Performance Optimization for the Origin 2000

`http://www.cs.utk.edu/~mucci/MPPopt.html`

Kevin London (`london@cs.utk.edu`)
Philip Mucci (`mucci@cs.utk.edu`)

University of Tennessee, Knoxville

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SGI Optimization Tutorial

Day 1

Getting Started

- First logon to an origin 2000. Today we will be using eckert.
- Copy the tutorials to your home area. They can be found in:

```
~london/arl_tutorial
```

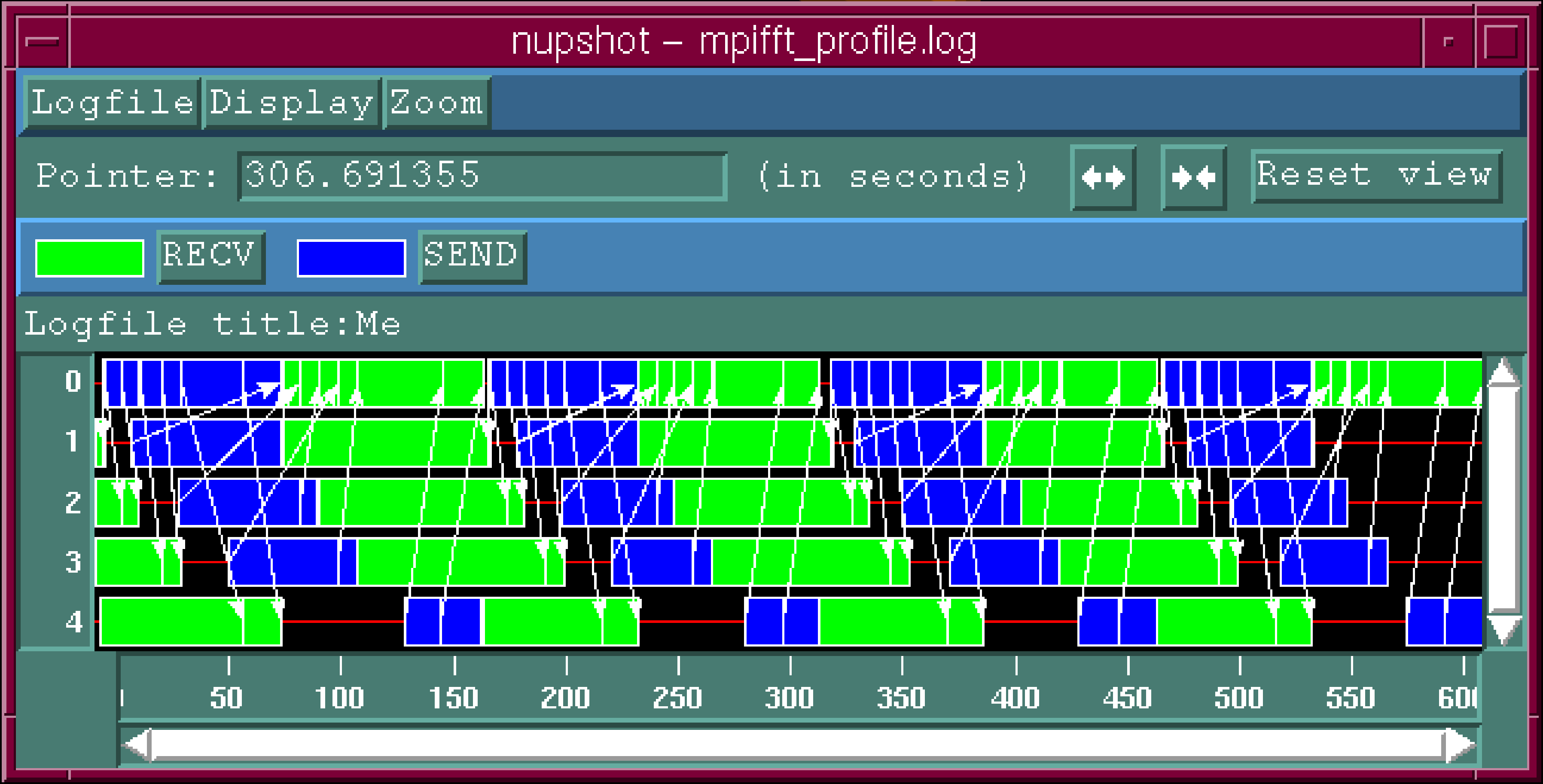
You can copy all the necessary files by:

```
Cp -rf ~london/arl_tutorial ~/.
```

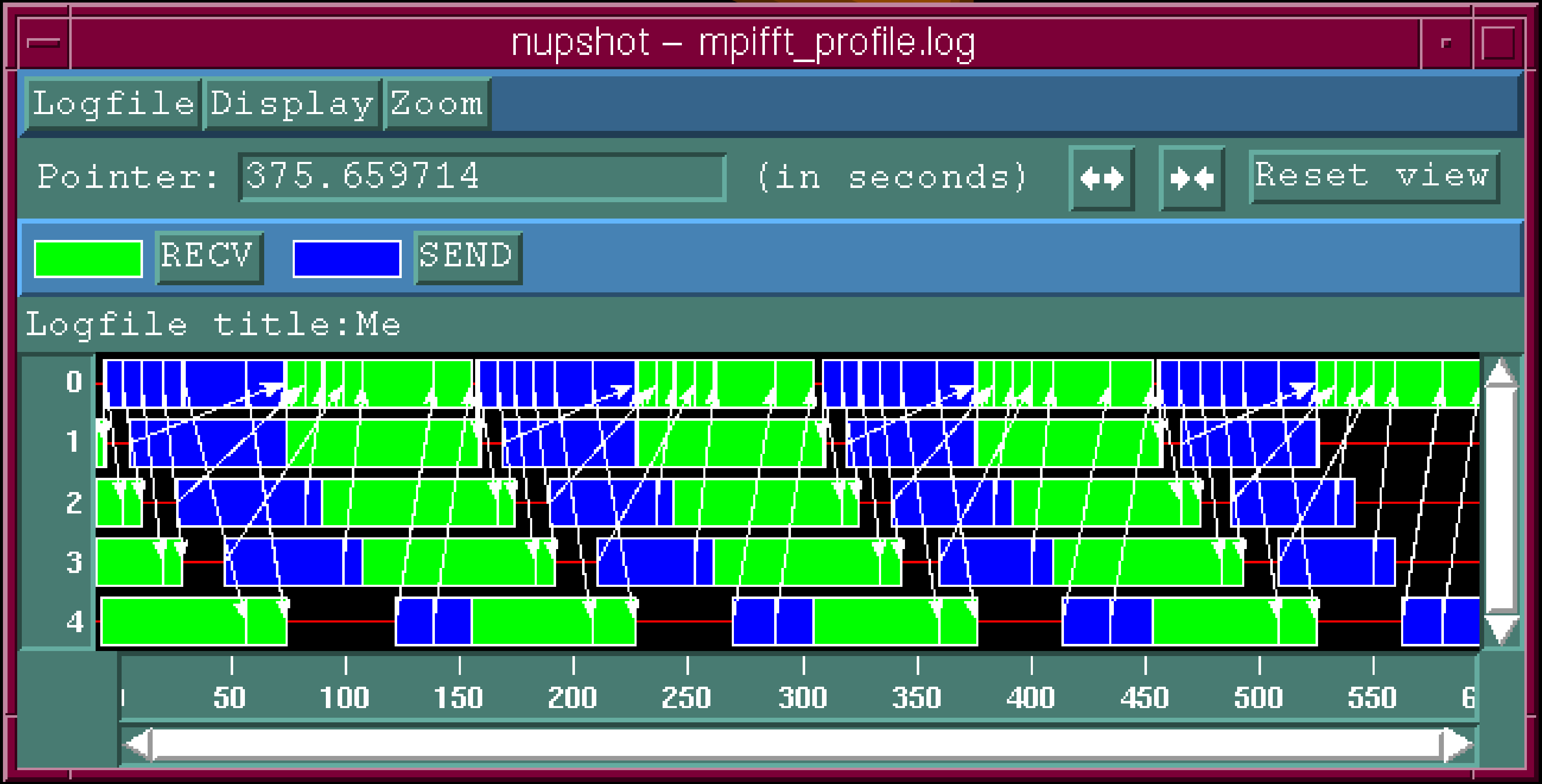
Getting Started (Continued)

