Keynote Lectures

Introduction to Belief functions – T. Denœux

Monday afternoon 14:00 – 15:45

The theory of belief functions originates from Dempster's early work on upper and lower probabilities applied to statistical inference (Dempster, 1968). It was further elaborated by Shafer (1976), who first introduced it as a formal framework for uncertain reasoning. Smets (1998) proposed a version of this theory, called the Transferable Belief Model (TBM), based on the introduction of new concepts such as unnormalized mass functions, the pignistic transformation and the least commitment principle. This first course provides a general introduction to the theory of belief functions. Main definitions and key results will be reviewed, after which some new concepts (such as the cautious rule of combination) will be introduced.

References:

A. P. Dempster. Upper and lower probabilities induced by a multivalued mapping. Annals of Mathematical Statistics, 38:325-339, 1967.

T. Denoeux. Conjunctive and Disjunctive Combination of Belief Functions Induced by Non Distinct Bodies of Evidence. Artificial Intelligence, Vol. 172, pages 234-264, 2008.

G. Shafer. A mathematical theory of evidence. Princeton University Press, Princeton, N.J., 1976.

Ph. Smets. The Transferable Belief Model for quantified belief representation. In D. M. Gabbay and Ph. Smets, editors, Handbook of Defeasible reasoning and uncertainty management systems, volume 1, pages 267-301. Kluwer Academic Publishers, Dordrecht, 1998.

Knowledge propagation in information fusion – A. Appriou

Monday afternoon 16:15 – 18:00

Information systems have to process more and more disparate complementary sources in an efficient way, in order to face the increased complexity of environments and requirements. Therefore they have to deal with individual believes expressed on heterogeneous frames of discernment that may have with each other uncertain or imprecise relations, so that it becomes unsuitable to look for a common one as usually proposed by classical data fusion theories. To face this context, the ability of the belief function theories to propagate knowledge from one frame of discernment to another is emphasized on the basis of a generic operator named “extension”. Furthermore, the latter provides a general formulation of the different operators that constitute a complete and coherent processing of multiple uncertain observations, from their modeling up to the required decision making. Therefore the particular conditions that lead to the traditional operators can be specified, in order to provide a federative view of

recent developments about sensitive problems faced in the framework of the uncertainty theories, such as information unreliability, source conflict, or adaptive decision making, for instance. The implementation of the generic operator is described, and a few examples illustrate a suitable management of uncertainty processing thanks to available tools.

Methods for building belief functions – T. Denœux

Tuesday morning 8:30 – 10:15

While a lot of effort has been put on the propagation and fusion of uncertain information represented as belief functions, less emphasis has been put on the initial modeling process itself, i.e., how to encode uncertain information in the belief function framework. This lectures reviews some formal methods and fundamental principles for building belief functions, including: the least commitment principle, the Generalized Bayes Theorem, belief function transformation methods (such as discounting or its extensions) and predictive belief functions (or how to formalize beliefs about future events based on statistical information).

Belief functions in the setting of Uncertainty Theories: convergences and discrepancies – D. Dubois

Tuesday morning 10:45 – 12:30

The modelling of uncertainty is motivated by two concerns: taming the variability of external phenomena and facing incomplete information in decision processes. These two concerns are related by the fact that in the face of variability, it is difficult to predict what the next state of the world will be. Yet the two concerns are distinct in the sense that variability is far from being the only cause of information incompleteness. However, the development of probability theory, as witnessed by the Bayesian school especially, tended to blur this distinction, suggesting that a unique probability distribution is enough to account for both randomness and incomplete information. More recently, new theories of uncertainty have emerged where partial ignorance is acknowledged and represented separately from randomness: the theories of evidence, possibility and imprecise probabilities, respectively. The aim of this talk is to provide a unified view of these approaches, and in particular, position belief functions in this landscape.

The basic tool for representing information incompleteness is set theory: an ill-known quantity is represented as a disjunctive set, i.e. a subset of mutually exclusive values representing an epistemic state, which in evidence theory is called a focal set. Introducing shades of plausibility within set-representations of incompleteness leads the the use of fuzzy sets. It is important to figure out that the reason why fuzzy set theory is relevant for uncertainty handling is because it is a set-based approach, not because it is fuzzy (i.e. gradual rather than abrupt).

