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Variable Elimination for Interval-Valued Influence Diagrams

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Abstract. Influence diagrams are probabilistic graphical models used to represent and solve decision problems under uncertainty. Sharp numerical values are required to quantify probabilities and utilities. Yet, real models are based on data streams provided by partially reliable sensors or experts. We propose an interval-valued quantification of these parameters to gain realism in the modelling and to analyse the sensitivity of the inferences with respect to perturbations of the sharp values. An extension of the classical influence diagrams formalism to support interval-valued potentials is provided. Moreover, a variable elimination algorithm especially designed for these models is developed and evaluated in terms of complexity and empirical performances.

Keywords: Influence diagrams · Bayesian networks · Credal networks · Sequential decision making · Imprecise probability

1 Introduction

Influence diagrams are probabilistic graphical models able to cope with decision problems with uncertainty. The parameters of an influence diagram are conditional probabilities for single variables given some other variables, or utilities depending on given sets of variables. The quantification of these parameters is based on a statistical processing of data or on the elicitation of expert knowledge.

Exactly as Bayesian networks, influence diagrams require sharp estimates of their parameters. Yet, when coping with expert knowledge, sharp values can be unfit to express judgements (e.g., which is the number modelling the probability for an option *more probable* than its negation?). This issue appears also when coping with scarce or missing data (e.g., probabilities conditional on rare events).

For reasons of this kind, in the last two decades, various extensions of Bayesian networks to support more general probabilistic statements have been proposed. These models have been developed in the field of possibility theory [2],

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