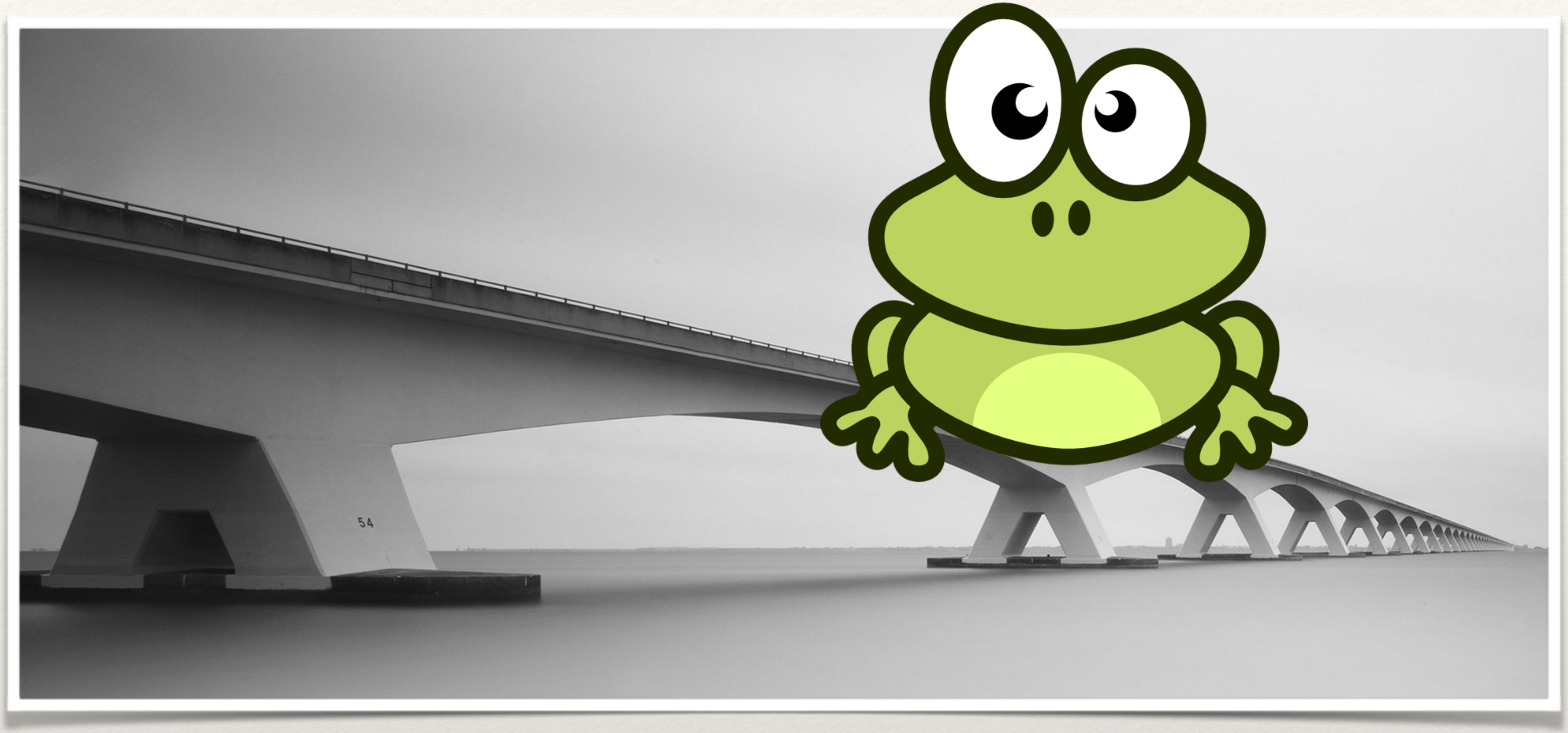


FrogWild!

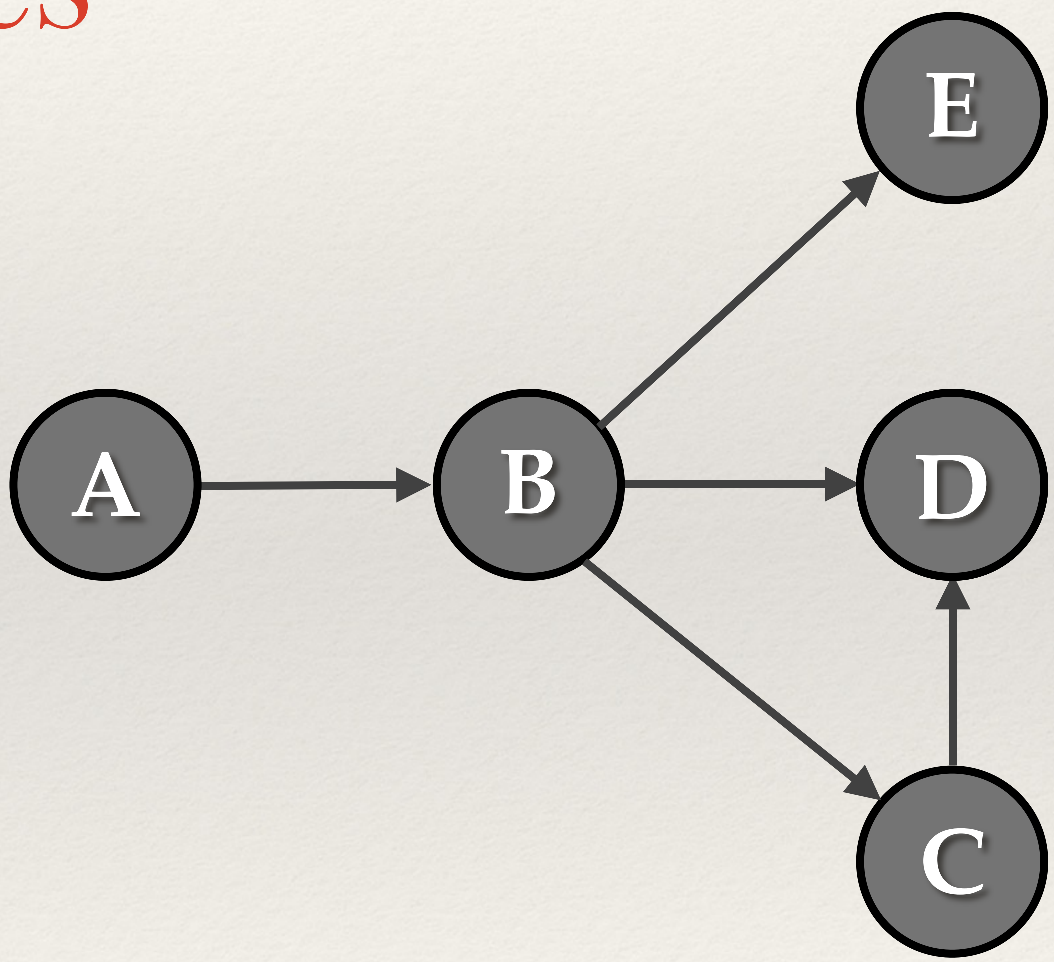
Fast PageRank Approximations on Graph Engines

Ioannis Mitliagkas
Michael Borokhovich
Alex Dimakis
Constantine Caramanis

Web Ranking

Given web graph

Find "important" pages



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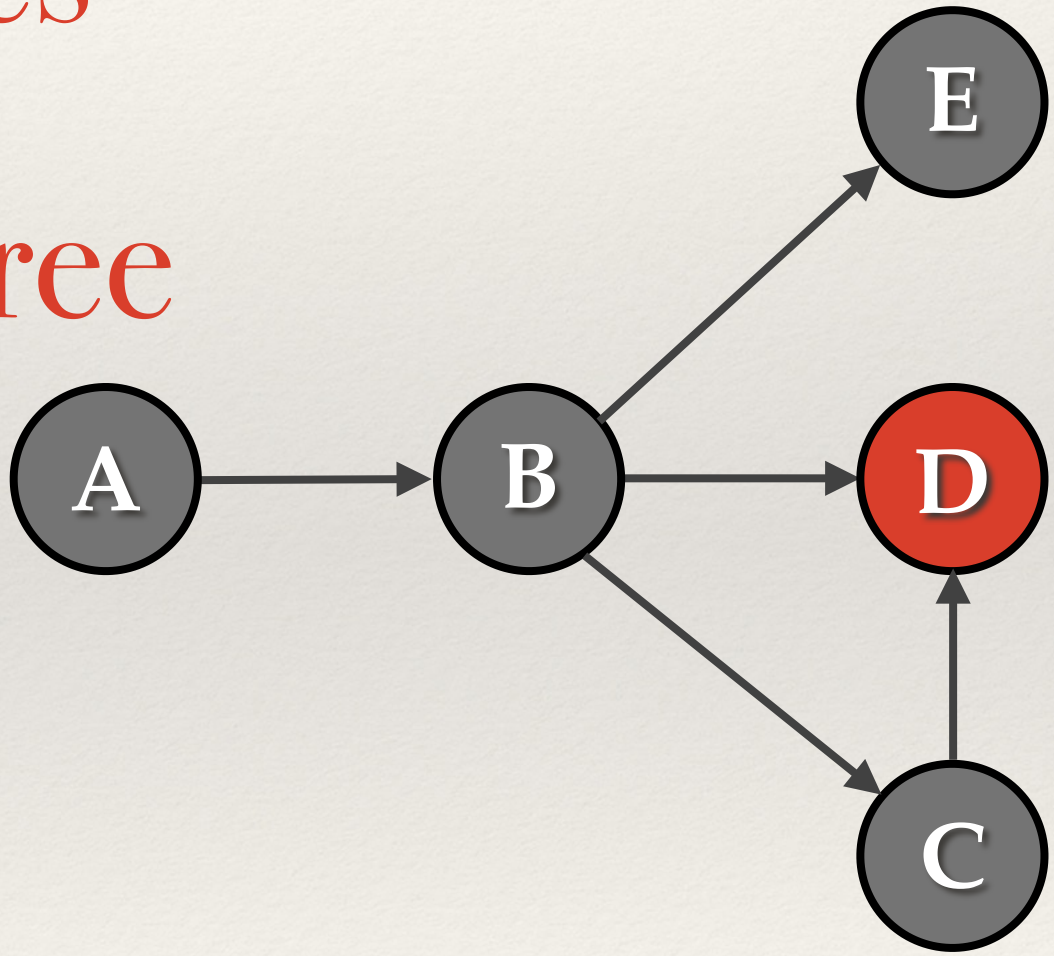
Rank Based on In-degree

Classic Approach



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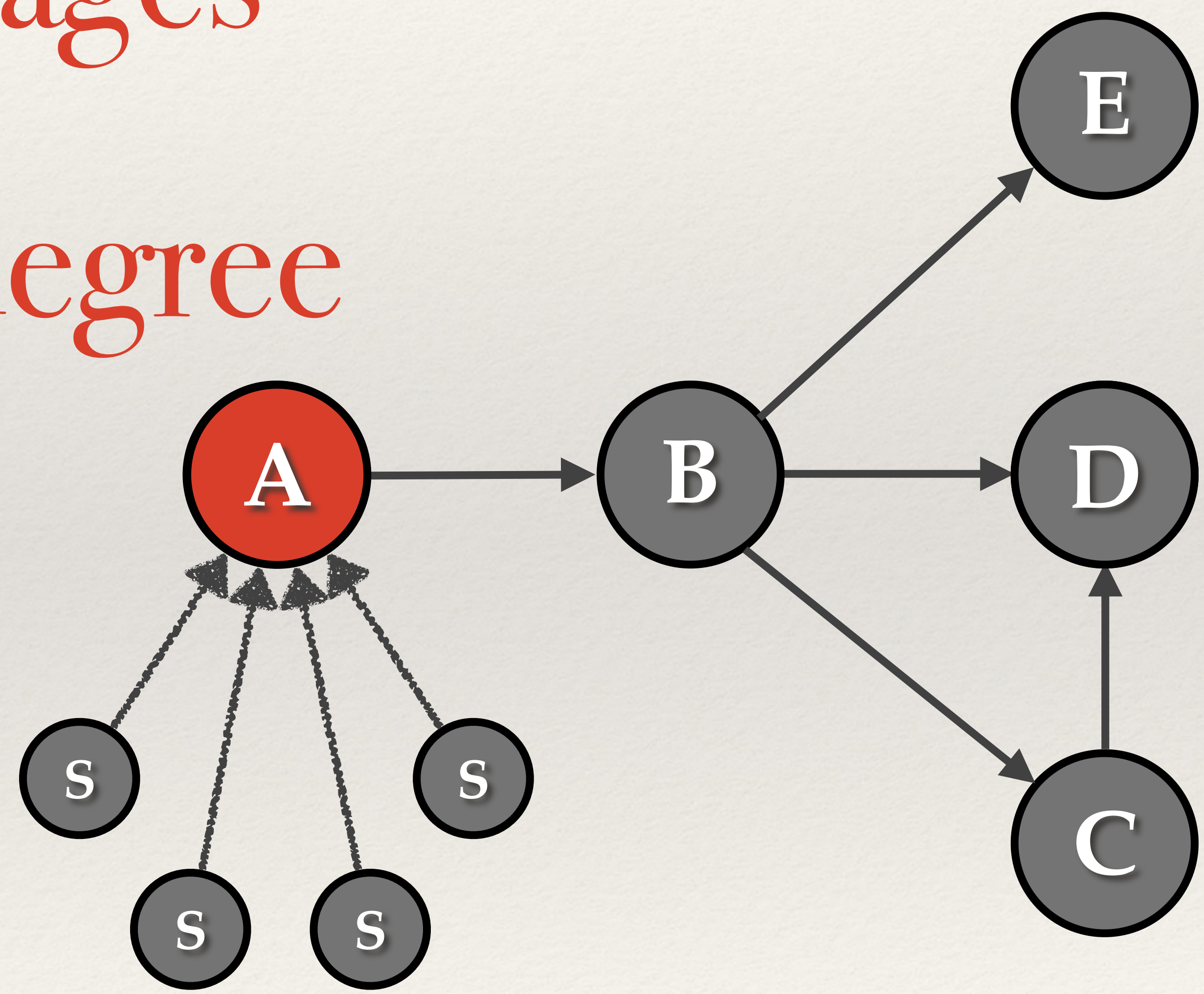


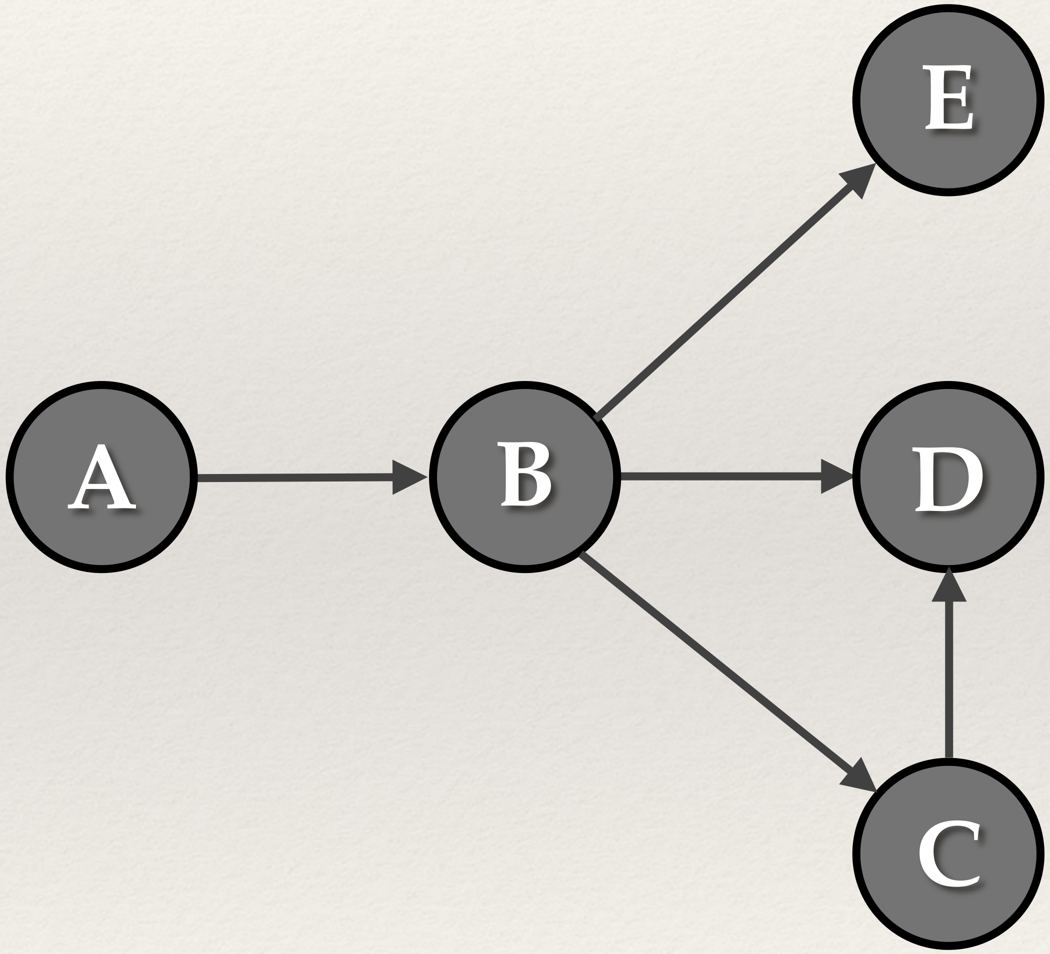
Susceptible

to manipulation by spammer networks

PageRank [Page et al., 1999]

Page Importance

Described by distribution π



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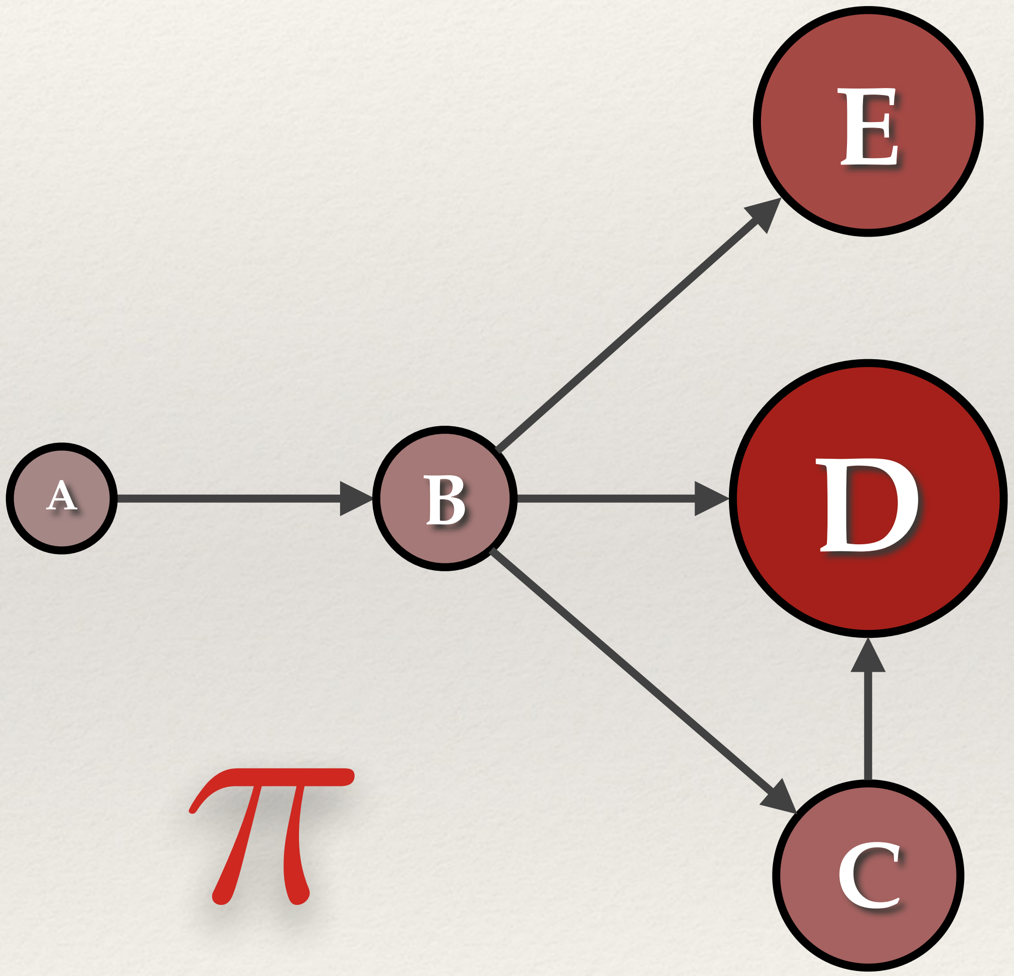
Recursive Definition