- For todays tutorial we will be using the files in `~/ARL_TUTORIAL/DAY1`
- We will be using some performance analysis tools to look at fft code written in MPI.

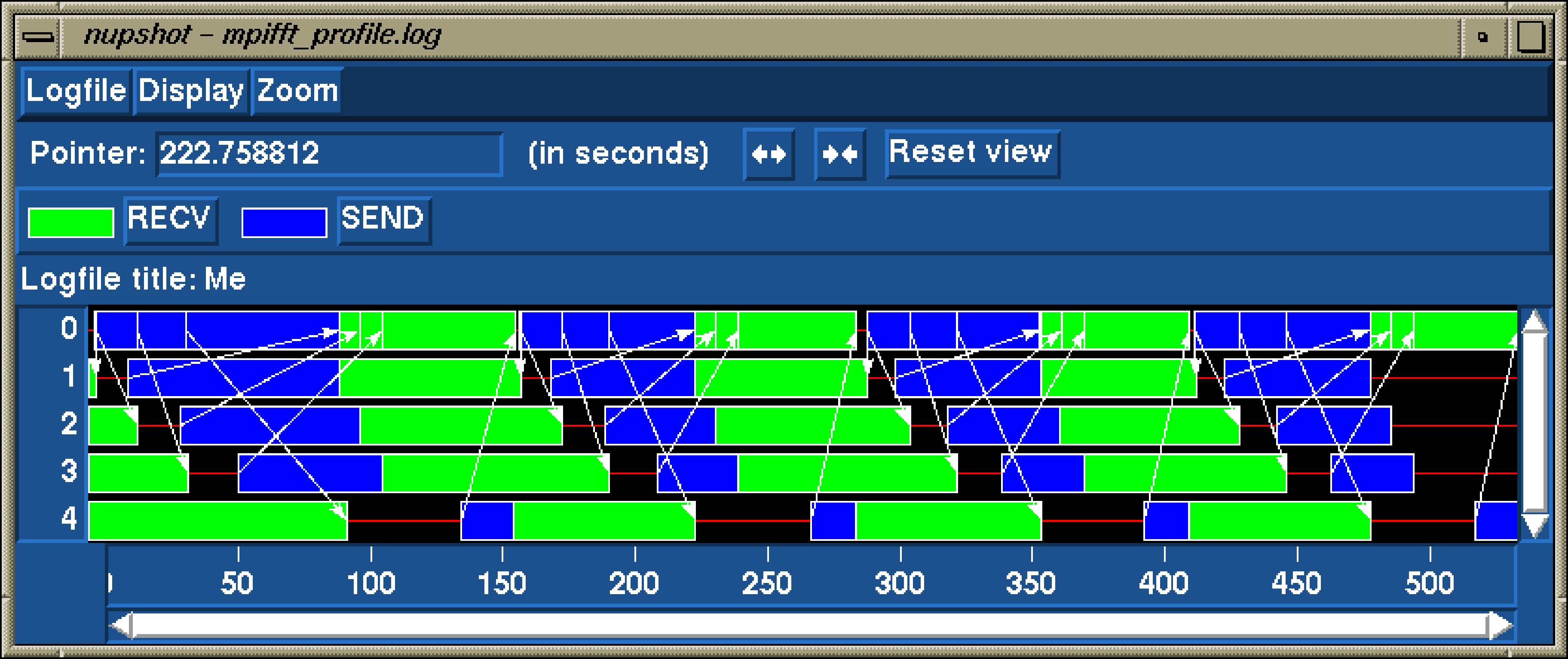
Version 1 of Mpifft



Version 2 of Mpifft



Version 3 of Mpifft



perfex

- `perfex` is useful for a first pass on your code
- Today run `perfex` on `mpifft` the following way:
  - `mpirun -np 5 perfex -mp -x -y -a mpifft`

Speedshop Tools

- `ssusage` -- allows you to collect information about your machines resources
- `ssrun` -- this is the command to run experiments on a program to collect performance data
- `prof` -- analyzes the performance data you have recorded using ssrun

Speedshop Experiment Types

- Statistical PC sampling with pcsamp experiments
- Statistical hardware counter sampling with _hwc experiments. (On R10000 systems with built-in hardware counters)
- Statistical call stack profiling with usertime
- Basic block counting with ideal

Speedshop Experiment Types

- Floating point exception trace with fpe

Using Speedshop Tools for Performance Analysis

The general steps for a performance analysis cycle are:

- Build the application
- Run experiments on the application to collect performance data
- Examine the performance data
- Generate an improved version of the program
- Repeat as needed

Using ssusage on Your Program

- Run your program with ssusage:
  - `ssusage <program_name>`
- This allows you to identify high user CPU time, high system CPU time, high I/O time, and a high degree of paging
- With this information you can then decide on which experiments to run for further study

ssusage (Continued)

- In this tutorial ssusage will be called like the following:
  - `ssusage mpirun -np 5 mpifft`
- The output will look something like this:
  - 38.31 real, 0.02 user, 0.08 sys, 0 majf, 117 minf, 0 sw, 0 rb, 0 wb, 172 vcx, 1 icx
  - Real-time, user-cpu time, system-cpu time, major page faults (those causing physical I/O), minor page faults (those requiring mapping only), swaps, physical blocks read and written, voluntary context switches and involuntary context switches.

