R in production

Code is run repeatedly

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The challenges

ICE CEAMI
CE CREAM
ICE
Cres

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SAMEC 9P 2, 90b
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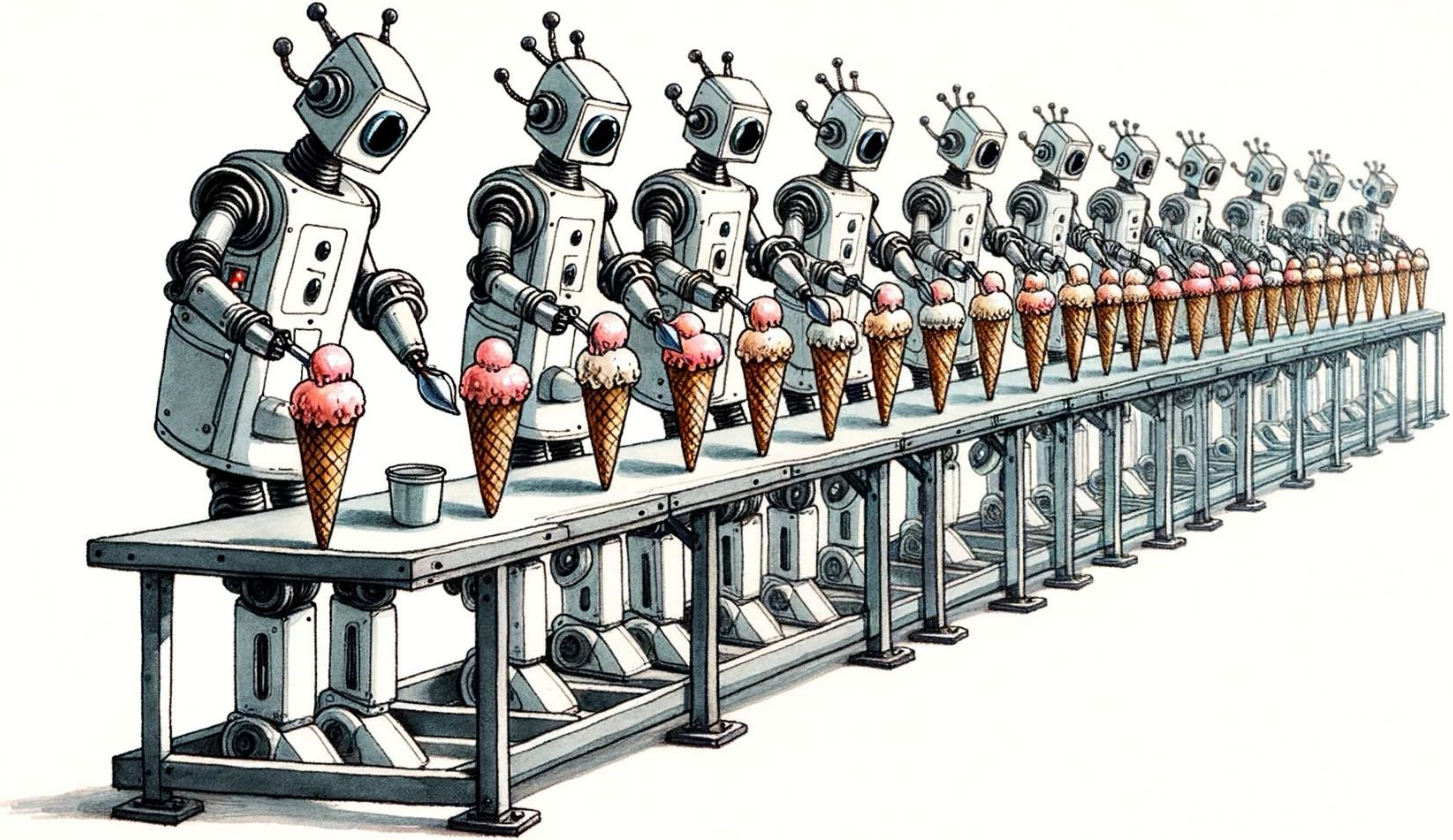
LUNTY CACTESSON
IDE
ICREREM



