

# **Unraveling uncertainty in benchmarking: Methods and open-source toolkit for analyzing and visualizing challenge results**

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Joint work with

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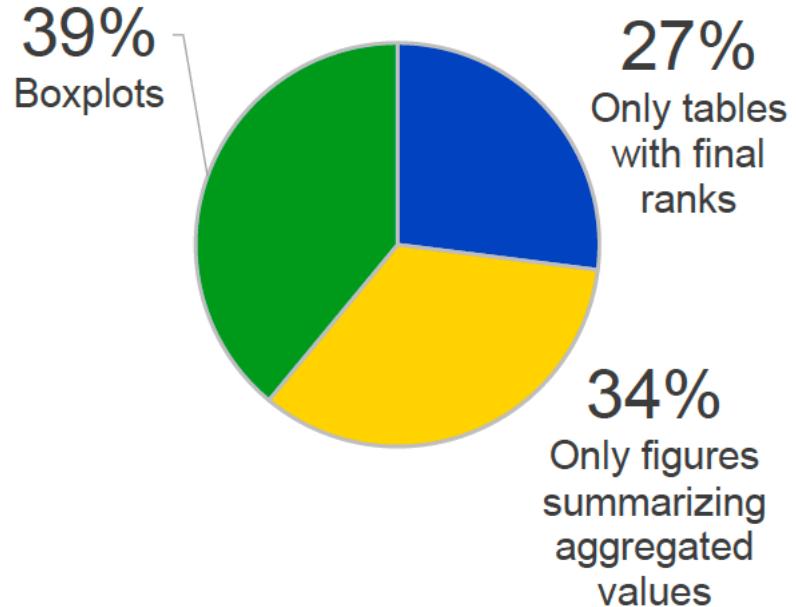
Data science seminar, Heidelberg, 11/06/2019

## Background

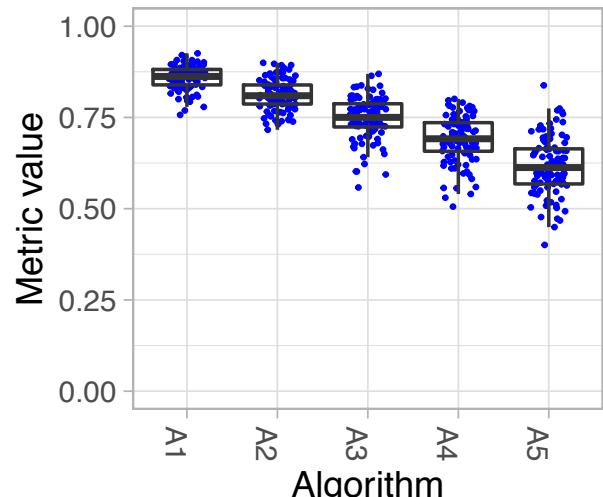
- *Grand challenges* as standard for validation of biomedical image analysis methods in a comparative manner
- Challenges compared to clinical trials
- Lack of common standards in design, analysis and reporting  
(Maier-Hein et al. *Nature Commun.* 2018)

## Common presentation of results

In 83 challenges analyzed in Maier-Hein et al. Nature Commun. 2018:

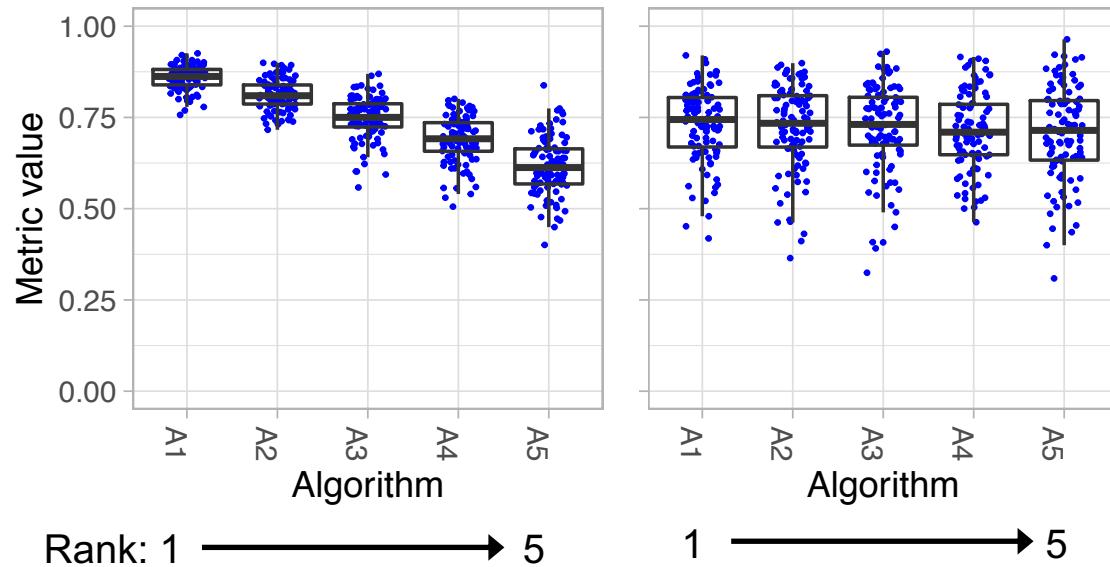


## Motivation: Why ranking lists are not enough

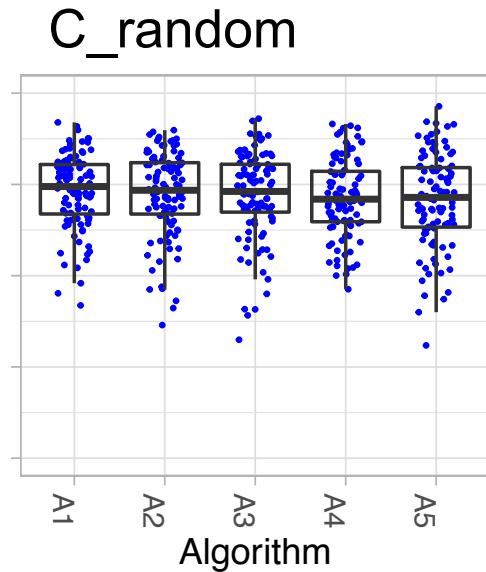
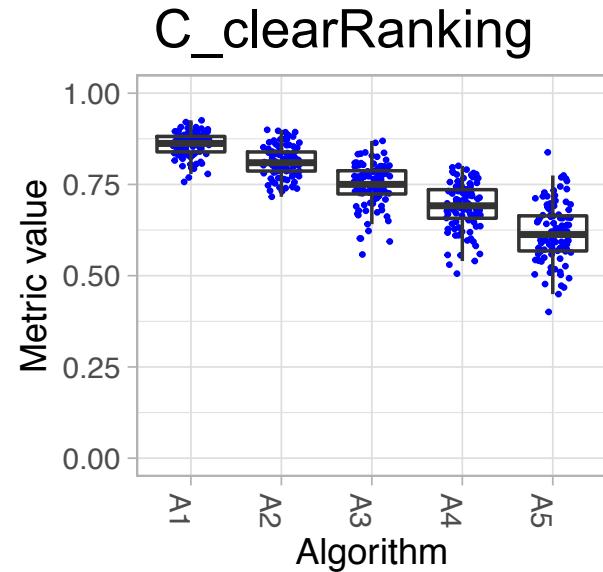


Rank: 1 → 5

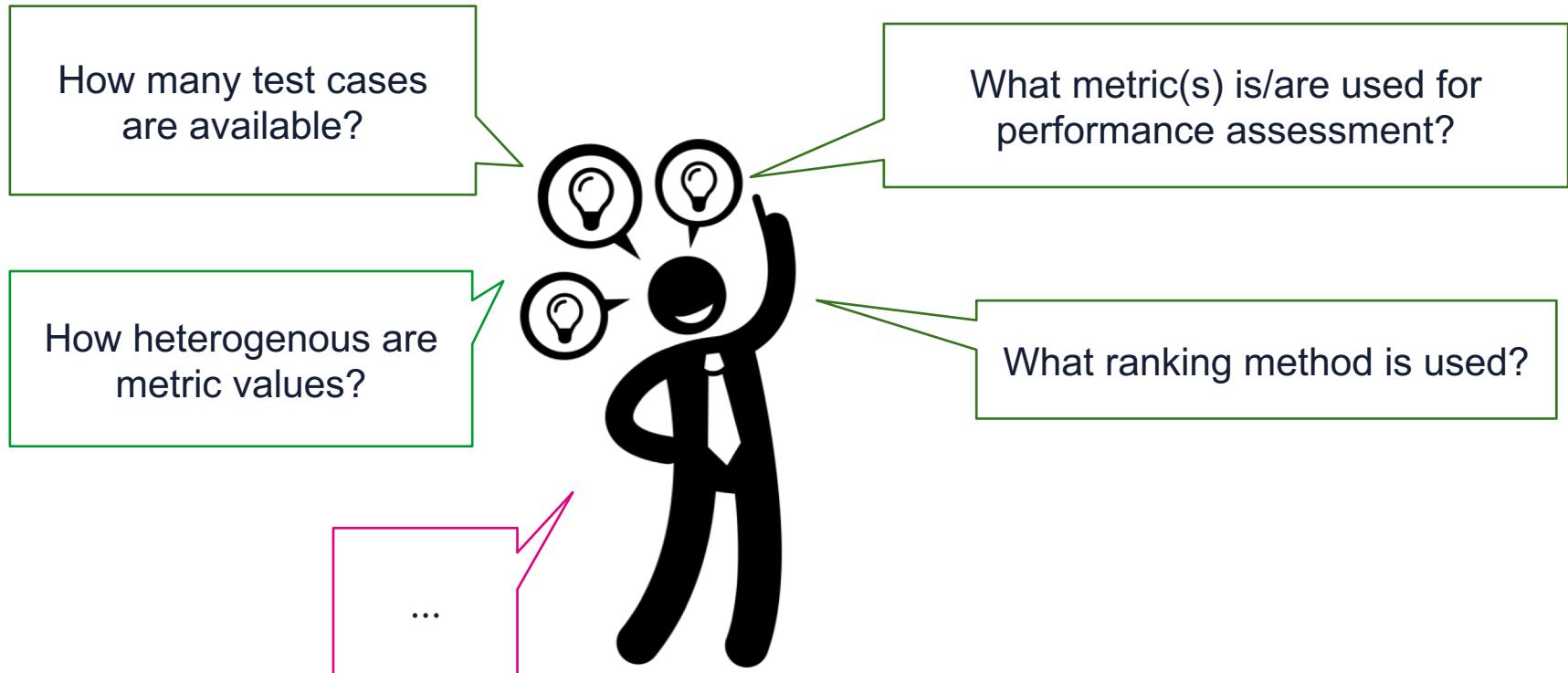
## Motivation: Why ranking lists are not enough



## Motivation: Why ranking lists are not enough



# The ranking in a challenge may be affected by ...



Icon created by the Noun Project

## Contribution

To help challenge organizers and participants gain further insights into algorithms' performances, we ...

