Detecting Task Phases from Power Traces

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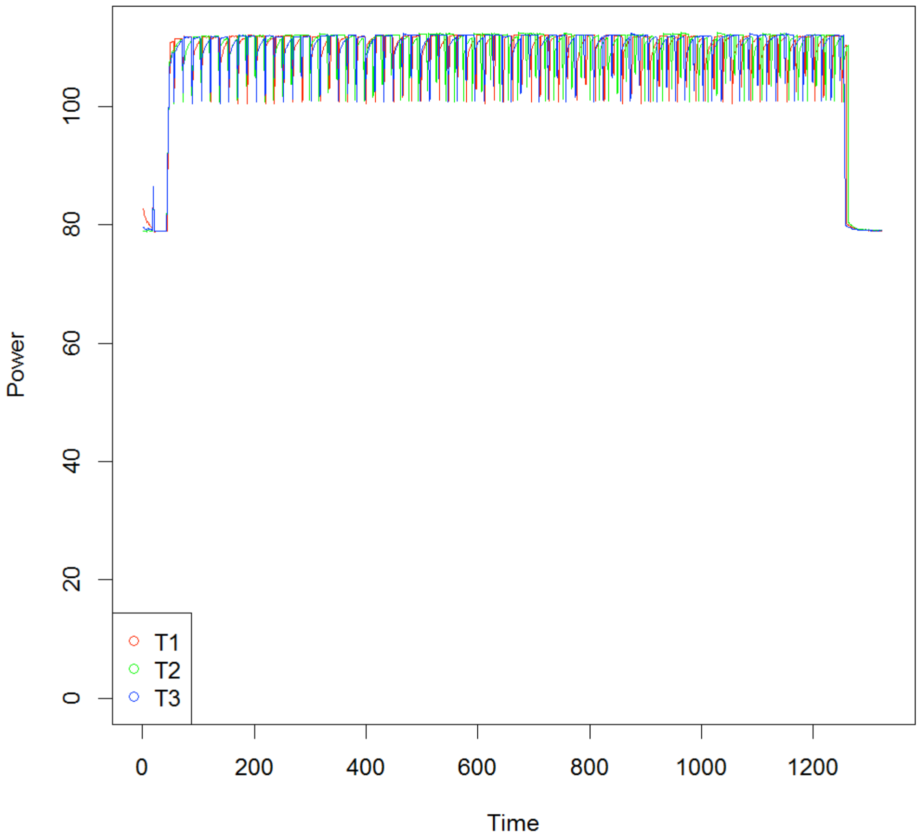
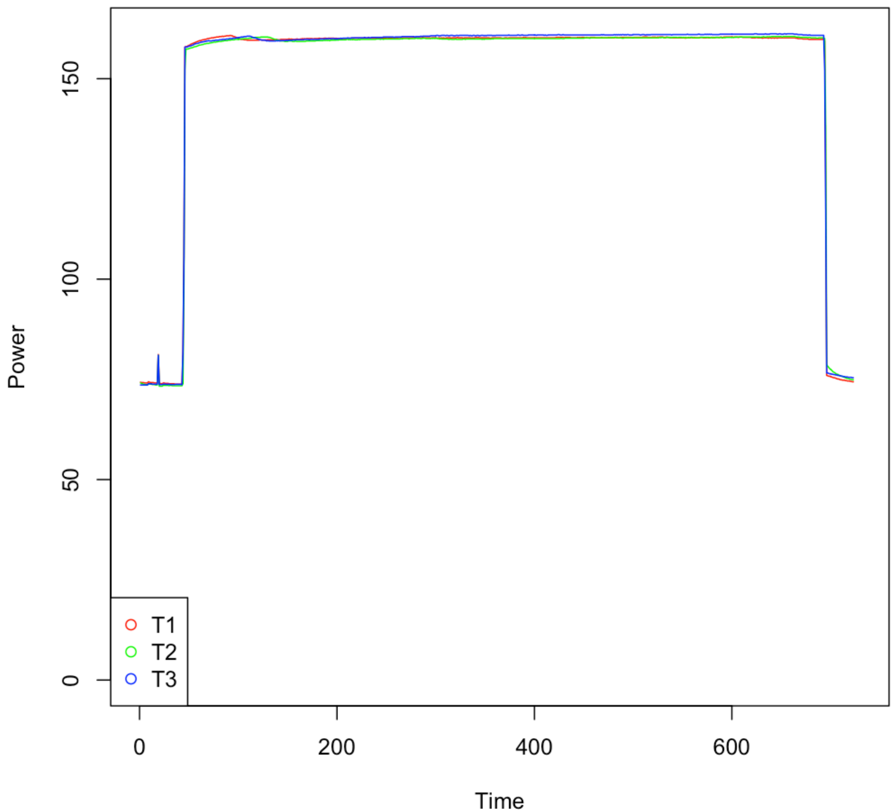
Workshop on Performance Modeling, Benchmarking, and Simulation @ SC
November 13, 2016

