

Groundedness in Logics With a Fixpoint Semantics

Public Defence

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- 1 Knowledge Representation and Reasoning (KRR)
- 2 KRR in Practice
- 3 My Contributions to KRR
- 4 Groundedness in Logics With a Fixpoint Semantics (English)
 - Chapter 3: Grounded Fixpoints
 - Chapter 4: Partial Grounded Fixpoints
 - Chapter 5: Set-Inductions and Locally Monotone Operators

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- ① Defining knowledge representation languages
- ② Defining inference methods
- ③ Implementing inference engines
- ④ Studying complexity, expressivity and succinctness
- ⑤ Relationships between languages/systems/inferences/...
- ⑥ Applications

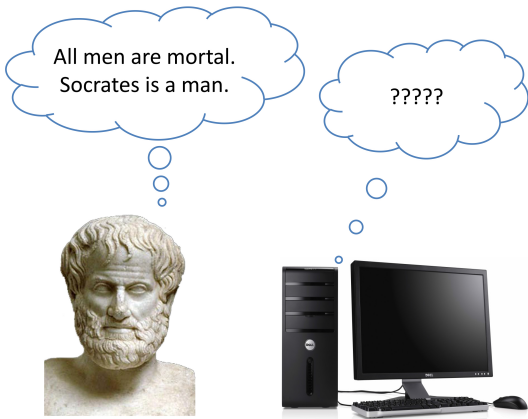
Goal

Representing knowledge about the world in a form that a computer system can utilise to solve complex tasks.

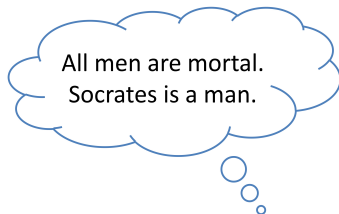
1. KR languages

Goal

Representing knowledge about the world in a form that a computer system can utilise to solve complex tasks.



1. KR Languages: First-Order Logic

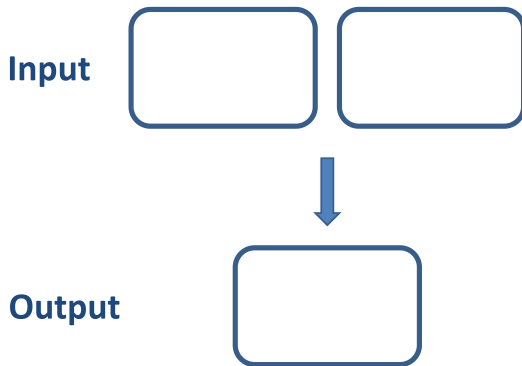


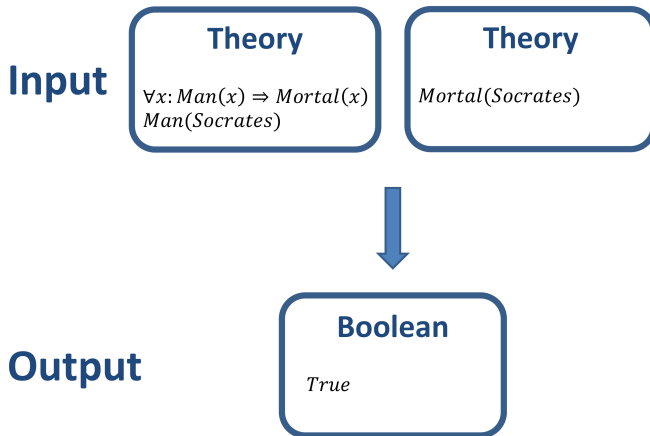
- First-order logic (FO):
 - All men are mortal: $\forall x : \text{Man}(x) \Rightarrow \text{Mortal}(x)$
 - Socrates is a man: $\text{Man}(\text{Socrates})$
- Certain types of knowledge inexpressible in FO

2. Inference Methods

Goal

*Representing knowledge about the world in a form that a computer system can utilise to solve **complex tasks**.*





Inference Methods: Model Expansion

Theory

$$\forall r \, c \, c': c \neq c' \Rightarrow On(r, c) \neq On(r, c')$$

$$\forall c \, r \, r': r \neq r' \Rightarrow On(r, c) \neq On(r', c)$$

...

