

# Per-class algorithm selection for black-box optimisation

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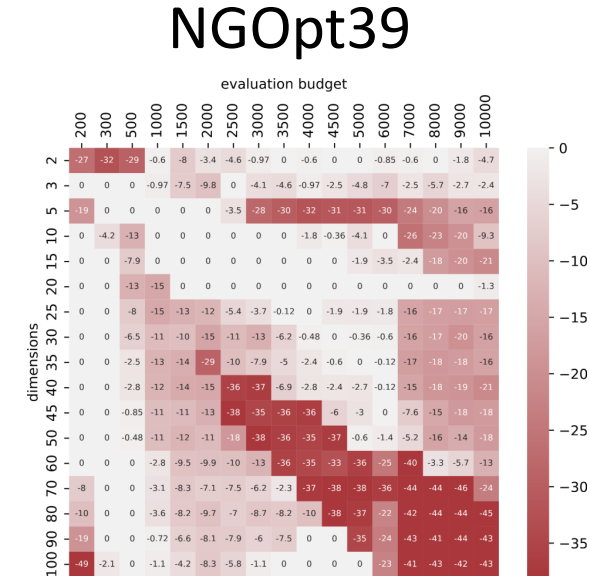
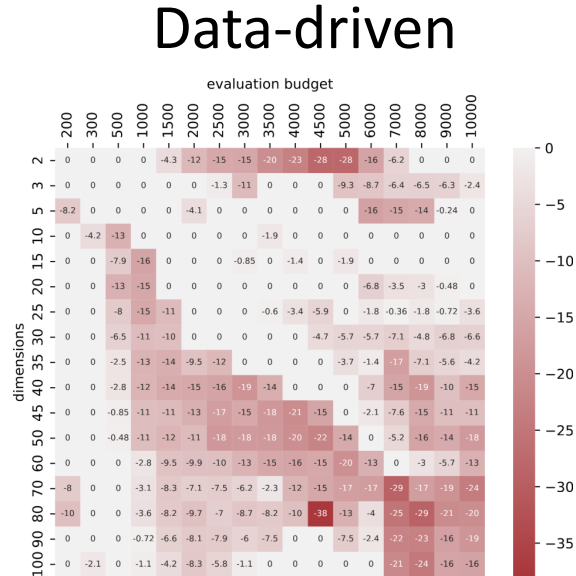
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# Summary

- Algorithm selection (AS) is great, e.g., for SAT → Mostly per-instance
- Black-box optimisation → No a priori instance-specific information
- Per-class AS → Use problem properties for AS over sets of instances

# Summary

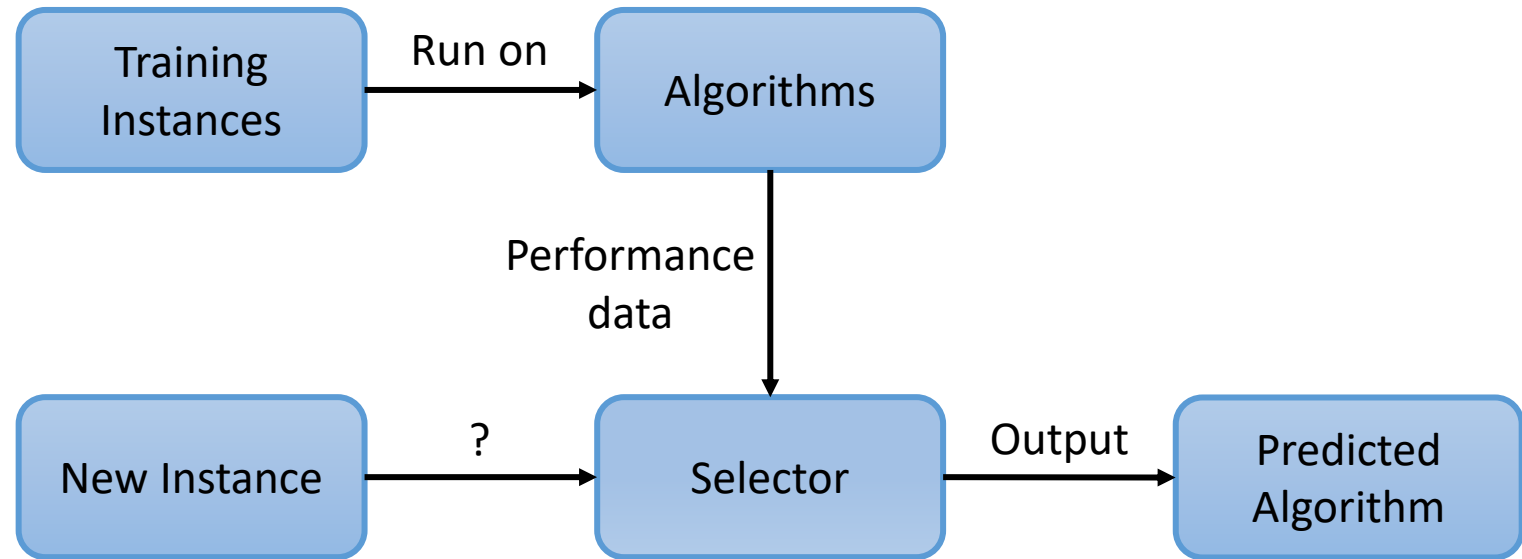
- General data-driven AS framework
  - Outperform hand-made SOTA system by Meta (NGOpt)
- Extensions to grey-box problems possible, to use more information



