ETC5521: Diving Deeply into Data Exploration

Exploring data having a space and time context Part I

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Outline

- What is temporal data?
- What is exploratory temporal data analysis?
- Using temporal objects in R: `tsibble`
- Data wrangling: aggregation, creating temporal components, missing values
- Plotting conventions: connect the dots; aspect ratio, landscape or portrait
- Calendar plots: arranging daily records into a calendar format
- Visual inference for temporal data
- tignostics: cognostics for temporal data
- Interactive graphics for temporal data
- Exploring longitudinal data, with the `brolgar` package

Philosophy

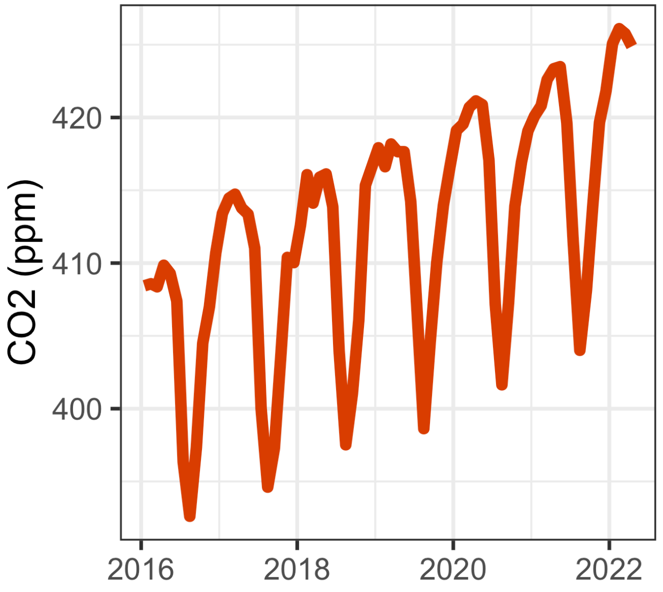
> Time series analysis is what you do after all the interesting stuff has been done!

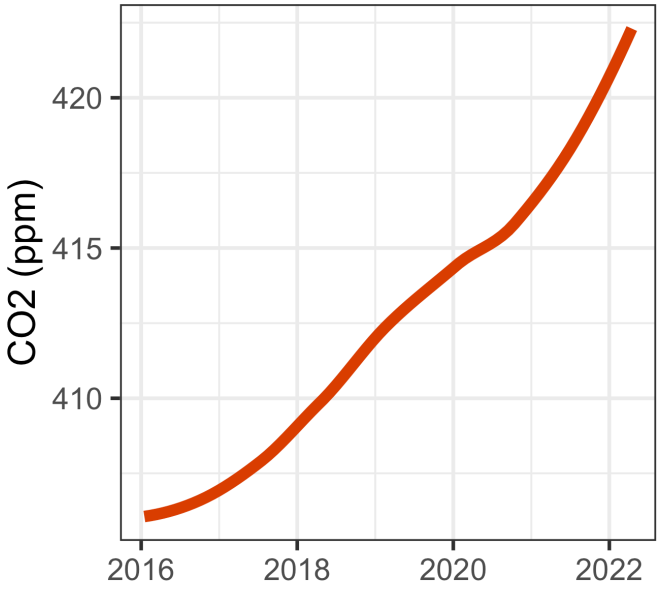
Heike Hofmann, 2005

Time series analysis focuses on modeling the temporal dependence. Data needs to have trend, seasonality, anomalies removed first.

> Exploratory temporal analysis involves exploring and discovering temporal trend, patterns related to seasons, and anomalies. And possibly also unusual temporal dependence.

What is temporal data?





- Temporal data has date/time/ordering index variable, call it time.
- A time variable has special structure:
  - it can have *cyclical* patterns, eg seasonality (summer, winter), an over in cricket
  - the cyclical patterns can be *nested*, eg postcode within state, over within innings
- Measurements are also NOT independent - yesterday may influence today.
- It still likely has non-cyclical patterns, trends and associations with other variables, eg temperature increasing over time, over is bowled by Elise Perry or Sophie Molineaux

`tsibble`: R temporal object

The `tsibble` package provides a data infrastructure for tidy temporal data with wrangling tools. Adapting the tidy data principles, `tsibble` is a data- and model-oriented object. In `tsibble`:

- Index is a variable with inherent ordering from past to present.
- Key is a set of variables that define observational units over time.
- Each observation should be uniquely identified by index and key.
- Each observational unit should be measured at a common interval, if regularly spaced.

Regular vs irregular

The Melbourne pedestrian sensor data has a regular period. Counts are provided for every hour, at numerous locations.

```
options(width=55)
pedestrian
```

```
# A tsibble: 66,037 x 5 [1h] <Australia/Melbourne>
# Key:       Sensor [4]
   Sensor     Date_Time           Date        Time Count
   <chr>      <dttm>              <date>     <int> <int>
 1 Birrarun… 2015-01-01 00:00:00 2015-01-01     0  1630
 2 Birrarun… 2015-01-01 01:00:00 2015-01-01     1   826
 3 Birrarun… 2015-01-01 02:00:00 2015-01-01     2   567
 4 Birrarun… 2015-01-01 03:00:00 2015-01-01     3   264
 5 Birrarun… 2015-01-01 04:00:00 2015-01-01     4   139
 6 Birrarun… 2015-01-01 05:00:00 2015-01-01     5    77
 7 Birrarun… 2015-01-01 06:00:00 2015-01-01     6    44
 8 Birrarun… 2015-01-01 07:00:00 2015-01-01     7    56
 9 Birrarun… 2015-01-01 08:00:00 2015-01-01     8   113
10 Birrarun… 2015-01-01 09:00:00 2015-01-01     9   166
# ℹ 66,027 more rows
```

In contrast, the US flights data, below, is irregular.

```
options(width=55)
library(nycflights13)
flights_ts <- flights |>
  mutate(dt = ymd_hm(paste(paste(year, month,
                             paste(hour, minute,
  as_tsibble(index = dt, key = c(origin, dest,
flights_ts
```

```
# A tsibble: 336,776 x 20 [!] <UTC>
# Key:       origin, dest, carrier, tailnum [52,807]
    year month   day dep_time sched_dep_time dep_delay
   <int> <int> <int>    <int>          <int>     <dbl>
 1  2013     1    30     2224           2000       144
 2  2013     2    17     2012           2010         2
 3  2013     2    26     2356           2000       236
 4  2013     3    13     1958           2005        -7
 5  2013     5    16     2214           2000       134
 6  2013     5    30     2045           2000        45
 7  2013     9    11     2254           2159        55
 8  2013     9    12       NA           2159        NA
 9  2013     9     8     2156           2159        -3
10  2013     1    26     1614           1620        -6
# ℹ 336,766 more rows
```

Is pedestrian traffic really regular?

Getting started

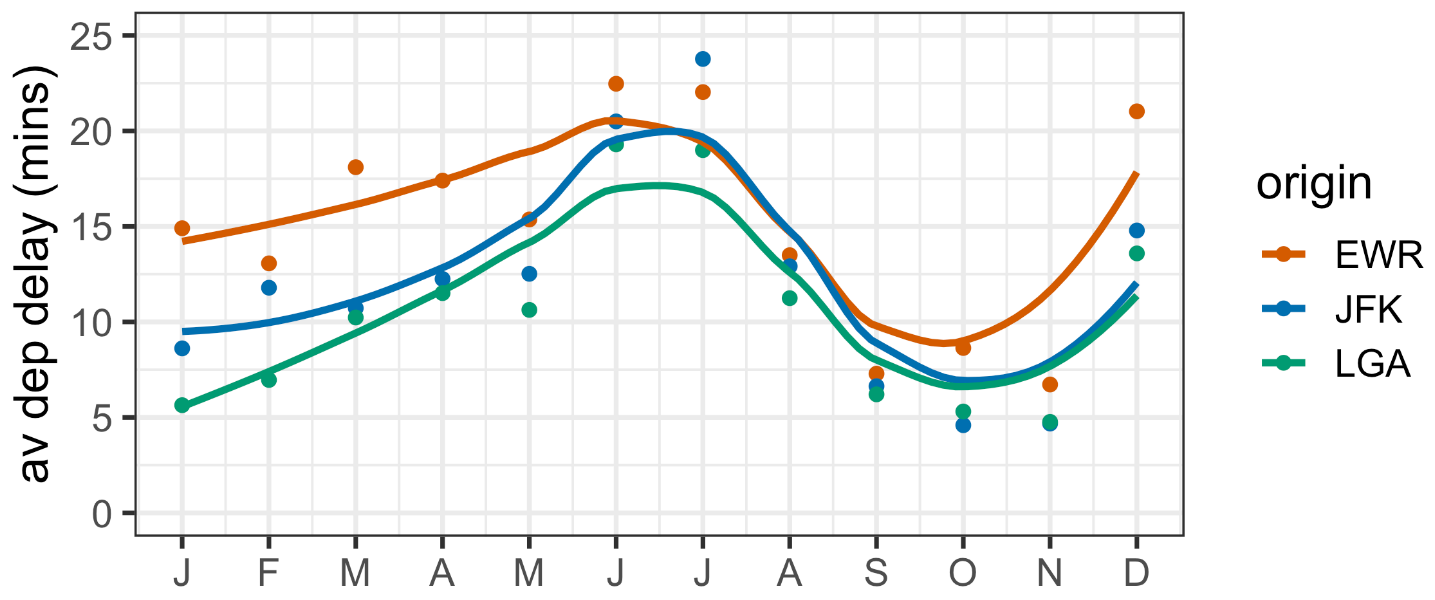
> Wrangling prior to analysing temporal data includes:
>
> - **aggregate** by temporal unit.
> - **construct temporal units** to study seasonality, such as month, week, day of the week, quarter, …
> - checking and imputing **missings**.

For the airlines data, you can aggregate by multiple quantities, eg number of arrivals, departures, average hourly arrival delay and departure delays.

