Reasoning about Configurable System Performance through the lens of Causality

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Abstract

Modern computer systems are highly configurable. They often are composed of heterogeneous components—each component consists of numerous configurations, giving a total variability space sometimes larger than the number of atoms in the universe. The performance of a system configured with different configuration options can widely vary. Thus, given the vast configuration space, understanding and reasoning about the performance behavior of such systems become challenging. These configuration options interact with each other within and across the system stack, and such interactions typically vary in different deployment environments or workload conditions. So, it becomes almost impossible to track down configuration options that should be set to different values to improve performance if the system's performance shows wide variability during operation time. As a result, existing performance models that rely on predictive machine learning models suffer from (i) *high cost*: given a deployment environment, regression-based performance models require a large number of configuration samples for accurate predictions, and more importantly, (ii) *unreliable predictions*: even if they predict performance for the environment where configurations are measured, since they may infer correlations as causation, they typically do not transfer well for predicting system performance behavior in a new environment (e.g., change of hardware from the canary environment to production).

The main problem we address here is to understand *why* the performance degradation is happening and *reason* based on a reliable model to improve it. To this end, this paper proposes a new methodology, called Unicorn, which initially learns a Causal Performance Model to reliably *capture intricate interactions* between options across software-hardware stack by tracing system-level performance events across the stack (hardware, software, cache, and tracepoint). Then, it uses them to *explain* how such interactions impact the variation in performance objectives causally. Given a limited sampling budget, Unicorn iteratively updates the learned performance model by estimating the causal effects of configuration options to performance objectives, then selecting the highest-impact options to adjust in order to address performance issues by improving the performance objective of interest without deteriorating other objectives in debugging task or recommend a near-optimal configuration.

We evaluated Unicorn on six highly configurable systems, including three on-device machine learning systems, a video encoder, a database, and a data analytics pipeline. In addition, we compared the results with state-of-the-art configuration optimization and debugging methods. The experimental results indicate that Unicorn can find effective repairs for performance faults and find configurations with near-optimal performance. Furthermore, unlike the existing methods, the learned causal performance models in Unicorn reliably predict performance for new environments where it has not been used during the learning process.

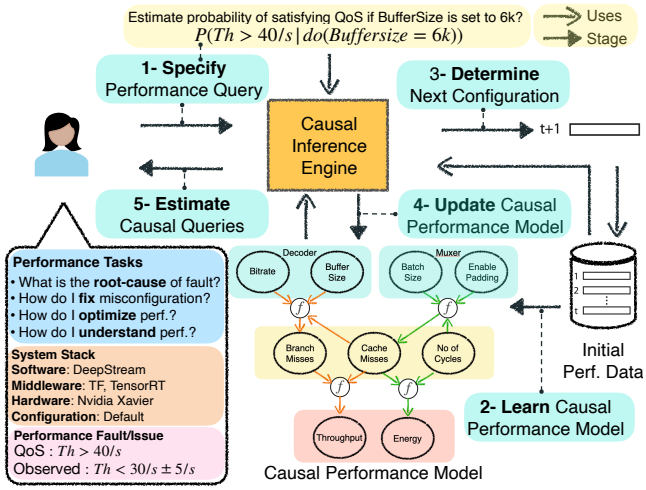


Figure 1. Overview of Unicorn

1 Introduction

Modern computer systems are typically composed of multiple components, each component has many configuration options, and they can seamlessly be deployed on various hardware platforms. The configuration space of highly configurable systems is combinatorially large with 100s if not 1000s of software and hardware configuration options that interact non-trivially with one another [36, 48, 97]. Developers of individual components typically have a very local, and thus limited, understanding regarding the performance behavior of such systems. Developers and users of the final system are often overwhelmed with the complexity of composing and configuring components, and thus, configuring these systems to achieve specific performance goals is challenging and error-prone.

Incorrect configuration (*misconfiguration*) elicits unexpected interactions between software and hardware resulting *non-functional faults*, i.e., faults in *non-functional* system properties such as latency and energy consumption. These non-functional faults—unlike regular software bugs—do not

cause the system to crash or exhibit an obvious misbehavior [69, 78, 92]. Instead, misconfigured systems remain operational while being compromised, resulting in severe performance degradation[1], for example, in execution time or energy consumption [14, 64, 68, 79].

Misconfigurations are not only causing major issues for interne-scale cloud systems [1], but also, they exist for many types of systems, including embedded systems. For example, a developer on NVIDIA's developer forum complained that *"I have a complicated system composed of multiple components running on Nvidia Nano and using several sensors and I observed several performance issues. [4]."* In another instance, a more experienced developer asks *"I'm quite upset with CPU usage on Jetson TX2, while running TCP/IP upload test program" [5].* After struggling in fixing the issues over the span of several days, the developer conclude: *there is a lot of knowledge required to optimize network stack and measure CPU load correctly. I tried to play with every configuration option explained in the kernel documents. I was able to reduce CPU load (mpstat) up to 77-83% IDLE with full CPU / max clock during.*" In addition, they would like to *understand* the impact of configuration options and their interactions: *"What is the effect of swap memory on increasing throughput? [2]".*

Existing works. Understanding the performance behavior of configurable systems can enable (i) performance debugging [32, 85], (ii) performance tuning [40, 43, 44, 66, 67, 72, 90, 94, 98], and (iii) architecture adaptation [6, 23, 24, 28, 42, 50, 53, 56]. A common strategy to build performance influence models in which regression-based models, of the form $f(c) = \beta_0 + \Sigma_i \phi(o_i) + \Sigma_{i..j} \phi(o_i..o_j)$, are used to build a model that explains the influence of individual options and their interactions [34, 76, 85, 94]. These approaches are adept at inferring the correlations between certain configuration options and performance objectives, however, they suffer from several issues: (i) the models require many performance measurements to provide reliable predictions, (ii) the models are not transferable for predicting performance for different environment, and (iii) the models provide incorrect explanations regarding important options and interactions that 'causes' performance variations.

Our approach. Based on the intuition and several experimental evidence presented in the following section, this paper proposes UNICORN–a methodology that enables reasoning about configurable system performance with causal inference and counterfactual reasoning. As depicted in Fig. 1, UNICORN first recovers the underlying causal structure (a model that consists of variables related to system performance across stack) by measuring the system variables under different configurations. The causal performance model allows users to (a) identify the root causes of performance faults, (b) estimate the effects of various configurable parameters on the performance objectives, and (c) prescribe candidate configurations to fix the performance fault or optimize system performance.

[1]we call them performance fault

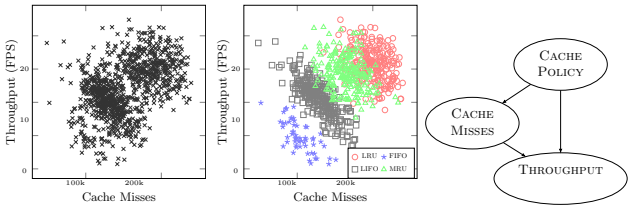


Figure 2. Simple example showing the effectiveness of causal reasoning in explaining the increase of Throughput with the decrease of Cache Misses. Observational data (Fig. 2a) (incorrectly) shows that as increase in Cache Misses leads to high throughput. Fig. 2c captures causal dependencies between different configuration option and system throughput. Thus, incorporating Cache Policy as a confounder correctly shows increase of Cache Misses correspond to decrease in throughput (Fig. 2b).

Contributions. Our contributions are as follows.

