A Dollar from 15 Cents: Cross-Platform Management for Internet Services

Christopher Stewart[†] Terence Kelly[*] Alex Zhang[*] Kai Shen[†]
[†]University of Rochester [*]Hewlett-Packard Laboratories

Abstract

As Internet services become ubiquitous, the selection and management of diverse server platforms now affects the bottom line of almost every firm in every industry. Ideally, such cross-platform management would yield high performance at low cost, but in practice, the performance consequences of such decisions are often hard to predict. In this paper, we present an approach to guide cross-platform management for real-world Internet services. Our approach is driven by a novel performance model that predicts application-level performance across changes in platform parameters, such as processor cache sizes, processor speeds, etc., and can be calibrated with data commonly available in today's production environments. Our model is structured as a composition of several empirically observed, parsimonious sub-models. These sub-models have few free parameters and can be calibrated with lightweight passive observations on a current production platform. We demonstrate the usefulness of our cross-platform model in two management problems. First, our model provides accurate performance predictions when selecting the next generation of processors to enter a server farm. Second, our model can guide platform-aware load balancing across heterogeneous server farms.

1 Introduction

In recent years, Internet services have become an indispensable component of customer-facing websites and enterprise applications. Their increased popularity has prompted a surge in the size and heterogeneity of the server clusters that support them. Nowadays, the management of heterogeneous server platforms affects the bottom line of almost every firm in every industry. For example, purchasing the right server makes and models can improve application-level performance while reducing cluster-wide power consumption. Such management decisions often span many server platforms that, in practice, cannot be tested exhaustively. Consequently, cross-platform management for Internet services has historically been ad-hoc and unprincipled.

Recent research [9,14,31,37,40,41,44] has shown that performance models can aid the management of Internet services by predicting the performance consequences of contemplated actions. However, past models for Internet services have not considered platform configurations such as processor cache sizes, the number of processors, and processor speed. The effects of such parameters are fundamentally hard to predict, even when data can be collected by any means. The effects are even harder to predict in real-world production environments, where data collection is restricted to passive measurements of the running system.

This paper presents a cross-platform performance model for Internet services, and demonstrates its use in making management decisions. Our model predicts application-level response times and throughput from a composition of several sub-models, each of which describes a measure of the processor's performance (henceforth, a processor metric) as a function of a system parameter. For example, one of our sub-models relates cache misses (a processor metric) to cache size (a system parameter). The functional forms of our sub-models are determined from empirical observations across several Internet services and are justified by reasoning about the underlying design of Internet services. Our knowledge-lean sub-models are called *trait models* because, like human personality traits, they stem from empirical observations of system behaviors and they characterize only one aspect of a complex system. Figure 1 illustrates the design of our cross-platform model.

The applicability of our model in real-world production environments was an important design consideration. We embrace the philosophy of George Box, "All models are wrong, but some [hopefully ours] are useful." [10] To reach a broad user base, our model targets third-party consultants. Consultants are often expected to propose good management decisions without *touching* their clients' production applications. Such inconvenient but realistic restrictions forbid source code instrumentation and controlled benchmarking. In many ways the challenge in such data-impoverished environments fits the words of the old adage, "trying to make a dollar from 15 cents." Typically, consultants must make do with data available from standard monitoring utilities and

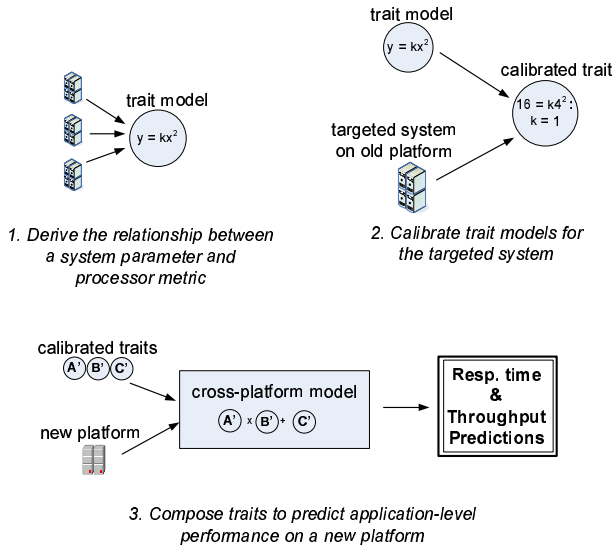


Figure 1: The design of our cross-platform performance model. The variable x represents a system parameter, *e.g.*, number of processors or L1 cache size. The variable y represents a processor metric (*i.e.*, a measure of processor performance), such as instruction count or L1 cache misses. Application-level performance refers to response time and throughput, collectively.

application-level logs. The simplicity of our sub-models allows us to calibrate our model using only such readily available data.

We demonstrate the usefulness of our model in the selection of high-performance, low-power server platforms. Specifically, we used our model (and processor power specifications) to identify platforms with high performance-per-watt ratios. Our model outperforms alternative techniques that are commonly used to guide platform selection in practice today. We also show that model-driven load balancing for heterogeneous clusters can improve response times. Under this policy, request types are routed to the hardware platform that our model predicts is best suited to their resource requirements.

The contributions of this paper are:

1. We observe and justify trait models across several Internet services.
2. We integrate our trait models into a cross-platform model of application-level performance.
3. We demonstrate the usefulness of our cross-platform model for platform selection and load balancing in a heterogeneous server farm.

The remainder of this paper is organized as follows. Section 2 overviews the software architecture, processing patterns, and deployment environment of the realistic Internet services that we target. Section 3 presents several trait models. Section 4 shows how we compose trait models into an established framework to achieve an accurate cross-platform performance prediction and compares our approach with several alternatives. Section 5 shows how trait-based performance models can guide the selection of server platforms and guide load balancing in a heterogeneous server cluster. Section 6 reviews related work and Section 7 concludes.

2 Background

Internet services are often designed according to a three-tier software architecture. A response to an end-user request may traverse software on all three tiers. The first tier translates end-user markup languages into and out of business data structures. The second tier (a.k.a. the business-logic tier) performs computation on business data structures. Our work focuses on this tier, so we will provide a detailed example of its operation below. The third tier provides read/write storage for abstract business objects. Requests traverse tiers via synchronous communication over local area networks (rather than shared memory) and a single request may revisit tiers many times [26]. Previous studies provide more information on multi-tier software architectures [29, 44].

