Cornell University

Asynchronous Large-Scale Graph Processing Made Easy

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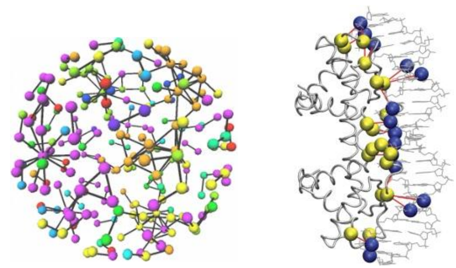
Cornell University

Graphs are ***ubiquitous***..

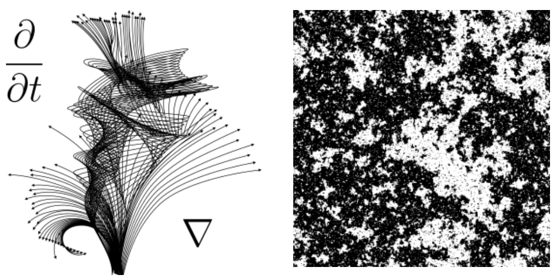
Social Networks

Web

Retail Advertising



DNA Analysis



Physical Simulations

Computer Vision

- Capture complex ***dependencies*** and ***interactions***

- Become ***essential*** in knowledge discovery and scientific studies

Existing Graph Processing Frameworks

GraphLab

GOLDENORB

Pregel

Naiad

PROJECT PEGASUS

APACHE GIRAPH

APACHE GIRAPH

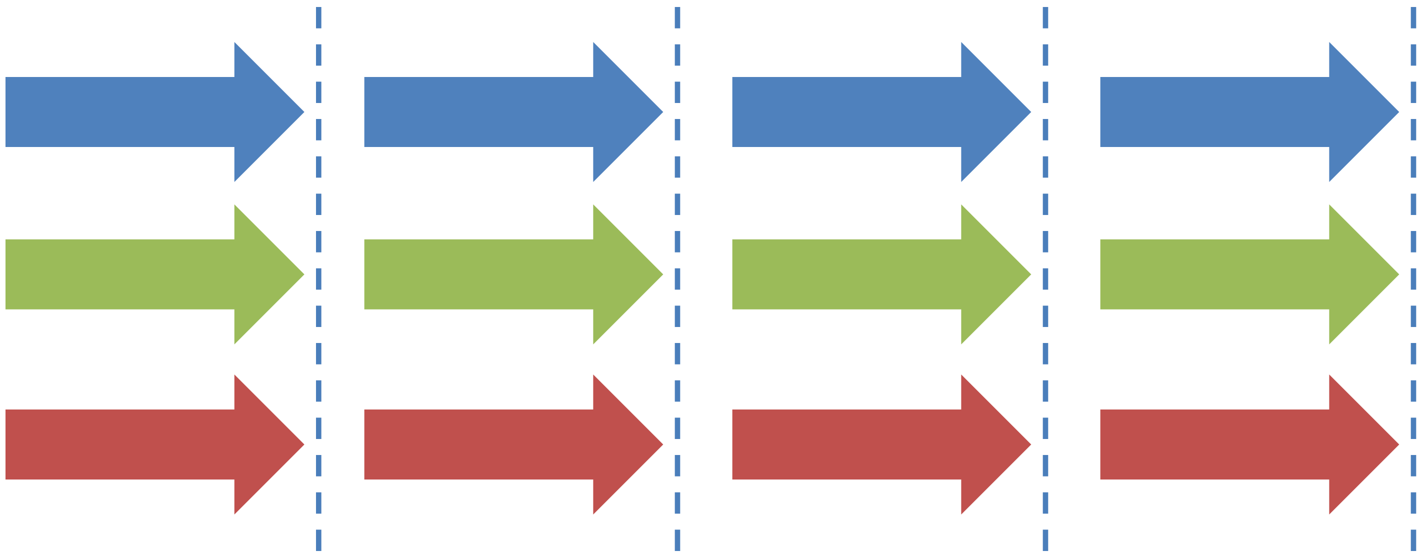
Galois

PrIter

Existing Graph Processing Frameworks

- Either follow BSP to compute ***synchronously***
  - Data is updated simultaneously and iteratively
  - Easy to program

Existing Graph Processing Frameworks



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Existing Graph Processing Frameworks

GraphLab

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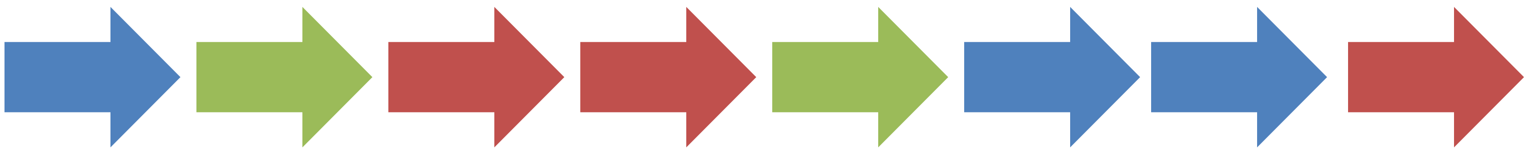
Galois

- Or compute ***asynchronously***
  - Data updates are (carefully) ordered
  - Data is updated using whatever available dependent state
  - Fast convergence

Existing Graph Processing Frameworks



- Or compute ***asynchronously***
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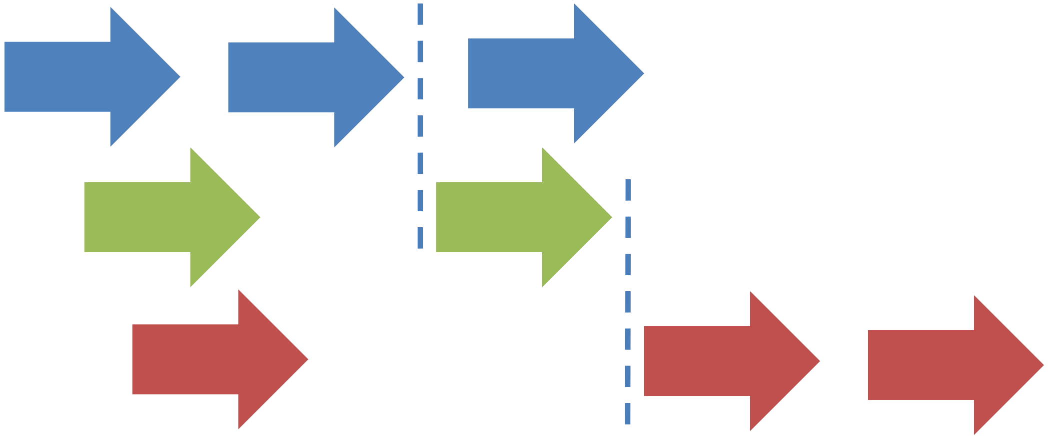
Existing Graph Processing Frameworks



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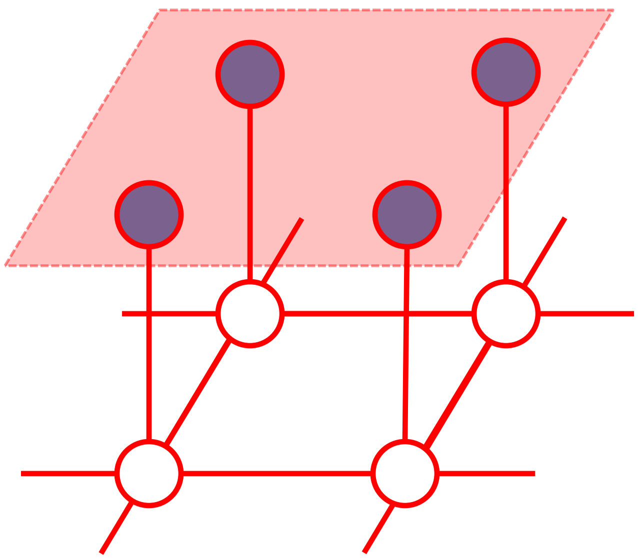
Research Goal:

A new graph computation framework that allows:

- *Sync. implementation for easy programming*
- *Async. execution for better performance*
    - ***Without** reimplementing everything*