Aggregating

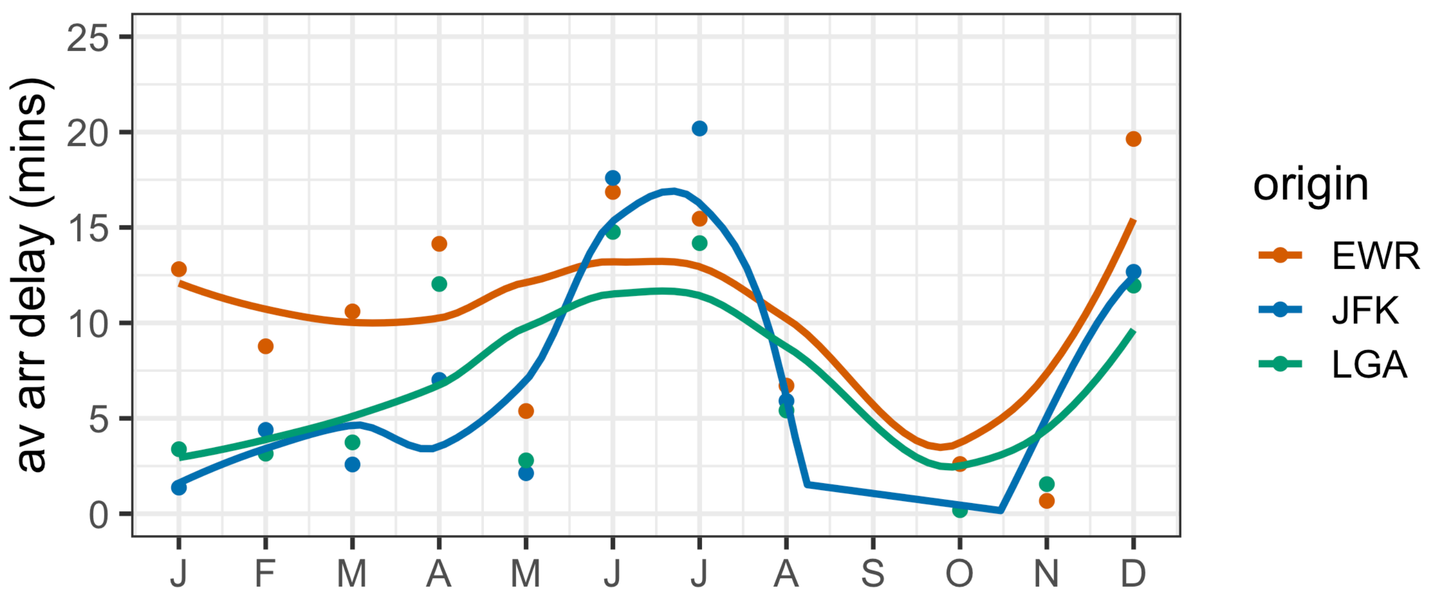
The US flights data already has some temporal components created, so aggregating by these is easy. Here is departure delay.

▶ Code



Aggregate by month, but examine arrival delays.

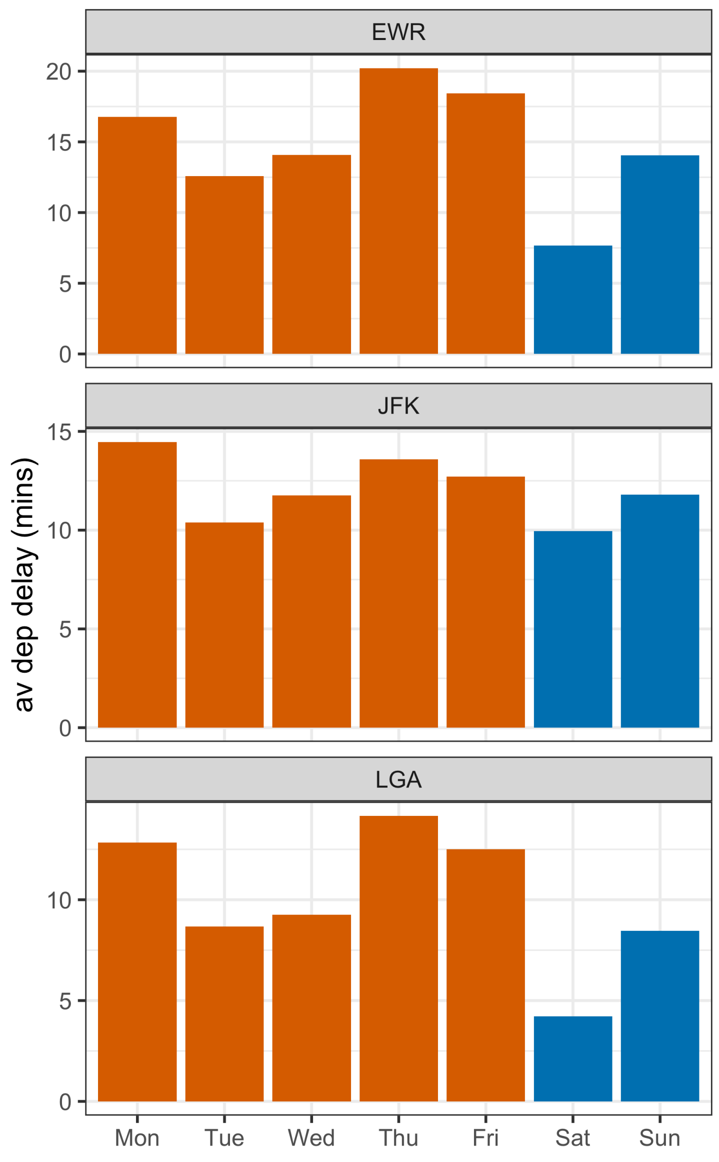
▶ Code



Constructing temporal units

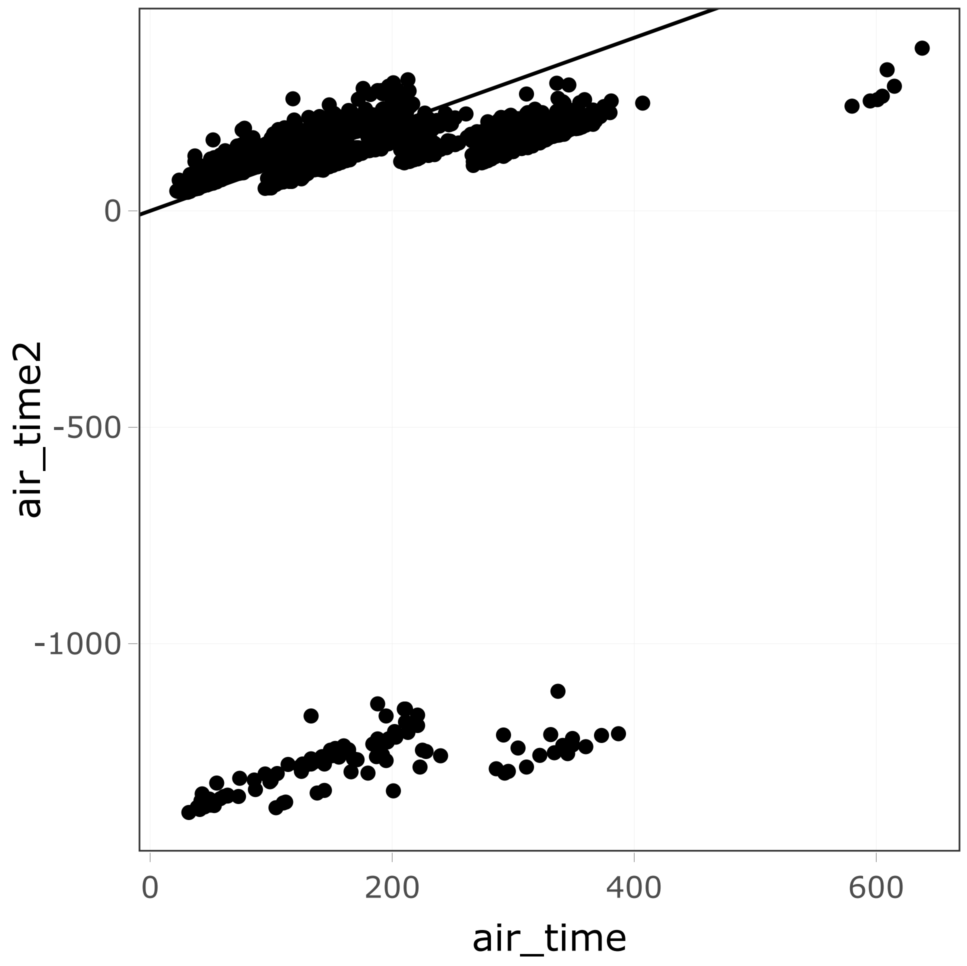
Week day vs weekend would be expected to have different patterns of delay, but this is not provided.

▶ Code



Be careful of times!

▶ Code



Why is this not what we expect?

Checking and filling missings (1/4)

```r
set.seed(328)
harvest <- tsibble(
  year = c(2010, 2011, 2013, 2011,
           2012, 2013),
  fruit = rep(c("kiwi", "cherry"),
              each = 3),
  kilo = sample(1:10, size = 6),
  key = fruit, index = year
)
harvest
```

```
# A tsibble: 6 x 3 [1Y]
# Key:       fruit [2]
   year fruit   kilo
  <dbl> <chr>  <int>
1  2011 cherry     2
2  2012 cherry     7
3  2013 cherry     1
4  2010 kiwi       6
5  2011 kiwi       5
6  2013 kiwi       8
```

```r
has_gaps(harvest, .full = TRUE)
```

```
# A tibble: 2 × 2
  fruit  .gaps
  <chr>  <lgl>
1 cherry TRUE
2 kiwi   TRUE
```

Can you see the gaps in time?

Both levels of the key have missings.

Checking and filling missings (2/4)

```
# A tsibble: 6 x 3 [1Y]
# Key:       fruit [2]
   year fruit   kilo
  <dbl> <chr>  <int>
1  2011 cherry     2
2  2012 cherry     7
3  2013 cherry     1
4  2010 kiwi       6
5  2011 kiwi       5
6  2013 kiwi       8
```

```r
count_gaps(harvest,  .full=TRUE)
```

```
# A tibble: 2 × 4
  fruit  .from   .to    .n
  <chr>  <dbl> <dbl> <int>
1 cherry  2010  2010     1
2 kiwi    2012  2012     1
```

One missing in each level, although it is a different year.

