Data Manipulation

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6/7/2019

The dplyr package is part of the tidyverse. It provides a grammar of data manipulation using a set of verbs for transforming tibbles (or data frames) in R or across various backend data sources.

```
library(dplyr, warn.conflicts = FALSE)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##     date
```

This section illustrates dplyr using the NYC flight departures data as a context.

```
library(nycflights13)
```

3.1 Data manipulation with dplyr

This section explores the main functions in dplyr which Hadley Wickham describes as a *grammar of data manipulation*—the counterpoint to his *grammar of graphics* in ggplot2.

The github repo for dplyr not only houses the R code, but also vignettes for various use cases. The introductory vignette is a good place to start and can by viewed by typing the following on the command line: vignette("dplyr", package = "dplyr") or by opening the dplyr.Rmd file in the vignettes directory of the dplyr repo. The material for this section is based on content from Hadley Wickham's Introduction to dplyr Vignette.

dplyr was designed to:

- provide commonly used data manipulation tools;

- have fast performance for in-memory operations;

- abstract the interface between the data manipulation operations and the data source.

dplyr operates on data frames, but it also operates on tibbles, a trimmed-down version of a data frame (tbl_df) that provides better checking and printing. Tibbles are particularly good for large data sets since they only print the first 10 rows and the first 7 columns by default although additional information is provided about the rows and columns.

The real power of dplyr is that it abstracts the data source, i.e., whether it is a data frame, a database, or Spark.

All the dplyr vignettes use the nycflights13 data which contain the 336,776 flights that departed from New York City in 2013. The flights tibble is one of several data sets in the package.

```
dim(flights)
```

```
## [1] 336776     19
```

```
flights # or print(flights)
```

```
## # 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 <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

The variable names in `flights` are self explanatory, but note that `flights` does not print like a regular data frame. This is because it is a *tibble*, which is designed for data with a lot of rows and/or columns, i.e., big data. The `print` function combines features of `head` and `str` in providing information about the tibble. Alternatively, we can use `str()` to give information about tibles or data frames.

```r
str(flights)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    336776 obs. of  19 variables:
##  $ year          : int  2013 2013 2013 2013 2013 2013 2013 2013 2013 2013 ...
##  $ 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  517 533 542 544 554 554 555 557 557 558 ...
##  $ sched_dep_time: int  515 529 540 545 600 558 600 600 600 600 ...
##  $ dep_delay     : num  2 4 2 -1 -6 -4 -5 -3 -3 -2 ...
##  $ arr_time      : int  830 850 923 1004 812 740 913 709 838 753 ...
##  $ sched_arr_time: int  819 830 850 1022 837 728 854 723 846 745 ...
##  $ 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 5708 79 301 ...
##  $ tailnum       : chr  "N14228" "N24211" "N619AA" "N804JB" ...
##  $ origin        : chr  "EWR" "LGA" "JFK" "JFK" ...
##  $ dest          : chr  "IAH" "IAH" "MIA" "BQN" ...
##  $ air_time      : num  227 227 160 183 116 150 158 53 140 138 ...
##  $ distance      : num  1400 1416 1089 1576 762 ...
##  $ hour          : num  5 5 5 5 6 5 6 6 6 6 ...
##  $ minute        : num  15 29 40 45 0 58 0 0 0 0 ...
##  $ time_hour     : POSIXct, format: "2013-01-01 05:00:00" "2013-01-01 05:00:00" ...
```

The `time_hour` variable in the `flights` data is encoded using the POSIXct format, which is identical to the format used for `time_hour` in the `weather` data of Section 3.1.4. The `time_hour` variable can be computed using the `make_datetime` function from the `ludridate` package with `year`, `month`, `day`, and `hour` as arguments. The flights table could be joined to the weather table using `time_hour` and `origin` as keys, which at least in principle allows us to model `dep_delay` in terms of the weather variables.

We could also define a `time_min` variable as follows:

```r
make_datetime(year = flights$year, month = flights$month, day = flights$day,
              hour = flights$hour, min = flights$minute)[1:5]
```

```
## [1] "2013-01-01 05:15:00 UTC" "2013-01-01 05:29:00 UTC"
## [3] "2013-01-01 05:40:00 UTC" "2013-01-01 05:45:00 UTC"
## [5] "2013-01-01 06:00:00 UTC"
```

This would allow us to model `dep_delay` at a finer level of granularity, but unfortunately the weather variables are only measured to the nearest hour.

3.1.1 Single Table Verbs

`dplyr` provides a suite of verbs for data manipulation:

- `filter`: select rows in a data frame;
- `arrange`: reorder rows in a data frame;
- `select`: select columns in a data frame;
- `distinct`: find unique values in a table;
- `mutate`: add new columns to a data frame;
- `summarise`: collapses a data frame to a single row;
- `sample_n`: take a random sample of rows.

Filter and Slice

`filter()` allows the selection of rows using Boolean operations, e.g., `&` or `|`.

