Towards Improving Merging Heuristics for Binary Decision Diagrams (BDDs)

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Binary Decision Diagrams - Basics

• A BDD encodes a function:



- Comparable to branching tree, but
- redundant nodes may be removed
- identical subtrees may be superimposed

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## BDDs for Combinatorial Optimization

Representation of solution space by directed acyclic multigraph with weighted and labeled arcs.

$$X = \{x_1, \ldots, x_n\}$$



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- Lee 1959: BDDs as compact representation for boolean functions.
- Hadzic and Hooker 2006: For post-optimality analysis.
- Bergman et al. 2013: Dual bounds from BDDs for the maximum independent set problem.
- For a compilation of resources: http://www.andrew.cmu.edu/user/vanhoeve/mdd/

- (Partial) solutions for a given problem.
- Carry length via arc costs.
- Define decisions via arc labels.

 $\mathsf{Longest} (\mathsf{shortest}) \mathsf{ path} \Leftrightarrow \mathsf{Maximal} (\mathsf{minimal}) \mathsf{ solution}.$ 

Decompose solution into parts i and impose an ordering  $\pi$ .

Assign to each subpart  $\pi_i$  of the solution a binary decision variable  $x_i$ .

Each subpart can be assigned costs  $c_{\pi_i}$ .

Given an *i*-partial assignment, the corresponding state  $s_i$  determines its feasible completions.

States are assigned to nodes in the BDD and determine the completing paths.

Allows superposition of nodes with same state, resulting into a **reduced BDD**.

#### Top-Down Construction of DD

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Keep BDDs polynomial in size  $\rightarrow$  longest paths then correspond to dual bounds.

Have to merge also nodes for which states are not the same.

**Research goal**: Improve BDD construction mechanisms so that tighter bounds can be achieved with the same BDD size.

Top-Down Construction of Relaxed DD



To build **relaxed** DD, merge some additional nodes as we go along.

Take the **union** of merged states

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To build **relaxed** DD, merge **X**<sub>4</sub> some additional nodes as we go along.

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X<sub>5</sub> Take the union of merged states.

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We consider

- top-down
- layerwise
- zero-suppressing long-arcs

construction of relaxed BDDs (Bergman et al. 2013) with max width  $\beta$  for the

- Maximum (Weighted) Independent Set Problem (MISP)
- Set Cover Problem (SCP)

**Merging:** Superimpose nodes in BDD while not losing feasible solutions. Different merging strategies to keep layer within maximum width:

- Bulk Merging
- Iterative Merging

# Minimum Longest Path (minLP) Value Bulk Merging ac

Bergman et al. (2013)

- Sort nodes in a layer descending by longest path length to them  $z^{lp}(u)$ .
- Merge the tail into one node so that the maximum width is not exceeded.

Rationale: Merge nodes that are unlikely to be part of longest path.

#### Classical minLP Selection





### Classical minLP Merging





#### minLP Ties

#### Example with $\beta = 10$ .



- Recall: State of nodes determines feasible completions.
- Define an informal **merging distance function** for pairwise merging of nodes *u* and *v*.
- Smaller distance between nodes should less likely increase the lengths of paths going through  $u \oplus v$ .

Initial motivation: Hamming distance between states.

- Idea: use upper bound directly from state s(u) to estimate remaining longest path length starting from given node u.
- For example, coarse upper bound in the MISP: cardinality of the set representing the state.

Given two nodes u, v in a layer with corresponding states s(u), s(v).

- 1. Hamming:  $d_H(u, v) = |s(u) \triangle s(v)|$ .
- 2. Increase in upper bound:  $d_{ub}(u, v) = \max\{z^{ub}(w) - z^{ub}(u), z^{ub}(w) - z^{ub}(v)\}.$
- 3. Upper bound:  $\tilde{d}_{\rm ub}(u,v) = z^{\rm ub}(w)$ .

## minLP/State Similarity Hybrid Merging Heuristic

minLP gives strong results. *Issue*: does not take similarity of states into account  $\rightarrow$  introduce iterative pairwise state similarity merging gently.



Region T extensible to the left by parameter  $\delta_l$  and to the right by parameter  $\delta_r$ . If  $\delta_l = \delta_r = 0$  we only consider ties.

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## minLP/State Similarity Hybrid Selection



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### minLP/State Similarity Hybrid Merging



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### Combine Bulk and Iterative Merging

- 1. Bulk merge  $\oplus B = w$ .
- 2. Pairwise iterative merging over nodes  $T \cup \{w\}$  choosing always the pair with minimum distance d(u, v).

#### Pure Tie Breaking MISP

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Strong results for small-width BDDs with pure tie breaking  $\delta_l = \delta_r = 0$  for unweighted MISP on 180 random graphs by Bergman and DIMACS instance set:



#### **DIMACS** Results

Table: Relative upper bounds of relaxed BDDs obtained with different merging heuristics and widths  $\beta \in \{10, 100\}$  for selected DIMACS instances.

	$\beta = 10$				$\beta = 100$			
inst	minLP	d <sub>H</sub>	$d_{ m ub}$	$\widetilde{d}_{ m ub}$	minLP	d <sub>H</sub>	d <sub>ub</sub>	$ ilde{d}_{ m ub}$
brock200_1	2.29	2.14	2.14	1.90	1.81	1.62	1.67	1.67
C500.9	3.05	3.00	2.81	2.47	2.61	2.46	2.40	2.28
gen400_p0.9_55	2.25	2.13	2.04	1.82	1.91	1.82	1.80	1.73
keller4	1.91	1.55	1.64	1.55	1.45	1.18	1.18	1.18
MANN_a45	1.34	1.34	1.21	1.30	1.08	1.32	1.27	1.19
p_hat300-3	2.19	2.11	2.08	1.86	1.86	1.75	1.81	1.69
p_hat700-2	2.59	2.45	2.32	2.18	2.14	1.98	1.95	1.93

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#### BDD Merging Heuristics

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Pure Tie Breaking SCP

#### Median increase in the lower bound value of 0.08.





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#### Weighted Problems

For weighted problems, ties are less likely to occur and  $\delta_I = \delta_r = 0$  degenerates to minLP. Raced parameters (0.185, 0.043) using irace on weighted DIMACS dataset, significant improvement but not so strong as before.



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- Results for MISP and SCP indiciate that state similarity based merging works well together with minLP when ties occur naturally.
- Work needs to be done for weighted problems, where we have virtually no ties, to achieve a larger effect.

#### References



David Bergman, Andre A Cire, Willem-Jan van Hoeve, and John N Hooker.

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# ευχαριστώ πολύ!