- propose methodology for visualizing results of challenges
- provide an open-source analysis and visualization toolkit

## Assessment data for a challenge analysis

Testcase_ID	Algorithm_name	Metric_value	Task_name
85	A1	0.7952	C_random
15	A4	0.6877	C_clearRanking
81	A3	0.7754	C_random
8	A5	0.6948	C_random
82	A2	0.8576	C_clearRanking
19	A2	0.5556	C_random
84	A1	0.5215	C_random

•

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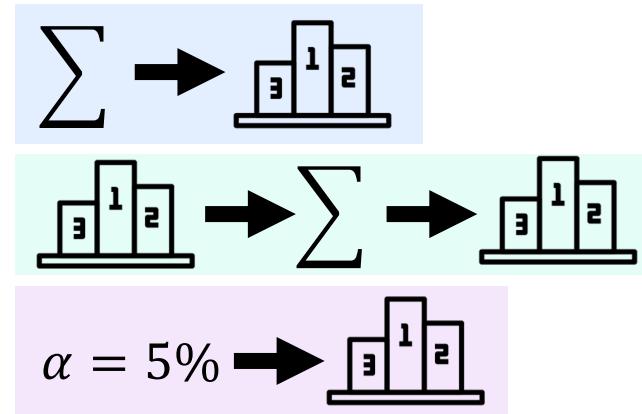
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# Ranking methods

Common methods:

- Aggregate-then-rank
- Rank-then-aggregate
- Test based procedures

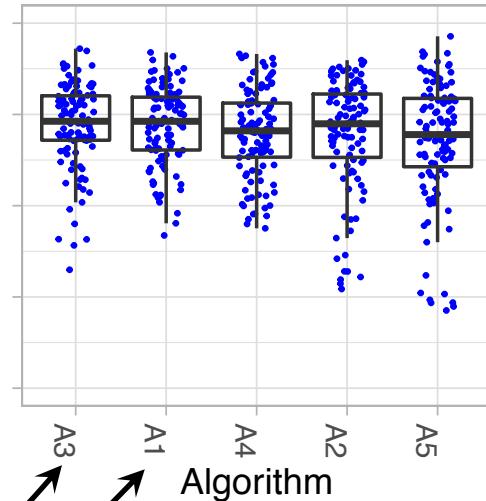
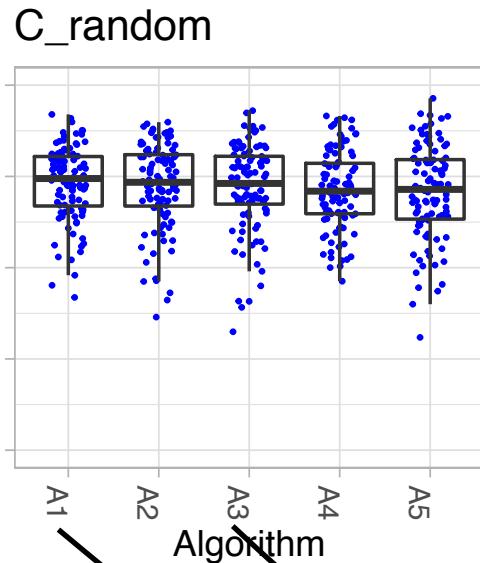
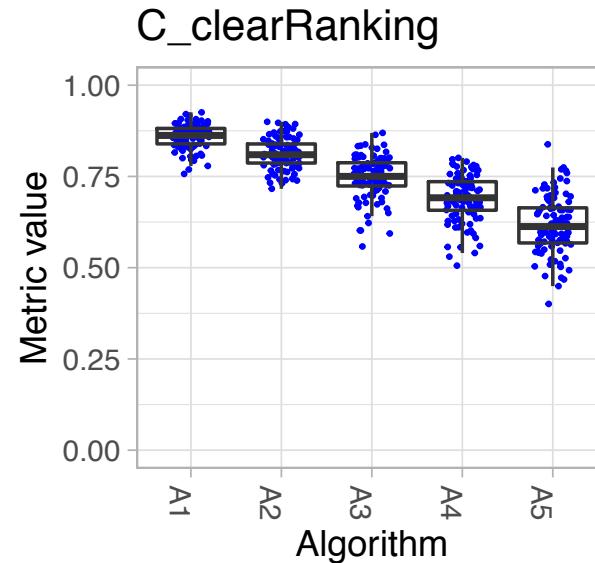


*Different strategies to obtain ranking may lead to different winners*

Maier-Hein et al. *Nature Commun.* 2018; Reinke et al. *MICCAI* 2018; Wiesenfarth et al., *ArXiv* 2019

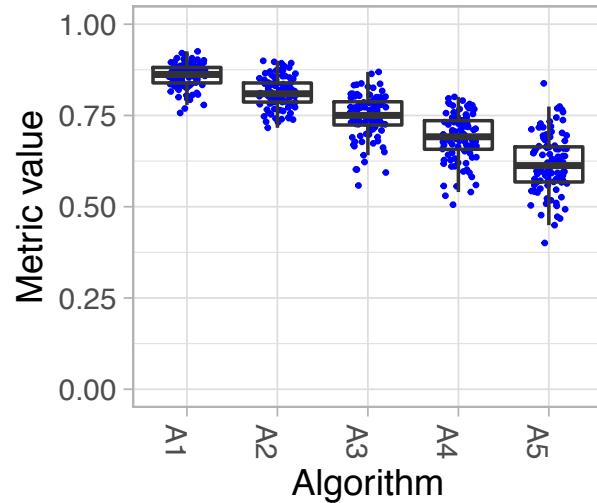
# **Visualization of raw assessment data: Understand distribution of metric values**

