A case study on modeling the performance of dense matrix computation:

Tridiagonalization in the EigenExa eigensolver on the K computer

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Background

Importance of performance modeling

- Performance modeling is one of important tasks in HPC including automatic performance tuning.
- Well constructed models can reduce the cost of tuning and help one to efficiently allocate limited computational resources.

Difficulties in performance modeling

- Performance behavior of a program (on large-scale parallel systems) is complicated; many factors (cost for arithmetic and communication) effect the execution time.
- Available information for modeling is usually limited.
- Verifying models is also not easy; comparison with actual (measured) timing results is impractical in some cases.

Related work

Dackland et al., 1996:

Performance modeling of the routine in ScaLAPACK by accumulating the estimation of low-level routines. (Model parameters was configured by theoretical performance of the target system and experiments.)

J. Demmel et al., 2012:

Performance model was used for evaluating the effectiveness of CA-QR/LU factorization on future machines. (Model was simple, and parameters was determined from expected theoretical peak performance.)

• A. Calotoiu et al., 2013:

General techniques for empirical performance modeling (Automatically selecting basis functions in model based on sampling data)

Overview of this study

Motivation

- During the development of the EigenExa eigensolver on the K computer, we have accumulated a lot of measured timing data.
- For a certain program, comparison of different approaches to performance modeling has not been sufficiently investigated.

Contribution

- For the tridiagonalization routine in EigenExa (named eigen_trd), we attempt to construct performance models.
- We consider four approaches to performance modeling and evaluate them by comparing with measured timing data.
- We also present some observations from measured data, which will be informative for further research for modeling.

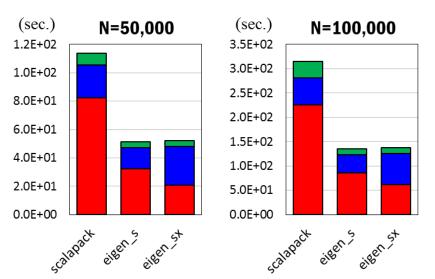
Outline

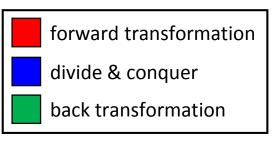
- 1. Introduction
- 2. Overview of eigen_trd
- 3. Measured results on the K computer
- 4. Approaches to performance modeling
- 5. Evaluation of the performance models
- 6. Conclusion

Overview of eigen_trd

Overview of EigenExa

- EigenExa eigensolver (main developer: T. Imamura)
 - Target problem: real symmetric dense eigenvalue problem
 - Target system: K computer and post-petascale systems
 - Two driver routines:
 - ✓ eigen_s: traditional approach based on tridiagonalization
 - ✓ eigen_sx: new approach employing penta-diagonalization

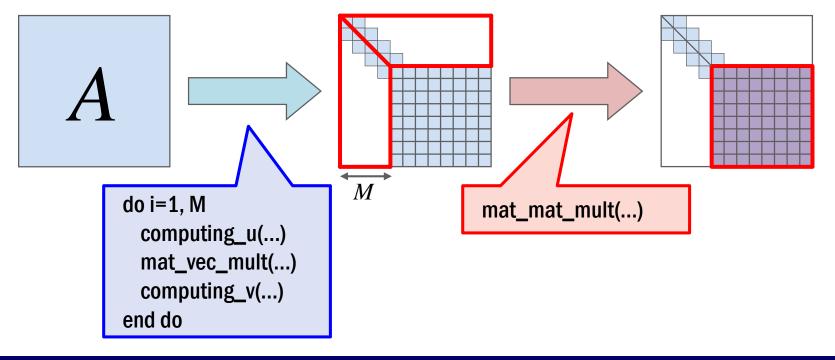




Evaluation using 4,800 nodes of Oakleaf-FX supercomputing system @ The Univ. of Tokyo (T. Fukaya & T. Imamura, PDSEC2015)

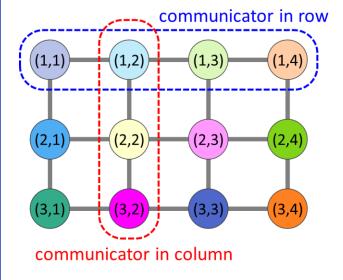
Overview of eigen_trd

- eigen_trd: tridiagonalization routine in EigenExa
 - Transform an input symmetric matrix into a tridiagonal matrix using orthogonal Householder transformations.
 - Employs Dongarra's method to reduce the memory access cost in symmetric matrix-vector multiplications.