Structure

7	5		9			6
2	3		8			4
8				3		1
5			7	2		
4		8	6		2	
		9	1			3
9		4				7
6			7		5	8
7			1	3	9	

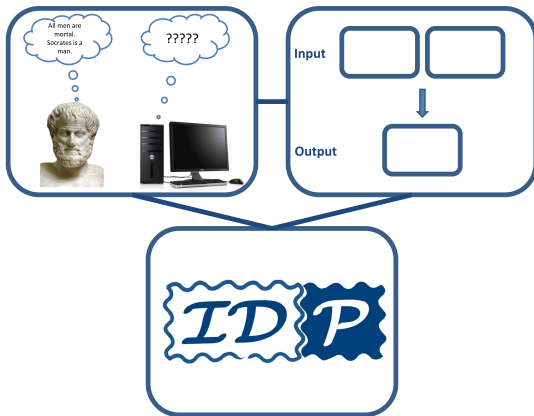
Structure

1	7	5	2	9	4	8	3	6
6	2	3	1	8	7	9	4	5
8	9	4	5	6	3	2	7	1
5	1	9	7	3	2	4	6	8
3	4	7	8	5	6	1	2	9
2	8	6	9	4	1	7	5	3
9	3	8	4	2	5	6	1	7
4	6	1	3	7	9	5	8	2
7	5	2	6	1	8	3	9	4

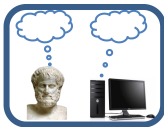
3. Inference Engines

Goal

*Representing knowledge about the world in a form that a **computer system** can utilise to **solve** complex tasks.*



4. Expressivity, Succinctness, Complexity



Inexpressive



Expressive

Lengthy



Succinct

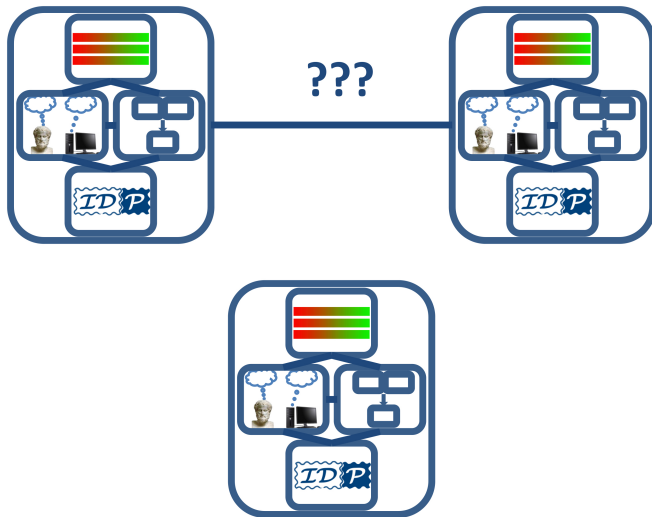


Complex

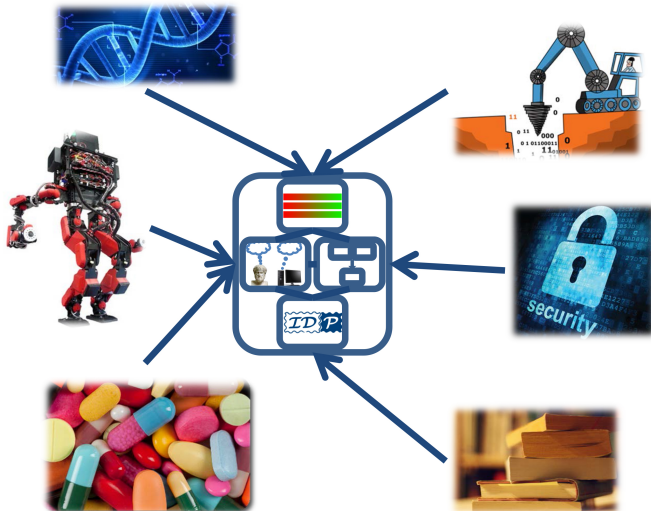


Simple

5. Relationship Between Languages/Systems/Inferences/...



6. Applications



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How to use IDP to solve real-world problems?

