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

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# Motivation

1. Internet services are increasingly popular
   - Customer-facing websites— e.g., Amazon and BestBuy.com
   - Essential enterprise applications— e.g., SAP and Salesforce.com

2. Data centers are increasingly complex
   - Comprise heterogeneous processor platforms
   - Energy costs affect ability to scale

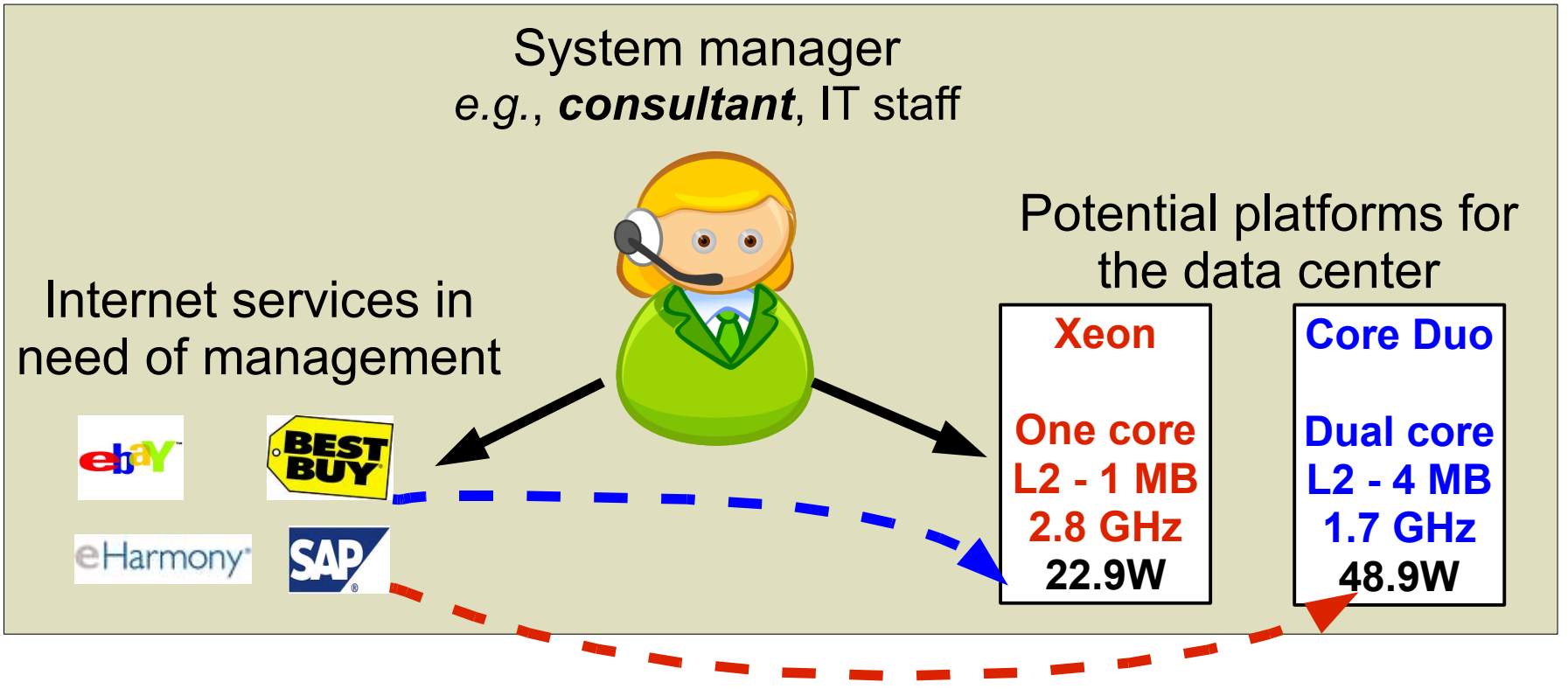
Decisions that span multiple platforms are commonplace in the data centers of almost every firm in every industry

One goal of such **cross-platform management** is to achieve *high performance at low cost*

