BOAT: Building Auto-Tuners with Structured Bayesian Optimization

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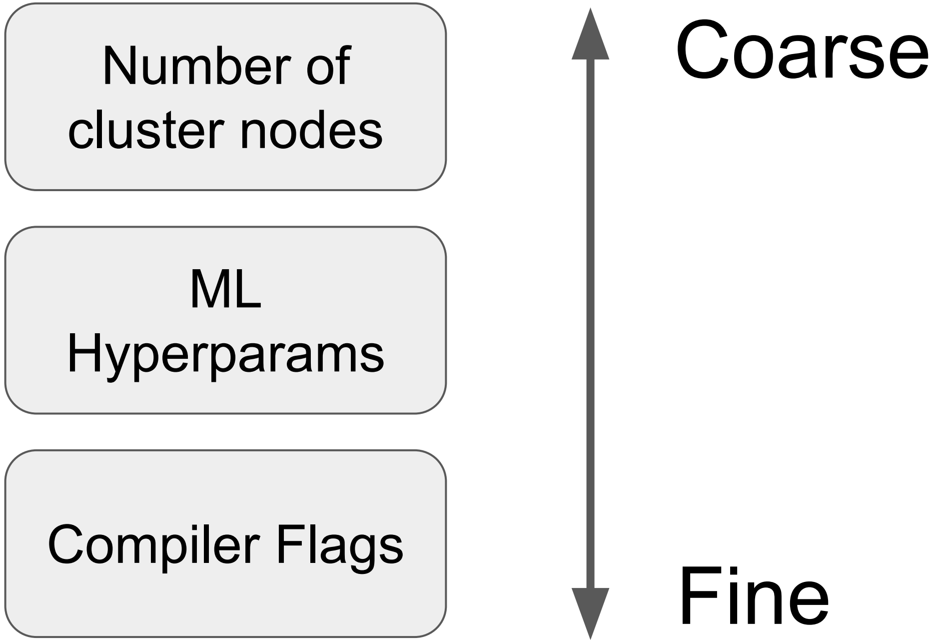
Presented by Jesse Mu

Parameters in large-scale systems



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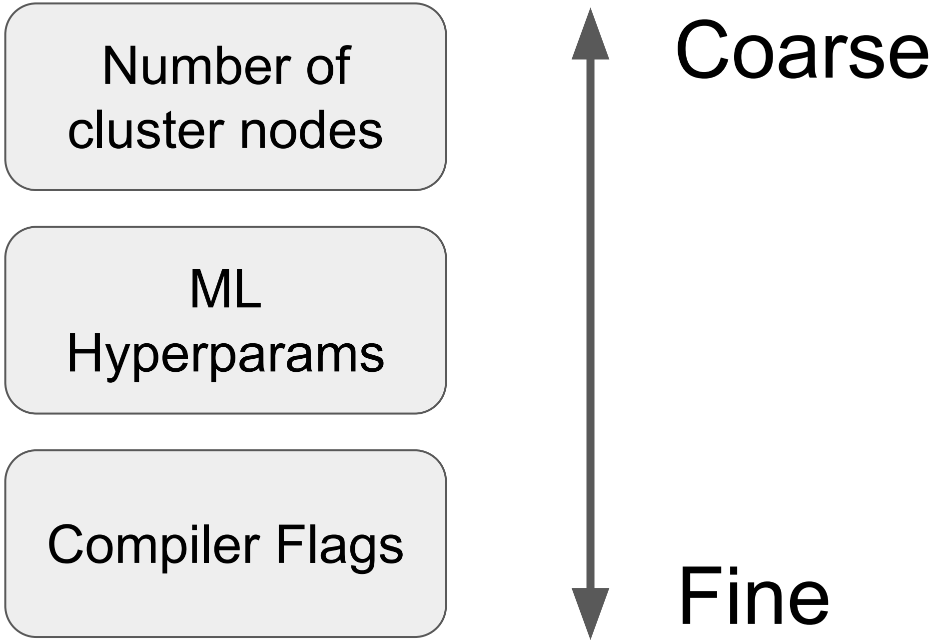

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Number of cluster nodes

ML Hyperparams

Compiler Flags

Coarse

Fine

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Minimize some cost function $f(\theta)$

...where cost is runtime, memory, I/O, etc

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- Bayesian optimization (e.g. SPEARMINT)
- *Structured* Bayesian optimization (this work: **B**esp**O**ke **A**uto-**T**uners)