Important pages are pointed to by

- important pages are pointed to by
  - important pages are pointed to by…



π

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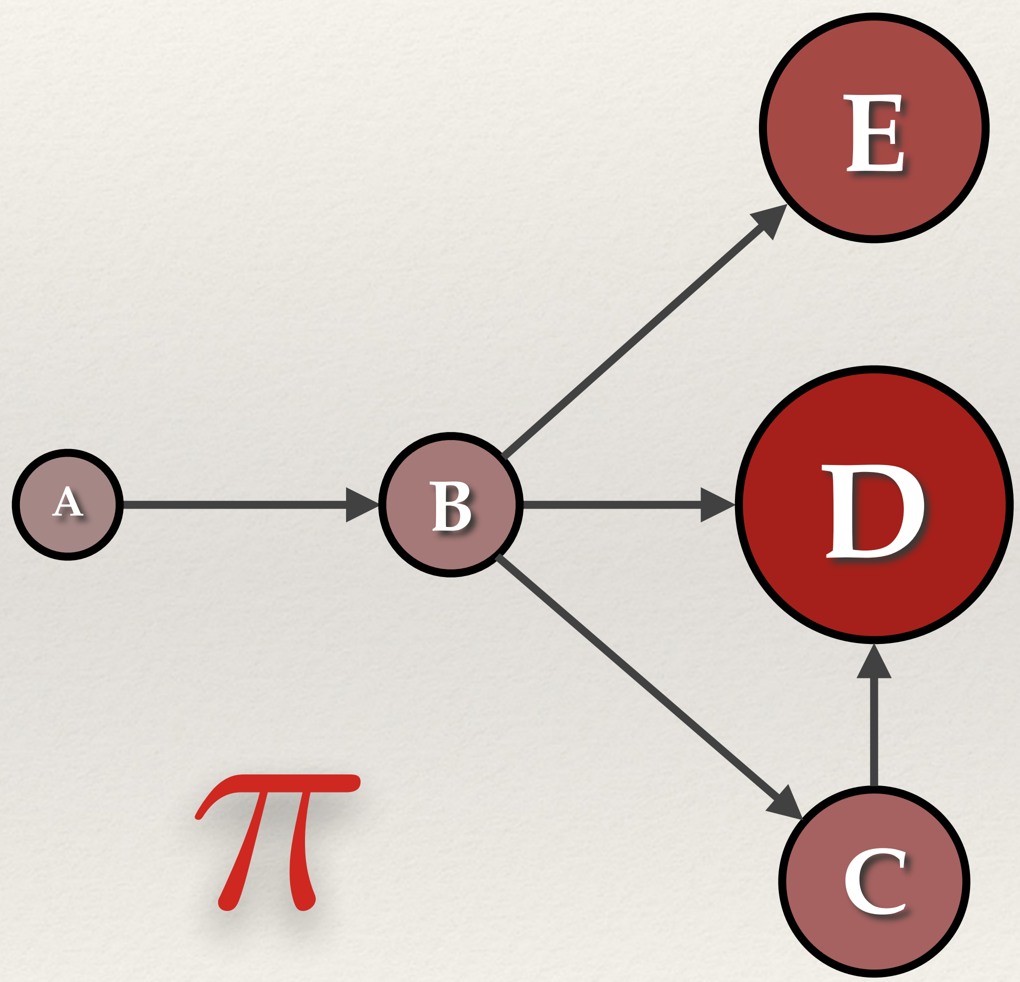
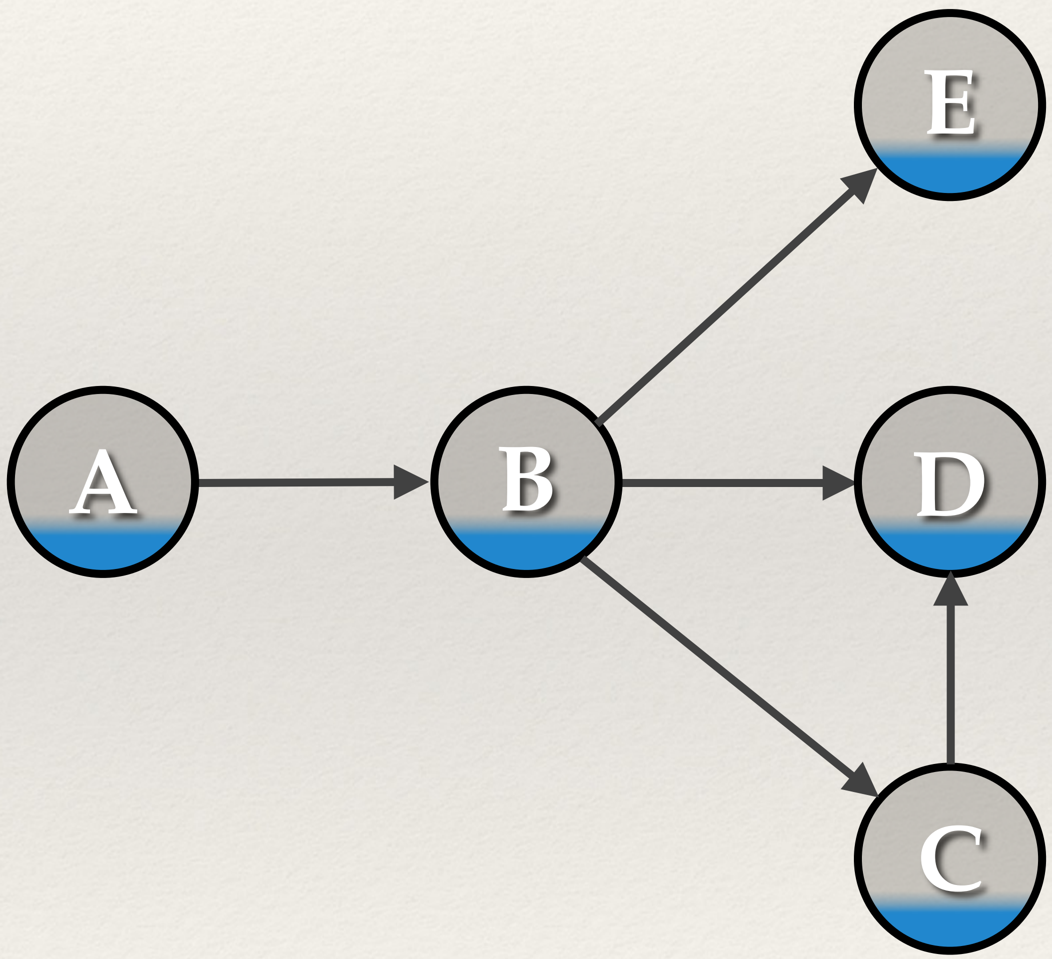


PageRank - Continuous Interpretation

Start: Gallon of water distributed evenly



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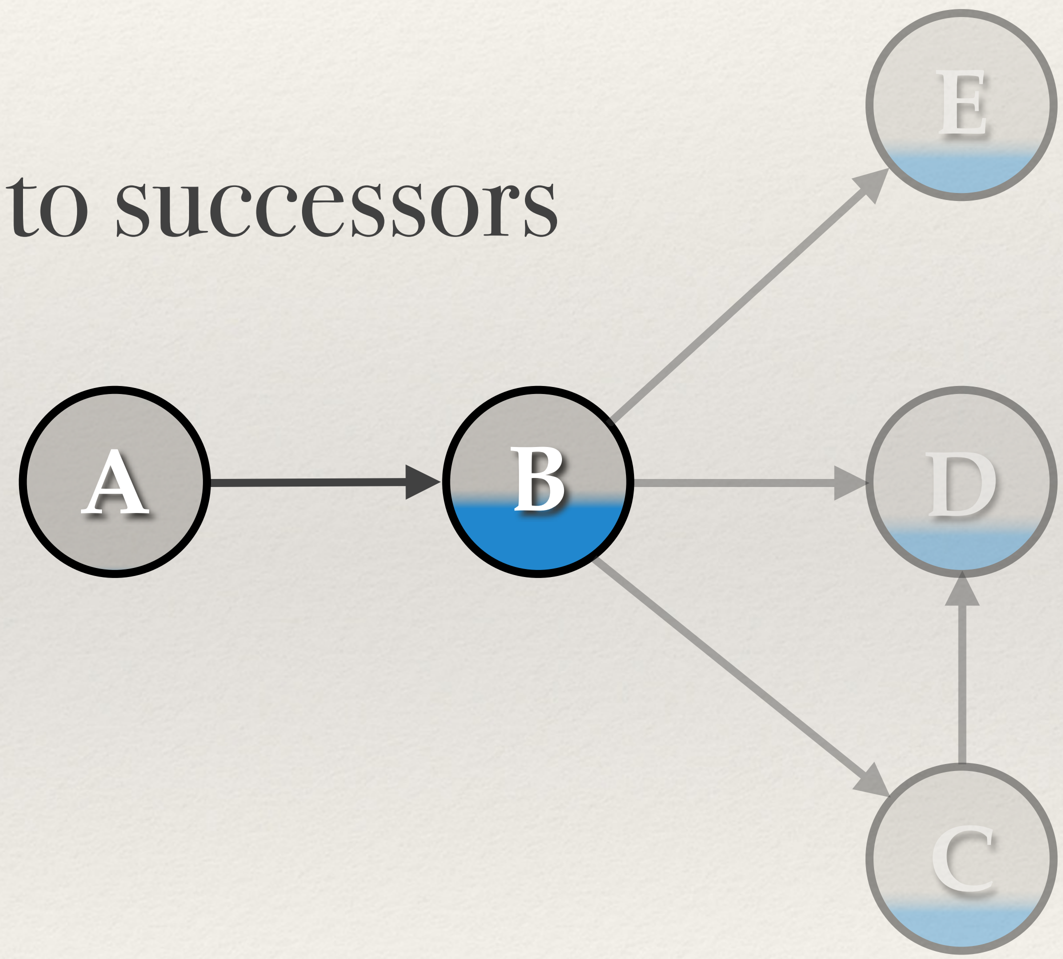
Start: Gallon of water distributed evenly

Every Iteration

Each vertex spreads water evenly to successors



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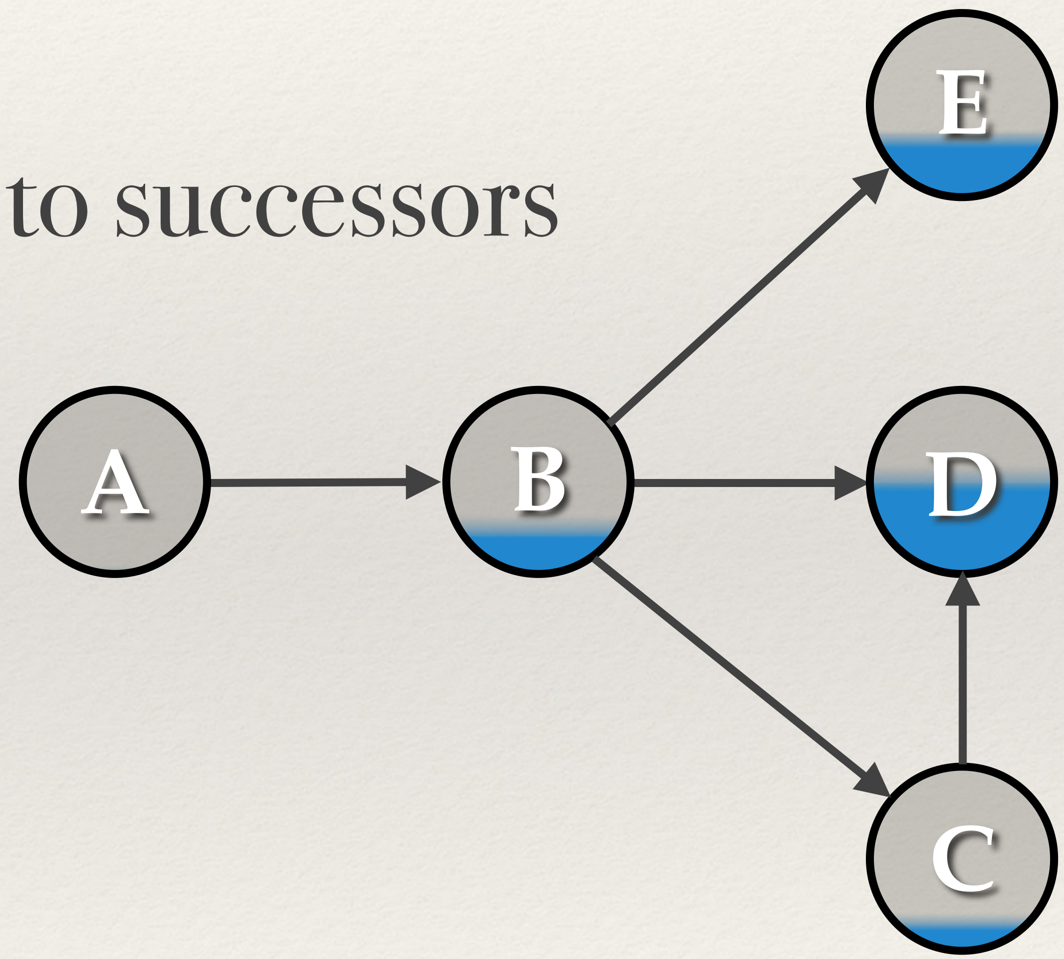

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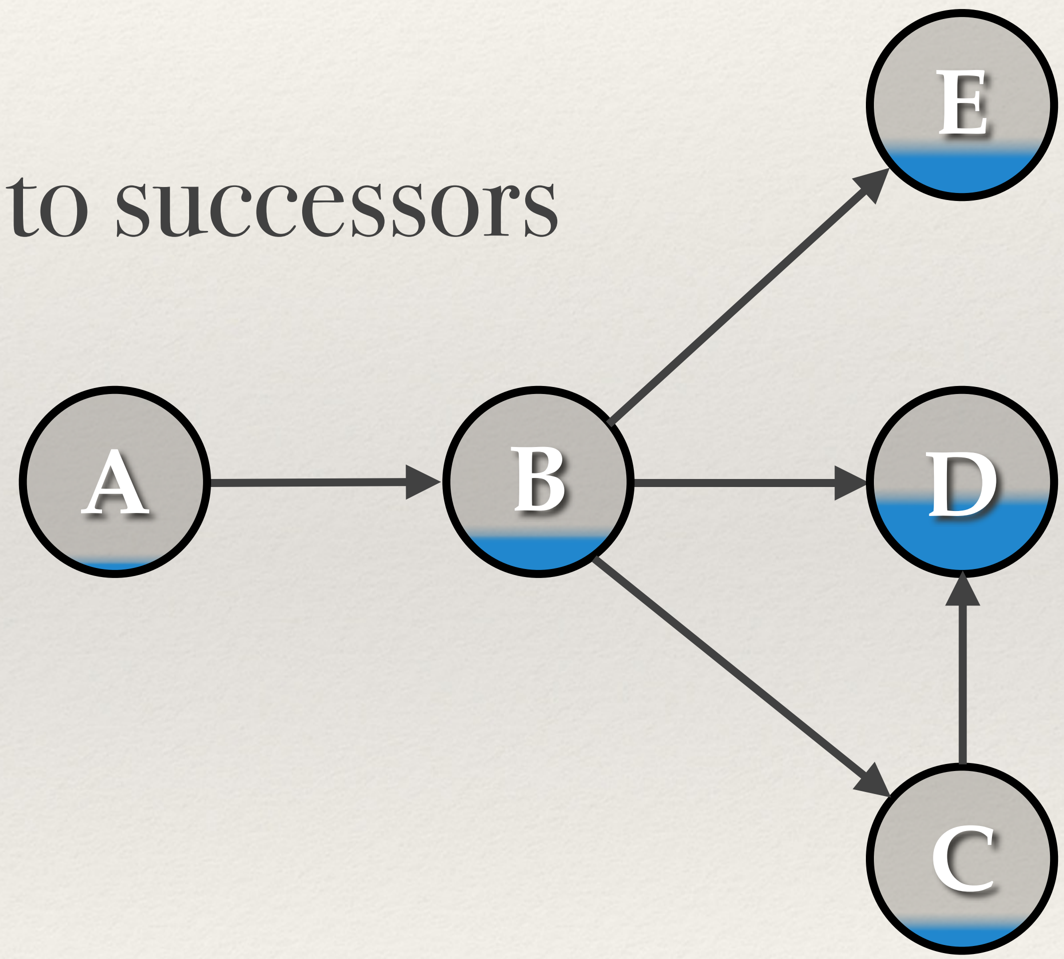
Start: Gallon of **water** distributed evenly

Every Iteration

Each vertex spreads water evenly to successors

Redistribute evenly

a fraction, $p_T = 0.15$, of all water



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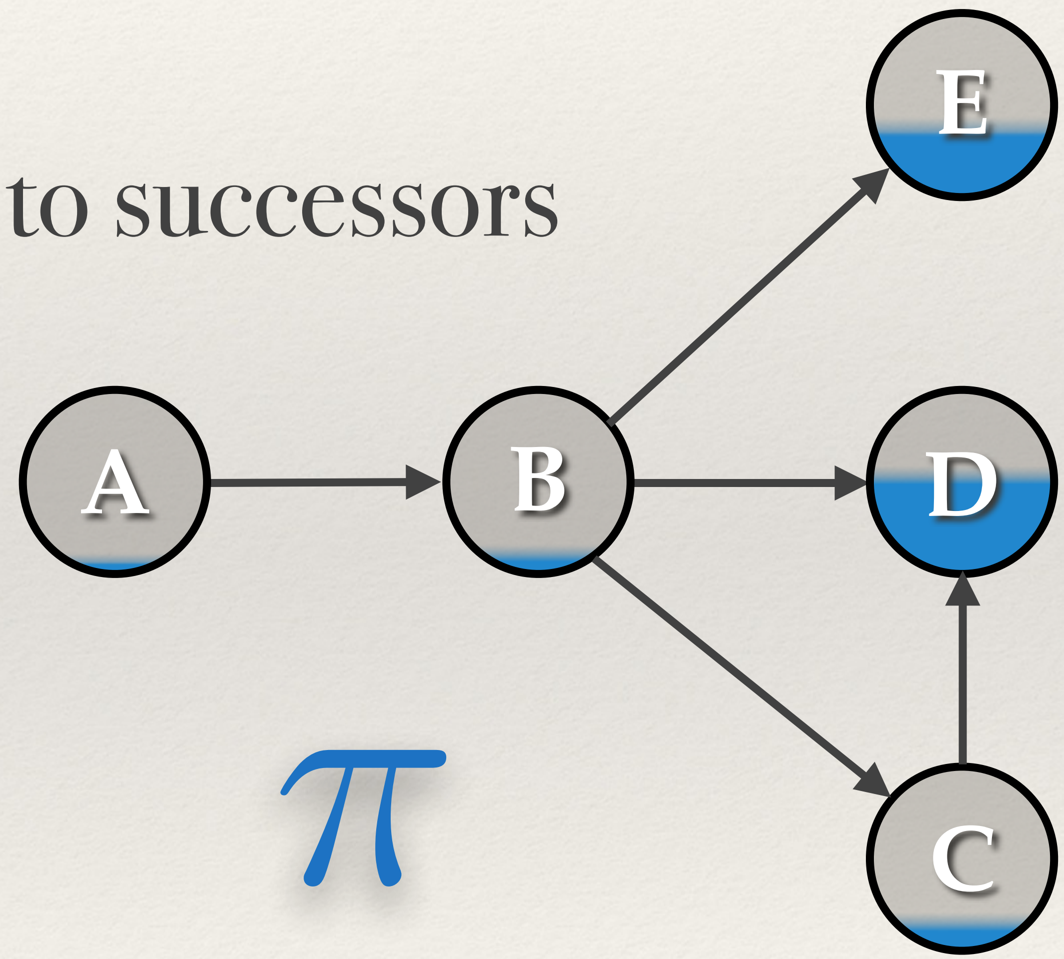


