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The University of Texas at Austin
Electrical and Computer Engineering

Data Partitioning Strategies for Graph Workloads on Heterogeneous Clusters

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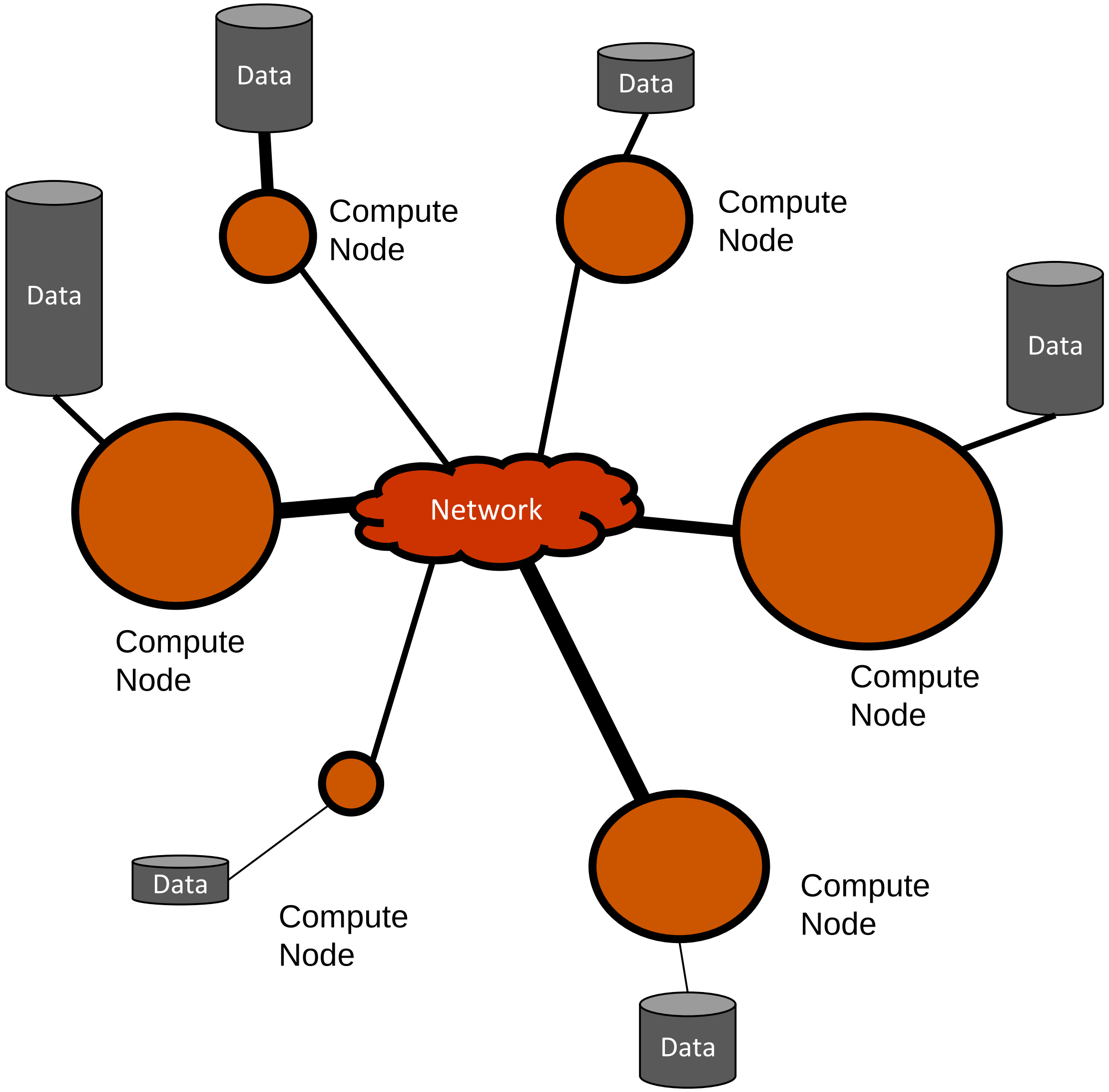
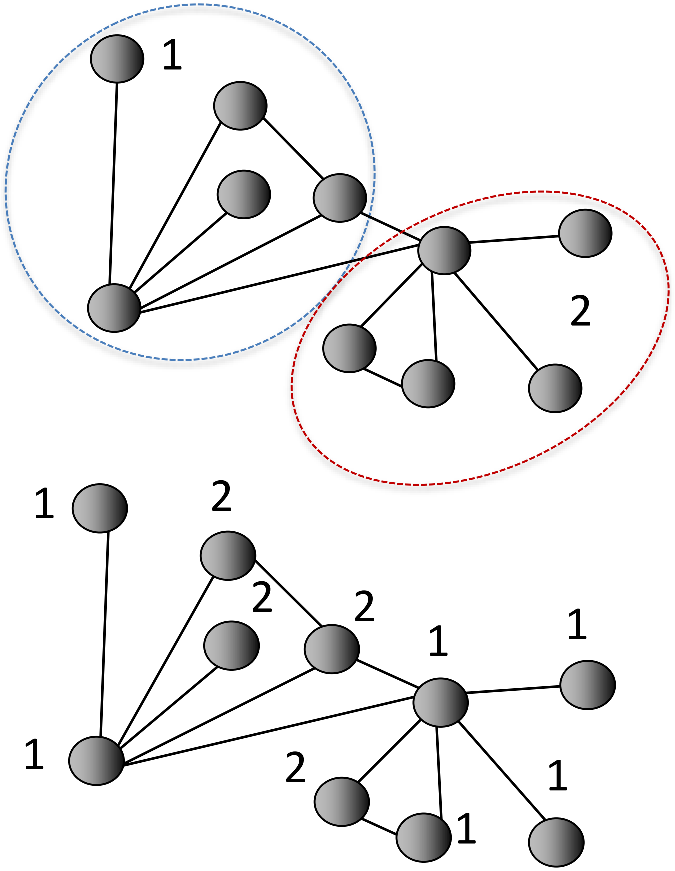
Motivation

- **Heterogeneity is pervasive in modern data centers [][]**
- **Graph analytics are a pervasive workload in the data center []**
  - Many frameworks available to efficiently and easily perform graph analytics [][][][]
- **Most frameworks are not equipped to deal with heterogeneity in the data center**



