

# **CSE 590: Special Topics Course ( Supercomputing )**

## **Lecture 7 ( Analyzing Distributed Memory Algorithms )**

**Rezaul A. Chowdhury  
Department of Computer Science  
SUNY Stony Brook  
Spring 2016**

# 2D Heat Diffusion

Let  $h_t(x, y)$  be the heat at point  $(x, y)$  at time  $t$ .

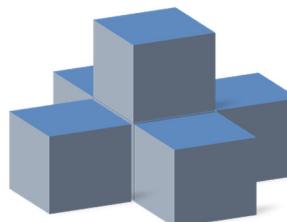
## Heat Equation

$$\frac{\partial h}{\partial t} = \alpha \left( \frac{\partial^2 h}{\partial x^2} + \frac{\partial^2 h}{\partial y^2} \right), \quad \alpha = \text{thermal diffusivity}$$

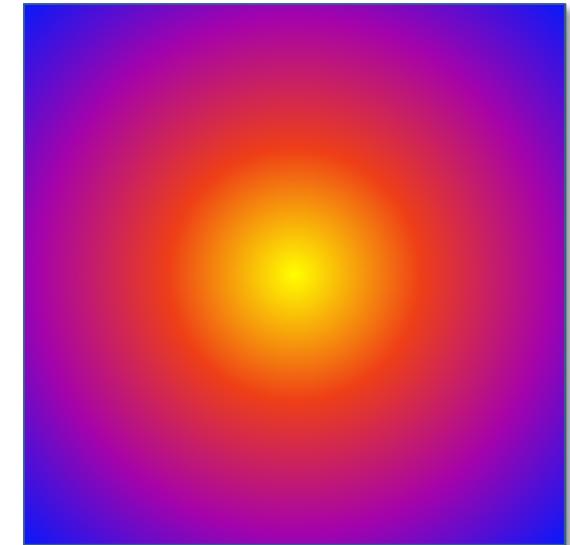
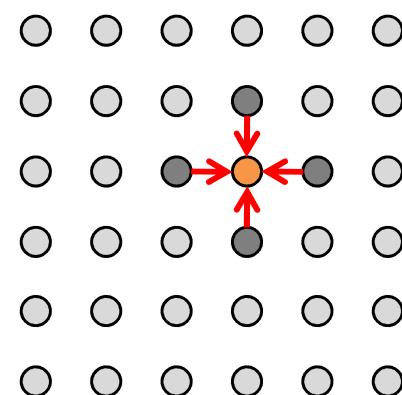
## Update Equation ( on a discrete grid )

$$h_{t+1}(x, y) = h_t(x, y) + c_x(h_t(x + 1, y) - 2h_t(x, y) + h_t(x - 1, y)) + c_y(h_t(x, y + 1) - 2h_t(x, y) + h_t(x, y - 1))$$

## 2D 5-point Stencil



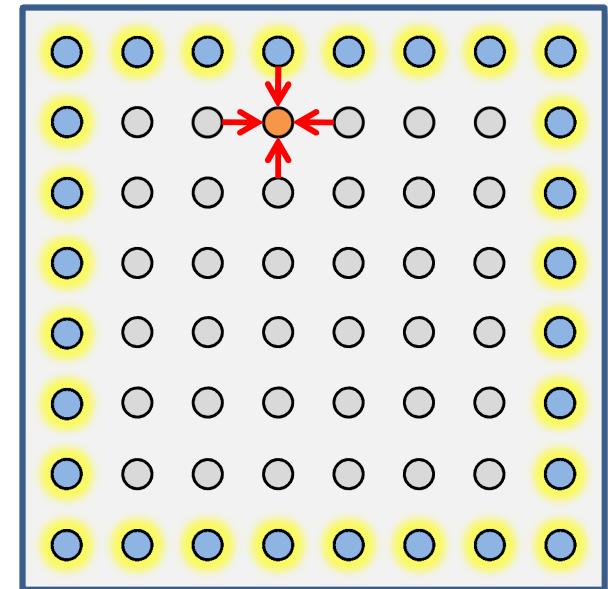
↑  
*time*



# Standard Serial Implementation

## Implementation Tricks

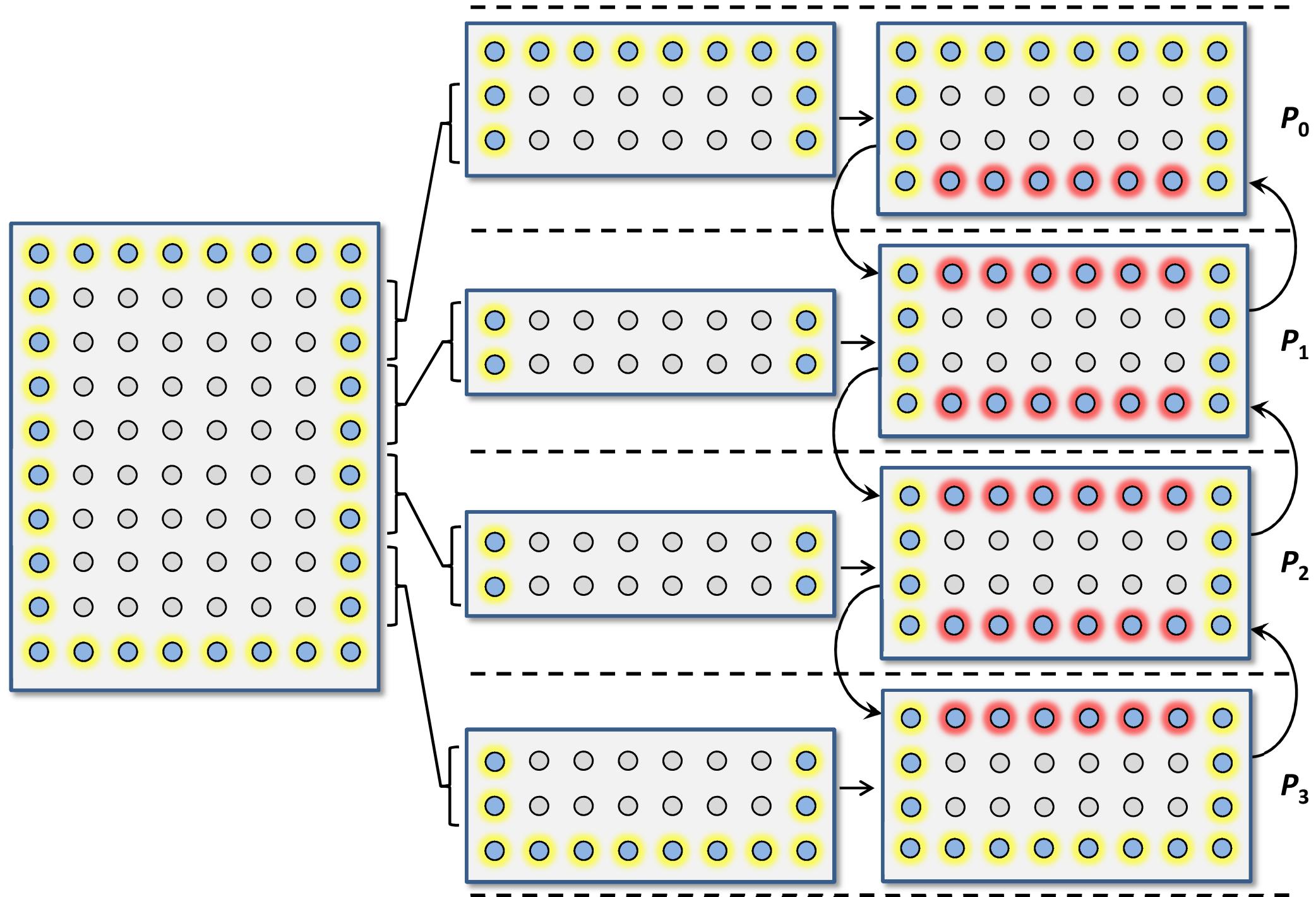
- Reuse storage for odd and even time steps
- Keep a halo of ghost cells around the array with boundary values



```
for ( int t = 0; t < T; ++t )
{
    for ( int x = 1; x <= X; ++x )
        for ( int y = 1; y <= Y; ++y )
            g[x][y] = h[x][y]
                + cx * ( h[x+1][y] - 2 * h[x][y] + h[x-1][y] )
                + cy * ( h[x][y+1] - 2 * h[x][y] + h[x][y-1] );

    for ( int x = 1; x <= X; ++x )
        for ( int y = 1; y <= Y; ++y )
            h[x][y] = g[x][y];
}
```

# One Way of Parallelization



# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}
```

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                            MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                            MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}

}

```

leave enough space  
for ghost cells

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )  
... ... ...  
... ... ...  
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];  
MPI_Status stat;  
MPI_Request sendreq[ 2 ], recvreq[ 2 ];  
... ... ...  
... ... ...  
for ( int t = 0; t < T; ++t )  
{  
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );  
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }  
  
    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );  
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }  
  
    for ( int x = 2; x < XX; ++x )  
        for ( int y = 1; y <= Y ; ++y )  
            g[x][y] = UPDATE( x, y );  
  
    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );  
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );  
  
    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }  
  
    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );  
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );  
  
    for ( int x = 1; x <= XX; ++x )  
        for ( int y = 1; y <= Y ; ++y )  
            h[x][y] = g[x][y];  
}
```

downward send and  
upward receive

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}

upward send and
downward receive
```

