

Power Signatures of High-Performance Computing Workloads

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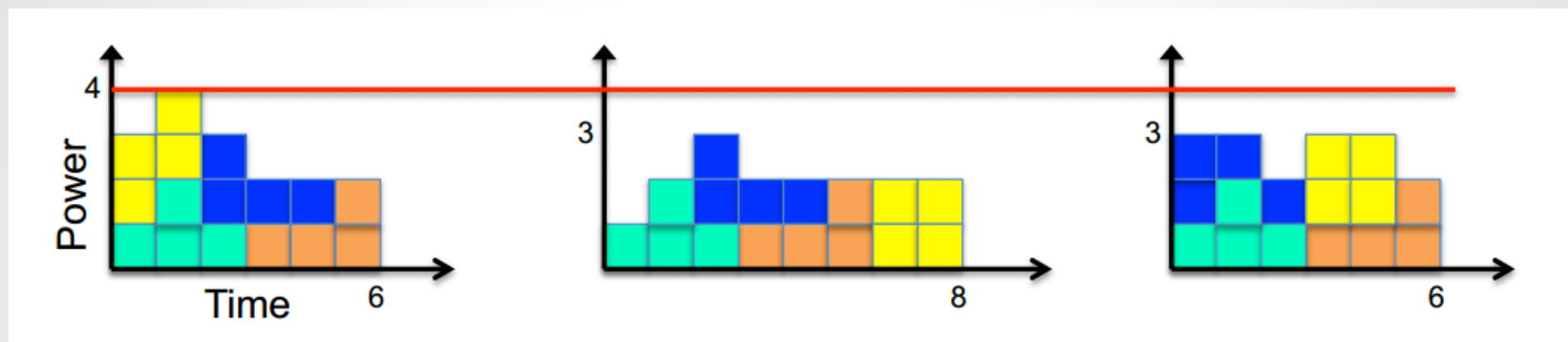
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Motivation

- Job scheduling as a Tetris game



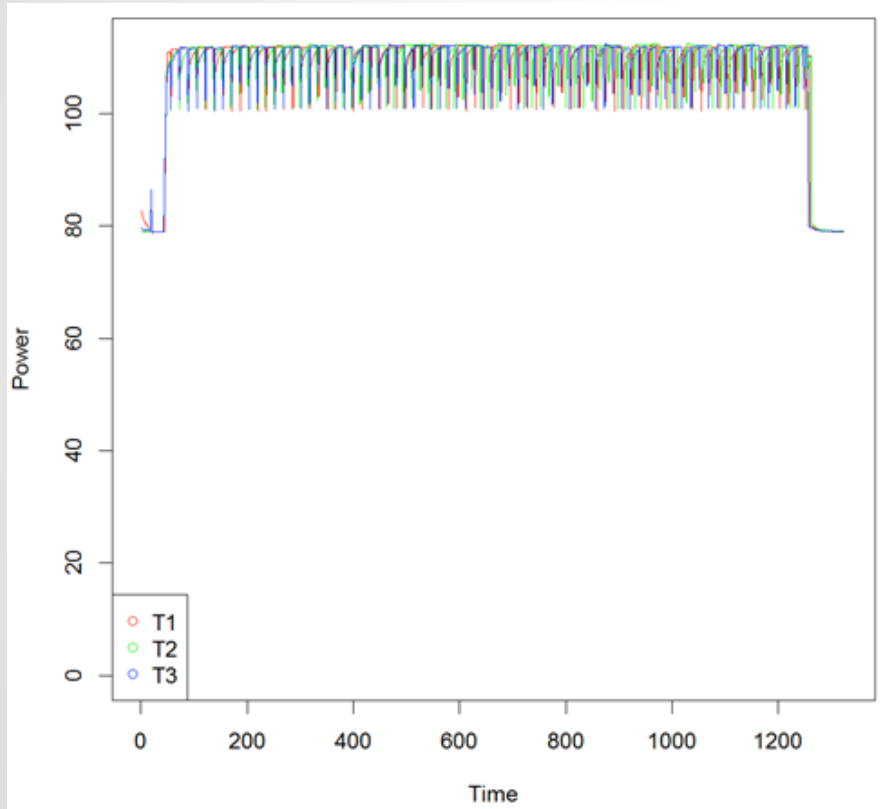
- Driven by power usage patterns.

