



Distributed Nonmonotonic Multi-Context Systems: Algorithms and Efficient Evaluation

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- Introduction to Multi-context Systems
- Basic Algorithm DMCS to Evaluate MCS
- Topological-based Optimized Algorithm DMCSOPT
- Streaming Models with DMCS-STREAMING
- Experimental Evaluation: Setup and Analysis
- Outlook



- What is a multi-context system? $M = (C_1, \ldots, C_n)$
 - a collection of contexts C_1, \ldots, C_n
- What is a context?

 $C_i = (L_i, kb_i, br_i)$

- ▶ a logic *L*_i
- the context's knowledge base kb_i
- a set br_i of bridge rules



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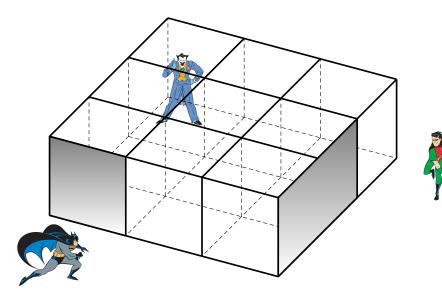
 $C_i = (L_i, kb_i, br_i)$

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- the context's knowledge base kb_i
- a set br_i of bridge rules
- What is a logic?

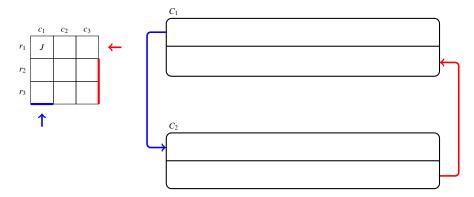
 $L = (\mathbf{KB}_L, \mathbf{BS}_L, \mathbf{ACC}_L)$

- set KB_L of well-formed knowledge bases
- set BS_L of possible belief sets
- ► acceptability function ACC_L : KB_L → 2^{BS_L} Which belief sets are accepted by a knowledge base?

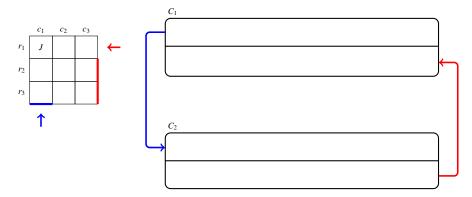




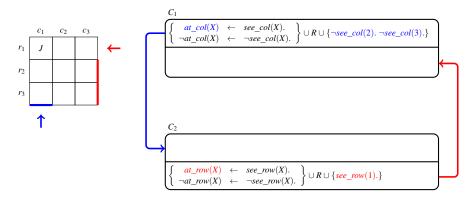




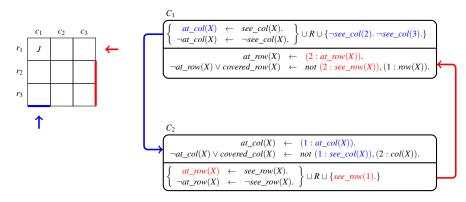








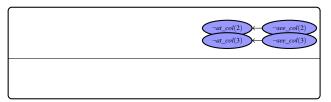


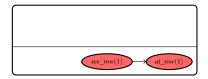




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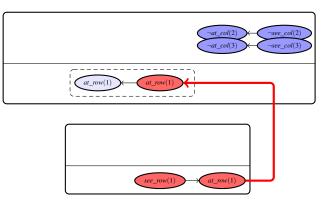






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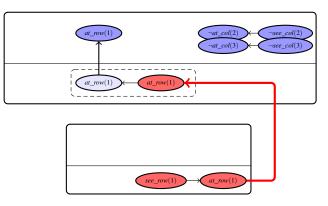
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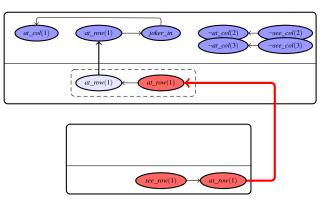
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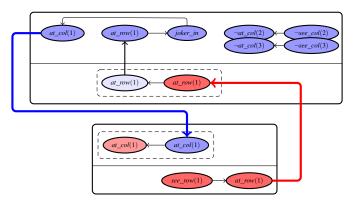
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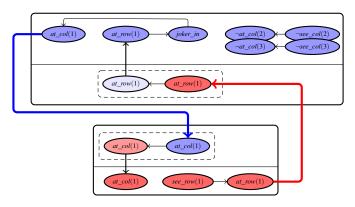
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Distributedness / Heterogeneity / Nonmonotonicity



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- \Rightarrow Power to model real life applications:
 - collaboration between business partners,
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Thus, algorithms to evaluate MCSs (compute equilibria) are of special interest!

