Evaluating Benchmark Subsetting Approaches

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Introduction

- Architects often select specific benchmarks to:
  - Reduce simulation time
  - Focus on specific characteristics (*e.g.*, memory behavior)
  - Build a benchmark suite

- Key challenge for selecting or subsetting benchmarks is:
  - To select a *representative* subset

Benchmark Subsetting Approaches

- Popular/emerging subsetting approaches include:
  - By principal component analysis (PCA)
  - By performance bottlenecks (Plackett and Burman)
  - By percentage of floating-point instructions (integer vs. floating-point)
  - Compute-bound or memory-bound
  - By programming language
  - Randomly

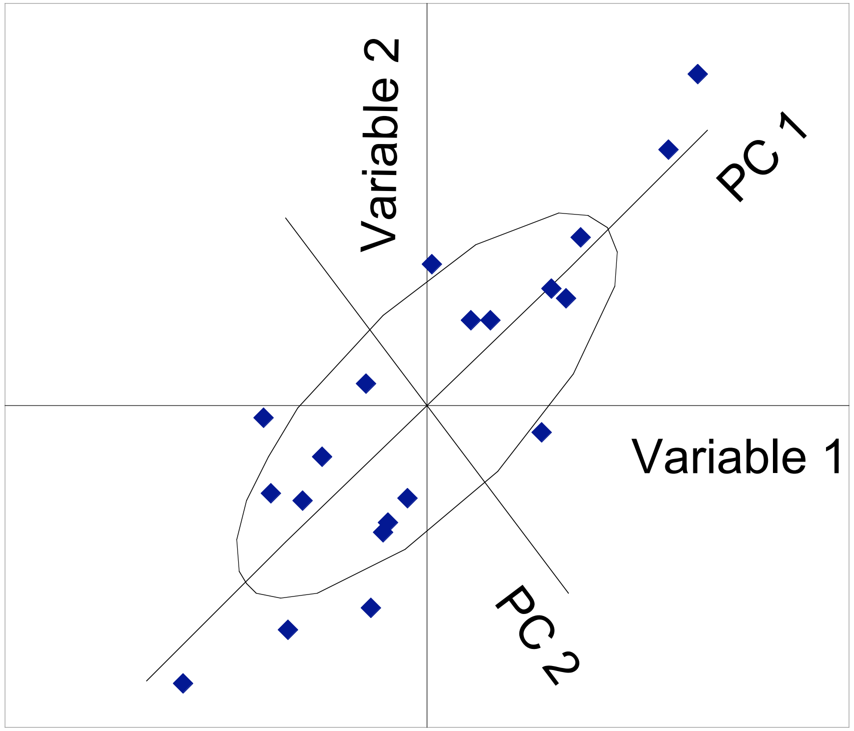
- But, which approach:
  - Produces the most accurate subset for a given subset size?
    - Absolute accuracy vs. relative accuracy
  - Produces the most accurate subset with the least profiling cost?
  - Most efficiently covers the space of benchmark characteristics?

Benchmark Subsetting Approach #1

- By principal component analysis (PCA):
  - Profile benchmarks to collect program characteristics
    - Instruction mix, amount of ILP, I/D footprints, data stream strides, *etc.*
  - Remove correlation between characteristics using Principal Component Analysis
    - Principal components are linear combinations of original characteristics
    - For more information on PCA, see [Eeckhout *et al.*, PACT 2002]
  - Cluster the benchmarks based on their principal components into N clusters
  - Select one representative benchmark from each cluster to form the subset

Removing Correlation using PCA

- Remove correlation between program characteristics
- Principal Components (PCs) are linear combination of original characteristics
- Var(PC1) ≥ Var(PC2) ≥ ...
- PC2 is less important to explain variation
- Reduce No. of variables
- Throw away PCs with negligible variance



$$PC1 = a_{11}x_1 + a_{12}x_2 + a_{13}x_3 + ...$$

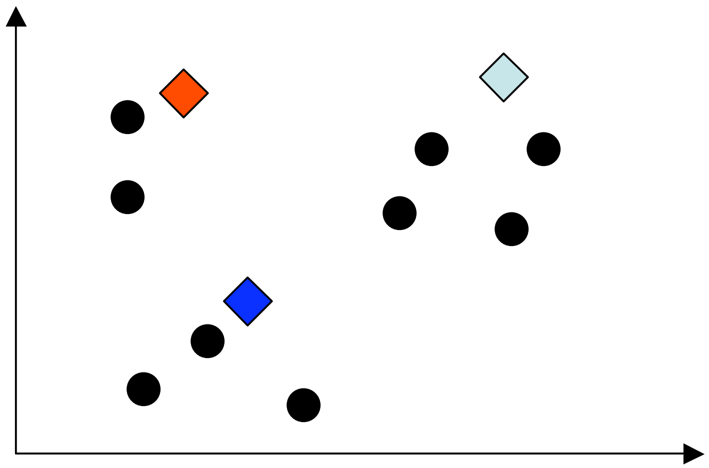
$$PC2 = a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + ...$$

