Code for QSS tidyverse Chapter 5: Discovery

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First Printing

Discovery

Textual Data

The Disputed Authorship of The Federalist Papers

```
## load the packages
library("tm")
library("SnowballC")
library("stringr")
library("tidytext")
library("tidyverse")
## the location of files from qss package
DIR_SOURCE <- system.file("extdata/federalist", package = "qss")</pre>
## loading the corpus
corpus_raw <- VCorpus(DirSource(directory = DIR_SOURCE, pattern = "fp"))</pre>
## the corpus object
corpus_raw
## <<VCorpus>>
## Metadata: corpus specific: 0, document level (indexed): 0
## Content: documents: 85
## A tidy version of the corpus
corpus_tidy <- tidy(corpus_raw) %>%
  select(id, text) %>%
  mutate(new_id = as.integer(str_sub(id, start = 3, end = 4)))
glimpse(corpus_tidy)
## Rows: 85
## Columns: 3
## $ id <chr> "fp01.txt", "fp02.txt", "fp03.txt", "fp04.t~
## $ text <chr> "AFTER an unequivocal experience of the ine~
## $ new_id <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, ~
```

```
tokens_raw <- corpus_tidy %>%
  ## tokenizes into words
  unnest_tokens(word, text, to_lower = TRUE) %>%
  ## stem the words
  mutate(stem = wordStem(word)) %>%
  ## remove any numbers in the strings
  mutate(word = str_replace_all(word, "\\d+", "")) %>%
  ## drop any empty strings
 filter(word != "")
## look at the result
glimpse(tokens_raw)
## Rows: 187,412
## Columns: 4
           <chr> "fp01.txt", "fp01.txt", "fp01.txt", "fp01.t~
## $ id
## $ word <chr> "after", "an", "unequivocal", "experience",~
## $ stem <chr> "after", "an", "unequivoc", "experi", "of",~
## load standard stop words
data("stop_words", package = "tidytext")
glimpse(stop_words)
## Rows: 1,149
## Columns: 2
           <chr> "a", "a's", "able", "about", "above", "acc~
## $ word
## $ lexicon <chr> "SMART", "SMART", "SMART", "SMART", "SMART"
## remove stopwords
tokens <- tokens_raw %>%
anti_join(stop_words, by = "word")
## the output is truncated here to save space
content(corpus_raw[[10]]) # Essay No. 10
    [1] "AMONG the numerous advantages promised by a well-constructed Union, none "
##
    [2] " deserves to be more accurately developed than its tendency to break and "
##
    [3] "
                control the violence of faction. The friend of popular governments never "
Document-Term Matrix
```

```
1 absurd
## 1
## 2
       1 accid
       1 acknowledg
## 3
## 4
       1 act
## 5
        1 actuat
## 6
        1 add
                        1
dtm <- cast_dtm(tokens_counts,</pre>
              document = new_id,
              term = stem,
              value = n)
dtm
## <<DocumentTermMatrix (documents: 85, terms: 4674)>>
## Non-/sparse entries: 37214/360076
## Sparsity
                  : 91%
## Maximal term length: 17
## Weighting
                  : term frequency (tf)
inspect(dtm[1:5, 1:8])
## <<DocumentTermMatrix (documents: 5, terms: 8)>>
## Non-/sparse entries: 16/24
## Sparsity
               : 60%
## Maximal term length: 10
## Weighting
            : term frequency (tf)
## Sample
##
      Terms
## Docs absurd accid acknowledg act actuat add addit address
    1 1 1
                    1 1
                                   1 1
                         0 0
                                   0 0
##
     2
          0
                0
                        3 0 0
##
                                                    0
##
     4
##
     5
           0
dtm.mat <- as.matrix(dtm)</pre>
```

Topic Discovery

Countri govern of revenu trade of excis import situat of respect nation of tax time direct articl subject collect commerc duti