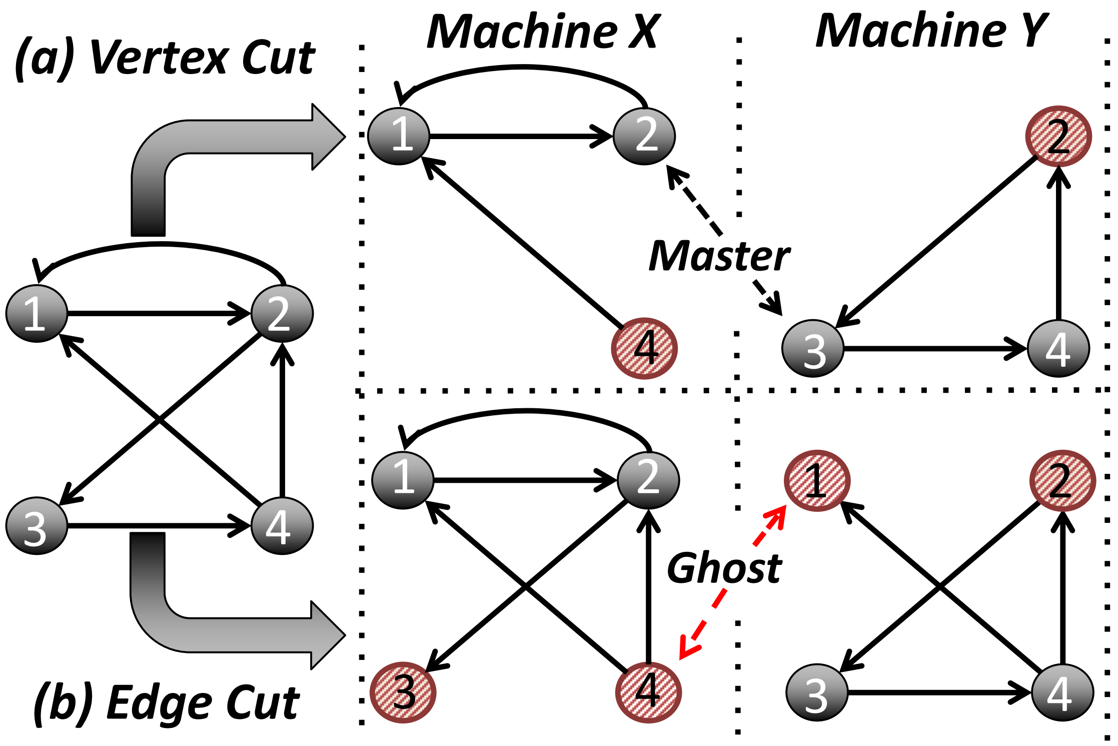
Background

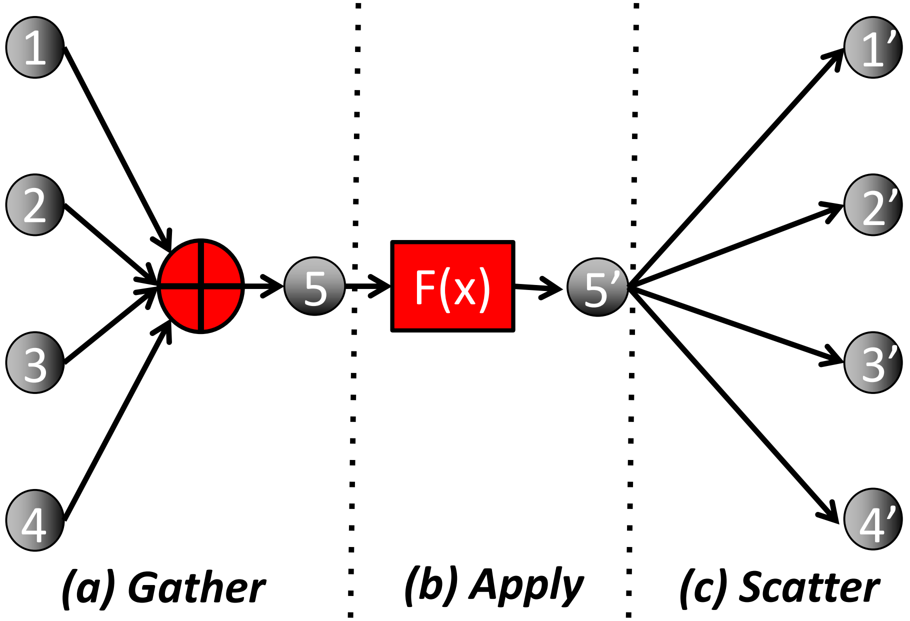
- **All work performed on PowerGraph[] framework**
- **Three relevant graph partitioning topics:**
  - Online vs. Offline Partitioning
  - Vertex vs. Edge Cut
  - Gather/Apply/Scatter



