Week 5: Beyond Bag-of-Words

POP77142 Quantitative Text Analysis for Social Scientists

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Overview

- Distributional hypothesis
- Keyword in context (KWIC)
- Word representations
- Embeddings

Words

Word Meanings

- In order to analyse text, it is helpful to understand the meanings of words.
- Even better if we could somehow ‘explain’ (represent) these meanings in a way that a computer can understand.
- Possible ways to represent word meanings:
  - Columns in document-term matrices;
  - Dictionary definitions;
  - Synonyms;
  - Similar words;
  - …

Back to DTM

- Here is a DTM showing the occurrences of 4 words in 4 plays by Shakespeare.

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

```r
dtm <- matrix(c(
  1, 114, 36, 20,
  0,  80, 58, 15,
  7,  62,  1,  2,
  13, 89,  4,  3
), nrow = 4, byrow = TRUE)
rownames(dtm) <- c("As You Like It", "Twelfth Night", "Julius Caesar", "Henry V")
colnames(dtm) <- c("battle", "good", "fool", "wit")
```

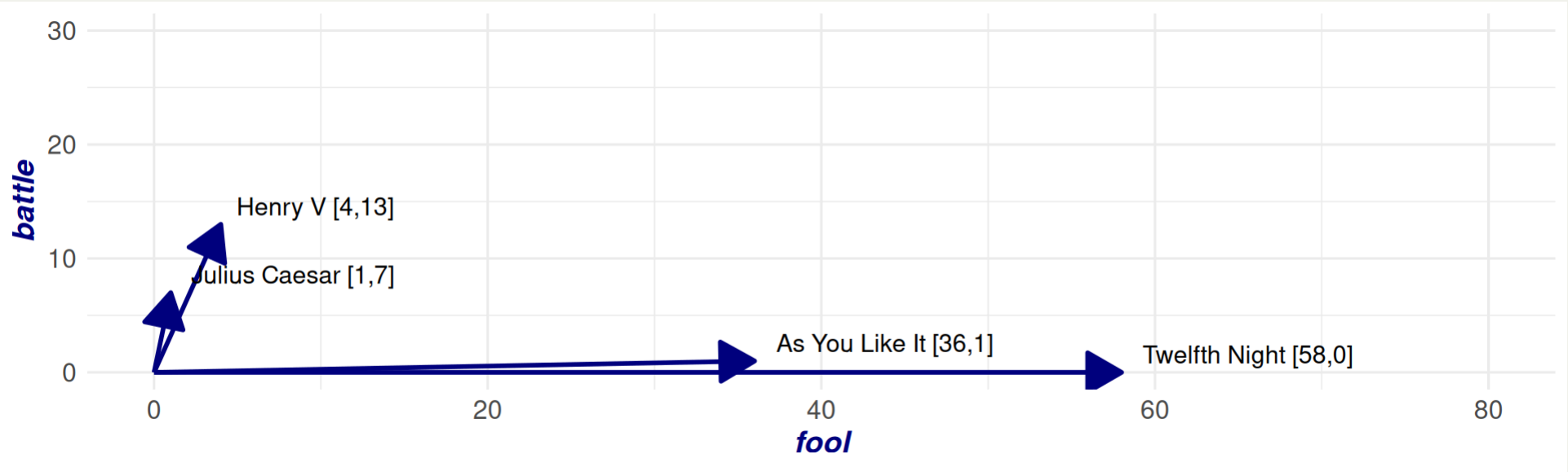
```r
dtm
```

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

Document Vectors

- It is easy to visualise documents/words in a limited number of dimensions.
- Here is a spatial visualisation of the the four Shakespeare plays in 2-dimensions, corresponding to the words *battle* and *fool*.

Plot | Code



Term-Document Matrix (TDM)

- An equivalent representation of texts as *document-term matrices* (DTMs), could be made with *term-document matrices* (TDMs).