# Challenges for Cross-Platform Management in the Real-World

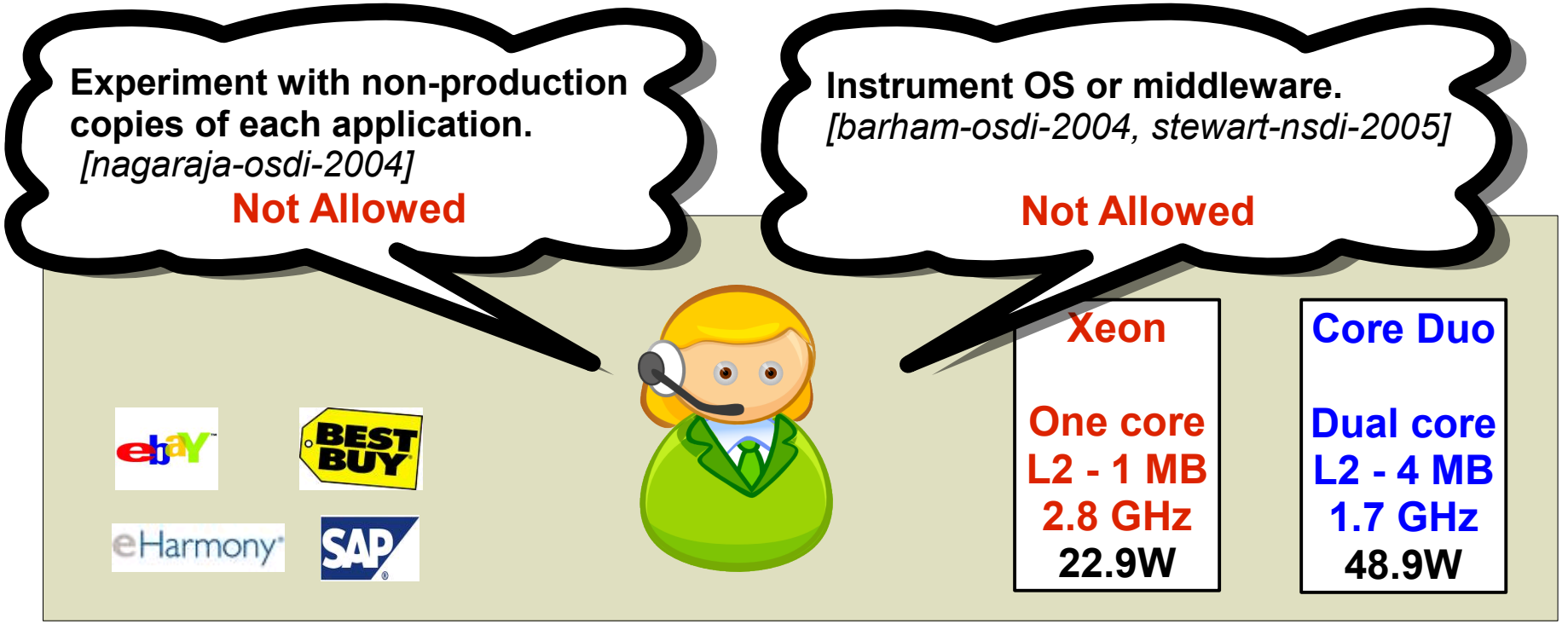
- Performance of an Internet service on a particular platform is hard to predict
  - Platform configurations like cache sizes and latencies, and number of cores have complex performance effects
  - Fluctuating workloads of Internet services place different demands on processors
- Data available for making decisions is constrained
  - Combination of security, trust, and politics
    - Are you a consultant? Hosting service? IT technician?
  - Invasive methods for system measurement are not allowed

# Motivating Example




Challenge #1: Which processor is most cost-effective for each service (*i.e.*, maximize throughput-per-watt)?

