Computational Social Science

Introduction to Natural Language Processing II

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Plan

1. Course updates
2. TF-IDF weighting
3. Vector representations of texts
4. Cosine similarity

Course updates

- Homework 2 due tonight
- Project proposals due next Wednesday
  - Complete quiz on Canvas

Working with text

Recap

- Introduction to Natural Language Processing
- Pre-processing texts
  - Tokenization, stemming, stop word removal
- The bag-of-words representation
  - N-grams

Working with text

Comparing documents

- The goal of today's lecture is to introduce methods for comparing documents
  - Re-weighting word counts to find distinctive words
  - Representing documents as vectors of word counts
  - Geometric interpretations of document vectors

Working with text

Limitations of word counts

- Word counts alone are an imperfect measure for comparing documents
  - Some words occur in most documents, providing little information about the document (recall Zipf's law)
  - Similarly, some words are very rare, providing little generalizable insight
  - We want to find words that help distinguish between documents

Working with text

Term-frequency inverse document-frequency (TF-IDF)

- Term-frequency inverse document-frequency (TF-IDF) is a way to weight word counts (“term frequencies”) to give higher weights to words that help distinguish between documents
  - Intuition: Adjust word counts to take into account how many documents a word appears in.

Working with text

Calculating term-frequency inverse document-frequency (TF-IDF)

- N = number of documents in the corpus
- $tf_{t,d}$ = number of times term t used in document d
- df_t = number of documents containing term t
- $idf_t = log(\frac{N}{df_t})$ = log of fraction of all documents containing t
  - $\frac{N}{df_t}$ is larger for terms occurring in fewer documents
  - The logarithm is used to penalize very high values
  - If a word occurs in all documents $df_t = N$, thus $idf_t = log\frac{N}{N} = log(1) = 0$.
- We then use these values to calculate $TFIDF_{t,d} = tf_{t,d} * idf_t$

Working with text

Loading data

Loading the word frequency objects created last lecture using `tidytext`.

Working with text

Computing TF-IDF in `tidytext`

We can easily compute TF-IDF weights using `tidy.text` by using the word-count object we created last lecture. Note the two document example is quite trivial. Many words have IDF scores equal to zero because they occur in both documents.

```
tidy.tfidf <- words %>% bind_tf_idf(word, title, n)
head(tidy.tfidf)
```

```
## # A tibble: 6 x 7
##   title              word          n total      tf   idf tf_idf
##   <chr>              <chr>     <dbl> <dbl>   <dbl> <dbl>  <dbl>
## 1 Elementary Forms totem      1250 78851 0.0159  0.693 0.0110
## 2 Elementary Forms religi      606 78851 0.00769 0      0
## 3 Elementary Forms anim        577 78851 0.00732 0      0
## 4 Elementary Forms religion    572 78851 0.00725 0      0
## 5 Elementary Forms form        542 78851 0.00687 0      0
## 6 Elementary Forms natur       542 78851 0.00687 0      0
```

Working with text

Take the stem “countri” for example (short for country, country’s, countries).

```
## # A tibble: 2 x 7
##   title                word        n total       tf   idf tf_idf
##   <chr>                <chr>   <dbl> <dbl>    <dbl> <dbl>  <dbl>
## 1 Communist Manifesto countri    26  4835 0.00538      0      0
## 2 Elementary Forms    countri    16 78851 0.000203     0      0
```

Working with text

The term "australia" has a relatively low term frequency but a higher IDF score, since it only occurs in *Elementary Forms*.

