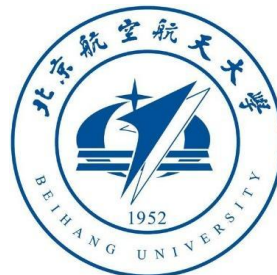


# MiniClean: A Single-Machine System for Cleaning Big Graphs

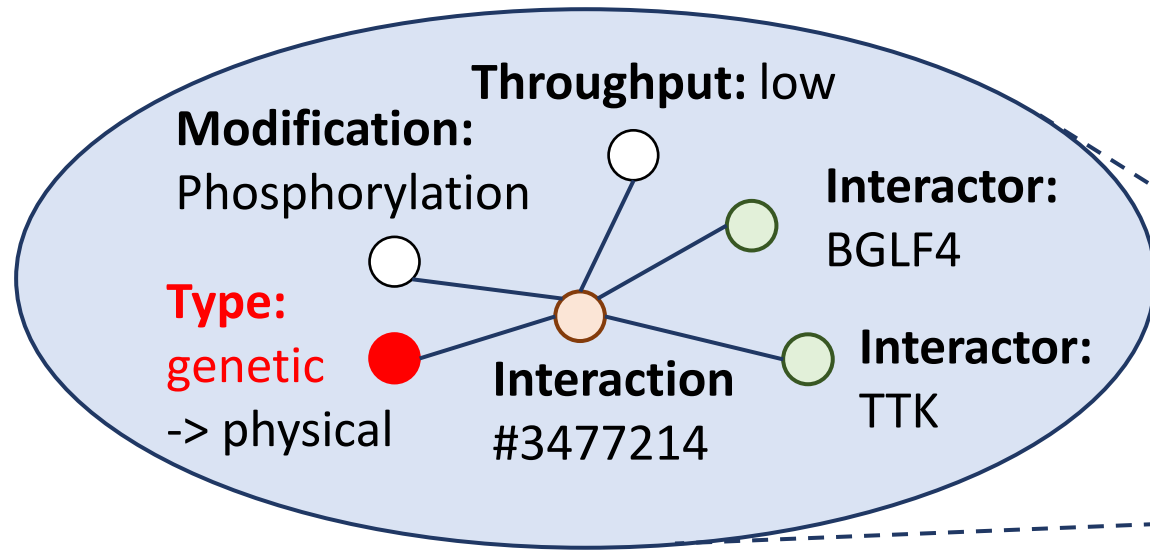
Wenchao Bai, Wenfei Fan, Jiahui Jin, Daji Li, Jian Li,  
Shuhao Liu, Mingliang Ouyang, Qiang Yuan

Shenzhen Institute of Computing Science, Southeast University,  
University of Edinburgh, Beihang University

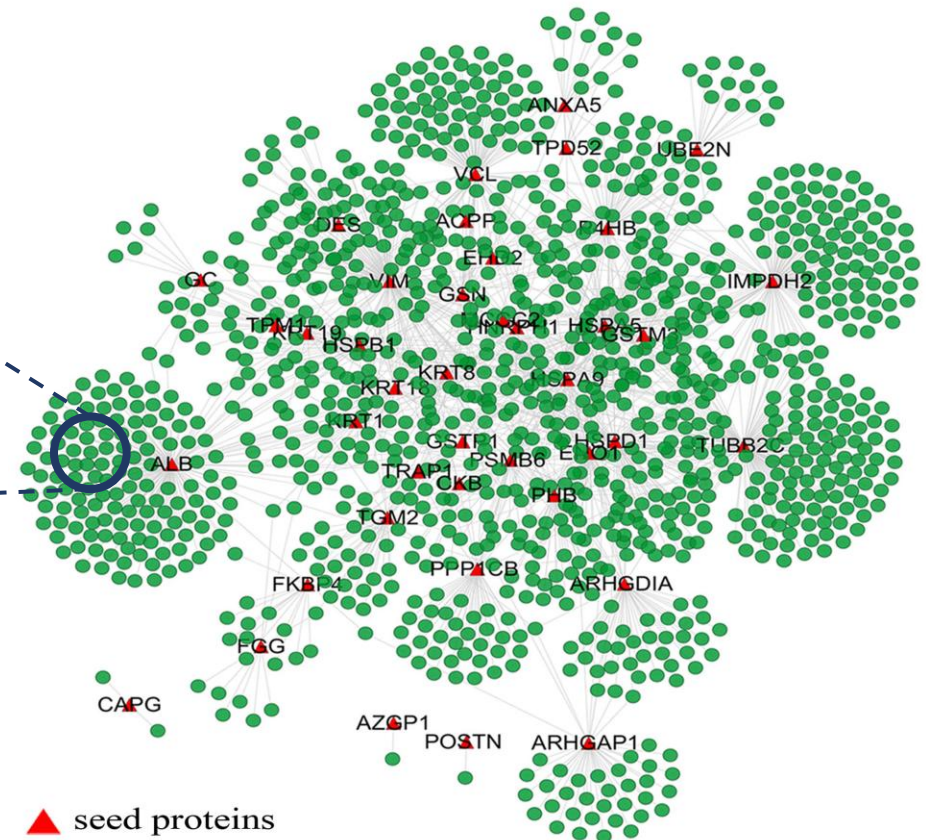


- **Introduction:** 00'00 – 08'55
- **Live Demo:** 08'55 – 12'21
- **Evaluation:** 12'21 – 13'38

# Graph Data Quality and Graph Applications



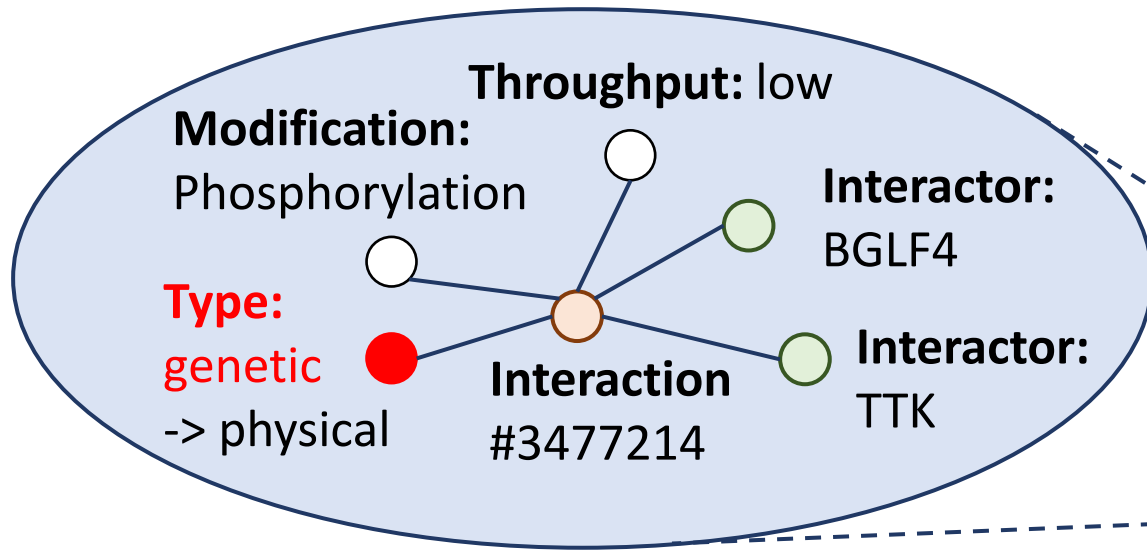
A mislabeled instance in BioGRID<sup>[2]</sup>



[1] Chen, Chen, et al. "Construction and analysis of protein-protein interaction networks based on proteomics data of prostate cancer." *International journal of molecular medicine* 37.6 (2016): 1576-1586.

