

TOWARDS AVERAGE-CASE ALGORITHMS FOR ABSTRACT ARGUMENTATION

Samer Nofal, Paul Dunne and Katie Atkinson

Computer Science Department, University of Liverpool, Ashton Street, Liverpool, U.K.

Keywords: Argumentation, Reasoning, Algorithms.

Abstract: Algorithms for abstract argumentation are created without extensive consideration of average-case analysis. Likewise, thorough empirical studies have been rarely implemented to analyze these algorithms. This paper presents average-case methods in the context of value-based argumentation frameworks. These methods solve decision problems related to arguments' acceptability. Experiments have shown indications of an improved average-case behavior in comparison to the naive ones.

1 INTRODUCTION

Argumentation frameworks (AFs) proposed in (Dung, 1995) have proven to be a useful abstract model for non monotonic reasoning. Since then, the interest in this model has been increasing for its promising applications (Bench-Capon and Dunne, 2007). However, AFs do not take into account the variable strength of arguments. To handle that issue, several developments have been proposed such as preference-based argumentation (Amgoud and Cayrol, 2002) and value-based argumentation frameworks (VAFs) (Bench-Capon, 2003). VAFs acknowledge social values promoted by arguments that play a role in persuasive practical reasoning where argument's weight is related to the significance of its value. VAFs seem to be applicable in various scenarios such as facilitating deliberation in democracies (Atkinson et al., 2006). Nevertheless, the main decision problems on acceptability in VAFs, as it is the case in AFs, are likely to be intractable (Dunne, 2010).

Average-case algorithms are well-established approaches in many other problems (e.g. quicksort). Being neglected in the context of abstract argumentation, we developed and experimented such methods that decide the acceptability of arguments in VAFs. As we show, these methods are characterized by in-exhaustible search at the average case. The paper is structured as follows: section 2 reviews basics of VAFs, in section 3 we introduce the new algorithm, experimental results are reported in section 4 and we conclude the paper in section 5.

2 PRELIMINARIES¹

A value-based argumentation framework is composed of: a finite set of arguments $Args$, an irreflexive binary relation $R \subset Args \times Args$, a non-empty set of values V and a function $val : Args \rightarrow V$ where cycles of attacks involve arguments mapped to at least two values. In VAFs, attacks are successful (or *defeats*) if the attacked-argument's value is not preferred to the value of the attacker argument according to some value order; a value order is called an *audience* in VAF's terminology. Therefore, the acceptance semantics in VAFs are amended accordingly based on the notion of *defeat*, unlike that of *attack* in AFs. Let $A \in Args$ attacks $B \in Args$ but $val(B)$ is preferred to $val(A)$ then, in VAFs, A does not defeat B . Recall that a preferred extension in AFs is intuitively defined as any maximal $S \subseteq Args$ where S is conflict free and defends itself. Hence, in AFs if $A \in Args$ attacks $B \in Args$ then $\{A\}$ is the only preferred extension. In VAFs, if $A \in Args$ attacks $B \in Args$ then we have two value orderings (or audiences). For the audience who prefers $val(B)$ to $val(A)$, $\{A, B\}$ is the preferred extension. As to the audience who prefers $val(A)$ to $val(B)$, $\{A\}$ is the preferred extension. In VAFs there are two types of argument acceptance: Objective Acceptance (OBA) and Subjective Acceptance (SBA). An argument $A \in Args$ is objectively acceptable if and only if for all value orders A is in every preferred extension (i.e. acceptable

¹We do not provide a detailed treatment of AFs and VAFs semantics due to space limitation, see (Dung, 1995) and (Bench-Capon, 2003) instead.

always, irrespective of the audience). On the other hand, an argument $A \in \text{Args}$ is subjectively acceptable if and only if for some value order A is in some preferred extension (i.e. accepted for some audience). In the case of $A \in \text{Args}$ attacks $B \in \text{Args}$, A is OBA while B is SBA.

3 AVERAGE-CASE METHODS

As in any intractable problem, there are classes of VAFs that could be solved in linear time. The following proposition identifies VAFs which allow for linear time reasoning, in particular, proposition 1 states that problem instances with unrestricted number of arguments sharing the same value are solvable trivially with only one property: none of the attacks involves arguments sharing the same value.

