Overview of Common Strategies for Parallelization

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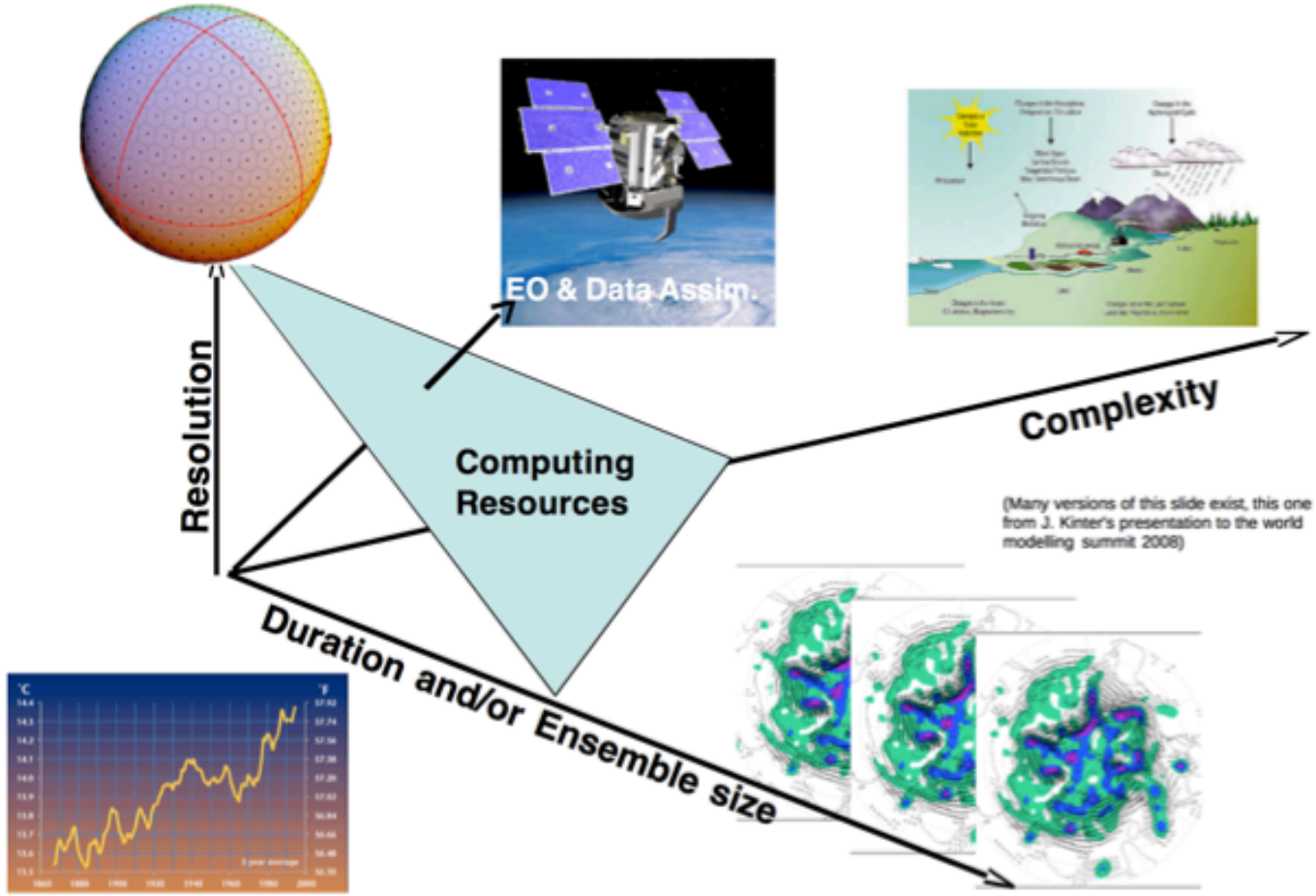
Fundamental Tools of Parallel Programming

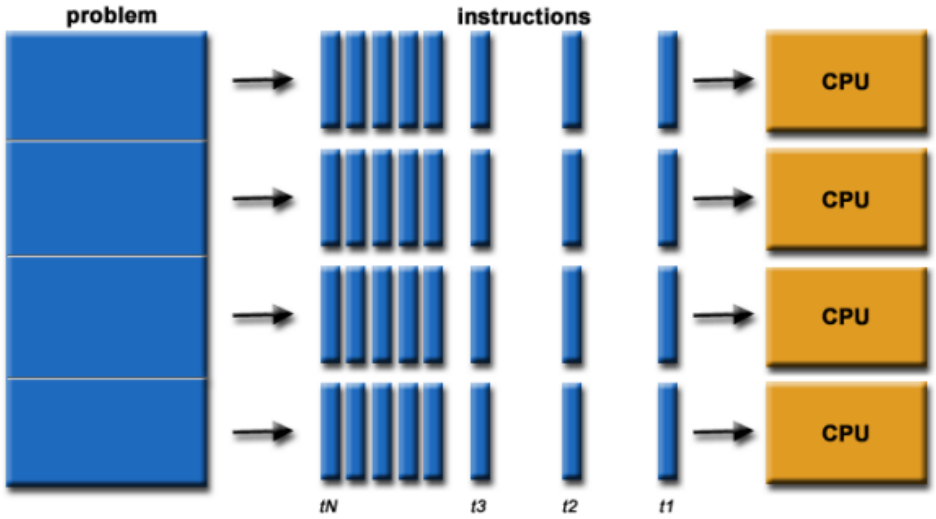
Parallelism - 101

- there are two main reasons to write a parallel program:
  - access to larger amount of memory (aggregated, going bigger)
  - reduce time to solution (going faster)


EO & Data Assim.
Resolution
Computing Resources
Complexity
Duration and/or Ensemble size
(Many versions of this slide exist, this one from J. Kinter's presentation to the world modelling summit 2008)

Concurrency

The first step in developing a parallel algorithm is to decompose the problem into tasks that can be executed concurrently



- A problem is broken into discrete parts that can be solved concurrently
- Each part is further broken down to a series of instructions
- Instructions from each part execute simultaneously on different processors
- An overall control / coordination mechanism is employed