Arithmetic & communication cost

| Computation | #flops per | | Bcast ocesses) | MPI_Allreduce $(\sqrt{P} \text{ processes})$ | | |
|--------------|--------------------------------------|------------|-------------------------|--|------------------------|--|
| Computation | process | #issues | #words | #issues | #words | |
| computing_u | $O\left(\frac{N^2}{\sqrt{P}}\right)$ | 2 <i>N</i> | $\frac{N^2}{\sqrt{P}}$ | N | O(N) | |
| mat_vec_mult | $\frac{2N^3}{3P}$ | | | 2 <i>N</i> | $\frac{N^2}{\sqrt{P}}$ | |
| computing_v | $O\left(\frac{N^2}{\sqrt{P}}\right)$ | N | $\frac{N^2}{2\sqrt{P}}$ | 2 <i>N</i> | O(N) | |
| mat_mat_mult | $\frac{2N^3}{3P}$ | | | | | |



process grid in EigenExa

(N: matrix size, P: # of processes, process grid: $\sqrt{P} \times \sqrt{P}$)

Measured results on the K computer

Evaluation conditions

Specifications of the K computer

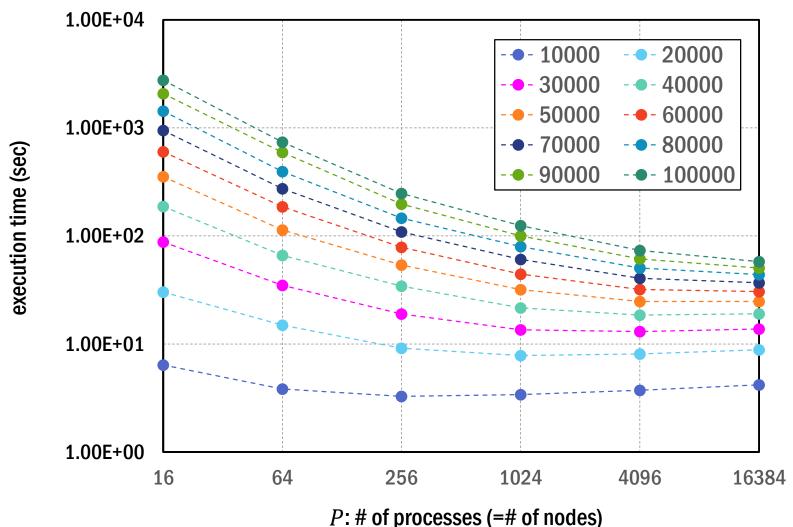
| Item | Specification/values | | | | |
|-------------------|---|--|--|--|--|
| CPU | SPARC64 VIIIfx (2.0GHz, 8cores) | | | | |
| Memory | DDR3 SDRAM (64GB/s) | | | | |
| Node | 1 CPU and 16 GB memory | | | | |
| Network | Torus fusion 6D mesh/torus (Tofu), 5 GB/s/link, bidirectional | | | | |
| System | 88,128 nodes (compute nodes: 82,944) | | | | |
| Peak FLOPS/system | 11.28PFLOPS | | | | |

Evaluation conditions (for details, see our paper)

- Fujitsu Fortran90 (mpifrtpx) compiler with "-Kfast,openmp -Cpp -Cfpp" and Fujitsu BLAS/LAPACK MPI libraries.
- Test matrix: $A_{i,j} = N + 1 \max(i,j)$

Measured timing data

Totally 60 timing results of eigen_trd on the K computer



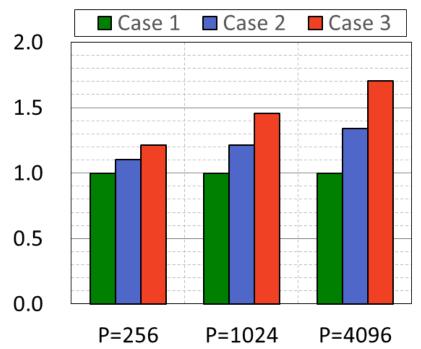
Difficulty in detailed measurement

```
subroutine function 1(...)
      MPI_Barrier(...) --- (*)
      t1 = MPI_Wtime()
        [computation]
      MPI_Barrier(...) --- (**)
      ct1 = MPI_Wtime()
        MPI_Allreduce(...)
      MPI_Barrier(...) --- (**)
      ct2 = MPI Wtime()
      g_{ctime1} = g_{ctime1} + (ct2 - ct1)
        [computation]
      MPI_Barrier(...) --- (*)
      t2 = MPI_Wtime()
      g_{time1} = g_{time1} + (t2 - t1)
end subroutine
```

Effect of synchronization on the measured timing results.