The **data** changes

The **schema** changes

date	temperature
05/01/2024	64.4
05/02/2024	68.0
05/03/2024	71.6
05/04/2024	66.2
05/05/2024	69.8
05/06/2024	73.4
05/07/2024	68.0
05/08/2024	71.6

The **schema** changes

date	**temp**
2024-05-01	18
2024-05-02	20
2024-05-03	22
2024-05-04	19
2024-05-05	21
2024-05-06	23
2024-05-07	20
2024-05-08	22

What changed? How is it likely to affect your code?

date	temperature
05/01/2024	64.4
05/02/2024	68.0
05/03/2024	71.6
05/04/2024	66.2
05/05/2024	69.8
05/06/2024	73.4
05/07/2024	68.0
05/08/2024	71.6

date	temp
2024-05-01	18
2024-05-02	20
2024-05-03	22
2024-05-04	19
2024-05-05	21
2024-05-06	23
2024-05-07	20
2024-05-08	22

Change	Impact
column name	probably errors
date format	might just work might error
temperature units	garbage predictions

A **package** changes

The **platform** changes

R/Python
System libraries
Operating system
Architecture

The **universe** changes

Concept drift
Model drift
Data drift

A **requirement** changes

Hard to mitigate

Universe

Schema

Unlikely to affect you

Requirements

Likely to affect you

Packages

Platform

Data

Easy to mitigate

1. Platform
2. Packages
3. Schema
4. Requirements

Platform

Insulate yourself from platform changes with a container

- Defines operating system + system dependencies
- Isolated
- Portable
- Immutable
- Scalable

Useful containers to know about

- GitHub action containers: https://docs.github.com/en/actions/writing-workflows/choosing-where-your-workflow-runs/choosing-the-runner-for-a-job
- https://github.com/rocker-org/rocker
- https://github.com/r-hub/rhub
- https://github.com/r-hub/evercran

We have never experienced a problem caused by using ubuntu-latest on GitHub

Packages

Mitigation strategy

- Right-size dependencies.
- Aggressively eliminate warnings and messages.
- Capture versions as part of deployment.
- Use a project-specific library renv.

Right-sizing dependencies

- I strongly believe you shouldn’t care at all about dependencies when you’re prototyping. It’s fine to take a dependency even if it’s one function that saves you 5 minutes.

- But more dependencies can make deployment more challenging, and can make your code more fragile.

