Utilizing Software Features for Algorithm Selection

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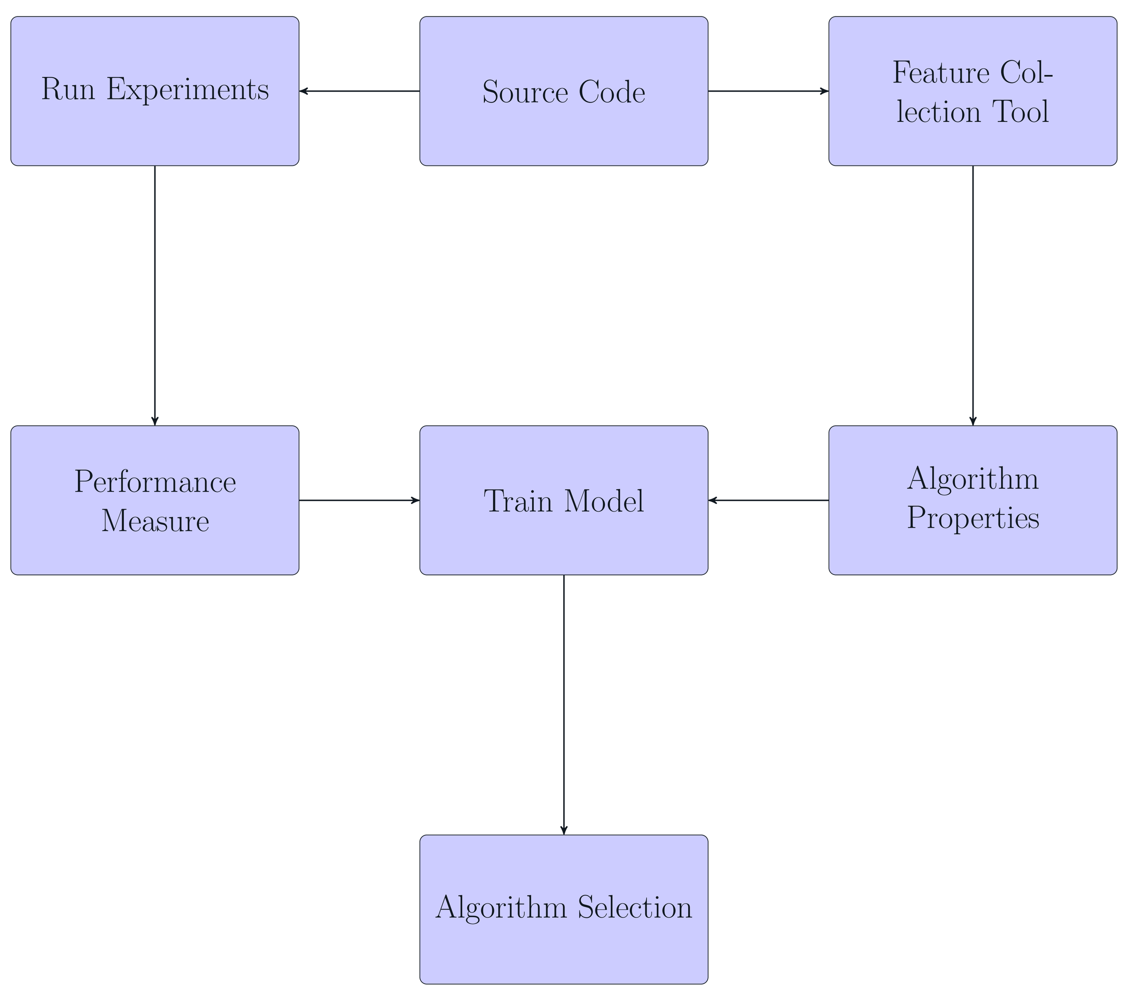
Motivation

- Goal – investigate whether algorithm selection can be improved if we utilize algorithm features along with instance features
- This iteration of the project uses static algorithm (software) features collected automatically
- Advantage – the number of performance models is constant no matter how many algorithms are used in scenario

Setup



- Performed experiments on seven ASlib scenarios (SAT11-INDU, OPENML-WEKA-2017, etc) as well as scenarios not currently in ASlib (SAT-2018)
- Created SAT18-EXP scenario using main track results with 400 benchmark instances from SAT 2018 competition. Converted data into ASlib format using scripts from COSEAL's aslib-spec repository
- SAT18-EXP has all solvers that participated in the competition, except for varisat since it was written in Rust (software metrics tool does not work)
- Obtained SAT18-EXP's instance features with SATzilla's feature collection tool[1]
- Modified scenarios due to lack of source code, ambiguity in solvers, lack of ability to take into the account parameter settings, and repeated runs
- Automatically collected algorithmic features for solvers written in C++ and Java such as cyclomatic complexity (average and total), maxindent complexity (average and total), lines of code (average and total), max indent (average and total), size in bytes (average and total), and number of files[2]
- Collected algorithmic features by selecting more relevant pieces of code (e.g., ignored code responsible for parallelism and certificate generation whenever possible)

Setup (cont.)