# Constraints in Production



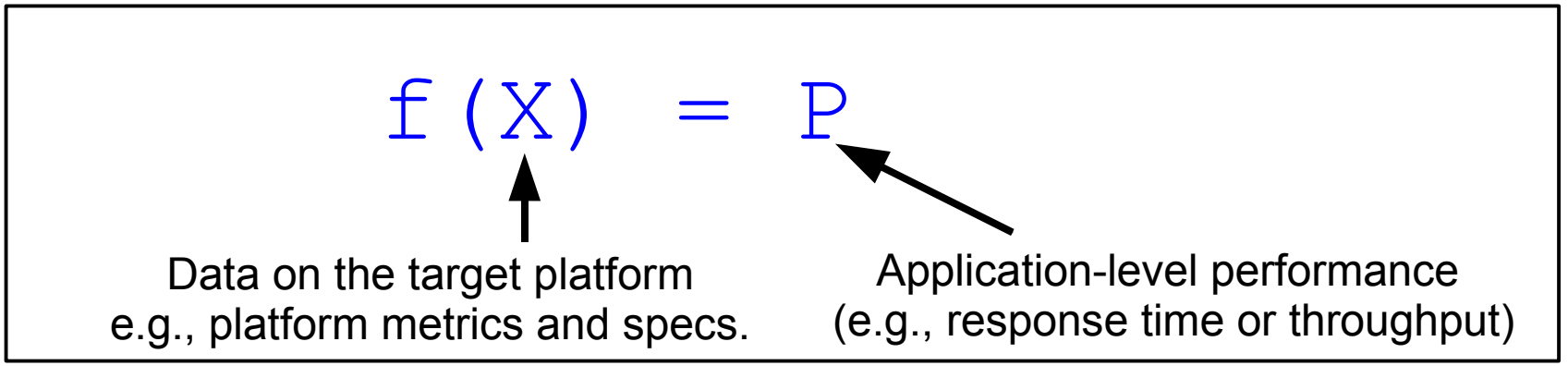

Challenge #2: Use only the limited data that can be collected non-intrusively with standard tools.

In the words of Tupac Shakur and the Digital Underground,

***"trying to make a dollar from 15 cents"***

# Making A Dollar from 15 Cents

Develop a cross-platform performance model using only data commonly available in production




- Convert seemingly useless production data into a surprisingly accurate guide on the performance consequences of cross-platform decisions

# Our Cross-Platform Performance Model

*Key concepts:*

***Trait models***— sub-models derived from empirical observations of a production system

***Existing expert knowledge***— textbooks and sound theory on the structure of both processors and Internet services

*Key principle:*

Derive trait models from production data for hard-to-characterize platform parameters and use expert knowledge to compose traits for performance prediction

# Outline

1. Motivation
2. Trait models— *empirically observed building blocks*
   - Identification and calibration
   - Example trait models
3. Our cross-platform model— *composition of trait models*
4. A Dollar from 15 cents— *cross-platform management*
5. Future work and conclusion

# Trait Models

Parsimonious sub-models that characterize only one aspect of a complex system *(like personality traits)*

Input: One platform configuration or workload property

Output: A processor metric— *e.g.,* cache misses or instructions

- Benefits of intentional simplicity
  - Easy to identify empirically— reduce a-priori knowledge
  - Few free parameters— calibrate with little data

# Deriving Trait Models

A trait model is the simplest functional form that yields low error for observed pairs of input parameters and output metrics

- Error metric is normalized residual error: $Err = \frac{|pred - act|}{act}$

- Empirical models can be misleading?

**Rigorous validation steps**

1. "Makes sense" based on system design principles
2. Observed for several applications/workloads
3. Practical calibration requirements

# Trait Model #1

**Input:** Cache size (*S*)

**Output:** Cache misses (*M*)

**Empirical Data from RUBiS**

| Cache Size | Cache Misses per (10K instr.) |
|---|---|
| 16K | 10.21 |
| 32 | 9.36 |
| 512 | 5.72 |
| 2048 | 4.53 |
| 4096 | 3.26 |
| 16384 | 1.25 |

Same workload for each test. Adequate resource provisioning

**Find the simplest functional form with low error on observed data**

| Functional form | Median Error |
|---|---|
| **Linear** | **0.73** |
| **Exponential** | **0.14** |
| **Logarithmic** | **0.09** |
| **Power law** | **0.02** |