The main point of the talk is to situate belief functions with respect to possibility theory, random set theory and imprecise probabilities
- in imprecise probability theory, the most general framework, information takes the form of a convex set of probability measures, all the larger as information is poor.
- in evidence theory, information is represented by random sets, albeit disjunctive ones (while random sets are often viewed as random objects). Belief functions correspond to special subsets of probabilities.

- in possibility theory, information is summarized by fuzzy sets or fuzzy intervals, then equivalent to nested random sets.

The talk will briefly point out differences and convergences between these uncertainty theories, namely:

- The fact that they use languages with distinct primitive notions which sometime makes the translation of notion from one framework to another difficult.
- The focus of belief functions on uncertain singular pieces of evidence as opposed to the use of imprecise probability for generic information.
- Practical representations from other theories that fit with belief functions : fuzzy intervals p-boxes, clouds.
- Conditioning and fusion rules for belief functions vs. for random sets, imprecise probabilities, and possibility theory.
- Impact on decision criteria under uncertainty.

REFERENCES

Basic references on alternative uncertainty theories

G. L.S. Shackle, Decision, Order and Time in Human Affairs, 2nd edition, Cambridge University Press, UK, 1961.

G. Shafer, A mathematical Theory of Evidence, Princeton University Press, 1976.

L. A. Zadeh, Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets and Systems, 1: 3-28, 1978.

D. Dubois and H. Prade, Possibility Theory, New York: Plenum, 1988

P. Smets and R. Kennes The transferable belief model, Artificial Intelligence, 66 (1994) 191-234.

P. Walley, Statistical Reasoning with Imprecise Probabilities, Chapman and Hall, 1991.

G. De Cooman, Possibility theory. Part I: Measure- and integral-theoretic groundwork; Part II: Conditional possibility; Part III: Possibilistic independence. Int. J. of General Systems, 25: 291-371, 1997.

References to the speaker's works

D. Dubois, H.T. Nguyen and H. Prade, Fuzzy sets and probability: misunderstandings, bridges and gaps. In D. Dubois and H. Prade, editors, Fundamentals of Fuzzy Sets. Boston, Mass: Kluwer, pages 343-438, 2000

D. Dubois and H. Prade, Possibility theory: Qualitative and quantitative aspects. In D. M. Gabbay and P. Smets P., Handbook of Defeasible Reasoning and Uncertainty Management Systems, Vol. 1., Dordrecht: Kluwer Academic, pages 169-226, 1998.

D. Dubois Possibility theory and statistical reasoning Computational Statistics & Data Analysis, 51, 47-69, 2006

D. Dubois, H. Prade. Formal representations of uncertainty. In: Decision-making Process-Concepts and Methods. Denis Bouyssou, Didier Dubois, Marc Pirlot, Henri Prade (Eds.), ISTE London & Wiley, Chap. 3, p. 85-156, 2009.

S. Destercke D.Dubois, E. Chojnacki, Unifying practical uncertainty representations – Part I: Generalized p-boxes. International Journal of Approximate Reasoning, 49, Issue 3, 2008, 649-663; Part II: Clouds. International Journal of Approximate Reasoning, 49, 2008, 664-677.

How to implement the belief functions – A. Martin

Tuesday afternoon 16:30 – 18:15

This lecture is a very practical one in order to show how we can easily implement the belief functions. This lecture is specially dedicated to the novices in the theory of belief functions. We will see different kind of implementations on Matlab based on simple examples.
Firstly, we will see how to use the Ph. Smets codes based on the natural ordering. In this context, we will show how to combine the basic belief assignments and how to decide.
Secondly, we will present how to work only with the focal elements with a general framework for power set and hyper power set. Finally, according to the time we will work on a practical example in order to see how to define the basic belief assignments.

The attendee could test on their own data. In order to facilitate this lecture, we ask to the attendee to bring their computing notebook with Matlab. A free test version of Matlab can be download on http://www.mathworks.com. You can upload the codes used in this lecture and many others on http://www.bfasociety.org/.

