BoGraph: Structured Bayesian Optimization From Logs for Systems with High-dimensional Parameter Space

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Abstract

Current auto-tuning frameworks struggle with tuning computer systems configurations due to their large parameter space, complex interdependencies, and high evaluation cost. Utilizing probabilistic models, Structured Bayesian Optimization (SBO) [18] has recently overcome these difficulties. SBO decomposes the parameter space by utilizing contextual information provided by system experts leading to fast convergence. However, the complexity of building probabilistic models has hindered its wider adoption. We propose BoGraph, a SBO framework that learns the system structure from its logs. BoGraph provides an API enabling experts to encode their knowledge of the system as performance models or components dependency. BoGraph takes in the learned structure and transforms it into a probabilistic graph model. Then it applies the expert-provided knowledge to the graph to further contextualize the system behavior. BoGraph probabilistic graph allows the optimizer to find efficient configurations faster than other methods. We evaluate BoGraph via a hardware architecture search problem, achieving an improvement in energy-latency objectives ranging from $5-7 \times$-factors improvement over the default architecture. With its novel contextual structure learning pipeline, BoGraph makes using SBO accessible for a wide range of other computer systems such as databases and stream processors.

1 Introduction

Modern computer systems facilitate the execution of a wide range of diverse workloads. This diversity forces system designers to expose tunable configurations to meet users’ demands. These configurations are everywhere in computer systems, such as compiler flags [3], hardware designs [12], and database knobs [58]. Tuning systems configuration is a tedious task due to the many parameters involved. For example, in our case study on hardware design optimization, there are over $2^{64}$ possible design decisions (see Table 2).

The complexity of optimizing these systems necessitates for auto-tuners to aid practitioners in improving the performance of their systems. However, current research into auto-tuners focuses on tuning configurations in the general sense, with the prime focus on optimizing neural network hyper-parameters [8, 45, 55], and often encounters significant challenges when applied to tuning computer systems specifically. This paper outlines significant challenges faced by current auto-tuners when optimizing computer systems, then proposes BoGraph, a framework designed to address these challenges.

1.1 Challenges and related work

Computer systems are expensive to evaluate

Firstly, popular optimization techniques that require many evaluations are expensive to conduct on computer systems. Computer systems are expensive to evaluate due to the high initialization cost and requiring expensive resources such as GPUs or multiple machines in a cluster [2]. Furthermore, evaluating a single experiment takes several minutes (see Figure 8a) to several hours and weeks [24, 41].

Some of the popular techniques under this umbrella are reinforcement learning (RL) [56], random search [8], evolutionary search (PetaBricks) [3], hill-climbing (OpenTuner) [4], or population-search [34]. In addition to being costly and time-consuming, these methods are hard to interpret and unstable as they are highly dependent on initializing seed [31]. These drawbacks render them unsuitable for optimizing computer systems. In particular, RL, which recently has enjoyed a surge in popularity, is methodologically ill-suited for the optimization task of system configuration. RL maintains a chain of decisions made to learn the dynamic between each decision [56]. However, in optimization, each evaluation is completely independent of the previous one (a full system restart is required), rendering the decision chain learned by the RL incorrect. RL is suitable for dynamic workloads or combinatorial problem solving, such as scheduling tasks [22, 41].

Computer systems are difficult to parallelize

Secondly, optimization techniques that rely on parallelization when applied to computer systems affect the measurement sensitivity. Computer systems are expensive and slow to evaluate; engineering them to launch many parallel instances is
non-trivial without impacting the measurement sensitivity. For example, parallelizing a system cluster to optimize its configuration [2] requires careful engineering to ensure each cluster is measured independently. This challenge renders optimization methods that exploit quick termination of experiments and massive parallelism such as AutoTVM [14], Hyperband [39] and BOHB [23] difficult to implement and expensive to use for computer systems optimization.

**Computer systems have a large number of parameters**

Thirdly, optimization methods using probabilistic models have proven effective in general auto-tuning but incapable of modeling the many configurations in computer systems. The most popular method is Bayesian Optimization (BO) [55] is an efficient technique for auto-tuning and used successfully (although in a limited setting) in computer systems, with the most notable example being CherryPick [2] and Spearmint [55]. BO models the system using a probabilistic model and searches the model for optimal configurations before testing these on the real system. However, BO struggles with systems that have > 10 configurations due to the computational complexity of its model [52]. Other methods such as Ernest [59] and RubberBand [42] use hand-crafted models to measure the proposed configurations’ effectiveness quickly leading to quick optimization. Hand-crafting models for systems with many parameters is an error-prone and difficult task even for experts. Computer systems often have many parameters. For example, our case study looks at 20 parameters, while larger systems such as Spark [64] have 100 knobs and PostgreSQL over 300 [43].

**Computer systems parameters dependency is complex**

Fourthly, methods that reduce the number of configurations and dimensions by using Factor Analysis [36] or Principled Component Analysis [60] as was done in OtterTune [57]. However, as the OtterTune experiment expanded to a real system [58] it was apparent that computer system parameters have complex interactions that standard dimensionality reduction methods fail to capture. The dependency between parameters is non-linear; often, parameters act as switches that change the system’s behavior or parameters with a large cut-off that causes the system to fail (e.g., system’s memory).

**Performance models might not always be available**

Finally, methods utilizing expert knowledge to improve sample efficiency and reduce dimensions without omitting configurations. Structured Bayesian optimization (SBO) [17, 18] contextualize the system behavior using probabilistic models provided by the system’s expert. SBO approach was highly successful in computer systems has significantly reduced the number of iterations needed to find optimal configurations while providing interpretable and stable models. Alternatively, Causal Bayesian Optimization (CBO) [1] used causal graphs to model the system behavior to aid the BO in optimizing a larger number of parameters. While these methods have shown promising results and were able to model high-dimensional systems, they suffer from a significant shortcoming: Firstly, they require hand-crafted probabilistic models of the system, which are often difficult to obtain without expertise in machine learning and systems. Secondly, experts often need repeated trials and errors in order to find the correct system structures. Finally, production level systems are too complex for experts to comprehend fully.

### 1.2 Our approach

Addressing these challenges, we designed BoGraph, a framework for optimizing systems that are expensive to evaluate and have many configurations. BoGraph is a SBO framework that learns a directed-acyclic-graph (DAG) of the system structure automatically from logs and expert knowledge. Combining SBO with structure discovery pipeline allows BoGraph to find optimal configurations from a few trials without needing to run parallel experiments. Furthermore, the structure allows it to model many configurations by decomposing the parameter space using the system structure. Finally, its flexibility allows using existing expert knowledge and augmenting it with models automatically driven from data.