	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

- In effect, the TDM is just the transpose of the DTM.

```
1 tdm <- t(dtm)
```

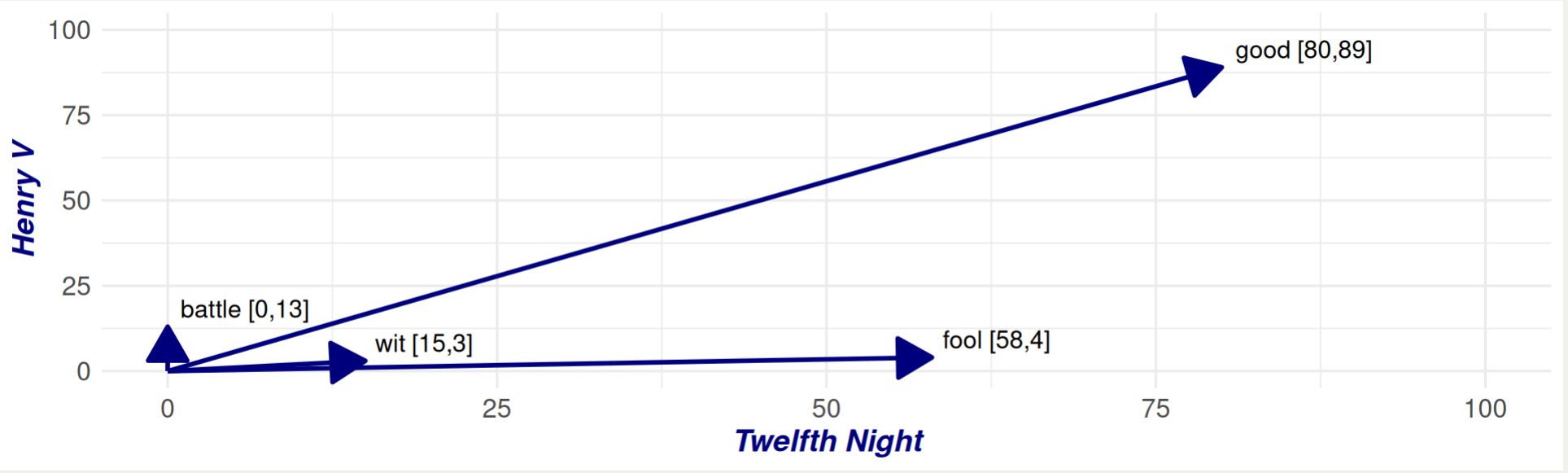
```
1 tdm
```

```
       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
```

Word Vectors

Similar to document vectors, we can also represent words as vectors.

Plot | Code



- Naturally, a 2-dimensional representation is rather limiting.

Distributional Hypothesis

Distributional Hypothesis

> You shall know a word by the company it keeps.
>
> J.R. Firth, 1957

- Words that occur in similar contexts tend to have similar meanings.
- Think about language acquisition in humans.
- Children don’t learn languages (word meanings) by studying dictionaries.
- They learn them by hearing and reading them in context.

Keyword in Context (KWIC)

- An intuitive first step would be to look at *contexts* of a word.
- One way, Keyword in Context (KWIC) approach from corpus linguistics.
- The idea is to pick a word and some window ($\pm n$ words) around it.

```r
dail_33 <- read.csv("../data/dail_33_small.csv.gz")
```

```r
dail_33_toks <- dail_33$text |>
  quanteda::tokens(remove_punct = TRUE) |>
  quanteda::tokens_tolower() |>
  quanteda::tokens_remove(quanteda::stopwords("en"))
```

```r
kwic_taoiseach <- quanteda::kwic(dail_33_toks, pattern = "taoiseach", window = 2)
```

```r
head(kwic_taoiseach, 10)
```

```
Keyword-in-context with 10 matches.
 [text28, 370] enacted apparently | taoiseach | tánaiste’s office
 [text32, 249] ireland background | taoiseach | asked attorney
 [text77, 477]         months ago | taoiseach | said build
  [text84, 57]     indeed elected | taoiseach | venue strange
  [text84, 81]   teams department | taoiseach | office tánaiste
 [text188, 25]      asking wanted | taoiseach | answer simple
 [text219, 77]     going election | taoiseach | call election
  [text273, 5]  minister tánaiste | taoiseach | minister state
 [text344, 10] expenditure reform | taoiseach | pursuant standing
  [text512, 7] expenditure reform | taoiseach | completed consideration
```

Keyword in Context (KWIC)

```r
vec_taoiseach <- c(
  # Contexts are stored as n-grams (bigrams for 2-word contexts)
  unlist(strsplit(kwic_taoiseach$pre, split = " ")),
  unlist(strsplit(kwic_taoiseach$post, split = " "))
) |>
  table() |>
  prop.table() |>
  sort(decreasing = TRUE)
```

```r
head(vec_taoiseach, 20)
```

```
   minister         ask        said  department  government    tánaiste 
0.016495321 0.014144115 0.013157531 0.012263151 0.011774469 0.009211194 
     deputy         can       thank        time       issue      raised 
0.008492001 0.008270711 0.007505417 0.007265686 0.005320179 0.005320179 
       know       asked    question          us         now        last 
0.005117330 0.004932921 0.004564105 0.004564105 0.004536444 0.004416578 
       give       aware 
0.004269052 0.004259831 
```

Could we have guessed the word from the provided context?

