Data manipulation with **dplyr**

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Data analysis is the process
by which data becomes
understanding, knowledge
and insight

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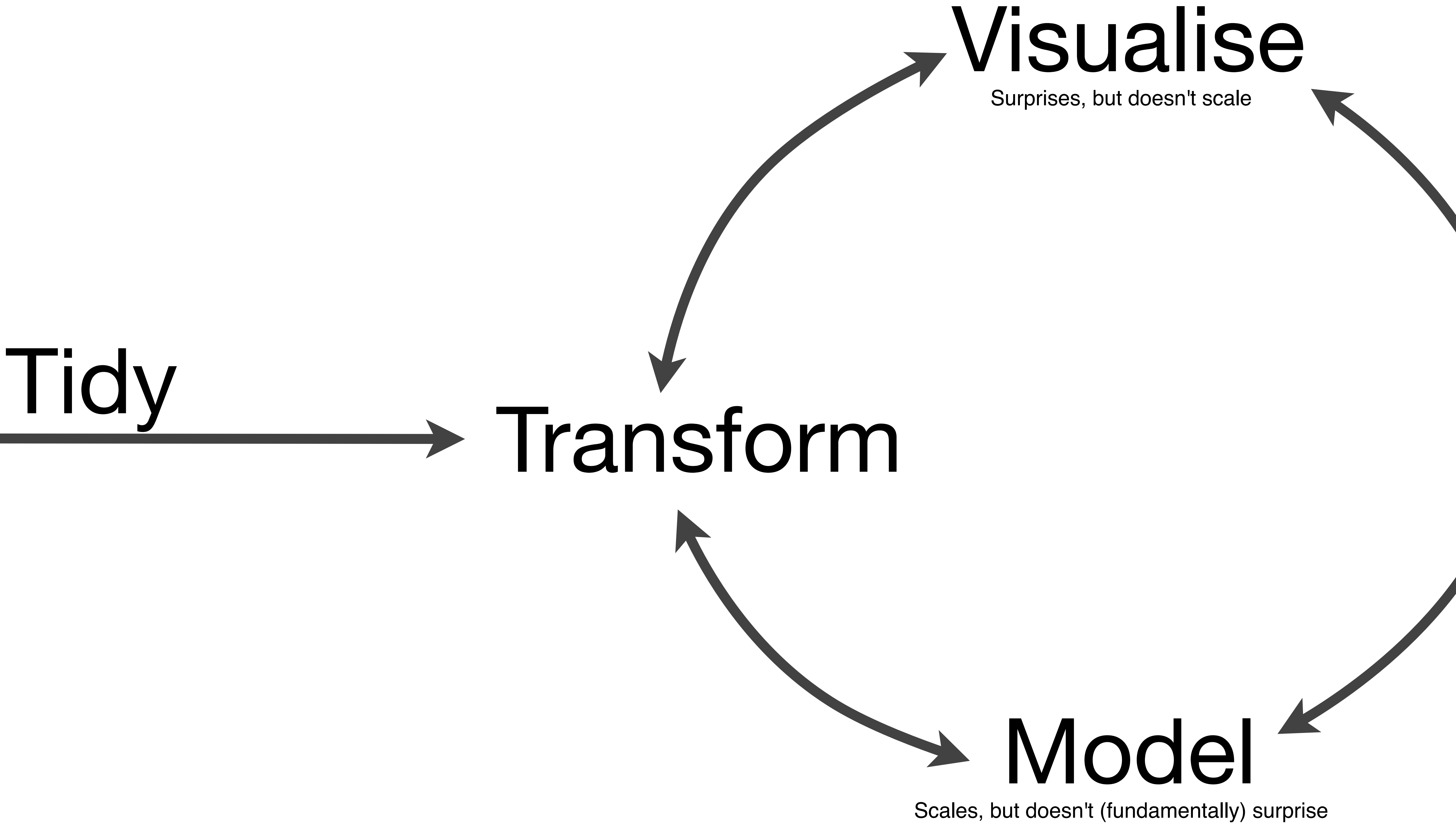


