The Toronto Analytics Job Landscape

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THIS PROJECT IS STILL UNDER CONSTRUCTION

The intention will be to mask the code as the project approaches completion.

Executive Summary

- This project was produced for the Text Analytics Workshop for the Winter 2018 Masters of Management Analytics Cohort at Queen's University
- The goal from the outset was to use text analytics techniques developed in class to examine jobs companies have posted on Indeed in Toronto and employ techniques discussed in class including document clustering, topic modelling, and visualization.

Project Rationale

- A open sourced project working with real world data was desired
- Other projects can be found scraping DS/Analytics jobs from Indeed. Typically word frequencies for keywords like Python or Hadoop are calculated
- Moving beyond that, we were interested in topic modelling and how the choice of words signals relationships between roles
- Job postings fit the 'bag of words' or ngram approach taught in class. Not many employers say **"We don't want someone who knows Python"**

```
library(feather)
library(tidyverse)
library(tidytext)
library(tm)
library(wordcloud)
library(widyr)
library(ggraph)
library(igraph)
library(knitr)
library(ggridges)
```

Gathering Data

- Beautiful Soup & Selenium were used in Python to access Indeed and scrape unsponsored job titles, companies, and postings
- `later number` unique jobs were scraped from the search terms: `analytics`,`etc`. . . .
- Jobs were passed from Python to R using Feather

```
rm(list=ls())
#list our data files
searches <- c("analytics",
```

```r
                "data analyst",
                "data scientist",
                "analytics strategy",
                "data insights",
                "marketing analytics",
                "analytics reporting",
                "machine learning",
                "business intelligence")

files <- paste("data/feather/",searches,".feather",sep="")

#read and collapse to data frame
datalist <- lapply(as.list(files),function(x){read_feather(x)})
test <- datalist[[1]]
data <- bind_rows(datalist,.id="search")
rm(datalist)

#fix quotations in column names
names(data) <- c("search","company","text","titles","urls")
data <- data %>% select(company,titles,text,search,urls)

#check if we have redundant jobs
sum(duplicated(data[,2:4]))
```

```
## [1] 755
```

```r
#examine the uniqueness of our data
NumJobs <- n_distinct(data$urls)

#reduce to distinct jobs and clean up search column
data <- data[!duplicated(data$urls),]
data$search <- plyr::mapvalues(data$search,
                               from=unique(data$search),
                               to=searches)
```

- Our data returned `NumJobs` unique jobs within our search.
- It's clear a considerable amount of cleaning is in order

```r
RemovePattern <- function(vector,pattern){gsub(pattern=pattern,replacement=" ",vector)}
data <- dmap(data,RemovePattern,"\n")
data <- dmap(data,RemovePattern,"\\(")
data <- dmap(data,RemovePattern,"\\)")
data <- dmap(data,RemovePattern,"\\{[a-zA-Z0-9]\\}")
```

```r
#investigate redundant jobs. Should return 200/each if they are all unique.

rollup <- data %>%
     group_by(search) %>%
     summarize(NumberUniquePostings=n())

str(rollup)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    9 obs. of  2 variables:
##  $ search              : chr  "analytics" "analytics reporting" "analytics strategy" "business intell
##  $ NumberUniquePostings: int  100 47 65 74 82 50 90 57 71
```

```r
#sort by search order
kable(left_join(data.frame(search=searches),rollup,by="search"))
```

search	NumberUniquePostings
analytics	100
data analyst	82
data scientist	90
analytics strategy	65
data insights	50
marketing analytics	71
analytics reporting	47
machine learning	57
business intelligence	74

- We expect 200 jobs for each result, and removing the duplicate jobs in the order they were searched.
- Interestingly, searching 200 jobs in analytics returns only 113 unique jobs, some redundancy exists.
- As we search overlapping terms, data sciencist, data insights, fewer and fewer unique jobs are returned
- Interestingly, each additional search term returns a surprising amount of new jobs. 75 jobs are shown for machine learning that were not found for data scientist, a fairly similar field.
- Business Intelligence seems to be fairly lateral to other search terms, returning many unique jobs