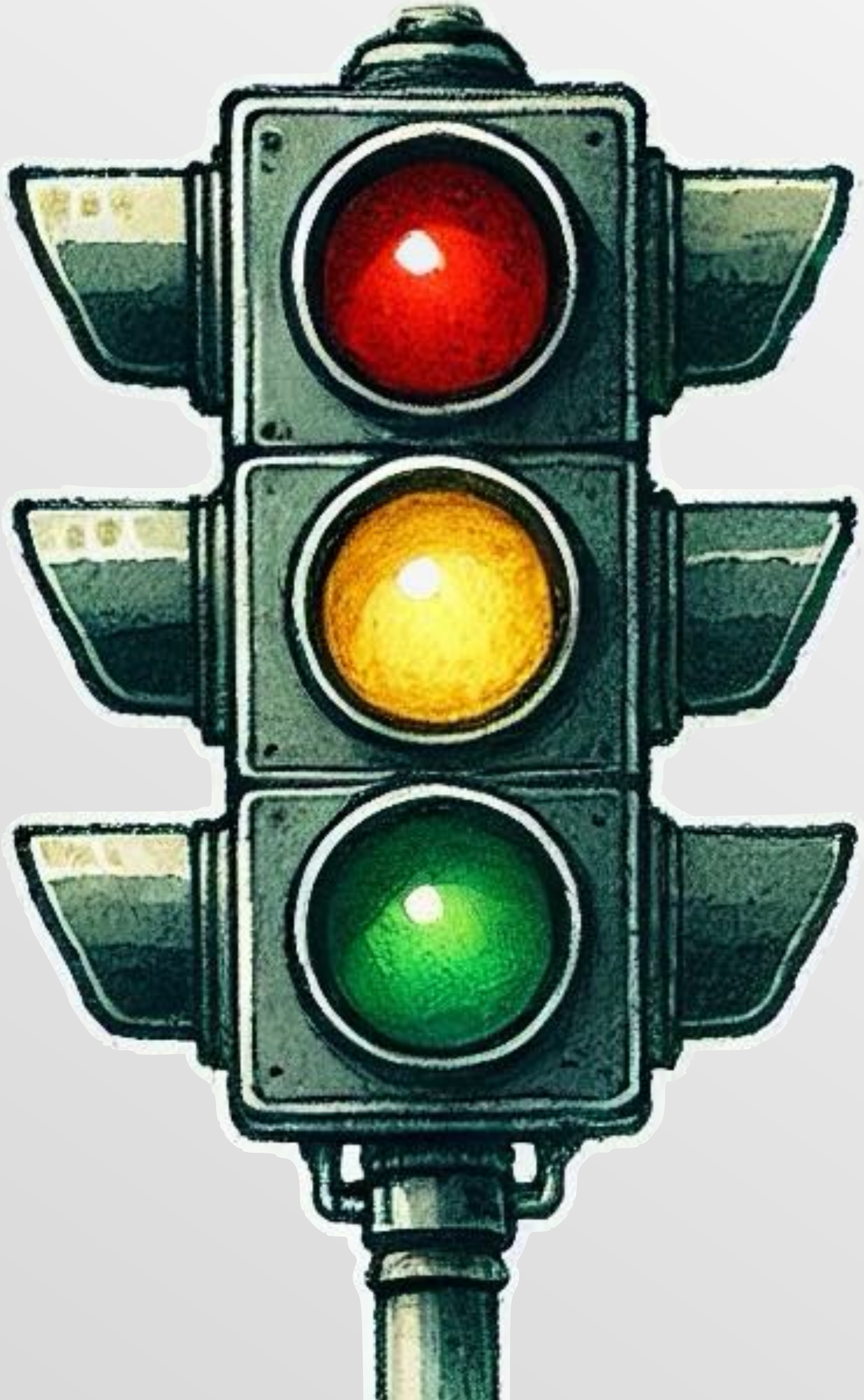
- So when you’ve got to the point of having something to deploy it’s worth taking a look at your dependencies to see if there any that you can now shed.

- https://www.tidyverse.org/blog/2019/05/itdepends/

How could you reduce dependencies here?

```r
library(tidyverse)

create_silly_story <- function(name, animal, color, food, place) {
  str_c(
    "Once upon a time, there was a magical ", animal, " named ", name, ".\n",
    name, " had a beautiful ", color, " mane that shimmered in the sunlight.\n",
    "Every day, ", name, " would prance through the fields of ", food, " near ", place, ".\n",
    "One day, ", name, " discovered a secret portal that led to a world made entirely of ", food, "!\n",
    name, " lived happily ever after, munching on ", food, " and spreading ", color, " joy wherever ", name, " went.\n"
  )
}
```

R’s condition hierarchy



Error

You must fix this before continuing

Warning

We’ll let it go this time, but you need to fix this

Message

FYI; no action needed

But still worth eliminating to make logs easier to read

Eliminate all warnings and messages

```r
options(warn = 1)
options(warn = 2)

# https://lifecycle.r-lib.org/
options(lifecycle_verbosity = "warning")
options(lifecycle_verbosity = "error")

# Tools of last resort
suppressWarnings()
suppressMessages()
```

