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The third and fourth international competitions on computational models of argumentation: Design, results and analysis

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Abstract. The International Competition on Computational Models of Argumentation (ICCMA) focuses on reasoning tasks in abstract argumentation frameworks. Submitted solvers are tested on a selected collection of benchmark instances, including artificially generated argumentation frameworks and some frameworks formalizing real-world problems. This paper presents the novelties introduced in the organization of the Third (2019) and Fourth (2021) editions of the competition. In particular, we proposed new tracks to competitors, one dedicated to dynamic solvers (i.e., solvers that incrementally compute solutions of frameworks obtained by incrementally modifying original ones) in ICCMA'19 and one dedicated to approximate algorithms in ICCMA'21. From the analysis of the results, we noticed that i) dynamic recomputation of solutions leads to significant performance improvements, ii) approximation provides much faster results with satisfactory accuracy, and iii) classical solvers improved with respect to previous editions, thus revealing advancement in state of the art.

Keywords: Argumentation, semantics, solver, dynamic framework

1. Introduction

Computational argumentation is a field of Artificial Intelligence (AI) that provides formalisms for reasoning with conflicting information. It finds applications in many different areas, ranging from healthcare [58] to explainable AI [80]. An *Abstract Argumentation Framework* (*AF* for short) [30] is one of the formalisms used in computational argumentation and can be represented as a simple pair $\mathcal{F} = (\mathsf{A}, \rightarrow)$, composed of a set of arguments and an attack relationship between them. Such a simple representation can be straightforwardly represented as a directed graph with nodes (arguments) and directed edges (attacks). We refer to [29] for a broader discussion on formal argumentation.

The *International Competition on Computational Models of Argumentation* (*ICCMA*)[1] aims to nurture

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research and development of implementations for computational models of argumentation. The objectives of the competition are to provide a forum for the empirical comparison of solvers, to highlight challenges to the community, to propose new directions for research, and to provide a core of common benchmark instances and a representation formalism that can aid in the comparison and evaluation of solvers. Similar competitions are organized in many other areas of AI. The *MiniZinc Challenge*[2] is an annual competition of *Constraint Programming* solvers on various benchmarks (since 2008). The annual *SAT Competition*[3] evaluates solvers for *Boolean Satisfiability* (SAT) problems (since 2002). The *International Planning Competition*[4] is a biennial challenge whose aim is to evaluate state-of-the-art planning systems empirically. As organizers of the third and fourth editions of the competition (ICCMA'19 and ICCMA'21), we proposed several novelties with respect to the two previous editions, which are described in [75] (ICCMA'15) and [42] (ICCMA'17), respectively.

With each reiteration of the competition, the organizers added new tracks that followed the latest developments in the field of computational argumentation. ICCMA'17 proposed a special track (called Dung's Triathlon) in which the solvers were required to deal with three consecutive enumeration problems, where the solution computed in the previous step could be used. The 2023 edition also features three special tracks: an approximate Track, a dynamic Track, and an ABA Track.[5] The 2019 competition introduced a new track to evaluate the effectiveness of solvers in recomputing extensions with minor adjustments to a starting AF. In this track, specifically designed for dynamic solvers and approaches [3,13], participants were allowed to use previous results to solve the problem more efficiently in a slightly modified framework rather than starting from scratch with each change. Typically, an AF represents a temporary "screenshot" of a debate, and new arguments and attacks can be added/retracted to account for new knowledge during the evolution of a discussion. If we consider disputes among users of online social networks [49], arguments/attacks are continuously added/retracted by users to express their point of view in response to the last utterance. The ICCMA'19 track challenged solvers to handle a single added or retracted attack per modification. This aimed to encourage the creation of specialized solvers for dynamic scenarios. This approach often leads to better performance. The second novelty in ICCMA'19 concerned the use of *Docker*.[6] Docker is a *platform-as-a-service* software that uses OS-level virtualization to deliver software in packages called *containers*. The software that hosts the containers is called "Docker Engine", which runs on Windows, Linux, and MacOS. In this case, our purpose is to encourage the packaging of solvers such that they can easily be run everywhere to ease the evaluation phase and allow for the recomputation of competition results. A container comes with all the needed software and libraries. An overview of these novelties has been described in [16] before ICCMA'19, while a preliminary summary of participants and benchmarks has been discussed in [17] after the competition.

In organizing ICCMA'21, we intended to keep the main novelties brought by ICCMA'19 and also planned the introduction of a new track dedicated to structured argumentation (more precisely, assumption-based argumentation [24,76]). Unfortunately, technical issues with the platform used for running the competition prevented us from using Docker, and a lack of participants caused us to cancel the tracks dedicated to dynamic and structured argumentation. On the contrary, the community showed interest in approximate algorithms, leading us to introduce a track dedicated to solvers using such al-

[2]MiniZinc Challenge: https://www.minizinc.org/challenge.html.
[3]SAT Competition: http://www.satcompetition.org.
[4]Planning competitions: https://tinyurl.com/uezhalg.
[5]ICCMA'23 Website: https://iccma2023.github.io/.
[6]Docker.com: https://www.docker.com.

gorithms. A preliminary description of the ICCMA'21 organization can be found in [54], while a short description of participants and results is available in [55].

The rest of this paper is structured as follows. In Section 2, we describe the necessary background about Abstract Argumentation, related work on dynamic frameworks and motivations for including them in the competition, and finally, Docker containers. Section 3 lists and describes the computational problems we included in ICCMA'19 and ICCMA'21, while Section 4 surveys the input and output format the solvers needed to adhere to (dynamic frameworks extend classical input formats). Section 5 describes the solvers that participated in the competition, how benchmarks were assembled, how we ranked the solvers according to the obtained results, and the adopted reference solver. In each section, we emphasize the differences between ICCMA'19 and ICCMA'21. Section 6 reports a detailed analysis of the results, including a comparison with the best ICCMA'17 solvers and between dynamic and non-dynamic solvers in ICCMA'19, to evaluate their speed-up. A similar comparison is made for ICCMA'19 solvers on ICCMA'21 benchmarks. Section 9 introduces lessons learned from organizing the competition, mainly concerning the virtualization of solvers and output parsing. Finally, Section 10 wraps up the paper with conclusions and final thoughts about future work.

2. Background and dynamic frameworks

We divide this section into two parts: fundamental notions about Abstract Argumentation are reported in Section 2.1, while Section 2.2 summarises the literature about dynamic AFs and related approaches.

2.1. Abstract argumentation

An *Abstract Argumentation Framework* (AF, for short) [30] is a tuple $\mathcal{F} = (\mathsf{A}, \rightarrow)$ where A is a set of arguments and $\rightarrow$ is a relation $\rightarrow \subseteq \mathsf{A} \times \mathsf{A}$. For two arguments $a, b \in \mathsf{A}$, the relation $a \rightarrow b$ means that argument a *attacks* argument b. An argument $a \in \mathsf{A}$ is *defended* by $S \subseteq \mathsf{A}$ (in $\mathcal{F}$) if for each $b \in \mathsf{A}$ such that $b \rightarrow a$ there is some $c \in S$ such that $c \rightarrow b$. A set $E \subseteq \mathsf{A}$ is *conflict-free* (in $\mathcal{F}$) if and only if there are no $a, b \in E$ with $a \rightarrow b$. E is *admissible* (in $\mathcal{F}$) if and only if it is conflict-free and each $a \in E$ is defended by E. Finally, the range of E in $\mathcal{F}$, i.e., $E^{\oplus}$, collects the same E and the set of arguments attacked by E: $E^{\oplus} = E \cup \{a \in \mathsf{A} | \exists b \in E : b \rightarrow a\}$. A directed graph can straightforwardly represent an AF: an example with five arguments is given in Fig. 1 (e.g., both arguments a and c attack b, but not vice-versa).

The *collective acceptability* of arguments depends on the definition of different *semantics*. Four of them are proposed by Dung in his seminal paper [30], namely the complete (**CO**), preferred (**PR**), stable (**ST**), and grounded (**GR**) semantics. In addition, other semantics have been defined in the literature that we also use for the competition: in particular, the semi-stable (**SST**) [25], stage (**STG**) [77], and ideal (**ID**) [31]. Semantics determine sets of jointly acceptable arguments, called *extensions*, by mapping each $\mathcal{F} = (\mathsf{A}, \rightarrow)$ to a set $\sigma(\mathcal{F}) \subseteq 2^{\mathsf{A}}$, where 2^{A} is the power set of A, and σ parametrically stands for any of the considered semantics. The extensions under complete, preferred, stable, semi-stable, stage, grounded, and ideal semantics are defined as follows. Given $\mathcal{F} = (\mathsf{A}, \rightarrow)$ and a set $E \subseteq \mathsf{A}$,

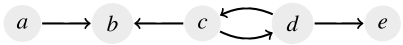


Fig. 1. An example of an AF represented as a directed graph.

- $E \in \mathbf{CO}(\mathcal{F})$ iff E is admissible in $\mathcal{F}$ and if $a \in \mathsf{A}$ is defended by E in $\mathcal{F}$ then $a \in E$,
- $E \in \mathbf{PR}(\mathcal{F})$ iff $E \in \mathbf{CO}(\mathcal{F})$ and there is no $E' \in \mathbf{CO}(\mathcal{F})$ such that $E' \supset E$,
- $E \in \mathbf{SST}(\mathcal{F})$ iff $E \in \mathbf{CO}(\mathcal{F})$ and there is no $E' \in \mathbf{CO}(\mathcal{F})$ such that $r(E'_{\mathcal{F}}) \supset E^{\oplus}$,
- $E \in \mathbf{ST}(\mathcal{F})$ iff $E \in \mathbf{CO}(\mathcal{F})$ and $E^{\oplus} = \mathsf{A}$,
- $E \in \mathbf{STG}(\mathcal{F})$ iff E is conflict-free in $\mathcal{F}$ and there is no E' that is conflict-free in $\mathcal{F}$ such that $r(E'_{\mathcal{F}}) \supset E^{\oplus}$,
- $E \in \mathbf{GR}(\mathcal{F})$ iff $E \in \mathbf{CO}(\mathcal{F})$ and there is no $E' \in \mathbf{CO}(\mathcal{F})$ such that $E' \subset E$,
- $E \in \mathbf{ID}(\mathcal{F})$ if and only if E is admissible, $E \subseteq \bigcap \mathbf{PR}(\mathcal{F})$ and there is no admissible $E' \subseteq \bigcap \mathbf{PR}(\mathcal{F})$ such that $E' \supset E$.

For a more detailed view of these semantics, please refer to [11]. Note that grounded and ideal extensions are uniquely determined and always exist [30,31]. Thus, they are also called *single-status* semantics. The other semantics introduced are *multi-status* semantics, where several extensions may exist. The stable semantics is the only case where an AF might possess no extension at all.

We report the definition of eight well-known problems in Abstract Argumentation, where the first six are decision problems:

- Credulous acceptance $Cred_\sigma$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$ and an argument $a \in \mathsf{A}$, is a contained in some $E \in \sigma(\mathcal{F})$?
- Sceptical acceptance $Scept_\sigma$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$ and an argument $a \in \mathsf{A}$, is a contained in all $E \in \sigma(\mathcal{F})$?
- Verification of an extension Ver_σ: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$ and a set of arguments $E \subseteq \mathsf{A}$, is $E \in \sigma(\mathcal{F})$?
- Existence of an extension $Exists_\sigma$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, is $\sigma(\mathcal{F}) \neq \varnothing$?
- Existence of non-empty extension $Exists_\sigma^{\neg\varnothing}$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, does there exist $E \neq \varnothing$ such that $E \in \sigma(\mathcal{F})$?
- Uniqueness of the solution $Unique_\sigma$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, is $\sigma(\mathcal{F}) = \{E\}$?
- Enumeration of extensions $Enum_\sigma$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, return all $E \in \sigma(\mathcal{F})$.
- Counting of extensions $Count_\sigma$: given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, return $|\sigma(\mathcal{F})|$.

Computational argumentation tools enable formalizing complex problems and understanding real-world situations where conflicting information must be considered to draw non-trivial conclusions. For example, verifying the acceptance of arguments and enumerating extensions is used in applications such as planning [67] and decision support [26]. For an in-depth discussion of the complexity results for the problems mentioned above, we refer to [32] and, in particular, to [51] for enumeration problems and [12,39] for counting problems.

2.2. *Motivations to dynamic frameworks*

In previous ICCMA editions, all the frameworks in each data set are static since all the AFs are sequentially passed as input to solvers, representing different and independent problem instances. Hence, all tasks are computed from scratch without taking any potentially useful knowledge from previous runs into account. However, AFs can be considered in practical applications as a temporary situation, which evolves when new knowledge becomes available that requires the addition or retraction of arguments and attacks. For example, users of online social networks [48] may engage in disputes and repeatedly add or retract arguments and attacks to express their point of view in response to the last move made by their adversaries in the ongoing digital conversation. Users often disclose as few arguments/attacks as possible in these situations. For this reason, ICCMA'19 also features additional tracks to evaluate solvers

on dynamic Dung's frameworks. The aim is to test those solvers dedicated to efficiently recomputing a solution after a minor change in the original AF. In this case, a problem instance consists of an initial framework (as for classical tracks) and an additional file storing a sequence of additions/deletions of attacks (between already existing arguments) on the initial framework, i.e. a list of modifications. This file has a simple text format, i.e. a sequence of $+att(a, b)$ (attack addition) or $-att(d, e)$ (attack deletion). The final single output must report the solution for the initial framework and each change. The dynamics of frameworks have attracted recent and broad interest in the computational argumentation community. We describe some related work, pointing to the research groups interested in organizing such a track.

In [23], the authors investigate the principles in which a grounded extension of a Dung's AF does not change when the set of arguments/attacks is changed. The authors of [28] study how the extensions can evolve when a new argument is considered. The focus is on adding a single argument interacting with a non-attacked argument. Several properties are defined for the change operations according to how the extensions are modified. For instance, a change operation can be *conservative* if the set of extensions is the same after a change. The work in [27] addresses the problem of revising AFs when a new argument is added. In particular, the authors focus on the impact of new arguments on the set of initial extensions, introducing various kinds of revision operators that have different effects on the semantics. For instance, a *decisive revision* allows for making a decision by providing a revised extensions' set with a unique non-empty extension. The authors of [13] propose a division-based method to divide the updated framework into two parts: "affected" and "unaffected". Only the status of affected arguments is recomputed after updates. A matrix-reduction approach similar to the previous division method is presented in [79]. In [2], the authors compute complete, preferred, stable, and grounded semantics on an AF, given a set of updates. This approach finds a reduced (updated) AF sufficient to compute an extension of the whole AF and uses state-of-the-art algorithms to recompute an extension of the reduced AF only. In [3], the same authors extend their dynamic techniques to improve the skeptical acceptance of arguments in preferred extensions.

Modifications of AFs are also studied in the literature as a base to compute *robustness* measures of frameworks [22,59,64]. In particular, by adding/removing an argument/attack, the set of extensions satisfying a given semantics may or may not change. For instance, one could be interested in computing the number of modifications needed to change this set or measure the number of modifications needed to have a different set of extensions satisfying a desired semantics. In the latter case, the user is interested in estimating how distant two different points of view are. A similar approach has also been proposed in [14], where the problem of revising argumentation frameworks according to the acquisition of new knowledge is taken into account. While attacks among the old arguments remain unchanged, new arguments and attacks among them can be added. In particular, the authors introduce the notion of *enforcing*, namely the process of modifying an AF (and possibly changing its semantics) to obtain a desired set of extensions.

Since in ICCMA'19, the inclusion of a dynamic track was launched for the first time; the changes have been limited to only attacks (that could be added or removed), which is an essential modification one can perform on an AF. Indeed, the dynamic challenge fostered some research, which was one of the motivations for the proposed dynamic challenge. See for instance [1,3,4,62].

2.3. Motivations to approximate algorithms

Generally speaking, approximate algorithms are methods that can compute the solution to a problem faster than what exact algorithms can normally perform, but with a risk of providing an incorrect solution

in some cases. This kind of approach had already been studied in the argumentation community before the organization of ICCMA 2021 [52,60,74]. Although not always correct, these algorithms can be highly necessary in situations where exact algorithms (e.g., SAT-based techniques) cannot solve the problem, or at least not fast enough to satisfy the needs of the users (e.g. if the argumentation framework is too large and the user expects a quick answer).

In the first organization of an approximate track at ICCMA, the focus was on the simplest problems related to the acceptability (credulous or skeptical) of arguments from the point of view of the nature of the answer, not from the point of view of complexity (see Section 3.2). However, some interesting ideas could be implemented for future ICCMA competitions, as discussed in Section 9.2.

3. The competition tracks and tasks

3.1. Tracks and tasks at ICCMA'19

ICCMA'19 let solvers participate in 7 classical tracks, the same as in ICCMA'17. Each track is named after the name of a semantics (**CO**, **PR**, **ST**, **SST**, **STG**, **GR**, and **ID**). Then, tasks are characterized by a problem and the semantics for which the problem is solved. In ICCMA'19, the following well-known problems are considered:

SE-σ: Given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, **return** some set $E \subseteq \mathsf{A}$ that is a σ-extension of $\mathcal{F}$.
EE-σ: Given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, **enumerate** all sets $E \subseteq \mathsf{A}$ that are σ-extensions of $\mathcal{F}$.
DC-σ: Given $\mathcal{F} = (\mathsf{A}, \rightarrow)$ and $a \in \mathsf{A}$, **decide** whether a is credulously accepted in $\mathcal{F}$ under σ.
DS-σ: Given $\mathcal{F} = (\mathsf{A}, \rightarrow)$ and $a \in \mathsf{A}$, **decide** whether a is sceptically accepted in $\mathcal{F}$ under σ.

For single-status semantics (**GR** and **ID**) the problem **EE** is equivalent to **SE**, and **DS** is equivalent to **DC**. Also, note that the **DC** problem returns the same results when computed for **CO** and **PR**, but to allow participation in the **PR** track without implementing tasks on the **CO** semantics (or vice versa), both the two tasks were maintained. The tasks selected in ICCMA'19 were:

CO: Complete Semantics (**SE**, **EE**, **DC**, **DS**);
PR: Preferred Semantics (**SE**, **EE**, **DC**, **DS**);
ST: Stable Semantics (**SE**, **EE**, **DC**, **DS**);
SST: Semi-stable Semantics (**SE**, **EE**, **DC**, **DS**);
STG: Stage Semantics (**SE**, **EE**, **DC**, **DS**);
GR: Grounded Semantics (only **SE** and **DC**);
ID: Ideal Semantics (only **SE** and **DC**).

The combination of problems with semantics amounts to 24 tasks overall. In addition, 4 new tracks were dedicated to the solution of problems over dynamic frameworks, this time using the semantics originally proposed in [30]: $\sigma \in \{$**CO**, **PR**, **ST**, **GR**$\}$. In this case, a problem instance consists of an initial framework and an additional file storing a sequence of additions/deletions of attacks (see Section 4 for more details). The dynamics tasks adopted in the competition are:

CO: Complete Semantics (**SE**, **EE**, **DC**, **DS**);
PR: Preferred Semantics (**SE**, **EE**, **DC**, **DS**);

ST: Stable Semantics (**SE**, **EE**, **DC**, **DS**);
GR: Grounded Semantics (only **SE** and **DC**).

In this case, the combination of problems with semantics amounts to a total of 14 tasks. Tasks in dynamic tracks are invoked by appending "*D*" to the end of the intended task: for instance, **EE-PR-D** denotes the enumeration task with the preferred semantics. In total, ICCMA'19 is composed of 11 tracks that collect 38 different tasks. Each participating solver can compete in an arbitrary set of tasks. If a solver supports all track's tasks (e.g. the track on complete semantics), it also automatically participates in the corresponding track.

3.2. Tracks and tasks at ICCMA'21

The first difference between ICCMA'19 and ICCMA'21 is the removal of the grounded semantics (**GR**) from the competition since it is not considered a challenging issue (recall that computing the grounded extension can be done linearly with respect to the number of arguments). Then, the competition was divided into two "main" tracks, one for exact algorithms and the other for approximate algorithms. In the exact track, the **EE** task was replaced with a counting task:

CE-σ: Given $\mathcal{F} = (\mathsf{A}, \rightarrow)$, **count** the sets $E \subseteq \mathsf{A}$ that are σ-extensions of $\mathcal{F}$.

Naturally, this new problem **CE** is trivial for single-status semantics (i.e. **ID** only, for ICCMA'21). Thus, the exact track consists of the following tasks:

CO: Complete Semantics (**SE**, **CE**, **DC**, **DS**);
PR: Preferred Semantics (**SE**, **CE**, **DC**, **DS**);
ST: Stable Semantics (**SE**, **CE**, **DC**, **DS**);
SST: Semi-stable Semantics (**SE**, **CE**, **DC**, **DS**);
STG: Stage Semantics (**SE**, **CE**, **DC**, **DS**);
ID: Ideal Semantics (only **SE** and **DS**).

In summary, the exact track of ICCMA'21 contains 6 sub-tracks (corresponding to the semantics), collecting 22 tasks.

The second track, dedicated to approximate algorithms, has 6 sub-tracks corresponding to the semantics. In this case, the focus is on decision problems. Therefore, the approximate track of ICCMA'21 consists of the following tasks:

CO: Complete Semantics (**DC**, **DS**);
PR: Preferred Semantics (**DC**, **DS**);
ST: Stable Semantics (**DC**, **DS**);
SST: Semi-stable Semantics (**DC**, **DS**);
STG: Stage Semantics (**DC**, **DS**);
ID: Ideal Semantics (only **DS**).

This approximate track thus contains 11 tasks, and ICCMA'21 consists, in total, of 2 tracks, 12 sub-tracks, and 33 tasks. Table 1 summarises all the tracks and tasks of ICCMA'19 and ICCMA'21.

Table 1
All tracks and tasks at ICCMA'19 and ICCMA'21

		CO					PR					ST					SST					STG					GR		ID		
		DC	DS	SE	EE	CE	DC	DS	SE	EE	CE	DC	DS	SE	EE	CE	DC	DS	SE	EE	CE	DC	DS	SE	EE	CE	DC	SE	DC	DS	SE
ICCMA'19	Classic	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓		✓
	Dynamic	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓												✓	✓			
ICCMA'21	Exact	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓		✓				✓	✓
	Approx.	✓	✓				✓	✓				✓	✓				✓	✓				✓	✓							✓	

4. Input and output formats

The file formats taken as input by solvers are described below. Benchmarks in ICCMA'19 and ICCMA'21 were available in two different formats (commonly used to represent AFs) to allow participating solvers to choose their preferred format during the competition.[7] The required output format is also briefly described. All the solvers needed to adhere to both input and output formats for facilitating the evaluation and comparison of results.

4.1. Input format

Each benchmark instance, that is, each AF, is represented in two different file formats: *trivial graph format* (`tgf`) and *aspartix format* (`apx`), both used in previous editions of ICCMA. `tgf`[8] is a simple text-based adjacency list file format for describing graphs. The format consists of a list of node labels and a # character followed by a list of edges, which specify node pairs and an optional edge label. For example, 1 2 # 1 2 represents a framework with two arguments and an attack from the first to the second one. The `apx` format is described in [37]. This format is more oriented to computational argumentation problems, but the encoded information is, in practice, very similar to `tgf`, even if arguments and attacks are always associated with a specific label. The previous example with arguments named *a* and *b* corresponds to "*arg(a). arg(b). att(a,b).*".

A novel format for dynamic AFs is introduced. For each (dynamic) problem instance, two files are required: the initial framework (either in `apx` or `tgf` format) and a text file with a list of changes to apply. The file with changes declares a list of modifications (one per line) of the initial framework. The file format with changes is inspired by the original `tgf` and `apx` formats. The format used for modifications is illustrated in the example below.

Example 4.1. The initial framework of Fig. 1 is provided in a file `myExample.apx` with the following content:

```
arg(a).
arg(b).
arg(c).
arg(d).
arg(e).
att(a,b).
att(c,b).
att(c,d).
att(d,c).
att(d,e).
```

The second file contains the list of modifications to be *sequentially* performed on the initial AF. The name of this file has to be the same as the first one but with a different extension .apxm instead of .apx. In this example, `myExample.apxm` is:

[7] The solvers that can "speak" the two format languages were required to select the one they wanted to be tested on in ICCMA'19. For ICCMA'21, the `apx` format was arbitrarily chosen.

