Multidimensional possibilistic models

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When dealing with practical problems in the field of artificial intelligence, one must cope with two basic issues: multidimensionality and uncertainty. The most widely used technique for it at present is offered by *graphical modelling*, sometimes characterised as a "marriage between probability theory and graph theory" [3], as it combines methodologies of both theories.

Nevertheless, it is well-known that (precise) probability theory is not always the optimal tool for modelling uncertainty, as it is not able to express imprecision (or even ignorance). Therefore many alternative theories for uncertainty modeling have emerged in recent decades. Among them, possibility theory is the most similar (from the formal point of view) to probability theory. Therefore, it seems quite natural that possibilistic graphical models have been studied since the early 1990s (e.g. [1, 2]).

In this contribution we will present a non-graphical approach (parameterised by a continuous t-norm) to the construction of multidimensional possibilistic models from sequences of low-dimensional ones. We will show that any of the previously presented graphical models, i.e., possibilistic trees, dependence trees and possibilistic belief networks (or possibilistic directed graphs), can be expressed using this technique. Furthermore, the dependence structure of these models can be visualised by their transformation into possibilistic belief networks.

Nevertheless, these models may differ from each other for different t-norms regarding two points of view. One of them is consistency with marginals: it may happen that application of the operator of composition based on, e.g., Gödel's t-norm, leads to a model consistent with the given marginals, while the same need not be true for that based on, e.g., product t-norm. This is caused by different conditional independence concepts induced by these models.

Another difference may even appear in the case of consistency of the resulting model with its marginals if we use it for decision making. Again, the optimal decision functions may be mutually different. Therefore probabilistic interpretation of these models must also be discussed to reveal the substance of these differences and to help us choose the proper model.

References

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