Exploring data

Into the tidyverse

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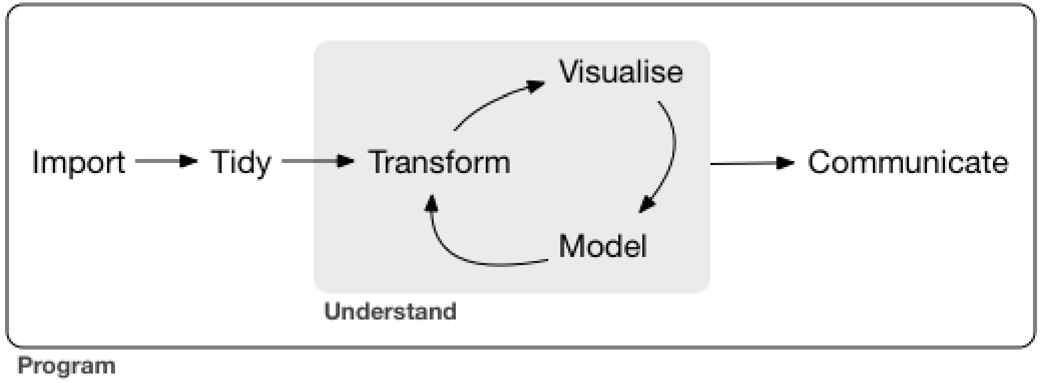
Data Science workflow

According to Hadley Wickham in R for Data Science:



First two weeks: data wrangling and visualization

Aspects of data **wrangling**:

- **import**: reading in data (e.g. `read_csv()`)
- **tidy**: rows = observations, columns = variables (i.e. **tabular** data)
- **transform**: filter observations, create new variables, summarize, etc.

What is Exploratory Data Analysis (EDA)?

(broadly speaking) EDA = questions about data + wrangling + visualization

R for Data Science: *"EDA is a state of mind"*, an iterative cycle:

- generate questions
- answer via transformations and visualizations

Example of questions?

- What type of **variation** do the variables display?
- What type of **relationships** exist between variables?

EDA is **NOT** a replacement for statistical inference and learning

EDA is an **important** and **necessary** step to build intuition

Now for an example...

Exploring MLB batting statistics

Import `Batting` table of historical MLB statistics from the `Lahman package`, explore using the `tidyverse`

```
library(tidyverse) # Load the tidyverse suite of packages
library(Lahman) # Load the Lahman package to access its datasets
Batting <- as_tibble(Batting) # Initialize the Batting dataset
```

Basic info about the `Batting` dataset:

```
dim(Batting) # displays same info as c(nrow(Batting), ncol(Batting))
```

```
## [1] 112184     22
```

```
class(Batting)
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

`tbl` (pronounced `tibble`) is the `tidyverse` way of storing tabular data, like a spreadsheet or `data.frame`

Always look at your data: view the first 6 (by default) rows with `head()`

```
head(Batting) # Try just typing Batting into your console, what happens?
```

```
## # A tibble: 6 × 22
##   playerID  yearID stint teamID lgID      G    AB     R     H   X2B   X3B    HR
##   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int> <int>
## 1 abercda01   1871     1 TRO    NA        1     4     0     0     0     0     0
## 2 addybo01    1871     1 RC1    NA       25   118    30    32     6     0     0
## 3 allisar01   1871     1 CL1    NA       29   137    28    40     4     5     0
## 4 allisdo01   1871     1 WS3    NA       27   133    28    44    10     2     2
## 5 ansonca01   1871     1 RC1    NA       25   120    29    39    11     3     0
## 6 armstbo01   1871     1 FW1    NA       12    49     9    11     2     1     0
## # ℹ 10 more variables: RBI <int>, SB <int>, CS <int>, BB <int>, SO <int>,
## #   IBB <int>, HBP <int>, SH <int>, SF <int>, GIDP <int>
```

Is our `Batting` dataset **tidy**?

- Each row = a player's season stint with a team (i.e. players can play for multiple teams in year)
- Each column = different measurement or recording about the player-team-season observation (can print out column names directly with `colnames(Batting)` or `names(Batting)`)

Can we explore how baseball has changed over time with `Batting`?

Let the data wrangling begin...

Summarize *continuous* (e.g. `yearID`, `AB`) and *categorical* (e.g. `teamID`, `lgID`) variables in different ways

Compute **summary statistics** for *continuous* variables with the `summary()` function:

```
summary(Batting$yearID)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##    1871    1938    1978    1969    2003    2022 
```

Compute **counts** of *categorical* variables with `table()` function:

```
table("Leagues" = Batting$lgID) # be careful it ignores NA values!
```

```
## Leagues
##    AA    AL    FL    NA    NL    PL    UA 
##  1893 51799   472   737 56800   149   334 
```

How do we remove the other leagues?

`dplyr` is a package within the `tidyverse` with functions for data wrangling

"Grammar of data manipulation": `dplyr` functions are **verbs**, datasets are **nouns**

- **We can `filter()` our dataset to choose observations meeting conditions**

