

Using the Troika Clique Partitioning Algorithm for Analyzing the cluster dynamics of market index correlation networks

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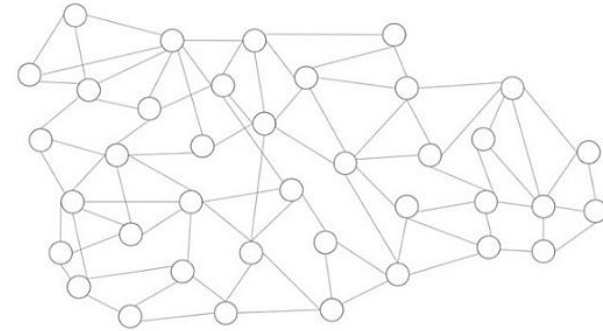


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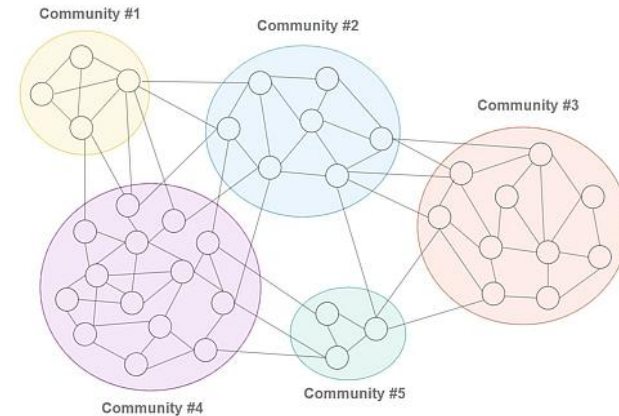
Clique Partitioning (CP) Problem

- Input: weighted undirected graph $G(V,E)$ with n nodes and m edges
- Method: a clustering (clique partitioning) algorithm
- Output: a partition of the nodes into disjoint clusters (node colours)
- Goal: group nodes into clusters which maximizes the weight of the partition

Input



Output



Figures from
timbr.ai

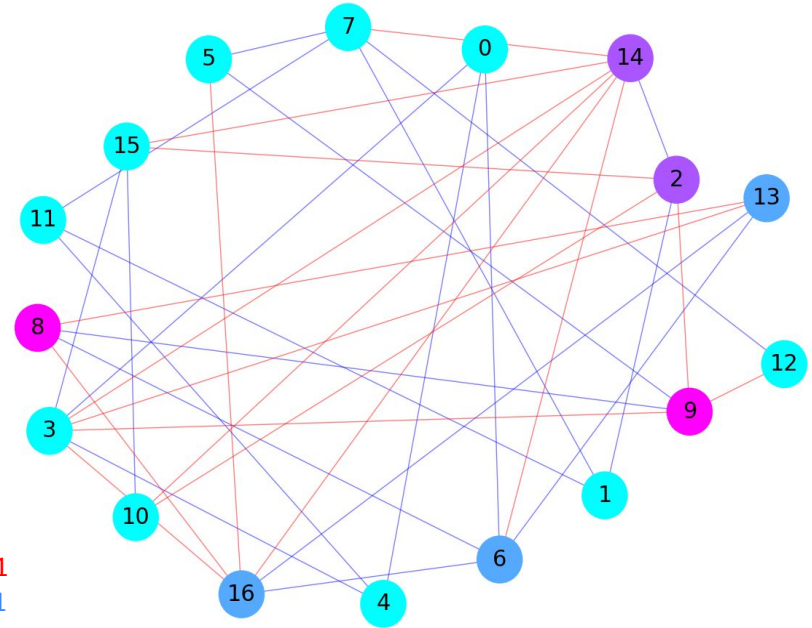
Grotschel & Wakabayashi (1989) A cutting plane algorithm for a clustering problem



How would you “clique partition” this graph?

Goal: Group nodes into clusters which maximizes the internal weight of the partition

~~Maximized Objective~~
~~Objective value = 4~~
Value = 16



Investment Portfolio Analogy

Objective:

- ▶ Maximize returns from a portfolio consisting of stocks and bonds.