Proposition 1. *Let $(\text{Args}, R, V, \text{val})$ be a VAF. Then unattacked arguments are OBA while the attacked ones are SBA if $\forall (A, B) \in R (\text{val}(A) \neq \text{val}(B))$.*

Proof. For those unattacked arguments the status of OBA is obvious. By contradiction we can prove that the remaining attacked arguments are SBA. Assume that not all of the attacked arguments are SBA, then one or more are either indefensible or OBA. OBA arguments are attacked by indefensible arguments, and the indefensible arguments are attacked by similar value arguments. Contradiction! ■

The naive approach needs to check all value orders (i.e. permutations of values in V) to determine the acceptability of an argument. Thus, the status of an argument will be computed in time proportional to $|V|!$ even if it works on a VAF with linear reasoning. This motivates us to look for a different approach that checks the minimum required value orders to find the acceptance status which results in algorithms with an improved average-case run-time complexity.

The idea of our algorithm is based on the notion that an argument's status is decided according to its attackers' statuses, this notion has been used in other aspects of AFs (see (Modgil and Caminada, 2009) for an overview). In deed, our algorithm searches the tree induced by the argument in question s.t. the argument is the root and its children are its attacker arguments and the children of these are their attackers and so on, provided that values are not repeated in a single branch unless the repetition happens in a row. We call such tree the *dispute tree*.

Definition 1. *Let $(\text{Args}, R, V, \text{val})$ be a VAF. Then T_A is the dispute tree induced by $A \in \text{Args}$ iff A is the root and $\forall B, C \in \text{Args} : B$ is a child of C iff $((B, C) \in R \wedge (\text{val}(B)$ does not appear on the directed path from C to $A \vee \text{val}(B) = \text{val}(C)))$.*

Example 1. *Consider the VAF in fig. 1 (a) (throughout the paper we use the argument-value syntax for nodes' labels). The dispute tree T_B is depicted in fig. 1 (b). Note that we do not consider attacks with repeated values unless they are in a row, for instance, in T_B the attack from A against C is dropped since A has the same value of B . The dropped attack is certainly unsuccessful if $V2$ is preferred to $V1$, and it is unreachable if $V1$ is preferred to $V2$.*

The new approach works on the dispute tree of arguments, it decides the status of an argument collectively based on its statuses under the superiority of each value in the dispute tree. Before presenting the strict methods it might be helpful to discuss an example just to capture the general idea.

Example 2. *Consider the VAF in fig. 1 (a). To decide the status of B , our algorithm decides its status as SBA since it is survived if $V1$ is most preferred (see fig. 1 (c)) and defeated when $V2$ is most preferred (see fig. 1 (d)). In other words, B is accepted for all audiences who prefer $V1$ but rejected by audiences who prefer $V2$. In total, its status is SBA.*

Every time a value is considered as most preferred the dispute tree changes accordingly, we refer to the new resulted tree as the *pruned dispute tree* under the superiority of some value.

Definition 2. *Let $(\text{Args}, R, V, \text{val})$ be a VAF, $A \in \text{Args}$, $v \in V$ and $T \subseteq T_A$. Then the pruned dispute tree T_v is defined as $\{(B, C) \in T \mid \text{val}(B) = \text{val}(C) \vee \text{val}(C) \neq v\}$*

Example 3. *Let T be the tree T_B in fig. 1 (b) and $v = V2$. Then $T_v = \{(C, B), (D, B), (E, D), (C, E)\}$.*

One more helpful term we have to define is related to the recursive nature of the new approach. The new method decides an argument's status on the basis of its attackers' statuses, and therefore, the status of an attacker is computed in the space of the dispute subtree that is branched from that attacker.

Definition 3. *Let $(\text{Args}, R, V, \text{val})$ be a VAF and $T \subseteq T_A$. Then the subtree $T(B)$ is defined as $\{(C, D) \in T \mid D = B \vee \text{there is a directed path in } T \text{ from } D \text{ to } B\}$.*

Example 4. *Let T be the tree T_v from example 3. Then $T(D) = \{(E, D), (C, E)\}$.*

The methods that decide the acceptability status for arguments in a VAF are presented in algorithms 1 and 2. Algorithm 1 decides the status of $A \in \text{Args}$ while algorithm 2 decides the status of A under the superiority of some value. With reference to algorithms 1 and 2, status_A and status'_A stand for the current provisional status of A and the status of A under the superiority of some value respectively.