Using ssrun on Your Program

- To collect performance data, call ssrun as follows:
  - `ssrun  flags  exp_type  prog_name  prog_args`
  - Flags are one or more valid flags
  - Exp_type   experiment name
  - Prog_name executable name
  - Prog_args   any arguments to the executable

Choosing an Experiment Type

- If you have high user CPU time, you should run `usertime`, `pcsamp`, `*_hwc` and `ideal` experiments
- If you have high system CPU time, you should run fpe if floating point exceptions are suspected
- High I/O time you should run ideal and then examine counts of I/O routines
- High paging you should run ideal then:
  - `prof -feedback`
  - Use `cord` to rearrange procedures

Running Experiments on a MPI Program

- Running experiments on MPI programs is a little different
- You need to setup a script to run experiments with them
  - `#!/Bin/sh`
  - `Ssrun -usertime mpifft`
- You then run the script by:
  - `mpirun -np 5 <script>`

Experiments That We Will Run for the Tutorial.

- `usertime`
- `fpcsamp`
- `ideal`
- `dsc_hwc` -- secondary data cache misses
- `tlb_hwc` -- TLB misses

usertime

- This experiment is already setup in `runmpifft` in the v[1-3] directories
- To run the experiment use:
  - `mpirun -np 5 runmpifft`
- This will give you 6 files in the directory: `mpifft.usertime.?????`
- To look at the results use:
  - `prof mpifft.usertime.?????`

usertime (Continued)

- Example output:

```
Cpu                                    : r10000
Fpu                                    : r10010
Clock                         : 195.0mhz
Number of cpus   : 32
Index  %samples  self  descendents  total              name
[1]        95.7%     0.00          17.82   594              _fork_child_handle
[2]        78.7%     0.00          14.67   489              slave_main
[3]        53.6%     0.72            9.27    333              slave_receive_data
```

%Samples is the total percentage of samples take in this function or its descendants. Self, and descendants are the time spent in that function and its descendants as determined by the number of samples in that function * the sample interval. Total is the number of samples.

fpcsamp

- To run this experiment you need to edit the runmpifft script and change the line:
  - `ssun -usertime mpifft` to:
  - `ssrun -fpcsamp mpifft`
- Once again this will give you 6 files in your directory:
  - `mpifft.fpcsamp.?????`
- To look at the results use:
  - `prof mpifft.fpcsamp.?????`

fpcsamp (Continued)

- Example output:

```
Samples   time     CPU      FPU      clock      n-cpu     s-interval countsize
  30990   30.99s  r10000  r10010  195.0mhz   32         1.0ms   2(bytes)
Each sample covers 4 bytes for every 1.0 ms ( 0.00% of 30.9900s)
--------------------------------------------------------------------------------
    -
Samples     time(%)          cum time(%)       procedure (dso:file)
4089         4.09s( 13.2)     4.09s( 13.2)        one_fft
    (mpifft:/home/army/london/eckert/arl_tutorial/day1/v1/slave.C)
3669         3.67s( 11.8)     7.76s( 25.0)        mpi_sgi_progress
    (/usr/lib32/libmpi.So:/xlvll/array/array_3.0/work/mpi/lib/libmpi/libmpi
    _n32_m4/adi/progress.C)
```

fpcsamp (Continued)

- Samples column shows the amount of samples were taken when the process was executing the function
- Time(%) covers the amount of time and percentage of time spent in this function
- Cum time(%) covers the amount of time up to and including this function and its percentage
- Procedure shoes where this function came from

ideal

- To run this experiment you need to edit the `runmpifft` script and change the line to:
  - `ssrun -ideal mpifft`
- This will leave 13 files in your directory
  - 6 `mpifft.ideal.?????`
  - `spifft.pixie`
  - 6 `lib*.pixn32` files for ex. `libmpi.so.pixn32`
- To view the results type:
  - `prof mpifft.ideal.?????`

ideal (Continued)

- Example output:

```
2332123106:  total number of cycles
  11.95961s:    total execution time
2924993455:   total number of instructions executed
    0.797:ratio of cycles / instruction
      195:              clock rate in mhz
  R10000:               target processor modeled
Cycles(%)               cum %  secs   instrns          calls  procedure(dso:file)
901180416(38.64)  38.64    4.62  1085714432 2048
     mpifft.Pixie:/home/army/london/eckert/arl_tutorial/day1/v1/slave.C)
```

ideal (Continued)

- Cycles (%) reports the number and procedure
- Cum% column shows the cumulative percentage of calls
- Secs column shows the number of seconds spent in the procedure
- Instrns column shows the number of instructions executed for the procedure
- Calls column reports the number of calls to the procedure
- Procedure column shows you which function and where it is coming from.

Secondary Data Cache Misses (dsc_hwc)

- To run this experiment you need to change the line in the `runmpifft` script to:
  - `ssrun -dsc_hwc mpifft`
- This will leave 6 files in your directory:
  - 6 `mpifft.fdsc_hwc.?????`
- To view the results type:
  - `prof mpifft.dsc_hwc.?????`

Secondary Data Cache Misses (dsc_hwc) (Continued)

- Example output:

```
Counter                          : sec cache D misses
Counter overflow value           : 131
Total number of ovfls            : 38925
Cpu                              : r10000
Fpu                              : r10010
Clock                            : 195.0 mhz
Number of cpus                   : 32
-------------------------------------------------------------------------
   --
Overflows(%)     cum overflows(%)   procedure (dso:file)
11411( 29.3)     11411( 29.3)       memcpy
   (/usr/lib32/libc.So.1:/xlv21/patches/3108/work/irix/lib/libx/libc_n32_
```

Secondary Data Cache Misses (dsc_hwc)

- Overflows(%) column shows the number of overflows caused by the function and percentage of misses in the whole program
- Cum overflows(%) column shows a cumulative number and percentage of overflows
- Procedure column shows the procedure and where it is found.

Translation Lookaside Buffer Misses (tlb_hwc)

- To run this experiment you need to change the line in the `runmpifft` script to:
  - `ssrun -tlb_hwc mpifft`
- This will leave 6 files in your directory:
  - 6 `mpifft.tlb_hwc.?????`
- To look at the results use:
  - `prof mpifft.tlb_hwc.?????`

Translation Lookaside Buffer Misses (tlb_hwc)

- Example output:

```
Counter                          : TLB misses
Counter overflow value           : 257
Total number of ovfls            : 120
Cpu                              : r10000
Fpu                              : r10010
Clock                            : 195.0 mhz
Number of cpus                   : 32
--------------------------------------------------------------------------------
   --
Overflows(%)      cum overflows(%)   procedure (dso:file)
25( 20.8)         25( 20.8)          mpi_sgi_barsync
   (/usr/lib32/libmpi.So:/xlvll/array/array_3.0/work/mpi/lib/libmpi/libmpi
   _n32_m4/sgimp/barsync.C)
```

