Topic 7: Word Embeddings

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This week's Rmd file here: https://github.com/MaRo406/EDS_231-text-sentiment/blob/main/topic_7.Rmd

Today we are using climbing incident data from this repo: https://github.com/ecaroom/climbing-accidents. Some analysis (in Excel) on the data was written up into a Rock and Ice magazine article.

But I've constructed our data set (link below) by pulling a few key variables including the full text of each incident report.

This is basically the most cutting edge of semantic analysis and vectorizes collections of words to see how far away they are compared to other words.

```
incidents_df<-read_csv("https://raw.githubusercontent.com/MaRo406/EDS_231-text-sentiment/825b159b6da4c7
```

```
## Rows: 2770 Columns: 4
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (3): ID, Accident Title, Text
## dbl (1): Publication Year
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

First, let's calculate the unigram probabilities, how often we see each word in this corpus.

```
unigram_probs <- incidents_df %>%
    unnest_tokens(word, Text) %>%
    anti_join(stop_words, by = 'word') %>%
    count(word, sort = TRUE) %>%
    mutate(p = n / sum(n))
unigram_probs
```

```
## # A tibble: 25,205 x 3
##    word         n       p
##    <chr>    <int>   <dbl>
##  1 rope      5129 0.00922
##  2 feet      5101 0.00917
##  3 climbing  4755 0.00855
##  4 route     4357 0.00783
```

```
##  5 climbers  3611 0.00649
##  6 climb     3209 0.00577
##  7 fall      3168 0.00569
##  8 climber   2964 0.00533
##  9 rescue    2928 0.00526
## 10 source    2867 0.00515
## # ... with 25,195 more rows
```

Next, we need to know how often we find each word near each other word – the skipgram probabilities. This is where we use the sliding window.

```
skipgrams <- incidents_df %>%
    unnest_tokens(ngram, Text, token = "ngrams", n = 5) %>%
    mutate(ngramID = row_number()) %>%
    tidyr::unite(skipgramID, ID, ngramID) %>%
    unnest_tokens(word, ngram) %>%
    anti_join(stop_words, by = 'word')

skipgrams
```

```
## # A tibble: 2,737,146 x 4
##    skipgramID `Accident Title`                                 `Publication Yea~ word
##    <chr>      <chr>                                                        <dbl> <chr>
##  1 1_1        Failure of Rappel Setup (Protection Pull~                     1990 color~
##  2 1_1        Failure of Rappel Setup (Protection Pull~                     1990 rocky
##  3 1_1        Failure of Rappel Setup (Protection Pull~                     1990 mount~
##  4 1_1        Failure of Rappel Setup (Protection Pull~                     1990 natio~
##  5 1_1        Failure of Rappel Setup (Protection Pull~                     1990 park
##  6 1_2        Failure of Rappel Setup (Protection Pull~                     1990 rocky
##  7 1_2        Failure of Rappel Setup (Protection Pull~                     1990 mount~
##  8 1_2        Failure of Rappel Setup (Protection Pull~                     1990 natio~
##  9 1_2        Failure of Rappel Setup (Protection Pull~                     1990 park
## 10 1_3        Failure of Rappel Setup (Protection Pull~                     1990 mount~
## # ... with 2,737,136 more rows
```

```
#calculate probabilities
skipgram_probs <- skipgrams %>%
    pairwise_count(word, skipgramID, diag = TRUE, sort = TRUE) %>%
    mutate(p = n / sum(n))
```

```
## Warning: `distinct_()` was deprecated in dplyr 0.7.0.
## Please use `distinct()` instead.
## See vignette('programming') for more help
```

Having all the skipgram windows lets us calculate how often words together occur within a window, relative to their total occurrences in the data. We do this using the point-wise mutual information (PMI). It's the logarithm of the probability of finding two words together, normalized for the probability of finding each of the words alone. PMI tells us which words occur together more often than expected based on how often they occurred on their own.

