CAPSANDRUNS: An Improved Method for Approximately Optimal Algorithm Configuration

Gellért Weisz András György Csaba Szepesvári



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- Zillions of practical algorithms ⇔ Little theory Want theoretical guarantees on the runtime of
 - the chosen configuration; and
 - the configuration process.
- Goal: find a near-optimal configuration solving 1δ fraction of the problems in the least expected time.
 - Since some instances (δ fraction) are hopelessly hard; don't want to solve those.

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Previous work (Kleinberg et al., 2017; Weisz et al., 2018): no capping of OPT: using OPT_0 instead of $OPT_{\delta/2}$.

Guarantees

- Previous work (Kleinberg et al., 2017; Weisz et al., 2018): with high probability,
 - (i) the algorithm finds an (ε, δ) -optimal configuration;
 - (ii) with total work

$$\tilde{O}\left(\mathrm{OPT}_0\frac{n}{\varepsilon^2\delta}\right)$$
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* Worst case lower bound: $\Omega\left(OPT_0\frac{n}{\varepsilon^2\delta}\right)$ (Kleinberg et al., 2017).

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- * Worst case lower bound: $\Omega\left(OPT_{0}\frac{n}{\varepsilon^{2}\delta}\right)$ (Kleinberg et al., 2017).
- This work with high probability finds an (ε, δ) -optimal configuration:
 - Total work (simplified version):

$$\tilde{O}\left(n \mathrm{OPT}_{\delta/2}\left(\frac{1}{\delta} + \max\left\{\frac{\sigma^2}{\max\{\varepsilon^2, \Delta^2\}}, \frac{r}{\max\{\varepsilon, \Delta\}}\right\}\right)\right) \ ,$$

where

- $\star~\Delta\sim$ gap between the best two configurations
- $\star~\sigma^2 \sim$ runtime variances,
- $\star~r\sim$ range of runtimes.

CAPSANDRUNS algorithm

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Phase I:

- For each configuration i find a runtime cap τ_i
 - that solves between 1δ and $1 \delta/2$ fraction of problem instances,
 - not wasting time on bad configurations.

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Phase II:

- Run a Bernstein race (Mnih et al., 2008) over the configurations.
 - Evaluate configurations in parallel, giving preference to better ones, shrinking confidence regions using Bernstein's inequality.

Experiments

Configuring SAT solvers (Weisz et al., 2018):



Factor of total runtime improvement from LEAPSANDBOUNDS to CAPSANDRUNS for various values of ε and δ .

STRUCTURED PROCRASTINATION	LeapsAndBounds	CAPSANDRUNS
20643 (± 5) days	1451 (± 83) days	586 (±7) days

Thank you!

Poster #201