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Performance Engineering of the Kernel Polynomial Method on Large-Scale CPU-GPU Systems

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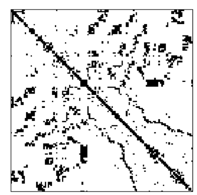
Prologue

What is this about?

The Kernel Polynomial Method (KPM)

Approximate the complete eigenvalue spectrum of a large sparse matrix.

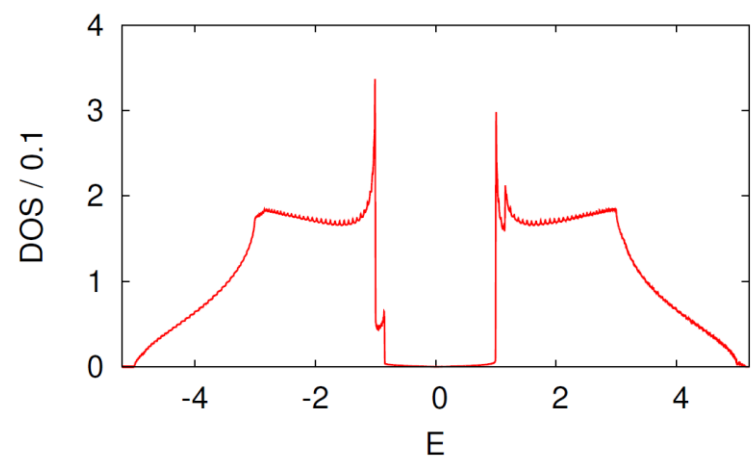
Large, Sparse



$$\boldsymbol{H}\,\boldsymbol{x} = \lambda\,\boldsymbol{x}$$

$$\underbrace{\{\lambda_1, \lambda_2, \dots, \lambda_k, \dots, \lambda_{n-1}, \lambda_n\}}$$

Good approximation to full spectrum
(e.g. Density of States)



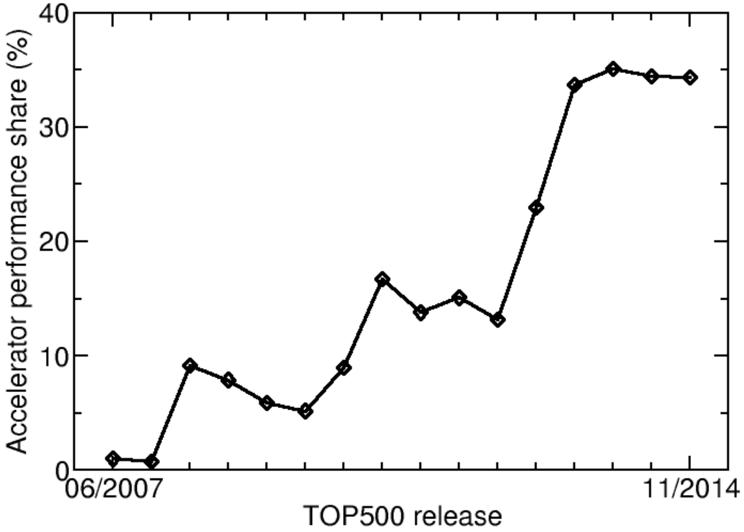
A. Weiße, G. Wellein, A. Alvermann, H. Fehske: **"The kernel polynomial method"**, Rev. Mod. Phys., vol. 78, p. 275, 2006.
E. di Napoli, E. Polizzi, Y. Saad: **"Efficient estimation of eigenvalue counts in an interval"**, Preprint. http://arxiv.org/abs/1308.4275

Why optimize for heterogeneous systems?

One third of TOP500 performance stems from accelerators.

But: Few <u>truly</u> heterogeneous software.

(Using both CPUs and accelerators.)



The Kernel Polynomial Method

Algorithmic Analysis

The Kernel Polynomial Method

Compute Chebyshev polynomials and moments.

