

STAT 412/612 Week 9 Homework

stringr and Regular Expressions

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3/22/2020

Question 1: Scrabble Words

1. Load into R the list of acceptable (2015) Scrabble words from https://dcgerard.github.io/stat_412_612/data/words.txt.

Hint: “NA” is an actual word. It means “no” or “not”.

```
library(tidyverse)
```

```
## -- Attaching packages ---- tidyverse 1.3.0 --
```

```
## <U+2713> ggplot2 3.3.0      <U+2713> purrr  0.3.3
## <U+2713> tibble  2.1.3      <U+2713> dplyr  0.8.3
## <U+2713> tidyr   1.0.0      <U+2713> stringr 1.4.0
## <U+2713> readr   1.3.1      <U+2713> forcats 0.4.0
```

```
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

```
text_mania <- read_tsv(file = "https://dcgerard.github.io/stat_412_612/data/words.txt",
                      na = character())
```

```
## Parsed with column specification:
## cols(
##   word = col_character()
## )
```

```
sample_n(text_mania,10)
```

```
## # A tibble: 10 x 1
##   word
##   <chr>
## 1 AROMATHERAPIST
## 2 UNTAPPED
```

```
## 3 ENTOMIC
## 4 SUBMISSIVELY
## 5 FRIGORIFIC
## 6 OILNUTS
## 7 BUSHLAND
## 8 MISSORTS
## 9 PAIOCKE
## 10 STRONGARMS
```

```
#check
text_mania %>%
  filter(is.na(word))
```

```
## # A tibble: 0 x 1
## # ... with 1 variable: word <chr>
```

2. How many words either begin or end in “X”?

Ans: 885 units

```
text_mania %>%
  filter(str_count(word, "^X") | str_count(word, "X$")) %>%
  nrow()
```

```
## [1] 885
```

3. How many words contain all of the vowels (A, E, I, O, and U)?

Ans: 3476 units

```
text_mania %>%
  filter(str_detect(word, "A") & str_detect(word, "E")
         & str_detect(word, "I") & str_detect(word, "O")
         & str_detect(word, "U")) -> text_vowels

nrow(text_vowels)
```

```
## [1] 3476
```

4. What are the shortest words that contain all of the vowels? (there should be five of them)

Ans: DOULEIA, EULOGIA, MIAOUED, MOINEAU and SEQUOIA

```
text_vowels %>%
  mutate(count = str_length(word)) %>% # the length of shortest words is seven.
  arrange(count) %>%
  filter(count == 7)
```

```
## # A tibble: 5 x 2
##   word      count
##   <chr>    <int>
## 1 DOULEIA      7
## 2 EULOGIA      7
## 3 MIAOUED      7
## 4 MOINEAU      7
## 5 SEQUOIA      7
```

5. Switch the first and last letters of all of the words. How many of them are still words?

Ans: 21287 units

```
text_mania %>%
  mutate(convert_word = str_replace_all
          (word, "^[A-Z](.*)([A-Z])$", "\\3\\2\\1")) %>%
  mutate( is_word = convert_word %in% word) %>%
  filter(is_word == TRUE) -> still_words

head(still_words)
```

```
## # A tibble: 6 x 3
##   word      convert_word is_word
##   <chr>    <chr>         <lgl>
## 1 AA      AA            TRUE
## 2 AB      BA            TRUE
## 3 ABA     ABA            TRUE
## 4 ABACA   ABACA           TRUE
## 5 ABAKA   ABAKA           TRUE
## 6 ABASIA  ABASIA          TRUE
```

```
count(still_words)
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1 21287
```

6. How many of the words that are still words after switching the first and last letters have *different* first and last letters?

Ans: 1696 units

```
still_words %>%
  mutate(same_first_last = str_sub(word, str_length(word), )
         == str_sub(word, 1, 1)) %>%
  # we can use "word" or "convert_word" columns.
  filter(same_first_last == FALSE) -> still_words_firstlast_different

count(still_words_firstlast_different)
```

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1  1696
```

7. What are the longest words that are still words after switching the first and last letters and where the first and last letters are different? You should end up with six words (three pairs of words).

```
still_words_firstlast_different %>%
  mutate(length = str_length(word)) %>%
  arrange(desc(length)) %>%
  head(6)
```

```
## # A tibble: 6 x 5
##   word          convert_word  is_word same_first_last length
##   <chr>         <chr>         <lgl>   <lgl>         <int>
## 1 DECOMMISSIONER RECOMMISSIONED TRUE    FALSE          14
## 2 DEMYTHOLOGISER REMYTHOLOGISED TRUE    FALSE          14
## 3 DEMYTHOLOGIZER REMYTHOLOGIZED TRUE    FALSE          14
## 4 RECOMMISSIONED DECOMMISSIONER TRUE    FALSE          14
## 5 REMYTHOLOGISED DEMYTHOLOGISER TRUE    FALSE          14
## 6 REMYTHOLOGIZED DEMYTHOLOGIZER TRUE    FALSE          14
```

Question 2 Bank Data

The US Federal Reserve publishes data on the largest commercial banks chartered in the United States.