```r
#normalize probabilities
normalized_prob <- skipgram_probs %>%
    filter(n > 20) %>%
    rename(word1 = item1, word2 = item2) %>%
    left_join(unigram_probs %>%
                  select(word1 = word, p1 = p),
              by = "word1") %>%
    left_join(unigram_probs %>%
                  select(word2 = word, p2 = p),
              by = "word2") %>%
    mutate(p_together = p / p1 / p2)

#Which words are most associated with "rope"?
normalized_prob %>%
    filter(word1 == "rope") %>%
    arrange(-p_together)
```

```
## # A tibble: 295 x 7
##    word1 word2        n          p      p1        p2 p_together
##    <chr> <chr>    <dbl>      <dbl>   <dbl>     <dbl>      <dbl>
##  1 rope  rope     25494 0.00340    0.00922 0.00922         40.0
##  2 rope  lengths    101 0.0000135  0.00922 0.0000575       25.4
##  3 rope  skinny      24 0.00000320 0.00922 0.0000144       24.2
##  4 rope  drag       211 0.0000281  0.00922 0.000138        22.1
##  5 rope  taut        98 0.0000131  0.00922 0.0000701       20.2
##  6 rope  coiled      60 0.00000800 0.00922 0.0000431       20.1
##  7 rope  thicker     21 0.00000280 0.00922 0.0000162       18.8
##  8 rope  trailing    68 0.00000907 0.00922 0.0000539       18.3
##  9 rope  fed         48 0.00000640 0.00922 0.0000413       16.8
## 10 rope  70m         31 0.00000414 0.00922 0.0000270       16.6
## # ... with 285 more rows
```

Now we convert to a matrix so we can use matrix factorization and reduce the dimensionality of the data.

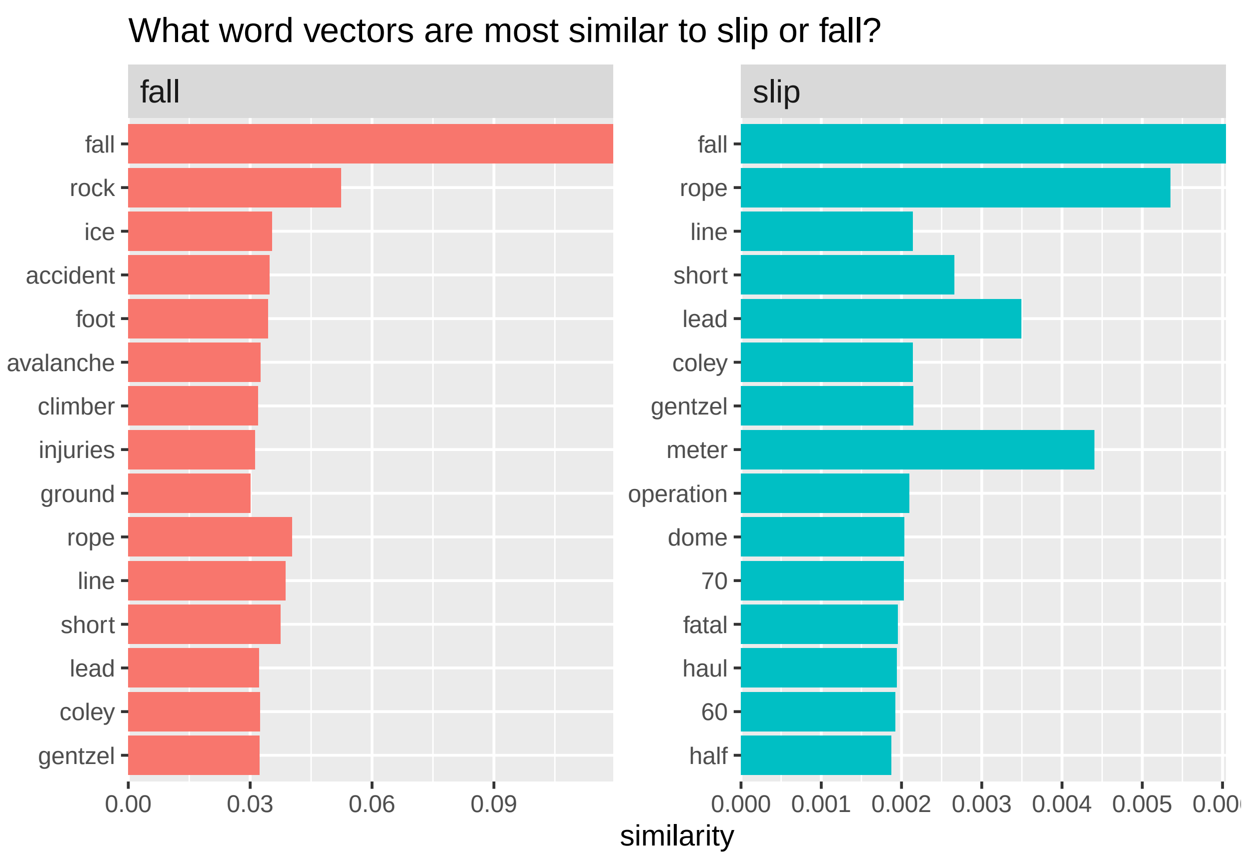
```r
pmi_matrix <- normalized_prob %>%
    mutate(pmi = log10(p_together)) %>%
    cast_sparse(word1, word2, pmi)

