Evaluating the Effectiveness of Model-Based Power Characterization

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synergy
systems, networking and energy efficiency

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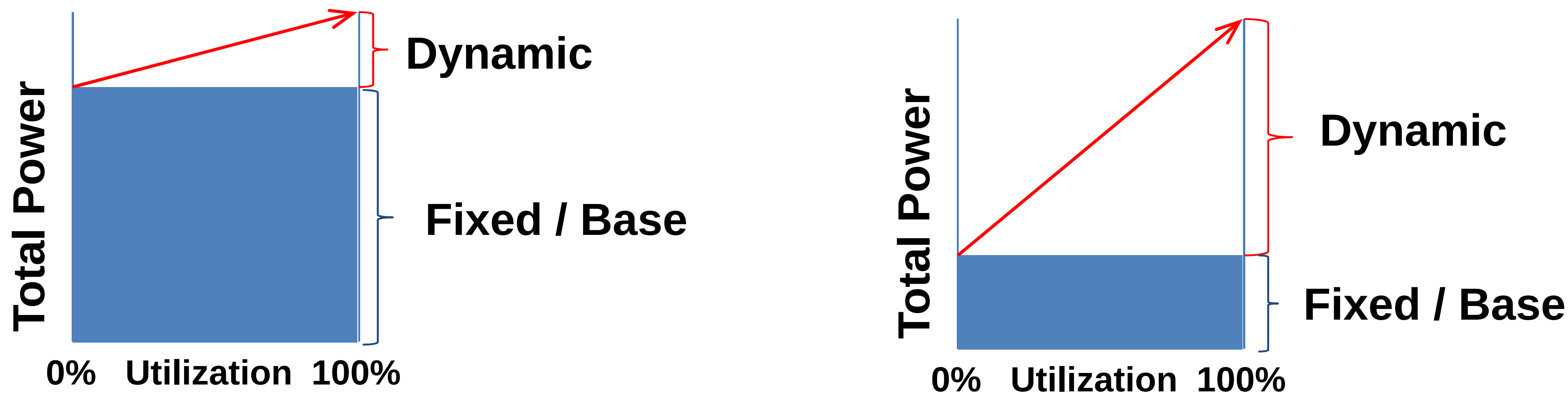
Motivation

- Computing platforms are ubiquitous
  – Sensors, mobile devices, PCs to data centers
  – Significant consumers of energy, slated to grow significantly
- Reducing energy consumption
  – Battery powered devices: goal of all day computing
  – Mains powered devices: reduce energy costs, carbon footprint

Detailed Power Characterization is Key

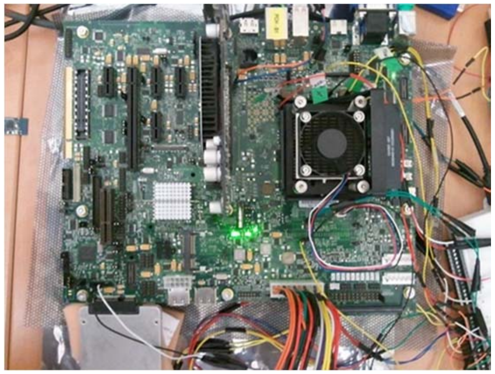
- Managing energy consumption within platforms
  – Requires visibility into where energy is being consumed
- Granularity of power characterization matters
  – “Total System Power” or “Individual Subsystem Power”
  – Depends on level of power optimizations desired
- Defining question, from the software stack perspective:
  – How can power consumption be characterized effectively
  – What are the limits: accuracy, granularity, complexity?
- Power characterization has been well studied
  – Need to revisit given the characteristics of modern platforms

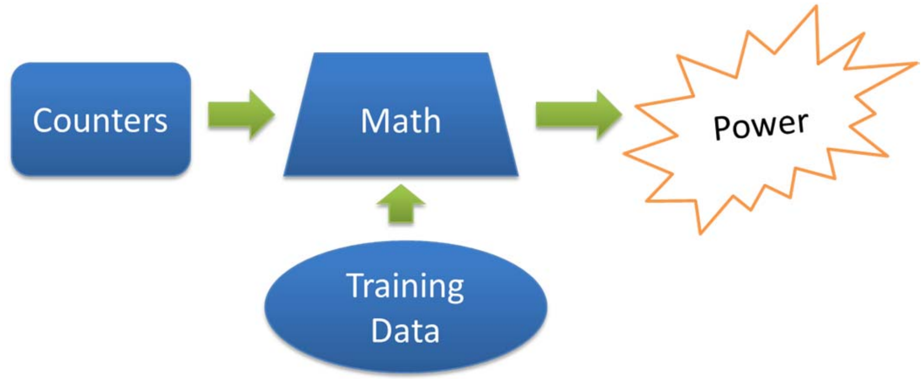
Modern Systems - Larger Dynamic Range



- Prior generation of computing platforms:
  - Systems with high base power -> small dynamic range
  - Dynamic component not critical to capture
- Modern platforms:
  - Increasing dynamic fraction
  - Critical to capture dynamic component for accuracy

