

Automatic Performance Tuning for the Multi-section with Multiple Eigenvalues Method for the Symmetric Eigenproblem

Takahiro Katagiri^{1,2}, Christof Voemel²,
James Demmel²

¹The University of Electro-communications, Japan

²The University of California at Berkeley, USA

PARA'06, Umea, Sweden

CP4, Monday, June 19, 2006, 14:00-14:20

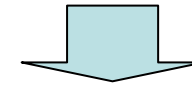
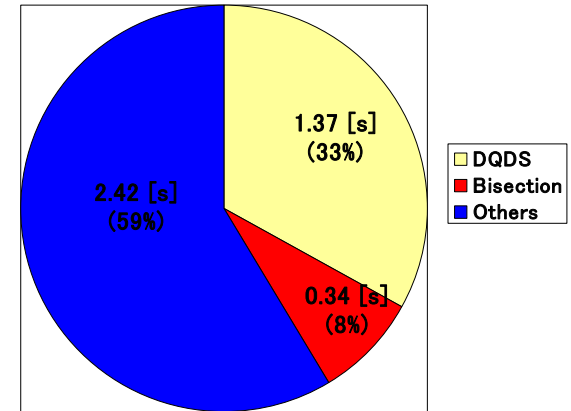
Outline

- Background
 - The bisection routine is bottle-neck in the current implementation of MRRR in LAPACK.
 - Multi-section with Multiple Eigenvalues (MME) Method
- Propose An Run-time Auto-tuning Function for MME
- Performance Evaluation Using the HITACHI SR8000
- Conclusion

Background

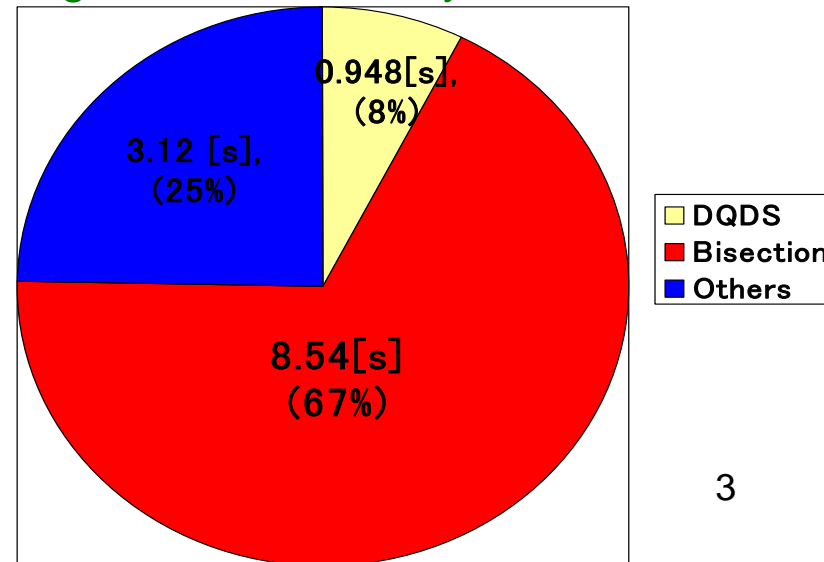
- In the current implementation of LAPACK4.0 MRRR routine, the most heaviest part is bisection routine, if the eigenvalues are tightly clustered.

T=(-1,2,-1) Matrix



Glued Wilkinson +21 Matrix

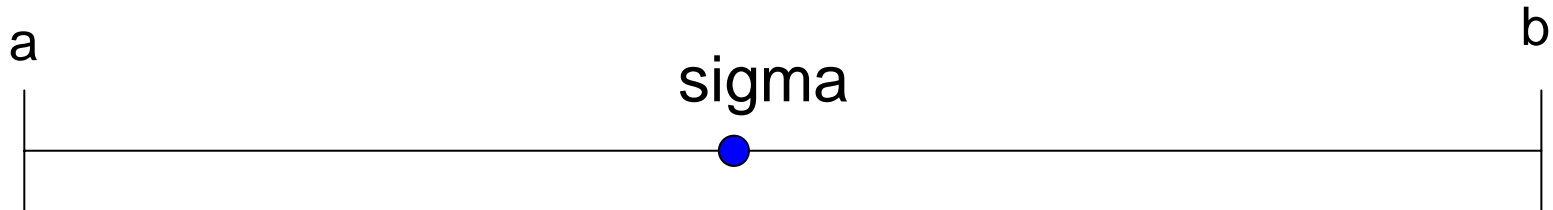
Eigenvalues are very clustered.



HITACHI SR8000
1node/8PE DATA

Bisection Method

- Target: Tridiagonal Symmetric Matrix
- The interval for all eigenvalues is given.
- The sigma is the search point to count the number of eigenvalues to narrow the interval.



$$\text{sigma} = a + (b - a) / 2$$

- Recently algorithm is used.
 - The count is correct except for floating point calculation error. [Demmel et.al, 1994]

The Bisection Kernel

```
S=0; NEG=0;
```

```
do J=1, N-1
```

```
  T = S - SIGMA
```

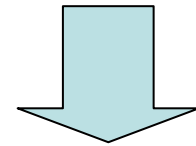
```
  DPLUS = D(J) + T
```

```
  S = T * LLD(J) / DPLUS
```

```
  if (DPLUS < 0) NEG = NEG + 1
```

```
enddo
```

:Loop Carried
Flow Dependency

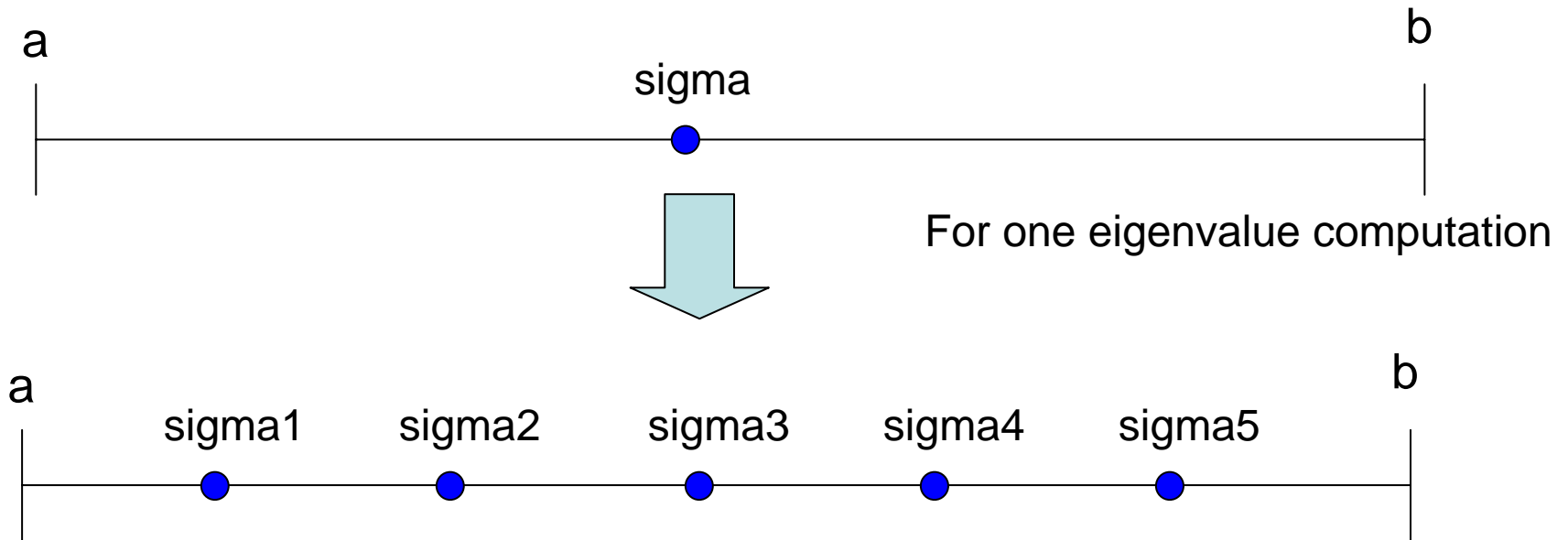


This cannot be
vectorized and
parallelized.

Multi-section

- **Multi-section** [Lo et.al.,1987][Simon,1989]

Bisection:



- **Merit:** The kernel can be parallelized and vectorized.
- **Drawback:** The parallelism strongly depends on the distribution of eigenvalue. (Guess that the bisection find the eigenvalue in early iteration time.)

The multi-section Kernel

```
S(1:ML)=0; NEG(1:ML)=0;
```

```
do I=1, ML
```

```
do J=1, N-1
```

```
T(I) = S(I) - SIGMA(I)
```

```
DPLUS(I) = D(J) + T(I)
```

```
S(I)=T(I)*LLD(J) / DPLUS(I)
```

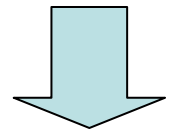
```
if (DPLUS(I)<0) NEG(I) = NEG(I) + 1
```

```
enddo
```

```
enddo
```

ML: The number of multi-section points.

