Data Transformation

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Introduction to Data Transformation

In order to visualize and (later) model data, we typically need to perform data transformation.

- Subset data by rows (observations) or columns (variables)
- Reorder the rows or columns of the data
- Calculate new variables from existing variables
- Calculate summary statistics of variables

One or more of these steps are often necessary to appropriately visualize or model a dataset.

Introduction to Data Transformation (cont'd)

This week, we will discuss data transformations on **tidy** data. That is, data that is already in a form where:

- Each variable has its own column
- Each observation has its own row
- Each value has its own cell

Next week, we will discuss more on tidy data and how to perform the data wrangling necessary to clean up *un*tidy data and turn it into tidy data.

`dplyr`: A grammar of data manipulation

Provides a powerful, flexible “grammar” of data manopulation.

- Identify the most important data manipulation verbs and make them easy to use from R
- Provide fast performance for in-memory data with under-the-hood C++ implementation
- Use the same interface whether the data is stored in-memory or in a database on disk

Part of the “tidyverse” with `ggplot2` and others.

Why use `dplyr`?

The `dplyr` package (mostly) doesn't implement any functionality that is missing or impossible to perform in base R.

However, code written with `dplyr`:

- Can be more expressive, concise, and human-readable
- Can be more explicit in your intentions for data manipulation
- Can be faster (sometimes) due to C++ implementation
- Can also be used with databases on disk
- Integrates with other `tidyverse` functions and packages

I will also show you how to perform the same functionality using base R.

Review of subsetting `data.frames` in R

- Simplifying (returns a vector)
  - Access individual columns using `df$name`
  - Access individual columns using `df[["name"]]`
- Preserving (returns a `data.frame`)
  - Subset rows using `df[i,]`
  - Subset rows using `df[c("name1", "name2")",]`
  - Subset columns using `df[,j]`
  - Subset columns using `df[,c("name1", "name2")]`
- You can subset both rows and columns at the same time
- Subsetting by a single column is always simplifying for `data.frames`
  - Change this behavior with `drop = FALSE`

```r
df <- data.frame(x=c(1L, 2L, 5L, 9L),
                 y=c('a', 'b', 'c', 'd'),
                 `z !`=c(1.11, 2.22, 3.33, 4.0),
                 row.names=c("Jo", "Ha", "Q", "Final"),
                 check.names=FALSE,
                 stringsAsFactors=FALSE)
df
```

```
##       x y  z !
## Jo    1 a 1.11
## Ha    2 b 2.22
## Q     5 c 3.33
## Final 9 d 4.00
```

```r
df$x
```

```
## [1] 1 2 5 9
```

```r
df[["y"]]
```

```
## [1] "a" "b" "c" "d"
```

```r
df$`z !`
```

```
## [1] 1.11 2.22 3.33 4.00
```

```r
df[["z !"]]
```

```
## [1] 1.11 2.22 3.33 4.00
```

```r
df[1:3,]
```

```
##    x y    z !
## Jo 1 a 1.11
## Ha 2 b 2.22
## Q  5 c 3.33
```

```r
df[c("Jo", "Ha", "Q"),]
```

```
##    x y    z !
## Jo 1 a 1.11
## Ha 2 b 2.22
## Q  5 c 3.33
```

```r
df[,2:3]
```

```
##       y  z !
## Jo    a 1.11
## Ha    b 2.22
## Q     c 3.33
## Final d 4.00
```

```r
df[,c("y","z !")]
```

```
##       y  z !
## Jo    a 1.11
## Ha    b 2.22
## Q     c 3.33
## Final d 4.00
```

```r
df[,"z !"]
```

```
## [1] 1.11 2.22 3.33 4.00
```

```r
df[,"z !",drop=FALSE]
```

```
##         z !
## Jo     1.11
## Ha     2.22
## Q      3.33
## Final 4.00
```

```r
df[1:3, c("y", "z !")]
```

```
##    y  z !
## Jo a 1.11
## Ha b 2.22
## Q  c 3.33
```

Verbs in `dplyr`

Provides most commonly used data manipulation actions.

