

# Merging or Computing Saturated Cost Partitionings?

A Merge Strategy for the Merge-and-Shrink Framework

Silvan Sievers, Thomas Keller, Gabriele Röger

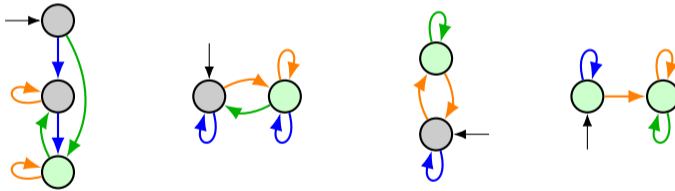
ICAPS 2024



**University  
of Basel**

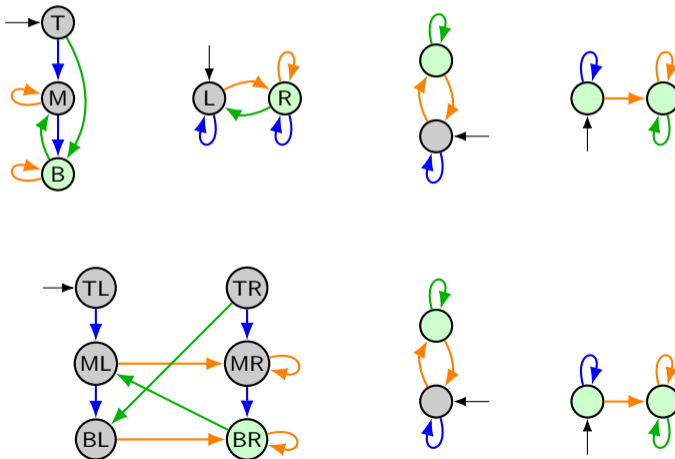
# Merge-and-Shrink Abstractions: Idea

Start from atomic factors (projections to single state variables)



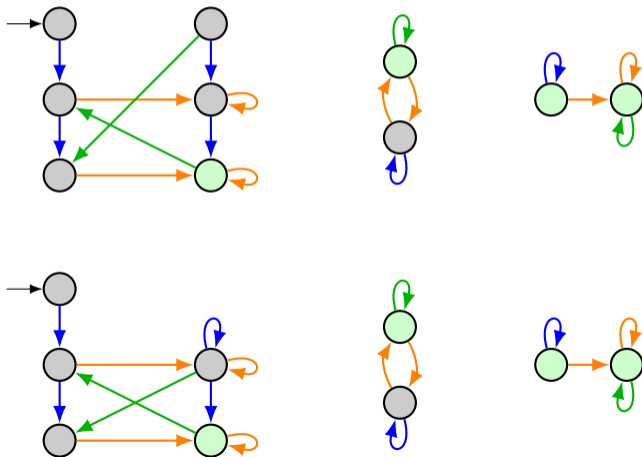
# Merge-and-Shrink Abstractions: Idea

Merge: replace two factors with their product



# Merge-and-Shrink Abstractions: Idea

Shrink: replace a factor by an abstraction of it



# Merge-and-Shrink Algorithm

Dräger et al. STTT 2006, Helmert et al. JACM 2014, Sievers & Helmert JAIR 2021

**Input:** FTS  $F$

**Output:** Heuristic for  $F$

```
1: function M&S( $F$ )
2:    $F' \leftarrow F$ 
3:   while not TERMINATE( $F'$ ) do
4:      $i, j \leftarrow$  MERGESTRATEGY( $F'$ )
5:     LABELREDUCTIONSTRATEGY( $F'$ )
6:     SHRINKSTRATEGY( $F', i, j$ )
7:      $k \leftarrow$  MERGE( $F', i, j$ )
8:     PRUNESTRATEGY( $F', k$ )
9:   return COMPUTEHEURISTIC( $F'$ )
```

- **Factor heuristic:** abstraction heuristic from single factor (= abstract transition system)
- Run until there is only a single factor and use its factor heuristic, or
- terminate early and use the maximum of the factor heuristics.

# Merge-and-Shrink with Saturated Cost Partitioning

Sievers et al. IJCAI 2020

- Saturated Cost Partitioning

(Seipp et al. JAIR 2020)

Admissible combination of heuristics.

- Typically better than maximum.
- Depends on the order in which the heuristics are considered.

# Merge-and-Shrink with Saturated Cost Partitioning

Sievers et al. IJCAI 2020

## ■ Saturated Cost Partitioning

(Seipp et al. JAIR 2020)

Admissible combination of heuristics.

■ Typically better than maximum.

■ Depends on the order in which the heuristics are considered.

