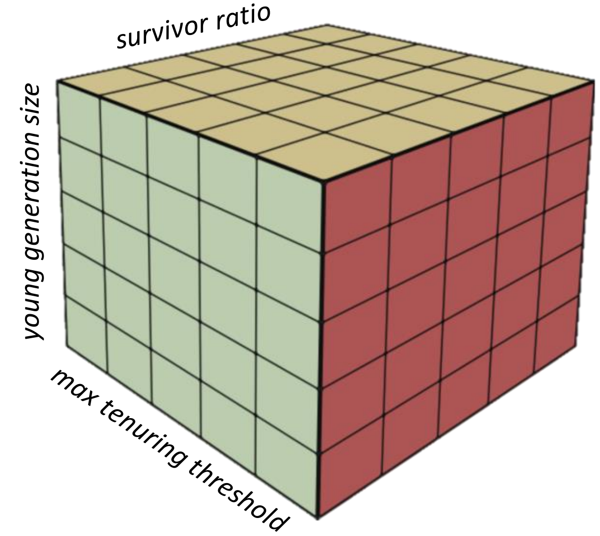
BOAT: Building Auto-Tuners with Structured Bayesian Optimization

Valentin Dalibard, Michael Schaarschmidt, Eiko Yoneki

Motivation

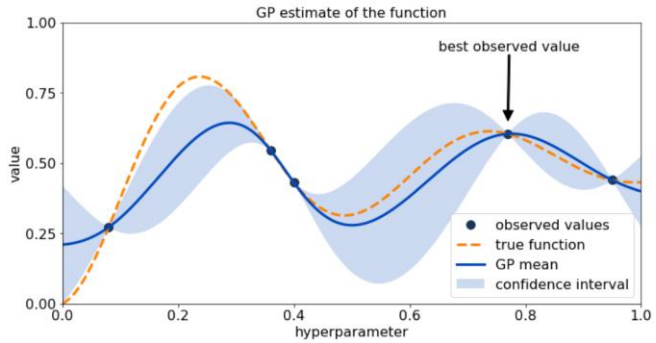
Problem



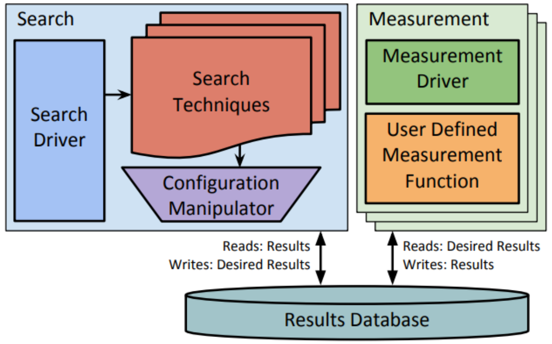
Modern systems require fine tuning a large number of hyperparameters