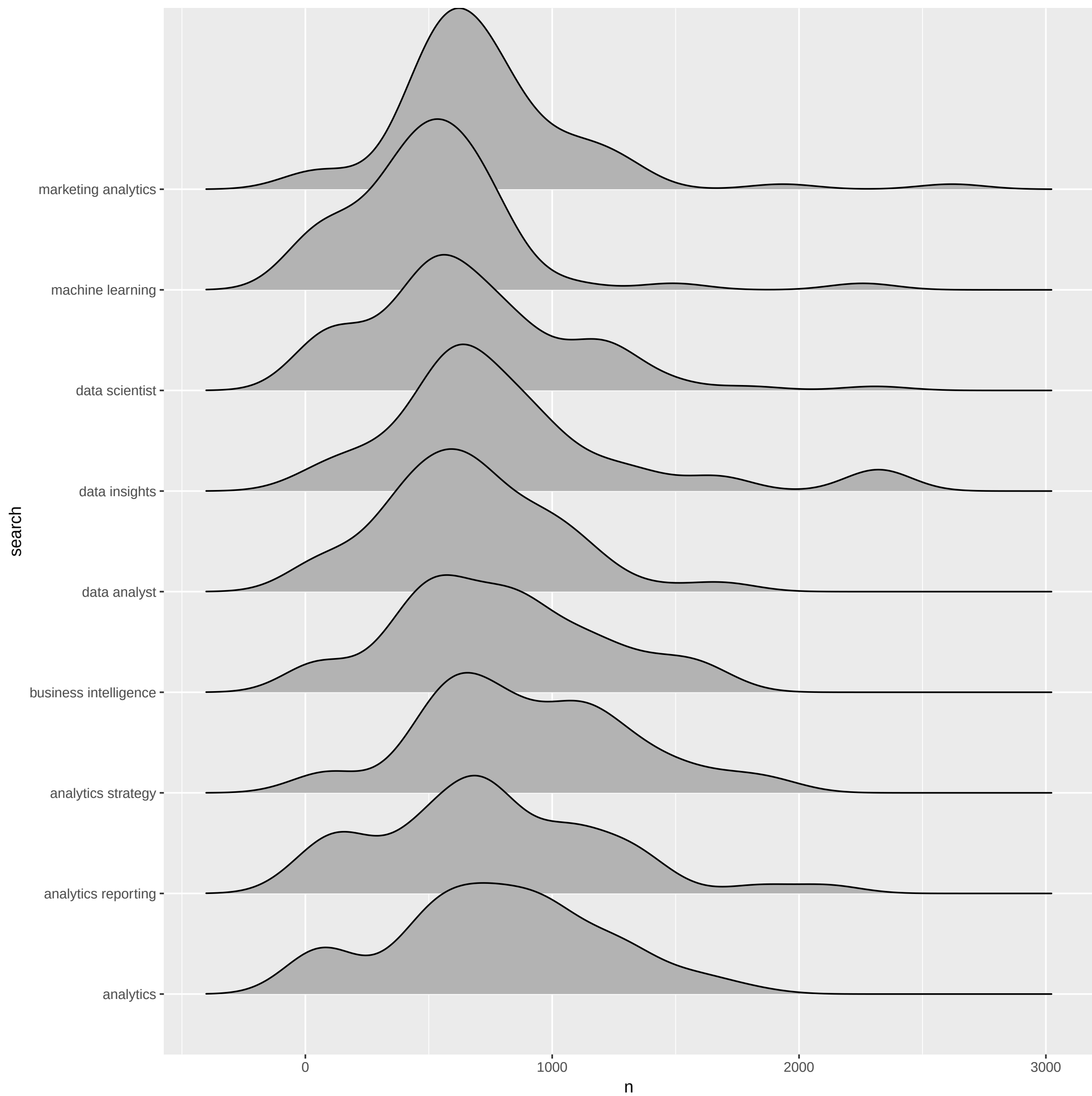
```r
kable(head(data %>% group_by(search,titles) %>% count(sort=TRUE),10))
```