$$M = A \times S^{B}$$

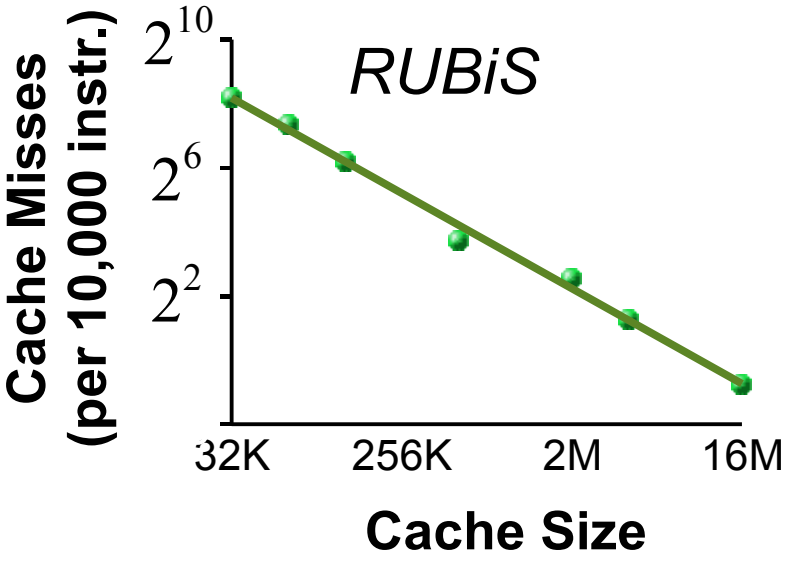
# Trait Model #1 Validation

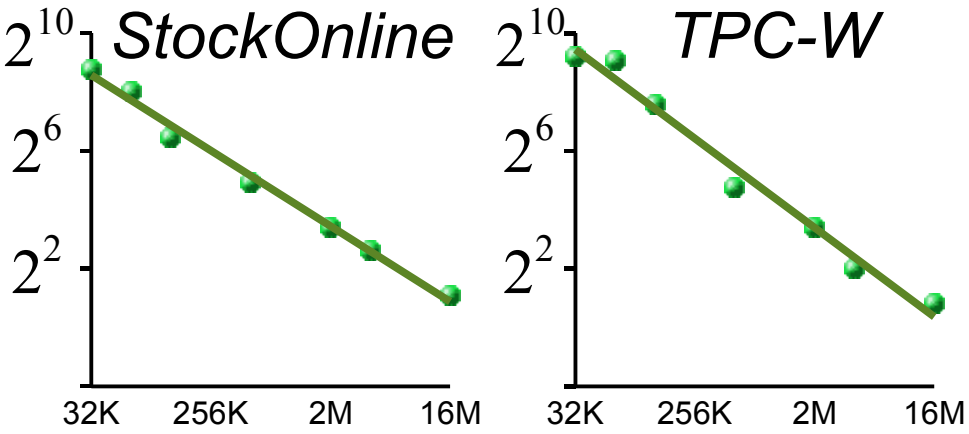
**Input:** **Cache size (*S*)**

**Output:** **Cache misses (*M*)**

**Relationship:** $M = A \times S^B$

1. **General:** Observed across 3 applications
2. **Makes Sense:** Heavy-tail reflects hard-to-remove cache misses
3. **Practical:** Calibrate with observations of cache misses on just 2 cache sizes



# Trait Model #2

**Input:** **Request-mix vector (<$N_1$, $N_2$, $N_k$>)**

**Output:** **Aggregate Instr. (*I*)**

**Empirical Data**

| Request Mix $N_1$ | $N_2$.... $N_k$ | | Aggr. Instr. |
|---|---|---|---|
| 18 | 42 | $Y_1$ | 280M |
| 33 | 36 | $Y_2$ | 311M |

**Relationship:** $$I = \sum_{type\ j} \alpha_k \cdot N_k$$

1. **General:** 3 applications and more than 500 request mixes

| | *Median Error* |
|---|---|
| RUBiS | 0.023 |
| StockOnline | 0.033 |
| TPCW | 0.025 |

2. **Makes Sense:** Request type influences code path
3. **Practical:** Nonstationarity [stewart-eurosys-2007] enables calibration from Apache logs

# Outline

1. Motivation

2. Trait models— *empirically observed building blocks*

3. Our cross-platform model— *composition of trait models*
   - Service time prediction
   - Response time prediction
   - Evaluate accuracy and compare to alternatives

4. A Dollar from 15 cents— *cross-platform management*

5. Future work and conclusion

# Composition Principles

- Expert knowledge about processors and Internet services
  1. Instruction and memory-access latencies are key components of the time spent processing end-user requests
     [hennessey & patterson] [karkhanis-isca-2004]
  2. Response time can be predicted using queuing models
     [doyle-usits-03] [stewart-nsdi-05] **[stewart-eurosys-07]**
- Rigorous evaluation validates composition
  - We target the business-logic tier where processor configurations affect performance the most

# Expert Knowledge on Processor Design

Average CPU service time for a particular mix of business-logic requests [hennessey & patterson]

$$s = \frac{I \times (CPI + [h_1 \cdot l_1 + h_2 \cdot l_2 + m_2 \cdot l_{mem}])}{clockrate \times \sum N_j}$$

- I → Aggregate instructions count
- CPI → Average number of cycles to execute an instruction (after registers are filled)
- h and l → accesses and latency in level k cache
- Clock rate → cycles per second available on the machine
- $N_j$ → number of requests of type j