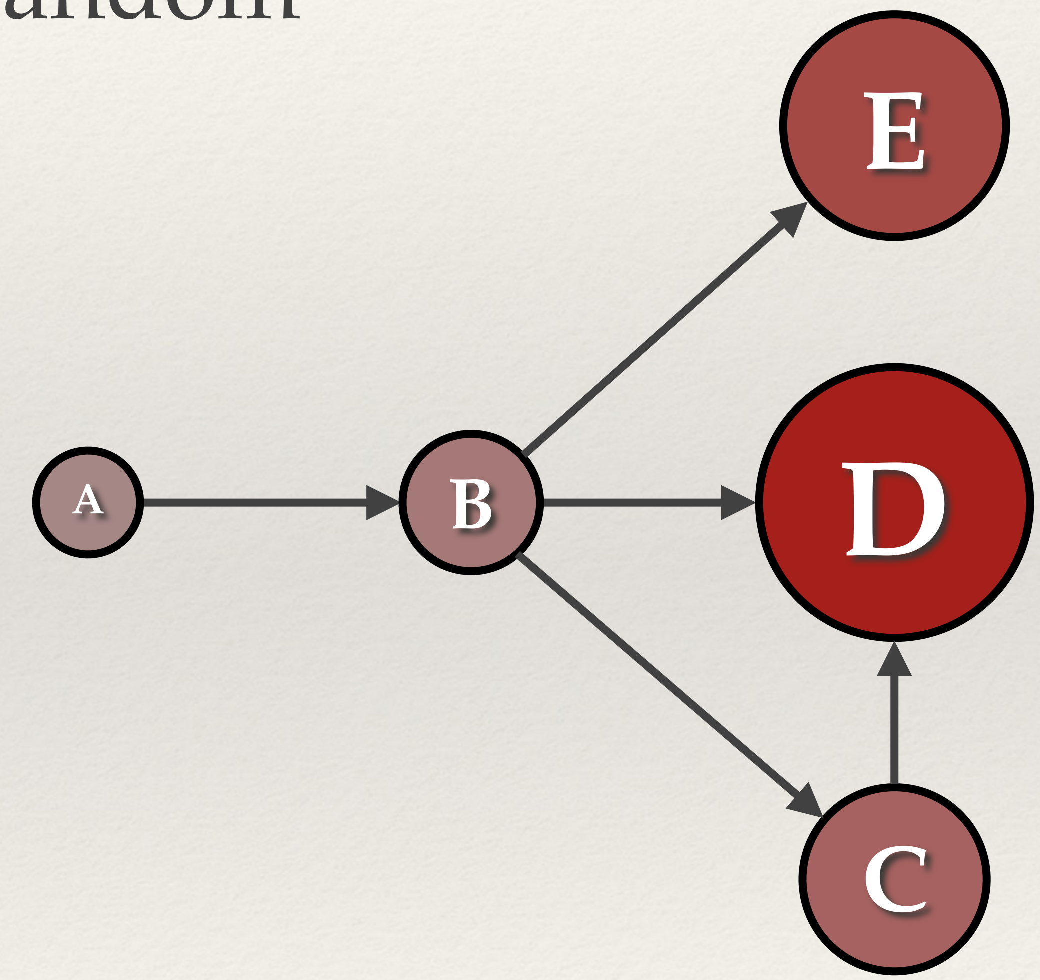
Repeat until convergence

Power Iteration employed usually

Discrete Interpretation

Frog walks randomly on graph

Next vertex chosen uniformly at random



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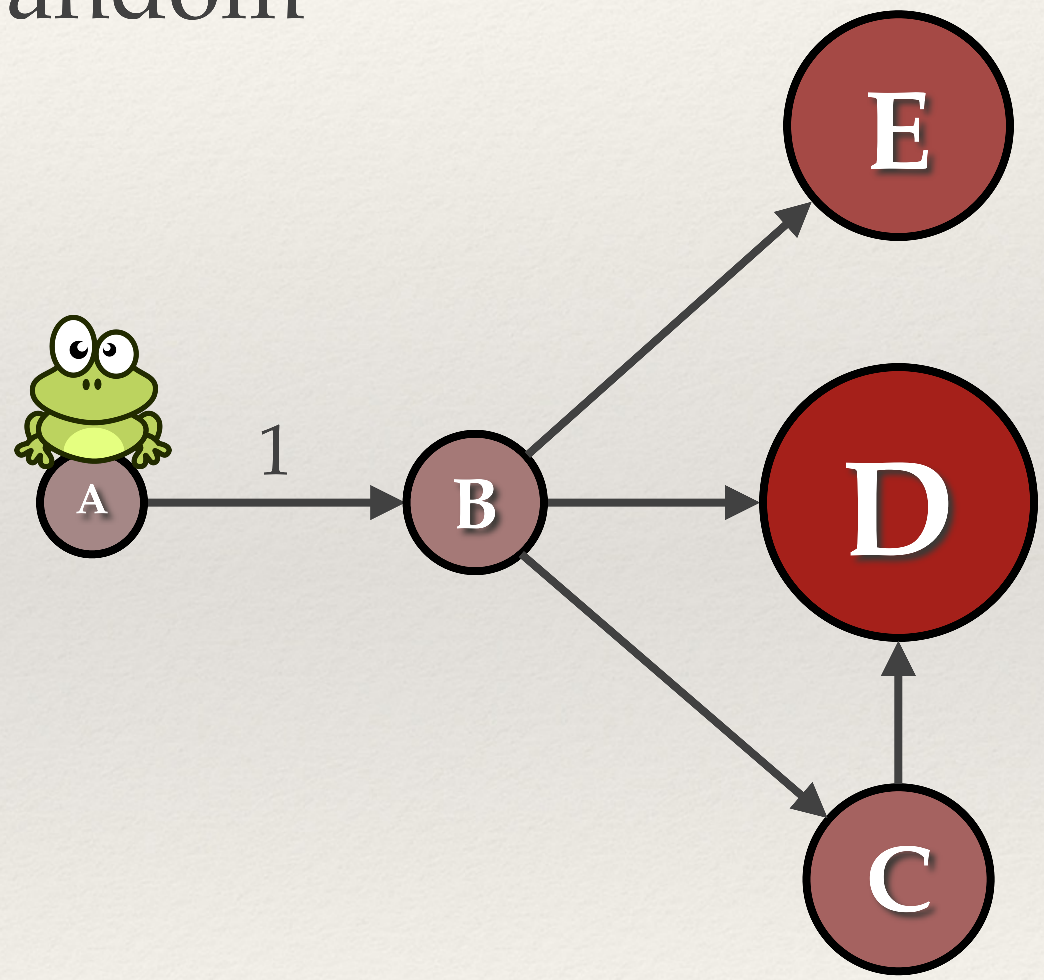

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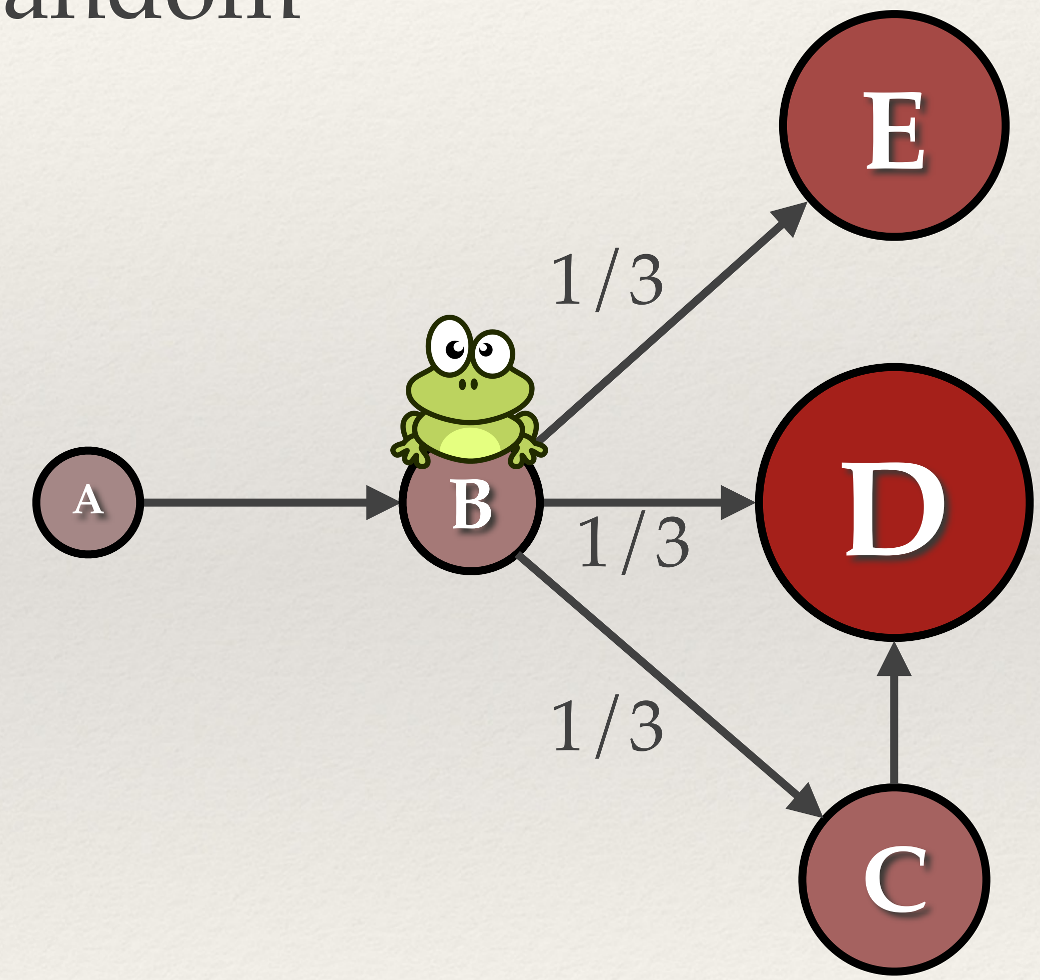

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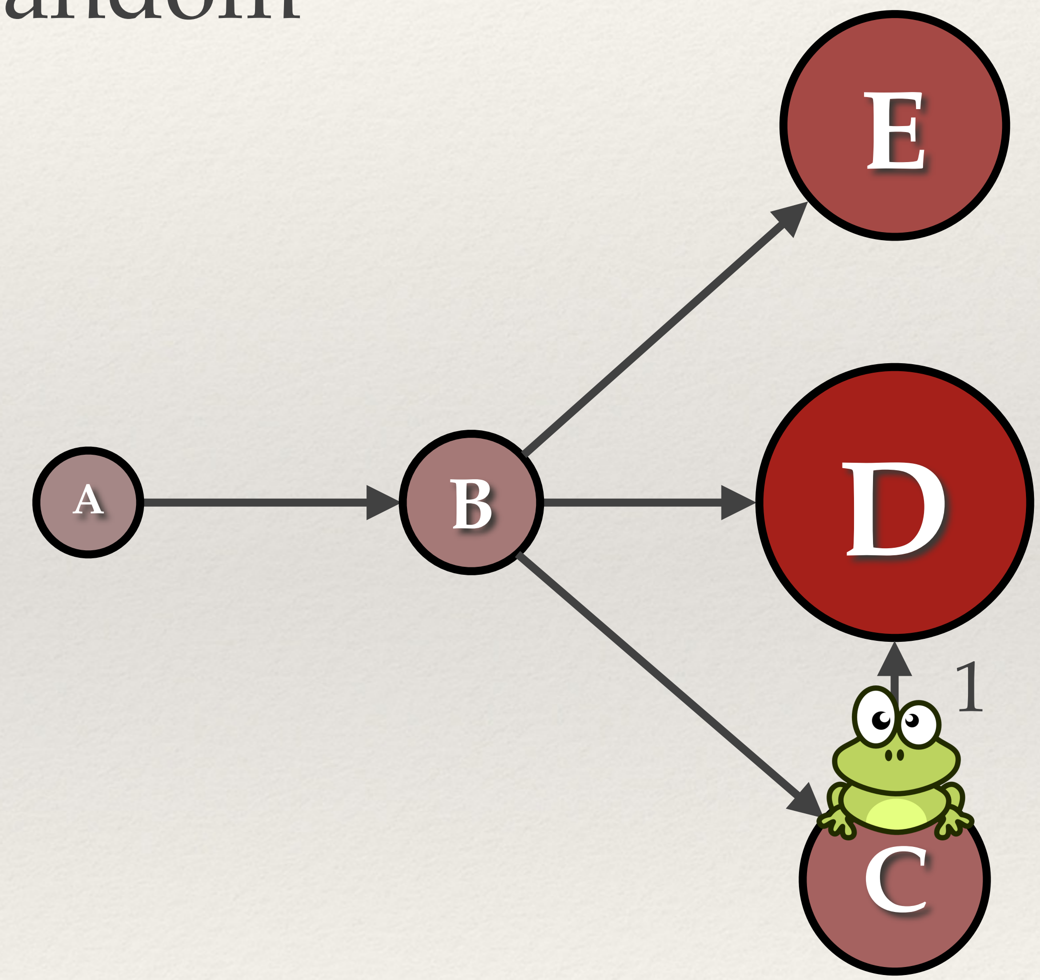
Teleportation

Every step: teleport w.p. p_T



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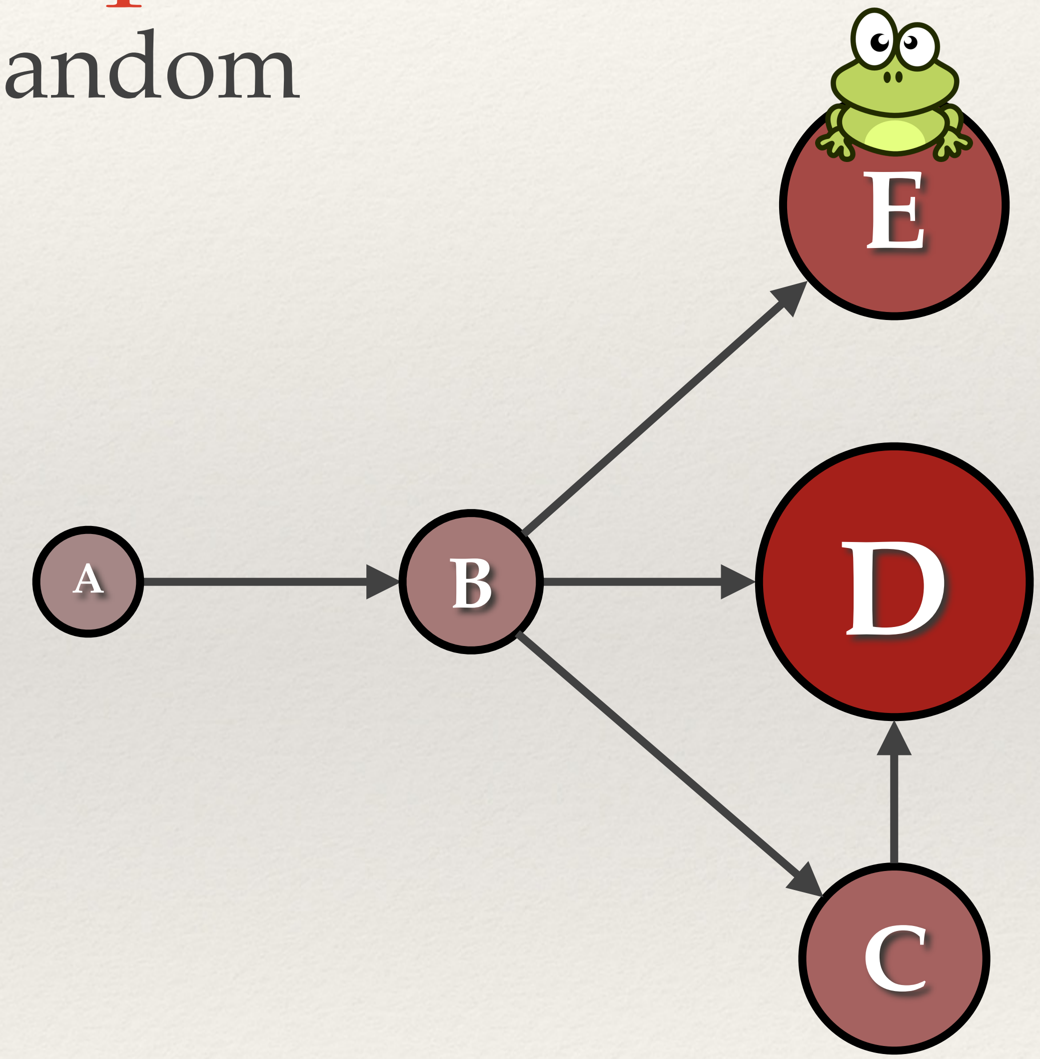

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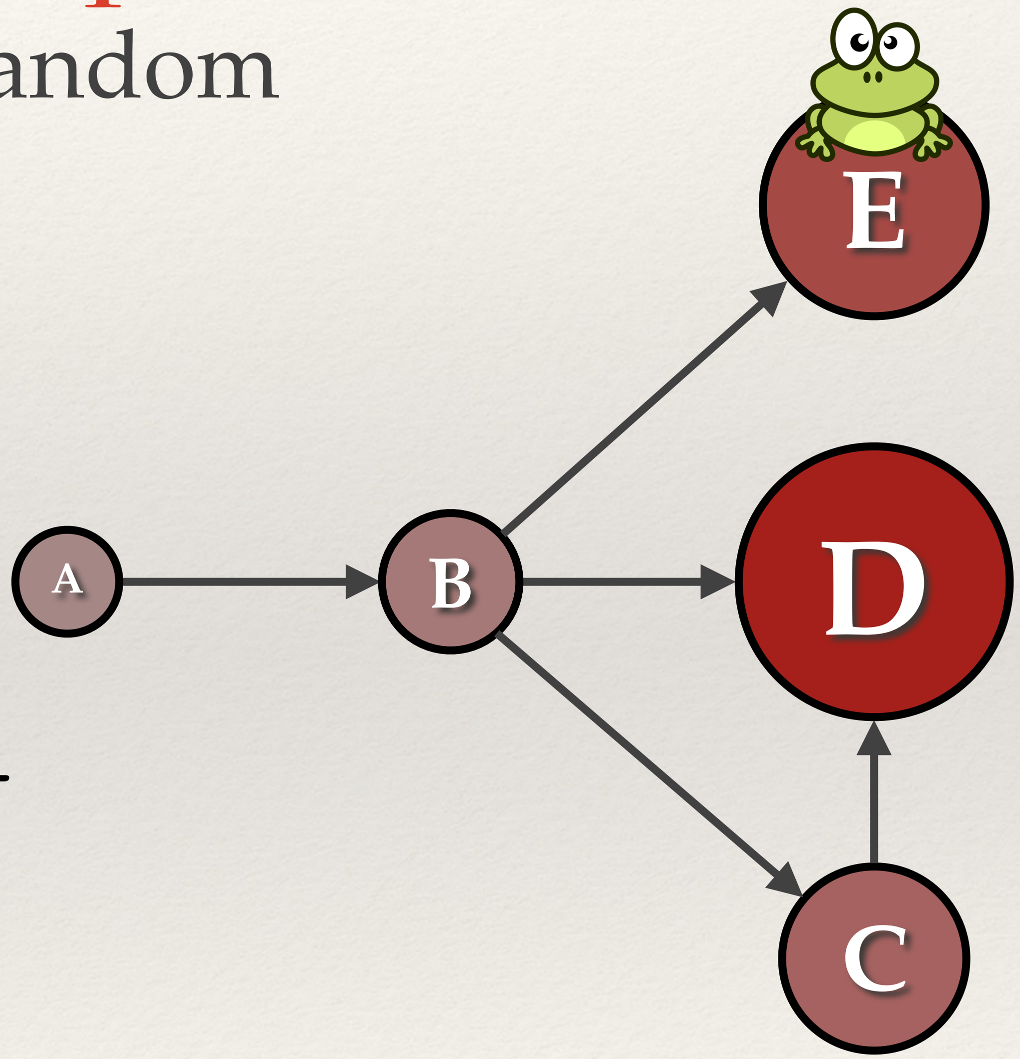
Frog location gives sample from π



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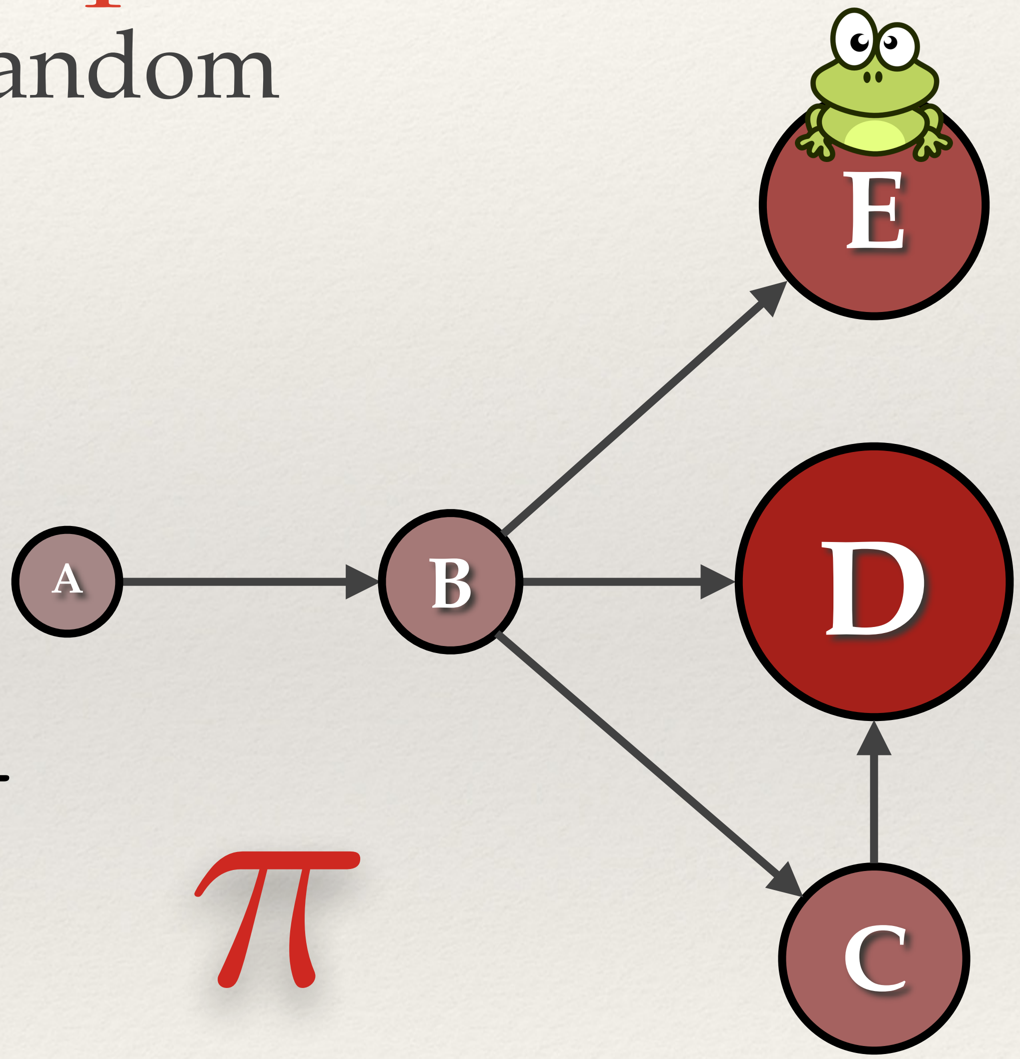
PageRank Vector

Many frogs, estimate vector π



PageRank Approximation

Looking for k "heavy nodes"