Evaluation of MCSs before this thesis

- Related works on distributed systems: either not truly distributed or homogeneous
 - Distributed Constraints Satisfaction Problems [Yokoo and Hirayama, 2000]
 - DisSAT: finding a single model [Hirayama and Yokoo, 2005]
 - Parallel algorithm for evaluating monotonic MCS [Roelofsen et al., 2004]
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- For distributed nonmonotonic MCS:
 - Only one proposal for evaluating MCSs in a centralized way using hex-programs
 - No implementation available
- Obstacles:
 - Abstraction of contexts
 - Information hiding and security aspects
 - Lack of system topology
 - Cyclic dependency between contexts



Towards Evaluation of MCSs

Our aims:

- Algorithms for evaluating equilibria of MCSs in a truly distributed way
- Optimization techniques
- Prototype implementation
- Benchmarking



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We fulfill these goals by exploiting and adapting methods from distributed systems area, with special care for MCSs:

- Dependencies between contexts
- Representation of partial knowledge
- Combination/join of local results



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Support notions:

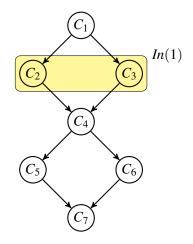
- Import Neighborhood and Closure
- Partial Belief States and Equilibria
- Joining Partial Belief States



Import Neighborhood and Closure

Import neighborhood of C_k

$$In(k) = \{c_i \mid (c_i : p_i) \in B(r), r \in br_k\}$$



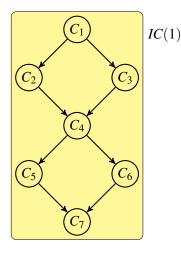


Import Neighborhood and Closure

Import neighborhood of C_k

$$In(k) = \{c_i \mid (c_i : p_i) \in B(r), r \in br_k\}$$

Import closure IC(k) of C_k is the smallest set *S* such that (i) $k \in S$ and (ii) for all $i \in S$, $In(i) \subseteq S$.





Let $M = (C_1, \ldots, C_n)$ be an MCS, and let $\epsilon \notin \bigcup_{i=1}^n \mathbf{BS}_i$



Partial Belief States and Equilibria

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A partial belief state of *M* is a sequence $S = (S_1, \ldots, S_n)$, where $S_i \in \mathbf{BS}_i \cup \{\epsilon\}$, for $1 \le i \le n$



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 $S = (S_1, \ldots, S_n)$ is a partial equilibrium of M w.r.t. a context C_k iff for $1 \le i \le n$,

- if $i \in IC(k)$ then $S_i \in ACC_i(kb_i \cup \{head(r) \mid r \in app(br_i, S)\})$
- otherwise, $S_i = \epsilon$

Intuitively, partial equilibria wrt. a context C_k cover the reachable contexts of C_k .

Joining Partial Belief States

Join $S \bowtie T$ of belief states *S* and *T*: like join of tuples in a database.

$$S = \begin{bmatrix} S_1 & \cdots & \epsilon & \cdots & s_j & \cdots & s_n \end{bmatrix}$$
$$T = \begin{bmatrix} \epsilon & \cdots & \epsilon & \cdots & T_i & \cdots & T_j & \cdots & \epsilon \end{bmatrix}$$
$$S \bowtie T = \begin{bmatrix} S_1 & \cdots & \epsilon & \cdots & T_i & \cdots & S_j = T_j & \cdots & S_n \end{bmatrix}$$

 $S \bowtie T$ is undefined, if $\epsilon \neq S_j \neq T_j \neq \epsilon$ for some *j*.

$$\mathcal{S} \bowtie \mathcal{T} = \{ S \bowtie T \mid S \in \mathcal{S}, T \in \mathcal{T} \}$$



