

# Introduction to Parallel Program Analysis

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# Outline

Parallel matrix-vector product

1D distribution

Analysis

2D distribution

# Parallel matrix-vector product

- ▶ Consider parallel matrix-vector multiplication
- ▶ Let  $A \in \mathbb{R}^{n \times n}$  and  $x \in \mathbb{R}^n$
- ▶ We wish to compute  $y = Ax$  in parallel and analyze scalability
- ▶ We consider 1D and 2D distribution schemes

# 1D distribution

- ▶ Assume that process  $i$  stores  $n_i$  rows of  $A$  and  $n_i$  rows of  $x$
- ▶ Then  $i$  computes  $y_i = A_i x_i$

$$\begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_{p-1} \end{bmatrix} = \begin{bmatrix} A_0 \\ A_1 \\ \vdots \\ A_{p-1} \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{p-1} \end{bmatrix}$$

$$A_i \in \mathbb{R}^{n_i \times n}, x, y \in \mathbb{R}^n$$

- ▶ Algorithm
  1. Process  $i$  gathers  $x$
  2. Process  $i$  computes  $y_i = A_i x_i$

## Analysis

- ▶ Step 1 can be done using all-to-all broadcast
  - ▶ Assume that all-to-all broadcast of  $m$  words takes time

$$t_s \log_2 p + t_w m(p - 1) \tag{1}$$

$t_s$  is start-up time,  $t_w$  is pre-word transfer time

- ▶ Assume  $n_i = n/p$ . Then  $m = n/p$ , and (1) becomes

$$\begin{aligned} t_s \log_2 p + t_w m(p - 1) &= t_s \log_2 p + t_w \frac{n}{p}(p - 1) \\ &\approx t_s \log_2 p + t_w n \end{aligned} \tag{2}$$

- ▶ Step 2 can be done in  $\approx (n/p)n$  operations:

$$\frac{n^2}{p} \tag{3}$$

For simplicity, we omit constants. For example, this computation is more like  $2n^2/p\gamma$ , where  $\gamma$  is the time per arithmetic operation

From (2, 3), the parallel time is

$$T_p = \frac{n^2}{p} + t_s \log_2 p + t_w n$$

Since the serial time is  $T_s = n^2$ , the speed up is

$$S = \frac{T_s}{T_p} = \frac{n^2}{\frac{n^2}{p} + t_s \log_2 p + t_w n} = \frac{1}{\frac{1}{p} + t_s \frac{\log_2 p}{n^2} + t_w \frac{1}{n}}$$

The efficiency is

$$E_{1D} := \frac{S}{p} = \frac{1}{1 + t_s \frac{p \log_2 p}{n^2} + t_w \frac{p}{n}} \quad (4)$$

## Scalability

- ▶ For fixed  $n$ ,  $E_{1D}$  decreases as  $p$  increases  
Not strongly scalable
- ▶ Denote the work for problem of size  $n$  by  $W(n) = n^2$   
Assume we double  $n$ . Then

$$W(2n) = 4n^2 = 4W(n)$$

- ▶ Since the work quadruples, we increase the number of processes to  $4p$   
Then

$$\begin{aligned} E'_{1D} &= \frac{1}{1 + t_s \frac{4p \log_2(4p)}{(2n)^2} + t_w \frac{4p}{2n}} = \frac{1}{1 + t_s \frac{p(2 + \log_2 p)}{n^2} + t_w \frac{2p}{n}} \\ &= \frac{1}{\underbrace{\left(1 + t_s \frac{p \log_2 p}{n^2} + t_w \frac{p}{n}\right)}_{\text{same as in } E_{1D}} + \left(t_s \frac{2p}{n^2} + t_w \frac{p}{n}\right)} \end{aligned}$$

► Obviously  $E'_{1D} < E_{1D}$  due to

$$t_s \frac{2p}{n^2} + t_w \frac{p}{n}$$



- ▶ Let  $M$  be the number of words that can be stored per node
- ▶ On  $p$  nodes, we can store  $pM$  words
- ▶ Let  $N$  be the size of the largest problem we can store on  $p$  nodes
- ▶ Assume we store  $N^2$  items, that is  $A$ . Then  $N^2 = pM$  and  $N = \sqrt{pM}$   
We ignore the storage for the  $x_i$
- ▶ Using  $n = N$  in (4), we obtain

$$E''_{1D} = \frac{1}{1 + t_s \frac{\log_2 p}{M} + t_w \frac{\sqrt{p}}{\sqrt{M}}} \quad (5)$$

- ▶  $\lim_{p \rightarrow \infty} E''_{1D} = 0$
- ▶ This algorithm does not scale well