[8] Trivial graph format: http://en.wikipedia.org/wiki/Trivial_Graph_Format.

```
arg(a).      arg(a).      arg(a).
arg(b).      arg(b).      arg(b).
arg(c).      arg(c).      arg(c).
arg(d).      arg(d).      arg(d).
arg(e).      arg(e).      arg(e).
att(a,b).    att(b,c).    att(b,c).
att(b,c).    att(c,b).    att(c,b).
att(c,b).    att(c,d).    att(c,d).
att(c,d).    att(d,c).    att(d,c).
att(d,c).    att(d,e).    att(d,e).
att(d,e).                 att(e,d).
```

Fig. 2. The three AFs obtained from the modifications in `myExample.apxm`.

```
1            1            1
2            2            2
3            3            3
4            4            4
5            5            5
#            #            #
1 2          2 3          2 3
2 3          3 2          3 2
3 2          3 4          3 4
3 4          4 3          4 3
4 3          4 5          4 5
4 5                       5 4
```

Fig. 3. The three AFs obtained from the modifications in `myExample.tgfm`.

```
+att(b,c).
-att(a,b).
+att(e,d).
```

Applying these changes to the initial file produces three frameworks, represented in Fig. 2.

A second example shows the same framework in the `tgf` format.

Example 4.2. Example 4.1 is considered using the `tgf` format. The file with modifications needs to have suffix .tgfm. Hence, the same changes are represented in `myExample.tgfm`:

```
+2 3
-1 2
+5 4
```

We obtain the three additional frameworks as shown in Fig. 3.

To generate the problem instances for the new tracks, a subset of the frameworks used in classical tracks was selected. A sequence of modifications was produced for each of the selected frameworks, where attacks were added only between existing arguments. No new argument was introduced during this process. Further details can be found in Section 5.3. For a modification file with n changes, a solver must compute solutions for n different frameworks by applying the modifications in sequence (starting at the top of the file).

```
[
 [a,d]
 [a,c,e]
]
```

Fig. 4. We here show the output format of both **EE** and **SE-D** tasks. In this specific example, the output corresponds to the result of the **EE-PR** task on the AF in Fig. 1.

4.2. Output format

The output format of ICCMA'17 has been retained, except for the **EE** task. The printed standard output for the **DC** and **DS** tasks was either `YES` or `NO`. For the **SE** task, the list of arguments belonging to the returned extension is encoded as, e.g., $[a1, a2, a4]$. For **EE**, the list of extensions is returned as illustrated in the example in Fig. 4. Solutions for **CE** (introduced in ICCMA'21) are simply the number of extensions printed on the standard output. Non-existence of solutions (e.g. in case of **ST**) was encoded by [ ], while an empty extension is simply described as [[ ]].

For the dynamic tracks, all answers were output in the form of a list where the first element represents the solution of the required task on the initial framework; each following element in this list is the answer returned for the $(i + 1)^{th}$ framework that incorporates the first i changes in the modification file, with $i \in [1..n]$ and n being the total number of changes in the modification file. **DC-**σ**-D** and **DS-**σ**-D** tasks returned a list of `YES` or `NO`, one for each modification including the initial framework; for example [`YES`, `YES`, `NO`]. The **SE-**σ**-D** tasks required a list as shown in Fig. 4: one extension found for each modification. The **EE-D** tasks needed one more level of indentation, i.e. Fig. 4 repeated for every modification and with one more pair of delimiting square parentheses, since a set of extensions needed to be returned for each modification.

5. Participants, benchmarks, evaluation, reference solver

This section will cover the solvers and their features, the benchmarks utilized in the competition, and the evaluation process used to rank the solvers.

5.1. Participants at ICCMA'19

For the third edition, the competition received 9 solver submissions from research groups in Austria, Finland, France, Germany, Italy, Romania, and the UK. Table 2 lists the solvers, related participants, and affiliations. Table 3 shows the tasks all the solvers participated in: 3 solvers were submitted to all the tracks, including dynamic ones. The authors of the solvers used different techniques to implement their applications. In particular, 4 solvers were based on transforming argumentation problems to SAT, 1 on the transformation to ASP, 1 relied on machine learning, and 3 were built on tailor-made algorithms. Following the alphabetical order, we provide a summary of each solver and refer the reader to the official abstract for a more detailed discussion.[9]

Argpref is a solver specialized in computing the ideal semantics. It implements a SAT-with-preferences approach to computing the backbone of a propositional encoding of admissible sets. Then, it applies polynomial-time post-processing to construct the ideal extension. Insights into the techniques used for the implementation are provided in [66].

[9]ICCMA'19 solvers: https://www.iccma2019.dmi.unipg.it/submissions.html.

Table 2
List of ICCMA'19 participants

Solver	Authors
Argpref	Alessandro Previti and Matti Järvisalo (Univ. of Helsinki, Finland)
Aspartix-V19	Wolfgang Dvořák, Anna Rapberger, Johannes P. Wallner and Stefan Woltran (TU Wien, Austria)
CoQuiAAS	Emmanuel Lonca, Jean Marie Lagniez (Univ. of Artois & CNRS, France), and Jean-Guy Mailly (Univ. Paris Descartes, France)
EqArgSolver	Odinaldo Rodrigues (King's College London, UK)
Mace4/Prover9	Adrian Groza, Liana Toderean, Emanuel Baba, Eliza Olariu, George Bogdan and Oana Avasi, (Tech. Univ. of Cluj-Napoca, Romania)
μ-toksia (2019)	Andreas Niskanen and Matti Järvisalo (Univ. of Helsinki, Finland)
Pyglaf (2019)	Mario Alviano (Univ. of Calabria, Italy)
Taas-dredd	Matthias Thimm (Univ. of Koblenz-Landau, Germany)
Yonas	Lars Malmqvist (Univ. of York, UK)

An early version of *Aspartix-V19* (simply Aspartix in the following) participated in ICCMA'15 and also was the reference solver in ICCMA'17. ASPARTIX delegates the main reasoning to an answer set programming (ASP) solver with argumentation semantics and reasoning tasks encoded via ASP rules. We refer to [35] for details on the version submitted to ICCMA'19.

CoQuiAAS v3.0 (simply CoQuiAAS in the following) participated in ICCMA'15, ICCMA'17 and ICCMA'19. Compared to the version used in ICCMA'17 (see [53] for details), the latest implementation of CoQuiAAS introduces changes also to handle dynamics. The full knowledge of the dynamics is exploited through a formula in which attacks can be activated/deactivated by using assumptions. CoQuiAAS has also been endowed with an integrated maximal satisfiable subsets (MSS) solver that took advantage of the approach proposed in [44] (the previous version resorted to an external solver). Other adjustments have been made to obtain an output compliant with the specifications of ICCMA'19.

EqArgSolver was first submitted to ICCMA'17 [68]. The version presented in ICCMA'19 has been improved with a series of changes aimed at increasing efficiency, readability, and software maintenance. First of all, the implementation of AFs and solutions has been moved to dedicated class objects. Then, to facilitate the representation of solutions, EqArgSolver associates each argument with an internal identifier determined by the position of the argument itself within the topological structure of the AF. The internal representation of solutions also changes, going from an approach with unordered maps (which was highly inefficient in terms of memory requirements) to the use of simple vectors of unsigned integers.

The *Mace4/Prover9* solver relies on the combined search capabilities of two tools: Prover9, an automated theorem prover for first-order and equational logic, and Mace4, which searches for finite models and counterexamples. The authors tuned search parameters for the specific task of labeling AFs. In the pre-processing phase, arguments receive a weight depending on the number of outgoing attacks and then are ordered in a decreasing way. The first argument in the ranking (the one that attacks the most) is set to *In*, and the satisfiability is checked using Mace4. If the test fails, that argument is changed to *Out*, and the next argument in the ranking is set to *In*. The procedure continues until either a solution is found or all arguments have been tested. This method is expected to work well in finding a single extension, as Mace4's domain size may cause a model explosion.

The μ-toksia solver made its debut in ICCMA'19; it is a purely SAT-based implementation, in the sense that all the reasoning by the system is performed by calls to a Boolean satisfiability (SAT) solver, including polynomial-time computations such as the grounded semantics, as well as incremental checks

Table 3
Tasks supported by each solver in ICCMA'19

	Dynamic	CO				PR				ST				SST				STG				GR		ID	
		DC	DS	SE	EE	DC	DS	SE	EE	DC	DS	SE	EE	DC	DS	SE	EE	DC	DS	SE	EE	DC	SE	DC	SE
Argpref																								✓	✓
Aspartix-V19		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
CoQuiAAS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
EqArgSolver		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓									✓	✓		
Mace4/Prover9		✓	✓	✓																					
μ-toksia (2019)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pyglaf (2019)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Yonas		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓									✓	✓		
Taas-dredd		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓									✓	✓		

for the persistence of (non-)solutions under changes in the dynamic tasks. As shown in a KR20 paper [63], for DC and DS tracks, μ-toksia was able to scale much more and resulted in the best solver when tested against ICCMA'17 benchmarks instances. For a careful explanation of its implementation, refer to [63].

The *Pyglaf* reasoner competed in ICCMA'17 and ICCMA'19. It reduces problems to circumscription by means of linear encodings. Circumscription is a non-monotonic logic formalizing common sense reasoning by means of a second-order semantics, which essentially enforces minimizing the extension of some predicates. The circumscription solver extends the SAT solver *glucose* and implements an algorithm based on unsatisfiable core analysis. A thorough implementation description can be found in [5].

Taas-dredd implements a DPLL-like approach (Davis, Putnam, Logemann, Loveland), which performs an exhaustive search iteratively trying possible acceptability values for the arguments until a valid labeling is found or backtracking is needed. The search order is guided by domain-independent heuristics that aim to minimize backtracking steps; information propagation is used to infer acceptability values once certain decisions are made. Additional information and source codes can be found on the Taas project web page.[10]

Yonas, first introduced in ICCMA'19, consists of an experimental abstract argumentation solver based on a combination of *Deep Reinforcement-learning* (DRL) and *Monte Carlo Tree Search* (MCTS). The implementation is realized in Python and PyTorch (a deep learning framework). The solver works with two main phases: pre-training and runtime. In the former phase, the DRL model is trained on a benchmark AFs set from ICCMA'17. During the runtime phase, the solver uses MCTS to search for solutions to a specific problem. The tree search is guided by a set of probabilities computed by the deep neural net, and the moves taken by MCTS feedback into the training of the neural net.

5.2. Participants in ICCMA'21

ICCMA'21 received 9 solver submissions as well from research groups in Austria, Finland, Germany, Italy, and the UK. The solvers and their developers are listed in Table 4, while Table 5 shows the solvers' participation in sub-tracks. The participation of a solver in a sub-track means that it solves all the tasks in

Table 4
List of ICCMA'21 participants

Solver	Authors
AFGCN	Lars Malmqvist (Univ. of York, UK)
A-Folio DPDB	Johannes K. Fichte (TU Dresden, Germany), Markus Hecher (TU Wien, Austria), Piotr Gorczyca (TU Dresden, Germany) and Ridhwan Dewoprabowo (TU Dresden, Germany)
Aspartix-V21	Wolfgang Dvořák (TU Wien, Austria), Matthias König (TU Wien, Austria), Johannes P. Wallner (TU Graz, Austria) and Stefan Woltran (TU Wien, Austria)
ConArg	Stefano Bistarelli, Fabio Rossi, Francesco Santini and Carlo Taticchi (Univ. of Perugia, Italy)
FUDGE	Matthias Thimm (Univ. of Koblenz-Landau, Germany), Federico Cerutti (Univ. of Brescia, Italy) and Mauro Vallati (Univ. of Huddersfield, UK)
HARPER++	Matthias Thimm (Univ. of Koblenz-Landau, Germany)
MatrixX	Maximilian Heinrich (University of Leipzig, Germany)
μ-toksia (2021)	Andreas Niskanen and Matti Järvisalo (Univ. of Helsinki, Finland)
Pyglaf (2021)	Mario Alviano (Univ. of Calabria, Italy)

[10]Taas project web page: http://taas.tweetyproject.org.

Table 5
Tasks supported by each solver in ICCMA'21

	Exact Track						Approximate Track					
	CO	PR	ST	SST	STG	ID	CO	PR	ST	SST	STG	ID
AFGCN							✓	✓	✓	✓	✓	✓
A-Folio DPDB	✓		✓									
Aspartix-V21	✓	✓	✓	✓	✓	✓						
ConArg	✓	✓	✓	✓	✓	✓						
FUDGE	✓	✓	✓			✓						
HARPER++							✓	✓	✓	✓	✓	✓
MatrixX	✓		✓									
μ-toksia (2021)	✓	✓	✓	✓	✓	✓						
Pyglaf (2021)	✓	✓	✓	✓	✓	✓						

Table 6
Tasks supported by solvers participating in the classical track of ICCMA'19 and in the exact track of ICCMA'21

	CO	PR	ST	SST	STG	ID
A-Folio DPDB	ICCMA'21		ICCMA'21			
Argpref						ICCMA'19
Aspartix	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19
	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21
ConArg	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21
CoQuiAAS	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19
EqArgSolver	ICCMA'19	ICCMA'19	ICCMA'19			
FUDGE	ICCMA'21	ICCMA'21	ICCMA'21			ICCMA'21
Mace4/Prover9	ICCMA'19					
MatrixX	ICCMA'21		ICCMA'21			
μ-toksia	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19
	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21
Pyglaf	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19	ICCMA'19
	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21	ICCMA'21
Yonas	ICCMA'19	ICCMA'19	ICCMA'19			
Taas-dredd	ICCMA'19	ICCMA'19	ICCMA'19			

the sub-track. We also summarize in Table 6 the tasks supported by all solvers participating in the classical and exact tracks of the ICCMA'19 and ICCMA'21 competitions. Three of the submitted solvers, namely Aspartix, μ-toksia, and Pyglaf, are an updated version of those participating in the 2019 competition. Similarly to ICCMA'19, various techniques are used by the solvers, namely 3 solvers use the transformation of argumentation problems to SAT, 1 uses a transformation to ASP, 1 uses constraint programming, 1 is based on machine learning, and finally 3 are built on tailor-made algorithms.

AFGCN[11] proposes an approximate algorithm based on a Graph Convolutional Network model, trained on data from the previous editions of ICCMA. It extends the work described in [60].

A-Folio DPDB[12] is a portfolio using a method specifically designed for counting problems, based on tree decompositions: if the tree-width is smaller than a given threshold, then DPDB [40] (an approach

[11] See http://argumentationcompetition.org/2021/downloads/afgcn.pdf.
[12] See http://argumentationcompetition.org/2021/downloads/a-folio-dpdb.pdf.

initially designed for model counting in propositional logic) is used to determine the number of extensions. If the tree-width is too large, then μ-toksia [63] is used to enumerate the extensions, and this enumeration is used to obtain the number of extensions. Finally, for other tasks (**SE**, **DC**, **DS**), μ-toksia is directly used.

Aspartix-V21 [34] (when clear from the context, we only write Aspartix), based on ASP encoding of abstract argumentation, is an update of Aspartix-V which already participated to ICCMA'15 and ICCMA'19.

ConArg[13] is a solver based on constraint programming. The solver submitted to ICCMA'21 is an update of the version that participated in previous editions. More details on the approach can be found in [18,21].

FUDGE [72] uses SAT reductions to solve argumentation problems. While most of the reductions are similar to standard approaches in the literature, reasoning with the preferred and ideal semantics benefits from a new method proposed by the authors of the solver [73]. Roughly speaking, it uses a characterization of skeptical acceptability under the preferred semantics, where only some specific admissible sets are used. It means that the solver can avoid the cost of computing all the maximal admissible sets.

HARPER++[14] is an approximate solver relying on the grounded extension. The idea is quite simple: for all the semantics considered, the **DC** task is solved by answering `YES` exactly for the arguments that belong to the grounded extension and `NO` otherwise, and for **DS** the answer is `NO` for arguments attacked by the grounded extension, and `YES` otherwise.

MatrixX [45] represents some properties of arguments (attacks and defence) as matrices and uses an approach inspired by Knuth's X algorithm for exact cover [47].

μ-toksia[15] is a solver based on SAT reductions; the solver submitted to ICCMA'21 is an updated version of the solver submitted to ICCMA'19. More details can be found in [63].

Pyglaf [6] transforms abstract argumentation tasks into circumscription and uses a SAT solver to obtain the result. Previous versions of the solver have been submitted to ICCMA'17 and ICCMA'19, see [5] for more details.

5.3. Benchmark selection for ICCMA'19

Starting from ICCMA'17, the competition welcomes argumentation solvers and the benchmarks on which the evaluations are performed. Six benchmarks have been submitted to ICCMA'17,[16] each of which focused on a specific theme, from generating particularly difficult instances to practical scenarios such as traffic networks and planning problems. Opening up to benchmarks in the competition goes toward testing the performance of argumentation solvers on real problems.

A total of 326 AF instances were selected for ICCMA'19 from the ones that were used in ICCMA'17[17] and two new benchmarks submitted to ICCMA'19.[18] The selected benchmarks serve two primary purposes. Firstly, we intend to assess the progress of solvers for argumentation problems in comparison to the previous edition of the competition. Thus, we have included instances from ICCMA'17. Secondly, we aim to scrutinize the behavior of different solvers with more practical benchmarks and closer to

[13] See http://argumentationcompetition.org/2021/downloads/conarg.pdf.
[14] See http://argumentationcompetition.org/2021/downloads/harper++.pdf.
[15] See http://argumentationcompetition.org/2021/downloads/mu-toksia.pdf.
[16] ICCMA'17 benchmark list: http://argumentationcompetition.org/2017/submissions.html#benchmarks.
[17] ICCMA'17 benchmark selection: http://argumentationcompetition.org/2017/benchmark_selection_iccma2017.pdf.
[18] A description of new ICCMA'19 benchmarks: https://iccma2019.dmi.unipg.it/submissions.html.

real-world instances. By doing so, we can identify the most effective solvers to offer solutions to real problems. While testing difficult instances can push solver limits, we aimed to compare solver performance across all collected benchmarks. As pointed out in [69], a good number of instances adopted in ICCMA'17 were too hard for all the solvers submitted in that competition. For example *SemBuster* is a group of 16 AFs, having between 60 and 7500 arguments, which were classified as 2 very easy, 1 easy, 3 medium, 9 hard, 1 too hard, for what concerning the **EE-PR** track [42]. However, 15 out of these 16 AFs could not be enumerated at all in the **EE-CO** track [69]. ICCMA'17 instances on which all the submitted solvers did not score more than 0 points were counted: out of 350 instances, we obtained 114 AFs in **EE-STG**, 69 in **EE-CO**, 53 in **EE-PR**, 41 in **EE-SST**, 30 in **EE-ST**. In practice, these AFs did not participate in the evaluation of the solvers (that is, 10-30% of the tested AFs). While none of the **DC** and **DS** tasks showed this characteristic, all the **SE** tasks (except **SE-CO**) presented more than 20 "void" instances. Even on 5 AFs in the **SE-GR** track, no solver could find a solution before the timeout (these instances have more than 500, 000 arguments).

The instances chosen for the competition, which avoided those that were overly hard, were selected using *ConArg* [18,21], a solver developed by some of the authors of this paper.[19] Only the instances ConArg could solve under extended time and memory conditions were selected from the benchmarks. ConArg used an allocation of 10 times the competition constraints' time limit and memory space to solve the problems (see Section 5.7). As a result, the dataset consists of relatively easy instances. Detailed results in Appendix A show that, in ICCMA'19, no instance was left unsolved by all the participants. Therefore, all the selected 326 AFs were practically used in the tests. ConArg was also used as the reference solver to check the correctness of solutions returned by participants. However, it should be noted that some of the chosen instances were still challenging, as 1315 out of 46618 attempts to solve various tasks per each solver and instance ended with timeouts.

About two third of the instances were selected from ICCMA'17 benchmarks (i.e., 204). The number of selected instances for each class of ICCMA'17 are reported in A; their features are summarised in [42]. The remaining instances (i.e., 122) came from the two new benchmarks that were submitted to ICCMA'19. Only those AFs that ConArg could solve with extended conditions were selected. The first new set of benchmark instances, named ICCMA19B1, was submitted by Bruno Yun and Madalina Croitoru. It is a practically oriented benchmark on logic-based AFs instantiated from inconsistent knowledge bases expressed using Datalog$^{\pm}$, a language widely used in the Semantic Web. In the competition, only those instances from the *Small* and *Medium* classes (as labeled by the authors proposing the benchmarks) were used. The second set of new benchmark instances, hereafter referred to as ICCMA19B2, was produced by a benchmark generator supplied by Billy D. Spelchan and Gao Yong. Instead of a random model generating directed graphs $D(n, q)$, where n is the number of vertices and p the edge probability, the authors propose $D(n, p, q)$, where q is the probability of the attack to be mutual. The motivation is that with $D(n, q)$, the existence of an extension in such a random AF is almost always guaranteed, making it less helpful in testing exact solvers (e.g. while testing the existence of a stable extension). In Table 7, we report the main statistics about the instances coming from these new datasets adopted in ICCMA'19. All such AFs are connected and have at least one cycle.

To sum up, Fig. 5 reports the distribution of benchmark instances: labels from A1 until T4 come from ICCMA'17, while the other three labels (S, M, and N) come from the two new benchmarks, de-

[19]For this reason, this solver did not participate in ICCMA'19. However, it participated in ICCMA'15, ICCMA'17 and ICCMA'21.

Table 7

Considering the instances selected from the new submitted benchmarks to be part of ICCMA'19 (one per row), the columns respectively report the minimum/maximum/median number of arguments, the minimum/maximum/median number of attacks, how many AFs are strongly connected over the total of selected AFs, and finally the minimum/maximum/median number of strongly connected components

	Min/Max/Med Ar.	Min/Max/Med At.	#isSC/total	Min/Max/Med #SCC
ICCMA19B1 (Small)	5/383/30	8/32768/296	33/105	1/61/4
ICCMA19B1 (Medium)	391/595/519	67,277/165,016/126,681	0/7	30/173/118
ICCMA19B2	100/320/176	2025/30,406/9160.5	10/10	1/1/1

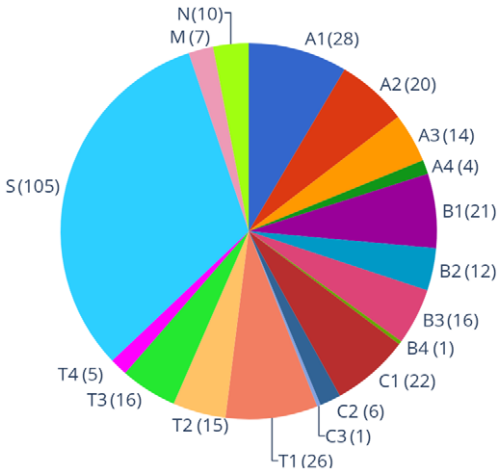


Fig. 5. The distribution of AF instances in the ICCMA'19 benchmark, selected from different benchmarks taken from ICCMA'17 (from A1 to T4), and from the two new submissions: *S*(mall) and *M*(edium) instances from ICCMA19B1, while *N* represents the instances from ICCMA19B2.

scribed in the following paragraphs.[20] A reports the exact number of frameworks selected from each sub-benchmark.

Dynamic-tasks benchmark-instances. All the introduced AFs and generators are intended for classical tasks in argumentation. Therefore, a generator was developed to produce benchmarks for dynamic tracks that create files with changes to AFs (see Section 4.1). Each addition/removal of an edge has an equal probability of 0.5. In removal, the attack to be deleted is selected among all the original attacks using a uniform distribution (it is impossible to remove a newly added attack). In case of addition, the two adjacent arguments are selected by using a uniform distribution, avoiding the generation of self-attacks and attacks that are already in. The generator reads both `apx` and `tgf` formats and produces `apxm`/`tgfm` modifications (see Section 4.1). The same 326 instances have been used for the dynamic tracks, including eight modifications to each AF, for a total of 2934 instances.

5.4. Benchmark selection for ICCMA'21

For the benchmark selection of ICCMA'21, a call for benchmarks was launched, which was unfortunately unsuccessful: no set of instances nor any generator was submitted. This leads to two paths:

[20] A more detailed description of these benchmark generators can be found on the website of ICCMA'19).