- **Input:** an MCS *M* and a starting context *C*_k
- **Output:** all partial equilibria of M wrt. C_k



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Input parameters for DMCS:

- V: set of "interesting" variables (to project the partial equilibria)
- hist: visited path



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Input parameters for DMCS:

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- hist: visited path

Strategy: DFS-traversal of *M* starting with C_k , visiting all C_i for $i \in IC(k)$

Distributedness: instances of DMCS

- running at each context node,
- communicating with each other for exchanging sets of belief states

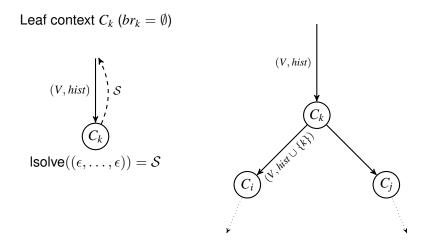


Leaf context
$$C_k$$
 ($br_k = \emptyset$)

$$(V, hist) \bigvee_{i=1}^{k} S$$
$$(C_k)$$
Isolve $((\epsilon, \dots, \epsilon)) = S$

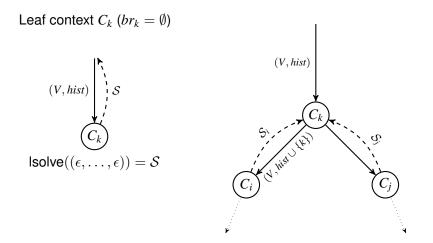


Intermediate context C_k ((i : p), (j : q) appear in br_k)



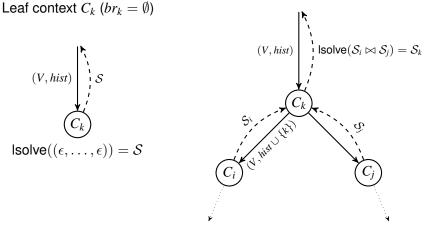


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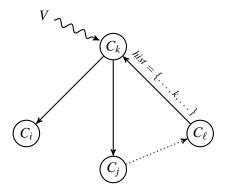




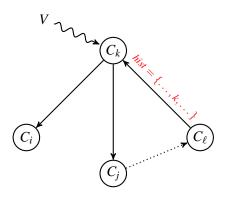
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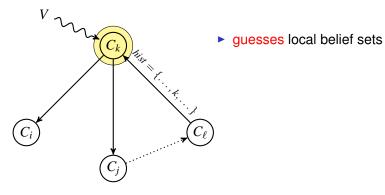




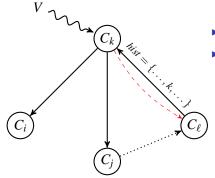






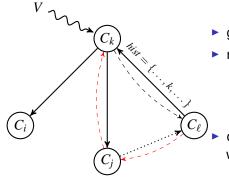






- guesses local belief sets
- returns them to invoking context

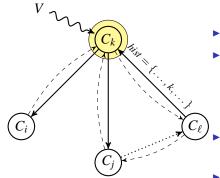




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- on the way back, partial belief states w.r.t. bad guesses will be pruned by \bowtie
- eventually, Ck will remove wrong guesses by calling lsolve on each received partial belief state



Scalability issues with the basic evaluation algorithm DMCS

- unaware of global context dependencies, only know (local) import neighborhood
- ► a context *C_i* returns a possibly huge set of partial belief states, which are the join of neighbor belief states of *C_i* plus local belief sets



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We address these issues by

- capturing inter-context dependencies (topology)
- providing a decomposition based on biconnected components
- characterizing minimal interface variables in each component
- develop the DMCSOPT algorithm which operates on query plans





Problem: How to go home?