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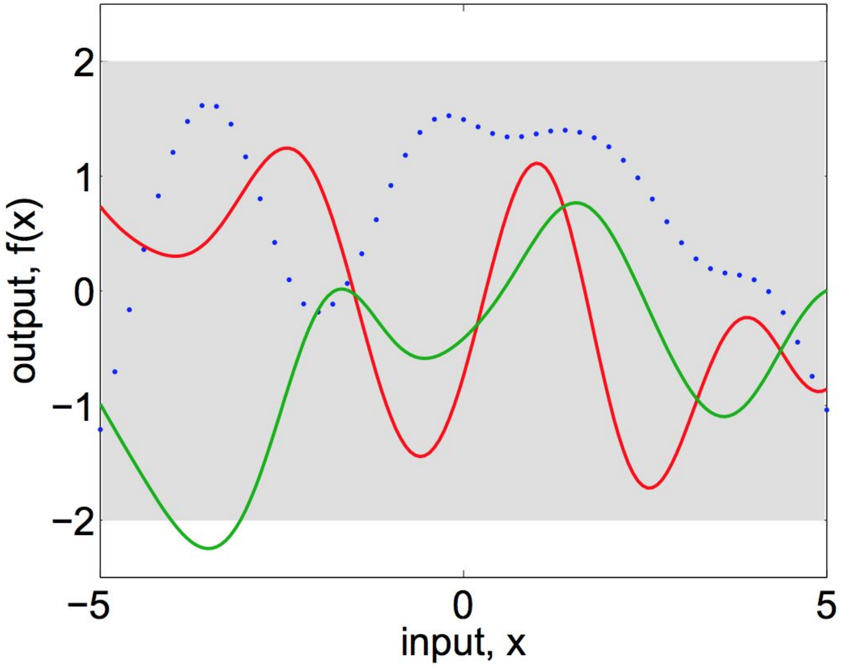
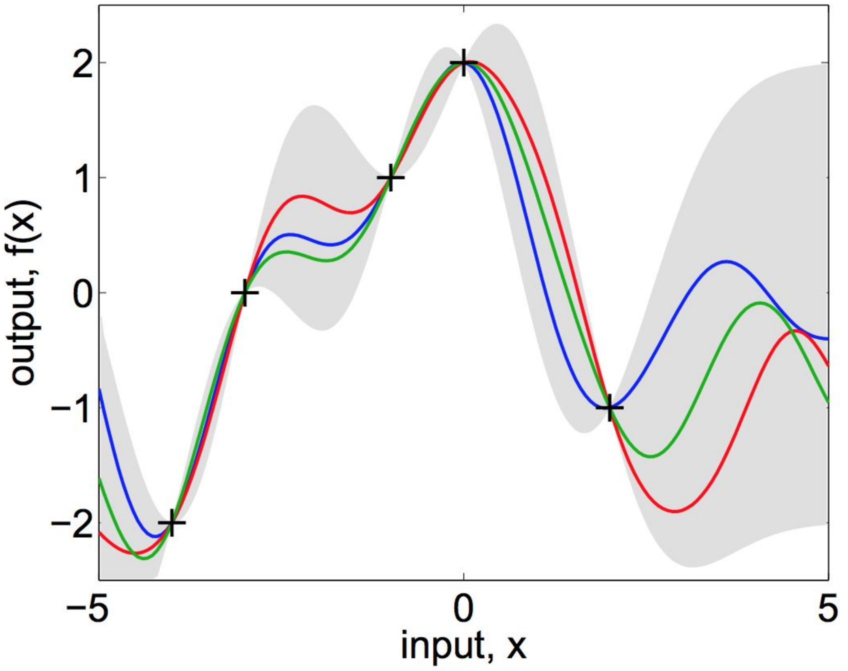
Gaussian Processes

Prior — Data → Posterior





From Carl Rasmussen’s 4F13 lectures
http://mlg.eng.cam.ac.uk/teaching/4f13/1718/gp%20and%20data.pdf

Algorithm 1 The Bayesian optimization methodology

Input: Objective function $f()$
Input: Acquisition function $\alpha()$
1: Initialize the Gaussian process G
2: **for** $i = 1, 2, \ldots$ **do**
3: Sample point: $\mathbf{x}_t \leftarrow \arg\max_{\mathbf{x}} \alpha(G(\mathbf{x}))$
4: Evaluate new point: $y_t \leftarrow f(\mathbf{x}_t)$
5: Update the Gaussian process: $G \leftarrow G \mid (\mathbf{x}_t, y_t)$
6: **end for**

Algorithm 1 The Bayesian optimization methodology

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e.g. expected increase over max perf.
(balance exploration vs exploitation)

