Data manipulation with **dplyr**

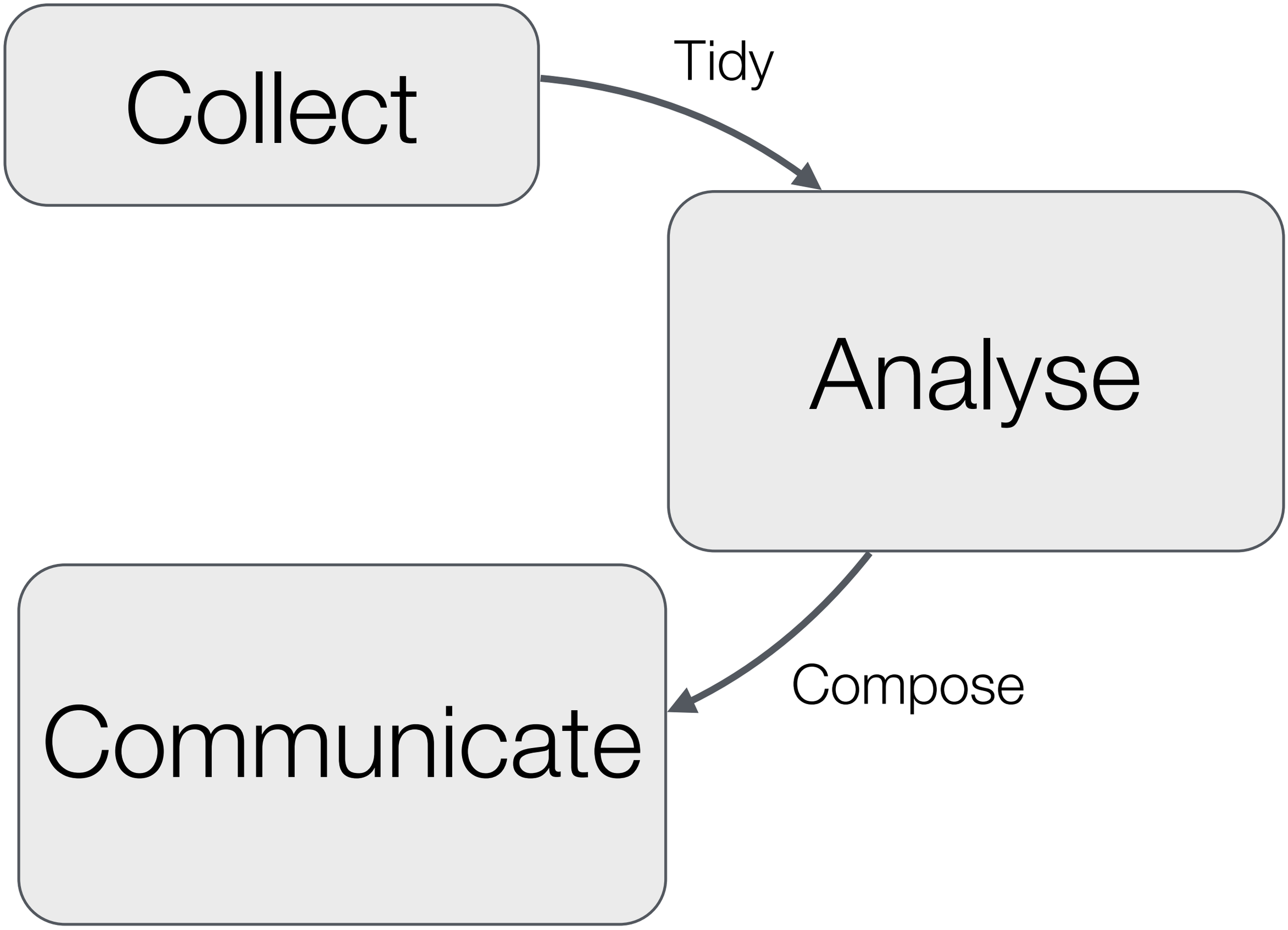
Hadley Wickham
@hadleywickham
Chief Scientist, RStudio