legislatur
garrison power
time armi stand
peac spain increas
establish respect
natur
constitut object
necess subject
nation

```
stemCompletion(c("revenu", "commerc", "peac", "armi"), corpus_raw)
##
      revenu
                              peac
                                         armi
                commerc
##
  "revenue" "commerce"
                           "peace"
                                     "armies"
tokens_counts <- bind_tf_idf(tokens_counts,</pre>
                            term = stem,
                            document = new id,
                            n = n
head(tokens_counts)
## # A tibble: 6 x 6
    new_id stem
                       n
                               tf idf
                                            tf_idf
##
     <int> <chr>
                      <int> <dbl> <dbl>
                                            <dbl>
##
## 1
         1 absurd
                      1 0.00186 1.73 0.00323
## 2
         1 accid
                          1 0.00186 3.75 0.00698
## 3
                         1 0.00186 1.55 0.00289
         1 acknowledg
## 4
         1 act
                          1 0.00186 0.400 0.000744
## 5
                          1 0.00186 2.14 0.00399
        1 actuat
## 6
         1 add
                          1 0.00186 1.35 0.00252
dtm_tfidf <- weightTfIdf(dtm)</pre>
dtm_tfidf
## <<DocumentTermMatrix (documents: 85, terms: 4674)>>
## Non-/sparse entries: 37044/360246
## Sparsity
                     : 91%
## Maximal term length: 17
                     : term frequency - inverse document frequency (normalized) (tf-idf)
## Weighting
## Top words for document 12
tokens_counts %>%
 filter(new_id == 12) %>%
slice max(tf idf, n = 10)
```

```
## # A tibble: 10 x 6
##
     new_id stem
                                      idf tf idf
                                  tf
                           n
      <int> <chr>
##
                       <int> <dbl> <dbl> <dbl>
## 1
                         11 0.0138
                                      1.22 0.0169
         12 revenu
         12 contraband
##
                           3 0.00376 4.44 0.0167
## 3
                           3 0.00376 4.44 0.0167
         12 patrol
## 4
        12 excis
                          5 0.00627 2.65 0.0166
## 5
        12 coast
                          3 0.00376 3.75 0.0141
## 6
        12 tax
                          8 0.0100
                                      1.31 0.0131
## 7
                         6 0.00752 1.73 0.0130
        12 trade
## 8
         12 cent
                          2 0.00251 4.44 0.0111
                           2 0.00251 4.44 0.0111
## 9
         12 gallon
                           8 0.0100 1.11 0.0111
## 10
         12 commerc
## Top words for document 24
tokens_counts %>%
 filter(new id == 24) %>%
 slice_max(tf_idf, n = 10)
## # A tibble: 10 x 6
##
     new id stem
                                  tf
                                      idf tf idf
                           n
      <int> <chr>
                       <int> <dbl> <dbl> <dbl>
##
## 1
                         6 0.00926 2.83 0.0262
         24 garrison
                           3 0.00463 4.44 0.0206
## 2
         24 dock
                           3 0.00463 4.44 0.0206
## 3
         24 yard
## 4
         24 settlement
                         3 0.00463 3.75 0.0174
## 5
                          4 0.00617 2.36 0.0146
         24 spain
## 6
                          7 0.0108
         24 armi
                                      1.26 0.0137
## 7
         24 frontier
                           3 0.00463 2.83 0.0131
## 8
         24 arsen
                           2 0.00309 3.75 0.0116
## 9
         24 western
                         3 0.00463 2.50 0.0116
## 10
         24 nearer
                           2 0.00309 3.34 0.0103
k <- 5 # number of clusters
## subset The Federalist papers written by Hamilton
hamilton \leftarrow c(1, 6:9, 11:13, 15:17, 21:36, 59:61, 65:85)
hamilton_docs <- filter(tokens_counts,</pre>
                       new_id %in% hamilton)
## convert into a document term matrix
## then calculate tf_idf
hamilton_dtm <- cast_dtm(hamilton_docs,</pre>
               document = new_id,
               term = stem,
               value = n) \%>\%
  weightTfIdf()
## check the output
hamilton dtm
## <<DocumentTermMatrix (documents: 51, terms: 3918)>>
## Non-/sparse entries: 22478/177340
## Sparsity
                    : 89%
```

```
## Maximal term length: 17
## Weighting
                     : term frequency - inverse document frequency (normalized) (tf-idf)
## run k-means, with a set seed for replication
set.seed(1234)
km.out <- kmeans(hamilton_dtm, centers = k)</pre>
km.out$iter # check the convergence; number of iterations may vary
## [1] 3
## How many documents per cluster?
table(km.out$cluster)
##
  1 2 3 4 5
   8 6 1 1 35
## label each centroid with the corresponding term
colnames(km.out$centers) <- colnames(hamilton_dtm)</pre>
for (i in 1:k) { # loop for each cluster
   print(str_c("CLUSTER ", i))
   print("Top 10 words: ")
    ## create a tibble of the cluster words
    ## print 10 most important terms
   cluster_centers <- enframe(km.out$centers[i, ]) %>%
    slice_max(value, n = 10)
   print(cluster_centers)
   print("Federalist Papers classified:") # extract essays classified
    ## create a tibble of cluster assignments
   cluster_docs <- enframe(km.out$cluster, "document", "cluster") %>%
      filter(cluster == i)
   print(as.vector(cluster_docs$document))
    cat("\n")
}
## [1] "CLUSTER 1"
## [1] "Top 10 words: "
## # A tibble: 10 x 2
##
     name
              value
##
      <chr>
                <dbl>
## 1 senat
              0.0222
## 2 presid 0.0194
## 3 governor 0.0118
## 4 pardon 0.0114
## 5 treati 0.0113
## 6 offic
              0.0104
## 7 appoint 0.0103
## 8 impeach 0.00974
## 9 nomin
              0.00950
## 10 vote
              0.00727
## [1] "Federalist Papers classified:"
```

```
## [1] "66" "68" "69" "74" "75" "76" "77" "79"
##
## [1] "CLUSTER 2"
## [1] "Top 10 words: "
## # A tibble: 10 x 2
##
     name
                 value
##
      <chr>>
                  <dbl>
## 1 armi
               0.0229
##
   2 militia
               0.0225
## 3 militari 0.0141
## 4 disciplin 0.00963
## 5 garrison 0.00805
## 6 peac
               0.00793
## 7 troop
               0.00758
## 8 liberti
               0.00619
## 9 corp
               0.00566
## 10 neighbor 0.00553
## [1] "Federalist Papers classified:"
## [1] "8" "24" "25" "26" "28" "29"
##
## [1] "CLUSTER 3"
## [1] "Top 10 words: "
## # A tibble: 10 x 2
##
     name
                   value
##
      <chr>
                   <dbl>
  1 northern
                  0.0607
##
   2 southern
                  0.0455
## 3 confederaci 0.0448
## 4 list
                  0.0326
## 5 frontier
                  0.0265
## 6 comprehens
                  0.0238
## 7 civil
                  0.0219
## 8 jersei
                   0.0218
## 9 pennsylvania 0.0216
## 10 navig
                  0.0200
## [1] "Federalist Papers classified:"
## [1] "13"
##
## [1] "CLUSTER 4"
## [1] "Top 10 words: "
## # A tibble: 10 x 2
##
     name
              value
##
      <chr>>
              <dbl>
##
  1 vacanc 0.0947
  2 recess 0.0552
##
   3 session 0.0483
## 4 senat
             0.0482
## 5 claus
             0.0465
## 6 fill
             0.0453
## 7 appoint 0.0312
## 8 expir
             0.0237
## 9 presid 0.0216
## 10 unfound 0.0192
## [1] "Federalist Papers classified:"
```

```
## [1] "67"
##
## [1] "CLUSTER 5"
## [1] "Top 10 words: "
## # A tibble: 10 x 2
##
     name
                 value
##
                 <dbl>
     <chr>
              0.00783
## 1 court
## 2 juri
               0.00490
## 3 tax
               0.00457
## 4 jurisdict 0.00395
              0.00373
## 5 taxat
## 6 elect
              0.00338
              0.00335
## 7 trial
## 8 land
              0.00334
## 9 revenu
               0.00327
               0.00316
## 10 claus
## [1] "Federalist Papers classified:"
  [1] "1" "6" "7" "9" "11" "12" "15" "16" "17" "21" "22"
## [12] "23" "27" "30" "31" "32" "33" "34" "35" "36" "59" "60"
## [23] "61" "65" "70" "71" "72" "73" "78" "80" "81" "82" "83"
## [34] "84" "85"
```

