Columbia University in the City of New York

Lecture 5: Data Wrangling II

Data Science for Business Analytics

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Outline

Relational data

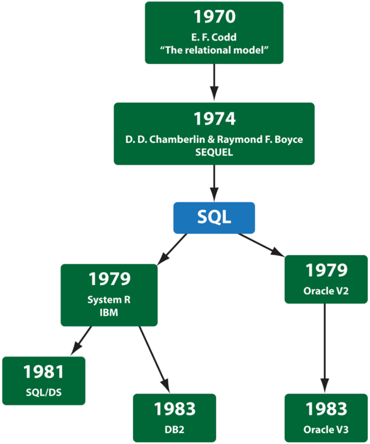
- Until now: analysis of a single table of data.
- Typically: multiple tables of data to be combined.

Multiple tables of data are called **relational data**:

- Because relations, not just the individual datasets, are important.
- Relations are always defined for a pair of tables.
- Relations of three or more tables are built from the relations between pairs.

RDMS

- Common place to find relational data.
- Oracle, MySQL, Microsoft SQL Server, PostgreSQL, IBM DB2, Microsoft Access, SQLite, and others.



nycflights13::flights

All 336,776 flights that departed from NYC in 2013 (US BTS):

```
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      2.00      830
##  2  2013     1     1      533            529      4.00      850
##  3  2013     1     1      542            540      2.00      923
##  4  2013     1     1      544            545     -1.00     1004
##  5  2013     1     1      554            600     -6.00      812
##  6  2013     1     1      554            558     -4.00      740
##  7  2013     1     1      555            600     -5.00      913
##  8  2013     1     1      557            600     -3.00      709
##  9  2013     1     1      557            600     -3.00      838
## 10  2013     1     1      558            600     -2.00      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>
```

nycflights13::airlines

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```
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.
```

nycflights13::airports

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```r
airports
```

```
## # A tibble: 1,458 x 8
##    faa   name                lat    lon   alt    tz dst   tzone
##    <chr> <chr>             <dbl>  <dbl> <int> <dbl> <chr> <chr>
##  1 04G   Lansdowne Airport  41.1 - 80.6  1044 -5.00 A     America/Ne~
##  2 06A   Moton Field Muni~  32.5 - 85.7   264 -6.00 A     America/Ch~
##  3 06C   Schaumburg Regio~  42.0 - 88.1   801 -6.00 A     America/Ch~
##  4 06N   Randall Airport    41.4 - 74.4   523 -5.00 A     America/Ne~
##  5 09J   Jekyll Island Ai~  31.1 - 81.4    11 -5.00 A     America/Ne~
##  6 0A9   Elizabethton Mun~  36.4 - 82.2  1593 -5.00 A     America/Ne~
##  7 0G6   Williams County ~  41.5 - 84.5   730 -5.00 A     America/Ne~
##  8 0G7   Finger Lakes Reg~  42.9 - 76.8   492 -5.00 A     America/Ne~
##  9 0P2   Shoestring Aviat~  39.8 - 76.6  1000 -5.00 U     America/Ne~
## 10 0S9   Jefferson County~  48.1 -123     108 -8.00 A     America/Lo~
## # ... with 1,448 more rows
```

nycflights13::planes

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```
planes
```

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

nycflights13::weather

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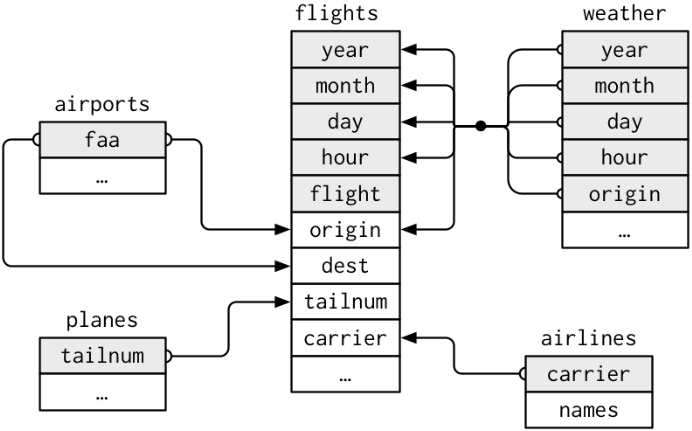
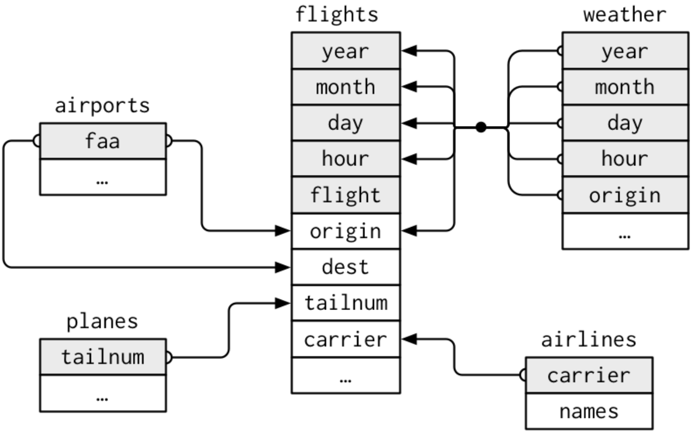
```
weather
```