Business-logic computations are often the bottleneck for Internet services. As an example, consider the business logic of an auction site: computing the list of currently winning bids can require complex considerations of bidder histories, seller preferences, and shipping distances between bidders and sellers. Such workloads are processor intensive, and their effect on application-level performance depends on the underlying platform's configuration in terms of cache size, on-chip cores, hyperthreading, etc. Therefore, our model, which spans a wide range of platform configurations, naturally targets the business-logic tier. Admittedly, application-level performance for Internet services can also be affected by disk and network workloads at other tiers. Previous works [14, 41] have addressed some of these issues, and we believe our model can be integrated with such works.

Internet services keep response times low to satisfy end-users. However as requests arrive concurrently, response times increase due to queuing delays. In production environments, resources are adequately provisioned to limit the impact of queuing. Previous analyses of several real enterprise applications [40] showed max CPU utilizations below 60% and average utilizations below 25%. Similar observations were made in [8]. Services are qualitatively different when resources are adequately provisioned compared to overload conditions. For example, contention for shared resources is more pronounced under overload conditions [29].

	Aggregate counts					
Time stamp	Type 1	Type 2	...	Instr. count ($x10^4$)	L1 miss	L2 miss
2:00pm	18	42	...	280322	31026	2072
2:01pm	33	36	...	311641	33375	2700

Table 1: Example of data available as input to our model. Oprofile [2] collects instruction counts and cache misses. Apache logs [1] supply frequencies of request types.

2.1 Nonstationarity

End-user requests can typically be grouped into a small number of types. For example, an auction site may support request types such as bid for item, sell item, and browse items. Requests of the same type often follow similar code paths for processing, and as a result, requests of the same type are likely to place similar demands on the processor. A request mix describes the proportion of end-user requests of each type.

Request mix nonstationarity describes a common phenomenon in real Internet services: the relative frequencies of request types fluctuate over long and short intervals [40]. Over a long period, an Internet service will see a wide and highly variable range of request mixes. On the downside, nonstationarity requires performance models to generalize to previously unseen transaction mixes. On the upside, nonstationarity ensures that observations over a long period will include more unique request mixes than request types. This diversity overconstrains linear models that consider the effects of each request type on a corresponding output metric (*e.g.*, instruction count), which enables parameter estimation using regression techniques like Ordinary Least Squares.

2.2 Data Availability

In production environments, system managers must cope with the practical (and often political) issues of trust and risk during data collection. For example, third-party consultants—a major constituent of our work—are typically seen as semi-trusted decision makers, so they are not allowed to perform controlled experiments that could pose availability or security risks to business-critical production systems. Similarly, managers of shared hosting centers are bound by business agreements that prevent them from accessing or modifying a service's source code. Even trusted developers of the service often relinquish their ability to perform invasive operations that could cause data corruption.

Our model uses data commonly available in most production environments, even in consulting scenarios. Specifically, we restrict our model inputs to logs of request arrivals and CPU performance counters. Table 1 provides an example of our model's inputs. Our model also uses information available from standard platform specification sheets such as the number of processors and on-chip cache sizes [6].

3 Trait Models

Trait models characterize the relationship between a system parameter and a processor metric. Like personality traits, they reflect one aspect of system behavior (*e.g.*, sensitivity to small cache sizes or reaction to changes in request mix). The intentional simplicity of trait models has two benefits for our cross-platform model. First, we can extract parsimonious yet general functional forms from empirical observations of the parameter and output metric. Second, we can automatically calibrate trait models with data commonly available in production environments.

Our trait models take the simplest functional form that yields low prediction error on the targeted system parameter and processor metric. We employ two sanity checks to ensure that our traits reflect authentic relationships—not just peculiarities in one particular application. First, we empirically validate our trait models across several applications. Second, we justify the functional form of our trait models by reasoning about the underlying structure of Internet services.

In this section, we observe two traits in the business logic of Internet services. First, we observe that a power law characterizes the miss rate for on-chip processor caches. Specifically, data-cache misses plotted against cache size on a log-log scale are well fit by a linear model. We justify such a heavy-tail relationship by reasoning about the memory access patterns of background system activities. Compared to alternative functional forms, a power law relationship achieves excellent prediction accuracy with few free model parameters.

Second, we observe that a linear request-mix model describes instruction count and aggregate cache misses. This trait captures the intuition that request type and volume are the primary determinants of runtime code paths. Our experiments demonstrate the resiliency of request mix models under a variety of processor configurations. Specifically, request-mix models remain accurate under SMP, multi-core, and hyperthreading processors.

3.1 Error Metric

The normalized residual error is the metric that we use to evaluate trait models. We also use it in the validation of our full cross-platform model. Let Y and $\hat{Y}$ represent observed and predicted values of the targeted output metric, respectively. The residual error, $E = Y - \hat{Y}$ tends toward zero for good models. The normalized residual error, $\frac{|E|}{Y}$, accounts for differences in the magnitude of Y.

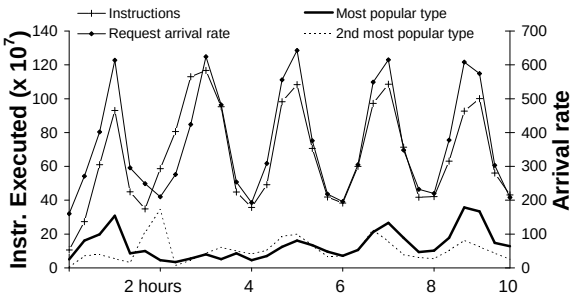


Figure 2: Nonstationarity during a RUBiS experiment. Request arrivals fluctuate in a sinusoidal fashion, which correspondingly affects the aggregate instructions executed. The ratio of the most popular request type to the second most popular type (*i.e.*, $\frac{freq_{most}}{freq_{2nd}}$) ranges from 0.13 to 12.5. Throughout this paper, a request mix captures per-type frequencies over a 30 second interval.

3.2 Testbed Applications

We study the business logic of three benchmark Internet Services. RUBiS is a J2EE application that captures the core functionalities of an online auction site [3]. The site supports 22 request types including browsing for items, placing bids, and viewing a user's bid history. The software architecture follows a three-tier model containing a front-end web server, a back-end database, and Java business-logic components. The StockOnline stock trading application [4] supports six request types. End users can buy and sell stocks, view prices, view holdings, update account information, and create new accounts. StockOnline also follows a three-tier software architecture with Java business-logic components. TPC-W simulates the activities of a transactional e-commerce bookstore. It supports 13 request types including searching for books, customer registration, and administrative price updates. Applications run on the JBoss 4.0.2 application server. The database back-end is MySQL 4.0. All applications run on the Linux 2.6.18 kernel.