$$PC3 = a_{31}x_1 + a_{32}x_2 + a_{33}x_3 + ...$$

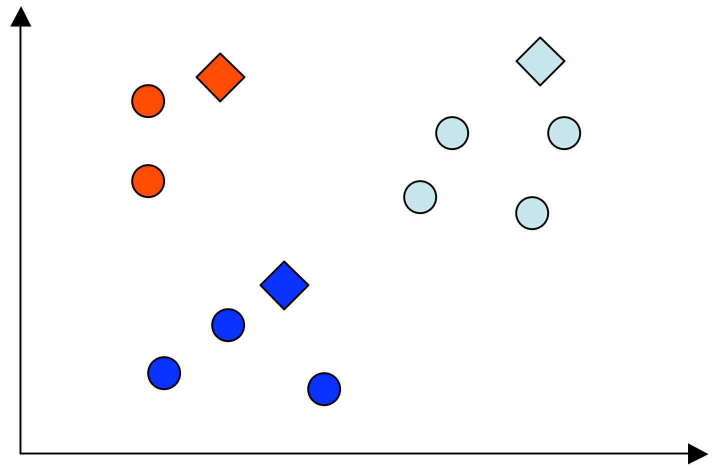
Clustering using k-means, Part 1

Cluster Analysis

K-Means Clustering algorithm



Step 1: Randomly select K cluster centroids

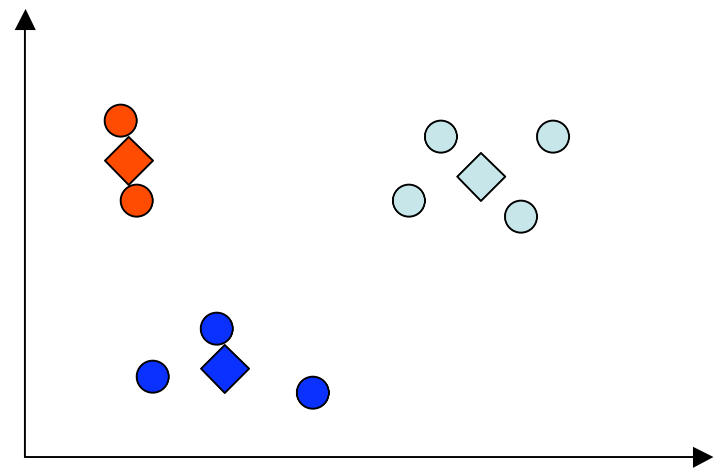


Step 2: Assign benchmarks to nearest cluster centroids

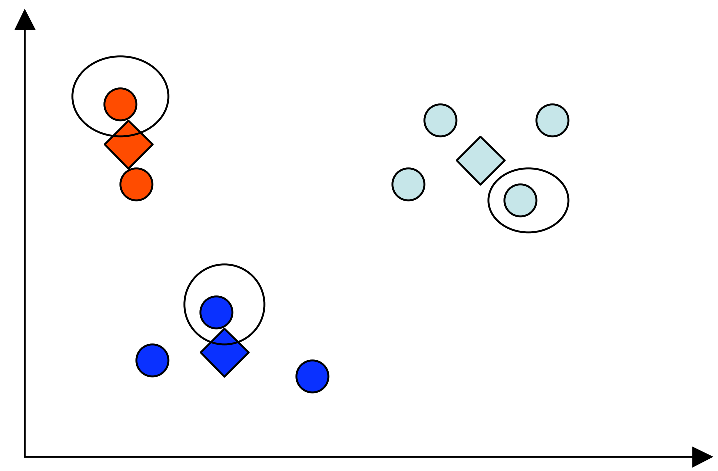
Clustering using k-means, Part 2

Cluster Analysis

K-Means Clustering algorithm



Step 3: Recalculate centroids and repeat Step 2 and 3 until algorithm converges



Step 4: Choose representative programs that are closest to the centroid of the clusters

Benchmark Subsetting Approach #2

- By performance bottlenecks (Plackett and Burman – P&B)
  - Use P&B design to quantify the magnitudes of all performance bottlenecks (CPI) in the processor and memory subsystem
    - Rank microarchitecture parameters based on their impact on overall performance
    - For more information on the P&B design, see [Yi *et al.*, HPCA 2003]
  - Cluster the benchmarks into N clusters based on:
    - Rank of magnitudes
    - Magnitudes
    - Percentage of CPI variation due to single bottlenecks
    - Percentage of CPI variation due to single bottlenecks and all interactions
  - Bottlenecks can be determined
    - Per benchmark
    - Across all benchmarks
  - Select one benchmark from each cluster to form the subset

Benchmark Subsetting Approaches #3 – #6

- By percentage of floating-point instructions (integer vs. floating-point)
  - SPECint vs. SPECfp
- Compute-bound vs. memory-bound
  - Compute-bound vs. memory-bound
    - Compute-bound: less than 6% L1 D$ miss rate for a 32KB cache
- By programming language
  - C vs. FORTRAN
- Randomly

Randomly choose benchmarks from each group
Form 30 different subsets for each group and report average results

Benchmark Subsetting Approach #7

- High-frequency
  - The de facto approach by computer architects
  - Form subsets based on descending order of frequency-of-use [Citron 2003, ISCA 2003 panel]
    - Choose most frequently used benchmark when subset size is 1
    - Choose two most frequently used benchmarks when subset size is 2
    - *etc*.

Methodology and Experimental Setup

- PCA profiling: ATOM
- Simulator:
  - SMARTS simulation framework (based on SimpleScalar)
    - U=1000 instructions, W=2000 instructions
    - 99.7% confidence interval, ±3% confidence level
  - P&B profiling: Added user-configurable latencies and throughputs