# This talk

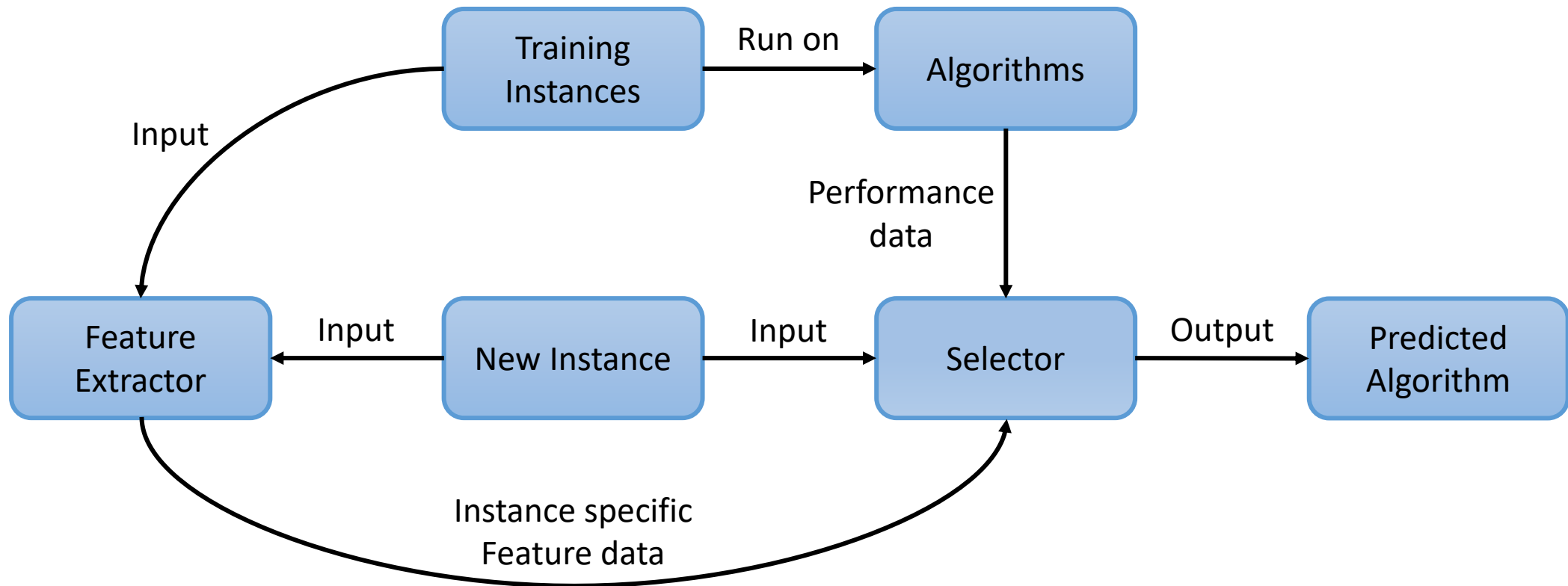
- Why we care about per-class algorithm selection
- How data-driven per-class algorithm selection works
- Comparison to hand-designed system
- Discussion of generality and extensibility

# Algorithm selection [Rice, Adv. in Comp. 1976]



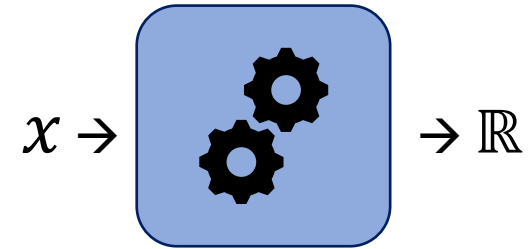
- No single algorithm is the best for every problem

# Per-instance algorithm selection

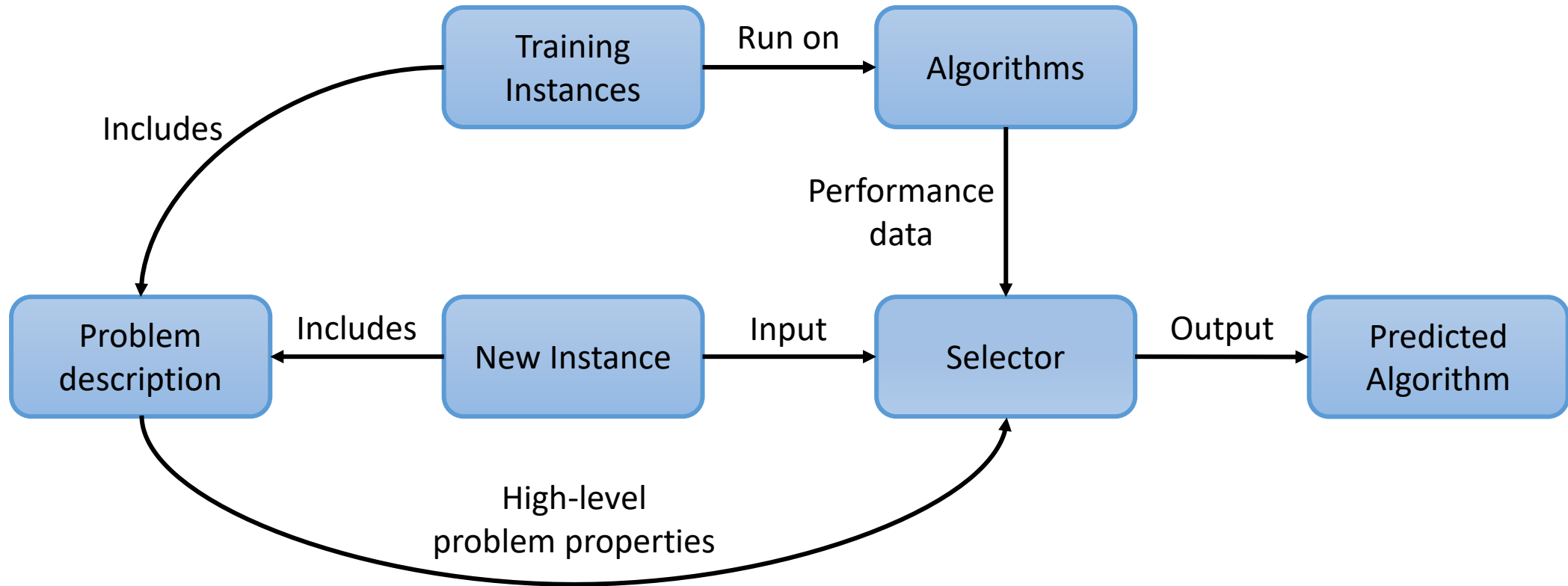


# Black-box optimisation

- Optimise a problem with unknown internals
- Use sampling strategy to find the optimum
  - Evolutionary algorithms
  - Bayesian optimisation
  - ...
- No a priori instance specific  $\rightarrow$  Costs function evaluations to compute
  - Description
  - Features