- **Online vs. Offline Partitioning**

Background

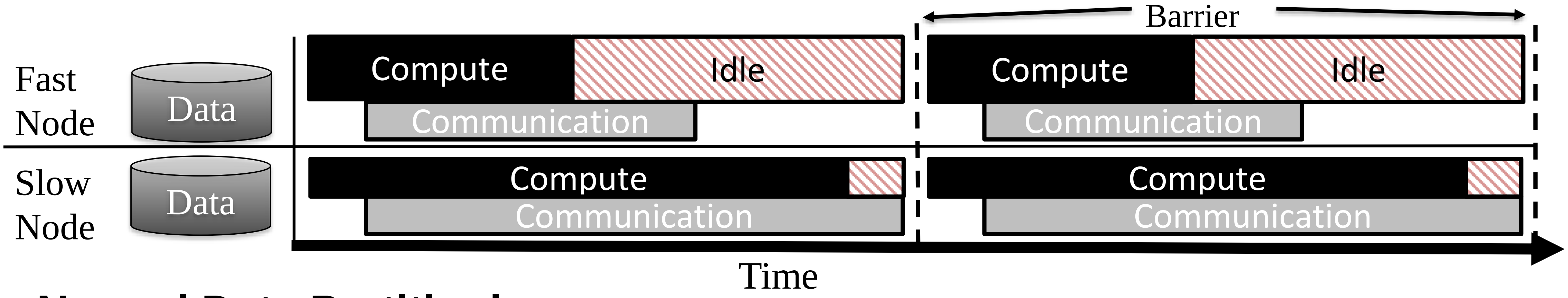




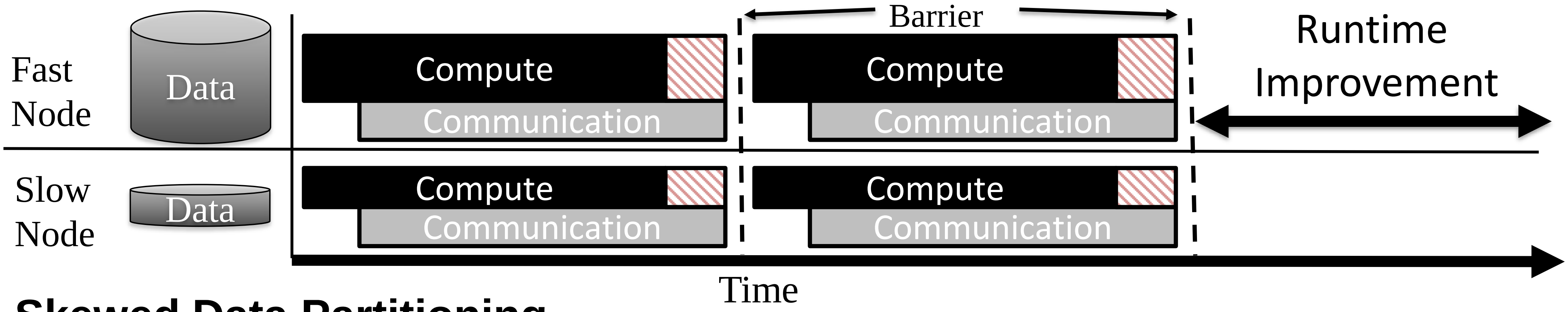
- **Vertex vs. Edge Cut**

- **Gather/Apply/Scatter**

Workload Skew in Heterogeneous Data Centers



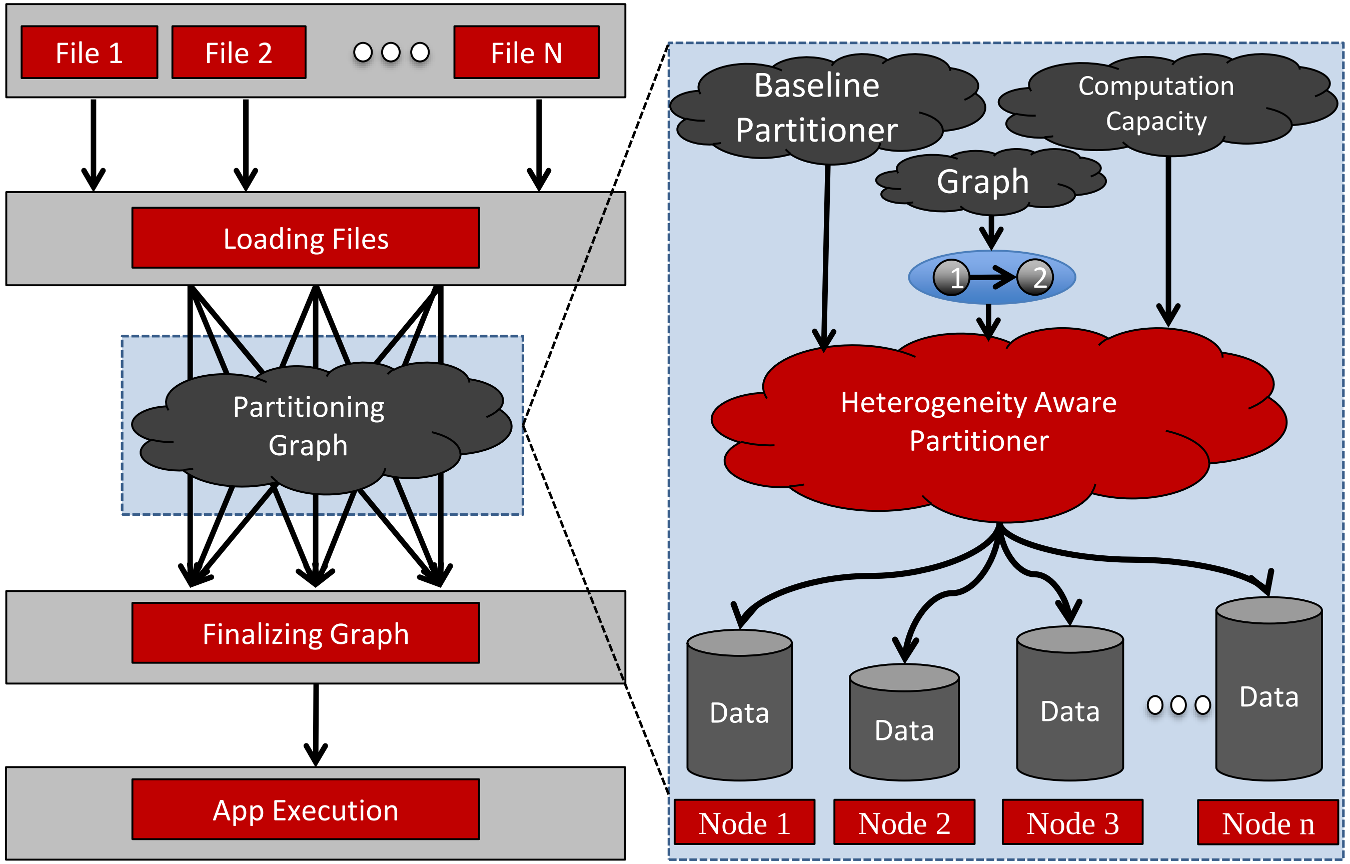
- **Normal Data Partitioning**



- **Skewed Data Partitioning**

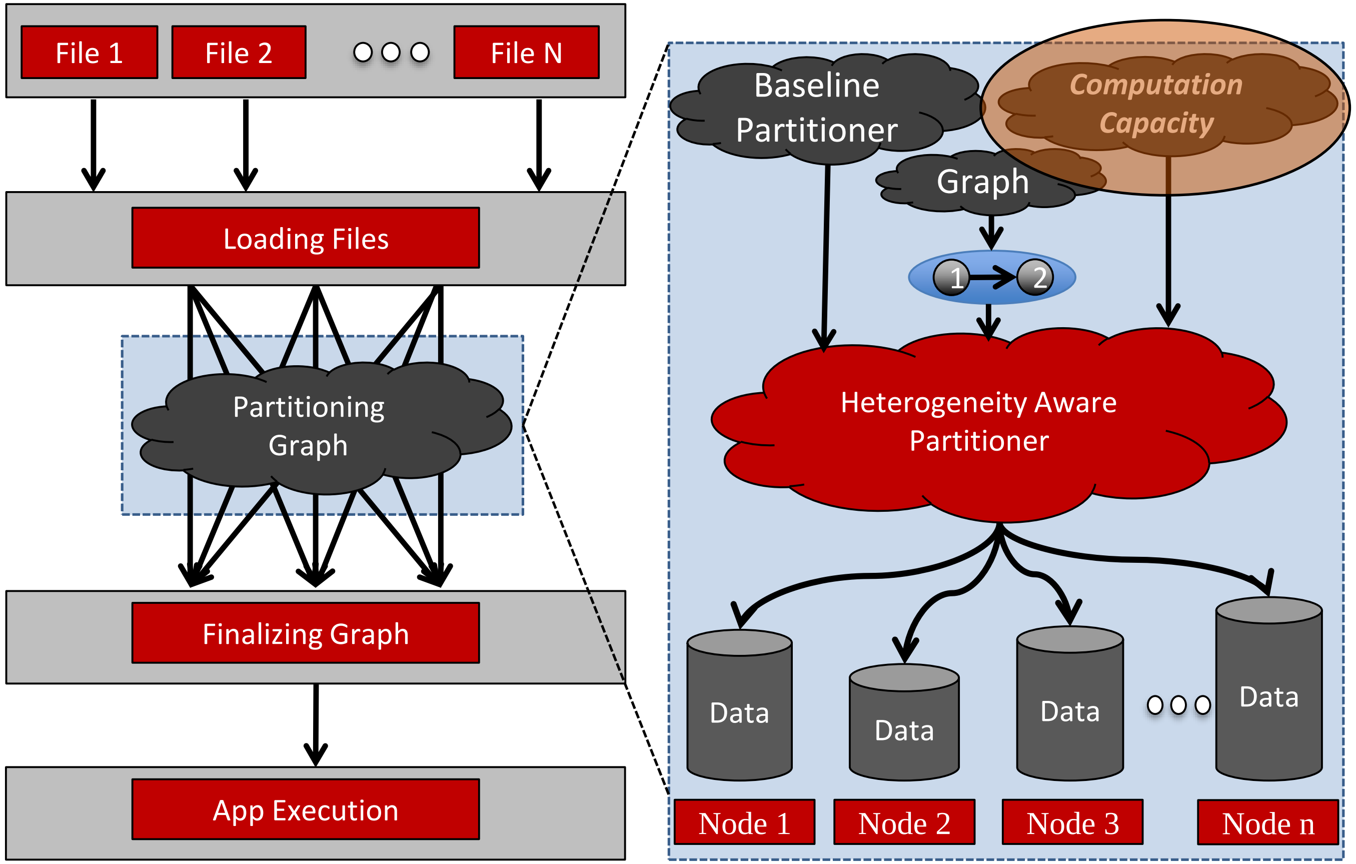
Heterogeneous Graph Analytics

- **Local node computation time dependent on data distribution**
- **To properly balance work, we need:**
  - Estimation of each node’s computational capacity
  - Partitioning algorithms that account for skewed computational capacity



Heterogeneous Computation Capacity

- **Computation capacity is complex**
- **Dependent on many factors:**
  - Hardware of the node
  - Nature of the graph
  - Nature of the algorithm
  - Communication patterns
- **Can we determine a simple, static estimate?**



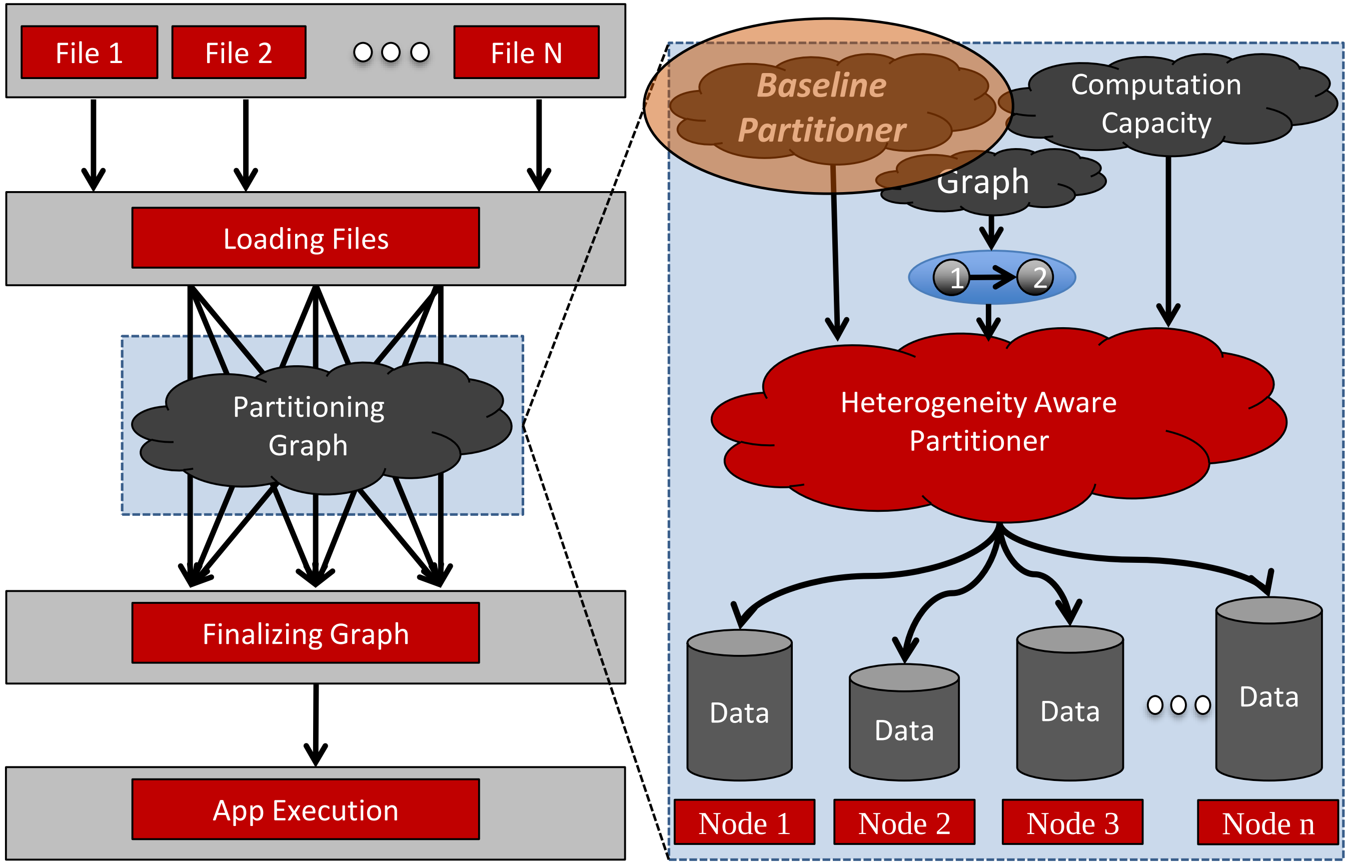
Skew Factor Calculation

Name	HW Threads	Memory	Network	Thread Skew Factor	Memory Skew Factor
c4.xlarge	4	7.5 GB	100 Mbps to 1.86 Gbps	1	1
c4.2xlarge	8	15 GB	100 Mbps to 1.86 Gbps	3	2
c4.4xlarge	16	30 GB	100 Mbps to 1.86 Gbps	7	4
c4.8xlarge	36	60 GB	up to 8.86 Gbps	17	8

- **Static estimate of node computational capacity could be based on:**
  - Threads: Logical compute threads on node (default N – 2)
  - Memory: Physical memory assigned to a node
  - Profiling: Local throughput of graph subset and algorithm
- **We will refer to the estimated ratios of computation capacity as the *skew factor* of the heterogeneous data center**

Heterogeneous Partitioning Algorithm

- **Online partitioning algorithms must be modified to support skew factor**
- **Easy to modify current online partitioning algorithms**
- **We have modified 5 popular algorithms from multiple sources**