Source: Dalibard et al., 2017

Existing Solutions

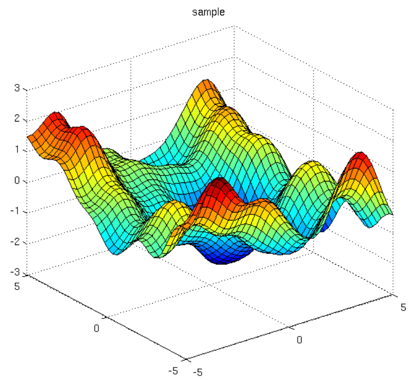


Bayesian optimization

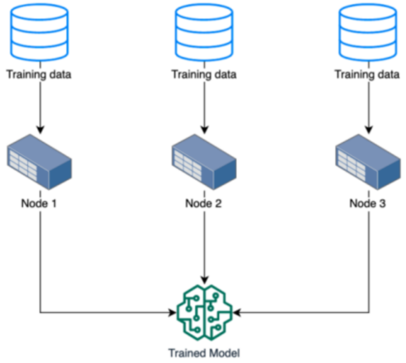


Auto-Tuners

Problems



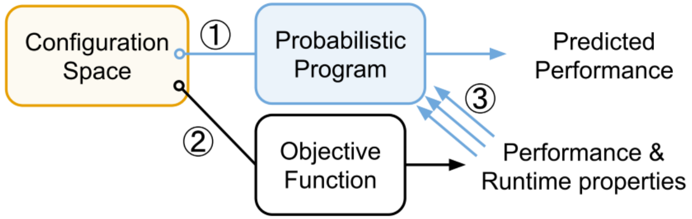
Configuration space too large



Time-consuming performance evaluation

BOAT: BespOke Auto-Tuner

Structured Bayesian Optimization



Source: Dalibard et al., 2017

BOAT Framework

```cpp
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 {
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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
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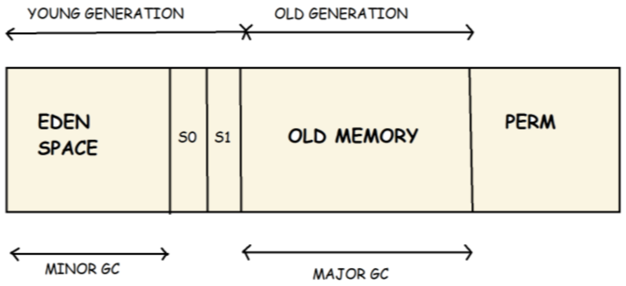
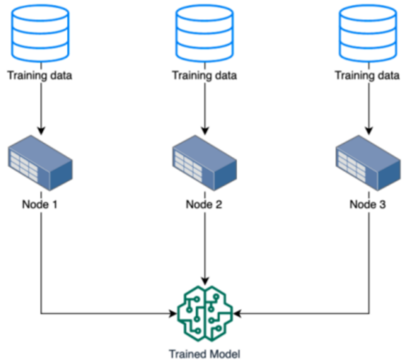
  // Print average prediction for Eden: 1536MB
  std::cout << eng.predict(1536) << std::endl;
}
```

Case Studies



Garbage collection



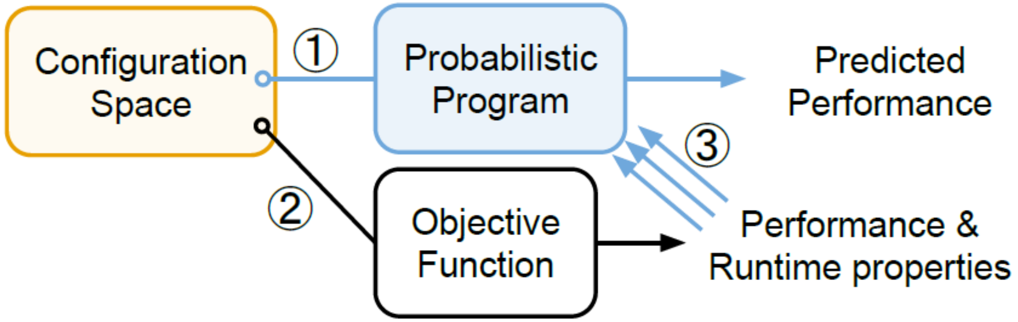
Distributed scheduling of neural network computation