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}
```

for ( int x = 2; x < XX; ++x )  
for ( int y = 1; y <= Y ; ++y )  
g[x][y] = UPDATE( x, y );

in addition to the ghost rows exclude  
the two outermost interior rows

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}
```

wait until data is received  
for the ghost rows

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}
```

update the two outermost interior rows

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );
}

for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

for ( int x = 1; x <= XX; ++x )
    for ( int y = 1; y <= Y ; ++y )
        h[x][y] = g[x][y];
}
```

wait until sending data is complete  
so that h can be overwritten

# MPI Implementation of 2D Heat Diffusion

```
#define UPDATE( u, v ) ( h[u][v] + cx * ( h[u+1][v] - 2* h[u][v] + h[u-1][v] ) + cy * ( h[u][v+1] - 2* h[u][v] + h[u][v-1] ) )
...
...
...
MPI_FLOAT h[ XX + 2 ][ Y + 2 ], g[ XX + 2 ][ Y + 2 ];
MPI_Status stat;
MPI_Request sendreq[ 2 ], recvreq[ 2 ];
...
...
...
for ( int t = 0; t < T; ++t )
{
    if ( myrank < p - 1 ) { MPI_Isend( h[ XX ], Y, MPI_FLOAT, myrank + 1, 2 * t, MPI_COMM_WORLD , & sendreq[ 0 ] );
                           MPI_Irecv( h[ XX + 1 ], Y, MPI_FLOAT, myrank + 1, 2 * t + 1, MPI_COMM_WORLD , & recvreq[ 0 ] ); }

    if ( myrank > 0 )      { MPI_Isend( h[ 1 ], Y, MPI_FLOAT, myrank - 1, 2 * t + 1, MPI_COMM_WORLD , & sendreq[ 1 ] );
                           MPI_Irecv( h[ 0 ], Y, MPI_FLOAT, myrank - 1, 2 * t , MPI_COMM_WORLD , & recvreq[ 1 ] ); }

    for ( int x = 2; x < XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            g[x][y] = UPDATE( x, y );

    if ( myrank < p - 1 ) MPI_Wait( &recvreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &recvreq[ 1 ], &stat );

    for ( int y = 1; y <= Y ; ++y ) { g[1][y] = UPDATE( 1, y ); g[XX][y] = UPDATE( XX, y ); }

    if ( myrank < p - 1 ) MPI_Wait( &sendreq[ 0 ], &stat );
    if ( myrank > 0 )      MPI_Wait( &sendreq[ 1 ], &stat );

    for ( int x = 1; x <= XX; ++x )
        for ( int y = 1; y <= Y ; ++y )
            h[x][y] = g[x][y];
}

now overwrite h
```

# Analysis of the MPI Implementation of Heat Diffusion

Let the dimension of the 2D grid be  $n_X \times n_Y$ , and suppose we execute  $n_T$  time steps. Let  $p$  be the number of processors, and suppose the grid is decomposed along  $X$  direction.

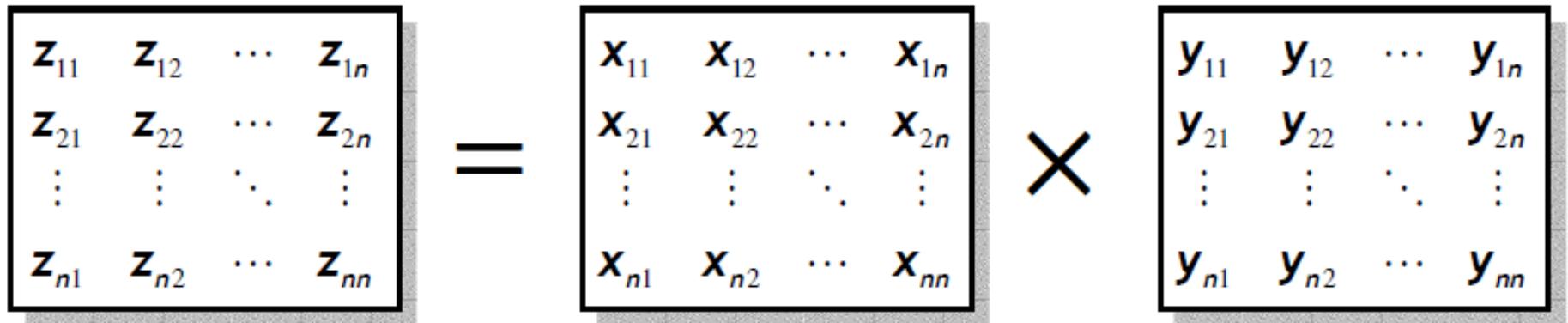
The computation cost in each time step is clearly  $\frac{n_X n_Y}{p}$ . Hence, the total computation cost,  $t_{comp} = \frac{n_T n_X n_Y}{p}$ .

All processors except processors 0 and  $p - 1$  send two rows and receive two rows each in every time step. Processors 0 and  $p - 1$  send and receive only one row each. Hence, the total communication cost,  $t_{comm} = 4n_T(t_s + n_Y t_w)$ , where  $t_s$  is the startup time of a message and  $t_w$  is the per-word transfer time.

Thus  $T_p = t_{comp} + t_{comm} = \frac{n_T n_X n_Y}{p} + 4n_T(t_s + n_Y t_w)$ , and  $T_1 = n_T n_X n_Y$ .

# Naïve Matrix Multiplication

$$z_{ij} = \sum_{k=1}^n x_{ik} y_{kj}$$



*Iter-MM( X, Y, Z, n )*

1. *for*  $i \leftarrow 1$  *to*  $n$  *do*
2.       *for*  $j \leftarrow 1$  *to*  $n$  *do*
3.           *for*  $k \leftarrow 1$  *to*  $n$  *do*
4.                $z_{ij} \leftarrow z_{ij} + x_{ik} \times y_{kj}$

# Naïve Matrix Multiplication

$$z_{ij} = \sum_{k=1}^n x_{ik} y_{kj}$$

$$\begin{matrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nn} \end{matrix} = \begin{matrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{matrix} \times \begin{matrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nn} \end{matrix}$$

Suppose we have  $p = n \times n$  processors, and processor  $P_{ij}$  is responsible for computing  $z_{ij}$ .

One master processor initially holds both  $X$  and  $Y$ , and sends all  $x_{ik}$  and  $y_{kj}$  for  $k = 1, 2, \dots, n$  to each processor  $P_{ij}$ . One-to-all Broadcast is a bad idea as each processor requires a different part of the input.

Each  $P_{ij}$  computes  $z_{ij}$  and sends back to master.

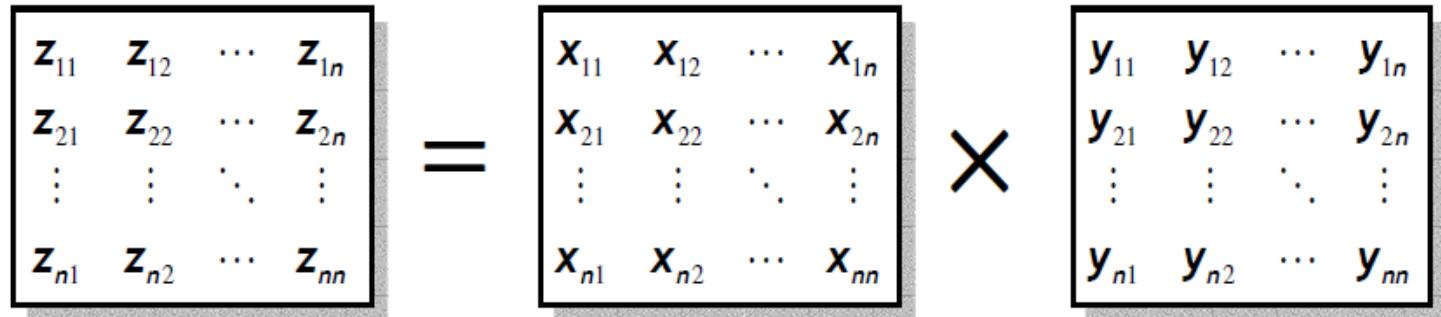
Thus  $t_{comp} = 2n$ , and  $t_{comm} = n^2(t_s + 2nt_w) + n^2(t_s + t_w)$ .

Hence,  $T_p = t_{comp} + t_{comm} = 2n + n^2(2t_s + t_w + 2nt_w)$ .

Total work,  $T_1 = 2n^3$ .

# Naïve Matrix Multiplication

$$z_{ij} = \sum_{k=1}^n x_{ik} y_{kj}$$



Observe that row  $i$  of  $X$  will be required by all  $P_{i,j}$ ,  $1 \leq j \leq n$ . So that row can be broadcast to the group  $\{P_{i,1}, P_{i,2}, \dots, P_{i,n}\}$  of size  $n$ .

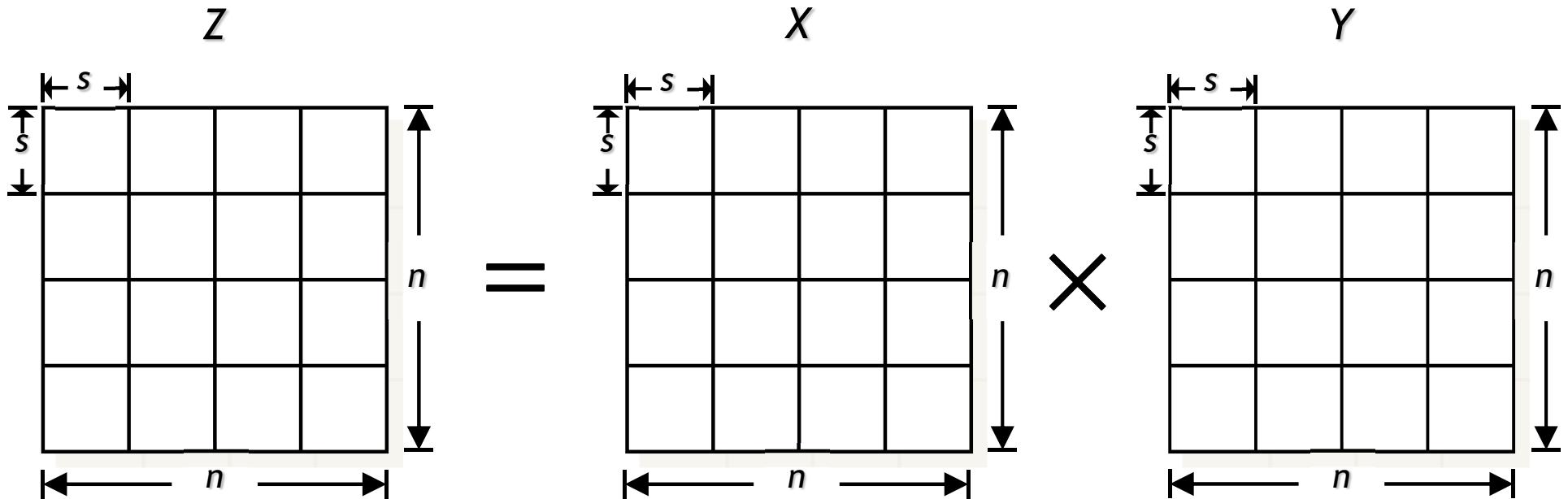
Similarly, for other rows of  $X$ , and all columns of  $Y$ .