# Per-class algorithm selection





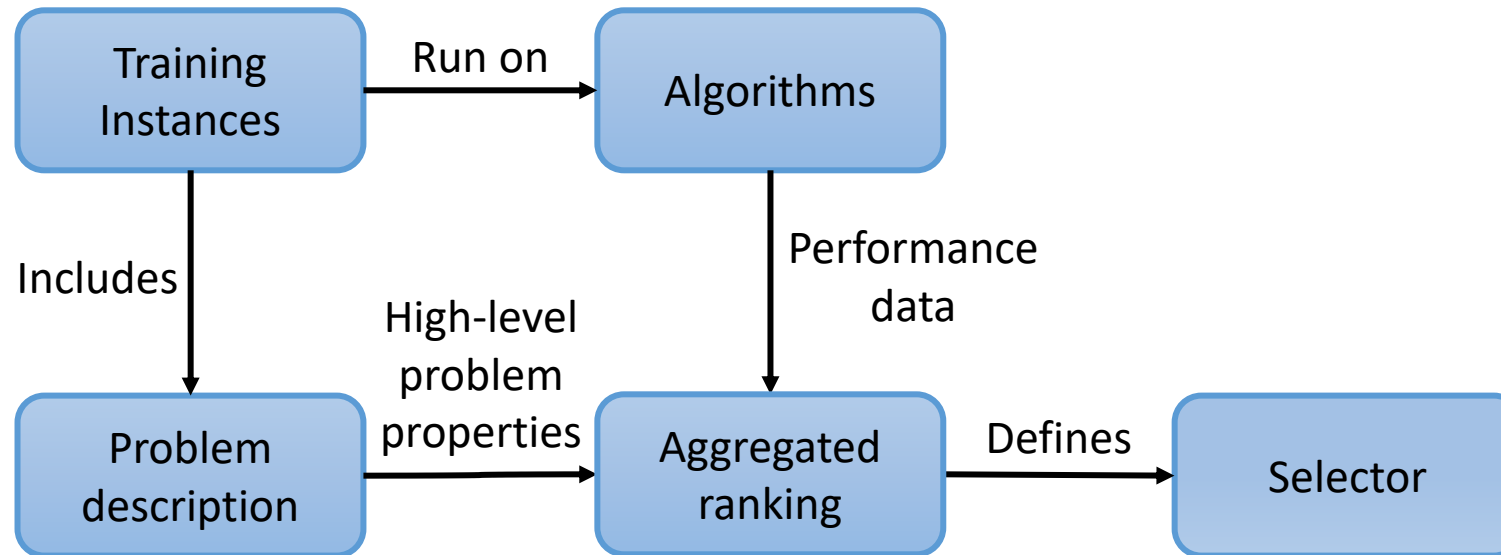
# Properties vs. features

- Features
  - Describe a problem instance
  - Differ across instances
  - Require function evaluations to determine
- Properties
  - Describe the higher level problem class or domain
  - Same across instances (in the same class/domain)
  - Known a priori

# Pros and cons to per-class algorithm selection

- No per-instance selection, but for larger groups
- Pro
  - Free – Can make a decision before doing any evaluations
  - General – Don't have to design features for each problem variant
- Con
  - Being less specific will usually mean lower performance


# Data-driven selector – Basic idea



# Considered problem properties

- Dimensions – Number of decision variables
- Budget – Number of function evaluations
  
- Properties we keep fixed
  - Variable type – Continuous
  - No constraints
  - No noise

# Comparison

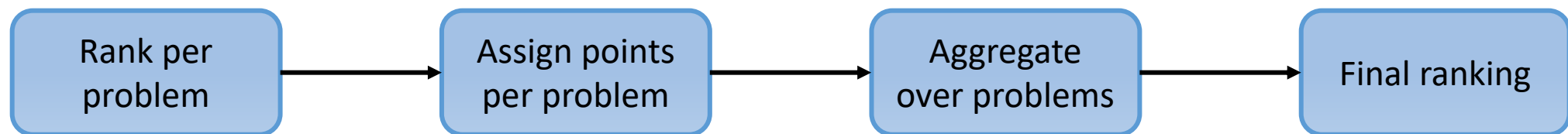
- NGOpt39  Nevergrad
  - Hand-designed competence map / selection wizard – “what is good where”  
[Meunier et al., TEVC 2022]
- Data-driven selector
  - Choose from the algorithms included in NGOpt39 based on performance data
- Same algorithms + implementation, different selection method