- Case 1: no barrier
- Case 2: barrier at (*)
- Case 3: barrier at (*) & (**)

Total execution time (N=50.000)

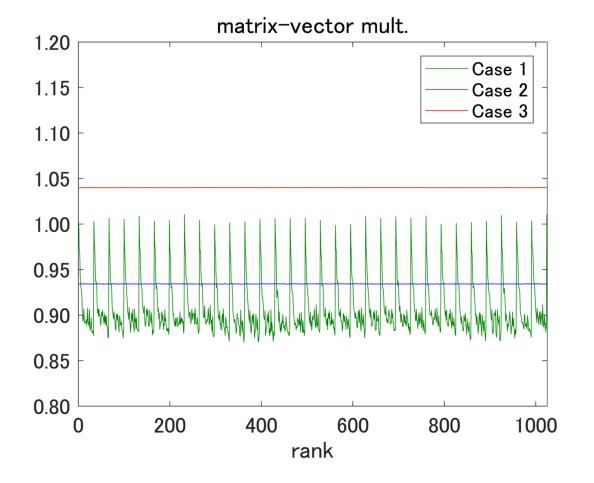


Case 1: no barrier

Case 2: barrier at (*)

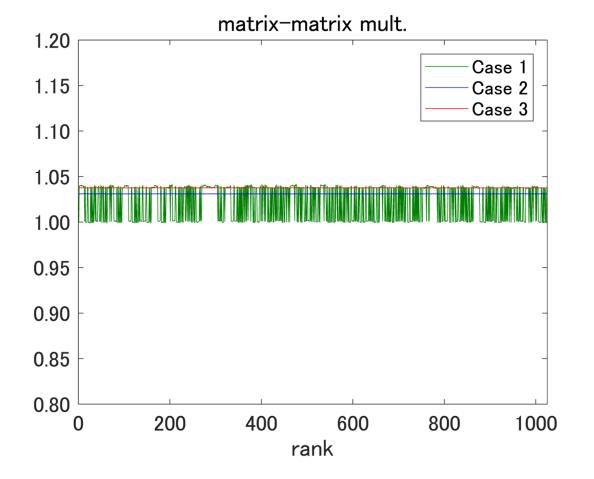
Case 3: barrier at (*) & (**)

```
subroutine function1(...)
     MPI_Barrier(...) --- (*)
     t1 = MPI_Wtime()
        [computation]
     MPI_Barrier(...) --- (**)
     ct1 = MPI Wtime()
        MPI_Allreduce(...)
     MPI_Barrier(...) --- (**)
     ct2 = MPI_Wtime()
     g ctime1 = g ctime1 + (ct2 - ct1)
        [computation]
     MPI_Barrier(...) --- (*)
     t2 = MPI Wtime()
     g_{time1} = g_{time1} + (t2 - t1)
end subroutine
```



- Case 1: no barrier
- Case 2: barrier at (*)
- Case 3: barrier at (*) & (**)

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subroutine function1(...)
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     ct1 = MPI Wtime()
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     g_{time1} = g_{time1} + (t2 - t1)
end subroutine
```

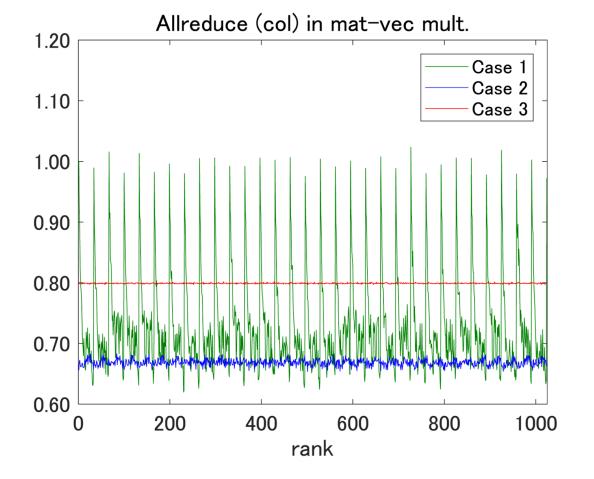


Case 1: no barrier

Case 2: barrier at (*)

Case 3: barrier at (*) & (**)

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     ct1 = MPI Wtime()
        MPI_Allreduce(...)
      MPI_Barrier(...) --- (**)
     ct2 = MPI_Wtime()
      g ctime1 = g ctime1 + (ct2 - ct1)
        [computation]
     MPI_Barrier(...) --- (*)
     t2 = MPI Wtime()
      g_{time1} = g_{time1} + (t2 - t1)
end subroutine
```