BoGraph’s structure discovery pipeline is a novel addition that learns the system’s dependencies as a DAG from the system’s logs. Furthermore, it allows experts to encode additional contextual knowledge of the system using BoGraph’s API, either by defining a structural dependency or a bespoke performance model. Finally, BoGraph combines this knowledge with the learned dependency DAG to build a probabilistic DAG model of the system. BoGraph differentiates itself from previous works by simplifying the process of using SBO by experts and non-experts alike.

We utilized BoGraph to tune the architecture design parameters of a hardware simulator gem5-Aladdin [29, 54] to optimize its energy-latency objectives. BoGraph tuned all exposed parameters, spanning the system’s cache, accelerator, and CPU parameters. BoGraph learned the dependencies between components purely from logs, which resulted in a faster convergence than other methods, where BoGraph found configurations in twenty iterations that took the next best auto-tuner a hundred iterations. It did that while improving the energy-latency utilization by 5 – 7 x-factors over the default, and no other method came close to its performance.

We summarize our main contributions as follows:

- An auto-tuner for high-dimensional problems and problems with expensive experimental cost.
- A SBO framework that automatically infers the system’s structure from logs and expert knowledge capable of modeling multiple optimization objectives.
- An API for experts to express the system’s dependencies or encode probabilistic models of its components.
- To our knowledge, the first work to optimize all the design choices in gem5-Aladdin and achieve an improvement in energy-latency by 5 – 7x over the default.
2 Background

2.1 Bayesian optimization

Bayesian Optimization (BO) [52] is an iterative sample efficient method for finding optimal configurations. Formulated as \( x^* = \text{argmin}(f(x^D)) \), where \( x^* \) is the optimal configuration, \( f(.) \) is the system being optimized, and \( x^D \) is the parameter space. Its efficiency comes from building a generative model of the system (surrogate model) to test optimization candidates rather than searching the real system directly. BO uses a utility function known as an acquisition function to find candidates from the surrogate model that optimizes the real system. The choice of the surrogate model and the acquisition function directly impact the number of iterations needed to optimize the objective.

Acquisition function

The acquisition function proposes configurations that balance exploring the system and optimizing it. There are several choices outlined in [52], our work uses quasi-Expected Improvement [21] to allow for optimizing over approximate samples from the model. The expected-improvement formula attempts to find points that improve on previously evaluated configurations while taking into account the uncertainty of the model. Points with higher uncertainty (unexplored areas) are more likely to be evaluated.

Surrogate model

The surrogate model determines BO’s convergence, and often the choice is a Gaussian Process (GP) [49] because it is sample efficient and generalizes to many problems. However, GP has a computational complexity of \( O(N^3) \) due to an expensive matrix inversion function. The complexity of the GP has hindered its ability to be utilized in high-dimensional spaces.

Alternative models

Random forest used in SMAC [32] handles large numbers of discrete variables often seen in computer systems. However, it does not scale when parameter bounds are either large discrete or continuous values. Addressing that, HyperMapper [44] integrates experts prior to the parameter space to reduce the parameter bounds. However, non-Bayesian methods underestimate the variance [52], which causes the acquisition function to be stuck in a local optimum. The variance is important to capture the noise in computer systems and judge the system’s structure to reduce models dimensions along the system’s structure to reduce models dimensions, enabling GP usage in higher dimensions and benefiting from its sample efficiency and principled variance.

2.2 Bayesian Network

BoGraph learns the system structure from logs using techniques from the Bayesian Network (BN) literature, see subsection 3.1. BN is a DAG where the nodes represent a distribution and edges their conditional dependency [20, 37]. The BN factorises the joint distribution of a node into a local distribution that depends only on the parent: \( P(X; G) = \prod_{i=1}^n P(X_i | X_{\text{parent}(i)}) \) where \( X_i \) is the \( i \)th node in the graph and \( \text{parent}(i) \) is the direct parent of the node. This property is what makes BN attractive to bring to the BO landscape; local factorization circumvents the curse of dimensionality and allows each node to scale independently.

Structure learning

Defining systems’ structure is a complicated process and error-prone, hence the need for an automated structure discovery method that learns from data. BN literature has many methods for learning the structure from data [51], with the BIC-score method being the most popular [62]. Scoring methods propose various DAGs and score them based on a trade-off between data fit and the complexity of the graph. However, scoring methods are combinatorial NP-hard methods [16]. Recently, NoTears [65] relaxed the combinatorial problem by mapping it into a continuous optimization problem. In NoTears, there is a function approximator that predicts a DAG and scores it. BoGraph supports BIC and NoTears, with NoTears being the default option in BoGraph, as it runs significantly faster and is easily parallelizable on GPUs [7] while producing comparable DAGs to the expensive BIC.

3 BoGraph Framework

BoGraph is an auto-tuning framework for systems with many configurations that discovers system structure and allows injecting interpretable models in the BO loop. It builds on the core idea of Structured Bayesian Optimization (SBO) [18] to utilize contextual knowledge in providing interpretable models that converge quickly. BoGraph’s core component is the probabilistic DAG creation pipeline that combines structure discovery with flexible modeling to provide the contextual knowledge.

Figure 1 shows BoGraph’s optimization process. The expert encodes any knowledge of the system and the target objectives. Then, BoGraph scans the system logs to learn a DAG of components’ dependency structure. Next, it combines the expert’s knowledge with the learned dependency DAG.
3.1 Structure discovery from logs

BoGraph’s first component is the structure discovery process shown in Figure 2 that learns a dependency DAG from the system logs. The pipeline first summarizes the logs and then learns the statistical dependency of the components using Bayesian Network (BN) [37].

3.1.1 Summarizing the logs

Computer systems generate a large number of logs used for monitoring and debugging by experts [9]. We assume the user provides a parser for the logs and their format as each system has different logging characteristics and is not in our work’s scope. BoGraph uses the parsers to extract additional knowledge of the system behavior. In the case study described in subsection 4.2, gem5-Aladdin [12] reports more than 1000 log entry. The large log itself is vulnerable to the curse of dimensionality, hence the need for summarization. BoGraph transform logs as seen in Listing 1 to the one seen in Table 1.

The first stage in the summarization process involves removing any metric with low variance between different executions, as they are not informative. All the remaining metrics are standardized to ensure the different measuring units do not skew the learning algorithm.

