

```
#pragma omp parallel for num_threads(NT)
    for (i=iimin;i<imax;i++) coll[i-iimin] = dt*(coll_term_f (i,I, F,g));
if (mpi_rank > 0) {
    MPI_Send(coll,N1,MPI_DOUBLE,0,0,MPI_COMM_WORLD)
} else {
    while (count < mpi_size) {
        MPI_Recv(tmp,N1,MPI_DOUBLE,MPI_ANY_SOURCE,0,MPI_COMM_WORLD,&mpi_status);
        sender = mpi_status.MPI_SOURCE;
        count++;
    }
}
```

# Introduction to parallel programming (for physicists)

FRANÇOIS GÉLIS & GRÉGOIRE MISGUICH, IPhT courses, June 2019.



université  
PARIS-SACLAY



IPhT, CEA-Saclay  
Itzykson room  
[courses.ipht.fr](http://courses.ipht.fr)

These slides (GM)

1. Introduction & hardware aspects (FG)
2. A few words about Maple & Mathematica
3. Linear algebra libraries
4. Fast Fourier transform
5. Python Multiprocessing
6. OpenMP
7. MPI (FG)
8. MPI+OpenMP (FG)

# Numerical Linear algebra



Here: a few simple examples  
showing how to call some parallel  
linear algebra libraries  
in numerical calculations

# (numerical) Linear algebra

- Basic Linear Algebra Subroutines: **BLAS**
  - vector op. (=level 1)
  - matrix-vector (=level 2)
  - matrix-matrix mult. & triangular inversion (=level 3)
  - Many implementations but standardized interface
  - Discussed here: **Intel MKL & OpenBlas**  
(multi-threaded = parallelized for shared-memory architectures)
- More advanced operations  
Linear Algebra Package: **LAPACK**  
(‘90, Fortran 77)
  - Call the BLAS routines
  - Matrix diagonalization, linear systems and eigenvalue problems
  - Matrix decompositions: LU, QR, SVD, Cholesky

<b>L</b>	<b>A</b>	<b>P</b>	<b>A</b>	<b>C</b>	<b>K</b>
<b>L</b>	<b>-A</b>	<b>P</b>	<b>-A</b>	<b>C</b>	<b>-K</b>
<b>L</b>	<b>A</b>	<b>P</b>	<b>A</b>	<b>-C</b>	<b>-K</b>
<b>L</b>	<b>-A</b>	<b>P</b>	<b>-A</b>	<b>-C</b>	<b>K</b>
<b>L</b>	<b>A</b>	<b>-P</b>	<b>-A</b>	<b>C</b>	<b>K</b>
<b>L</b>	<b>-A</b>	<b>-P</b>	<b>A</b>	<b>C</b>	<b>-K</b>

- Many implementations

Used in most scientific softwares & libraries  
(Python/Numpy, Maple, Mathematica, Matlab, ...)

# A few other useful libs

... for BIG matrices

- **ARPACK**

=Implicitly Restarted Arnoldi Method (~Lanczos for Hermitian cases)

Large scale eigenvalue problems. For (usually **sparse**) nxn matrices with n which can be as large as  $10^8$ , or even more !

Ex: iterative algo. to find the largest eigenvalue, without storing the matrix M (just provide  $v \rightarrow Mv$ ).

Can be used from Python/SciPy

- **PARPACK**

= parallel version of ARPACK

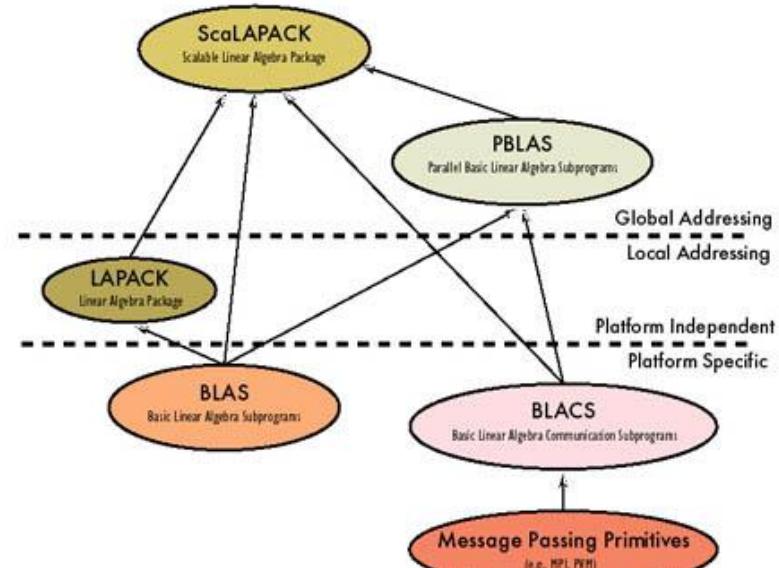
for distributed memory architectures (the matrices are stored over several nodes)

- **ScaLAPACK**

Parallel version of LAPACK for distributed memory architectures

# ScaLAPACK

A Software Library for Linear Algebra Computations on Distributed-Memory Computers



# Two multi-threaded implementations of BLAS & Lapack

## OpenBLAS

- Open source License (BSD)
- Based on GotoBLAS2  
[Created by GAZUSHIGE GOTO, Texas Adv. Computing Center, Univ. of Texas]
- Can be used from Fortran, C, C++, Python/Numpy, ...

## Intel's implementation (=part of the MKL lib.)

- Commercial license
- Included in *Intel® Parallel Studio XE* (compilers, libraries, ...), which is free for students
- Included in *Intel® Performance Libraries* (libraries only, without compiler), free for every one.
- Installed in most/many computing centers / intel-based clusters
- Included in `intel-python`, which is free for *all* users
- Can be used from Fortran, C, C++ or Python/Numpy

# Lapack/Intel-MKL

Code examples in C or FORTRAN:

[https://software.intel.com/sites/products/documentation/doclib/mkl\\_sa/11/mkl\\_lapack\\_examples/](https://software.intel.com/sites/products/documentation/doclib/mkl_sa/11/mkl_lapack_examples/)

## [Intel® Math Kernel Library LAPACK Examples](#)

This document provides code examples for LAPACK (Linear Algebra PACKage) routines that solve problems in the following fields:

### [Linear Equations](#)

Examples for several LAPACK routines that solve systems of [linear equations](#).

### [Linear Least Squares Problems](#)

Examples for some of the LAPACK routines that find solutions to [linear least squares problems](#).

### [Symmetric Eigenproblems](#)

[Symmetric Eigenproblems](#) has examples for LAPACK routines that compute eigenvalues and eigenvectors of real symmetric and complex Hermitian matrices.

### [Nonsymmetric Eigenproblems](#)

[Nonsymmetric Eigenproblems](#) provides examples for ?geev, one of several LAPACK routines that compute eigenvalues and eigenvectors of general matrices.

### [Singular Value Decomposition](#)

Examples for LAPACK routines that compute the [singular value decomposition](#) of a general rectangular matrix.

# Lapack-MKL example in Fortran

DGELSD/from Intel's website (part 1/3)

```
* The routine computes the minimum-norm solution to a real linear least
* squares problem: minimize  $\|b - Ax\|$  using the singular value
* decomposition (SVD) of A. A is an m-by-n matrix which may be
* rank-deficient.
*
* Several right hand side vectors b and solution vectors x can be
* handled
* in a single call; they are stored as the columns of the m-by-nrhs
* right
* hand side matrix B and the n-by-nrhs solution matrix X.
*
```

```
* The effective rank of A is determined by counting the number of
* singular
* values which are less than rcond times
```

```
* Example Program Results.
```

```
=====
```

```
* DGELSD Example Program Results
```

```
* Minimum norm solution
```

```
* -0.69 -0.24 0.06
* -0.80 -0.08 0.21
* 0.38 0.12 -0.65
* 0.29 -0.24 0.42
* 0.29 0.35 -0.30
*
```

```
(...)
```

Here minimize  $\|\vec{b} - A\vec{x}\|_2$  with  
A a rectangular matrix and  $\vec{b}$  a  
vector.

Naming convention of the LAPACK routines : XYYZZZ

X:	S	REAL
	D	DOUBLE PRECISION
	C	COMPLEX
	Z	COMPLEX*16 or DOUBLE COMPLEX
YY:	BD	bidiagonal
	DI	diagonal
	GB	general band
	GE	general
	GG	general matrices, generalized problem (i.e., a pair of general
		matrices)
	GT	general tridiagonal
	(...)	

