### ST720 Data Science

Converting to and from non-tidy formats

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#### Introduction

- ► Tidy (text) data let us use the popular suite of tidy tools such as dplyr, tidyr, and ggplot2 to explore and visualize text data.
- However, most NLP tools in R are not compatible. ('https://cran.r-project.org/web/views/NaturalLanguageProcessing.html')

### Introduction

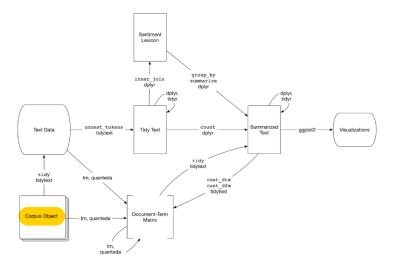


Figure 1: A flowchart of a typical text analysis

### Tidying a document-term matrix

- most common structures that text mining packages work with is the document-term matrix (or DTM).
  - each row represents one document (such as a book or article),
  - each column represents one term, and
  - each value (typically) contains the number of appearances of that term in that document.
- DTMs are usually implemented as sparse matrices, and can be stored in a more efficient format.

### Tidying a document-term matrix

- ▶ DTM objects cannot be used directly with tidy tools, and tidytext package provides two verbs.
  - tidy() turns a document-term matrix into a tidy data frame.
  - cast() turns a tidy one-term-per-row data frame into a matrix.
    - cast\_sparse(): converting to a sparse matrix from Matrix.
    - cast dtm(): converting to a DocumentTermMatrix object from tm
    - cast\_dfm(): converting to a dfm object from quanteda.

# Tidying DocumentTermMatrix objects

DocumentTermMatrix class in the tm package is the most popular.

```
library(tm)

data("AssociatedPress", package = "topicmodels")
AssociatedPress

## <<DocumentTermMatrix (documents: 2246, terms: 10473)>>
## Non-/sparse entries: 302031/23220327

## Sparsity : 99%

## Maximal term length: 18

## Weighting : term frequency (tf)
```

- Dataset contains documents (each of them an AP article) and terms (distinct words).
- ▶ This DTM is 99% sparse (99% of document-word pairs are zero).

# Tidying DocumentTermMatrix objects

▶ Access the terms with Terms() function.

# Tidying DocumentTermMatrix objects

▶ To make it tidy, we use tidy() function.

```
ap_td <- tidy(AssociatedPress)
print(ap_td, n = 5)</pre>
```

- ► A tidy three-column tbl\_df: document, term, and count. (similar to the melt() {reshape2} for non-sparse matrices.
- Only the non-zero values are included in the tidied output. No 0 for count.

# Sentiment Analysis with tidy data.

```
ap_sentiments <- ap_td %>%
  inner_join(get_sentiments("bing"), by = c(term = "word"))
ap_sentiments
```

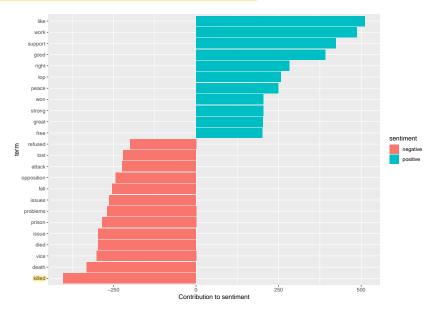
```
## # A tibble: 30,094 x 4
##
     document term count sentiment
##
       <int> <chr> <dbl> <chr>
## 1
           1 assault 1 negative
##
           1 complex 1 negative
           1 death 1 negative
##
##
           1 died 1 negative
##
           1 good 2 positive
##
           1 illness 1 negative
## 7
           1 killed
                       2 negative
##
           1 like
                       2 positive
##
           1 liked 1 positive
## 10
           1 miracle
                       1 positive
## # ... with 30,084 more rows
```

# Sentiment Analysis with tidy data.

▶ Visualize which words from the AP articles most often contributed to positive or negative sentiment.

```
ap_sentiments %>%
  count(sentiment, term, wt = count) %>%
  ungroup() %>%
  filter(n >= 200) %>%
  mutate(n = ifelse(sentiment == "negative", -n, n)) %>%
  mutate(term = reorder(term, n)) %>%
  ggplot(aes(term, n, fill = sentiment)) +
  geom_bar(stat = "identity") +
  ylab("Contribution to sentiment") +
  coord_flip()
```

# Sentiment Analysis with tidy data.



- ► Alternative implementations of document-term matricesis dfm (document-feature matrix) class from the quanteda package.
- ► Example in quanteda: presidential inauguration speeches