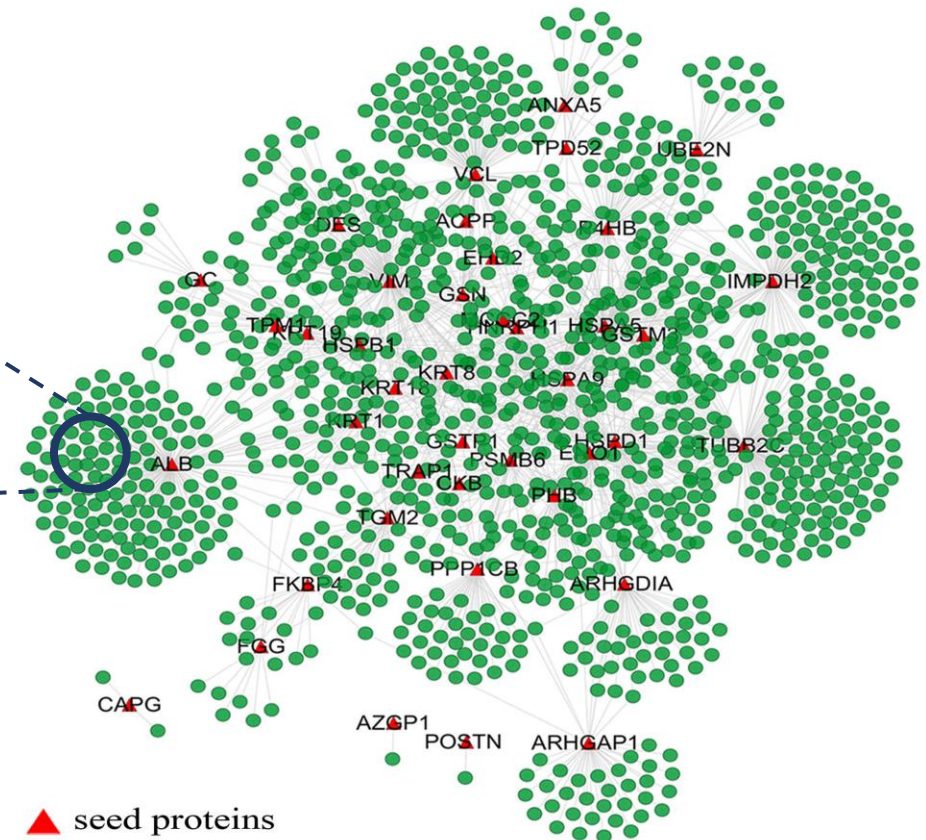
[2] [BioGRID | Database of Protein, Chemical, and Genetic Interactions](#)

# Graph Data Quality and Graph Applications



A mislabeled instance in BioGRID<sup>[2]</sup>

- *Errors (e.g., duplicates, conflicts) are common.*
- *Errors can misguide data-driven decision making.*



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# Approaches to Graph Cleaning

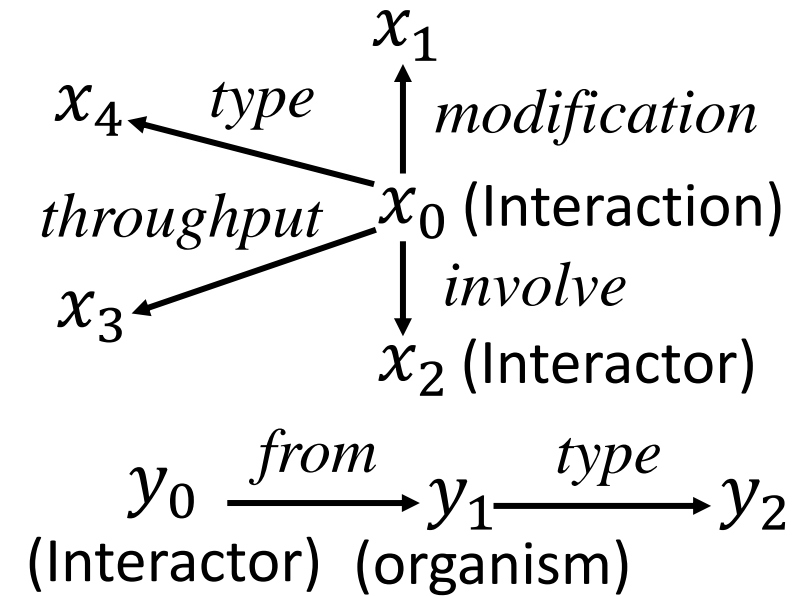
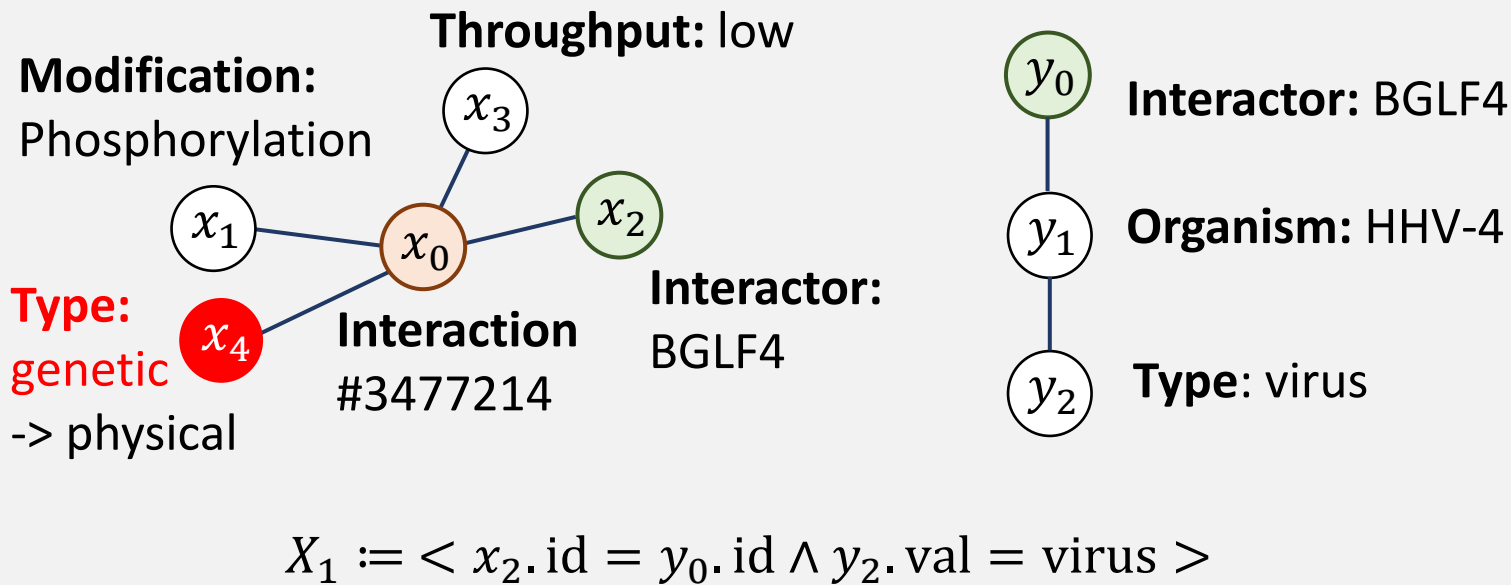
- **Strawman 1:** ML models (e.g., Ditto, KGClean).
  - Transform graphs into embeddings.
  - Detect errors (duplicates/conflicts) via binary classification.
  - Predictions are probabilistic and hard to explain.
- **Strawman 2:** Logic rules.
  - Apply rules via pattern matching and predicate verification.
  - Deduce dependencies to detect and correct errors.
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- **Our Solution:** ML models + Logic rules.
  - $M_1(x_0, x_1) > \delta_1 \wedge X_1 \rightarrow x_4.\text{val} = \text{physical}$
  - $x_4.\text{val} = \text{genetic} \wedge X_2 \rightarrow M_2(x_0, x_3) > \delta_2$