- We propose UNICORN, a novel approach that instead of relying on correlations between system variables and performance objectives, constructs a causal performance model and enable reasoning about system performance in a reliable fashion using the mathematics of causality.
- We evaluate UNICORN in terms of its *effectiveness, transferability*, and *scalability* and compared with state-of-the-art performance debugging and optimization using six real-world highly configurable systems (three machine learning systems, a video encoder, and a database system) deployed on 3 architecturally different NVIDIA Jetson devices.
- We offer a manually curated performance fault dataset (called Jetson Faults) and accompanying code required to reproduce our findings at https://git.io/JtFNG.

2 Causal Performance Modeling and Analyses: Motivating Scenarios

In this section, we, first, point out reliability and stability issues with existing performance analyses practices via a simple as well as a large-scale real scenario. We then define a new abstraction that enables us to perform causal reasoning in systems. We, finally, show the effectiveness of causality vs correlation for performance tasks that address the issues.

A simple scenario: Fig. 2 shows a simple scenario where the observational data indicates that throughput is positively correlated with increased Cache Misses (as in Fig. 2 a). A simple ML model built on this data will predict with high confidence that larger Cache Misses leads to higher throughput—this is misleading as higher Cache Misses should, in theory, lower throughput. However, segregating the same data on Cache Policy (as in Fig. 2 b) reveals that within each group of Cache Misses, as Cache Misses increases, the throughput decreases. One would expect such behavior as the more Cache Misses the higher number of access to external memory and therefore, the throughput would be expected to decrease.

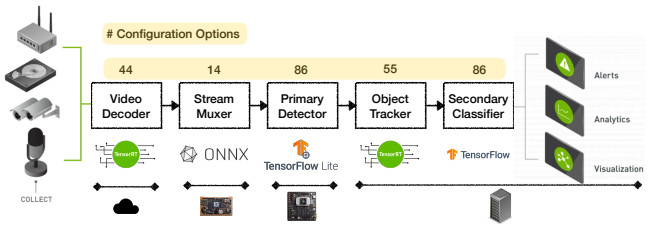


Figure 3. An example of a highly-configurable composed system, DeepStream [70]. It is a data analytics pipeline with several configurable components: a (i) Video Decoder; (ii) Stream Muxer, a plugin that accepts input streams and converts them to sequential batch frames; (iii) Primary Detector, which transforms the input frames based on input NN requirements and does model inference to detect objects; (iv) Object Tracker, which supports multi-object tracking; (v) Secondary Classifier, which improves performance by avoiding re-inferencing on the same objects in every frame.

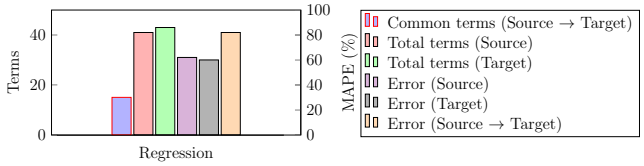


Figure 4. Regression models do not generalize well as the number of common terms, total terms and prediction error of the structural causal models change from source (Xavier) to target (TX2). The rank correlation between source and target is 0.07 (p-value=0.73).

The system resource manager may change the cache policy based on some criteria; this means that for the same number of cache misses, the throughput may be lower or higher, however, in all policies, the increases of cache misses result in a decrease in throughput. Thus, Cache Policy acts as a confounder that explains the relation between Cache Misses and throughout, which a correlation-based model will not be able to capture. In contrast, a causal performance model, as shown in Fig. 2 c, finds the relation between Cache misses, Cache Policy, and throughput and thus can reason about the observed behavior correctly.

In reality, performance analysis using causal reasoning for heterogeneous multi-component systems is non-trivial. In particular, there are two main challenges: (i) end-to-end performance analysis is not possible by reasoning about individual components in isolation, (ii) intra-component analysis may not be sufficient as severe performance bottlenecks may happen due to sub-optimal interactions of configuration options across components. Next, we use a highly configurable multi-stack system to motivate why causal reasoning is a better choice for understanding the performance behavior of complex systems and then illustrate Unicorn with the example.

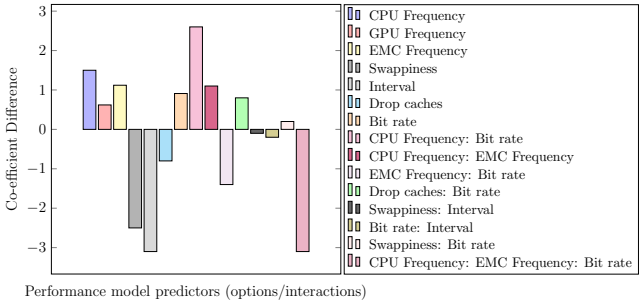


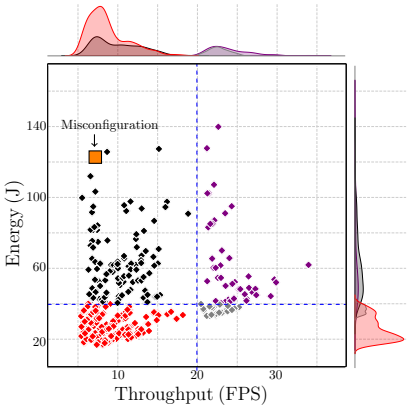
Figure 5. Visualizing co-efficient differences from the source (Xavier) regression model to the target (TX2) regression model for the common terms and interactions (shown by ":").

Scenario involving highly configurable multi-stack system: We deployed a data analytics pipeline, DeepStream [2], on NVIDIA Jetson Xavier hardware as shown in Fig. 3. DeepStream has many components, and each component has many configuration options, resulting in many variants of the same system. In particular, the variability comes from: (i) the configuration options of each software component in the pipeline, (ii) configurable low-level libraries that implement functionalities required by different components (e.g., the choice of tracking algorithm in the tracker or different neural architectures), (iii) the configuration options associated with each component's deployment stack (e.g., CPU frequency of NVIDIA Xavier). Further, there exist many configurable events that can be measured/observed at the OS level by the event tracing system. Such huge variabilities make performance analysis challenging. Moreover, configuration options among the components *interact* with each other, making the performance analysis tasks even harder.

In particular, we focus on two performance tasks: (i) *Performance Debugging*: It starts with an observed performance issue (e.g., slow execution), and the task is involved replacing the current configurations in the deployed environment with another configuration that fixes the observed performance issue; (ii) *Performance Optimization*: Here, no performance issue is observed; however, one wants to get a near-optimal performance by finding a configuration that enables the best tradeoff in the multi-objective space (e.g., throughput vs. energy consumption vs. accuracy in DeepStream). To better understand the potential of the proposed approach, we show the limitations of existing correlation-based approaches for these tasks in the context of DeepStream Framework.

In particular, we measured (i) application performance metrics including throughput and energy consumption by instrumenting the DeepStream code, and (ii) 145 system-wide performance events (hardware, software, cache, and tracepoint) using *perf* and measured the data for 2000 configurations of DeepStream. We measured the performance data

[2]https://developer.nvidia.com/deepstream-sdk



(a) Performance Distribution

Config. Option	Value
CPU Cores	2
CPU Frequency (GHz)	0.1
EMC Frequency (GHz)	1.6
GPU Frequency (GHz)	0.7
Scheduler Policy	NOOP
Scheduler Runtime (μs)	950k
Scheduler Child	1
Batch Timeout	1
Batch Size	1
Interval	1
Cache Size	5
DirtyBackground Ratio	5
Dirty Ratio	10
Drop Caches	0
Cache Pressure	500
Swappiness	60
GPU Memory Growth	def.
Logical Devices	50
Swap Memory (Gb)	1
Throughput (FPS)	6.8
Energy (J)	122

(b) Misconfiguration

Figure 6. (a) Multi-objective performance distribution when DeepStream is deployed on NVIDIA Jetson Xavier (b) Misconfiguration that caused the multi-objective non-functional fault (shown as the example fault in □ in the performance distribution.

in two different hardware environments, Jetson Xavier and TX2. More specifically, the configuration space of the system included (i) Software level (Decoder: 44, Stream Muxer: 14, Detector: 52), (ii) 206 Kernel level (e.g., Swappiness, Scheduler Policy, etc.), and (iii) 4 Hardware options (CPU Freq, active cores). We used 8 camera streams as the workload. We used x286 as the decoder, TrafficCamNet model that uses ResNet 18 architecture for the detector. This model is pre-trained in 4 classes on a dataset of 150k frames and has an accuracy of 83.5% for detecting and tracking cars from a traffic camera's viewpoint. The 4 classes are Vehicle, BiCycle, Person, and Roadsign. We use the Keras (Tensorflow backend) pre-trained model from TensorRT. We used NvDCF tracker, which uses a correlation filter-based online discriminative learning algorithm to a single object and uses a data association algorithm for multi-object tracking. As it is depicted in Fig. 6a, performance behavior of DeepStream, like other highly configurable systems, is non-linear, multi-modal, non-convex [49].