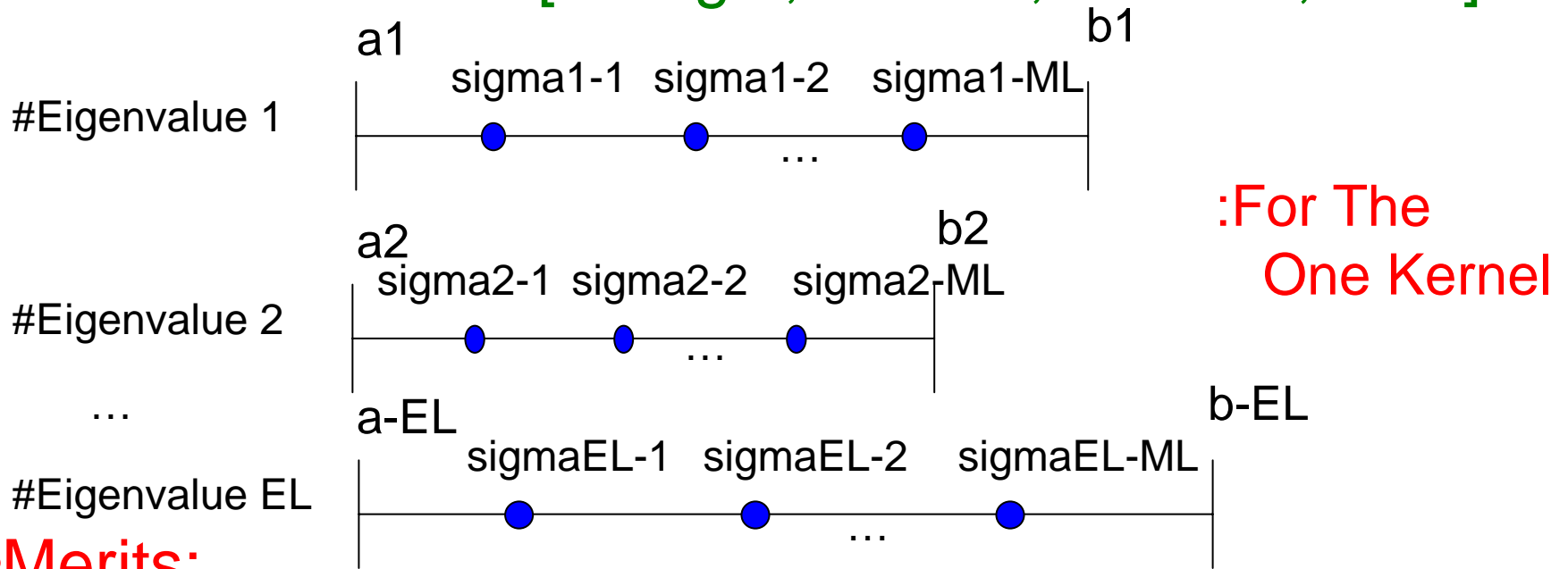
:There is no dependency for T(I), DLPAS(I), and S(I).



The loop I can be vectorized & parallelized.

Multi-section with Multiple Eigenvalues (MME) Method

- **MME Method** [Katagiri, Voemel, Demmel, 2006]



- **Merits:**

- The kernel can be parallelized and vectorized.
- The outer loop length can keep long, even if we take small multi-section points (ML) --- **EL-times to normal multi-section.**

➡ The search efficiency & parallelism keep high compared to multi-section.

- **Drawback:**

There is no merit for no multiple eigenvalue case.

The MME Kernel

```
S(1:EL*ML)=0; NEG(1:EL*ML)=0;
```

```
do I=1, EL*ML
```

EL: The number of
Eigenvalues.

ML: The number of
multi-section points.

```
do J=1, N-1
```

```
T(I) = S(I) - SIGMA(I)
```

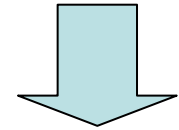
```
DPLUS(I) = D(J) + T(I)
```

```
S(I) = T(I)*LLD(J) / DPLUS(I)
```

```
if (DPLUS(I)<0) NEG(I) = NEG(I) + 1
```

```
enddo
```

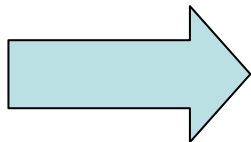
```
enddo
```



- (1) The loop I can be vectorized & parallelized.
- (2) The loop length of I is longer than multi-section.

The Parameter Setting Problem of MME

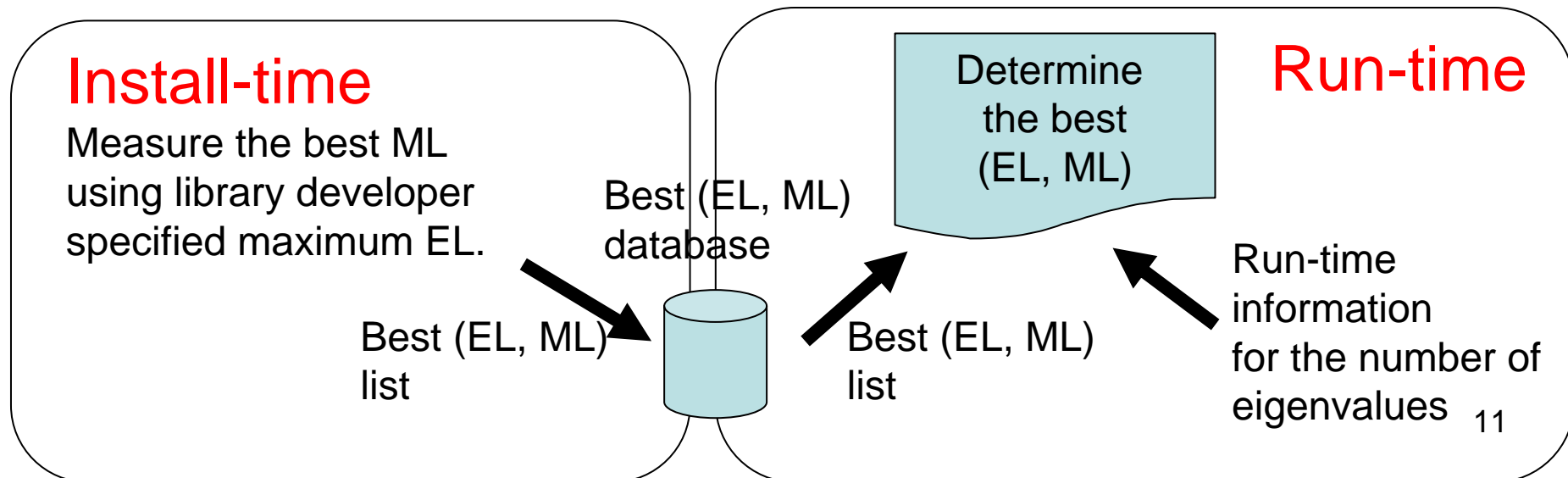
- **Parameter Setting Problem:** How should we set the two parameters for EL and ML?
- **Conventional Problem:** Multi-section points (ML) depends on the computer architecture. Hence, we can determine the ML before the routine is called.
- **New Problem:** However, the number of multiple eigenvalues (EL) depends on the numerical characteristics for input matrices.



A run-time tuning function is needed to tune MME.

Overall of the New Run-time Auto-tuning Function

- **Type:** Run-time parameter setting with (1)run-time information for the number of eigenvalues using (2)tuned parameters (Install-time Optimization) in install-time.
- **Method:** Using an empirical auto-tuning method for install-time auto-tuning to the eigenvalue calculation routine (*DLARRB*) using the MME kernel with a random tri-diagonal matrix.



Overall of the Install-time Optimization Method

1. Measure the normal multi-section kernel time, then find the best ML. Thus, find the best of ml in $[1, \dots, MAXML]$ with $EL=1$.
2. Let the best multi-section point be ML^* . : Check multi-section time
3. do $el=2, MAXEL$
 1. Find the best ML using the routine using the MME kernel with el for ml in $[1, \dots, MLE]$, where MLE in $[1, \dots, MAXML]$ and $MLE \leq ML^*$. If ($el > ML^*$), then $ml=1$ is only measured. Let the best ML be ML^*_el , and the time be T_{el} . : Check main problem time
 2. do $co-el=1, el-1$: Check co-problem time
 1. Find the best set ($EL^*_co-best, ML^*_co-best$) using the routine with MME kernel. The parameters is fixed as ($EL(co-el), ML(co-el)$) with el . Let the best time be $T_{co-best}$.
 2. If ($T_{co-best} < T_{el}$) then
 ($EL(el), ML(el)$) = ($EL^*_co-best, ML_{co-best}$); :Co-problem fast
 else
 ($EL(el), ML(el)$) = (el, ML^*_el); :Main problem fast

Note: The comparison is done by the time per eigenvalues.

For example, if the time is t with el and ml , the comparison is done by t / el .

Performance Evaluation (1/3)

- **Machine:** The HITACHI SR8000 1node/8PEs
(A SMP for 8PEs)
- **Theoretical Peak:** 8GFLOPS/node
- **Compiler:** HITACHI Fortran90 V01-04-/B
- **Compiler Option:** -opt=4 -parallel=4
- **Test Matrices:**
 - #1: $T = (-1, 2, -1)$ dimensioned 2100
 - #2: $T = (\text{Rnd}[0:1])$ dimensioned 2100
 - #3: $T = W +$ dimensioned 2100
 - #4: $T = \text{Glued } W +$ dimensioned 21, 100times.
The glue value is 0.1. Total dimension of the matrix is 2100.