```
mlb_batting <- filter(Batting, lgID %in% c("AL", "NL"))
nrow(Batting) - nrow(mlb_batting) # Difference in rows
```

```
## [1] 3585
```

- **We can `select()` variables of interest**

```
sel_batting <- select(Batting, yearID, lgID, G, AB, R, H, HR, BB, SO)
head(sel_batting, n = 3)
```

```
## # A tibble: 3 × 9
##   yearID lgID      G    AB     R     H    HR    BB    SO
##    <int> <fct> <int> <int> <int> <int> <int> <int> <int>
## 1   1871 NA        1     4     0     0     0     0     0
## 2   1871 NA       25   118    30    32     0     4     0
## 3   1871 NA       29   137    28    40     0     2     5
```

- **We can `arrange()` our dataset to sort observations by variables**

```r
hr_batting <- arrange(Batting, desc(HR)) # use desc() for descending order
head(hr_batting, n = 3)
```

```
## # A tibble: 3 × 22
##   playerID  yearID stint teamID lgID      G    AB     R     H   X2B   X3B    HR
##   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int> <int>
## 1 bondsba01   2001     1 SFN    NL      153   476   129   156    32     2    73
## 2 mcgwima01   1998     1 SLN    NL      155   509   130   152    21     0    70
## 3 sosasa01    1998     1 CHN    NL      159   643   134   198    20     0    66
## # ℹ 10 more variables: RBI <int>, SB <int>, CS <int>, BB <int>, SO <int>,
## #   IBB <int>, HBP <int>, SH <int>, SF <int>, GIDP <int>
```

- **We can `summarize()` our dataset to one row based on functions of variables**

```r
summarize(Batting, max(stint), median(AB))
```

```
## # A tibble: 1 × 2
##   `max(stint)` `median(AB)`
##          <int>        <dbl>
## 1            5           45
```

- **We can `mutate()` our dataset to create new variables** (mutate is a weird name...)

```
new_batting <- mutate(Batting, batting_avg = H / AB, so_to_bb = SO / BB)
head(new_batting, n = 1)
```

```
## # A tibble: 1 × 24
##   playerID  yearID stint teamID lgID      G    AB     R     H   X2B   X3B    HR
##   <chr>      <int> <int> <fct>  <fct> <int> <int> <int> <int> <int> <int> <int>
## 1 abercda01   1871     1 TRO    NA        1     4     0     0     0     0     0
## # ℹ 12 more variables: RBI <int>, SB <int>, CS <int>, BB <int>, SO <int>,
## #   IBB <int>, HBP <int>, SH <int>, SF <int>, GIDP <int>, batting_avg <dbl>,
## #   so_to_bb <dbl>
```

How do we perform several of these actions?

```
head(arrange(select(mutate(Batting, BA = H / AB), playerID, BA), desc(BA)), n = 1)
```

```
## # A tibble: 1 × 2
##   playerID    BA
##   <chr>    <dbl>
## 1 snowch01     1
```

That's awfully annoying to do, and also difficult to read...

Enter the pipeline

The `%>%` (*pipe*) operator is used in the `tidyverse` (from `magrittr`) to chain commands together

`%>%` directs the **data analyis pipeline**: output of one function pipes into input of the next function

```
Batting %>%
  filter(lgID %in% c("AL", "NL"),
         AB > 300) %>%
  mutate(batting_avg = H / AB) %>%
  arrange(desc(batting_avg)) %>%
  select(playerID, yearID, batting_avg) %>%
  head(n = 5)
```

```
## # A tibble: 5 × 3
##   playerID  yearID batting_avg
##   <chr>      <int>       <dbl>
## 1 duffyhu01   1894       0.440
## 2 barnero01   1876       0.429
## 3 lajoina01   1901       0.426
## 4 keelewi01   1897       0.424
## 5 hornsro01   1924       0.424
```

More pipeline actions!

Instead of `head()`, **we can `slice()` our dataset to choose the observations based on the position**

```
Batting %>%
  filter(lgID %in% c("AL", "NL"),
         AB > 300) %>%
  mutate(so_to_bb = SO / BB) %>%
  arrange(so_to_bb) %>%
  select(playerID, yearID, so_to_bb) %>%
  slice(c(1, 2, 10, 100))
```

```
## # A tibble: 4 × 3
##   playerID  yearID so_to_bb
##   <chr>      <int>    <dbl>
## 1 roweja01    1882   0
## 2 seweljo01   1932   0.0536
## 3 holloch01   1922   0.0862
## 4 collied01   1918   0.178
```

Grouped operations

We `group_by()` to split our dataset into groups based on a variable's values

```
Batting %>%
  filter(lgID %in% c("AL", "NL")) %>%
  group_by(yearID) %>%
  summarize(hr = sum(HR), so = sum(SO), bb = sum(BB)) %>%
  arrange(desc(hr)) %>%
  slice(1:5)
```