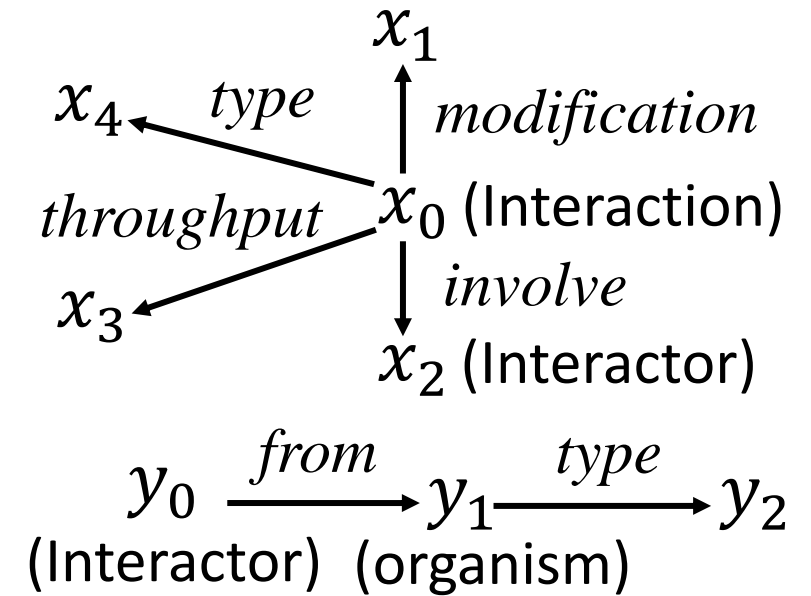
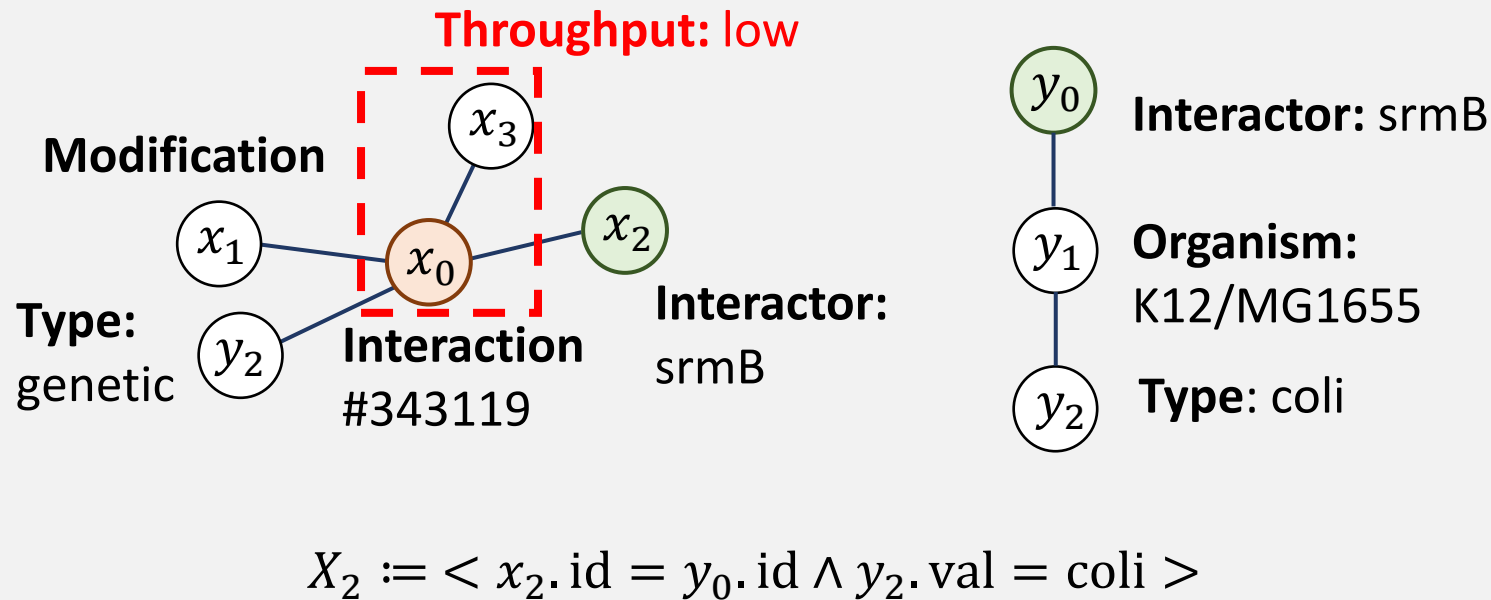


# Approaches to Graph Cleaning



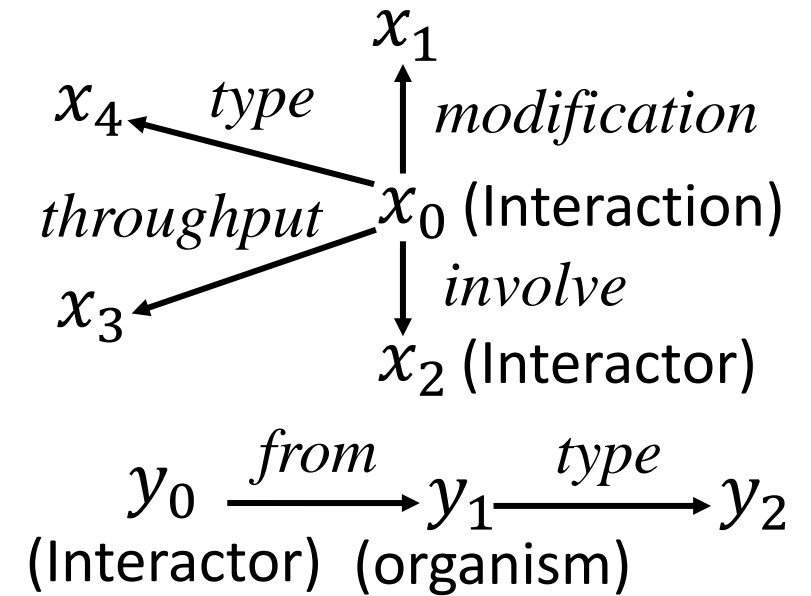
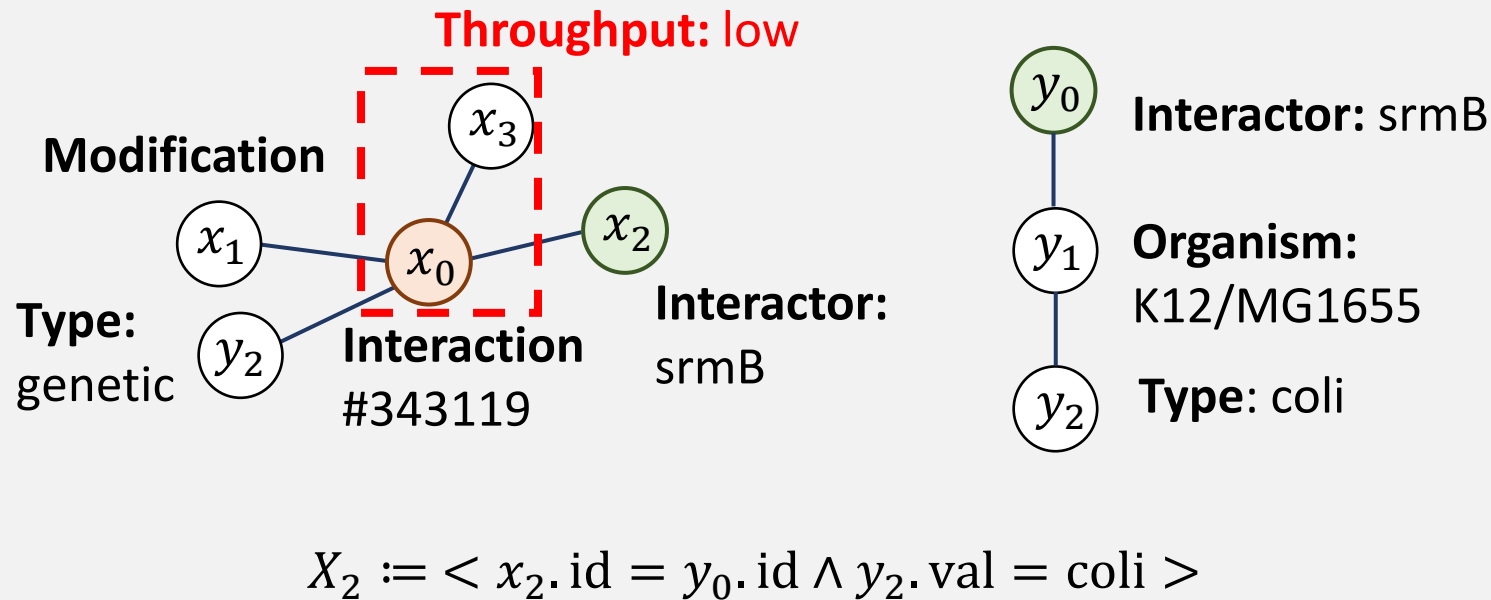
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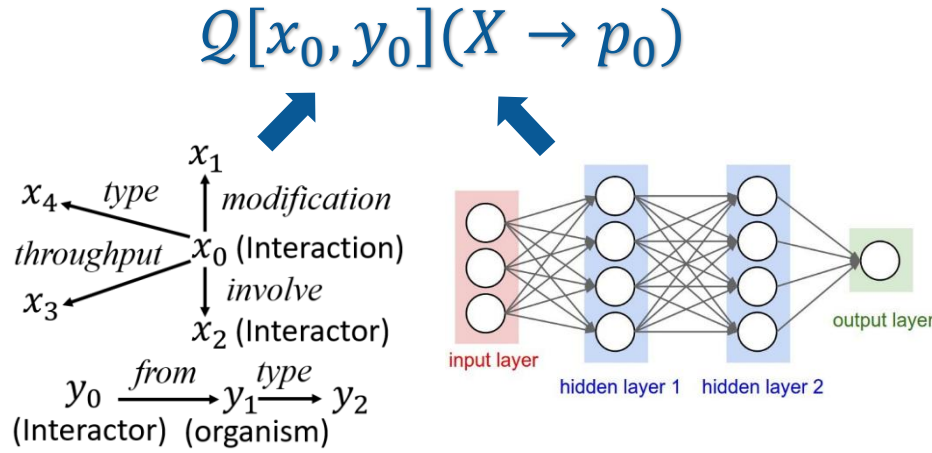