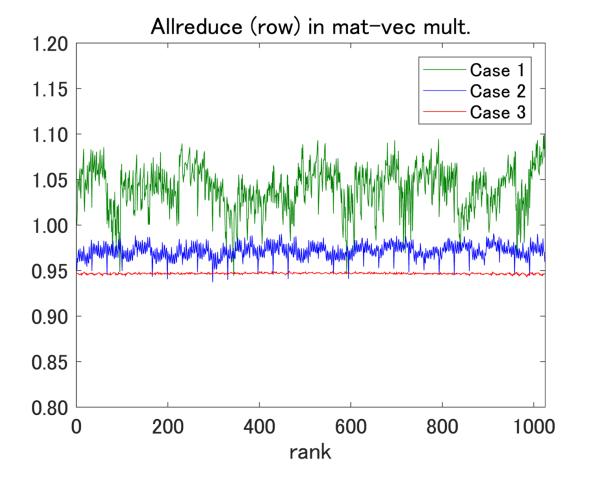


Case 1: no barrier

Case 2: barrier at (*)

Case 3: barrier at (*) & (**)

```
subroutine function1(...)
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        [computation]
     MPI_Barrier(...) --- (*)
     t2 = MPI Wtime()
     g_{time1} = g_{time1} + (t2 - t1)
end subroutine
```



Approaches to Performance modeling

Assumption and goal of modeling

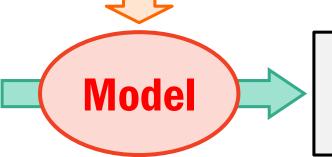
Assumption

- Target machine is given: K computer, information of the machine is limited (in next slides).
- Target program is given: eigen_trd in EigenExa, information of the program (computational and communication pattern) is already known.

◆Goal

available information of the target machine and program

- matrix size: N
- number of nodes: P



Execution time:

 $T_{\rm trd}(N,P)$

Situations

We attempt modeling in four situations:

- 1. The target machine does not exist: only the **specifications** of the machine are available.
- 2. Simple benchmark programs can be run using a part of the target machine: results of **BLAS routines** and **MPI ping-pong** are available.
- 3. Specified benchmark programs can be run using limited computational resources: results of modified version of the target program (without MPI routines) and MPI collective routines are available.
- 4. The target program can be run using sufficient resources: measured results of the target program are available.

In each situation, available information for modeling is different.

Situation 1

Modeling in Situation 1

Specifications of the K computer

| Symbol | Item | Specification |
|---------|-----------------------|----------------------------------|
| F | FLOPS/node | 1.28×10^{11} (flop/sec) |
| B_{M} | Memory bandwidth/node | 6.40×10^{10} (byte/sec) |
| B_N | Network bandwidth | 5.00×10^9 (byte/sec) |
| L | Network latency | 9.20×10^{-7} (sec) |

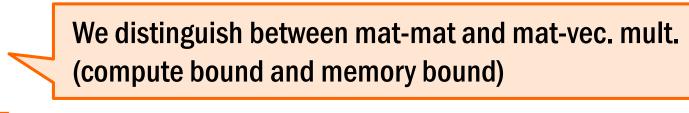
Main idea

$$T_{\text{trd}}(N, P) = T_{\text{flop}}(N, P) + T_{\text{comm}}(N, P)$$
time for arithmetic time for communication

We separately model the time for arithmetic and communication.

Modeling the time for arithmetic

 $T_{\text{fl}op}$ = (time for one operation) · (# of operations)



$$T_{\text{flop}}(N,P) = \gamma_{\text{mm}} \cdot \frac{2N^3}{P} + \gamma_{\text{mv}} \cdot \frac{2N^3}{P}$$
mat-mat mult.

B/F ratio in symmetric mat-vec mult. is 4flops/8bytes.

$$\gamma_{\rm mm} = \frac{1}{F}, \ \gamma_{\rm mv} = \frac{2}{B_M}$$

Modeling the time for communication

$$T_{\text{p2p}}(w) = \alpha + \beta \cdot w$$

w: data size

$$T_{\text{comm}}(N,P) = \alpha \cdot M_{\text{p2p}}(N,P) + \beta \cdot W_{\text{p2p}}(N,P)$$
total number of issues

We assume MPI_Allreduce and MPI_Bcast are operated along with a binary tree.

