GraBi: Communication-Efficient and Workload-Balanced Partitioning for Bipartite Graphs

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Outline

- ☑ Background
- ☐ Motivation
- ☐ Design of GraBi
  - ➢ Vertical Partitioning: Vertex-vector Chunking
  - ➢ Horizontal Partitioning: Vertex-chunk Assignment
- ☐ Evaluation
- ☐ Conclusion

Graph Partitioning

Graph partitioning distributes vertices and edges over computing nodes.

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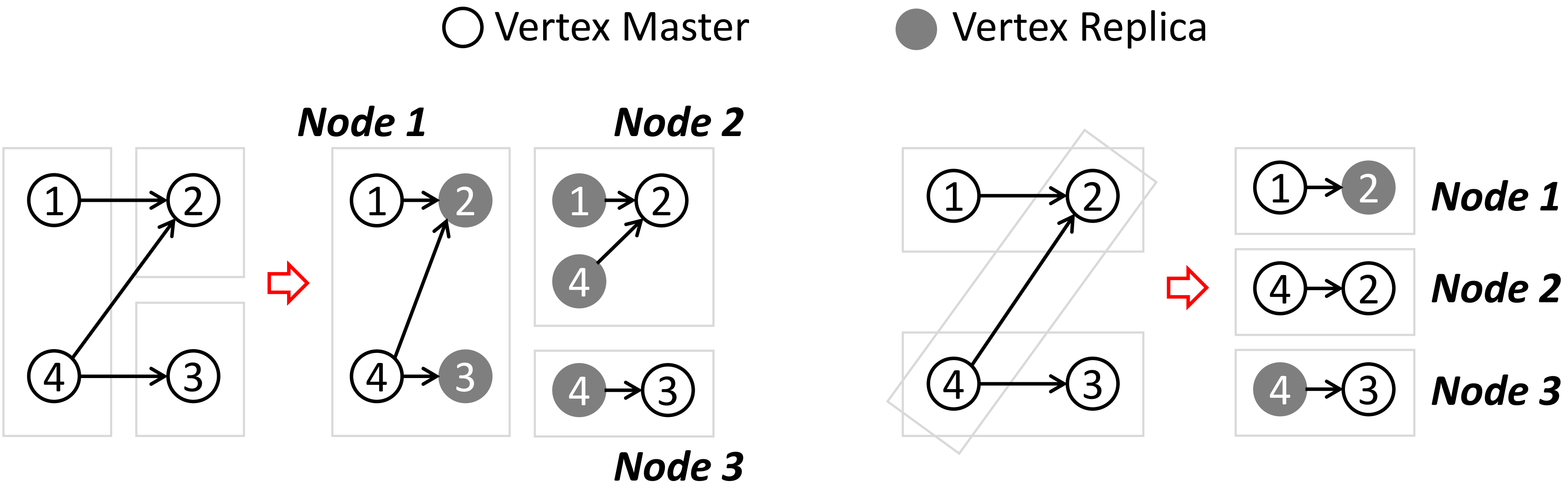

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(b) Vertex-cut

- Edge-cut equally distributes vertices among nodes.
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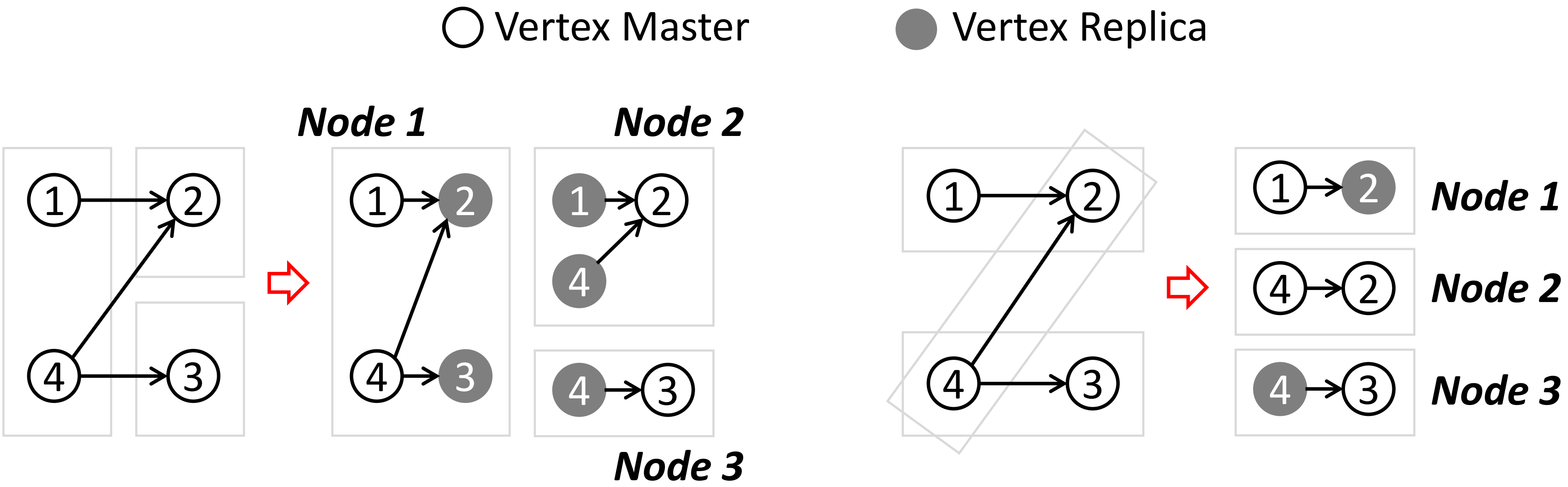

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- replication factor (λ): the average number of replicas per vertex.

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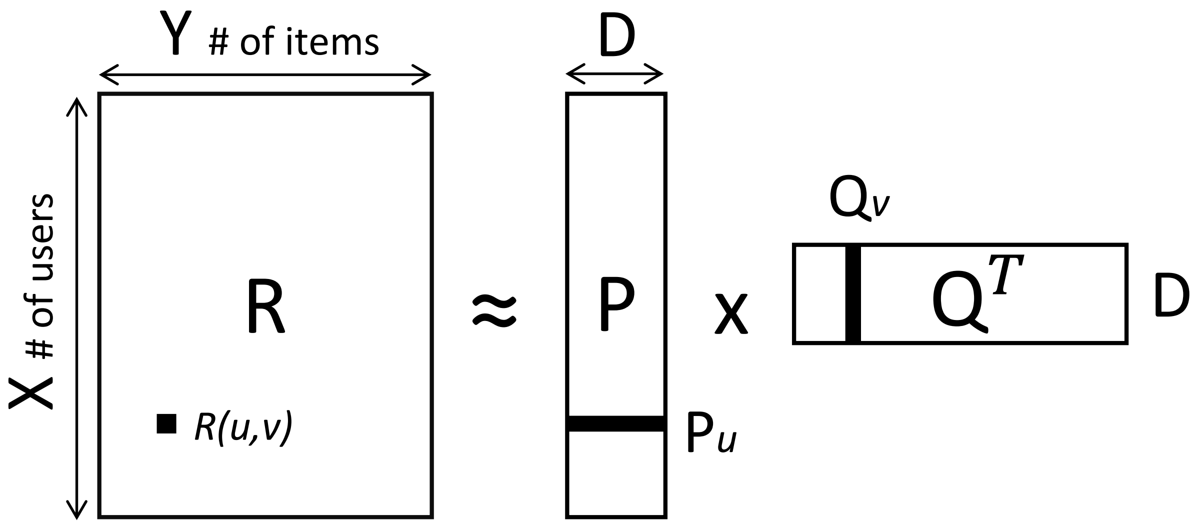
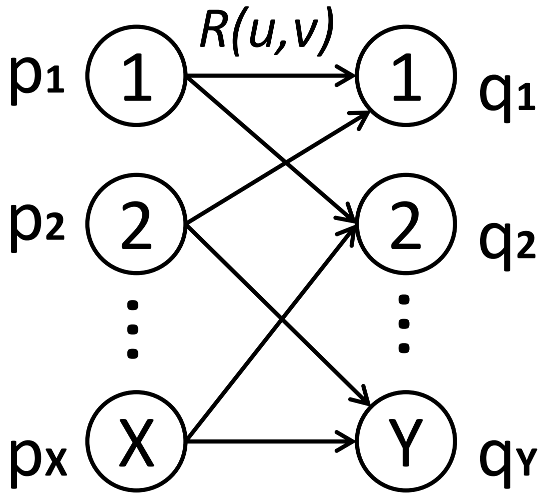


(a) View of Matrix



(b) View of Graph

Observations

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- The users of $PowerGraph^{[2]}$ can configure each vertex value as a vector of thousands of elements

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- In $Netflix$[3], the number of users is about 27x that of movies.
- In $English\ Wikipedia$[4], the number of articles is about 98x that of words.

