Lecture 3: Collective communication

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CME 194 Stanford University

April 8, 2013

Outline

Cost model

Broadcast

Reduce

Distributed vector norms

Homework 1

Recall $\alpha + \beta n$ model:

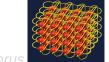
- Can only send one message at a time
- ► Cost depends on *latency*, α , message length, n, and bandwidth, $1/\beta$



Will assume network is fully-connected,



but, in practice, topology is usually fat-tree



or multi-dimensional torus

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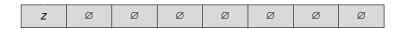


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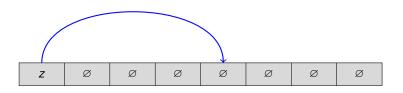
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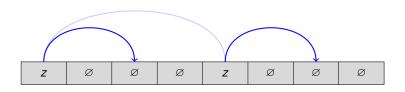
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Total cost is $(\alpha + \beta n) \log_2 p$



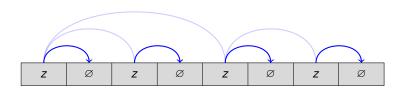
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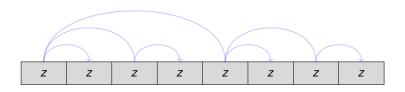
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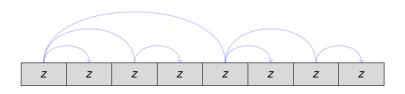
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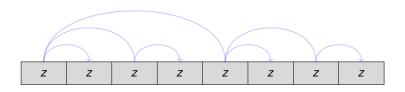
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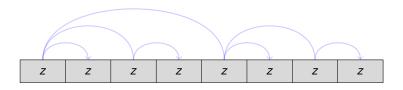
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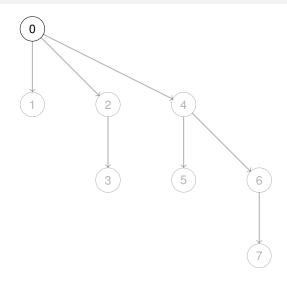
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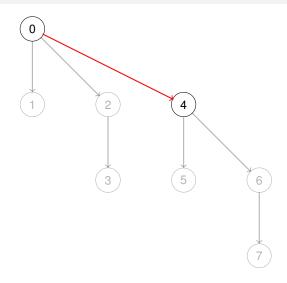
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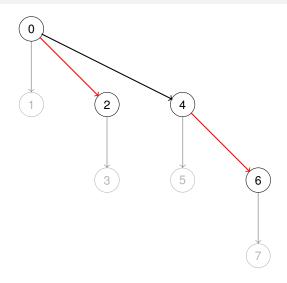


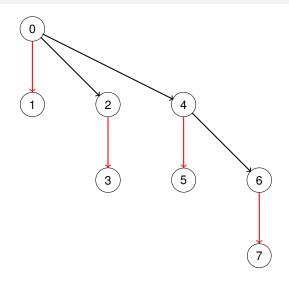
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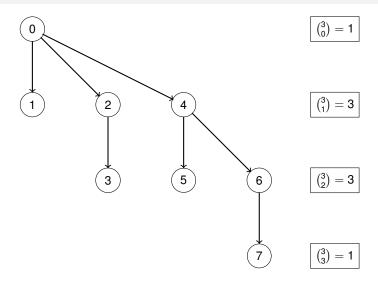
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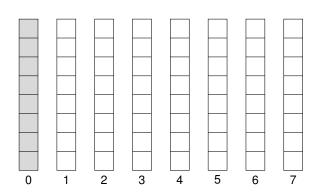