Structured Bayesian Optimization

Bayesian Optimization

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

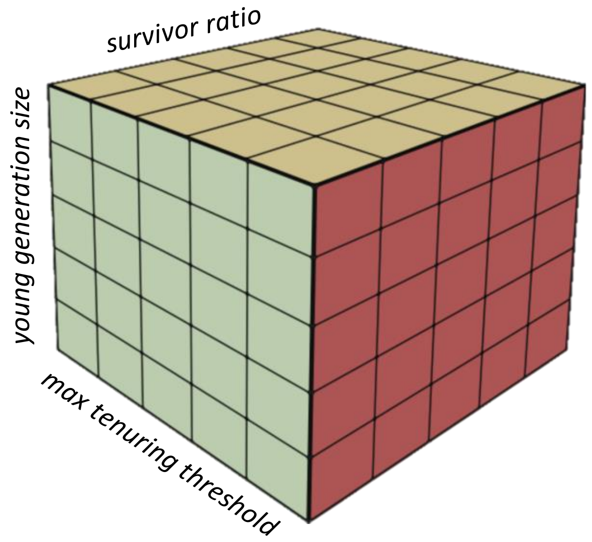
Structured Bayesian Optimization



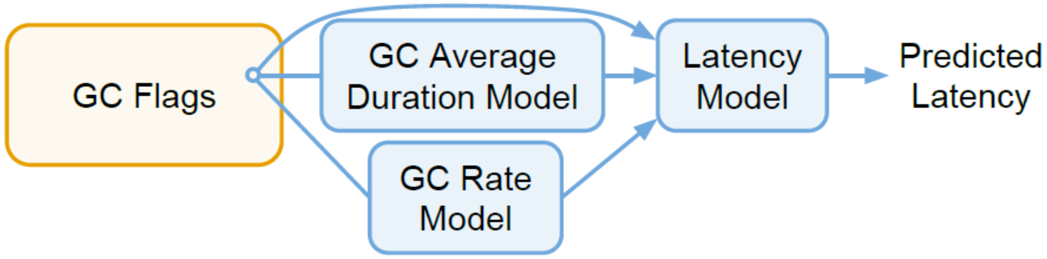
Source: Dalibard et al., 2017

Probabilistic Model: Garbage Collection

GC Configuration Space



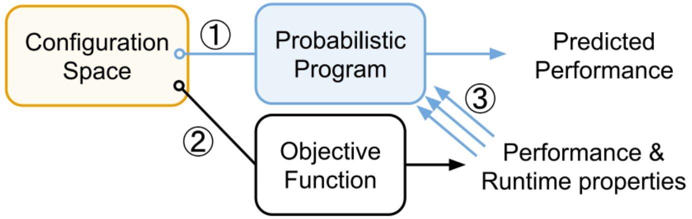
Dataflow of GC Model



Source: Dalibard et al., 2017

BOAT: BespOke Auto-Tuner

Structured Bayesian Optimization



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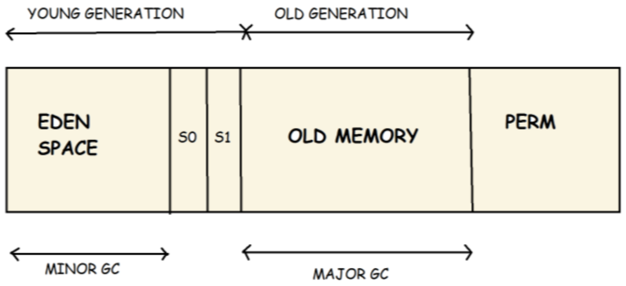