Eliminate all messages and warnings in this code

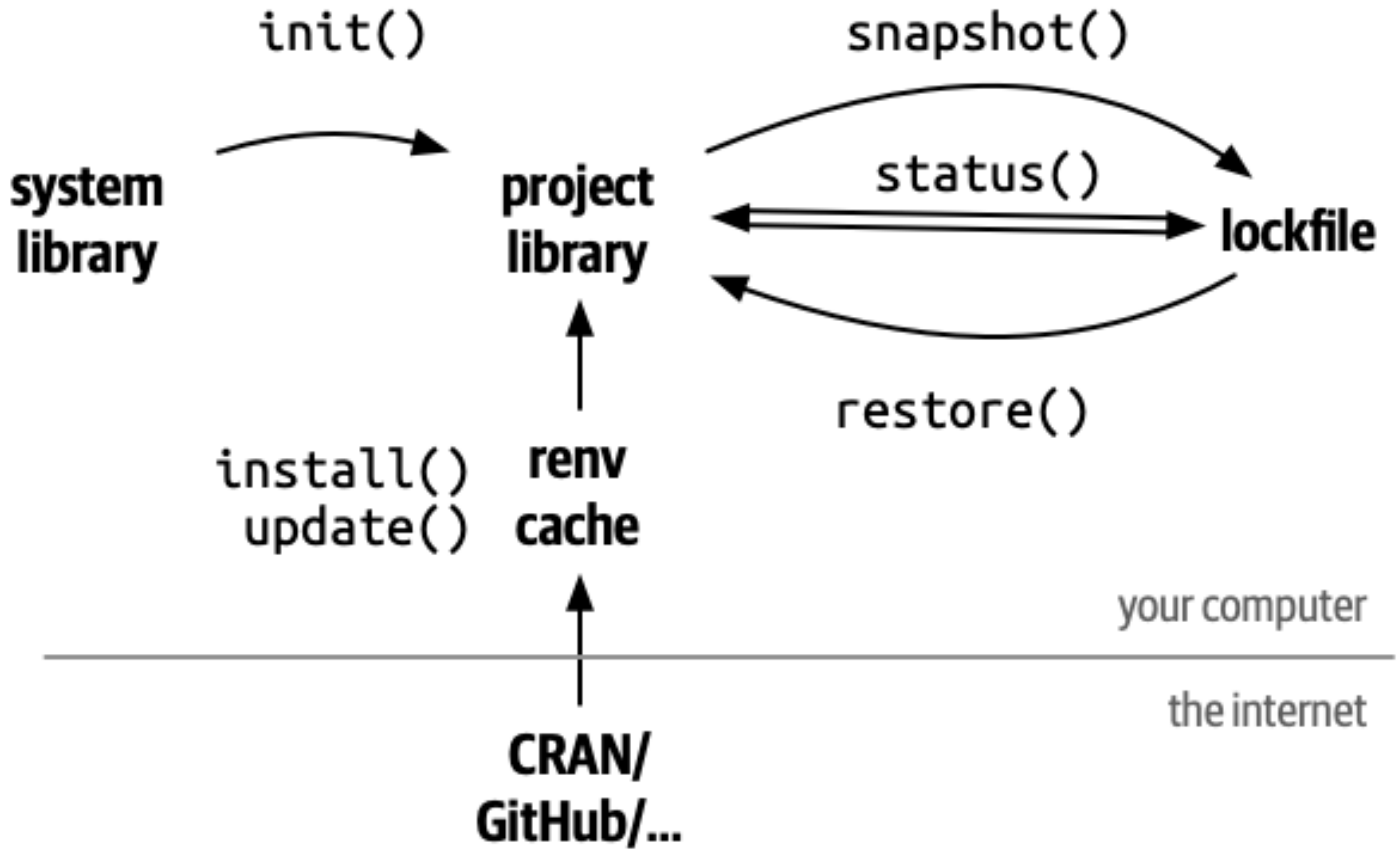
```
library(dplyr)
library(readr)

df1 ← data.frame(x = c(1, 1, 2), y = 1:3)
df2 ← data.frame(x = c(1, 2, 2), z = letters[1:3])
left_join(df1, df2)

path ← tempfile()
write_csv(df1, path)
read_csv(path)
```

Capturing versions at deployment

- Ensures that deployed code continues to work regardless of how packages change. 100% needed.
- Handled automatically on deploy by Posit Connect, and manually with rsconnect::write_manifest() for other cases.
- But what about on your machine? What happens when your code production code needs a change after a year and you can no longer even get it to run?