The workload generators bundled with RUBiS, StockOnline, and TPC-W produce synthetic end-user requests according to fixed long-term probabilities for each request type. Our previous work showed that the resulting request mixes are qualitatively unlike the nonstationary workloads found in real production environments [40]. In this work, we used a nonstationary sequence of integers to produce a nonstationary request trace for each benchmark application. We replayed the trace in an open-arrival fashion in which the aggregate arrival rate fluctuated. Figure 2 depicts fluctuations in the aggregate arrival rate and in the relative frequencies of transaction types during a RUBiS experiment. Our nonstationary sequence of integers is publicly available [5] and can be used to produce nonstationary mixes for any application with well-defined request types.

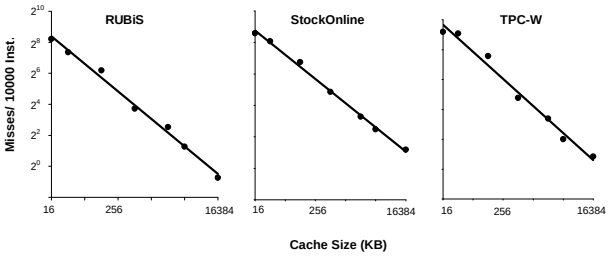


Figure 3: Cache misses (per 10k instructions) plotted against cache size on a log-log plot. Measurements were taken from real Intel servers using the Oprofile monitoring tool [2]. The same nonstationary workload was issued for each test. Cache lines were 64 bytes.

3.3 Trait Model of Cache Size on Cache Misses

Figure 3 plots data-cache miss rates relative to cache size on a log-log scale. Using least squares regression, we calibrated linear models of the form $ln(Y) = Bln(X) + A$. We observe low residual errors for each application in our testbed. Specifically, the largest normalized residual error observed for RUBiS, StockOnline, and TPCW is 0.08, 0.03, and 0.09 respectively. The calibrated B parameters for RUBiS, StockOnline, and TPCW are -0.83, -0.77, and -0.89 respectively. Log-log linear models with slopes between (-2, 0) are known as *power law distributions* [19, 33, 43]

We justify our power-law trait model by making observations on its rate of change, shown in Equation 1.

$$\frac{dY}{dX} = Be^{A}X^{B-1} \quad (1)$$

For small values of X, the rate of change is steep, but as X tends toward infinity the rate of change decreases and slowly (*i.e.*, with a heavy tail) approaches zero. The heavy-tail aspect of a power law means the rate of change decreases more slowly than can be described using an exponential model. In terms of cache misses, this means a power-law cache model predicts significant miss rate reductions when *small* caches are made larger, but almost no reductions when *large* caches are made larger. The business logic tier for Internet services exhibits such behavior by design. Specifically, per-request misses due to lack of capacity are significantly reduced by larger L1 caches. However, garbage collection and other infrequent-yet-intensive operations will likely incur misses even under large cache sizes.

A power law relationship requires the calibration of only two free parameters (*i.e.*, A, and B), which makes it practical for real-world production environments. However, there are many other functional forms that have only two free parameters; how does our trait model compare to alternatives? Table 2 compares logarithmic,

		Log	Exp.	Power law	Log -normal
RUBiS	lowest	0.011	0.105	0.005	0.001
	median	0.094	0.141	0.028	0.027
	highest	0.168	0.254	0.080	0.072
Stock	lowest	0.013	0.010	0.010	0.012
	median	0.075	0.099	0.023	0.024
	highest	0.026	0.142	0.034	0.042
TPCW	lowest	0.046	0.044	0.011	0.007
	median	0.109	0.084	0.059	0.060
	highest	0.312	0.146	0.099	0.101

Table 2: Normalized residual error of cache models that have fewer than three free parameters. The lowest, median, and highest normalized residuals are reported from observations on seven different cache sizes.

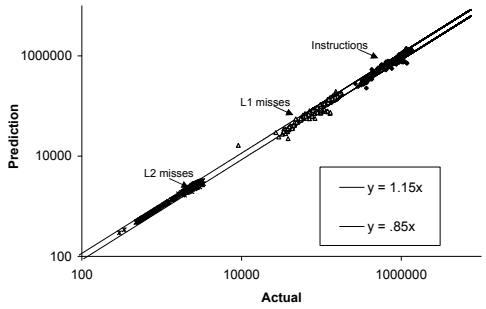


Figure 4: RUBiS instruction count and aggregate cache misses (L1 and L2) plotted against a linear request mix model's predictions. Measurements were taken from a single processor Intel Pentium D server. Lines indicate 15% error from the actual value. Collected with OProfile [2] at sampling rate of 24000.

exponential, and power law functional forms. Power law models have lower median normalized residual error than logarithmic and exponential models for each application in our testbed. Also, we compare against a generalized (quadratic) log-normal model, $ln(Y) = B_2 ln(X)^2 + B_1 ln(X) + A$. This model allows for an additional free parameter (B_2) in calibration, and is expected to provide a better fit, though it cannot be calibrated from observations on one machine. Our results show that the additional parameter does not substantially reduce residual error. For instance, the median residual error for the power law distribution is approximately equal to that of the generalized log-normal distribution. We note that other complex combinations of these models may provide better fits, such as Weibull or power law with exponential cut-off. However, such models are hard to calibrate with the limited data available in production environments.

3.4 Trait Models of Request Mix on Instructions and Cache Misses

Figure 4 plots a linear combination of request type frequencies against the instruction count, L1 misses, and L2 misses for RUBiS. Our parsimonious linear combination has only one model parameter for each request type, as shown below.

$$C_k = \sum_{\text{types } j} \alpha_{jk} N_j \quad (2)$$

Where C_k represents one of the targeted processor metrics and N_j represents the frequency of requests of type j. The model parameter α_{jk} transforms request-type frequencies into demand for processor resources. Intuitively, α_{jk} represents the typical demand for processor resource k of type j. We refer to this as a request-mix model, and we observe excellent prediction accuracy. The 90th percentile normalized error for instructions, L1 misses, and L2 misses were 0.09, 0.10, 0.06 respectively.

Request-mix models are justifiable, because business-logic requests of the same type typically follow similar code paths. The number of instructions required by a request will likely depend on its code path. Similarly, cold-start compulsory misses for each request will depend on code path, as will capacity misses due to a request's working set size. However, cache misses due to sharing between requests are not captured in a request-mix model. Such misses are not present in the single processor tests in Figure 4.

Table 3 evaluates request-mix models under platform configurations that allow for shared misses. The first three columns report low normalized error when resources are adequately provisioned (below 0.13 for all applications), as they would be in production environments. However under maximum throughput conditions, accuracy suffers. Specifically, we increased the volume of the tested request mixes by a factor of 3. Approximately 50% of the test request mixes achieved 100% processor utilization. Normalized error increased for the L1 miss metric to 0.22–0.34. These results are consistent with past work [29] that attributed shared misses in Internet services to contention for software resources. In the realistic, adequately provisioned environments that we target, such contention is rare. We conclude that request-mix models are most appropriate in realistic environments when resources are not saturated.