Can we:

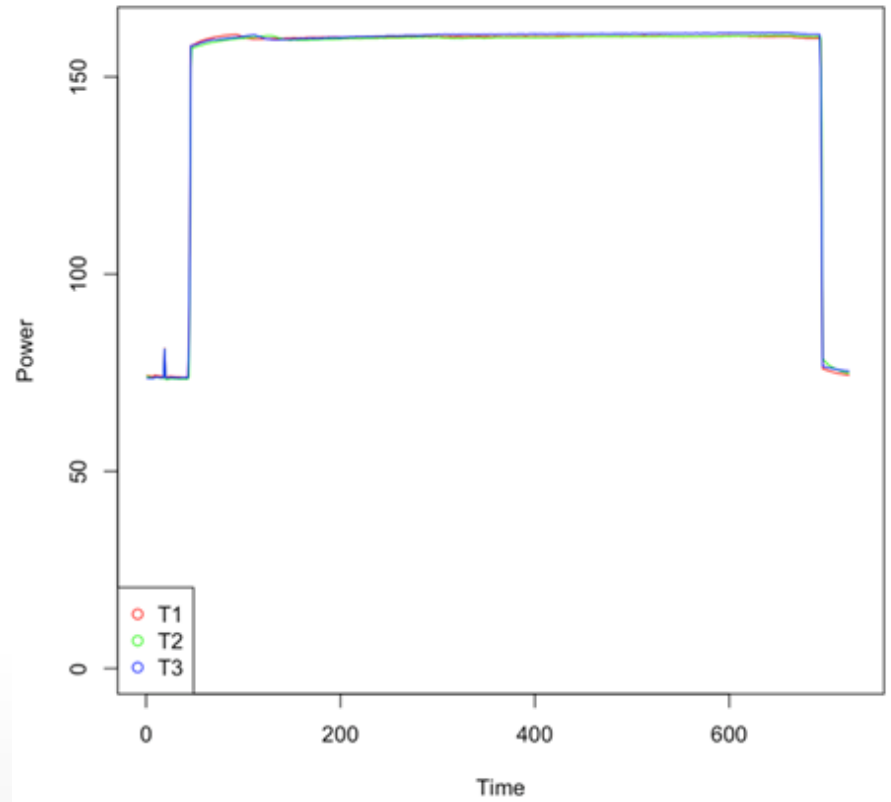
- Associate a pattern with each application?
- Enhance scheduler with pattern information?

Motivation

- Qualitative patterns in applications' traces



FFT



CUBLAS

Talk Outline

- Research questions
- What is a power signature?
- Methodology:
 - Signature validation
 - Experimental setup
- Results
- Current and future work

Research Questions

- Can we summarize HPC workloads' power behavior into distinctive signatures?
- Is such a signature consistent across
 - runs?
 - input data?
 - hardware configurations?
 - hardware platforms?
- How well (quantitatively) does a signature distinguish a workload?

What is a power signature?

A. The trace itself: vector of power measurements.

B. Statistical summary of the trace

Time-series-based Signature

How do we quantify the difference between two traces?

1. Mean Squared Difference (MSD)

- Match power observations pairwise, and take MSD
- Traces must be same length

2. Dynamic Time Warping (DTW)

- Identifies similarities of two time series
- Accounts for offsets and differences in periodic frequency

Feature-based Signature

What features are useful?

- Basic statistics:
 - 2-vector: $\langle \text{Maximum}, \text{Median} \rangle$
 - (Divide each by trace's minimum power)
 - Call this **MaxMed**
- More involved statistics that have been found useful in time-series clustering:
 - Standard Deviation + 11 other features
 - Augmented with **MaxMed**, call this **stat14**.

Signature Validation

- Clustering: “optimally” partition a set of traces
- Classification: automatically identify the label (e.g. workload) of a trace

Signature Validation: Clustering

- Input:
 - Data points (traces)
 - Notion of distance (signature)
- Output: Partition

Algorithms:

- kmeans: centroid-based clustering
- dbscan: density-based clustering
- hclust: hierarchical clustering
 - dendrograms

Signature Validation: Clustering

Our signature is good if the partition is good.
How do we know a partition is good?