```
# The following is equivalent to filter(flights, month == 1, day == 1).
filter(flights, month == 1 & day == 1)
```

```
## # A tibble: 842 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 832 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 <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

```
# In base R this would be done as:
# flights[flights$month == 1 & flights$day == 1, ]
```

Using the `|` operator is also easy.

```
filter(flights, month == 1 | month == 2)
```

```
## # A tibble: 51,955 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 51,945 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 <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

Rows can also be selected by position using slice:

```r
slice(flights, 1:3)
```

```
## # A tibble: 3 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
## # ... with 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 <dbl>, minute <dbl>,
## #   time_hour <dttm>
```

Arrange

`arrange()` orders a data frame by a set of column names (or more complicated expressions). If you provide more than one column name, each additional column will be used to break ties in the values of preceding columns:

```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 <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

```
# Or with `arr_delay` descending:
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 <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

Select and Rename

`select()` allows you to focus on the variables of interest:

```
# Select columns by name
select(flights, year, month, day)
```

```
## # A tibble: 336,776 x 3
##     year month   day
##    <int> <int> <int>
##  1  2013     1     1
##  2  2013     1     1
##  3  2013     1     1
##  4  2013     1     1
##  5  2013     1     1
##  6  2013     1     1
##  7  2013     1     1
##  8  2013     1     1
##  9  2013     1     1
## 10  2013     1     1
## # ... with 336,766 more rows
```

```
# Select all columns between year and day (inclusive)
select(flights, year:day)
```

```
## # A tibble: 336,776 x 3
##     year month   day
##    <int> <int> <int>
##  1  2013     1     1
##  2  2013     1     1
##  3  2013     1     1
##  4  2013     1     1
##  5  2013     1     1
##  6  2013     1     1
##  7  2013     1     1
##  8  2013     1     1
##  9  2013     1     1
## 10  2013     1     1
## # ... with 336,766 more rows
```

```
# Select all columns except those from year to day (inclusive)
select(flights, -(year:day))
```

```
## # A tibble: 336,776 x 16
##    dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay
##       <int>          <int>     <dbl>    <int>          <int>     <dbl>
##  1      517            515         2      830            819        11
##  2      533            529         4      850            830        20
##  3      542            540         2      923            850        33
##  4      544            545        -1     1004           1022       -18
##  5      554            600        -6      812            837       -25
##  6      554            558        -4      740            728        12
##  7      555            600        -5      913            854        19
##  8      557            600        -3      709            723       -14
##  9      557            600        -3      838            846        -8
## 10      558            600        -2      753            745         8
## # ... with 336,766 more rows, and 10 more variables: carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

`dplyr::select()` is similar to `base::select()`, but is included in `dplyr` to have a comprehensive, consistent architecture for data manipulation.

It is possible to rename variables with `select`, but `rename` is a better choice since `select` drops any unnamed variables:

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

```
## # 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 <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tail_num <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

Distinct

`distinct()` finds unique values in a table:

```
distinct(flights, tailnum)
```

```
## # A tibble: 4,044 x 1
##    tailnum
##    <chr>
##  1 N14228
##  2 N24211
##  3 N619AA
##  4 N804JB
##  5 N668DN
##  6 N39463
##  7 N516JB
##  8 N829AS
##  9 N593JB
## 10 N3ALAA
## # ... with 4,034 more rows
```

```
distinct(flights, origin, dest)
```

```
## # A tibble: 224 x 2
##    origin dest
##    <chr>  <chr>
##  1 EWR    IAH
##  2 LGA    IAH
##  3 JFK    MIA
##  4 JFK    BQN
##  5 LGA    ATL
##  6 EWR    ORD
##  7 EWR    FLL
##  8 LGA    IAD
##  9 JFK    MCO
## 10 LGA    ORD
## # ... with 214 more rows
```

This is similar to `base::unique()` but is faster.

Mutate and Transmute

`mutate()` transforms variables, i.e., adds new columns that are functions of existing columns.

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

```
## # 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 <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>, gain <dbl>, speed <dbl>
```

`dplyr::mutate()` works similarly to `base::transform()`, but `transform()` does not allow you to refer to columns that you've just created. For example, the following would not work with `transform()`, since the second argument depends on the first:

```
mutate(flights,
       gain = arr_delay - dep_delay,
       gain_per_hour = gain / (air_time / 60))
```

```
## # 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 <int>,
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dttm>, gain <dbl>, gain_per_hour <dbl>
```

Note: The new variables are not actually part of `flights` as can be seen by printing `flights`, but the new tibble can be used as part of a workflow. Alternately, a new tibble, e.g., `flights_gain` could be created by: `flights_gain <- mutate(...)`.

If you only want to keep the new variables, use `transmute()`:

```
transmute(flights,
          gain = arr_delay - dep_delay,
          gain_per_hour = gain / (air_time / 60)
)
```

```
## # A tibble: 336,776 x 2
##     gain gain_per_hour
##    <dbl>         <dbl>
##  1     9          2.38
##  2    16          4.23
##  3    31         11.6
##  4   -17         -5.57
##  5   -19         -9.83
##  6    16          6.4
##  7    24          9.11
##  8   -11        -12.5
##  9    -5         -2.14
## 10    10          4.35
## # ... with 336,766 more rows
```

Now let's add a time_min variables to the flights data using the four time variables. The modulo operator is used in which the quotient (hour) and remainder (min) are extracted from `sched_dep_time`.

```
mutate(flights,
       time_min = make_datetime(year, month, day,
                                sched_dep_time %/% 100,
                                sched_dep_time %% 100))$time_min[1:5]
```

```
## [1] "2013-01-01 05:15:00 UTC" "2013-01-01 05:29:00 UTC"
## [3] "2013-01-01 05:40:00 UTC" "2013-01-01 05:45:00 UTC"
## [5] "2013-01-01 06:00:00 UTC"
```

Sample

`sample_n()` and `sample_frac()` are used to take a random sample of rows for a fixed number and a fixed fraction, respectively.

