

Knowledge Compilation of Logic Programs Using Approximation Fixpoint Theory

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Presenter: Joost Vennekens

ICLP 2015

Content

- 1 Knowledge Compilation
- 2 Bottom-Up Knowledge Compilation for Monotone Logic Programs
- 3 Bottom-Up Knowledge Compilation for Non-Monotone Logic Programs
- 4 Knowledge Compilation: An Algebraical Perspective
- 5 Conclusion

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Knowledge Compilation: What?

- Given:
 - Theory \mathcal{T} in language \mathcal{L} .
- Find:
 - Equivalent theory \mathcal{T}' in language \mathcal{L}' with attractive properties.

Knowledge Compilation: What?

- Given:
 - Theory \mathcal{T} in language \mathcal{L} .
- Find:
 - Equivalent theory \mathcal{T}' in language \mathcal{L}' with attractive properties.
E.g., if \mathcal{L}' is the language of **SDDs**: the following inference methods are polytime:
 - Validity checking,
 - Consistency checking,
 - Equivalence checking,
 - Model enumeration,
 - (Weighted) model counting.
 - ...

Knowledge Compilation: Why?

- Compile once, evaluate often.
- Reuse (off-line) compilation.
- Reduction of problems in \mathcal{L} to problems in \mathcal{L}' .

Knowledge Compilation: How?

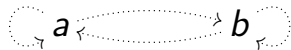
- In this talk, \mathcal{L} is the language of propositional logic programs (parametrised well-founded semantics)
- \mathcal{L}' is the language of SDDs (Sentential Decision Diagrams) (but it could be any representation of propositional formulas)
- State of the art:
 - Transform logic program \mathcal{P} to CNF (completion + loop breaking formulas)
 - Transform the CNF to an SDD

Knowledge Compilation: How?

- In this talk, \mathcal{L} is the language of propositional logic programs (parametrised well-founded semantics)
- \mathcal{L}' is the language of SDDs (Sentential Decision Diagrams) (but it could be any representation of propositional formulas)
- State of the art:
 - Transform logic program \mathcal{P} to CNF (completion + loop breaking formulas)
 - Transform the CNF to an SDD
- Disadvantages
 - Many auxiliary variables are introduced
 - Expensive pre-processing (loop breaking) not always feasible

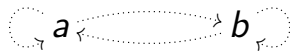
Example

$$\left\{ \begin{array}{l} R(x, y) \leftarrow E(x, y). \\ R(x, y) \leftarrow E(x, z) \wedge R(z, y). \end{array} \right\}$$



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$$\left\{ \begin{array}{l} R(x, y) \leftarrow E(x, y). \\ R(x, y) \leftarrow E(x, z) \wedge R(z, y). \end{array} \right\}$$



$$R(a, a) \Leftarrow E(a, a) \vee (E(a, b) \wedge R(b, a)) \vee (E(a, a) \wedge R(a, a)).$$

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$$R(a, a) \Rightarrow E(a, a) \vee (E(a, b) \wedge R(b, a) \wedge T_1) \vee (E(a, a) \wedge R(a, a) \wedge \mathbf{f}).$$

$$R(a, b) \Rightarrow E(a, b) \vee (E(a, a) \wedge R(a, b) \wedge \mathbf{f}) \vee (E(a, b) \wedge R(b, b) \wedge T_2).$$

$$R(b, b) \Rightarrow E(b, b) \vee (E(b, a) \wedge R(a, b) \wedge \neg T_2) \vee (E(b, b) \wedge R(b, b) \wedge \mathbf{f}).$$

$$R(b, a) \Rightarrow E(b, a) \vee (E(b, b) \wedge R(b, a) \wedge \mathbf{f}) \vee (E(b, a) \wedge R(a, a) \wedge \neg T_1).$$

Example

$$\left\{ \begin{array}{l} R(x, y) \leftarrow E(x, y). \\ R(x, y) \leftarrow E(x, z) \wedge R(z, y). \end{array} \right\}$$



$$R(a, a) \Leftrightarrow E(a, a) \vee (E(a, b) \wedge E(b, a)).$$

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Situation

- IJCAI'15 “Anytime inference in probabilistic logic programs with $T_{\mathcal{P}}$ -compilation” (Vlasselaer et al):
 - New *bottom-up* knowledge compilation for positive logic programs
 - Improved efficiency
 - Enables *approximate inference*
- This paper:
 - Generalisation for *generalised logic program under parametrised well-founded semantics*
 - Generalisation to algebraical setting (*Approximation Fixpoint Theory*)

