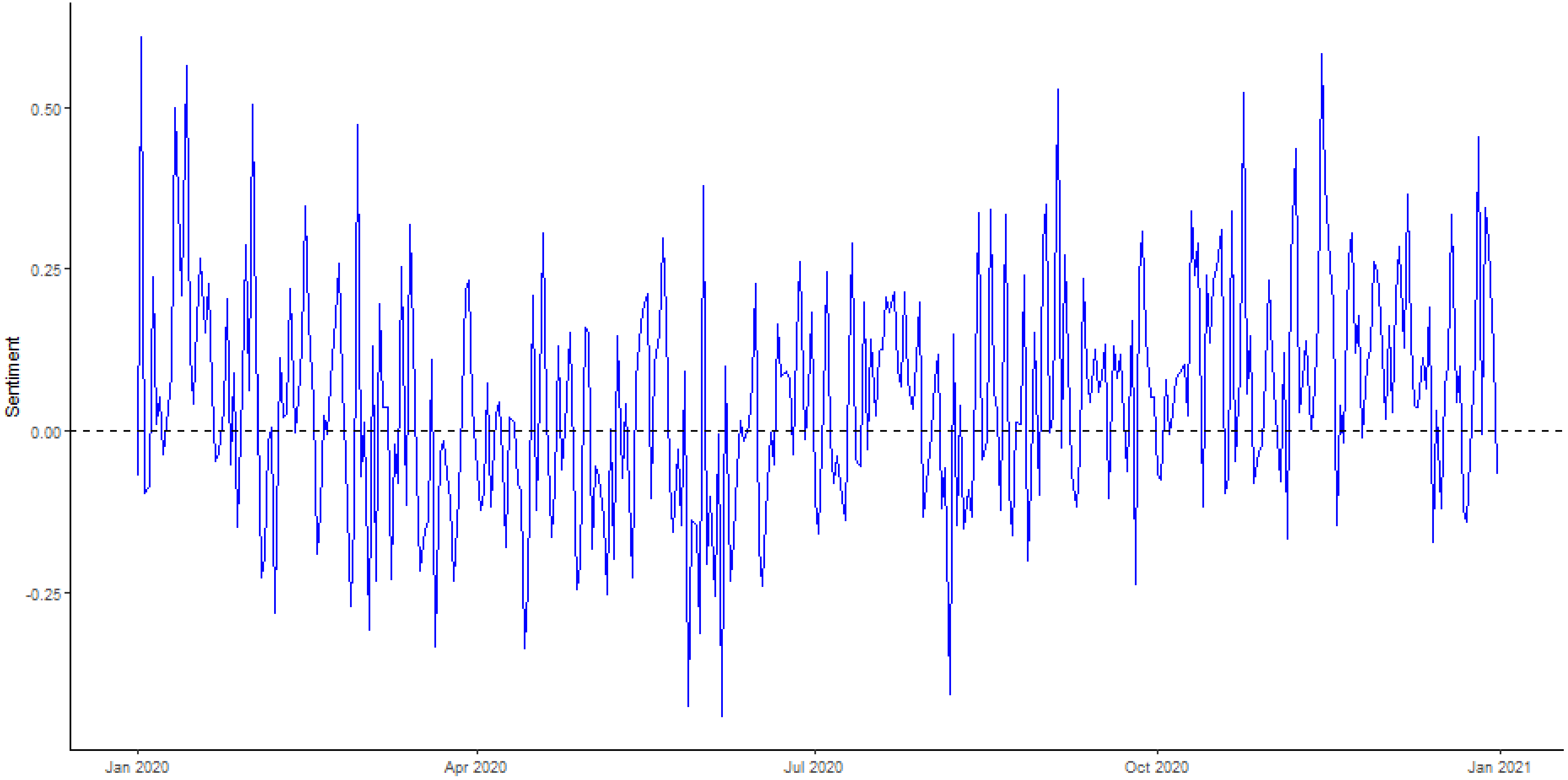
Applying weighted dictionaries

We can now use `tidyverse` function to group and summarise sentiment, for example per day:

```r
p_guardian_sentiment_afinn <- guardian_afinn_sentiments %>%
  group_by(day) %>%
  summarise(sentiment = mean(value)) %>%
  ggplot(aes(x = day, y = sentiment)) +
  geom_line(color = "blue") +
  geom_hline(yintercept = 0, linetype = "dashed") +
  theme_classic() +
  labs(x = NULL, y = "Sentiment")
```

Applying weighted dictionaries

```
p_guardian_sentiment_afinn
```



Validating dictionaries

Now to the one million dollar question: Do the values we just computed actually represent sentiment?