```
sample_n(flights, 10)
```

```
## # A tibble: 10 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     4    23     1011           1010         1     1244
##  2  2013     5    21     1517           1444        33     1911
##  3  2013     8    19     1254           1300        -6     1406
##  4  2013     9     7     1551           1559        -8     1746
##  5  2013     9    24      946           1000       -14     1130
##  6  2013    12    18     1142           1129        13     1456
##  7  2013     8    28     1458           1450         8     1623
##  8  2013     8    11      604            605        -1      834
##  9  2013     6    15      604            610        -6     1008
## 10  2013     7    29     1154           1200        -6     1333
## # ... with 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 <dbl>, minute <dbl>,
## #   time_hour <dttm>
```

```
sample_frac(flights, 0.01)
```

```
## # A tibble: 3,368 x 19
##     year month   day dep_time sched_dep_time dep_delay arr_time
##    <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     6    23      914            915        -1     1158
##  2  2013     4    15     1602           1605        -3     1730
##  3  2013     9    11     2024           2025        -1     2400
##  4  2013     9     6      550            600       -10      834
##  5  2013    11     2      851            900        -9      958
##  6  2013     8    16     1028           1030        -2     1342
##  7  2013     8     9     1124           1125        -1     1431
##  8  2013     7     7     2244           1835       249       38
##  9  2013    11    25     1458           1505        -7     1754
## 10  2013     7     2     1824           1824         0     2133
## # ... with 3,358 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 <dbl>,
## #   minute <dbl>, time_hour <dttm>
```

The argument `replace = TRUE` samples with replacement, e.g., for a bootstrap sample. The `weight` argument allows you to weight the observations.

The above verbs have a common syntax.

- the first argument is a data frame (or tibble);
- subsequent arguments describe what to do to the data frame;
- the result is data frame (or tibble).

These properties allow the user to form a workflow chain or pipeline with the verbs and other compatible functions.

3.1.2 Grouped Operations

These above verbs become very powerful when you apply them to groups of observations within a dataset. In `dplyr`, this is done by the `group_by()` function. It breaks a dataset into specified groups of rows. When you then apply the verbs above on the resulting object they'll be automatically applied "by group."

We now split the complete dataset into individual planes and then summarise each plane by counting the number of flights and computing the average distance and arrival delay.

```r
by_tailnum <- group_by(flights, tailnum)
delay <- summarise(by_tailnum,
  count = n(),
  dist = mean(distance, na.rm = TRUE),
  delay = mean(arr_delay, na.rm = TRUE))
delay <- filter(delay, count > 20, dist < 2000)
delay
```

```
## # A tibble: 2,962 x 4
##    tailnum count  dist    delay
##    <chr>   <int> <dbl>    <dbl>
##  1 <NA>     2512  710.  NaN
##  2 N0EGMQ    371  676.    9.98
##  3 N10156    153  758.   12.7
##  4 N102UW     48  536.    2.94
##  5 N103US     46  535.   -6.93
##  6 N104UW     47  535.    1.80
##  7 N10575    289  520.   20.7
##  8 N105UW     45  525.   -0.267
##  9 N107US     41  529.   -5.73
## 10 N108UW     60  534.   -1.25
## # ... with 2,952 more rows
```

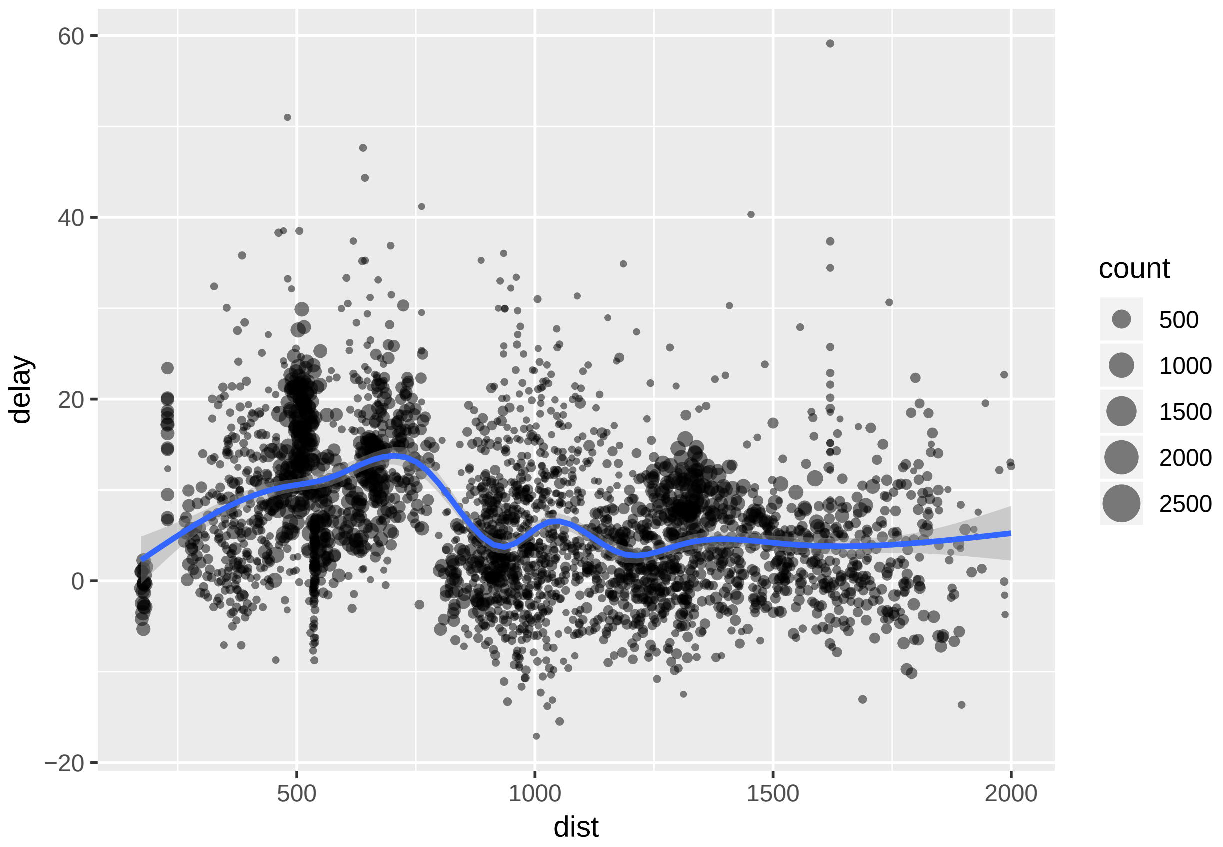
We can then see if the average delay is related to the average distance flown by a plane.