Content

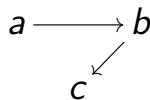
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Reachability

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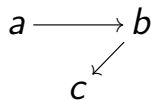
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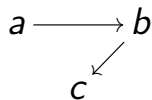
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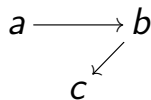
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$R(a, b) =$	f	t
$R(b, a) =$	f	f
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$R(c, a) =$	f	f
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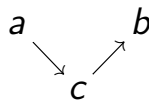
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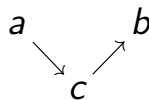
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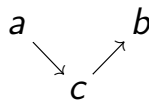
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...			

Observations

- For every graph: similar process.
- Lots of overlap.
- Least fixpoint computation = sequence of interpretations.
- **Idea:** Generalise this. Execute this fixpoint computation once, symbolically.

Parametrised well-founded semantics

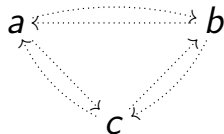
- \mathcal{P} : parametrised logic program
 - Σ_d : defined symbols
 - Σ_p : parameter symbols
- For every Σ_p -interpretation I : \mathcal{P} defines the well-founded model of \mathcal{P} in context I (a Σ_d -interpretation), denoted $WFM(\mathcal{P}, I)$
- = **Parametrised well-founded semantics**

Symbolic Interpretations

- Σ_d -interpretation: mapping $\Sigma_d \rightarrow \{\mathbf{t}, \mathbf{f}\}$: state in the least fixpoint computation
- Symbolic Σ_d -interpretation \mathcal{A} : mapping $\Sigma_d \rightarrow \{\text{formulas over } \Sigma_p\}$ (modulo equivalence)
- Will be a state in a symbolic least fixpoint computation

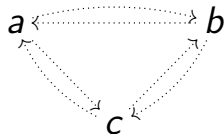
Symbolic Least Fixpoint Computation

$$\left\{ \begin{array}{l} R(x, y) \leftarrow E(x, y). \\ R(x, y) \leftarrow E(x, z) \wedge R(z, y). \end{array} \right\}$$



Symbolic Least Fixpoint Computation

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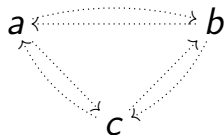
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Symbolic Least Fixpoint Computation

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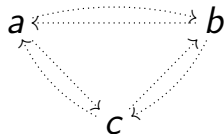
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$$R(a, b) = \mathbf{f} \quad E(a, b) \quad E(a, b) \vee (E(a, c) \wedge E(c, a)) \vee \dots$$

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Negation

- Least fixpoint computation only works for monotone logic programs.
- What about negation?
- For the standard (non-parametrised) well-founded semantics: solved by Van Gelder, Ross and Schlipf (1991).

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$s = \mathbf{t}$$

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$s = \mathbf{t}$$

$$p = \mathbf{u}$$

$$q = \mathbf{u}$$

$$r = \mathbf{u}$$

...

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$s = t$$

$p =$	u	t
$q =$	u	u
$r =$	u	u
\dots		

Rule application

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\} \quad s = t$$

$p =$	u	t	t
$q =$	u	u	t
$r =$	u	u	u
...			

Rule application

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$s = t$$

$p =$	u	t	t	t
$q =$	u	u	t	t
$r =$	u	u	u	f
...				

Rule application

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$s = \mathbf{f}$$

$$p = \mathbf{u}$$

$$q = \mathbf{u}$$

$$r = \mathbf{u}$$

...

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$s = \mathbf{f}$$

$p =$	u	f
$q =$	u	f
$r =$	u	u
...		

Unfounded set

Well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\} \quad s = \mathbf{f}$$

$p =$	u	f	f
$q =$	u	f	f
$r =$	u	u	t
...			

Rule application

Observations

- For every Σ_p -interpretation: similar process
- Lots of overlap
- Well-founded model computation = sequence of partial interpretations
- **Idea:** Generalise this. Execute this fixpoint computation once, symbolically.

