

# Exploiting Unfounded Sets for HEX-Program Evaluation

Thomas Eiter, Michael Fink, Thomas Krennwallner,  
Christoph Redl, Peter Schüller

redl@kr.tuwien.ac.at



TECHNISCHE  
UNIVERSITÄT  
WIEN  
Vienna University of Technology

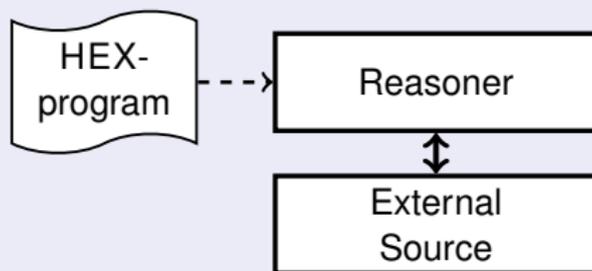


September 27, 2012

# Motivation

## HEX-Programs

- Extend ASP by **external sources**
- **Scalability problems** due to **minimality checking**



## Contribution

- Exploit **unfounded sets** for **minimality checking**
- Search for unfounded sets encoded as **separate search problem**
- Much **better scalability**

# Outline

- 1 Introduction
- 2 Answer Set Computation
- 3 Optimization and Learning
- 4 Implementation and Evaluation
- 5 Conclusion

# Outline

- 1 Introduction
- 2 Answer Set Computation
- 3 Optimization and Learning
- 4 Implementation and Evaluation
- 5 Conclusion

# 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

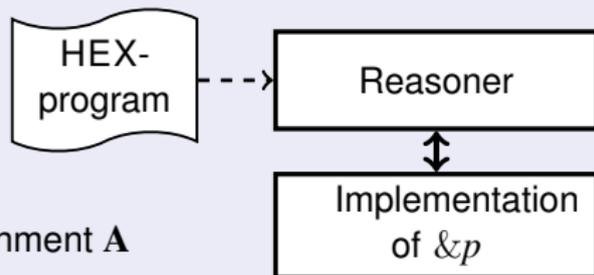
$t_j$  ... terms

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  $\mathbf{A}$

iff  $f_{\&p}(\mathbf{A}, q_1, \dots, q_k, t_1, \dots, t_l) = 1$ .



# Examples

## *&rdf*

### The *&rdf* External Atom

- Input: URL
- Output: Set of triplets from RDF file

External knowledge base is a set of RDF files on the web:

$$\mathit{addr}(\mathit{http://.../data1.rdf}).$$

$$\mathit{addr}(\mathit{http://.../data2.rdf}).$$

$$\mathit{bel}(X, Y) \leftarrow \mathit{addr}(U), \mathit{\&rdf}[U](X, Y, Z).$$

# Examples

## *&rdf*

### The *&rdf* External Atom

- Input: URL
- Output: Set of triplets from RDF file

External knowledge base is a set of RDF files on the web:

$$\begin{aligned} &addr(\text{http://.../data1.rdf}). \\ &addr(\text{http://.../data2.rdf}). \\ &bel(X, Y) \leftarrow addr(U), \&rdf[U](X, Y, Z). \end{aligned}$$

## *&diff*

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

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

# Semantics of HEX-Programs

## Definition (FLP-Reduct [Faber et al., 2004])

For an interpretation  $\mathbf{A}$  over a program  $\Pi$ , the **FLP-reduct**  $f\Pi^{\mathbf{A}}$  of  $\Pi$  wrt.  $\mathbf{A}$  is the set  $\{r \in \Pi \mid \mathbf{A} \models b, \text{ for all } b \in B(r)\}$  of all rules whose body is satisfied under  $\mathbf{A}$ .

## Definition (Answer Set)

An interpretation  $\mathbf{A}$  is an **answer set** of program  $\Pi$  iff it is a subset-minimal model of the FLP reduct  $f\Pi^{\mathbf{A}}$ .