1. Look at the partition qualitatively:
Are workloads grouped together?
2. Quantitatively compare partition to some
“ideal” reference.
 - Example ideal reference: grouped by workload

Signature Validation: Classification

Algorithm: Random forest

Leave-one-out accuracy measures a signature's utility

Bonus: Variable importance measures

Experimental Setup

255 power traces from 13 benchmarks.

- (Baseline)
- SystemBurn*:
 - FFT1D
 - FFT2D
 - TILT
 - DGEMM
 - GUPS
 - SCUBLAS
 - DGEMM+SCUBLAS
- Synthetic: Power Model Calibration**
- Sort
- Prime95
- Graph500
- Stream
- Linpack-CBLAS

** Rivoire et al, Hot Power, 2008

* Josh Lothian et al., ORNL Technical Report, 2013

Experimental Setup

	S1 (RR)	S2 (OC)	S3 (LC)	S4 (RF)
CPU	AMD Athlon 65 X2 4800+ @ 2.5 GHz	Intel Core i5-750 @ 2.67GHz	Intel Core i5-750 @ 2.67GHz	Intel Core i7-3770 @ 3.40GHz
RAM	4 GB	8 GB	8 GB	8 GB
GPU	GeForce 9800gt	GeForce GTX 285	GeForce GTX 650 Ti 1GB	GeForce GTX 670 2GB
Power	115–195 W	120–226 W	85–252 W	74–309 W

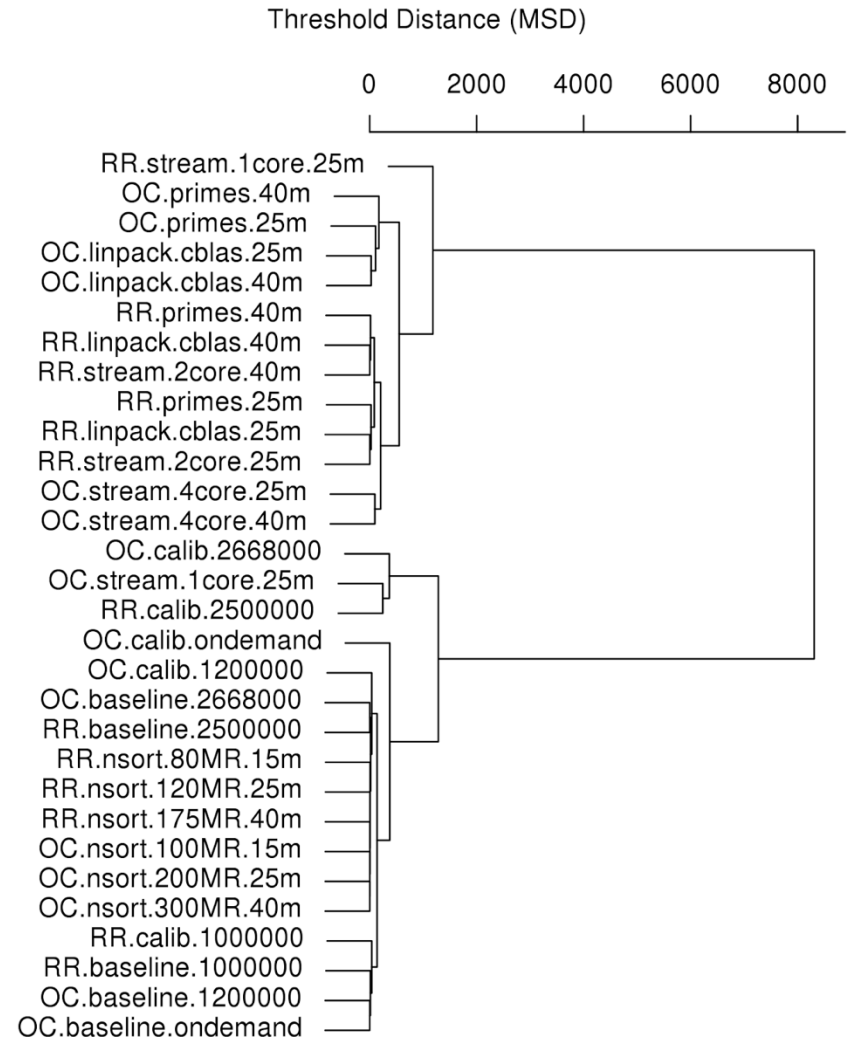
Watts Up? Pro power meter reports power consumption once per second.

