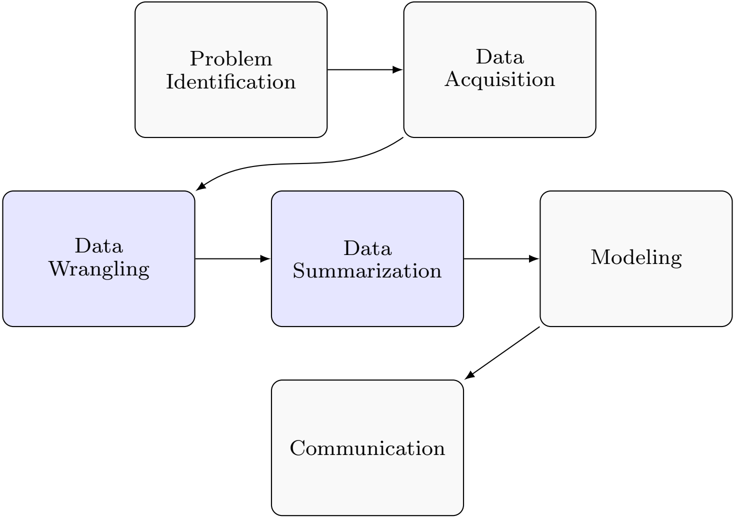
An Introduction to R with the Tidyverse

ART Forum 2019

Preamble

- This is *an* introduction to R.
- My goal is to get you doing as much in R as quickly as possible.
- Materials at github.com/marcdotson/introduction-to-r.

Data Analysis Process



R and Data Manipulation

Data Description and Visualization

Cleaning Data and Summarization

R/RStudio

R is an open-source programming language for statistical computing, data analysis, and data science.

cran.r-project.org

RStudio is an integrated development environment (IDE) that makes it easier to use R.

rstudio.com

Go to our shared RStudio Cloud project bit.ly/31qxlsJ.

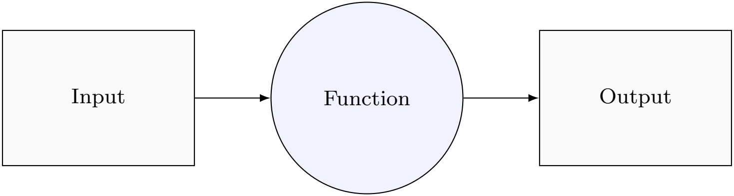
Orientation

- *Console:* Where you run code.
- *Source:* Create and save R scripts and send code to the Console.

```
# Use comments to explain (the why of) your code.
2 * (18 - 7)
```

- *Environment:* A snapshot of what you have loaded.
- *Help:* Look up documentation.

Functions



- Functions are composed of arguments that tell the function how to operate.
- Using a function is referred to as a "call" or a "function call."
- Don't forget you have *Help*.

Packages

- A package is a collection of functions, documentation, and sometimes data.
- There are a number of packages that are part of base R.
- You can install other packages from CRAN.
- Not all packages are created equal.

The Tidyverse

"The tidyverse is an opinionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures."

readr – importing data
dplyr – manipulating data
tidyr – cleaning data
ggplot2 – visualizing data

```
# Load the (already installed) tidyverse.
library(tidyverse)
```

Importing Data

- Let's import `store_data.csv`.

```
store_data <- read_csv("store_data.csv")
```

- Note that `store_data` now appears in our Environment. The Environment lists objects we've assigned a name in our script.
- You should always use an R Project to organize your work and set your working directory (where R looks for data to import).

Data Frames

- Data frames are the most common data structure in R.

  ```
  store_data
  ```

- What can we learn by printing `store_data`?

Data Manipulation

- The heart of data wrangling is data manipulation.
  - Filter observations.
  - Arrange observations.
  - Select variables.
  - Mutate variables (i.e., recode or create new variables).
  - Join data frames.
- One of the most-used packages, dplyr provides a consistent grammar of data manipulation with functions (a.k.a., verbs) that mirror SQL.

The Pipe

- Part of the common philosophy for the tidyverse is that:
  1. Each function should do one specific thing well.
  2. Each function should have a data frame as an input and a data frame as an output.
- This allows us to to `%>%` together functions in consecutive lines of code so that it is easy for humans to read.

Filter Observations

- We often want to filter our data by keeping certain observations.

```
store_data %>%
  filter(gender == "Female")

store_data %>%
  filter(store_spend > 100)
```

- How would we filter by `gender == "Female"` and `store_spend > 100`?
- Why are we putting quotes around `"Female"` but not `gender`?