## Dot- and boxplot: Distribution of metric values

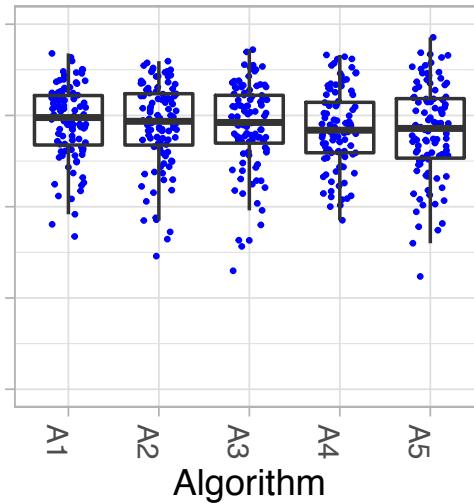


## Dot- and boxplot: Distribution of metric values

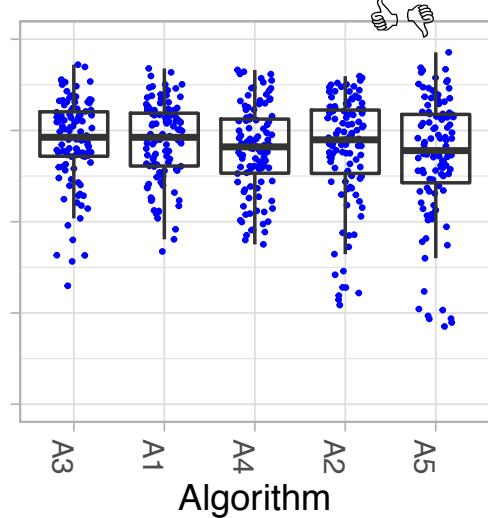
C\_clearRanking



C\_random

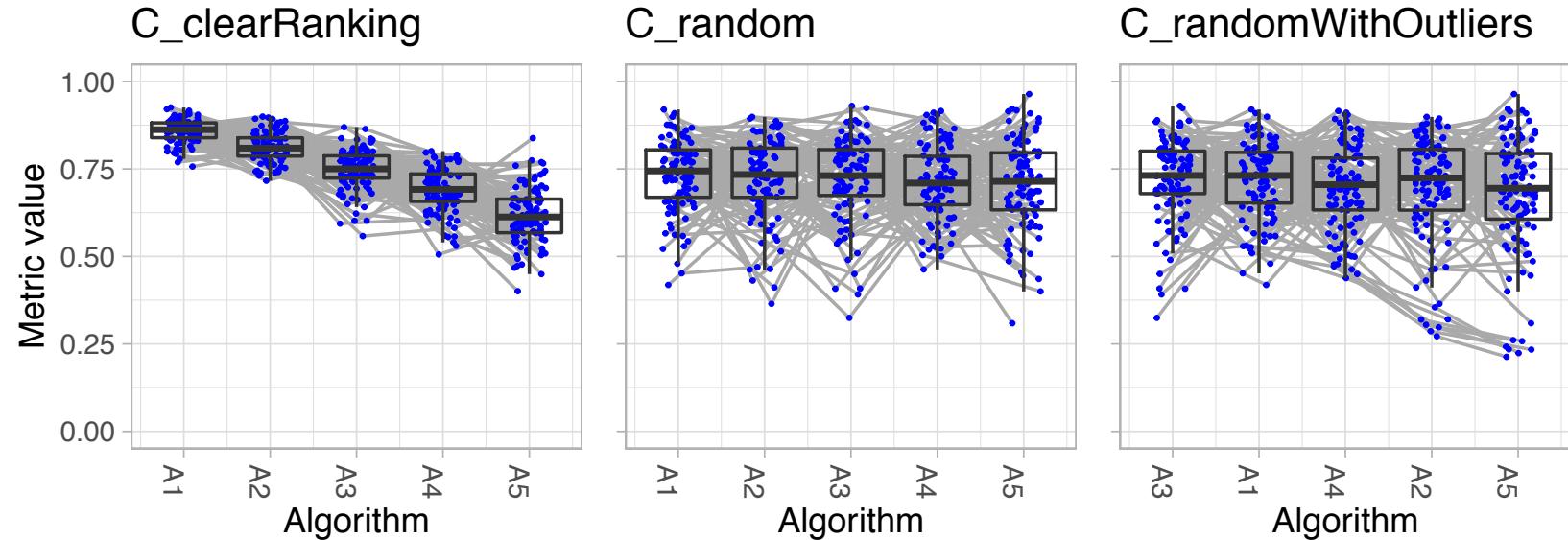


C\_randomWithOutliers



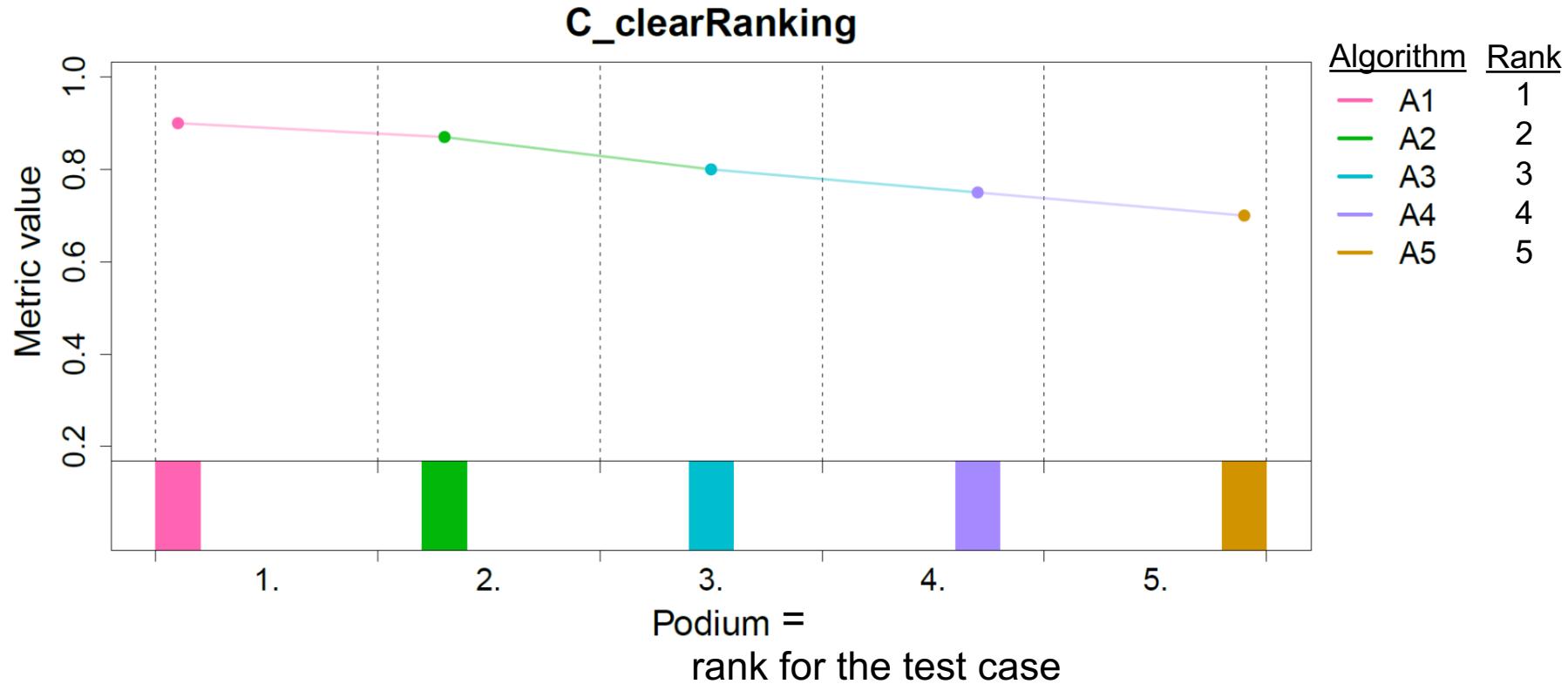
+ Helps identify implausible values / inconsistencies in the data

## Dot- and boxplot: Distribution of metric values

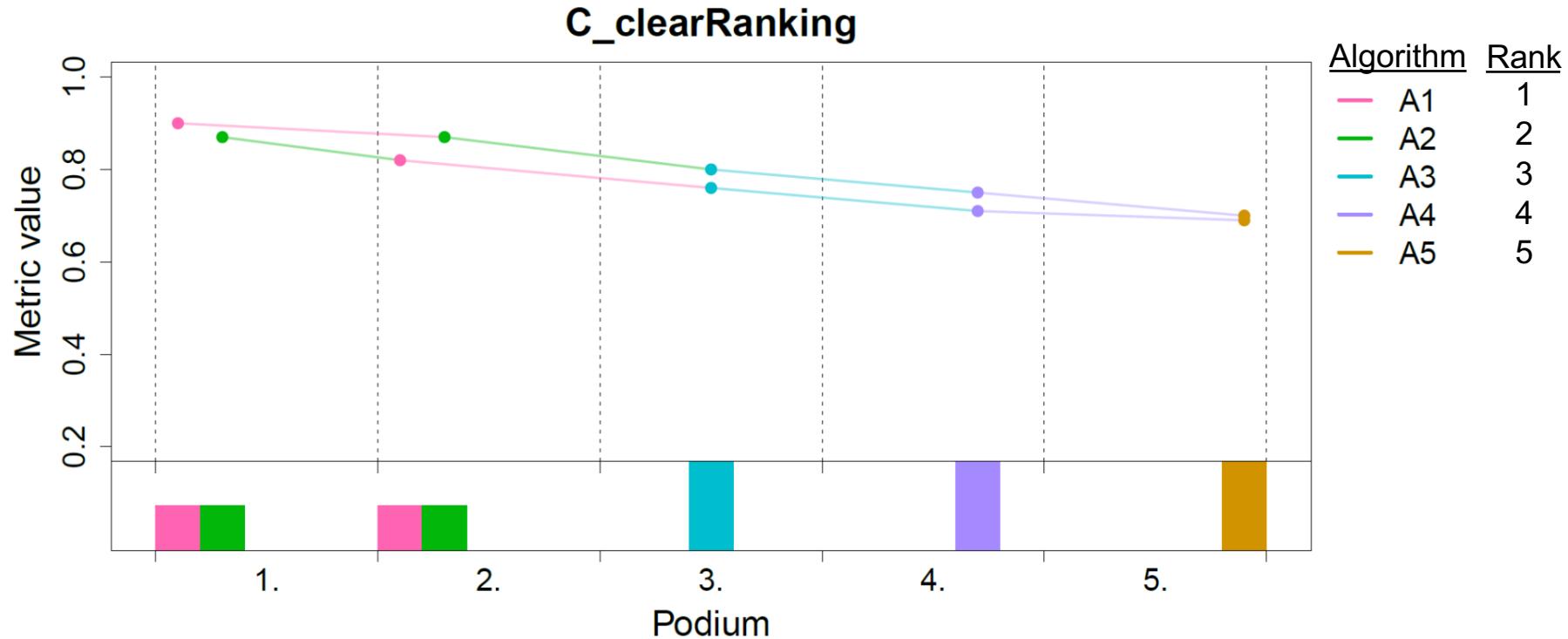


- + Helps identify implausible values / inconsistencies in the data
- Connection of metric values from the same test case?

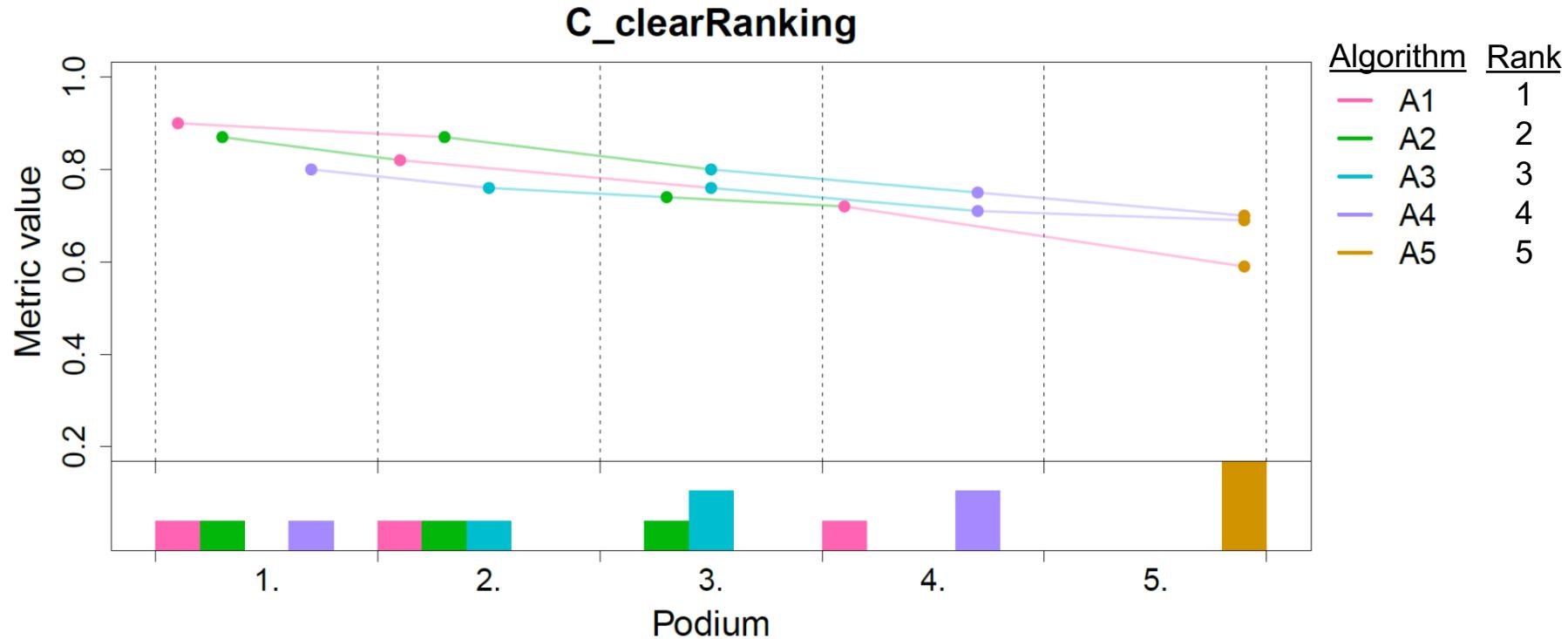
# Podium plot: Combined view of metric values and ranking



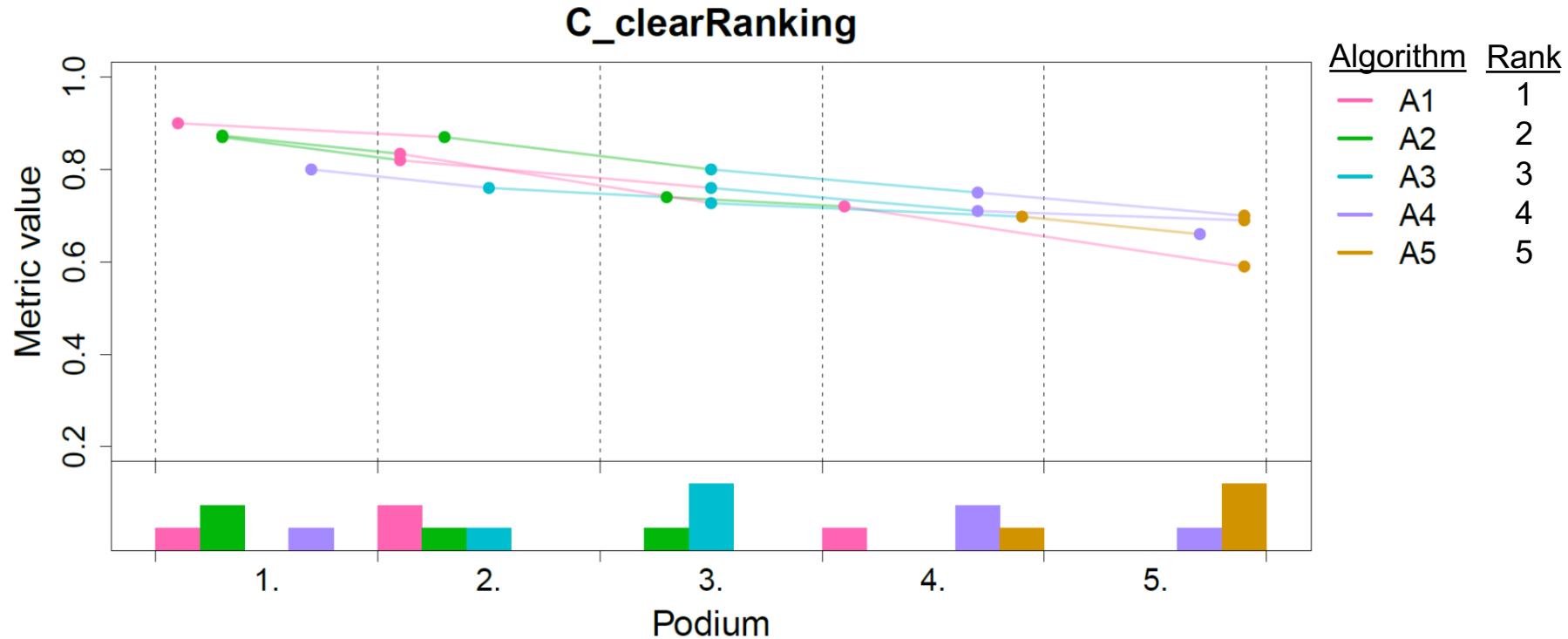
# Podium plot: Combined view of metric values and ranking