Clustering Results

- OCRR data
 - n=30
 - 6 workloads (different input configurations)
- Algorithm: hclust
- Signature: raw trace
- Distance: MSD

2-clustering:

- Top: Stream, Prime95, Linpack-CBLAS (CPU-intensive)
- Bottom: Calib, Baseline, Sort

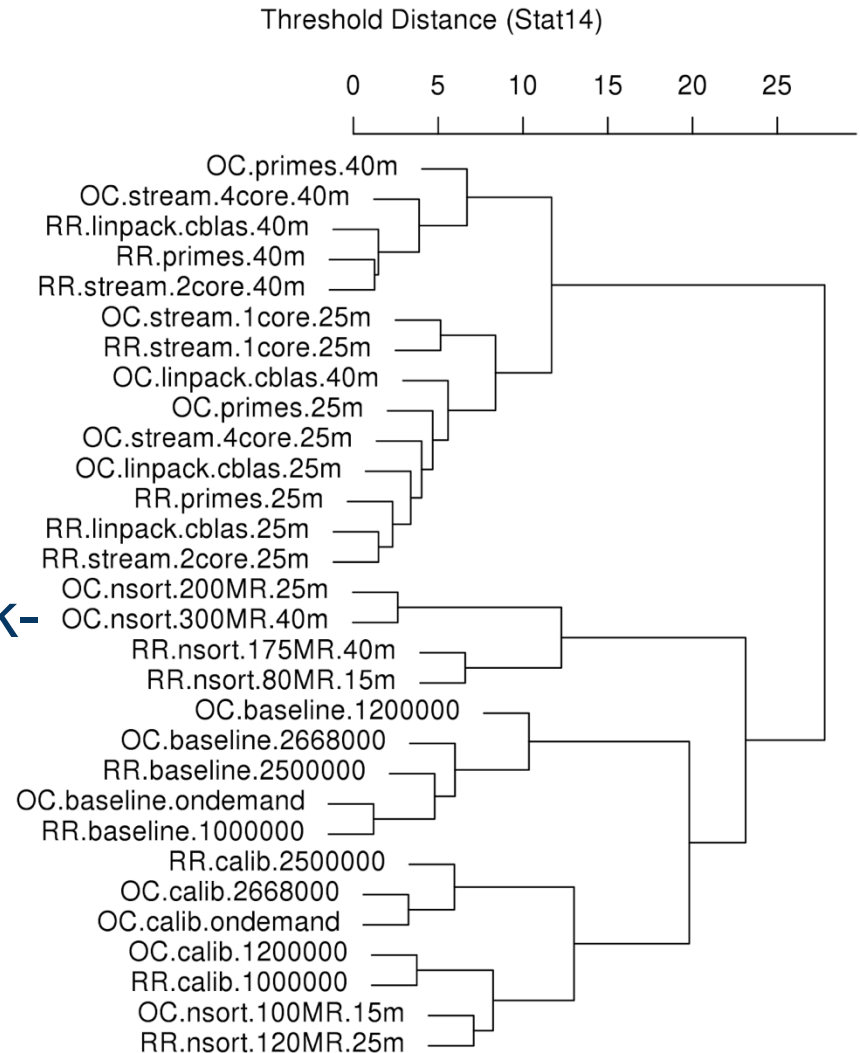


Clustering Results

- OCRR data
 - n=30
 - 6 workloads (different input configurations)
- Algorithm: hclust
- Signature: **stat14**
- Distance: Manhattan

4-clustering:

- Stream, Prime95, Linpack-CBLAS
- Sort
- Baseline
- Calib



Clustering Metric

Ideal clustering: by workload.

