Module 11: Working with Strings and Date/Time Variables

Managing and Manipulating Data Using R

Introduction

What we will do today

Load the packages we will use today (output omitted)

- **you must run this code chunk after installing these packages**

```
library(tidyverse)
library(stringr)
library(lubridate)
library(nycflights13)
```

If package not yet installed, then must install before you load. Install in "console" rather than .Rmd file

- Generic syntax: `install.packages("package_name")`
- Install "tidyverse": `install.packages("stringr")`

Note: when we load package, name of package is not in quotes; but when we install package, name of package is in quotes:

- `install.packages("tidyverse")`
- `library(tidyverse)`

Load data we will use today

- Western Washington University student list data

```
load(url("https://github.com/ksalazar3/HED696C_Rclass/raw/master/data/prospect_
```

- Jeopardy text data Link

```
jeopardy <- read_csv("https://raw.githubusercontent.com/ksalazar3/HED696C_Rclas
#> Rows: 216930 Columns: 7
#> -- Column specification ------------------------------------------------
#> Delimiter: ","
#> chr  (5): Round, Category, Value, Question, Answer
#> dbl  (1): Show Number
#> date (1): Air Date
#>
#> 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 mess
```

Working with Strings

String basics

What are strings?

String refers to a “data type” used in programming to represent text rather than numbers (although it can include numbers)

- Strings have `character` types

```
string1<- "Apple"
typeof(string1) #type is charater
#> [1] "character"
```

- Create strings using `" "`

```
string2 <- "This is a string"
```

- If string contains a quotation, use `' " " '`

```
string3 <- 'example of a "quote" within a string'
```

- To print a string, use `writeLines()`

```
print(string3) #will print using \
#> [1] "example of a \"quote\" within a string"
writeLines(string3)
#> example of a "quote" within a string
```

Common uses of strings

Basic uses:

- Names of files and directories

```
acs_tract <- read_csv("https://raw.githubusercontent.com/ksalazar3/HED696C_Rcla
#> New names:
#> Rows: 11504 Columns: 30
#> -- Column specification
#> ------------------------------------------------------ Delimiter: "," chr
#> (4): tract_name, tract, race_brks_nonwhiteasian, inc_brks dbl (26): ...1,
#> pop_total, pop_total_25plus, median_household_income, pop_wh...
#> 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 messag
#> * `` -> `...1`
```

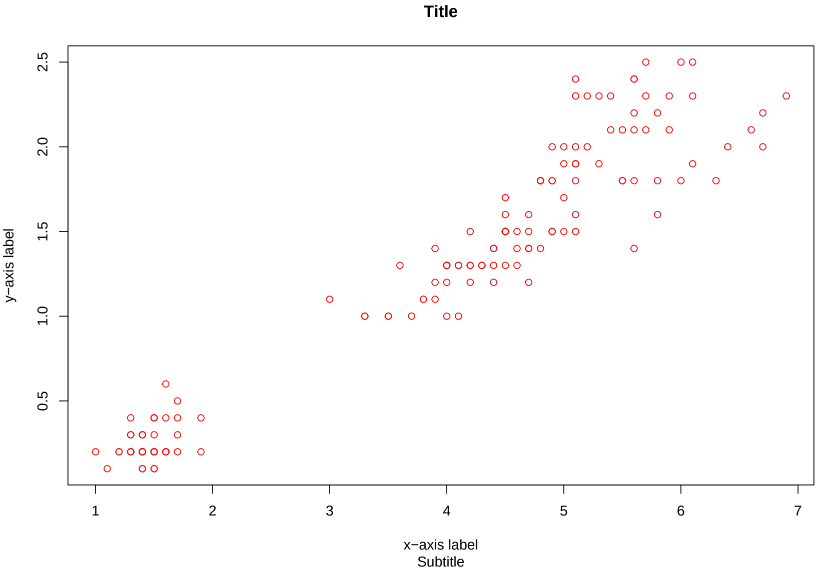
- Names of elements in data objects

```
num_vec <- 1:5
names(num_vec) <- c('uno', 'dos', 'tres', 'cuatro', 'cinco')
num_vec
#>    uno    dos   tres cuatro  cinco
#>      1      2      3      4      5
```

