



# Strengthening Relaxed Decision Diagrams for Maximum Independent Set Problem: Novel Variable Ordering and Merge Heuristics

Mohsen Nafar and Michael Römer



## Decision Diagrams (Exact)

- a **graphical representation of the solution space**
- **generic**: require a **Dynamic Programming** formulation
- **exponential size**

## Approximate Decision Diagrams (restricted and relaxed)

- **linear size**
- obtain (combinatorial) **primal and dual bounds**
- put in **generic exact algorithms (e.g. B&B or P&B)**
- **quality of the bounds depend on heuristic strategies**  
for **1. node selection** and **2. variable ordering**

## Maximum Independent Set Problem (MISP)

- **NP-hard** combinatorial problem
- Problem: Given a graph  $G = (V, E)$ , find the largest  $I \subseteq V$  subset of its vertices such that  
 $\forall v, u \in I, (u, v) \notin E$

- IP formulation:

$$\begin{aligned} & \text{Maximize} && \sum_{v \in V} x_v \\ & \text{S.t.} && x_u + x_v \leq 1, \forall (u, v) \in E \\ & && x_v \in \{0, 1\} \end{aligned}$$

# Learning more about Decision Diagrams for Optimization

- A gentle introduction:

TUTORIALS IN  
OPERATIONS RESEARCH  
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## An Introduction to Decision Diagrams for Optimization




*Willem-Jan van Hove*

Tepper School of Business, Carnegie Mellon University, vanhoeve@andrew.cmu.edu

- A survey:

[Home](#) > [INFORMS Journal on Computing](#) > [Vol. 34, No. 4](#) >

## Decision Diagrams for Discrete Optimization: A Survey of Recent Advances

Margarita P. Castro , Andre A. Cire , J. Christopher Beck 

Published Online: 22 Mar 2022 | <https://doi.org/10.1287/ijoc.2022.1170>

# Some Decision Diagram based Solvers



## **DDO, a Generic and Efficient Framework for MDD-based Optimization**

By Xavier Gillard, Pierre Schaus, Vianney  
Coppé

Developed in Rust

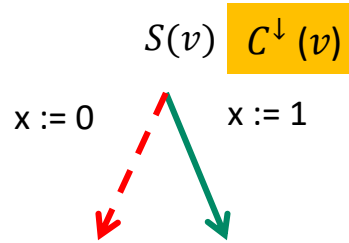
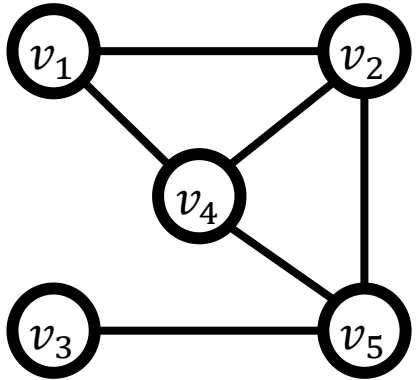


## **Peal-and-Bound: Solving Discrete Optimization Problems with Decision Diagrams and Separation**

PhD Thesis by Isaac Rudich (August 2024)