```r
library(ggplot2)
ggplot(delay, aes(dist, delay)) +
  geom_point(aes(size = count), alpha = 1/2) +
  geom_smooth() +
  scale_size_area()
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

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



The average delay increases for short distance (with a lot of variation), but then levels out.

This course does not focus on graphics, but we will use simple graphics in various workflows. The principal graphics packages that integrate into workflows include:

- Grammar of graphics

`ggplot2` is a plotting system for R, based on the Leland Wilkinson's grammar of graphics It takes care of many of the details that make plotting a hassle (like drawing legends) as well as providing a powerful model of graphics that makes it easy to produce complex multi-layered graphics.

- Interactive grammar of graphics

`ggvis` makes it easy to describe interactive web graphics in R. It combines:

- a grammar of graphics from ggplot2,

- reactive programming from shiny, and

- data transformation pipelines from dplyr.

You use `summarise()` with aggregate functions, which take a vector of values and return a single number. There are many useful examples of such functions in base R, e.g., `mean()`, `sum()`, and `sd()`.

`dplyr` adds:

- `n()`: the number of observations in the current group;
- `n_distinct(x)`: the number of unique values in `x`;
- `first(x)`, `last(x)`, and `nth(x, n)`: the first, last, and nth observation in `x`.

You can also use your own functions.

For example, we could use these to find the number of planes and the number of flights that go to each possible destination:

```
destinations <- group_by(flights, dest)
summarise(destinations,
  planes = n_distinct(tailnum),
  flights = n()
)
```

```
## # A tibble: 105 x 3
##    dest  planes flights
##    <chr>  <int>   <int>
##  1 ABQ      108     254
##  2 ACK       58     265
##  3 ALB      172     439
##  4 ANC        6       8
##  5 ATL     1180   17215
##  6 AUS      993    2439
##  7 AVL      159     275
##  8 BDL      186     443
##  9 BGR       46     375
## 10 BHM       45     297
## # ... with 95 more rows
```

When you group by multiple variables, each summary peels off one level of the grouping. Thus, you can progressively roll-up a dataset:

```
daily <- group_by(flights, year, month, day)
(per_day   <- summarise(daily, flights = n()))
```

```
## # A tibble: 365 x 4
## # Groups:   year, month [12]
##     year month   day flights
##    <int> <int> <int>   <int>
##  1  2013     1     1     842
##  2  2013     1     2     943
##  3  2013     1     3     914
##  4  2013     1     4     915
##  5  2013     1     5     720
##  6  2013     1     6     832
##  7  2013     1     7     933
##  8  2013     1     8     899
##  9  2013     1     9     902
## 10  2013     1    10     932
## # ... with 355 more rows
```

```
(per_month <- summarise(per_day, flights = sum(flights)))
```

```
## # A tibble: 12 x 3
## # Groups:   year [1]
##     year month flights
##    <int> <int>   <int>
##  1  2013     1   27004
##  2  2013     2   24951
##  3  2013     3   28834
##  4  2013     4   28330
##  5  2013     5   28796
##  6  2013     6   28243
##  7  2013     7   29425
##  8  2013     8   29327
##  9  2013     9   27574
## 10  2013    10   28889
## 11  2013    11   27268
## 12  2013    12   28135
```

```
(per_year  <- summarise(per_month, flights = sum(flights)))
```

```
## # A tibble: 1 x 2
##    year flights
##   <int>   <int>
## 1  2013  336776
```

3.1.3 Chaining

The `dplyr` API is *functional*, i.e., the function calls don't have *side-effects*. That means you must always save intermediate results, which doesn't lead to elegant code. One solution is to do it step-by-step.

```
a1 <- group_by(flights, year, month, day)
a2 <- select(a1, arr_delay, dep_delay)
```

```
## Adding missing grouping variables: `year`, `month`, `day`
```

```
a3 <- summarise(a2,
  arr = mean(arr_delay, na.rm = TRUE),
  dep = mean(dep_delay, na.rm = TRUE))
a4 <- filter(a3, arr > 30 | dep > 30)
a4
```

```
## # A tibble: 49 x 5
## # Groups:   year, month [11]
##     year month   day   arr   dep
##    <int> <int> <int> <dbl> <dbl>
##  1  2013     1    16  34.2  24.6
##  2  2013     1    31  32.6  28.7
##  3  2013     2    11  36.3  39.1
##  4  2013     2    27  31.3  37.8
##  5  2013     3     8  85.9  83.5
##  6  2013     3    18  41.3  30.1
##  7  2013     4    10  38.4  33.0
##  8  2013     4    12  36.0  34.8
##  9  2013     4    18  36.0  34.9
## 10  2013     4    19  47.9  46.1
## # ... with 39 more rows
```

This is not a good idea for big data.