Running Example: Belief Propagation

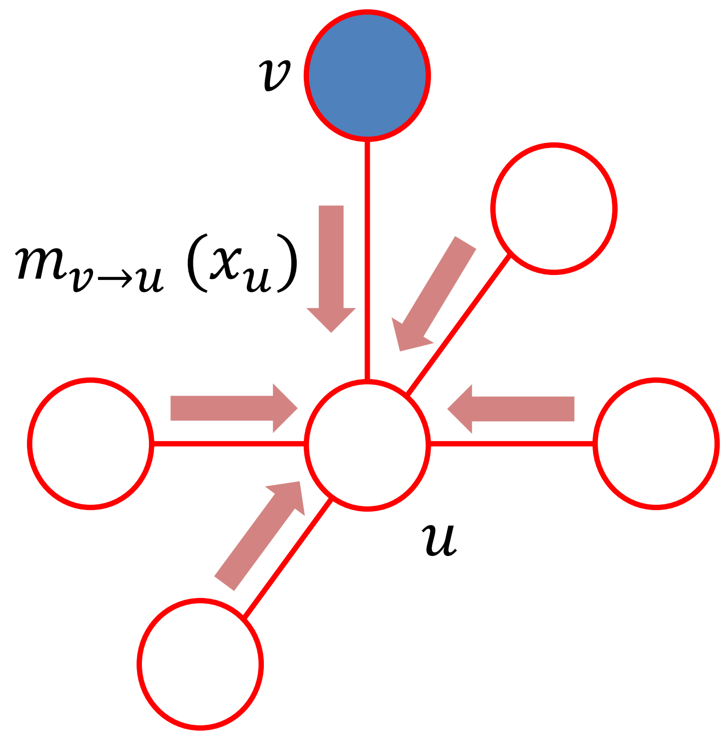
- Core procedure for many inference tasks in graphical models
  - Example: MRF for Image Restoration



Running Example: Belief Propagation

- Based on message passing to update local belief of each vertex:

$$b_u(x_u) \propto \phi_u(x_u) \prod_{e_{w,u} \in E} m_{w \to u}(x_u) \quad (1)$$



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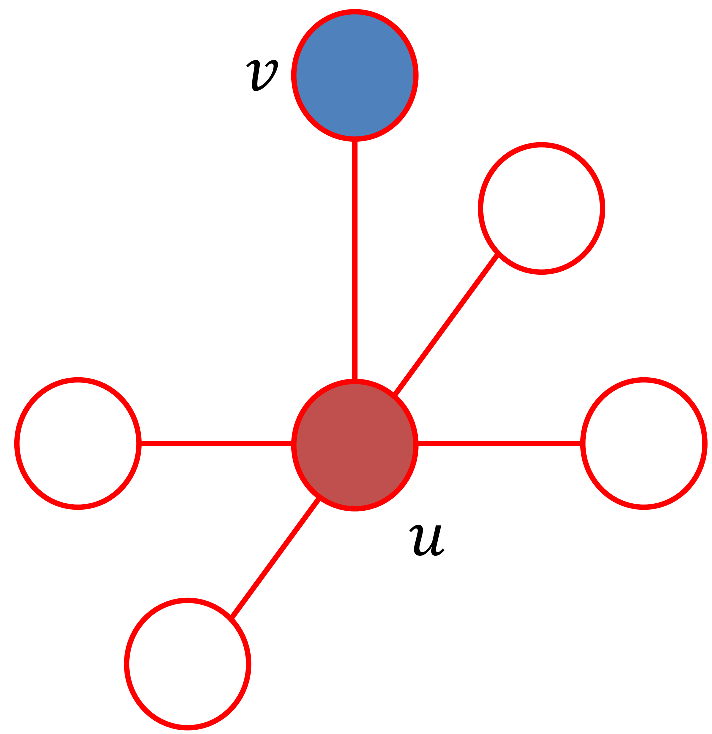

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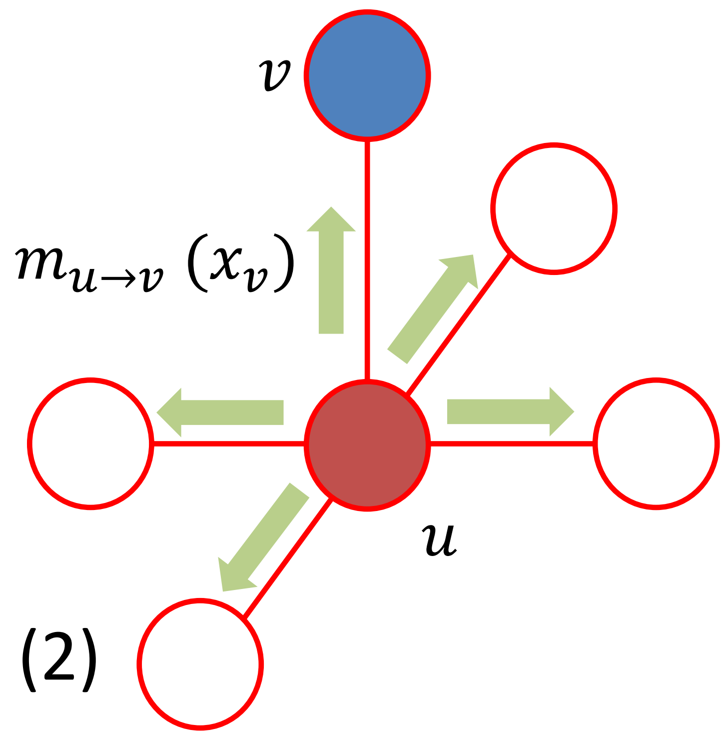
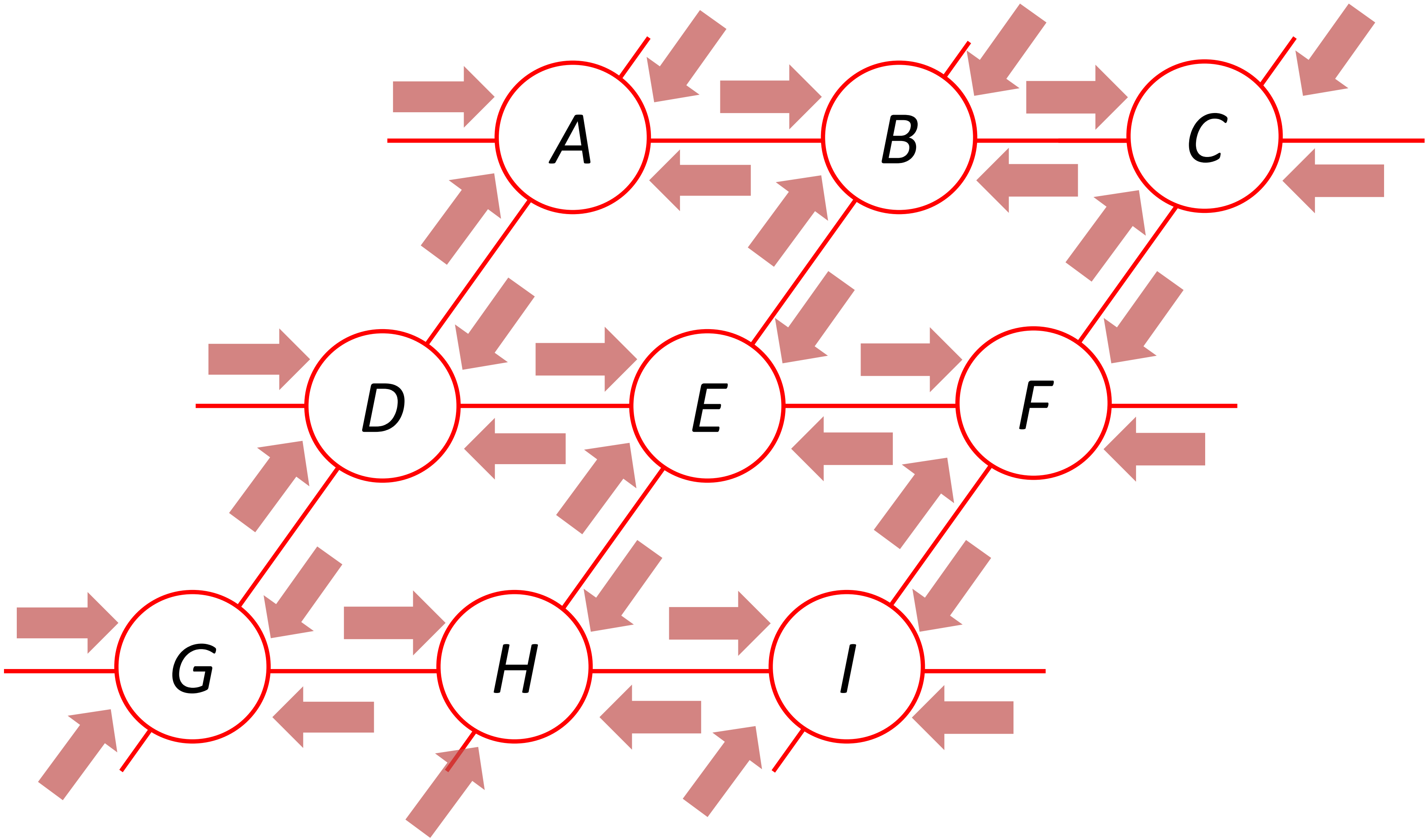
$$m_{u \to v}(x_v) \propto \sum_{x_u \in \Omega} \phi_{u,v}(x_u, x_v) \cdot \frac{b_u(x_u)}{m_{v \to u}(x_u)} \quad (2)$$