- `filter()` subsets data by rows/observations
- `arrange()` reorders data by rows/observations
- `select()` subsets data by columns/variables
- `mutate()` creates new columns/variables
- `summarise()` calculates summary statistics

Each can be applied over levels of a categorical variable with `group_by()`.

Each takes a `data.frame` as the first argument and outputs a new `data.frame`.

Loading dplyr

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

Name masking and namespaces in R

Several functions are "masked" when `dplyr` is loaded.

They can still be accessed by fully qualifying their names:

- `stats::filter()`
- `stats::lag()`

Name masking and namespaces in R (cont'd)

Each package in R creates its own namespace.

R finds functions based on the order packages are loaded.

You can see this search path with `search()`:

```r
search()
```

```
##  [1] ".GlobalEnv"        "package:dplyr"     "package:stats"
##  [4] "package:graphics"  "package:grDevices" "package:utils"
##  [7] "package:datasets"  "package:methods"   "Autoloads"
## [10] "package:base"
```

Name masking and namespaces in R (cont'd)

When name conflicts occur, a warning about masked names is given.

You can always use `package::function()` to find the right one.

Example dataset

Today we will explore the `flights` dataset also used in the homework and the **R4DS** book.

```
library(nycflights13)
flights
```

Note that `flights` is actually a `tibble`, which is simply a special type of `data.frame`.

I will use `data.frame` to refer to both interchangeably. We will discuss the differents in more depth later in the course.

Subsetting rows with `filter()`

Get only flights from October.

In base R:

```
flights[flights$month == 10,]
```

In `dplyr`:

```
filter(flights, month == 10)
```

```r
filter(flights, month == 10)
```

```
## # A tibble: 28,889 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013    10     1      447            500       -13      614
##  2  2013    10     1      522            517         5      735
##  3  2013    10     1      536            545        -9      809
##  4  2013    10     1      539            545        -6      801
##  5  2013    10     1      539            545        -6      917
##  6  2013    10     1      544            550        -6      912
##  7  2013    10     1      549            600       -11      653
##  8  2013    10     1      550            600       -10      648
##  9  2013    10     1      550            600       -10      649
## 10  2013    10     1      551            600        -9      727
## # ... with 28,879 more rows, and 12 more variables: sched_arr_time <
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Why flights$month vs month?

Like ggplot2, dplyr uses non-standard evaluation to facilitate ease of interactive programming.

In base R:

```
flights[flights$month == 10,]
```

In dplyr:

```
filter(flights, month == 10)
```

This approach is useful for interactive data analysis, but can cause problems when used within user-defined functions.

We may discuss more on non-standard evaluation later in the course if there is interest.

Anatomy of `filter()`

```
filter(data, condition1, condition2, condition3, ...)
```

- The first argument is the data
- The following arguments are vectorized logical expressions
- Additional arguments are joined by `&` (AND)
- Rows that evaluate to `TRUE` are kept
- Rows that evluate to `FALSE` or `NA` are dropped

Review of logical operators in R

- Standard comparison operators: `==`, `!=`, `>`, `<`, `>=`, `<=`.
  - Remember to use == instead of = when doing comparisons
- `dplyr::near()` for checking floating point equality
- `dplyr::between()` is a synonym for `a <= x & x <= b`
- `&`, `|`, and `!` are vectorized AND, OR, and NOT
  - Non-vectorized versions (for `if` statements) are `&&` and `||`
- `%in%` checks if an element exists in a set
  - E.g., `x %in% c(a,b)` is equivalent to `x == a | x == b`
- `is.na` to check for missing values
  - Remember that `NA == NA` evaluates to `NA`

Get only flights from Alaska Airlines or Hawaiian Airlines.

In base R:

```r
flights[flights$carrier %in% c("AS", "HA"),]
```

In `dplyr`:

```r
filter(flights, carrier %in% c("AS", "HA"))
```

```r
filter(flights, carrier %in% c("AS", "HA"))
```

```
## # A tibble: 1,056 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      724            725        -1     1020
##  2  2013     1     1      857            900        -3     1516
##  3  2013     1     1     1808           1815        -7     2111
##  4  2013     1     2      722            725        -3      949
##  5  2013     1     2      909            900         9     1525
##  6  2013     1     2     1818           1815         3     2131
##  7  2013     1     3      724            725        -1     1012
##  8  2013     1     3      914            900        14     1504
##  9  2013     1     3     1817           1815         2     2121
## 10  2013     1     4      725            725         0     1031
## # ... with 1,046 more rows, and 12 more variables: sched_arr_time <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Get only flights from Alaska Airlines or Hawaiian Airlines.

