A systematic approach to data cleaning with R

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Demos and other materials

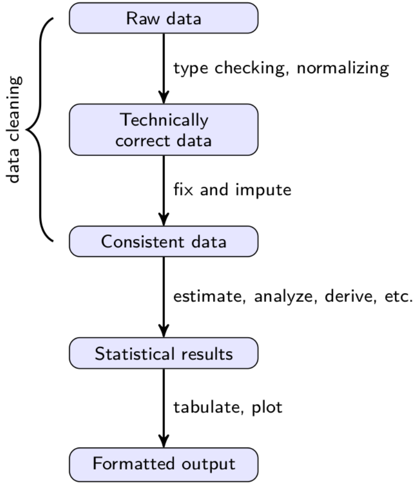
https://github.com/markvanderloo/satRday

Contents

- The statistical value chain
- From raw data to technically correct data
  - Strings and encoding
  - Regexp and approximate matching
  - Type coercion
- From technically correct data to consistent data
  - Data validation
  - Error localization
  - Correction, imputation, adjustment

The statistical value chain

Statistical value chain



Concepts

Technically correct data

- Well-defined format (data structure)
- Well-defined types (numbers, date/time,string, categorical...)
- Statistical units can be identified (persons, transactions, phone calls...)
- Variables can be identified as properties of statistical units.
- Note: tidy data $\subset$ technically correct data

Consistent data

- Data satisfies demands from domain knowledge
- (more on this when we talk about validation)

From raw to technically correct data

Dirty tabular data

Demo

Coercing while reading: `/table`

Tabular data: long story short

- `read.table`: R's swiss army knife
  - fairly strict (no sniffing)
  - Very flexible
  - Interface could be cleaner (see this talk)
- `readr::read_csv`
  - Easy to switch between strict/lenient parsing
  - Compact control over column types
  - Fast
  - Clear reports of parsing failure

Really dirty data

Demo

Output file parsing: `/parsing`

A few lessons from the demo

- (base) R has great text processing tools.
- Need to work with regular expressions[1]
- Write many small functions extracting single data elements.
- Don't overgeneralize: adapt functions as you meet new input.
- Smart use of existing tools (`read.table(text=)`)

[1] Mastering Regular Expressions (2006) by Jeffrey Friedl is a great resource

Packages for standard format parsing

- **`jsonlite`**: parse JSON files
- **`yaml`**: parse yaml files
- **`xml2`**: parse XML files
- **`rvest`**: scrape and parse HTML files

Some tips on regular expressions with R

- `stringr` has *many* useful shorthands for common tasks.
- Generate regular expressions with `rex`

```
library(rex)
# recognize a number in scientific notation
rex(one_or_more(digit)
    , maybe(".",one_or_more(digit))
    , "E" %or% "e"
    , one_or_more(digit))
```

```
## (?:[[:digit:]])+(?:\.(?:[[:digit:]])+)?(?:E|e)(?:[[:dig
```

Regular expressions

Express a *pattern* of text, e.g.

$$\texttt{"(a|b)c*"} = \{\texttt{"a"}, \texttt{"ac"}, \texttt{"acc"}, \ldots, \texttt{"b"}, \texttt{"bc"}, \texttt{"bcc"}, \ldots\}$$

Task	**`stringr`** function:
string detection	`str_detect(string, pattern)`
string extraction	`str_extract(string, pattern)`
string replacement	`str_extract(string, pattern, replacement)`
string splitting	`str_split(string, pattern)`