Notice how `tsibble` handles this summary so neatly.

Checking and filling missings (3/4)

```
# A tsibble: 6 x 3 [1Y]
# Key:       fruit [2]
   year fruit   kilo
  <dbl> <chr>  <int>
1  2011 cherry     2
2  2012 cherry     7
3  2013 cherry     1
4  2010 kiwi       6
5  2011 kiwi       5
6  2013 kiwi       8
```

Make the implicit missing values explicit.

```r
harvest <- fill_gaps(harvest,
                     .full=TRUE)
harvest
```

```
# A tsibble: 8 x 3 [1Y]
# Key:       fruit [2]
   year fruit   kilo
  <dbl> <chr>  <int>
1  2010 cherry    NA
2  2011 cherry     2
3  2012 cherry     7
4  2013 cherry     1
5  2010 kiwi       6
6  2011 kiwi       5
7  2012 kiwi      NA
8  2013 kiwi       8
```

Checking and filling missings (4/4)

```
# A tsibble: 6 x 3 [1Y]
# Key:       fruit [2]
   year fruit   kilo
  <dbl> <chr>  <int>
1  2011 cherry     2
2  2012 cherry     7
3  2013 cherry     1
4  2010 kiwi       6
5  2011 kiwi       5
6  2013 kiwi       8
```

We have already seen `na_ma()` function, that imputes using a moving average. Alternatively, `na_interpolation()` uses the previous and next values to impute.

```
harvest_nomiss <- harvest |>
  group_by(fruit) |>
  mutate(kilo =
    na_interpolation(kilo)) |>
  ungroup()
harvest_nomiss
```

```
# A tsibble: 6 x 3 [1Y]
# Key:       fruit [2]
   year fruit   kilo
  <dbl> <chr>  <int>
1  2011 cherry     2
2  2012 cherry     7
3  2013 cherry     1
4  2010 kiwi       6
5  2011 kiwi       5
6  2013 kiwi       8
```

Plotting conventions

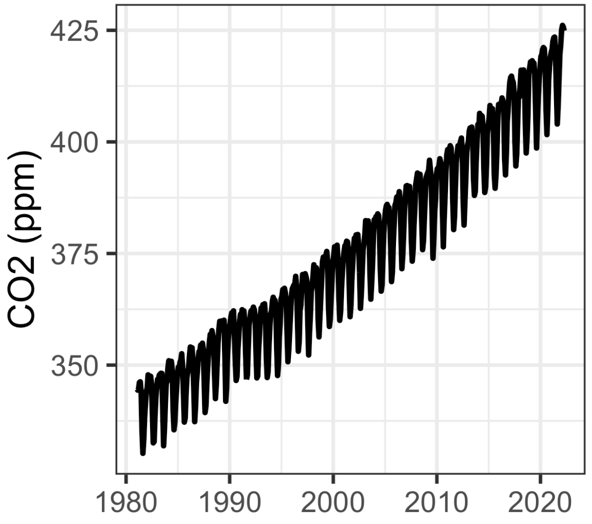
Conventions

- **lines**: connecting sequential time points reminding the reader that the temporal dependence is important.
- **aspect ratio**: wide or tall? Cleveland, McGill, McGill (1988) argue the average line slope in a line chart should be 45 degrees, which is called banking to 45 degrees. But this is refuted in Talbot, Gerth, Hanrahan (2012) that the conclusion was based on a flawed study. Nevertheless, aspect ratio is an inescapable skill for designing effective plots. For time series, typically a wide aspect ratio is good.
- **conventions**:
  - time on the horizontal axis,
  - ordering of elements like week day, month. Most software organises by alphabetical order, so this needs to be controlled.

Aspect ratio

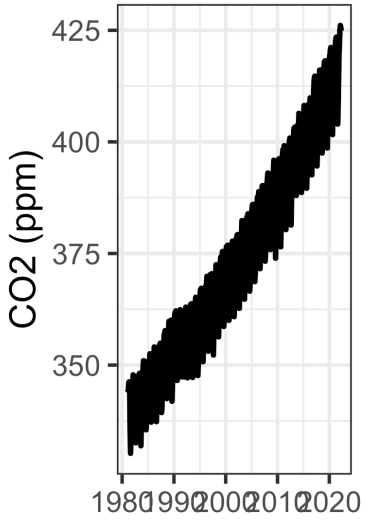
learn R

1 to 1 (may be useless)