search	titles	n
data scientist	Data Scientist	26
data analyst	Data Analyst	14
business intelligence	Business Intelligence Analyst	11
analytics	Data Scientist	9
machine learning	Machine Learning Engineer	8
analytics	Data Analyst	7
data analyst	Data Scientist	6
data scientist	Data Engineer	5
machine learning	Machine Learning Developer	4
business intelligence	Business Analyst	3

```r
kable(head(data %>% count(company,sort=TRUE),10))
```

company	n
Deloitte	17
BMO Financial Group	15
RBC	14
Scotiabank	14
Rogers Communications	9
TELUS Communications	9
Canadian Tire: Corporate	8
Centre for Addiction and Mental Health	8
Bell	7
KPMG LLP	6

```
#how long are our jobs
data %>%
     unnest_tokens(token="words",output="unigrams",input=text) %>%
     group_by(urls) %>%
     count(search,urls,sort=TRUE) %>%
     filter(n<3000) %>%
     ggplot(aes(x=n,y=search))+geom_density_ridges()
```



- We see that there are alot of 0 information jobs, postings with only a few words, let's look at what some of those are.

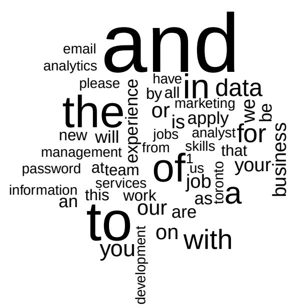
```
MinWords <- 300

empty_urls <- data %>%
```

```
    unnest_tokens(token="words",output="unigrams",input=text) %>%
    group_by(urls) %>%
    count(urls,sort=TRUE) %>%
    filter(n < MinWords)

# data %>%
#      filter(urls %in% empty_urls$urls) %>%
#      head()

data <- data %>%
    filter(!urls %in% empty_urls$urls)
```

- We see here a variety of failed scrapings, or 0 info postings

```
long_postings <- data %>%
    unnest_tokens(token="words",output="unigrams",input=text) %>%
    group_by(urls) %>%
    count(urls,sort=TRUE) %>%
    filter(n >3000)
```

```
unigrams <- data %>%
    unnest_tokens(token="words",output="unigrams",input=text) %>%
    group_by(unigrams) %>%
    count(unigrams,sort=TRUE)

wordcloud(unigrams$unigrams,unigrams$n,max.words=50)
```



- Looking at a simple word frequency, we see out of the box our data is very messy
- The boiler plate at the end of each job posting, encouraging people to apply, discussing company acolades and culture distort our analysis. Let's spend some time cleaning up *common stopwords*, *job specific words* and *html*

```
#what words to avoid
stop <- read.csv("stopwords.csv",stringsAsFactors = FALSE)
stop <- rbind(stop,data.frame(words=stopwords("en")))


#process n-grams
unigrams <- data %>%
    unnest_tokens(token="words",output="unigrams",input=text) %>%
    group_by(unigrams) %>%
    filter(!unigrams %in% stop$words) %>%
```

```
    count(unigrams,sort=TRUE)

#visualize
wordcloud(unigrams$unigrams,unigrams$n,max.words=50)
```

- We are starting to look better. Let's take a look at our bigrams.

```
#look a bi-grams
bigrams_totals <- data %>%
    unnest_tokens(token="ngrams",n=2,output="tokens",input=text) %>%
    separate(col=tokens,into=c("word1","word2"),sep=" ") %>%
    filter(!word1 %in% stop$words, !word2 %in% stop$words) %>%
    unite(tokens,word1,word2,sep=" ") %>%
    count(tokens,sort=TRUE)
```

```r
#kable(head(bigrams_totals,20))

wordcloud(bigrams_totals$tokens,bigrams_totals$n,max.words=10)
```


```r
#determine how frequent each word occurs across job postings. Don't skip stop words yet.
unigrams_freq <- data %>%
     unnest_tokens(token="words",output="tokens",input=text) %>%
     select(urls,tokens) %>%
     distinct() %>%
     filter(!tokens %in% stop$words) %>%
     group_by(tokens) %>%
     count(tokens,sort=TRUE) %>%
     ungroup() %>%
```

```r
    mutate(frequency=n/NumJobs)

kable(head(unigrams_freq,20))
```