Property of the log. BoGraph exploits the structured property of the logs to summarize the data further. The convention in computer systems is that the log name corresponds to where the log was generated in the system [26, 63]. For example, in the case study on gem5-Aladdin, the structure is Component.SubComponent.Measurement, as shown in Listing 1. BoGraph groups all entries under SubComponent together, as they are likely to depend on each other. Then it applies Factor Analysis (FA) [36] to compress linearly dependent components down to a single statistic. This aggressive compression works because logs generated at the SubComponent level are dependent on each other. BoGraph applies FA recursively starting from SubComponent, up to the top level of the log entry. A user who wants BoGraph to keep all the metrics without decomposition (to understand the system better) can disable the recursion. In the gem5-Aladdin case study, we grouped at the component level as it produced comparable optimizations to grouping subcomponent but was faster and easier to visualize.

This process is applied to the whole logs, which includes previous evaluation of the system. At the end of this stage, BoGraph produces a summary of the logs similar to the one reported in Table 1 for the structure learning algorithm.

Listing 1: Sample of gem5’s logs

| EXP | L2     | CPU    | MEM_CTRLs | MEMBUS | TOL2BUS | CPU |
|-----|--------|--------|-----------|--------|---------|-----|
| 0   | -0.26  | -0.80  | -0.00     | ...    | ...     |     |
| 1   | -1.39  | -0.81  | -0.48     | ...    | ...     |     |
|     | ...    | ...    | ...       | ...    | ...     |     |
Figure 3: The discovered structure after optimizing gem5-Aladdin on the STENCIL3D task. The maximum dimensionality is ten at the "Avg Power" node, instead of twenty parameters jointly optimizing EDP without context. See subsubsection 4.2.4 for further discussion of this figure.

3.1.2 Learning the dependency DAG

The next stage is to learn the dependency of the components from the summarized logs.

Bayesian Network (BN) is known and established for the task of discovering structure from data [51] using statistical association tests. The dependency DAG does not guarantee the causation order of components. However, it does capture the relationship between nodes that moves together. This correlation-based relationship is simpler to derive from data alone without expert knowledge [37, 47]. We do encode specific causal links in the dependency DAG. For example, we enforce that the parameters are always the root node and the optimization objectives are the sink nodes. The correlation-based structure of the inner system components is not guaranteed to be causally correct, but it is suitable for an optimization problem. In optimization problems, modeling the intermediate node in the graph will capture whether a parameter improves or regresses the intermediate nodes. However, the model will not capture the causation between the intermediate node. For example, whether the CPU slows down the L2 cache or vice-versa. Nevertheless, this does not matter since the beginning and end of the graph are causally correct. The intermediate models will still correctly break down the configuration dimensions and provide context to know which subset of the parameters impact the system.

BoGraph modular design enables the usage of any structure learning algorithm, with two popular ones already integrated: the BIC score [62], and NoTears [65]. The goal of these algorithms is to find a DAG that maximizes the likelihood of the data given the graph while penalizing complex graphs max score(G; D) = ℓ(θ; D) − penalty(G), where θ is the parameters of the graph. We encode a set of restrictions in these algorithms that ensures the system’s parameters are not allowed to have children to ensure the causal flow of the optimization task. These structure learning algorithms are expensive to compute, with BIC score being NP-Hard algorithm and NoTears has a complexity of O(N^3). BoGraph takes an optional update scheduler that decides when to perform structure learning. By default, it performs structure learning update every quarter of the optimization budget.

At this stage, BoGraph also includes any expert-defined edges. Figure 3 shows the discovered structure from gem5 logs with the included expert edges, the details of the figure are further discussed in subsubsection 4.2.4.

3.1.3 The pipeline overhead

BoGraph structure discovery pipeline is invoked in full every time the structure needs updating (a configurable choice, set to every quarter of the available budget). Once the structure is discovered, only the summarization pipeline is invoked every iteration.

BoGraph maintains the system trace (previous evaluation, previous configurations, and detailed logs) on disk. First, the cost of performing this pipeline is dwarfed by the high evaluation cost of the real system. Secondly, this enables BoGraph in the future to learn from other distributed instances. Finally, it provides a fault-tolerance mechanism for when the instance has to restore from a checkpoint.

Optimizing this overhead is out of the scope of this work. Each system provides logs separately, and production systems already have log parsers in place for monitoring purposes and can be reused by BoGraph. Furthermore, BoGraph can run a helper instance to run the pipeline on a separate machine and communicate only the summarized information to the BoGraph main loop, for these reasons, we did not measure the overhead of this operation.
3.2 Bayesian Network as a Surrogate Model

The dependency structure found using BN structure learning has few quirks making it unsuitable for BO problems. The sampling in BN scales exponentially [38], while BO’s acquisition functions need to generate a large number of samples before proposing optimization candidates. Furthermore, BN is designed for inference tasks rather than regression tasks. BN regression is limited to parametric regression models with fixed degrees of freedom, making BN too rigid. BoGraph utilizes BN to learn the system’s structure but then places generalizable models such as Gaussian Process (GP) [49], that are optimized for batch sampling with efficient $O(N^2)$ implementation for sampling [27]. GPs and Bayesian Neural Networks [40] learn the polynomial complexity that offers a regularized fit for the data and generalize to unseen one. Finally, BoGraph relies on sampling to approximate the posterior allowing any integration of any model capable of producing samples offering a larger degree of freedom to express expert knowledge.

BoGraph maps each node in the dependency DAG in Figure 3 to a probabilistic model that approximates it in Figure 4. The process finds a graph $G_E$ with the same edges and nodes to the dependency DAG $G$ produced by the BN but replaced with probabilistic models. The nodes $n \in G_E$ approximate the nodes $v \in G$ such that $P(n|D_n) \approx P(v|D_v)$ and follows $P(G_E|D) \approx P(G|D)$. BoGraph effectively uses the BN DAG as a blueprint to know where to place general-purpose probabilistic models, allowing combining the best of both worlds: BN’s effective structure learning and general-purpose models’ flexibility. Finally, BoGraph adds any expert predefined probabilistic model to $G_E$ and then trains the model on the system logs. Each node in the probabilistic DAG is compartmentalized, where each node predicts a single value conditioned on its parents directly. An exciting effect is that any node can be the primary optimization target, which provides free multi-objective modeling.

At the end of this stage, BoGraph has produced a probabilistic model that captures both the system’s expert understanding and any structure discovered from the logs.