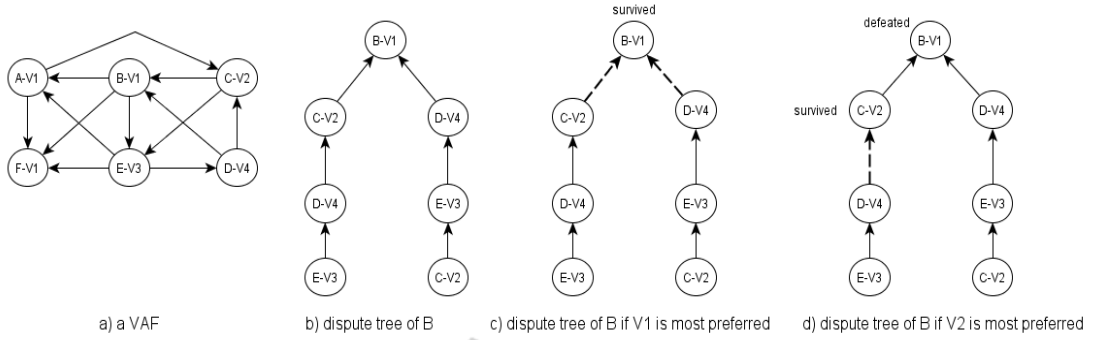


Figure 1: Referenced by examples 1, 2, 3, and 4.

Algorithm 1: $\text{DecideStatus}(A \in \text{Args}, T \subseteq T_A)$.

```

1: for all  $v \in V : \exists(B, C) \in T \text{ s.t. } (val(B) = v \vee val(C) = v)$ 
   do
2:    $status'_A \leftarrow \text{StatusAtValue}(A, T, v)$ 
3:   if ( $status_A$  is 2 or null)  $\wedge$   $status'_A = 2$  then
4:      $status_A \leftarrow 2$ 
5:   else
6:     if ( $status_A$  is 0 or null)  $\wedge$   $status'_A = 0$  then
7:        $status_A \leftarrow 0$ 
8:     else
9:       if  $status'_A = 1 \wedge T$  is not chain then
10:         $status'_A \leftarrow \text{DecideStatus}(A, T, v)$ 
11:        if ( $status_A$  is 2 or null)  $\wedge$   $status'_A = 2$  then
12:           $status_A \leftarrow 2$ 
13:        else
14:          if ( $status_A$  is 0 or null)  $\wedge$   $status'_A = 0$  then
15:             $status_A \leftarrow 0$ 
16:          else
17:            return 1
18:        else
19:          return 1
20: return  $status_A$ 
    
```

Algorithm 2: $\text{StatusAtValue}(A \in \text{Args}, T \subseteq T_A, v \in V)$.

```

1:  $status'_A \leftarrow 2$ 
2: for all  $B \in \text{Args}$  s.t.  $(B, A) \in T$  do
3:   if  $val(A) \neq v \vee val(B) = val(A)$  then
4:      $status'_B = \text{StatusAtValue}(B, T(B), v)$ 
5:     if  $status'_B = 2 \wedge (val(A) = val(B) \vee val(B) = v)$  then
6:       return 0
7:   else
8:     if  $status'_B \neq 0$  then
9:        $status'_A = 1$ 
10: return  $status'_A$ 
    
```

Example 5. Consider the VAF in fig. 2 (a), to find the acceptability status of F the values $\{V1, V2, V3, V4\}$ are to be investigated. An important note: trees in fig. 2 are constructed from left to right while statuses are decided from bottom to top. Now, if $V1$ is most preferred then the status of F is defeated as depicted in fig. 2 (b). In the same way, F is defeated if $V2$ and $V3$ are most preferred respectively (see fig. 2 (c)

and fig. 2 (d)). However, if $V4$ is most preferred then F is undecided (fig. 2 (e)). At this stage, two more value orders are to be explored, namely, $V1$ is preferred to $V3$ and $V3$ is preferred to $V1$. In fact, F is also defeated in the latter two cases (fig. 2 (f) and fig. 2 (g)), and therefore, the status of F is indefensible. The naive method needs to check 24 value orders (i.e. $|V|!$) to decide F 's status, but our algorithms find the status after checking only 6 value orders.

In the remainder of this section, the correctness proof of algorithms 1 and 2 is outlined. These algorithms are recursive and so the proof is naturally inductive. These proofs identify the base and inductive cases that are directly provable from the definition of SBA/OBA and the definitions presented in this paper. In fact, algorithm 2 is a depth first search procedure that visits attacker arguments until it stops and returns 0 for defeated status (i.e. not in any preferred extension), 1 for undecided status or 2 for survived status (i.e. member in a preferred extension).