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[3] http://www.netflixprize.com/community/viewtopic.php?pid=9857
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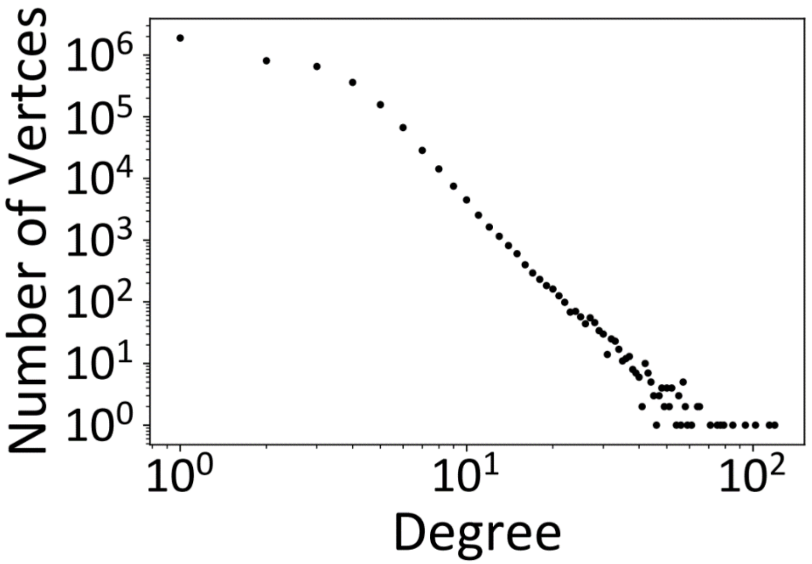
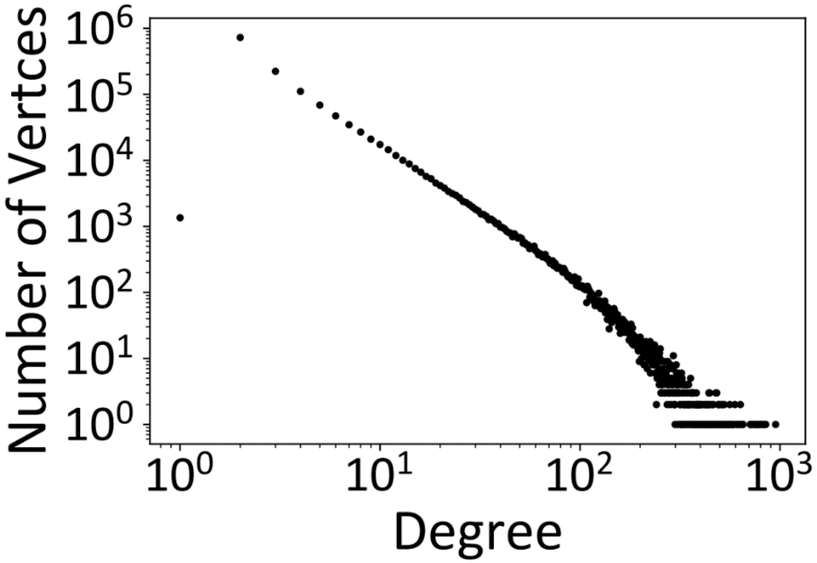
➢ Both the two vertex-subsets in $DBLP^{[1]}$ exhibit power-law degree distribution.



(a) Author Degree Distribution



(b) Publication Degree Distribution

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Opportunities

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- **Observation 3**: Within a vertex-subset, the vertices usually exhibit power-law degree distribution

⇨ *The vertices of different degrees should be* distinguished.

Overview of GraBi

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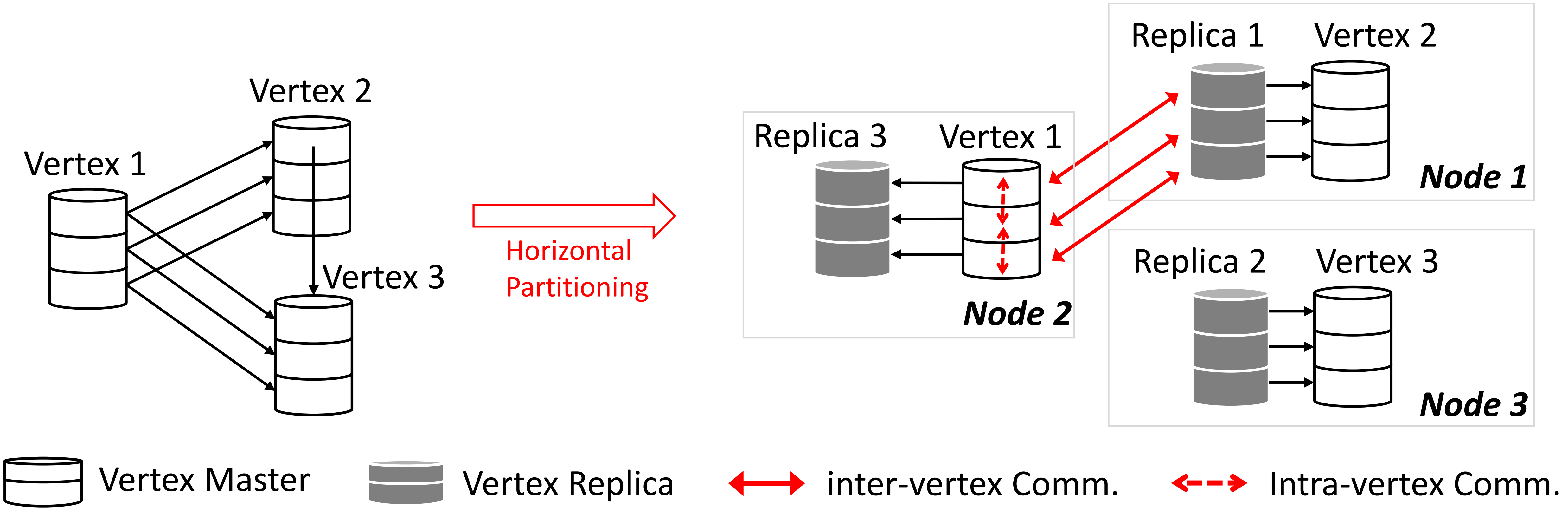
- GraBi comprehensively exploits the above three features of bipartite graphs and MLDM algorithms.

- GraBi partitions a bipartite graph first vertically, and then horizontally, to realize high-quality partitioning.

Vertical Partitioning: Vertex-vector Chunking



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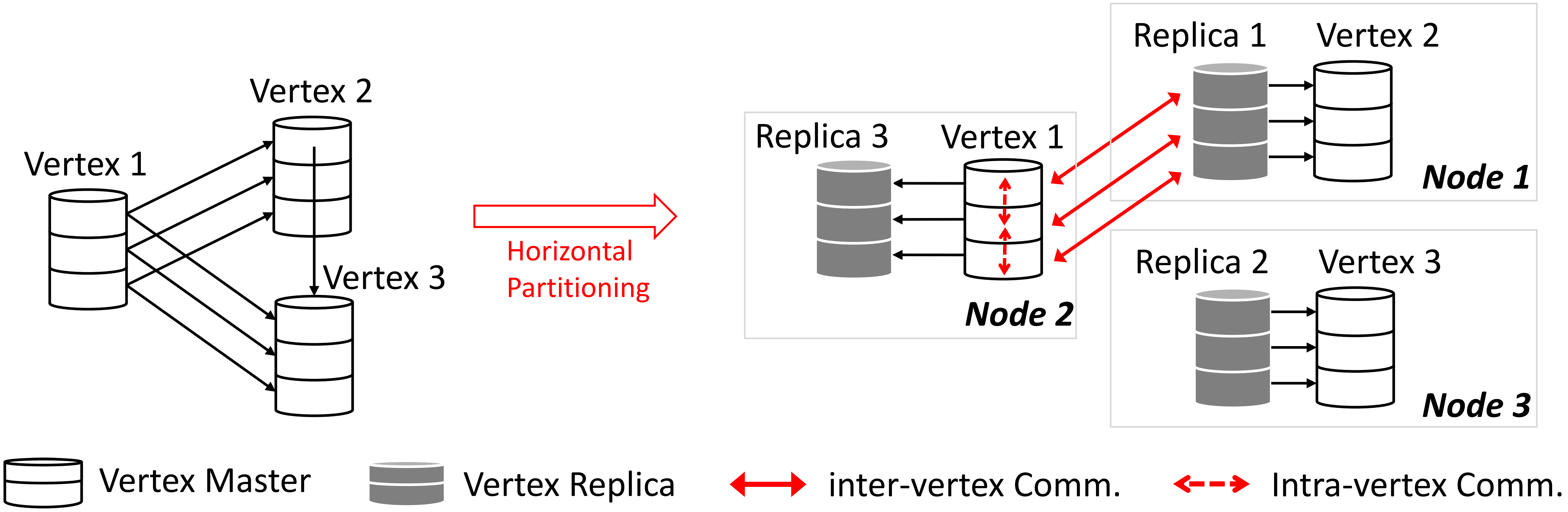

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is assigned to a computing node.