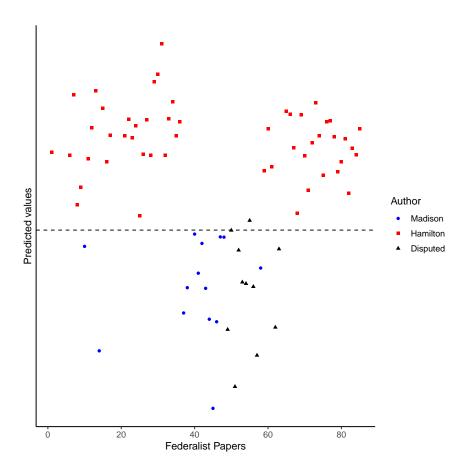
Authorship Prediction

```
## essays written by Madison, Jay, or joint:
## "hamilton" defined earlier
madison \leftarrow c(10, 14, 37:48, 58)
jay \leftarrow c(2:5, 64)
joint <- c(18:20)
## the specific words of interest
STYLE_WORDS <- c("although", "always", "commonly", "consequently",
                 "considerable", "enough", "there", "upon",
                 "while", "whilst")
## add a variable for the author
tokens raw <- tokens raw %>%
 mutate(author = case_when(new_id %in% hamilton ~ "Hamilton",
                             new_id %in% madison ~ "Madison",
                             new_id %in% jay ~ "Jay",
                             new_id %in% joint ~ "Joint",
                            TRUE ~ "Disputed"))
## Average word use per thousand words by author
tfm <- tokens_raw %>%
  group_by(author, word) %>%
  ## total term use per author
  summarize(n = n()) \%
 ungroup() %>%
  group_by(author) %>%
  ## average term use by author per 1000 words
```

```
mutate(tf_thou = n / sum(n) * 1000) %>%
  ## just the words of interest
  filter(word %in% STYLE_WORDS) %>%
  ## drop n for pivoting
  select(-n) %>%
  ## reshape
  pivot_wider(names_from = word,
             values from = tf thou) %>%
  mutate_at(vars(always:consequently), replace_na, 0)
tfm
## # A tibble: 5 x 11
## # Groups: author [5]
    author although always commonly consequently considerable
     <chr>
               <dbl> <dbl>
                              <dbl>
                                           <dbl>
## 1 Disput~ 0.137
                      0.228 0.0456
                                           0.365
                                                         0.228
## 2 Hamilt~ 0.00904 0.551 0.190
                                          0.0361
                                                         0.416
                      0.955 0.119
             0.597
                                           0.477
                                                         0.119
## 3 Jay
## 4 Joint NA
                      0.355
                             0.178
                                                         0.355
## 5 Madison 0.196
                      0.171
                              0
                                           0.318
                                                         0.122
## # ... with 5 more variables: there <dbl>, upon <dbl>,
## # whilst <dbl>, enough <dbl>, while <dbl>
## Create new data set for regression
## Average word use per thousand words by author per document
reg_data <- tokens_raw %>%
 group_by(author, new_id, word) %>%
  ## total term use per author-document
  summarize(n = n()) \%>\%
  ## average term use by author per 1000 words per document
  mutate(tf_thou = n / sum(n) * 1000) %>%
  ## just the words of interest
  filter(word %in% STYLE WORDS) %>%
  ## create the outcome variable
  mutate(author outcome = case when(author == "Hamilton" ~ 1,
                                   author == "Madison" ~ -1,
                                   TRUE ~ NA_real_)) %>%
  ## drop n to reshape
  select(-n) %>%
  pivot_wider(names_from = word,
             values_from = tf_thou) %>%
  mutate_at(vars(always:`while`), replace_na, 0) %>%
  ungroup()
hm.fit <- lm(author_outcome ~ upon + there + consequently + whilst,
            data = reg_data)
hm.fit
##
## Call:
## lm(formula = author_outcome ~ upon + there + consequently + whilst,
```

```
##
       data = reg_data)
##
## Coefficients:
   (Intercept)
##
                         upon
                                       there consequently
##
        -0.1955
                        0.2128
                                      0.1180
                                                    -0.5964
         whilst
##
##
        -0.9090
hm.fitted <- fitted(hm.fit) # fitted values</pre>
sd(hm.fitted)
## [1] 0.7029763
Cross-Validation
library(modelr)
## add author predictions
author_data <- reg_data %>%
  add_predictions(hm.fit) %>%
  mutate(pred_author = if_else(pred >= 0, "Hamilton", "Madison"))
## correct predictions rate
author data %>%
  filter(!is.na(author_outcome)) %>%
  group_by(author) %>%
  summarize(`Proportion Correct` = mean(author == pred_author))
## # A tibble: 2 x 2
   author 'Proportion Correct'
##
     <chr>>
                              <dbl>
## 1 Hamilton
                                  1
## 2 Madison
                                  1
ham_mad <- filter(reg_data, !is.na(author_outcome))</pre>
n <- nrow(ham_mad)</pre>
hm.classify <- as.vector(rep(NA, n), mode = "list") # a container list</pre>
for (i in 1:n) {
  ## fit the model to the data after removing the ith observation
    sub.fit <- lm(author_outcome ~ upon + there +</pre>
                    consequently + whilst,
                  data = ham_mad[-i, ]) # exclude ith row
    ## predict the authorship for the ith observation
    hm.classify[[i]] <- slice(ham_mad, i) %>% add_predictions(sub.fit)
}
## create output table, calculate prediction rate
bind_rows(hm.classify) %>%
  mutate(pred_author = if_else(pred >= 0, "Hamilton", "Madison")) %>%
  group_by(author) %>%
  summarize(`Proportion Correct` = mean(author == pred_author))
```

```
## # A tibble: 2 x 2
     author 'Proportion Correct'
##
     <chr>>
                             <dbl>
##
## 1 Hamilton
                             1
                             0.786
## 2 Madison
plot_data <- filter(author_data, !(author %in% c("Jay", "Joint")))</pre>
ggplot(plot_data,
       aes(x = new_id, y = pred,
           color = author, shape = author)) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_point() +
  scale_y_continuous(breaks = seq(10, 80, by = 10),
                     minor_breaks = seq(5, 80, by = 5)) +
  scale_color_manual(values = c("Madison" = "blue",
                                "Hamilton" = "red",
                                "Disputed" = "black")) +
  scale_shape_manual(values = c("Madison" = 16, "Hamilton" = 15,
                                 "Disputed" = 17)) +
  labs(color = "Author", shape = "Author",
       x = "Federalist Papers", y = "Predicted values")
```



