Week 4: Data Wrangling

MTH 365: Introduction to Data Science

May 31, 2024

Recommended Reading

- *Modern Data Science with R* Ch. 4: Data Wrangling
- *Modern Data Science with R* Ch. 5: Tidy Data and Iteration
- Wickham, Hadley. (2014). "Tidy Data". *Journal of Statistical Software* 59(10). Available on BlueLine.
- https://srvanderplas.github.io/stat-computing-r-python/part-wrangling/00-wrangling.html

```r
library(tidyverse)
```

Data structure and semantics

- Most statistical datasets are tables made up of *rows* and *columns*. A dataset is a collection of *values*: these can be *numbers* (quantiative) or character *strings* (qualitative)

What is Data Wrangling?

Data Wrangling can be defined as the process of cleaning, organizing, and transforming raw data into the desired format for analysts to use for prompt decision making. Also known as data cleaning.

Why do you need this "Data Wrangling" Skill?

- Data wrangling helps to improve data usability as it converts data into a compatible format for the end system.
- It helps to quickly build data flows within an intuitive user interface and easily schedule and automate the data-flow process.
- Integrates various types of information and their sources (like databases, web services, files, etc.)
- Help users to process very large volumes of data easily and easily share data-flow techniques.

Messy Data

Five main ways tables of data tend not to be tidy:

1. Column headers are values, not variable names.
2. Multiple variables are stored in one column.
3. Variables are stored in both rows and columns.
4. Multiple types of observational units are stored in the same table.
5. A single observational unit is stored in multiple tables.

Tidy data

"Tidy" data is a standard way of mapping the meaning of a dataset to its structure.

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

Any other arrangement of the data is called "messy".

Real datasets can, and often do, violate the three principles of tidy data in almost every way imaginable! Even they do, sometimes we don't need the whole data for analysis.

dplyr

dplyr is a grammar of data manipulation, providing a consistent set of verbs that help you solve the most common data manipulation challenges

There are some of the primary dplyr verbs, representing distinct data analysis tasks:

`filter()`: Select specified rows of a data frame, produce subsets

`arrange()`: Reorder the rows of a data frame

`select()`: Select particular columns of a data frame

`mutate()`: Add new or change existing columns of the data frame (as functions of existing columns)

`summarise()`: Create collapsed summaries of a data frame

`group_by`: Introduce structure to a data frame

Example: Gapminder

Gapminder is an independent Swedish foundation with no political, religious or economic affiliations. **Gapminder is a fact tank, not a think tank.** Gapminder fights devastating misconceptions about global development. Gapminder produces free teaching resources making the world understandable based on reliable statistics. Gapminder promotes a fact-based worldview everyone can understand. Gapminder collaborates with universities, UN, public agencies and non-governmental organizations.

```r
library(dslabs)
data(gapminder)
glimpse(gapminder)
```

```
## Rows: 10,545
## Columns: 9
## $ country          <fct> "Albania", "Algeria", "Angola", "Antigua and Barbuda"~
## $ year             <int> 1960, 1960, 1960, 1960, 1960, 1960, 1960, 1960, 1960,~
## $ infant_mortality <dbl> 115.40, 148.20, 208.00, NA, 59.87, NA, NA, 20.30, 37.~
## $ life_expectancy  <dbl> 62.87, 47.50, 35.98, 62.97, 65.39, 66.86, 65.66, 70.8~
## $ fertility        <dbl> 6.19, 7.65, 7.32, 4.43, 3.11, 4.55, 4.82, 3.45, 2.70,~
## $ population       <dbl> 1636054, 11124892, 5270844, 54681, 20619075, 1867396,~
## $ gdp              <dbl> NA, 13828152297, NA, NA, 108322326649, NA, NA, 966778~
## $ continent        <fct> Europe, Africa, Africa, Americas, Americas, Asia, Ame~
## $ region           <fct> Southern Europe, Northern Africa, Middle Africa, Cari~
```

1. select()

```
gapminder %>% select(gdp, region) %>% head()
```

```
##              gdp          region
## 1             NA Southern Europe
## 2    13828152297 Northern Africa
## 3             NA   Middle Africa
## 4             NA       Caribbean
## 5   108322326649   South America
## 6             NA    Western Asia
```

```
gapminder_short = select(gapminder, gdp, region)
```

