Efficient Processing of Large Graphs via Input Reduction

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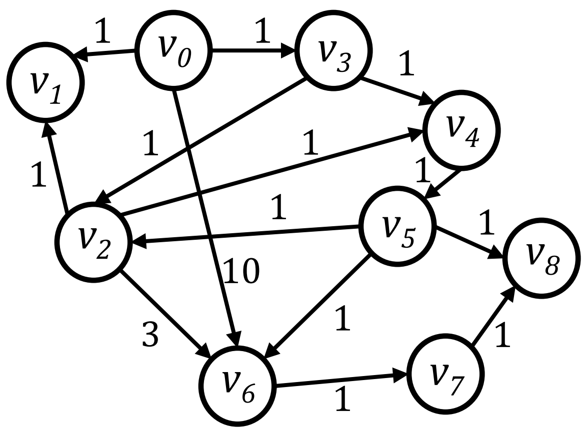
Graph Processing

- Iterative graph algorithms
  - Vertices are processed over continuously
  - Highly parallel execution



t	v_0	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8
t_0	0	∞	∞	∞	∞	∞	∞	∞	∞
t_1	0	1	∞	1	∞	∞	10	∞	∞
t_2	0	1	2	1	2	∞	10	11	∞
t_3	0	1	2	1	2	3	5	11	12
t_4	0	1	2	1	2	3	4	6	4
t_5	0	1	2	1	2	3	4	5	4
t_6	0	1	2	1	2	3	4	5	4

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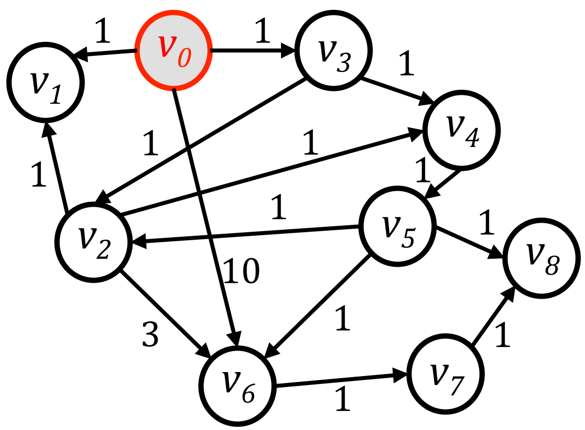

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t_0	**0**	∞	∞	∞	∞	∞	∞	∞	∞
t_1	0	1	∞	1	∞	∞	10	∞	∞
t_2	0	1	2	1	2	∞	10	11	∞
t_3	0	1	2	1	2	3	5	11	12
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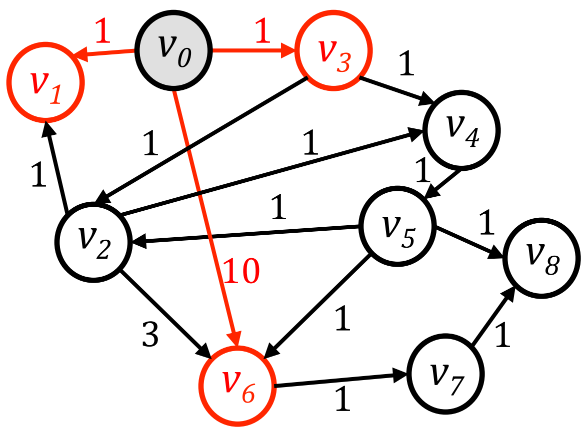

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t_1	0	**1**	∞	**1**	∞	∞	**10**	∞	∞
t_2	0	1	2	1	2	∞	10	11	∞
t_3	0	1	2	1	2	3	5	11	12
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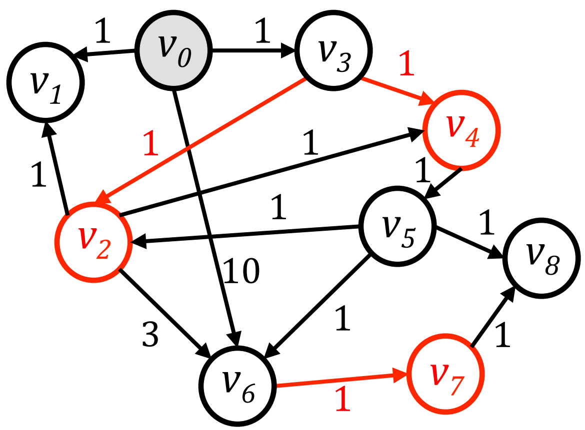

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t_2	0	1	**2**	1	**2**	∞	10	**11**	∞
t_3	0	1	2	1	2	3	5	11	12
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Graph Processing

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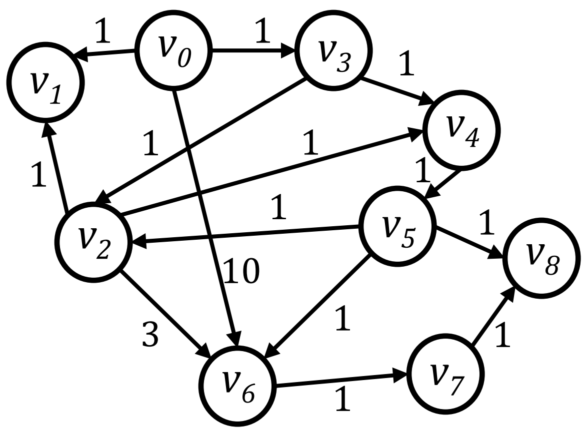
  - Vertices are processed over continuously
  - Highly parallel execution
- Challenging due to ever-growing graph sizes



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Graph Processing

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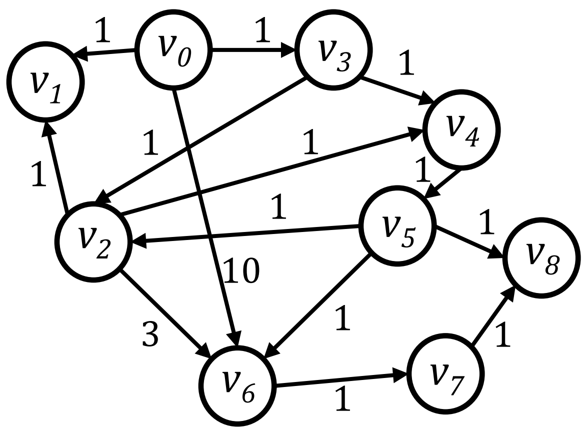
  - Highly parallel execution
- Challenging due to ever-growing graph sizes
- Convergence speed is dependent on initializations



t	v_0	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8
t_0	0	∞	∞	∞	∞	**3**	∞	∞	∞
t_1	0	1	∞	1	∞	3	4	∞	4
t_2	0	1	2	1	2	3	4	6	4
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How to find better initializations?

Key Idea

- Compute initial values using a smaller signature of the original graph
  - Generate smaller graph using light-weight input reduction techniques

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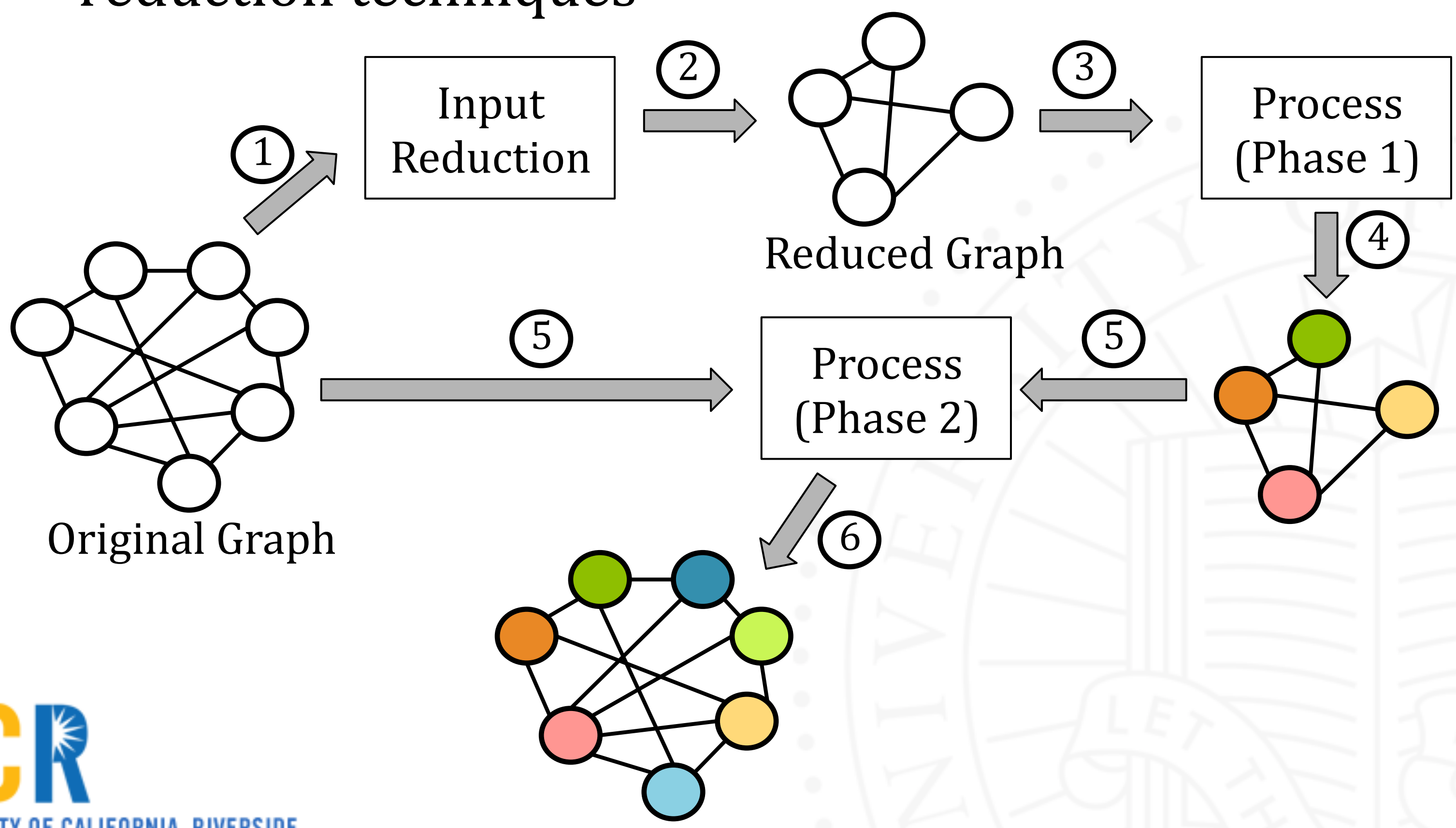

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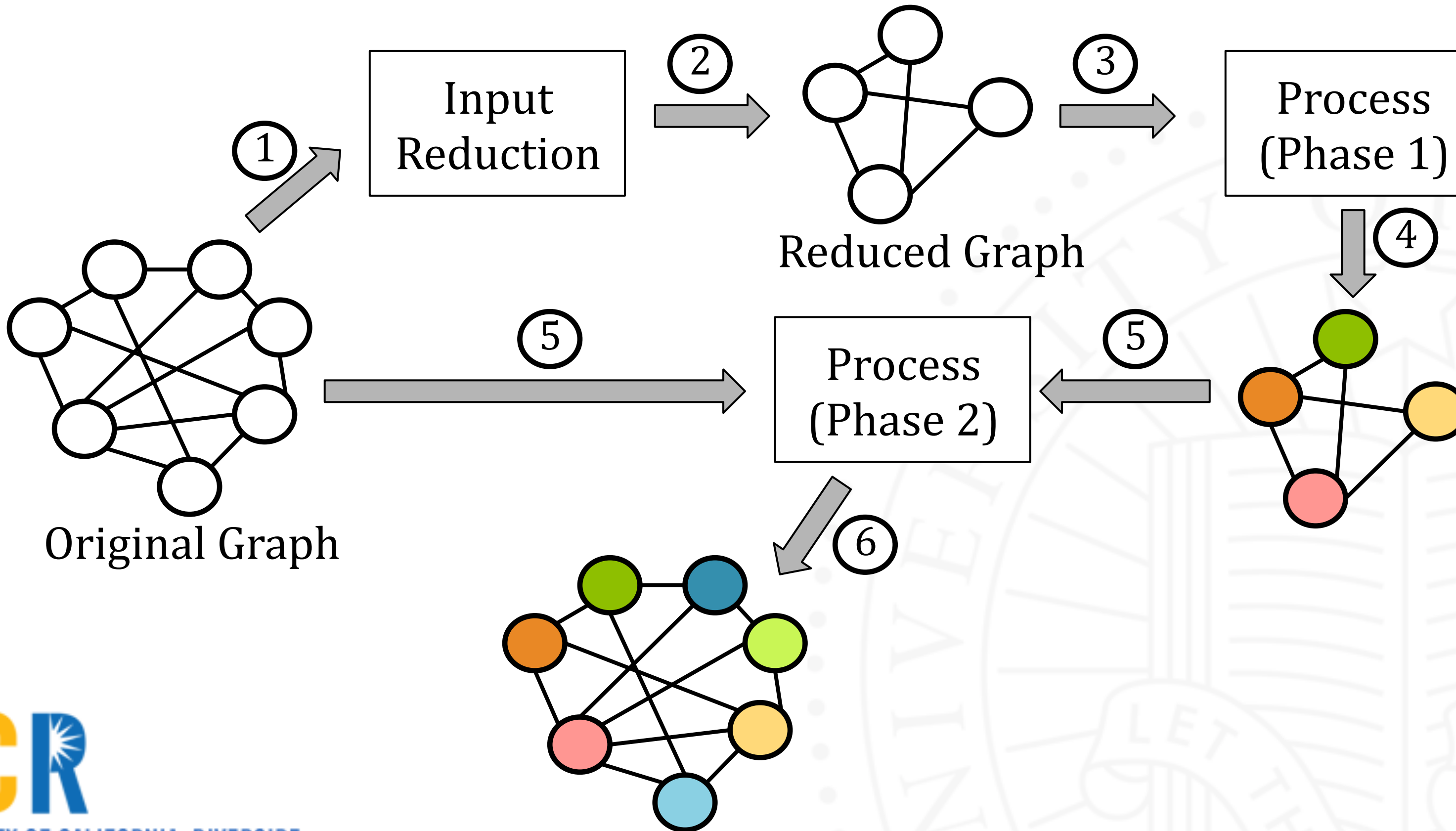
Key Idea

time(Input Reduction)
+ time(Phase 1) **<** **time(Original)**
+ time(Phase 2)



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Outline

- Input Reduction
- Vertex Transformations
- Correctness of Results
- Evaluation
- Conclusion

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Input Reduction

- Must be light-weight & general
  - Multilevel graph partitioning [SC’95, SC’01]
    - Matching based contraction [ICPP’95, JPDC’98]
    - Pruning based on edge costs affecting paths [ICDM’10]
  - Gate graph for shortest paths problem [ICDM’11]
- Develop vertex level transformations
  - Easily parallelizable using the vertex centric graph processing systems

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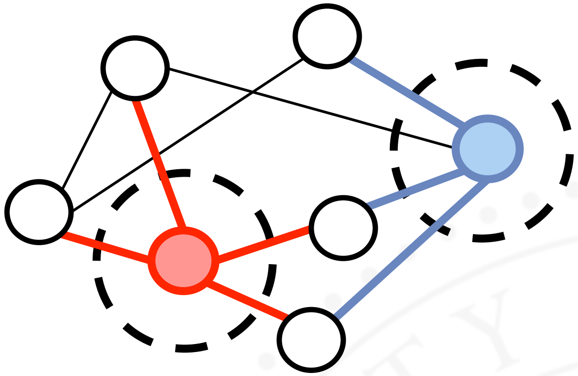
Vertex Transformations

- Maintain structural integrity of the graph
  - Preserve the overall connectivity
- Light-weight
  - Local
  - Non-interfering



