

# Answer Set Programming with External Sources: Algorithms and Efficient Evaluation

PhD Defense

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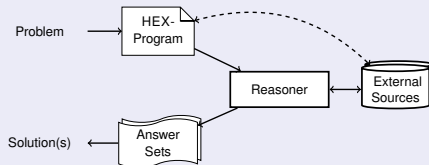


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# Motivation

## HEX-Programs

- Extend ASP by **external sources**:

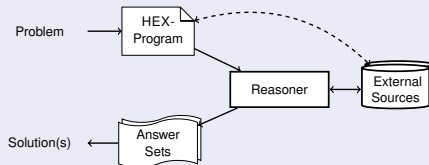


**Example:**  $p(X, Y) \leftarrow url(U), \&rdf[U](X, Y, Z)$

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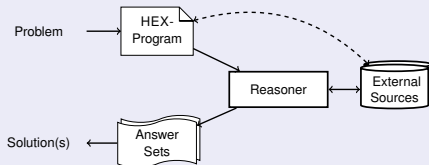
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- Traditional algorithm based on a **translation to ASP**  $\Rightarrow$  natural, **but ...**

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## Two Main Problems

- **Limited scalability** due to blind guessing
- **Restrictive syntactic conditions** due to use of an ordinary ASP grounder

# Motivation

## Applications of HEX-Programs

- Multi-context Systems
- **DL-programs** – Integration of ASP with ontologies
- Constraint ASP solving
- **ACTHEX** – Programs with action atoms
- Physics simulation (e.g. AngryBirds agent)
- Route planning
- ...

## Contributions

- New **genuine evaluation algorithms** based on **conflict-driven algorithms**  
⇒ significantly **better scalability**
- New **safety concept** and **grounding algorithm**  
⇒ **more convenience for the user**

# Outline

- 1 Motivation
- 2 HEX-Programs
- 3 Propositional HEX-Program Solving
  - Basic Evaluation Algorithm
  - Concrete Learning Functions
  - Minimality Check
- 4 Grounding and Domain Expansion
  - Liberal Domain-Expansion Safety
  - Grounding Algorithm
  - Evaluation Heuristics
- 5 The DLVHEX System
  - Implementation
  - Evaluation of the Learning-Based Algorithm
  - Evaluation of the Grounding Algorithm
- 6 Conclusion and Outlook

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# HEX-Programs

HEX-programs extend ordinary ASP programs by **external sources**

## Definition (HEX-programs)

A **HEX-program** consists of rules of form

$$a_1 \vee \dots \vee a_n \leftarrow b_1, \dots, b_m, \text{not } b_{m+1}, \dots, \text{not } b_n,$$

with classical literals  $a_i$ , and classical literals or an external atoms  $b_j$ .

## Definition (External Atoms)

An **external atom** is of the form

$$\&p[q_1, \dots, q_k](t_1, \dots, t_l),$$

$p$  ... external predicate name

$q_i$  ... predicate names or constants

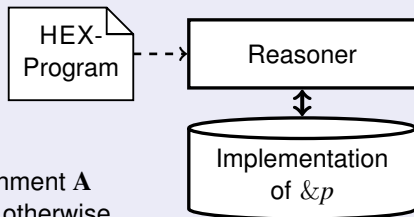
$t_j$  ... terms

Semantics:

$1 + k + l$ -ary Boolean **oracle function**  $f_{\&p}$ :

$\&p[q_1, \dots, q_k](t_1, \dots, t_l)$  is *true* under assignment  $\mathbf{A}$

if  $f_{\&p}(\mathbf{A}, q_1, \dots, q_k, t_1, \dots, t_l) = 1$  and *false* otherwise.





# HEX-Programs

## Definition (Answer Set)

An interpretation  $\mathbf{A}$  is an **answer set** of program  $\Pi$  if it is a subset-minimal model of the FLP-reduct  $f\Pi^{\mathbf{A}} = \{r \in \Pi \mid \mathbf{A} \models B(r)\}$  [Faber et al., 2011].

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## Example

$\&diff[p, q](X)$ : all elements  $X$ , which are in the extension of  $p$  but not of  $q$ :

$$\begin{aligned}
 dom(X) &\leftarrow \#int(X) \\
 n(X) &\leftarrow dom(X), \&diff[dom, s](X) \\
 s(X) &\leftarrow dom(X), \&diff[dom, n](X) \\
 &\leftarrow s(X1), s(X2), s(X3), X1 \neq X2, X1 \neq X3, X2 \neq X3
 \end{aligned}$$

# Traditional Evaluation Method

## Evaluating Program $\Pi$

- 1 Replace external atoms  $\&g[\vec{y}](\vec{x})$  by ordinary ones  $e_{\&g[\vec{y}]}(\vec{x})$  and guess their values  $\Rightarrow$  guessing program  $\hat{\Pi}$
- 2 For each candidate, check if it is a compatible set
- 3 If yes: check if it is also a subset-minimal model of the reduct

## Definition (Compatible Set)

A compatible set of a program  $\Pi$  is an assignment  $\hat{\mathbf{A}}$

- (i) which is an answer set [Gelfond and Lifschitz, 1991] of  $\hat{\Pi}$ ; and
- (ii)  $f_{\&g}(\hat{\mathbf{A}}, \vec{y}, \vec{x}) = 1$  if  $\mathbf{Te}_{\&g[\vec{y}]}(\vec{x}) \in \hat{\mathbf{A}}$  and  $f_{\&g}(\hat{\mathbf{A}}, \vec{y}, \vec{x}) = 0$  otherwise for all external atoms  $\&g[\vec{y}](\vec{x})$  in  $\Pi$ .

# Traditional Evaluation Method

## Example

HEX-Program  $\Pi$ :

$$\begin{aligned} & p(c_1); \text{dom}(c_1); \text{dom}(c_2); \text{dom}(c_3) \\ & p(X) \leftarrow \text{dom}(X), \&empty[p](X) \end{aligned}$$

$\&empty[p](t)$  with  $t = c_1$  ( $t = c_2$ ) is true iff<sub>def</sub> extension of  $p$  is empty (not empty)

Guessing program  $\hat{\Pi}$ :

$$\begin{aligned} & p(c_1); \text{dom}(c_1); \text{dom}(c_2); \text{dom}(c_3) \\ & p(X) \leftarrow \text{dom}(X), e_{\&empty[p]}(X) \\ & e_{\&empty[p]}(X) \vee \neg e_{\&empty[p]}(X) \leftarrow \text{dom}(X) \end{aligned}$$

8 candidates, e.g.:

$$\begin{aligned} & \{\mathbf{T}p(c_1), \mathbf{T}p(c_2), \mathbf{T}dom(c_1), \mathbf{T}dom(c_2), \mathbf{T}dom(c_3), \\ & \mathbf{F}e_{\&empty[p]}(c_1), \mathbf{T}e_{\&empty[p]}(c_2), \mathbf{F}e_{\&empty[p]}(c_3)\} \end{aligned}$$

Compatibility check: **passed**  $\Rightarrow$  **compatible set**

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# Algorithm for Ground HEX-Program Evaluation

## Conflict-Driven Nogood Learning in ASP

- Successful SAT-solving technique adopted to ASP [Drescher et al., 2008]
- Program  $\hat{\Pi}$  is represented as a **set of nogoods**
- Derive additional nogoods from **conflicts**

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## Conflict-Driven Nogood Learning in ASP

- Successful SAT-solving technique adopted to ASP [Drescher et al., 2008]
- Program  $\hat{\Pi}$  is represented as a **set of nogoods**
- Derive additional nogoods from **conflicts**

## Idea

- Learn **additional nogoods** from external source evaluation
- Defined as **learning functions** of kind

$$\Lambda: \mathcal{E} \times 2^{\mathcal{D}(\Pi)} \mapsto 2^{2^{\mathcal{D}(\Pi)}}$$

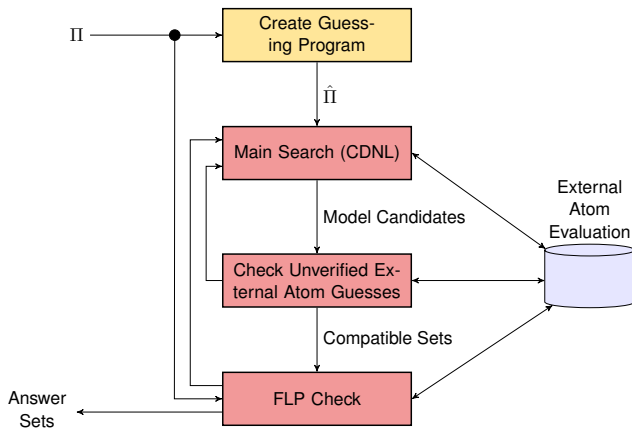
where

$\mathcal{E}$  ... set of all external predicates with input list in  $\Pi$

$\mathcal{D}(\Pi)$  ... set of all signed literals

- Concept of **correctness of learning functions** wrt. a program

# Overall Algorithm





## Algorithm Hex-Eval

**Input:** A HEX-program  $\Pi$ **Output:** All answer sets of  $\Pi$  $\hat{\Pi} \leftarrow \Pi$  with all external atoms  $\&g[\vec{y}]$  replaced by  $e_{\&g[\vec{y}]}(\vec{x})$ Add guessing rules for all replacement atoms to  $\hat{\Pi}$  $\nabla \leftarrow \emptyset$  // set of dynamic nogoods $S \leftarrow \emptyset$  // set of all compatible sets**while**  $\hat{C} \neq \perp$  **do** $\hat{C} \leftarrow \perp$  $inconsistent \leftarrow false$ **while**  $\hat{C} = \perp$  **and**  $inconsistent = false$  **do** $\hat{A} \leftarrow \text{Hex-CDNL}(\Pi, \hat{\Pi}, \nabla)$ **if**  $\hat{A} = \perp$  **then** $inconsistent \leftarrow true$ **else** $compatible \leftarrow true$ **for all external atoms with input list**  $\&g[\vec{y}]$  **in**  $\Pi$  **do**Evaluate  $\&g[\vec{y}]$  under  $\hat{A}$  $\nabla \leftarrow \nabla \cup \Lambda(\&g[\vec{y}], \hat{A})$ Let  $\hat{A}[\&g[\vec{y}]](\vec{x}) = 1 \Leftrightarrow Te_{\&g[\vec{y}]}(\vec{x}) \in \hat{A}$ **if**  $\exists \vec{x} : f_{\&g}(\hat{A}, \vec{y}, \vec{x}) \neq \hat{A}[\&g[\vec{y}]](\vec{x})$  **then** $\text{Add } \hat{A} \text{ to } \nabla$  $\text{Set } compatible \leftarrow false$ **if**  $compatible$  **then**  $\hat{C} \leftarrow \hat{A}$ **if**  $inconsistent = false$  **then**//  $\hat{C}$  is a compatible set of  $\Pi$  $\nabla \leftarrow \nabla \cup \{\hat{C}\}$ **if**  $FLPCheck(\Pi, \hat{C}, \nabla)$  **then** $S \leftarrow S \cup \{\hat{C}\}$ **return**  $\{\{Ta \in \hat{C} \mid a \in A(\Pi)\} \mid \hat{C} \in S\}$ 

## Algorithm Hex-CDNL

**Input:** A program  $\Pi$ , its guessing program  $\hat{\Pi}$ , a set of correct nogoods  $\nabla$  of  $\Pi$ **Output:** An answer set of  $\hat{\Pi}$  (candidate for a compatible set of  $\Pi$ ) which is a solution to all nogoods  $d \in \nabla$ , or  $\perp$  if none exists $A \leftarrow \emptyset$  // assignment over  $A(\hat{\Pi}) \cup BA(\hat{\Pi}) \cup BA(sh(\hat{\Pi}))$  $dl \leftarrow 0$  // decision level**while**  $true$  **do** $(A, \nabla) \leftarrow \text{Propagation}(\hat{\Pi}, \nabla, A)$ **if**  $\delta \subseteq A$  **for some**  $\delta \in \Delta_{\hat{\Pi}} \cup \Theta_{sh(\hat{\Pi})} \cup \nabla$  **then****if**  $dl = 0$  **then** **return**  $\perp$  $(\epsilon, k) \leftarrow \text{Analysis}(\delta, \hat{\Pi}, \nabla, A)$  $\nabla \leftarrow \nabla \cup \{\epsilon\}$  $A \leftarrow A \setminus \{\sigma \in A \mid k < dl(\sigma)\}$  $dl \leftarrow k$ **else if**  $A^T \cup A^F = A(\hat{\Pi}) \cup BA(\hat{\Pi}) \cup BA(sh(\hat{\Pi}))$  **then** $U \leftarrow \text{UnfoundedSet}(\hat{\Pi}, A)$ **if**  $U \neq \emptyset$  **then**let  $\delta \in \lambda_{\hat{\Pi}}(U)$  such that  $\delta \subseteq A$ **if**  $\{\sigma \in \delta \mid 0 < dl(\sigma)\} = \emptyset$  **then** **return**  $\perp$  $(\epsilon, k) \leftarrow \text{Analysis}(\delta, \hat{\Pi}, \nabla, A)$  $\nabla \leftarrow \nabla \cup \{\epsilon\}$  $A \leftarrow A \setminus \{\sigma \in A \mid k < dl(\sigma)\}$  $dl \leftarrow k$ **else****return**  $A^T \cap A(\hat{\Pi})$ **else if** *Heuristic decides to evaluate*  $\&g[\vec{p}]$  **then**Evaluate  $\&g[\vec{p}]$  under  $A$  and set  $\nabla \leftarrow \nabla \cup \Lambda(\&g[\vec{p}], A)$ **else if** *Heuristic decides to do a UFS check* **then**Let  $\Pi' \subseteq \Pi$  s.t.  $\hat{A}$  is complete and compatible over  $\hat{\Pi}'$  $FLPCheck(\Pi', A, \nabla)$ **else** $\sigma \leftarrow \text{Select}(\hat{\Pi}, \nabla, A)$  $dl \leftarrow dl + 1$  $A \leftarrow A \circ (\sigma)$

# Algorithm for Ground HEX-Program Evaluation

Restricting to learning functions that are correct for  $\Pi$ , the following results hold.