SGI Optimization Tutorial

Day 2

More Info on Tools

- http://www.cs.utk.edu/~browne/perftools-review
- http://www.nhse.org/ptlib

Getting the new files

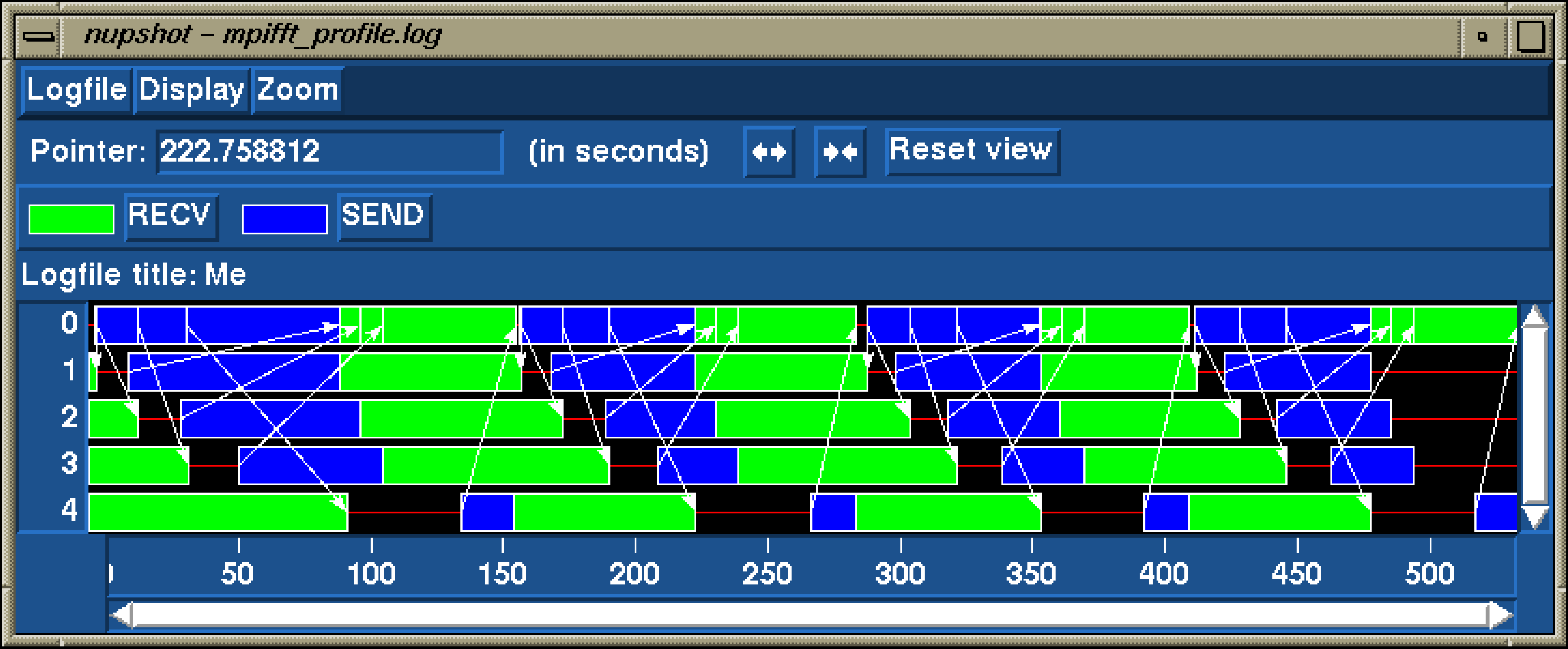
- You need to cd into `~/ARL_TUTORIAL/DAY1`
- Then

```
    cp ~london/ARL_TUTORIAL/DAY1/make* .
```

Outline

- nupshot tutorial
- vampir tutorial
- matrix multiply tutorial

Nupshot view



nupshot

- `nupshot` is distributed with the mpich distribution.
- `nupshot` can read alog and picl-1 log files.
- A good way to get a quick overview of how your well the communication in your program is doing.

Using nupshot

- The change to the makefile in using mpe is in the link line you need to call `-llmpi` before `-lmpi`
- MPE for the tutorial is located in:
  - `/home/army/london/ECKERT/nup_mpe/lib`
- Next if you have csh/tcsh
  - `source ~london/NUP_SOURCE`

Using nupshot (continued)

- This file has the following stuff adding to your environment:
  - setenv TCL_LIBRARY /ha/cta/unsupported/SPE/profiling/tcl7.3-tk3.6/lib
  - setenv TK_LIBRARY /ha/cta/unsupported/SPE/profiling/tcl7.3-tk3.6/lib
  - set path = ($path /ha/cta/unsupported/SPE/profiling/nupshot
- These will setup the correct TCL/TK libraries and that nupshot is in your path.
- Then you need to set your display and use xhost to authorize eckert to connect to your display.

Using nupshot (continued)

- For example:
  - `setenv DISPLAY heat04.ha.md.us`
  - On heat04 type `xhost +eckert`
- If you don't use csh/tcsh all the variables need to be set up by hand and you can do it this way:
  - `DISPLAY=heat04.ha.md.us`
  - `export DISPLAY`

Running the example

- To make the example go into the DAY1 directory and type:
  - `make clean`
  - `make`
- This will link in the mpe profiling library and make the executables.
- To run the executables go into the v1, v2 and v3 directories and type:
  - `mpirun -np 5 mpifft`

Running the Example (continued)

- If everything works out right, you will see a line to stdout like the following:
  - `Writing logfile.`
  - `Finished writing logfile.`
- This will leave a `mpifft.alog` file in your directory.
- To view it type `nupshot` and click on the logfile button. And use the open button to view the logfile.

Running the Example (continued)

- This will bring up a timeline window, you can also get a mountain range view by clicking on Display, then on configure and click on add and mountain ranges.
- The mountain ranges view is a histogram of the states the processors are in at any one time.
- If you click and hold in the timeline display on a MPI call it will tell you the start/stop time and total amount of time spent in that call.

Vampir Tutorial (Getting Started)

- Setup environment variables for the vampir tracing tools.
  - setenv PAL_ROOT /home/army/london/ECKERT/vampir-trace
- In your makefile you need to link in the vampir library
  - -L/home/army/london/ECKERT/vampir-trace/lib -lVT
- This needs to be linked in before mpi.
- Then run your executable like normal.

Vampir Tutorial Creating a logfile

- To setup the tutorial for vampir go into the DAY1 directory and do the following:
  - `rm make.def`
  - `ln -s make_vampir.sgi make.def`
  - `make`
- Then run the executables using
  - `mpirun -np 5 mpifft`
- If everything goes right you will see:
  - `Writing logfile mpifft.bpv`
  - `Finished writing logfile.`

Vampir Tutorial Viewing the Logfile

- This will leave 1 file, mpifft.bpv in your directory.
- We now need to setup our variables again.
  - setenv PAL_ROOT /home/army/london/ECKERT/vampir
  - setenv DISPLAY <your display>
  - set path = ($path /home/army/london/ECKERT/vampir/bin)
- Then create a directory for VAMPIR defaults
  - mkdir ~/.VAMPIR_defaults
  - cp /home/army/london/ECKERT/vampir/etc/VAMPIR2.cnf ~/VAMPIR_defaults/.

