Integration of probabilistic relational modeling and reasoning into Protégé

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In probabilistic relational models (PRMs) [2, 3] slots of classes and instances are represented by probability distributions. During reasoning using these models, values of unknown slots are calculated via Bayesian inference [1]. Advantages of PRMs over pure logic modeling techniques are:

- relational domains with inherent uncertainty on parameters and structure can be represented,
- parameters of probability distributions and model structure can be adjusted or learned given observation data.

The relational domain, that will be used in the presentation, consists of an ontology of scene-entities. Static and dynamic scenes within an indoor table top scenario will be modeled. Reasoning methods on PRMs will be shown, which enables the application of scene interpreation, -explanation and -prediction. The PRM reasoner is written as Protégé Plugin.

In the presentation domain, scenes are modeled as hierarchies of scene entities ranging from basic physical objects (e.g. plates) to aggregations of various levels (e.g. covers, table configurations). The reasoner provides answers on existence and features of partly observed or hypothesized scene entities. In a cyclic process reasoning results can be delivered back to a low-level image analysis to guide the retrieval of more evidence in order to improve the accuracy of the scene interpretation (selective perception). This conceptual framework was outlined in [5].

Classes and Instances of PRMs are also known as Bayesian Network Fragments (BNFs). BNFs were introduced as relational extension to Bayesian networks, and allow the probabilistic modeling of domains, which exhibit varying number of variables and modular reoccurrence patterns in data. BNFs reside within the knowledge base representing classes of scene entities. The knowledge base is built as ontology of a taxonomic class-hierarchy, which is utilized by interpretation steps changing the abstraction level of scene entity models. During the interpretation process, scene-specific Bayesian networks (scene graphs) are composed of copies of BNFs specifying entity instances. A generated network represents relations between domain entities, in our setting basically a partonomy of scene entities. Entities within a scene graph can be hypothesized or observed, (partially) backed by evidence.

Within the proposed framework, BNFs consist of random variables, which model inter alia features of scene entities. Certain features of scene entities such as positions of objects or timemarks of processes are modeled as continuous random variables [4]. The conditional distributions of random variables can be defined with arbitrary functionality, e.g. including euclidean plane transformations of positions for rotation invariant constellation models. Each BNF further contains an existence probability, which reflects the belief on occurence of the entity within an assumed scene and is conditioned on features of the same and relating entities (e.g. the existence of a cover depends on the spatial configuration of associated plate and cup).

The interpretation algorithm, we put forth, generates scene graphs of scene entities by processing a number of model construction steps, which exploit the partonomic and taxonomic hierarchies of the enitity classes within the knowledge base: bottom-up *aggregation* of entities, top-down *expansion* of entities, *generalization* of entities and *specialization* of entities. The construction of scene graphs is guided by the given evidence and a metric measuring the confidence of scene assessments. During the incremental interpretation process this score allows to compare alternative partial scene explanations for following only the promising ones to keep the reasoning computationally inexpensive.

Resulting scene graphs provide explanations of scenes and can be queried by Bayesian inference to obtain expectations on unobserved (features of) scene entities. The application of this approach will be shown by examples within the table top domain.

References

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