Slides: Data Manipulation and Transformation

Actuarial Data Science Online Textbook

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Reading List

- R for Data Science Online Book, Chapters 5, 13
- Applied predictive Modelling, 3.3 (only transformations to resolve outliers), 3.4

Introduction

Motivation

- It is rare that you get the data in exactly the right form you need.
- You'll need to create some new variables or summaries, or
- you just want to rename the variables or reorder the observations in order to make the data a little easier to work with.

Using R to manipulate data

- R package: `dplyr` (a core member of `tidyverse`) for data manipulation and transformation[1]
- Data: `nycflights13` package, flights departing New York City in 2013
- We use `ggplot2` to help us understand the data.

```r
#install.packages("nycflights13")
library(nycflights13)
library(tidyverse)
```

1. dplyr overwrites some functions in base R. If you want to use the base version of these functions after loading dplyr, you'll need to use their full names: stats::filter() and stats::lag()

Data

```
flights #tibble, tweaked data frame to work better in tidyverse
```

year <int>	month <int>	day <int>	dep_time <int>	sched_dep_time <int>	dep_delay <dbl>
2013	1	1	517	515	2
2013	1	1	533	529	4
2013	1	1	542	540	2
2013	1	1	544	545	-1
2013	1	1	554	600	-6
2013	1	1	554	558	-4
2013	1	1	555	600	-5
2013	1	1	557	600	-3
2013	1	1	557	600	-3
2013	1	1	558	600	-2

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```
view(flights) # will open the dataset in the RStudio viewer
```

Types of variables

- `int` stands for integers.
- `dbl` stands for doubles, or real numbers.
- `chr` stands for character vectors, or strings.
- `dttm` stands for date-times (a date + a time).
- `lgl` stands for logical, vectors that contain only TRUE or FALSE.
- `fctr` stands for factors, which R uses to represent categorical variables with fixed possible values.
- `date` stands for dates.

Data Manipulation Functions

Functions for data manipulation

Functions in `dplyr` package

- `%>%` Pipe operator
- `glimpse()` A glimpse into the data and its structure
- `filter()` Pick observations by their values
- `arrange()` Reorder the rows
- `select()` Pick variables by their names
- `summarise()` Collapse many values down to a single
- `group_by()` Changes the scope of each function above from operating on the entire dataset to operating on it group-by-group

Filter: Introduction

```r
#The first argument is the name of the data frame.
#The subsequent arguments are the expressions that filter the data frame.
filter(flights, month == 1, day == 1)
```

year	month	day	dep_time	sched_dep_time	dep_delay
<int>	<int>	<int>	<int>	<int>	<dbl>
2013	1	1	517	515	2
2013	1	1	533	529	4
2013	1	1	542	540	2
2013	1	1	544	545	-1
2013	1	1	554	600	-6
2013	1	1	554	558	-4
2013	1	1	555	600	-5
2013	1	1	557	600	-3
2013	1	1	557	600	-3
2013	1	1	558	600	-2

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```r
# use the assignment operator, <- to save the result
#jan1 <- filter(flights, month == 1, day == 1)
# Save and print the result at the same time
#(dec25 <- filter(flights, month == 12, day == 25))
```

Filter: Comparisons

To use filtering effectively, you have to know how to select the observations that you want using the comparison operators. R provides the standard suite:

- `>` bigger than
- `>=` bigger than or equal to
- `<` less than
- `<=` less than or equal to
- `!=` not equal
- `==` equal[1]

1. Be cautions when using `==: floating point numbers`. Consider using `near()`

Filter: Logical Operators

- Multiple arguments to `filter()` are combined with "and": every expression must be true in order for a row to be included in the output.

Other types of combinations using Boolean operators:

- `&` is "and"
- `|` is "or"
- `!` is "not"
- `x %in% y` select every row where `x` is one of the values in `y`

According to De Morgan's law,

- `!(x & y)` is the same as `!x | !y`
- `!(x | y)` is the same as `!x & !y`

Exercise 1

- Find all flights that departed in November or December.

```
filter(flights, month %in% c(11, 12))
```

year <int>	month <int>	day <int>	dep_time <int>	sched_dep_time <int>	dep_delay <dbl>
2013	11	1	5	2359	6
2013	11	1	35	2250	105
2013	11	1	455	500	-5
2013	11	1	539	545	-6
2013	11	1	542	545	-3
2013	11	1	549	600	-11
2013	11	1	550	600	-10
2013	11	1	554	600	-6
2013	11	1	554	600	-6
2013	11	1	554	600	-6

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```
#Alternatively, use the following
#filter(flights, month == 11 | month == 12)
```

Exercise 2

- Find flights that weren't delayed (on arrival or departure) by more than two hours.