Request-mix models can be calibrated with timestamped observations of the targeted processor metric and logs of request arrivals, both of which are commonly available in practice. Past work [40] demonstrated that unrealistic stationary workloads are not sufficient for calibration. Request-mix models can require many observations before converging to good parameters. For the real and benchmark applications that we have seen, request mix models based on ten hours of log files are typically sufficient.

	2-way SMP (L1 miss)	Dual-core (L2 miss)	Hyperthreading (L1 miss)	Max tput (L1 miss)
RUBiS	0.044	0.030	0.045	0.349
Stock	0.060	0.077	0.096	0.276
TPCW	0.035	0.084	0.121	0.223

Table 3: Median normalized residual error of a request-mix model under different environments. Evaluation spans 583 request mixes from a nonstationary trace. The target architectural metric is shown in parenthesis. All tests were performed on Pentium D processors. Hyperthreading was enabled in the system BIOS. 2-way SMP and dual-cores were enabled/disabled by the operating system scheduler. The "max tput" test was performed on a configuration with 2 processors and 4 cores enabled with hyperthreading on.

4 Cross-Platform Performance Predictions

Section 3 described trait models, which are parsimonious characterizations of only one aspect of a complex system. In this section, we will show that trait models can be composed to predict application-level performance for the whole system. Our novel composition is formed from expert knowledge about the structure of Internet services. In particular, we note that instruction and memory-access latencies are key components of the processing time of individual requests, and that Internet services fit many of the assumptions of a queuing system. Our model predicts application-level performance across workload changes and several platform parameters including: processor speed, number of processors (*e.g.*, on-chip cores), cache size, cache latencies, and instruction latencies. Further, our model can be calibrated from the logs described in Table 1. Source code access, instrumentation, and controlled experiments are not required. We attribute the low prediction error of our model to accurate trait models (described in Section 3) and a principled composition based on the structure of Internet services.

The remainder of this section describes the composition of our cross-platform model, then presents the test platforms that we use to validate our model. Finally, we present results by comparing against alternative modeling techniques. In Section 5, we complete the challenge of turning 15-cent production data into a dollar by using our model to guide management decisions like platform selection and load balancing.

4.1 Composition of Traits

The amount of time spent processing an end-user request, called service time, depends on the instructions and memory accesses necessary to complete the request. Average CPU service time can be expressed as

$$s = \frac{I \times (\text{CPI} + (H_1C_1 + H_2C_2 + M_2C_{\text{mem}}))}{\text{CPU speed} \times \text{number of requests}}$$

where I is the aggregate number of instructions required by a request mix, CPI is the average number of cycles per instruction (not including memory access delays), H_k is the percentage of hits in the L_k cache per instruction, M_k is the percentage of misses in the L_k cache per instruction, and C_k is the typical cost in cycles of accesses to the L_k cache [22]. *CPI*, *CPUspeed*, and C_k are typically released in processor spec sheets [6]. Recent work [16] that more accurately approximates CPI and C_k could transparently improve the prediction accuracy of our model.

This model is the basis for our cross-platform performance prediction. Subsequent subsections will extend this base to handle changes in application-level workload and cache size parameters, and to predict the application-level performance.

4.1.1 Request Mix Adjustments

In Section 3, we observed that both instruction counts and cache misses, at both L1 and L2, are well modeled as a linear combination of request type frequencies:

$$I = \sum_{\text{types } j} \alpha_{Ij} N_j \quad \text{and} \quad \#M_k = \sum_{\text{types } j} \alpha_{M_k j} N_j$$

where I is the number of instructions for a given volume and mix of requests, N_j is the volume of requests of type j, and $\#M_k$ is the number of misses at cache level k. The intuition behind these models is straightforward: α_{Ij}, for example, represents the typical number of instructions required to serve a request of type j. We apply ordinary least squares regression to a 10-hour trace of nonstationary request mixes to calibrate values for the α parameter. After calibration, the acquired $\hat{\alpha}$ parameters can be used to predict performance under future request mixes. Specifically, we can predict both instruction count and aggregate cache misses for an unseen workload represented by a new vector N' of request type frequencies.

4.1.2 Cache Size Adjustments

Given L1 and L2 cache miss rates observed on the current hardware platform, we predict miss rates for the cache sizes on a new hardware platform using the power-law cache model: $M_k = e^A S_k^B$ where S_k is the size of the level-k cache.

We calibrate the power law under the most strenuous test possible: using cache-miss observations from only an L1 and L2 cache. This is the constraint under which many consultants must work: they can measure an application running in production on only a single hardware platform. Theoretically, the stable calibration of

power law models desires observations of cache misses on 5 cache sizes [19]. Calibration from only two observations skews the model's predictions for smaller cache sizes [33]. However in terms of service time prediction, the penalty of such inaccuracies—L1 latency—is low.

4.1.3 Additional Service Time Adjustments

Most modern processors support manual and/or dynamic frequency adjustments. Administrators can manually throttle CPU frequencies to change the operation of the processor under idle and busy periods. Such manual policies override the *CPUspeed* parameter in processor spec. sheets. However, power-saving approaches in which the frequency is automatically adjusted only during idle periods are not considered in our model. Such dynamic techniques should not affect performance during the busy times in which the system is processing end-user requests.

We consider multi-processors as one large virtual processor. Specifically, the *CPUspeed* parameter is the sum of cycles per second across all available processors. We do not distinguish between the physical implementations of logical processors seen by the OS (*e.g.*, SMT, multi-core, or SMP). We note however that our model accuracy could be improved by distinguishing between cores and hyperthreads.

4.1.4 Predicting Response Times

Service time is not the only component of a request's total response time; often the request must wait for resources to become available. This aspect of response time, called queuing delay, increases non-linearly as the demand for resources increases. Queuing models [27] attempt to characterize queuing delay and response time as a function of service time, request arrival rate, and the availability of system resources. Our past work presented a queuing model that achieves accurate response time prediction on *real* Internet services [40]. That particular model has two key advantages: 1) it considers the weighted impact of request mix on service times and 2) it can be easily calibrated in the production environments that we target. It is a model of aggregate response time y for a given request mix and is shown below:

$$y = \sum_{j=1}^{n} s_j N_j + \sum_{r} \left(\frac{1}{\lambda} \cdot \frac{U_r^2}{1-U_r} \right) \cdot \sum_{j=1}^{n} N_j$$

where λ and U_r respectively denote the aggregate count of requests in the given mix (*i.e.*, arrival rate) and the average utilization of resource r, respectively. Utilization is the product of average service time and arrival rate. The first term reflects the contribution of service times to aggregate response time, and the second considers queuing delays. For average response time, divide y by λ. The parameter s_j captures average service time for type j and can be estimated via regression procedures using observations of request response times and resource utilizations [40]. Note that y reflects aggregate response time for the whole system; s_j includes delays caused by other resources— not just processing time at the business-logic tier. Our service time predictions target the portion of s_j attributed to processing at the business-logic tier only.

