Dwarfs on Accelerators

Enhancing OpenCL Benchmarking for Heterogeneous Computing Architectures

THE AUSTRALIAN NATIONAL UNIVERSITY

Beau Johnston and Josh Milthorpe
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Trends in Supercomputing – A view from the Top500

1. Summit – GV100
2. Sunway TaihuLight
3. Sierra – GV100
4. Tianhe-2A
5. ABCI – V100
6. Piz Daint – P100
7. Titan – K20x
8. Sequoia
9. Trinity – Phi
10. Cori – Phi

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- 7 / 10 use accelerators
- Newest is Summit – based on IBM Power9 with NVLINK and CAPI
- All devices have an OpenCL runtime
- Small but representative benchmark suite is needed

OpenCL – The Language of Heterogeneous Computing

- Open Computing Language (OpenCL) is an open standard.
- Allows computationally intensive codes – kernels – to be written once and run on any compliant accelerator.
- Most vendors are compliant to basic standards.
- Application code can be written directly in OpenCL, and
- Can be used as a back-end for higher level languages – OpenMP runtime implemented for TI Keystone II DSP architecture[1].
- Increased relevancy for FPGA programming

[1] Mitra, G. et al. 2014. Implementation and optimization of the OpenMP accelerator model for the TI Keystone II architecture. International workshop on openmp (2014), 202–214.

Extended Open Dwarfs Benchmark Suite

- Extended Open Dwarfs (EOD) Benchmark Suite
- Based off the OpenDwarfs benchmark suite[2]
- Benchmarks selected following diversity analysis and 13 Berkeley Dwarfs taxonomy
- Built in OpenCL
- Purpose of OpenDwarfs was a to characterize a diverse set of parallel applications and architectures using a common language, but had deficiencies. . .

[2]Krommydas, K. OpenDwarfs: Characterization of dwarf-based benchmarks on fixed and reconfigurable architectures. Journal of Signal Processing Systems, vol. 85, no. 3, pp. 373-392, 2016

EOD Extensions

- Selection of problem size is critically affects HPC benchmarking
- Highest impact on CPU architectures.
- A major contribution of the work is facilitating 4 different problem sizes for all applications presented in the suite.
- Selected according to levels of cache
    - **tiny** : $<$ 32 KiB L1
    - **small**: $<$ 256 KiB L2
    - **medium**: $<$ 8192 L3
    - **large**: $>$ 8192 L3

EOD Extensions – Continued

- Diverse:
  - 4 different problem sizes per application
  - Added applications – currently 11 and 37 kernels
  - Real applications sampled from Bioinformatics, Computational Biology, Computational Chemistry and other fields
- Reproducible: Minimum of 2 sec runs per benchmark
- Precise:
  - High resolution timers with LibSciBench
  - Reported with one cycle resolution and roughly 6 ns of overhead
  - Also allows collection of energy and hardware events
- Portable:
  - Based on an OpenCL backend
  - Tested on a wide range of hardware
  - Consistent tuning – i.e. workgroup size arguments

Applications

Table 1: List of Extended OpenDwarfs Applications and their respective dwarfs

Dwarf	Extended OpenDwarfs Application
Dense Linear Algebra	LU Decomposition
Sparse Linear Algebra	Compressed Sparse Row
Spectral Methods	DWT2D, FFT
N-Body Methods	Gemnoui
Structured Grid	Speckle Reducing Anisotropic Diffusion
Unstructured Grid	Computational Fluid Dynamics
Map Reduce	K-Means
Combinational Logic	Cyclic-Redundancy Check
Graph Traversal	Breadth First Search
Dynamic Programming	Smith-Waterman
Backtrack and Branch and Bound	N-Queens
Graphical Methods	Hidden Markov Models
Finite State Machines	Temporal Data Mining

Hardware

Name	Vendor	Type	Series	Core Count	Clock Frequency (MHz) (min/max/turbo)	Cache (KiB) (L1/L2/L3)	TDP (W)	Launch Date
Xeon E5-2697 v2	Intel	CPU	Ivy Bridge	24∗	1200/2700/3500	32/256/30720	130	Q3 2013
i7-6700K	Intel	CPU	Skylake	8∗	800/4000/4300	32/256/8192	91	Q3 2015
i5-3550	Intel	CPU	Ivy Bridge	4∗	1600/3380/3700	32/256/6144	77	Q2 2012
Titan X	Nvidia	GPU	Pascal	3584†	1417/1531/–	48/2048/–	250	Q3 2016
GTX 1080	Nvidia	GPU	Pascal	2560†	1607/1733/–	48/2048/–	180	Q2 2016
GTX 1080 Ti	Nvidia	GPU	Pascal	3584†	1480/1582/–	48/2048/–	250	Q1 2017
K20m	Nvidia	GPU	Kepler	2496†	706/–/–	64/1536/–	225	Q4 2012
K40m	Nvidia	GPU	Kepler	2880†	745/875/–	64/1536/–	235	Q4 2013
FirePro S9150	AMD	GPU	Hawaii	2816‖	900/–/–	16/1024/–	235	Q3 2014
HD 7970	AMD	GPU	Tahiti	2048‖	925/1010/–	16/768/–	250	Q4 2011
R9 290X	AMD	GPU	Hawaii	2816‖	1000/–/–	16/1024/–	250	Q3 2014
R9 295x2	AMD	GPU	Hawaii	5632‖	1018/–/–	16/1024/–	500	Q2 2014
R9 Fury X	AMD	GPU	Fuji	4096‖	1050/–/–	16/2048/–	273	Q2 2015
RX 480	AMD	GPU	Polaris	4096‖	1120/1266/–	16/2048/–	150	Q2 2016
Xeon Phi 7210	Intel	MIC	KNL	256‡	1300/1500/–	32/1024/–	215	Q2 2016