tokens	n	frequency
experience	507	0.7971698
will	480	0.7547170
work	473	0.7437107
data	472	0.7421384
new	443	0.6965409
team	442	0.6949686
business	435	0.6839623
skills	432	0.6792453
information	409	0.6430818
years	388	0.6100629
help	387	0.6084906
search	384	0.6037736
working	378	0.5943396
2017	376	0.5911950
1	366	0.5754717
email	365	0.5738994
canada	358	0.5628931
support	355	0.5581761
development	353	0.5550314
analytics	351	0.5518868

```r
#determine how frequent each bigram is across job postings. Don't skip stop words yet.
bigrams_freq <- data %>%
    unnest_tokens(token="ngrams",n=2,output="tokens",input=text) %>%
    select(urls,tokens) %>%
    distinct() %>%
    separate(col=tokens,into=c("word1","word2"),sep=" ") %>%
    filter(!word1 %in% stop$words, !word2 %in% stop$words) %>%
    unite(tokens,word1,word2,sep=" ") %>%
    group_by(tokens) %>%
    count(tokens,sort=TRUE) %>%
    ungroup() %>%
    mutate(frequency=n/NumJobs)

kable(head(bigrams_freq,20))
```

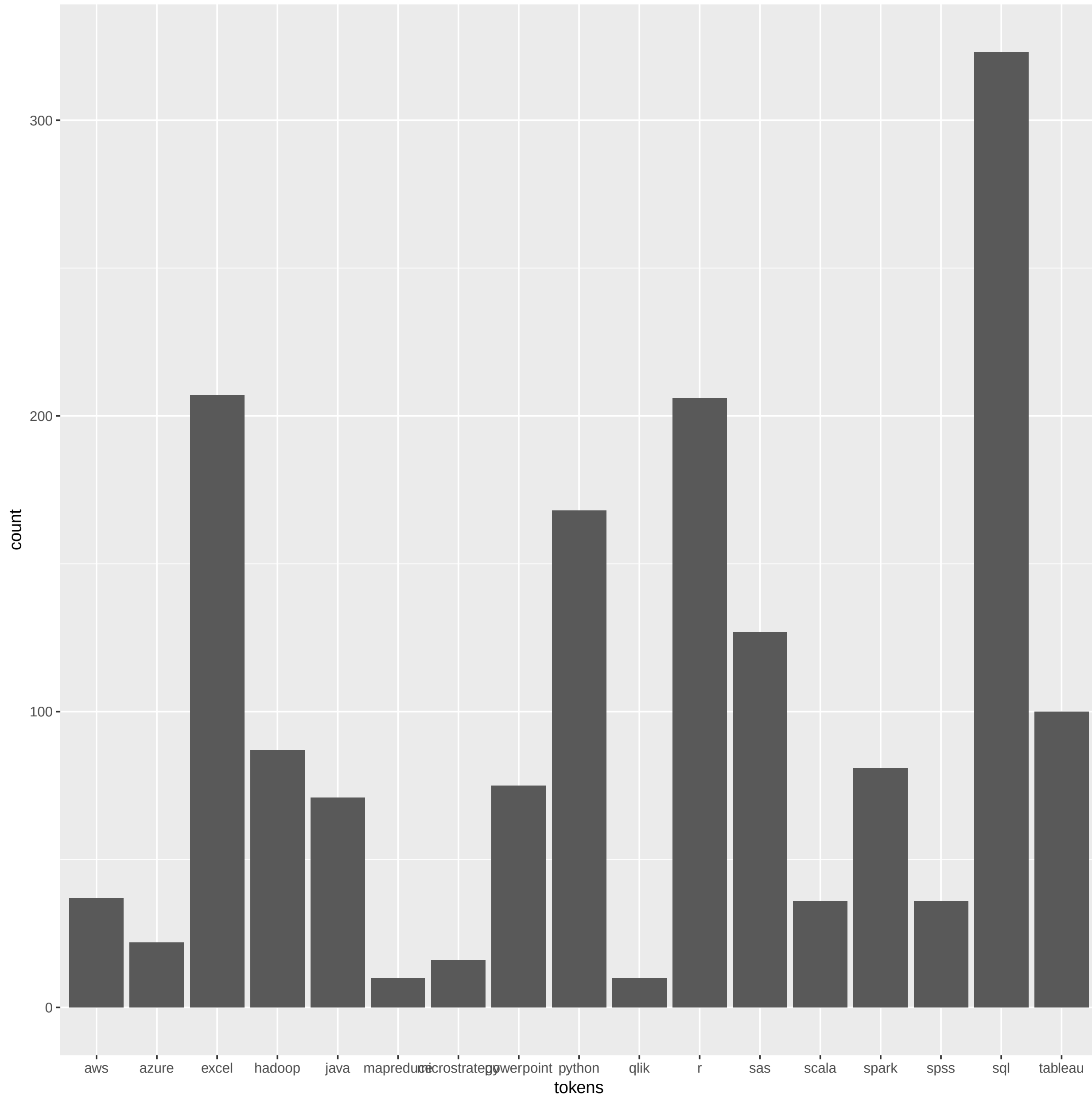
tokens	n	frequency
communication skills	190	0.2987421
computer science	179	0.2814465
2 c2	143	0.2248428
b.scorecardresearch.com p	143	0.2248428
c1 2	143	0.2248428
http b.scorecardresearch.com	143	0.2248428
p c1	143	0.2248428
title keywords	143	0.2248428
579216298929618 ev	142	0.2232704
6486505 c4	142	0.2232704