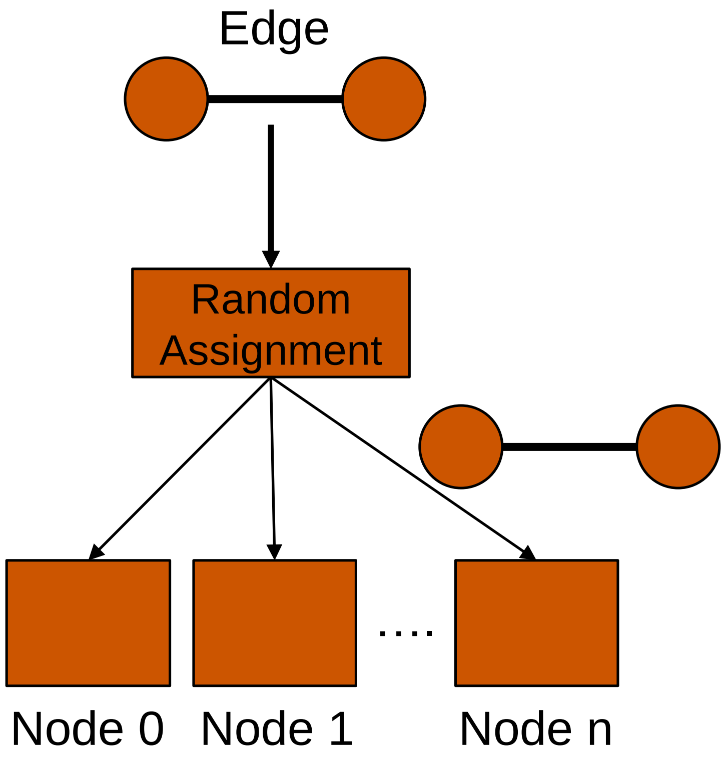


Problem Formulation

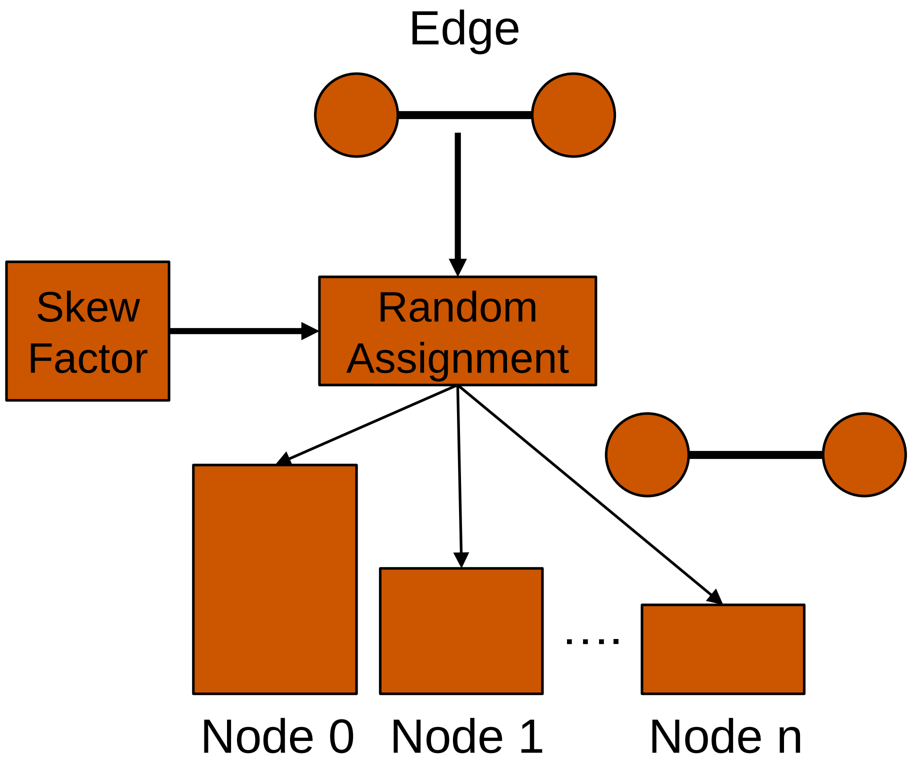
- **Statically estimated based on:**
  - Threads: Logical compute threads on node (default N – 2)
  - Memory: Physical memory assigned to a node
  - Profiling: Local throughput of graph subset and algorithm