```
## # A tibble: 26,130 x 15
##    origin  year month   day  hour  temp  dewp humid wind_dir
##    <chr>  <dbl> <dbl> <int> <int> <dbl> <dbl> <dbl>    <dbl>
##  1 EWR     2013  1.00     1     0  37.0  21.9  54.0      230
##  2 EWR     2013  1.00     1     1  37.0  21.9  54.0      230
##  3 EWR     2013  1.00     1     2  37.9  21.9  52.1      230
##  4 EWR     2013  1.00     1     3  37.9  23.0  54.5      230
##  5 EWR     2013  1.00     1     4  37.9  24.1  57.0      240
##  6 EWR     2013  1.00     1     6  39.0  26.1  59.4      270
##  7 EWR     2013  1.00     1     7  39.0  27.0  61.6      250
##  8 EWR     2013  1.00     1     8  39.0  28.0  64.4      240
##  9 EWR     2013  1.00     1     9  39.9  28.0  62.2      250
## 10 EWR     2013  1.00     1    10  39.0  28.0  64.4      260
## # ... with 26,120 more rows, and 6 more variables: wind_speed <dbl>,
## #   wind_gust <dbl>, precip <dbl>, pressure <dbl>, visib <dbl>,
## #   time_hour <dttm>
```

nycflights13

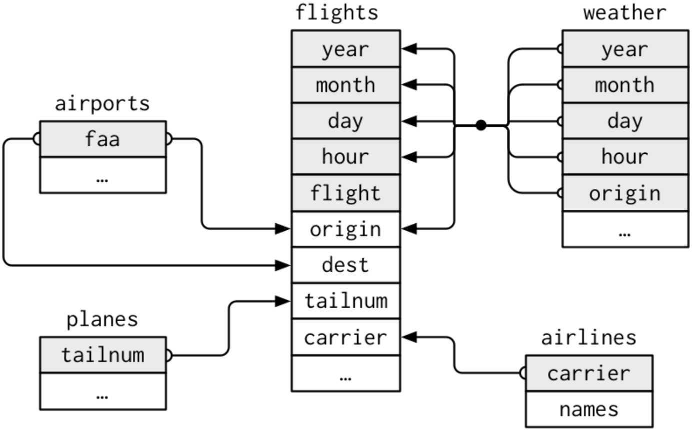


Exercise 1



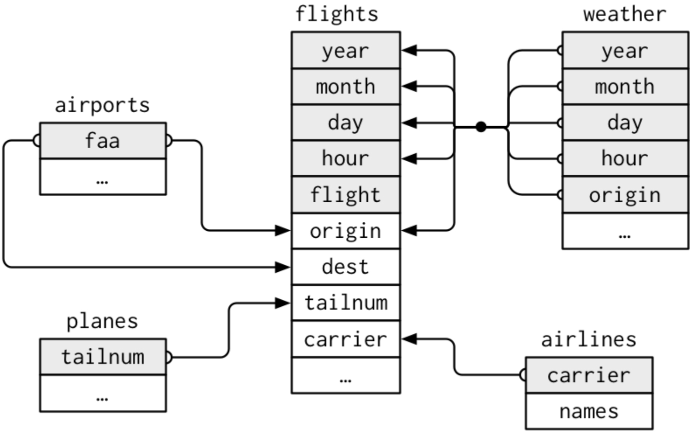
Imagine you wanted to draw (approximately) the route each plane flies from its origin to its destination. What variables would you need? What tables would you need to combine?

Exercise 2



I forgot to draw the relationship between `weather` and `airports`. What is the relationship and how should it appear in the diagram?

Exercise 3



`weather` only contains information for the origin (NYC) airports. If it contained weather records for all airports in the USA, what additional relation would it define with `flights`?

Keys

- Variables used to connect pair of tables.
- Uniquely identifies an observation.
- Either a single variable (e.g., `tailnum` for `planes`) or multiple variables (e.g., `year`, `month`, `day`, `hour`, and `origin` for `weather`).

Two types of **keys**:

- A **primary key** uniquely identifies an observation **in its own table** (e.g., `planes$tailnum`).
- A **foreign key** uniquely identifies an observation **in another table** (e.g., `flights$tailnum`).

Note that:

- A variable can be both a primary key *and* a foreign key.
- A primary key and the corresponding foreign key in another table form a **relation**.
- Relations are typically one-to-many (e.g., flights and planes).

Is a given key primary?

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

```
## # A tibble: 0 x 2
## # ... with 2 variables: tailnum <chr>, n <int>
```

```
weather %>%
  count(year, month, day, hour, origin) %>%
  filter(n > 1)
```

```
## # A tibble: 0 x 6
## # ... with 6 variables: year <dbl>, month <dbl>, day <int>,
## #   hour <int>, origin <chr>, n <int>
```

No explicit primary key?


```r
flights %>%
  count(year, month, day, flight) %>%
  filter(n > 1)
```

```
## # A tibble: 29,768 x 5
##     year month   day flight     n
##    <int> <int> <int>  <int> <int>
##  1  2013     1     1      1     2
##  2  2013     1     1      3     2
##  3  2013     1     1      4     2
##  4  2013     1     1     11     3
##  5  2013     1     1     15     2
##  6  2013     1     1     21     2
##  7  2013     1     1     27     4
##  8  2013     1     1     31     2
##  9  2013     1     1     32     2
## 10  2013     1     1     35     2
## # ... with 29,758 more rows
```

- Solution: add one with `mutate()` and `row_number()`.
- This is called a **surrogate key**.

Outline

Combining tables

Three families of verbs 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.
- **Set operations**, which treat observations as if they were set elements.

Create a narrower dataset


```r
flights2 <- flights %>%
  select(year:day, hour, origin, dest, tailnum, carrier)
flights2
```

```
## # A tibble: 336,776 x 8
##     year month   day  hour origin dest  tailnum carrier
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>
##  1  2013     1     1  5.00 EWR    IAH   N14228  UA
##  2  2013     1     1  5.00 LGA    IAH   N24211  UA
##  3  2013     1     1  5.00 JFK    MIA   N619AA  AA
##  4  2013     1     1  5.00 JFK    BQN   N804JB  B6
##  5  2013     1     1  6.00 LGA    ATL   N668DN  DL
##  6  2013     1     1  5.00 EWR    ORD   N39463  UA
##  7  2013     1     1  6.00 EWR    FLL   N516JB  B6
##  8  2013     1     1  6.00 LGA    IAD   N829AS  EV
##  9  2013     1     1  6.00 JFK    MCO   N593JB  B6
## 10  2013     1     1  6.00 LGA    ORD   N3ALAA  AA
## # ... with 336,766 more rows
```

A simple example


```r
flights2 %>%
  select(-origin, -dest) %>%
  left_join(airlines, by = "carrier")
```

```
## # A tibble: 336,776 x 7
##     year month   day  hour tailnum carrier name
##    <int> <int> <int> <dbl> <chr>   <chr>   <chr>
##  1  2013     1     1  5.00 N14228  UA      United Air Lines Inc.
##  2  2013     1     1  5.00 N24211  UA      United Air Lines Inc.
##  3  2013     1     1  5.00 N619AA  AA      American Airlines Inc.
##  4  2013     1     1  5.00 N804JB  B6      JetBlue Airways
##  5  2013     1     1  6.00 N668DN  DL      Delta Air Lines Inc.
##  6  2013     1     1  5.00 N39463  UA      United Air Lines Inc.
##  7  2013     1     1  6.00 N516JB  B6      JetBlue Airways
##  8  2013     1     1  6.00 N829AS  EV      ExpressJet Airlines Inc.
##  9  2013     1     1  6.00 N593JB  B6      JetBlue Airways
## 10  2013     1     1  6.00 N3ALAA  AA      American Airlines Inc.
## # ... with 336,766 more rows
```

Why mutating join?

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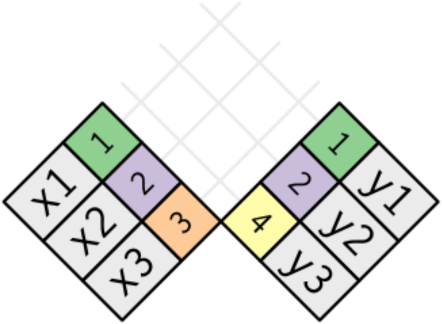
```r
flights2 %>%
  select(-origin, -dest) %>%
  mutate(name = airlines$name[match(carrier, airlines$carrier)])
```

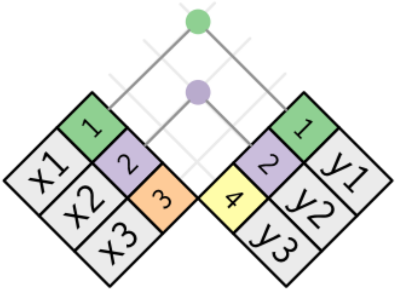
```
## # A tibble: 336,776 x 7
##     year month   day  hour tailnum carrier name
##    <int> <int> <int> <dbl> <chr>   <chr>   <chr>
##  1  2013     1     1  5.00 N14228  UA      United Air Lines Inc.
##  2  2013     1     1  5.00 N24211  UA      United Air Lines Inc.
##  3  2013     1     1  5.00 N619AA  AA      American Airlines Inc.
##  4  2013     1     1  5.00 N804JB  B6      JetBlue Airways
##  5  2013     1     1  6.00 N668DN  DL      Delta Air Lines Inc.
##  6  2013     1     1  5.00 N39463  UA      United Air Lines Inc.
##  7  2013     1     1  6.00 N516JB  B6      JetBlue Airways
##  8  2013     1     1  6.00 N829AS  EV      ExpressJet Airlines Inc.
##  9  2013     1     1  6.00 N593JB  B6      JetBlue Airways
## 10  2013     1     1  6.00 N3ALAA  AA      American Airlines Inc.
## # ... with 336,766 more rows
```

Understanding mutating joins


