

Configuring *irace* using surrogate configuration benchmarks

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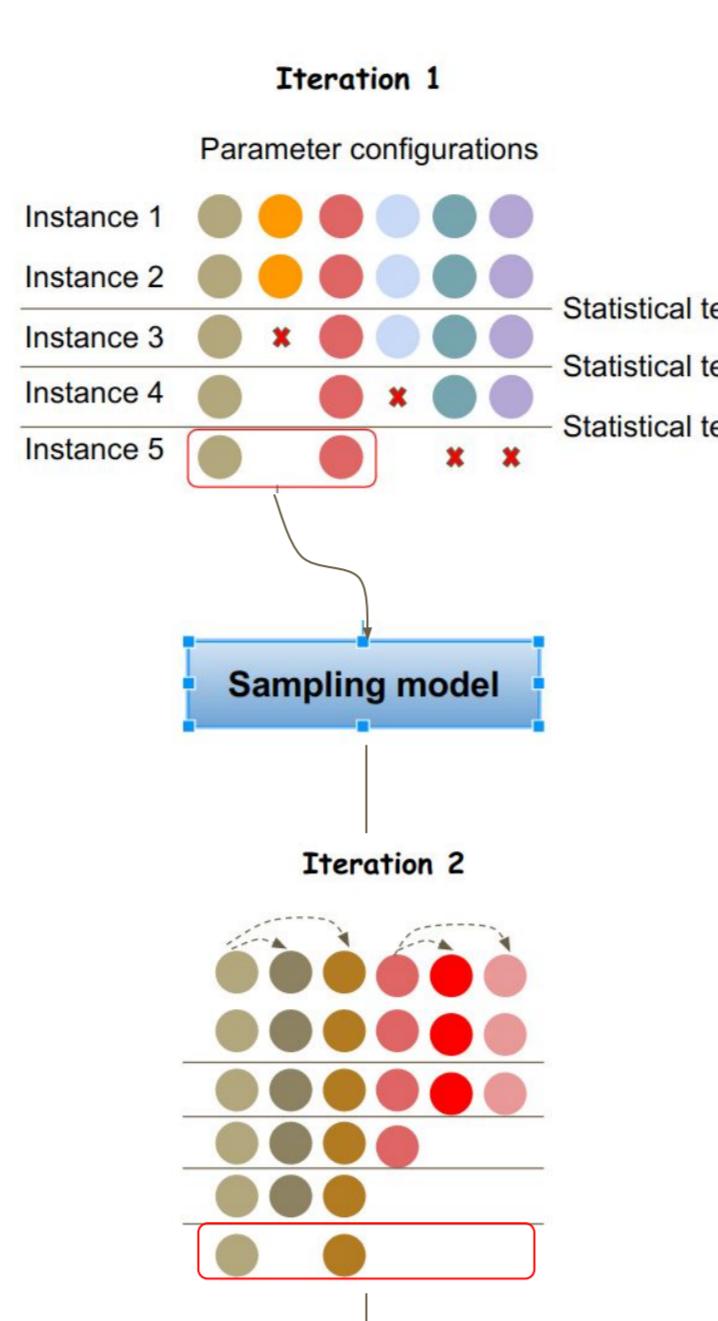
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1. *irace* parameters

Parameter	Type	Domain	Default value
N_{iter}	int	[1, 50]	$2 + \log_2 n^{params}$
μ	int	[1, 20]	5
T_{first}	int	[4, 20]	5
N_{min}	int	[1, 20]	$2 + \log_2 n^{params}$
<i>test_type</i>	categorical	{F-test, t-test, t-test-holm, t-test-bonferroni}	F-test
<i>confidence_level</i>	real	[0.5, 0.99]	0.95
<i>enable_soft_restart</i>	categorical	{true, false}	true
<i>enable_elitist</i>	categorical	{true, false}	true
<i>elitist_instances</i>	int	[1, 10]	1



2. Meta-tuning and algorithm configuration benchmarks

Use an automatic algorithm configurator to configure the parameters of a configurator