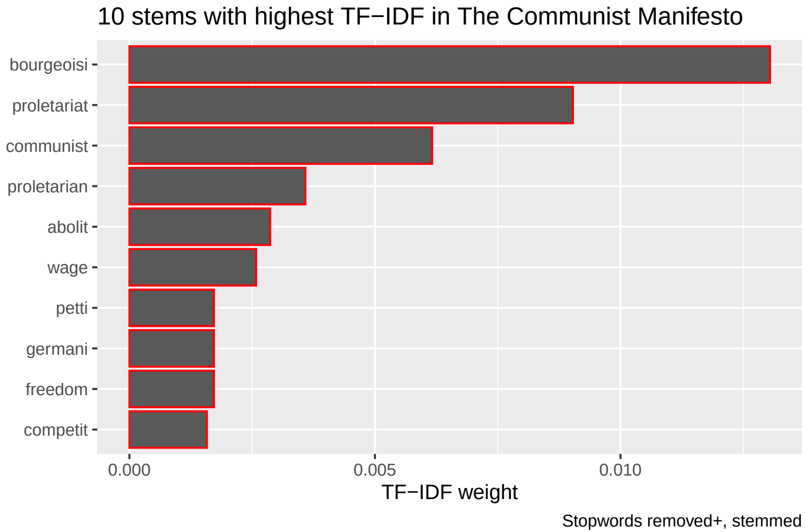
```
## # A tibble: 1 x 7
##   title             word           n total      tf   idf   tf_idf
##   <chr>             <chr>      <dbl> <dbl>   <dbl> <dbl>    <dbl>
## 1 Elementary Forms australia     108 78851 0.00137 0.693 0.000949
```

Working with text

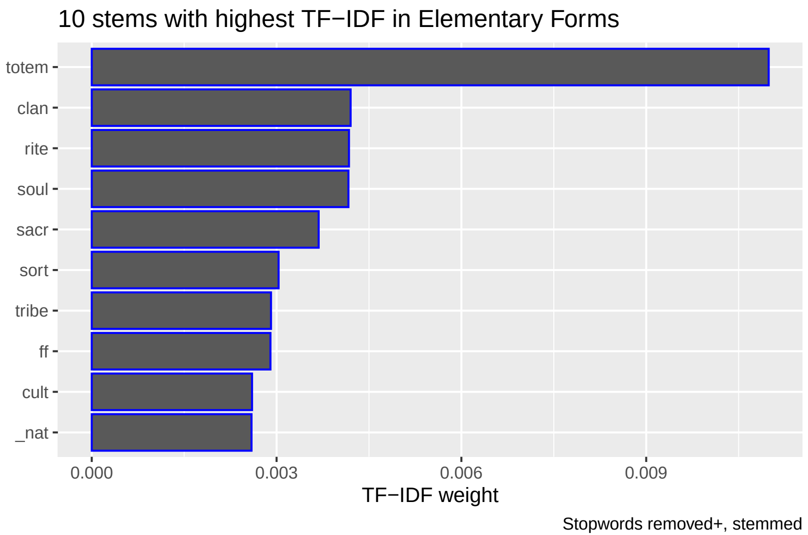
In this case *all* words unique to one document will have the same IDF score, $\sim log(2/1)$.

```
## # A tibble: 6 x 7
##   title              word      n total      tf   idf  tf_idf
##   <chr>              <chr> <dbl> <dbl>   <dbl> <dbl>   <dbl>
## 1 Elementary Forms totem  1250 78851 0.0159  0.693 0.0110
## 2 Elementary Forms clan    478 78851 0.00606 0.693 0.00420
## 3 Elementary Forms rite    475 78851 0.00602 0.693 0.00418
## 4 Elementary Forms soul    474 78851 0.00601 0.693 0.00417
## 5 Elementary Forms sacr    419 78851 0.00531 0.693 0.00368
## 6 Elementary Forms sort    345 78851 0.00438 0.693 0.00303
```

Working with text



Working with text



Vector representations of texts

The document-term matrix (DTM)

- A frequently used bag-of-words representation of a text corpus is the *Document-Term Matrix*:
  - Each row* is a document (a unit of text)
  - Each column is a term (word)
  - For a given DTM X, each cell $X_{i,j}$ indicates the number of times a term i occurs in document j, $tf_{i,j}$.
    - This can be the raw term counts or TF-IDF weighted counts.
- Most cells are empty so it is usually stored as a sparse matrix to conserve memory.