```r
x <- tribble(~key, ~val_x,
             1, "x1",
             2, "x2",
             3, "x3")
y <- tribble(~key, ~val_y,
             1, "y1",
             2, "y2",
             4, "y3")
```



Inner join



key	val_x	val_y
1	x1	y1
2	x2	y2

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

```
## # A tibble: 2 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1  1.00 x1    y1
## 2  2.00 x2    y2
```

Outer joins

An **outer join** keeps observations that appear in at least one of the tables:

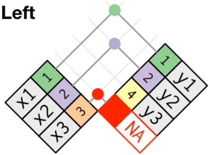
- A **left join** keeps all observations in `x`.
- A **right join** keeps all observations in `y`.
- A **full join** keeps all observations in `x` and `y`.

They work by adding to each table an additional "virtual" observation which

- has a key that always matches (if no other key matches),
- and a value filled with `NA`.

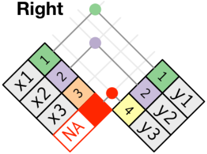
Outer joins II

Left



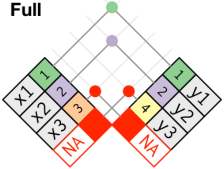
key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA

Right



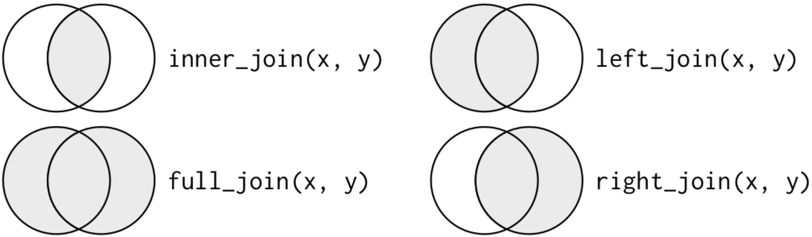
key	val_x	val_y
1	x1	y1
2	x2	y2
4	NA	y3

Full



key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA
4	NA	y3

A Venn diagram for joins

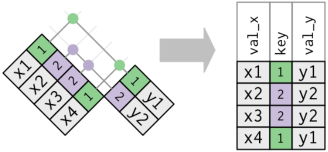


Duplicate keys

Two possibilities:

1. One table has duplicate keys.
   - Useful to add in additional information as there is typically a one-to-many relationship.
2. Both tables have duplicate keys.
   - Usually an error because in neither table do the keys uniquely identify an observation.
   - When you join duplicated keys, you get all possible combinations (i.e., the Cartesian product).

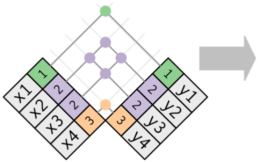
One table has duplicate keys




```r
x <- tribble(~key, ~val_x,
             1, "x1",
             2, "x2",
             2, "x3",
             1, "x4")
y <- tribble(~key, ~val_y,
             1, "y1",
             2, "y2")
left_join(x, y, by = "key")
```

```
## # A tibble: 4 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1  1.00 x1    y1
## 2  2.00 x2    y2
## 3  2.00 x3    y2
```

Both tables have duplicate keys



key	val_x	val_y
1	x1	y1
2	x2	y2
2	x2	y3
2	x3	y2
2	x3	y3
3	x4	y4

```r
x <- tribble(~key, ~val_x, 1, "x1", 2, "x2", 2, "x3", 3, "x4")
y <- tribble(~key, ~val_y, 1, "y1", 2, "y2", 2, "y3", 3, "y4")
left_join(x, y, by = "key")
```

```
## # A tibble: 6 x 3
##     key val_x val_y
##   <dbl> <chr> <chr>
## 1  1.00 x1    y1
## 2  2.00 x2    y2
## 3  2.00 x2    y3
## 4  2.00 x3    y2
## 5  2.00 x3    y3
## 6  3.00 x4    y4
```

Defining the key columns

Default uses all variables that appear in both tables (**natural**):

```
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
##    <dbl> <dbl> <int> <dbl> <chr>  <chr> <chr>   <chr>   <dbl> <dbl>
##  1  2013  1.00     1  5.00 EWR    IAH   N14228  UA       NA    NA
##  2  2013  1.00     1  5.00 LGA    IAH   N24211  UA       NA    NA
##  3  2013  1.00     1  5.00 JFK    MIA   N619AA  AA       NA    NA
##  4  2013  1.00     1  5.00 JFK    BQN   N804JB  B6       NA    NA
##  5  2013  1.00     1  6.00 LGA    ATL   N668DN  DL       39.9  26.1
##  6  2013  1.00     1  5.00 EWR    ORD   N39463  UA       NA    NA
##  7  2013  1.00     1  6.00 EWR    FLL   N516JB  B6       39.0  26.1
##  8  2013  1.00     1  6.00 LGA    IAD   N829AS  EV       39.9  26.1
##  9  2013  1.00     1  6.00 JFK    MCO   N593JB  B6       39.0  26.1
## 10  2013  1.00     1  6.00 LGA    ORD   N3ALAA  AA       39.9  26.1
## # ... with 336,766 more rows, and 8 more variables: humid <dbl>,
## #   wind_dir <dbl>, wind_speed <dbl>, wind_gust <dbl>, precip <dbl>,
## #   pressure <dbl>, visib <dbl>, time_hour <dttm>
```

Using a character vector

Like a natural join, but uses only some of the common variables:

```
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  5.00 EWR    IAH   N14228  UA        1999 Fixe~
##  2   2013     1     1  5.00 LGA    IAH   N24211  UA        1998 Fixe~
##  3   2013     1     1  5.00 JFK    MIA   N619AA  AA        1990 Fixe~
##  4   2013     1     1  5.00 JFK    BQN   N804JB  B6        2012 Fixe~
##  5   2013     1     1  6.00 LGA    ATL   N668DN  DL        1991 Fixe~
##  6   2013     1     1  5.00 EWR    ORD   N39463  UA        2012 Fixe~
##  7   2013     1     1  6.00 EWR    FLL   N516JB  B6        2000 Fixe~
##  8   2013     1     1  6.00 LGA    IAD   N829AS  EV        1998 Fixe~
##  9   2013     1     1  6.00 JFK    MCO   N593JB  B6        2004 Fixe~
## 10   2013     1     1  6.00 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>
```

Using a named character vector

With `by = c("a" = "b")`, `left_join` matches variable `a` in table `x` to variable `b` in table `y`:

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