1. Read in the provided `fed_large_c_bank_ratings.csv` file to answer the following questions

```
US_commercial_banks <- read.csv(file = "../data/fed_large_c_bank_ratings.csv")
sample_n(US_commercial_banks, 10)
```

```
##              name rank charter
## 1 SIMMONS BK/SIMMONS FIRST NAT CORP    84    SMB
## 2 ALDEN ST BK/              1637    SMB
## 3 TENNESSEE ST BK/TENNESSEE ST BSHRS  925    SMB
## 4 OAKSTAR BK/OAKSTAR BSHRS    651    SMB
## 5 NANO BANC/ALLEGiant UNITED HOLDS LLC  793    SMB
## 6 ADAMS B&TC/ADAGE LLC    774    SMB
## 7 COMMENCEMENT BK/          1490    SMB
## 8 BANK OF FAYETTE CTY/MOSCOW BSHRS    952    SMB
## 9 WEST MI CMNTY BK/NORTHSTAR FNCL GRP 1021    SMB
## 10 FARMERS BK OF NORTHERN MO/NORTHERN MO BSHRS 1507    SMB
```

```
##      consolidated_assets
## 1              17659
## 2              345
## 3              678
## 4              996
## 5              815
## 6              839
## 7              388
## 8              656
## 9              596
## 10             383
```

2. Many of the banks have more than one name. Separate out the multiple names into different columns called name and alternate name, ignore any additional names, and update the data frame.

```
US_commercial_banks %>%
  separate("name", into = c("name", "alternate_name"), sep = "/") ->
  US_commercial_banks_V02
```

```
## Warning: Expected 2 pieces. Additional pieces discarded in 1 rows [15].
```

```
head(US_commercial_banks_V02)
```

```
##      name      alternate_name rank charter
## 1  BANK OF NY MELLON  BANK OF NY MELLON CORP    10    SMB
## 2  STATE STREET B&TC    STATE STREET CORP    11    SMB
## 3  GOLDMAN SACHS BK USA  GOLDMAN SACHS GROUP THE    12    SMB
## 4      ALLY BK            ALLY FNCL    15    SMB
## 5    NORTHERN TC        NORTHERN TR CORP    20    SMB
## 6    REGIONS BK        REGIONS FC    22    SMB
##      consolidated_assets
## 1              311387
## 2              242148
## 3              228836
## 4              167492
## 5              135885
## 6              125641
```

```
# recheck if they have additional names
# US_commercial_banks_V02 %>%
# mutate(add_name = str_detect(alternate_name, "/")) %>%
# filter(add_name == TRUE)
```

3. How many bank names begin with a digit?

Ans: 2

```
US_commercial_banks_V02 %>%
  filter(str_detect(name, "^\\d")) %>%
  nrow()
```

```
## [1] 2
```

4. How many bank names have the word “BANK” in them?

Ans: 41

```
US_commercial_banks_V02 %>%
  filter(str_detect(name, "BANK")) %>%
  nrow()
```

```
## [1] 41
```

