

# Data analysis for benchmarking combinatorial solvers with R.

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# Tools and Libraries

- ▶ R — programming language for data science
- ▶ RStudio — IDE for R (<https://www.rstudio.com/>)
- ▶ RNotebook — Feature of RStudio allowing to interleave text, R and resulting plots / tables
- ▶ tidyverse (<https://www.tidyverse.org/>)
  - ▶ ggplot2 — library for plotting
  - ▶ dplyr — library for data manipulation

# What to Measure and Store

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- ▶ running time (wall clock system-time and user-time)
- ▶ memory usage
- ▶ how often did X happen
- ▶ proof size (number of steps file size)
- ▶ hash of input file
- ▶ computer name
- ▶ current date and time
- ▶ return code
- ▶ solver name
- ▶ instance name
- ▶ path of instance file
- ▶ instance category
- ▶ instance scaling parameter
- ▶ solver parameters
- ▶ used timeout
- ▶ ...

## Storing and Importing Data — Best Practice

- ▶ use standard machine readable formats (CSV, SQLite)
- ▶ following standards saves manual work for import  
(CSV = **comma** separated file, no space after commas, etc.)
- ▶ include table headers (avoid ' ', '-', and special characters)
- ▶ compress files individually ('.csv.gz' instead of '.zip')
- ▶ store information about used units (ms / s, byte / KB / MB, etc.)
- ▶ if CSV import takes long, use R's own format for local use
- ▶ less files are easier to handle  
(usually first normal form sufficient, for our use case)

# Data Transformation

my favourite operations:

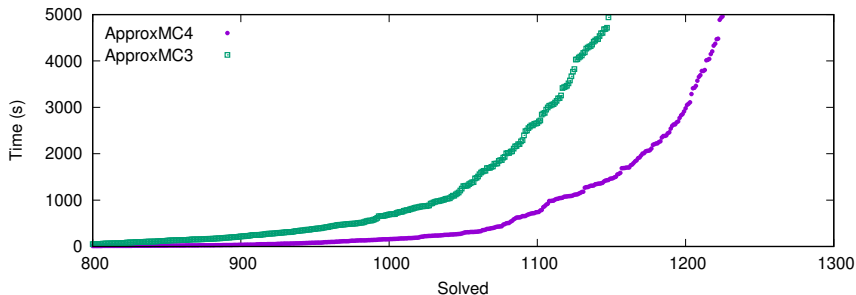
- ▶ `filter` — filters data
- ▶ `mutate` — change or create columns
- ▶ `arrange` — sort data
- ▶ `group_by` — group data for use with summarise
- ▶ `summarise` — collect statistics of grouped data
- ▶ `join` — combine columns of two tables
- ▶ `bind_rows` — append rows of to tables
- ▶ `pivot_wider` — create columns by removing rows
- ▶ `pivot_longer` — create rows by removing columns
- ▶ `distinct` — remove duplicate rows

cheat sheets: <https://www.rstudio.com/resources/cheatsheets/>

# Tables

- ▶ easy way to show small number of data points
- ▶ usually used for accumulated data  
(number of time outs, speed-up, min, max, median, mean, quantiles)
- ▶ create table in R, export to latex, don't touch afterwards  
`print(xtable(dataframe, type = "latex"), file = "tabel.tex")`

# Cactus Plot / Cumulative Plot

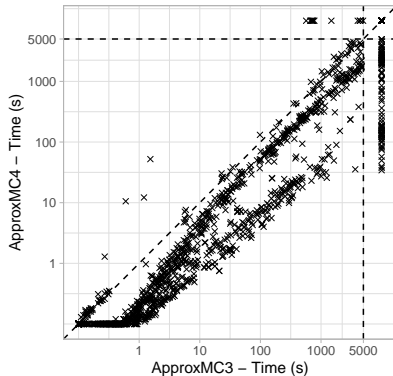


- ▶ used to compare many different algorithms / solvers
- ▶ shows number of solved instances at different timeouts
- ▶ pitfall: suggests that one solver is always better than other (usually not true)