If you want to save storage, another way is to wrap the function calls inside each other.

```
filter(
  summarise(
    select(
      group_by(flights, year, month, day),
      arr_delay, dep_delay
    ),
    arr = mean(arr_delay, na.rm = TRUE),
    dep = mean(dep_delay, na.rm = TRUE)
  ),
  arr > 30 | dep > 30
)
```

```
## Adding missing grouping variables: `year`, `month`, `day`
```

```
## # A tibble: 49 x 5
## # Groups:   year, month [11]
##     year month   day   arr   dep
##    <int> <int> <int> <dbl> <dbl>
##  1  2013     1    16  34.2  24.6
##  2  2013     1    31  32.6  28.7
##  3  2013     2    11  36.3  39.1
##  4  2013     2    27  31.3  37.8
##  5  2013     3     8  85.9  83.5
##  6  2013     3    18  41.3  30.1
##  7  2013     4    10  38.4  33.0
##  8  2013     4    12  36.0  34.8
##  9  2013     4    18  36.0  34.9
## 10  2013     4    19  47.9  46.1
## # ... with 39 more rows
```

However, this is difficult to read because the order of the operations is from inside to out. Thus, the arguments are a long way away from the function. To get around this problem, `dplyr` provides the `%>%` operator. `x %>% f(y)` turns into `f(x, y)` so you can use it to rewrite multiple operations that you can read left-to-right, top-to-bottom:

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

```
## Adding missing grouping variables: `year`, `month`, `day`
```

```
## # A tibble: 49 x 5
## # Groups:   year, month [11]
##     year month   day   arr   dep
##    <int> <int> <int> <dbl> <dbl>
##  1  2013     1    16  34.2  24.6
##  2  2013     1    31  32.6  28.7
##  3  2013     2    11  36.3  39.1
##  4  2013     2    27  31.3  37.8
##  5  2013     3     8  85.9  83.5
##  6  2013     3    18  41.3  30.1
##  7  2013     4    10  38.4  33.0
##  8  2013     4    12  36.0  34.8
##  9  2013     4    18  36.0  34.9
## 10  2013     4    19  47.9  46.1
## # ... with 39 more rows
```

The `%>%` R operator is somewhat like UNIX pipes in which the standard output of one command becomes the standard input of the next. Thus, we sometimes call %>% the R pipe operator.

However, %>% is very powerful since it can be used with many R functions including graphics functions in R packages such as ggplot2 and ggvis.