Prior work

We can identify applications based on *power traces*





Task Type Recognition

- Collapse each trace into a vector of statistical features
- Use classifier to guess best matching task type
- We leverage existing classifier based on **random forest** of decision trees (accuracy 85-90%)

[Combs et al., E2SC 2014]

Limitations

- Operates on entire traces, with no insight into local behavior
- Can’t recognize novel combinations of known task types
- Doesn’t allow resource management policies to dynamically adapt to finer-grained phases of a job
- **Goal:** automatically partition a trace into concatenated *phases* and recognize the task type of each

Steps in Phase Recognition

1. Identify **change points** in power trace
   Ex: `t={20, 150, 300, 430}`
2. Identify intervals as **candidate phases**
   Ex: `[0, 20); [20, 150); [0, 150)…`
3. **Predict the task type** of each candidate phase
   Ex: `[0, 20): idle; [20, 150): FFT…`
4. Choose the best **final partition** of the trace

```
[0, 150): FFT
[150, 300): sort
[300, 430): GUPS
[430, end): idle
```

Experimental Setup

- Dataset of 388 traces from 21 “kernels”
  - **NPB:** bt, cg, ft, lu, sp, ua
  - **Mahout data analytics:** ALS, bayes, SGD, kmeans
  - **SystemBurn:** Tilt, fft1d, fft2d, dgemm, gups, scublas
  - **Other:** Nsort (external sort), primes95, STREAM, graph500, baseline (idle)
- Iteratively and randomly:
  - Remove 5 traces from dataset and concatenate to form a “test trace”
  - Build random forest from remaining traces
  - Partition test trace into kernels
- Correctness metric: how many data points in the trace were assigned to the right kernel?