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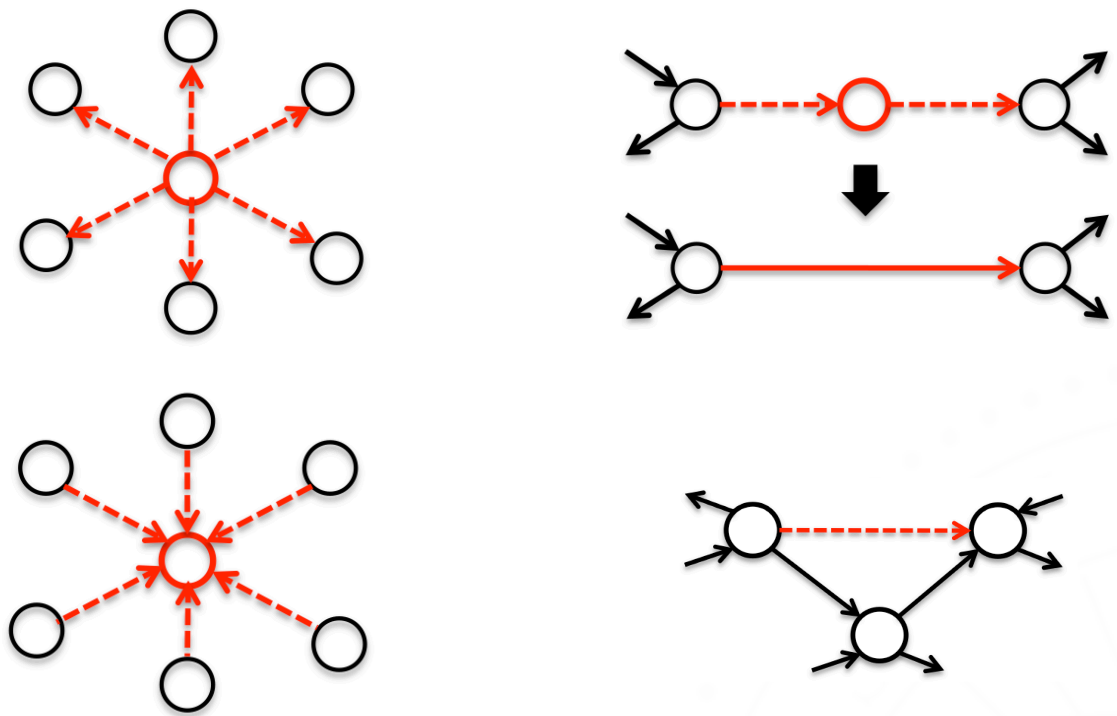
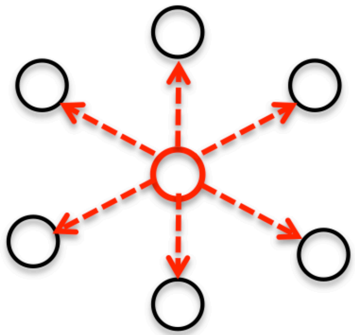
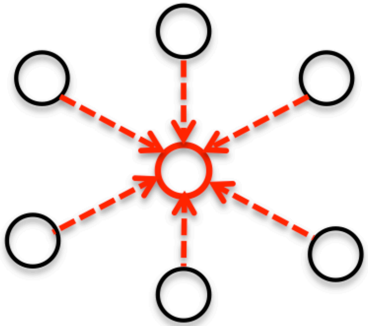
Vertex Transformations



Vertex Transformations

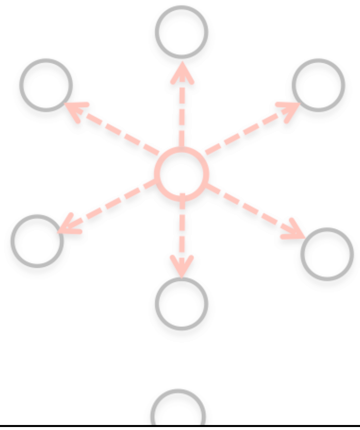


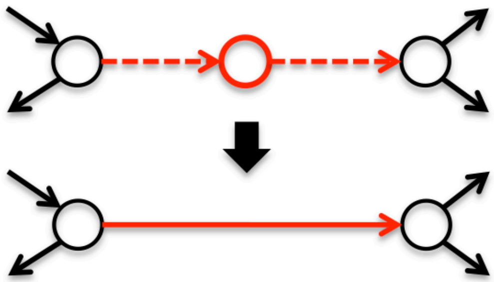
if (inDegree(v) $=0$) **then**
$\triangleright$ apply $\mathcal{T}_1$: drop $v \to *$
$\mathcal{E}' \leftarrow \mathcal{E}' \setminus$ outEdges(v)



if (outDegree(v) $=0$) **then**
$\triangleright$ apply $\mathcal{T}_2$: drop $* \to v$
$\mathcal{E}' \leftarrow \mathcal{E}' \setminus$ inEdges(v)

Vertex Transformations





if (inDegree(v) = outDegree(v) = 1) **then**
$\triangleright$ apply $\mathcal{T}_3$: bypass v
$\mathcal{E}' \leftarrow (\mathcal{E}' \setminus \{u \rightarrow v, v \rightarrow w\}) \cup \{u \rightarrow w\}$
where $\{u \rightarrow v, v \rightarrow w\} \subseteq \mathcal{E}'$

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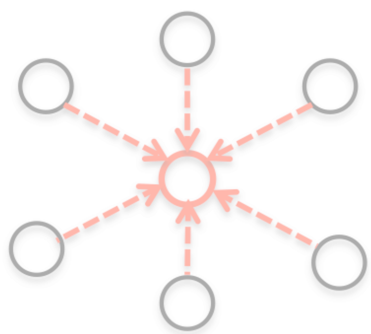
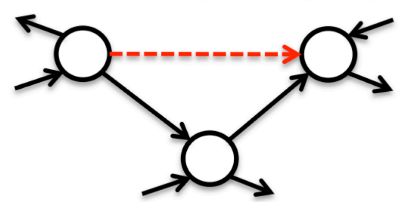
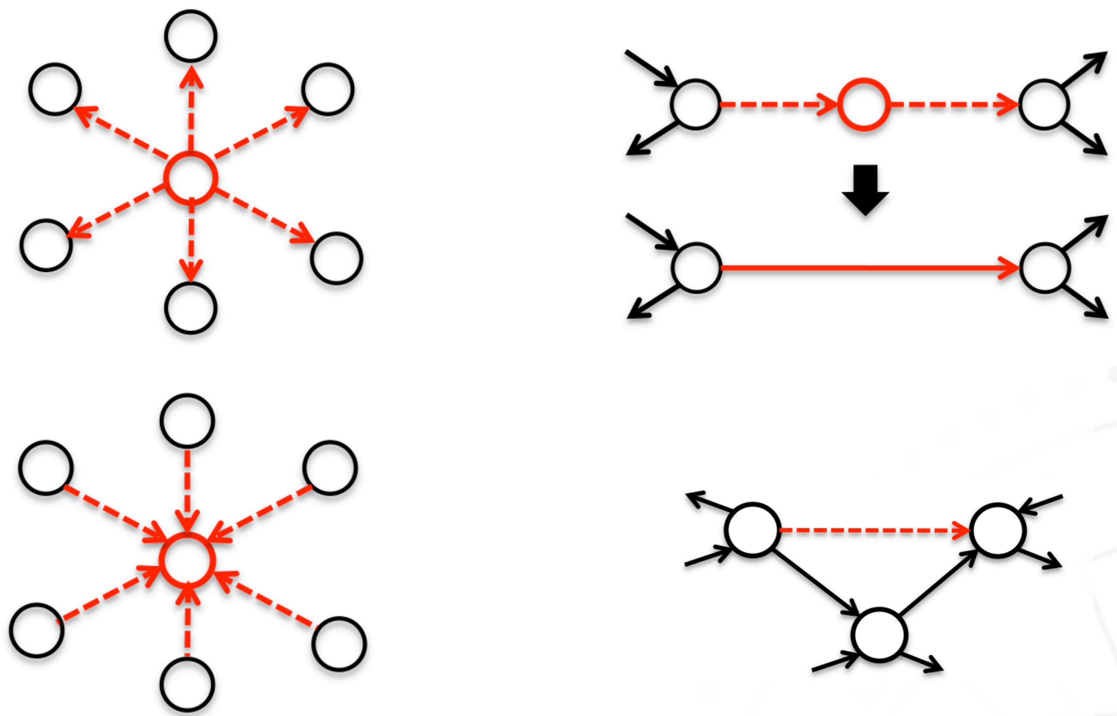
Vertex Transformations

if ($w \in \text{outNeighbors}(v)$ s.t. w is unchanged **and**
outNeighbors(v) $\cap$ inNeighbors(w) $\neq \phi$) **then**
$\triangleright$ apply $\mathcal{T}_5$: drop $v \to w$
$$\mathcal{E}' \leftarrow \mathcal{E}' \setminus \{(v \to w)\}$$





Vertex Transformations



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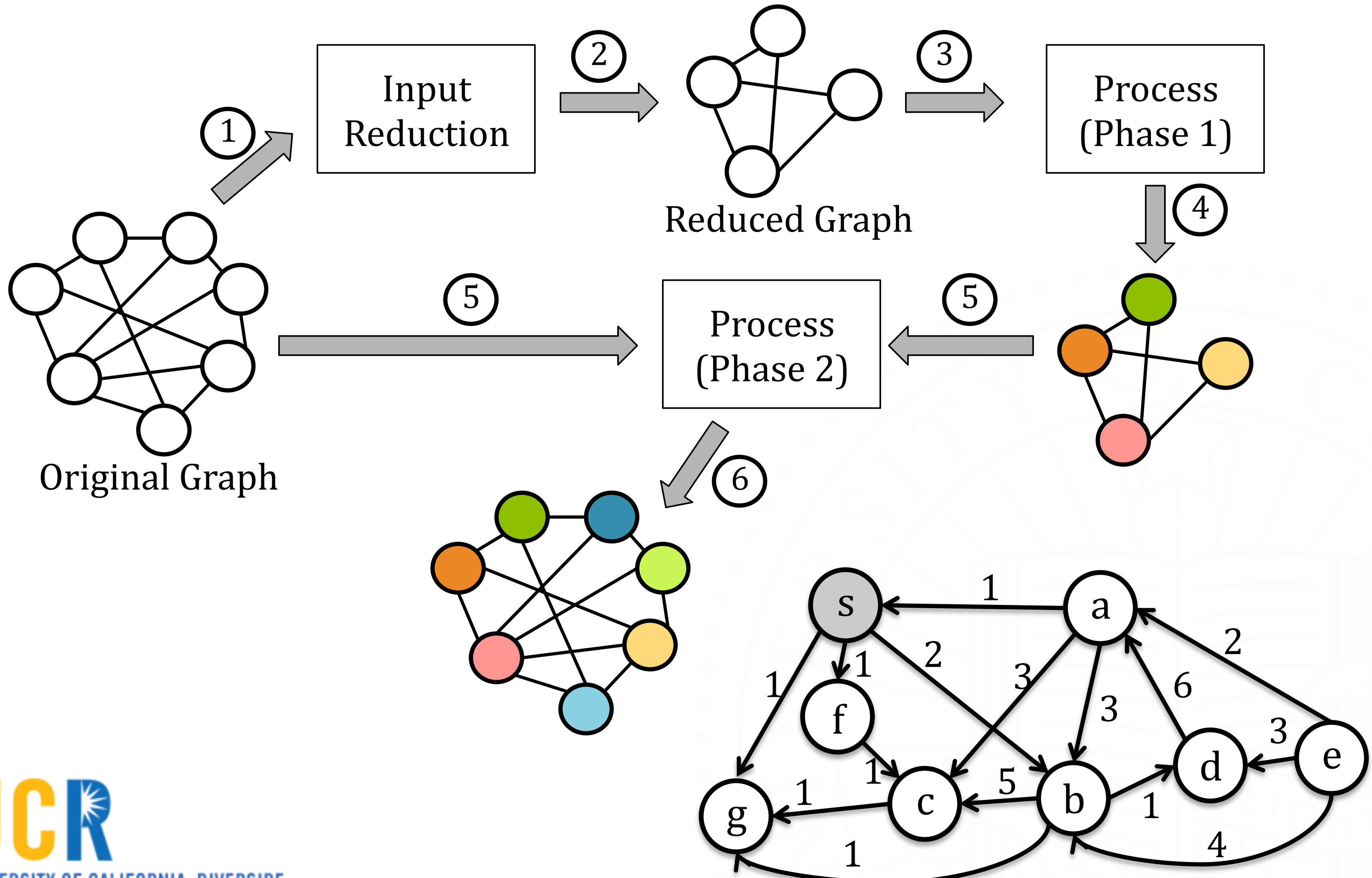
Other Details

- More vertex transformations
  - Some relax structural integrity
- Order of transformations
  - Unified graph reduction algorithm

Processing workflow



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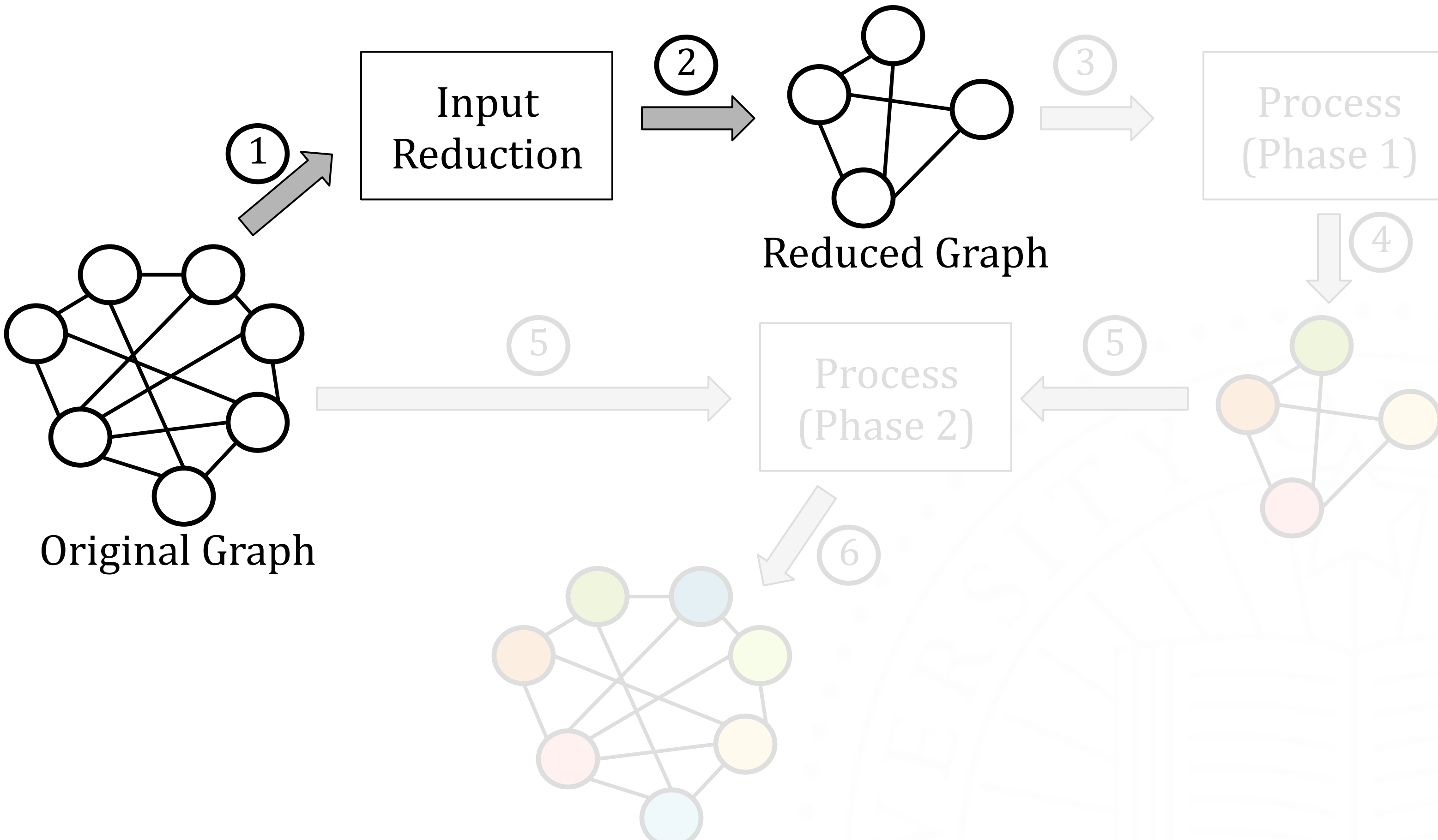