$$M_{\text{p2p}}(N,P) = 8N \log_2 \sqrt{P}, \ W_{\text{p2p}}(N,P) = \frac{5N^2}{2\sqrt{P}} \log_2 \sqrt{P}$$

$$\alpha = L, \quad \beta = \frac{8}{B_N}$$

Obtained model in Situation 1

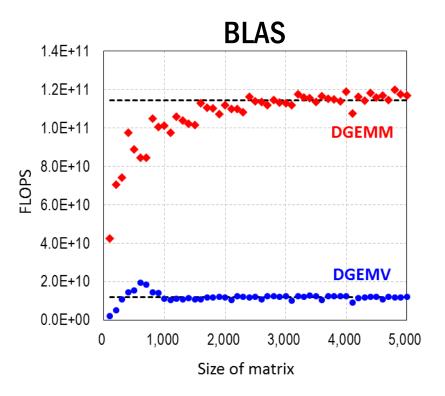
$$T_{\text{trd}}(N,P) = \left(\frac{1}{F} + \frac{2}{B_M}\right) \cdot \frac{2N^3}{P} + L \cdot 8N \log_2 \sqrt{P} + \frac{8}{B_N} \cdot \frac{5N^2}{2\sqrt{P}} \log_2 \sqrt{P}$$

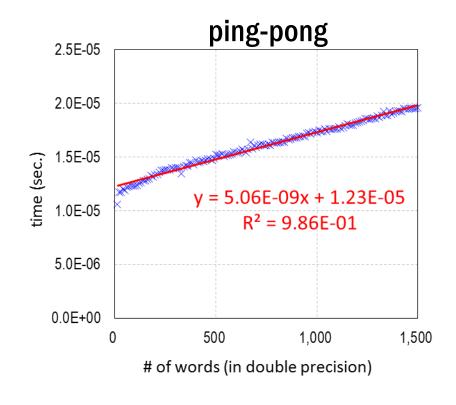
| Symbol | Item | Specification | | |
|---------|-----------------------|----------------------------------|--|--|
| F | FLOPS/node | 1.28×10^{11} (flop/sec) | | |
| B_{M} | Memory bandwidth/node | $6.40 	imes 10^{10}$ (byte/sec) | | |
| B_N | Network bandwidth | 5.00×10^9 (byte/sec) | | |
| L | Network latency | 9.20×10^{-7} (sec) | | |

Situation 2

Modeling in Situation 2

Benchmark results of BLAS & MPI ping-pong



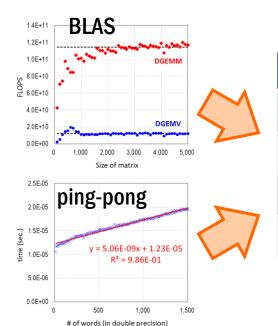


Main idea

We employ the same approach in Situation 1, but model parameters are determined from benchmark results.

Obtained model in Situation 2

$$T_{\text{trd}}(N,P) = (\gamma_{\text{mm}} + \gamma_{\text{mv}}) \cdot \frac{2N^3}{P} + \alpha \cdot 8N \log_2 \sqrt{P} + \beta \cdot \frac{5N^2}{2\sqrt{P}} \log_2 \sqrt{P}$$



| Parameter | Value | | | |
|------------------|------------------------|--|--|--|
| $\gamma_{ m mm}$ | 8.77×10^{-12} | | | |
| $\gamma_{ m mv}$ | 4.23×10^{-11} | | | |
| α | 1.23×10^{-5} | | | |
| β | 5.06×10^{-9} | | | |

B/F ratio in dsymv is 1/2 that in dgemv.

By LS fitting.

Situation 3

Modeling in Situation 3

Execution of specified benchmark program

- A modified version of eigen_trd without MPI routines (Program can finish, but result is nonsense.)
- MPI collective routines using \sqrt{P} processes.

◆ Main idea

$$T_{\text{trd}}(N,P) = T_{\text{flop}}(N,P) + T_{\text{al}}(N,P) + T_{\text{bc}}(N,P)$$

$$\underbrace{\text{time for MPI_Allreduce}}_{\text{time for MPI_Bcast}}$$

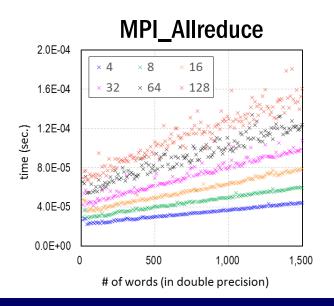
- $T_{\text{flop}}(N, P)$ is directly measured by the modified program.
- $T_{\rm al}(N,P)$ and $T_{\rm bc}(N,P)$ are modeled using the benchmark results of MPI collective routines.