5. Convert the abbreviation “BK” to the word “BANK”. What are the relative proportions of names that have “BANK” as the first word, the last word, somewhere other than first or last, or not at all?

```
US_commercial_banks_V02 %>%
  mutate(name = str_replace_all(name, "BK", "BANK")
         , position_banks = if_else(str_detect(name, "^BANK "), "first",
                                   if_else(str_detect(name, " BANK$"), "last",
                                   if_else(str_detect(name, " BANK "), "middle", "none")))) -> US_commercial_banks_V03
```

```
US_commercial_banks_V03 %>%
  group_by(position_banks) %>%
  summarize(proportions = n()/nrow(US_commercial_banks_V02))
```

```
## # A tibble: 4 x 2
##   position_banks proportions
##   <chr>          <dbl>
## 1 first          0.056
## 2 last           0.664
## 3 middle         0.096
## 4 none           0.184
```

```
# traditional method
US_commercial_banks_V02 %>%
  mutate(name = str_replace_all(name, "BK", "BANK")) %>%
  filter(str_detect(name, "^BANK ")) -> first_banks

nrow(first_banks) #21 have "BANK" as the first word
```

```
## [1] 21
```

```
prop_first <- (nrow(first_banks)/ nrow(US_commercial_banks_V02))*100
prop_first
```

```
## [1] 5.6
```

```
# traditional method
```

```
US_commercial_banks_V02 %>%
  mutate(name = str_replace_all(name, "BK", "BANK")) %>%
  filter(str_detect(name, " BANK$")) -> last_banks
```

```
nrow(last_banks) #249 have "BANK" as the last word
```

```
## [1] 249
```

```
prop_last<- (nrow(last_banks)/ nrow(US_commercial_banks_V02))*100
prop_last
```

```
## [1] 66.4
```

```
# traditional method
```

```
US_commercial_banks_V02 %>%
  mutate(name = str_replace_all(name, "BK", "BANK")) %>%
  filter(str_detect(name, " BANK ")) -> middle_banks
```

```
nrow(middle_banks) #36 have "BANK" neither in the first nor in the last word
```

```
## [1] 36
```

```
prop_middle <- (nrow(middle_banks)/ nrow(US_commercial_banks_V02))*100
prop_middle
```

```
## [1] 9.6
```

```
# traditional method
```

```
US_commercial_banks_V02 %>%
  mutate(name = str_replace_all(name, "BK", "BANK")) %>% #
  anti_join(first_banks) %>%
  anti_join(last_banks) %>%
  anti_join(middle_banks) -> no_banks
```

```
## Joining, by = c("name", "alternate_name", "rank", "charter",
## "consolidated_assets")Joining, by = c("name", "alternate_name", "rank",
## "charter", "consolidated_assets")Joining, by = c("name", "alternate_name",
## "rank", "charter", "consolidated_assets")
```

```
nrow(no_banks) # 69 have no bank words
```

```
## [1] 69
```

```
prop_no <- (nrow(no_banks)/ nrow(US_commercial_banks_V02))*100  
prop_no
```