Network Data

Marriage Network in Renaissance Florence

```
## load from QSS
data("florentine", package = "qss")
## print out the adjacency (sub)matrix for the first 5 families
florentine[1:5, 1:5]
##
       FAMILY ACCIAIUOL ALBIZZI BARBADORI BISCHERI
## 1 ACCIAIUOL
                     0
                              0
## 2
     ALBIZZI
                      0
                              0
                                        0
                                                 0
## 3 BARBADORI
                      0
                              0
                                        0
                                                 0
## 4 BISCHERI
                      0
                              0
                                        0
                                                 0
## 5 CASTELLAN
                              0
                                        1
                      0
## Count ties for each family
florentine %>%
 group_by(FAMILY) %>%
 rowwise() %>%
 summarize(connections = sum(c_across(ACCIAIUOL:TORNABUON)))
## # A tibble: 16 x 2
## # Groups: FAMILY [16]
     FAMILY connections
##
##
     <chr>
                     <int>
## 1 ACCIAIUOL
                         1
## 2 ALBIZZI
                         3
## 3 BARBADORI
                         2
## 4 BISCHERI
                         3
## 5 CASTELLAN
                         3
## 6 GINORI
                         1
## 7 GUADAGNI
                         4
## 8 LAMBERTES
## 9 MEDICI
                         6
## 10 PAZZI
                         1
## 11 PERUZZI
                         3
## 12 PUCCI
                         0
## 13 RIDOLFI
                         3
                         2
## 14 SALVIATI
## 15 STROZZI
                         4
## 16 TORNABUON
```