# Incorporating Trait Models

- Prediction across cache sizes and request mixes

$$s = \frac{I \times (CPI + h_1 \cdot l_1 + h_2 \cdot l_2 + m_2 \cdot l_{mem})}{clockrate \times \sum N_j}$$

**Trait model #2**
(in paper)

$$I = \sum_{type\ j} \alpha_j \cdot N_j$$

$$M_i = \sum_{type\ j} \alpha_{ij} \cdot N_j$$

**Trait model #1**

$$M = A \times S^B$$

- Accesses at level i equals misses at i-1

# Expert Knowledge on Queuing Models

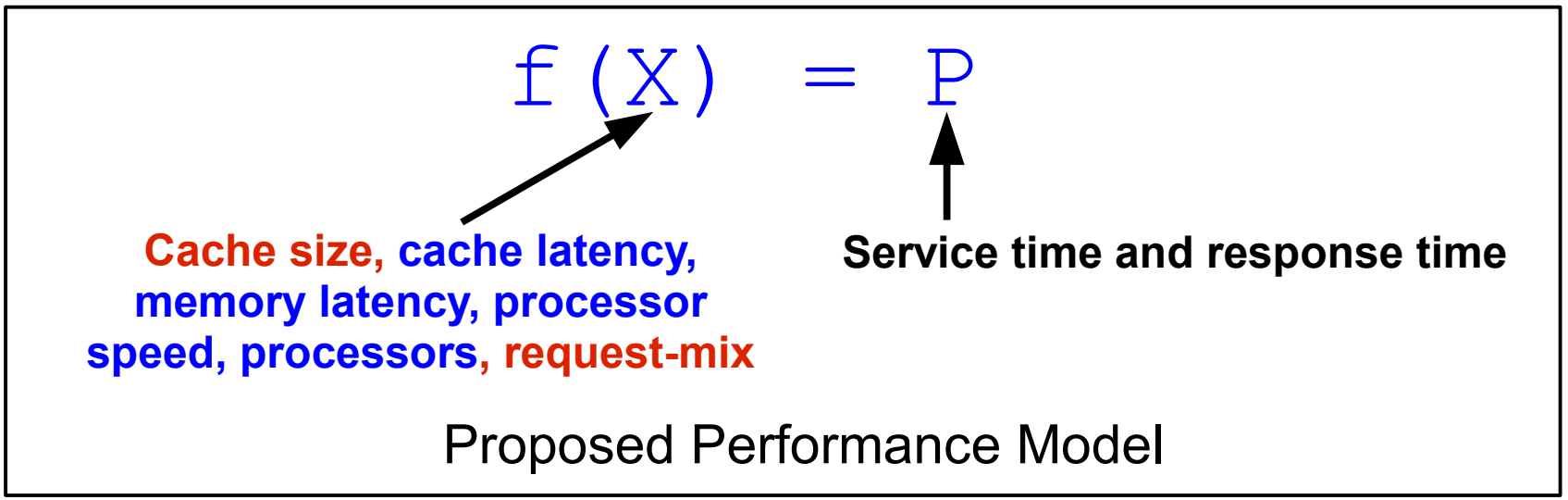
- Response time = service time + queuing delay
- Request-mix M/M/1 queuing model

  [stewart-eurosys-2007]

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

  - Accounts for request mix in waiting time
    - Intuition: other requests utilize resource r which detracts from the time available to service it
  - Validated with traces from *real* Internet services

# Our Performance Model (Bird's Eye)




- Prototype originally implemented in R (ported to VBA)
- Basic data collection tools: Sysstat, Oprofile, Apache
  - Formatted with ~483 lines of Perl
  - Timestamped data— ORCA Data collector (Adrian Cockcraft)