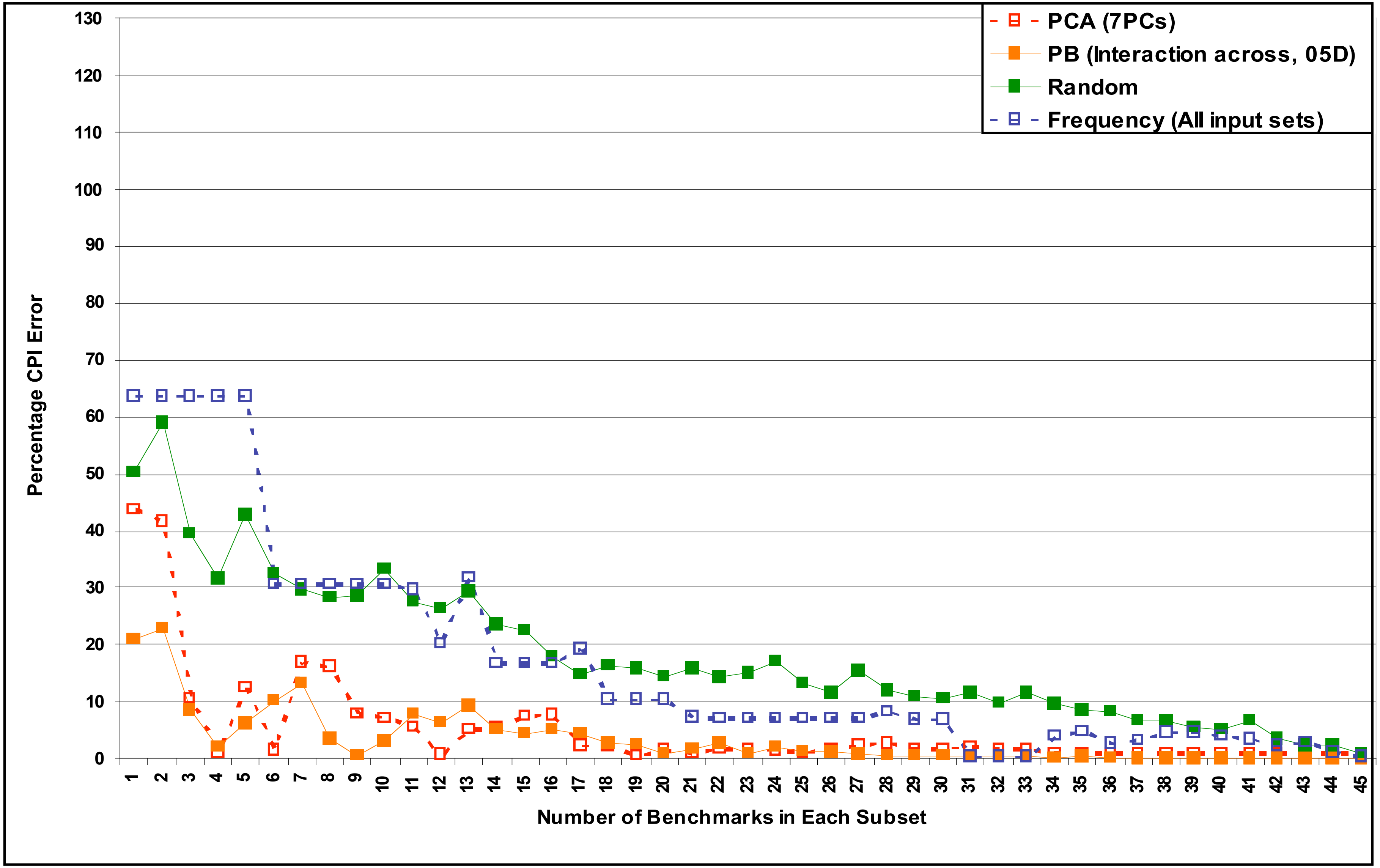
- Benchmark information
  - All SPEC CPU 2000 benchmarks and input sets
    - Except *vpr-place* and *perlbmk-perfect* crash SMARTS
  - Benchmark-input pair used synonymously with benchmark

- Processor configurations:
  - 4 4-way issue configurations, 4 8-way configurations
  - For each issue width, configurations represent range of configurations