Use a project-specific library

- (Remember, a library is your collection of R packages)
- renv essentially gives you the ability to have a separate library for each project
- This guarantees reproducibility but is quite a lot of hassle — if you want a new version of a package to be available in every project, you need to install it in every project.
- That’s why this is the last option!


init()
snapshot()
system library
project library
status()
lockfile
restore()
install()
update()
renv cache
your computer
the internet
CRAN/ GitHub/...

Your turn

Return to the **diamonds** project.

Call renv::init() to create a private library.

Change setup-r-dependencies action to setup-renv.

Redeploy and check that your code works.

Add a new chunk that uses dplyr to show the five most expensive diamonds. What do you need to do to get this to work in production?

You should regularly update your renv environments

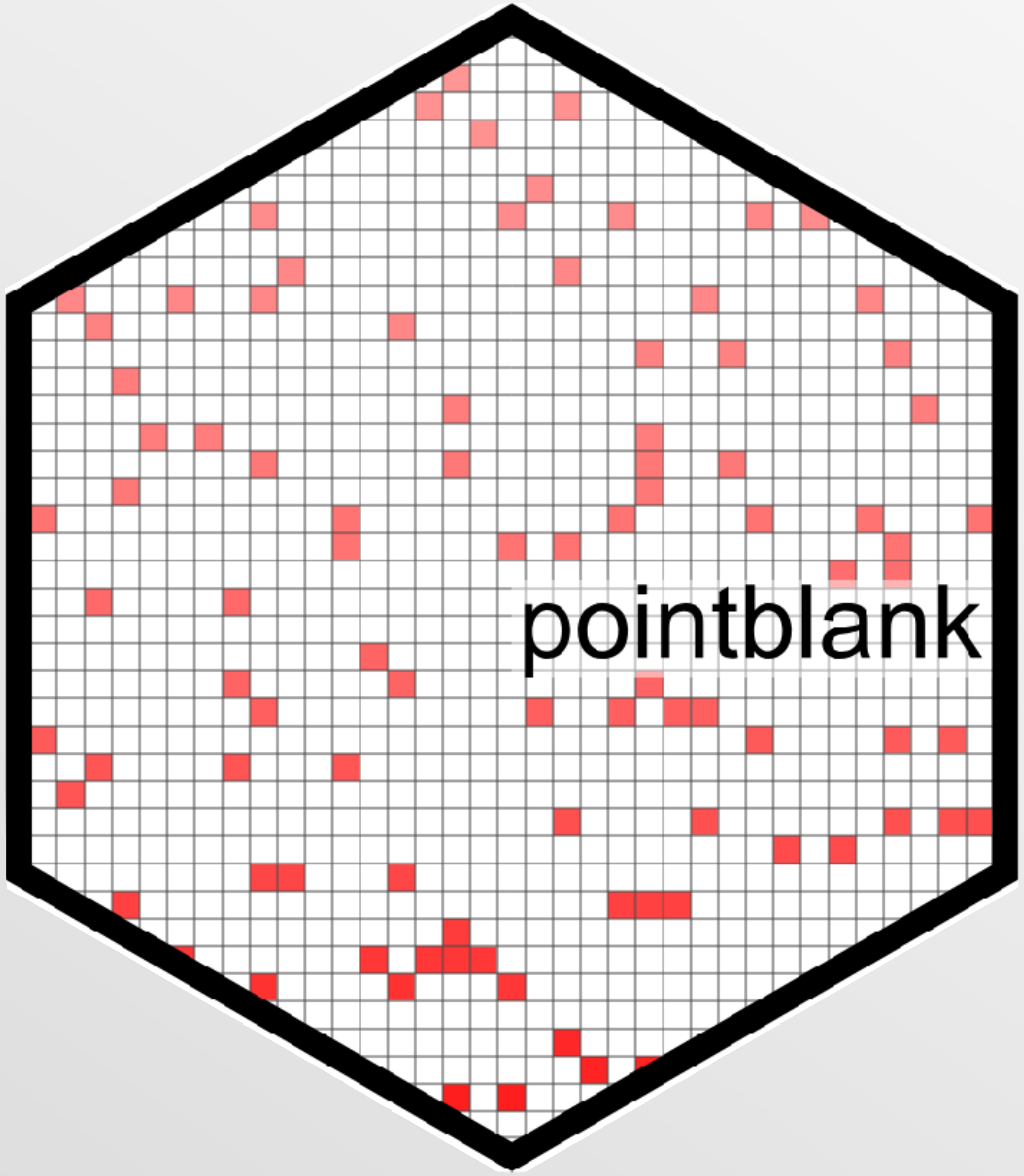
```r
renv::update()
# check the code works
renv::snapshot()
```