Investments:

- ▶ Stocks
- ▶ Bonds

Variables:

- ▶ s = Amount invested in stocks
- ▶ b = Amount invested in bonds



Integer Programming (IP) Formulation

Maximize Returns:

$$\text{Returns} = 1.2s + 1.1b$$

Constraints:

1. Total investment limit:

$$s + b \leq 100,000$$

2. Diversification:

$$s \geq 0, \quad b \geq 20000$$

3. Integer constraint:

$$s, b \in \mathbb{Z}$$



Optimal Solution

Solution:

- ▶ Optimal investment in stocks (s): \$80,000
- ▶ Optimal investment in bonds (b): \$20,000

Calculated Returns:

$$\text{Max Returns} = 1.2 \times 100000 + 1.1 \times 20000 = \$116,000$$

Remarks:

- ▶ This allocation maximizes the returns under the given constraints.
- ▶ Preference is given to stocks due to higher returns per dollar invested.



Clique Partitioning IP Formulation

Given partition P , for every pair of nodes (i, j) , their cluster assignment is either same (represented by $x_{ij} = 0$) or different (represented by $x_{ij} = 1$). The weight of the undirected edge between nodes (i, j) is represented as w_{ij} .

$$\text{RP}^*(G) : \max_{x_{ij}} W = \sum_{(i,j) \in E} w_{ij}(1 - x_{ij})$$

Constraints:

$$\text{s.t. } x_{ik} + x_{jk} \geq x_{ij} \quad \forall (i, j, k) \in T_+^k \quad T_+^k = \{(i, j, k) \in T \mid w_{ik} > 0 \vee w_{jk} > 0\}$$

$$x_{jk} + x_{ij} \geq x_{ik} \quad \forall (i, j, k) \in T_+^j \quad T_+^j = \{(i, j, k) \in T \mid w_{jk} > 0 \vee w_{ij} > 0\}$$

$$x_{ij} + x_{ik} \geq x_{jk} \quad \forall (i, j, k) \in T_+^i \quad T_+^i = \{(i, j, k) \in T \mid w_{ij} > 0 \vee w_{ik} > 0\}.$$

$$x_{ij} \in \{0, 1\} \quad \forall (i, j) \in E$$



Existing Methods

Exact Methods:

- Solving IP formulation using commercial solvers (Miyauchi et al. 2018)
- Exact branch-and-cut exploring facet inequalities (Simanchev et al. 2019)

Heuristic Methods:

- Combo (Sobolevsky et al. 2019)
- Merge-divide memetic clique partitioning algorithm (Lu et al. 2021)



Troika

Inspiration: Bayan algorithm for Community Detection (Aref et al. 2022)



Troika

Branch-and-Cut Implementation

- **Node Triple Method:** Branch on sets of three nodes to explore feasible space.
- **Upper Bound:** Use linear programming relaxation to establish upper bounds.
- **Lower Bound:** Employ heuristic search to construct lower bounds.

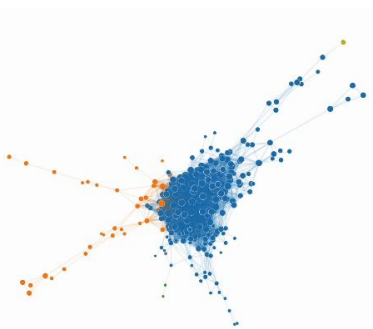


Applying Troika to Market Index Correlation Network

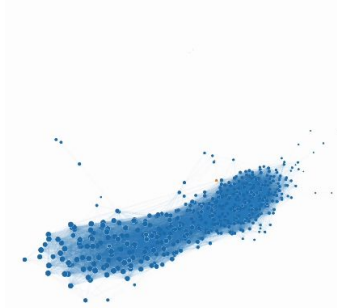
- Correlation Matrix
- Fisher Transform
- Thresholding
- Signed Networks



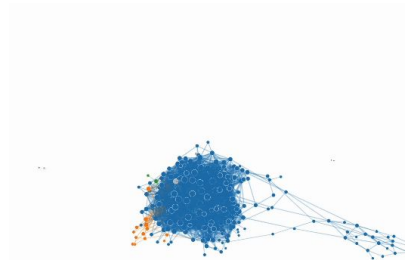
Yearly Clustering Results of S&P 500 (2019-2023)