Basic algorithm and algorithmic optimizations:

Exploit knowledge from all software layers!

for $r = 0$ to $R-1$ **do** — Application: Loop over random initial states

$\quad |v\rangle \leftarrow |\mathrm{rand}()\rangle$

$\quad$ Initialization steps and computation of η_0, η_1

$\quad$ **for** $m = 1$ to $M/2$ **do** — Algorithm: Loop over moments

$\quad\quad \mathrm{swap}(|w\rangle, |v\rangle)$

$\quad\quad |u\rangle \leftarrow H|v\rangle$

$\quad\quad |u\rangle \leftarrow |u\rangle - b|v\rangle$

$\quad\quad |w\rangle \leftarrow -|w\rangle$

$\quad\quad |w\rangle \leftarrow |w\rangle + 2a|u\rangle$

$\quad\quad \eta_{2m} \leftarrow \langle v|v\rangle$

$\quad\quad \eta_{2m+1} \leftarrow \langle w|v\rangle$

$\quad$ **end for**

end for

Building blocks: (Sparse) linear algebra library

▷ spmv()
▷ axpy()
▷ scal()
▷ axpy()
▷ nrm2()
▷ dot() — Dot Product

-1 **do**

steps and computation of η_0, η_1

$M/2$ **do**

$, |v\rangle)$

$(H - b\mathbb{1})|v\rangle - |w\rangle$ &

$= \langle v|v\rangle$ &

$= \langle w|v\rangle$ ▷ aug_spmv()

$= \langle w|v\rangle$ ▷ aug_spmmv()

Augmented Sparse Matrix Vector Multiply

Augmented Sparse Matrix Multiple Vector Multiply

Analysis of the Algorithmic Optimization

- **Minimum code balance of vanilla algorithm:**
  complex double precision values, 32-bit indices, 13 non-zeros per row, application: topological insulators

$$B_{vanilla} = 3.39\ Bytes/Flop$$ (B = inverse computational intensity)

- **Identified bottleneck: Memory bandwidth**
  ➔ Decrease memory transfers to alleviate bottleneck

- **Algorithmic optimizations reduce code balance:**

$$B_{aug\_spmv} = 2.23\ B/F$$ kernel fusion

$$B_{aug\_spmmv}(R) = 1.88/R + 0.35\ B/F$$ put *R* vectors in block

Consequences of Algorithmic Optimization

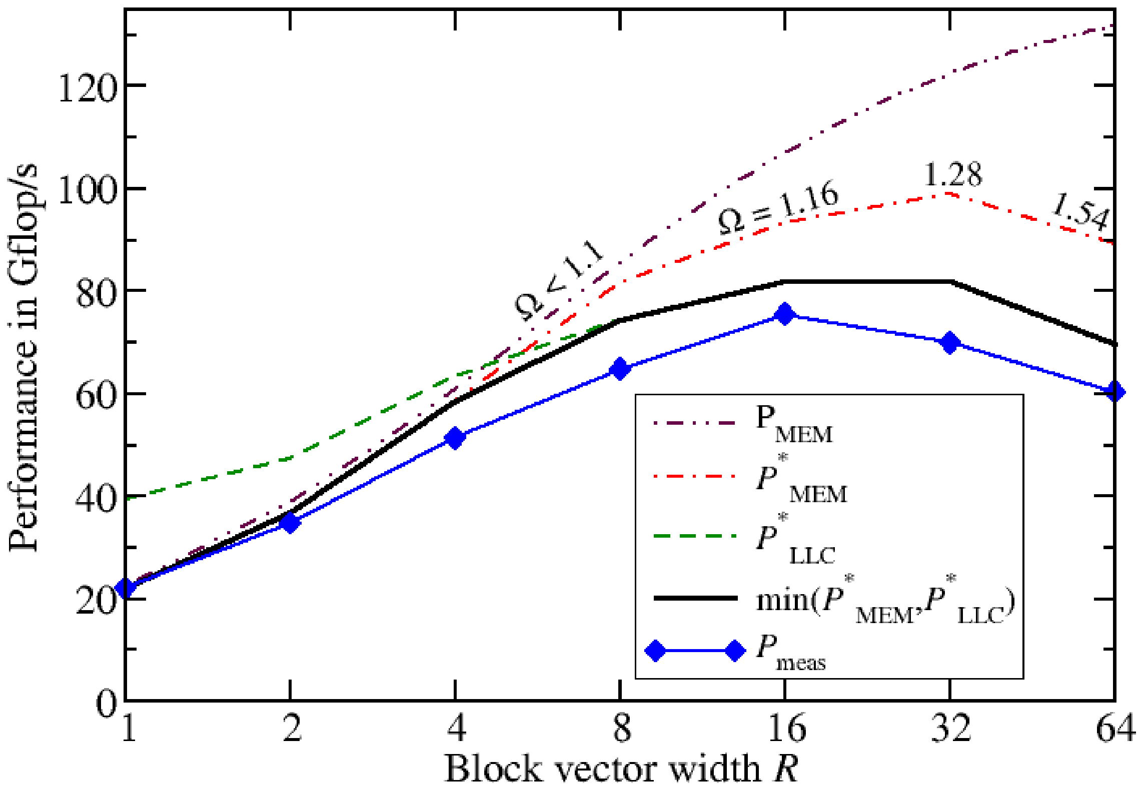
- **Mitigation of the relevant bottleneck**
  ➔ Expected speedup