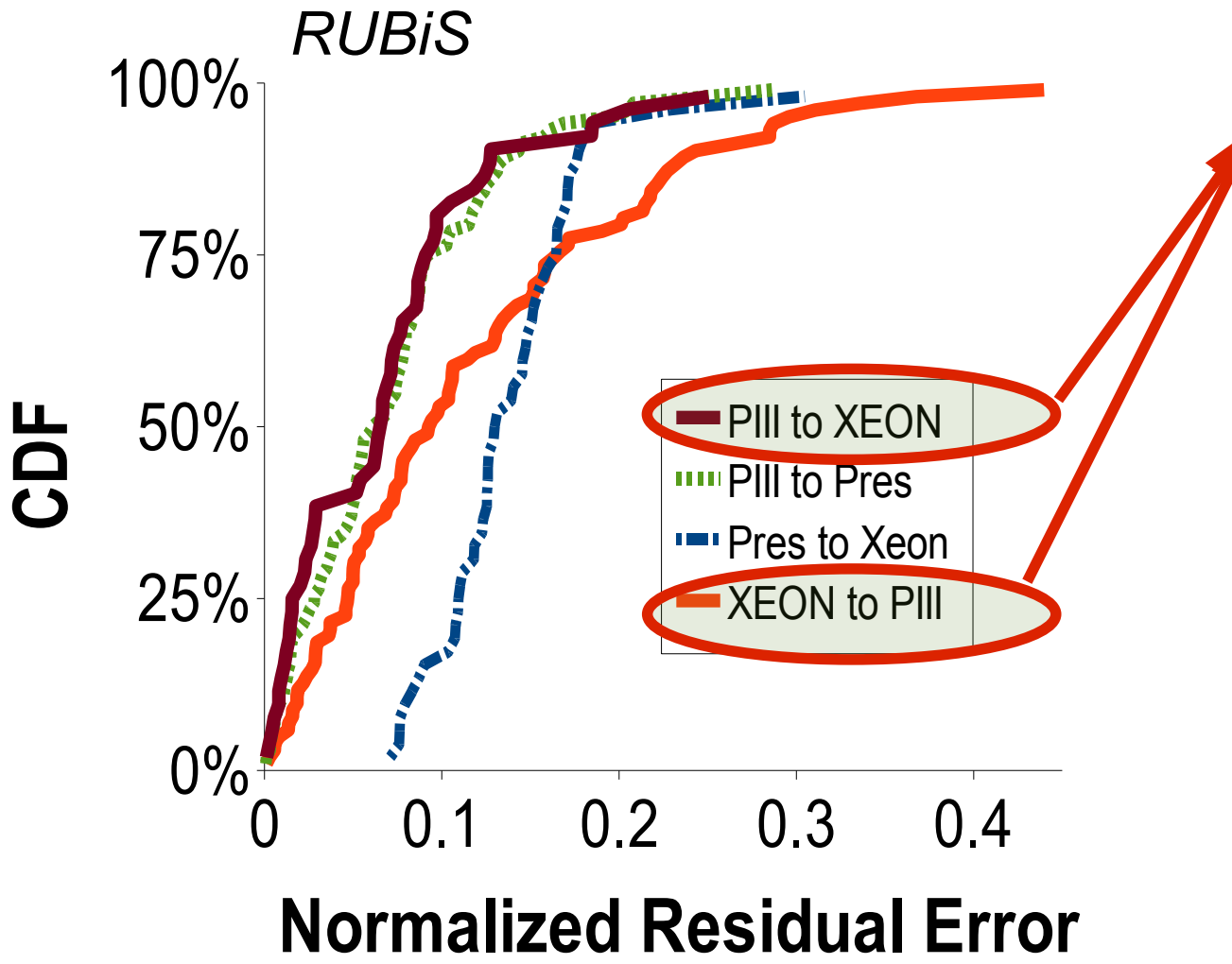
# Experimental Setup

- Test platforms
  - **PIII** (Coppermine)
    - 32 KB L1
    - 128 KB L2 cache
  - **Pres** (P4 Prescott)
    - 16 KB L1
    - 512 KB L2 cache
  - **XEON** (PentiumD)
    - 32 KB L1
    - 2 MB L2 cache
  - **More in Paper**
- Request mixes
  - 10-hour nonstationary sequence of requests
  - 1 request mix equals 30 second interval
  - **First 5 hours calibrate model on one platform**
  - **Evaluate on 2nd 5 hours on a different platform**