- **Statically estimated based on:**

Random Skewed Partitioner



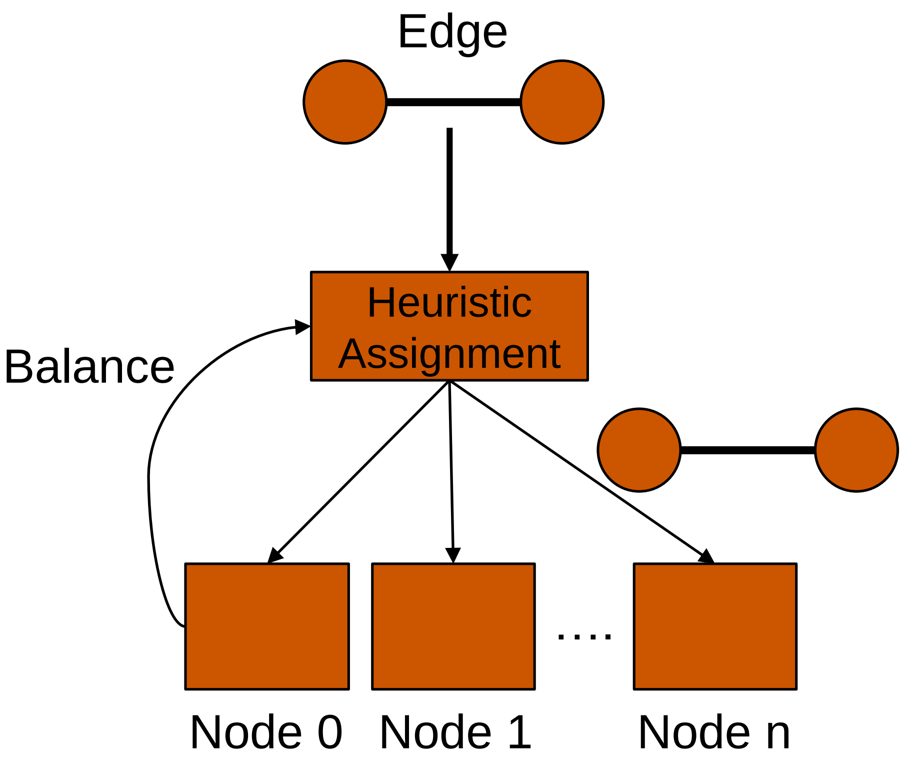
- **Original**



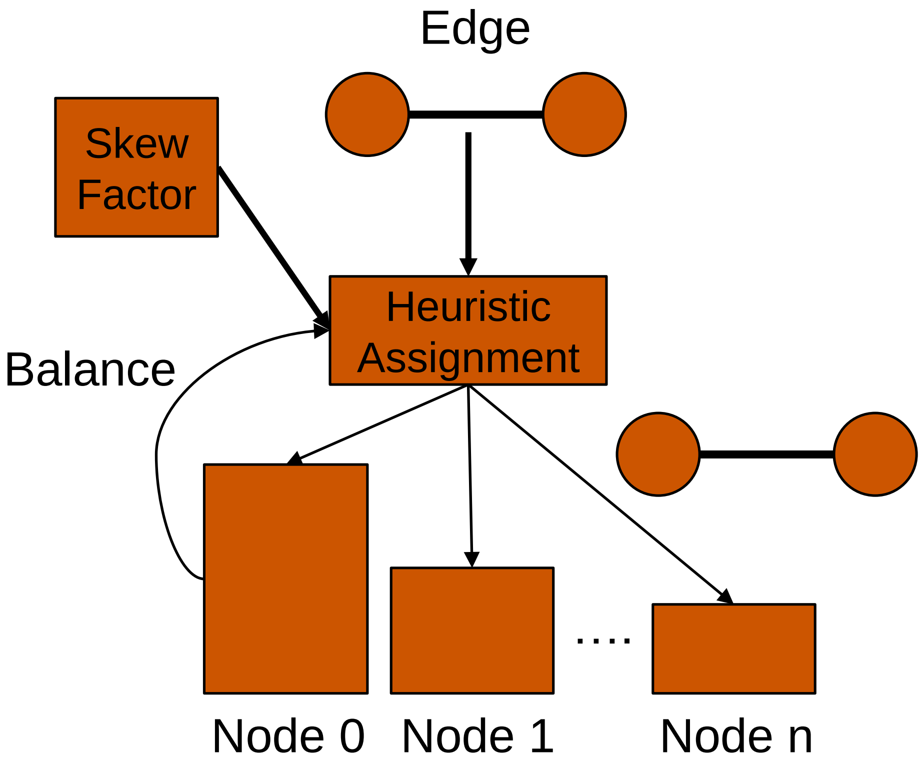
- **Skewed**

- **Random assignment of edges to nodes**

Greedy Skewed Partitioner



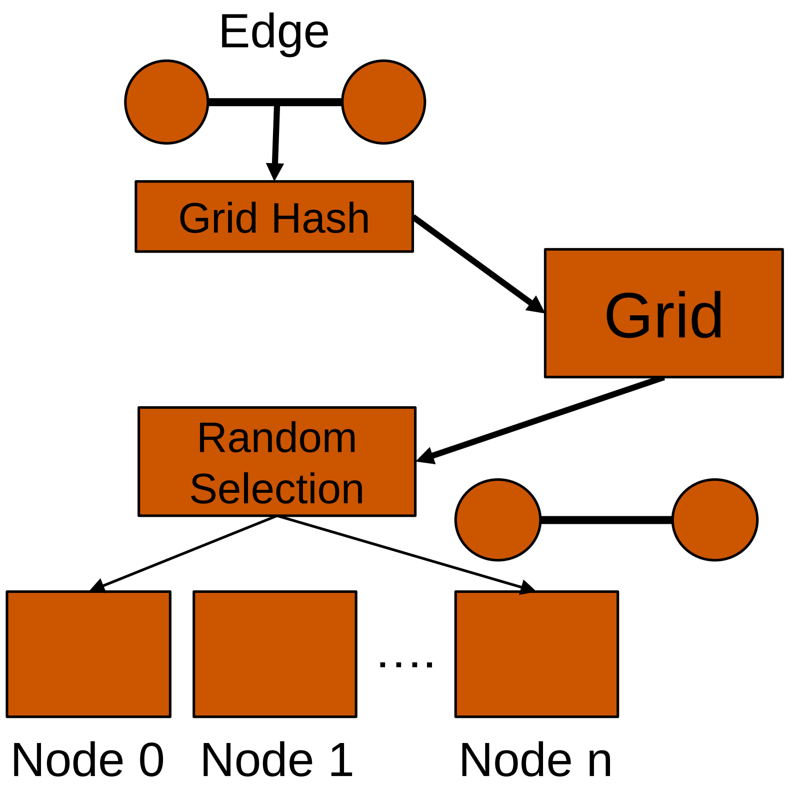
- **Original**



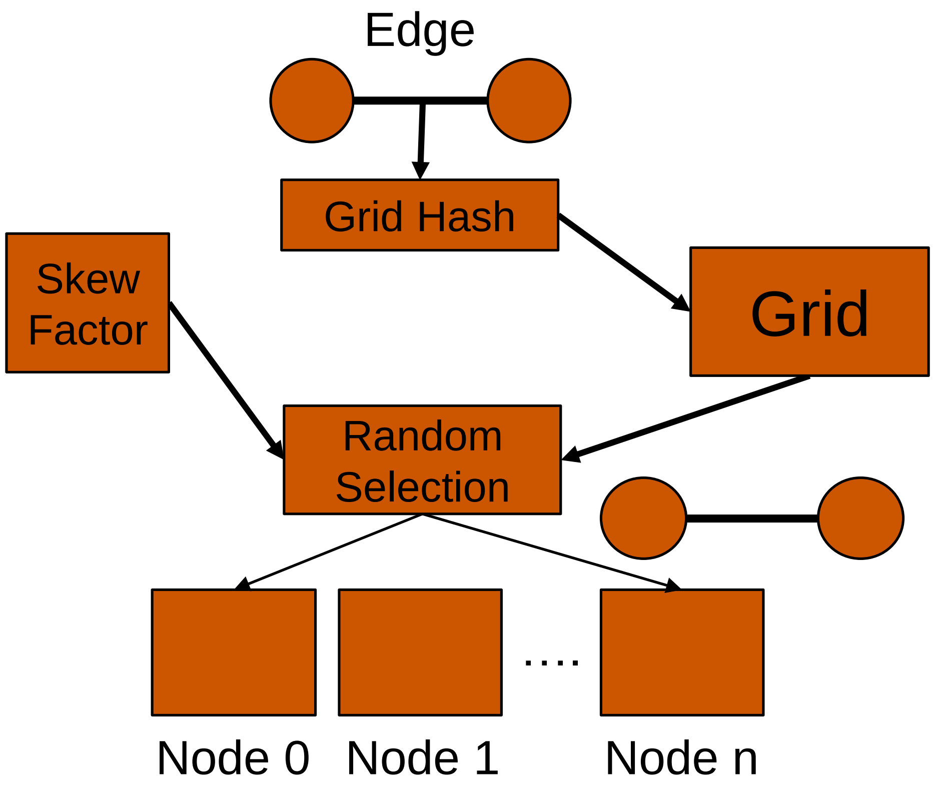
- **Skewed**

- **Greedy decision using current distribution of edges**
  - Either locally or coordinated

Grid Skewed Partitioner



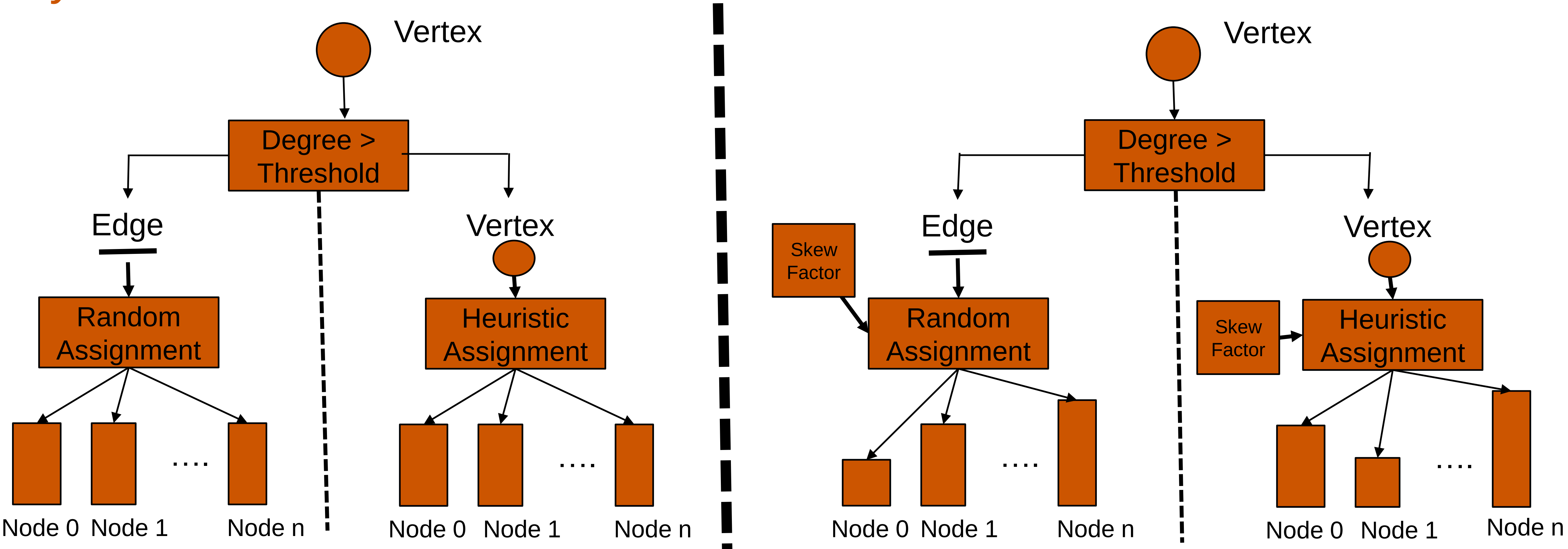
- **Original**



- **Skewed**

- **Greedy decision using current distribution of edges**
  - Either locally or coordinated