```
filter(flights, !(arr_delay > 120 | dep_delay > 120))
```

year <int>	month <int>	day <int>	dep_time <int>	sched_dep_time <int>	dep_delay <dbl>
2013	1	1	517	515	2
2013	1	1	533	529	4
2013	1	1	542	540	2
2013	1	1	544	545	-1
2013	1	1	554	600	-6
2013	1	1	554	558	-4
2013	1	1	555	600	-5
2013	1	1	557	600	-3
2013	1	1	557	600	-3
2013	1	1	558	600	-2

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```
#Alternatively, use the following
#filter(flights, arr_delay <= 120, dep_delay <= 120)
```

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Filter: Missing Values

- NA represents an unknown value so missing values are “contagious”: almost any operation involving an unknown value will also be unknown.
- `filter()` only includes rows where the condition is `TRUE`; it excludes both FALSE and NA values. If you want to preserve missing values, ask for them explicitly:

```
df <- tibble(x = c(1, NA, 3))
filter(df, x > 1)
```

x
<dbl>
3

1 row

```
filter(df, is.na(x) | x > 1)
```

x
<dbl>
NA
3

2 rows

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Arrange

- `arrange()`: Order by column names (or more complicated expressions)
- Use `desc()` to re-order by a column in descending order
- Missing values are always sorted at the end

```
arrange(flights, year)
```

year <int>	month <int>	day <int>	dep_time <int>	sched_dep_time <int>	dep_delay <dbl>
2013	1	1	517	515	2
2013	1	1	533	529	4
2013	1	1	542	540	2
2013	1	1	544	545	-1
2013	1	1	554	600	-6
2013	1	1	554	558	-4
2013	1	1	555	600	-5
2013	1	1	557	600	-3
2013	1	1	557	600	-3
2013	1	1	558	600	-2

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

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Select

- `select()` allows you to select a useful subset based on the names of the variables.

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

year <int>	month <int>	day <int>
2013	1	1
2013	1	1
2013	1	1
2013	1	1
2013	1	1
2013	1	1
2013	1	1
2013	1	1
2013	1	1
2013	1	1

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```
#select(flights, year:day)
#select(flights, -(year:day))
```

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`Select`: Useful functions

- `starts_with("abc")`: matches names that begin with “abc”.
- `ends_with("xyz")`: matches names that end with “xyz”.
- `contains("ijk")`: matches names that contain “ijk”.
- `matches()`: selects variables that match a regular expression.
- `everything()`

Other related functions:

- `rename()`: rename variables
- `mutate()`: create new variables with functions of existing variables

Summarise

```r
summarise(flights, delay = mean(dep_delay, na.rm = TRUE))
```

delay
<dbl>
12.63907

1 row

`Summarise`: with `group-by`

- This changes the unit of analysis from the complete dataset to individual groups.