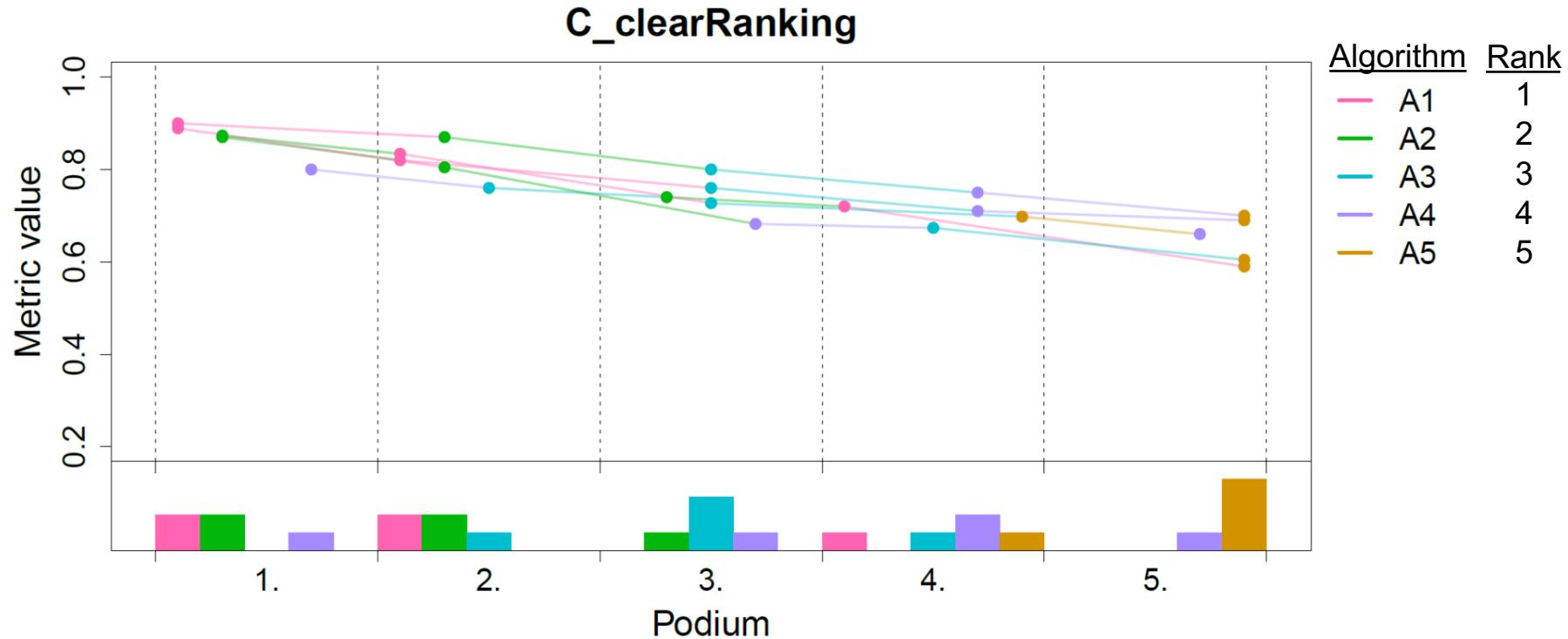
# Podium plot: Combined view of metric values and ranking



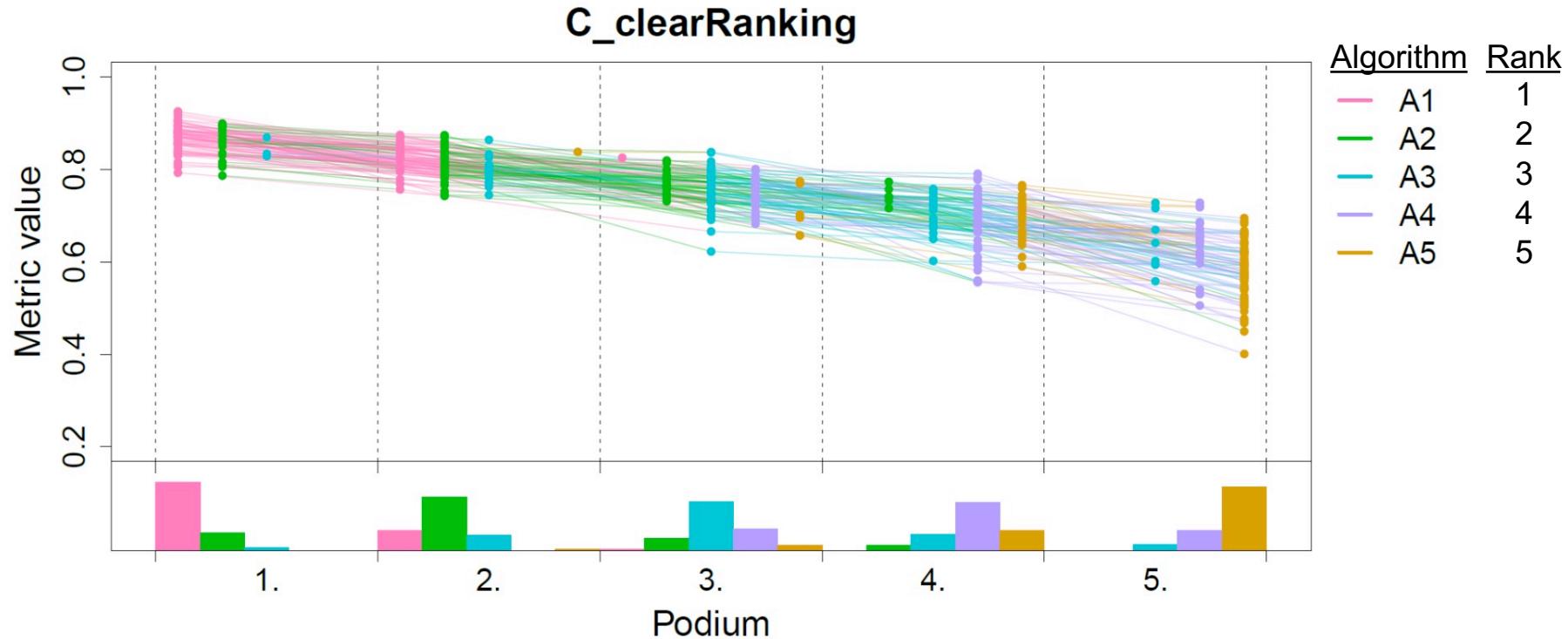
# Podium plot: Combined view of metric values and ranking



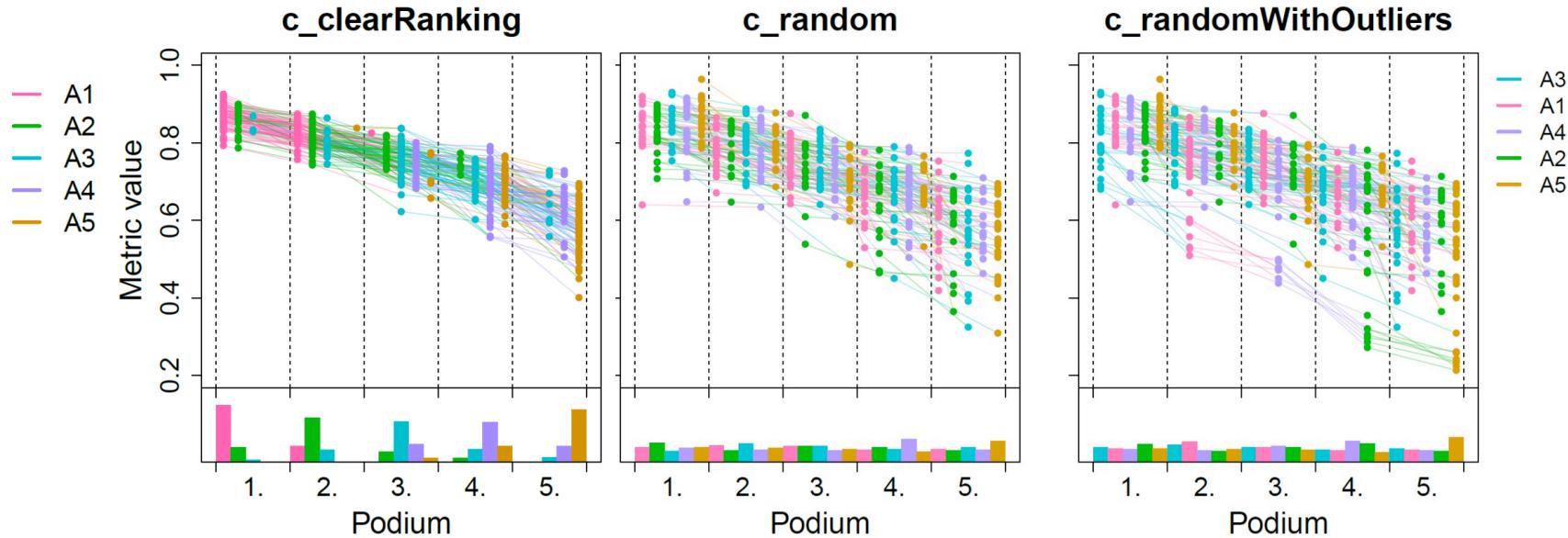
# Podium plot: Combined view of metric values and ranking



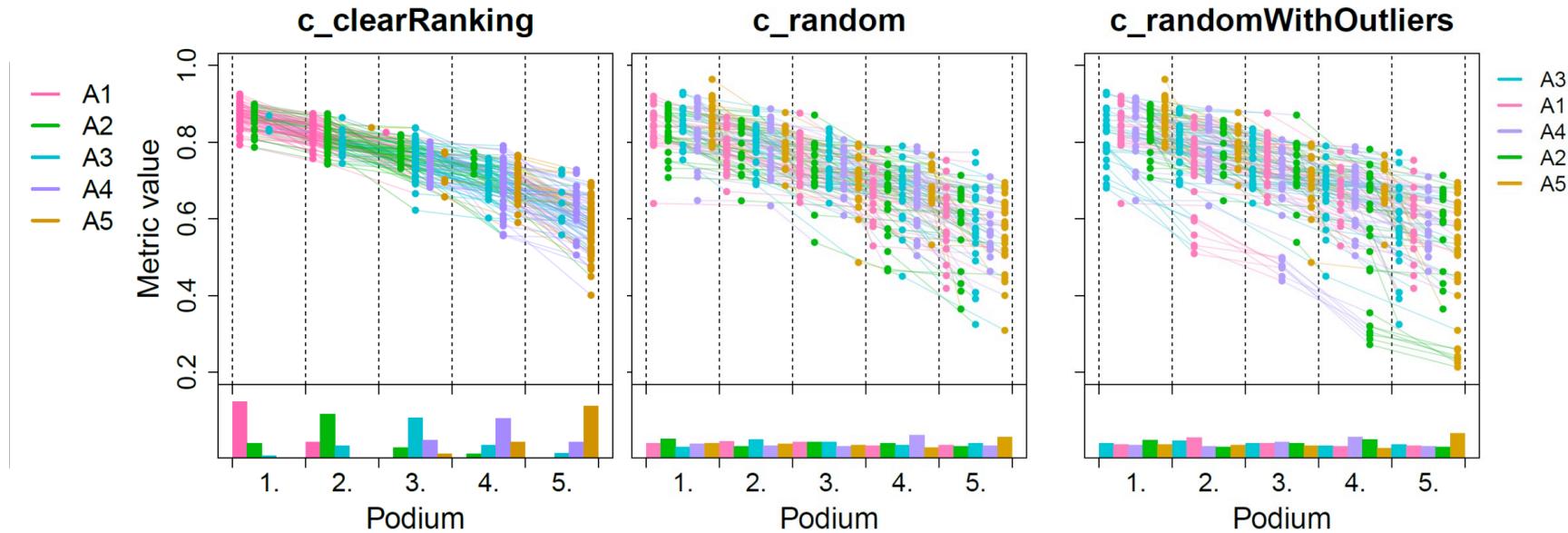
# Podium plot: Combined view of metric values and ranking



