Data Wrangling and Data Analysis
Exploratory Data Analysis

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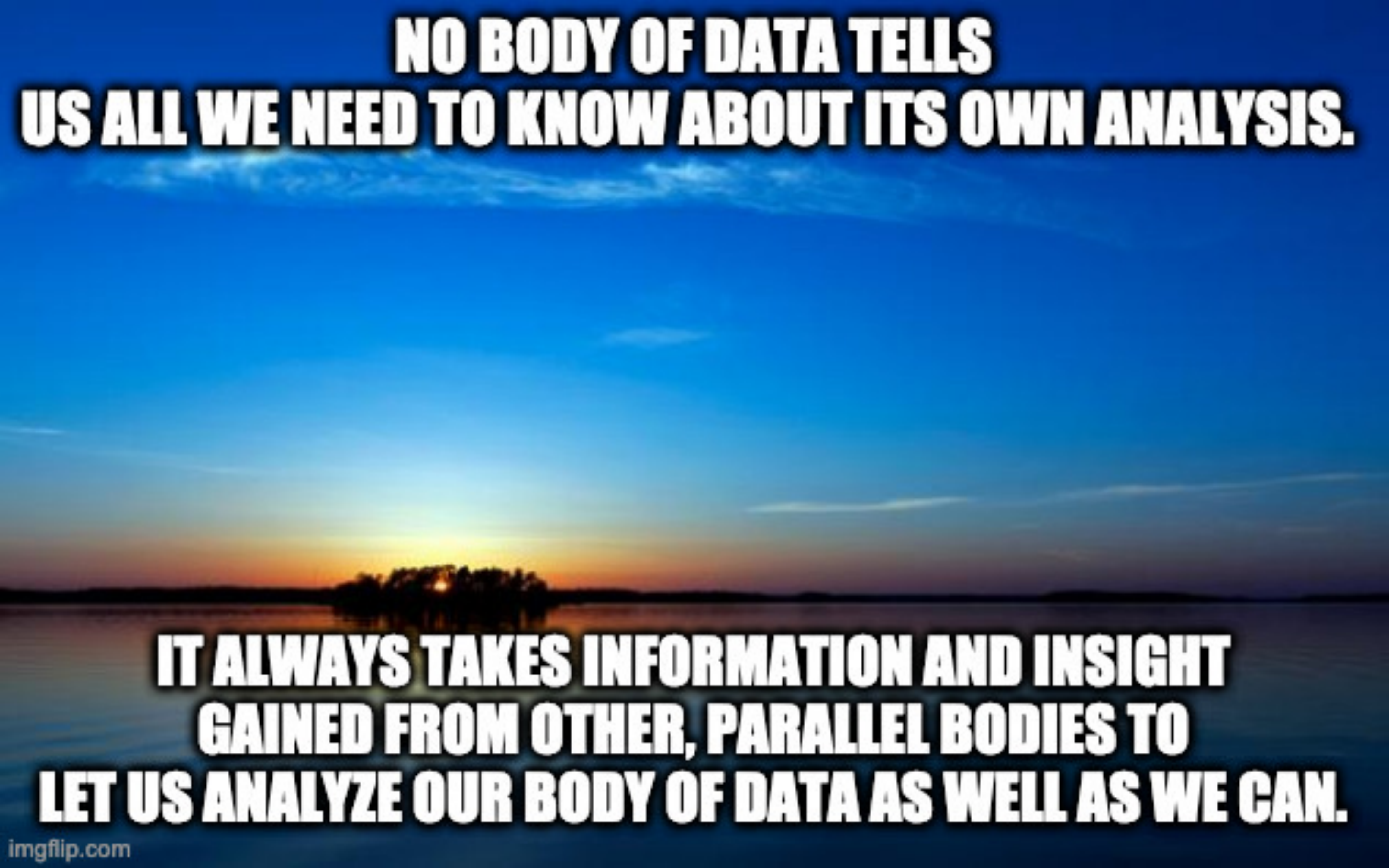
John Tukey (1915 – 2000)

- Data Scientist patient zero
- Inventor of:
  - The boxplot
  - The term “exploratory data analysis”
  - The Fast Fourier Transform
  - “Tukey’s test”
  - The word “bit”
  - So, so much more (Wikipedia)



- John Tukey 1970, EDA

Where it fits in

- Data visualization principles
- The grammar of graphics
- **Exploratory data analysis (EDA)**

- Goal: know how to create and improve data visualizations, and know how to use them for exploration

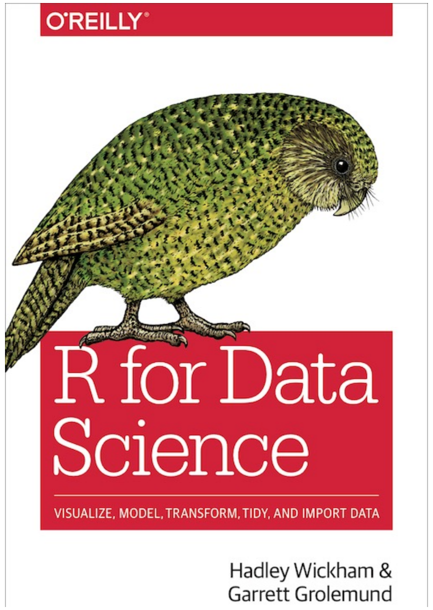
Reading materials for this week

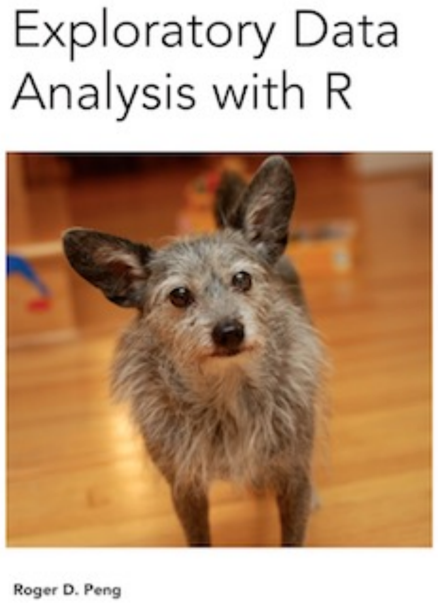
- **R for Data Science (R4DS)**

  (Wickham & Grolemund 2017(ish) **)**
- https://r4ds.had.co.nz
- Chapters 3,5, 7

Optional:

- **Exploratory Data Analysis with R** *(Peng 2020)*
- https://bookdown.org/rdpeng/exdata/





Exploratory vs. confirmatory

Exploratory vs confirmatory

Exploratory analysis

- Generate new insights
- Create new hypotheses
- Analysis may depend on data

Confirmatory analysis

- Test theory
- A priori hypothesis
- Analysis predefined
- Example: registered report

Exploratory vs confirmatory

You work at Google and your colleague has implemented a new search algorithm for German searches. Your task is to check whether this algorithm performs better than the existing one.

- **Confirmatory.**
- Theory testing, hypothesis: new works better than old
- Analysis can be defined in advance: which outcome variables, how to sample from the population, which method?
- Full analysis script could be written before the data even exists

Exploratory vs confirmatory

You have obtained access to your company's customer relations database. Your task is to find data-driven ways in which your company can improve customer retainment.

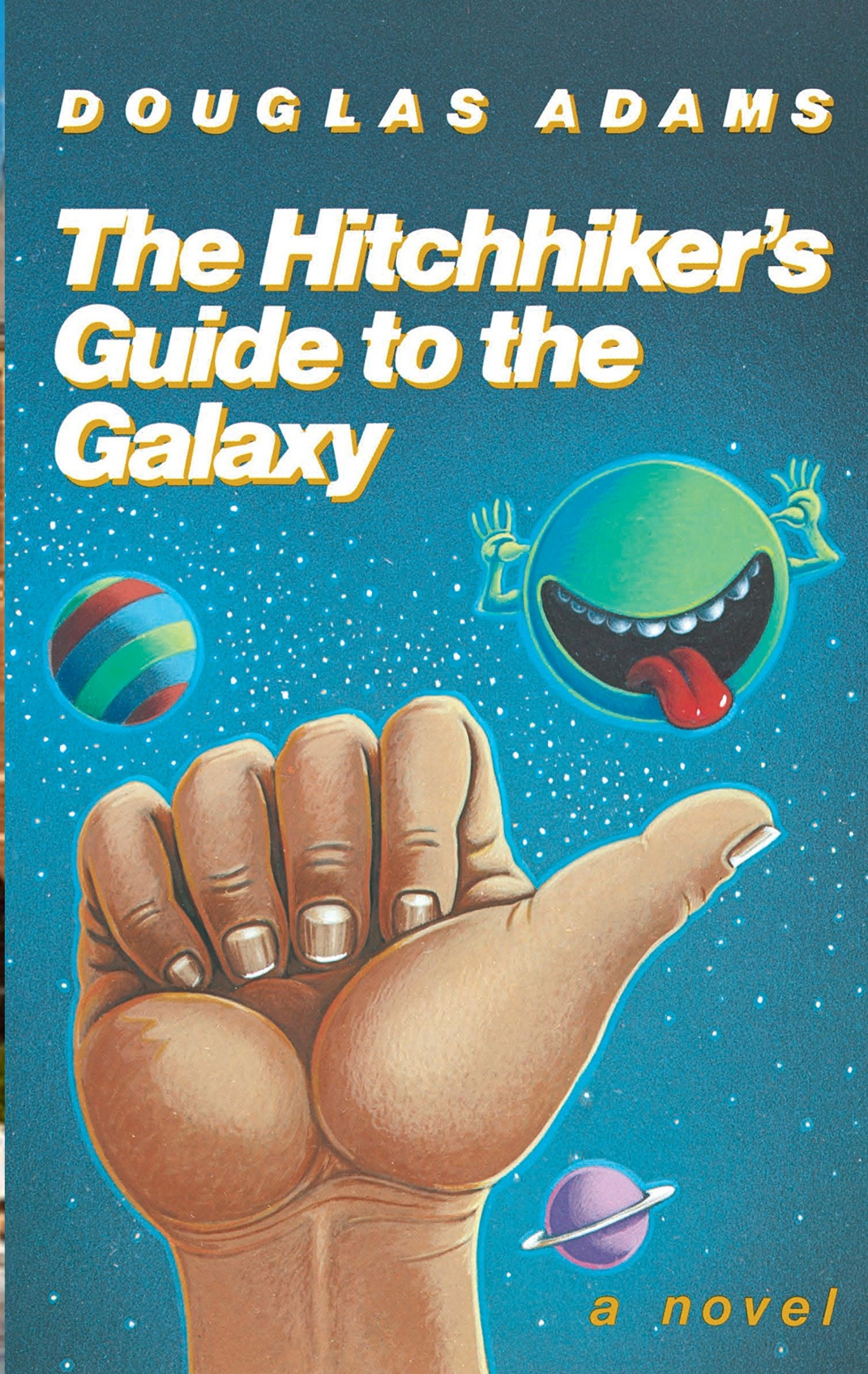
- **Exploratory.**
- Generate new insights - at which touchpoint do customers drop out?
- Create new hypotheses - there may be two types of customers who drop out
- Analysis cannot be defined in advance, task is to explore associations between features

Exploratory vs confirmatory

- Both are necessary and complementary
- Typical scientific questions: exploratory -> confirmatory
- Then build on the tested theories to generate new insights: confirmatory -> exploratory?

- This lecture: **exploratory analysis**


I amsterda


DOUGLAS ADAMS
The Hitchhiker's Guide to the Galaxy
a novel

Some good advice on data exploration

Tukey’s approach to EDA

- Look at center and spread
- Find comparisons
- “Straightening and flattening”:
- Use logarithms and other transforms
- Use models and residuals

hinges.

If we have 9 values in all, the 5th from either end will be the median, since $\frac{1}{2}(1 + 9) = 5$. Since $\frac{1}{2}(1 + 5) = 3$, the third from either end will be a hinge. If we have 13 values, the 7th will be the median—and the 4th from each end a hinge. In folded form, a particular set of 13 values appears as follows:

−3.2						1.5						9.8
	−1.7				1.2		1.8				6.4	
		−0.4		0.3				2.4		4.3		
			0.1						3.0			

The five summary numbers are, in order, −3.2, 0.1, 1.5, 3.0, and 9.8, one at each folding point.