Info-theoretic measure of partition similarity:
Aadjusted Normalized Mutual Information

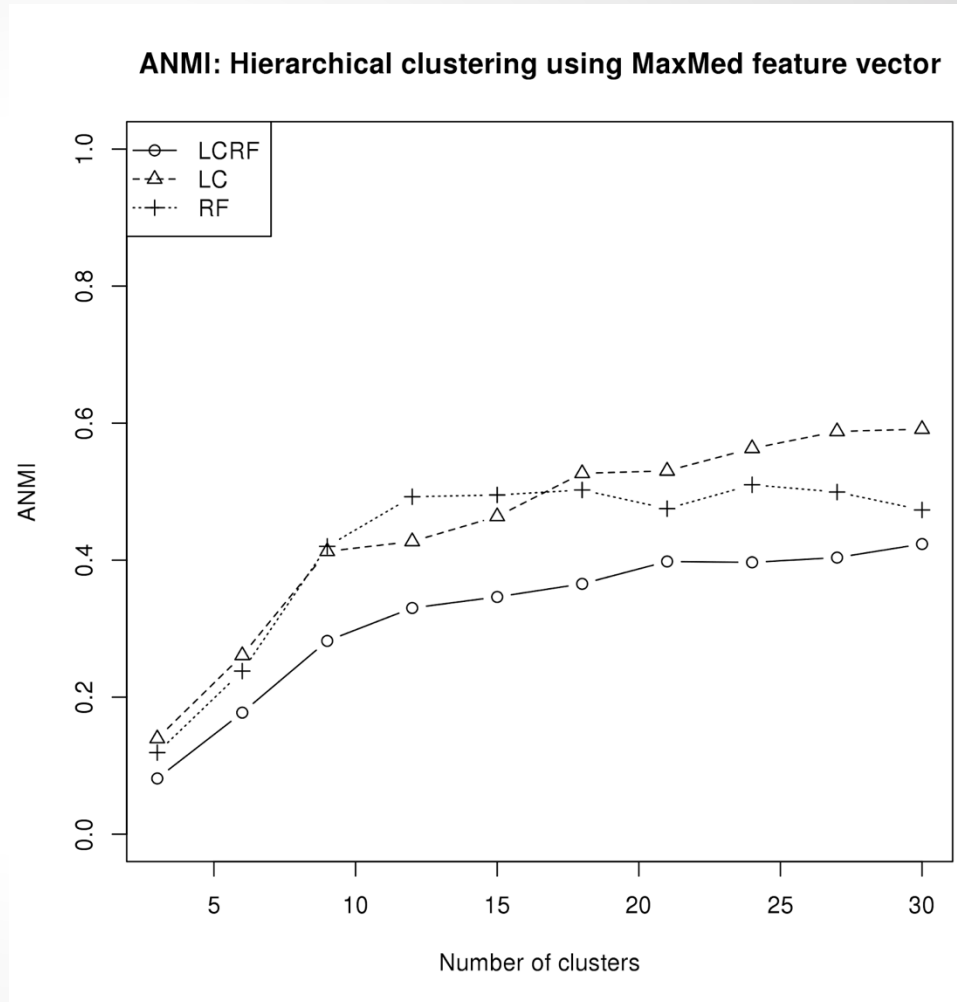
(Derived from NMI)

- $NMI = (\text{Mutual information}) / (\text{Joint entropy})$
- NMI is between 0 (worst) and 1 (best)
- Expected ANMI of two random partitions is 0.

Clustering Results

- Data:
 - LCRF (n=225)
 - LC (n=111)
 - RF (n=114)
- Algorithm: hclust
- Signature: **MaxMed**

