AutoML: Beyond AutoML

Best Practices for Algorithm Configuration

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- if done wrong, waste of time and compute resources

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- Validate the eventually returned configuration on your test instances

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Best Practice 1: Never trust your algorithm

Explicitly check and use external software to:

- ensure resource limitations
- terminate your algorithm
- verify returned solutions
- measure performance

Pitfall 2: File System

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Best Practice 2: Don't use the Shared File System

To relieve the file system of a HPC cluster:

- design well which files are required and which are not
- use a local (SSD) disc

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In practice, it can be hard to prevent over-tuning, e.g., by

- using larger instance sets
- tuning on the target hardware

Best Practice 3: Check for Over-Tuning

Check for over-tuning by validating your final configuration on

- many random seeds
- a large set of unused test instances
- a different hardware

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Best Practice 4: Ensure Homogeneity

Algorithm configurators should only run on homogeneous instance sets. Different degrees of homogeneity:

- Strong homogeneity: all instances agree on the ranking of configurations
- Weak homogeneity: all instances agree on the top-performing configurations

More Pitfalls and Best Practices

 \dots can be found in <code>[Eggensperger et al. 2019]</code>