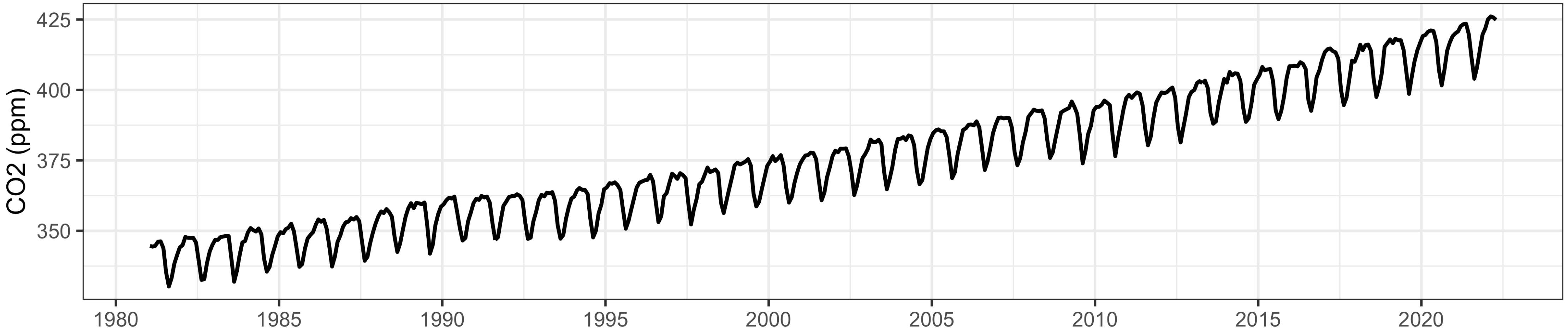


CO2 at
Point Barrow,
Alaska

tall & skinny: trend



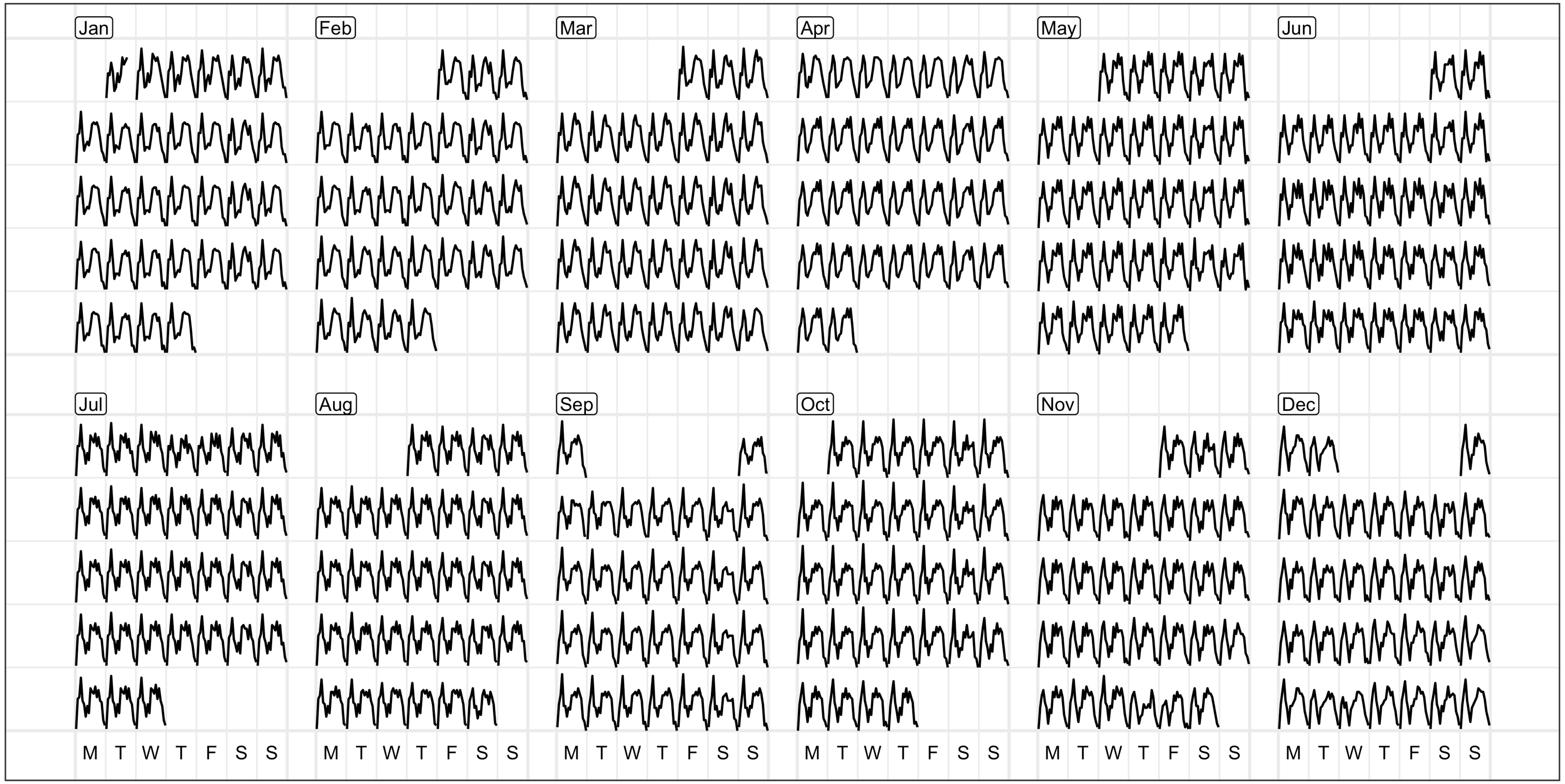
short & wide: seasonality



Calendar plot

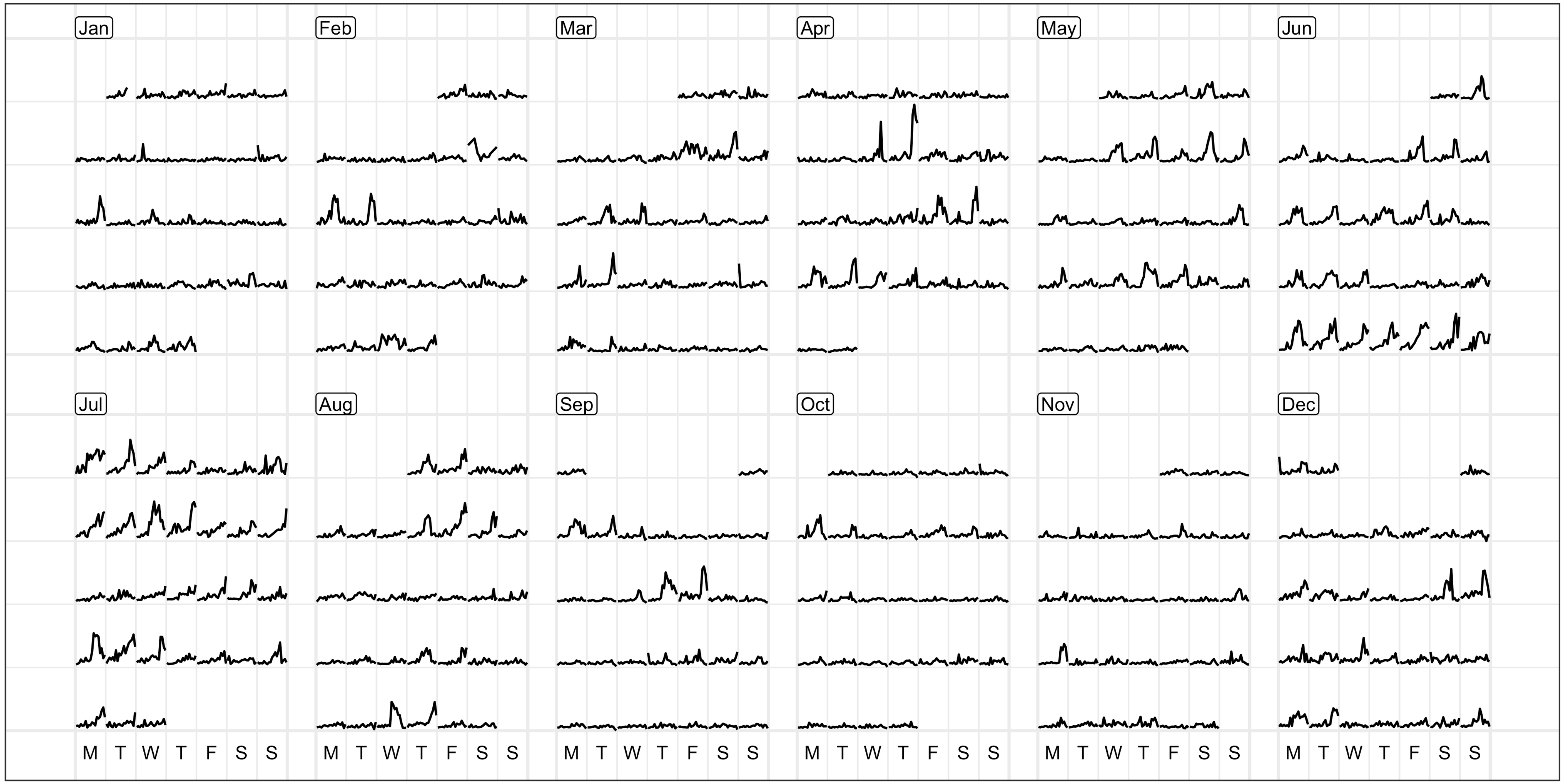
Case study: NYC flights (1/2)

About calendars | What do we see? | R



Case study: NYC flights (2/2)