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- *Generalizability (ML)*
- *Reliability (Logic)*
- *Explainability (Logic)*



# Graph Cleaning Rules (GCRs)

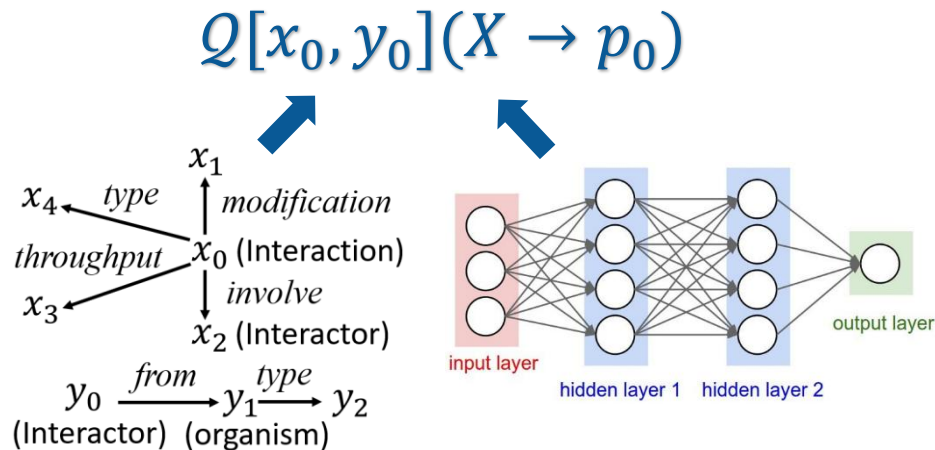


- ✓  $Q[x_0, y_0]$ : dual star pattern
- ✓  $X \rightarrow p_0$ : dependency
- ✓  $X$ : precondition (conjunction of predicates)
- ✓  $p_0$ : consequence (predicate)

## Dependency deduction:

- ML predicates  $M(x.\bar{A}, y.\bar{B})$ : for ML classification & regression
- Variable and constant predicates  $x.A \oplus y.B, x.A \oplus c$ : for value associations

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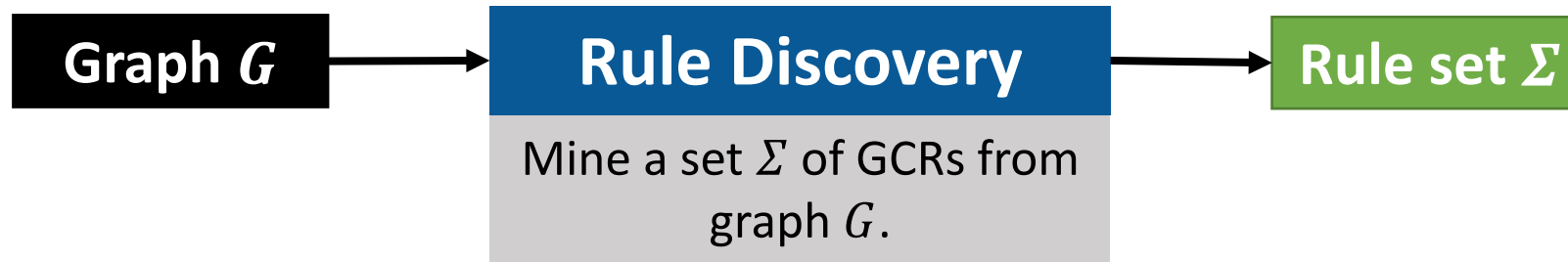
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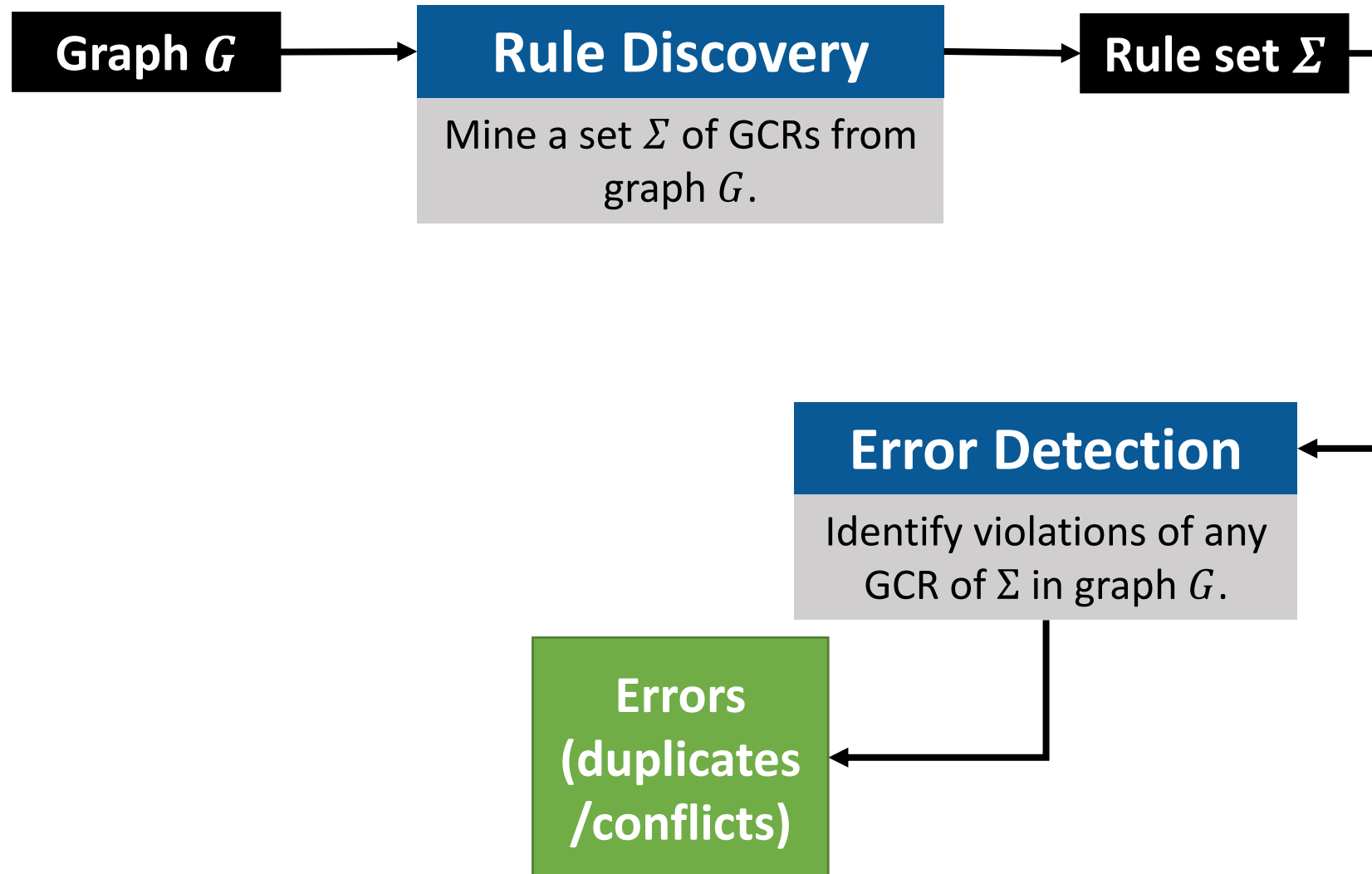
### Functionalities