Power Characterization: Measure or Model



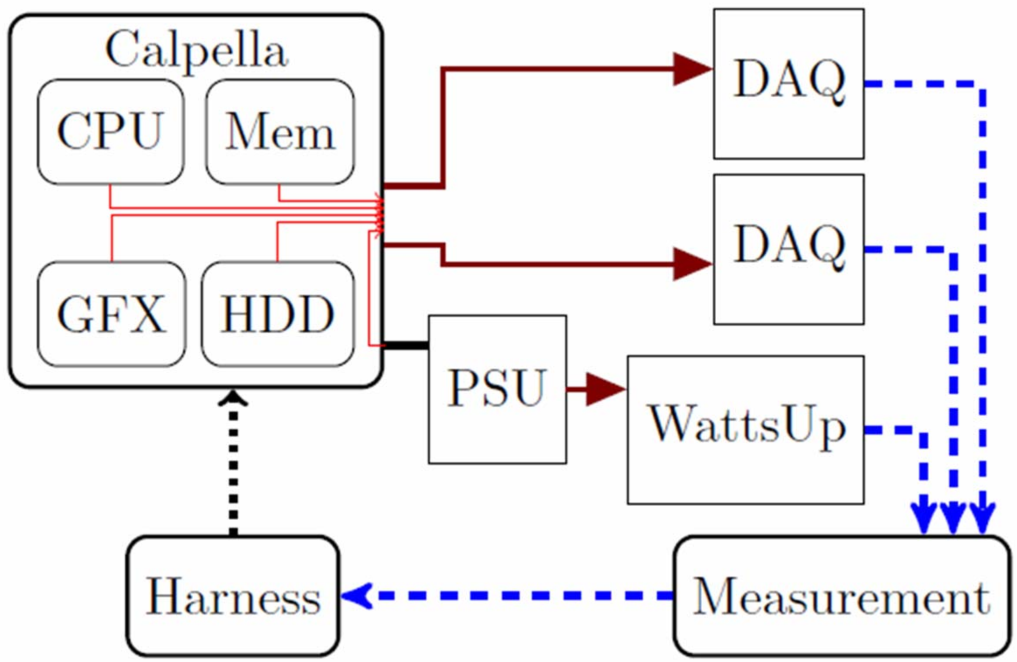


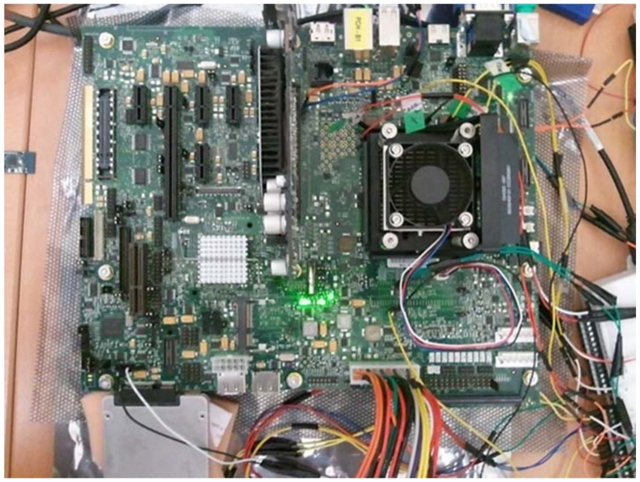
- Two options: Directly measured, or indirectly modeled
  - Modeling preferred because of less hardware complexity
- Many different power models have been proposed
  - Linear regression, learning, stochastic, ..
- Question: how good are these models?
  - Component level as well as system level power predictions

Outline

- Describe power measurement infrastructure
  - Fine grained, per component breakdown
- Present different power models
  - Linear regression (prior work), complex models
- Compare models with real measurements
  - Different workloads (SpecCPU, PARSEC, synthetic)
- Results: Power modeling -> high error
  - Reasons range from complexity, hidden states
  - Modeling errors will only get worse with variability