## Proposition

*If for input  $\Pi$ ,  $\hat{\Pi}$  and  $\nabla$ , Algorithm Hex-CDNL returns*

- (i) an interpretation  $\mathbf{A}$ , then  $\mathbf{A}$  is an answer set of  $\hat{\Pi}$  and a solution to  $\nabla$ ;*
- (ii)  $\perp$ , then  $\Pi$  has no compatible set that is a solution to  $\nabla$ .*

## Theorem (Soundness and Completeness of Algorithm Hex-Eval)

*Algorithm Hex-Eval computes all answer sets of  $\Pi$ .*

# Concrete Learning Functions: Uninformed Learning

**Idea:** learn that input implies output

## Definition

The learning function for a general external predicate with input list  $\&g[\vec{p}]$  in program  $\Pi$  under assignment  $\mathbf{A}$  is defined as

$$\Lambda_g(\&g[\vec{p}], \mathbf{A}) = \{ \mathbf{A}|_{\vec{p}} \cup \{ \mathbf{Fe}_{\&g[\vec{y}]}(\vec{x}) \} \mid \vec{x} \in \text{ext}(\&g[\vec{y}], \mathbf{A}) \}$$

## Example

$\&diff[p, q](X)$  with  $\text{ext}(p, \mathbf{A}) = \{a, b\}$ ,  $\text{ext}(q, \mathbf{A}) = \{a, c\}$

Learn:  $\{ \mathbf{Tp}(a), \mathbf{Tp}(b), \mathbf{Fp}(c), \mathbf{Tq}(a), \mathbf{Fq}(b), \mathbf{Tq}(c), \mathbf{Fe}_{\&diff[p, q]}(b) \}$

## Lemma

*For all assignments  $\mathbf{A}$ , the nogoods  $\Lambda_g(\&g[\vec{p}], \mathbf{A})$  are correct wrt.  $\Pi$ .*

# Concrete Learning Functions: Monotonicity

**Idea:** learn that parts of the input imply output

## Definition

The learning function for an external predicate  $\&g$  with input list  $\vec{p}$  in program  $\Pi$  under assignment  $\mathbf{A}$ , such that  $\&g$  is monotonic in  $\vec{p}_m \subseteq \vec{p}$ , is defined as

$$\Lambda_m(\&g[\vec{p}], \mathbf{A}) = \left\{ \left\{ \mathbf{T}a \in \mathbf{A}|_{\vec{p}_m} \right\} \cup \mathbf{A}|_{\vec{p}_n} \cup \left\{ \mathbf{F}e_{\&g[\vec{y}]}(\vec{x}) \right\} \mid \vec{c} \in \text{ext}(\&g[\vec{y}], \mathbf{A}) \right\}$$

## Example

$\&xdiff[p, q](X)$  with  $\text{ext}(p, \mathbf{A}) = \{a, b\}$ ,  $\text{ext}(q, \mathbf{A}) = \{a, c\}$ , monotonic in  $p$

Learn:  $\left\{ \mathbf{T}p(a), \mathbf{T}p(b), \mathbf{T}q(a), \mathbf{F}q(b), \mathbf{T}q(c), \mathbf{F}e_{\&xdiff[p, q]}(b) \right\}$

## Lemma

For all assignments  $\mathbf{A}$ , the nogoods  $\Lambda_m(\&g[\vec{p}], \mathbf{A})$  are correct wrt.  $\Pi$ .

# Minimality of Answer Sets

## Recall

An interpretation  $\mathbf{A}$  is an **answer set** of program  $\Pi$  if it is a subset-minimal model of the FLP reduct  $f\Pi^{\mathbf{A}} = \{r \in \Pi \mid \mathbf{A} \models B(r)\}$ .

## 2-Step Algorithm

- 1 Compute a **compatible set** (=answer set candidate) [Eiter et al., 2012]
- 2 Check minimality

## Traditional Approach

- 1 Given a compatible set
- 2 Explicitly construct the **reduct**
- 3 Search for smaller models

# Minimality of Answer Sets

## Example

Let  $\Pi$  be the following program:

$$dom(a); dom(b)$$

$$p(a) \leftarrow dom(a), \&g[p](a)$$

$$p(b) \leftarrow dom(b), \&g[p](b)$$

Let  $\&g$  implement the mapping:  $\emptyset \mapsto \{b\}; \{a\} \mapsto \{a\}; \{b\} \mapsto \emptyset; \{a, b\} \mapsto \{a, b\}$

Guessing program  $\hat{\Pi}$ :

$$dom(a); dom(b)$$

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4 candidates, e.g.:  $\{\mathbf{T}dom(a), \mathbf{T}dom(b), \mathbf{T}p(a), \mathbf{T}e_{\&g[p]}(a)\}$

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→ **passes** compatibility check but **fails** minimality check



# Using Unfounded Sets [Faber, 2005]

## Definition (Unfounded Set)

A set of atoms  $U$  is an **unfounded set** of  $\Pi$  wrt. (partial) assignment  $\mathbf{A}$ , if for all  $a \in U$  and all  $r \in \Pi$  with  $a \in H(r)$  at least one of the following holds:

- 1  $\mathbf{A} \not\models B(r)$
- 2  $\mathbf{A} \dot{\cup} \neg.U \not\models B(r)$
- 3  $\mathbf{A} \models h$  for some  $h \in H(r) \setminus U$

(where  $\mathbf{A} \dot{\cup} \neg.U = (\mathbf{A} \setminus \{\mathbf{T}a \mid a \in U\}) \cup \{\mathbf{F}a \mid a \in U\}$ )

## Definition (Unfounded-Free Assignments)

An assignment  $\mathbf{A}$  is **unfounded-free** wrt. program  $\Pi$ , if there is no unfounded set  $U$  of  $\Pi$  wrt.  $\mathbf{A}$  such that  $\mathbf{T}a \in \mathbf{A}$  for some  $a \in U$ .

## Theorem

*A model  $\mathbf{A}$  of a program  $\Pi$  is an answer set iff it is unfounded-free.*

# Using Unfounded Sets

Encode the search for unfounded sets as SAT instance

## Unfounded Set Search Problem – Basic Encoding

**Nogood Set**  $\Gamma_{\Pi, \mathbf{A}} = \Gamma_{\Pi, \mathbf{A}}^N \cup \Gamma_{\Pi, \mathbf{A}}^O$  over atoms  $A(\hat{\Pi}) \cup \{h_r, l_r \mid r \in \Pi\}$  consisting of a **necessary part**  $\Gamma_{\Pi, \mathbf{A}}^N$  and an **optimization part**  $\Gamma_{\Pi, \mathbf{A}}^O$

- $\Gamma_{r, \mathbf{A}}^R = \Gamma_{r, \mathbf{A}}^H \cup \Gamma_{r, \mathbf{A}}^C$
- $\Gamma_{r, \mathbf{A}}^H = \left\{ \{\mathbf{T}h_r\} \cup \{\mathbf{F}h \mid h \in H(r)\} \right\} \cup \left\{ \{\mathbf{F}h_r, \mathbf{T}h\} \mid h \in H(r) \right\}$
- $\Gamma_{r, \mathbf{A}}^C = \begin{cases} \left\{ \{\mathbf{T}h_r\} \cup \right. \\ \quad \left. \{\mathbf{F}a \mid a \in B_o^+(r), \mathbf{A} \models a\} \cup \{\mathbf{t}a \mid a \in B_e(\hat{r})\} \cup \right. \\ \quad \left. \{\mathbf{T}h \mid h \in H(r), \mathbf{A} \models h\} \right\} & \text{if } \mathbf{A} \models B(r), \\ \emptyset & \text{otherwise} \end{cases}$

**Intuition:** solutions of  $\Gamma_{\Pi, \mathbf{A}}$  correspond to **potential** unfounded sets of  $\Pi$  wrt.  $\mathbf{A}$

# Using Unfounded Sets

Each unfounded set corresponds to a solution of  $\Gamma_{\Pi, \mathbf{A}}$

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Formally:

## Proposition

*Let  $U$  be an unfounded set of a program  $\Pi$  wrt. assignment  $\mathbf{A}$  such that  $\mathbf{A}^T \cap U \neq \emptyset$ . Then  $I_\Gamma(U, \Gamma_{\Pi, \mathbf{A}}, \Pi, \mathbf{A})$  is a solution to  $\Gamma_{\Pi, \mathbf{A}}$ .*

where  $I_\Gamma(U, \Gamma_{\Pi, \mathbf{A}}, \Pi, \mathbf{A})$  is defined as follows:

## Definition (Induced Assignment of an Unfounded Set wrt. $\Gamma_{\Pi, \mathbf{A}}$ )

Let  $U$  be an unfounded set of a program  $\Pi$  wrt. assignment  $\mathbf{A}$ . The *assignment induced by  $U$  wrt.  $\Gamma_{\Pi, \mathbf{A}}$* , denoted  $I_\Gamma(U, \Gamma_{\Pi, \mathbf{A}}, \Pi, \mathbf{A})$ , is

$$I_\Gamma(U, \Gamma_{\Pi, \mathbf{A}}, \Pi, \mathbf{A}) = I_\Gamma^0(U, \Pi, \mathbf{A}) \cup \{\mathbf{F}a \mid a \in A(\Gamma_{\Pi, \mathbf{A}}), \mathbf{T}a \notin I_\Gamma^0(U, \Pi, \mathbf{A})\},$$

where

$$I_\Gamma^0(U, \Pi, \mathbf{A}) = \{\mathbf{T}a \mid a \in U\} \cup \{\mathbf{T}h_r \mid r \in \Pi, H(r) \cap U \neq \emptyset\} \cup \{\mathbf{T}e_{\&g[\vec{y}]}(\vec{x}) \mid e_{\&g[\vec{y}]}(\vec{x}) \in A(\hat{\Pi}), \mathbf{A} \dot{\cup} \neg.U \models \&g[\vec{y}](\vec{x})\}.$$

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**Not** every solution of  $\Gamma_{\Pi, A}$  corresponds to an unfounded set, but ...

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## Proposition

*Let  $S$  be a solution to  $\Gamma_{\Pi, \mathbf{A}}$  such that*

*(a)  $\mathbf{T}e_{\&[\vec{y}]}(\vec{x}) \in S$  and  $\mathbf{A} \not\models \&[\vec{p}](\vec{c})$  implies  $\mathbf{A} \dot{\cup} \neg.U \models \&[\vec{y}](\vec{x})$ ; and*

*(b)  $\mathbf{F}e_{\&[\vec{y}]}(\vec{x}) \in S$  and  $\mathbf{A} \models \&[\vec{p}](\vec{c})$  implies  $\mathbf{A} \dot{\cup} \neg.U \not\models \&[\vec{y}](\vec{x})$ ,*

*where  $U = \{a \mid a \in A(\Pi), \mathbf{T}a \in S\}$ . Then  $U$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ .*

# Using Unfounded Sets

**Not** every solution of  $\Gamma_{\Pi, \mathbf{A}}$  corresponds to an unfounded set, but ...

## Proposition

Let  $S$  be a solution to  $\Gamma_{\Pi, \mathbf{A}}$  such that

- (a)  $\mathbf{T}e_{\&[\vec{y}]}(\vec{x}) \in S$  and  $\mathbf{A} \not\models \&[\vec{p}](\vec{c})$  implies  $\mathbf{A} \dot{\cup} \neg.U \models \&[\vec{y}](\vec{x})$ ; and
  - (b)  $\mathbf{F}e_{\&[\vec{y}]}(\vec{x}) \in S$  and  $\mathbf{A} \models \&[\vec{p}](\vec{c})$  implies  $\mathbf{A} \dot{\cup} \neg.U \not\models \&[\vec{y}](\vec{x})$ ,
- where  $U = \{a \mid a \in A(\Pi), \mathbf{T}a \in S\}$ . Then  $U$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ .

Therefore:

## Our Approach

- 1 Compute a solution  $S$  of  $\Gamma_{\Pi, \mathbf{A}}$
- 2 Check if post-conditions (a) and (b) hold for  $S$
- 3 If yes:  $S$  represents an unfounded set  
If no: goto 1 and continue with next solution of  $\Gamma_{\Pi, \mathbf{A}}$

# Optimization and Learning

## Optimization

- Generate **additional nogoods**  $\Gamma_{\Pi, A}^O$  to prune search space
- **Advanced encoding**  $\Omega_{\Pi}$  which is **reusable for all compatible sets**

## Learning

- **Nogood exchange**: search for compatible sets  $\leftrightarrow$  UFS search
- Learn nogoods from **detected unfounded sets**

## Decision Criterion

- Ordinary ASP solver has already performed a UFS-check
- For some programs this is sufficient
- **Criterion**: positive cycles through external atoms (**e-cycles**)



# Outline

- 1 Motivation
- 2 HEX-Programs
- 3 Propositional HEX-Program Solving
  - Basic Evaluation Algorithm
  - Concrete Learning Functions
  - Minimality Check
- 4 **Grounding and Domain Expansion**
  - Liberal Domain-Expansion Safety
  - Grounding Algorithm
  - Evaluation Heuristics
- 5 The DLVHEX System
  - Implementation
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# Liberal Safety: Motivation

## Safety in HEX-Programs

- Ordinary safety **not** sufficient due to **value invention**
- Current notion of **strong safety**: **no value invention** by cyclic external atoms
- But: **unnecessarily restrictive**

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$$\Pi = \{p(\text{hexhex}); p(Y) \leftarrow p(X), \&tail[X](Y)\}$$

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## Example

$$\Pi = \{p(\text{hexhex}); p(Y) \leftarrow p(X), \text{tail}[X](Y)\}$$

## Contribution

- New **more liberal safety criteria**
- Still guarantee **finite groundability**
- Based on a **modular framework**  $\Rightarrow$  **extensibility of the approach**

# Liberal Safety

## Monotone Grounding Operator

$$G_{\Pi}(\Pi') = \bigcup_{r \in \Pi} \{r\theta \mid \mathbf{A} \subseteq \mathcal{A}(\Pi'), \mathbf{A} \not\models \perp, \mathbf{A} \models B^+(r\theta)\},$$

where  $\mathcal{A}(\Pi') = \{\mathbf{T}a, \mathbf{F}a \mid a \in A(\Pi')\} \setminus \{\mathbf{F}a \mid a \leftarrow . \in \Pi\}$   
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Program  $\Pi$ :

$$\begin{aligned} r_1 &: s(a); & r_2 &: \text{dom}(ax); & r_3 &: \text{dom}(axx) \\ r_4 &: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y) \end{aligned}$$

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# Liberal Safety

## Two Concepts

- A **term** is **bounded** if  $G_{\Pi}(\Pi')$  contains only finitely many substitutions for it
- An **attribute** is **de-safe** if  $G_{\Pi}(\Pi')$  contains only finitely many values at this attribute position

## Idea

- 1 Start with empty set of **bounded terms**  $B_0$  and **de-safe attributes**  $S_0$
- 2 For all  $n \geq 0$  until  $B_n$  and  $S_n$  do not change anymore
  - a Identify additional bounded terms  $\Rightarrow B_{n+1}$   
(assuming that  $B_n$  are bounded and  $S_n$  are de-safe)
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Step 2a realized by **term bounding functions (TBFs)**  $b(\Pi, r, S, B)$

$\Rightarrow$  TBFs are **a flexible means** that however must fulfill certain **conditions**

# Liberal Safety: Modularity

Modular composition of TBFs:

## Proposition

*If  $b_i(\Pi, r, S, B)$ ,  $1 \leq i \leq \ell$ , are TBFs,  
then  $b(\Pi, r, S, B) = \bigcup_{1 \leq i \leq \ell} b_i(\Pi, r, S, B)$  is a TBF.*

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Operator  $G$  is a **witness** for **finite groundability**:

## Proposition

*If  $\Pi$  is a de-safe program, then  $G_{\Pi}^{\infty}(\emptyset)$  is finite.*

## Theorem (Finite Restrictability of DE-Safe Programs)

*Let  $\Pi$  be a de-safe program. Then  $\Pi$  is finitely restrictable and  $G_{\Pi}^{\infty}(\emptyset) \equiv^{pos} \Pi$ .*

The results hold for **any** TBF!