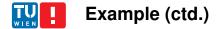


- Problem: How to go home?
- Possible solutions:
 - Car
 - Train





- Problem: How to go home?
- Possible solutions:
 - Car: slower than train
 - Train: should bring some food
- Spike and Mickey have additional information from Tyke and Minnie



 Minnie wants Mickey to come back as soon as possible.

$$kb_{4} = \{car_{4} \lor train_{4} \leftarrow \}$$

$$br_{4} = \{train_{4} \leftarrow (5 : want_sooner_{5})\}$$

$$kb_{5} = \{want_sooner_{5} \leftarrow soon_{5}\}$$

$$br_5 = \left\{ soon_5 \leftarrow (4 : train_4) \right\}$$







2

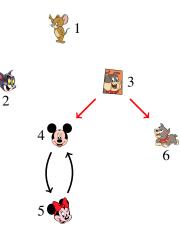




- Spike is responsible for buying provisions, if they go by train.
- If his son Tyke is sick, then Spike must attend to him as fast as possible.

$$kb_{3} = \begin{cases} car_{3} \lor train_{3} \leftarrow \\ train_{3} \leftarrow urgent_{3} \\ sandwiches_{3} \lor chocolate_peanuts_{3} \leftarrow train_{3} \\ coke_{3} \lor juice_{3} \leftarrow train_{3} \end{cases}$$
$$br_{3} = \begin{cases} urgent_{3} \leftarrow (6:sick_{6}) \\ train_{3} \leftarrow (4:train_{4}) \end{cases};$$

$$kb_6 = \left\{ sick_6 \lor fit_6 \leftarrow \right\}$$
$$br_6 = \emptyset.$$

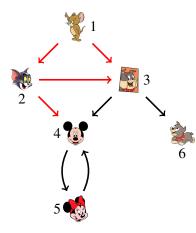




- Jerry is the leader of the group.
- Jerry is allergic to peanuts.
- Tom wants to get home somehow and doesn't want coke.

$$kb_{1} = \begin{cases} car_{1} \leftarrow not \ train_{1} \\ \perp \leftarrow peanuts_{1} \end{cases}$$
$$br_{1} = \begin{cases} train_{1} \leftarrow (2 : train_{2}), (3 : train_{3}) \\ peanuts_{1} \leftarrow (3 : chocolate_peanuts_{3}) \end{cases}$$

$$kb_{2} = \{ \perp \leftarrow not \, car_{2}, not \, train_{2} \} \text{ and} \\ br_{2} = \begin{cases} car_{2} \leftarrow (3 : car_{3}), (4 : car_{4}) \\ train_{2} \leftarrow (3 : train_{3}), (4 : train_{4}), \\ not \ (3 : coke_{3}) \end{cases} \end{cases}$$

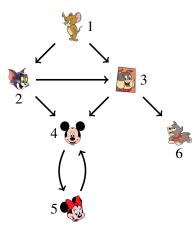




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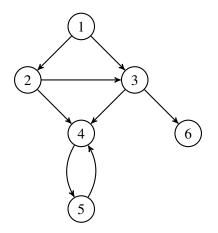
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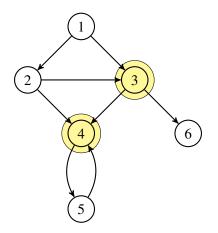
One equilibrium is $S = ({train_1}, {train_2}, {train_3, urgent_3, juice_3, sandwiches_3}, {train_4}, {soon_5, want_sooner_5}, {sick_6})$





Jerry decides after gathering information.

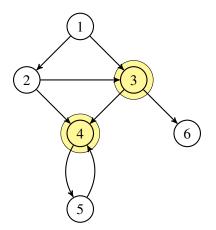




- Jerry decides after gathering information.
- Mickey and Spike do not want to bother the others.



MCS Decomposition: Cut vertex



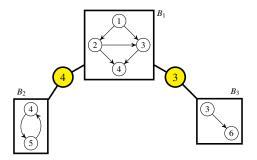
A vertex *c* of a weakly connected graph *G* is a *cut vertex*, if $G \setminus c$ is disconnected



Based on cut vertices, we can decompose the MCS into a *block tree*: provides a "high-level" view of the dependencies (edge partitioning)



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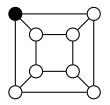


- ▶ *B*¹ induced by {1,2,3,4}
- ▶ *B*² induced by {4,5}
- ▶ *B*₃ induced by {3,6}

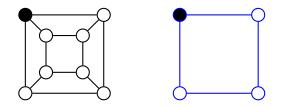


cycle breaking by creating a spanning tree of a cyclic MCS

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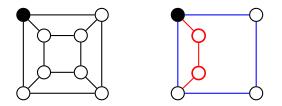