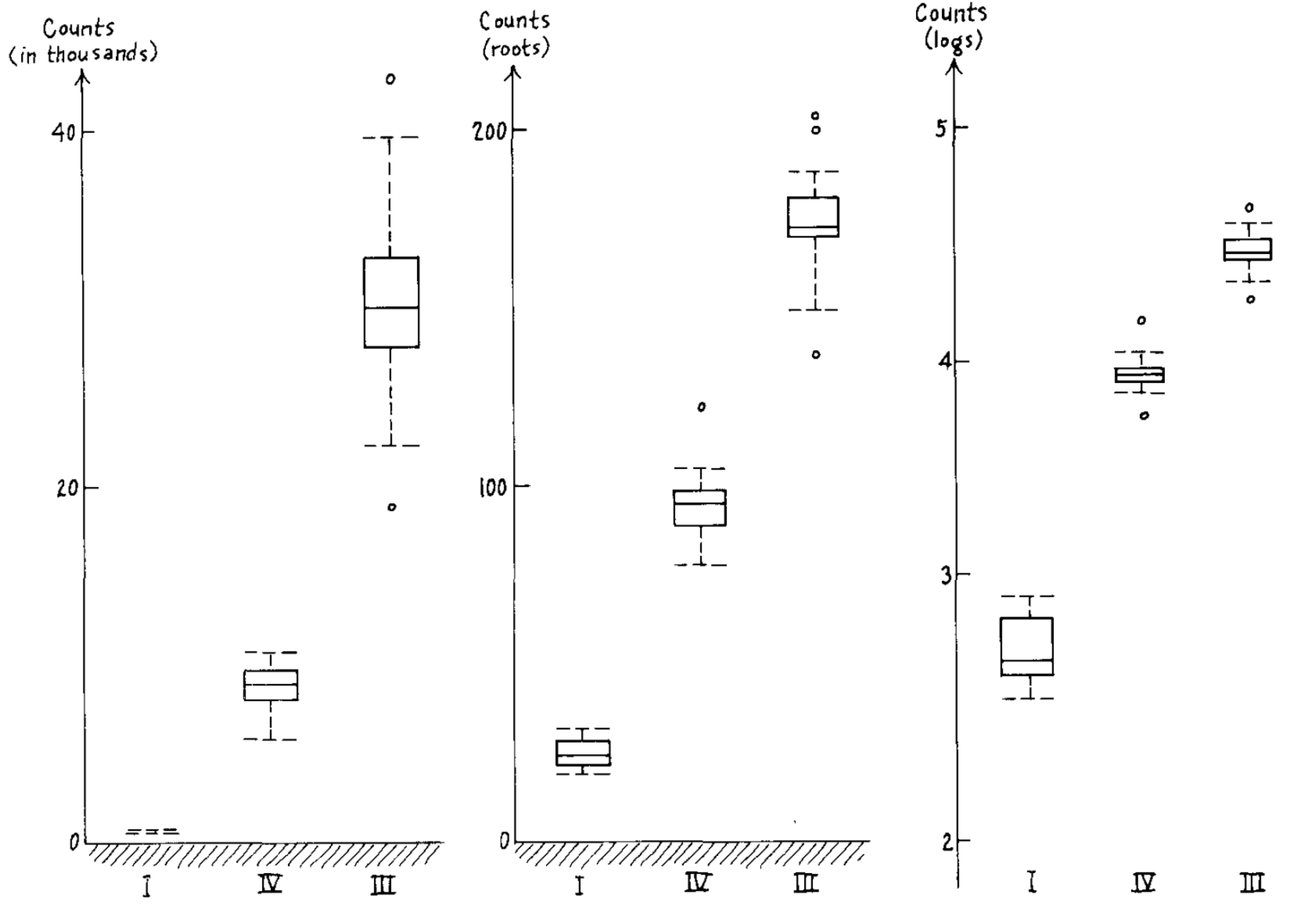
We usually symbolize the 5 numbers (extremes, hinges, median) that make up a

5-number summary

by a simple summary scheme like this:

#13			
M7		1.5	
H4	0.1		3.0
1	−3.2		9.8

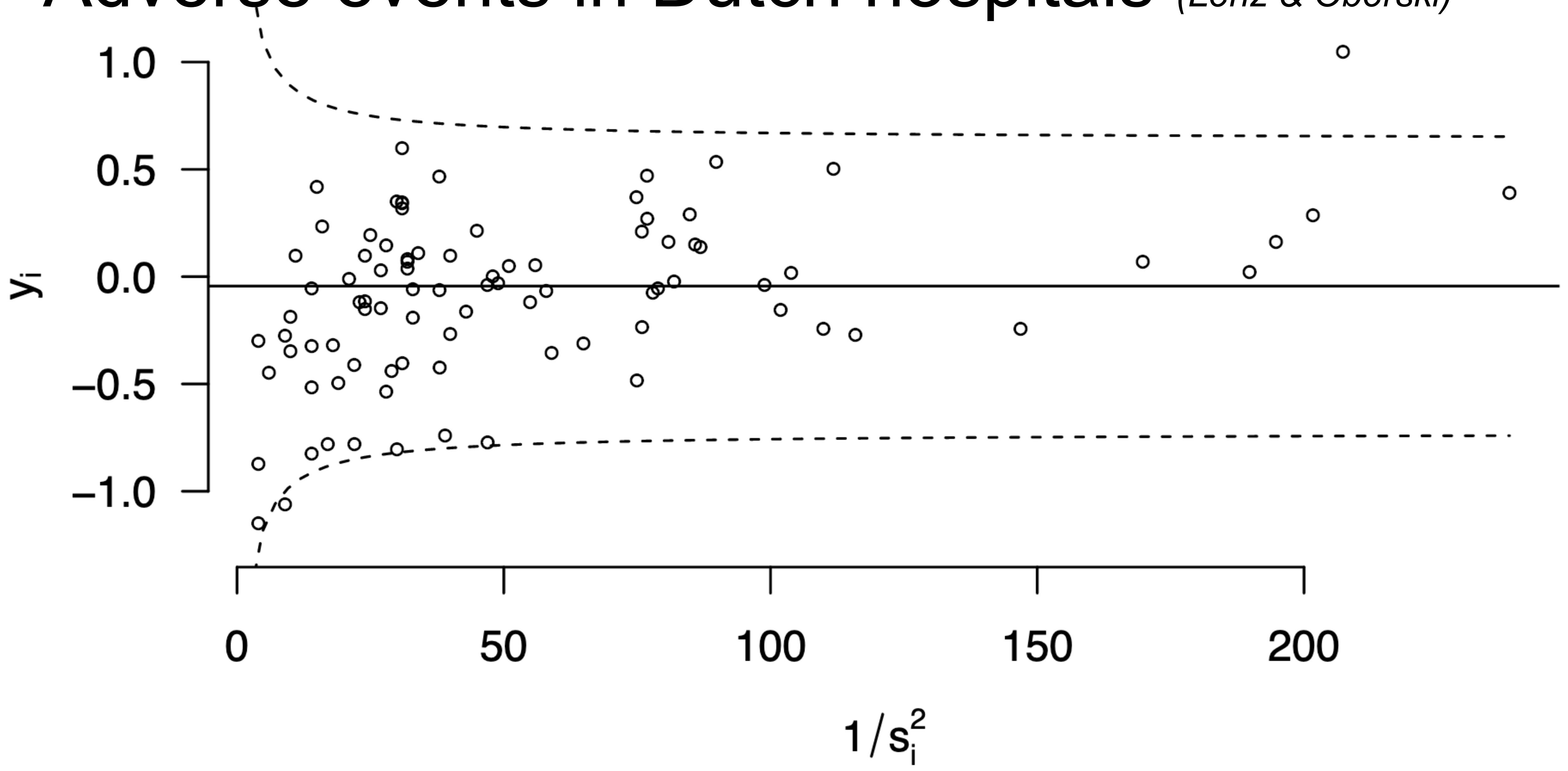
(Tukey 1970)



Counts (in thousands)
40
20
0
I
IV
III
Counts (roots)
200
100
0
I
IV
III
Counts (logs)
5
4
3
2
I
IV
III

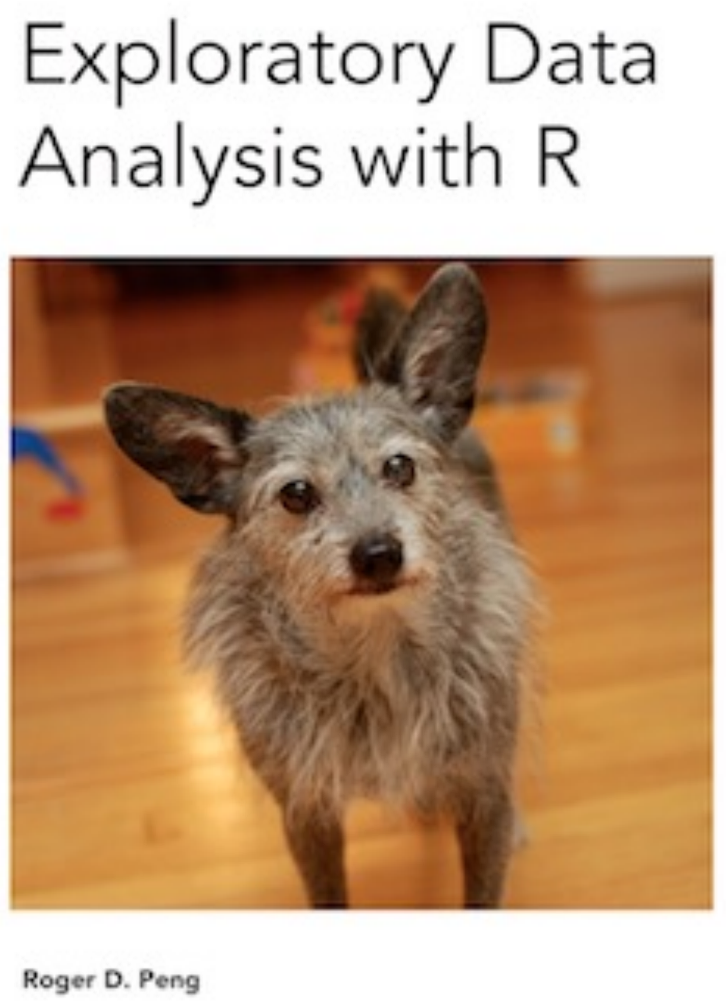
(Tukey 1970)

Adverse events in Dutch hospitals *(Lenz & Oberski)*



Peng's EDA checklist

1. Formulate your question
2. Read in your data
3. Check the packaging, (run str())
4. Look at the top and the bottom of your data
5. Check your "n"s
6. Validate with at least one external data source
7. Try the easy solution first
8. Challenge your solution
9. Follow up



Example exploration of current corona cases in the Netherlands

Dataset: COVID-19 case counts in The Netherlands

CoronaWatchNL collects numbers on COVID-19 disease count cases in **The Netherlands**. The numbers are collected from various sources on a daily base, like RIVM (National Institute for Public Health and the Environment), LCPS (Landelijk Coördinatiecentrum Patiënten Spreiding), NICE (Nationale Intesive Care Evaluatie), and the National Corona Dashboard. This project standardizes, and publishes data and makes it **Findable, Accessible, Interoperable, and Reusable (FAIR)**. We aim to collect a complete time series and prepare a dataset for reproducible analysis and academic use.

Read data, check packaging

```
url_icu <-
"https://raw.githubusercontent.com/J535D165/CoronaWatchNL/master/data-
ic/data-nice/NICE_IC_long_latest.csv"

icu <- read_csv(url_icu)
```

```
> dim(icu)
[1] 1935    3
```

Look at top and bottom

```
> icu %>% tail
# A tibble: 6 x 3
  Datum      Type                          Aantal
  <date>     <chr>                          <dbl>
1 2020-09-28 Toename ontslag (ziekenhuis)       0
2 2020-09-28 Totaal opnamen (IC)              144
3 2020-09-28 Toename opnamen (IC)               7
4 2020-09-28 Totaal ontslag (IC)               56
5 2020-09-28 Cumulatief opnamen (IC)         3261
6 2020-09-28 Toename ontslag (overleden)        0
```

Look at top and bottom

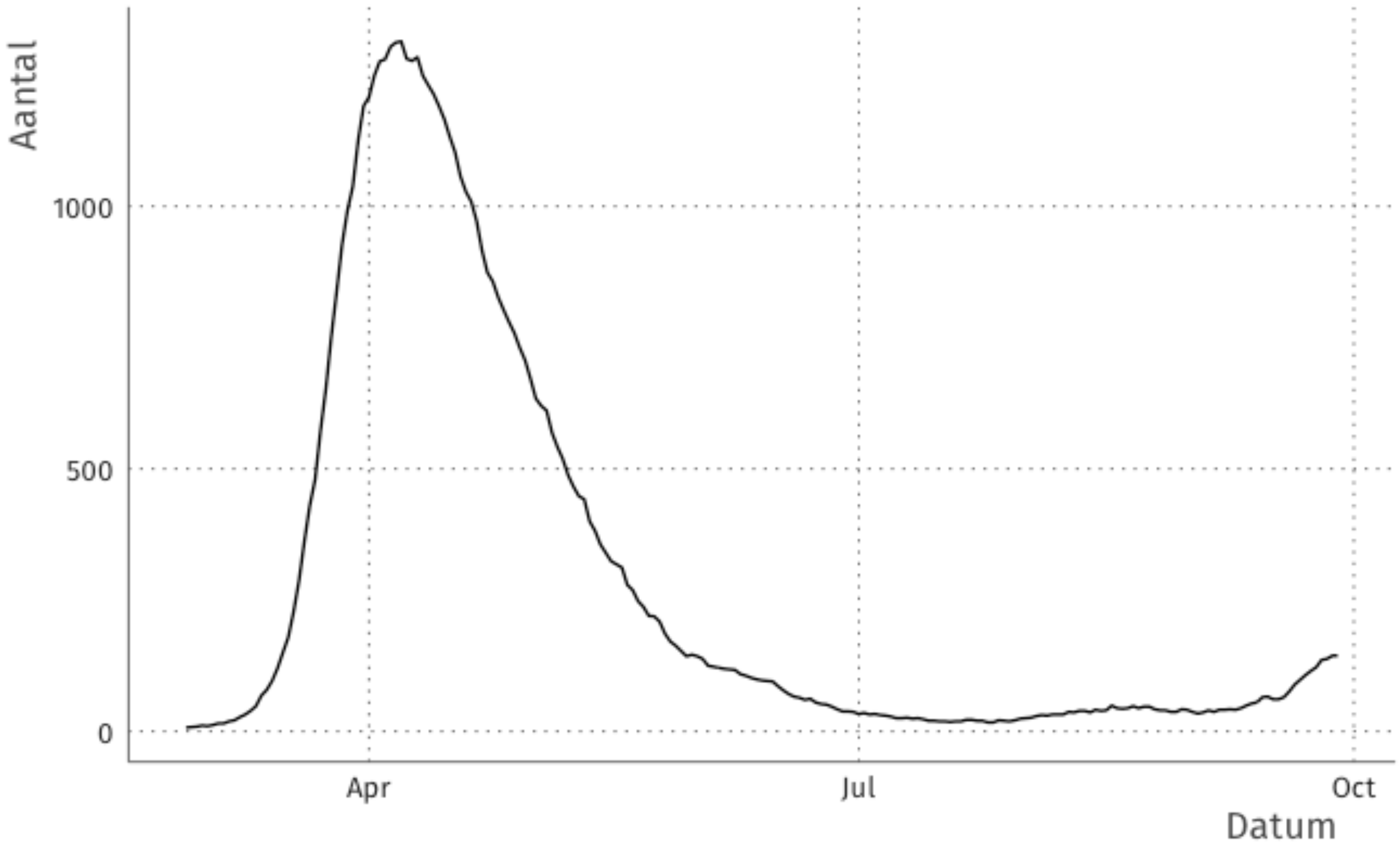
```
> icu %>% head
# A tibble: 6 x 3
  Datum      Type                                 Aantal
  <date>     <chr>                                 <dbl>
1 2020-02-27 Totaal ingezette IC's                     5
2 2020-02-27 Cumulatief opnamen (IC)                   7
3 2020-02-27 Totaal ontslag (IC)                       0
4 2020-02-27 Cumulatief ontslag (ziekenhuis)           0
5 2020-02-27 Cumulatief ontslag (overleden)            0
6 2020-02-27 Toename ontslag (overleden)               0
```