Undirected Graph and Centrality Measures

```
library("igraph") # load the package

## Convert column to rownames, treat as matrix
florence <- florentine %>%
   column_to_rownames(var = "FAMILY") %>%
```

```
as.matrix()
## Convert adjacency matrix to graph object
florence <- graph.adjacency(florence, mode = "undirected", diag = FALSE)
plot(florence) # plot the graph (default visualization)
degree(florence)
## ACCIAIUOL ALBIZZI BARBADORI BISCHERI CASTELLAN
                                                   GINORI
                  3 2
## GUADAGNI LAMBERTES
                      MEDICI
                                       PERUZZI
                                                    PUCCT
                                  PAZZI
                            6
                                     1
                  1
##
    RIDOLFI SALVIATI
                       STROZZI TORNABUON
##
closeness(florence)
##
    ACCIAIUOL
                 ALBIZZI
                          BARBADORI
                                      BISCHERI
                                                CASTELLAN
## 0.018518519 0.022222222 0.020833333 0.019607843 0.019230769
       GINORI
                GUADAGNI LAMBERTES
                                        MEDICI
## 0.017241379 0.021739130 0.016949153 0.024390244 0.015384615
                   PUCCI
                            RIDOLFI
                                      SALVIATI
## 0.018518519 0.004166667 0.022727273 0.019230769 0.020833333
    TORNABUON
## 0.02222222
1 / (closeness(florence) * 15)
## ACCIAIUOL ALBIZZI BARBADORI BISCHERI CASTELLAN
                                                   GINORI
## 3.600000 3.000000 3.200000 3.400000 3.466667
                                                 3.866667
## GUADAGNI LAMBERTES MEDICI
                                  PAZZI
                                       PERUZZI
                                                    PUCCI
## 3.066667 3.933333 2.733333 4.333333 3.600000 16.000000
   RIDOLFI SALVIATI STROZZI TORNABUON
##
## 2.933333 3.466667 3.200000 3.000000
betweenness(florence)
## ACCIAIUOL ALBIZZI BARBADORI BISCHERI CASTELLAN
                                                   GINORI
## 0.000000 19.333333 8.500000 9.500000 5.000000 0.000000
## GUADAGNI LAMBERTES
                       MEDICI
                                 PAZZI
                                        PERUZZI
                                                    PUCCI
RIDOLFI SALVIATI STROZZI TORNABUON
## 10.333333 13.000000 9.333333 8.333333
plot(florence, vertex.size = closeness(florence) * 1000,
    main = "Closeness")
plot(florence, vertex.size = betweenness(florence),
```

Twitter Following Network

```
## load the data
data("twitter.following", package = "qss")
data("twitter.senator", package = "qss")
## rename to be shorter
follow <- twitter.following</pre>
senator <- twitter.senator</pre>
## examine
head(follow)
##
        following
                         followed
## 1 SenAlexander
                         RoyBlunt
## 2 SenAlexander
                      SenatorBurr
## 3 SenAlexander
                      JohnBoozman
## 4 SenAlexander SenJohnBarrasso
## 5 SenAlexander
                      SenBennetCO
## 6 SenAlexander
                      SenDanCoats
head(senator)
##
         screen name
                                name party state
## 1
        SenAlexander Lamar Alexander
                                          R
## 2
            RoyBlunt
                           Roy Blunt
                                               MO
## 3
        SenatorBoxer Barbara Boxer
                                          D
                                               CA
## 4 SenSherrodBrown
                     Sherrod Brown
                                         D
                                               OH
## 5
         SenatorBurr
                       Richard Burr
                                          R
                                               NC
## 6 SenatorBaldwin Tammy Baldwin
                                               WI
twitter_adj <- graph_from_edgelist(as.matrix(follow),</pre>
                                   directed = TRUE)
```

Directed Graph and Centrality

```
senator <- mutate(senator,</pre>
         indegree = degree(twitter_adj, mode = "in"),
         outdegree = degree(twitter_adj, mode = "out"))
## with slice and arrange
arrange(senator, desc(indegree)) %>%
  slice(1:3) %>%
  select(name, party, state, indegree, outdegree)
##
                  name party state indegree outdegree
           Tom Cotton
                                         64
                         R
                                AR
                                                   15
## 2 Richard J. Durbin
                           D
                                IL
                                         60
                                                   87
## 3
        John Barrasso
                          R
                                WY
                                                   79
```

```
## with slice_max
slice_max(senator, order_by = indegree, n = 3) %>%
  arrange(desc(indegree)) %>%
 select(name, party, state, indegree, outdegree)
##
                  name party state indegree outdegree
## 1
            Tom Cotton
                           R
                                AR
                                          64
## 2 Richard J. Durbin
                                IL
                                          60
                                                    87
                           D
                                          58
                                                    79
         John Barrasso
                           R.
                                WY
## 4
          Joe Donnelly
                                IN
                                          58
                                                    9
                           D
## 5
       Orrin G. Hatch
                           R.
                                UT
                                          58
                                                    50
# Define scales to reuse for the plots
scale_color_parties <- scale_color_manual("Party",</pre>
                                            values = c(R = "red",
                                                        D = "blue"
                                                        I = "green"),
                                           labels = c(R = "Republican",
                                                      D= "Democrat",
                                                      I = "Independent"))
scale_shape_parties <- scale_shape_manual("Party",</pre>
                                           values = c(R = 16,
                                                      D = 17
                                                      I = 4),
                                           labels = c(R = "Republican",
                                                      D= "Democrat",
                                                      I = "Independent"))
## Calculate closeness measures and graph
senator %>%
  mutate(closeness_in = closeness(twitter_adj,
                                           mode = "in"),
         closeness_out = closeness(twitter_adj,
                                            mode = "out")) %>%
  ggplot(aes(x = closeness_in, y = closeness_out,
             color = party, shape = party)) +
  geom_point() +
  scale_color_parties +
  scale_shape_parties +
  labs(main = "Closeness", x = "Incoming path",
       y = "Outgoing path") +
  theme_classic(base_size = 22) +
  theme(legend.position = "none")
## Calculate betweenness measures and graph
senator %>%
  mutate(betweenness_dir = betweenness(twitter_adj,
                                                directed = TRUE),
         betweenness_undir = betweenness(twitter_adj,
                                                  directed = FALSE)) %>%
  ggplot(aes(x = betweenness_dir,
             y = betweenness_undir, color = party,
             shape = party)) +
  geom_point() +
```

```
scale_color_parties +
scale_shape_parties +
labs(main = "Betweenness", x = "Directed", y = "Undirected") +
theme_classic(base_size = 22)
```