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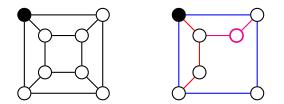
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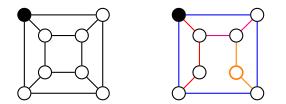
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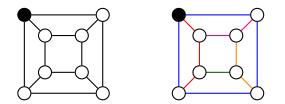
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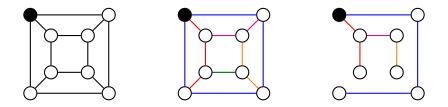
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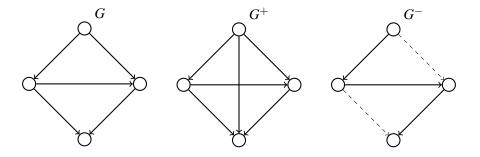


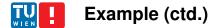
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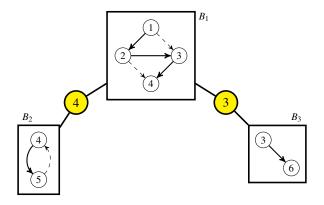
cycle breaker edges cb(G, P): remove last edge from each path P_i in G

Optimization: Avoid Unnecessary Calls

transitive reduction of a digraph G is the graph G^- with the smallest set of edges whose transitive closure G^+ equals the one of G



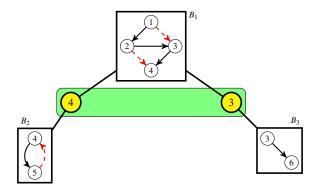




- B_1 : acyclic \rightarrow apply transitive reduction
- ► B₂: cyclic → apply ear decomposition, then apply transitive reduction (already reduced)
- B₃: acyclic and already reduced



Optimization: Minimal Interface

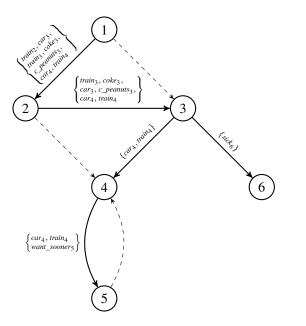


In a pruned block B', take all variables from

- the minimal interface in B'
- child cut vertices c
- removed edges E

Outcome: query plan for the MCS to restrict calls and partial belief states







- Operate on the (optimized) query plan
- Does not need to break cycle
- Proceed on the leaf and intermediate cases almost similar to DMCS
- …Except: guessing for removed edges because of cycles

Motivation for Streaming Models in MCS

For large context knowledge bases, we still face scalability issues:

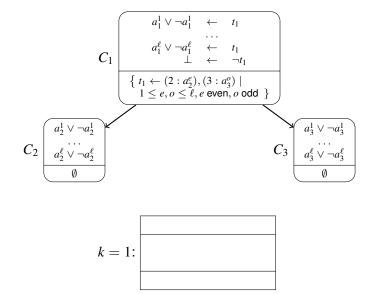
- potentially many models: exhaust memory at combination- or at solving-time
- synchronous evaluation (one context may block the parent)
- this is mainly due to computing all (partial) equilibria

Motivation for Streaming Models in MCS

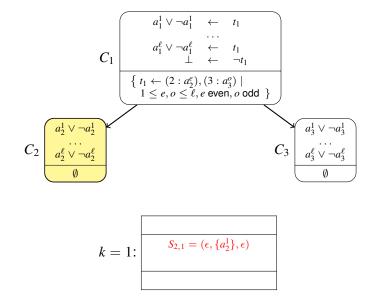
For large context knowledge bases, we still face scalability issues:

- potentially many models: exhaust memory at combination- or at solving-time
- synchronous evaluation (one context may block the parent)
- this is mainly due to computing all (partial) equilibria
- Idea: Adapt existing algorithms with streaming mode:
 - request at most k partial equilibria (obtain some instead of all answers)
 - allow for asynchronous communication
 - allow to request further partial equilibria: communication in multiple rounds











$$C_{1} \qquad \begin{array}{c} a_{1}^{1} \lor \neg a_{1}^{1} \leftarrow t_{1} \\ & \ddots \\ a_{1}^{\ell} \lor \neg a_{1}^{\ell} \leftarrow t_{1} \\ & \perp \leftarrow \neg t_{1} \\ \hline \\ f_{1} \leftarrow (2 : a_{2}^{e}), (3 : a_{3}^{o}) \mid \\ 1 \le e, o \le \ell, e \text{ even}, o \text{ odd } \end{array}$$