3.3 Structured Bayesian Optimization

Algorithm 1  BoGraph Bayesian Optimization loop

```
Input: acquisition function $\alpha$, system $E$, budget
repeat
    [find structure and build DAG model $M$ from logs]
    $M = \text{BoGraph}(E, \text{logs})$
    [select next point $x_{n+1}$ to evaluate]
    $x_{n+1} = \alpha(s_{\text{sample}}(M))$
    [submit $x_{n+1}$ to be evaluated]
    $E.update(x_{n+1})$
until budget = 0
```

Optimization loop. Algorithm 1 details the optimization loop. BoTorch’s probabilistic DAG combines several models’ posterior, producing a complicated posterior that cannot be optimized directly. Instead, we use quasi-acquisition functions that optimize the estimate from samples rather than the model directly. BoTorch [6] provides a suite of utility functions for BO frameworks, including quasi-acquisition functions and samplers. We use BoTorch’s Sobol sequence sampler to generate an estimate of the posterior, then use the quasi-Expected Improvement acquisition function to optimize the estimates and produce optimization candidates.

Sampling process. Allowing general probabilistic models comes at the cost that exact inference and closed-form acquisition function optimization are not possible anymore. Instead, BoGraph approximates the inference from the model by sampling and optimizing over the samples. The sampling in probabilistic DAG is different from typical probabilistic models and shown in Algorithm 2. First, BoGraph finds all the nodes with a direct path from the parameters to the objective. Then, it creates a cache to hold all the samples and avoid recomputing them for nodes with multiple children. Next, each node condition on the parents prediction of the samples, and finally output the posterior of the objectives.

3.4 BoGraph API

BoGraph API streamlines the process of expressing system designers’ knowledge by providing both high and low-level APIs. Listing 2 shows several of the functions BoGraph that enable experts to encode their knowledge in several ways: A high-level DAG API for expressing the dependencies between parameters and metrics. The API extends the popular library for building graphs, networkX [28] as such provides the ability to read all the popular methods for defining directed graphs. And a lower-level API that allows expressing experts’ knowledge using Pyro [11], the probabilistic programming language. By default, BoGraph uses a GP as the metric model if no probabilistic model is defined. The GP implementation we use is GPYtorch [27] a performant GP implementation. The user can override the kernel of the GP to inject any prior
Algorithm 2 Sampling the probabilistic DAG

Input: sampler s, DAG model M, system SY
initialize a samples cache Q
find all nodes along the path to the objective in M
path = M.path(SY.objects)
for node n in path.nodes do
  if n ∈ SY.params
    {a parameter node: sample the parameter space}
    p_samples = s.sample(n.space())
    {cache generated samples}
    Q ∪ (n.key, p_samples)
  else
    {an objective node: condition on parents output}
    cond = n.predict(Q[n.parents()])
    Q ∪ (n.key, cond)
  end if
end for
Return: Q[SY.objects]

information about the objective function distribution; this is only recommended for advanced users.

3.5 Summary

BoGraph simplifies the process of integrating SBO in systems for faster optimizer convergence. The main loop performs structure learning of the system’s components by processing the logs and transforming it into a probabilistic model. The framework exposes an API that allows experts to encode dependency structure and probabilistic models.

4 Evaluation

In this paper, we presented BoGraph as a framework able to tune many parameters by capturing system dependency. We evaluated BoGraph on these two systems:

1. Synthetic function optimization: a benchmark to explore BoGraph expert injection, learning structure, and visualizing on a simple system, subsection 4.1.1.
2. A System-on-a-chip (SoC): a case study that explores optimizing a search space of 2^64 combinations. SoCs are integrated circuits used for bespoke workload and have many design decisions with complex trade-offs. We optimized the design of gem5-Aladdin to improve energy-latency utilization. subsection 4.2.

Evaluation goals. We evaluated the following claims:

- BoGraph can converge towards optimal configurations faster than other states of the art, subsection 4.2.3.
- It integrates expert knowledge, which results in fewer evaluations required to find optimal configurations, subsection 4.1.1.
- It captures the system behavior and decompose a large number of parameters, subsection 4.2.4.
- It produces system structures and interpretable models, subsection 4.2.4 and subsection 4.1.2.
- The overhead of running BoGraph is lower than running a full system evaluation, subsection 4.2.2.

Time budget vs. the number of evaluation comparison.

Often in auto-tuning literature, the auto-tuner is given a time budget to tune the system. We argue that in the context of computer systems, the number of iterations is more informative of the monetary cost of the optimization. As described in subsection 1.1 computer systems are expensive to evaluate and restart. Therefore, the goal is to minimize the required number of evaluations rather than simply reach optimization.

Setup. We ran the experiments on a machine with 8GB VRAM RTX3060TI, Intel i7 8700k, and 32GB RAM. BoGraph is built on PyTorch v1.9 [46], GP from GPyTorch v1.2 [27], samplers from BoTorch v0.5 [6], probabilistic models from Pyro v1.7 [11], and CausalNex v0.11 [7] for the NoTears implementation.

4.1 Synthetic experiment

Problem setup. The first set of evaluations is a function from the engineering design literature [25]. We took both forms of the Forrester function \( f(x) = (6x - 2)^2 \sin(12x - 4) \) and the alternative form \( f_{alt}(x) = 0.5 f(x) + 10(x - 0.5) + 5 \), and combined them to create a 2D function: \( f(2D(x_1, x_2) = f(x_1) + falt(x_2) \). The optimization goal is to recover the global minimum point. Despite Forrester2D simplicity, it demonstrates the primary ideas of BoGraph without the complexity of a larger system, as we can assume computer systems performance is the sum of the performance of each component.
We evaluated the following four models to determine BoGraph’s ability to make use of expert’s knowledge:

- **Standard GP**: A baseline GP without any learning.
- **NoPrior**: Structure learning enabled.
- **StructPrior**: Dependency structure known in advance.
- **FullPrior**: Dependency structure with a deterministic model that defines each forester function.

### 4.1.1 Performance

Figure 5 shows the best-found minimum after observing forty points, and as expected, models with added expert knowledge are more robust and with better configuration found given the same budget. Worth noting, all models do converge to the global minimum after eighty steps. FullStruct produced the optimal value consistently since it had full parametric knowledge of the system. On the other hand, StructPrior was able to reach the optimal value most of the time; an unlucky initialization seed can cause the model not to fit quickly.

### 4.1.2 Interpretability

Finding optimal configuration is primarily the goal of any auto-tuners. However, when off-the-shelf optimizers fail without providing any reasoning, it is challenging to debug it. First, we inspect the structure found in the NoPrior model. Figure 6 shows two graphs, on the left is the initial graph that is used in the first twenty iterations of the model run, and on the right is the model that BoGraph learned from data. We can see it did correctly identify the relation between parameters and their corresponding metric. This aspect makes structure learning very attractive - we can identify potential further engineering work in both the underlying system and the modeling procedure.