## Example

Program  $\Pi$ :  $dom(a).dom(b).$

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

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

where  $\&g$  implements the following mapping:

$$\emptyset \mapsto \{b\}; \{a\} \mapsto \{a\}; \{b\} \mapsto \emptyset; \{a, b\} \mapsto \{a, b\}$$

$\mathbf{A} = \{\mathbf{T}dom(a), \mathbf{T}dom(b), \mathbf{T}p(a), \mathbf{F}p(b)\}$  is a model but no subset-minimal model of  $f\Pi^{\mathbf{A}} = \{dom(a); dom(b); p(a) \leftarrow dom(a), \&g[p](a)\}$

# Outline

- 1 Introduction
- 2 Answer Set Computation**
- 3 Optimization and Learning
- 4 Implementation and Evaluation
- 5 Conclusion

# Answer Set Computation

## 2-Step Algorithm

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

# Answer Set Computation

## 2-Step Algorithm

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

## The Naive Minimality Check

- 1 Let  $\mathbf{A}$  be a compatible set
- 2 Compute  $f_{\Pi}^{\mathbf{A}}$
- 3 Check if there is a smaller model than  $\mathbf{A}$

**Problem:** Reduct has usually many models

**Note:** In practice, smaller models are rarely found

# Answer Set Computation

## 2-Step Algorithm

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

## The Naive Minimality Check

- 1 Let **A** be a compatible set
- 2 Compute  $f\Pi^A$
- 3 Check if there is a smaller model than **A**

**Problem:** Reduct has usually many models

**Note:** In practice, smaller models are rarely found

## Complexity

Minimality check is Co-NP-complete, lifting the overall answer set existence problem to  $\Pi_2^P$   
(in presence of disjunctions and/or nonmonotonic external atoms)

# Using Unfounded Sets [Faber, 2005]

## Definition (Unfounded Set)

A set of atoms  $X$  is an **unfounded set** of  $\Pi$  wrt. (partial) assignment  $\mathbf{A}$ , iff for all  $a \in X$  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  $\mathbf{A} \dot{\cup} \neg.X \not\models B(r)$
- 3  $\mathbf{A} \models h$  for some  $h \in H(r) \setminus X$

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

## Definition (Unfounded-free Assignments)

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

## 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

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

- $N_{\Pi}^{\mathbf{A}} = \{\{\mathbf{F}a \mid \mathbf{T}a \in \mathbf{A}\}\} \cup (\bigcup_{r \in \Pi} R_r^{\mathbf{A}})$
- $R_{r,\mathbf{A}} = H_{r,\mathbf{A}} \cup C_{r,\mathbf{A}}$ , where
- $H_{r,\mathbf{A}} = \{\{\mathbf{T}h_r\} \cup \{\mathbf{F}h \mid h \in H(r)\}\} \cup \{\{\mathbf{F}h_r, \mathbf{T}h\} \mid h \in H(r)\}$
- $C_{r,\mathbf{A}} = \begin{cases} \{\{\mathbf{T}h_r\} \cup \\ \{\mathbf{F}a \mid a \in B_o^+(r), \mathbf{A} \models a\} \cup \{\mathbf{t}a \mid a \in B_e(\hat{r})\} \cup \\ \{\mathbf{T}h \mid h \in H(r), \mathbf{A} \models h\}\} & \text{if } \mathbf{A} \models B(r), \\ \{\} & \text{otherwise} \end{cases}$

**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  $\Gamma_{\Pi}^{\mathbf{A}}$

## Definition (Induced Assignment of an Unfounded Set)

Let  $U$  be an unfounded set of a program  $\Pi$  wrt. assignment  $\mathbf{A}$ .