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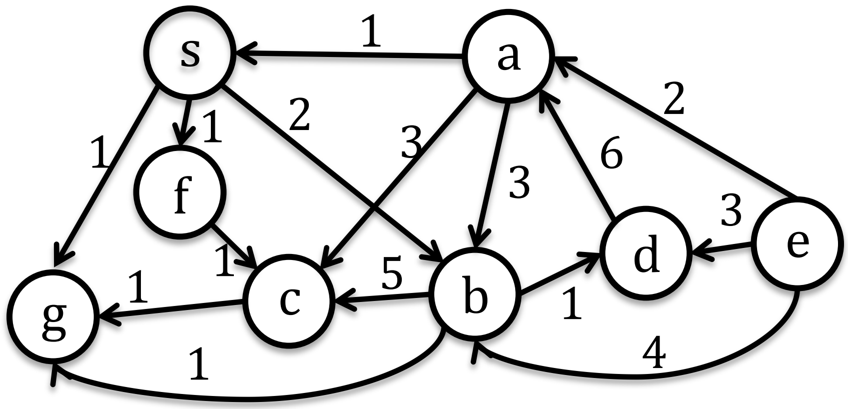
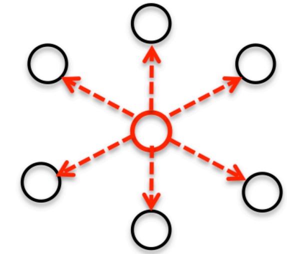
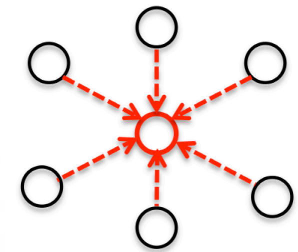
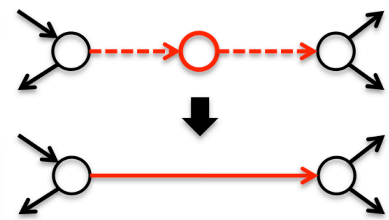
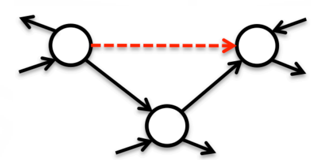
Input Reduction











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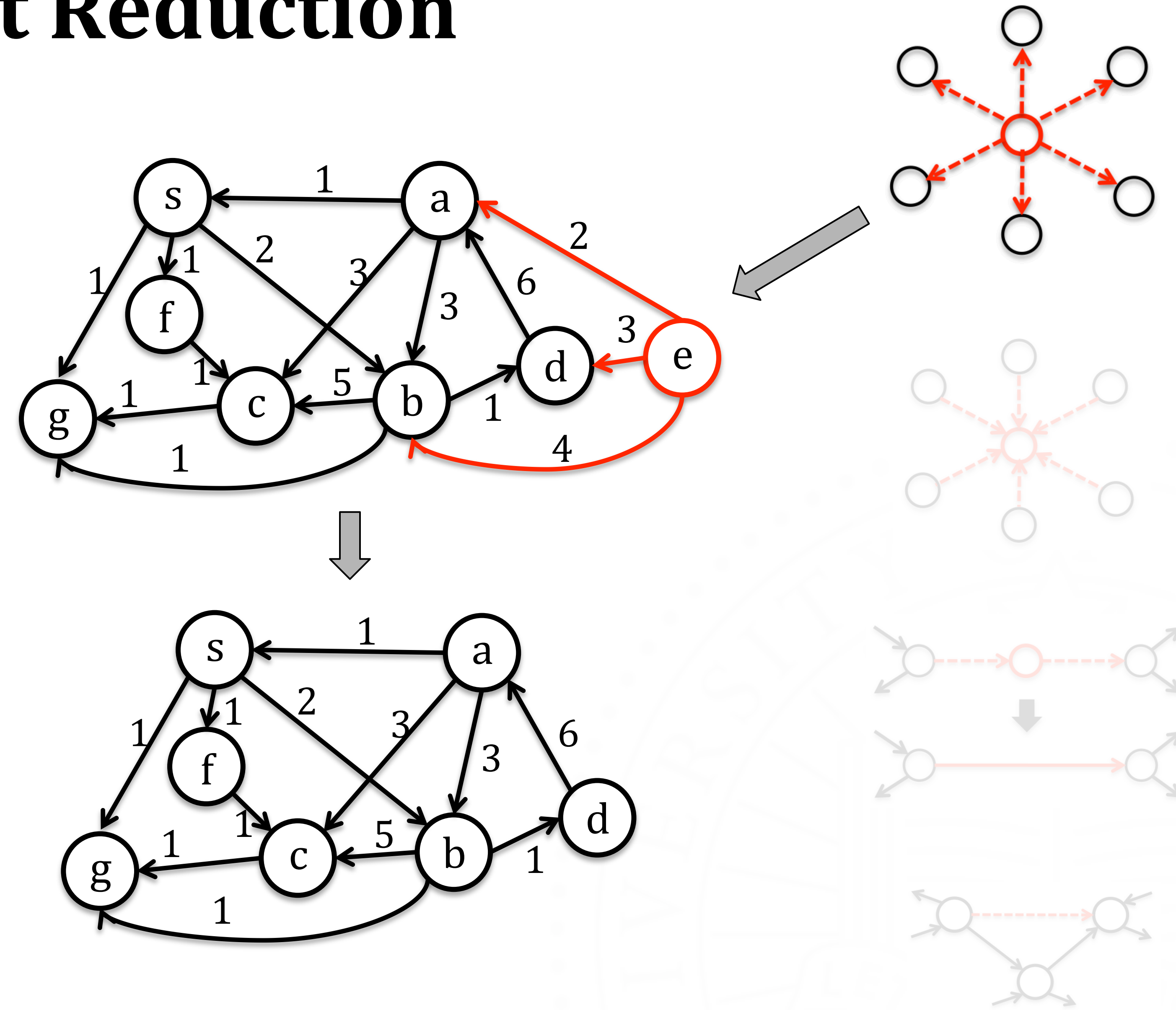

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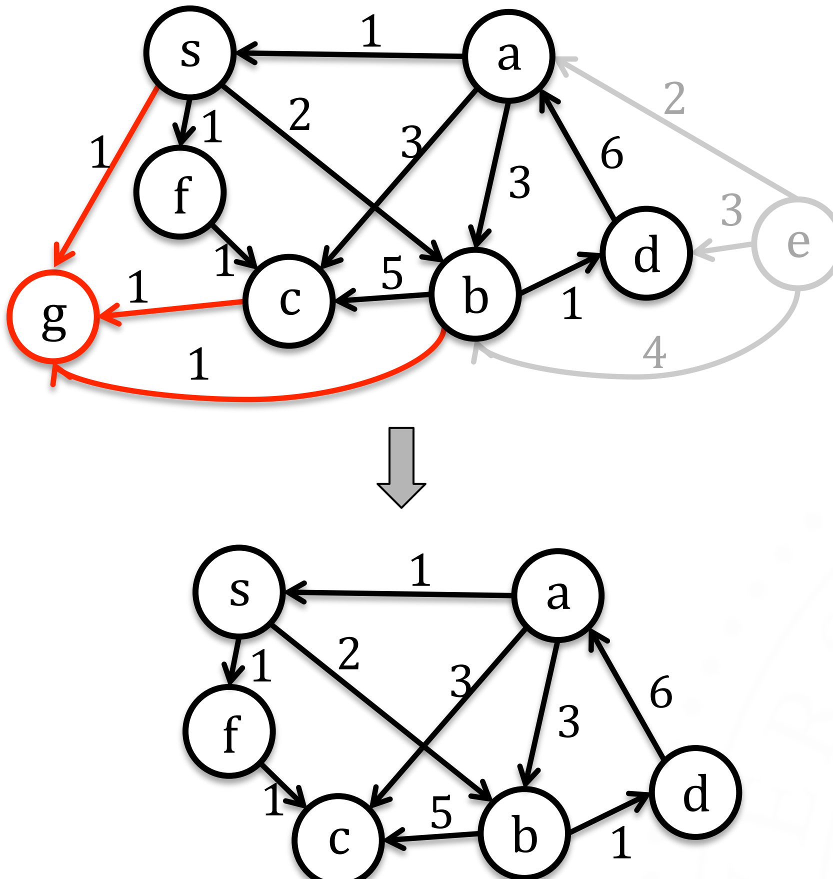

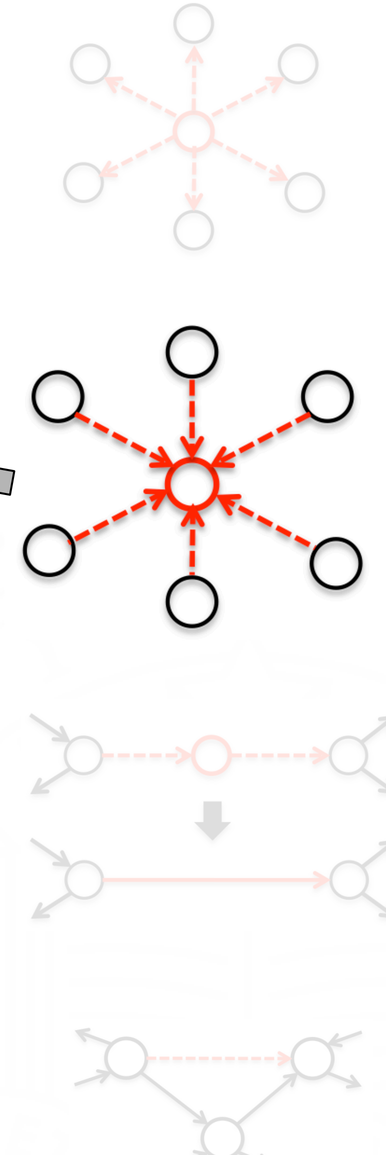

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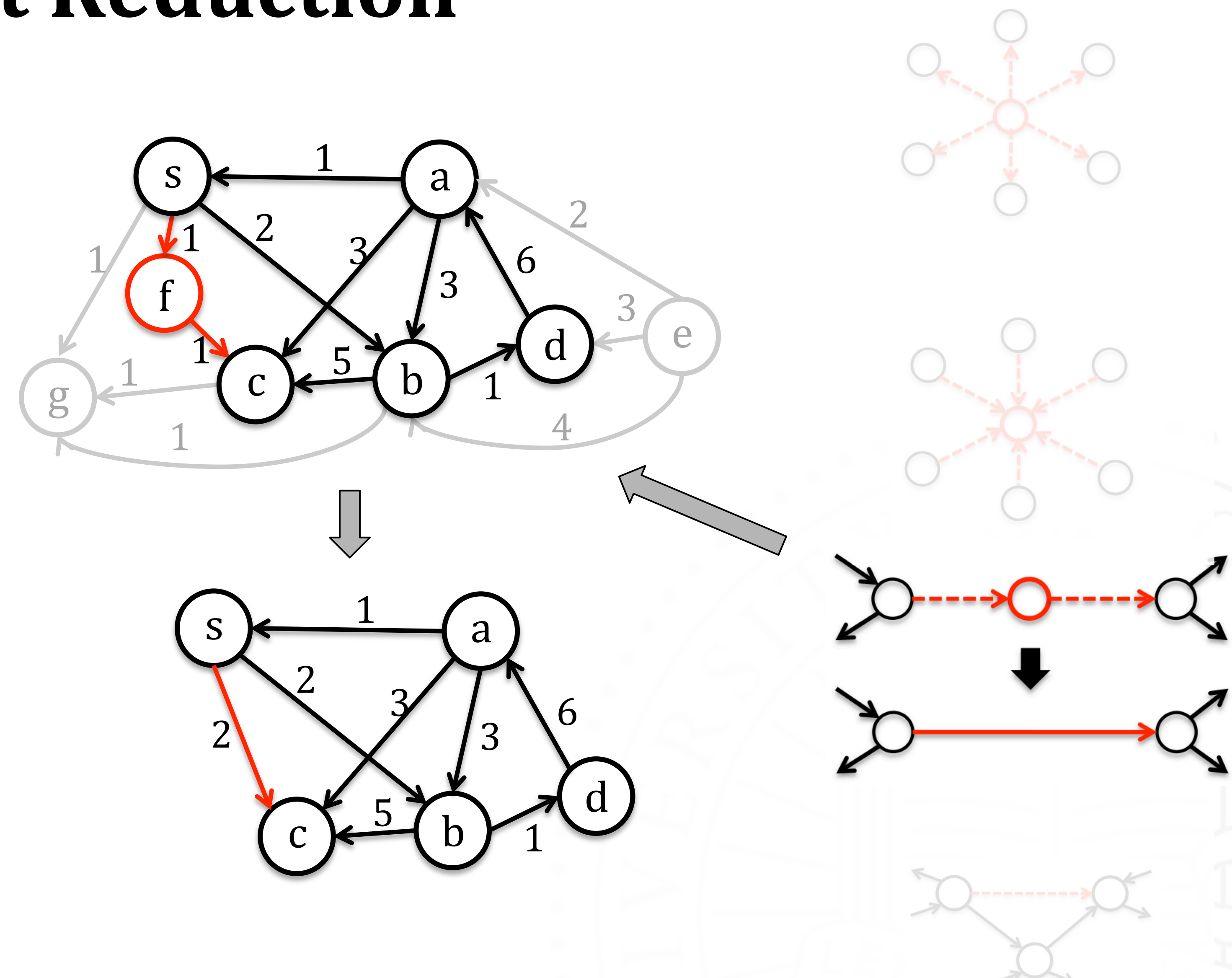

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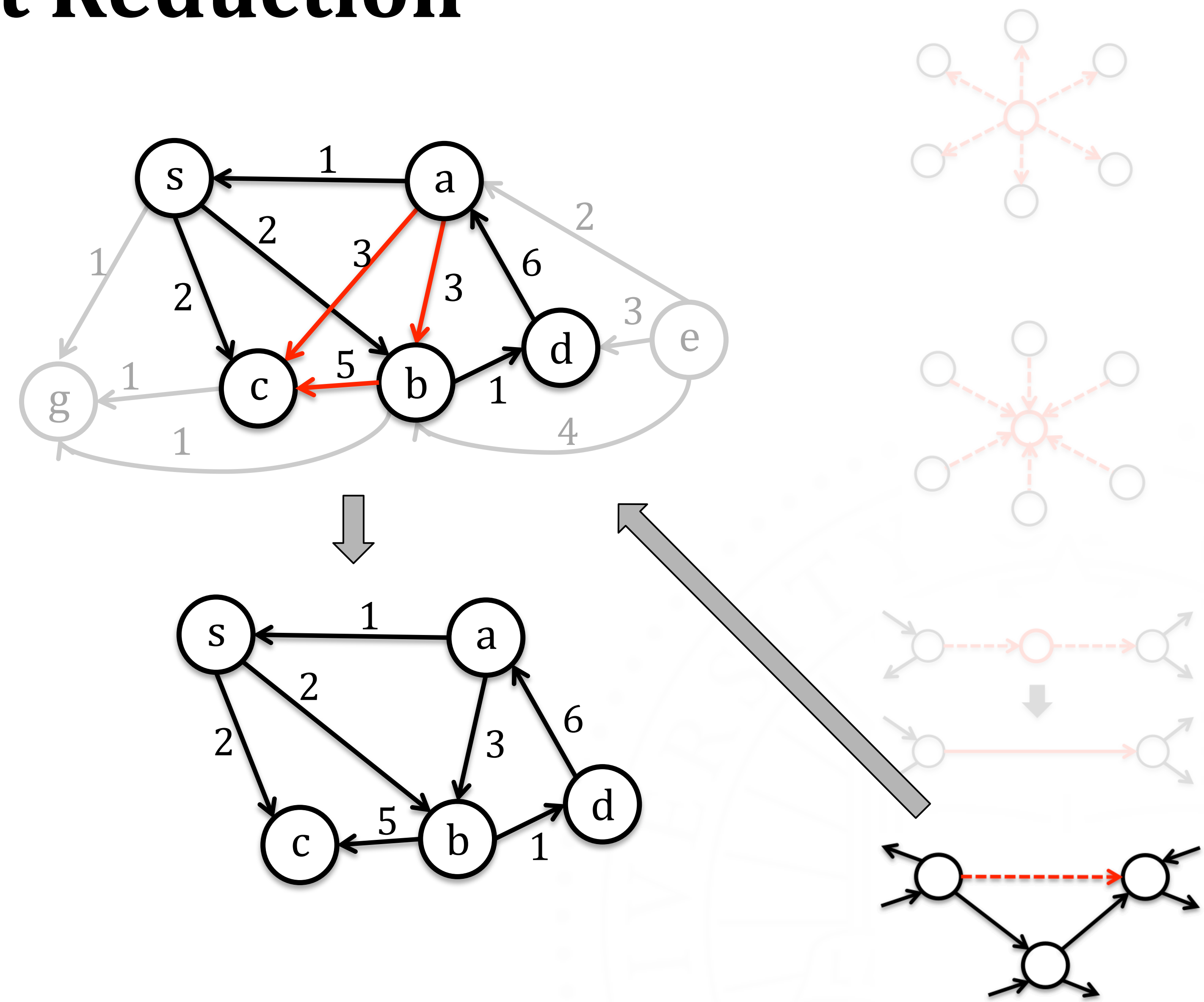