Arrange Observations

- Arrange observations to reveal helpful information and check data.

```
store_data %>%
  arrange(store_trans)

store_data %>%
  arrange(desc(store_trans))
```

Select Variables

- Sometimes we only care about keeping certain variables, especially when working with a large dataset.

```
store_data %>%
  select(store_spend, age, gender)
```

Mutate Variables

- We can also recode existing variables or create new variables.

```
store_data %>%
  mutate(store_spend = store_spend / 100)
```

- Note how we can overwrite variables in a data frame as well as objects if we use the same name.

Join Data Frames

- In the simplest case, a common variable (like an ID) allows us to join two data frames.

```
sat_data <- read_csv("sat_data.csv")

crm_data <- store_data %>%
  left_join(sat_data, by = "id")
```

- Print `crm_data`.
- Other common joins include:
  - `inner_join` to keep everything that has a matching common variable in both the left and right data frames.
  - `anti_join` to keep everything that *doesn't* have a matching common variable in both the left and right data frames.

Exercise

In *consecutive lines of code*, do the following.

1. Join `store_data`, `sat_data`, and `online_data` `by = "id"`.
2. Filter the data to keep only observations in the `"US"`.
3. Select `id`, `store_spend`, `online_spend`, and `gender`.
4. Create `total_spend = store_spend + online_spend`.
5. Find who has the highest `total_spend`.
6. Practice reading this code (read `%>%` as "then").

R and Data Manipulation

Data Description and Visualization

Cleaning Data and Summarization

Data Summarization

- Data summarization includes the following.
  - Describing data with numerical summaries (i.e., statistics).
  - Visualizing data with graphical summaries.
- How we summarize depends on the whether the data is discrete or continuous.
  - Discrete is also called qualitative or categorical.
  - Continuous is also called quantitative or numerical.
- We will use both dplyr and ggplot2 to summarize data.

Describing Discrete Data

- The simplest numeric summary for a discrete variable is a count.

```
crm_data %>%
  count(gender)
```

- Now get a count by both gender and country to produce a "tidy" cross-tab.

Visualizing Discrete Data

- Perhaps the most popular package, ggplot2 uses a consistent grammar of graphics built with layers.
  1. Data – Data to visualize.
  2. Aesthetics – Mapping graphical elements to data.
  3. Geometries – Or “geom,” the graphic representing the data.
- Let’s plot our previous summary (note how `+` is different from `%>%`).

```
ggplot(crm_data, aes(x = gender)) +
  geom_bar()
```

  - Let’s visualize a second variable. Add the aesthetic `fill = country`.
  - The geom `position` argument is set to `"stack"` by default. Try `"fill"` instead.

Describing Continuous Data

- The simplest numeric summary for a continuous variable is a mean.

```
crm_data %>%
  summarize(avg_store_spend = mean(store_spend))
```

- Note that `summarize()` is a more general version of `count()`.
- Compute the mean of both `store_spend` and `sat_overall`.
- We can also compute the mode, median, variance, standard deviation, minimum, maximum, etc.

Visualizing Continuous Data

- Let's plot the distribution of `store_spend`.

```
ggplot(crm_data, aes(x = store_spend)) +
  geom_histogram()
```

- Change the geom `bins` argument to `10`.
- Visualize the relationship between `store_spend` and `sat_overall`.

```
crm_data %>%
  ggplot(aes(x = store_spend, y = sat_overall)) +
  geom_point()
```

- As part of the aesthetic, `log(store_spend + 1)`.
- Play with the `size` and `alpha` geom arguments.
- Add a `geom_smooth()` layer.

Describing Discrete and Continuous Data

- Grouped summaries provide a powerful solution for describing a combination of discrete and continuous data.

```
crm_data %>%
  group_by(gender, country) %>%
  summarize(
    n = n(),
    avg_store_spend = mean(store_spend),
    avg_sat_overall = mean(sat_overall)
  ) %>%
  arrange(desc(avg_store_spend))
```

- Grouping by a discrete variable is equivalent to filtering the data separately for each value of the group variable.
- `count()` is a wrapper around a grouped summary with `n()`.

Visualizing Discrete and Continuous Data

- There are geoms specific to visualizing the relationship between discrete and continuous data.
- Use `geom_boxplot()` and `geom_density()` to visualize the relationship between `gender` and `sat_overall`.

Adding Layers

- There are numerous options to quickly create impressive visuals.

```
crm_data %>%
  ggplot(
    aes(
      x = log(store_spend + 1),
      y = sat_overall,
      color = gender
    )
  ) +
  geom_jitter(size = 2, alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE) +
  facet_wrap(~ country) +
  ggtitle("Store Spend by Overall Satisfaction")
```

Exercise

In *consecutive lines of code*, do the following.