Parametrised well-founded semantics

- \mathcal{P} : parametrised logic program
 - Σ_d : defined symbols
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- = Parametrised well-founded semantics
- Now: compute $PWFM(\mathcal{P})$

Symbolic Partial Interpretations

- Partial interpretation: mapping $\Sigma_d \rightarrow \{\mathbf{t}, \mathbf{f}, \mathbf{u}, \mathbf{i}\}$: state in the well-founded model computation.
- Alternative representation: mapping $\Sigma_d \rightarrow \{\mathbf{t}, \mathbf{f}\} \times \{\mathbf{t}, \mathbf{f}\}$ (certain, possible)
 - $(\mathbf{t}, \mathbf{t}) = \mathbf{t}$
 - $(\mathbf{f}, \mathbf{f}) = \mathbf{f}$
 - $(\mathbf{f}, \mathbf{t}) = \mathbf{u}$
 - $(\mathbf{t}, \mathbf{f}) = \mathbf{i}$
- Symbolic partial interpretation:
mapping $\Sigma_d \rightarrow \{\text{formulas over } \Sigma_p\} \times \{\text{formulas over } \Sigma_p\}$
(modulo equivalence)
- Will be a state in a symbolic well-founded model computation

Symbolic well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

Symbolic well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$$p_c = \quad \mathbf{f}$$

$$p_p = \quad \mathbf{t}$$

$$q_c = \quad \mathbf{f}$$

$$q_p = \quad \mathbf{t}$$

$$r_c = \quad \mathbf{f}$$

$$r_p = \quad \mathbf{t}$$

...

Symbolic well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$p_c =$	f	f \vee s
$p_p =$	t	t
$q_c =$	f	f
$q_p =$	t	t
$r_c =$	f	f
$r_p =$	t	t
...		

Rule application

Symbolic well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$p_c =$	f	s	s
$p_p =$	t	t	t
$q_c =$	f	f	s
$q_p =$	t	t	t
$r_c =$	f	f	f
$r_p =$	t	t	¬s
...			

Rule application

Symbolic well-founded model construction

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

$p_c =$	f	s	s	s
$p_p =$	t	t	t	s
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$r_c =$	f	f	f	f
$r_p =$	t	t	¬s	¬s
...				

Unfounded set

Symbolic well-founded model construction

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$p_c =$	f	s	s	s	s
$p_p =$	t	t	t	s	s
$q_c =$	f	f	s	s	s
$q_p =$	t	t	t	s	s
$r_c =$	f	f	f	f	¬s
$r_p =$	t	t	¬s	¬s	¬s
...					

Rule application

Symbolic well-founded model

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

Symbolic interpretation: $p \mapsto s, q \mapsto s, r \mapsto \neg s$

Knowledge Compilation

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

Propositional theory: $(p \Leftrightarrow s) \wedge (q \Leftrightarrow s) \wedge (r \Leftrightarrow \neg s)$

Knowledge Compilation

$$\left\{ \begin{array}{l} p \leftarrow q \vee s \\ q \leftarrow p \\ r \leftarrow \neg p \end{array} \right\}$$

Non-recursive logic program:

$$\left\{ \begin{array}{l} p \leftarrow s. \\ q \leftarrow s. \\ r \leftarrow \neg s. \end{array} \right\}$$

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Background: Approximation Fixpoint Theory

- Algebraical theory
- Defines different types of fixpoints of lattice operators
 - Supported fixpoints
 - (Partial) stable fixpoints
 - Kripke-Kleene fixpoint
 - Well-founded fixpoint
- Captures semantics of many logical formalisms
 - Logic programming
 - Autoepistemic logic (Moore, 1985)
 - Default logic (Reiter, 1980)
 - Dung's argumentation frameworks (Dung, 1995)
 - Abstract dialectical frameworks (Brewka and Woltran, 2013)

(Denecker, Marek, Truszczyński, 2000)

Background: Approximation Fixpoint Theory

- Given:
 - Complete lattice $\langle L, \leq \rangle$
 - Bilattice $\langle L^2, \leq_p \rangle$
 - Lattice operator $O : L \rightarrow L$
 - Approximator $A : L^2 \rightarrow L^2$
- Define:
 - **Supported fixpoint**: fixpoint of O
 - **A-Kripke-Kleene fixpoint**: $\text{lfp}_{\leq_p} A$
 - **Partial A-stable fixpoint**: pair (x, y) such that $x = \text{lfp}(A(\cdot, y)_1)$ and $y = \text{lfp}(A(x, \cdot)_2)$
 - **A-well-founded fixpoint**: least precise partial A-stable fixpoint
 - **A-stable fixpoint** of O : fixpoint x of O such that (x, x) is a partial A-stable fixpoint