Tidy

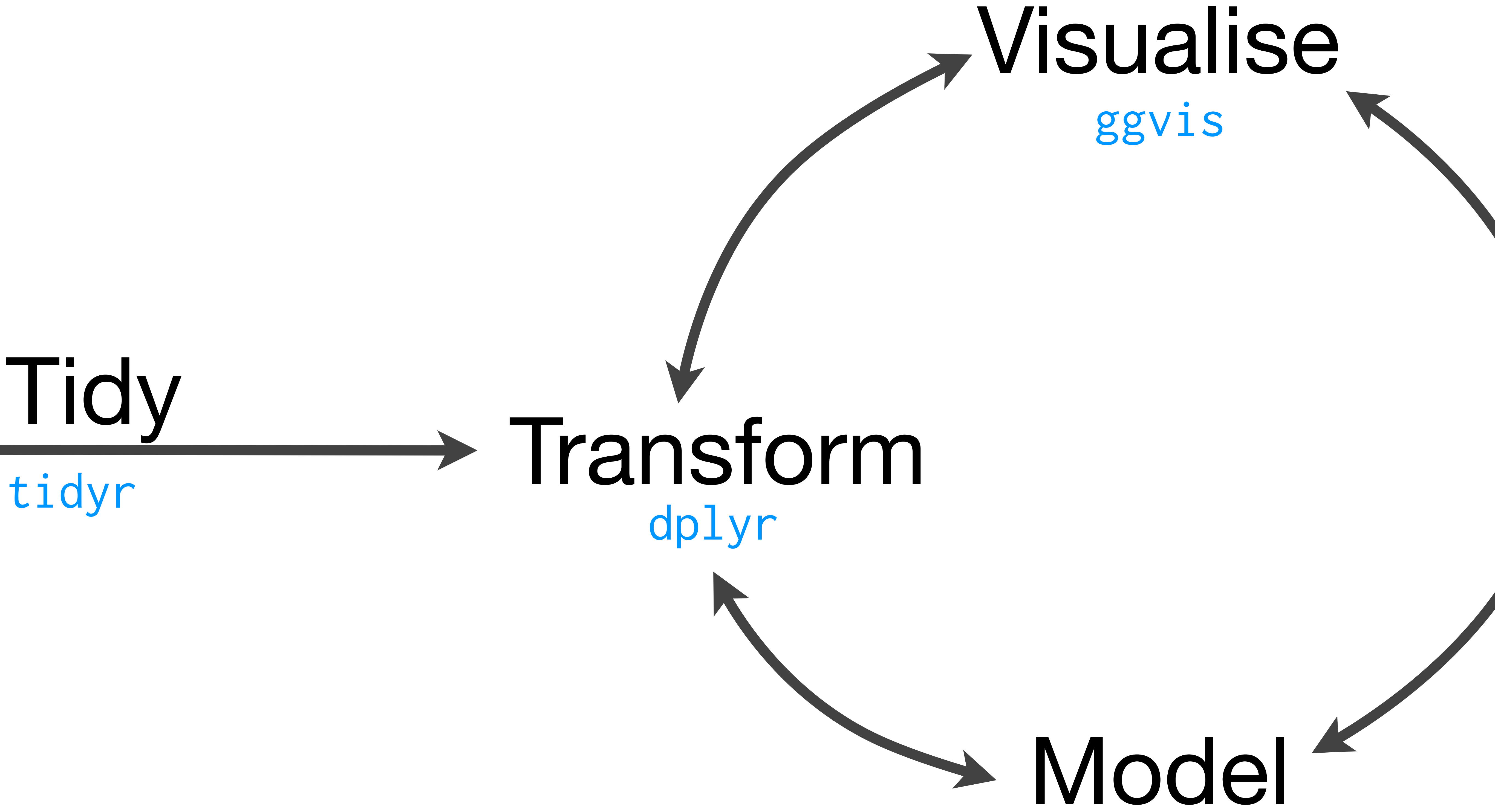
Transform

Visualise

Surprises, but doesn't scale

Model

Scales, but doesn't (fundamentally) surprise



Visualise

ggvis

Tidy

tidyr

Transform

dplyr

Model

1. Flights data
2. One table verbs & grouped summaries
3. Data pipelines
4. Grouped mutate/filter & window functions
5. Joins (two table verbs)
6. Do
7. Databases

The bad news:
It's going to be frustrating

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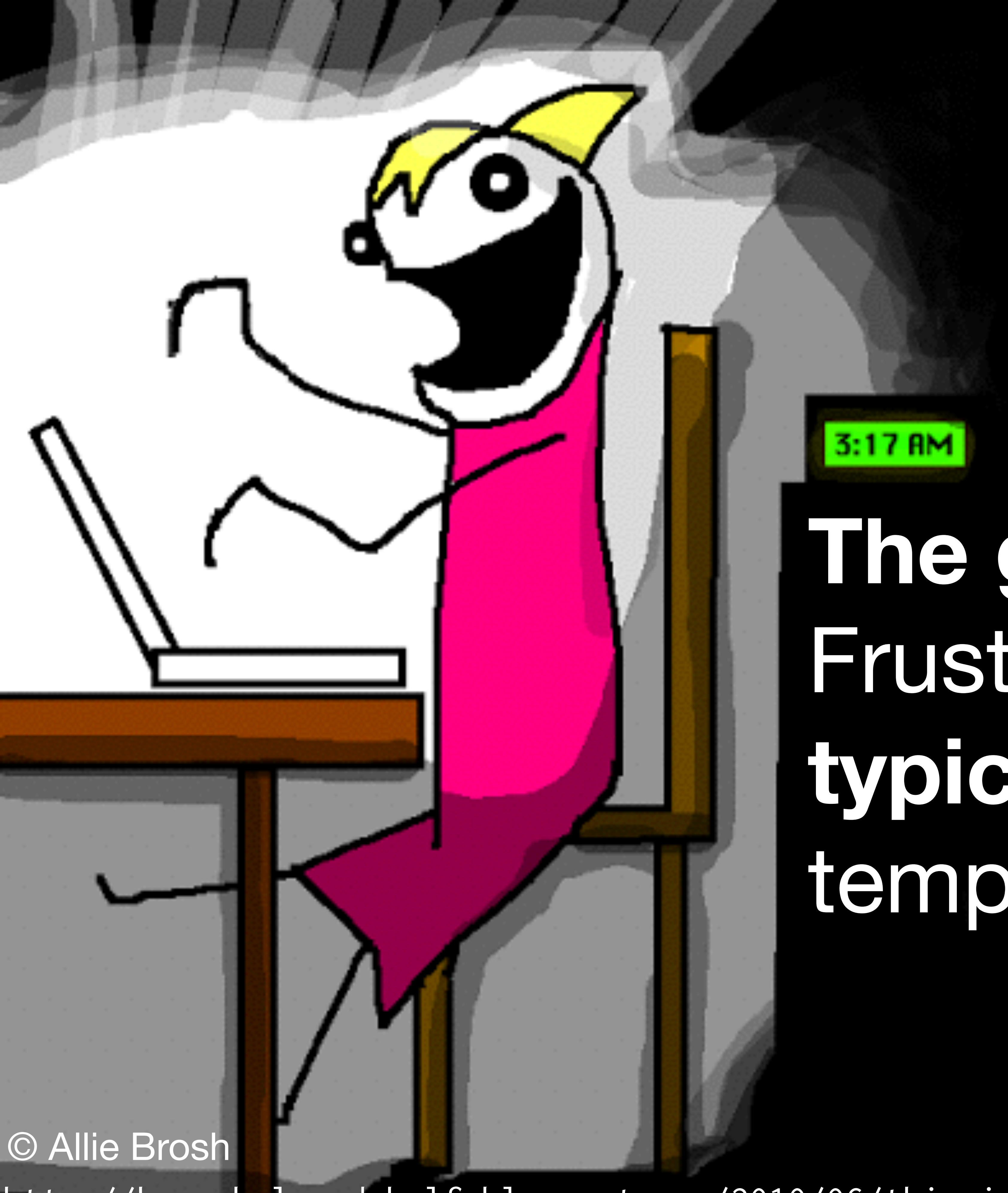
http://hyperboleandahalf.blogspot.com/2010/09/four-levels-of-social-entrapment.html



The good news: Frustration is **typical** and temporary

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http://hyperboleandahalf.blogspot.com/2010/06/this-is-why-ill-never-be-adult.html

Flights data

Rstudio projects

- Isolate code and results from different projects. Restart where you left off.
- Double-click `dplyr-tutorial.Rproj` file to open. (One R file for each section)
- (If you don’t use RStudio, just change working directories)

Flights data

- `flights` [227,496 x 14]. Every flight departing Houston in 2011.
- `weather` [8,723 x 14]. Hourly weather data.
- `planes` [2,853 x 9]. Plane metadata.
- `airports` [3,376 x 7]. Airport metadata.

```
library(dplyr)
library(ggplot2)

flights <- tbl_df(read.csv("flights.csv",
  stringsAsFactors = FALSE))
flights$date <- as.Date(flights$date)

weather <- tbl_df(read.csv("weather.csv",
  stringsAsFactors = FALSE))
weather$date <- as.Date(weather$date)

planes <- tbl_df(read.csv("planes.csv",
  stringsAsFactors = FALSE))

airports <- tbl_df(read.csv("airports.csv",
 stringsAsFactors = FALSE))
```

Your turn

Introduce yourself to your neighbour.