tokens	n	frequency
c2 6486505	142	0.2232704
cancel alerts	142	0.2232704
centre 2017	142	0.2232704
company city	142	0.2232704
cv 2.0	142	0.2232704
description searchclose	142	0.2232704
get updated	142	0.2232704
help centre	142	0.2232704
resumesemployers post	142	0.2232704
searchclose find	142	0.2232704

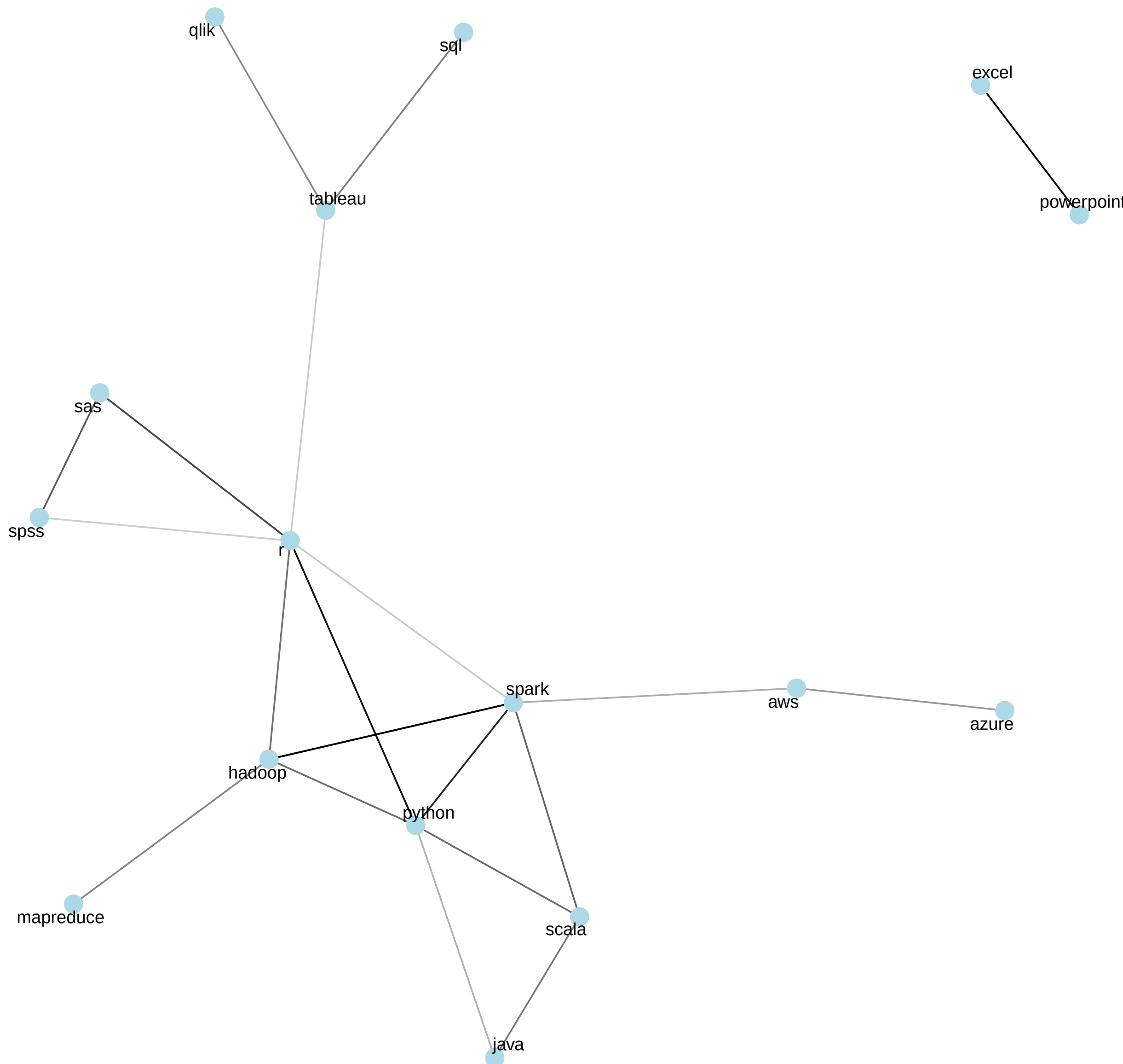
```
skills <- c("sas","python","sql","r","spss",
            "hadoop","spark","java","scala","aws","c++",
            "excel","powerpoint","mapreduce",
          "qlik","tableau","microstrategy","azure")

data %>%
     unnest_tokens(token="words",output="tokens",input=text) %>%
     filter(tokens %in% skills) %>%
     pairwise_count(tokens,urls,sort=TRUE) %>%
     head()
```

```
## # A tibble: 6 × 3
##        item1      item2     n
##        <chr>      <chr> <dbl>
## 1     python          r    84
## 2          r     python    84
## 3     python        sql    73
## 4        sql     python    73
## 5      excel powerpoint    68
## 6 powerpoint      excel    68
```

```
data %>%
     unnest_tokens(token="words",output="tokens",input=text) %>%
     filter(tokens %in% skills) %>%
     ggplot(aes(x=tokens)) +
     geom_bar()
```




```
#pairwise correlation
data %>%
    unnest_tokens(token="words",output="tokens",input=text) %>%
    filter(tokens %in% skills) %>%
    pairwise_cor(tokens,urls,sort=TRUE) %>%
    filter(correlation > .2) %>%
    graph_from_data_frame() %>%
    ggraph(layout = "fr") +
    geom_edge_link(aes(edge_alpha = correlation), show.legend = FALSE) +
    geom_node_point(color = "lightblue", size = 5) +
    geom_node_text(aes(label = name), repel = TRUE) +
    theme_void()
```




```
#creating tokens - once we come up with list of stop words, should use anti_join here to remove them
#
# data_token <- data %>%
#      unnest_tokens(word,text)
#
# #creating unique document identifiers for each job posting
# data_token$ID <- paste(data_token$company,data_token$titles,sep="_")
#
# #removing useless columns -
# data_token <- data_token[,-(1:4)]
# head(data_token)
#
# #frequency of words by document
#
```