# Liberal Safety: Relations to Other Notions

We defined a TBF  $b_{synsem} = b_{syn}(\Pi, r, S, B) \cup b_{sem}(\Pi, r, S, B)$

Using TBF  $b_{synsem}$ , de-safety is strictly **more general** than many other approaches:

## Theorem

*Every strongly de-safe [Eiter et al., 2006] program is de-safe.*

## Theorem

*Every VI-restricted program [Calimeri et al., 2007] is de-safe.*

## Theorem

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**Further techniques** can often be integrated by customized TBFs!



# Grounding Algorithm

## Algorithm GroundHEX

**Input:** A liberally de-safe HEX-program  $\Pi$

**Output:** A ground HEX-program  $\Pi_g$  s.t.  $\Pi_g \equiv \Pi$

Choose a set  $R$  of *de-safety-relevant* external atoms in  $\Pi$

$\Pi_p \leftarrow \Pi \cup \{r_{inp}^a \mid a = \&g[\vec{Y}](\vec{X}) \text{ in } r \in \Pi\} \cup \{r_{guess}^a \mid a = \&g[\vec{Y}](\vec{X}) \notin R\}$

Replace all external atoms  $\&g[\vec{Y}](\vec{X})$  in all rules  $r$  in  $\Pi_p$  by  $e_{r, \&g[\vec{Y}]}(\vec{X})$

**repeat**

$\Pi_{pg} \leftarrow \text{GroundASP}(\Pi_p)$  // partial grounding

// evaluate all de-safety-relevant external atoms

**for**  $a = \&g[\vec{Y}](\vec{X}) \in R$  **in a rule**  $r \in \Pi$  **do**

$\mathbf{A}_{ma} \leftarrow \{\mathbf{T}p(\vec{c}) \mid a(\vec{c}) \in A(\Pi_{pg}), p \in \vec{Y}_m\} \cup \{\mathbf{F}p(\vec{c}) \mid a(\vec{c}) \in A(\Pi_{pg}), p \in \vec{Y}_a\}$

// do this under all relevant assignments

**for**  $\mathbf{A}_{nm} \subseteq \{\mathbf{T}p(\vec{c}), \mathbf{F}p(\vec{c}) \mid p(\vec{c}) \in A(\Pi_{pg}), p \in \vec{Y}_n\}$  **s.t.**  $\nexists a : \mathbf{T}a, \mathbf{F}a \in \mathbf{A}_{nm}$  **do**

$\mathbf{A} \leftarrow (\mathbf{A}_{ma} \cup \mathbf{A}_{nm} \cup \{\mathbf{T}a \mid a \leftarrow \cdot \in \Pi_{pg}\}) \setminus \{\mathbf{F}a \mid a \leftarrow \cdot \in \Pi_{pg}\}$

**for**  $\vec{y} \in \{\vec{c} \mid r_{inp}^a(\vec{c}) \in A(\Pi_{pg})\}$  **do**

$O \leftarrow \{\vec{x} \mid f_{\&g}(\mathbf{A} \cup \mathbf{A}_{nm}, \vec{y}, \vec{x}) = 1\}$

// add the respective ground guessing rules

$\Pi_p \leftarrow \Pi_p \cup \{e_{r, \&g[\vec{Y}]}(\vec{x}) \vee ne_{r, \&g[\vec{Y}]}(\vec{x}) \leftarrow \cdot \mid \vec{x} \in O\}$

**until**  $\Pi_{pg}$  *did not change*

Remove input auxiliary rules and external atom guessing rules from  $\Pi_{pg}$

Replace all  $e_{\&g[\vec{Y}]}(\vec{x})$  in  $\Pi$  by  $\&g[\vec{Y}](\vec{x})$

**return**  $\Pi_{pg}$

# Program Decomposition

## Traditional HEX-Algorithms

- Program decomposition sometimes **necessary**
- Intuition: program is split **whenever value invention may occur**

## Example

Program II:

$$\begin{aligned} f: d(a); d(b); d(c); \quad & r_1: s(Y) \leftarrow \&diff[d, n](Y), d(Y) \\ & r_2: n(Y) \leftarrow \&diff[d, s](Y), d(Y) \\ & r_3: c(Z) \leftarrow \&count[s](Z) \end{aligned}$$

needs to be partitioned into evaluation units

$$\mathbf{1} \quad u_1 = \{f, r_1, r_2\}$$

$$\mathbf{2} \quad u_2 = \{r_3\}$$

where  $u_2$  depends on  $u_1$

# Program Decomposition

## New Evaluation Heuristics GreedyGEG

**Now:** program decomposition **not necessary**

**But:** worst-case of grounder can sometimes **be avoided by splitting**

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Splitting might be **good for the grounder** but **bad for the solver**

⇒ Aim at **two contrary goals**

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---

### Algorithm GreedyGEG

---

**Input:** A liberally de-safe HEX-program  $\Pi$

**Output:** A generalized evaluation graph  $\mathcal{E} = \langle V, E \rangle$  for  $\Pi$

Let  $V$  be the set of (subset-maximal) strongly connected components of  $G = \langle \Pi, \rightarrow_m \cup \rightarrow_n \rangle$

Update  $E$

**while**  $V$  was modified **do**

**for**  $u_1, u_2 \in V$  such that  $u_1 \neq u_2$  **do**

**if** there is no indirect path from  $u_1$  to  $u_2$  (via some  $u' \neq u_1, u_2$ ) or vice versa **then**

**if** no de-relevant  $\&[\vec{y}](\vec{x})$  in some  $u_2$  has a nonmonotonic predicate input from  $u_1$  **then**

$V \leftarrow (V \setminus \{u_1, u_2\}) \cup \{u_1 \cup u_2\}$

                Update  $E$

**return**  $\mathcal{E} = \langle V, E \rangle$

---

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# Implementation



# DLVHEX

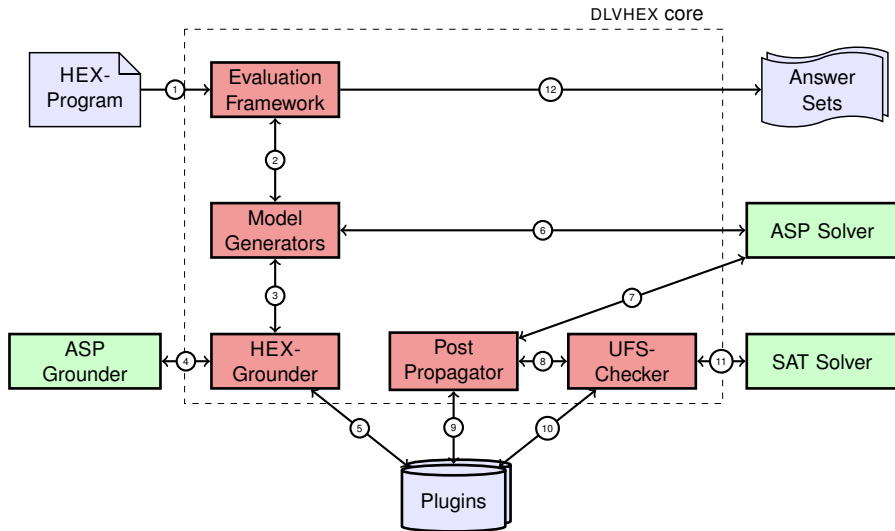
## Implementation

- Platform-independent (Linux, OS X, MS Windows)
- Written in C++ (core: 130k lines of code)
- External sources loaded via plugin interface

## Technology

- Backend: GRINGO and CLASP from Potassco
- CLASP serves also as SAT solver for UFS search
- Alternatively: self-made grounder and solver built from scratch

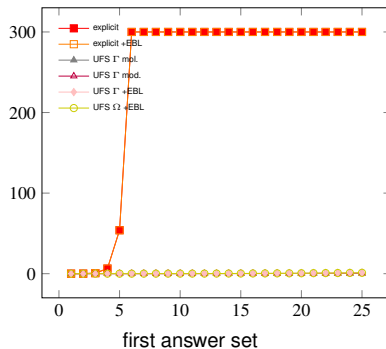
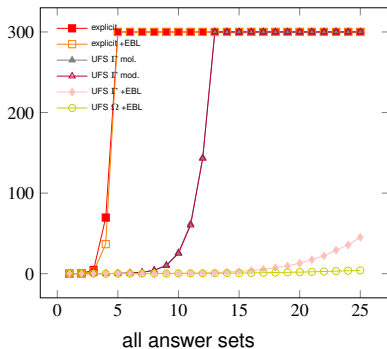
# System Architecture





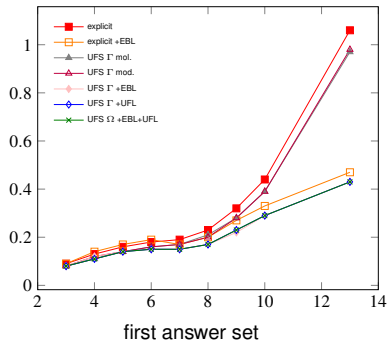
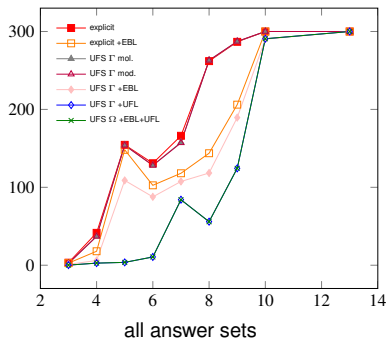
# Evaluation of the Learning-Based Algorithm

## Set Partitioning

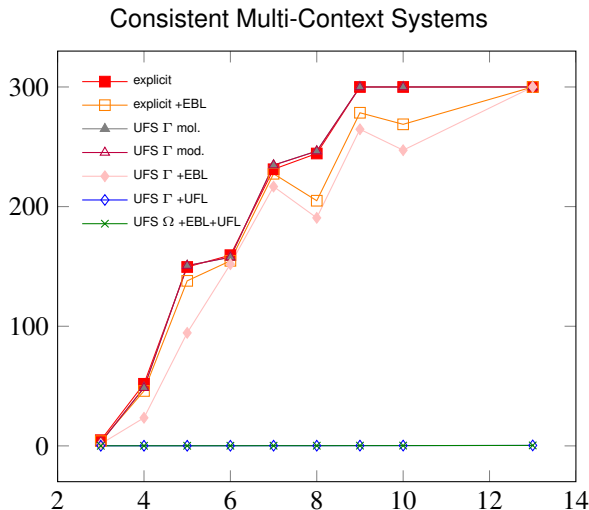


# Evaluation of the Learning-Based Algorithm

## Inconsistent Multi-Context Systems

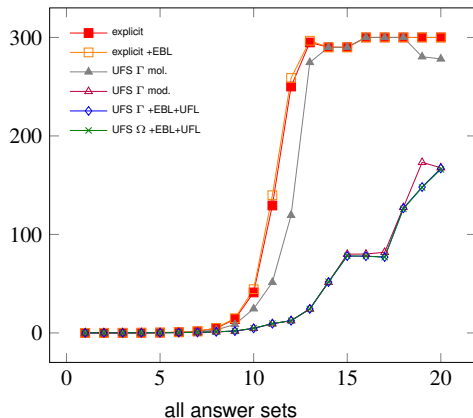


# Evaluation of the Learning-Based Algorithm



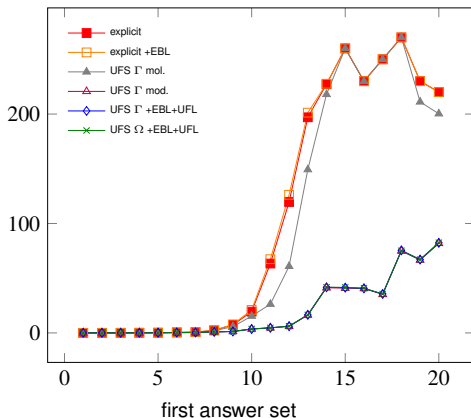
# Evaluation of the Learning-Based Algorithm

## Abstract Argumentation



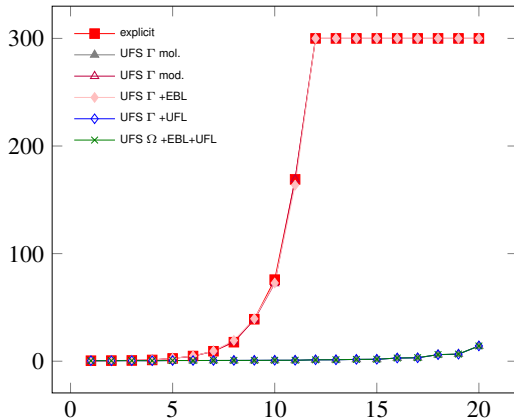
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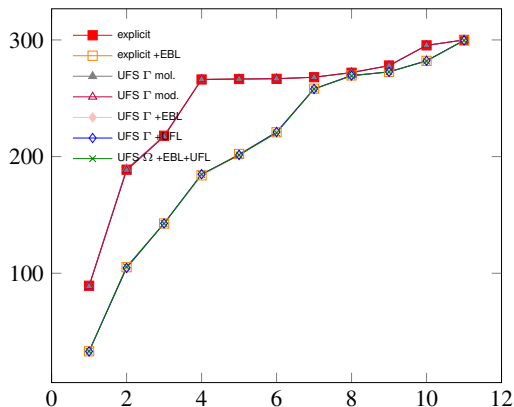
# Evaluation of the Learning-Based Algorithm

