Every normal logic program has a 2-valued Minimal Hypotheses semantics

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Outline

1. Introduction
2. Building a semantics
3. Minimal Hypotheses semantics
4. Conclusions and Future Work

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Every NLP has a 2-valued MH semantics
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Every NLP has a 2-valued MH semantics
Knowledge can be written in sentences
  - Sentences can be translated into logic formalisms
  - Logic Programs are one such formalism for KR
  - LP = Normal Logic Rules + Integrity Constraints
Background (1/2)

- Knowledge can be written in sentences
- Sentences can be translated into logic formalisms
  - Logic Programs are one such formalism for KR
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Logic Rule (LR)

A LR is of the form \( h \leftarrow b_1, \ldots, b_n, \text{not } c_1, \ldots, \text{not } c_m \) with \( m, n \geq 0 \) and finite, and where \( b_i, c_j \) are ground atoms.

Notation: \( \text{head}(r) = h \) and \( \text{body}(r) = \{b_1, \ldots, b_n, \text{not } c_1, \ldots, \text{not } c_m\} \).

Normal Logic Program (NLP)

A NLP is a (countable) set of Normal Logic Rules (NLRs), where a NLR \( r \) is s.t. \( \text{head}(r) \) is a ground atom.

Integrity Constraint (IC)

A IC is a LR \( r \) such that \( \text{head}(r) = \bot \).
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The Problem (1/2)

- Ideally, KR Declarativity with LPs would allow:
  - Full separation of concerns of rules, i.e., KR role of NLRs ≠ KR role of ICs, i.e.,
    - Normal Logic Rules ⇔ Define space of candidate solutions
    - Integrity Constraints ⇔ Prune out undesired candidates
  - Semantics is what determines which sets of beliefs (models) are candidates
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Semantics is what determines which sets of beliefs (models) are candidates
According to this Ideal KR Declarativity view...

...since only ICs are allowed to prune out candidate models...

...LPs with no ICs (i.e., NLPs) should always allow, at least, one model...

...otherwise NLRs would be allowed to play the role of ICs too

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Common semantics for NLPs

- **2-valued: Stable Models**
  - Classically Supported, but...
  - Lacks guarantee of model existence — undermining liveness
    cannot provide semantics to arbitrarily updated/merged programs
  - Lacks relevance
    does not allow for top-down query-answering proof-procedures
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    does not allow use of tabling methods to speed up computations

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Goal: Desired Semantics (1/2)

- 2-valued semantics
  - Guarantee of model existence
    (e.g., for liveness in the face of updates)
  - Relevance
    Truth of a literal is determined solely by the literals in its call-graph
  - Cumulativity
    Atoms true in all models can be safely added to program as facts

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Closed World **Assumption**

Programs with stratified negation have only one model. . .
. . . which hints that. . .
. . . non-determinism (more than one model) comes from “non-stratification” of negation
I.e., negated literals *in loop* play important semantic role
Need for a different kind of **Assumption** for non-stratified negation
A model can be seen as set of *assumed hypotheses* + their conclusions
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Maximal skepticism $\rightarrow$ atomic beliefs must have support

CWA is particular case

- **Support**
  - Classical
    - belief in atom requires a rule for it (head) with *all* body literals true
    - OR
  - (new) Layered (Stratified)
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Classical Support $\Rightarrow$ Layered Support

Maximal skepticism $\rightarrow$ minimal atomic beliefs

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Positive hypotheses or negative hypotheses?
Traditionally, maximum negative hypotheses, but...

Problem with negative hypotheses

\[ a \leftarrow \neg a \]

Assuming neg. hyp. \( \neg a \) leads to contradiction: \( a \)
Assuming pos. hyp. \( a \) does \not{} lead to contradiction!

No explicit \( \neg a \) can be derived since we are using NLPs

Minimum positive hypotheses it is, then!
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Assumable hypotheses of program:

\[ Hyps = \text{(positive)} \, \text{atoms} \, \text{of negative literals in loop} \]

- Select a minimal subset \( H \) of \( Hyps \) assumed true such that
- \( H \) is enough to propagate 2-valuedness to all literals
- If so, an MH-model is the \( M = \) consequences of \( H \)
- Propagation of truth-values via deterministic polynomial-time Remainder operator (generalization of \( T_P \) operator)
Minimal Hypotheses semantics — Intuitive definition

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Propagation of truth-values via deterministic polynomial-time Remainder operator (generalization of \( T_P \) operator)
MH semantics — Example

Vacation example

beach ← not mountain
mountain ← not travel
travel ← not beach, passport_ok
passport_ok ← not expired_passport
expired_passport ← not passport_ok
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    \text{expired\_passport} & \leftarrow \text{not passport\_ok} \\
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\text{travel} & \leftrightarrow \text{not beach} \\
\text{passport\_ok} & \phantom{\leftrightarrow \text{not beach}}
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- `mountain` ← `not travel`
- `travel` ← `not beach`
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Reasoning as Query Answering

- In the MH 2-v semantics, models are the deductive consequences of a specialized abduction for NLPs
- Existential query answering (a.k.a. brave reasoning) “is there a model (min. hyps+conseqs.) where query is true?”

More efficient with Relevant semantics, e.g. MH (not SM)

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Every NLP has a 2-valued MH semantics
**Conclusions**

- **NLR ≠ ICs**
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- **Minimum positive hypotheses**: generalization of maximum negative hypotheses
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  - relevance, cumulativity, existence (liveness in face of updates)
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- Implementation of MH semantics-based system (ongoing)
- Further comparisons: MH vs RSMs, MH vs PStable, others
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- Applications: Semantic Web, KR (adding regular abduction), combination of 2-v with 3-v
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Thank you
Disjunctive Logic Programs (1/2)

- Disjunctive LPs (DisjLPs): rules are of the form

\[ h_1 \lor \ldots \lor h_q \leftarrow b_1, \ldots, b_n, \text{not } c_1, \ldots, \text{not } c_m \]

with \( q \geq 1, m, n \geq 0 \) and finite, and where \( h_k, b_i, c_j \) are atoms

- Can be transformed into NLPs via Shifting Rule

\[ a \lor b \leftarrow \text{Body} \]
\[ a \leftarrow \text{not } b, \text{Body} \]
\[ b \leftarrow \text{not } a, \text{Body} \]

- Shifting Rule produces loops over default negation
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Disjunctions / Shifting Rule / Loops

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b \lor c & \quad b \leftarrow \text{not } c \quad c \leftarrow \text{not } b \\
c \lor a & \quad c \leftarrow \text{not } a \quad a \leftarrow \text{not } c
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\]

Basis of MH intuition = conceptually reverse the Shifting Rule:
Loops (any kind of loops) encode disjunction of hypotheses
Disjunctions / Shifting Rule / Loops

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Disjunctive Logic Programs (2/2)

Disjunctions / Shifting Rule / Loops

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**Motivation for the Layered Negative Reduction**

**Variation of the vacation example**

<table>
<thead>
<tr>
<th>beach</th>
<th>not mountain</th>
</tr>
</thead>
<tbody>
<tr>
<td>mountain</td>
<td>not travel</td>
</tr>
<tr>
<td>travel</td>
<td>not beach</td>
</tr>
</tbody>
</table>

Three MHs: \{beach, travel, not mountain\}, \{beach, not travel, mountain\}, \{not beach, travel, mountain\}.

**Variation of the vacation example with fourth friend**

<table>
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Two MHs: \{beach, travel, not mountain\}, \{beach, not travel, mountain\}.

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