```

Case Studies



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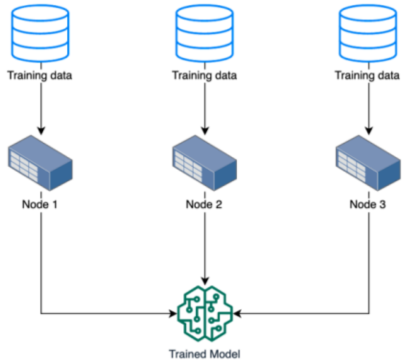
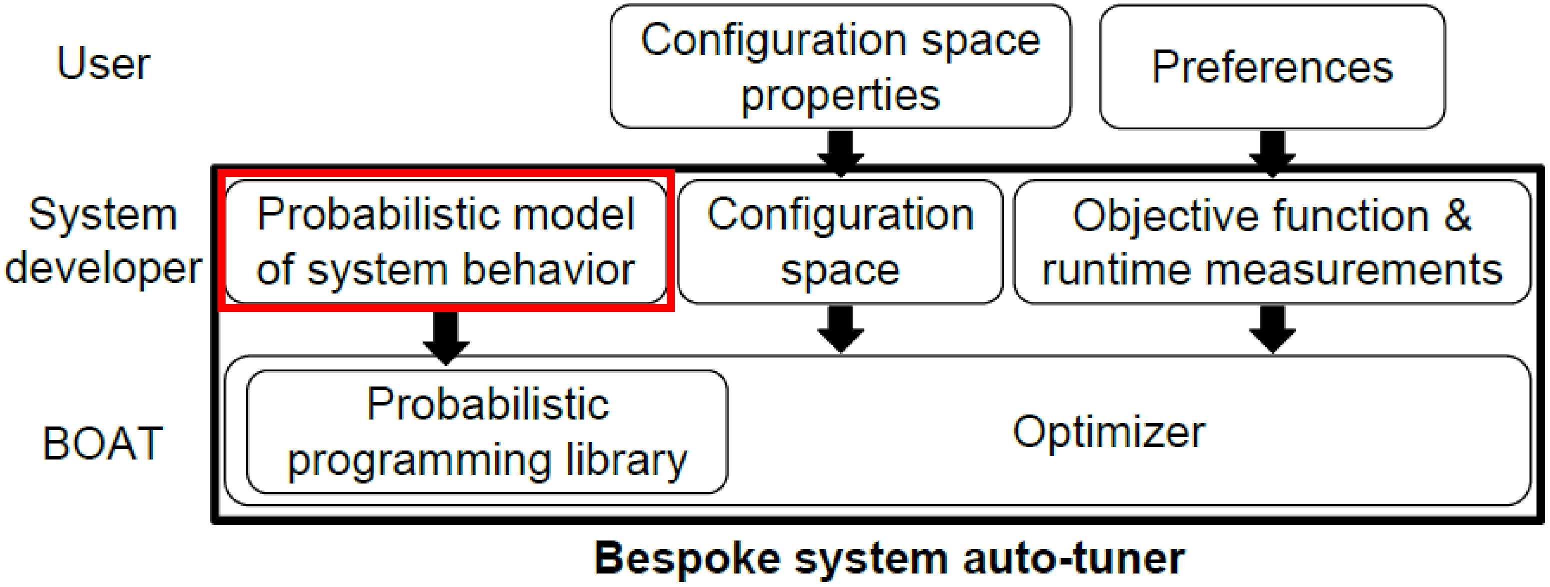


Distributed scheduling of neural network computation

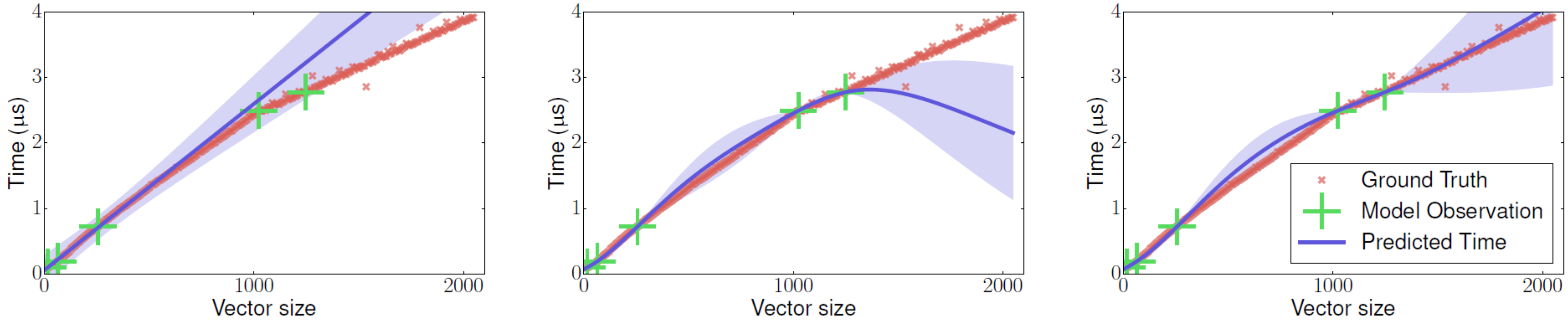
Source: Dalibard et al., 2017

BOAT Framework



Source: Dalibard et al., 2017

Semi-Parametric Models in BOAT



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

Source: Dalibard et al., 2017

Probabilistic Models in BOAT

Semi-Parametric Model

