BOAT
Building Auto-Tuners with Structured Bayesian Optimization

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Motivation

The complexity of modern Machine Learning systems has led to a sharp increase in the number and sensitivity of hyper-parameters necessary to tune them

Problems:

- The curse of dimensionality
- Training time limits fitness evaluations
- Highly distributed

Classical Bayesian Optimization

Non-parametric Model

- Grows in complexity based on the data
- Can model any function given enough samples

Acquisition Function

- Encodes the exploration-exploitation trade-off
- It is not guaranteed to converge, especially in high-dimensional spaces

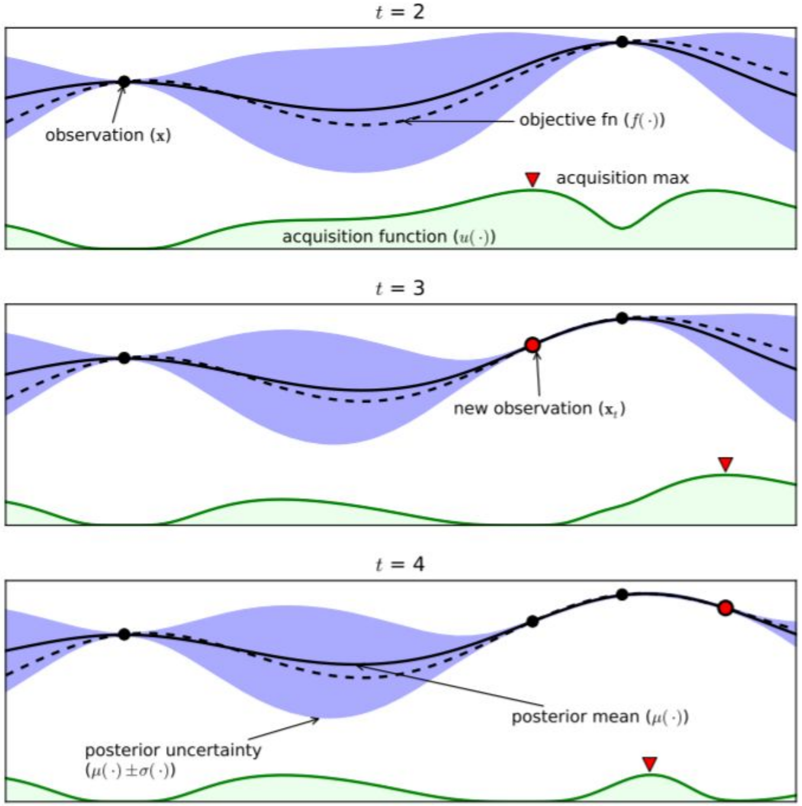
Gaussian Process

- Common non-parametric model
- Entirely defined by its mean and covariance function

Bayesian Optimization

Input: Objective function $f()$
Input: Acquisition function $\alpha()$

```
Initialize the Gaussian process G
for i = 1, 2, ... do
    Sample point: x_t ← arg max_x α(G(x))
    Evaluate new point: y_t ← f(x_t)
    Update the Gaussian process: G ← G | (x_t, y_t)
end for
```



Limitations

Bayesian Optimization is not guaranteed to converge in high-dimensional (>10) domains

Reasons:

- The curse of dimensionality
  - Tackled by SBO
- Non-convergence of the acquisition function
  - Requires complex decomposition and algorithms

Structured Bayesian Optimization

- Probabilistic Programming
  - Draw values from random distributions
  - Constrain variable values to those observed
  - Output variable distribution

```
# Draw from distributions
bias = uniform_draw(0.0, 1.0)
flip = bernoulli_draw(bias)

# Observe an outcome
observe(flip, true)

# Output the resulting distribution
predict(bias)
```

Listing 4.1: A very simple probabilistic program.

- SBO:
  - Structured Bayesian Optimization allows for the injection of domain knowledge into Bayesian Optimization
  - In the form of a probabilistic program