Original BP Implementation



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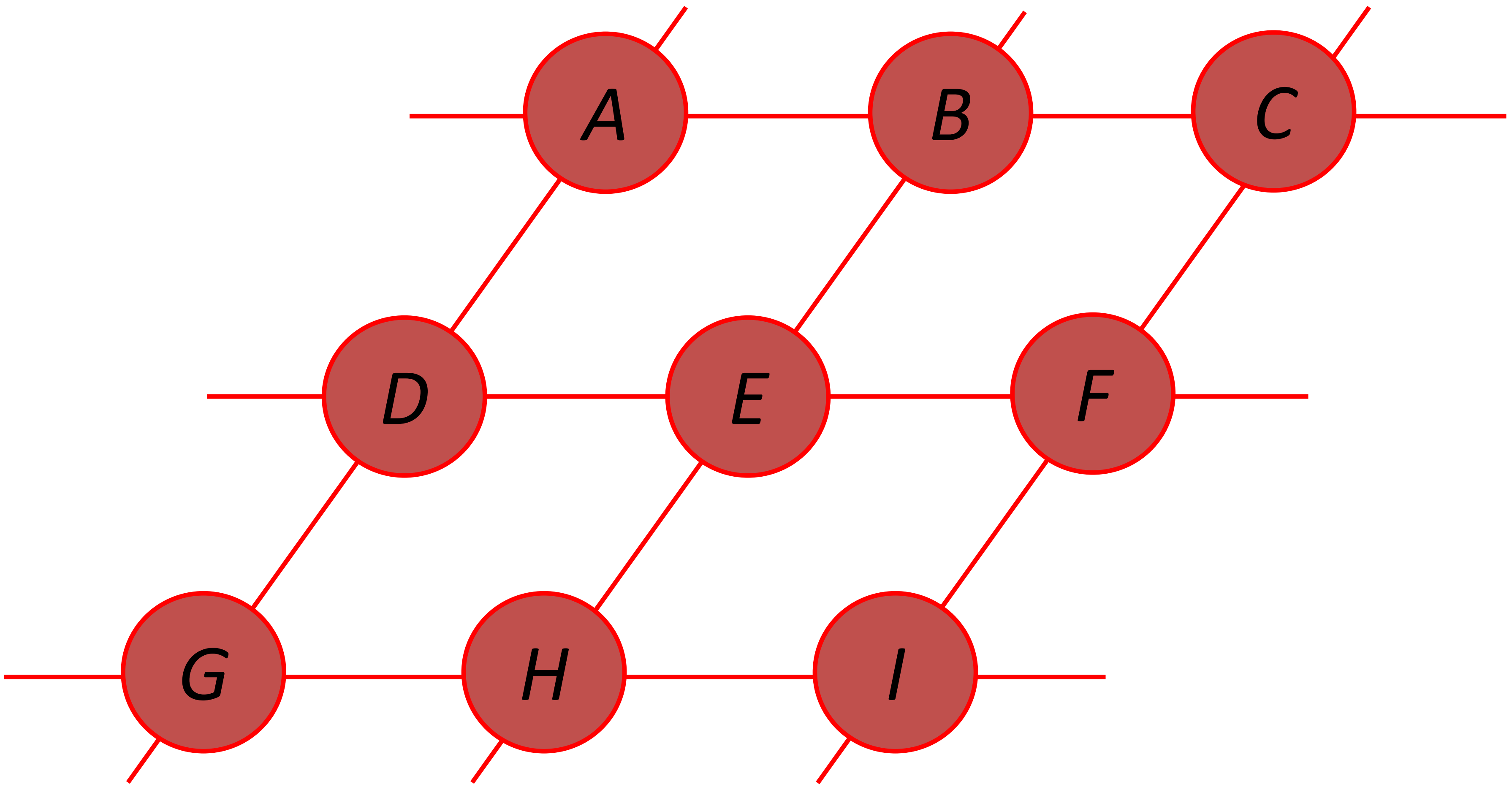

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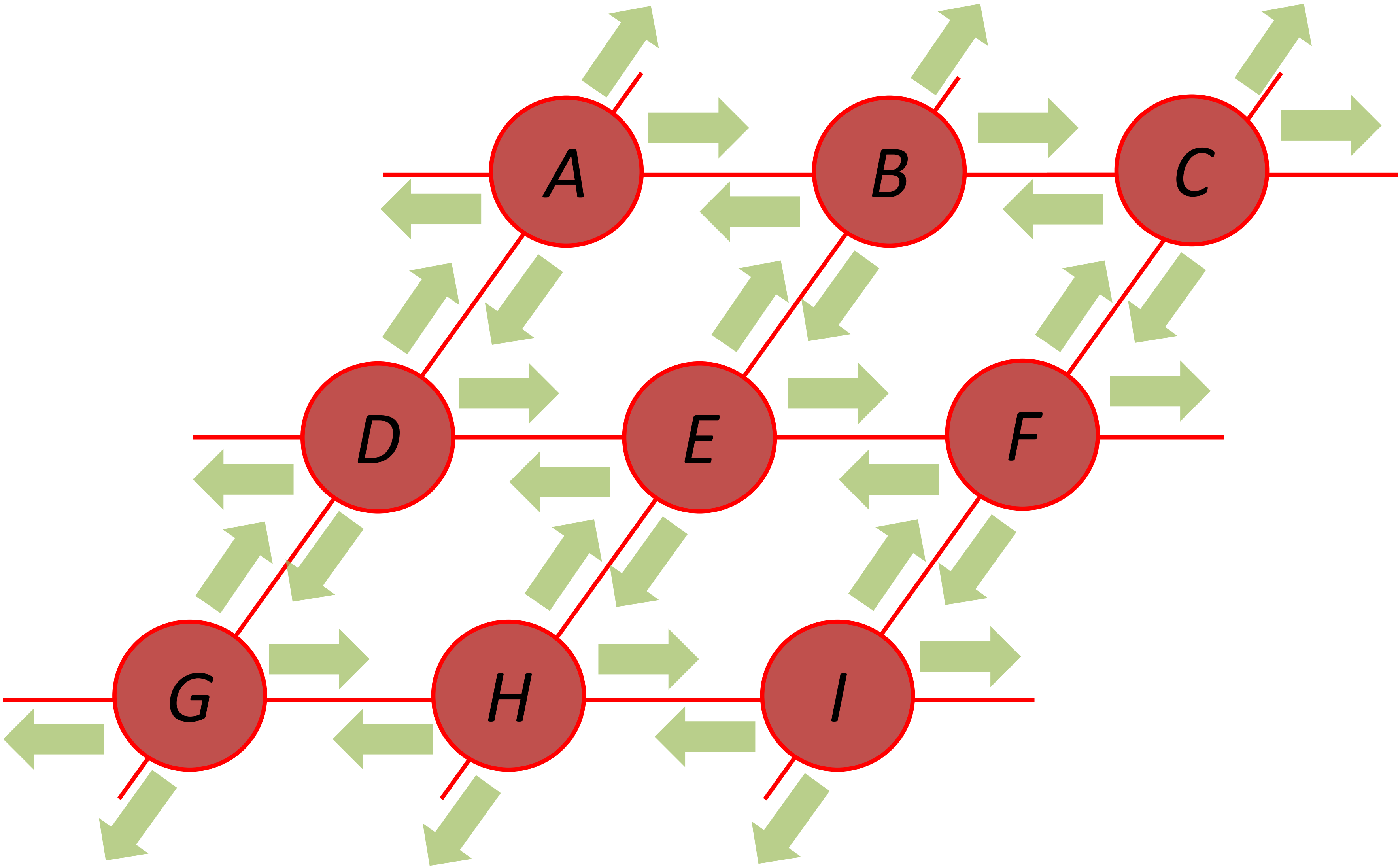
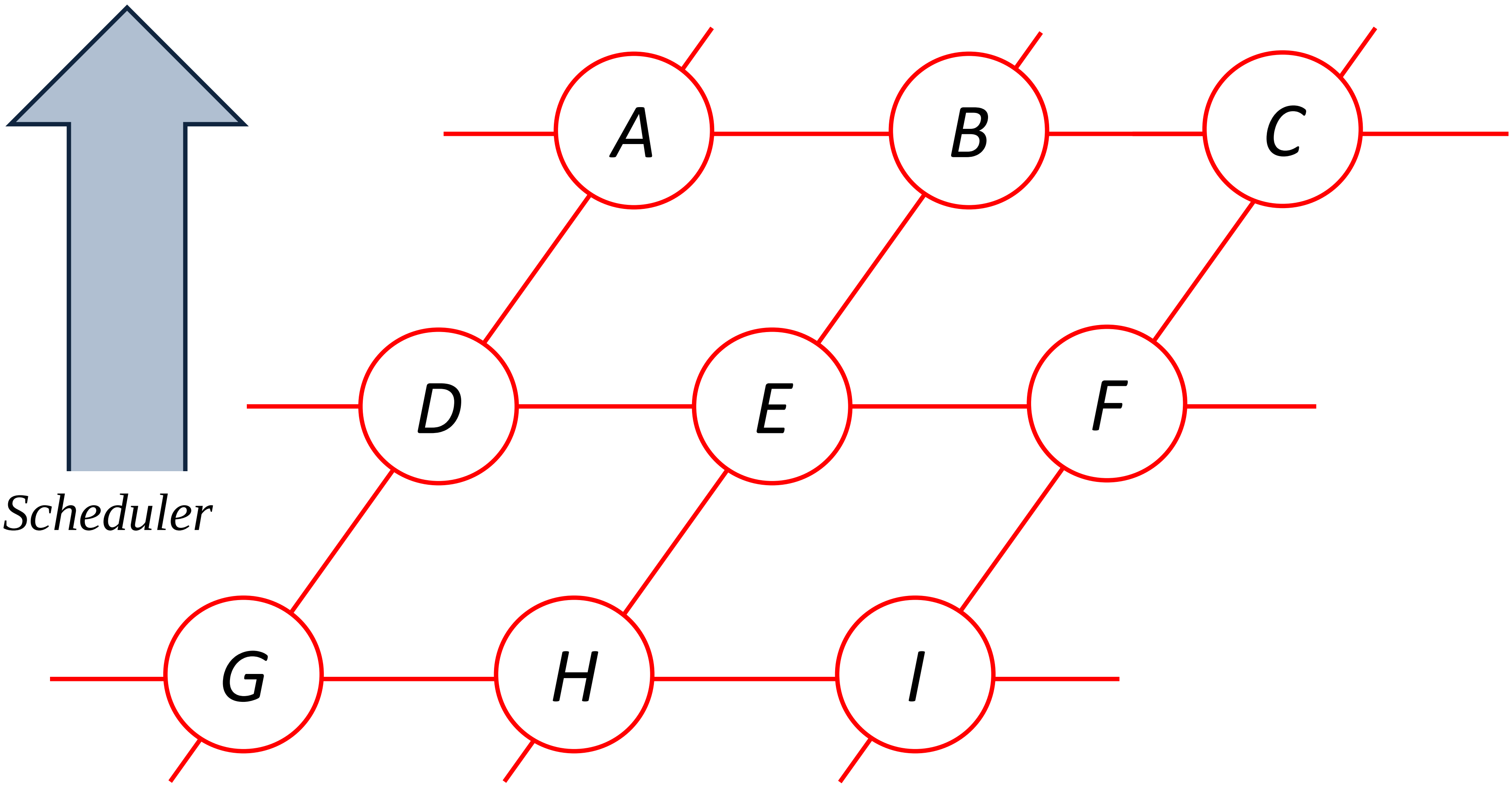