# Training

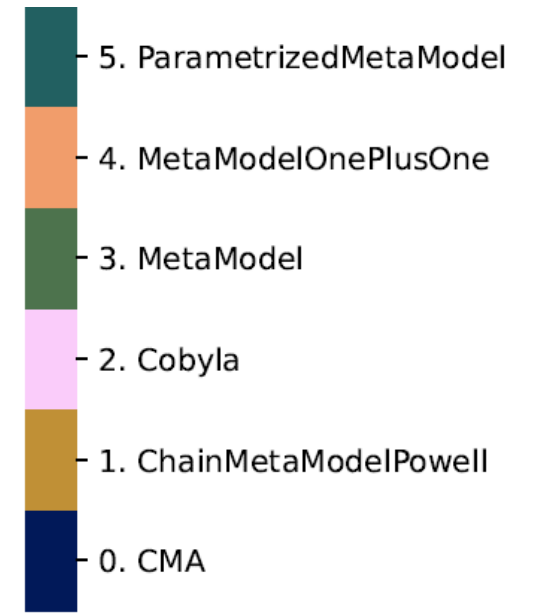
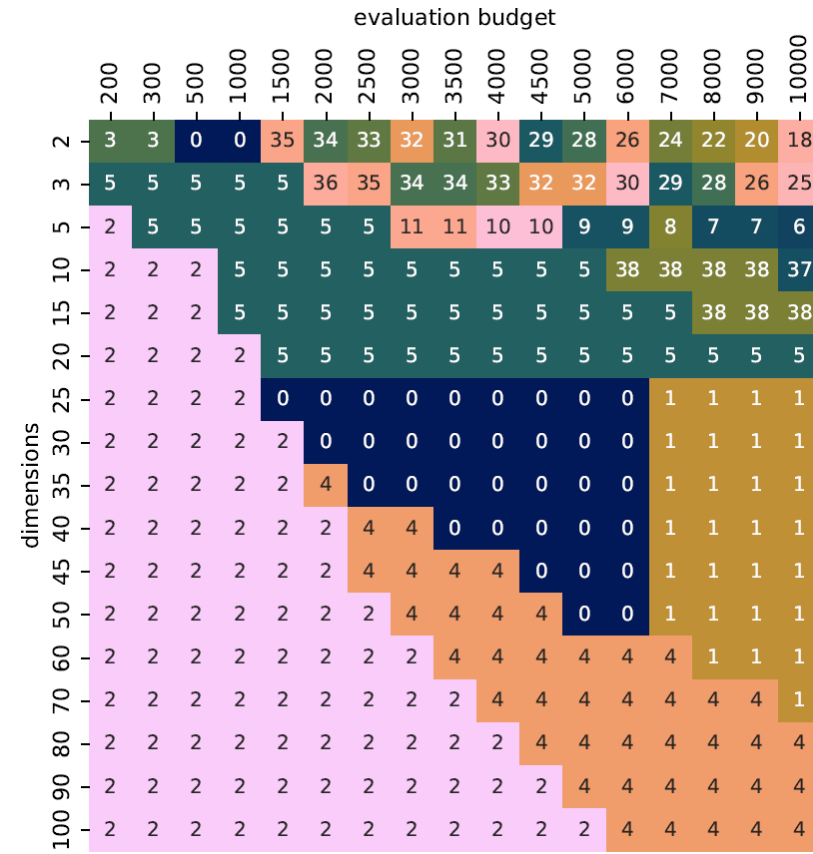
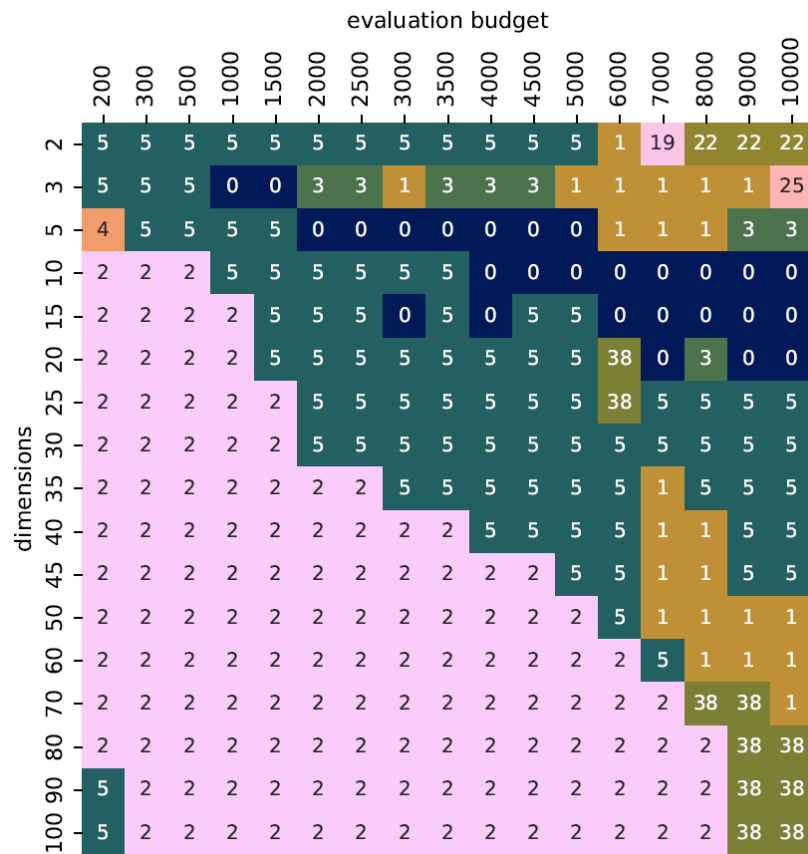
- Budgets: [1,...,10000]
- Dimensions: [1,...,100]
- Algorithms: All those used by NGOpt39 in this domain (34 total)
- Problems: 24 BBOB functions, instance 1, 25 repetitions each  
[Hansen et al. Tech. Rep. 2009]

# Ranking

- Per budget-dimension pair
  - Give an algorithm 1 point for each run in the top 25 per problem
  - Runs below the top 25 tied with the 25<sup>th</sup> best run are also awarded a point
  - Algorithm with most points is chosen for the budget-dimension pair



# Data-driven vs. NGOpt39





# Testing

- Budgets: [200, 300, 500, 1000, ..., 5000, 6000, ..., 10000]
- Dimensions: [2, 3, 5, 10, ..., 50, 60, ..., 100]
- Algorithms:
  - 5 per budget-dimension pair
  - All those chosen by NGOpt39, or in the top 4 performers (excluding NGOpt39)
- Problems: 828 MA-BBOB functions, 1 repetition each