- ✓ Conflict resolution
- ✓ Entity resolution
- ✓ ML explanation

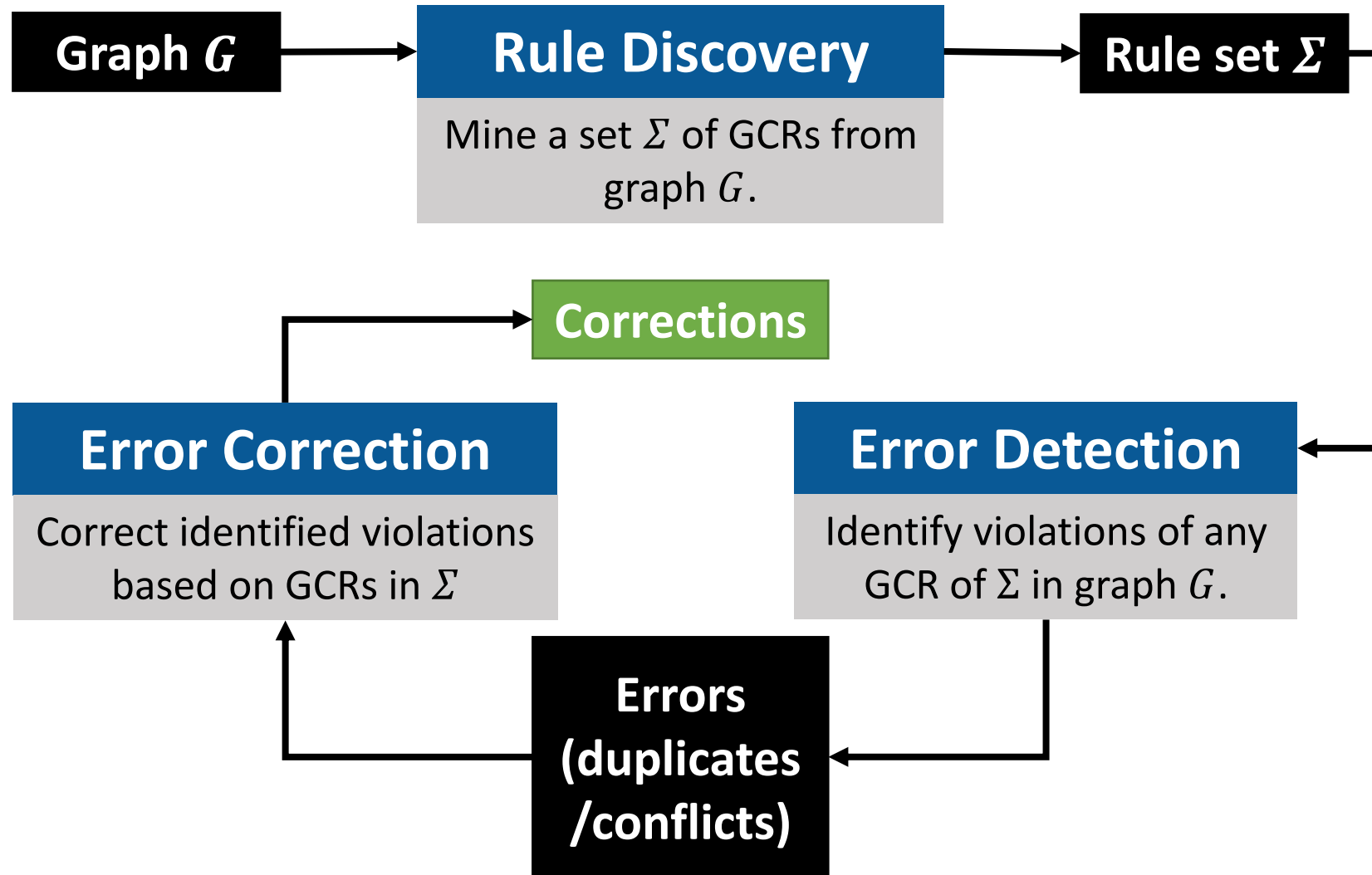
# Cleaning with GCRs



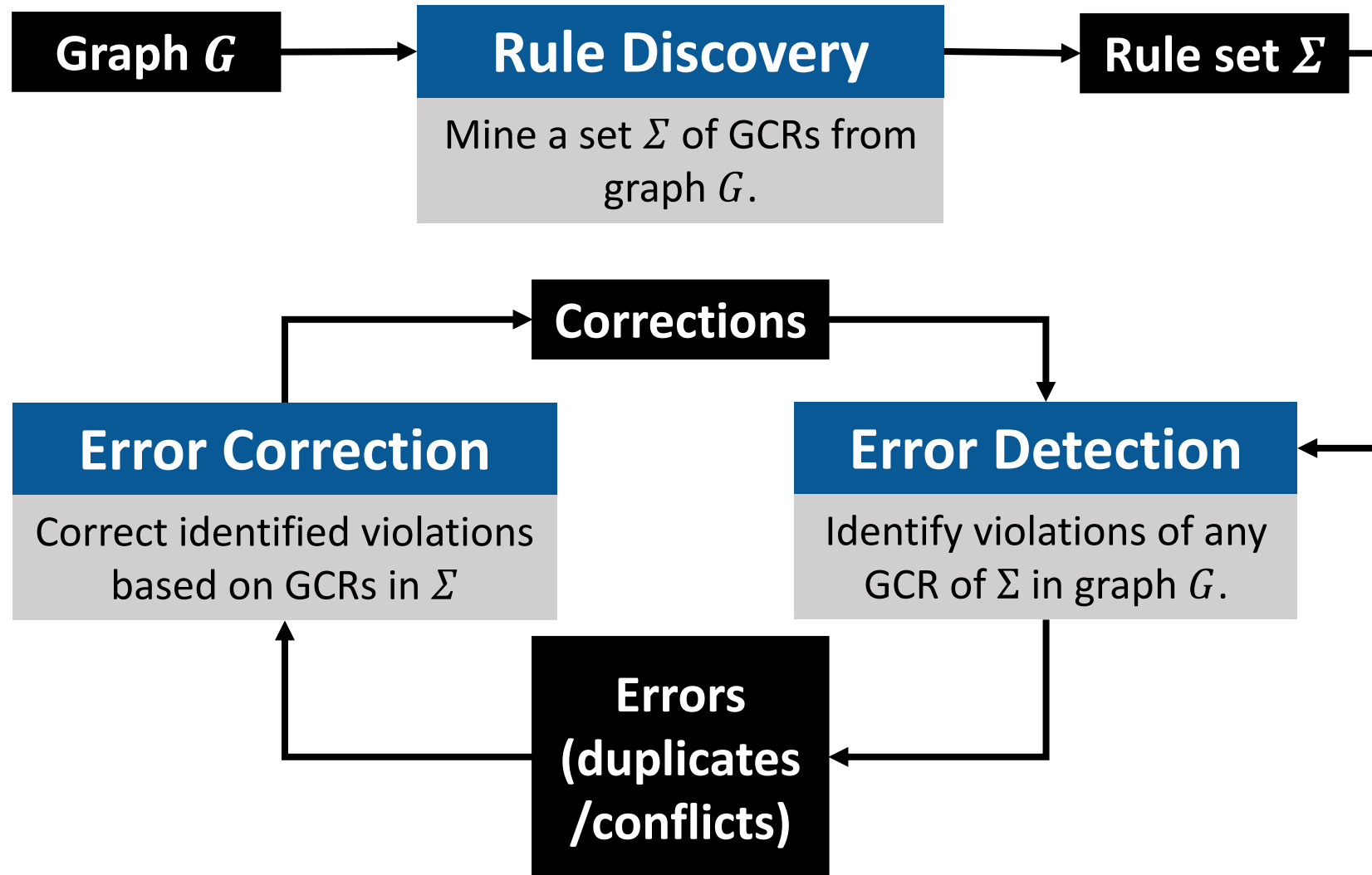
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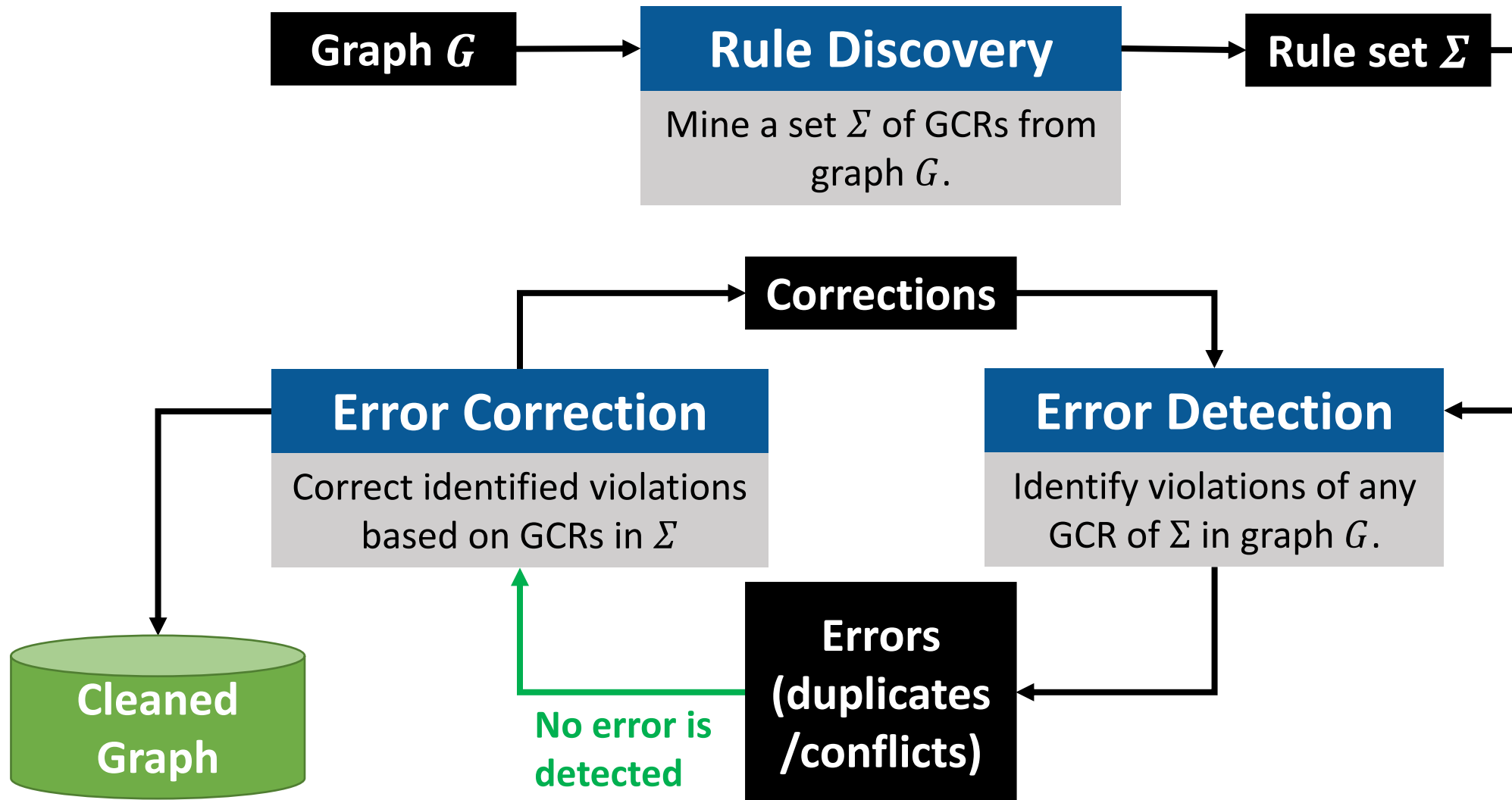


