

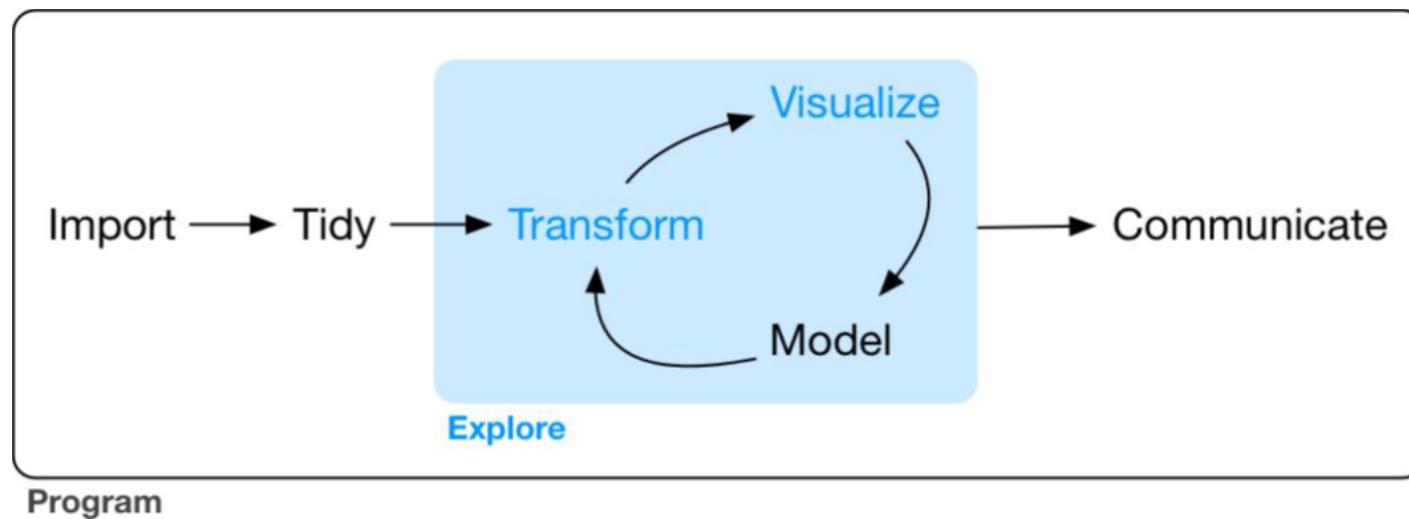
IE6600 Computation and Visualization for Analytics

dplyr: data wrangle with relational data

updated: 2022-06-29

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Goal



Wickham, Hadley, and Garrett Grolemund. R For Data Science. OReilly, 2017.

Introduction

It's rare that a data analysis involves only a single table of data. Typically you have many tables of data, and you must combine them to answer the questions that you're interested in. Collectively, multiple tables of data are called relational data because it is the relations, not just the individual datasets, that are important.

To work with relational data you need verbs that work with pairs of tables. There are two most common families of verbs designed to work with relational data:

- Mutating joins, which add new variables to one data frame from matching observations in another.
- Filtering joins, which filter observations from one data frame based on whether or not they match an observation in the other table.

Prerequisites

```
library(tidyverse)  
library(nycflights13)
```

nycflights13

`airlines` lets you look up the full carrier name from its abbreviated code:

```
head(airlines)
```

```
## # A tibble: 6 × 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.
```

`airports` gives information about each airport, identified by the faa airport code:

```
airports
```

```
## # A tibble: 1,458 × 8
##   faa   name          lat    lon   alt    tz dst  tzone
##   <chr> <chr>         <dbl> <dbl> <dbl> <dbl> <chr> <chr>
## 1 04G   Lansdowne Airport  41.1  -80.6  1044   -5 A   America/...
## 2 06A   Moton Field Municipal Airport  32.5  -85.7   264   -6 A   America/...
## 3 06C   Schaumburg Regional  42.0  -88.1   801   -6 A   America/...
## 4 06N   Randall Airport    41.4  -74.4   523   -5 A   America/...
## 5 09J   Jekyll Island Airport  31.1  -81.4    11   -5 A   America/...
## 6 0A9   Elizabethton Municipal Airport  36.4  -82.2  1593   -5 A   America/...
## 7 0G6   Williams County Airport  41.5  -84.5   730   -5 A   America/...
## 8 0G7   Finger Lakes Regional Airport  42.9  -76.8   492   -5 A   America/...
## 9 0P2   Shoestring Aviation Airfield  39.8  -76.6  1000   -5 U   America/...
## 10 0S9   Jefferson County Intl  48.1 -123.    108   -8 A   America/...
## # ... with 1,448 more rows
```