Validate with external source

Check n’s

```
> icu %>% group_by(Type) %>% summarize(n())

# A tibble: 9 x 2
  Type                            `n()`
  <chr>                           <int>
1 Cumulatief ontslag (overleden)    215
2 Cumulatief ontslag (ziekenhuis)   215
3 Cumulatief opnamen (IC)           215
4 Toename ontslag (overleden)       215
5 Toename ontslag (ziekenhuis)      215
6 Toename opnamen (IC)              215
7 Totaal ingezette IC's             215
8 Totaal ontslag (IC)               215
9 Totaal opnamen (IC)               215
```

```r
icu %>%
  filter(Type == "Totaal opnamen (IC)")  %>%
  ggplot(aes(Datum, Aantal)) + geom_line() +
  theme_fira()
```



Understand what you’re looking at

Bezetting IC units

	IC-units in Nederland		
	gem.	min.	max.
bedden	14	1	35
intensivisten (in fte)	7	1	18
verpleegkundigen (in fte)	50	10	152

(84 ICUs)

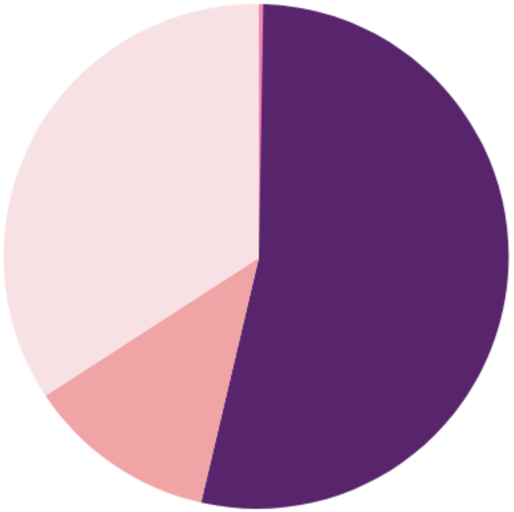
Back-of-the-envelope:

$14 \times 84 \approx 1200$ beds

Geometric average:
$\sqrt{1 \times 35} \approx 6$ beds

Understand what you’re looking at

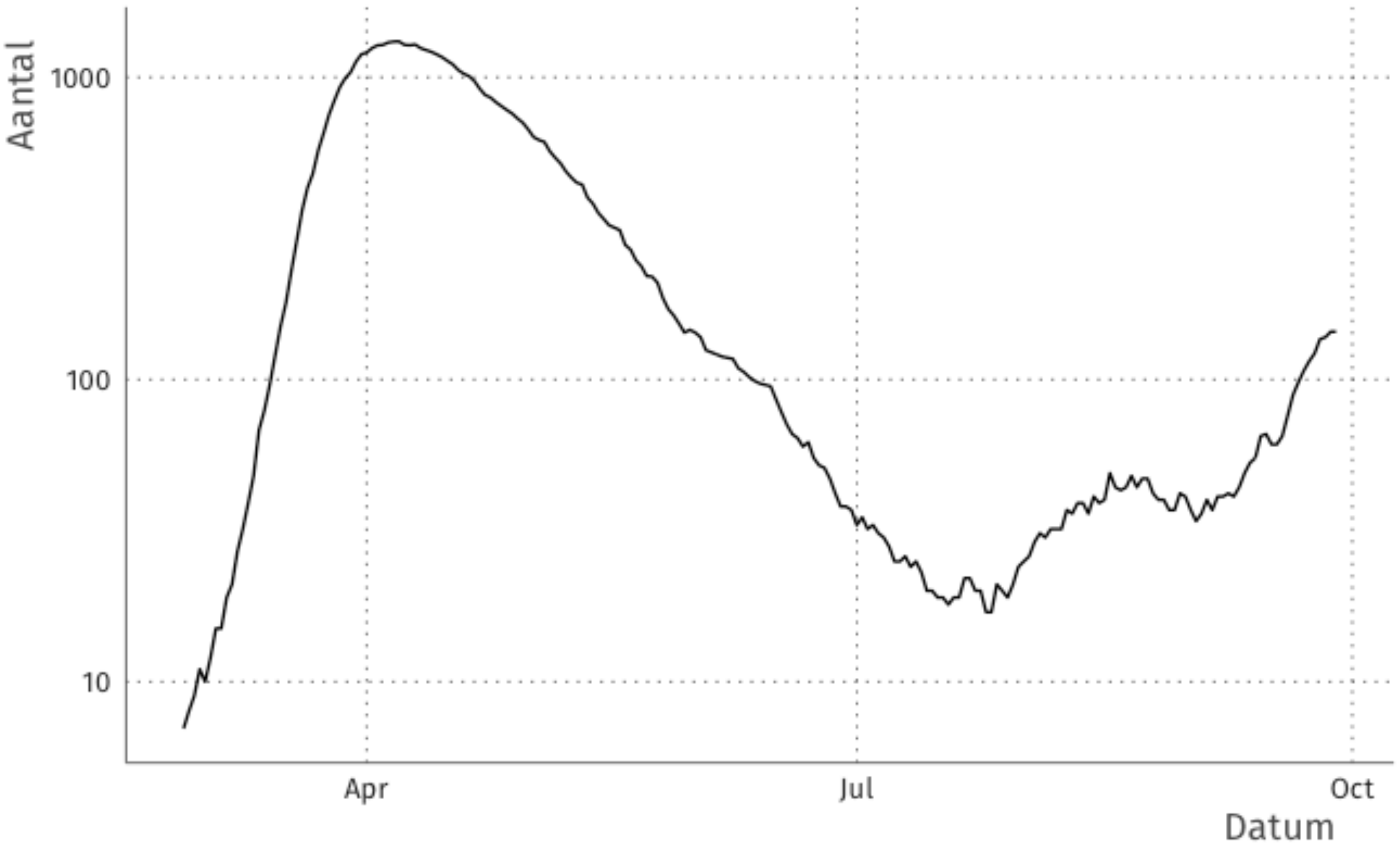
Aantal opnamen per opnametype



IC-units in Nederland

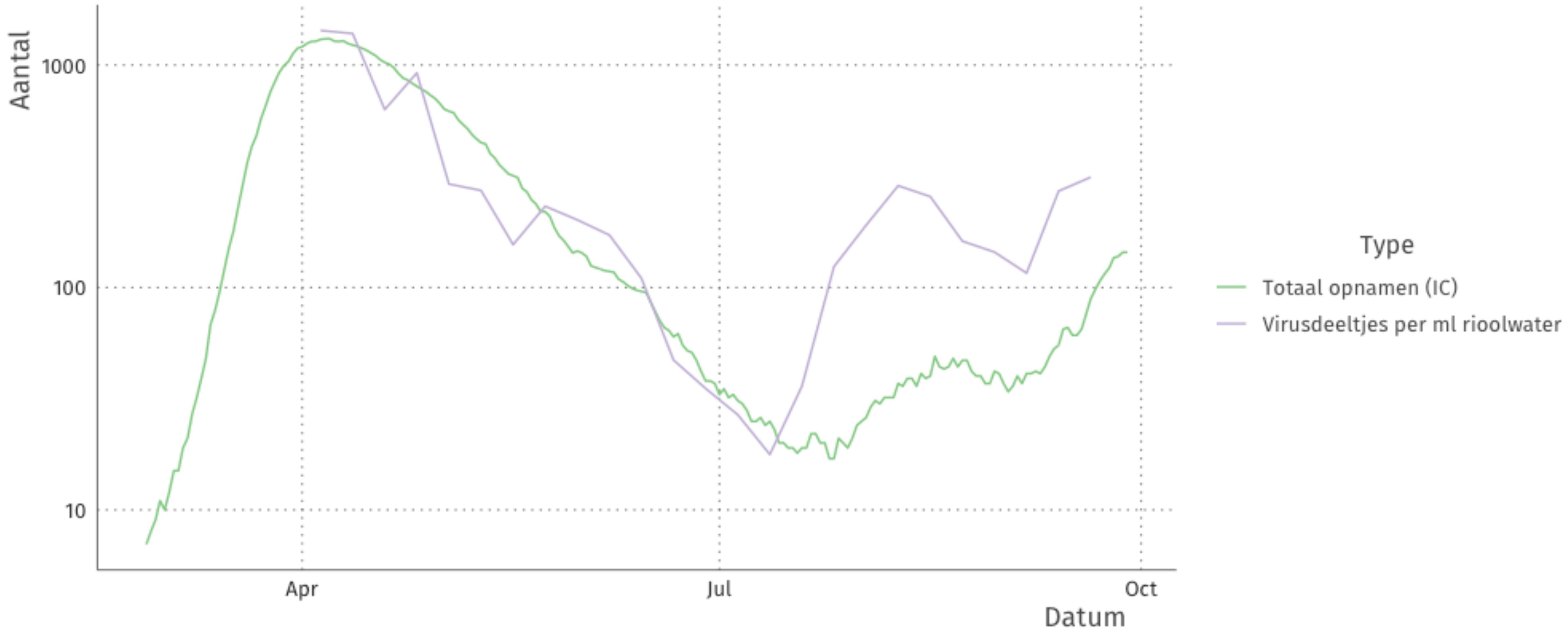
	IC-units in Nederland	
Type	**aantal**	**%**
Alle opnamen	**73.979**	**100**
Medisch	39.654	53,6
Spoed chirurgie	8.632	11,7
Geplande chirurgie	25.499	34,5
Overige	194	0,3

```
icu %>%
  filter(Type == "Totaal opnamen (IC")  %>%
  ggplot(aes(Datum, Aantal)) + geom_line() +
  theme_fira() + scale_y_log10()
```



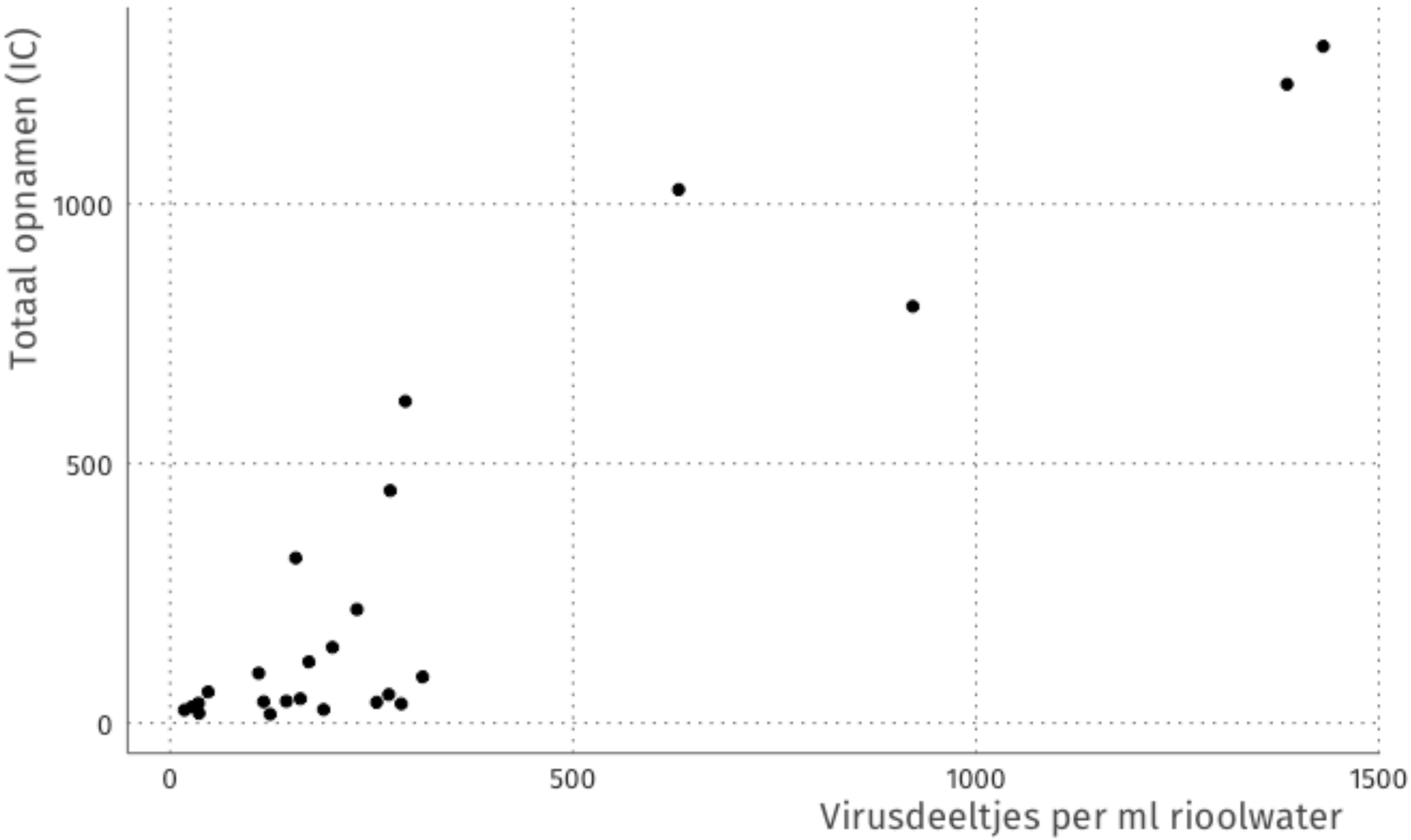
```
url_sewage <-
"https://raw.githubusercontent.com/J535D165/CoronaWatchNL/master/data-dashboard/data-sewage/RIVM_NL_sewage_counts.csv"

sewage <- read_csv(url_sewage)


joined <- bind_rows(sewage, icu)
```

```
joined %>%
  filter(Type == "Totaal opnamen (IC)" |
           Type == "Virusdeeltjes per ml rioolwater")  %>%
  ggplot(aes(Datum, Aantal, color = Type)) + geom_line() +
  scale_y_log10() +
  theme_fira() + scale_color_brewer(type = "qual")
```