```
## # A tibble: 336,776 x 15
##     year month   day  hour origin dest  tailnum carrier name      lat
##    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr>   <dbl>
##  1  2013     1     1  5.00 EWR    IAH   N14228  UA      George~  30.0
##  2  2013     1     1  5.00 LGA    IAH   N24211  UA      George~  30.0
##  3  2013     1     1  5.00 JFK    MIA   N619AA  AA      Miami ~  25.8
##  4  2013     1     1  5.00 JFK    BQN   N804JB  B6      <NA>     NA
##  5  2013     1     1  6.00 LGA    ATL   N668DN  DL      Hartsf~  33.6
##  6  2013     1     1  5.00 EWR    ORD   N39463  UA      Chicag~  42.0
##  7  2013     1     1  6.00 EWR    FLL   N516JB  B6      Fort L~  26.1
##  8  2013     1     1  6.00 LGA    IAD   N829AS  EV      Washin~  38.9
##  9  2013     1     1  6.00 JFK    MCO   N593JB  B6      Orland~  28.4
## 10  2013     1     1  6.00 LGA    ORD   N3ALAA  AA      Chicag~  42.0
## # ... with 336,766 more rows, and 5 more variables: lon <dbl>,
## #   alt <int>, tz <dbl>, dst <chr>, tzone <chr>
```

Other implementations

`base::merge()` can perform all four types of mutating join:

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)`

Advantages of the specific dplyr verbs:

- More clearly convey the intent of your code.
- Considerably faster and don't mess with the order of the rows.

Other implementations II

SQL is the inspiration for dplyr's conventions:

dplyr	SQL
`inner_join(x, y, by = "z")`	`SELECT * FROM x INNER JOIN y USING (z)`
`left_join(x, y, by = "z")`	`SELECT * FROM x LEFT OUTER JOIN y USING (z)`
`right_join(x, y, by = "z")`	`SELECT * FROM x RIGHT OUTER JOIN y USING (z)`
`full_join(x, y, by = "z")`	`SELECT * FROM x FULL OUTER JOIN y USING (z)`

Note that:

- "INNER" and "OUTER" are optional, and often omitted.
- Joining different variables between the tables, e.g. `inner_join(x, y, by = c("a" = "b"))` uses a slightly different syntax in SQL: `SELECT * FROM x INNER JOIN y ON x.a = y.b`.

Filtering joins

Similar to mutating joins, but affect the observations rather than the variables:

- `semi_join(x, y)` **keeps** all observations in `x` that have a match in `y`.
  - Useful for matching filtered summary tables back to the original rows.
- `anti_join(x, y)` **drops** all observations in `x` that have a match in `y`.
  - Useful for diagnosing join mismatches.

Flights that went to top destinations

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

```
## # A tibble: 141,145 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      542            540      2.00      923
##  2  2013     1     1      554            600     -6.00      812
##  3  2013     1     1      554            558     -4.00      740
##  4  2013     1     1      555            600     -5.00      913
##  5  2013     1     1      557            600     -3.00      838
##  6  2013     1     1      558            600     -2.00      753
##  7  2013     1     1      558            600     -2.00      924
##  8  2013     1     1      558            600     -2.00      923
##  9  2013     1     1      559            559      0         702
## 10  2013     1     1      600            600      0         851
## # ... with 141,135 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>
```

But it's difficult to extend that approach to multiple variables.

Semi-join

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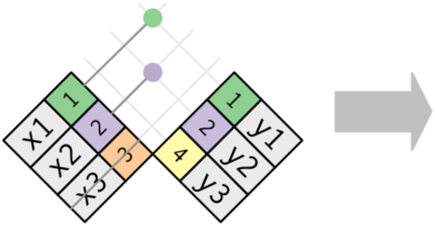
Only keeps rows in x having a match in y:

```
flights %>% semi_join(top_dest)
```

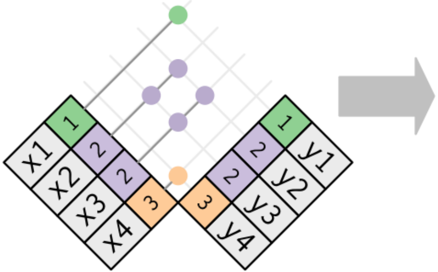
```
## Joining, by = "dest"

## # A tibble: 141,145 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      542            540      2.00      923
##  2  2013     1     1      554            600     -6.00      812
##  3  2013     1     1      554            558     -4.00      740
##  4  2013     1     1      555            600     -5.00      913
##  5  2013     1     1      557            600     -3.00      838
##  6  2013     1     1      558            600     -2.00      753
##  7  2013     1     1      558            600     -2.00      924
##  8  2013     1     1      558            600     -2.00      923
##  9  2013     1     1      559            559      0         702
## 10  2013     1     1      600            600      0         851
## # ... with 141,135 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>
```

Visually understand the semi-join



key	val_x
1	x1
2	x2



key	val_x
1	x1
2	x2
2	x3
3	x4

flights without match in planes


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

```
## # A tibble: 722 x 2
##    tailnum     n
##    <chr>   <int>
##  1 <NA>     2512
##  2 N725MQ    575
##  3 N722MQ    513
##  4 N723MQ    507
##  5 N713MQ    483
##  6 N735MQ    396
##  7 N0EGMQ    371
##  8 N534MQ    364
##  9 N542MQ    363
```

Set operations

- Used the least frequently
- Work with a complete row, comparing the values of every variable.
- Expect the `x` and `y` inputs to have the same variables, and treat the observations like sets.

The three 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`.

Intersect and union


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

```
intersect(df1, df2)
```

```
## # A tibble: 1 x 2
##       x     y
##   <dbl> <dbl>
## 1  1.00  1.00
```

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

```
## # A tibble: 3 x 2
##       x     y
##   <dbl> <dbl>
## 1  1.00  2.00
## 2  2.00  1.00
## 3  1.00  1.00
```

Setdiff


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

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

```
## # A tibble: 1 x 2
##       x     y
##   <dbl> <dbl>
## 1  2.00  1.00
```

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

```
## # A tibble: 1 x 2
##       x     y
##   <dbl> <dbl>
## 1  1.00  2.00
```

Outline

Warm-up

- Does every year have 365 days?
- Does every day have 24 hours?
- Does every minute have 60 seconds?

Refering to an instant in time

Three types of date/time data:

- A **date**. Tibbles print this as `<date>`.
- A **time** within a day. Tibbles print this as `<time>`.
- A **date-time** is a date plus a time: it uniquely identifies an instant in time (typically to the nearest second). Tibbles print this as `<dttm>`. Elsewhere in R these are called POSIXct.

In R:

- Focus on dates/date-times because no "native" class for times.
- If you need one, look at the **hms** package.

Use the simplest possible data type satisfying your needs!

Creating date/times

The **lubridate** package:

- Makes it easier to work with dates and times in R,
- is not part of core tidyverse because you only need it when you're working with dates/times.