- ① Collect knowledge about the problem domain
- ② Model the knowledge in the IDP language
- ③ Map your problem to one or more inference methods
- ④ Run the system

Case study: Course scheduling

1. Collecting knowledge

- Every course consists of several (at least one) sessions.
- Every session is given in a room with capacity at least as high as the number of students enrolled for that session.
- Instructors can only teach one session simultaneously.
- ...

2. Modelling knowledge

- Every **course** consists of several (at least one) **sessions**.
- Every session is given in a **room** with **capacity** at least as high as the number of **students** enrolled for that session.
- **Instructors** can only teach one session simultaneously.
- ...

Vocabulary:

- **Types:** *course, session, room, capacity(\mathbb{N}), student, instructor, time ...*

2. Modelling knowledge

- Every course **consists of** several (at least one) sessions.
- Every session is **given in** a room with **capacity** at least as high as the number of students **enrolled for** that session.
- Instructors can only **teach** one session simultaneously.
- ...

Vocabulary:

- Types: *course*, *session*, *room*, *capacity*(\mathbb{N}), *student*, *instructor*, *time* ...
- **Relations/Functions:**
 - *partOf*(*session*, *course*)
 - *locationOf*(*session*) \rightarrow *room*
 - *capacityOf*(*room*) $\rightarrow \mathbb{N}$
 - *enrolledIn*(*student*, *session*)
 - *teacherOf*(*session*) \rightarrow *instructor*
 - ...

2. Modelling knowledge

- Every course consists of several (at least one) sessions.
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- ...

$\forall c[\text{course}] : \exists s[\text{session}] : \text{partOf}(s, c)$

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$\forall c[\text{course}] : \exists s[\text{session}] : \text{partOf}(s, c)$

$\forall s[\text{session}] : \text{capacityOf}(\text{locationOf}(s)) \geq \#\{st[\text{student}] : \text{enrolledIn}(st, s)\}.$

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$\forall s_1, s_2[\text{session}] : \text{teacherOf}(s_1) = \text{teacherOf}(s_2) \Rightarrow \text{noOverlap}(s_1, s_2).$

3. Choosing inference methods

- Verifying whether a given schedule is valid
 - Model checking
- Finding a valid schedule
 - (Optimal) model expansion
- Updating scheduling when unexpected events occur
 - Revision
- Interactively (with a domain expert) crafting a schedule
 - E.g., propagation, explanation