Validating the results is arguably the most important task of not just dictionary-based methods, but also automated content analysis in general. Three common ways of validations include:

- Comparing the results with (manual) gold standards
- Computing data fit indices
- Invesigating meaningful relationships of results with other variables in the data (e.g., a terrorism dictionary should lead to higher scores in the aftermath of terrorist attacks)

Validating dictionaries with oolong

The `oolong` package provides a simple way for gold-standard validation directly in R. As it is still in early active development, the latest development version is usually the best choice:

```r
remotes::install_github("chainsawriot/oolong")
```

As always, load it with `library()`:

```r
library(oolong)
```

Validating dictionaries with oolong

We first create a random sample of our data for the gold standard test with the `gs()` function, indicating the construct to validate. Note that it is suggested to use at least 1% of the data for validation, but for demonstration purposes, let's stick to a smaller number of 20 articles:

```r
gs_test <- gs(input_corpus = guardian_corpus, construct = "positive",
              exact_n = 20, userid = "Julian")

gs_test
```

```
##
## -- oolong (gold standard generation) -------------------------------------------
## :) Julian
## i GS: n = 20, 0 coded.
## i Construct:  positive.
##
## -- Methods --
```

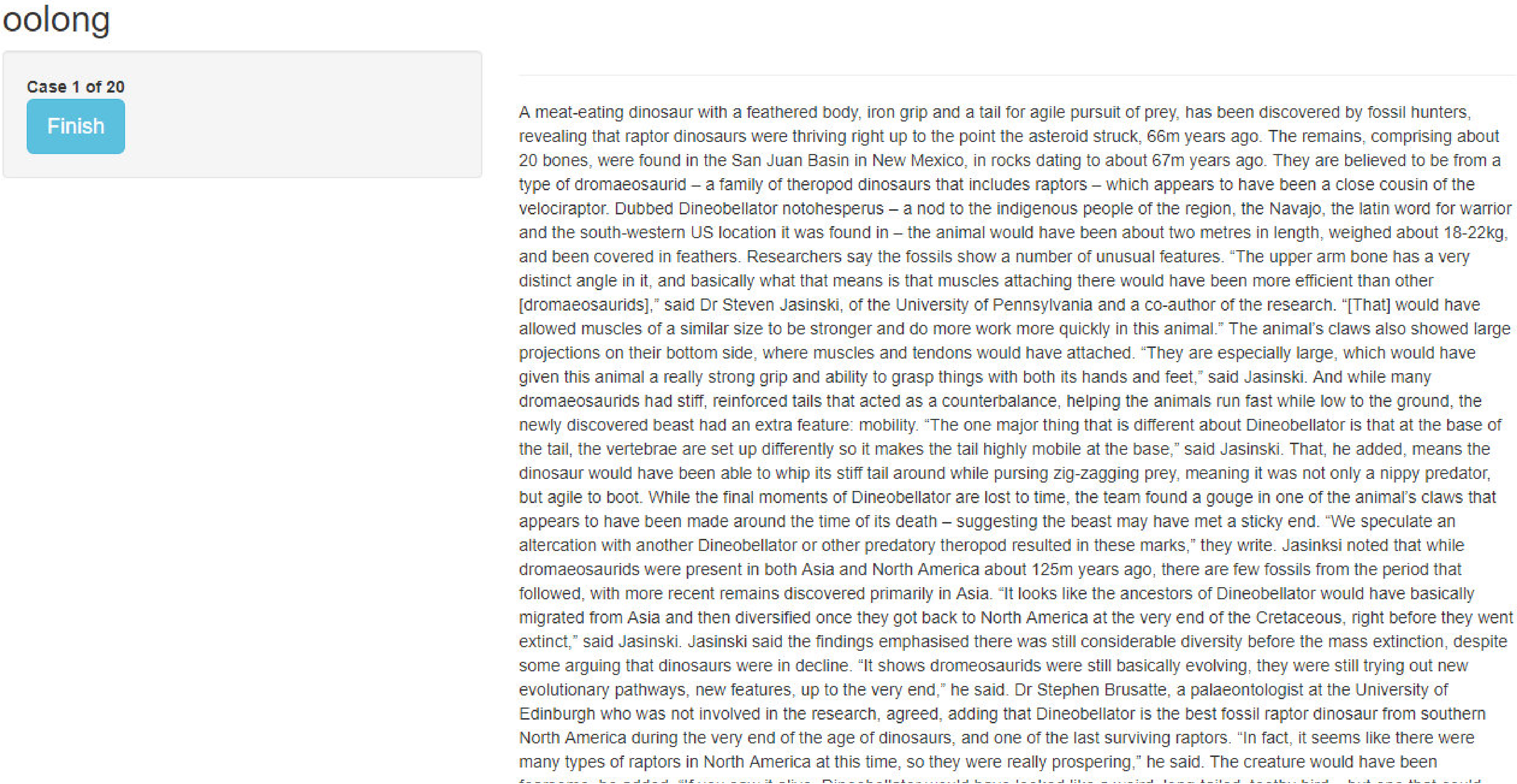
Validating dictionaries with `oolong`

As outlined in the resulting object, we can now start coding the data (and thus providing a manual gold standard) by using the method `$do_gold_standard_test()`:

```
gs_test$do_gold_standard_test()
```

This opens a coding window in RStudio's *Viewer* pane:

Validating dictionaries with `oolong`



A meat-eating dinosaur with a feathered body, iron grip and a tail for agile pursuit of prey, has been discovered by fossil hunters, revealing that raptor dinosaurs were thriving right up to the point the asteroid struck, 66m years ago. The remains, comprising about 20 bones, were found in the San Juan Basin in New Mexico, in rocks dating to about 67m years ago. They are believed to be from a type of dromaeosaurid – a family of theropod dinosaurs that includes raptors – which appears to have been a close cousin of the velociraptor. Dubbed Dineobellator notohesperus – a nod to the indigenous people of the region, the Navajo, the latin word for warrior and the south-western US location it was found in – the animal would have been about two metres in length, weighed about 18-22kg, and been covered in feathers. Researchers say the fossils show a number of unusual features. “The upper arm bone has a very