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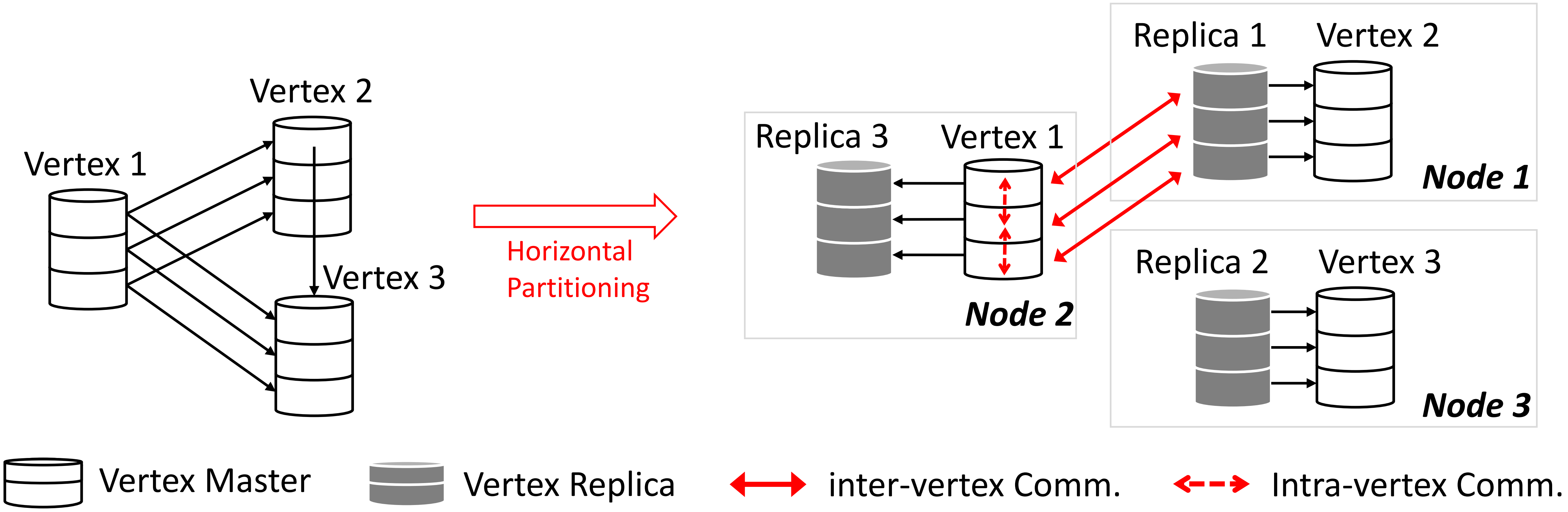

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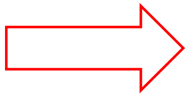

- Inter-vertex Communication happens between computing nodes
- Intra-vertex Communication happens within a computing node

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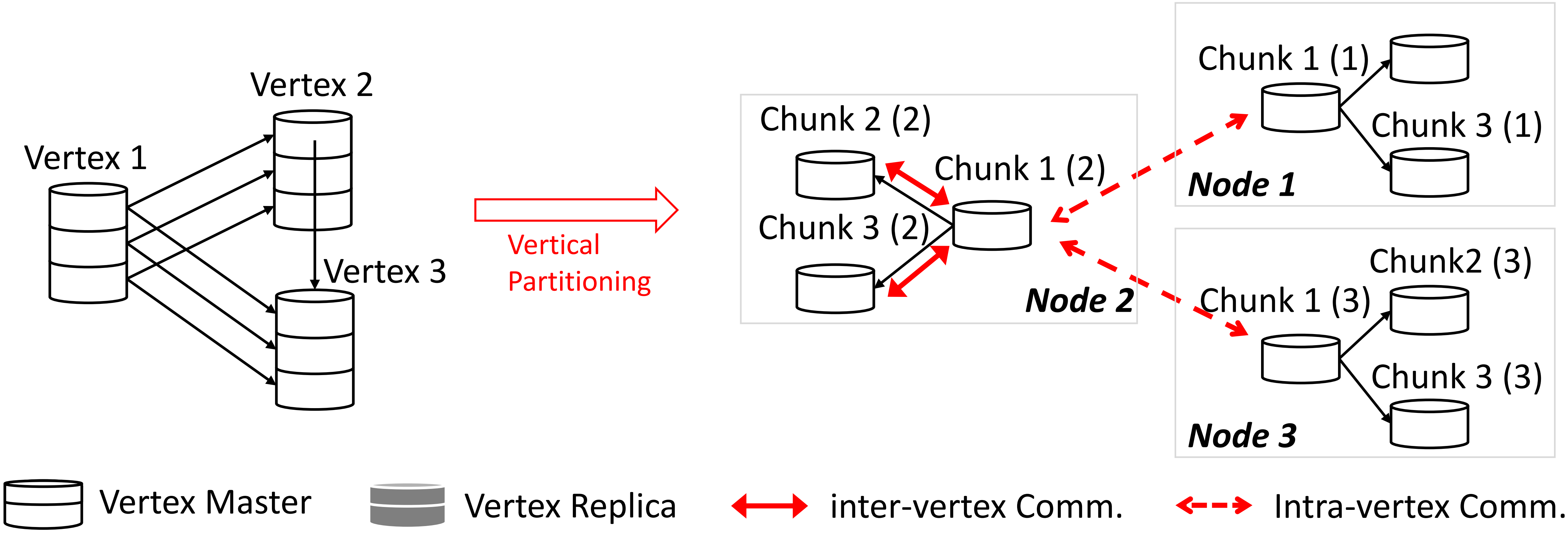

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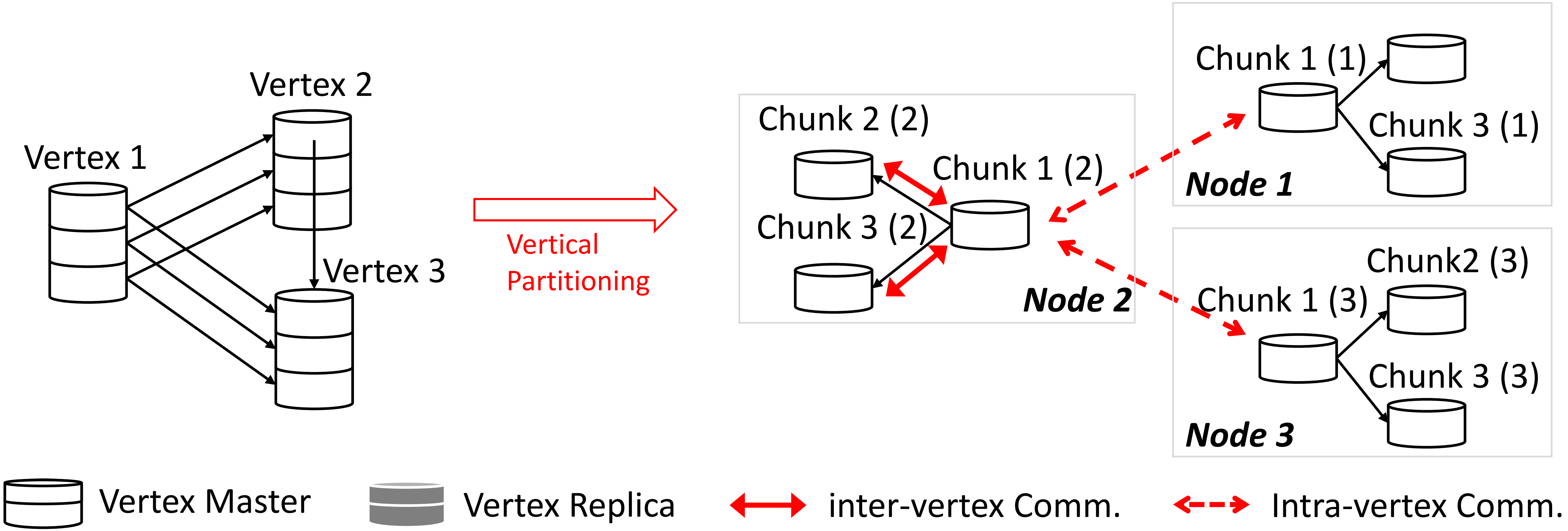

The whole vector of a vertex is divided into vertex-chunks.