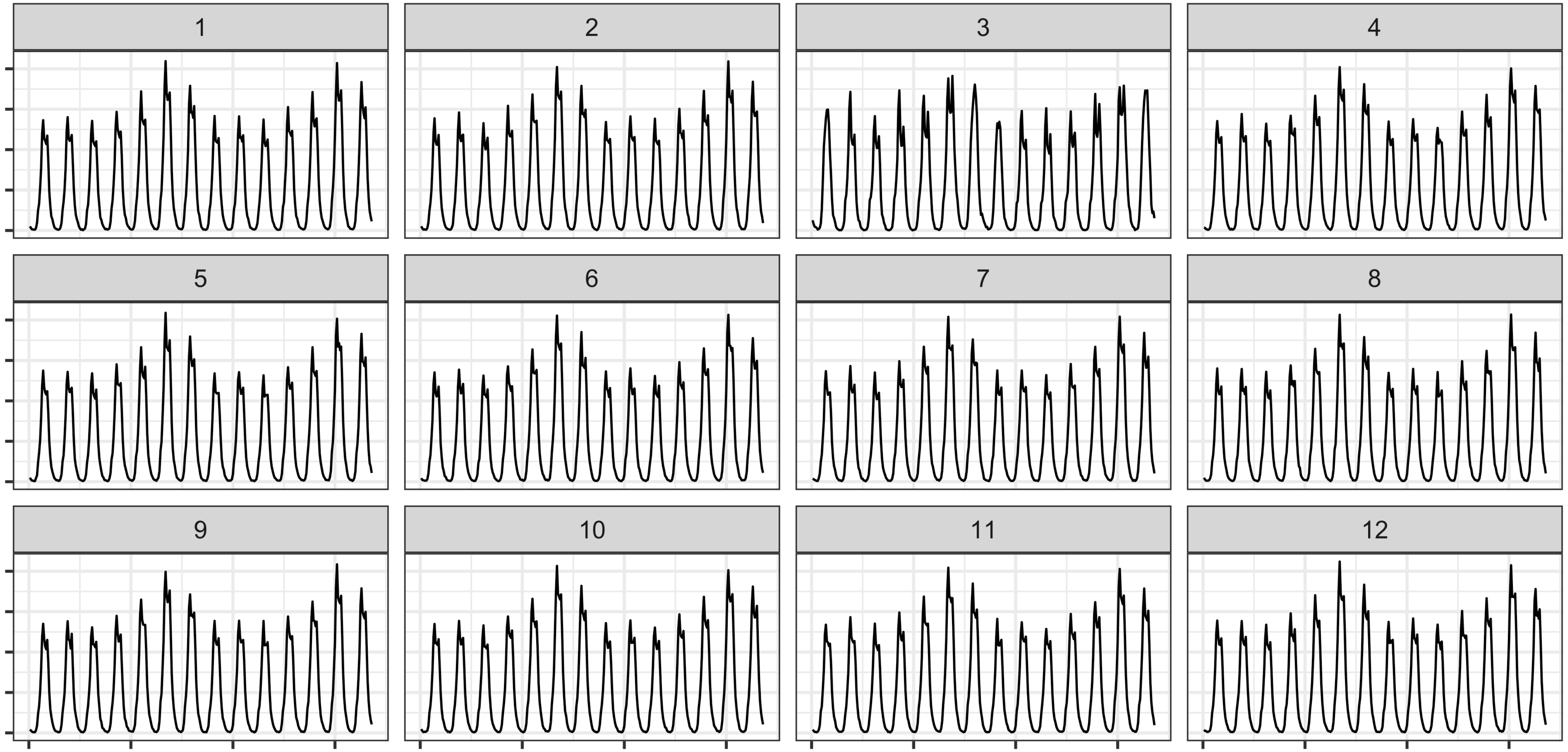
What do we see? R



Visual inference

Temporal patterns: simulation

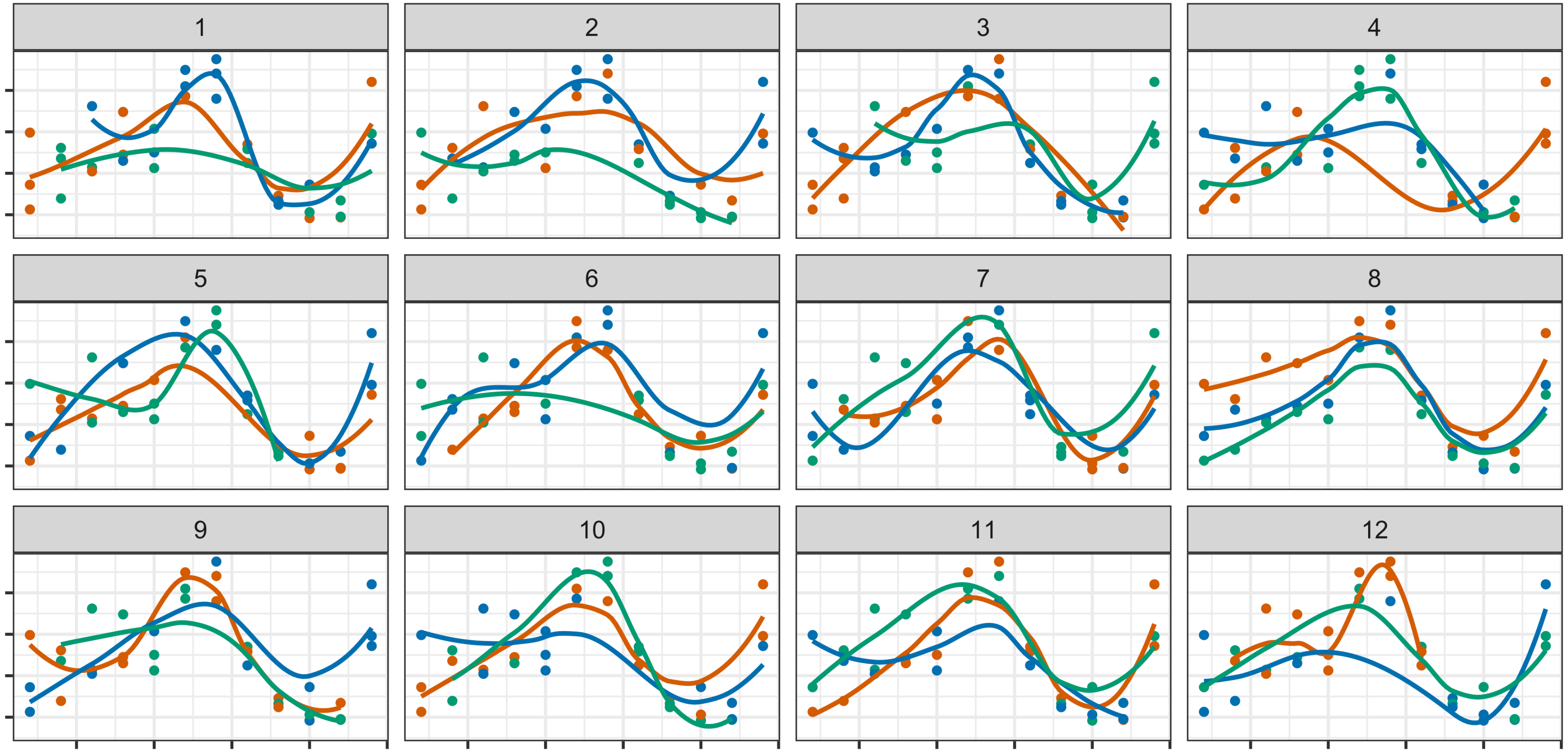
▶ Code



1. Decide on a model
2. Simulate from the model to generate nulls

Association: permutation

▶ Code



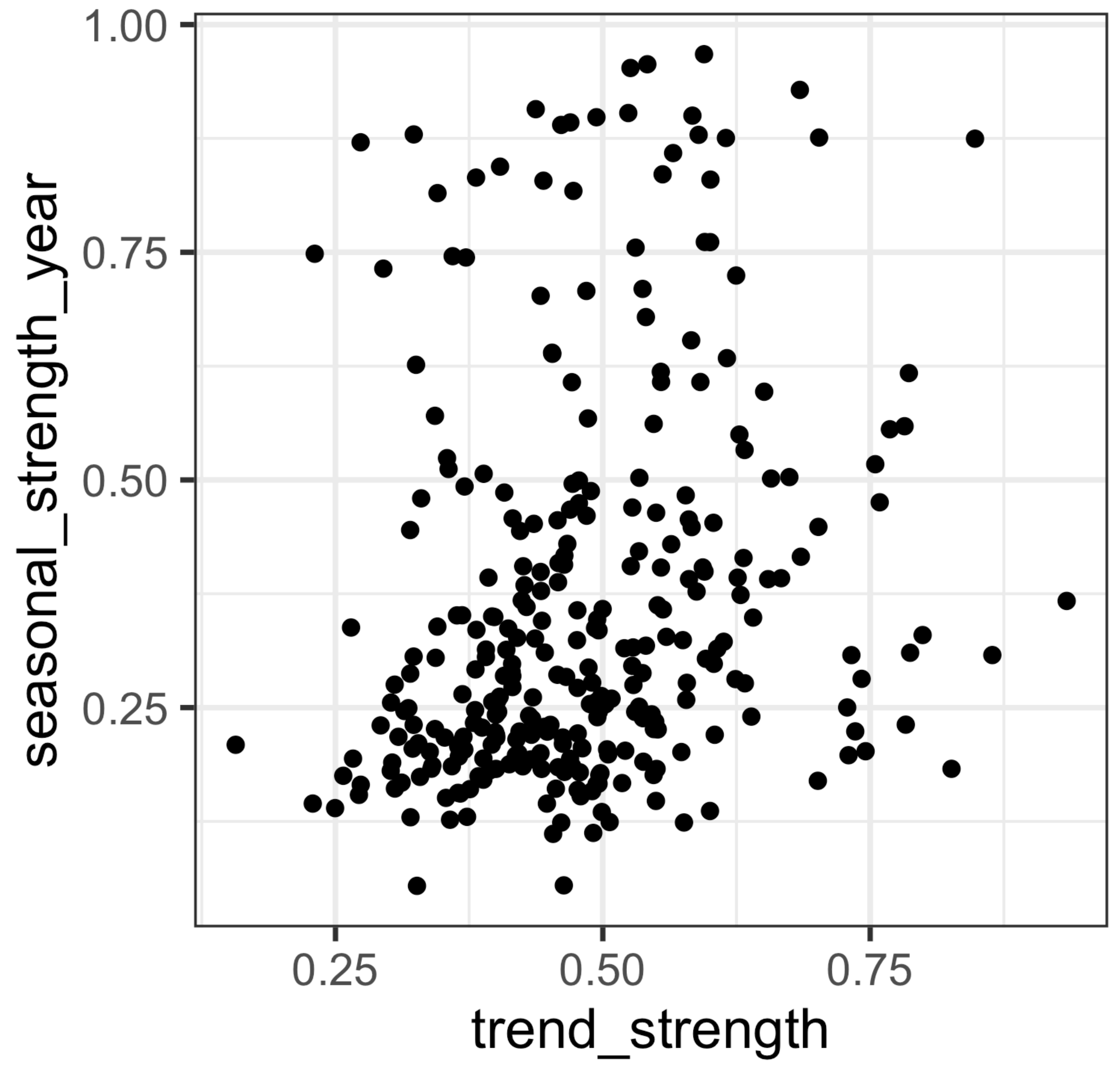
Break association between variables. Here `origin` is permuted which breaks association with `dep_delay`, while keeping `month` fixed.

Which plot has the biggest difference between the three groups?

Tignostics

`feasts`: time series features

▶ Code



The `feasts` package provides functions to calculate tignostics for time series.

Remember scagnostics?

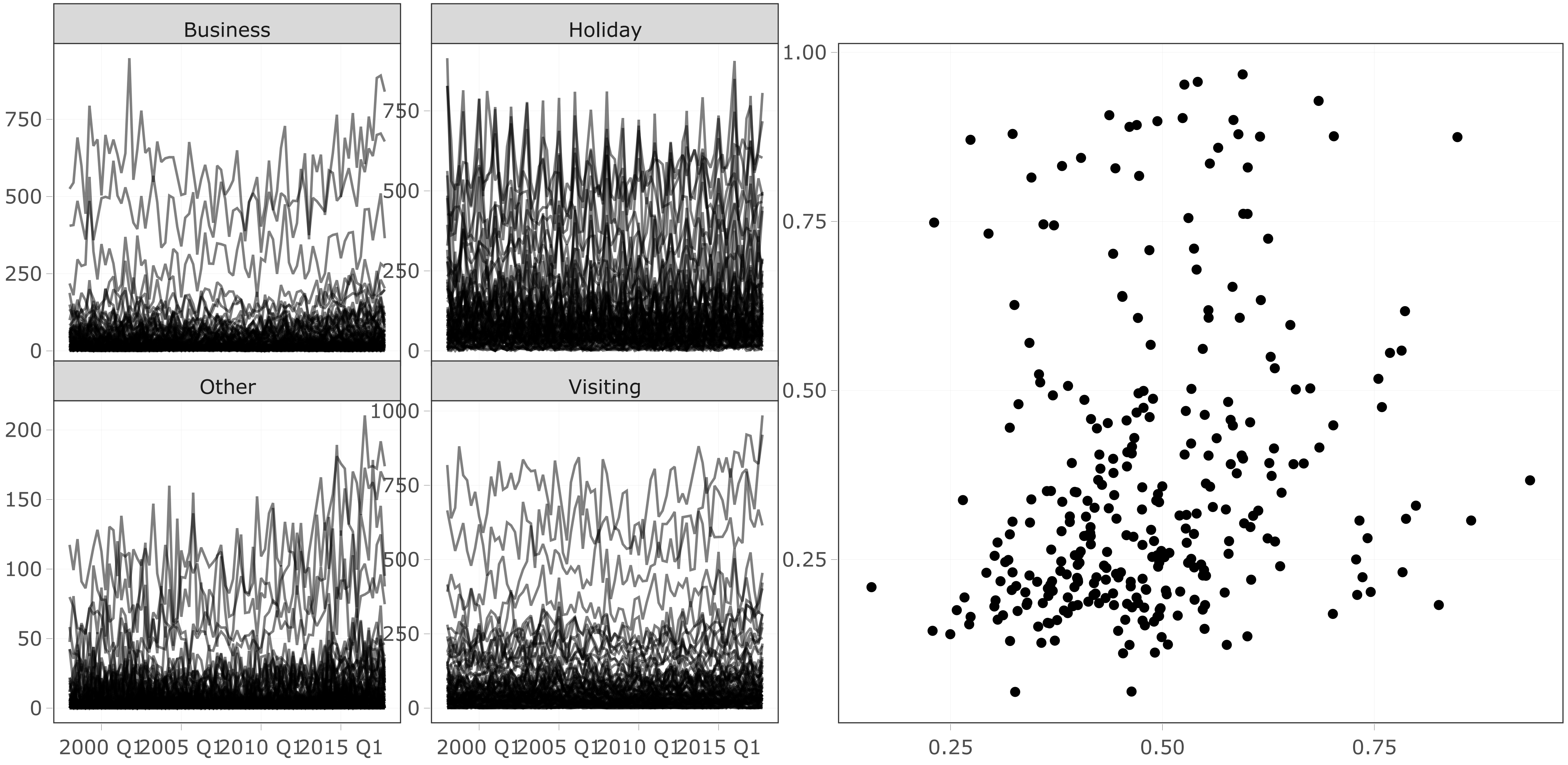
Compute tignostics for each series, for example,

- trend
- seasonality
- linearity
- spikiness
- peak
- trough

Interactivity

Interactive exploration with `tsibbletalk`

- Code



Wrapping series

Pedestrian counts at Bourke St Mall, has a daily seasonality.

