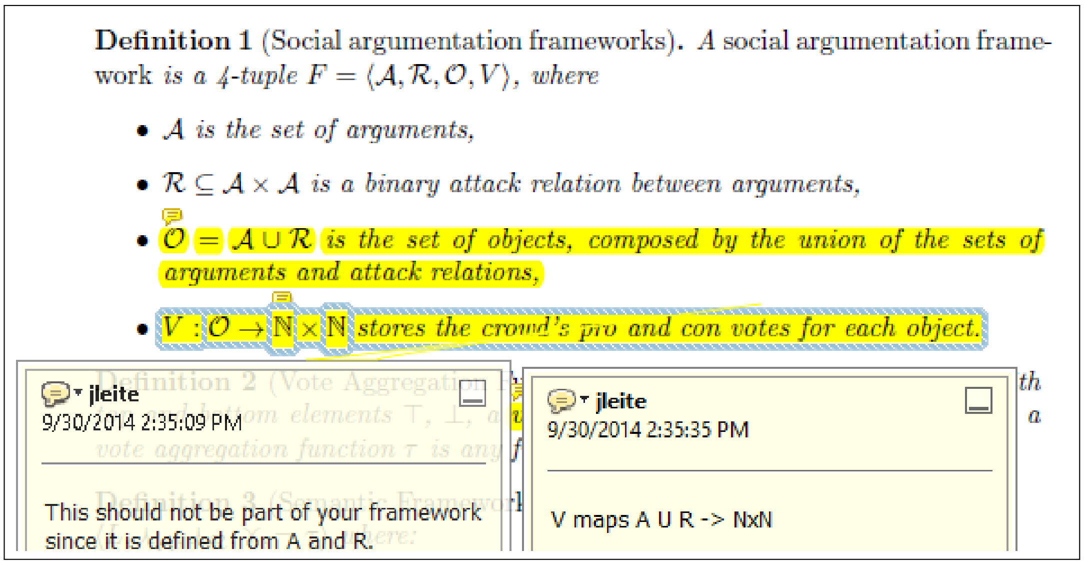
Discussion on comments



Definition 1 (Social argumentation frameworks). *A social argumentation framework is a 4-tuple* $F = \langle \mathcal{A}, \mathcal{R}, \mathcal{O}, V \rangle$*, where*

- $\mathcal{A}$ *is the set of arguments,*
- $\mathcal{R} \subseteq \mathcal{A} \times \mathcal{A}$ *is a binary attack relation between arguments,*
- $\mathcal{O} = \mathcal{A} \cup \mathcal{R}$ *is the set of objects, composed by the union of the sets of arguments and attack relations,*
- $V : \mathcal{O} \to \mathbb{N} \times \mathbb{N}$ *stores the crowd's pro and con votes for each object.*

jleite
9/30/2014 2:35:09 PM

This should not be part of your framework since it is defined from A and R.

jleite
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V maps A U R -> NxN

- I understand that $\mathcal{O}$ may seem verbose at the first sight. But please recall the discussions we had on the report regarding the new classes of vote aggregation functions, before last summer. In the report we had a bunch of functions defined on social voting. For every trivial operation, we had to define one function over $\mathcal{A}$ and another one over $\mathcal{R}$. Thus we had agreed on adding $\mathcal{O}$ to the framework, in order to eliminate this triviality.

  Even though to a lesser extent, in the current work we still benefit from this notion. So for the time being I keep the definition as it is if you've no further objections.

Definition 2 (Vote Aggregation Function). *Given a totally ordered set L with top and bottom elements $\top$, $\bot$, a voting function V and a set of objects $\mathcal{O}$, a vote aggregation function τ is any function such that $\tau : \mathcal{O} \times 2^{\mathcal{O}} \to L$.*

Definition 3 (Semantic Framework). … $\langle L, \curlywedge_{\mathcal{A}}, \curlywedge_{\mathcal{R}}, \curlyvee, \neg, \tau \rangle$ *where:*

- *L is a totally ordered set with top … all possible valuations of an argu…*

jleite
9/30/2014 2:37:15 PM

what is a voting function? And where is it used in this definition?

- V's definition is given in Definition 1, but you're right that it wasn't clear enough. Hopefully it reads well now.

  As you state it's not used in this definition, but concrete functions from this class of functions (as in Definition 5) will be defined given a voting function. That's why I thought we should better include it here as well. But maybe I'm mistaken.