In base R:

```r
flights[flights$carrier == "AS" | flights$carrier == "HA",]
```

In `dplyr`:

```r
filter(flights, carrier == "AS" | carrier == "HA")
```

```r
filter(flights, carrier == "AS" | carrier == "HA")
```

```
## # A tibble: 1,056 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      724            725        -1     1020
##  2  2013     1     1      857            900        -3     1516
##  3  2013     1     1     1808           1815        -7     2111
##  4  2013     1     2      722            725        -3      949
##  5  2013     1     2      909            900         9     1525
##  6  2013     1     2     1818           1815         3     2131
##  7  2013     1     3      724            725        -1     1012
##  8  2013     1     3      914            900        14     1504
##  9  2013     1     3     1817           1815         2     2121
## 10  2013     1     4      725            725         0     1031
## # ... with 1,046 more rows, and 12 more variables: sched_arr_time <i
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Get only flights between Honolulu and JFK.

In base R:

```r
flights[flights$origin == "JFK" & flights$dest == "HNL",]
```

In `dplyr`:

```r
filter(flights, origin == "JFK" & dest == "HNL")
```

```r
filter(flights, origin == "JFK" & dest == "HNL")
```

```
## # A tibble: 342 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      857            900        -3     1516
##  2  2013     1     2      909            900         9     1525
##  3  2013     1     3      914            900        14     1504
##  4  2013     1     4      900            900         0     1516
##  5  2013     1     5      858            900        -2     1519
##  6  2013     1     6     1019            900        79     1558
##  7  2013     1     7     1042            900       102     1620
##  8  2013     1     8      901            900         1     1504
##  9  2013     1     9      641            900      1301     1242
## 10  2013     1    10      859            900        -1     1449
## # ... with 332 more rows, and 12 more variables: sched_arr_time <int
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Get only flights between Honolulu and JFK.

In base R:

```
flights[flights$origin == "JFK" & flights$dest == "HNL",]
```

In `dplyr`:

```
filter(flights, origin == "JFK", dest == "HNL")
```

```r
filter(flights, origin == "JFK", dest == "HNL")
```

```
## # A tibble: 342 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      857            900        -3     1516
##  2  2013     1     2      909            900         9     1525
##  3  2013     1     3      914            900        14     1504
##  4  2013     1     4      900            900         0     1516
##  5  2013     1     5      858            900        -2     1519
##  6  2013     1     6     1019            900        79     1558
##  7  2013     1     7     1042            900       102     1620
##  8  2013     1     8      901            900         1     1504
##  9  2013     1     9      641            900      1301     1242
## 10  2013     1    10      859            900        -1     1449
## # ... with 332 more rows, and 12 more variables: sched_arr_time <int
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Reordering rows with `arrange()`

Sort by flights that departed with least delay (most ahead of schedule):

In base R:

```
flights[order(flights$dep_delay),]
```

In `dplyr`:

```
arrange(flights, dep_delay)
```

```r
arrange(flights, dep_delay)
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013    12     7     2040           2123       -43       40
##  2  2013     2     3     2022           2055       -33     2240
##  3  2013    11    10     1408           1440       -32     1549
##  4  2013     1    11     1900           1930       -30     2233
##  5  2013     1    29     1703           1730       -27     1947
##  6  2013     8     9      729            755       -26     1002
##  7  2013    10    23     1907           1932       -25     2143
##  8  2013     3    30     2030           2055       -25     2213
##  9  2013     3     2     1431           1455       -24     1601
## 10  2013     5     5      934            958       -24     1225
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Use `desc()` to sort by a variable in descending order