# MA-BBOB – Many affine combinations

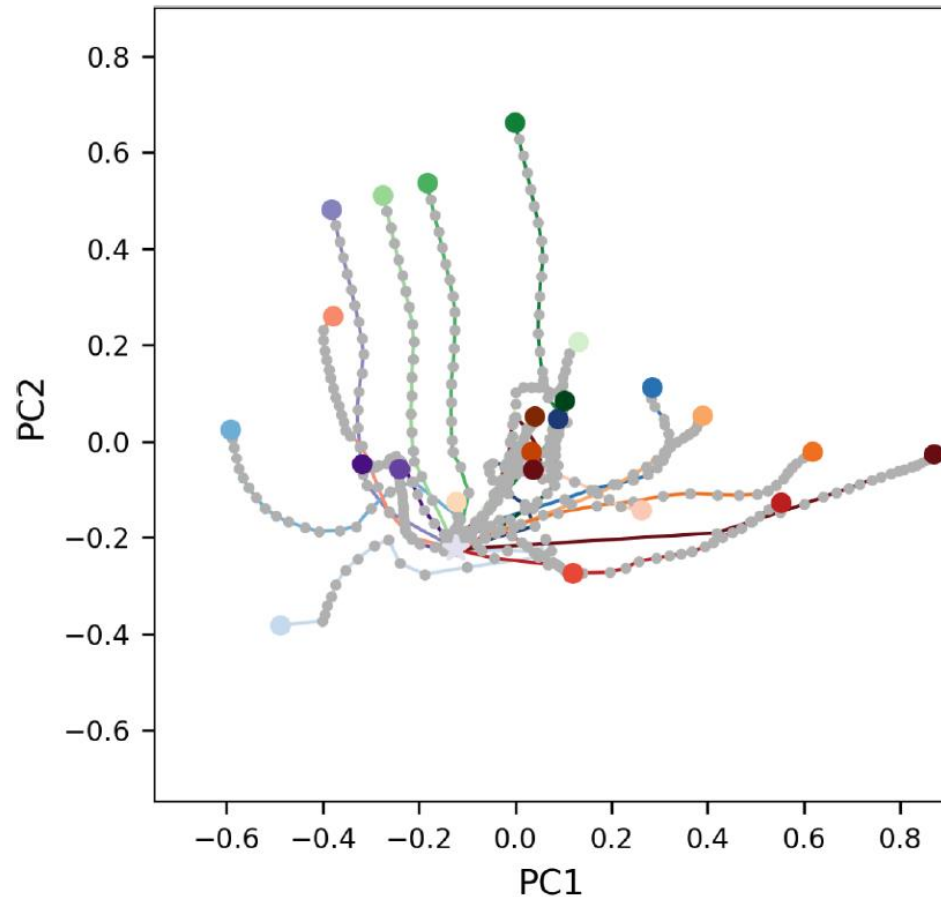


Fig. from [Dietrich and Mersmann, PPSN 2022]

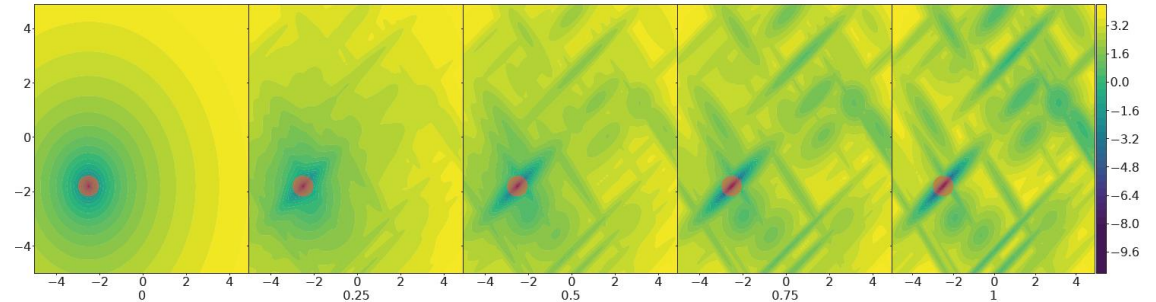
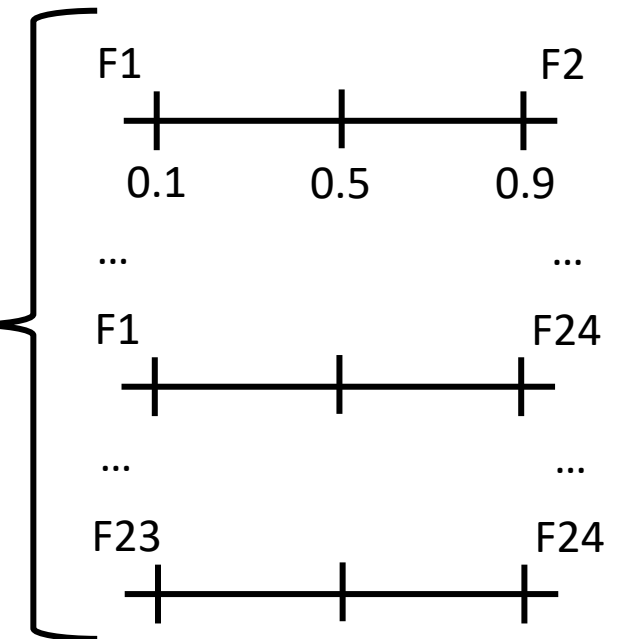


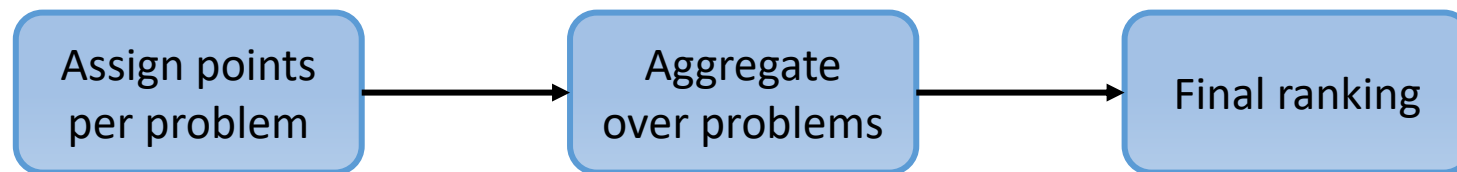
Fig. from [Vermetten et al., GECCO 2023]