1. Join `store_data`, `sat_data`, and `online_data` `by = "id"`.
2. Filter the data to keep only observations in the `"CA"`.
3. Create `total_spend = store_spend + online_spend`.
4. Assign this final data frame to `ca_crm_data`.

Use `ca_crm_data` to explore the following questions.

1. How many men and women are there?
2. Is there a relationship between `credit_score` and `sat_overall`?
3. What is the average `total_spend` by `gender`?
4. Is the relationships between `total_spend` and `sat_overall` different for men and women?

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Tidy Data

- Tidy data is defined as follows:
  1. Each observation has its own row.
  2. Each variable has its own column.
  3. Each value has its own cell.
- Fourth (sort of), each table has one type of observational unit.
- This may seem obvious or simple, but this common philosophy is at the heart of the *tidy*verse.
- It also means we will often prefer long datasets to wide datasets.

Gather Columns

- The most common problem with messy data is when columns are really values. Where is this problem in `online_data`?
- Use tidyr to `gather()` the columns into key-value variable pairs.

```
online_data <- online_data %>%
  gather(
    key = week,
    value = visits,
    week1_visit:week4_visit
  )
```

- Note how this makes a wide dataset long (or at least long*er*) by iteratively transposing and stacking data.

Spread Columns

- If the data has the opposite problem (i.e., values that should really be columns), `spread()` key-value pairs into columns.

```
online_data %>%
  spread(key = week, value = visits)
```

Separate and Unite Columns

- If two (or more) values are in one column, `separate()` the values into two (or more) columns.

  ```
  online_data <- online_data %>%
    separate(year_mo, c("year", "month"))
  ```

- When two (or more) values should be in one column, `unite()` the values into one column.

  ```
  online_data %>%
    unite(year_mo, year, month)
  ```

Wrangling ↔ Summarization

- Tidy data changes how we can summarize.

```
online_data %>%
  group_by(id) %>%
  summarize(total_visits = sum(visits)) %>%
  left_join(sat_data, by = "id")
```

- Continue the consecutive lines of code to visualize the relationship between `total_visits` and `sat_overall` by `country`.
- What's the difference between assigning `color` as an aesthetic at the ggplot vs. the geom layer?

Inspecting Data

- What is the data structure for `online_data`?
- What about the data structure for `faithful`?
- How do we inspect data (whether or not its a tibble)?

```
str(faithful)
summary(faithful)
class(faithful)
dim(faithful)
names(faithful)
head(faithful)
tail(faithful)
```

- We could also coerce data into a tibble: `as_tibble(faithful)`.

Data Types and Coercion

- We can also coerce data types.
  - Numeric (i.e., double) with `as.numeric()`
  - Integer with `as.integer()`
  - Character with `as.character()`
  - Factor with `as.factor()`
- Why would we want to coerce a data type?

```
online_data %>%
  filter(visits > 700) %>%
  ggplot(aes(x = id, y = visits)) +
  geom_col()
```

- The `x` in a bar/column plot needs to be discrete. Coerce `id` to be a factor and try the plot again.

Missing Values

- Missing values are (and should be) encoded as `NA`.
- `NA` is treated in a particular way.

```
online_data %>%
  group_by(year) %>%
  summarize(avg_visits = mean(visits))
```

- Add the argument `na.rm = TRUE` to the `mean()` function.
- Because `NA` is a special character, it can be referenced.

```
online_data2 <- online_data %>%
  filter(visits != is.na(visits))

unique(online_data2$visits)
```

Exercise

In *consecutive lines of code*, do the following.

1. Using the latest `online_data`, separate `week` into two variables.
2. Use `select()` to get rid of the variable with "visit" repeated.
3. Group by `id` and compute the `total_visits`.
4. Join this `online_data` with `store_data` and `sat_data`.
5. Overwrite `crm_data` with this final data frame.

Use the new `crm_data` to explore the following questions.

1. Visualize the average `total_visits` by `country` and `gender`. Which group has the highest average `total_visits`?
2. What's the relationship between `total_visits` and `store_spend`? Is this different for each `country`?

Epilogue

- The tidyverse represents the state of the art for data wrangling and summarization in R and serves as the foundation for a growing number of additional packages (e.g., tidytext).
- *R for Data Science* r4ds.had.co.nz
- DataCamp datacamp.com
- Cheatsheets rstudio.com/resources/cheatsheets
- The tidyverse tidyverse.org
- Watch Hadley Wickham explain

Advanced Topics

- Iteration r4ds.had.co.nz/iteration.html
- List Columns adv-r.had.co.nz
- Database Queries tidyverse.org/articles
- Tidymodels tidyverse.org/articles
- *Advanced R* adv-r.had.co.nz