October 2014

Please download slides, code & data from bit.ly/rday-strata14

Data **analysis**: data → knowledge

Data **science**: knowledge → action


Collect
Tidy
Analyse
Compose
Communicate

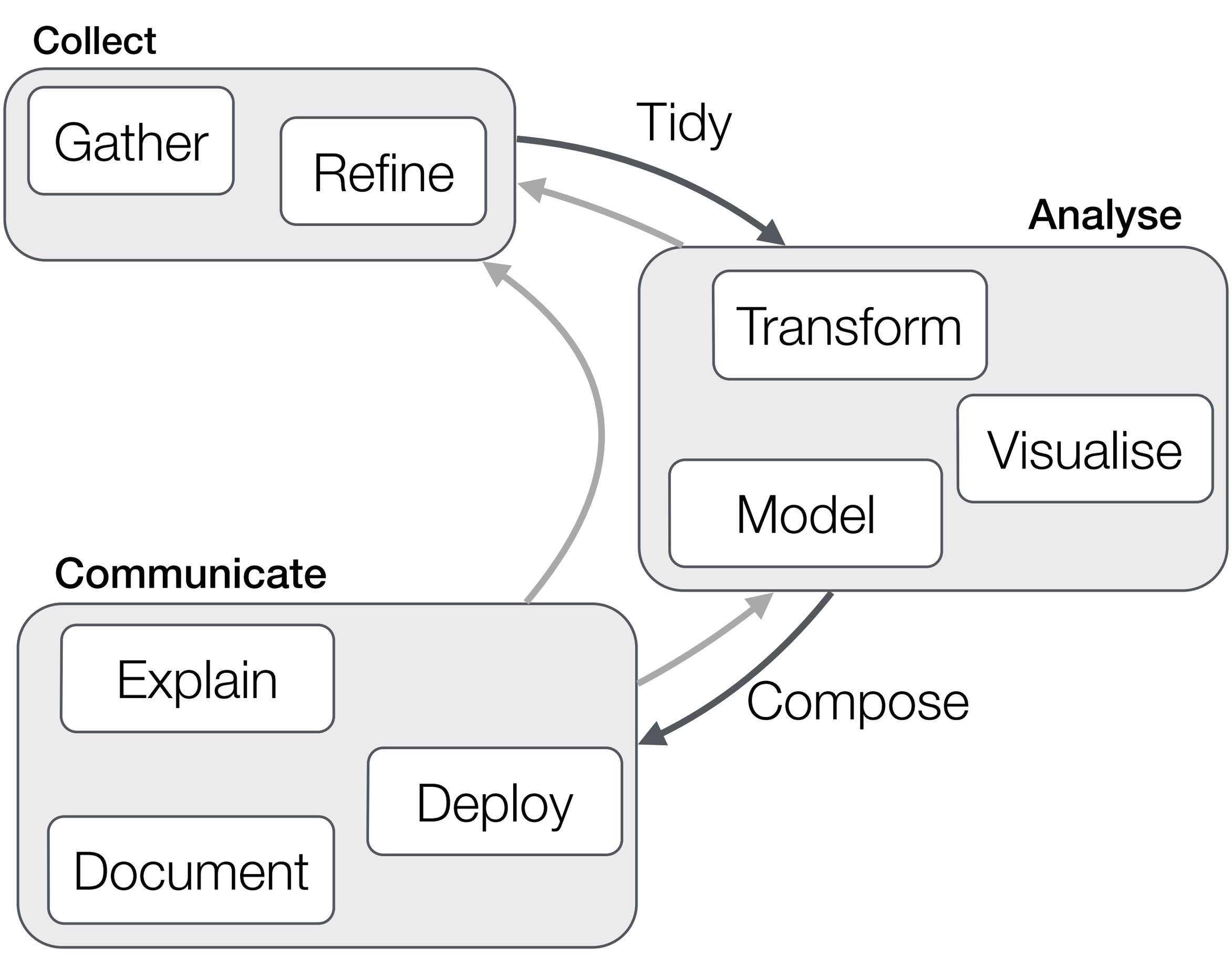
Collect

Tidy

Analyse

Compose

Communicate


Collect
Gather
Refine
Tidy
Analyse
Transform
Visualise
Model
Communicate
Explain
Deploy
Document
Compose

