

# Integrating Defeasible Argumentation and Machine Learning Techniques (Preliminary Report)

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## Abstract

The field of machine learning (ML) is concerned with the question of how to construct algorithms that automatically improve with experience. In recent years many successful ML applications have been developed, such as datamining programs, information-filtering systems, etc. Although ML algorithms allow the detection and extraction of interesting patterns of data for several kinds of problems, most of these algorithms are based on *quantitative* reasoning, as they rely on training data in order to infer so-called target functions.

In the last years *defeasible argumentation* has proven to be a sound setting to formalize common-sense *qualitative* reasoning. This approach can be combined with other inference techniques, such as those provided by machine learning theory.

In this paper we outline different alternatives for combining defeasible argumentation and machine learning techniques. We suggest how different aspects of a generic argument-based framework can be integrated with other ML-based approaches.

## 1 Introduction and motivations

The ability to generate and collect data has increased exponentially in the last years. Automating transactional databases has resulted in an explosive growth of information, motivating the evolution of several *datamining* techniques. Simply stated, datamining refers to *extracting or mining knowledge from large amounts of data*. This knowledge constitutes non-trivial and potentially useful information that can be obtained in many cases by applying *machine learning* (ML) techniques.

The field of machine learning is concerned with the question of how to construct algorithms that automatically improve with experience [Mit97]. In recent years many successful ML applications have been developed, such as datamining programs, information-filtering systems, etc. Although ML algorithms allow the detection and extraction of interesting patterns of data for several kinds of problems, most of these algorithms provide an output based on *quantitative* evidence (i.e. training data), whereas the inference process which led to this output is commonly unknown (i.e. ‘black-box’ metaphor).

In the last years *defeasible argumentation* [CML00, PV99, SL92] has proven to be a sound setting to formalize common-sense *qualitative* reasoning. This approach can be combined with other inference techniques, such as those provided by machine learning theory.

In this preliminary report we explore different alternatives for developing applications which combine defeasible argumentation and machine learning techniques. We suggest how different

aspects of a generic argument-based framework can be integrated with other ML-based approaches. The paper is structured as follows. First, we briefly introduce the components of most argument-based framework and then outline possible directions for the integration of ML techniques and defeasible argumentation. Next, we describe a particular setting suitable for the application of such approach, namely text mining problems. Finally, we discuss some promising research lines that are currently being pursued.

## 2 Integrating ML and argument-based frameworks

Argument-based frameworks [SL92, CML00, PV99] provide a sound formalization of defeasible reasoning, and have found a wide acceptance in many areas such as development of legal reasoning applications, multiagent systems, etc. As pointed out in [CRL00], most argument-based frameworks share a number of common notions, namely:

1. **Knowledge Base formalized in an underlying logical language:** Most argument-based frameworks involve a knowledge base  $K = (\Pi, \Delta)$  which provides *background knowledge* for an intelligent agent formalized in a first-order logical language  $L$ . This background knowledge typically involves a set  $\Pi$  of *strict rules* and *facts* and a set  $\Delta$  of *defeasible rules*.
2. **Argument:** An *argument* is a defeasible proof obtained from the knowledge base  $K$  by applying suitable (defeasible) inference rules associated with the underlying logical language  $L$ .
3. **Dialectical reasoning:** Given two arguments  $A$  and  $B$ , conflict (or attack) among arguments arises whenever  $A$  and  $B$  cannot be simultaneously accepted (typically because of some kind of logical contradiction). Many argument systems provide a preference criterion which defines a partial order among arguments, allowing to determine whether  $A$  should be preferred over  $B$ . This defines a *defeat* relationship. Given the set  $Args$  of arguments obtained from a knowledge base  $K$ , it holds that  $attacks \subseteq Args \times Args$ , and  $defeats \subseteq attacks$ . In order to determine whether a given argument  $A$  is ultimately undefeated (or *warranted*), a dialectical process is recursively carried out, where defeaters for  $A$ , defeaters for these defeaters, and so on, are taken into account.

Next we will outline different approaches that we are currently considering to model the above issues in the context of ML techniques.

- **Building a defeasible knowledge base from training data:**

Recently there have been some approaches to obtaining defeasible rules from training data, particularly in the context of Inductive Logic Programming (ILP). In [IK97], the authors present a method to generate non-monotonic rules with exceptions from positive/negative examples and background knowledge in Inductive Logic Programming. The form of the programs to be learnt is the one of *extended logic programs*, which incorporates both strict negation and negation as failure that can be effectively used in the presence of incomplete information. Default rules are generated as specializations of general rules that cover positive examples, whereas exceptions to general rules are identified from negative examples and are then generalized to rules for cancellation of defaults. The resulting learning system LELP allows also to learn hierarchical defaults by recursively calling an exception identification algorithm.

In [GS01], the authors investigate the feasibility of Knowledge Discovery from Data-bases (KDD) in order to facilitate the discovery of defeasible rules for legal decision making. In particular they argue in favour of Defeasible Logic as an appropriate formal system in which the extracted principles should be encoded.