Hybrid Skewed Partitioner

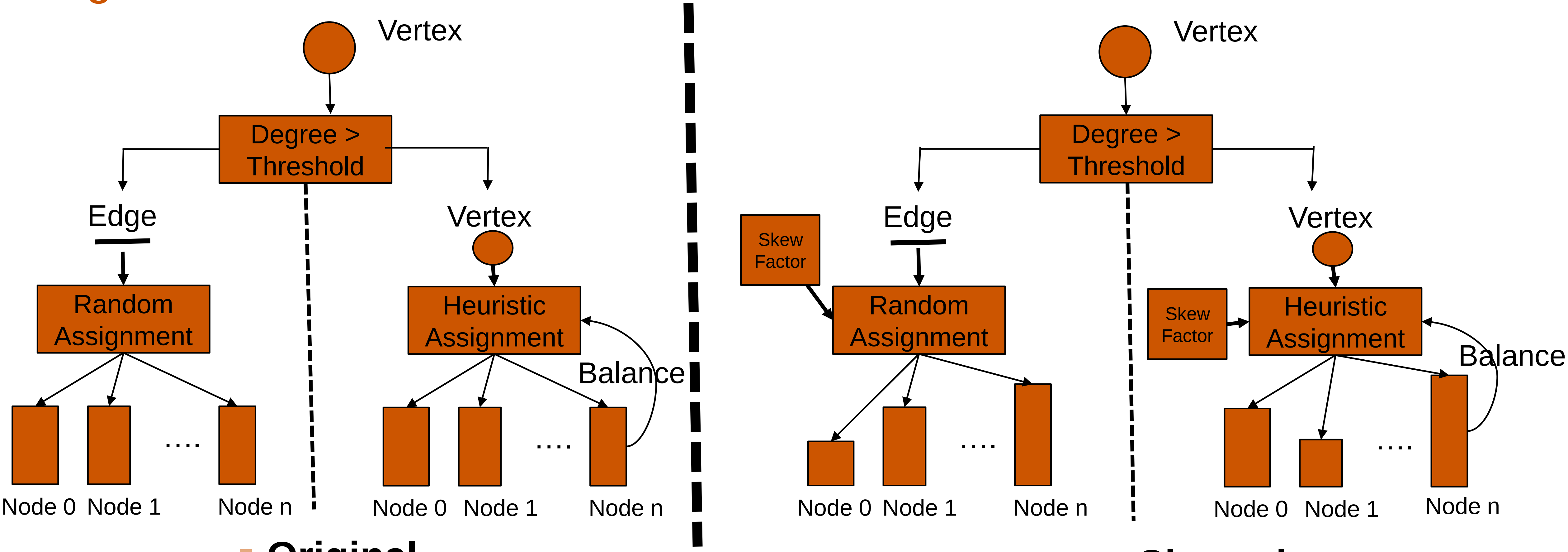


- **Original**

- **Skewed**

- **Random assignment of edges/verticies to nodes based on degree**

Ginger Skewed Partitioner



- **Original**
- **Skewed**

- **Random assignment of edges/verticies to nodes based on degree**

Experimental Setup

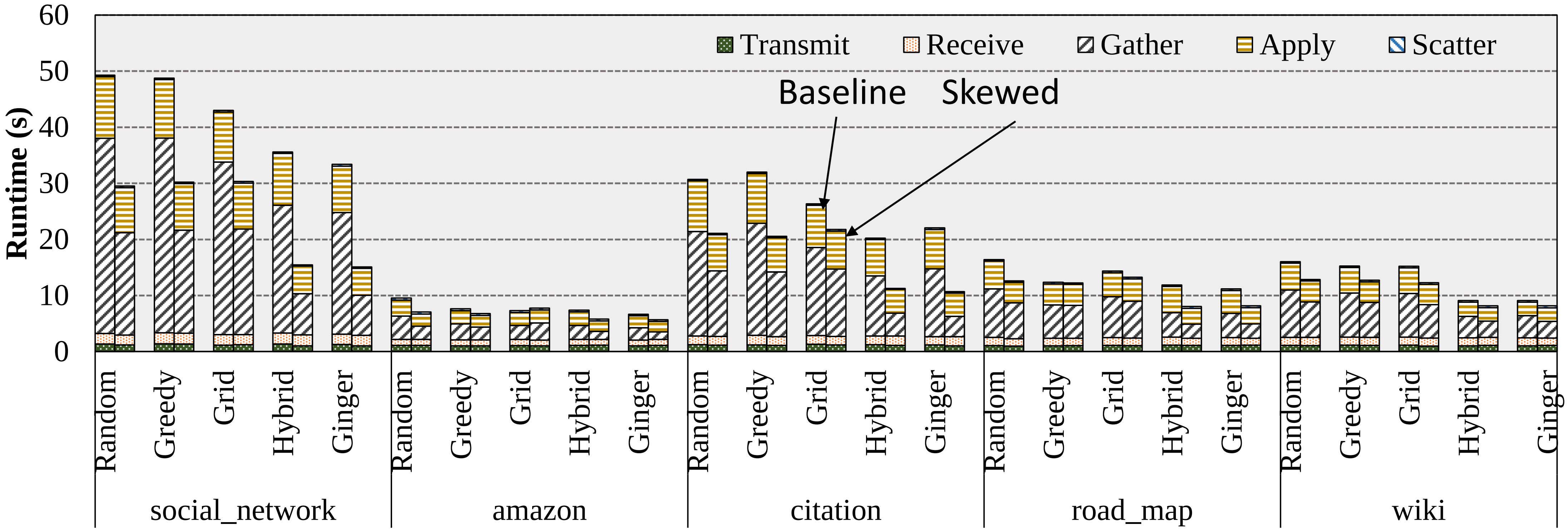
- **Algorithms**
  - Graph: PageRank (PR), Connected Components (CC), Triangle Count (TC)
  - Matrix: Stochastic Gradient Descent (SGD), Alternating Least Squares (ALS)
- **Data Sets**

Name	Vertices	Edges	Size (Uncompressed)	Type	Algorithms
amazon	403,394	3,384,388	46MB	Directed Graph	PR,CC,TC
citation	3,774,768,NA	16,518,948	268MB	Directed Graph	PR,CC,TC
netflix	NA	NA	100MB	Sparse Matrix	ALS,SGD
road-map	1,379,917	1,921,660	84MB	Undirected Graph	PR,CC,TC
social-network	4,847,571	68,993,773	1.1GB	Directed Graph	PR,CC,TC
twitter	41,000,000	1,400,000,000	25GB	Directed Graph	PR,CC,TC
wiki	2,394,385	5,021,410	64MB	Directed Graph	PR,CC,TC

Experimental Setup

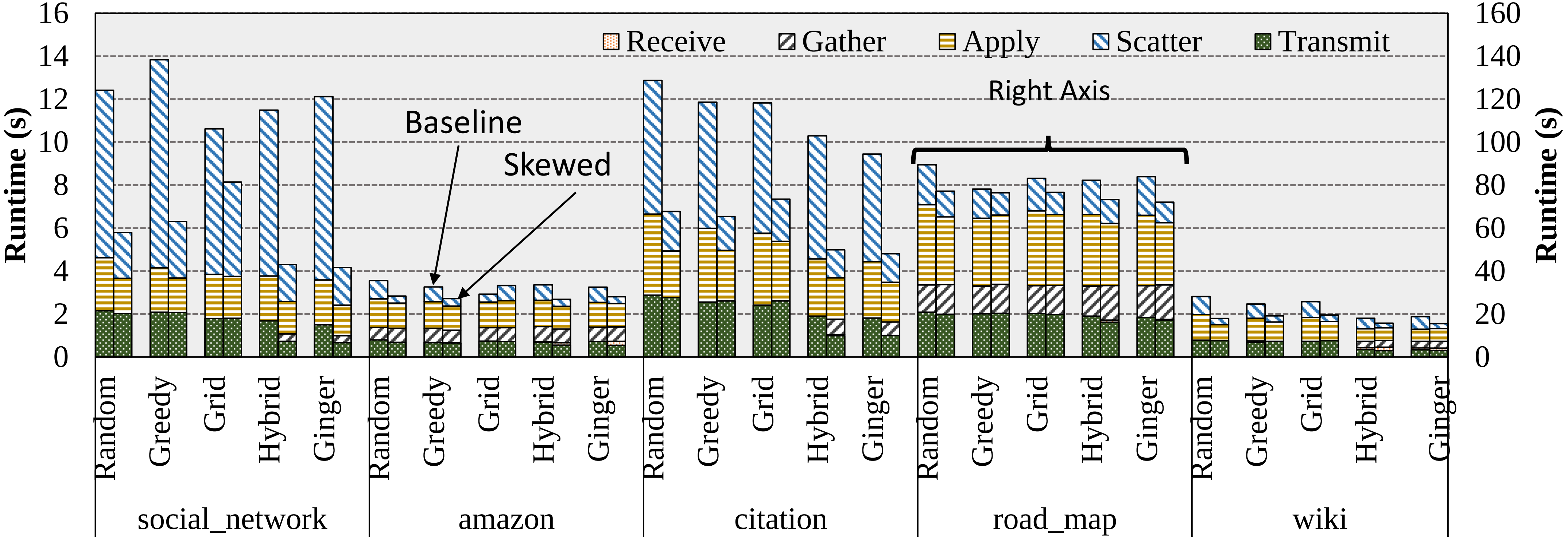
- **Data Center**
  - Graph: PageRank (PR), Connected Components (CC), Triangle Count (TC)
  - Matrix: Stochastic Gradient Descent (SGD), Alternating Least Squares (ALS)
- **Skew Factor**
  - Results use Thread Based Skew Factor