} Eigenvalue
Distribution
: Sparse

← Very Clustered

Performance Evaluation (2/3)

- **Target Process:** All eigenvalues and all eigenvalues for the tri-diagonal matrix
- **Target routine:**
Total execution time for bisection and MME routines in **LAPACK4.0 *DSTEGR*** (Hereafter, *GR*) .
There are two implementations in *GR*:
 - **DQDS mode:** DQDS for full accuracy of eigenvalues.
Using one bisection part.
 - *DLARRV* (Modifying the eigenvector accuracy)
 - **Aggressive bisection mode:** Using two bisection parts.
 - *DRARRE* (Roughly eigenvalue calculated)
 - *DLARRV* (Modifying the eigenvector accuracy)

Performance Evaluation (3/3)

- Static Parameter Tuning (Hand-tuning)
 - Using a fixed parameter set until the GR routine ends.
 - $EL=(1, 2, 3, 4, 8, 16, 32)$: 7 kinds
 - $ML=(1, 2, 4, 8, 16, 24)$: 6 kinds
 - The best time of $EL*ML= 42$ kinds of combinations is obtained.
- The Proposed Run-time Auto-tuning
 - Using different parameter set according to run-time information.
 - Install-time Optimization
 - Parameters:
 - $EL=(1, 2, \dots, 32)$: 32 kinds
 - $ML=(1, 2, \dots, 24)$: 24 kinds
 - Searching space is $EL*ML=768$. By using the empirical method, the searching space is reduced.
 - Benchmark Matrix in Install-time Optimization
 - The eigenvalue calculation routine with the MME kernel for a tri-diagonal matrix:
 - Dimension: 10,500 : <- L1 Cache Limitation
 - A uniform random matrix with [0:1]
 - One execution time is measured for the target routine.

The Auto-Tuned Parameter

Auto-Tuning
Time:
129
[second]

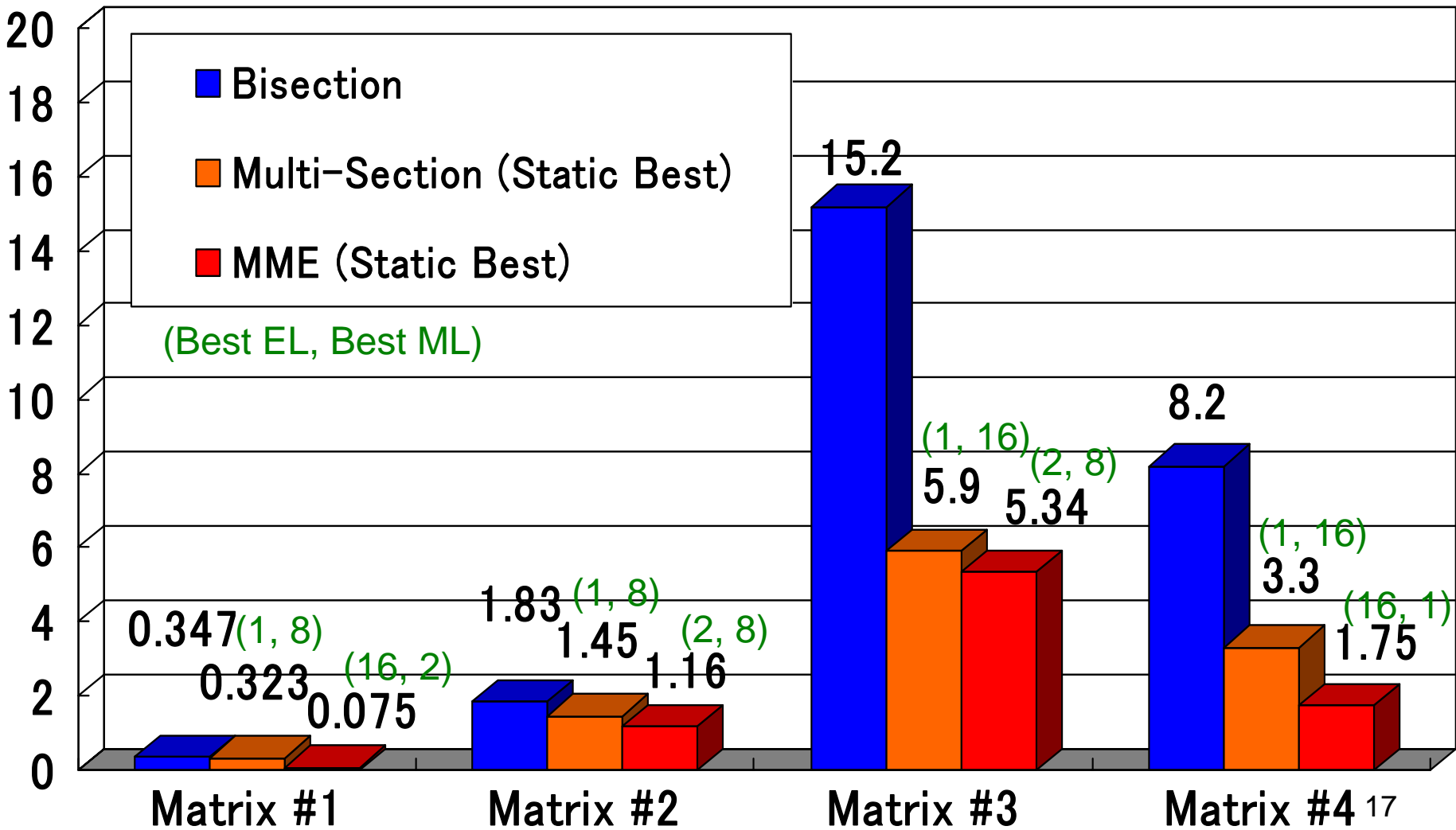
#Eig.	EL	ML
1	1	16
2	2	8
3	3	4
4	4	4
5	5	3
6	5	3 :Co-Prob. Fast
7	7	2
8	8	2
9	9	1
10	10	1
11	11	1
12	12	1
13	13	1
14	14	1
15	15	1
16	16	1
17	16	1 :Co-Prob. Fast
18	16	1 :Co-Prob. Fast
19	16	1 :Co-Prob. Fast
20	16	1 :Co-Prob. Fast

#Eig.	EL	ML
21	21	1
22	22	1
23	23	1
24	24	1
25	24	1:Co-Prob. Fast
26	13	1:Co-Prob. Fast
27	27	1
28	14	1:Co-Prob. Fast
29	29	1
30	15	1:Co-Prob. Fast
31	15	1:Co-Prob. Fast
32	16	1:Co-Prob. Fast

Effect on Static Tuned MME (1/2)

– DQDS Mode : SR8000, N=2100

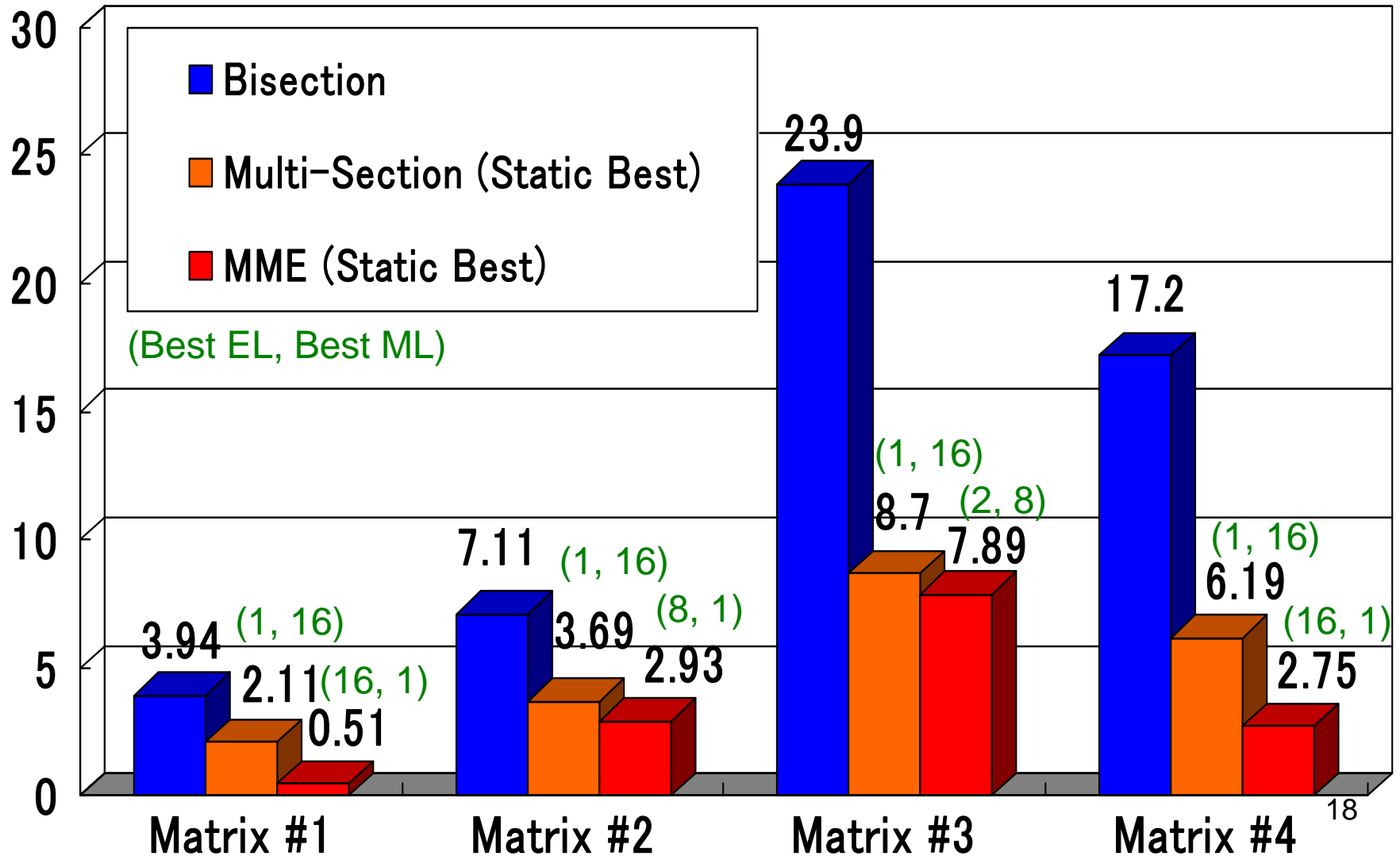
Time in Second



Effect on Static Tuned MME (2/2)