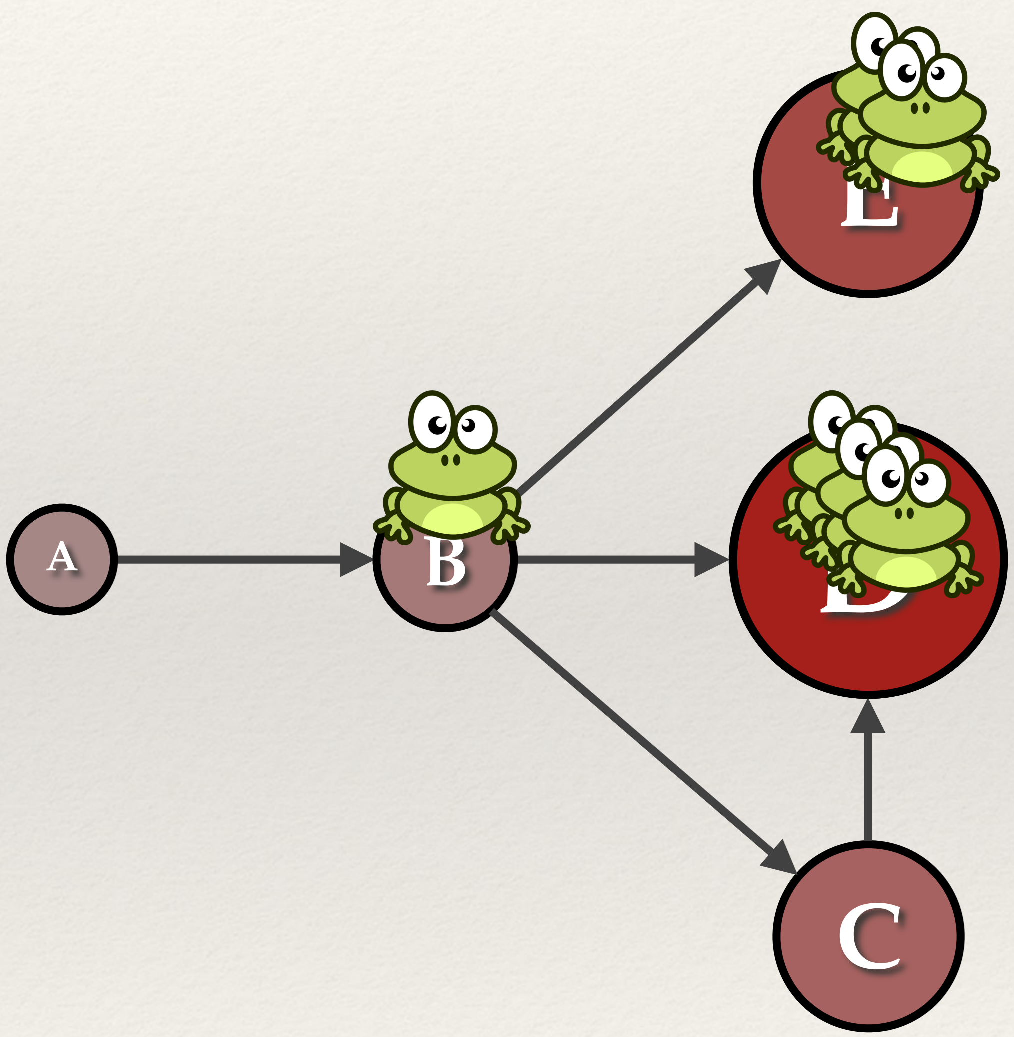
Do not need full PageRank vector

Random Walk Sampling

Favors heavy nodes

Captured Mass Metric

For node set S: $\pi(S)$



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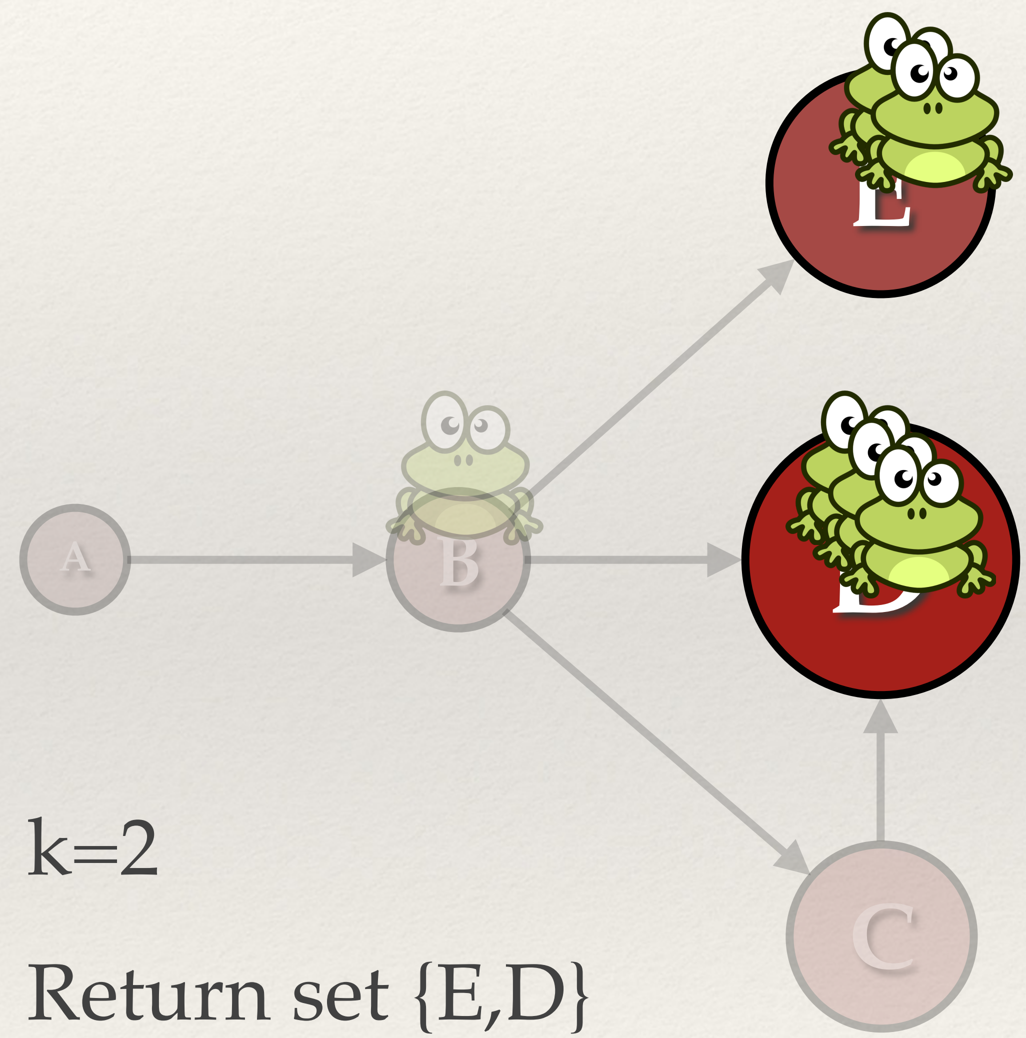


Captured Mass Metric

For node set S: $\pi(S)$

k=2

Return set {E,D}

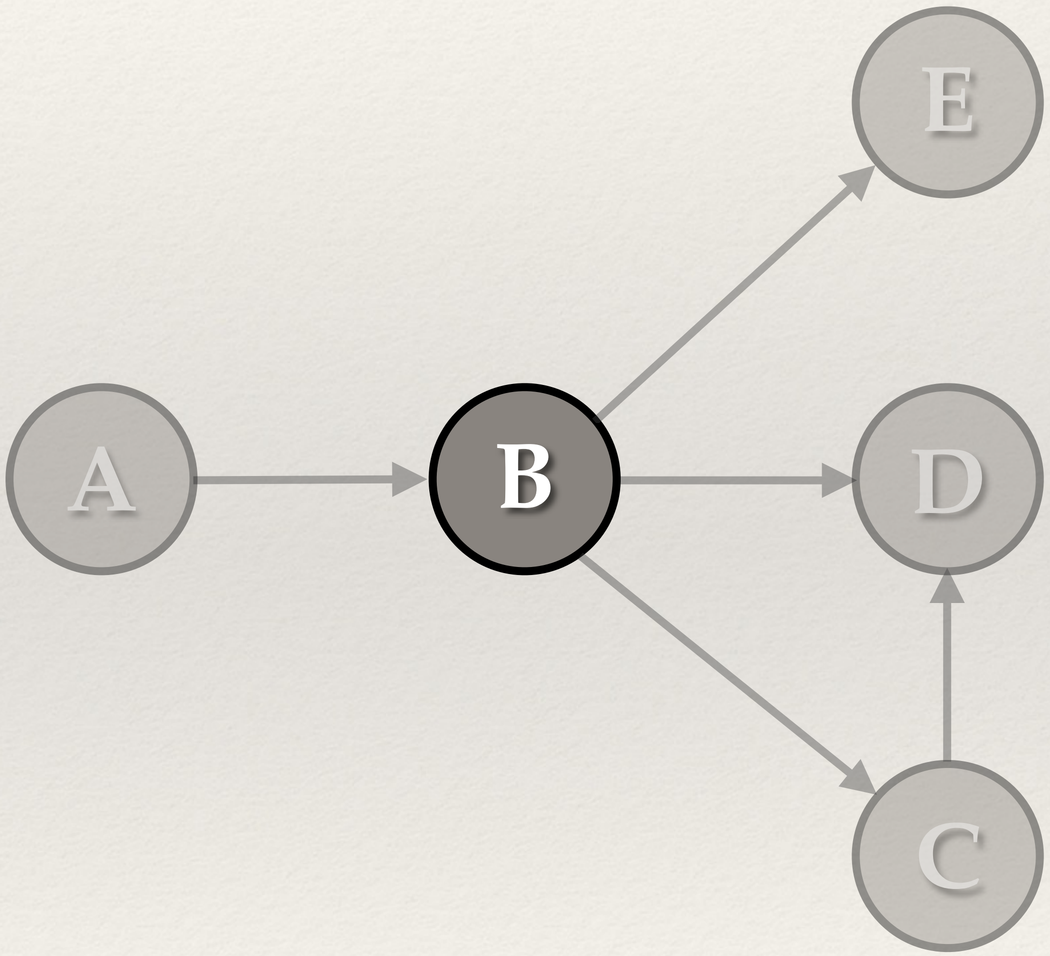
Captured mass $= \pi(\{E,D\})$

Platform

Graph Engines

- Engine splits graph across cluster
- **Vertex program** describes logic

GAS abstraction



Other approaches:
Giraph [Avery, 2011], Galois [Nguyen et al., 2013], GraphX [Xin et al., 2013]

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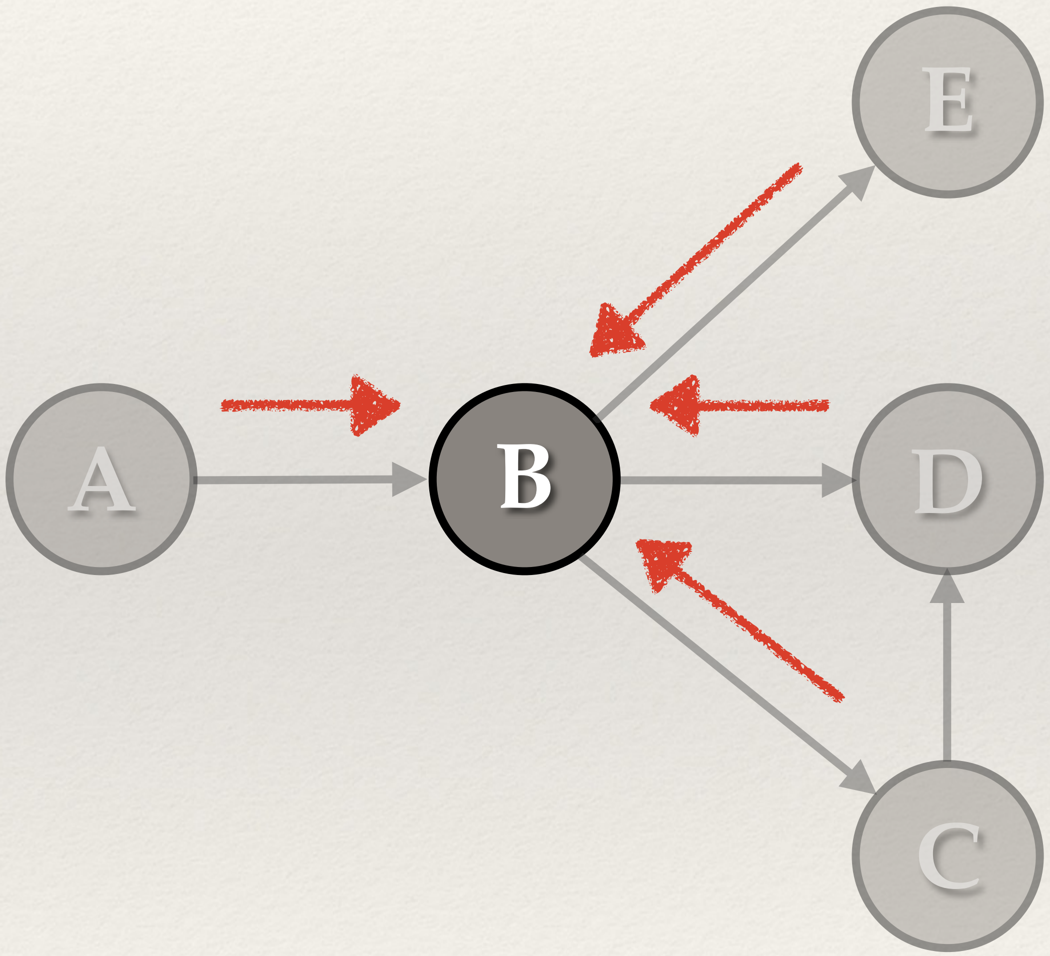

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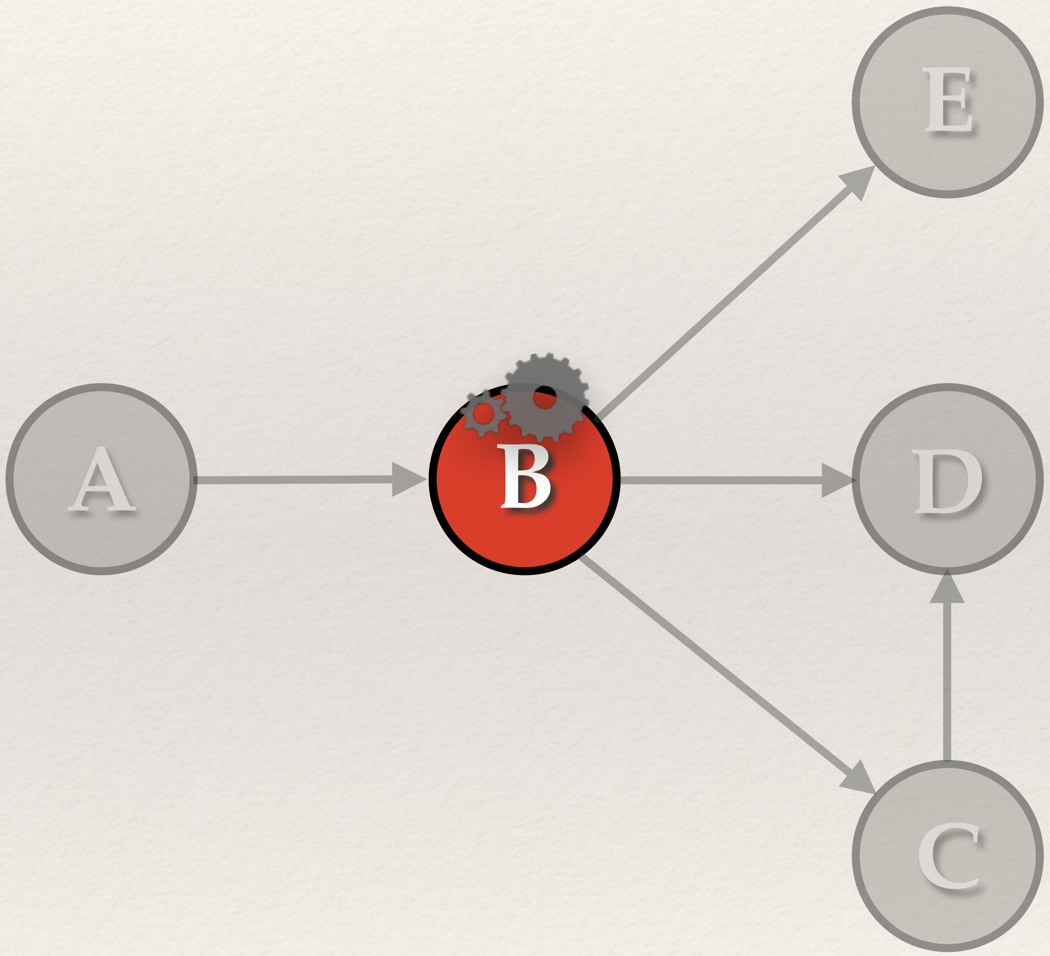
2. Apply



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Graph Engines

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GAS abstraction

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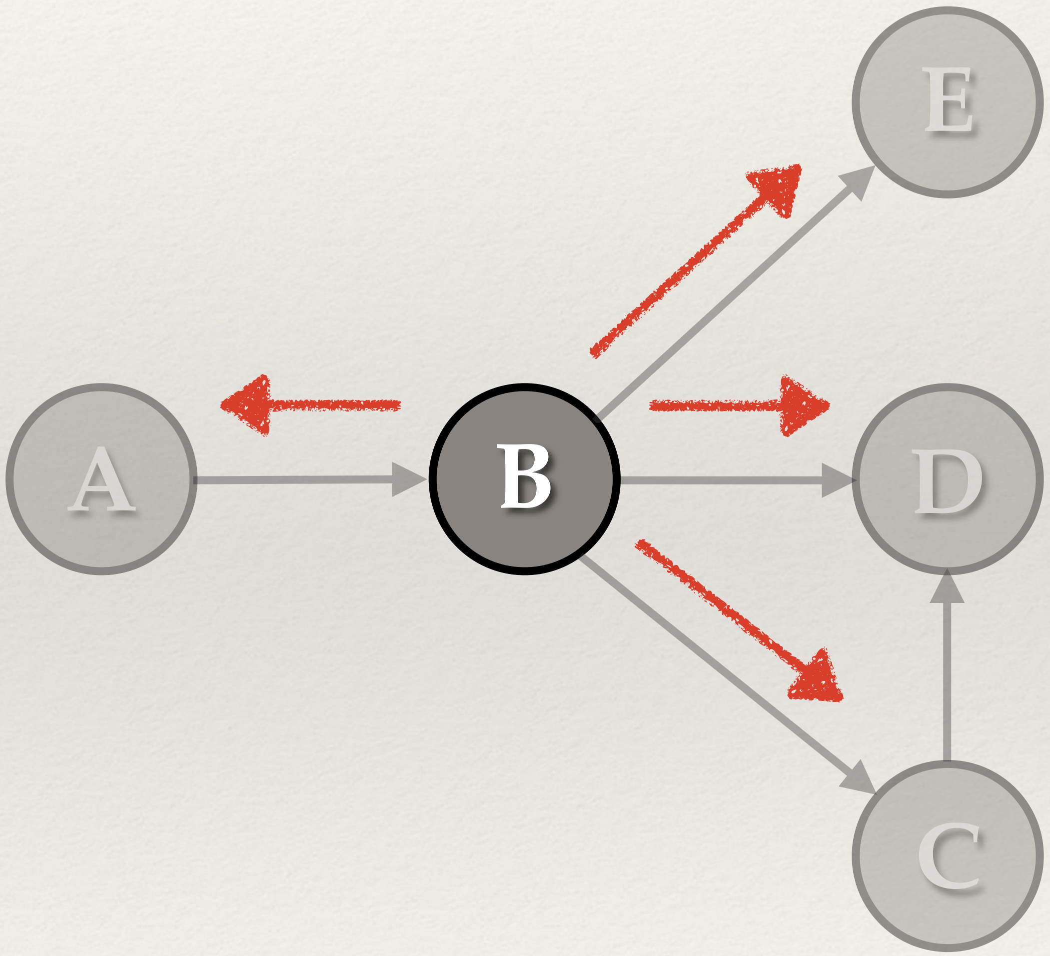
3. Scatter



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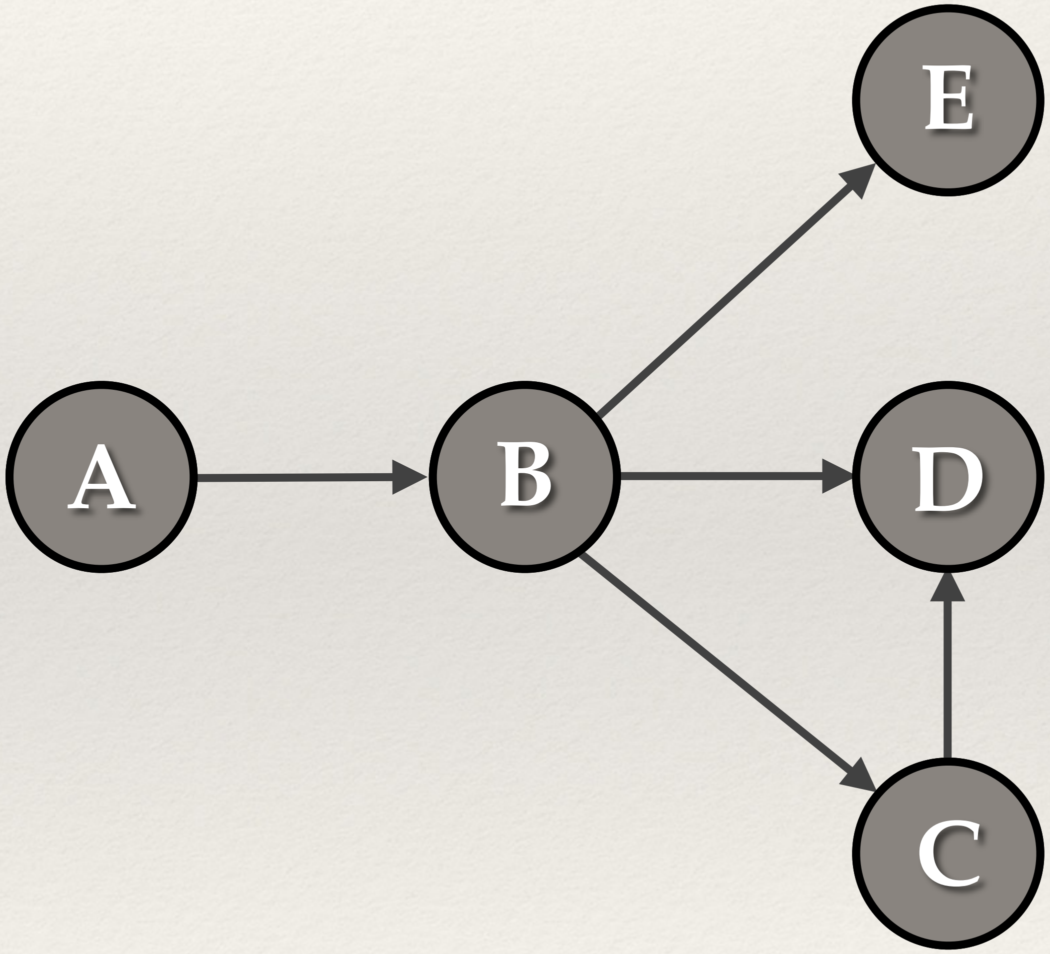
Edge Cuts