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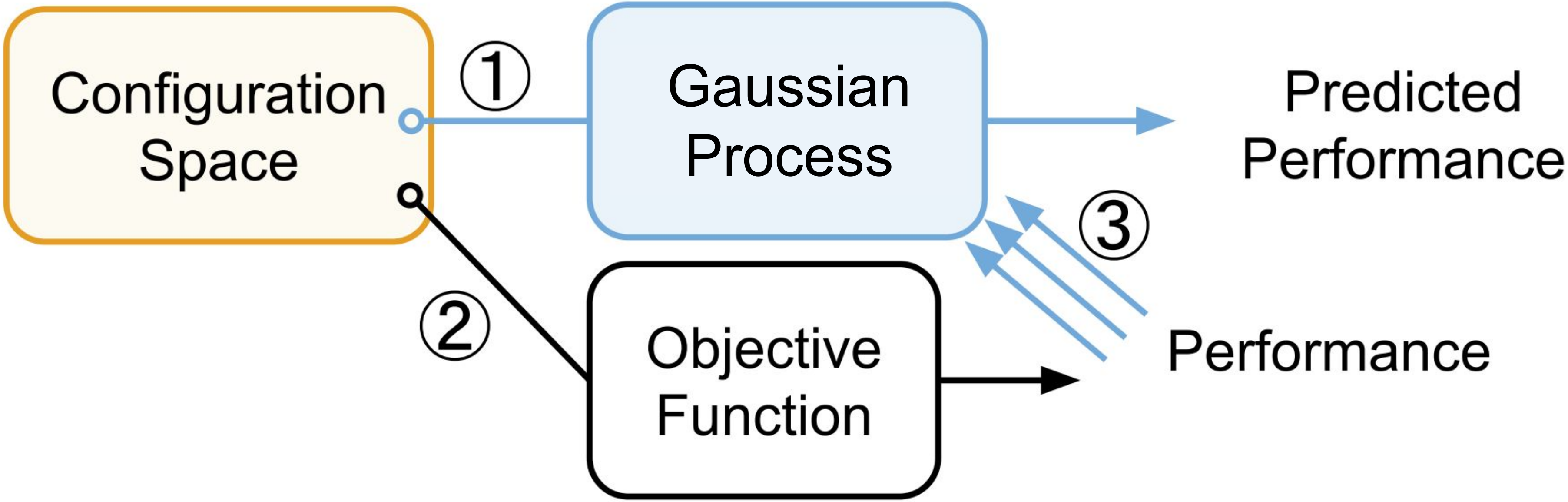
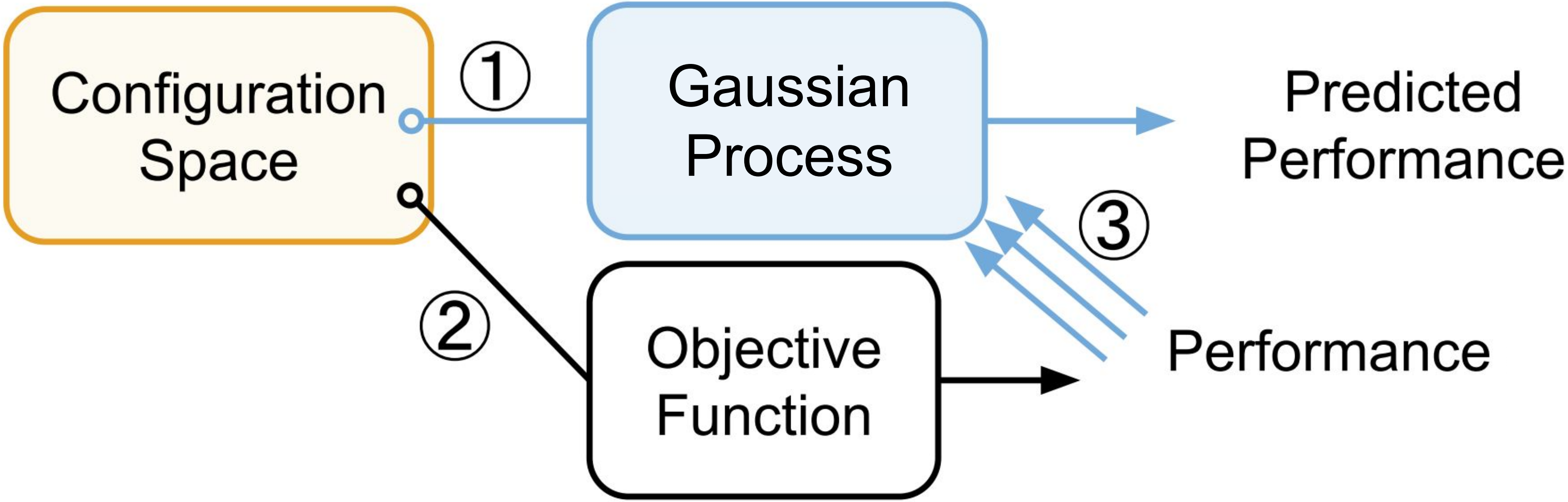
Bayesian Optimization



Structured Bayesian Optimization (SBO)



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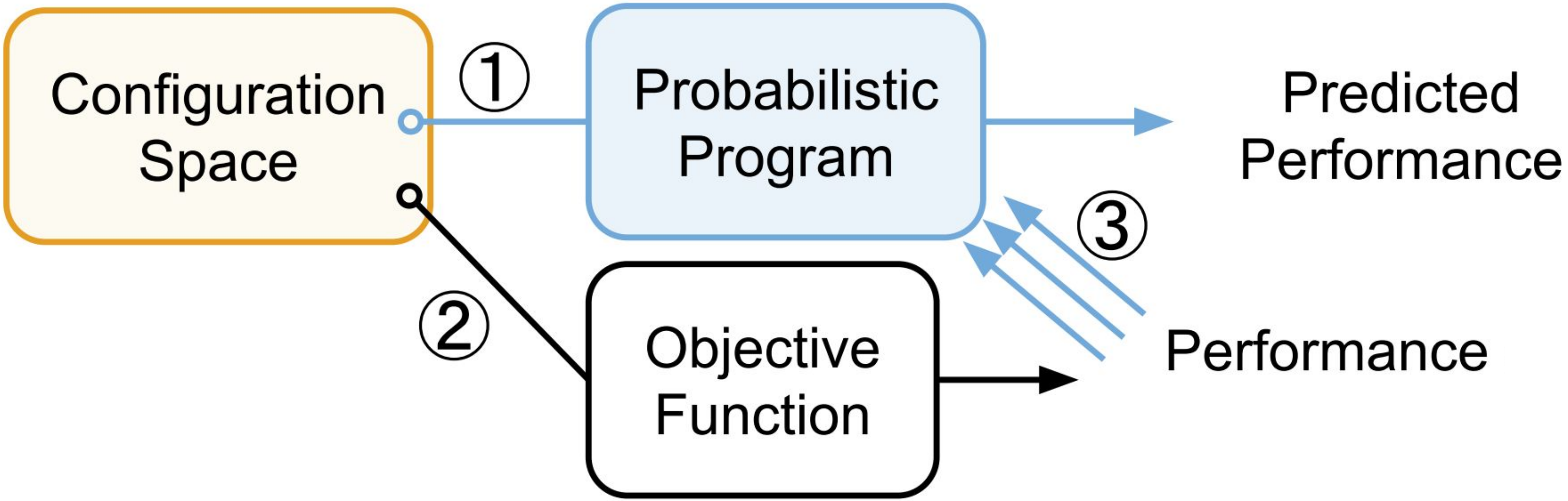