4.2 Evaluation Setup

We empirically evaluate our service and response time predictions for RUBiS, StockOnline, and TPC-W. First, we compare against alternative methods commonly used in practice. Such comparisons suggest that our model is immediately applicable for use in real world problems. Then we compare against a model recently proposed in the research literature [25]. This comparison suggests that our principled modeling methodology provides some benefits over state-of-the-art models.

4.2.1 Test Platforms

We experiment with 4 server machines that allow for a total of 11 different platform configurations. The various servers are listed below:

PIII Dual-processor PIII Coppermine with 1100 MHz clock rate, 32 KB L1 cache, and 128 KB L2 cache.

PRES Dual-processor P4 Prescott with 2.2 GHz clock rate, 16 KB L1 cache, and 512 KB L2 cache.

PD4 Four-processor dual-core Pentium D with 3.4 GHz clock rate, 32 KB L1 cache, 4 MB L2 cache, and 16 MB L3 cache.

XEON Dual-processor dual-core Pentium D Xeon that supports hyperthreading. The processor runs at 2.8 GHz and has a 32 KB L1 cache and 2 MB L2 cache.

We used a combination of BIOS features and OS scheduling mechanisms to selectively enable/disable hyperthreading, multiple cores, and multiple processors on the XEON machine, for a total of eight configurations. We describe configurations of the XEON using notation of the form "#H/#C/#P." For example, 1H/2C/1P means hyperthreading disabled, multiple cores enabled, and multiple processors disabled. Except where otherwise noted, we calibrate our models using log files from half of a 10-hour trace on the PIII machine. Our log files contain aggregate response times, request mix information, instruction count, aggregate L1 cache misses, and aggregate L2 cache misses. The trace contains over 500 mixes cumulatively. Request mixes from the remaining half of the trace were used to evaluate the normal-

ized residual error $\frac{|\text{predicted}-\text{actual}|}{\text{actual}}$ on the remaining ten platforms/configurations. Most mixes in the second half of the trace constitute extrapolation from the calibration data set; specifically, mixes in the second half lie outside the convex hull defined by the first half.

4.2.2 Alternative Models Used In Practice

Because complex models are hard to calibrate in data-constrained production environments, the decision support tools used in practice have historically preferred simplicity to accuracy. Commonly used tools involve simple reasoning about the linear consequences of platform parameters on CPU utilization and service times.

Processor Cycle Adjustments Processor upgrades usually mean more clock cycles per second. Although the rate of increase in clock speeds of individual processor cores has recently slowed, the number of cores per system is increasing. Highly-concurrent multi-threaded software such as business-logic servers processing large numbers of simultaneous requests can exploit the increasing number of available cycles, so the net effect is a transparent performance improvement. A common approach to predicting the performance impact of a hardware upgrade is simply to assume that CPU service times will decrease in proportion to the increase in clock speed. For service time prediction, this implies

$$\text{st}_{\text{new}} = \text{st}_{\text{orig}} \times \frac{\text{cycles}_{\text{orig}}}{\text{cycles}_{\text{new}}} \quad (3)$$

However, this approach does not account for differences in cache sizes on the old and new CPUs. Section 3 has shown that changes to the cache size have non-linear effects on the number of cache misses for business-logic servers, which in turn affects CPU service times and CPU utilization. Furthermore, cache miss latencies differ across hardware platforms, and these differences too may affect CPU service times.

Benchmark-Based Adjustments A more sophisticated approach used widely in practice is to predict performance using ratios of standard application benchmark scores. Specifically, these approaches measure the service times and maximum throughput for a target application on both the new and original platform. This application's performance is expected to be representative of a larger class of applications. This model is shown below:

$$\text{st}_{\text{new}} = \text{st}_{\text{orig}} \times \frac{\text{TPC score}_{\text{orig}}}{\text{TPC score}_{\text{new}}} \quad (4)$$

This approach improves on the processor cycle adjustments by considering the effect of caching and other architectural factors. However, modern business-logic servers can vary significantly from standard benchmark applications. Indeed, standard benchmarks differ substantially *from one another* in terms of CPI and miss frequencies [39]!

Workload Adjustments Workload fluctuations are ubiquitous in Internet services, and we frequently wish to predict the effects of workload changes on system resources. One typical approach is to model CPU utilization as a linear function of request volume.

$$\text{utilization}_{\text{new}} = \text{utilization}_{\text{orig}} \times \frac{\text{request rate}_{\text{new}}}{\text{request rate}_{\text{orig}}} \quad (5)$$

The problem with this approach is that while it accounts for changes in the aggregate volume of requests, it ignores changes in the *mix of request types*. We call such a model a scalar performance model because it treats workload as a scalar request rate rather than a vector of type-specific rates. Nonstationarity clearly poses a serious problem for scalar models. For example, if request volume doubles the model will predict twice as much CPU utilization. However if the increase in volume was due entirely to a lightweight request type, actual utilization may increase only slightly.

4.3 Results

4.3.1 Accuracy of Service Time Predictions

We first consider the problem of predicting average per-request CPU service times of an application on a new hardware platform given observations of the application running on our PIII platform. We compare our method with three alternatives: 1) the naïve cycle-based adjustment of Equation 3 with linear workload adjustments of Equation 5, 2) a variant in which we first predict service time as a function of request mix using a linear weighted model and then apply the cycle-based adjustment, and 3) the benchmark-based method of Equation 4 with request mix workload adjustments.

Table 4 shows the prediction error for RUBiS. Our method has less error than the benchmark-based method for all target platforms. In all cases except one, our method has lower error than its three competitors. Most often, our model has less than one third the error of competing approaches. The results for StockOnline and TPC-W are similar. Table 5 shows that our predictions are always the most accurate for the StockOnline application. Our results for TPC-W (Table 6) show consistently low error for our model (always below 0.17).