Sort by flights that departed with most delay:

In base R:

```
flights[order(flights$dep_delay, decreasing=TRUE),]
```

In `dplyr`:

```
arrange(flights, desc(dep_delay))
```

```r
arrange(flights, desc(dep_delay))
```

```
## # A tibble: 336,776 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     9      641            900      1301     1242
##  2  2013     6    15     1432           1935      1137     1607
##  3  2013     1    10     1121           1635      1126     1239
##  4  2013     9    20     1139           1845      1014     1457
##  5  2013     7    22      845           1600      1005     1044
##  6  2013     4    10     1100           1900       960     1342
##  7  2013     3    17     2321            810       911      135
##  8  2013     6    27      959           1900       899     1236
##  9  2013     7    22     2257            759       898      121
## 10  2013    12     5      756           1700       896     1058
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

Subsetting columns with select()

Keep only date and delay columns.

In base R:

```
flights[,c("year","month","day","dep_delay","arr_delay")]
```

In dplyr:

```
select(flights, year, month, day, dep_delay, arr_delay)
```

```r
select(flights, year, month, day, dep_delay, arr_delay)
```

```
## # A tibble: 336,776 x 5
##     year month   day dep_delay arr_delay
##    <int> <int> <int>     <dbl>     <dbl>
##  1  2013     1     1         2        11
##  2  2013     1     1         4        20
##  3  2013     1     1         2        33
##  4  2013     1     1        -1       -18
##  5  2013     1     1        -6       -25
##  6  2013     1     1        -4        12
##  7  2013     1     1        -5        19
##  8  2013     1     1        -3       -14
##  9  2013     1     1        -3        -8
## 10  2013     1     1        -2         8
## # ... with 336,766 more rows
```

Keep first 9 columns (`year` through `arr_delay`).

In base R:

```
flights[,1:9]
```

In `dplyr`:

```
select(flights, 1:9)
```

Keep first 9 columns (`year` through `arr_delay`) by name.

In base R:

```
flights[,which(names(flights)=="year"):
          which(names(flights)=="arr_delay")]
```

In `dplyr`:

```
select(flights, year:arr_delay)
```

```r
select(flights, year:arr_delay)
```

```
## # A tibble: 336,776 x 9
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 336,766 more rows, and 2 more variables: sched_arr_time <
## #   arr_delay <dbl>
```

Keep all columns except tail number and flight number.

In base R:

```
flights[,-c(which(names(flights)=="tailnum"),
            which(names(flights)=="flight"))]
```

In `dplyr`:

```
select(flights, -tailnum, -flight)
```

```r
select(flights, -tailnum, -flight)
```

```
## # A tibble: 336,776 x 17
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 336,766 more rows, and 10 more variables: sched_arr_time
## #   arr_delay <dbl>, carrier <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dttm>
```

Useful functions for selecting column/variable names

- `dplyr::starts_with("arr")`
  - matches column names that begin with "arr"
- `dplyr::ends_with("time")`
  - matches column names that end with "time"
- `dplyr::contains("dep")`
  - matches column names that contain "dep"
- `dplyr::num_range("x", 1:3)`
  - matches "x1", "x2", and "x3"

Keep only columns starting with “arr”.

In base R:

```
flights[,substr(names(flights), 1, 3) == "arr"]
```

In `dplyr`:

```
select(flights, starts_with("arr"))
```

```r
select(flights, starts_with("arr"))
```

```
## # A tibble: 336,776 x 2
##    arr_time arr_delay
##       <int>     <dbl>
##  1      830        11
##  2      850        20
##  3      923        33
##  4     1004       -18
##  5      812       -25
##  6      740        12
##  7      913        19
##  8      709       -14
##  9      838        -8
## 10      753         8
## # ... with 336,766 more rows
```

Rename columns with rename()

rename() is a variant of select() that keeps all variables/columns while renaming the specified ones.