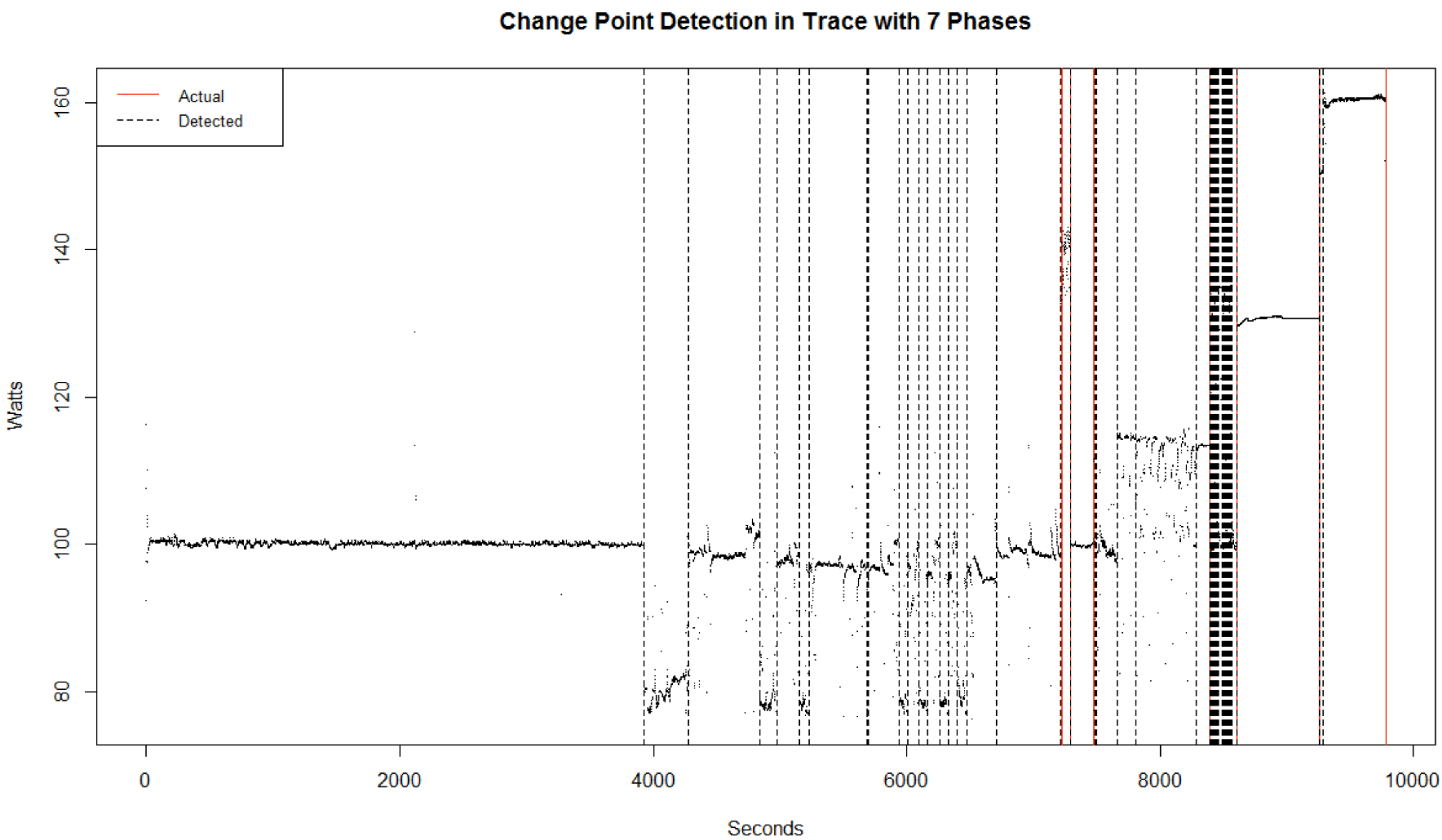
Change Point Detection

- **Definition:** detecting abrupt changes in the statistical properties of a time series
- **Hypothesis:** Since we've shown that different task types have different statistical properties, the boundaries between different task types should also be *change points*
- **Goal:** detect a superset of the actual phase boundaries
  - We can weed out spurious change points in later steps…
  - ...at the cost of computational complexity

Change Point Detection Algorithm

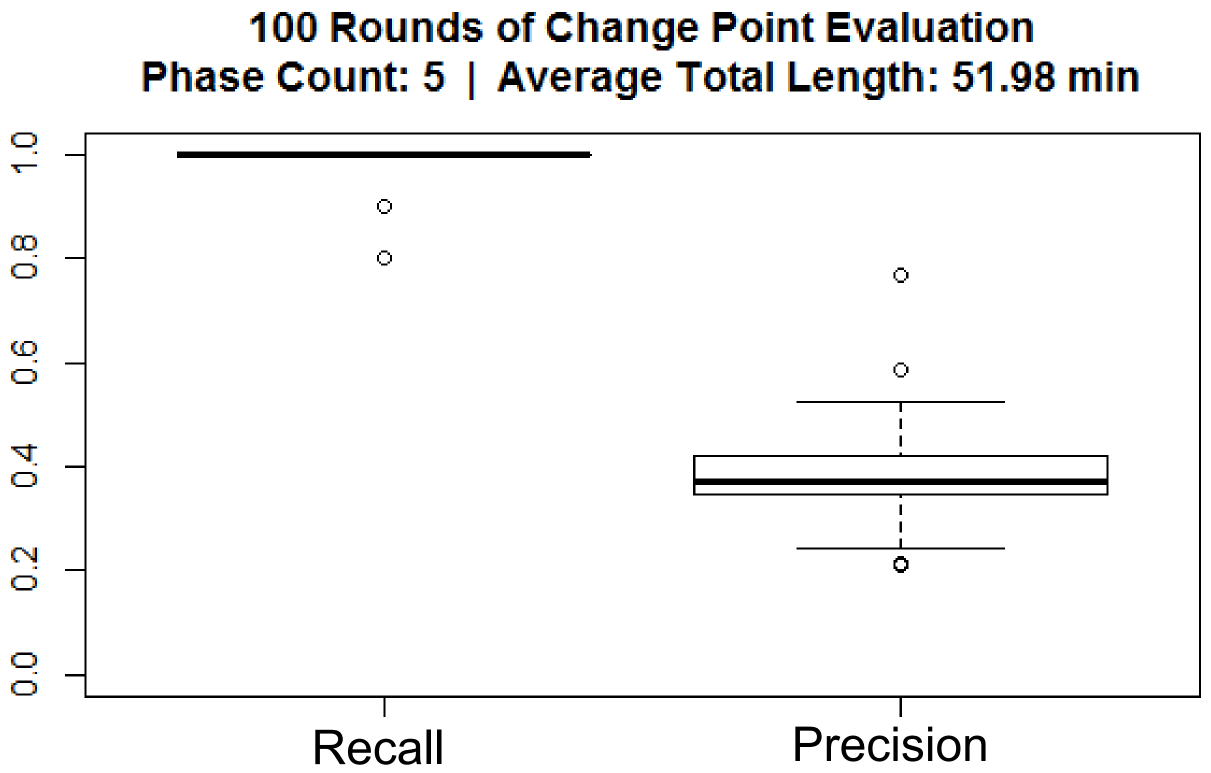
- Evaluated variants of *binary segmentation* [Scott and Knott, 1974]
- Basic idea:
  - Find best single changepoint in dataset; stop if none found
  - Recursively use to partition dataset and repeat
- Our best variant: *wild binary segmentation (WBS)* [Fryzlewicz, 2014]
  - Search for “best changepoint” in random intervals of different lengths
  - Better for irregularly spaced / short phases