## Document-feature matrix of: 58 documents, 9,357 features (91.

```
inaug_td <- tidy(inaug_dfm)
inaug_td</pre>
```

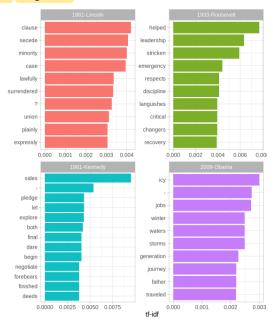
```
## # A tibble: 44,709 x 3
##
     document
                   term
                                 count
## <chr>
                   <chr>
                                 <dbl>
   1 1789-Washington fellow-citizens
##
##
   2 1797-Adams fellow-citizens
##
   3 1801-Jefferson fellow-citizens
##
   4 1809-Madison fellow-citizens
##
   5 1813-Madison fellow-citizens
##
   6 1817-Monroe fellow-citizens
##
   7 1821-Monroe fellow-citizens
##
   8 1841-Harrison fellow-citizens
                                   11
   9 1845-Polk fellow-citizens
##
## 10 1849-Taylor fellow-citizens
## # ... with 44,699 more rows
```

▶ Find the words most specific to each of the inaugural speeches.

```
inaug_tf_idf <- inaug_td %>%
  bind_tf_idf(term, document, count) %>%
  arrange(desc(tf_idf))

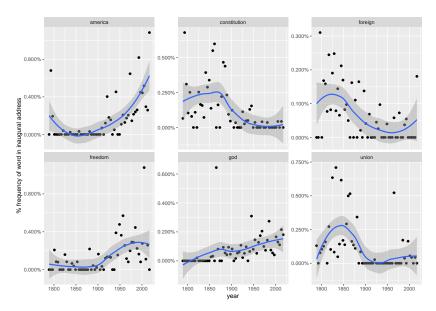
print(inaug_tf_idf, n = 5)
```

```
## # A tibble: 44.709 x 6
##
                            document
                                                                                                                                                                                                   count
                                                                                                                                                                                                                                                                                                   idf tf idf
                                                                                                                            term
                                                                                                                                                                                                                                                                    tf
## <chr>
                                                                                                                            <chr>
                                                                                                                                                                                                    <dbl> <db> <db> <db> <db > <db
## 1 1793-Washington arrive
                                                                                                                                                                                                                            1 0.00680 4.06 0.0276
## 2 1793-Washington upbraidings
                                                                                                                                                                                                                           1 0.00680 4.06 0.0276
## 3 1793-Washington violated
                                                                                                                                                                                                                           1 0.00680 3.37 0.0229
## 4 1793-Washington willingly
                                                                                                                                                                                                                           1 0.00680 3.37 0.0229
## 5 1793-Washington incurring
                                                                                                                                                                                                                           1 0.00680 3.37 0.0229
## # ... with 4.47e+04 more rows
```



 Pick several words and visualize how they changed in frequency over time.

```
year term counts <- inaug td %>%
 extract(document, "year", "(\\d+)", convert = TRUE) %>%
 complete(year, term, fill = list(count = 0)) %>%
 group by(year) %>%
 mutate(year_total = sum(count))
print(year term counts, n = 5)
## # A tibble: 542,706 x 4
## # Groups: year [58]
##
     year term count year_total
## <int> <chr> <dbl> <dbl>
## 1 1789 - 2 1538
## 2 1789 ,
           70 1538
## 3 1789 : 8 1538
## 4 1789 :
                     1538
## 5 1789 !
                      1538
## # ... with 5.427e+05 more rows
```



### Casting tidy text data into a DTM

► Tidied AP dataset and cast it back into a document-term matrix using the cast\_dtm() function.

```
ap_td %>%
    cast_dtm(document, term, count)

## <<DocumentTermMatrix (documents: 2246, terms: 10473)>>
## Non-/sparse entries: 302031/23220327
## Sparsity : 99%
## Maximal term length: 18
## Weighting : term frequency (tf)
```

# Casting tidy text data into a DFM

► Similarly, we could cast the table into a dfm object from quanteda's dfm with cast\_dfm().

```
ap_td %>%
  cast_dfm(document, term, count)
```

## Document-feature matrix of: 2,246 documents, 10,473 features

# Casting tidy text data into a matrix

## [1] "Matrix"

Some tools simply require a sparse matrix:

```
library(Matrix)

m <- ap_td %>%
    cast_sparse(document, term, count)

class(m)

## [1] "dgCMatrix"
## attr(,"package")
```

