Distributed Parallel Inference on Large Factor Graphs

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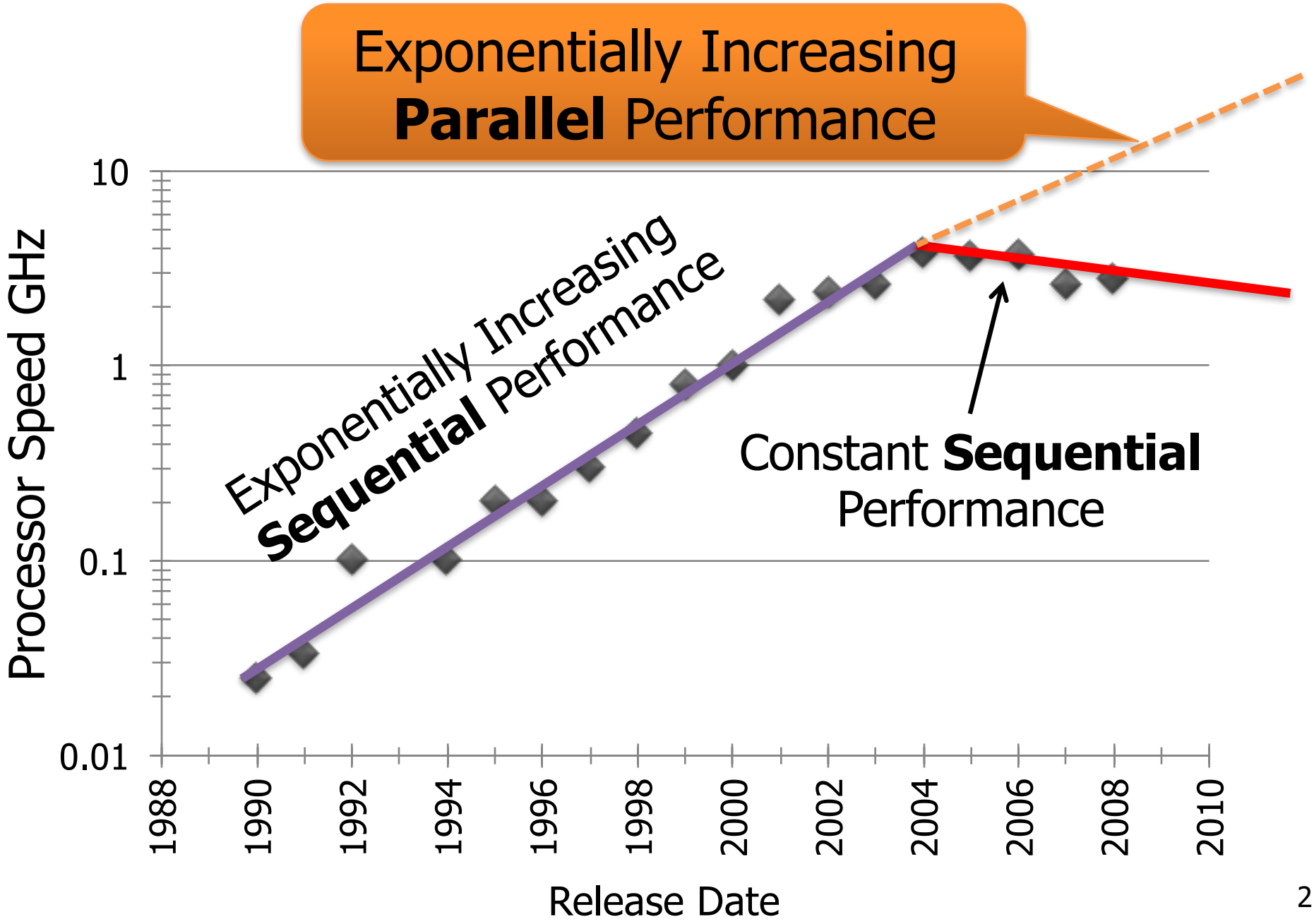
Exponential Parallelism



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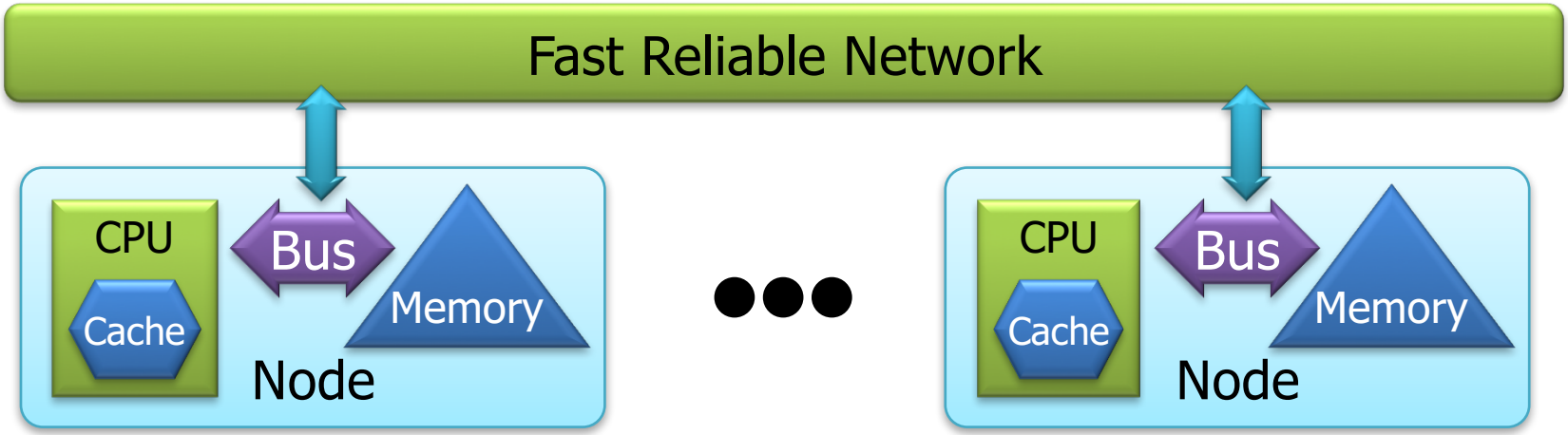
Distributed Parallel Setting

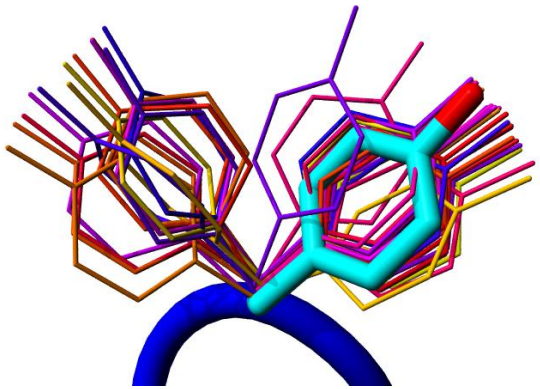


- Opportunities:
  - Access to larger systems: 8 CPUs → 1000 CPUs
  - Linear Increase:
    - RAM, **Cache Capacity,** and **Memory Bandwidth**
- Challenges:
  - Distributed state, Communication and Load Balancing

Graphical Models and Parallelism

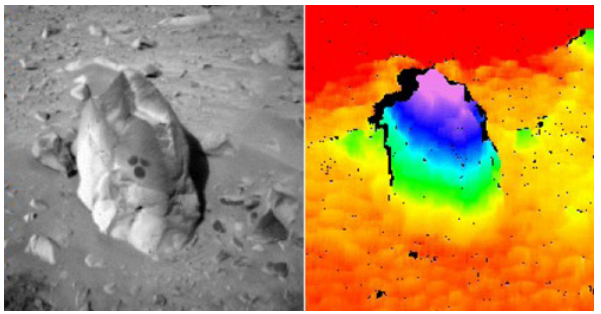
*Graphical models provide a common language for **general purpose** parallel algorithms in machine learning*

- A parallel **inference algorithm** would improve:



Protein Structure Prediction

Movie Recommendation

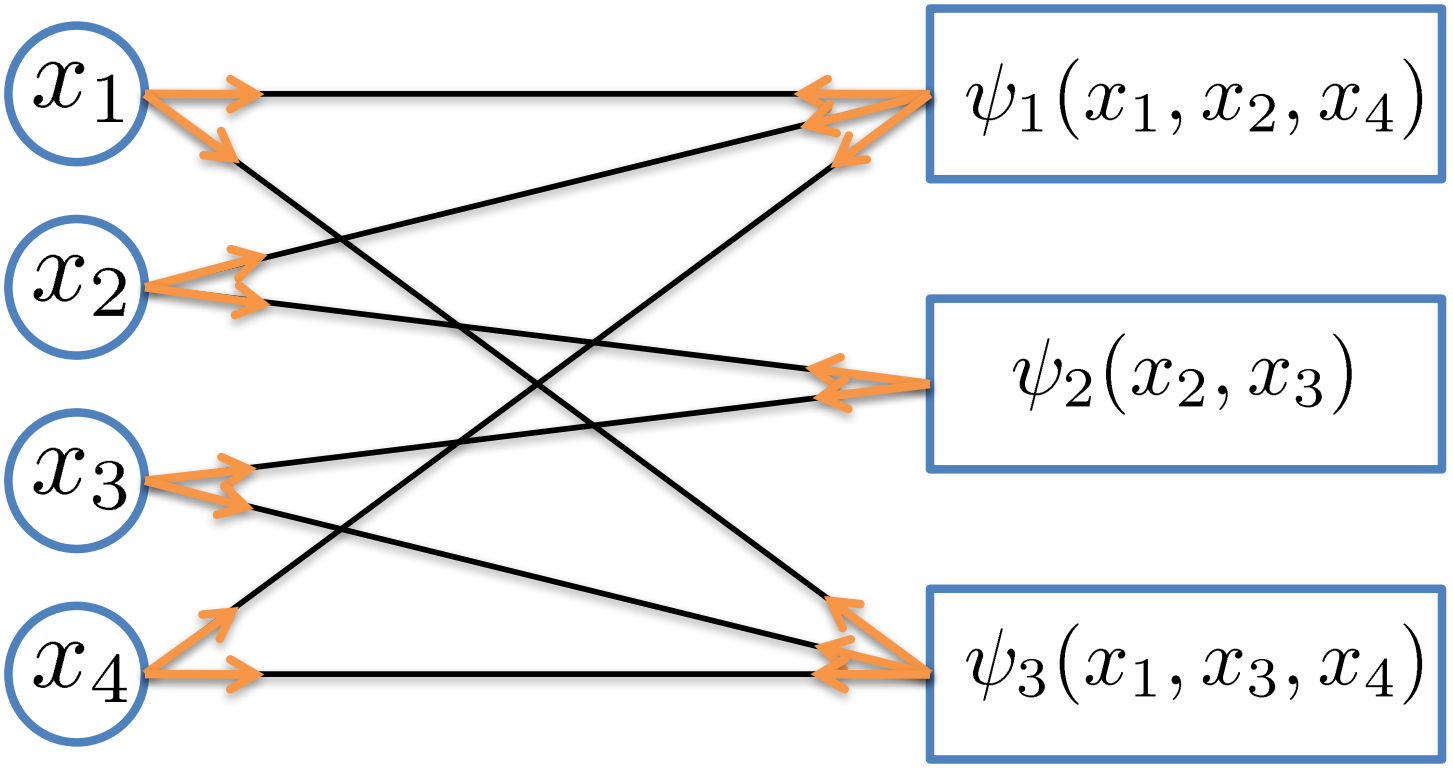


Computer Vision

Inference is a key step in **Learning** Graphical Models

Belief Propagation (BP)

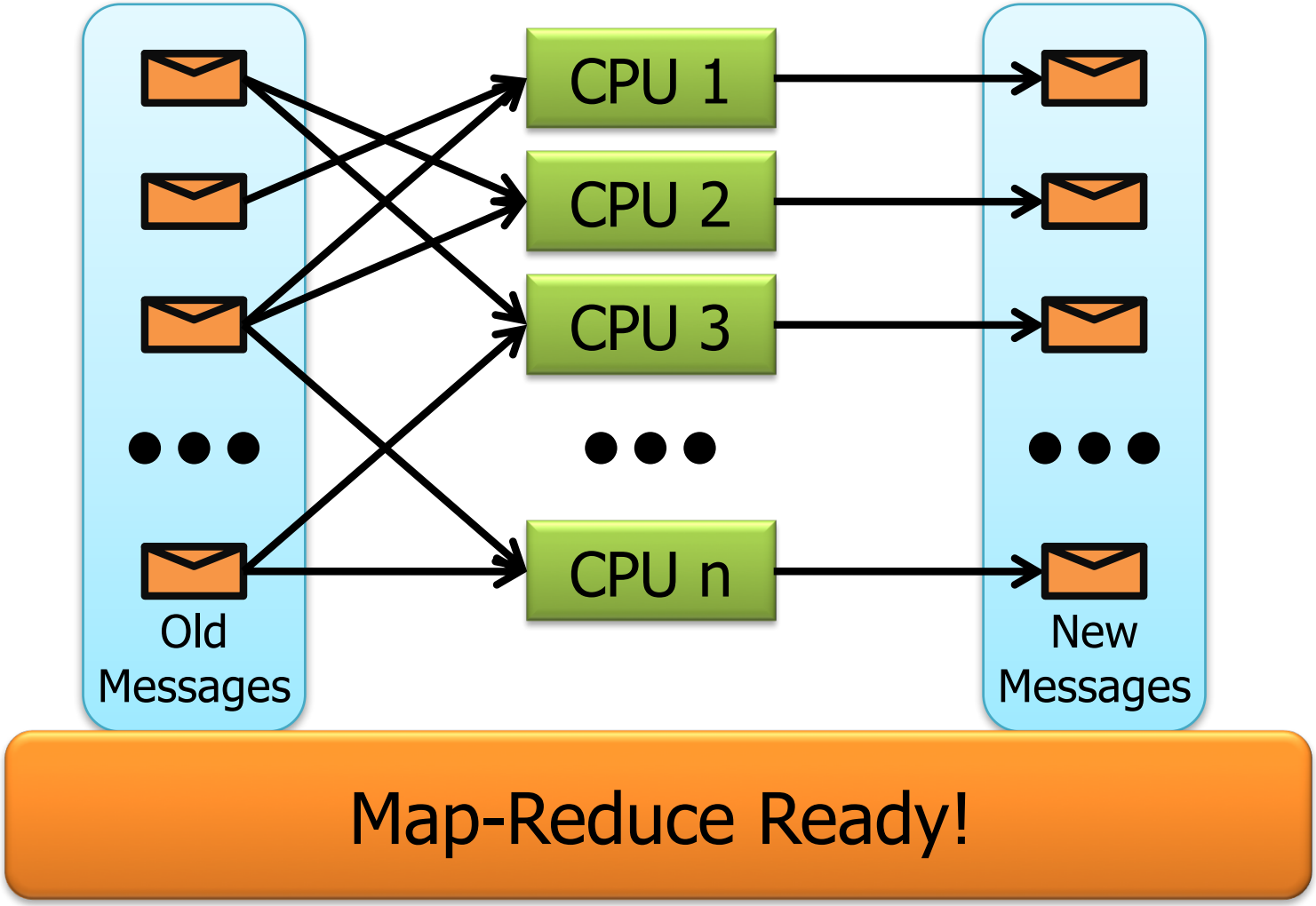
- Message passing algorithm



Naturally Parallel Algorithm

Parallel Synchronous BP

- Given the old messages all new messages can be computed in parallel:



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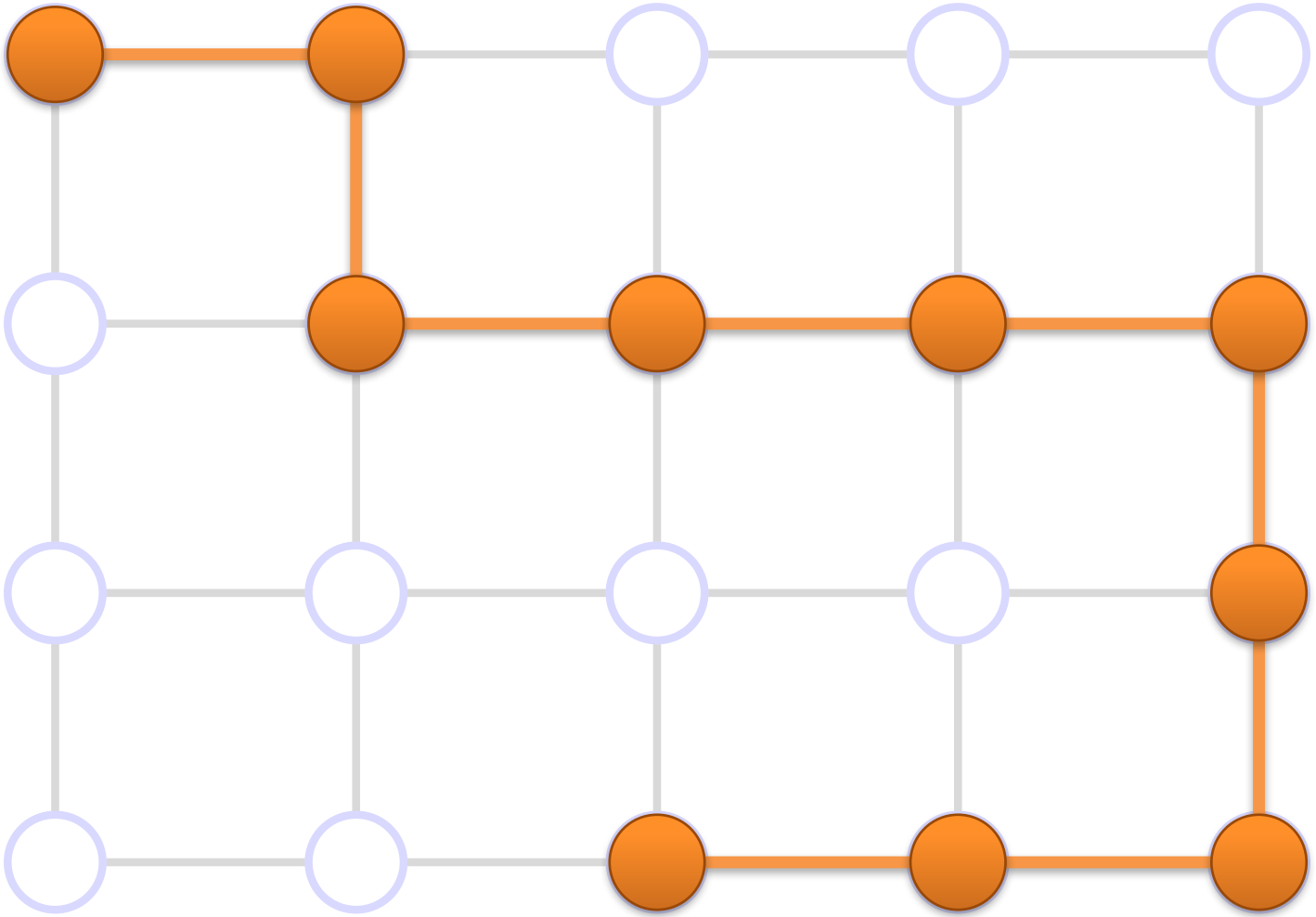
Hidden Sequential Structure



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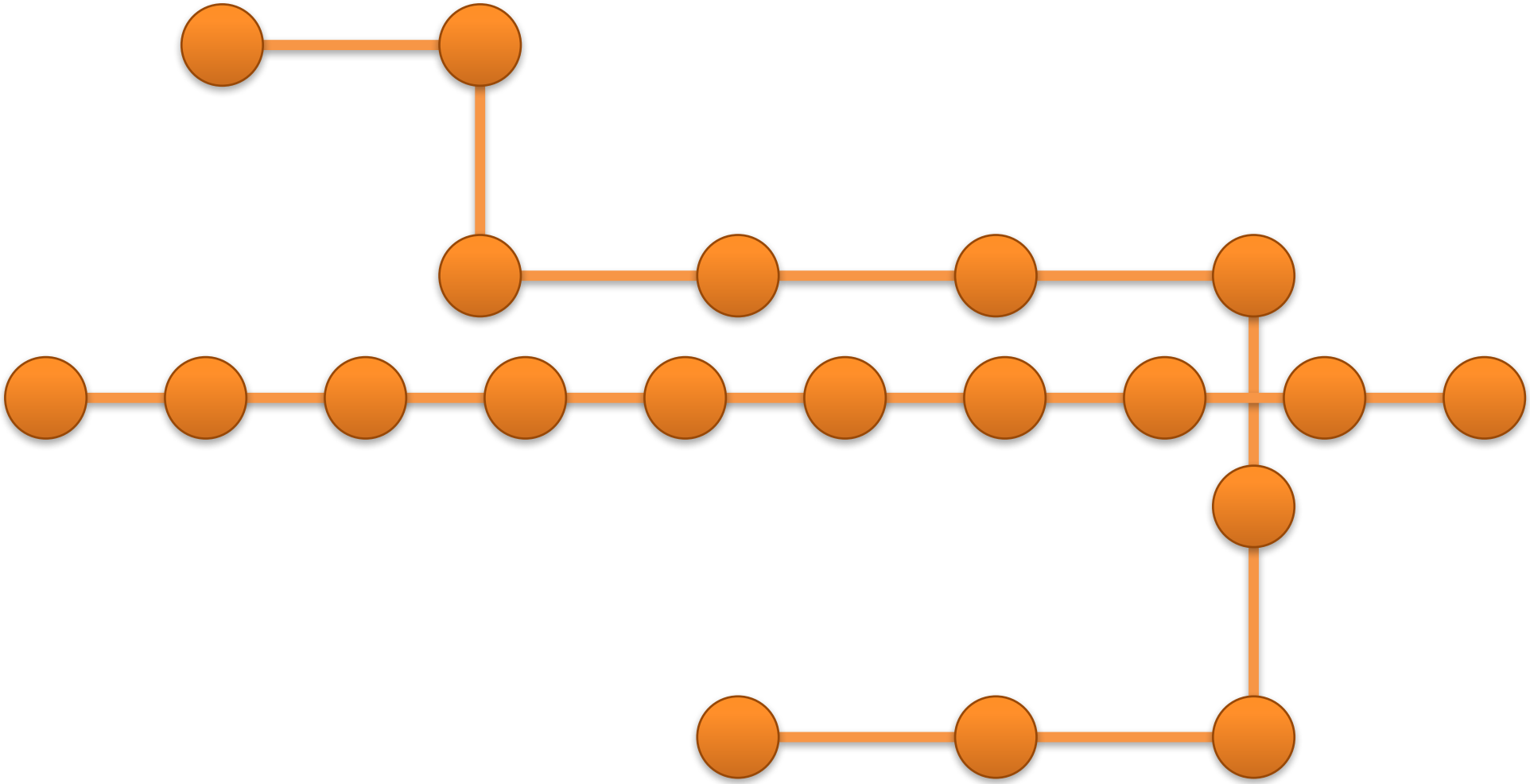
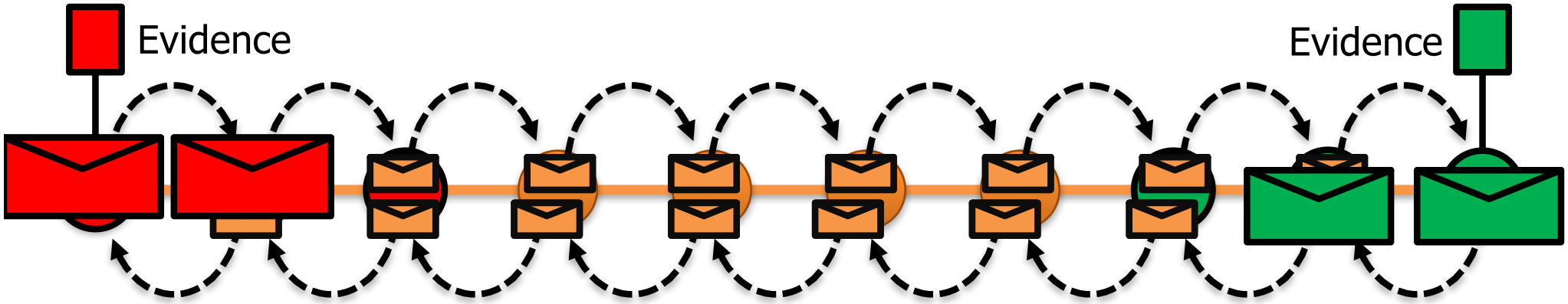
Hidden Sequential Structure



Hidden Sequential Structure



- Running Time:

$$\frac{2n \text{ Messages Calculations}}{p \text{ Processors}} \times (n \text{ Iterations to Converge}) = \frac{2n^2}{p}$$

Time for a single parallel iteration

Number of Iterations

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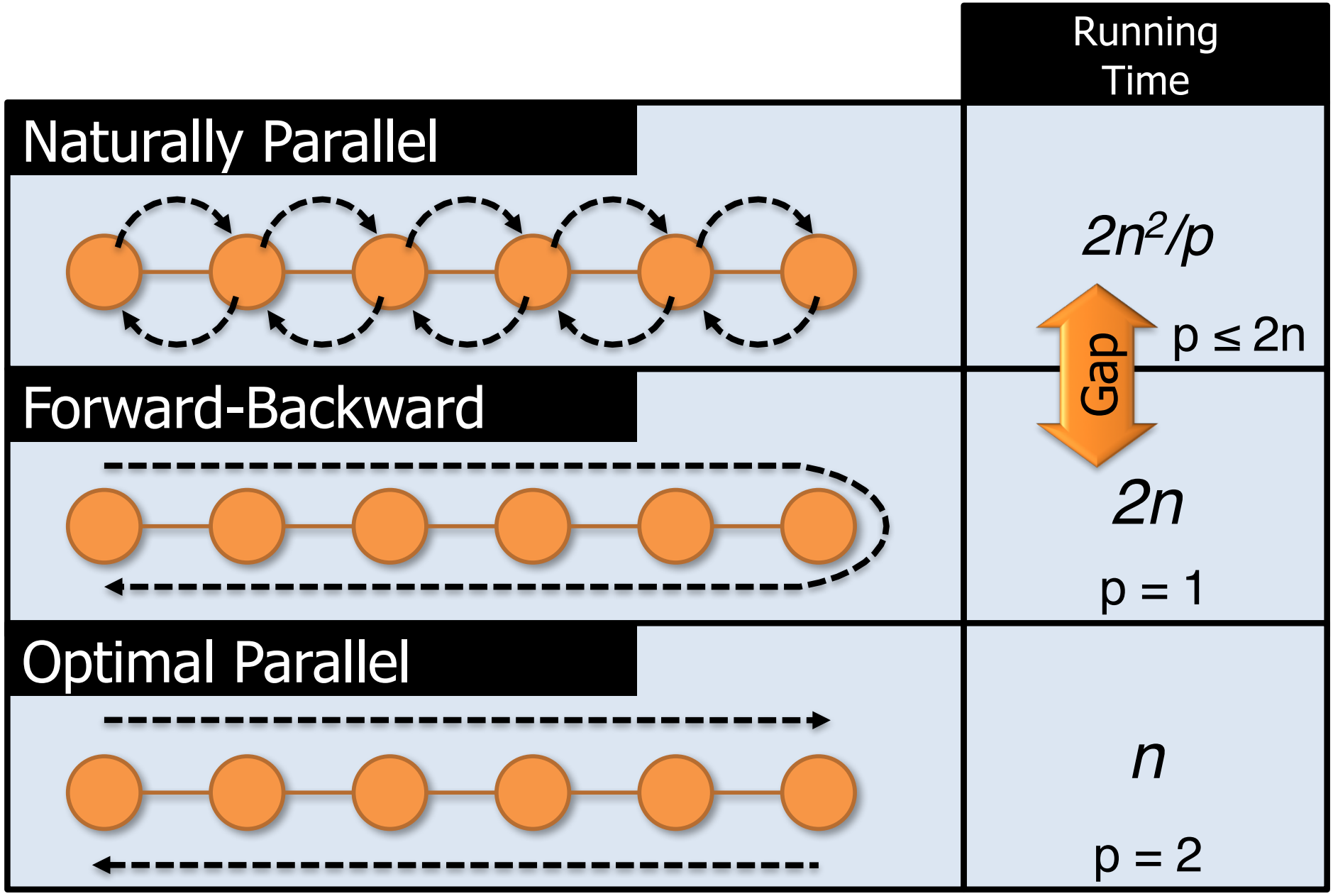
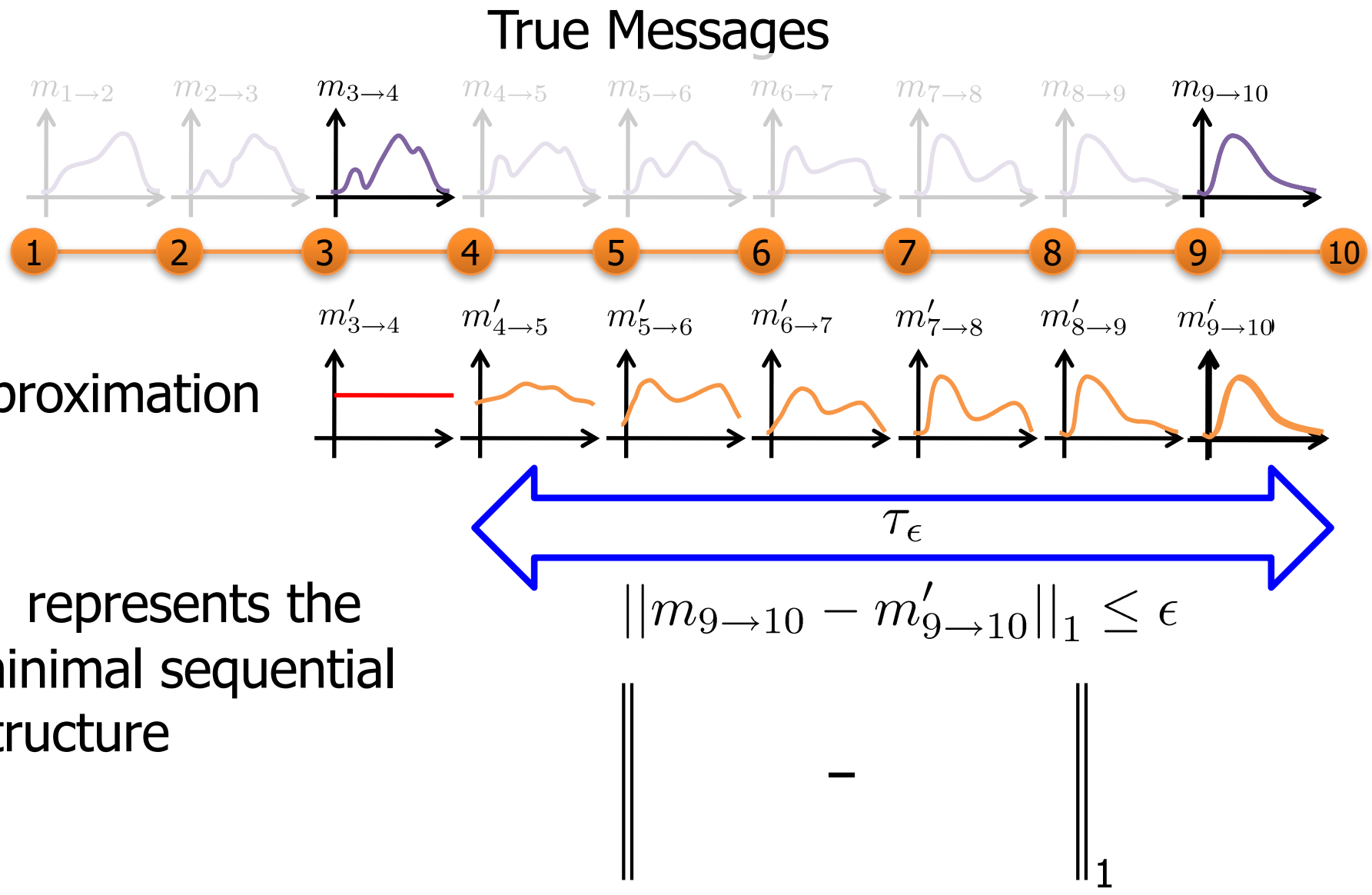
Optimal Sequential Algorithm