```
# data_count <- data_token %>%
#      count(ID,word,sort=TRUE)
#
# #creating table of total count of words in each document
# data_count2 <- data_count %>%
#      group_by(ID) %>%
#      summarise(total = sum(n))
#
# #joining the total count information with primary dataset
# data_count <- right_join(data_count,data_count2)
#
# #creating the correlation column so we can filter out words <1% or >80% of docs
# data_count <- data_count %>%
#      mutate(correlation = n/total) %>%
#      arrange(desc(correlation))
#
# #Note for Gage: I'm noticing something odd for some of these postings. Look at the head of the data f
#
# head(data_count)
#
#
# #Correlation filters
# minCor = 0.01
# maxCor = 0.80
#
# #filter out words <1% or >80% of docs
# data_count <- data_count %>%
#      filter(correlation > minCor & correlation < maxCor)
#
# #casting tidy text data into DTM
# data_dtm <- data_count %>%
#      cast_dtm(ID,word,n)
#
# #creating TDM
# data_tdm <- t(data_dtm)
#
# #reducing sparsity of TDM before clustering
# dim(data_tdm)
# data_clean <- removeSparseTerms(data_tdm,sparse = 0.80)
# data_m <- as.matrix(data_clean)
# data_df <- as.data.frame(data_m)
#
# #looking at most popular words, min freq of 20
# findFreqTerms(data_tdm,lowfreq=20)
#
# #accumulator of clustering results
# clust_results <- data.frame()
#
# #run kmeans for all clusters up to 15
# set.seed(50)
# for(i in 1:10) {
#      k_clust <- kmeans(data_m, centers=i, iter.max =100)
#      #Combine cluster number and cluster together, write to df
```

```
#      clust_results <- rbind(clust_results,cbind(i,k_clust$tot.withinss))
# }
# names(clust_results) <- c("cluster","results")
#
# #scree elbow plot
# ggplot(clust_results,aes(x=cluster,y=results,group=1))+
# geom_point()+geom_line()+scale_x_continuous(name='# of clusters',limits = c(1, 10))
#
# #if you want specific points look at