### 4.1.3 Model divergence

We inspect each component of BoGraph to see what it learned. Since BoGraph transforms each node to a probabilistic model, it can be sampled, tested using model scoring methods (see [35] for scoring methods), and visualized to debug what is learned. The Figure 7 shows samples of each node in the NoPrior model and their ability to fully capture the real function, which shows that the model does not diverge from the data generating process. Inspecting each model provides insight into which part of the graph is not capturing its objective, enabling the expert to debug the auto-tuner when it fails to converge.

### 4.2 Optimizing gem5-Aladdin EDP

Systems-on-a-chip (SoCs) are integrated circuits that provide bespoke computing on a single microchip. An example of its usage is smartphones, IoT, and autonomous vehicles. SoC designers experiment with different designs to meet each use case’s objective. Synthesizing chips for experiments is very expensive; hence several simulators emerged that promises a high degree of accuracy [12, 15, 53]. The simulator itself is expensive to run and has a large number of design choices hence the need for BoGraph.
Table 2: The gem5-aladdin parameters from their sweeper [30]. Producing over $2^{64}$ unique combination. Some parameters take large values such as cache_size; their search space is pruned by transforming it to a function to power of two.

| Parameter                          | Min  | Max  |
|------------------------------------|------|------|
| CYCLE TIME                         | 1    | 10   |
| PIPELINING                         | 0    | 1    |
| CACHE SIZE (POWER OF TWO)          | 14   | 17   |
| CACHE ASSOC (POWER OF TWO)         | 0    | 5    |
| CACHE LINE SZ (POWER OF TWO)       | 5    | 7    |
| CACHE Hit Latency                  | 1    | 5    |
| CACHE Queue Size                   | 16   | 256  |
| CACHE BANDWIDTH                    | 2    | 18   |
| TLB Hit Latency                    | 1    | 32   |
| TLB Miss Latency                   | 1    | 32   |
| TLB ENTRIES (POWER OF TWO)         | 0    | 5    |
| TLB ASSOC (POWER OF TWO)           | 0    | 5    |
| TLB PAGE SIZE                      | 1024 | 32768|
| TLB Max Outstanding Walks          | 2    | 16   |
| TLB Bandwidth                      | 2    | 16   |
| L2CACHE Size (POWER OF TWO)        | 17   | 21   |
| ENABLE L2                          | 0    | 1    |
| PIPELINED DMA                      | 0    | 1    |
| READY Mode                         | 0    | 1    |
| IGNORE Cache Flush                 | 0    | 1    |

4.2.1 Problem setup

The topic of optimizing SoCs’ design to reduce the energy, power, and total area is of a great interest to the community [48]. A recent work [10] used BO to choose between seven predefined cache interfaces (search space of $2^7$) to improve the accelerator’s cycles.

We note that optimizing the cycle is problematic. Improving the cycle forces the optimizer to find configurations that abuse the fact by slowing down the simulator both energy and cycles improve, leading to slower hardware. Instead, we focus on optimizing the latency $\text{latency} = \frac{1}{\text{sim\_seconds}}$ and energy consumption and tune all exposed parameters in the system simulator. We optimized the gem5-Aladdin [54] system-accelerator co-design parameters detailed in Table 2 to reduce Aladdin’s the Energy-delay Product (EDP) where $\text{EDP} = \text{energy} \times \text{latency}^2$ [5].

Expert knowledge. We provided BoGraph with our knowledge of the EDP function: directed edges from power and latency to EDP; and the EDP deterministic formula.

Benchmark. All experiments were evaluated on the full MachSuite benchmark [50] to provide a comparison against the standard literature in co-designing accelerator, and hardware [48, 54]. The tasks provide a range of data-intensive, compute-intensive, and mixed workloads. We refer to [50] for a full description of each task.

Simulator setup. We used the default MESI Two Level Aladdin protocol, which builds against x86 ISA the CPU models TimingSimpleCPU, O3CPU, and AtomicSimpleCPU, and estimated power consumption using gem5’s MathExprPowerModel which deterministically calculate the power consumption based on a formula taking into account the design.

Baselines. Each baseline ran against every task independently for a hundred evaluation, with each experiment repeated three times. The baseline aimed to represent the diverse set of philosophies in the auto-tuner literature; the following provides a short summary of each:

- **Default**: the settings provided by the simulator.
- **BoTorch** [6]: A performant GP implementation. Showing the effectiveness of BoGraph with everything else being equal as BoGraph shares BoTorch’s samplers and acquisition functions.
- **Random** [8]: Effective when only a subset of the dimensions is impactful.
- **DeepGP** [19]: Provides unsupervised structure discovery in the latent space. We configured a two-layer GP with 64 inducing points (the maximum that fits on our GPU). We built DeepGP using GPyTorch [27] and BoTorch.
- **PBT Tuner** [33]: Trains a large population of different models while constantly evaluating and keeping best performing models. Using the NNI [45] implementation.

We could not compare against BOAT [18] due to changes in the underlying libraries, which requires significant effort to update. Similarly, CBO [1] is tightly coupled to the problem described in their paper, which requires significant engineering effort to reuse in a different context. We have plans to compare against SMAC [32] as it builds a random forest of the search space and combines an ensemble of pre-trained optimization techniques. BoGraph allows injecting expert knowledge and pre-trained models. For a fair comparison, we will need to provide similar models. This comparison will be the basis of future work.

4.2.2 Execution time

This set of experiments investigate the time it takes to perform a single task execution run and compares it to the overhead of using an auto-tuner. The comparison in Figure 8 shows the time it takes for average task execution, compared to the average optimization time for each of the baseline methods. All the tasks beside aes/aes take at least five times the time to optimize for the slowest model, DeepGP, showing that execution time dominates optimization time. gem5-Aladdin not only has an enormous combination of configurations ($\approx 2^{64}$) but also each execution for a non-trivial task takes at least a minute. Hence the need for auto-tuners that perform better than simple parameter sweeps.
Table 3: ELLPACK performance using the median best configuration proposed by each model. The lower the values, the better.

| MODEL   | LOG EDP | LATENCY (1/sec) | POWER (mWatts) | POWER/OPS | AREA     |
|---------|---------|-----------------|----------------|-----------|----------|
| BoGraph | 8.12 ± 0.28 | 11.06 ± 0.19 | 27.37 ± 11.59 | 0.65 ± 0.28 | 3.54 ± 2.06 |
| PBTTuner| 9.39 ± NA  | 18.53 ± NA  | 34.92 ± NA  | 0.84 ± NA  | 6.10 ± NA  |
| DeepGP  | 10.14 ± 0.27 | 11.06 ± 3.92 | 203.15 ± 46.34 | 4.86 ± 1.11 | 110.81 ± 55.96 |
| BoTorch | 10.44 ± 0.62 | 11.06 ± 3.90 | 108.46 ± 102.97 | 2.59 ± 2.46 | 54.90 ± 29.93 |
| RANDOM  | 10.74 ± 0.19 | 18.32 ± 4.81 | 143.94 ± 194.83 | 3.44 ± 4.66 | 64.36 ± 52.80 |
| DEFAULT | 14.50 ± 0  | 94.80 ± 0  | 220.34 ± 0 | 5.13 ± 0  | 35.18 ± 0  |

4.2.3 EDP Optimization

Overview. Figure 9 examines the improvement in the EDP from the default configurations across all tasks. BoGraph always found configurations that outperformed every other method, and in every task outperformed the default between 5 and 7 x-factors depending on the task.