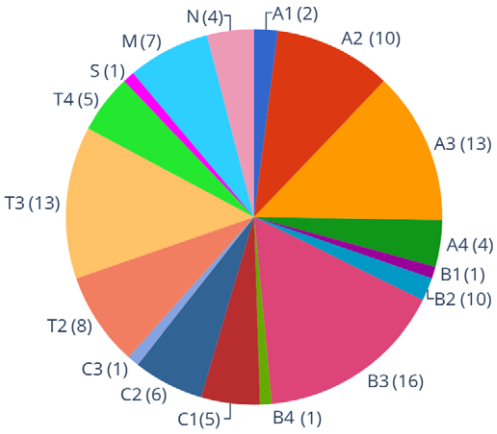
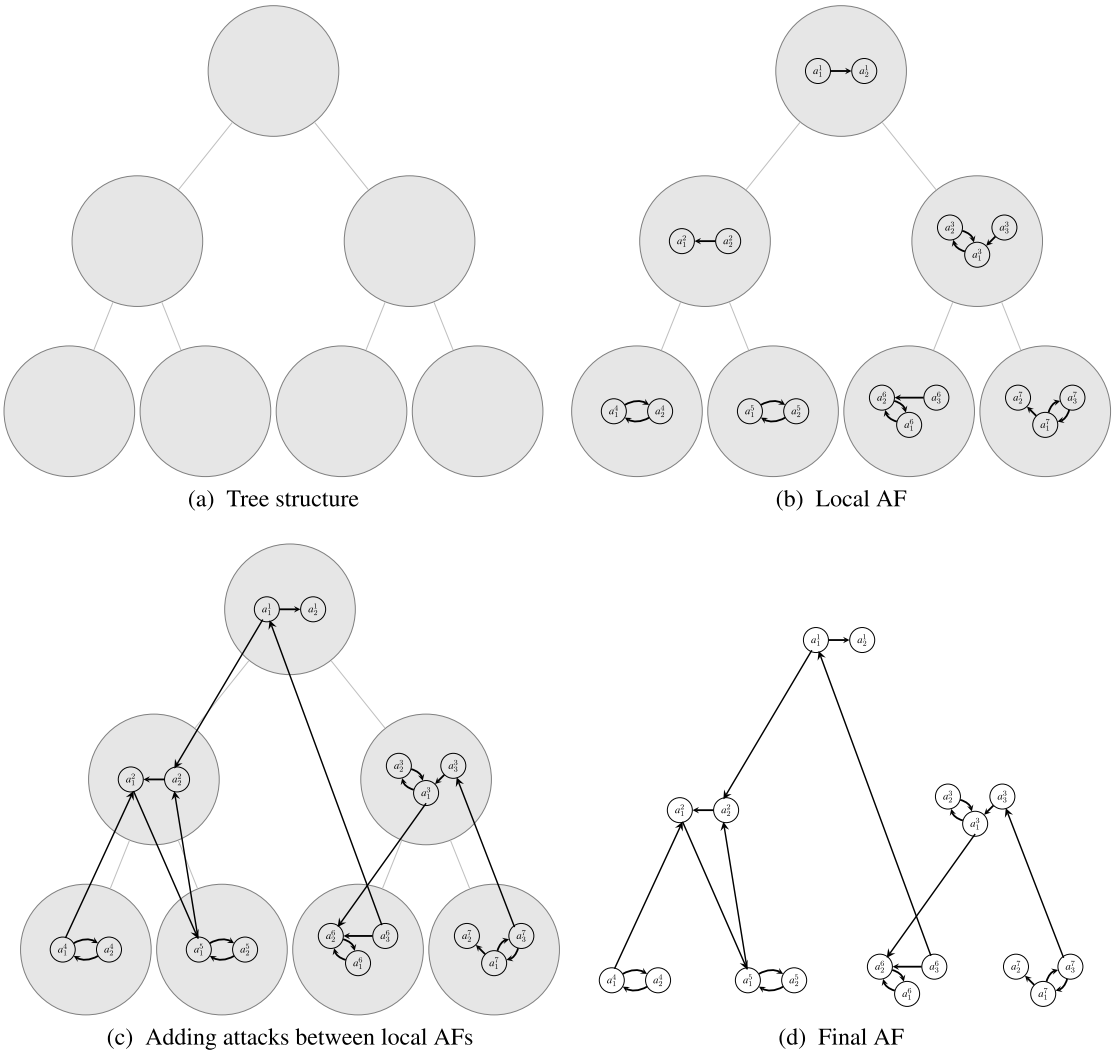


Fig. 6. The distribution of AF instances in the ICCMA'21 benchmark, selected from different benchmarks taken from ICCMA'19. A1 to T4 represent the instances from ICCMA'17, *S*(mall) and *M*(edium) are the instances from ICCMA19B1, while *N* represents the instances from ICCMA19B2.

selecting a subset of ICCMA'19 instances and generating new ones. The ICCMA'19 instances were selected to be challenging enough to distinguish efficient solvers while still being solvable by some of them. Building the benchmark for ICCMA'21 in this way also allows for evaluating solver evolution from 2019 to 2021. Then, the hardest instances among the ones used at ICCMA'19 were selected, ranking the instances by two criteria: for a given AF $\mathcal{F}$, we counted how many times a solver reached the timeout on $\mathcal{F}$ (for any problem and any semantics) during ICCMA'19. We also computed the average runtime of all solvers for solving any problem under any semantics on $\mathcal{F}$. Then, we selected all the AFs such that the number of timeouts is greater or equal to 6, or the average runtime is greater or equal to 60 seconds. This means that all the instances that can be considered too easy (having almost no timeout or being solved in under a minute) were discarded, leading to a set of 107 AFs. Their distribution is described in Fig. 6. Most of them are actually instances from ICCMA'17 (datasets A1 to T4), while only 12 AFs have been selected from those submitted in response to the call for benchmarks at ICCMA'19. Detailed numbers of instances are provided in Appendix A.

ICCMA'21 also proposed a new approach for generating AFs considering underlying tree structures. More precisely, a tree $\mathcal{T}$ that will be used as a skeleton for the AF is first constructed (Fig. 7a). $\mathcal{T}$ is a perfectly balanced d-tree of height h generated randomly, where d and h are fixed and given as parameters. Then, each node of the tree is associated with a fresh local AF graph (fresh in the sense where each AF's arguments are disjointed, see Fig. 7b). To link local AFs together, for each AF $\mathcal{A}_N$ rooted to a node N of $\mathcal{T}$, attacks between arguments of $\mathcal{A}_N$ and arguments coming from AFs present in the left or right subtree of N are added (Fig. 7c). The final AF is the set of local AFs and the added attacks (see Fig. 7d).

The number of arguments k that are used to be linked to outside AFs is fixed and is given as a parameter. For a given AF $\mathcal{A}_N$, let A be the set of arguments selected to be linked. Then, for each AF $\mathcal{A}'_N$ present in the left or right sub-tree of N, a percentage r of arguments A' of $\mathcal{A}'_N$ are selected to interact with A. r is chosen randomly between $[l, u]$ such that $0 \leqslant l < u \leqslant 1$ and l, u are given as parameters. Once A and A' are identified, each pair $(a, a') \in A \times A'$ is considered and the attack (a, a') or (a', a) is added with a probability one-half.



(a) Tree structure (b) Local AF

(c) Adding attacks between local AFs (d) Final AF

Fig. 7. AFs generation process.

For the local AF, two random generators have been considered that are based on the following random graph generators:[21]

- Barabasi-Albert preferential attachment model [10] with n_b nodes and m_b being the number of edges to attach from a new node to existing nodes;
- Erdöz-Rényi [38] (or binomial graph) with n_e nodes and p_e being the probability for edge creation.

The values n_b, m_b and n_e are integers and p_e is between]0, 1]. Let us observe that Barabasi-Albert only constructs undirected graphs, which differs from what is required to construct AFs. To overcome this issue, two graphs called the attack graph A and the defense graph D were constructed to generate an AF. Then, for each lexicographically ordered edge (a_1, a_2) of A (respectively D) an attack (a_1, a_2)

[21] Those graphs were generated through the `NetworkX` library (*networkx.org*).

(respectively (a_2, a_1) is added. In order to keep the correct number of edges, A and D are generated with $\lceil \frac{1}{2} \times m_b \rceil$ (respectively $\lceil \frac{1}{2} \times m_r \rceil$) edges for the Barabasi-Arbert model.

The numbers that are used for generating the local AFs have default values $n_b = 1000$, $m_b = 70$, $n_e = 300$, and $p_e = 0.1$. Then, two last parameters are used for generating the tree structure: these parameters are d (tree depth) and w (tree-width). Finally, once these parameters are fixed, the last thing to decide is the type of the local AFs. For a given instance, either all they are of type Erdös-Rényi, or all are of type Barabasi-Albert, or they are randomly chosen between one of them.

The details of the distribution of these instances are available online in a CSV file where the first column indicates the type of the local AFs (E for Erdös-Rényi, B for Barabasi-Albert, and BE for the random choice of one of them), the second and third columns give the tree depth and tree-width, and the last column gives the number of instances.[22] With all the combinations of parameters, we have 180 types of instances: 60 for each local AF type (E, B, BE). These 60 types of instances correspond to the combination of $d \in \{5, \ldots, 10\}$ and $w \in \{1, \ldots, 10\}$.

The motivation for developing this benchmark generation model was twofold: first of all, it seemed intuitive that (some) large debates could be split into smaller, loosely connected debates. This is the case, for instance, in presidential elections, where arguments about (e.g.) the economy are strongly connected, arguments about environmental issues are strongly connected, but arguments about the economy are (comparatively) only loosely connected to the ones about the environment. This is based solely on intuition, as there is no formal evidence to support it for the moment. The second motivation was that community-based graphs could offer interesting instances that can be solved by "clever" algorithms that take into account the properties of the graph while being hard for purely SAT-based approaches.[23] The challenges posed by community-based instances have already been observed in other domains (e.g. SAT, [61]), as well as the ability of the proposed model to provide challenging instances (see [56]).

Notes. A tool has been developed by the organizers of ICCMA'21 specifically for the purpose of translating from APX to TGF format. The source code and the description of how to use the tool are available online.[24]

Approximate track benchmark selection. The set of benchmarks used for the approximate track is a subset of the ones used for the complete track, containing all the instances for which the winner of ICCMA'19 (μ-toksia) could determine the result in 4 hours. The arguments in the acceptance request are the same as those in the exact tracks.

5.5. Scores and ranking at ICCMA'19

Each solver was given 4 GB of RAM to compute the results of tasks in both the classical and dynamic tracks. The timeout to compute an answer for the dynamic track was 5 minutes for each framework/change: half of the time in the classical track for a single instance, that is 10 minutes. Time and memory limits mimic previous competitions (also to have some comparison). All runs were done on Intel Sandy Bridge CPUs with 16 cores clocked at 2.6 GHz and 64 GB of RAM, using up to all 16 cores for different runs.

[22] See http://argumentationcompetition.org/2021/distribution_instances_2021.csv.

[23] This has been confirmed by the success of A-FOLIO-DPDB, which used a tailored approach following a measurement of the treewidth of instances. See Section 7.1 for more details.

[24] https://github.com/crillab/apx2tgf

The solvers were given all instances in the tracks they participated in to solve. For each instance, a solver got (0, 1] points if it delivered the correct result (it could be incomplete, see below); −5 points if it delivered an incorrect result; 0 points if the result was empty (e.g. the timeout was reached without an answer) or if it was not parsable (e.g. some unexpected error message). For **SE**, **DC**, and **DS**, the assigned score was 1 if the solver returned the correct answer (respectively "yes", "no", or just an extension). For **EE**, a solver received a (0, 1] fraction of points depending on the fraction of found enumerated extensions (1 if it returned all of them).

For the dynamic tracks, a result was considered correct and complete if, for n changes in a file, $n + 1$ correct and complete results were provided by a solver (initial AF plus modifications). In ICCMA'19, there are 8 changes per file, so $n = 8$. The score for a correct and complete result was 1, as usual. A partial (incomplete) result was considered correct if it gave fewer than $n + 1$ answers, but each of the given answers was correct and complete (with respect to the corresponding static tasks). These rules applied to all the problems (**SE**, **DC**, **DS**, **EE**) in the dynamic track. A correct but incomplete result scored a value in (0, 1], depending on the fraction of correct sub-solutions returned. If the considered dynamic task involved enumeration (i.e. **EE**) and the last solution a solver provided was correct but partial, then the whole answer was evaluated as if the last problem instance was not solved at all, considering the answer as partial and correct, and assigning a fraction of $1/n$ points, depending on the fraction of returned enumerated extensions. This exception does not penalize solvers that incrementally enumerate extensions; otherwise, the last solution would globally count as incomplete if a timeout occurs during enumeration. If any sub-solutions were incorrect, the overall output was considered incorrect (−5 points). Otherwise, if no answer was given, 0 points were assigned (for instance, due to a timeout).

The ranking of solvers for a track was based on the sum of scores over all tasks of a considered track. Ties were broken by the solver's total time to return the correct results. Note that to ensure that each task had the same impact on the evaluation of a track, all tasks for one semantics had the same number of instances.

5.6. Scores and ranking at ICCMA'21

For the 2021 edition, the competition has been run on a computer cluster where each machine has an Intel Xeon E5-2637 v4 CPU and 128GB of RAM. The runtime limit for each instance is 600 seconds for the "exact" track and 60 seconds for the "approximate" track. The memory limit is the machine's memory, i.e. 128GB. Each sub-track has one ranking, i.e., six rankings for the "exact" track and six rankings for the "approximate" track. To be ranked, a solver must participate in the full sub-track (without obligation to participate in all the (sub)tracks). The scoring system is slightly different between both tracks.

For the "exact" track, any wrong result on an instance i in a sub-track conducts to the exclusion of the solver from the said sub-track. It does not prevent the solver from being ranked for other sub-tracks if there are no wrong results for these other ones. Then, the score of a solver $\mathcal{S}$ on the instance i is

$$Score(\mathcal{S}, i) = \begin{cases} 1 & \text{the correct answer is given in the runtime limit} \\ 0 & \text{timeout or non-parsable output} \end{cases}$$

On the contrary, wrong results do not lead to an exclusion in the "approximate" track:

$$Score(\mathcal{S}, i) = \begin{cases} 1 & \text{the correct answer is given in the runtime limit} \\ 0 & \text{wrong result, timeout or non-parsable output} \end{cases}$$

Then, the score of the solver $\mathcal{S}$ for the task $\mathcal{T}$ is

$$Score(\mathcal{S}, \mathcal{T}) = \sum_{i \in \mathcal{T}} Score(\mathcal{S}, i)$$

and the score for the sub-track $\mathcal{ST}$ is

$$Score(\mathcal{S}, \mathcal{ST}) = \sum_{T \in \mathcal{ST}} Score(\mathcal{S}, \mathcal{T}).$$

When two solvers have the same score for a given sub-track, the cumulated runtime over the instances correctly solved is used as a tie-break rule (the fastest is the best).

5.7. Reference solvers

In the ICCMA argumentation competitions, only a reference solver is usually used to check the results correctness. For instance, solutions for all instances in ICCMA'15 were computed using Tweety [71,75], a collection of libraries for logical aspects of artificial intelligence and knowledge representation, while Aspartix-D was employed as the reference solver in ICCMA'17 [37,42]. No proof can be given that ConArg has no errors, but 100% of the competition's instances were solved by obtaining the same results as the solvers able to solve such instances. In ICCMA'19, ConArg [18,21], was utilized as the reference solver of the competition. The output of solvers was compared among themselves and with the output produced by ConArg to ensure the correctness and completeness of the answers. Additionally, ConArg was used to select benchmark instances, as mentioned in Section 5.3. ConArg (i.e., *arg*umentation with *con*straints) is a Constraint-programming tool developed by some of the authors of this paper, based on *Gecode*,[25] an efficient C++ toolkit for developing constraint-based systems and applications. ConArg and *Conarglib* (its software-library version) are among the official projects supported by Gecode. The two main goals of this tool are to *i)* to solve further problems linked to weighted problems [19], and *ii)* to improve its performance over classical semantics, by using a benchmark assembled with random graph-models [20].

In [29], the authors classify the ConArg approach among "reduction-based implementations", where first the problem is reduced to the target formalism (in this case, constraints), then a solver for that formalism is executed and, finally, the obtained output is interpreted as solutions of the original problem. The search phase takes advantage of classical techniques in Constraint-programming, such as local consistency, different heuristics for trying to assign values to variables, and complete search-tree with branch-and-bound. Models in Gecode are implemented using *spaces*. A space is home to *variables*, *propagators* (implementations of constraints), and *branchers* (implementations of branching, describing the shape of the search tree).

To prevent any issues caused by instances that the reference solver could not solve, the organizers of the ICCMA'19 competition aimed to avoid their usage. The authors of [69] proved that nearly 23% of all AFs of ICCMA'17 could not be enumerated by any solver, and some participant in the competition was erroneously scored positively for instances that no solver could solve. For this reason, one of the criteria for selecting instances in ICCMA'19 was that they had to be solvable by the reference solver. Since ConArg is not the best performance solver, it used 10 times the time and 10 times the memory

[25] http://www.gecode.org.

space granted in the competition constraint to solve the problems. As shown in [69], ConArg solved 76.92% (20 out of 26) of the problems solved by only one solver in ICCMA'17, which, in our opinion, guarantees to have not only easy instances.

Concerning the ICCMA'21 competition, a tool named RUBENS,[26] developed by some authors of this paper was used to perform initial checks on the submitted solvers. RUBENS is a library designed to generate test cases automatically using translation rules. It comes with some pre-built test generators and an interface allowing users to create new ones with minimal effort. The RUBENS checker then executes the software to be tested on the generated test cases, and if the software produces an unexpected result, an error message is thrown. Using this tool allowed us to discover some issues in two solvers, providing the authors with few instances and allowing them to correct their solvers before the competition. A reference solver was not taken into consideration for the exact track. Instead, the obtained results for each instance were examined to identify any inconsistencies. This allowed us to discover that another solver was incorrect for a sub-track. Unfortunately, this solver could not be fixed in time to participate in the considered sub-track. The same methods could not be used for the approximate track due to the incomplete nature of the algorithms. Therefore, the 2019 version of μ-toksia was considered a reference solver, as described in Section 5.4. The correctness of the solvers in ICCMA'21 was ensured by taking advantage of the work done by the organizers of the 2019 edition. For both complete and incomplete ICCMA'21 tracks, the global results were aggregated by a dedicated tool, mETRICS.[27]

6. Results and analysis for ICCMA'19

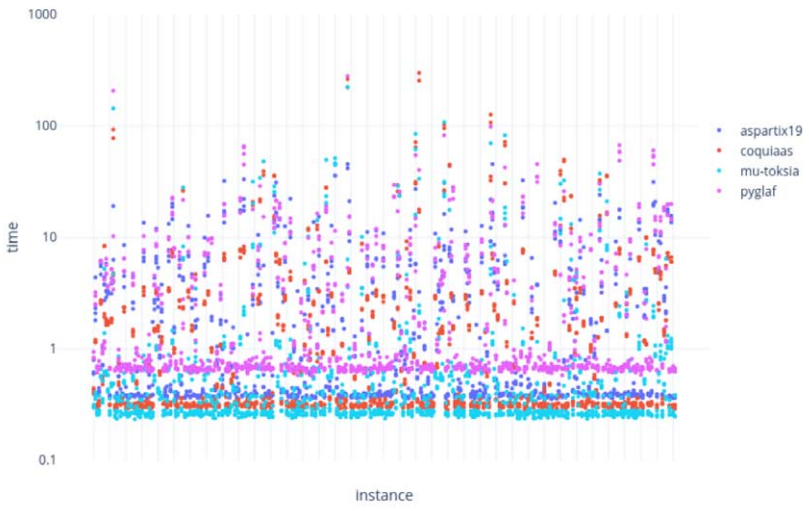
The detailed results and ranking of solvers for all tracks can be found on the dedicated page of the competition website.[28] In Appendix B, we report some tables aggregating results per semantics. In the global ranking for the static tracks, the solvers μ-toksia, CoQuiAAS, Aspartix, and Pyglaf reached the first, second, third, and fourth positions, respectively. μ-toksia got the highest score for every single track as well. As a reminder, μ-toksia, CoQuiAAS, and Pyglaf use a SAT-based implementation, while Aspartix relies on an ASP solver. For the dynamic tracks, the first and second positions are still held by μ-toksia, and CoQuiAAS, respectively. In this case, CoQuiAAS performed better than μ-toksia on the complete and grounded tracks.

Figure 8 shows the time (on a logarithmic scale) taken to solve each non-dynamic instance that was solved correctly by each solver;[29] failed instances, for example, due to exceeding the memory limit or timeout, are not shown. The results are again aggregated by semantics. We can see that Pyglaf is slightly above the other lines in the case of "easy" instances (less than a second), while Yonas is visibly above all, i.e. it takes significantly longer. The other solvers are very close to each other.

Figure 9 shows the same results this time considering dynamic tracks: **CO-D** and **ST-D**, thus aggregated by semantics and with solution time on a logarithmic scale. In non-dynamic tracks, μ-toksia is first, CoQuiAAS second, and Pyglaf third. We omit the detailed results for the sake of brevity and refer the interested reader to the ICCMA'19 website for full results. The figures show that CoQuiAAS is faster in the case of "easy" instances (less than one second), but the difference is a matter of some tenths of a

[26] https://github.com/crillab/rubens.
[27] https://github.com/crillab/metrics.
[28] ICCMA'19 results: https://iccma2019.dmi.unipg.it/results.html.
[29] For this and following figures in this section, more semantics are shown in C.

(a) **CO**

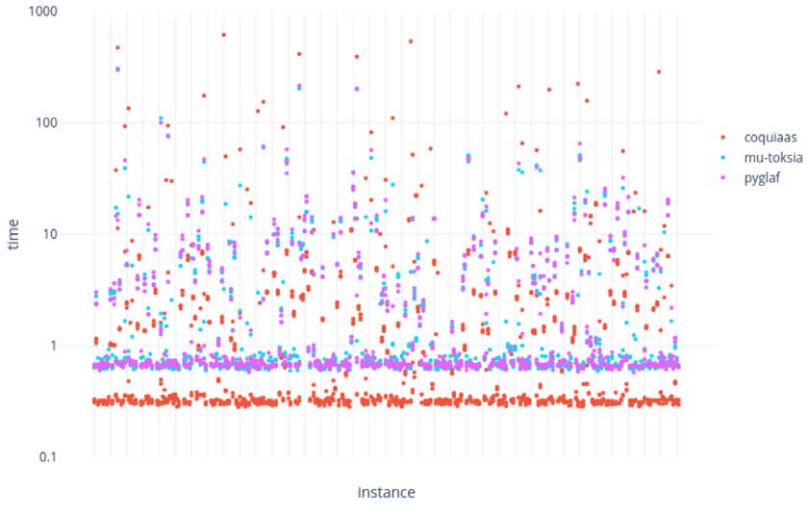


(b) **SST**

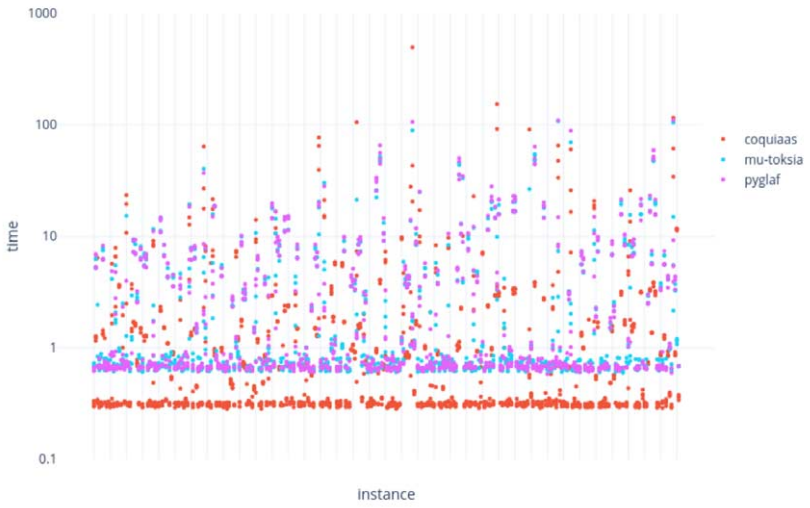
Fig. 8. Time [s] taken for each correctly solved instance in the tracks for the semantics **CO** and **SST** – ICCMA'19.

second at most. μ-toksia and Pyglaf show similar performance in such instances. The difference is larger for more difficult instances.