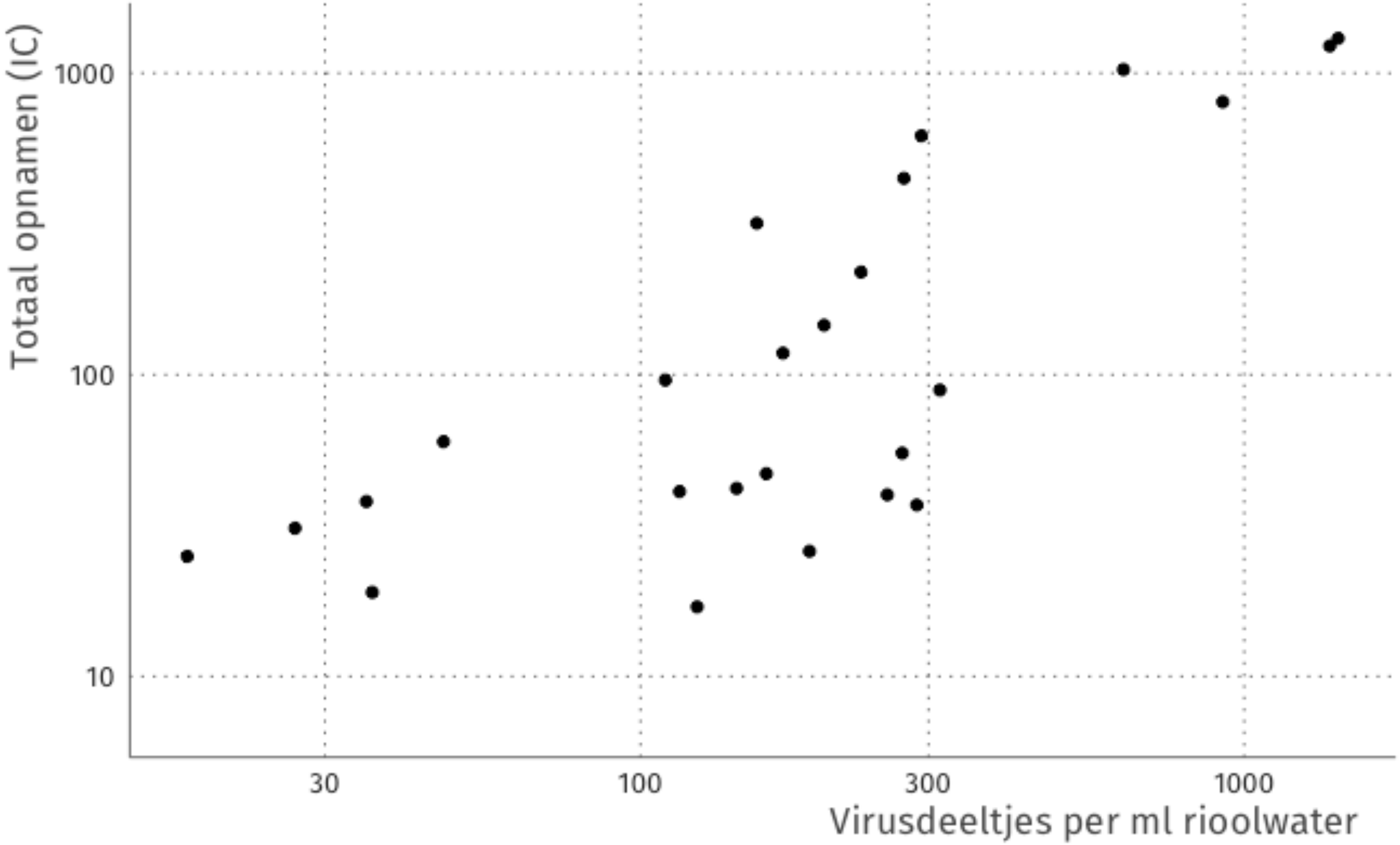


```
joined_wide <- joined %>%
  filter(Type == "Totaal opnamen (IC)" |
           Type == "Virusdeeltjes per ml rioolwater") %>%
  pivot_wider(names_from = Type, values_from = Aantal)
```

```r
joined_wide %>%
ggplot(aes(`Virusdeeltjes per ml rioolwater`, `Totaal opnamen (IC)`)) +
  geom_point() + theme_fira()
```

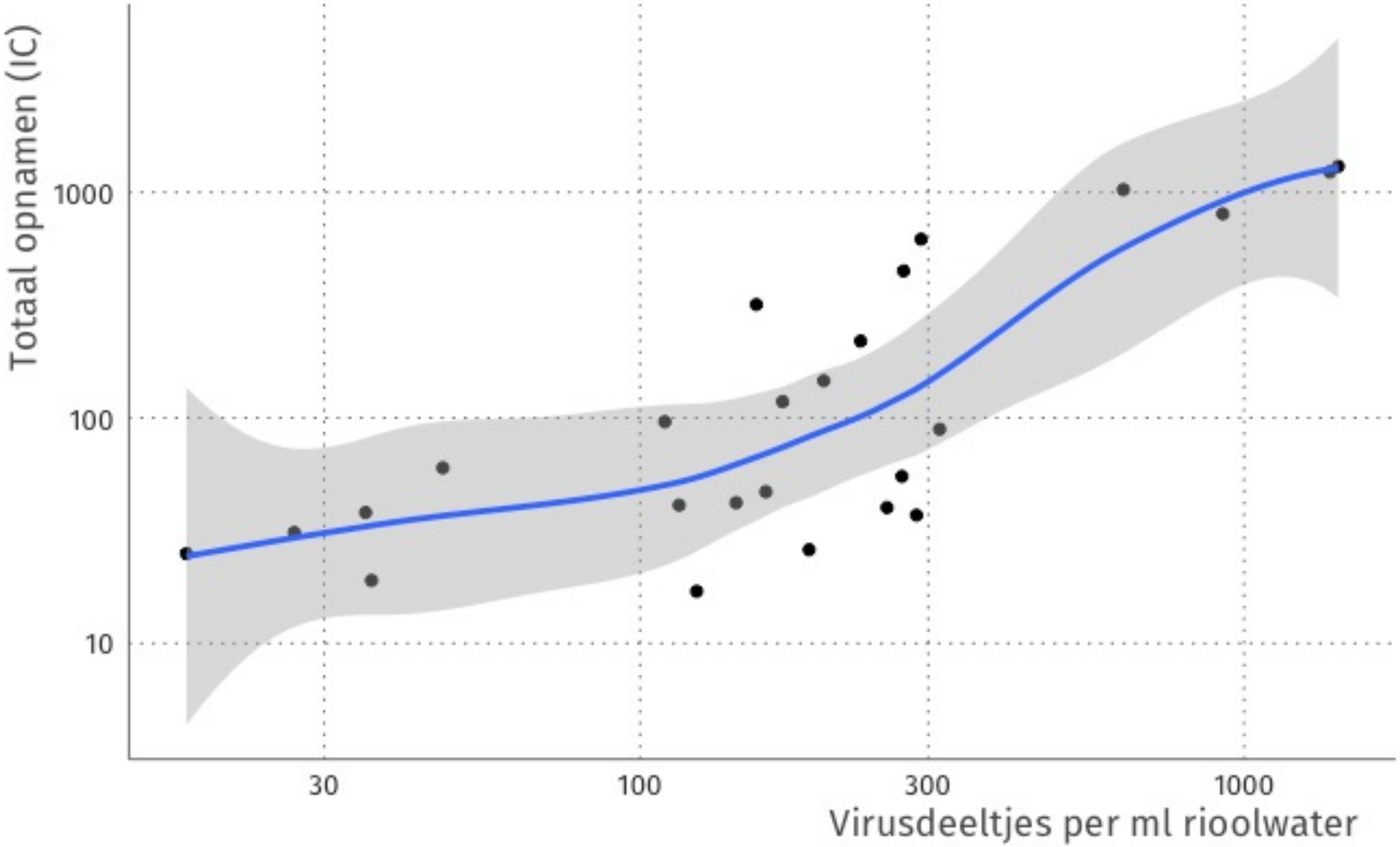


```
joined_wide %>%
ggplot(aes(`Virusdeeltjes per ml rioolwater`, `Totaal opnamen (IC)`)) +
  geom_point() + scale_y_log10() + scale_x_log10() + theme_fira()
```

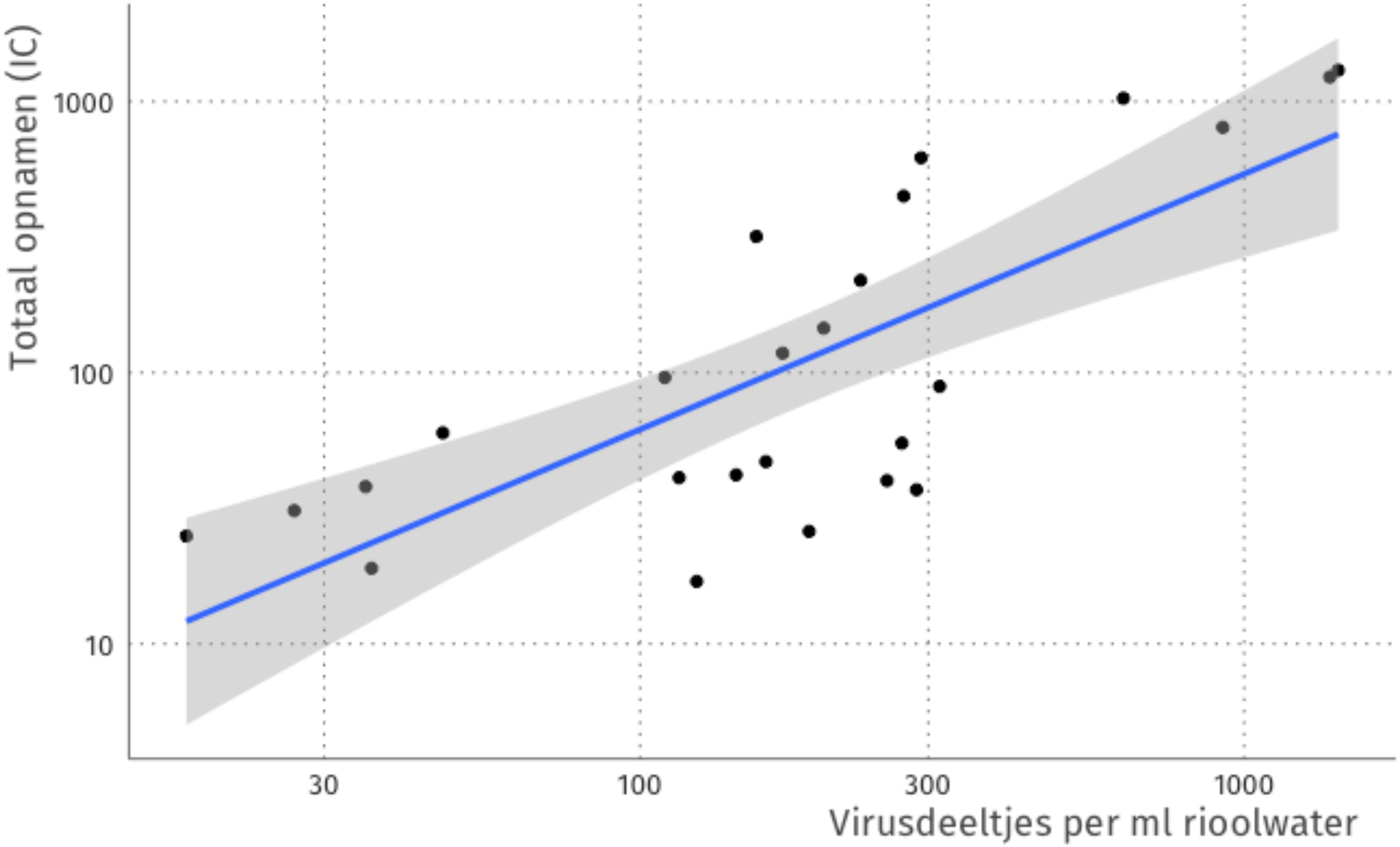


“straightening”

```
joined_wide %>%
ggplot(aes(`Virusdeeltjes per ml rioolwater`, `Totaal opnamen (IC)`)) +
  geom_point() + geom_smooth() +
  scale_y_log10() + scale_x_log10() + theme_fira()
```



```
joined_wide %>%
ggplot(aes(`Virusdeeltjes per ml rioolwater`, `Totaal opnamen (IC)`)) +
  geom_point() + geom_smooth(method = “lm”) +
  scale_y_log10() + scale_x_log10() + theme_fira()
```



