R crash course - Data frames

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Data Frame Basics

Exploring Data Frames

Exercise Solution

Munging Data with `dplyr`

Exercise Solution

Reshape Data with `tidyr`

Exercise Solution

Combining Data with `joins`

Dependencies

- Latest version ($\geq$ `3.1.2`) of `R` (*free* from `https://www.r-project.org/`)
- Latest version of `Rstudio` (also *free* from `https://www.rstudio.com/`)
- A bunch of *free* packages

```
# The single tidyverse package now includes
# dplyr and tidyr
install.packages('tidyverse')
# install.packages('dplyr')
# install.packages('tidyr')
install.packages('nycflights13')  # sample data frame
```

Data Frames: Introduction

- Data frames are the primary representation of data in `R`
- You can think of a data frame as a two-dimensional *table* of data
- It helps your sanity to always think of data frames as a table where

  ```
  Each column represents a variable/feature
  Each row represents an observation/instance
  ```

- Conceptually, a data frame is also a collection of vectors, i.e., each column is a vector that belongs to the (parent) data frame
- The fastest path to achieving `R`-ninja status is to get familiar with data frames

Data Frames: First Impression

- Let's load an existing data frame to take a look at

```
# install data package (only need to do once)
install.packages('nycflights13')
```

```
# load data package to workspace
library('nycflights13')
```

- The `nycflights13` package contains a single data frame named `flights`
- Contains data (16 variables) on all 336,776 flights that departed NYC (i.e. JFK, LGA, or EWR) in 2013
- See documentation for details on what the 16 variables are

```
?flights
```

Data Frames: First Impression (cont'd)

```
str(flights)  # take a peek at the data frame
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    336776 obs
##  $ year          : int  2013 2013 2013 2013 2013 2013 20
##  $ month         : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ day           : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ dep_time      : int  517 533 542 544 554 554 555 557
##  $ sched_dep_time: int  515 529 540 545 600 558 600 600
##  $ dep_delay     : num  2 4 2 -1 -6 -4 -5 -3 -3 -2 ...
##  $ arr_time      : int  830 850 923 1004 812 740 913 70
##  $ sched_arr_time: int  819 830 850 1022 837 728 854 72
##  $ arr_delay     : num  11 20 33 -18 -25 12 19 -14 -8 8
##  $ carrier       : chr  "UA" "UA" "AA" "B6" ...
##  $ flight        : int  1545 1714 1141 725 461 1696 507
##  $ tailnum       : chr  "N14228" "N24211" "N619AA" "N80
##  $ origin        : chr  "EWR" "LGA" "JFK" "JFK" ...
##  $ dest          : chr  "IAH" "IAH" "MIA" "BQN" ...
##  $ air_time      : num  227 227 160 183 116 150 158 53
```

Some Question

- What questions could you ask (and answer) with this data?
  - how many flights were there each day?
  - what was the mean departure delay for flights every month/day?
  - what is the proportion of annual departures from each of the three airports?
  - what else?
- By the end of this session, we'll have the tools to answer most (if not all) of the questions you can come up with!

Data Frame Basics

`tibble`

- A `tibble` is a trimmed down version of `data.frame` that is more convenient to work with
- Throughout this course, we will use the terms `tibble` and data frames interchangably, which is technically incorrect, but easier to read

Simple Example

- Use `tibble()` function (from `tidyverse`) to create a `tibble` data frame
- Arguments of `tibble()` are vectors or lists (of equal length) that constitute each column (variable)
- For example, let's create a data frame of the following table:

Age	Personality	Income
24	Good	2000
22	Bad	5800
23	Good	4200
25	Bad	1500
22	Good	6000

Simple Example (cont'd)

- We'll save the data frame to an object (I'll call mine `data`)

```
data <- tibble(  # start tibble()
  age = c(24, 22, 23, 25, 22),
  personality = c('g', 'b', 'g', 'b', 'g'),
  income = c(2000, 5800, 4200, 1500, 6000)
)  # finish the tibble() function
```

- Note that the new lines are just a matter of coding style, i.e., it makes the code easier to read
- The same data frame can be created in a single line:

```
data <- tibble(age = c(24, 22, 23, 25, 22),
personality = c('g', 'b', 'g', 'b', 'g'), income
= c(2000, 5800, 4200, 1500, 6000))
```

Simple Example (cont'd)

- Let's take a look at our new data frame

```r
data
```

```
## # A tibble: 5 × 3
##     age personality income
##   <dbl>       <chr>  <dbl>
## 1    24           g   2000
## 2    22           b   5800
## 3    23           g   4200
## 4    25           b   1500
## 5    22           g   6000
```