Power Measurement Infrastructure





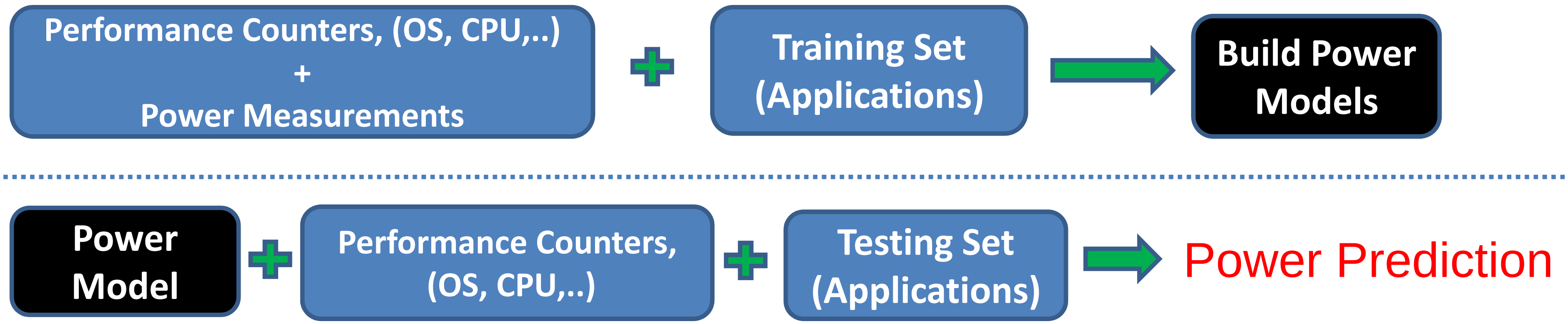
- Highly instrumented Intel "Calpella" Platform
  - Nehalem core i7, core i5, 50 sense resistors
  - High precision NI DAQs, 16bit / 1.25MS/s, 32 ADCs

Prior Work in Power Modeling

- Total System Power Modeling
  - *[Economou MOBS'06]* - Regression model, MANTIS
    - AMD blade: < 9% error across benchmarks
    - Itanium server: <21% error
  - *[Riviore HotPower '08]* – Compare regression models
    - Core2Duo/XEON, Itanium, Mobile FileServer, AMD Turion
    - Mean error < 10% across SPEC CPU/JBB benchmarks
- Subsystem Models
  - *[Bircher ISPASS '07]* – linear regression models
    - P4 XEON system: Error < 9% across all subsystems

Prior work: single-threaded workloads, systems with high base power, less complex systems.

Power Modeling Methodology



- Counters: CPU + OS/Device counters
  - For CPU: measure only 4 (programmable) + 2 (fixed)
  - Remove uncorrelated counters, add based on coefficients
- Benchmarks: "training set" and "testing set"
  - *k* X 2-fold cross-validation (do this n = 10 times)
  - Removes any bias in choosing training and testing set