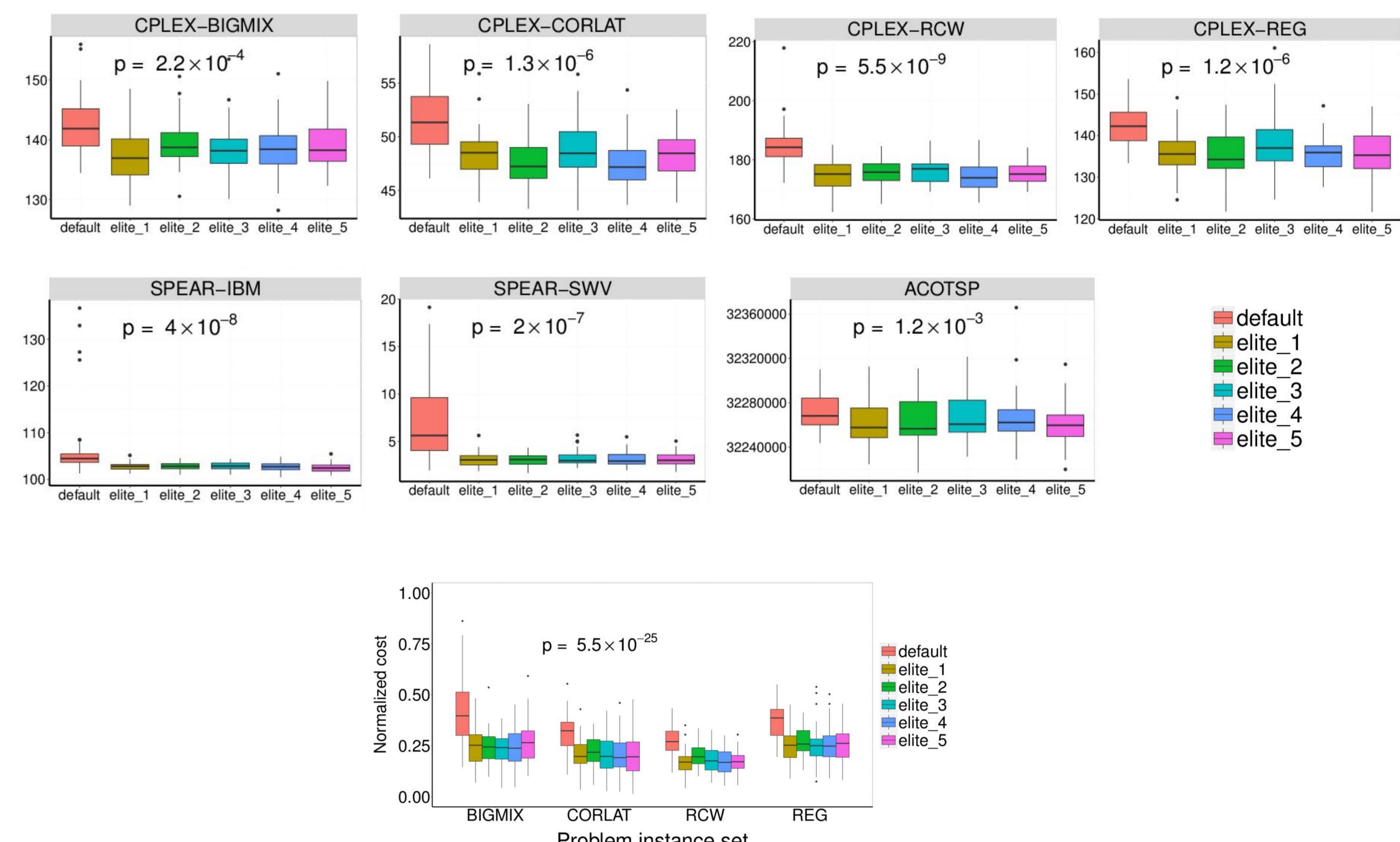
Algorithm configuration benchmarks for meta-tuning:

- Real benchmarks: extremely expensive
 - An *irace* run on SPEAR-IBM (budget: 5000 runs) → 2 CPU days
 - A meta-tuning on SPEAR-IBM (budget: 5000 *irace* runs) → 27.5 CPU years
- Artificial benchmark set
 - Unclear how to generate
 - Unclear how to match characteristics of real configuration tasks
- Surrogate benchmarks
 - A prediction model: configuration x instance → performance value
 - Build on real benchmark data

3. Empirical Performance Model (Hutter, Xu, Hoos & Leyton-Brown, 2014a)

- Random Forest regression model
- Training: 1000 random configurations x all problem instances

Algorithm	# Parameters (int/real/categorical/conditional)	Problem instance set (#instances)	Performance measure
CPLEX	76 (18/7/45/4)	BIGMIX (1000) REG (1000) CORLAT (1000) RCW (1000)	Running time
SPEAR	28 (4/12/10/9)	IBM (765) SWV (604)	Running time
Ant Colony Optimization	11 (4/4/3/5)	TSP (50)	Solution quality



Meta-tuning becomes computationally feasible

- An *irace* run on SPEAR-IBM (budget: 5000 runs) → 5 CPU minutes
- A meta-tuning on SPEAR-IBM (budget: 5000 *irace* runs) → 7.5 CPU days

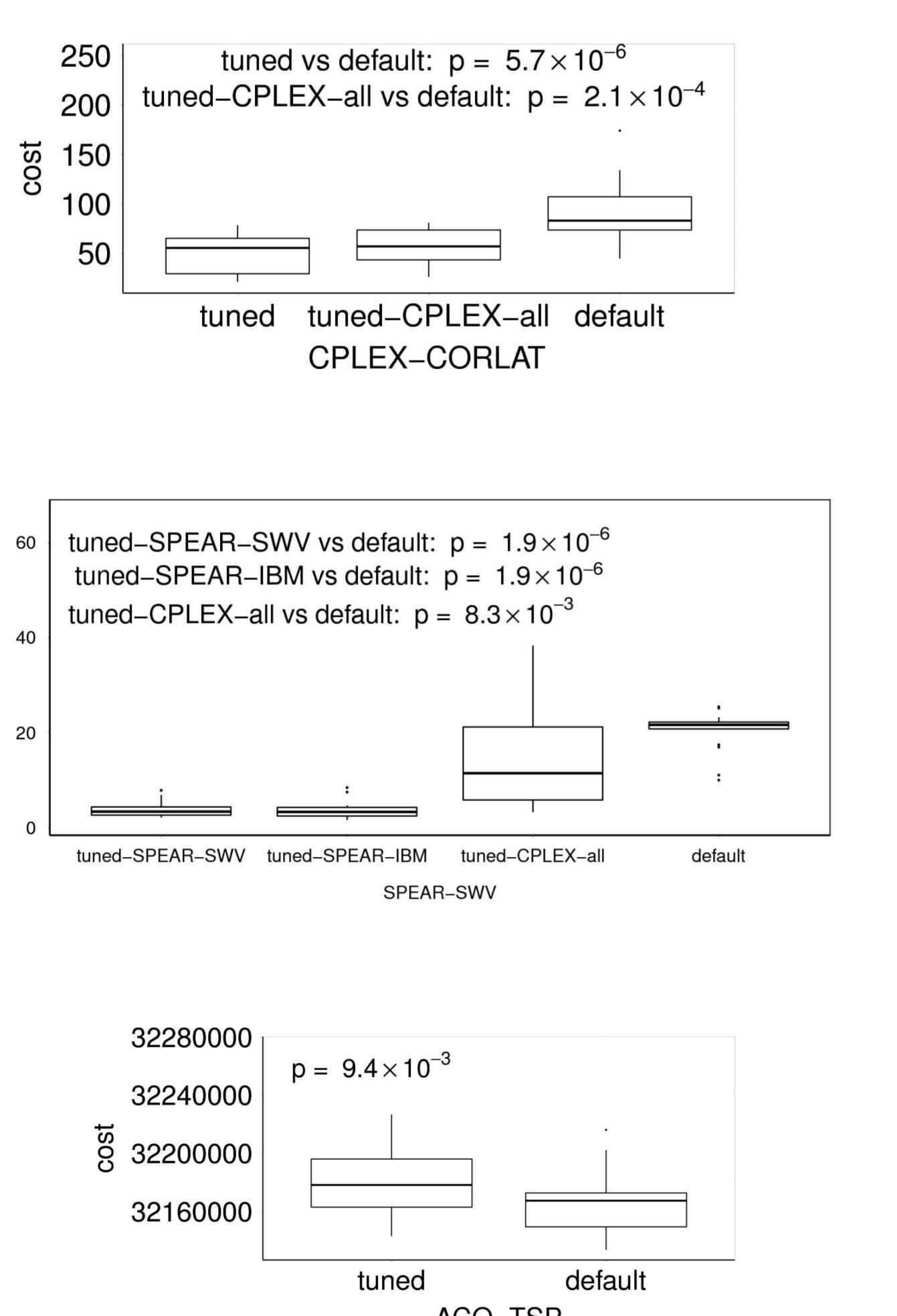
Consistency between surrogate and real benchmarks