ZZZ: Type of computation. Here LSD stands for minimum norm solution to a linear least squares problem using the singular value decomposition of A and a divide and conquer method

# Lapack-MKL example in Fortran

(part 2/3)

```
* .. Parameters .
INTEGER M, N, NRHS
PARAMETER ( M = 4, N = 5, NRHS = 3 )
INTEGER LDA, LDB
PARAMETER ( LDA = M, LDB = N )
INTEGER LWMAX
PARAMETER ( LWMAX = 1000 )

* .. Local Scalars ..
INTEGER INFO, LWORK, RANK
DOUBLE PRECISION RCOND

* .. Local Arrays ..
* IWWORK dimension should be at least
* 3*MIN(M,N)*NLVL + 11*MIN(M,N),
* Where
* NLVL = MAX( 0, INT(LOG_2( MIN(M,N) / (SMLSIZ+1))) ) + 1
* and SMLSIZ = 25
INTEGER IWORK( 3*M*0+11*M )
DOUBLE PRECISION A( LDA, N ), B( LDB, NRHS ), S( M ),
    WORK( LWMAX )
```

```
DATA A/
$ 0.12, -6.91, -3.33, 3.97,
$ -8.19, 2.22, -8.94, 3.33,
$ 7.69, -5.12, -6.72, -2.74,
$ -2.26, -9.08, -4.40, -7.92,
$ -4.71, 9.96, -9.98, -3.20
$ /
DATA B/
$ 7.30, 1.33, 2.68, -9.62, 0.00,
$ 0.47, 6.58, -1.71, -0.79, 0.00,
$ -6.28, -3.42, 3.46, 0.41, 0.00
$ /
* .. External Subroutines ..
EXTERNAL DGELSD
EXTERNAL PRINT_MATRIX
* .. Intrinsic Functions ..
INTRINSIC INT, MIN
```

Lapack routines require you to provide some memory space to work (in the form of array(s)). Here: WORK, double precision array of size LWORK (see next slide).

M, N: size of A  
NRHS: number of vectors  $\vec{b}$  for which the problem must me solved.

# Lapack-MKL example in Fortran

(part 3/3)

```
*     .. Executable Statements ..
WRITE(*,*) 'DGELSD Example Program
Results'
*   Negative RCOND means using
default (machine precision) value
RCOND = -1.0
*
*   Query the optimal workspace.
*
LWORK = -1
CALL DGELSD( M, N, NRHS, A, LDA, B,
LDB, S, RCOND, RANK, WORK, LWORK,
IWORK, INFO )
LWORK = MIN( LWMAX, INT( WORK( 1 ) ) )
*
*   Solve the equations A*X = B.
*
CALL DGELSD( M, N, NRHS, A, LDA, B,
LDB, S, RCOND, RANK, WORK, LWORK,
IWORK, INFO )
*
*   Check for convergence.
*
IF( INFO.GT.0 ) THEN
WRITE(*,*) 'The algorithm computing
```

```
SVD failed to converge;
WRITE(*,*) 'the least squares solution
could not be computed.'
STOP
END IF
*
*   Print minimum norm solution.
*
CALL PRINT_MATRIX( 'Minimum norm
solution', N, NRHS, B, LDB )
*
*   Print effective rank.
*
WRITE(*,'(/A,16)') ' Effective rank =
', RANK
*
*   Print singular values.
*
CALL PRINT_MATRIX( 'Singular values',
1, M, S, 1 )
STOP
END
*
*   End of DGELSD Example.
```

First call to DGELSD with  
LWORK=-1 → LAPACK returns  
the optimal size LWORK of the  
workspace array WORK.

Actual calculation

Compilation and output :

```
$ ifort -mkl DGELSD_example.f
$ ./a.out
DGELSD Example Program
Results

Minimum norm solution
-0.69  -0.24   0.06
-0.80  -0.08   0.21
 0.38   0.12  -0.65
 0.29  -0.24   0.42
 0.29   0.35  -0.30

Effective rank =          4

Singular values
 18.66  15.99  10.01   8.51
```

# Lapack/Intel-MKL

## zheevd example in C

```
#include <stdlib.h>
#include <stdio.h>
#include <mkl.h>
// C-wrapper to the Fortran Lapack lib. :
#include <mkl_lapacke.h>
int main() {
    const int n=2000;           prints the num. of threads

    printf("Matrix size=%i\n",N);
    printf("Number of threads=%i\n",
mkl_get_max_threads());      ←

    MKL_INT N = n, LDA = n, info,i,j;
    double w[N];               ←
    MKL_Complex16* a;
    a=malloc(N*LDA*sizeof(MKL_Complex16));

    srand(999); /* dense random matrix */
    for (i=0; i < N; i++)
        for(j = 0; j<N; j++)
            a[i*LDA+j].real=rand(),a[i*LDA+j].imag=rand();
    }
```

```
// LAPACKE_zheevd: computes all
// eigenvalues and eigenvectors of a
// complex Hermitian matrix A using divide
// and conquer algorithm

info = LAPACKE_zheevd( LAPACK_ROW_MAJOR,
'V', 'L', N, a, LDA, w );
/* Check for convergence */
if( info > 0 ) {
    printf( "The algorithm failed to compute
eigenvalues.\n" );
    exit( 1 );
}
/* Print the extreme eigenvalues */
printf("Smallest eigen value=%6.2f\n",w[0]);
printf("Largest value=%6.2f\n\n",w[N-1]);
}
```

w: array containing  
the eigen. vals.

Call to Lapack.  
This version takes care of the  
workspace memory management  
(contrary to the Fortran version)

# OpenBLAS/LAPACK

## zheevd example in C

```
#include <stdlib.h>
#include <stdio.h>
#include <omp.h>
// C-wrapper to the Fortran Lapack lib.
#include <lapacke.h>
int main() {
const int N=2000;

printf("Matrix size=%i\n",N);
printf("Number of threads=%i\n",
omp_get_max_threads());

int LDA=N, info,i,j;
double w[N];
lapack_complex_double* a;
a=malloc(N*LDA*sizeof(lapack_complex_double))
;

srand(999); /* Dense random matrix */
for (i=0; i < N; i++)
    for(j = 0; j<N; j++)
a[i*LDA+j]=lapack_make_complex_double(rand()
,rand());
```

```
// LAPACKE_zheevd: computes all
// eigenvalues and eigenvectors of a
// complex Hermitian matrix A using divide
// and conquer algorithm

info = LAPACKE_zheevd( LAPACK_ROW_MAJOR,
'V', 'L', N, a, LDA, w );

/* Check for convergence */
if( info > 0 ) {
    printf( "The algorithm failed to compute
eigenvalues.\n" );
    exit( 1 );
}
/* Print the extreme eigenvalues */
printf("Smallest eigen value=%6.2f\n",w[0]);
printf("Largest value=%6.2f\n\n",w[N-1]);
```

# OpenBLAS/CBLAS

## dgemm example in C

```
#include <stdio.h>
#include <stdlib.h>
#include <cblas.h>
int main() {
int N=10000,N2,i,j;
N2=N*N;
//Memory allocation for the arrays:
double *A, *B, *C;
A = (double *)malloc( N2*sizeof( double ) );
B = (double *)malloc( N2*sizeof( double ) );
C = (double *)malloc( N2*sizeof( double ) );

for (i = 0; i < (N2); i++)
    A[i] = (double)(i+1),
    B[i] = (double)(-i-1),
    C[i] = 0.0;

printf ("Computing matrix product using OpenBLAS dgemm
function via CBLAS interface ... \n");
cblas_dgemm(CblasRowMajor, CblasNoTrans, CblasNoTrans,
            N, N, N, 1.0, A, N, B, N, 1.0, C, N);
printf ("done.\n\n");
return 0;
}
```

Matrix-matrix multiplication (BLAS) of double precision general matrices

Specify the « order » of the matrix elements in memory:

$A[i][j]=A[j+LDA*i]$  row-major  
(C/C++ order)

$A[i][j]=A[i+LDA*j]$  column-major  
(=Fortran order)