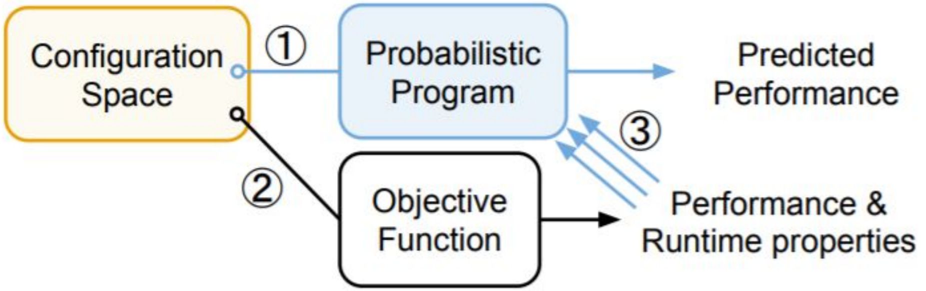


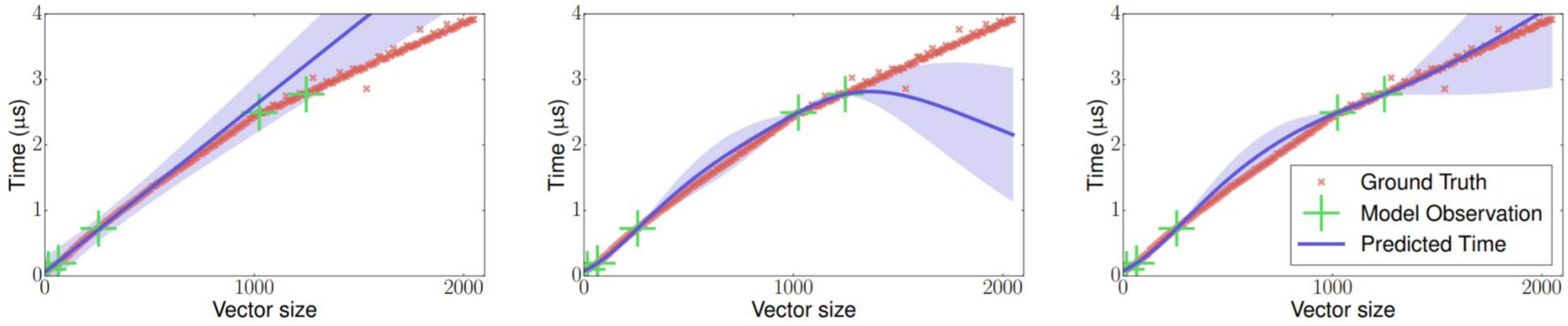
Figure 1: Procedure of Structured Bayesian Optimization

Semi-Parametric Models

- Semi-Parametric Model:
  - Custom parametric model is encoded in probabilistic program
  - Non-parametric program learns the difference between the actual data and the parametric program

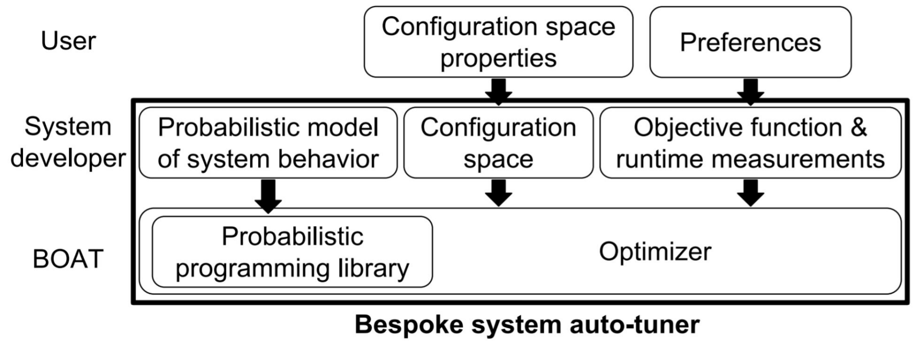
```
double predict(int ygs, int sr, int mtt) {
  return gp.predict({ygs, sr, mtt}) +  parametric(ygs, sr);
}

double observe(int ygs, int sr, int mtt, double observed_rate){
  return gp.observe({ygs, sr, mtt},
                    observed_rate - parametric(ygs,  sr));
}
```



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

BOAT Architecture



Boat is meant to allow for the easy construction of a bespoke auto-tuner by defining semi-parametric models of the system.

It requires defining:

- The configuration space
- Objective function and metrics
- **Probabilistic Program to model system behaviour**

Efficiency

In order to make high-dimensional optimization problems tractable BOAT has several restrictions

- The larger model must be split into multiple components
- Components should only predict one value
- **Components should be assembled into a model assuming conditional independence**

Garbage Collection Case Study

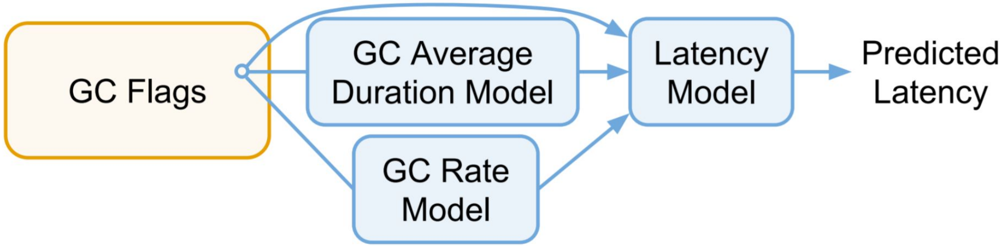


Figure 2: Dataflow of our garbage collection model

```
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;
};
```