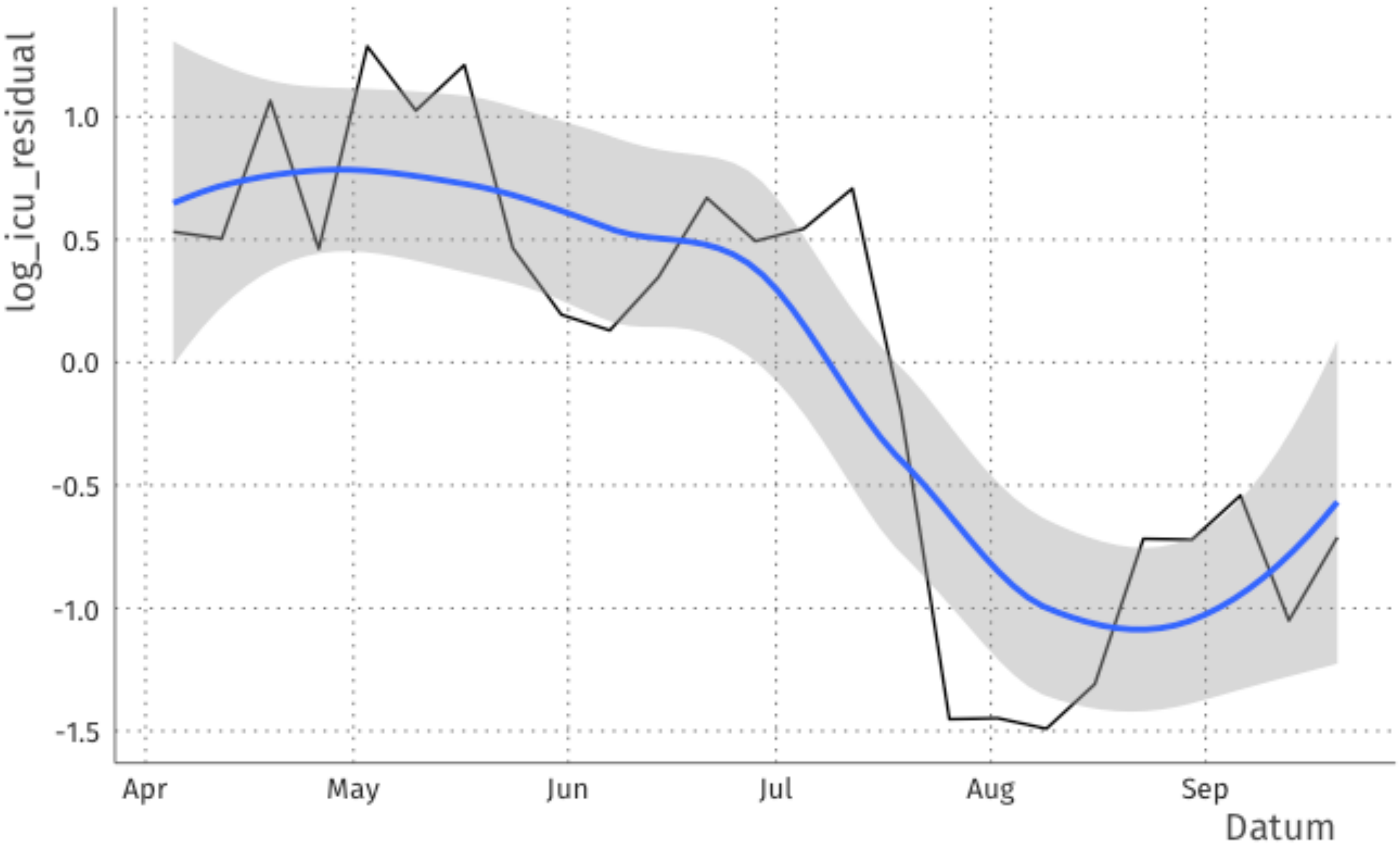
Looking at **residuals**

```
joined_wide <- joined_wide %>%
  mutate(
    log_icu = log(`Totaal opnamen (IC)` + 1),
    log_sewage = log(`Virusdeeltjes per ml rioolwater` + 1))

fit_lm <- lm(log_icu ~ log_sewage, data = joined_wide)

joined_wide <- joined_wide %>%
  mutate(log_icu_predicted = predict(fit_lm, newdata = .),
         log_icu_residual = log_icu - log_icu_predicted)
```

```
joined_wide %>%
      filter(!is.na(log_icu_residual)) %>%
      ggplot(aes(Datum, log_icu_residual)) +
      geom_line() + theme_fira()
```

“flattening”

```
joined_wide %>%
      filter(!is.na(log_icu_residual)) %>%
      ggplot(aes(Datum, log_icu_residual)) +
      geom_line() + geom_smooth() + theme_fira()
```



“flattening”

Using some standard plots for EDA

Visual EDA: two questions

- Variation: How are the features distributed?
  - Univariate
  - Specific: among people, among time, among flights
  - General: among the unit of measurement, among examples
  - In tabular data, generally one example/unit per row

- Association: What type of covariation occurs in the data?
  - Which features covary? When A is high, is B high?
  - Multidimensional, multivariate.

Visual EDA: two questions

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```r
library(nycflights13)
flights
#> # A tibble: 336,776 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
#> 1  2013     1     1      517            515         2      830            819
#> 2  2013     1     1      533            529         4      850            830
#> 3  2013     1     1      542            540         2      923            850
#> 4  2013     1     1      544            545        -1     1004           1022
#> 5  2013     1     1      554            600        -6      812            837
#> 6  2013     1     1      554            558        -4      740            728
#> # … with 3.368e+05 more rows, and 11 more variables: arr_delay <dbl>,
#> #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

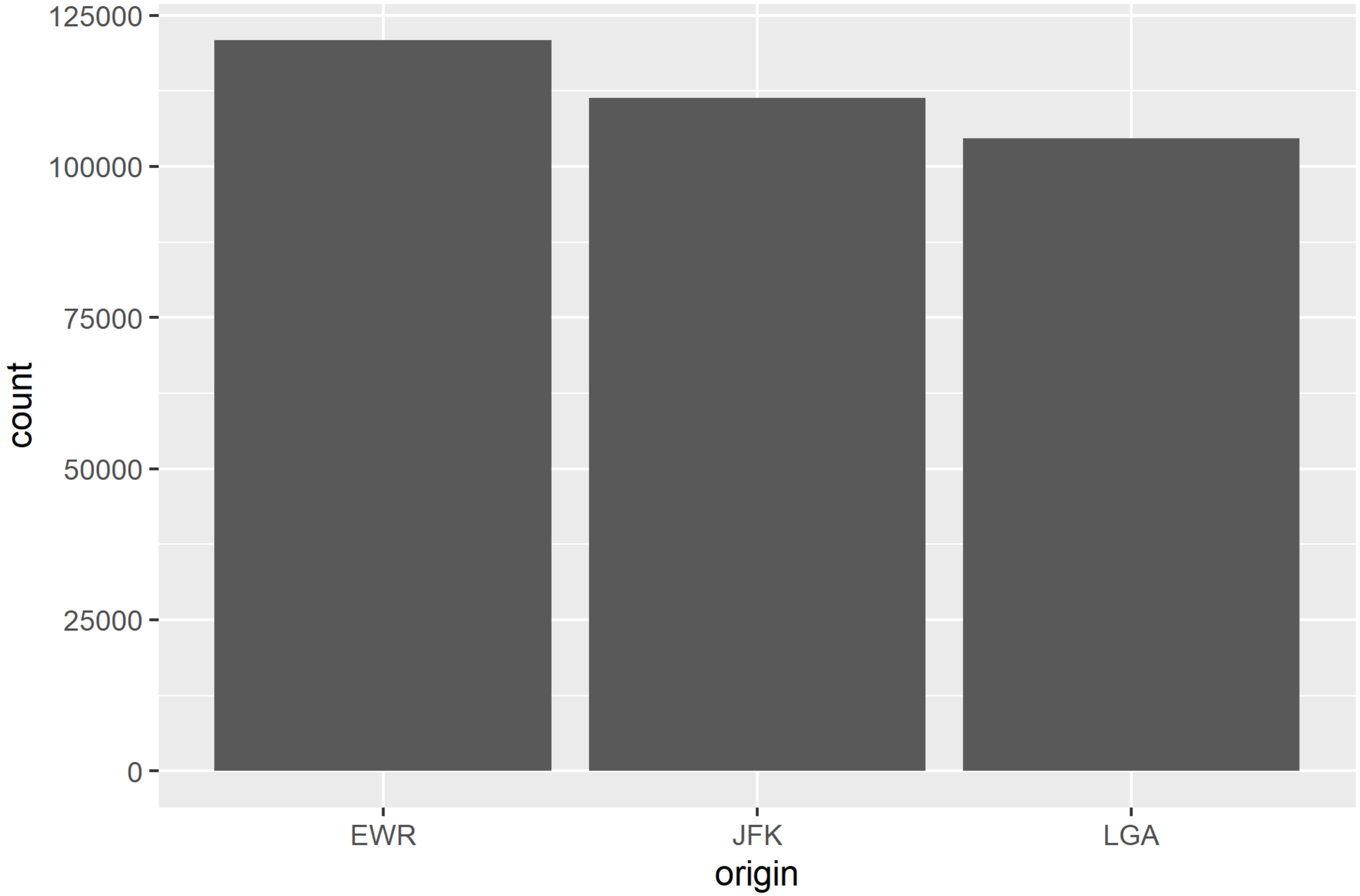
Bar chart

- X position: feature of interest
- Y position: count of occurrences (statistical transformation)
- Geom: bars/rectangle

- For categorical features e.g., flight origin

Bar chart

```
ggplot(data = flights) +
  geom_bar(mapping = aes(x = origin))
```



Bar chart

- Fewest flights depart from LGA
- Almost 125000 flights from EWR

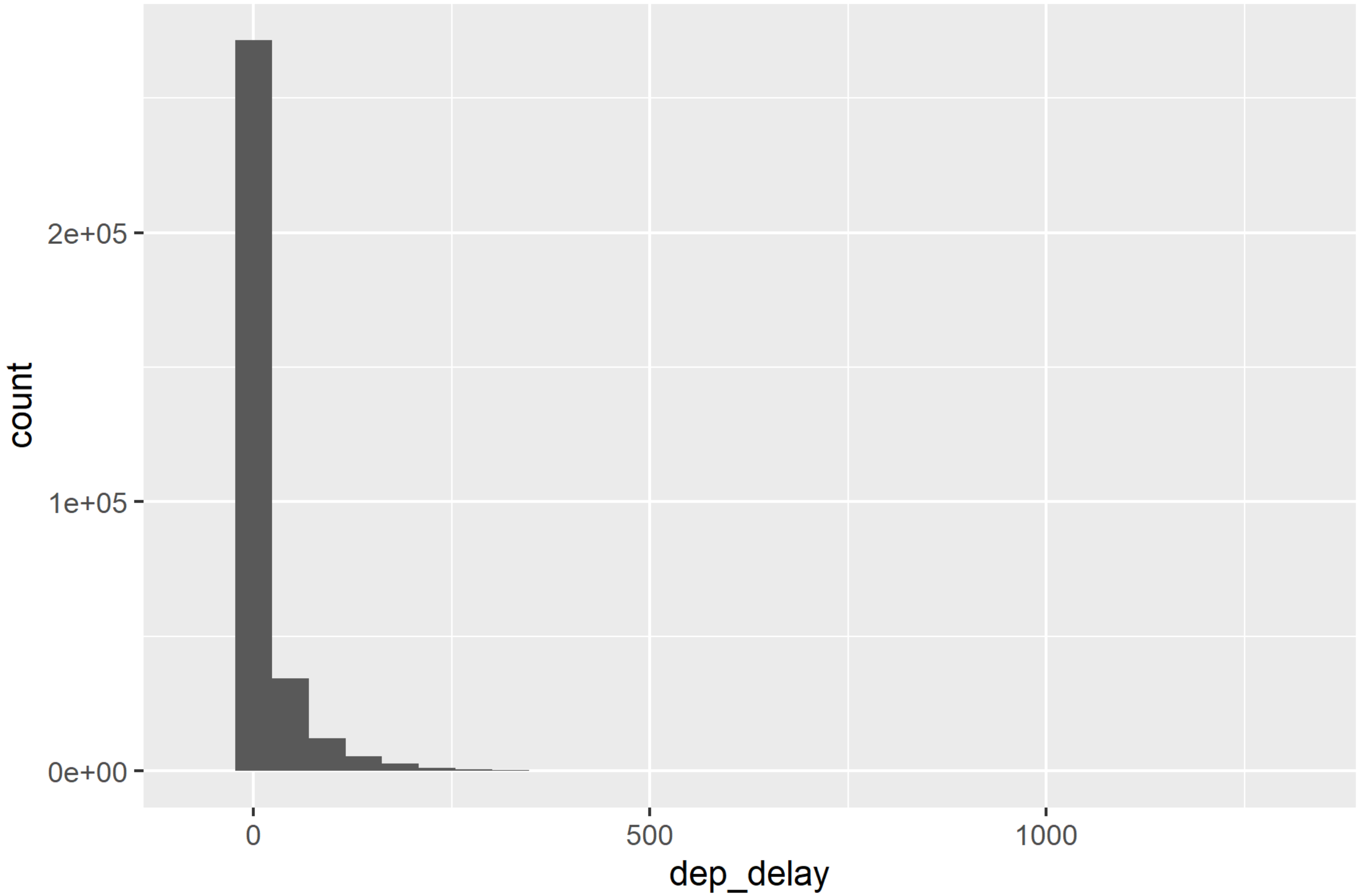
Histogram

- X position: feature of interest
- Y position: count of occurrences **in bins** (statistical transformation)
- Geom: bars/rectangle