The **assignment induced by  $U$** , denoted  $I(U, \Gamma_{\Pi}^{\mathbf{A}})$ , is

$$I(U, \Gamma_{\Pi}^{\mathbf{A}}) = I'(U, \Gamma_{\Pi}^{\mathbf{A}}) \cup \{\mathbf{F}a \mid a \in A(\Gamma_{\Pi}^{\mathbf{A}}), \mathbf{T}a \notin I'(U, \Gamma_{\Pi}^{\mathbf{A}})\}, \text{ where}$$

$$I'(U, \Gamma_{\Pi}^{\mathbf{A}}) = \{\mathbf{T}a \mid a \in U\} \cup \{\mathbf{T}h_r \mid r \in \Pi, H(r) \cap U \neq \emptyset\} \cup \\ \{\mathbf{T}e_{\&g[\vec{p}]}(\vec{c}) \mid e_{\&g[\vec{p}]}(\vec{c}) \in A(\hat{\Pi}), \mathbf{A} \dot{\cup} \neg.U \models \&g[\vec{p}](\vec{c})\}.$$

## Proposition

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

# Using Unfounded Sets

**Not** each 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)  $\mathbf{T}e_{\&g[\vec{p}]}(\vec{c}) \in S$  and  $\mathbf{A} \not\models \&g[\vec{p}](\vec{c})$  implies  $\mathbf{A} \dot{\cup} \neg.U \models \&g[\vec{p}](\vec{c})$ ; and
- (b)  $\mathbf{F}e_{\&g[\vec{p}]}(\vec{c}) \in S$  and  $\mathbf{A} \models \&g[\vec{p}](\vec{c})$  implies  $\mathbf{A} \dot{\cup} \neg.U \not\models \&g[\vec{p}](\vec{c})$

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

## Our Approach

- 1 Compute a solution  $S$  of  $\Gamma_{\Pi}^{\mathbf{A}}$
- 2 Check if truth value of external atom replacement  $e_{\&g[\vec{p}]}(\vec{c})$  in  $S$  is equal to truth value of  $\&g[\vec{p}](\vec{c})$  under  $\mathbf{A} \dot{\cup} \neg.U$
- 3 If yes:  $S$  represents an unfounded set
- 4 If no: continue with next solution of  $\Gamma_{\Pi}^{\mathbf{A}}$

# Outline

- 1 Introduction
- 2 Answer Set Computation
- 3 Optimization and Learning**
- 4 Implementation and Evaluation
- 5 Conclusion

# Optimization and Learning

## Optimization

Generate **additional nogoods**  $O_{\Pi}^{\mathbf{A}}$  to prune search space

- **Restrict search** to atoms which are true in  $\mathbf{A}$
- Try to **avoid changes of truth values** of external atoms

## Learning

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

# Outline

- 1 Introduction
- 2 Answer Set Computation
- 3 Optimization and Learning
- 4 Implementation and Evaluation**
- 5 Conclusion

# Implementation

## Implementation

- Prototype implementation: DLVHEX
- Written in C++
- External sources loaded via plugin interface

## Technology

- Basis: Gringo and CLASP
- CLASP serves also as SAT solver for UFS search
- Alternatively: self-made grounder and solver built from scratch

# Benchmark Results

$n$		5	6	7	8	9	10	11	12	13	...	20
all AS	explicit	10.9	94.3	—	—	—	—	—	—	—	—	—
	+EBL	4.3	34.8	266.1	—	—	—	—	—	—	—	—
	UFS	0.2	0.3	0.8	1.8	4.5	11.9	32.4	92.1	273.9	—	—
	+EBL	0.1	0.1	0.2	0.2	0.3	0.4	0.6	0.8	1.2	...	11.1
first AS	explicit	0.7	4.3	26.1	163.1	—	—	—	—	—	—	—
	+EBL	0.8	4.9	31.1	192.0	—	—	—	—	—	—	—
	UFS	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	...	0.5
	+EBL	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	...	0.3

Figure: Set Partitioning

$n$	all answer sets		first answer set	
	Explicit	UFS	Explicit	UFS
5	1.47	1.13	0.70	0.62
6	4.57	2.90	1.52	1.27
7	19.99	10.50	3.64	2.77
8	80.63	39.01	9.46	6.94
9	142.95	80.66	30.12	20.97
10	240.46	122.81	107.14	63.50