## Default Reasoning over DL-KBs (Bird-Penguin)



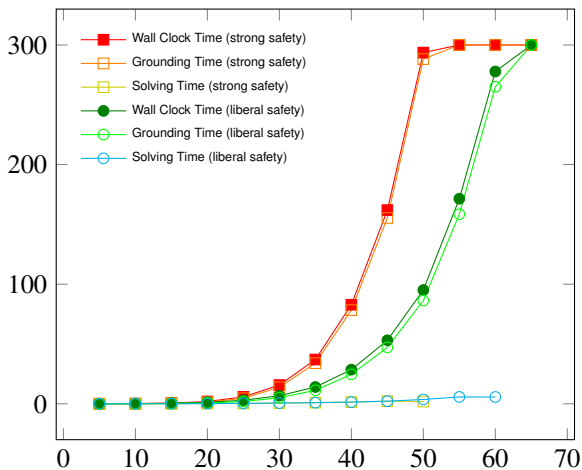
# Evaluation of the Learning-Based Algorithm

## Default Reasoning over DL-KBs (Wine)



# Evaluation of the Grounding Algorithm

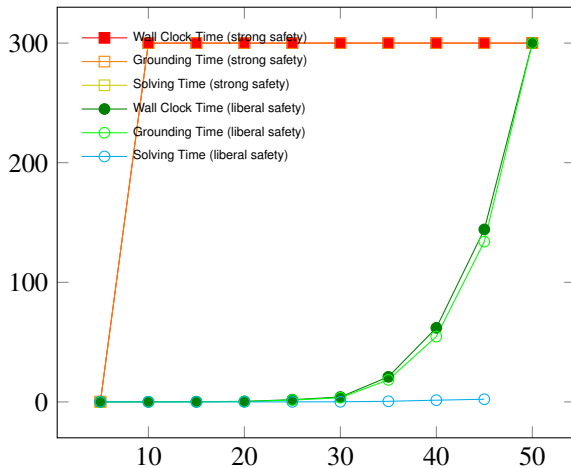
## Reachability





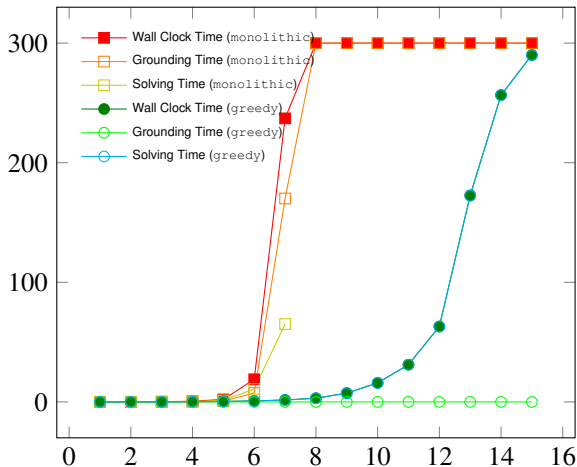
# Evaluation of the Grounding Algorithm

## Merge Sort



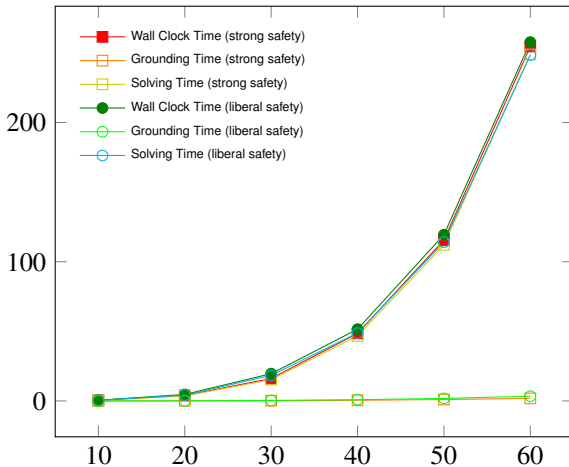
# Evaluation of the Grounding Algorithm

## Argumentation with Subsequent Processing



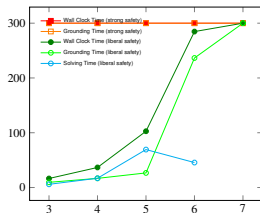
# Evaluation of the Grounding Algorithm

## Set Partitioning Liberal Safety

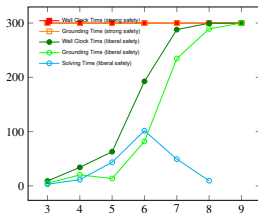


# Evaluation of the Grounding Algorithm

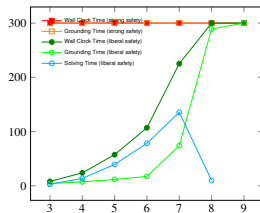
## Route Planning



full map



subway and tram



subway only

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# Conclusion

## HEX-Programs – ASP Programs with External Sources

- Useful for many **applications**:  
multi-context systems, semantic web, route planning, etc.
- **But**:  
traditional algorithms suffer both **scalability** and **expressiveness limitations**

## Contributions

- **Learning-based algorithm** based on **customizable** learning functions
  - Tight integration with **UFS-based minimality-checking algorithm**
  - **Decision criterion** which sometimes allows for **skipping the minimality check**
  - New **notion of safety** based on a **flexible framework**  $\Rightarrow$  **liberal de-safety**
  - **Grounding algorithm** for liberally de-safe HEX-programs
- $\Rightarrow$  Significant improvement of **efficiency** and **expressiveness**

# Outlook

## Future Work

- Further improvement of **efficiency** and **user's convenience**
  - Application-specific **learning functions**
  - Pruning of the search space in **minimality check**
  - Improvement of the **grounding algorithm**
  - Refine and extend existing **term bounding functions**
- Integration of **language extensions**,  
e.g. ASP extensions and modularity techniques
- Long term goal: **tight integration** of **grounding and solving**

# References I



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# Concrete Learning Functions: Functionality

**Idea:** multiple output tuples exclude each other

## Definition

The learning function for a functional external predicate  $\&g$  with input list  $\vec{p}$  in program  $\Pi$  under assignment  $\mathbf{A}$  is defined as

$$\Lambda_f(\&g[\vec{p}], \mathbf{A}) = \left\{ \left\{ \mathbf{Te}_{\&g[\vec{y}]}(\vec{x}), \mathbf{Te}_{\&g[\vec{y}]}(\vec{x}') \right\} \mid \vec{x} \neq \vec{x}' \right\}$$

## Example

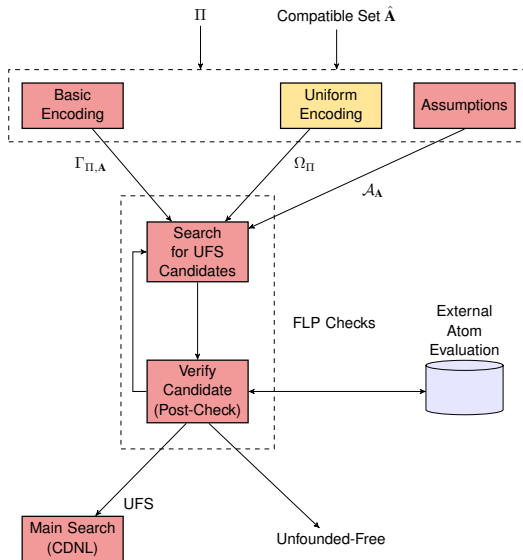
$\&concat[ab, c](X)$

Learn:  $\left\{ \mathbf{Te}_{\&concat[ab, c]}(abc), \mathbf{Te}_{\&concat[ab, c]}(ab) \right\}$

## Lemma

*For all assignments  $\mathbf{A}$ , if  $\&g$  is functional, the nogoods  $\Lambda_f(\&g[\vec{p}], \mathbf{A})$  are correct wrt.  $\Pi$ .*

# Using Unfounded Sets



# Exchanging Nogoods between UFS and Main Search

## Definition

A nogood of the form  $N = \{\mathbf{T}t_1, \dots, \mathbf{T}t_n, \mathbf{F}f_1, \dots, \mathbf{F}f_m, \circ e_{\&g[\vec{y}]}(\vec{x})\}$ , where  $\circ$  is **T** or **F**, is a **valid input-output-relationship**, if for all assignments  $\mathbf{A}$ ,  $\mathbf{T}t_i \in \mathbf{A}$ , for  $1 \leq i \leq n$ , and  $\mathbf{F}f_i \in \mathbf{A}$ , for  $1 \leq i \leq m$ , implies  $\mathbf{A} \models \&g[\vec{y}](\vec{x})$  if  $\circ = \mathbf{F}$ , and  $\mathbf{A} \not\models \&g[\vec{y}](\vec{x})$  if  $\circ = \mathbf{T}$ .

## Definition (Nogood Transformation $\mathcal{T}$ )

Nogood transformation  $\mathcal{T}$  for a valid input-output relationship  $N$ :

$$\mathcal{T}(N, \mathbf{A}) = \begin{cases} \emptyset & \text{if } \mathbf{F}t_i \in \mathbf{A} \text{ for some } 1 \leq i \leq n, \\ \{\{\mathbf{F}t_1, \dots, \mathbf{F}t_n\} \cup \{\circ e_{\&g[\vec{y}]}(\vec{x})\}\} \cup \\ \quad \{\mathbf{T}f_i \mid 1 \leq i \leq m, \mathbf{A} \models f_i\} & \text{otherwise.} \end{cases}$$

## Proposition

*Let  $N$  be a valid input-output relationship, and let  $U$  be an unfounded set wrt.  $\Pi$  and  $\mathbf{A}$ . Then  $I(U, \Gamma_{\Pi}^{\mathbf{A}})$  is a solution to  $\mathcal{T}(N, \mathbf{A})$ .*

# Exchanging Nogoods between UFS and Main Search

## Example (Set Partitioning)

Consider the program  $\Pi$ :

$$s(a) \leftarrow \text{domain}(a), \&\text{diff}[\text{domain}, n](a)$$

$$n(a) \leftarrow \text{domain}(a), \&\text{diff}[\text{domain}, s](a)$$

$$\text{domain}(a) \leftarrow$$

Let

$$\mathbf{A}^T = \{\text{domain}(a), s(a), e_{\&\text{diff}[n]}(a)\}$$

Suppose the main search has learned  $N = \{\mathbf{T}\text{domain}(a), \mathbf{F}n(a), \mathbf{F}e_{\&\text{diff}[n]}(a)\}$ .

Then  $\mathcal{T}(N, \mathbf{A}) = \{\{\mathbf{F}\text{domain}(a), \mathbf{F}e_{\&\text{diff}[n]}(a)\}\}$ .

# Learning Nogoods from Unfounded Sets

## Example

Consider the program  $\Pi = \{p \leftarrow \&id[p](); x_1 \vee x_2 \vee \dots \vee x_k \leftarrow\}$ .

Set  $\{p\}$  is an unfounded set wrt.  $\mathbf{A} = \{\mathbf{T}p, \mathbf{T}e_{\&id}()\}$ , regarding just the first rule.

The same is true for any  $\mathbf{A}' \supset \mathbf{A}$  regarding  $\Pi$ .

## Proposition

*If  $U$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ , then every answer set of  $\Pi$  is a solution to the nogoods in  $L(U, \Pi, \mathbf{A})$ , where*

$$L(U, \Pi, \mathbf{A}) = \{\{\sigma_0, \sigma_1, \dots, \sigma_j\} \mid \sigma_0 \in \{\mathbf{T}a \mid a \in U\}, \sigma_i \in H_i \text{ for all } 1 \leq i \leq j\}$$

# Learning Nogoods from Unfounded Sets

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Consider the program  $\Pi = \{p \leftarrow \&id[p](); x_1 \vee x_2 \vee \dots \vee x_k \leftarrow\}$ .

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## Example (cont'd)

Reconsider program  $\Pi = \{p \leftarrow \&id[p](); x_1 \vee x_2 \vee \dots \vee x_k \leftarrow\}$

Suppose the UFS  $U = \{p\}$  wrt.  $\mathbf{A} = \{\mathbf{T}p, \mathbf{T}x_1\} \cup \{\mathbf{F}a_i \mid 1 < i \leq k\}$  was found

The learned UFS nogood is:  $L(U, \mathbf{A}, \Pi) = \{\mathbf{T}p\}$



## Algorithm FLPCheck

**Input:** A program  $\Pi$ , a compatible set  $\hat{\Lambda}$ , a set of correct nogoods  $\nabla$  of  $\Pi$

**Output:** *true* iff  $\mathbf{A}$  is an answer set of  $\Pi$  and *false* otherwise, learned nogoods added to  $\nabla$

**if** encoding  $\Gamma$  **then**

    SAT instance is  $\Gamma_{\Pi}^{\mathbf{A}}$   
    Let  $\mathcal{T}(N) = \mathcal{T}_{\Gamma}(N)$

**if** encoding  $\Omega$  **then**

    SAT instance is  $\Omega_{\Pi}$  with assumptions  $\mathcal{A}_{\mathbf{A}}$   
    Let  $\mathcal{T}(N) = \mathcal{T}_{\Omega}(N)$

**for**  $C \in \text{Comp}$  **do**

**if** there is an  $e$ -cycle of  $\Pi_C$  under  $\rightarrow_p^d$  **then**

**while** SAT instance has more solutions **do**

            Let  $S$  be the next solution of the SAT instance

            Let  $U$  be the unfounded set candidate encoded by  $S$

$\text{isUFS} \leftarrow \text{true}$

**for** all external atoms  $\&[\bar{y}](\bar{x})$  in  $\Pi_C$  **do**

            Evaluate  $\&[\bar{y}]$

$\nabla \leftarrow \nabla \cup \Lambda(\&[\bar{y}], \mathbf{A})$

            Add  $\mathcal{T}(N)$  to the SAT instance for all  $N \in \Lambda(\&[\bar{y}], \mathbf{A})$

**if**  $\mathbf{T}e_{\&[\bar{y}]}(\bar{x}) \in S, \mathbf{A} \not\models \&[\bar{y}](\bar{x})$  and  $\mathbf{A} \dot{\cup} \neg.U \not\models \&[\bar{y}](\bar{x})$  **then**