The communication complexity of broadcasting  $m$  units of data to a group of size  $n$  is  $(t_s + mt_w) \log n$ .

As before, each  $P_{i,j}$  computes  $z_{ij}$  and sends back to master.

Hence,  $t_{comm} = 2n(t_s + nt_w) \log n + n^2(t_s + t_w)$ .

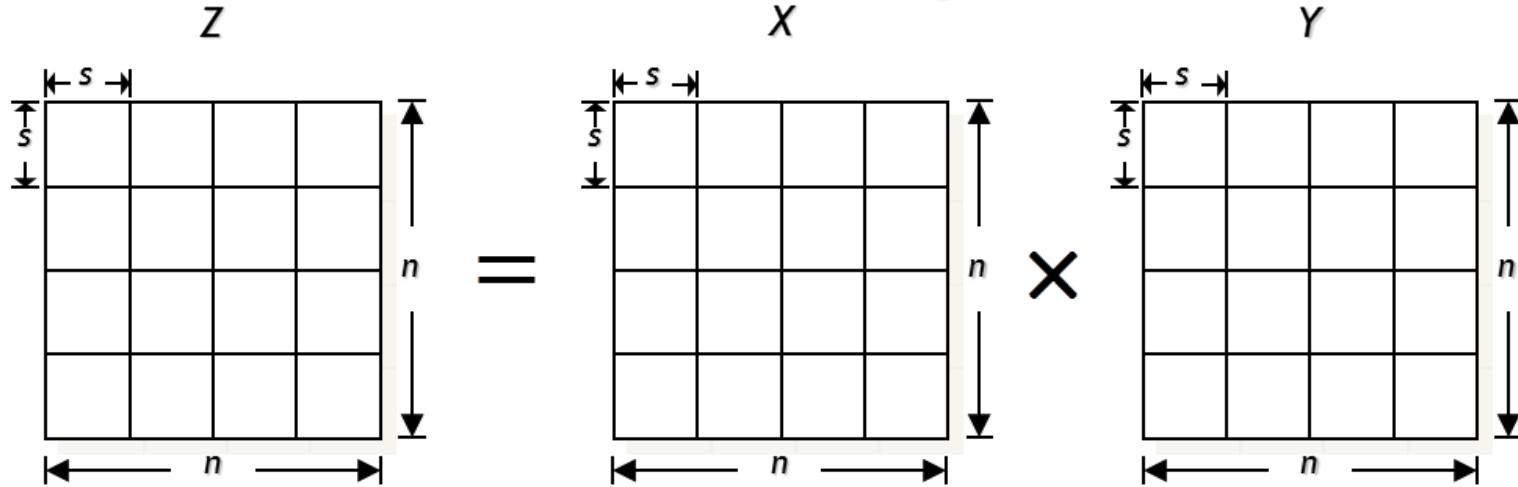
# Block Matrix Multiplication



*Block-MM(  $X, Y, Z, n$  )*

1. *for*  $i \leftarrow 1$  *to*  $n / s$  *do*
2.     *for*  $j \leftarrow 1$  *to*  $n / s$  *do*
3.         *for*  $k \leftarrow 1$  *to*  $n / s$  *do*
4.             *Iter-MM(  $X_{ik}, Y_{kj}, Z_{ij}, s$  )*

# Block Matrix Multiplication



Suppose  $p = \frac{n}{s} \times \frac{n}{s}$ , and processor  $P_{ij}$  computes block  $Z_{ij}$ .

One master processor initially holds both  $X$  and  $Y$ , and sends all blocks  $X_{ik}$  and  $Y_{kj}$  for  $k = 1, 2, \dots, \frac{n}{s}$  to each processor  $P_{ij}$ .

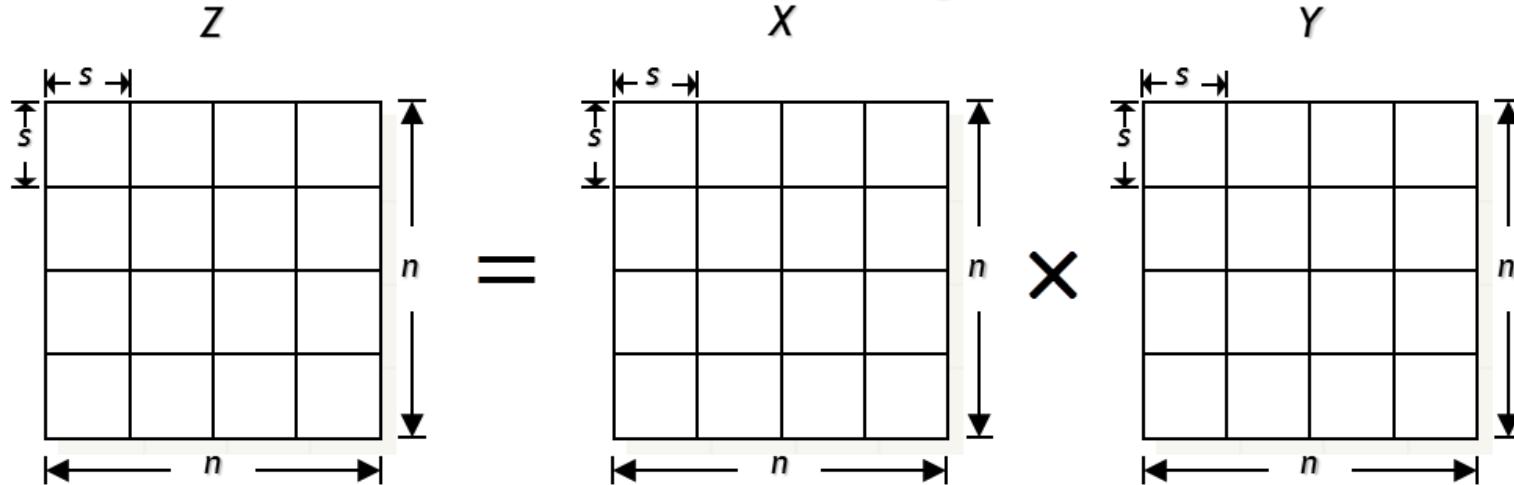
Thus  $t_{comp} = \frac{n}{s} (2s^3 + s^2) = O(ns^2)$ ,

and  $t_{comm} = \left(\frac{n}{s}\right)^2 (2(t_s + nst_w) + (t_s + s^2 t_w))$ . ( w/o broadcast )

For  $s = \sqrt{n}$ ,  $t_{comp} = O(n^2)$ , and  $t_{comm} = O(nt_s + n^{2.5}t_w)$

For  $s = n^{\frac{2}{3}}$ ,  $t_{comp} = O(n^{2+\frac{1}{3}})$ , and  $t_{comm} = O\left(n^{\frac{2}{3}}t_s + n^{2+\frac{1}{3}}t_w\right)$

# Block Matrix Multiplication



Now consider one-to-group broadcasting.

Block row  $i$  of  $X$ , i.e., blocks  $X_{ik}$  for  $k = 1, 2, \dots, \frac{n}{s}$ , will be required by  $\frac{n}{s}$  different processors, i.e., processors  $P_{ij}$  for  $j = 1, 2, \dots, \frac{n}{s}$ .

Similarly, for other block rows of  $X$ , and all block columns of  $Y$ .

As before, each  $P_{ij}$  computes block  $Z_{ij}$  and sends back to master.

$$\text{Hence, } t_{comm} = \frac{n}{s} (t_s + nst_w) \log\left(\frac{n}{s}\right) + \left(\frac{n}{s}\right)^2 (t_s + s^2 t_w).$$

# Cannon's Algorithm

We decompose each matrix

into  $\sqrt{p} \times \sqrt{p}$  blocks of size

$\frac{n}{\sqrt{p}} \times \frac{n}{\sqrt{p}}$  each.

We number the processors  
from  $P_{0,0}$  to  $P_{\sqrt{p}-1, \sqrt{p}-1}$ .

Initially,  $P_{ij}$  holds  $A_{ij}$  and  $B_{ij}$ .

We rotate block row  $i$  of  $A$  to  
the left by  $i$  positions, and  
block column  $j$  of  $B$  upward  
by  $j$  positions.

So,  $P_{ij}$  now holds  $A_{i,j+i}$  and  
 $B_{i+j,j}$ .