```
library(lubridate)
today()
now()
```

```
## [1] "2018-03-25"
## [1] "2018-03-25 22:24:29 CEST"
```

Three other (usual) ways to create a date/time:

- From a string.
- From individual date-time components.
- From an existing date/time object (i.e., with `as_datetime(today())` or conversely `as_date(now())`).

From a string


```r
ymd("2017-01-31")
mdy("January 31st, 2017")
dmy("31-Jan-2017")

ymd_hms("2017-01-31 20:11:59")
mdy_hm("01/31/2017 08:01")
```

```
## [1] "2017-01-31"
## [1] "2017-01-31"
## [1] "2017-01-31"
## [1] "2017-01-31 20:11:59 UTC"
## [1] "2017-01-31 08:01:00 UTC"
```

Additionally:

```r
ymd(20170131)
ymd(20170131, tz = "UTC")
```

```
## [1] "2017-01-31"
## [1] "2017-01-31 UTC"
```

From individual components


```
flights %>%
  select(year, month, day, hour, minute, dep_time) %>%
  mutate(departure = make_datetime(year, month, day, hour, minute))
```

```
## # A tibble: 336,776 x 7
##     year month   day  hour minute dep_time departure
##    <int> <int> <int> <dbl>  <dbl>    <int> <dttm>
##  1  2013     1     1  5.00   15.0      517 2013-01-01 05:15:00
##  2  2013     1     1  5.00   29.0      533 2013-01-01 05:29:00
##  3  2013     1     1  5.00   40.0      542 2013-01-01 05:40:00
##  4  2013     1     1  5.00   45.0      544 2013-01-01 05:45:00
##  5  2013     1     1  6.00    0        554 2013-01-01 06:00:00
##  6  2013     1     1  5.00   58.0      554 2013-01-01 05:58:00
##  7  2013     1     1  6.00    0        555 2013-01-01 06:00:00
##  8  2013     1     1  6.00    0        557 2013-01-01 06:00:00
##  9  2013     1     1  6.00    0        557 2013-01-01 06:00:00
## 10  2013     1     1  6.00    0        558 2013-01-01 06:00:00
## # ... with 336,766 more rows
```

Remark

For dep_time and others such as arr_time:

```
make_datetime_100 <- function(year, month, day, time) {
  make_datetime(year, month, day, time %/% 100, time %% 100)}
```

From individual components II

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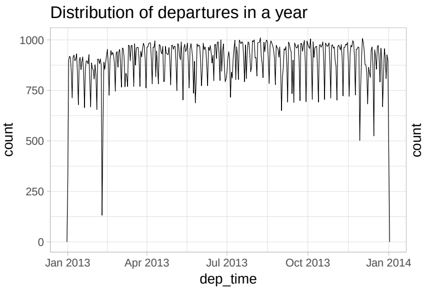
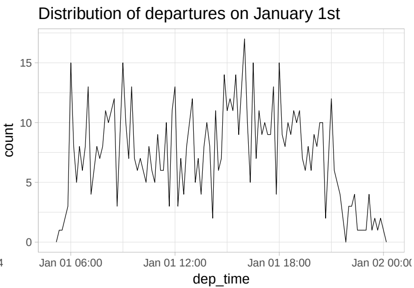
```r
flights_dt <- flights %>% filter(!is.na(dep_time), !is.na(arr_time)) %>%
  mutate(dep_time = make_datetime_100(year, month, day, dep_time),
         arr_time = make_datetime_100(year, month, day, arr_time)) %>%
  select(origin, dest, ends_with("delay"), ends_with("time"))

flights_dt %>% ggplot(aes(dep_time)) +
  geom_freqpoly(binwidth = 86400) + # 86400s = 1d
 ggtitle("Distribution of departures in a year")
flights_dt %>% filter(dep_time < ymd(20130102)) %>%
  ggplot(aes(dep_time)) + geom_freqpoly(binwidth = 600) + # 600s = 10mn
  ggtitle("Distribution of departures on January 1st")
```



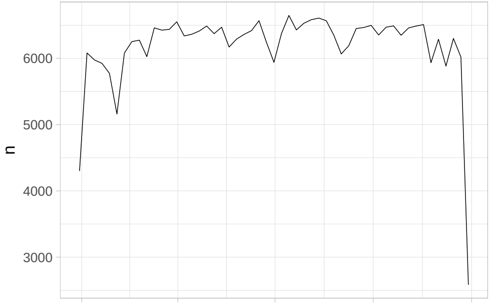


Rounding

- floor_date() rounds down
- round_date() rounds to
- ceiling_date() rounds up

Takes a vector of dates to adjust and then the name of the unit:

```
flights_dt %>%
  count(week = floor_date(dep_time, "week")) %>%
  ggplot(aes(week, n)) +
    geom_line()
```



Getting/setting components of a date/time

Getting the components:

```r
datetime <- ymd_hms("2016-07-08 12:34:56")
c(year(datetime), month(datetime), mday(datetime),
  yday(datetime), wday(datetime))
```

```
## [1] 2016    7    8  190    6
```

Setting the components:

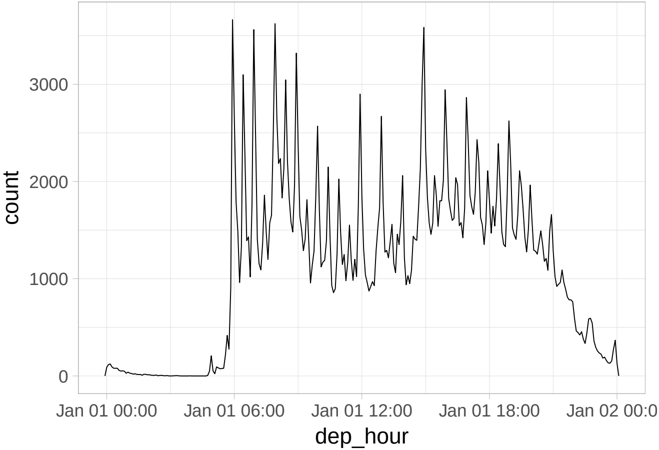
```r
year(datetime) <- 2020
datetime
month(datetime) <- 01
datetime
hour(datetime) <- hour(datetime) + 1
datetime
```

```
## [1] "2020-07-08 12:34:56 UTC"
## [1] "2020-01-08 12:34:56 UTC"
## [1] "2020-01-08 13:34:56 UTC"
```

Alternatively, use e.g. `update(datetime, year = 2020)`.

Flights distribution over the day


```r
flights_dt %>%
  mutate(dep_hour = update(dep_time, yday = 1)) %>%
  ggplot(aes(dep_hour)) +
    geom_freqpoly(binwidth = 300)
```



Time spans

Goal: to do arithmetic (i.e., subtraction, addition, and division) with dates/times.

Three classes that represent time spans:

- **durations** (number of seconds).
- **periods** (human units like weeks and months).
- **intervals** (a starting and ending point).

Durations

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- A **duration** always record a time span in seconds.
- Larger units created at the standard rate (60s/mn, 60mn/h, 24h/d, 7d/w, 365d/y)

```
dseconds(15)
dminutes(10)
dhours(c(12, 24))
ddays(0:5)
dweeks(3)
dyears(1)
```

```
## [1] "15s"
## [1] "600s (~10 minutes)"
## [1] "43200s (~12 hours)" "86400s (~1 days)"
## [1] "0s"                 "86400s (~1 days)"  "172800s (~2 days)"
## [4] "259200s (~3 days)" "345600s (~4 days)" "432000s (~5 days)"
## [1] "1814400s (~3 weeks)"
## [1] "31536000s (~52.14 weeks)"
```

Durations arithmetics

You can add and multiply durations:

```
2 * dyears(1)
dyears(1) + dweeks(12) + dhours(15)
```

```
## [1] "63072000s (~2 years)"
## [1] "38847600s (~1.23 years)"
```

You can add and subtract durations to and from days:

```
tomorrow <- today() + ddays(1)
last_year <- today() - dyears(1)
```

What happens here?