– Aggressive Bisection Mode: SR8000, N=2100

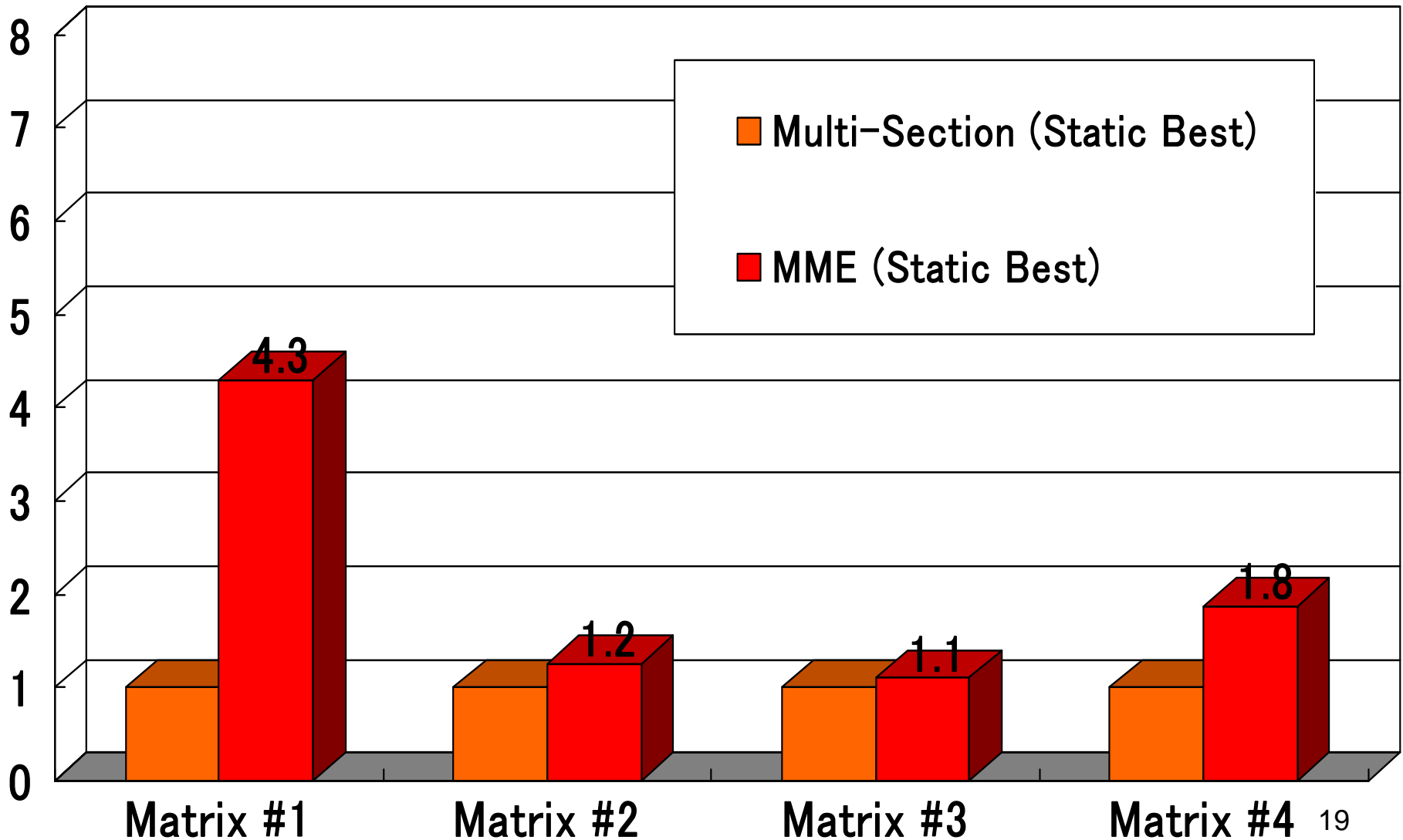
Time in Second



Speedup of Static Tuned MME (1/2)

– DQDS mode : SR8000, N=2100

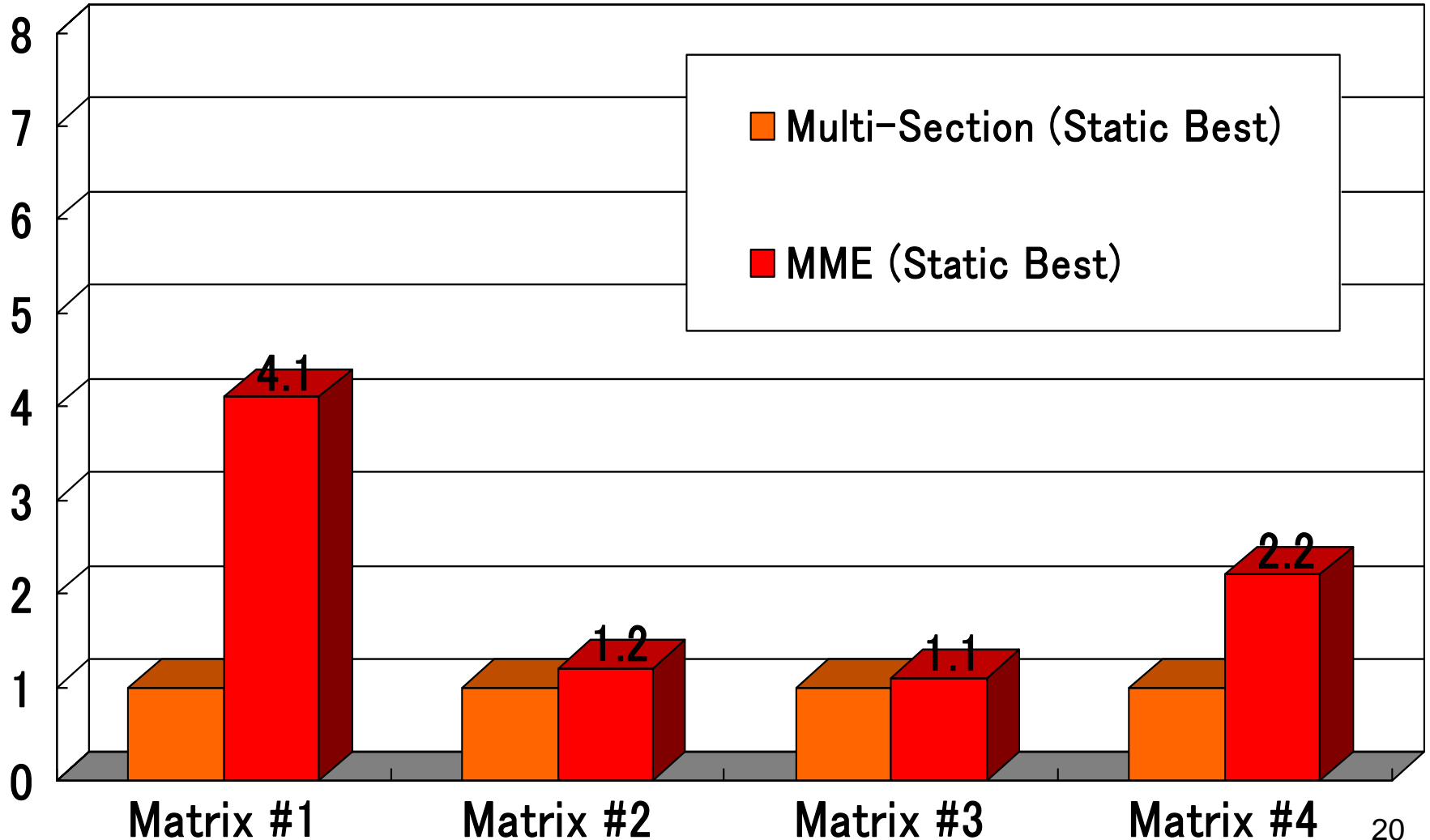
Speedup



Speedup of Static Tuned MME (2/2)