- For continuous features, e.g., departure delay in minutes

Histogram

```
ggplot(data = flights) +
  geom_histogram(mapping = aes(x = dep_delay))
```

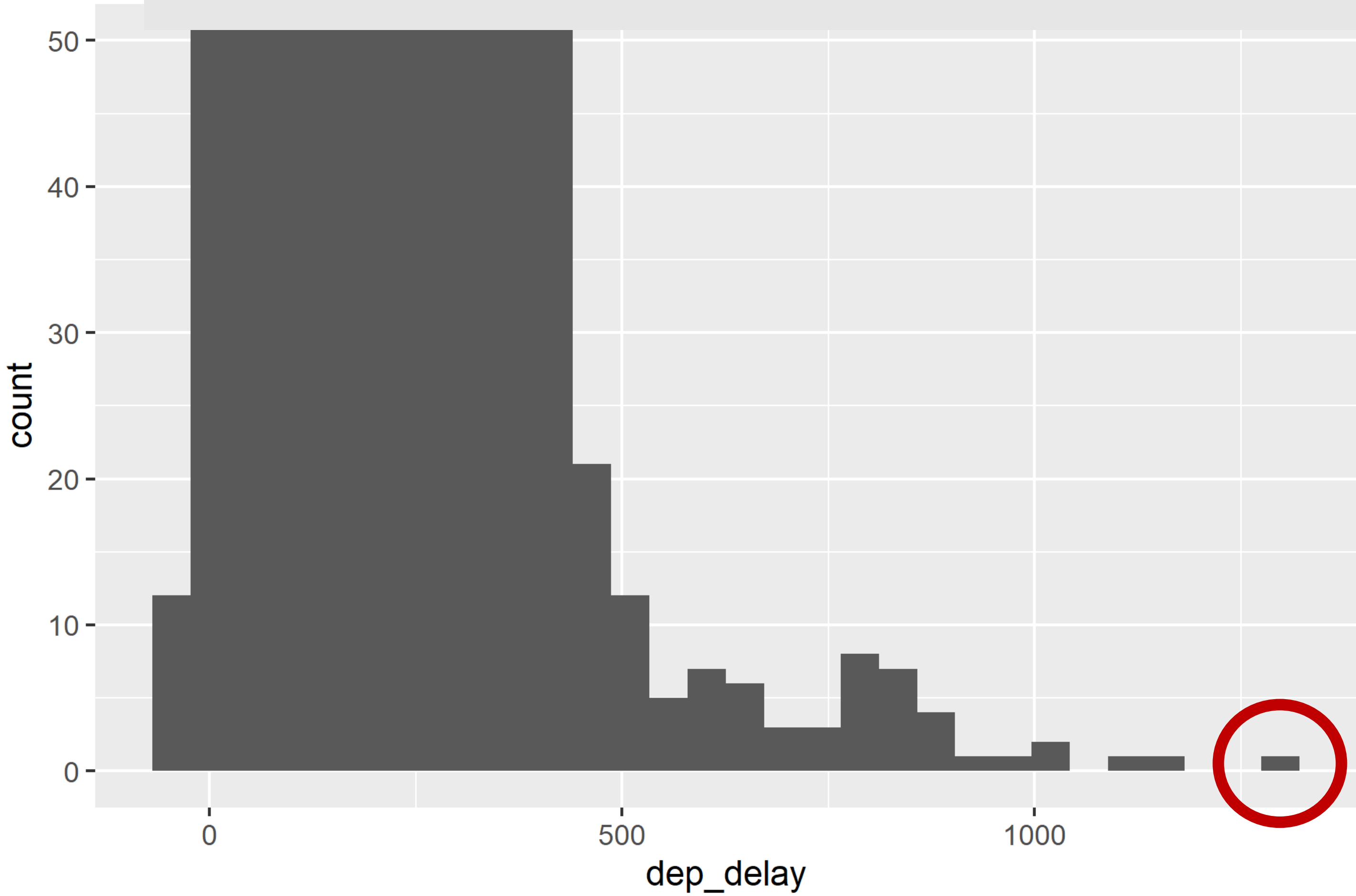


Histogram

- New question: why the strange distribution? What happens at the tail end?

Histogram (zoomed)

```
ggplot(data = flights) +
  geom_histogram(mapping = aes(x = dep_delay)) +
  coord_cartesian(ylim = c(0, 50))
```



That’s a long delay!

Histogram

- Most flights are approximately on time
- There are even some flights that depart early
- There are a few flights with more than 1000 minutes delay

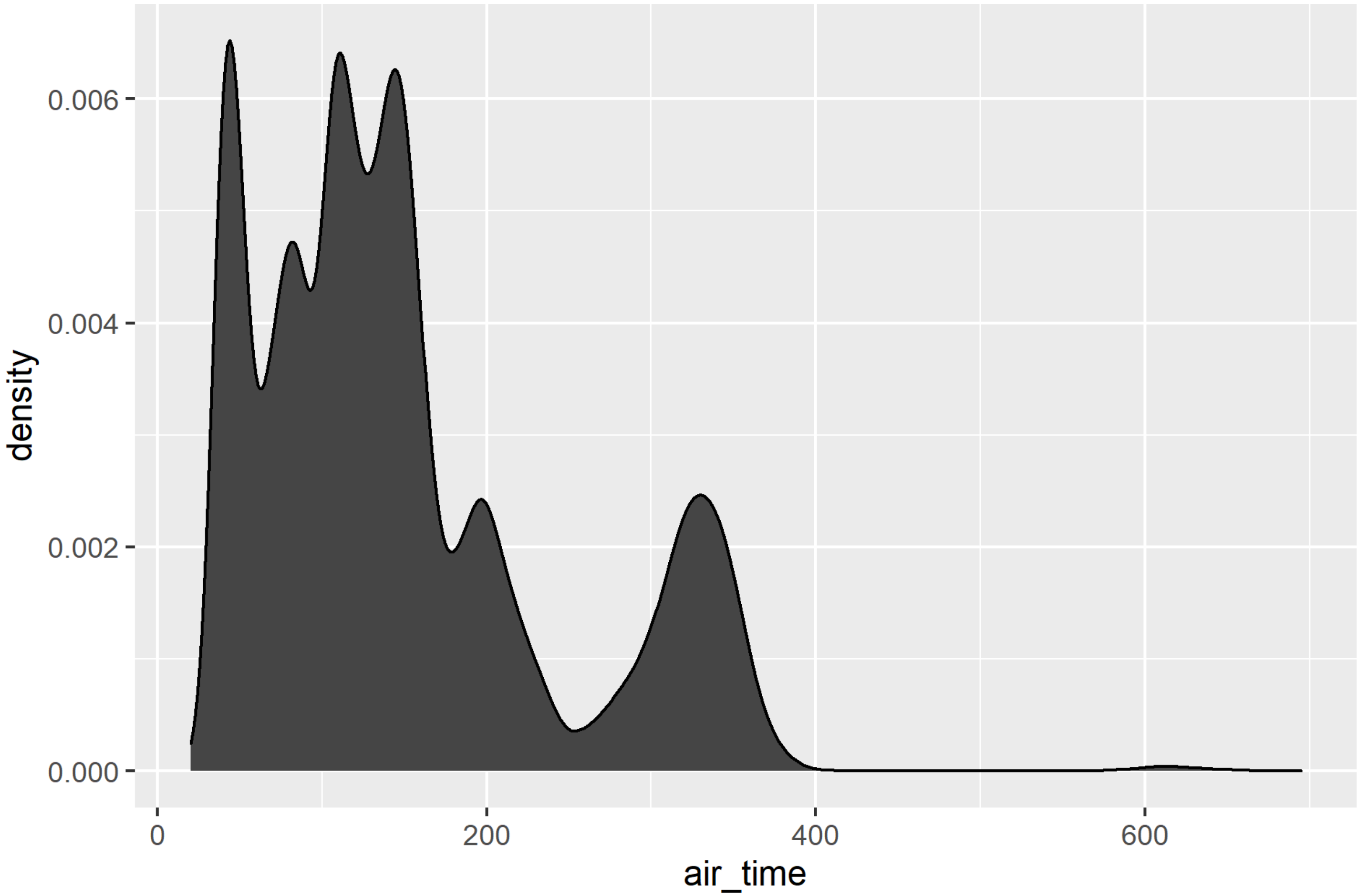
Density

- X position: feature of interest
- Y position: density (statistical transformation, smoothed histogram)
- Geom: polygon / line

- For continuous features, e.g., airtime in minutes

Density

```
ggplot(data = flights) +
  geom_density(mapping = aes(x = air_time))
```



Density

- Most flights from NY are under 200 minutes (3.3 hours)
- Few flights are between 200 and 250 minutes
- Quite some flights are between 250 and 400 minutes
- Some flights are over 600 minutes (weird bump? Remember!)

- Air times are not normally distributed!

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- **Association: What type of covariation occurs in the data?**
  - Which features covary? When A is high, B is high?
  - Multidimensional, multivariate.

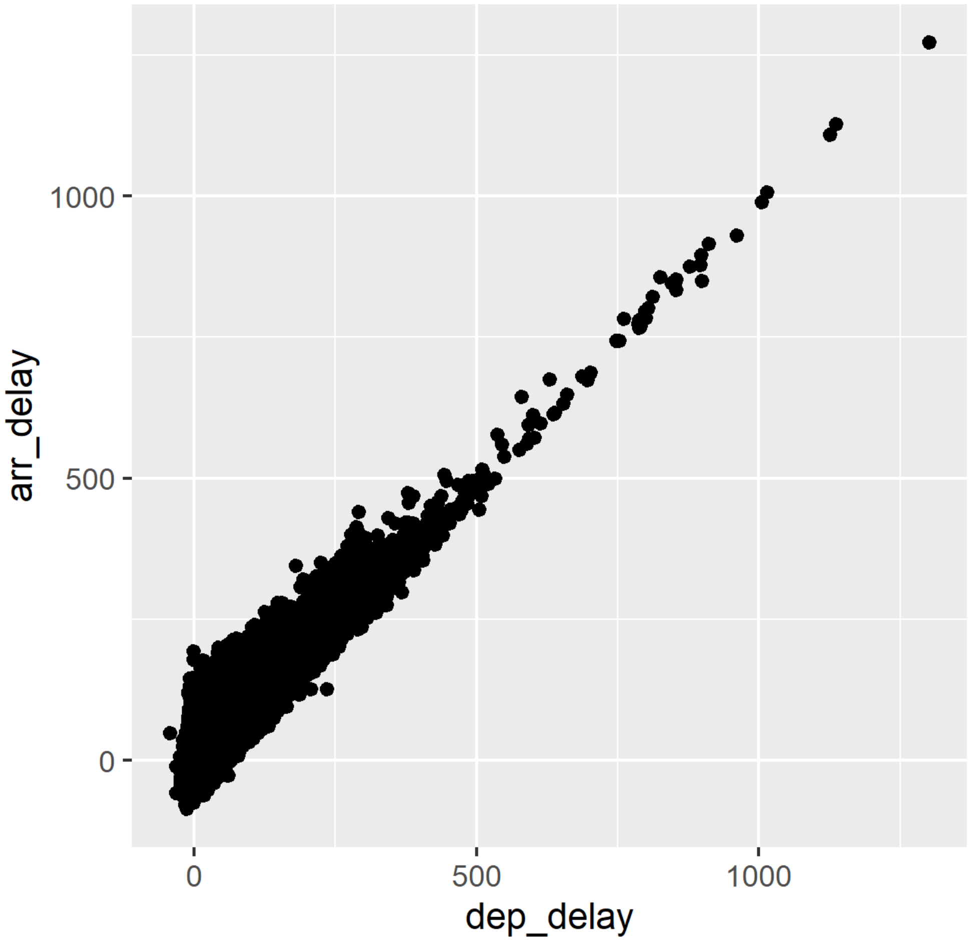
Scatter plot

- X position: feature A of interest (in regression, generally predictor)
- Y position: feature B of interest (in regression, outcome)
- Geom: points/dots

- For continuous features, e.g., departure delay in minutes and arrival delay in minutes

Scatter plot

```
ggplot(data = flights) +
  geom_point(aes(x = dep_delay, y = arr_delay))
```