`planes` gives information about each plane, identified by its tailnum:

```
planes
```

```
## # A tibble: 3,322 × 9
##   tailnum year type      manufacturer model engines seats speed engine
##   <chr>   <int> <chr>      <chr>         <chr>   <int> <int> <int> <chr>
## 1 N10156  2004 Fixed wing multi... EMBRAER      EMB-...     2    55    NA Turbo...
## 2 N102UW  1998 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 3 N103US  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 4 N104UW  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 5 N10575  2002 Fixed wing multi... EMBRAER      EMB-...     2    55    NA Turbo...
## 6 N105UW  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 7 N107US  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 8 N108UW  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 9 N109UW  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## 10 N110UW  1999 Fixed wing multi... AIRBUS INDU... A320...     2   182    NA Turbo...
## # ... with 3,312 more rows
```

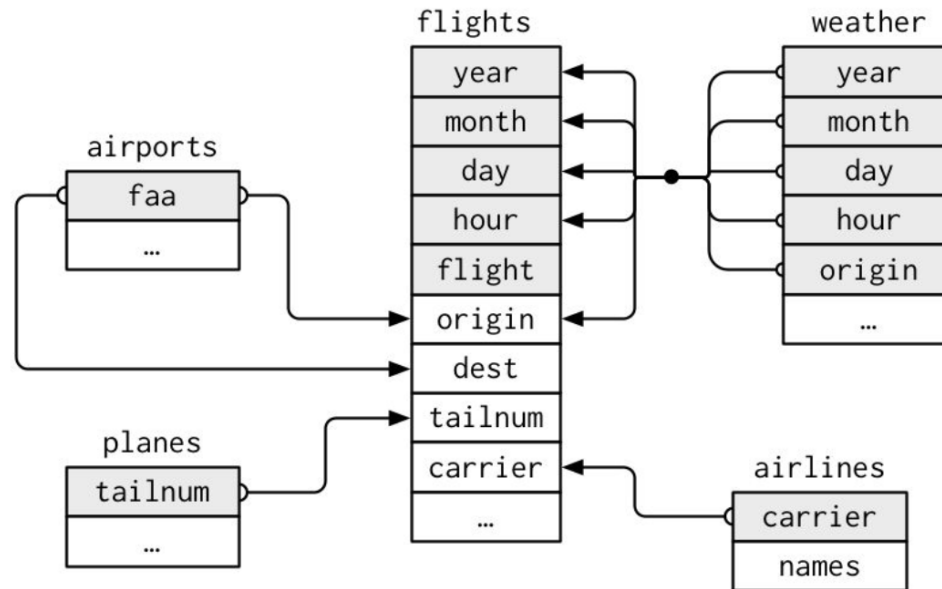

`weather` gives the weather at each NYC airport for each hour:

```
weather
```

```
## # A tibble: 26,115 × 15
##   origin year month   day hour temp dewp humid wind_dir wind_speed
##   <chr>   <int> <int> <int> <int> <dbl> <dbl> <dbl>    <dbl>    <dbl>
## 1 EWR     2013     1     1     1 39.0 26.1 59.4      270     10.4
## 2 EWR     2013     1     1     2 39.0 27.0 61.6      250      8.06
## 3 EWR     2013     1     1     3 39.0 28.0 64.4      240     11.5
## 4 EWR     2013     1     1     4 39.9 28.0 62.2      250     12.7
## 5 EWR     2013     1     1     5 39.0 28.0 64.4      260     12.7
## 6 EWR     2013     1     1     6 37.9 28.0 67.2      240     11.5
## 7 EWR     2013     1     1     7 39.0 28.0 64.4      240     15.0
## 8 EWR     2013     1     1     8 39.9 28.0 62.2      250     10.4
## 9 EWR     2013     1     1     9 39.9 28.0 62.2      260     15.0
## 10 EWR    2013     1     1    10 41    28.0 59.6      260     13.8
## # ... with 26,105 more rows, and 5 more variables: wind_gust <dbl>, precip <dbl>,
## #   pressure <dbl>, visib <dbl>, time_hour <dtm>
```

nycflights13 Entity Relationship Diagram

One way to show the relationships between the different tables is with a drawing:
If you have taken database management, you would be familiar with.



Wickham, Hadley, and Garrett Grolemund. R For Data Science. OReilly, 2017.

For `nycflights13`:

- flights connects to planes via a single variable, tailnum.
- flights connects to airlines through the carrier variable.
- flights connects to airports in two ways: via the origin and dest variables.
- flights connects to weather via origin (the location), and year, month, day, and hour (the time).