Developed in Julia

# Top-Down Compilation of Exact DD for MISP



$$x_1 = v_1$$

$$x_2 = v_2$$

$$x_3 = v_3$$

$$x_4 = v_4$$

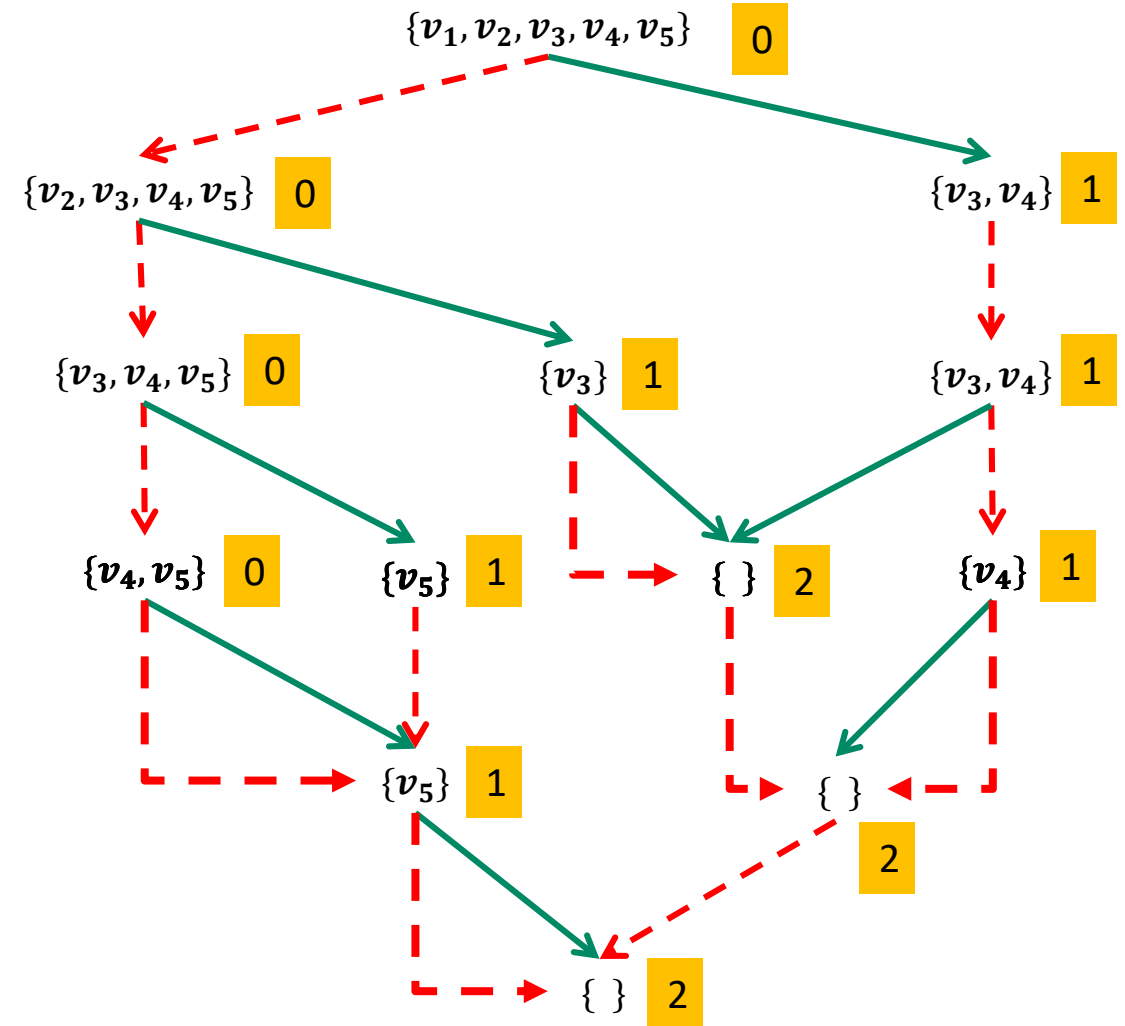
$$x_5 = v_5$$

For the MISP:

State  $S$ : Admissible vertices

State transition  $f(S, x_i)$ :

$$f(S, x_i) = \begin{cases} S & \text{for } x_i = 0 \\ S \setminus N(x_i) & \text{for } x_i = 1 \end{cases}$$



# Top-Down Compilation of Relaxed DD for MISP

## Dual Bounds via Relaxed Decision Diagrams

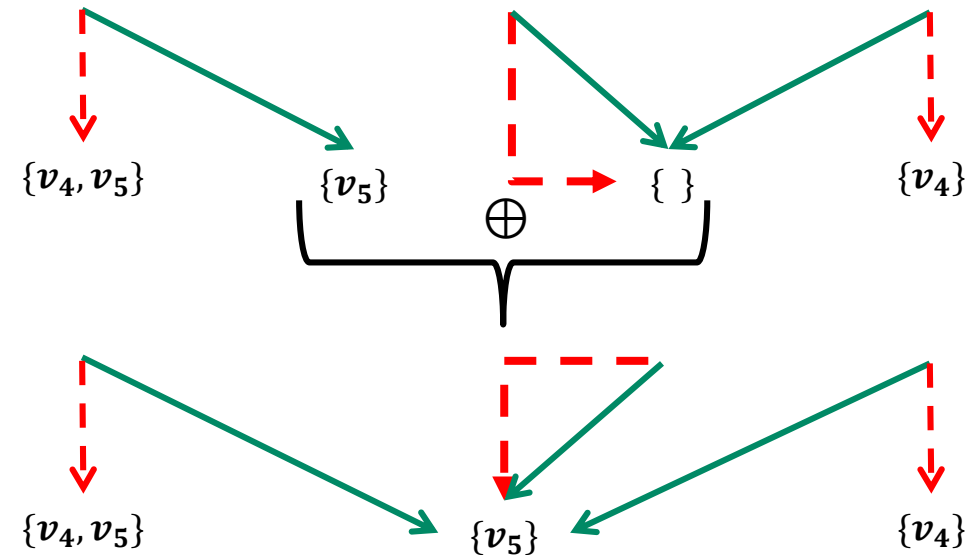
- given a maximum permitted width  $W$
- if the width of a layer exceeds  $W$ : **merge nodes** until  $W$  is respected
- to obtain the state of the merged nodes, apply a problem-specific merge operation ( $\oplus$ ) that ensures a **valid relaxation**:

Merging nodes introduces errors

How can we control (decrease) the error?