Collect

Gather

Refine

Tidy

Analyse

Transform

`dplyr`

Visualise

Model

`ggvis`

Compose

Communicate

Explain

`shiny` `knitr`

Deploy

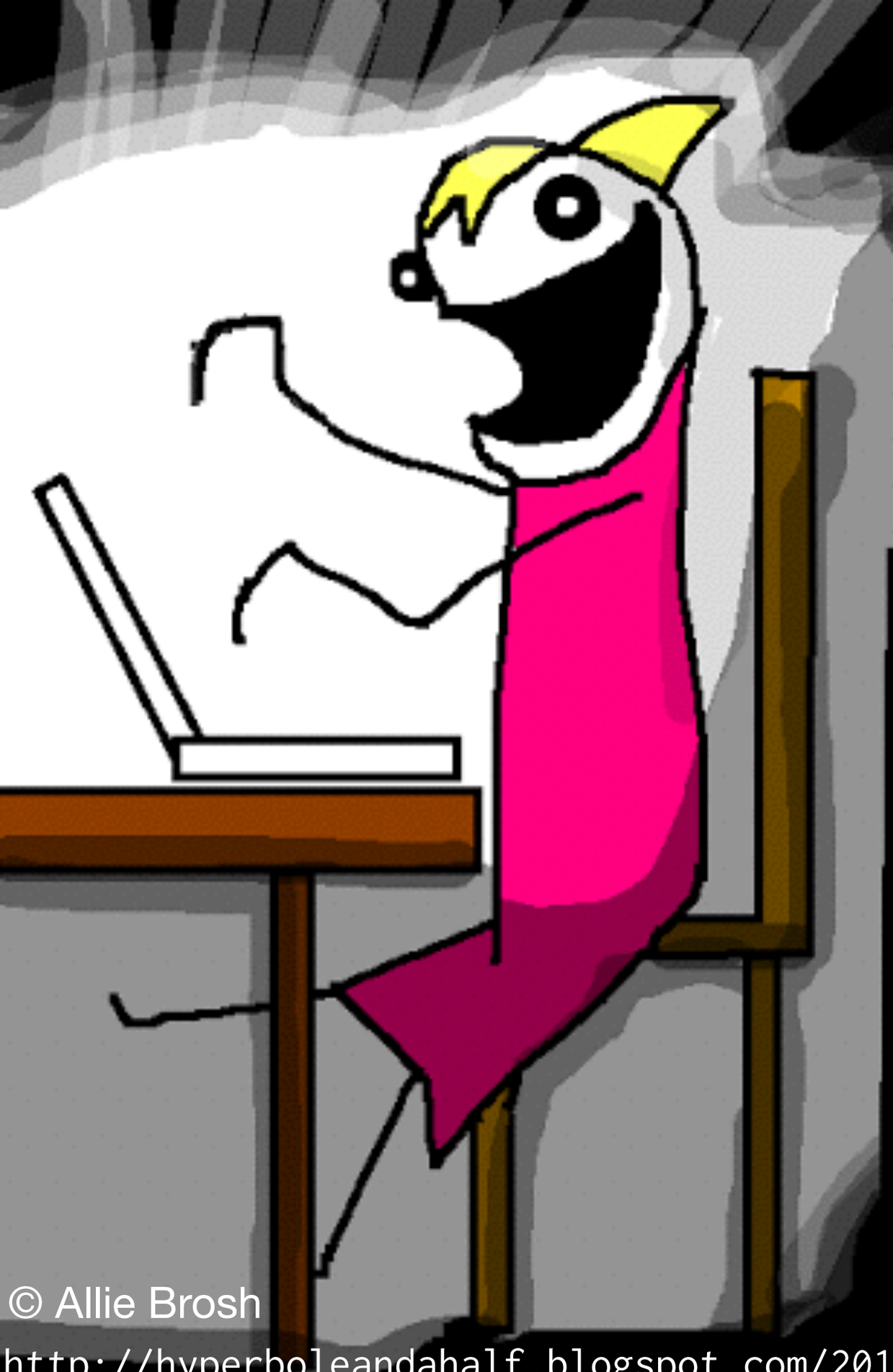
`packrat`

Document

1. Flights data
2. One table verbs & grouped summaries
3. Data pipelines
4. Joins (two table verbs)
5. Databases

The bad news:
It’s going to be frustrating

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



The good news:
Frustration is
typical and
temporary

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

```
# Complete list at http://bit.ly/rday-strata14

install.packages("dplyr"
install.packages("nycflights13")

stopifnot(packageVersion("dplyr") > "0.3")
```

Flights data

Flights data

- `flights` [336,776 x 16]. Every flight departing NYC in 2013.
- `weather` [8,719 x 14]. Hourly weather data.
- `planes` [3,322 x 9]. Plane metadata.
- `airports` [1,397 x 7]. Airport metadata.
- `airlines` [16 x 2]. Airline names

Your turn

Introduce yourself to your neighbour.