What questions might you want to answer with this data?

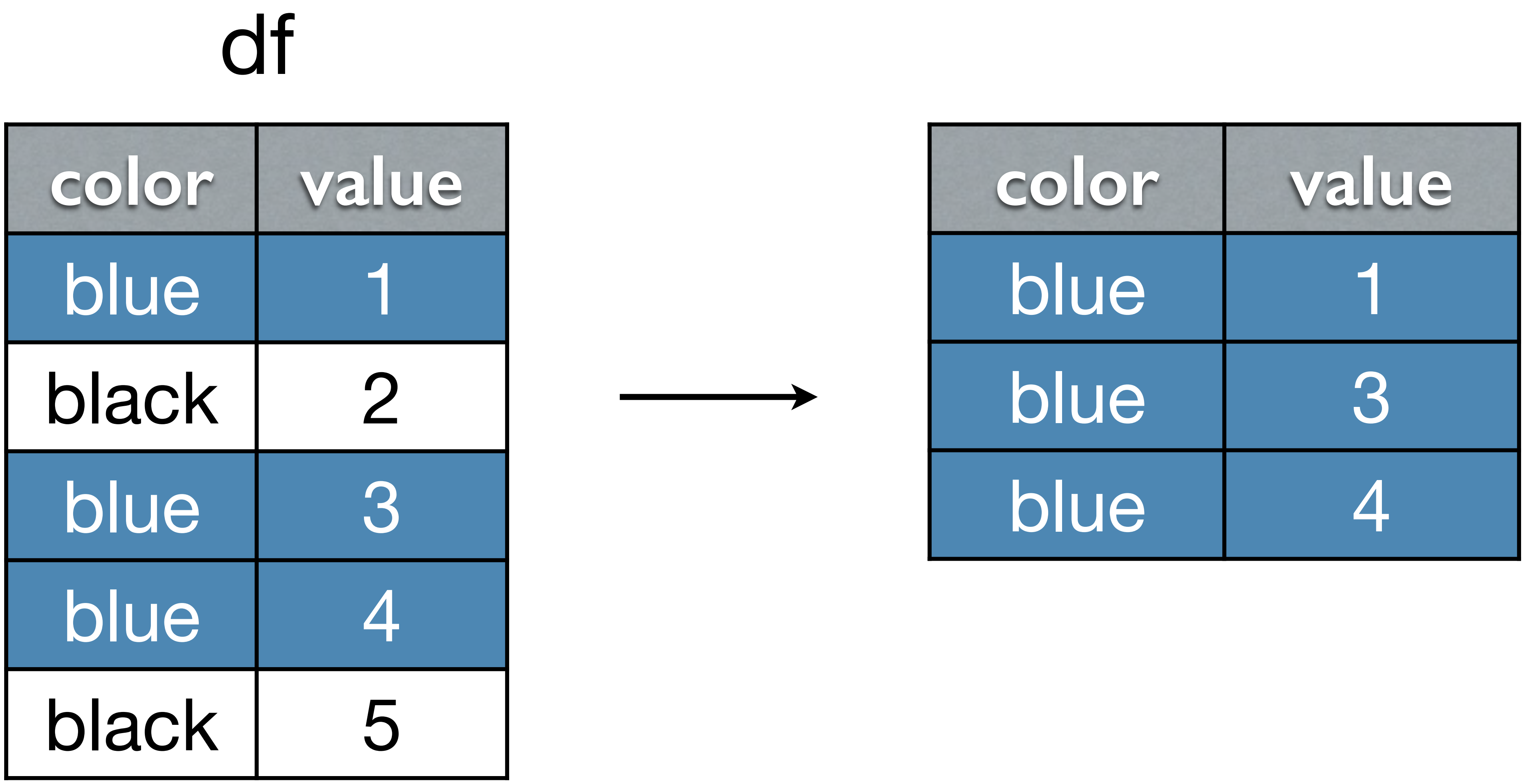
One table verbs

- **filter**: keep rows matching criteria
- **select**: pick columns by name
- **arrange**: reorder rows
- **mutate**: add new variables
- **summarise**: reduce variables to values

Structure

- First argument is a data frame
- Subsequent arguments say what to do with data frame
- Always return a data frame
- (Never modify in place)

```
df <- data.frame(
  color = c(”blue”, ”black”, ”blue”, ”blue”, ”black”),
  value = 1:5)
```



df

color	value
blue	1
black	2
blue	3
blue	4
black	5

color	value
blue	1
blue	3
blue	4

```
filter(df, color == ”blue”)
```

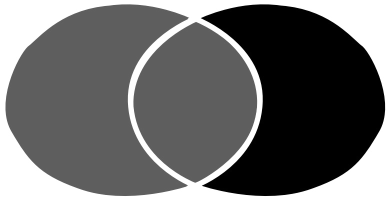
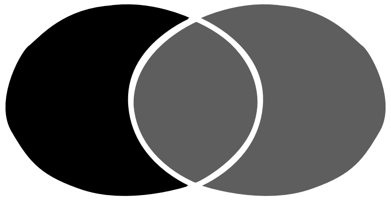
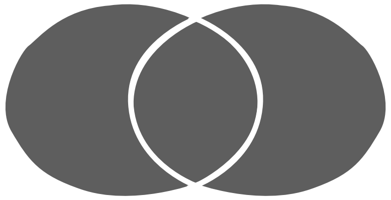
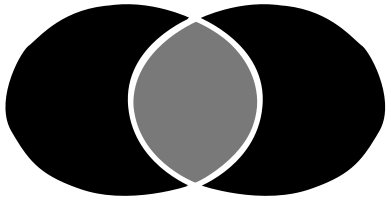
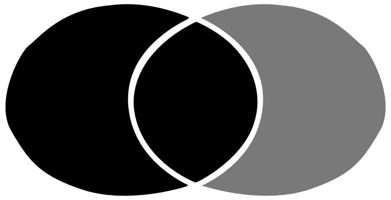
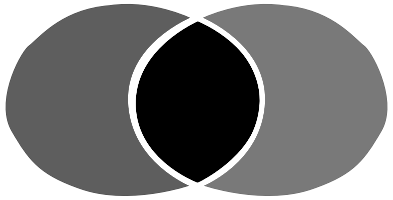
df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

color	value
blue	1
blue	4

```
filter(df, value %in% c(1, 4))
```

	a
	b
	a | b
	a & b
	a & !b
	xor(a, b)

```
x > 1
x >= 1
x < 1
x <= 1
x != 1
x == 1
x %in% (”a”, ”b”)
```