Common uses of strings

- Text elements displayed in plots, graphs, maps

```
plot(iris$Petal.Length, iris$Petal.Width, main = 'Title', sub = 'Subtitle',
     xlab = 'x-axis label', ylab = 'y-axis label', col = 'red')
```



String basics

We will use the `stringr` library for working with strings, rather than Base R

- `stringr` functions have intuitive names and all begin with `str_`
- Base R functions for working with strings can be inconsistent (avoid using them)

Basic functions:

- String length using `str_length()`

```
#example 1
string2 <- "This is a string"
str_length(string2)
#> [1] 16

#example 2
str_length(c("a", "strings are fun", NA))
#> [1]  1 15 NA
```

Combining strings

- Combining strings using `str_c()`

```
#example 1
x_var <- "x"
y_var <- "y"

str_c(x_var, y_var)
#> [1] "xy"

#example 2
str_c("x", "y")
#> [1] "xy"
```

- Use `sep` argument to control how strings are seperated when combined

```
str_c("x", "y", sep= ", ")
#> [1] "x, y"
```

- `NA` are still contagious, if you want a string “NA” rather than `NA` use `str_replace_na()`

```
street_dir<- c("East", "West", NA)
str_c("Direction: ", street_dir)
#> [1] "Direction: East" "Direction: West" NA
str_c("Direction: ", str_replace_na(street_dir))
#> [1] "Direction: East" "Direction: West" "Direction: NA"
```

Subsetting strings

-Extract parts of a string using `str_sub()`, which uses `start` and `end` arguments to extract the position of the substring wanted

```
fruits<- c("Apple", "Banana", "Orange")

#first three elements
str_sub(fruits, 1, 3) #end argument in inclusive
#> [1] "App" "Ban" "Ora"

#last three elements
str_sub(fruits, -3, -1) #neg nums count backwards from end
#> [1] "ple" "ana" "nge"
```

- **Task: extract 6-digit zip code from `zip9` in `wwlist`**

```
wwlist %>% mutate(
  zip=str_sub(zip9, 1, 5)
)
```

Lower-case and Upper-case functions

- Changing strings to lower or upper case

```
str_to_lower("HELLO")
#> [1] "hello"
str_to_upper("hello")
#> [1] "HELLO"
```

- **Task: lower-case `hs_name` in `wwlist`**

```
wwlist %>% select(receive_date, hs_name) %>%
  mutate(
  hs_name_lwr=str_to_lower(hs_name),
)
#> # A tibble: 268,396 x 3
#>    receive_date hs_name                      hs_name_lwr
#>    <date>       <chr>                        <chr>
#>  1 2016-05-31   Ingraham High School         ingraham high school
#>  2 2016-05-31   Kentwood Senior High School  kentwood senior high school
#>  3 2016-05-31   Archbishop Thomas J Murphy HS archbishop thomas j murphy hs
#>  4 2016-05-31   Garfield High School         garfield high school
#>  5 2016-05-31   Lake Stevens High School     lake stevens high school
#>  6 2016-05-31   Franklin High School         franklin high school
#>  7 2016-05-31   Hockinson High School        hockinson high school
#>  8 2016-05-31   Nathan Hale High School      nathan hale high school
#>  9 2016-05-31   Sultan High School           sultan high school
#> 10 2016-05-31   Sandpoint High School        sandpoint high school
#> # ... with 268,386 more rows
#> # i Use `print(n = ...)` to see more rows
```

Student Exercises

1. Combine `school_type` and `school_category` in the `wwlist` dataframe to create one school type + category varibale. Be sure to seperate type and category using a comma AND deal with contagious NAs by using string “NA” if `school_type` and/or `school_category` are `NA`.
2. The last four digits of `zip9` indicate the delivery route within the 5-digit zip code area. Create a new `route` variable that extracts the last four digits from `zip9`.