- **Other bottlenecks become relevant**
  ➔ Achieved speedup may not be $B_{vanilla}/B_{aug\_spmmv}$

- **Block vectors are best stored interleaved**
  ➔ May impose larger changes to the codebase

- `aug_spmmv()` **no part of standard libraries**
  ➔ Implementation by hand is necessary

CPU roofline performance model



$P = \frac{b}{B}$ **Gflop/s**

→ Performance limit for bandwidth-bound code

b = max. bandwidth = 50 GB/s
B = code balance

$\Omega = \frac{\text{Actual data transfers}}{\text{Minimum data transfers}}$

S. Williams, A. Waterman, D. Patterson: **"Roofline: An insightful visual performance model for multicore architectures"**, *Commun. ACM*, vol. 52, p. 65, 2009.

Implementation

How to harness a heterogeneous machine in an efficient way?

Implementation

Algorithmic optimizations lead to a *potential* speedup.

➔ We “merely” need an efficient implementation!

Data or task parallelism?

- **MAGMA: task parallelism between devices**
  `http://icl.cs.utk.edu/magma/`
- **Kernel fusion Task parallelism**

➔ Data-parallel approach suits our needs

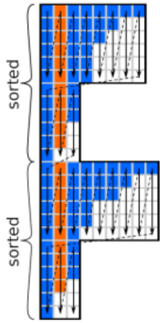
Implementation

Data-parallel heterogeneous work distribution

- **Static work-distribution by matrix rows/entries**
- **Device workload ←→ device performance**

SELL-C-σ sparse matrix storage format

- **Unified format for all relevant devices**
- **Currently no runtime-exchange of matrix data (dynamic load balancing, future work)**