Residual BP Implementation



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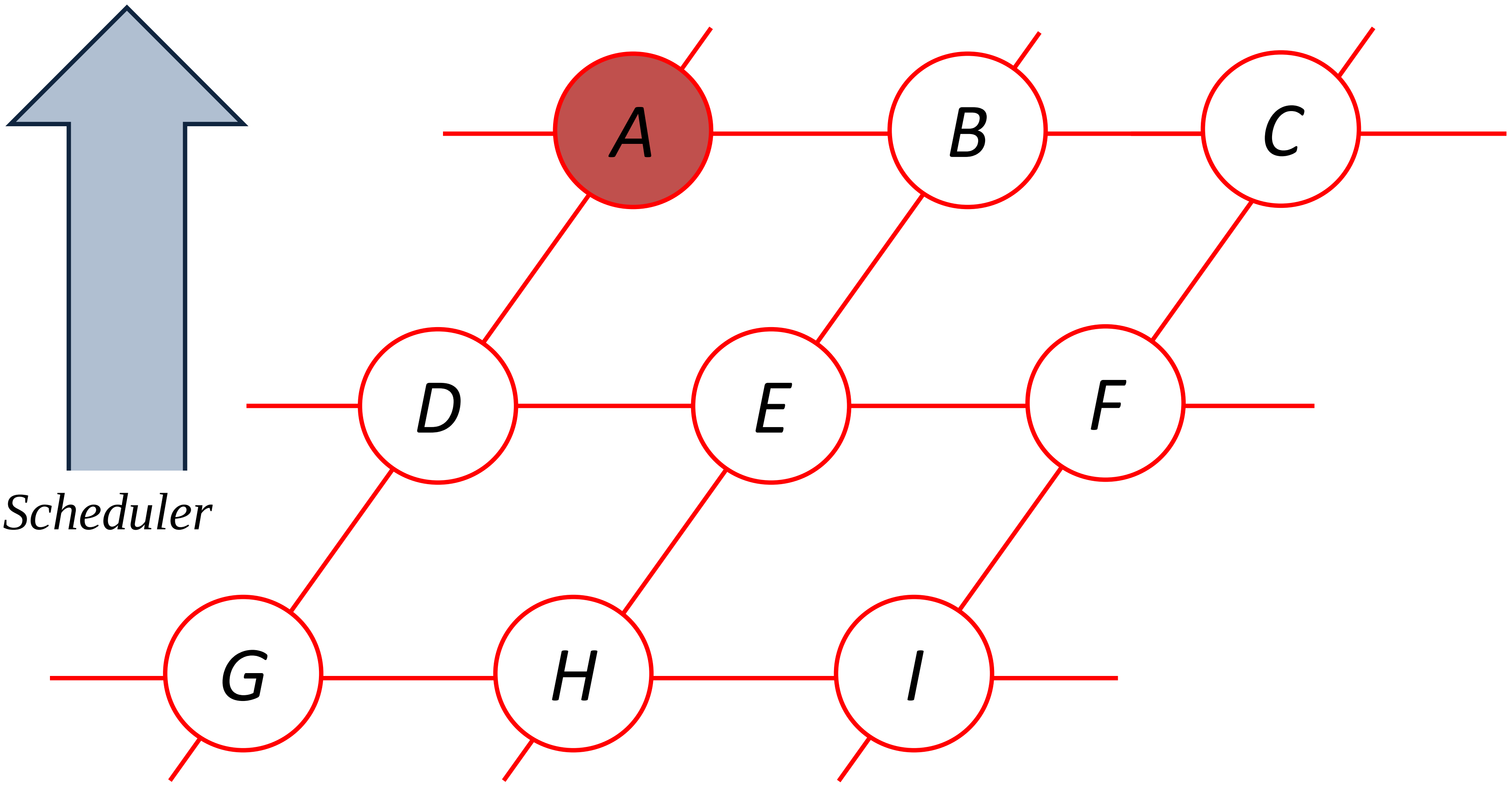

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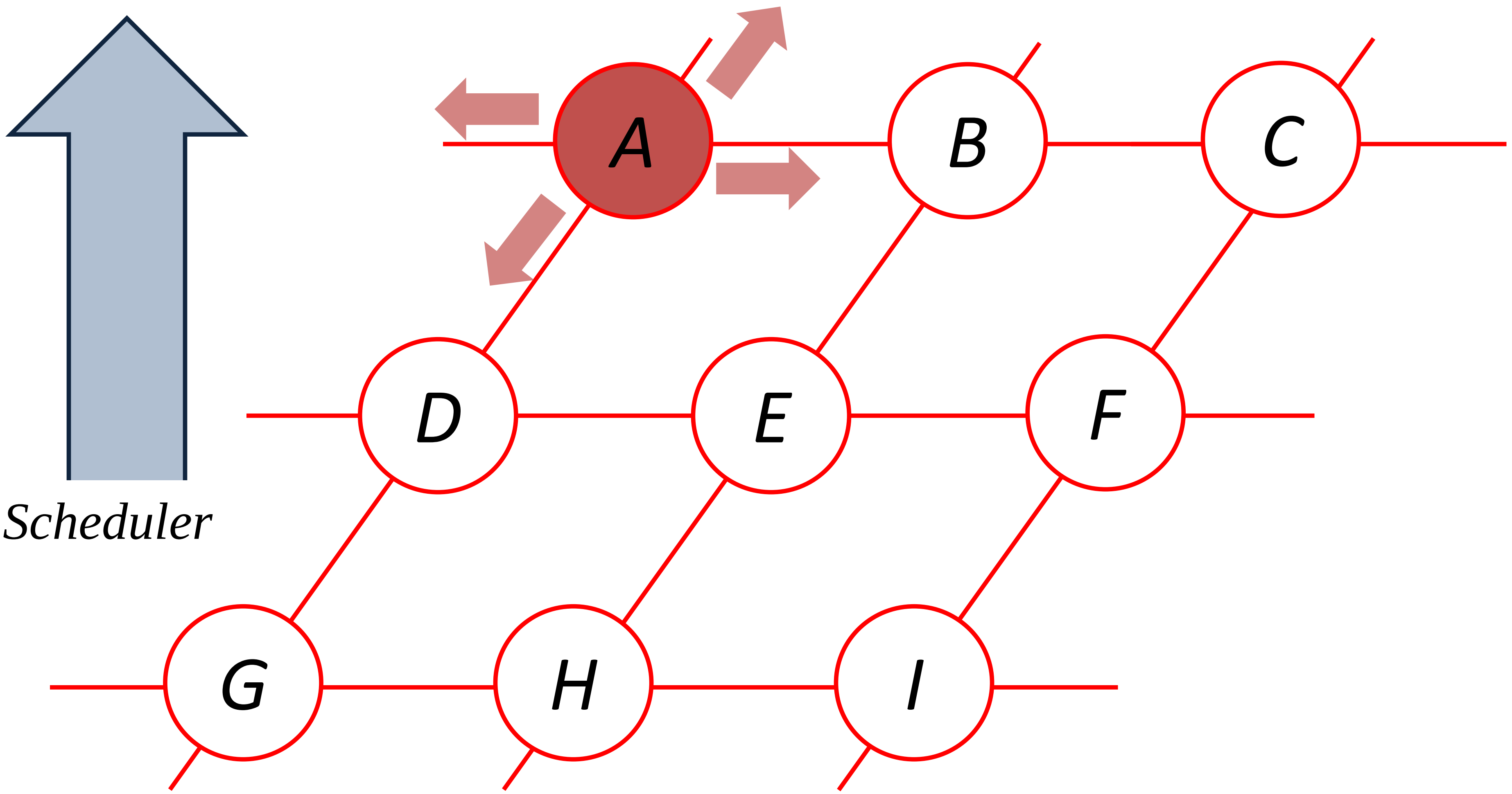