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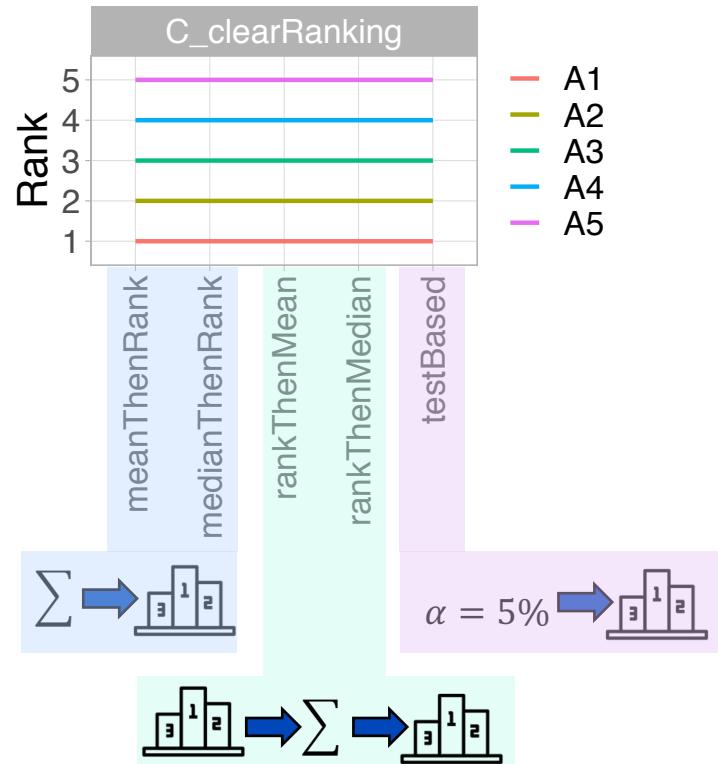
# Podium plot: Combined view of metric values and ranking



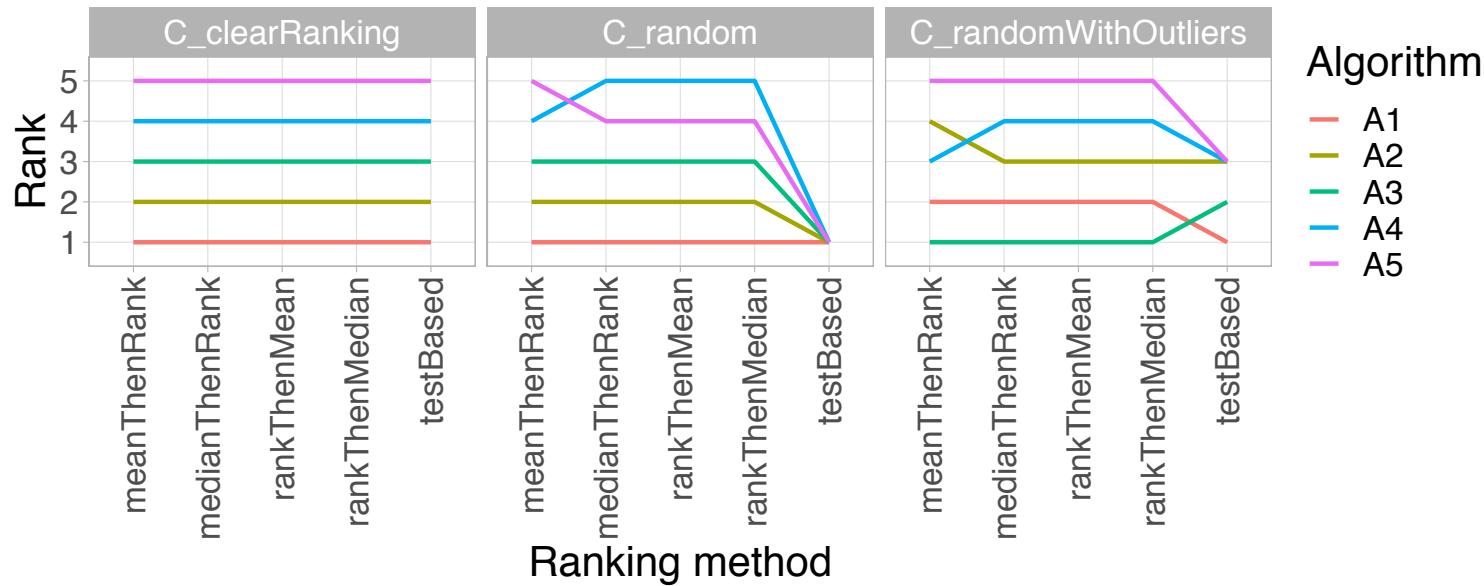
- + Connects metric values from the same test case
- + Allows identification of influential test cases
- Relatively complex

# **Ranking robustness and uncertainty**

# Line plot: Ranking robustness with regard to ranking method



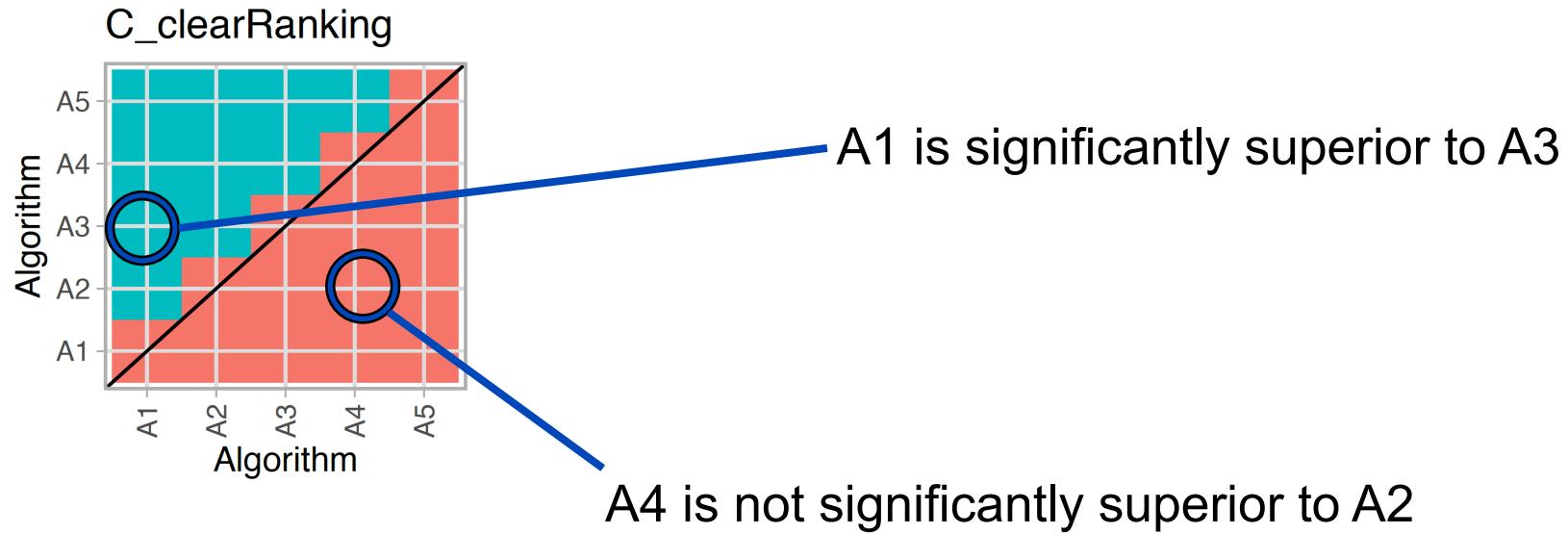
# Line plot: Ranking robustness with regard to ranking method



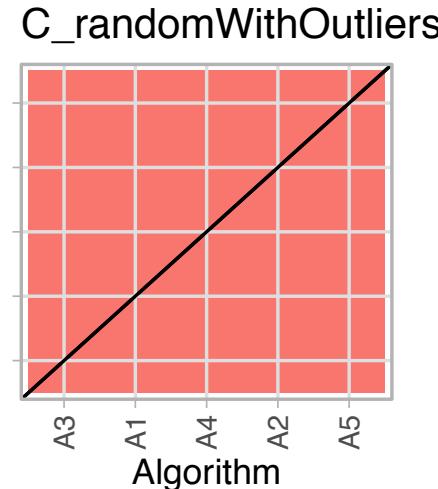
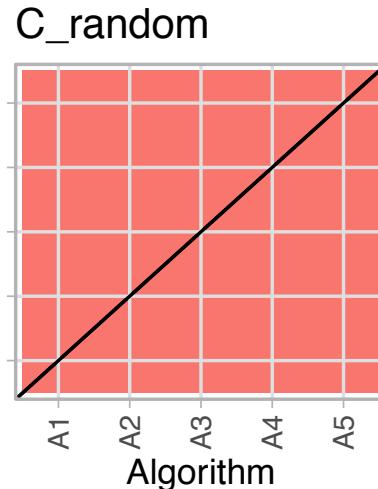
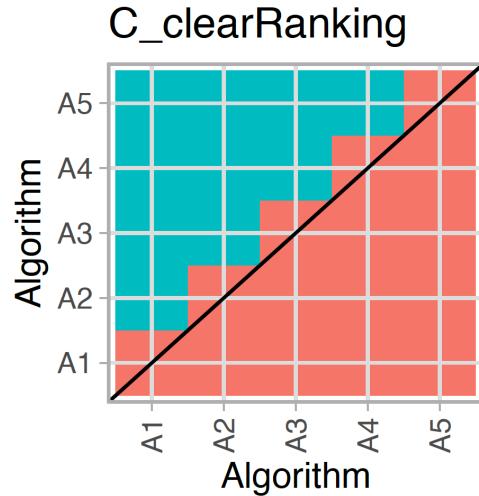
Can be modified to assess robustness with regard to metric, across tasks, ...