$\text{isUFS} \leftarrow \text{false}$

**if**  $\mathbf{F}e_{\&[\bar{y}]}(\bar{x}) \in S, \mathbf{A} \models \&[\bar{y}](\bar{x})$  and  $\mathbf{A} \dot{\cup} \neg.U \models \&[\bar{y}](\bar{x})$  **then**

$\text{isUFS} \leftarrow \text{false}$

**if**  $\text{isUFS}$  **then**

            Let  $N \in L_1(U, \Pi_C, \mathbf{A})$  be a nogood learned from the UFS

$\nabla \leftarrow \nabla \cup \{N\}$  **return false**

**return true**

# Minimality Checking Algorithm

## Theorem (Soundness and Completeness of Algorithm FLPCheck)

- (i) *Algorithm FLPCheck returns true if and only if the restriction  $\mathbf{A}$  of  $\hat{\mathbf{A}}$  to ordinary atoms is an answer set of  $\Pi$ .*
- (ii) *All answer sets of  $\Pi$  are solutions to all nogoods added to  $\nabla$  by FLPCheck.*

# Decision Criterion for Necessity of Minimality Checking

## Idea

- Ordinary ASP solver has already performed a (restricted) minimality check
- Thus many unfounded sets are already detected
- This is sufficient for many programs

# Decision Criterion for Necessity of Minimality Checking

## Idea

- Ordinary ASP solver has already performed a (restricted) minimality check
- Thus many unfounded sets are already detected
- This is sufficient for many programs

## Criterion

- **E-cycles:**  
Only **positive cycles** which involve **predicate parameters** of external atoms require additional checks
- Criterion can be applied **component-wise**

# Atom Dependency Graph

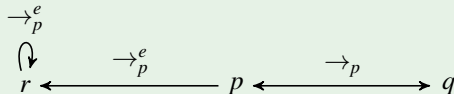
## Definition (Positive Atom Dependencies)

For a ground program  $\Pi$  and ground atoms  $p(\vec{c})$ ,  $q(\vec{d})$ , we say:

- (i)  $p(\vec{c})$  **depends positively** on  $q(\vec{d})$  ( $p(\vec{c}) \rightarrow_p q(\vec{d})$ ) if for some rule  $r \in \Pi$  we have  $p(\vec{c}) \in H(r)$  and  $q(\vec{d}) \in B^+(r)$ ; and
- (ii)  $p(\vec{c})$  **depends externally** on  $q(\vec{d})$  ( $p(\vec{c}) \rightarrow_p^e q(\vec{d})$ ) if for some rule  $r \in \Pi$  we have  $p(\vec{c}) \in H(r)$  and there is a  $\&g[q_1, \dots, q_n](\vec{d}) \in B^+(r) \cup B^-(r)$  with  $q_i = q$  for some  $i \in \{1, \dots, n\}$ .

## Example

$\Pi = \{r \leftarrow \&id[r](); \quad p \leftarrow \&id[r](); \quad p \leftarrow q; \quad q \leftarrow p\}$



# Cuts

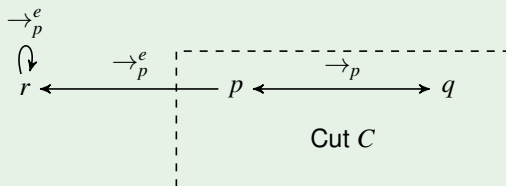
## Definition (Cut)

Let  $U$  be an UFS of  $\Pi$  wrt.  $\mathbf{A}$ . A set of atoms  $C \subseteq U$  is a **cut**, if

- (i) for all  $a \in C, b \in U$ :  $b \not\rightarrow_p^e a$ ; and
- (ii) for all  $a \in C, b \in U \setminus C$ :  $b \not\rightarrow_p a$  and  $a \not\rightarrow_p b$ .

## Example (ctd.)

$\Pi = \{r \leftarrow \&d[r](); \quad p \leftarrow \&d[r](); \quad p \leftarrow q; \quad q \leftarrow p\}$



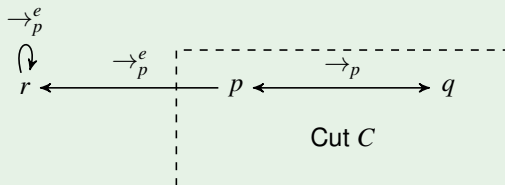
# Cuts

## Lemma (Unfounded Set Reduction Lemma)

Let  $U$  be an UFS of  $\Pi$  wrt.  $\mathbf{A}$  and let  $C$  be a cut. Then  $Y = U \setminus C$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ .

## Example (ctd.)

$\Pi = \{r \leftarrow \&id[r](); \quad p \leftarrow \&id[r](); \quad p \leftarrow q; \quad q \leftarrow p\}$



UFS  $U = \{p, q, r\}$  wrt.  $\mathbf{A} = \{\mathbf{T}p, \mathbf{T}q, \mathbf{T}r\}$   
 $\Rightarrow$  UFS  $U' = \{p, q, r\} \setminus \{p, q\} = \{r\}$  wrt.  $\mathbf{A}$

# External-Atom Input Unfoundedness

## Lemma (External-Atom Input Unfoundedness)

*Let  $U$  be an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ . If there are no  $x, y \in U$  s.t.  $x \rightarrow_p^e y$ , then  $U$  is an unfounded set of  $\hat{\Pi}$  wrt.  $\hat{\mathbf{A}}$ .*

## Example

$\Pi = \{r \leftarrow \&id[r](); \quad p \leftarrow \&id[r](); \quad p \leftarrow q; \quad q \leftarrow p\}$

UFS  $U_1 = \{p, q\}$  wrt.  $\mathbf{A}' = \{\mathbf{T}p, \mathbf{T}q, \mathbf{F}r\}$  is already detected when

$\hat{\Pi} = \{e_{\&id[r]}() \vee \neg e_{\&id[r]}() \leftarrow; \quad r \leftarrow e_{\&id[r]}(); \quad p \leftarrow e_{\&id[r]}(); \quad p \leftarrow q; \quad q \leftarrow p\}$  is evaluated

UFS  $U_2 = \{p, q, r\}$  wrt.  $\mathbf{A}'' = \{\mathbf{T}p, \mathbf{T}q, \mathbf{T}r\}$  is **not** detected during model generation phase of the ordinary part as  $p, r \in U_2$  and  $p \rightarrow_p^e r$



# E-Cycles

## Definition (Cycle and E-Cycle)

A **cycle** under a binary relation  $\circ$  is a sequence of elements  $C = c_0, \dots, c_{n+1}$  ( $n \geq 0$ ) s.t.  $(c_i, c_{i+1}) \in \circ$  for all  $i \in \{0, \dots, n\}$  and  $c_0 = c_{n+1}$ .

Let  $\rightarrow_p^d = \rightarrow_p \cup \leftarrow_p \cup \rightarrow_p^e$  ( $\leftarrow_p$  is the inverse of  $\rightarrow_p$ ).

A cycle  $c_0, \dots, c_{n+1}$  in  $\rightarrow_p^d$  is called an **e-cycle**, if it contains e-edges.

## Proposition (Relevance of e-cycles)

*Suppose  $U$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$  which contains no e-cycle under  $\rightarrow_p^d$ . Then there exists an unfounded set of  $\hat{\Pi}$  wrt.  $\hat{\mathbf{A}}$ .*

## Corollary

*If there is no e-cycle under  $\rightarrow_p^d$  and  $\hat{\Pi}$  has no unfounded set wrt.  $\hat{\mathbf{A}}$ , then  $\mathbf{A}$  is unfounded-free for  $\Pi$ .*

# E-Cycles

## Example (Programs without E-Cycles)

$$\Pi_1 = \{out(X) \leftarrow \&diff[set_1, set_2](X)\} \cup F \quad (F \dots \text{set of facts})$$
$$\Pi_2 = \{str(Z) \leftarrow dom(Z), str(X), str(Y), \text{not } \&concat[X, Y](Z)\}$$

# E-Cycles

## Example (Programs without E-Cycles)

$$\Pi_1 = \{out(X) \leftarrow \&diff[set_1, set_2](X)\} \cup F \quad (F \dots \text{set of facts})$$

$$\Pi_2 = \{str(Z) \leftarrow dom(Z), str(X), str(Y), \text{not } \&concat[X, Y](Z)\}$$

## Proposition (Unfoundedness of Cyclic Input Atoms)

*If  $U$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$  and  $U$  contains no cyclic input atoms, then  $\hat{\Pi}$  has an unfounded set wrt.  $\hat{\mathbf{A}}$ .*

# Program Decomposition

Let  $\mathcal{C}$  be a partitioning of the ordinary atoms  $A(\Pi)$  of  $\Pi$  into  $\subseteq$ -maximal strongly connected components under  $\rightarrow_p \cup \rightarrow_p^e$ .

## Definition (Associated Programs)

For each  $C \in \mathcal{C}$ , the program **associated with  $C$**  is defined as

$$\Pi_C = \{r \in \Pi \mid H(r) \cap C \neq \emptyset\} .$$

## Proposition

*Let  $U$  be a nonempty unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ . Then for some  $\Pi_C$  with  $C \in \mathcal{C}$  we have that  $U \cap C$  is an unfounded set of  $\Pi_C$  wrt.  $\mathbf{A}$ .*

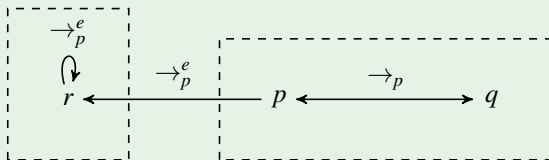
## Proposition

*Let  $U$  be a nonempty unfounded set of  $\Pi_C$  wrt.  $\mathbf{A}$  such that  $U \subseteq C$ . Then  $U$  is an unfounded set of  $\Pi$  wrt.  $\mathbf{A}$ .*

# Program Decomposition

## Example

$\Pi = \{r \leftarrow \&id[r](); \quad p \leftarrow \&id[r](); \quad p \leftarrow q; \quad q \leftarrow p\}$



$\mathcal{C} = \{C_1, C_2\}$  with  $C_1 = \{p, q\}$  and  $C_2 = \{r\}$

$\Pi_{C_1} = \{p \leftarrow \&id[r](); p \leftarrow q; q \leftarrow p\}$

$\Pi_{C_2} = \{r \leftarrow \&id[r]()\}$ .

Let  $U = \{p, q, r\}$  be an UFS wrt.  $\mathbf{A} = \{\mathbf{T}p, \mathbf{T}q, \mathbf{T}r\}$

Then  $U \cap \{r\} = \{r\}$  is also an unfounded set of  $\Pi_{C_2}$  wrt.  $\mathbf{A}$

# Liberal Safety: Concrete TBF

## Definition (Syntactic Term Bounding Function)

$t \in b_{syn}(\Pi, r, S, B)$  if

- (i)  $t$  is a constant in  $r$ ; or
- (ii) there is an ordinary atom  $q(s_1, \dots, s_{ar(q)}) \in B^+(r)$  s.t.  $t = s_j$ , for some  $1 \leq j \leq ar(q)$  and  $q \upharpoonright j \in S$ ; or
- (iii) for some external atom  $\&g[\vec{X}](\vec{Y}) \in B^+(r)$ , we have that  $t = Y_i$  for some  $Y_i \in \vec{Y}$ , and for each  $X_i \in \vec{X}$ ,
 
$$\begin{cases} X_i \in B, & \text{if } \tau(\&g, i) = \mathbf{const}, \\ X_i \upharpoonright 1, \dots, X_i \upharpoonright ar(X_i) \in S, & \text{if } \tau(\&g, i) = \mathbf{pred}. \end{cases}$$

# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$r_1: s(a); \quad r_2: \text{dom}(ax); \quad r_3: \text{dom}(axx)$$

$$r_4: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y)$$

■  $B_1(r_2, \Pi, b_{syn}) = \{ax\}, B_1(r_3, \Pi, b_{syn}) = \{axx\}, B_1(r_4, \Pi, b_{syn}) = \{x\}$

# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$\begin{aligned} r_1 &: s(a); & r_2 &: \text{dom}(ax); & r_3 &: \text{dom}(axx) \\ r_4 &: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y) \end{aligned}$$

- $B_1(r_2, \Pi, b_{syn}) = \{ax\}, B_1(r_3, \Pi, b_{syn}) = \{axx\}, B_1(r_4, \Pi, b_{syn}) = \{x\}$
- $\Rightarrow S_1(\Pi) = \{\text{dom} \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright 1 2\}$



# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$\begin{aligned} r_1 &: s(a); & r_2 &: \text{dom}(ax); & r_3 &: \text{dom}(axx) \\ r_4 &: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y) \end{aligned}$$

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- $\Rightarrow S_1(\Pi) = \{\text{dom} \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright 2\}$
- $B_2(r_4, \Pi, b_{syn}) = \{Y\}, B_2(r_1, \Pi, b_{syn}) = \{a\}$

# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$\begin{aligned} r_1 &: s(a); & r_2 &: \text{dom}(ax); & r_3 &: \text{dom}(axx) \\ r_4 &: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y) \end{aligned}$$

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- $B_2(r_4, \Pi, b_{syn}) = \{Y\}, B_2(r_1, \Pi, b_{syn}) = \{a\}$
- $\Rightarrow S_2(\Pi) \supseteq \{s \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright_{\circ} 1\}$

# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$\begin{aligned} r_1 &: s(a); & r_2 &: \text{dom}(ax); & r_3 &: \text{dom}(axx) \\ r_4 &: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y) \end{aligned}$$

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- $\Rightarrow S_2(\Pi) \supseteq \{s \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright_{\circ} 1\}$
- $X \in B_3(r_4, \Pi, b_{syn})$

# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$\begin{aligned} r_1 &: s(a); & r_2 &: \text{dom}(ax); & r_3 &: \text{dom}(axx) \\ r_4 &: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y) \end{aligned}$$

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- $\Rightarrow S_1(\Pi) = \{\text{dom} \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright 2\}$
- $B_2(r_4, \Pi, b_{syn}) = \{Y\}, B_2(r_1, \Pi, b_{syn}) = \{a\}$
- $\Rightarrow S_2(\Pi) \supseteq \{s \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright 1\}$
- $X \in B_3(r_4, \Pi, b_{syn})$
- $\Rightarrow \&cat[X, x]_{r_4} \upharpoonright 1 \in S_3(\Pi)$

# Liberal Safety: Concrete TBF

## Example

Program  $\Pi$ :

$$r_1: s(a); \quad r_2: \text{dom}(ax); \quad r_3: \text{dom}(axx)$$

$$r_4: s(Y) \leftarrow s(X), \&cat[X, x](Y), \text{dom}(Y)$$

- $B_1(r_2, \Pi, b_{syn}) = \{ax\}, B_1(r_3, \Pi, b_{syn}) = \{axx\}, B_1(r_4, \Pi, b_{syn}) = \{x\}$
- $\Rightarrow S_1(\Pi) = \{\text{dom} \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright 2\}$
- $B_2(r_4, \Pi, b_{syn}) = \{Y\}, B_2(r_1, \Pi, b_{syn}) = \{a\}$
- $\Rightarrow S_2(\Pi) \supseteq \{s \upharpoonright 1, \&cat[X, x]_{r_4} \upharpoonright 1\}$
- $X \in B_3(r_4, \Pi, b_{syn})$
- $\Rightarrow \&cat[X, x]_{r_4} \upharpoonright 1 \in S_3(\Pi)$

We also provide a TBF which exploits [semantic properties](#) of external sources

# Grounding Algorithm

## Definition (Input Auxiliary Rule)

Let  $\Pi$  be a HEX-program, and let  $a = \&g[\vec{Y}](\vec{X})$  be some external atom with input list  $\vec{Y}$  occurring in a rule  $r \in \Pi$ . Then, for each such atom, a rule  $r_{inp}^a$  is composed:

- The head is  $H(r_{inp}^a) = \{g_{inp}(\vec{Y})\}$ , where  $g_{inp}$  is a fresh predicate.
- The body  $B(r_{inp}^a)$  contains each  $b \in B^+(r) \setminus \{a\}$  such that  $a$  joins  $b$  in  $\vec{Y}$ , and  $b$  is de-safety-relevant if it is an external atom.