- Assign vertices to machines
- Cross-machine edges require network communication
- Pregel, GraphLab 1.0
- High-degree nodes generate large volume of traffic
- Computational load imbalance



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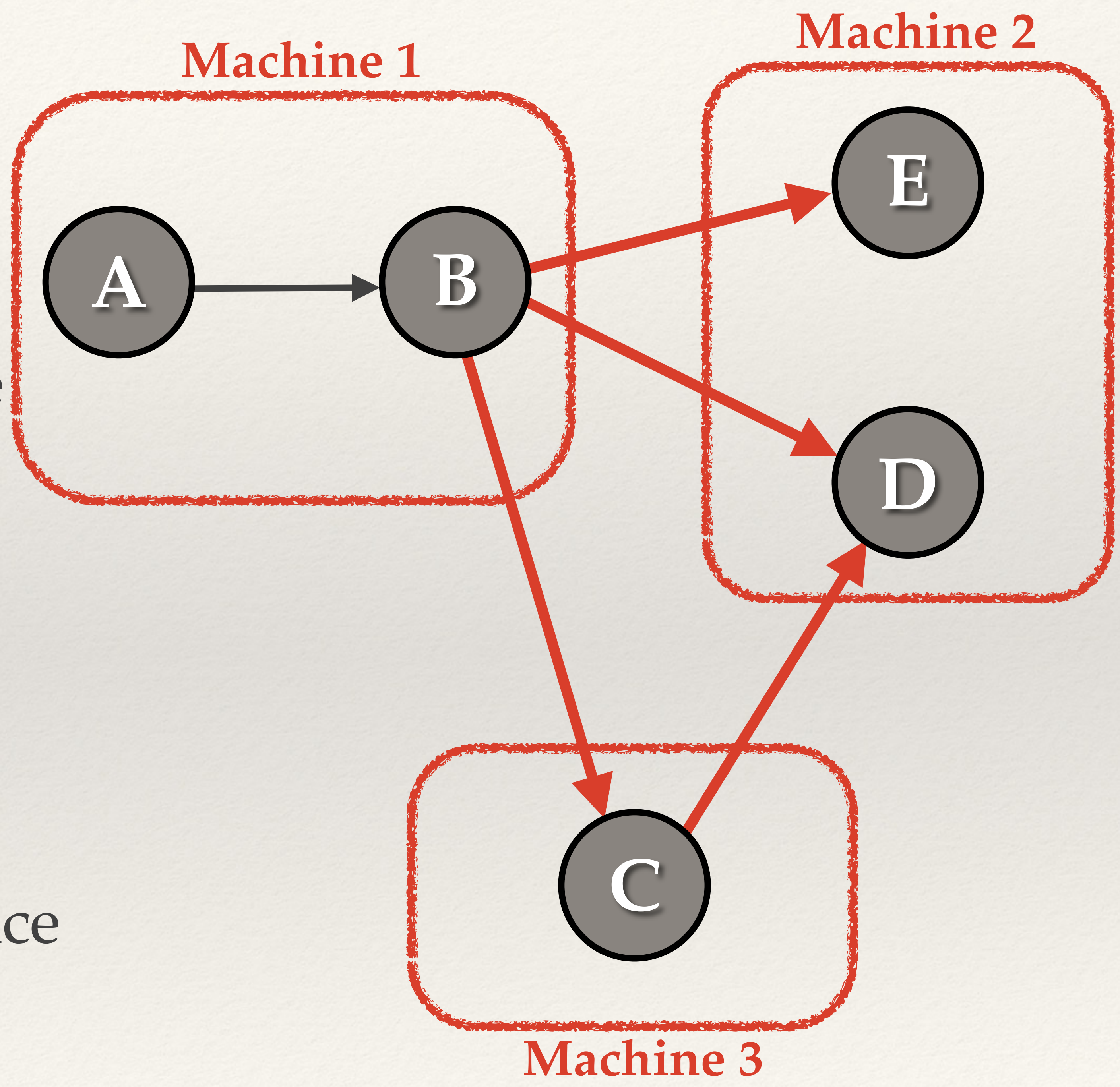
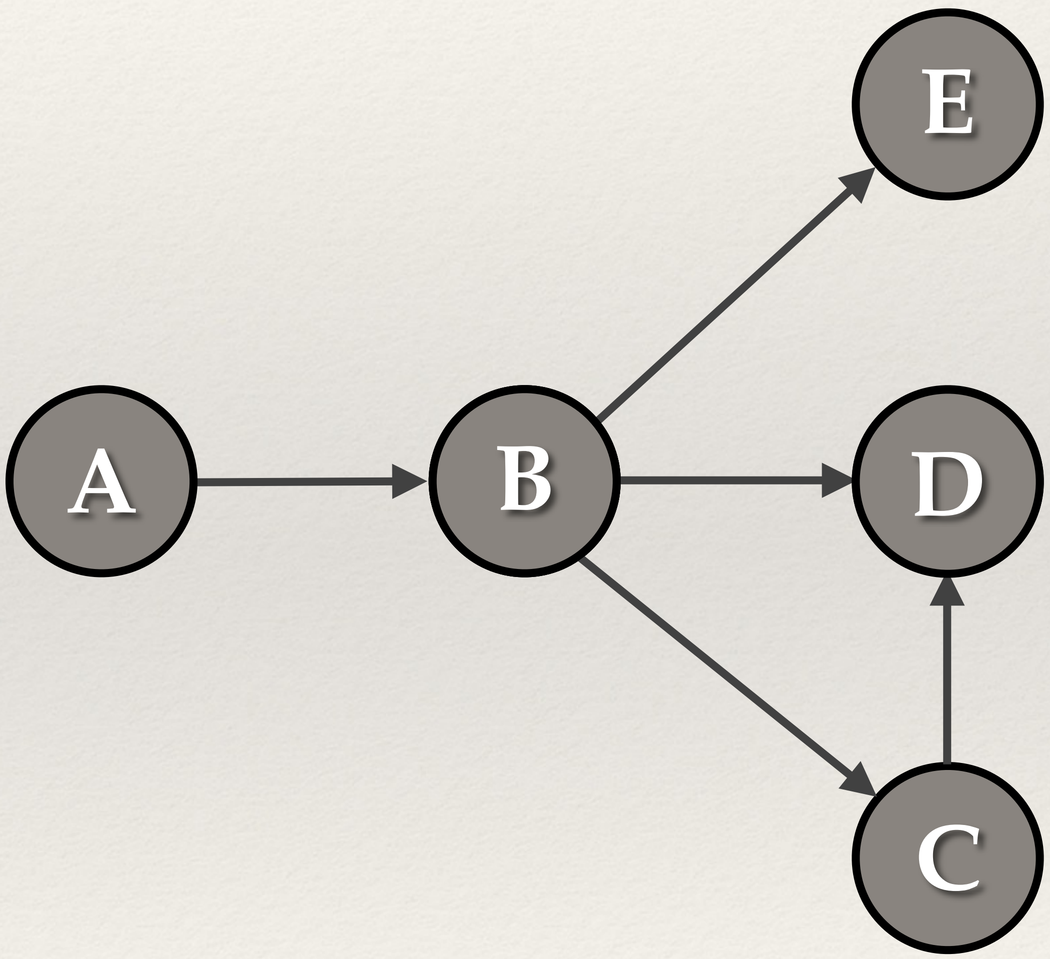


Vertex Cuts

- Assign edges to machines
- High-degree nodes replicated
- One replica designated master
- Need for synchronization
  1. Gather
  2. Apply [on master]
  3. Synchronize mirrors
  4. Scatter
- GraphLab 2.0 - PowerGraph
- Balanced - Network still bottleneck



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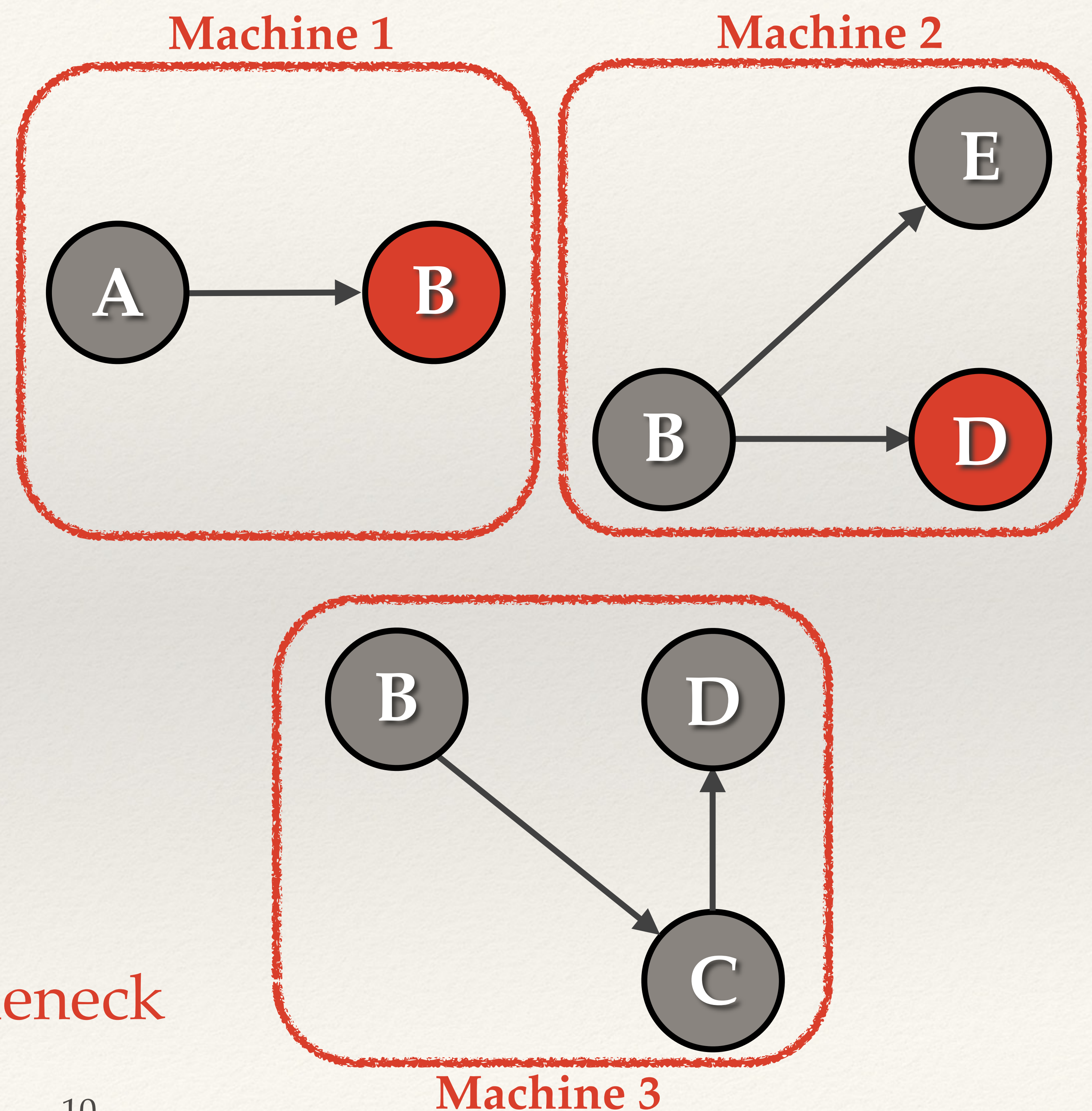

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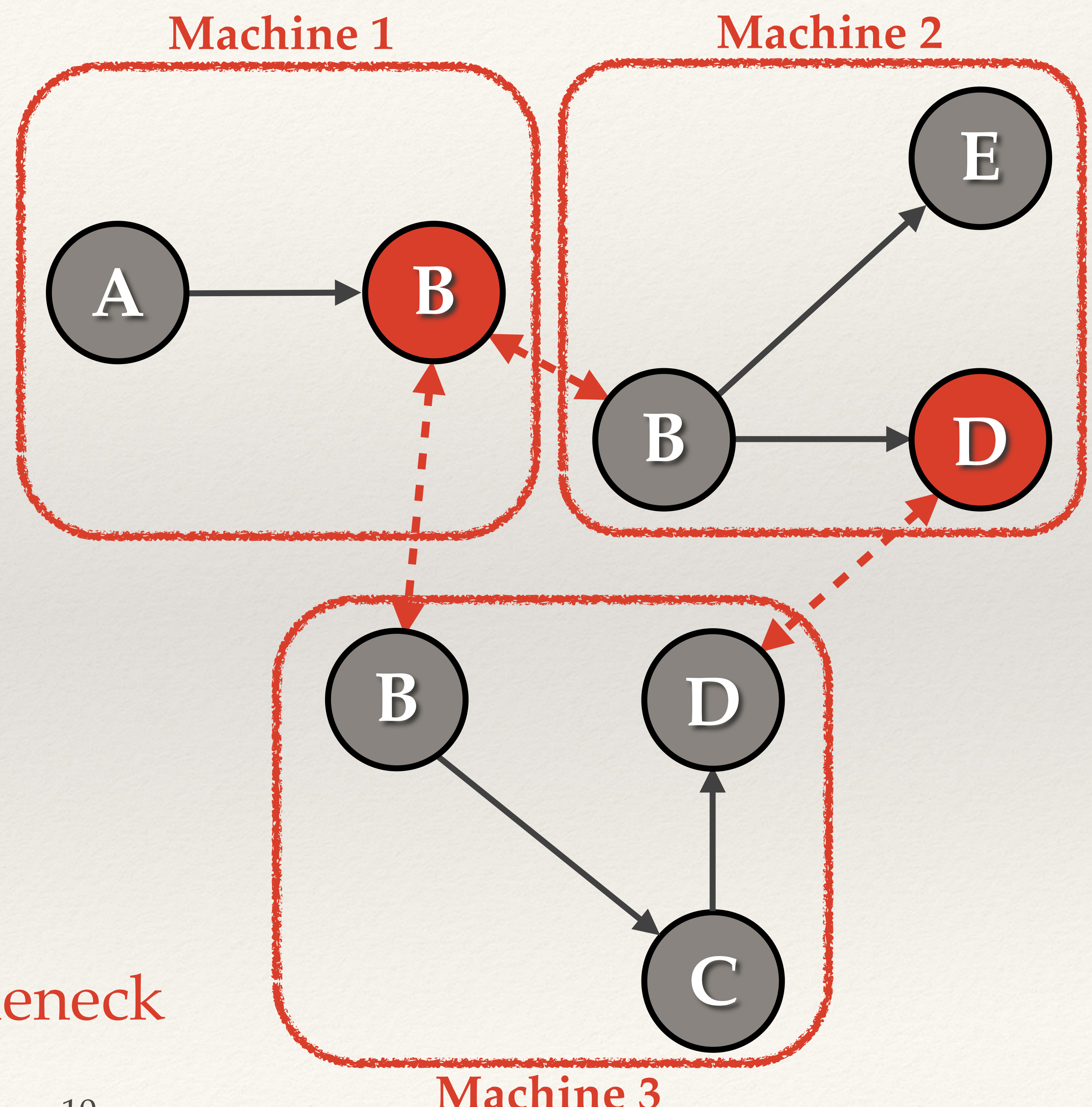


Random Walks on GraphLab

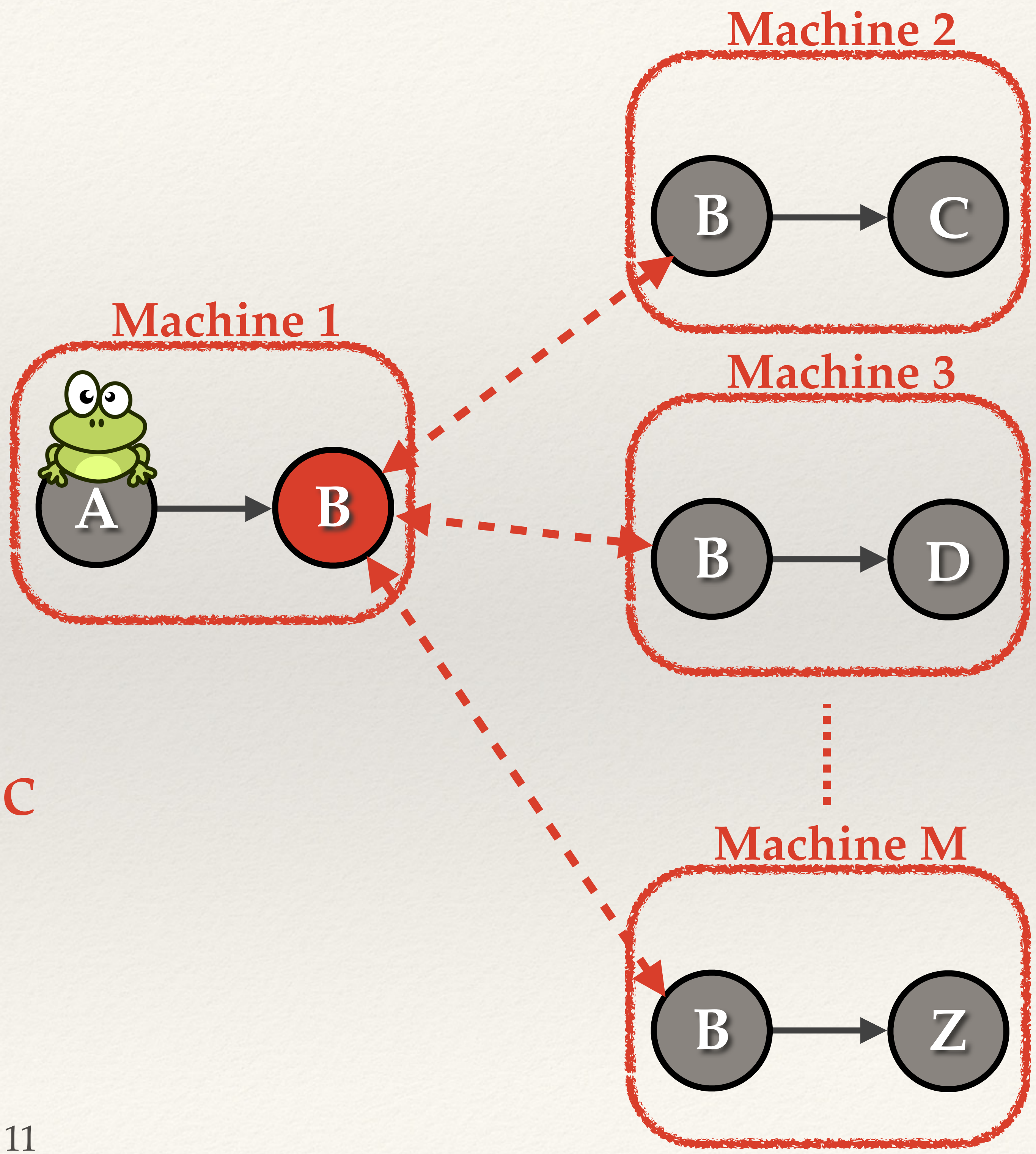
Master node decides step

Decision synced to all mirrors

Only machine M needs it

Unnecessary network traffic

Average replication factor ~8



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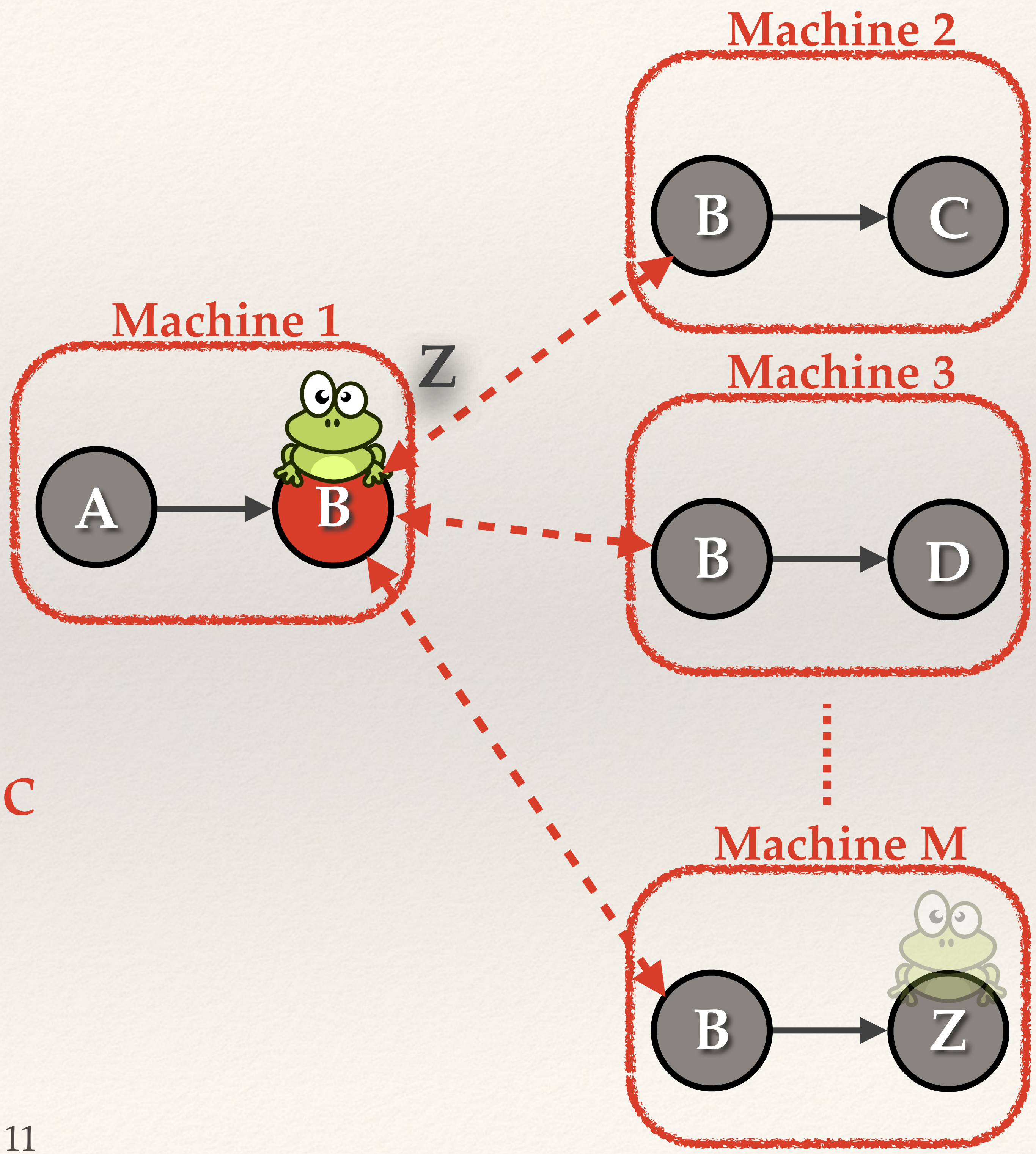