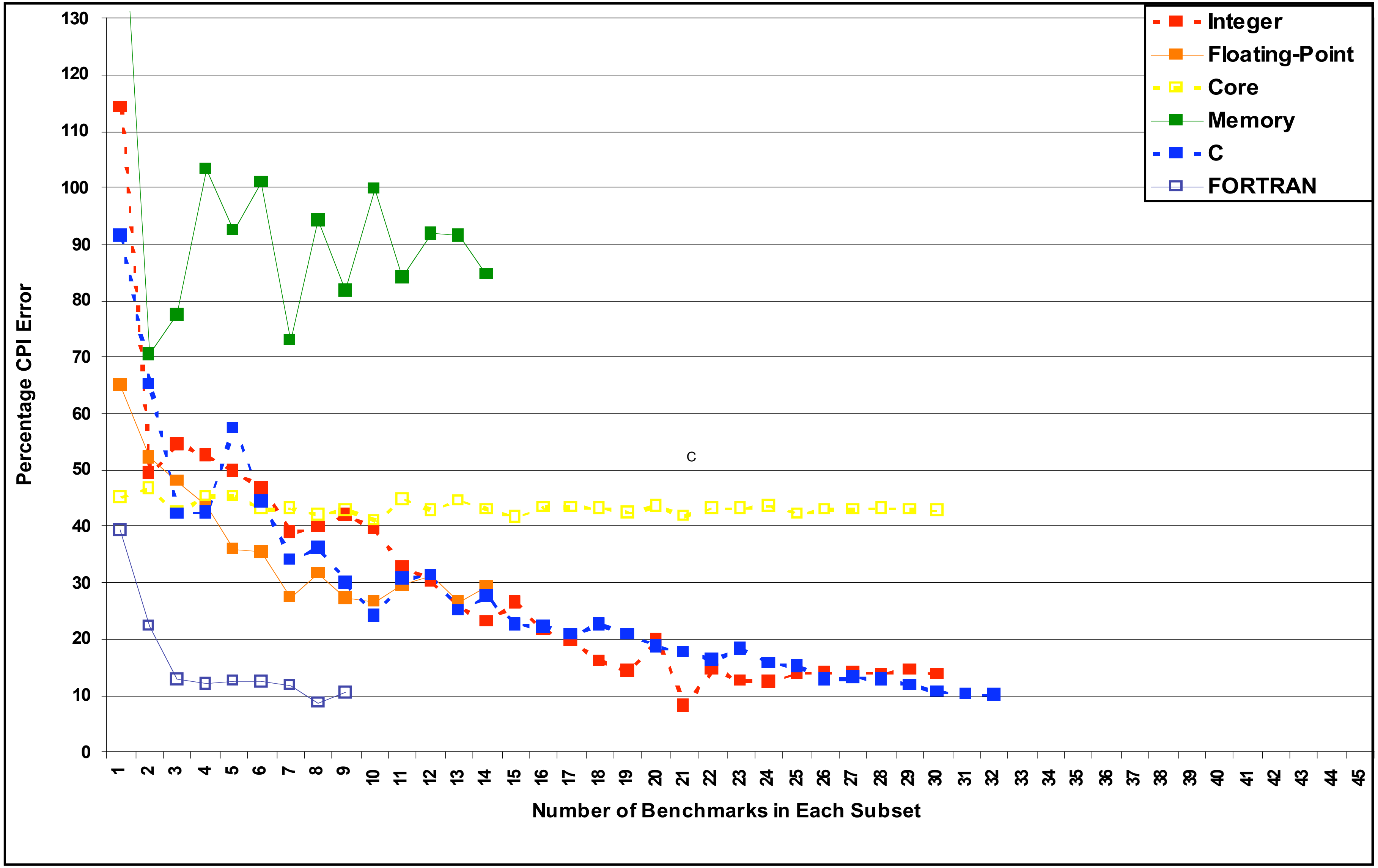
Quantifying Representativeness

- Absolute accuracy
  - Important when extrapolating results of subset for performance prediction of entire suite
  - Error in estimated CPI or EDP when using subset vs. full suite
- Relative accuracy
  - Important when comparing alternative designs during early design space exploration studies
  - Error in estimated speedup when using subset vs. full suite
- Coverage of the workload space
  - Important when selecting a subset of programs when designing a benchmark suite
  - Minimum Euclidean distance of the benchmark's characteristics of each subset away all individual benchmarks

