Validatetools

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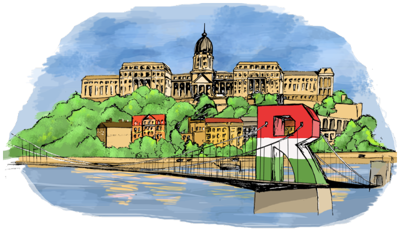


Who am I?

- Data scientist / Methodologist Statistics Netherlands (aka CBS).
- Author of several R-packages, including `whisker`, `validate`, `errorlocate`, `docopt`, `tableplot`, `chunked`, `ffbase`,...
- Co-author of *Statistical Data Cleaning with applications in R (2018)* (sorry for the plug, but relevant for this talk...)

CAUTION: BAD DATA
BAD DATA QUALITY MAY RESULT IN FRUSTRATION AND LEAD TO DROP KICKING YOUR COMPUTER

Data cleaning...

A large part of your and our job is spent in data-cleaning:

- getting your data in the right shape (e.g. `tidyverse`)
- checking validity (e.g. `validate`, `dataMaid`, `errorlocate`)
- impute values for missing or erroneous data (e.g. `VIM`, `simputation`)
- see data changes, improvements (e.g. `daff`, `lumberjack`)

Desirable data cleaning properties:

- Reproducible data checks
- Automate repeated data checking (e.g. monthly/quarterly stats)
- Monitor data improvements / changes.
- But **How?**

RULES

Cleaning philosophy

- **“Explicit is better than implicit”**.
- Make data knowledge as **explicit** as possible.
- Store these as **validation rules**.

Advantages:

- Easy checking of rules
- Data quality statistics: how often is each rule violated?
- Allows for reasoning on rules: which variables are involved in errors?
- Simplifies rule changes and additions.

Rules

- Data rules are solidified domain knowledge.
- In statistical production: much domain knowledge available.
- Many rules, many diverse subpopulations.
- Real world knowledge e.g. :
  - age is not negative.
  - human age is less then 150 years.
- Expert knowledge, e.g:
  - `IF profit > 0 THEN turnover > 0`
  - `IF married THEN age > 16`

R package validate

With package validate you formulate explicit rules that data must conform to:

```r
library(validate)
check_that( data.frame(age=160, job = "no", income = 3000)
  age >= 0,
  age < 150,
  job %in% c("yes", "no"),
  if (job == "yes") age >= 16,
  if (income > 0) job == "yes"
)
```

Rules (2)

A lot of datacleaning packages are using validate rules to facilitate their work.

- `validate`: validation **checks** and data **quality stats** on data.
- `errorlocate` to find **errors** in variables (in stead of records)
- `rspa` data **correction** under data constraints
- `deductive` deductive **correction**
- `dcmodify` deterministic **correction** and **imputation**.

Why-o-why `validatetools`?

- We have package `validate`, what is the need?

In “real life”

- We have large data analysis processes with many steps.
- Often many rules (> 100) on many variables (> 20) and many observations (> 0.5M) with diverse subpopulations.
- Results often in redundant or (partially) contradictive rule sets...

Because we'd like to...

- clean up rule sets (kind of meta-cleaning. . .).
- detect and resolve problems with rules:
  - Detect **conflicting** rules.
  - Remove **redundant** rules.
  - **Substitute** values and **simplify** rules.
  - Detect **unintended** rule interactions.
- check the rule set using formal logic (without any data!).
- solve these kind of fun problems :-)

Formal logic

Rule set S

A validation rule set S is a conjunction of rules r_i, which applied on record $\boldsymbol{x}$ returns `TRUE` (valid) or `FALSE` (invalid)

$$S(\boldsymbol{x}) = r_1(\boldsymbol{x}) \wedge \cdots \wedge r_n(\boldsymbol{x})$$

Note

- a record has to comply to each rule r_i.
- it is thinkable that two or more r_i are in conflict, making each record invalid.