```
flights2 <- flights
names(flights2)[names(flights2)=="year" |
                  names(flights2)=="month" |
                  names(flights2)=="day"] <- c("YEAR","MONTH","DAY")
```

```
rename(flights, YEAR=year, MONTH=month, DAY=day)
```

```r
rename(flights, YEAR=year, MONTH=month, DAY=day)
```

```
## # A tibble: 336,776 x 19
##     YEAR MONTH   DAY dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 336,766 more rows, and 12 more variables: sched_arr_time
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>
```

New variables with `mutate()`

Create a new variable giving the average air speed (in mph) of each flight.

In base R:

```
flights2 <- flights
flights2$speed <- flights2$distance / flights2$air_time * 60
```

In `dplyr`:

```
mutate(flights, speed = distance / air_time * 60)
```

```r
mutate(flights, speed = distance / air_time * 60)
```

```
## # A tibble: 336,776 x 20
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 336,766 more rows, and 13 more variables: sched_arr_time
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>, speed <dbl>
```

Create two new variables giving (1) the average air speed (in mph) of each flight and (2) the amount of time gained in the air.

In base R:

```
flights2 <- flights
flights2$speed <- flights2$distance / flights2$air_time * 60
flights2$gain <- flights2$arr_delay - flights2$dep_delay
```

In `dplyr`:

```
mutate(flights,
       speed = distance / air_time * 60,
       gain = arr_delay - dep_delay)
```

```r
mutate(flights,
       speed = distance / air_time * 60,
       gain = arr_delay - dep_delay)
```

```
## # A tibble: 336,776 x 21
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      533            529         4      850
##  3  2013     1     1      542            540         2      923
##  4  2013     1     1      544            545        -1     1004
##  5  2013     1     1      554            600        -6      812
##  6  2013     1     1      554            558        -4      740
##  7  2013     1     1      555            600        -5      913
##  8  2013     1     1      557            600        -3      709
##  9  2013     1     1      557            600        -3      838
## 10  2013     1     1      558            600        -2      753
## # ... with 336,766 more rows, and 14 more variables: sched_arr_time
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <
## #   minute <dbl>, time_hour <dttm>, speed <dbl>, gain <dbl>
```

Anatomy of `mutate()`

```
mutate(data, var1 = expr1, var2 = expr2, ...)
```

- The first argument is the data
- The following arguments are named vectorized expressions that output a vector of the same length
- When used with `data.frames`, you can use variables created in the same `mutate()` call in the subsequent expressions

Useful functions for creating variables

- Arithmetic such as `+`, `-`, `*`, `/`, `^`, etc.
  - These are vectorized and will recycle shorter variables
- Modular arithmetic such as `%%` and `%/%`
  - Useful for breaking apart integers (e.g., time into hours + minutes)
- Logs such as `log()`, `log2()` and `log10`
  - Useful for data with multiplicative variance
- Offsets such as `dplyr::lead()` and `dplyr::lag()`
  - Useful for running differences and data over time points
- Cumulative summaries such as `cumsum()`, `cumprod()`, `cummax()`, and `cummin()`
  - Also `dplyr::cummean()` for running means
- Logical operators such as '`==`, `!=`, `>`, `<`, `>=`, `<=`, etc.
  - Useful for turning continuous variables into categorical
- `dplyr::n()` gives the number of observations
  - `n()` can only be used inside `mutate()`, `filter()` and `summarise()`

New variables with `transmute()`

`transmute()` is a variant of `mutate()` that keeps only the new variables and drops the rest.

In base R:

```
data.frame(distance = flights$distance,
           speed = flights$distance / flights$air_time * 60,
           gain = flights$arr_delay - flights$dep_delay,
           gain_per_mile = (flights$arr_delay - flights$dep_delay) /
             flights$distance)
```

In `dplyr`:

```
transmute(flights,
          distance = distance,
          speed = distance / air_time * 60,
          gain = arr_delay - dep_delay,
          gain_per_mile = gain / distance)
```

```r
transmute(flights,
          distance = distance,
          speed = distance / air_time * 60,
          gain = arr_delay - dep_delay,
          gain_per_mile = gain / distance)
```