# Cleaning with GCRs





# Cleaning with GCRs



## Single-machine solutions are often preferred:

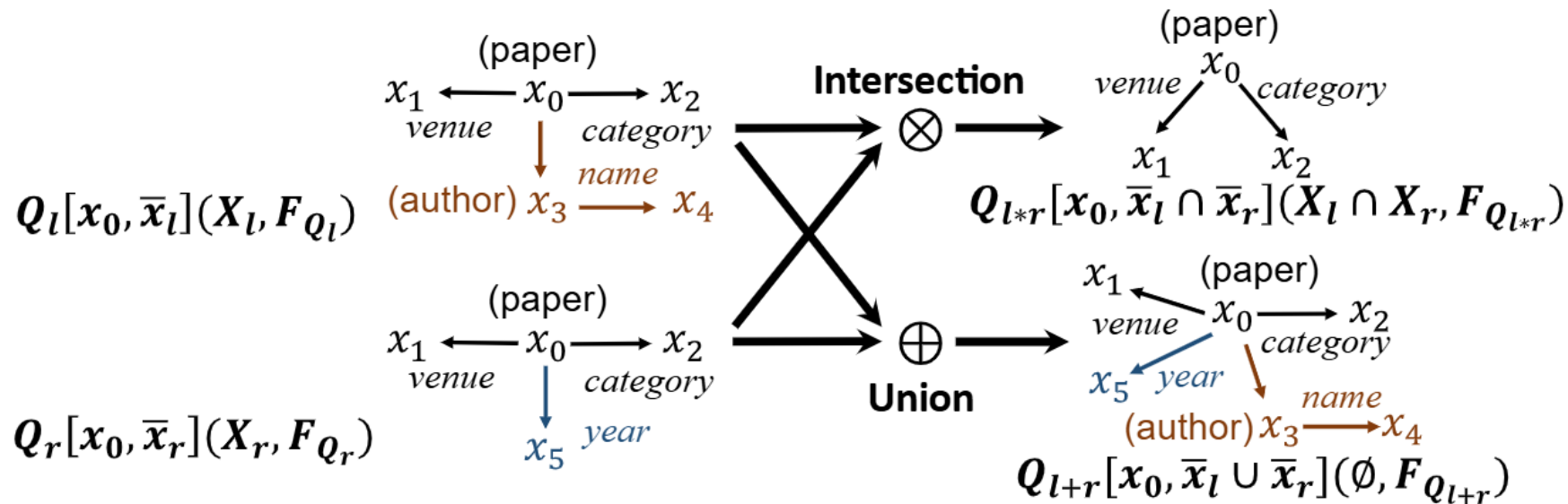
- **Physical constraints on deployed hardware.**
  - A cluster on premise may not be feasible, e.g., at an edge location.
- **A cloud deployment is not viable.**
  - Prohibitive cost: network bandwidth at \$0.05–0.09 per GB<sup>[1]</sup>.
  - Privacy concerns.

[1] <https://aws.amazon.com/pricing>

# Single-Machine Graph Cleaning: Challenges

- **Computation heavy.**
  - > 9h processing time on a 32-node cluster.
- **Excessive intermediate data.**
  - > 150GB intermediate result, way exceeding the memory capacity of a typical machine.
- **Parallel model for maximum resource utilization.**
  - Idle caused by I/O, data transfer, and task dependencies.

# Optimization 1: Bundled Processing



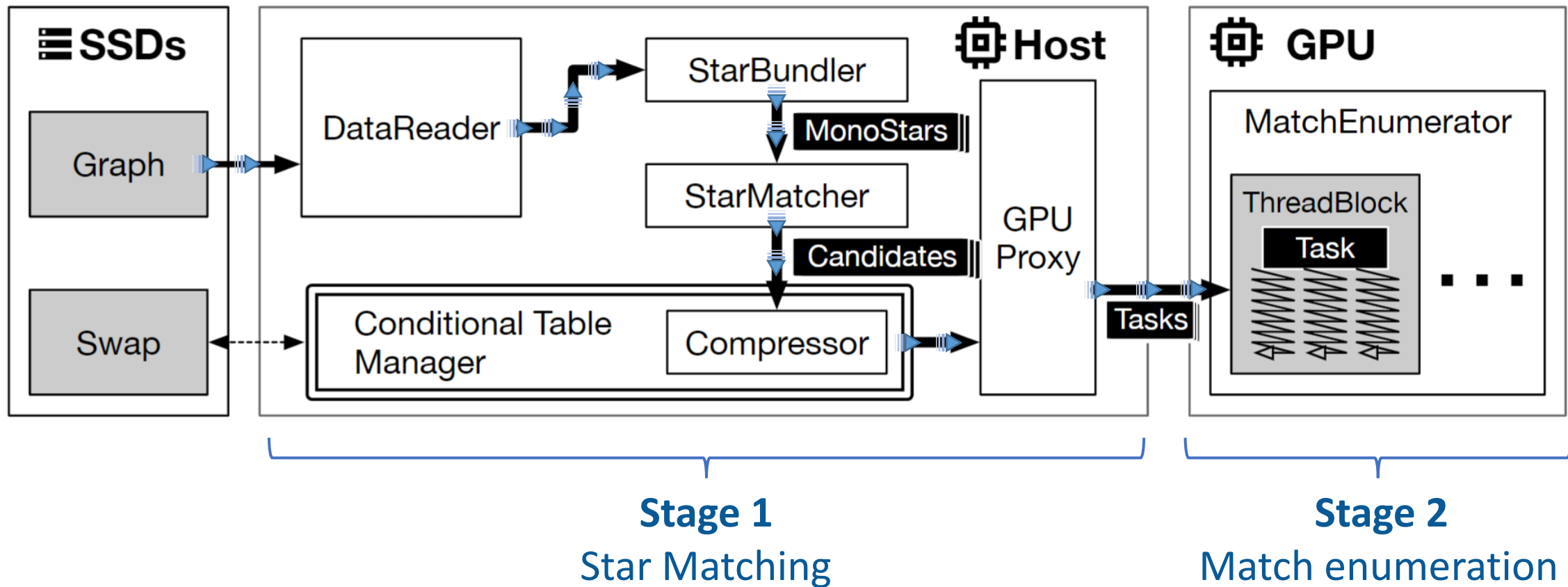
- ✓ **Motivation:** Repetitive computation by matching common substructures.
- ✓ **Solution:** Bundle similar patterns into a group and match them together.