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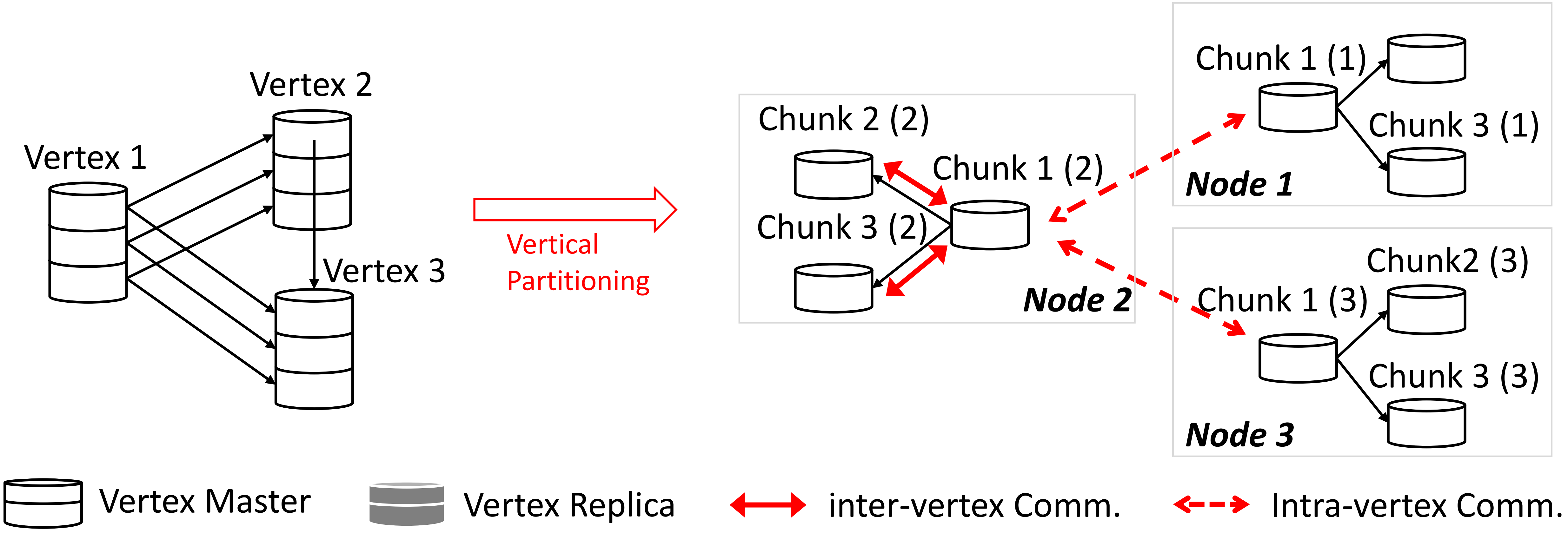

The whole vector of a vertex is divided into vertex-chunks.

- Inter-vertex Communication happens within a computing node
- Intra-vertex Communication happens between computing nodes

Vertical Partitioning: Vertex-vector Chunking

➢ **Number of Layers *L***

- L=1, horizontal partitioning, inter-vertex communication dominates
- L=N, vertical partitioning, intra-vertex communication dominates

→ $\boldsymbol{L}$ **= 1, 2, … ,*N***

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L is set as the *Greatest Common Divisor* (GCD) of D and N
D is the number of elements in each vector, *N* is the number of computing nodes.

→ Each vertex-chunk consists of D/L elements, Each layer is assigned to N/L nodes.

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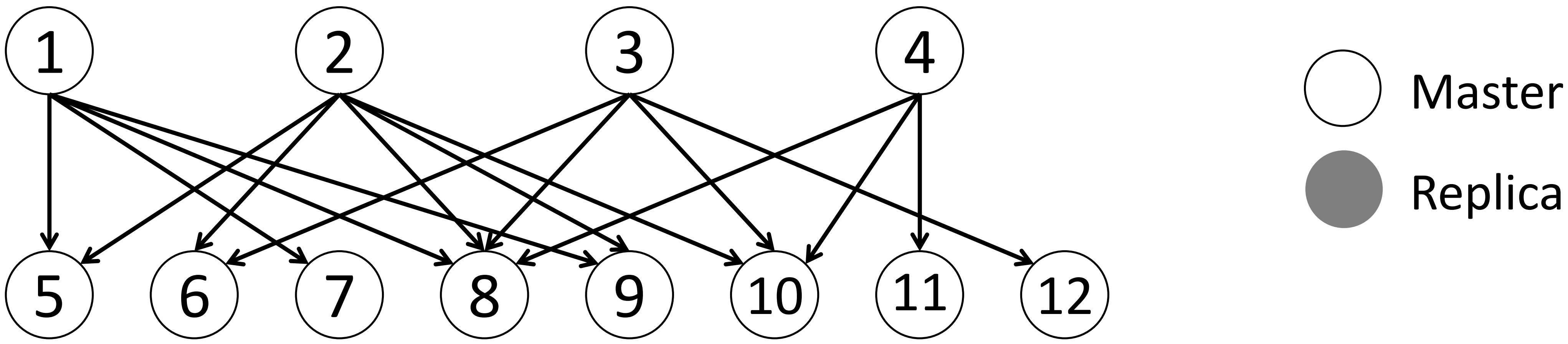
The vertical partitioning stage, *Vertex-vector Chunking*, is simple element-grouping for every vectored vertex.

Horizontal Partitioning: Vertex-chunk Assignment



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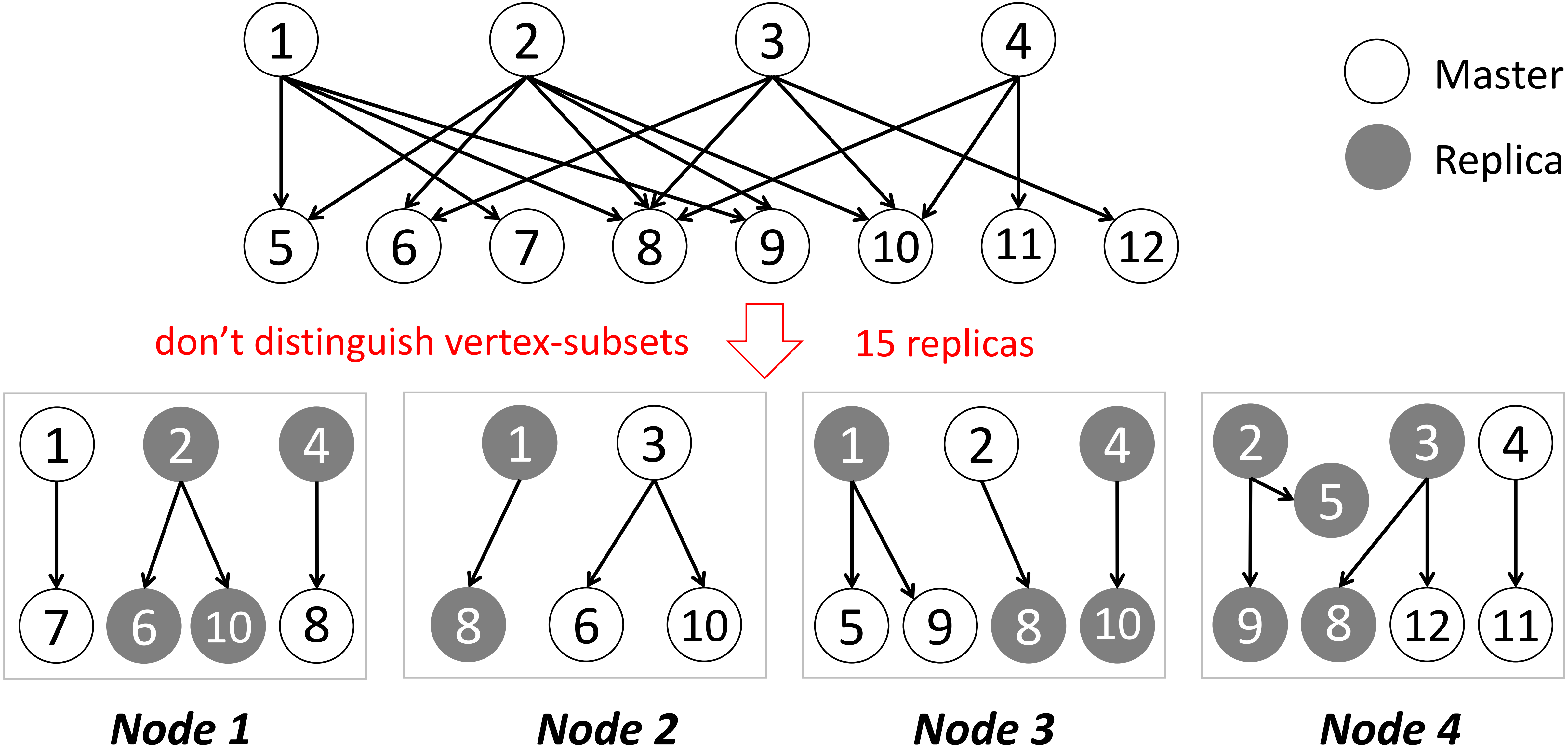