Execution Time



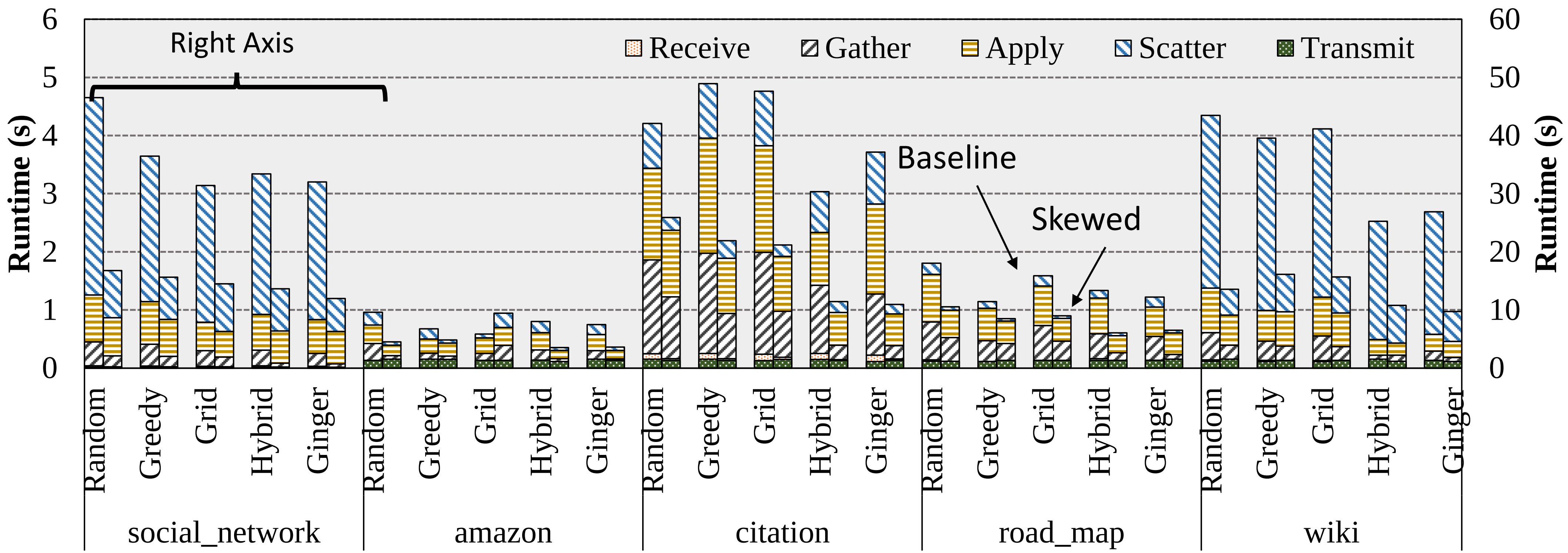
- **Pagerank**

Execution Time



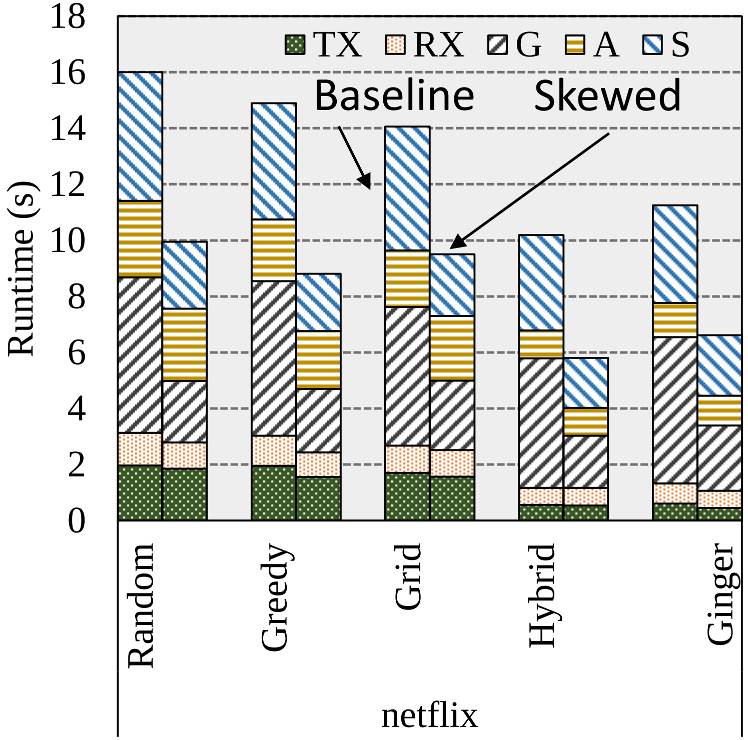
- **Connected Components**

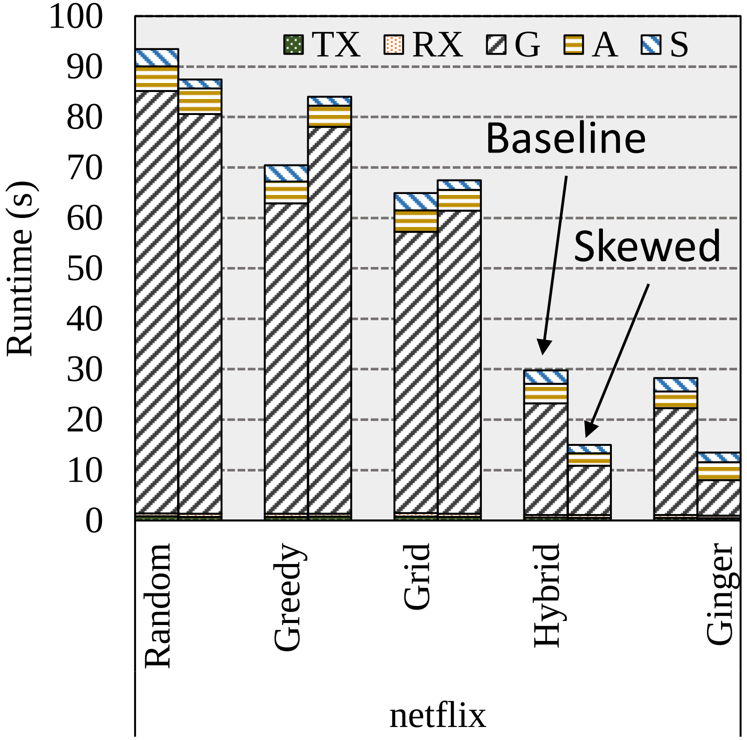
Execution Time



- **Triangle Count**

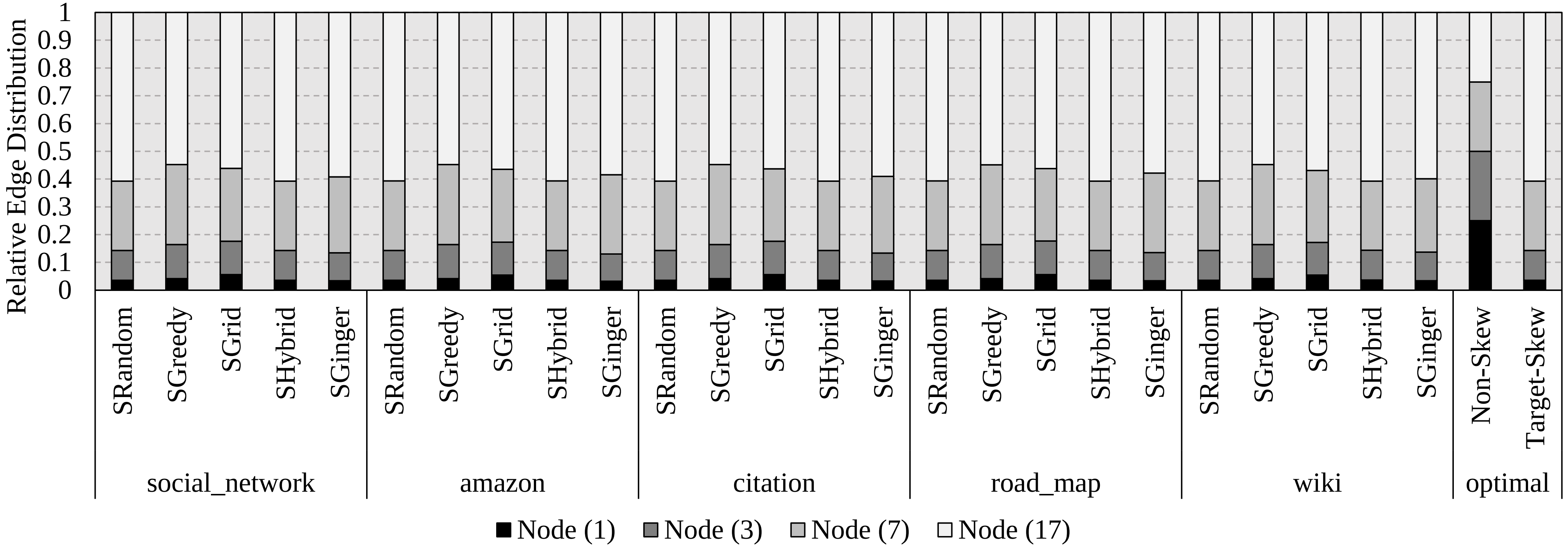
Execution Time





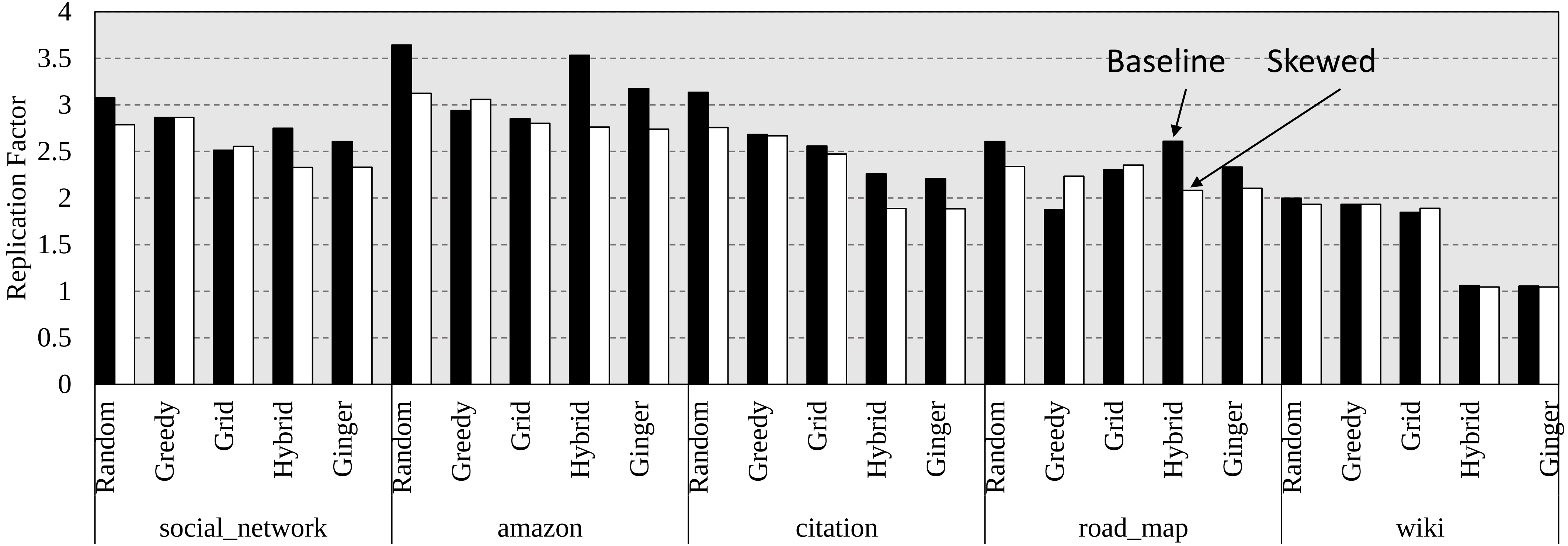
- **Stochastic Gradient Descent**
- **Alternating Least Squares**