Using Vampir

- To start up Vampir use
  - `vampir &`

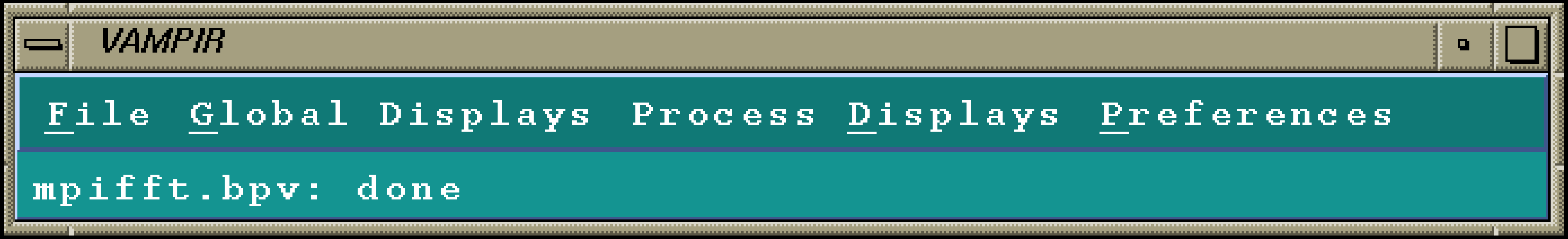
From the “File” menu, select “Open Tracefile…”. A file selection box will appear. Choose mpifft.bpv

We’ll start by viewing the timeline for the the entire run. From the “Global Displays” menu, select “Global Timeline”.   A window with the timeline will pop up.

Zoom in on a section of the timeline:

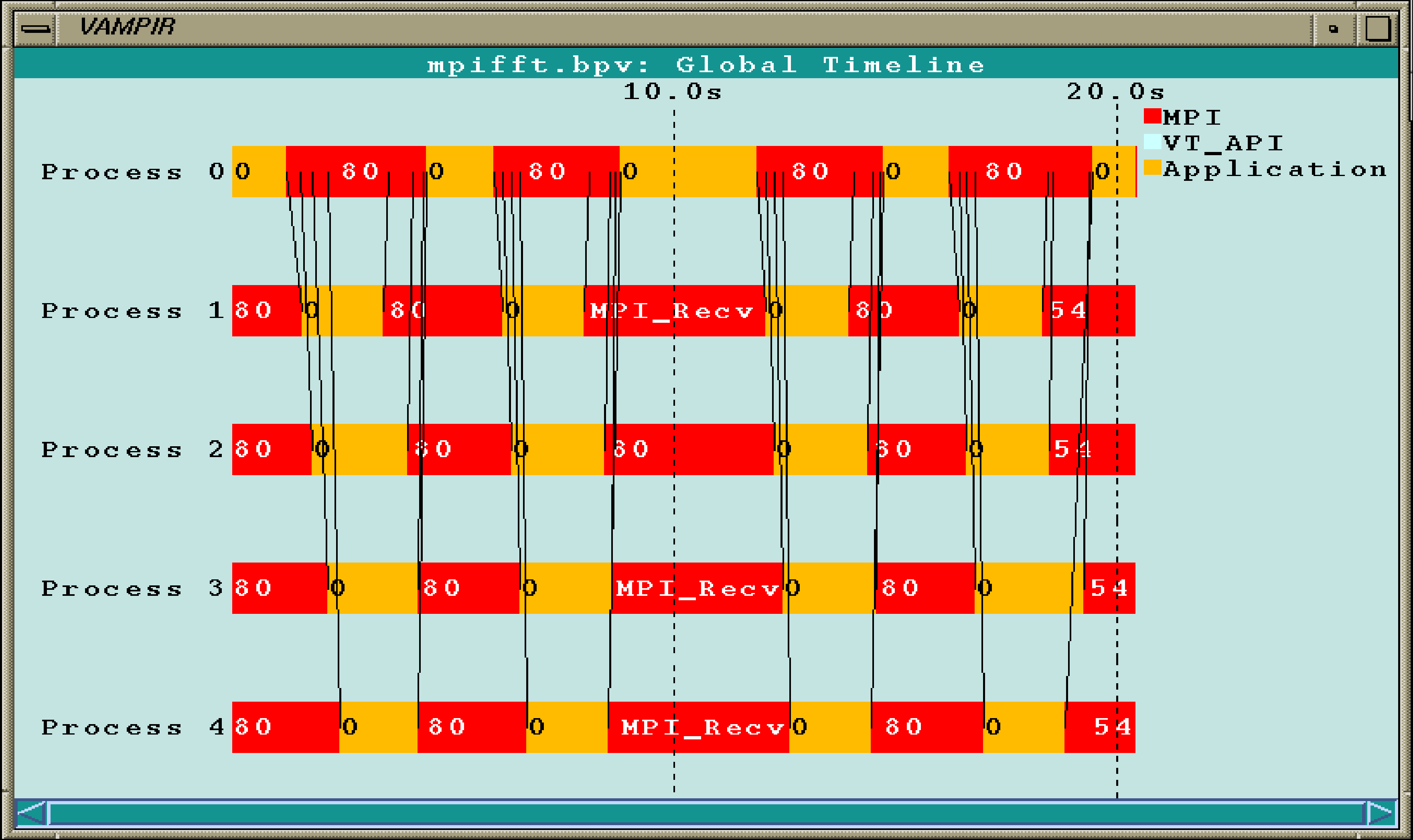
Click and drag over a portion of the timeline with the left mouse button. This part will be magnified. If you zoom in close enough you will see the MPI calls.

