Topic 7: Word Embeddings

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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.

```
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.
```

```
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
```

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

```r
    unnest_tokens(word, ngram) %>%
    anti_join(stop_words, by = 'word')

skipgrams
```

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

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

```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
```

```
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)
```

```
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",])
```

```
climbdata_plot <-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 = "Climbing data: What word vectors are most similar to slip or fall?")
```

```
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
```

```
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:

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?

```
library(data.table)
```

```
##
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

## The following object is masked from 'package:purrr':
##
##     transpose
```

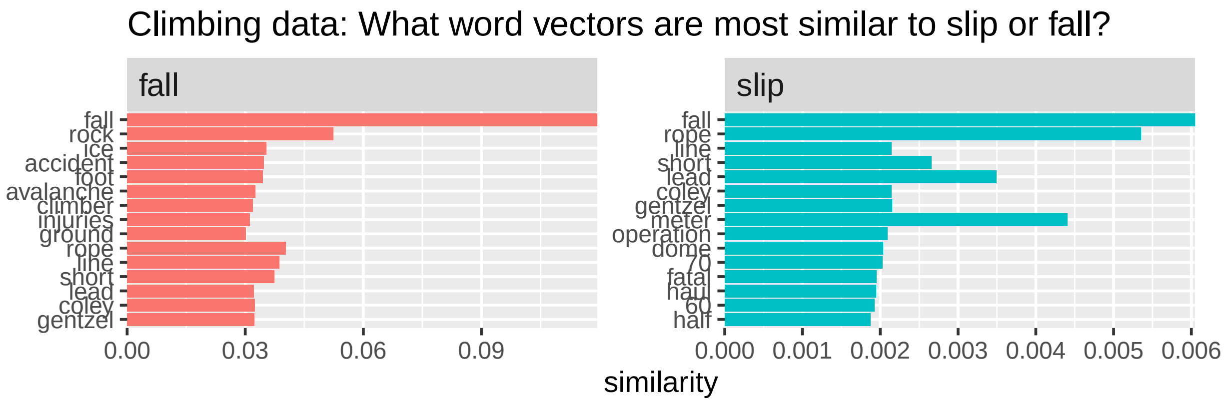
```r
data_glove<-fread(here::here("dat","glove.6B",'glove.6B.300d.txt'), header = FALSE)
data_glove <- data_glove %>%
  remove_rownames() %>%
  column_to_rownames(var = "V1")
```

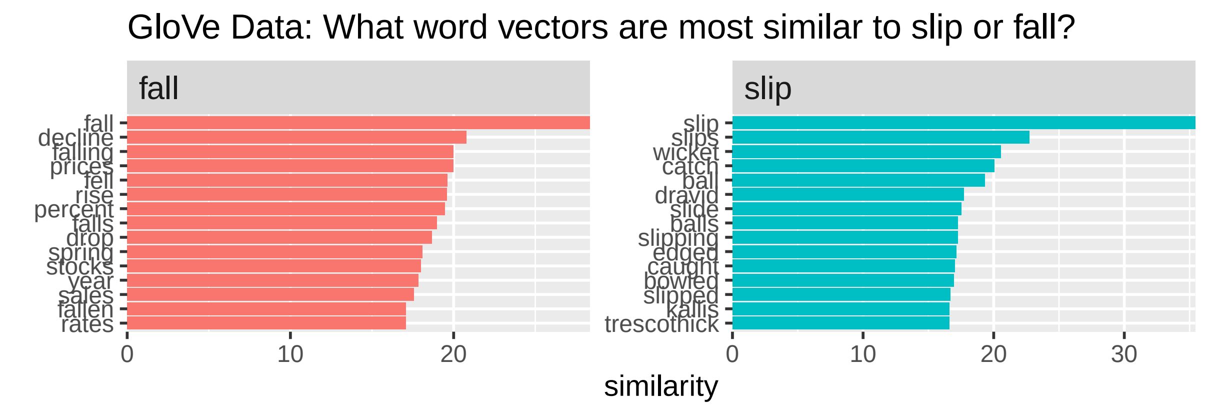
```r
data_glove <- as.matrix(data_glove)

fall_2 <- search_synonyms(data_glove,data_glove["fall",])
slip_2 <- search_synonyms(data_glove,data_glove["slip",])
```

```r
glovedata_plot <- slip_2 %>%
    mutate(selected = "slip") %>%
    bind_rows(fall_2 %>%
                  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 = "GloVe Data: What word vectors are most similar to slip or fall?")

climbdata_plot / glovedata_plot
```





The climbing data slip and fall histograms show that the word vectors caught climbing related terms such as accident, rope and line. The GloVe data shows economic-related terms(prices, stocks, rates) for fall and cricket-related terms/players (Dravid, wicket, edged) for slip because slip is common fielding position in cricket. This is due to the GloVe data being more expansive than just climbing.

```
snow_danger <- data_glove["snow",] + data_glove["danger",]
search_synonyms(data_glove, 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
```

```
no_snow_danger <- data_glove["danger",] - data_glove["snow",]
search_synonyms(data_glove, 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
```

The GloVe data shows more weather and climate related incidents rather than climbing incidents in the addition equation and more macroeconomic related terms in the subtraction equation.

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

```
king_man <- data_glove["king",] - data_glove["man",]
search_synonyms(data_glove, 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
```

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

```
batman_superman <- data_glove["batman",] + data_glove["superman",]
search_synonyms(data_glove, batman_superman)
```

```
## # A tibble: 400,000 x 2
##    token      similarity
##    <chr>           <dbl>
##  1 batman           81.5
##  2 superman         79.8
##  3 spider-man       57.5
##  4 superhero        55.9
##  5 superboy         50.9
```

```
##   6 marvel           50.6
##   7 comics           48.6
##   8 x-men            48.0
##   9 supergirl        46.8
##  10 luthor           45.6
## # ... with 399,990 more rows
```

```r
cricket_baseball <- data_glove["cricket",] - data_glove["baseball",]
search_synonyms(data_glove, cricket_baseball)
```

```
## # A tibble: 400,000 x 2
##     token      similarity
##     <chr>           <dbl>
##   1 cricket          38.5
##   2 wicket           28.8
##   3 indies           28.6
##   4 lanka            28.2
##   5 sri              28.0
##   6 overs            28.0
##   7 marylebone       27.9
##   8 list-a           27.8
##   9 waca             27.6
##  10 wickets          27.5
## # ... with 399,990 more rows
```

```r
air_water <- data_glove["air",] - data_glove["water",]
search_synonyms(data_glove, air_water)
```

```
## # A tibble: 400,000 x 2
##     token   similarity
##     <chr>        <dbl>
##   1 air           32.5
##   2 dyess         24.3
##   3 nhut          24.0
##   4 usaf          23.6
##   5 afb           23.6
##   6 macdill       23.3
##   7 aviano        23.0
##   8 f-16          22.6
##   9 norad         22.5
##  10 raaf          22.5
## # ... with 399,990 more rows
```