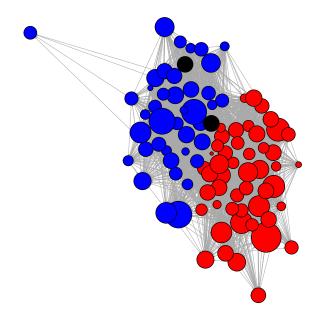
```
0.009
                                                                          40
Outgoing path
                                                                      Undirected
                                                                                                                     Party
    0.006
                                                                                                                         Republican
Democrat
                                                                                                                         Independent
   0.003
   0.000
                                                       0.0020
        0.0016
                    0.0017
                               0.0018
                                            0.0019
                             Incoming path
                                                                                         Directed
```

```
## Calculate the pagerank
senator <- mutate(senator,</pre>
                  page_rank = page_rank(twitter_adj)[["vector"]])
## Create igraph object
net <- graph_from_data_frame(d = follow,</pre>
                             vertices = senator,
                             directed=T)
## View the new object
## IGRAPH 40efe1f DN-- 91 3859 --
## + attr: name (v/c), party (v/c), state (v/c),
## | indegree (v/n), outdegree (v/n), page_rank (v/n)
## + edges from 40efe1f (vertex names):
## [1] Lamar Alexander->Roy Blunt
## [2] Lamar Alexander->Richard Burr
## [3] Lamar Alexander->John Boozman
   [4] Lamar Alexander->John Barrasso
## [5] Lamar Alexander->Michael F. Bennet
## [6] Lamar Alexander->Daniel Coats
## [7] Lamar Alexander->Susan M. Collins
## + ... omitted several edges
## look at some network edges, nodes, and node (vertex) attributes
```

+ 6/3859 edges from 40efe1f (vertex names):

head(E(net)) ## E() for edges

```
## [1] Lamar Alexander->Roy Blunt
## [2] Lamar Alexander->Richard Burr
## [3] Lamar Alexander->John Boozman
## [4] Lamar Alexander->John Barrasso
## [5] Lamar Alexander->Michael F. Bennet
## [6] Lamar Alexander->Daniel Coats
head(V(net)) ## V() for vertex
## + 6/91 vertices, named, from 40efe1f:
## [1] Lamar Alexander Roy Blunt
                                       Barbara Boxer
## [4] Sherrod Brown Richard Burr
                                       Tammy Baldwin
head(V(net)$party)
## [1] "R" "R" "D" "D" "R" "D"
## Code will not run as-is
## Adding hypothetical weights to edges
E(net)$weight <- hypothetical_weights_vector</pre>
## Vector of colors of the nodes based on party
col <- senator %>%
  mutate(col = case_when(party == "R" ~ "red",
                         party == "D" ~ "blue",
                         TRUE ~ "black")) %>%
  select(col) %>% pull()
## plot the new object
## with node size based on page_rank
plot(net, vertex.size = V(net)$page_rank*1000,
     vertex.label = NA, vertex.color = col,
     edge.arrow.size = 0.1,
     edge.width = 0.5)
```



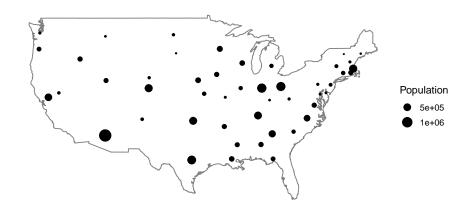
```
PageRank <- function(n, A, d, pr) { # function takes 4 inputs</pre>
    deg <- degree(A, mode = "out") # outdegree calculation</pre>
    for (j in 1:n) {
        pr[j] \leftarrow (1 - d) / n + d * sum(A[,j] * pr / deg)
   return(pr)
}
while (condition) {
    LOOP CONTENTS HERE
}
nodes <- 4
## adjacency matrix with arbitrary values
adj \leftarrow matrix(c(0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0),
              ncol = nodes, nrow = nodes, byrow = TRUE)
adj
        [,1] [,2] [,3] [,4]
##
## [1,]
               1
## [2,]
           1
                0
                     1
                          0
## [3,]
         0
                          0
## [4,]
           0
              1
                     0
```

```
adj <- graph.adjacency(adj) # turn it into an igraph object
d <- 0.85 # typical choice of constant
pr <- rep(1 / nodes, nodes) # starting values</pre>
## maximum absolute difference; use a value greater than threshold
diff <- 100
## while loop with 0.001 being the threshold
while (diff > 0.001) {
   pr.pre <- pr # save the previous iteration</pre>
   pr \leftarrow PageRank(n = nodes, A = adj, d = d, pr = pr)
   diff <- max(abs(pr - pr.pre))</pre>
}
pr
## [1] 0.2213090 0.4316623 0.2209565 0.1315563
Spatial Data
The 1854 Cholera Outbreak in London
Spatial Data in R
data("us.cities", package = "maps")
glimpse(us.cities)
## Rows: 1,005
## Columns: 6
                <chr> "Abilene TX", "Akron OH", "Alameda CA"~
## $ name
## $ country.etc <chr> "TX", "OH", "CA", "GA", "NY", "OR", "N~
## $ long
                <dbl> -99.74, -81.52, -122.26, -84.18, -73.8~
                <int> 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, ~
## $ capital
## Filter just the continental US capitals
capitals <- filter(us.cities,</pre>
                  capital == 2,
                  !country.etc %in% c("HI", "AK"))
## Convert the USA map data from maps package to a dataframe
usa_map <- map_data("usa")</pre>
## Plot the map and capitals
ggplot() +
 geom_map(map = usa_map) +
 borders(database = "usa") +
  geom_point(aes(x = long, y = lat, size = pop),
            data = capitals) +
```