Vampir Startup Screen



mpifft.bpv: done

Vampir Timeline Display

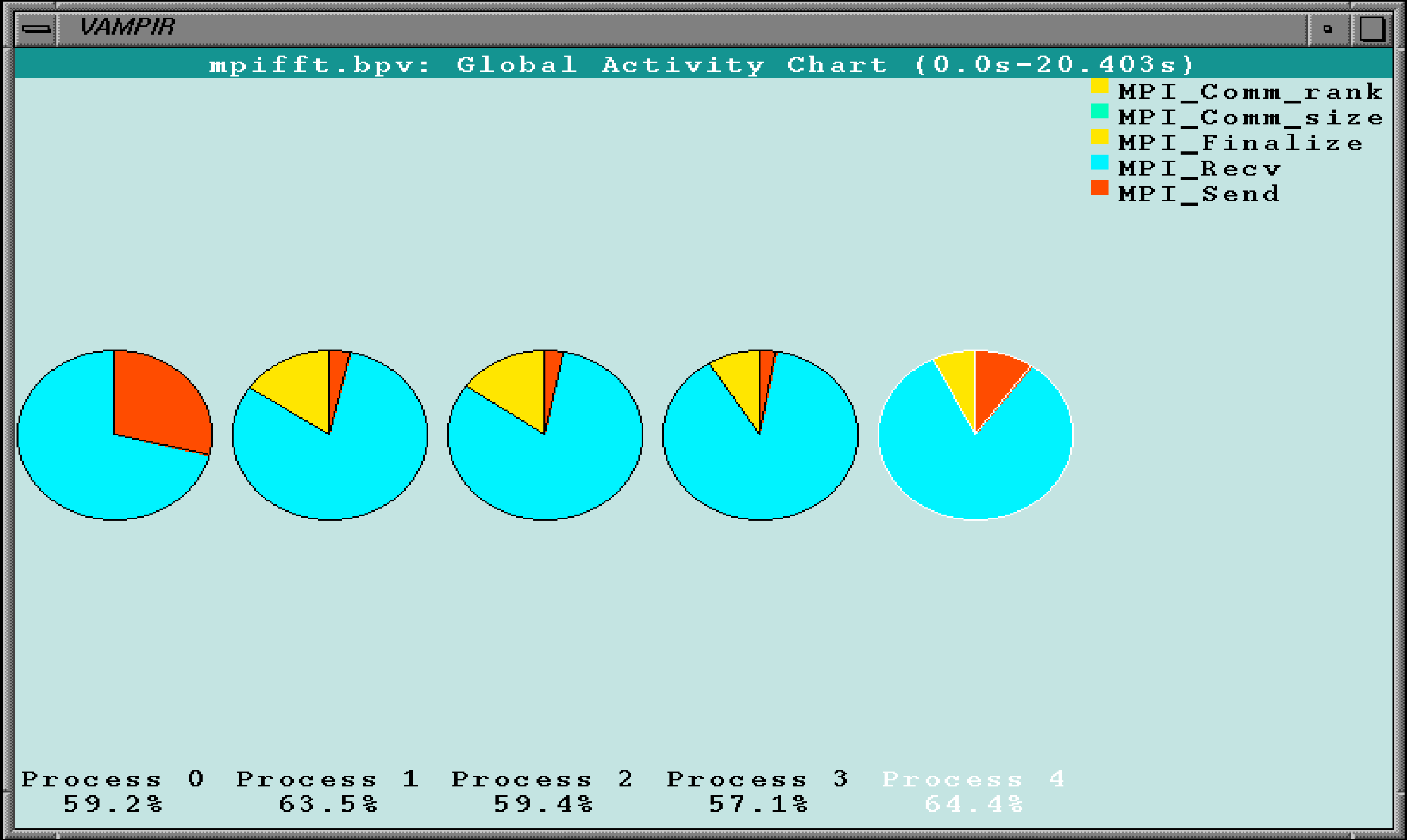


Using Vampir viewing statistics for selected portion of the timeline.

View process statistics for the selected portion of the timeline.

- From the “Global Displays” menu, select “Global Activity Chart”.
- A new window will open.
- Press the right mouse button within this window.
- Select “Use Timeline Portion”.
- Scroll the timeline, using the scroll bar at the bottom of the timeline window, and watch what happens in both displays.
- Press the right mouse button in the “Global Activity Chart” and select “Close”.

Vampir Global Activity Chat



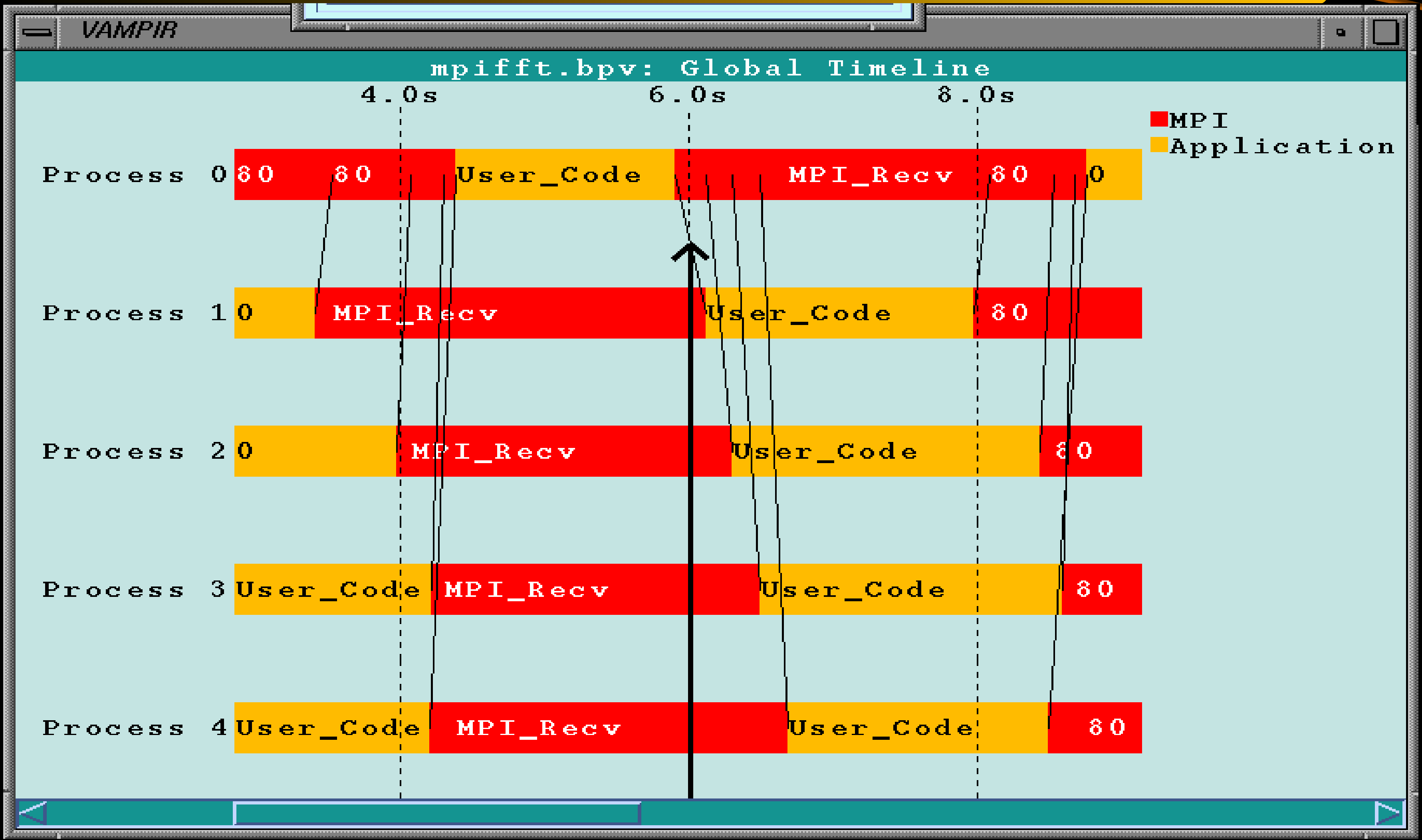
Vampir, additional info on messages

Obtain additional information on messages.

