

Practical Strategies for R-Based Research in Secure Data Environments

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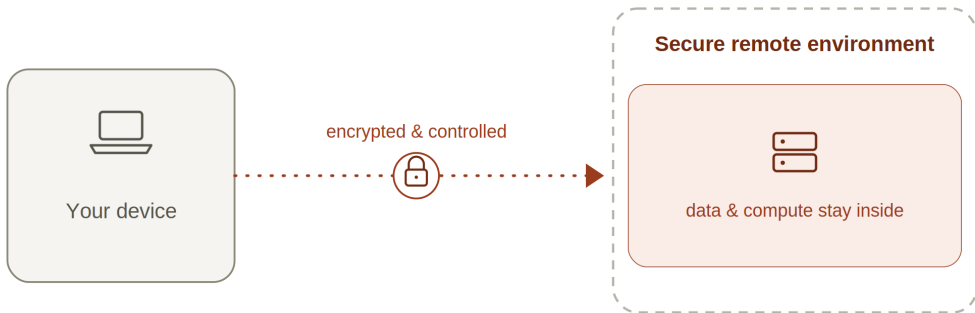
useR! Conference, July 2026, Warsaw, Poland

Motivation

- ▶ Sensitive data requires secure computing environments
- ▶ Security restrictions create practical challenges for researchers
- ▶ R can help overcome many of these challenges

What are secure remote access systems?

- ▶ Controlled environments for working with sensitive data remotely
- ▶ Commonly used for administrative, health, and other confidential data
- ▶ Strict controls govern access, software, and data exports



Out of Despair project

- ▶ Population-based study using large-scale administrative register data
- ▶ Analysis conducted in the FIONA secure remote access environment
- ▶ Presentation will have examples relating to the project



Health register



Education register



Income & benefits



Population register

Why secure environments change R workflows

Several factors reshape how R is used day-to-day in these settings:



Limited
computational
resources



Restricted
external access



Data governance



Slower workflow

Why R works well in secure environments

R's design lines up well with what these environments demand:



Rich ecosystem



Highly flexible



Open source



Reproducible

Efficient data handling for large datasets

- ▶ Large register datasets may not fit fully into memory
- ▶ Focus on early filtering and selecting only necessary variables
- ▶ Use efficient formats and tools (`arrow`, `fst`, `data.table`)



Example of a register

- ▶ Register of doctor visits
- ▶ 3 653 451 rows and 116 columns
- ▶ Many of the columns not relevant

id	visit start		visit end		icd10 code	
1	12-04-2018	12:00:00	12-04-2018	12:36:00	Z00.00	...
1	02-11-2018	09:30:00	02-11-2018	10:03:00	E11.9	...
2	21-04-2016	15:00:00	21-04-2016	15:24:00	I10	...
3	17-01-2014	13:00:00	17-01-2014	13:16:00	J45.909	...
⋮	⋮		⋮		⋮	⋮

arrow example

Filtering a dataset before loading the result into memory:

```
dt <- open_dataset("data/panel_dataset.parquet") %>%  
  select(id, visit_start, visit_end, icd10) %>%  
  filter(grepl("^F", icd10)) %>%  
  collect()
```

data.table example

Comparison for creating a new variable in dataset with 3 million rows:

Tidyverse

```
panel <- panel %>%  
  mutate(.row = row_number()) %>%  
  left_join(  
    data %>% select(id = time),  
    by = join_by(id, month >= time)  
  ) %>%  
  summarise(  
    times = sum(!is.na(time)),  
    .by = .row  
  ) %>%  
  right_join(  
    panel %>% mutate(.row = row_number()),  
    by = ".row"  
  ) %>%  
  select(-.row)
```

Time: 44 s

data.table

```
panel[  
  , attempts :=  
    records[  
      .SD,  
      on = .(id, time <= month),  
      .N,  
      by = .EACHI  
    ]$N  
]
```

Time: 20 s

Efficient computation in constrained systems

- ▶ Shared compute environments limit scalability
- ▶ Inefficient code quickly becomes a bottleneck
- ▶ Use parallelisation when appropriate (`future`, `furrr`, `future.apply`)



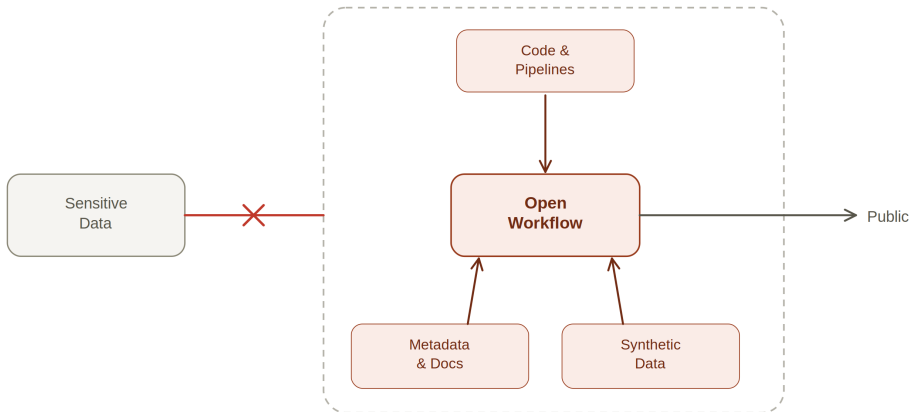
future example

Using parallelisation when fitting nested cross-validation using `mlr3`:

```
future::plan("multisession", workers = 5)
rr <- resample(
  tsk,
  at,
  rsmp_cv
)
future::plan("sequential")
```

Open science without open data

- ▶ Sensitive data cannot be shared publicly
- ▶ Transparency shifts from data → workflow



AI and advanced computation in secure environments

- ▶ Modern AI and computational tools offer new opportunities
- ▶ Secure environments impose practical limits on their use
- ▶ Service providers should offer secure, local alternatives to external tools

Conclusion

- ▶ Secure data environments introduce inconveniences
- ▶ Optimise code and analyses (e.g. `data.table`, `arrow`, parallelisation)
- ▶ Publish code along with detailed workflows and documentation.

Thank you!
Questions? Suggestions?



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