ParamILS: An Automatic Algorithm Configuration Framework

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JAIR'09

Reading

Comprehensive journal paper on a seminal work

Check website for specific sections to read 👀

Feel free to read more at your own interest 😊

Integer programing and SAT

Integer program (IP) max $c \cdot z$ s.t. $Az \leq b$ $z \in \mathbb{Z}^n$

SAT

 $(x_1 \lor x_4) \land (x_1 \lor \bar{x}_3 \lor \bar{x}_8)$ $\land (x_1 \lor x_8 \lor x_{12}) \land (x_2 \lor x_{11})$

Tons of applications:





Robust ML

MAP estimation



Clustering



Routing



Scheduling

Algorithm configuration

Solvers come with tons of tunable parameters Tuning by hand is notoriously **slow**, **tedious**, and **error-prone** Can we **automatically** optimize parameters?

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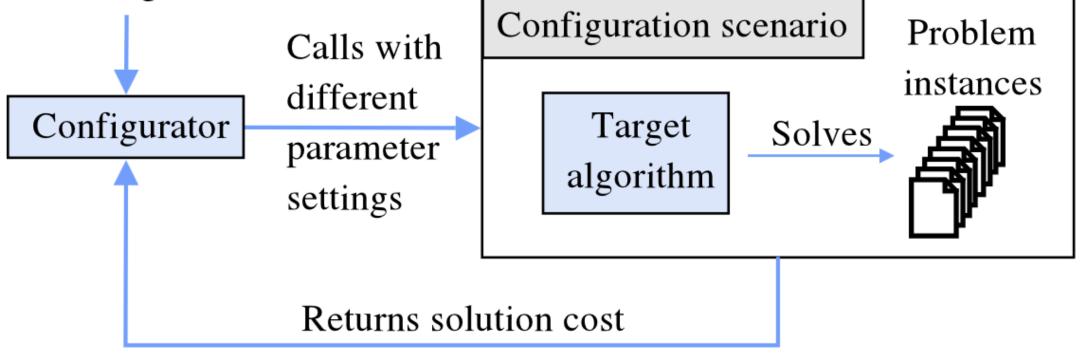
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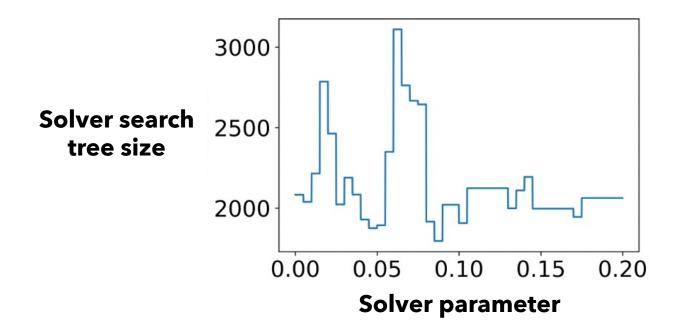
Algorithm configuration pipeline

Parameter domains





Key challenge



- Solver performance is **extremely volatile**
- Gradients are often **uninformative**

Outline

1. Introduction

2. Setup

- 3. ParamILS
- 4. Experiments
- 5. Spectrum auctions

Setup: Parameterized algorithm

Algorithm \mathcal{A} with k parameters

 i^{th} parameter setting from a set Θ_i Assume $|\Theta_i|$ is finite (e.g., by discretizing continuous parameters)

 $\Theta \subseteq \Theta_1 \times \cdots \times \Theta_k$ is the set of all feasible configurations In experiments, $|\Theta|$ as large as $1.38 \cdot 10^{37}$

 $\mathcal{A}(\boldsymbol{\theta})$ is the algorithm with parameters $\boldsymbol{\theta} \in \boldsymbol{\Theta}$

Setup: Modeling the application domain

Set of problem instances Π

• E.g., $\pi \in \Pi$ is a routing integer program

Application-specific distribution \mathcal{D} over problem instances, e.g.:

- Distribution over Bay Area routing problems
- Uniform distribution over benchmark dataset



Setup: Measuring performance

 $o(\theta, \pi, \kappa)$: runtime of $\mathcal{A}(\theta)$ on instance π with runtime cap κ

 κ_{max} : maximum runtime after which any run will be terminated

 $c(\boldsymbol{\theta})$: overall cost of running algorithm with parameters $\boldsymbol{\theta}$

- E.g., expected runtime $c(\boldsymbol{\theta}) = \mathbb{E}_{\pi \sim \mathcal{D}}[o(\boldsymbol{\theta}, \pi, \kappa_{\max})]$
- If $\mathcal D$ is the uniform distribution over a benchmark set Π , equivalent to

$$c(\boldsymbol{\theta}) = \frac{1}{|\Pi|} \sum_{\pi \in \Pi} o(\boldsymbol{\theta}, \pi, \kappa_{\max})$$