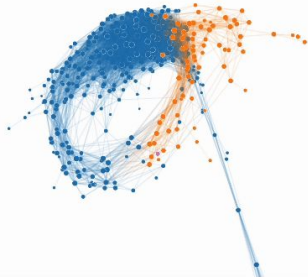
2019



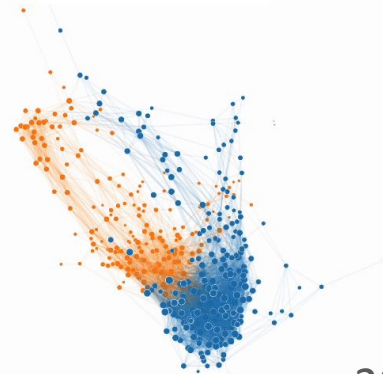
2020



2021



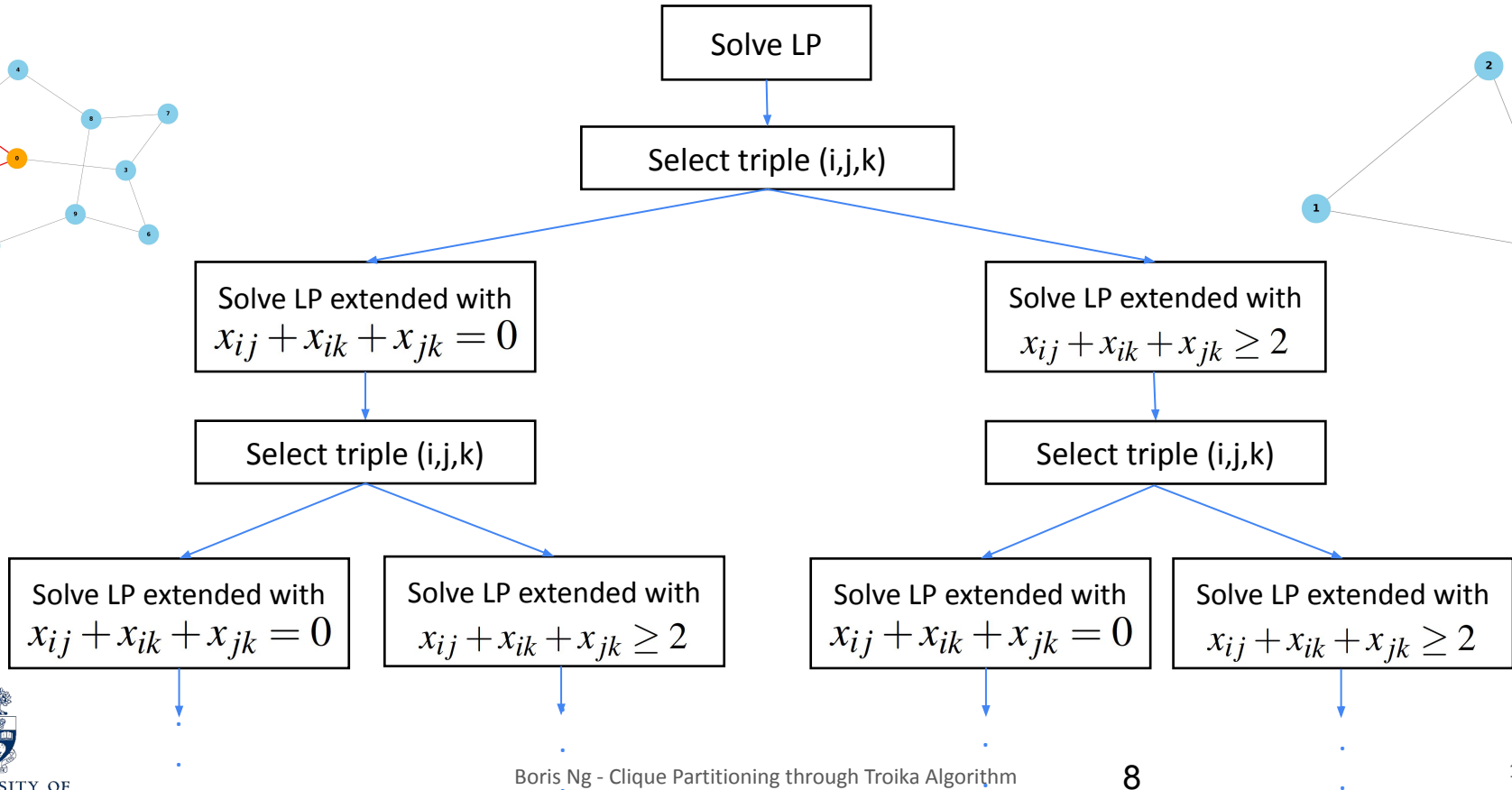
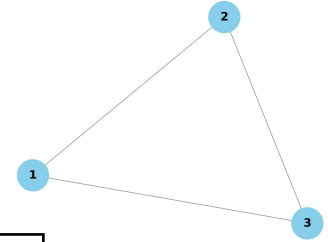
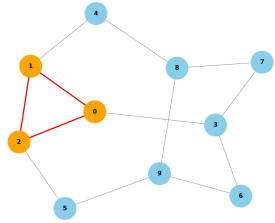
2022