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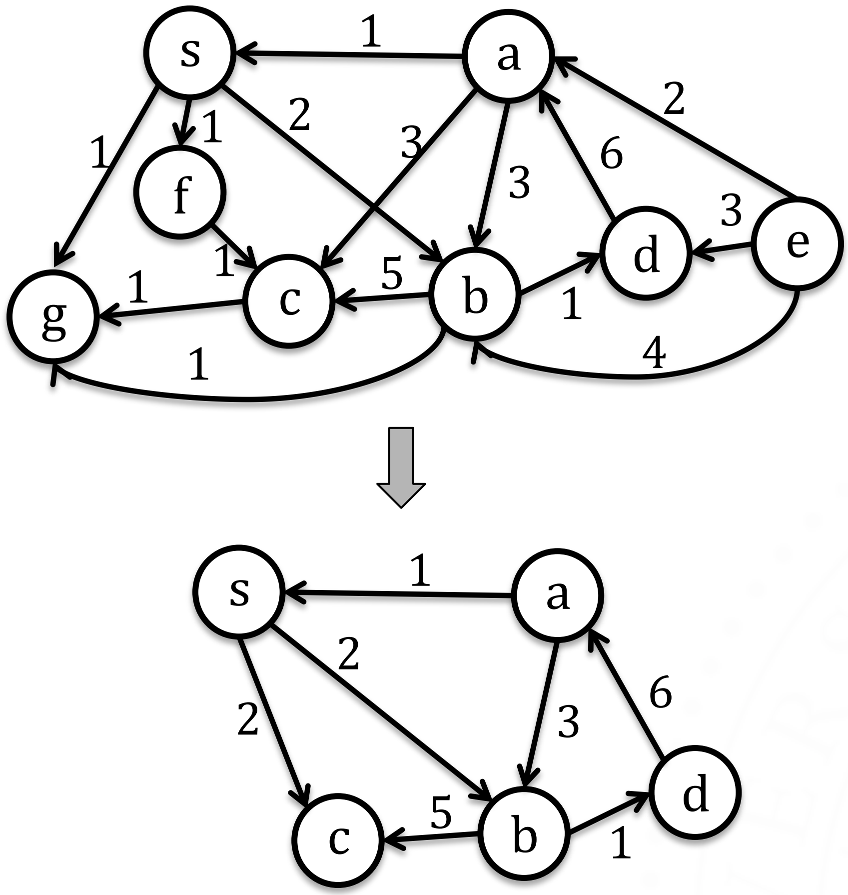
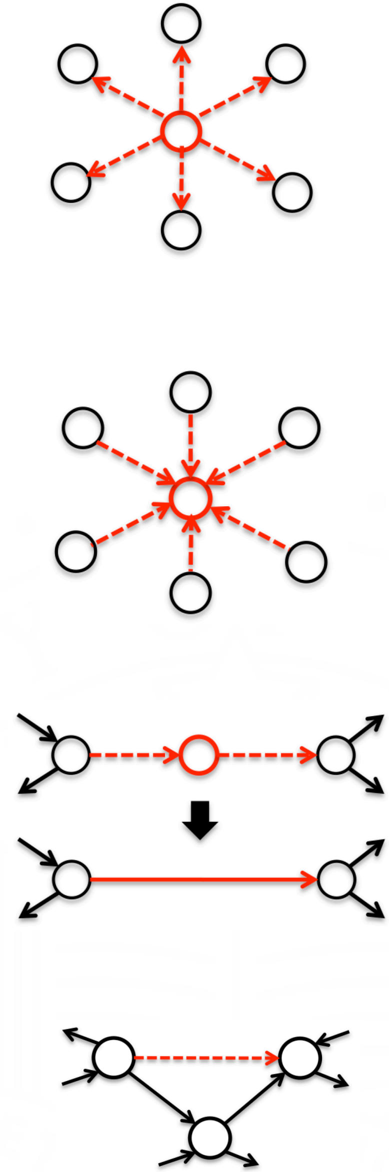
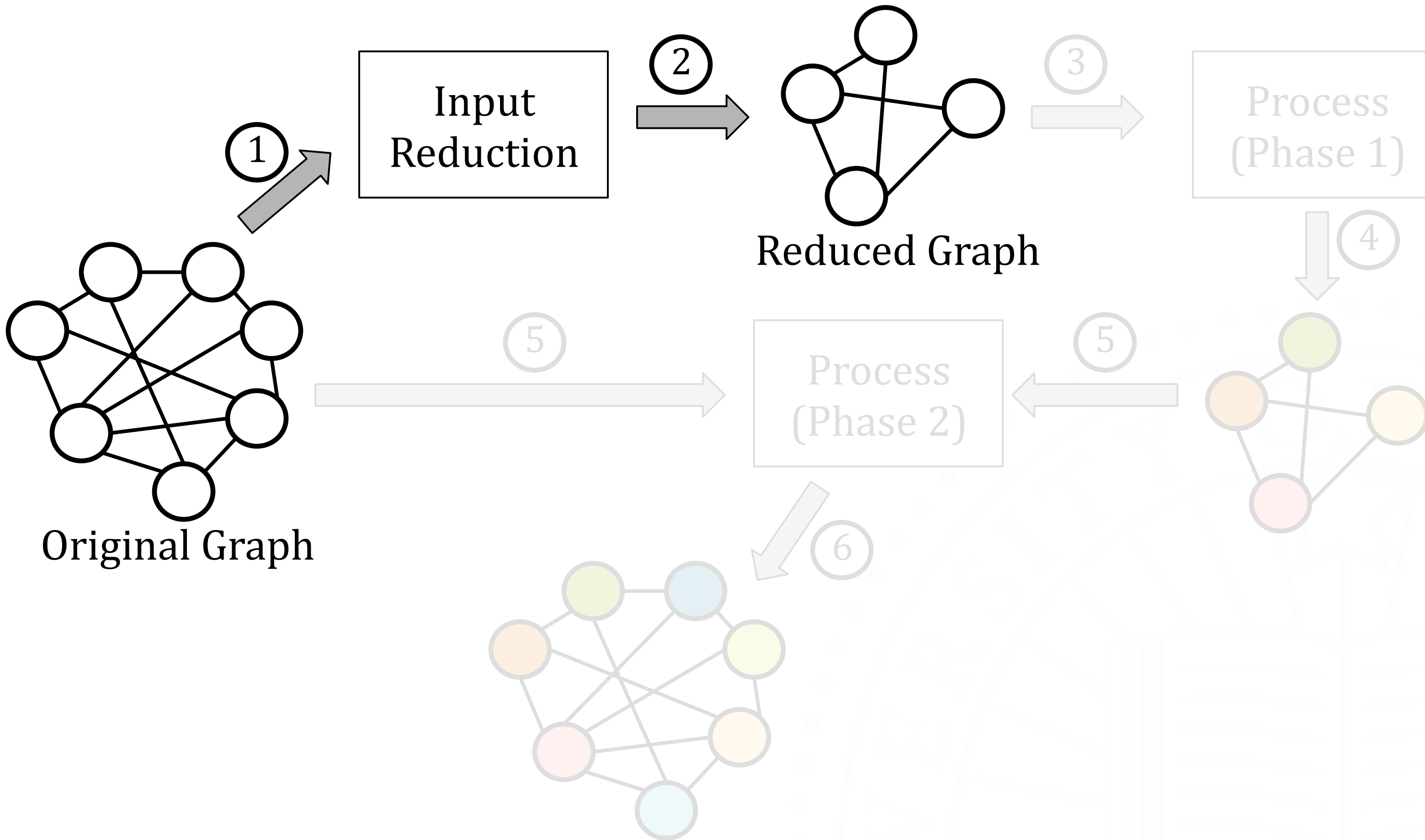




Workflow



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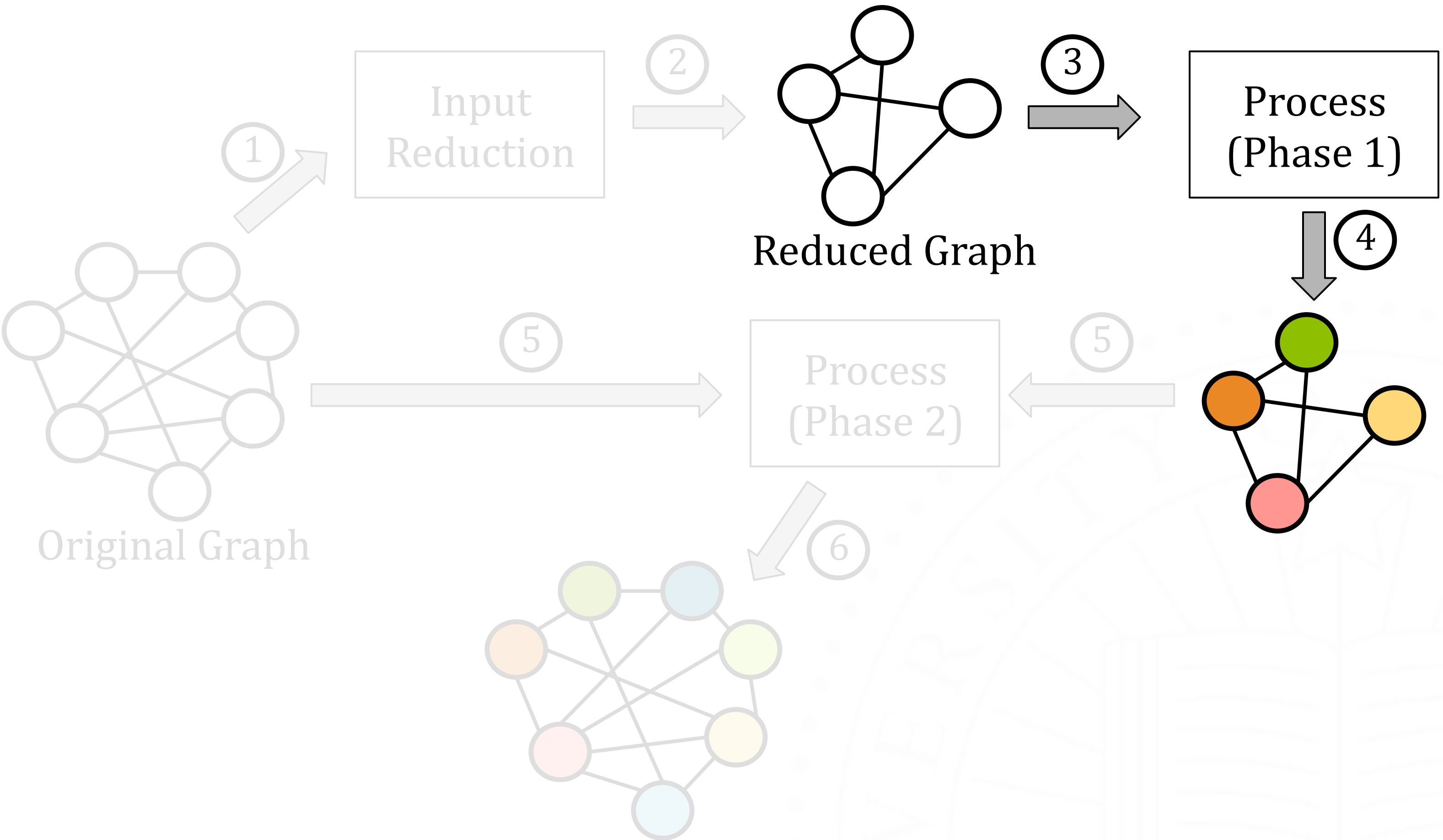

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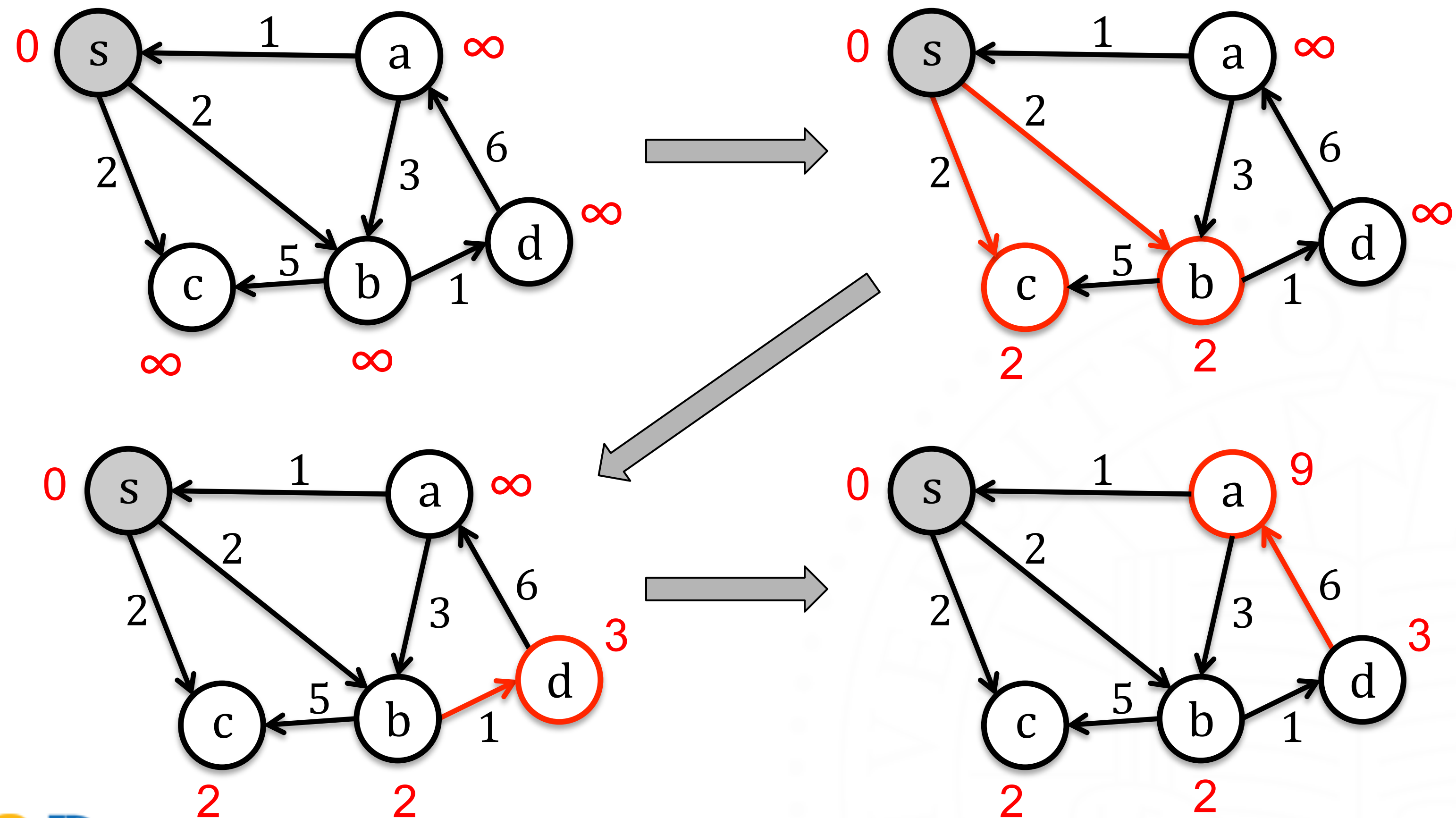
Processing Reduced Graph