Proposition 2. Let (Args, R, V, val) be a VAF, $A \in \text{Args}$ and $v \in V$ is the most preferred value. Then algorithm 2 decides the acceptability of A w.r.t preferred semantics as 0, 1 or 2 where $0 \equiv (A \notin \text{any preferred extension})$, $1 \equiv \text{undecided}$ and $2 \equiv (A \in \text{some preferred extension})$.

Proof (outline). In the base case the algorithm stops and returns 2 for one of three reasons. Firstly, if there is no attacker at all (line 2). Secondly, if the value of the attacked argument is most preferred then attacks from arguments promoting a different value are not successful (line 3). Thirdly, if all attackers promote a repeated value that breaks the current value order (see def. 1 for dispute trees). The inductive case: given an attacker with a defined status, if the status of the attacker argument is 2 and either its value is v (the most preferred value) or its value is equal to the attacked argument's value then the status of the attacked argument is 0 (line 6), otherwise, if the attacker's status is not equal to 0 then the attacked argument's status is

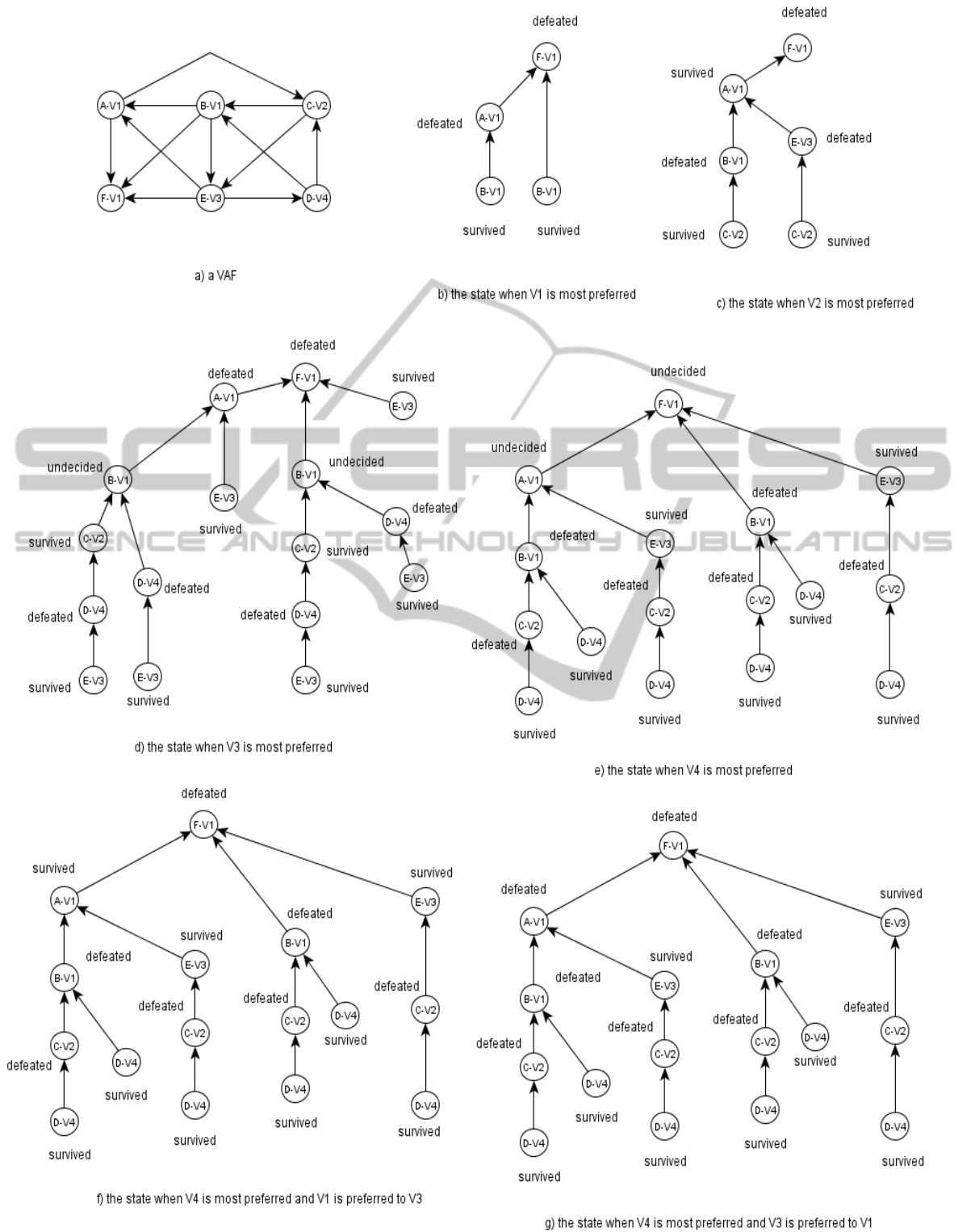


Figure 2: Progress of algorithms in example 5.

undecided (line 9) unless there is another attacker that defeats it. ■

Algorithm 1 is also a recursive procedure that returns: 0 for indefensible status, 1 for SBA status or 2

for OBA status.