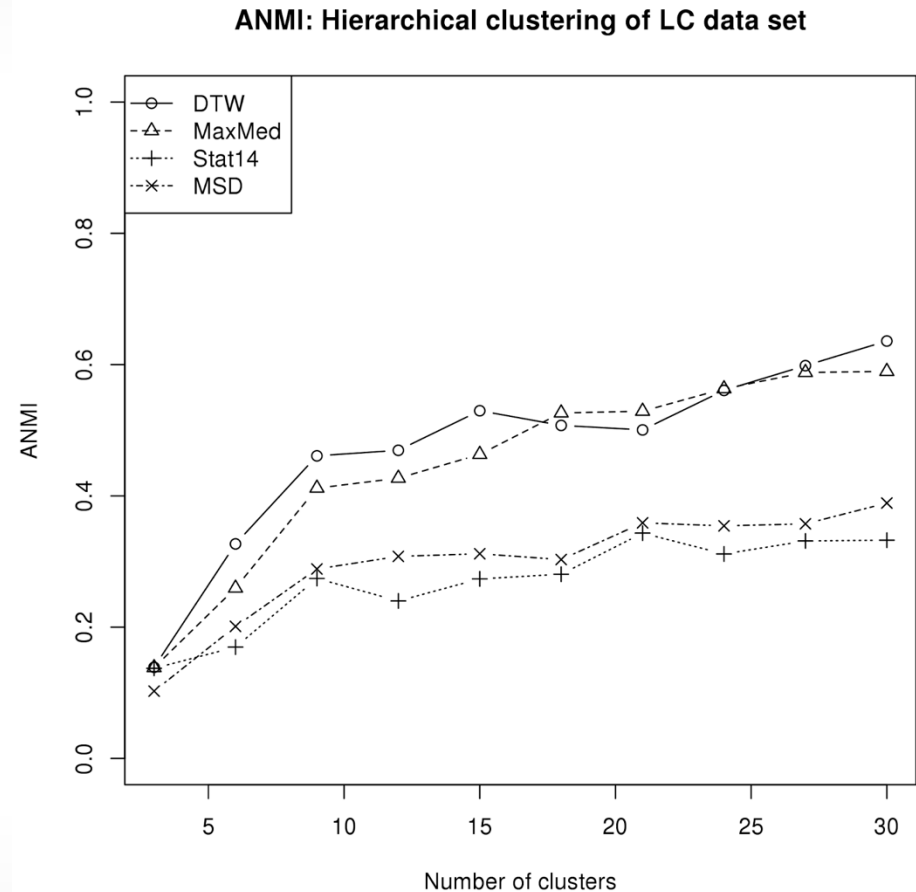
Signatures may be more consistent *within* hardware platform



Clustering Results

- Data: LC (n=111)
- Algorithm: hclust

MaxMed and **DTW** signature methods are more effective than **Stat14** and **MSD**



Classification Results

- Trained a random forest classifier on LCRF data (n=225)
- Using **MaxMed** or **Stat14** yields leave-one-out accuracy >80%