Student Excercises (Solutions)

1. Combine `school_type` and `school_category` in the `wwlist` dataframe to create one school type + category varibale. Be sure to seperate type and category using a comma AND deal with contagious NAs by using string "NA" if `school_type` and/or `school_category` are `NA` .

```
wwlist %>% select(school_type, school_category) %>%
  mutate(
    type_cat= str_c(str_replace_na(school_type), str_replace_na(school_category
  )
#> # A tibble: 268,396 x 3
#>    school_type school_category type_cat
#>    <chr>       <chr>           <chr>
#>  1 public      Regular School  public, Regular School
#>  2 public      Regular School  public, Regular School
#>  3 <NA>        <NA>            NA, NA
#>  4 public      Regular School  public, Regular School
#>  5 public      Regular School  public, Regular School
#>  6 public      Regular School  public, Regular School
#>  7 public      Regular School  public, Regular School
#>  8 public      Regular School  public, Regular School
#>  9 public      Regular School  public, Regular School
#> 10 public      Regular School  public, Regular School
#> # ... with 268,386 more rows
#> # i Use `print(n = ...)` to see more rows
```

Student Excercises (Solutions)

1. The last four digits of `zip9` indicate the delivery route within the 5-digit zip code area. Create a new `route` variable that extracts the last four digits from `zip9`.

```
wwlist %>% select(zip9) %>%
  mutate(
  route=str_sub(zip9, -4, -1)
)
#> # A tibble: 268,396 x 2
#>    zip9       route
#>    <chr>      <chr>
#>  1 98103-3528 3528
#>  2 98030-7964 7964
#>  3 98290-8659 8659
#>  4 98105-0002 0002
#>  5 98252-9327 9327
#>  6 98108-1809 1809
#>  7 98685-3135 3135
#>  8 98125-4543 4543
#>  9 98294-1529 1529
#> 10 83864-2304 2304
#> # ... with 268,386 more rows
#> # i Use `print(n = ...)` to see more rows
```

Regular Expressions

What are regular expressions (e.g., regex)?

Regular expressions are an entirely different and concise “language” used to describe patterns in strings

- One of the most powerful and sophisticated data science tools!
- They have a wide range of uses
- They are universal: can be used and are consistent across any programming language (e.g., R, Python, JavaScript)
- **BUT** they take a while to wrap your head around and can get really complex really quickly!

I will attempt to give an approachable introduction to regular expressions

- I still stuggle with regular expression tasks!
- My favorite tool for building, testing, debugging regular expressions: web regex app

Basic Matches

The simplest patterns match exact (sub)strings!

- `str_view()` shows the first match; `str_view_all` shows all the matches

```
x <- c("apple", "banana", "pear")
# str_view(x, "an") #uncomment to view outside of beamer presentation
```

- To detect matches in a column of a dataframe, use `str_detect` and `filter()`
  - `str_detect` determines a match and returns a logical vector the same length as the input

Task: Detect whether high school names abbreviate "high school" as "HS"?

```
wwlist %>%
  select(hs_name) %>%
  filter(str_detect(hs_name, "HS"))
#> # A tibble: 9,072 x 1
#>    hs_name
#>    <chr>
#>  1 Archbishop Thomas J Murphy HS
#>  2 Lewis and Clark HS-Spokane
#>  3 Health Sci & Human Services HS
#>  4 Lewis and Clark HS-Spokane
#>  5 Cascade HS - Leavenworth
#>  6 Auburn Mountainview HS
#>  7 Newport HS- Bellevue
#>  8 Newport HS- Bellevue
#>  9 East Valley HS-Spokane Valley
#> 10 Marysville Pilchuck Pathway HS
```

Basic Matches

The next step-up in complexity is using `.` which matches any character (including white space but except a newline)

Task: Detect whether there are any "HS" abbreviations that have *any* character before and after the abbreviation?

```
wwlist %>%
  select(hs_name) %>%
  filter(str_detect(hs_name, ".HS."))
#> # A tibble: 4,919 x 1
#>    hs_name
#>    <chr>
#>  1 Lewis and Clark HS-Spokane
#>  2 Lewis and Clark HS-Spokane
#>  3 Cascade HS - Leavenworth
#>  4 Newport HS- Bellevue
#>  5 Newport HS- Bellevue
#>  6 East Valley HS-Spokane Valley
#>  7 Liberty HS-Renton
#>  8 East Valley HS-Yakima
#>  9 West Valley HS-Spokane
#> 10 Newport HS- Bellevue
#> # ... with 4,909 more rows
#> # i Use `print(n = ...)` to see more rows
```

Anchors

Regular expressions will match any part of a string. Sometimes it's useful to *anchor* the regular expression so that it matches from the start or the end of the string:

- `^` will match the start of the string
- `$` will match the end of the string

```
x <- c("apple", "banana", "pear")
str_detect(x, "^a")
#> [1]  TRUE FALSE FALSE
str_detect(x, "a$")
#> [1] FALSE  TRUE FALSE
```

Escapes

Regular expressions use special characters (i.e., `.`, `\`) to match patterns in strings. If you're trying to match an actual character exactly rather than use it's special behavior, you need to use an *escape*

- The double backslash `\\` is used to *escape* special behavior for these characters

```r
# To create the regular expression, we need \\
dot <- "\\."

# But the expression itself only contains one:
writeLines(dot)
#> \.

# And this tells R to look for an explicit .
str_detect(c("abc", "a.c", "bef"), "a\\.c")
#> [1] FALSE  TRUE FALSE
```

- for a full list of escape characters type the following into your console: `?"'"`

Common special patterns

There are other “special patterns” that will match more than one character and can be really useful.

Matching characters

- `.` matches any character
- `\d` matches any digit (or `\D` for non-digits)
- `\s` matches any whitespace such as space, tab, newline (or `\S` fir non-whitepsace)

Matching alternates

- `[abe]` matches one of a, b, or e
- `[^ab3]` matches anything but a, b, e
- `[a-f]` matches range

Tools: other `stringr` Functions

I only highlighted a few `stringr` functions in this lecture. But there are many functions that are helpful in applying regular expressions to real data problems (i.e., determining match, finding positions of matches, extracting context of matches, replacing values based on matches)

- `stringr` cheat sheet
- Some common functions:

Task	Function
Detect matches	`str_detect`, `str_which`, `str_count`, `str_locate`
Subset strings	`str_sub`, `str_subset`, `str_extract`, `str_match`
Mutate strings	`str_sub`, `str_replace`, `str_to_lower`, `str_to_upper`
Join or split strings	`str_c`, `str_dup`, `str_plit_fixed`

Examples

Task: Look for any Jeopardy categories that begin with a digit

```
jeopardy %>%
  select(Category) %>%
  filter(str_detect(Category, "^\\d"))
#> # A tibble: 6,294 x 1
#>    Category
#>    <chr>
#>  1 3-LETTER WORDS
#>  2 3-LETTER WORDS
#>  3 3-LETTER WORDS
#>  4 3-LETTER WORDS
#>  5 3-LETTER WORDS
#>  6 1994 FILMS
#>  7 1994 FILMS
#>  8 1994 FILMS
#>  9 1994 FILMS
#> 10 1994 FILMS
#> # ... with 6,284 more rows
#> # i Use `print(n = ...)` to see more rows
```

Examples

Task: Look for any Jeopardy categories that may contain a year variable as a sequence of 4 digits. Create a new `year_category` indicator variable if the Jeopardy category involves a year.

```
jeopardy1 <- jeopardy %>%
  select(Category) %>%
  mutate(
    year_category=str_detect(Category, "[0-9][0-9][0-9][0-9]")
)
```

- Print some observations

```
jeopardy1 %>%
  select(Category, year_category) %>%
  filter(year_category==TRUE)
#> # A tibble: 3,347 x 2
#>    Category   year_category
#>    <chr>      <lgl>
#>  1 1994 FILMS TRUE
#>  2 1994 FILMS TRUE
#>  3 1994 FILMS TRUE
#>  4 1994 FILMS TRUE
#>  5 1994 FILMS TRUE
#>  6 THE 1930s  TRUE
#>  7 THE 1930s  TRUE
#>  8 THE 1930s  TRUE
#>  9 THE 1930s  TRUE
#> 10 THE 1930s  TRUE
```

Why are string manipulations and regular expressions useful?

Basic examples:

- Dealing with identification numbers (leading or trailing zeros)

```
typeof(acs_tract$fips_county_code)
#> [1] "double"

acs_tract <- acs_tract %>%
  mutate(char_county=
  str_pad(as.character(fips_county_code), side = "left" ,3, pad="0"))
```

- Complex reshaping (tidying) of data
  - Problem: multiple variables crammed into the column names
    - new_ prefix = new cases
    - sp/rel/sp/ep describe how the case was diagnosed
    - m/f gives the gender
    - digits are age ranges

```
who %>% pivot_longer(
  cols = new_sp_m014:newrel_f65,
  names_to = c("diagnosis", "gender", "age"),
  names_pattern = "new_?(.*)_(.)(.*)",
  values_to = "count"
)
```

Why are string manipulations and regular expressions useful?