Algorithm configuration goal

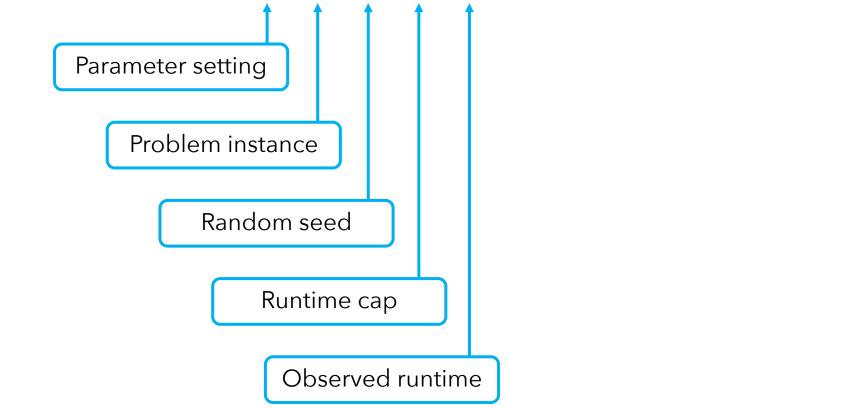
Goal: Find parameter setting $\boldsymbol{\theta}$ with low cost $c(\boldsymbol{\theta})$

Challenges:

- Distribution ${\mathcal D}$ may be unknown
- Do not know analytical form of *c*
- *c* may be nonconvex, non-Lipschitz, ...



Sequence of runs $\mathbf{R} = ((\boldsymbol{\theta}_1, \pi_1, s_1, \kappa_1, o_1), \dots, (\boldsymbol{\theta}_n, \pi_n, s_n, \kappa_n, o_n))$



Empirical cost

Sequence of runs $\mathbf{R} = ((\boldsymbol{\theta}_1, \pi_1, s_1, \kappa_1, o_1), \dots, (\boldsymbol{\theta}_n, \pi_n, s_n, \kappa_n, o_n))$

Empirical cost $\hat{c}(\boldsymbol{\theta}, \mathbf{R}) = \operatorname{average}(\{o_i : \boldsymbol{\theta} = \boldsymbol{\theta}_i\})$

Could be replaced by another statistic, e.g., median

Goal: Find θ with low empirical (training) cost $\hat{c}(\theta, \mathbf{R})$

- Ideally, this should lead to low **actual** cost $c(\theta)$
- Later this quarter: statistical guarantees for bounding $|c(\theta) \hat{c}(\theta, \mathbf{R})|$

Key questions

- 1. Which parameter configurations $\Theta' \subseteq \Theta$ should we evaluate?
- 2. Which instances $\Pi_{\theta'} \subseteq \Pi$ should we use to evaluate $\theta' \in \Theta'$?
- 3. Which cutoff times κ_i should we use for each run?

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ParamILS:

A seminal general-purpose algorithm configuration procedure

- Begins with a **default** parameter configuration
- Performs **local search** in configuration space
 - Changes the setting of **one parameter at a time**
 - Keeps those changes resulting in performance improvements
- After finding a **local minimum**:

Randomly changes some parameters in order to escape

BasicILS

Step 1: Randomly search for good initial configuration

- i. $\boldsymbol{\theta}_0$: initial configuration
- ii. For i = 1, ..., r:
 - a. $\boldsymbol{\theta} \leftarrow random(\boldsymbol{\Theta})$
 - b. if $BETTER(\boldsymbol{\theta}, \boldsymbol{\theta}_0), \boldsymbol{\theta}_0 \leftarrow \boldsymbol{\theta}$

Essentially, run $\mathcal{A}(\boldsymbol{\theta})$ on some random instances and compare $\hat{c}(\boldsymbol{\theta}, \mathbf{R})$ and $\hat{c}(\boldsymbol{\theta}_0, \mathbf{R})$



Step 2: Search for better configuration in neighborhood of $\boldsymbol{\theta}_0$

 $\boldsymbol{\theta}_{\text{ils}} \leftarrow \text{IterativeFirstImprovement}(\boldsymbol{\theta}_0)$

IterativeFirstImprovement($\boldsymbol{\theta}$):

Repeat:

- i. $\boldsymbol{\theta}' \leftarrow \boldsymbol{\theta}$
- ii. Find best parameter setting θ'' in the neighborhood of θ' according to \hat{c}

 ${\boldsymbol{\theta}}^{\prime\prime}$ differs from ${\boldsymbol{\theta}}^{\prime}$ in one component



Step 2: Search for better configuration in neighborhood of $\boldsymbol{\theta}_0$

 $\boldsymbol{\theta}_{\text{ils}} \leftarrow \text{IterativeFirstImprovement}(\boldsymbol{\theta}_0)$

IterativeFirstImprovement($\boldsymbol{\theta}$):

Repeat:

i. $\boldsymbol{\theta}' \leftarrow \boldsymbol{\theta}$

ii. Find best parameter setting θ'' in the neighborhood of θ' according to \hat{c}

iii. Set $\boldsymbol{\theta} = \boldsymbol{\theta}^{\prime\prime}$

Until $\theta' = \theta \implies$ found a local minimum

BasicILS

Step 3 (repeat as many times as you can):