```
## # A tibble: 336,776 x 4
##    distance speed  gain gain_per_mile
##       <dbl> <dbl> <dbl>         <dbl>
##  1     1400  370.     9       0.00643
##  2     1416  374.    16       0.0113
##  3     1089  408.    31       0.0285
##  4     1576  517.   -17      -0.0108
##  5      762  394.   -19      -0.0249
##  6      719  288.    16       0.0223
##  7     1065  404.    24       0.0225
##  8      229  259.   -11      -0.0480
##  9      944  405.    -5      -0.00530
## 10      733  319.    10       0.0136
## # ... with 336,766 more rows
```

Summary statistics with summarise()

Get the mean departure and arrival delay.

In base R:

```
data.frame(mean_dep_delay = mean(flights$dep_delay,
                                  na.rm=TRUE),
           mean_arr_delay = mean(flights$arr_delay,
                                  na.rm=TRUE))
```

In dplyr:

```
summarise(flights,
          mean_dep_delay = mean(dep_delay, na.rm=TRUE),
          mean_arr_delay = mean(arr_delay, na.rm=TRUE))
```

```r
summarise(flights,
          mean_dep_delay = mean(dep_delay, na.rm=TRUE),
          mean_arr_delay = mean(arr_delay, na.rm=TRUE))
```

```
## # A tibble: 1 x 2
##   mean_dep_delay mean_arr_delay
##            <dbl>          <dbl>
## 1           12.6           6.90
```

Anatomy of `summarise()`

```
summarise(data, summary1 = expr1, summary2 = expr2, ...)
```

- The first argument is the data
- The following arguments are expressions that output a single value from a vector of values
- It is particularly important to consider missing values when summarizing data
- Also available as `summarize()`

Useful functions for calculating summary statistics

- Measures of location such as `mean()` and `median()`
- Measures of spread such as `sd()`, `var()`, `IQR()`, and `mad()`
- Measures of rank such as `min()`, `max()`, and `quantile()`
- Counts such as:
  - `dplyr::n()` gives the number of observations
  - `sum(!is.na(x))` gives the number of non-missing values
  - `dplyr::n_distinct()` gives the number of unique values
- Remember that `sum(x == 10)` gives the count of `x == 10`
  - What does `mean(x == 10)` calculate?

Calculate the proportion of flights delayed more than 2 hours on arrival.

```
summarise(flights, mean(arr_delay > 120, na.rm=TRUE))
```

Calculate the number of unique airline carriers.

```
summarise(flights, n_distinct(carrier))
```

Calculate the proportion of flights with missing air times.

```
summarise(flights, sum(is.na(air_time)) / n())
```

```r
summarise(flights, mean(arr_delay > 120, na.rm=TRUE))
```

```
## # A tibble: 1 x 1
##   `mean(arr_delay > 120, na.rm = TRUE)`
##                                    <dbl>
## 1                                 0.0307
```

```r
summarise(flights, n_distinct(carrier))
```

```
## # A tibble: 1 x 1
##   `n_distinct(carrier)`
##                   <int>
## 1                    16
```

```r
summarise(flights, sum(is.na(air_time)) / n())
```

```
## # A tibble: 1 x 1
##   `sum(is.na(air_time))/n()`
##                        <dbl>
## 1                     0.0280
```

Grouped transformations with `group_by()`

`summarise()` and the other data manipulation verbs in `dplyr` become much more powerful when paired with `group_by()`.

Count the number of flights from each carrier.

```
summarise(group_by(flights, carrier), n())
```

Calculate the average arrival delay for each carrier.

```
summarise(group_by(flights, carrier),
          mean(arr_delay, na.rm=TRUE))
```

You can group by multiple variables.

Use `ungroup()` to ungroup a grouped dataset.