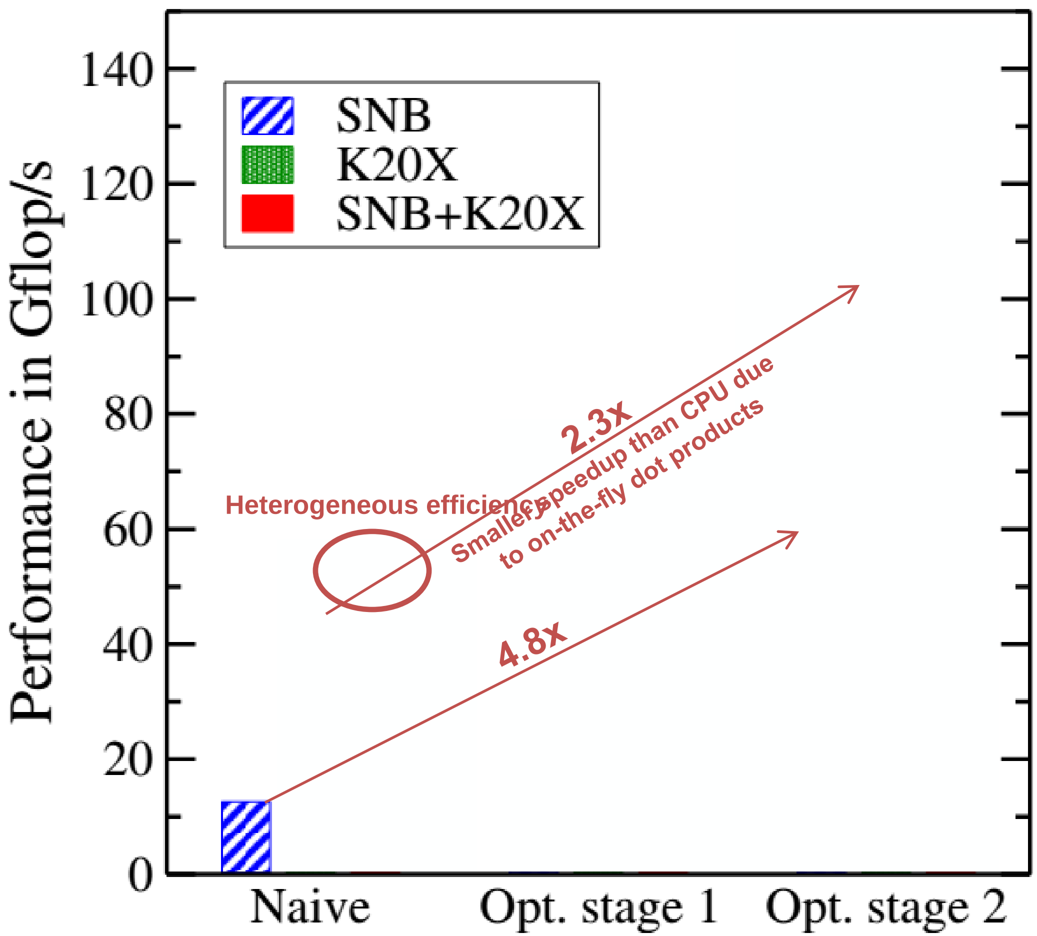


M. Kreutzer, G. Hager, G. Wellein, H. Fehske, A. R. Bishop, **"A unified sparse matrix data format for efficient general sparse matrix-vector multiplication on modern processors with wide SIMD units"**, *SIAM J. Sci. Comput.*, vol. 36, p. C401, 2014