Indexing: The $ Operator

- The $ operator lets you reference elements of an object (e.g., column vectors of a data frame) in R

```
data$age
```

```
## [1] 24 22 23 25 22
```

```
data$personality
```

```
## [1] "g" "b" "g" "b" "g"
```

Indexing: The [Operator

- The [operator, similar to the $ operator, lets you reference elements of an object (e.g., column vectors of a data frame) either by name *or by index*

```
data['age']
```

```
## # A tibble: 5 × 1
##     age
##   <dbl>
## 1    24
## 2    22
## 3    23
## 4    25
## 5    22
```

Indexing: The [Operator (cont'd)

```
data[1]
```

```
## # A tibble: 5 × 1
##       age
##     <dbl>
## 1      24
## 2      22
## 3      23
## 4      25
## 5      22
```

Indexing: The [[Operator (cont'd)

- Note that when using the [operator, unlike $, you get a new data frame of the indexed column, *not* a vector.
- Use the [[operator if you want a vector instead

```
data[[1]]
```

```
## [1] 24 22 23 25 22
```

Indexing: Numeric Row/Column

- Since a data frame is a table of data, you can treat it like a matrix, and index its entries by `[row #, col #]` notation

```
data[2, 3]  # item in row 2 column 3
```

```
## # A tibble: 1 × 1
##   income
##    <dbl>
## 1   5800
```

```
data[, 2]  # entire column 2
```

```
## # A tibble: 5 × 1
##   personality
##         <chr>
## 1           g
## 2           b
## 3           g
```

Indexing: Named Variables

- Since the columns represent variables with names, you can index columns by a string representing variable names

```
data[, 'age']  # entire 'age' column
```

```
## # A tibble: 5 × 1
##     age
##   <dbl>
## 1    24
## 2    22
## 3    23
## 4    25
## 5    22
```

```
# entries 3~5 of 'personality' column
data[3:5, 'personality']
```

```
## # A tibble: 3 × 1
```

Indexing: Vectors

- As with vectors/matrices, you can index a data frame with vectors (either numeric or string)

```
data[1:3, c('age', 'income')]
```

```
## # A tibble: 3 × 2
##     age income
##   <dbl>  <dbl>
## 1    24   2000
## 2    22   5800
## 3    23   4200
```

```
data[c(1,4), 2:3]
```

```
## # A tibble: 2 × 2
##   personality income
##         <chr>  <dbl>
## 1           g   2000
```

Conditional Indexing

- Pick out entries that match specific criteria by first creating a binary vector for indexing

```
# find the 22-year-olds
ind <- data$age == 22
data[ind, ]  # index rows by binary vector ind
```

```
## # A tibble: 2 × 3
##     age personality income
##   <dbl>       <chr>  <dbl>
## 1    22           b   5800
## 2    22           g   6000
```

Chained Indexing

- Note that
  - when you index rows of a single column, the result is a vector
  - when you index multiple columns, the result is a new data frame
- You can chain indices to pin-point elements of a data frame
- For example, all of the following operations are (almost) equivalent – can you tell how the first two are different from the last two?

```
# (Almost) Equivalent operations to get the age of
# third observation (row 3)
data[3, 1]  # if you know that 'age' is column 1
data[3, 'age']
data[3,]$age  # get 'age' of row 3
data$age[3]  # get third observation of 'age' variable
```

Column (Variable) Names

- To see the column name of a data frame, use the `colnames()` function
- The column names can be changed by directly assigning a new vector of names to the `colnames()` function

```r
colnames(data)
```

```
## [1] "age"         "personality" "income"
```

```r
colnames(data) <- c('age', 'attitude', 'income')
data
```

```
## # A tibble: 5 × 3
##     age attitude income
##   <dbl>    <chr>  <dbl>
## 1    24        g   2000
## 2    22        b   5800
## 3    23        g   4200
```

Write Data Frames to Files

- Use `write_tsv()` to write data frames to tab-separated (text) files
- The syntax is

  `write_tsv(x, path = "")`

- For example, to save our sample data to a file named `data.tsv` with the entries of each row separated by a tab character, write

```
write_tsv(data, path='data.tsv')
```

- Recall, the default directory is the current working directory, specified with `setwd()`, and retrieved with `getwd()`
- For more options, see documentation

```
?write_tsv
```