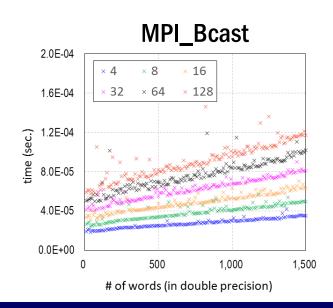
Time of MPI collective routines

•
$$T_{\rm al}(N,P) = \alpha_{\rm al}(\sqrt{P}) \cdot 5N + \beta_{\rm al}(\sqrt{P}) \cdot \frac{N^2}{\sqrt{P}}$$

• $T_{\rm bc}(N,P) = \alpha_{\rm bc}(\sqrt{P}) \cdot 3N + \beta_{\rm bc}(\sqrt{P}) \cdot \frac{3N^2}{2\sqrt{P}}$
total number of issues total amount of data

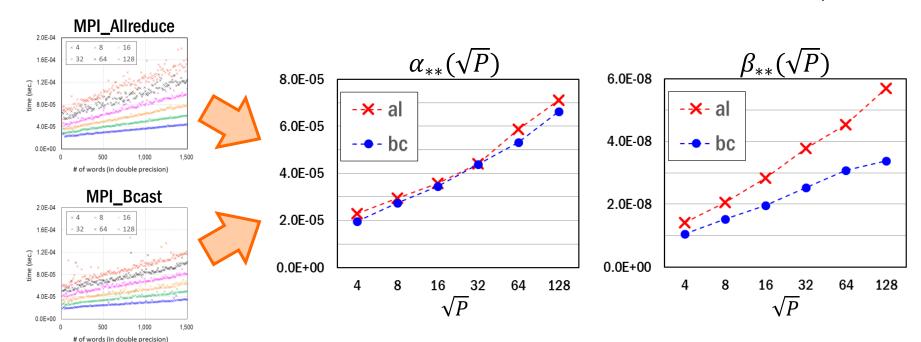
We determine the model parameters from benchmark results.





Obtained model in Situation 3

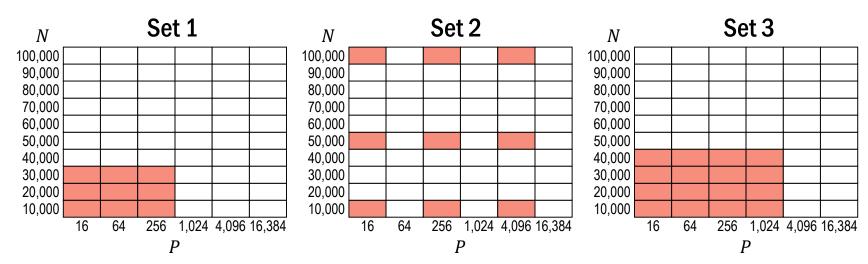
$$\begin{split} T_{\mathrm{trd}}(N,P) &= T_{\mathrm{flop}}(N,P) & \qquad \mathbf{Measured} \\ &+ \alpha_{\mathrm{al}} \big(\sqrt{P} \big) \cdot 5N + \beta_{\mathrm{al}} \big(\sqrt{P} \big) \cdot \frac{N^2}{\sqrt{P}} \\ &+ \alpha_{\mathrm{bc}} \big(\sqrt{P} \big) \cdot 3N + \beta_{\mathrm{bc}} \big(\sqrt{P} \big) \cdot \frac{3N^2}{2\sqrt{P}} \end{split}$$



Situation 4

Modeling in Situation 4

A number of measured timing results of eigen_trd



Main idea

 We construct a model as a linear combination of basis functions of N and P:

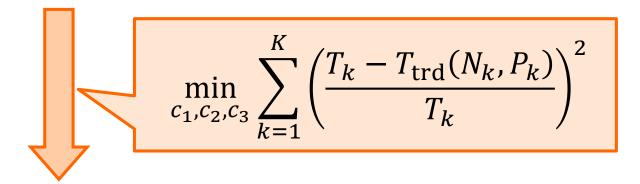
$$T_{\mathrm{trd}}(N,P) = \sum c_i \cdot F_i(N,P)$$
.

 We determine the model parameters by LS fitting using the sample data.