We also show the cumulative amount of time, expressed in seconds, taken to solve each instance (among those correctly solved) of a track. Figure 10 displays the results for the classical tracks, while Fig. 11 reports the results for the dynamic tracks. What emerges for the non-dynamic tracks is that



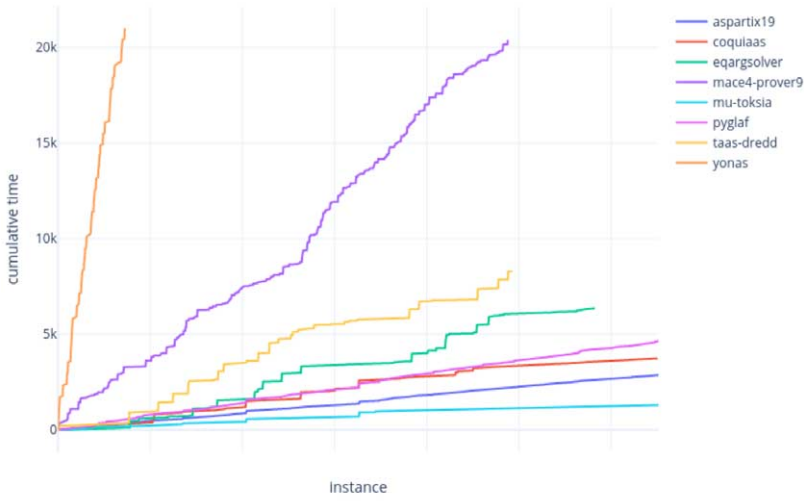
(a) **CO**



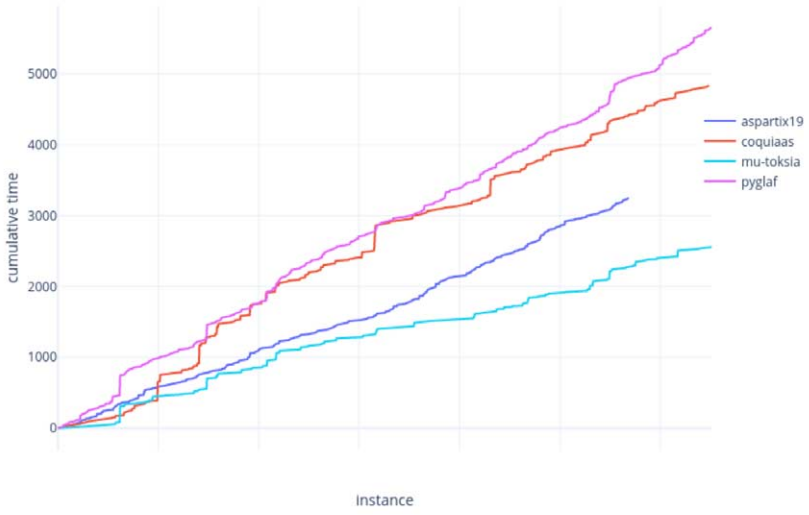
(b) **SST**

Fig. 9. Time [s] taken for each correctly solved instance in the dynamic tracks for the semantics **CO** and **SST** – ICCMA'19.

Yonas takes longer than all the other solvers, whose performances are, in turn, more similar to each other. Between the three solvers taking part in the dynamic track, μ-toksia and Pyglaf are remarkably faster than CoQuiAAS concerning the overall time taken to correctly solve instances in the preferred track. On the other hand, CoQuiAAS performs better than the other solvers for the stable and grounded tracks.



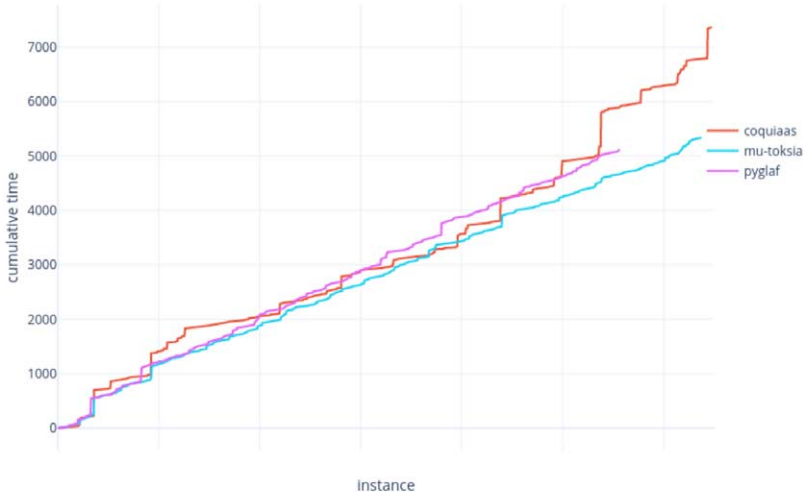
(a) **CO**



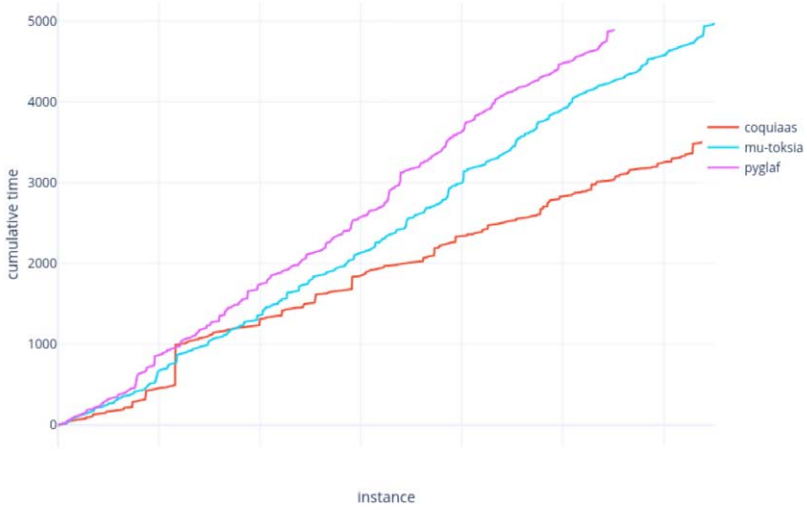
(b) **SST**

Fig. 10. Cumulative time [s] taken to correctly solve all instances in the **CO** and **SST** tracks – ICCMA'19.

The hardest instances in the classical tracks were *n320p5q2_n.apx* (**DC-CO**, **EE-PR**, **DC-PR**, **DC-ST**), *n256p3q08n.apx* (**EE-SST**, **EE-STG**), in which three solvers timed out. Another hard instance was *n256p5q2_e.apx*, where three solvers took more than 5 minutes to find a solution in 10 different tracks. These three instances belong to the dataset in ICCMA19B2.



(a) **CO**



(b) **SST**

Fig. 11. Cumulative time [s] taken to correctly solve all instances in the dynamic **CO** and **SST** tracks – ICCMA'19.

Concerning the dynamic tracks, in **EE-CO** with instances *n256p3q08n.apx* and *n320p5q2_n.apx*, all three participants timed out. While previous instances were hard to solve for all the three participants also in other tasks, with the following instances, only CoQuiAAS timed out in at least a track: *A-2-stb_422_250.apx*, *B-3-WS_300_16_70_30.apx*, *B-3-stb_339_393.apx*, *B-3-stb_428_430.apx*, *C-2-stb_304_352.apx*, *n160p3q24e.apx*, *A-2-WS_300_16_70_30.apx*, *B-3-stb_327_100.apx*.

6.1. Statistical significance of results

To determine whether the runtime differences of the solvers are significant, we conducted a Wilcoxon signed-rank test [78], a non-parametric test for paired samples which compares the probability that a random value from the first group is greater than its dependent value from the second group. In our case, each group contains the execution time of a solver, given a particular task, against all instances solved by both solvers. The results obtained are trustworthy since the following assumptions are fulfilled: i) the dependent variable is continuous, ii) paired observations are randomly and independently drawn, and iii) paired observations come from the same population. Upon comparison, the test generates a p-value for each sample pair, and statistical significance is determined if the p-value falls below a certain threshold, most commonly 0.05. Performing tests to compare the runtimes for all solvers participating in ICCMA'17, 19, and 21 was not possible due to the different machine configurations on which the performance of the solvers was computed, which results in execution times that are not directly comparable. Therefore, we conducted the test on participant solvers in the ICCMA'19 classic tracks.[30] We discuss below the results of tests.

For most of the results (354 out of 383 tests), we obtain p-value < 0.05. In other words, the difference between the sample change and the expected change is big enough to be statistically significant. For the remaining 29 solver pairs with p-value $\geqslant 0.05$, we cannot exclude the hypothesis that the difference between their runtimes follows a symmetric distribution around zero. This means that there is no evidence of a statistically significant difference between the two distributions, and it cannot be concluded with sufficient confidence that there is a dissimilarity between the performances of the two compared solvers. Two solvers in particular, μ-toksia and Mace4-Prover9, frequently present high p-values when tested with the other solvers.

Table 8 shows the results of the Wilcoxon signed-rank tests, conducted between Mace4-Prover9 and other solvers, that presented a p-value $\geqslant 0.05$. Mace4-Prover9 performs closely to the solvers listed in the table for the tasks it participates in. For instance, in the SE-CO task, Mace4-Prover9 and eqargsolver are ranked sixth and seventh, respectively. It is worth noting that *mu*-toksia, the best overall solver in ICCMA'19, never appears in Table 8, so its performance compared to Mace4-Prover9 cannot be questioned.

Table 8
Wilcoxon signed-rank test results between Mace4-Prover9 and other ICCMA'19 classic track solvers, where p-value $\geqslant 0.05$

Task	Solver_1	Solver_2	p-value
DC-CO	Mace4-Prover9	Aspartix-V19	0.566
DC-CO	Mace4-Prover9	EqArgSolver	0.570
DC-CO	Mace4-Prover9	Pyglaf	0.112
DS-CO	Mace4-Prover9	Aspartix-V19	0.363
DS-CO	Mace4-Prover9	CoQuiAAS	0.874
DS-CO	Mace4-Prover9	EqArgSolver	0.320
SE-CO	Mace4-Prover9	Aspartix-V19	0.319
SE-CO	Mace4-Prover9	CoQuiAAS	0.752
SE-CO	Mace4-Prover9	EqArgSolver	0.780

[30] Wilcoxon signed-rank test results for ICCMA'19 classic tracks: https://iccma2019.dmi.unipg.it/wilcoxon/all_res_wilcoxon.txt.

Table 9
Wilcoxon signed-rank test results between Taas-dredd and other ICCMA'19 classic track solvers, where p-value $\geqslant 0.05$

DC-CO	Taas-dredd	EqArgSolver	0.358
DC-CO	Taas-dredd	μ-toksia	0.220
DC-PR	Taas-dredd	EqArgSolver	0.262
DC-PR	Taas-dredd	μ-toksia	0.192
DC-ST	Taas-dredd	CoQuiAAS	0.265
DC-ST	Taas-dredd	EqArgSolver	0.979
DS-PR	Taas-dredd	EqArgSolver	0.495
DS-PR	Taas-dredd	μ-toksia	0.608
DS-ST	Taas-dredd	Aspartix-V19	0.095
DS-ST	Taas-dredd	Pyglaf	0.222
EE-CO	Taas-dredd	Aspartix-V19	0.280
EE-CO	Taas-dredd	CoQuiAAS	0.568
EE-CO	Taas-dredd	μ-toksia	0.137
EE-PR	Taas-dredd	Aspartix-V19	0.666
EE-PR	Taas-dredd	CoQuiAAS	0.458
EE-ST	Taas-dredd	Pyglaf	0.179
SE-CO	Taas-dredd	μ-toksia	0.223
SE-PR	Taas-dredd	Pyglaf	0.983
SE-ST	Taas-dredd	Pyglaf	0.579

The findings in Table 9 suggest a statistically non-significant difference in performance between μ-toksia and Taas-dredd, which, however, ranked first and last, respectively, for the tasks DC-CO, DC-PR, DS-PR, EE-CO and SE-CO. It appears that Taas-dredd's behaviour varies considerably depending on the benchmark instances, possibly due to the quality of the heuristics used. Nevertheless, when compared on average, Taas-dredd performs much worse than μ-toksia for all tasks and again, these results do not undermine the validity of the rankings obtained.

6.2. *Comparison with ICCMA'17 solvers*

The first four solvers in ICCMA'17 were compared with the overall winner of ICCMA'19 to quantify the improvements of solvers achieved in two years. The past solvers were also dockerized by asking the participants of ICCMA'17 for those older versions (the participant himself dockerized Pyglaf).

Table 10 shows the scores for Argmat-sat, ArgSemSAT, CoQuiAAS'17, Pyglaf'17, and μ-toksia'19 on the ICCMA'19 benchmark instances. It can be noted that CoQuiAAS'17 has a negative score due to his erroneous behaviour in some tasks of ICCMA'17. μ-toksia also ranks first among these solvers, obtaining two points more than Pyglaf in 2017. Except for the **EE** and **ST** tracks, Argmat-sat performed very well as well. μ-toksia shows better time performance for 20 out of 24 tasks compared to Argmat-sat, while memory consumption is better for Argmat-sat in 15 out of 24 tracks. Only considering completed problem instances, the total time for μ-toksia is 8.2% less than Argmat-sat, while the maximum memory consumption is 112% more for Argmat-sat.[31] B, Table 21 provides detailed results about Argmat-sat '17, Pyglaf '17, and μ-toksia in terms of the total time taken to solve the instances in a task, and the maximum memory consumption across all instances in a given task.

[31] This could mean that Argmast-sat performs better on larger instances due to possible memory exhaustion by μ-toksia.

Table 10
Scores of the first four solvers from ICCMA'17 against the best performer of ICCMA'19: μ-toksia

	Argmat-sat '17	ArgSemSAT '17	CoQuiAAS '17	Pyglaf '17	μ-toksia '19
DC-CO	326	326	326	326	326
DC-GR	326	326	326	326	326
DC-ID	326	–	104	325	326
DC-PR	326	326	323	326	326
DC-SST	326	326	64	325	326
DC-ST	326	317	−550	326	326
DC-STG	326	–	69	326	326
DS-CO	326	326	326	326	326
DS-PR	326	326	266	326	326
DS-SST	326	326	−923	326	326
DS-ST	242	316	20	326	326
DS-STG	326	–	−898	326	326
EE-CO	325	323	311	326	326
EE-PR	326	326	−352	326	326
EE-SST	326	325	−428	325	326
EE-ST	326	321	236	325	325
EE-STG	326	–	−445	326	325
SE-CO	326	325	326	326	326
SE-GR	326	326	326	326	326
SE-ID	326	–	−400	325	326
SE-PR	326	326	−390	326	326
SE-SST	326	326	−517	326	326
SE-ST	326	318	236	326	326
SE-STG	326	–	−547	326	326
Total	7739	5831	−2191	7820	**7822**

6.3. *Comparison between dynamic and non-dynamic solvers*

Finally, the performance of dynamic versions of solvers was compared to the performance of their static equivalents. The benchmark instances and eight modifications each were used for comparison (see Section 5.3). Instances suitable for non-dynamic solvers were also generated by applying the modifications. This comparison considered the total time taken to solve each instance and its modifications for the successfully solved instances, and it was performed for the three solvers submitted to dynamic tracks, namely CoQuiAAS, μ-toksia, and Pyglaf. In Appendix B, Table 22 shows the performance differences – the performance advantage of the dynamic solvers is evident.

On average, the dynamic versions of CoQuiAAS, μ-toksia, and Pyglaf improved their performance over their non-dynamic versions by respectively 81.87%, 27.61%, and 86.54%. The difference between μ-toksia and the other two solvers is probably because it already shows excellent performance in its non-dynamic version, thus outlining a performance limit for both non-dynamic and dynamic tools. In C, Fig. 26a, Fig. 26b and Fig. 26c report the sum of the times of successful instances considering a solver and its dynamic version, respectively, CoQuiAAS, μ-toksia and Pyglaf. Figure 12 shows the percentage improvement per task by considering the three different solvers.

We also show the differences in performance of CoQuiAAS, μ-toksia, Pyglaf, and their dynamic version with respect to the single problem and the semantics. Figure 13 reports the sum of the times,

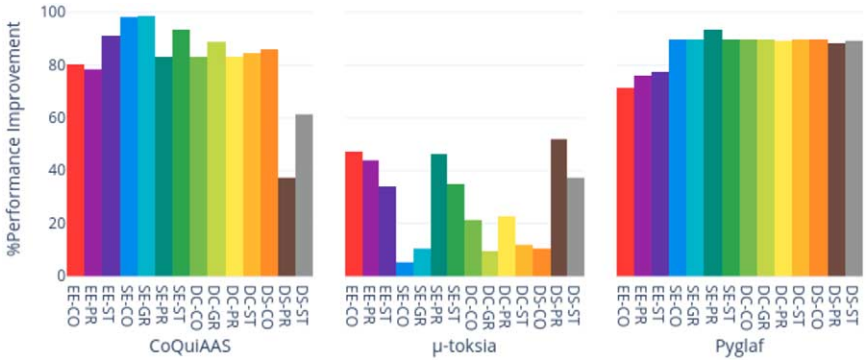


Fig. 12. Percentage performance-improvement of a dynamic solver over its non-dynamic version. Values on the ordinate are computed as $100 - (T_{dynamic} \times 100 \div T_{non\text{-}dynamic})$, where T corresponds to the sum of all solved instances in each task. The bars in the chart correspond to tasks in the legend, read in top-bottom firstly, left-right secondly direction.

aggregated by problem, of successful instances considering a solver and its dynamic version. In Appendix C, Figs 27a to 27c report the sum of the times, aggregated by semantics, of successful instances considering a solver and its dynamic version.

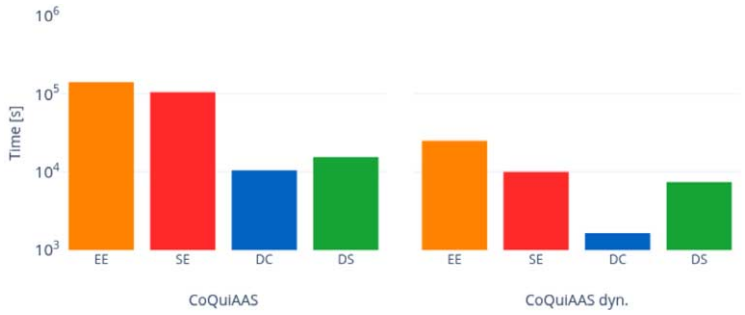
7. Results and analysis for ICCMA'21

Now we describe the results of ICCMA'21. More specifically, we focus on the track dedicated to exact algorithms in Section 7.1 and on the track dedicated to approximate algorithms in Section 7.2. The detailed results (ranking and cumulated runtime) for each pair (problem, semantics) can be found in [55].

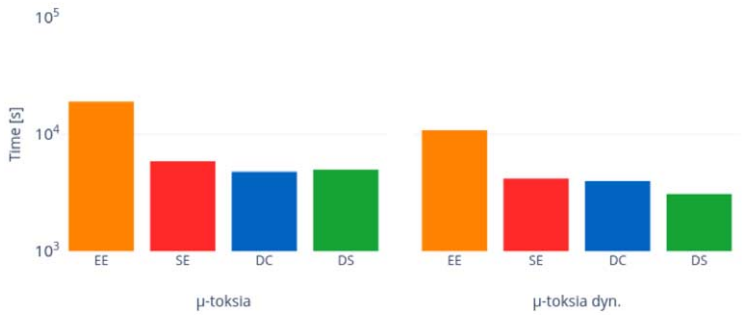
7.1. Exact track

Compared to the previous edition, the main result of the competition is that there is no global winner (μ-toksia, in 2019). Indeed, A-Folio-DPDB won two sub-tracks (**CO** and **ST**), PYGLAF won two sub-tracks (**PR**, **SST**), ASPARTIX-V21 won one sub-track (**STG**) and FUDGE won one sub-track (**ID**). This is a combination of new solvers (A-Folio-DBDP, FUDGE) and updated versions of solvers that already participated in ICCMA (ASPARTIX and PYGLAF). While all these solvers use some reduction to SAT or ASP in some cases, A-Folio-DPDB is the first ICCMA winner based on tree-width analysis of the instances.

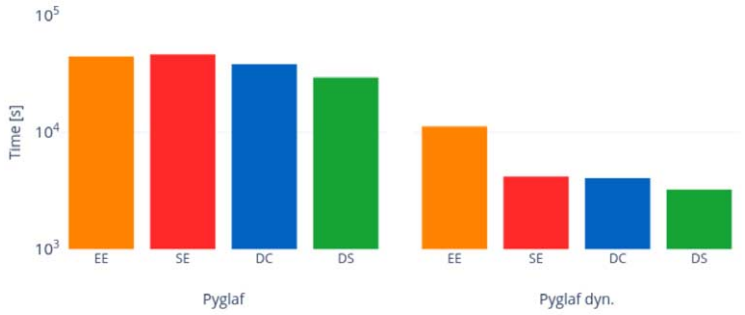
Figure 14 shows the runtime of solving each instance in the exact track for each solver participating in the sub-tracks dedicated to the complete and semi-stable semantics (other semantics are plotted in C). We observe that some groups of instance seem (in general) easier than some other ones. The data is plotted such that instances are sorted in the lexicographical order. This means that the instances on the left side correspond to some of the instances selected from ICCMA'19 (their benchmark names start with A and B), while the instances at the center correspond mainly to the new instances generated for ICCMA'21. This is in line with the intuition that the new instances should be hard for solvers that do not consider the AFs' structure. However, notice that the other instances selected from ICCMA'19 (on the right side, with benchmark names starting with M, n, S, or T) are in some cases easy (e.g. Fig. 14a) and in some cases hard, even harder than the new instances from ICCMA'21 (e.g. Fig. 14b).



(a) CoQuiAAS



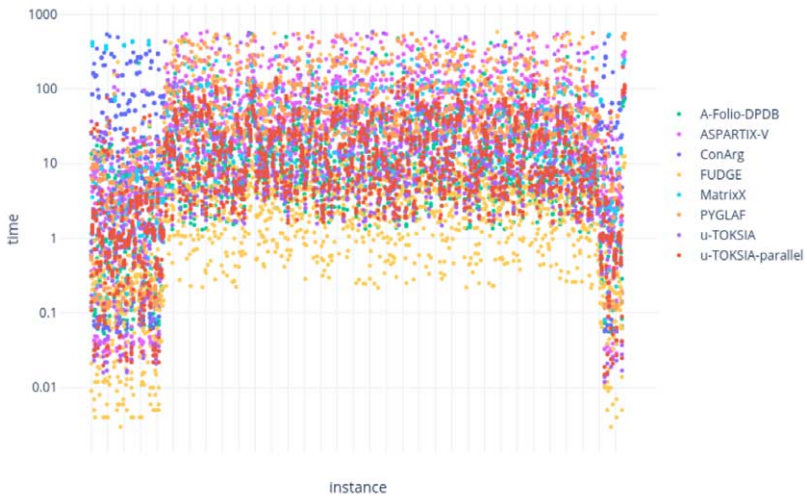
(b) μ-toksia



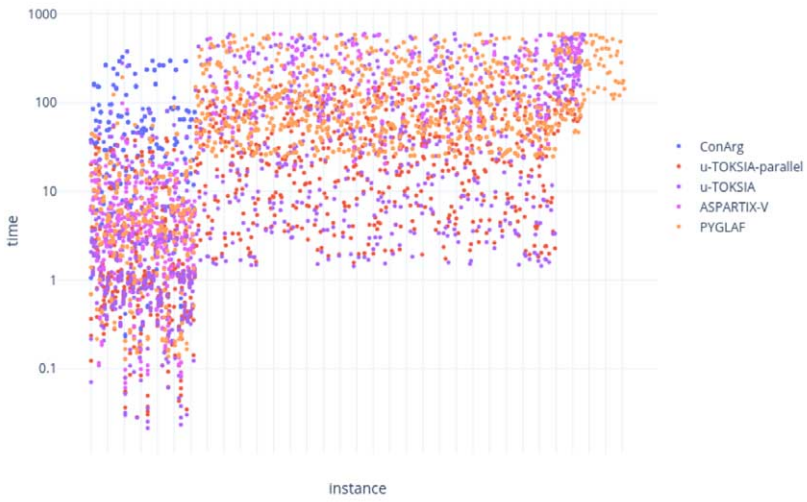
(c) Pyglaf

Fig. 13. The sum of the time (logarithmic scale) aggregated by the problem of successful instances for each track, considering CoQuiAAS, μ-toksia, and Pyglaf, together with their dynamic versions. Times are reported in Table 22 in B.