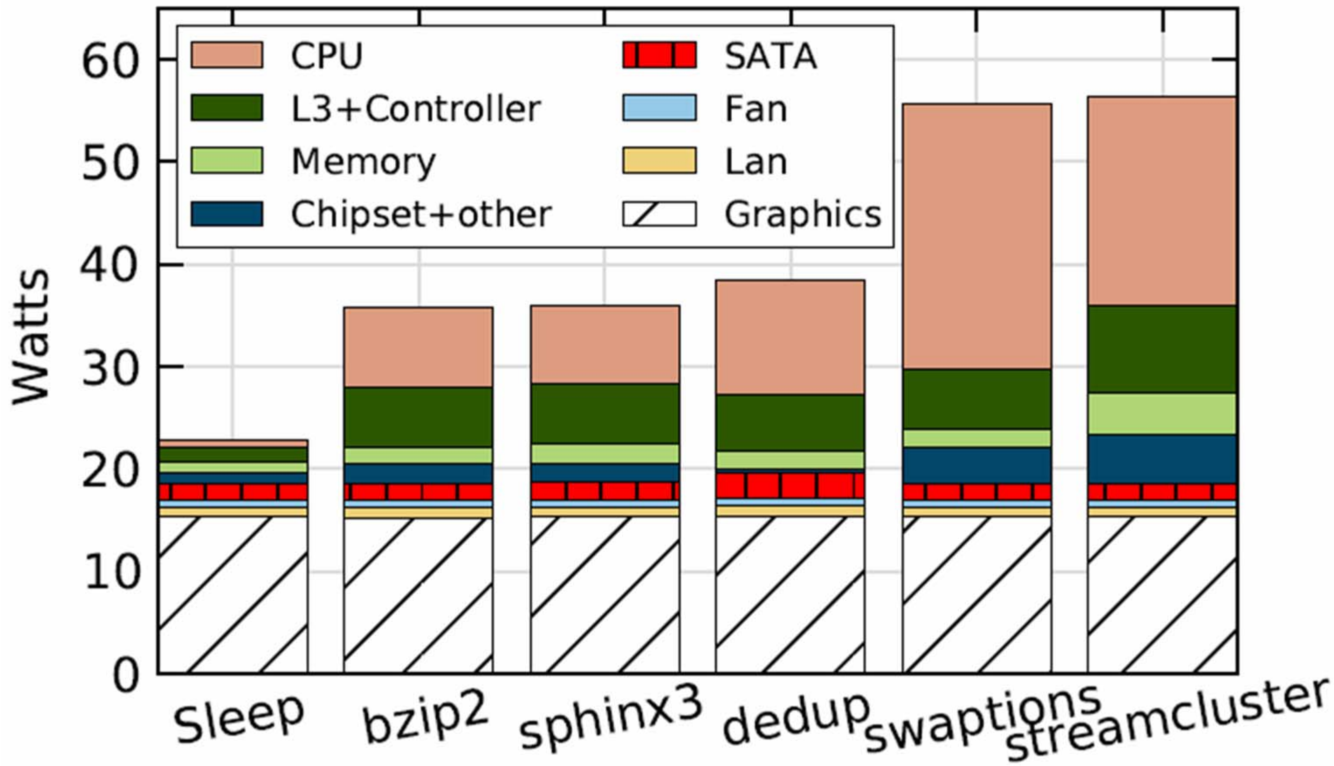
Power Consumption Models

- “MANTIS” [Prior Work] – Linear Regression
  - Uses domain knowledge for counter selection
- “Linear-lasso” – Linear Regression
  - Counters selection: “MANTIS” + Lasso/GLMNET
- “nl-poly-lasso” – Non Linear Regression (NLR)
  - Counters selection: “MANTIS” + Lasso/GLMNET
- “nl-poly-exp-lasso” – NLR + Poly term + Exp. Term
  - Counters selection: “MANTIS” + Lasso/GLMNET
- “svm_rbf” – Support Vector Machines
  - Unlike Lasso, SVM does not force model to be sparse.

Benchmarks

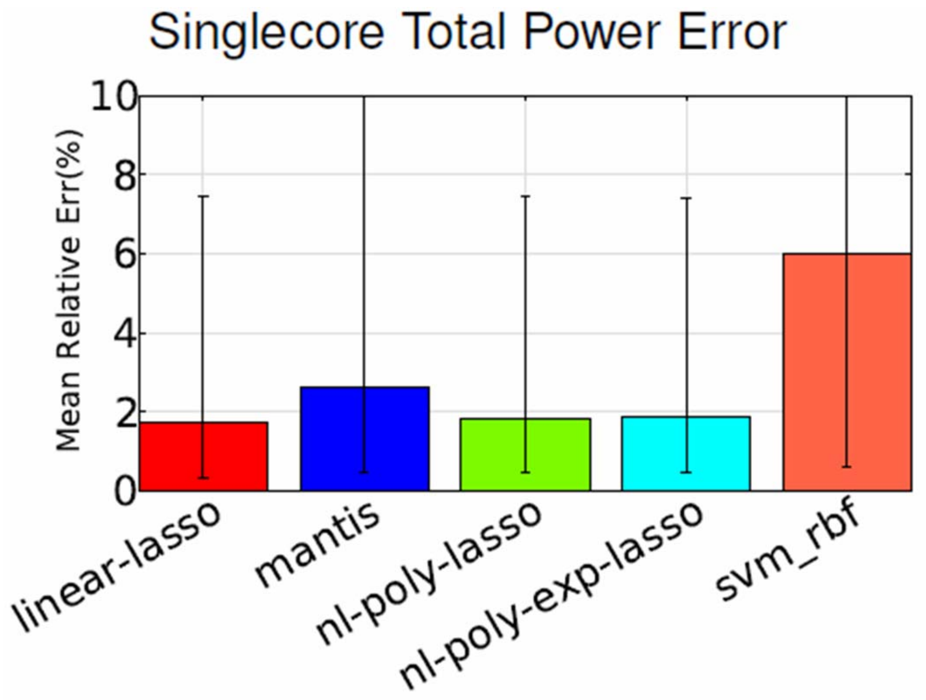
- “SpecCPU” – 22 Benchmarks, single-threaded
  - More CPU centric
- “PARSEC” – emerging multi-core workloads
  - Include file-dedup, x264 encoding
- Specific workloads – specific subsystems
  - “Bonnie” – I/O heavy benchmark
  - “Linux Build” – Multi threaded parallel build
  - StressTestApp, CPULoad, memcached