– Aggressive bisection mode : SR8000, N=2100

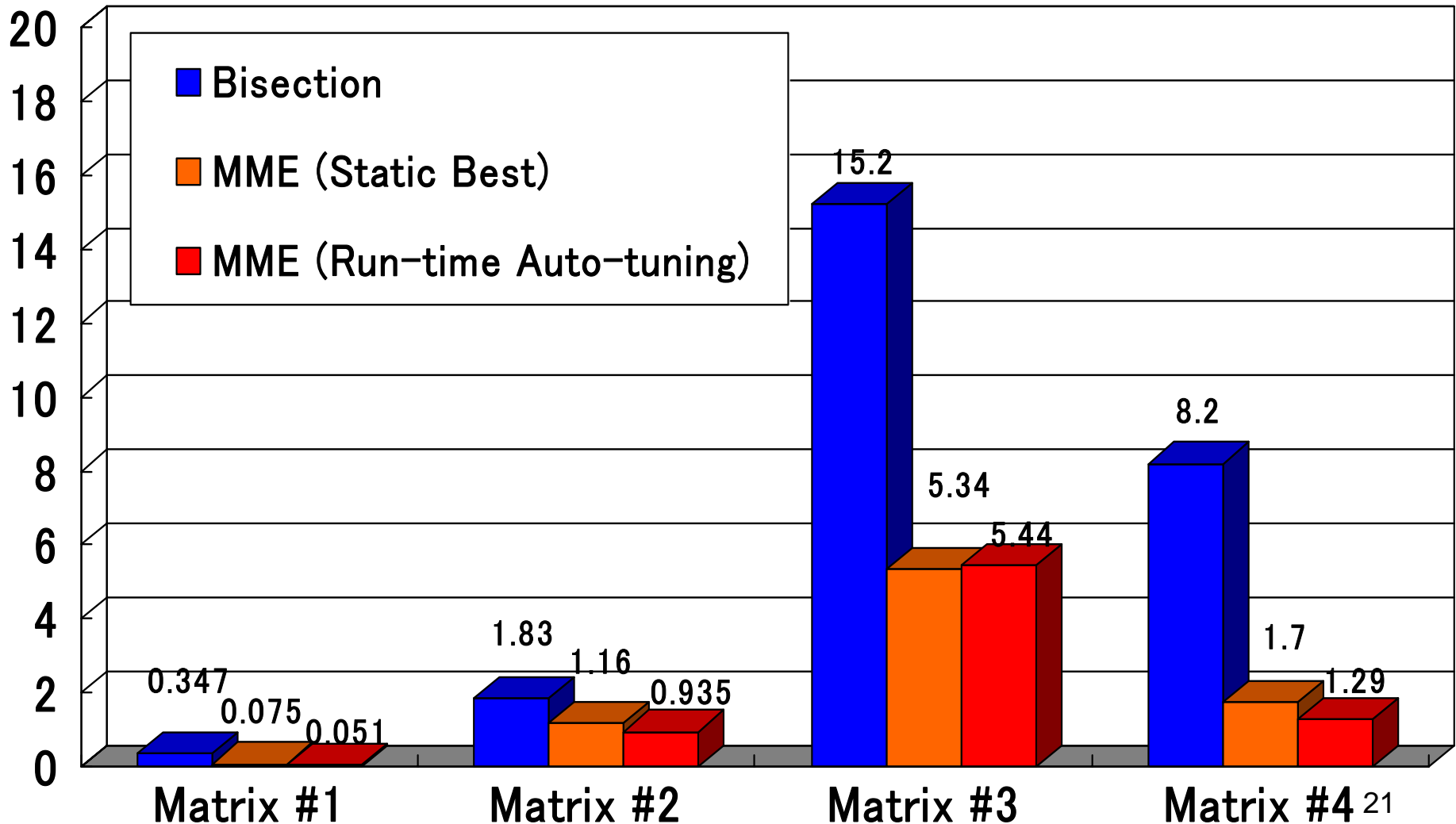
Speedup



Effect on Run-time Auto-Tuning to MME (1/2)

– DQDS mode : SR8000, N=2100

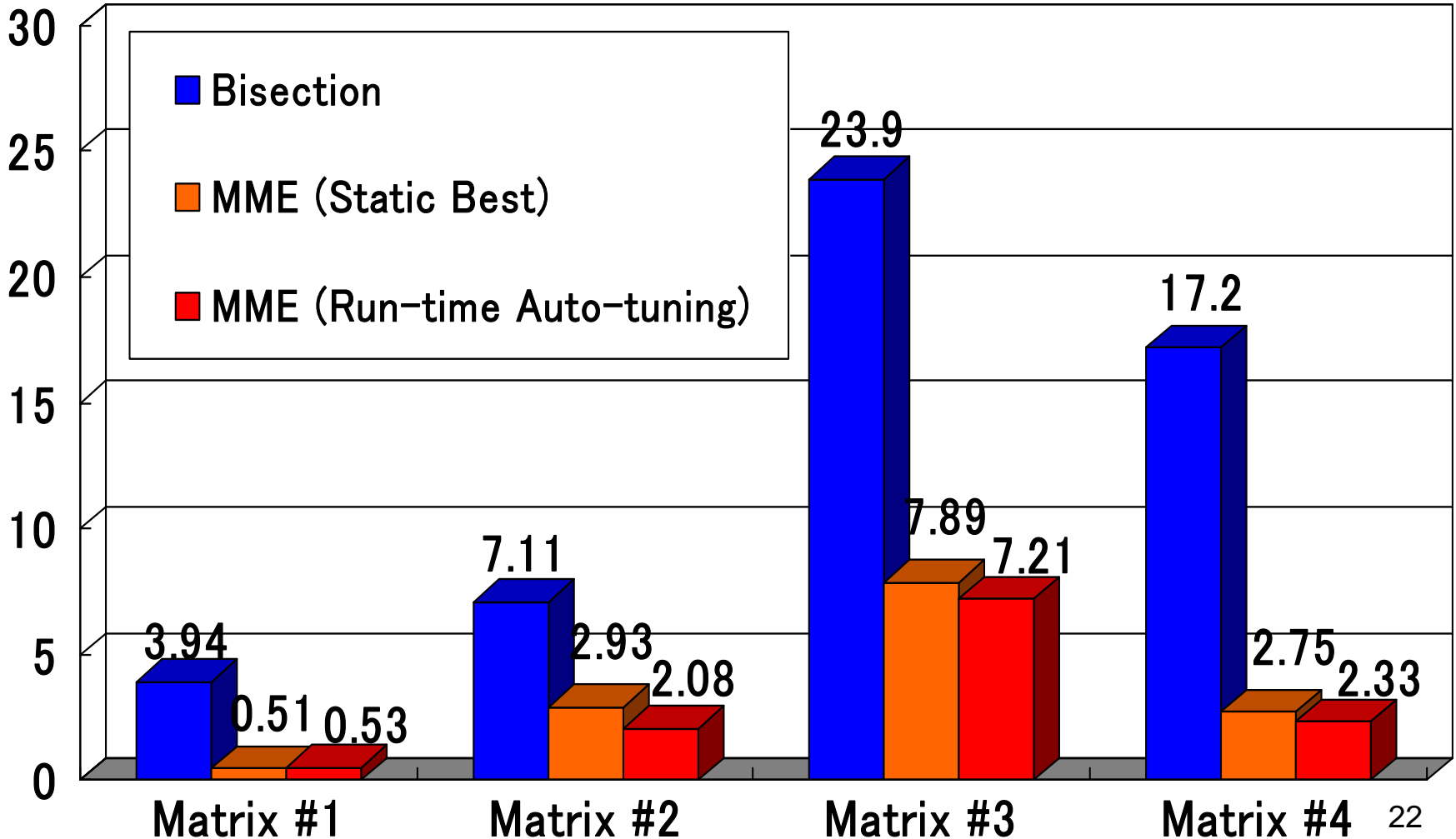
Time in Second



Effect on Run-time Auto-Tuning to MME (2/2)

– Aggressive bisection mode : SR8000, N=2100

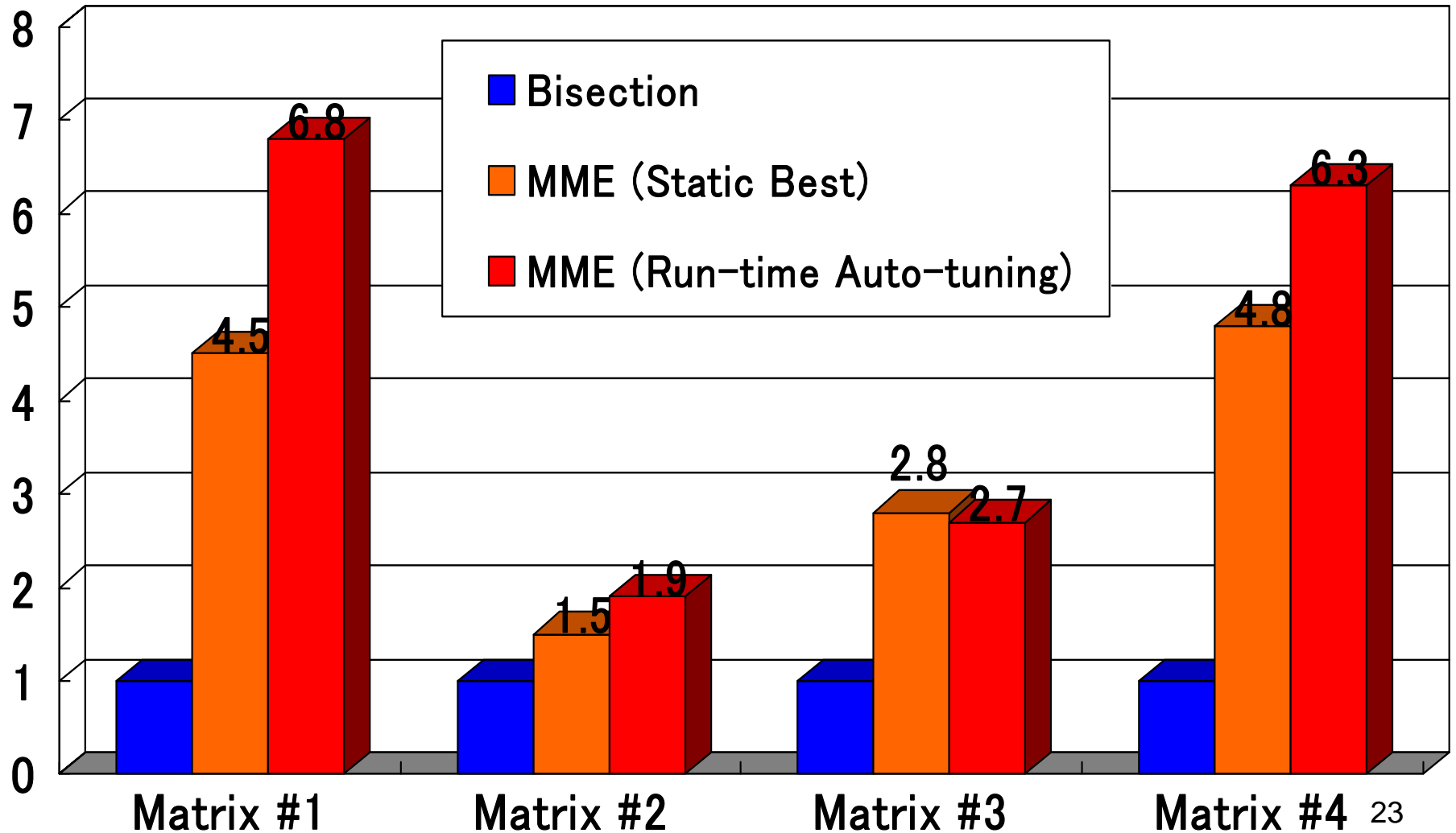
Time in Second



Speedup of Run-time Auto-Tuning to MME (1/2)