In the context of obtaining defeasible rules by means of induction-based techniques, the work of Peter Flach [Fla98] provides an interesting survey of several approaches to computational induction and provides a descriptive theory of induction as a logical framework system. Several rule systems for conjectural reasoning are axiomatized and semantically characterized.

- **Building arguments:**

Finding hypotheses which explain unseen instances is central to most ML algorithms. Interestingly, in argument-based frameworks an argument is also understood as providing “a hypothesis supporting a given conclusion” [SL92]. We contend that argument-based reasoning and many ML techniques share this common notion. Many theoretical results from argument theory could therefore be applied in a ML context.

*Analytical learning* methods [Mit97] (like explanation-based learning) offer the advantage of generalizing more accurately from less data by using prior knowledge to guide learning. However, they can be misled when given incorrect or insufficient prior knowledge. On the other hand, *inductive learning* methods (like neural nets, decision tree learning, inductive logic programming) offer the advantage that they require no explicit prior knowledge and learn regularities based solely on the training data. However, they can fail when given insufficient training data, and can be misled by the implicit inductive bias they must adopt in order to generalize beyond the observed data. A combined analytical and inductive ML method that overcomes the pitfalls associated with each separate approach (yet conserving their individual advantages) should be as follows: given a set of training examples  $D$  of some target function  $f$  (possibly containing errors), a domain theory  $B$  (possibly containing errors), and a space of candidate hypothesis  $H$ , determines which hypothesis  $h$  fits best the training examples and domain theory.

We think that defeasible argumentation can be used to improve ML approaches as the one described above as it provides a sound formalization for both expressing and reasoning with uncertain and incomplete information. From the set of examples  $D$  and theory  $B$ , a knowledge base  $(\Pi, \Delta)$  can be induced as explained above. The hypothesis  $h$  can be expressed as an argument structure  $\langle A, h \rangle$  where  $A$  stands for both the relevant part of the background theory and relevant features of  $D$ .

- **Dialectical reasoning and ML:**

The process of defeasible argumentation always involves the analysis of conflicting arguments in a dialectical setting. As explained before, such setting relies on a *defeat* relationship for comparing conflicting arguments. Determining whether an argument is ultimately accepted requires a recursive analysis in which defeaters, defeaters for these defeaters, and so on, are taken into account [CML00].

In many formalizations of argumentation the notion of defeat is considered as an abstract relationship (i.e. a partial order  $\preceq$  among arguments). Some approaches (e.g. [SL92]) rely on the notion of *specificity* for defining defeat. In this context, ML techniques provide sound alternatives for considering *numeric attributes* or *probabilistic values* for deciding between conflicting hypotheses [Mit97]. We think that such approaches could provide the

basis for defining new comparison criteria in the context of argument-based frameworks. In the same line of reasoning, contrasting conflicting hypotheses is a common situation in many ML algorithms. In this setting defeasible argumentation provides a useful theoretical background for contrasting such hypotheses, making easier to identify *fallacious* patterns of reasoning which might lead to incorrect results.

### 3 Text mining: a case study

Datamining is the process of discovering interesting patterns from large amounts of data [HK00]. In *textual datamining* the needs of the user may vary from looking for a specific piece of text to getting familiarized with a subject area [Hon97]. Basic approaches for information retrieval and data mining involve the following strategies:

- *Searching using keywords*: This is done by automatically indexing the documents by frequency of term appearance. This approach is used by web crawlers [BP00] and traditional information retrieval systems [FBY92].
- *Exploration of the document collection supported by organizing the documents in some manner*: For each document, an internal representation is obtained and then the documents are arranged into clusters by some similarity measure [Ras92]. This process can be done by using ML techniques such as neural networks [GL01a, GL01b, Hon97, KKL<sup>+</sup>00] or bayesian classifiers [BP97, PB97].
- *Filtering*: It refers to discarding uninteresting documents from an incoming document flow [MMLP97].

Each approach has its pros and cons. Searching using keywords is easy to implement but can lead to retrieve unrelated documents or, even worse, to not discover related documents (this can be measured using some metric such as precision and recall [FBY92]). Clustering of documents can be efficiently implemented by neural nets but may require retraining in the presence of new examples; besides, in this case the model is not understandable by a human programmer because it is compiled as a set of numerical weights. Filtering is difficult because of the dynamic nature of user interests and document flow [GL01a].

Some recent approaches propose using argumentation to analyze structured text in the form of XML documents [BH01, Hun01]. As explained in the previous section, we feel that the integration of defeasible argumentation and ML can tackle many of the problems described above, thus enhancing existing algorithms for text mining.

### 4 Conclusions and future work

The success of argumentation-based approaches is partly due to the sound setting it provides for *qualitative reasoning*. Although numeric attributes offer an useful source of information for *quantitative reasoning* in several knowledge domains, they have been mostly neglected in the defeasible argumentation community. This is maybe due to the historical origins of argumentative reasoning, which were more related to legal (qualitative) reasoning rather than to number-based attributes as those used in rule-based production systems.

We think that integrating ML techniques with argumentation frameworks would be highly desirable, as it would provide a combination of both analytical and inductive ML methods capable of tackling the pitfalls of each separately yet conserving their advantages, making them

more attractive and suitable for other research and application areas. Part of our current research work is focused on these aspects.

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