PRACTICAL USES OF EXISTENTIAL RULES IN KNOWLEDGE REPRESENTATION

Part 3: Applications of Rules in AI

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Outline

Goal

Show some example where either **rules** or **related ideas** were crucial to achieve the state of the art

- Horn-$\mathcal{ALC}$ reasoning
- PLP
- Data integration
- Stream reasoning

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Take-home message

1. Rules can be used also in uncertain scenarios
2. A declarative approach is (often) intuitive and **decreases** the development time
3. Robust and scalable reasoning tools are crucial
4. AI communities should talk to each other!

2^{nd} Scenario: Probabilistic Logic Programming

PLP

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Basic idea: Reason over facts which may be true with a certain probability

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State of the art

Several PLP formalisms exist. **ProbLog** (Raedt, Kimmig, and Toivonen 2007) is one of the most popular ones

ProbLog

Definition

A ProbLog program $\mathcal{P}$ is a triple $(\mathcal{R}, \mathcal{F}, \pi)$ where $\mathcal{R}$ is set of (function-free) rules, $\mathcal{F}$ is a set of facts and $\pi : \mathcal{F} \rightarrow [0, 1]$ is the function that labels facts with probabilities.

Key problem

Given $\mathcal{P}$ and query q as input, what is $Pr(q)$ (the probability of q)?

General Approach

It has been shown that computing $Pr(q)$ can be expressed using Weighted Model Counting (WMC) over weighted logical formulas (Vlasselaer et al. 2016)

The Grounding Problem

ProbLog2, a state-of-the-art engine, proceeds as follows:

1. Find relevant **ground** program for q with backward chaining
2. Execute a custom implementation of fixpoint operator $T_{\mathcal{P}}$:
   - $T_{\mathcal{P}}$ proceeds bottom-up, akin to chase procedures
   - $T_{\mathcal{P}}$ incrementally computes, for each inferred fact f, a propositional formula λ_f which "remembers" all the possible ways f can be inferred
3. After $T_{\mathcal{P}}$ has finished, it computes WMC for λ_q

Problem

Grounding can be a major performance bottleneck with large knowledge bases

Datalog to the rescue

Some ideas developed for Datalog can be useful (Tsamoura, Gutiérrez-Basulto, and Kimmig 2020)

First idea

Don't ground $\mathcal{P}$ with backward chaining. Rewrite it with **magic sets** (Bancilhon et al. 1985)

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First idea

Don't ground $\mathcal{P}$ with backward chaining. Rewrite it with **magic sets** (Bancilhon et al. 1985)

Second idea

Apply **semi-naïve evaluation** (Abiteboul, Hull, and Vianu 1995) on the non-ground program to reduce the number of duplicates

Magic sets

Consider database I and program P. Our goal is to answer query Q

Idea

The main idea is to rewrite P into P' where additional **magic** relations restrict the derivations to facts relevant for answering Q

Magic sets

Consider database I and program P. Our goal is to answer query Q

Example 1

Consider the rules below and assume we want to answer $Q = lives(linda, X)$

$$married(X, Y), lives(X, Z) \rightarrow lives(Y, Z) \quad (r_1)$$

$$married(X, Y) \rightarrow married(Y, X) \quad (r_2)$$

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The rewriting procedure produces the program

$$mgc_1(Y), married(X, Y), lives(X, Z) \rightarrow lives(Y, Z) \quad (r_3)$$

$$mgc_1(X) \rightarrow mgc_2(X) \quad (r_4)$$

$$mgc_2(Y), married(X, Y) \rightarrow married(Y, X) \quad (r_5)$$

Then, we can reason on $I \cup \{mgc_1(linda)\}$

Semi naïve evaluation

Semi naïve evaluation is a well-known technique to avoid the recomputation of duplicate derivation during the materialization

Naïve Evaluation

Input: Facts I, program P

while true do

  $J := I$;

  for $r \in P$ **do**

    Let r be $B \to H$

    $J := J \cup \{H\sigma \mid B\sigma \subseteq I\}$;

  if $J = I$ **then** **return** J ;

Semi Naïve Evaluation

Input: Facts I, program P

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while true do

  $J := I$;

  for $r \in P$ **do**

    Let r be $B \to H$;

    $J := J \cup \{H\sigma \mid B\sigma \subseteq I \wedge B\sigma \cap \Delta \neq \emptyset\}$;

  if $J = I$ **then** **return** J;

  $\Delta := J \setminus I$;

New approach

Tsamoura et al. (2020) proposed a new procedure:

1. ~~Find relevant **ground** program for q with backward chaining~~. Use Magic Set to obtain a **non-ground** program

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   - Leverage semi-naïve evaluation
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   - Leverage semi-naïve evaluation
   - Introduce extra rules to compute the probability (λ–transformation)
3. After $T_{\mathcal{P}}$ has finished, compute WMC for λ_q