Find all flights:

To SFO or OAK

In January

Delayed by more than an hour

That departed between midnight and five am.

Where the arrival delay was more than twice the departure delay

```
filter(flights, dest %in% c("SFO", "OAK"))
filter(flights, dest == "SFO" | dest == "OAK")
# Not this!
filter(flights, dest == "SFO" | "OAK")

filter(flights, date < "2001-02-01")

filter(flights, hour >= 0, hour <= 5)
filter(flights, hour >= 0 & hour <= 5)

filter(flights, dep_delay > 60)

filter(flights, arr_delay > 2 * dep_delay)
```

df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

color
blue
black
blue
blue
black

```
select(df, color)
```

df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

value
1
2
3
4
5

```
select(df, -color)
```

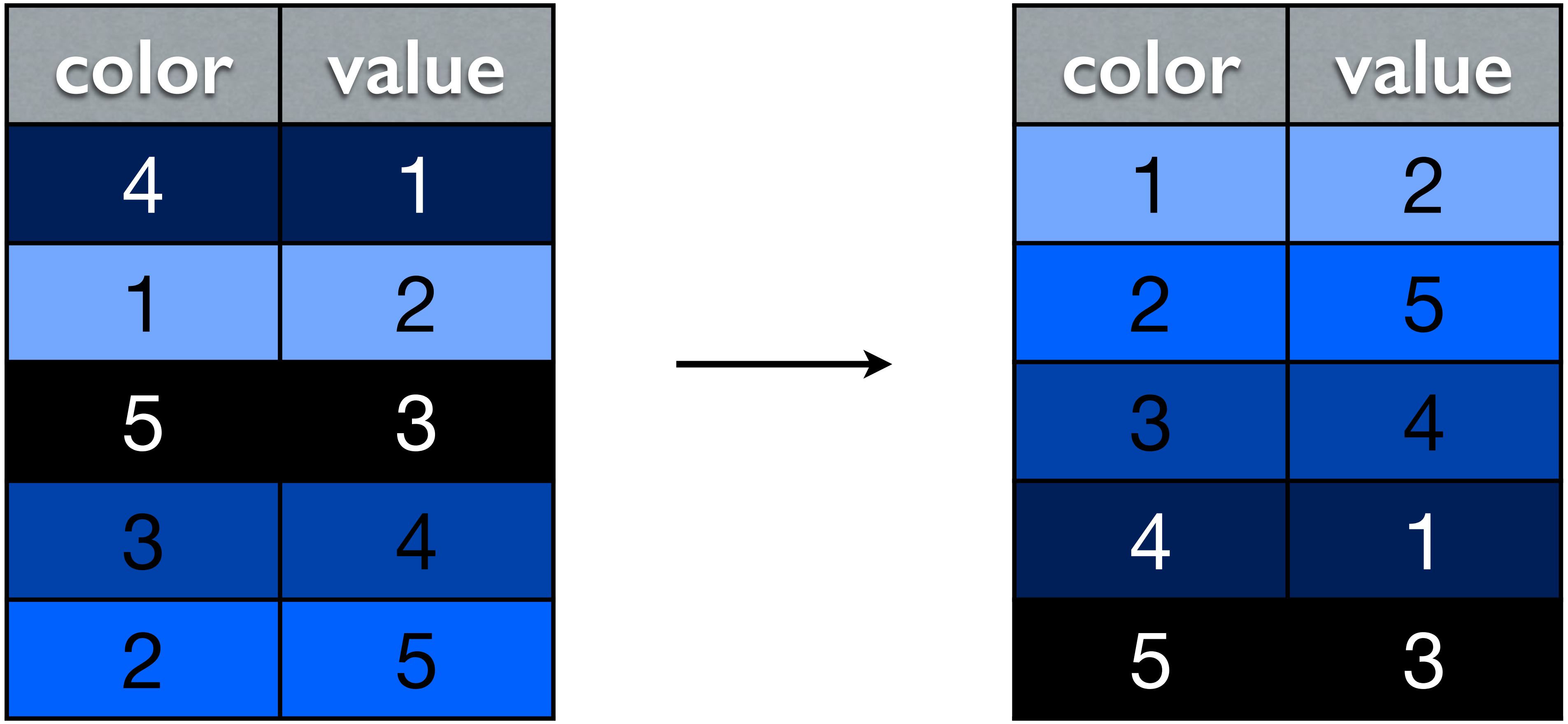
Your turn

Read the help for `select()`. What other ways can you select variables?

Write down three ways to select the two delay variables.

```
select(flights, arr_delay, dep_delay)
select(flights, arr_delay:dep_delay)
select(flights, ends_with("delay”))
select(flights, contains("delay”))
```