#remove missing data
pmi_matrix@x[is.na(pmi_matrix@x)] <- 0
#run SVD using irlba() which is good for sparse matrices
pmi_svd <- irlba(pmi_matrix, 100, maxit = 500) #Reducing to 100 dimensions
#next we output the word vectors:
word_vectors <- pmi_svd$u
rownames(word_vectors) <- rownames(pmi_matrix)
```

```r
search_synonyms <- function(word_vectors, selected_vector) {
dat <- word_vectors %*% selected_vector

similarities <- dat %>%
        tibble(token = rownames(dat), similarity = dat[,1])
```

```
similarities %>%
       arrange(-similarity) %>%
        select(c(2,3))
}
```

```
fall <- search_synonyms(word_vectors,word_vectors["fall",])
slip <- search_synonyms(word_vectors,word_vectors["slip",])
```

```
slip %>%
    mutate(selected = "slip") %>%
    bind_rows(fall %>%
                  mutate(selected = "fall")) %>%
    group_by(selected) %>%
    top_n(15, similarity) %>%
    ungroup %>%
    mutate(token = reorder(token, similarity)) %>%
    ggplot(aes(token, similarity, fill = selected)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~selected, scales = "free") +
    coord_flip() +
    theme(strip.text=element_text(hjust=0, size=12)) +
    scale_y_continuous(expand = c(0,0)) +
    labs(x = NULL, title = "What word vectors are most similar to slip or fall?")
```



```r
# take semantics of snow and danger and see what happens when they are added together
snow_danger <- word_vectors["snow",] + word_vectors["danger",]
search_synonyms(word_vectors, snow_danger)
```

```
## # A tibble: 9,104 x 2
##    token      similarity
##    <chr>           <dbl>
##  1 snow           0.396
##  2 avalanche      0.131
##  3 conditions     0.0918
##  4 soft           0.0806
##  5 wet            0.0783
##  6 ice            0.0769
##  7 icy            0.0735
##  8 slope          0.0703
##  9 fresh          0.0604
## 10 blindness      0.0596
## # ... with 9,094 more rows
```

```r
# remove snow and association of snow from danger and see what happens
no_snow_danger <- word_vectors["danger",] - word_vectors["snow",]
search_synonyms(word_vectors, no_snow_danger)
```

```
## # A tibble: 9,104 x 2
##    token     similarity
##    <chr>          <dbl>
##  1 avalanche     0.0882
##  2 danger        0.0547
##  3 rockfall      0.0540
##  4 gulch         0.0534
##  5 class         0.0507
##  6 hazard        0.0403
##  7 hazards       0.0394
##  8 occurred      0.0376
##  9 potential     0.0373
## 10 mph           0.0361
## # ... with 9,094 more rows
```

Assignment

Download a set of pretrained vectors, GloVe, and explore them.

Grab data here:

Use the last three chunks of this markdown to produce the assignment.

```r
wiki_data <- read_table(file = here('data/glove/glove.6B.300d.txt'),
                        col_names = FALSE)
```

```
##
## -- Column specification --------------------------------------------------------
## cols(
```