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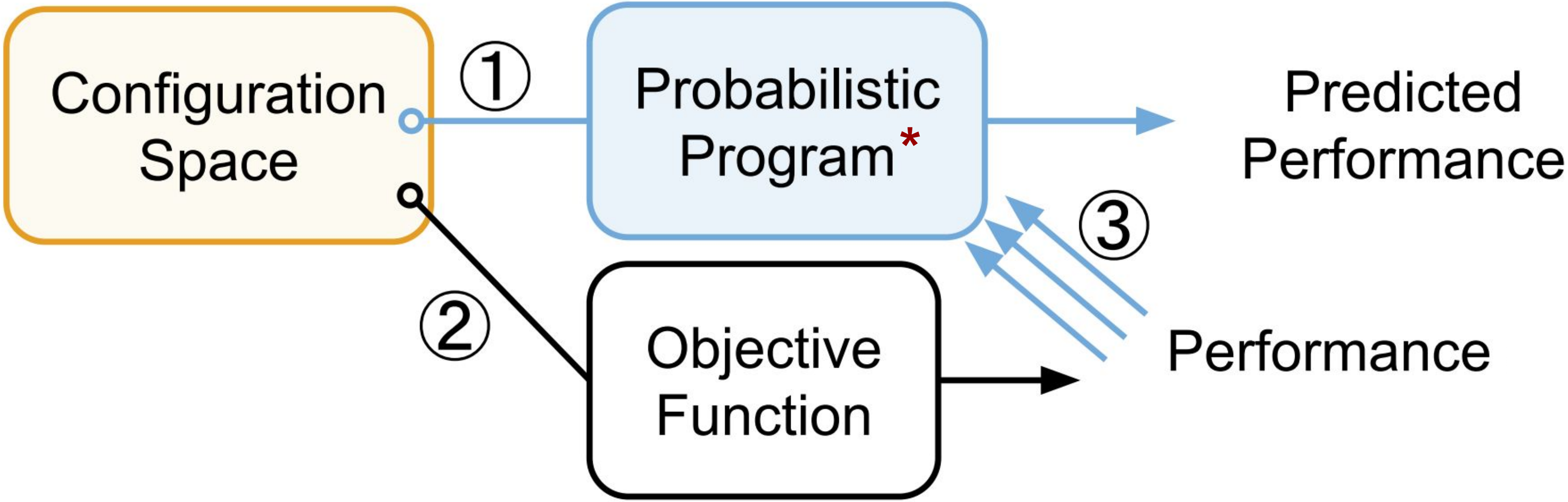

*Developer-specified, *semi-parametric* model of performance from observed performance + arbitrary runtime characteristics

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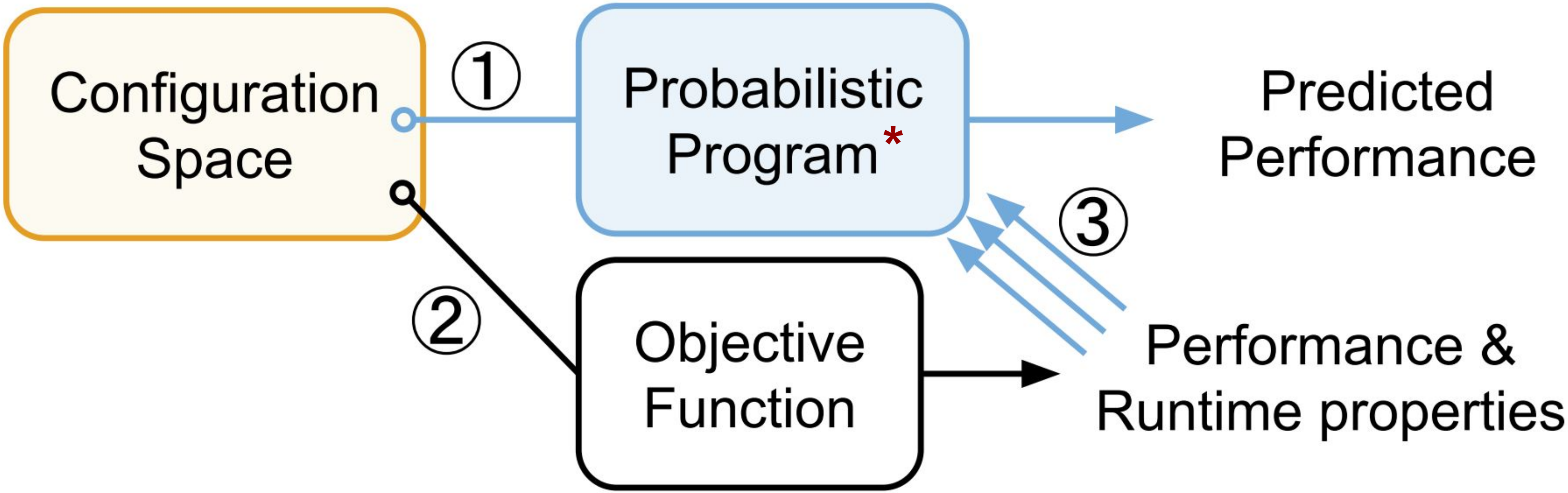

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Probabilistic Models for SBO