scale size area ensures: 0 = no area

scale_size_area() +

```
coord_quickmap() +
theme_void(base_size = 12) +
labs(x = "", y = "",
    size = "Population")
```





head(usa_map)

```
## 1 -101.4078 29.74224 1 1 1 main <NA>
## 2 -101.3906 29.74224 1 22 main <NA>
## 3 -101.3620 29.65056 1 3 main <NA>
## 4 -101.3505 29.63911 1 4 main <NA>
## 5 -101.3219 29.63338 1 5 main <NA>
## 6 -101.3047 29.64484 1 6 main <NA>
```

dim(usa_map)

[1] 7243 6

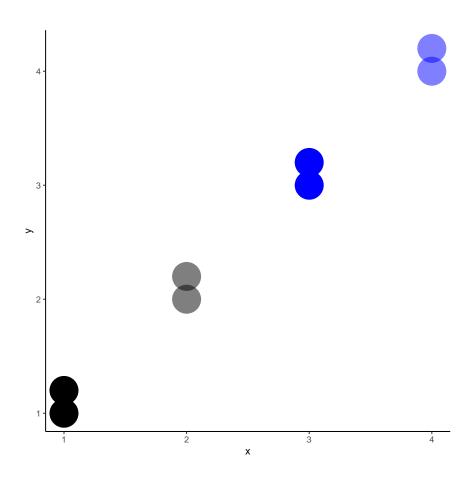
```
allcolors <- colors()
head(allcolors) # some colors</pre>
```

```
## [1] "white" "aliceblue" "antiquewhite"
## [4] "antiquewhite1" "antiquewhite2" "antiquewhite3"
```

length(allcolors) # number of color names

[1] 657

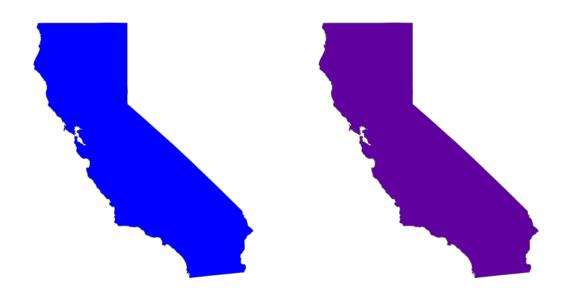
```
red <- rgb(red = 1, green = 0, blue = 0) # red
green <- rgb(red = 0, green = 1, blue = 0) # green
blue <- rgb(red = 0, green = 0, blue = 1) # blue</pre>
c(red, green, blue) # results
## [1] "#FF0000" "#00FF00" "#0000FF"
black <- rgb(red = 0, green = 0, blue = 0) # black</pre>
white <- rgb(red = 1, green = 1, blue = 1) # white
c(black, white) # results
## [1] "#000000" "#FFFFFF"
rgb(red = c(0.5, 1), green = c(0, 1), blue = c(0.5, 0))
## [1] "#800080" "#FFFF00"
## semi-transparent blue
blue.trans <- rgb(red = 0, green = 0, blue = 1, alpha = 0.5)
## semi-transparent black
black.trans <- rgb(red = 0, green = 0, blue = 0, alpha = 0.5)</pre>
## Sample data with color and alpha column
sample_data \leftarrow tibble(x = rep(1:4, each = 2),
              y = x + rep(c(0, 0.2), times = 2),
              color = rep(c("#000000", "#0000FF"), each = 4),
              alpha = c(1, 1, 0.5, 0.5, 1, 1, 0.5, 0.5))
## plot it
ggplot(aes(x = x, y = y, color = color, alpha = alpha),
       data = sample_data) +
  geom_point(size = 15) +
  scale_color_identity() +
  scale_alpha_identity()
```



United States Presidential Elections

```
## Load the data
data("pres08", package = "qss")
## Calculate vote-share
pres08 <- pres08 %>%
  mutate(Dem = Obama / (Obama + McCain),
         Rep = McCain / (Obama + McCain))
## Set the purple shade
cal_color <- filter(pres08, state == "CA") %>%
  mutate(purple_shade = rgb(red = Rep,
                            green = 0,
                            blue = Dem)) %>%
  select(purple_shade) %>% pull()
## Plot California as blue
ggplot() +
  borders(database = "state", regions = "California", fill = "blue") +
  coord_quickmap() +
  theme_void()
## Plot California as purple shade
ggplot() +
```