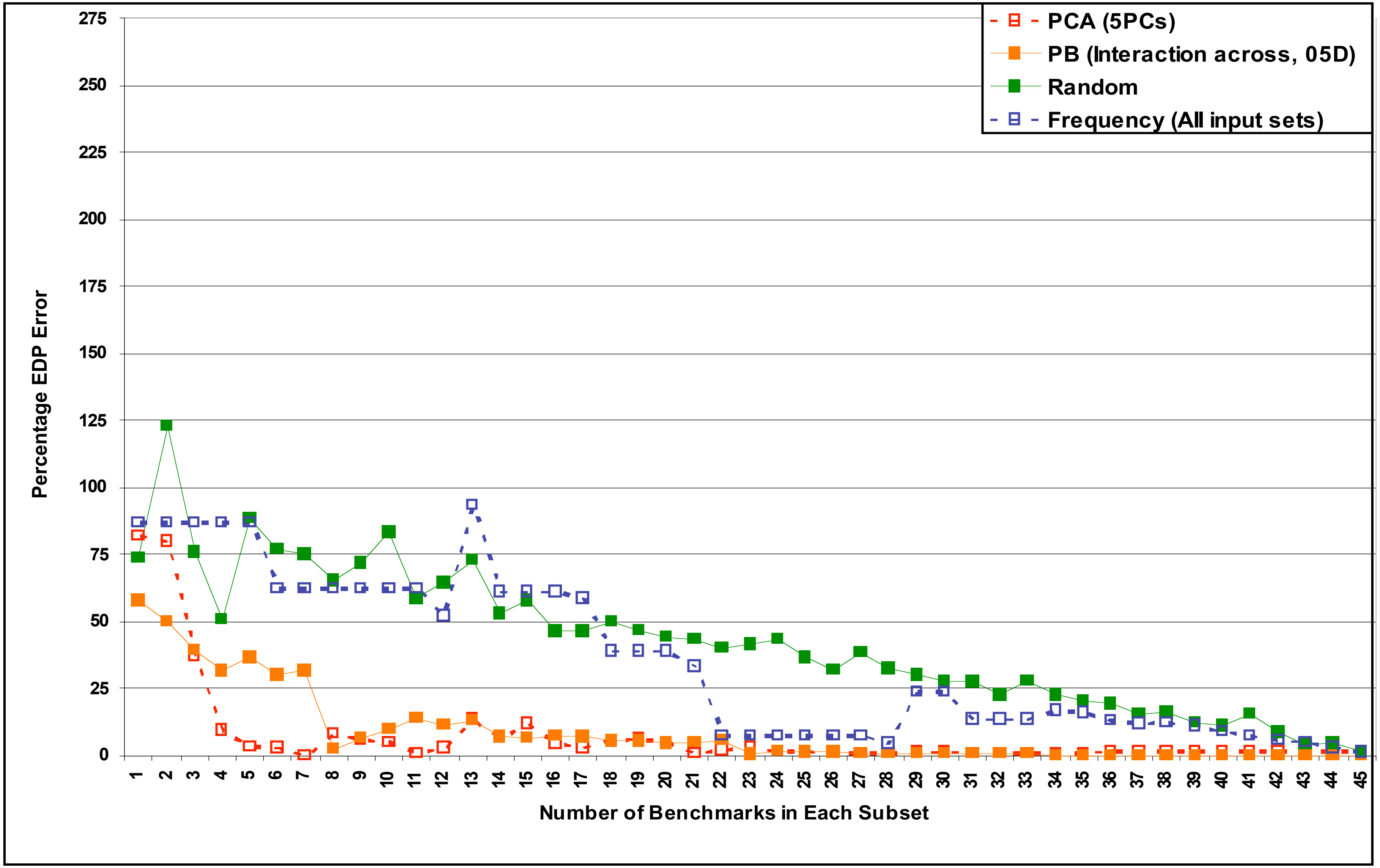
Absolute CPI Accuracy, Part 1



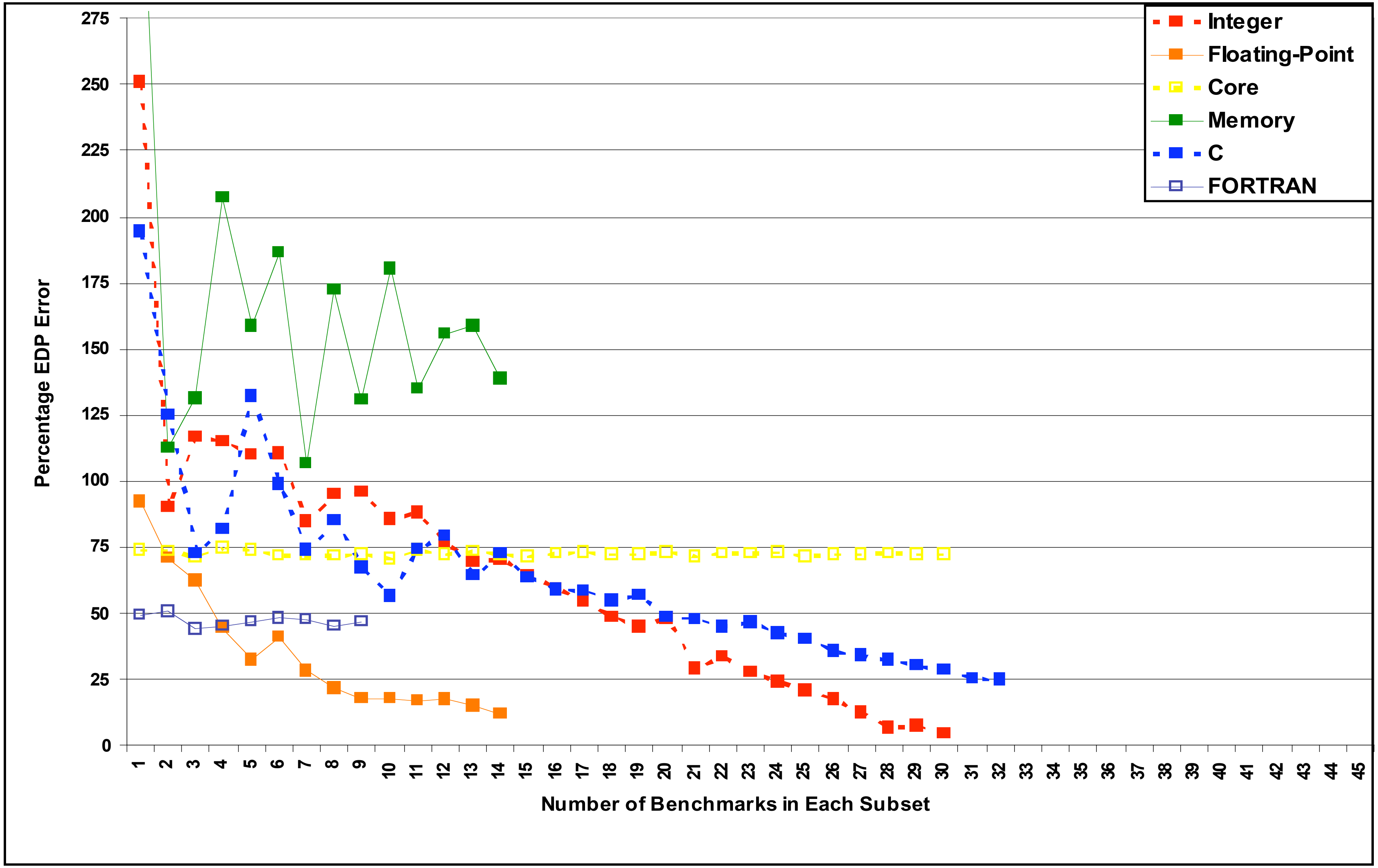
Absolute CPI Accuracy, Part 2



Absolute EDP Accuracy, Part 1



Absolute EDP Accuracy, Part 2



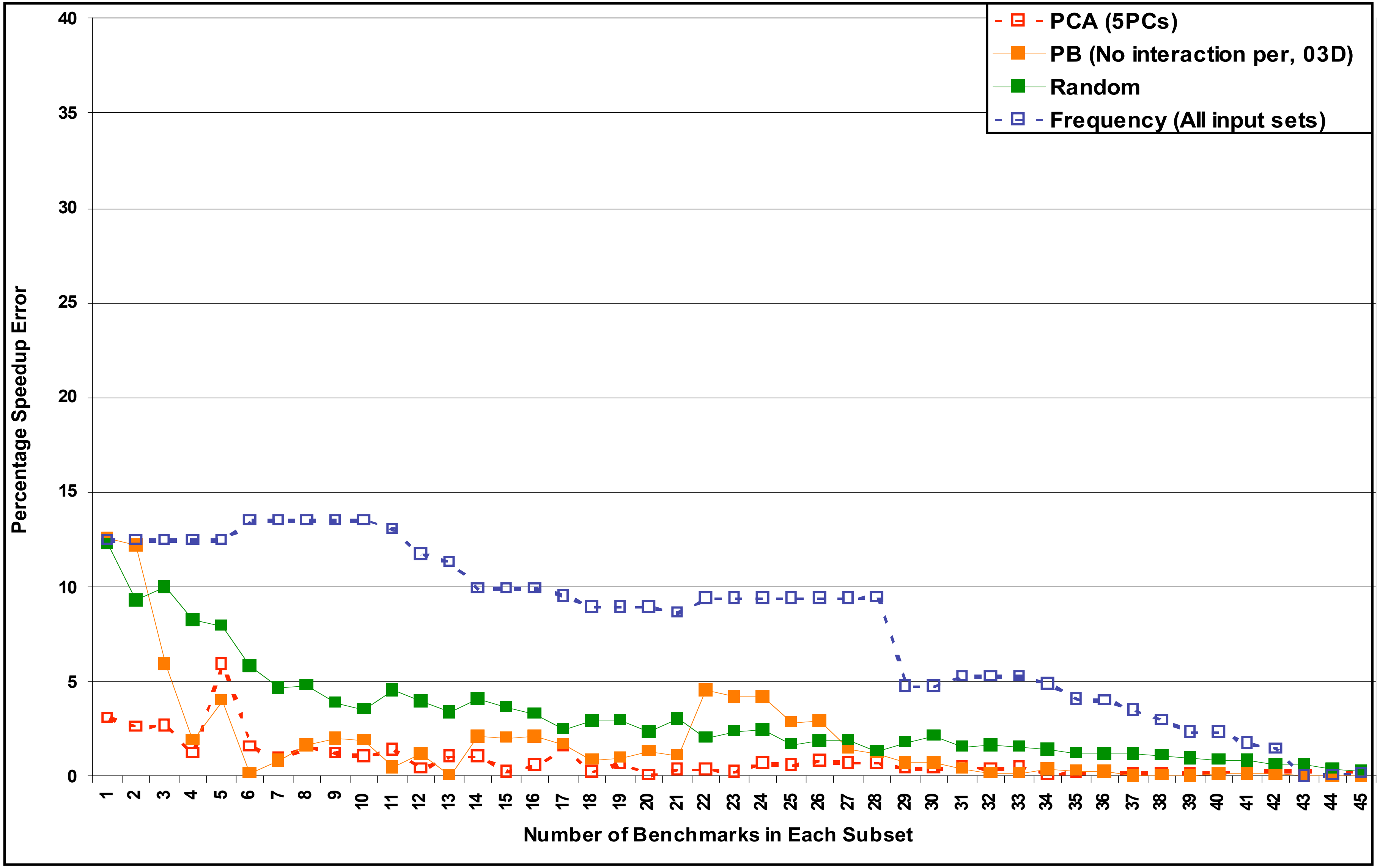
Key Conclusions for Absolute Accuracy

- Most accurate approaches:
  - PCA with 7 principal components
  - P&B using Top 5 bottlenecks
  - If want < 5% CPI error, need at least 17 benchmark-input pairs (1/3 of the entire suite)
- Int vs. float, compute vs. memory, language, and random approaches have poor and inconsistent CPI/EDP
  - Results based on these approaches may be misleading
- High-frequency approach
  - Overly optimistic DL1 and L2 cache hit rates
  - Some subsets may be pessimistic about branch prediction accuracy