Next, we examine the performance of ELLPACK task, our highest performing task. We provide the detailed results of other tasks in the supplementary materials as they follow a similar story.

Table 3 shows that BoGraph found configurations with the least power consumption and fastest execution. Other methods could not reduce the power even if they reduced the latency because the EDP formula favors latency (the latency is weighted twice). Without providing the context needed to learn that power is an important factor to improve the EDP, the tuners will be stuck in that local minima. BoGraph captured both objectives, the latency and power while avoiding the local minima areas by utilizing the additional knowledge it has. We included the area measurements to ensure that the models were not proposing unrealistic chip sizes; the area was optimized by proxy since gem5’s power estimator penalizes large chips.

Convergence. Figure 10 examines the rate of improvement over the default, an important metric when comparing auto-tuners. As expected, all methods show high variance in the initial first ten iterations as they are configured to sample at random until they observe ten observations. Then the behavior between models diverges. All the baseline methods: PBTTuner, DeepGP, BoTorch, and Random get stuck in a local minimum and do not improve over the optimization. This confirms the hypothesis stated in subsection 1.1 the complexity of the system configurations and the many parameters render most methods obsolete. However, BoGraph outlearned all methods at every iteration and was the only one to find the most performant configuration.

BoGraph improvement jumps at every 20th step in Figure 10 are caused by the structure learning algorithm. We set the update frequency to 20 after examining the dimensions and learning time relationship in subsection 4.2.5. Another interesting jump happened after the 60th step, as it did not
happen immediately but gradually; we believe this is caused by the final structure that allowed the acquisition function to explore a space that was not obvious initially.

4.2.4 Structure discovery

Optimizing gem5-Aladdin shows how BoGraph helps shield the end-user of the difficulty in defining probabilistic model manually. However, BoGraph strength also is in its interpretability and providing knowledge back to the user. There are over 1000 metric reported in a typical gem5 statistics file as each component provide its detailed statistics. The knowledge we injected was the EDP formula, and the edges between AVGPOWER to EDP, and LATENCY to EDP. BoGraph took the prior specification as a starting point but kept learning about the system structure while optimizing it. The ability to show the learned structure informs the designers of their system’s behavior during runtime.

Figure 3 looks at the structure discovered from tuning the ELLPACK task. Interestingly, the model learned that only ten of the exposed twenty parameters had impacted the system’s performance. The reduced structure mirrors what often experts tune manually in the system [48], BoGraph reached this heuristic purely from learning from logs while showing why that relationship holds.

4.2.5 Structure learning for dimensional reduction

Here we investigate the gains and costs of performing structure learning in BoGraph. The goal of structure learning is to reduce the max dimensionality of the surrogate model by decomposing the search space along the system structure. We define max dimension of a DAG $G$ to be $MD = \forall_{n \in G} \max(\text{indegree}(n))$ (lower is better), each node later becomes a probabilistic model. The variance is of three runs.
direct path from parameters to objectives.

Figure 11 visualizes the relationship between learning the structure of every optimization step and the average time it takes it. It was conducted separately of the BoGraph loop using data collected at random to understand the cost of structure learning in the average case and started after observing fifteen observations mimicking a typical BoGraph run. After every evaluation observation, the algorithm detected more correlations between objectives, leading to reduced dimensions up until a stable structure plateau. The average cost did not increase since we are looking only at a few data points (sub 100) due to the main requirement of this research, the ability to converge as quickly as possible with the least number of evaluations needed.

4.3 Discussion

We have shown BoGraph ability to learn the structure from system logs, propose optimal configurations, and provide an API to inject expert knowledge into the optimization process. BoGraph is a tool that transforms a black box problem into a gray box one, providing insight into the system’s behavior under different configurations. This power, as expected, comes at the cost of increased inference and search time. However, we think the increased cost is justified in large systems when comparing the number of iterations needed to optimize against other baselines, and the insight reported back is valuable to any system designer and maintainer. Furthermore, the surrogate model captures the relationship between components in the system, which is invariant of the hardware or environment changes. BoGraph is general purpose and can work just as well on other systems such as databases that also exhibit a hierarchical logging structure [63] similar to gem5.

5 Future work and limitation.

BoGraph is still evolving, with aims to apply to different problem spaces, evaluate it on a multi-objective problem, and improve its exploration strategy.

- **Structured acquisition function.** While BoGraph produces a structured model, we used an off-the-shelf sampler to approximate the DAG and optimize the samples jointly using a standard acquisition function. This approach is expensive and ignores the structure of the model instead of using an optimizer that considers the independence between samples can produce numerically stable results faster.

- **Multi-objective optimization.** Modeling multiple-objectives is trivial in BoGraph as a result of using DAGs as an internal data structure. For example, rather than sampling the model’s EDP node in Figure 3 BoGraph can sample any node in its graph, allowing it to model as many objectives for optimization. Multi-objective modeling is an interesting opportunity for computer system objectives often compete (latency vs. throughput, energy vs. latency, etc). Once multiple objectives are modeled, they can be optimized using off-the-shelf multi-objective utility functions such as expected hypervolume improvement function [21].

- **Application domains.** We have shown BoGraph ability to find meaningful structure from logs and use that to optimize gem5-Aladdin. Follow-up work is to extend the case study to include a hardware-accelerator co-design for neural networks specifically [61], this will allow producing chips tailored for popular ML models for autonomous vehicles and embedded devices. Other computer systems will benefit from BoGraph ability to capture dependency and tune large number of configurations such as databases knobs [58] and stream processors [13].