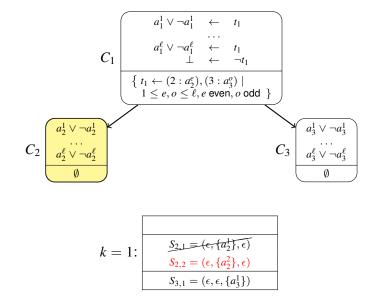
$$C_{2} \qquad \begin{array}{c} a_{2}^{1} \lor \neg a_{2}^{1} \\ \vdots \\ a_{2}^{\ell} \lor \neg a_{2}^{\ell} \\ \emptyset \end{array}$$

$$k = 1: \qquad \begin{array}{c} s_{2,1} = (\epsilon, \{a_{2}^{1}\}, \epsilon) \\ \hline \\ S_{3,1} = (\epsilon, \epsilon, \{a_{3}^{1}\}) \end{array}$$



$$C_{1} = \frac{a_{1}^{1} \vee \neg a_{1}^{1} \leftarrow t_{1}}{\sum_{\substack{a_{1}^{1} \vee \neg a_{1}^{1} \leftarrow t_{1} \\ \perp \leftarrow \neg t_{1} \\ \perp \leftarrow \neg t_{1}}} C_{1} = \frac{a_{1}^{1} \vee \neg a_{1}^{1}}{\sum_{\substack{a \in \neg \neg a_{1}^{2} \\ 1 \leq e, o \leq \ell, e \text{ even}, o \text{ odd } }}} C_{2} = C_{2} = \frac{a_{2}^{1} \vee \neg a_{2}^{1}}{\emptyset} = C_{3} = \frac{a_{3}^{1} \vee \neg a_{3}^{1}}{\sum_{\substack{a \in \neg \neg a_{2}^{1} \\ a_{3}^{1} \vee \neg a_{2}^{1} \\ 0 \end{bmatrix}}} C_{2} = \frac{a_{2}^{1} \vee \neg a_{2}^{1}}{\emptyset} = C_{3} = \frac{a_{3}^{1} \vee \neg a_{3}^{1}}{0} = C_{3} = \frac{a_{$$





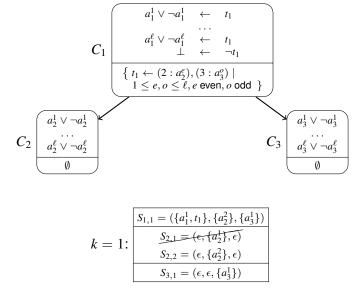


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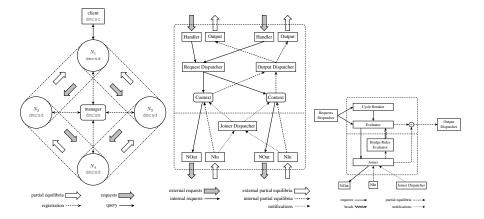
$$k = 1: \frac{S_{1,1} = (\{a_1^1, t_1\}, \{a_2^2\}, \{a_3^1\})}{S_{2,1} = (\epsilon, \{a_2^1\}, \epsilon)}$$
$$S_{2,2} = (\epsilon, \{a_2^2\}, \epsilon)$$
$$S_{3,1} = (\epsilon, \epsilon, \{a_3^1\})$$





Trade-off: recomputation!!!

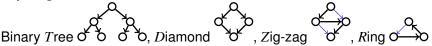






Experiments: Benchmark Setup

Topologies:



Other quantitative parameters:

- n: system size
- s: local theory size
- b: number of interface atoms
- r: maximal number of bridge rules

Local theories' structure:



A local theory has 2^m answer sets, where $m \in [0, s/2]$.



Parameter choice (based on some initial testing):

- n was chosen based on the topology:
 - $T: n \in \{7, 10, 15, 31, 70, 100\}$
 - $\blacktriangleright D: n \in \{4, 7, 10, 13, 25, 31\}$
 - $\blacktriangleright Z: n \in \{4, 7, 10, 13, 25, 31, 70\}$
 - $R: n \in \{4, 7, 10, 13, 70\}$

▶ *s*, *b*, *r* are fixed to either 10, 5, 5 or 20, 10, 10, respectively.



