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Modeling semantics of inconsistent qualitative knowledge for quantitative Bayesian network inference[☆]

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Abstract

We propose a novel framework for performing quantitative Bayesian inference based on qualitative knowledge. Here, we focus on the treatment in the case of inconsistent qualitative knowledge. A hierarchical Bayesian model is proposed for integrating inconsistent qualitative knowledge by calculating a prior belief distribution based on a vector of knowledge features. Each inconsistent knowledge component uniquely defines a model class in the hyperspace. A set of constraints within each class is generated to describe the uncertainty in ground Bayesian model space. Quantitative Bayesian inference is approximated by model averaging with Monte Carlo methods. Our method is firstly benchmarked on ASIA network and is applied to a realistic biomolecular interaction modeling problem for breast cancer bone metastasis. Results suggest that our method enables consistently modeling and quantitative Bayesian inference by reconciling a set of inconsistent qualitative knowledge.

Keywords: Qualitative knowledge modeling; Inconsistent knowledge integration; Bayesian networks; Bayesian inference; Monte Carlo simulation

1. Introduction

Bayesian reasoning provides a probabilistic approach to inference. In Bayesian framework, quantities of interest are described by probabilities and optimal decisions can be made by reasoning about these probabilities together with the observation or evidence. Bayesian reasoning is important to machine learning because it provides a quantitative approach to weighting the evidence supporting alternative hypotheses. Numerous algorithms have been proposed for learning the Bayesian network structure and parameter from the observed data. These algorithms produce a single Bayesian model by maximizing its probability given the training data, i.e. maximum a posterior approximation. In realistic problem, learning Bayesian model by training data requires relatively large amount of observed data comparing to the size of network. However, the data basis is often very sparse and it is hardly sufficient to select one adequate model due to the model uncertainty, thus, selecting a single model may induce overfitting to the data and can lead to strongly biased inference results. It is therefore preferable to adopt a full Bayesian approach with model averaging.

Besides the training data, the prior background knowledge provides many ways to adjust uncertainties. The prior background knowledge includes qualitative and quantitative knowledge which describes the entities and their relationships with different levels of abstraction. Quantitative knowledge can be exemplified by a probability elicitation procedure from a domain expert. In most domains, this is particularly difficult due to the limitations of expert knowledge in this level. In contrast, qualitative knowledge, which only provides loose constraints with uncertainty on the entities and their relations exist in many science and engineering domains. For example, in biomedicine, the statement: “*Gene CTGF, IL11 and OPN cooperatively activate bone metastasis in breast cancer*”, entities are gene *CTGF, IL11, OPN* and *Bone metastasis in breast cancer*, their qualitative relation: *cooperatively activate*. In some cases, there are properties which further specify the qualitative relationship. In “*The risk of lung cancer among smokers is approximately* 10 *times higher than non-smokers*”,