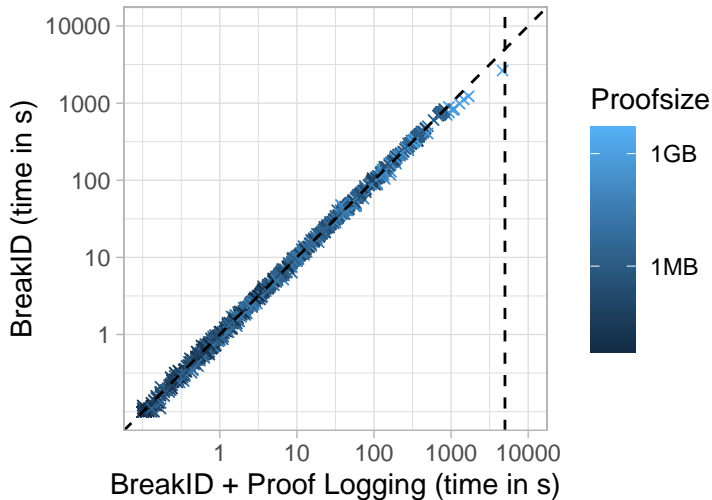


# Scatter Plot

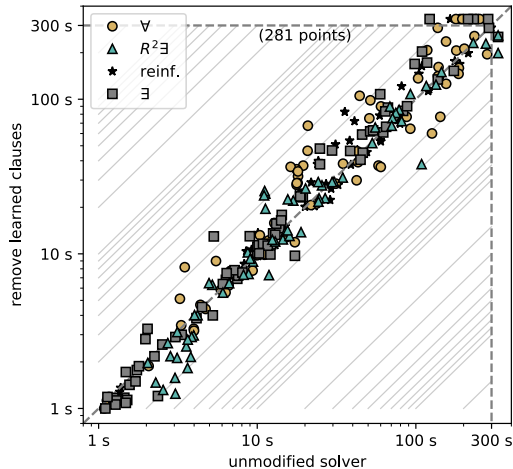
- ▶ used to compare two algorithms / solvers
- ▶ use log-log plot with 1:1 ratio
- ▶ can add points for timeout / error
- ▶ allows to see speed-up
- ▶ pitfall: where are points to be better?
- ▶ pitfall: difficult to see how many points are in point cloud



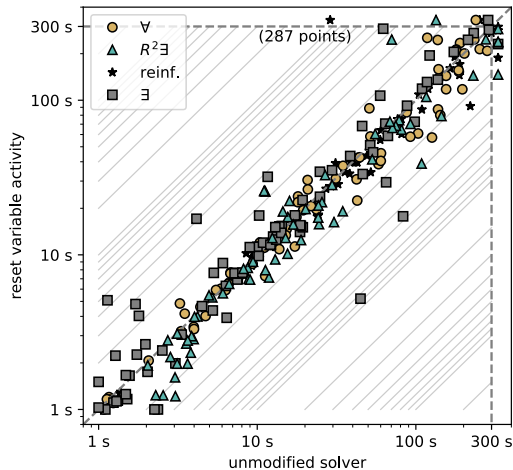
## Scatter Plot — Variation in Running Time



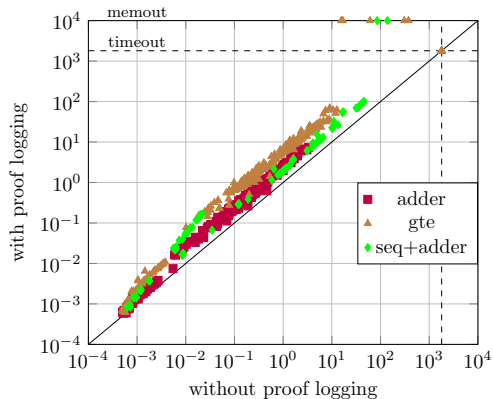
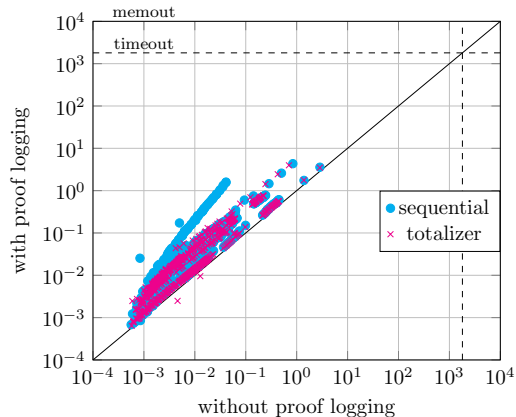
# Scatter Plot — Solvers as Chaotic System (1)