2. filter()

```
gapminder2000 = gapminder %>%
  filter(year == 2000)
head(gapminder2000)
```

```
##                country year infant_mortality life_expectancy fertility
## 1              Albania 2000             23.2            74.7      2.38
## 2              Algeria 2000             33.9            73.3      2.51
## 3               Angola 2000            128.3            52.3      6.84
## 4  Antigua and Barbuda 2000             13.8            73.8      2.32
## 5            Argentina 2000             18.0            74.2      2.48
## 6              Armenia 2000             26.6            71.3      1.30
##   population          gdp continent          region
## 1    3121965   3686649387    Europe Southern Europe
## 2   31183658  54790058957    Africa Northern Africa
## 3   15058638   9129180361    Africa   Middle Africa
## 4      77648    802526701  Americas       Caribbean
## 5   37057453 284203745280  Americas   South America
## 6    3076098   1911563665      Asia    Western Asia
```

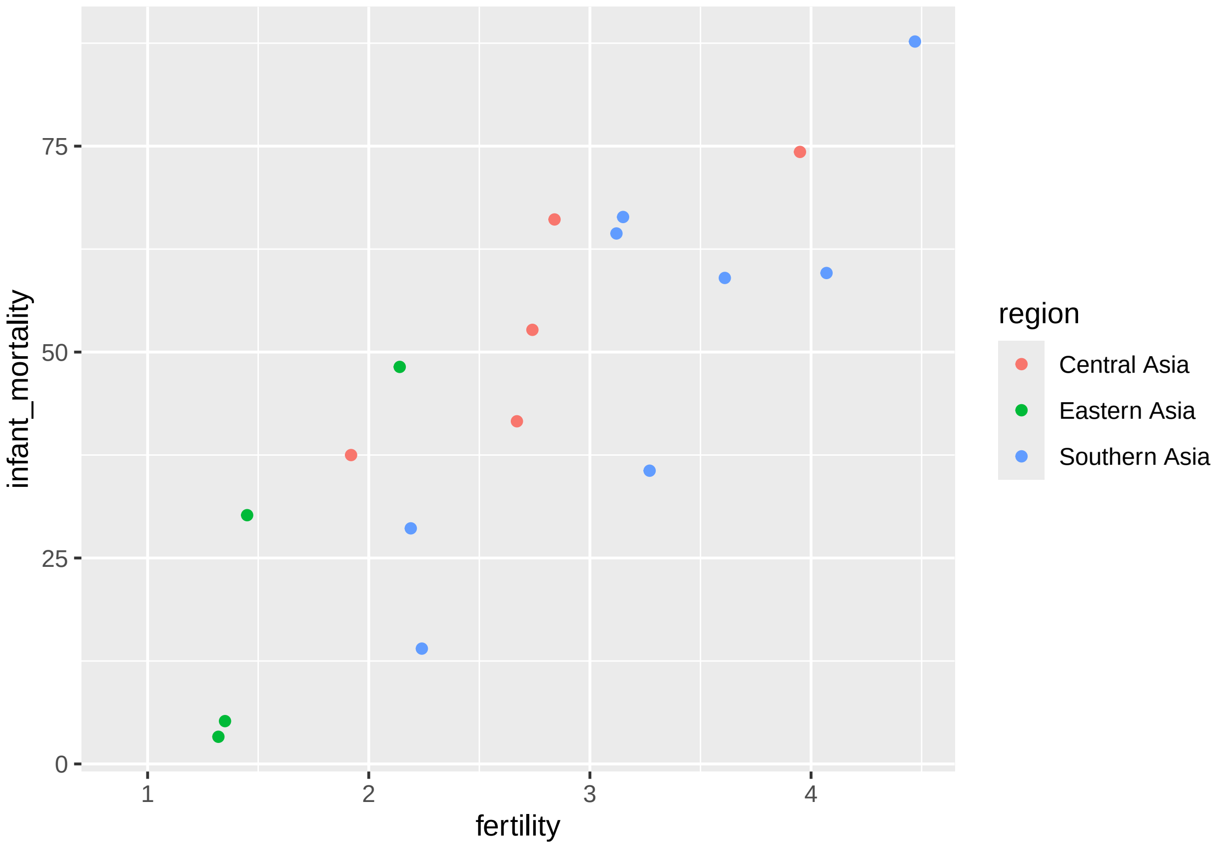
Now, let’s take a look at the scatter plot between fertility and infant_mortality for year 2000 only.

```
ggplot(gapminder2000, aes(x = fertility, y = infant_mortality)) +
  geom_point(aes(color = region))
```