df

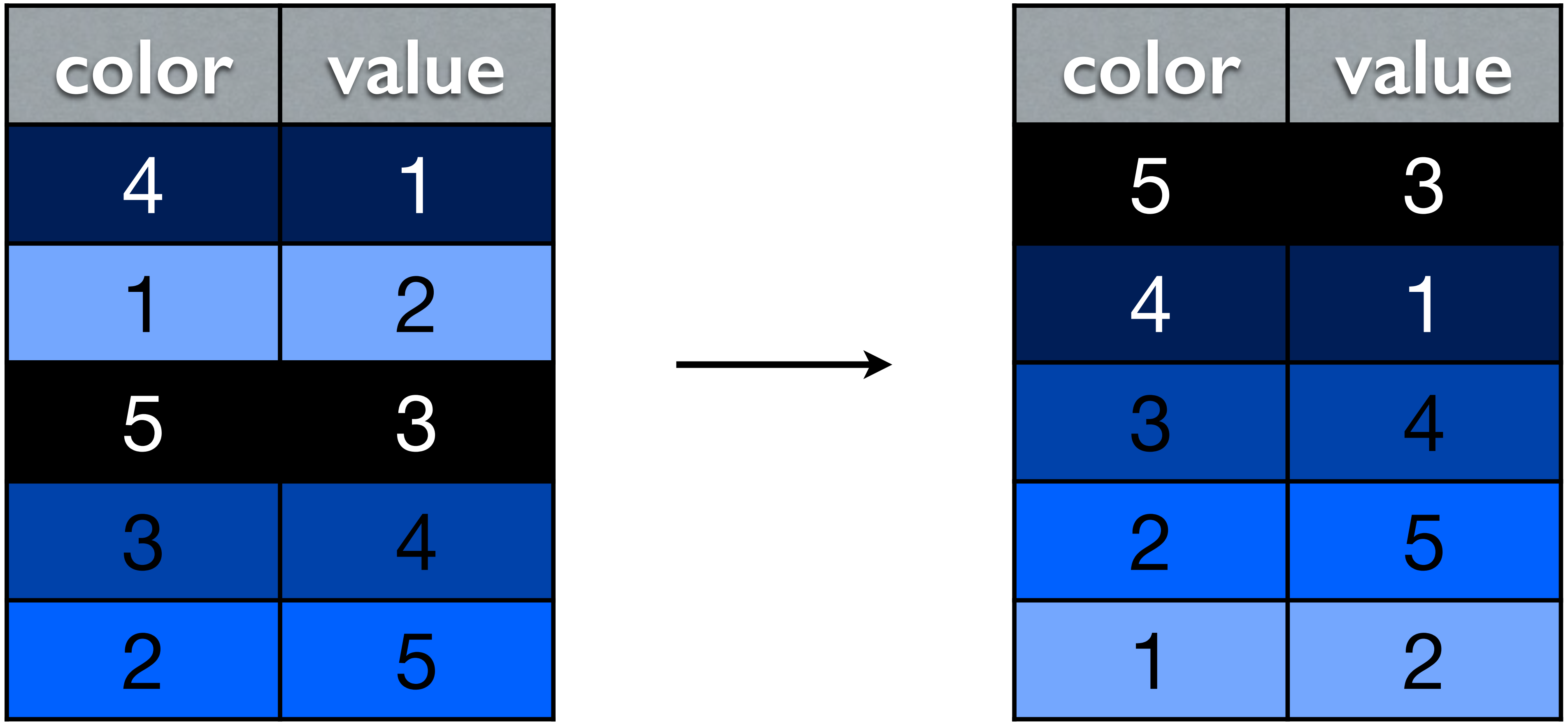


color	value
4	1
1	2
5	3
3	4
2	5

color	value
1	2
2	5
3	4
4	1
5	3

```
arrange(df, color)
```

df



color	value
4	1
1	2
5	3
3	4
2	5

color	value
5	3
4	1
3	4
2	5
1	2

```
arrange(df, desc(color))
```

Your turn

Order the flights by departure date and time.

Which flights were most delayed?

Which flights caught up the most time during the flight?

```
arrange(flights, date, hour, minute)

arrange(flights, desc(dep_delay))
arrange(flights, desc(arr_delay))

arrange(flights, desc(dep_delay - arr_delay))
```

df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

color	value	double
blue	1	2
black	2	4
blue	3	6
blue	4	8
black	5	10

```
mutate(df, double = 2 * value)
```

df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

color	value	double	quadruple
blue	1	2	4
black	2	4	8
blue	3	6	12
blue	4	8	16
black	5	10	20

```
mutate(df, double = 2 * value,
    quadruple = 2 * double)
```

Your turn

Compute speed in mph from time (in minutes) and distance (in miles). Which flight flew the fastest?

Add a new variable that shows how much time was made up or lost in flight.

How did I compute hour and minute from dep?

(Hint: you may need to use `select()` or `View()` to see your new variable)

```
flights <- mutate(flights,
  speed = dist / (time / 60))
arrange(flights, desc(speed))

mutate(flights, delta = dep_delay - arr_delay)

mutate(flights,
 hour = dep %/% 100,
 minute = dep %% 100)
```

Grouped summarise

df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

total
15

```
summarise(df, total = sum(value))
```

df

color	value
blue	1
black	2
blue	3
blue	4
black	5

→

color	total
blue	8
black	7

```
by_color <- group_by(df, color)
summarise(by_color, total = sum(value))
```