Word Representations

Word Vectors

- Vectors for representing words are called **embeddings**.
- It is more often used to refer to *dense vectors*.
- But *sparse vectors* are also embeddings.
- What is the problem with sparse vectors?

```
1 length(vec_taoiseach)
```

```
[1] 9537
```

```
1 median(vec_taoiseach)
```

```
[1] 1.844083e-05
```

In practice, it would be even larger (as we excluded all zero counts), of length V (vocabulary size).

Co-occurrence Matrix

- Instead of using TDM, we could represent words as a **co-occurrence matrix**.
- It is also knows as **term-term matrix**, **word-word matrix**, or **term-context matrix**.
- The idea is to count how many times a word occurs in the context of another word.
- The matrix would, thus, has a dimensionality of $V \times V$.
- Context can be defined in many ways:
  - Same document,
  - Same sentence,
  - An arbitrary window of $\pm n$ words.

Example: Co-occurrence Matrix

```r
dail_33_fcm <- dail_33_toks |>
  # Create feature co-occurrence matrix (fcm)
  quanteda::fcm(
    window = 2,
    context = "window",
    count = "frequency",
    tri = FALSE
  )
```

```r
dail_33_fcm
```

```
Feature co-occurrence matrix of: 157,414 by 157,414 features.
               features
features        seanad éireann accepted finance bill 2024 without
  seanad            58     565       19       7  530   33      29
  éireann          565     184        5      16   50    6       5
  accepted          19       5       98      20   69    1      16
  finance            7      16       20     176 1134   27      28
  bill             530      50       69    1134 2056  535     340
  2024              33       6        1      27  535   78      47
  without           29       5       16      28  340   47     274
  recommendation     5       4      101      12   36   15      16
  wish               7       5        7      17  141    7      12
  advise             1       8        0       4   12    0       1
               features
features        recommendation wish advise
  seanad                     5    7      1
  éireann                    4    5      8
  accepted                 101    7      0
  finance                   12   17      4
  bill                      36  141     12
```

Example: Co-occurrence Matrix

- Let's zoom in on some words that we saw frequently in the context of *taoiseach*.

```
taoiseach_fcm <- dail_33_fcm |>
  quanteda::fcm_select(
    pattern = c("taoiseach", "tánaiste", "minister", "party", "election", "government"),
    selection = "keep"
  )
```

```
taoiseach_fcm
```

```
Feature co-occurrence matrix of: 6 by 6 features.
            features
features     minister government tánaiste taoiseach party election
  minister       7792       4988     1204      1789   670       85
  government     4988       4896      517      1277  1185      168
  tánaiste       1204        517       68       999    81        9
  taoiseach      1789       1277      999       308   131       67
  party           670       1185       81       131   700       60
  election         85        168        9        67    60      154
```

Weighting Terms

- Oftentimes raw frequencies are difficult to interpret.
- Words that occur frequently in text (e.g. stopwords) are not very informative.
- There is a paradox in that words that occur in the context of another word likely carry as little information as the words that occur *too* frequently.
- How do we address this?
  - For DTM/TDM, we can use **tf-idf** (term frequency-inverse document frequency) weighting.
  - For co-occurrence matrices, we can use **pointwise mutual information** (PMI).

Pointwise Mutual Information (PMI)

- The intuition behind PMI is that the best way to weight the association between two words is to compare the observed co-occurrence with the expected co-occurrence.
- In probability terms it is how often two events (w - word and c - context) co-occur compared to how often we would expect them to if they were independent:

$$PMI(w, c) = \log_2 \frac{P(w, c)}{P(w)P(c)}$$

- This ratio gives us an estimate of how much the two words co-occur than we would expect them by chance.