- Prediction accuracy
- Benchmark homogeneity (KendallW)
- Important parameters and pairwise interactions (fANOVA, Hutter et al 2014b)

Post-analysis

- fANOVA (Hutter et al 2014b), ablation (Fawcett et al 2016), manual testing
- Most important parameters: N_{iter} , N_{min} , *elitist*
- Complex interactions between *irace* parameters
- Best *irace* versions exploit a more intense search than the default version.

4. Mixed results on real benchmarks



6. Ongoing works

- Try a new surrogate modelling method: Eggensperger, Lindauer, Hoos, Hutter & Leyton-Brown, 2017
 - Quantile Random Forest regression model + Hyper-parameter tuning
 - Training data: Trajectories of different automatic algorithm configurators + incumbents' performance + random data points
 - New benchmarks (*aclib2*)
- Collect more benchmarks
- Define quantitative characteristics of an algorithm configuration benchmark
- Meta-tuning on *irace* with capping
- Study relation between *irace* parameters and benchmark characteristics
- Study other state-of-the-art configurators

References

- C. Fawcett and H. H. Hoos. Analysing differences between algorithm configurations through ablation. *Journal of Heuristics*, 22(4):431–458 (2016)
- Dang, N., Pérez Cáceres, L, De Causmaecker, P. and Stützle, T. Configuring *irace* using surrogate configuration benchmarks. In: GECCO2017, pp. 243-250 (2017)
- F. Hutter, L. Xu, H. H. Hoos, and K. Leyton-Brown. Algorithm runtime prediction: Methods & evaluation. *Artificial Intelligence*, 206:79–111 (2014a)
- F. Hutter, H. H. Hoos, and K. Leyton-Brown. An efficient approach for assessing hyperparameter importance. In Proc. of the 31th Int. Conf. on Machine Learning, vol. 32, pp. 754–762 (2014b)
- K. Eggensperger, F. Hutter, H. H. Hoos, and K. Leyton-Brown. Efficient benchmarking of hyperparameter optimizers via surrogates. In: AAAI, pp. 1114–1120. AAAI Press (2015)
- Eggensperger, K., Lindauer, M., Hoos, H.H., Hutter, F. and Leyton-Brown, K. Efficient Benchmarking of Algorithm Configuration Procedures via Model-Based Surrogates. arXiv preprint arXiv:1703.10342 (2017)
- M. López-Ibáñez, J. Dubois-Lacoste, L. Pérez Cáceres, T. Stützle, and M. Birattari. The *irace* package: Iterated racing for automatic algorithm configuration. *Operations Research Perspectives*, pp. 43–58 (2016)