Impact

The new procedure removes the need for grounding, which was a performance bottleneck

Performance improvement

Some key results from (Tsamoura, Gutiérrez-Basulto, and Kimmig 2020)

- The runtime of query answering was two order of magnitude and 25% faster than ProbLog2 in the best and worst cases, respectively
- VLog enabled the computation on much larger DBs than what was possible before

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Lesson learned

Well-known ideas developed for rule-based query answering can be re-used as-is for other problems as well

3^{rd} Scenario: Entity Resolution

Entity Resolution

Entity resolution is the task of recognizing and linking entities across different tables. It is a well-known task in database literature (96+ papers between 2009-2014, see (Papadakis, Ioannou, and Palpanas 2020))

- Magellan (Konda et al. 2016)
- Deep Learning (Mudgal et al. 2018)
- Crowd-sourcing (Das et al. 2017)
- Embeddings (Cappuzzo, Papotti, and Thirumuruganathan 2020)
- ...

Entity Resolution in Practice

Scientific advancement requires an extensive analysis of prior knowledge in the literature, but this is **time consuming**

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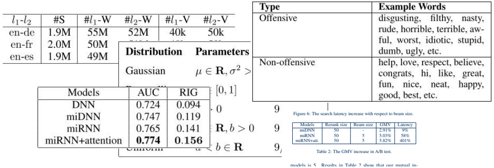
AI can help!

Long-term vision: Develop an accurate and large-scale KB of scientific knowledge

A KB of Scientific Knowledge

valuable experimental knowledge



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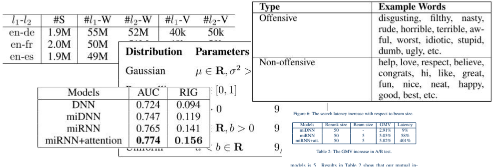
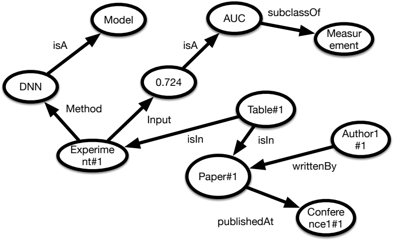
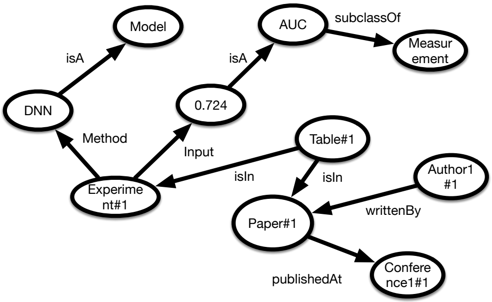




Advantages



Potential use cases:

- Retrieve experimental results with entity-based search
- Exploit co-authorship networks
- Identify potential inconsistencies across papers

Tab2Know: General pipeline

Tab2Know is a recent work to construct a KB from tables in scientific papers (Kruit, He, and Urbani 2020)

Key features:

- Heuristic-based methods to recognize and extract tables from PDFs

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- **(Focus of today)** logic-based reasoning for **entity resolution**

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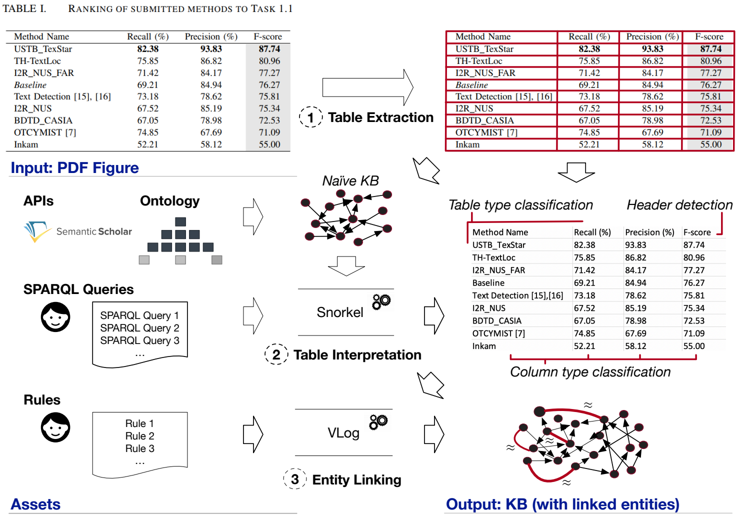