*Sometimes the rows and columns are reversed, resulting in a *Term-Document Matrix* or *TDM*

Vector representations of texts

Casting a `tidytext` object into a DTM

```
X <- texts %>% unnest_tokens(word, text) %>%
    anti_join(stop_words) %>% count(title, word) %>%
    cast_dtm(title, word, n)
print(X)
```

```
## <<DocumentTermMatrix (documents: 2, terms: 11525)>>
## Non-/sparse entries: 12663/10387
## Sparsity           : 45%
## Maximal term length: NA
## Weighting          : term frequency (tf)
```

Note: This matrix is not weighted by TF-IDF, although we could apply the weights if desired.

Vector representations of texts

Viewing the DTM

The object created is a class unique to the `tidytext` package. We can inspect this to see what it contains.

```
class(X)
```

```
## [1] "DocumentTermMatrix"    "simple_triplet_matrix"
```

```
dim(X)
```

```
## [1]     2 11525
```

```
X$dimnames[1]
```

```
## $Docs
## [1] "Communist Manifesto" "Elementary Forms"
```

```
#X$dimnames[2] # prints all columns as a long list
X$dimnames[[2]][1:50] # first 50 columns
```

```
##  [1] "1"                 "10"                "1830"              "1846"
##  [5] "1847"              "1888"              "18th"              "2"
##  [9] "3"                 "4"                 "5"                 "6"
## [13] "7"                 "8"                 "9"                 "_a"
```

Vector representations of texts

Viewing the DTM

The easiest way to see the actual DTM is to cast it to a matrix.

```
Xm <- as.matrix(X)
```

Vector representations of texts

Geometric interpretation

- Each text is a vector in N-dimensional space, where N is the total number of unique words (column of the DTM)
- Each word is a vector in D-dimensional space, where D is the number of documents (rows of the DTM)

See https://web.stanford.edu/~jurafsky/slp3/6.pdf for more details on the vector-space model

Vector representations of texts

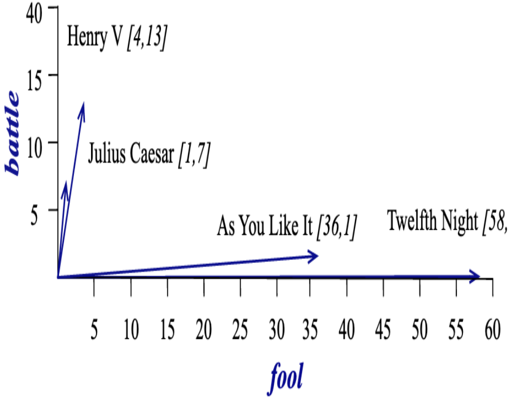
Document vectors

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

This example from Jurafsky and Martin shows a Term-Document Matrix (TDM) pertaining to four key words from four Shakespeare

Vector representations of texts

Document vectors



Here vectors for each play are plotted in two-dimensional space.
The y- and x-axes indicate the number of times the words "battle"

Vector representations of texts

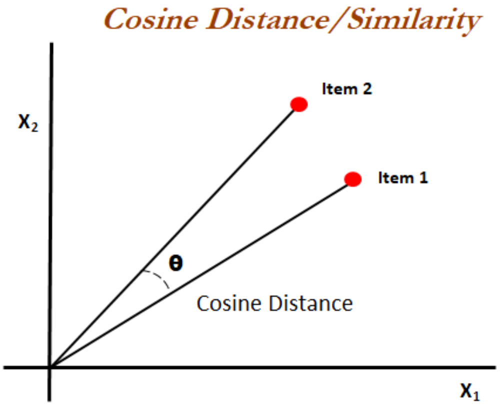
Word vectors

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

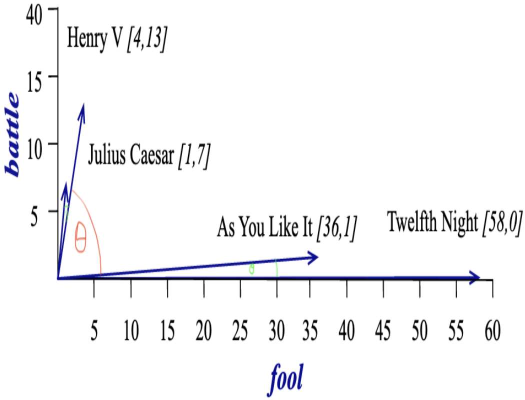
Figure 6.5 The term-document matrix for four words in four Shakespeare plays. The red boxes show that each word is represented as a row vector of length four.