Base R: `grep` `grepl` | `regexpr` `regmatches` | `sub` `gsub` | `strsplit`

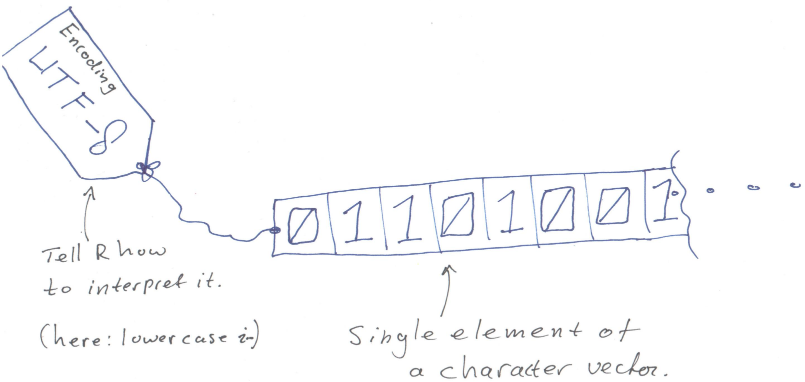
String normalization

Bring a text string in a standard format, e.g.

- Standardize upper/lower case (casefolding)
  - `stringr`: `str_to_lower`, `str_to_upper`, `str_to_title`
  - `base R`: `tolower`, `toupper`
- Remove accents (transliteration)
  - `stringi`: `stri_trans_general`
  - `base R`: `iconv`
- Re-encoding
  - `stringi`: `stri_encode`
  - `base R`: `iconv`
- Uniformize encoding (unicode normalization)
  - `stringi`: `stri_trans_nfkc` (and more)

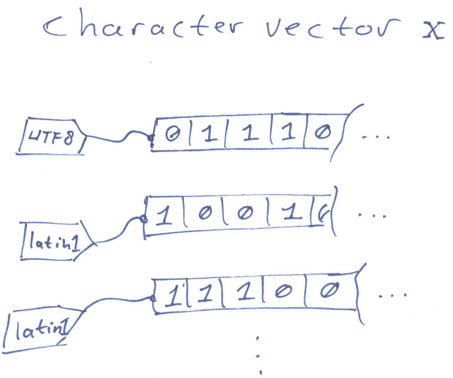
Encoding

Encoding in R



Encoding in R

`Encoding(X) <- "UTF-8"` only changes the labels, not the data



Use iconv() to change the encoding.

Encoding in R

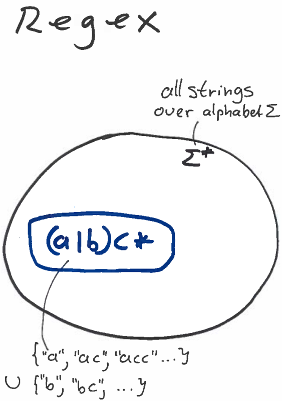
Demo

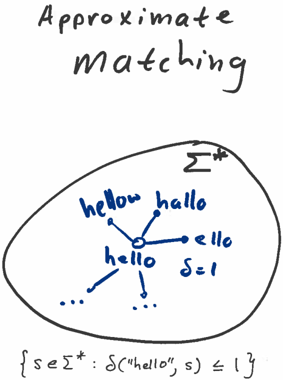
Normalization, re-encoding, transliteration: `/strings`

A few tips

Detect encoding	`stringi::stri_enc_detect`
Conversion options	`iconvlist()` `stringi::stri_enc_list()`

Approximate text matching





Approximate text matching

Demo

Approximate matching and normalization: `/matching`

Approximate text matching: edit-based distances

	Allowed operation			
Distance	substitution	deletion	insertion	transposition
Hamming	✔	✖	✖	✖
LCS	✖	✔	✔	✖
Levenshtein	✔	✔	✔	✖
OSA	✔	✔	✔	✔*
Damerau-Levenshtein	✔	✔	✔	✔

*Substrings may be edited only once.

"leela" → "leea" → "leia"

```
stringdist::stringdist("leela","leia",method="dl")
```

```
## [1] 2
```

Some pointers for approximate matching

- Normalisation and approximate matching are complementary
- See my useR2014 talk or paper on stringdist for more distances
- The fuzzyjoin package allows fuzzy joining of datasets

Other good stuff

- lubridate: extract dates from strings

```
lubridate::dmy("17 December 2015")
```

```
## [1] "2015-12-17"
```

- tidyr: many data cleaning operations to make your life easier
- readr: Parse numbers from text strings

```
readr::parse_number(c("2%","6%","0.3%"))
```

```
## [1] 2.0 6.0 0.3
```

From technically correct to consistent data

The mantra of data cleaning

- Detection (data conflicts with domain knowledge)
- Selection (find the value(s) that cause the violation)
- Correction (replace them with better values)

Detection, AKA data validation

Informally:

Data Validation is checking data against (multivariate) expectations about a data set.