EOD Evaluation

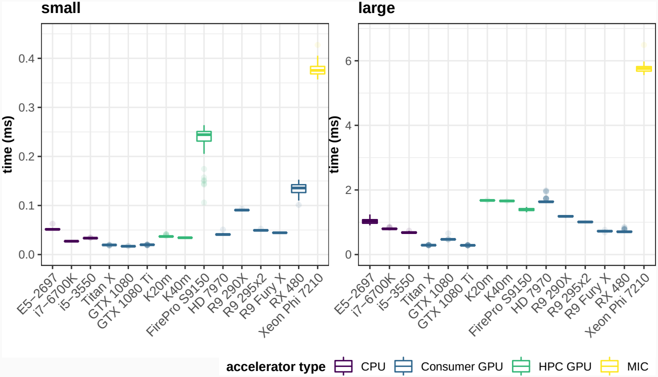

Figure 1: Comparison of performance on 2 sizes of csr application.

EOD Evaluation – Continued

- Just a sample of 1 of 11 applications
- Similar breakdown of 37 kernels
- 15 devices
- Time, performance events and energy (x50)
- Many more results and discussions presented in the full paper

What now?

- Small benchmark suite
- Wide diversity of scientific application codes
- Forms a large range of result times

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But,

- How representative?
- Work since publishing uses EOD to study:
    1. workload characterization
    2. performance prediction
    3. scheduling

Workload characterisation with AIWC

- Architecture-Independent Workload Characterisation (AIWC)[3]
- Plugin for OclGrind – an Extensible OpenCL device simulator[4]
- Beta available – https://github.com/BeauJoh/Oclgrind – and will be merged into default OclGrind

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[3] B. Johnston and J. Milthorpe, "OpenCL Performance Prediction using Architecture-Independent Features," arXiv:1805.04207 [cs.SE]

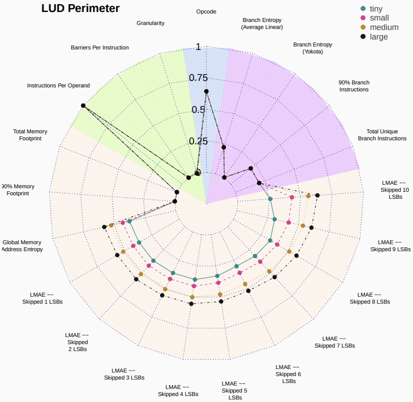
[4] J. Price and S. McIntosh-Smith, "Oclgrind: An extensible opencl device simulator," in Proceedings of the 3rd International Workshop on OpenCL, 2015, p. 12.

Overview of AIWC

- Simulation of OpenCL kernels occur on LLVM IR – SPIR
- AIWC tracks and measures hardware agnostic events
- Large number of metrics collected (34)
- Over a wide spectrum computation, thread communication and memory access patterns

AIWC Example

- 4 major types: Compute, Parallelism, Memory, Control
- Various number of metrics per type: based on statistical measurements – distributions, entropy and absolute counts