For MISP:  $\oplus = \cup$

$$i. e. S_1 \oplus S_2 \oplus \dots \oplus S_k = S_1 \cup S_2 \cup \dots \cup S_k$$



The error (hence quality of the bounds) depends on:  
1. node selection, 2. variable ordering

# Some Related Works on Variable Ordering

## Using Machine Learning

- using Reinforcement Learning (Cappart et. al 2019, 2021, 2023) [MISP]
- Algorithm selection (Karahalios and van Hoeve 2021)

## Classical methods (no machine learning)

- generic: look-ahead (Bergman et al. 2016, book)
- specific [MISP]: state information, i.e. MIN (Bergman et al. 2016, book)

## This paper:

→ use **graph-theoretical** information from **induced subgraphs corresponding to states**

# Some Related Works on Node Selection

## Strategies based on Sorting

(keep the best  $W-1$  nodes, merge the rest)

- by objective function value (SO)
- using state information
- using binary classifiers, look-ahead (Frohner and Raidl 2019) [MISP]
- tie-breaking strategies for nodes with identical values (Frohner and Raidl 2020) [MISP]

## Strategies based on Grouping

(group nodes according to state similarity)

- using labeling functions (Horn et al. 2021)
- using problem-specific distances (de Weerd et al. 2021)
- using unsupervised clustering (Nafar and Römer 2024)
- approximate equivalence using lookahead, merge and reduce (Nafar and Römer 2024)

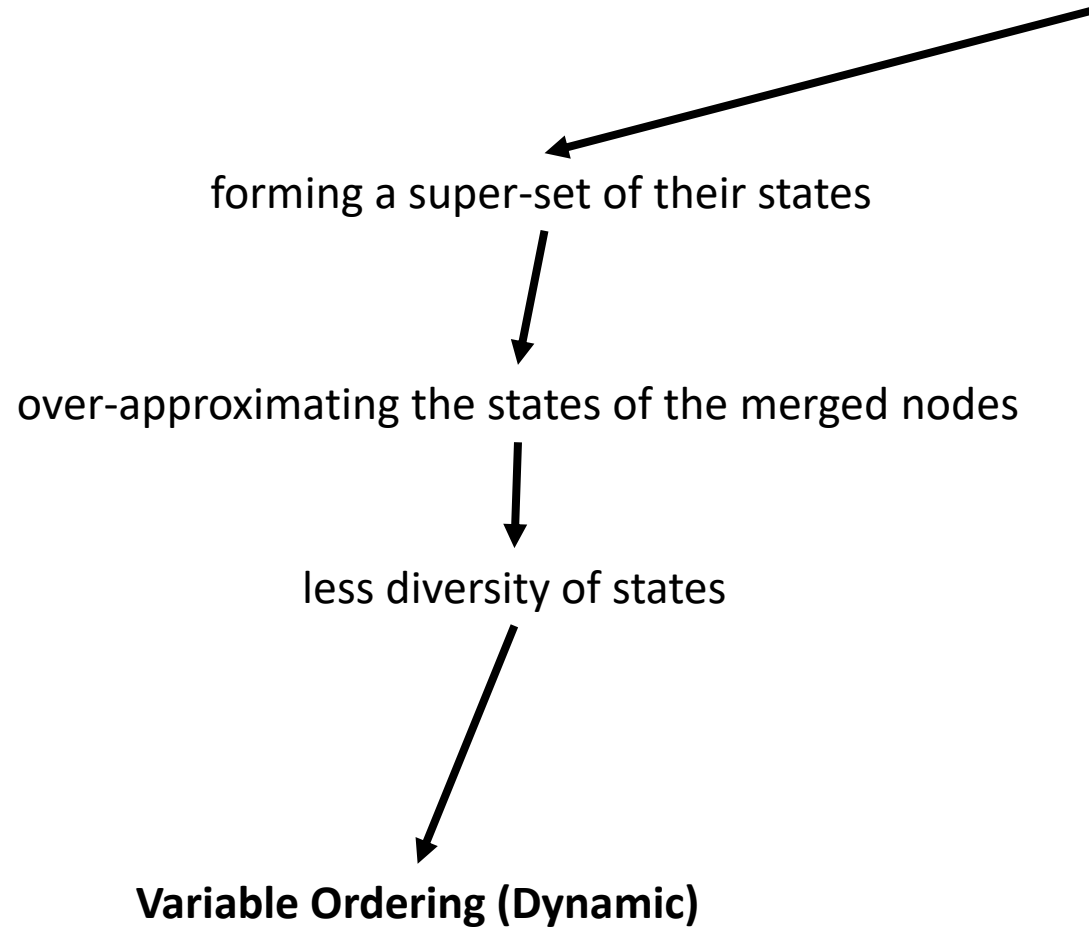
## This paper:

→ use **Border Tie (BT)** merging for improving the **node selection**



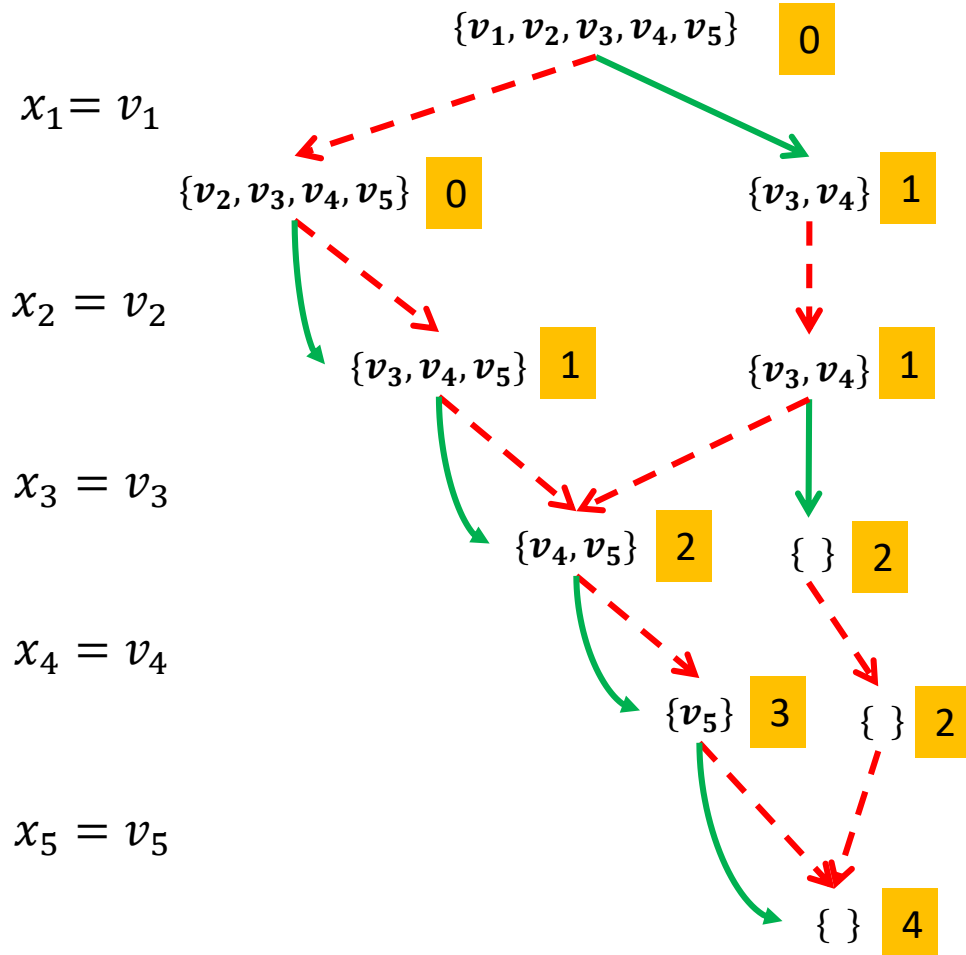
# Errors in relaxed DDs for MISP

- Errors in a merged node is a **“two-sided” over-approximation** of all the nodes in the merge:

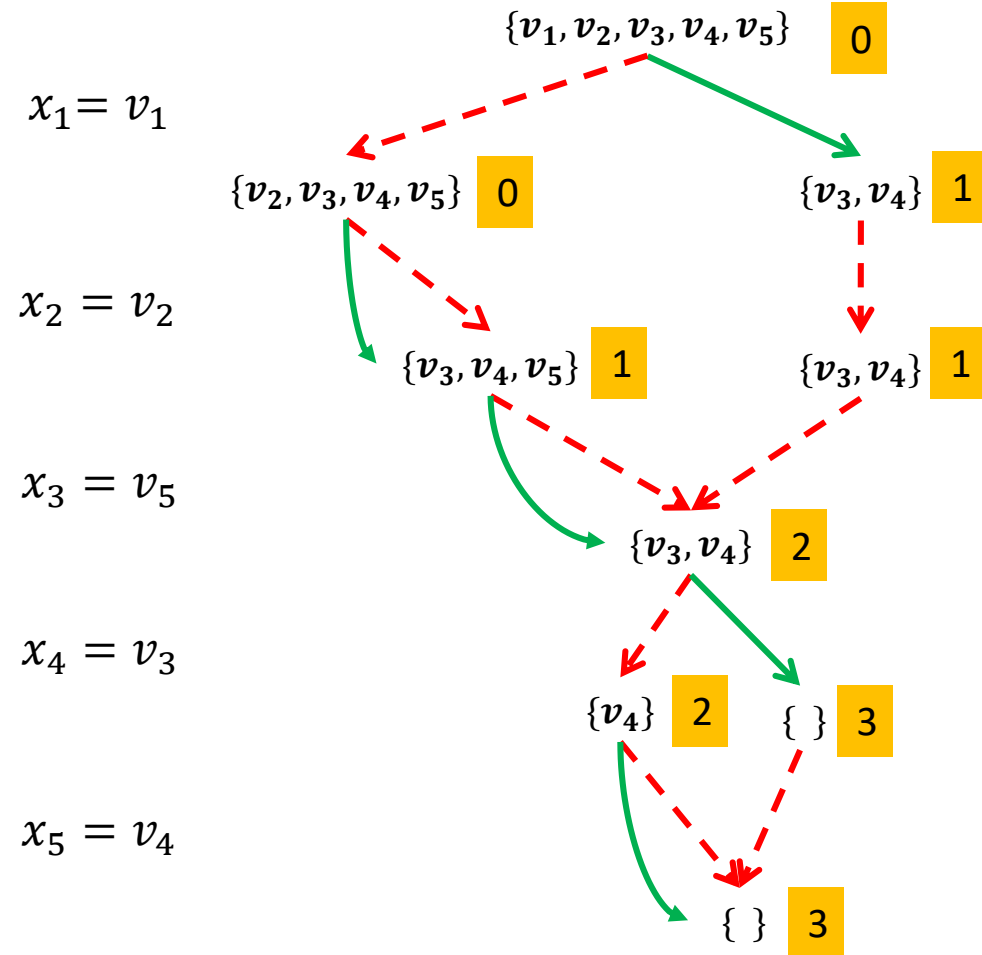


# Relaxed DDs for MISP instance

- no particular variable ordering



- MIN** variable ordering



# Current Degree Sum: CDS Variable Ordering

• Change the **point of view**: Original problem



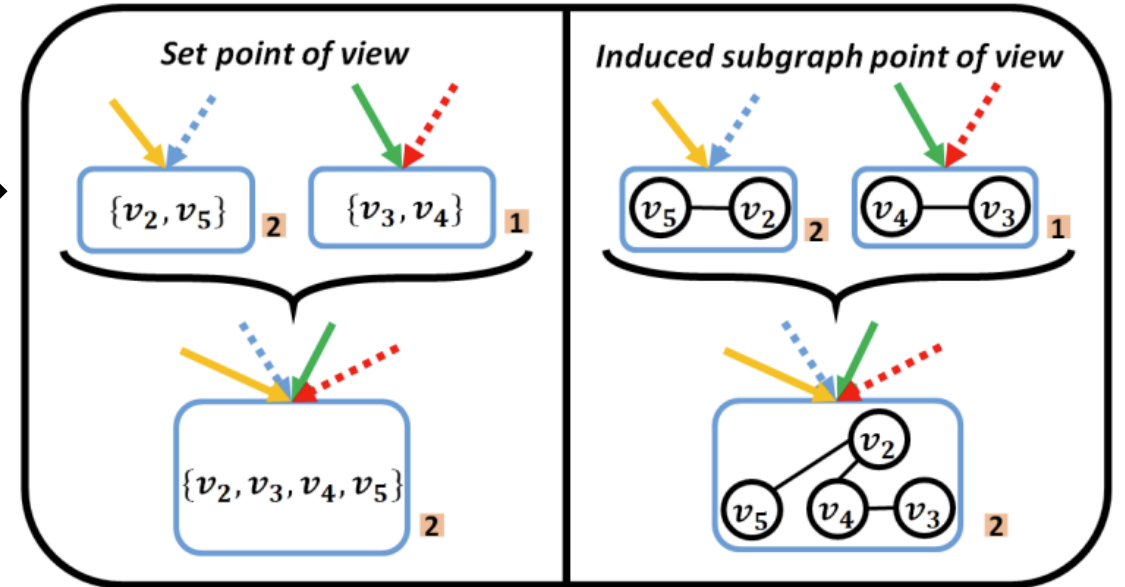
• Original problem: More information



1. Less Diversity (similar states)

2. More intersection with optimum solutions

3. Potentially smaller layers



But layers have more than one graph!!!