2023

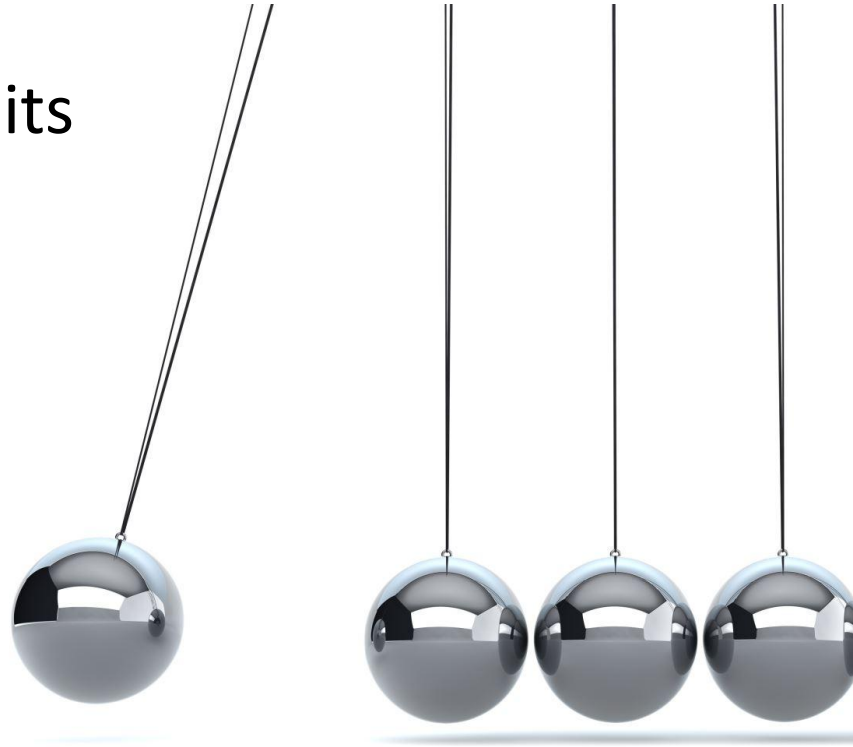


How does Troika work? Branching on Node Triples



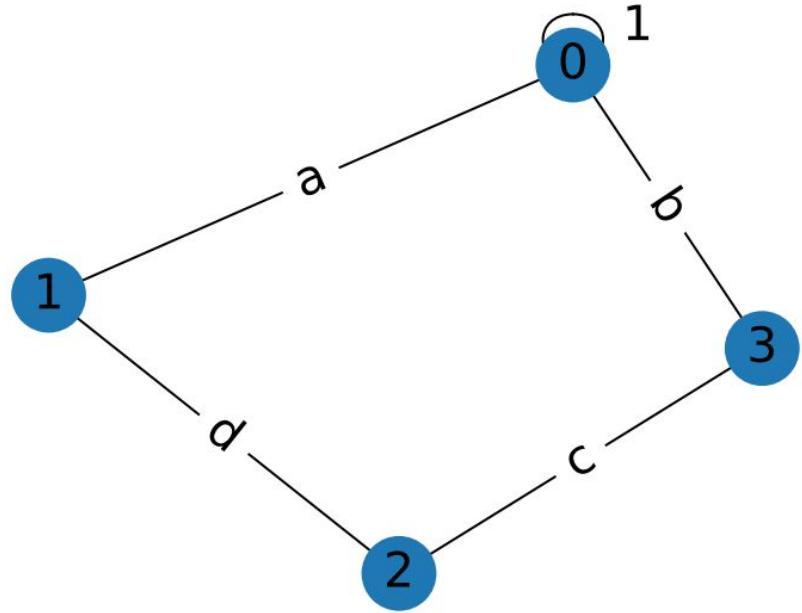
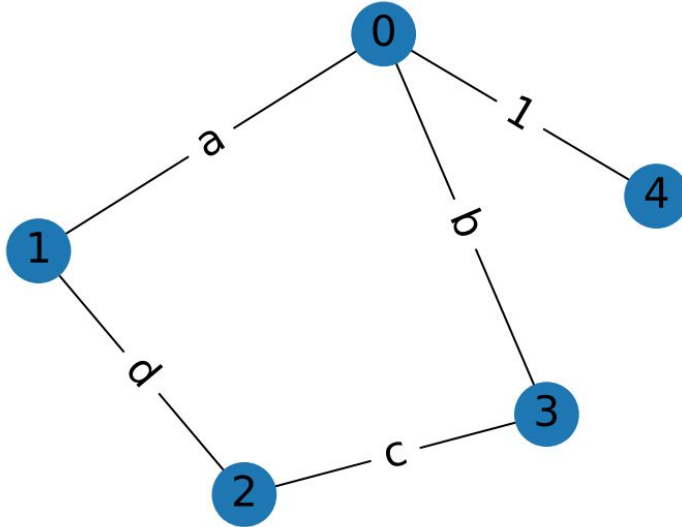
Pushing the computational limits