```
struct GCRateModel : public SemiParametricModel<GCRateModel> {
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}
```

Source: Dalibard et al., 2017

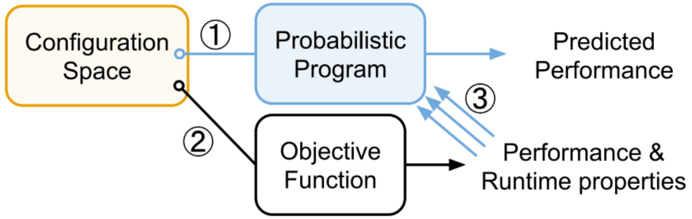
Directed Acyclic Graph Model

```
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;
};

int main() {
  CassandraModel model;
  // Observe a measurement
  std::unordered_map<std::string, double> m;
  m["rate"] = 0.40; m["duration"] = 0.15; m["latency"] = 15.1;
  int ygs = 5000, sr = 7, mtt = 2;
  model.observe(m, ygs, sr, mtt);
  /* Prints distributions (mean and stdev) of rate, duration
     and latency with a larger young generation size (ygs)*/
  std::cout << model.predict(6000, sr, mtt) << std::endl;
  // Print corresponding expected improvement of the latency
  std::cout << model.expected_improvement(
      "latency", 15.1, 6000, sr, mtt) << std::endl;
}
```

BOAT: BespOke Auto-Tuner

Structured Bayesian Optimization



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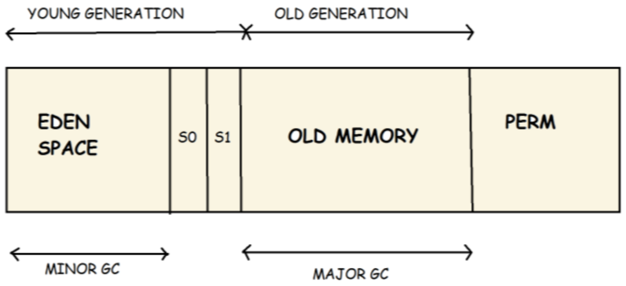
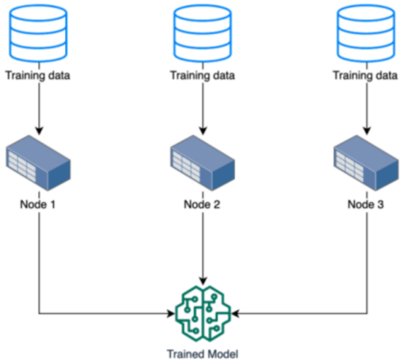
Case Studies



Garbage Collection

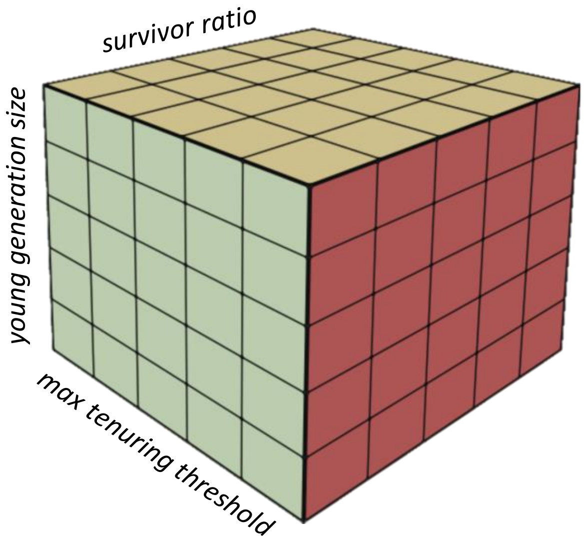


Distributed scheduling of neural network computation

Source: Dalibard et al., 2017

Case Study: Garbage Collection

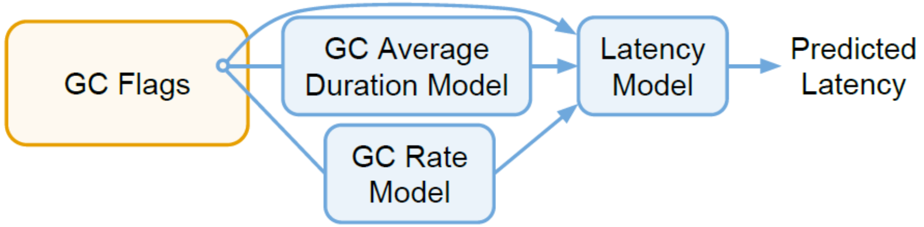
Configuration Space



Objective Function

cassandra

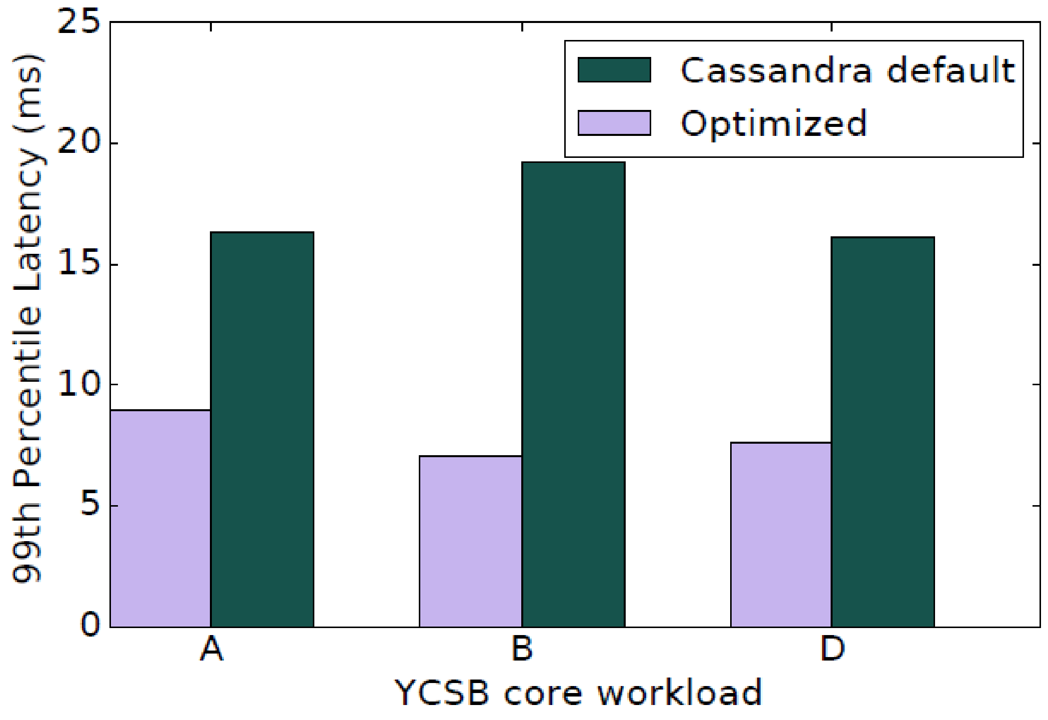
Model



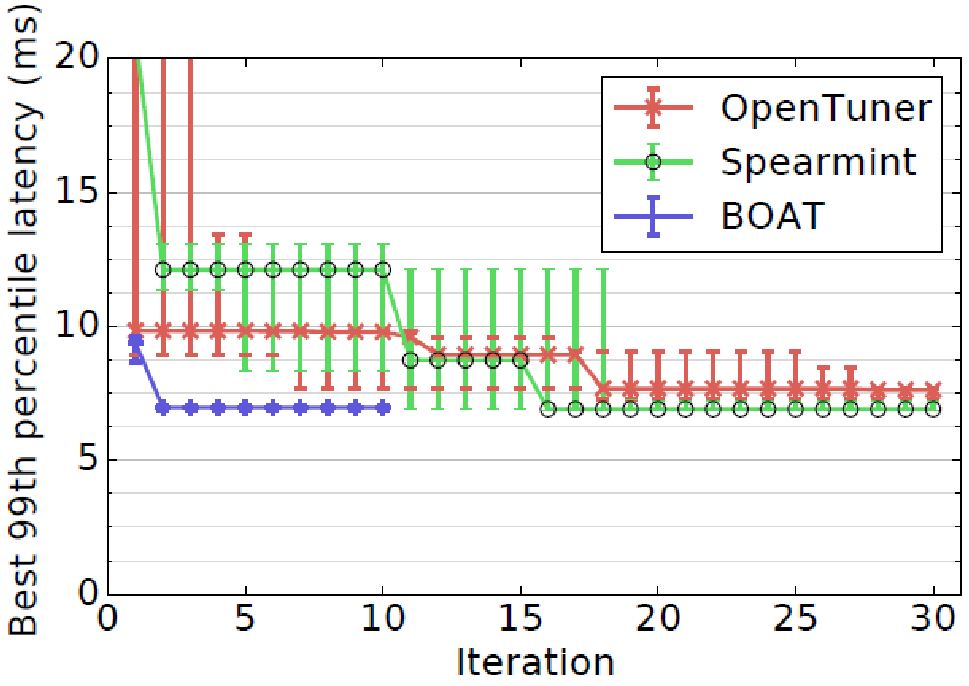