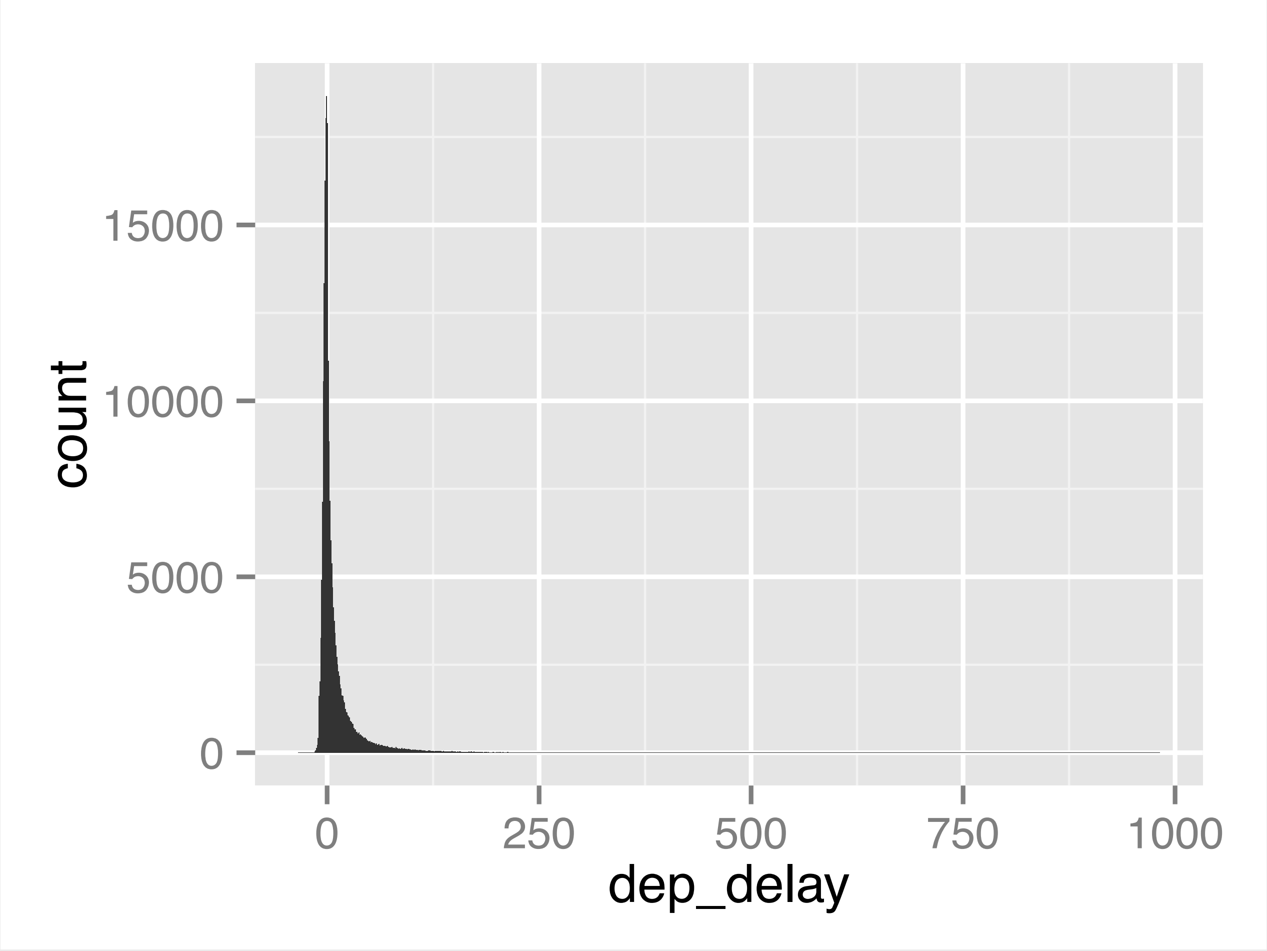
```
by_date <- group_by(flights, date)
by_hour <- group_by(flights, date, hour)
by_plane <- group_by(flights, plane)
by_dest <- group_by(flights, dest)
```

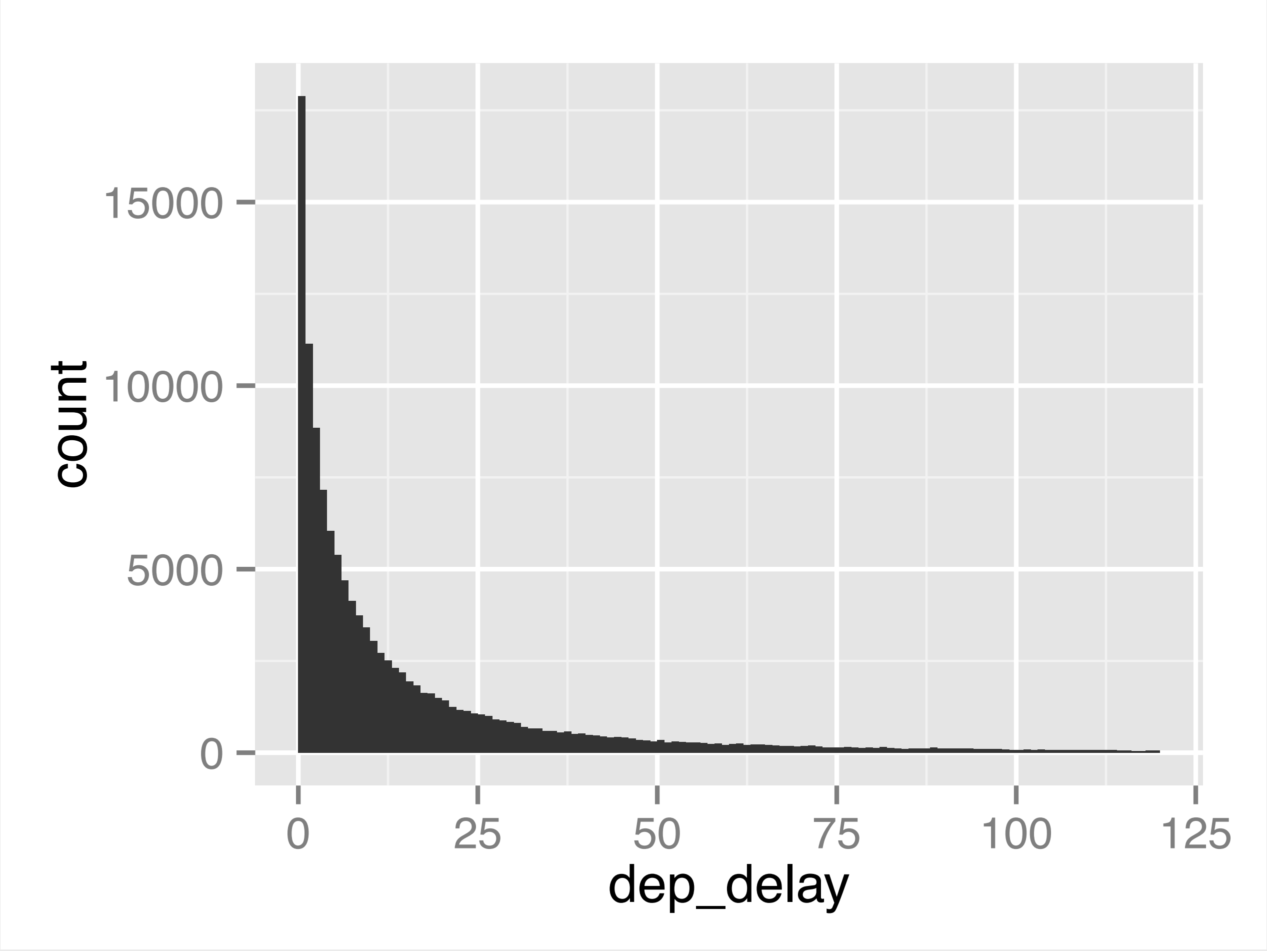
Summary functions

- min(x), median(x), max(x), quantile(x, p)
- n(), n_distinct(x), sum(x), mean(x)
- sum(x > 10), mean(x > 10)
- sd(x), var(x), ~~iqr~~ IQR(x), mad(x)