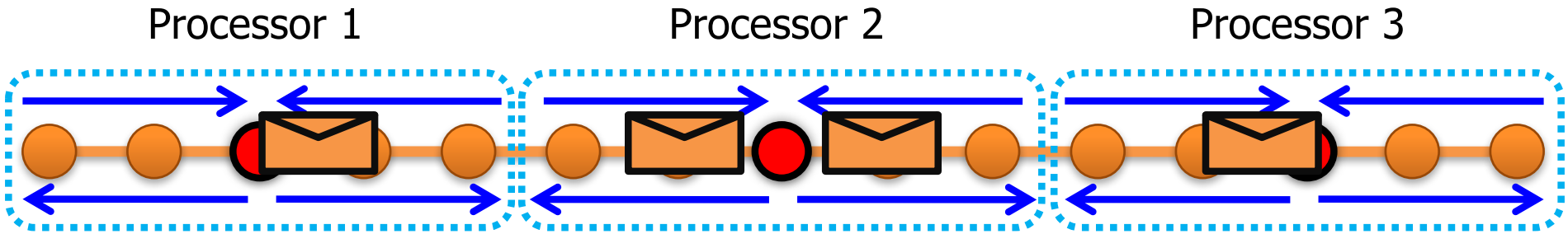
Parallelism by Approximation



τ_ε -Approximation

- τ_ε represents the minimal sequential structure

Optimal Parallel Scheduling



- In [AIStats 09] we demonstrated that this algorithm is **optimal**:

Synchronous $O\left(\frac{n}{p} + \tau_\epsilon\right)$ Optimal Schedule

$O\left(\frac{n\tau_\epsilon}{p}\right)$

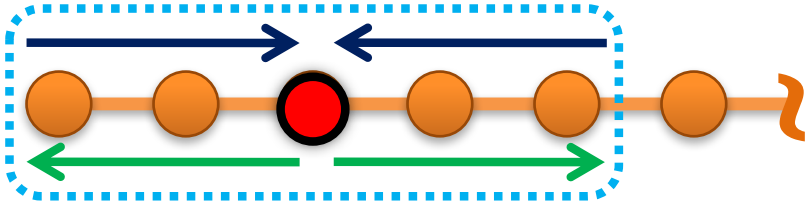
Gap

Parallel Component

Sequential Component

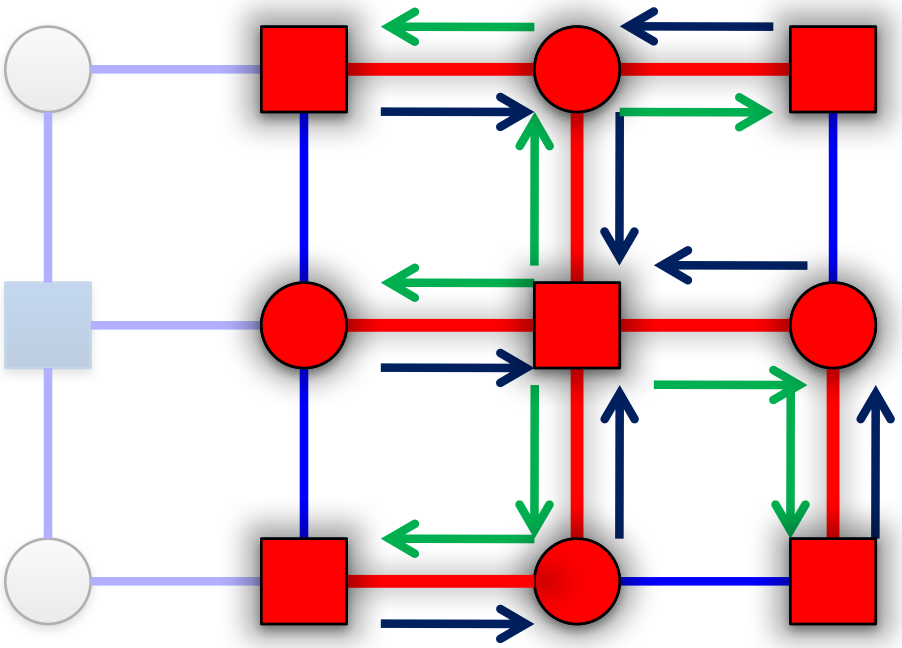
The Splash Operation

- Generalize the optimal chain algorithm:



to arbitrary cyclic graphs:

1) Grow a BFS Spanning tree with fixed size
2) Forward Pass computing all messages at each vertex
3) Backward Pass computing all messages at each vertex



Running Parallel Splashes

- Partition the graph
- Schedule Splashes locally
- Transmit the messages along the boundary of the partition

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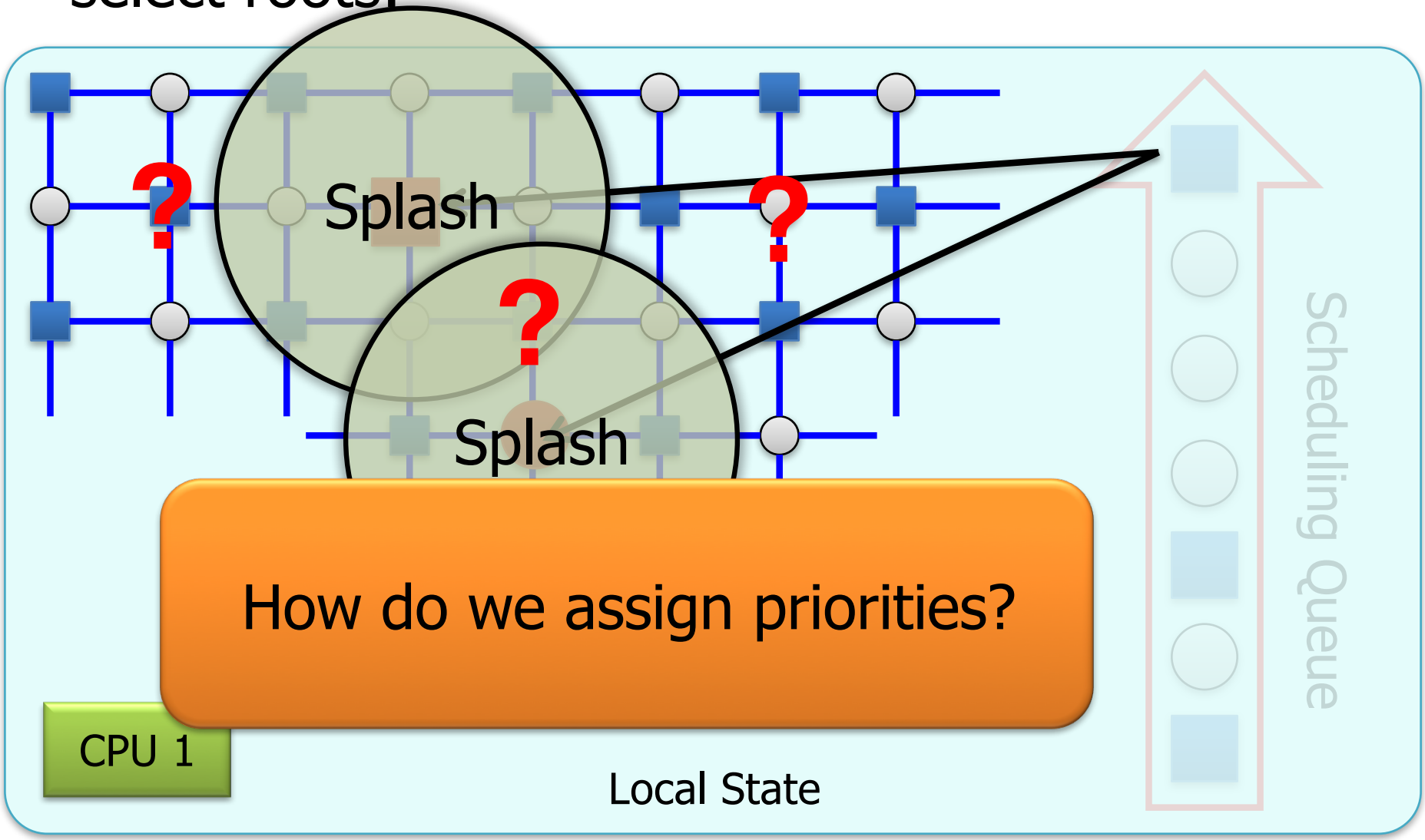
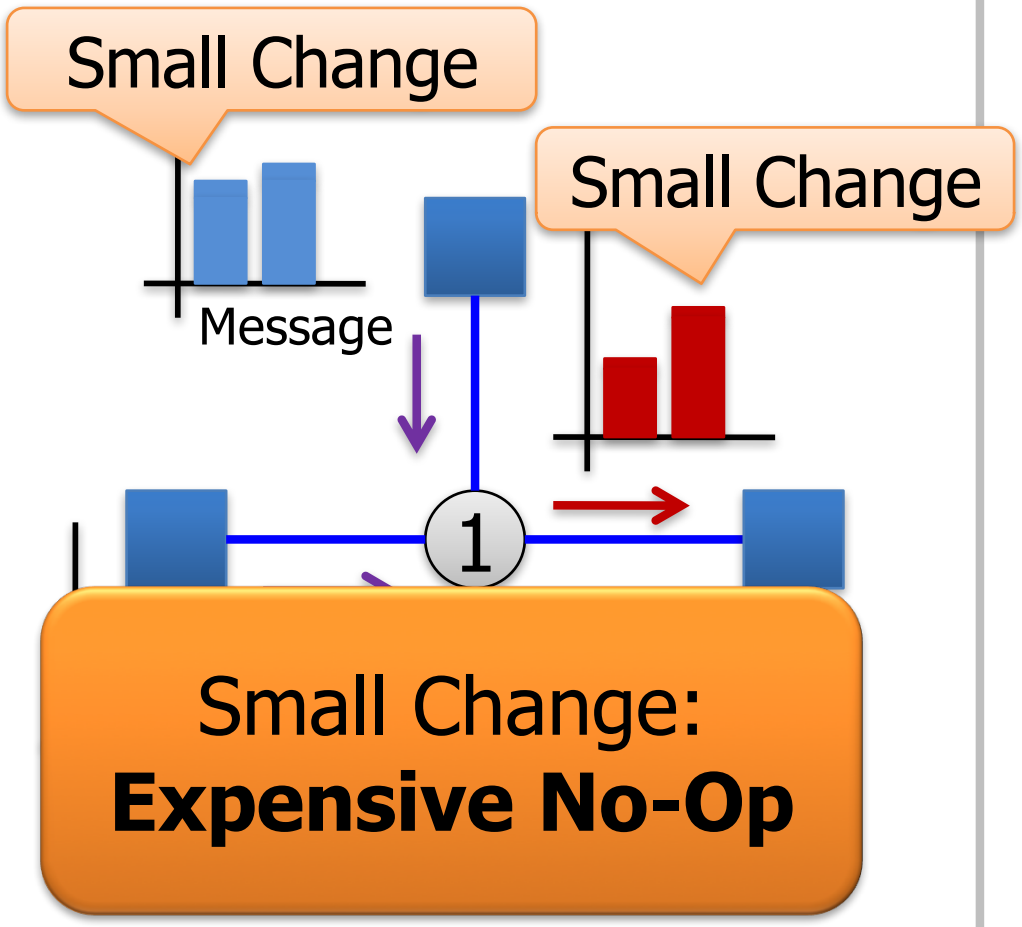
Where do we Splash?