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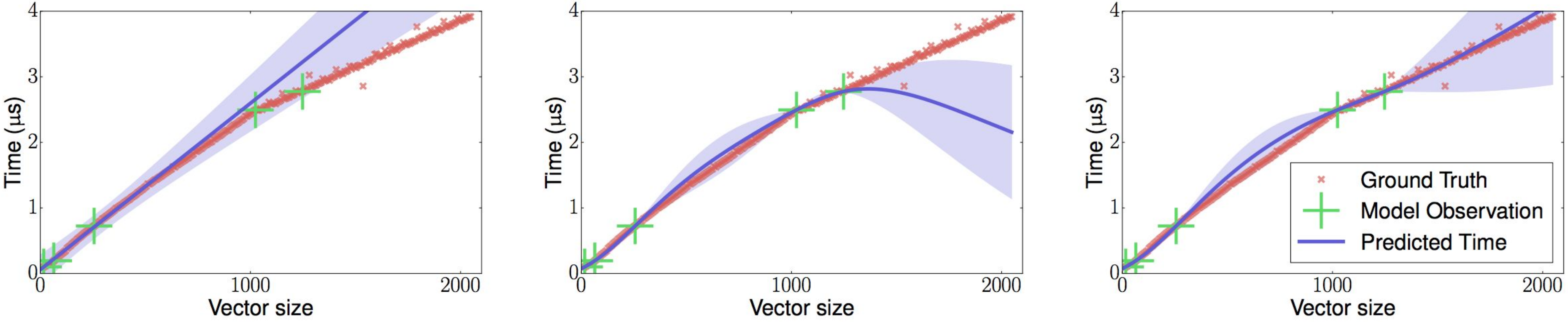

(a) Parametric (Linear regression) (b) Non-parametric (Gaussian process) (c) Semi-parametric (Combination)

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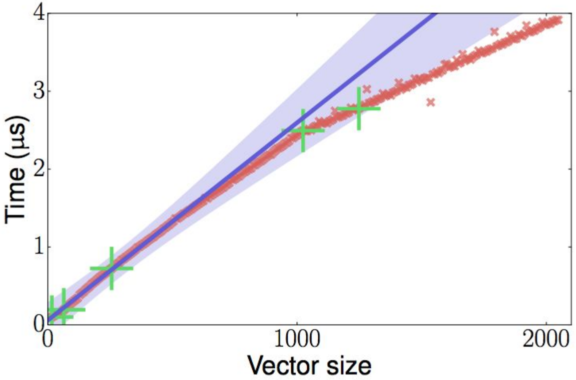
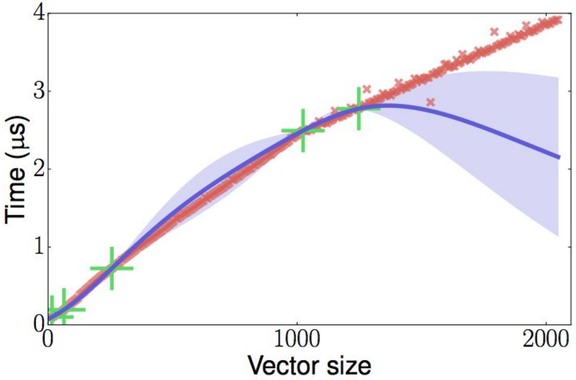
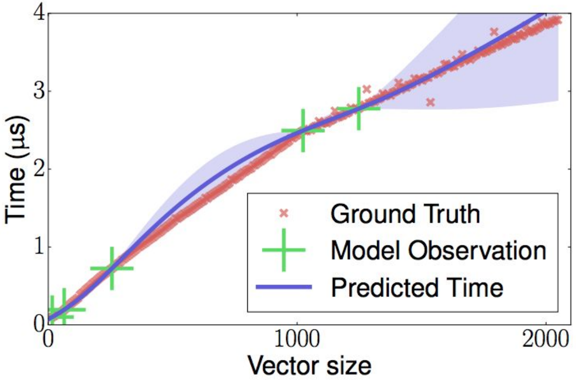


(a) Parametric (Linear regression)



(b) Non-parametric (Gaussian process)



(c) Semi-parametric (Combination)

Too restrictive

Too generic

Just right

Semi-parametric models in SBO

- Specify the parametric component *only* (GP for free)

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```
struct GCRateModel : public SemiParametricModel<GCRateModel> {
  GCRateModel() {
    allocated_mbs_per_sec =
     std::uniform_real_distribution<>(0.0, 5000.0)(generator);
    // Omitted: also sample the GP parameters
  }
  double parametric(double eden_size) const {
    // Model the rate as inversly proportional to Eden's size
    return allocated_mbs_per_sec / eden_size;
  }
};
```

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};
```

Prior: malloc rate ~ Uniform(0, 5000)

Semi-parametric models in SBO

```
int main() {
  // Example: observe two measurements and make a prediction
  ProbEngine<GCRateModel> eng;
  eng.observe(0.40, 1024);  // Eden: 1024MB, GC rate: 0.40/sec
  eng.observe(0.25, 2048);  // Eden: 2048MB, GC rate: 0.25/sec
  // Print average prediction for Eden: 1536MB
  std::cout << eng.predict(1536) << std::endl;
}
```