Now, let's try to combine filter function and ggplot function. Start with the gapminder dataset, filter the data for year 2000 and region in Central Asia, Eastern Asia, and Southern Asia. Then make a plot of fertility and infant mortality and use color to indicate different regions.

```
gapminder %>% filter(year == 2000) %>%
  filter(region %in% c("Central Asia", "Eastern Asia", "Southern Asia")) %>%
  ggplot(aes(x = fertility, y = infant_mortality)) +
  geom_point(aes(color = region))
```

```
## Warning: Removed 2 rows containing missing values or values outside the scale range
## (`geom_point()`).
```



3. `mutate()`

Example: We'd like to calculate the gross domestic product per capita. Here are the variables in our data - write an expression to do this calculation.

```
gapminder = gapminder %>% mutate(GDP_pc = gdp/population)
head(gapminder)
```

```
##                country year infant_mortality life_expectancy fertility
## 1              Albania 1960           115.40           62.87      6.19
## 2              Algeria 1960           148.20           47.50      7.65
## 3               Angola 1960           208.00           35.98      7.32
## 4  Antigua and Barbuda 1960               NA           62.97      4.43
## 5            Argentina 1960            59.87           65.39      3.11
## 6              Armenia 1960               NA           66.86      4.55
##   population          gdp continent          region   GDP_pc
## 1    1636054           NA    Europe Southern Europe       NA
## 2   11124892  13828152297    Africa Northern Africa 1242.992
## 3    5270844           NA    Africa  Middle Africa        NA
## 4      54681           NA  Americas       Caribbean       NA
## 5   20619075 108322326649  Americas   South America 5253.501
## 6    1867396           NA      Asia    Western Asia       NA
```

Next, how do we find out which countries have the high GDP per capital?

4. arrange()

Right now, the data is sorted by country, then year. We could use the `arrange()` command to resort in terms of another variable.

```
GDP_only = gapminder %>% select(country, year, GDP_pc, continent)
head(GDP_only)
```

```
##               country year   GDP_pc continent
## 1             Albania 1960       NA    Europe
## 2             Algeria 1960 1242.992    Africa
## 3              Angola 1960       NA    Africa
## 4 Antigua and Barbuda 1960       NA  Americas
## 5           Argentina 1960 5253.501  Americas
## 6             Armenia 1960       NA      Asia
```

```
GDP_only %>% arrange(GDP_pc) %>% head()
```

```
##   country year   GDP_pc continent
## 1 Liberia 1995 54.88963    Africa
## 2 Liberia 1996 58.24203    Africa
## 3 Liberia 1994 59.06140    Africa
## 4   China 1962 72.36223      Asia
## 5 Liberia 1993 75.97131    Africa
## 6   China 1961 78.33912      Asia
```

```
GDP_only %>% arrange(desc(GDP_pc)) %>% head()
```

```
##                country year   GDP_pc continent
## 1 United Arab Emirates 1980 61340.89      Asia
## 2 United Arab Emirates 1981 59716.61      Asia
## 3 United Arab Emirates 1977 58532.69      Asia
## 4           Luxembourg 2007 57017.14    Europe
## 5 United Arab Emirates 1975 56279.40      Asia
## 6           Luxembourg 2008 56218.31    Europe
```

```
GDP_only %>% arrange(continent, desc(GDP_pc)) %>% head()
```

```
##             country year   GDP_pc continent
## 1 Equatorial Guinea 2011 8527.472    Africa
## 2 Equatorial Guinea 2009 8519.694    Africa
## 3        Seychelles 2011 8506.595    Africa
## 4 Equatorial Guinea 2008 8303.419    Africa
## 5 Equatorial Guinea 2010 8205.302    Africa
## 6        Seychelles 2010 8168.815    Africa
```