To show major shortcomings of existing state-of-the-art performance models, we built performance influence models that have extensively been used in the systems' literature [31, 32, 34, 51, 55, 58, 65, 86, 87] and it is the standard approach in industry [55, 58]. Specifically, we built non-linear regression models with forward and backward elimination using a stepwise training method on the DeepStream performance data. We then performed several sensitivity analyses and identified the following issues:

1. **Performance influence models could not reliably predict performance in unseen environments.** Performance behavior of configurable systems varies across environments, e.g., when we deploy a software on a new hardware with a different microarchitecture or when the workload changes [46, 51–53, 94]. When building a performance model, it is important to capture predictors (options and interactions that appear in the performance influence models of form $f(c) = \beta_0 + \Sigma_i \phi(o_i) + \Sigma_{i..j} \phi(o_i..o_j)$) that transfer well, i.e., remain *stable* across environmental changes. Such characteristic is expected from performance models since the models are learned based on one environment (e.g., staging) and are desirable to reliably predict performance in another environment (e.g., production). Therefore, if the predictors in a performance model become unstable, even if they produce accurate predictions in the current environment, there is no guarantee that it performs well in other environments, i.e., they become unreliable for performance predictions and performance optimizations due to large prediction errors. To investigate how transferable performance influence models are across environments, we performed a thorough analysis when learning a performance model for DeepStream deployed on two different hardware platforms that have two different microarchitectures. Note that such environmental changes are common, and it is known that performance behavior changes when in addition to a change of hardware resources (e.g., higher CPU frequency), we have major differences in terms of architectural constructs [19, 22], also supported by a thorough empirical study [51]. The results in Fig. 4 indicate that the number of stable predictors is too small with respect to the total number of predictors that appear in the learned regression models.

2. **Performance influence models could produce incorrect explanations.** In addition to performance predictions, where developers are interested to know the effect of configuration changes on performance objectives, they are also interested to estimate and explain the effect of a change in particular *configuration options* (e.g., changing *CachePolicy*) toward performance variations. It is therefore desirable that the strength of the predictors in performance models, determined by their coefficients, remain consistent across environments [22, 51]. In the context of our simple scenario in Fig. 2, the performance influence model that has been learned indicates that $0.16 \times CacheMisses$ is the most influential term that determines throughput, however, the (causal) model in Fig. 2 (c) show that there the interactions between configuration options *CachePolicy* and system event *CacheMisses* is a more reliable predictor of the throughput, indicating that the performance influence model, due to relying on superficial correlational statistics, incorrectly explains factors that influence performance behavior of the system. We performed a thorough analysis and found out that a very low Spearman rank correlation between predictors coefficients, indicating that a performance model based on regression could be highly unstable and thus would produce unreliable explanations as well as unreliable estimation of the effect of change in specific options for performance debugging purposes.

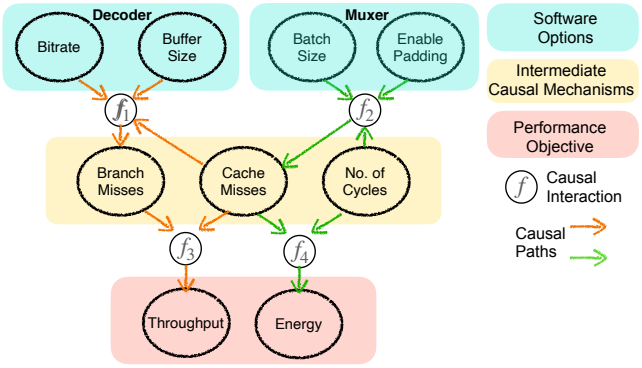


Figure 7. A Causal Performance Model for DeepStream.

Causal Performance Models. We hypothesize that the reason behind the above-mentioned issues is the inability of correlation-based models to capture causally relevant predictors in the learned performance models. Hence, we introduce a new abstraction for performance modeling, called **Causal Performance Model (CPM)**, that gives us the leverage for performing causal reasoning in the systems performance domain. A CPM is an instantiation of Graphical Models [73] with new types and structural constraints to enable performance modeling. Formally, CPMs (cf., Fig. 7) are Directed Acyclic Graphs (DAGs) [73] with (i) performance variables, (ii) functional nodes that define functional dependencies between performance variables, and (iii) causal links that interconnect performance nodes with each other via functional nodes, and (iv) structural constraints to define assumptions we require in performance modeling. In particular, we defined three new variable types: (1) Software-level configuration options associated with a software component in the composed system (e.g., Bitrate in the decoder component of DeepStream), (2) intermediate performance variables relating the effect of configuration options to performance objectives including middleware traces (e.g., Context switches), performance events (e.g., CacheMisses), and hardware-level options (e.g., CPU frequency), and (3) end-to-end performance objectives (e.g., Throughout, Energy consumption). We also characterize the functional nodes with polynomial models to be explainable, although, in a generic form, they could be characterized with any functional forms, e.g., neural networks [80, 99]. We also defined two specific constraints over CPMs to characterize the assumptions in performance modeling: (i) defining variables that can be intervened (note that some performance variables can only be observed (e.g., CacheMisses) or in some cases where a variable can be intervened, the user may want to restrict the variability space, e.g., the cases where the user may want to use prior experience, restricting the variables that do not have a major impact to performance objectives); (ii) structural constraints, e.g., configuration options do not cause other options. Note that such constraints enable incorporating domain knowledge and enable further sparsity that facilitates learning with low sample sizes.

How causal reasoning can fix the reliability and explainability issues in current performance analyses practices. The causal performance models contain more detail than the joint distribution of all variables in the model. For example, the CPM in Fig. 7 encodes not only *BranchMisses* and *Throughput* readings are dependent but also that lowering *CacheMisses* causes the *Throughput* of DeepStream to increase and not the other way around. The arrows in causal performance models correspond to the assumed direction of causation, and the absence of an arrow represents the absence of direct causal influence between variables, including configuration options, system events, and performance objectives. The only way we can make predictions about how performance distribution changes for a system when deployed in another environment or when its workload changes are if we know how the variables are causally related. This information about causal relationships is not captured in non-causal models, such as regression-based models. Using the encoded information in CPMs, we can benefit from analyses that are only possible when we explicitly employ causal models, in particular, interventional and counterfactual analyses [74, 75]. For example, imagine that in a hardware platform, we deploy the DeepStream and observed that the system throughput is below 30/s and BufferSize as one of the configuration options was determined dynamically between 8k-20k. The system maintained may be interested in estimating the likelihood of fixing the performance issue in a counterfactual world where the BufferSize is set to a fixed value, 6k. The estimation of this counterfactual query is only possible if we have access to the underlying causal model because setting a specific option to a fixed value is an intervention as opposed to conditional observations that have been done in the traditional performance model for performance predictions.