Source: Dalibard et al., 2017

Case Study: Garbage Collection

BOAT vs. Cassandra Default



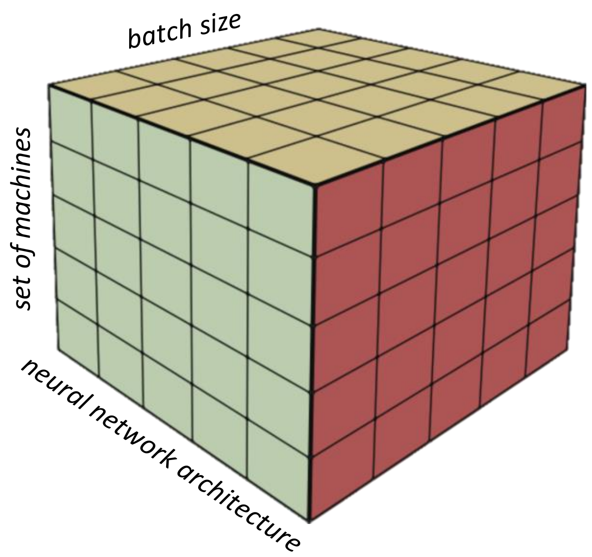
BOAT vs. Generic Auto-Tuners



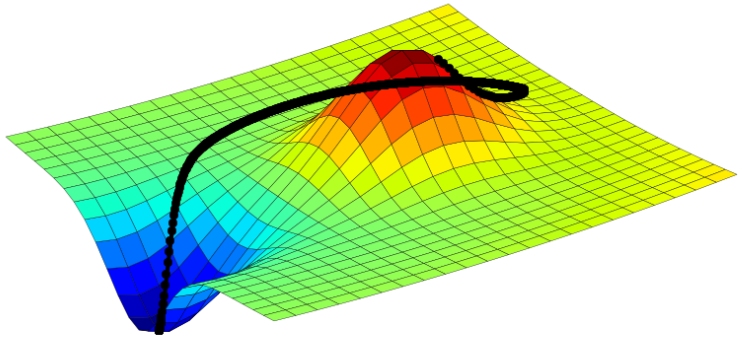
Source: Dalibard et al., 2017

Case Study: Neural Networks

Configuration Space

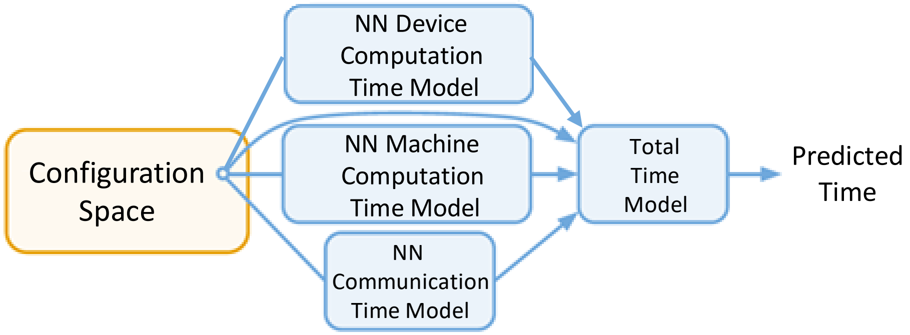


Objective Function



Average time for SGD

Model



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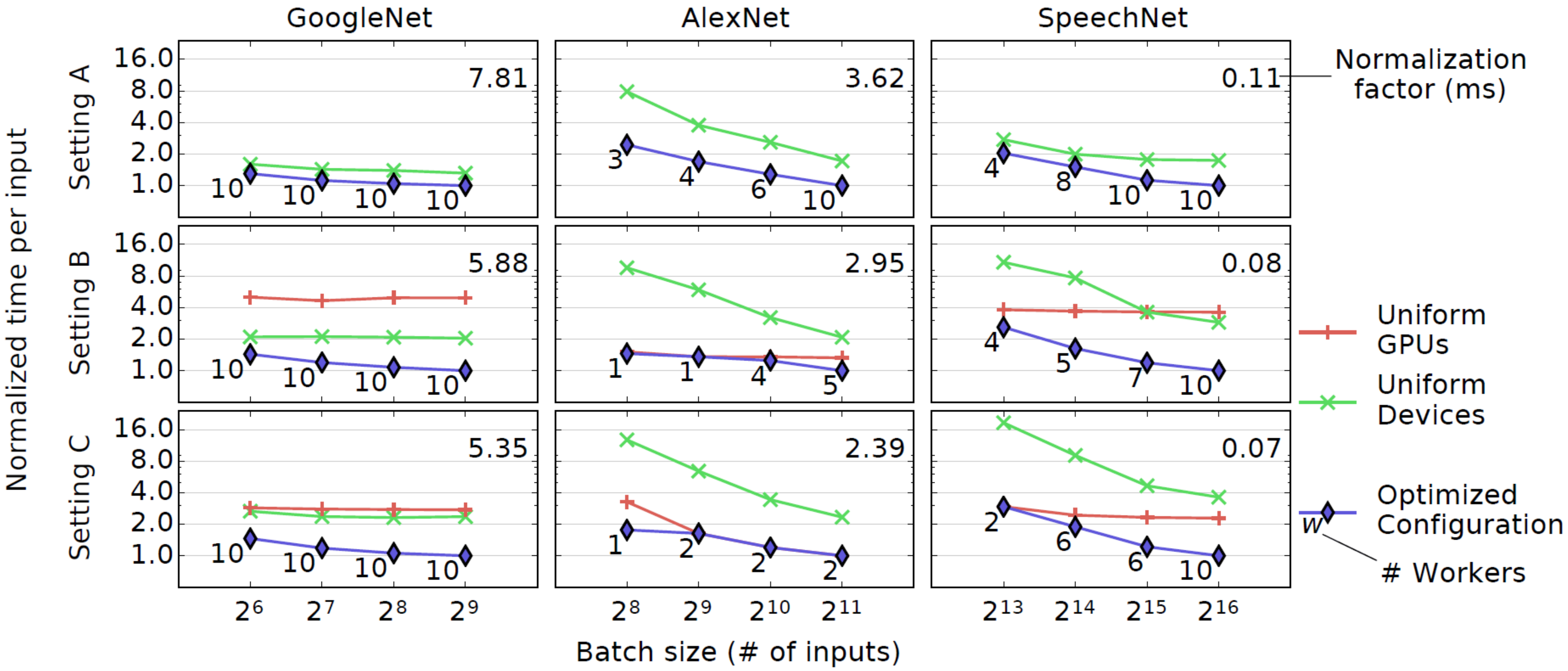
Case Study: Neural Networks



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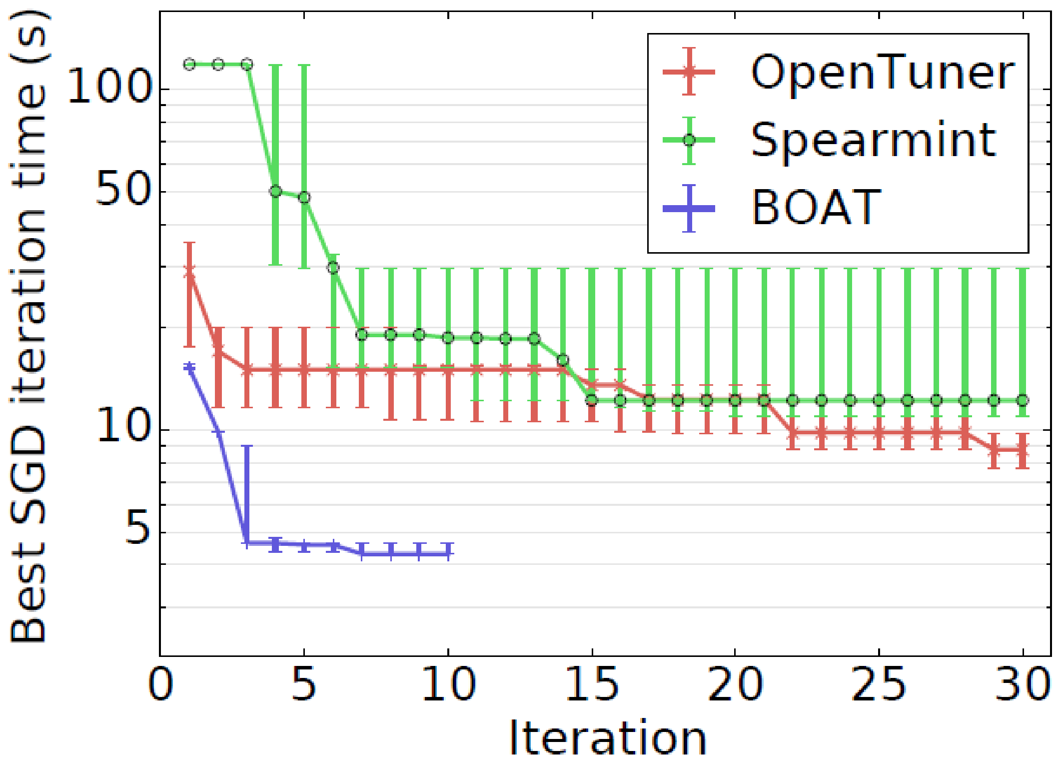
Case Study: Neural Networks



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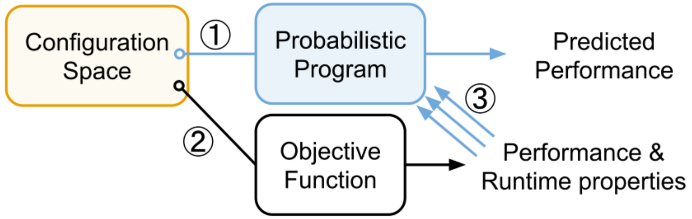
Summary

Structured Bayesian Optimization



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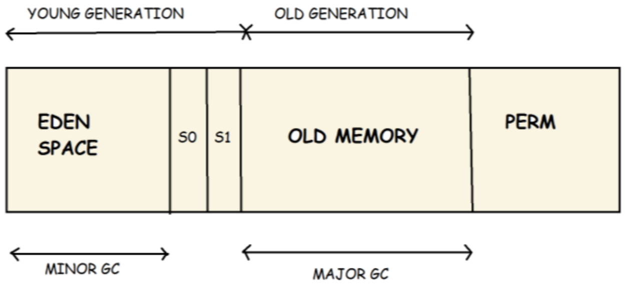
Case Studies



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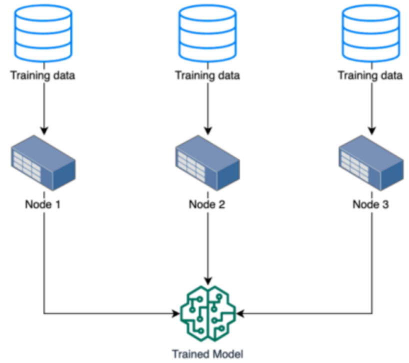

Distributed scheduling of neural network computation

BOAT: 6 Years Later…

Framework

Go to file | Code

90b7583 on May 23, 2017 · 12 commits

6 years ago

6 years ago

6 years ago

6 years ago

6 years ago

About

No description, website, or topics provided.

- Readme
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Releases

Paper

BOAT: Building auto-tuners with structured Bayesian optimization

Authors: Valentin Dalibard, Michael Schaarschmidt, Eiko Yoneki

Publication date: 2017/4/3