Key for relational data table

There are two types of keys:

- A primary key uniquely identifies an observation in its own table.
- A foreign key uniquely identifies an observation in another table.

Primary key (PK)

For example, `planes$tailnum` is a primary key because it uniquely identifies each plane in the `planes` table.

```
planes
```

```
## # A tibble: 3,322 × 9
##   tailnum year type      manufacturer model engines seats speed engine
##   <chr>   <int> <chr>      <chr>          <chr>   <int> <int> <int> <chr>
## 1 N10156  2004 Fixed wing multi... EMBRAER    EMB-...     2    55    NA Turbo...
## 2 N102UW  1998 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 3 N103US  1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 4 N104UW  1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 5 N10575  2002 Fixed wing multi... EMBRAER    EMB-...     2    55    NA Turbo...
## 6 N105UW  1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 7 N107US  1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 8 N108UW  1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 9 N109UW  1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## 10 N110UW 1999 Fixed wing multi... AIRBUS    INDU... A320...     2   182    NA Turbo...
## # ... with 3,312 more rows
```

If we would like to find one plane with tailnumber "N110UW"

```
planes %>%  
  filter(tailnum=="N110UW")
```

```
## # A tibble: 1 × 9  
##   tailnum year type manufacturer model engines seats speed engine  
##   <chr>   <int> <chr>      <chr>      <chr>   <int> <int> <int> <chr>  
## 1 N110UW  1999 Fixed wing multi ... AIRBUS INDU... A320...     2   182    NA Turbo...
```

Of course, the PK can be a combination of variables: `c(year, month, day, hour, minute, origin)`

```
flights %>%  
  filter(year==2013, month==1, day==5, hour==5, minute==40, origin=="JFK")
```

```
## # A tibble: 1 × 19  
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time  
##   <int> <int> <int>   <int>         <int>      <dbl>    <int>         <int>  
## 1  2013     1     5     537           540        -3      831           850  
## # ... with 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,  
## #   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,  
## #   hour <dbl>, minute <dbl>, time_hour <dtm>
```

Foreign key

For example, `flights$tailnum` is a foreign key because it appears in the `flights` table where it matches each flight to a unique plane in the `plane` table. Which means in the table `flights`, the `tailnum` is a foreign key not a PK; but in the table `plane`, the `tailnum` is a PK

```
flights %>%  
  filter(tailnum=="N110UW")
```

```
## # A tibble: 40 × 10  
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time  
##   <int> <int> <int>   <int>         <int>         <dbl>   <int>         <int>  
## 1  2013     1    10       620             630         -10     855             831  
## 2  2013    10     6       959             959          0    1214            1207  
## 3  2013    10     9      1639            1540          59    1830            1742  
## 4  2013    10    24      1600            1550          10    1756            1752  
## 5  2013    11     6      1546            1544           2    1741            1750  
## 6  2013    11     9      1458            1500          -2    1649            1656  
## 7  2013    11    10       818             825          -7    1007            1029  
## 8  2013    11    13      1540            1544          -4    1738            1750  
## 9  2013    11    21      1222            1200          22    1413            1359  
## 10 2013    11    26      1603            1544          19    1842            1750
```


Mutate Join

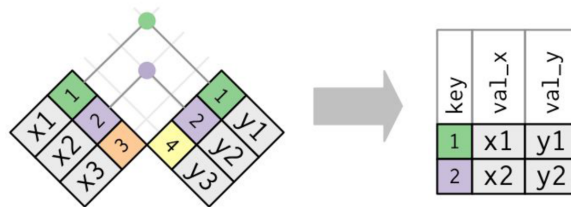
Data table

| x | | y | |
|---|----|---|----|
| 1 | x1 | 1 | y1 |
| 2 | x2 | 2 | y2 |
| 3 | x3 | 4 | y3 |

```
x <- tribble(  
  ~key, ~val_x,  
  1, "x1",  
  2, "x2",  
  3, "x3"  
)
```

```
y <- tribble(  
  ~key, ~val_y,  
  1, "y1",  
  2, "y2",  
  4, "y3"  
)
```

Inner join



Base R function:

```
merge(x, y, by="key")
```

```
#or  
x %>%  
  merge(y, by="key")
```

dplyr `inner_join()` function:

```
inner_join(x, y, by="key")
```

```
## # A tibble: 2 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1    x1    y1
## 2     2    x2    y2
```

```
#or
x %>%
  inner_join(y, by="key")
```

```
## # A tibble: 2 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1    x1    y1
## 2     2    x2    y2
```

