

# Argumentation Random Field

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**Abstract.** We propose a new approach to integrating probabilities and argumentation, based on Markov Random Fields, and building on the connection between conditional independence and the labelling status of arguments. Such a system overcomes the main limitation of Markov logic networks, namely that only consistent theory can be ascribed non-zero probability. Our approach provides a principled technique for the merger of probabilities and argumentation, and holds promise in allowing for the learning of an argumentation system<sup>3</sup>.

## 1 Overview

Conflicting information is commonplace in domains such as intelligence analysis and decision support, making argumentation a natural choice for driving the reasoning process. However, most argumentation frameworks have propositional or predicate logic underpinnings, making it difficult to cope with uncertainty and argument strength. While work does exist which has utilised argument weights to facilitate reasoning in such complex domains, such approaches suffer from several limitations, often adopting an ad-hoc approach to weight propagation (c.f. the weakest link principle). More rigorous approaches often fail to explain the origin of argument weights and probabilities.

In this paper we suggest a different approach to reasoning with argument and probabilities. Our departure point is the analogy between local Markov properties (conditional independence given neighbours) in Markov Random Fields (also known as Markov Networks), and the status of an argument based on the status of its neighbours.

A Markov random field [4] is a graphical model which encodes local Markov properties — a random variable is independent of all other variables given its neighbours — as an undirected graph to establish probabilities of all valuations to the variables. Echoing the local Markov properties, Dung’s argumentation semantics [2] can be recovered by applying a list of acceptability rules based on a graphical model of argument interaction. For example, “A is labelled IN (accepted) if all its attackers are labelled OUT (rejected)” [1]. Such rules, which assign acceptability to an argument given the status of its neighbours, also satisfy local Markov properties. Moreover, the construction of arguments as proof networks [7] also admits the local Markov properties — the establishment of a conclusion is independent of all other rules given the premises of the rules for the conclusion. These two observations allow us to construct *Markov Argumentation Random Fields* (MARF). With MARF, we can model the acceptability interaction

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of premises, conclusions, inference rules, and argument attacks quantitatively through potential functions. Simple operations on these potentials facilitate the computation of a coherent probabilistic interpretation of the argumentation outcome — the argumentation structure along with the acceptability status assigned to premises, conclusions, inference rules and arguments.

Our approach can be viewed as an extension to Markov Logic [6] which builds a Markov random field for classic first order logic. While Markov Logic allows inconsistencies in a knowledge base, it will assign zero probabilities to all inconsistent formulae sets. MARF allows inconsistencies, and assigns non-zero probabilities to inconsistent sets, thus enabling the modelling of how inconsistent information interacts probabilistically: MARF produces an argumentation structure [7] over these inconsistent formulae which describes how one statement reinstates another as in abstract argumentation.

[3] has some commonalities with our work; it establishes probabilities for individual arguments based on the probabilities assigned to classic boolean interpretations of a logical language. These probabilities are used to derive probabilities of subgraphs of the abstract argument framework as per its semantics [5]. Unlike [3], we begin by modelling the dependency of arguments with respect to both acceptability rules and proof network construction rules. Critically, our approach allows us to drill into the details of acceptability assignments of interacting arguments. MARF therefore provides flexibility in designing inference; and the ability to learn parameters within the system.

Work into MARF can be extended in several directions. First, we intend to study how potential functions for argumentation schemes can be constructed, which capture interactions between premises, conclusions and critical questions. Second, we seek to learn the parameters of the MARF given exemplar argumentation structures. Representing and learning reasoning structures enable more effective intelligence analysis support in making sense of conflicting information. We also wish to further investigate whether argument reinstatement will lead to a better reasoning mechanism than Markov Logic due to the presence of non-zero probabilities in inconsistent sets.

## References

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