- Use the original iterative algorithm



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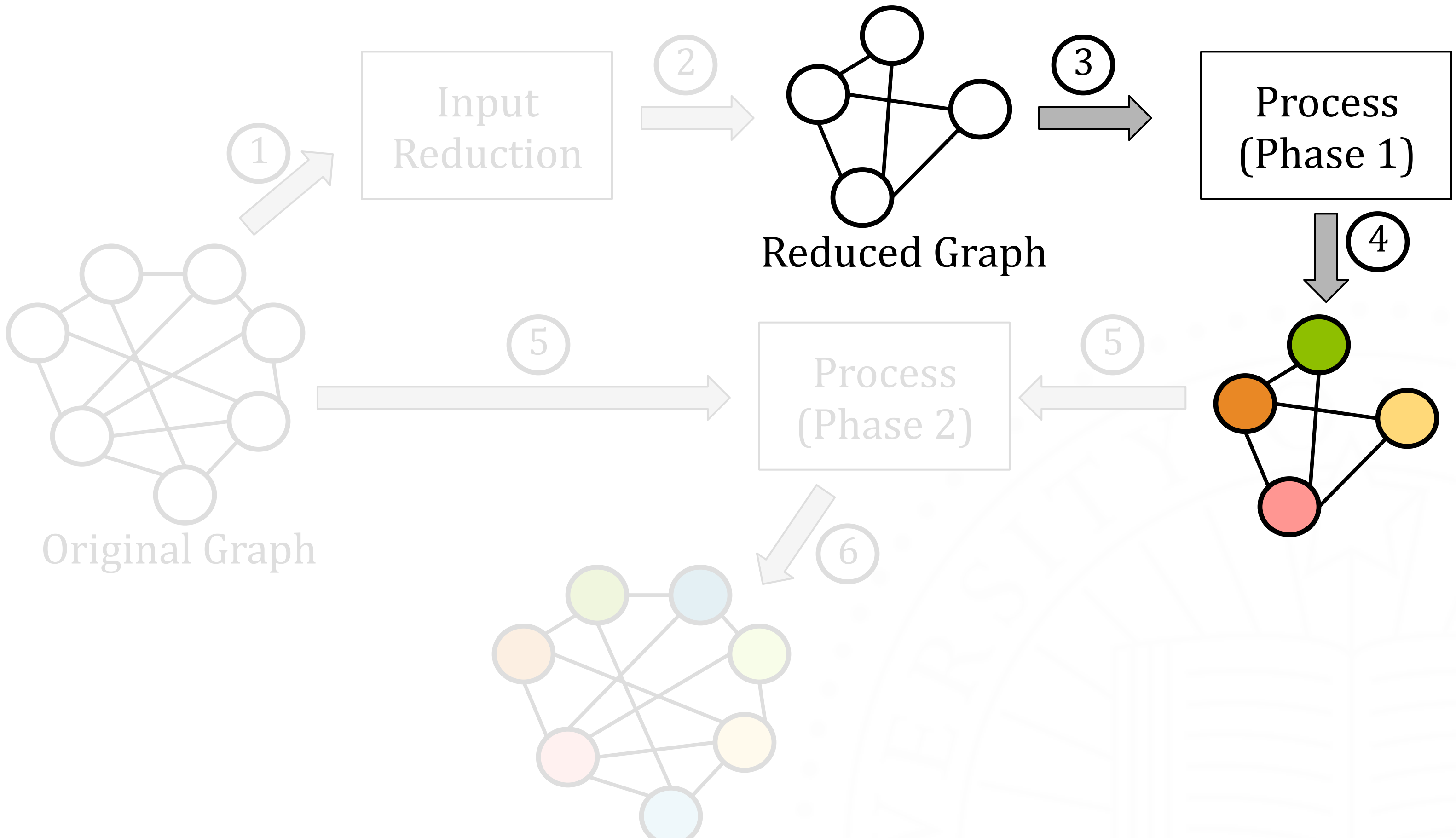
Workflow



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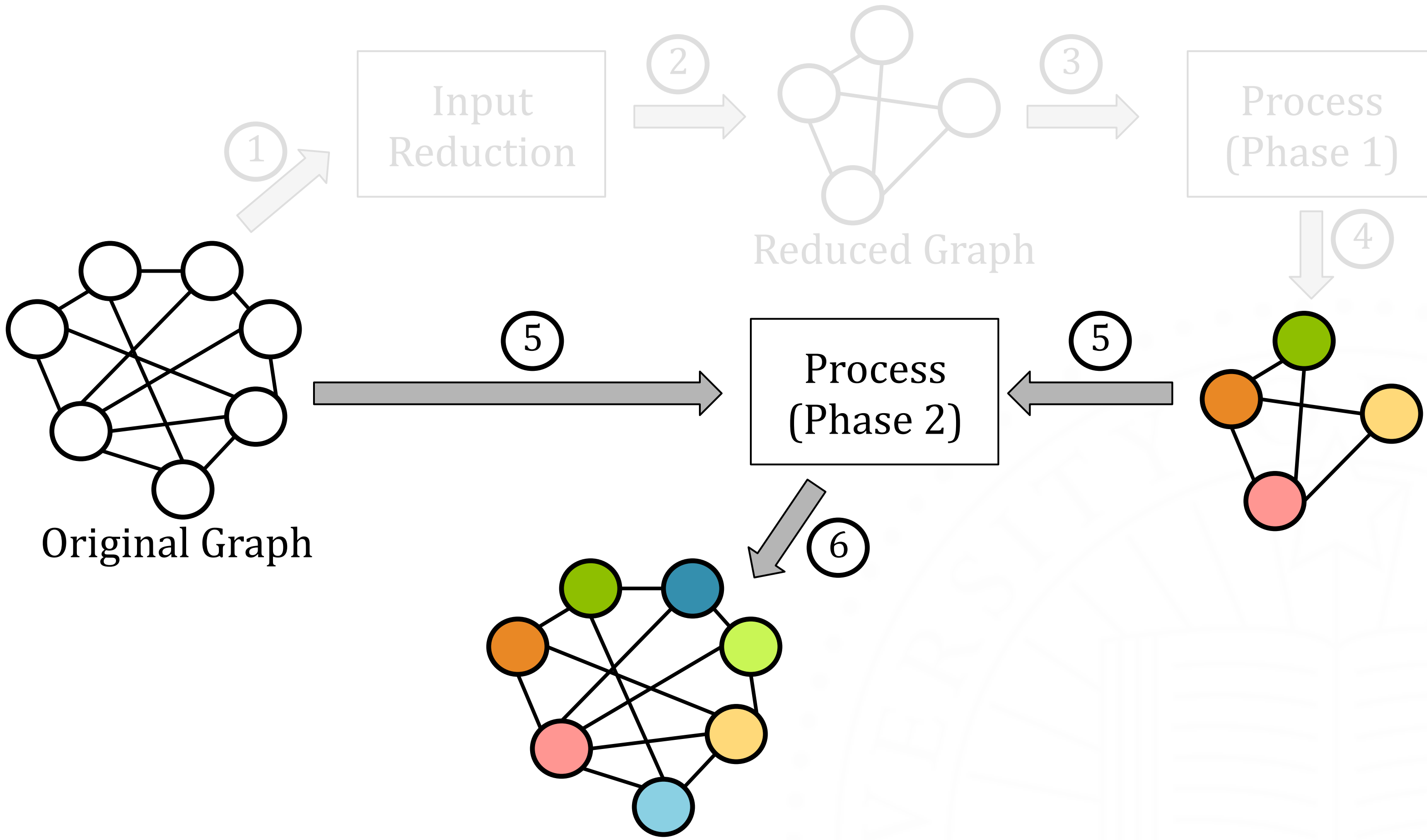
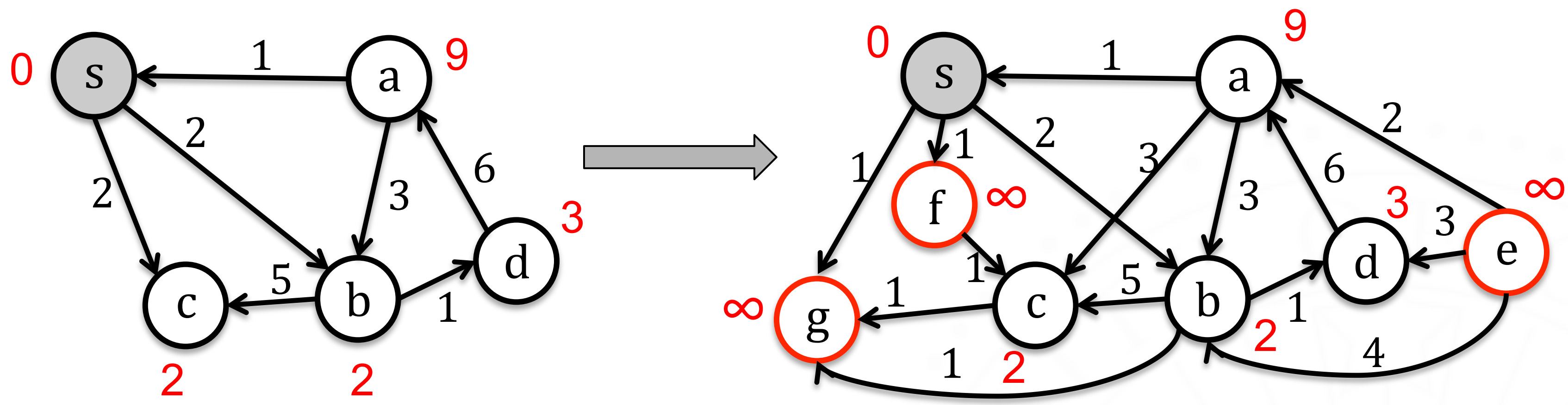


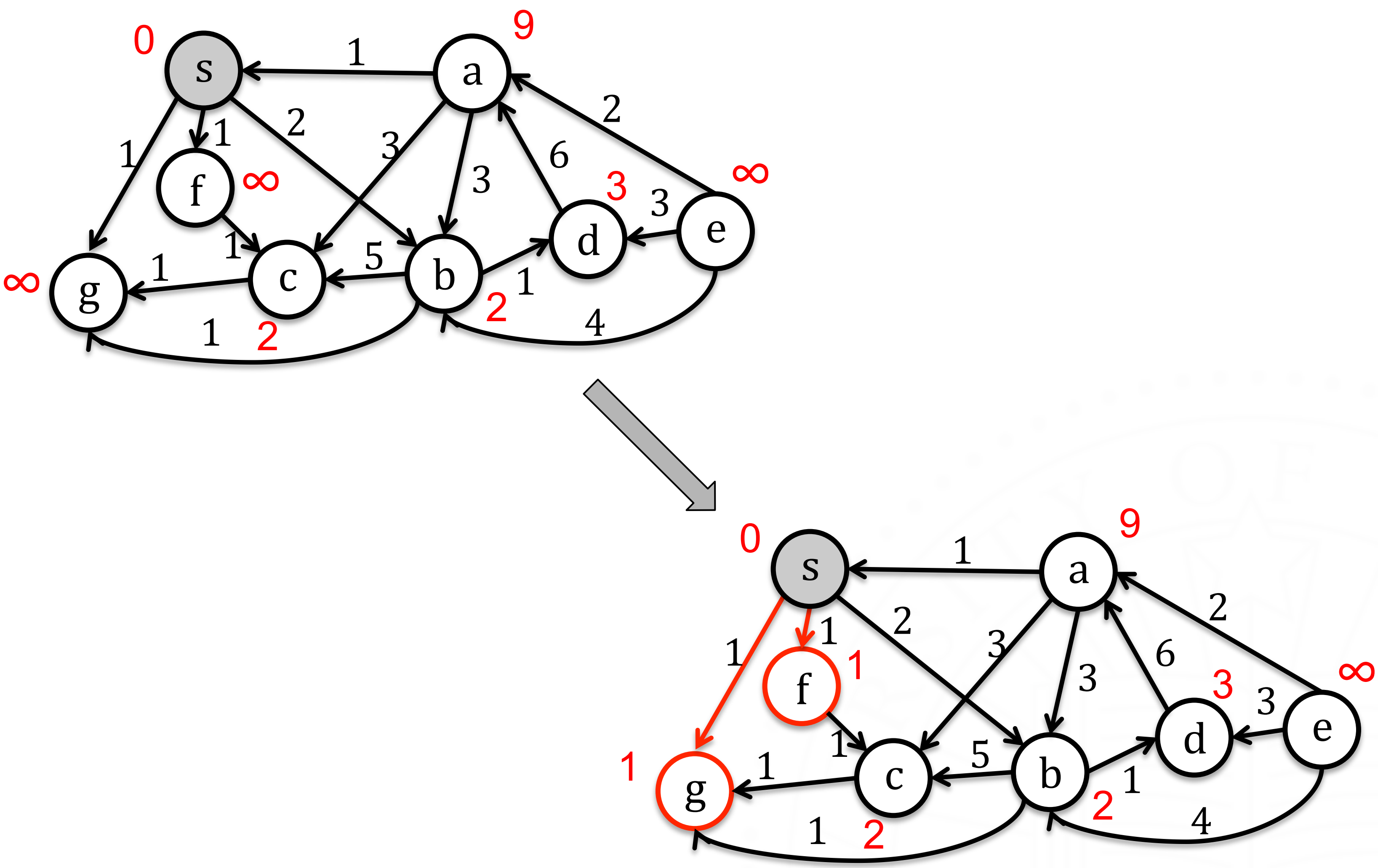
1
Input Reduction
2
Reduced Graph
3
Process (Phase 1)
4
Original Graph
5
Process (Phase 2)
5
6