CPMs are not only capable of predicting system performance in certain environments, they encode the causal structure of the underlying system performance behavior, i.e., the data-generating mechanism behind system performance. Therefore, the causal model can reliably transfer across environments [81]. To demonstrate this for CPMs as a particular characterization of causal models, we performed a similar sensitivity analysis to regression-based models and observed that CPMs can reliably predict performance in unseen environments (see Fig. 8). In addition, as opposed to PIMs that are only capable of performance predictions, CPMs can be used for several downstream heterogeneous performance tasks. For example, using a CPM, we can determine the *causal effects* of configuration options on performance objectives. Using the estimated causal effects, one can determine the effect of change in a particular set of options towards performance objectives and therefore can select the options with the highest effects to fix a performance issue, i.e., bring back

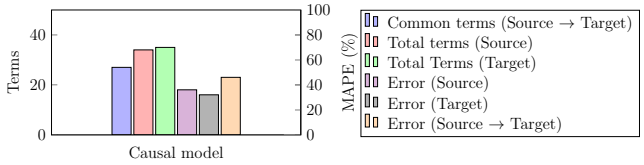


Figure 8. Causal models generalize better as the number of common terms, total terms and prediction error of the structural does not change much from source (Xavier) to target (TX2). The rank correlation between source and target is 0.49 (p-value=0.76).

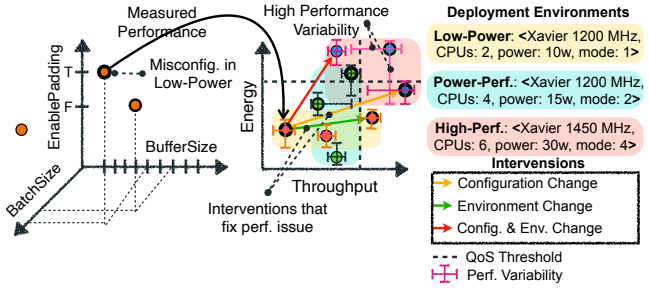


Figure 9. Mapping configuration space to multi-objective performance space

the performance objective that has violated a specific quality of service constraint without sacrificing other objectives. CPMs are also capable of predicting performance behavior by calculating conditional expectation, $E(Y|X)$, where Y indicates performance objectives, e.g., throughput, and $X = x$ is the system configurations that have not been measured.

3 Unicorn

This section presents Unicorn–our methodology for performance analyses of highly configurable and composable systems with causal reasoning.

Overview. Unicorn works in five stages, implementing an active learning loop (cf. Fig. 1): (i) Users or developers of a highly-configurable system *specify*, in a human-readable language, the performance task at hand in terms of a query in the Inference Engine. For example, a DeepStream user may have experienced a throughput drop when they have deployed it on NVIDIA Xavier in low-power mode (cf. Fig. 9). Then, Unicorn's main process starts by (ii) collecting some predetermined number of samples and *learning a causal performance model*; Here, a sample contains a system configuration and its corresponding measurement—including low-level system events and end-to-end system performance. Given a certain budget, which in practice either translates to time [47] or several samples [49], Unicorn, at each iteration, (iii) *determines the next configuration(s)* and measures system performance when deployed with the determined configuration–i.e. new sample; accordingly, (iv) the *learned*

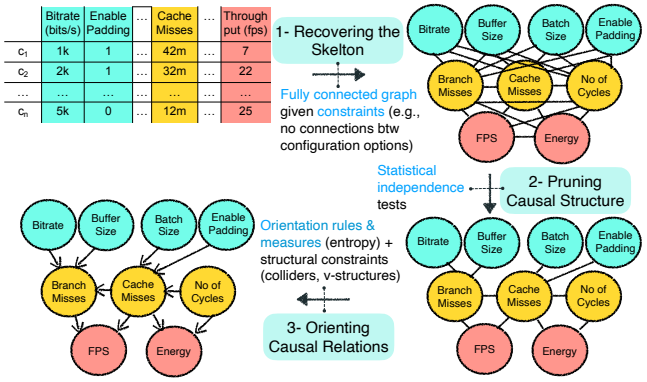


Figure 10. Causal model learning from performance data.

causal performance model is incrementally updated, reflecting a model that captures the underlying causal structure of the system performance. Unicorn terminates if either budget is exhausted or the same configuration has been selected a certain number of times consecutively, otherwise, it continues from stage-iii. Finally, (v) to automatically derive the quantities which are needed to conduct the performance tasks, the specified performance queries are *translated* to formal causal queries, and they will be *estimated* based on the final causal model.

Stage-I: Formulate Performance Queries. Unicorn enables *developers* and *users* of highly-configurable systems to conduct performance tasks, including performance debugging, optimization, and tuning in the following scenarios. In particular, they need to answer several performance queries: (i) What configuration options *caused* the performance fault? (ii) What are *important options and their interactions* that influence performance? (iii) How to *optimize* one quality or navigate *tradeoffs* among multiple qualities in a reliable and explainable fashion? (iv) How can we *understand* what options and possible interactions are most responsible for the performance degradation in production?

At this stage, the performance queries are translated to formal causal queries using the interface of the causal inference engine in Unicorn. Note that in the current implementation of Unicorn, this translation is performed manually, however, this process could be made automatically by creating a grammar for specifying performance queries and the translations can be made between the performance query into the well-defined causal queries, note that such translation has been done in domains such as genomics [25].

Stage-II: Learn Causal Performance Model In this stage, Unicorn learns a CPM (see Section 2) that explains the causal relations between configuration options, the intermediate causal mechanism, and performance objectives. Here, we use an existing structure learning algorithm called *Fast Causal Inference* (hereafter, FCI) [89]. We selected FCI because: (i) it accommodates for the existence of unobserved

confounders [30, 71, 89], i.e., it operates even when there are latent common causes that have not been, or cannot be, measured. This is important because we do not assume absolute knowledge about configuration space, hence there could be certain configurations we could not modify or system events we have not observed. (ii) FCI, also, accommodates variables that belong to various data types such as nominal, ordinal, and categorical data common across the system stack (cf. Fig. 9). To build the CPM, we, first, gather a set of initial samples (cf. Table Fig. 10). To ensure reliability [19, 22], we measure each configuration multiple times, and we use their median for the causal model learning. As depicted in Fig. 10, UNICORN implements three steps for causal structure learning: (i) recovering the skeleton of the CPM by enforcing structural constraints; (ii) pruning the recovered structure using standard statistical tests of independence. In particular, we use mutual info for discrete variables and Fisher z-test for continuous variables. (iii) orienting undirected edges using entropy [17, 18, 30, 71, 89].

Phase-III: Iterative Sampling At this stage, UNICORN determines the next configuration to be measured. UNICORN first estimates the causal effects of configuration options towards performance objectives using the learned causal performance model. Then, UNICORN iteratively determines the next system configuration using the estimated causal effects as a heuristic. Specifically, UNICORN determines the value assignments for options with a probability that is determined proportionally based on their associated causal effects. The key intuition is that such changes in the options are more likely to have a larger effect on performance objectives, and therefore we can learn more about the performance behavior of the system. Given the exponentially large configuration space and the fact that the span of performance variations is determined by a small percentage of configurations, if we had ignored such estimates for determining the change in configuration options, the next configurations would result in considerable variations in performance objectives comparing with the existing data. Therefore, measuring the next configuration would not provide additional information for the causal model.