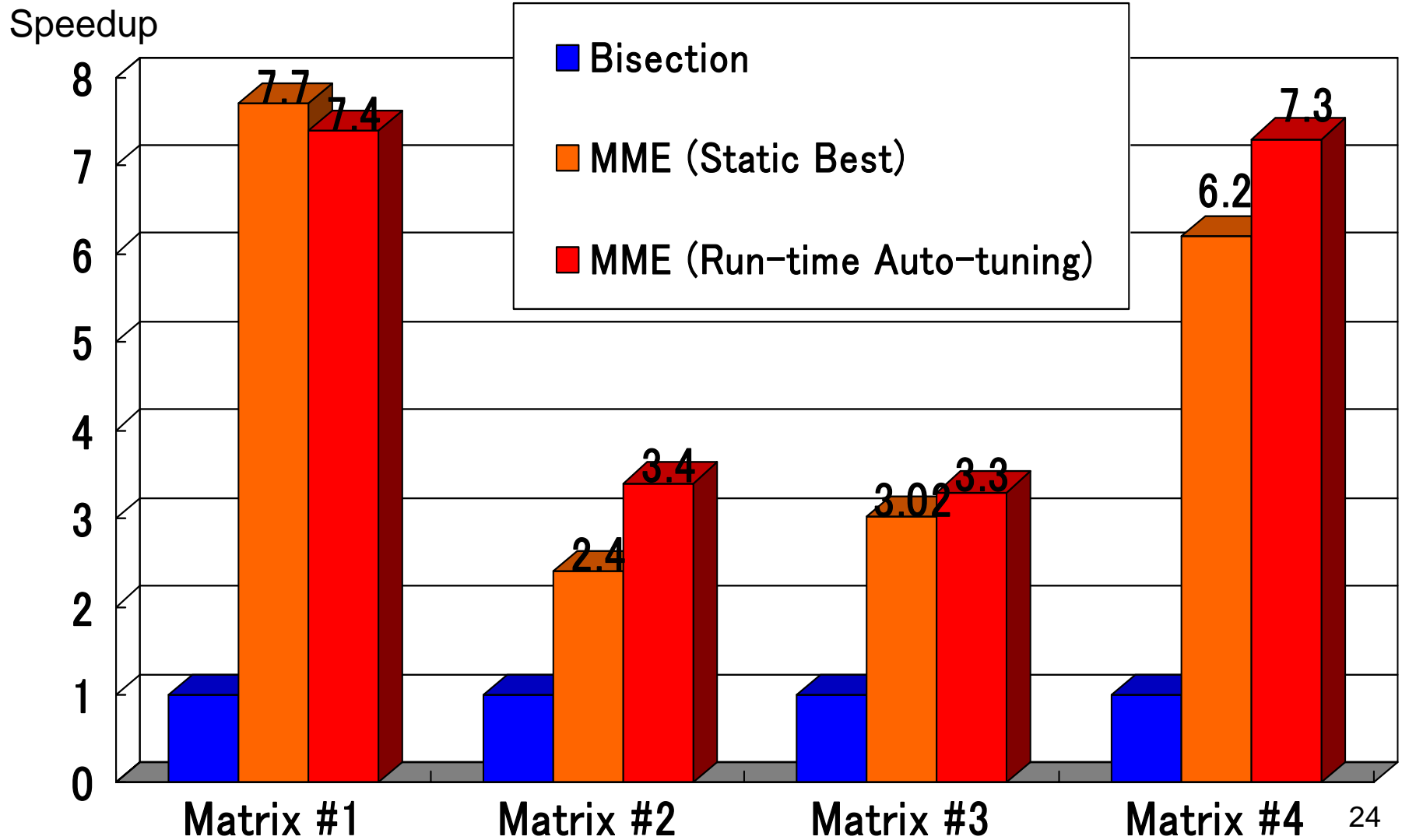
– DQDS mode : SR8000, N=2100

Speedup



Speedup of Run-time Auto-Tuning to MME (2/2)

– Aggressive bisection mode : SR8000, N=2100



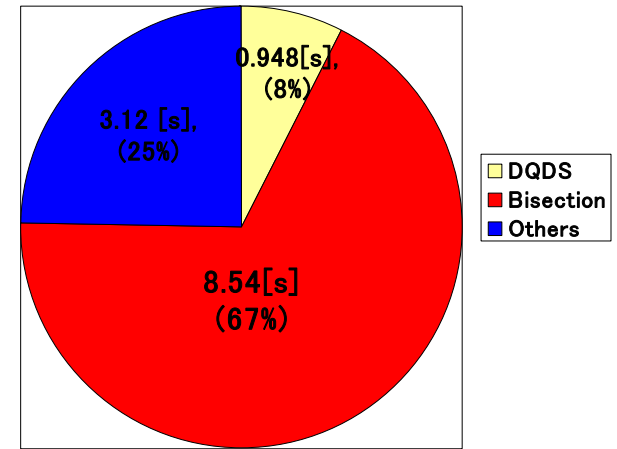
Conclusion (1/2)

- Most of performance using the run-time auto-tuning was almost same as the static best case of MME.
 - Some cases of the run-time auto-tuning were faster than the static tuned cases. There was a case of **1.7x** speedup to the static best MME.
 - **Static tuning is impossible to use actual numerical libraries:** The best parameter strongly depends on input matrix.
 - So, the proposed run-time auto-tuning method is crucial function for numerical libraries.

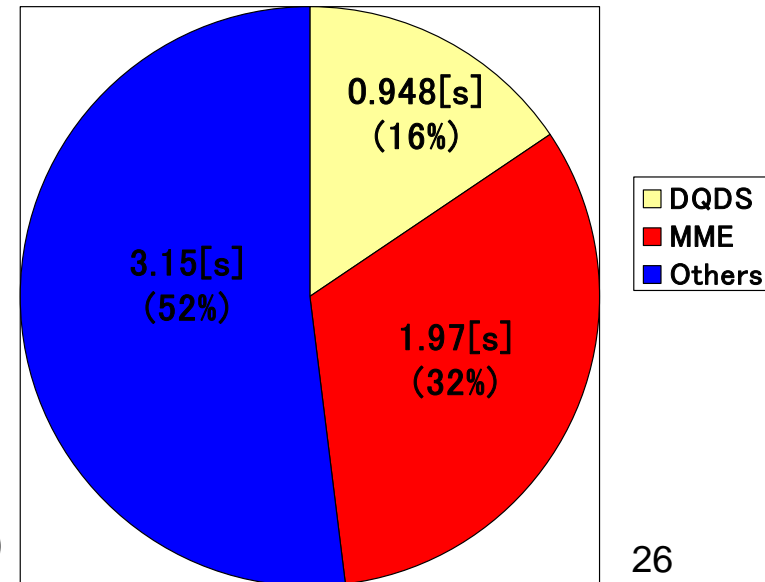
Conclusion (2/2)

- The bisection routine is not bottle-neck any more on the HITACHI SR8000.
- The routines of DQDS and other part (may be DLARRF, which is computing of RRR of child cluster) will be bottle-neck on the HITACHI SR8000.
- We need to parallelize them.