# Compilation of the OpenBLAS examples – use of make & makefile

```
#specify below the path to the OpenBLAS library files (like libopenblas.a and cblas.h)
OPEN_BLAS_LIB= ../OpenBLAS

#specify below the path to the lapacke.h header file
LAPACKE_INC= ../OpenBLAS/lapack-netlib/LAPACKE/include

dgemm_example_mini.exe: dgemm_example_mini.c
    gcc $< -o $@ -L $(OPEN_BLAS_LIB) -I $(OPEN_BLAS_LIB) -lopenblas -pthread

zheevd_example.exe: zheevd_example.c
    gcc $< -o $@ -I $(LAPACKE_INC) -L $(OPEN_BLAS_LIB) -lopenblas -fopenmp -lgfortran

clean:
    \rm *.exe

all: dgemm_example.exe zheevd_example.exe
```

makefile  
\$< : 1st pre-requisite (usually the source file)  
\$@ : target (executable name)

-j option: use several threads/cores to compile multiple files in parallel

To compile: make dgemm\_example.exe or make all or make -j 2 all

# Check parallelism (1)

```
$ make dgemm_example.exe  
gcc dgemm_example.c -o dgemm_example.exe -L ../OpenBLAS -I ../OpenBLAS  
-lopenblas -fopenmp -lrt
```

```
$ export OMP_NUM_THREADS=1; ./dgemm_example.exe 2000
```

Initializing the matrices ... done.

Computing matrix product using OpenBLAS dgemm function via CBLAS interface... done.

**Elaspe time (s): 0.719543**

**22.2308 GFlops**

```
$ export OMP_NUM_THREADS=10; ./dgemm_example.exe 2000
```

Initializing the matrices ... done.

Computing matrix product using OpenBLAS dgemm function via CBLAS interface... done.

**Elaspe time (s): 0.0814542**

**196.38 GFlops**

Close to the peak power of the CPU  
(here Xeon E5-2630 v2 @ 2.60GHz / 15360 KB Cache).  
Check with **cat /proc/cpuinfo** )

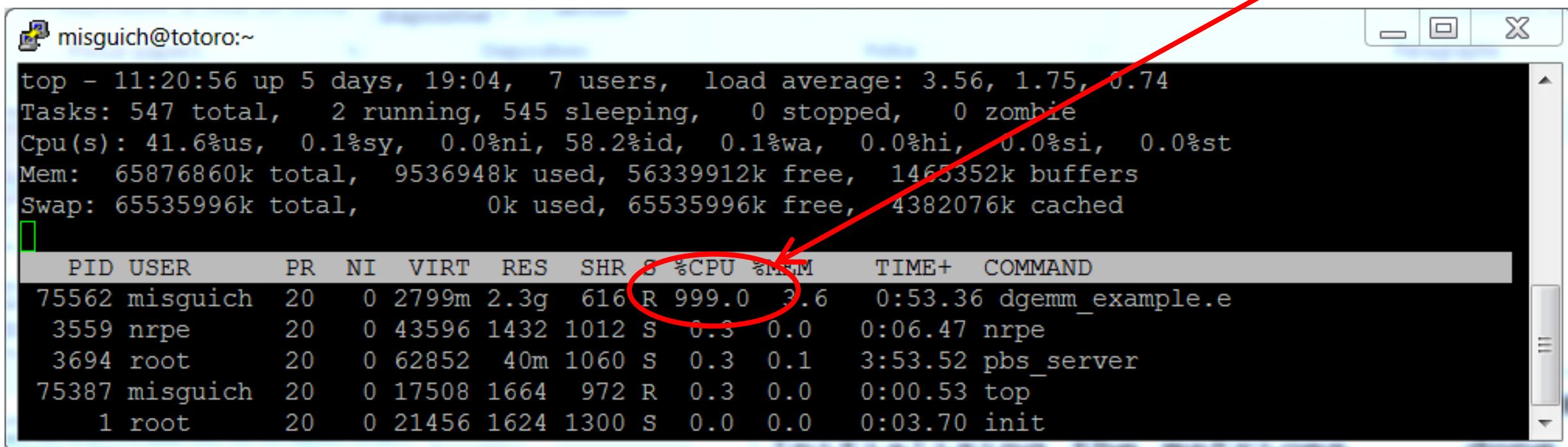
# Check parallelism (2)

Environment variable to specify the # of threads  
(if not specified in the code)

```
$ export OMP_NUM_THREADS=10; ./dgemm_example.exe 10000
Initializing the matrices ... done.
Computing matrix product using OpenBLAS dgemm function via CBLAS interface... done.
Elaspe time (s) : 9.45623
211.49 GFlops
```

1 process with ~10 threads running

Top



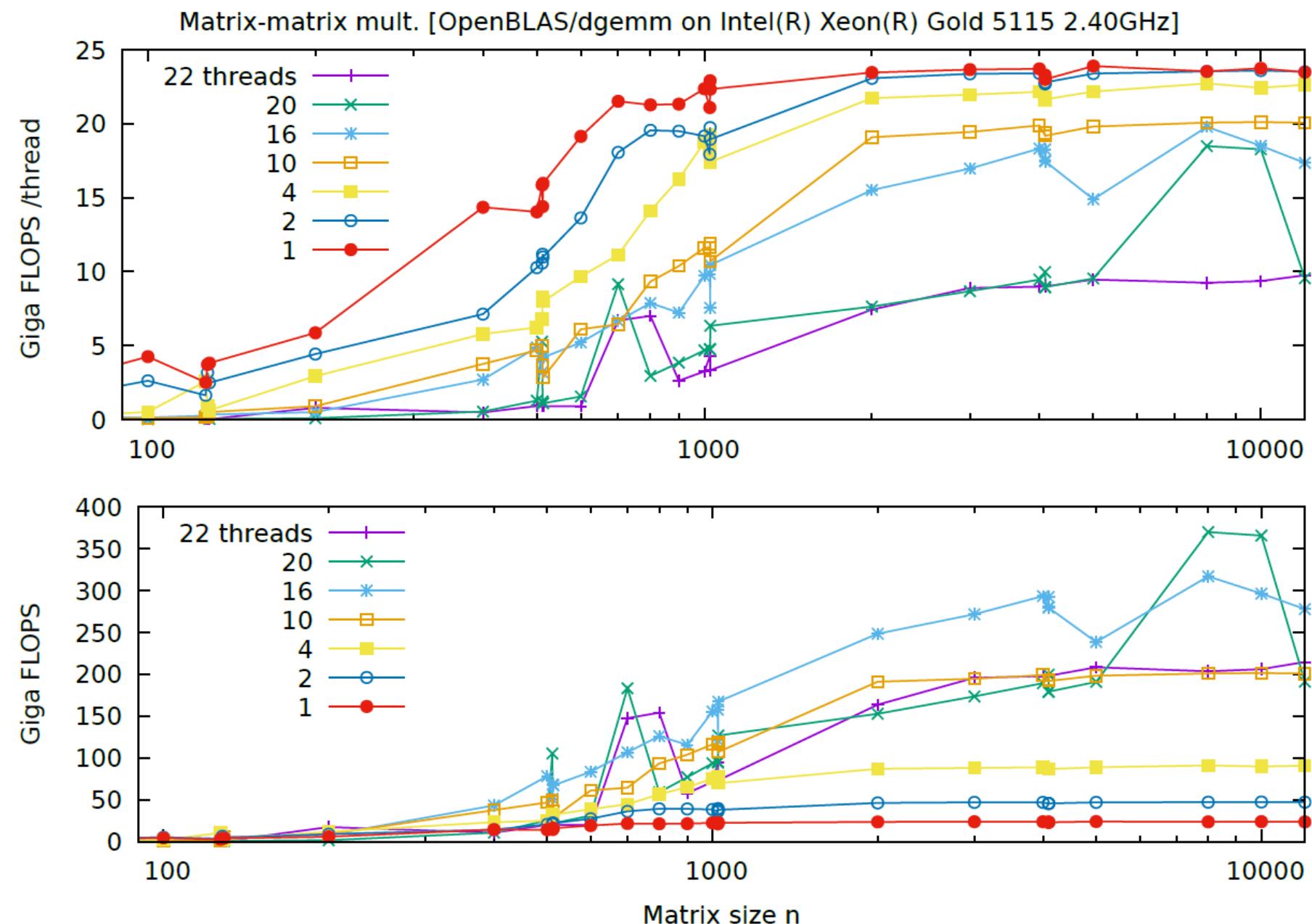
The screenshot shows the terminal window of the top command. At the top, it displays system statistics: load average (3.56, 1.75, 0.74), tasks (547 total, 2 running, 545 sleeping, 0 stopped, 0 zombie), CPU usage (41.6%us, 0.1%sy, 0.0%ni, 58.2%id, 0.1%wa, 0.0%hi, 0.0%si, 0.0%st), memory usage (65876860k total, 9536948k used, 56339912k free, 1465352k buffers, 65535996k total swap, 0k used, 65535996k free, 4382076k cached). Below this is a header for the process list:

PID	USER	PR	NI	VIRT	RES	SHR	S	%CPU	%MEM	TIME+	COMMAND
75562	misguich	20	0	2799m	2.3g	616	R	999.0	3.6	0:53.36	dgemm_example.e
3559	nrpe	20	0	43596	1432	1012	S	0.3	0.0	0:06.47	nrpe
3694	root	20	0	62852	40m	1060	S	0.3	0.1	3:53.52	pbs_server
75387	misguich	20	0	17508	1664	972	R	0.3	0.0	0:00.53	top
1	root	20	0	21456	1624	1300	S	0.0	0.0	0:03.70	init

A red circle highlights the %CPU column header, and a red arrow points from the text "1 process with ~10 threads running" above to this circle. Another red arrow points from the same text to the "R" in the status column of the first process row.

# OpenBLAS performance

## dgemm (from C)



# Anatomy of High-Performance Matrix Multiplication

KAZUSHIGE GOTO

The University of Texas at Austin  
and

ROBERT A. VAN DE GEIJN

The University of Texas at Austin

## High-performance BLAS

---

Now *OpenBLAS*

We present the basic principles which underlie the high-performance implementation of the matrix-matrix multiplication that is part of the widely used GotoBLAS library. Design decisions are justified by successively refining a model of architectures with multilevel memories. A simple but effective algorithm for executing this operation results. Implementations on a broad selection of architectures are shown to achieve near-peak performance.

Categories and Subject Descriptors: G.4 [Mathematical Software]: —*Efficiency*

General Terms: Algorithms; Performance

Additional Key Words and Phrases: linear algebra, matrix multiplication, basic linear algebra subprograms



# Armadillo: C++ library for linear algebra & scientific computing

Example of (symmetric) matrix diagonalization

Can call OpenBLAS or MKL

```
#include <iostream>
#include <armadillo>
using namespace arma;
int main() {
    const int N=5000;
    size_t dim=N;
    mat A(dim, dim,
arma::fill::randu);
    vec eigval;
    mat eigvec;
    eig_sym(eigval,eigvec,A);
    cout<<"1st
eigenvalue=<<eigval[0]
<<"\tLast=<<eigval[dim-
1]<<endl;
return 0;
```



# Armadillo: C++ library for linear algebra & scientific computing

## Matrix-matrix multiplication

```
#include <iostream>
#include <armadillo>
using namespace arma;
int main() {
const int N=10000;
size_t dim=N;
mat A(dim, dim, arma::fill::randu);
mat B(dim, dim, arma::fill::randu);
mat C=A*B;
return 0;
}
```



# Armadillo: C++ library for linear algebra & scientific computing

## compilation

```
ARMA_INC=/usr/local/install/armadillo-9.200.6/include
```

```
ARMA_LIB=/usr/local/install/armadillo-9.200.6/lib64/
```

```
diag.exe: diag.cpp
```

```
g++ -std=gnu++11 $< -o $@ -I $(ARMA_INC) -L $(ARMA_LIB) -larmadillo
```

```
mult.exe: mult.cpp
```

```
g++ -std=gnu++11 $< -o $@ -I $(ARMA_INC) -L $(ARMA_LIB) -larmadillo
```



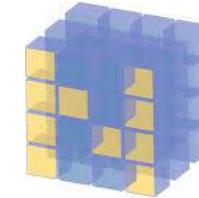
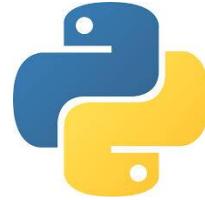
# Armadillo: C++ library for linear algebra & scientific computing

checking what linear algebra library that is actually used

```
$ ldd diag.exe
linux-vdso.so.1 => (0x00007ffeddd7c000)
libarmadillo.so.9 => /usr/local/install/armadillo-9.200.6/lib64/libarmadillo.so.9 (0x00007f2c30549000)
libstdc++.so.6 => /usr/local/install/gcc-4.8.0/lib64/libstdc++.so.6 (0x00007f2c3023f000)
libm.so.6 => /lib64/libm.so.6 (0x000000338f200000)
libgcc_s.so.1 => /usr/local/install/gcc-4.8.0/lib64/libgcc_s.so.1 (0x00007f2c30010000)
libc.so.6 => /lib64/libc.so.6 (0x000000338e200000)
libmkl_rt.so => /opt/intel/composer_xe_2013.5.192/mkl/lib/intel64/libmkl_rt.so
(0x00007f2c2fb02000)
libhdf5.so.6 => /usr/lib64/libhdf5.so.6 (0x0000003390a00000)
libz.so.1 => /lib64/libz.so.1 (0x000000338ee00000)
/lib64/ld-linux-x86-64.so.2 (0x000000338de00000)
libdl.so.2 => /lib64/libdl.so.2 (0x000000338ea00000)
```

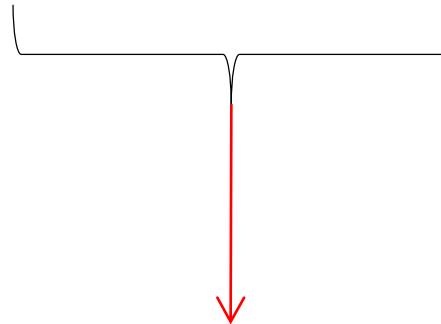
MKL used here

# BLAS & Lapack from Python/Numpy



L	A	P	A	C	K
L	-A	P	-A	C	-K
L	A	P	A	-C	-K
L	-A	P	-A	-C	K
L	A	-P	-A	C	K
L	-A	-P	A	C	-K

Python → Numpy → LinAlg → LAPACK → BLAS



Different possible implementations

- standard BLAS/LAPACK (Netlib)
- ATLAS (Automatically Tuned Linear Algebra Software)
- OpenBLAS
- MKL
- ...

} Multi-threaded /parallel

# Python/Numpy linalg

Check the version of Lapack & BLAS numpy is linked to:

```
>>> import numpy as np  
>>> np.__config__.show()
```

```
Python 2.7.5 (default, Mar 20 2015, 15:33:03)  
[GCC 4.4.7 20120313 (Red Hat 4.4.7-11)] on linux2  
Type "help", "copyright", "credits" or "license"  
for more information.  
>>> import numpy as np  
>>> np.__config__.show()  
lapack_opt_info:  
    libraries = ['openblas', 'openblas']  
    library_dirs = ['/usr/local/lib']  
    define_macros = [('HAVE_CBLAS', None)]  
    language = c  
blas_opt_info:  
    libraries = ['openblas', 'openblas']  
    library_dirs = ['/usr/local/lib']  
    define_macros = [('HAVE_CBLAS', None)]  
    language = c  
openblas_info:  
    libraries = ['openblas', 'openblas']  
    library_dirs = ['/usr/local/lib']  
    define_macros = [('HAVE_CBLAS', None)]  
    language = c  
(. . .)
```

# Python/Numpy linalg

What if my numpy version is *not* linked to a parallel linear algebra lib. ?

- Install OpenBLAS:

```
> sudo apt-get install libopenblas-dev
```

(this will hopefully replace the previous BLAS lib. by OpenBLAS in Numpy)

- Or the Intel Python distribution

<https://software.intel.com/en-us/articles/installing-intel-free-libs-and-python-apt-repo>

(...)

```
> sudo apt-get install intelpython3
```



The corresponding numpy will be using the MKL lib.