Change Point Detection Example



Change Point Detection Results

- “Correct” change point: within 3 samples of actual task type transition

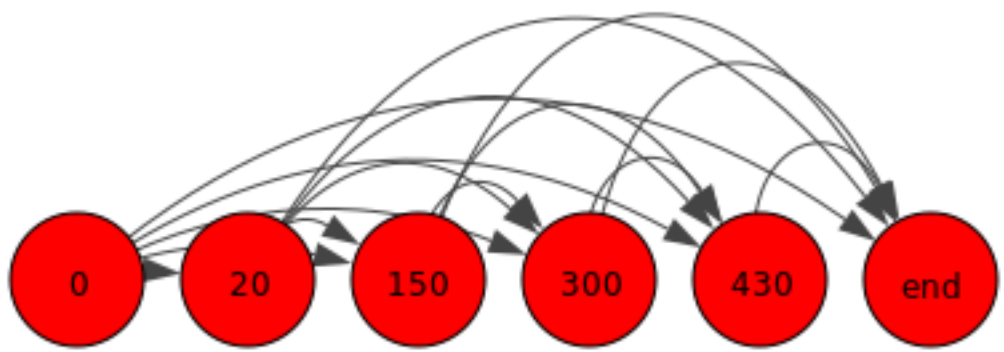


Candidate Phase Identification

- Identify pairs of change points as *candidate phases*.
- **Minimal approach:** consecutive pairs only
  - Computationally simplest
  - …but will always fail to recognize internally complex task types
- **Maximal approach:** all possible pairs
  - Computationally expensive
  - ...but guarantees inclusion of all real phases if change point algorithm worked
- **Our approach:** maximal (computationally tractable for our traces)

Final Partition

- **Build graph:** nodes for change points, edges for candidate phases



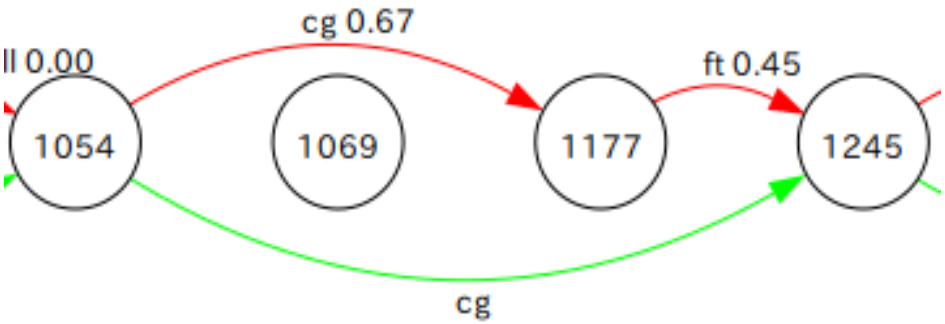
- **Weight edges** based on confidence of task type prediction [see next slide]
- **Compute longest path** to get final partition