4. Running the system

IDP Web-IDE File Configure main() Run Help IDP Homepage

```
61 }
62
63 Diploma = {
64   anne,aardrijkskunde;
65   bert,biologie; bert,lo;
66   chris,chemie;
67   dirk,economie;
68   erik,engels; erik,nederlands;
69   frans,frans; frans,latijn;
70   gert,fysica; gert,wiskunde;
71   hans,geschiedenis;
72   ilona,godsdienst;
73   jenny,informatica;
74 }
75
76 LesurenPerWeek = {
77   wetwisk,aardrijkskunde ↔ 1; wetwisk,biologie ↔ 2;
78   wetwisk,chemie ↔ 2; wetwisk,economie ↔ 0;
79   wetwisk,engels ↔ 3; wetwisk,frans ↔ 4;
80   wetwisk,fysica ↔ 2; wetwisk,geschiedenis ↔ 2;
81   wetwisk,godsdienst ↔ 2; wetwisk,informatica ↔ 1;
82   wetwisk,latijn ↔ 0; wetwisk,lo ↔ 2;
83   wetwisk,nederlands ↔ 4; wetwisk,wiskunde ↔ 6;
84 }
85
86 /* structure S */
87
88
89 theory T : V {
90   // Een leerkracht geeft les aan een groep op een bepaald tijdstip
91   // GeefLes(Docent(groep,vak),groep,dag,uur) ← Les(vak,groep,dag,uur). }
92
93   // Een vak moet per week het juiste aantal lesuren gegeven worden
94   // vak groep : # { dag uur : Les(vak,groep,dag,uur) }
95   = LesurenPerWeek(groep,vak).
96
97   // Een leerkracht kan op een tijdstip maar 1 les geven
98   // leerkracht dag uur : # { groep : GeefLes(leerkracht,groep,dag,uur) } < 2.
99
100   // Een leerkracht moet een diploma hebben voor de vakken die hij/zij geeft
101   // leerkracht groep vak : Docent(groep,vak) = leerkracht
102   ⇒ Diploma(leerkracht,vak).
103
104   // Geen les op woensdagnamiddag
105   // (3 vak groep uur : Les(vak,groep,Woensdag,uur) ∧ uur > 4).
106
107   // Een groep kan per tijdstip maar 1 les krijgen
108   // groep dag uur : # { vak : Les(vak,groep,dag,uur) } < 2.
109 }
110
111 procedure main(){
112   print(modelexpand(T,S)[1])
113 }
114
115
116
```

```
Warnings: Verifying and/or autocompleting structure S
Warning: Variables uur dag vak groep are not quantified. At
tmp2471.tidp:91:5
Warning: Derived sort Dag for variable dag. At tmp2471.tidp:94:20
Warning: Derived sort Groep for variable groep. At tmp2471.tidp:94:19
Warning: Derived sort Uur for variable uur. At tmp2471.tidp:94:24
Warning: Derived sort Vak for variable vak. At tmp2471.tidp:94:5
Warning: Derived sort Dag for variable dag. At tmp2471.tidp:98:16
Warning: Derived sort Groep for variable groep. At
tmp2471.tidp:98:29
Warning: Derived sort Leerkracht for variable leerkracht. At
tmp2471.tidp:98:5
Warning: Derived sort Uur for variable uur. At tmp2471.tidp:98:20
Warning: Derived sort Uur for variable uur. At
tmp2471.tidp:101:16
Warning: Derived sort Dag for variable dag. At tmp2471.tidp:108:11
Warning: Derived sort Groep for variable groep. At
tmp2471.tidp:108:5
Warning: Derived sort Uur for variable uur. At tmp2471.tidp:108:19
Warning: Derived sort Vak for variable vak. At tmp2471.tidp:108:24
structure : V {
  Dag = { 1..3 }
  Groep = { "wetwisk" }
  Leerkracht = { "anne"; "bert"; "chris"; "dirk"; "erik"; "frans"; "ge
  Lesuren = { 0..8 }
  Uur = { 1..7 }
  Vak = { "aardrijkskunde"; "biologie"; "chemie"; "economie"; "engels"
  Diploma = { "anne"; "aardrijkskunde"; "bert"; "biologie"; "bert"; "lo";
  GeefLes = { "anne"; "wetwisk"; 4, 5; "bert"; "wetwisk"; 2, 5; "chris"; "wet
  Les = { "aardrijkskunde"; "wetwisk"; 4, 5; "biologie"; "wetwisk"; 2, 5; "
  Volgt = { "wetwisk"; "aardrijkskunde"; "wetwisk"; "biologie"; "wetwisk
  Donderdag = 2
  Docent = { "wetwisk"; "aardrijkskunde";
  >"anne"; "wetwisk"; "biologie"; "bert"; "wetwisk"; "chemie";
  >"chris"; "wetwisk"; "economie"; "dirk"; "wetwisk"; "engels";
  >"erik"; "wetwisk"; "frans"; "frans"; "wetwisk"; "fysica";
  >"gert"; "wetwisk"; "geschiedenis"; "hans"; "wetwisk"; "godsdienst";
  >"ilona"; "wetwisk"; "informatica"; "jenny"; "wetwisk"; "latijn";
  >"frans"; "wetwisk"; "lo"; "bert"; "wetwisk"; "nederlands";
  >"erik"; "wetwisk"; "wiskunde"; "gert" }
  Donderdag = 4
  LesurenPerWeek = { "wetwisk"; "aardrijkskunde";
  >1; "wetwisk"; "biologie"; "wetwisk"; "chemie";
  >2; "wetwisk"; "economie"; "wetwisk"; "engels";
  >3; "wetwisk"; "frans"; "wetwisk"; "fysica";
  >2; "wetwisk"; "geschiedenis"; "wetwisk"; "godsdienst";
  >2; "wetwisk"; "informatica"; "wetwisk"; "latijn";
  >0; "wetwisk"; "lo"; "wetwisk"; "nederlands";
  >4; "wetwisk"; "wiskunde"; "wetwisk"; "gert" }
  Maandag = 1
  Vrijdag = 5
  Woensdag = 3
}
```