1. **Graph Pre-processing** ←
2. Search Termination Criteria
3. Variable fixing
4. Implied branching
5. Parallel processing of the separating sets
6. Node Triple Selection



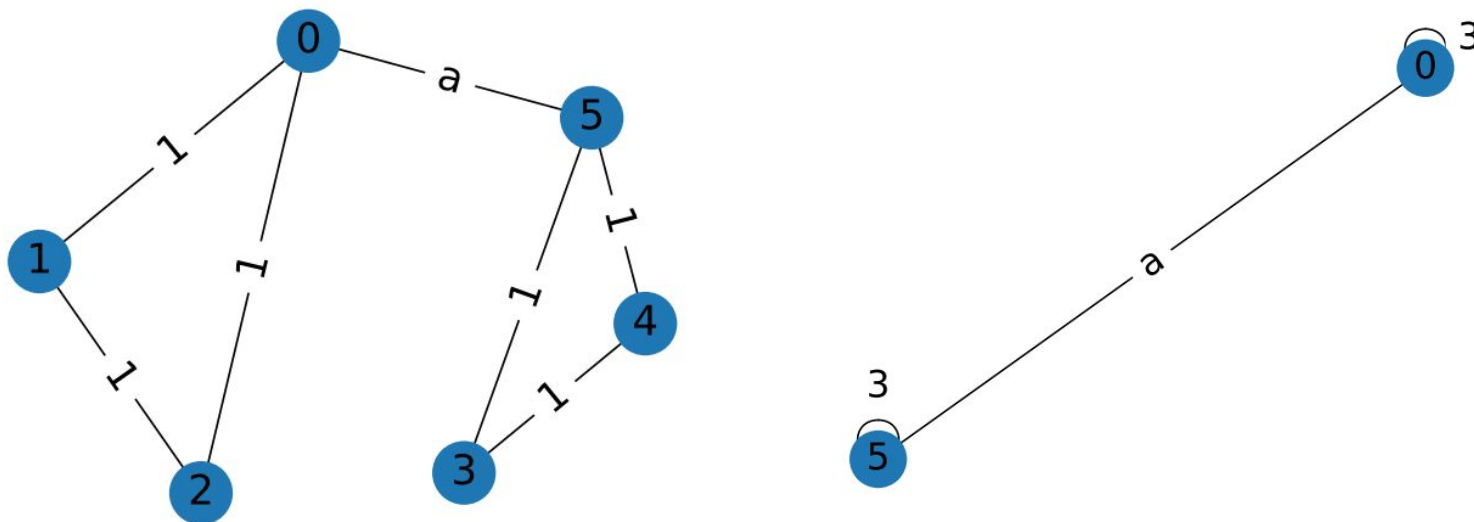
Graph Pre-processing

1. Pendant Node Reduction



Graph Pre-processing

2. Pendant Clique Reduction



Experimental Setup

- Datasets:
 - ABR Graphs: Aggregation of Binary Relations for qualitative data analysis.
 - MCF Graphs: Machine Cell Formation problems in manufacturing
 - Barabási-Albert Graphs: Scale-free networks to model real-world structures

Sorensen & Letchford (2017) CP-lib: Benchmark instances of the clique partitioning problem
Barabási & Albert (1999) Emergence of scaling in random networks