Data distribution



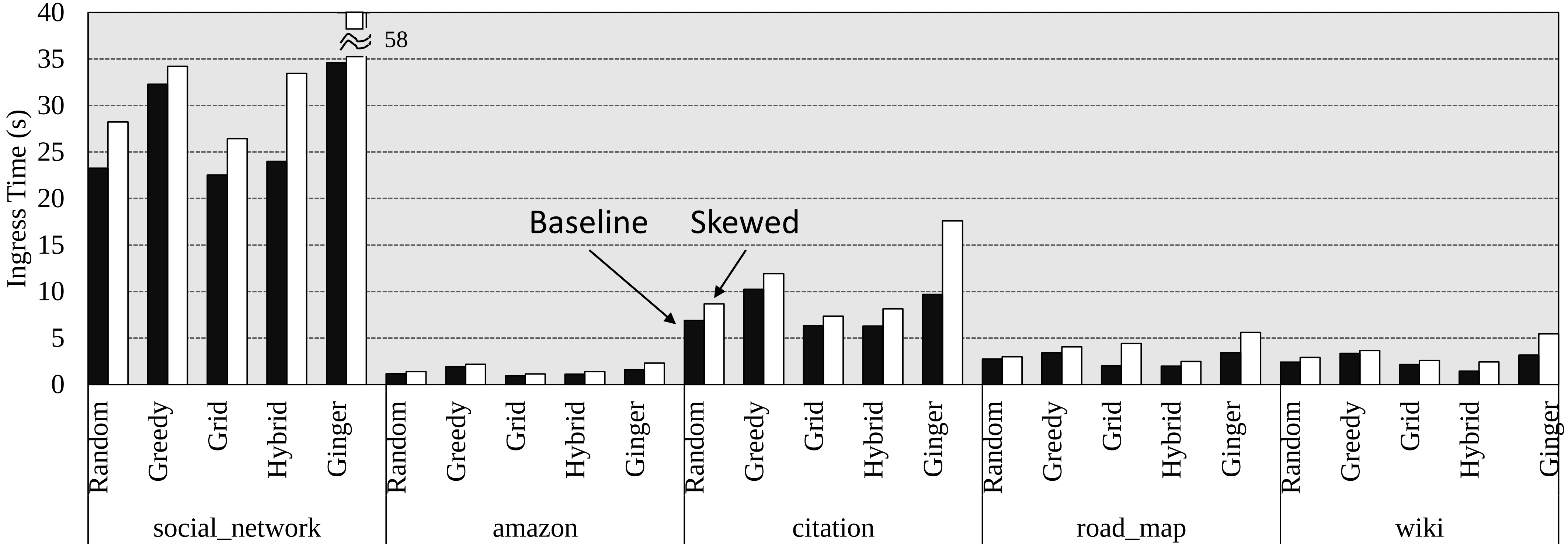
- **Ideal distribution 17-7-3-1**

Results



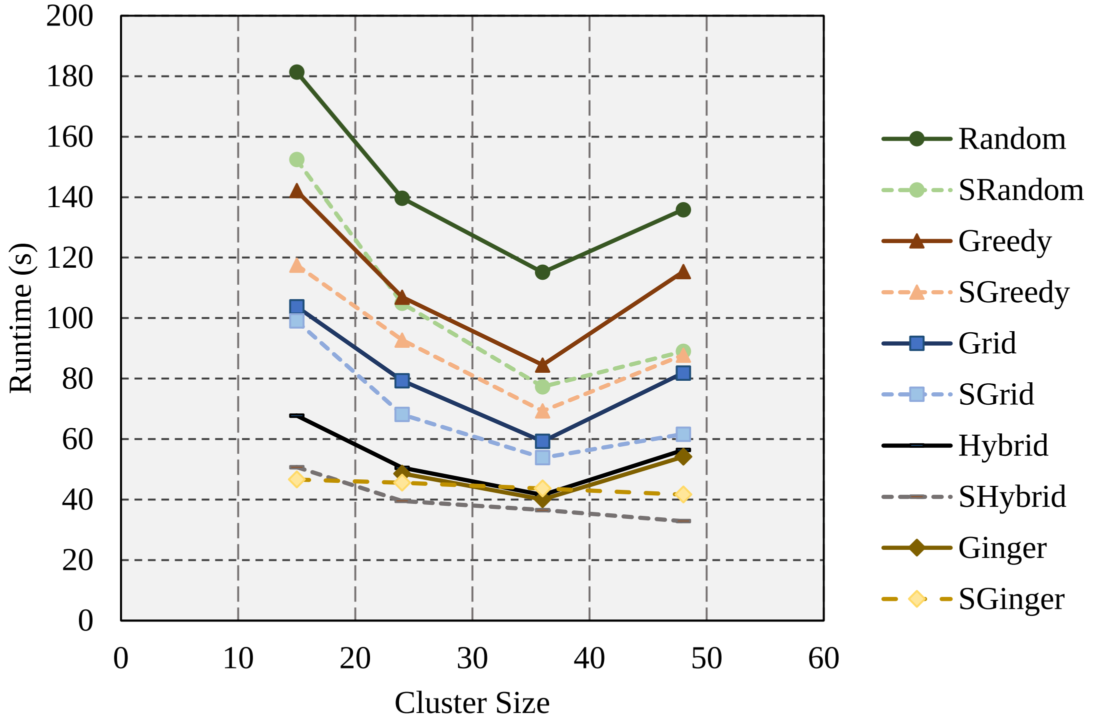
- **Skewed approach generally decreases network communication**

Results

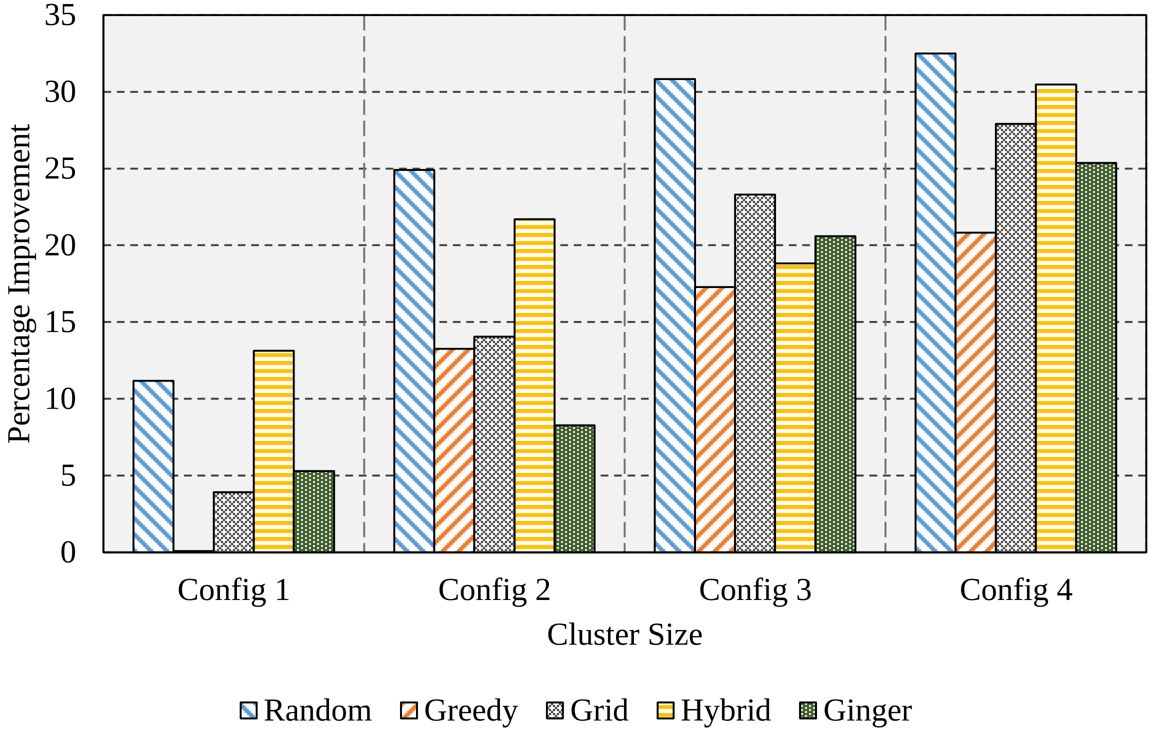


- **Data Ingress Time**

Scale-out Results



- **Extremely large Twitter graph**
- **No benefits after 36 nodes**



Configuration Name	C4.2xlarge	C4.4xlarge	C4.8xlarge
Config 1	12	8	4
Config 2	8	8	8
Config 3	4	8	12
Config 4	3	5	16

Future Work

- **Incorporate better network model**
- **Profile based partitioning scheme**
  - How do we sample graph inputs?

Conclusion

- **Simple, static throughput estimation can greatly improve performance**
- **We modify 5 existing on-line graph partitioning strategies for heterogeneous environments**
- **Our modified algorithms improve runtime by as much as 64% and on average 32% on Amazon EC2**
- **We show that our strategies also work up to 48 nodes, achieving 18% performance improvement on scale-out**

Thank You!

References

[1] S. Garg, S. Sundaram, and H. D. Patel. Robust heterogeneous data center design: A principled approach. *SIGMETRICS Perform. Eval. Rev.*, 39(3):28–30, Dec. 2011.

[2] B.-G. Chun, G. Iannaccone, G. Iannaccone, R. Katz, G. Lee, and L. Niccolini. An energy case for hybrid datacenters. *SIGOPS Oper. Syst. Rev.*, 4(1):76–80, Mar. 2010.

[1] J. E. Gonzalez, Y. Low, H. Gu, D. Bickson, and C. Guestrin. Powergraph: Distributed graph-parallel computation on natural graphs. In *OSDI*, pages 17–30. USENIX Association, 2012.