DEMO

```
pp <- p_bourke |>
        as_tsibble(index = time) |>
        ggplot(aes(x=time, y=count)) +
          geom_line() +
          theme(aspect.ratio=0.5)


ui <- fluidPage(tsibbleWrapUI("tswrap"))
server <- function(input, output, session) {
  tsibbleWrapServer("tswrap", pp, period = "1
}

shinyApp(ui, server)
```

Famous data: Lynx

Annual numbers of lynx trappings for 1821–1934 in Canada. Almost 10 year cycle.

Explore periodicity by wrapping series on itself.

DEMO

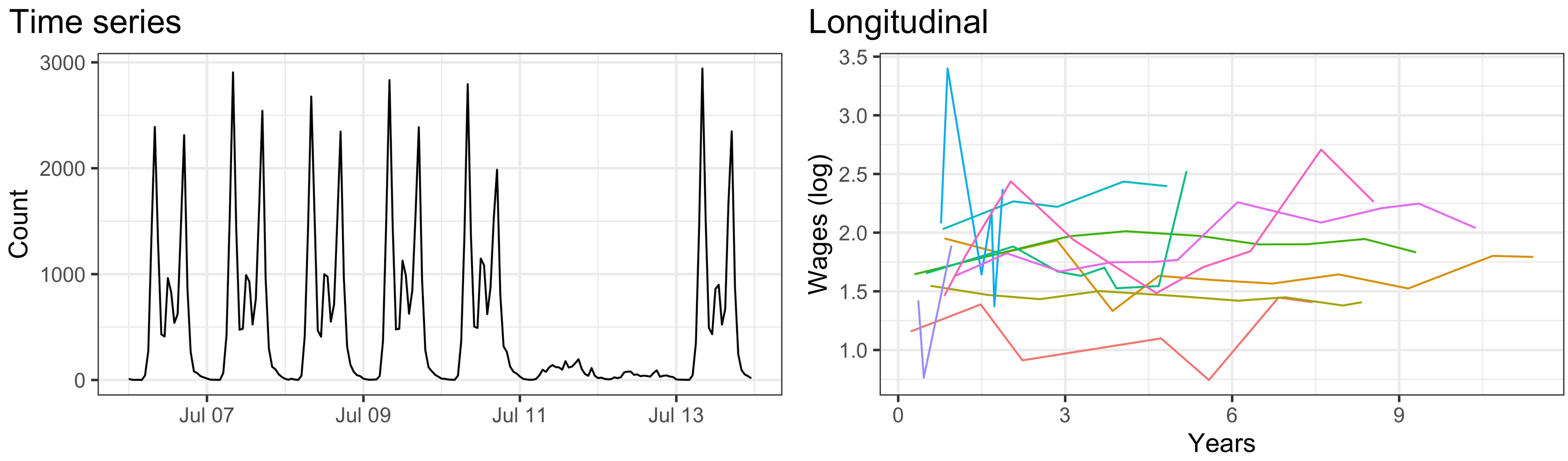
```
lynx_tsb <- as_tsibble(lynx) |>
  rename(count = value)
pl <- ggplot(lynx_tsb,
  aes(x = index, y = count)) +
  geom_line(size = .2)

ui <- fluidPage(
  tsibbleWrapUI("tswrap"))
server <- function(input, output,
                   session) {
  tsibbleWrapServer("tswrap", pl,
       period = "1 year")
}
shinyApp(ui, server)
```

Longitudinal data

Longitudinal vs time series

> Longitudinal data tracks the same sample of individuals at different points in time. It often has different lengths and different time points for each individual.

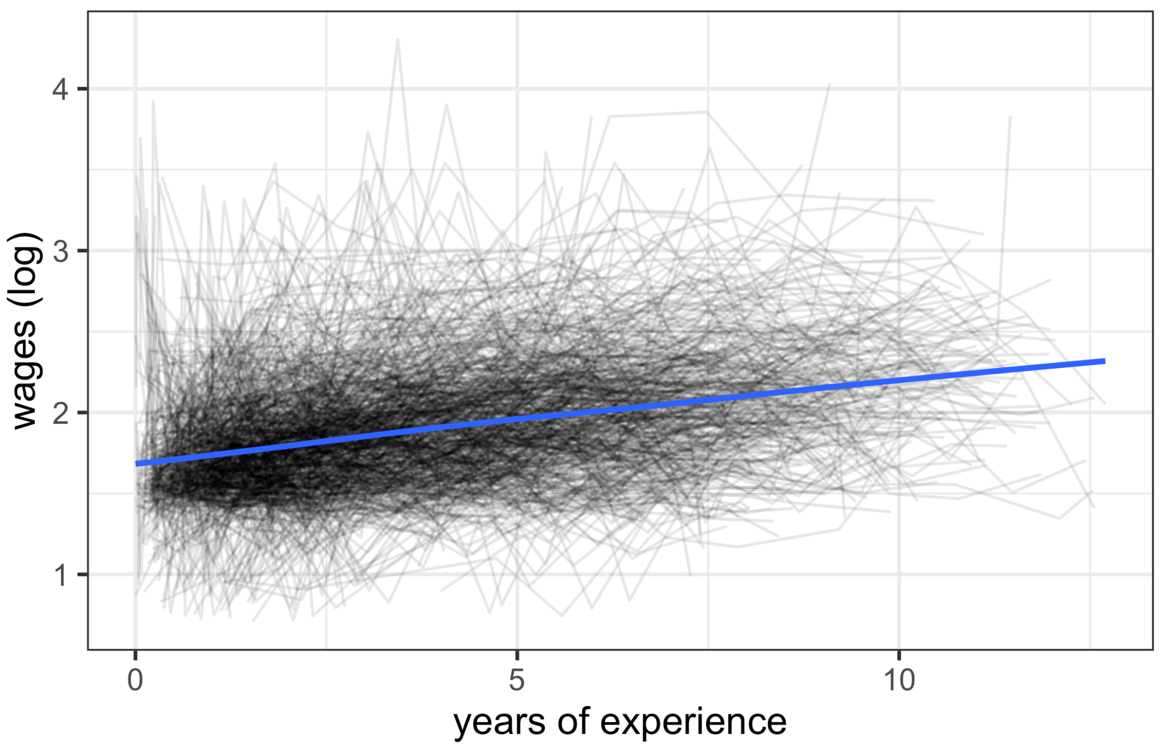


When the time points are the same for each individual, it is usually referred to as panel data. When different individuals are measured at each time point, it is called cross-

Overall trend

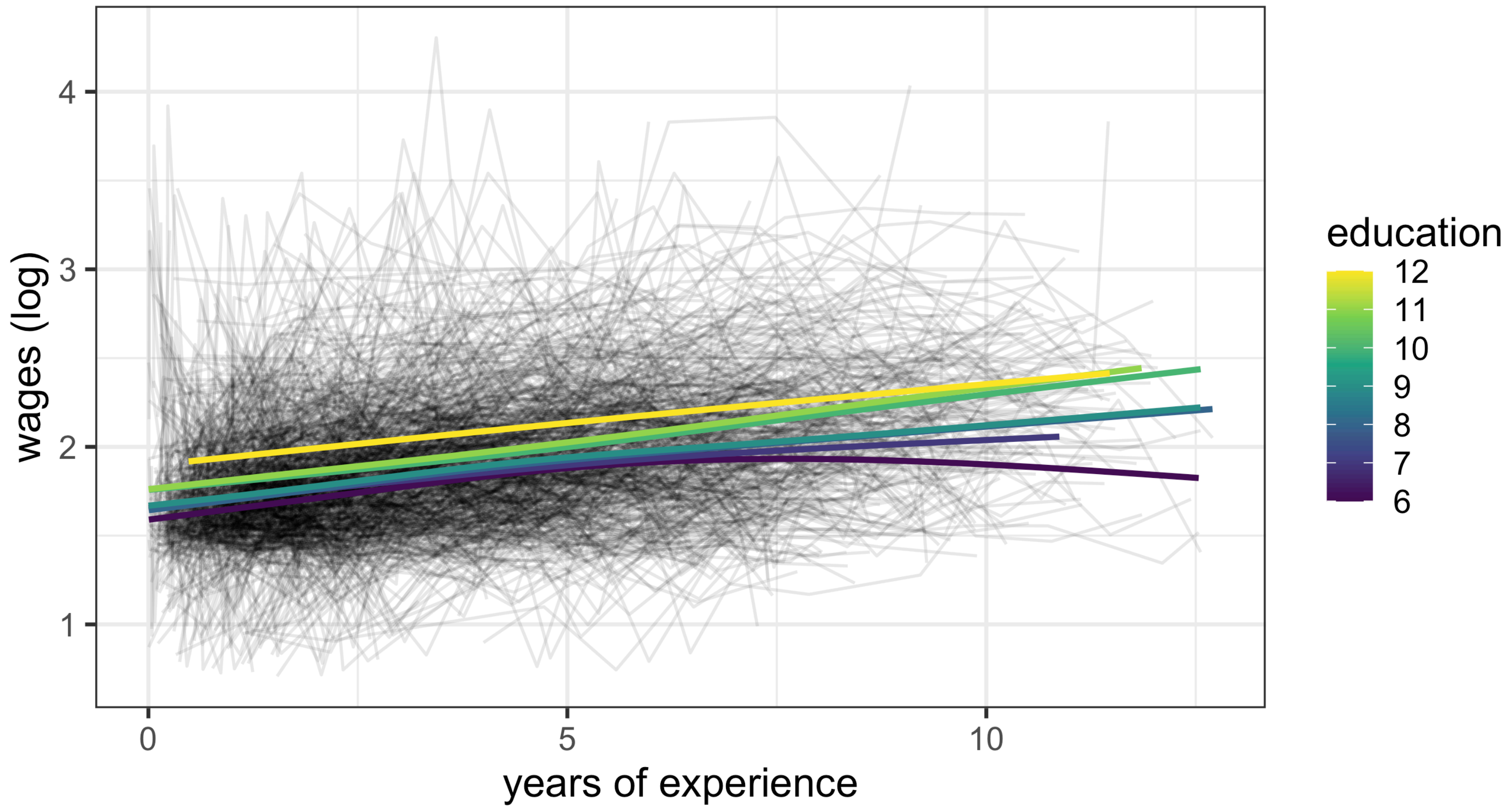
Log(wages) of 888 individuals, measured at various times in their employment US National Longitudinal Survey of Youth.