Glued Wilkinson +21 Matrix



Glued Wilkinson +21 Matrix
With MME on the 1node/8PEs

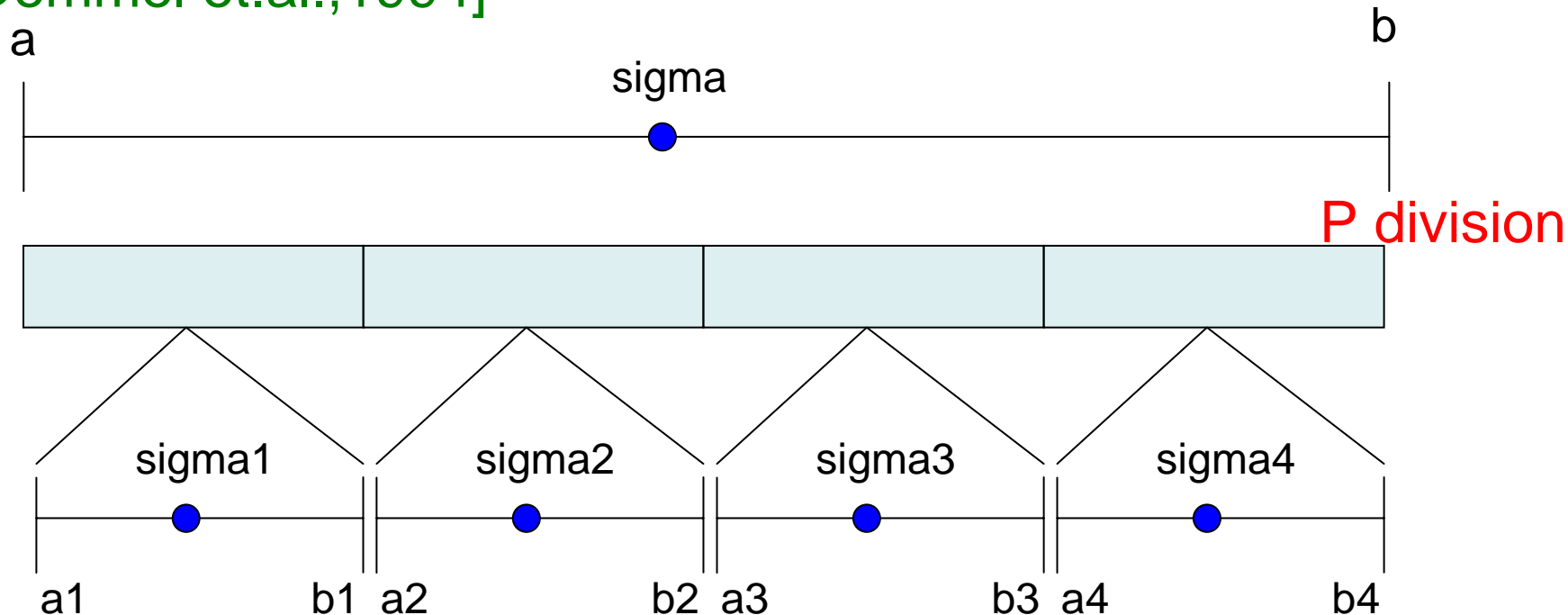


Future work

- Evaluation of performance for the empirical run-time auto-tuning method using several SMP parallel environments.
- Implementation of the run-time auto-tuning method using LAPACK API.
- Adapt and evaluate the run-time auto-tuning framework to the other numerical kernels.

Parallelizing The Bisection Kernel (1 / 2)

- **Method 1** : Dividing The Interval for Bisection
[Demmel et.al.,1994]



- **Drawbacks:**

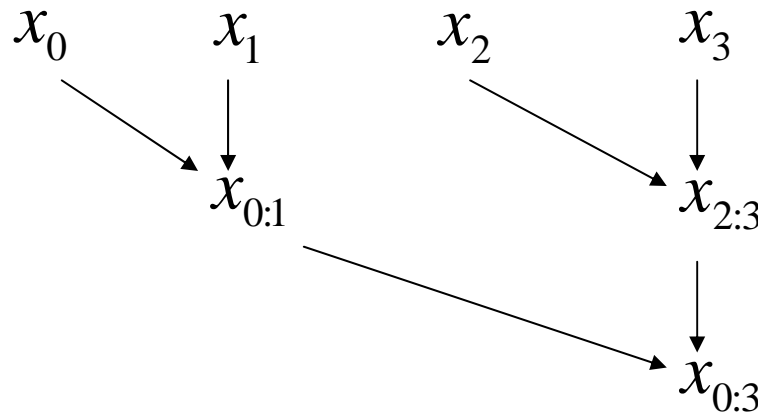
- The kernel can not be vectorized.
- The parallel efficiency will be down, if eigenvalues are clustered.

Parallelizing The Bisection Kernel (2 / 2)

- **Method 2** : Cyclic Reduction Method (Parallel Prefix Method) for the polynomials of

$$p_k(x) = \det(T_k - xI) \quad [\text{Ren, 1996}]$$

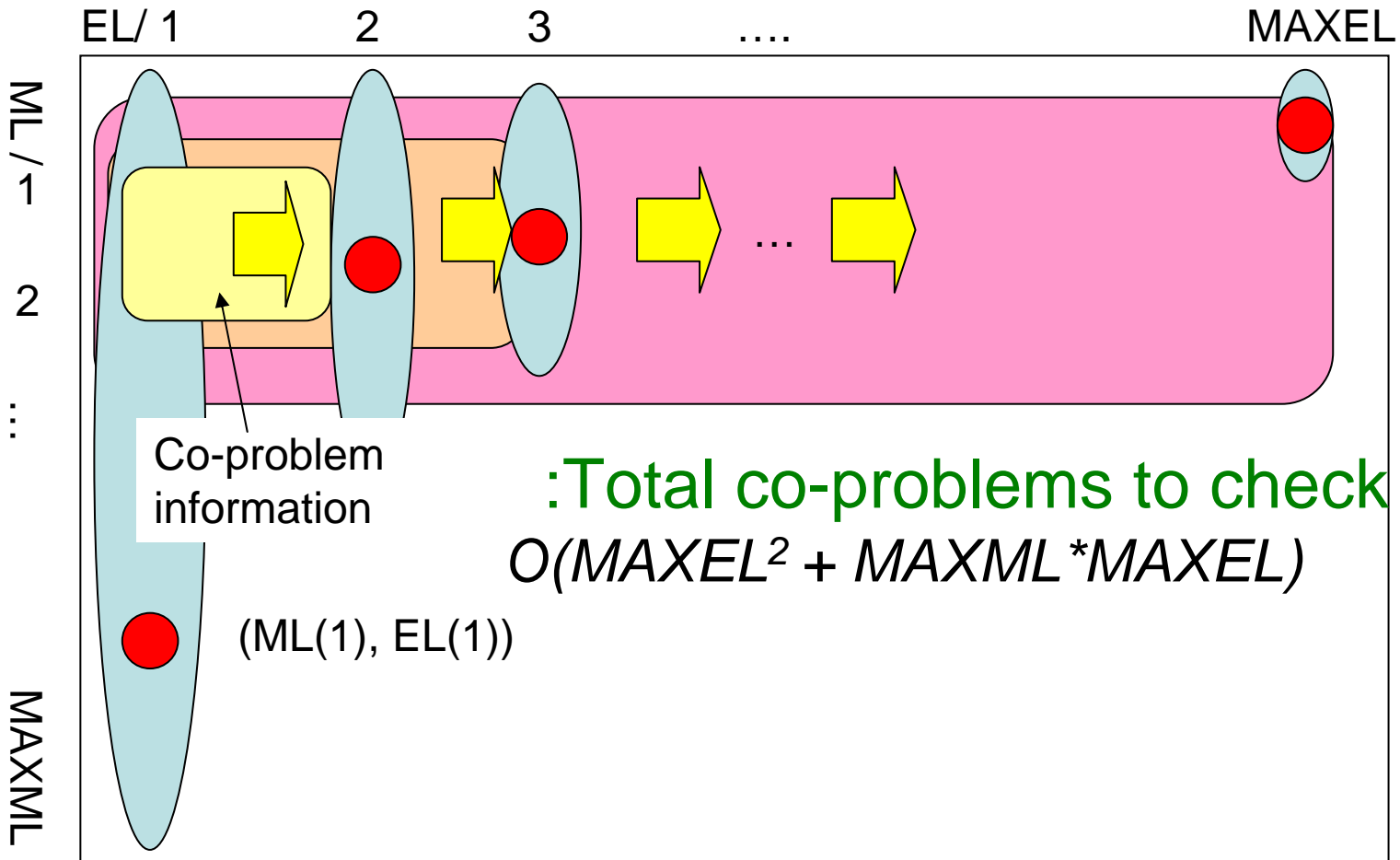
$$\longrightarrow p_k(x) = \det(a_k - x) p_{k-1}(x) - b_{k-1}^2 p_{k-2}(x)$$



O(log k) Parallelism

- **Merit**: The kernel can be parallelized and vectorized.
- **Drawback**: The method has numerical instability.