distinct angle in it, and basically what that means is that muscles attaching there would have been more efficient than other [dromaeosaurids],” said Dr Steven Jasinski, of the University of Pennsylvania and a co-author of the research. “[That] would have allowed muscles of a similar size to be stronger and do more work more quickly in this animal.” The animal’s claws also showed large projections on their bottom side, where muscles and tendons would have attached. “They are especially large, which would have given this animal a really strong grip and ability to grasp things with both its hands and feet,” said Jasinski. And while many dromaeosaurids had stiff, reinforced tails that acted as a counterbalance, helping the animals run fast while low to the ground, the newly discovered beast had an extra feature: mobility. “The one major thing that is different about Dineobellator is that at the base of the tail, the vertebrae are set up differently so it makes the tail highly mobile at the base,” said Jasinski. That, he added, means the dinosaur would have been able to whip its stiff tail around while pursing zig-zagging prey, meaning it was not only a nippy predator, but agile to boot. While the final moments of Dineobellator are lost to time, the team found a gouge in one of the animal’s claws that appears to have been made around the time of its death – suggesting the beast may have met a sticky end. “We speculate an altercation with another Dineobellator or other predatory theropod resulted in these marks,” they write. Jasinksi noted that while dromaeosaurids were present in both Asia and North America about 125m years ago, there are few fossils from the period that followed, with more recent remains discovered primarily in Asia. “It looks like the ancestors of Dineobellator would have basically migrated from Asia and then diversified once they got back to North America at the very end of the Cretaceous, right before they went extinct,” said Jasinski. Jasinski said the findings emphasised there was still considerable diversity before the mass extinction, despite some arguing that dinosaurs were in decline. “It shows dromeosaurids were still basically evolving, they were still trying out new evolutionary pathways, new features, up to the very end,” he said. Dr Stephen Brusatte, a palaeontologist at the University of Edinburgh who was not involved in the research, agreed, adding that Dineobellator is the best fossil raptor dinosaur from southern North America during the very end of the age of dinosaurs, and one of the last surviving raptors. “In fact, it seems like there were many types of raptors in North America at this time, so they were really prospering,” he said. The creature would have been