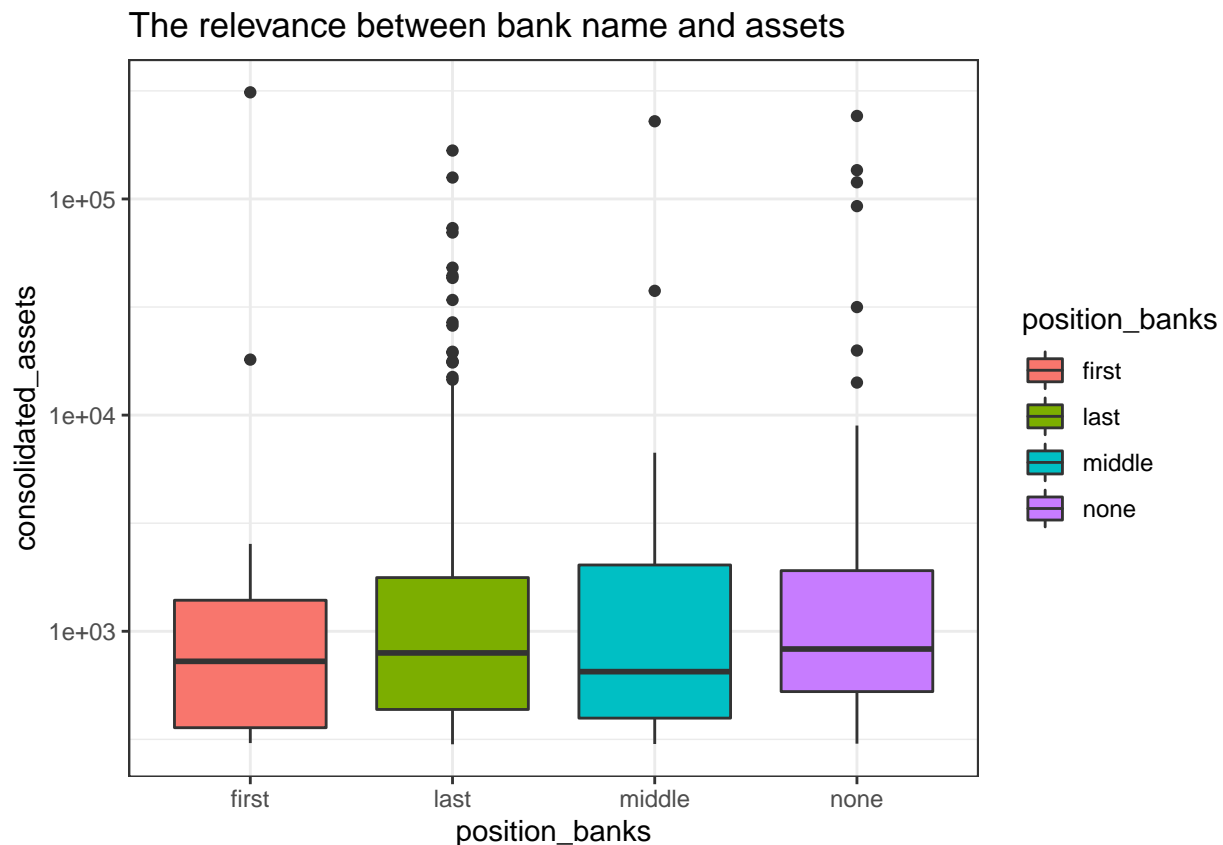
```
## [1] 18.4
```

6. Extra Credit: Use a boxplot to compare the distributions of the log of the combined total assets of the banks based on where the word “BANK” appears in their name. Does position seem to make a difference?

Ans: the position of the bank’s name does not have inseparable effects on total assets.

```
US_commercial_banks_V03 %>%  
  ggplot(aes(x = position_banks, y = consolidated_assets, fill = position_banks))+  
  geom_boxplot()+  
  scale_y_log10()+  
  theme_bw()+  
  ggtitle("The relevance between bank name and assets")
```

```
## Warning: Removed 1 rows containing non-finite values (stat_boxplot).
```




```
# Note:
# 1e+03 = 1 * 10^3 = 1000
# 1e+04 = 1 * 10^4 = 10000
# 1e+05 = 1 * 10^5 = 100000
# 1e-03 = 1 * 10^(-3) = 0.001
```

Extra Credit Question: Create your own date parser.

1. Create a function called `my_d_parser()` that takes as input a string of eight digits and a format (specified by with a `#Y`, `#m`, and `#d`; for `YYYY`, `MM`, and `DD`, respectively) and returns a vector of length 3 where the first element is the year, the second is the month, and the third is the day.

Hints:

- I used the following functions: `str_replace()`, `str_locate()`, `rank()`, `c()`, `str_match()`, `as.numeric()`.
- Thinking in reverse order, you need to create a regex pattern based on the order of the terms in the input format you can use to parse the input string into vector of year, month, and day.
- Start by using regex to convert the input format (`#Y`, `#m`, `#d`) into a new regex string
- * As an example, use regex to replace “`#Y`” with “`([0-9]{4})`”
- Create a vector with the order of the elements in the input format.
- Create a vector of the matches for the input string with the new parsing regex
- Using the vector you created for the order of the input format to return the elements matching year, month, and day
- Make sure each element of the output vector is a number.
 - You are not allowed to use any pre-built date parsers.
 - You have to use regular expressions.
 - Test out your parser on the following three inputs.

```
my_d_parser <- function(string, pattern) {
  pattern_2 <- str_replace(pattern, "#Y", "YYYY")
  pattern_2 <- str_replace(pattern_2, "#m", "mm")
  pattern_2 <- str_replace(pattern_2, "#d", "dd")

  y_index <- str_locate(pattern_2, "YYYY")
  year <- as.numeric(str_sub(string, y_index[1], y_index[2]))

  m_index <- str_locate(pattern_2, "mm")
  month <- as.numeric(str_sub(string, m_index[1], m_index[2]))

  d_index <- str_locate(pattern_2, "dd")
  day <- as.numeric(str_sub(string, d_index[1], d_index[2]))

  return(c(year, month, day))
}
```

```
pattern <- "#Y, #d, #m"
string <- "2021, 12, 02"
my_d_parser(string, pattern)
```

```
## [1] 2021    2   12
```

```
pattern <- "#d-#Y,#m"  
string <- "01-2020,05"  
my_d_parser(string, pattern)
```

```
## [1] 2020    5    1
```

```
pattern <- "#m/#d/#Y"  
string <- "05/29/2017"  
my_d_parser(string, pattern)
```

```
## [1] 2017    5   29
```

```
#another solution
```

```
my_d_parser_anotherway <- function(string, pattern){  
  str_replace(pattern, pattern = "#Y", "([0-9]{4})") %>% #{} exactly{n}  
    str_replace(pattern = "#m", "([0-9]{2})") %>%  
    str_replace(pattern = "#d", "([0-9]{2})") -> pattern_V02  
  
  dpattern <- str_locate(pattern, "#d")[1]  
  mpattern <- str_locate(pattern, "#m")[1]  
  ypattern <- str_locate(pattern, "#Y")[1]  
  combined <- rank(c(ypattern, mpattern, dpattern))  
  str_match(string = string, pattern = pattern_V02)[, -1] %>%  
    as.numeric() -> finalparser  
  return(finalparser[combined])  
}
```