## Significance map: Ranking uncertainty using hypothesis tests

*Test cases can be considered as a finite sample from a larger population*



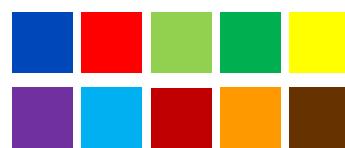
# Significance map: Ranking uncertainty using hypothesis tests



- + Winner significantly superior to others?
- Difference between algorithms relevant?
- Little power to detect differences when # test cases small

# Ranking uncertainty using bootstrapping

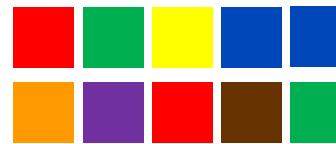
1. Use available data set to generate 1000 bootstrap data sets



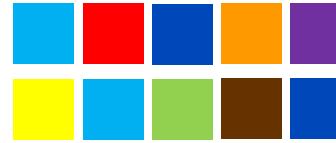
$n$  test cases

resample  
→

$b=1$



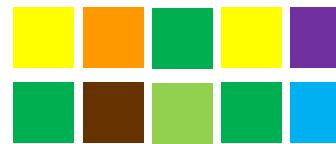
$b=2$



⋮

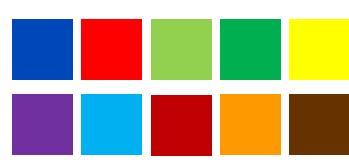
⋮

$b=1000$

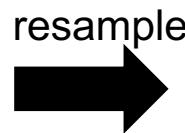


## Ranking uncertainty using bootstrapping

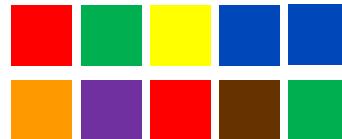
1. Use available data set to generate 1000 bootstrap data sets
2. Perform ranking on each bootstrap data set



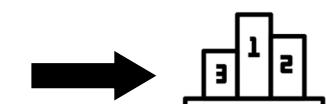
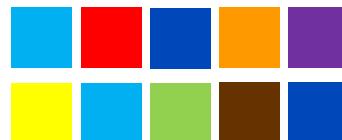
$n$  test cases



$b=1$



$b=2$

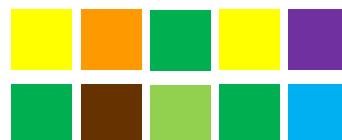


⋮

⋮

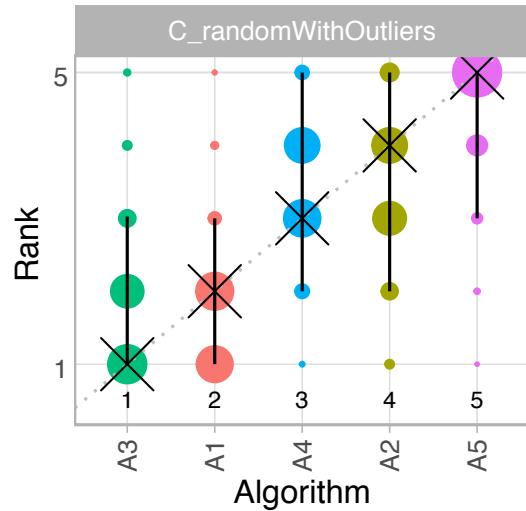
⋮

$b=1000$



## Blob plots: Ranking uncertainty using bootstrapping

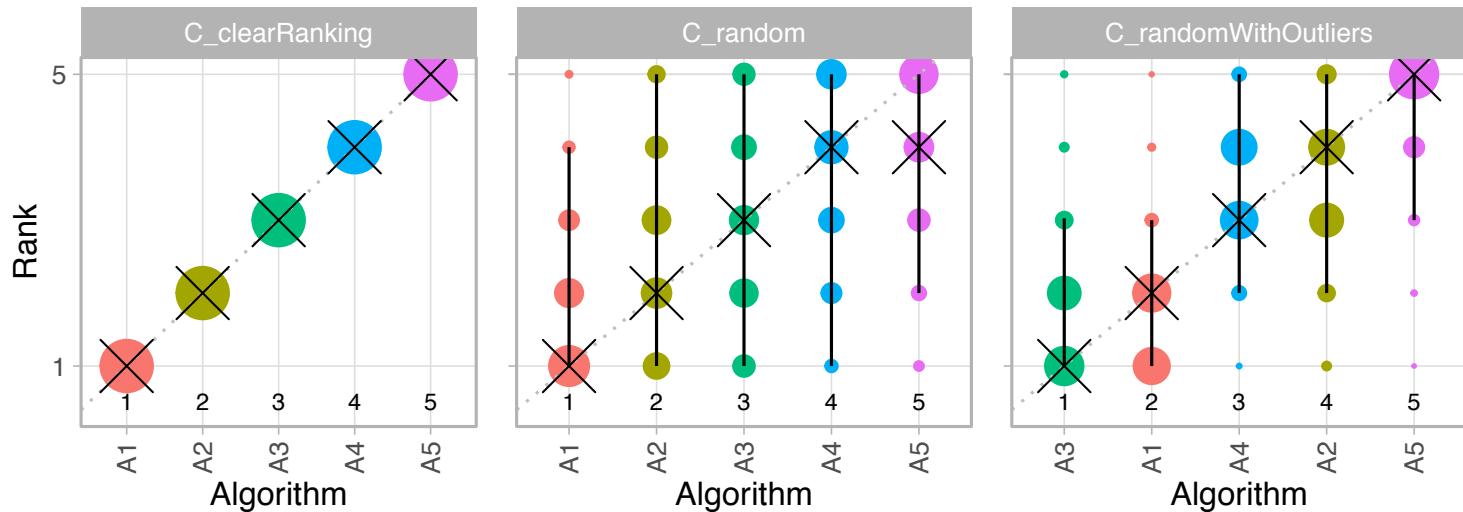
% ● 10 ● 25 ● 50 ● 75 ● 100



+ What range of ranks for each algorithm is supported by the data?

## Blob plots: Ranking uncertainty using bootstrapping

% ● 10 ● 25 ● 50 ● 75 ● 100



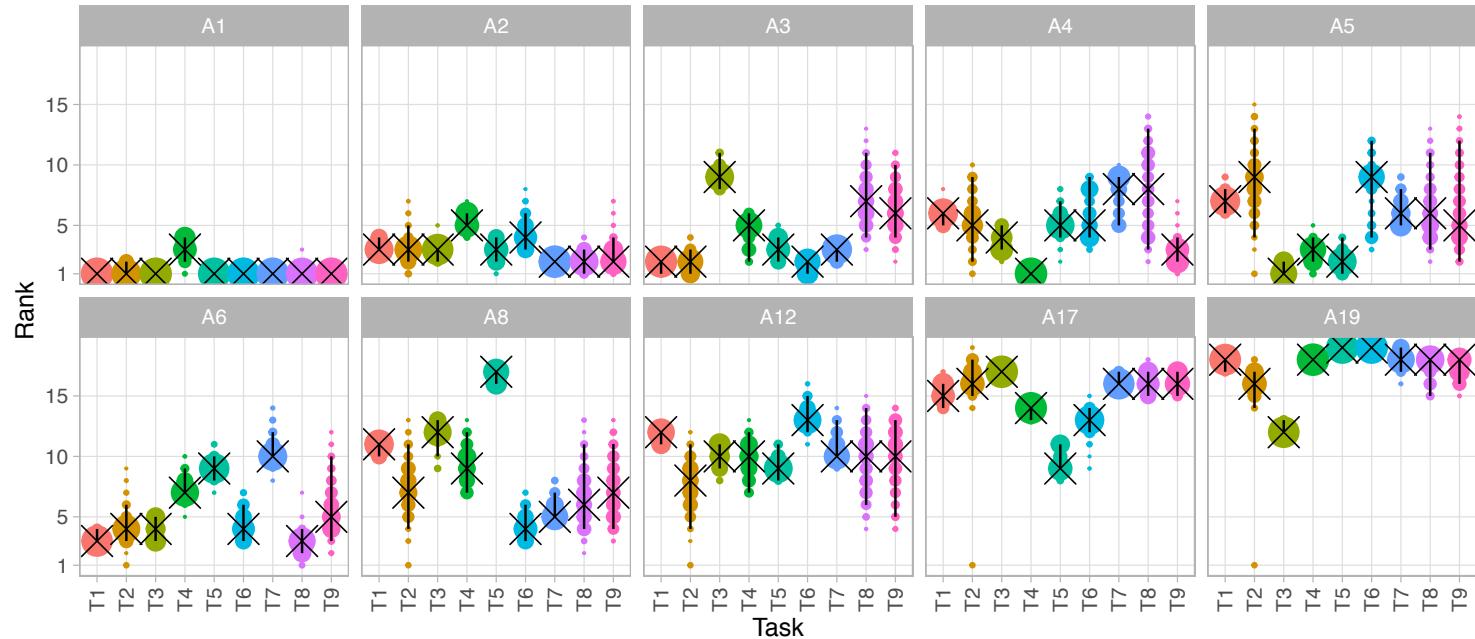
- + What range of ranks for each algorithm is supported by the data?
- Not sensible for very few test cases
- Difference between algorithms relevant?

# **Multi-task challenges**

## Multi-task challenges

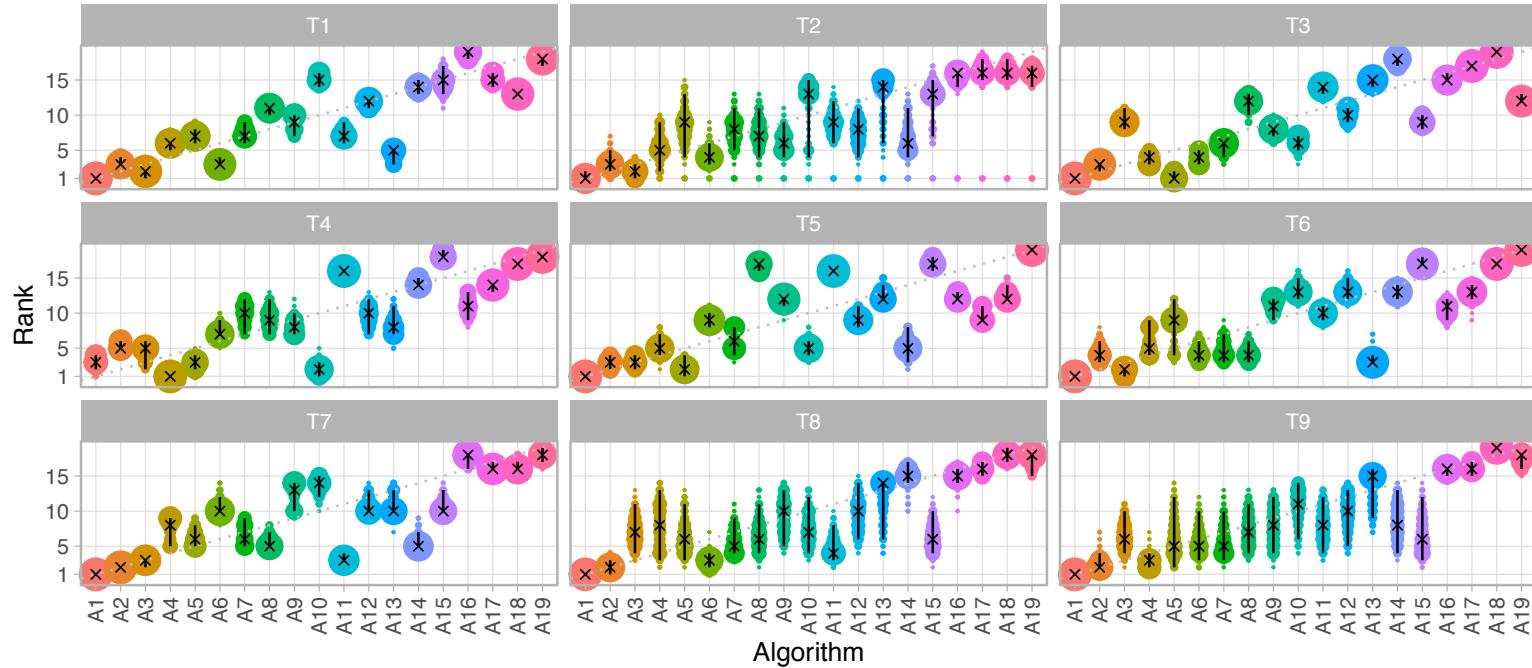
- Allow assessment of ...
  - generalizability of algorithms across tasks
  - which task yields clear separation of algorithms
  - similarity of tasks with regard to rankings
  - ...
- For illustration:
  - Subset of algorithms and tasks of *Medical Segmentation Decathlon* (2018)
  - Anonymized algorithms  $A_i$ , anonymized tasks T1-T9