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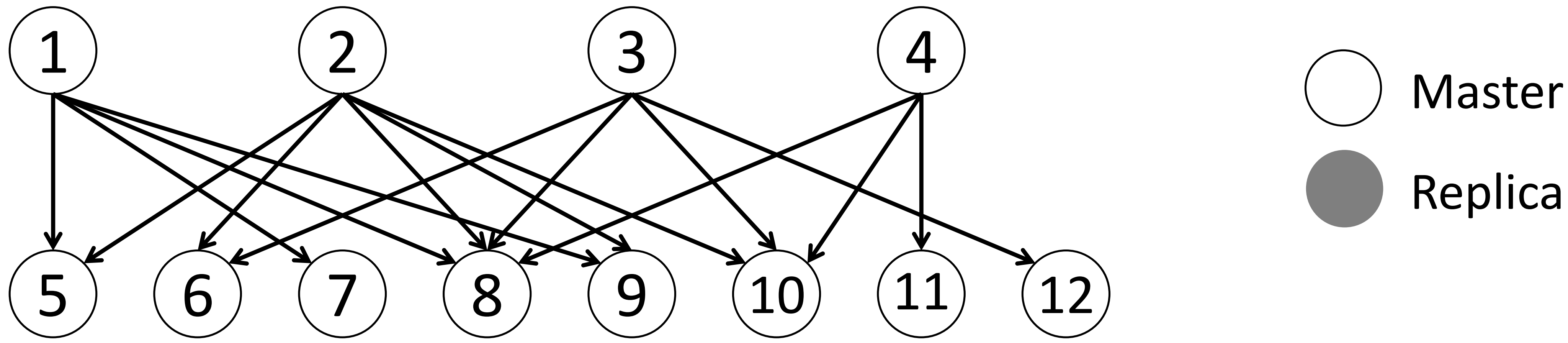

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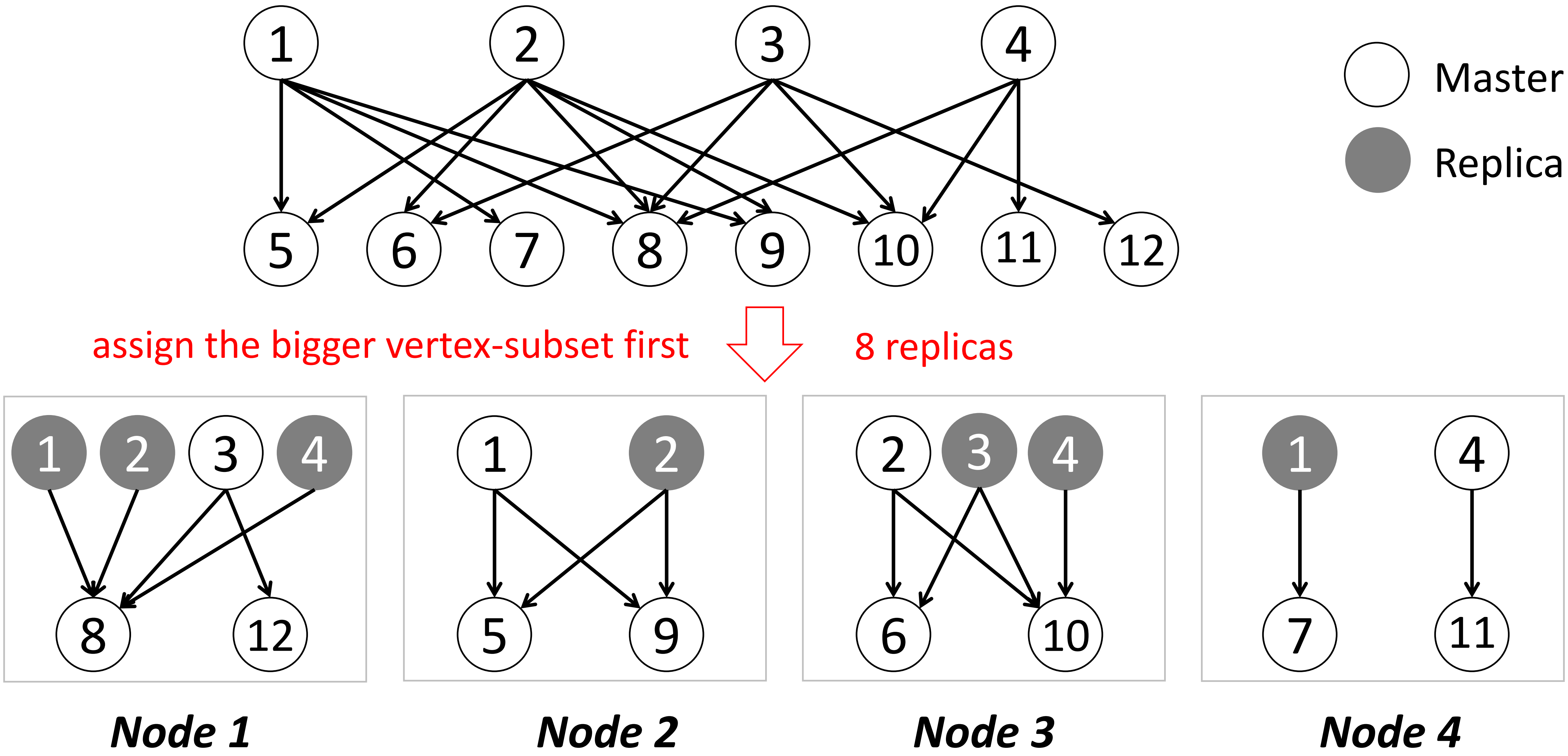

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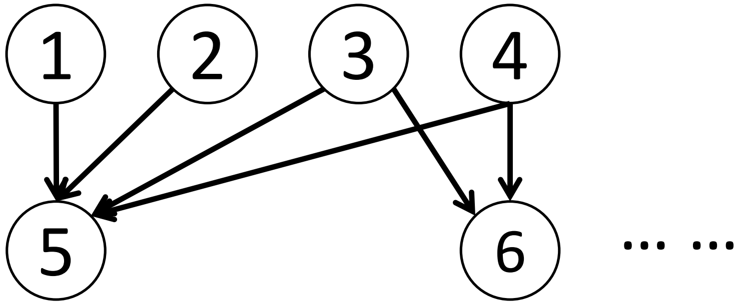


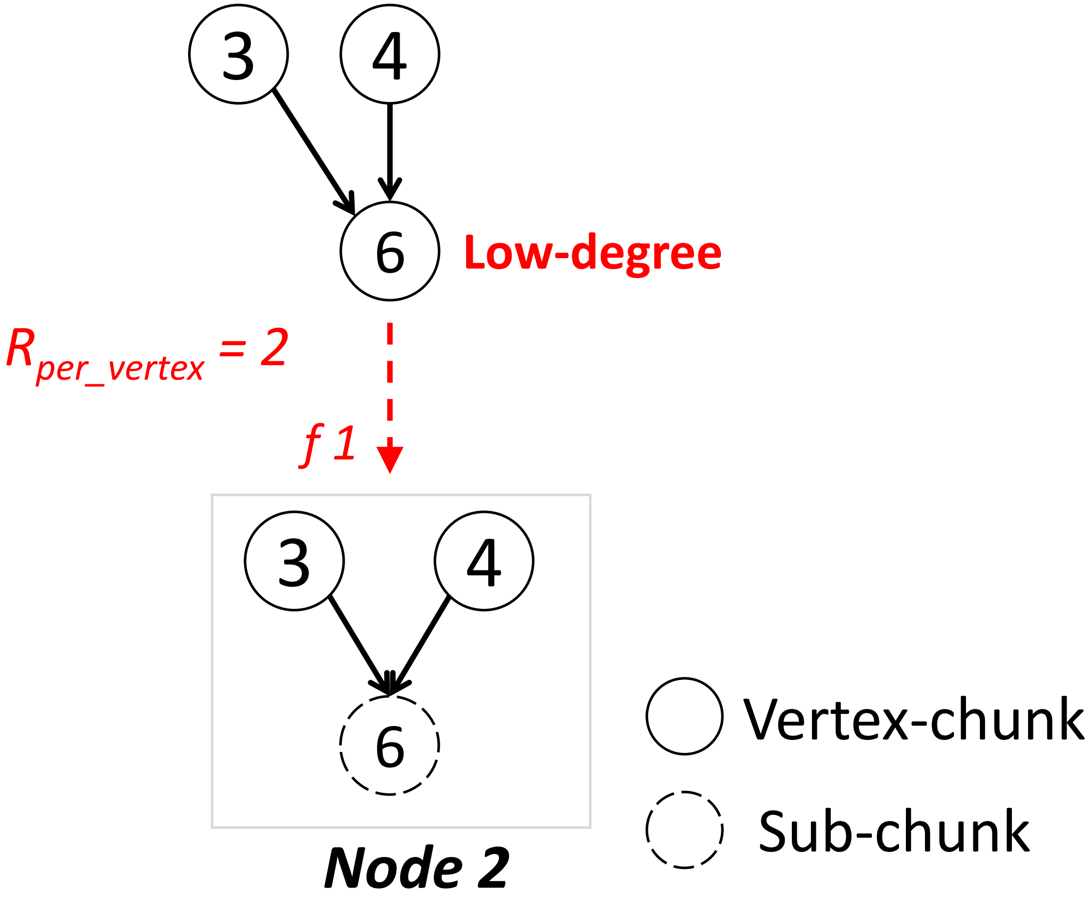
$$R_{per\_vertex} = \alpha \times \left(\frac{|E|}{|U|}\right)$$