A <sub>0,0</sub>	A <sub>0,1</sub>	A <sub>0,2</sub>	A <sub>0,3</sub>
A <sub>1,0</sub>	A <sub>1,1</sub>	A <sub>1,2</sub>	A <sub>1,3</sub>
A <sub>2,0</sub>	A <sub>2,1</sub>	A <sub>2,2</sub>	A <sub>2,3</sub>
A <sub>3,0</sub>	A <sub>3,1</sub>	A <sub>3,2</sub>	A <sub>3,3</sub>

(a) Initial alignment of A

B <sub>0,0</sub>	B <sub>0,1</sub>	B <sub>0,2</sub>	B <sub>0,3</sub>
B <sub>1,0</sub>	B <sub>1,1</sub>	B <sub>1,2</sub>	B <sub>1,3</sub>
B <sub>2,0</sub>	B <sub>2,1</sub>	B <sub>2,2</sub>	B <sub>2,3</sub>
B <sub>3,0</sub>	B <sub>3,1</sub>	B <sub>3,2</sub>	B <sub>3,3</sub>

(b) Initial alignment of B

A <sub>0,0</sub>	A <sub>0,1</sub>	A <sub>0,2</sub>	A <sub>0,3</sub>
B <sub>0,0</sub>	B <sub>1,1</sub>	B <sub>2,2</sub>	B <sub>3,3</sub>
A <sub>1,1</sub>	A <sub>1,2</sub>	A <sub>1,3</sub>	A <sub>1,0</sub>
B <sub>1,0</sub>	B <sub>2,1</sub>	B <sub>3,2</sub>	B <sub>0,3</sub>
A <sub>2,2</sub>	A <sub>2,3</sub>	A <sub>2,0</sub>	A <sub>2,1</sub>
B <sub>2,0</sub>	B <sub>3,1</sub>	B <sub>0,2</sub>	B <sub>1,3</sub>
A <sub>3,3</sub>	A <sub>3,0</sub>	A <sub>3,1</sub>	A <sub>3,2</sub>
B <sub>3,0</sub>	B <sub>0,1</sub>	B <sub>1,2</sub>	B <sub>2,3</sub>

(c) A and B after initial alignment

A <sub>0,1</sub>	A <sub>0,2</sub>	A <sub>0,3</sub>	A <sub>0,0</sub>
B <sub>1,0</sub>	B <sub>2,1</sub>	B <sub>3,2</sub>	B <sub>0,3</sub>
A <sub>1,2</sub>	A <sub>1,3</sub>	A <sub>1,0</sub>	A <sub>1,1</sub>
B <sub>2,0</sub>	B <sub>3,1</sub>	B <sub>0,2</sub>	B <sub>1,3</sub>
A <sub>2,3</sub>	A <sub>2,0</sub>	A <sub>2,1</sub>	A <sub>2,2</sub>
B <sub>3,0</sub>	B <sub>0,1</sub>	B <sub>1,2</sub>	B <sub>2,3</sub>
A <sub>3,0</sub>	A <sub>3,1</sub>	A <sub>3,2</sub>	A <sub>3,3</sub>
B <sub>0,0</sub>	B <sub>1,1</sub>	B <sub>2,2</sub>	B <sub>3,3</sub>

(d) Submatrix locations after first shift

# Cannon's Algorithm

$P_{ij}$  now holds  $A_{i,j+i}$  and

$B_{i+j,j}$ .

$P_{ij}$  multiplies these two submatrices, and adds the result to  $C_{i,j}$ .

Then in each of the next  $\sqrt{p} - 1$  steps, each block row of  $A$  is rotated to the left by 1 position, and each block column of  $B$  is rotated upward by 1 position. Each  $P_{ij}$  adds the product of its current submatrices to  $C_{i,j}$ .

$A_{0,0}$ $B_{0,0}$	$A_{0,1}$ $B_{1,1}$	$A_{0,2}$ $B_{2,2}$	$A_{0,3}$ $B_{3,3}$
$A_{1,1}$ $B_{1,0}$	$A_{1,2}$ $B_{2,1}$	$A_{1,3}$ $B_{3,2}$	$A_{1,0}$ $B_{0,3}$
$A_{2,2}$ $B_{2,0}$	$A_{2,3}$ $B_{3,1}$	$A_{2,0}$ $B_{0,2}$	$A_{2,1}$ $B_{1,3}$
$A_{3,3}$ $B_{3,0}$	$A_{3,0}$ $B_{0,1}$	$A_{3,1}$ $B_{1,2}$	$A_{3,2}$ $B_{2,3}$

(c) A and B after initial alignment

$A_{0,1}$ $B_{1,0}$	$A_{0,2}$ $B_{2,1}$	$A_{0,3}$ $B_{3,2}$	$A_{0,0}$ $B_{0,3}$
$A_{1,2}$ $B_{2,0}$	$A_{1,3}$ $B_{3,1}$	$A_{1,0}$ $B_{0,2}$	$A_{1,1}$ $B_{1,3}$
$A_{2,3}$ $B_{3,0}$	$A_{2,0}$ $B_{0,1}$	$A_{2,1}$ $B_{1,2}$	$A_{2,2}$ $B_{2,3}$
$A_{3,0}$ $B_{0,0}$	$A_{3,1}$ $B_{1,1}$	$A_{3,2}$ $B_{2,2}$	$A_{3,3}$ $B_{3,3}$

(d) Submatrix locations after first shift

$A_{0,2}$ $B_{2,0}$	$A_{0,3}$ $B_{3,1}$	$A_{0,0}$ $B_{0,2}$	$A_{0,1}$ $B_{1,3}$
$A_{1,3}$ $B_{3,0}$	$A_{1,0}$ $B_{0,1}$	$A_{1,1}$ $B_{1,2}$	$A_{1,2}$ $B_{2,3}$
$A_{2,0}$ $B_{0,0}$	$A_{2,1}$ $B_{1,1}$	$A_{2,2}$ $B_{2,2}$	$A_{2,3}$ $B_{3,3}$
$A_{3,1}$ $B_{1,0}$	$A_{3,2}$ $B_{2,1}$	$A_{3,3}$ $B_{3,2}$	$A_{3,0}$ $B_{0,3}$

(e) Submatrix locations after second shift

$A_{0,3}$ $B_{3,0}$	$A_{0,0}$ $B_{0,1}$	$A_{0,1}$ $B_{1,2}$	$A_{0,2}$ $B_{2,3}$
$A_{1,0}$ $B_{0,0}$	$A_{1,1}$ $B_{1,1}$	$A_{1,2}$ $B_{2,2}$	$A_{1,3}$ $B_{3,3}$
$A_{2,1}$ $B_{1,0}$	$A_{2,2}$ $B_{2,1}$	$A_{2,3}$ $B_{3,2}$	$A_{2,0}$ $B_{0,3}$
$A_{3,2}$ $B_{2,0}$	$A_{3,3}$ $B_{3,1}$	$A_{3,0}$ $B_{0,2}$	$A_{3,1}$ $B_{1,3}$

(f) Submatrix locations after third shift

# Cannon's Algorithm

Initial arrangement makes

$\sqrt{p} - 1$  block rotations of  $A$

and  $B$ , and one block matrix multiplication per processor.

In each of the next  $\sqrt{p} - 1$

steps, each processor

performs one block matrix

multiplication, and sends and

receives one block each.

$$t_{comp} = 2\sqrt{p} \left( \frac{n}{\sqrt{p}} \right)^3 = O\left(\frac{n^3}{p}\right),$$

$$t_{comm} = 4(\sqrt{p} - 1)$$

$$\times \left( t_s + \left( \frac{n}{\sqrt{p}} \right)^2 t_w \right).$$

$A_{0,0}$	$A_{0,1}$	$A_{0,2}$	$A_{0,3}$
$B_{0,0}$	$B_{1,1}$	$B_{2,2}$	$B_{3,3}$
$A_{1,1}$	$A_{1,2}$	$A_{1,3}$	$A_{1,0}$
$B_{1,0}$	$B_{2,1}$	$B_{3,2}$	$B_{0,3}$
$A_{2,2}$	$A_{2,3}$	$A_{2,0}$	$A_{2,1}$
$B_{2,0}$	$B_{3,1}$	$B_{0,2}$	$B_{1,3}$
$A_{3,3}$	$A_{3,0}$	$A_{3,1}$	$A_{3,2}$
$B_{3,0}$	$B_{0,1}$	$B_{1,2}$	$B_{2,3}$

(c) A and B after initial alignment

$A_{0,1}$	$A_{0,2}$	$A_{0,3}$	$A_{0,0}$
$B_{1,0}$	$B_{2,1}$	$B_{3,2}$	$B_{0,3}$
$A_{1,2}$	$A_{1,3}$	$A_{1,0}$	$A_{1,1}$
$B_{2,0}$	$B_{3,1}$	$B_{0,2}$	$B_{1,3}$
$A_{2,3}$	$A_{2,0}$	$A_{2,1}$	$A_{2,2}$
$B_{3,0}$	$B_{0,1}$	$B_{1,2}$	$B_{2,3}$
$A_{3,0}$	$A_{3,1}$	$A_{3,2}$	$A_{3,3}$
$B_{0,0}$	$B_{1,1}$	$B_{2,2}$	$B_{3,3}$

(d) Submatrix locations after first shift

$A_{0,2}$	$A_{0,3}$	$A_{0,0}$	$A_{0,1}$
$B_{2,0}$	$B_{3,1}$	$B_{0,2}$	$B_{1,3}$
$A_{1,3}$	$A_{1,0}$	$A_{1,1}$	$A_{1,2}$
$B_{3,0}$	$B_{0,1}$	$B_{1,2}$	$B_{2,3}$
$A_{2,0}$	$A_{2,1}$	$A_{2,2}$	$A_{2,3}$
$B_{0,0}$	$B_{1,1}$	$B_{2,2}$	$B_{3,3}$
$A_{3,1}$	$A_{3,2}$	$A_{3,3}$	$A_{3,0}$
$B_{1,0}$	$B_{2,1}$	$B_{3,2}$	$B_{0,3}$

(e) Submatrix locations after second shift

$A_{0,3}$	$A_{0,0}$	$A_{0,1}$	$A_{0,2}$
$B_{3,0}$	$B_{0,1}$	$B_{1,2}$	$B_{2,3}$
$A_{1,0}$	$A_{1,1}$	$A_{1,2}$	$A_{1,3}$
$B_{0,0}$	$B_{1,1}$	$B_{2,2}$	$B_{3,3}$
$A_{2,1}$	$A_{2,2}$	$A_{2,3}$	$A_{2,0}$
$B_{1,0}$	$B_{2,1}$	$B_{3,2}$	$B_{0,3}$
$A_{3,2}$	$A_{3,3}$	$A_{3,0}$	$A_{3,1}$
$B_{2,0}$	$B_{3,1}$	$B_{0,2}$	$B_{1,3}$

(f) Submatrix locations after third shift

## Cannon's Algorithm

What if initially, one master processor (say,  $P_{0,0}$ ) holds all data (i.e., matrices  $A$  and  $B$ ), and the same processor wants to collect the entire output matrix (i.e.,  $C$ ) at the end?