- Statistical approaches are the most reliable way to subset benchmarks

Computing Relative Accuracy

- Compute the average speedup across entire benchmark suite for the following enhancements:
  - 4X larger ROB and LSQ
  - Next-line prefetching with prefetch buffers
  - 4X larger DL1 and L2 caches, 8-way associativity, same hit latency
- Compute the average speedup across benchmarks in each subset
- Compute speedup error when using a subset and when using the entire suite
  - Relative error = $(\text{Speedup}_{w/SS} - \text{Speedup}_{wo/SS}) / \text{Speedup}_{wo/SS} * 100$

Relative CPI Accuracy (ROB), Part 1



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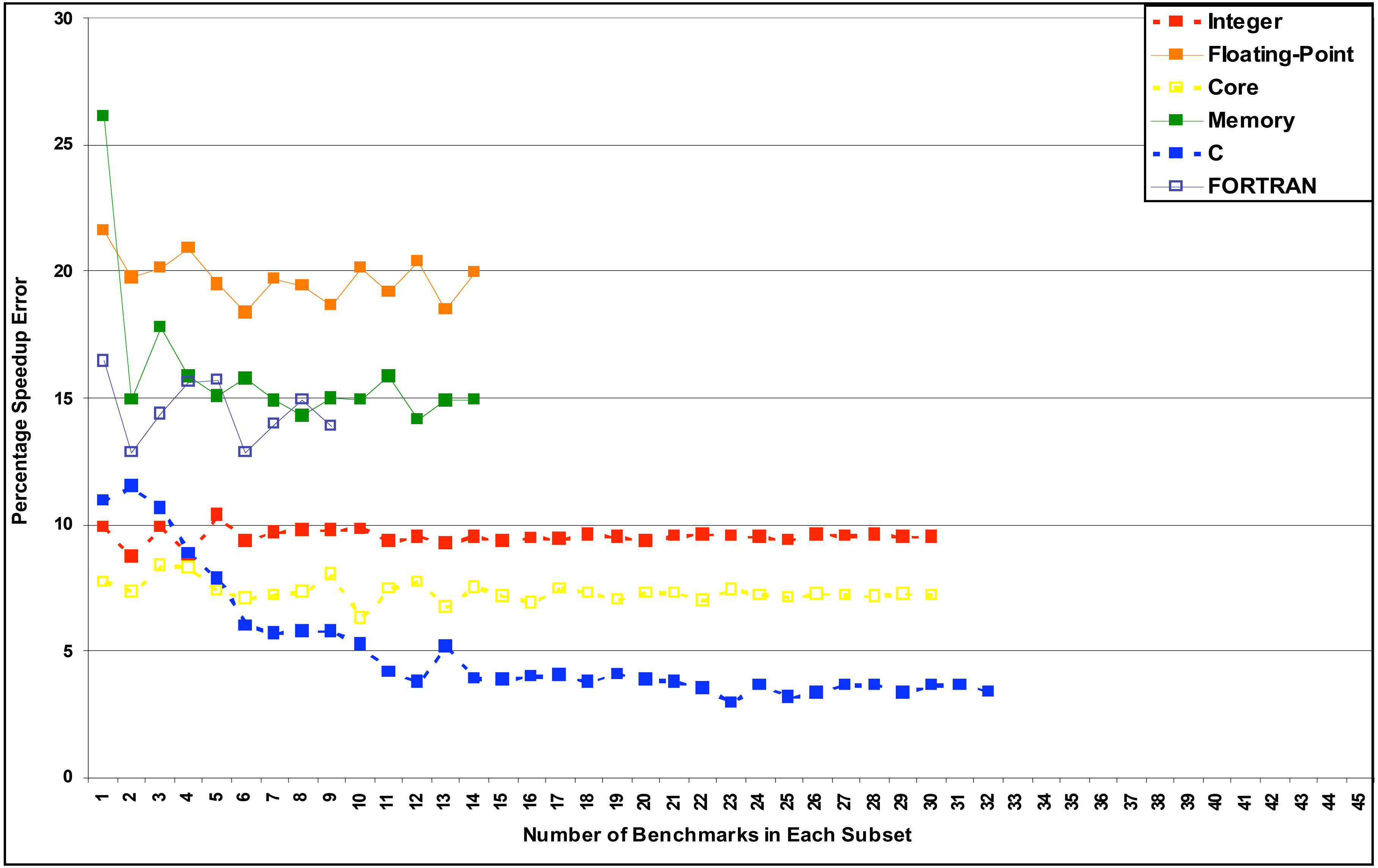
Relative CPI Accuracy (ROB), Part 2



