Syntactico-Semantic Reasoning using PCFG, MEBN, and PR-OWL

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Abstract

Probabilistic context free grammars (PCFG) have been the core of the probabilistic reasoning based parsers for several years especially in the context of the NLP. Multi entity bayesian networks (MEBN) a First Order Logic probabilistic reasoning methodology and is widely adopted and used method for uncertainty reasoning. Further upper ontology like Probabilistic Ontology Web Language (PR-OWL) built using MEBN takes care of probabilistic ontologies which model and capture the uncertainties inherent in the domain's semantic information. The paper attempts to establish a link between probabilistic reasoning in PCFG and MEBN by proposing a formal description of PCFG driven by MEBN leading to usage of PR-OWL modeled ontologies in PCFG parsers.

Keywords: Syntactico-Semantic Reasoning, MEBN, PR-OWL, PCFG

1. Introduction

This section introduces the concepts and terminologies of PCFG (Probabilistic Context Free Grammar) and MEBN (Multi Entity Bayesian Network) theory. Section 2 formally puts forth the proposed mapping between PCFG and MEBN theory. Section 3 discusses the need for mapping and a use case of application of Mapping defined in Section 2.

A PCFG (Probabilistic Context Free Grammar) [1], probabilistically driven context free grammar is a quintuple $G_{PCFG} = (M, T_{PCFG}, S, P)$, where

- $M_{PCFG} = \{N^i : i = 1, \ldots, n\}$ is a set of nonterminals
- $T_{PCFG} = \{w^k : k = 1, \ldots, v\}$ is a set of terminals
- $R_{PCFG} = \{N^i \rightarrow \zeta \in (M_{PCFG} \cup T_{PCFG})^*\}$ is a set of rules
- $S_{PCFG} = N^1$ is the start symbol
- $P_{PCFG}$ is a corresponding set of probabilities on rules such that
  \[ \forall i \sum_j P(N^i \rightarrow \zeta) = 1 \]
For a PCFG in chomsky normal form (CNF)
- \( R_{PCFG} = \{N \rightarrow NN', N \rightarrow w\} \)
- \( \forall i \sum_{r,s} P(N_i \rightarrow NN') + \sum_k P(N_i \rightarrow w') = 1 \)

A simple PCFG in CNF would look like

\[
\begin{align*}
S &\rightarrow \text{NP VP 1.0} \\
\text{NP} &\rightarrow \text{NP PP 0.4} \\
\text{PP} &\rightarrow \text{P NP 1.0} \\
\text{VP} &\rightarrow \text{V NP 0.7} \\
\text{VP} &\rightarrow \text{VP PP 0.3} \\
\text{NP} &\rightarrow \text{<some noun 2> 0.18} \\
\text{NP} &\rightarrow \text{<some noun 1> 0.1} \\
\text{NP} &\rightarrow \text{<some noun 3> 0.04} \\
\text{NP} &\rightarrow \text{<some noun 4> 0.18} \\
\text{NP} &\rightarrow \text{<some noun 5> 0.1} \\
\text{V} &\rightarrow \text{<some verb> 1.0} \\
\text{P} &\rightarrow \text{<some preposition> 1.0}
\end{align*}
\]

A MEBN (Multi Entity Bayesian Network) theory \[3\] \( T \) is a set of MFrags \( \{F_1, F_2, F_3, \ldots, F_r\} \).

A M_frag \( F_i \) is a quintuple \( F_i = (C_{MEBN}^i, I_{MEBN}^i, R_{MEBN}^i, G_{MEBN}^i, D_{MEBN}^i) \) where

- \( C_{MEBN}^i \) is a finite set of values a context can take form as a value, context serves as a constraints.
- \( I_{MEBN}^i \) is a set of input random variables
- \( R_{MEBN}^i \) is a finite set of resident random variables
- \( G_{MEBN}^i \) is a directed acyclic graph representing the dependency between input random variables and resident random variables conditional on context random variables in one to one correspondence similar to bayesian network.
- \( D_{MEBN}^i \) is a set of local conditional probability distributions where each member of \( R_{MEBN}^i \) has its own conditional probability distribution in set \( D_{MEBN}^i \).
- Sets \( C_{MEBN}^i, I_{MEBN}^i \) and \( R_{MEBN}^i \) are pairwise disjoint.