```
##   .default = col_double(),
##   X1 = col_character()
## )
## i Use `spec()` for the full column specifications.
```

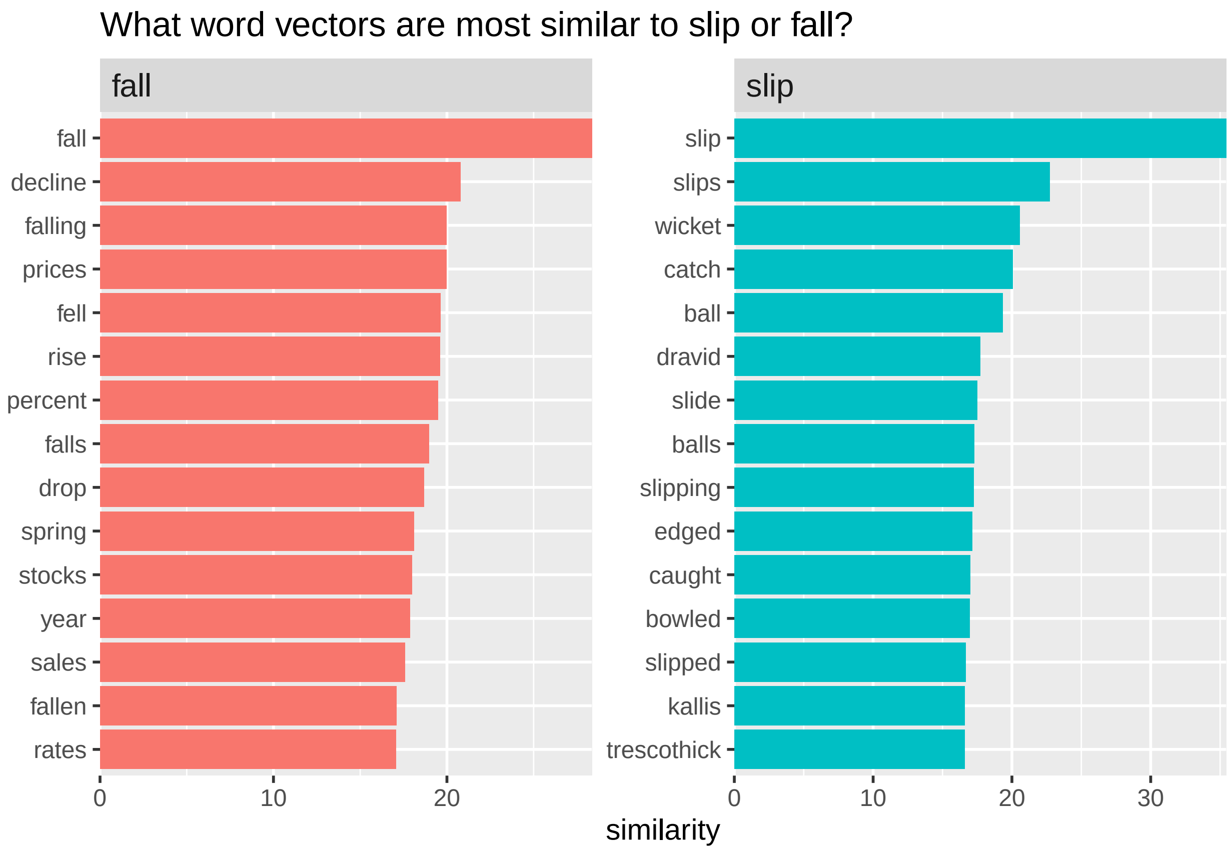
```r
wiki_data <- wiki_data %>%
  column_to_rownames(var = "X1")
#rownames(wiki_data) <- wiki_data$X1

word_vectors <- as.matrix(x = wiki_data)
```

```r
search_synonyms <- function(word_vectors, selected_vector) {
dat <- word_vectors %*% selected_vector

similarities <- dat %>%
        tibble(token = rownames(dat), similarity = dat[,1])

similarities %>%
       arrange(-similarity) %>%
        select(c(2,3))
}
```

1. Recreate the analyses in the last three chunks (find-synonyms, plot-synonyms, word-math) with the GloVe embeddings. How are they different from the embeddings created from the climbing accident data? Why do you think they are different?

```r
fall <- search_synonyms(word_vectors,word_vectors["fall",])
slip <- search_synonyms(word_vectors,word_vectors["slip",])
```

```r
slip %>%
    mutate(selected = "slip") %>%
    bind_rows(fall %>%
                  mutate(selected = "fall")) %>%
    group_by(selected) %>%
    top_n(15, similarity) %>%
    ungroup %>%
    mutate(token = reorder(token, similarity)) %>%
    ggplot(aes(token, similarity, fill = selected)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~selected, scales = "free") +
    coord_flip() +
    theme(strip.text=element_text(hjust=0, size=12)) +
    scale_y_continuous(expand = c(0,0)) +
    labs(x = NULL, title = "What word vectors are most similar to slip or fall?")
```



These graphs vary wildly from the climbing incident data with words close to fall being much more associated with financial words or closer to the word itself like "falling". Slip also has much similar words, like "slips", but also seems to have a greater variety of similar words. We did not remove variations of words in this data so that is why we are getting slips, falling, and more.