```
one_pm <- ymd_hms("2016-03-12 13:00:00", tz = "America/New_York")
one_pm
one_pm + ddays(1)
```

```
## [1] "2016-03-12 13:00:00 EST"
## [1] "2016-03-13 14:00:00 EDT"
```

Periods

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Work with "human" times, like days (no fixed length in secs):

```
one_pm
one_pm + days(1)
```

```
## [1] "2016-03-12 13:00:00 EST"
## [1] "2016-03-13 13:00:00 EDT"
```

```
seconds(15)
minutes(10)
hours(c(12, 24))
days(7)
months(1:3)
weeks(3)
years(1)
```

```
## [1] "15S"
## [1] "10M 0S"
## [1] "12H 0M 0S" "24H 0M 0S"
## [1] "7d 0H 0M 0S"
## [1] "1m 0d 0H 0M 0S" "2m 0d 0H 0M 0S" "3m 0d 0H 0M 0S"
## [1] "21d 0H 0M 0S"
## [1] "1y 0m 0d 0H 0M 0S"
```

Periods arithmetics

Add and multiply periods:

```
10 * (months(6) + days(1))
days(50) + hours(25) + minutes(2)
```

```
## [1] "60m 10d 0H 0M 0S"
## [1] "50d 25H 2M 0S"
```

Add periods to dates:

```
# A leap year
ymd("2016-01-01") + dyears(1)
ymd("2016-01-01") + years(1)

# Daylight Savings Time
one_pm + ddays(1)
one_pm + days(1)
```

```
## [1] "2016-12-31"
## [1] "2017-01-01"
## [1] "2016-03-13 14:00:00 EDT"
## [1] "2016-03-13 13:00:00 EDT"
```

Dividing periods

- What should `dyears(1) / ddays(365)` return ?
- What should `years(1) / days(1)` return ?

Dividing periods

- What should `dyears(1) / ddays(365)` return ?
- What should `years(1) / days(1)` return ?

```r
years(1) / days(1)
```

```
## estimate only: convert to intervals for accuracy

## [1] 365.25
```

Intervals

The **interval** (i.e., a duration with a starting point):

```
next_year <- today() + years(1)
(today() %--% next_year) / ddays(1)
```

```
## [1] 365
```

How many periods fall into an interval:

```
(today() %--% next_year) %/% days(1)
```

```
## Note: method with signature 'Timespan#Timespan' chosen for function '%/%',
##  target signature 'Interval#Period'.
##  "Interval#ANY", "ANY#Period" would also be valid
```

```
## [1] 365
```

Summary

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	date				date time				duration				period				interval				number			
date	-								-	+			-	+							-	+		
date time					-				-	+			-	+							-	+		
duration	-	+			-	+			-	+		⁄									-	+	×	⁄
period	-	+			-	+							-	+							-	+	×	⁄
interval												⁄				⁄								
number	-	+			-	+			-	+	×		-	+	×		-	+	×		-	+	×	⁄

Pick the simplest data structure that solves your problem:

- If you only care about physical time, use a duration.
- If you need to add human times, use a period.
- If you need to figure out how long a span is in human units, use an interval.

Time zones


```r
Sys.timezone()
```

```
## [1] "Europe/Paris"
```

```r
length(OlsonNames())
```

```
## [1] 592
```

```r
head(OlsonNames())
```

```
## [1] "Africa/Abidjan"     "Africa/Accra"       "Africa/Addis_Ababa"
## [4] "Africa/Algiers"     "Africa/Asmara"      "Africa/Asmera"
```

Same instant in different time zones


```r
(x1 <- ymd_hms("2015-06-01 12:00:00", tz = "America/New_York"))
(x2 <- ymd_hms("2015-06-01 18:00:00", tz = "Europe/Copenhagen"))
(x3 <- ymd_hms("2015-06-02 04:00:00", tz = "Pacific/Auckland"))
```

```
## [1] "2015-06-01 12:00:00 EDT"
## [1] "2015-06-01 18:00:00 CEST"
## [1] "2015-06-02 04:00:00 NZST"
```

```r
x1 - x2
x1 - x3
```

```
## Time difference of 0 secs
## Time difference of 0 secs
```

UTC:

```r
x4 <- c(x1, x2, x3)
x4
```

```
## [1] "2015-06-01 18:00:00 CEST" "2015-06-01 18:00:00 CEST"
## [3] "2015-06-01 18:00:00 CEST"
```

Changing the time zone

Keep the instant in time:

```
x4a <- with_tz(x4, tzone = "Australia/Lord_Howe")
x4a
x4a - x4
```

```
## [1] "2015-06-02 02:30:00 +1030" "2015-06-02 02:30:00 +1030"
## [3] "2015-06-02 02:30:00 +1030"
## Time differences in secs
## [1] 0 0 0
```

Change the instant in time:

```
x4b <- force_tz(x4, tzone = "Australia/Lord_Howe")
x4b
x4b - x4
```

```
## [1] "2015-06-01 16:00:00 +1030" "2015-06-01 16:00:00 +1030"
## [3] "2015-06-01 16:00:00 +1030"
## Time differences in hours
## [1] -10.5 -10.5 -10.5
```

Outline

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Factors

- Used to work with categorical variables (i.e., that have a fixed and known set of possible values.
- Useful to display character vectors in a non-alphabetical order.

The **forcats** package:

- Range of helpers for working with factors.
- Not part of the core tidyverse, so we need to load it explicitly.

```
library(forcats)
```

Creating factors

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Imagine that you have a variable that records month:

```
x1 <- c("Dec", "Apr", "Jan", "Mar")
```

Using a string to record this variable has two problems:

1. Twelve possible months and nothing saving you from typos.
2. It doesn't sort in a useful way:

```
x2 <- c("Dec", "Apr", "Jam", "Mar")
sort(x1)
```

```
## [1] "Apr" "Dec" "Jan" "Mar"
```

Creating factors II

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Start by creating a list of the valid **levels**:

```
month_levels <- c("Jan", "Feb", "Mar", "Apr", "May", "Jun",
                  "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")
```

Then create a factor:

```
y1 <- factor(x1, levels = month_levels)
y1
```

```
## [1] Dec Apr Jan Mar
## Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

```
sort(y1)
```

```
## [1] Jan Mar Apr Dec
## Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

```
factor(x1) ## without levels
```

```
## [1] Dec Apr Jan Mar
## Levels: Apr Dec Jan Mar
```

Creating factors III

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Notice:

```
y2 <- factor(x2, levels = month_levels)
y2
```

```
## [1] Dec  Apr  <NA> Mar
## Levels: Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
```

Other ordering:

```
f1 <- factor(x1, levels = unique(x1))
f1

f2 <- x1 %>% factor() %>% fct_inorder()
f2
```

```
## [1] Dec Apr Jan Mar
## Levels: Dec Apr Jan Mar
## [1] Dec Apr Jan Mar
## Levels: Dec Apr Jan Mar
```

To access the set of valid levels directly: `levels(f2)`.

forcats::gss_cat

Sample from the General Social Survey:

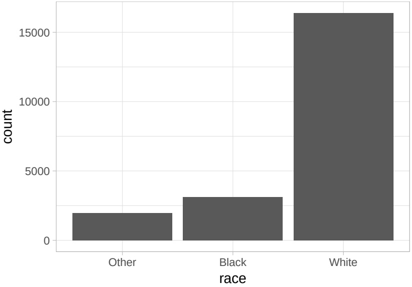
```
gss_cat
```

```
## # A tibble: 21,483 x 9
##     year marital    age race  rincome  partyid  relig  denom  tvhours
##    <int> <fct>    <int> <fct> <fct>    <fct>    <fct>  <fct>    <int>
##  1  2000 Never m~    26 White $8000 t~ Ind,nea~ Prote~ South~      12
##  2  2000 Divorced    48 White $8000 t~ Not str~ Prote~ Bapti~      NA
##  3  2000 Widowed     67 White Not app~ Indepen~ Prote~ No de~       2
##  4  2000 Never m~    39 White Not app~ Ind,nea~ Ortho~ Not a~       4
##  5  2000 Divorced    25 White Not app~ Not str~ None   Not a~       1
##  6  2000 Married     25 White $20000 ~ Strong ~ Prote~ South~      NA
##  7  2000 Never m~    36 White $25000 ~ Not str~ Chris~ Not a~       3
##  8  2000 Divorced    44 White $7000 t~ Ind,nea~ Prote~ Luthe~      NA
##  9  2000 Married     44 White $25000 ~ Not str~ Prote~ Other        0
## 10  2000 Married     47 White $25000 ~ Strong ~ Prote~ South~       3
## # ... with 21,473 more rows
```

More info with ?gss_cat.

Levels of a factor stored in a tibble


```r
ggplot(gss_cat, aes(race)) + geom_bar()
```

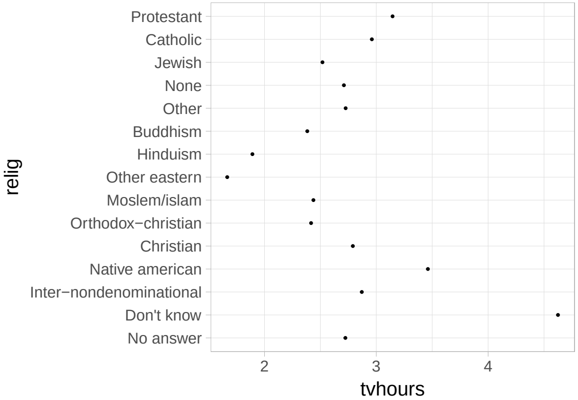



```r
gss_cat %>% count(race)
```

```
## # A tibble: 3 x 2
##   race      n
##   <fct> <int>
## 1 Other  1959
## 2 Black  3129
## 3 White 16395
```

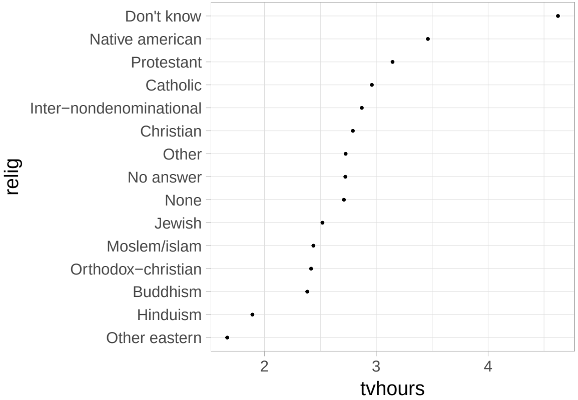
What's wrong here?


```r
relig_summary <- gss_cat %>%
  group_by(relig) %>%
  summarise(age = mean(age, na.rm = TRUE),
            tvhours = mean(tvhours, na.rm = TRUE),
            n = n())
ggplot(relig_summary, aes(tvhours, relig)) + geom_point()
```



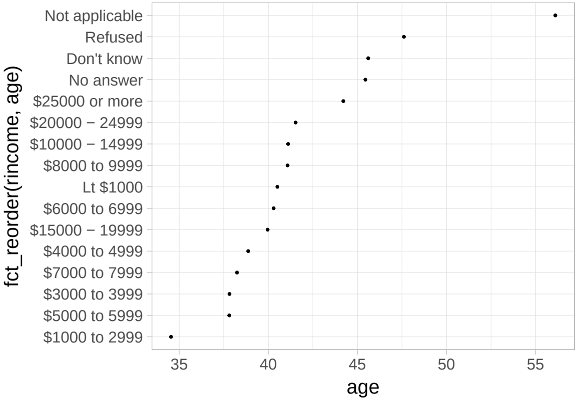
Modifying factor order

```
relig_summary %>%
  mutate(relig = fct_reorder(relig, tvhours)) %>%
  ggplot(aes(tvhours, relig)) + geom_point()
```



What's wrong here?


```r
rincome_summary <- gss_cat %>%
  group_by(rincome) %>%
  summarise(age = mean(age, na.rm = TRUE),
            tvhours = mean(tvhours, na.rm = TRUE),
            n = n())
ggplot(rincome_summary, aes(age, fct_reorder(rincome, age))) + geom_point()
```



Modify factor order II

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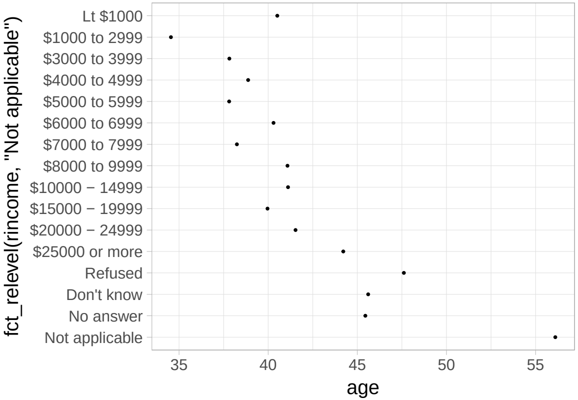
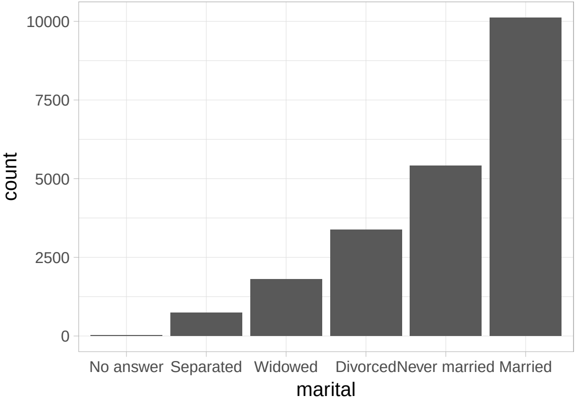
```r
ggplot(rincome_summary, aes(age, fct_relevel(rincome,
                                               "Not applicable"))) +
  geom_point()
```



Why do you think the average age for "Not applicable" is so high?

Modify factor order III