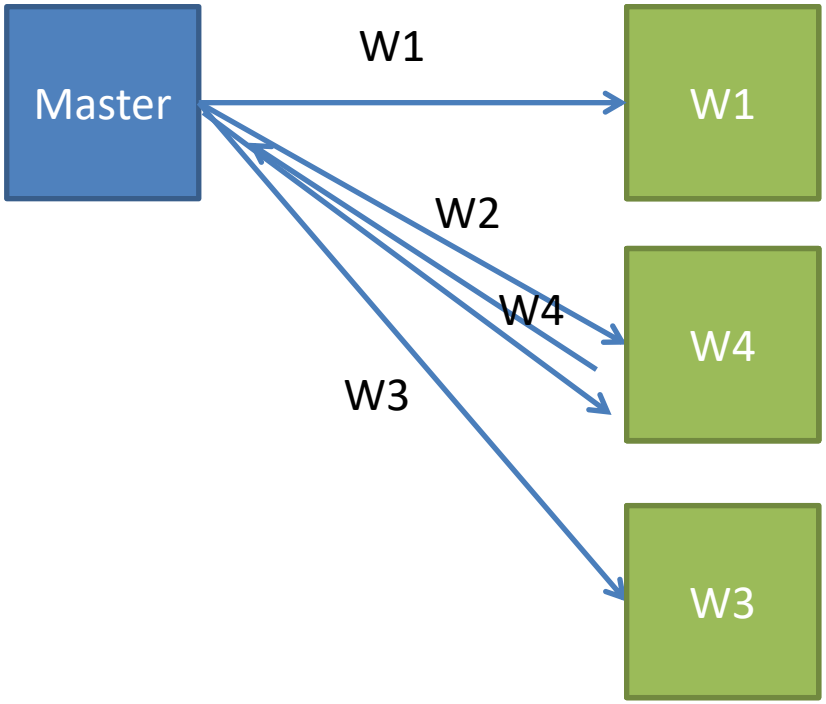
Fundamental Steps of Parallel Design

- Identify portions of the work that can be performed concurrently
- Mapping the concurrent pieces of work onto multiple processes running in parallel
- Distributing the input, output and intermediate data associated within the program
- Managing accesses to data shared by multiple processors
- Synchronizing the processors at various stages of the parallel program execution

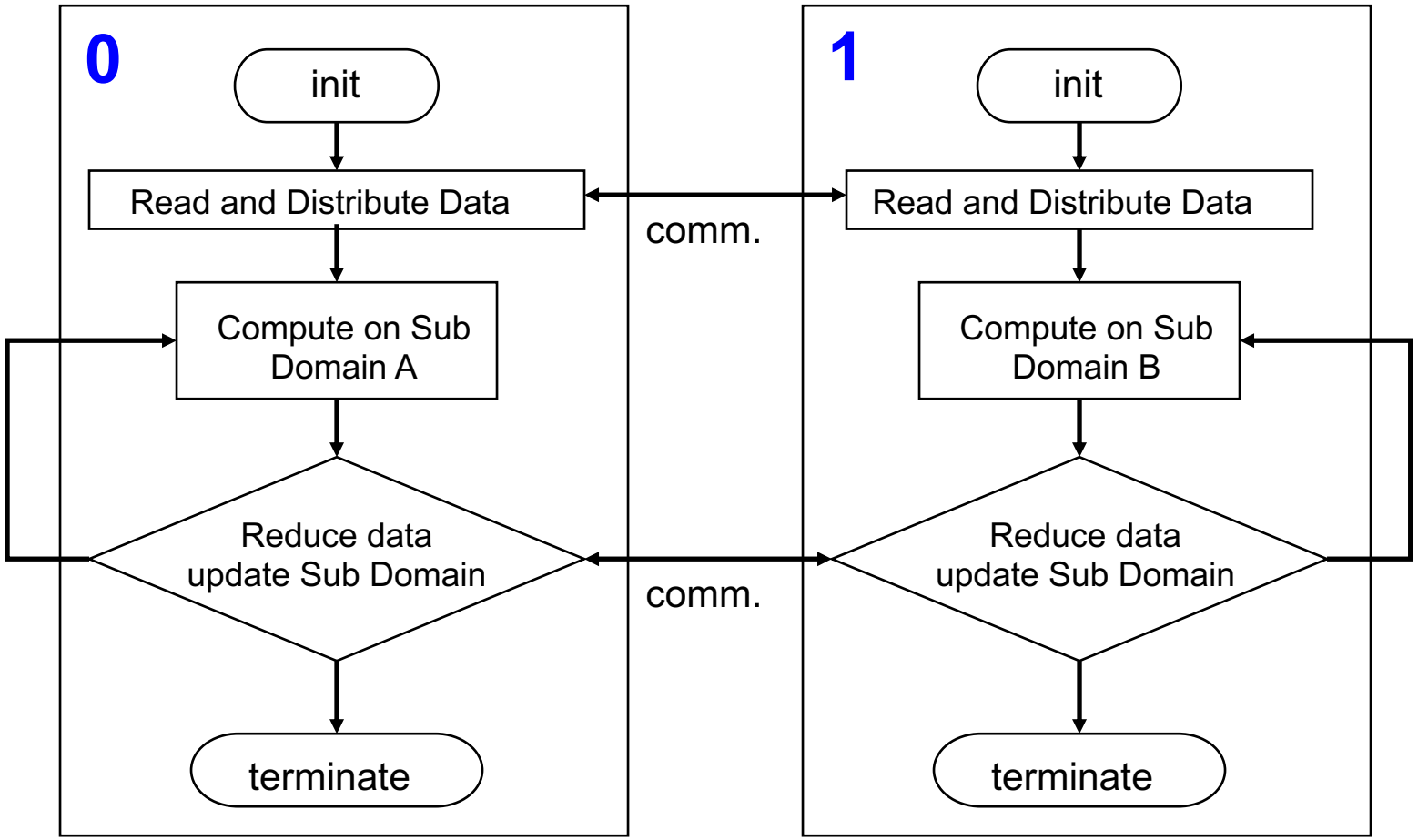
Easy Parallel Computing

- Farming, embarrassingly parallel
  - Executing multiple instances on the same program with different inputs/initial cond.
  - Reading large binary files by splitting the workload among processes
  - Searching elements on large data-sets
  - Other parallel execution of embarrassingly parallel problem (no communication among tasks)
- Ensemble simulations (weather forecast)
- Parameter space (find the best wing shape)