scaling the axes then use seq(1:10)
#
# ## above plot shows that at about 3 clusters, any additional clusters would lose significance
#
# #need to create principal components, regular kmeans will kick out an error because it uses princomp
# pc <- prcomp(data_m)
# plot(pc,xlab="Principal Components")
# summary(pc)
# comp <- data.frame(pc$x[,1:12])
# plot(comp)
#
# #Let's look at 3 clusters
# kmeans3 <- kmeans(comp,centers=3)
#
# #Plot clusters
# library(cluster)
# clusplot(comp, kmeans3$cluster, color=TRUE, shade=TRUE,
#          labels=2, lines=0, main="K-means cluster plot")
#
# ###hierarchical clustering
#
# #calculate distance
# data_dist <- dist(data_df,method="euclidean")
#
# #creating and plotting hierarchical cluster
# hc <- hclust(data_dist)
# plot(hc)
# rect.hclust(hc,k=8,border="red")
```

```
# freqs_to_use <- data %>%
#      unnest_tokens(token="words",output="tokens",input=text) %>%
#      select(urls,tokens) %>%
#      distinct() %>%
#      filter(!tokens %in% stop$words) %>%
#      group_by(tokens) %>%
#      count(tokens,sort=TRUE) %>%
#      ungroup() %>%
#      mutate(frequency=n/NumJobs) %>%
#      filter(frequency>MinFreq & frequnecy<MaxFreq)
#
# unis <- data %>%
#      unnest tokens %>%
#      select(-c(list of cols to drop)) %>%
#      filter(tokens %in% freqs_to_use$tokens) %>% #this takes care of stop words too
#      count() %>%
#      spread(tokens, but not the keys you use) # this should result in the features being words
```

```
# # and the rows being different jobs. This is a dtm.
#
# bigrams <-# same process. Look at the separate/unite functions for getting rid of stop words
#
# datatocluster <- bind_cols(bigrams,unis)
# #the result of this is a data frame where your rows are each job, maybe you need a key to identify
# # and each column is a unigram or bigram, and the data is how many times it was mentioned in the job
#
# #do the same clustering
#
# #when you now do this route, all your stop words should be gone.
```