Current Degree Sum: CDS

$$\sum_{s \in L} dg_s(v_i)$$

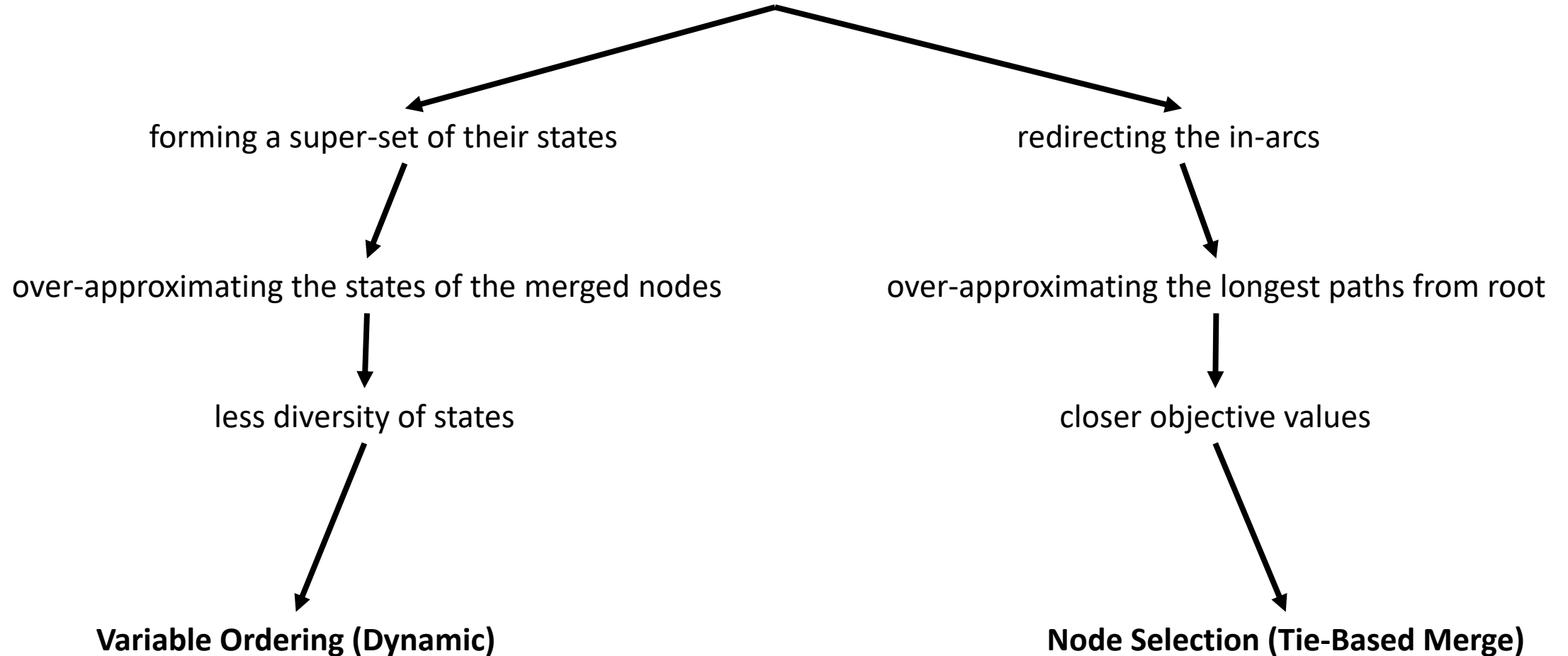
**HOW?!**

Vertex with lower degree, if one graph (state)



# Errors in relaxed DDs for MISP

- Errors in a merged node is a **“two-sided” over-approximation** of all the nodes in the merge:

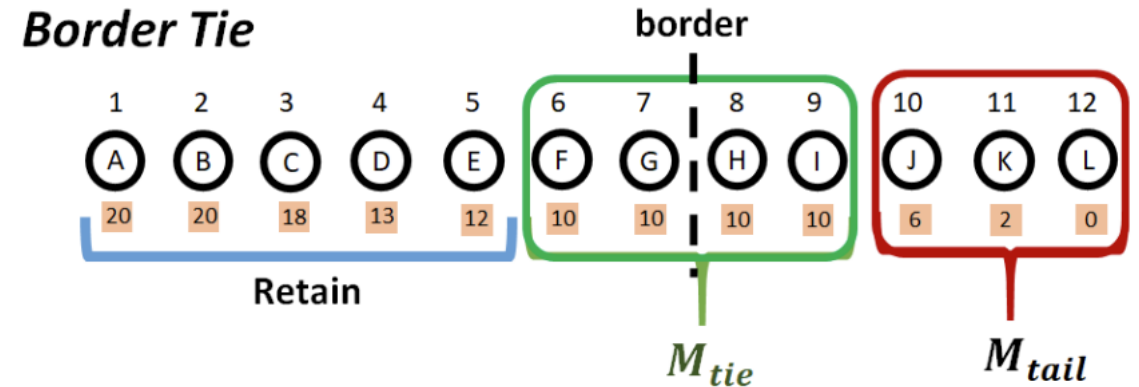
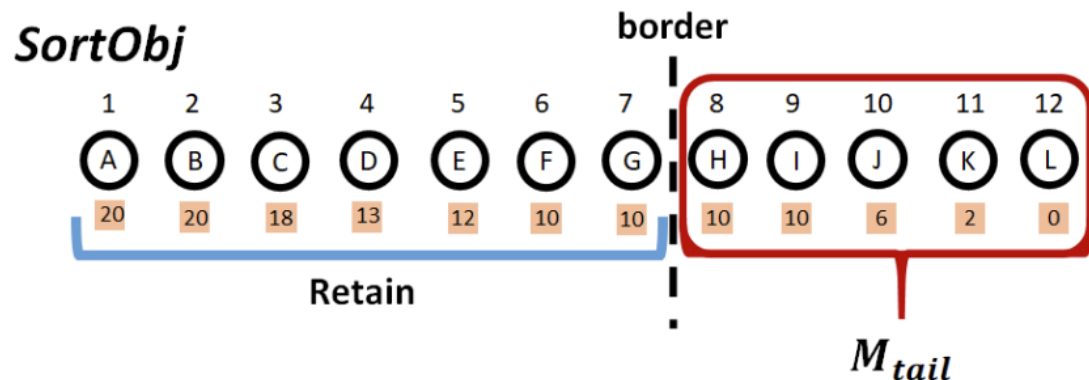


# Node Selection in relaxed DDs for MISP

**Definition 1.** (Border Tie). Let the nodes in a layer of a DD be sorted according to some criterion  $C$  and  $SortC$  be its corresponding sorted list, and let  $W$  be the given maximum width. A subsequence of  $SortC$  in which all nodes have the same criterion value and which includes  $SortC [W - 1]$  and  $SortC [W]$  is called a Border Tie.