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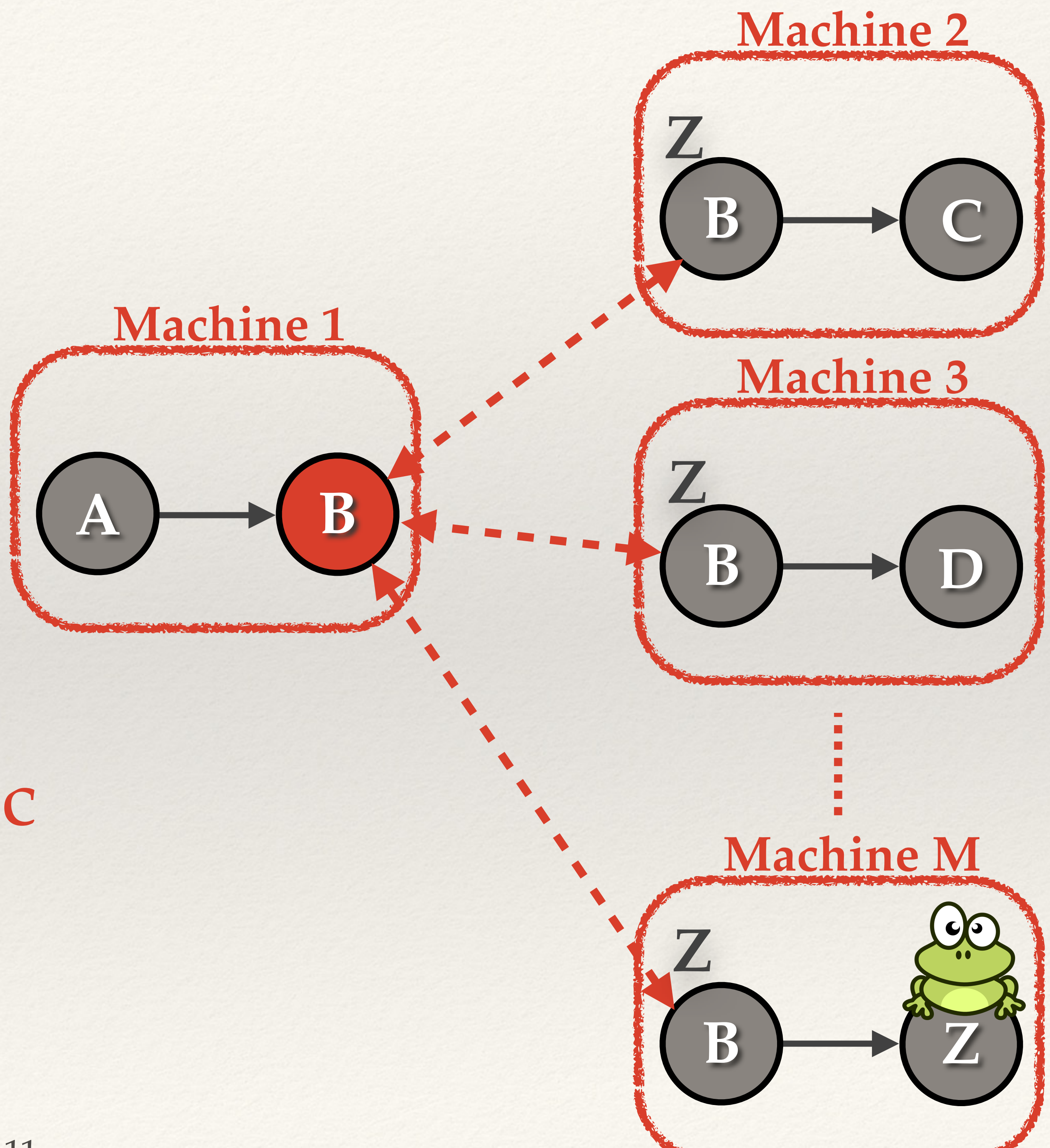


Objective

Faster PageRank approximation on GraphLab

Idea

Only synchronize the mirror that will receive the frog

Doable, but requires

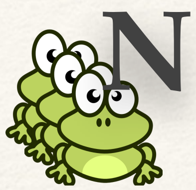
1. Serious engine hacking
2. Exposing an ugly/complicated API to programmer

Simpler

Pick mirrors to synchronize at random!

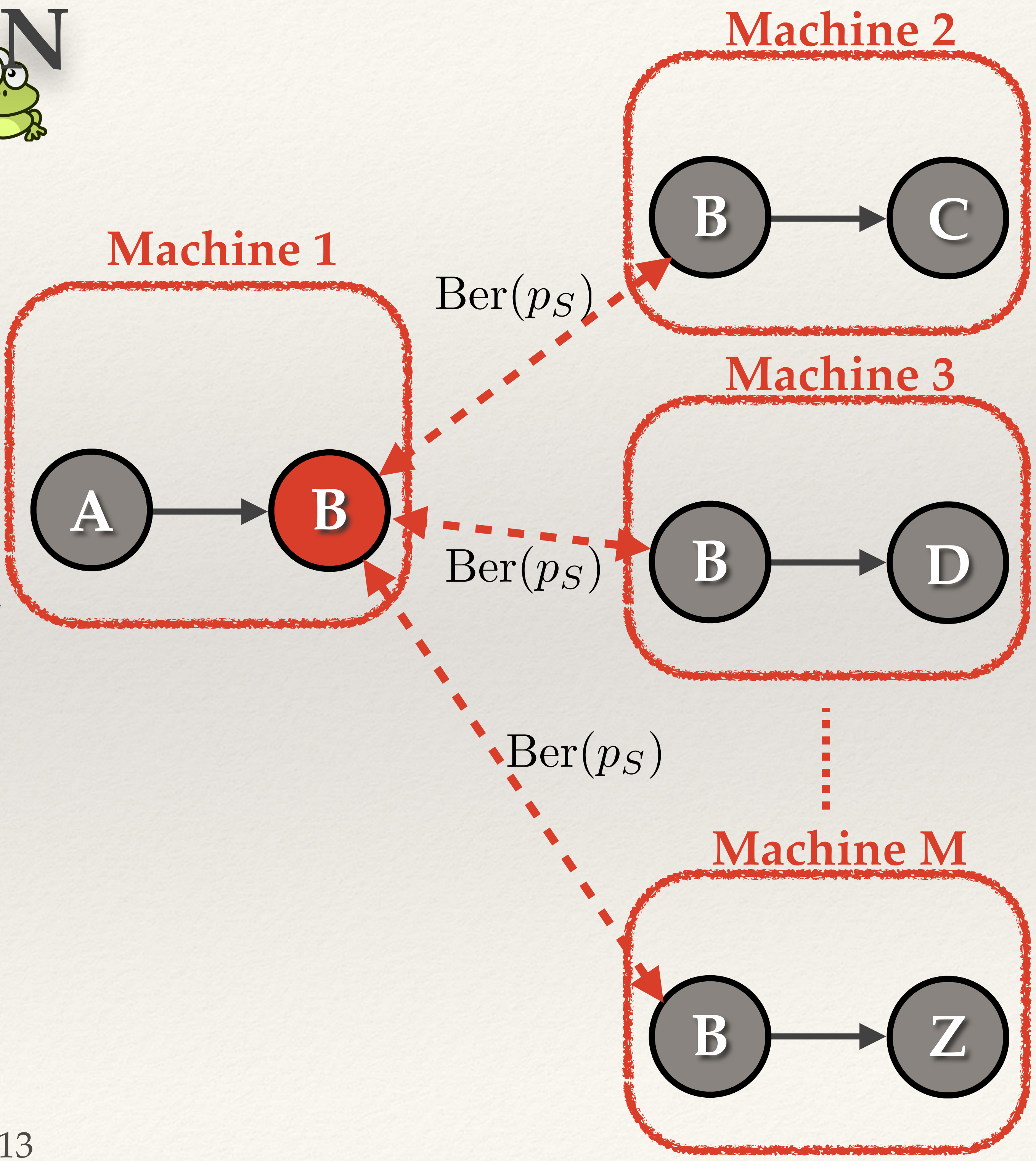
Synchronize independently with probability p_S

FrogWild!

Release N frogs in parallel 

Vertex Program

1. Each frog dies w.p. p_T (gives sample)
   Assume K frogs survive
2. For every mirror, draw bridge w.p. p_S
3. Spread frogs evenly among synchronized mirrors.



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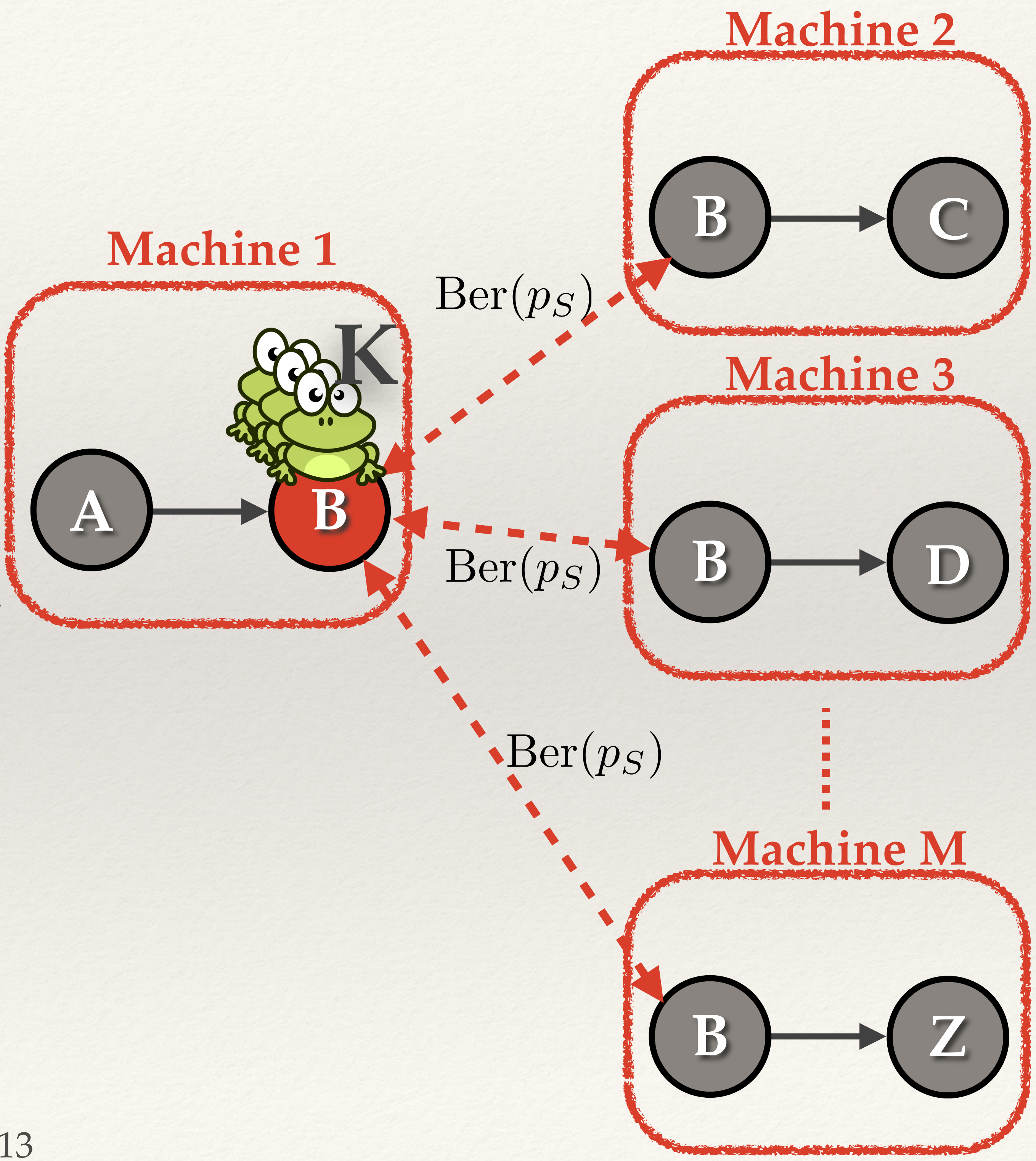

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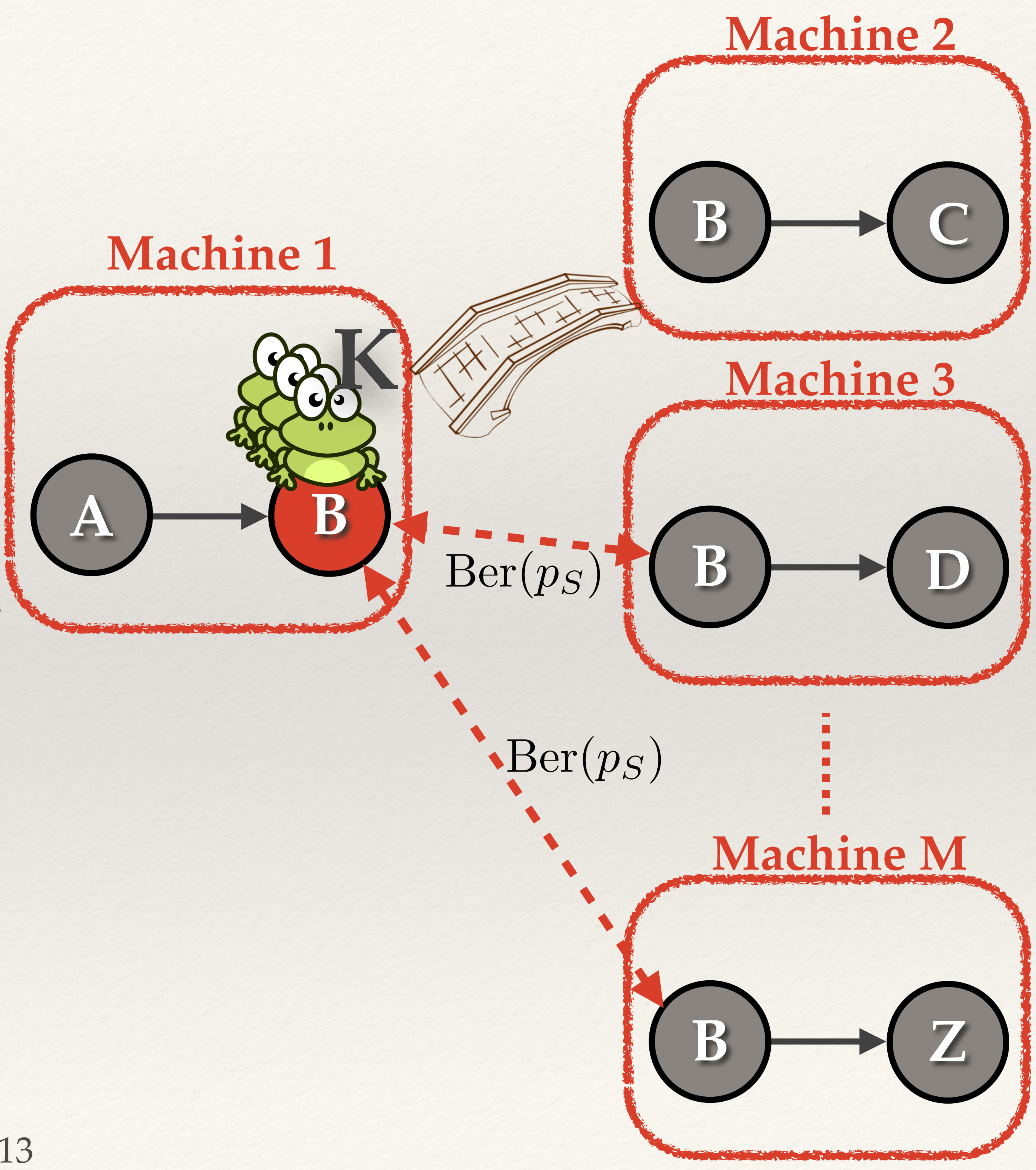

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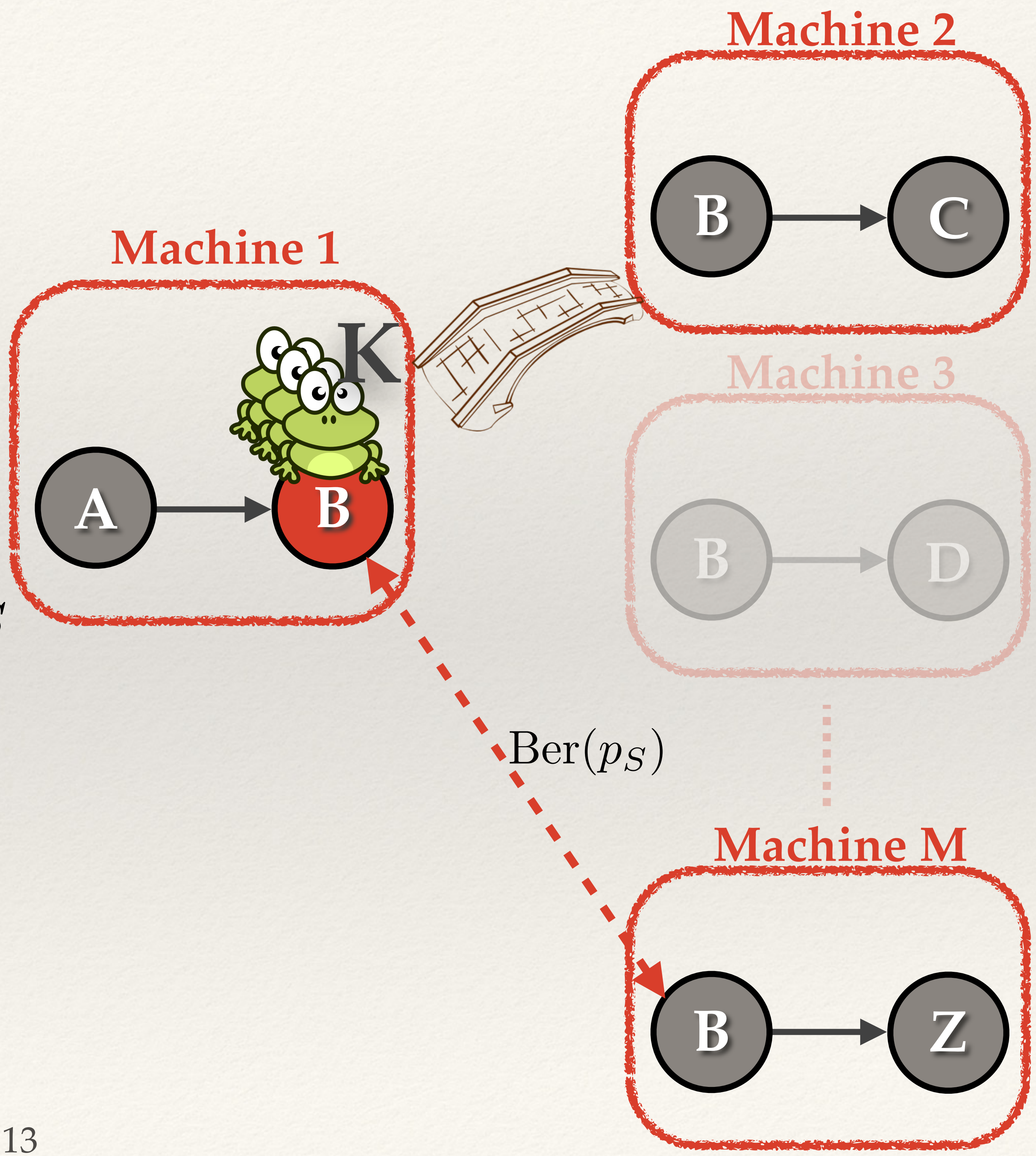