Master/Slave



A Parallel Program on Distributed Memory

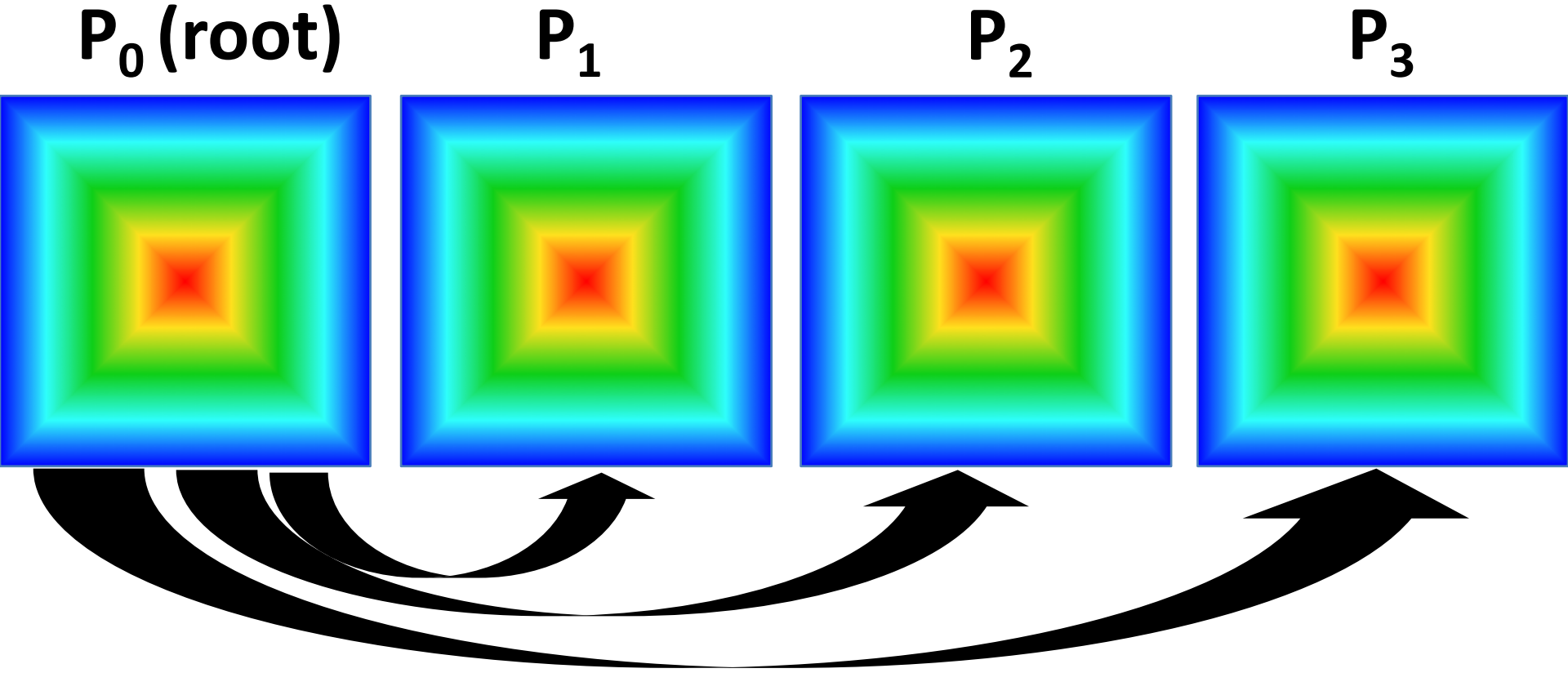


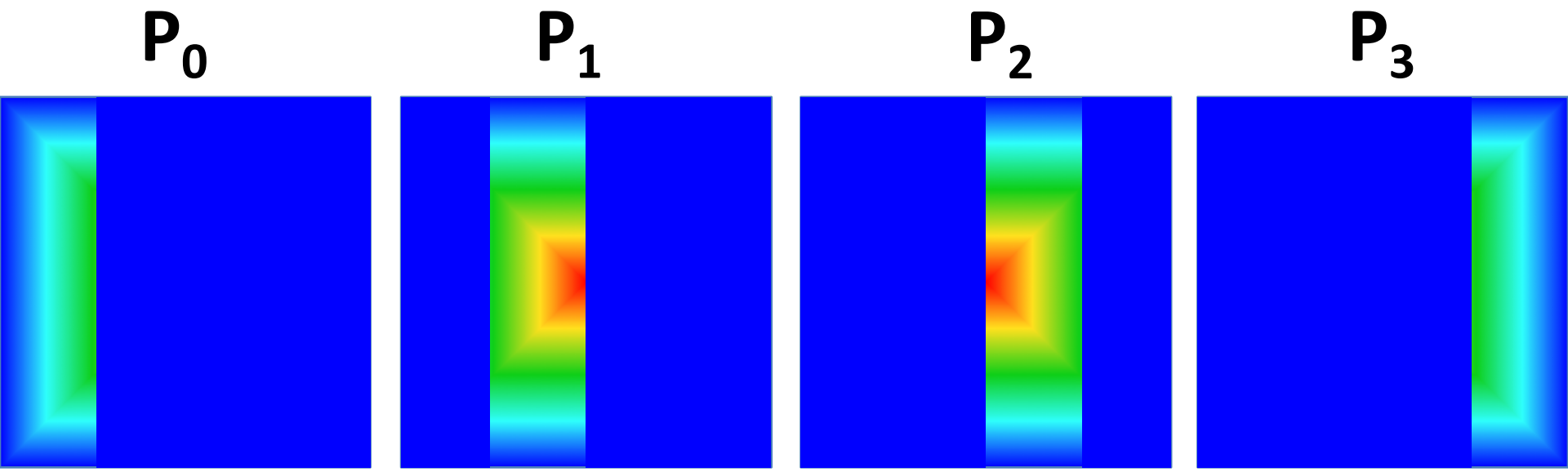
Distributed Data Vs Replicated Data

- Replicated data distribution is useful if it helps to reduce the communication among process at the cost of bounding scalability
- Distributed data is the ideal data distribution but not always applicable for all data-sets
- Usually complex application are a mix of those techniques => distribute large data sets; replicate small data

P_0

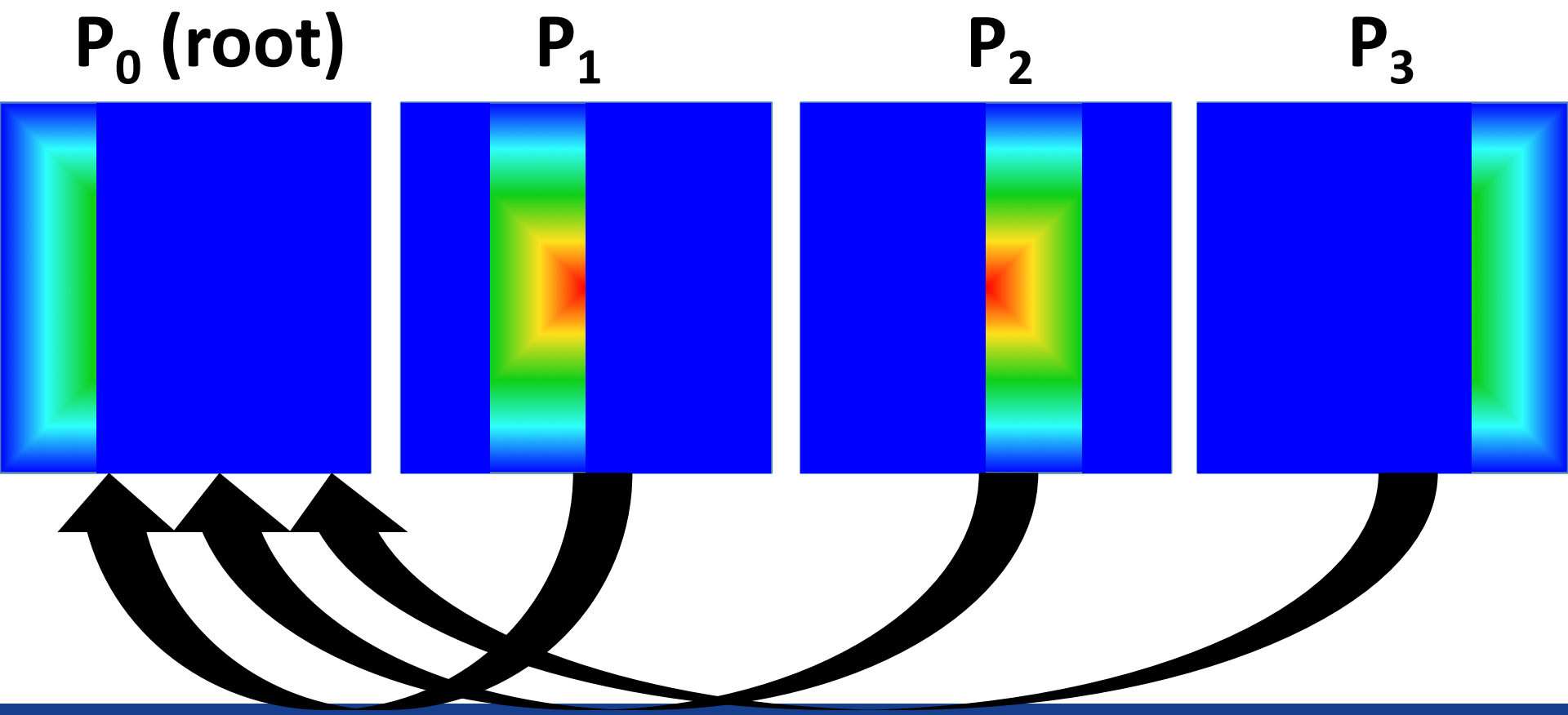
call MPI_BCAST(...)