Target Processor	Cycle pred scalar	Cycle pred req-mix	Bench-mark	Our Method
PRES	0.48	0.35	0.30	**0.06**
PD4	0.24	0.17	0.32	**0.07**
XEON 1H/1C/1P	0.63	0.49	0.27	**0.10**
XEON 1H/1C/2P	0.43	0.28	0.24	**0.08**
XEON 1H/2C/1P	0.39	0.30	0.26	**0.02**
XEON 1H/2C/2P	0.36	0.27	0.57	**0.03**
XEON 2H/1C/1P	0.42	0.28	0.24	**0.02**
XEON 2H/1C/2P	0.12	**0.05**	0.29	0.24
XEON 2H/2C/1P	0.35	0.22	0.32	**0.02**
XEON 2H/2C/2P	0.18	0.13	0.38	**0.09**

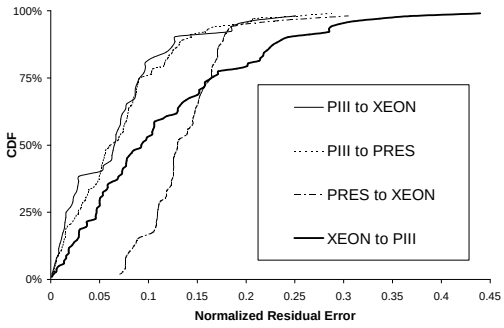
Table 4: Median normalized residual error of service time predictions for RUBiS. Models are calibrated on our PIII platform from half of a 10-hour nonstationary trace. The numbers presented are the median error when the models are used to predict the second half of the nonstationary trace on the targeted platforms. The median across platforms for our method is 0.07.

Target Processor	Cycle pred scalar	Cycle pred req-mix	Bench-mark	Our Method
PRES	0.35	0.23	0.56	**0.18**
PD4	0.38	0.28	0.42	**0.12**
XEON 1H/1C/1P	0.55	0.41	0.21	**0.10**
XEON 1H/1C/2P	0.48	0.38	0.34	**0.12**
XEON 1H/2C/1P	0.44	0.39	0.35	**0.09**
XEON 1H/2C/2P	0.36	0.26	0.71	**0.12**
XEON 2H/1C/1P	0.48	0.38	0.34	**0.17**
XEON 2H/1C/2P	0.22	0.16	0.52	**0.14**
XEON 2H/2C/1P	0.45	0.37	0.47	**0.15**
XEON 2H/2C/2P	0.36	0.29	0.39	**0.02**

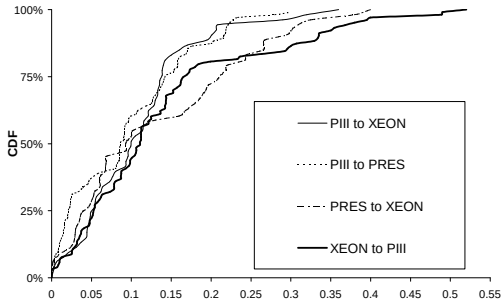
Table 5: Median normalized residual error of service time predictions for StockOnline. The median across platforms for our method is 0.12.

Target Processor	Cycle pred scalar	Cycle pred req-mix	Bench-mark	Our Method
PRES	0.48	0.35	–	**0.11**
PD4	0.28	0.24	–	**0.09**
XEON 1H/1C/1P	0.38	0.32	–	**0.13**
XEON 1H/1C/2P	0.23	0.16	–	**0.13**
XEON 1H/2C/1P	0.22	0.16	–	**0.12**
XEON 1H/2C/2P	0.27	0.22	–	**0.17**
XEON 2H/1C/1P	0.28	0.23	–	**0.06**
XEON 2H/1C/2P	0.24	0.20	–	**0.11**
XEON 2H/2C/1P	0.20	**0.15**	–	0.16
XEON 2H/2C/2P	0.18	0.21	–	**0.14**

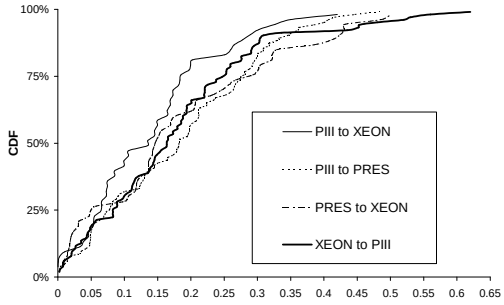
Table 6: Median normalized residual error of service time predictions for TPC-W. Note, the benchmark method is not applicable for TPC-W, since observations on the new platform are required for calibration. The median across platforms for our method is 0.13.



(a) RUBiS



(b) StockOnline



(c) TPCW

Figure 5: Cumulative distributions of normalized residual error for response time predictions across nonstationary request mixes. Mean response times on the PIII, P4, and XEON were 256, 106, and 93 ms respectively. XEON shortens XEON 2H/2T/2P according to our naming conventions.

4.3.2 Accuracy of Response Time Predictions

Figure 5 shows the prediction accuracy of our queuing model. For predictions from PIII to XEON, our model converts median service time error of 0.09, 0.02, and 0.14 into response time predictions with median error of 0.06, 0.09, and 0.13, for RUBiS, TPC-W, and StockOnline respectively. Even though response time is a more complex metric, our prediction error remains low.

Figure 5 also demonstrates the robustness of our method. The 85th percentile of our prediction error for RUBiS is always below 0.21 no matter which platforms we use for calibration and validation. For StockOnline and TPC-W, the 85th percentile prediction error is below 0.29 and 0.30, respectively.

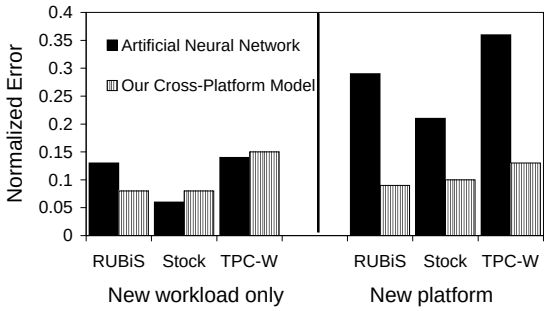


Figure 6: Comparison of an artificial neural network to our cross-platform model. The median normalized error for predictions of average response time are reported. We trained the ANN on several subsets of the training data. The reported values are from the training subset that yielded the lowest prediction error for each application.

4.3.3 Comparison to Neural Net Model

Ipek *et al.* used an artificial neural network to predict performance across changes in platform parameters [25]. Artificial neural networks can be automatically calibrated without knowledge of the form of the functional relationship between input parameters and output variables. Also, they operate with categorical and continuous data. However, the limited amount of available data for cross-platform management for real-world Internet services presents a challenge for neural networks. Neural networks require many observations of the input parameters and output variables in order to learn the underlying structure of the system. In contrast, our composition of trait models is based on our knowledge of the underlying structure of Internet services.