## Blob plot stratified by algorithm



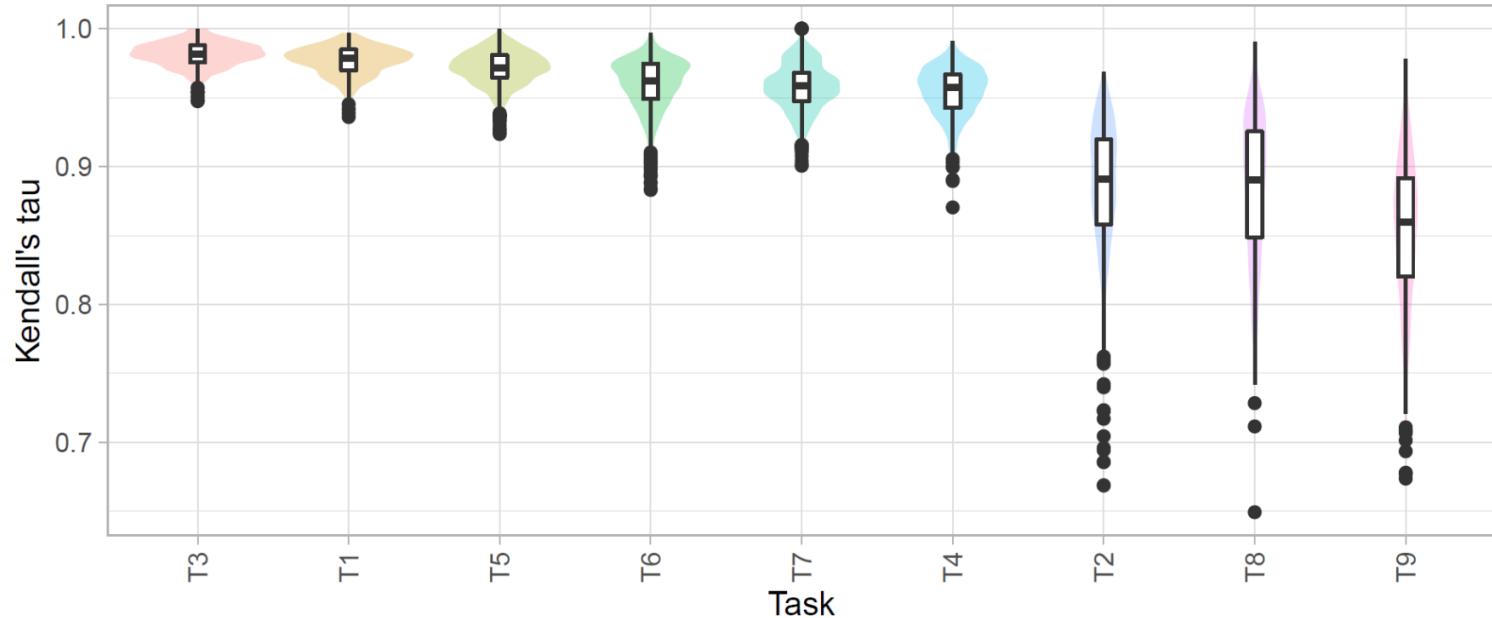
- + What range of ranks is supported by the data within and across tasks?
- + In which task does algorithm rank favorably or unfavorably?

## Blob plot stratified by task



+ Which task yields clear separation of algorithms?

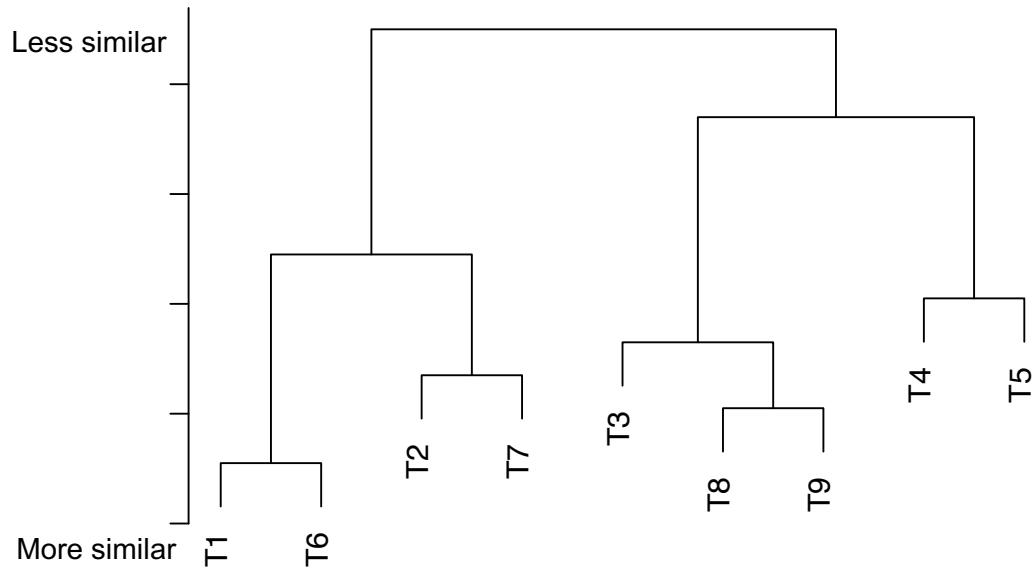
## Violin plot: Overall ranking stability of a task



+ Compares ranking stability of entire ranking lists across tasks

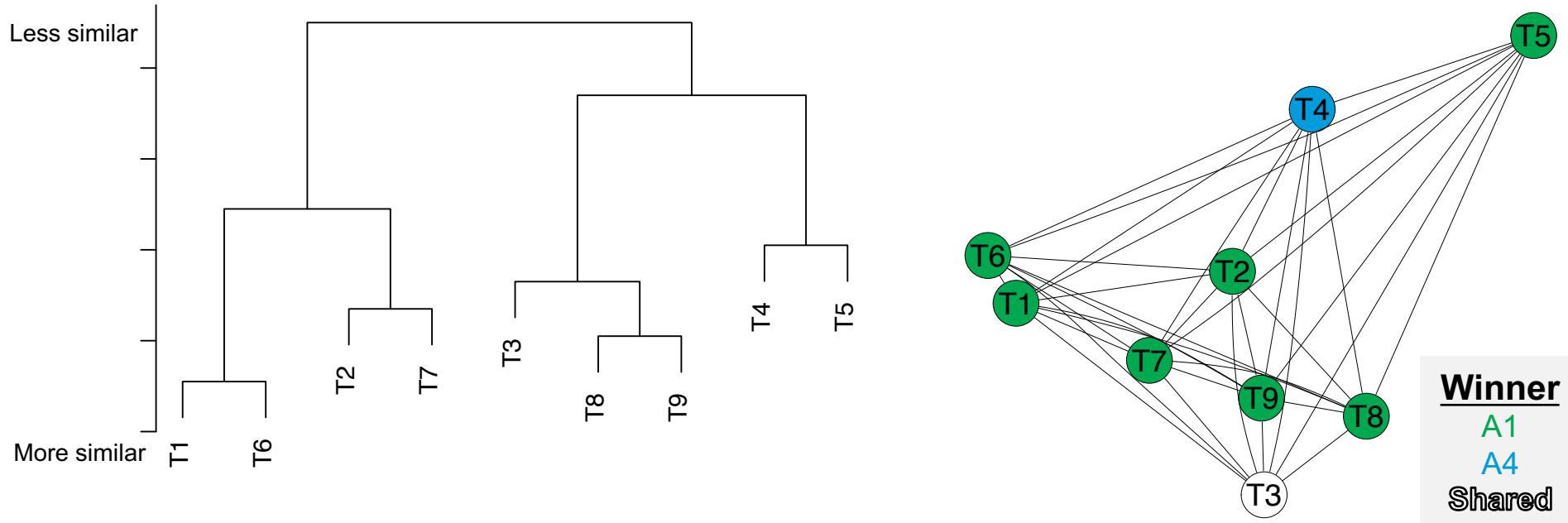
## Dendrogram:

## Similarity of tasks with regard to ranking



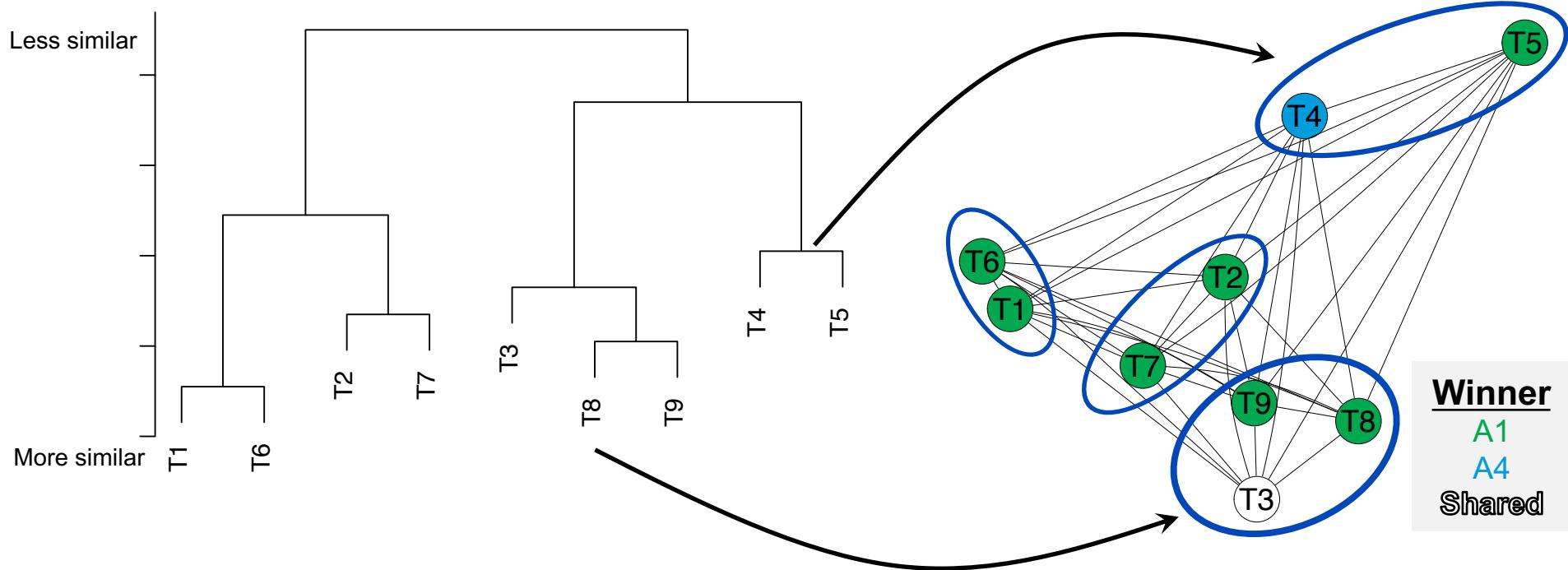
+ Group tasks according to similarity of their ranking lists