Read Data Frames from Files

- To read data frames that exist as text files, use the general `read_table()` function
- Note that specific options for `read_table()` will depend on the structure of the text file you wish to read (e.g., comma-separated or tab-separated)
- Some shortcuts for pre-defined for (commonly used) formats

```
read_csv(file)             # comma-separated values
read_tsv(file)             # tab-separated values
read_delim(file, delim)    # custom delimiters
```

Read Data Frames from Files (cont'd)

- For example, to read the `tsv` file we just saved,

```
data <- read_tsv('data.tsv', col_names = TRUE)
```

```
## Parsed with column specification:
## cols(
##   age = col_integer(),
##   personality = col_character(),
##   income = col_integer()
## )
```

- Notice how `read_tsv()` guesses the type of your columns
- It's good practice to specify column types manually so that
  1. you know exactly what you want, and
  2. you get what you want

Specify types for columns

- You can use the output message from the previous `read_tsv()` call as a boiler plate input to the `col_types` parameter, e.g.,

```
data <- read_tsv('data.tsv', col_types = cols(
  age = col_double(),
  personality = col_character(),
  income = col_double()
), col_names = TRUE)
```

- Or, you can use a compact specification,

```
data <- read_tsv('data.tsv', col_types = 'dcd',
                 col_names = TRUE)
```

- See the documentation for more details

```
?read_delim
```

Read Data from Online Database

- `read_*()` can also load data frames from an online database
- While loading data directly from the web is not recommended, this can be useful when making a local copy of an online database
- For example, to make a local copy of the dataset saved in `https://goo.gl/MGzatX`

```
address <- 'https://goo.gl/MGzatX'
data <- read_tsv(address)
write_tsv(data, path='data.tsv')
```

- Note that you can read data in one format (e.g., comma-separated) and save the local copy in another (e.g., tab-separated)

Exploring Data Frames

Example Data

- We'll use a sample dataset from `https://goo.gl/epWdDj`
- First, load the data into your workspace

```
address <- 'https://goo.gl/MaHL7q'
autompg <- read_tsv(address)
```

```
## Parsed with column specification:
## cols(
##   mpg = col_double(),
##   cylinders = col_integer(),
##   displacement = col_double(),
##   horsepower = col_character(),
##   weight = col_integer(),
##   accel = col_double(),
##   year = col_integer(),
##   origin = col_integer(),
##   model = col_character(),
##   make = col_character()
```

Display Structure with `str()`

- The `str()` function is useful for exploring the overall structure of a data frame

```r
str(autompg)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    398 obs. of
##  $ mpg         : num  18 15 18 16 17 15 14 14 14..
##  $ cylinders   : int  8 8 8 8 8 8 8 8 8 8 ...
##  $ displacement: num  307 350 318 304 302 429 45..
##  $ horsepower  : chr  "130.0" "165.0" "150.0" ""..
##  $ weight      : int  3504 3693 3436 3433 3449 4..
##  $ accel       : num  12 11.5 11 12 10.5 10 9 8...
##  $ year        : int  70 70 70 70 70 70 70 70 70..
##  $ origin      : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ model       : chr  "chevrolet chevelle malib"..
##  $ make        : chr  "chevrolet" "buick" "plym"..
##  - attr(*, "spec")=List of 2
##   ..$ cols   :List of 10
```

Factors

- Note that some variables should be `factors` – a data frame representation of categorical variables
- Use `factor()` to force varaible into factor variables

```
autompg$year <- factor(autompg$year)
autompg$model <- factor(autompg$model)
autompg$make <- factor(autompg$make)
```

- The entries of a `factor` variable is defined by `levels`

```
levels(autompg$make)
```

`unique` values

- Use `unique()` to list the unique values of any variable

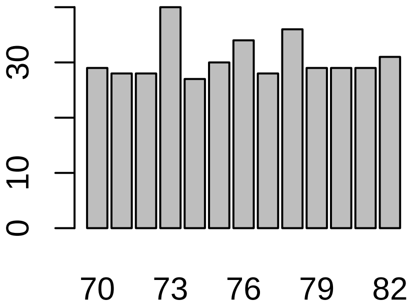
```r
unique(autompg$cylinders)
```

```
## [1] 8 4 6 3 5
```