Phase-IV: Update Causal Performance Model At each iteration, UNICORN measures the configuration that is determined by Phase-III and updates the causal performance model (CPM) incrementally. Since the causal model uses limited observational data, there may be a discrepancy between the underlying performance model and the learned CPM, note that this issue exist in all domains using data-driven models, including causal reasoning [74]. The more accurate the causal graph, the more accurate the proposed intervention will be [17, 18, 30, 71, 89]. Therefore, in case our repairs do not fix the faults, we update the observational data with this new configuration and repeat the process. Over time, the estimations of causal effects will become more accurate.

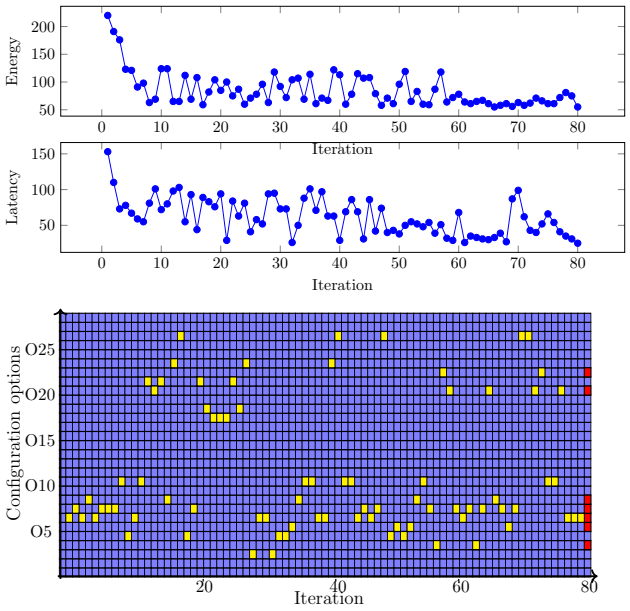


Figure 11. Incremental update of Latency and Energy using UNICORN for debugging a multi-objective fault (top two plots). Yellow-colored nodes indicate the configuration option values recommended by UNICORN (bottom plot). Red colored nodes indicate the recommended fixes from the fault (Iteration 1.)

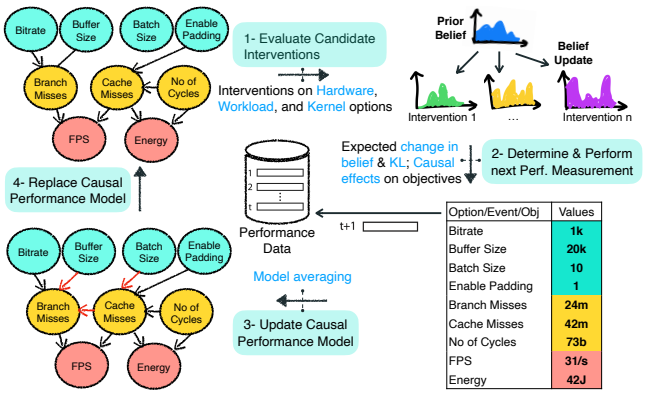


Figure 12. Causal model update.

We terminate the incremental learning once we achieve the desired performance.

The reason behind this initial sampling is to learn an initial causal model and given that our sampling budget is limited, we maximize the information in the causal model iteratively following a Bayesian approach where at iteration t the current causal model is considered as prior and given the new sample it gets updated.

Phase-V: Estimate Performance Queries At this stage, given the learned causal performance model, UNICORN's inference engine estimates the user-specified queries using the mathematics of causal reasoning–do-calculus. Specifically,

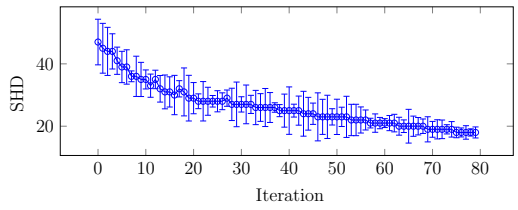


Figure 13. SHD of the obtained causal model by UNICORN and ground truth causal model iteratively decreases.

the causal inference engine provides a quantitative estimate for the identifiable queries on the current causal model and may return some queries as unidentifiable. It also determines what assumptions or new measurements are required to answer the "unanswerable" questions, so, the user can decide to incorporate these new assumptions by defining more constraints or increase the sampling budgets.

Implementation. There are generic causal modeling and inference tools developed and maintained by industry (e.g., Microsoft's DoWhy [83], IBM's CausalLib [84], Uber's CausalML [93]), and academia (e.g., Ananke [12], Causal Fusion [11]); these tools only implement the core machinery in causal reasoning including different causal modeling, structure learning, inference, counterfactuals, and estimation tasks. We implemented UNICORN by integrating and building on top of (i) *Semopy* [82] for predictions with causal models, (ii) *Ananke* [12] for estimating the causal effects, (iii) *CausalML* [93] for counterfactual reasoning, *PyCausal* [77] for structure learning. In particular, we integrated the tools into a seamless pipeline to provide users with the following capabilities for performance modeling and analyses: (i) **Modeling**: specifying the causal variables and constraints needed for learning a correct causal performance model (see Section 2); (ii) **Analyses**: Iterative sampling, model learning and update, estimation of performance queries, and early stopping; and (iii) **User interface**: visualization, annotations, interactions with PCM models, and query estimations.

4 Case Study

Prior to a systematic evaluation in Section 5, here, we show how UNICORN can enable performance debugging in a real-world scenario discussed in [3], where a developer migrated a real-time scene detection system from NVIDIA TX1 to a more powerful hardware, TX2. However, the developer, surprisingly, experienced 4× worse latency in the new environment (from 17 frames/sec in TX1 to 3 frames/sec in TX2). After two days of discussions, the performance issue was diagnosed with a misconfiguration–an incorrect setting of a compiler option and two hardware options. Here, we assess whether and how UNICORN could facilitate the performance debugging by comparing with (i) the fix suggested

Problem [3]: For a real-time scene detection task, TX2 (faster platform) only processed 4 frames/sec whereas TX1 (slower platform) processed 17 frames/sec, i.e., the latency is 4× worse on TX2.
Observed Latency (frames/sec): 4 FPS
Expected Latency (frames/sec): 22-24 FPS *(30-40% better)*

Configuration Options	UNICORN	SMAC	BUGDOC	Forum	ACE†
CPU Cores	✓	✓	✓	✓	3%
CPU Frequency	✓	✓	✓	✓	6%
EMC Frequency	✓	✓	✓	✓	13%
GPU Frequency	✓	✓	✓	✓	22%
Scheduler Policy	·	✓	✓	·	·
Sched rt runtime	·	·	✓	·	·
Sched child runs	·	·	✓	·	·
Dirty bg. Ratio	·	·	·	·	·
Dirty Ratio	·	·	✓	·	·
Drop Caches	·	✓	✓	·	·
CUDA_STATIC	✓	✓	✓	✓	55%
Cache Pressure	·	·	·	·	·
Swappiness	·	✓	✓	·	1%
Latency (TX2 frames/sec)	**28**	24	20	23	
Latency Gain (over TX1)	**65%**	42%	21%	39%	
Latency Gain (over default)	**7×**	6×	5×	5.75×	
Resolution time	**22 mins**	4 hrs	3.5 hrs	2 days	

Figure 14. Using UNICORN on a real-world performance issue.

by NVIDIA in the forum, and two academic performance debugging approaches– BUGDOC [61] and SMAC [45].

