

Abstract

Goal: a semantic parser that is **not constrained** by a fixed formal ontology and purely logical inference

- 1) Formal language: **First Order Logic**
- 2) Ontology: use Distributional Semantics to generate the **relevant part of a “graded” on-the-fly ontology**
- 3) Inference: **Probabilistic Logic** inference

Tasks:

- 1) Recognizing Textual Entailment (**RTE**) using Markov Logic Networks (**MLNs**)
- 2) Semantic Textual Similarity (**STS**) using Probabilistic Soft Logic (**PSL**)

Inference

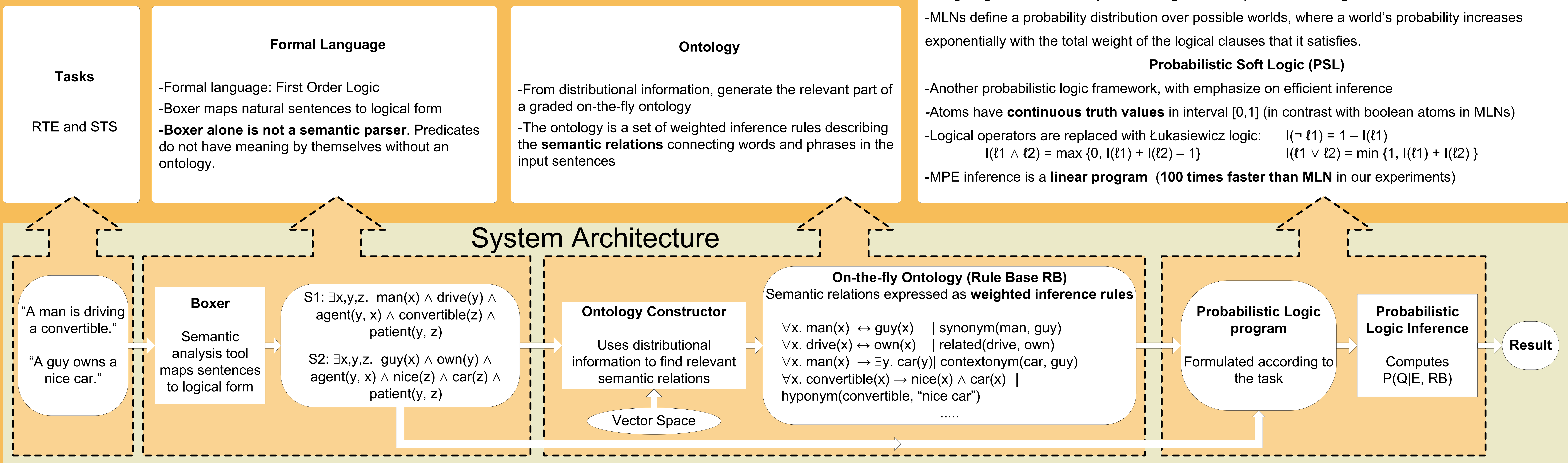
- Given input sentences and the generated ontology, Inference draws conclusions and answers queries
- Standard theorem provers are insufficient because the **ontology is “graded”** not binary
- Probabilistic logic solves this problem because it accepts **weighted** first order logic formulas
- Given the input sentences, and the rule base, we build a probabilistic logic program whose solution is the answer to the target task
- A probabilistic Logic program is an evidence set E, set of rules R and a query Q
- Inference computes **Pr(Q|E, R)**
- The probabilistic logic frameworks we use are MLNs for the RTE task and PSL for the STS task

Markov Logic Networks (MLNs)

- Given a set of weighted first-order logic formula, MLNs construct complex undirected graphical model
- Weighting the rules is a way of softening them compared to hard logical constraints.
- MLNs define a probability distribution over possible worlds, where a world’s probability increases exponentially with the total weight of the logical clauses that it satisfies.

Probabilistic Soft Logic (PSL)

- Another probabilistic logic framework, with emphasize on efficient inference
- Atoms have **continuous truth values** in interval [0,1] (in contrast with boolean atoms in MLNs)
- Logical operators are replaced with Łukasiewicz logic: $I(\neg \ell_1) = 1 - I(\ell_1)$
 $I(\ell_1 \wedge \ell_2) = \max\{0, I(\ell_1) + I(\ell_2) - 1\}$ $I(\ell_1 \vee \ell_2) = \min\{1, I(\ell_1) + I(\ell_2)\}$
- MPE inference is a **linear program** (**100 times faster than MLN** in our experiments)



Task1: RTE using MLNs

- Task: Given T, H, find if T Entails, Contradicts or not related (Neutral) to H
- Inference: compute $\text{Pr}(T|H, RB)$, $\text{Pr}(\neg T|H, RB)$
- Entailment decision = F ($\text{Pr}(T|H, RB)$, $\text{Pr}(\neg T|H, RB)$) where F is trained
- Computational overhead: reduce size of the ground network by removing unnecessary ground atoms ^[MLN_NL]

Task2: STS using PSL

- Task: Given S1, S2, find their semantic similarity score
- Adapt PSL for the STS task: replace PSL conjunction with an average, and change the grounding accordingly ^[STS_PSL]
- Inference: compute $\text{Pr}(S1|S2, RB)$, $\text{Pr}(S2|S1, RB)$
- Similarity score = F ($\text{Pr}(S1|S2, RB)$, $\text{Pr}(S2|S1, RB)$) where F is trained

Evaluation

System	SICK-RTE(acc)	SICK-STS(corr)
Distribution-only	0.60	0.65
Logic-only	0.71	0.68
Logic+Distribution	0.73	0.70

Conclusion

We propose a Semantic Parser that does not require a fixed ontology.
Ontology is generated from distributional information, and tasks are performed using Probabilistic Logic inference.