Processor  $P_{0,0}$  initially sends  $A_{i,j}$  and  $B_{i,j}$  to processor  $P_{i,j}$ , and at the end processor  $P_{i,j}$  sends back  $C_{i,j}$  to  $P_{0,0}$ .

Since there are  $p$  processors, and each submatrix has size  $\frac{n}{\sqrt{p}} \times \frac{n}{\sqrt{p}}$ , the additional communication complexity:

$$3p \times \left( t_s + \left( \frac{n}{\sqrt{p}} \right)^2 t_w \right) = 3(pt_s + n^2 t_w).$$

So, the communication complexity increases by a factor of  $\sqrt{p}$ .

## Floyd-Warshall's All-Pairs Shortest Paths

Let  $G = (V, E, w)$  be a weighted directed graph with vertex set  $V = \{v_1, v_2, \dots, v_n\}$ , edge set  $E$ , and weight function  $w$ .

The weight of edge  $(v_i, v_j) \in E$  is given by  $w(v_i, v_j)$ .

We construct an  $n \times n$  matrix  $A$  as follows:

$$A(i, j) = a_{ij} = \begin{cases} 0, & \text{if } i = j, \\ \infty, & \text{if } (v_i, v_j) \notin E, \\ w(v_i, v_j), & \text{otherwise.} \end{cases}$$

Floyd-Warshall's algorithm takes matrix  $A$  as input, and returns another  $n \times n$  matrix  $D$  as output with

$D(i, j) = d_{ij}$  = shortest distance from  $v_i$  to  $v_j$  in  $G$ .

# Floyd-Warshall's All-Pairs Shortest Paths

*FW-APSP( A, n )*

1.  $D^{(0)} \leftarrow A$
2. *for*  $k \leftarrow 1$  *to*  $n$  *do*
3.     *for*  $i \leftarrow 1$  *to*  $n$  *do*
4.         *for*  $j \leftarrow 1$  *to*  $n$  *do*
5.              $d_{i,j}^{(k)} \leftarrow \min \{ d_{i,j}^{(k-1)}, d_{i,k}^{(k-1)} + d_{k,j}^{(k-1)} \}$
6. *return*  $D^{(n)}$

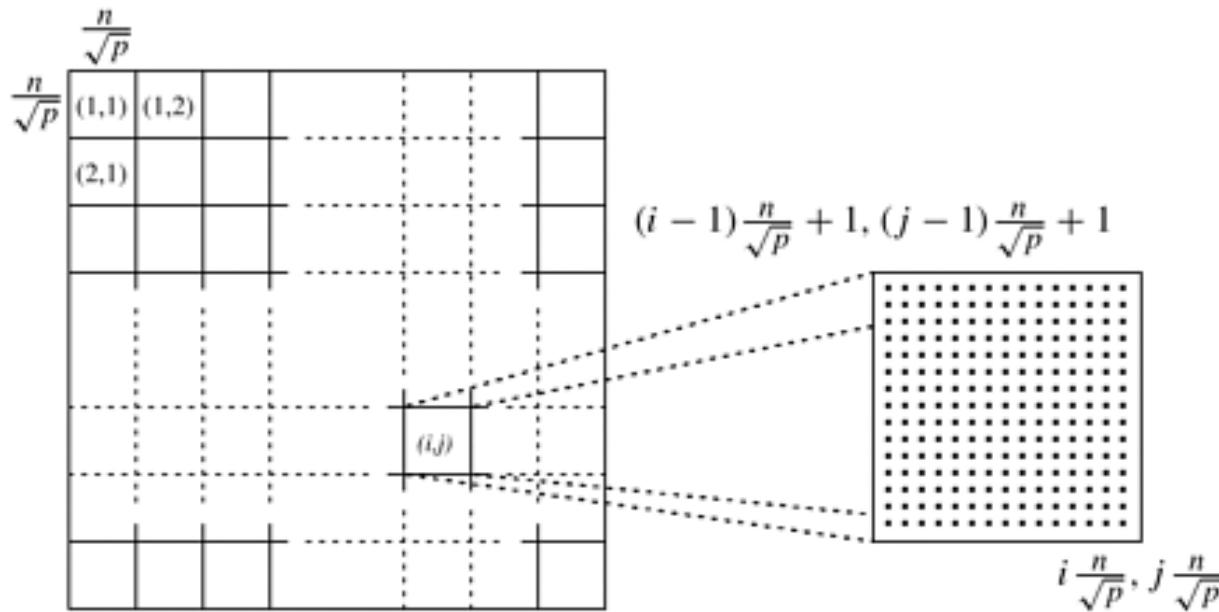
- can be solved using only  $\Theta(n^2)$  extra space, e.g., using only two  $n \times n$  matrices for storing the values of  $D$
- can be solved in-place in  $A$
- serial running time is  $\Theta(n^3)$

# Distributed Memory Implementation

Let  $p$  be the number of processing nodes.

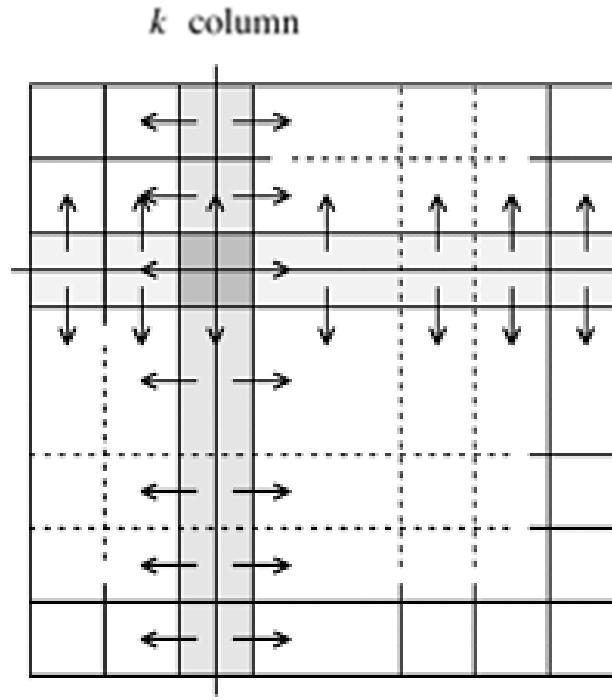
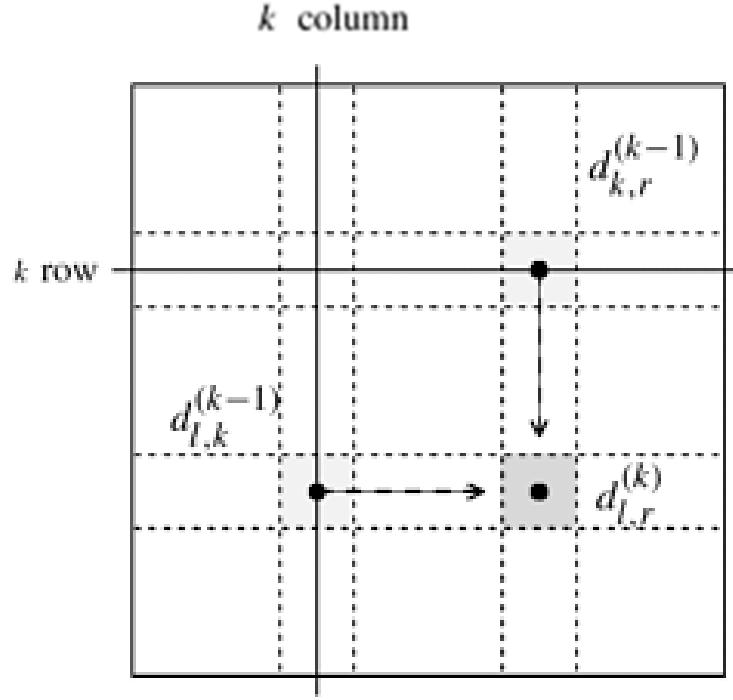
We divide  $D^{(k)}$  into  $\sqrt{p} \times \sqrt{p}$  blocks of size  $\frac{n}{\sqrt{p}} \times \frac{n}{\sqrt{p}}$  each.

We assign block  $(i, j)$  to processor  $P_{i,j}$  for  $1 \leq i, j \leq \sqrt{p}$ .