Key Conclusions for Relative Accuracy

- Conclusions are similar to those for absolute accuracy
  - PCA and P&B are more accurate
  - Other 5 approaches are not accurate
- Accuracy generally improves with larger subset sizes
- Similar results across all processor configurations
- Key difference: Relative error is lower than absolute error
  - Relative error is typically < 20% for most approaches/subset sizes
  - Absolute error is typically > 20% for most approaches/subset sizes
  - Less variation in CPI across configurations (*i.e.*, for relative accuracy) than across benchmarks (*i.e.*, for absolute accuracy)
    - Matched-pairs comparison

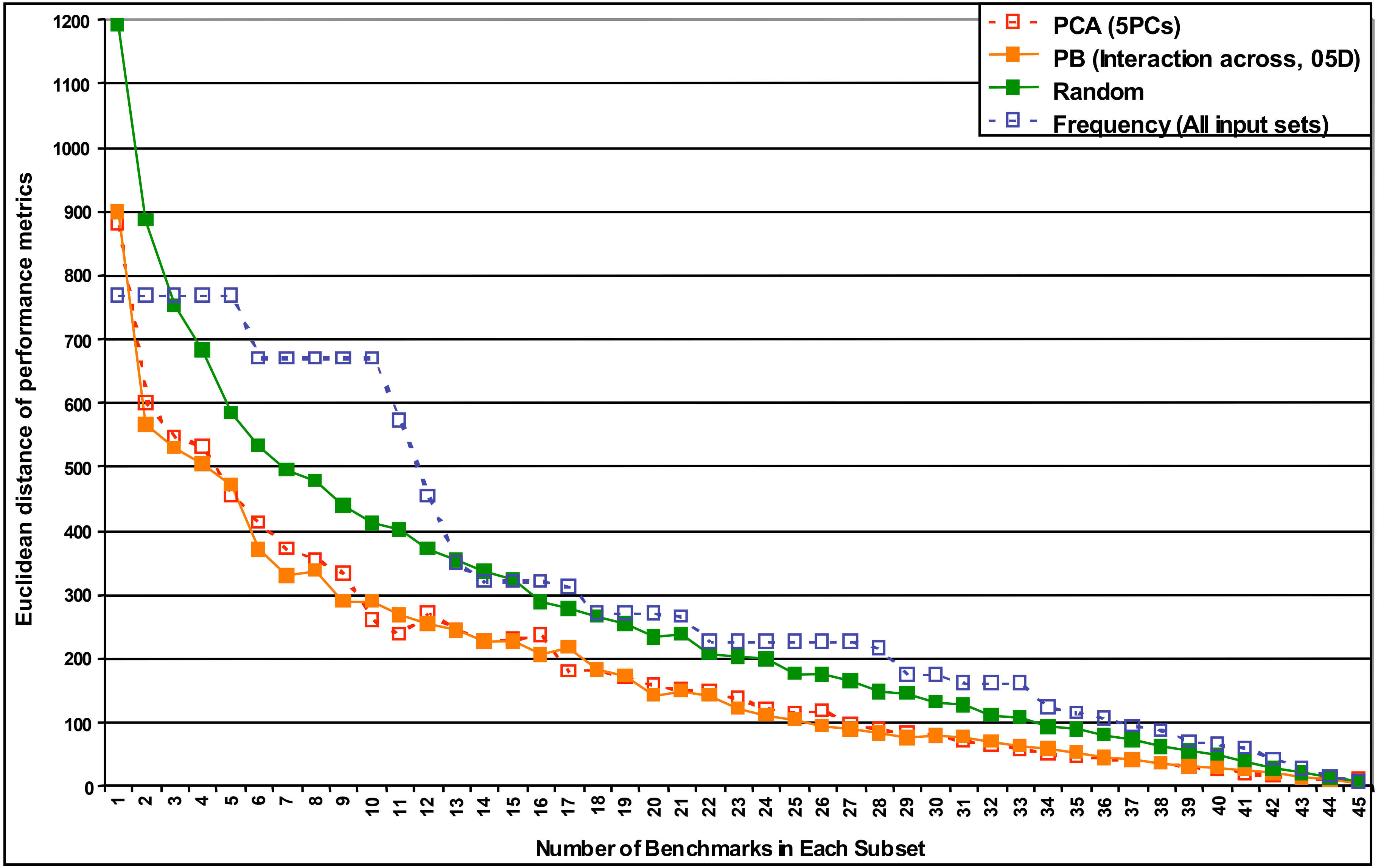
Computing Coverage

- Vectorize the performance and power metrics for each benchmark
  - Performance metrics: IPC; branch prediction accuracy; L1 D-cache, L1 I-cache, L2 cache hit rates, D-TLB, and I-TLB hit rates
  - Power metrics: Power for rename logic, branch predictor, reorder buffer, load-store queue, register file, L1 D-cache, L1 I-cache, L2 cache, functional units, result bus, and clock network
- Normalize each metric and scale to 100
  - Normalize performance metrics to maximum possible value
    - Maximum IPC = Issue width
  - Normalize power metrics to their percentage of the total power consumption
- Compute the Euclidean distance between each benchmark NOT in the subset to each benchmark IN the subset
- For each benchmark NOT in the subset, assign the minimum Euclidean distance as its distance
- Sum the Euclidean distances for all benchmarks NOT in the subset and assign that number as the total minimum Euclidean distance for that subset size