On Fig. 15, which shows the cumulative runtime (in seconds) for the exact track (under the semantics **CO** and **SST** – other semantics are provided in C), the observations are consistent with the rankings of the competition. More precisely, well-ranked solvers solve more instances in less time, while the last-



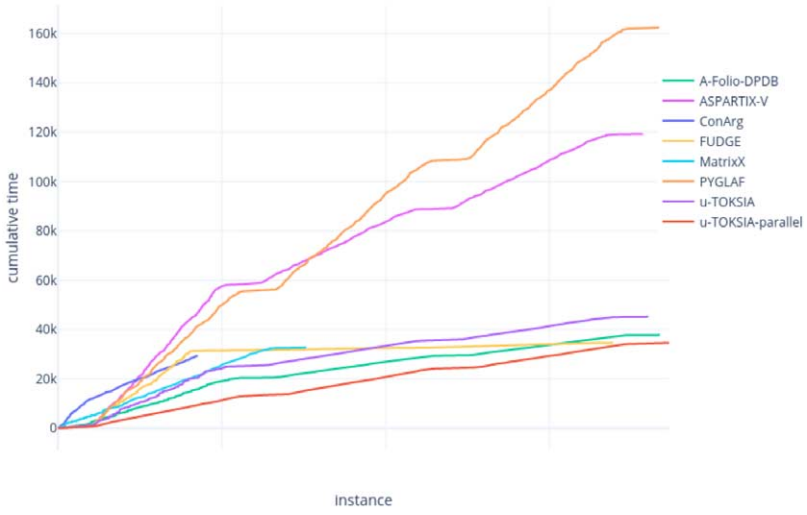
(a) **CO**



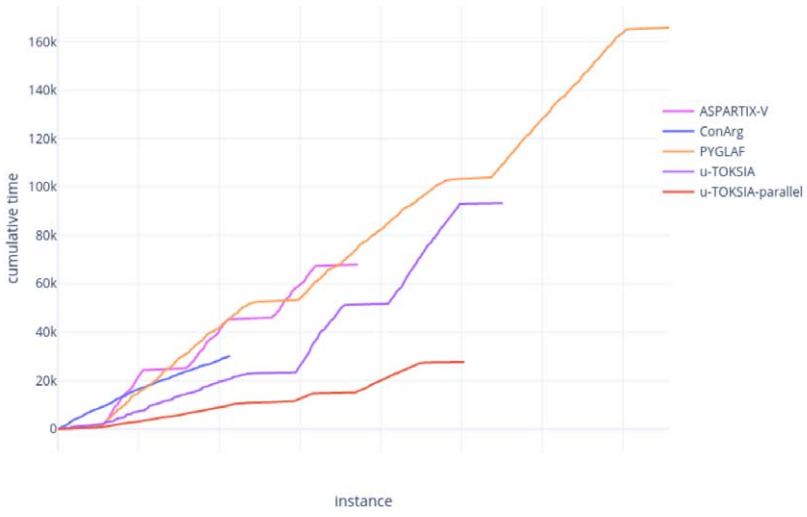
(b) **SST**

Fig. 14. Time [s] taken for each correctly solved instance in the exact track for the semantics **CO** and **SST** – ICCMA'21.

ranked solvers either fail to solve many instances or require much more time. Interestingly, some solvers seem more efficient on "easy" instances but cannot solve more challenging ones. Consider, for instance, μ-toksia (and its parallel version) for the semi-stable semantics (Fig. 15b), and compare it with Pyglaf. μ-toksia's accumulated runtime is much lower than Pyglaf's, but the former has provided an answer for much fewer instances (hence their final ranking).



(a) **CO**



(b) **SST**

Fig. 15. Cumulative time [s] taken to correctly solve all instances in the exact track for the semantics **CO** and **SST** – ICCMA'21.

7.1.1. Comparison with ICCMA'19 best solver

Finally, we have compared μ-toksia (the winner from ICCMA'19) with the best solvers from ICCMA'21, i.e. the ones who performed best on any pair (problem, semantics). As can be seen from Table 11, μ-toksia'19 globally performs better on the instances from ICCMA'21 than the competitors of this edition (including the 2021 version of μ-toksia). One possible explanation for the different per-

Table 11
Scores of the ICCMA'19 winner (μ-toksia) against the best solvers from ICCMA'21

	μ-toksia'19	PYGLAF'21	FUDGE'21	A-Folio-DPDB'21	μ-toksia'21	ASPARTIX-V21
DC-CO	586	557	414	584	522	506
DC-PR	587	557	414	n/a	523	506
DC-ST	585	548	505	585	504	472
DC-SST	582	485	n/a	n/a	481	210
DC-STG	569	149	n/a	n/a	219	245
DS-CO	586	585	587	587	587	587
DS-ID	497	120	258	n/a	108	202
DS-PR	582	425	371	n/a	275	173
DS-ST	587	511	452	575	386	395
DS-SST	580	482	n/a	n/a	230	212
DS-STG	578	164	n/a	n/a	226	256
SE-CO	583	586	587	587	587	587
SE-ID	499	118	234	n/a	108	104
SE-PR	583	210	298	n/a	305	266
SE-ST	585	508	457	577	387	399
SE-SST	583	442	n/a	n/a	285	215
SE-STG	583	504	n/a	n/a	236	271
Total	9735/9979	6951/9979	4577/6457	3495/3522	5969/9979	5606/9979
Percentage	97.55	69.66	70.88	99.23	59.82	56.18

formance of the two versions of μ-toksia is the use of different SAT solvers in the implementation: μ-toksia'19 include Glucose (version 4.1) [8] as the core SAT engine, while μ-toksia'21 exploit CryptoMiniSat (version 5.8.0) [70].

We have only considered **SE**, **DC** and **DS** for this comparison, since μ-toksia (2019) does not support **CE**. A possible way to solve **CE** with this version of the solver would have been to enumerate the extensions (**EE**) and count their numbers ourselves. However, this would have induced an additional runtime related to the input/output operations required to parse the set of extensions provided by μ-toksia. For this reason, the comparison on **CE** would not have been fair.

The number of instances to be solved for each pair (problem, semantics) is the same (587). In all the cases, μ-toksia'19 is close to 100% of solved instances, which means that even when another solver outperforms it, the difference between them is small. On the contrary, in some cases, most other solvers are far from 100% of solved instances. Only A-Folio-DPDB has a higher percentage of solved instances, which is unsurprising since this particular solver is based on μ-toksia'19.

7.1.2. On parallel computing

For the first time at ICCMA'21, there was a submission of a solver relying on parallel computing. Indeed, μ-toksia was submitted in two versions: one where there is only one SAT solver for computing the extensions and one where four threads run in parallel various SAT solvers (or, more precisely, the same SAT solver with different parameters). Only the single-threaded version was considered for the ICCMA ranking, but it is still interesting to discuss the performance of the multi-threaded solver (hereafter named μ-toksia-parallel).

More precisely, for each sub-track, the score of μ-toksia-parallel is compared with the score of (the single-threaded) μ-toksia and the score of the sub-track winner. These scores are summarised in Table 12. In all the cases, μ-toksia-parallel outperforms the single-threaded version. Furthermore, in two

Table 12
Relative performance of μ-toksia-parallel, μ-toksia, and the winner of each sub-track

Solver	Score	Solver	Score	Solver	Score
(a) Complete Semantics		(b) Preferred Semantics		(c) Semi-stable Semantics	
μ-toksia-parallel	1868	μ-toksia-parallel	1322	PYGLAF	1515
A-Folio DPDB	1838	PYGLAF	1299	μ-toksia-parallel	1216
μ-toksia	1803	μ-toksia	1210	μ-toksia	1103
(d) Stable Semantics		(e) Stage Semantics		(f) Ideal Semantics	
A-Folio DPDB	1862	ASPARTIX-V21	879	FUDGE	492
μ-toksia-parallel	1737	μ-toksia-parallel	807	μ-toksia-parallel	465
μ-toksia	1441	μ-toksia	788	μ-toksia	216

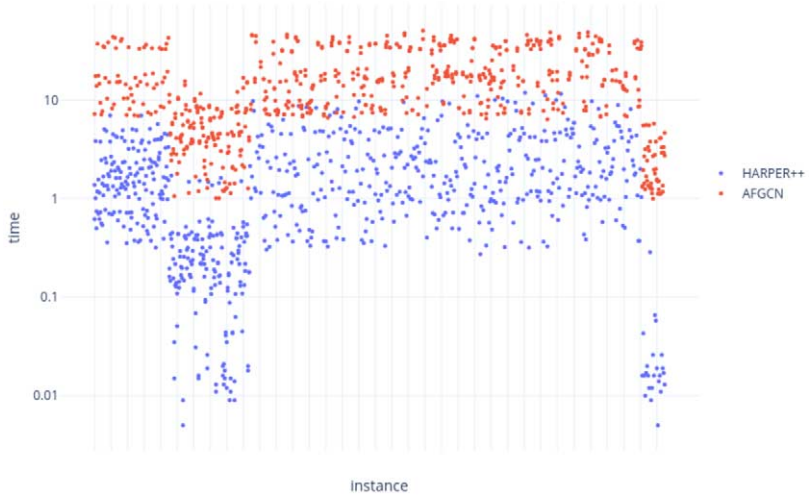


Fig. 16. Time [s] taken for each correctly solved instance in the approximate track for the complete semantics – ICCMA'21.

cases (the complete and preferred semantics), it even outperforms the winner of the sub-track (namely A-Folio DPDB for the complete semantics and PYGLAF for the preferred semantics).

7.2. Approximate track

For the track dedicated to approximate algorithms, HARPER++ won two sub-tracks (**CO**, **ID**), while AFGCN won the other sub-tracks. However, an essential difference between both solvers is their runtime: AFCGN is much slower than HARPER++ in all cases, as can be seen in Fig. 16 (runtime for each instance, for the complete semantics) and Fig. 17 (cumulative runtime for the complete semantics).[32] This comes from the fact that HARPER++ mainly relies on the grounded extension, which can be computed in linear time (in the number of arguments). The detailed results for each pair (problem, semantics) are described in [55]: it shows that, in general, HARPER++ is more accurate for skeptical reasoning (**DS**) while AFGCN is more accurate for credulous reasoning (**DC**).

[32] Figures for the other semantics are given in C.

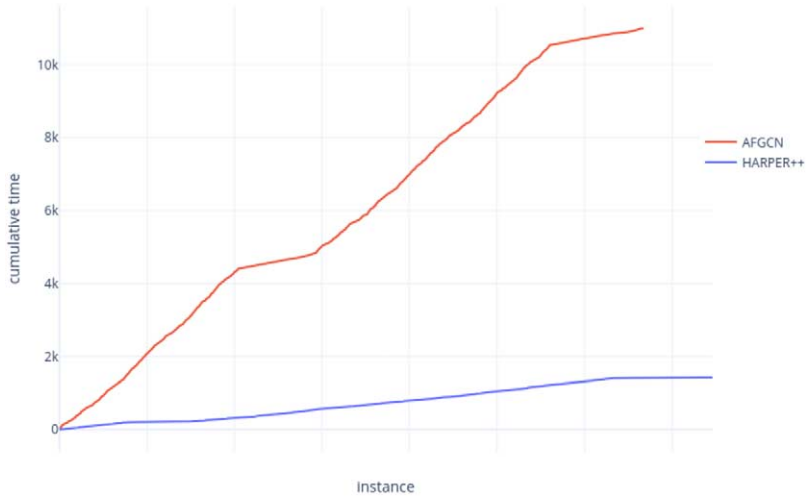


Fig. 17. Cumulative time [s] taken to correctly solve all instances in the approximate track for the complete semantics – ICCMA'21.

8. Contributions of solvers to the state of the art

While the above results show the performance of each solver individually, they do not show how much each solver contributed to the state of the art, as defined by all solvers. While an individual solver may have the best overall performance, it may perform only marginally better than others, albeit consistently. Conversely, a solver may not have outstanding performance across the entire set of instances but beat every other solver on a small subset – without it, the state of the art would be significantly worse for those instances.

The Shapley value was computed for each solver in each non-dynamic track to assess their contributions to the state of the art [41,50]. Briefly, the Shapley value is the average increase in performance we see by adding the solver in question to any subset of the other solvers. It is a game theory concept with various desirable properties that guarantee a fair credit allocation to each solver. Table 13 shows the results for all solvers across all tracks for both years.

In 2019, μ-toksia, the overall best solver, ranks last regarding Shapley value. This indicates that while it has great overall performance, there is no case where it is much better than all the other solvers – it only slightly improves the ICCMA'19 state of the art. On the other hand, Taas-dredd, which ranks last overall, is second in terms of Shapley value, just behind Pyglaf. While in many cases, it does not perform well, there are cases where it performs much better than the other solvers, making a significant contribution to the state of the art.

The ranking of solvers for the 2021 competition in terms of Shapley value closely follows the ranking of individual performance when aggregated by sub-track. For the global results, the Shapley value is correlated to both the solver's individual performance and the number of tracks it participated in (for instance, Pyglaf and μ-toksia have a higher value than A-Folio DPDB, which participated only in two sub-tracks).

We see a similar picture for most of the individual tracks. These results reveal the recipe for a competition-winning solver – achieve good performance across all instances with a tried-and-tested approach rather than using a new heuristic that works well in only a few cases. They also show the value

Table 13
Shapley values of all solvers across all tracks and years in terms of score

Year/Track	Algorithm	Shapley Value
2019	Pyglaf	6652
	Taas-dredd	6187
	Argpref	3371
	Mace4/Prover9	2726
	Aspartix	1832
	Yonas	1832
	EqArgSolver	1517
	CoQuiAAS	99.25
	μ-toksia	1.014
2021/Approximate	AFGCN	1378
	HARPER++	983.5
2021/Exact	Pyglaf	1056
	μ-toksia	667.5
	μ-toksia-parallel	632.7
	Aspartix	619.9
	FUDGE	520.1
	A-Folio DPDB	454.5
	ConArg	0.4524
	MatrixX	0

of the Shapley analysis – we can identify solvers that are much better than anything else on some parts of the competition instances, allowing us to give credit to novel and very different approaches.

Finally, it is worth noting that the solvers in ICCMA'19, and especially ICCMA'21, have shown a significant improvement in terms of correctness in comparison to the 2015 and 2017 editions, where several participants provided incorrect answers.

9. Lessons learned

Organizing and running a competition requires a lot of effort and dedication. In this section, we give some of our insights into what could be improved in the hope that it will be helpful for the organizers of future competitions in AI.

9.1. ICCMA 2019

The requirement for all submitted solvers to use Docker in ICCMA'19 saved much work in setting up solvers and ensuring they ran correctly. However, Docker containers cannot be run directly on most HPC infrastructure because of Docker's security deficiencies. To leverage our HPC infrastructure to provide the large amount of computational resources required, the Docker containers were converted to Singularity containers,[33] which could be run without problems. The underlying virtualization is the same, and the conversion is straightforward; for the purposes of this competition, Docker and Singularity are equivalent.

[33] Singularity website: https://sylabs.io/singularity/.

JSON inspires the standardized output format required for submitted solvers but does not entirely conform to the JSON standard. Various pre-processing steps were implemented in ICCMA'19 that transformed the output format into JSON and handled simple cases directly. While this allowed us to use a standard JSON parser, the additional steps could have been avoided with simple modifications to the output format. It can be recommended that competition organizers require standard formats as far as possible to avoid implementing custom parsers.

As can be seen from the results of the competitions held in 2017 and 2019, the performance of participants relying on SAT varies greatly depending on the implementation of the SAT solver itself. Concerning solvers submitted to ICCMA'19, Argpref implements MiniSAT 2.2.0, a SAT-with-preferences based approach [36], μ-toksia and Pyglaf are both dependant on the Boolean SAT solver Glucose (version 4.1) [7,8], and Taas-dredd implements the DPLL-algorithm (Davis-Putnam-Logemann-Loveland) backtracking algorithm for SAT solving [15, Chapter 3]. In ICCMA'21, Pyglaf is still based on Glucose, FUDGE uses the SAT solver CaDiCaL 1.3.1,[34] while, differently from the 2019 edition, μ-toksia includes CryptoMiniSat (version 5.8.0) [70] as the underlying SAT solver.

Selecting the benchmarks to use could lead to errors in the evaluation phase. As shown in [69], 23% of AFs from ICCMA'17 could not be enumerated by any solver. To avoid potential issues, ICCMA'19 instances were limited to those solvable by ConArg, the reference solver. Indeed, the reference solver had a different time and memory limitation than the participant in the competition; ConArg was given 10 times the time and memory space used in the competition to solve problems. So, despite Conarg not having the best time and memory performance of other solvers, the benchmarks also included difficult (enough) instances. Indeed, ConArg is developed and maintained by some of the ICCMA'19 organizers, hence the decision to use it as a reference solver.

9.2. ICCMA 2021

The organizers of the 2021 edition appreciated the use of Docker in ICCMA'19. However, a part of the community did not receive it well. Furthermore, some technical difficulties were encountered, which prevented the organizers from using Docker again for ICCMA 2021. As a result, various issues arose when setting up the competition environment, such as ensuring that all the submitted solvers were correctly compiling or running.

The exceptional results of μ-toksia 2019 (even when compared to more recent solvers submitted to ICCMA 2021) may give the impression that choosing the "best" SAT solver is enough to solve all the argumentation problems. However, experimental evaluations [43,46] have shown that no SAT solver is strictly dominating the other ones for solving argumentation tasks, but each solver has its own strengths and weaknesses, depending on the problem to be solved, the semantics, and the instance. An exact characterization of which SAT solver is the best for each of these combinations is still an open question.

Moreover, beyond the SAT-based approaches, other approaches have been studied in the literature (e.g., based on graph decomposition [57] or backdoors [33]). These approaches seem promising but were mainly absent from ICCMA. However, let us notice that the success of A-FOLIO-DPDB for the counting task (using a technique based on the graph treewidth) confirms the interest of such approaches. So, we believe that one of the main challenges for the near future of the ICCMA competition is to provide challenging benchmarks that could not be solved by "simply" plugging a SAT solver but would require a more fine-grained analysis of the graph properties like those mentioned here. We have started this effort with our community-based benchmark generation approach.

[34] CaDiCaL documentation: https://fmv.jku.at/cadical/.

We envision two last directions for improving the competition. Regarding the main track, it seems important to be able to guarantee the results of the solvers, e.g., providing not only a YES/NO answer to decision problems but also completing them with a certificate. This effort has been started by the recent ICCMA 2023, which requires a certificate with positive answers for credulous acceptability and negative answers for skeptical acceptability. Finding certificates for other cases is a challenge, but inspiration could be taken from other communities (e.g. in SAT competitions, UNSAT instances are certified as well[35]).

Finally, regarding the approximate track, various important questions should be investigated, like the possibility of giving guarantees about the proximity between the correct result and the answer provided by the algorithms or approximate algorithms for computing one extension or the set of (skeptically or credulously) accepted arguments.

10. Conclusion

This paper described the 2019 and 2021 editions of the International Competition on Computational Models of Argumentation. In particular, we have outlined the submitted solvers, benchmarks, ranking design, and results obtained by solvers. To evaluate the improvement of solvers over time, we have also compared the top 2019 solvers with the ones that participated in ICCMA'17, and similarly for the best solvers of 2021 with the winner of ICCMA'19. The top solver in 2019, i.e., μ-toksia, shows better performance when compared by using the same ranking criteria with respect to solvers in ICCMA'17; this can also be appreciated in terms of the total time taken to solve instances, which is often less than 2017 solvers, while memory consumption is often higher – there is a clear improvement in state of the art between the two competitions. Notably, μ-toksia'19 also outperforms the solvers from ICCMA'21, including the updated version of μ-toksia that participated in ICCMA'21. We further compared the performance of dynamic solvers to their non-dynamic counterparts in ICCMA'19. The performance improvement is quite significant, suggesting that dynamic solvers should be used whenever possible, for example, to compute semantics frequently during the evolution of debates. The competition results are easily reproducible, as all submitted solvers are publicly available in Docker containers. Finally, we described the results of the track dedicated to approximate algorithms newly introduced at ICCMA'21. We showed that both approaches participating in this track offer interesting results regarding accuracy and runtime.

Several changes were implemented between ICCMA'19 and ICCMA'21 to enhance the competition's significance and meet community expectations. The organizers of ICCMA'21 decided not to utilize Docker as a platform for standardizing solver execution due to technical challenges and reservations from part of the community. Moreover, the absence of participants in the dynamic track led to its removal in ICCMA'21, where an approximate track replaced it. As for individual tasks, ICCMA'21 replaced the enumeration of grounded extensions (which is not a difficult challenge) with a counting task. Finally, contrary to what happened in ICCMA'19, where the organizers used ConArg as a reference solver to evaluate the correctness of the participants, the results of each solver in the exact track of ICCMA'21 were checked for inconsistencies against all the other participants.

ICCMA provides an opportunity to advance research in computational argumentation by fostering the development of efficient solvers capable of addressing real-world problems. The competition's benchmarks comprise large frameworks that are not typically representative of real-life scenarios involving

[35] See https://satcompetition.github.io/2023/certificates.html.

conflicting information, which can usually be modeled through smaller graphs. Therefore, other crucial factors should also be considered, such as the ability to generalize and ease of use for non-expert end-users. The best solver to use might not be the fastest one, but instead, the solver that comes with APIs for several programming languages, web interfaces, and easy-to-follow manuals or guides. In future competitions, having a criterion that considers these usability parameters would be beneficial. On the other hand, there exist particular applications of argumentation theory (for instance, to produce/enhance explanations for neural networks [9,65]) in which the input data reaches a significant size. In this case, a separate consideration must be made as the solvers' performance will still play a fundamental role in addressing related problems. In future competitions, it would be interesting to use neural networks as benchmarks to test the behavior of solvers.

Acknowledgements

We want to thank all the participants of ICCMA'19 and ICCMA'21 for submitting their solvers and benchmarks and thus directly participating in advancing computational models of argumentation. We also thank the ICCMA steering committee for providing support and help in setting up the competition. Finally, we would like to thank Dr. Theofrastos Mantedalis for the help provided in organizing ICCMA'19.

We thank the Advanced Research Computing Center at the University of Wyoming for providing the computational resources used for the 2019 edition and the analysis of the results. Lars Kotthoff is supported by NSF grant 1813537. We thank the Centre de Recherche en Informatique de Lens at the Université d'Artois for running the 2021 edition on its computer cluster, which was funded by the French Ministry of Research and the Région Hauts de France through CPER DATA.

Appendix A. Benchmark selection

Benchmark selection for ICCMA 2019. We report the number of frameworks we selected from each sub-benchmark to assemble the benchmark of ICCMA'19. A1 to T4 are benchmarks also used in ICCMA'17 (we point the interested reader to the website of ICCMA'17), while S, M (ICCMA19B1), and N (ICCMA19B2) are the two new benchmarks described in Section 5.3: A1 (28), A2 (20), A3 (14), A4 (4), B1 (21), B2 (12), B3 (16), B4 (1), C1 (22), C2 (6), C3 (1), T1 (26), T2 (15), T3 (16), T4(5), S (105), M (7), N (10).

Benchmark selection for ICCMA 2021. Now we report the number of instances selected from each dataset for ICCMA'21. Regarding the instances from ICCMA'19, recall that A1 to T4 are actually the benchmarks from ICCMA'17, while S and M are the datasets from ICCMA19B1, and N comes from ICCMA19B2: A1 (2), A2 (10), A3 (13), A4 (4), B1 (1), B2 (10), B3 (16), B4 (1), C1 (5), C2 (6), C3 (1), T2 (8), T3 (13), T4 (5), S (1), M (7), N (4).

