Post Training Survey Data Analysis

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Introduction

Here's an example of analysis of survey data for a training held at the San Jose Conservation Corps. We'll be using it to generate a word cloud to study the keywords used in the survey responses to the question, "What skills did you hope to learn/improve on through this training session?"

Code for Survey Analysis

First, let's load all of the relevant libraries.

```
library(pacman)
## Warning: package 'pacman' was built under R version 4.1.2
p_load(dplyr, tidytext, tidyverse, stringi, wordcloud, igraph, ggraph)
Let's load the survey data.
df <- read.csv("training_response_sample.csv")</pre>
head(df)
##
        id
## 1 hI7d5
## 2 AkW3n
## 3 h3Q9s
## 4 BKFrF
## 5 lpzep
## 6 vroUV
##
                                                                                        skills_gain
## 1
                                                                 Learn about environmental justice
## 2
## 3
                                                                            Awareness of pollution
## 4
             My knowledge about can i help my community with contamination and how to prevent it
## 5
            I learned about different neighborhoods and how economically it impacts some areas.
```

Looking at Individual Tokens

Let's see what the attendees think of the training in terms of commonly used words related to the skills they hope to gain and/or work on.

6 More awareness of enviro injustices in San Jose area, and the tools to combat this at work

Data Preparation and Processing

Break down the words into individual tokens

```
# Tokenize the words
data_words<- df %>% unnest_tokens(word, skills_gain) %>%
  anti_join(stop_words) %>% count(word, sort = T)
## Joining, by = "word"
# Removing words related to the title of the training or the city of
# "San Jose" (a bigram and name that makes no sense when separated into tokens)
data_words_small <- data_words[-c(1,2, 25,31),]</pre>
data_words_small
##
               word n
## 3
          awareness 2
## 4
          knowledge 2
## 5
           learning 2
## 6
          pollution 2
## 7
            ability 1
## 8
              check 1
## 9
              clean 1
## 10
             combat 1
## 11
          community 1
## 12 contamination 1
## 13
       economically 1
## 14
        electronics 1
## 15
             enviro 1
## 16
        environment 1
## 17
          expanding 1
## 18
         experience 1
## 19
         government 1
## 20
         hazardous 1
## 21
            impacts 1
## 22
         injustices 1
## 23
             issues 1
## 24
                 job 1
## 26
              learn 1
## 27
            learned 1
## 28
              legal 1
## 29 neighborhoods 1
## 30
            prevent 1
## 32
              stuff 1
## 33
       surroundings 1
## 34
              teach 1
## 35
              tools 1
## 36
              waste 1
Visualization
Make a word cloud out of it
data_words_small %>% with(wordcloud(word, n, max.words = 40, scale = c(2.5, 0.25)))
```

```
government contamination impacts neighborhoods economically injustices clean surroundings expanding teach environment ability learnedlegal tools community check check awareness awareness awareness awareness combat hazardous learning by pollution electronics knowledge
```

Bigrams

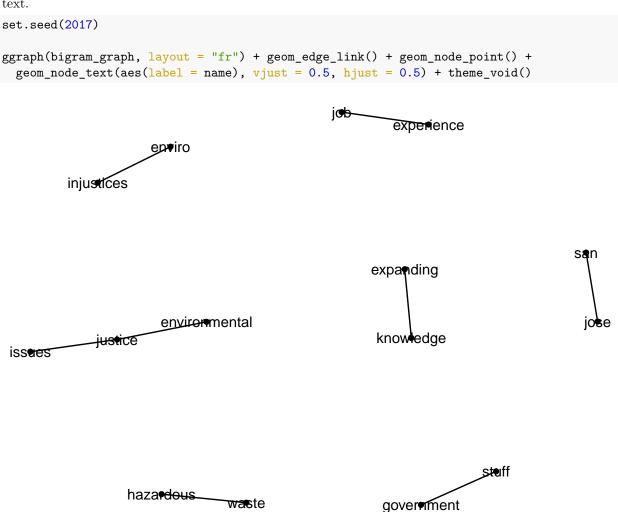
```
## id bigram
## 1 hI7d5 learn about
## 2 hI7d5 about environmental
## 3 hI7d5 environmental justice
## 5 h3Q9s awareness of
## 6 h3Q9s of pollution
## 7 BKFrF my knowledge
```

Get bi-grams into separate words so we can remove stop words

```
count(word1, word2, sort = TRUE)
head(bigram_counts)
##
             word1
                         word2 n
## 1 environmental
                       justice 3
## 2
            enviro injustices 1
## 3
         expanding knowledge 1
## 4
        government
                         stuff 1
## 5
         hazardous
                         waste 1
## 6
               job experience 1
Looks like most of the words are titles and names linked to those titles. Let's bring both words in the bi-grams
together.
bigrams_united <- bigrams_filtered %>%
  unite(bigram, word1, word2, sep = " ")
head(bigrams united)
##
        id
                           bigram
## 1 hI7d5 environmental justice
## 2 vroUV
               enviro injustices
## 3 vroUV
                         san jose
## 4 1fMAt
                   job experience
## 5 1fMAt
             expanding knowledge
## 6 1kY4J
                 hazardous waste
Visualization
Create an igraph object from tidy data
library(igraph)
# original counts
head(bigram_counts)
##
             word1
                         word2 n
## 1 environmental
                       justice 3
            enviro injustices 1
## 3
         expanding knowledge 1
## 4
        government
                         stuff 1
         hazardous
## 5
                         waste 1
               job experience 1
# only look at relatively common combinations
bigram_graph <- bigram_counts %>% graph_from_data_frame()
bigram_graph
## IGRAPH e296986 DN-- 15 8 --
## + attr: name (v/c), n (e/n)
## + edges from e296986 (vertex names):
## [1] environmental->justice
                                   enviro
                                                ->injustices
## [3] expanding
                    ->knowledge
                                  government
                                                ->stuff
## [5] hazardous
                     ->waste
                                   job
                                                ->experience
## [7] justice
                     ->issues
                                   san
                                                ->jose
```

We can convert an igraph object into a ggraph with the "ggraph" fcn. Then, add layers to it - nodes, edges,

text.



NOTE: The analysis isn't as useful here as there aren't enough responses to fully get a diverse portfolio of bigrams. However, despite the small population of the survey respondents (at the time this survey was deployed), we can see some common word associations within the responses of the training attendees.

Here, we can see that when it comes to the environment, there's a strong drive among attendees to address social injustices and issues related to the environment. We also see a desire to gain knowledge and work experience on how to tackle these issues with a brief mention of government policy (?) and San Jose itself (the city at which the attendees are based at).