Advanced examples:

- Web-scraping
  - Find and scrape all linked pages of recruiters assigned by states: (https://gobama.ua.edu/staff/)
  - Parsing raw HTML to convert it into tabular data
- Natural Language Processing
  - Analyzing university president speeches for promotion of interdisciplinary research (IDR)
  - Predict sentiment of promotion of IDR

Working with Dates and Times

Working with date/time variables

Working with dates and times in data management seems simpler than it really is!

- Does every year have 365 days?
- Does every day have 24 hours?
- Does every minute have 60 seconds?

These details matter for:

- Calculating changes over time
- Analyzing longitudinal data
- Predicting the occurance/timing of events

There are three ways you're likely to create a date/time variable:

- From a string (most common)
- From date and time individual components
- From an existing date/time object

Creating Date/Times

Creating Date/Times from strings

The most common way you're likely to create Date/Time variables is from primary/secondary data where dates and times are recorded and/or stores as strings.

For Dates:

- Use `lubridate` "helpers" to identify the order of year/month/day

```
ymd("2017/01/31")
#> [1] "2017-01-31"

mdy("January 31st, 2017")
#> [1] "2017-01-31"

dmy("31-01-2017")
#> [1] "2017-01-31"

ymd(20170131)
#> [1] "2017-01-31"
```

For Dates:

- Use `lubridate` "helpers" to identify the order of year/month/day **AND** hours/minutes/seconds

```
ymd_hms("2017-01-31 20:11:59")
#> [1] "2017-01-31 20:11:59 UTC"

mdy_hm("01/31/2017 08:01")
#> [1] "2017-01-31 08:01:00 UTC"
```

Creating Date/Times from individual variables

What if your dates and times are recorded across multiple columns/variables?

EX: NYC flights data

```
flights %>%
  select(year, month, day, hour, minute)
#> # A tibble: 336,776 x 5
#>     year month   day  hour minute
#>    <int> <int> <int> <dbl>  <dbl>
#>  1  2013     1     1     5     15
#>  2  2013     1     1     5     29
#>  3  2013     1     1     5     40
#>  4  2013     1     1     5     45
#>  5  2013     1     1     6      0
#>  6  2013     1     1     5     58
#>  7  2013     1     1     6      0
#>  8  2013     1     1     6      0
#>  9  2013     1     1     6      0
#> 10  2013     1     1     6      0
#> # ... with 336,766 more rows
#> # i Use `print(n = ...)` to see more rows
```

- Create a date variable using `make_date()`

```
flights1<- flights %>%
  select(year, month, day) %>%
  mutate(
    depart= make_date(year, month, day)
```

Using Date/Time Variables

Time spans

Arithmatic with dates works differently than with any numeric type!

There are three date/time classes that represent time spans:

- Durations: represent the duration of time to an exact number of seconds
- Periods: represent the period of time such as weeks/months/years
- Intervals: represent a starting and end point in time

Durations

When you subtract two dates, the result is a `difftime` object

- A `difftime` object records time span as seconds (not intuitive)
- Use `as.duration` to make the difftime object more intuitive (but records time span in seconds)

```
# How old is Karina?
k_age <- today() - ymd(19890321)
k_age
#> Time difference of 12312 days

typeof(k_age)
#> [1] "double"
class(k_age)
#> [1] "difftime"

as.duration(k_age)
#> [1] "1063756800s (~33.71 years)"
```

- Durations uses "constructers"

Time spans

Periods

Periods don't record time spans in exact seconds and are more intuitive to the way we think about time!

```
one_pm <- ymd_hms("2016-03-12 13:00:00", tz = "America/New_York")

one_pm # 1pm
#> [1] "2016-03-12 13:00:00 EST"
one_pm + days(1) #1pm
#> [1] "2016-03-13 13:00:00 EDT"

one_pm + years(1)
#> [1] "2017-03-12 13:00:00 EDT"
```