Appendix B. Detailed results

Results for ICCMA 2019. Tables 14 to 20 show the aggregated results of solvers by each different semantics (**CO**, **PR**, **ST**, **SST**, **STG**, **GR** and **ID**): for example **SE**, **SE**, **DC** and **DS** tasks related to

Table 14
Results of the **CO** track, aggregating **EE**, **SE**, **DC**, and **DS** tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Aspartix	1304	0	0	0	0	0	0	2873.198	94019584	1304
CoQuiAAS	1302	0	0	0	0	2	0	5060.037	969428992	1302
EqArgSolver	1166	0	0	0	0	138	0	97244.536	474550272	1166
μ-toksia	1304	0	0	0	0	0	0	1309.272	90816512	1304
Pyglaf	1304	0	0	0	0	0	0	4660.723	50774016	1304
Taas-dredd	987	10	203	0	0	104	0	77462.209	99794944	−163.190
Yonas	1200	0	0	0	0	86	18	238724.722	9999351808	1035.829

Table 15
Results of the **PR** track, aggregating all the tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Aspartix	1299	0	5	0	0	0	0	4346.610	92950528	1274
CoQuiAAS	1301	0	0	0	0	3	0	6601.919	93622272	1301
EqArgSolver	1166	0	0	0	0	138	0	96887.766	3063808	1166
μ-toksia	1304	0	0	0	0	0	0	1405.415	89145344	1304
Pyglaf	1257	0	47	0	0	0	0	5656.699	82247680	1022
Taas-dredd	863	15	236	0	0	190	0	143690.076	99987456	−436.032
Yonas	1009	177	1	0	0	94	23	363580.659	9979367424	836.678

Table 16
Results of the **ST** track, aggregating all the tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Aspartix	1304	0	0	0	0	0	0	2111.697	86528000	1304
CoQuiAAS	1303	0	0	1	0	0	0	1978.757	65941504	1303
EqArgSolver	1160	0	0	0	0	144	0	100895.672	3059712	1160
μ-toksia	1304	0	0	0	0	0	0	999.592	78954496	1304
Pyglaf	1304	0	0	0	0	0	0	4863.809	98836480	1304
Taas-dredd	791	13	278	0	0	222	0	170496.572	99676160	-718.032
Yonas	915	185	12	0	1	163	28	411195.085	9995333632	700.669

Table 17
Results of the **SST** track, aggregating all the tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Aspartix	1138	21	139	0	5	1	0	4868.853	59879424	428.699
CoQuiAAS	1298	0	0	1	0	5	0	8137.338	94203904	1298
μ-toksia	1303	0	0	0	0	1	0	3226.112	88989696	1303
Pyglaf	1303	0	0	0	0	1	0	6317.506	92397568	1303

Table 18
Results of the **STG** track, aggregating all the tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Aspartix	1215	24	65	0	0	0	0	3841.746	87470080	882.219
CoQuiAAS	1289	0	0	1	0	14	0	15855.341	99647488	1289
μ-toksia	1303	0	0	0	0	1	0	3191.954	75272192	1303
Pyglaf	1300	0	2	0	0	2	0	7479.289	95862784	1290

Table 19
Results of the **GR** track, aggregating all the tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Aspartix	652	0	0	0	0	0	0	930.546	3080192	652
CoQuiAAS	652	0	0	0	0	0	0	434.905	3055616	652
EqArgSolver	652	0	0	0	0	0	0	256.632	3059712	652
μ-toksia	652	0	0	0	0	0	0	238.776	3059712	652
Pyglaf	360	0	292	0	0	0	0	1900.577	409772032	−1100
Taas-dredd	502	0	150	0	0	0	0	218.212	3059712	−248
Yonas	652	0	0	0	0	0	0	5736.522	3055616	652

Table 20
Results of the **ID** track, aggregating all the tasks – ICCMA'19

Solver	#Corr	#Cra	#Inc	#Fail	#Inv	#TO	#OOM	Time	Memory	Score
Argpref	652	0	0	0	0	0	0	4241.309	46161920	652
Aspartix	648	0	1	0	0	3	0	5232.252	82718720	643
CoQuiAAS	651	0	0	0	0	1	0	3615.624	86106112	651
μ-toksia	652	0	0	0	0	0	0	1594.610	93822976	652
Pyglaf	650	0	0	0	0	2	0	8133.248	82640896	650

the complete semantics are aggregated in Table 14. The columns *Solver*, *#Corr*, *#Cra*, *#Inc*, *#Fail*, *#Inv*, *#TO*, *#OOM*, *Time*, *Memory*, and *Score* correspond to: the name of the solver, the number of correct answers, number of crashes, number of incorrect answers, number of failures, number of invalid answers, number of timeouts, number of out-of-memory, running time (total, seconds), used memory (max) and final score, respectively. In detail, #Cra refers to the number of times the solver crashed due to memory issues, #Fail corresponds to all those runs that did not produce an answer (e.g. because of timeouts), #Inc refers to syntactically correct but wrong answers, and #Inv is the number of syntactically incorrect answers.

Table 21 provides detailed results about Argmat-sat '17, Pyglaf '17, and μ-toksia in terms of the total time to solve the instances in a task and the maximum memory consumption across all instances in a given task.

From Table 22 we extracted Fig. 12: it shows the performance improvement between ICCMA'19 dynamic-solvers and their non-dynamic version.

Results for ICCMA 2021. We show the results aggregated for each sub-track (i.e. each semantics). Detailed results for each task (**CE**, **SE**, **DS**, **DC**) are described in [55].

Exact Track. Table 23 to 28 show, respectively, the results for the complete, preferred, semi-stable, stable, stage and ideal semantics for the exact track. The score of the solvers at the competition corresponds to the number of correctly solved instances within the time limit (#CORR). Only Table 27 contains a column #Inc, since **CE-STG** is the only task with incorrect results.

PYGLAF was removed from the **STG** sub-track ranking because of wrong results on **CE-STG**. In Table 27, we give all the results for the **STG** sub-track, including the information about PYGLAF, with the details on the number of incorrectly solved instances.

Approximate Track. Table 29 to 34 show, respectively, the results for the complete, preferred, semi-stable, stable, stage and ideal semantics.

Table 21

The total time to solve instances in a track (T), and the max memory-consumption (M) recorded among all the tested instances, comparing Pyglaf'17, Argsemsat '17, and μ-toksia. In bold, we highlighted the best performance for each track

	Argmat-sat '17 (T)	Pyglaf '17 (T)	μ-toksia (T)	Argmat-sat '17 (M)	Pyglaf '17 (M)	μ-toksia '19 (M)
DC-CO	247.606	868.639	**144.566**	**2744320**	101429248	3059712
DC-GR	186.649	816.788	**118.020**	**2748416**	408502272	3059712
DC-ID	1219.777	3689.534	**779.923**	359321600	408530944	**93822976**
DC-PR	224.471	909.690	**143.485**	**2748416**	101511168	3059712
DC-SST	646.953	1176.023	**382.811**	63500288	410750976	**61640704**
DC-ST	198.537	936.490	**134.863**	**2748416**	103944192	3059712
DC-STG	677.609	1129.134	**304.506**	220917760	320135168	**3059712**
DS-CO	289.909	824.397	**119.092**	**2748416**	407949312	3059712
DS-PR	329.712	1291.082	**260.691**	**2744320**	408477696	3055616
DS-SST	**350.531**	820.685	439.937	**41095168**	410763264	71610368
DS-ST	228.015	982.555	**197.775**	**2748416**	407928832	3059712
DS-STG	439.977	465.708	**398.004**	**24285184**	298020864	50610176
EE-CO	1234.672	1699.336	**926.960**	**58286080**	408096768	90816512
EE-PR	1140.984	1793.324	**782.133**	335994880	408428544	**89145344**
EE-SST	**694.502**	1343.793	2050.861	**62275584**	410533888	88989696
EE-ST	1225.934	1340.969	**483.222**	**64880640**	408113152	78954496
EE-STG	**708.887**	1237.260	2213.428	217391104	319905792	**75272192**
SE-CO	186.475	837.489	**118.654**	**2748416**	408133632	3055616
SE-GR	188.254	831.678	**120.756**	**2744320**	408457216	3055616
SE-ID	1212.473	4094.385	**814.687**	359583744	409243648	**93466624**
SE-PR	290.008	1774.713	**219.106**	**2748416**	408219648	3059712
SE-SST	**334.826**	1050.739	352.503	**40849408**	410308608	62005248
SE-ST	256.407	938.164	**183.732**	**2752512**	408113152	3059712
SE-STG	433.657	605.012	**276.016**	24702976	319684608	**3059712**

Table 22

For each task in ICCMA'19, the sum of the times using the dynamic version of a solver (**D**) and the non-dynamic solver on the same instances

	CoQuiAAS **D**	CoQuiAAS	μ-toksia **D**	μ-toksia	Pyglaf **D**	Pyglaf
EE-CO	11245.699	57452.466	4014.1	7614.729	4091.292	14305.657
EE-PR	11016.949	51246.702	3840.326	6852.05	4005.905	16698.682
EE-ST	2978.907	33066.517	3041.083	4592.005	3118.97	13687.683
SE-CO	415.898	22150.552	991.753	1047.821	957.432	9382.833
SE-GR	220.476	16073.153	939.169	1047.905	971.831	9340.286
SE-PR	7990.63	46583.326	1128.106	2094.996	1118.985	16863.551
SE-ST	1392.604	21310.391	1103.307	1692.002	1125.505	10655.019
DC-CO	556.403	3263.978	998.394	1264.71	1016.12	9614.515
DC-GR	218.591	1944.182	955.222	1056.546	972.122	9395.487
DC-PR	552.116	3215.875	976.361	1263.765	1002.714	9319.65
DC-ST	322.382	2048.395	1056.926	1200.064	1064.172	10090.488
DS-CO	416.792	2912.148	945.012	1057.074	976.008	9437.691
DS-PR	5563.113	8859.674	1066.52	2218.847	1091.149	9354.401
DS-ST	1479.013	3841.023	1081.253	1718.16	1185.033	10822.633

Table 23
Results of the exact **CO** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#TO	#OOM	#Corr	Time
1	A-Folio DPDB	356	154	1838	256865.269137
2	PYGLAF	506	7	1835	471672.364965
3	μ-toksia	545	0	1803	366929.58568
4	ASPARTIX-V21	561	0	1787	457280.325126
5	FUDGE	653	0	1695	417615.509689
6	MatrixX	1589	0	759	746642.199855
7	ConArg	1920	0	428	806693.680245

Table 24
Results of the exact **PR** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#TO	#OOM	#Corr	Time
1	PYGLAF	1049	0	1299	763331.549189
2	μ-toksia	1130	8	1210	781100.071756
3	FUDGE	1158	0	1190	778747.086111
4	ASPARTIX-V21	1296	0	1052	893080.384484
5	ConArg	1919	0	429	1078990.372535

Table 25
Results of the exact **SST** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#TO	#OOM	#Corr	Time
1	PYGLAF	675	158	1515	608878.736437
2	μ-toksia	1242	3	1103	837705.709219
3	ASPARTIX-V21	1604	0	744	1030815.676415
4	ConArg	1920	0	428	799122.13297

Table 26
Results of the exact **ST** track, aggregating all the tasks – ICCMA '21

Rank	Solver	#TO	#OOM	#Corr	Time
1	A-Folio-DPDB	403	83	1862	399310.875341
2	PYGLAF	605	0	1743	584282.048277
3	FUDGE	763	0	1585	628810.979216
4	μ-toksia	902	4	1441	693282.745979
5	ASPARTIX-V21	919	0	1429	713113.490005
6	ConArg	1919	0	429	569940.064742
7	MatrixX	2089	0	259	988008.858822

Table 27
Results of the exact **STG** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
n/a	PYGLAF	40	1078	0	1230	788942.719787
1	ASPARTIX-V21	0	1469	0	879	980538.66247
2	μ-toksia	0	1556	4	788	1006700.226719
3	ConArg	0	1923	0	425	321370.304013

Table 28
Results of the exact **ID** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#TO	#OOM	#Corr	Time
1	FUDGE	682	0	492	464947.160094
2	ASPARTIX-V21	868	0	306	543003.026772
3	PYGLAF	936	0	238	581959.560274
4	μ-toksia	952	6	216	574761.838951
5	ConArg	960	0	214	601182.943059

Table 29
Results of the approximate **CO** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
1	HARPER++	366	0	0	747	1635.459946
2	AFGCN	84	361	0	668	34155.56654

Table 30
Results of the approximate **PR** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
1	AFGCN	90	150	0	567	18392.00973
2	HARPER++	369	0	0	438	742.960579

Table 31
Results of the approximate **SST** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
1	AFGCN	64	135	0	522	15762.23359
2	HARPER++	370	0	0	351	671.55106

Table 32
Results of the approximate **ST** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
1	AFGCN	120	198	0	637	23900.77196
2	HARPER++	454	0	0	457	932.037855

Table 33
Results of the approximate **STG** track, aggregating all the tasks – ICCMA'21

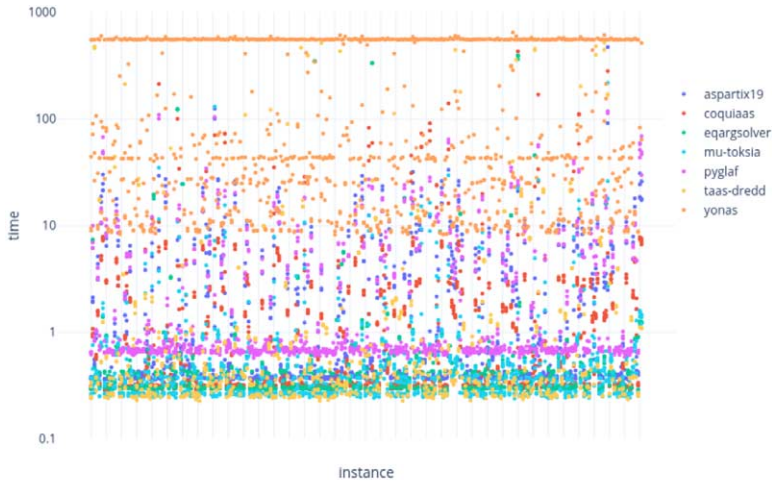
Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
1	AFGCN	71	0	0	392	4530.34336
2	HARPER++	114	0	0	349	98.217632

Table 34
Results of the approximate **ID** track, aggregating all the tasks – ICCMA'21

Rank	Solver	#Inc	#TO	#OOM	#Corr	Time
1	HARPER++	2	0	0	108	9.848397
2	AFGCN	2	0	0	108	470.655630

Appendix C. Additional figures

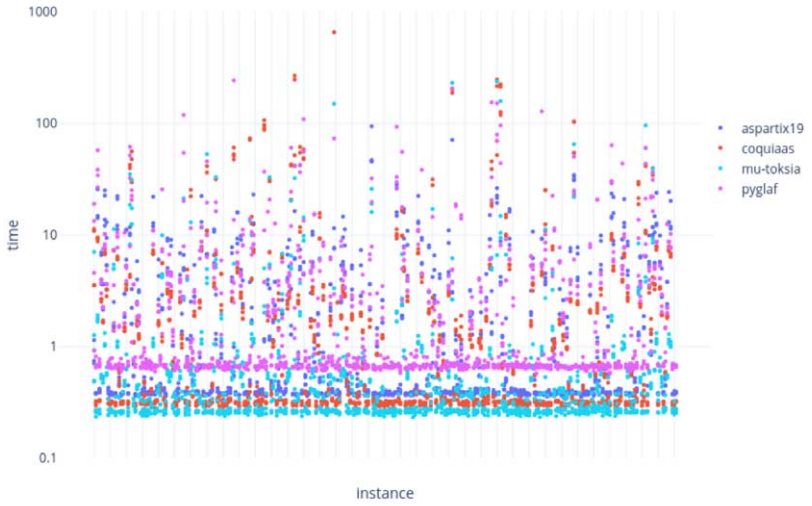
C.1. ICCMA'19



(a) **PR**

(b) **ST**

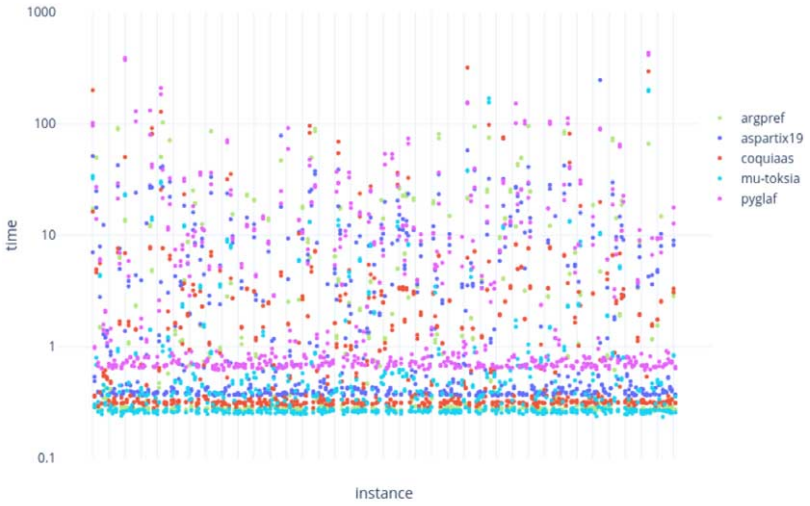
Fig. 18. Time [s] taken for each correctly solved instance in the classical and dynamic track – ICCMA'19.



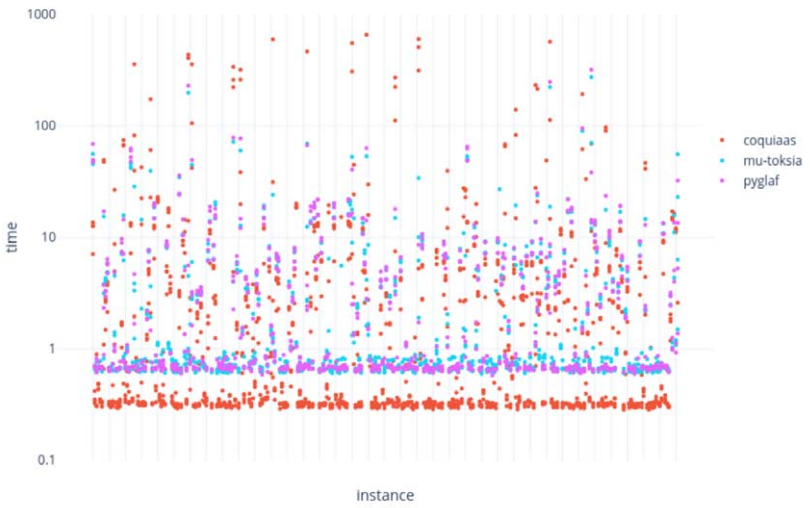
(a) **STG**

(b) **GR**

Fig. 19. Time [s] taken for each correctly solved instance in the classical and dynamic track – ICCMA'19 (cont.).

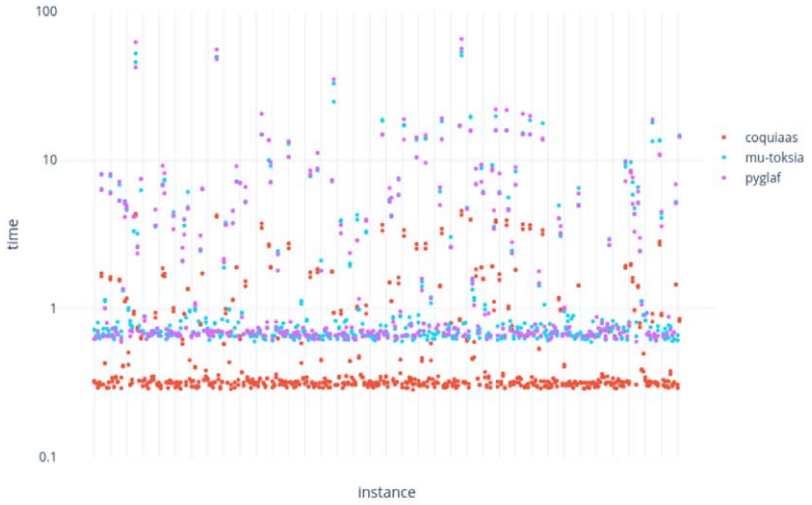


(a) **ID**



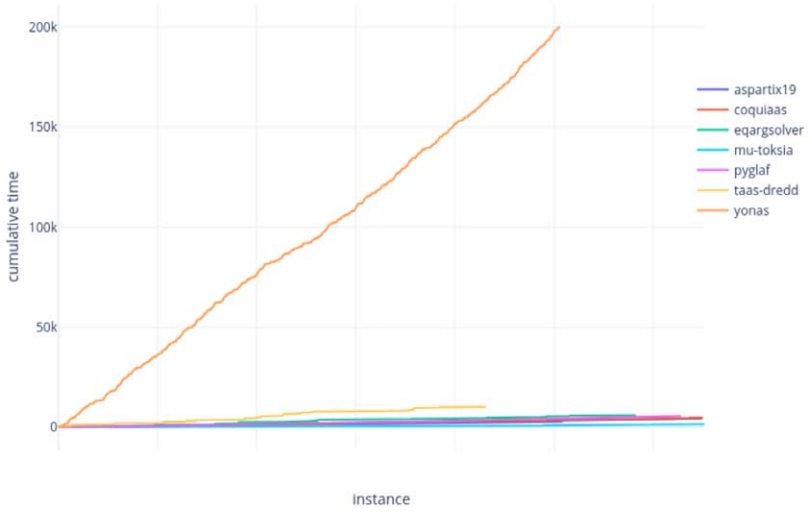
(b) **PR-D**

Fig. 20. Time [s] taken for each correctly solved instance in the classical and dynamic tracks – ICCMA'19 (cont.).



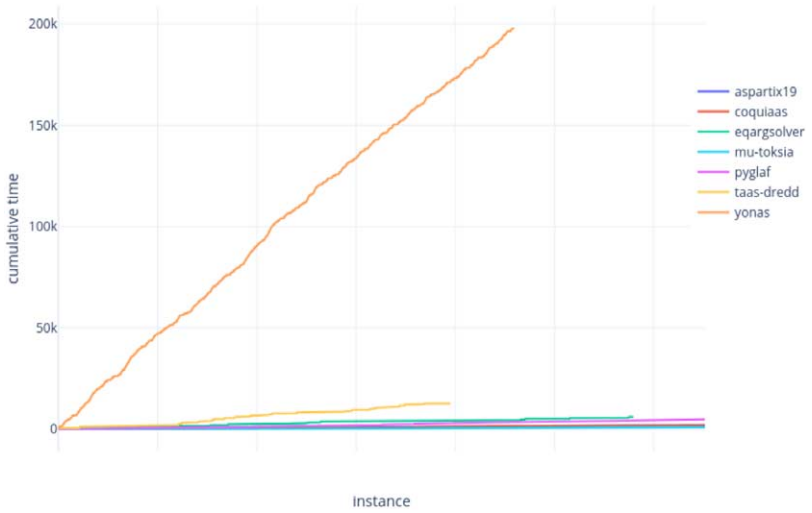
(a) **GR-D**

Fig. 21. Time [s] taken for each correctly solved instance in the classical and dynamic tracks – ICCMA'19 (cont.).

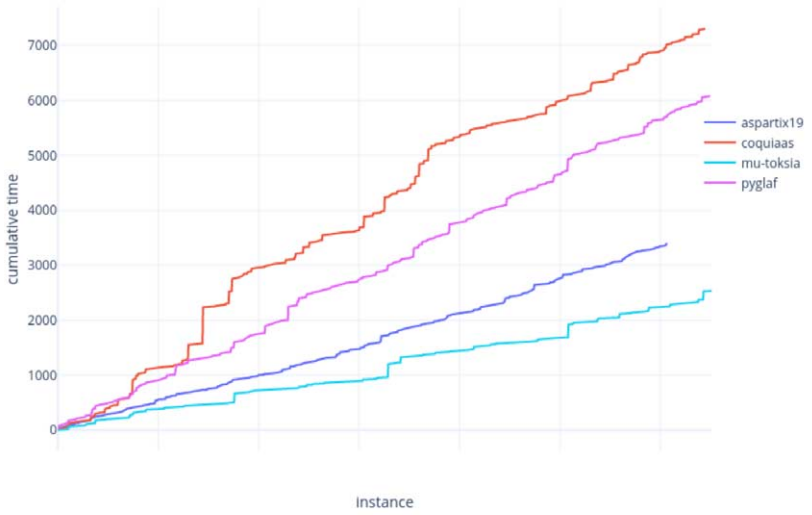


(a) **PR**

Fig. 22. Cumulative time [s] taken to solve all instances in the classical and dynamic tracks correctly – ICCMA'19.