Our selection  
of combined  
BBOB functions

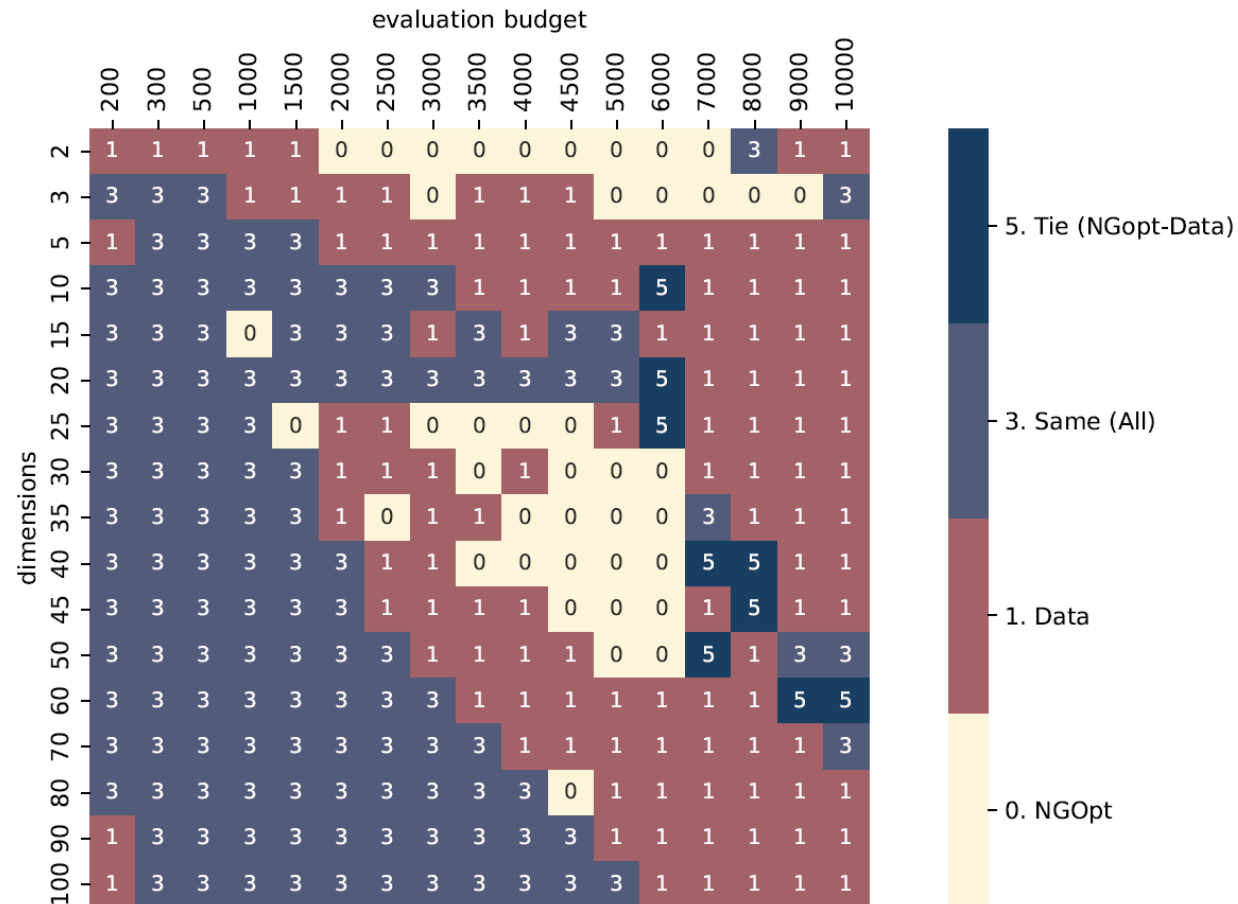


# Test ranking

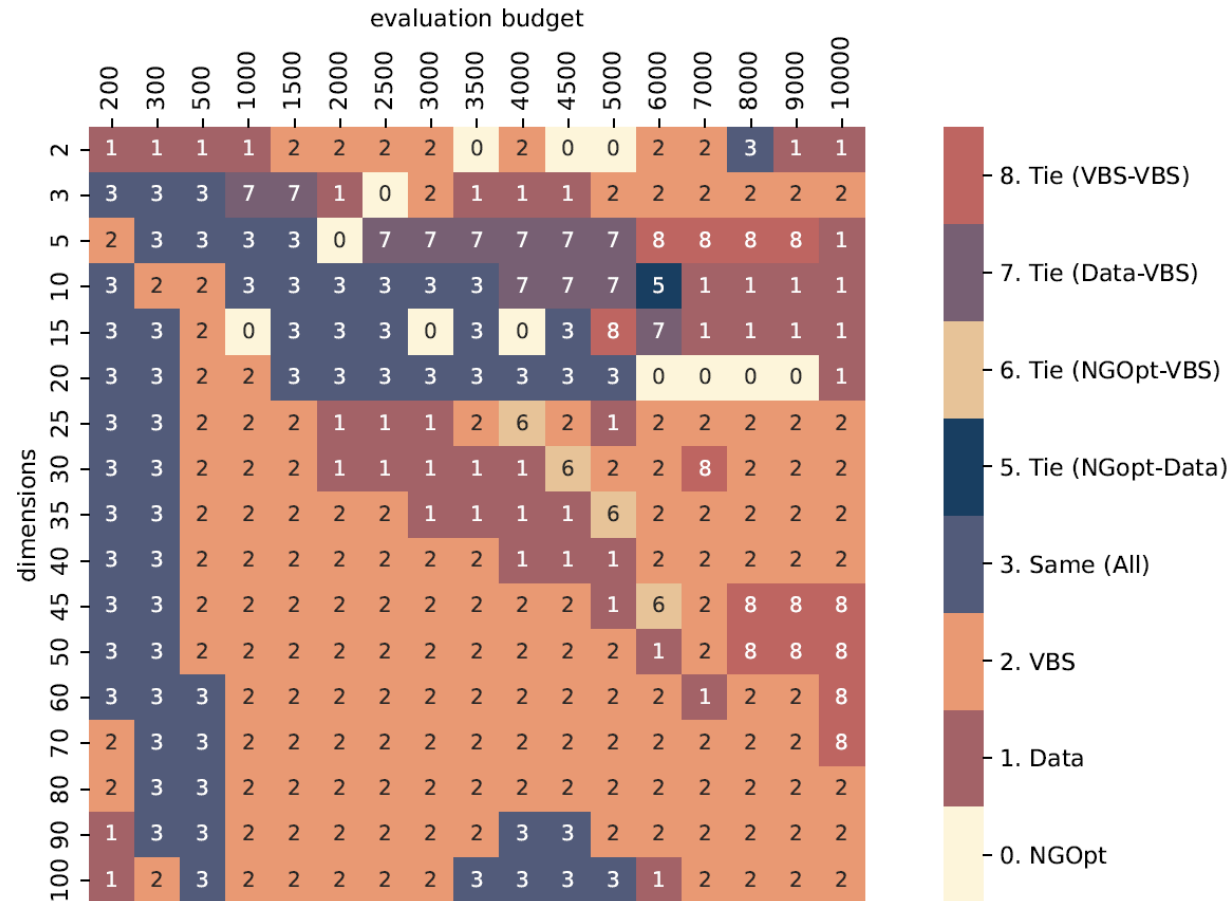
- One run per algorithm per problem
- Per budget-dimension pair
  - Give an algorithm 1 point for each problem where it is the best
  - Algorithms tied with the best algorithm on a problem also get a point
  - Algorithm with most points is chosen for the budget-dimension pair