## Definition (External Atom Guessing Rule)

For HEX-program  $\Pi$  and  $a = \&g[\vec{Y}](\vec{X})$ , construct  $r_{guess}^a$ :

- The head is  $H(r_{guess}^a) = \{e_{r, \&g[\vec{Y}]}(\vec{X}), ne_{r, \&g[\vec{Y}]}(\vec{X})\}$ .
- The body  $B(r_{guess}^a)$  contains
  - (i) each  $b \in B^+(r) \setminus \{a\}$  such that  $a$  joins  $b$  and  $b$  is de-safety-relevant if it is an external atom; and
  - (ii)  $g_{inp}(\vec{Y})$ .

# Grounding Algorithm

## Example

Program II:

$$\begin{array}{ll}
 f: d(a); d(b); d(c); & r_1: s(Y) \leftarrow \&diff[d, n](Y), d(Y) \\
 & r_2: n(Y) \leftarrow \&diff[d, s](Y), d(Y) \\
 & r_3: c(Z) \leftarrow \&count[s](Z)
 \end{array}$$

# Grounding Algorithm

## Example

Program  $\Pi$ :

$$\begin{aligned} f: d(a); d(b); d(c); \quad & r_1: s(Y) \leftarrow \&diff[d, n](Y), d(Y) \\ & r_2: n(Y) \leftarrow \&diff[d, s](Y), d(Y) \\ & r_3: c(Z) \leftarrow \&count[s](Z) \end{aligned}$$

$\Pi_p$  at the beginning of the first iteration:

$$\begin{aligned} f: d(a); d(b); d(c) \quad & r_1: s(Y) \leftarrow e_1(Y), d(Y) \\ g_1: e_1(Y) \vee ne_1(Y) \leftarrow d(Y); \quad & r_2: n(Y) \leftarrow e_2(Y), d(Y) \\ g_2: e_2(Y) \vee ne_2(Y) \leftarrow d(Y); \quad & r_3: c(Z) \leftarrow e_3(Z) \end{aligned}$$

$(e_1(Y), e_2(Y), e_3(Z))$  short for  $e_{r_1, \&diff[d, n]}(Y)$ ,  $e_{r_2, \&diff[d, s]}(Y)$ ,  $e_{r_3, \&count[s]}(Z)$ , resp.)

Evaluates  $\&count[s](Z)$  under all  $\mathbf{A} \subseteq \{s(a), s(b), s(c)\}$

Adds rules  $\{e_3(z) \vee ne_3(z) \leftarrow . \mid z \in \{0, 1, 2, 3\}\}$



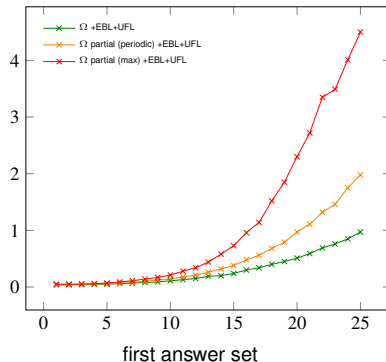
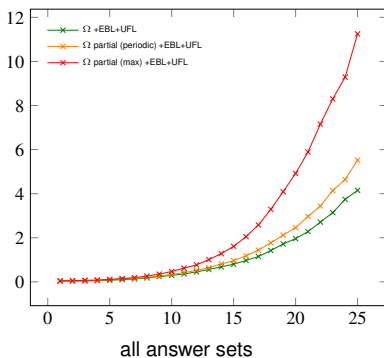
# Grounding Algorithm

## Theorem (Correctness of Algorithm GroundHEX)

*If  $\Pi$  is a liberally de-safe HEX-program, then  $\text{GroundHEX}(\Pi) \equiv^{pos} \Pi$ .*

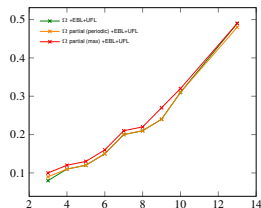
# Evaluation of the Learning-Based Algorithm wrt. Partial Assignments

## Set Partitioning

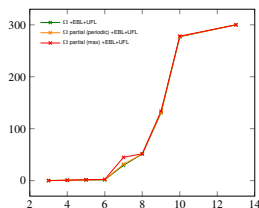


# Evaluation of the Learning-Based Algorithm wrt. Partial Assignments

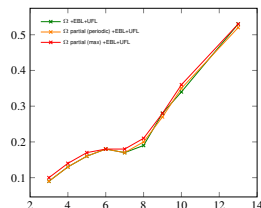
## Multi-Context Systems



consistent (no answer sets)



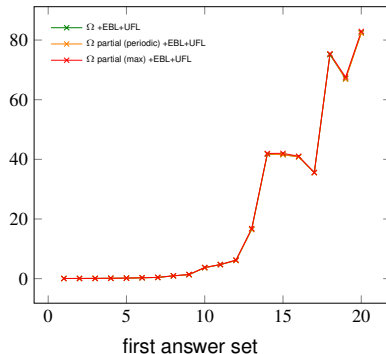
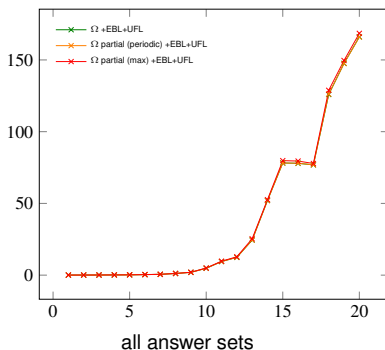
inconsistent, all answer sets



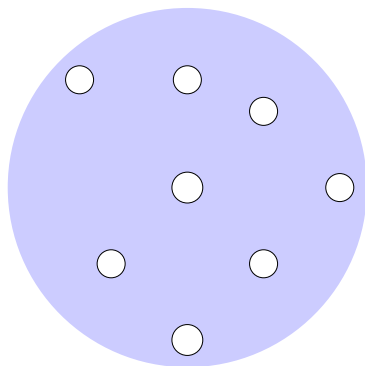
inconsistent, first answer set

# Evaluation of the Learning-Based Algorithm wrt. Partial Assignments

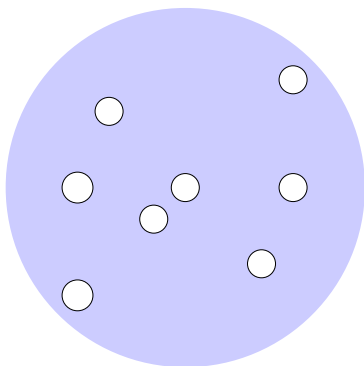
## Abstract Argumentation



# Unfounded Sets – Interesting Observations

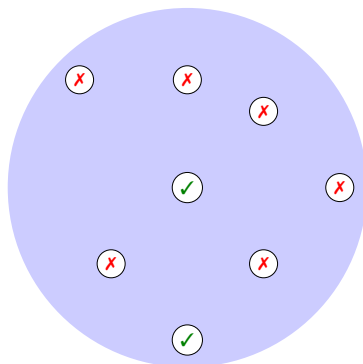


**Explicit Check**  
Search for Smaller Models  
of the Reduct

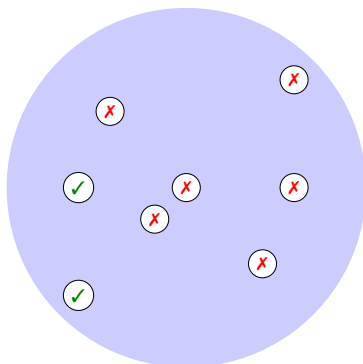


**UFS-based Check**  
Search for Unfounded Sets

# Unfounded Sets – Interesting Observations

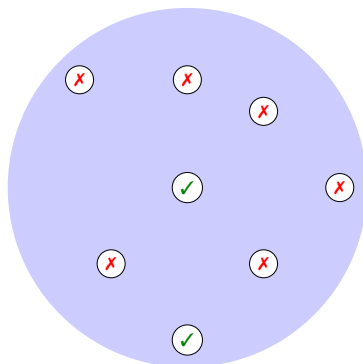


**Explicit Check**  
Search for Smaller Models  
of the Reduct

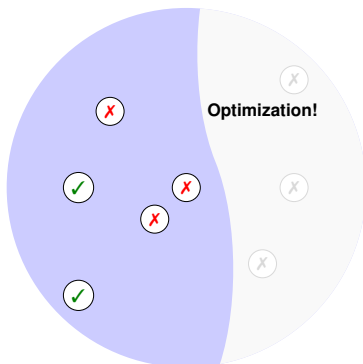


**UFS-based Check**  
Search for Unfounded Sets

# Unfounded Sets – Interesting Observations

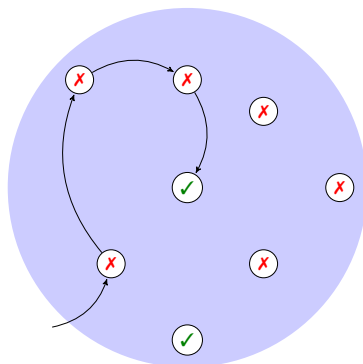


**Explicit Check**  
Search for Smaller Models  
of the Reduct

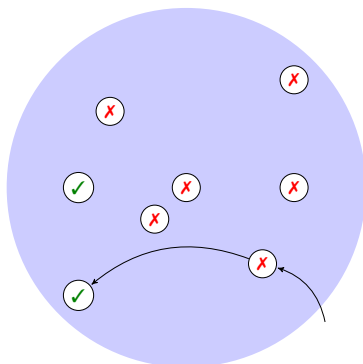


**UFS-based Check**  
Search for Unfounded Sets

# Unfounded Sets – Interesting Observations



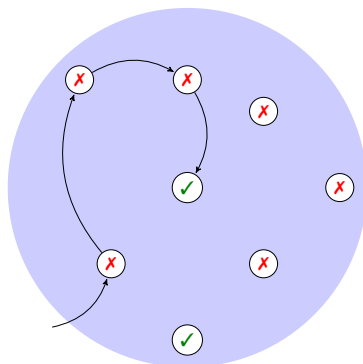
**Explicit Check**  
Search for Smaller Models  
of the Reduct



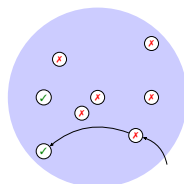
**UFS-based Check**  
Search for Unfounded Sets



# Unfounded Sets – Interesting Observations

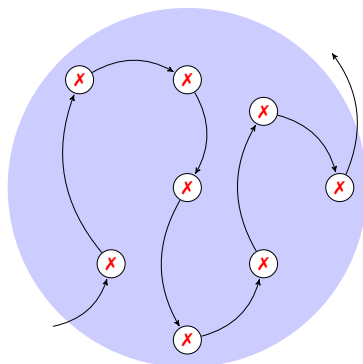


**Explicit Check**  
Search for Smaller Models  
of the Reduct

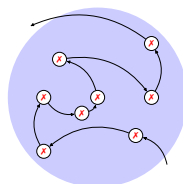


**UFS-based Check**  
Search for Unfounded Sets

# Unfounded Sets – Interesting Observations



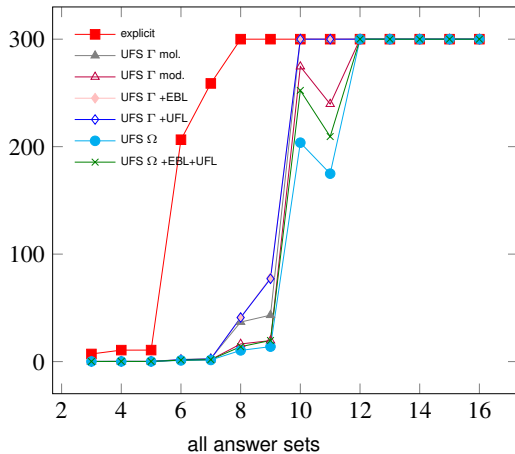
**Explicit Check**  
Search for Smaller Models  
of the Reduct



**UFS-based Check**  
Search for Unfounded Sets

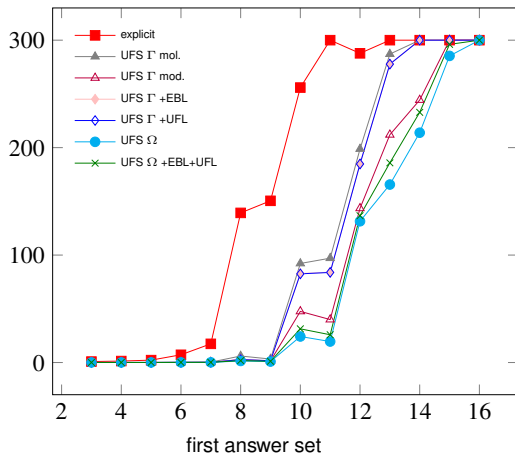
# Evaluation of the Learning-Based Algorithm