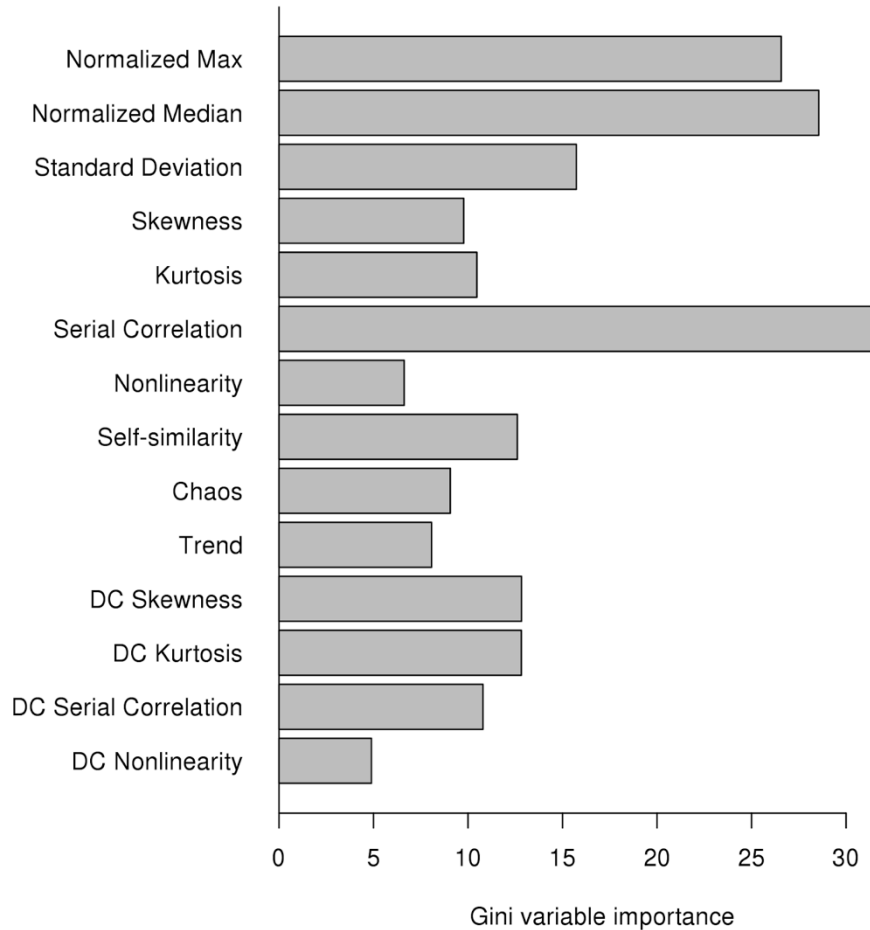
Classification Results

Gini variable importance suggests:

- **MaxMed** is a good subset of **Stat14**

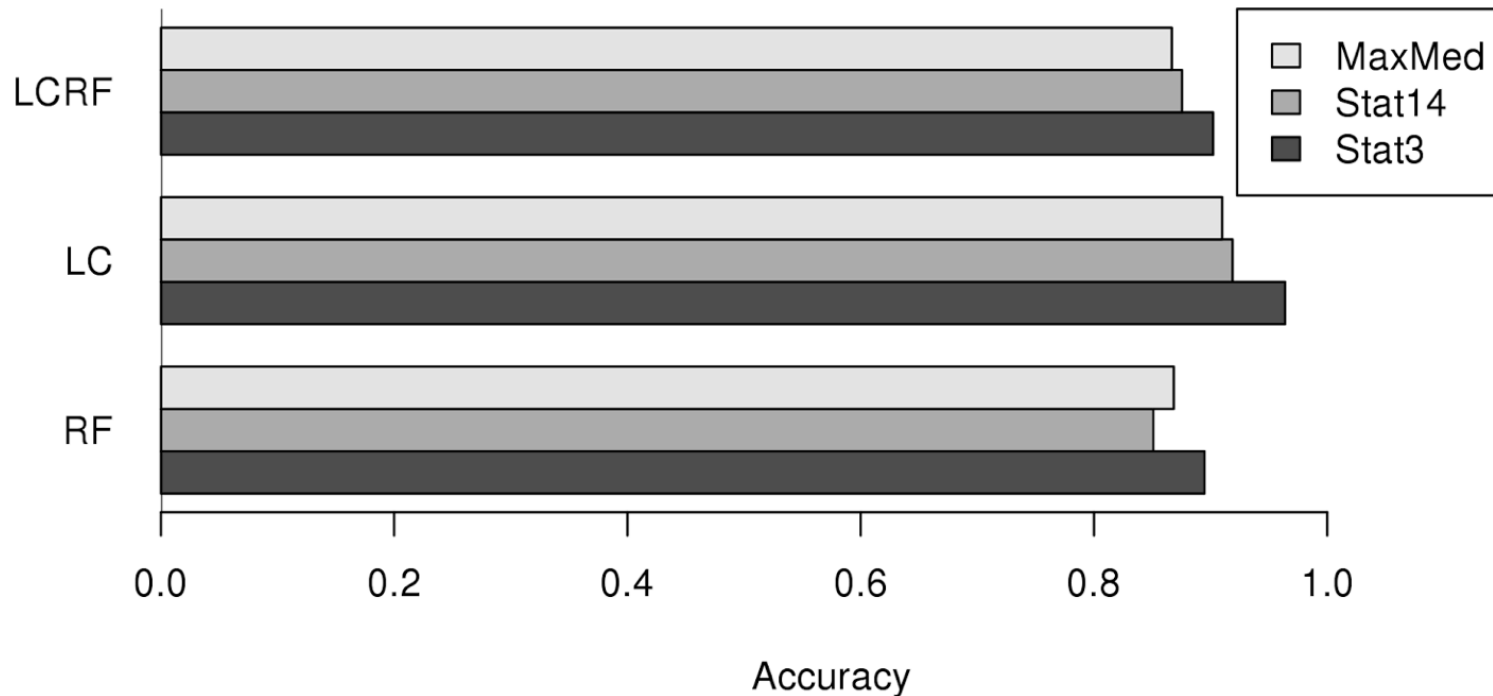
- Try **Stat3**:
< Normalized
Maximum,
Normalized Median,
Serial Correlation