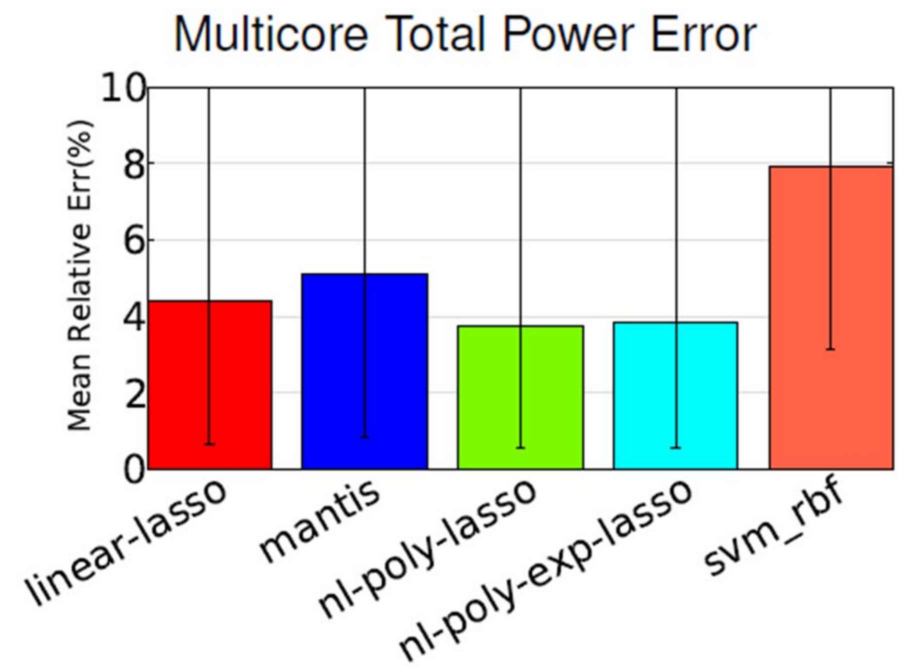
"Calpella" Platform – Power Breakdown



- Subsystem level power breakdown
  - – PSU power not shown, GPU constant
  - – Large dynamic range – 23W (Idle) to 57W (stream)!

Modeling Total System Power

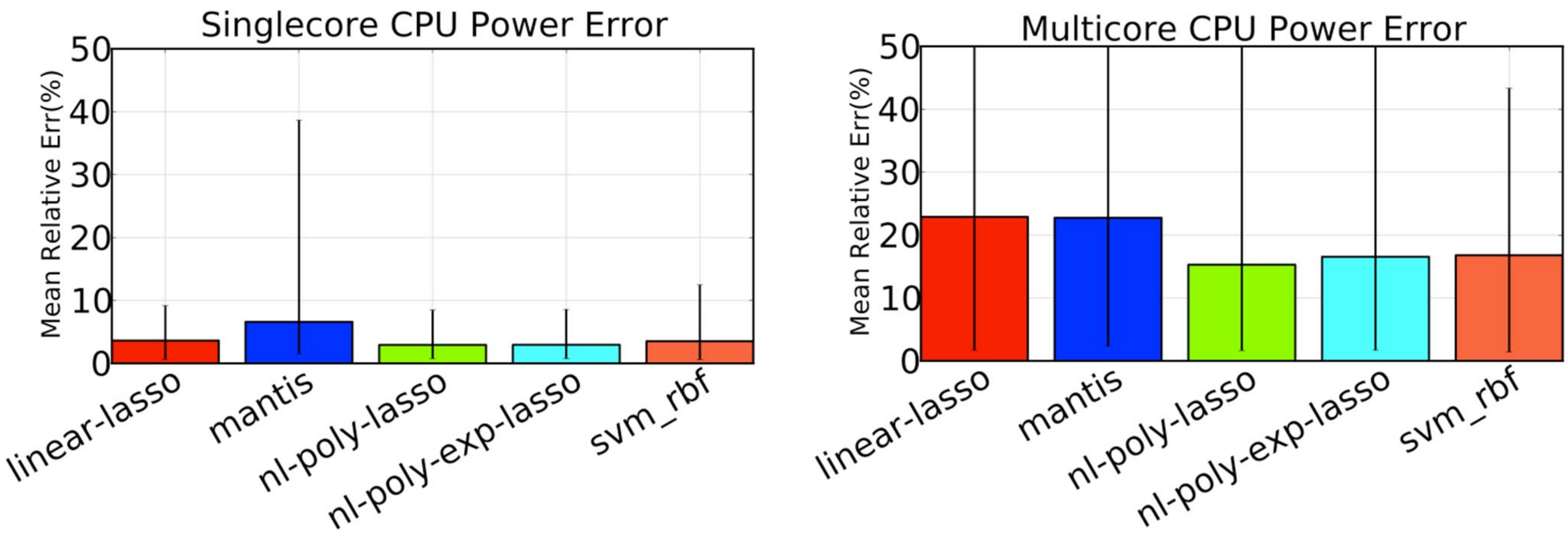




Error bars indicate max-min per-benchmark mean error

- Increased Complexity -> Single core to Multi-Core
  - Modeling error increases significantly
  - Mean Modeling Error < 10%, worse error > 15%