Findings. Fig. 14 illustrates our findings. We find that:

- UNICORN could diagnose the root cause of the misconfiguration and recommends a fix within 24 minutes. Using the recommended configuration fixes from UNICORN, we achieved a throughput of 28 frames/sec (65% higher than TX1 and 7× higher than the fault). This, surprisingly, exceeds the developers' initial expectation of 30 – 40% improvement.
- BUGDOC (a diagnosis approach) has the least improvement compared to other approaches (21% improvement over TX1), while taking 3.5 hours to suggest the fix. BUGDOC also changed several unrelated options (depicted by ✓) not endorsed by the domain experts.
- Using SMAC (an optimization approach), we aimed to find a configuration that achieves optimal throughput. However, after converging, SMAC recommended a configuration which achieved 24 frames/sec (42% better than TX1 and 6× better than the fault), however, could not outperform the configuration suggested by UNICORN and even took 4 hours (6× longer than UNICORN to converge). In addition, SMAC changed several unrelated options (✓ in Fig. 14).

Why UNICORN works better (and faster)? UNICORN discovers the misconfigurations by constructing a causal model (a simplified version of this is shown in Fig. 14). This causal model rules out irrelevant configuration options and focuses on the configurations that have the highest (direct or indirect) causal effect on latency, e.g., we found the root-cause

CUDA STATIC in the causal graph which indirectly affects latency via context-switches (an intermediate system event); this is similar to other relevant configurations that indirectly affected latency (via energy consumption). Using counterfactual queries, UNICORN can reason about changes to configurations with the highest average causal effect (ACE) (last column in Fig. 14). The counterfactual reasoning occurs no additional measurements, significantly speeding up inference as shown in Fig. 14, UNICORN accurately finds all the configuration options recommended by the forum (depicted by ✔ in Fig. 14).

5 Evaluations

We examine the following: (i) **Effectiveness** (Section 6)–sample efficiency and performance gain. (ii) **Transferability** (Section 7) across environments, and (iii) **Scalability** (Section 8) to large configuration spaces.

Systems. We selected six configurable systems including a video analytic pipeline, three deep learning-based systems (for image, speech, and NLP), a video encoder, and a database, see Table 1. We use heterogeneous deployment platforms, including NVIDIA TX1, TX2, and XAVIER, each having different resources (compute, memory) and microarchitectures.

Configuration. We choose a wide range of configuration options and system events (see Table 1), following NVIDIA's configuration guides/tutorials and other related work [35]. As opposed to prior work that only can support binary options due to scalability issues (e.g., [95, 96], we included options with binary, discrete, and continuous.

Ground truth. To ensure reliable and replicable results, following the common practice [19, 22, 51, 55], we measured 2000 samples for each 15 deployment settings (5 systems and 3 hardware) and repeated each measurement 5 times and recorded the median. We curated a ground truth of performance issues, called JETSON FAULTS, for each of the studied software and hardware systems using the measured ground truth data. By definition, non-functional faults are located in the tail of performance distributions [33, 57]. We, therefore, selected and labeled configurations that are worse than the 99th percentile as '*faulty*.' Fig. 15 shows the total 494 faults discovered across different software. Out of these 494 NF-FAULTS, 43 are faults with multiple types (both energy and latency). Of all the 451 single-objective and 43 multi-objective NF-FAULTS discovered in this study, only 2 faults had a single root cause, 411 faults had five or more root causes, and 81 remaining faults had two to four root causes. *Initial samples*: 25–10% of the total sampling budget.

Baselines. We evaluate UNICORN for two performance tasks, including **Task 1. Performance Debugging and Repair** and **Task 2. Performance Optimization**. We compare UNICORN against state-of-the-art, including **CBI** [88], a feature selection algorithm for fixing performance issues; **DD** [7], a delta debugging technique, that minimizes the difference between a pair of configurations; **EnCore** [101] learns to debug from correlational information about misconfigurations; **BugDoc** [61] infers the root causes and derive succinct explanations of failures using decision trees; **SMAC** [45], A sequential model-based auto-tuning approach; and **PESMO** [41], A multi-objective Bayesian optimization approach.

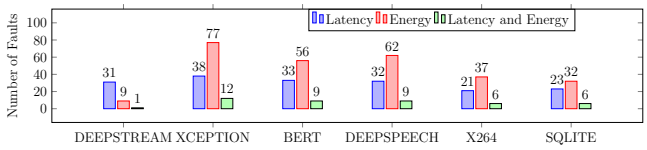


Figure 15. Distribution of 451 single-objective and 43 multi-objective non-functional faults across different software systems used in our study.

Table 1. Overview of the subject systems used in our study.

System	Workload	$\|C\|$	$\|O\|$	$\|\mathcal{S}\|$	$\|\mathcal{H}\|$	$\|\mathcal{W}\|$	$\|\mathcal{P}\|$
DEEPSTREAM	Video analytics pipeline for detection and tracking from 20 camera streams	2461	53	19	2	1	2
XCEPTION [16]	Image recognition system to classify 5000/5000 test images from CIFAR10	6443	28	19	3	3	3
DEEPSPEECH [39]	Speech-to-text from 0.5/1932 hours of Common Voice Corpus5.1 (English) data	6112	28	19	3	1	3
BERT [21]	NLP system for sentiment analysis of 1000/25000 test reviews from IMDb	6188	28	19	3	1	3
x264	Encodes a 20 second 11.2 MB video of resolution 1920 x 1080 from UGC	17248	32	19	3	1	3
SQLITE	DBMS for sequential reads and writes, random reads, batch writes and deletions	15680	242	288	3	3	3

* C: Configurations, O: Options, $\mathcal{S}$: System Events, $\mathcal{H}$: Hardware, $\mathcal{W}$: Workload, $\mathcal{P}$: Objectives

Evaluation Metrics. (i) **Recall**, the percentage of true root-causes that are correctly predicted, (ii) **Precision**, the percentage of true root-causes among the predicted ones, (iii) Accuracy, weighted Jaccard similarity between the predicted and true root-causes, where the weight vector was derived based on the causal effects of options to performance based on the ground-truth CPM. For example, if A is the recommended configuration by an approach and B is the configuration that fixes the performance issue in the ground truth data, we measure $accuracy = \frac{\sum_{ACE}(A \cap B)}{\sum_{ACE}(A \cup B)}$. (iv) **Gain**, percentage improvement of suggested fix over the observed fault– $\Delta_{gain} = \frac{NFP_{FAULT} - NFP_{NOFAULT}}{NFP_{FAULT}} \times 100$, where NFP_{FAULT} the observed faulty performance and $NFP_{NO\ FAULT}$ is the performance of suggested fix. (v) **Error**: Single objective: the absolute difference between the best suggested and the optimal in ground truth; Multi-objective: hypervolume error [104]. (vi) **Time**, overhead of an approach in terms of wallclock time in hours to converge and suggest a fix.

6 Effectiveness and Sample Efficiency

Setting: We only show the partial results, however, our results generalize to all evaluated settings. *Debugging*: latency faults in TX2 and energy faults in Xavier. *Optimization (single-objective)*: comparison with SMAC in TX2 for Xception for both latency and energy. *Optimization (multi-objective)*: comparison with PESMO in TX2. We repeat the entire debugging and optimization tasks 3 times.

Results (debugging). Tables 2a and 2b shows Unicorn *significantly outperforms correlation-based methods in all cases.* For example, in Deepstream on TX2, Unicorn achieves 6% more accuracy, 12% more precision, and 10% more recall compared to the next best method, BugDoc. We observed latency gains as high as 88% (9% more than BugDoc) on TX2 and energy gain of 86% (9% more than BugDoc) on Xavier for Xception. We observe similar trends in energy faults and multi-objective faults.The results confirm that Unicorn *can recommend repairs for faults that significantly improve latency and energy usage.* Applying the changes to the configurations recommended by Unicorn increases the performance drastically.