Basic plots

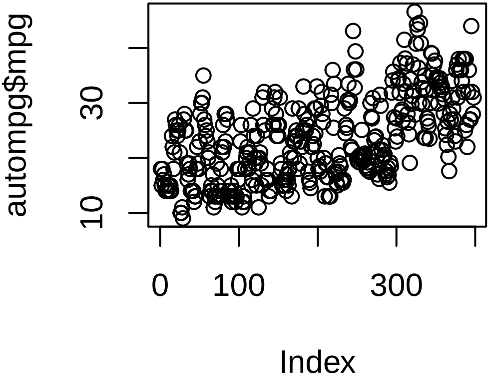
- Use `plot()` to generate quick and dirty (but sometimes helpful) plots
- By default, `plot()` will generate histograms of categorical variables (`factors`) and scatter plots (with respect to row index) of continuous variables

```
plot(autompg$year)
```



Basic `plots` (cont'd)

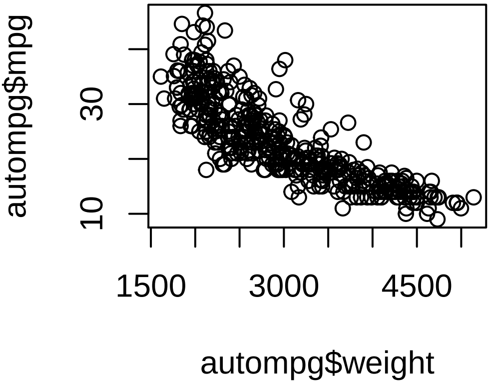
```
plot(autompg$mpg)
```



Basic plots (cont'd)

- Use syntax `plot(x, y)` to plot two variables

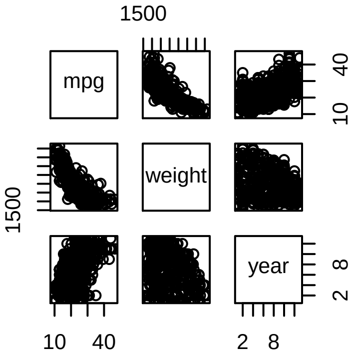
```
plot(autompg$weight, autompg$mpg)
```



Plotting pairs

- To plot more than two variables against each other, use `pairs()`

```
pairs(autompg[, c('mpg', 'weight', 'year')])
```



- Note that you can plot the entire data frame with `pairs(autompg)`

Data Frame Basics: Exercise

- From the `autompg` data
  - create a new data frame with all the buick vehicles (i.e., `make=="buick"`)
  - generate a `summary()` of the buick vehicles' `mpg`
  - make the `cylinders` variable of the buick data frame into a factor
  - plot a histogram of the buick's `cylinders`
- These are just (very) basic operations
- For more complicated operations, we'll use `dlyr` and `tidyr` (both part of `tidyverse` and covered next)
- For more sophisticated plots, we'll use `ggplot2` (covered in the next session)

Exercise Solution

WARNING

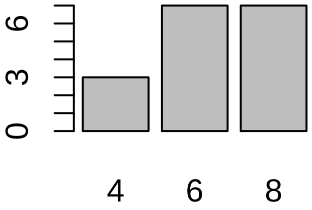
- Solutions to the exercise are presented in the next slide
- Try the exercise before proceeding!

Solution

```
buick_index <- autompg$make == 'buick'
buick <- autompg[buick_index, ]
summary(buick$mpg)
```

```
##     Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     12.0    14.0    17.7    19.2    22.4    30.0
```

```
buick$cylinders <- factor(buick$cylinders)
plot(buick$cylinders)
```



Munging Data with `dplyr`

Introduction to dplyr

- dplyr is a package that provides a convenient framework (along with a handful of useful functions) for wrangling data (frames)
- dplyr is a part of the tidyverse, so if you load tidyverse, dplyr is also loaded
- You can also, but don't have to, install and load the dplyr as a standalone package like you would any other R package

```
# Install, if you haven't already.
# Only need to do this once on a single machine.
install.packages('dplyr')
# load package into workspace
library('dplyr')
```

- We'll primarily use the flights data frame from the nycflights13 package in this part

Work with `tibble`

- To be consistent, and avoid surprises, make sure you're working with a `tibble` and **NOT** a `data.frame`.
- Since `tibble`s are just an opinionated `data.frame`, you can make sure you're working with a `tibble` by converting your `data.frame`s to `tibble`s with `as_tibble()`

```
flights <- as_tibble(flights)
```

Verbs

- A *verb* in the world of `dplyr` is a function that takes a data frame as its first argument, and returns another data frame as a result
- For example, the `head()` function can be considered a verb

```
head(flights, n = 10)
```

- Note that the result of the `head()` function is another data frame (in this case, with 3 rows)
- The **core idea of `dplyr`** is that most of your data manipulation needs can be satisfied with 5 basic verbs (or 4, depending on how you categorize them)