We implemented an artificial neural network (ANN) as described in [25]. We used 16 hidden states, a learning rate 0.0001, a momentum value of 0.5, and we initialized the weights uniformly. The output variable for the ANN was the average response time. The training set for the ANN consisted of observations on the PIII and PRES platforms. The validation set consisted of observations under new transaction mixes on the PRES and XEON platforms.

Figure 6 shows the median prediction error of the ANN compared to our model on the validation set. Our model has comparable accuracy, within 0.02, under situations in which the ANN predicts only the effects of workload changes. However, the ANN has up to 3X the error of our model when predicting response time on the unseen XEON platform. Observations on two platforms are not enough for the ANN to learn the relationship between platform parameters and response time. These results suggest that our methodology, a composition of trait models, may be better suited for cross-platform management in data-constrained production environments.

5 Enhanced System Management

In this section, we use our model to improve cross-platform management decisions for Internet services. In general, such management decisions can have significant consequences on the bottom line for service providers, which completes our metaphor of creating a dollar from 15 cents. We explore two specific management problems often encountered in real-word production environments.

- *Platform Selection* When building or augmenting a server cluster, service providers wish to select platforms that will maximize performance relative to a cost. We look at the problem of choosing the hardware platform that yields maximum response-time-bounded throughput per watt. This problem is challenging because architectural features and configuration options that enhance performance also increase power consumption. Of course, the problem could also be solved by testing the application of interest on each target processor configuration, but such exhaustive testing is typically too expensive and time consuming in real-world scenarios.
- *Platform-Aware Load Balancing for Heterogeneous Servers* Service providers wish to extract maximum performance from their server infrastructure. We show that naïvely distributing arriving requests across all machines in a server cluster may yield sub-optimal performance for certain request types. Specifically, certain types of requests execute most efficiently only under certain platform configurations in the server cluster. Our cross-platform performance predictions can identify the best platform for each request type.

5.1 Platform Selection

Our metric for platform selection is throughput per watt. We leverage our performance model of application-level response time to predict the maximum request arrival rate that does not violate a bound on aggregate response time. Given an expected request mix, we iteratively query our model with increased aggregate arrival rates. The response-time-bounded throughput is the maximum arrival rate that does not exceed the response time bound. The other half of our metric for platform selection is power consumption, which we acquire from processor spec sheets [6]. Admittedly, processor specs are not the most accurate source for power consumption data [17, 21], but they will suffice for the purpose of demonstrating our model's ability to guide management decisions.

For this test, we compare our model against the other cross-platform prediction methods commonly used in practice. The competing models are not fundamentally

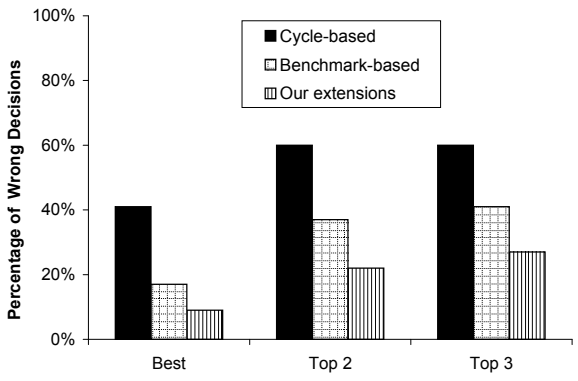


Figure 7: Probability of incorrect decisions for model-driven platform selection.

Processor	Rankings			
	actual	our method	cycle-based	bench-mark
PD4	1	**1**	**1**	**1**
XEON 2H/2C/2P	2	**2**	6	**2**
XEON 2H/2C/1P	3	4	**3**	5
XEON 2H/1C/1P	4	3	**4**	3
XEON 2H/1C/2P	5	**5**	**5**	6
XEON 1H/1C/1P	6	7	7	7
PRES	7	6	2	4
XEON 1H/2C/1P	8	**8**	**8**	**8**
XEON 1H/1C/2P	9	**9**	**9**	**9**
XEON 1H/2C/2P	10	**10**	**10**	**10**

Table 7: Platform rankings of the response-time-bounded throughput per watt on RUBiS. Response time bound was 150ms. Power consumption data was taken from [6]. Actual response-time-bounded throughput was measured as a baseline.

intended to model response time, so we apply our queueing model to each. Specifically, the difference in results in this section come from the different methods of service time prediction presented in Section 4. We calibrate performance models on the PIII platform, and show results for the RUBiS auction service. Table 7 compares the measured throughput per watt to the predictions of each method. The absolute value of the difference between the actual ranking and the predicted ranking (*i.e.*, $|pred - act|$), is never greater than 1 with our method. Comparatively, the cycle-based and benchmark approach have mis-rankings of 5 and 3 respectively. In practice, mis-rankings could cause service providers to purchase an inefficient platform. One way to measure the cost of such mis-predictions is to measure the net loss in throughput per watt between the mis-predicted platform and the properly ranked platform, *i.e.*, $\frac{tpw_{predicted\ rank\ k}}{tpw_{actual\ rank\ k}} \times 100\%$. The maximum loss is only 5% for our method, but is 45% and 12% for the cycle-based and benchmark methods, respectively.

Often in practice, platform selections are made from a few properly priced platforms. We divided our platform into subsets of five, and then predicted the best platform in the subset. We report how often each performance prediction method does *NOT* correctly identify the best, the top two, and the top three platforms. Figure 7 shows that our method selects the best processor configuration for 230 of 252 (91%) combinations. More importantly, alternative methods are 2X and 4X more likely to make costly wrong decisions. For the problems of correctly identifying the top two and top three platforms, our approach yields the correct decision for all but 25% of platform subsets whereas our competitors are wrong more than 41% and 60% of the time.

5.2 Platform-Aware Load Balancing

In this section, we first observe that *the best processor for one request type may not be the best processor for another*. Second, we show that the techniques described in Section 4 enable black-box ranking of processors for each request type. Our techniques complement advanced type-based load distribution techniques, like locality-aware request distribution, in heterogeneous clusters and do not require intrusive instrumentation or benchmarking. A mapping of request type to machine can be made with the limited data available to consultants.

Table 8 shows the expected and actual response time for four request types that contribute significantly to the overall response time of RUBiS. These types were chosen because they are representative of different demands for processor resources in RUBiS. The first type represents requests for static content. Since XEON and PRES have similar clock rates there is not much difference between their processing power on this request type. *Search Items by Region* has a large working set and benefits from fewer L2 cache misses on XEON. *View Item* has a small working set size that seems to fit mostly within the larger L1 cache of XEON. *Lookup user information*, however, has unique cache behavior. Its working set is medium-sized consisting of user information, user bid histories, and user items currently for sale. This request type seems to benefit more from the lower-latency 512KB cache of PRES, than it does from the larger 32KB L1 cache of Xeon.