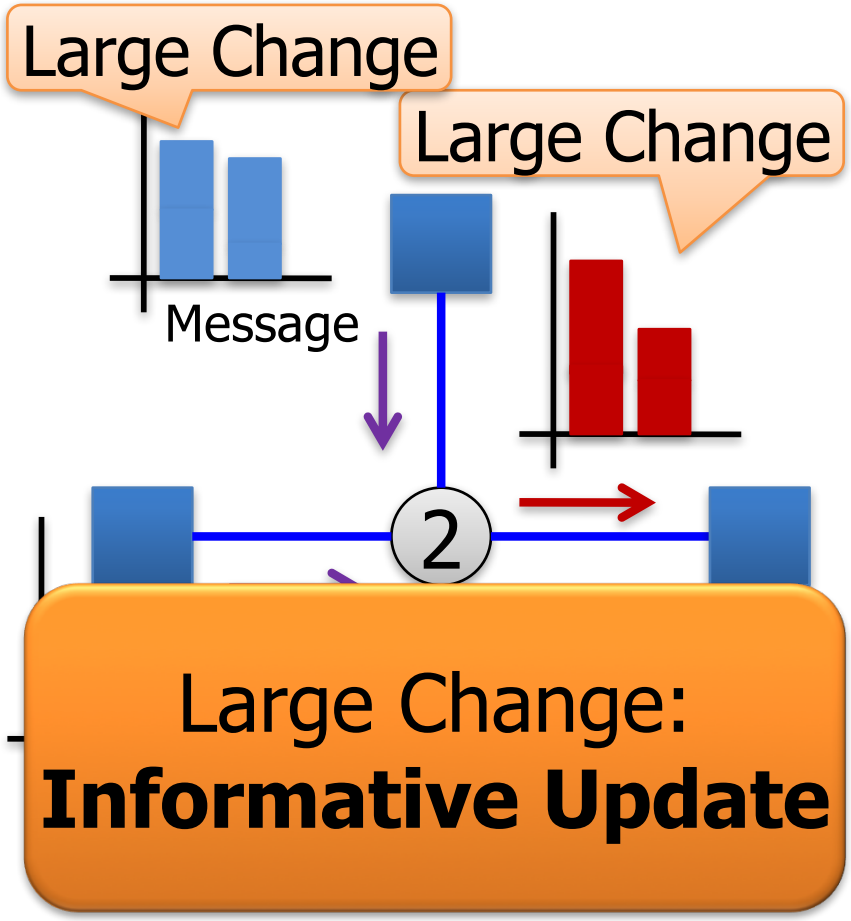
- Assign priorities and use a scheduling queue to select roots:



Message Scheduling

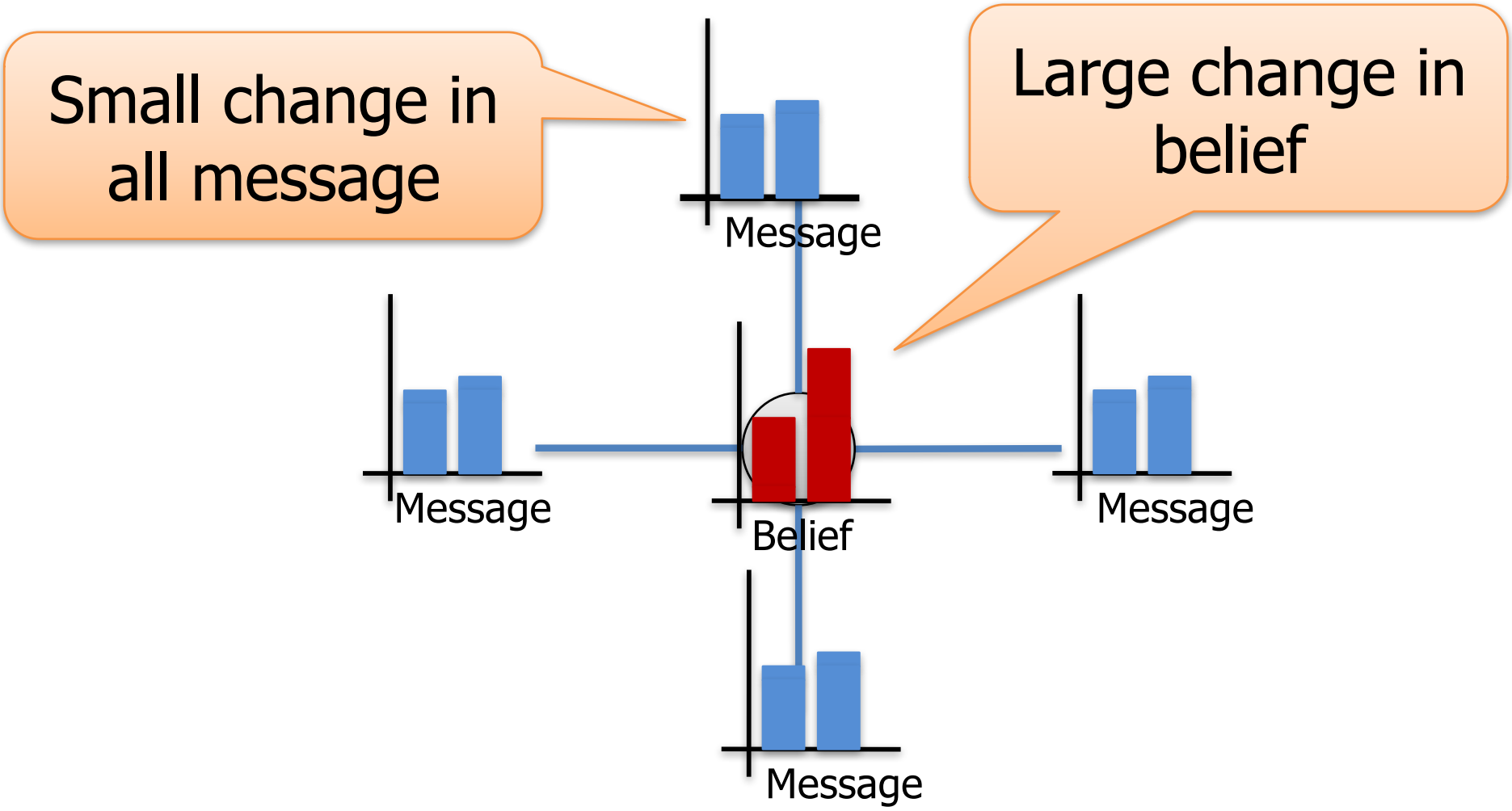
- Residual Belief Propagation [Elidan et al., UAI 06]:
  - Assign priorities based on change in inbound messages





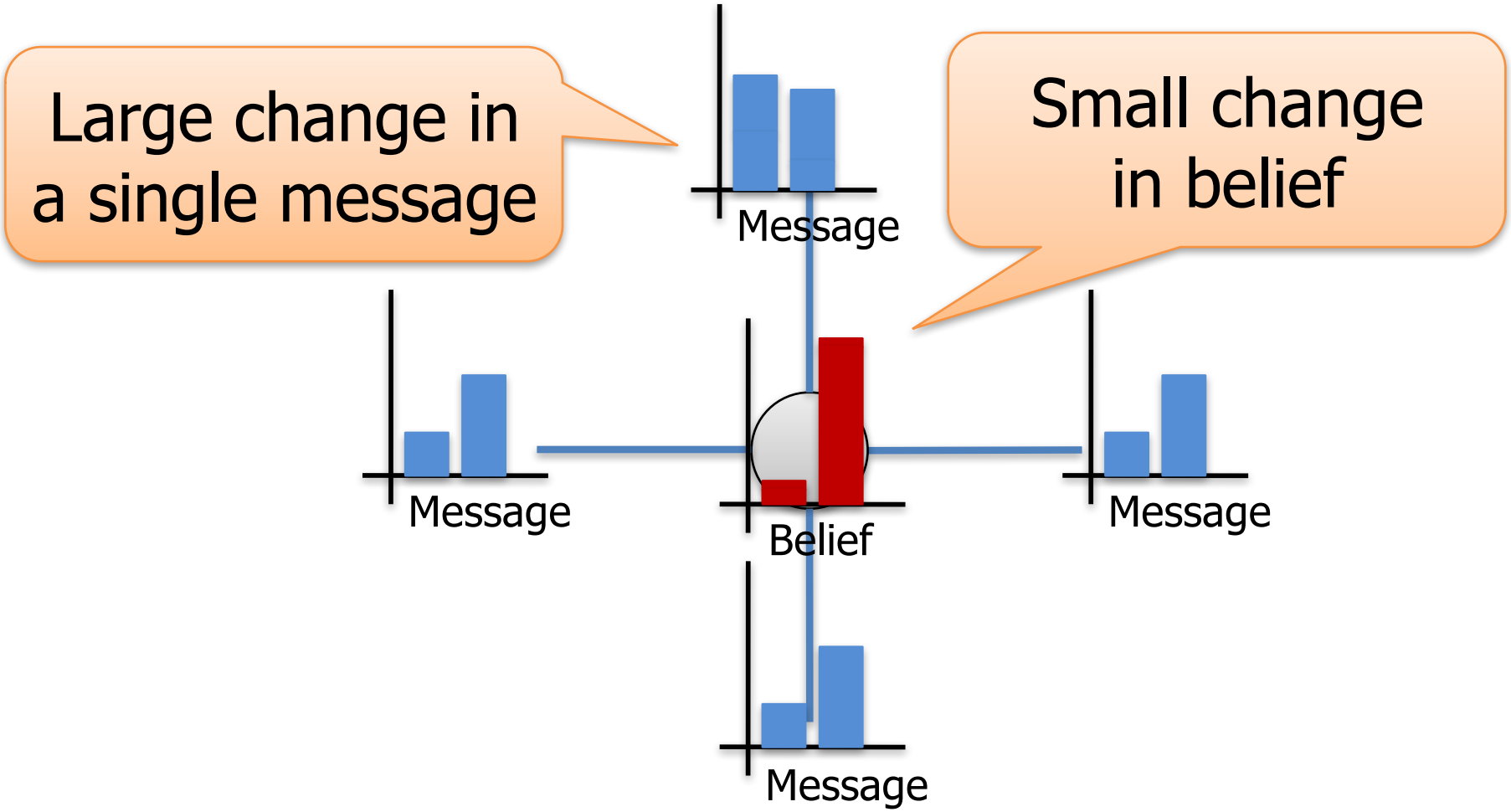
Problem with Message Scheduling

- Small changes in messages do not imply small changes in belief:



Problem with Message Scheduling

- Large changes in a single message do not imply large changes in belief:

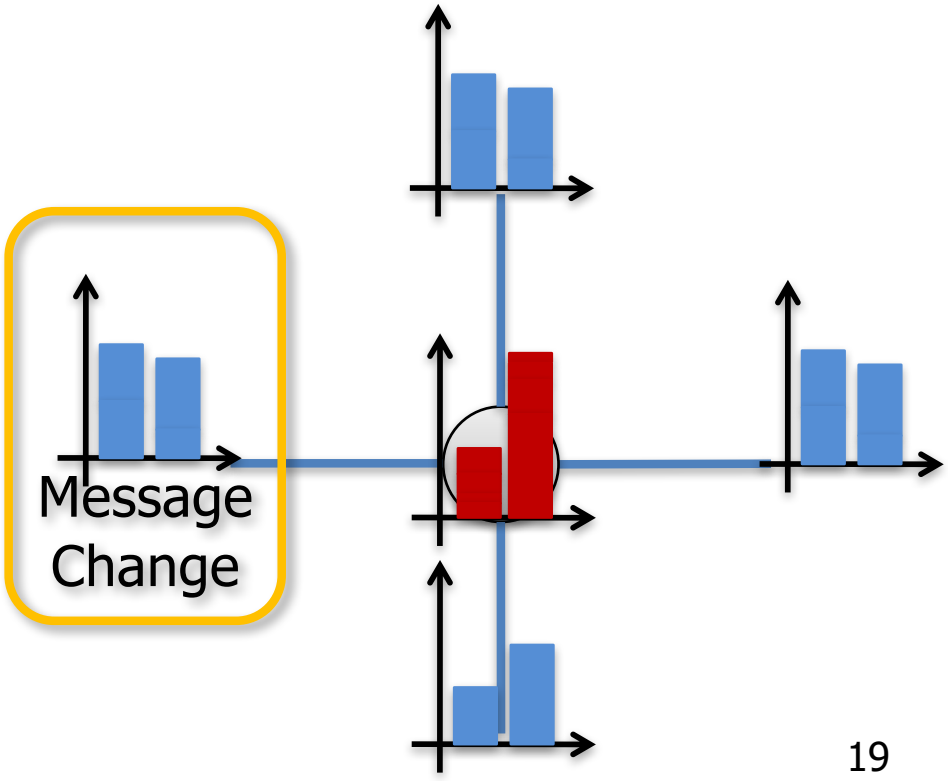


Belief Residual Scheduling

- Assign priorities based on the cumulative change in belief:

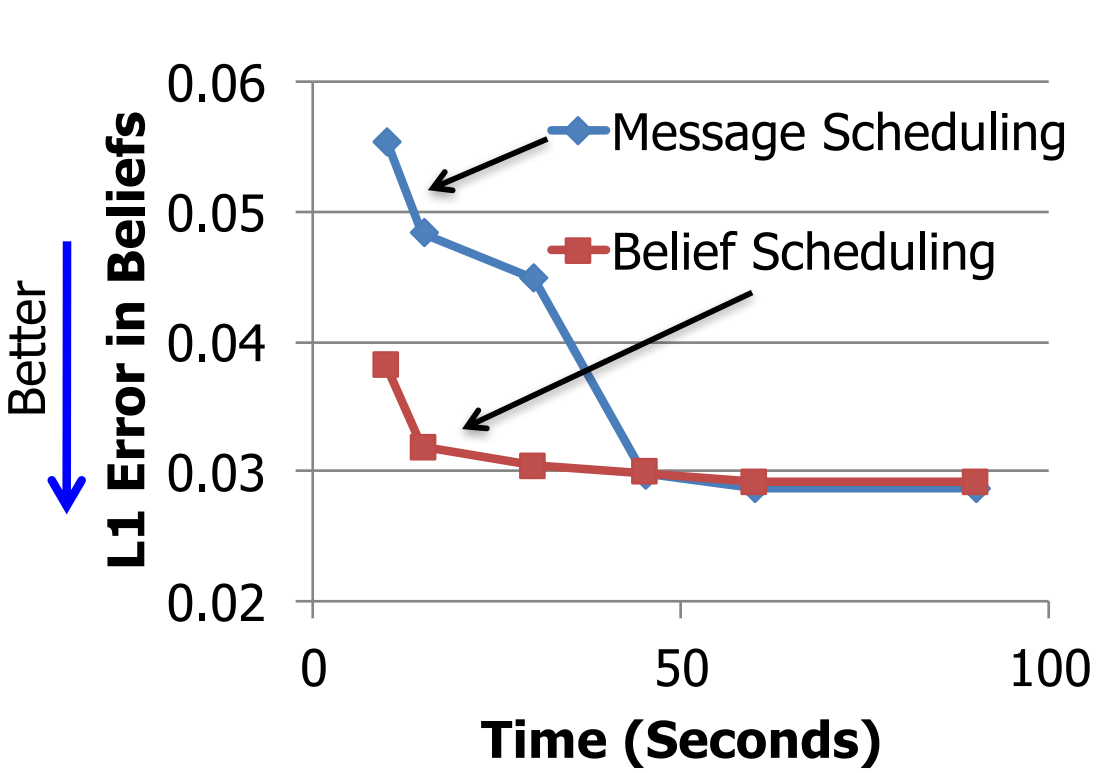
$$r_v = \left\| \; - \; \right\|_1 + \left\| \; - \; \right\|_1 + \left\| \; - \; \right\|_1$$