Background: Approximation Fixpoint Theory

- Given: (Logic programming)
 - Complete lattice $\langle L, \leq \rangle$ (Lattice of interpretations: $\langle 2^{\Sigma_d}, \subseteq \rangle$)
 - Bilattice $\langle L^2, \leq_p \rangle$ (Partial interpretations)
 - Lattice operator $O : L \rightarrow L$ (T_P)
 - Approximator $A : L^2 \rightarrow L^2$ (Ψ_P)
- Define:
 - Supported fixpoint: fixpoint of O (Supported model) (Clark, 1978)
 - A-Kripke-Kleene fixpoint: $\text{lfp}_{\leq_p} A$ (Kripke-Kleene semantics) (Fitting, 1985)
 - Partial A-stable fixpoint: pair (x, y) such that $x = \text{lfp}(A(\cdot, y)_1)$ and $y = \text{lfp}(A(x, \cdot)_2)$ (Partial stable model)
 - A-well-founded fixpoint: least precise partial A-stable fixpoint (Well-founded model) (Van Gelder, Ross and Schilpf, 1988)
 - A-stable fixpoint of O : fixpoint x of O such that (x, x) is a partial A-stable fixpoint (Stable model) (Gelfond and Lifschitz, 1988)

Background: Approximation Fixpoint Theory

- **Well-founded induction** (Denecker and Vennekens, 2007):
 - Algebraical generalisation of well-founded model computation
 - Constructive characterisation of the well-founded fixpoint
 - Sequence of bilattice elements (partial interpretations)
 - Transitions similar to “rule application” and “unfounded set computation”

Extending AFT

- 1 Studied the link between well-founded inductions of different operators
- 2 (For logic programming): defined symbolic versions of $T_{\mathcal{P}}$ and $\Psi_{\mathcal{P}}$ (called $\mathcal{T}_{\mathcal{P}}$ and $\Psi_{\mathcal{P}}$ respectively)
- 3 Applying (1): well-founded induction of $\Psi_{\mathcal{P}}$: fixpoint procedure to compute the parametrised well-founded model

Extending AFT

- 1 Studied the link between well-founded inductions of different operators
- 2 (For logic programming): defined symbolic versions of $T_{\mathcal{P}}$ and $\Psi_{\mathcal{P}}$ (called $\mathcal{T}_{\mathcal{P}}$ and $\mathcal{\Psi}_{\mathcal{P}}$ respectively)
- 3 Applying (1): well-founded induction of $\mathcal{\Psi}_{\mathcal{P}}$: fixpoint procedure to compute the parametrised well-founded model
- 4 **Any-time algorithm** for approximate inference

Theorem

Let \mathcal{P} be a parametrised logic program with parametrised well-founded model $(\mathcal{A}, \mathcal{A})$. Let $(\mathcal{A}_i, \mathcal{A}'_i)_{i \leq \beta}$ be a well-founded induction of $\mathcal{\Psi}_{\mathcal{P}}$. Then

$$WMC(\mathcal{A}_i, \varphi, W) \leq WMC(\mathcal{A}, \varphi, W) \leq WMC(\mathcal{A}'_i, \varphi, W).$$

Content

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- 2 Bottom-Up Knowledge Compilation for Monotone Logic Programs
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- 5 Conclusion

Advantages

Advantages of this approach for **logic programming**

- No auxiliary variables needed
- Preserves equivalence
- No loop-breaking preprocessing
- Any-time algorithm
- Works with any type of circuits (“propositional formulas modulo equivalence”) that support bottom-up compilation

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Advantages of using **AFT**

- Paves the way for knowledge compilation for autoepistemic logic, default logic, abstract argumentation, ...
- Knowledge compilation for Kripke-Kleene semantics
- Simple (but abstract) proofs of correctness

Conclusion

Main contributions:

- Lifted knowledge compilation principles to *general* logic programs
- Lifted knowledge compilation principles to *AFT*

Work in progress:

- Implementation and experiments
- Knowledge compilation for stable semantics