Five basic verbs

- The five basic verbs of `dplyr` and associated actions are presented below

verb	action
`filter()`	select a subset of *rows* by specified conditions
`select()`	select a subset of *columns*
`mutate()`	create a *new column* (often from existing columns)
`arrange()`	reorder (sort) *rows* by values of specified *column*(s)
`summarize()`	aggregate values and reduce to single value

- Some verbs have additional options or convenient wrappers

Selecting Rows: `filter()`

- Select a subset of *rows*
- Multiple conditions can be used
- Use `&` to specify `AND` conditions
- Use `|` to specify `OR` conditions
- `AND(&)/OR(|)` operations can be used together (where default behavior for multiple conditions is `AND`)

```
filter(flights, tailnum == 'N14228' & arr_delay > 10)
filter(flights,
       tailnum == 'N14228' |  tailnum == 'N24211')
filter(flights,
       tailnum == 'N14228' |  tailnum == 'N24211',
       arr_delay > 10)
```

Selecting Rows: `slice()`

- To select rows by numerical index (position), use `slice()`
- For example, to select the first 10 rows

```
slice(flights, 1:10)
```

- or to select the last 10 rows

```
slice(flights, (n() - 9):n())
```

- Use `n()` inside a `dplyr` verb to to indicate the *number of rows* of the data frame

Selecting Columns: `select()`

- Select a subset of *columns*
- Either specify the columns that you want to select

```
select(flights, carrier, tailnum)
```

- Or specify the columns you wish to drop

```
select(flights, -year, -month, -day)
```

Selecting Columns: `select()` (cont'd)

- `dplyr` provides useful helper functions you can use to `select()` columns that match specific criteria such as
  - `starts_with(x)`: names that start with `x`
  - `ends_with(x)`: names that end with `x`
  - `contains(x)`: names that contain `x`
  - `matches(x)`: names that match the (regular expression) `x`
- See the documentation for more details

```
?dplyr::select
```

- While you can assign new column names with `select()` the convenience function `rename()` lets you rename columns while retaining the rest of the data frame

```
select(flights, tail_num = tailnum)
rename(flights, tail_num = tailnum)
```

Create New Columns: `mutate()`

- Create new columns, usually as a function of existing columns
- You can refer to new columns you just created, inside the same `mutate()` function

```
mutate(flights, gain = arr_delay - dep_delay,
       speed = distance / air_time * 60,
       # use the gain column we just created
       # to create yet another gain_per_hour column
       gain_per_hour = gain / (air_time / 60)
       )
```

- Use `transmute()` to create a new data frame *just from* the new column(s)

```
transmute(flights, gain = arr_delay - dep_delay)
```

Sorting Rows by Column Value: `arrange()`

- Reorder the rows of a data frame by the specified column's value
- Multiple conditions are arranged from left to right
- Use `desc()` to arrange in descending order

```
arrange(flights, year, month, day)
arrange(flights, year, desc(month), day)
arrange(flights, year, month, desc(day))
arrange(flights, year, desc(month), desc(day))
```

Aggregate Data: `summarize()`

- Aggregate/collapse the data into a single row
- Think of as applying a function to columns

```
summarize(flights, delay = mean(dep_delay))
# Note that the mean function need help
# handling NA values
summarize(flights,
          delay = mean(dep_delay, na.rm = TRUE))
```

- More useful as a grouped operation (see next)

Grouped Operations

- If a data frame is *grouped*, operations are applied to each group separately, and the results are combined back to a single data frame
- Use the `group_by()` verb to specify variables to use for generating groups

```
flights_by_day <- group_by(flights, day)
```

- Some verbs have specific behavior when applied to grouped data

verb	group specific action
`arrange()`	sort rows within each group
`slice()`	extract rows within each group
`summarize()`	aggregate values group-wise

Grouped slice()

- Retrieve the first 2 departures (rows) of each day

```
slice(flights_by_day, 1:2)
```

```
## Source: local data frame [62 x 19]
## Groups: day [31]
##
##      year month   day dep_time sched_dep_time
##     <int> <int> <int>    <int>          <int>
## 1    2013     1     1      517            515
## 2    2013     1     1      533            529
## 3    2013     1     2       42           2359
## 4    2013     1     2      126           2250
## 5    2013     1     3       32           2359
## 6    2013     1     3       50           2145
## 7    2013     1     4       25           2359
## 8    2013     1     4      106           2245
## 9    2013     1     5       14           2359
```