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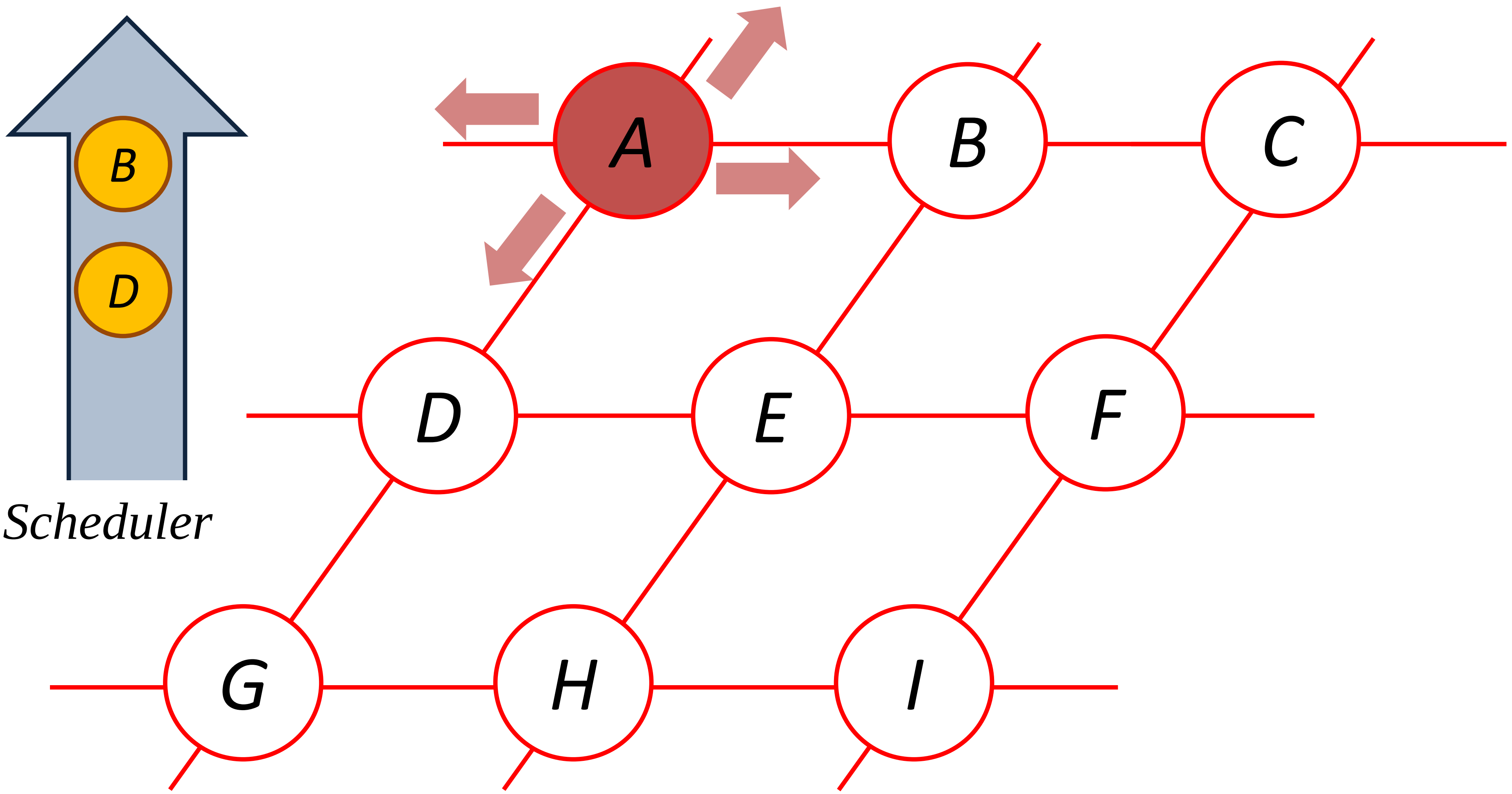

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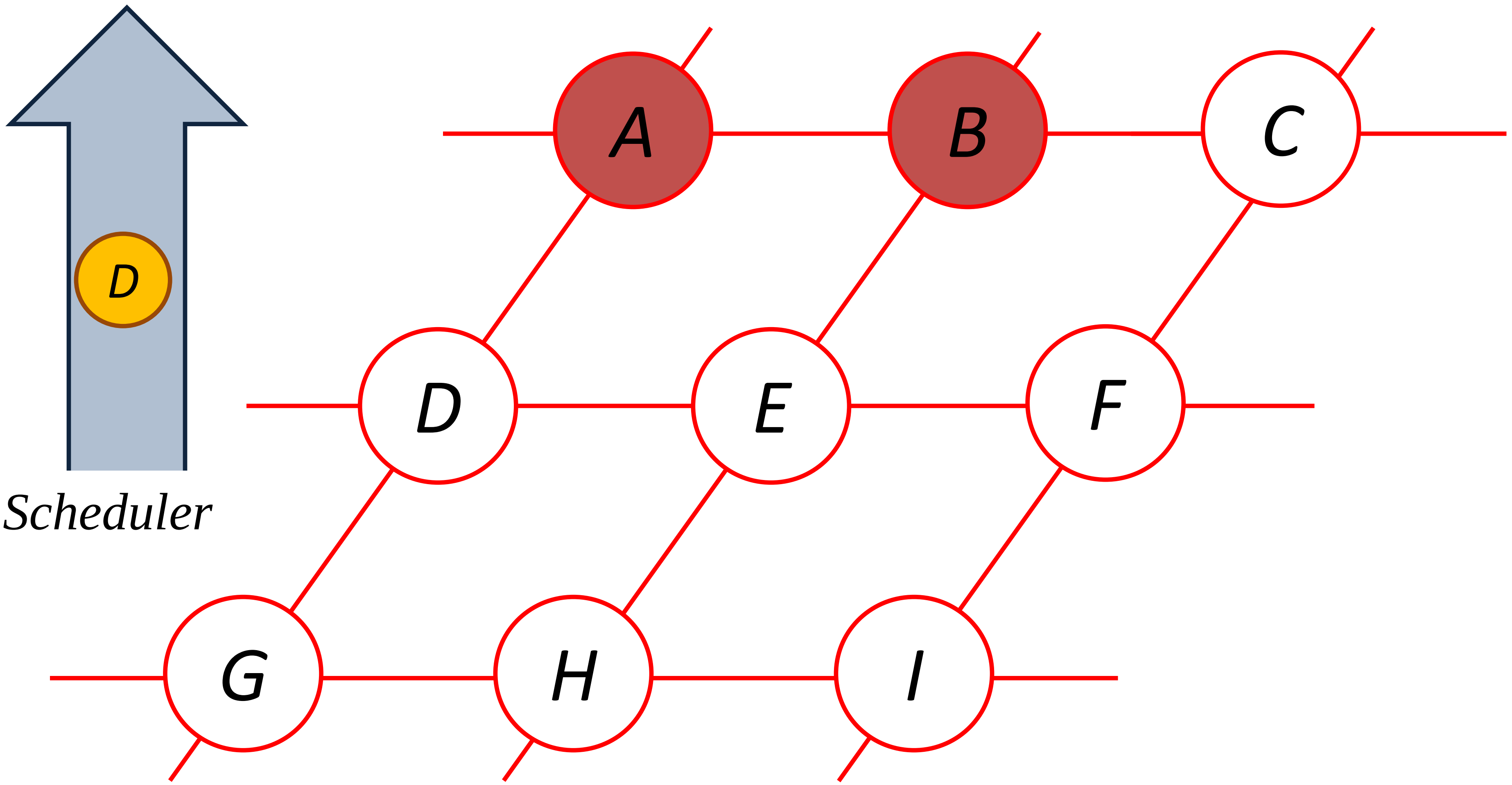