**Input:** FTS  $F$

**Output:** Heuristic for  $F$

```
1: function M&SWITHSCP( $F$ )
2:    $F' \leftarrow F, H \leftarrow \emptyset$ 
3:   while not TERMINATE( $F'$ ) do
4:      $i, j \leftarrow$  MERGESTRATEGY( $F'$ )
5:     LABELREDUCTIONSTRATEGY( $F'$ )
6:      $\omega \leftarrow$  SCPOORDERSTRATEGY( $F'$ )
7:      $H \leftarrow H \cup \{h_{\omega}^{SCP}\}$ 
8:     SHRINKSTRATEGY( $F', i, j$ )
9:      $k \leftarrow$  MERGE( $F', i, j$ )
10:    PRUNESTRATEGY( $F', k$ )
11:  return COMPUTEMAXHEURISTIC( $H$ )
```

We want to devise a merge strategy that works well in M&S with cost partitioning.



## Evaluating Merge Candidates

For evaluating a pair of factors, we locally assess the value of merging them and of using them as individual heuristics:

$$h_{prod}^{init} = h_F^{\mathcal{T}^\otimes}(s_0)$$

$$h_{mFactor}^{init} = \max(h_F^{\mathcal{T}^i}(s_0), h_F^{\mathcal{T}^j}(s_0))$$

$$h_{mSCP}^{init} = \max(h_{\langle \mathcal{T}_F^i, \mathcal{T}_F^j \rangle}^{SCP}(s_0), h_{\langle \mathcal{T}_F^j, \mathcal{T}_F^i \rangle}^{SCP}(s_0))$$

## Evaluating Merge Candidates

For evaluating a pair of factors, we locally assess the value of merging them and of using them as individual heuristics:

$$h_{prod}^{init} = h_F^{T^\otimes}(s_0)$$

$$h_{mFactor}^{init} = \max(h_F^{T^i}(s_0), h_F^{T^j}(s_0))$$

$$h_{mSCP}^{init} = \max(h_{\langle T_F^i, T_F^j \rangle}^{SCP}(s_0), h_{\langle T_F^j, T_F^i \rangle}^{SCP}(s_0))$$

$$h_{prod}^{avg} = \text{AVG}(h_F^{T^\otimes})$$

$$h_{mFactor}^{avg} = \max(\text{AVG}(h_F^{T^j}), \text{AVG}(h_F^{T^i}))$$

$$h_{mSCP}^{avg} = \max(\text{AVG}(h_{\langle T_F^i, T_F^j \rangle}^{SCP}), \text{AVG}(h_{\langle T_F^j, T_F^i \rangle}^{SCP}))$$

## Two New Merge Strategies

- **maximum factor scoring function (mFactor)** prefers candidates whose product heuristic improves most compared to the maximum over the two factor heuristics:

$$\text{Maximize } h_{prod} - h_{mFactor}$$

**Rationale:** greedy decision for the best immediate improvement without looking ahead to the future transformations by M&S.

## Two New Merge Strategies

- **maximum factor scoring function (mFactor)** prefers candidates whose product heuristic improves most compared to the maximum over the two factor heuristics:

$$\text{Maximize } h_{prod} - h_{mFactor}$$

**Rationale:** greedy decision for the best immediate improvement without looking ahead to the future transformations by M&S.

- **maximum SCP scoring function (mSCP)** adapts the same concept to the integration of cost partitioning into M&S.

$$\text{Maximize } h_{prod} - h_{mSCP}$$

# Comparison

	mFactor		mSCP	
	init	avg	init	avg
$h^{M\&S}$	889	860	<b>902</b>	875
$h_{SCP}^{M\&S}$	916	902	<b>990</b>	909

## Comparison

	mFactor		mSCP	
	init	avg	init	avg
$h^{M\&S}$	889	860	<b>902</b>	875
$h_{SCP}^{M\&S}$	916	902	<b>990</b>	909

Additional experiments:

- Stopping the M&S algorithm when there is no good merge candidate leads to worse coverage, because continuing merging factors can lead to better factor heuristics in later iterations.
- Adding SCP heuristics for each pair of remaining factors does not pay off.

# State-of-the-art Strategies

			SCC		mSCP	
	DFP	sbM	DFP	sbM		SCC
$h^{M\&S}$	882	920	922	913	902	<b>926</b>
$h_{SCP}^{M\&S}$	915	965	950	956	990	<b>1006</b>

**DFP** Dräger et al. SPIN 2006, Sievers et al. AAI 2014

**sbM** sbMIASM; Fan et al. SoCS 2014, Sievers et al. ICAPS 2016

**SCC** Sievers et al. ICAPS 2016

# Summary

- New merge strategy for M&S with saturated cost partitioning.
- Improves the state of the art of M&S.
- Even better if integrated with the SCC merge strategy.