# Python/Numpy linalg

Matrix diagonalization example

```
import numpy as np
import numpy.random as npr
import time
npr.seed(2019)
n=3000
A = npr.randn(n,n)
t = time.time()
v = np.linalg.eigvals(A)
td = time.time() - t
print(" Time=%0.4f s" % (td))
```

Specify the #of threads using an environment variable (bash shell):

```
> export OMP_NUM_THREADS=4
```

# Performance vs #of cores & matrix dim.

## Matrix diagonalization

```
import numpy as np
import numpy.random as npr
import time

npr.seed(2019)

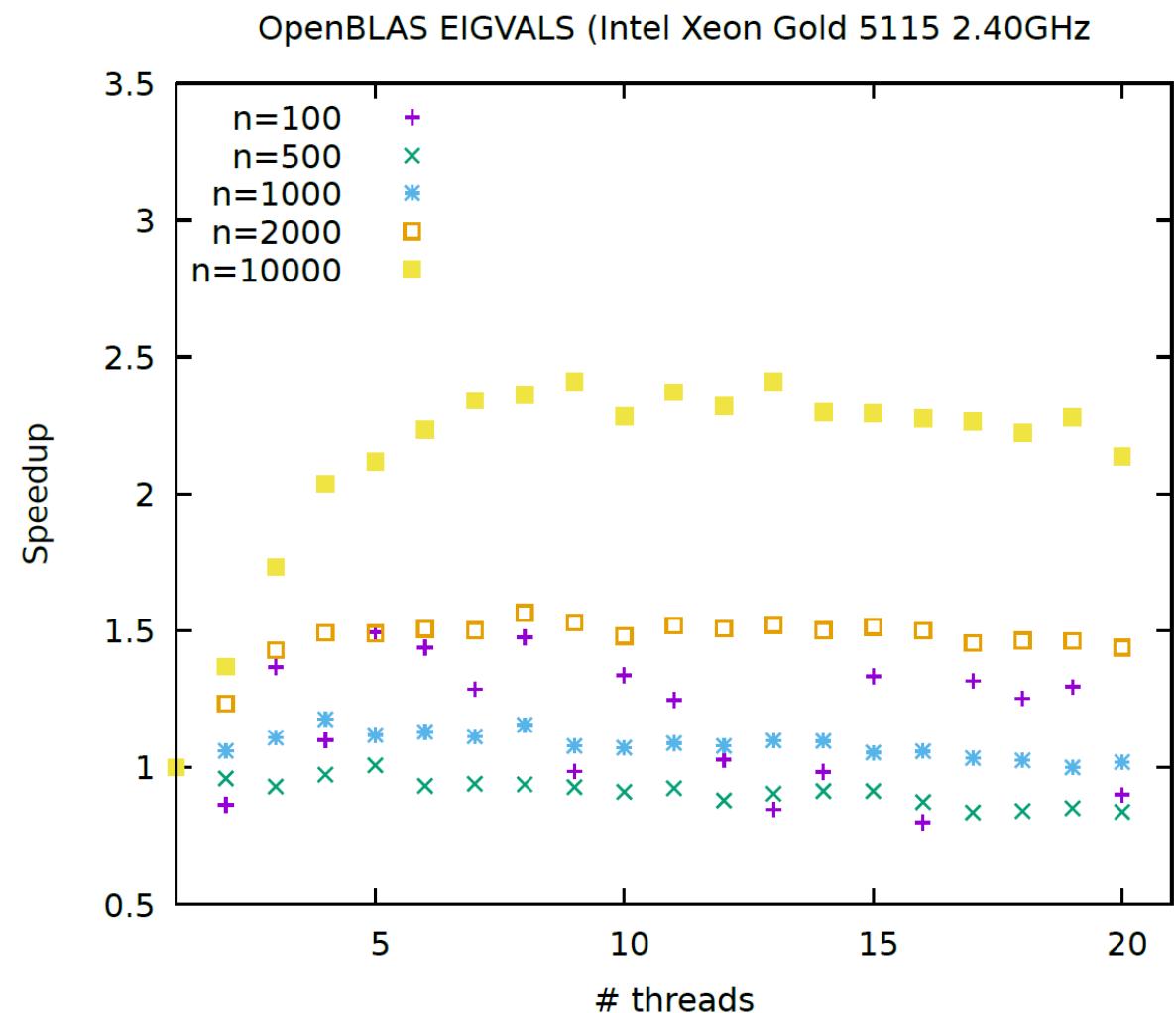
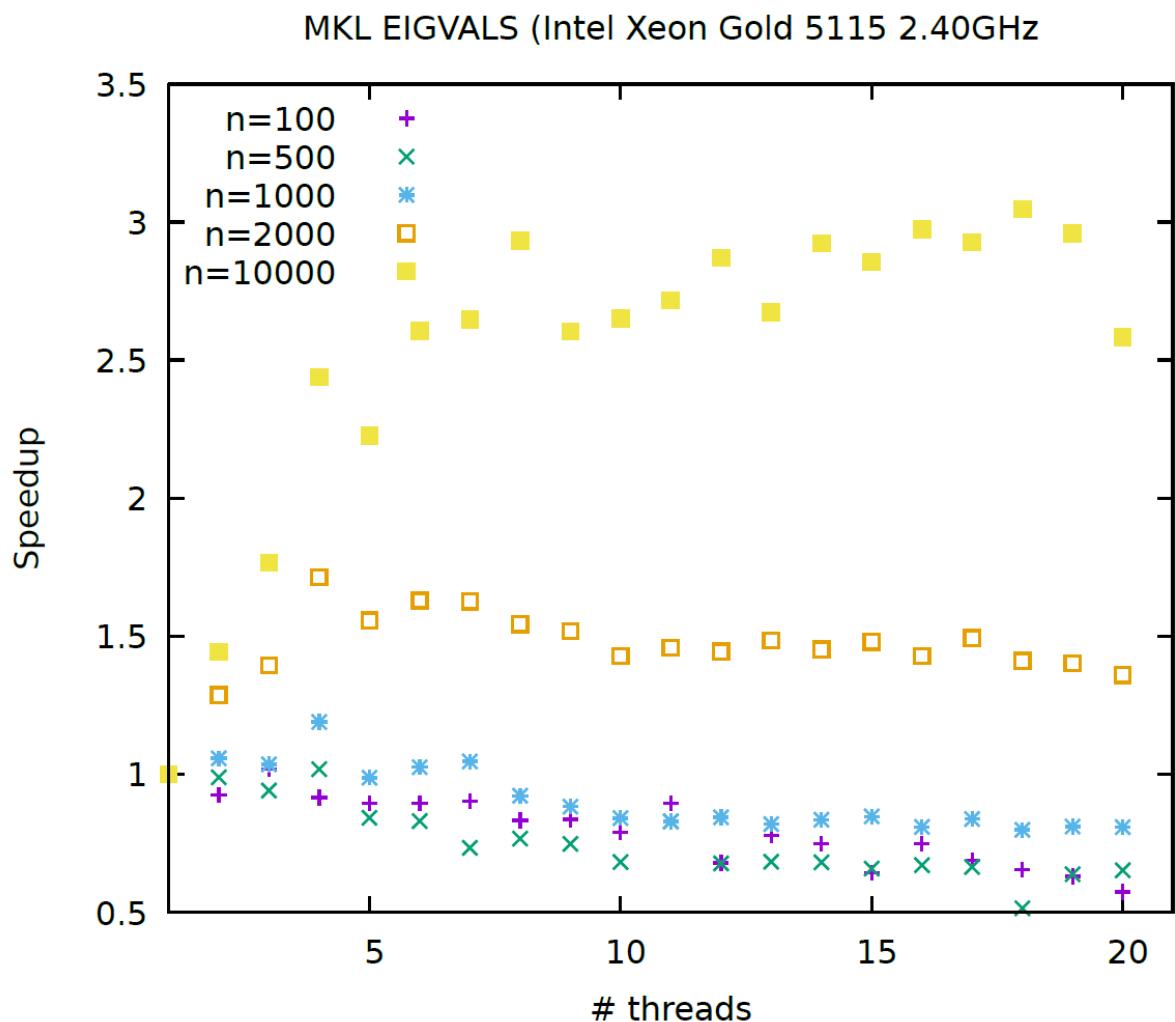
sizes=[10,20,100,200,300,400,500,600,700,800,900
,1000,2000,4000,8000,10000,12000]

with open("Eigvals.dat",'w') as my_file:
    my_file.write("#\ntime\n")
    for n in sizes:
        A = npr.randn(n,n)
        t = time.time()
        v=np.linalg.eigvals(A)
        td = time.time() - t
        print("Eigenvals of (%d,%d) matrix in
%0.4f s" % (n, n, td))
        my_file.write(str(n)+"\t"+str(td)+"\n")
```

```
Eigenvals of (10,10) matrix in 0.0008 s
Eigenvals of (20,20) matrix in 0.0002 s
Eigenvals of (50,50) matrix in 0.0006 s
Eigenvals of (100,100) matrix in 0.0359 s
Eigenvals of (200,200) matrix in 0.0393 s
Eigenvals of (300,300) matrix in 0.0996 s
Eigenvals of (400,400) matrix in 0.1522 s
Eigenvals of (500,500) matrix in 0.2451 s
Eigenvals of (600,600) matrix in 0.3967 s
Eigenvals of (700,700) matrix in 0.4587 s
Eigenvals of (800,800) matrix in 0.5750 s
Eigenvals of (900,900) matrix in 0.6680 s
Eigenvals of (1000,1000) matrix in 0.7734 s
Eigenvals of (2000,2000) matrix in 2.4721 s
Eigenvals of (3000,3000) matrix in 7.4194 s
Eigenvals of (4000,4000) matrix in 14.2675 s
Eigenvals of (6000,6000) matrix in 39.1304 s
Eigenvals of (8000,8000) matrix in 68.1390 s
Eigenvals of (10000,10000) matrix in 109.9833 s
Eigenvals of (12000,12000) matrix in 195.2025 s
```