### DTM of Jane Austen's books

## Weighting

```
library(janeaustenr)
austen_dtm <- austen_books() %>%
  unnest_tokens(word, text) %>%
  count(book, word) %>%
  cast dtm(book, word, n)
austen_dtm
## <<DocumentTermMatrix (documents: 6, terms: 14520)>>
## Non-/sparse entries: 40379/46741
## Sparsity
                      : 54%
## Maximal term length: 19
```

: term frequency (tf)

documents: 50

data("acq")

## Content:

- ► Some data structures are designed to store document collections before tokenization, often called a "corpus".
- ▶ acq corpus in tm package contains 50 articles from Reuters.

```
## <<VCorpus>>
## Metadata: corpus specific: 0, document level (indexed): 0
```

▶ A corpus object is a list, with each item containing both text and metadata.

10 <NA> 1987-02-27 02:08:27 ""

Let's tidy.

```
acq_td <- tidy(acq)
acq_td</pre>
```

```
## # A tibble: 50 x 16
##
     author datetimestamp
                           description heading id
                                                          langu
                                <chr>
                                                    <chr> <chr>
##
   <chr>
            <dttm>
                                            <chr>
##
   1 <NA> 1987-02-27 00:18:06
                                            COMPUT~ 10
                                                          en
   2 <NA> 1987-02-27 00:19:15
                                11 11
                                            OHIO M~ 12
##
                                                          en
                                            MCLEAN~ 44
##
   3 <NA> 1987-02-27 00:49:56
                                                          en
   4 By Ca~ 1987-02-27 00:51:17
                                11 11
                                            CHEMLA~ 45
##
                                                          en
   5 <NA> 1987-02-27 01:08:33
                                            <COFAB~ 68
##
                                                          en
   6 <NA> 1987-02-27 01:32:37 ""
##
                                            TNVEST~ 96
                                                          en
##
   7 By Pa~ 1987-02-27 01:43:13
                                            AMERIC~ 110
                                                          en
   8 <NA> 1987-02-27 01:59:25 ""
##
                                            HONG K~ 125
                                                          en
##
   9 <NA> 1987-02-27 02:01:28 ""
                                            LIEBER~ 128
                                                          en
```

## # ... with 40 more rows, and 9 more variables: topics <chr>,
## # lewissplit <chr>, cgisplit <chr>, oldid <chr>, places <na
## # people <lgl>, orgs <lgl>, exchanges <lgl>, text <chr>

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► Then use unnest\_tokens() to find the most common words or the ones most specific to each article.

```
acq_tokens <- acq_td %>%
  select(-places) %>%
  unnest_tokens(word, text) %>%
  anti_join(stop_words, by = "word")
```

Most common words

```
acq_tokens %>%
 count(word, sort = TRUE)
## # A tibble: 1,566 x 2
##
    word
               n
## <chr> <int>
##
  1 dlrs
             100
   2 pct
         70
##
##
   3 mln
             65
   4 company 63
##
   5 shares 52
##
   6 reuter 50
##
## 7 stock 46
## 8 offer 34
##
   9 share 34
## 10 american 28
## # ... with 1,556 more rows
```

▶ tf-idf

```
acq_tokens %>%
  count(id, word) %>%
  bind_tf_idf(word, id, n) %>%
  arrange(desc(tf_idf))
```

```
## # A tibble: 2,853 x 6
##
     id
          word
                               idf tf idf
                     n
                          tf
##
     <chr> <chr> <int> <dbl> <dbl> <dbl>
##
   1 186
          groupe
                     2 0.133 3.91
                                   0.522
##
   2 128 liebert
                     3 0.130 3.91 0.510
   3 474 esselte 5 0.109 3.91 0.425
##
##
   4 371 burdett 6 0.103 3.91
                                   0.405
   5 442
          hazleton 4 0.103 3.91
                                   0.401
##
   6 199 circuit 5 0.102 3.91
                                   0.399
##
   7 162
          suffield
                     2 0.1
                              3.91
                                   0.391
##
                              3.91
                                   0.391
##
   8 498
          west
                     3 0.1
##
   9 441
          rmj
                   8 0.121 3.22
                                   0.390
  10 467
                     3 0.0968
                              3.91
                                   0.379
##
          nursery
## # ... with 2,843 more rows
```

# Summary

- ► Text analysis requires working with a variety of tools, many of which have inputs and outputs that aren't in a tidy form.
- Should know how to convert between a tidy text data frame and sparse document-term matrices, as well as how to tidy a Corpus object containing document metadata.
- ▶ This conversion tools are an essential part of text analysis as shown in the next chapter, Tompic model.