```r
by_day <- group_by(flights, year, month, day)
summarise(by_day, delay = mean(dep_delay, na.rm = TRUE))
```

year <int>	month <int>	day <int>	delay <dbl>
2013	1	1	11.54892601
2013	1	2	13.85882353
2013	1	3	10.98783186
2013	1	4	8.95159516
2013	1	5	5.73221757
2013	1	6	7.14801444
2013	1	7	5.41720430
2013	1	8	2.55307263
2013	1	9	2.27647715
2013	1	10	2.84499462

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Summarise: Exercise with multiple operations

- Explore the relationship between the distance and average delay for each location
- There are three steps to prepare this data:
  - Group flights by destination
  - Summarise to compute distance, average delay, and number of flights
  - Filter to remove noisy points (counts below or equal to 20) and Honolulu ("HNL") airport, which is almost twice as far away as the next closest airport

Please have a try!

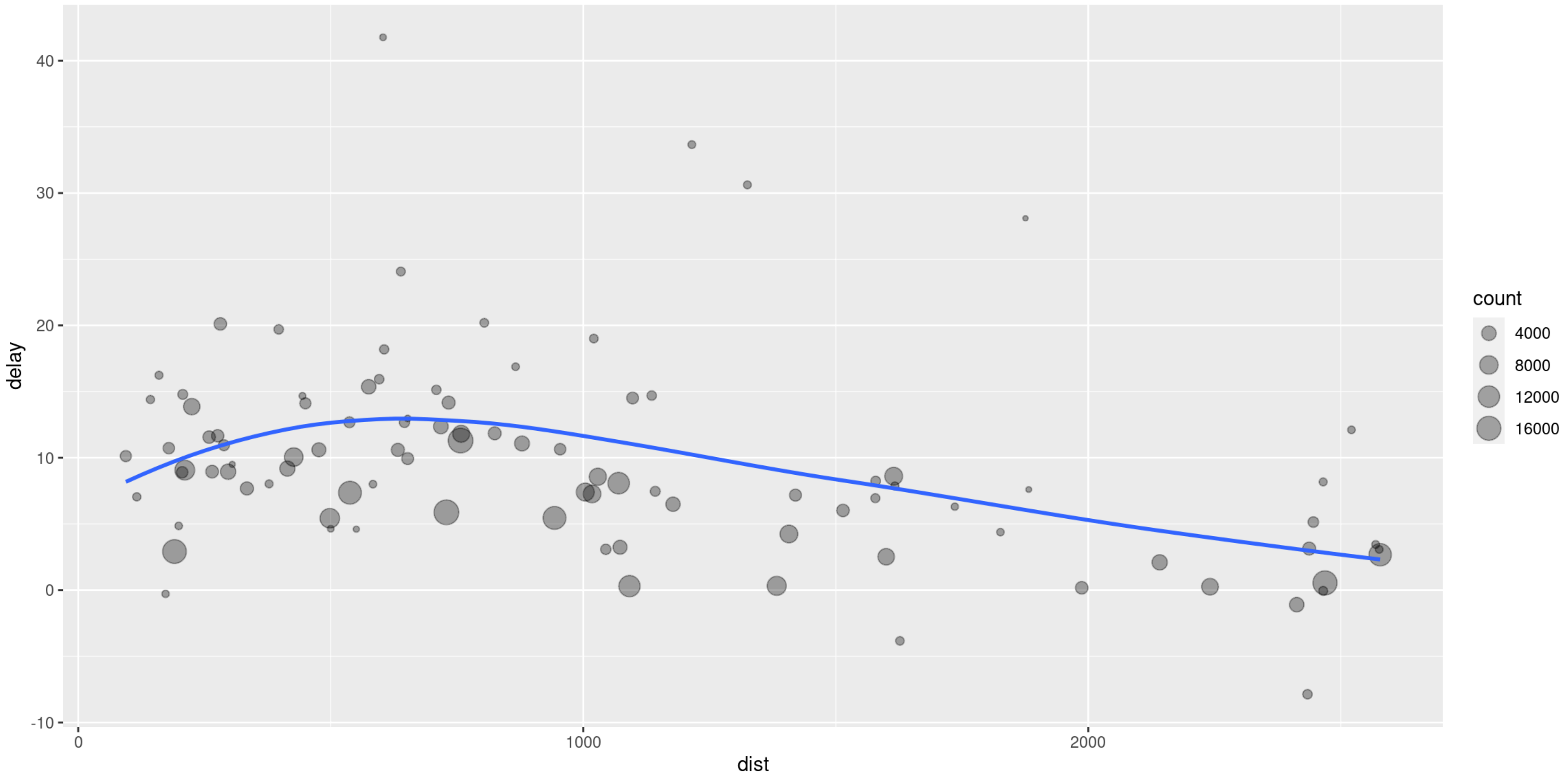
Exercise: code

```r
by_dest <- group_by(flights, dest)
delay <- summarise(by_dest,
  count = n(),
  dist = mean(distance, na.rm = TRUE),
  delay = mean(arr_delay, na.rm = TRUE)
)
delay <- filter(delay, count > 20, dest != "HNL")

# It looks like delays increase with distance up to ~750 miles
# and then decrease. Maybe as flights get longer there's more
# ability to make up delays in the air?
plot=ggplot(data = delay, mapping = aes(x = dist, y = delay)) +
  geom_point(aes(size = count), alpha = 1/3) +
  geom_smooth(se = FALSE)
#> `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```

Exercise: plot

```
print(plot)
```



Exercise: Another way to do it using pipe %>%

```
delays <- flights %>%
  group_by(dest) %>%
  summarise(
    count = n(),
    dist = mean(distance, na.rm = TRUE),
    delay = mean(arr_delay, na.rm = TRUE)
  ) %>%
  filter(count > 20, dest != "HNL")
```