## Optimization 2: Data Compression

Conditional succinct matches						Unfolded matches			
Matches			Conditions			$x_0.\text{id}$	...	$x_4.\text{val}$	...
$x_0.\text{id}$	$x_1.\text{val}$	$x_2.\text{val}$	$x_4.\text{val}$	$x_0.\text{title}$	$x_5.\text{val}$	$u_3$	...	J	...
$u_3$	OSDI	CS	{J, S}	MR	null	$u_3$	...	S	...
$u_4$	OSDI	CS	{J, S}	GFS	null	...	...	...	...
$u_1$	OSDI	null	{M, P, J, S}	TF	2016	Filtered out by $x_2.\text{val} = \text{CS}$			
$u_2$	OSDI	null	{M, P, J, S}	tf	2016				

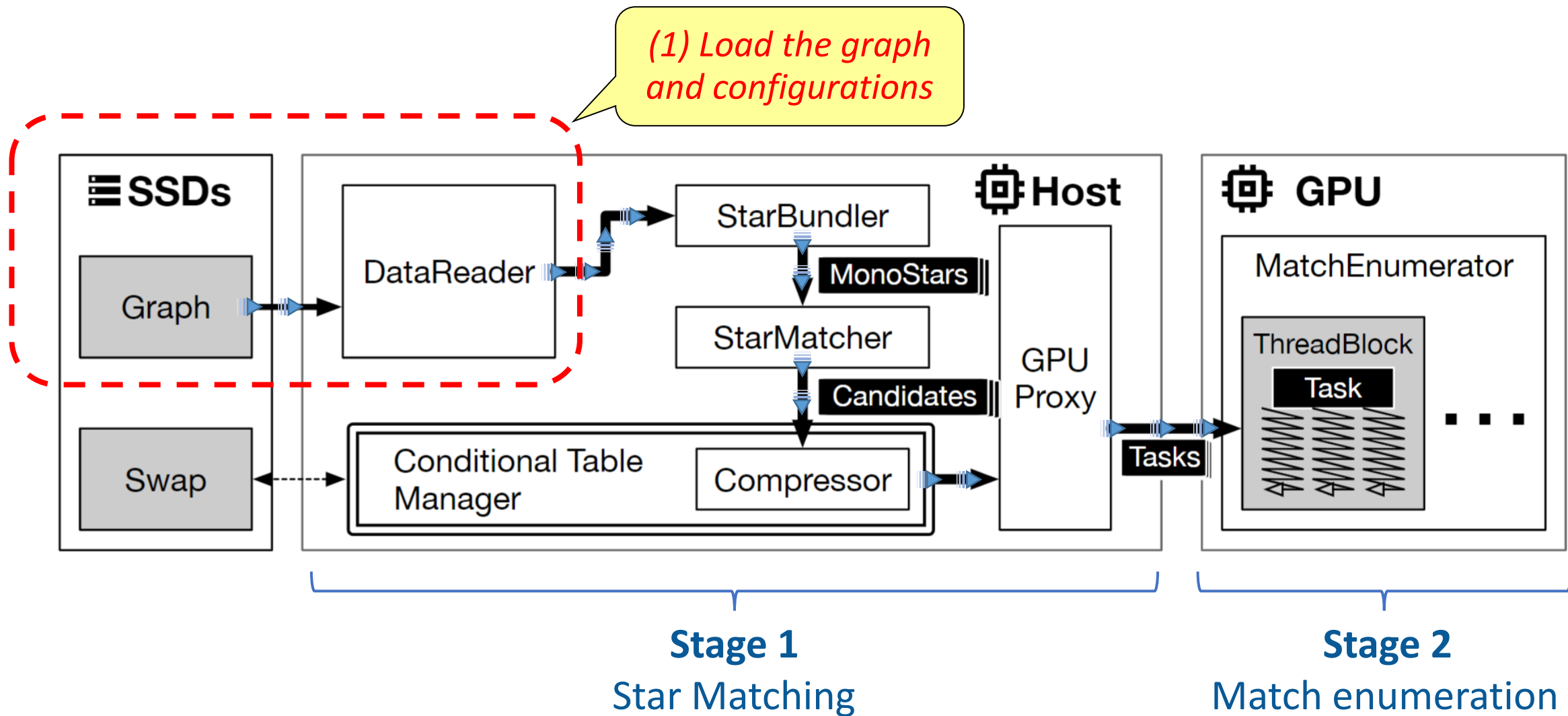
- ✓ **Motivation:** Intermediate data has up to  $O(|V|^{|Q|})$  materialized candidates.
- ✓ **Solution:** Conditional succinct table for compression.