Mapping Results

- Use default values for missing vertices



Processing Original Graph



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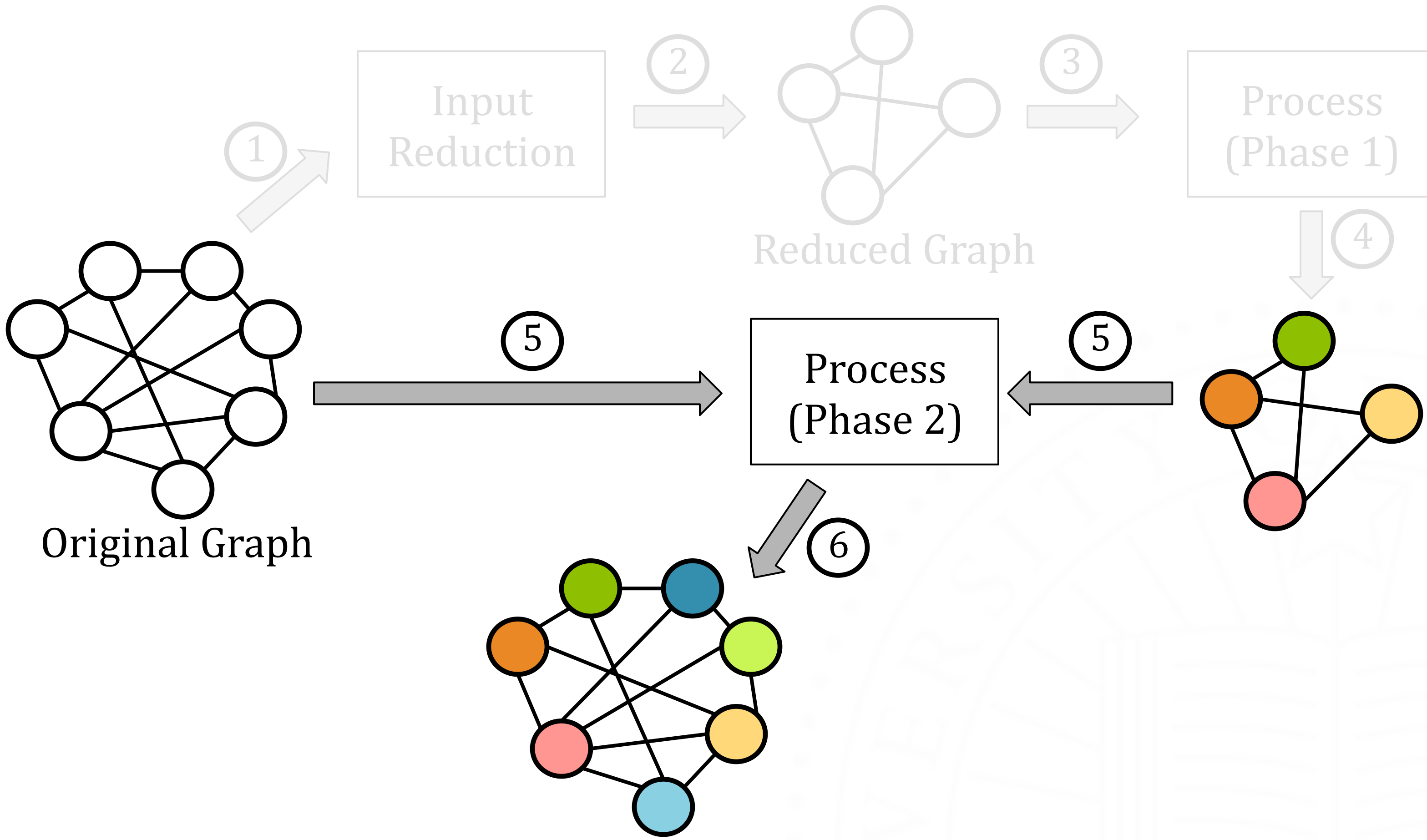

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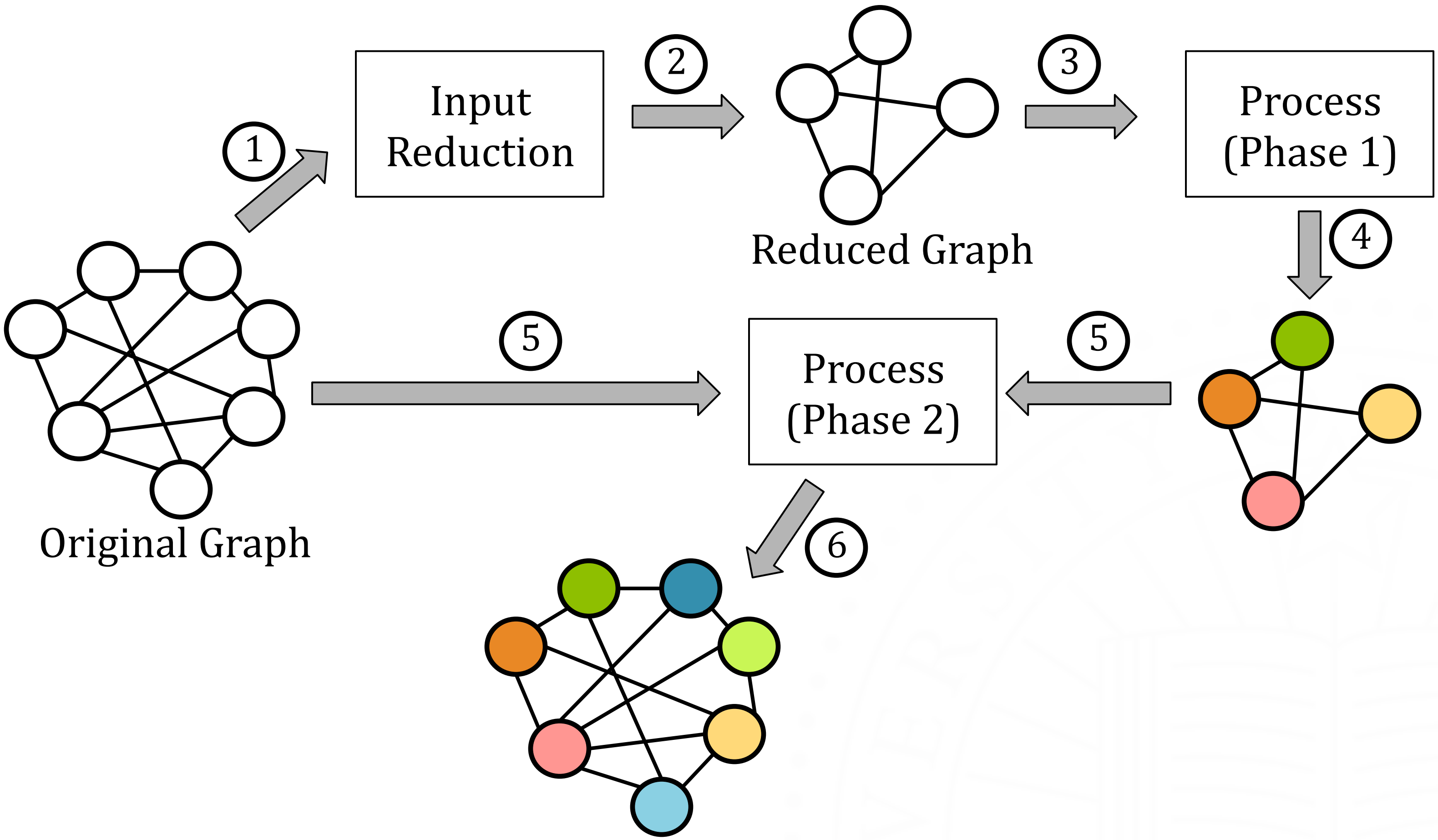

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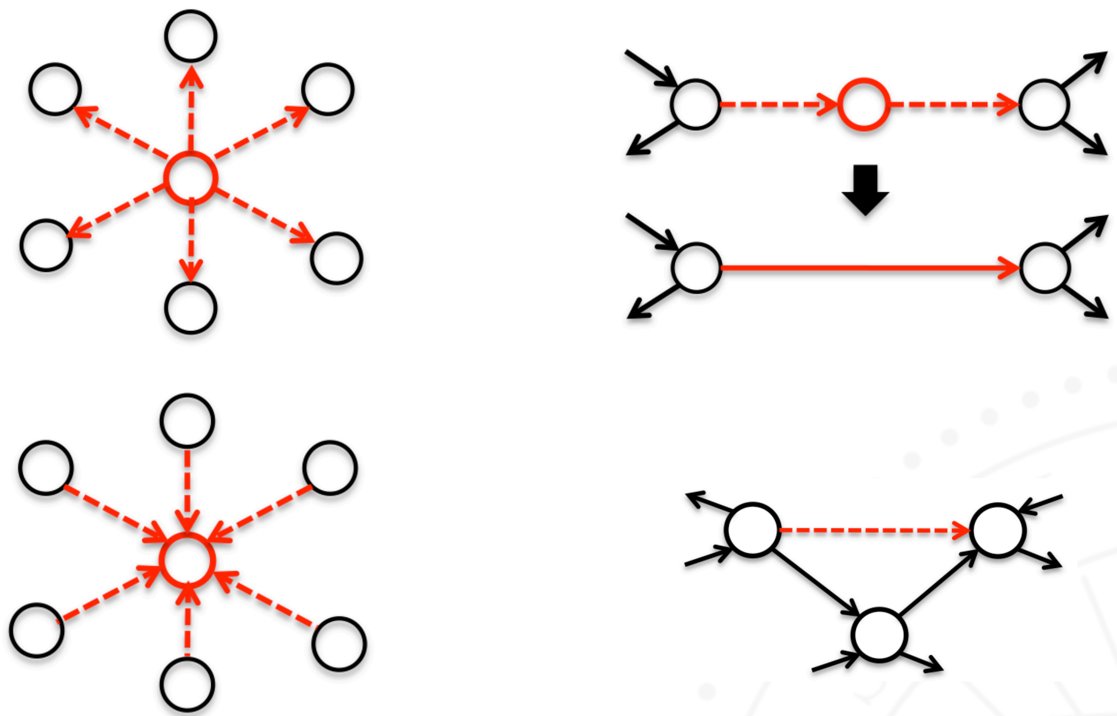
Correctness: SSSP Example



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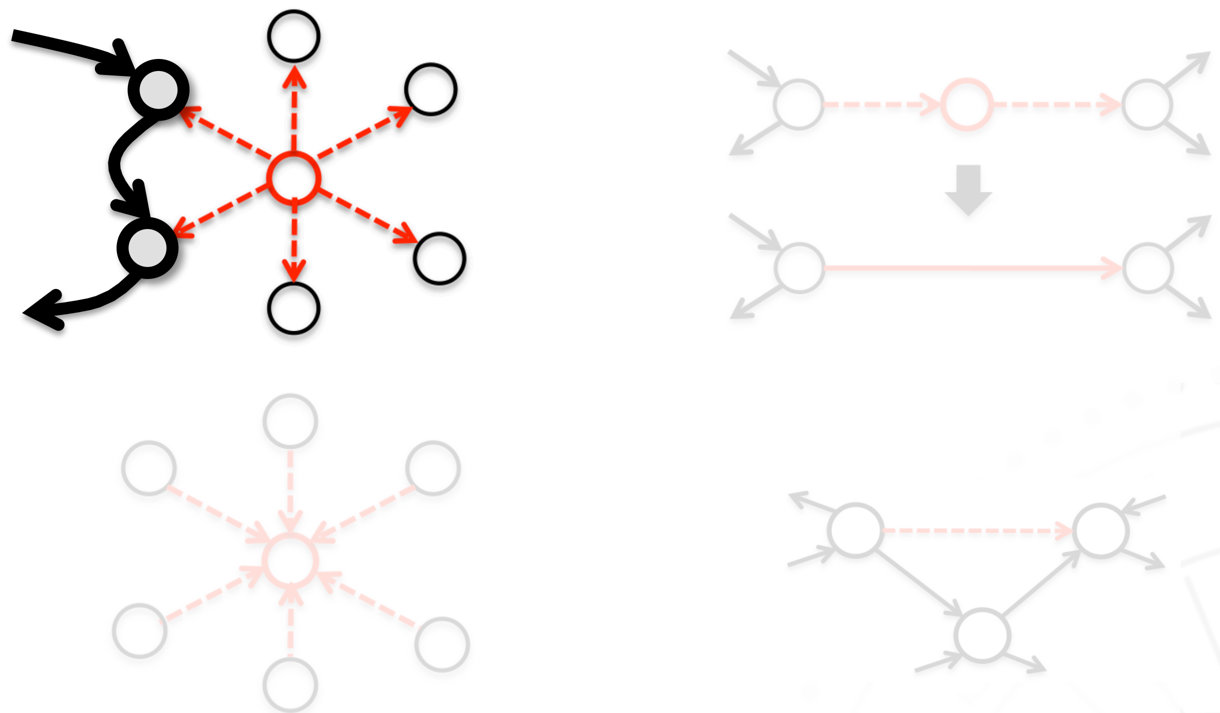

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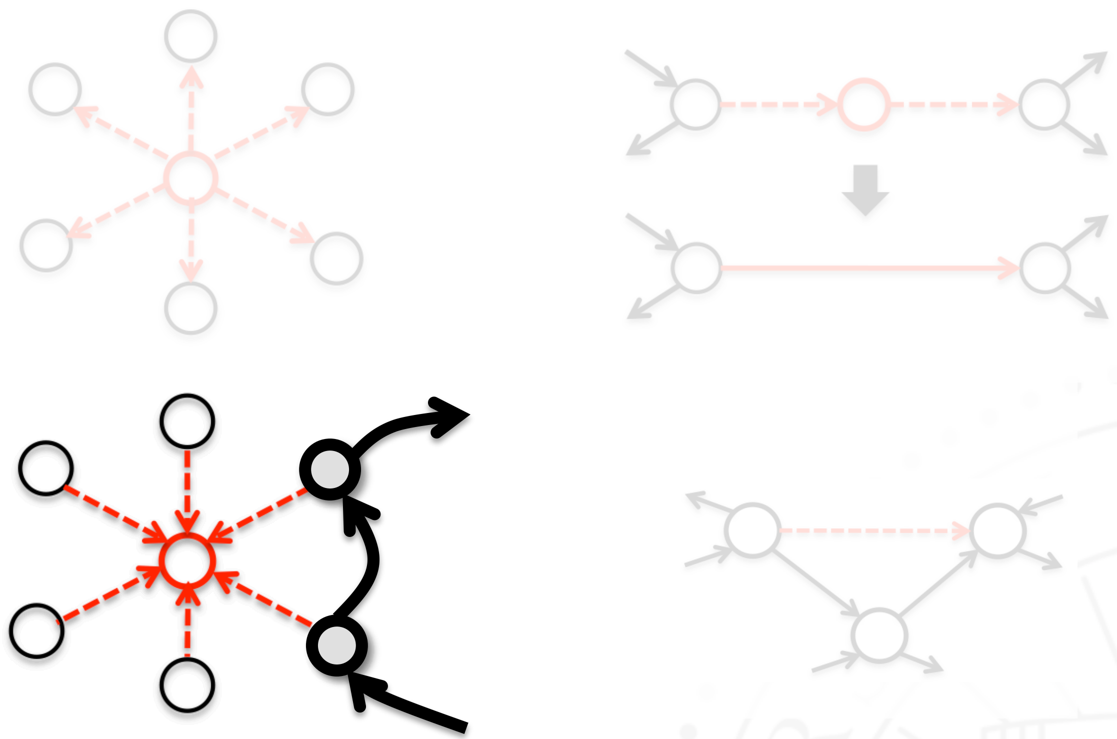

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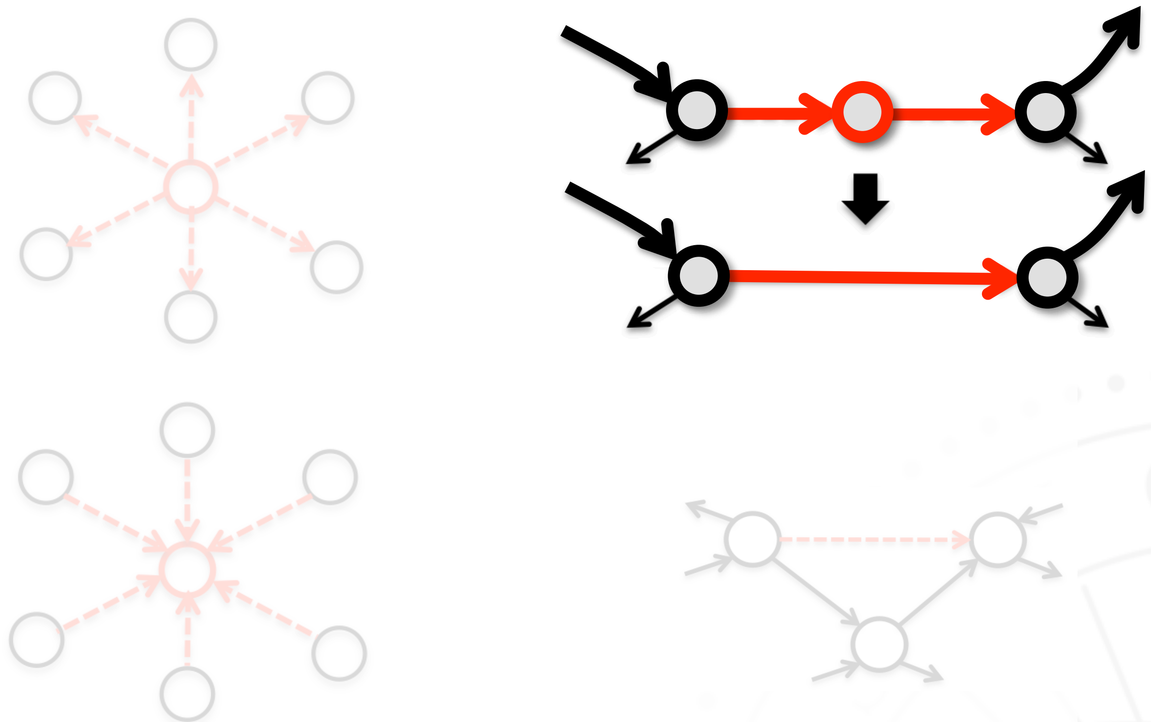