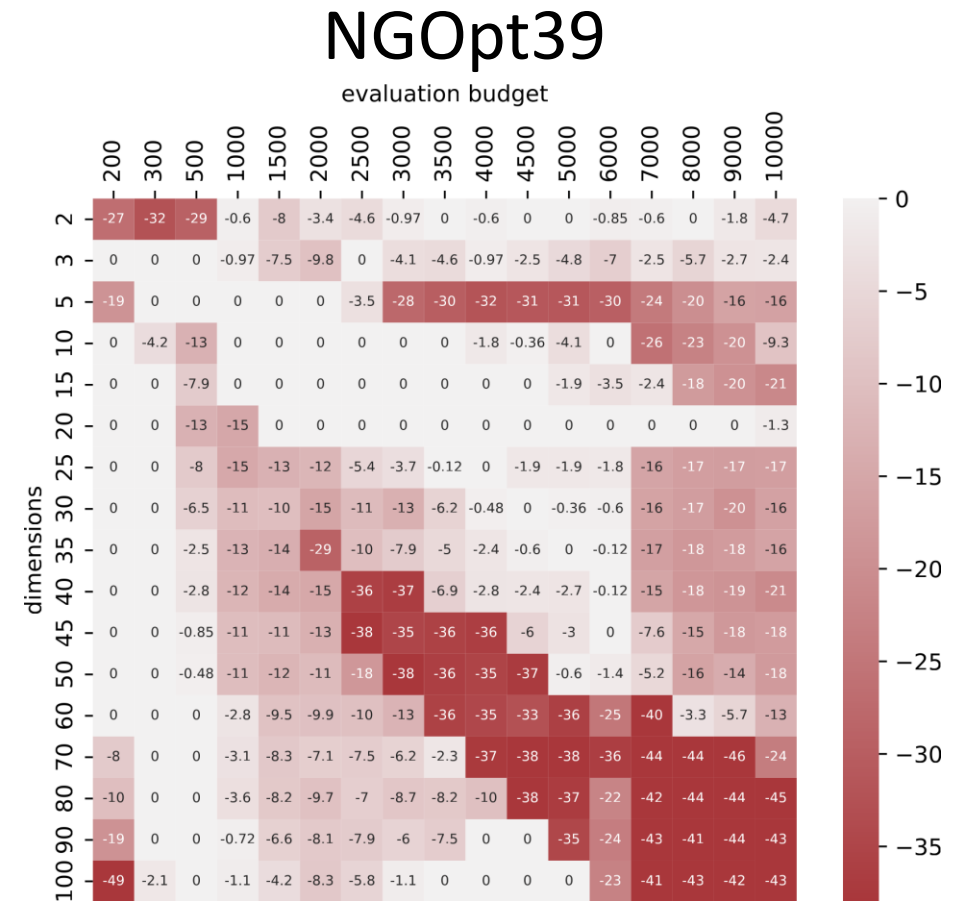
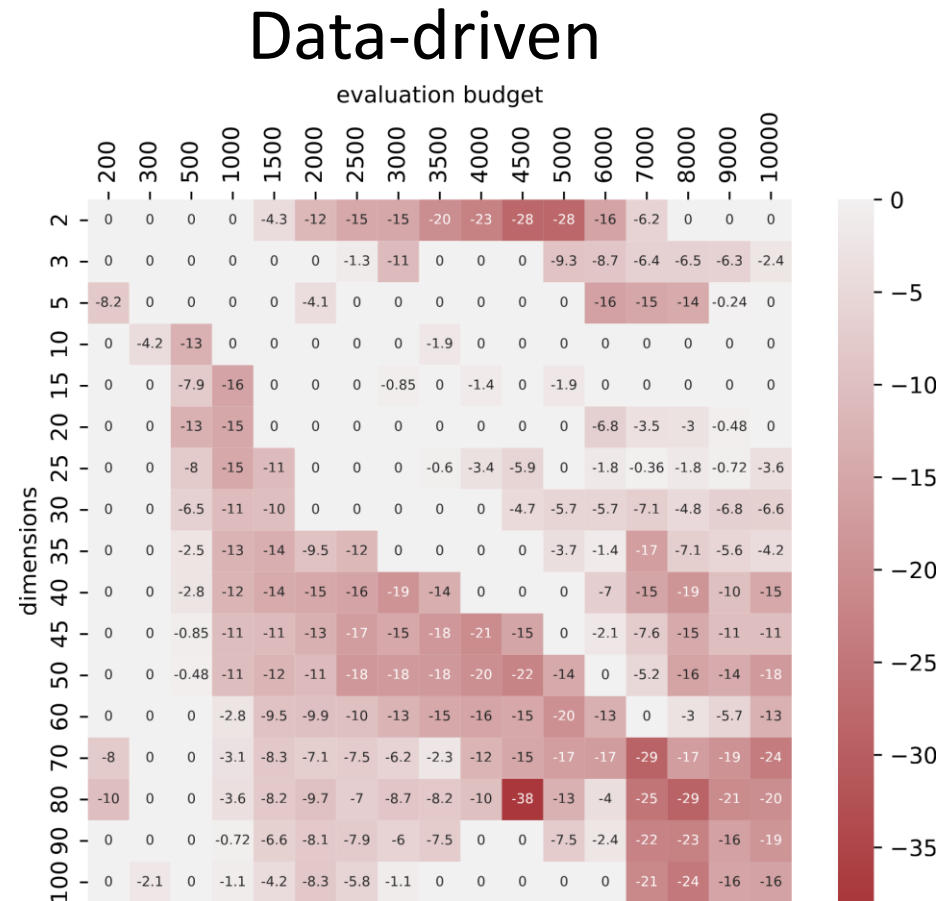
# Data-driven vs. NGOpt39 on MA-BBOB