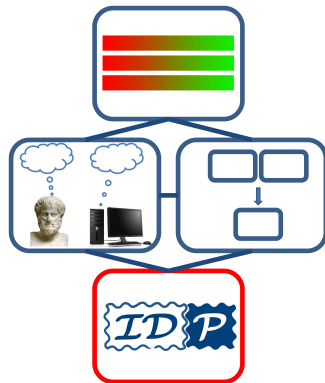
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Various research topics

- 1 The IDP Knowledge Base System
- 2 Symmetry
- 3 The Linear Time Calculus
- 4 Applications of KRR in Data Mining
- 5 FO(C)
- 6 Knowledge Compilation
- 7 Groundedness

1. The IDP Knowledge Base System

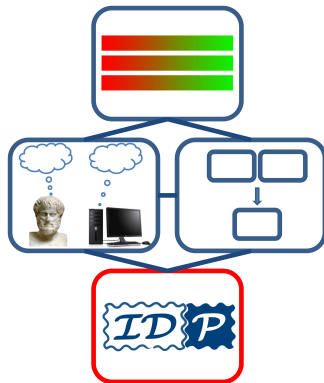
- The IDP language: rich extension of FO
- Many inferences methods
- Ground-and-solve



- **Predicate Logic as a Modelling Language: The IDP System** B. De Cat, B. Bogaerts, M. Bruynooghe and M. Denecker, 2015 (accepted)
- **Meta-level Representations in the IDP Knowledge Base System: Towards Bootstrapping Inference Engine Development** B. Bogaerts, J. Jansen, B. De Cat, G. Janssens, M. Bruynooghe and M. Denecker, LaSh, 2014
- **MiniSat(ID) for Satisfiability Checking and Constraint Solving** B. De Cat, B. Bogaerts and M. Denecker, ALP Newsletter, 2014.
- **Model Expansion in the Presence of Function Symbols Using Constraint Programming** B. De Cat, B. Bogaerts, J. Devriendt and M. Denecker, ICTAI, 2013

2. Symmetry

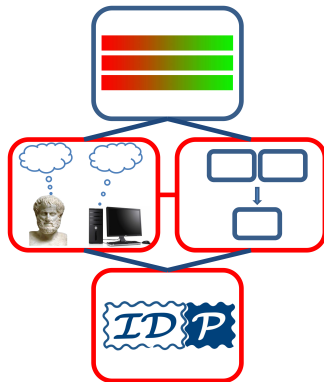
- Detecting and exploiting symmetries
- Increased efficiency



- **BreakIDGlucose: On The Importance of Row Symmetry** J. Devriendt, B. Bogaerts and M. Bruynooghe, CSPSAT, 2014
- **Symmetry Propagation: Improved Dynamic Symmetry Breaking in SAT** J. Devriendt, B. Bogaerts, C. Mears, B. De Cat and M. Denecker, ICTAI, 2012

3. The Linear Time Calculus

- Language: temporal version of the IDP language for modelling dynamic domains
- Inferences: progression, simulation, verification of invariants, ...
- Implementation in IDP