call evolve(dtfact)

call MPI_Gather(…, …, …)



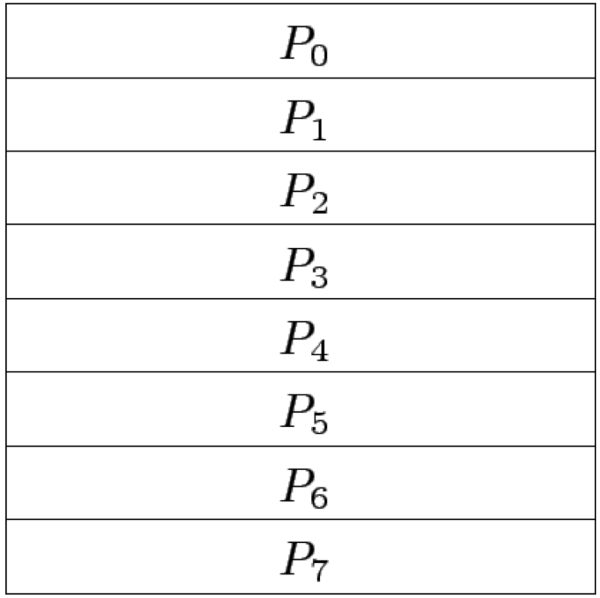
Replicated data

- Compute domain (and workload) distribution among processes
- Master-slaves: P_0 drives all processes
- Large amount of data communication
  - at each step P_0 distribute data to all processes and collect the contribution of each process
- Problem size scaling limited in memory capacity

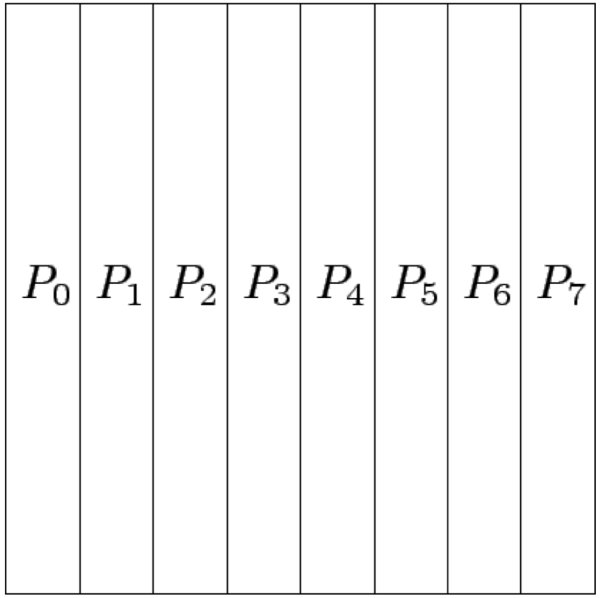
Static Data Partitioning

The simplest data decomposition schemes for dense matrices are 1-D block distribution schemes.

row-wise distribution

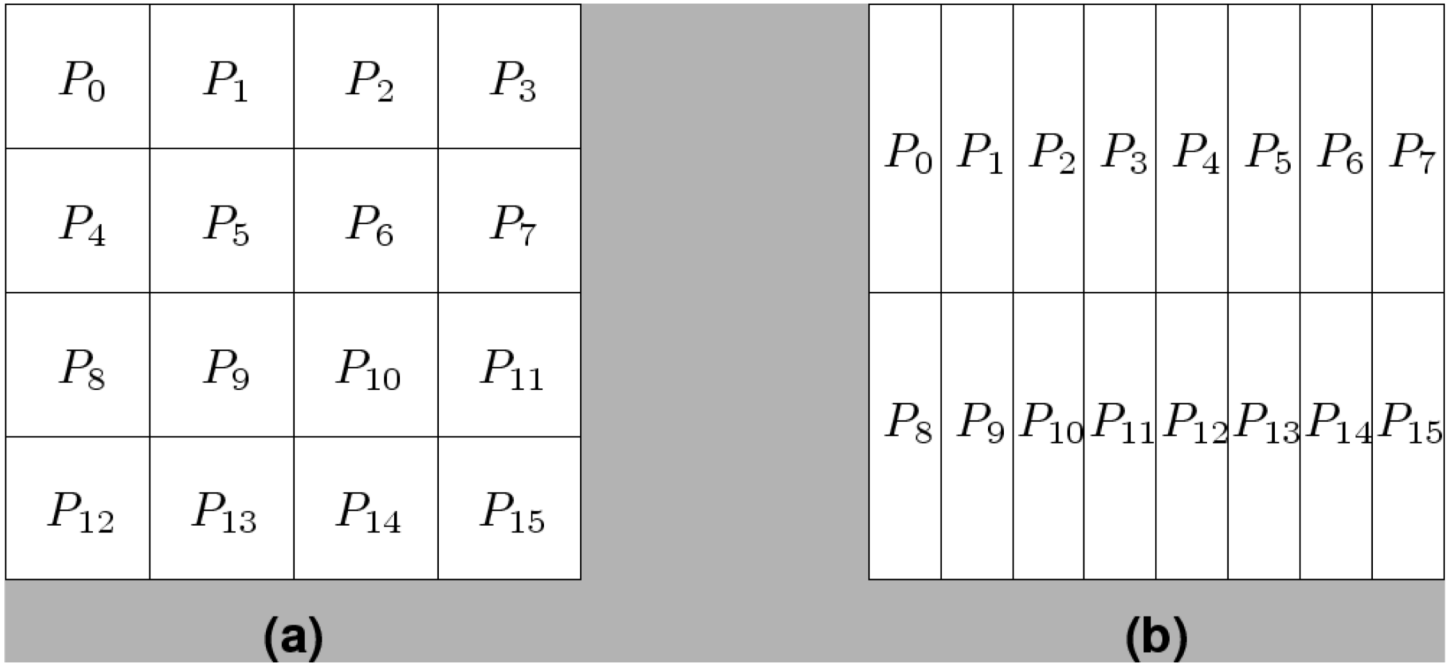


column-wise distribution



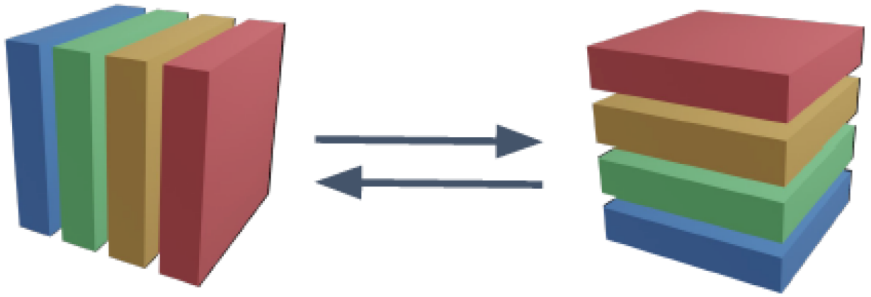
Block Array Distribution Schemes

Block distribution schemes can be generalized to higher dimensions as well.