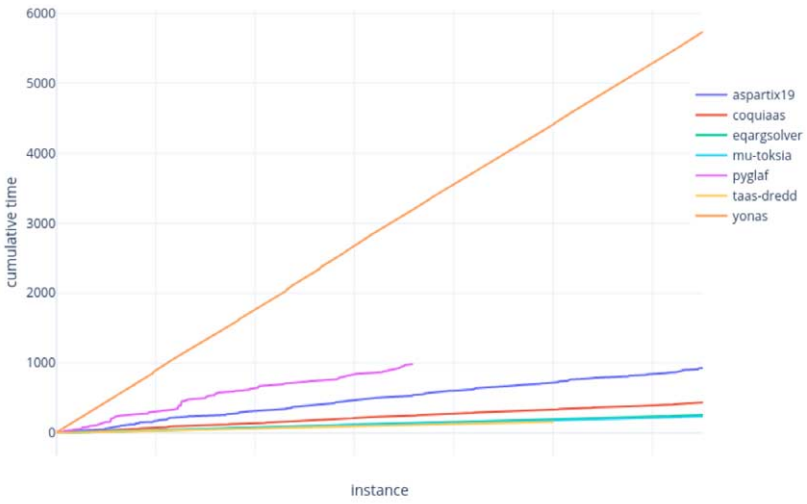


(a) **ST**

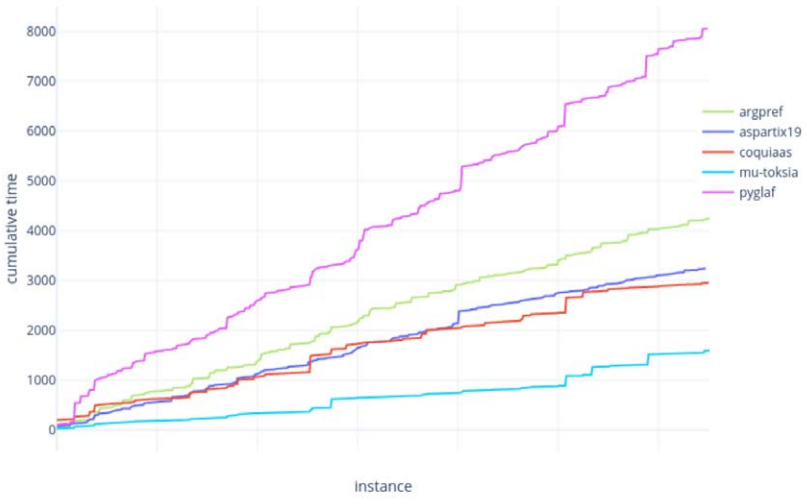


(b) **STG**

Fig. 23. Cumulative time [s] taken to correctly solve all instances in the classical and dynamic tracks – ICCMA'19 (cont.).

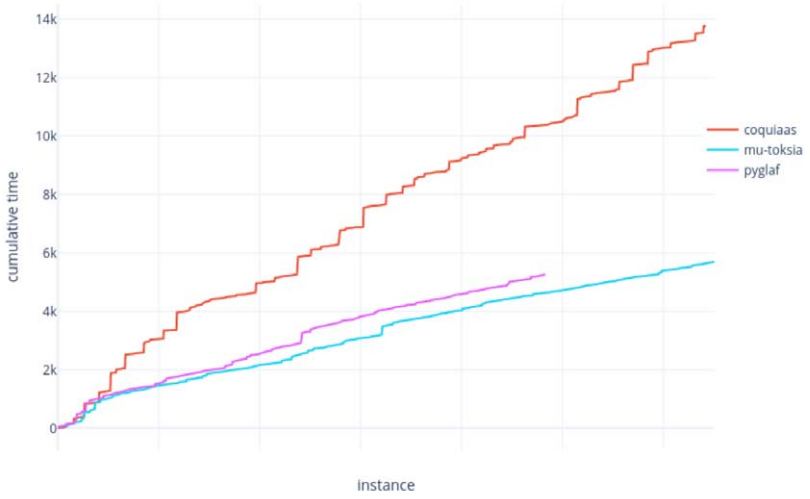


(a) **GR**

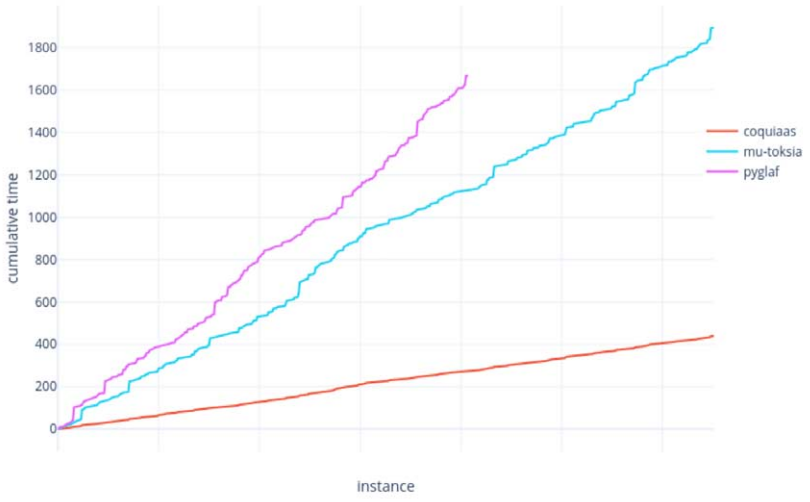


(b) **ID**

Fig. 24. Cumulative time [s] taken to correctly solve all instances in the classical and dynamic tracks – ICCMA'19 (cont.).

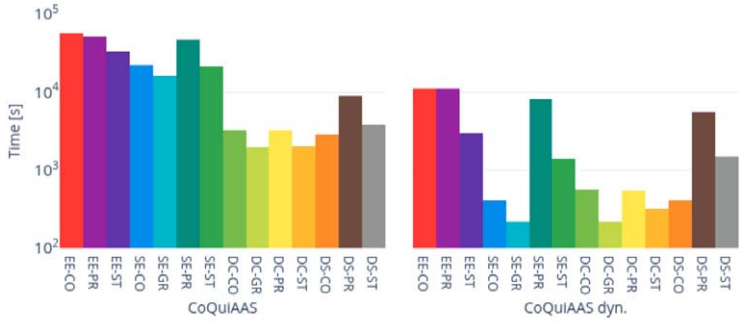


(a) **PR-D**

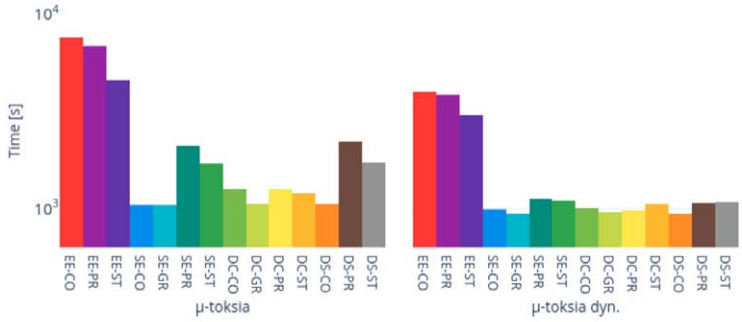


(b) **GR-D**

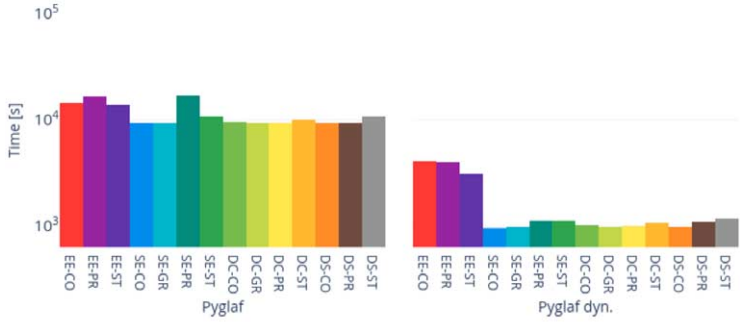
Fig. 25. Cumulative time [s] taken to correctly solve all instances in the classical and dynamic tracks – ICCMA'19 (cont.).



(a) **PR**



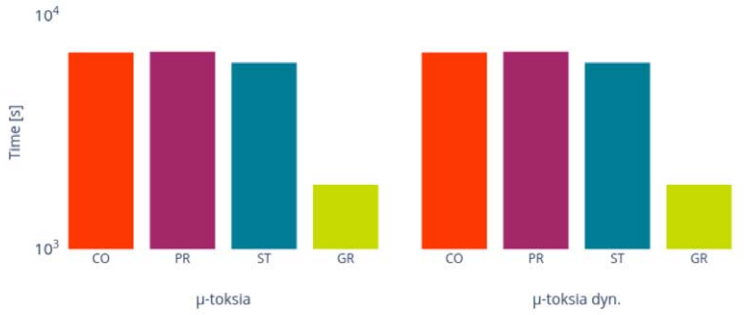
(b) **ST**



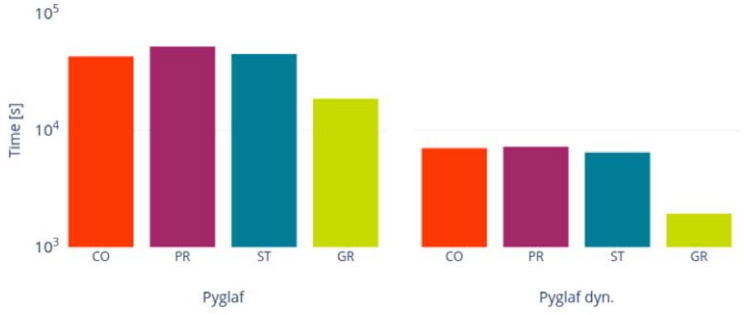
(c) **STG**

Fig. 26. The sum of the time (logarithmic scale) of successful instances for each track, considering CoQuiAAS, μ-toksia, and Pyglaf, together with their dynamic versions. The bars in the chart correspond to tasks in the legend, read in top-bottom firstly, left-right secondly direction. Times are reported in Table 22 in B – ICCMA'19.

(a) **PR**



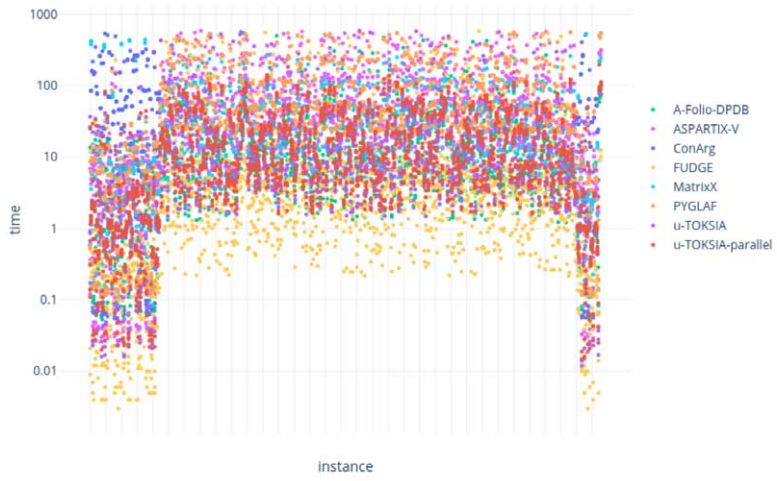
(b) **ST**



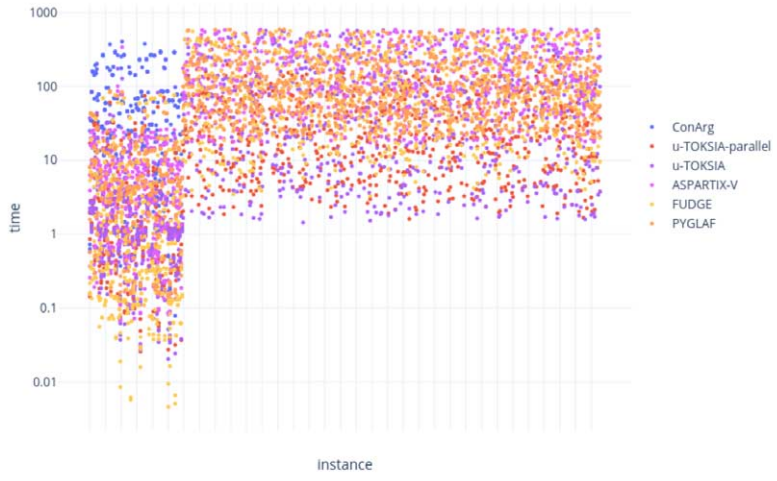
(c) **STG**

Fig. 27. The sum of the time (logarithmic scale) aggregated by semantics of successful instances for each track, considering CoQuiAAS, μ-toksia and Pyglaf, together with their dynamic versions. Times are reported in Table 22 in B – ICCMA'19.

C.2. ICCMA'21



(a) **CO**



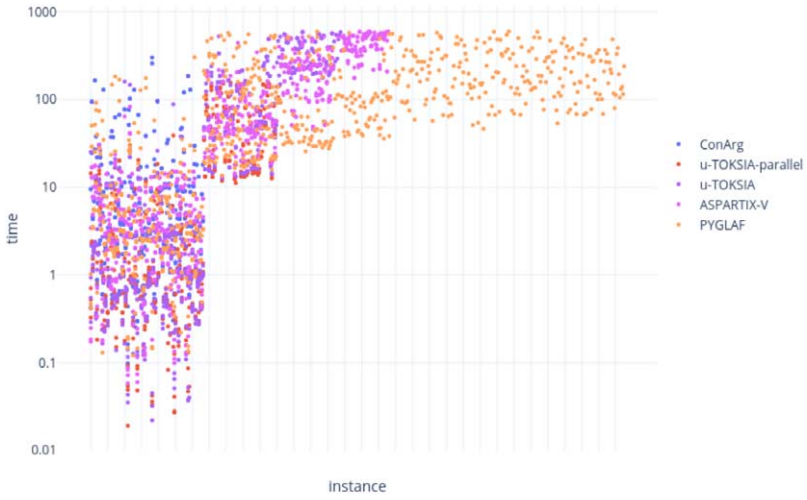
(b) **PR**

Fig. 28. Time [s] taken for each correctly solved instance in the exact track – ICCMA'21.

(a) **ST**

(b) **SST**

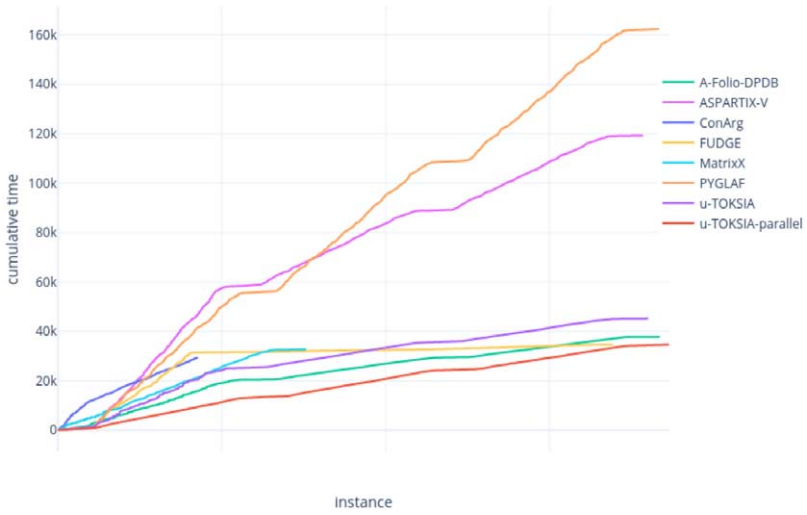
Fig. 29. Time [s] taken for each correctly solved instance in the exact track – ICCMA'21 (cont.).



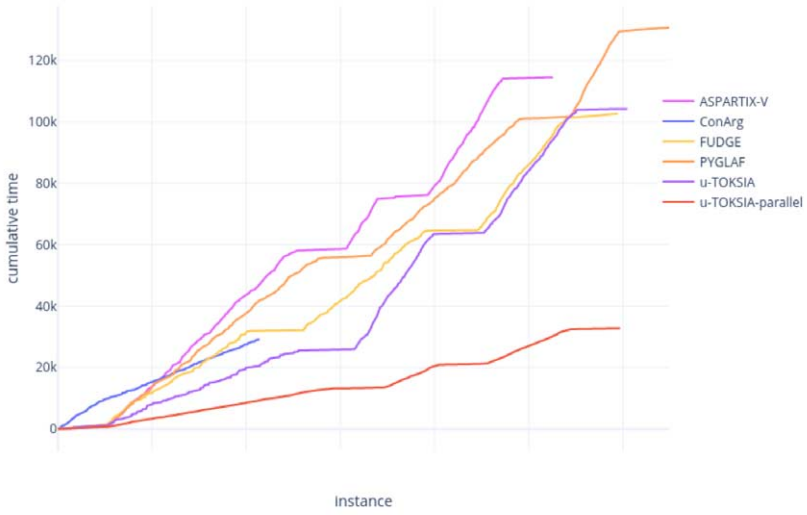
(a) **STG**

(b) **ID**

Fig. 30. Time [s] taken for each correctly solved instance in the exact track – ICCMA'21 (cont.).

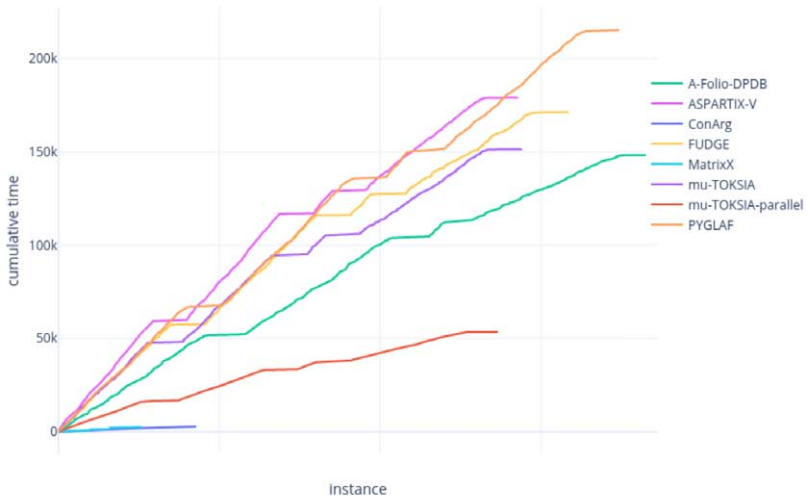


(a) **CO**



(b) **PR**

Fig. 31. Cumulative time [s] taken to solve all instances in the exact track correctly – ICCMA'21.



(a) **ST**

(b) **SST**

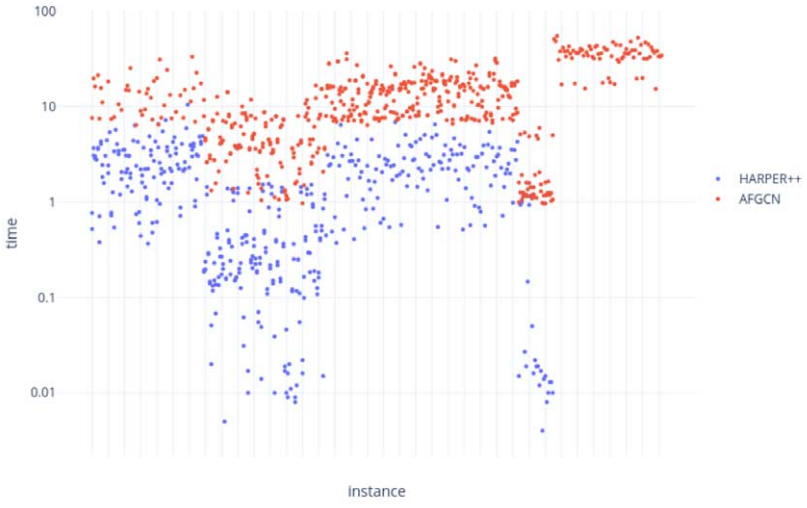
Fig. 32. Cumulative time [s] taken to solve all instances in the exact track correctly – ICCMA'21 (cont.).

(a) **STG**

(b) **ID**

Fig. 33. Cumulative time [s] taken to solve all instances in the exact track correctly – ICCMA'21 (cont.).

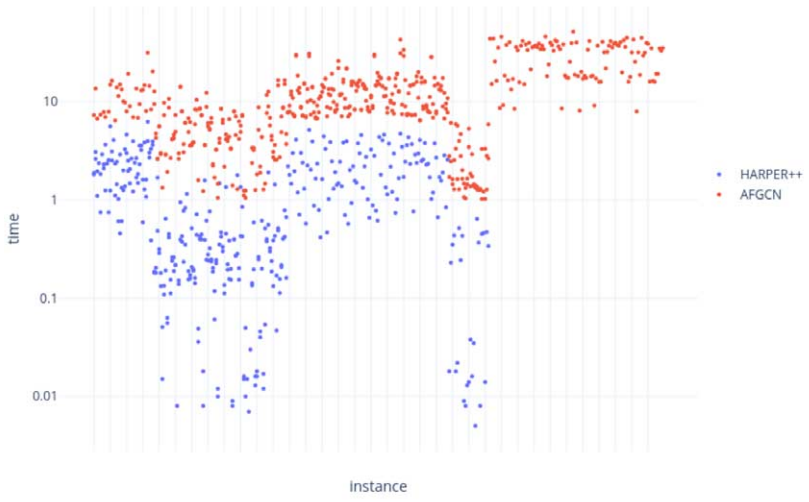
(a) **CO**



(b) **PR**

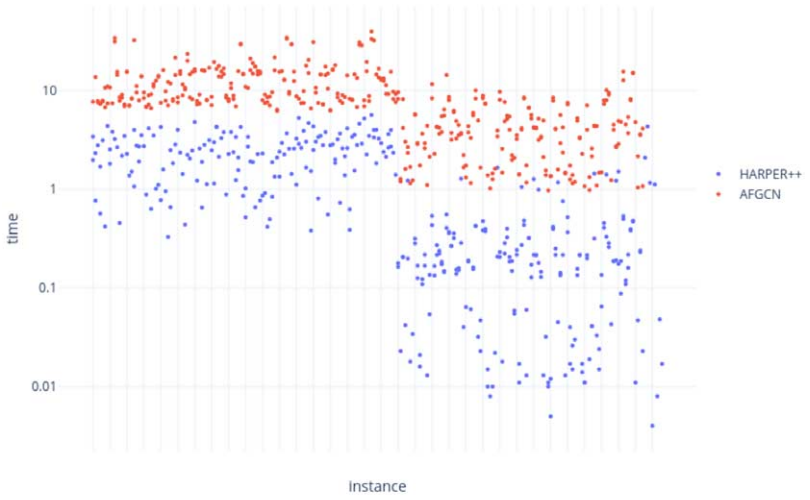
Fig. 34. Time [s] taken for each correctly solved instance in the approximate track – ICCMA'21.

(a) **ST**

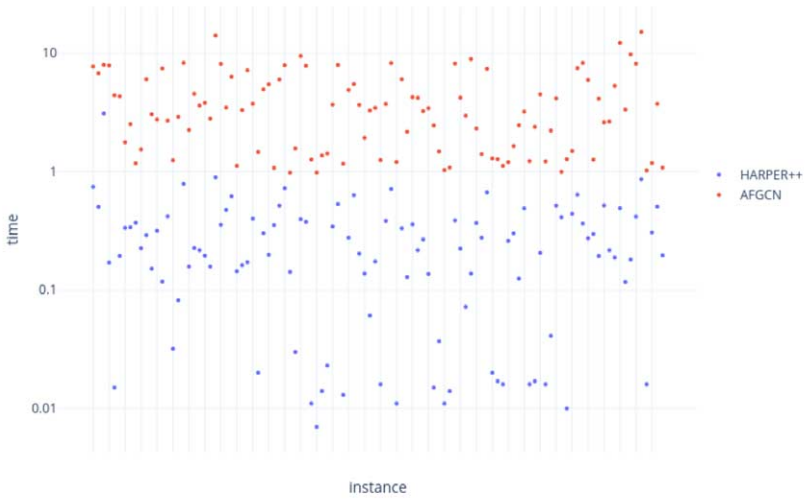


(b) **SST**

Fig. 35. Time [s] taken for each correctly solved instance in the approximate track – ICCMA'21 (cont.).