Download our workloads

**www.cs.rochester.edu/u/stewart/models.html**

# Accuracy Across Cache Configurations

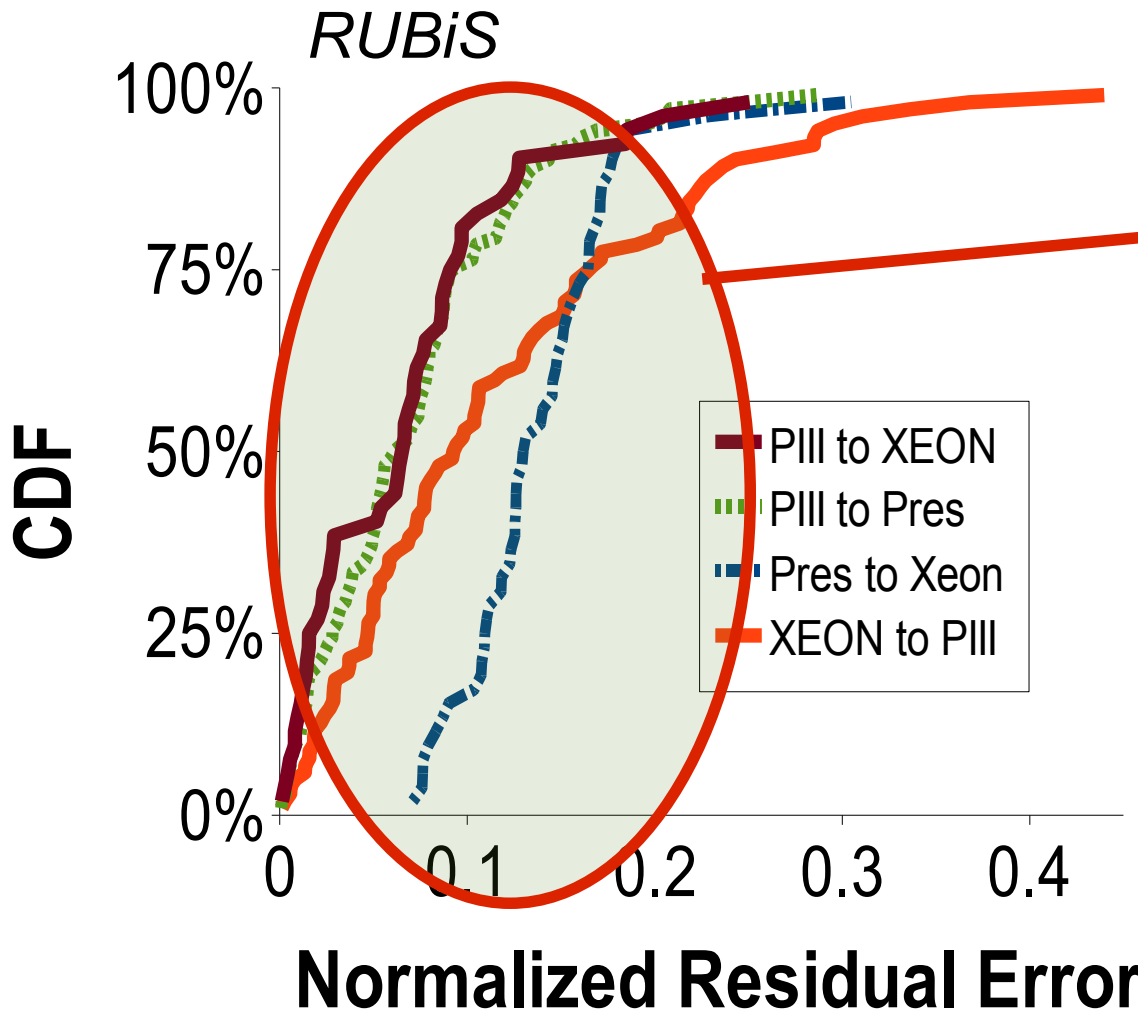



- **Accurate from "smaller caches to larger" and vice versa**

Median Error

- PIII to Xeon
  - RUBiS = 0.06
  - Stock = 0.13
  - TPC-W = 0.09
- XEON to PIII
  - RUBiS = 0.09
  - Stock = 0.11
  - TPC-W = 0.14

# Accuracy Across Request Mixes




- **Accurate for a wide range of request mixes**

Median 75th Percentile Error

- RUBiS = 0.15
- Stock = 0.17
- TPC-W = 0.16

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2. Trait models— *empirically observed building blocks*
3. Our cross-platform model— *composition of trait models*
4. A Dollar from 15 cents— *cross-platform management*
   - Maximum throughput-per-watt processor selection (see paper)
   - Platform-aware load balancing
5. Future work and conclusion

# Heterogeneity in Data Centers

- Makeup of data centers changes over time
  - New platforms are introduced piecewise
  - Old platforms die or become too inefficient