Composing semi-parametric models

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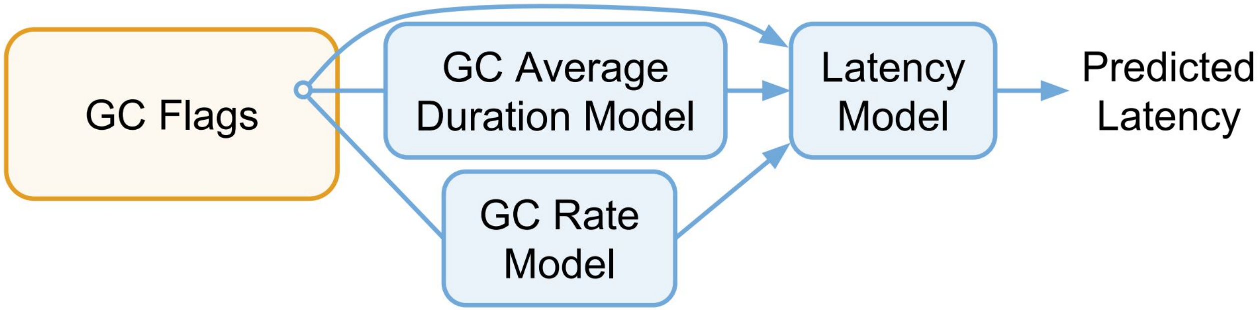
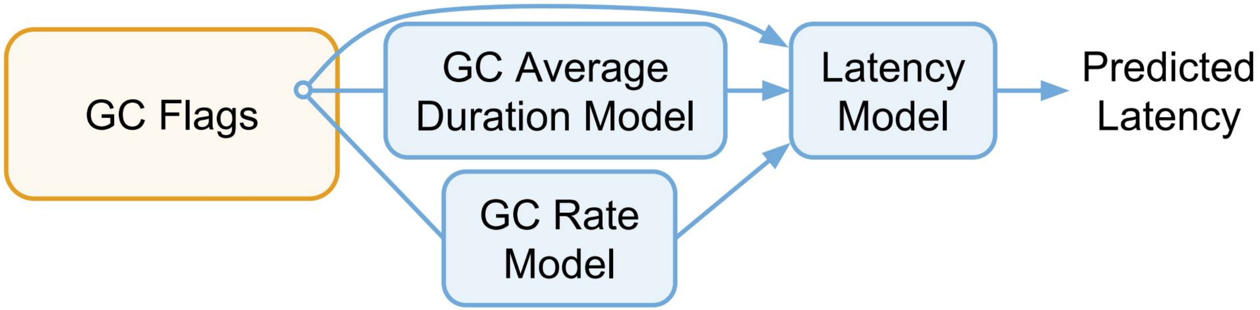


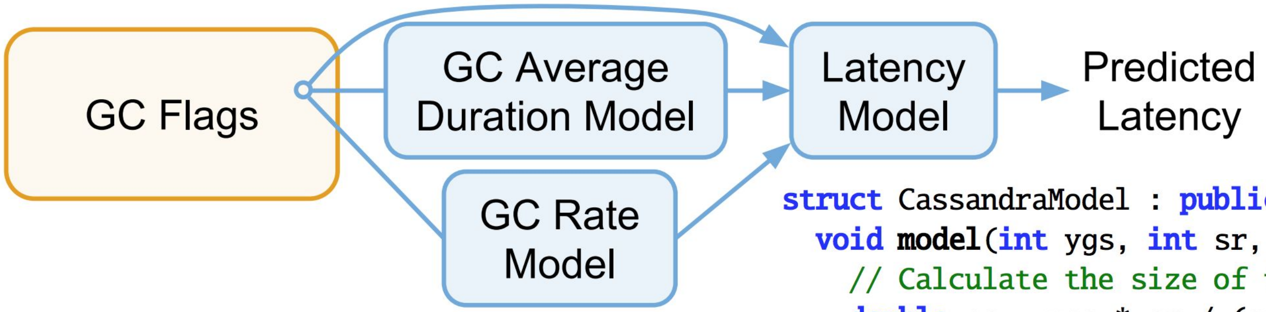
Composing semi-parametric models



Dataflow DAG

Inference exploits conditional independence between models

Composing semi-parametric models




```
struct CassandraModel : public DAGModel<CassandraModel> {
  void model(int ygs, int sr, int mtt){
    // Calculate the size of the heap regions
    double es = ygs * sr / (sr + 2.0);// Eden space's size
    double ss = ygs / (sr + 2.0);     // Survivor space's size
    // Define the dataflow between semi-parametric models
    double rate =     output("rate", rate_model, es);
    double duration = output("duration", duration_model,
                             es, ss, mtt);
    double latency =  output("latency", latency_model,
                             rate, duration, es, ss, mtt);
  }
  ProbEngine<GCRateModel> rate_model;
  ProbEngine<GCDurationModel> duration_model;
  ProbEngine<LatencyModel> latency_model;
};
```

Dataflow DAG

Inference exploits conditional independence between models

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1. Configuration space (i.e. possible params)
2. Objective function + runtime measurements
3. *Semi-parametric* model of system

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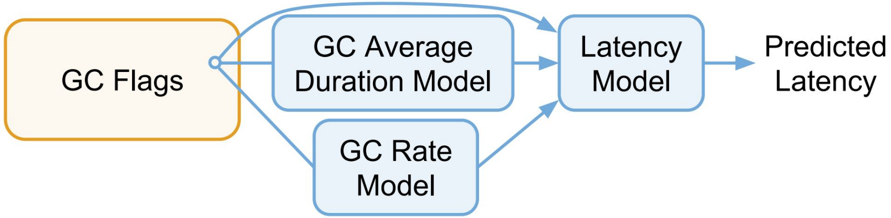
Key: try generic system, before optimizing with structure