MEBN Theory is queried using first order logic constructs, connectives, and operators. Every query on MEBN involves the construction of situation specific Bayesian network (SSBN) from the set of MFrags belonging to the concerned MTheory. MEBN theory has been widely adopted and used in various fields \[2\]. MEBN theory has been mapped with Relational Model of Relational Databases \[11\].

Given the probabilistic approach of formally defined systems like PCFG and MEBN theory for uncertainty reasoning in syntactic and semantic aspects respectively. A mapping between these two formal system lays the foundation for syntactico-semantic reasoning.

2. Mapping between PCFG and MEBN:
In order to establish a connecting link between PCFG and MEBN, we need to find mapping between the members of quintuples of PCFG and MEBN. The process can be outlined in two steps.

Step 1: Mapping of Non Terminals, Terminals in PCFG to the set of Context, Input, and Random variables in the MEBN theory.

Step 2: Mapping between PCFG rule probabilities and set of local conditional probability distributions defined in MEBN.

Step 1:

For a mapping to exist between a PCFG and a MEBN, primarily there has to be a relation between the non terminals and terminal symbols of the entire system.

Every Non Terminal shall have an equivalent input variable in the MEBN set of MFrags such that,

\[ M_{PCFG} \subset \bigcup_{i} U_{MEBN} \]

If not, shall be introduced.

Every derivation of grammar rule shall be part of \( \epsilon \), a infinite set of entity identifiers symbols across all MFrags of the MEBN theory. \( \epsilon \) being a infinite set of entity identifier symbols under MEBN theory,

\[ \forall (N \rightarrow NN') \in R_{PCFG}, \ \forall (N \rightarrow w') \in R_{PCFG}, \ \forall NN' \in \epsilon \text{ and } w' \in \epsilon \]

An additional resident random variable hasProbability(\( \theta \)), \( \theta_{i} \ldots \theta_{k} \) are ordinary variables of MFragment \( F_i \), dependant on input random variables shall be introduced in every MFragment \( F_i \) of MEBN theory.

Step 2:

In MEBN theory if \( \{\epsilon_{i}, \epsilon_{2}, \ldots, \epsilon_{n}\} \), a non empty finite set of entity identifier symbols then a partial world \( W \) of a resident random variable \( RV \) is the set of all instances of the parents of random variable \( RV \) and the context variables of the MFragment \( F_i \) that can be obtained by substituting \( \epsilon_{i} \) for ordinary variables \( \{\theta_{i} \ldots \theta_{j}\} \) of \( F_i \). A partial world state \( S_{w} \) for partial world \( W \) is the set of assignments of values for each one of the random variable of the MFragment \( F_i \) in the partial world.

A local distribution \( \pi_{RV} \) for a resident random variable \( RV \) in MFragment \( F_i \) in addition to specifying a subset of values for \( RV(\epsilon) \) provides a probability distribution function \( \pi_{RV(\epsilon)}(\alpha | S_{w}) \geq 0 \) and
\[ \sum_{\alpha} \pi_{RV(\alpha|S_w)} = 1, \text{ where } \alpha \text{ is finite subset which ranges over the set } \{ \xi_1, \xi_2, \ldots, \xi_n \} \cup \{ T, F \}. \]  

“T”, “F” denote truth values TRUE and FALSE respectively.

Combined probability distribution across PCFG and MEBN theory shall be based on conflation of probabilities from PCFG and MEBN theory.

\[ P_{PCFG-MEBN}(N \rightarrow N^s) = \& (P(N \rightarrow N^s), \pi_{RV(\alpha|S_w)}) \text{ where } N N^s \in \alpha \]

\[ P_{PCFG-MEBN}(N \rightarrow w^t) = \& (P(N \rightarrow w^t), \pi_{RV(\alpha|S_w)}) \text{ where } w^t \in \alpha \]

\&() is a probability conflation function[4] which combines probabilities and normalizes with least shannon’s information loss.

For a MEBN theory T, a set of MFrags \{ F_1, F_2, F_3, \ldots, F_n \}, there exists a joint unique probability distribution on the set of instances of the random variables of its MFrags that is consistent with the local probability distributions assigned within the M_frag[3].