Figure: Argumentation (plain)

# Benchmark Results

c#contexts	(no answer sets)				
	explicit check		UFS check		
	plain	+EBL	plain	+EBL	+UFL
3	8.61	4.68	7.31	2.44	0.50
4	86.55	48.53	80.31	25.98	1.89
5	188.05	142.61	188.10	94.45	4.62
6	209.34	155.81	207.14	152.32	14.39
7	263.98	227.99	264.00	218.94	49.42
8	293.64	209.41	286.38	189.86	124.23
9	—	281.98	—	260.01	190.56
10	—	274.76	—	247.67	219.83

Figure: Consistent MCSs

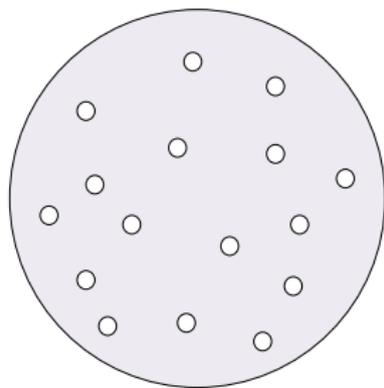
c#contexts	enumerating all answer sets					finding first answer set				
	explicit check		UFS check			explicit check		UFS check		
	plain	+EBL	plain	+EBL	+UFL	plain	+EBL	plain	+EBL	+UFL
3	9.08	6.11	6.29	2.77	0.85	4.01	2.53	3.41	1.31	0.57
4	89.71	36.28	80.81	12.63	5.27	53.59	16.99	49.56	6.09	1.07
5	270.10	234.98	268.90	174.23	18.87	208.62	93.29	224.01	32.85	3.90
6	236.02	203.13	235.55	179.24	65.49	201.84	200.06	201.24	166.04	28.34
7	276.94	241.27	267.82	231.08	208.47	241.09	78.72	240.72	66.56	16.41
8	286.61	153.41	282.96	116.89	69.69	201.10	108.29	210.61	103.11	30.98
9	—	208.92	—	191.46	175.26	240.75	112.08	229.14	76.56	44.73
10	—	—	—	289.87	289.95	—	125.18	—	75.24	27.05

Figure: Inconsistent MCSs

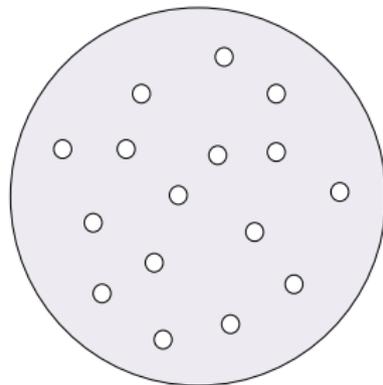
# Benchmark Results

## Interesting Observations

- Search space for UFS check potentially smaller than for explicit check
- Even if they have the same size the UFS check is mostly faster:
  - Less overhead (SAT vs. ASP instance)
  - Easier for the solver to jump from one candidate to the next one



candidate smaller models  
of the reduct

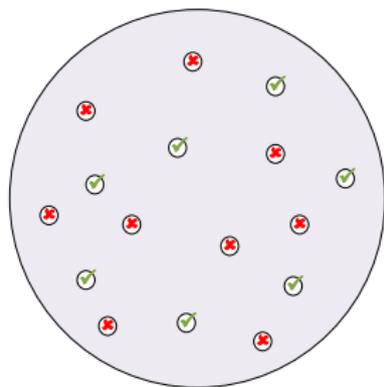


candidate unfounded sets

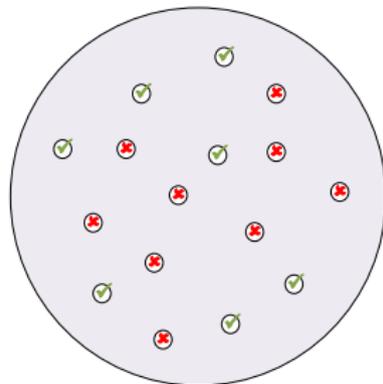
# Benchmark Results

## Interesting Observations

- Search space for UFS check potentially smaller than for explicit check
- Even if they have the same size the UFS check is mostly faster:
  - Less overhead (SAT vs. ASP instance)
  - Easier for the solver to jump from one candidate to the next one