Source: Grama et al., "Introduction to Parallel Computing", 2<sup>nd</sup> Edition

# Distributed Memory Implementation

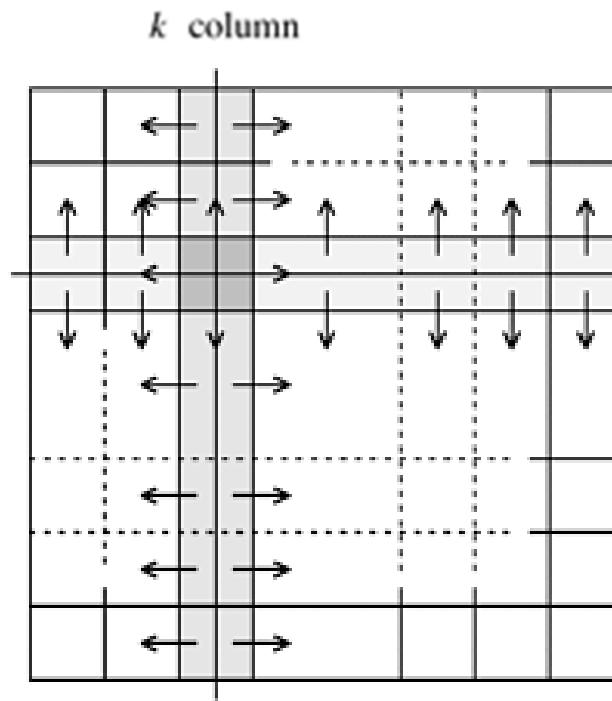
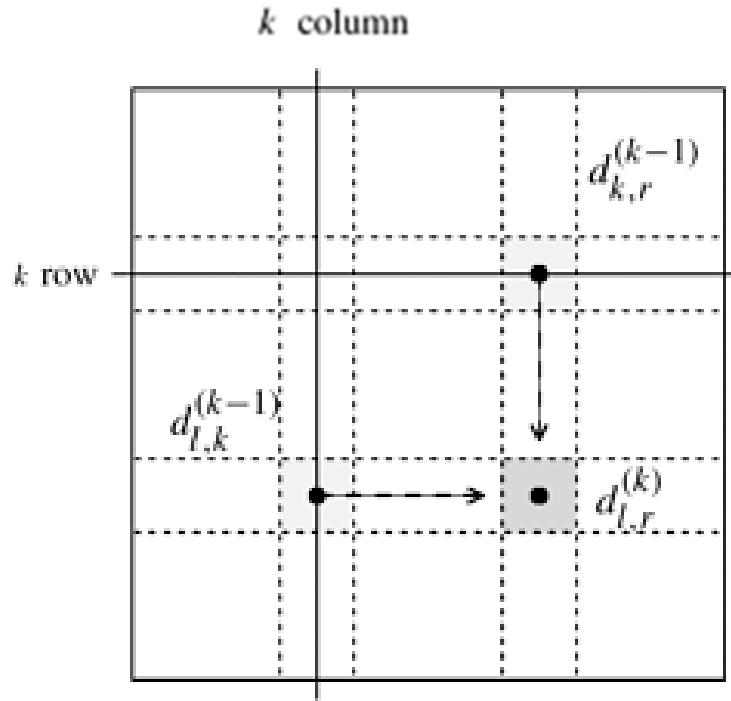


Source: Gramma et al.,  
“Introduction to Parallel Computing”,  
2nd Edition

During the computation of  $D^{(k)}$  each processor  $P_{i,j}$  requires

- a segment ( of length  $\frac{n}{\sqrt{p}}$  ) from row  $k$  of  $D^{(k-1)}$  which belongs to a processor in block column  $j$
- a segment ( of length  $\frac{n}{\sqrt{p}}$  ) from column  $k$  of  $D^{(k-1)}$  which belongs to a processor in block row  $i$

# Distributed Memory Implementation



Source: Gramma et al.,  
“Introduction to Parallel Computing”,  
2nd Edition

After the computation of  $D^{(k-1)}$  if processor  $P_{i,j}$

- contains a segment from row  $k$  of  $D^{(k-1)}$ , it broadcasts that segment to all processors in block column  $j$
- contains a segment from column  $k$  of  $D^{(k-1)}$ , it broadcasts that segment to all processors in block row  $i$

# Distributed Memory Implementation

*FW-APSP-2D-Block(  $D^{(0)}$  )*

1. *for*  $k \leftarrow 1$  *to*  $n$  *do*
2.     *parallel*: each node  $P_{i,j}$  does the following:
  3.         if it contains a segment of row  $k$  of  $D^{(k-1)}$ ,  
broadcasts that segment to nodes  $P_{*,j}$
  4.         if it contains a segment of column  $k$  of  $D^{(k-1)}$ ,  
broadcasts that segment to nodes  $P_{i,*}$
  5.         waits until all nodes receive the needed segments ( global sync )
  6.         computes its part of the  $D^{(k)}$  matrix

In each iteration of the for loop ( assuming  $t_s$  and  $t_w$  to be constants )

- **Line 3:** communication complexity =  $\Theta\left(\frac{n}{\sqrt{p}} \log \sqrt{p}\right)$  ( why? )
- **Line 4:** communication complexity =  $\Theta\left(\frac{n}{\sqrt{p}} \log \sqrt{p}\right)$  ( why? )
- **Line 5:** communication complexity =  $\Theta(\log p)$  ( sync )
- **Line 6:** computation complexity =  $\Theta(n^2/p)$

# Distributed Memory Implementation

*FW-APSP-2D-Block(  $D^{(0)}$  )*

1. *for*  $k \leftarrow 1$  *to*  $n$  *do*
2.     *parallel*: each node  $P_{i,j}$  does the following:
  3.         if it contains a segment of row  $k$  of  $D^{(k-1)}$ ,  
broadcasts that segment to nodes  $P_{*,j}$
  4.         if it contains a segment of column  $k$  of  $D^{(k-1)}$ ,  
broadcasts that segment to nodes  $P_{i,*}$
  5.         waits until all nodes receive the needed segments ( global sync )
  6.         computes its part of the  $D^{(k)}$  matrix

Overall:

$$t_{comm} = \Theta\left(n \times \frac{n}{\sqrt{p}} \log p\right) = \Theta\left(\frac{n^2}{\sqrt{p}} \log p\right)$$

$$\text{and } t_{comp} = \Theta\left(n \times \frac{n^2}{p}\right) = \Theta\left(\frac{n^3}{p}\right)$$

$$\text{Hence, } T_p = t_{comp} + t_{comm} = \Theta\left(\frac{n^3}{p} + \frac{n^2}{\sqrt{p}} \log p\right)$$

# Improved Distributed Memory Implementation

*FW-APSP-2D-Block(  $D^{(0)}$  )*

1. *for*  $k \leftarrow 1$  *to*  $n$  *do*
2.     *parallel*: each node  $P_{i,j}$  does the following:
  3.         if it contains a segment of row  $k$  of  $D^{(k-1)}$ ,  
broadcasts that segment to nodes  $P_{*,j}$
  4.         if it contains a segment of column  $k$  of  $D^{(k-1)}$ ,  
broadcasts that segment to nodes  $P_{i,*}$
  5.         waits until all nodes receive the needed segments ( global sync )
  6.         computes its part of the  $D^{(k)}$  matrix

The global synchronization in line 5 can be removed without affecting the correctness of the algorithm.

The trick is to use *pipelining*.

# Pipelined 2D Block Mapping FW-APSP

*FW-APSP-Pipelined-2D-Block(  $D^{(0)}$  )*

1. *for*  $k \leftarrow 1$  *to*  $n$  *do*
2.     *parallel*: each node  $P_{i,j}$  does the following:
  3.         if it contains a segment of row  $k$  of  $D^{(k-1)}$ , sends that segment to nodes  $P_{i-1,j}$  ( if  $i > 1$  ) and  $P_{i+1,j}$  ( if  $i < \sqrt{p}$  )
  4.         if it contains a segment of column  $k$  of  $D^{(k-1)}$ , sends that segment to nodes  $P_{i,j-1}$  ( if  $j > 1$  ) and  $P_{i,j+1}$  ( if  $j < \sqrt{p}$  )
  5.         waits only until it receives the two segments it needs
  6.         computes its part of the  $D^{(k)}$  matrix, and at any point if it receives data from any direction it stores them locally, and forwards them in the opposite direction

After the computation of row 1 & col 1, all relevant segments of  $D^{(1)}$  reach  $P_{\sqrt{p},\sqrt{p}}$  after  $\Theta((n/\sqrt{p}) \times \sqrt{p}) = \Theta(n)$  time units. (how?)  
Successive rows & cols follow after time  $\Theta(n^2/p)$  in pipelined mode.  
Hence,  $P_{\sqrt{p},\sqrt{p}}$  completes computation in time  $\Theta(n^3/p) + \Theta(n)$ .

# Pipelined 2D Block Mapping FW-APSP

*FW-APSP-Pipelined-2D-Block(  $D^{(0)}$  )*

1. *for*  $k \leftarrow 1$  *to*  $n$  *do*
2.     *parallel*: each node  $P_{i,j}$  does the following:
  3.         if it contains a segment of row  $k$  of  $D^{(k-1)}$ , sends that segment to nodes  $P_{i-1,j}$  ( if  $i > 1$  ) and  $P_{i+1,j}$  ( if  $i < \sqrt{p}$  )
  4.         if it contains a segment of column  $k$  of  $D^{(k-1)}$ , sends that segment to nodes  $P_{i,j-1}$  ( if  $j > 1$  ) and  $P_{i,j+1}$  ( if  $j < \sqrt{p}$  )
  5.         waits only until it receives the two segments it needs
  6.         computes its part of the  $D^{(k)}$  matrix, and at any point if it receives data from any direction it stores them locally, and forwards them in the opposite direction

When  $P_{\sqrt{p},\sqrt{p}}$  completes iteration  $n - 1$ , it sends the relevant values of row  $n$  and column  $n$  to other nodes.

These values reach  $P_{1,1}$  in time  $\Theta(n)$ .

$$\text{Hence, } T_p = t_{comp} + t_{comm} = \Theta\left(\frac{n^3}{p}\right) + \Theta(n) = \Theta\left(\frac{n^3}{p} + n\right)$$

# Parallel QuickSort: A Shared-Memory Version

**Input:** An array  $A[ q : r ]$  of distinct elements.

**Output:** Elements of  $A[ q : r ]$  sorted in increasing order of value.

*Par-Randomized-Looping-QuickSort (  $A[ q : r ]$  )*

1.  $m \leftarrow r - q + 1$
2. *if*  $m > 1$  *then*
3.      $k \leftarrow 0$
4.     *while*  $\max\{ r - k, k - q \} > 3m / 4$  *do*
5.         select a random element  $x$  from  $A[ q : r ]$
6.          $k \leftarrow \text{Par-Partition} ( A[ q : r ], x )$
7.         *spawn* *Par-Randomized-Looping-QuickSort (  $A[ q : k - 1 ]$  )*
8.         *Par-Randomized-Looping-QuickSort (  $A[ k + 1 : r ]$  )*
9.         *sync*

# Parallel QuickSort: Distributed-Memory Version

**Input:** An array  $A[ q : r ]$  of distinct elements distributed among processing nodes  $P_s, P_{s+1}, \dots, P_t$  such that each node contains between  $\alpha/2$  and  $2\alpha$  elements, where  $\alpha = n / p = \text{orig } \# \text{elems} / \text{orig } \# \text{nodes}$ .