Grouped summarize()

- Retrieve (1) number of departures (observations), (2) average distance, and (3) average arrival delay for each day (i.e., for flights grouped by day)

```
summarize(flights_by_day,  count = n(),
          dist = mean(distance, na.rm=TRUE),
          delay = mean(arr_delay, na.rm=TRUE))
```

```
##   day count dist   delay
## 1   1 11036 1039  7.3637
## 2   2 10808 1047  6.7681
## 3   3 11211 1041  4.4699
## 4   4 11059 1038 -1.7827
## 5   5 10858 1038  0.4925
## 6   6 11059 1041 -1.7489
```

Multiple (Chained) Operations

- Consider the following task

  find days when the mean arrival delay OR departure delay was greater than 30

- We can achieve the desired result with three operations
  1. **`group_by`** date (`year`, `month`, `day`)
  2. **`summarize`** mean arrival/departure delay
  3. **`filter`** summarized results (i.e., mean `arr_delay` > 30 | mean `dep_delay` > 30)
- Note that `dplyr` verbs do **not** modify the original data frame
  - This is generally a good thing, since it guarantees the integrity of your data
  - But it makes multiple operations on a data frame difficult
- There are two (acceptable) ways to apply multiple operations on a data frame, and one is definitely prefered to the other

Multiple Operations: The OK Way

- One way to perform multiple operations is to save intermediate data frames as new data frames
- This method delivers desired results, but makes your workspace quite messy (i.e., you'll end up with a workspace full of intermediate results)

```
flights_by_date <- group_by(flights, year, month, day)
summary_by_date <- summarize(
  flights_by_date,
  arr = mean(arr_delay, na.rm=TRUE),
  dep = mean(dep_delay, na.rm=TRUE))
big_delay_dates <- filter(
  summary_by_date,
  arr > 30 | dep > 30)
```

- This method might be prefered if you need the intermediate results in the future
- If not, there is a better way to chain multiple operations with

The Pipe Operator %>%

- The pipe operator, aka the 'magic' operator, takes the output from the verb on its left-hand side, and uses it as the first argument (data frame) for the verb on the right-hand side

```
big_delay_dates <- flights %>%
  group_by(year, month, day) %>%
  summarize(arr = mean(arr_delay, na.rm=TRUE),
            dep = mean(dep_delay, na.rm=TRUE)) %>%
  filter(arr > 30 | dep > 30)
```

- No need to save intermediate results
- Easier to read (i.e., you can follow the operations step-by-step without too much mental accounting)

The Pipe Operator %>% – Best Practice

- Always using the pipe operator – across multiple lines – makes it easier to add/remove/move things around, even for single expressions, i.e.,

```
flights_by_date <- flights %>%
  group_by(year, month, day)
```

`dplyr`: Exercise

- With the `flights` data
  1. find the average speed (`distance / air_time * 60`) by each carrier (ignore `NA`), and sort the data in descending order of average speed
  2. find the number of flights and average flight time of all flights greater than 10 hours by each carrier in April

Exercise Solution

WARNING

- Solutions to the exercise are presented in the next slide
- Try the exercise before proceeding!

Solution 1

```
speed_by_carrier <- flights %>%
  group_by(carrier) %>%
  mutate(speed = distance / air_time * 60) %>%
  summarize(avg_speed = mean(speed, na.rm=TRUE)) %>%
  arrange(desc(avg_speed))
speed_by_carrier
```

```
## # A tibble: 6 × 2
##   carrier avg_speed
##     <chr>     <dbl>
## 1      HA     480.4
## 2      VX     446.2
## 3      AS     443.7
## 4      F9     425.2
## 5      UA     420.9
## 6      DL     418.5
```

Solution 2

```
april_long_flights <- flights %>%
  group_by(month, carrier) %>%
  filter(month == 4 & hour > 10) %>%
  summarize(avg = mean(hour, na.rm=TRUE), count = n())
april_long_flights
```

```
## Source: local data frame [6 x 4]
## Groups: month [1]
##
##   month carrier   avg count
##   <int>   <chr> <dbl> <int>
## 1     4      9E 16.68  1170
## 2     4      AA 15.55  1704
## 3     4      AS 18.00    30
## 4     4      B6 16.89  3012
## 5     4      DL 15.81  2747
## 6     4      EV 16.08  3048
```

Reshape Data with `tidyr`

Introduction to `tidyr`

- Recall, the prefered way to think about a data frame:

  ```
  Each column represents a variable/feature
  Each row represents an observation/instance
  ```

- Consider the following (fictional) data frame of students' homework grades

ID	HW1	HW2	HW3
jamie	6	7	3
cersei	8	5	2
hodor	9	10	9

- What are the variables of this data?
- What are the potential issues with this representation?
- What are the benefits of this representation?