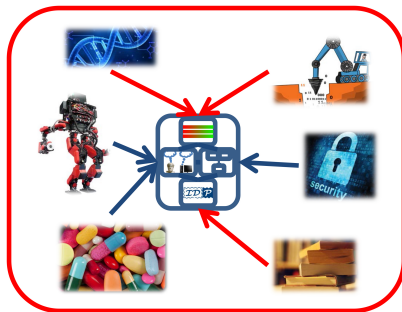


- [Simulating Dynamic Systems Using Linear Time Calculus Theories](#) B. Bogaerts, B. De Cat, J. Jansen, M. Bruynooghe, B. De Cat, J. Vennekens and M. Denecker, TPLP 14(4-5), 2014.

4. Applications of KRR in Machine Learning and Data Mining

Applications of IDP:

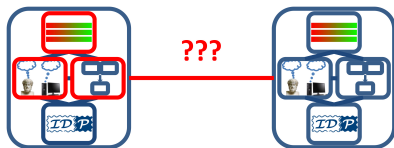
- Stenmatology
- Phylogenetic trees
- Finite state automata



- **Predicate Logic as a Modeling Language: Modeling and Solving some Machine Learning and Data Mining Problems with IDP³** M. Bruynooghe, H. Blockeel, B. Bogaerts, B. De Cat, S. De Pooter, J. Jansen, A. Labarre, J. Ramon, M. Denecker and S. Verwer, TPLP, 2015. (accepted)
- **Analyzing manuscript traditions using constraint-based data mining** T. Andrews, H. Blockeel, B. Bogaerts, M. Bruynooghe, M. Denecker, S. De Pooter, C. Macé and J. Ramon, CoCoMiLe, 2012.
- **Modeling Machine Learning and Data Mining Problems with FO(\cdot)** H. Blockeel, B. Bogaerts, M. Bruynooghe, B. De Cat, S. De Pooter, M. Denecker, A. Labarre, J. Ramon and S. Verwer, ICLP Technical Communication, 2012.

5. FO(C)

- Language for expressing complex cause-effect relationships
- Studied complexity of inference in FO(C)
- (Inference by) reduction of FO(C) to the IDP language

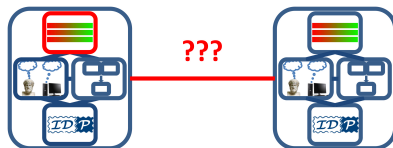


- **Inference in the FO(C) Modelling Language** B. Bogaerts, J. Vennekens, M. Denecker and J. Van den Bussche, ECAI, 2014
- **FO(C) and Related Modelling Paradigms** B. Bogaerts, J. Vennekens, M. Denecker and J. Van den Bussche, NMR, 2014
- **FO(C): A Knowledge Representation Language of Causality** B. Bogaerts, J. Vennekens, M. Denecker and J. Van den Bussche, ICLP technical communication, 2014

6. Knowledge Compilation

Knowledge Compilation:

- Compares languages by studying complexity of inference and relative succinctness
- Provides transformations between these languages



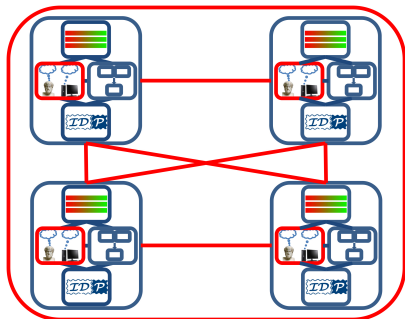
Our addition:

- Transformation from logic programs into Boolean circuits
 - Efficient (polynomial)
 - No auxiliary variables
 - Exploits the constructive nature of well-founded semantics
 - Enables approximate inference
- Theory is developed in *Approximation Fixpoint Theory*

- Knowledge compilation of logic programs using approximation fixpoint theory B. Bogaerts, G. Van den Broeck, TPLP 15(4-5), 2015 (conditionally accepted).