- *$min : 2^{\mathbb{N}} \to \mathbb{N}$ b… nimum value amongst the natural numb… iven as the input.*

Why not keep the lower case?

- *$\mathcal{T} = \{\tau(a, \mathcal{A}) | a \in \mathcal{A}\}$ be the multiset of social support values of all arguments.*

- Well τ is a function, $\mathcal{T}$ is a multiset and we've used capital letters for set/multiset symbols up to now. Am I missing something?

Does it make sense to maximize/minimize the constants?

Definition 7 (Normalized dataset). *Given a SAF $F = \langle \mathcal{A}, \mathcal{R}, \mathcal{O}, V \rangle$ and a semantic framework $\mathcal{S} = \langle L, \curlywedge_{\mathcal{A}}, \curlywedge_{\mathcal{R}}, \curlyvee, \neg, \tau \rangle$, the generic variance mapping $Var : 2^{\mathbb{N}} \to \mathbb{N}$ and constants $r_1, r_2, r_3, r_4 \in \mathbb{R}^+$, the multiset of m… valuations $\mathcal{D}$ is said to be normalized dataset if the following conditions ho…*

- I'm not sure what you have in mind by "maximizing/minimizing the constants". I had some preliminary idea on the topic, maybe we're thinking the same thing.

  So I'm assuming if somehow we agree on a set of *normalized data sets*, we may utilize them as our training set. We may optimize the parameters with them, and thus fix an interval with respect to normalized sets regarding the two concepts of interest, *the range* and *the distribution*.

If what you meant was *maximizing the lower bound* and *minimizing the upper bound* with a similar process, then I suppose we're on the same page.

This is fine. However, keep in mind that, within some other context, we might lift this property, e.g. when cleaning up irrelevant arguments...

Property 2 (Guarantee for the existence of arguments). *An argument with some social strength should never be diminished to the value of zero through normalization.*

$$d \neq \perp \Rightarrow \rho(d) \neq 0$$

As it is, this chapter is rather uninteresting. It says close to nothing...

2.3 Classes of Normalizing Mappings

Here we define some concrete classes of normalizing mappings which all adhere to a subset of desired properties defined in the previous section.

The purpose of this section is just to display that different envisioned uses may require functions that satisfy different collections of properties.

- I completely agree with your comment regarding Property 2. Indeed this was the whole purpose of Subsection 2.3 i.e. stating that with respect to the context of interest, we may decide to relinquish some properties.

  I understand your criticism on the section being too preliminary, which is surely the case. But once again my only goal for now is stating the aforementioned need. Once we're satisfied with the state of the characterization and the properties, I'll put more effort on the concrete contexts of interests and associated set of properties.

how are they different from a partition?

Very crudely, our objective via utilizing cluster analysis is to identify groups of objects that are very similar with regard to their values. Before going into more detail, firstly we need to formally define what a *cluster* is. In the literature, there are many definitions with respect to clusters. In our context we will define them closely to the *partitions* from the classical set theory via updating the definition accordingly with respect to multisets.

Definition 8 (Cluster). *A family of multisets $\mathcal{C}$ is a clustering of a multiset X and every element C of $\mathcal{C}$ is a cluster if and only if all of the following conditions hold:*

- *Set of clusters does not contain the empty set.*

$$\emptyset \notin \mathcal{C}$$

- *(Collectively exhaustive) The sum of the multisets in $\mathcal{C}$ is equal to X.*

$$\biguplus_{C \in \mathcal{C}} C = X$$

- *(Mutually exclusive) Distinct multisets do not contain shared elements.*

$$(C_i, C_j \in \mathcal{C}) \wedge (C_i \neq C_j) \implies (C_i \wedge C_j = \emptyset)$$

- If you are questioning the clusters in the current formalization, then the answer is *they're almost the same*. The only thing is that in set theory partitions are defined over sets. We've to define clusters over multisets so we've to do minor modifications to the generic partition definition. For instance when formalizing *collective exhaustiveness* property you would use union of sets, however here we utilize the multiset summation.

  On the other hand, if you were inquiring about how partitions differ from clusters with respect to the machine learning literature, then they might greatly differ. That's because as you know there is no single definition of clusters that's agreed upon. For instance some clustering methods use a fuzzy definition where a datapoint d may belong to a cluster X with degree 0.3 and to a cluster Y with 0.7. There are also *transparent clustering* methods which are binary wrt. membership but let datapoints belong to multiple clusters, etc.