α is an amplification factor

Horizontal Partitioning: Vertex-chunk Assignment

A set of
Hash Functions

f 4 f 3 f 2 f 1



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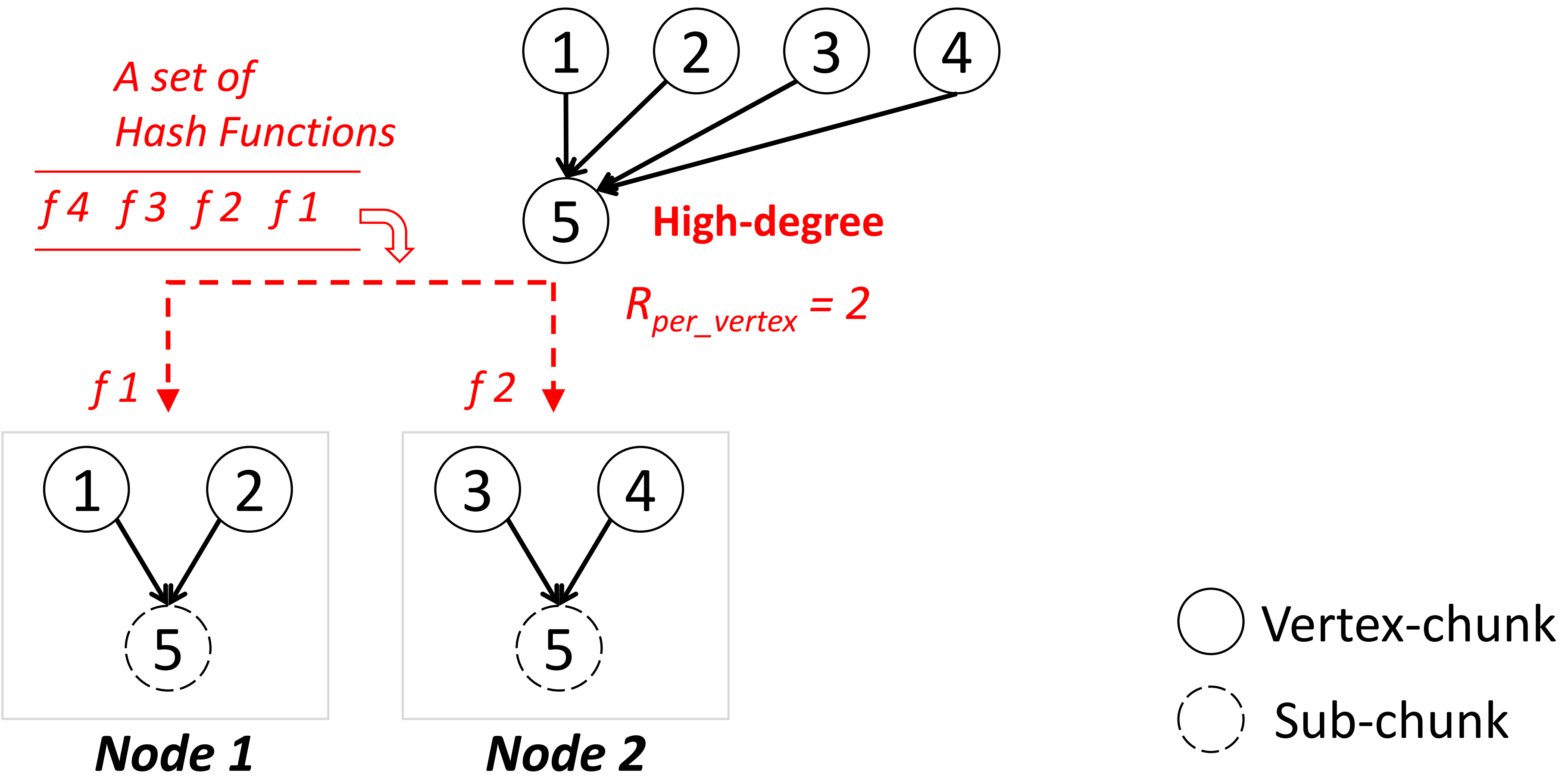

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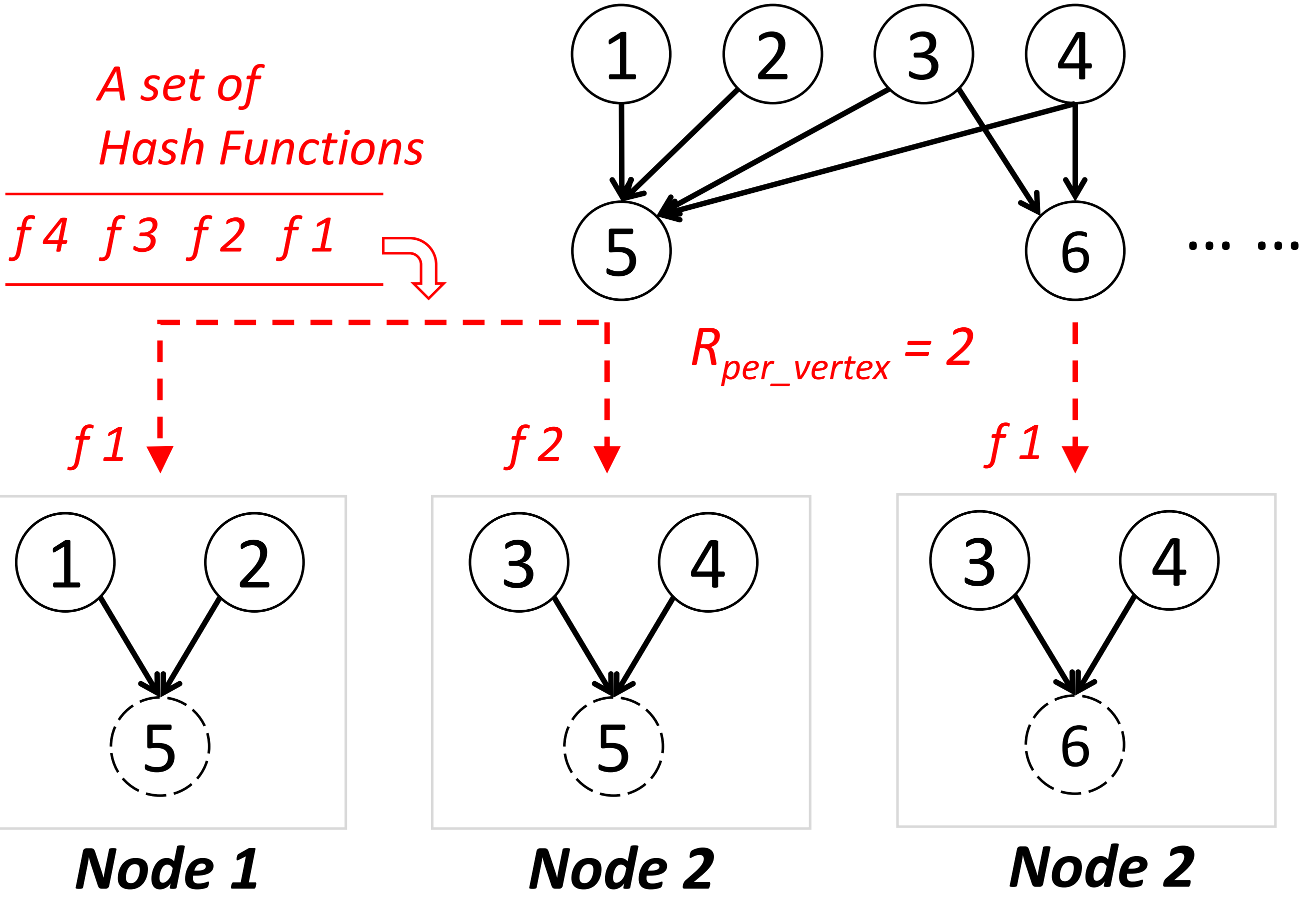
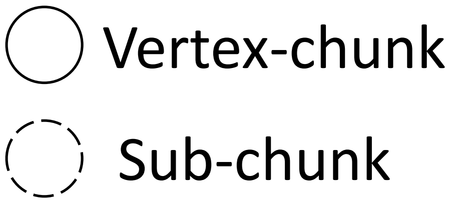


Global Table

vertex ID	functions
5	1, 2
6	1
…	…
k	1,2,4



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- **Vertical Partitioning:**

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GraBi

- **Fine-grained, high-quality**
- **Light-weight**
- **Generalizable to most MLDM algorithms**

Experimental Setup

- **Implementation**

- GraBi is implemented on a open-source distributed graph-processing system $PowerLyra$[1].
- The two important parameters in GraBi, L and α, are set as 4 and 2 respectively.