If the keys are different

```
x <- tribble(  
  ~key, ~val_x,  
  1, "x1",  
  2, "x2",  
  3, "x3"  
)
```

```
y1 <- tribble(  
  ~key1, ~val_y,  
  1, "y1",  
  2, "y2",  
  4, "y3"  
)
```

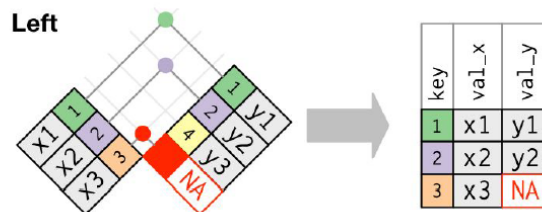
Base function:

```
merge(x, y1, by.x="key", by.y="key1")
```

dplyr function:

```
inner_join(x, y1, by=c("key"="key1"))
```

Left join



Base R function:

```
merge(x, y, by="key", all.x=TRUE)
```

```
#or  
x %>%  
  merge(y, by="key", all.x=TRUE)
```

dplyr `left_join()` function:

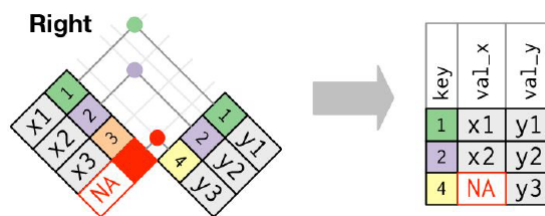
```
left_join(x, y, by="key")
```

```
## # A tibble: 3 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1   x1    y1
## 2     2   x2    y2
## 3     3   x3    <NA>
```

```
#or
x %>%
  left_join(y, by="key")
```

```
## # A tibble: 3 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1   x1    y1
## 2     2   x2    y2
## 3     3   x3    <NA>
```

Right join



Base R function:

```
merge(x, y, by="key", all.y=TRUE)
```

```
#or  
x %>%  
  merge(y, by="key", all.y=TRUE)
```


dplyr `right_join()` function:

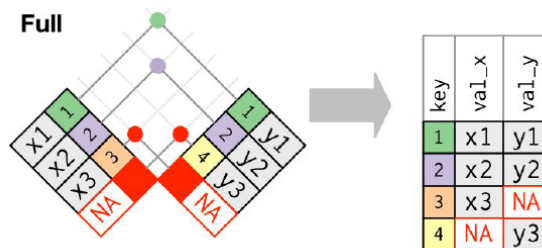
```
right_join(x, y, by="key")
```

```
## # A tibble: 3 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1  x1    y1
## 2     2  x2    y2
## 3     4 <NA>   y3
```

```
#or
x %>%
  right_join(y, by="key")
```

```
## # A tibble: 3 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1  x1    y1
## 2     2  x2    y2
## 3     4 <NA>   y3
```

Full join



Base R functoin:

```
merge(x, y, by="key",  
      all.x=TRUE,  
      all.y = TRUE)
```

```
#or  
x %>%  
  merge(y, by="key",  
        all.x=TRUE,  
        all.y = TRUE)
```

dplyr `full_join()` function:

```
full_join(x, y, by="key")
```

```
## # A tibble: 4 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1  x1    y1
## 2     2  x2    y2
## 3     3  x3    <NA>
## 4     4 <NA>   y3
```

```
#or
x %>%
  full_join(y, by="key")
```

```
## # A tibble: 4 × 3
##   key val_x val_y
##   <dbl> <chr> <chr>
## 1     1  x1    y1
## 2     2  x2    y2
## 3     3  x3    <NA>
## 4     4 <NA>   y3
```

Filtering Joins

Filtering Joins

- `semi_join(x, y)` *keeps* all observations in x that have a match in y.
- `anti_join(x, y)` *drops* all observations in x that have a match in y.

Question?

If we would like to find all the flight information from top 8 busiest destinations?

Step 1: Find the top 8 "dest"

```
busy.dest <- flights %>%  
  count(dest, sort=T) %>%  
  head(8)  
busy.dest
```

```
## # A tibble: 8 × 2  
##   dest      n  
##   <chr> <int>  
## 1 ORD    17283  
## 2 ATL    17215  
## 3 LAX    16174  
## 4 BOS    15508  
## 5 MCO    14082  
## 6 CLT    14064  
## 7 SFO    13331  
## 8 FLL    12055
```