Book: Proceedings of the 26th International Conference on World Wide Web

Pages: 479-488

Description: Due to their complexity, modern systems expose many configuration parameters which users must tune to maximize performance. Auto-tuning has emerged as an alternative in which a black-box optimizer iteratively evaluates configurations to find efficient ones. Unfortunately, for many systems, such as distributed systems, evaluating performance takes too long and the space of configurations is too large for the optimizer to converge within a reasonable time.

Total citations: Cited by 88

Scholar articles: BOAT: Building auto-tuners with structured Bayesian optimization
V Dalibard, M Schaarschmidt, E Yoneki - Proceedings of the 26th International Conference on …, 2017
Cited by 88 · Related articles · All 10 versions

Sources: GitHub, Google Scholar

Some Thoughts on the Paper

- Extension of neural network case study beyond system perspective: Investigate whether BOAT could be used to increase model accuracy through hyperparameter selection (e.g. in image recognition tasks)

- No discussion about potential limitations and problems of the approach
  - What if the modularization of the overall system is not possible or the input-output relationships are unknown?
  - Are there situations in which the added knowledge could have a negative impact on the performance of the system (thinking of reward shaping in RL)?
  - …

- Little technical depth on how BOAT maximizes the expected improvement and performs inference

Questions / Discussion

References

- V. Dalibard, M. Schaarschmidt, and E. Yoneki: BOAT: Building Auto-Tuners with Structured Bayesian Optimization, WWW, 2017.
- Valentin Dalibard. A framework to build bespoke auto-tuners with structured Bayesian optimisation. PhD thesis, University of Cambridge (UCAM-CL-TR-900), January 2017.

Image Sources

- V. Dalibard, M. Schaarschmidt, and E. Yoneki: BOAT: Building Auto-Tuners with Structured Bayesian Optimization, WWW, 2017.
- https://miro.medium.com/max/1072/1*tkpDTzQKwekXbSd0L_e9Aw.png
- https://cds.cern.ch/record/2702355/files/step1.png
- Jason Ansel et al. Opentuner: an extensible framework for program autotuning. In Proceedings of the 23rd international conference on Parallel architectures and compilation, pages 303-316. ACM, 2014.
- https://thegradient.pub/content/images/size/w1600/2019/11/kernel_cookbook-2.png
- https://www.studytrails.com/2021/02/10/distributed-machine-learning-2-architecture/
- https://iq.opengenus.org/content/images/2018/05/jvm_memory.png
- https://upload.wikimedia.org/wikipedia/commons/thumb/5/5e/Cassandra_logo.svg/1200px-Cassandra_logo.svg.png
- https://ozzieliu.com/assets/img/gradientdescent.png
- https://github.com/VDalibard/BOAT
- https://scholar.google.com/citations?view_op=view_citation&hl=de&user=39qZ_EsAAAAJ&citation_for_view=39qZ_EsAAAAJ:l7t_Zn2s7bgC
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