5. summarize()

If we want to compare summary statistics, we might use `summarize()`.

```
summary(GDP_only)
```

```
##                country          year          GDP_pc             continent   
##  Albania            :   57   Min.   :1960   Min.   :   54.89   Africa  :2907  
##  Algeria            :   57   1st Qu.:1974   1st Qu.:  532.48   Americas:2052  
##  Angola             :   57   Median :1988   Median : 1719.03   Asia    :2679  
##  Antigua and Barbuda:   57   Mean   :1988   Mean   : 5583.94   Europe  :2223  
##  Argentina          :   57   3rd Qu.:2002   3rd Qu.: 6689.21   Oceania : 684  
```

```
##  Armenia            :   57   Max.   :2016   Max.   :61340.89
##  (Other)            :10203                 NA's   :2972
```

```
GDP_only %>% summarise(avg = mean(GDP_pc),
                       min = min(GDP_pc),
                       max = max(GDP_pc),
                       sd = sd(GDP_pc))
```

```
##   avg min max sd
## 1  NA  NA  NA NA
```

```
GDP_only %>% filter(GDP_pc != "NA") %>%
  summarise(avg = mean(GDP_pc),
            min = min(GDP_pc),
            max = max(GDP_pc),
            sd = sd(GDP_pc),
            N = n())
```

```
##        avg      min      max       sd    N
## 1 5583.936 54.88963 61340.89 8339.741 7573
```

Wait, why are these NAs?

The `summarize()` function sometimes go with group_by function. Instead giving the summary information for the whole data, with a group_by function, it provides the summary information by groups.

```
GDP_only %>% filter(GDP_pc != "NA") %>%
  group_by(continent) %>%
  summarise(avg = mean(GDP_pc),
            min = min(GDP_pc),
            max = max(GDP_pc),
            sd = sd(GDP_pc),
            N = n())
```

```
## # A tibble: 5 x 6
##   continent    avg   min    max     sd     N
##   <fct>      <dbl> <dbl>  <dbl>  <dbl> <int>
## 1 Africa      904.  54.9  8527.  1289.  2270
## 2 Americas   5426. 370.  38656.  6315.  1703
## 3 Asia       5979.  72.4 61341.  9547.  1720
## 4 Europe    12708. 299.  57017. 10506.  1434
## 5 Oceania    5579. 426.  25439.  6240.   446
```

Try it for yourself

(a). Start with the gapminder dataset, filter the data for country United States and Canada, then select fertility, infant mortality and year to be included. Then make a scatterplot of fertility and infant mortality and use color to indicate different years. Note: think about a question, whether the order of filter and select matters?

(b). Show the summary statistics (mean, sd, min, max) of GDP_pc for year 2010 for different region. Hint: You cannot use the GDP_only data, why?

Joining Data

Table joins allow us to combine information stored in different tables, keeping what we need while discarding what we don't

Simple Data Example

```
df1 <- data.frame(
  id = 1:6,
  trt = rep(c("A", "B", "C"),
  rep=c(2,1,3)),
  value = c(5,3,7,1,2,3))

df1
```

```
##   id trt value
## 1  1   A     5
## 2  2   B     3
## 3  3   C     7
## 4  4   A     1
## 5  5   B     2
## 6  6   C     3
```

```
df2 <- data.frame(
  id=c(4,4,5,5,7,7),
  stress=rep(c(0,1), 3),
  bpm = c(65,125,74,136,48,110))

df2
```

```
##   id stress bpm
## 1  4      0  65
## 2  4      1 125
## 3  5      0  74
## 4  5      1 136
## 5  7      0  48
## 6  7      1 110
```

left_join() All elements in the left data set are kept

Mon-matches are filled in by NA

`right_join()` works symmetric

```
left_join(df1, df2, by="id")
```

```
##   id trt value stress bpm
## 1  1   A     5     NA  NA
## 2  2   B     3     NA  NA
## 3  3   C     7     NA  NA
## 4  4   A     1      0  65
## 5  4   A     1      1 125
## 6  5   B     2      0  74
## 7  5   B     2      1 136
## 8  6   C     3     NA  NA
```