Example: PMI

- Let's try to work out some PMI values for the co-occurrence matrix we created above.
- To simplify our calculations, let's say these are the only words in our vocabulary.

```
1 taoiseach_fcm
```

```
Feature co-occurrence matrix of: 6 by 6 features.
            features
features     minister government tánaiste taoiseach party election
  minister       7792       4988     1204      1789   670       85
  government     4988       4896      517      1277  1185      168
  tánaiste       1204        517       68       999    81        9
  taoiseach      1789       1277      999       308   131       67
  party           670       1185       81       131   700       60
  election         85        168        9        67    60      154
```

- First, let's calculate the margins:

```
1 # Row (word) margins
2 w <- rowSums(as.matrix(taoiseach_fcm))
```

```
1 # Column (context) margins
2 c <- colSums(as.matrix(taoiseach_fcm))
```

```
1 # Column (context) margins
2 total <- sum(w)
```

Example: PMI

```
1 w
```

```
minister government   tánaiste  taoiseach      party   election
   16528      13031       2878       4571       2827        543
```

```
1 c
```

```
minister government   tánaiste  taoiseach      party   election
   16528      13031       2878       4571       2827        543
```

```
1 total
```

```
[1] 40378
```

$$P(w = taoiseach, c = party) = \frac{131}{40378} = 0.0032$$

$$P(w = taoiseach) = \frac{4571}{40378} = 0.1132$$

$$P(c = party) = \frac{2827}{40378} = 0.07$$

$$PPMI(w = taoiseach, c = party) = \log_2 \frac{0.0032}{0.1132 \times 0.07} = -1.31$$

Embeddings

Word Embeddings

- The problem with all word vectors (embeddings) calculated so far is that they are high-dimensional.
- In the extreme they are of dimension V (vocabulary size).
- This has a number of disadvantages:
  - Difficulty of interpretation.
  - Computationally inefficient.
- What we would like to have instead are word embeddings of some dimensionality K such that $K < V$.
- But which would retain the useful properties that we discussed (convey the word meanings).

Development of Word Embeddings

- Learning vector representations of words has long been an active area of research in NLP (e.g. Bengio et al. (2003))
- However, the field really took off after the introduction of **Word2Vec** by Mikolov et al. (2013).
- Other populat implemenations include **GloVe** (Global Vectors for Word Representation) by Pennington et al. (2014)
- There can be a trade-off between general-purpose embeddings trained on large corpora (e.g. Wikipedia) and domain-specific embeddings trained on smaller corpora.
- However, pretrained embeddings have been shown to be quite robust and reliable for some political science tasks (e.g. Rodriguez & Spirling, 2022).