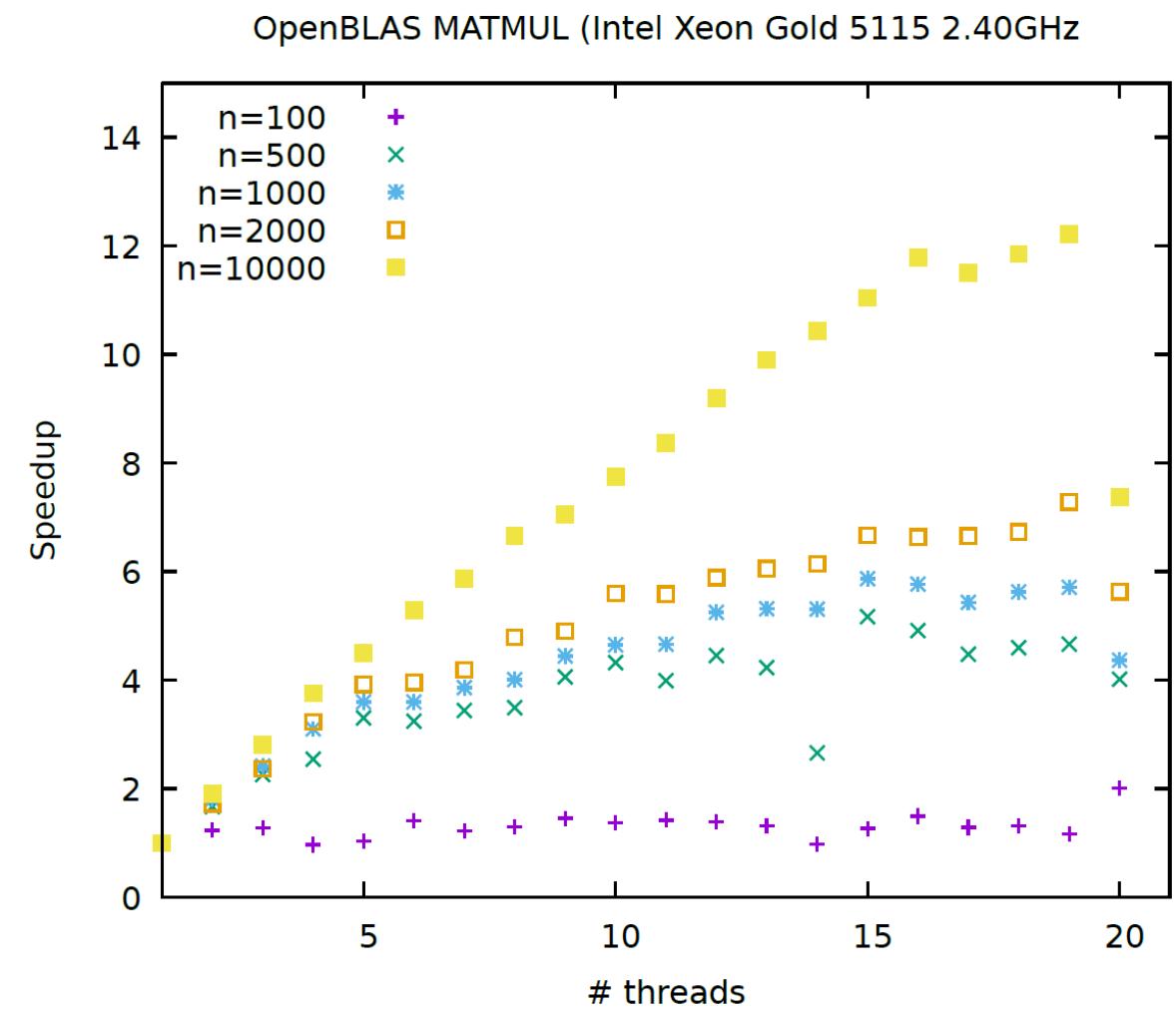
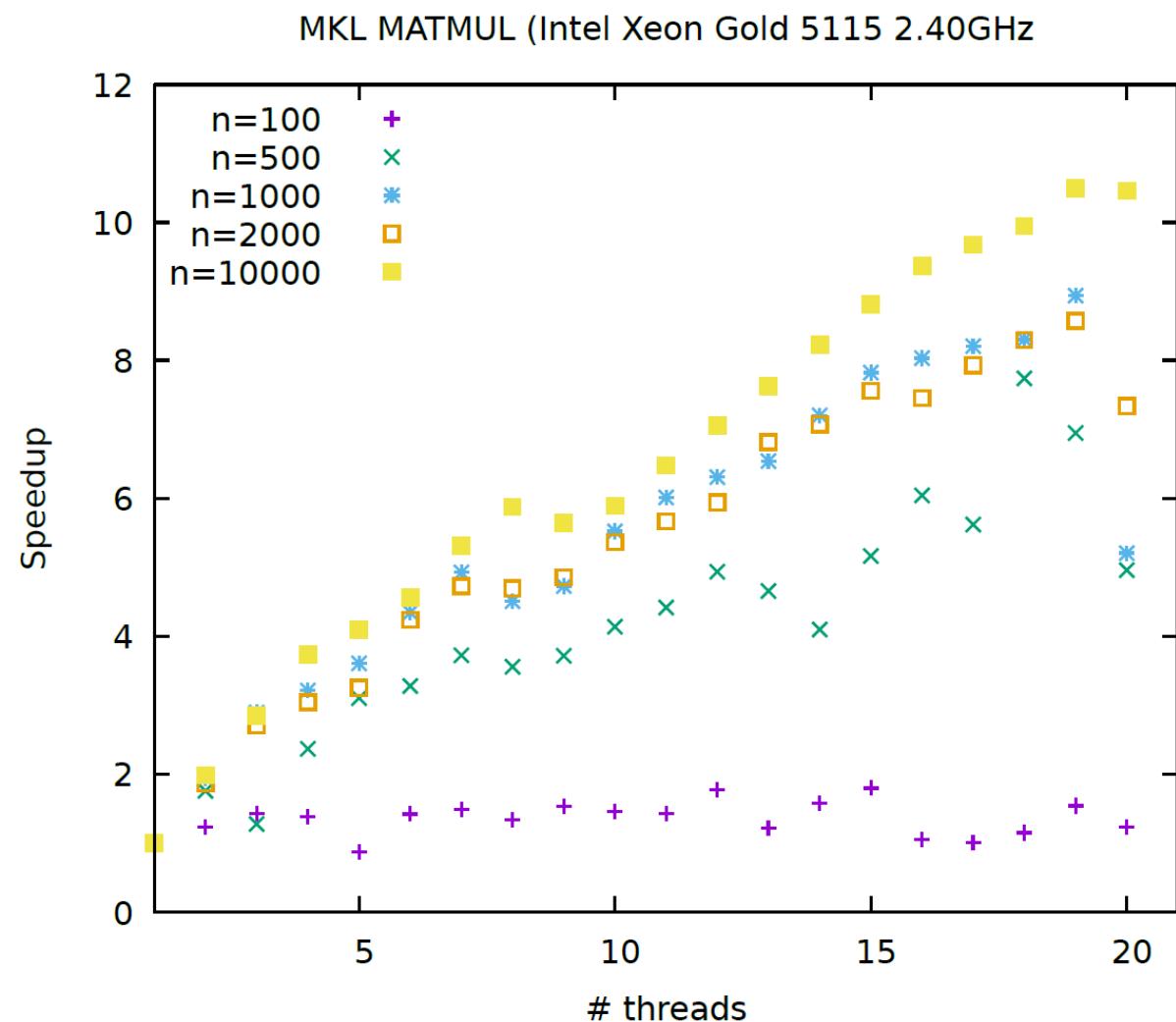
# Performance vs #of cores & matrix dim.