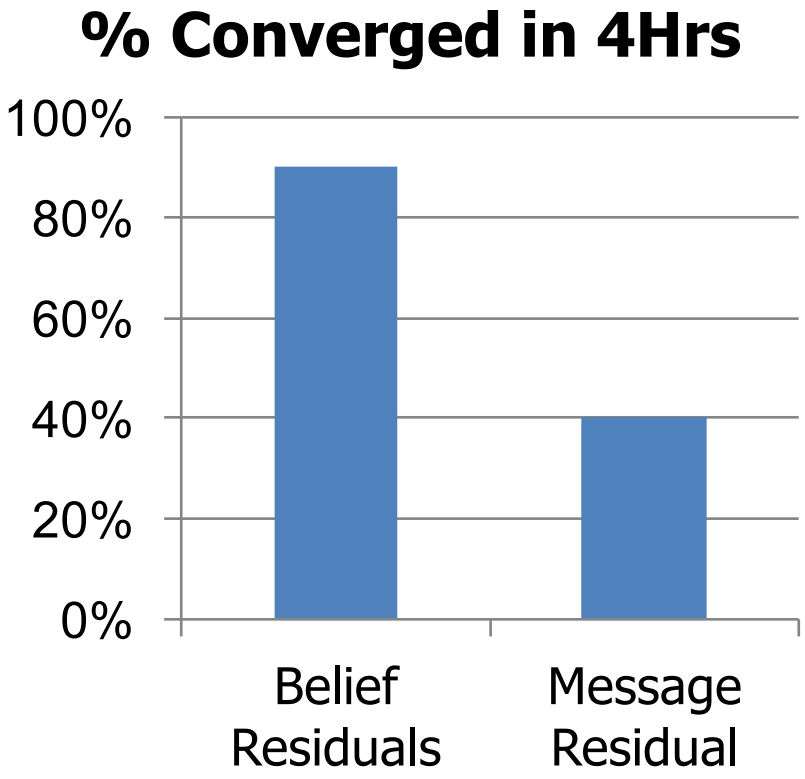
A vertex whose belief has changed substantially since last being updated will likely produce informative new messages.



Message vs. Belief Scheduling

- Belief scheduling improves accuracy more quickly
- Belief scheduling improves convergence





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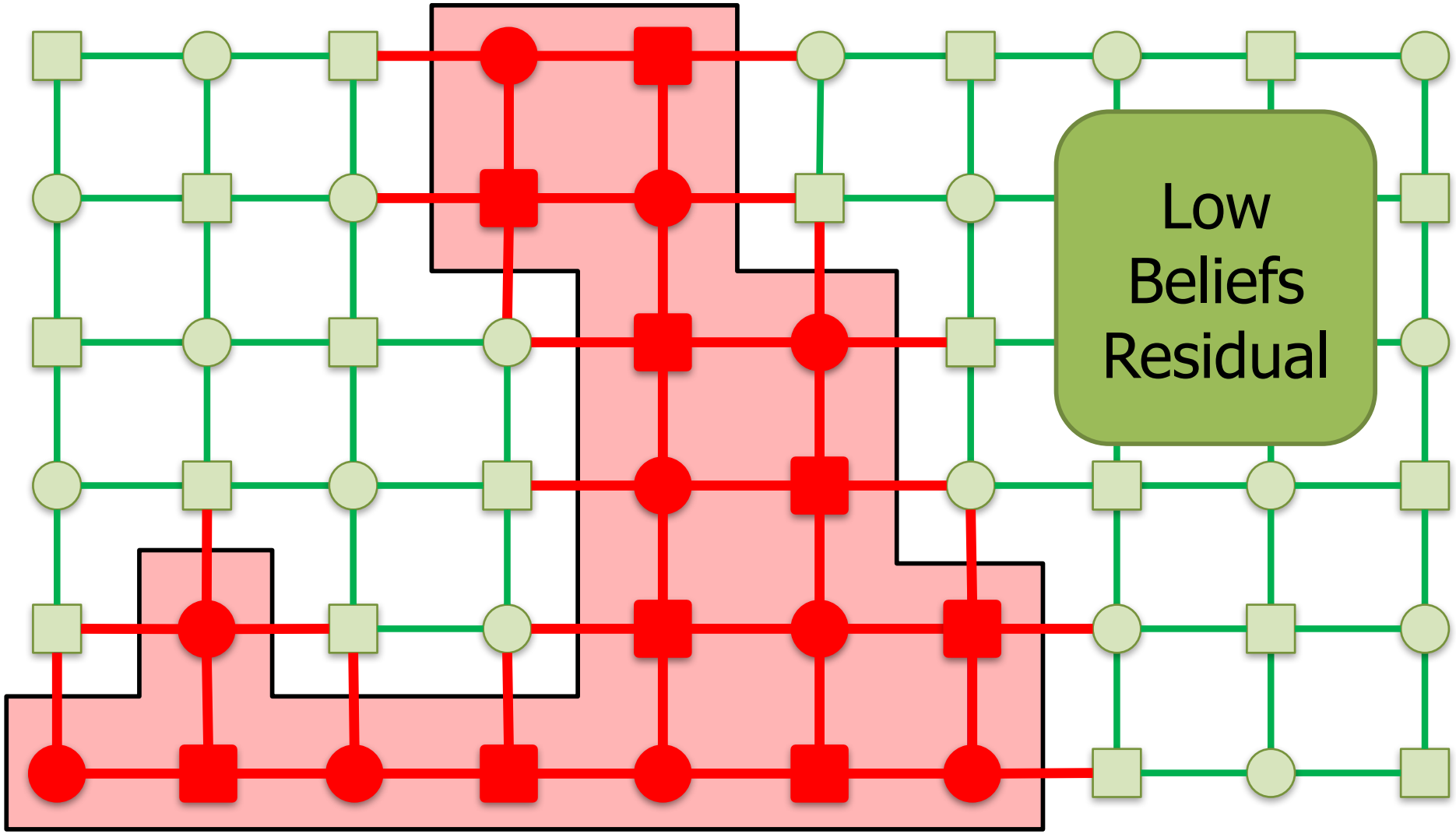
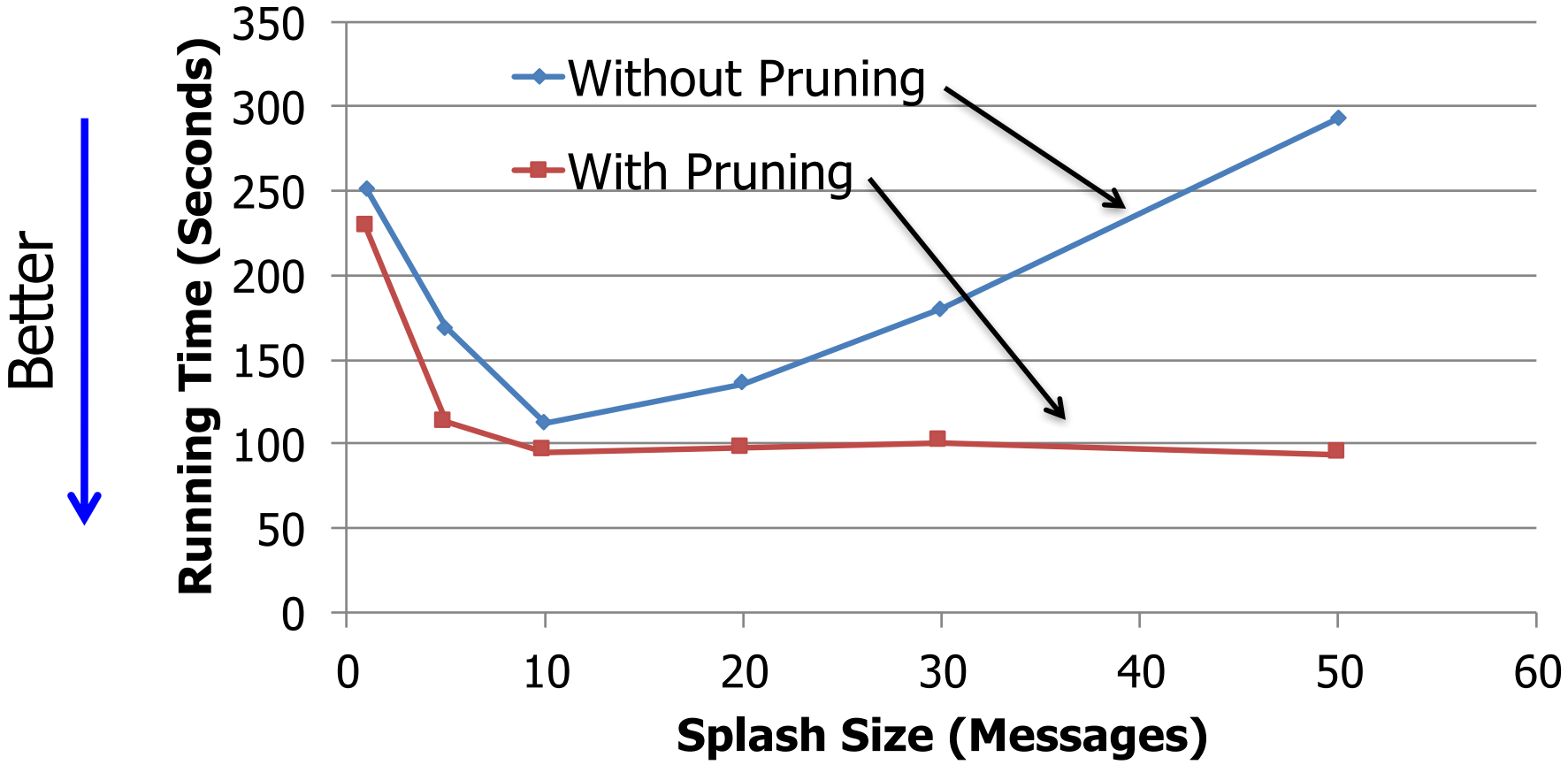
Splash Pruning

- Belief residuals can be used to **dynamically** reshape and resize Splashes:

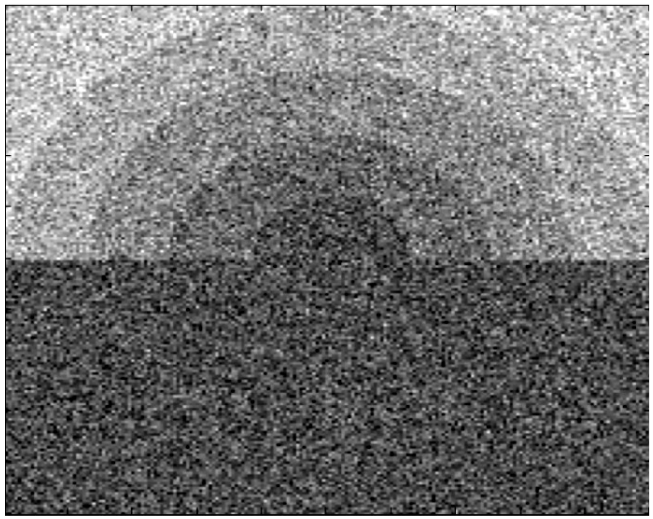


Splash Size

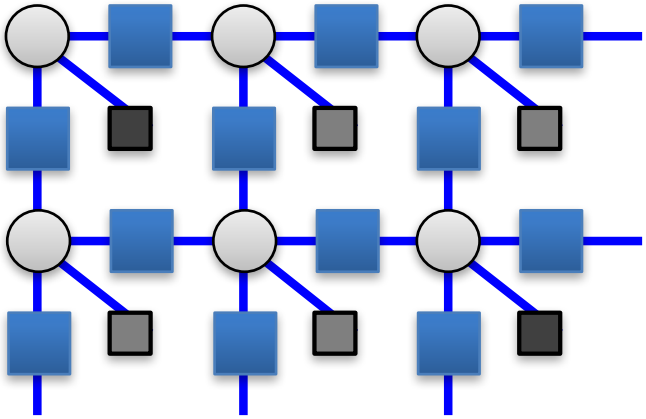
- Using **Splash Pruning** our algorithm is able to dynamically select the **optimal** splash size