## 2D distribution

- ▶ Consider a 2D grid of processes
- ▶ For simplicity, assume  $q \times q = p$  processes
- ▶ Process  $(i, j)$  stores submatrix  $A_{ij} \in \mathbb{R}^{n_i \times m_i}$
- ▶ Process  $(j, j)$  stores subvector  $x_j \in \mathbb{R}^{n_j}$
- ▶ This distribution can be visualized as

$$\begin{array}{cccc}
 A_{0,0}, x_0 & A_{0,1} & \dots & A_{0,q-1} \\
 A_{1,0} & A_{1,1}, x_1 & \dots & A_{1,q-1} \\
 \vdots & \vdots & \dots & \vdots \\
 A_{q-1,0} & A_{q-1,1} & \dots & A_{q-1,q-1}, x_{q-1}
 \end{array}$$

# Algorithm

1. Process  $(j, j)$  broadcasts  $x_j$  along column  $j$

$$\begin{array}{cccc}
 A_{0,0}, x_0 & A_{0,1}, x_1 & \cdots & A_{0,q-1}, x_{q-1} \\
 A_{1,0}, x_0 & A_{1,1}, x_1 & \cdots & A_{1,q-1}, x_{q-1} \\
 \vdots & \vdots & & \\
 A_{q-1,0}, x_0 & A_{q-1,1}, x_1 & \cdots & A_{q-1,q-1}, x_{q-1}
 \end{array}$$

2. Process  $(i, j)$  computes  $A_{ij}x_j$
3. Process  $(i, i)$  does "sum" reduction across row  $i$ . Then  $(i, i)$  contains  $y_i$ :

$$y_i = A_{i,0}x_0 + A_{i,1}x_1 + \cdots + A_{i,q-1}x_{q-1}$$

# Analysis

Assume  $n_i, m_i = n/q$

- ▶ Assume one-to-all broadcast of  $m$  words takes

$$(t_s + t_w m) \log_2 p \quad (6)$$

Here  $m = n/q = n/\sqrt{p}$  and we broadcast along  $q = \sqrt{p}$  nodes  
Then (6) becomes

$$\begin{aligned} (t_s + t_w m) \log_2 p &= \left( t_s + t_w \frac{n}{q} \right) \log_2 q \\ &= \left( t_s + t_w \frac{n}{\sqrt{p}} \right) \log_2 \sqrt{p} \\ &= \frac{1}{2} \left( t_s + t_w \frac{n}{\sqrt{p}} \right) \log_2 p \end{aligned} \quad (7)$$

- ▶  $A_{ij}x_j$  takes

$$\left(\frac{n}{q}\right)^2 = \frac{n^2}{p} \tag{8}$$

- ▶ All-to-one reduction is like one-to-all broadcast:

$$\frac{1}{2} \left( t_s + t_w \frac{n}{\sqrt{p}} \right) \log_2 p \tag{9}$$

We ignore the time for summations

The parallel time is (7) + (8) + (9):

$$T_p = \frac{n^2}{p} + \left( t_s + t_w \frac{n}{\sqrt{p}} \right) \log_2 p$$

Speedup is

$$S = \frac{T_s}{T_p} = \frac{n^2}{\frac{n^2}{p} + \left(t_s + t_w \frac{n}{\sqrt{p}}\right) \log_2 p} = \frac{1}{\frac{1}{p} + \left(t_s + t_w \frac{n}{\sqrt{p}}\right) \frac{\log_2 p}{n^2}}$$

Efficiency is

$$E_{2D} = \frac{1}{1 + t_s \frac{p \log_2 p}{n^2} + t_w \frac{\sqrt{p} \log_2 p}{n}} \quad (10)$$

What happens if we increase  $n$  to  $2n$  and  $p$  to  $4p$  compared to increasing in

$$E_{1D} = \frac{1}{1 + t_s \frac{p \log_2 p}{n^2} + t_w \frac{p}{n}} ?$$

- ▶ As before, assume  $n = \sqrt{pM}$   
Then

$$\begin{aligned} E''_{2D} &= \frac{1}{1 + t_s \frac{p \log_2 p}{pM} + t_w \frac{\sqrt{p} \log_2 p}{\sqrt{pM}}} \\ &= \frac{1}{1 + t_s \frac{\log_2 p}{M} + t_w \frac{\log_2 p}{\sqrt{M}}} \end{aligned}$$

- ▶  $\log_2$  is a very slowly growing function, and can be considered as a constant here
- ▶ As  $p$  increases, the efficiency decreases very slowly and much slower than  $E'_{1D}$  in (5)
- ▶ For practical purposes, this algorithm scales well