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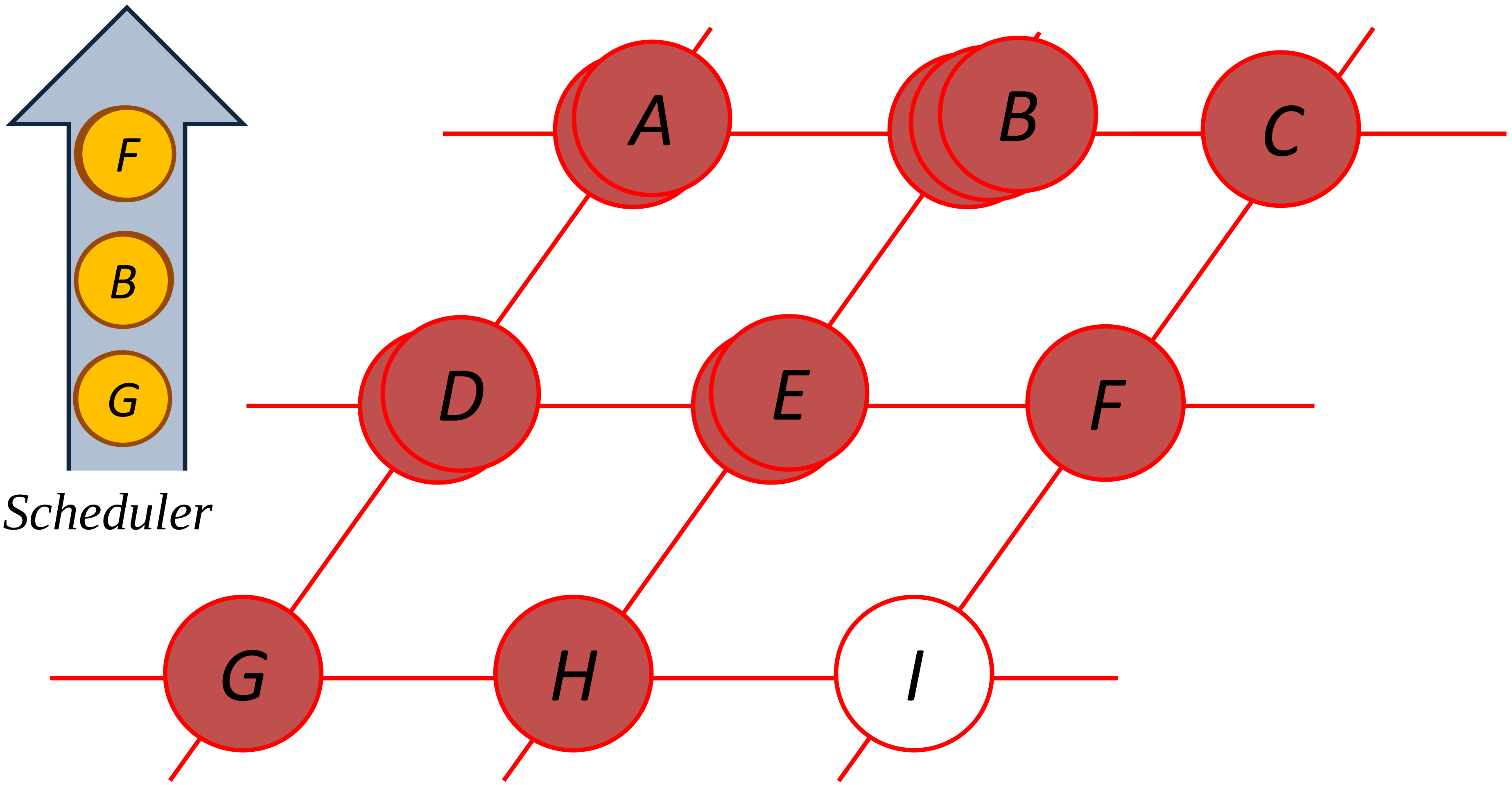

Comparing Original and Residual BPs

Algorithm 1: Original BP Algorithm

Initialize $b_u^{(0)}$ as ϕ_u for all $u \in V$;
Calculate the message $m_{u\to v}^{(0)}$ using $b_u^{(0)}$ according to Eq. 2 for all $u \to v \in E$;
Initialize $t = 0$;
repeat
  $t = t + 1$;
  foreach $u \in V$ **do**
    Calculate $b_u^{(t)}$ using $m_{w\to u}^{(t-1)}$ according to Eq. 1 ;
    foreach outgoing edge $e_{u,v}$ *of* u **do**
      Calculate $m_{u\to v}^{(t)}$ using $b_u^{(t)}$ according to Eq. 2 ;
    end
  end
until $\forall u \in V, ||b_u^{(t)} - b_u^{(t-1)}|| \le \epsilon$;

Algorithm 2: Residual BP Algorithm

Initialize $b_u^{(new)}$ as ϕ_u and $b_u^{(old)}$ as uniform distribution for all $u \in V$;
Initialize $m_{u\to v}^{(old)}$ as uniform distribution for all $u \to v \in E$;
Calculate message $m_{u\to v}^{(new)}$ using $b_u^{(new)}$ according to Eq. 2 for all $u \to v \in E$;
repeat
  $u = \arg\max_v (\max_{(w,v)\in E} ||m_{w\to v}^{\text{new}} - m_{w\to v}^{\text{old}}||)$;
  Set $b_u^{(old)}$ to $b_u^{(new)}$;
  Calculate $b_u^{(new)}$ using $m_{w\to u}^{(new)}$ according to Eq. 1 ;
  foreach outgoing edge $e_{u,v}$ *of* u **do**
    Set $m_{u\to v}^{(old)}$ to $m_{u\to v}^{(new)}$;
    Calculate $m_{u\to v}^{(new)}$ using $b_u^{(new)}$ according to Eq. 2 ;
  end
until $\forall u \in V, ||b_u^{(new)} - b_u^{(old)}|| \le \epsilon$;

- Computation logic is actually identical: Eq 1 and 2
- Only differs in when/how to apply this logic

GRACE:

- *Separate **vertex-centric computation** from **execution policies***
- *Customizable BSP-style runtime that enables asynchronous execution features*