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➢ Counterparts

- Hybrid-cut (Observation 3)
- Bi-cut (Observation 2)
- 3D-partitioner (Observation 1+ Observation 2)

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- **Bipartite Graphs**

Graph	|U|	|V|	|E|	|U/V|
DBLP	4,000K	1,426K	8.6M	2.81
Netflix	480K	18K	100.5M	27.02
LiveJournal	7,489K	3,201K	112.3M	2.34
Yahoo	1,001K	625K	256.8M	1.60
Orkut	8,731K	2,783K	327.0M	3.14

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- **MLDM Algorithms**

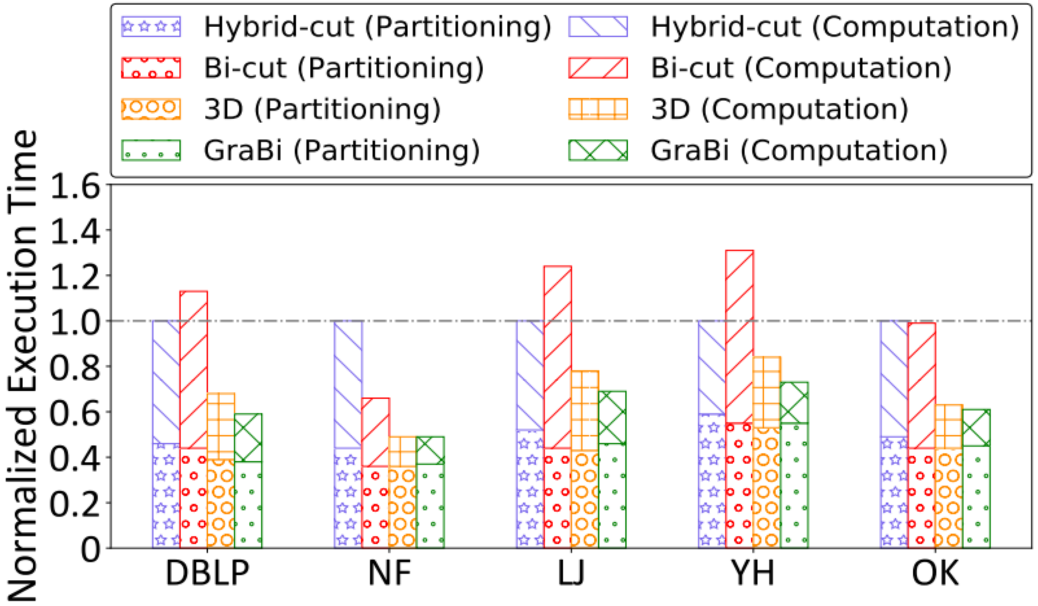
Alternating Least Squares (ALS)

Stochastic Gradient Descent (SGD)

Non-negative Matrix Factorization (NMF)

Overall Performance

➢ **Total Execution Time**



- GraBi improves the execution time by an average of 1.65x over Hybrid-cut, 1.70x over Bi-cut, and 1.09x over 3D-partitioner respectively.
- GraBi surpasses Hybrid-cut and Bi-cut in both the partitioning and computation phases.
- GraBi outperforms 3D-partitioner in the computation phase, but slightly underperforms in the partitioning phase.

Partitioning Phase

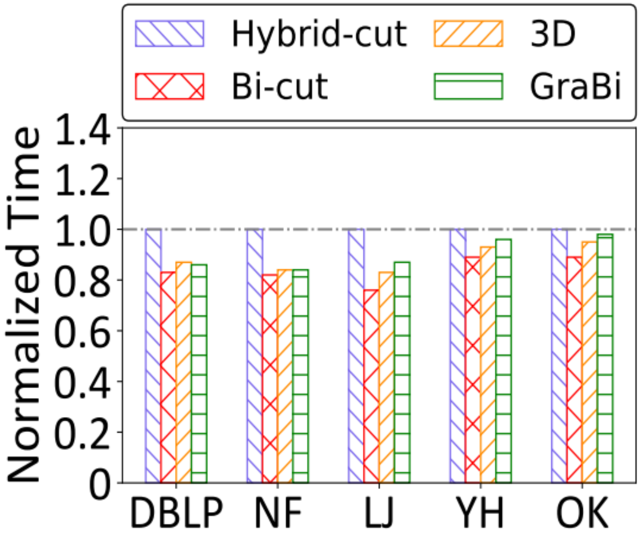
➢ **Replication Factor**

Graph	Hybrid-cut	Bi-cut	3D-partitioner	GraBi
DBLP	2.74	3.08	1.38	1.45
Netflix	3.37	2.14	1.16	1.20
LiveJournal	2.64	3.47	1.30	1.52
Yahoo	3.34	4.43	1.53	1.56
Orkut	3.34	4.43	1.53	1.56

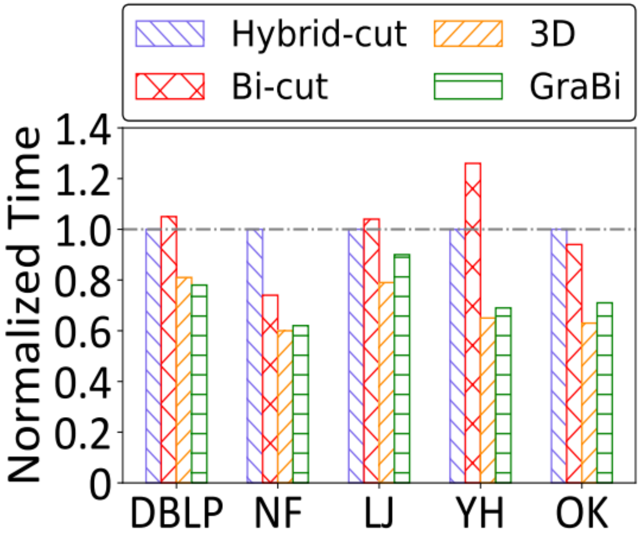
- A lower replication factor represents higher partitioning quality.
- The average of Hybrid-cut, Bi-cut, 3Dpartitioner, and GraBi are 3.06, 3.28, 1.36, and 1.45 respectively.

Partitioning Phase

➢ **Graph Partitioning Time**



(a) Loading & Distributing Time

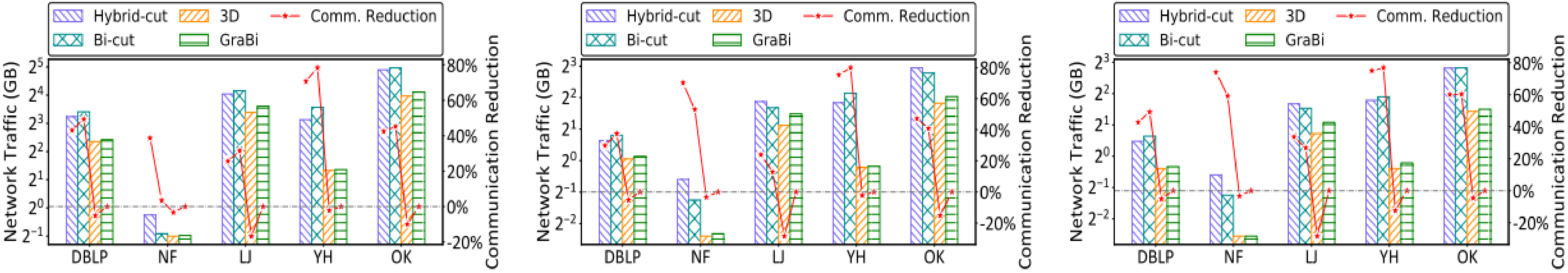


(b) Finalizing Time

- Bi-cut has the shortest loading & distributing time, and Hybrid-cut has the longest.
- The finalizing time is almost proportional to the corresponding replication factor.