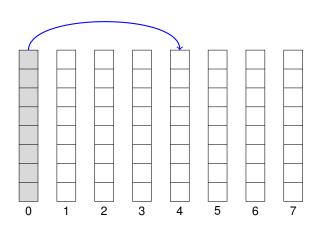


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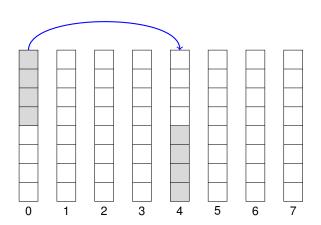
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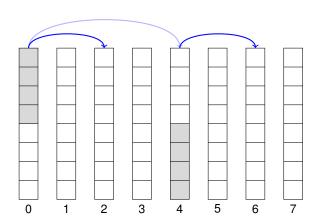
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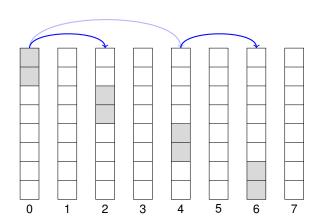
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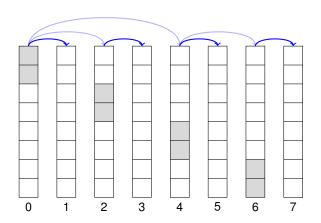
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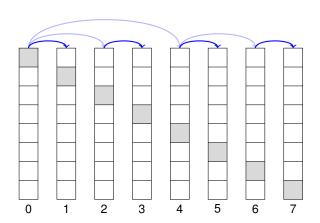
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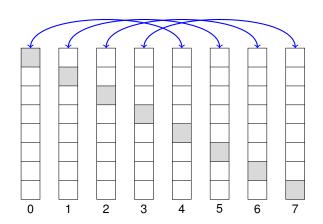
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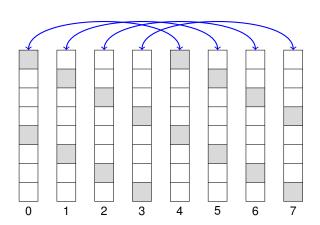
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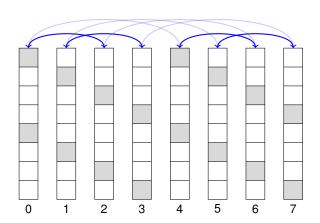
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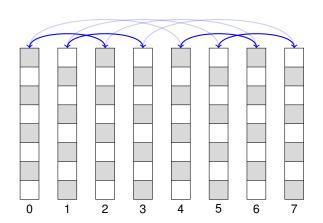
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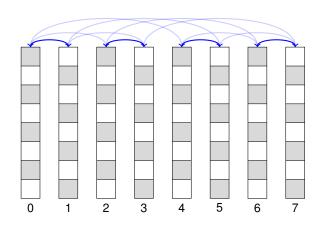
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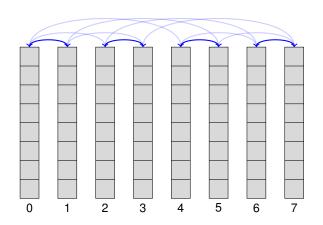
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type, int root, MPI_Comm comm )
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Broadcasts n items of type type from process with rank root with respect to communicator comm.

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$$x = \sum_{i=0}^{p-1} \hat{x}_i$$

Can run Broadcast algorithms in reverse (with summation).

Therefore, same communication costs

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Reduces each process in communicator comm's *n* items from sendBuf into process root's recvBuf using binary operation implied by op, e.g., MPI_SUM or MPI_MAX.

Related routines are MPI_Allreduce (give every process the result) and MPI_Reduce_scatter (give every process a subset of the result)

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$$\alpha := \mathbf{y}^H \mathbf{x}$$

- ► Each process gets subset of *x* and *y*, e.g., *x_i* and *y_i*
- ► Then $\alpha = \sum_{i=0}^{p-1} y_i^H x_i = \sum_{i=0}^{p-1} \hat{\alpha}_i$
- ▶ Have each process form $\hat{\alpha}_i := y_i^H x_i$ then Reduce
- Work is $2\frac{n}{p} + (\alpha + \beta) \log_2 p$ with binomial Reduce

Setting y = x yields parallel $||x||_2$.

Setting y = ones(n, 1) yields parallel $||x||_1$

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- Generate random distributed vector x and compute its two-norm
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