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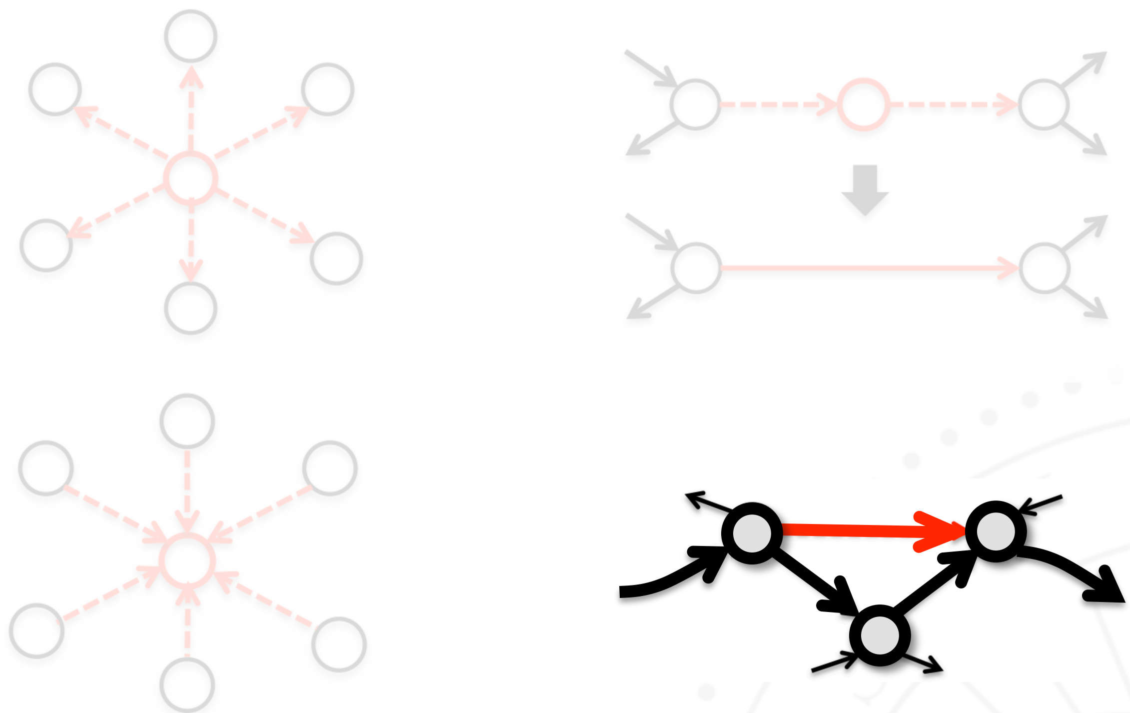

Correctness

- Transformation properties
  - Level of vertices, edges and components
  - Allow developing & reasoning for new transformations
- Algorithm behavior can be reasoned
  - Phase 2 initializations
  - Properties of aggregation function

- Correctness argued for algorithms used
  - 5 accurate and 1 approximate

Evaluation

- Techniques independent of frameworks & processing environment
  - Incorporated in Galois [PLDI'11]
  - Single machine: 24-core, 32GB RAM
- 6 benchmarks
  - PR, SSSP, SSWP, CC, GC, CD
- 4 input graphs
  - Friendster (|E| = 2.6B), Twitter (|E| = 1.5B), UKDomain (|E| = 936M), RMAT-24 (|E| = 268M)

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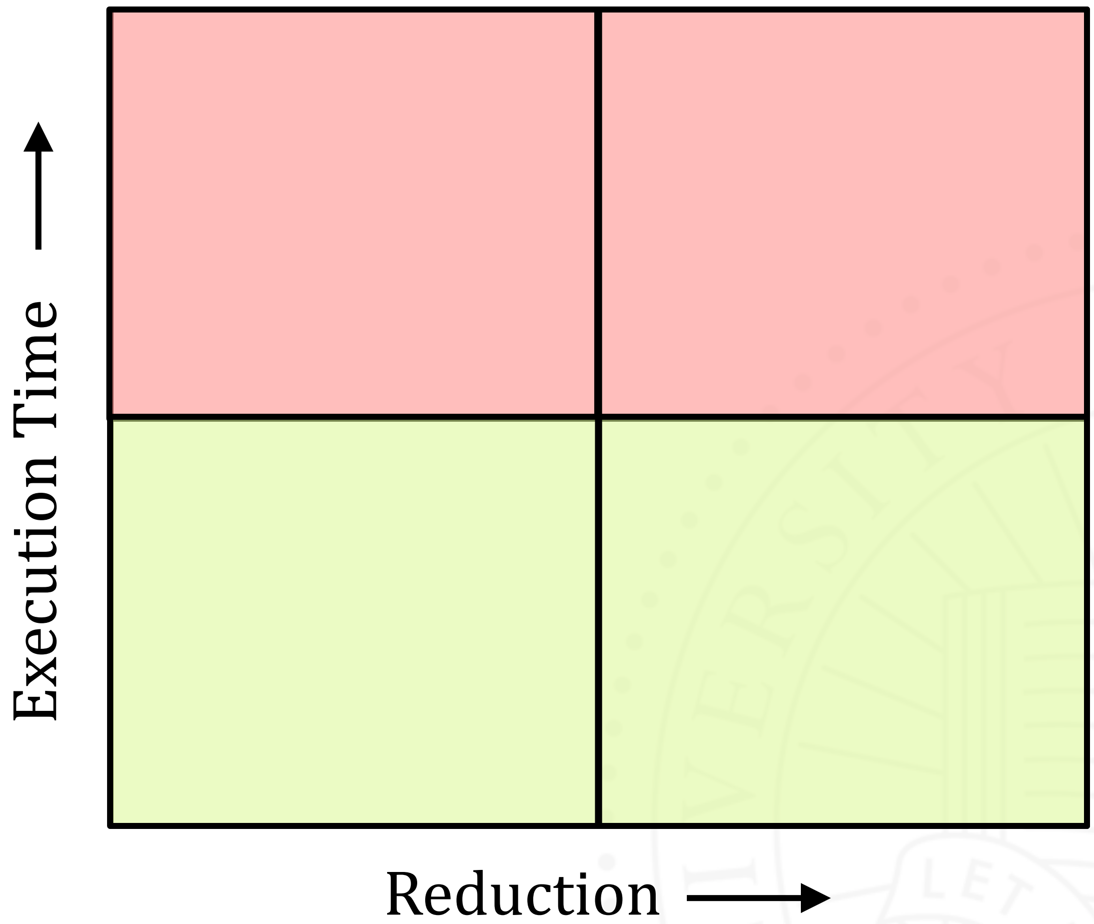
Reduction

- $$ERP = \frac{|E_{REDUCED}|}{|E_{ORIGINAL}|} \times 100$$



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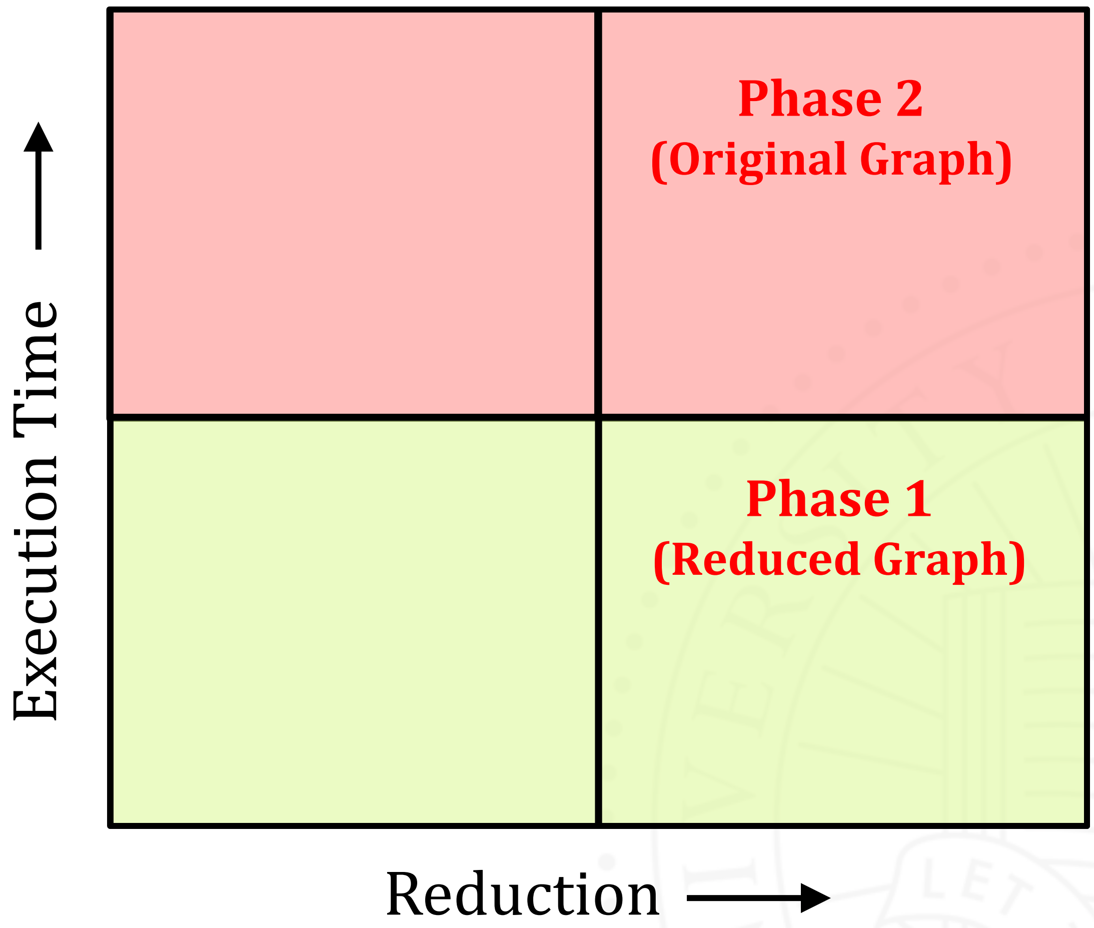

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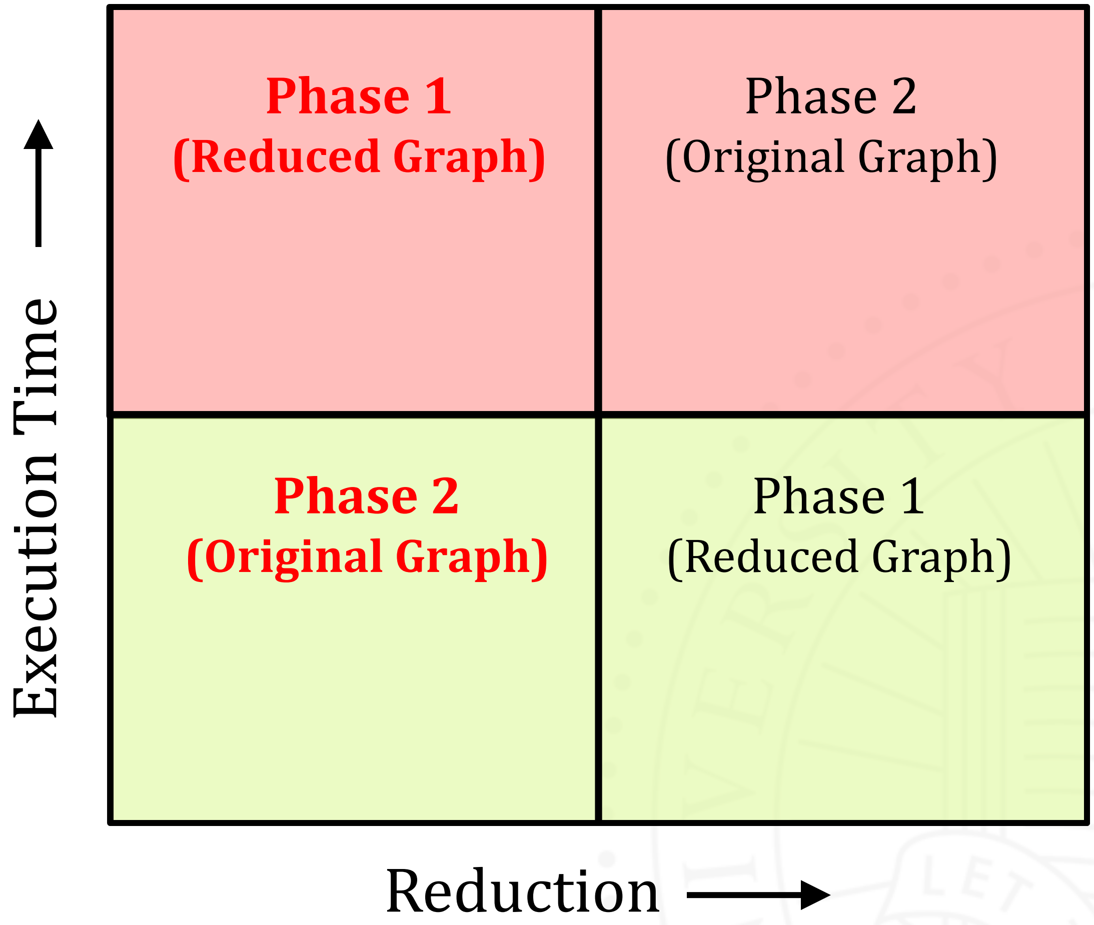
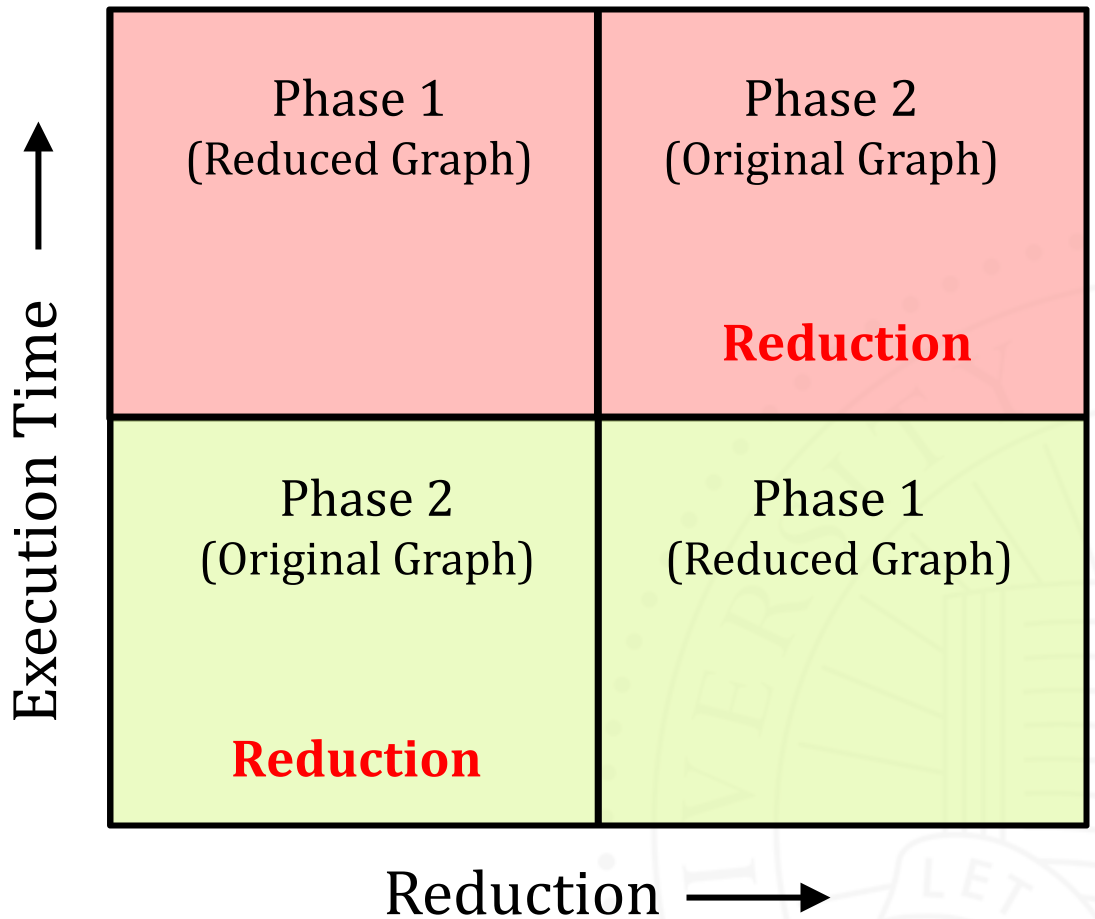