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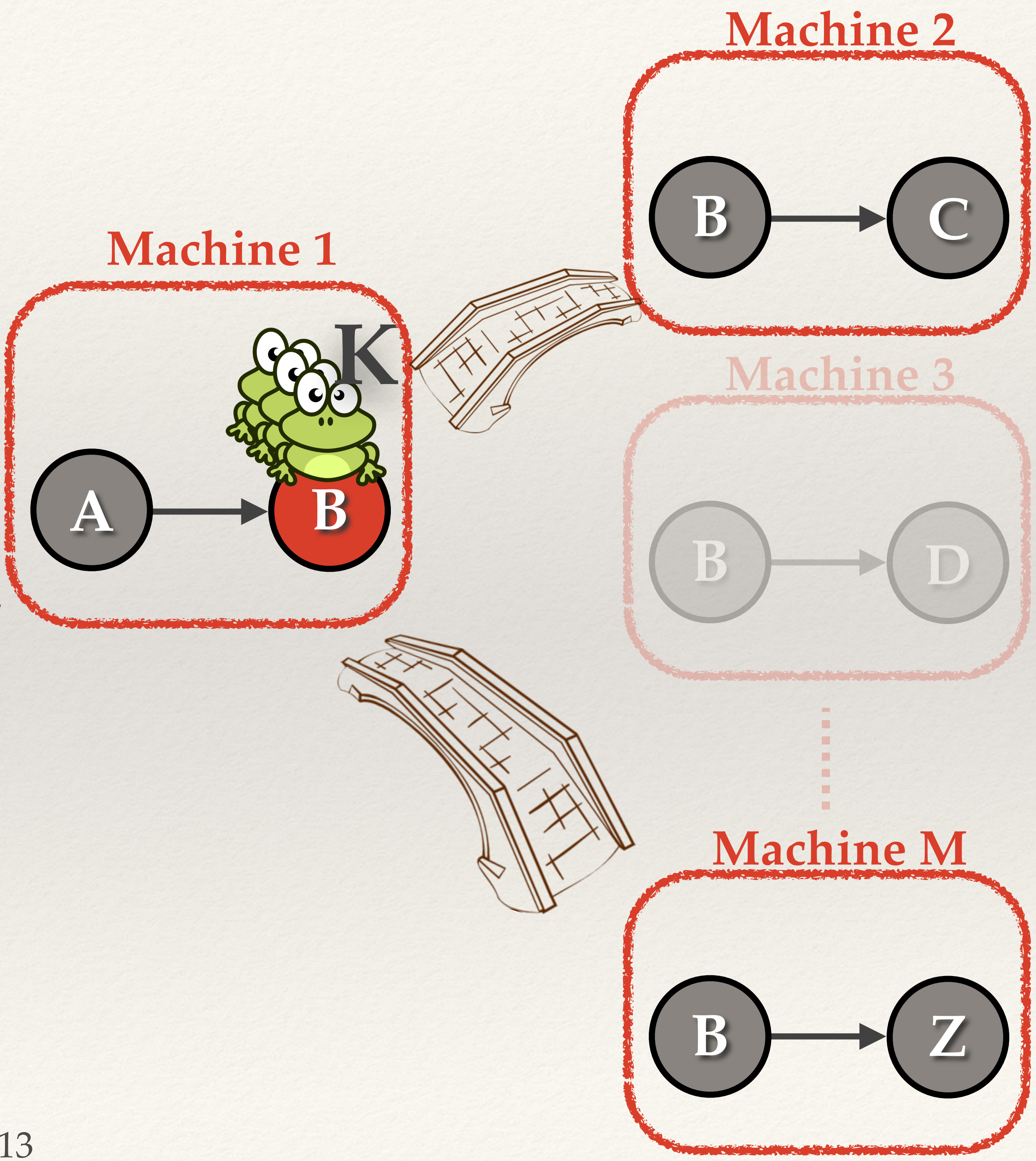

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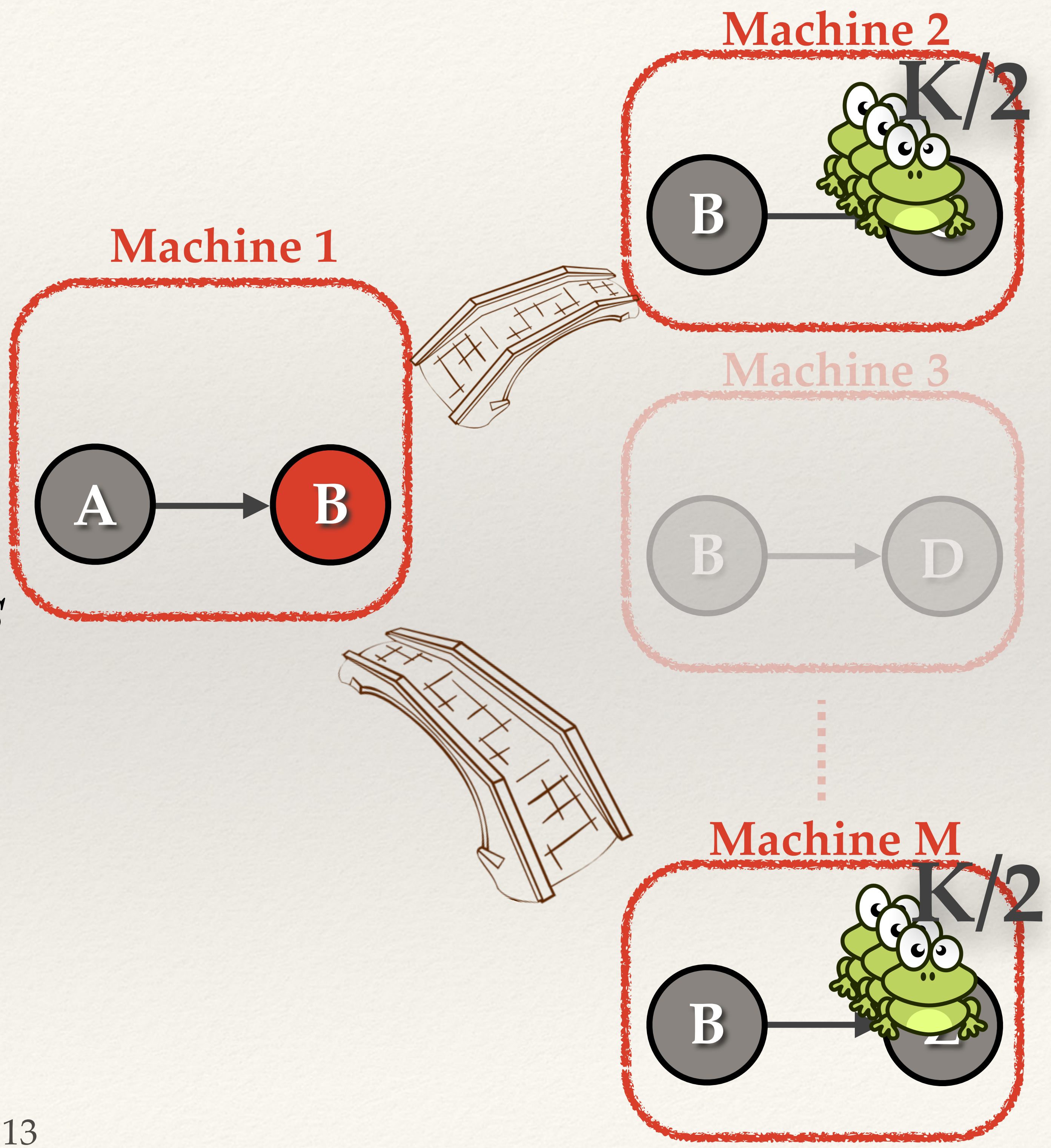

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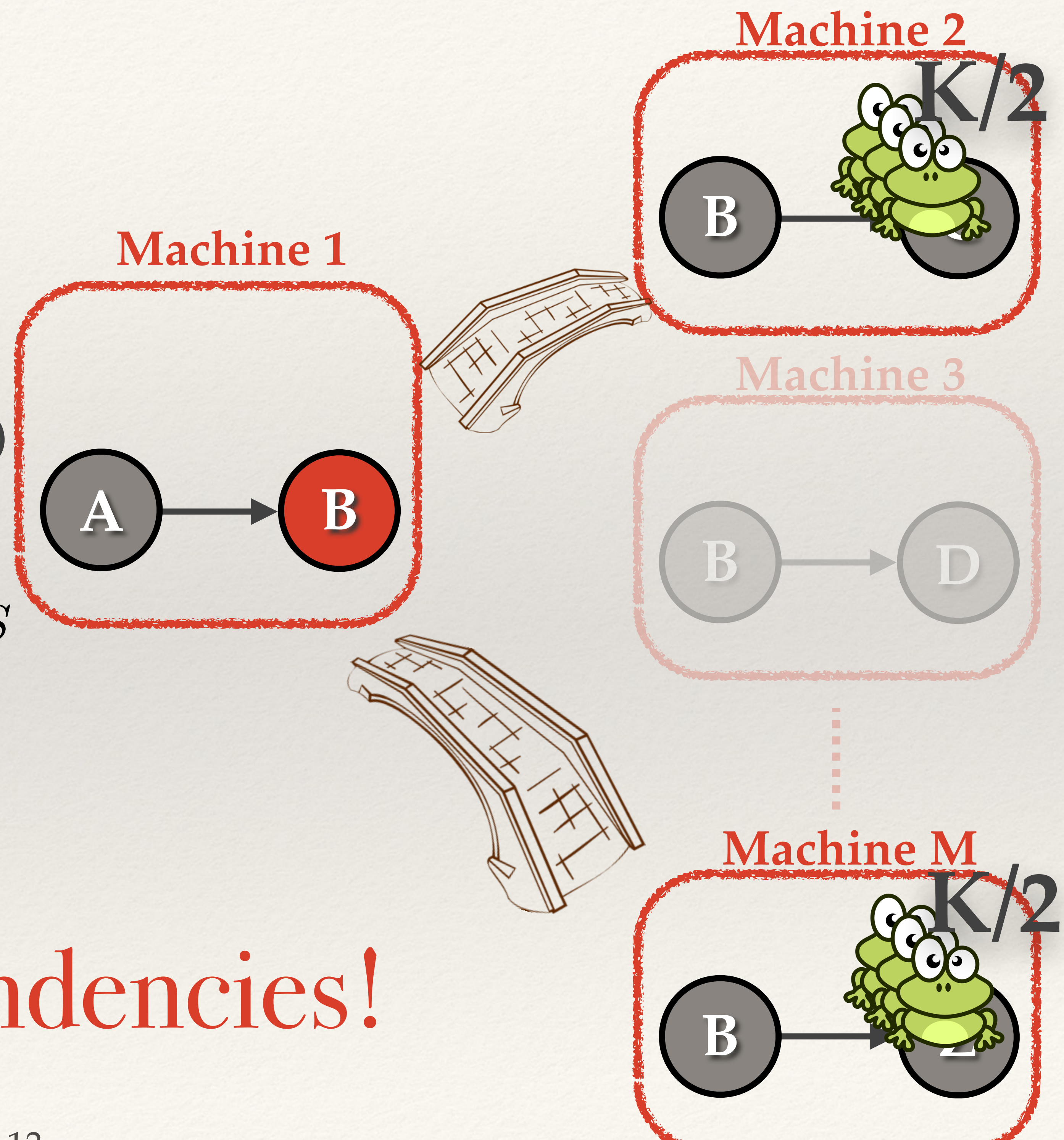


Bridges introduce **dependencies!**

Contributions

1. Algorithm for approximate PageRank
2. Modification of GraphLab
   Exposes very simple API extension (p_S).
   Allows for randomized synchronization.
3. Speedup of 7-10x
4. Theoretical guarantees for solution despite introduced dependencies

Theoretical Guarantee

Mass Captured by top-k set, S, of estimate from N frogs after t steps

$$\pi(S) \geq \mathrm{OPT} - 2\epsilon \quad \text{w.p. } 1-\delta$$

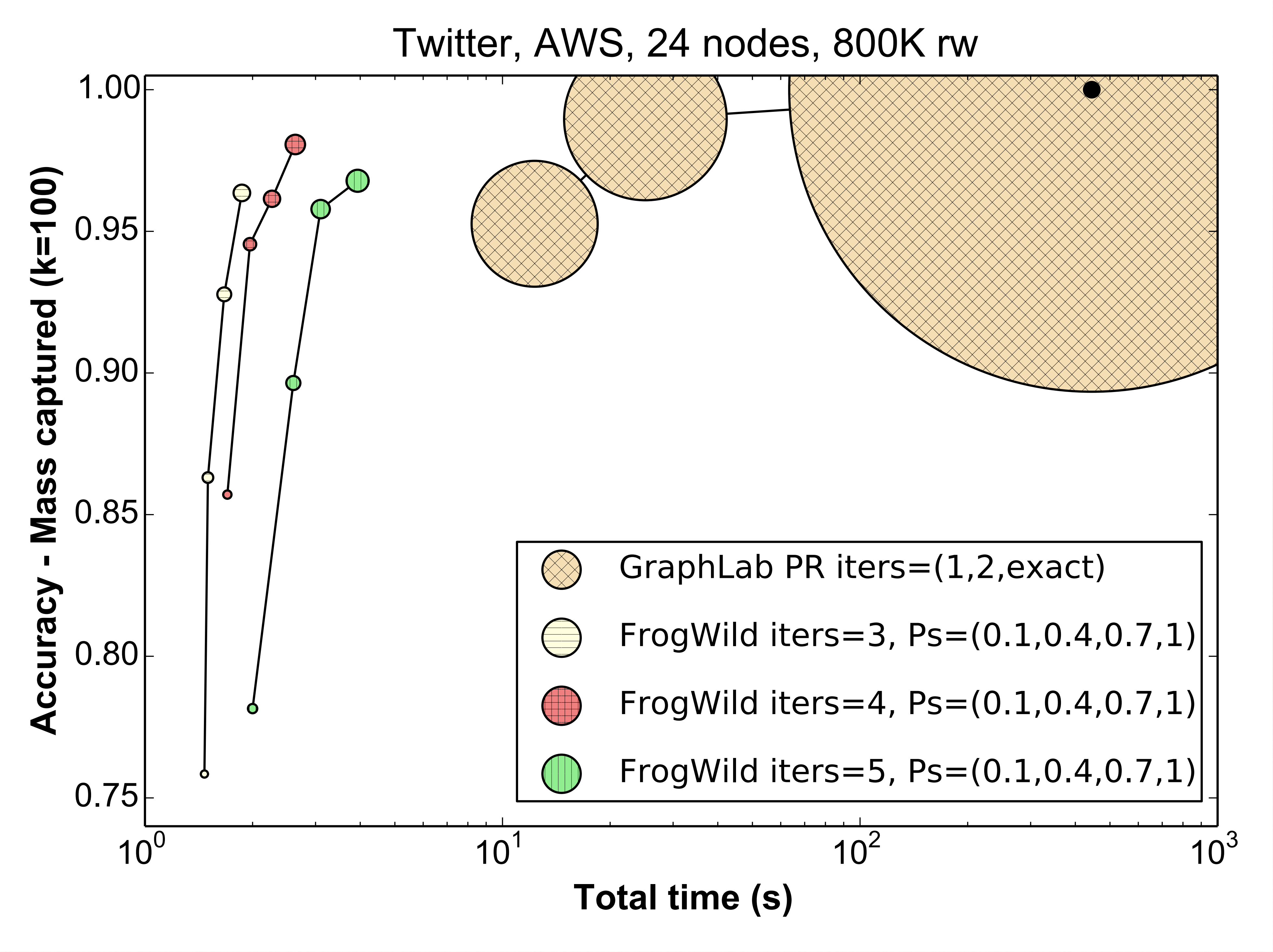
where $$\epsilon < \sqrt{k}\lambda_2^t + \sqrt{\frac{k}{\delta}\left[\frac{1}{N} + (1-p_S^2)p_\cap(t)\right]}$$

probability two Frogs meet at first t steps

$$p_\cap(t) \leq \frac{1}{n} + \frac{t\|\pi\|_\infty}{p_T},$$

Experiments

Experimental Results



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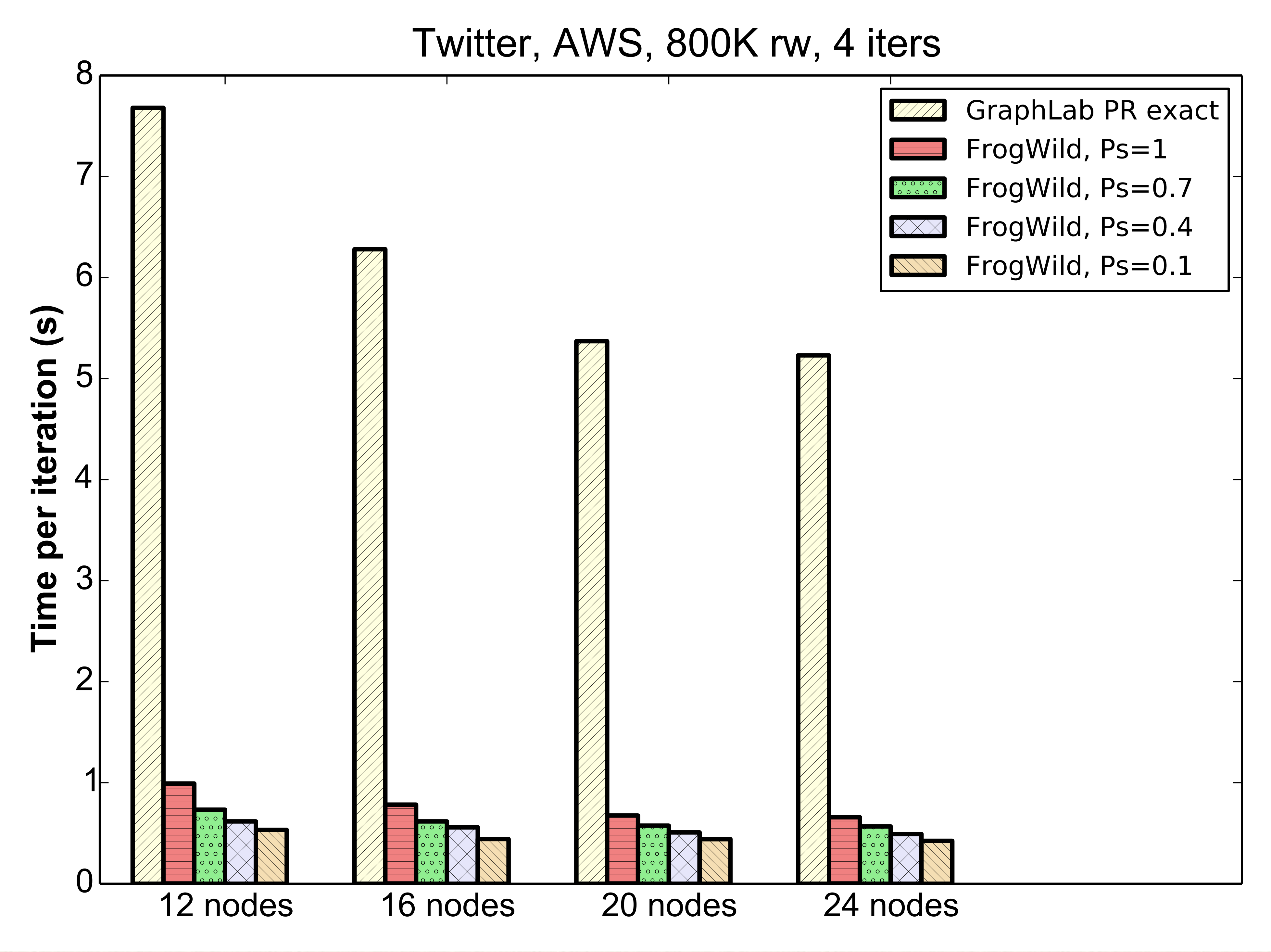

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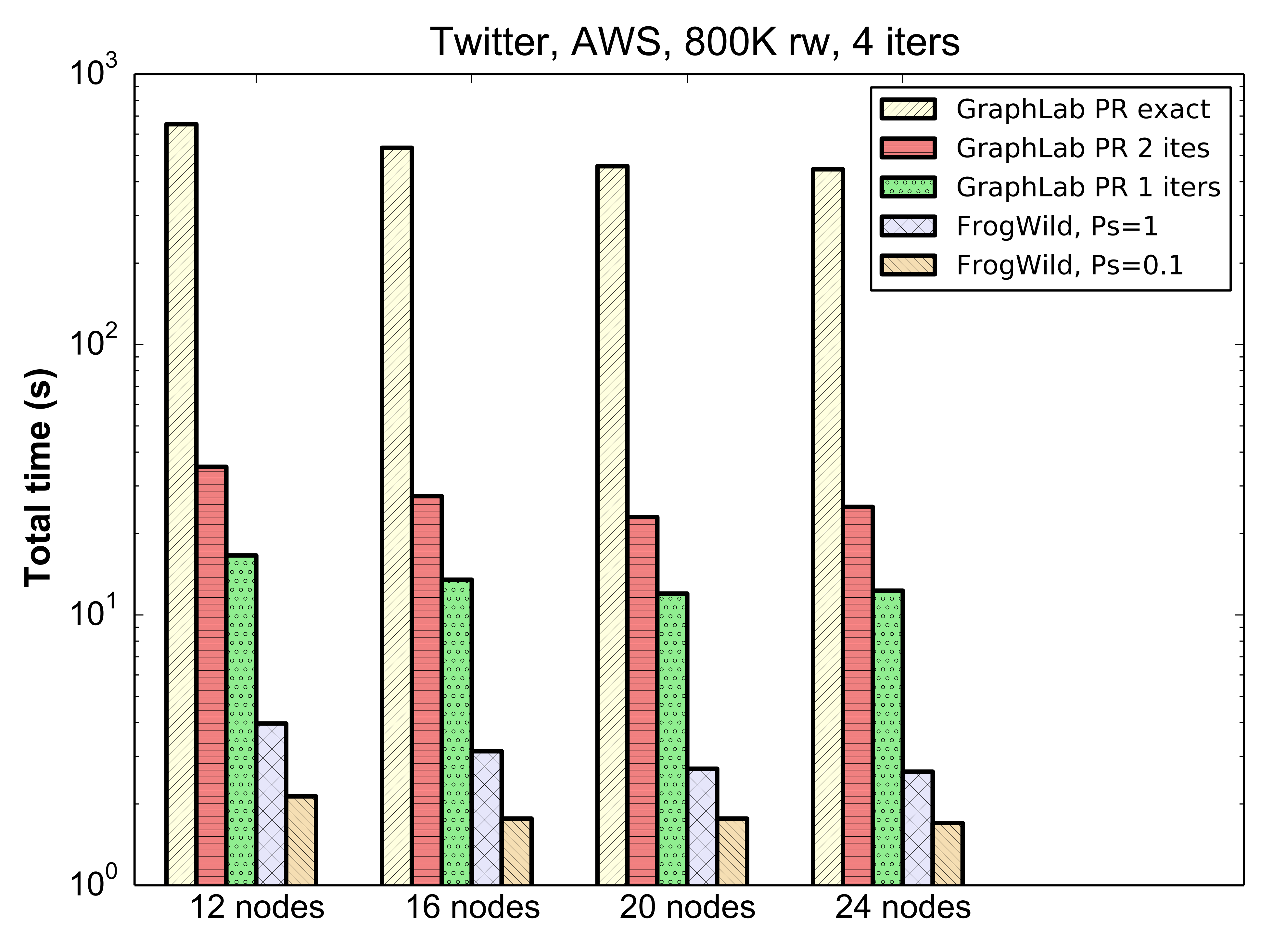

Thank you!