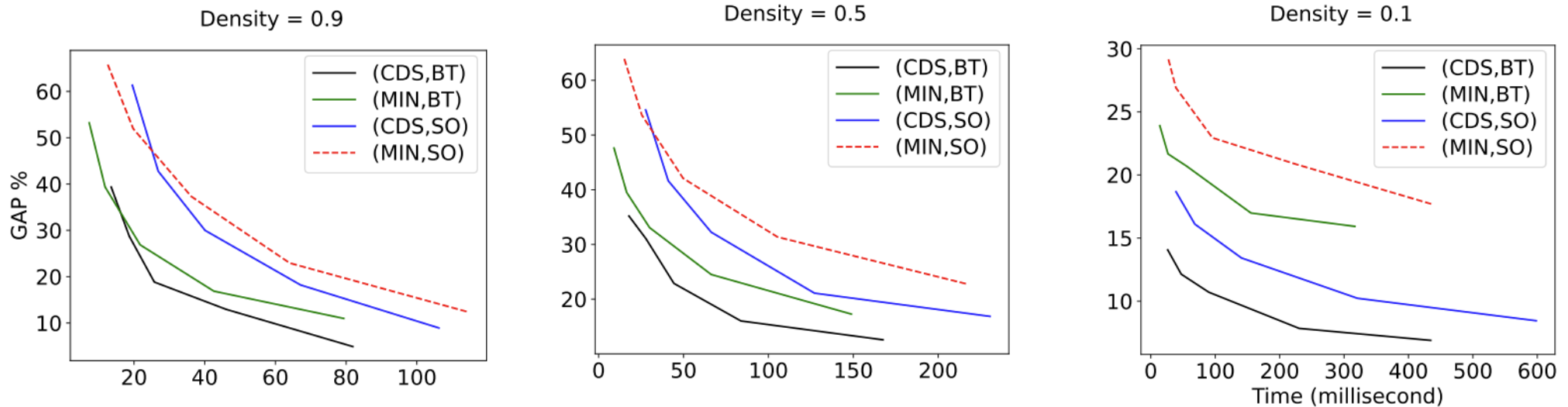
1. keep the best  $W-1$  nodes according to objective value
2. merge the rest

1. keep the best  $W-1$  nodes according to objective value
2. merge border tie nodes (if any)
3. merge the rest (if any)

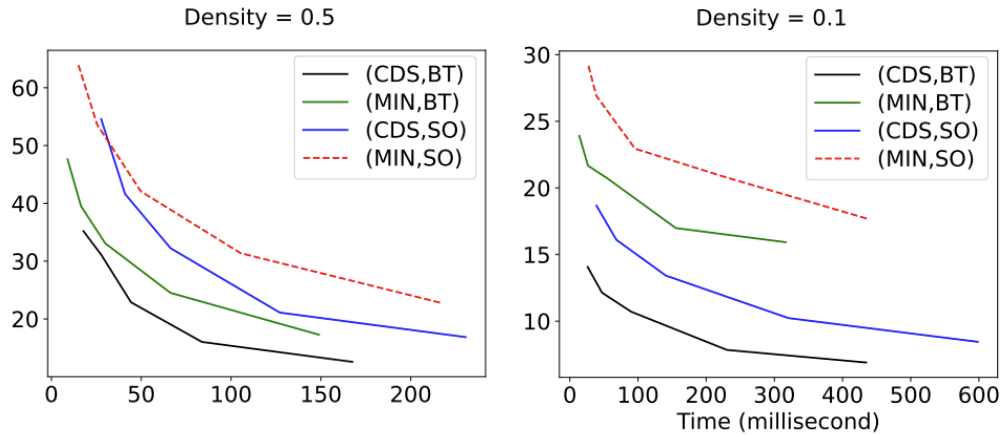


# Computational Results: Gap-Time (Dual bounds)

- random graph instances, 20 instance per density each with 100 vertices
- Comparing the bounds obtained with our approaches to those with the standard approaches



# Computational Results: DD Sizes



| Density    | Average DD Size (nodes) |          |              |          |
|------------|-------------------------|----------|--------------|----------|
|            | (MIN,SO)                | (CDS,SO) | (MIN,BT)     | (CDS,BT) |
| <b>0.1</b> | 73513                   | 76190    | <b>58059</b> | 59069    |
| <b>0.2</b> | 71324                   | 73190    | <b>56393</b> | 57173    |
| <b>0.3</b> | 68484                   | 69470    | <b>54020</b> | 55253    |
| <b>0.4</b> | 65088                   | 66580    | <b>51870</b> | 53049    |
| <b>0.5</b> | 62053                   | 63355    | <b>50456</b> | 51356    |
| <b>0.6</b> | 58946                   | 59661    | <b>47715</b> | 47505    |
| <b>0.7</b> | 55058                   | 56040    | <b>43606</b> | 45629    |
| <b>0.8</b> | 50808                   | 51466    | <b>35334</b> | 36025    |
| <b>0.9</b> | 45770                   | 47272    | <b>37578</b> | 41607    |

- SO vs **BT**: smaller DD + more merged nodes, but better dual bounds: *Success?!*
- MIN vs **CDS**: control the diversity of the states to reduce the destructive effect of merge: *Success?!*