Valuation-Based Systems – P. Shenoy

Wednesday morning 8:30 – 10:15

A valuation-based system is an abstract way of describing many uncertainty calculi such as Bayesian probability theory, Dempster-Shafer belief functions, Zadeh[1]s possibility theory, and Spohn[1]s kappa calculus. The main elements of valuation-based systems are variables and their state spaces, a set of valuations where each valuation describes knowledge regarding a subset of variables, an operation for combining valuations, and an operation for marginalizing valuations. In calculi where double counting leads to erroneous results, it is important that the set of valuations do not include double counting of knowledge. The combination of all valuations, the joint valuation, then represents the totality of all knowledge. If we wish to discern what the joint valuation entails for a variable of interest, we can compute the marginal of the joint valuation for the variable of interest (by marginalizing all variables but the variable of interest from the joint valuation). This is often referred to as making inferences. One major advantage of viewing uncertain calculi through the lens of valuation-based systems is that it simplifies the understanding of uncertain calculi. Thus, one who is familiar with, say, Bayesian probability theory, can understand the essence of other uncertain calculi, such as Dempster-Shafer belief functions, etc. It also helps to dispel myths, such as one calculus is [3]superior[2] to another, and to transfer concepts and algorithms from one calculus to another. The theory of valuation-based systems was initially developed for describing the process of computing marginals of the joint valuation without explicitly computing the joint valuation through a process called local computation. It has since been extended to include a removal operation, which can be considered as an inverse of the combination operation. Using the removal operation, one can describe valuations called conditionals. Also, it has been extended to include the concept of conditional independence, which ensures that there is no double counting of knowledge. Finally, valuation-based systems can also be used to describe decision-making calculi such as Bayesian decision theory, retrieval in relational databases, etc.

The applications of belief functions in a situation analysis process – Eloi Bossé

Wednesday morning 10:45 – 12:30

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Belief functions for signal and image analysis – O. Collot

Wednesday afternoon 16:30 – 18:15

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Statistics and Information Fusion – P.A. Monney

Thursday morning 8:30 – 10:15

In this presentation, statistical data will be analyzed from an information fusion perspective, which will require the application of several important features of belief functions theory. In this context, numerous inference methods will be explained and the concepts necessary for a thorough explanation of these methods will be provided. The approach used for inference will allow us to shed some light on the interpretation of the likelihood function and Fisher's fiducial distribution. It will be shown that Bayesian inference is a special case of the inference method used for one of the models presented, called functional models. However, the semantic of the model gives a different meaning to the Bayesian posterior distribution. Inference results are used to compute the probability that logical arguments proving certain propositions about the parameter are true. This combination of logical reasoning and probability theory provides statistical inference theory with an algebraic flavor that has only recently been put forward. Statistical decision making in the general context of belief functions theory will also be briefly touched upon, in particular the relationship with classical Neyman-Pearson test theory. Multiple examples will be used throughout the presentation to illustrate the different methods and to demonstrate their applicability.

Classification, clustering, data analysis – T. Denœux

Thursday morning 10:45 – 12:30

In the last 15 years, a lot of work has been devoted to the development of new classification and clustering methods based on the theory of belief functions. The expressive power of belief functions can be exploited at two levels: to model imprecision and uncertainty of input data, and to express uncertainty on the output of a classification or clustering algorithm. Several methods will be presented, including: the evidential k nearest neighbor rule, evidential neural networks, the evidential c-means (ECM) algorithm, as well as more recent methods for multi-label clustering and ensemble classification and clustering.

Belief functions for dynamical systems – E. Ramasso

Thursday afternoon 16:30 – 18:15

Dynamical systems are encountered in many areas such as automatic control, gesture analysis, expression and gait recognition, among others. Given some data generated from real dynamical systems, one is interesting in solving two main problems:
- estimating mathematical models of these systems (with embedded noise filtering)
- automatically recognizing which model is the correct one at a given instant (inference)

A recent focus on belief functions has been made these last years in order to propose solutions to these problems. These functions have been shown to be particularly suited to the cases where:
- not enough data are available for a reliable estimation of models
- systems' states are imprecisely known

This lecture aims at presenting the main tools for dynamical systems analysis in belief functions framework with some real applications.