**Output:** Elements of  $A[ q : r ]$  sorted in increasing order of value distributed among the nodes in the following order:  $P_s, P_{s+1}, \dots, P_t$ .

*Distributed-Randomized-Looping-QuickSort (  $A[ q : r ]$ ,  $\alpha, s, t$  )*

1. *if*  $s = t$  *then* sort  $A[ q : r ]$  locally on  $P_s$  using serial quicksort
2. *else*
3.    $m \leftarrow r - q + 1, k \leftarrow 0$
4.   *while*  $\max\{ r - k, k - q \} > 3m / 4$  *do*
5.     select a random element  $x$  from  $A[ q : r ]$
6.      $k \leftarrow \text{Distributed-Rank} ( A[ q : r ], x, s, t )$
7.     Find an  $i$ , and redistribute  $A[ q : r ]$  among the nodes as evenly as possible such that
  - ( a ) all elements  $\leq x$  are stored among nodes  $P_s$  to  $P_i$ ,
  - ( b ) all elements  $> x$  are stored among nodes  $P_{i+1}$  to  $P_t$ , and
  - ( c ) no node stores fewer  $\alpha/2$  or more than  $2\alpha$  elements
7.     *parallel:* *Distributed-Randomized-Looping-QuickSort (  $A[ q : k ]$ ,  $\alpha, s, i$  )*

*Distributed-Randomized-Looping-QuickSort (  $A[ k + 1 : r ]$ ,  $\alpha, i + 1, t$  )*

# Distributed QuickSort: Example

First Step	$P_0$	$P_1$	$P_2$	$P_3$	$P_4$	
	7 13 18 2 17 1 14 20 6 10 15 9 3 16 19 4 11 12 5 8					pivot selection
	pivot=7					

	$P_0$	$P_1$	$P_2$	$P_3$	$P_4$	
	7 2 18 13 1 17 14 20 6 10 15 9 3 4 19 16 5 12 11 8					after local rearrangement
	7 2 1 6 3 4 5 18 13 17 14 20 10 15 9 19 16 12 11 8					after global rearrangement

Second Step	$P_0$	$P_1$	$P_2$	$P_3$	$P_4$	
	7 2 1 6 3 4 5 18 13 17 14 20 10 15 9 19 16 12 11 8					pivot selection
	pivot=5			pivot=17		

	$P_0$	$P_1$	$P_2$	$P_3$	$P_4$	
	1 2 7 6 3 4 5 14 13 17 18 20 10 15 9 19 16 12 11 8					after local rearrangement
	1 2 3 4 5 7 6 14 13 17 10 15 9 16 12 11 8 18 20 19					after global rearrangement

Image Source: Grama et al., "Introduction to Parallel Computing", 2<sup>nd</sup> Edition

# Distributed QuickSort: Example

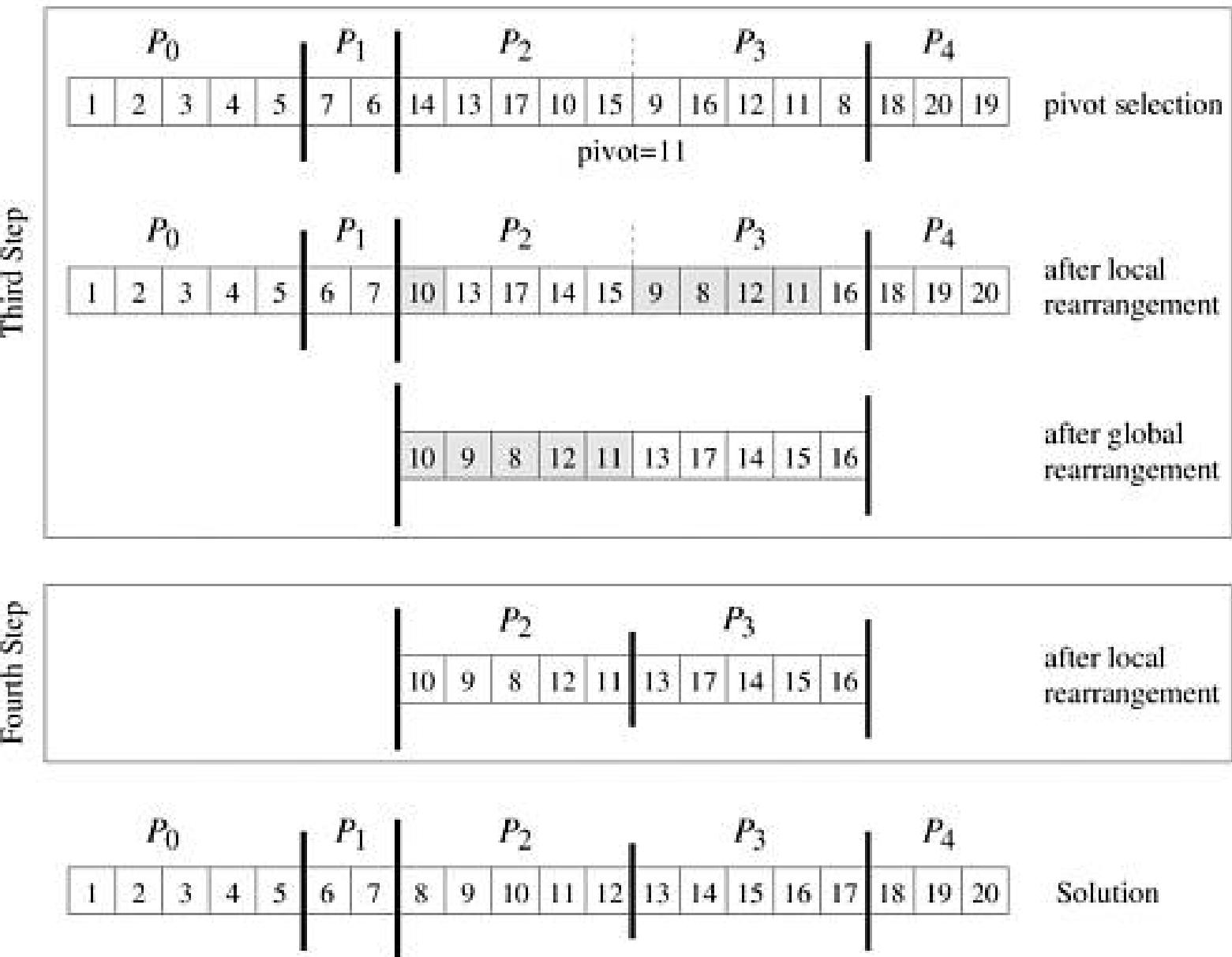


Image Source: Grama et al., "Introduction to Parallel Computing", 2<sup>nd</sup> Edition

# Distributed QuickSort: Distributed Rank & Partition

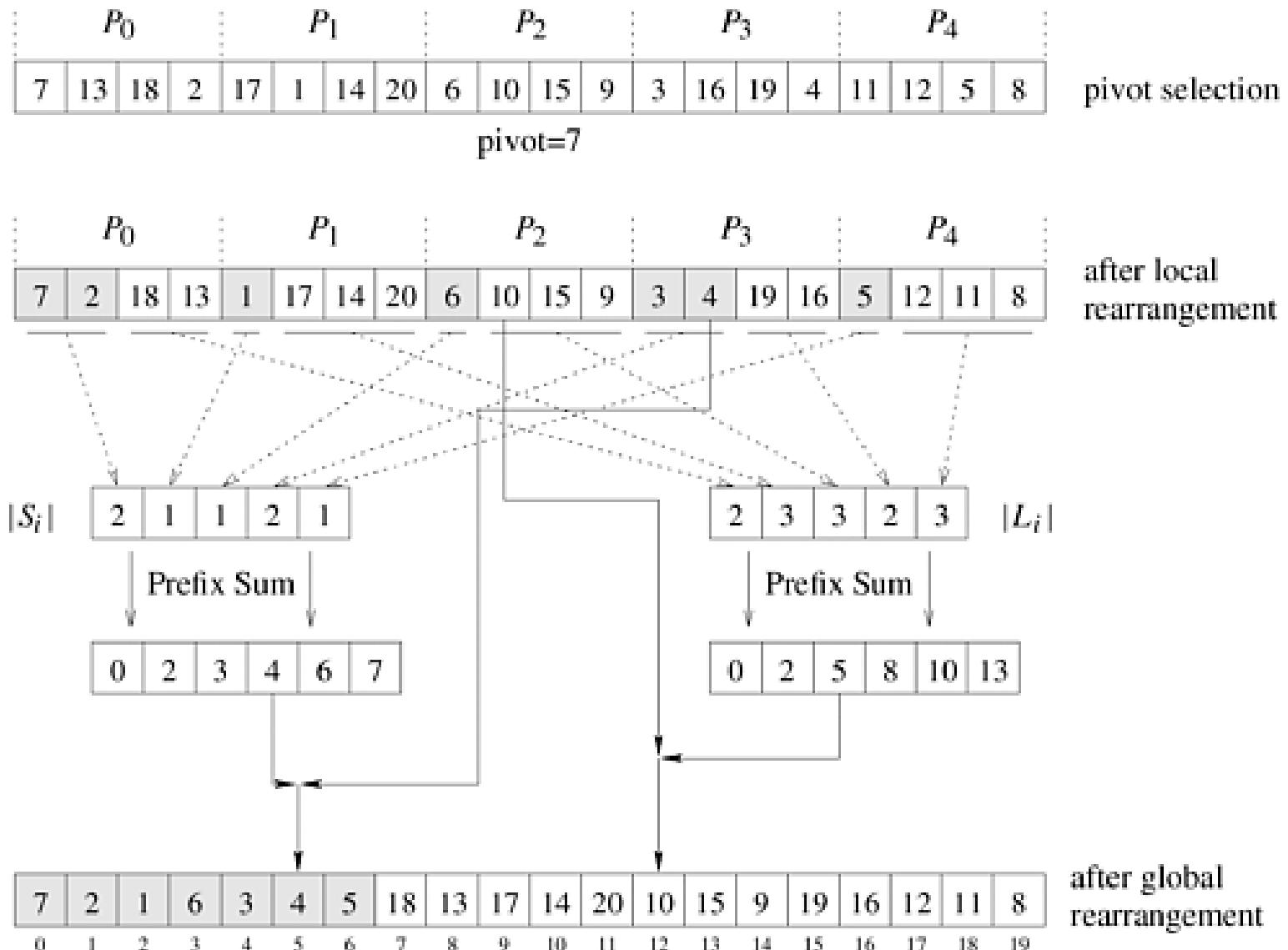


Image Source: Grama et al., "Introduction to Parallel Computing", 2<sup>nd</sup> Edition