Introduction to `tidyr`: An Example

- For data manipulation/visualization we often prefer to have data in the *long* form
- The *long* form of the previous data would be

ID	HW	Score
jamie	1	6
jamie	2	7
⋮	⋮	⋮
hodor	2	10
hodor	3	9

- `tidyr` is a package that provides a tools for converting data between *long* and *wide* forms

Introduction to `tidyr`: Getting Started

- `tidyr` is also part of the `tidyverse`, so if you load `tidyverse`, `tidyr` is also loaded
- You can also, but don't have to, install and load `tidyr` as a standalone package like you would any other `R` package

```
# Install, if you haven't already.
# Only need to do this once on a single machine.
install.packages('tidyr')
```

```
# load package into workspace
library('tidyr')
```

Introduction to tidyr: Getting Started (cont'd)

- Create some random data

```
grades <- tibble(
  ID = c('jamie', 'cersei', 'hodor'),
  HW1 = runif(3, 1, 10),
  HW2 = runif(3, 1, 10),
  HW3 = runif(3, 1, 10),
  info = c('male/lannister',
           'female/lannister',
           'male/stark'))
grades
```

```
## # A tibble: 3 × 5
##        ID   HW1   HW2   HW3             info
##     <chr> <dbl> <dbl> <dbl>            <chr>
## 1   jamie 2.861 9.140 7.650   male/lannister
## 2 cersei 3.570 8.571 5.319 female/lannister
## 3   hodor 9.690 8.234 7.008       male/stark
```

Create *long* data with gather()

- With the `grades` data, we would like to create a data frame in the form of

ID	info	HW	score
-	-	-	-

- The verb for gathering multiple columns into key-value pairs in `tidyr` is `gather()`
- The syntax is

```
gather(data, key, value, ...)
```

- where the `...` should be replaced by column specifications

Create *long* data with gather() (cont'd)

```r
grades.tidy <- grades %>%
  gather(HW, score, HW1:HW3)
grades.tidy
```

```
## # A tibble: 6 × 4
##       ID              info    HW score
##    <chr>             <chr> <chr> <dbl>
## 1  jamie    male/lannister   HW1 2.861
## 2 cersei  female/lannister   HW1 3.570
## 3  hodor        male/stark   HW1 9.690
## 4  jamie    male/lannister   HW2 9.140
## 5 cersei  female/lannister   HW2 8.571
## 6  hodor        male/stark   HW2 8.234
```

Split a Column to Multiple Variables with separate()

- Often, there will be column that you'd prefer to split into multiple variables, e.g., splitting a date column to year, month, and day
- From the grades data, notice that the info column combines two variables: sex and house
- We can split such columns to multiple variables with the separate() verb in tidyr

```
grades.split <- grades.tidy %>%
  separate(info, into = c('sex', 'house'), sep = '/')
grades.split
```

```
## # A tibble: 3 × 5
##       ID    sex     house    HW score
##    <chr>  <chr>     <chr> <chr> <dbl>
## 1  jamie   male lannister   HW1 2.861
## 2 cersei female lannister   HW1 3.570
## 3  hodor   male     stark   HW1 9.690
```

Chaining `tidyr` verbs

- Note that `tidyr` operations are also verbs that can be chained with the pipe operator %>%
- For example, we can do the previous operations on the `grades` data with the chained operation

```
grades.final <- grades %>%
  gather(HW, score, HW1:HW3) %>%
  separate(info, into=c('sex', 'house'), sep='/')
```

- `tidyr` verbs can also be chained with `dplyr` verbs (and any other function that qualifies as a verb, i.e., takes a data frame as the first argument and results in a new data frame)

Exercise

- Create some random data

```
address <- 'https://goo.gl/0hFk2w'
finance <- read_tsv(address)
```

1. Tidy the data to fit the form

ID	type	year	amount
-	-	-	-

2. Find the mean and total Income/Expense for each ID across all years

Exercise Solution

WARNING

- Solutions to the exercise are presented in the next slide
- Try the exercise before proceeding!