▶ Code



Wages tend to increase as time in the workforce gets longer, on average.

▶ Code



The higher the education level achieved, the higher overall wage, on average.

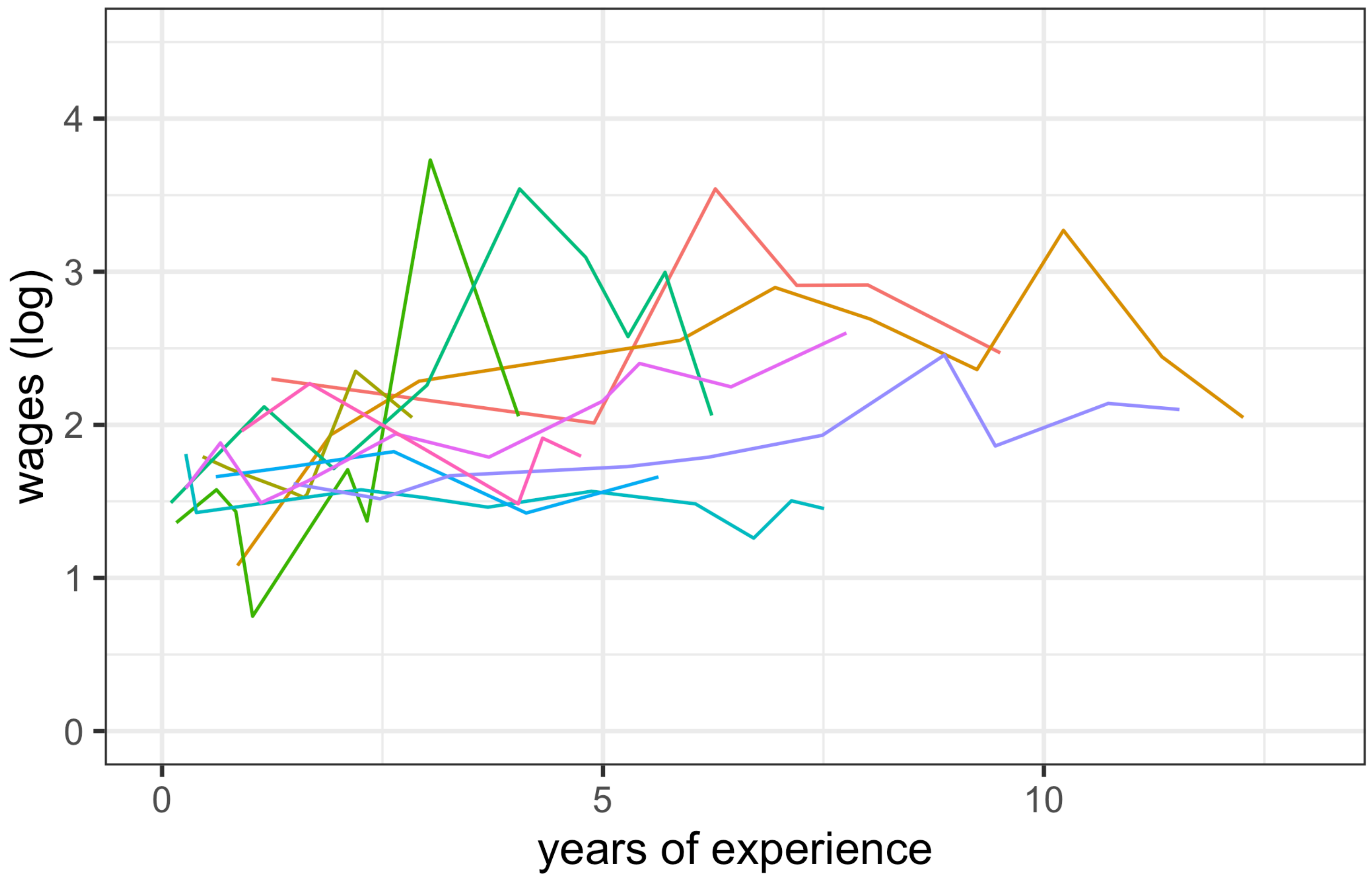
Eating spaghetti

`brolgar` uses `tsibble` as the data object, and provides:

- sampling individuals
- longnostics for individuals
- diagnostics for statistical models

Sample 1 | Sample 2 | Sample 3

▶ Code



Few individuals experience wages like the overall trend.

Individual patterns

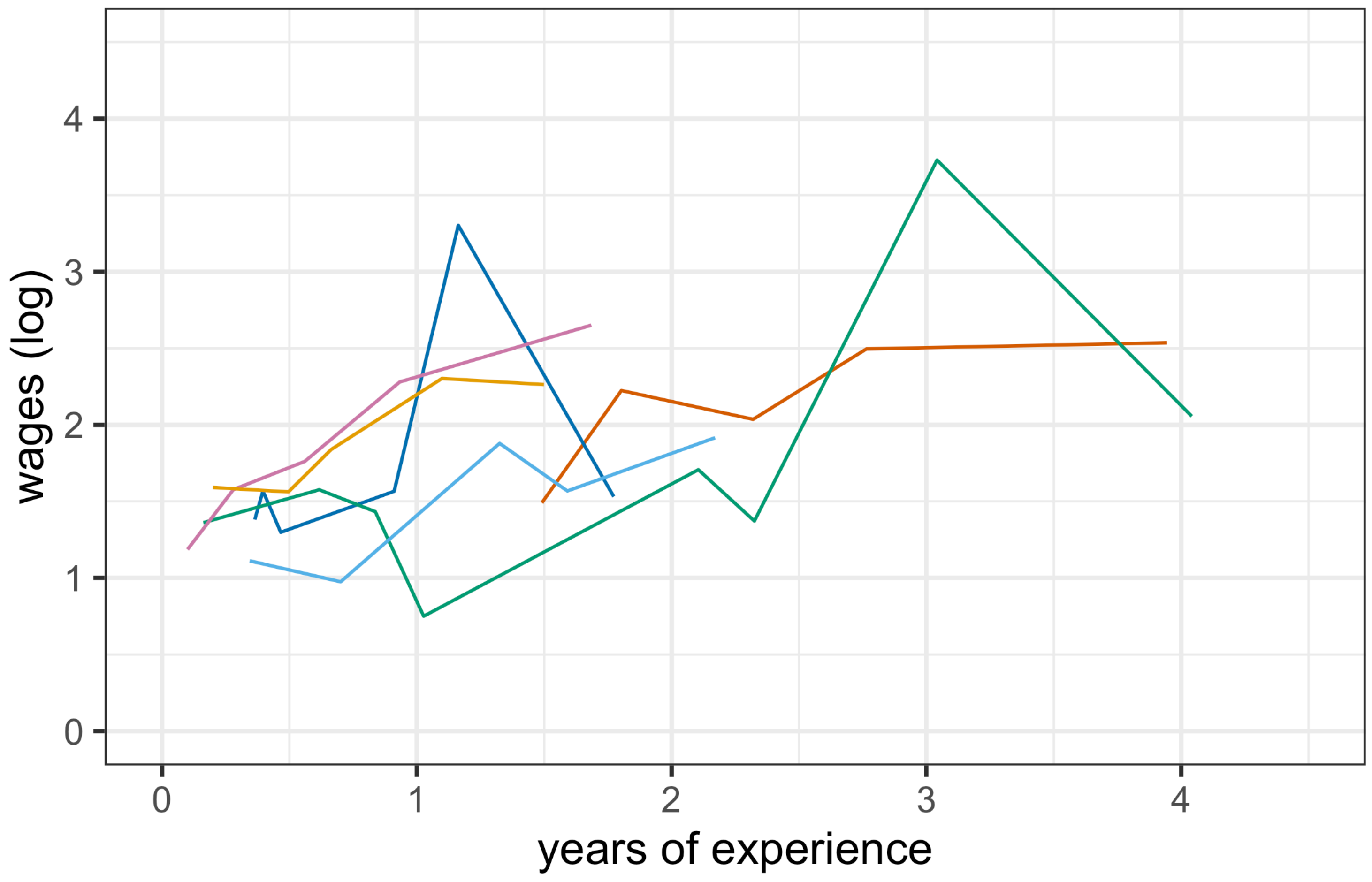
Remember scagnostics?