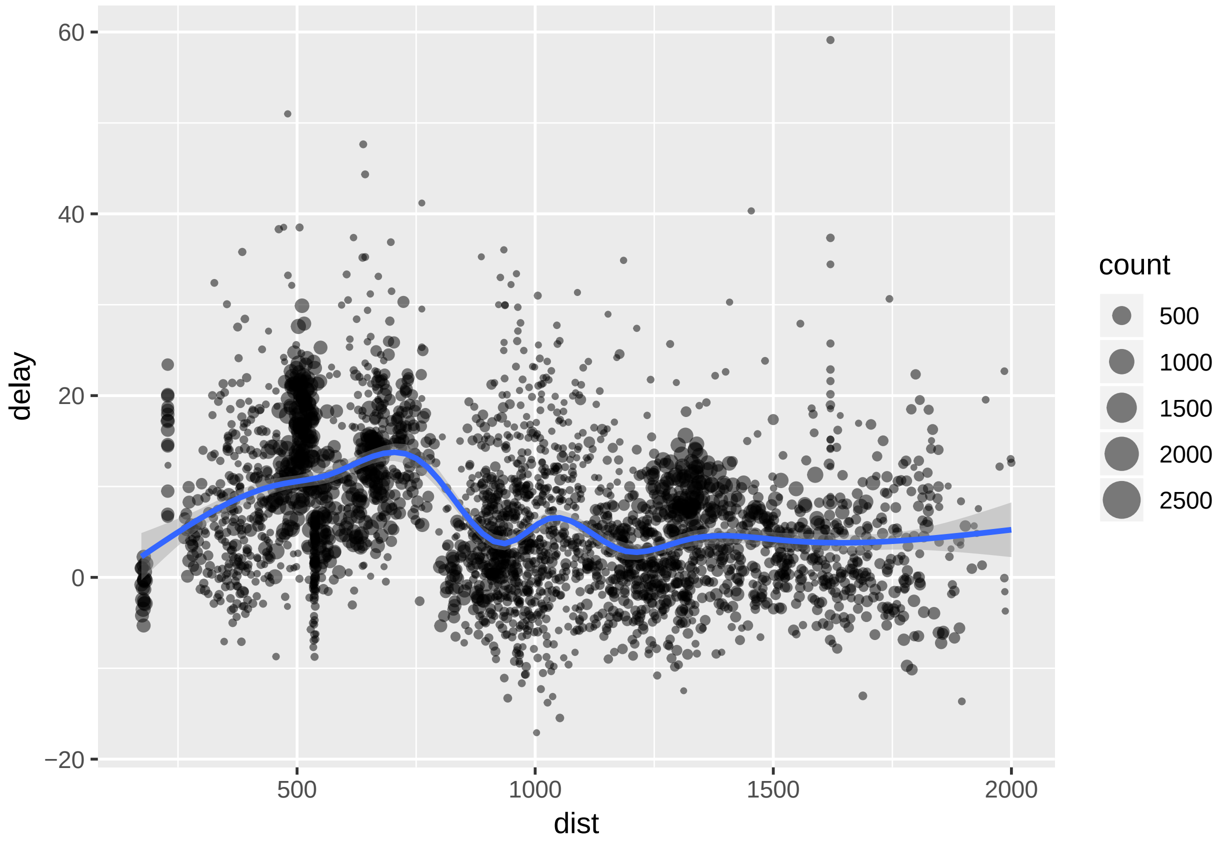
Let's redo our grouped tailnum example using %>%:

```
group_by(flights, tailnum) %>%
  summarise(
    count = n(),
    dist = mean(distance, na.rm = TRUE),
    delay = mean(arr_delay, na.rm = TRUE)) %>%
  filter(
    count > 20, dist < 2000) %>%
  ggplot(
    aes(dist, delay)) +
    geom_point(aes(size = count), alpha = 1/2) +
    geom_smooth() +
    scale_size_area()
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

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



What makes this work is that the first argument is a data frame and the output is a data frame. Do you see the potential of building very powerful workflows?

3.1.4 Combining Tables

It's rare that a data analysis involves only a single table of data. In practice, you'll normally have many tables that contribute to an analysis, and you need flexible tools to combine them.

The material for this section is extracted from Hadley Wickham's dplyr Two-table Vignette.

In `dplyr`, there are three families of verbs that work with two tables at a time:

- Mutating joins, which add new variables to one table from matching rows in another.

- Filtering joins, which filter observations from one table based on whether or not they match an observation in the other table.

- Set operations, which combine the observations in the data sets as if they were set elements.

This discussion assumes that you have tidy data, where the rows are observations and the columns are variables (see Section 3.3). The discussion here will be limited to mutating joins.

All two-table verbs work similarly. The first two arguments are `x` and `y`, and provide the tables to combine. The output is always a new table with the same type as `x`

Mutating joins

Mutating joins allow you to combine variables from multiple tables. For example, take the `nycflights13` data. In one table we have flight information with an abbreviation for carrier, and in another we have a mapping between abbreviations and full names. You can use a join to add the carrier names to the flight data:

```r
# Drop unimportant variables so it's easier to understand the join results.
flights2 <- flights %>%
  select(year:day, hour, origin, dest, tailnum, carrier)
airlines
```

```
## # A tibble: 16 x 2
##    carrier name
##    <chr>   <chr>
##  1 9E      Endeavor Air Inc.
##  2 AA      American Airlines Inc.
##  3 AS      Alaska Airlines Inc.
##  4 B6      JetBlue Airways
##  5 DL      Delta Air Lines Inc.
##  6 EV      ExpressJet Airlines Inc.
##  7 F9      Frontier Airlines Inc.
##  8 FL      AirTran Airways Corporation
##  9 HA      Hawaiian Airlines Inc.
## 10 MQ      Envoy Air
## 11 OO      SkyWest Airlines Inc.
## 12 UA      United Air Lines Inc.
## 13 US      US Airways Inc.
## 14 VX      Virgin America
## 15 WN      Southwest Airlines Co.
## 16 YV      Mesa Airlines Inc.
```

```r
flights2 %>%
  left_join(airlines)
```

```
## Joining, by = "carrier"
## # A tibble: 336,776 x 9
##     year month   day  hour origin dest  tailnum carrier name
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr>
##  1  2013     1     1     5 EWR    IAH   N14228  UA      United Air Lines I~
##  2  2013     1     1     5 LGA    IAH   N24211  UA      United Air Lines I~
##  3  2013     1     1     5 JFK    MIA   N619AA  AA      American Airlines ~
##  4  2013     1     1     5 JFK    BQN   N804JB  B6      JetBlue Airways
##  5  2013     1     1     6 LGA    ATL   N668DN  DL      Delta Air Lines In~
##  6  2013     1     1     5 EWR    ORD   N39463  UA      United Air Lines I~
##  7  2013     1     1     6 EWR    FLL   N516JB  B6      JetBlue Airways
##  8  2013     1     1     6 LGA    IAD   N829AS  EV      ExpressJet Airline~
##  9  2013     1     1     6 JFK    MCO   N593JB  B6      JetBlue Airways
## 10  2013     1     1     6 LGA    ORD   N3ALAA  AA      American Airlines ~
## # ... with 336,766 more rows
```

Controlling how the tables are matched

In addition to x and y, each mutating join takes an argument by that controls which variables are used to match observations in the two tables. There are several ways to specify it.

- NULL, the default. dplyr will will use all variables that appear in both tables, a natural join. For example, the flights and weather tables match on their common variables: year, month, day, hour and origin.