Validating dictionaries with `oolong`

After you have finished coding the data, `$lock()` it to perform the actual gold standard test:

```
gs_test$lock()
```

Validating dictionaries with oolong

We can now apply our dictionary as before by using the `$turn_gold()` method. This creates a `quanteda` corpus:

```
gs_corpus <- gs_test$turn_gold()
gs_corpus
```

```
## Corpus consisting of 20 documents and 1 docvar.
## 2476 :
## "A meat-eating dinosaur with a feathered body, iron grip and ..."
##
## 2501 :
## "Three weeks ago, Tony Robinson completed a six-part series f..."
##
## 4695 :
## "My husband and I run a quirky, colourful music bar in Herefo..."
##
## 487 :
## "It’s time to go rogue with your eyeliner. Many SS20 catwalks..."
##
## 8787 :
## "The funniest sketch I’ve ever seen … Siblings – a hilarious ..."
##
```

Validating dictionaries with oolong

Let's apply the dictionary just as before:

```r
gs_dict <- gs_corpus %>%
  tokens() %>%
  dfm() %>%
  dfm_weight(scheme = "prop") %>%
  dfm_lookup(liu_dict)

gs_dict
```

```
## Document-feature matrix of: 20 documents, 2 features (2.50% sparse) and 1 docvar.
##       features
## docs     positive   negative
##   2476 0.02156334 0.01617251
##   2501 0.02357724 0.01788618
##   4695 0.02657807 0.02214839
##   487  0.04215852 0.02866779
##   8787 0.01980198 0.03217822
##   2874 0.03694268 0.05095541
## [ reached max_ndoc ... 14 more documents ]
```

Validating dictionaries with `oolong`

We need one value per document to compare our manual codings to:

```r
gs_values <- gs_dict %>%
  convert("data.frame") %>%
  mutate(sentiment = positive - negative) %>%
  pull(sentiment)

gs_values
```

```
##  [1]  0.0053908356  0.0056910569  0.0044296788  0.0134907251 -0.0123762376
##  [6] -0.0140127389 -0.0078843627  0.0189393939  0.0091324201  0.0132248220
## [11] -0.0241545894 -0.0245231608  0.0035569106 -0.0186766275 -0.0126715945
## [16]  0.0009569378 -0.0103412616  0.0017889088 -0.0063391442 -0.0343137255
```

Validating dictionaries with oolong

Finally, use the `summarize_oolong()` function to get the test results:

```r
gs_results <- summarize_oolong(gs_test, target_value = gs_values)

gs_results
```

Validating dictionaries with `oolong`

The summary objects also includes a `plot()` method that displays various important measures at once:

```
plot(gs_results)
```

Dictionaries and beyond

Improve dictionary-based methods by:

- Including negating bigrams
- Removing common sources of error (phrases like "good bye", etc.)
- Minding the context the dictionary was developed for
- *Always* (re-)validating dictionaries

Dictionaries provide a simple way for classifying documents into latent constructs. Supervised machine learning classification may drastically improve such classifications, but also come with increased effort. For example, look at Rudkowsky et al., 2018 for a word embeddings approach towards sentiment analysis.

Exercise solutions

Exercise solutions

Exercise 1: Text description

First, load the tweets (remember to explicitly read in Twitter IDs as character):

```
btw_tweets <- read_csv("data/tweets_btw.csv",
                       col_types = list(id = col_character()))
```

Then, create a corpus:

```
btw_corpus <- corpus(btw_tweets, docid_field = "id", text_field = "text")
```

Exercise solutions

There are of course multiple possibilites to text preprocessing. This way, we remove most of (probably) unwanted features:

```
btw_tokens <- tokens(btw_corpus,
                     remove_punct = TRUE, remove_symbols = TRUE,
                     remove_numbers = TRUE, remove_url = TRUE,
                     remove_separators = TRUE) %>%
  tokens_tolower() %>%
  tokens_remove(c(stopwords("german", "nltk"), "rt", "#*", "@*")) %>%
  tokens_select(min_nchar = 2) %>%
  tokens_keep("\\w+", valuetype = "regex")
```