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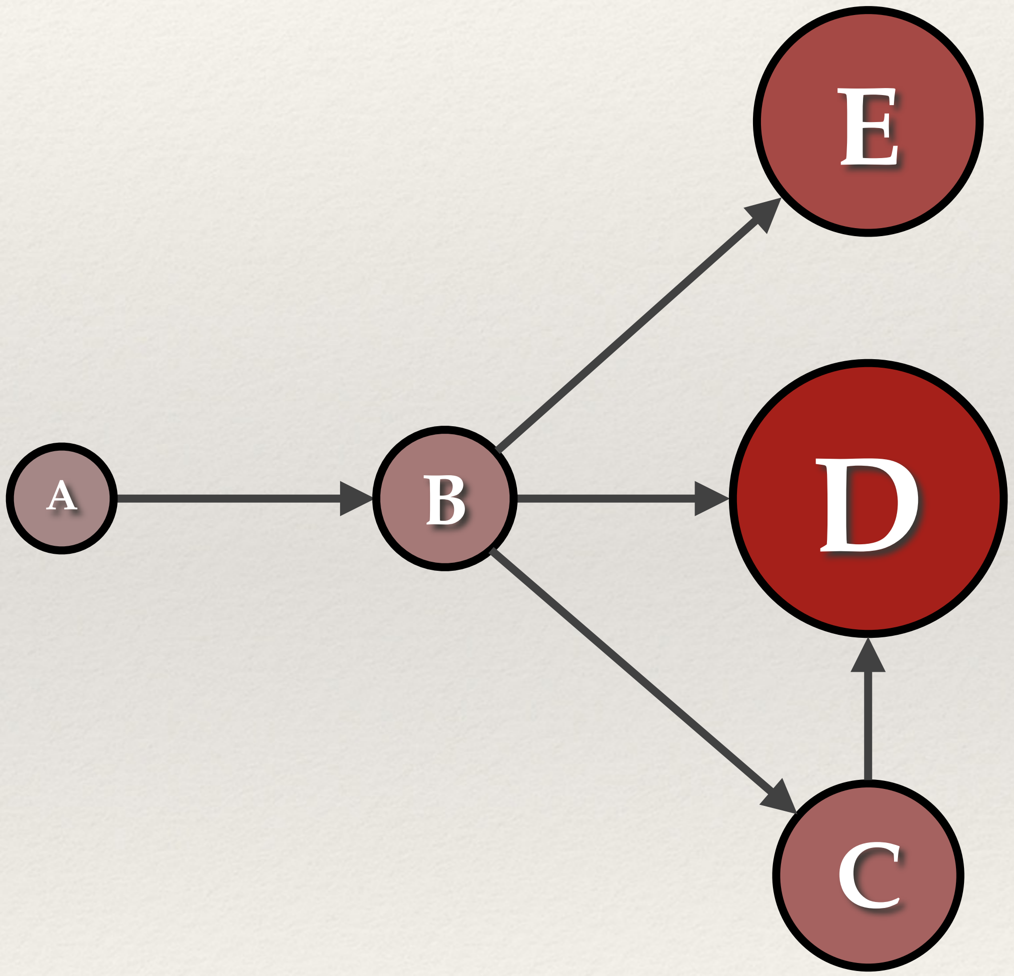
Backup Slides

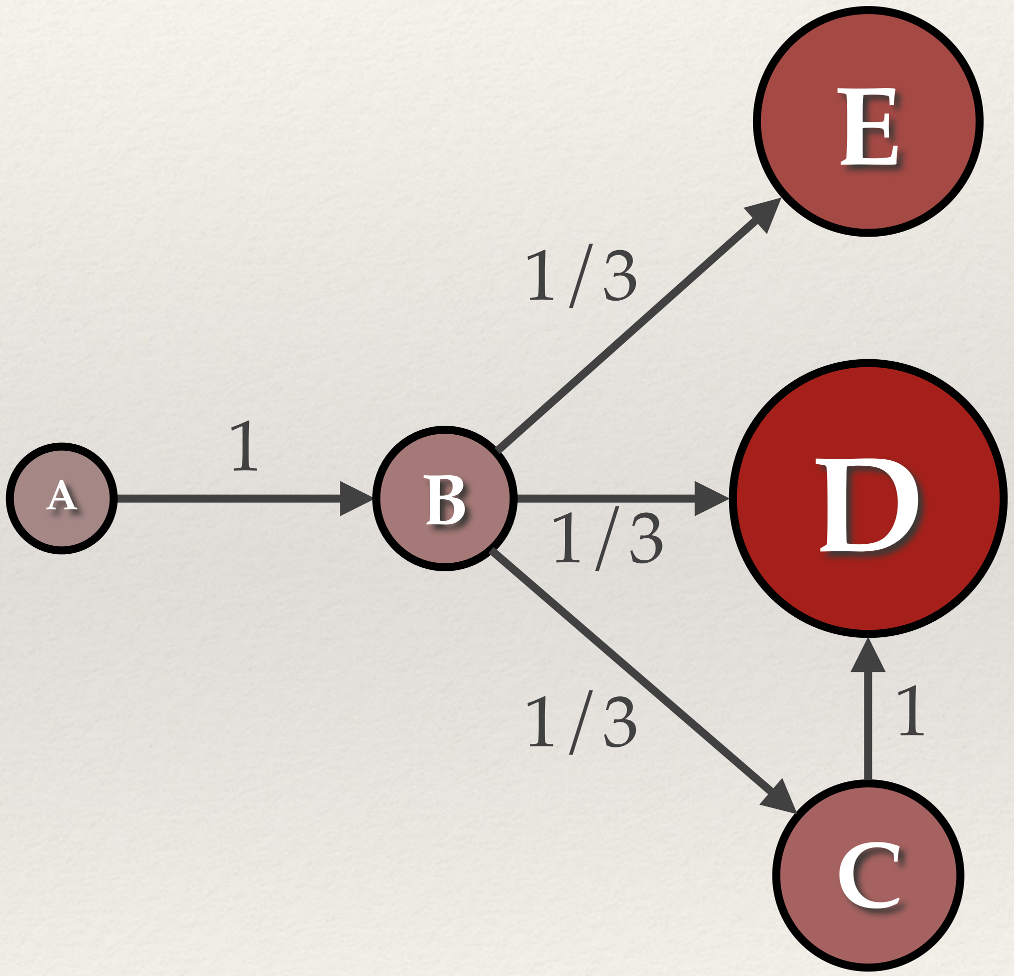
PageRank [Page et al., 1999]



PageRank [Page et al., 1999]

Normalized Adjacency Matrix

$$P_{ij} = \frac{1}{\mathrm{d}_{\mathrm{out}}(j)}, \quad (j, i) \in G$$



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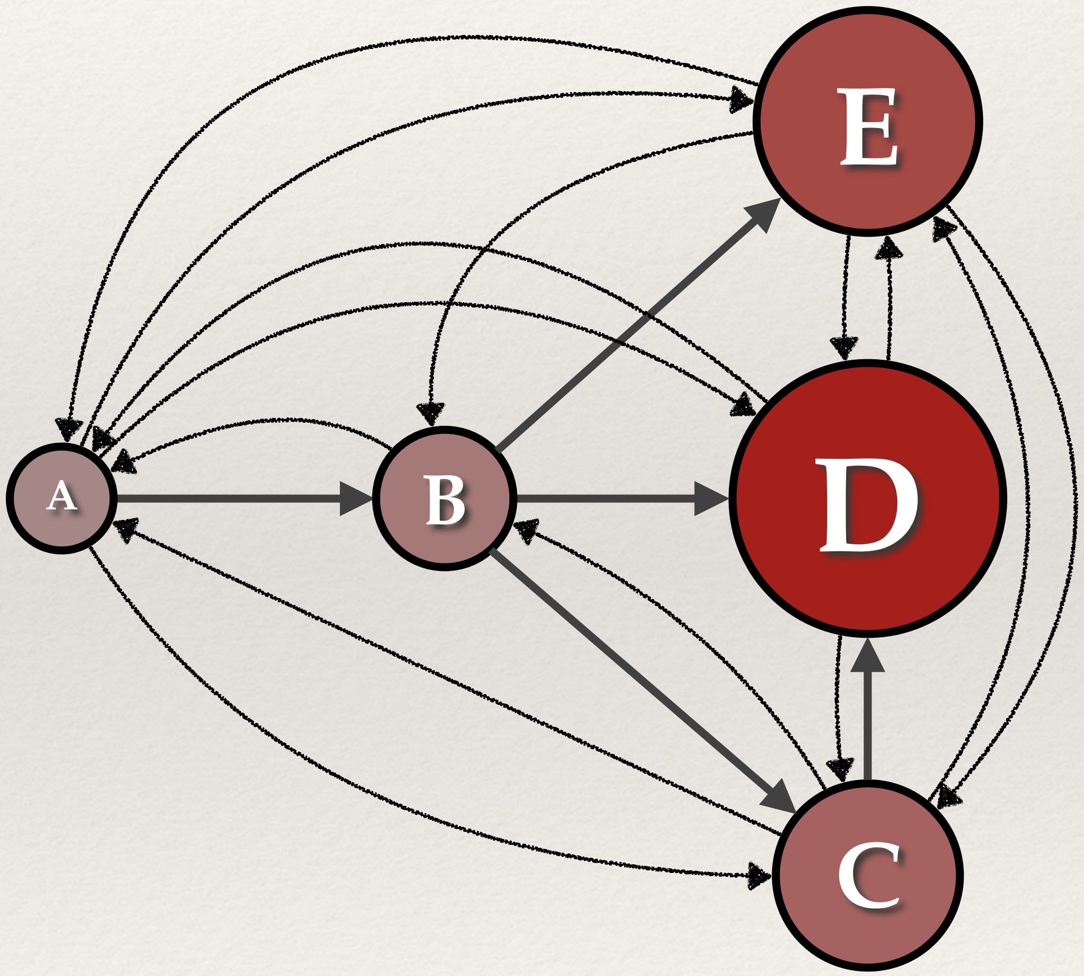
Augmented Matrix $p_T \in [0, 1]$

$$Q_{ij} = (1 - p_T) P_{ij} + \frac{p_T}{n}$$



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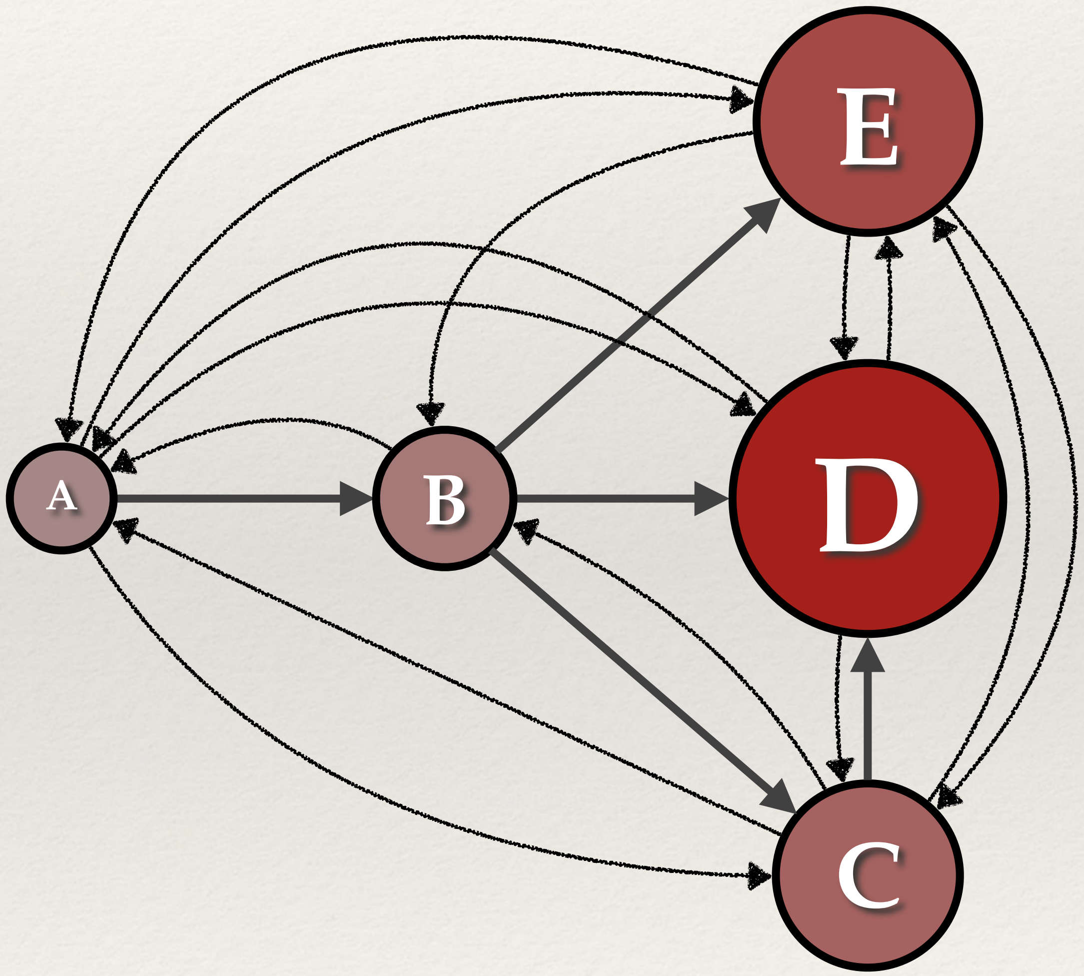
$$Q_{ij} = (1 - p_T) P_{ij} + \frac{p_T}{n}$$

PageRank Vector $\pi = Q\pi$



PageRank [Page et al., 1999]

Normalized Adjacency Matrix

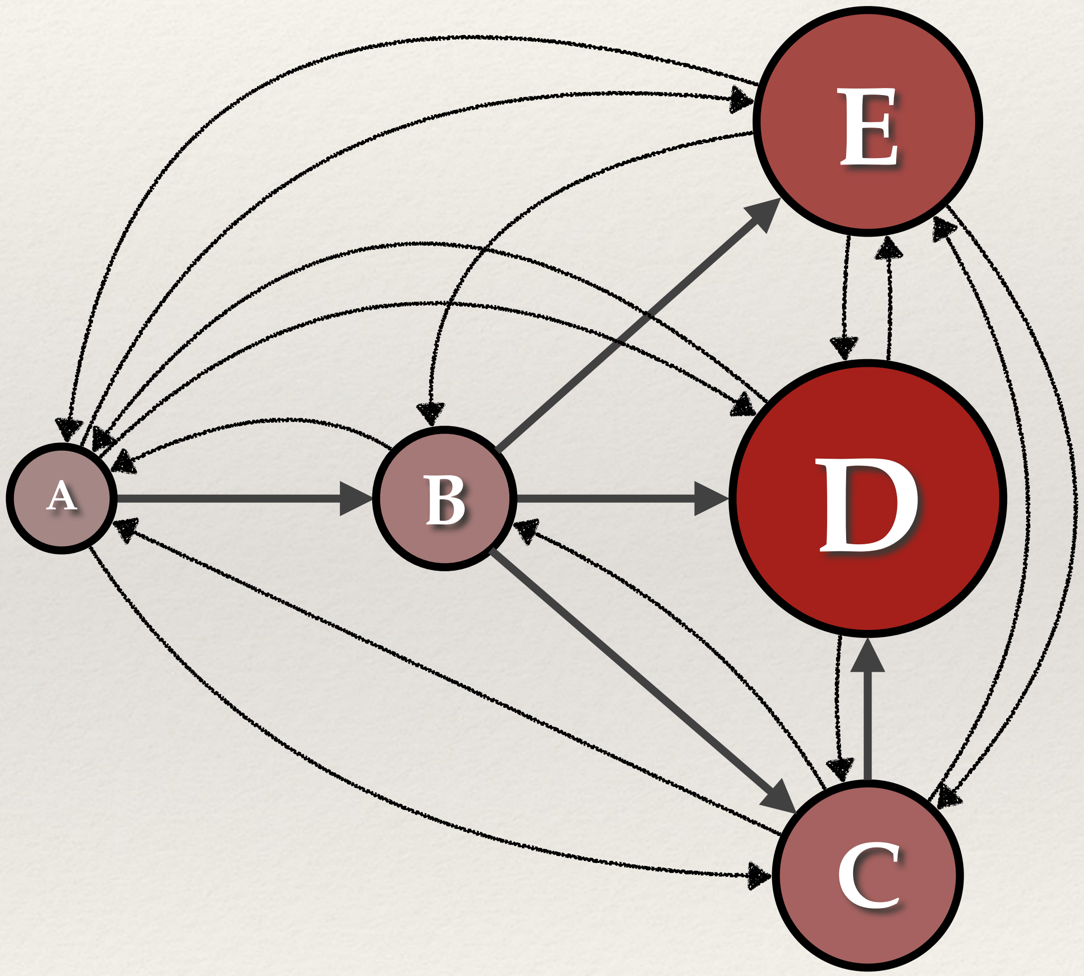
$$P_{ij} = \frac{1}{\mathrm{d_{out}}(j)}, \quad (j, i) \in G$$

Augmented Matrix $p_T \in [0, 1]$

$$Q_{ij} = (1 - p_T)P_{ij} + \frac{p_T}{n}$$

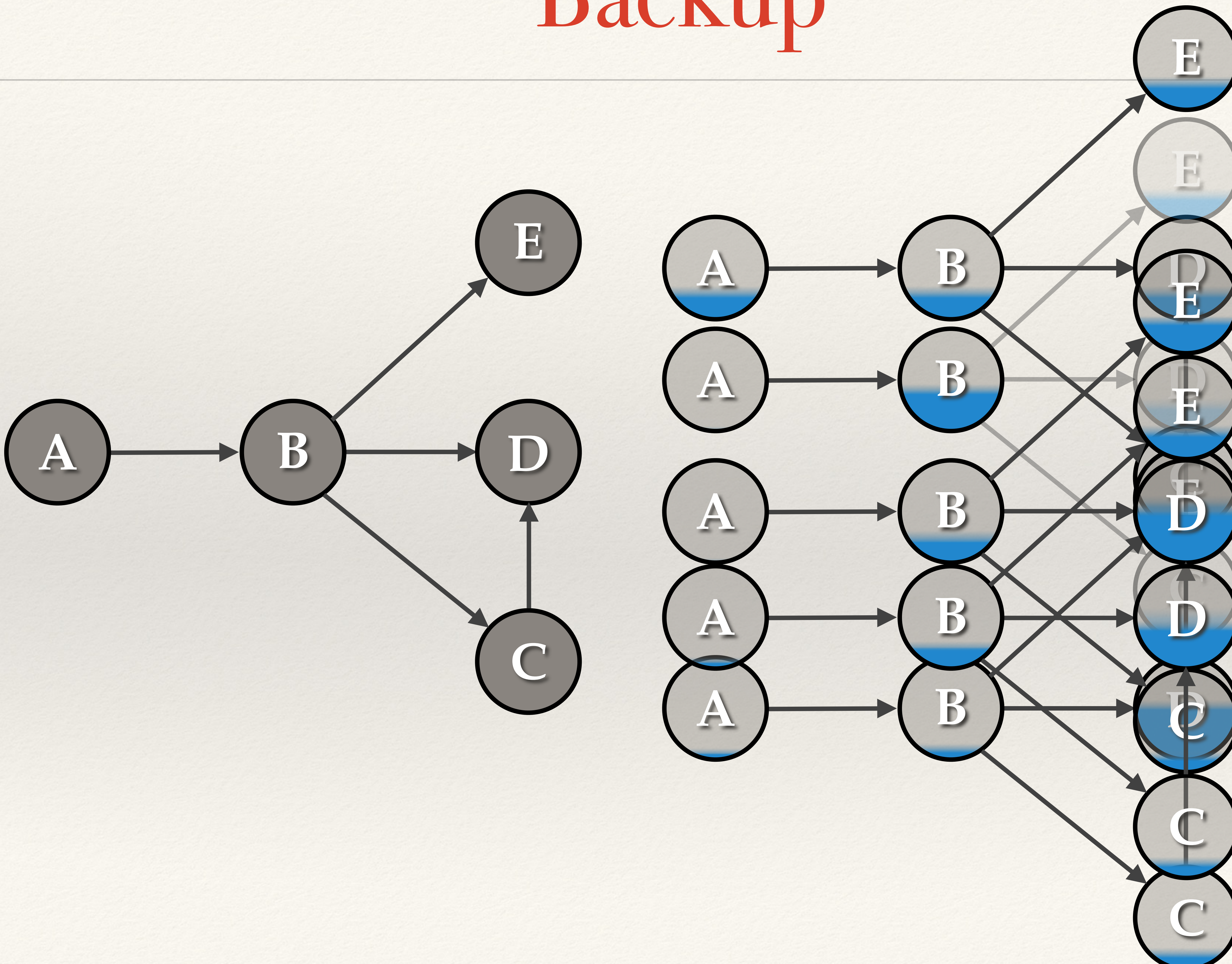
PageRank Vector $\pi = Q\pi$

Power Method $Q^t p^0 \to \pi$



Here be dragons.

Backup



Backup