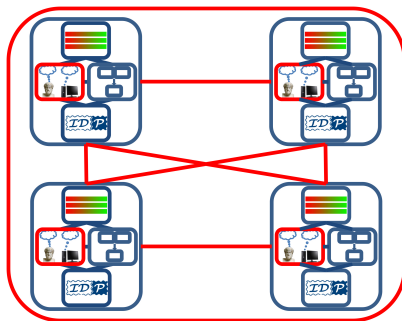
Approximation Fixpoint Theory (AFT)

- Abstract algebraical framework (Denecker, Marek, Truszczyński)
- Describes semantics ...
 - Supported semantics
 - Stable semantics
 - Kripke-Kleene semantics
 - Well-founded semantics
- ... of different logics
 - logic programming
 - autoepistemic logic (AEL)
 - default logic
 - Dung's argumentation frameworks
 - abstract dialectical frameworks



7. Groundedness

- Extension of AFT
- (Partial) grounded fixpoints: abstract concept that captures common intuitions from several fields
- Used to classify semantics in these fields
- Refined constructive semantics (for AEL)



- **Grounded Fixpoints and Their Applications in Knowledge Representation** B. Bogaerts, J. Vennekens and M. Denecker, Artificial Intelligence 224, 2015.
- **Partial Grounded Fixpoints** B. Bogaerts, J. Vennekens and M. Denecker, IJCAI, 2015.
- **Grounded Fixpoints** B. Bogaerts, J. Vennekens and M. Denecker, AAI, 2015.
- **On Well-Founded Set-Inductions and Locally Monotone Operators** B. Bogaerts, J. Vennekens and M. Denecker. (unpublished)

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- Different research domains:
 - Logic programming,
 - Autoepistemic logic,
 - Default logic,
 - Dung's argumentation frameworks,
 - Abstract dialectical frameworks.
- Similar intuitions: facts (or models)
 - are *grounded*,
 - are supported by *cycle-free* arguments,
 - are not *unfounded*,
 - can be built *from the ground up*.

- Completion semantics (Clark, 1978) **ungrounded models**
- Perfect model semantics (Przymusinski, 1988)
- Well-founded semantics (Van Gelder et. al., 1988)
- Stable semantics (Gelfond and Lifschitz, 1988)

$\{p \leftarrow p\}$: **self-supporting model** $\{p\}$

- Expansion semantics (Moore, 1985) **ungrounded expansions**
- “Honest theories” (Halpern and Moses, 1985)
- Moderately grounded expansions (Konolige, 1988)
- Strongly grounded expansions (Konolige, 1988)
- Constructive tightly grounded autoepistemic reasoning (Niemelä, 1991)
- Stable semantics (Denecker, Marek and Truszczyński, 2000)
- Well-founded semantics (Denecker, Marek and Truszczyński, 2000)

$\{Kp \Rightarrow p\}$: **self-supporting expansions in which p is known**

- What is the problem with logic programs as $\{p \leftarrow p\}$ or AEL theories such as $\{Kp \Rightarrow p\}$?
- Algebraical study (fixpoint theory)
- Application to logic programming, autoepistemic logic, default logic, Dung's argumentation frameworks and abstract dialectical frameworks

Grounded fixpoints

Given

- Complete lattice $\langle L, \leq \rangle$: every set $S \subseteq L$ has a least upper bound $\bigvee S$ and a greatest lower bound $\bigwedge S$
- Operator $O : L \rightarrow L$

Definition (Grounded)

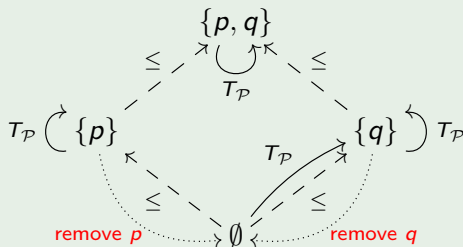
We call $x \in L$ *grounded* for O if for each $v \in L$ such that $O(x \wedge v) \leq v$, it holds that $x \leq v$.