Modeling Subsystem Power – CPU

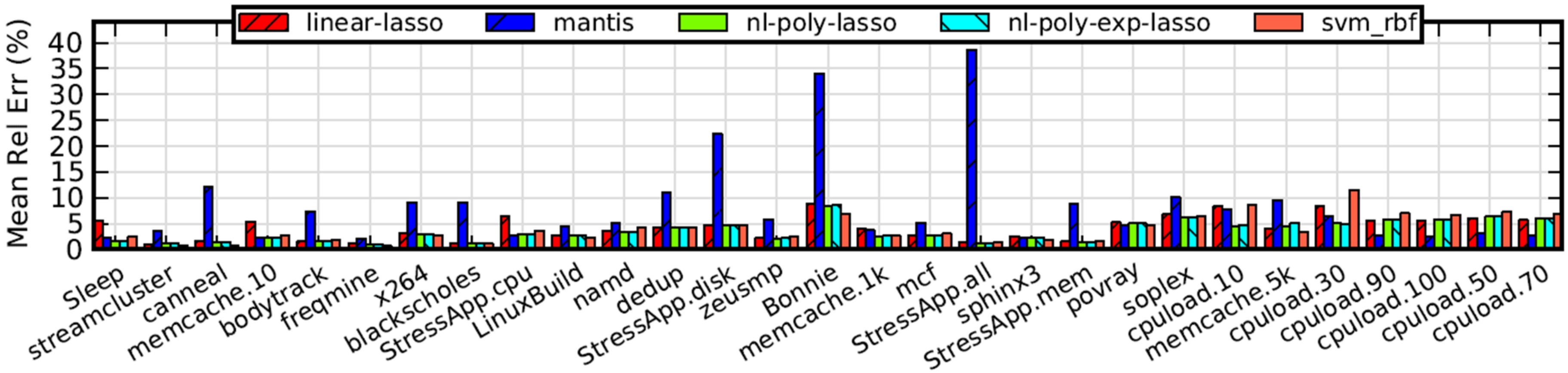


Error bars indicate max-min per-benchmark mean error

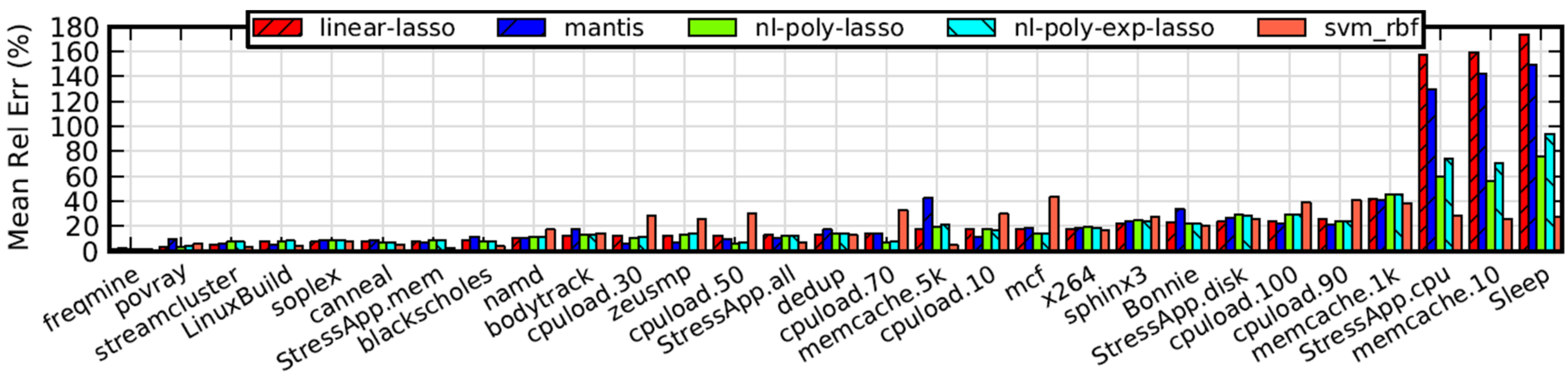
- Increased Complexity -> Single core to Multi-Core
  - CPU Power modeling error increases significantly
  - Multicore - Mean Error ~20%, worst case > 150%
  - Simplest case: HT and TurboBoost are Disabled

CPU Power: Single -> Multicore

Single-core:



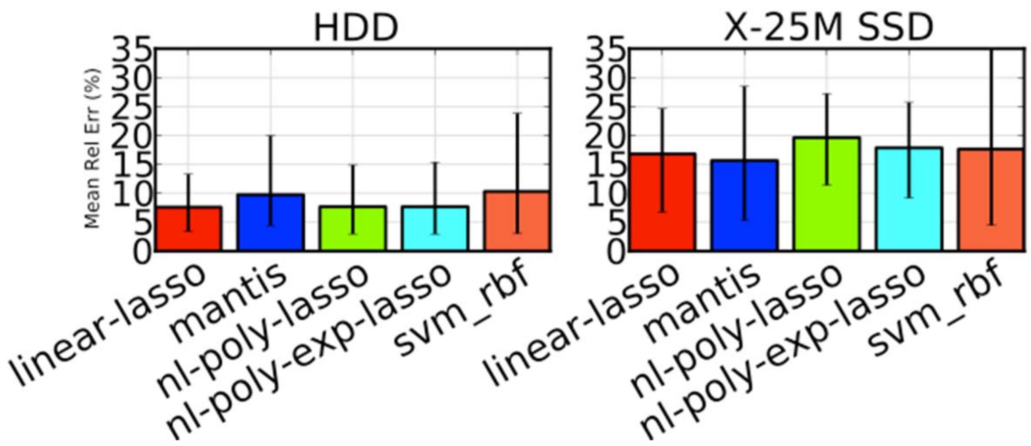
Multi-core:



CMP inherently increases prediction complexity

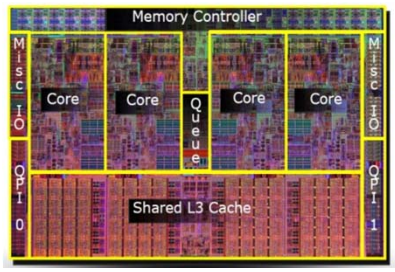
Accurate Power Modeling is Challenging

- Hidden system states
  - SSDs: wear leveling, TRIM, delayed writes, erase cycles
  - Processors: aggressive clock gating, “Turbo Boost”
- Increasing system complexity
  - Too many states: Nehalem CPU has hundreds of counters
  - Interactions hard to capture: resource contention
- E.g. consider SSDs vs traditional HDDs



Power Prediction Error
on SSD is 2X higher than HDD!

Adding Hardware Variability to the Mix



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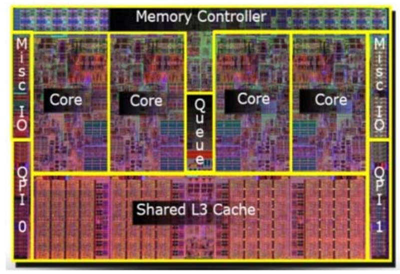

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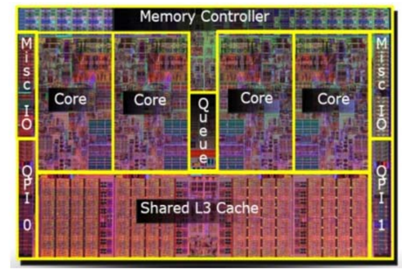

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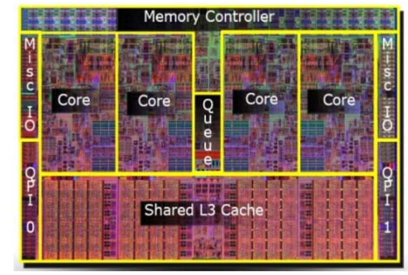
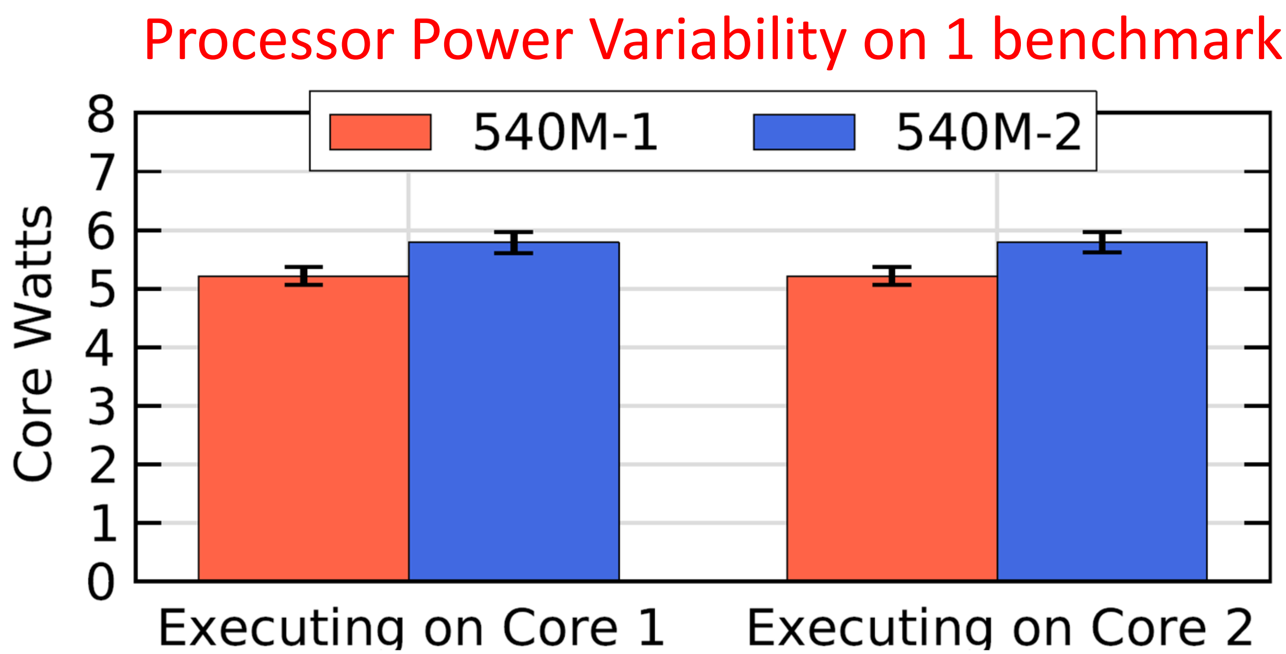