Vertex-Centric Programming Model

- Update vertex data value based on received messages
- Generate new messages for outgoing edges
- Send out messages to neighbors and vote for halt

```
List<Msg> Proceed(List<Msg> msgs) {
 Distribution newBelief = potent;
 for (Msg m in msgs) {
  newBelief = times(newBelief, m.belief);
 }
 List<Msg> outMsgs(outDegree);
 for (Edge e in outgoingEdges) {
  Distribution msgBelief;
  msgBelief = divide(newBelief, Msg[e]);
  msgBelief = convolve(msgBelief, e.potent);
  msgBelief = normalize(msgBelief);
  outMsg[e] = new Msg(msgBelief);
 }
 if (L1(newBelief, belief) < eps) voteHalt();
 belief = newBelief;
 return outMsgs;
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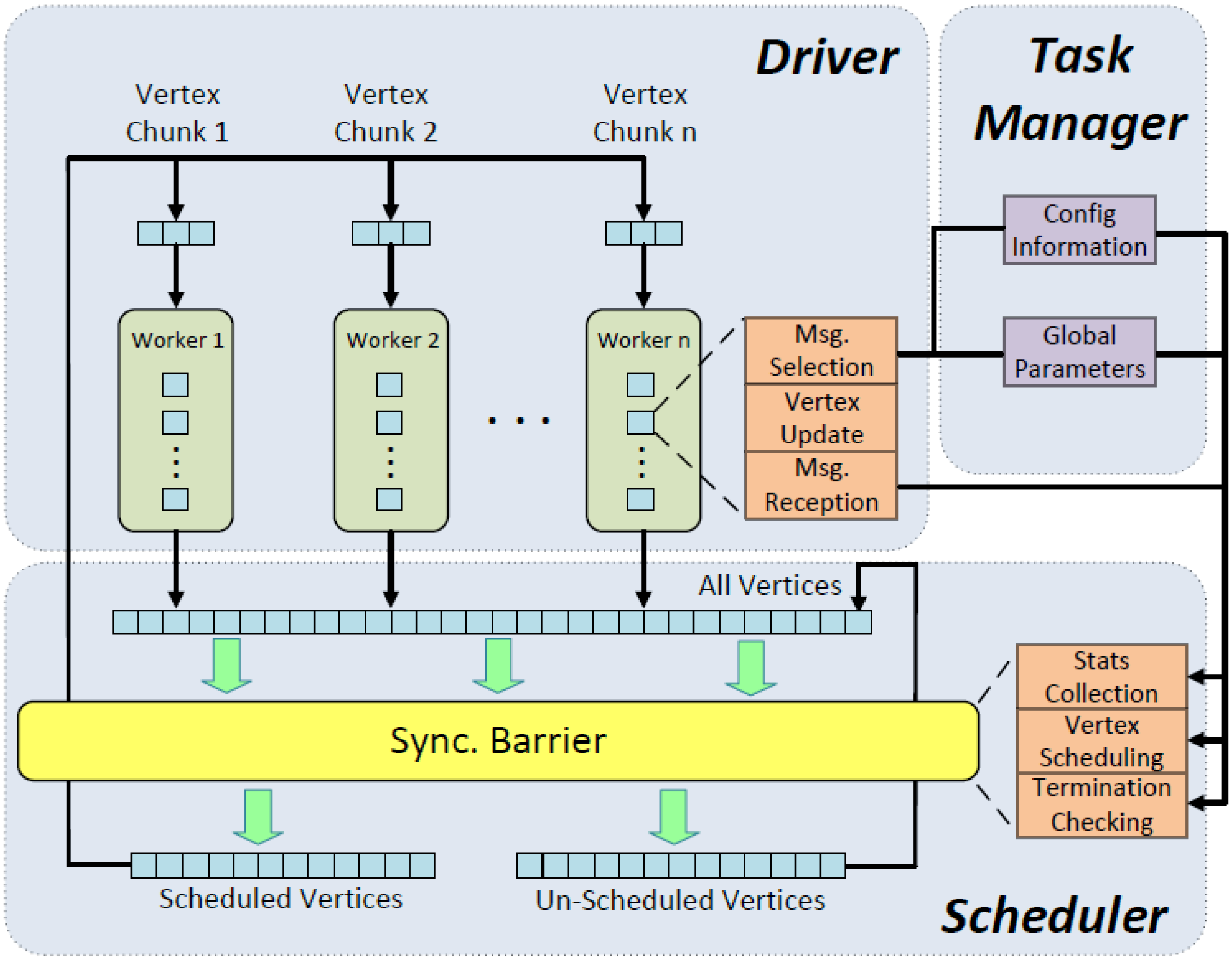
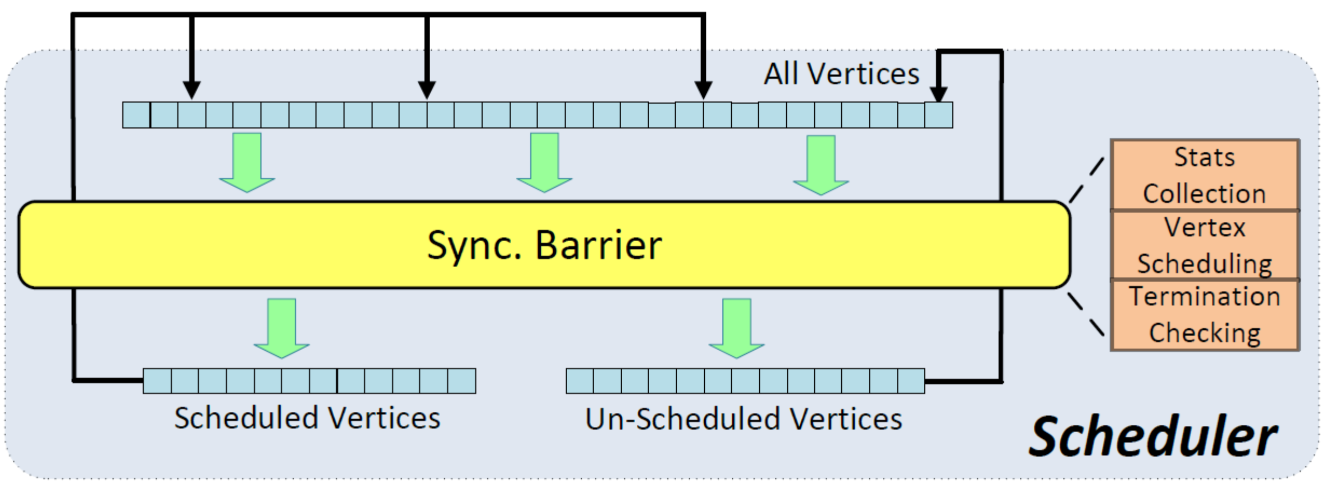
Customizable BSP-Style Runtime



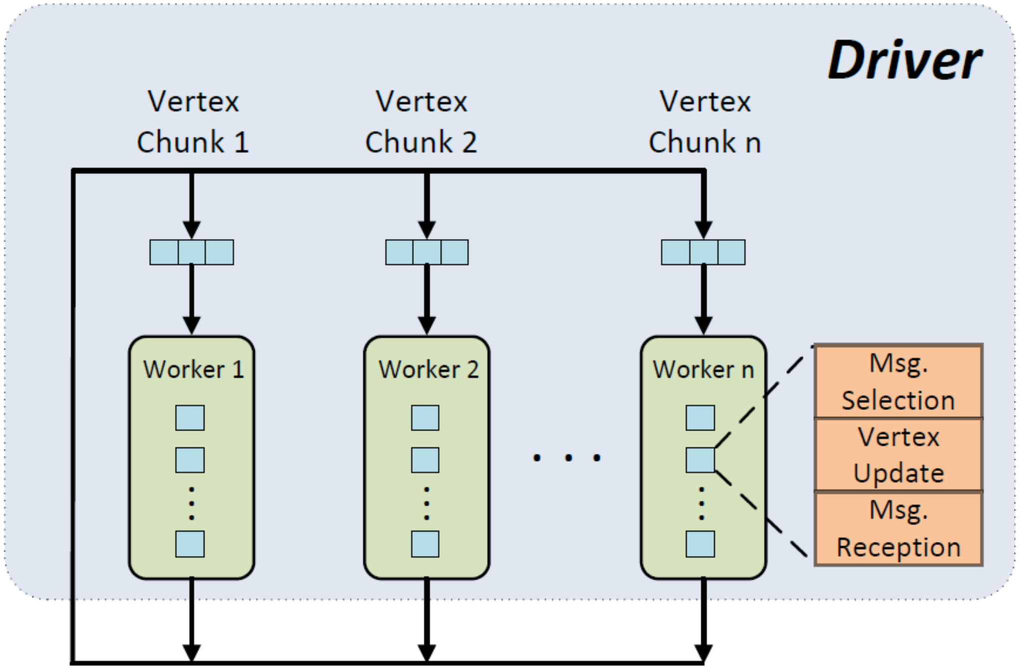
Scheduler

- At each tick barrier:
  - Check if the computation can stop
  - Collect graph data snapshot
  - Schedule the subset of vertices for the next tick



Driver

- For each worker:
  - Get a partition of the graph
  - Apply update function for scheduled vertices
  - Send newly generated messages to neighbors



- When update a vertex:
  - Choose which received messages to use
  - Specify what to do with the newly received messages

Back to Original BP

- Schedule all vertices at the tick barrier

```
void OnPrepare(List<Vertex> vertices) {
    scheduleAll(true);
}
```

- Use the message received from the last tick

```
Msg OnSelectMsg(Edge e) {
    return PrevRecvdMsg(e);
}

void OnRecvMsg(Edge e, Message msg) {
    // Do nothing since every vertex
    // will be scheduled
}
```

Back to Residual BP

- Schedule only one vertex with the highest residual
- Use the most recently received message

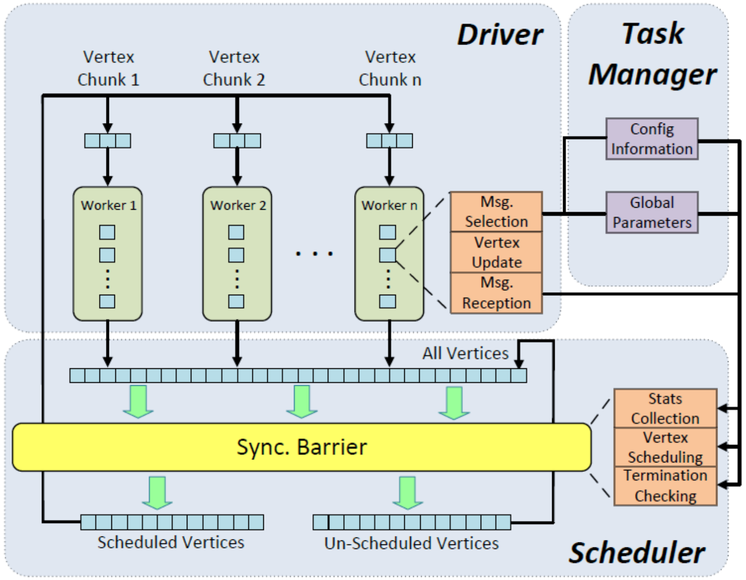
```
void OnPrepare(List<Vertex> vertices) {
   Vertex selected = vertices[0];
   for (Vertex vtx in vertices)
      if (vtx.priority > selected.priority)
       selected = vtx;
   Schedule(selected);
}