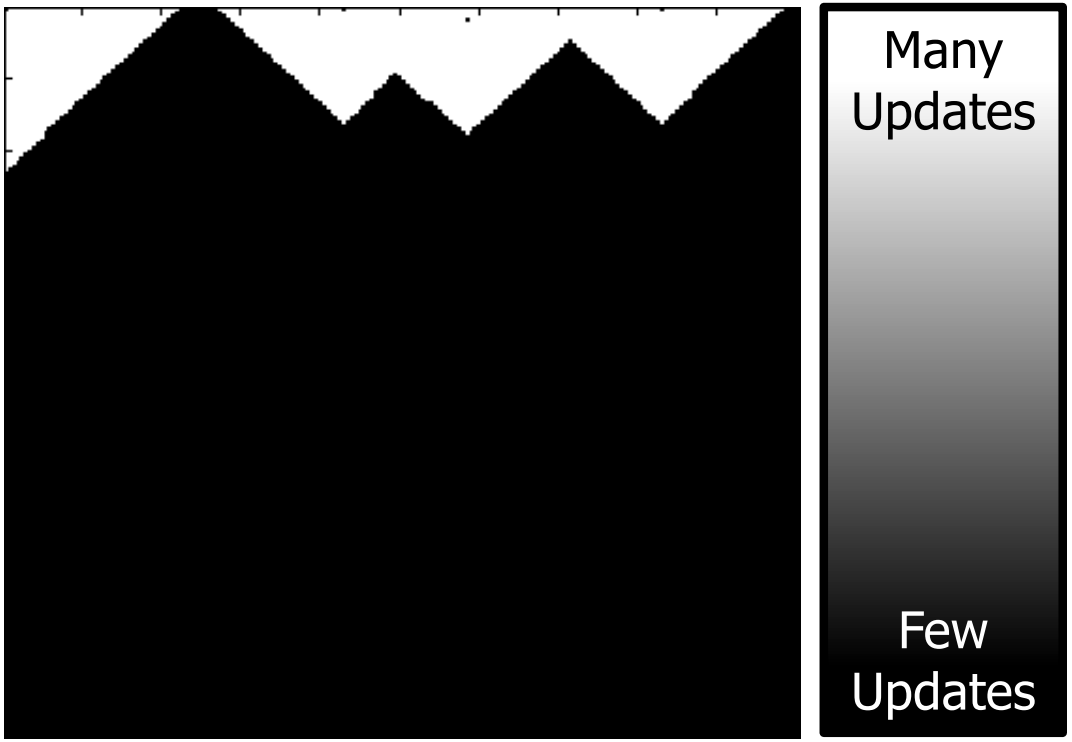
Example



Synthetic Noisy Image



Factor Graph



Vertex Updates

Algorithm identifies and focuses on hidden sequential structure

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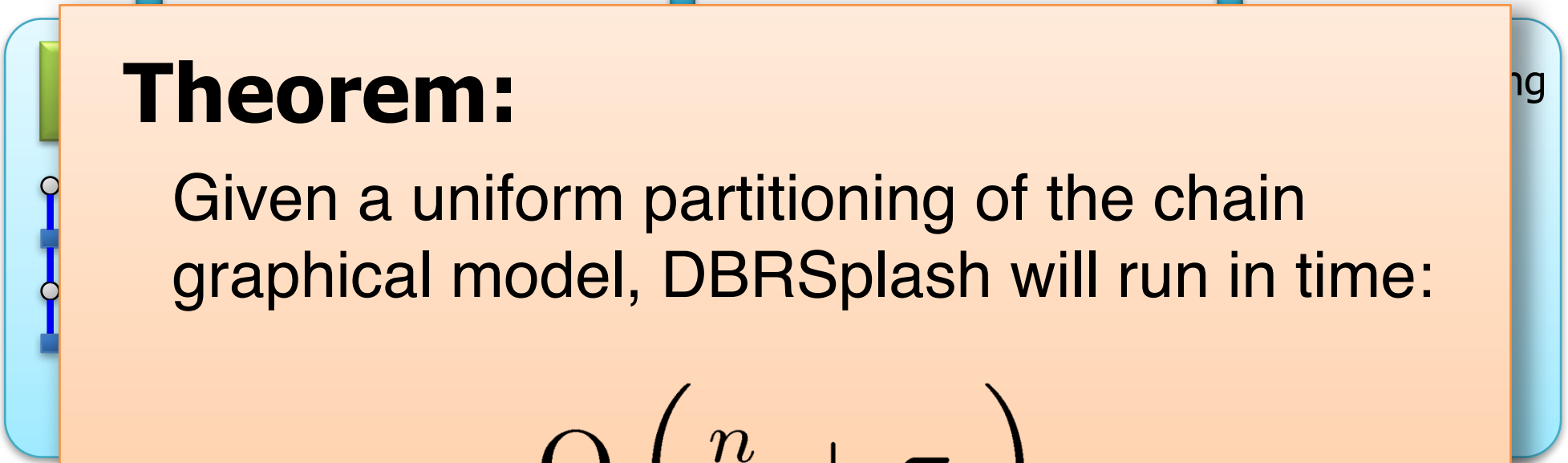
Distributed Belief Residual Splash Algorithm

Fast Reliable Network



Theorem:

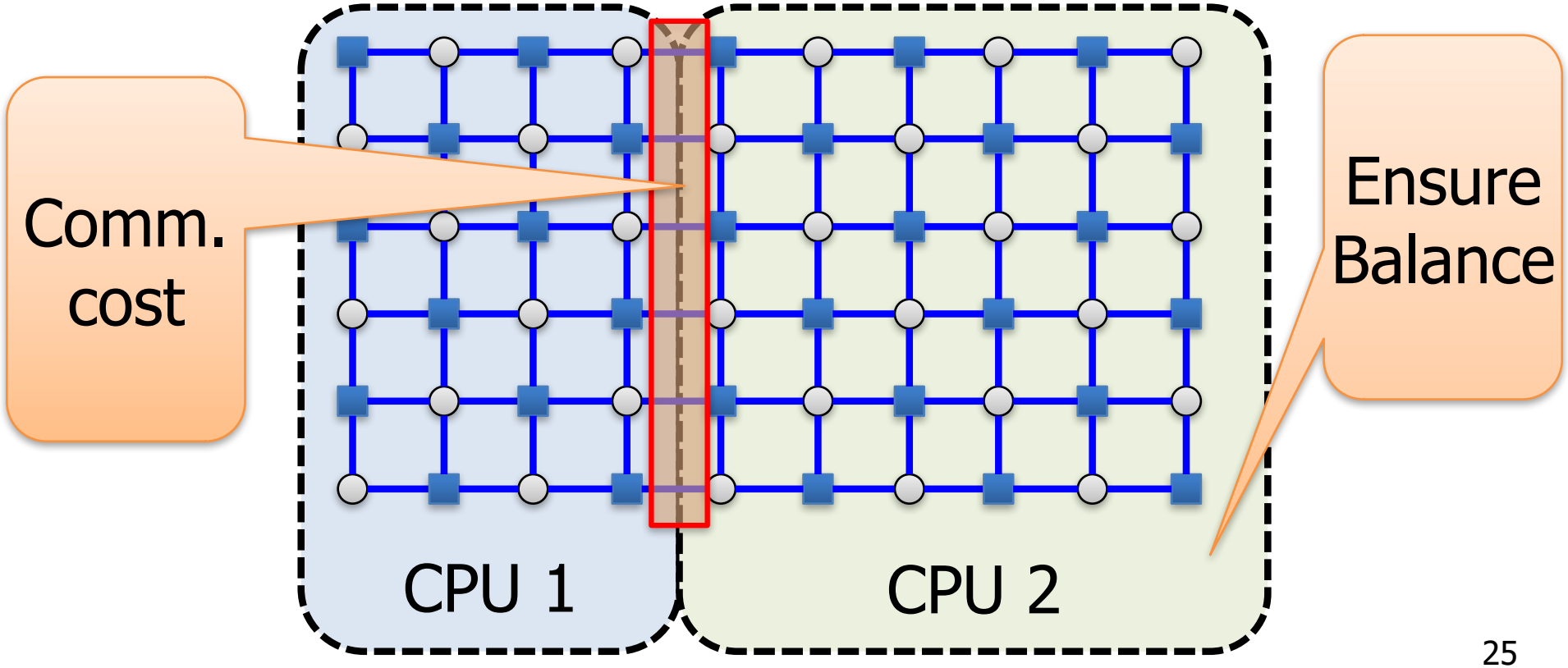
Given a uniform partitioning of the chain graphical model, DBRSplash will run in time:

$$\mathrm{O}\left(\frac{n}{p} + \tau_\epsilon\right)$$

retaining optimality.

Partitioning Objective

- The partitioning of the factor graph determines:
  - Storage, Computation, and Communication
- Goal:
  - Balance **Computation** and Minimize **Communication**



The Partitioning Problem

- Objective:

Minimize Communication

$$\text{minimize:} \quad \sum_{(i,j)\in \text{Cut Edges}} c_{ij}$$

Ensure Balance

$$\text{subj. to:} \quad \sum_{i\in \text{Largest Block}} w_i \leq \frac{\gamma}{p} \sum_{v\in V} w_v$$

- Depends on:

Update counts are not known!

Work: $w_i = \text{Updates}_i \times \text{Size}(i) \times \text{Degree}(i)$

Comm: $c_{ij} = (\text{Updates}_i + \text{Updates}_j) \times \text{MessageSize}(i,j)$

- NP-Hard → METIS fast partitioning heuristic

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Unknown Update Counts

- Determined by belief scheduling
- Depends on: graph structure, factors, …
- Little correlation between past & future update counts

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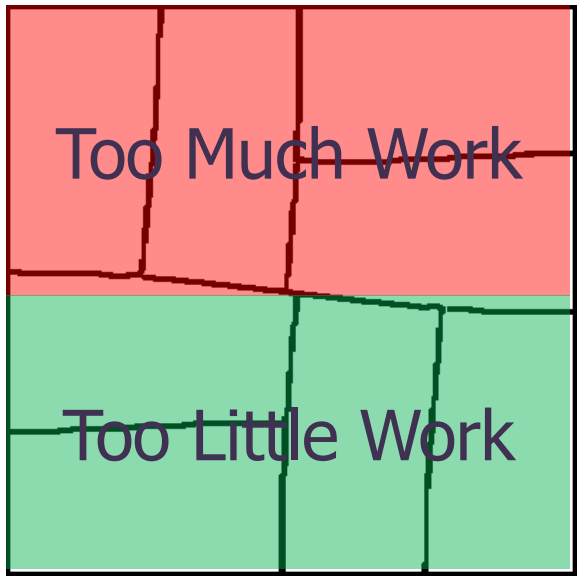
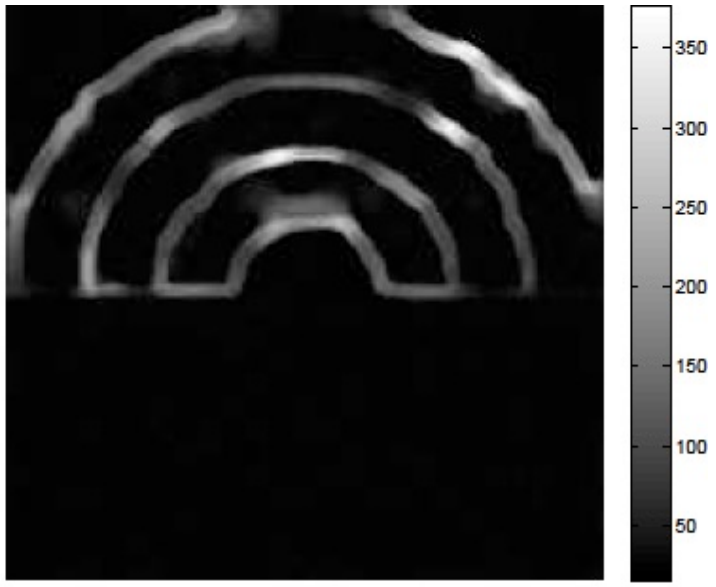
Uniformed Cuts