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Missing values

- `na.rm=TRUE` removes the missing values

```
flights %>%
  group_by(year, month, day) %>%
  summarise(mean = mean(dep_delay, na.rm = TRUE))
```

year <int>	month <int>	day <int>	mean <dbl>
2013	1	1	11.54892601
2013	1	2	13.85882353
2013	1	3	10.98783186
2013	1	4	8.95159516
2013	1	5	5.73221757
2013	1	6	7.14801444
2013	1	7	5.41720430
2013	1	8	2.55307263
2013	1	9	2.27647715
2013	1	10	2.84499462

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Useful Summary functions

- Measures of location (central tendency): `mean(x)`, `median(x)`
- Measures of spread (variability): `sd(x)`, `IQR(x)`[1]
- Measures of rank: `min(x)`, `quantile(x, 0.25)`, `max(x)`
- Measures of position: `first(x)`, `nth(x, 2)`, `last(x)`
- Counts: `n()`, `sum(!is.na(x))`, `n_distinct(x)`
  - `count(tailnum, wt = distance)`, "count" (sum) the total number of miles a plane flew
- Counts and proportions of logical values: `sum(x > 10)`, `mean(y == 0)`

1. The interquartile range (IQR) is a measure of variability, based on dividing a data set into quartiles. Q1 is the "middle" value in the first half of the rank-ordered data set. Q2 is the median value in the set. Q3 is the "middle" value in the second half of the rank-ordered data set. The interquartile range is equal to Q3 minus Q1.

Grouping by multiple variables

```r
daily <- group_by(flights, year, month, day)
#n() returns the size of the current group
(per_day   <- summarise(daily, flights = n()))
```

year	month	day	flights
<int>	<int>	<int>	<int>
2013	1	1	842
2013	1	2	943
2013	1	3	914
2013	1	4	915
2013	1	5	720
2013	1	6	832
2013	1	7	933
2013	1	8	899
2013	1	9	902
2013	1	10	932

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Ungrouping

```r
daily %>%
  ungroup() %>%            # no longer grouped by date
  summarise(flights = n())  # all flights
```

flights
<int>
336776

1 row

Relational Data

Relational Data

- **Relational data**: multiple tables of data that are related.

Three families of verbs designed to work with relational data:

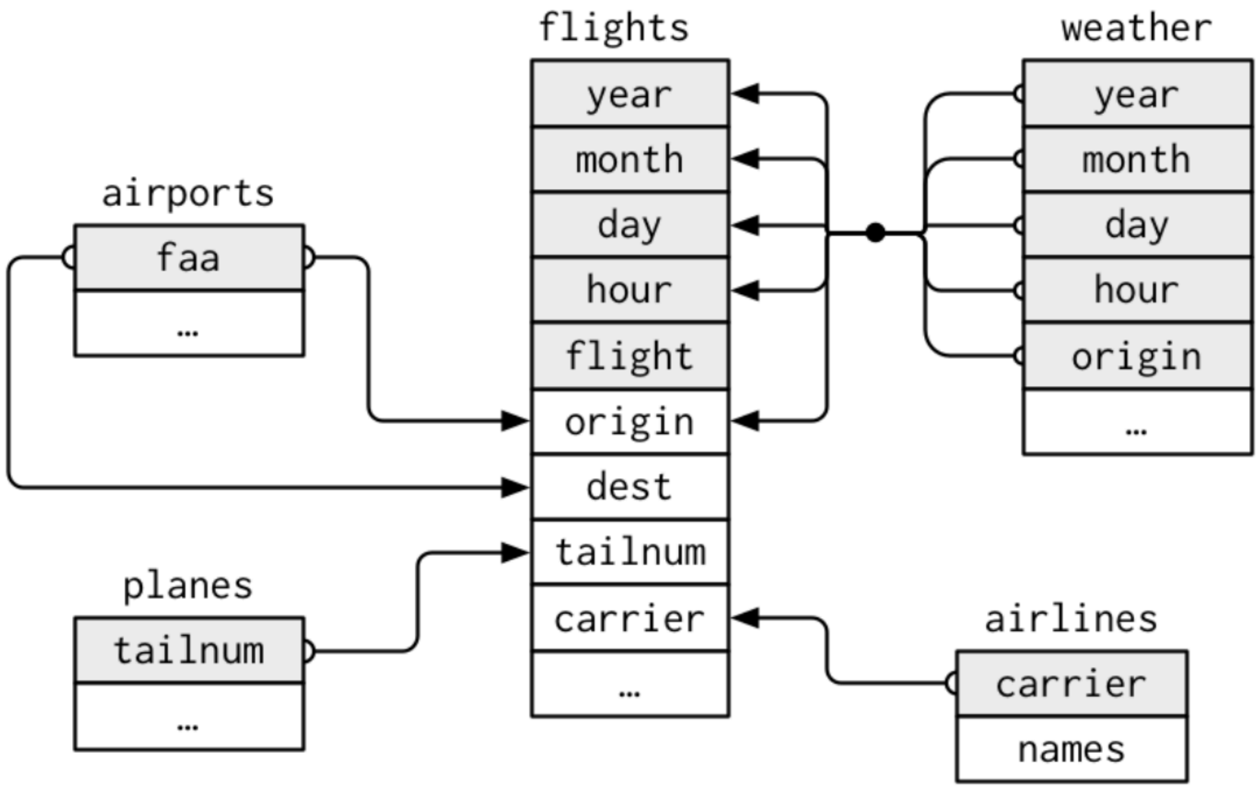
- **Mutating joins**: add new variables to one data frame from matching observations in another.
- **Filtering joins**: filter observations from one data frame based on whether or not they match an observation in the other table.
- **Set operations**: treat observations as if they were set elements.
- Other similar database system: SQL