Obtained model in Situation 4

$$T_{\text{trd}}(N,P) = c_1 \cdot \frac{N^3}{P} + c_2 \cdot N \log_2 \sqrt{P} + c_3 \cdot \frac{N^2}{\sqrt{P}} \log_2 \sqrt{P}$$

Sample data:
$$(T_k, N_k, P_k)$$
 $k = 1, ... K$



| Set | c_1 | c_2 | c_3 | |
|-----|------------------------|-----------------------|-----------------------|--|
| 1 | 4.06×10^{-11} | 5.10×10^{-5} | 4.18×10^{-8} | |
| 2 | 4.07×10^{-11} | 5.58×10^{-5} | 3.41×10^{-8} | |
| 3 | 4.01×10^{-11} | 5.21×10^{-5} | 3.92×10^{-8} | |

Summary of modeling in each situation

Summary of modeling in each situation

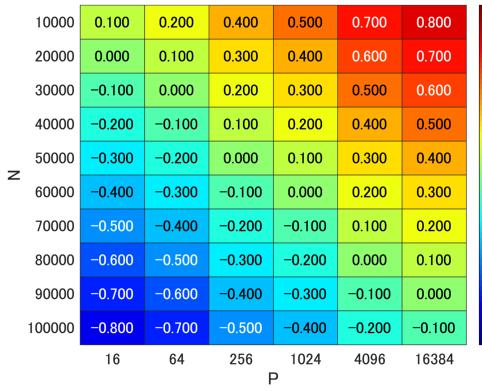
| | Model form | Features | Required resources |
|---|---|--|--------------------------|
| 1 | $T_{\text{flop}}(N, P) + T_{\text{comm}}(N, P)$ | Parameters: determined from specifications | Nothing |
| 2 | $T_{\text{flop}}(N, P) + T_{\text{comm}}(N, P)$ | Parameters: determined from benchmark results of BLAS & MPI ping-pong | 2 nodes |
| 3 | $T_{\text{flop}}(N, P)$ + $T_{\text{al}}(N, P)$ + $T_{\text{bc}}(N, P)$ | T_{flop}: measured by modified eigen_trd Parameters: determined from benchmark results of MPI collective routines | Up to \sqrt{P} nodes |
| 4 | $\sum_{i=1}^{3} c_i \cdot F_i(N, P)$ | Parameters: determined by LS fitting using sample data | Depending on sample data |

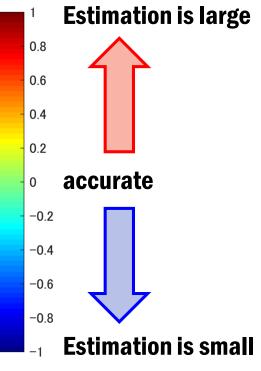
Evaluation of the performance models

Evaluation metric

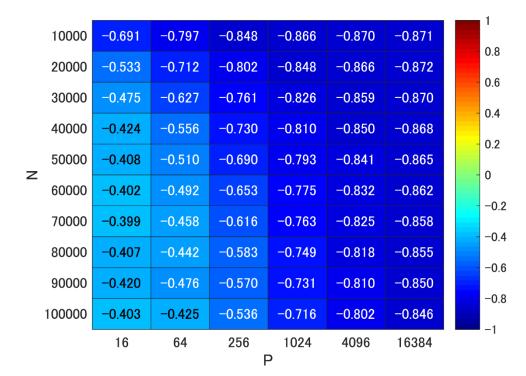
Compare the estimation with measured timing data

$$(relative error) = \frac{(estimated time) - (measured time)}{(measured time)}$$





| | Model form | Features | Required resources |
|---|---|--|--------------------|
| 1 | $T_{\text{flop}}(N, P) + T_{\text{comm}}(N, P)$ | Parameters: determined from specifications | Nothing |



- Accurate modeling using only the specifications is quite difficult.
- Estimation by the model is much smaller than the actual time.
 (Because theoretical performance was used.)

| | Model form | Features | Required resources |
|---|---|--|--------------------|
| 2 | $T_{\text{flop}}(N, P) + T_{\text{comm}}(N, P)$ | Parameters: determined from benchmark results of BLAS & MPI ping-pong | 2 nodes |



- Estimation error is about 20% for some cases.
- Error tends to be larger when P is large and N is small.
 (Difficulty of estimation of communication cost?)

| | Model form | Features | Required resources |
|---|---|---|------------------------|
| 3 | $T_{\text{flop}}(N, P)$ + $T_{\text{al}}(N, P)$ + $T_{\text{bc}}(N, P)$ | • T_{flop} : measured by modified eigen_trd • Parameters: determined from benchmark results of MPI collective routines | Up to \sqrt{P} nodes |



- For all cases excepting P is large and N is small, estimation is accurate. (error is in 5~10%.)
- One of main reasons for accurate estimation would be the measurement of the time for $T_{\rm flop}$.

| | Model form | Features | Required resources | |
|---|--------------------------------------|--|--------------------------|--|
| 4 | $\sum_{i=1}^{3} c_i \cdot F_i(N, P)$ | Parameters: determined by LS fitting using sample data | Depending on sample data | |