Process Flow of the Install-time Optimization Method

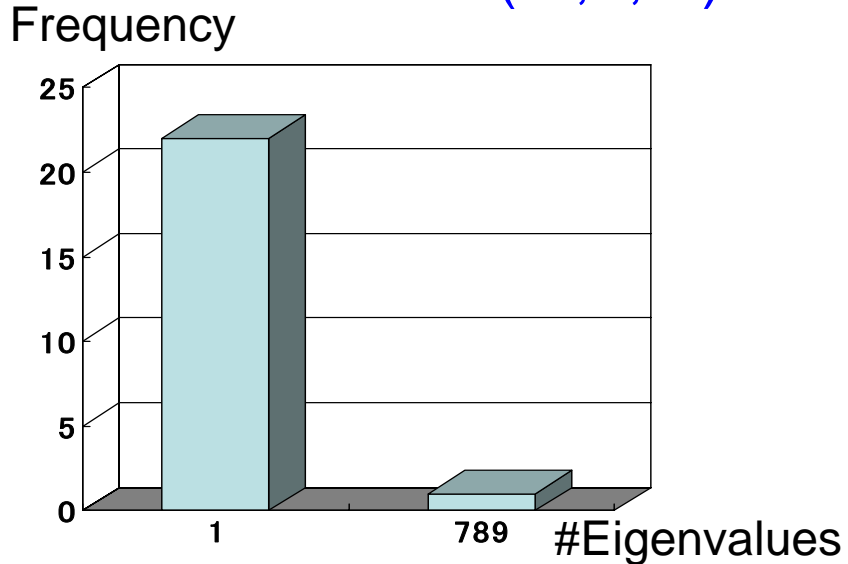


Run-time Auto-tuning Details

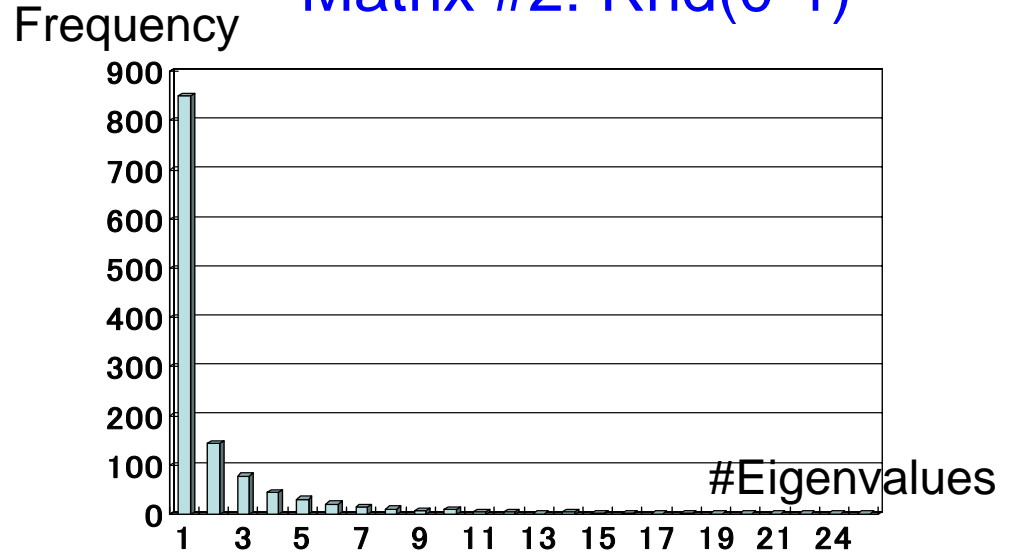
1. Check the required number of eigenvalues. Let the number be el .
2. Search the list of $(EL(el), ML(el))$ for el in $[1, \dots, MAXEL]$.
3. If $(el \leq MAXEL)$, then $(EL(el), ML(el))$ are the best parameter set.
4. If $(el > MAXEL)$, then $(EL(MAXEL), ML(MAXEL))$ are the predicted best parameter set.

The Distribution of The Number of Eigenvalues in *dlarrb* routine (DQDS Mode)

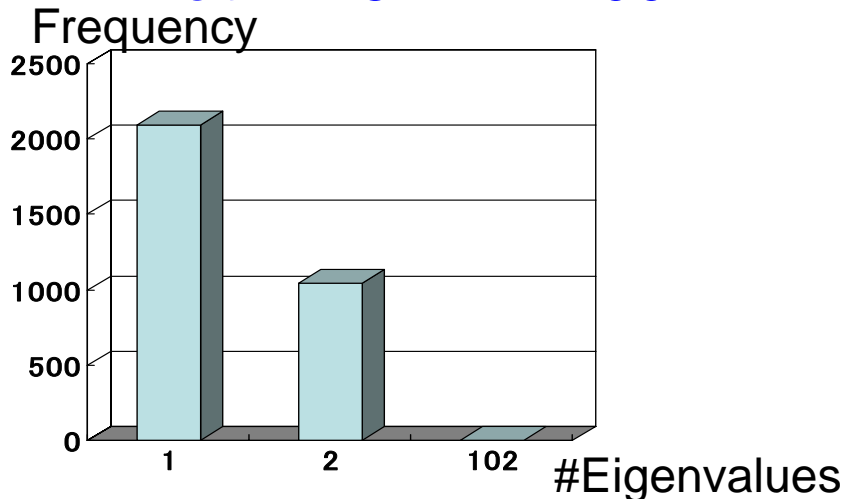
Matrix #1: (-1,2,-1)



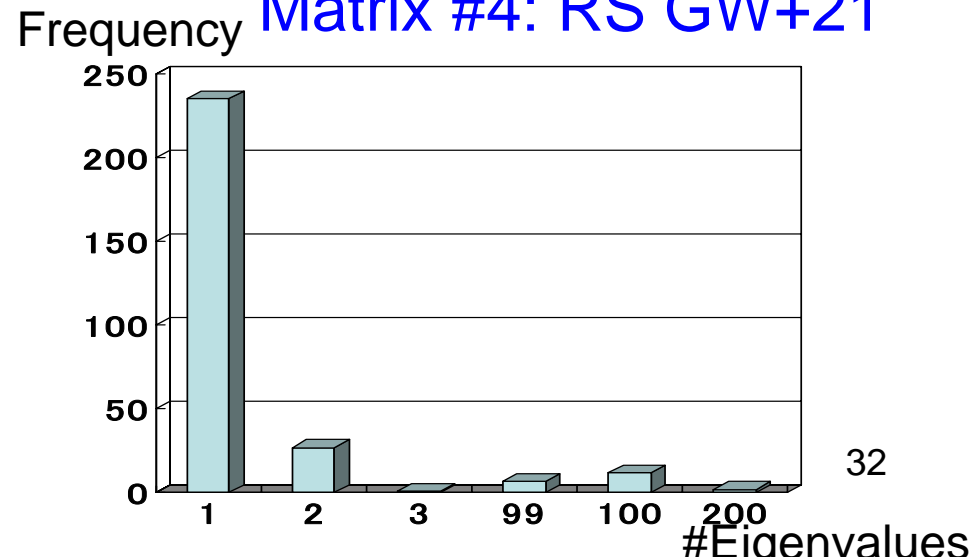
Matrix #2: Rnd(0-1)



Matrix #3: W+2100



Matrix #4: RS GW+21



Appendix A: A Static Tuning Log

Matrix #4, Using dqds case

EL/	1 (MS)	2	3	4	8	16	32
ML/ 1 /	8.200	5.418	4.127	3.432	2.361	<u>1.758</u>	<u>1.760</u>
2 /	6.348	4.249	3.261	6.357	<u>1.961</u>	1.968	1.962
4 /	4.674	3.034	<u>2.392</u>	<u>2.010</u>	2.075	2.098	2.114
8 /	3.532	<u>2.376</u>	3.200	8.200	2.662	2.703	2.797
16 /	<u>3.305</u>	3.975	4.183	4.236	4.355	4.427	4.569
24 /	5.488	5.183	6.035	5.616	5.774	5.971	6.106

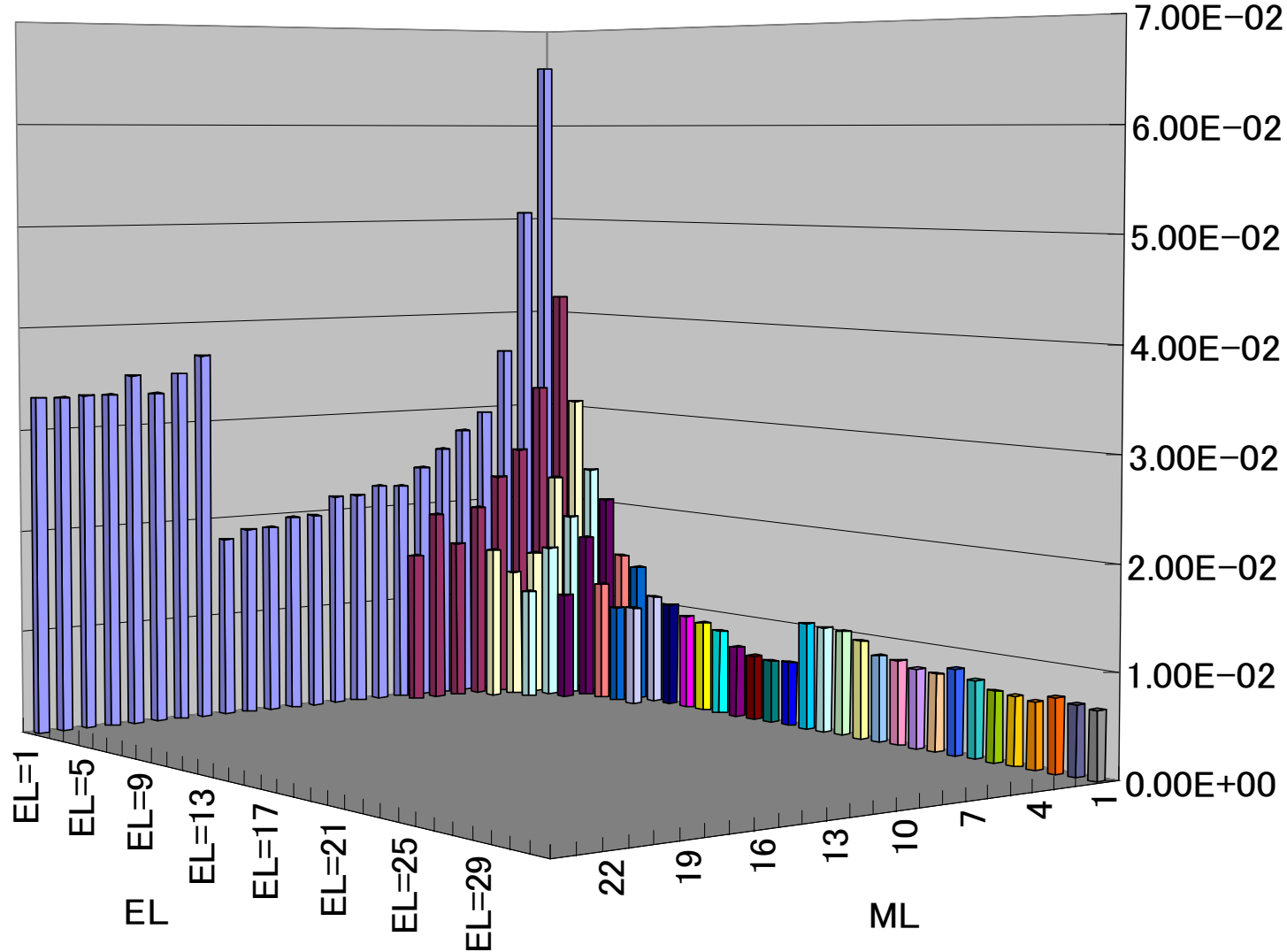
EL*ML=16 is an empirical condition on the HITACHI SR8000

Appendix B: Auto-tuning Log

– Main Problem

Main Problem

Time in Second



Appendix B: Auto-tuning Log

– Co-Problem

Time in Second