Computation Phase

➢ **Network Traffic**

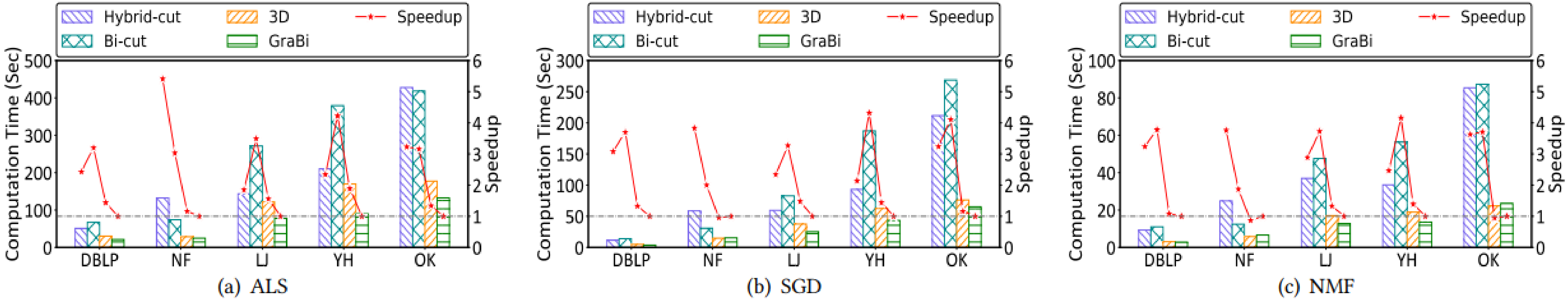


(a) ALS (b) SGD (c) NMF

- GraBi reduces the network traffic in Hybrid-cut and Bi-cut by an average of 45% and 49% respectively.
- GraBi incurs more network traffic than 3D-partitioner by an average of 11%.

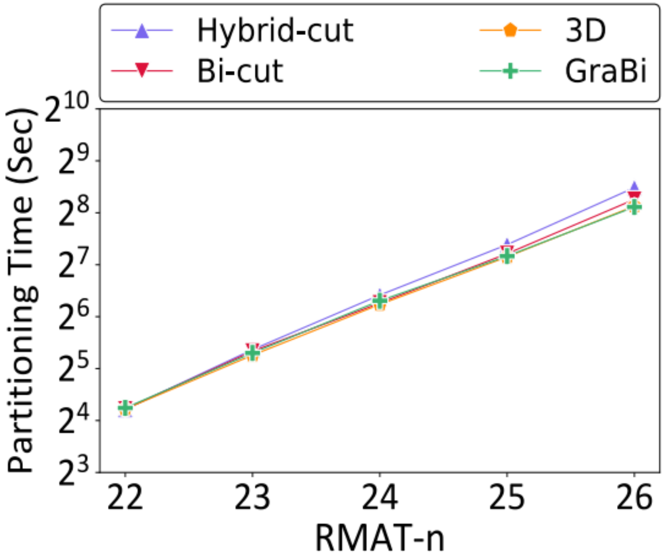
Computation Phase

➢ **Graph Computation Time**

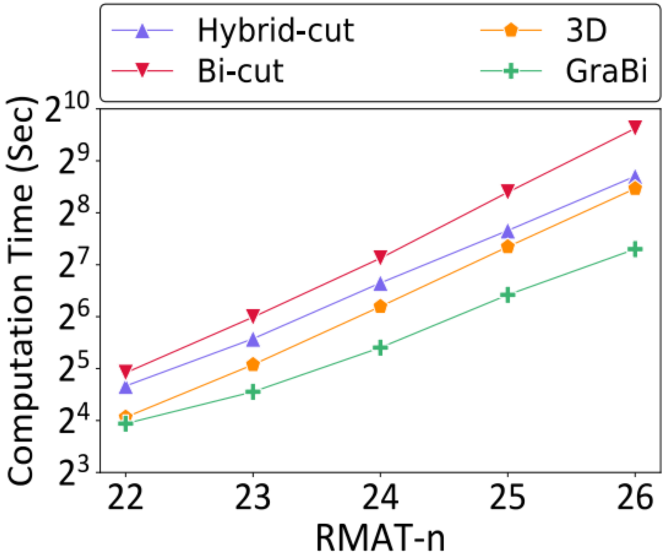


- GraBi outstrips Hybrid-cut, Bi-cut, and 3D-partitioner by an average of 3.12x, 3.41x, and 1.30x respectively.

Scalability



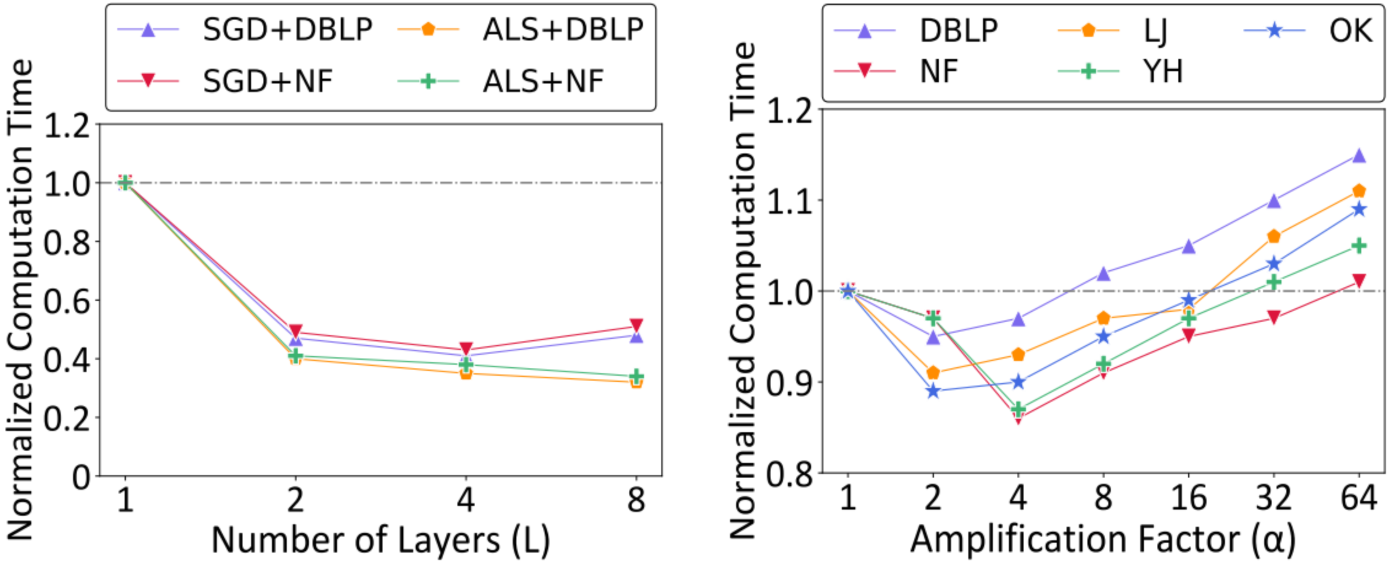
(a) Partitioning Time



(b) Computation Time

- As to the partitioning phase, the scalability of 3D-partitioner and GraBi is better than Hybrid-cut and Bi-cut.
- As to the computation phase, the scalability Hybrid-cut of and GraBi is better than Bi-cut and 3D-partitioner.

Impact of Parameters

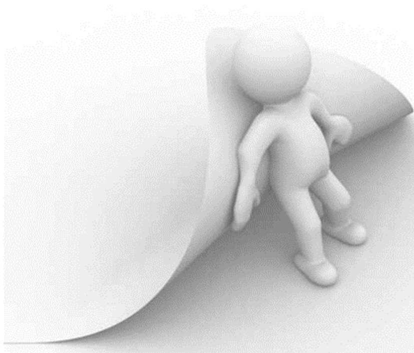


(a) Impact of L on ALS and SGD (b) Impact of α on ALS

- ALS and SGD algorithms behave best at different values of L.
- The impact of α is moderate and stable within a wide value range.

Conclusion

GraBi is a *communication-efficient* and *workload-balanced* partitioning framework for bipartite graphs.



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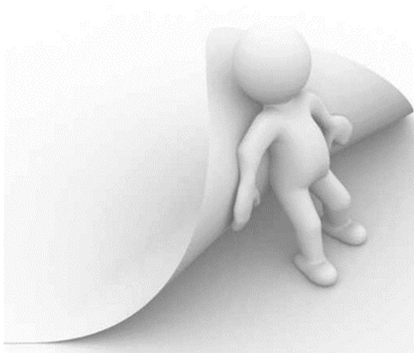
Observation 1 ⇨ Divide a bipartite graph into several layers ⇨ Efficient Communication



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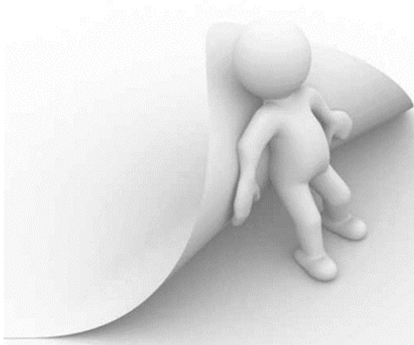

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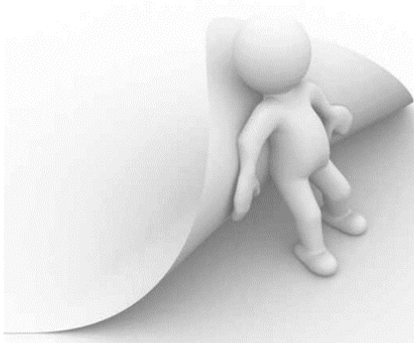
Observation 3 ⇨ Decompose each high-degree vertex-chunk into sub-chunks ⇨ Workload Balance



Thank You !