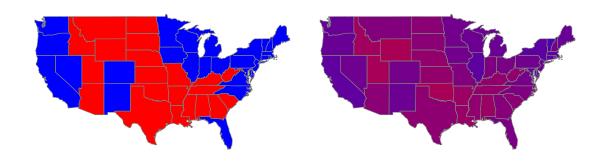
```
borders(database = "state", regions = "California", fill = cal_color) +
coord_quickmap() +
theme_void()
```



```
## prepare the presidential data for merge
## by changing case of the state variable
## and removing unneeded states (plus DC)
pres08 <- mutate(pres08, state = str_to_lower(state.name)) %>%
 filter(!(state %in% c("hawaii",
                         "d.c.",
                         "alaska")))
## take the states map data, remove DC
states <- map_data("state") %>%
 filter(!(region %in% c("hawaii",
                         "district of columbia",
                         "alaska"))) %>%
  ## merge with the presidential data
  full_join(pres08, by = c("region" = "state")) %>%
  ## create a party winner variable
  ## and a shade of winning variable
  mutate(party = if_else(Dem > Rep, "Dem", "Rep"),
         purple_shade = rgb(red = Rep,
                            green = 0,
                            blue = Dem))
## Check the data
glimpse(states)
```

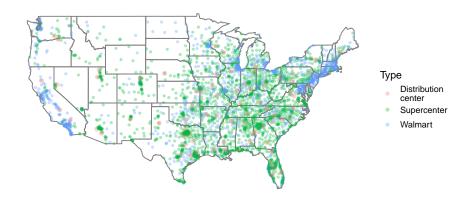
```
<chr> "alabama", "alabama", "alabama", "ala~
## $ region
## $ subregion
                                                                                                                                            ## $ state.name <chr> "Alabama", 
## $ Obama
                                                                                                                                            <int> 39, 39, 39, 39, 39, 39, 39, 39, 3°
                                                                                                                                            <int> 60, 60, 60, 60, 60, 60, 60, 60, 60, 6~
## $ McCain
## $ EV
                                                                                                                                            <int> 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9~
## $ Dem
                                                                                                                                             <dbl> 0.3939394, 0.3939394, 0.3939394, 0.39~
                                                                                                                                            <dbl> 0.6060606, 0.6060606, 0.6060606, 0.60~
## $ Rep
## $ party
                                                                                                                                            <chr> "Rep", "Rep"
## $ purple_shade <chr> "#9B0064", "#9B0064", "#9B0064", "#9B~
```

```
### Plot with red/blue
ggplot(states) +
 geom_polygon(aes(group = group, x = long, y = lat,
                   fill = party)) +
 borders(database = "state") +
  coord quickmap() +
  scale_fill_manual(values = c("Rep" = "red", "Dem" = "blue"),
                    guide = "none") +
 theme_void() +
  labs(x = "", y = "")
## Plot with shading
ggplot(states) +
 geom_polygon(aes(group = group, x = long, y = lat,
                  fill = purple_shade)) +
 borders(database = "state") +
  scale fill identity() +
  coord_quickmap() +
  theme_void() +
  labs(x = "", y = "")
```



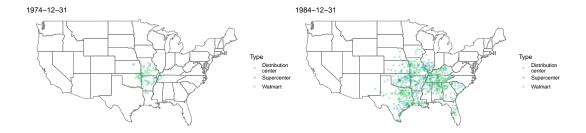
Expansion of Walmart

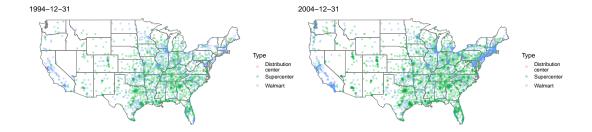
```
## Load the data
data("walmart", package = "qss")
## add a "size" column for larger points for Distribution Centers
## Then recode the "type" levels
walmart <- walmart %>%
 mutate(size = if_else(type == "DistributionCenter", 2, 1),
        type = recode(type, "DistributionCenter" = "Distribution \ncenter",
                       "SuperCenter" = "Supercenter",
                       "Wal-MartStore" = "Walmart"))
## Map it
ggplot() +
 borders(database = "state") +
 geom_point(aes(x = long, y = lat, color = type, size = size),
             data = walmart,
             alpha = 1 / 3) +
  coord_quickmap() +
  scale_size_identity() +
 theme_void(base_size = 12) + # remove all extra formatting
  labs(color = "Type") # change the label for the legend
```



Animation in R

```
walmart.map(walmart, as.Date("1974-12-31"))
walmart.map(walmart, as.Date("1984-12-31"))
walmart.map(walmart, as.Date("1994-12-31"))
walmart.map(walmart, as.Date("2004-12-31"))
```





```
library(gganimate)
library(lubridate)
## Round down to year from opendate
walmart <- walmart %>%
  mutate(year = floor_date(opendate, unit = "year"))
## Create the animation
walmart_animated <-</pre>
  ggplot() +
    borders(database = "state") +
    geom_point(aes(x = long, y = lat,
                   color = type),
               data = walmart) +
    coord_quickmap() +
    theme_void() +
    transition_states(states = year,
                    transition_length = 0,
                    state_length = 1) +
  shadow_mark()
## show the animation
walmart_animated
## save the animation
anim_save("DISCOVERY/walmart.gif")
```