Validation rules

Often these expectations can be expressed as a set of simple *validation rules*.

Data validation

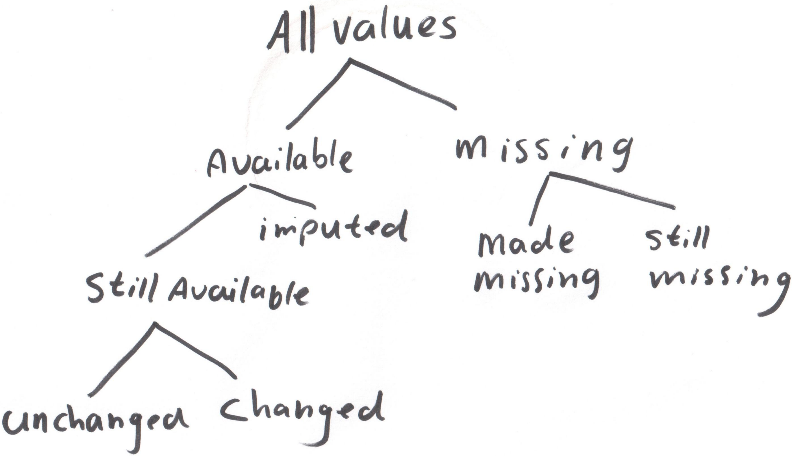
Demo

The `validate` package `/validate`

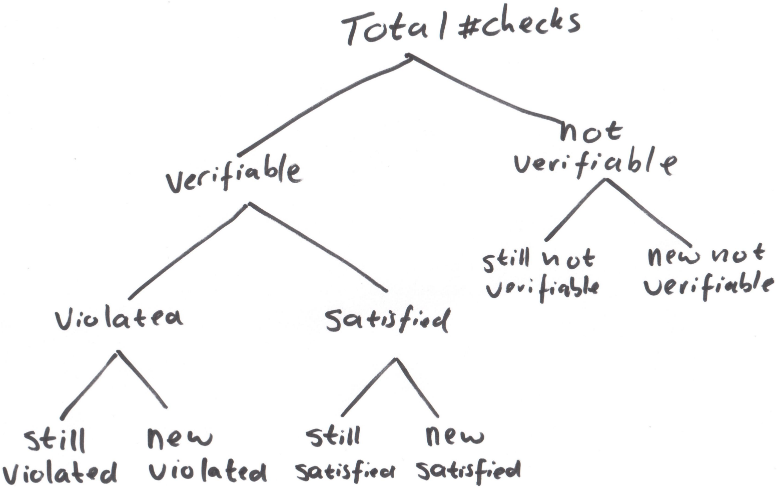
The `validate` package, in summary

- Make data validation rules explicit
- Treat them as objects of computation
  - store to / read from file
  - manipulate
  - annotate
- Confront data with rules
- Analyze/visualize the results

Tracking changes when altering data



Tracking changes in rule violations



Use rules to correct data

Main idea

Rules restrict the data. Sometimes this is enough to derive a correct value uniquely.

Examples

- Correct typos in values under linear restrictions
  - $123 + 45 \neq 177$, but $123 + \underline{54} = 177$.
- Derive imputations from values under linear restrictions
  - $123 + \texttt{NA} = 177$, compute $177 - 123 = 54$.

Both can be generalized to systems $\mathbf{Ax} \leq \mathbf{b}$.

Deductive correction and imputation

Demo

The `deductive` package: `/deductive`.

Selection, or: error localization

Fellegi and Holt (1976)

Find the least (weighted) number of fields that can be imputed such that all rules can be satisfied.