Proposition 3. *Let $(Args, R, V, val)$ be a VAF and $A \in Args$. Then algorithm 1 decides the acceptability status of A w.r.t preferred semantics as 0, 1 or 2 where $0 \equiv indefensible$, $1 \equiv SBA$ and $2 \equiv OBA$.*

Proof (outline). In the base case the algorithm stops for one of two reasons. Firstly, if there are no values left for investigation then the algorithm returns whatever status (0 or 2) it ends with (line 1). Secondly, the algorithm stops and returns 1 when the status at the superiority of some value ($status'_A$) is not equal to the provisional status ($status_A$) provided that either $status'_A \neq 1$ or the current tree T is a chain (line 19). Inductive case: if the current provisional status ($status_A$) is 0 or 2 then it is unchanged as long as the computed status at the superiority of some value ($status'_A$) is 0 or 2 respectively (lines 12 and 15). Otherwise, the provisional status ($status_A$) is 1 (line 17). ■

The worst-case scenario of these algorithms is not better than the naive one. But as we are concerned with the average-case scenario, experiments have suggested a better average-case run-time; in the subsequent section we report these results.

4 EXPERIMENTS

We implemented the algorithms presented in section 3 using Java language on a Linux-based cluster of 4 CPUs and 16GB of system memory. We built VAFs randomly for these experiments; the random generator made all decisions randomly with approximately equal probability. These decisions include choosing the number of arguments, number of values and number of attacks, which arguments attack which others and finally which argument is mapped to which value. As to the correctness, we tested the algorithm with 200,000 VAFs where $|V|$ ranges from 2 to 7 and $|Args|$ ranges from 2 to 15.

Concerning the analysis, we ran three experiments. The first experiment was to show how our algorithm compares to the naive approach. For this purpose, we randomly generated 9844 VAFs grouped by $|V|$. Table 1 details each group while table 2 presents the measures of value orders averages and CPU time averages (in milliseconds) for each group under naive and new approaches. The second experiment was to show how our algorithm's behavior is affected by the increase of $|V|$. Figures 3 and 4 show the behavior in terms of averages of value orders and averages of CPU time respectively. The charts in figures 3 and 4 are obtained from 9753 VAFs where the number of attacks against any argument is limited up to 4, $|Args|$ is 30 and $|V|$ ranges from 2 to 20. The last experiment

was to evaluate, in the context of the new algorithm, the correlation between the number of attacks against any single argument and the performance measured by the average of CPU time and the average of value orders. The results of last experiment are presented in figures 5 and 6 where the charts plot 9500 VAFs with $|Args|$ as 20, $|V|$ as 4 and the number of attacks against any argument ranges from 2 to 20. As an illustration on how to read these figures, the point (15,83.22) in figure 3 means that for a group of VAFs (actually 724 cases) with $|V| = 15$ the algorithm needs to check on average 83.22 value orders until it decides the acceptability status.

Table 1: Random VAFs.

group	$ V $	$ VAFs $	$range(Args)$	$range(R)$
1	2	1284	2-12	0-45
2	3	1400	3-15	0-58
3	4	1505	4-17	1-87
4	5	1422	5-18	3-927
5	6	1405	7-20	8-109
6	7	1404	8-20	10-135
7	8	996	8-20	13-140
8	9	428	9-20	20-138

Table 2: Comparisons.

group	new algorithm		naive algorithm	
	value orders	CPU time	value orders	CPU time
1	1.66	0.04	0.03	2.00
2	2.37	0.11	0.15	6.00
3	3.10	0.33	1.06	24.00
4	3.83	0.91	7.17	120.00
5	4.53	3.46	31.20	720.00
6	5.12	11.00	221.36	5,040.00
7	5.60	32.91	2,438.76	40,320.00
8	5.92	103.40	45,676.53	362,880.00

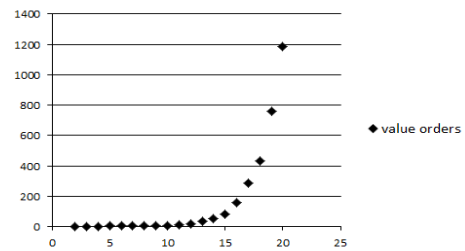


Figure 3: The effect of increase in $|V|$.