6 Conclusion

This work presents BoGraph, a general Structured Bayesian Optimization framework for systems with many parameters and long execution times. BoGraph exploits the inherent structure in the system to build a dependency graph that reduces the dimensionality of each component. The decomposability allows tuning a larger number of parameters, providing interpretable optimization suggestions and a natural way to encode expert knowledge in its graph. We demonstrated BoGraph efficiency by exploring the co-design of a system accelerator and produced configurations that optimized energy-latency utility by 5 – 7 x-factors over the default where no other method came close.

Availability

The code will be available through open-source and for artifact evaluation upon paper acceptance.

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References

[1] Virginia Aglietti, Xiaoyu Lu, Andrei Paleyes, and Javier González. Causal Bayesian Optimization. In International Conference on Artificial Intelligence and Statistics, pages 3155–3164. PMLR, 2020.
[2] Omid Alipourfard, Hongqiang Harry Liu, Jianshu Chen, Shivaram Venkataraman, Minlan Yu, and Ming Zhang. CherryPick: Adaptively Unearthing the Best Cloud Configurations for Big Data Analytics, 2017.

[3] Jason Ansel and Cy Chan. PetaBricks. XRDS: Crossroads, The ACM Magazine for Students, 17(1):32, 2010.

[4] Jason Ansel, Shoaib Kamil, Kalyan Veeramachaneni, Jonathan Ragan-Kelley, Jeffrey Bosboom, Una-May O’Reilly, and Saman Amarasinghe. OpenTuner. In Proceedings of the 23rd International Conference on Parallel Architectures and Compilation - PACT ’14, pages 303–316, 2014.

[5] Omid Azizi, Aqeel Mahesri, Benjamin C Lee, Sanjay J Patel, and Mark Horowitz. Energy-performance tradeoffs in processor architecture and circuit design: A marginal cost analysis. ACM SIGARCH Computer Architecture News, 38(3):26–36, 2010.

[6] Maximilian Balandat, Brian Karrer, Daniel R. Jiang, Samuel Daulton, Benjamin Letham, Andrew Gordon Wilson, and Eytan Bakshy. BoTorch: A Framework for Efficient Monte-Carlo Bayesian Optimization. arXiv:1910.06403 [cs, math, stat], December 2020.

[7] Paul Beaumont, Ben Horsburgh, Philip Pilgerstorfer, Angel Droth, Richard Oentaryo, Steven Ler, Hiep Nguyen, Gabriel Azvedo Ferreira, Zain Patel, and Wesley Leong. CausalNex, 2021.

[8] James Bergstra and Yoshua Bengio. Random search for hyper-parameter optimization. Journal of machine learning research, 13(Feb):281–305, 2012.

[9] Betsy Beyer, Chris Jones, Jennifer Petoff, and Niall Richard Murphy. Site Reliability Engineering: How Google Runs Production Systems. “O’Reilly Media, Inc.”, 2016.

[10] Kshitij Bhardwaj, Marton Havasi, Yuan Yao, David M. Brooks, José Miguel Hernández Lobato, and Gu-Yeon Wei. Determining optimal coherency interface for many-accelerator socs using bayesian optimization. IEEE Computer Architecture Letters, 18(2):119–123, 2019.

[11] Eli Bingham, Jonathan P. Chen, Martin Jankowiak, Fritz Obermeyer, Neeraj Pradhyan, Theofanis Karaletos, Rohit Singh, Paul Szerlip, Paul Horsfall, and Noah D. Goodman. Pyro: Deep Universal Probabilistic Programming. October 2018.

[12] Nathan Binkert, Bradford Beckmann, Gabriel Black, Steven K Reinhardt, Ali Saidi, Arkapava Basu, Joel Hestness, Derek R Hower, Tushar Krishna, and Somayeh Sardashti. The gem5 simulator. ACM SIGARCH computer architecture news, 39(2):1–7, 2011.

[13] Paris Carbone, Asterios Katsifodimos, Stephan Ewen, Volker Markl, Seif Haridi, and Kostas Tzoumas. Apache flink: Stream and batch processing in a single engine. Bulletin of the IEEE Computer Society Technical Committee on Data Engineering, 36(4), 2015.

[14] Tianqi Chen, Lianmin Zheng, Eddie Yan, Ziheng Jiang, Thierry Moreau, Luí Ceze, Carlos Guestrin, and Arvind Krishnamurthy. Learning to optimize tensor programs. arXiv preprint arXiv:1805.08166, 2018.

[15] Yu-Hsin Chen, Tien-Ju Yang, Joel Emer, and Vivienne Sze. Eyeriss v2: A Flexible Accelerator for Emerging Deep Neural Networks on Mobile Devices. arXiv:1807.07928 [cs], May 2019.

[16] Max Chickering, David Heckerman, and Chris Meek. Large-sample learning of Bayesian networks is NP-hard. Journal of Machine Learning Research, 5, 2004.

[17] Valentin Dalibard. A Framework to Build Bespoke Auto-Tuners with Structured Bayesian Optimisation. Technical Report, Cambridge University, Department of Computer Science and Technology, November 2016.

[18] Valentin Dalibard, Michael Schaal, and Eiko Yoneki. BOAT: Building auto-tuners with structured Bayesian optimization. In Proceedings of the 26th International Conference on World Wide Web - WWW ’17, pages 479–488, New York, New York, USA, 2017. ACM Press.

[19] Andreas Damianou and Neil D Lawrence. Deep gaussian processes. In Artificial Intelligence and Statistics, pages 207–215. PMLR, 2013.

[20] Adnan Darwiche. Modeling and Reasoning with Bayesian Networks. Cambridge Univ. Press, Cambridge, reprinted edition, 2009.

[21] Samuel Daulton, Maximilian Balandat, and Eytan Bakshy. Differentiable expected hypervolume improvement for parallel multi-objective Bayesian optimization. arXiv preprint arXiv:2006.05078, 2020.

[22] X Dutreilh, S Kirgizov, O Melekhova ICAS 2011, undefined The, and undefined 2011. Using reinforcement learning for autonomic resource allocation in clouds: Towards a fully automated workflow. academia.edu.

[23] Stefan Falkner, Aaron Klein, and Frank Hutter. BOHB: Robust and efficient hyperparameter optimization at scale. arXiv preprint arXiv:1807.01774, 2018.

[24] Avrilia Floratou, Ashvin Agrawal, Bill Graham, Sriram Rao, and Karthik Ramasamy. Dhalion: Self-regulating stream processing in heron. Proceedings of the VLDB Endowment, 10(12):1825–1836, 2017.
[25] Alexander Forrester, Andras Sobester, and Andy Keane. 
*Engineering Design via Surrogate Modelling: A Practical Guide*. John Wiley & Sons, 2008.