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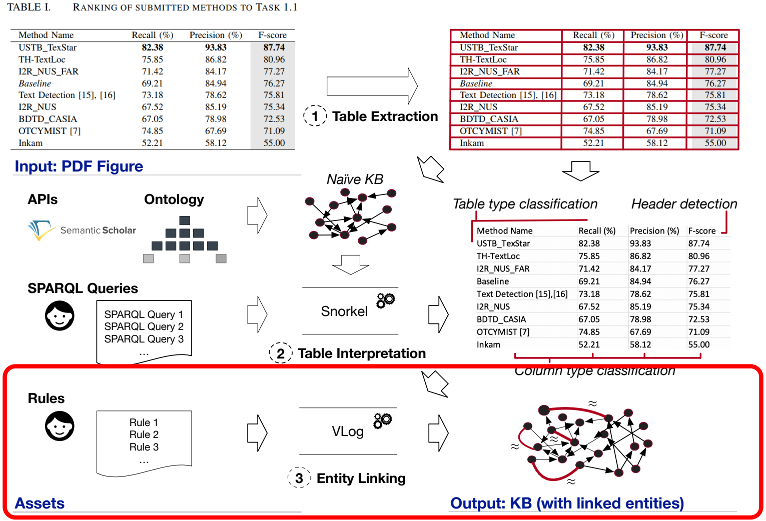

Method Name	Recall (%)	Precision (%)	F-score
USTB_TexStar	**82.38**	**93.83**	**87.74**
TH-TextLoc	75.85	86.82	80.96
I2R_NUS_FAR	71.42	84.17	77.27
Baseline	69.21	84.94	76.27
Text Detection [15], [16]	73.18	78.62	75.81
I2R_NUS	67.52	85.19	75.34
BDTD_CASIA	67.05	78.98	72.53
OTCYMIST [7]	74.85	67.69	71.09
Inkam	52.21	58.12	55.00

A declarative approach

Terminology

Tuple Generating Dependency (TGD): $bicycle(X) \rightarrow \exists Y.partOf(X, Y) \wedge Wheel(Y)$
Equality Generating Dependency (EGD): $email(X, Y) \wedge email(X, Z) \rightarrow Y \approx Z$

Tab2Know's approach: Use TGDs and EGDs to perform entity resolution

TGDs

They can be used to create new entities from the cells and columns

EGDs

They can be used to infer that entities mentioned in different cells are the same

Output

After reasoning is completed, newly introduced entities are used to populate a KB

A declarative approach: TGDs

Two types of entities: One for columns, one for cells

$$type(X, \text{Column}) \rightarrow \exists Y.colEntity(X, Y) \quad (r_1)$$

$$type(X, \text{Cell}) \rightarrow \exists Y.cellEntity(X, Y) \quad (r_2)$$

A declarative approach: EGDs

Avoid that the same entity is represented with multiple labeled nulls

$$ceNoTypLabel(X, L) \wedge ceNoTypLabel(Y, L) \rightarrow X \approx Y \qquad (r_3)$$

$$eNoTypLabel(X, C, L), eNoTypLabel(Y, C, L) \rightarrow X \approx Y \qquad (r_4)$$

$$eTableLabel(X, T, L), eTableLabel(Y, T, L) \rightarrow X \approx Y \qquad (r_5)$$

$$eTypLabel(X, S, L), eTypLabel(Y, S, M), STR\_EQ(L, M) \rightarrow X \approx Y \qquad (r_6)$$

$$eAuthLabel(X, A, L), eAuthLabel(Y, A, M), STR\_EQ(L, M) \rightarrow X \approx Y \qquad (r_7)$$

- Special built-in predicates (STR_EQ) encode string similarities
- Other predicates include authors of the paper
- Program can be easily extended with other rules → rapid KB construction

Preliminary results

Input

Approach was tested on a collection with 142k CS open-access papers and 73k tables (IJCAI, ECAI, etc.)

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- EGDs reduced number of “column” entities of 65% and of “cell” entities of 55%
- Every rule contributed by linking some entities
- On a sample of 541 entities, average precision was 97%

Lessons learned

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2. Rules can be easily changed or adapted depending on the performance
3. VLog was scalable enough to perform rapid prototyping with large KGs
4. Support to built-in predicates was crucial

4^{th} Scenario: Stream Reasoning

A few of slides are a modified version of Harald Beck's ISWC17 presentation, used with permission

Motivation

Stream reasoning: add reasoning on top of stream processing. Central question: **“What is true now?”** (Margara et al. 2014)

- E.g. public transport: What are the current expected arrival times?
- Is there currently a good connection between two lines?

