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BSC Tools update

Using clustering and Folding

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Outline

(Computation Structure detection

- Short intro
- Aggregative Refinement
- Tracking program evolution
- Scaling clustering algorithm

(Instantaneous performance metric

- Clustering + Folding



Clustering

(Identification of computation structure

- CPU burst = region between consecutive runtime calls
 - Described with performance hardware counters
 - Associated with call stack data

(Using DBSCAN density-cluster algorithm

- Data not necessarily Gaussian





Outputs

Scatter Plot of Clustering Metrics



Clusters Distribution Along Time



Cluster Statistics

CLUSTER	1	2	3	4	5	6
% Time	36.29	29.52	10.13	9.68	3.73	1.71
Avg. Burst Dur. (ms)	220.46	177.70	60.81	29.09	38.71	44.83
IPC	0.53	0.50	0.62	0.77	0.66	0.59
MIPS	1210.07	1164.36	1403.19	1743.32	1499.47	1338.24
L1M/KINSTR	22.72	32.63	12.65	8.39	16.12	6.86
L2M/KINSTR	0.59	1.23	1.08	0.61	1.23	1.73
Mem.BW (MB/s)	90.77	182.65	193.32	136.33	236.15	295.71

Code Linking

CLUSTER	CODE SECTION
1	solve_nmm.f:[2037 - 2310]
2	solve_nmm.f:[1478 - 1782]
	solve_nmm.f:[2030 - 1782]
3	solve_nmm.f:[1241 - 1345]
4	solve_nmm.f:[2771 - 2865]
	solve_nmm.f:[2388 - 2489]
5	solve_nmm.f:[1478 - 1569]
6	solve_nmm.f:[1607 - 1633]



Using clusters to understand apps behavior (GROMACS)





Using clusters to understand apps behavior (GROMACS)







Identifying main code regions (PARSEK)









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DBSCAN characteristics

(Two parameters

- Epsilon: search radius
- MinPoints: minimum cluster density





DBSCAN Eps selection

(Which results are better?



285,961,719 ns





193,574,087 ns

THREAD 1.56

THREAD 1.64.1

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DBSCAN single *Eps* limitation





Refinement Algorithm Approach

- (Analogy between DBSCAN and hierarchical clustering
 - Iterative bottom up construction of a pseudo-dendogram
- (Cluster Sequence Score as target
 - Similar to X-means approach to decide K-means k parameter







Automatic Refinement of Parallel Application Structure Detection (ICPADS 2011)

BT A 4 tasks









VAC4 128 tasks





VAC4 128 tasks







VAC4 128 tasks



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Correlating multiple runs

(Use and correlate information from different runs

- Analysis of input parameters
- Code improvements
- Using different machines, compilers, flags, libraries
- Scalability studies
- Even for the same run: time evolution
- (Scatter plot = performance picture
 - Identifies objects and their weight
 - Correlation \rightarrow image tracking
- (Based on heuristics
 - Code regions evolve smoothly (things keep closer)
 - No common callstack means not the same region
 - Time sequence identify regions within and between runs



Barcelona Supercomputing Centre On the usefulness of object tracking techniques in performance analysis (UPC-DAC-RR-2012-18)

Scenario 1: Analysing scalability (WRF)

(**1**28 vs. 256





1.2

DBSCAN (Eps=0.018, MinPoints=10) Trace 'WRF.MN.256p.chop2.clustered2.prv'





Scenario 2: Comparing machines & compilers (CG-POP)



PowerPC, xlc



Intel, ifort







Scenario 3: Problem size impact (NAS-BT)

NOISE

NOISE

Region 1 1e+08 Region 2 Instructions Completed Region 3 Region 4 1e+07 Region 5 Region 6 1e+06 100000 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 IPC

Class W









Class B





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Sampling input data

(First target: online clustering

- Centralised approach (global clustering at the MRNet frontend)
- Data reduction trough sampling
- Data classification based on the samples clustering

All processes







8 representatives + 15% random



75% less data 6s down from 2m



Hierarchical DBSCAN

- 1. Local clustering
 - Up to 20-30k points per local process
- 2. Generate models
 - Convex hull, medial axis...
- Merge the hulls over the MRNet 3.
 - Intersect?
- Broadcast the global model 4.
- 5. Classify data locally using the global model
 - Point inside the hull?











PEPC 4K tasks, 3095134 points, 273 tasks (16 way tree, 256 leaves, 12k points per local clustering) \rightarrow clustering time 28.6 sec



Distributed tree-based implementation of DBSCAN cluster algorithm for parallel applications analysis (UPC-DAC-RR-2011-38) tro Nacional de Supercomputación

Comparison (parsek)

31515 points









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Comparison (WRF)

74240 points





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Can I get very detailed perf. data with low overhead?

- (Application granularity vs. detailed granularity
 - Samples: hardware counters + callstack
- (Folding: based on known structure: iterations, routines, clusters;
 - Project all samples into one instance
- (Extremely detailed time evolution of hardware counts, rates and callstack with minimal overhead
 - Correlate many counters
 - Instantaneous CPI stack models



Task 4 Thread 0 -- COPY_FACES:[{copy_faces.f}:{4,7}-{320,9}]



Unveiling Internal Evolution of Parallel Application Computation Phases (ICPP 2011)

Correlating with sources: which line should I look?







The "benefits" of Fortran 90 intrinsic (PEPC)



Interchanging loops (MR. GENESIS)





Pre-computing float data – loop split (PMEMD)

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Conclusions

(Performance analytics

- Data analytics applied to raw performance data
- From data to insight
 - Information is on variability and distribution
- Huge room for research

(Showed results of some techniques

- Clustering enables focusing the analysis and open many different uses on the analysis
- Folding makes possible to compute instantaneous performance metric functions with low overhead
- Tracking helps detecting movement in the performance space
 - Sequence of "frames" along many factors (not just time)



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