- Trained all models on Teton High-Performance Computing cluster[3]
- Combined software and instance features by constructing $n \times m$ dataframe, where n is the number of instances times number of solvers, and m is the number of instance and software features
- Utilized server scripts from aslib-r[4] for tuning hyperparameters for individual models. Tuning for combined models was done similarly (e.g., nested cross-validation and so on).

Results

- Combined model is a Random Forest regression model that utilizes both instance and software features
- Individual model is the standard model that uses instance features only
- Models with pair regression method available in LLAMA[5] were also used to see if combined regression model performs better than a slightly modified individual model
- **mcp** and **par10** gaps show the normalized fraction of the gap closed by different methods
- A value of 0 corresponds to the single best solver and a value of 1 to the virtual best. Negative values indicate performance worse than the single best solver
- OPENML was grayed out for par10 table since this metric does not make sense for the scenario

mcp gap (color scale −1.0 −0.5 0.0 0.5 1.0)

	combined regression	individual pair regression	individual regression
TSP−LION2015	**0**	−0.17	−0.11
SAT18−EXP	0.59	0.6	**0.61**
SAT11−RAND	0.88	**0.92**	0.91
SAT11−INDU	**0.41**	0.39	0.31
SAT11−HAND	0.58	**0.67**	0.64
SAT03−16_INDU	0.46	**0.5**	0.44
OPENML−WEKA−2017	−0.42	**0.22**	−0.51
GRAPHS−2015	0.45	**0.62**	0.56

par10 gap (color scale −1.0 −0.5 0.0 0.5 1.0)

	combined regression	individual pair regression	individual regression
TSP−LION2015	**0**	−0.42	−0.22
SAT18−EXP	0.29	0.29	**0.32**
SAT11−RAND	0.46	**0.49**	0.48
SAT11−INDU	**0.13**	0.12	0.05
SAT11−HAND	0.24	**0.28**	**0.28**
SAT03−16_INDU	**0.13**	**0.13**	0.12
OPENML−WEKA−2017			
GRAPHS−2015	0.12	**0.19**	0.15

Summary

- Building algorithm selection models with current static features produces mixed and inconsistent results
- Some scenarios (OPENML) are improved, some stay about same (SAT01-16_INDU), and others worsen (SAT11-RAND)
- Performing pair regression with instance features gives a much larger improvement on some scenarios compared to combined regression model

Future Work

- Build pair regression models that use both software and instance features to see if they perform any better (currently running experiments)
- Perform feature selection (forward and backward) to find out which software features will be filtered out
- Investigate better static algorithmic features (a lot of minisat hacked solvers have very similar values).
- Take into the account data structures and Object-Oriented properties
- Collect dynamic algorithmic features that characterize only the parts of software that were executed during runtime (stack trace)
- Find a way to automatically analyze more relevant pieces of source code related to computation (e.g., ignore code used for GUIs and so on)
- Add feature costs for algorithm properties

References

[1] L Xu et al. "SATzilla2012: Improved algorithm selection based on cost-sensitive classification models". In: *Proceedings of SAT Challenge 2012: Solver and Benchmark Descriptions* (Jan. 2012), pp. 55–58.

[2] *Metrix++ is a tool to collect and analyse code metrics.* URL: https://metrixplusplus.github.io/home.html.

[3] *Advanced Research Computing Center (2018) Teton Computing Environment, Intel x86_64 cluster. University of Wyoming, Laramie, WY.* URL: https://doi.org/10.15786/M2FY47.

[4] Bernd Bischl et al. "ASlib: A benchmark library for algorithm selection". In: *Artif. Intell.* 237 (2016), pp. 41–58. DOI: 10.1016/j.artint.2016.04.003. URL: https://doi.org/10.1016/j.artint.2016.04.003.

[5] Lars Kotthoff. *LLAMA: Leveraging Learning to Automatically Manage Algorithms.* Tech. rep. arXiv:1306.1031. arXiv, June 2013. URL: http://arxiv.org/abs/1306.1031.