Experimental Setup

- Performance Metrics:
 - Solution Quality
 - Computational time
-

- Methods Compared:
 - Troika
 - Gurobi IP Formulation
 - Combo Algorithm

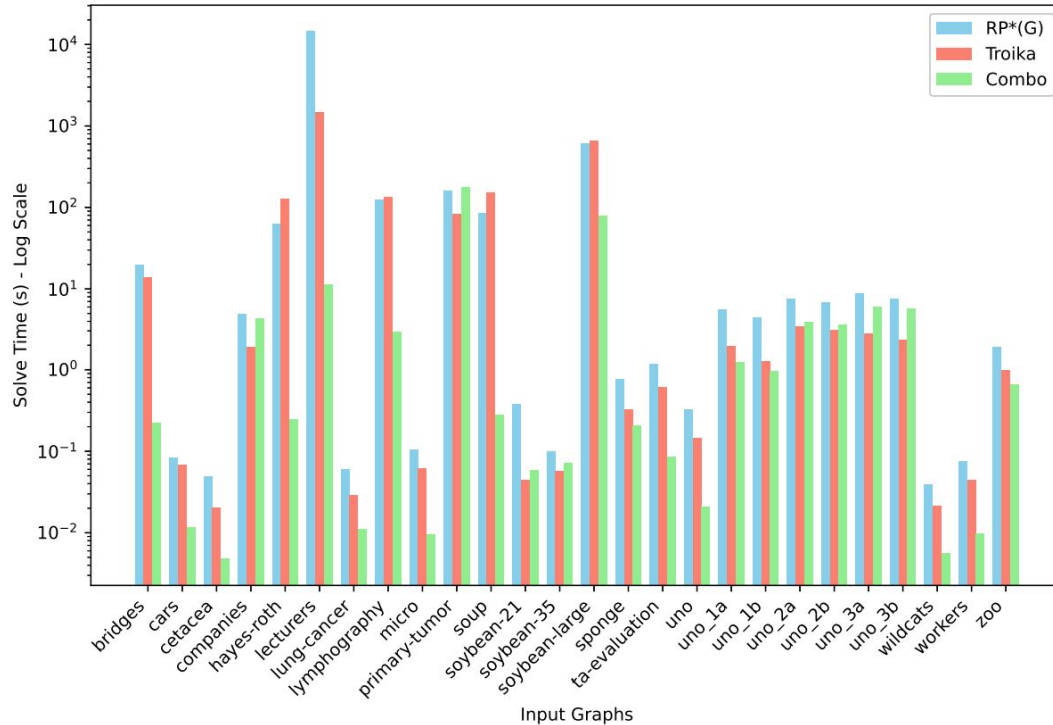
Sorensen & Letchford (2017) CP-lib: Benchmark instances of the clique partitioning problem

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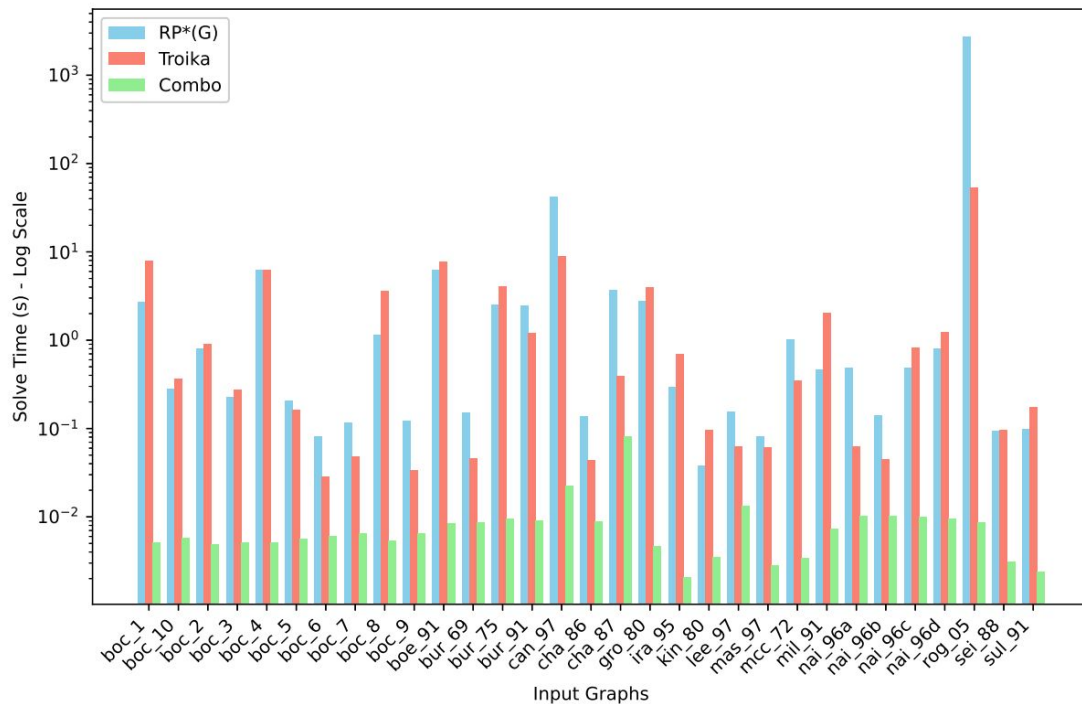
Solve Time