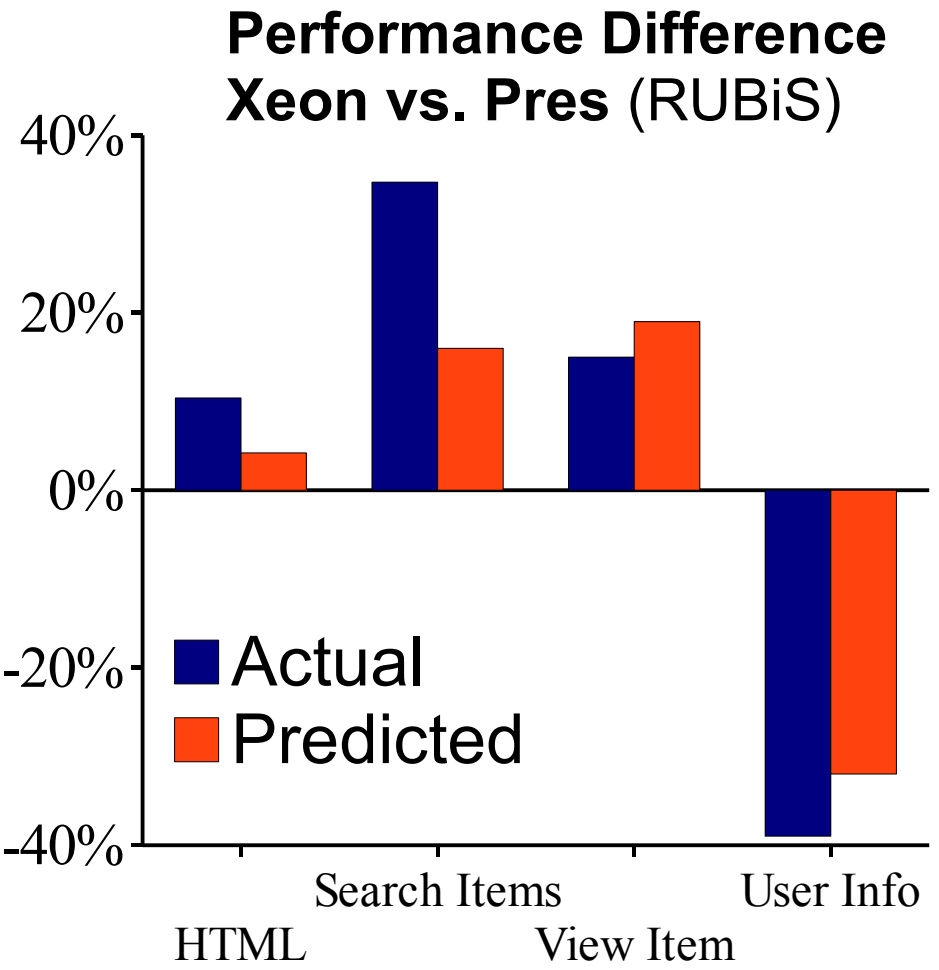
- *Load balancing across heterogeneous platforms*
  - In practice— Weighted round robin
    - Alternatively, designate a homogeneous cluster for each application
  - Research solutions— Locality-aware scheduling
    - Issues requests with similar patterns (same type) to same machine
    - [pai-asplos-1998][amza-usits-2003][elinkety-eurosys-2007]
    - ***Suit software to best utilize hardware***

# Platform-Aware Load Balancing

- **Distribute requests to the platform best configured to their architectural demands**
  - Request-type granularity
- Example: Xeon vs. Pres
  - Xeon larger L1 & L2
  - Pres lower L2 latency

*The best processor varies with request type*

*Our model can be used to predict per-type performance*



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# Future Work

- Can single-parameter trait models capture the intentions of system designers?
  - Intuition: The performance difference between empirical observations that vary on only one parameter most often reflects design intentions
  - Benefit: Detect unintended performance degradations (*performance anomalies*) without a-priori knowledge on the intended effects of every parameter
    - [augillera-sosp-2003][chen-nsdi-2004][reynolds-nsdi-2006]
  - Results: Found 5 anomalies in Linux; 4 in RUBiS/JBoss

# Take Away Points

1. Presented a cross-platform performance model for Internet services
   - Composition of single-parameter ***trait models*** that are:
   1. derived from empirical data and
   2. calibrated with data commonly available in production
2. Our model can guide the management of today's heterogeneous data centers

Nonstationary workload:
**http://www.cs.rochester.edu/u/stewart/models.html**