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Way to proceed:

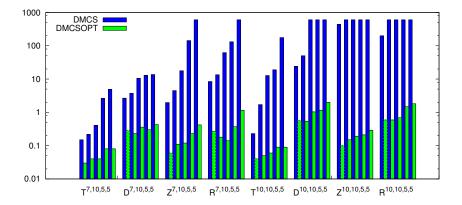
- test 5 instances per parameter setting
- run DMCS, DMCSOPT on non-streaming and streaming mode (DMCS-STREAMING)
- ▶ in streaming mode, run with different package sizes: 1,10,100
- measure:
 - total number of returned partial equilibria
 - total running time (in secs)
 - running time to get the first set of answers (in streaming mode)



- Comparing DMCS and DMCSOPT
- Comparing streaming and non-streaming modes
- Effect of the package size
- Role of the topologies

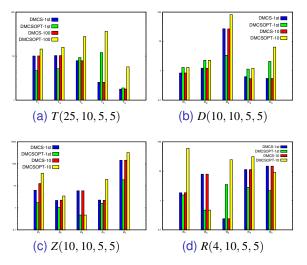


DMCS vs. DMCSOPT (non-streaming)





DMCS vs. DMCSOPT (streaming)

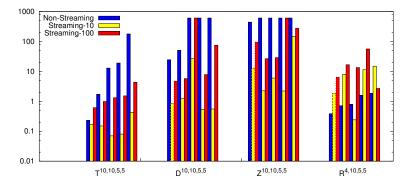


stream N partial equilibria: not a fair comparison due to projection

first return: might have the above effect from intermediate contexts



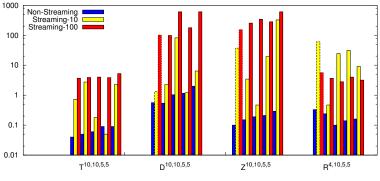
Streaming vs. Nonstreaming (DMCS)



- Streaming wins in most of the cases
- Ring behaves irregularly!



Streaming vs. Nonstreaming (DMCSOPT)

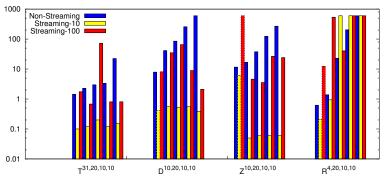


with small systems and local theories

Streaming loses because of recomputation



Streaming vs. Nonstreaming (DMCSOPT)

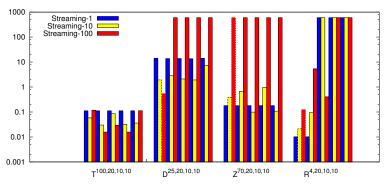


with large systems and local theories

- Streaming starts gaining back...
- ...but does not always win, again due to recomputation



Effect of the Package Size



Average time to find 1 partial equilibrium in streaming mode

- ▶ k = 1 looks ok, too large package size is not always a good idea
- Ring behaves irregularly



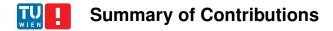
Topological aspects that affect the performance:

- (i) number of connections
- (ii) structure of block trees and cut vertices
- (iii) cyclicity

Observations:

$$T >_{\mathsf{DMCS}}^{(i,ii)} D >_{\mathsf{DMCS}}^{(i)} Z >_{\mathsf{DMCS}}^{(iii)} R$$

$$T >_{\text{DMCSOPT}}^{(i,ii)} Z >_{\text{DMCSOPT}}^{(ii)} D >_{\text{DMCSOPT}}^{(iii)} R$$



Exploration of an area that had not been considered before:

design, implement, and analyze truly distributed algorithms to evaluate partial equilibria of Heterogeneous Multi-Context Systems.



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- Algorithms DMCS, DMCSOPT, DMCS-STREAMING,
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Thus establish another step to bring MCSs to real life applications!



- Implementation issues for DMCS
- Grounding-on-the-fly for non-ground ASP-based MCS
- Conflict learning in DMCS
- Query answering in MCS
- Distributed Heterogeneous Stream Reasoning



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Thank you very much for your attention!



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