# Optimization 3: Pipelined Architecture

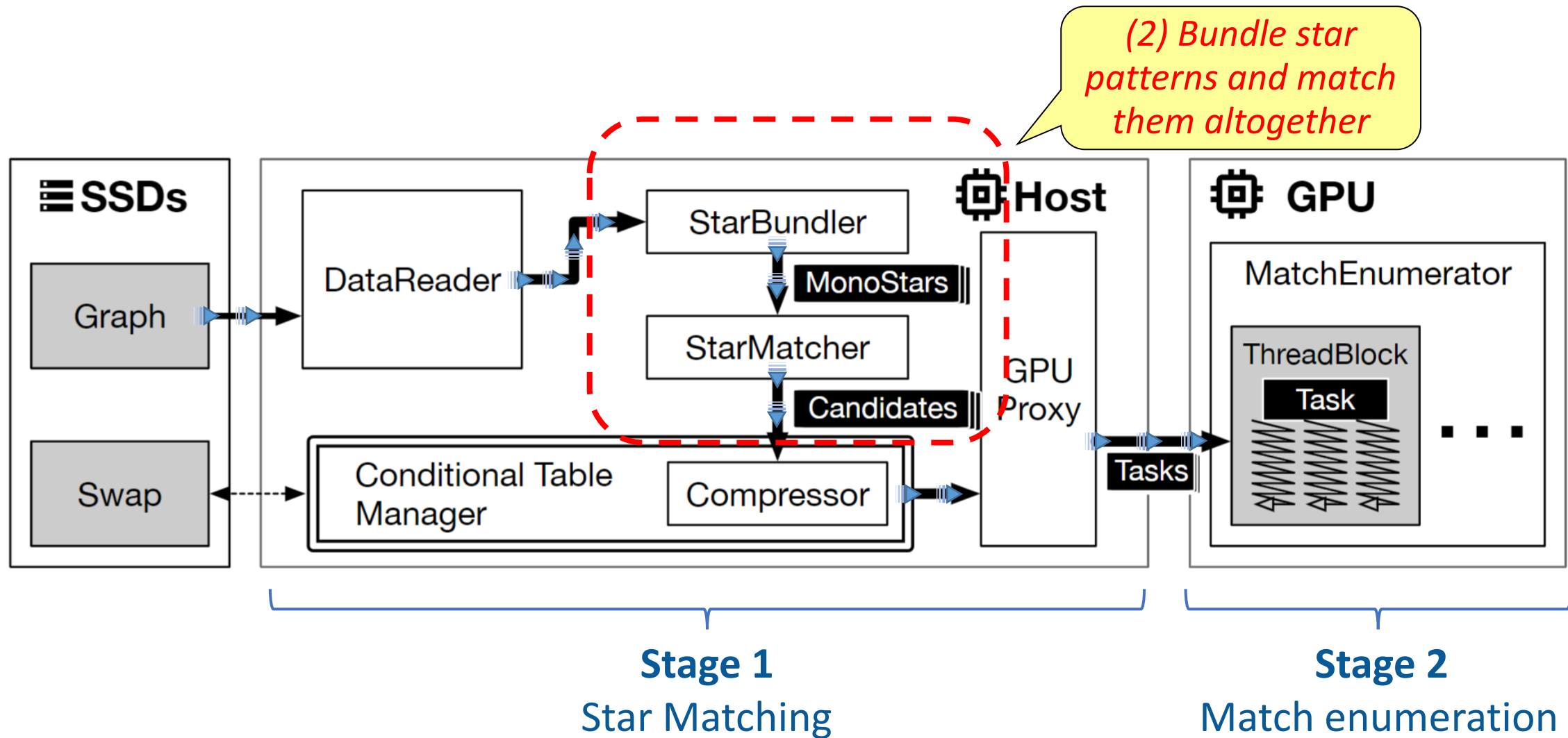




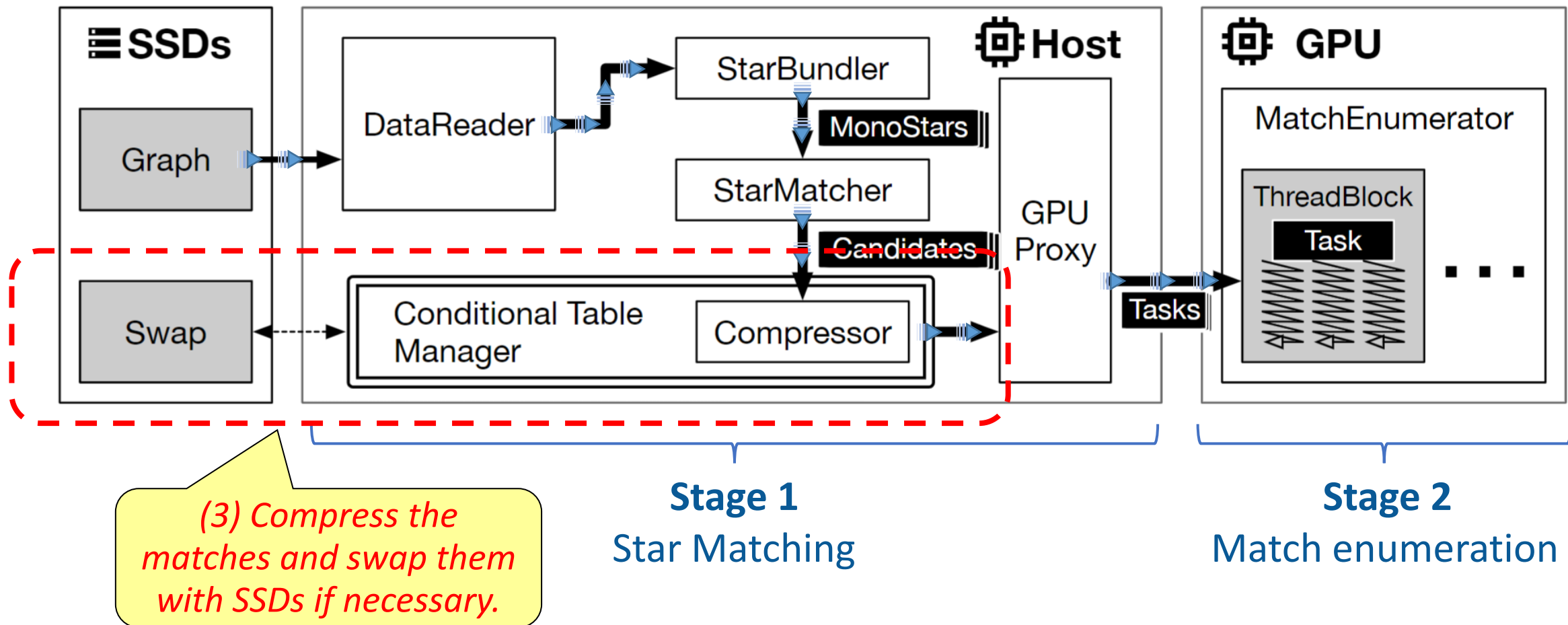
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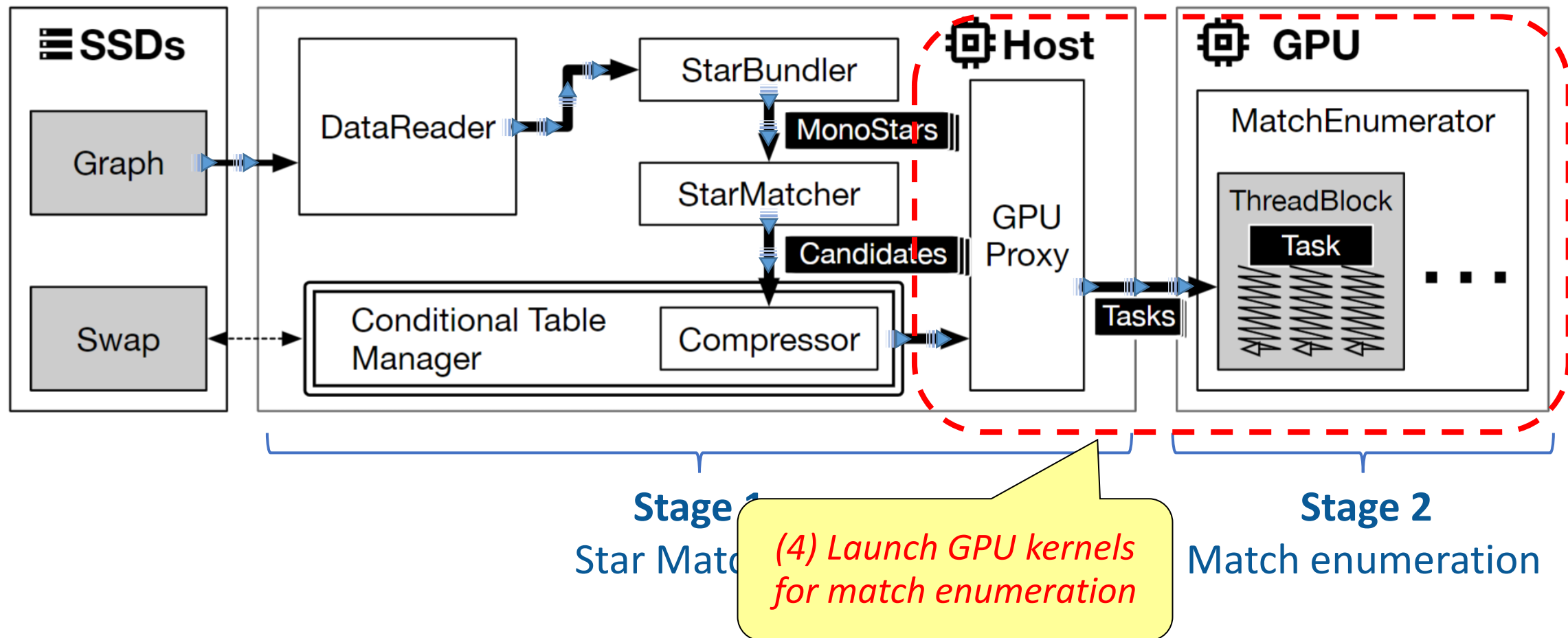
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In our demonstration, we will walk the participants through

- **Data management:** visualize the input graph and GCRs;
- **GCR discovery:** configure and launch a rule discovery task;
- **GCR application:** inspect the errors detected/corrected by each GCR.

*We will use BioGRID, a real PPI graph in our demonstration.*

# System Evaluation: Accuracy

System	BioGRID			SemScholar		
	Time	ER-F1(%)	CR-F1(%)	Time	ER-F1(%)	CR-F1(%)
MiniClean	312.7s	97.5	97.2	4089.1s	94.6	70.6
Ditto	7.7×	91.0	N/A	4.3×	90.3	N/A
KGClean	11.9×	N/A	54.9	11.9×	N/A	29.8

- **ER tasks:** outperforms ER model *Ditto* by 4.3%--6.5%.
- **CR tasks:** outperforms CR model *KGClean* by 40.4%--42.3%.
- **Efficiency:** 11.9× faster than ML baselines.



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$\Delta = 6.5\%$        $\Delta = 4.3\%$

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Single-machine (BioGRID)		Scalability (SemScholar)		Ablation study (SemScholar)	
System	Time (s)	System	Time (s)	System	Time (s)
Blaze	OOM	GCRClean-32-Node	8.09×	noBundle	1.35×
MiniGraph	65.34×	MiniClean-2-GPU	0.64×	noPipelinedPar	1.26×
Hyperblocker	11.92×	MiniClean-4-GPU	0.48×	noIndPar	1.12×
MiniClean-1-GPU	259.6s	MiniClean-1-GPU	4251.08s	MiniClean-2-GPU	2993.7s

- **Single-machine**: 65.34× faster than **MiniGraph**; 11.92× faster than **Hyperblocker**.
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**Welcome to play with MiniClean!**