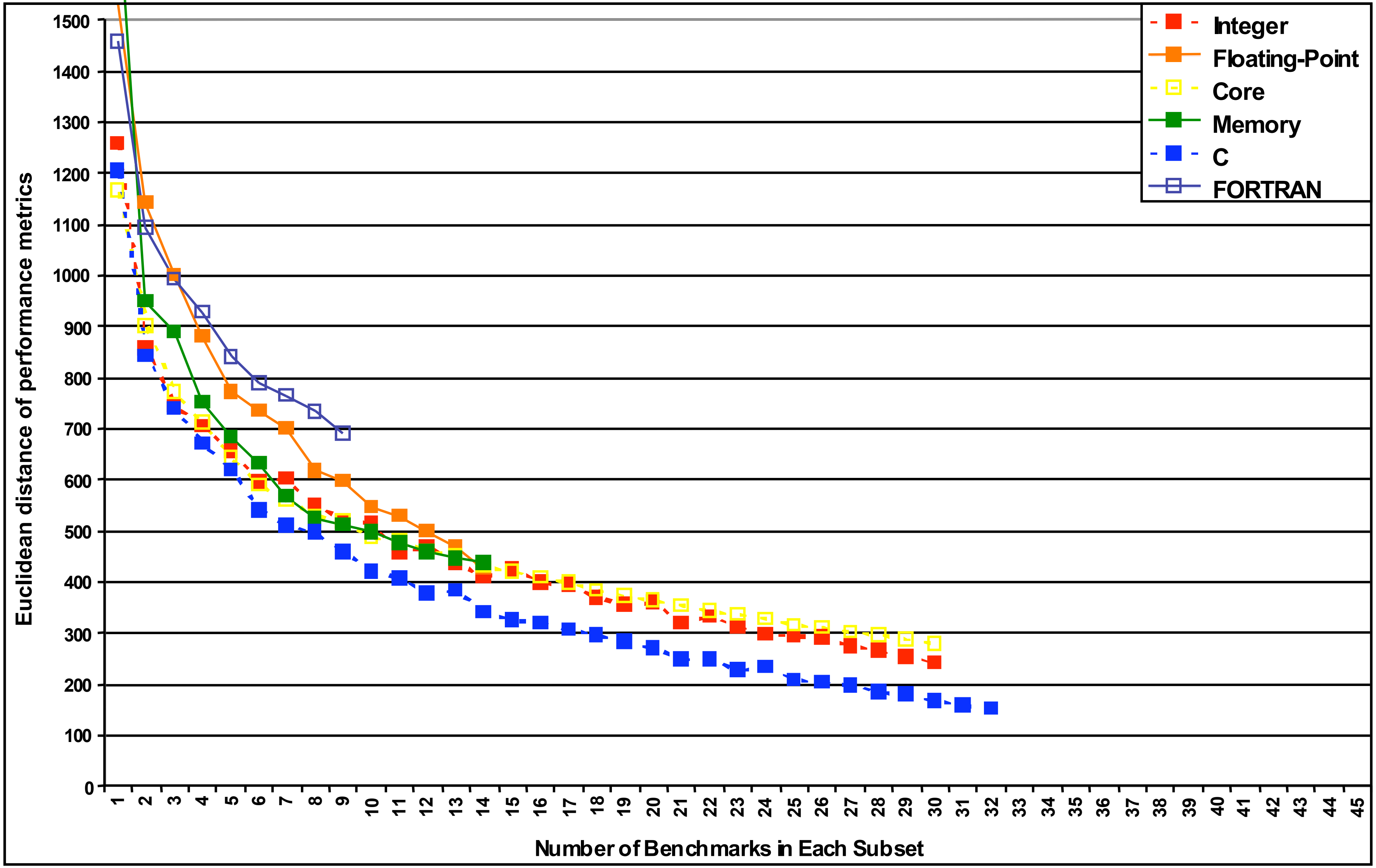
Coverage Intuition

- Total Euclidean distance represents how well the benchmarks in the subset are spread throughout the entire space of benchmarks
- A smaller total Euclidean distance means that benchmarks that are not in the subset are very close to a benchmark in the subset
  - Benchmarks not in the subset are accurately represented by a benchmark in the subset
  - Or, from the viewpoint of coverage, the benchmarks in the subset effectively cover the benchmark suite

Performance Coverage, Part 1



Performance Coverage, Part 2



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Key Conclusions for Coverage

- Conclusions are similar to those for absolute accuracy
  - PCA and P&B have good coverage
  - Other 5 approaches do not have good coverage
  - Same conclusions for absolute/relative accuracy and coverage
- Coverage generally improves with larger subset sizes
- Similar results across all processor configurations
- Smaller Euclidean distances for power metrics:
  - Smaller maximum values for power metrics
  - Less variability in power results

Accuracy vs. Profiling Cost

- Subsetting approaches have different accuracies, but what is their profiling cost?
  - PCA
    - Specialized functional simulator or instrumentation
    - Single run or many runs
    - Requires a couple of months to gather profiling data
  - P&B
    - Requires performance simulator
    - 88 very different processor configurations (*i.e.*, some very slow)
    - Requires several months to gather profiling data
  - No profiling cost for the other 5 approaches

- Based on accuracy and profiling cost, we recommend using PCA to subset benchmark suites

Conclusions

- Computer architects frequently use subsetting…
  … but accuracy of subsetting approaches is unknown
  - Absolute accuracy
  - Relative accuracy
  - Coverage

- PCA and P&B design
  - Have the best absolute and relative CPI/EDP accuracy
  - Error less than 5% for 20+ benchmark-input pairs
  - Most efficiently cover the space of performance and power characteristics
- Other 5 approaches have poor accuracy and coverage

- PCA has the highest accuracy at the lowest profiling cost

Thank you

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