## Scatter Plot — Solvers as Chaotic System (2)



# Scatter Plot — Overhead



# Empirical Asymptotic Scaling – Basics

from theory: this algorithm runs in time  $O(n^2)$

⇒ can we empirically evaluate asymptotic behaviour?

problems:

- ▶ humans bad at judging curves
- ▶ polynomial with high enough degree will fit everything

assumptions:

- ▶  $f(n) = an^b + g(n)$
- ▶  $g(n) \ll an^b$

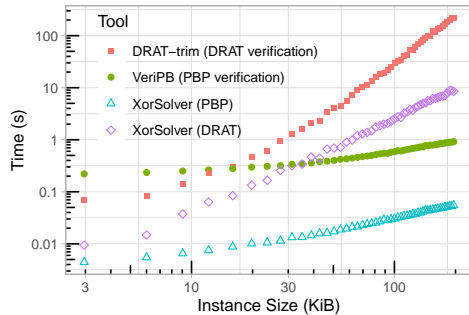
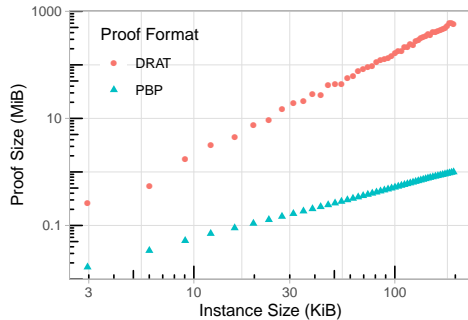
idea:

- ▶ plot  $y = \log(f(n))$  against  $x = \log(n)$
- ▶  $\log(f(n)) \approx \log(an^b) = \log(a) + b \log(n)$
- ▶ ⇒ we should see a straight line ( $y \approx \log(a) + bx$ )

# Empirical Asymptotic Scaling – Challenges

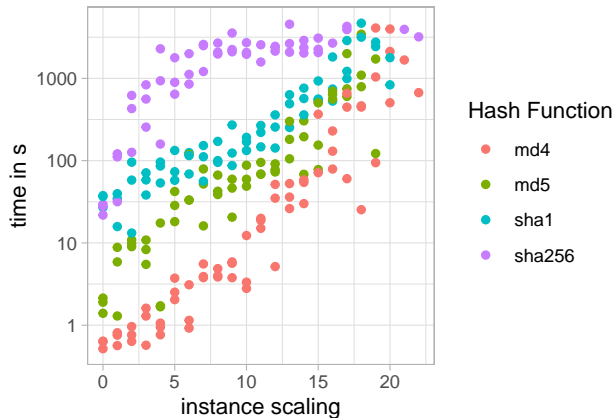
- ▶ need  $g(n) \ll an^b$ , is chosen  $n$  large enough?  
 $f(n) = n + 0.1^{1'000'000} n^2$
- ▶ running time jumps when exceeding CPU cache limits  
 $f(n) = n^2$  if  $n > 512$  else  $0.1n^2$
- ▶ data can be “noisy”  
 $f(n) = \varepsilon(n) \cdot n^2$
- ▶ choice of scaling parameter  
e.g.: number of variables, number of clauses, file size
  
- ▶ can't **proof** asymptotic behaviour, only says what scaling is plausible
- ▶ can highlight problems in implementation (expected  $n^2$  but got  $n^3$ )
- ▶ might show data **not** meeting assumptions (e.g.  $f(n) = 2^n$ )

# Empirical Asymptotic Scaling – Polynomial Example





# Empirical Asymptotic Scaling – Exponential Example



# Box-plot

- ▶ used to visualize variation
- ▶ box ranges between quantiles, bold line is median, whiskers not standardized (1.5 IQR, all data points), points beyond whiskers are called outliers