Evaluation: Cassandra GC



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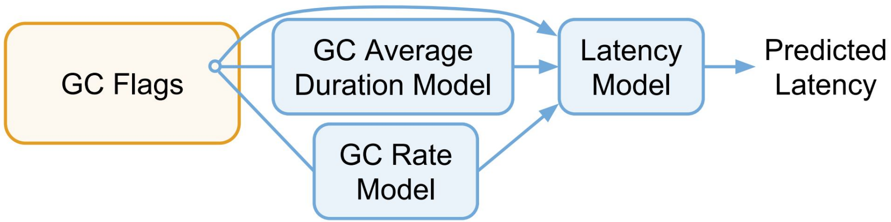

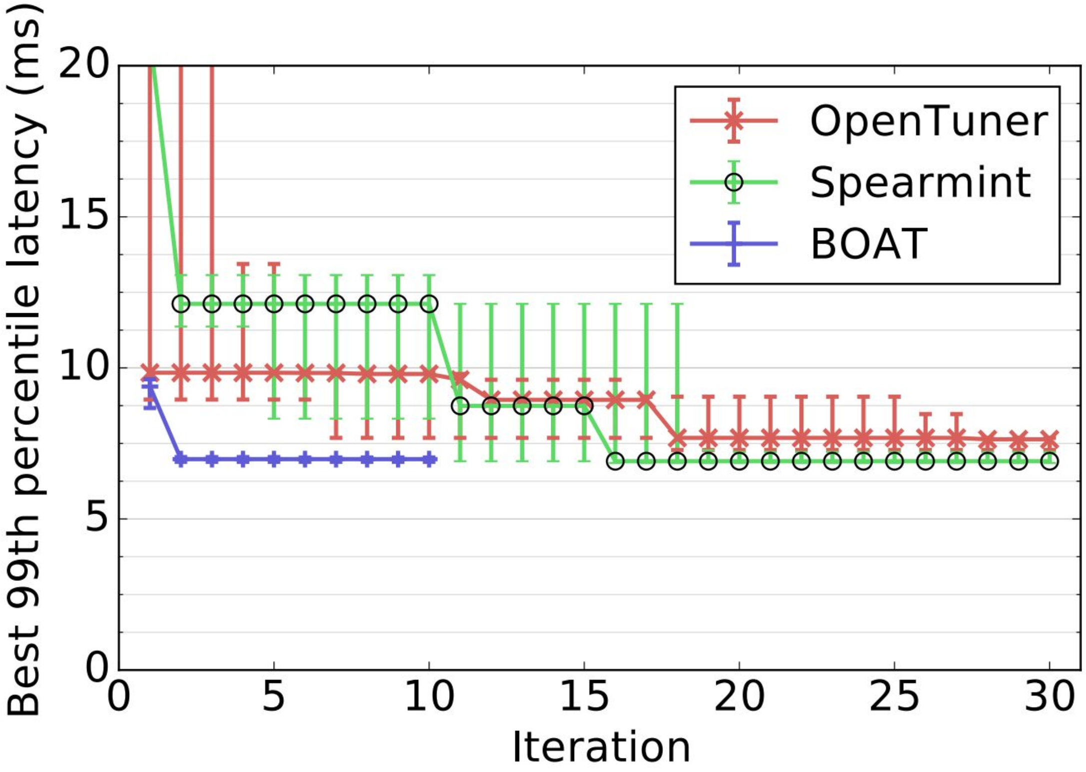

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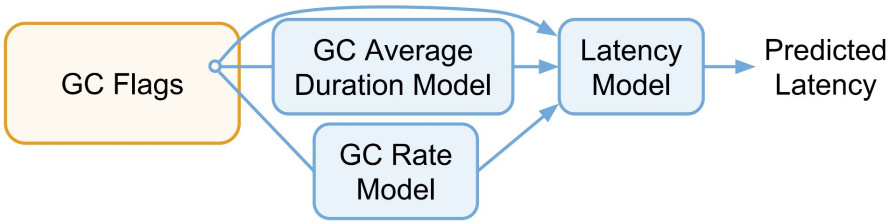