What questions might you want to answer with this 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)

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

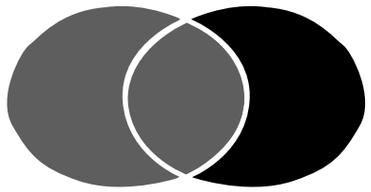
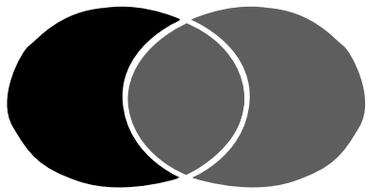
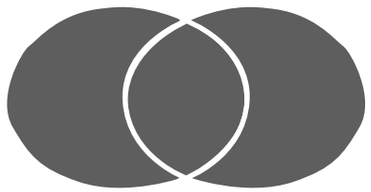
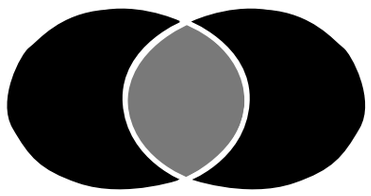
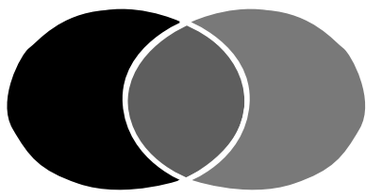
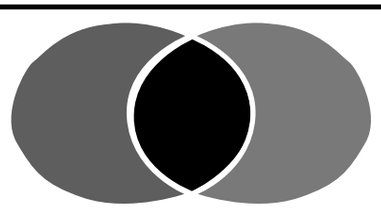
```
filter(df, color == "blue")
```

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, c(arr_delay, dep_delay))
select(flights, dep_delay, dep_delay + 1)
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 summaries

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))
```

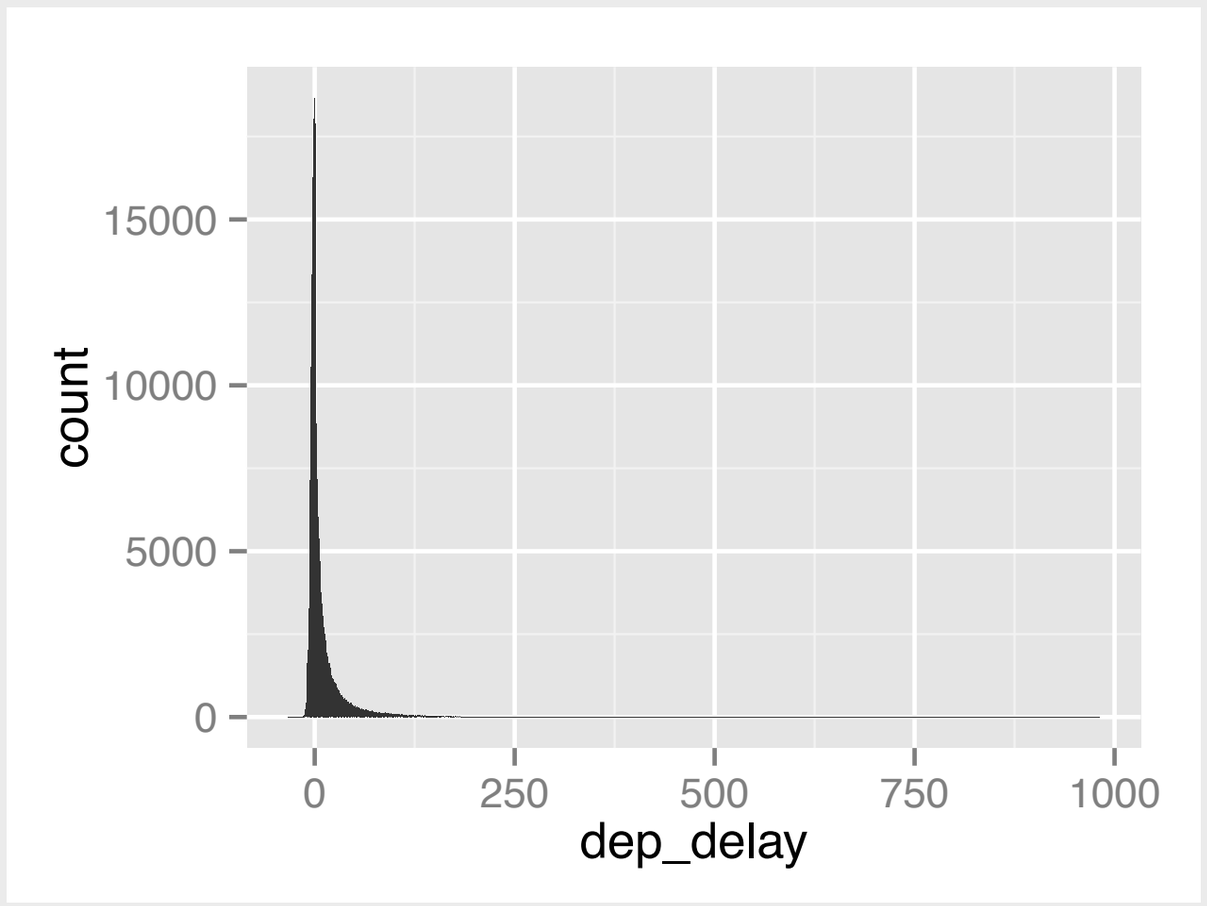
```
flights <- mutate(flights,
  date = as.Date(ISOdate(year, month, day)))