```
# take semantics of snow and danger and see what happens when they are added together
snow_danger <- word_vectors["snow",] + word_vectors["danger",]
search_synonyms(word_vectors, snow_danger)
```

```
## # A tibble: 400,000 x 2
##    token      similarity
##    <chr>           <dbl>
##  1 snow             57.6
##  2 rain             40.6
##  3 danger           40.5
##  4 snowfall         34.8
##  5 weather          34.4
##  6 winds            34.0
##  7 rains            34.0
##  8 fog              33.6
##  9 landslides       33.3
## 10 threat           33.0
## # ... with 399,990 more rows
```

```
# remove snow and association of snow from danger and see what happens
no_snow_danger <- word_vectors["danger",] - word_vectors["snow",]
search_synonyms(word_vectors, no_snow_danger)
```

```
## # A tibble: 400,000 x 2
##    token        similarity
##    <chr>             <dbl>
##  1 danger             23.3
##  2 risks              20.2
##  3 imminent           18.7
##  4 dangers            17.9
##  5 risk               17.8
##  6 32-team            17.6
##  7 mesdaq             17.5
##  8 inflationary       17.4
##  9 risking            17.2
## 10 2001-2011          17.0
## # ... with 399,990 more rows
```

Snow and danger together seems to have a lot more weather words than in the climbing data. When snow asscociation is removed from danger it seems to focus on risk and some other, more random words.

2. Run the classic word math equation, "king" - "man" = ?

```r
no_king_man <- word_vectors["king",] - word_vectors["man",]
search_synonyms(word_vectors, no_king_man)
```

```
## # A tibble: 400,000 x 2
##    token       similarity
##    <chr>            <dbl>
##  1 king              35.3
##  2 kalākaua          26.8
##  3 adulyadej         26.3
##  4 bhumibol          25.9
##  5 ehrenkrantz       25.5
##  6 gyanendra         25.2
##  7 birendra          25.2
##  8 sigismund         25.1
##  9 letsie            24.7
## 10 mswati            24.0
## # ... with 399,990 more rows
```

We get a lot of words that are likely the word "king" in other languages.

3. Think of three new word math equations. They can involve any words you'd like, whatever catches your interest.

```r
no_baseball_bat <- word_vectors["baseball",] - word_vectors["bat",]
search_synonyms(word_vectors, no_baseball_bat)
```

```
## # A tibble: 400,000 x 2
##    token        similarity
##    <chr>             <dbl>
##  1 baseball           31.0
##  2 basketball         30.1
```

```
##  3 football           26.5
##  4 nba                25.6
##  5 soccer             25.5
##  6 nfl                23.8
##  7 nhl                22.3
##  8 ncaa               22.3
##  9 hockey             22.2
## 10 professional       22.0
## # ... with 399,990 more rows
```

```
no_surfing_wave <- word_vectors["surfing",] - word_vectors["wave",]
search_synonyms(word_vectors, no_surfing_wave)
```

```
## # A tibble: 400,000 x 2
##    token                 similarity
##    <chr>                      <dbl>
##  1 surfing                     34.1
##  2 windsurfing                 26.5
##  3 snorkeling                  26.1
##  4 http://thomas.loc.gov       24.7
##  5 snowboarding                24.3
##  6 kayaking                    24.3
##  7 http://www.boston.com       23.4
##  8 snorkelling                 23.1
##  9 biking                      22.9
## 10 skateboarding               22.4
## # ... with 399,990 more rows
```

```
no_santa_barbara <- word_vectors["santa",] - word_vectors["barbara",]
search_synonyms(word_vectors, no_santa_barbara)
```

```
## # A tibble: 400,000 x 2
##    token    similarity
##    <chr>         <dbl>
##  1 santa          31.9
##  2 fe             22.5
##  3 fé             19.4
##  4 clarita        19.1
##  5 catarina       18.9
##  6 são            18.8
##  7 cruz           18.7
##  8 unión          17.9
##  9 rio            17.7
## 10 vitória        17.4
## # ... with 399,990 more rows
```