

# Exploring the Reduction of Configuration Spaces of Workflows

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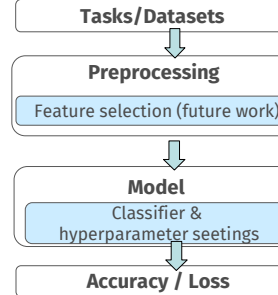
Workshop Neuro-symbolic Metalearning and AutoML @ ECML PKDD 2023  
Based on article in Proc. of The 26th Int. Conf. on Discovery Science (DS2023)

## Objectives

### Objective

- Examine the performance of a large set of workflows (portfolio), ML algorithms + hyperparameters, on selected datasets (i.e., obtain metadata of past experiments with workflows).
- Apply the workflow reduction method to the portfolio & obtain the reduced set of workflows
- Compare the performance of the initial and reduced portfolios on a new dataset (use leave-one-out evaluation)

## Workflows studied



1690 different workflows

41 datasets from OpenML

4 classification algorithms

# hyperparam. settings

Classif. Alg.	Description	#Workflows
SVM	SVM	300
LogR	Logistic Regression	220
LD	Linear Discriminant	90
RF	Random Forest	1080

## Workflow Reduction

Our method is an improved/ revised version of Abdulrahman et al. (2019).

### Phase 1 - Prune Low (PL):

- Use a given portfolio of workflows;
- Use the existing performance metadata obtained in prior tests;
- Identify the top performing workflows (pipelines) for each dataset: top 5% of workflows based on accuracy and top 5% of workflows based on A3R (combines accuracy and time));
- Remove all workflows that are not top performers.

### Phase 2 - Prune Redundant (PR)

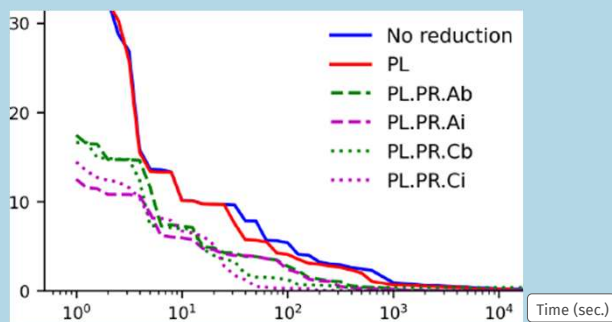
- Eliminate the workflows that are redundant

Two types of redundancy tests: Two modes:  
 - cover test (PR.C); - batch (b);  
 - cover + accuracy test (PR.A); - iterative reduction (i).

## Generating Predictions

- We use the **average ranking method (AR\*)** (Abdulrahman et al. 2018), as the **workflow recommendation method**. It is easy to define different configuration spaces (sets of workflows).
- Method AR\* **converts each portfolio of workflows into a ranking** using the available performance metadata.
- The **ranking is followed to generate class predictions** for the target dataset.
- This enables to **calculate the performance/loss**, as tests proceed.
- Evaluation** follows the **leave-one-out (LOO)** strategy for each dataset. The mean loss is returned.

## Resulting Loss Curves



Loss curves different variants of the reduction method

## Results

Mean loss (area under loss curve)

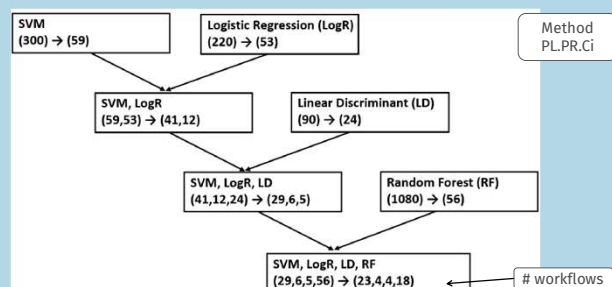
Reduction method	Size SVM	Size LogR	Size LD	Size RF	Size total	Size %	MIL %	Loss 10 <sup>6</sup> %
No reduction	300	220	90	1080	1690	100.0	6.57	0.00
PL	247	202	70	727	1248	73.7	6.30	0.00
PL.PR.Ab	216	81	37	137	471	27.9	3.31	0.02
PL.PR.Ai	123	38	17	88	266	15.7	3.18	0.02
PL.PR.Cb	26	1	3	26	56	3.3	3.02	0.38
PL.PR.Ci	23	4	4	18	49	2.9	3.42	0.06

Effects of reduction on the portfolio size and loss

Reduction method	Elim. None	Elim. SVM	Elim. LogR	Elim. LD	Elim. RF
No reduction	6.57	7.99	6.72	6.65	3.83
PL	6.30	7.80	6.47	6.36	3.83
PL.PR.Ab	3.31	7.32	3.26	3.34	3.77
PL.PR.Ai	3.18	7.96	3.17	3.32	3.76
PL.PR.Cb	3.02	7.08	3.20	3.27	4.35
PL.PR.Ci	3.42	7.30	3.76	3.23	4.36

Ablation study: Effects of eliminating certain subsets of workflows on loss

## Iterative Reduction



## Conclusions and Future Work

### Conclusions

- The reduction method PL.PR.Ci It identified **49 useful workflows** out of 1690. Final loss 0.38%.
- The reduction method PL.PR.Ai is **safer to use**: It identified **266 useful workflows**. Final loss 0.02%.
- The workflows compete for place in the selected set. SVM workflows occupy more places than e.g., LogR. Ablation study confirms that they are more important than e.g., LogR.

### Future Work

- Examine the **effects of preprocessing** (feature selection)
- Transfer the final portfolio** to other MTL/AutoML systems
- Exploit** the reduction method in other MTL/AutoML systems