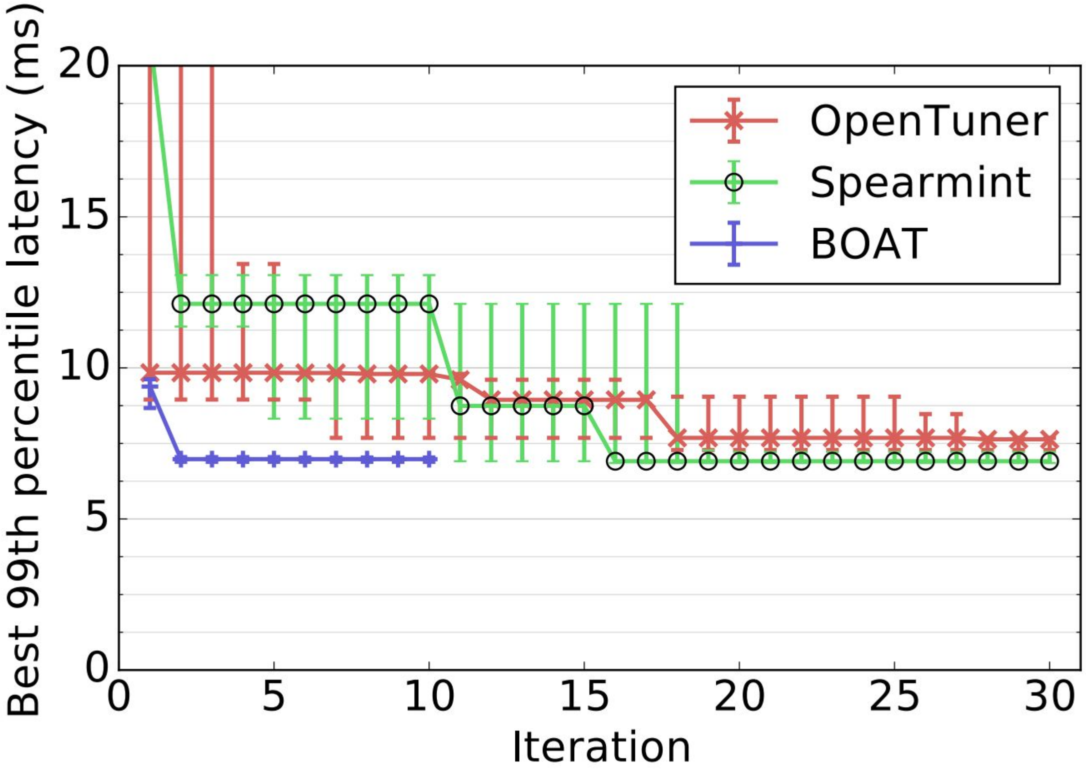

Best params outperform Cassandra defaults by 63%

Existing systems converge but take 6x longer

Evaluation: Neural Net SGD

Load balancing, worker allocation over 10 machines = **30 params**

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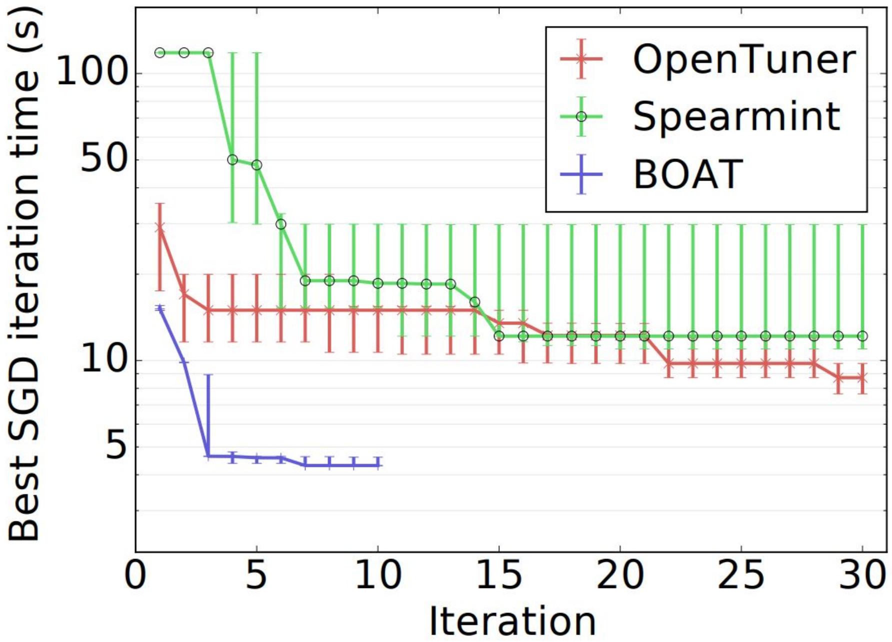

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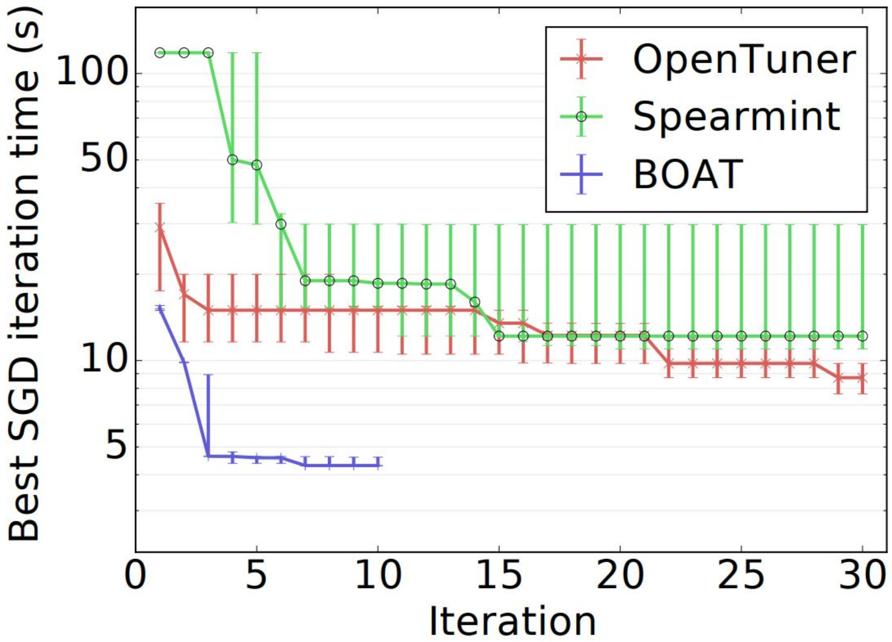

Default configuration: 9.82s

OpenTuner: 8.71s

BOAT: **4.31s**

Existing systems don't converge!

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  - Unsurprising that expert-developed models optimize better!
    - Tradeoff: developer hours vs machine hours
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    - More details about tradeoff between parametric model and generic GP
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- **Implementation**
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  - Key for system adoption: make interface as high-level as possible
- **Evaluation**
  - What happens when # params >> 30?
  - “DAGModels help debugging”...how?