```r
summarise(group_by(flights, carrier),
          mean(arr_delay, na.rm=TRUE))
```

```
## # A tibble: 16 x 2
##    carrier `mean(arr_delay, na.rm = TRUE)`
##    <chr>                             <dbl>
##  1 9E                                7.38
##  2 AA                                0.364
##  3 AS                               -9.93
##  4 B6                                9.46
##  5 DL                                1.64
##  6 EV                               15.8
##  7 F9                               21.9
##  8 FL                               20.1
##  9 HA                               -6.92
## 10 MQ                               10.8
## 11 OO                               11.9
## 12 UA                                3.56
## 13 US                                2.13
## 14 VX                                1.76
## 15 WN                                9.65
## 16 YV                               15.6
```

Piping with the pipe operator

Combining multiple `dplyr` verbs becomes much more expressive when used with the pipe operator %>%.

The pipe operator takes the return value of the expression on the LHS and turns it into the first argument of the function on the RHS.

```
foo(bar(baz(x)))
```

is the same as

```
baz(x) %>% bar() %>% foo()
```

is the same as

```
x %>% baz() %>% bar() %>% foo()
```

Piping with the pipe operator (cont'd)

```
summarise(group_by(flights, carrier),
          mean(arr_delay, na.rm=TRUE))
```

becomes

```
group_by(flights, carrier) %>%
          summarise(mean(arr_delay, na.rm=TRUE))
```

or

```
flights %>%
  group_by(carrier) %>%
  summarise(mean(arr_delay, na.rm=TRUE))
```

```r
flights %>%
  group_by(carrier) %>%
  summarise(mean(arr_delay, na.rm=TRUE))
```

```
## # A tibble: 16 x 2
##    carrier `mean(arr_delay, na.rm = TRUE)`
##    <chr>                             <dbl>
##  1 9E                                7.38
##  2 AA                                0.364
##  3 AS                               -9.93
##  4 B6                                9.46
##  5 DL                                1.64
##  6 EV                               15.8
##  7 F9                               21.9
##  8 FL                               20.1
##  9 HA                               -6.92
## 10 MQ                               10.8
## 11 OO                               11.9
## 12 UA                                3.56
## 13 US                                2.13
## 14 VX                                1.76
## 15 WN                                9.65
## 16 YV                               15.6
```

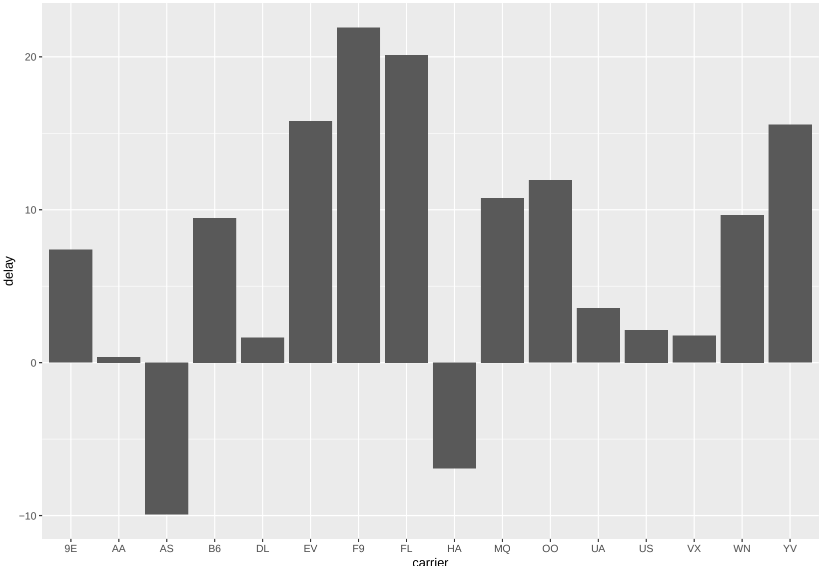
Data transformation + visualization

You can chain together `dplyr` verbs with `ggplot2` too.

Visualize the average delay for each carrier.