```
str(weather)
```

```
## Classes 'tbl_df', 'tbl' and 'data.frame':    26115 obs. of  15 variables:
##  $ origin    : chr  "EWR" "EWR" "EWR" "EWR" ...
##  $ year      : num  2013 2013 2013 2013 2013 ...
##  $ month     : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ day       : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ hour      : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ temp      : num  39 39 39 39.9 39 ...
##  $ dewp      : num  26.1 27 28 28 28 ...
##  $ humid     : num  59.4 61.6 64.4 62.2 64.4 ...
##  $ wind_dir  : num  270 250 240 250 260 240 240 250 260 260 ...
##  $ wind_speed: num  10.36 8.06 11.51 12.66 12.66 ...
##  $ wind_gust : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ precip    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ pressure  : num  1012 1012 1012 1012 1012 ...
##  $ visib     : num  10 10 10 10 10 10 10 10 10 10 ...
##  $ time_hour : POSIXct, format: "2013-01-01 01:00:00" "2013-01-01 02:00:00" ...
```

```
flights2 %>%
  left_join(weather)
```

```
## Joining, by = c("year", "month", "day", "hour", "origin")

## # A tibble: 336,776 x 18
##     year month   day  hour origin dest  tailnum carrier  temp  dewp humid
##    <dbl> <dbl> <int> <dbl> <chr>  <chr> <chr>   <chr>   <dbl> <dbl> <dbl>
##  1  2013     1     1     5 EWR    IAH   N14228  UA       39.0  28.0  64.4
##  2  2013     1     1     5 LGA    IAH   N24211  UA       39.9  25.0  54.8
##  3  2013     1     1     5 JFK    MIA   N619AA  AA       39.0  27.0  61.6
##  4  2013     1     1     5 JFK    BQN   N804JB  B6       39.0  27.0  61.6
##  5  2013     1     1     6 LGA    ATL   N668DN  DL       39.9  25.0  54.8
##  6  2013     1     1     5 EWR    ORD   N39463  UA       39.0  28.0  64.4
##  7  2013     1     1     6 EWR    FLL    N516JB  B6       37.9  28.0  67.2
##  8  2013     1     1     6 LGA    IAD    N829AS  EV       39.9  25.0  54.8
##  9  2013     1     1     6 JFK    MCO    N593JB  B6       37.9  27.0  64.3
## 10  2013     1     1     6 LGA    ORD    N3ALAA  AA       39.9  25.0  54.8
## # ... with 336,766 more rows, and 7 more variables: wind_dir <dbl>,
## #   wind_speed <dbl>, wind_gust <dbl>, precip <dbl>, pressure <dbl>,
## #   visib <dbl>, time_hour <dttm>
```

- A character vector, by = "x". Like a natural join, but uses only some of the common variables. For example, flights and planes have year columns, but they mean different things so we only want to join by tailnum.

```
flights2 %>%
  left_join(planes, by = "tailnum")
```

```
## # A tibble: 336,776 x 16
##    year.x month   day  hour origin dest  tailnum carrier year.y type
##     <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>    <int> <chr>
##   1   2013     1     1     5 EWR    IAH    N14228  UA          1999 Fixe~
##   2   2013     1     1     5 LGA    IAH    N24211  UA          1998 Fixe~
##   3   2013     1     1     5 JFK    MIA    N619AA  AA          1990 Fixe~
##   4   2013     1     1     5 JFK    BQN    N804JB  B6          2012 Fixe~
##   5   2013     1     1     6 LGA    ATL    N668DN  DL          1991 Fixe~
##   6   2013     1     1     5 EWR    ORD    N39463  UA          2012 Fixe~
##   7   2013     1     1     6 EWR    FLL    N516JB  B6          2000 Fixe~
##   8   2013     1     1     6 LGA    IAD    N829AS  EV          1998 Fixe~
##   9   2013     1     1     6 JFK    MCO    N593JB  B6          2004 Fixe~
## 10   2013     1     1     6 LGA    ORD    N3ALAA  AA            NA <NA>
## # ... with 336,766 more rows, and 6 more variables: manufacturer <chr>,
## #   model <chr>, engines <int>, seats <int>, speed <int>, engine <chr>
```

Note that the year columns in the output are disambiguated with a suffix.

- A named character vector: by = c("x" = "a"). This will match variable x in table x to variable a in table y. The variables from use will be used in the output.

Each flight has an origin and destination airport, so we need to specify which one we want to join to:

```
flights2 %>%
  left_join(airports, c("dest" = "faa"))
```

```
## # A tibble: 336,776 x 15
##     year month   day  hour origin dest  tailnum carrier name    lat   lon
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr> <dbl> <dbl>
##   1  2013     1     1     5 EWR    IAH    N14228  UA      Geor~  30.0 -95.3
##   2  2013     1     1     5 LGA    IAH    N24211  UA      Geor~  30.0 -95.3
##   3  2013     1     1     5 JFK    MIA    N619AA  AA      Miam~  25.8 -80.3
##   4  2013     1     1     5 JFK    BQN    N804JB  B6      <NA>    NA    NA
##   5  2013     1     1     6 LGA    ATL    N668DN  DL      Hart~  33.6 -84.4
##   6  2013     1     1     5 EWR    ORD    N39463  UA      Chic~  42.0 -87.9
##   7  2013     1     1     6 EWR    FLL    N516JB  B6      Fort~  26.1 -80.2
##   8  2013     1     1     6 LGA    IAD    N829AS  EV      Wash~  38.9 -77.5
##   9  2013     1     1     6 JFK    MCO    N593JB  B6      Orla~  28.4 -81.3
## 10  2013     1     1     6 LGA    ORD    N3ALAA  AA      Chic~  42.0 -87.9
## # ... with 336,766 more rows, and 4 more variables: alt <int>, tz <dbl>,
## #   dst <chr>, tzone <chr>
```