To sum up, the outcome of the experiments shows that the new algorithm has a better average case behavior than the naive methods as stated by table 2. Negatively, figures 3 and 4 point that the average case complexity of the new algorithm might be exponential, which is not surprising since the problem has been proven to be hard. Finally, figures 5 and 6 show that the increase in the number of attacks against any

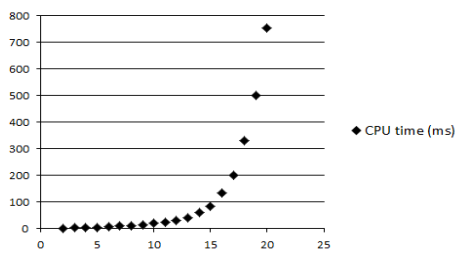
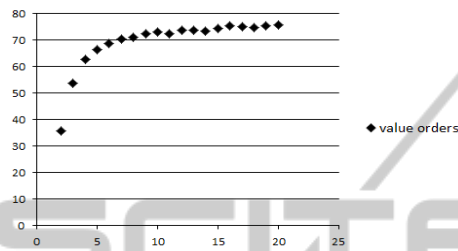
Figure 4: The effect of increase in $|V|$.

Figure 5: The effect of increase in attacks per argument.

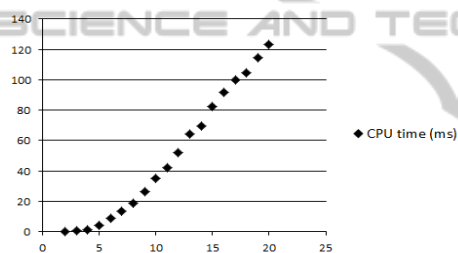


Figure 6: The effect of increase in attacks per argument.

single argument has no extreme impact on the behavior of the new algorithm.

5 CONCLUSIONS

In this paper we argued that hard computations of abstract argumentation developments is not the end of the story. In light of experiments conducted, average-case algorithms seem to be candidate methods towards practical implementation of argument systems. This work developed average-case algorithms for an instance of AFs developments: value-based argumentation frameworks. From an experimental algorithmic point of view, the results of this work illustrate the relative performance of the new approaches compared to the naive methods.

As future work, we plan to investigate average-case approaches for classical problems in AF and the decision problems that have arisen in the context of AF developments such as extended AFs (Modgil, 2009). Another direction for future work is to ex-

plore the role of heuristics, which might lead to better average-case algorithms. For instance, in our approach attackers are traversed in an arbitrary order while presumably it could be more efficient if the attackers are visited in an ascending order according to the number of their attackers. However, the influence of heuristics on the overall performance would be unclear. To be cost-effective, heuristics computations must not exceed the wasted computations imposed by the arbitrary order.

ACKNOWLEDGEMENTS

We would like to thank the anonymous reviewers for their comments that help improve the paper.

REFERENCES

- Amgoud, L. and Cayrol, C. (2002). A reasoning model based on the production of acceptable arguments. *Annals of Mathematics and Artificial Intelligence*, 34:197–215.
- Atkinson, K., Bench-Capon, T., and McBurney, P. (2006). Parmenides: facilitating deliberation in democracies. *Artificial Intelligence and Law*, 14(4):261–275.
- Bench-Capon, T. (2003). Persuasion in practical argument using value-based argumentation frameworks. *Logic and Computation*, 13(3):429–448.
- Bench-Capon, T. and Dunne, P. (2007). Argumentation in artificial intelligence. *Artificial Intelligence*, 171:619–641.
- Dung, P. (1995). On the acceptability of arguments and its fundamental role in non monotonic reasoning, logic programming and n-person games. *Artificial Intelligence*, 77(2):321–357.
- Dunne, P. (2010). Tractability in value-based argumentation. In *proceedings of Computational models of arguments*, pages 195–206.
- Modgil, S. (2009). Reasoning about preferences in argumentation frameworks. *Artificial Intelligence*, 173:901–934.
- Modgil, S. and Caminada, M. (2009). Proof theories and algorithms for abstract argumentation frameworks. In Rahwan, I. and Simari, G. R., editors, *Argumentation in AI*, pages 105–129. Springer-Verlag.