Intuition

- $L = 2^F$, $\leq = \subseteq$
- In this case: x is grounded for O if it only contains facts that are sanctioned by O : whenever we remove facts from x , at least one of them is rederived.

Example

$$\mathcal{P} = \left\{ \begin{array}{l} p \leftarrow p. \\ q \leftarrow \neg p \vee q. \end{array} \right\}$$



Properties of grounded fixpoints

Proposition

All grounded fixpoints of O are minimal fixpoints of O .

Proposition

A monotone operator has exactly one grounded fixpoint, namely its least fixpoint.

Proposition

All A -stable fixpoints of O are grounded fixpoints of O .

Proposition

The well-founded fixpoint of a symmetric approximator A of O approximates all grounded fixpoints of O .

Grounded fixpoints in logic programming

- Study of existing semantics: stable and two-valued well-founded semantics are “grounded”
- Closely related to unfounded sets
- Grounded fixpoints induce a new semantics
 - Two-valued
 - Purely algebraical
 - Simple
 - Easily extensible
- Study complexity

Other applications of grounded fixpoints

- Autoepistemic logic
- Default logic
- Dung's argumentation frameworks
- Abstract dialectical frameworks

- Abstract algebraical definition of groundedness
- Studied relation with other types of fixpoints from AFT
- Corresponds to intuitions in many different domains
- Study of existing semantics
- New induced semantics with attractive properties

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- Grounded fixpoints: limited to two-valued setting
- Sometimes partial fixpoints (three-valued models) are interesting:
 - Central objects of study
 - More general
 - As an analysis tool (e.g., in debugging)

Definition

Let A be an approximator of O . A point $(x, y) \in L^c$ is *A-grounded* if for every $v \in L$ with $A(x \wedge v, y \wedge v)_2 \leq v$, also $y \leq v$.

Properties of partial grounded fixpoints

Proposition

If A is a symmetric approximator of O , then x is grounded for O if and only if (x, x) is A -grounded.

Proposition

All consistent (partial) A -stable fixpoints are A -grounded.

Theorem

The well-founded fixpoint of a symmetric approximator A of O is the least precise A -grounded fixpoint.

Proposition

If A and B are approximators of O and $A \leq_p B$, then all consistent B -grounded points are also A -grounded.

Application (Logic Programming)

- Study semantical relationship with well-founded and stable models
- Closely related to unfounded sets
- Study complexity

- 1 Knowledge Representation and Reasoning (KRR)
- 2 KRR in Practice
- 3 My Contributions to KRR
- 4 Groundedness in Logics With a Fixpoint Semantics (English)**
 - Chapter 3: Grounded Fixpoints
 - Chapter 4: Partial Grounded Fixpoints
 - Chapter 5: Set-Inductions and Locally Monotone Operators

- Denecker and co-authors
 - strongly argued for a constructive semantics for various non-monotonic logics (LP, AEL, ...)
 - claimed that the well-founded semantics is always strong enough to construct the intended model for “sound” theories
- Claim was proven for logic programs (viewed as inductive definitions) (Denecker and Vennekens, 2014)
- Claim was made (without proof) for AEL (Denecker, Marek and Truszczyński, 2011)
- However ...

- ... still in 2011, Hanne Vlaeminck came up with this example:

Example

$$\{q \Leftrightarrow \neg Kp, r \Leftrightarrow \neg Kq\}.$$

- Clear intended model
- Well founded semantics fails to identify it (construction is too weak)
- The unique grounded fixpoint

Goal

Refine well-founded semantics to

- *Maintain advantages of a constructive semantics*
- *Also capture this kind of examples*

- Generalisation (AEL): monotonically stratified theories
- Generalisation (AFT): locally monotone operator
- New constructive semantics (AFT): well-founded set-semantics based on groundedness

Theorem

All locally monotone operators O have a unique grounded fixpoint; this fixpoint is the unique element in the well-founded set of O .

Questions?

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