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Semantic Web: RDF Stream Processing - SPARQL extensions: C-SPARQL, CQELS, $\text{SPARQL}_{\text{Stream}}, \ldots$ Typical: Window operators select snapshots of recent data

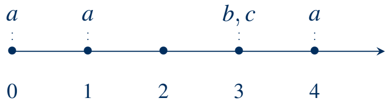
- Window examples: `[RANGE 3m]`, `[TRIPLES 2]`

Goals & Challenges

- Goal: expressive stream reasoning solutions
  (1) based on model-based semantics
  (2) high performance
- Central challenge: **throughput vs. expressiveness**

LARS: A Logic for Analytic Reasoning over Streams

LARS (Beck, Dao-Tran, and Eiter 2018) is a logic-based frameworks to reason on streams



- Stream $S = (T, \upsilon)$
  - **Timeline** T closed interval in $\mathbb{N}$, $t \in T$ **time point**
  - **Evaluation** function $\upsilon : T \rightarrow 2^{\mathcal{A}}$ (sets of atoms)

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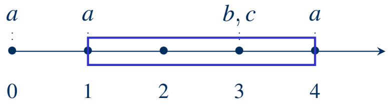

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  - $\alpha = \boxplus^w \beta$: means that β must hold on the substream defined by a window function with arg w (e.g., last w time points)
  - $\alpha = \Diamond\beta$: means that β must holds at **some** time point

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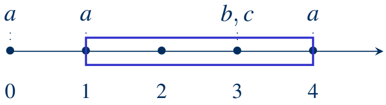

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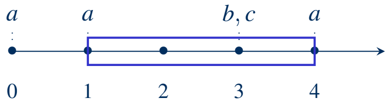

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Plain LARS

Plain LARS (Bazoobandi, Beck, and Urbani 2017)

Focus on positive non-ground LARS programs where for each rule $\alpha \leftarrow \beta_1, \ldots, \beta_n$ we have:

- head α: atom a or $@_t a$
- body elements: $\beta_i ::= a \mid @_t\, a \mid \boxplus^w @_t\, a \mid \boxplus^w \Diamond\, a \mid \boxplus^w \Box\, a$

From LARS to Datalog

Observation

LARS rules can be rewritten into Datalog rules

- How do we represent time?
  - Increase arity of the relations, e.g., $P(X) \rightarrow P(X,T)$
- How can we translate LARS rules?
  - $@_S P(X)$ as $P(X,S)$
  - $\boxplus^2 \Diamond P(X) \rightarrow Q(X)$ as $P(X,T) \rightarrow Q(X)$ and $P(X,T-1) \rightarrow Q(X)$

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Semi-naïve evaluation (SNE)

One key novelty of (Bazoobandi, Beck, and Urbani 2017) is to show how to replicate SNE in a stream

From LARS to Datalog

- For formula $\varphi = \alpha, \beta_i$ in any rule $\alpha \leftarrow \beta_1, \ldots, \beta_n$, consider **annotated ground formulas** $\varphi\sigma_{[c,h]}$, where
  - $\varphi\sigma$ is the **ground instance** of φ due to **substitution** σ
  - $[c, h]$ is an annotation stating that $\varphi\sigma$ holds from **consideration time** c to **horizon time** h

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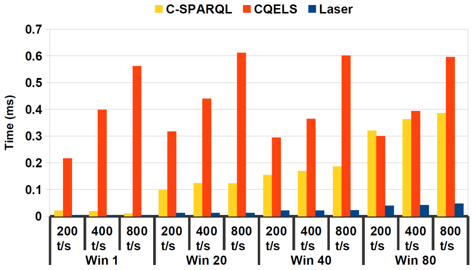
- Horizon time can be extended in the future, e.g., at time point t, $\boxplus^3 \Diamond p(a)$ can be annotated as $\boxplus^3 \Diamond p(a)_{[t,t+3]}$
- When computing substitution σ for instantiating rule $B_1 \wedge B_2 \wedge \ldots B_n \rightarrow H$ at time point t, at least one $B_i\sigma_{[c,h]}$ has $c = t$, i.e., has been derived at the current time point

Laser: Implementation & Evaluation

Evaluation: Time per triple

- Compare to C-SPARQL, CQELS, and Ticker
- Micro benchmarks to test **(1)** $q(A,B) \leftarrow \boxplus^n \Diamond p(A,B)$ (resp. $\Box$); elementary data join; multiple rules; **(2)** small show case example requiring LARS features.
- Window sizes: 1s to 80s; stream rate: 200 to 800 triples/second



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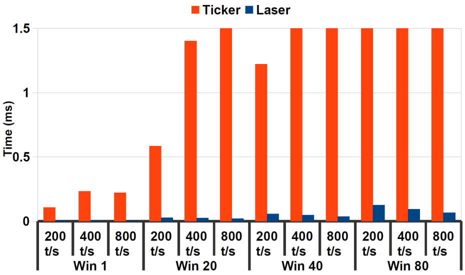

(2)

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We have described cases where rules turned out to be very useful

- In some scenarios, existential quantification was necessary (data integration). In others, Datalog rules were enough (PLP, stream reasoning)
- Sometimes, the tools could be directly used (data integration). In other cases, some modifications are required (PLP)
- Finally, we have seen how sometimes **ideas**, rather systems, can make the difference

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