We will also need a DFM:

```
btw_dfm <- dfm(btw_tokens)
```

Exercise solutions

The rest is just applying the various text and word metrics function. For example, get a list of most frequent words per account:

```
textstat_frequency(btw_dfm, n = 3, groups = author)
```

```
##               feature frequency rank docfreq       group
## 1                 the        26    1      21   ABaerbock
## 2               heute        23    2      23   ABaerbock
## 3                mehr        22    3      21   ABaerbock
## 4               heute        32    1      30 ArminLaschet
## 5                 the        23    2       8 ArminLaschet
## 6 ministerpräsident        22    3      22 ArminLaschet
## 7               heute        85    1      81   OlafScholz
## 8                mehr        76    2      67   OlafScholz
## 9              müssen        66    3      63   OlafScholz
```

Exercise solutions

Or all collocations in the tweets:

```
textstat_collocations(btw_tokens)
```

```
##                    collocation count count_nested length   lambda        z
## 1                       ab uhr    17            0      2 6.394060 16.01189
## 2                 bürger innen    16            0      2 5.769122 14.72774
## 3    sagt bundesfinanzminister    13            0      2 5.455357 14.10808
## 4       herzlichen glückwunsch    15            0      2 8.716410 13.77752
## 5                   geht's los    12            0      2 7.930611 13.42734
## 6         unserer gesellschaft    10            0      2 5.676450 13.21986
## 7           bürgerinnen bürger    12            0      2 7.832576 12.93256
## 8                gleich geht's     8            0      2 6.689422 12.36857
## 9                   live dabei     8            0      2 5.419750 11.97853
## 10                dafür sorgen    11            0      2 6.067464 11.93917
## 11                 vielen dank     7            0      2 6.261835 11.88686
## 12           europäische union     7            0      2 6.153480 11.80651
## 13              gutes gespräch     6            0      2 6.469644 11.37955
## 14                 seit jahren     7            0      2 5.498415 11.16812
## 15                      of the     9            0      2 4.135198 10.64397
## 16       gesellschaft respekts     6            0      2 6.237010 10.63205
##  [ reached 'max' / getOption("max.print") -- omitted 665 rows ]
```

Exercise solutions

For keyness, you first need to group the DFM per author and then set the target account:

```
btw_dfm %>%
  dfm_group(author) %>%
  textstat_keyness(target = "ABaerbock")
```

```
##        feature      chi2            p n_target n_reference
## 1         from 25.808169 3.770891e-07        9           0
## 2           is 23.007328 1.613850e-06       15           8
## 3         born 22.494735 2.107204e-06        8           0
## 4  klimaschutz 20.384591 6.333776e-06       14           8
## 5       jewish 19.187319 1.184980e-05        7           0
## 6       kinder 18.305508 1.881623e-05       16          12
## 7           to 17.086892 3.570791e-05       18          16
## 8           of 16.084673 6.057230e-05       21          22
## 9         girl 15.888712 6.717818e-05        6           0
## 10  herzlichen 15.709383 7.385688e-05       13           8
## 11        this 15.176496 9.791462e-05        8           2
## 12         and 13.632950 2.222504e-04       18          19
## 13        been 12.603943 3.849338e-04        5           0
## 14    deported 12.603943 3.849338e-04        5           0
## 15        more 12.603943 3.849338e-04        5           0
```

Exercise solutions

```
btw_dfm %>%
  dfm_group(author) %>%
  textstat_keyness(target = "OlafScholz")
```

```
##                  feature      chi2            p n_target n_reference
## 1  bundesfinanzminister 30.994409 2.587728e-08       45           0
## 2                   uhr 22.347416 2.275190e-06       43           3
## 3                 innen 21.986248 2.746111e-06       60           9
## 4                  geht 20.749690 5.234004e-06       58           9
## 5          gesellschaft 20.142413 7.188483e-06       33           1
## 6                 dafür 19.743496 8.856255e-06       59          10
## 7               respekt 18.771061 1.473867e-05       31           1
## 8               schaltet 15.130191 1.003456e-04       22           0
## 9                    spd 15.015281 1.066442e-04       32           3
## 10                  gibt 13.852374 1.977467e-04       36           5
## 11              schaffen 13.301928 2.651333e-04       23           1
## 12                  live 13.100998 2.951384e-04       32           4
## 13       kanzlerkandidat 13.064438 3.009554e-04       19           0
## 14                  plan 12.376033 4.348801e-04       18           0
## 15                  sagt 11.234277 8.030039e-04       49          12
## 16                  ganz 11.201510 8.173081e-04       29           4
## 17        ostdeutschland 10.311353 1.322143e-03       15           0
```