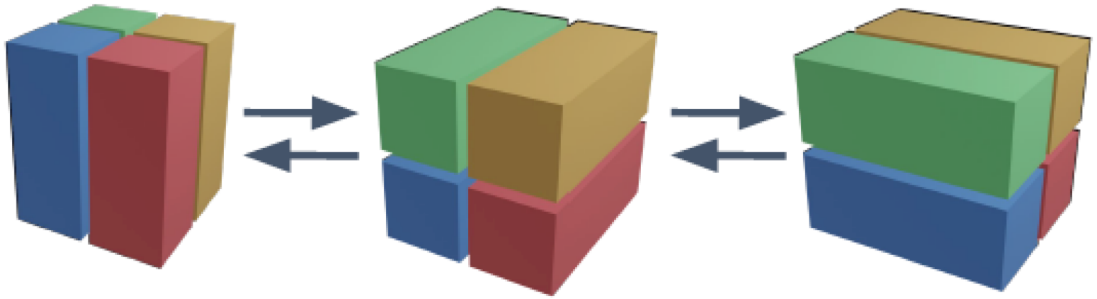


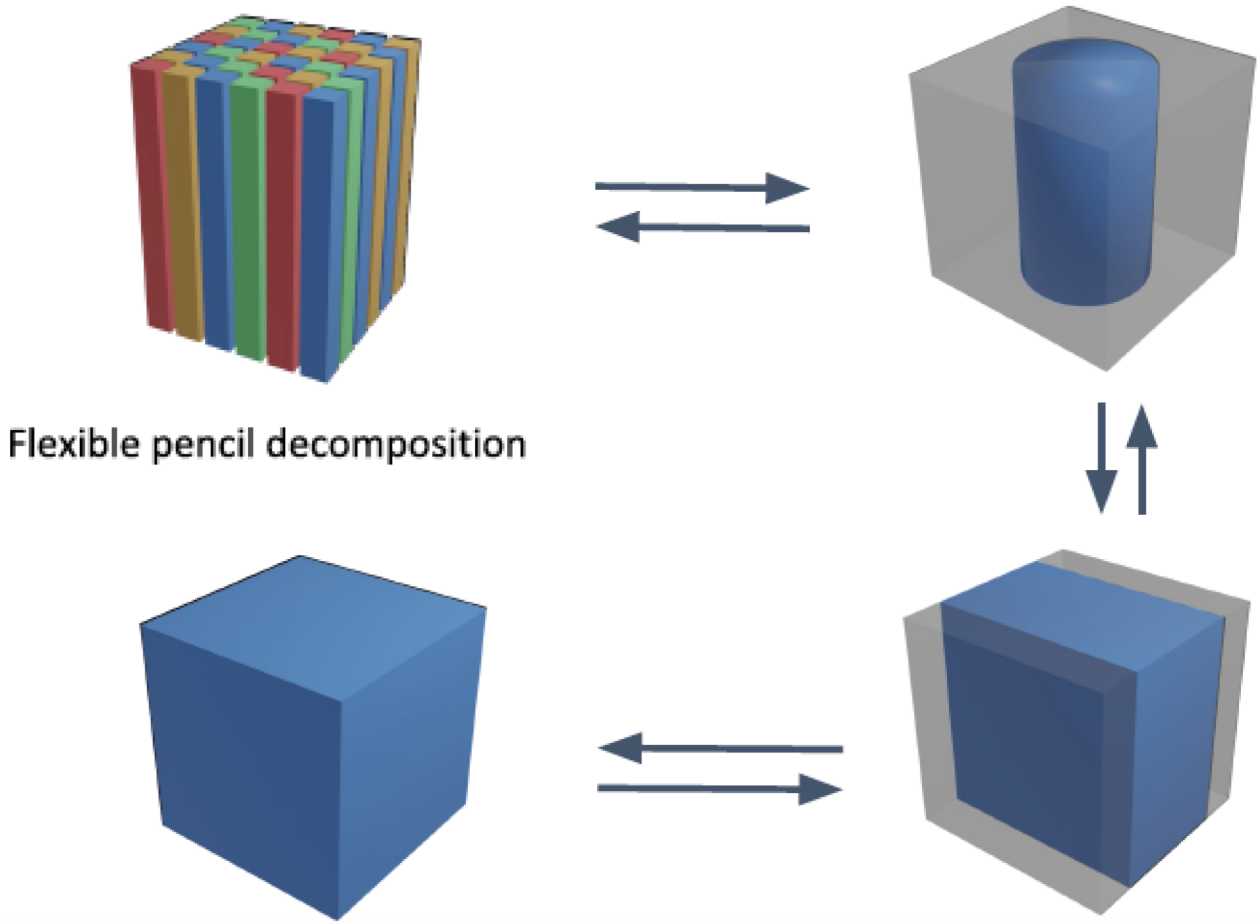
Degree to which tasks/data can be subdivided is limit to concurrency and parallel execution!!

Slab decomposition:



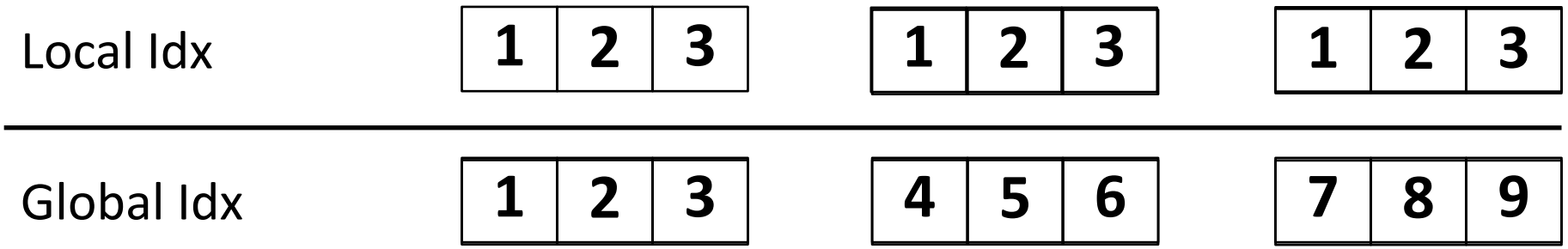
Pencil decomposition:



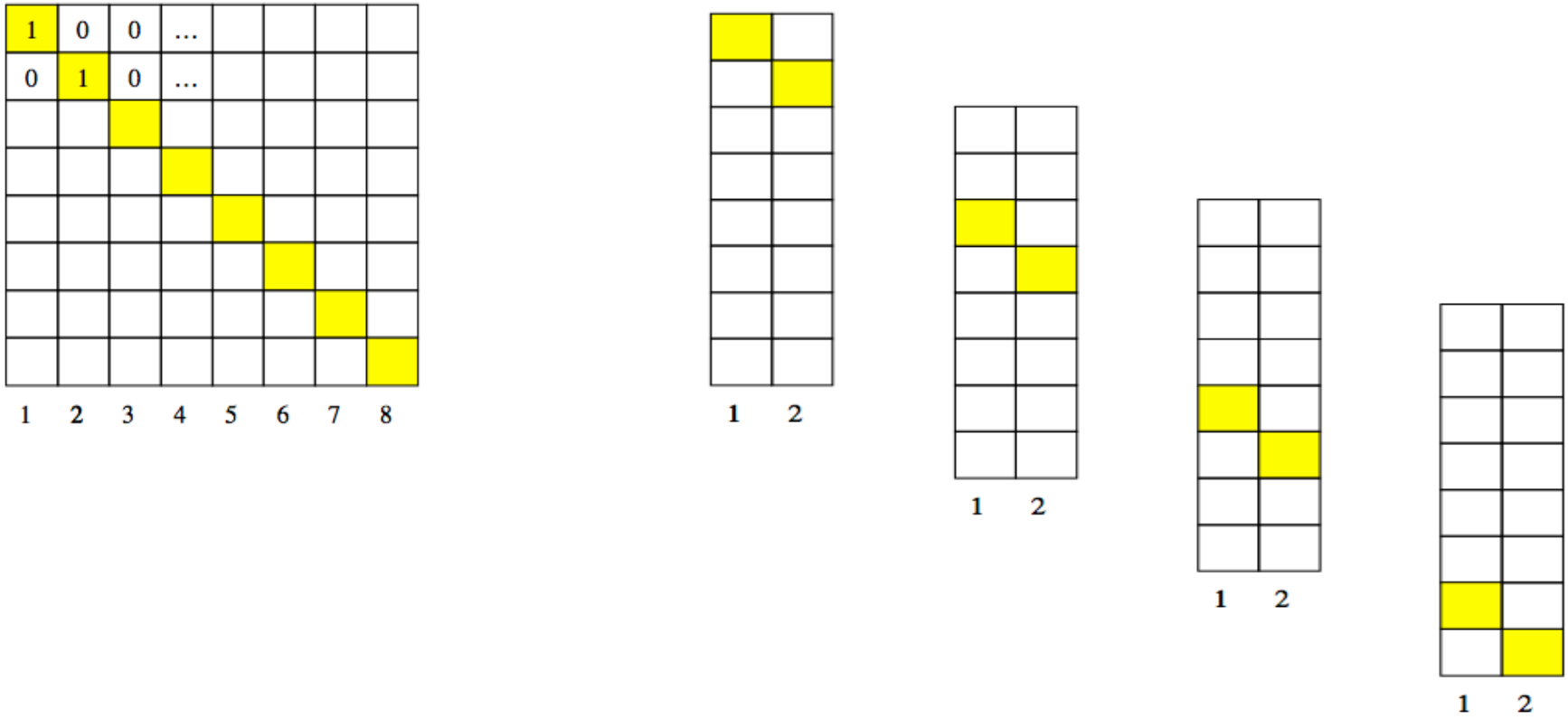

Flexible pencil decomposition

Global Vs Local Indexes

- In sequential code you always refer to global indexes
- With distributed data you must handle the distinction between global and local indexes (and possibly implementing utilities for transparent conversion)



Domain Decomposition



Identity Matrix /1

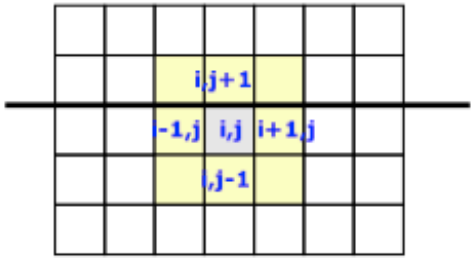
```
// Initialization of a Indenty Matrix
for( i = 0; i < SIZE; i++ ){
  for( j = 0; j < SIZE; j++ ){

    if( i == j ) mat[ i * SIZE + j ] = 1.0;
    else mat[ i * SIZE + j ] = 0.0;
  }
}
```

Identity Matrix /1

```
   […]
   int size_loc = SIZE / npes;

// NO!!!! double * mat = malloc( SIZE * SIZE * sizeof(double) );

    double * mat = malloc( SIZE * size_loc * sizeof(double) );
    int i, j;

   // Initialization of the distributed Indenty Matrix
    for( i = 0; i < size_loc; i++ ){
      for( j = 0; j < SIZE; j++ ){

        int i_global = rank * size_loc + i;

        if( i_global == j ) mat[ i * SIZE + j ] = 1.0;
        else mat[ i * SIZE + j ] = 0.0;
      }
    }
```