```
library(ggplot2)
flights %>%
  group_by(carrier) %>%
  summarise(delay=mean(arr_delay, na.rm=TRUE)) %>%
  ggplot(aes(x=carrier, y=delay)) + geom_col()
```

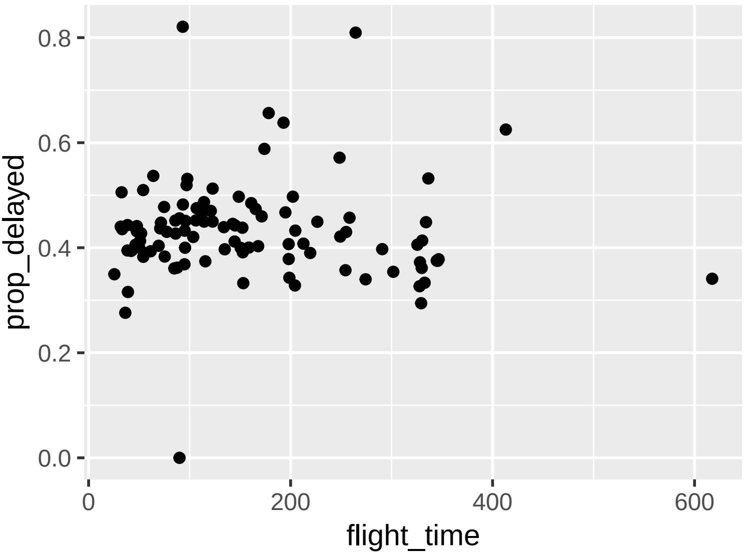
```r
flights %>%
  group_by(carrier) %>%
  summarise(delay=mean(arr_delay, na.rm=TRUE)) %>%
  ggplot(aes(x=carrier, y=delay)) + geom_col()
```



For each destination, visualize the proportion of delayed arriving flights versus the average flight time in the air.

```r
flights %>%
  group_by(dest) %>%
  summarise(prop_delayed = mean(arr_delay > 0, na.rm=TRUE),
            flight_time = mean(air_time, na.rm=TRUE),
            count = n()) %>%
  ggplot(aes(x=flight_time, y=prop_delayed)) + geom_point()
```

```
## Warning: Removed 1 rows containing missing values (geom_point
```



Map the number of flights from each destination to an aesthetic.

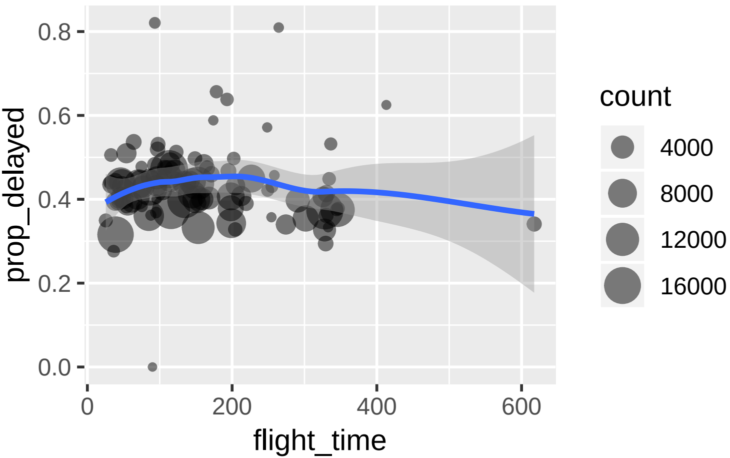
Add a smooth fitted line.

```
flights %>%
  group_by(dest) %>%
  summarise(prop_delayed = mean(arr_delay > 0, na.rm=TRUE),
            flight_time = mean(air_time, na.rm=TRUE),
            count = n()) %>%
  ggplot(aes(x=flight_time,
             y=prop_delayed)) +
  geom_point(aes(size=count), alpha=1/2) +
  geom_smooth()
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'

## Warning: Removed 1 rows containing non-finite values (stat_sm

## Warning: Removed 1 rows containing missing values (geom_point
```



Exercises

- For carriers that flew more than 1000 flights in 2013, find the number of flights that weren't delayed on arrival.
- Find the average distance flown by each carrier in each month of 2013.
- Plot to total miles flown each month in 2013.
- Plot the proportion of flights delayed by 10 minutes or more for each hour of the day.
- Plot the total distance flown versus the total time in arrival delays for each plane.
- Plot the relationship between the total time in the air and the total distance flown for each plane.
- Plot the average speed flown versus the average distance flown for each destination.
- Find the fastest plane.