General matrix diagonalization

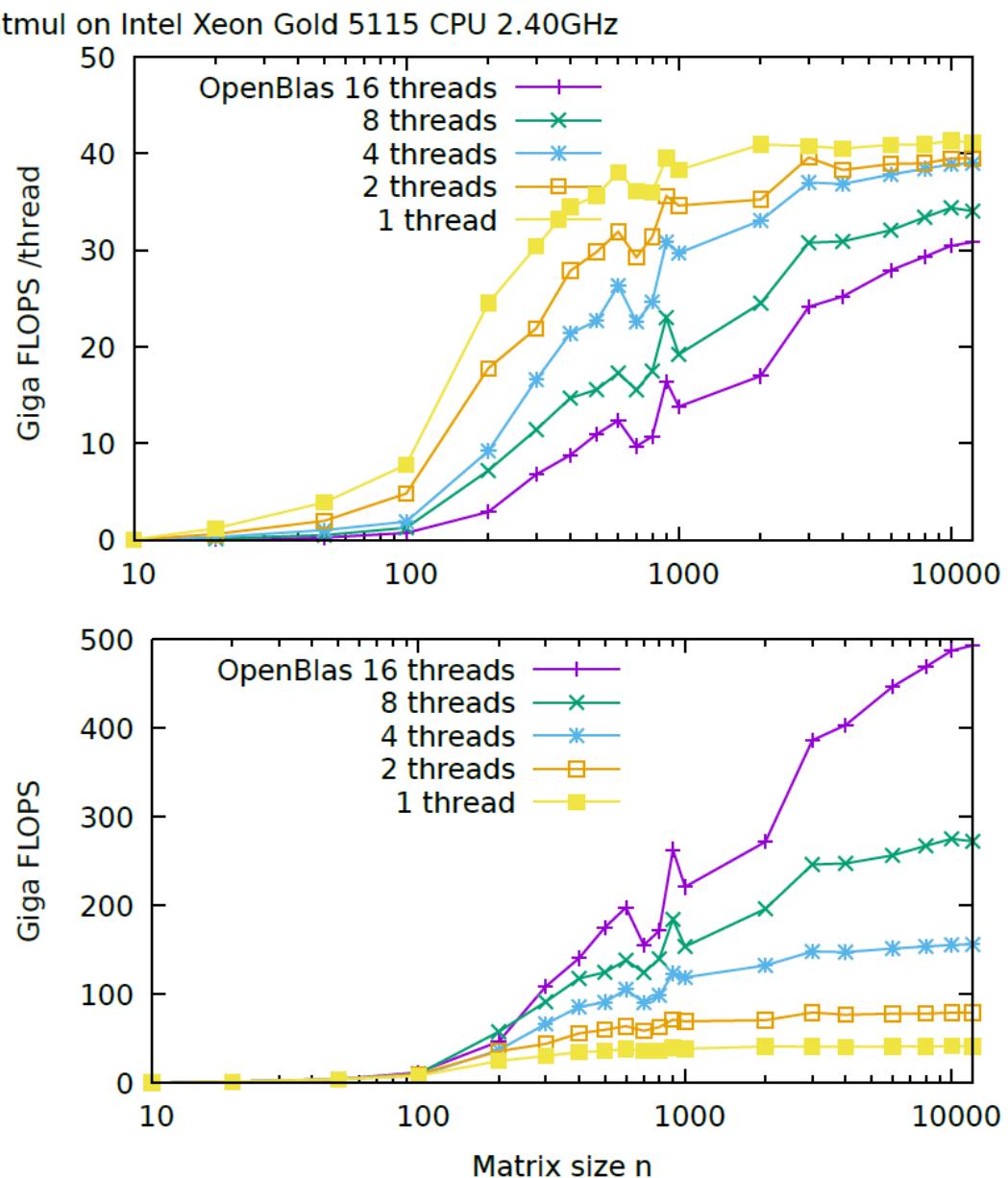
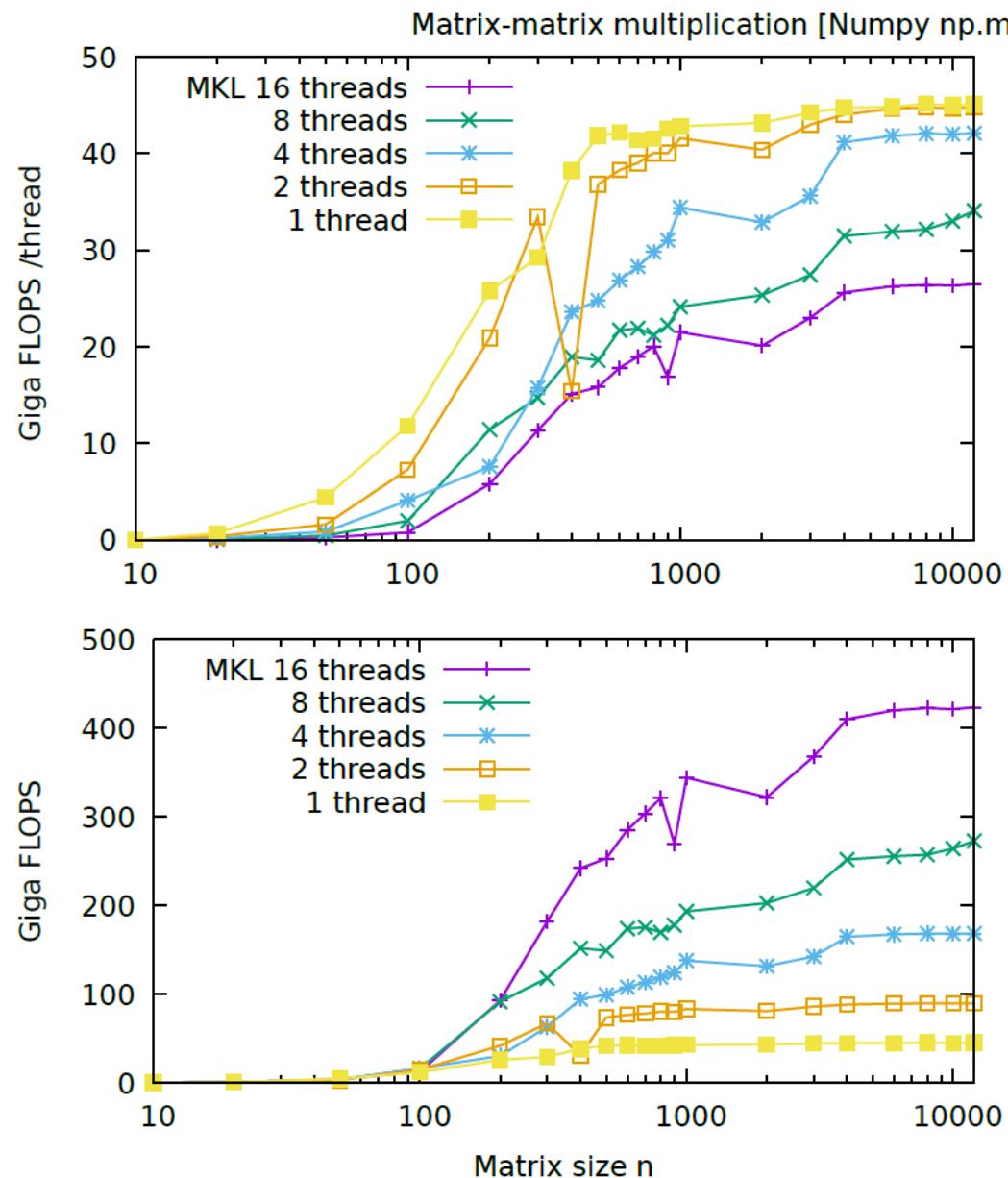