P4

- Variability in hardware is increasing
  - Identical parts, not necessarily identical in power, perf.
  - Can be due to: manufacturing, environment, aging, …
  - “Model one, apply to other instances” may not hold
- Experiment: Measure CPU power variability
  - Identical dual-core Core i5-540M -- 540M-1, 540M-2
  - Same benchmark, different configurations, 5 runs each

Variability Leads to Higher Modeling Error



- 12% Variability across 540M-1 and 540M-2
  - 20% modeling error + 12% variability ➔ 34% error!
- Part variability slated to increase in the future

Summary

- Power characterization using modeling
  - Becoming infeasible for complex modern platforms
  - Total power: 1%-5% (single core) to 10%-15% error (multi-core)
  - Per-component model predictions even worse:
    - CPU 20% - 150% error
    - Memory 2% - 10% error, HDD 3% - 22% error, and SSD 5% - 35% error
- Challenge: hidden state and system complexity
- Variability in components makes it even worse

Need low cost instrumentation solutions for accurate power characterization.

Questions?

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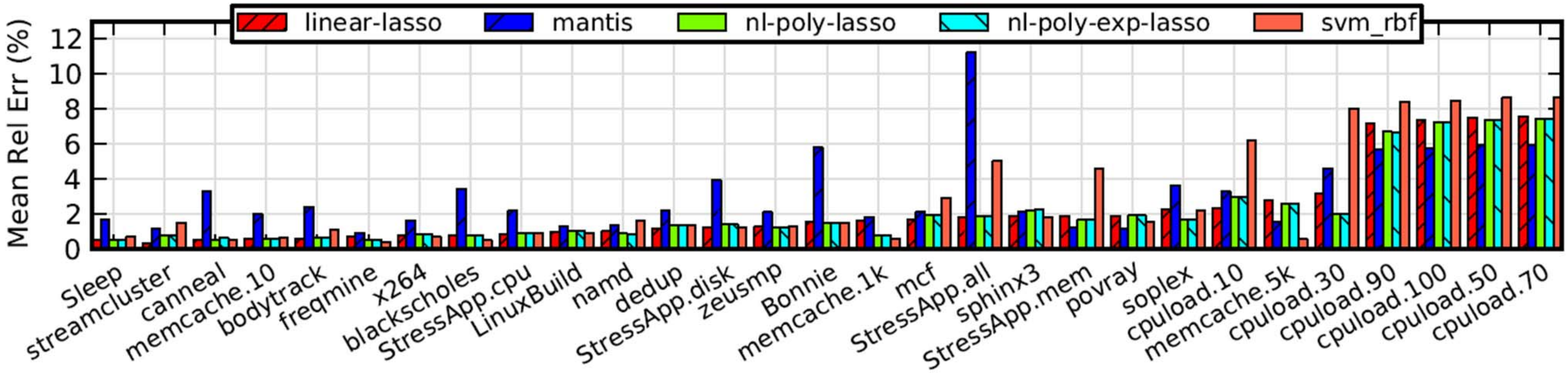
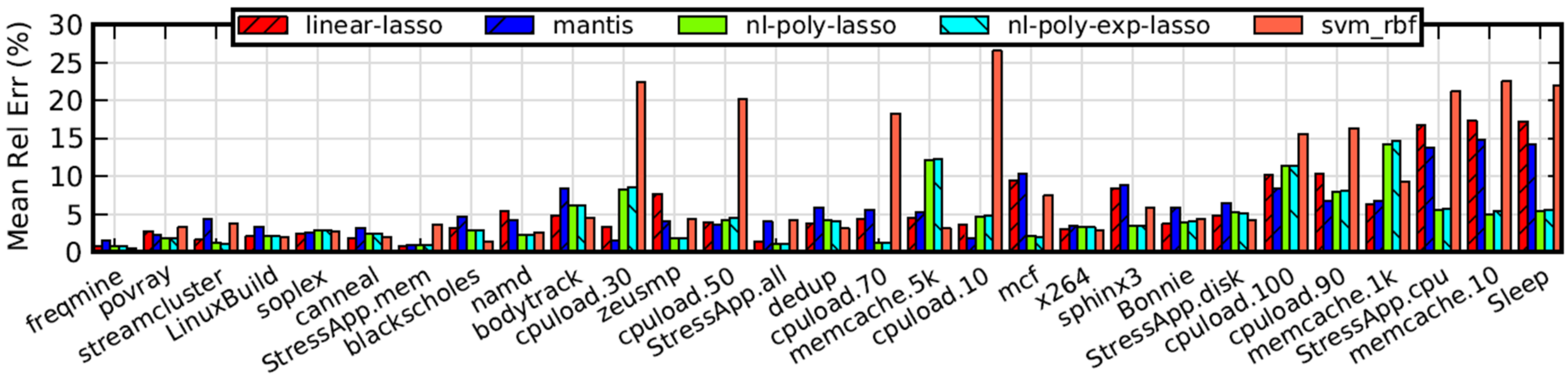
Total Power: Single -> Multicore

Single-core:



Multi-core:



Increase in error, sensitivity to individual benchmarks