Step 2: Retrieve flight information with these top 8 "dest"

```
flights %>%  
  filter(dest%in%busy.dest$dest)
```

```
## # A tibble: 119,712 × 19  
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time  
##   <int> <int> <int>   <int>         <int>         <dbl>   <int>         <int>  
## 1  2013     1     1     554           600         -6     812           837  
## 2  2013     1     1     554           558         -4     740           728  
## 3  2013     1     1     555           600         -5     913           854  
## 4  2013     1     1     557           600         -3     838           846  
## 5  2013     1     1     558           600         -2     753           745  
## 6  2013     1     1     558           600         -2     924           917  
## 7  2013     1     1     558           600         -2     923           937  
## 8  2013     1     1     559           559          0     702           706  
## 9  2013     1     1     600           600          0     851           858  
## 10 2013     1     1     600           600          0     837           825  
## # ... with 119,702 more rows, and 11 more variables: arr_delay <dbl>,  
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,  
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
```

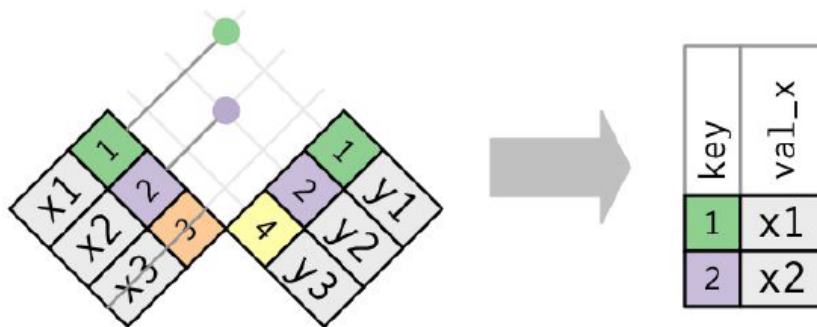

Semi-join

What if we use `semi_join()` to do the step 2

```
flights %>%  
  semi_join(busy.dest, by="dest")
```

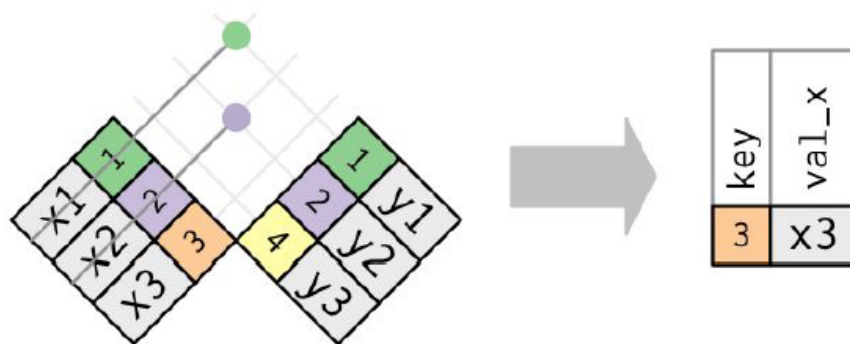
```
## # A tibble: 119,712 × 19  
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time  
##   <int> <int> <int>   <int>         <int>         <dbl>   <int>         <int>  
## 1  2013     1     1     554           600          -6     812           837  
## 2  2013     1     1     554           558          -4     740           728  
## 3  2013     1     1     555           600          -5     913           854  
## 4  2013     1     1     557           600          -3     838           846  
## 5  2013     1     1     558           600          -2     753           745  
## 6  2013     1     1     558           600          -2     924           917  
## 7  2013     1     1     558           600          -2     923           937  
## 8  2013     1     1     559           559           0     702           706  
## 9  2013     1     1     600           600           0     851           858  
## 10 2013     1     1     600           600           0     837           825  
## # ... with 119,702 more rows, and 11 more variables: arr_delay <dbl>,  
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,  
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
```

Semi-join (cont'd)



`semi_join(x, y)` keeps all observations in x that have a match in y .

Anti-join



`anti_join(x, y)` drops all observations in *x* that have a match in *y*.

What if we would like to find the rest of the "dest" information

```
flights %>%  
  anti_join(busy.dest, by="dest")
```

```
## # A tibble: 217,064 × 19  
##   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time  
##   <int> <int> <int>   <int>         <int>         <dbl>   <int>         <int>  
## 1  2013     1     1     517           515           2     830           819  
## 2  2013     1     1     533           529           4     850           830  
## 3  2013     1     1     542           540           2     923           850  
## 4  2013     1     1     544           545          -1    1004          1022  
## 5  2013     1     1     557           600          -3     709           723  
## 6  2013     1     1     558           600          -2     849           851  
## 7  2013     1     1     558           600          -2     853           856  
## 8  2013     1     1     559           600          -1     941           910  
## 9  2013     1     1     559           600          -1     854           902  
## 10 2013     1     1     601           600           1     844           850  
## # ... with 217,054 more rows, and 11 more variables: arr_delay <dbl>,  
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,  
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
```