## Conformant Planning



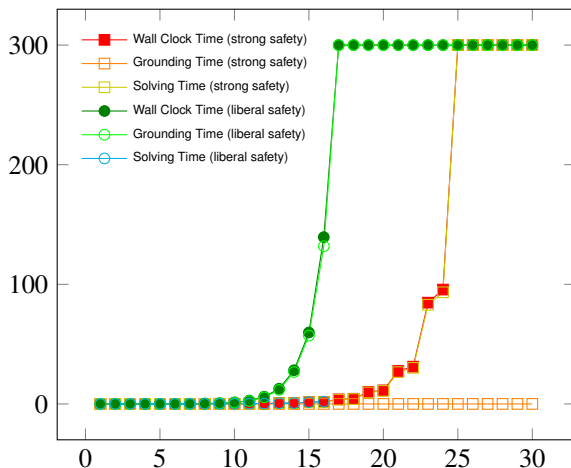
# Evaluation of the Learning-Based Algorithm

## Conformant Planning



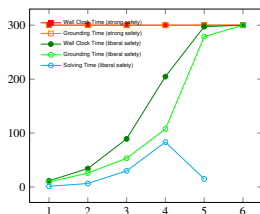
# Evaluation of the Grounding Algorithm

Default Reasoning over DL-KBs with Nonmonotonic External Atom (Bird-Penguin)

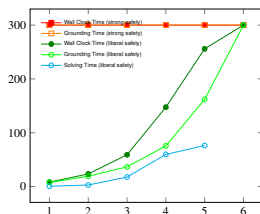


# Evaluation of the Grounding Algorithm

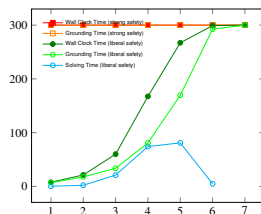
## Pair Route Planning



full map



subway and tram



subway only

# Evaluation of the Learning-Based Algorithm

domain	All Answer Sets						First Answer Set					
	explicit		UFS $\Gamma$	UFS $\Gamma$		$\Omega$	explicit		UFS $\Gamma$	UFS $\Gamma$		UFS $\Omega$
		+EBL	mol.	mod.	+EBL	+EBL		+EBL	mol.	mod.	+EBL	+EBL
1 (1)	0.05 (0)	0.05 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)
2 (1)	0.28 (0)	0.20 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.09 (0)	0.10 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)
3 (1)	4.65 (0)	2.82 (0)	0.06 (0)	0.05 (0)	0.05 (0)	0.05 (0)	0.70 (0)	0.70 (0)	0.04 (0)	0.04 (0)	0.04 (0)	0.04 (0)
4 (1)	69.66 (0)	36.64 (0)	0.14 (0)	0.14 (0)	0.06 (0)	0.06 (0)	6.34 (0)	6.35 (0)	0.04 (0)	0.04 (0)	0.05 (0)	0.05 (0)
5 (1)	300.00 (1)	300.00 (1)	0.33 (0)	0.32 (0)	0.09 (0)	0.07 (0)	54.02 (0)	53.80 (0)	0.05 (0)	0.05 (0)	0.05 (0)	0.05 (0)
6 (1)	300.00 (1)	300.00 (1)	0.77 (0)	0.81 (0)	0.12 (0)	0.10 (0)	300.00 (1)	300.00 (1)	0.04 (0)	0.05 (0)	0.06 (0)	0.06 (0)
7 (1)	300.00 (1)	300.00 (1)	1.73 (0)	1.78 (0)	0.20 (0)	0.13 (0)	300.00 (1)	300.00 (1)	0.06 (0)	0.06 (0)	0.06 (0)	0.07 (0)
8 (1)	300.00 (1)	300.00 (1)	4.35 (0)	4.17 (0)	0.31 (0)	0.16 (0)	300.00 (1)	300.00 (1)	0.07 (0)	0.06 (0)	0.07 (0)	0.07 (0)
9 (1)	300.00 (1)	300.00 (1)	10.42 (0)	10.21 (0)	0.47 (0)	0.23 (0)	300.00 (1)	300.00 (1)	0.08 (0)	0.07 (0)	0.08 (0)	0.09 (0)
10 (1)	300.00 (1)	300.00 (1)	26.31 (0)	25.13 (0)	0.53 (0)	0.29 (0)	300.00 (1)	300.00 (1)	0.09 (0)	0.09 (0)	0.11 (0)	0.12 (0)
15 (1)	300.00 (1)	300.00 (1)	300.00 (1)	300.00 (1)	2.83 (0)	0.79 (0)	300.00 (1)	300.00 (1)	0.19 (0)	0.15 (0)	0.27 (0)	0.26 (0)
20 (1)	300.00 (1)	300.00 (1)	300.00 (1)	300.00 (1)	12.98 (0)	1.95 (0)	300.00 (1)	300.00 (1)	0.38 (0)	0.29 (0)	0.57 (0)	0.57 (0)
25 (1)	300.00 (1)	300.00 (1)	300.00 (1)	300.00 (1)	45.18 (0)	4.11 (0)	300.00 (1)	300.00 (1)	0.70 (0)	0.47 (0)	1.09 (0)	1.08 (0)

Table: Set Partitioning

# Evaluation of the Learning-Based Algorithm

#ctx	All Answer Sets							$\Omega$
	explicit		UFS $\Gamma$	UFS $\Gamma$				
	+EBL	mol.	mod.	+EBL	+UFL	+EBL+UFL		
3 (9)	3.29 (0)	2.70 (0)	2.44 (0)	2.34 (0)	1.09 (0)	0.14 (0)	0.14 (0)	
4 (14)	41.57 (1)	17.94 (0)	37.04 (1)	37.03 (1)	6.05 (0)	2.71 (0)	0.61 (0)	
5 (11)	154.55 (5)	148.11 (5)	154.17 (5)	153.94 (5)	108.87 (2)	3.65 (0)	1.28 (0)	
6 (18)	130.90 (7)	102.57 (6)	128.26 (7)	128.12 (7)	87.75 (4)	10.61 (0)	1.55 (0)	
7 (13)	166.14 (5)	118.04 (5)	157.67 (5)	157.06 (5)	107.50 (4)	84.08 (2)	29.47 (0)	
8 (6)	261.96 (5)	143.75 (2)	262.95 (5)	263.00 (5)	118.36 (2)	55.86 (1)	51.13 (1)	
9 (14)	286.74 (13)	206.10 (9)	287.10 (12)	287.32 (12)	189.48 (8)	124.34 (5)	130.56 (6)	
10 (12)	300.00 (12)	300.00 (12)	300.00 (12)	300.00 (12)	290.18 (11)	290.69 (11)	277.05 (11)	

#ctx	First Answer Set						
	explicit		UFS $\Gamma$	UFS $\Gamma$			$\Omega$
	+EBL	mol.	mod.	+EBL	+UFL	+EBL+UFL	
3 (9)	0.09 (0)	0.09 (0)	0.08 (0)	0.08 (0)	0.08 (0)	0.08 (0)	0.09 (0)
4 (14)	0.13 (0)	0.14 (0)	0.11 (0)	0.12 (0)	0.12 (0)	0.11 (0)	0.13 (0)
5 (11)	0.16 (0)	0.17 (0)	0.14 (0)	0.14 (0)	0.14 (0)	0.14 (0)	0.16 (0)
6 (18)	0.18 (0)	0.19 (0)	0.16 (0)	0.16 (0)	0.15 (0)	0.15 (0)	0.18 (0)
7 (13)	0.19 (0)	0.17 (0)	0.17 (0)	0.17 (0)	0.15 (0)	0.15 (0)	0.17 (0)
8 (6)	0.23 (0)	0.20 (0)	0.21 (0)	0.20 (0)	0.17 (0)	0.17 (0)	0.19 (0)
9 (14)	0.32 (0)	0.27 (0)	0.28 (0)	0.28 (0)	0.22 (0)	0.23 (0)	0.28 (0)
10 (12)	0.44 (0)	0.33 (0)	0.39 (0)	0.39 (0)	0.29 (0)	0.29 (0)	0.34 (0)

Table: Inconsistent Multi-Context Systems



# Evaluation of the Learning-Based Algorithm

#ctx	explicit		UFS $\Gamma$		UFS $\Omega$		UFS $\Omega$ +EBL+UFL
		+EBL	mol.	mod.	+EBL	+UFL	
3 (6)	4.78 (0)	3.97 (0)	2.96 (0)	2.97 (0)	1.65 (0)	0.08 (0)	0.08 (0)
4 (10)	51.90 (1)	45.91 (1)	48.71 (1)	48.59 (1)	23.48 (0)	0.10 (0)	0.11 (0)
5 (8)	149.53 (3)	137.95 (3)	150.80 (3)	150.64 (3)	94.45 (1)	0.10 (0)	0.12 (0)
6 (6)	159.41 (3)	154.69 (3)	157.62 (3)	157.72 (3)	151.89 (3)	0.12 (0)	0.15 (0)
7 (12)	231.23 (9)	227.45 (9)	234.74 (9)	234.63 (9)	216.75 (8)	0.17 (0)	0.20 (0)
8 (5)	244.39 (4)	204.92 (3)	246.42 (4)	246.34 (4)	190.60 (3)	0.17 (0)	0.21 (0)
9 (8)	300.00 (8)	278.44 (7)	300.00 (8)	300.00 (8)	264.65 (6)	0.22 (0)	0.24 (0)
10 (11)	300.00 (11)	268.78 (9)	300.00 (11)	300.00 (11)	247.16 (8)	0.25 (0)	0.31 (0)

Table: Consistent Multi-Context Systems

# Evaluation of the Learning-Based Algorithm

#args	All Answer Sets					
	explicit	+EBL	UFS $\Gamma^*$ mol.	UFS $\Gamma^*$ mod.	+EBL+UFL	$\Omega$ +EBL+UFL
1 (30)	0.06 (0)	0.06 (0)	0.05 (0)	0.05 (0)	0.05 (0)	0.05 (0)
2 (30)	0.08 (0)	0.07 (0)	0.06 (0)	0.06 (0)	0.06 (0)	0.07 (0)
3 (30)	0.11 (0)	0.10 (0)	0.08 (0)	0.08 (0)	0.08 (0)	0.09 (0)
4 (30)	0.19 (0)	0.19 (0)	0.14 (0)	0.12 (0)	0.12 (0)	0.13 (0)
5 (30)	0.32 (0)	0.32 (0)	0.26 (0)	0.18 (0)	0.18 (0)	0.19 (0)
6 (30)	0.71 (0)	0.72 (0)	0.55 (0)	0.33 (0)	0.33 (0)	0.36 (0)
7 (30)	1.58 (0)	1.66 (0)	1.16 (0)	0.52 (0)	0.51 (0)	0.56 (0)
8 (30)	4.75 (0)	5.04 (0)	3.06 (0)	1.09 (0)	1.08 (0)	1.15 (0)
9 (30)	14.02 (0)	14.97 (0)	8.65 (0)	1.86 (0)	1.84 (0)	1.95 (0)
10 (30)	41.10 (0)	44.38 (0)	24.53 (0)	4.73 (0)	4.58 (0)	4.79 (0)
11 (30)	129.35 (1)	139.80 (2)	51.39 (0)	9.34 (0)	9.34 (0)	9.48 (0)
12 (30)	250.16 (12)	258.82 (17)	119.44 (0)	12.49 (0)	12.38 (0)	12.39 (0)
13 (30)	294.91 (27)	296.67 (27)	274.65 (19)	24.26 (0)	24.33 (0)	24.44 (0)
14 (30)	290.01 (29)	290.01 (29)	290.00 (29)	51.38 (3)	51.65 (3)	51.98 (3)
15 (30)	290.01 (29)	290.01 (29)	290.00 (29)	79.93 (3)	78.00 (3)	78.19 (3)
16 (30)	300.00 (30)	300.00 (30)	300.00 (30)	80.10 (4)	77.91 (4)	77.95 (4)
17 (30)	300.00 (30)	300.00 (30)	300.00 (30)	81.90 (5)	77.04 (5)	76.85 (5)
18 (30)	300.00 (30)	300.00 (30)	300.00 (30)	127.43 (8)	126.57 (8)	125.91 (8)
19 (30)	300.00 (30)	300.00 (30)	280.39 (28)	173.16 (13)	148.13 (10)	147.62 (10)
20 (30)	300.00 (30)	300.00 (30)	278.20 (27)	167.72 (12)	167.02 (12)	166.07 (12)

Table: Abstract Argumentation

# Evaluation of the Learning-Based Algorithm

#args	explicit		First Answer Set		$\Omega$	
		+EBL	UFS $\Gamma^*$ mol.	UFS $\Gamma^*$ mod.	+EBL+UFL	+EBL+UFL
1 (30)	0.05 (0)	0.05 (0)	0.05 (0)	0.05 (0)	0.05 (0)	0.05 (0)
2 (30)	0.07 (0)	0.07 (0)	0.06 (0)	0.06 (0)	0.06 (0)	0.06 (0)
3 (30)	0.09 (0)	0.09 (0)	0.08 (0)	0.08 (0)	0.07 (0)	0.08 (0)
4 (30)	0.14 (0)	0.14 (0)	0.12 (0)	0.10 (0)	0.10 (0)	0.12 (0)
5 (30)	0.22 (0)	0.22 (0)	0.21 (0)	0.15 (0)	0.15 (0)	0.17 (0)
6 (30)	0.46 (0)	0.47 (0)	0.42 (0)	0.27 (0)	0.27 (0)	0.29 (0)
7 (30)	0.76 (0)	0.79 (0)	0.68 (0)	0.37 (0)	0.37 (0)	0.40 (0)
8 (30)	2.34 (0)	2.44 (0)	1.98 (0)	0.89 (0)	0.90 (0)	0.94 (0)
9 (30)	7.35 (0)	7.82 (0)	5.76 (0)	1.36 (0)	1.28 (0)	1.34 (0)
10 (30)	19.47 (0)	21.05 (0)	15.37 (0)	3.54 (0)	3.53 (0)	3.68 (0)
11 (30)	63.39 (1)	67.39 (1)	26.30 (0)	4.61 (0)	4.66 (0)	4.69 (0)
12 (30)	119.65 (4)	126.18 (4)	60.88 (0)	6.11 (0)	6.11 (0)	6.13 (0)
13 (30)	197.04 (14)	201.27 (15)	149.25 (3)	16.34 (0)	16.49 (0)	16.50 (0)
14 (30)	227.27 (22)	227.72 (22)	218.00 (17)	41.28 (2)	41.68 (2)	41.76 (2)
15 (30)	260.02 (26)	260.02 (26)	260.01 (26)	40.92 (2)	41.38 (2)	41.62 (2)
16 (30)	230.04 (23)	230.04 (23)	230.02 (23)	40.63 (3)	40.69 (3)	40.84 (3)
17 (30)	250.03 (25)	250.03 (25)	250.01 (25)	35.24 (2)	35.60 (2)	35.57 (2)
18 (30)	270.02 (27)	270.02 (27)	270.01 (27)	74.89 (5)	75.47 (5)	75.10 (5)
19 (30)	230.06 (23)	230.06 (23)	211.12 (21)	66.58 (4)	67.03 (4)	67.04 (4)
20 (30)	220.07 (22)	220.07 (22)	200.29 (20)	81.81 (5)	82.33 (5)	82.45 (5)