Note

- Solutions need not be unique.
- Random one chosen in case of degeneracy.
- Lowest weight need not guarantee smallest number of altered variables.

Error localization

Demo

The **`errorlocate`** package: `/errorlocate`

Notes on `errorlocate`

- For in-record rules
- Support for
  - linear (in)equality rules
  - Conditionals on categorical variables (if male then not pregnant)
  - Mixed conditionals (has job then age $>= 15$)
  - Conditionals w/linear predicates (staff > 0 then staff cost > 0)
- Optimization is mapped to MIP problem.

Missing values

Mechanisms (Rubin):

- **MCAR**: missing completely at random
- **MAR**: $P(Y = \texttt{NA})$ depends on value of X
- **MNAR**: $P(Y = \texttt{NA})$ depends on value of Y

Imputation

Purpose of imputation vs prediction

- Prediction: estimate a single value (often for a single use)
- Imputation: estimate values such that the completed data set allows for valid inference[a]

[a] This is very difficult!

Imputation methods

- Deductive imputation
- Imputation based on predictive models
- Donor imputation (knn, pmm, sequential/random hot deck)

Predictive model-based imputation

$$\hat{y} = \hat{f}(\boldsymbol{x}) + \epsilon$$

e.g.Linear regression

$$\hat{y} = \alpha + \boldsymbol{x}^T\hat{\beta} + \epsilon$$

- Residual:
  - $\epsilon = 0$ Impute expected value
  - ϵ drawn from observed residuals e
  - $\epsilon \sim N(0,\sigma)$ parametric residual, $\hat{\sigma}^2 = \mathrm{var}(e)$
- Multiple imputation (Bayesian bootstrap)
  - Draw β from parametric distribution, impute multiple times.

Donor imputation (hot deck)

Method variants:

- **Random hot deck:** copy value from random record.
- **Sequential hot deck:** copy value from previous record.
- *k*-**nearest neighbours:** draw donor from *k* neares neigbours
- **Predictive mean matching:** copy value closest to prediction

Donor pool variants:

- per variable
- per missing data pattern
- per record

Note on multivariate donor imputation

Many multivariate methods seem relatively *ad hoc*, and more theoretical and empirical comparisons with alternative approaches would be of interest.

Andridge and Little (2010) *A Review of Hot Deck Imputation for Survey Non-response*. Int. Stat. Rev. **78**(1) 40–64

Demo time

Demo

Imputation `/imputation`

- **`VIM`**: visualisation, GUI, extensive methodology
- **`simputation`**: simple, scriptable interface to common methods

Methods supported by `simputation`

- Model based (optionally add [non-]parametric random residual)
  - linear regression
  - robust linear regression
  - CART models
  - Random forest
- Donor imputation (including various donor pool specifications)
  - k-nearest neigbour (based on gower's distance)
  - sequential hotdeck (LOCF, NOCB)
  - random hotdeck
  - Predictive mean matching
- Other
  - (groupwise) median imputation (optional random residual)
  - Proxy imputation (copy from other variable)

Credits

- `deductive` Mark van der Loo, Edwin de Jonge
- `errorlocate` Edwin de Jonge, Mark van der Loo
- `gower` Mark van der Loo
- `jsonlite` Jeroen Ooms, Duncan Temple Lang, Lloyd Hilaiel
- `magrittr` Stefan Milton Bache, Hadley Wickham
- `rex` Kevin Ushey Jim Hester, Robert Krzyzanowski
- `simputation` Mark van der Loo
- `stringdist` Mark van der Loo, Jan van der Laan, R Core, Nick Logan
- `stringi` Marek Gagolewski, Bartek Tartanus
- `stringr` Hadley Wickham, RStudio
- `tidyr` Hadley Wickham, RStudio
- `validate` Mark van der Loo, Edwin de Jonge
- `VIM` Matthias Templ, Andreas Alfons, Alexander Kowarik, Bernd Prantner
- `xml2` Hadley Wickham, Jim Hester, Jeroen Ooms, RStudio, R foundation