The Aggregation of Binary Relation (ABR) dataset



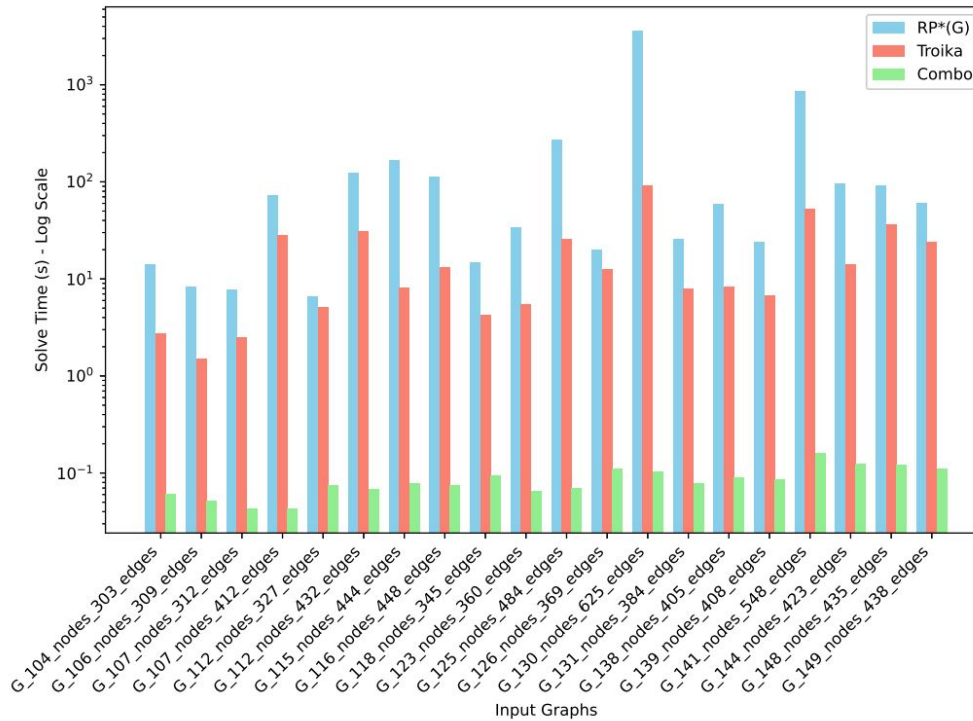
Solve Time

The Machine Cell Formation (MCF) dataset



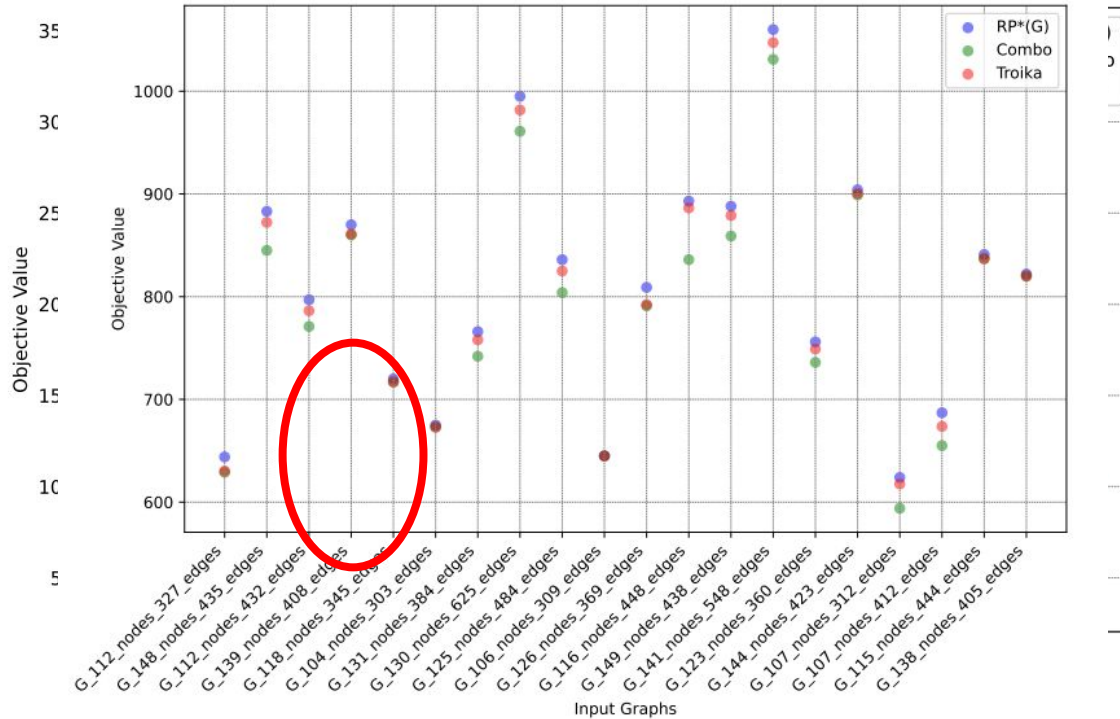
Solve Time

The Barabási-Albert Graphs dataset



Accuracy

The Ma Barabási-Albert Graph (MCB) dataset



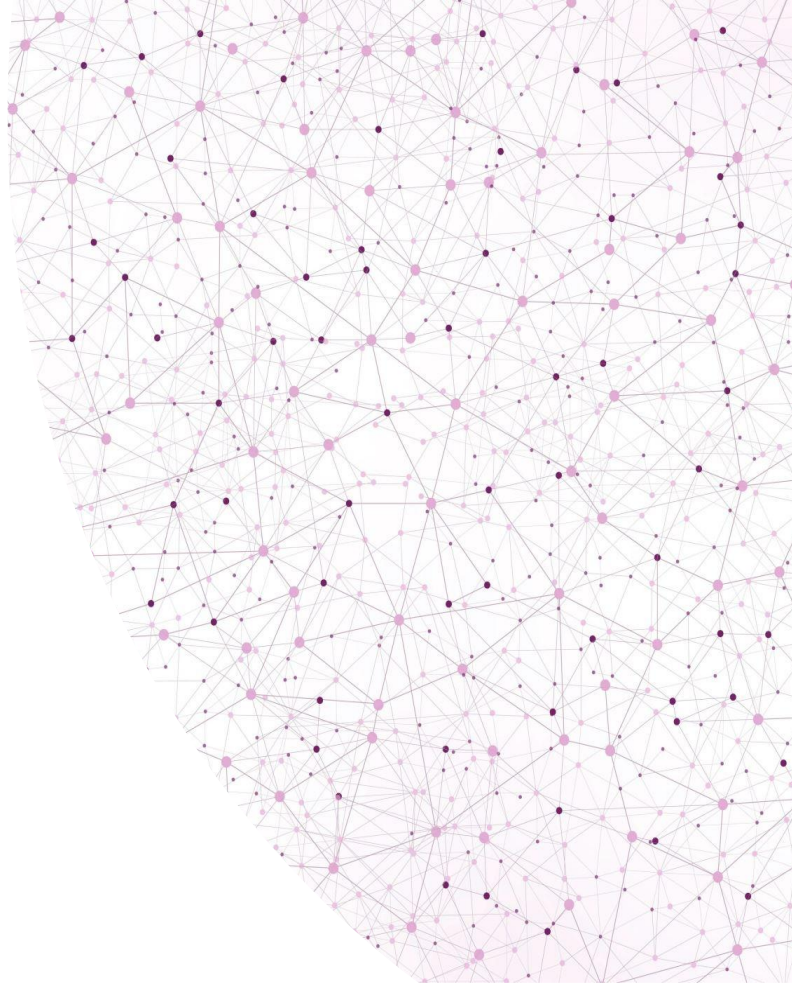
Experimental Results

- *Troika* is **5.8, 27 and 14.8 times faster** than *Gurobi IP Formulation* on average on ABR, MCF and Barabási-Albert graphs respectively
- *Troika* achieves **98.85% optimality**, compared to *Combo's* 96.65% on both MCF and Barabási-Albert graphs.



Final Note

- Troika offers efficient and effective solution for the clique partitioning problem
- Troika demonstrates a balance in terms of solve time and solution quality



Acknowledgements

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