We could also treat the rows of this matrix as vector representations of each word. We will return to this idea next week.

Cosine similarity



Cosine similarity



Cosine similarity

$\vec{u}$ and $\vec{v}$ are vectors representing texts (e.g. rows from a DTM matrix). We can compute the cosine of the angle between these two vectors using the following formula:

$$cos(\theta) = \frac{\vec{u} \cdot \vec{v}}{\|\vec{u}\|\|\vec{v}\|} = \frac{\sum_i \vec{u}_i \vec{v}_i}{\sqrt{\sum_i \vec{u}_i^2}\sqrt{\sum_i \vec{v}_i^2}}$$

The value range from 0 (complete dissimilarity) to 1 (identical), since all values are non-negative.

Cosine similarity

```r
u <- c(1,2,3,4)
v <- c(0,1,0,1)

sum(u*v) / (sqrt(sum(u^2)) * sqrt(sum(v^2)))
```

```
## [1] 0.7745967
```

```r
# Same result using matrix multiplication
u %*% v / (sqrt(u %*% u) * sqrt(v %*% v))
```

```
##           [,1]
## [1,] 0.7745967
```

Cosine similarity

Making a function

```
cosine.sim <- function(u,v) {
  numerator <- u %*% v
  denominator <- sqrt(u %*% u) * sqrt(v %*% v)
  return (numerator/denominator)
}

cosine.sim(u,v)
```

```
##           [,1]
## [1,] 0.7745967
```

Cosine similarity

Cosine similarity between Marx and Durkheim

We can use the two columns of the DTM matrix defined above as arguments to the similarity function.

```
print(cosine.sim(Xm[1,], Xm[2,]))
```

```
##           [,1]
## [1,] 0.6012744
```

Cosine similarity

Cosine similarity for a larger corpus

Let's consider another example with a slightly larger corpus of texts.

```
m <- gutenberg_metadata %>%
    filter(author == "Shakespeare, William" & language == "en")
plays <- gutenberg_download(2235:2269)

plays <- plays %>% left_join(m, by = "gutenberg_id") %>%
    filter(gutenberg_id != 2240) # Removing a duplicate
```

Cosine similarity

From text to DTM

```
## <<DocumentTermMatrix (documents: 33, terms: 4815)>>
## Non-/sparse entries: 72441/86454
## Sparsity           : 54%
## Maximal term length: 15
## Weighting          : term frequency (tf)
## [1]   33 4815
```

Cosine similarity

Extracting TF-IDF matrix

```
DTMd <- as.matrix(DTM)
write.csv(DTMd %>% as.data.frame(), "../data/shakespeare.csv", row.name

# Run line below if using tf-idf weights as
# some columns contain zeros and must be removed
#DTMd <- DTMd[,colSums(DTM) > 0]
```

Cosine similarity

Normalizing columns

We can simplify the cosine similarity calculation if we normalize each column by its length (the denominator in the above calculation.)