Solution 1

```r
finance <- finance %>%
  gather(year, amount, 2:7) %>%
  separate(year, c('type', 'year'), sep='_')
finance
```

```
## # A tibble: 8 × 4
##      ID   type  year  amount
##   <chr>  <chr> <chr>   <dbl>
## 1  leia Income  2013  4174.3
## 2   han Income  2013 11064.9
## 3  luke Income  2013 11341.8
## 4  leia Income  2014 17343.7
## 5   han Income  2014 -5023.7
## 6  luke Income  2014  3547.0
## 7  leia Income  2015  3027.6
## 8   han Income  2015  -757.4
```

Solution 2

```r
finance.summary <- finance %>%
  group_by(ID, type) %>%
  summarize(mean=mean(amount), total=sum(amount))
finance.summary
```

```
## Source: local data frame [6 x 4]
## Groups: ID [?]
##
##      ID    type  mean total
##   <chr>   <chr> <dbl> <dbl>
## 1   han Expense  8170 24509
## 2   han  Income  1761  5284
## 3  leia Expense  8818 26453
## 4  leia  Income  8182 24546
## 5  luke Expense 12820 38461
## 6  luke  Income  8803 26408
```

Combining Data with `joins`

Basic concatenations

- `rbind`: concatenate rows
- `cbind`: concatenate columns
- For data frames, `bind_rows()` and `bind_cols()` from `dplyr` is usually much faster.

Example (with matrix, but works with data frames too)

```r
A <- matrix(1:4, 2, 2)
B <- matrix(5:8, 2, 2)
rbind(A, B)
```

```
##      [,1] [,2]
## [1,]    1    3
## [2,]    2    4
## [3,]    5    7
## [4,]    6    8
```

```r
cbind(A, B)
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    3    5    7
## [2,]    2    4    6    8
```

Introduction to `joins`

- Sometimes, you will find relevant data across multiple datasets, e.g., a list of grades in one dataset and a list of contact information in another
- In such cases, you may want to `join` the two datasets into a single data frame prior to further analysis
- For a successful `join` you must determine
  1. One or more variables that uniquely identify matching observations (rows) in both datasets
  2. How you wish to join the data, i.e.,
     - **Left/right join** Retain one of the datasets entirely, while only keeping matching entries of the other, possibly resulting in a few missing values (`NA`)
     - **Inner join** Retain only complete matches, possibly dropping some rows of both datasets
     - **Outer (full) join** Retain all rows of both datasets, but potentially resulting in many missing values (`NA`)

Example Datasets

- For illustration, let's create two data frames

```
info <- tibble(
  name=c('tony', 'tony', 'rey'),
  job=c('scientist', 'tiger', 'scavenger'),
  score=rnorm(3)
)

power <- tibble(
  name=c('tony', 'hank', 'rey'),
  job=c('scientist', 'scientist', 'scavenger'),
  strength=rexp(3)
)
```

- How is an observation (row) uniquely identified?

Left/Right join

- Retain rows of one dataset, and match the rows of the other

```
left_join(info, power, by=c('name', 'job'))
```

```
## # A tibble: 3 × 4
##     name       job   score strength
##    <chr>     <chr>   <dbl>    <dbl>
## 1   tony scientist  1.7708   0.5130
## 2   tony     tiger -0.9516       NA
## 3    rey scavenger  0.6836   0.2724
```

```
right_join(info, power, by=c('name', 'job'))
```

```
## # A tibble: 3 × 4
##     name       job  score strength
##    <chr>     <chr>  <dbl>    <dbl>
## 1   tony scientist 1.7708   0.5130
## 2   hank scientist     NA   1.4199
```

Inner join

- Retain only the rows that have matches on both datasets

```r
inner_join(info, power, by=c('name', 'job'))
```

```
## # A tibble: 2 × 4
##    name       job  score strength
##   <chr>     <chr>  <dbl>    <dbl>
## 1  tony scientist 1.7708   0.5130
## 2   rey scavenger 0.6836   0.2724
```

Outer (Full) `join`

- Retain all rows

```r
full_join(info, power, by=c('name', 'job'))
```

```
## # A tibble: 4 × 4
##    name       job   score strength
##   <chr>     <chr>   <dbl>    <dbl>
## 1  tony scientist  1.7708   0.5130
## 2  tony     tiger -0.9516       NA
## 3   rey scavenger  0.6836   0.2724
## 4  hank scientist      NA   1.4199
```

Reference

- A great "cheat sheet" for wrangling data with `dplyr` and `tidyr` is available for free at `https://www.rstudio.com/wp-content/uploads/2015/02/data-wrangling-cheatsheet.pdf`