Performance results

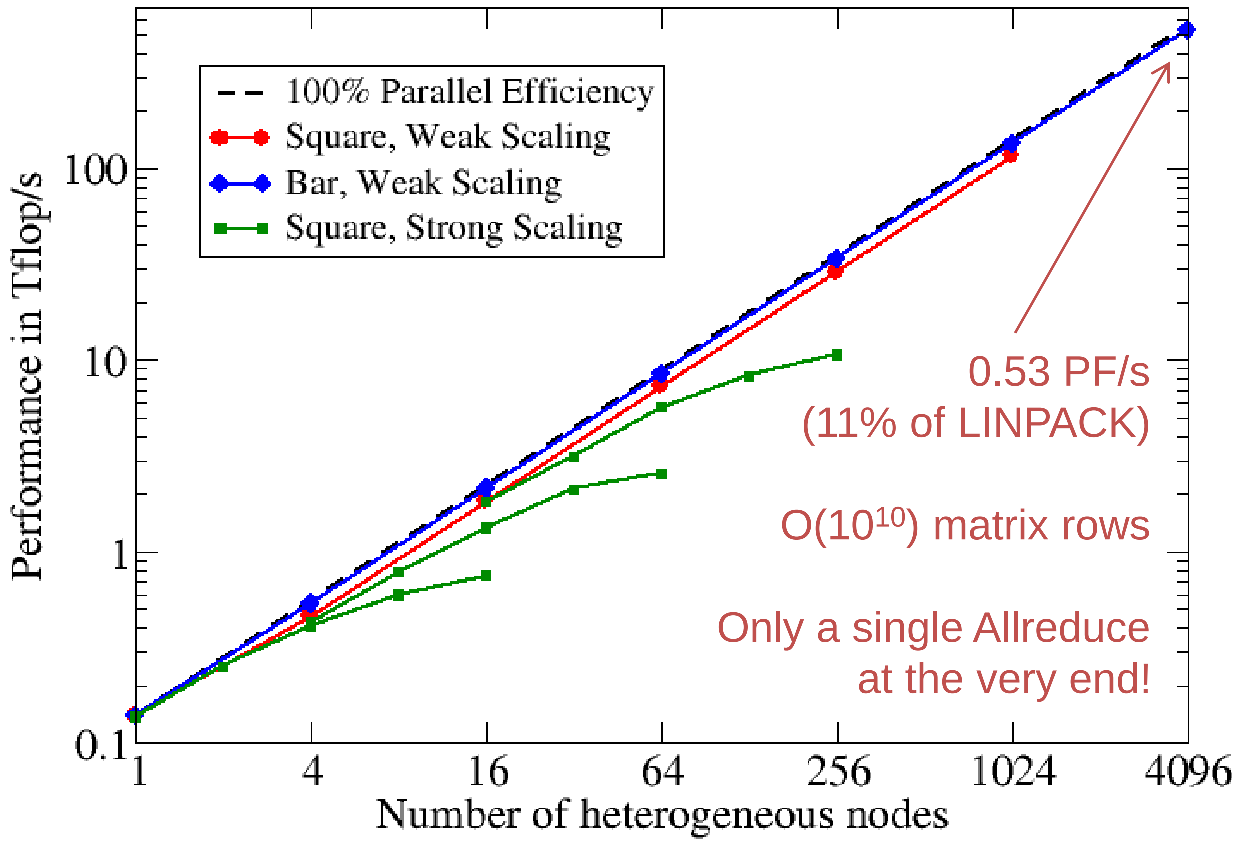
Does all this really pay off?

Single-node Heterogeneous Performance



SNB: Intel Xeon Sandy Bridge, K20X: Nvidia Tesla K20X, Complex double precision matrix/vectors (topological insulator)

Large-scale Heterogeneous Performance



CRAY XC30 – Piz Daint*

- 5272 nodes, each w/
  - 1 octacore Intel Sandy Bridge
  - 1 Nvidia Kepler K20x
- Peak: 7.8 Pflop/s
- LINPACK: 6.3 Pflop/s
- Largest system in Europe

*Thanks to CSCS/O. Schenk/T. Schulthess for granting access and compute time

Epilogue

Try it out! (If you want...)

Download our building block library and KPM application: `http://tiny.cc/ghost`

GHOST *General, Hybrid, and Optimized Sparse Toolkit*

- **MPI + OpenMP + SIMD + CUDA**
- **Transparent data-parallel heterogeneous execution**
- **Affinity-aware task parallelism (checkpointing, comm. hiding, etc.)**
- **Support for block vectors**
  - Automatic code generation for common block vector sizes
  - Hand-implemented tall skinny dense matrix kernels
- **Fused kernels (arbitrarily "augmented SpMMV")**
- **SELL-C-σ heterogeneous sparse matrix format**
- **Various sparse eigensolvers implemented and downloadable**

. . .

Backup Slides

Only in the unlikely case I was too fast...

Conclusions

- Model-guided performance engineering of KPM on CPU and GPU
- Decoupling from main memory bandwidth
- Optimized node-level performance
- Embedding into massively-parallel application code
- Fully heterogeneous peta-scale performance for a sparse solver

Outlook

- Applications besides KPM
- Automatic (& dynamic) load balancing
- Optimized GPU-CPU-MPI communication
- Further optimization techniques (cache blocking, ...)
- Performance engineering for Xeon Phi (already supported