>



Classification Results

- **Stat3** classifier labels traces with >85% accuracy



Conclusions

- We evaluated different types of signatures:
 - Time-series-based
 - **Feature-based**
- Some workloads have unique signatures, some workloads are less easily distinguished from others.
- Signatures can distinguish workloads across hardware platforms, but are more effective given data from a single machine type.

Current and Future Work

- Expand to:
 - Heterogeneous workloads
 - MPI/distributed workloads
 - Finer-grained or coarser-grained samples
- Online workload recognition
- Workload-aware energy-efficient scheduling

Acknowledgements

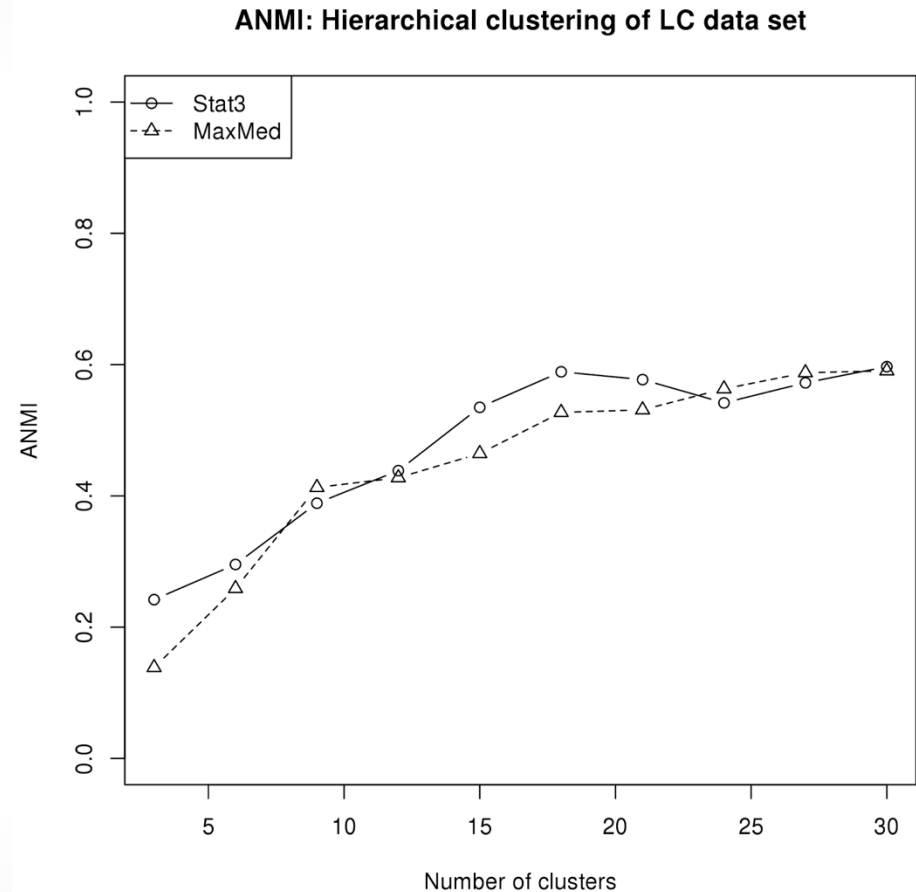


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Afterthought: Clustering Again

- Data: LC (n=111)
- Algorithm: hclust

Stat3 is *not* obviously better than **MaxMed** for clustering



Backup: More Clustering Results

- Data: LCRF (n=225)
- Algorithm: hclust

The result holds for multiple platforms:

MaxMed and **DTW** signature methods are more effective than **Stat14** and **MSD**