8.0

0.6

0.4

0.2

0

-0.2

-0.4

-0.6

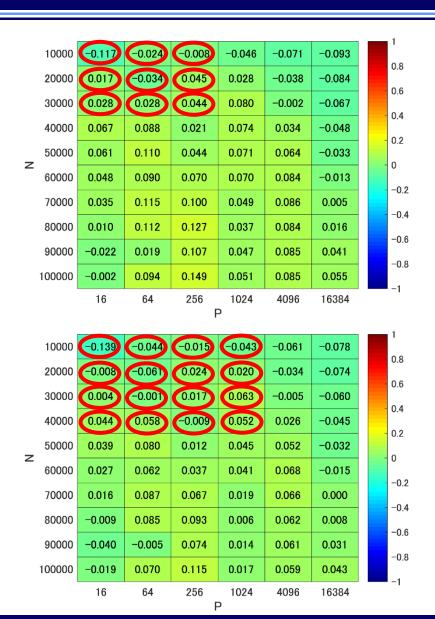
-0.8

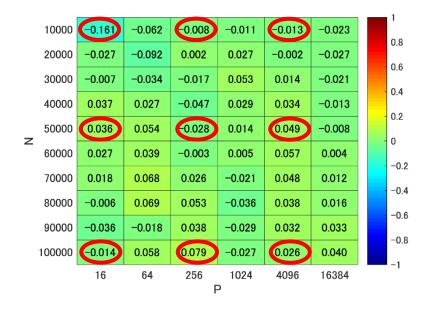
Sample data used for fitting



 For every case, estimation is very accurate. (error is within 10%)

Effect of sample data set in Situation 4



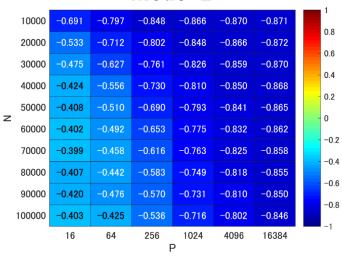


No significant differences are found.

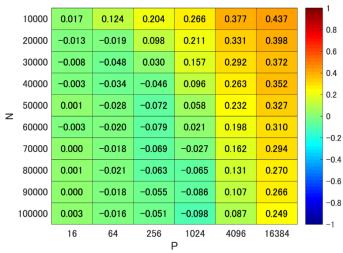
(Differences of sample data set rarely impacted the accuracy of estimation.)

Overall comparison

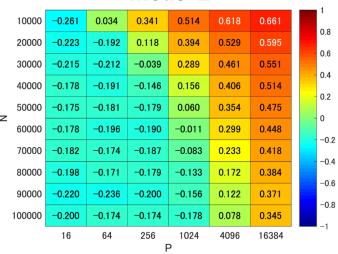




Model 3



Model 2



Model 4 (data set 1)

| | | \ | | | | | , | 4 |
|---|--------|----------|--------|--------|--------|--------|--------|------|
| | 10000 | -0.117 | -0.024 | -0.008 | -0.046 | -0.071 | -0.093 | 1 |
| | 20000 | 0.017 | -0.034 | 0.045 | 0.028 | -0.038 | -0.084 | 0.8 |
| | 30000 | 0.028 | 0.028 | 0.044 | 0.080 | -0.002 | -0.067 | 0.6 |
| | 40000 | 0.067 | 0.088 | 0.021 | 0.074 | 0.034 | -0.048 | 0.4 |
| z | 50000 | 0.061 | 0.110 | 0.044 | 0.071 | 0.064 | -0.033 | 0.2 |
| | 60000 | 0.048 | 0.090 | 0.070 | 0.070 | 0.084 | -0.013 | 0 |
| | 70000 | 0.035 | 0.115 | 0.100 | 0.049 | 0.086 | 0.005 | -0.2 |
| | 80000 | 0.010 | 0.112 | 0.127 | 0.037 | 0.084 | 0.016 | -0.4 |
| | 90000 | -0.022 | 0.019 | 0.107 | 0.047 | 0.085 | 0.041 | -0.6 |
| | 100000 | -0.002 | 0.094 | 0.149 | 0.051 | 0.085 | 0.055 | -0.8 |
| | , | 16 | 64 | 256 | 1024 | 4096 | 16384 | -1 |
| | | | | | | | | |

-0.2

-0.4

Conclusion

Summary and future work

- We attempted to model the performance of eigen_trd (tridiagonalization routine) in EigenExa on the K computer.
- We considered 4 situations, where different limited information is available for performance modeling.
- We evaluated the estimation by each model comparing with the measured timing data.
- Evaluation with other dense matrix computation and on other computer systems remains to be investigated.