```
## # A tibble: 5 × 4
##   yearID    hr    so    bb
##    <int> <int> <int> <int>
## 1   2019  6776 42823 15895
## 2   2017  6105 40104 15829
## 3   2021  5944 42145 15794
## 4   2000  5693 31356 18237
## 5   2016  5610 38982 15088
```

`group_by()` is only useful in a pipeline (e.g. with `summarize()`), and pay attention to its behavior

`ungroup()` can solve your problems afterwards

Putting it all together...

We'll create a **tidy** dataset where each row = a year with the following variables:

- total HRs (homeruns), SOs (strikeouts), and BBs (walks)
- year's BA = total H / total AB
- only want AL and NL leagues

```
year_batting_summary <- Batting %>%
  filter(lgID %in% c("AL", "NL")) %>%
  group_by(yearID) %>%
  summarize(total_hits = sum(H, na.rm = TRUE),
            total_hrs = sum(HR, na.rm = TRUE),
            total_sos = sum(SO, na.rm = TRUE),
            total_walks = sum(BB, na.rm = TRUE),
            total_atbats = sum(AB, na.rm = TRUE)) %>%
  mutate(batting_avg = total_hits / total_atbats)
head(year_batting_summary, n = 2)
```

```
## # A tibble: 2 × 7
##   yearID total_hits total_hrs total_sos total_walks total_atbats batting_avg
##    <int>      <int>     <int>     <int>       <int>        <int>       <dbl>
## 1   1876       5338        40       589         336        20121       0.265
## 2   1877       3705        24       726         345        13667       0.271
```

Top three years with the most HRs?

```
year_batting_summary %>%
  arrange(desc(total_hrs)) %>%
  slice(1:3)
```

```
## # A tibble: 3 × 7
##   yearID total_hits total_hrs total_sos total_walks total_atbats batting_avg
##    <int>      <int>     <int>     <int>       <int>        <int>       <dbl>
## 1   2019      42039      6776     42823       15895       166651       0.252
## 2   2017      42215      6105     40104       15829       165567       0.255
## 3   2021      39484      5944     42145       15794       161941       0.244
```

Top three years with highest batting average?

```
year_batting_summary %>%
  arrange(desc(batting_avg)) %>%
  slice(1:3)
```

```
## # A tibble: 3 × 7
##   yearID total_hits total_hrs total_sos total_walks total_atbats batting_avg
##    <int>      <int>     <int>     <int>       <int>        <int>       <dbl>
## 1   1894      17809       629      3333        5870        57577       0.309
## 2   1895      16827       488      3621        5120        56788       0.296
## 3   1930      25597      1565      7934        7654        86571       0.296
```

Best and worst strikeout to walk ratios?

```r
year_batting_summary %>%
  mutate(so_to_bb = total_sos / total_walks) %>%
  arrange(so_to_bb) %>%
  slice(c(1, n()))
```

```
## # A tibble: 2 × 8
##   yearID total_hits total_hrs total_sos total_walks total_atbats batting_avg
##    <int>      <int>     <int>     <int>       <int>        <int>       <dbl>
## 1   1893      15913       460      3341        6143        56898       0.280
## 2   1879       6171        58      1843         508        24155       0.255
## # ℹ 1 more variable: so_to_bb <dbl>
```

We can make better looking tables... **`rename()` variables in our dataset**

```r
year_batting_summary %>%
  select(yearID, batting_avg) %>%
  rename(Year = yearID, `Batting AVG` = batting_avg) %>%
  slice(c(1, n()))
```

```
## # A tibble: 2 × 2
##    Year `Batting AVG`
##   <int>         <dbl>
## 1  1876         0.265
## 2  2022         0.243
```

Grammar of tables preview

We can go one step further - **and use the new `gt` package** to create a nice-looking table for presentation

```
library(gt)
year_batting_summary %>%
  select(yearID, batting_avg) %>%
  rename(Year = yearID,
         `Batting AVG` = batting_avg) %>%
  arrange(desc(`Batting AVG`)) %>%
  slice(c(1:3, (n()-2):n())) %>%
  gt() %>%
  tab_header(
    title = "Best / worst MLB Seasons by AVG"
    subtitle = "Top / bottom three are presen
  )
```

Best / worst MLB Seasons by AVG

Top / bottom three are presented

Year	Batting AVG
1894	0.3093075
1895	0.2963126
1930	0.2956764
1908	0.2389593
1888	0.2387601
1968	0.2366924

Note the `gt` display is different in these slides due to the `xaringan` package formatting

Enough with tables!

Data visualization

"The simple graph has brought more information to the data analyst's mind than any other device." — Tukey

- **TOMORROW**: the **grammar of graphics**
- Use `ggplot2` to visually explore our data
- More intuitive than base `R` plotting!
- Will walkthrough different types of visualizations for 1D, 2D, continuous, categorical, facetting, etc.
- `tidyverse` verbs and `%>%` leads to natural pipeline for EDA