Table 8 also shows our ability to predict the best machine on a per-request-type basis. We achieve this by us-

Response Time Per-type (ms)				
	PRES		Dual-core Xeon	
	actual	predict	actual	predict
Browse.html	53	49	**48**	**47**
Search Items by Reg.	423	411	**314**	**354**
View Item	102	110	**89**	**92**
Lookup User Info	**80**	**75**	132	109

Table 8: Expected response time of each request-type when issued in isolation. Predictions are based on log file observations from PIII. The dual-core Xeon is a single processor. Request mix consisted of only requests of the tested type at a rate of ten requests per second.

ing the techniques described in Section 4. In particular, we calibrate the parameters of our business-logic traits using only lightweight passive observations of a system serving a realistic nonstationary workload. Then, we predict performance under a workload mix that consists of only one type of request. This is done for each machine and request type in the system.

6 Related Work

Our contributions in this paper span model-driven system management, workload characterization, and performance modeling. The general literature on these topics is vast; this section briefly reviews certain related works.

6.1 Model-Driven Management

Networked services are now too complex for ad-hoc, human-centric management. Performance predictions, the by-product of performance models, offer a convenient abstraction for principled, human-free management. Our previous work [41] presented a whole-system performance model capable of guiding the placement and replication of interacting software components (*e.g.*, web server, business-logic components, and database) across a cluster. Shivam *et al.* [34, 37] model scientific applications on a networked utility. Their model can be used to guide the placement of compute and I/O-bound tasks and the order in which workflows execute. Doyle *et al.* provide a detailed model of file system caching for standard web servers that is used to achieve resource management objectives such as high service quality and performance isolation [14]. Magpie [9] models the control flow of requests through distributed server systems, automatically clustering requests with similar behavior and detecting anomalous requests. Aguilera *et al.* [7] perform bottleneck analysis under conditions typical of real-world Internet services. Thereska and Ganger [42] investigate real-world causes for inaccuracies in storage system models and study their effect on management policies. Finally, our most recent work proposed a model of application-level performance that could predict the effects of combining two or more applications onto the same machine (*i.e.*, consolidation).

The contribution of this work is a practical method for performance prediction across platform and workload parameters that can be used to guide cross-platform decisions for real-world Internet services.

6.2 Workload Characterization

Internet services have certain innate resource demands that span hardware platforms, underlying systems software, and even the end-user input supplied to them. Previous work [32, 36] advocated separating the characterization of application-specific demands from the characterization of underlying systems and high-level inputs. Our trait models continue in this tradition by providing parsimonious and easy-to-calibrate descriptions of an application's demand for hardware resources. We believe trait models exist and can be derived for other types of applications, such as databases and file systems.

Characterizations of application resource demand that have functional forms similar to our trait models have been observed in past research. Saavedra & Smith model the execution time of scientific FORTRAN programs as a weighted linear combination of "abstract operations" such as arithmetic and trigonometric operations [35]. Our request-mix models characterize much higher level business-logic operations in a very different class of applications. Another difference is that Saavedra & Smith calibrate their models using direct measurements obtained through invasive application instrumentation whereas we analyze lightweight passive observations to calibrate our models.

Chow considers the optimal design of memory hierarchies under the *assumption* of a power-law relationship between cache size and miss rates [13]. Smith presents very limited empirical evidence, based on a single internal Amdahl benchmark, that appears to be roughly consistent with Chow's assumption [38]. Thiebaut and Hartstein *et al.* explore a special case of Chow's assumption from a theoretical standpoint [20, 43]. This prior work is primarily concerned with the *design* of cache hierarchies and typically employs traces of memory accesses. We compose a power-law model with request-mix models and queuing models to *predict* the impact on response times of both workload changes and architectural changes. Furthermore we employ only passive observations of a running application to estimate power-law parameters.

The growing commercial importance of Java-based middleware and applications has attracted considerable attention in the architecture community. Recent stud-

ies investigate interactions between Java benchmarks and architectural features including branch prediction, hyperthreading, and the CPU cache hierarchy [11, 24, 29]. One important difference between these investigations and our work is that they focus on throughput whereas we emphasize application-level response times. Also, our work incorporates expert knowledge about Internet services via a novel composition of trait models. We demonstrated, in Section 4.3.3, that our composition improves cross-platform performance prediction when only limited production data is available.

6.3 Cross-Platform Performance Models

Chihaia & Gross report that simple analytic memory models accurately predict the execution times of scientific codes across hardware architectures [12]. We predict response times in business-logic servers across platforms, and we too find that succinct models suffice for our purposes. More sophisticated approaches typically fall into one of two categories: Knowledge-free machine learning techniques [23, 25, 30] and detailed models based on deep knowledge of processor design [16, 28, 32].

Detailed knowledge-intensive models typically require more extensive calibration data than is available to consultants in the practical scenarios that motivate our work, *e.g.*, data available only through simulated program execution. Knowledge-free machine learning methods, on the other hand, typically offer only limited insight into application performance: The structure and parameters of automatically-induced models are often difficult to explain in terms that are meaningful to a human performance analyst or useful in an IT management automation problem such as the type-aware load distribution problem of section 5.2. Furthermore the accuracy of knowledge-free data-mining approaches to cross-platform performance prediction has been a controversial subject: See, *e.g.*, Ein-Dor & Feldmesser for sweeping claims of accuracy and generality [15] and Fullerton for a failure to reproduce these results [18].

Our contribution is a principled composition of concise and justifiable models that are easy to calibrate in practice, accurate, and applicable to online management as well as offline platform selection.

7 Conclusion

This paper describes a model-driven approach for cross-platform management of real-world Internet services. We have shown that by composing *trait models*—parsimonious, easy-to-calibrate characterizations of one aspect of a complex system—we can achieve accurate cross-platform performance predictions. Our trait models themselves are typically accurate to within 10% and our application-level performance predictions are typically accurate to within 15%. Our approach relies only on lightweight passive observations of running production systems for model calibration; source code access, invasive instrumentation, and controlled benchmarking are not required. Applied to the problem of selecting a platform that offers maximal throughput per watt, our approach correctly identifies the best platform 91% of the time whereas alternative approaches choose a sub-optimal platform 2x–4x more frequently. Finally, we have shown that our model can improve load balancing in a heterogeneous server cluster by assigning request types to the most suitable platforms.

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