### 3. Need for Mapping PCFG and MEBN

Conventionally PCFGs have been very useful in probabilistic reasoning in the context of parsing the strings to recognize a specific pattern. Often natural languages processing tasks benefited from PCFGs. The rationale behind using probability with CFGs is to resolve a most probable parse sequence from possible set of parses available for a given string. The PCFGs are very helpful in achieving the stochasticity with which humans usually process the pattern recognition problems. Probabilistic Grammars were further augmented with Markov Random fields [7] CFGs and PCFGs focus on syntactic and structural patterns while completely ignoring semantic context during parsing. See figure 1 and 2 where constituency parse trees obtained from stanford's corenlp[5] parser (http://corenlp.run) for two different sentences are syntactically similar but semantically different. The parsers currently could not accommodate the semantic information associated with the vocabulary in the sentences. The phrases “the cake batter with the chocolate” , “the cake batter with the spatula” are semantically very different while syntactically the same.

Semantic information is modelled as ontologies. OWL is the main language to build ontologies. The proposed integration of PCFG and MEBN theory paves a way towards usage of PR-OWL [6] with PCFG since PR-OWL is an upper ontology for specifying probabilistic ontologies expressed as MEBN Theory. Probabilistic ontologies capture the inherent uncertainties of the real world information, enabling probabilistic reasoning through MEBN theory modelling of the ontology classes, properties and relations. Carvalho et al defined and described the process of constructing probabilistic ontologies using MEBN theory, which they called PR-OWL (Probabilistic-Ontology Web Language).
The approach proposed in the paper is an attempt to enable PCFGs parse sentences taking into consideration the semantic information associated with. It is quite evident by the “Principle of Semantic Compositionality” that semantic and syntactic information goes together to give a sentence a meaning understandable by humans [8]. Though it’s a different opinion that “Principle of Semantic Compositionality” is contested for it being not true all the times especially when context is introduced in the semantic meaning [9]. The work by [10] clearly points out differences in the way, how the “Principle of Semantic Compositionality” should be interpreted.
Sentence 1: Alice mixed the cake batter with the chocolate
4. Summary

PCFGs have been the answer to the amphibology in natural language. MEBN theory has evolved as an extension to Bayesian networks with first order logic expressivity. MEBN theory is used in constructing probabilistic ontologies for uncertainty reasoning in knowledge bases and semantic information databases modelled as ontologies. Mapping between PCFG and MEBN would serve as a bridge linking the probabilistic reasoning in syntactic, structural oriented systems to probabilistic reasoning in semantic and probabilistic ontologies, a syntactico-semantic reasoning. Additionally, PR-OWL being the frontrunner in modelling probabilistic ontologies using MEBN’s first order logic expressivity can augment with PCFGs using the mapping described in this paper. Further, the work reported in the paper needs intricacies involved in PR-OWL’s inheritance and polymorphism support w.r.t OWL to be touched upon.
References

[1] Jelinek, Frederick, John D. Lafferty, and Robert L. Mercer. "Basic methods of probabilistic context free grammars." Speech Recognition and Understanding. Springer, Berlin, Heidelberg, 345-360. (1992)

[2] Patnaikuni, Patnaik, R. Shrinivasan, and Sachin R. Gengaje. "Survey of Multi Entity Bayesian Networks (MEBN) and its applications in probabilistic reasoning." International Journal of Advanced Research in Computer Science 8.5 (2017).

[3] Laskey, Kathryn Blackmond. "MEBN: A language for first-order Bayesian knowledge bases." Artificial intelligence 172.2-3. 140-178. (2008)

[4] Hill, Theodore. "Conflations of probability distributions." Transactions of the American Mathematical Society 363.6 : 3351-3372. (2011)

[5] Manning, Christopher, et al. "The Stanford CoreNLP natural language processing toolkit." Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations. (2014).

[6] Carvalho, Rommel N., Kathryn B. Laskey, and Paulo CG Costa. "PR-OWL–a language for defining probabilistic ontologies." International Journal of Approximate Reasoning 91: 56-79. (2017)

[7] Zhu, Long Leo, and Yuanhao Chen. "Unsupervised learning of probabilistic grammar-markov models for object categories." Pattern Analysis and Machine Intelligence, IEEE Transactions on 31.1:114-128. (2009)

[8] Pelletier, Francis Jeffry. "The principle of semantic compositionality." Topoi 13.1:11-24. (1994)

[9] Pelletier, F. J. "Context, compositionality, and brevity." Brevity: 178-197. (2013)

[10] Szabo, Zoltan Gendler. "The case for compositionality." The oxford handbook on compositionality: 64-80. (2012)

[11] Parka, Cheol Young, and Kathryn Blackmond Laskey. "MEBN-RM: A Mapping between Multi-Entity Bayesian Network and Relational Model." arXiv preprint arXiv:1806.02455 (2018).