Formal logic (2)

Rule $r_i(x)$

A rule a disjunction of atomic clauses:

$$r_i(x) = \bigvee_j C_i^j(x)$$

with:

$$C_i^j(\boldsymbol{x}) = \begin{cases} \boldsymbol{a}^T\boldsymbol{x} \leq b \\ \boldsymbol{a}^T\boldsymbol{x} = b \\ x_j \in F_{ij}\text{with } F_{ij} \subseteq D_j \\ x_j \not\in F_{ij}\text{with } F_{ij} \subseteq D_j \end{cases}$$

Rule types

- *linear* restrictions
- *categorical* restrictions
- *if* statements with linear and categorical restrictions

If statement is Modus ponens:

$$\begin{aligned} & \text{if } P \text{ then } Q \\ \Leftrightarrow \quad & P \implies Q \\ \Leftrightarrow \quad & \neg P \vee Q \end{aligned}$$

Example

```r
rules <- validator(
  example = if (job == "yes") income > 0
)
```

$$r_{\text{example}}(x) = \text{job} \notin \text{"yes"} \lor \text{income} > 0$$

```r
print(rules)
```

```
## Object of class 'validator' with 1 elements:
##  example: !(job == "yes") | (income > 0)
```

Mixed Integer Programming

Each problem we try to solve, can be translated into a mip problem, which can be readily solved using a mip solver.

`validatetools` uses `lpSolveApi`.

$$\begin{aligned} \text{Minimize } f(\mathbf{x}) &= 0; \\ \text{s.t. } \mathbf{R}\mathbf{x} &\leq \mathbf{d} \end{aligned}$$

with $\boldsymbol{R}$ and $\boldsymbol{d}$ the rule definitions and $f(\boldsymbol{x})$ is the specific problem that is solved.

Problem: infeasibility

Problem

One or more rules in conflict:

- $S(x)$ always is ‘FALSE, **no data correct**
- *happens more often than you think*

```
library(validatetools)
rules <- validator( is_adult = age >=21
                  , is_child = age < 18
                  )
is_infeasible(rules)
```

```
## [1] TRUE
```

KEEP CALM

AND

RESOLVE CONFLICT

Conflict, and now?

```r
# Find out which rule would remove the conflict
detect_infeasible_rules(rules)
```

```
## [1] "is_adult"
```

```r
# And itś conflicting rule(s)
is_contradicted_by(rules, "is_adult")
```

```
## [1] "is_child"
```

- One of these rules needs to be removed
- Which one? Depends on human assessment. . .

Detecting and removing redundant rules

- Rule r_1 may imply r_2, so r_2 can be removed.
- Simplifies rule set!

```
rules <- validator( r1 = age >= 18
                  , r2 = age >= 12
                  )
detect_redundancy(rules)
```

```
##    r1    r2
## FALSE  TRUE
```

```
remove_redundancy(rules)
```

```
## Object of class 'validator' with 1 elements:
##  r1: age >= 18
```

Value substitution

```r
rules <- validator( r1 = if (gender == "male") weight > 50
                  , r2 = gender %in% c("male", "female")
                  )

substitute_values(rules, gender = "male")
```

```
## Object of class 'validator' with 2 elements:
##  r1           : weight > 50
##  .const_gender: gender == "male"
```

Conditional statement

A bit more complex reasoning, but still classical logic:

```r
rules <- validator( r1 = if (income > 0) age >= 16
                  , r2 = age < 12
                  )
# age > 16 is always FALSE so r1 can be simplified
simplify_conditional(rules)
```

```
## Object of class 'validator' with 2 elements:
##  r1: income <= 0
##  r2: age < 12
```

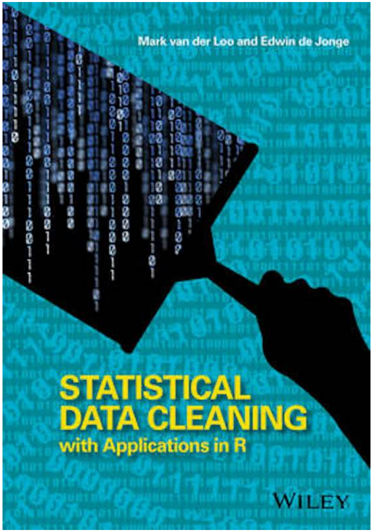
All to gether now!:

`simplify_rules` applies all simplification methods to the rule set

```r
rules <- validator( r1 = if (age < 16) income == 0
                  , r2 = job %in% c("yes", "no")
                  , r3 = if (job == "yes") income > 0
                  )
simplify_rules(rules, job = "yes")
```

```
## Object of class 'validator' with 3 elements:
##  r1        : age >= 16
##  r3        : income > 0
##  .const_job: job == "yes"
```

Interested?


Mark van der Loo and Edwin de Jonge
STATISTICAL DATA CLEANING
with Applications in R
WILEY

SDCR

M. van der Loo and E. de Jonge (2018) *Statistical Data Cleaning with applications in R* Wiley, Inc.

validatetools

- Available on CRAN

More theory?

← See book

Thank you for your attention! / Köszönöm a figyelmet!