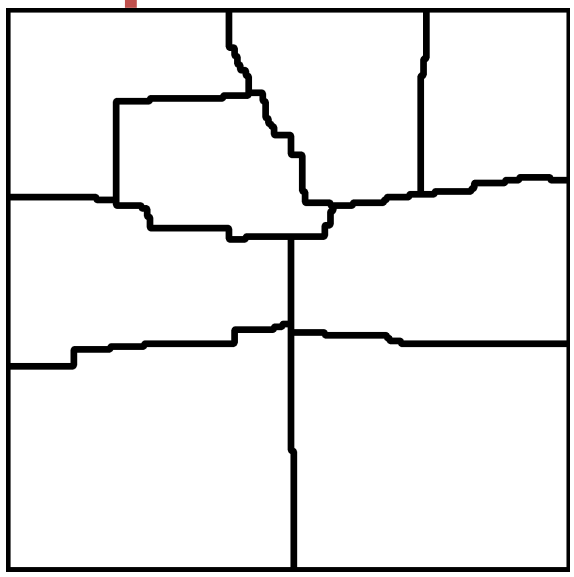
Uninformed Cut



Update Counts

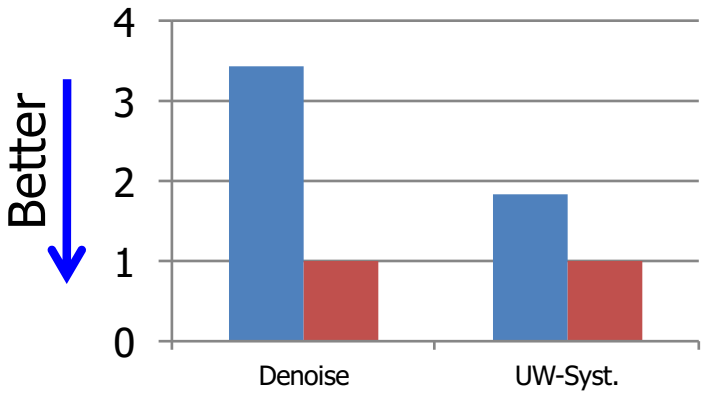


Optimal Cut

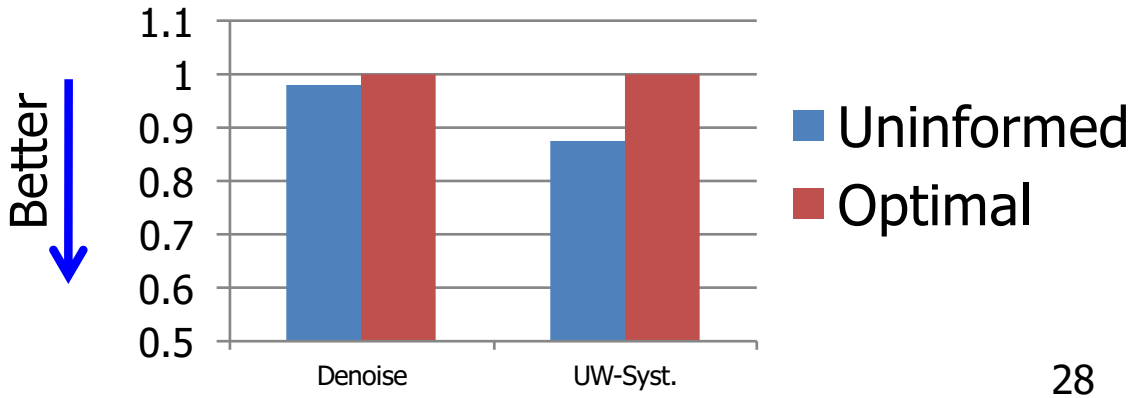


- Greater imbalance & lower communication cost

Work Imbalance

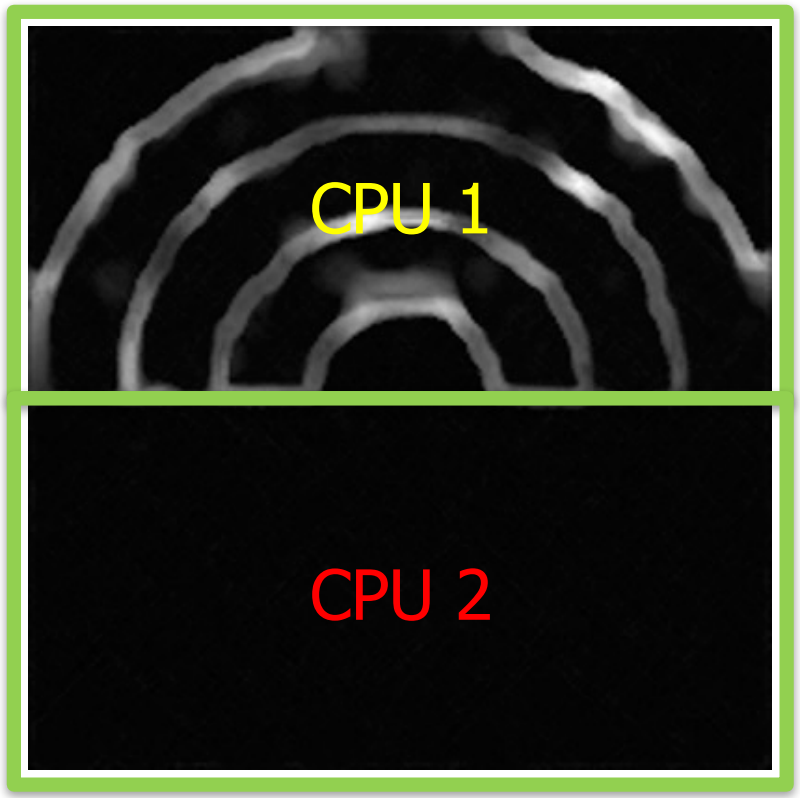


Communication Cost

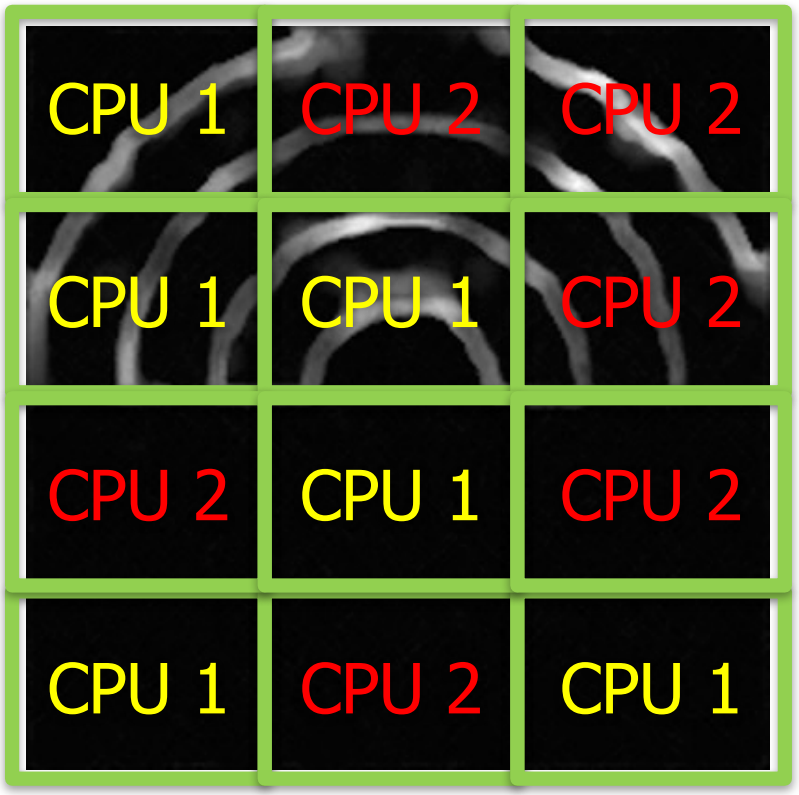


Over-Partitioning

- Over-cut graph into *k*p* partitions and randomly assign CPUs
  - Increase balance
  - Increase communication cost (More Boundary)



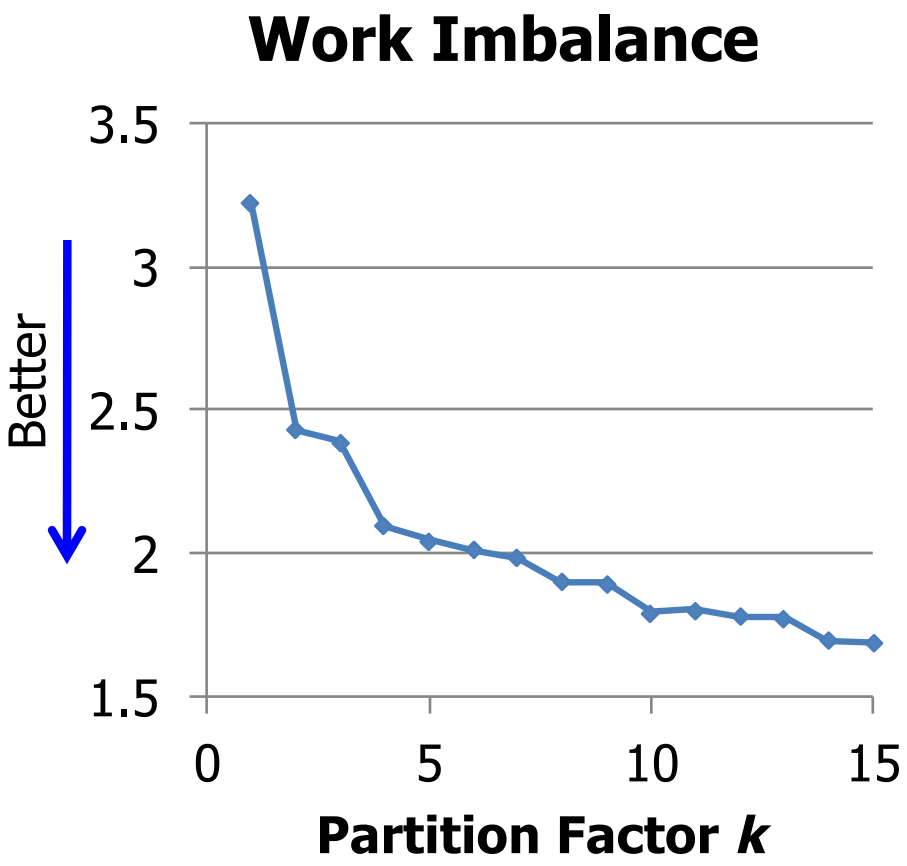
Without Over-Partitioning

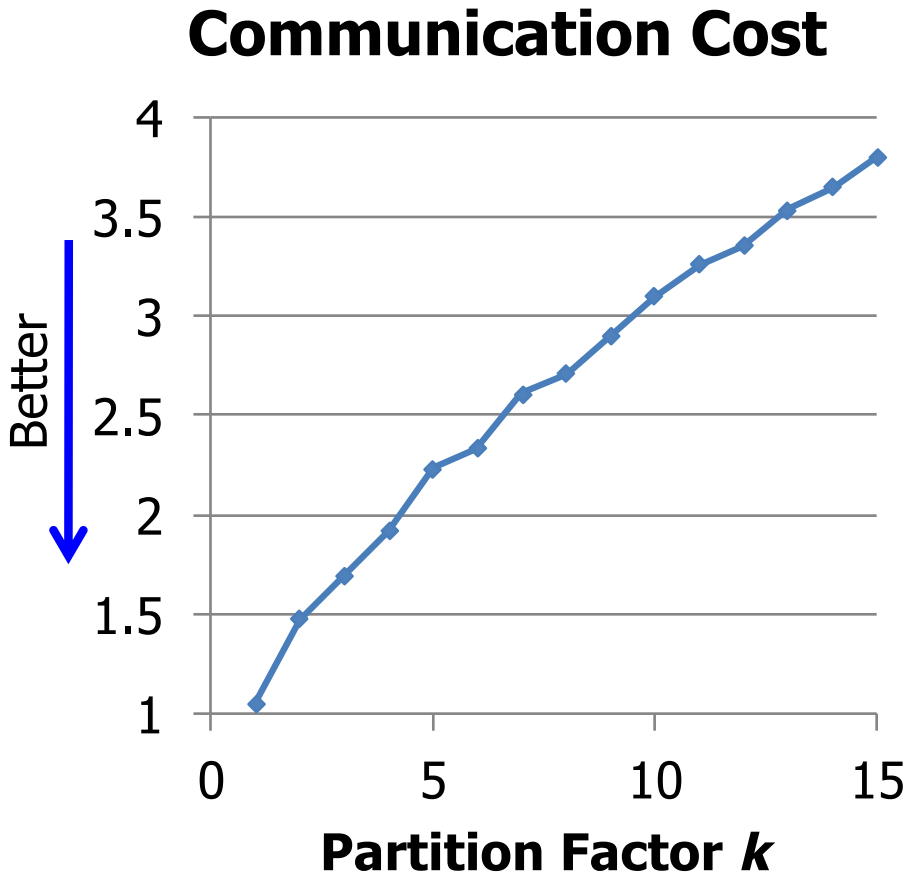


k=6

Over-Partitioning Results

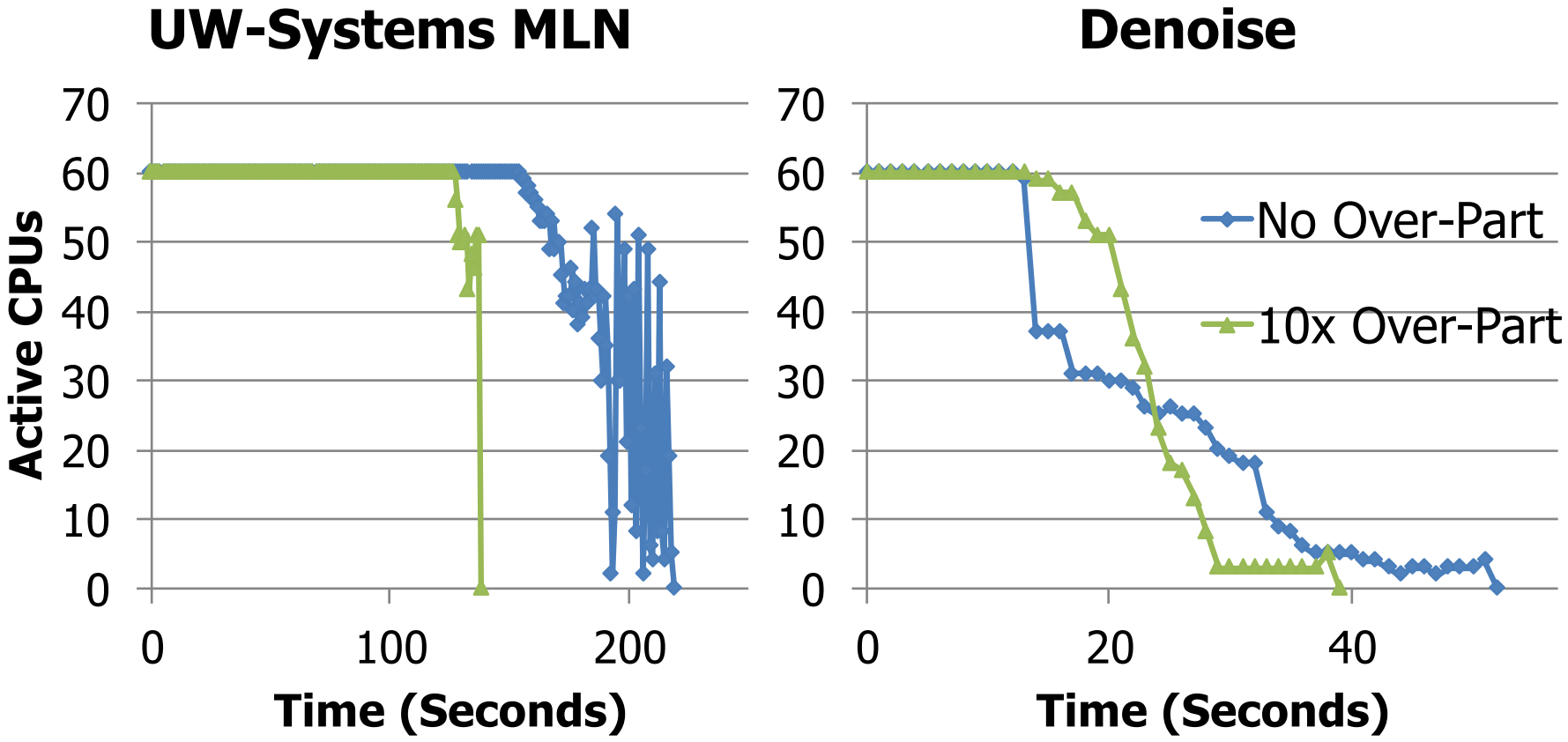
- Provides a simple method to trade between work balance and communication cost



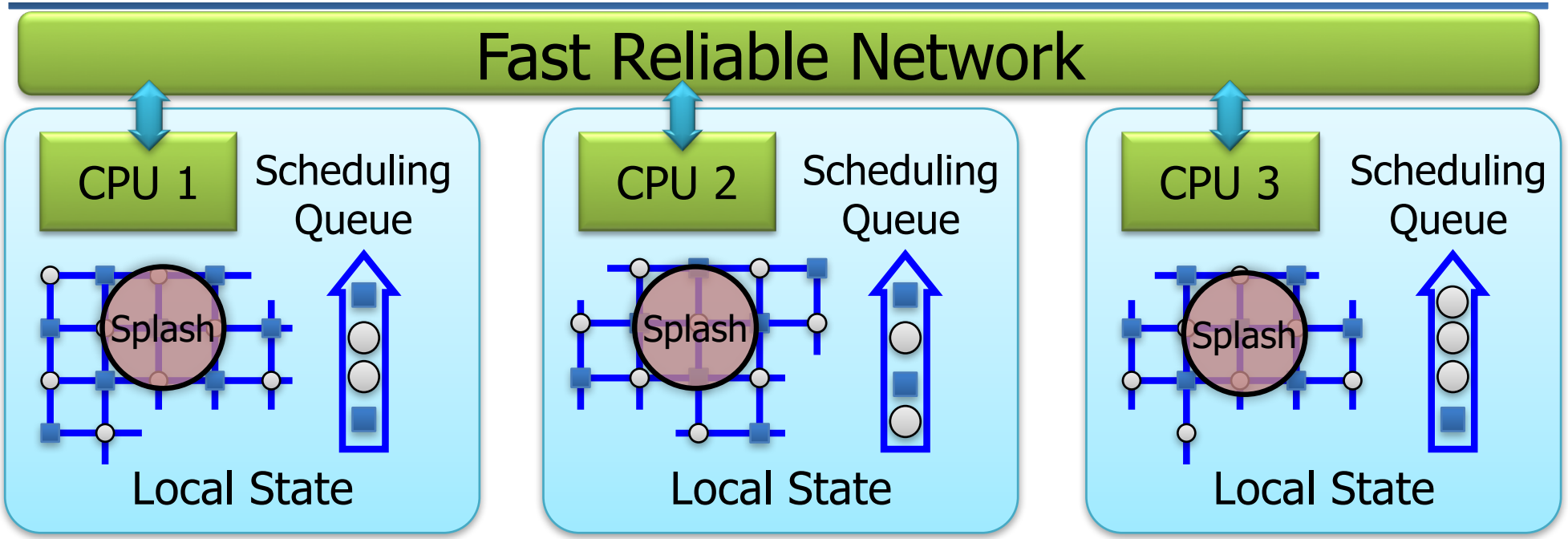


CPU Utilization

- Over-partitioning improves CPU utilization:



DBRSplash Algorithm



- Over-Partition factor graph
  - Randomly assign pieces to processors
- Schedule Splashes locally using belief residuals
- Transmit messages on boundary