Edge Weights

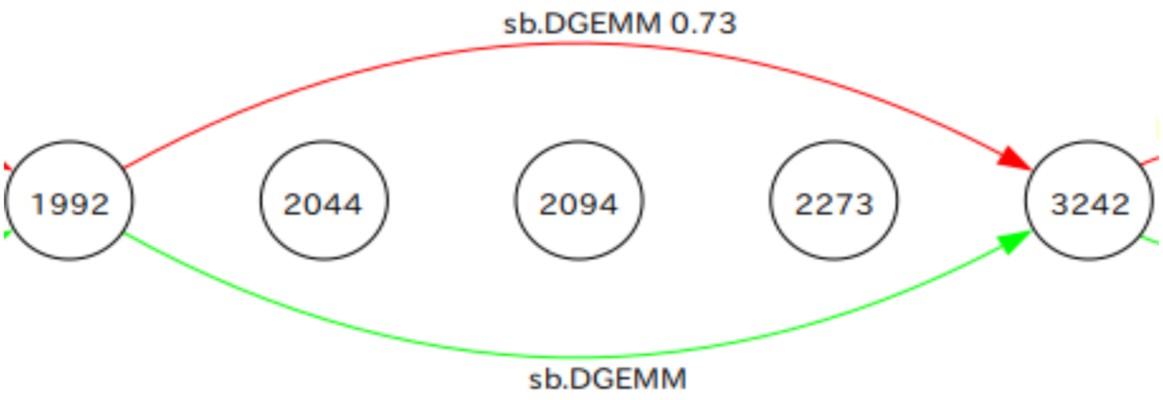
- Use internal properties of random forest
- **Certainty:** what fraction of trees voted for this task type?
- **Proximity:** how similar is this phase's path through the trees to the paths taken by others in its type?
- **Weight by** interval length

```
0.5 * (certainty +
proximity to traces of predicted
type) * interval_length
```

