On the Relationship Between Bipolar Gradual Argumentation Frameworks and Neural Networks (Extended Abstract)

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Motivated by the flexibility and learning performance of neural networks, there has been increasing interest in using them to approximate argumentation tasks [3, 9, 4, 5]. In the context of strength-based argumentation frameworks, there is a family of argumentation models that is actually very close to neural networks. These models are often called bipolar gradual argumentation models (BAG for short). Some recent examples can be found in [2, 8, 1, 6]. The models basically consist of weighted directed graphs with two types of edges. Nodes correspond to abstract arguments that can be accepted or rejected to a certain degree. Every node is associated with a *base score* that reflects its initial weight when ignoring all other arguments. Edges can be attacking or supporting and may have a weight that reflects the strength of the relationship between the arguments. The end goal is to assign strength values to every argument such that the strength of every argument is consistent with the strength of its attackers and supporters. To this end, gradual argumentation models define an update function that iteratively updates the strength values until they converge. The strength of every argument is initialized with its base score and updated based on the strength of its attackers and supporters. Usually, attackers should decrease and supporters should increase the strength of the affected argument based on their own respective strengths. Intuitively, the final strength values correspond to a fixed-point of the update function in which all strength values are in balance.

It is interesting to note that for finite acyclic graphs, gradual argumentation frameworks can be seen as neural networks that take some inputs (base score of the arguments without ingoing edges) and compute an output (final strength of arguments without outgoing edges) by performing some transformations on the inputs (intermediate arguments). It is then natural to ask, can we transfer results between these two seemingly different fields to their mutual benefit? As a first step in this direction, multilayer perceptrons (MLPs for short) have recently been analyzed from an argumentation perspective [7]. MLPs process inputs on layered acyclic graphs by successively performing linear and non-linear transformations. Their mechanics are extremely close to the Euler-based semantics for gradual argumentation that has been investigated in [1]. As it turns out, the MLP update function can be generalized to arbitrary graphs and, in this way, can be used to interpret arbitrary BAGs. Interestingly, it satisfies all semantical properties that the Euler-based semantics satisfies, but also solves some symmetry- and bias-problems of the Euler-based semantics. Figure 1 compares semantical properties from the literature satisfied by the Df-QuAD [8], Euler-based [1], quadratic energy [6] and MLP-based semantics [7].

Property	DfQ	Euler	QEM	MLP
Anonymity	✓	✓	✓	✓
Independence	✓	✓	✓	✓
Directionality	✓	✓	✓	✓
Equivalence	✓	✓	✓	✓
Stability	✓	✓	✓	✓
Neutrality	✓	✓	✓	✓
(Strict) Monotony	(✓)	✓	✓	✓

Property	DfQ	Euler	QEM	MLP
(Strict) Reinforcement	(✓)	✓	✓	✓
Resilience	(✓)	✓	✓	✓
Franklin	✓	✓	✓	✓
Weakening	(✓)	✓	✓	✓
Strengthening	(✓)	✓	✓	✓
Duality	✓	×	✓	✓
Open-Mindedness	×	×	✓	(✓)

Fig. 1. Properties fully satisfied (✓), satisfied when excluding base scores 0 and 1 ((✓)), not satisfied even when excluding base scores 0 or 1 (x).

So far, previous work on convergence guarantees for BAGs could be applied to generalize the mechanics of MLPs to arbitrary graphs, which is interesting for the theory of MLPs. This generalization gave rise to a new BAG semantics with strong semantical guarantees, which is interesting for the theory of BAGs. Currently, we are working on using learning ideas for neural networks to advance the state of the art in learning BAGs from data [10]. Ideas from the field of argumentation like sets of attacks or supports may then again lead to novel ideas for additional structure in neural networks that may improve the learning performance in the future. In the workshop, I would like to present some of the previous findings in more detail, report on our ongoing work on exploiting the relationship between neural networks and BAGs to learn BAGs from data and discuss these ideas with the argument strength community.

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