# Distributed QuickSort

*Distributed-Randomized-Looping-QuickSort (  $A[ q : r ]$ ,  $\alpha$ ,  $s$ ,  $t$  )*

1. *if*  $s = t$  *then* sort  $A[ q : r ]$  locally on  $P_s$  using serial quicksort
2. *else*
3.    $m \leftarrow r - q + 1$ ,  $k \leftarrow 0$
4.   *while*  $\max\{ r - k, k - q \} > 3m / 4$  *do*
5.     select a random element  $x$  from  $A[ q : r ]$
6.      $k \leftarrow \text{Distributed-Rank} ( A[ q : r ], x, s, t )$
7.     Find an  $i$ , and redistribute  $A[ q : r ]$  among the nodes as evenly as possible such that
  - ( a ) all elements  $\leq x$  are stored among nodes  $P_s$  to  $P_i$ ,
  - ( b ) all elements  $> x$  are stored among nodes  $P_{i+1}$  to  $P_t$ , and
  - ( c ) no node stores fewer than  $\alpha/2$  or more than  $2\alpha$  elements
8.     *parallel:* *Distributed-Randomized-Looping-QuickSort (  $A[ q : k ]$ ,  $\alpha$ ,  $s$ ,  $i$  )*  
*Distributed-Randomized-Looping-QuickSort (  $A[ k + 1 : r ]$ ,  $\alpha$ ,  $i + 1$ ,  $t$  )*

**Lines 5-6 ( assuming  $t_s$  and  $t_w$  to be constants )**

- communication complexity =  $O(p + \log p)$  ( why? )
- computation complexity =  $O\left(\frac{n}{p}\right)$  ( why? )
- overall =  $O\left(\frac{n}{n} + p + \log p\right)$

# Distributed QuickSort

*Distributed-Randomized-Looping-QuickSort (  $A[ q : r ]$ ,  $\alpha$ ,  $s$ ,  $t$  )*

1. *if*  $s = t$  *then* sort  $A[ q : r ]$  locally on  $P_s$  using serial quicksort
2. *else*
3.    $m \leftarrow r - q + 1$ ,  $k \leftarrow 0$
4.   *while*  $\max\{ r - k, k - q \} > 3m / 4$  *do*
5.     select a random element  $x$  from  $A[ q : r ]$
6.      $k \leftarrow \text{Distributed-Rank} ( A[ q : r ], x, s, t )$
7.     Find an  $i$ , and redistribute  $A[ q : r ]$  among the nodes as evenly as possible such that
  - ( a ) all elements  $\leq x$  are stored among nodes  $P_s$  to  $P_i$ ,
  - ( b ) all elements  $> x$  are stored among nodes  $P_{i+1}$  to  $P_t$ , and
  - ( c ) no node stores fewer than  $\alpha/2$  or more than  $2\alpha$  elements
8.     *parallel:* *Distributed-Randomized-Looping-QuickSort (  $A[ q : k ]$ ,  $\alpha$ ,  $s$ ,  $i$  )*  
*Distributed-Randomized-Looping-QuickSort (  $A[ k + 1 : r ]$ ,  $\alpha$ ,  $i + 1$ ,  $t$  )*

**Line 7** ( assuming  $t_s$  and  $t_w$  to be constants )

- communication complexity =  $O\left(p + \log p + \frac{n}{p}\right)$  ( why? )
- computation complexity =  $O(1)$  ( why? )
- overall =  $O\left(\frac{n}{n} + p + \log p\right)$

# Distributed QuickSort

*Distributed-Randomized-Looping-QuickSort (  $A[ q : r ]$ ,  $\alpha$ ,  $s$ ,  $t$  )*

1. *if*  $s = t$  *then* sort  $A[ q : r ]$  locally on  $P_s$  using serial quicksort
2. *else*
3.    $m \leftarrow r - q + 1$ ,  $k \leftarrow 0$
4.   *while*  $\max\{ r - k, k - q \} > 3m / 4$  *do*
5.     select a random element  $x$  from  $A[ q : r ]$
6.      $k \leftarrow \text{Distributed-Rank} ( A[ q : r ], x, s, t )$
7.     Find an  $i$ , and redistribute  $A[ q : r ]$  among the nodes as evenly as possible such that
  - ( a ) all elements  $\leq x$  are stored among nodes  $P_s$  to  $P_i$ ,
  - ( b ) all elements  $> x$  are stored among nodes  $P_{i+1}$  to  $P_t$ , and
  - ( c ) no node stores fewer  $\alpha/2$  or more than  $2\alpha$  elements
8.     *parallel:* *Distributed-Randomized-Looping-QuickSort (  $A[ q : k ]$ ,  $\alpha$ ,  $s$ ,  $i$  )*  
*Distributed-Randomized-Looping-QuickSort (  $A[ k + 1 : r ]$ ,  $\alpha$ ,  $i + 1$ ,  $t$  )*

Depth of the shared-memory version is  $O(\log n)$  w.h.p.

Same bound applies to the distributed-memory version.

$$\text{Hence, } T_p = O\left(\left(\frac{n}{p} + p + \log p\right) \log n\right) = O\left(\frac{n \log n}{p} + p \log n\right) \text{ (w.h.p.)}$$

# Distributed Sample Sort

**Task:** Sort  $n$  distinct keys using  $p$  processing nodes.

**Steps:**

1. **Initial Distribution:** The master node scatters the  $n$  keys among  $p$  processing nodes as evenly as possible.
2. **Pivot Selection:** Each node sorts its local keys, and selects  $q - 1$  evenly spaced keys from its sorted sequence. The master node gathers these *local pivots* from all nodes, locally sorts those  $p(q - 1)$  keys, selects  $p - 1$  evenly spaced global pivots from them, and broadcasts them to all nodes.
3. **Local Bucketing:** Each node inserts the global pivots into its local sorted sequence using binary search, and thus divides the keys among  $p$  buckets.
4. **Distribute Local Buckets:** For  $1 \leq i \leq p$ , each node sends bucket  $i$  to node  $i$ .
5. **Local Sort:** Each node locally sorts the elements it received in step 4.
6. **Final Collection:** The master node collects all sorted keys from all nodes, and for  $1 \leq i < p$ , places all keys from node  $i$  ahead of all keys from node  $i + 1$ .

## Bound on Bucket Sizes

**Theorem:** If each node selects  $q - 1$  evenly spaced keys in step 2, then no node will sort more than  $\frac{n}{p} + \frac{n}{q}$  keys (in the worst case) in step 5.

**Proof:** Homework.

# Analyzing Distributed Sample Sort

**Steps:** ( assuming  $q = \Theta(p)$ , and  $t_s$  and  $t_w$  constants )

1. **Initial Distribution:**  $O\left(\log p + \frac{n}{p}(p - 1)\right) = O(n + \log p)$  [ **comm:** scatter ]
2. **Pivot Selection:**  $O\left(\frac{n}{p} \log \frac{n}{p} + pq \log(pq)\right) = O\left(\frac{n}{p} \log \frac{n}{p} + p^2 \log p\right)$  [ **comp:** sort ]  
 $O(\log p + (q - 1)(p - 1) + (p - 1) \log p) = O(p^2)$  [ **comm:** gather, broadcast ]
3. **Local Bucketing:**  $O\left((p - 1) \log \frac{n}{p}\right) = O(p \log n)$  [ **comp:** binary search ]
4. **Distribute Local Buckets:**  $O\left(\frac{n}{p} + \left(\frac{n}{p} + \frac{n}{q}\right)\right) = O\left(\frac{n}{p}\right)$  [ **comm:** send, receive ]
5. **Local Sort:**  $O\left(\left(\frac{n}{p} + \frac{n}{q}\right) \log \left(\frac{n}{p} + \frac{n}{q}\right)\right) = O\left(\frac{n}{p} \log \frac{n}{p}\right)$  [ **comp:** sort ]
6. **Final Collection:**  $O\left((p - 1) \left(\frac{n}{p} + \frac{n}{q}\right)\right) = O(n)$  [ **comm:** receive ]

# Analyzing Distributed Sample Sort

**Overall:**

$$t_{comp} = O\left(\frac{n}{p} \log \frac{n}{p} + p^2 \log p + p \log n\right)$$

$$t_{comm} = O(n + p^2)$$

$$T_p = t_{comp} + t_{comm} = O\left(n + \frac{n}{p} \log \frac{n}{p} + p^2 \log p + p \log n\right)$$

**Overall ( excluding steps 1 and 6 ):**

$$t_{comp} = O\left(\frac{n}{p} \log \frac{n}{p} + p^2 \log p + p \log n\right)$$

$$t_{comm} = O\left(\frac{n}{p} + p^2\right)$$

$$T_p = t_{comp} + t_{comm} = O\left(\frac{n}{p} \log \frac{n}{p} + p^2 \log p + p \log n\right)$$