- 1. $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta}_{\text{ils}}$
- 2. for s rounds do random exploration:

 $\boldsymbol{\theta} \leftarrow \text{random } \boldsymbol{\theta}' \text{ in the neighborhood of } \boldsymbol{\theta}$

- 3. $\theta \leftarrow \text{ITERATIVEFIRST}\text{IMPROVEMENT}(\theta)$
- 4. if $BETTER(\boldsymbol{\theta}, \boldsymbol{\theta}_{ils})$, set $\boldsymbol{\theta}_{ils} \leftarrow \boldsymbol{\theta}$
- 5. With some small probability, restart: $\theta \leftarrow random(\Theta)$

Return best $\boldsymbol{\theta}$ the algorithm ever found according to \hat{c}

Adaptive capping

Solving IPs can take forever...

- We want to give up as early as we can
- But still correctly evaluate BETTER(θ_1, θ_2)

Without a good way to **cap** runs, will waste time on bad θ 's

Adaptive capping

Illustrative example:

• θ_1 takes 10 seconds total to solve 100 instances $\hat{c}(\theta_1, \mathbf{R}) = \frac{1}{100} \cdot 10 = 0.1$ • θ_2 takes at least 11 seconds to solve the first instance $\hat{c}(\theta_2, \mathbf{R}) \ge \frac{1}{100} \cdot (11 + 0 + 0 + \cdots 0) = 0.11$

99 zeros

• Can stop evaluating $\boldsymbol{\theta}_2$ 11 seconds into the first run

Simple adaptive capping

BETTER($\boldsymbol{\theta}_1$, $\boldsymbol{\theta}_2$):

- 1. Evaluate $\boldsymbol{\theta}_1$ on N random instances to compute $\hat{c}(\boldsymbol{\theta}_1, \mathbf{R})$
- 2. Evaluate θ_2 on N random instances to compute $\hat{c}(\theta_2, \mathbf{R})$ But give up after $N \cdot \hat{c}(\theta_1, \mathbf{R})$ seconds and return θ_1
- 3. If didn't give up, return

$$\begin{cases} \boldsymbol{\theta}_1 & \text{if } \hat{c}(\boldsymbol{\theta}_1, \mathbf{R}) < \hat{c}(\boldsymbol{\theta}_2, \mathbf{R}) \\ \boldsymbol{\theta}_2 & \text{else} \end{cases}$$

Many ways **cap more aggressively** and improve this further

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Experiments: example

Average runtime

Scenario	SimpleLS(100)	BasicILS(100)		<i>p</i> -value
	Performance	Performance	Avg. # ILS iterations	
Saps-SWGCP	0.5 ± 0.39	0.38 ± 0.19	2.6	$9.8\cdot10^{-4}$
Saps-QCP	3.60 ± 1.39	3.19 ± 1.19	5.6	$4.4\cdot 10^{-4}$
Spear-QCP	0.4 ± 0.39	0.36 ± 0.39	1.64	0.008

- SAPS and SPEAR: SAT solvers
- SWGCP: graph coloring problems
- QCP: quasi-group completion problem
- SimpleLS: local search w/o randomization
 - Should get stuck in local minima

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Spectrum auctions

Later work by the same UBC lab (and others):

- In 2016-17, FCC held an auction to repurpose radio spectrum
 - Broadcast television \rightarrow wireless internet
 - In total, the auction yielded \$19.8 billion



Kevin-Leyton Brown UBC



llya Segal Stanford

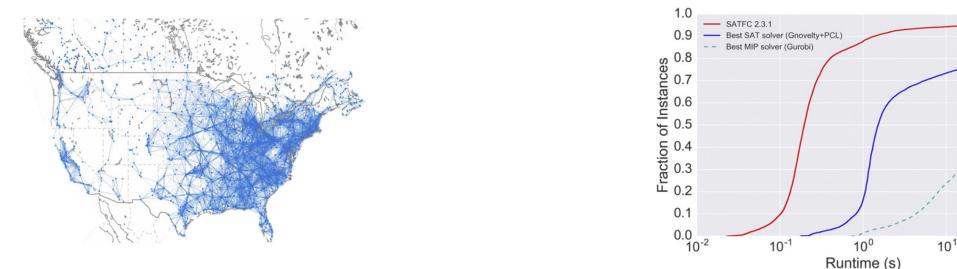


Paul Milgrom Stanford

And many others!

Spectrum auctions

• The auction involves solving huge graph coloring problems



- SATFC uses algorithm configuration + portfolio selection
- Simulations indicate SATFC saved the government billions

 10^{2}



ParamILS: a seminal general-purpose configuration procedure

Combines local search with random exploration

Speedups for **IP** and **SAT** solvers

Inspired later breakthroughs for **spectrum auctions**