[26] Qiang Fu, Jieming Zhu, Wenlu Hu, Jian-Guang Lou, Rui Ding, Qingwei Lin, Dongmei Zhang, and Tao Xie. Where do developers log? an empirical study on logging practices in industry. In *Companion Proceedings of the 36th International Conference on Software Engineering*, pages 24–33, 2014.

[27] Jacob R. Gardner, Geoff Pleiss, David Bindel, Kilian Q. Weinberger, and Andrew Gordon Wilson. GPyTorch: Blackbox Matrix-Matrix Gaussian Process Inference with GPU Acceleration. *arXiv:1809.11165 [cs, stat]*, January 2019.

[28] Frank Hutter, Holger Hoos, and Kevin Leyton-Brown. An evaluation of sequential model-based optimization for expensive blackbox functions. In *Proceedings of the 15th Annual Conference Companion on Genetic and Evolutionary Computation*, pages 1209–1216, 2013.

[29] Max Jaderberg, Valentin Dalibard, Simon Osindero, Wojciech M. Zaremba, Jeff Donahue, Ian Graph, Oriol Vinyals, Tim Green, Iain Dunning, and Karen Simonyan. Population based training of neural networks. *arXiv preprint arXiv:1711.09846*, 2017.

[30] David A Kenny. Measuring model fit. 2015.

[31] Paul Kline. *An Easy Guide to Factor Analysis*. Routledge, 2014.

[32] HT Li, Guang Jin, JL Zhou, Zhong-bao ZHOU, and Da-qing LI. Survey of Bayesian network inference algorithms. *Systems and Computers in China*, 30(5):935–939, 2008.

[33] Ujval Misra, Richard Liaw, Lisa Dunlap, Romil Bhardwaj, Kirthivasan Kandasamy, Joseph E. Gonzalez, Ion Stoica, and Alexey Tumanov. RubberBand: Cloud-based hyperparameter tuning. In *Proceedings of the Sixteenth European Conference on Computer Systems*, pages 327–342, Online Event United Kingdom, April 2021. ACM.

[34] Judea Pearl. The do-calculus revisited. *arXiv preprint arXiv:1210.4852*, 2012.

[35] Daphne Koller and Nir Friedman. *Probabilistic Graphical Models: Principles and Techniques*. MIT press, 2009.

[36] Luigi Nardi, David Koeplinger, and Kunle Olukotun. Practical Design Space Exploration. *arXiv:1810.05236 [cs, math, stat]*, July 2019.

[37] Carl Edward Rasmussen and Christopher K. I. Williams. *Gaussian Processes for Machine Learning*. Adaptive Computation and Machine Learning. MIT Press, Cambridge, Mass., 3. print edition, 2008.
[50] Brandon Reagen, Robert Adolf, Yakun Sophia Shao, Gu-Yeon Wei, and David Brooks. Machsuite: Benchmarks for accelerator design and customized architectures. In 2014 IEEE International Symposium on Workload Characterization (IISWC), pages 110–119. IEEE, 2014.

[51] Mauro Scanagatta, Antonio Salmerón, and Fabio Stella. A survey on Bayesian network structure learning from data. Progress in Artificial Intelligence, pages 1–15, 2019.

[52] Bobak Shahriari, Kevin Swersky, Ziyu Wang, Ryan P Adams, and Nando De Freitas. Taking the human out of the loop: A review of Bayesian optimization. Proceedings of the IEEE, 104(1):148–175, 2015.

[53] Yakun Sophia Shao, Brandon Reagen, Gu-Yeon Wei, and David Brooks. Aladdin: A pre-rtl, power-performance accelerator simulator enabling large design space exploration of customized architectures. In 2014 ACM/IEEE 41st International Symposium on Computer Architecture (ISCA), pages 97–108. IEEE, 2014.

[54] Yakun Sophia Shao, Sam Likun Xi, Vijayalakshmi Srinivasan, Gu-Yeon Wei, and David Brooks. Co-designing accelerators and soc interfaces using gem5-aladdin. In 2016 49th Annual IEEE/ACM International Symposium on Microarchitecture (MICRO), pages 1–12. IEEE, 2016.

[55] Jasper Snoek, Hugo Larochelle, and Ryan P Adams. Practical bayesian optimization of machine learning algorithms. In Advances in Neural Information Processing Systems, pages 2951–2959, 2012.

[56] Richard S. Sutton and Andrew G. Barto. Reinforcement Learning : An Introduction. MIT Press, Cambridge Mass., 1998.

[57] Dana Van Aken, Andrew Pavlo, Geoffrey J. Gordon, and Bohan Zhang. Automatic Database Management System Tuning Through Large-scale Machine Learning. In Proceedings of the 2017 ACM International Conference on Management of Data - SIGMOD ’17, pages 1009–1024, New York, New York, USA, 2017. ACM Press.

[58] Dana Van Aken, Dongsheng Yang, Sebastien Brillard, Ari Fiorino, Bohan Zhang, Christian Bilien, and Andrew Pavlo. An inquiry into machine learning-based automatic configuration tuning services on real-world database management systems. Proceedings of the VLDB Endowment, 14(7):1241–1253, March 2021.

[59] Shivaram Venkataraman, Zongheng Yang, Michael Franklin, Benjamin Recht, and Ion Stoica. Ernest: Efficient performance prediction for large-scale advanced analytics. In 13th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 16), pages 363–378, 2016.

[60] Svante Wold, Kim Esbensen, and Paul Geladi. Principal component analysis. Chemometrics and intelligent laboratory systems, 2(1-3):37–52, 1987.

[61] Sam Xi, Yuan Yao, Kshitij Bhardwaj, Paul Whatmough, Gu-Yeon Wei, and David Brooks. Smaug: End-to-end full-stack simulation infrastructure for deep learning workloads. ACM Transactions on Architecture and Code Optimization (TACO), 17(4):1–26, 2020.

[62] Shulin Yang and Kuo-Chu Chang. Comparison of score metrics for Bayesian network learning. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 32(3):419–428, 2002.

[63] Ding Yuan, Soyeon Park, and Yuanyuan Zhou. Characterizing logging practices in open-source software. In 2012 34th International Conference on Software Engineering (ICSE), pages 102–112. IEEE, 2012.

[64] Matei Zaharia, Mosharaf Chowdhury, Michael J Franklin, Scott Shenker, and Ion Stoica. Spark: Cluster computing with working sets. HotCloud, 10(10-10):95, 2010.

[65] Xun Zheng, Bryon Aragam, Pradeep Ravikumar, and Eric P Xing. Dags with no tears: Continuous optimization for structure learning. arXiv preprint arXiv:1803.01422, 2018.