Reduction

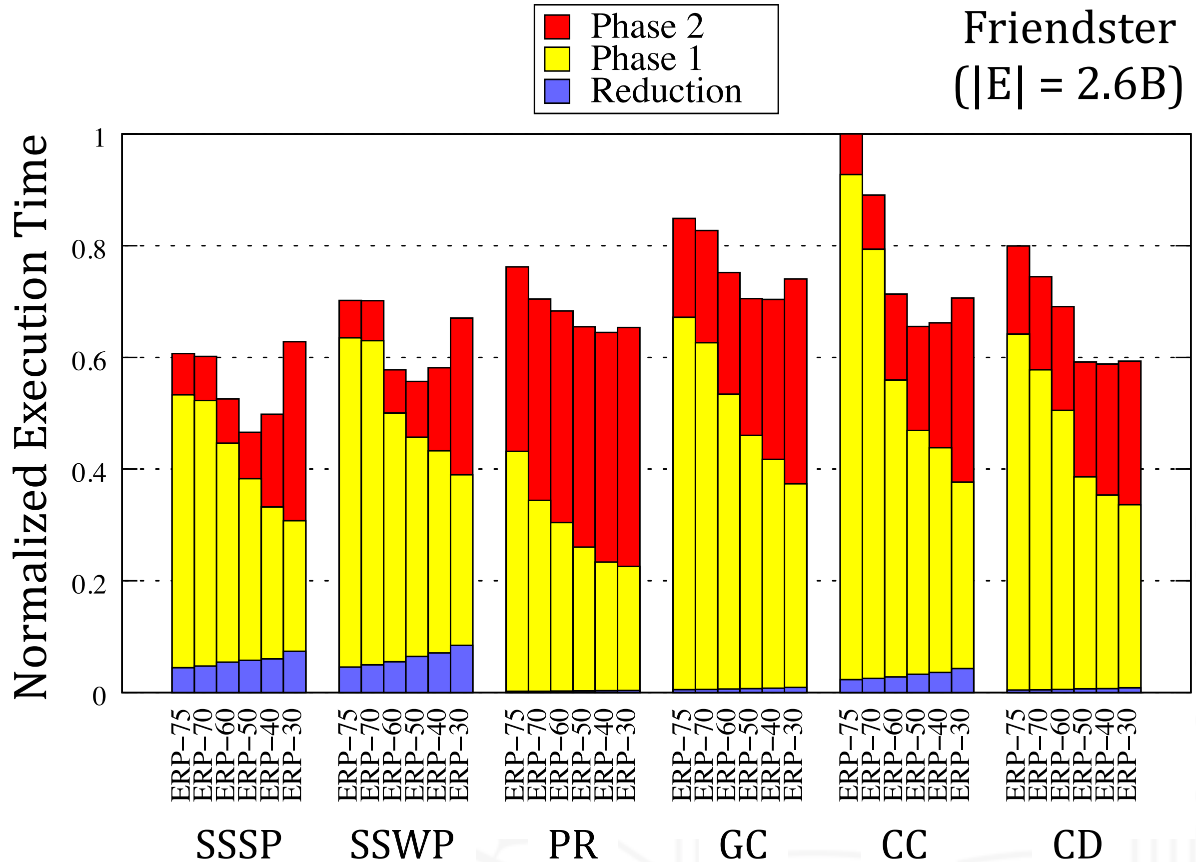
- $ERP = \frac{|E_{REDUCED}|}{|E_{ORIGINAL}|} \times 100$



Execution Time

- Speedups over parallel versions
- Speedups increase as ERP decreases up to an extent
- 1.3x - 1.7x for 75% - 50%
- Structural dissimilarity for very low ERP

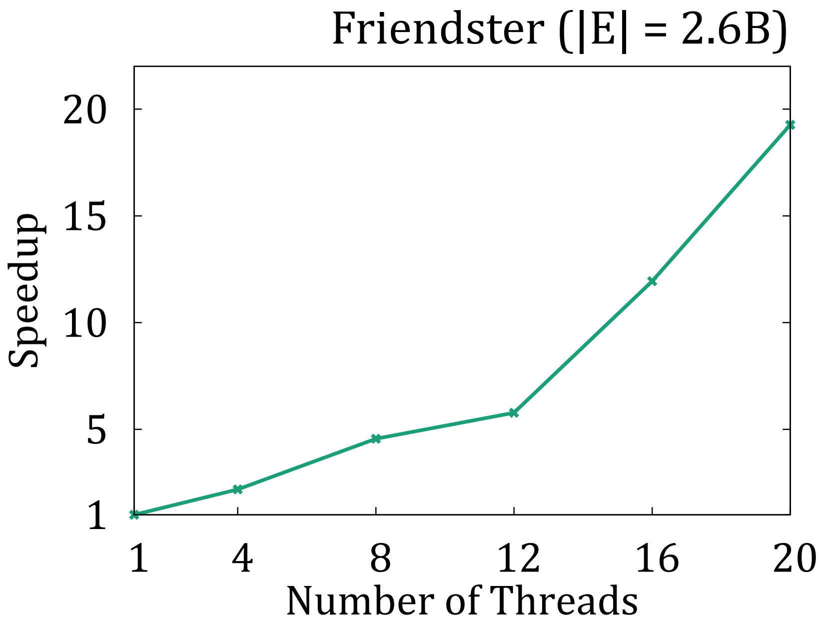
Friendster (|E| = 2.6B)

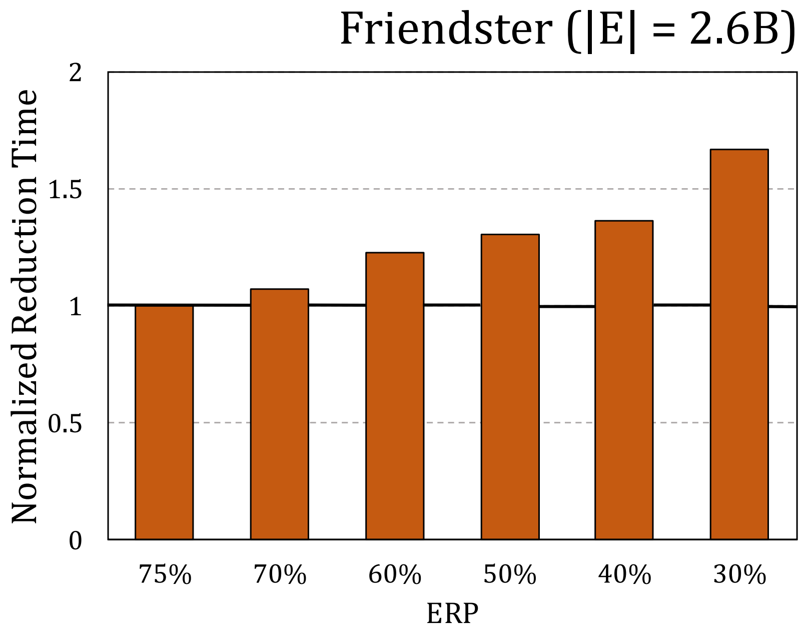


$$ERP = \frac{|E_{REDUCED}|}{|E_{ORIGINAL}|} \times 100$$

Input Reduction

- Transformations are local, i.e., parallelizable
- Higher reduction requires more work





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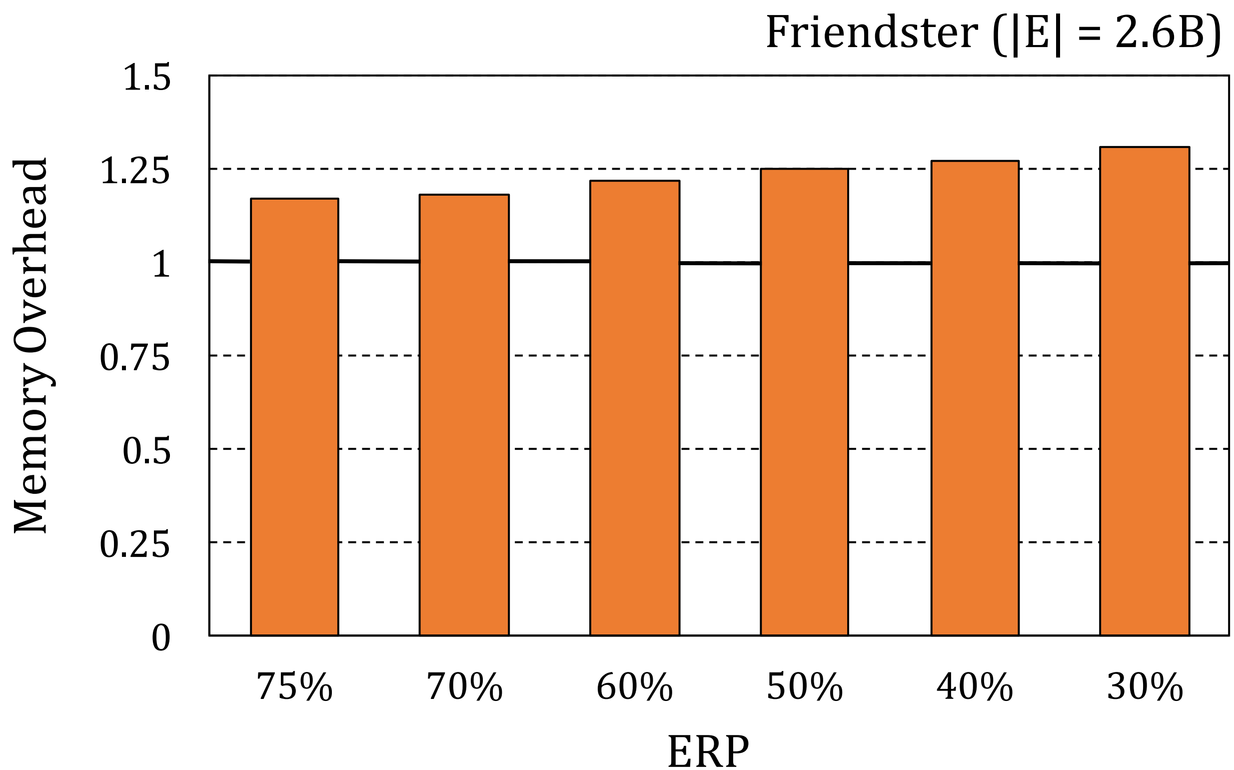
Memory Overhead

- Tracking dissimilar elements
  - Newly added vertices & edges



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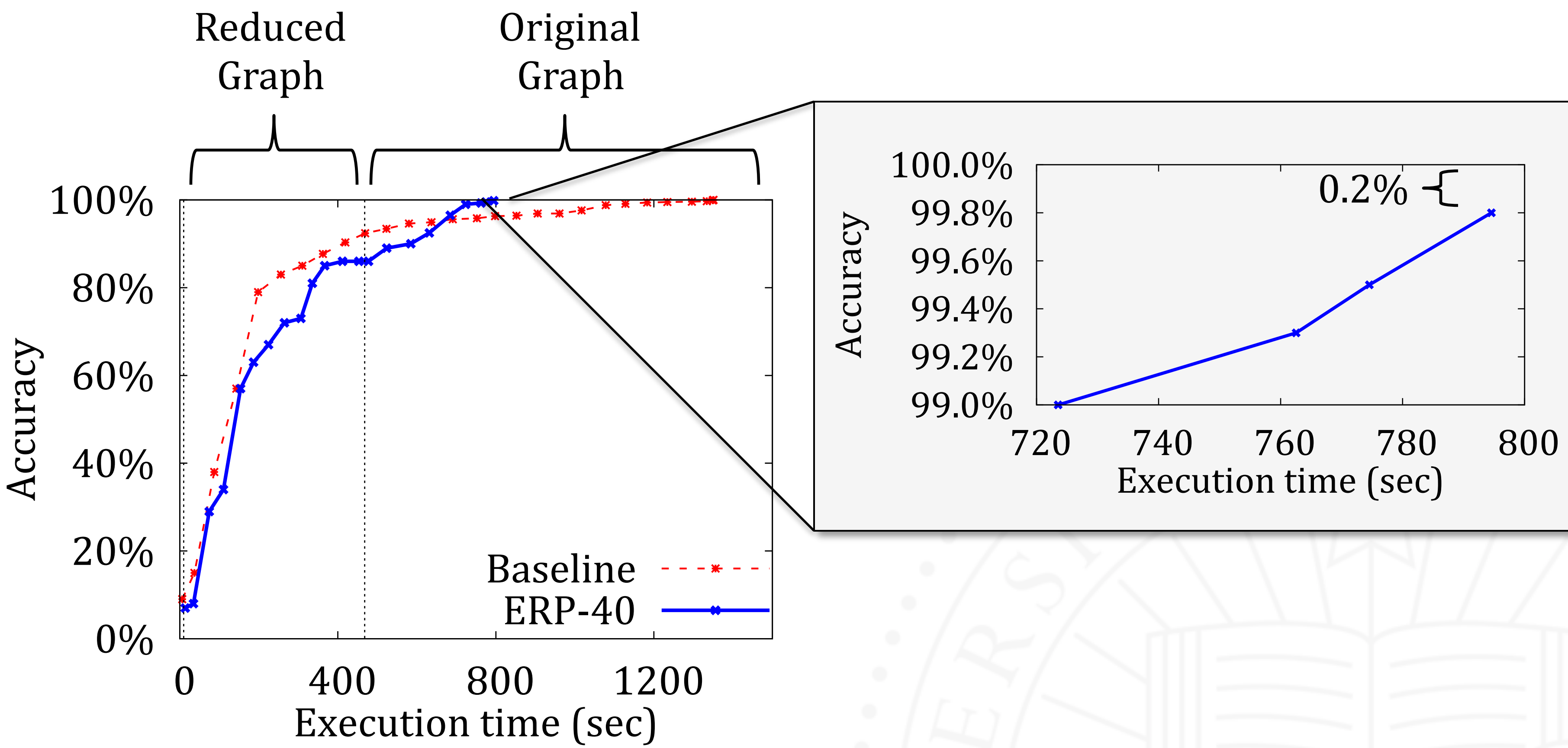
Community Detection



Friendster (|E| = 2.6B)

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More Results

- Contribution of individual transformations
  - Some transformations more useful than others
  - Different graphs benefit from different transformations
- Improvement in scalability
- Results for all inputs

Conclusion

- Input reduction using transformations that are
  - Light-weight
  - Parallelizable
  - General
- Correctness reasoned using fine-grained transformation properties
- Achieve 1.25-2.14x speedups

Thanks

- GRASP
  - http://grasp.cs.ucr.edu/

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