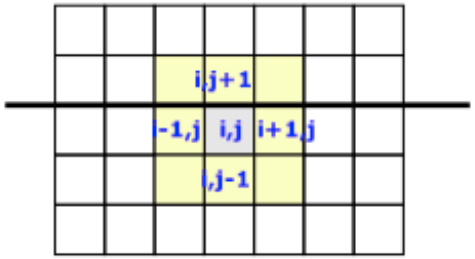
Again on Domain Decomposition

sub-domain boundaries

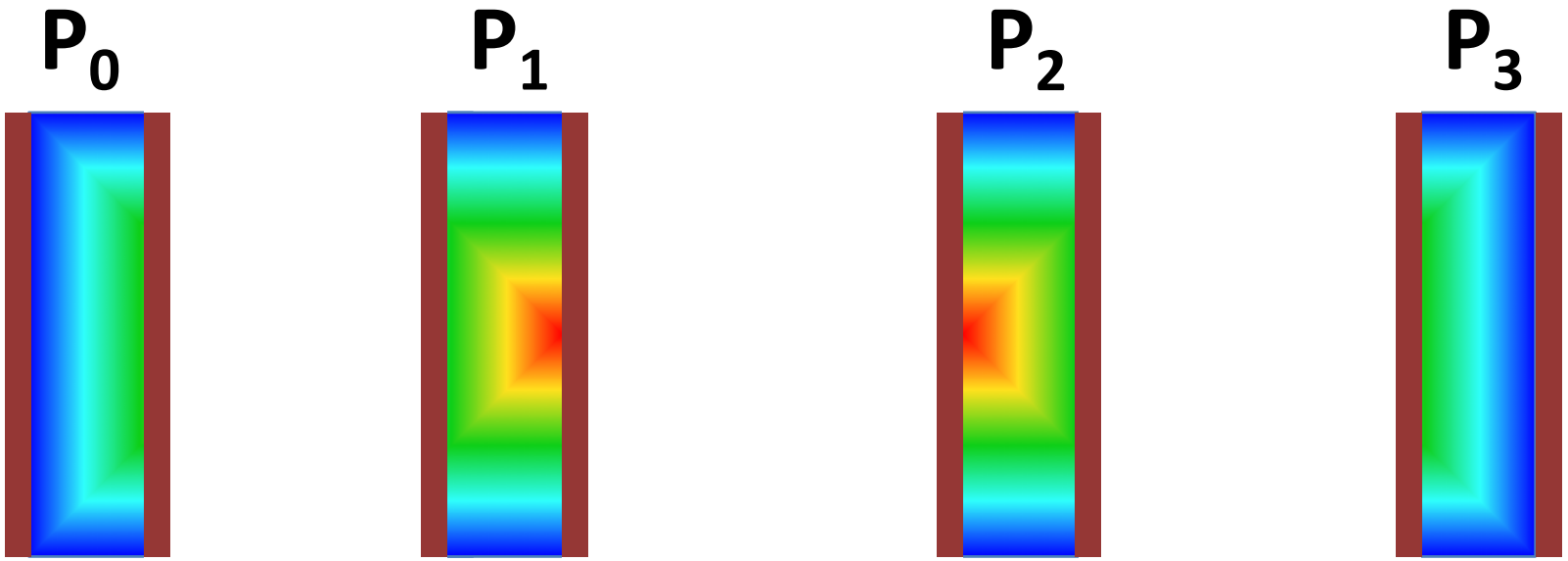


Again on Domain Decomposition

sub-domain boundaries



The Transport Code - Parallel Version

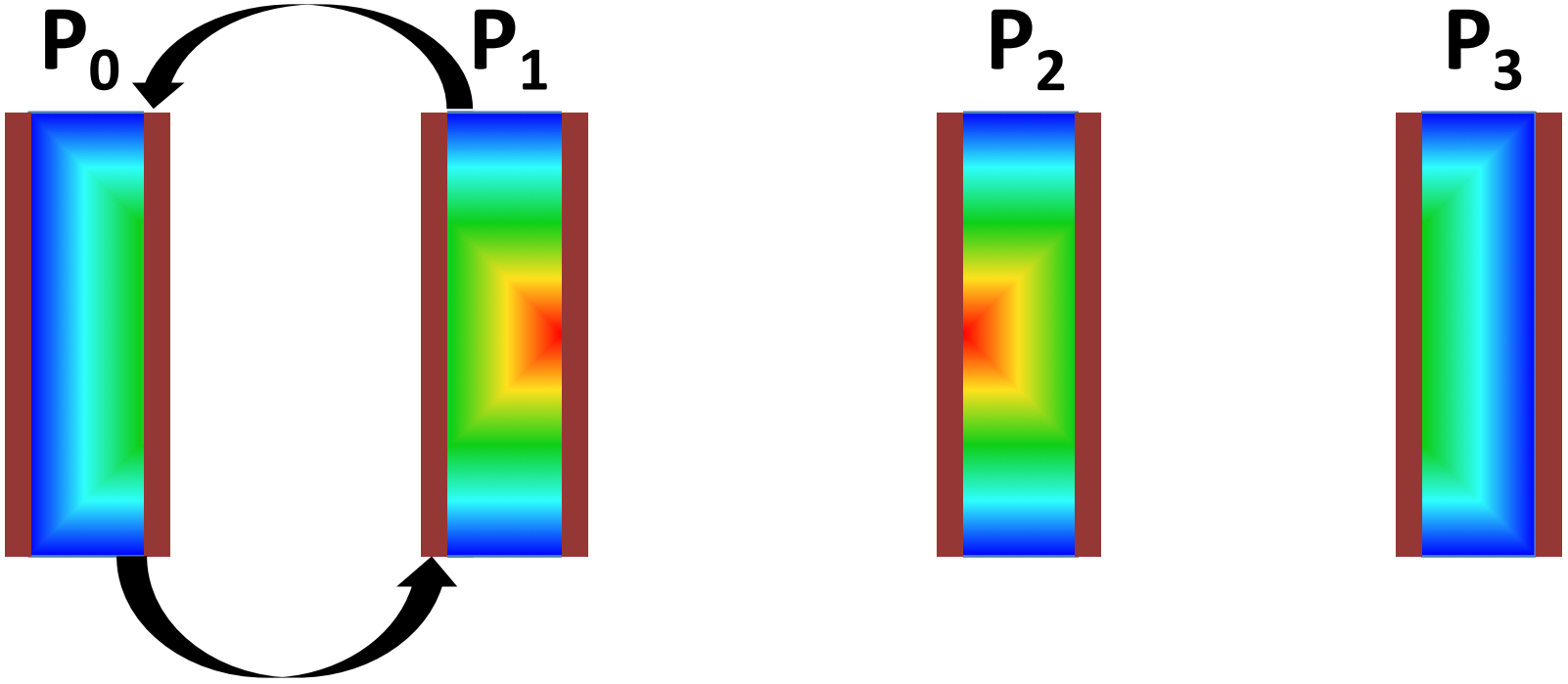


call evolve(dtfact)

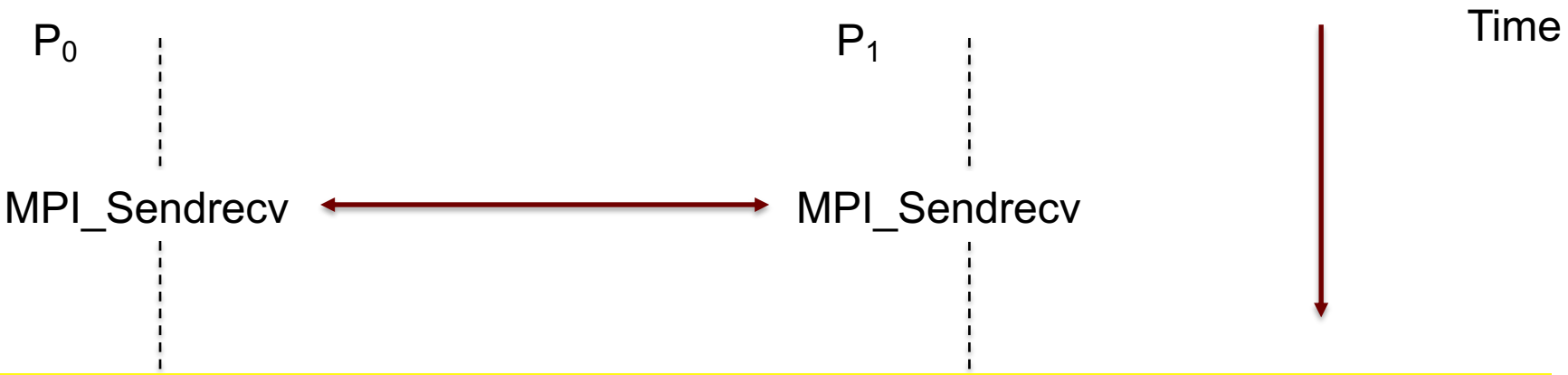
Distributed Matrix /1

```
   […]
   int size_loc = SIZE / npes;

// NO!!!! double * mat = malloc( SIZE * SIZE *
sizeof(double) );

 double * mat;
 mat = malloc( SIZE *( size_loc + 2 ) * sizeof(double) );
```