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Smoking cause lung cancer and the influence is 10 *times higher to non-smokers*. In recent studies (Chang & Stetter, 2007a, 2007b), it is shown that qualitative knowledge can be used and translated into a set of constraints on the Bayesian model space. This set of constraints defines the model uncertainty in structure and parameter space respectively. The model uncertainty represented by the qualitative knowledge enables the full Bayesian approach where a class of Bayesian networks which are consistent with the semantics of the set of qualitative hypotheses are drawn according to the model uncertainty. The probabilistic network inference and reasoning can be derived by performing quantitative prediction and inference in each of the Bayesian model and these quantitative results are averaged weighted by the model posterior probability. This approach has been successfully applied to both well-known benchmark model and real-world application. However, one significant drawback of this qualitative knowledge-driven probabilistic network modeling and inference approach is its incapability of dealing with inconsistent qualitative knowledge. It is well-known that knowledge are often inconsistent, i.e. in the same domain, there may exist contradicting qualitative statements on dependency, causality and parameters over a set of entities. Therefore, it is imperative to develop methods for reconciling inconsistent qualitative knowledge and for modeling Bayesian networks and performing quantitative prediction. In this paper, we propose a novel framework for performing quantitative Bayesian inference with model averaging based on the inconsistent qualitative statements as a coherent extension of framework of quantitative Bayesian inference based on a set of consistent hypotheses introduced in Chang and Stetter (2007b). Our method interprets the qualitative statements by a vector of knowledge features whose structure can be represented by a hierarchical Bayesian network. The prior probability for each qualitative knowledge component is calculated as the joint probability distribution over the features and can be decomposed into the production of the conditional probabilities of the knowledge features. These knowledge components define multiple Bayesian model classes in the hyperspace. Within each class, a set of constraints on the ground Bayesian model space can be generated. Therefore, the distribution of the ground model space can be decomposed into a set of weighted distributions determined by each model class. This framework is used to perform full Bayesian inference which can be approximated by Monte Carlo methods, but is analytically tractable for smaller networks and statement sets. In Section 2, we introduce some related works which have been previously reported and related to our approach. We also clarify the contribution of this approach comparing to the approach proposed previously in Chang and Stetter (2007b). In Section 3, we propose the hierarchical knowledge model for modeling and integrating qualitative knowledge. In Section 4, we describe the quantitative Bayesian inference method with model averaging based on the inconsistent qualitative knowledge. In Section 5, we firstly benchmarked our method with ASIA network by reconciling a set of inconsistent hypotheses with regard to the interactions between pairs of variables to model Bayesian networks and performing quantitative inference based on these Bayesian networks. Then we apply our method to integrate a set of realistic inconsistent knowledge with regard to the TGFβ-Smad signaling pathway in the breast cancer bone metastasis network for constructing the Bayesian models and performing quantitative inference. Conclusions and further discussion are provided in Section 6.

2. Related works

Previous reported methods for Bayesian inference are exclusively based on the quantitative data. In these data-driven Bayesian inference approach, the structure and parameter are learned by certain model selection criterion which select a model with local maximum score and make quantitative predictions on this model. It is clear that model selection scheme is insufficient to make good predictions especially when the data is sparse. In this case, full Bayesian approach with Bayesian model averaging shall be used to provide better generalization. Bayesian inference approaches based on the qualitative knowledge potentially provide a way to take into account the model uncertainty with Bayesian model averaging. Several algorithms have been proposed to perform qualitative Bayesian network modeling and inference based on soly qualitative knowledge (Druzdzel & Henrion, 1993; Renooij, Gaag, & Parsons, 2002). These algorithms perform qualitative inference with sign propagation, therefore, they are useful in producing qualitative inference. However, the major limitations of these approaches are two-fold: (1) Since qualitative signs are used in these approach, sign operations are performed for qualitative inference. Therefore, ambiguous sign is easily propagate through the network by simple sign propagation and meaningful inference results cannot be generated in this case. (2) In these approaches, no quantitative information can be gained from the qualitative settings through sign propagation, i.e. model uncertainty is not taken into account. Moreover, neither of these approaches can deal with inconsistent qualitative knowledge.

In our approach, qualitative knowledge is well formulized to construct the prior distribution over the structure and parameter space. The inputs are only qualitative statements with certain fuzzy cause-effect relationships between the domain variables. The uncertainty in these statements are modeled and translated into belief distribution on the Bayesian model space. Therefore, each Bayesian model in the space produces a quantitative prediction which will be weighted by the models belief assignment in the space. The novelty of our approach is that we take advantage of model uncertainty modeling and full Bayesian approach with model averaging to produce quantitative predictions and inference based on only qualitative information. Further quantitative information from data is not needed. This is especially useful when there are sparse data in the domain. Moreover, the approach described in this paper is a coherent extension of the methods introduced in Chang and Stetter (2007b), in that inconsistent qualitative knowledge can be integrated to model the uncertainty in the knowledge space, thus, multiple classes of Bayesian networks can be constructed for performing the quantitative inference weighted