Msg OnSelectMsg(Edge e) {
   return GetLastRecvdMsg(e);
}

void OnRecvMsg(Edge e, Message msg) {
   Distn lastBelief = GetLastUsedMsg(e).belief;
   float residual = L1(newBelief, msg.belief);
   UpdatePrior(GetRecVtx(e), residual, sum);
}
```

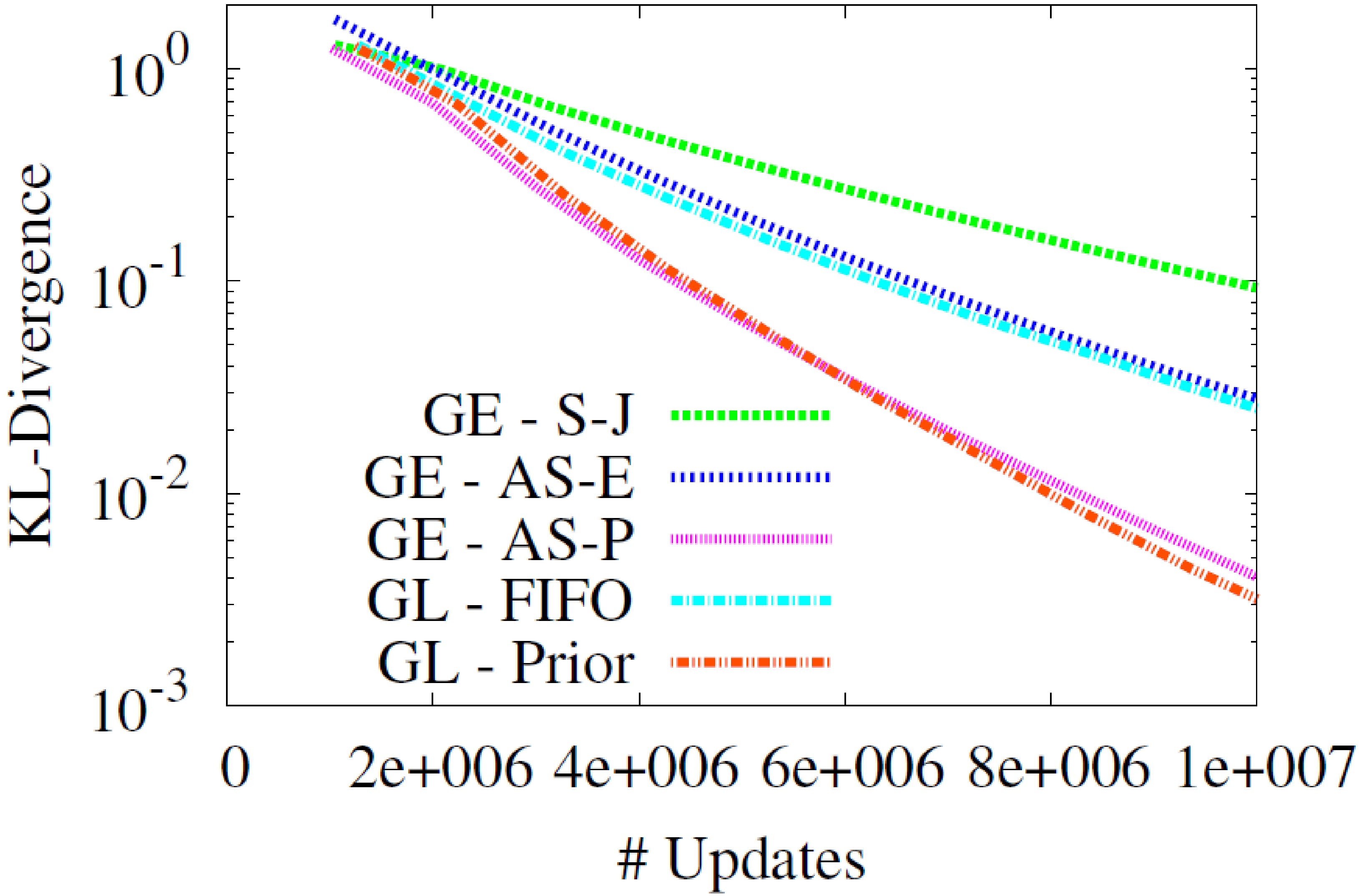
Experimental Setup

- Implementation
  - Multi-core prototype
  - Static graph partitioning
  - Four execution policies
    - Jacobi, Gauss-Seidel, Eager, Prioritized



- Hardware: 8 quad-cores with 128GB RAM

Results: Image Restoration with BP



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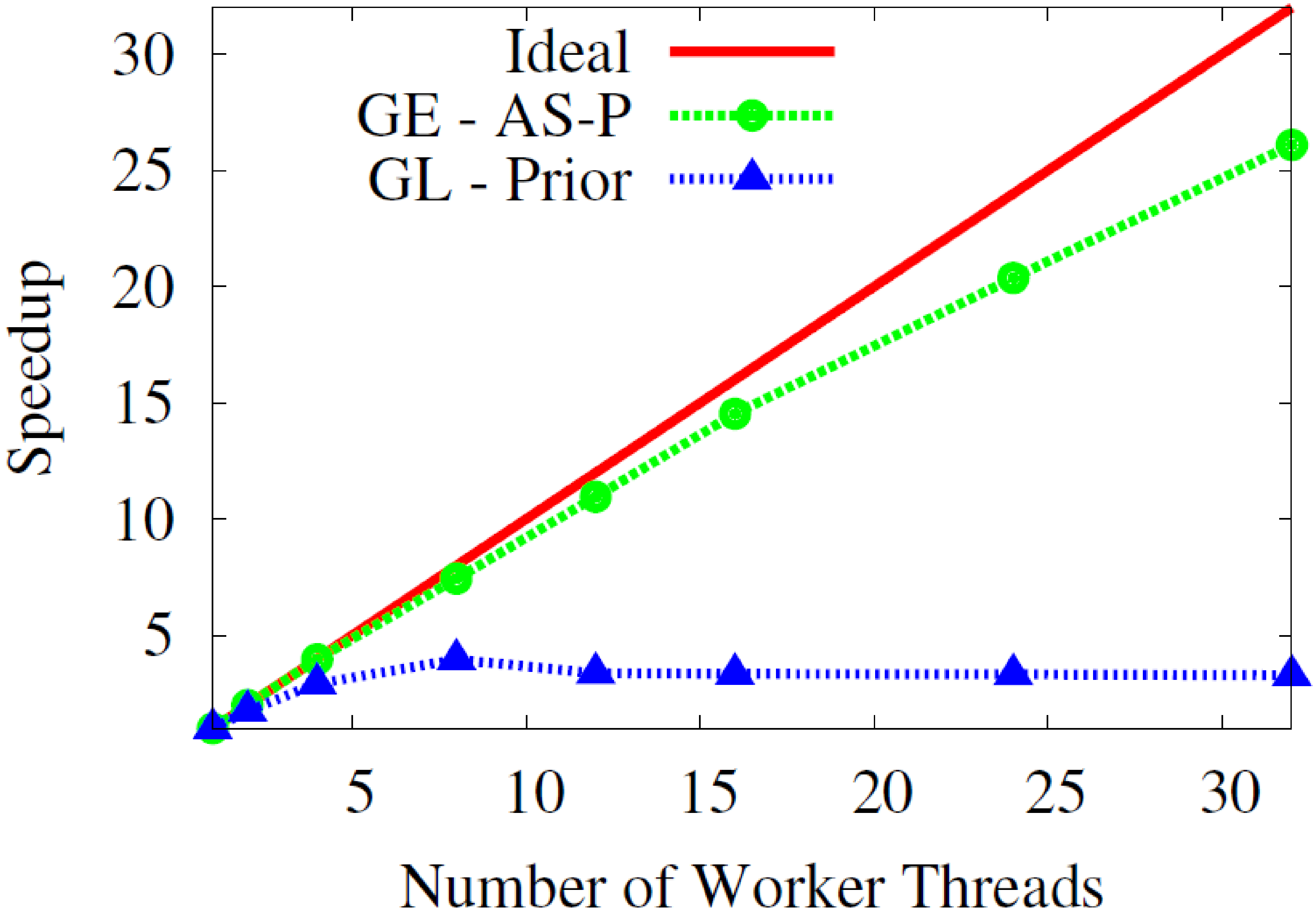

Conclusions

Thank you!

- Graph processing: Code synchronously while execute asynchronously (if it is better)

- We can make such a development cycle easy
  - Code-once with vertex-centric programming model
  - Customizable BSP-style runtime to allow switching with various execution policies

http://www.cs.cornell.edu/bigreddata/grace/