candidate smaller models  
of the reduct

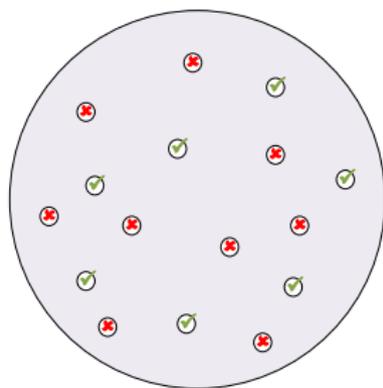


candidate unfounded sets

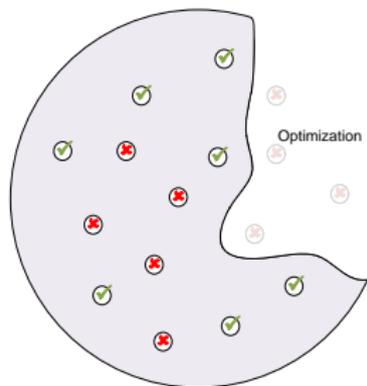
# Benchmark Results

## Interesting Observations

- Search space for UFS check potentially smaller than for explicit check
- Even if they have the same size the UFS check is mostly faster:
  - Less overhead (SAT vs. ASP instance)
  - Easier for the solver to jump from one candidate to the next one



candidate smaller models  
of the reduct

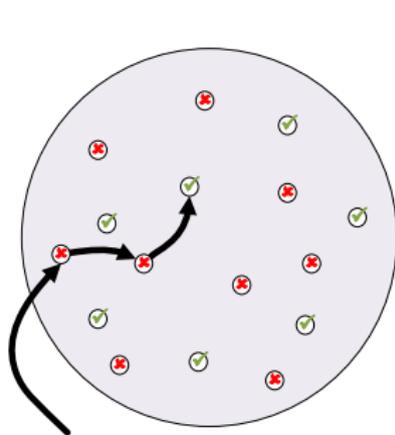


candidate unfounded sets

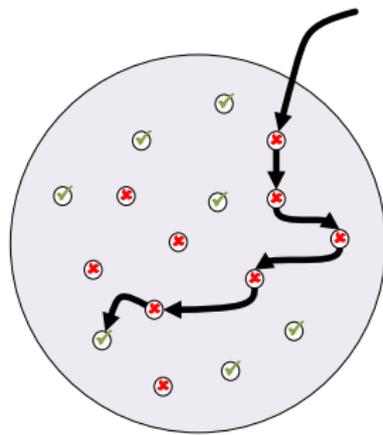
# Benchmark Results

## Interesting Observations

- Search space for UFS check potentially smaller than for explicit check
- Even if they have the same size the UFS check is mostly faster:
  - Less overhead (SAT vs. ASP instance)
  - Easier for the solver to jump from one candidate to the next one