Data set

- `nycflights13` contains five tibbles that are related to each other:
  - `flights`: gives information about each flight
  - `airlines`: lets you look up the full carrier name
  - `airports`: gives information about each airport, identified by the `faa` airport code
  - `planes`: gives information about each plane, identified by its `tailnum`
  - `weather`: gives the weather at each NYC airport for each hour

Table Relations

- Each relation always concerns a pair of tables
- Understand the chain of relations between the tables that you are interested in.



Keys

- Primary key: uniquely identifies an observation in its own table.
  - For example, `planes$tailnum` is a primary key because it uniquely identifies each plane in the planes table.
- Foreign key: uniquely identifies an observation in another table.
  - For example, `flights$tailnum` is a foreign key because it appears in the flights table where it matches each flight to a unique plane.
- A variable can be both a primary key and a foreign key. For example, origin is part of the weather primary key, and is also a foreign key for the airport table.

Identify the primary keys

- `count()` the primary keys and look for entries where `n` is greater than one.

```
planes %>%
  count(tailnum) %>%
  filter(n > 1)
```

0 rows

Add a primary key

- What's the primary key in the `flights` table?
  - None
- Surrogate key:add one primary key with `mutate()` and `row_number()`
- A primary key and the corresponding foreign key in another table form a **relation**.
- Relations are typically one-to-many. You can model many-to-many relations with a many-to-1 relation plus a 1-to-many relation.

Exercise: Add a surrogate key to flights

```r
flights %>%
  arrange(year, month, day, sched_dep_time, carrier, flight) %>%
  mutate(flight_id = row_number()) %>%
  #TThis makes it possible to see every column in a data frame.
  glimpse()
```

```
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, 559, 558, 559, 558, 558, 557, …
$ sched_dep_time <int> 515, 529, 540, 545, 558, 559, 600, 600, 600, 600, 600, …
$ dep_delay      <dbl> 2, 4, 2, -1, -4, 0, -2, -1, -2, -2, -3, NA, 1, 0, -5, -…
$ arr_time       <int> 830, 850, 923, 1004, 740, 702, 753, 941, 849, 853, 838,…
$ sched_arr_time <int> 819, 830, 850, 1022, 728, 706, 745, 910, 851, 856, 846,…
$ arr_delay      <dbl> 11, 20, 33, -18, 12, -4, 8, 31, -2, -3, -8, NA, -6, -7,…
$ carrier        <chr> "UA", "UA", "AA", "B6", "UA", "B6", "AA", "AA", "B6", "…
$ flight         <int> 1545, 1714, 1141, 725, 1696, 1806, 301, 707, 49, 71, 79…
$ tailnum        <chr> "N14228", "N24211", "N619AA", "N804JB", "N39463", "N708…
$ origin         <chr> "EWR", "LGA", "JFK", "JFK", "EWR", "JFK", "LGA", "LGA",…
$ dest           <chr> "IAH", "IAH", "MIA", "BQN", "ORD", "BOS", "ORD", "DFW",…
$ air_time       <dbl> 227, 227, 160, 183, 150, 44, 138, 257, 149, 158, 140, N…
$ distance       <dbl> 1400, 1416, 1089, 1576, 719, 187, 733, 1389, 1028, 1005…
$ hour           <dbl> 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6…
$ minute         <dbl> 15, 29, 40, 45, 58, 59, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
$ time_hour      <dttm> 2013-01-01 05:00:00, 2013-01-01 05:00:00, 2013-01-01 0…
$ flight_id      <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, …
```