# Computational Results: Branch-and-Bound

| Density    | Time (Seconds) |             |          |              |
|------------|----------------|-------------|----------|--------------|
|            | (MIN,SO)       | (CDS,SO)    | (MIN,BT) | (CDS,BT)     |
| <b>0.1</b> | 872.3          | 821.9       | 445.8    | <b>320.9</b> |
| <b>0.2</b> | 126.4          | 94.0        | 85.5     | <b>56.4</b>  |
| <b>0.3</b> | 31.0           | 26.8        | 24.3     | <b>17.0</b>  |
| <b>0.4</b> | 10.1           | 9.3         | 8.6      | <b>5.9</b>   |
| <b>0.5</b> | 4.3            | 3.5         | 4.0      | <b>2.5</b>   |
| <b>0.6</b> | 1.92           | 1.70        | 1.57     | <b>1.4</b>   |
| <b>0.7</b> | 1.11           | 1.01        | 0.93     | <b>0.89</b>  |
| <b>0.8</b> | 0.73           | 0.70        | 0.81     | <b>0.66</b>  |
| <b>0.9</b> | 0.60           | <b>0.56</b> | 0.65     | 0.61         |

- Any combination containing **BT** or **CDS** or both is better than (MIN,SO)

| Density  | <b>0.1</b>  | <b>0.2</b>  | <b>0.3</b>  | <b>0.4</b>  | <b>0.5</b>  | <b>0.6</b>   | <b>0.7</b>  | <b>0.8</b> | <b>0.9</b> | Average      |
|----------|-------------|-------------|-------------|-------------|-------------|--------------|-------------|------------|------------|--------------|
| (CDS,SO) | 5.7         | 25.61       | 13.42       | 8.4         | 18.3        | 11.4         | 9.0         | 4.1        | <b>6.6</b> | 11.43        |
| (MIN,BT) | 48.8        | 32.3        | 21.4        | 15.6        | 6.2         | 18.2         | 16.2        | -10.9      | -8.3       | 15.52        |
| (CDS,BT) | <b>63.2</b> | <b>55.3</b> | <b>45.2</b> | <b>42.0</b> | <b>40.6</b> | <b>25.52</b> | <b>19.8</b> | <b>9.5</b> | -1.6       | <b>33.30</b> |

# Computational Results: Branch-and-Bound

(MIN,BT) better **bounds** and **solution times**  
 than (CDS,SO), but more subproblems to solve:  
**good quality bounds is not the only factor?!**

**Hypothesis:** the intuitions behind the design of  
**CDS** (more intersections with optimal solutions)

| Density    | Node Size (Sub-problem Solved in B&B) |            |          |              |
|------------|---------------------------------------|------------|----------|--------------|
|            | (MIN,SO)                              | (CDS,SO)   | (MIN,BT) | (CDS,BT)     |
| <b>0.1</b> | 63880                                 | 39051      | 34183    | <b>17150</b> |
| <b>0.2</b> | 15454                                 | 6623       | 9088     | <b>3816</b>  |
| <b>0.3</b> | 5906                                  | 3053       | 3830     | <b>1700</b>  |
| <b>0.4</b> | 2609                                  | 1581       | 1814     | <b>802</b>   |
| <b>0.5</b> | 1452                                  | 796        | 947      | <b>450</b>   |
| <b>0.6</b> | 702                                   | 397        | 440      | <b>266</b>   |
| <b>0.7</b> | 399                                   | 256        | 283      | <b>195</b>   |
| <b>0.8</b> | 291                                   | 210        | 245      | <b>173</b>   |
| <b>0.9</b> | 247                                   | <b>174</b> | 224      | 178          |

**(CDS,BT):** benefits of both, (good bounds, more intersections): solved subproblems reduced by 50%

| Density  | <b>0.1</b>  | <b>0.2</b>   | <b>0.3</b>  | <b>0.4</b>  | <b>0.5</b>  | <b>0.6</b>  | <b>0.7</b>  | <b>0.8</b>  | <b>0.9</b>  | Average     |
|----------|-------------|--------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| (CDS,SO) | 38.8        | 57.1         | 48.3        | 39.4        | 45.2        | 43.3        | 35.7        | 27.7        | 29.6        | 40.6        |
| (MIN,BT) | 46.4        | 41.1         | 35.1        | 30.4        | 34.7        | 37.3        | 29.0        | 15.8        | 9.3         | 31.0        |
| (CDS,BT) | <b>73.1</b> | <b>75.30</b> | <b>71.2</b> | <b>69.2</b> | <b>68.9</b> | <b>62.0</b> | <b>51.0</b> | <b>40.3</b> | <b>27.6</b> | <b>59.8</b> |

# Conclusions

- We proposed for MISP:
  - a novel variable ordering approach which is based-on graph theoretical information obtained from induced subgraphs corresponding to states
  - a new tie-based node selection approach
- These simple ideas yield considerably stronger dual bounds than the standard and most commonly used approaches
- As was shown in multiple previous papers, better bounds translate into faster exact algorithms such as branch-and-bound

# References



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