Your turn

How might you summarise `dep_delay` for each day? Brainstorm for 2 minutes.





```
by_date <- group_by(flights, date)
delays <- summarise(by_date,
  mean = mean(dep_delay),
  median = median(dep_delay),
  q75 = quantile(dep_delay, 0.75),
  over_15 = mean(dep_delay > 15),
  over_30 = mean(dep_delay > 30),
  over_60 = mean(dep_delay > 60)
 )
```

```
by_date <- group_by(flights, date)
delays <- summarise(by_date,
  mean = mean(dep_delay, na.rm = TRUE),
  median = median(dep_delay, na.rm = TRUE),
  q75 = quantile(dep_delay, 0.75, na.rm = TRUE),
  over_15 = mean(dep_delay > 15, na.rm = TRUE),
  over_30 = mean(dep_delay > 30, na.rm = TRUE),
  over_60 = mean(dep_delay > 60, na.rm = TRUE)
 )
```

```
# OR

by_date <- group_by(flights, date)
no_missing <- filter(flights, !is.na(dep))
delays <- summarise(no_missing,
 mean = mean(dep_delay),
  median = median(dep_delay),
  q75 = quantile(dep_delay, 0.75),
  over_15 = mean(dep_delay > 15),
  over_30 = mean(dep_delay > 30),
  over_60 = mean(dep_delay > 60)
 )
```

Data pipelines

```
# Downside of functional interface is that it's
# hard to read multiple operations:
hourly_delay <- filter(
  summarise(
    group_by(
      filter(
        flights,
        !is.na(dep_delay)
      ),
      date, hour
    ),
    delay = mean(dep_delay),
    n = n()
  ),
  n > 10
)
```

```
# Solution: the pipe operator from magrittr
# x %>% f(y) -> f(x, y)

hourly_delay <- flights %>%
  filter(!is.na(dep_delay)) %>%
  group_by(date, hour) %>%
  summarise(delay = mean(dep_delay), n = n()) %>%
  filter(n > 10)

# Hint: pronounce %>% as then
```

Your turn

Create data pipelines to answer the following questions:

Which destinations have the highest average delays?

Which flights (i.e. carrier + flight) happen every day? Where do they fly to?

On average, how do delays (of non-cancelled flights) vary over the course of a day?
(Hint: hour + minute / 60)

```
flights %>%
  group_by(dest) %>%
  summarise(
    arr_delay = mean(arr_delay, na.rm = TRUE),
    n = n()) %>%
  arrange(desc(arr_delay))

# Nifty trick to see more data
.Last.value %>% View()

# It would be nice to plot these on a map...
```

```
flights %>%
  group_by(carrier, flight, dest) %>%
  tally(sort = TRUE) %>% # Save some typing
  filter(n == 365)

flights %>%
  group_by(carrier, flight, dest) %>%
  summarise(n = n()) %>%
  arrange(desc(n)) %>%
  filter(n == 365)

# Slightly different answer
flights %>%
  group_by(carrier, flight) %>%
  filter(n() == 365)
```

```
per_hour <- flights %>%
  filter(cancelled == 0) %>%
  mutate(time = hour + minute / 60) %>%
  group_by(time) %>%
  summarise(
    arr_delay = mean(arr_delay, na.rm = TRUE),
    n = n()
  )

qplot(time, arr_delay, data = per_hour)
qplot(time, arr_delay, data = per_hour, size = n) + scale_size_area()
qplot(time, arr_delay, data = filter(per_hour, n > 30), size = n) +
scale_size_area()

ggplot(filter(per_hour, n > 30), aes(time, arr_delay)) +
  geom_vline(xintercept = 5:24, colour = "white", size = 2) +
  geom_point()
```

Grouped mutate/filter

Groupwise variables

- Creating new variables within a group is also often useful.
- Sometime that's a combination of aggregation and recycling, e.g. `z = (x - mean(x)) / sd(x)`
- Other times you need a **window function**
- More details in `vignette("window-functions")`

```
# Example:

planes <- flights %>%
  filter(!is.na(arr_delay)) %>%
  group_by(plane) %>%
  filter(n() > 30)

planes %>%
  mutate(z_delay =
    (arr_delay - mean(arr_delay)) / sd(arr_delay)) %>%
  filter(z_delay > 5)

planes %>% filter(min_rank(arr_delay) < 5)
```

Window functions

- Aggregation function:
  n inputs → 1 output
- Window function:
  n inputs → n outputs
- (Excludes functions that could operate row by row)

Types of window functions

- **Ranking and ordering**
- **Offsets: lead & lag**
- Cumulative aggregates
- Rolling aggregates

Your turn

What's the difference between `min_rank()`, `row_number()` and `dense_rank()`?

For each plane, find the two most delayed flights. Which of the three rank functions is most appropriate?

```
min_rank(c(1, 1, 2, 3))
dense_rank(c(1, 1, 2, 3))
row_number(c(1, 1, 2, 3))

flights %>% group_by(plane) %>%
  filter(row_number(desc(arr_delay)) <= 2)

flights %>% group_by(plane) %>%
  filter(min_rank(desc(arr_delay)) <= 2)

flights %>% group_by(plane) %>%
  filter(dense_rank(desc(arr_delay)) <= 2)
```

```
daily <- flights %>%
  group_by(date) %>%
  summarise(delay = mean(dep_delay, na.rm = TRUE))

# What's the day-to-day change?
daily %>% mutate(delay - lag(delay))

# If not ordered by date already
daily %>% mutate(delay - lag(delay), order_by = date)
```

Other uses

- Was there a change? `x != lag(x)`
- Percent change? `(x - lag(x)) / x`
- Fold-change? `x / lag(x)`
- Previously false, now true? `!lag(x) & x`

Two table verbs

```
# Motivation: how can we show airport delays on
# a map?  Need to connect to airports dataset

location <- airports %>%
  select(dest = iata, name = airport, lat, long)

flights %>%
  group_by(dest) %>%
  filter(!is.na(arr_delay)) %>%
  summarise(
    arr_delay = mean(arr_delay),
    n = n()
  ) %>%
  arrange(desc(arr_delay)) %>%
  left_join(location)
```

Joining datasets

name	instrument
John	guitar
Paul	bass
George	guitar
Ringo	drums
Stuart	bass
Pete	drums