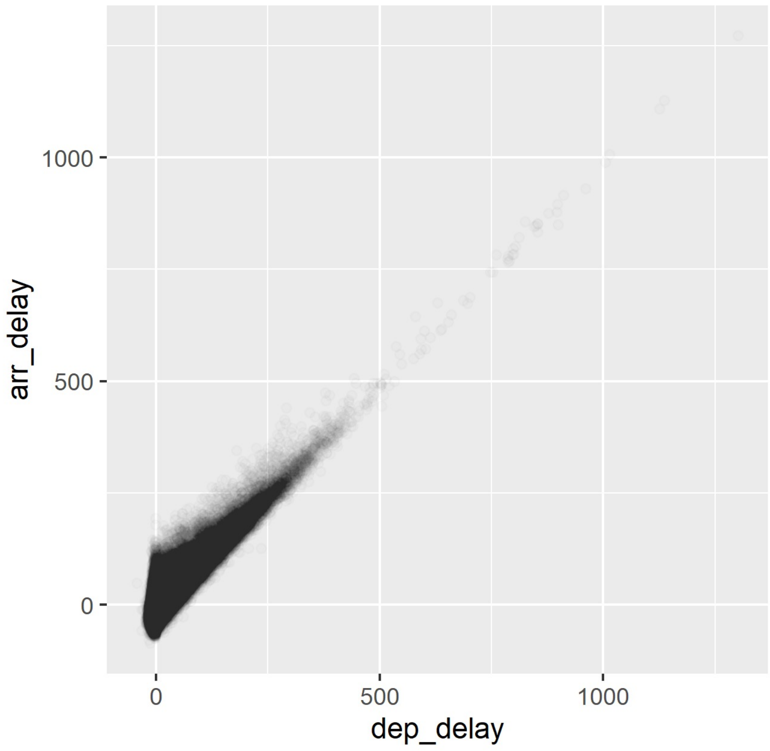


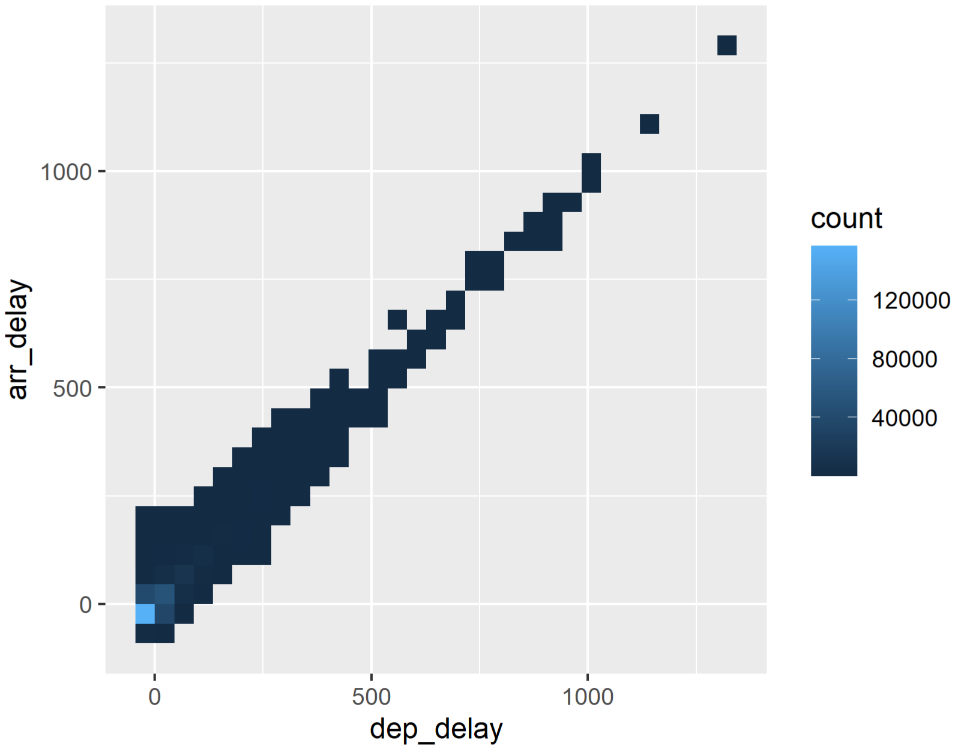
Scatter plot

- Departure and arrival delay correlate strongly
- Arrival delay is generally higher than departure delay
- Only a few delays are above 500 minutes

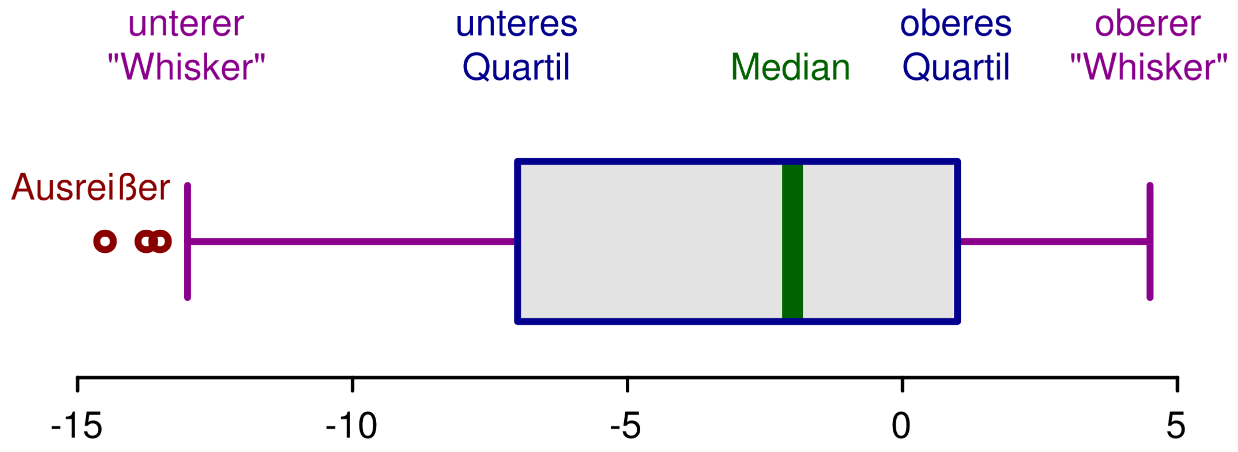
Solutions to overplotting

- Transparency (`alpha`) or binning (`geom_bin2d`)





Box plot (Tukey)



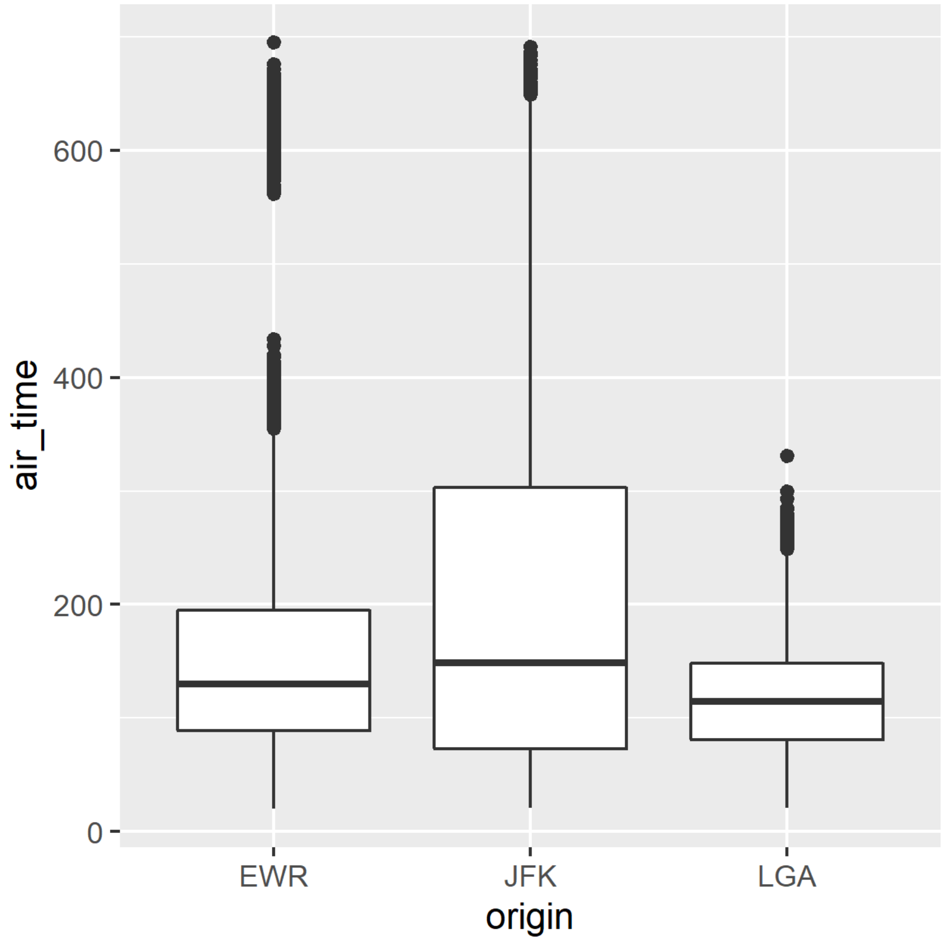
- X position: feature A of interest
- Y position: feature B of interest
- Geom: rectangles for box, lines (whiskers), points for outliers

- Statistical transformations:
- median, 25% and 75% percentile
  (**i**nter **q**uartile **r**ange, IQR),
  1.5×IQR for “whiskers”

- Continuous vs. categorical, e.g., origin and airtime

Box plot

```
ggplot(data = flights) +
  geom_boxplot(aes(x = origin, y = air_time))
```

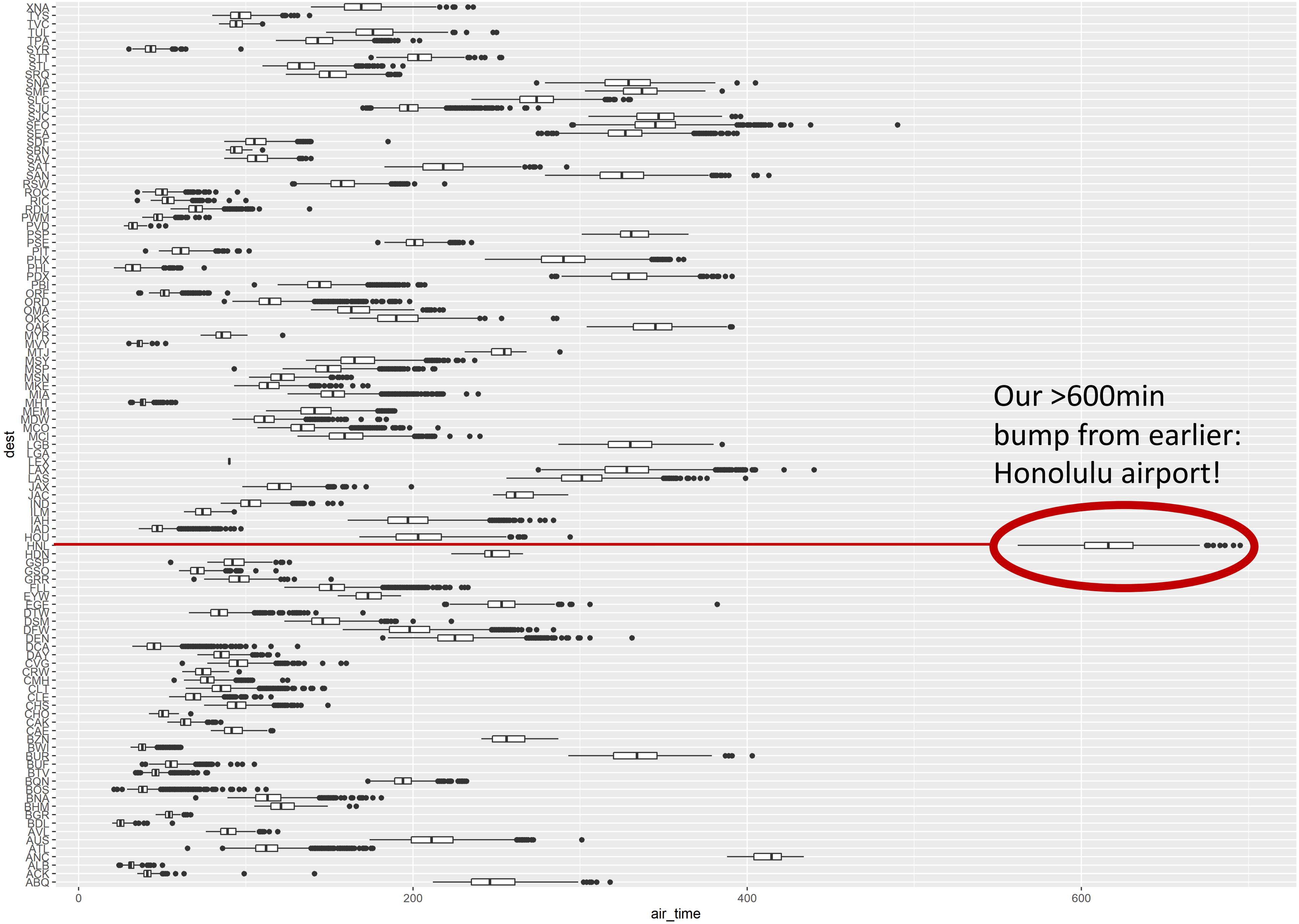


Box plot

- Flights from LGA do not have the >600 minute bump
- Flights from JFK take longest, on average (median)
- Flight times from JFK have largest IQR

- Let’s look at destination rather than origin?