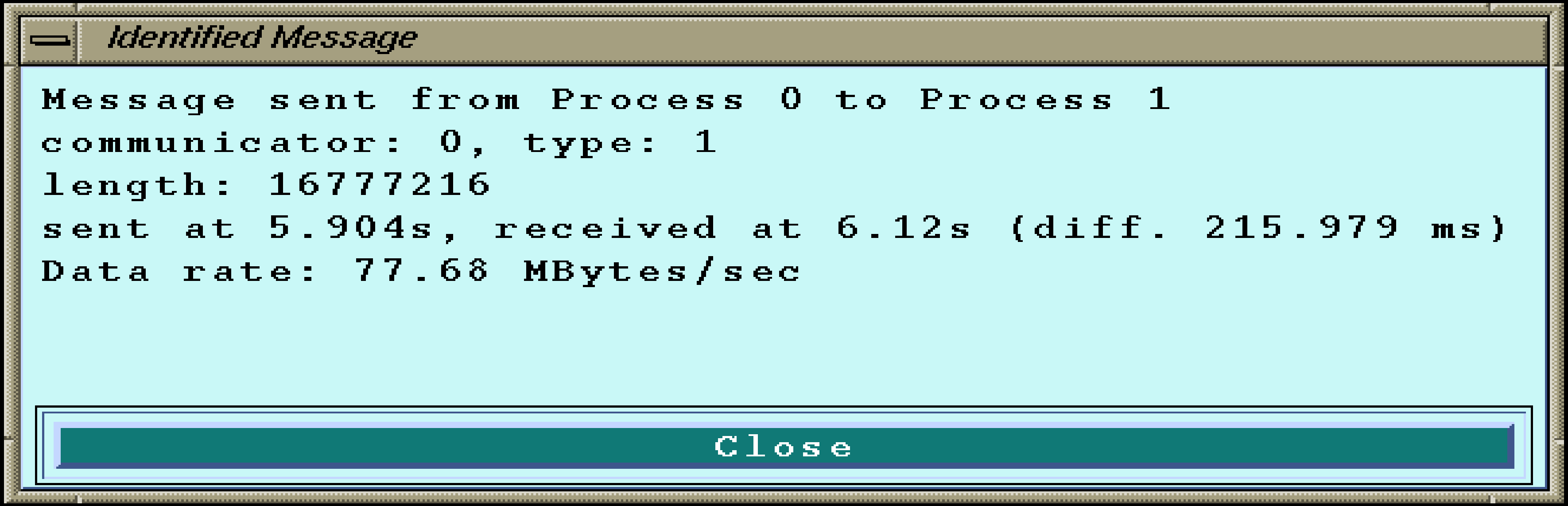
- Click on the "Global Timeline" window with the right mouse button.
- From the pop-up menu, select "Identify Message".
- Messages are drawn as lines between processes. Click on any message with the left mouse button. A window with message information should pop up.
- Press the "Close" button when finished reading.

- To exit VAMPIR from the "File" menu select "Exit".

Identifying a message in Vampir



Identifying messages in Vampir



```
Message sent from Process 0 to Process 1
communicator: 0, type: 1
length: 16777216
sent at 5.904s, received at 6.12s (diff. 215.979 ms)
Data rate: 77.68 MBytes/sec
```

Matrix-Matrix Multiply Demo

- These exercises are to get you familiar with some of the code optimizations that we went over early today.
- All of these exercises are located in the DAY2 directory.

Exercise 1

- This first exercise will use a simple matrix-matrix inner product multiplication to demonstrate various optimization techniques.

Matrix-Matrix Multiplication - Simple Optimization by Cache Reuse

Purpose: The exercise is intended to show how the reuse of data that has been loaded into cache by some previous instruction can save time and thus increase the performance of your code.

Information: Perform the matrix multiplication **A=A+B*C** using the code segment below as a template and ordering the ijk loops in to the following orders(ijk, jki, kij, and kji). In the file **matmul.f**, one ordering has been provided for you (**ijk**), as well as high performance BLAS routine **dgemm** which does double precision general matrix multiplication. **dgemm** and other routines can be obtained from Netlib. The cariables in the matmul routine (reproduced on the next page) are chosen for compatibility with the BLAS routines and have the following meanings: the variables ii, jj,kk, reflect the sizes of the matrix A (ii by jj), B(ii by kk) and C(kk by jj); the variables lda, ldb, and ldc are the leading dimensions of each of those matrices and reflect the total size of the allocated matrix, not just the part of the matrix used.

Example of the loop

```
subroutine ijk ( A, ii, jj, lda, B, kk, ldb, C, ldc)
double precision A(lda, *), B(ldb,*),C(ldc,*)
integer=i,j,k
do i=1,ii
    do j=1,jj
        do k=1,kk
            A(i,j) = A(i,j)+B(i,k)*C(k,j)
        enddo
    enddo
enddo
```

Instructions for the exercise

Instructions: For this exercise, use the files provided in the directory **matmul1-f**. You will need to work on the file **matmul.f**. If you need help, consult **matmul.f.ANS**, where there is one possible solution.

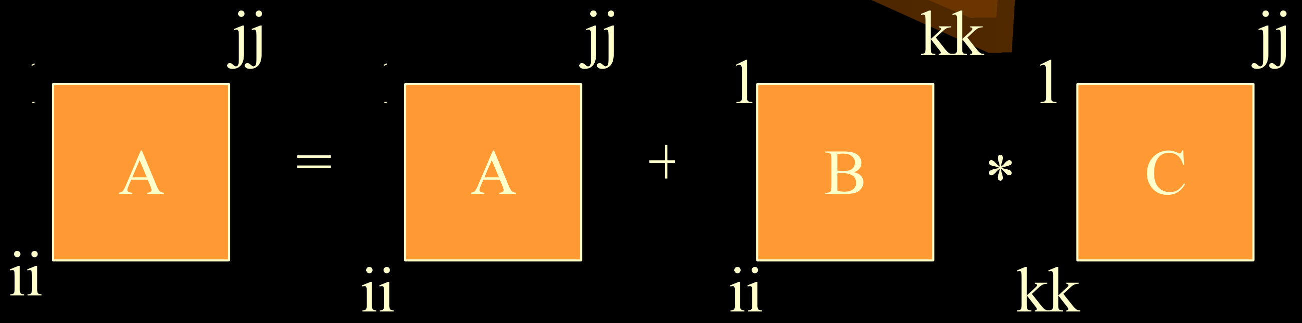
(a)Compile the code: **make matmul** and run the code, making note of the Mflops you get.