# Dendrogram/Network: Similarity of tasks with regard to ranking



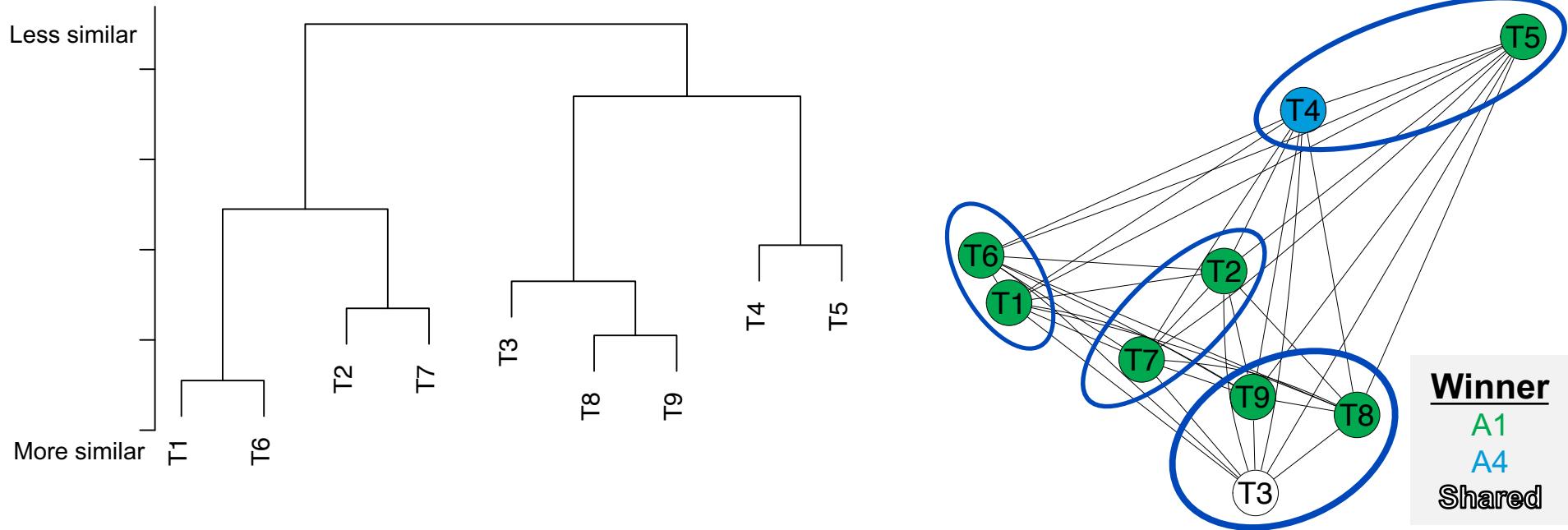
+ Group tasks according to similarity of their ranking lists

# Dendrogram/Network: Similarity of tasks with regard to ranking



+ Group tasks according to similarity of their ranking lists

# Dendrogram/Network: Similarity of tasks with regard to ranking



- + Group tasks according to similarity of their ranking lists
- Depend on chosen distance measure and agglomeration method/layout engine

## Open-source framework: *challengeR*

# Open-source toolkit *challengeR*

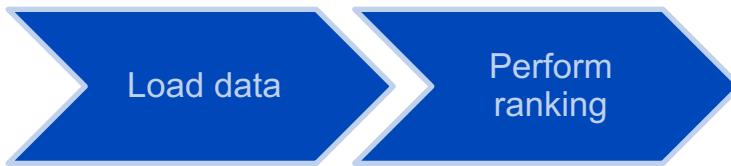


Load data

Testcase_ID	Algorithm_name	Metric_value	Task_name
85	A1	0.7952	c_random
15	A4	0.6877	c_clearRanking
81	A3	0.7754	c_random
8	A5	0.6948	c_random
82	A2	0.8576	c_clearRanking
19	A2	0.5556	c_random
84	A1	0.5215	c_random

```
data_matrix = read.csv(file.choose())
challenge = data_matrix %>% as.challenge(
  case="Testcase_ID", algorithm="Algorithm_name",
  value="Metric_value",
  by="Task_name", # (only for multi-task)
  smallBetter = FALSE)
```

# Open-source toolkit *challengeR*



```
ranking = challenge %>% testThenRank(. . .)
ranking = challenge %>% aggregateThenRank(. . .)
ranking = challenge %>% rankThenAggregate(. . .)

# Consensus ranking for multiple tasks:
meanRanks = ranking %>% consensus(method = "euclidean")
```

# Open-source toolkit *challengeR*



```
ranking_bootstrapped = ranking %>% bootstrap(...)
```

# Open-source toolkit *challengeR*



```
report(ranking_bootstrapped,  
       consensus=meanRanks,  
       format = "PDF",  
       ...)
```

# Open-source toolkit *challengeR*



**Alternatively all in a single call:**

```
data_matrix %>% as.challenge(...) %>%  
  test(...) %>% rank(...) %>% bootstrap(...) %>% report(...)
```

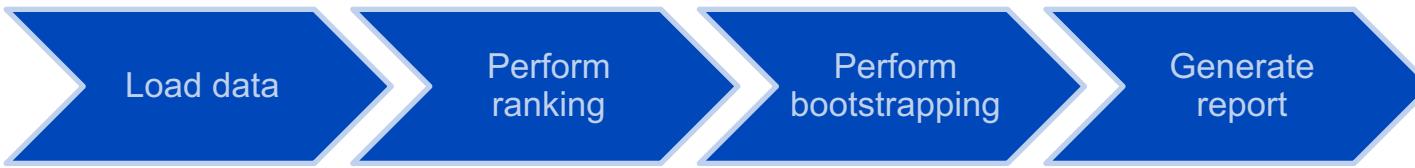
# Open-source toolkit *challengeR*



**Alternatively all in a single call:**

```
data_matrix %>% as.challenge(...) %>%  
  aggregate(...) %>% rank(...) %>% bootstrap(...) %>% report(...)
```

# Open-source toolkit challengeR



## Benchmarking report for Task1

created by challengeR 0.0.27 (Wiesenthärl, Renate, Carsten, Maren Rehm @ Kopp-Schroeder, 2019)

08 October, 2019

This document presents a comprehensive report on a benchmark study. Input data comprises raw metric values for 19 different algorithms and 10 test cases.

- Visualization of assessment data: Dot- and boxplots, violin plots and ranking heatmap
- Visualization of ranking stability: Box plots, Violin plots, significance maps and line plots
- Statistical analysis: Wilcoxon signed rank test, Kruskal-Wallis test, Friedman test.

Algorithms are ordered according to their ranking scheme.

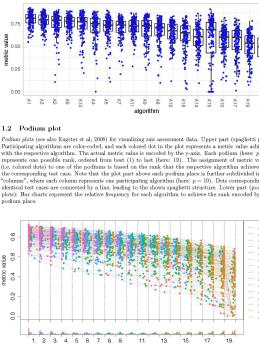
Ranking test:

	prop	significance	rank
A1	0.042034	1	1
A2	0.048907	1	2
A3	0.059477	3	3
A4	0.060000	1	4
A5	0.070043	5	5
A6	0.070048	7	6
A7	0.070050	7	7
A8	0.070052	10	8
A9	0.070055	12	9
A10	0.070056	14	10
A11	0.070057	16	11
A12	0.070058	16	12
A13	0.070059	18	13
A14	0.070060	18	14
A15	0.070061	18	15
A16	0.070062	18	16
A17	0.070063	18	17
A18	0.070064	18	18
A19	0.070065	18	19

### 1 Visualization of raw assessment data

#### 1.1 Dot- and boxplot

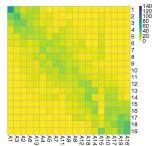
Dot- and boxplots for visualizing raw assessment data separately for each algorithm. Boxplots represent data corresponding to individual test cases.



2

#### 1.3 Ranking heatmap

Ranking heatmap for visualizing raw assessment data. Each cell ( $i, A_j$ ) shows the absolute frequency of test cases in which algorithm  $A_j$  achieved rank  $i$ .



#### 2 Visualization of ranking stability

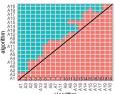
##### 2.1 Box plot for visualizing ranking stability

Algorithms are ordered, and the area of each blob at position  $(A_i, \text{rank } j)$  is proportional to the relative frequency  $A_i$  achieved rank  $j$  across  $k = 100$  bootstrap samples. The median rank for each algorithm is indicated by a thick cross. 95% bootstrap intervals across bootstrap samples are indicated by black lines.



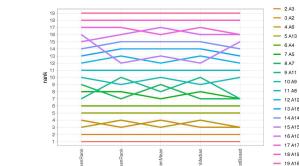
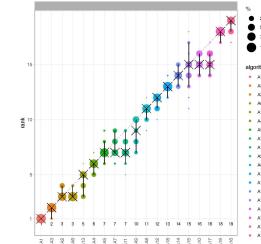
##### 2.3 Significance maps for visualizing ranking stability based on statistical significance

Significance maps depict incidence matrices of pairwise significant test results for the matched Wilcoxon signed rank test. The rows and columns are ordered by the mean rank of the algorithms. The diagonal line separates significant values of the algorithms or the rows are significantly larger than those from the columns. The diagonal line is colored red, while the off-diagonal cells are colored green.



##### 2.4 Ranking robustness with respect to ranking methods

The ranking is based on the raw assessment data. The y-axis is the mean rank of each algorithm. Each algorithm is represented by one colored line. The only ranking method encoded on the x-axis, the height of the line represents the corresponding test case. Colored bars below the x-axis indicate the mean rank of all methods.



### 3 Reference

Wiesenthärl, M., Hainke, A., Oetjen, M., Jägerle, L. and Kopp-Schroeder, A., Analyzing and visualizing results of challenges. *Journal*.

M. J. A. Erteler, T. Schröer, and F. Leisch, "Exploratory and inferential analysis of benchmark experiments," *International Conference on Data Analysis and Applications*, Berlin, Germany, Technical Report 30, 2018. [Online]. Available: <http://epub.kit.edu/research/de/30/>.

# Open-source toolkit *challengeR*: Single plots

ranking %>%

- boxplot(...)
- podium(...)
- rankingHeatmap(...)
- significanceMap(...)
- ...

ranking\_bootstrapped %>%

- violin(...)
- ...

## Summary

- Uncertainty and robustness of rankings needs to be assessed
- Open-source toolkit (R package)
  - Available on <https://github.com/wiesenfa/challengeR>
  - Computes rankings for diverse ranking methods
  - Generates an automatic report
- Wiesenfarth, Reinke, Landmann, Cardoso, Maier-Hein & Kopp-Schneider (2019).  
Methods and open-source toolkit for analyzing and visualizing challenge results.  
*arXiv preprint arXiv:1910.05121*

## Summary

- Anyone already tried to use it?
- Feedback / problems / feature requests?
- Contributions welcome!

m.wiesenfarth@dkfz.de