Compute longnostics for each subject, for example,

- Slope, intercept from simple linear model
- Variance, standard deviation
- Jumps, differences

Increasing | Decreasing | Consistent | Volatile

▶ Code



Individual summaries

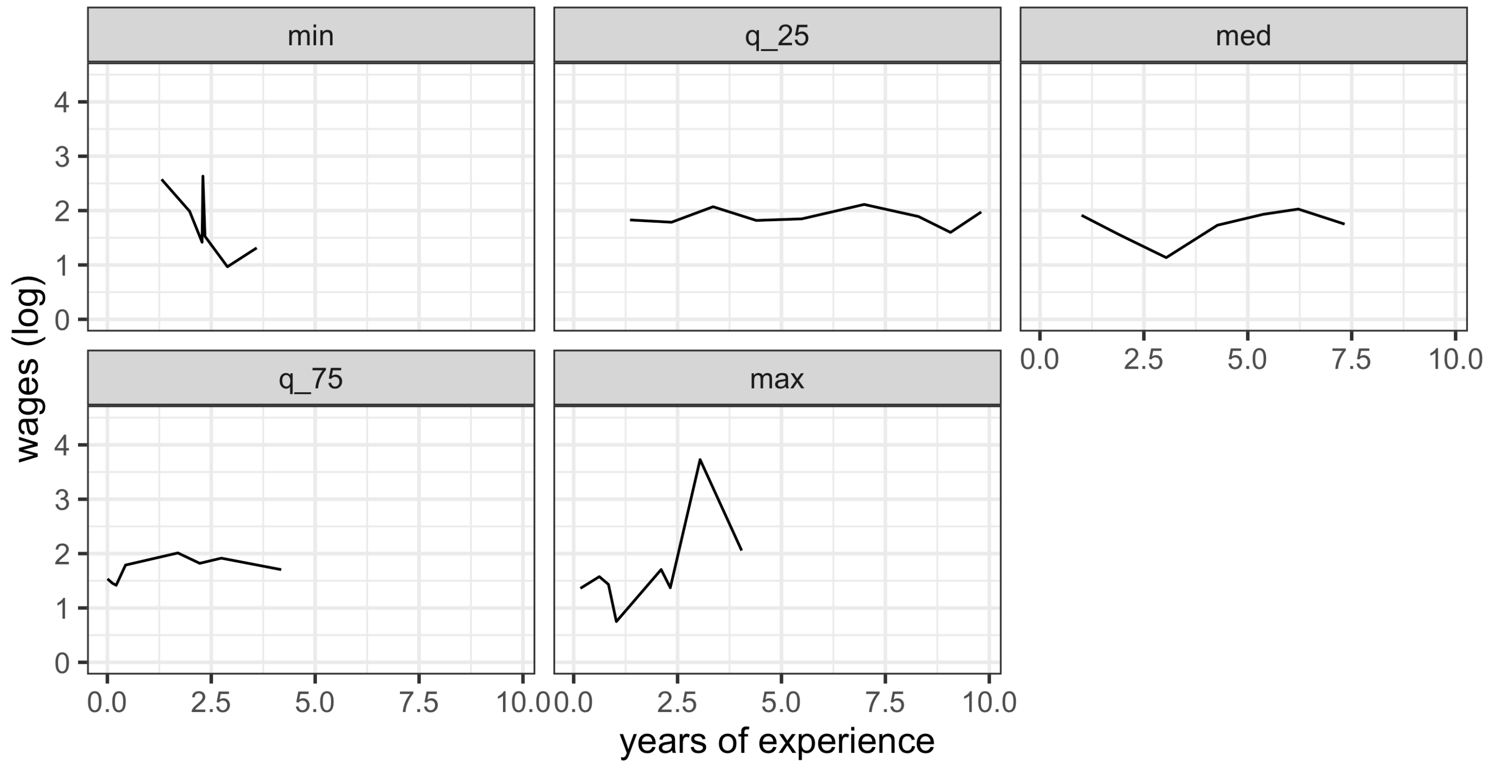
A different style of five number summary: What does average look like? What do extremes look like?

Find those individuals who are representative of the min, median, maximum, etc of a particular feature, e.g. trend, using `keys_near()`. This reports the individual who is closest to a particular statistic.

`wages_threenum()` returns the three individuals: min, max and closest to the median value, for a particular feature.

`wages_fivenum()` returns the five individuals: min, max and closest to the median, Q1 and Q3 values, for a particular feature.

▶ Code

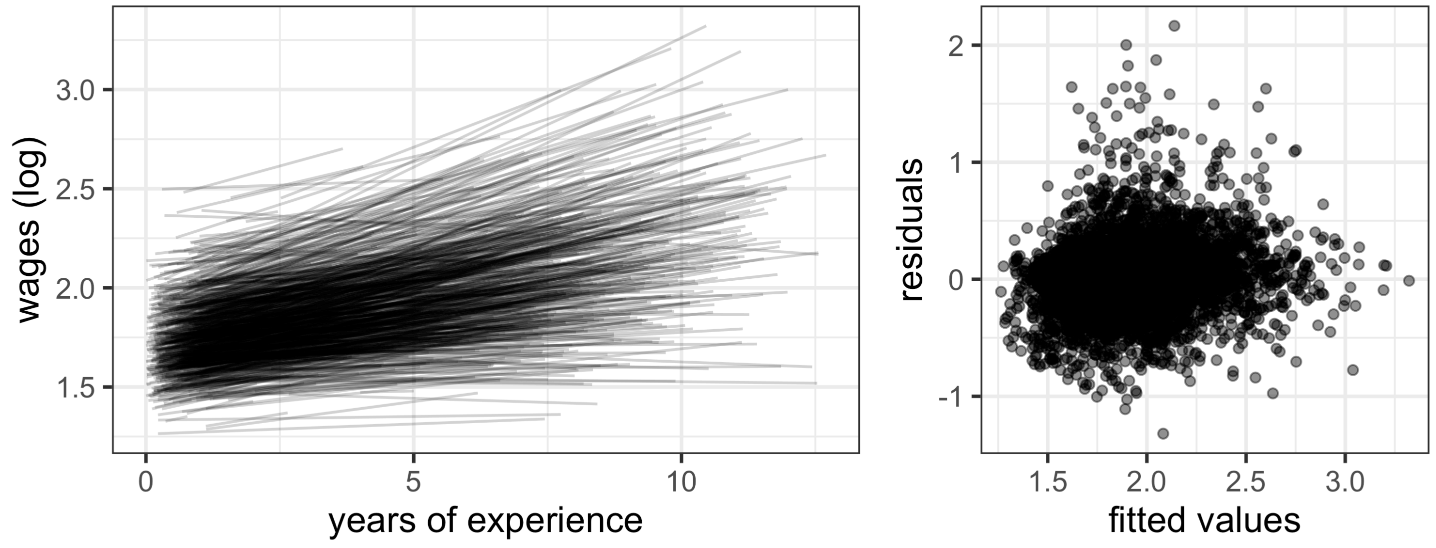


Assessing model fits

Fit a mixed effect model, education as fixed effect, subject random effect using slope.

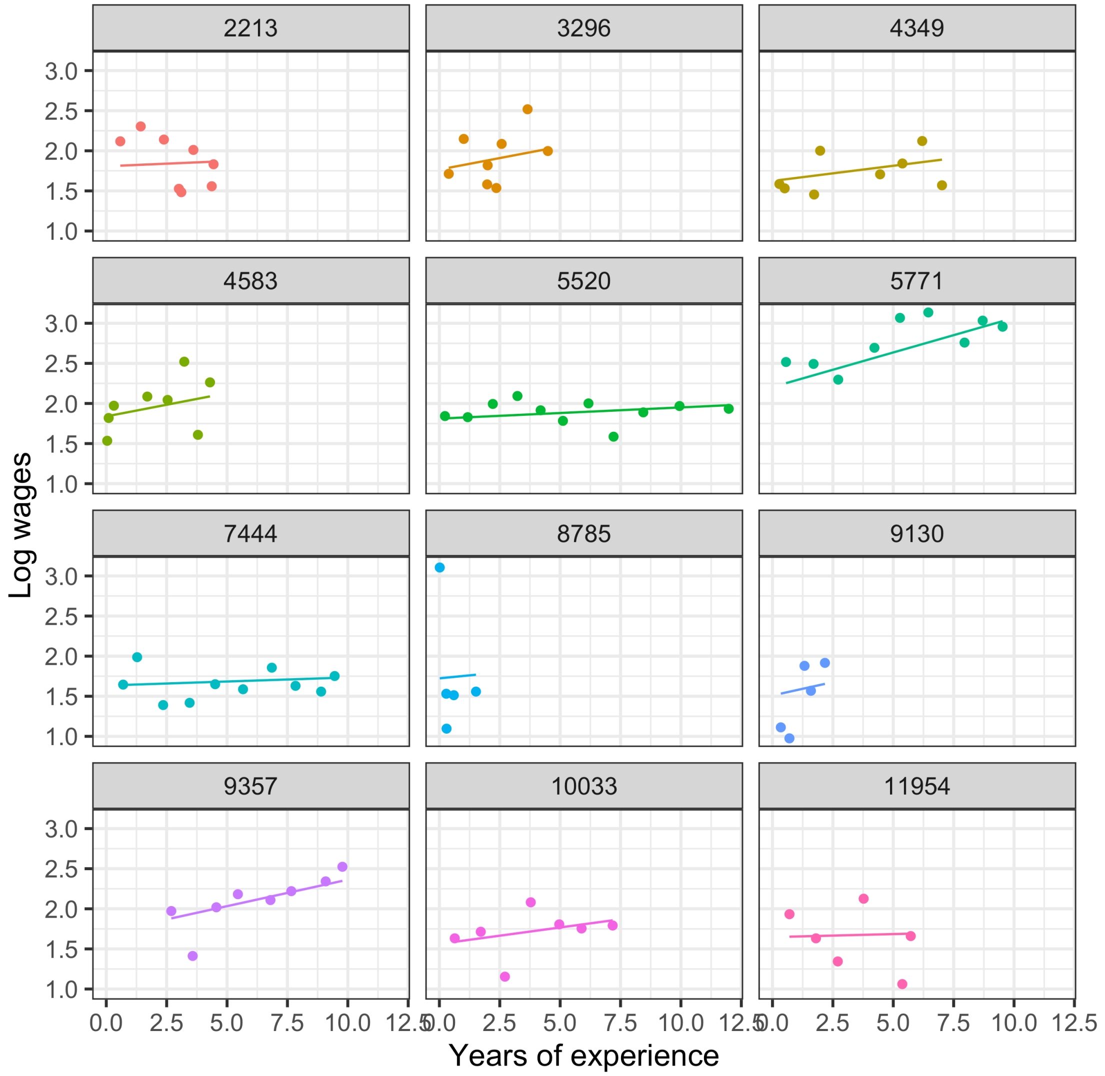
Summary of the fit

▶ Code



Diagnosing the fit: each individual model

▶ Code



Resources

- Wang, Cook, Hyndman (2019) A New Tidy Data Structure to Support Exploration and Modeling of Temporal Data
- Wang, Cook, Hyndman, O'Hara-Wild (2019) tsibble
- O'Hara-Wild, Hyndman, Wang (2020). fabletools: Core Tools for Packages in the 'fable' Framework
- O'Hara-Wild, Hyndman, Wang (2024). feasts: Feature Extraction and Statistics for Time Series
- Tierney, Cook, Prvan (2020) Browse Over Longitudinal Data Graphically and Analytically in R