Table: Abstract Argumentation

# Evaluation of the Learning-Based Algorithm

#cnt	explicit	+EBL	UFS $\Gamma$ mol.	UFS $\Gamma$ mod.	+EBL	+UFL	$\Omega$ +EBL+UFL
1 (1)	0.47 (0)	0.50 (0)	0.48 (0)	0.49 (0)	0.49 (0)	0.48 (0)	0.48 (0)
2 (1)	0.57 (0)	0.49 (0)	0.57 (0)	0.55 (0)	0.48 (0)	0.48 (0)	0.51 (0)
3 (1)	0.70 (0)	0.55 (0)	0.75 (0)	0.74 (0)	0.53 (0)	0.54 (0)	0.50 (0)
4 (1)	1.17 (0)	0.48 (0)	1.17 (0)	1.17 (0)	0.48 (0)	0.47 (0)	0.58 (0)
5 (1)	2.57 (0)	0.61 (0)	2.68 (0)	2.65 (0)	0.63 (0)	0.65 (0)	0.60 (0)
6 (1)	4.81 (0)	0.64 (0)	4.59 (0)	4.84 (0)	0.65 (0)	0.65 (0)	0.63 (0)
7 (1)	9.26 (0)	0.69 (0)	9.32 (0)	9.40 (0)	0.66 (0)	0.71 (0)	0.70 (0)
8 (1)	17.68 (0)	0.71 (0)	18.28 (0)	19.30 (0)	0.70 (0)	0.74 (0)	0.70 (0)
9 (1)	39.01 (0)	0.76 (0)	38.59 (0)	39.48 (0)	0.79 (0)	0.75 (0)	0.77 (0)
10 (1)	75.80 (0)	0.86 (0)	72.34 (0)	72.72 (0)	0.86 (0)	0.84 (0)	0.87 (0)
11 (1)	168.96 (0)	0.88 (0)	169.03 (0)	163.63 (0)	0.85 (0)	0.88 (0)	0.91 (0)
12 (1)	300.00 (1)	1.28 (0)	300.00 (1)	300.00 (1)	1.30 (0)	1.28 (0)	1.31 (0)
13 (1)	300.00 (1)	1.38 (0)	300.00 (1)	300.00 (1)	1.30 (0)	1.37 (0)	1.46 (0)
14 (1)	300.00 (1)	1.74 (0)	300.00 (1)	300.00 (1)	1.68 (0)	1.67 (0)	1.67 (0)
15 (1)	300.00 (1)	1.79 (0)	300.00 (1)	300.00 (1)	1.77 (0)	1.79 (0)	1.77 (0)
16 (1)	300.00 (1)	2.94 (0)	300.00 (1)	300.00 (1)	2.95 (0)	2.94 (0)	2.94 (0)
17 (1)	300.00 (1)	3.15 (0)	300.00 (1)	300.00 (1)	3.17 (0)	3.27 (0)	3.16 (0)
18 (1)	300.00 (1)	6.08 (0)	300.00 (1)	300.00 (1)	6.08 (0)	6.15 (0)	6.13 (0)
19 (1)	300.00 (1)	6.67 (0)	300.00 (1)	300.00 (1)	6.48 (0)	6.63 (0)	6.50 (0)
20 (1)	300.00 (1)	14.08 (0)	300.00 (1)	300.00 (1)	14.23 (0)	14.15 (0)	14.11 (0)

Table: Default Reasoning over DL-KBs (Bird-Penguin)

# Evaluation of the Learning-Based Algorithm

Ontology	explicit		UFS $\Gamma$	UFS $\Gamma$	$\Omega$		
		+EBL	mol.	mod.	+EBL	+UFL	+EBL+UFL
wine_00 (34)	89.30 (9)	33.11 (3)	89.29 (9)	88.75 (9)	33.19 (3)	33.00 (3)	33.15 (3)
wine_01 (34)	188.79 (18)	105.22 (10)	189.51 (18)	188.18 (18)	104.80 (9)	104.59 (10)	105.47 (10)
wine_02 (34)	217.87 (22)	142.67 (14)	217.32 (22)	217.13 (22)	142.79 (14)	142.75 (14)	142.65 (14)
wine_03 (34)	266.10 (30)	183.98 (18)	266.15 (30)	266.14 (30)	183.69 (18)	184.91 (18)	184.73 (18)
wine_04 (34)	266.52 (30)	202.22 (19)	266.47 (30)	266.48 (30)	201.19 (18)	201.46 (19)	201.32 (19)
wine_05 (34)	266.67 (30)	220.87 (21)	266.83 (30)	266.83 (30)	221.21 (21)	221.07 (21)	220.33 (21)
wine_06 (34)	268.03 (30)	258.18 (26)	268.08 (30)	267.98 (30)	257.76 (26)	257.99 (26)	257.96 (26)
wine_07 (34)	271.86 (30)	269.57 (30)	271.97 (30)	272.14 (30)	269.43 (30)	269.45 (30)	269.20 (30)
wine_08 (34)	278.06 (30)	272.57 (30)	278.16 (30)	277.81 (30)	272.37 (30)	272.57 (30)	272.72 (30)
wine_09 (34)	295.35 (31)	282.05 (30)	295.32 (30)	295.35 (31)	282.27 (30)	282.19 (30)	281.87 (30)
wine_10 (34)	300.00 (34)	299.45 (32)	300.00 (34)	300.00 (34)	299.55 (32)	299.63 (32)	299.58 (32)

Table: Default Reasoning over DL-KBs (Wine)

# Evaluation of the Grounding Algorithm

#	With Domain Predicate			Without Domain Predicates		
	wall clock	ground	solve	wall clock	ground	solve
15 (10)	0.59 (0)	0.28 (0)	0.08 (0)	0.49 (0)	0.23 (0)	0.06 (0)
25 (10)	5.78 (0)	4.67 (0)	0.33 (0)	2.94 (0)	1.90 (0)	0.35 (0)
35 (10)	36.99 (0)	33.99 (0)	1.00 (0)	14.02 (0)	11.30 (0)	0.95 (0)
45 (10)	161.91 (0)	155.40 (0)	2.18 (0)	53.09 (0)	47.19 (0)	2.22 (0)
55 (10)	300.00 (10)	300.00 (10)	n/a	171.46 (0)	158.58 (0)	5.74 (0)
65 (10)	300.00 (10)	300.00 (10)	n/a	300.00 (10)	300.00 (10)	n/a

Table: Reachability

# Evaluation of the Grounding Algorithm

#	With Domain Predicate			Without Domain Predicates		
	wall clock	ground	solve	wall clock	ground	solve
5 (10)	0.22 (0)	0.04 (0)	0.10 (0)	0.10 (0)	0.01 (0)	0.04 (0)
6 (10)	1.11 (0)	0.33 (0)	0.54 (0)	0.10 (0)	0.01 (0)	0.04 (0)
7 (10)	9.84 (0)	4.02 (0)	4.42 (0)	0.11 (0)	0.01 (0)	0.05 (0)
8 (10)	115.69 (0)	61.97 (0)	42.30 (0)	0.12 (0)	0.01 (0)	0.05 (0)
9 (10)	300.00 (10)	300.00 (10)	n/a	0.14 (0)	0.01 (0)	0.07 (0)
10 (10)	300.00 (10)	300.00 (10)	n/a	0.15 (0)	0.08 (0)	0.01 (0)
15 (10)	300.00 (10)	300.00 (10)	n/a	0.23 (0)	0.14 (0)	0.01 (0)
20 (10)	300.00 (10)	300.00 (10)	n/a	0.47 (0)	0.35 (0)	0.02 (0)
25 (10)	300.00 (10)	300.00 (10)	n/a	1.90 (0)	1.58 (0)	0.06 (0)
30 (10)	300.00 (10)	300.00 (10)	n/a	4.11 (0)	3.50 (0)	0.12 (0)
35 (10)	300.00 (10)	300.00 (10)	n/a	20.98 (0)	18.45 (0)	0.51 (0)
40 (10)	300.00 (10)	300.00 (10)	n/a	61.94 (0)	54.62 (0)	1.46 (0)
45 (10)	300.00 (10)	300.00 (10)	n/a	144.22 (2)	133.99 (2)	2.26 (0)
50 (10)	300.00 (10)	300.00 (10)	n/a	300.00 (10)	300.00 (0)	n/a

Table: Merge Sort

# Evaluation of the Grounding Algorithm

#	monolithic			greedy		
	wall clock	ground	solve	wall clock	ground	solve
4 (30)	0.57 (0)	0.11 (0)	0.38 (0)	0.25 (0)	0.01 (0)	0.18 (0)
5 (30)	2.12 (0)	0.67 (0)	1.26 (0)	0.44 (0)	0.01 (0)	0.37 (0)
6 (30)	18.93 (0)	7.45 (0)	10.86 (0)	0.88 (0)	0.01 (0)	0.80 (0)
7 (30)	237.09 (9)	170.12 (9)	65.12 (0)	1.65 (0)	0.01 (0)	1.57 (0)
8 (30)	300.00 (30)	300.00 (30)	n/a	3.13 (0)	0.01 (0)	3.05 (0)
9 (30)	300.00 (30)	300.00 (30)	n/a	7.41 (0)	0.02 (0)	7.31 (0)
10 (30)	300.00 (30)	300.00 (30)	n/a	15.92 (0)	0.02 (0)	15.81 (0)
11 (30)	300.00 (30)	300.00 (30)	n/a	31.19 (0)	0.02 (0)	31.05 (0)
12 (30)	300.00 (30)	300.00 (30)	n/a	63.16 (0)	0.02 (0)	62.95 (0)
13 (30)	300.00 (30)	300.00 (30)	n/a	172.75 (1)	0.03 (0)	172.38 (1)
14 (30)	300.00 (30)	300.00 (30)	n/a	256.60 (18)	0.01 (0)	256.44 (18)
15 (30)	300.00 (30)	300.00 (30)	n/a	290.01 (29)	< 0.005 (0)	290.00 (29)

Table: Argumentation with Subsequent Processing



# Evaluation of the Grounding Algorithm

#	With Domain Predicate			Without Domain Predicates		
	wall clock	ground	solve	wall clock	ground	solve
10 (1)	0.49 (0)	0.01 (0)	0.39 (0)	0.52 (0)	0.02 (0)	0.41 (0)
20 (1)	3.90 (0)	0.05 (0)	3.62 (0)	4.67 (0)	0.10 (0)	4.23 (0)
30 (1)	16.12 (0)	0.18 (0)	15.32 (0)	19.59 (0)	0.36 (0)	18.32 (0)
40 (1)	48.47 (0)	0.48 (0)	46.71 (0)	51.55 (0)	0.90 (0)	48.74 (0)
50 (1)	115.56 (0)	1.00 (0)	112.14 (0)	119.40 (0)	1.79 (0)	114.11 (0)
60 (1)	254.66 (0)	1.84 (0)	248.88 (0)	257.78 (0)	3.35 (0)	248.51 (0)

Table: Set Partitioning

# Evaluation of the Grounding Algorithm

#	Full Map															
	With Domain Predicate								Without Domain Predicates							
	wall clock	ground	solve solution (%)	length changes	lunch (%)				wall clock	ground	solve solution (%)	length changes	lunch (%)			
3 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	16.44 (0)	9.46 (0)	5.81 (0)	76.00	152.21	3.92	0.00	
4 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	36.60 (0)	16.69 (0)	16.90 (0)	52.00	213.00	5.31	3.85	
5 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	102.71 (0)	26.63 (0)	69.26 (0)	52.00	281.27	7.58	11.54	
6 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	284.69 (38)	236.43 (38)	45.56 (0)	16.00	368.12	9.00	100.00	
7 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	

#	Subway and Tram															
	With Domain Predicate								Without Domain Predicates							
	wall clock	ground	solve solution (%)	length changes	lunch (%)				wall clock	ground	solve solution (%)	length changes	lunch (%)			
3 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	8.91 (0)	4.88 (0)	3.01 (0)	96.00	125.19	3.38	0.00	
4 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	34.05 (2)	20.11 (2)	11.41 (0)	92.00	192.80	4.65	0.00	
5 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	62.98 (0)	13.57 (0)	43.58 (0)	90.00	284.89	7.53	46.67	
6 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	192.58 (11)	81.96 (11)	101.66 (0)	74.00	361.86	8.95	100.00	
7 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	287.99 (38)	234.55 (38)	49.27 (0)	24.00	410.17	10.50	100.00	
8 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	299.75 (48)	289.34 (48)	9.48 (0)	4.00	418.00	12.00	100.00	
9 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	

#	Subway Only															
	With Domain Predicate								Without Domain Predicates							
	wall clock	ground	solve solution (%)	length changes	lunch (%)				wall clock	ground	solve solution (%)	length changes	lunch (%)			
3 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	8.08 (0)	4.10 (0)	2.91 (0)	100.00	127.16	2.62	0.00	
4 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	23.87 (0)	7.31 (0)	13.72 (0)	100.00	206.78	4.16	12.00	
5 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	57.30 (0)	11.69 (0)	39.37 (0)	100.00	317.08	7.20	90.00	
6 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	107.05 (0)	17.32 (0)	78.33 (0)	100.00	364.32	8.46	100.00	
7 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	225.16 (9)	73.97 (9)	135.58 (0)	82.00	405.27	9.61	100.00	
8 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	299.90 (48)	289.15 (48)	9.83 (0)	4.00	353.00	9.00	100.00	
9 (50)	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	n/a	300.00 (50)	300.00 (50)	0.00 (0)	0.00	n/a	n/a	n/a	

Table: Route Planning