Schema

Mitigation strategy

- Social
  - Make friends with the folks who provide your data!
  - Establish data contracts (go to Nick’s talk! Wed 10:20 AM)
- Technical
  - Aggressively check that your data looks as expected

Pointblank provides a flexible tool for validating data



There are six ways to use it

- Canned data report
- Data quality reporting
- Pipeline data validation
- Expectations in unit tests
- Custom control flow
- Rmd integration

We’ll focus on two

- **Canned data report**
- Data quality reporting
- **Pipeline data validation**
- Expectations in unit tests
- Custom control flow
- Rmd integration

scan_data() produces a handy report

```r
report <- pointblank::scan_data(mtcars)
report
pointblank::export_report(mtcars, "mtcars-report.html")

# Interactions/correlations sections are slow for large datasets
# so you can drop them with this code
pointblank::scan_data(ggplot2::diamonds, sections = "OVMS")
```

Pipeline validation throws an error if data isn’t as you expect

- Check variable types:
  col_is_numeric(), **col_is_character()**, ...

- Check missingness (if you don’t expect any):
  col_vals_not_null()

- Check ranges/valid values:
  col_is_between(), **col_vals_in_set()**

- Special purpose:
  col_vals_expr(), **col_vals_regex()**

- Custom: **specially()**
  e.g. specially(\(df) nrow(anti_join(df, ref) == 0)

What would you validate for the ice cream data?

```r
library(dplyr)

data <- tribble(
  ~date,          ~temperature,
  "2024-05-01",  64.4,
  "2024-05-02",  68.0,
  "2024-05-03",  71.6,
  "2024-05-04",  66.2,
  "2024-05-05",  69.8,
  "2024-05-06",  73.4,
  "2024-05-07",  68.0,
  "2024-05-08",  71.6
)
data <- data |> mutate(date = as.Date(date))
```

Some ideas

```
library(pointblank)

data ▷
  col_is_date(date) ▷
  col_is_numeric(temperature) ▷
  col_vals_not_null(date) ▷
  col_vals_between(temperature, 30, 120)
```

Your turn

```
# You can download USD ⟷ EUR exchange range data from this API
url ← "https://data-api.ecb.europa.eu/service/data/EXR/
D.USD.EUR.SP00.A?
format=csvdata&detail=dataonly&startPeriod=2024-08-08"

# Assume you want to download this data daily.
# Write some pointblank code to ensure that you get an
# error if the data format changes
```

Advanced workflows

https://github.com/posit-conf-2023/ds-workflows-r/blob/main/materials/project/01_data_clean_validate/01_data_clean_validate.rmd#L192C3-L192C21

Requirements

No great insights, but...

- Adopt the mindset that a successful project will attract changes and will require upkeep.
- If you are using GitHub (or similar) internally, issues and projects are a great way to track desired changes.
- Do your best to **batch** and **time box** projects.
- Invest in refactoring.

What is refactoring?

- Rewriting code so the reduces are the same but the internals are better: easier to read or easier to maintain.
- Second order benefit is improving your programming skills.
- Common tasks:
  - Enforce common style
  - Fix any kludges you added in the heat of the moment
  - Reduce code by using packages

Your turn

What other techniques for handling changing requirements have you found useful in your career?