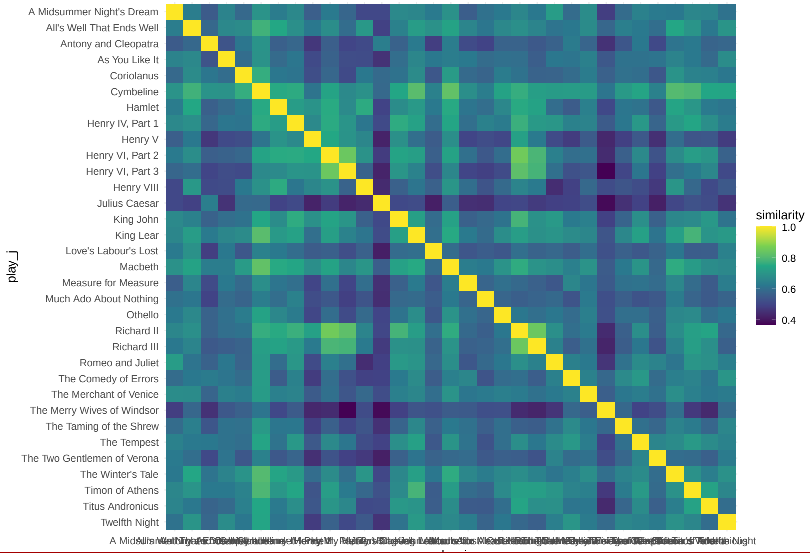
```
normalize <- function(v) {
  return (v/sqrt(v %*% v))
}

# Normalizing every column in the matrix
for (i in 1:dim(DTMd)[1]) {
  DTMd[i,] <- normalize(DTMd[i,])
}
```

Cosine similarity

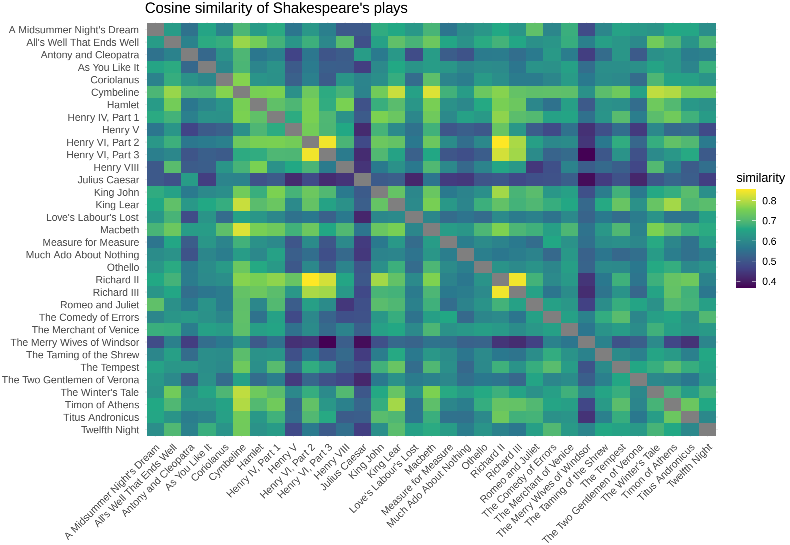
Calculating cosine similarity using matrix multiplication

```
sims <- DTMd %*% t(DTMd)
```

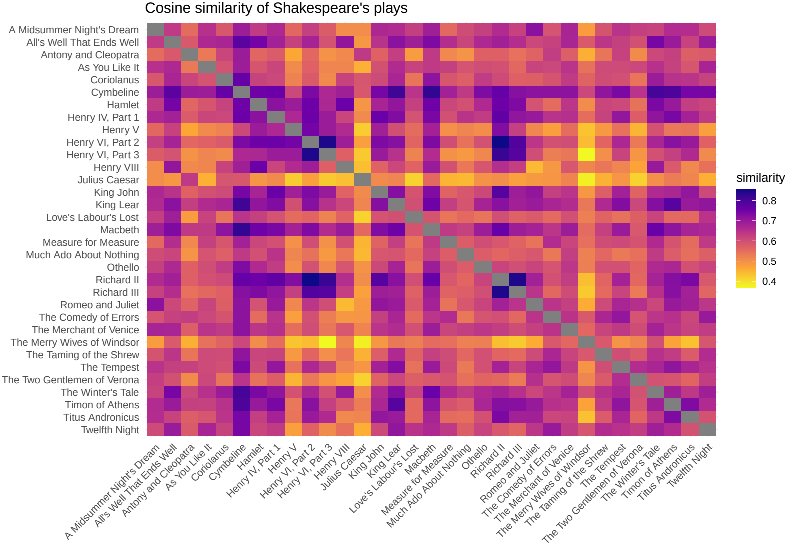
Cosine similarity



Cosine similarity



Cosine similarity



Next week

- Word embeddings