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)
```

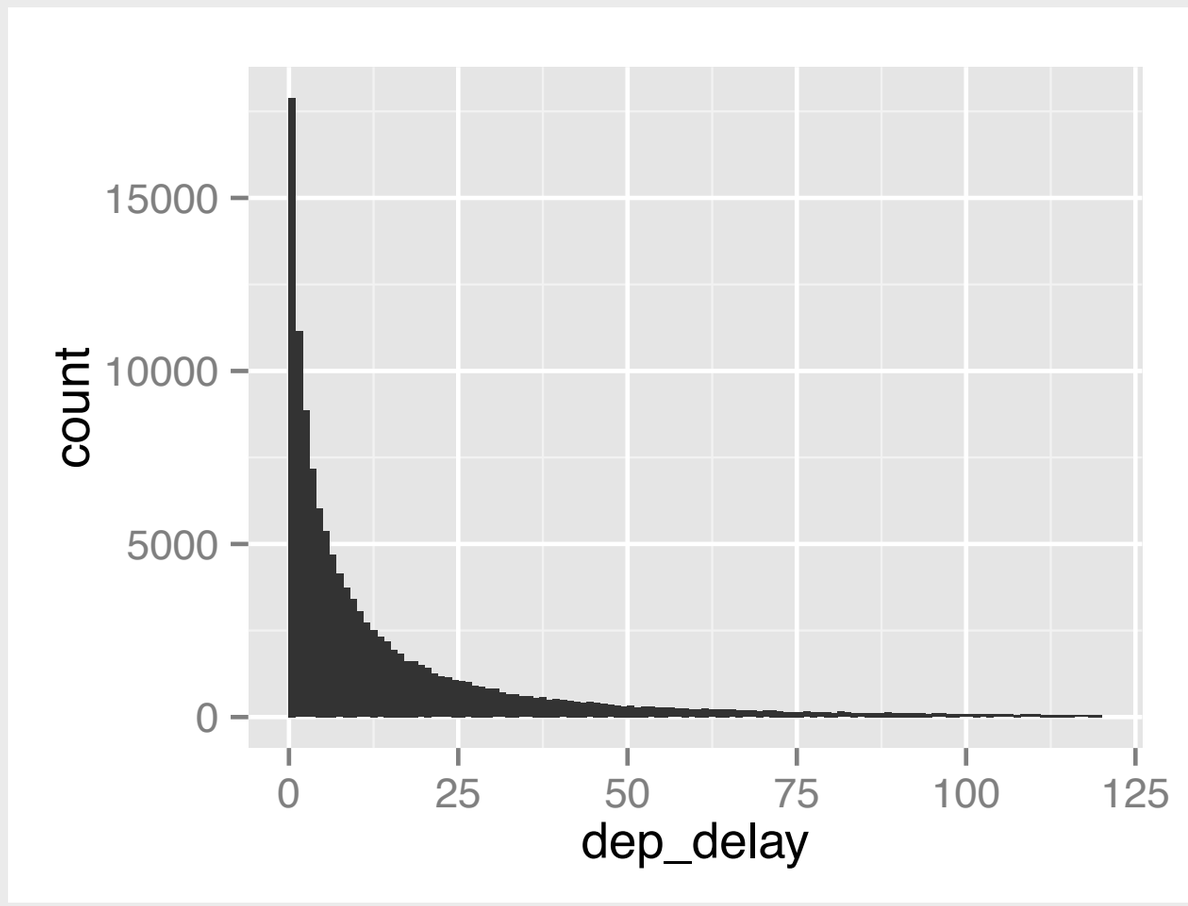
Summary functions

- `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(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_delay))
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)
)
```

Your turn

There's probably significant variation between the three airports in NYC. Can you redo the analysis to look at delays by airport?

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()
```

Two table verbs

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

location <- airports %>%
  select(dest = faa, 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

=

?

```
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 departing in NYC?

Use graphics to explore.

```
qplot(temp, delay, data = delay_weather)
qplot(wind_speed, delay, data = delay_weather)
qplot(wind_gust, delay, data = delay_weather)
qplot(is.na(wind_gust), delay, 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)

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.

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")

# Learn about do
# Learn about window functions
# Learn about set operations
```

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

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