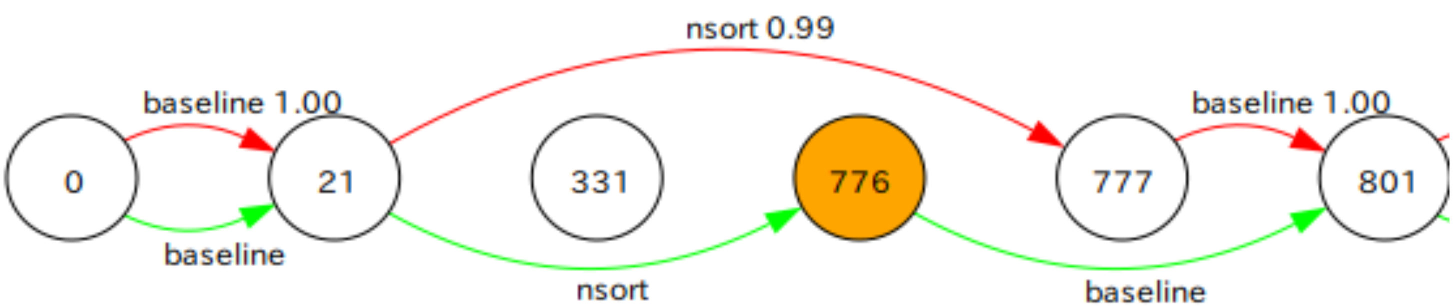
Examples



ll 0.00
cg 0.67
ft 0.45
1054
1069
1177
1245
cg



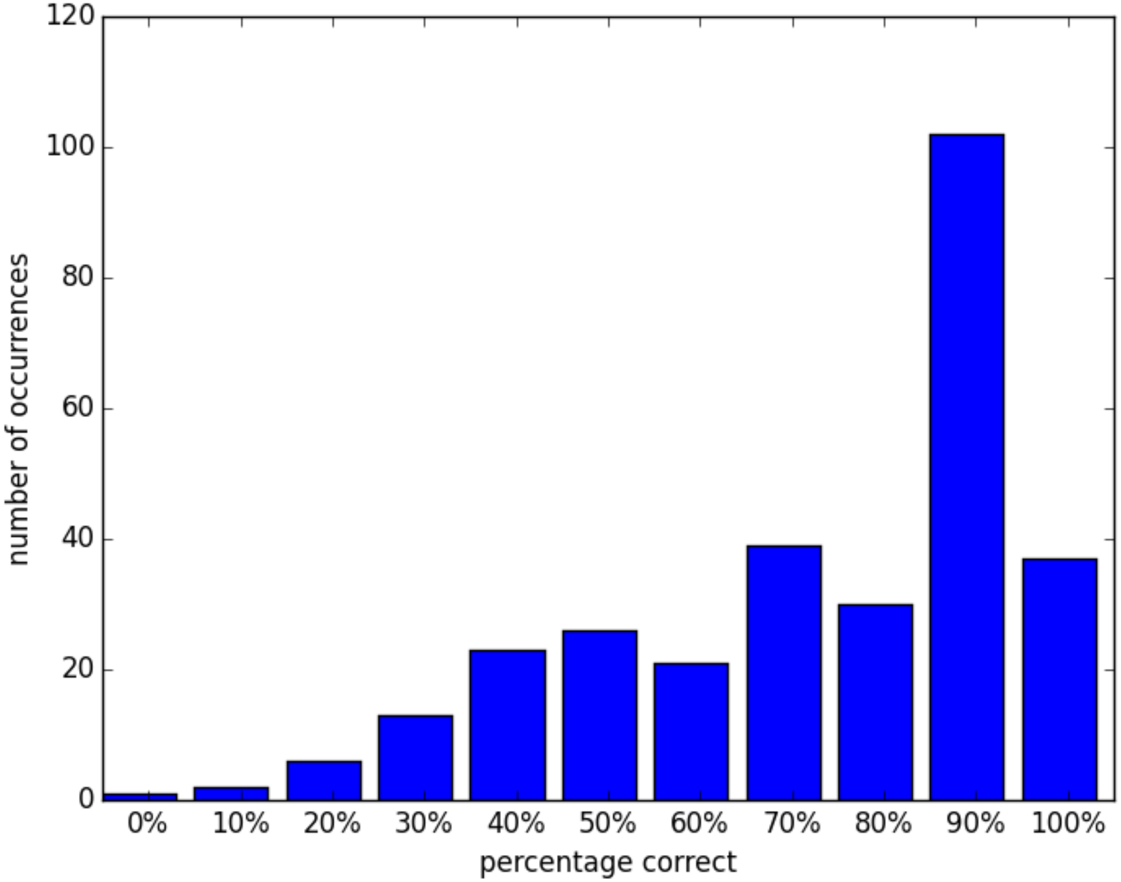
sb.DGEMM 0.73
1992
2044
2094
2273
3242
sb.DGEMM