```
gss_cat %>%
  mutate(marital = marital %>% fct_infreq() %>% fct_rev()) %>%
  ggplot(aes(marital)) + geom_bar()
```



Modifying factor levels

More powerful than changing the orders of the levels is changing their values:

- To clarify labels for publication.
- To collapse levels for high-level displays.

What's wrong here?

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```r
gss_cat %>% count(partyid)
```

```
## # A tibble: 10 x 2
##    partyid                n
##    <fct>              <int>
##  1 No answer            154
##  2 Don't know             1
##  3 Other party          393
##  4 Strong republican   2314
##  5 Not str republican  3032
##  6 Ind,near rep        1791
##  7 Independent         4119
##  8 Ind,near dem        2499
##  9 Not str democrat    3690
## 10 Strong democrat     3490
```

Modifying factor levels II

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```r
gss_cat %>%
  mutate(partyid = fct_recode(partyid,
    "Republican, strong"    = "Strong republican",
    "Republican, weak"      = "Not str republican",
    "Independent, near rep" = "Ind,near rep",
    "Independent, near dem" = "Ind,near dem",
    "Democrat, weak"        = "Not str democrat",
    "Democrat, strong"      = "Strong democrat")) %>%
  count(partyid)
```

```
## # A tibble: 10 x 2
##    partyid                   n
##    <fct>                 <int>
##  1 No answer               154
##  2 Don't know                1
##  3 Other party             393
##  4 Republican, strong     2314
##  5 Republican, weak       3032
##  6 Independent, near rep  1791
##  7 Independent            4119
##  8 Independent, near dem  2499
##  9 Democrat, weak         3690
## 10 Democrat, strong       3490
```

Collapsing factors

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```r
gss_cat %>%
  mutate(partyid = fct_recode(partyid,
    "Republican, strong"    = "Strong republican",
    "Republican, weak"      = "Not str republican",
    "Independent, near rep" = "Ind,near rep",
    "Independent, near dem" = "Ind,near dem",
    "Democrat, weak"        = "Not str democrat",
    "Democrat, strong"      = "Strong democrat",
    "Other"                 = "No answer",
    "Other"                 = "Don't know",
    "Other"                 = "Other party" )) %>% count(partyid)
```

```
## # A tibble: 8 x 2
##   partyid                   n
##   <fct>                 <int>
## 1 Other                   548
## 2 Republican, strong     2314
## 3 Republican, weak       3032
## 4 Independent, near rep  1791
## 5 Independent            4119
## 6 Independent, near dem  2499
## 7 Democrat, weak         3690
## 8 Democrat, strong       3490
```

Collapsing factors II

```r
gss_cat %>%
  mutate(partyid = fct_collapse(partyid,
    other = c("No answer", "Don't know", "Other party"),
    rep = c("Strong republican", "Not str republican"),
    ind = c("Ind,near rep", "Independent", "Ind,near dem"),
    dem = c("Not str democrat", "Strong democrat")
  )) %>%
  count(partyid)
```

```
## # A tibble: 4 x 2
##   partyid     n
##   <fct>   <int>
## 1 other     548
## 2 rep      5346
## 3 ind      8409
## 4 dem      7180
```

Collapsing factor III


```r
gss_cat %>%
  mutate(relig = fct_lump(relig)) %>%
  count(relig)
```

```
## # A tibble: 2 x 2
##   relig          n
##   <fct>      <int>
## 1 Protestant 10846
## 2 Other      10637
```

```r
gss_cat %>%
  mutate(relig = fct_lump(relig, n = 3)) %>%
  count(relig, sort = TRUE)
```

```
## # A tibble: 4 x 2
##   relig          n
##   <fct>      <int>
## 1 Protestant 10846
## 2 Catholic    5124
## 3 None        3523
## 4 Other       1990
```

Outline

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String basics


```
library(stringr) # package for string manipulation

# To create strings
string1 <- "This is a string"
string2 <- 'To get a "quote" inside a string, use single quotes'
```

Backslash as escape character:

```
double_quote <- "\"" # or '"'
single_quote <- '\'' # or "'"
```

The printed representation is not the string itself:

```
x <- c("\"", "\\")
x
writeLines(x)
```

```
## [1] "\"" "\\"
## "
## \
```

More on strings

Special characters:

- Use `"\n"`, for newline, or,`"\t"`, for tab.
- Complete list by requesting help on `"` (`?'"'`, or `?"'"`)

Other usefuls things:

```
(x <- "\u00b5") # Non-English characters
```

```
## [1] "µ"
```

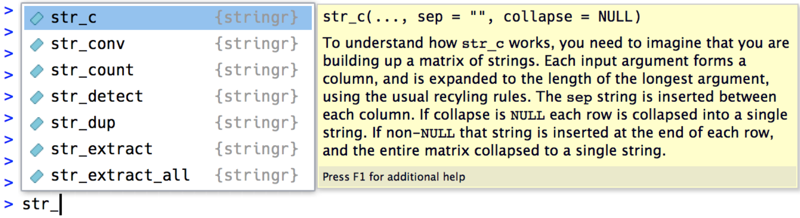
```
c("one", "two", "three") # Character vectors
```

```
## [1] "one"   "two"   "three"
```

```
str_length(c("a", "R for data science", NA)) # String length
```

```
## [1]  1 18 NA
```

stringr autocomplete



More on strings II

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Combining strings:

```
str_c("x", "y")
str_c("x", "y", "z")
str_c("x", "y", sep = ", ")
```

```
## [1] "xy"
## [1] "xyz"
## [1] "x, y"
```

Missing values:

```
x <- c("abc", NA)
str_c("|-", x, "-|")
```

```
## [1] "|-abc-|" NA
```

```
str_c("|-", str_replace_na(x), "-|")
```

```
## [1] "|-abc-|" "|-NA-|"
```

More on strings III

Recycling:

```
str_c("prefix-", c("a", "b", "c"), "-suffix")
```

```
## [1] "prefix-a-suffix" "prefix-b-suffix" "prefix-c-suffix"
```

Collapsing a vector of strings:

```
str_c(c("x", "y", "z"), collapse = ", ")
```

```
## [1] "x, y, z"
```

Subsetting strings

```
x <- c("Apple", "Banana", "Pear")
str_sub(x, 1, 3)
```

```
## [1] "App" "Ban" "Pea"
```

```
str_sub(x, -3, -1)
```

```
## [1] "ple" "ana" "ear"
```

```
str_sub("a", 1, 5)
```

```
## [1] "a"
```

```
str_sub(x, 1, 1) <- str_to_lower(str_sub(x, 1, 1))
x
```

```
## [1] "apple"  "banana" "pear"
```

See also `str_to_upper()` or `str_to_title()`.

Locales

```r
# Turkish has two i's: with and without a dot, and it
# has a different rule for capitalising them:
str_to_upper(c("i", "ı"))
```

```
## [1] "I" "I"
```

```r
str_to_upper(c("i", "ı"), locale = "tr")
```

```
## [1] "İ" "I"
```

The locale:

- An ISO 639 language code, which is a two or three letter abbreviation
- If blank, R uses the current locale, as provided by your operating system.

Regular expressions

A language that allows you to describe patterns in strings.
Allows you for instance to:

- Determine which strings match a pattern.
- Find the positions of matches.
- Extract the content of matches.
- Replace matches with new values.
- Split a string based on a match.

Read the chapter on strings from the book!