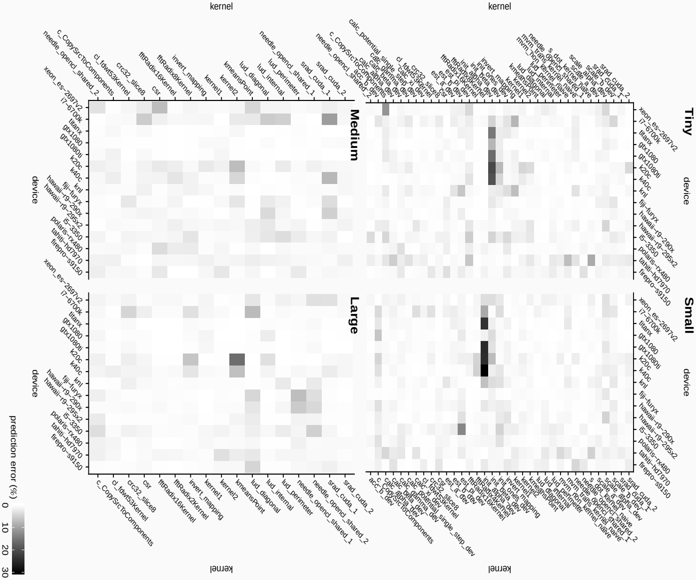


Performance Prediction – Combining EOD and AIWC

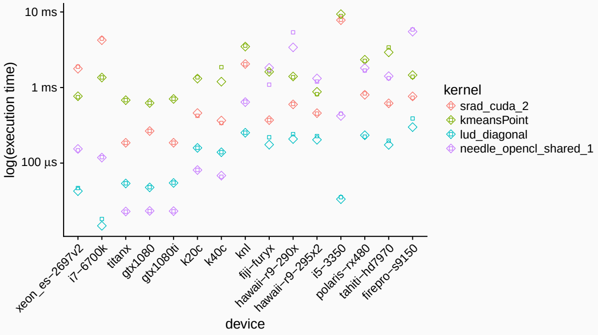
- Development of a regression model can now occur!
- AIWC's 34 metrics form input variables
- EOD response variables
- R language and Ranger – a Random Forest implementation – was used
- Performs recursive partitioning of high dimensional data
- Accepts 3 parameters:
    - num.trees – number of trees grown in forest – 10-10k by 500
    - mtry – number of features tried to split in a node – 1-34
    - min.node.size – minimal size per tree – 1-50
- Optimal model needs careful tuning[5]

[5] B. Johnston, G. Falzon and J. Milthorpe, "OpenCL Performance Prediction using Architecture-Independent Features,", High Performance Computing and Simulation (HPCS 2018), Jul 2018, Orléans, France.

Performance Prediction Example



Scheduling



- 4 random kernels.
- square → mean measured time
- diamond → mean predicted time
- order is important!

Conclusions

- Completed essential curation of the OpenDwarfs benchmark suite:
    - Increased application diversity
    - Tested on 15 devices
    - High precision measurements of time, energy and hardware events
- Required for:
    - Evaluating OpenCL on wide-range of parallel architectures
    - Workload characterization
    - Performance prediction
    - Scheduling

Open Questions and Next Steps

- Do you have real applications to add to EOD? Perhaps in biological, numerical computing or stochastic simulations?
- These workloads can test the extremes of EOD and prediction coverage? Poor predictions finds holes in the model → missing benchmark in EOD
- What about new hardware – Especially FPGA? Spare hours on a super-computer?
- Large applications that could benefit from using the predictive model?

- We should collaborate!

Thanks

- The University of Bristol's High Performance Computing Research group for the use of "The Zoo" Research cluster
- Oracle
- ANU VC Travel Grant
- You!

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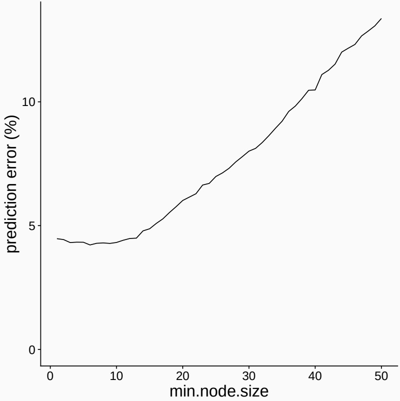
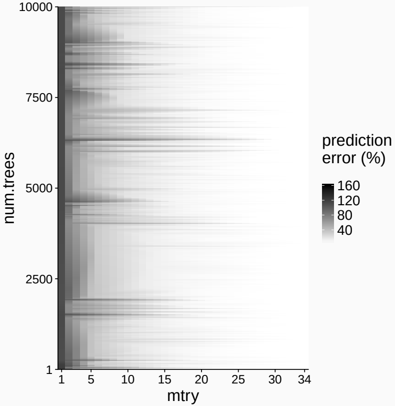
min.node.size



- Full coverage of min.node.size with fixed tuning parameters: num.trees = 300 and mtry = 30
- Smallest out-of-bag prediction error for values < 15
- Selection made to fix min.node.size = 9

num.trees and mtry

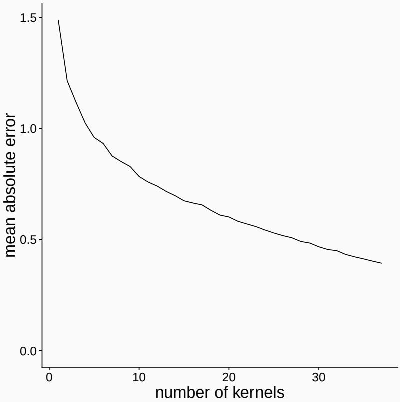
- optim_sa function used to find global minimum
- Full coverage achieved – 4 outer-most points and 8 random starting internal points
- intermediate results used and interpolation performed – using akima
- Model performance varies significantly for last 2 variables
- mtry $>$ 25, offers good fit
- num.trees less impact – fewer



Choosing Parameters for the Future

- num.trees=500, mtry=32, and min.node.size=9 look good
- train on a random selection of N kernels and test on remainder
- see paper for details but final values are num.trees = 505, mtry = 30 and min.node.size = 9

Increased Training Data



- How many kernels to add for training – what's enough?
- Another study performed to see how error changes w.r.t. number of kernels in training
- Uses random selection for each random count – again see paper for full details
- Error tapers off for more kernels!
- gradient still significant at 37 kernels → could still benefit from more.

Prediction Accuracy