Figure 17a and Figure 17b demonstrate the sample efficiency results for different systems. We observe that for both latency and energy faults Unicorn achieved significantly higher gains with significantly less number of samples. For Xception, Unicorn required an 8x lower number of samples to obtain 32% higher gain than DD. The higher gain in Unicorn with a relatively lower number of samples in comparison to correlation-based methods indicates that Unicorn causal reasoning is more effective in guiding the search in the objective space. Unicorn does not waste budget with evaluating configurations with lower causal effects and finds a fix faster.

Unicorn *can resolve misconfiguration faults significantly faster than correlation-based approaches.* In Tables 2a and 2b, the last two columns indicate the time taken (in hours) by each approach to diagnosing the root cause. For all methods, we set a maximum budget of 4 hours. We find that, while other approaches use the entire budget to diagnose and resolve the faults, Unicorn can do so significantly faster, e.g., Unicorn is 13× faster in diagnosing and resolving faults in energy usage for x264 deployed on Xavier and 10× faster for latency faults for Bert on TX2.

Results (optimization). Fig. 16(a) and 16(b) demonstrate the single-objective optimization results—Unicorn finds configurations with optimal latency and energy for both cases. Fig. 16(a) illustrates that the optimal configuration discovered by Unicorn has 43% lower latency (12 seconds) than that of SMAC (21 seconds). Here, Unicorn reaches near-optimal configuration by only exhausting one-third of the entire budget. In Fig. 16(b), the optimal configuration discovered by Unicorn and SMAC had almost the same energy, but Unicorn reached this optimal configuration 4x faster than

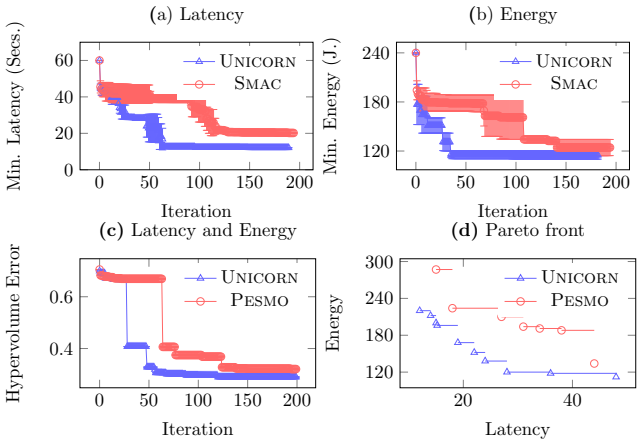


Figure 16. Unicorn vs. optimization with SMAC and PESMO.

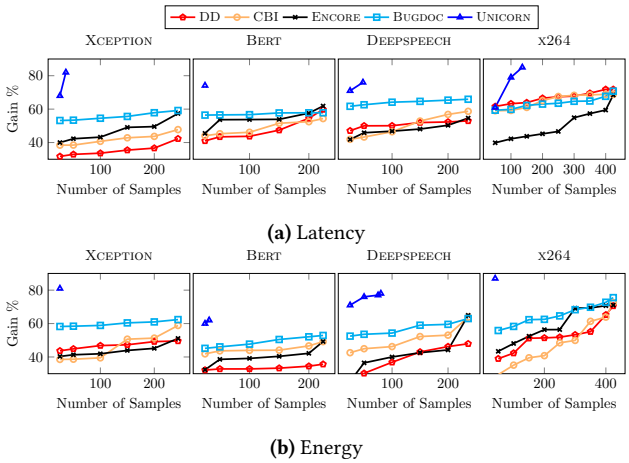


Figure 17. Unicorn has significantly higher sampling efficiency than other baselines in debugging non-functional faults.

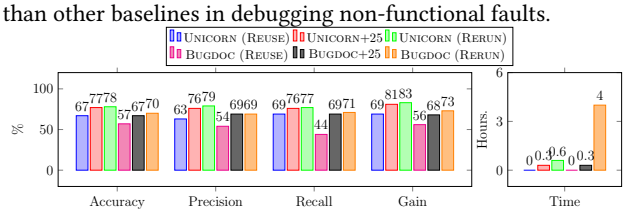


Figure 18. Accuracy, Precision, Recall and Gain of debugging non-functional faults (Xavier to TX2)

SMAC. In both single-objective optimizations, the iterative variation of Unicorn is less than SMAC–i.e., Unicorn finds more stable configurations. Figure 16(c) compares Unicorn with PESMO to optimize both latency and energy in TX2 (for image recognition). Here, Unicorn has 12% lower hypervolume error than PESMO and reaches the same level of hypervolume error of PESMO 4x times faster. Fig.16(d) illustrates the optimal Pareto front obtained by Unicorn and PESMO. The Pareto front by Unicorn has higher coverage as it discovered a higher number of Pareto optimal configurations with lower energy and latency value than PESMO.

Table 2. Efficiency of UNICORN compared to other approaches. Cells highlighted in **blue** indicate improvement over faults.

(a) Single objective performance fault in latency and energy consumption.

			Accuracy					Precision					Recall					Gain					Time†	
			UNICORN	CBI	DD	ENCORE	BUGDOC	UNICORN	CBI	DD	ENCORE	BUGDOC	UNICORN	CBI	DD	ENCORE	BUGDOC	UNICORN	CBI	DD	ENCORE	BUGDOC	UNICORN	Others
TX2	Latency	Deepstream	**87**	61	62	65	81	**83**	66	59	60	71	**80**	61	65	60	70	**88**	66	67	68	79	**0.8**	4
		XCEPTION	**86**	53	42	62	65	**86**	67	61	63	67	**83**	64	68	69	62	**82**	48	42	57	59	**0.6**	4
		BERT	**81**	56	59	60	57	**76**	57	55	61	73	**71**	74	68	67	65	**74**	54	59	62	58	**0.4**	4
		DEEPSPEECH	**81**	61	59	60	72	**76**	58	69	61	71	**81**	73	61	63	69	**76**	59	53	55	66	**0.7**	4
		x264	**83**	59	63	62	62	**82**	69	58	65	66	**78**	64	67	63	72	**85**	69	72	68	71	**1.4**	4
XAVIER	Energy	Deepstream	**91**	81	79	77	87	**81**	61	62	64	73	**85**	63	61	62	75	**86**	68	62	61	78	**0.7**	4
		XCEPTION	**84**	66	63	63	81	**78**	56	58	66	65	**80**	69	55	63	68	**83**	59	50	51	62	**0.4**	4
		BERT	66	59	53	63	**72**	**70**	62	64	64	65	**79**	61	54	63	66	**62**	49	36	49	53	**0.5**	4
		DEEPSPEECH	**73**	68	63	72	71	**75**	55	59	54	68	**78**	53	52	59	71	**78**	64	48	65	63	**1.2**	4
		x264	**77**	71	70	74	74	**83**	63	53	61	66	**78**	67	53	54	72	**87**	73	71	76	76	**0.3**	4

(b) Multi-objective non-functional faults in *Energy, Latency.*

		Accuracy				Precision				Recall				Gain (Latency)				Gain (Energy)				Time†	
		UNICORN	CBI	ENCORE	BUGDOC	UNICORN	CBI	ENCORE	BUGDOC	UNICORN	CBI	ENCORE	BUGDOC	UNICORN	CBI	ENCORE	BUGDOC	UNICORN	CBI	ENCORE	BUGDOC	UNICORN	Others
Energy + Latency	XCEPTION	**89**	76	81	79	**77**	53	54	62	**81**	59	59	62	**84**	53	61	65	**75**	38	46	44	**0.9**	4
	BERT	71	72	**73**	71	**77**	42	56	63	**79**	59	62	65	**84**	53	59	61	**67**	41	27	48	**0.5**	4
	DEEPSPEECH	**86**	69	71	72	**80**	44	53	62	**81**	51	59	64	**88**	55	55	62	**77**	43	43	41	**1.1**	4
	x264	**85**	73	83	81	**83**	50	54	67	**80**	63	62	61	**75**	62	64	66	**76**	64	66	64	**1**	4