+

name	band
John	T
Paul	T
George	T
Ringo	T
Brian	F

=

?

```r
x <- data.frame(
  name = c("John", "Paul", "George", "Ringo", "Stuart", "Pete"),
  instrument = c("guitar", "bass", "guitar", "drums", "bass",
     "drums")
)

y <- data.frame(
  name = c("John", "Paul", "George", "Ringo", "Brian"),
  band = c("TRUE", "TRUE", "TRUE",  "TRUE", "FALSE")
)
```

x

name	instrument
John	guitar
Paul	bass
George	guitar
Ringo	drums
Stuart	bass
Pete	drums

+

y

name	band
John	T
Paul	T
George	T
Ringo	T
Brian	F

=

name	instrument	band
John	guitar	T
Paul	bass	T
George	guitar	T
Ringo	drums	T

```
inner_join(x, y)
```

x

name	instrument
John	guitar
Paul	bass
George	guitar
Ringo	drums
Stuart	bass
Pete	drums

+

y

name	band
John	T
Paul	T
George	T
Ringo	T
Brian	F

=

name	instrument	band
John	guitar	T
Paul	bass	T
George	guitar	T
Ringo	drums	T
Stuart	bass	NA
Pete	drums	NA

```
left_join(x, y)
```

x

name	instrument
John	guitar
Paul	bass
George	guitar
Ringo	drums
Stuart	bass
Pete	drums

+

y

name	band
John	T
Paul	T
George	T
Ringo	T
Brian	F

=

name	instrument
John	guitar
Paul	bass
George	guitar
Ringo	drums

```
semi_join(x, y)
```

x

name	instrument
John	guitar
Paul	bass
George	guitar
Ringo	drums
Stuart	bass
Pete	drums

+

y

name	band
John	T
Paul	T
George	T
Ringo	T
Brian	F

=

name	instrument
Stuart	bass
Pete	drums

```
anti_join(x, y)
```

Type	Action
inner	Include only rows in **both** x and y
left	Include all of x, and matching rows of y
semi	Include rows of x that match y
anti	Include rows of x that **don’t** match y

```
# Let's combine hourly delay data with weather
# information

hourly_delay <- flights %>%
  group_by(date, hour) %>%
  filter(!is.na(dep_delay)) %>%
  summarise(
    delay = mean(dep_delay),
    n = n()
  ) %>%
  filter(n > 10)
delay_weather <- hourly_delay %>% left_join(weather)
```

Your turn

What weather conditions are associated with delays leaving in Houston?

Use graphics to explore.

```
qplot(temp, dep, data = delay_weather)
qplot(wind_speed, dep, data = delay_weather)
qplot(gust_speed, dep, data = delay_weather)
qplot(is.na(gust_speed), dep, data = delay_weather,
  geom = "boxplot”)
qplot(conditions, dep, data = delay_weather,
  geom = "boxplot”)
qplot(events, dep, data = delay_weather,
  geom = "boxplot”)
```

Your turn

Are older planes more likely to be delayed? Explore the data and answer with a plot.

(Hint: I'd recommend by starting with some checking of the plane data)

Do

The workhorse function

- If one of the specialised verbs doesn’t do what you need, you can use `do()`
- It’s slower, but general purpose.
- Equivalent to `ddply()` and `dlply()`, and is particularly useful in conjunction with models

How it works

- Two variations: unnamed (for functions that return data frames), and named (for functions that return anything else)
- Uses a pronoun, `.`, to represent the current group

```
# Derived from http://stackoverflow.com/a/23341485/16632
library(dplyr)
library(zoo)
df <- data.frame(
  houseID = rep(1:10, each = 10),
  year = 1995:2004,
  price = ifelse(runif(10 * 10) > 0.50, NA, exp(rnorm(10 * 10)))
)

df %>%
  group_by(houseID) %>%
  do(na.locf(.))

df %>%
  group_by(houseID) %>%
  do(head(., 2))

df %>%
  group_by(houseID) %>%
  do(data.frame(year = .$year[1]))
```

```
# Named usage allows us to put any object into
# a column: creates a ”list-column”. This is valid
# in R, but data frame methods don’t always expect.

df <- data.frame(x = 1:5)
df$y <- list(1:2, 2:3, 3:4, 4:5, 5:6)

df
str(df)

tbl_df(df)

# Doesn’t work
df <- data.frame(
  x = 1:5,
  y = list(1:2, 2:3, 3:4, 4:5, 5:6)
)
```

```
# Goal fit a linear model to each day, predicting
# delay from time of day

usual <- flights %>%
  mutate(time = hour + minute / 60) %>%
  filter(hour >= 5, hour <= 20)

models <- usual %>%
  group_by(date) %>%
  do(
    mod = lm(dep_delay ~ time, data = .)
  )

# See 5-do.R for more details
```

Future work

- Labelling is still a little wonky
- Parallel? (like plyr)
- Better tools for working with models

Databases

Other data sources

- PostgreSQL, Greenplum, redshift
- MySQL, MariaDB
- SQLite
- MonetDB, BigQuery
- *Oracle*, *SQL Server, ImpalaDB*

Getting started

- Easiest to dip your toe in database waters with SQLite. No setup required!
- dplyr provides `copy_to()`, which makes it easy to get data from R into DB
- You can work with database tables just like data frames. dplyr translates the SQL for you.

```
hflights_db <- src_sqlite("hflights.sqlite3",
  create = TRUE)

copy_to(
  dest = hflights_db,
  c         e(flights),
  n          flights",
  indexes = list(
    c("date", "hour"),
    "pla    "
    "des
    "arr
  ), temporary = FALSE
)
```

Start with variables needed to join tables

Default is to create temporary tables

```
# DEMO
```

Learning SQL

- Learn how to use SELECT.
- Learn how indices work. (http://www.sqlite.org/queryplanner.html)
- Learn how SELECT works. (http://tech.pro/tutorial/1555/10-easy-steps-to-a-complete-understanding-of-sql)
- Make friends with an expert

When to use?

- Obviously, good idea to use if you data already in database. Better to pull from live db than to use static exports.
- If data fits in memory, using local data frame will always be faster. Only use DB for “big” data.
- Correct indexes are key to good filter + join performance. Talk to a DBA!

Where next

```
browseVignettes(package = ”dplyr”)

# Translate plyr to dplyr
http://jimhester.github.io/plyrToDplyr/

# Common questions & answers
http://stackoverflow.com/questions/tagged/dplyr?sort=frequent
```