Data exchange among processes

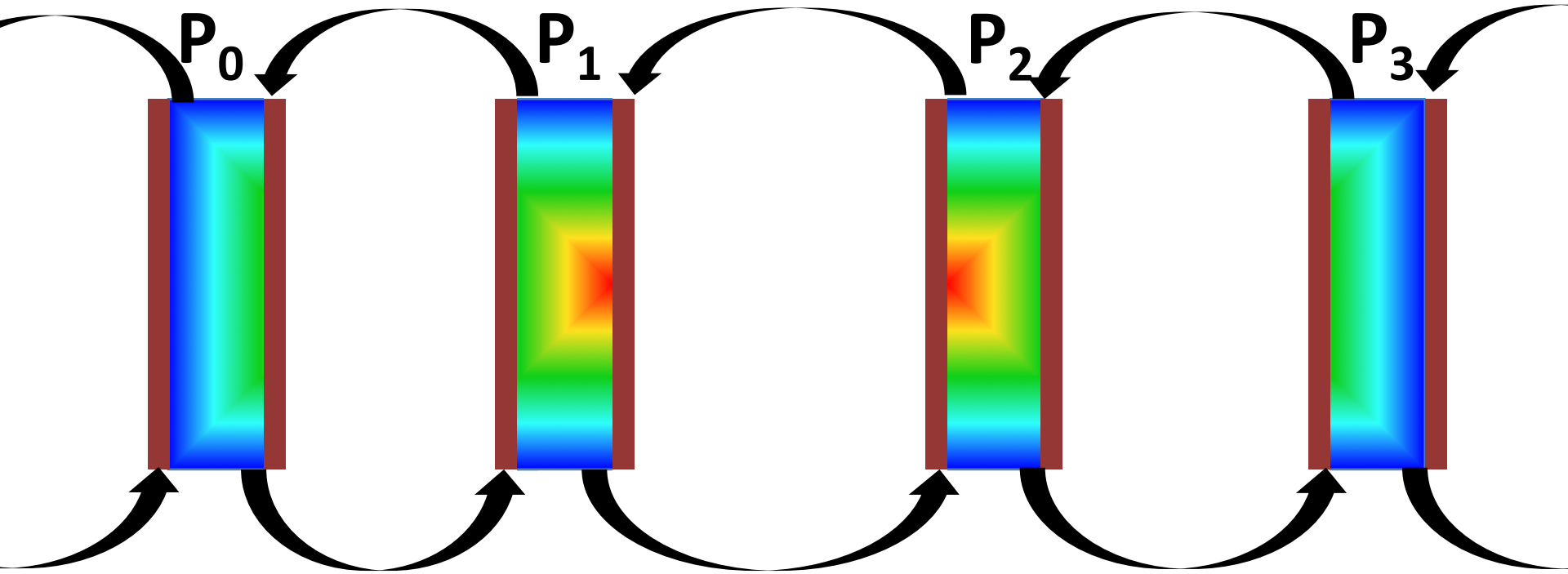


Efficient Data Exchange Between 2 Processes




```
[…]

int * buf_s = (int *) malloc( N * sizeof(int) );

int * buf_r = (int *) malloc( N * sizeof(int) );

init_buffer( buf_s, N );

MPI_Sendrecv( buf_s, N, MPI_INT, !rank, 100, buf_r, N, MPI_INT, !rank, 100,
              MPI_COMM_WORLD, MPI_STATUS_IGNORE );
```

proc_down = mod(proc_me - 1 + nprocs , nprocs)

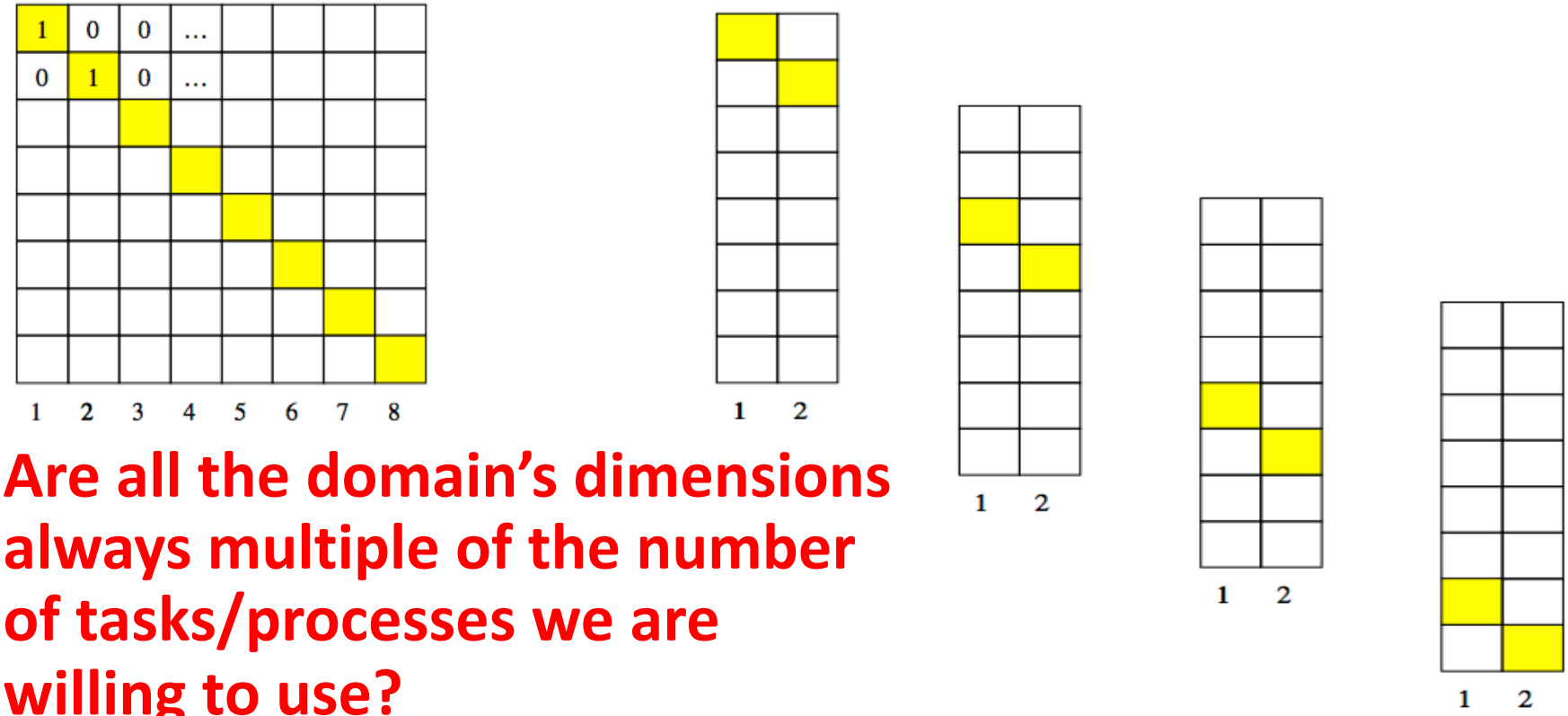


proc_up = mod(proc_me + 1 , nprocs)

Distributed Data

- Global and Local Indexes
- Ghost Cells Exchange Between Processes
  - Compute Neighbor Processes
- Parallel Output

Collaterals to Domain Decomposition /1



Are all the domain's dimensions always multiple of the number of tasks/processes we are willing to use?

Identity Matrix /1

```
[…]
int size_loc = SIZE / npes;

 rest = offset = SIZE % npes;

 if( rank < rest ){
   size_loc += 1; offset = 0;
 }

 double * mat = malloc( SIZE * size_loc * sizeof(double) );
 int i, j;

// Initialization of the distributed Indenty Matrix
 for( i = 0; i < size_loc; i++ ){
   for( j = 0; j < SIZE; j++ ){

     int i_global = rank * size_loc + i + offset;

     if( i_global == j ) mat[ i * SIZE + j ] = 1.0;
     else mat[ i * SIZE + j ] = 0.0;
   }
 }
```