inner_join() Only matches from both data sets are kept

```
inner_join(df1, df2, by="id")
```

```
##   id trt value stress bpm
## 1  4   A     1      0  65
```

```
## 2  4    A     1       1 125
## 3  5    B     2       0  74
## 4  5    B     2       1 136
```

full_join() All ids are kept, missings are filled in with NA

```r
full_join(df1, df2, by="id")
```

```
##    id  trt value stress bpm
## 1   1    A     5     NA  NA
## 2   2    B     3     NA  NA
## 3   3    C     7     NA  NA
## 4   4    A     1      0  65
## 5   4    A     1      1 125
## 6   5    B     2      0  74
## 7   5    B     2      1 136
## 8   6    C     3     NA  NA
## 9   7 <NA>    NA      0  48
## 10  7 <NA>    NA      1 110
```

Traps of joins

Sometimes we unexpectedly cannot match values: missing values, different spelling, …

Be very aware of things like a trailing or leading space

Join can be along multiple variables, e.g. by = c("ID", "Date")

Joining variable(s) can have different names, e.g. by = c("State" = "Name")

Always make sure to check dimensions of data before and after a join

Check on missing values; help with that: anti_join

anti_join() Return all rows from `x` without a match in `y`

```r
anti_join(df1, df2, by="id") # no values for id in df2
```

```
##   id trt value
## 1  1   A     5
## 2  2   B     3
## 3  3   C     7
## 4  6   C     3
```

```r
anti_join(df2, df1, by="id") # no values for id in df1
```

```
##   id stress bpm
## 1  7      0  48
## 2  7      1 110
```

Example: Linking Data: NYC flights

The R package `nycflights13` contains data about all flights that departed one of the three New York City airports (JFK, LGA, and EWR) in 2013. As you can probably imagine, this isn't a small dataset.

```r
#install.packages('nycflights13')
library(nycflights13)
data(flights)
```

```r
names(flights)
```

```
##  [1] "year"           "month"          "day"            "dep_time"
##  [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
##  [9] "arr_delay"      "carrier"        "flight"         "tailnum"
## [13] "origin"         "dest"           "air_time"       "distance"
## [17] "hour"           "minute"         "time_hour"
```

```r
glimpse(flights)
```

```
## Rows: 336,776
## Columns: 19
## $ year           <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2~
## $ month          <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ day            <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ dep_time       <int> 517, 533, 542, 544, 554, 554, 555, 557, 557, 558, 558, ~
## $ sched_dep_time <int> 515, 529, 540, 545, 600, 558, 600, 600, 600, 600, 600, ~
## $ dep_delay      <dbl> 2, 4, 2, -1, -6, -4, -5, -3, -3, -2, -2, -2, -2, -2, -1~
## $ arr_time       <int> 830, 850, 923, 1004, 812, 740, 913, 709, 838, 753, 849,~
## $ sched_arr_time <int> 819, 830, 850, 1022, 837, 728, 854, 723, 846, 745, 851,~
## $ arr_delay      <dbl> 11, 20, 33, -18, -25, 12, 19, -14, -8, 8, -2, -3, 7, -1~
## $ carrier        <chr> "UA", "UA", "AA", "B6", "DL", "UA", "B6", "EV", "B6", "~
## $ flight         <int> 1545, 1714, 1141, 725, 461, 1696, 507, 5708, 79, 301, 4~
## $ tailnum        <chr> "N14228", "N24211", "N619AA", "N804JB", "N668DN", "N394~
## $ origin         <chr> "EWR", "LGA", "JFK", "JFK", "LGA", "EWR", "EWR", "LGA",~
## $ dest           <chr> "IAH", "IAH", "MIA", "BQN", "ATL", "ORD", "FLL", "IAD",~
## $ air_time       <dbl> 227, 227, 160, 183, 116, 150, 158, 53, 140, 138, 149, 1~
## $ distance       <dbl> 1400, 1416, 1089, 1576, 762, 719, 1065, 229, 944, 733, ~
## $ hour           <dbl> 5, 5, 5, 5, 6, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6~
## $ minute         <dbl> 15, 29, 40, 45, 0, 58, 0, 0, 0, 0, 0, 0, 0, 0, 0, 59, 0~
## $ time_hour      <dttm> 2013-01-01 05:00:00, 2013-01-01 05:00:00, 2013-01-01 0~
```

