Abstract Argumentation with Markov Networks (Extended Abstract)

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Markov networks are one of the main families of probabilistic graphical models and have various applications in uncertain reasoning and machine learning (Khot et al. 2015; Fisher, Christen, and Wang 2016; Gayathri, Easwarakumar, and Elias 2017). One of the most popular applications in the area of knowledge representation and reasoning are probably Markov Logic Networks that combine logic and probability theory (Richardson and Domingos 2006). This extended abstract summarizes the main results from (Potyka 2020a), which showed how classical abstract argumentation problems can be encoded as Markov networks. The main contributions of this work are: 1) explaining how classical argumentation problems can be encoded as Markov networks and how inference tasks in classical argumentation frameworks can be reduced to inference tasks in Markov networks; 2) a semantical analysis of the resulting probabilistic graphical models from a probabilistic argumentation perspective; and 3) a natural generalization to bipolar argumentation frameworks that respects both properties for classical and probabilistic argumentation frameworks. In the following, we describe each contribution in more detail and give some ideas for future research directions.

1) Intuitively, Markov networks decompose joint probability distributions into a product of local factors that depend only on a subset of the random variables. The encoding in (Potyka 2020a) introduces one random variable for every argument that can take the values in, out and $\mathrm{undecided}$. A joint assignment to the random variables corresponds to a classical labelling in argumentation. The basic idea of the encoding is to introduce one factor for each argument that depends on the argument itself and its attackers in the argumentation graph. If the labelling is locally consistent with the conditions of an argumentation semantics, the factor returns 1. Otherwise, it will return 0 and in this way make the probability of the labelling 0. In this way, we can, for example, link the problems of credulous and sceptical reasoning under complete and stable semantics to marginal probability computations, and computing the number of labellings to computing the partition function of Markov networks. Similarly, finding labellings under grounded, preferred and semi-stable semantics can be linked to MAP-queries in Markov networks. All problems are well understood for Markov networks (Koller and Friedman 2009) and the connection allows transfering exact and approximate computation algorithms for Markov networks to the argumentation setting.

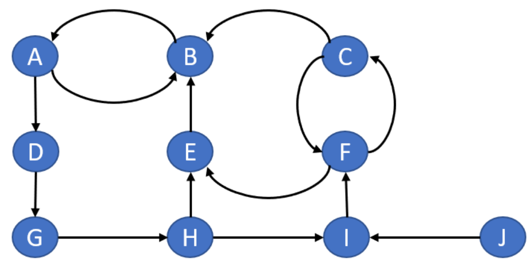

Figure 1: Argumentation framework (edges represent attacks).

2) As it turns out, the Markov networks that result from the encoding are not only interesting for transferring algorithms for Markov networks to argumentation frameworks, but can be seen as interesting probabilistic argumentation models in their own right. To illustrate this, Figure 1 shows a classical argumentation framework and Table 1 some of the resulting marginal probabilities of arguments for the Markov networks that resulted from different semantics. As we show in (Potyka 2020a), the Markov networks respect several of the properties proposed by Hunter and Thimm for probabilistic argumentation (Hunter and Thimm 2017). For example, the probability of attackers defines an upper bound for attacked arguments and unattacked arguments have probability 1 (are accepted) in accordance with classical argumentation.

3) The generalization to the bipolar argumentation setting is driven by the idea to treat attack and supports equally. Existing bipolar semantics often favor one or the other. The new semantics, called the *deductive semantics*, defines symmetrical conditions for the effects of attackers and supporters. If an argument is accepted (rejected), then all attackers (supporters) must be rejected. Furthermore, if an supporter (attacker) of an argument is accepted, then the argument must be accepted (rejected). The deductive semantics still respects the idea of supported and mediated attacks introduced in (Cayrol and Lagasquie-Schiex 2013). Following similar ideas as before, it can be encoded as a Markov network again and its corresponding probabilistic semantics still satisfies some basic properties by Hunter and Thimm that can be transferred to the bipolar setting naturally. In particular, due to the symmetrical treatment of attack and

$\mathcal{A}$	c	g	p	ss	s
$P(A = \text{in})$	$\frac{3}{6}$	0.22	0.6	0.67	$\frac{2}{3}$
$P(A = \text{out})$	$\frac{1}{6}$	0.03	0.34	0.32	$\frac{1}{3}$
$P(B = \text{in})$	$\frac{1}{6}$	0.03	0.34	0.32	$\frac{1}{3}$
$P(B = \text{out})$	$\frac{3}{6}$	0.22	0.6	0.67	$\frac{2}{3}$
$P(C = \text{in})$	$\frac{1}{6}$	0.03	0.34	0.32	$\frac{1}{3}$
$P(C = \text{out})$	$\frac{3}{6}$	0.34	0.55	0.64	$\frac{2}{3}$
$P(D = \text{in})$	$\frac{1}{6}$	0.03	0.34	0.32	$\frac{1}{3}$
$P(D = \text{out})$	$\frac{3}{6}$	0.22	0.6	0.67	$\frac{2}{3}$
$P(E = \text{in})$	$\frac{1}{6}$	0.03	0.34	0.32	$\frac{1}{3}$
$P(E = \text{out})$	$\frac{3}{6}$	0.34	0.55	0.64	$\frac{2}{3}$
$P(F = \text{in})$	$\frac{3}{6}$	0.34	0.55	0.64	$\frac{2}{3}$
$P(F = \text{out})$	$\frac{1}{6}$	0.03	0.34	0.32	$\frac{1}{3}$
$P(I = \text{in})$	0	0	0	0	0
$P(I = \text{out})$	1	1	1	1	1
$P(J = \text{in})$	1	1	1	1	1
$P(J = \text{out})$	0	0	0	0	0

Table 1: Marginal probabilities (rounded) under different semantics for Figure 1. Note that $P(X = \text{undecided}) = 1 - P(X = \text{in}) - P(X = \text{out})$.

support, each attack property has a symmetrical support property. For example, while the probability of attackers continues to define an upper bound for attacked arguments, the probability of supporters defines a lower bound for supported arguments.

There are several directions for future work. From an algorithmic perspective, it is interesting to combine algorithms for Markov networks (which may be stronger for combinatorial tasks like sceptical inference or counting labellings) with classical argumentation algorithms to advance the state-of-the-art. In particular, lifted inference ideas (Kersting 2012) may be fruitful to exploit symmetries in argumentation graphs. Current reasoning algorithms for argumentation problems are mainly based on SAT (Dvorák et al. 2012), ASP (Egly, Gaggl, and Woltran 2008) or CSP (Lagniez, Lonca, and Mailly 2015) encodings. Another potentially interesting application is to use learning algorithms for Markov networks to learn argumentation frameworks from data. A similar application of Bayesian networks has been considered in (Kido and Okamoto 2017). Motivated by the new bipolar semantics, two other novel semantics have been introduced that treat attack and support almost equally as well, but are more decisive in the sense that they allow less labellings with undecided arguments (Potyka 2020b; Potyka 2021).

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