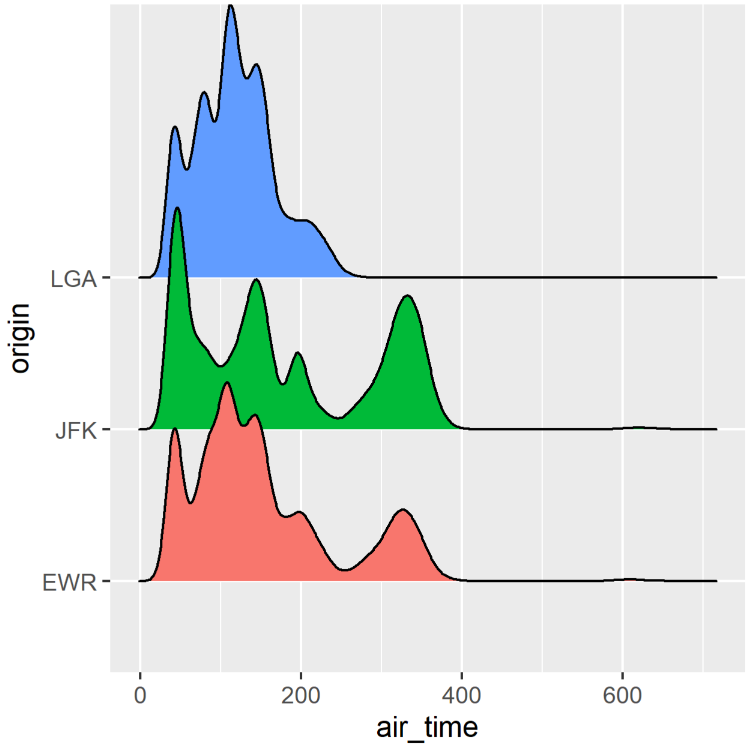
Box plot by destination



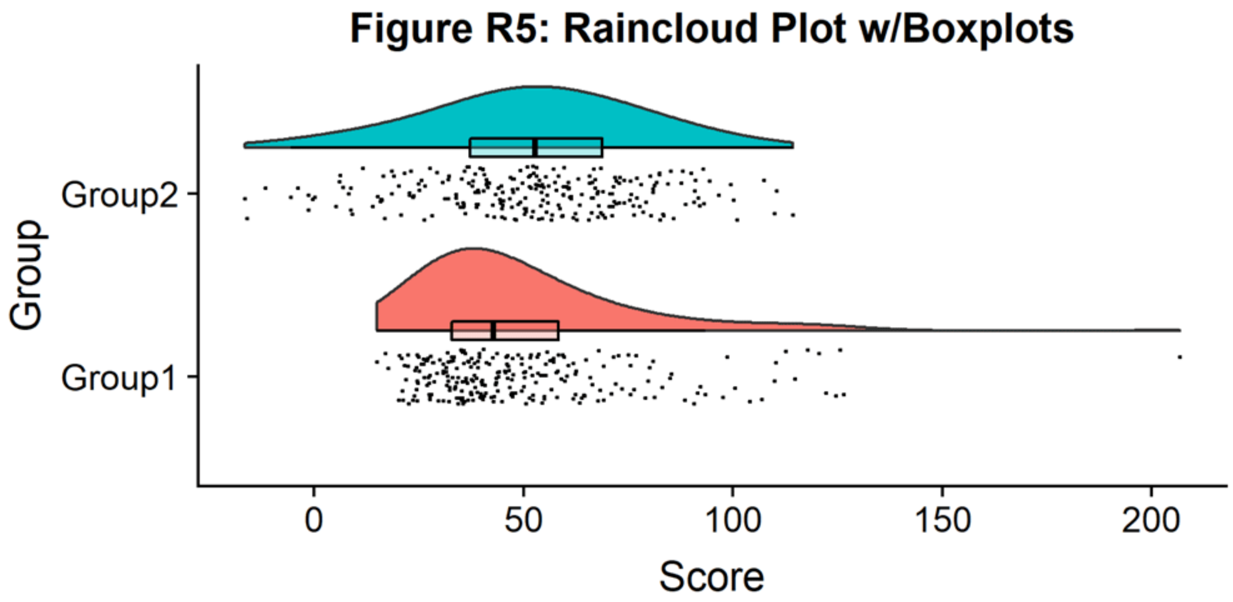
Our >600min bump from earlier: Honolulu airport!

Many options available for categorical vs continuous

ggridges (ridgeline plot)



Raincloud plot

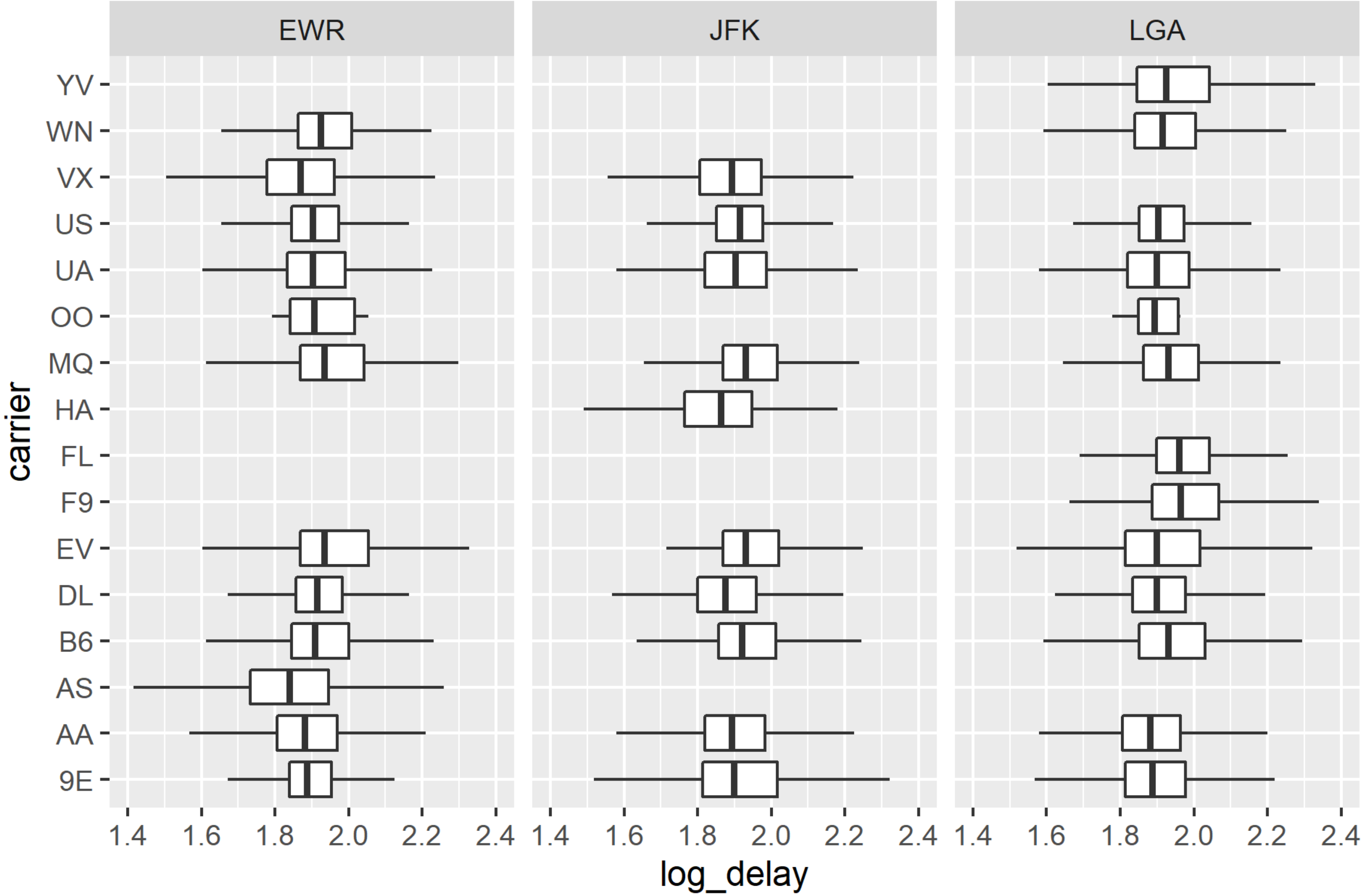


Facets

- Faceting a plot means creating a subplot per category
- Also called “small multiples” (tufte)
- Allows for another categorical variable in the visualisation
- Danger: clutter

```
+ facet_wrap(~feature)
```

Boxplot of (log) delay by carrier, faceted by origin



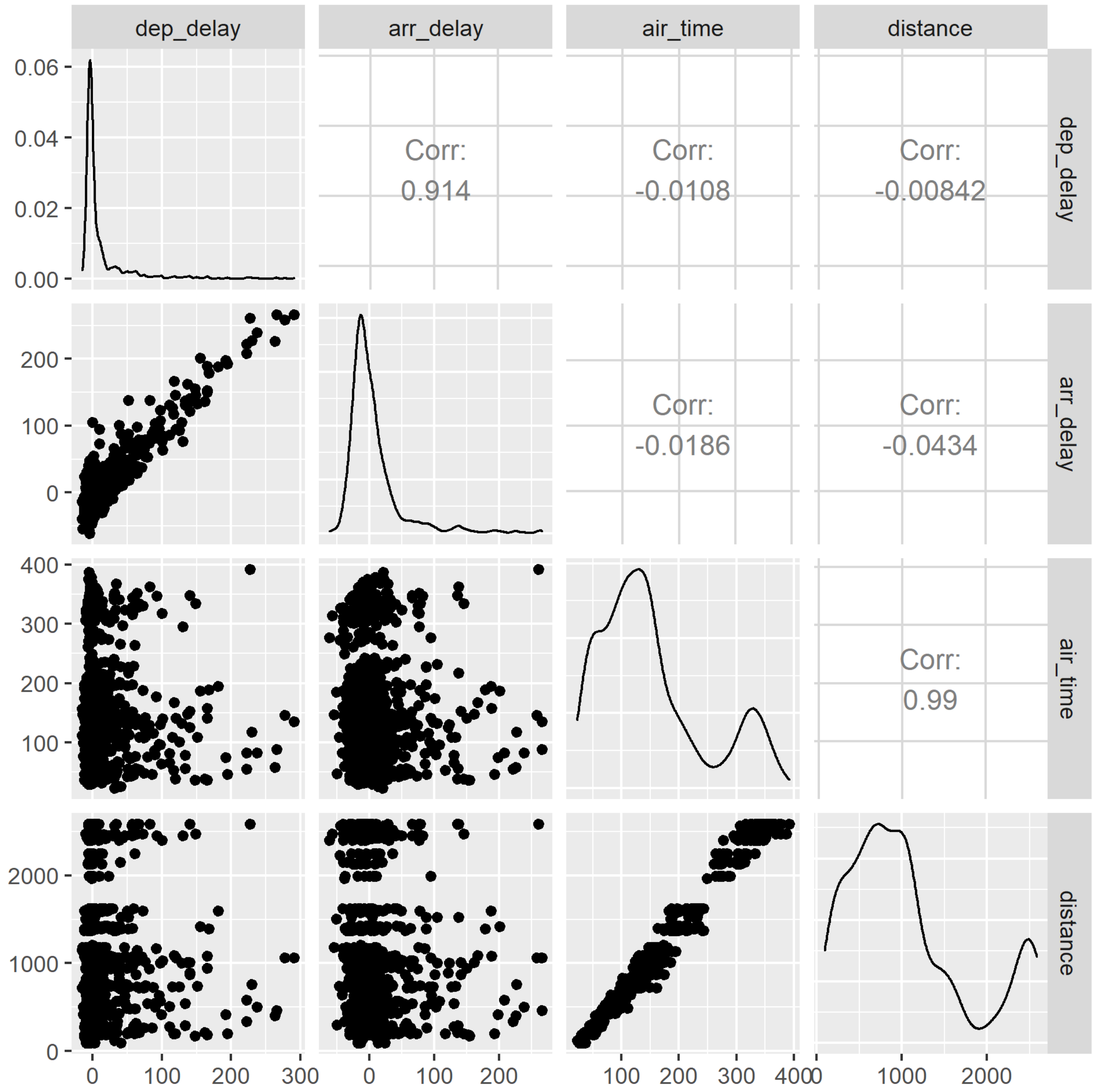
Facets

- Some carriers do not fly from some airports (missing data)
- Delays are quite similar across origin airports and carriers

Pairs plot

- Pairs plot: a scatter plot for each variable
- Multivariate
- Difficult in ggplot: facet by variable (not a feature in the original dataset)
- Data frame needs to be
- Package available: GGally (`ggpairs`)

Pairs plot



dep_delay
arr_delay
air_time
distance
0.06
0.04
0.02
0.00
Corr:
0.914
Corr:
-0.0108
Corr:
-0.00842
Corr:
-0.0186
Corr:
-0.0434
Corr:
0.99
200
100
0
400
300
200
100
2000
1000
0
0
100
200
300
0
100
200
100
200
300
400
0
1000
2000

Pairs plot

- Air time and distance correlate strongly
- Departure and arrival delay correlate strongly
- Air time / distance do not correlate with delay

- In other words: distance cannot predict delays well

Conclusion

- Exploration is key to understanding things you did not know already
- EDA walks a fine line between seeing useful and less useful things (overfitting, if you like)
- Some useful principles are:
  - Peng's checklist
  - Understanding what you're seeing
  - Finding interesting comparisons
  - "Straightening and flattening" (using models and residuals)
  - Standard graphs to look at variation and association