Suppose we want to know more about the airline (`carrier`). In the data set, each carrier is stored using a two-letter code.

```r
table(flights$carrier)
```

```
##
##    9E    AA    AS    B6    DL    EV    F9    FL    HA    MQ    OO    UA    US
## 18460 32729   714 54635 48110 54173   685  3260   342 26397    32 58665 20536
##    VX    WN    YV
##  5162 12275   601
```

- Why use a two-letter code instead of the airline name?
- Can we *link* the airline names to the letter codes?

```r
data(airlines)
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.
```

Use a common variable, called a *key*, to link the data.

`inner_join()`

```r
flights_carrier = flights %>%
  inner_join(airlines, by = c("carrier" = "carrier"))
head(flights_carrier)
```

```
## # A tibble: 6 x 20
##    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      554            600        -6      812            837
## 6  2013     1     1      554            558        -4      740            728
## # i 12 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 <dttm>, name <chr>
```

Did it work?

```r
names(flights_carrier)
```

```
##  [1] "year"           "month"          "day"            "dep_time"
##  [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
##  [9] "arr_delay"      "carrier"        "flight"         "tailnum"
## [13] "origin"         "dest"           "air_time"       "distance"
## [17] "hour"           "minute"         "time_hour"      "name"
```

```r
glimpse(flights_carrier)
```

```
## Rows: 336,776
## Columns: 20
## $ year           <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2~
## $ month          <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ day            <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ dep_time       <int> 517, 533, 542, 544, 554, 554, 555, 557, 557, 558, 558, ~
## $ sched_dep_time <int> 515, 529, 540, 545, 600, 558, 600, 600, 600, 600, 600, ~
## $ dep_delay      <dbl> 2, 4, 2, -1, -6, -4, -5, -3, -3, -2, -2, -2, -2, -2, -1~
## $ arr_time       <int> 830, 850, 923, 1004, 812, 740, 913, 709, 838, 753, 849,~
## $ sched_arr_time <int> 819, 830, 850, 1022, 837, 728, 854, 723, 846, 745, 851,~
## $ arr_delay      <dbl> 11, 20, 33, -18, -25, 12, 19, -14, -8, 8, -2, -3, 7, -1~
```

```
## $ carrier        <chr> "UA", "UA", "AA", "B6", "DL", "UA", "B6", "EV", "B6", "~
## $ flight         <int> 1545, 1714, 1141, 725, 461, 1696, 507, 5708, 79, 301, 4~
## $ tailnum        <chr> "N14228", "N24211", "N619AA", "N804JB", "N668DN", "N394~
## $ origin         <chr> "EWR", "LGA", "JFK", "JFK", "LGA", "EWR", "EWR", "LGA",~
## $ dest           <chr> "IAH", "IAH", "MIA", "BQN", "ATL", "ORD", "FLL", "IAD",~
## $ air_time       <dbl> 227, 227, 160, 183, 116, 150, 158, 53, 140, 138, 149, 1~
## $ distance       <dbl> 1400, 1416, 1089, 1576, 762, 719, 1065, 229, 944, 733, ~
## $ hour           <dbl> 5, 5, 5, 5, 6, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6~
## $ minute         <dbl> 15, 29, 40, 45, 0, 58, 0, 0, 0, 0, 0, 0, 0, 0, 0, 59, 0~
## $ time_hour      <dttm> 2013-01-01 05:00:00, 2013-01-01 05:00:00, 2013-01-01 0~
## $ name           <chr> "United Air Lines Inc.", "United Air Lines Inc.", "Amer~
```

```
#this added the column "names" from the "airlines" dataframe.
```

Your Turn!

1. Create a new data set, `flights2` that contains the carrier name, year, month, day, departure delay, arrival delay, origin airport, destination airport, and flight number.
2. How many unique flight routes does United Airlines run that depart the New York area?
3. How many unique destinations does United Airlines serve from the New York Area?
4. How many unique flight routes does United Airlines run from each of the three area airports?
5. What is the average departure delay of a United Airlines flight leaving any New York area airport?
6. What is the average departure delay of a United Airlines flight leaving JFK? LGA? EWR?