Overview

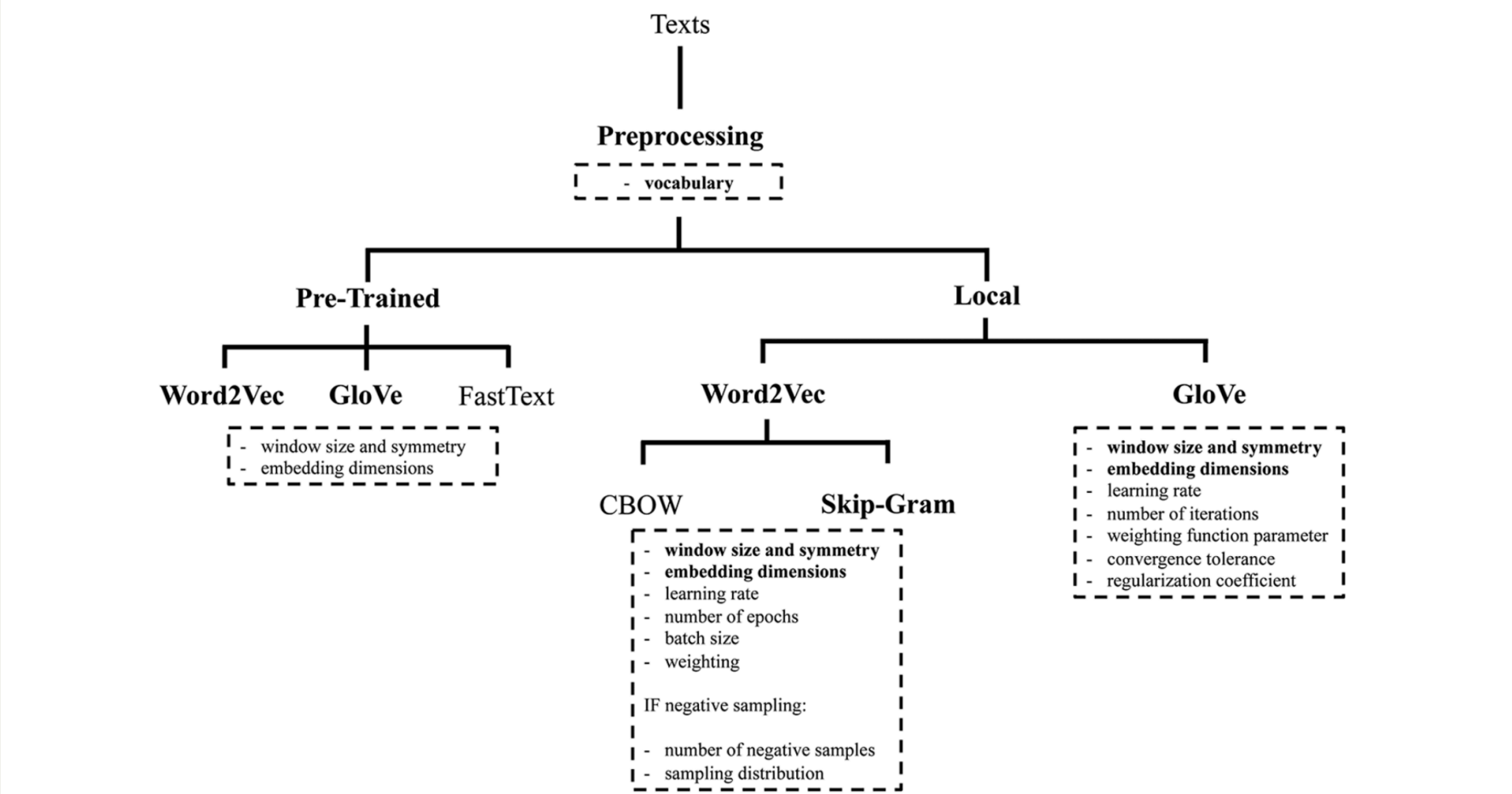


Figure 1. Decision flowchart for embeddings. Branches are either/or approaches. Boxes list decisions to be made under those approaches. Decisions in bold are ones we evaluate below.

(Rodriguez & Spirling, 2022)

Example: GloVe

- GloVe is an unsupervised learning algorithm for obtaining vector representations for words.
- We can use `text2vec` package to fit a GloVe model to our co-occurrence matrix.

```
library("text2vec")
```

```
# Fit GloVe model
glove <- text2vec::GloVe$new(
  rank = 50,
  x_max = 10
)
wv <- glove$fit_transform(
  x = dail_33_fcm,
  n_iter = 10,
  convergence_tol = 0.01,
  n_threads = 8
)
```

```
INFO  [14:31:49.809] epoch 1, loss 0.1111
INFO  [14:31:51.948] epoch 2, loss 0.0856
INFO  [14:31:54.062] epoch 3, loss 0.0756
INFO  [14:31:56.273] epoch 4, loss 0.0710
INFO  [14:31:58.393] epoch 5, loss 0.0681
INFO  [14:32:00.516] epoch 6, loss 0.0661
INFO  [14:32:02.648] epoch 7, loss 0.0647
INFO  [14:32:04.772] epoch 8, loss 0.0636
INFO  [14:32:06.892] epoch 9, loss 0.0627
INFO  [14:32:09.012] epoch 10, loss 0.0620
```

Example: GloVe

- Let's examine some of the resultant word vectors.

```
wv_context <- glove$components
dim(wv_context)
```

```
[1]     50 157414
```

```
word_vectors <- wv + t(wv_context)
```

```
head(word_vectors["taoiseach",])
```

```
[1] -0.4027613  0.3048856 -0.7087512 -0.3784644 -0.1840084 -0.2217320
```

```
head(word_vectors["tánaiste",])
```

```
[1] -0.3436311  0.4836179 -0.3490796 -0.1104271 -0.0773500 -0.3662451
```

Example: GloVe

- Let's calculate cosine similarity between some word vectors.

```
cos_sim <- function(vec_a, vec_b) {
  sum(vec_a * vec_b) / (sqrt(sum(vec_a^2)) * sqrt(sum(vec_b^2)))
}
```

```
sim_taoiseach_tanaiste <- cos_sim(
  word_vectors["taoiseach",],
  word_vectors["tánaiste",]
)
sim_taoiseach_tanaiste
```

```
[1] 0.9602767
```

```
sim_taoiseach_minister <- cos_sim(
  word_vectors["taoiseach",],
  word_vectors["minister",]
)
sim_taoiseach_minister
```

```
[1] 0.8963921
```

Next

- Tutorial: Word embeddings
- Final Project: Due 23:59 on Wednesday, 23rd April (submission on Blackboard)