Mutating Joins

- Mutating join allows you to combine variables from two tables. It first matches observations by their keys, then copies across variables from one table to the other.
- Add columns from y to x:
  - `inner_join()`: keeps observations that appear in both tables.
  - `left_join()`: keeps all observations in x.
  - `right_join()`: keeps all observations in y.
  - `full_join()`: keeps all observations in x and y.

```r
flights %>%
  select(year:day, hour, tailnum, carrier) %>%
  left_join(airlines, by = "carrier") #by = "key"
```

year <int>	month <int>	day <int>	hour <dbl>	tailnum <chr>	carrier <chr>
2013	1	1	5	N14228	UA
2013	1	1	5	N24211	UA
2013	1	1	5	N619AA	AA
2013	1	1	5	N804JB	B6
2013	1	1	6	N668DN	DL
2013	1	1	5	N39463	UA

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Mutating Joins: The Key Columns

- When you join duplicated keys, you get all possible combinations.
- Defining the key columns
  - `by=NULL`: uses all variables that appear in both tables, the so called natural join
  - `by = "x"`: uses only some of the common variables.
  - `by = c("a" = "b")`: match variable a in table x to variable b in table y

Mutating Joins: `base::merge()`

dplyr	**merge**
inner_join(x, y)	merge(x, y)
left_join(x, y)	merge(x, y, all.x = TRUE)
right_join(x, y)	merge(x, y, all.y = TRUE)
full_join(x, y)	merge(x, y, all.x = TRUE, all.y = TRUE)

- dplyr's joins are considerably faster and don't mess with the order of the rows.

Filtering Joins

- Filtering joins match observations in the same way as mutating joins, but affect the observations, not the variables.
- There are two types:
  - 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.

Exercise 1

- Questions:
  - find the top ten most popular destinations
  - match it back to `flights`

```r
top_dest <- flights %>%
  count(dest, sort = TRUE) %>%
  head(10)

flights %>%
  semi_join(top_dest)
```

year <int>	month <int>	day <int>	dep_time <int>	sched_dep_time <int>	dep_delay <dbl>
2013	1	1	542	540	2
2013	1	1	554	600	-6
2013	1	1	554	558	-4
2013	1	1	555	600	-5
2013	1	1	557	600	-3
2013	1	1	558	600	-2
2013	1	1	558	600	-2
2013	1	1	558	600	-2
2013	1	1	559	559	0
2013	1	1	600	600	0

Exercise 2

- Question: when connecting flights and planes, what are the flights that don't have a match in planes?

```r
flights %>%
  anti_join(planes, by = "tailnum") %>%
  count(tailnum, sort = TRUE)
```

tailnum <chr>	n <int>
NA	2512
N725MQ	575
N722MQ	513
N723MQ	507
N713MQ	483
N735MQ	396
N0EGMQ	371
N534MQ	364
N542MQ	363
N531MQ	349

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Join problems

- Start by identifying the variables that form the primary key in each table.
- Check that none of the variables in the primary key are missing. If a value is missing then it can't identify an observation!
- Check that your foreign keys match primary keys in another table. The best way to do this is with an anti_join().

Set Operations

- `intersect(x, y)`: return only observations in both x and y.
- `union(x, y)`: return unique observations in x and y.
- `setdiff(x, y)`: return observations in x, but not in y.

Examples

```r
df1 <- tribble(
  ~x, ~y,
   1,  1,
   2,  1
)
df2 <- tribble(
  ~x, ~y,
   1,  1,
   1,  2
)
intersect(df1, df2)
```

x <dbl>	y <dbl>
1	1

1 row

```r
union(df1, df2)
```

x <dbl>	y <dbl>
1	1
2	1
1	2

3 rows

```r
setdiff(df1, df2) #setdiff(df2, df1)
```