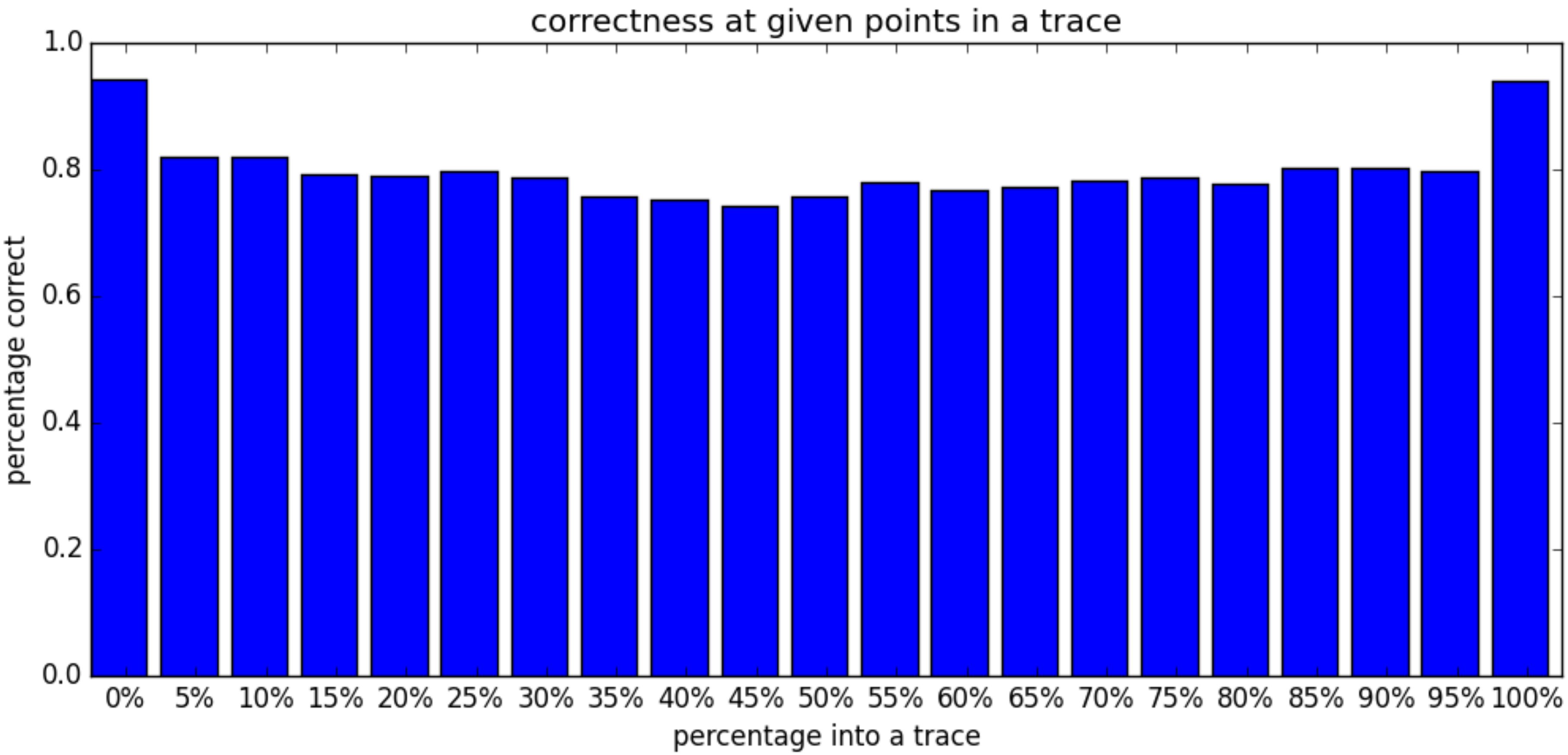
nsort 0.99
baseline 1.00
baseline 1.00
0
21
331
776
777
801
baseline
nsort
baseline

Correctness: Histogram

- Metric: number of data points attributed to the right "kernel" over 300 runs



Correctness throughout the length of the trace



Conclusions

- Can break a trace into its constituent phases with high accuracy (mean 78%)
- Possible improvement
  - Prune candidate phases to reduce computational complexity
  - Use internal measures of trace complexity to tune target number of change points
  - Explore other methods of computing edge weights
  - Try higher frequency power measurements (RAPL).
- Possible extensions
  - Adapt to mix of known and unknown task types
  - Online recognition

Questions?

Test Machines (Single-Node)

	LC	RF
CPU	Intel Core i5-750 @2.67Ghz	Intel Core i7-3770 @ 3.40Ghz
RAM	8GB	8GB
GPU	GeForce GTX 650 Ti 1GB	GeFroce GTX 670 2GB
Power	85-252W	74-309W

Random Forest Feature Vector

- Normalized Max
- Normalized Min
- Standard Deviation
- Skewness
- Kurtosis
- Serial Correlation
- Nonlinearity
- Self-similarity
- Chaos
- Trend
- Skewness of detrended trace
- Kurtosis of detrended trace
- Serial Correlation of detrended trace
- Nonlinearity of detrended trace
- 4 Fourier Coefficients, skipping first

Trace Complexity

- We define the complexity of a single trace as log(number_of_change_points) / log(trace_length)
- Different thresholds can be used to determine the change in power required to define a single change point.
  - Based on Standard Deviation
  - Based on range
  - Based on Interquartile Range
  - Based on mean absolute deviation

Complexity results