(b) Edit **matmul.f** and alter the orderings of the loops, **make**, run and repeat for the various loop orderings. Make a note of the Mflops so you can compare them at then end.

Exercise 1 (continued)

- Which loop ordering achieved the best performance and why? (ijk, jki,kij, kji)

Explanations: To explain the reason for these timing and performance figures, the multiplication operation needs to be examined more closely. The matrices are drawn below, with the dimensions of rows and columns indicated. The ii indicates the size of the dimension which is traveled when we do the i loop, the jj indicates the dimension traveled when we do the j loop and the kk indicates the dimension traveled when we do the k loop.



The pairs of routines with the same innermost loop (e.g. jki and kji) should have similar results. Let’s look at jki and kji again. These two routines achieve the best performance, and have the i loop as the innermost loop. Looking at the diagram, this corresponds to traveling down the columns of 2 (A and B) of the 3 matrices that are used in the calculations. Since in Fortran, matrices are stored in memory column by column, going down a column simply means using the next contiguous data item, which usually will already be in the cache. Most of the data for the i loop should already be in the cache for both the A and B matrices when it is needed.

Some improvements to the simple loops approach to matrix multiplication which are implemented by dgemm include loop unrolling (some of the innermost loops are expanded so that not so many branch instructions are necessary), and blocking (data is used as much as possible while it is in cache). These methods will be explored later in Exercise 2.

Exercise 2 Matrix-Matrix Multiplication Optimization using Blocking and Unrolling of Loops

Purpose: This exercise is intended to show how to subdivide data into blocks and unroll loops. Subdividing data into blocks helps them to fit into cache memory better. Unrolling loops decreases the number of branch instructions. Both of these methods sometimes increase performance. A final example shows how matrix multiplication performance can be improved by combining methods of subdividing data into blocks, unrolling loops, and using temporary variables and controlled access patterns.

Information: The matrix multiplication **A = A + B * C** can be executed using the simple code segment below. This loop ordering **kji** should correspond to one of the best access ordering the six possible simple **i, j, k** style loops.

```
subroutine kji  ( A, ii, jj, lda, B, kk, ldb, C, ldc )
double precision A( lda, *), B(ldb, *), C(ldc, *)
integer i, j, k
do k = 1, kk
      do j = 1, jj
            do i = 1, ii
                  A(i,j) = A(i,j) +B(i,k) * C(k,j)
            enddo
      enddo
enddo
return
enddo
```

However, this is not the best optimization technique. Performance can be improved further by blocking and unrolling the loops. The first optimization will demonstrate the effect of loop unrolling. In the instructions, you will be asked to add code to unroll the j, k, and i loops by two, so that you have, for example, **do j = 1, jj, 2**, and add code to compensate for all the loops that you are skipping, for example, **A (i,j) = A(i,j) + B(i,k) *C(k,j) + B(i,k+1) * C(k+1, j)**. Think of multiplying a 2x2 matrix to figure out the unrolling.

The second optimization will demonstrate the effect of blocking, so that, as much as possible, the blocks that are being handled can be kept completely in cache memory. Thus each loop is broken up into blocks (ib, beginning of an i block, ie, end of an i block) and the variables travel from the beginning of the block to the end of the block for each i,j,k. Use blocks of size 32 to start with, if you wish you can experiment with the size of the block to obtain the optimal size.

The next logical step is to combine these two optimizations into a routine which is both blocked and unrolled and you will be asked to do this.

The final example tries to extract the core of the BLAS **dgemm** matrix-multiply routine. The blocking and unrolling are retained, but the additional trick here is to optimize the innermost loop. Make sure that it only references items in columns and that it does not reference anything that would not be in a column. To that end, B is copied and transposed into the temp matrix **T(k,i) = B(i,k)**. Then multiplying **B(i,k)*C(k,j)** is equivalent to multiplying **T(k,i)*C(k,j)** (notice the k index occurs only in the row). Also, we do not store the result in **A(i,j)=A(i,j)+B(i,k)*C(k,j)** but in a temporary variable **T1=T1+T(k,j)*C(k,j)**. The effect of this is the inner k-loop has no extraneous references. After the inner loop has executed, **A(i,j)** is set to its correct value.

mydgemm:

```
do kb = 1, kk, blk
    ke = min(kb+blk-1,kk)
    do ib = 1, ii, blk
        ie = min(ib+blk-1, ii)
        do i = ib,ie
            do k = kb, ke
                T(k-kb+1, i-ib+1) = B(i,k)
            enddo
        enddo
        do jb = 1, jj, blk
            je = min(jb+blk-1, jj)
            do j = jb, je, 2
                do i = ib, ie, 2
                    T1 = 0.0d0
                    T2 = 0.0d0
                    T3 = 0.0d0
                    T4 = 0.0d0
                    do k = kb, ke
                        T1 = T1 + T (k-kb+1,i-ib+1)*C(k,j)
                        T2 = T2 + T(k-kb+1, i-ib+2)*C(k,j)
                        T3 = T3 + T(k-kb+1, i-ib+1)*C(k,j+1)
                        T4 = T4 +T(k-kb+1, i-ib+2)*C(k,j+1)
                    enddo
                    A(i,j) = A(i,j)+T1
                    A(i+1,j) = A(i+1, j)+T2
                    A(i,j+1) = A(i, j+1)+T3
                    A(i+1, j+1) = A(i+1, j+1) +T4
                enddo
            enddo
        enddo
    enddo
enddo
```

Instructions: For this exercise, use the files provided in the directory matmul2-f. You will need to edit the file matmul.f. One possible solution has been provided in the file matmul.f.ANS.

•Compile by typing **make matmul** and execute **matmul**, recording the Mflops values returned for **kji, dgemm** and **mydgemm**. You will get some "0.000" values. Those are from areas where you are expected to edit the code and are not doing anything currently.

•Note: In order to speed up your execution, you can comment out each routine after you have finished recording its execution rates. For example, you could comment out the **kji, dgemm** and **mydgemm** routines now and you would not have to wait for them to execute in future runs.

•Edit **matmul.f** and uncomment and correct the routine **kjib** which should be a blocked version of kji (use blocks of size 32). Compile and execute the code, recording the Mflops values.

•Edit **matmul.f** and uncomment and correct the routine **kjiu** which should be an unrolled version of **kji.** Compile and execute the code, recording the Mflops values.

•Which optimizations achieved the best performance?

•Why was this performance achieved? (Review the information about **dgemm** and **mydgemm** for the answer)

•Why is the performance of **dgemm** worse than that of **mydgemm**? (**mydgemm** extracts the core of **dgemm** to make it somewhat simpler to understand. In doing so it throws away the parts of **dgemm** which are generic and applicable to any size matrix. Since **mydgemm** cannot handle arbitrary size matrices it is somewhat faster than **dgemm** but less useful)..