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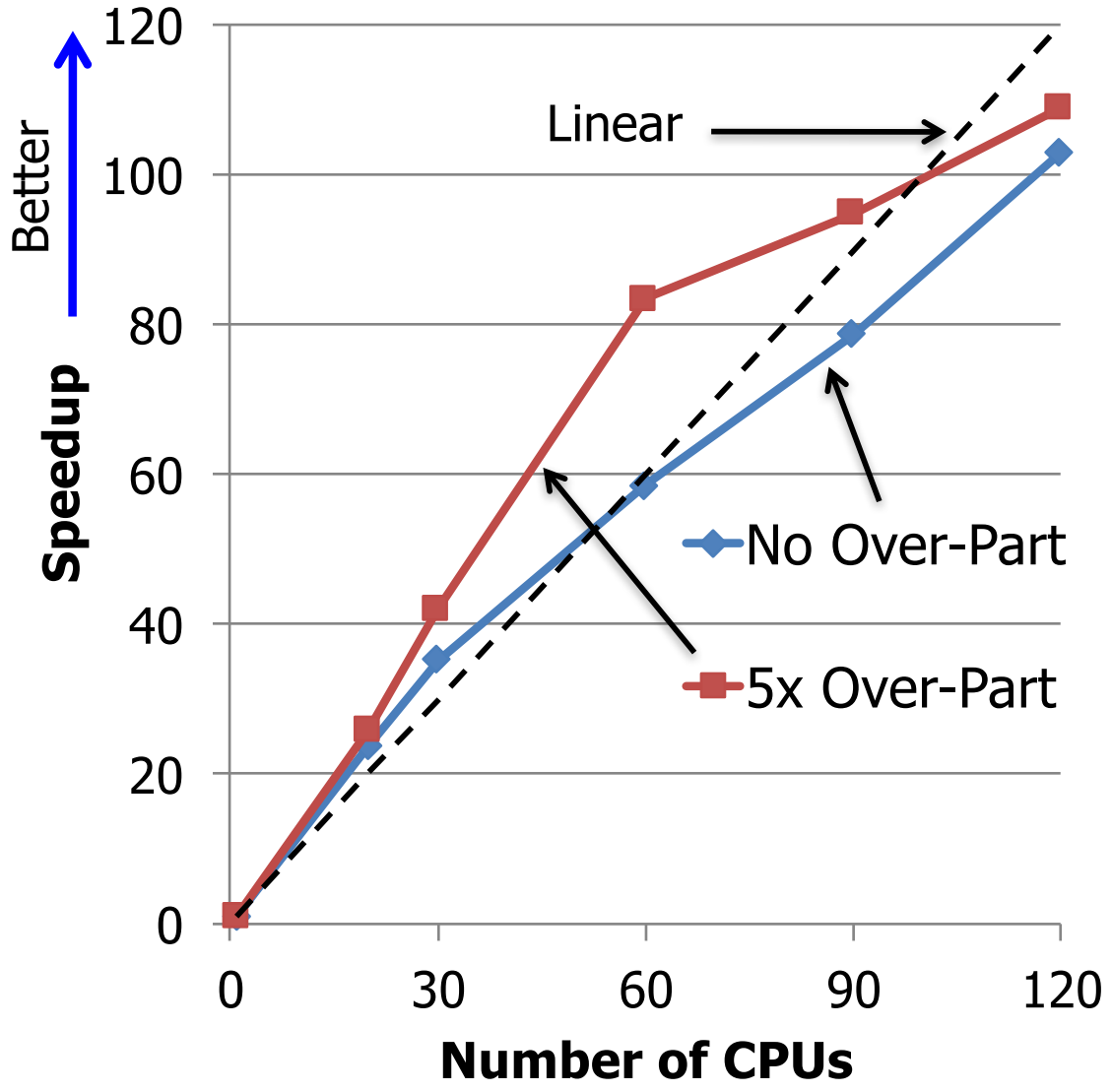
Experiments

- Implemented in C++ using MPICH2 as a message passing API
- Ran on Intel OpenCirrus cluster: 120 processors
  - 15 Nodes with 2 x Quad Core Intel Xeon Processors
  - Gigabit Ethernet Switch
- Tested on Markov Logic Networks obtained from Alchemy [Domingos et al. SSPR 08]
  - Present results on largest UW-Systems and smallest UW-Languages MLNs

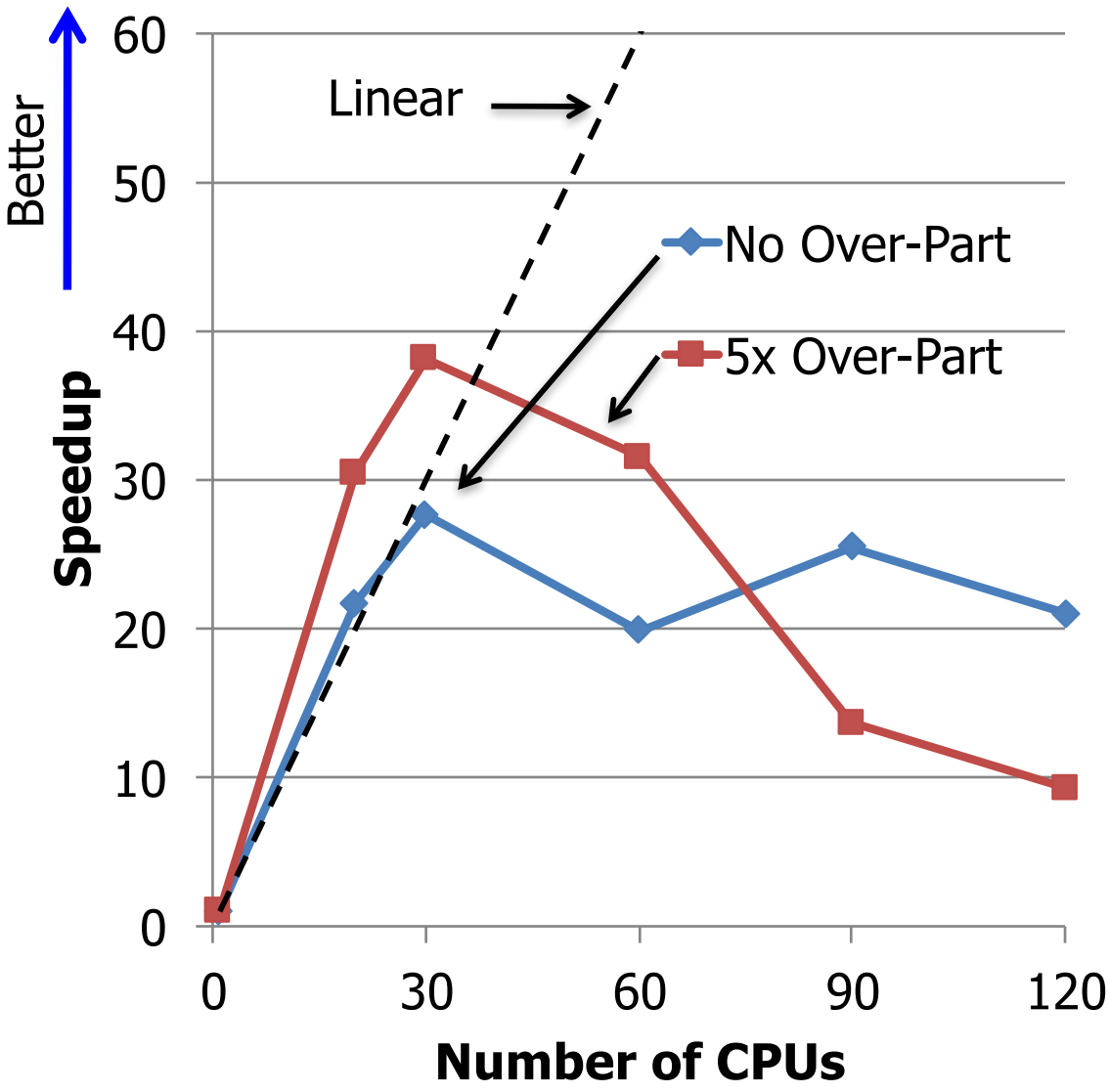
Parallel Performance (Large Graph)

- UW-Systems
  - 8K Variables
  - 406K Factors
- Single Processor Running Time:
  - 1 Hour
- Linear to Super-Linear up to 120 CPUs
  - Cache efficiency



Parallel Performance (Small Graph)

- UW-Languages
  - 1K Variables
  - 27K Factors
- Single Processor Running Time:
  - 1.5 Minutes
- Linear to Super-Linear up to 30 CPUs
  - Network costs quickly dominate short running-time



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Summary

- **Splash Operation** generalization of the optimal parallel schedule on chain graphs
- **Belief**-based scheduling
  - Addresses message scheduling issues
  - Improves accuracy and convergence
- **DBRSplash** an efficient **distributed** parallel inference algorithm
  - Over-partitioning to improve work balance
- Experimental results on large factor graphs:
  - **Linear** to **super-linear** speed-up using up to 120 processors

Thank You

Acknowledgements

Intel Research Pittsburgh: OpenCirrus Cluster

AT&T Labs

DARPA

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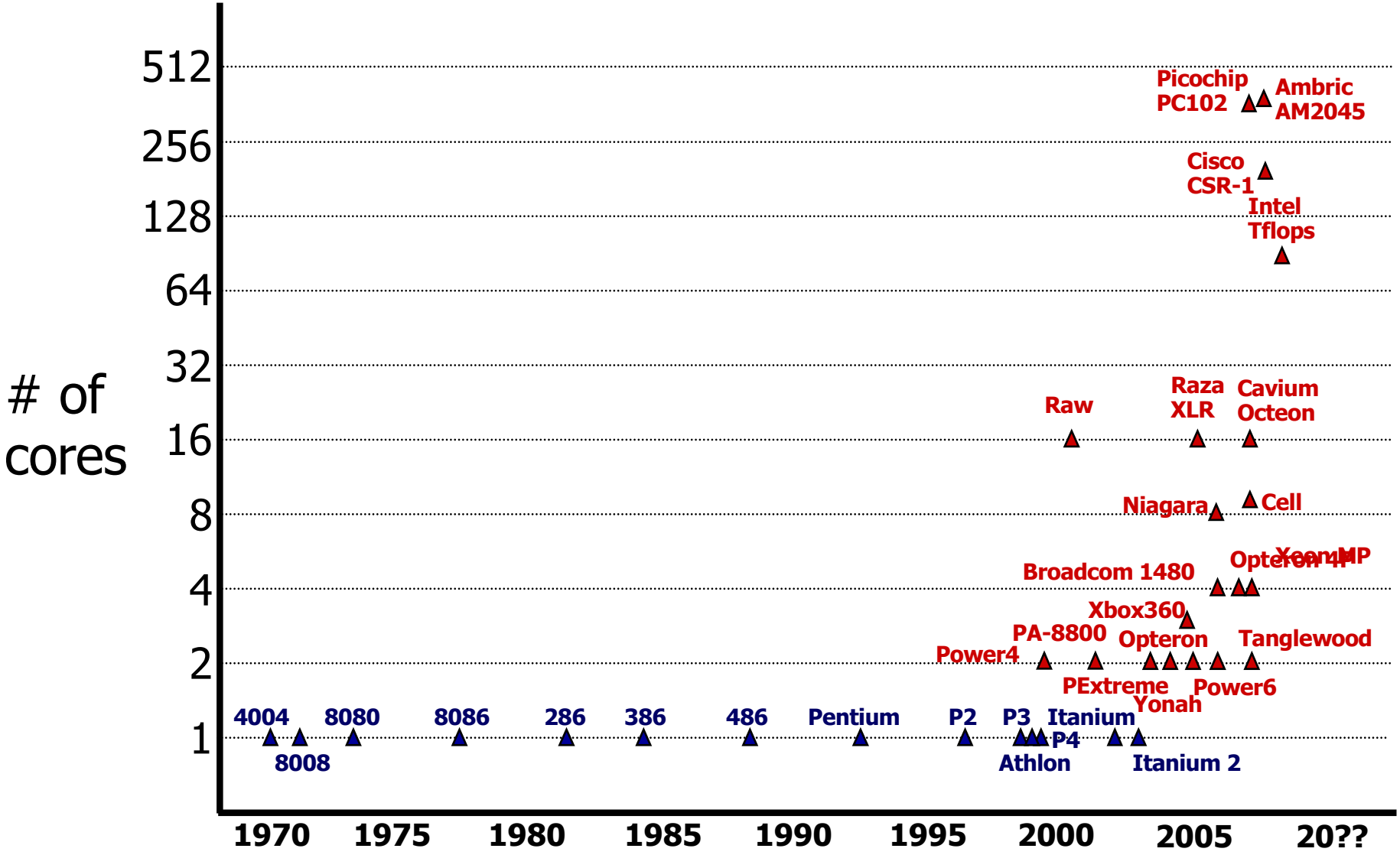
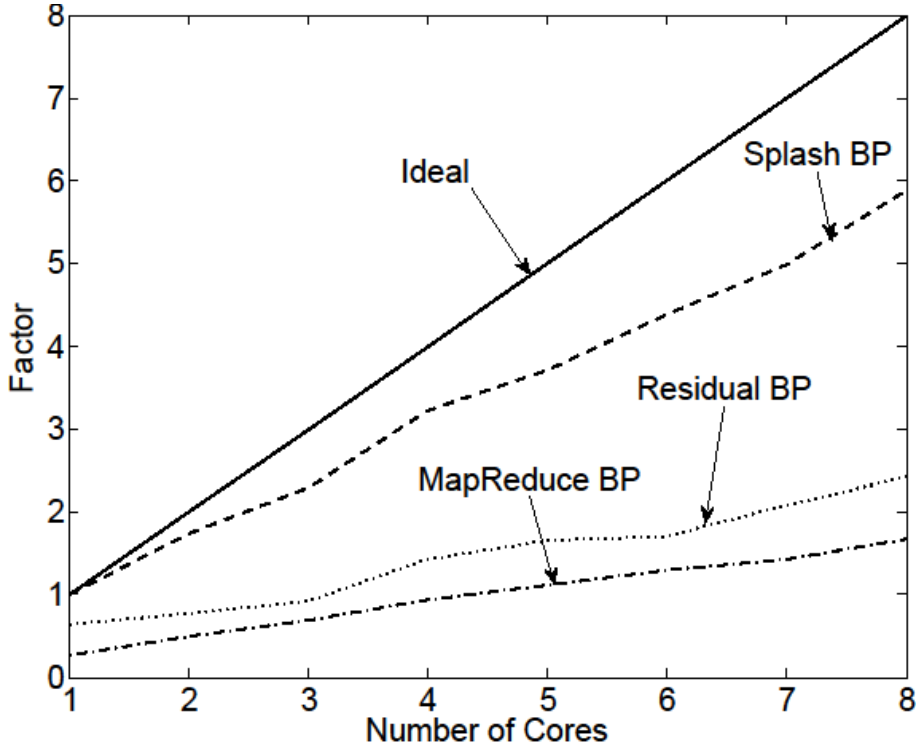
Exponential Parallelism

- From Saman Amarasinghe:



AIStats09 Speedup

3D –Video Prediction



Protein Side-Chain Prediction