Exercise solutions

```r
btw_dfm %>%
  dfm_group(author) %>%
  textstat_keyness(target = "ArminLaschet")
```

```
##                     feature      chi2            p n_target n_reference
## 1         ministerpräsident 91.332497 0.000000e+00       22           1
## 2       nordrhein-westfalen 69.321275 1.110223e-16       16           0
## 3                        de 36.070796 1.902772e-09       12           3
## 4                  gespräch 27.794642 1.348992e-07       13           7
## 5  modernisierungsjahrzehnt 27.315149 1.728519e-07        7           0
## 6                        la 22.329953 2.295973e-06        7           1
## 7                düsseldorf 18.054805 2.146362e-05        5           0
## 8     nrw-ministerpräsident 18.054805 2.146362e-05        5           0
## 9                        et 13.617375 2.241018e-04        5           1
## 10                    tweet 13.462455 2.433851e-04        4           0
## 11                 wolfgang 13.462455 2.433851e-04        4           0
## 12                 minister 13.045333 3.040411e-04        7           4
## 13                     with 10.847924 9.890656e-04        8           7
## 14                    armin 10.508752 1.188105e-03        5           2
## 15                   freund  9.455777 2.104851e-03        4           1
## 16              präsidenten  9.455777 2.104851e-03        4           1
## 17                austausch  9.446190 2.115881e-03        8           8
```

Exercise solutions

Exercise 2: Applying dictionaries

Create the dictionary by creating a list of the two constructs and pass it to the `dictionary()` function:

```
liu_dict <- dictionary(list(
  positive = positive_words,
  negative = negative_words
))
```

Exercise solutions

Weighting the DFM before applying the dictionary gives the proportion of *construct terms* in the document:

```r
guardian_dfm %>%
  dfm_weight(scheme = "prop") %>%
  dfm_lookup(liu_dict)
```

```
## Document-feature matrix of: 10,000 documents, 2 features (0.92% sparse) and 5 docvars.
##       features
## docs   positive   negative
##    1 0.02152080 0.03873745
##    2 0.03658537 0.02439024
##    3 0.02188184 0.01969365
##    4 0.02828283 0.03232323
##    5 0.01991150 0.01880531
##    6 0.03152174 0.01630435
## [ reached max_ndoc ... 9,994 more documents ]
```

Exercise solutions

Weighting the DFM after applying the dictionary gives the proportion of *constructs* in the document (ignoring all other terms):

```
guardian_dfm %>%
  dfm_lookup(liu_dict) %>%
  dfm_weight(scheme = "prop")
```

```
## Document-feature matrix of: 10,000 documents, 2 features (0.92% sparse) and 5 docvars.
##     features
## docs  positive  negative
##    1 0.3571429 0.6428571
##    2 0.6000000 0.4000000
##    3 0.5263158 0.4736842
##    4 0.4666667 0.5333333
##    5 0.5142857 0.4857143
##    6 0.6590909 0.3409091
## [ reached max_ndoc ... 9,994 more documents ]
```