† Wallclock time in hours

7 Transferability

Setting. We reuse the CPM constructed from a source environment, e.g., TX1, to resolve a non-functional fault in a target environment, e.g., XAVIER. We evaluated UNICORN for debugging energy faults for XCEPTION and used XAVIER as the source and TX2 as the target, since they have different microarchitectures, expecting to see large differences in their performance behaviors. We only compared with BUGDOC as it discovered fixes with higher energy gain in XAVIER than other correlation-based baseline methods (see Table 2a). We compared UNICORN and BUGDOC in the following scenarios: (I) REUSE: reusing the recommended configurations from Source to Target, (II) +25: reusing the performance models (i.e., causal model and decision tree) learned in Source and fined-tuned the models with 25 new samples in Target, and (III) RERUN: we rerun UNICORN and BUGDOC from scratch to resolve energy faults in Target. For optimization tasks, we use three larger additional XCEPTION workloads: 10000 (10k), 20000 (20k), and 50000 (50k) test images (previous experiments used 5000 (5k) test images). We evaluated three variants of SMAC and UNICORN: (1) SMAC and UNICORN (REUSE), where we *reuse* the near-optimum found with a 5K tests image on the larger workloads; (2) SMAC +10% and UNICORN +10%, where we rerun with 10% budget in target and update the CPM with 10% additional budget; and (3) SMAC +20% and UNICORN +20%, where we rerun with 20% budget in target and update the model with 20% additional budget.

Results. Fig. 18 indicates the results in resolving energy faults in TX2. We observe that UNICORN +25 obtains 8% more accuracy, 7% more precision, 5% more recall and 8% more gain than BUGDOC (RERUN). Here, BUGDOC takes significantly longer than UNICORN, i.e., BUGDOC (RERUN) exceeds the 4-hour budget in whereas UNICORN takes at most 20 minutes to fix the energy faults. We have to rerun BugDoc every time the hardware changes, and this limits its practical usability. In contrast, UNICORN incrementally updates the internal causal model with new samples from the newer hardware to learn new relationships. Therefore, it is less sensitive and much faster. Since UNICORN uses causal models to infer candidate fixes using only the available observational data, it tends to be much faster than BugDoc. We also observe that with little updates, UNICORN +25 (20 minutes) achieves a similar performance of UNICORN (RERUN) (36 minutes). Since the causal mechanisms are sparse, the CPM from XAVIER in UNICORN quickly reaches a fixed structure in TX2 using incremental learning by judiciously evaluating the most promising fixes until the fault is resolved.

Our experimental results demonstrate that UNICORN performs better than the two variants of three SMAC (c.f. Figure 19). SMAC (REUSE) performs the worst when the workload changes. With 10K images, reusing the near-optimal configuration from 5K images results in a latency gain of 10%, compared to 12% with UNICORN in comparison with the default configuration. We observe that UNICORN + 20% achieves

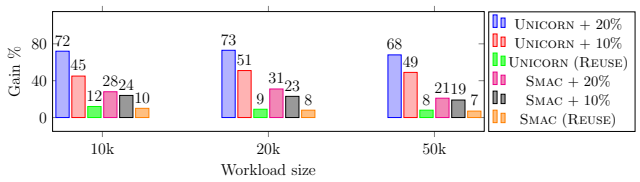


Figure 19. Unicorn finds configurations with higher gain when workloads are changed for performance optimization task.

44%, 42%, and 47% higher gain than SMAC + 20% for workload sizes of 10k, 20k, and 50k images, respectively.

8 Scalability

Setting. We evaluated Unicorn for scalability with sqlite (large configuration space) and Deepstream (large composed system). In sqlite, we conducted the evaluation in three scenarios: (a) selecting the most relevant software/hardware options and events (34 configuration options and 19 system events), (b) selecting all modifiable software and hardware options and system events (242 configuration options and 19 events), and (c) selecting not only all modifiable software and hardware options and system events but also intermediate `tracepoint events` (242 configuration options and 288 events). In Deepstream, there are two scenarios: (a) 53 configuration options and 19 system events, and (b) 53 configuration options and 288 events when we select all modifiable software and hardware options, and system/tracepoint events.

Table 3. Scalability for sqlite and Deepstream on Xavier

System	Configs	Events	Paths	Queries	Degree	Gain (%)	Time/Fault (in sec.) Discovery	Query Eval	**Total**
sqlite	34	19	32	191	3.6	93	9	14	**291**
	242	19	111	2234	1.9	94	57	129	**1345**
	242	288	441	22372	1.6	92	111	854	**5312**
Deepstream	53	19	43	497	3.1	86	16	32	**1509**
	53	288	219	5008	2.3	85	97	168	**3113**

Results. In large systems, there are significantly more causal paths and therefore, causal learning and estimations of queries take more time. The results in Table 3 indicate that Unicorn can scale to a much larger configuration space without an exponential increase in runtime for any of the intermediate stages. This can be attributed to the sparsity of the causal graph (average degree of a node for sqlite in Table 3 is at most 3.6, and it reduces to 1.6 when the number of configurations increase and reduces from 3.1 to 2.3 in Deepstream when systems events are increased).

9 Related Work

Performance Faults in Configurable Systems. Previous empirical studies have shown that a majority of performance issues are due to misconfigurations [37], with severe consequences in production environments [62, 91], and configuration options that cause such performance faults force the users to tune the systems themselves [103]. Previous works have used static and dynamic program analysis to identify the influence of configuration options on performance [60, 95, 96] and to detect and diagnose misconfigurations [8, 9, 100, 102]. Unlike Unicorn, none of the white-box analysis approaches target configuration space across system stack, where it limits their applicabilities in identifying the true causes of a performance fault.

Statistical and Model-based Debugging. Debugging approaches such as Statistical Debugging [88], HOLMES [15], XTREE [59], BugDoc [61], EnCore [61], Rex [63], and PerfLearner [38] have been proposed to detect root causes of system faults. These methods make use of statistical diagnosis and pattern mining to rank the probable causes based on their likelihood of being the root causes of faults. However, these approaches may produce correlated predicates that lead to incorrect explanations.

Causal Testing and Profiling. Causal inference has been used for fault localization [10, 27], resource allocations in cloud systems [29], and causal effect estimation for advertisement recommendation systems [13]. More recently, AID [26] detects root causes of a intermittent software failure using fault injection as interventions. Causal Testing and Holmes [54] modifies the system inputs to observe behavioral changes and utilizes counterfactual reasoning to find the root causes of bugs. Causal profiling approaches like CoZ [20] points developers where optimizations will improve performance and quantifies their potential impact. Causal inference methods like X-Ray [8] and ConfAid [9] had previously been applied to analyze program failures. All approaches above are either orthogonal or complimentary to Unicorn, mostly they focus on functional bugs (e.g., Causal Testing) or if they are performance related, they are not configuration-aware (e.g., CoZ).

10 Conclusion

Modern computer systems are highly-configurable with thousands of interacting configurations with a complex performance behavior. Misconfigurations in these systems can elicit complex interactions between software and hardware configuration options, resulting in non-functional faults. We propose Unicorn, a novel approach for diagnostics that learns and exploits the causal structure of configuration options, system events, and performance metrics. Our evaluation shows that Unicorn effectively and quickly diagnoses the root cause of non-functional faults and recommends high-quality repairs to mitigate these faults.

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