# Speedup vs #of cores & matrix dim.

Matrix-matrix multiplication

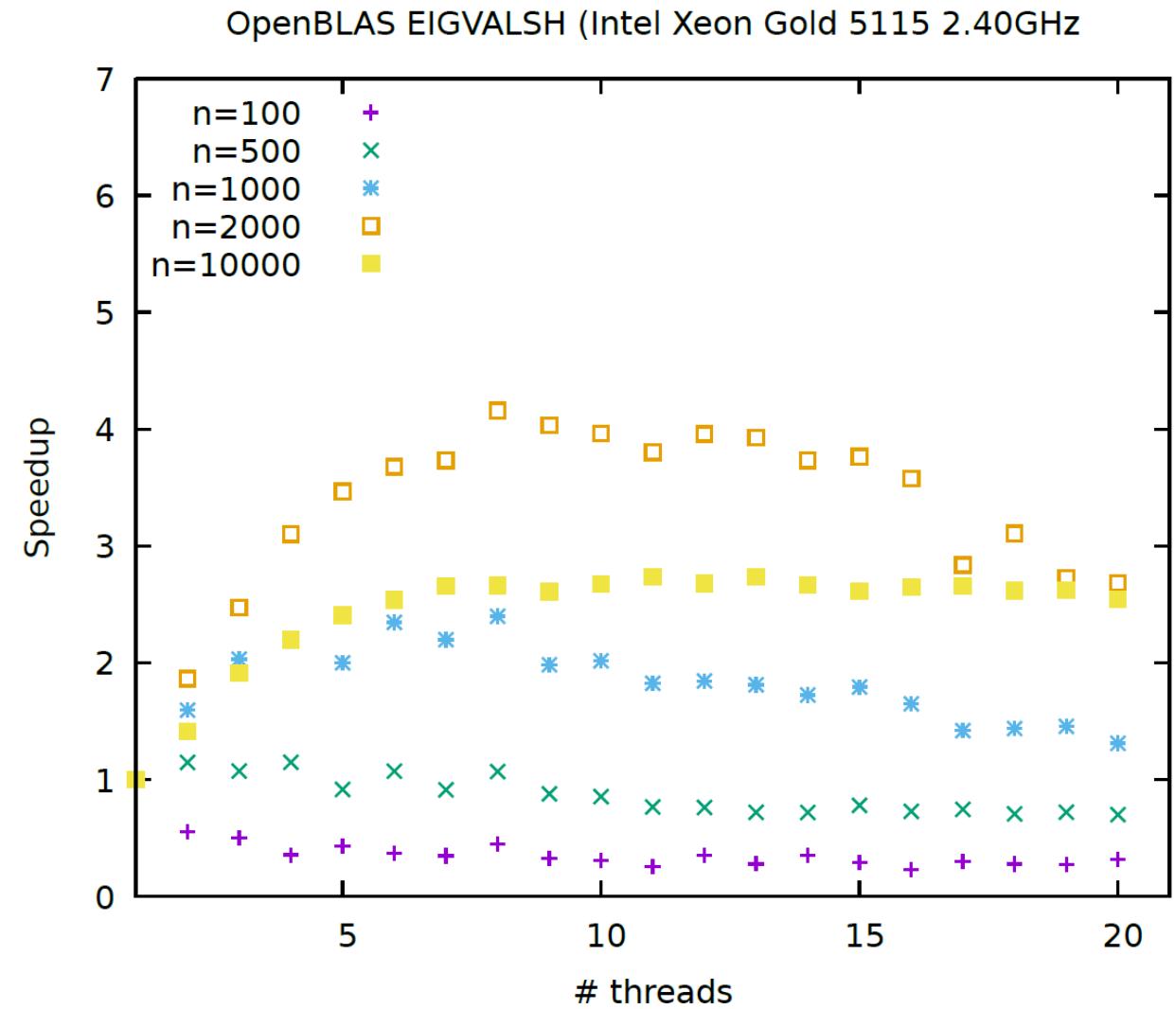
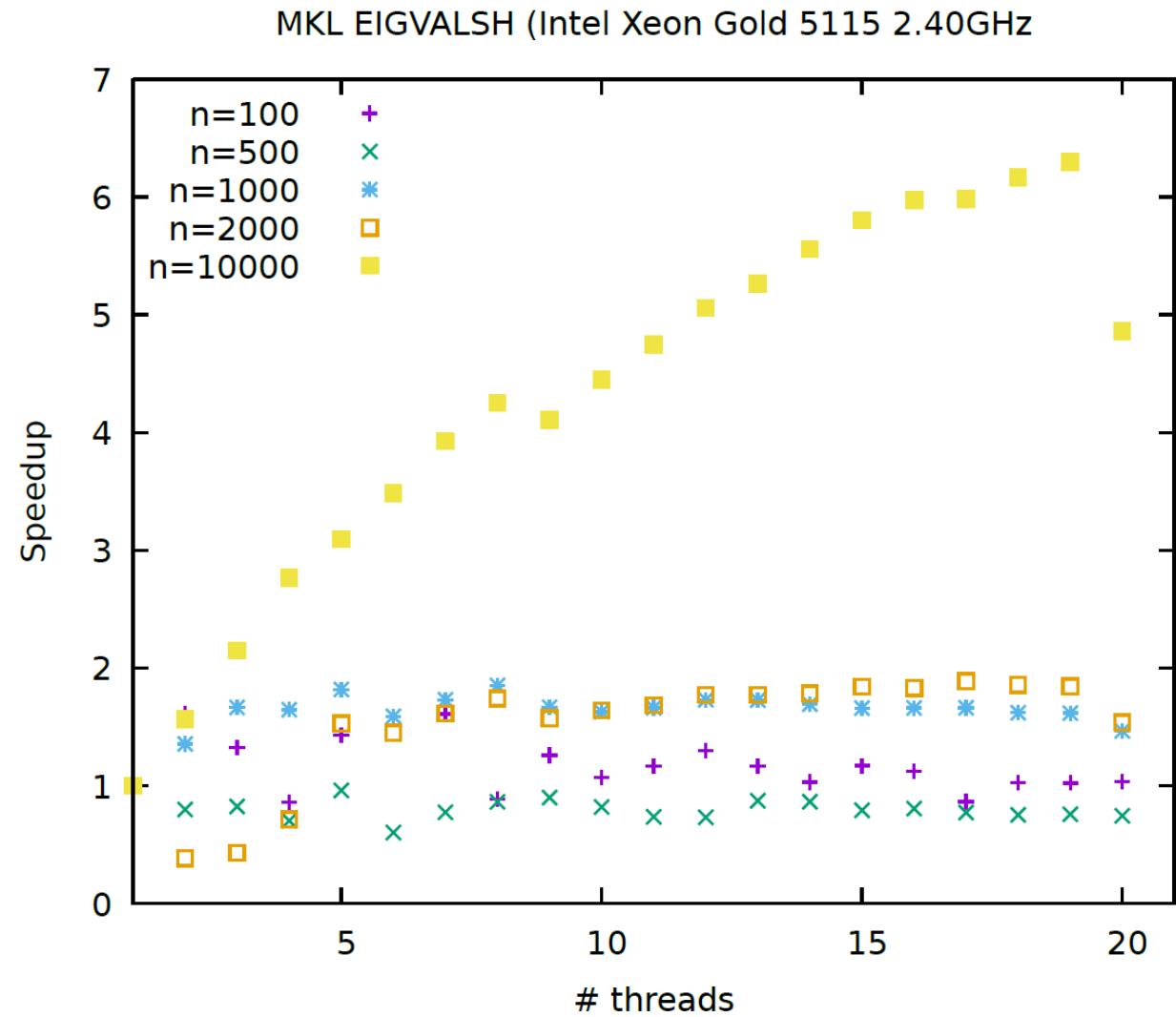


# Matrix-matrix multiplication - OpenBLAS & MKL performance



# Speedup vs #of cores & matrix dim.

Hermitian matrix diagonalization



# Speedup vs #of cores & matrix dim.

Matrix Singular Value Decomposition