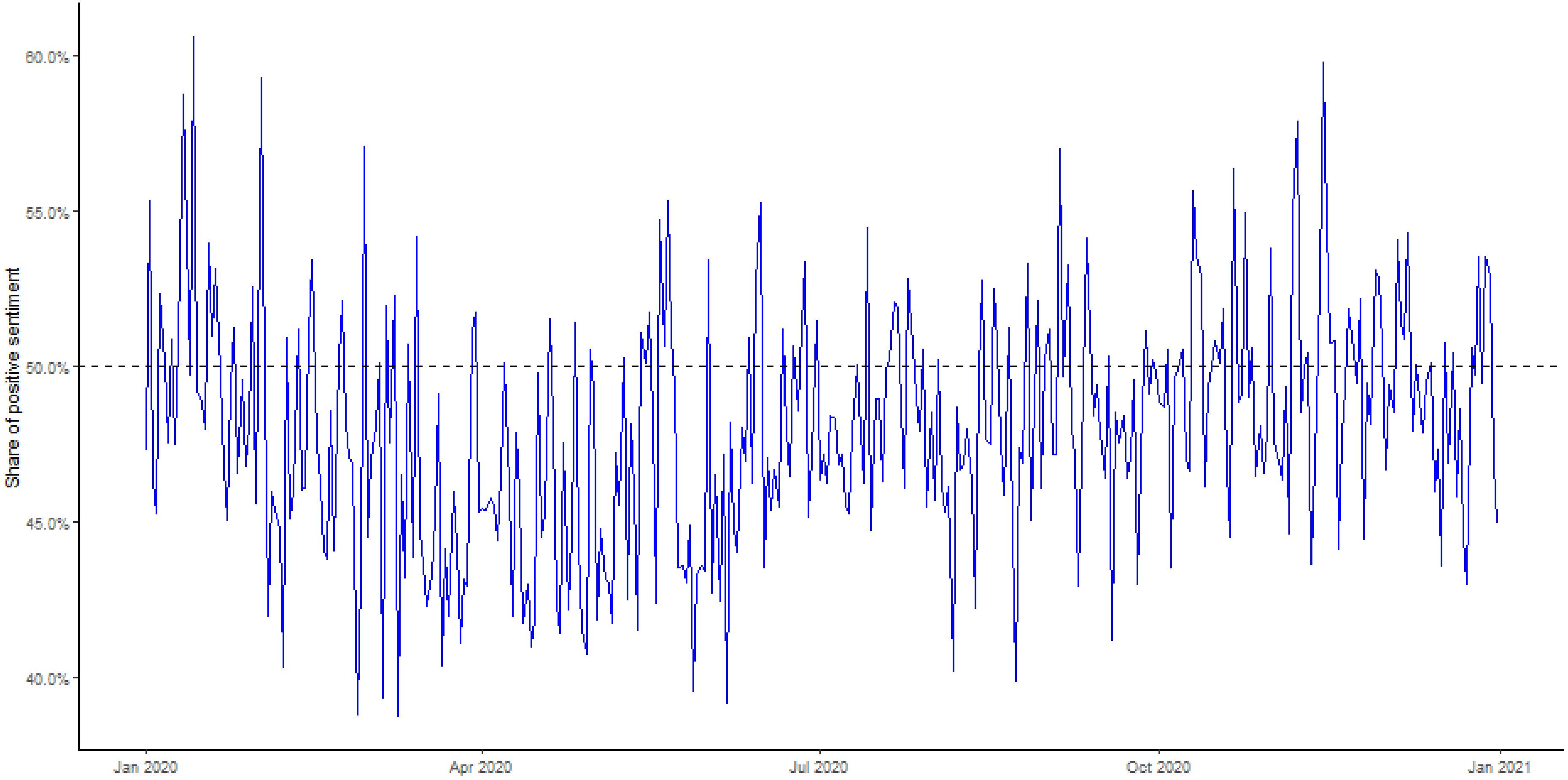
Exercise solutions

If we use the second way (proportion of constructs), we only need to plot one category; 50% then marks the transition from predominantly positive to predominantly negative sentiment:

```r
p_guardian_sentiment_liu <- guardian_dfm %>%
  dfm_group(day) %>%
  dfm_lookup(liu_dict) %>%
  dfm_weight(scheme = "prop") %>%
  tidy() %>%
  filter(term == "positive") %>%
  mutate(day = as.Date(document)) %>%
  ggplot(aes(x = day, y = count)) +
  geom_line(color = "blue") +
  geom_hline(yintercept = .5, linetype = "dashed") +
  theme_classic() +
  scale_y_continuous(labels = scales::percent) +
  labs(x = NULL, y = "Share of positive sentiment")
```

Exercise solutions

```
p_guardian_sentiment_liu
```



Thanks

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