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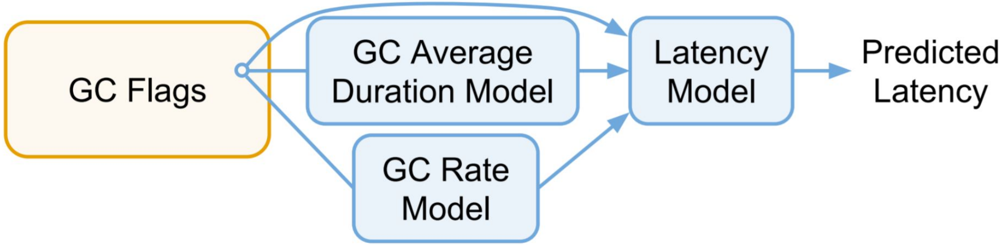

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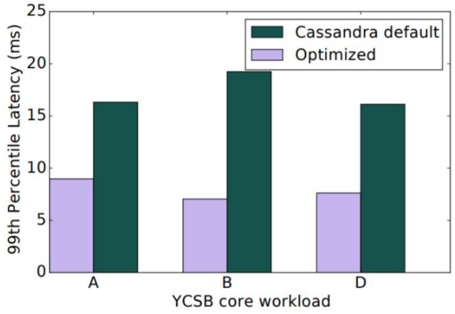

Figure 5: Results for YCSB workloads A, B and D.

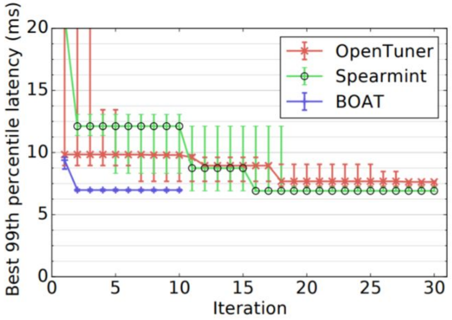

Figure 6: Convergence of the frameworks on workload B.

Neural Network Case Study

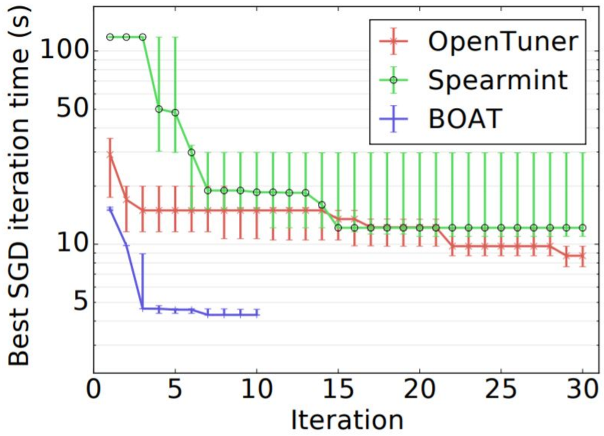

Figure 8: Convergence of the frameworks on Setting C using SpeechNet with a 2^{16} batch size.

Optimizes BOAT for the notoriously difficult NN scheduling problem

- **Up to 32 dimensions, compared to 10**
- Highly distributed
- Difficult to evaluate
- **Greatly outperforms generic auto-tuners**

Recap

Classical Bayesian Optimization

Non-Parametric model

Acquisition Function

Recap

Classical Bayesian Optimization

Non-Parametric model

Acquisition Function

Semi-Parametric Model

Probabilistic Programming

Structured Bayesian Optimization

Related Work

Since Publication:

- ProBO:
  - Probabilistic-programming-language agnostic
  - Coming up next
- Arrow:
  - Same idea as BOAT, applied to cloud VM architectures
- BoTorch:
  - Bayesian Optimization which can leverage the PyTorch to more efficiently solve the acquisition function
  - Uses probabilistic models implemented in PyTorch

Authors Future Work Ideas:

- Allow for easier modelling of “stacked” systems where each layer depends on the previous
- Allow for use in real-time systems
- Allow for more general modelling

Critique

- Opentuner can also be customised
  - A comparison against Opentuner with a similar amount of customization and time investment could have helped strengthen the evaluation
  - Could have shown that it is either easier to customize or faster for the same amount of effort
- The Neural Network example is significantly more complex than presented in the paper, it requires different algorithms for the acquisition function alongside decomposition tricks
  - Does not lower the impact of successfully optimizing a 32 dimensional problem
  - It does indicate that solving such problems is more complex than simply defining probabilistic programs
- No mention in the final paper that the probabilistic programming library cannot handle models with more than 5 parameters, strongly implied by the encouragement to slowly add structure
- My future work ideas:
  - New acquisition function, several have been proposed
  - Rebuilding the framework structure on top of BoTorch

Questions?