# Wins compared to the VBS on MA-BBOB



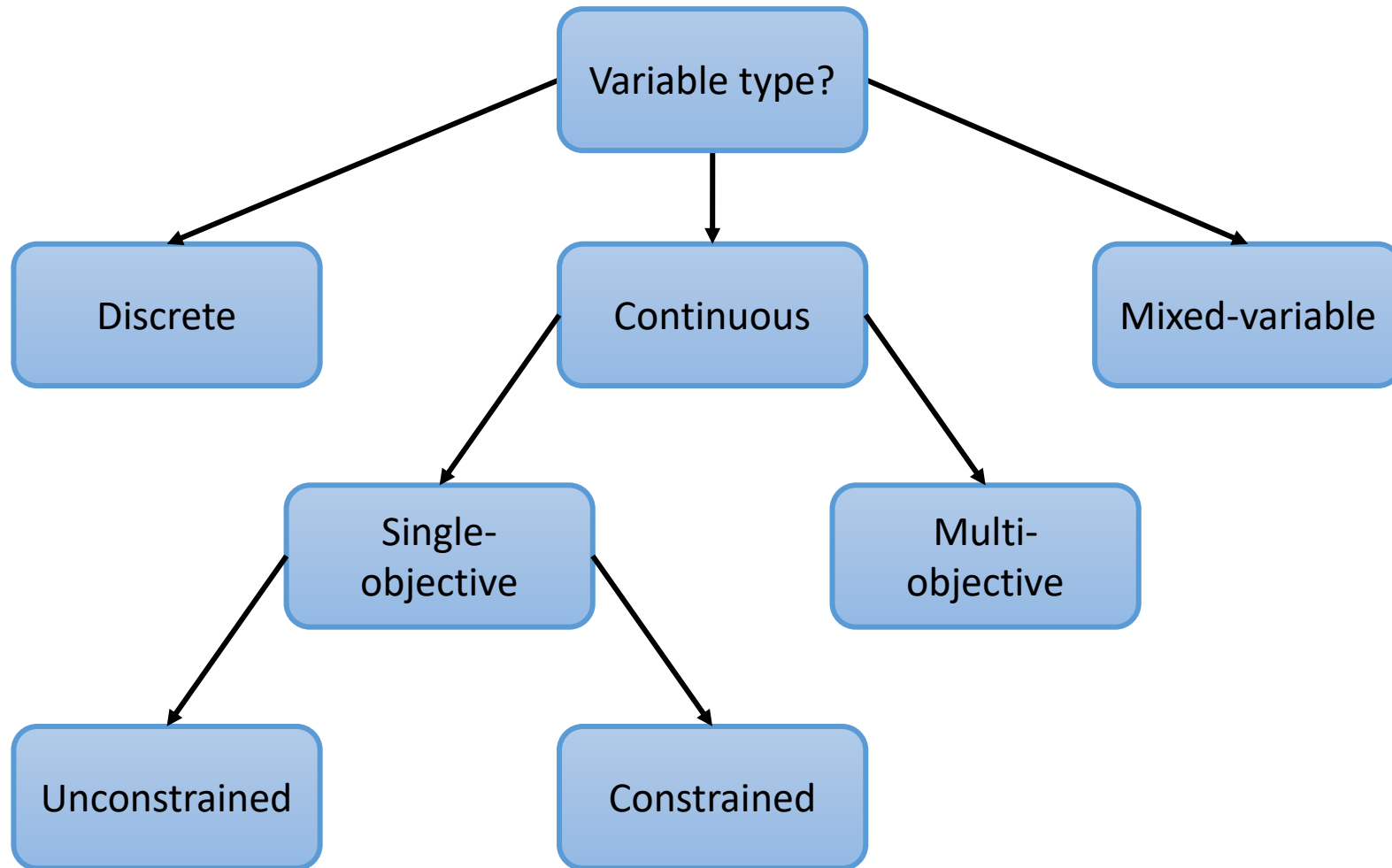
# Loss to the VBS on MA-BBOB (% of problems)



# Moving forward

- Improve training instance set for generalisability
- Progressively add algorithms
- Evaluate different selection methods, e.g., for:
  - Worst case performance

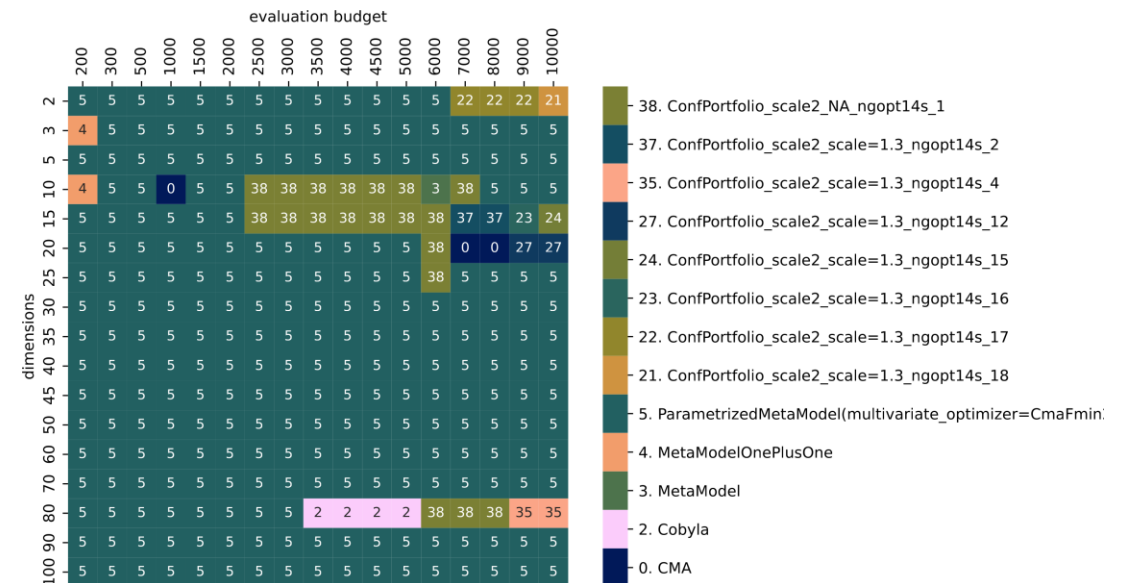
# Generalisation to other problem domains





# Extension to grey-box setting

- Include user provided properties in the data-driven analysis
- Property needs to be known for the training data
- E.g., multimodal (F15-F24 in BBOB)



# Take home

- Per-class algorithm selection for black-box optimisation works
- Data-driven system improves over hand-designed selectors
- General conceptual framework → No features, no problem
  - Problems with constraints, multiple objectives, ... → No problem!
- Extendable to grey-box setting
  - Have a multimodal problem?
    - Selection based on multimodal problems in the data

# References

- [Dietrich and Mersmann 2022] Dietrich, K., Mersmann, O. (2022). Increasing the Diversity of Benchmark Function Sets Through Affine Recombination. In: Rudolph, G., Kononova, A.V., Aguirre, H., Kerschke, P., Ochoa, G., Tušar, T. (eds) Parallel Problem Solving from Nature – PPSN XVII. PPSN 2022. Lecture Notes in Computer Science, vol 13398. Springer, Cham. [https://doi.org/10.1007/978-3-031-14714-2\\_41](https://doi.org/10.1007/978-3-031-14714-2_41)
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