candidate smaller models  
of the reduct

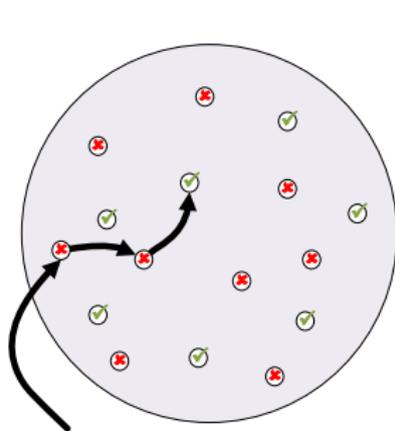


candidate unfounded sets

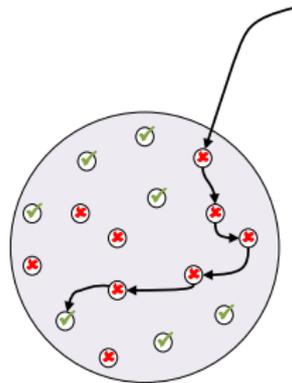
# Benchmark Results

## Interesting Observations

- Search space for UFS check potentially smaller than for explicit check
- Even if they have the same size the UFS check is mostly faster:
  - Less overhead (SAT vs. ASP instance)
  - Easier for the solver to jump from one candidate to the next one



candidate smaller models  
of the reduct

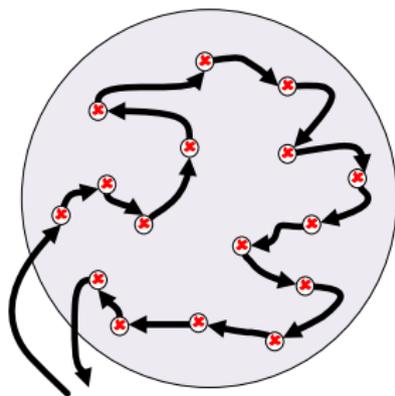


candidate unfounded sets

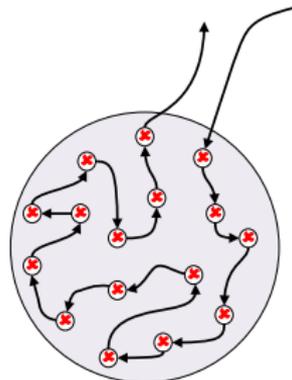
# Benchmark Results

## Interesting Observations

- Search space for UFS check potentially smaller than for explicit check
- Even if they have the same size the UFS check is mostly faster:
  - Less overhead (SAT vs. ASP instance)
  - Easier for the solver to jump from one candidate to the next one



candidate smaller models  
of the reduct



candidate unfounded sets

# Outline

- 1 Introduction
- 2 Answer Set Computation
- 3 Optimization and Learning
- 4 Implementation and Evaluation
- 5 Conclusion**

# Conclusion

## Evaluating HEX-Programs

- Compute a **compatible set**, then check if it is **unfounded-free**
- Encoded as **nogood set** consisting of a **necessary** and **optimization part**
- Unfounded sets allow for **learning** nogoods

## Implementation and Evaluation

- Prototype implementation based on Gringo and CLASP
- Experiments show significant **improvements by UFS-based minimality check**
- Further speedup by **optimization part** and **learning**

## Future Work

- Unfounded set check over **partial interpretations**
- **Decision criterion** for necessity of UFS-check
- **Further restriction of search space** to the relevant part

# References

 Eiter, T., Fink, M., Krennwallner, T., and Redl, C. (2012).

Conflict-driven ASP solving with external sources.

*Theory and Practice of Logic Programming: Special Issue ICLP.*

To appear.

 Eiter, T., Ianni, G., Schindlauer, R., and Tompits, H. (2005).

A uniform integration of higher-order reasoning and external evaluations in answer-set programming.

*In In Proceedings of the 19th International Joint Conference on Artificial Intelligence (IJCAI-05, pages 90–96. Professional Book.*

URL:

<http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.128.8944>.

 Faber, W. (2005).

Unfounded sets for disjunctive logic programs with arbitrary aggregates.

*In In Logic Programming and Nonmonotonic Reasoning, 8th International Conference (LPNMR'05), 2005, pages 40–52. Springer Verlag.*

 Faber, W., Leone, N., and Pfeifer, G. (2004).

Recursive aggregates in disjunctive logic programs: Semantics and complexity.

*In In Proceedings of European Conference on Logics in Artificial Intelligence (JELIA, pages 200–212. Springer.*