```
flights2 %>%
  left_join(airports, c("origin" = "faa"))
```

```
## # A tibble: 336,776 x 15
##     year month   day  hour origin dest  tailnum carrier name    lat   lon
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr> <dbl> <dbl>
##  1  2013     1     1     5 EWR    IAH   N14228  UA      Newa~  40.7 -74.2
##  2  2013     1     1     5 LGA    IAH   N24211  UA      La G~  40.8 -73.9
##  3  2013     1     1     5 JFK    MIA   N619AA  AA      John~  40.6 -73.8
##  4  2013     1     1     5 JFK    BQN   N804JB  B6      John~  40.6 -73.8
##  5  2013     1     1     6 LGA    ATL   N668DN  DL      La G~  40.8 -73.9
##  6  2013     1     1     5 EWR    ORD   N39463  UA      Newa~  40.7 -74.2
##  7  2013     1     1     6 EWR    FLL   N516JB  B6      Newa~  40.7 -74.2
##  8  2013     1     1     6 LGA    IAD   N829AS  EV      La G~  40.8 -73.9
##  9  2013     1     1     6 JFK    MCO   N593JB  B6      John~  40.6 -73.8
## 10  2013     1     1     6 LGA    ORD   N3ALAA  AA      La G~  40.8 -73.9
## # ... with 336,766 more rows, and 4 more variables: alt <int>, tz <dbl>,
## #   dst <chr>, tzone <chr>
```

Types of join

There are four types of mutating join, which differ in their behavior when a match is not found. We'll illustrate each with a simple example:

```
(df1 <- data_frame(x = c(1, 2), y = 2:1))
```

```
## Warning: `data_frame()` is deprecated, use `tibble()`.
## This warning is displayed once per session.
```

```
## # A tibble: 2 x 2
##       x     y
##   <dbl> <int>
## 1     1     2
## 2     2     1
```

```
(df2 <- data_frame(x = c(1, 3), a = 10, b = "a"))
```

```
## # A tibble: 2 x 3
##       x     a b
##   <dbl> <dbl> <chr>
## 1     1    10 a
## 2     3    10 a
```

`inner_join(x, y)` only includes observations that match in both `x` and `y`.

```
df1 %>% inner_join(df2) # %>% knitr::kable()
```

```
## Joining, by = "x"
```

```
## # A tibble: 1 x 4
##       x     y     a b
##   <dbl> <int> <dbl> <chr>
## 1     1     2    10 a
```

`left_join(x, y)` includes all observations in `x`, regardless of whether they match or not. This is the most commonly used join because it ensures that you don't lose observations from your primary table.

```
df1 %>% left_join(df2)
```

```
## Joining, by = "x"
```

```
## # A tibble: 2 x 4
##       x     y     a b    
##   <dbl> <int> <dbl> <chr>
## 1     1     2    10 a    
## 2     2     1    NA <NA> 
```

`right_join(x, y)` includes all observations in `y`. It's equivalent to `left_join(y, x)`, but the columns will be ordered differently.

```
df1 %>% right_join(df2)
```

```
## Joining, by = "x"
```

```
## # A tibble: 2 x 4
##       x     y     a b    
##   <dbl> <int> <dbl> <chr>
## 1     1     2    10 a    
## 2     3    NA    10 a    
```

```
df2 %>% left_join(df1)
```

```
## Joining, by = "x"
```

```
## # A tibble: 2 x 4
##       x     a b         y
##   <dbl> <dbl> <chr> <int>
## 1     1    10 a         2
## 2     3    10 a        NA
```

`full_join()` includes all observations from `x` and `y`.

```
df1 %>% full_join(df2)
```

```
## Joining, by = "x"
```

```
## # A tibble: 3 x 4
##       x     y     a b    
##   <dbl> <int> <dbl> <chr>
## 1     1     2    10 a    
## 2     2     1    NA <NA> 
## 3     3    NA    10 a    
```

The left, right and full joins are collectively know as outer joins. When a row doesn't match in an outer join, the new variables are filled in with missing values.

Each two-table verb has a straightforward SQL equivalent. The correspondences between R and SQL are:

- `inner_join()`: `SELECT * FROM x JOIN y ON x.a = y.a`
- `left_join()`: `SELECT * FROM x LEFT JOIN y ON x.a = y.a`
- `right_join()`: `SELECT * FROM x RIGHT JOIN y ON x.a = y.a`
- `full_join()`: `SELECT * FROM x FULL JOIN y ON x.a = y.a`

`x` and `y` don't have to be tables in the same database. If you specify `copy = TRUE`, `dplyr` will copy the `y` table into the same location as the `x` variable. This is useful if you've downloaded a summarized dataset and determined a subset for which you now want the full data.

You should review the coercion rules, e.g., factors are preserved only if the levels match exactly and if their levels are different the factors are coerced to character.

At this time, `dplyr` does not provide any functions for working with three or more tables.

See the complete set of vignettes on the `dplyr` repo for other examples.