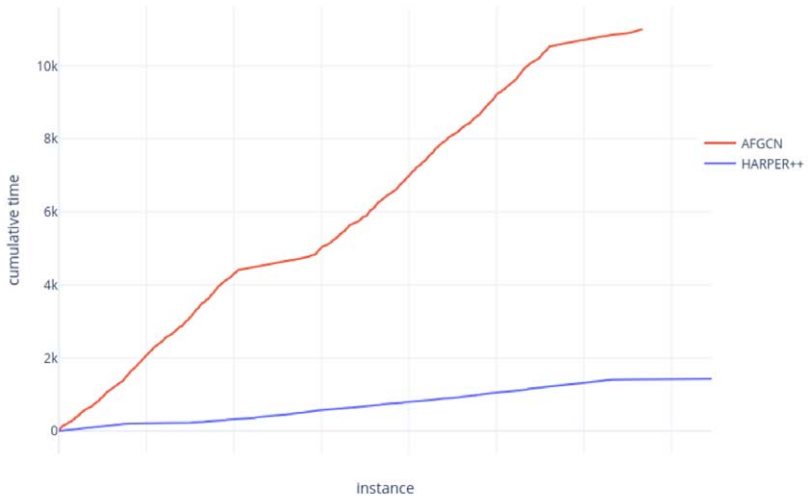


(a) **STG**

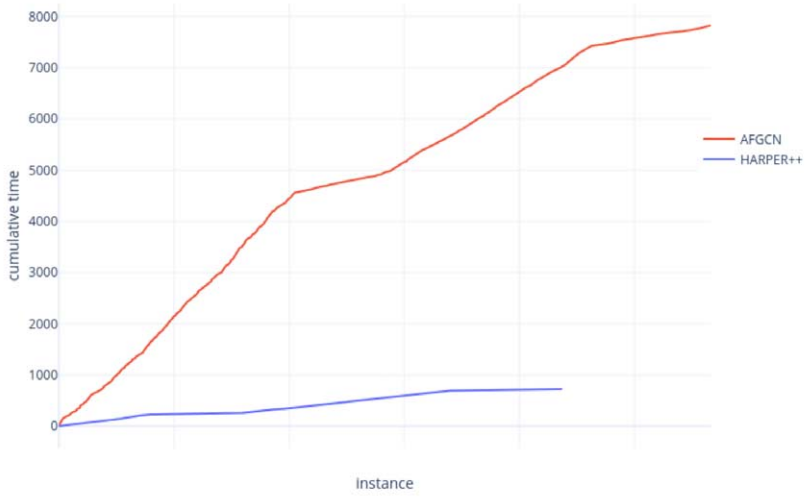


(b) **ID**

Fig. 36. Time [s] taken for each correctly solved instance in the approximate track – ICCMA'21 (cont.).

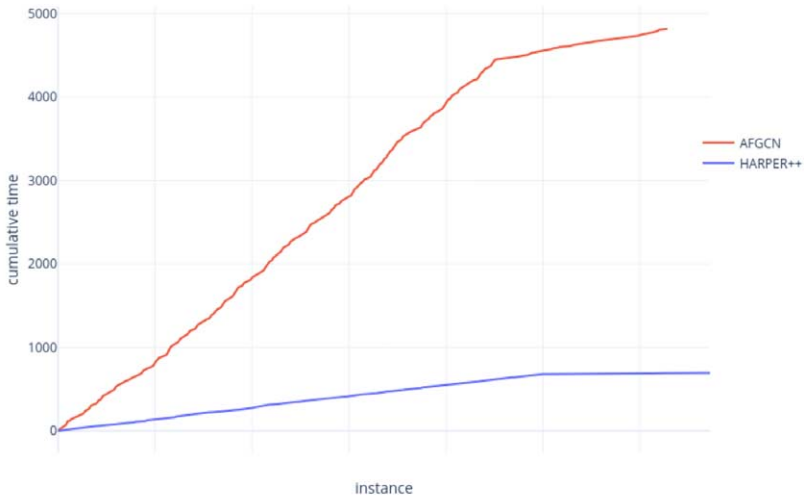


(a) **CO**

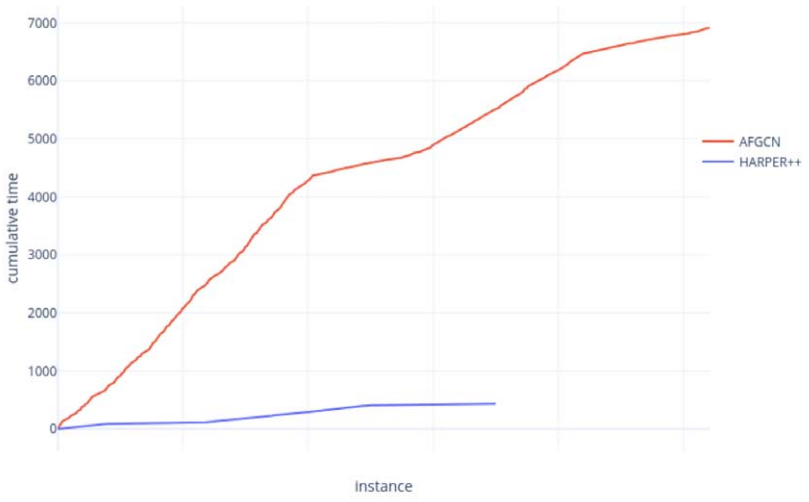


(b) **PR**

Fig. 37. Cumulative time [s] taken to solve all instances in the approximate track correctly – ICCMA'21.

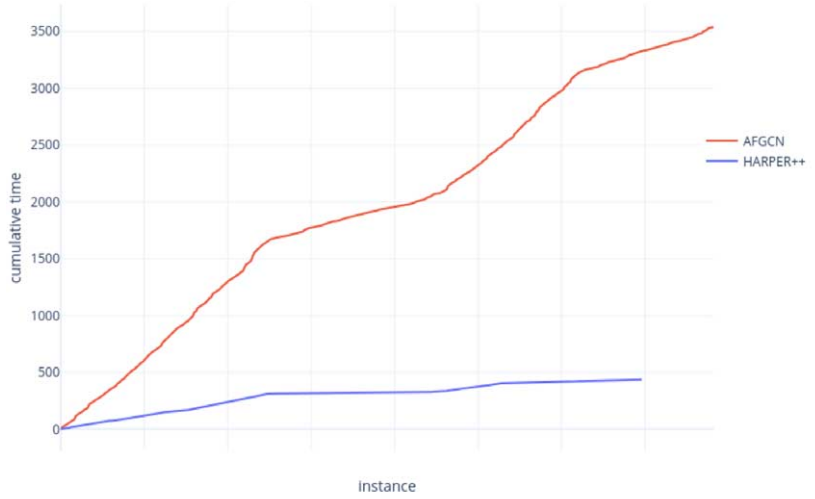


(a) **ST**



(b) **SST**

Fig. 38. Cumulative time [s] taken to correctly solve all instances in the approximate track – ICCMA'21 (cont.).



(a) **STG**

(b) **ID**

Fig. 39. Cumulative time [s] taken to solve all instances in the approximate track correctly – ICCMA'21 (cont.).

References

[1] G. Alfano and S. Greco, Incremental skeptical preferred acceptance in dynamic argumentation frameworks, *IEEE Intell. Syst.* **36**(2) (2021), 6–12. doi:10.1109/MIS.2021.3050521.

[2] G. Alfano, S. Greco and F. Parisi, Efficient computation of extensions for dynamic abstract argumentation frameworks: An incremental approach, in: *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017*, Melbourne, Australia, August 19–25, 2017, C. Sierra, ed., ijcai.org, 2017, pp. 49–55, https://doi.org/10.24963/ijcai.2017/8. doi:10.24963/IJCAI.2017/8.

[3] G. Alfano, S. Greco and F. Parisi, An efficient algorithm for skeptical preferred acceptance in dynamic argumentation frameworks, in: *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019*, Macao, China, August 10–16, 2019, S. Kraus, ed., ijcai.org, 2019, pp. 18–24. doi:10.24963/ijcai.2019/3.

[4] G. Alfano, S. Greco, F. Parisi, G.I. Simari and G.R. Simari, On the incremental computation of semantics in dynamic argumentation, *FLAP* **8**(6) (2021), 1749–1792, https://collegepublications.co.uk/ifcolog/?00048.

[5] M. Alviano, Argumentation reasoning via circumscription with Pyglaf, *Fundam. Informaticae* **167**(1–2) (2019), 1–30. doi:10.3233/FI-2019-1808.

[6] M. Alviano, The pyglaf argumentation reasoner (ICCMA2021), *CoRR*, (2021), https://arxiv.org/abs/2109.03162 arXiv:2109.03162.

[7] G. Audemard and L. Simon, Predicting learnt clauses quality in modern SAT solvers, in: *IJCAI 2009, Proceedings of the 21st International Joint Conference on Artificial Intelligence*, Pasadena, California, USA, July 11–17, 2009, C. Boutilier, ed., 2009, pp. 399–404, http://ijcai.org/Proceedings/09/Papers/074.pdf.

[8] G. Audemard and L. Simon, On the glucose SAT solver, *Int. J. Artif. Intell. Tools* **27**(1) (2018), 1840001:1–1840001:25. doi:10.1142/S0218213018400018.

[9] H. Ayoobi, N. Potyka and F. Toni, SpArX: Sparse argumentative explanations for neural networks, in: *ECAI 2023–26th European Conference on Artificial Intelligence, September 30 – October 4, 2023, Kraków, Poland – Including 12th Conference on Prestigious Applications of Intelligent Systems (PAIS 2023)*, K. Gal, A. Nowé, G.J. Nalepa, R. Fairstein and R. Radulescu, eds, Frontiers in Artificial Intelligence and Applications, Vol. 372, IOS Press, 2023, pp. 149–156. doi:10.3233/FAIA230265.

[10] A. Barabási and R. Albert, Emergence of scaling in random networks, *Science* **286**(5439) (1999), 509–512. doi:10.1126/science.286.5439.509.

[11] P. Baroni, M. Caminada and M. Giacomin, An introduction to argumentation semantics, *Knowl. Eng. Rev.* **26**(4) (2011), 365–410. doi:10.1017/S0269888911000166.

[12] P. Baroni, P.E. Dunne and M. Giacomin, On extension counting problems in argumentation frameworks, in: *Computational Models of Argument: Proceedings of COMMA 2010, Desenzano del Garda*, Italy, September 8–10, 2010, P. Baroni, F. Cerutti, M. Giacomin and G.R. Simari, eds, Frontiers in Artificial Intelligence and Applications, Vol. 216, IOS Press, 2010, pp. 63–74. doi:10.3233/978-1-60750-619-5-63.

[13] P. Baroni, M. Giacomin and B. Liao, On topology-related properties of abstract argumentation semantics. A correction and extension to dynamics of argumentation systems: A division-based method, *Artif. Intell.* **212** (2014), 104–115, https://doi.org/10.1016/j.artint.2014.03.003. doi:10.1016/j.artint.2014.03.003.

[14] R. Baumann and G. Brewka, Expanding argumentation frameworks: Enforcing and monotonicity results, in: *Computational Models of Argument: Proceedings of COMMA 2010, Desenzano del Garda*, Italy, September 8–10, 2010, P. Baroni, F. Cerutti, M. Giacomin and G.R. Simari, eds, Frontiers in Artificial Intelligence and Applications, Vol. 216, IOS Press, 2010, pp. 75–86. doi:10.3233/978-1-60750-619-5-75.

[15] A. Biere, M. Heule, H. van Maaren and T. Walsh (eds), *Handbook of Satisfiability, Frontiers in Artificial Intelligence and Applications*, Vol. 185, IOS Press, 2009. ISBN 978-1-58603-929-5.

[16] S. Bistarelli, L. Kotthoff, F. Santini and C. Taticchi, Containerisation and dynamic frameworks in ICCMA'19, in: *Proceedings of the Second International Workshop on Systems and Algorithms for Formal Argumentation (SAFA 2018) Co-Located with the 7th International Conference on Computational Models of Argument (COMMA 2018)*, Warsaw, Poland, September 11, 2018, M. Thimm, F. Cerutti and M. Vallati, eds, CEUR Workshop Proceedings, Vol. 2171, CEUR-WS.org 2018, pp. 4–9, https://ceur-ws.org/Vol-2171/paper_1.pdf.

[17] S. Bistarelli, L. Kotthoff, F. Santini and C. Taticchi, A first overview of ICCMA'19, in: *Proceedings of the Workshop on Advances in Argumentation in Artificial Intelligence 2020 Co-Located with the 19th International Conference of the Italian Association for Artificial Intelligence (AIxIA 2020), CEUR Workshop Proceedings*, Vol. 2777, CEUR-WS.org 2020, pp. 90–102.

[18] S. Bistarelli, F. Rossi and F. Santini, A ConArg-based library for abstract argumentation, in: *29th IEEE International Conference on Tools with Artificial Intelligence, ICTAI 2017*, Boston, MA, USA, November 6–8, 2017, IEEE Computer Society, 2017, pp. 374–381. doi:10.1109/ICTAI.2017.00065.

[19] S. Bistarelli, F. Rossi and F. Santini, A novel weighted defence and its relaxation in abstract argumentation, *Int. J. Approx. Reason.* **92** (2018), 66–86, https://doi.org/10.1016/j.ijar.2017.10.006. doi:10.1016/j.ijar.2017.10.006.

[20] S. Bistarelli, F. Rossi and F. Santini, Not only size, but also shape counts: Abstract argumentation solvers are benchmark-sensitive, *J. Log. Comput.* **28**(1) (2018), 85–117, https://doi.org/10.1093/logcom/exx031. doi:10.1093/logcom/exx031.

[21] S. Bistarelli and F. Santini, ConArg: A constraint-based computational framework for argumentation systems, in: *IEEE 23rd International Conference on Tools with Artificial Intelligence, ICTAI 2011*, Boca Raton, FL, USA, November 7–9, 2011, IEEE Computer Society, 2011, pp. 605–612. doi:10.1109/ICTAI.2011.96.

[22] S. Bistarelli, F. Santini and C. Taticchi, On looking for invariant operators in argumentation semantics, in: *Proceedings of the Thirty-First International Florida Artificial Intelligence Research Society Conference, FLAIRS 2018*, Melbourne,

Florida, USA, May 21–23 2018, K. Brawner and V. Rus, eds, AAAI Press, 2018, pp. 537–540, https://aaai.org/ocs/index.php/FLAIRS/FLAIRS18/paper/view/17671.
[23] G. Boella, S. Kaci and L.W.N. van der Torre, Dynamics in argumentation with single extensions: Abstraction principles and the grounded extension, in: *Proceedings*, Symbolic and Quantitative Approaches to Reasoning with Uncertainty, 10th European Conference, ECSQARU 2009, Verona, Italy, July 1–3, 2009, C. Sossai and G. Chemello, eds, Lecture Notes in Computer Science, Vol. 5590, Springer, 2009, pp. 107–118. doi:10.1007/978-3-642-02906-6_11.
[24] A. Bondarenko, P.M. Dung, R.A. Kowalski and F. Toni, An abstract, argumentation-theoretic approach to default reasoning, *Artif. Intell.* **93** (1997), 63–101. doi:10.1016/S0004-3702(97)00015-5.
[25] M.W.A. Caminada, W.A. Carnielli and P.E. Dunne, Semi-stable semantics, *J. Log. Comput.* **22**(5) (2012), 1207–1254, https://doi.org/10.1093/logcom/exr033. doi:10.1093/logcom/exr033.
[26] L. Carstens, X. Fan, Y. Gao and F. Toni, An overview of argumentation frameworks for decision support, in: *Graph Structures for Knowledge Representation and Reasoning – 4th International Workshop, GKR 2015, Revised Selected Papers*, Buenos Aires, Argentina, July 25, 2015, M. Croitoru, P. Marquis, S. Rudolph and G. Stapleton, eds, Lecture Notes in Computer Science, Vol. 9501, Springer, 2015, pp. 32–49. doi:10.1007/978-3-319-28702-7_3.
[27] C. Cayrol, F.D. de Saint-Cyr and M. Lagasquie-Schiex, Revision of an argumentation system, in: *Principles of Knowledge Representation and Reasoning: Proceedings of the Eleventh International Conference, KR 2008*, Sydney, Australia, September 16–19, 2008, G. Brewka and J. Lang, eds, AAAI Press, 2008, pp. 124–134, http://www.aaai.org/Library/KR/2008/kr08-013.php.
[28] C. Cayrol, F.D. de Saint-Cyr and M. Lagasquie-Schiex, Change in abstract argumentation frameworks: Adding an argument, *J. Artif. Intell. Res.* **38** (2010), 49–84, https://doi.org/10.1613/jair.2965. doi:10.1613/jair.2965.
[29] F. Cerutti, S.A. Gaggl, M. Thimm and J.P. Wallner, Foundations of implementations for formal argumentation, *FLAP* **4**(8) (2017), http://www.collegepublications.co.uk/downloads/ifcolog00017.pdf.
[30] P.M. Dung, On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games, *Artif. Intell.* **77**(2) (1995), 321–358. doi:10.1016/0004-3702(94)00041-X.
[31] P.M. Dung, P. Mancarella and F. Toni, Computing ideal sceptical argumentation, *Artif. Intell.* **171**(10–15) (2007), 642–674, https://doi.org/10.1016/j.artint.2007.05.003. doi:10.1016/j.artint.2007.05.003.
[32] W. Dvorák and P.E. Dunne, Computational problems in formal argumentation and their complexity, *FLAP* **4**(8) (2017), http://www.collegepublications.co.uk/downloads/ifcolog00017.pdf.
[33] W. Dvorák, M. Hecher, M. König, A. Schidler, S. Szeider and S. Woltran, Tractable abstract argumentation via backdoor-treewidth, in: *Thirty-Sixth AAAI Conference on Artificial Intelligence, AAAI 2022, Thirty-Fourth Conference on Innovative Applications of Artificial Intelligence, IAAI 2022, the Twelveth Symposium on Educational Advances in Artificial Intelligence, EAAI 2022 Virtual Event, February 22 – March 1, 2022*, AAAI Press, 2022, pp. 5608–5615, https://doi.org/10.1609/aaai.v36i5.20501. doi:10.1609/AAAI.V36I5.20501.
[34] W. Dvorák, M. König, J.P. Wallner and S. Woltran, Aspartix-V21, *CoRR* (2021), https://arxiv.org/abs/2109.03166 arXiv:2109.03166.
[35] W. Dvorák, A. Rapberger, J.P. Wallner and S. Woltran, ASPARTIX-V19 – an answer-set programming based system for abstract argumentation, in: *Foundations of Information and Knowledge Systems – 11th International Symposium, FoIKS 2020, Proceedings*, Dortmund, Germany, February 17–21, 2020, A. Herzig and J. Kontinen, eds, Lecture Notes in Computer Science, Vol. 12012, Springer, 2020, pp. 79–89. doi:10.1007/978-3-030-39951-1_5.
[36] N. Eén and N. Sörensson, An extensible SAT-solver, in: *Theory and Applications of Satisfiability Testing, 6th International Conference, SAT 2003. Santa Margherita Ligure, Italy, May 5-8, 2003 Selected Revised Papers*, E. Giunchiglia and A. Tacchella, eds, Lecture Notes in Computer Science, Vol. 2919, Springer, 2003, pp. 502–518. doi:10.1007/978-3-540-24605-3_37.
[37] U. Egly, S.A. Gaggl and S. Woltran, Answer-set programming encodings for argumentation frameworks, *Argument Comput.* **1**(2) (2010), 147–177. doi:10.1080/19462166.2010.486479.
[38] P. Erdös and A. Rényi, On random graphs. I, *Publ. Math. Debrecen* **6** (1959), 290–297. doi:10.5486/PMD.1959.6.3-4.12.
[39] J.K. Fichte, M. Hecher and A. Meier, Counting complexity for reasoning in abstract argumentation, in: *The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, the Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, the Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019*, Honolulu, Hawaii, January 27 – February 1, 2019, AAAI Press, 2019, pp. 2827–2834, https://doi.org/10.1609/aaai.v33i01.33012827. doi:10.1609/AAAI.V33I01.33012827.
[40] J.K. Fichte, M. Hecher, P. Thier and S. Woltran, Exploiting database management systems and treewidth for counting, *Theory Pract. Log. Program.* **22**(1) (2022), 128–157. doi:10.1017/S147106842100003X.
[41] A. Fréchette, L. Kotthoff, T.P. Michalak, T. Rahwan, H.H. Hoos and K. Leyton-Brown, Using the Shapley value to analyze algorithm portfolios, in: *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, February 12-17, 2016*, D. Schuurmans and M.P. Wellman, eds, AAAI Press, Phoenix, Arizona, USA, 2016, pp. 3397–3403, https://doi.org/10.1609/aaai.v30i1.10440. doi:10.1609/AAAI.V30I1.10440.

[42] S.A. Gaggl, T. Linsbichler, M. Maratea and S. Woltran, Design and results of the second international competition on computational models of argumentation, *Artif. Intell.* **279** (2020), https://doi.org/10.1016/j.artint.2019.103193. doi:10.1016/j.artint.2019.103193.

[43] S. Gning and J. Mailly, On the impact of SAT solvers on argumentation solvers, in: *Proceedings of the Third International Workshop on Systems and Algorithms for Formal Argumentation Co-Located with the 8th International Conference on Computational Models of Argument (COMMA 2020)*, September 8, 2020, S.A. Gaggl, M. Thimm and M. Vallati, eds, CEUR Workshop Proceedings, Vol. 2672, CEUR-WS.org, 2020, pp. 68–73, https://ceur-ws.org/Vol-2672/paper_7.pdf.

[44] É. Grégoire, Y. Izza and J. Lagniez, Boosting MCSes enumeration, in: *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018*, Stockholm, Sweden, July 13–19, 2018, J. Lang, ed., ijcai.org, 2018, pp. 1309–1315. doi:10.24963/ijcai.2018/182.

[45] M. Heinrich, The MatrixX Solver for Argumentation Frameworks, *CoRR*, (2021), arXiv:2109.14732. https://arxiv.org/abs/2109.14732.

[46] J. Klein and M. Thimm, Revisiting SAT techniques for abstract argumentation, in: *Computational Models of Argument – Proceedings of COMMA 2020*, Perugia, Italy, September 4–11, 2020, H. Prakken, S. Bistarelli, F. Santini and C. Taticchi, eds, Frontiers in Artificial Intelligence and Applications, Vol. 326, IOS Press, 2020, pp. 251–262. doi:10.3233/FAIA200509.

[47] D.E. Knuth, Dancing links, in: *Millennial Perspectives in Computer Science*, J.W. Jim Davies Bill Roscoe, ed., Proceedings of the 1999 Oxford-Microsoft Symposium in Honour of Sir Tony Hoare, Bloomsbury Publishing, 2000, pp. 187–214.

[48] N. Kökciyan, N. Yaglikci and P. Yolum, Argumentation for resolving privacy disputes in online social networks: (extended abstract), in: *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*, Singapore, May 9–13, 2016, C.M. Jonker, S. Marsella, J. Thangarajah and K. Tuyls, eds, ACM, 2016, pp. 1361–1362, http://dl.acm.org/citation.cfm?id=2937160.

[49] N. Kökciyan, N. Yaglikci and P. Yolum, An argumentation approach for resolving privacy disputes in online social networks, *ACM Trans. Internet Techn.* **17**(3) (2017), 27:1–27:22. doi:10.1145/3003434.

[50] L. Kotthoff, A. Fréchette, T.P. Michalak, T. Rahwan, H.H. Hoos and K. Leyton-Brown, Quantifying algorithmic improvements over time, in: *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018*, Stockholm, Sweden, July 13–19, 2018, J. Lang, ed., ijcai.org, 2018, pp. 5165–5171, https://doi.org/10.24963/ijcai.2018/716. doi:10.24963/IJCAI.2018/716.

[51] M. Kröll, R. Pichler and S. Woltran, On the complexity of enumerating the extensions of abstract argumentation frameworks, in: *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017*, Melbourne, Australia, August 19–25, 2017, C. Sierra, ed., ijcai.org, 2017, pp. 1145–1152, https://doi.org/10.24963/ijcai.2017/159. doi:10.24963/IJCAI.2017/159.

[52] I. Kuhlmann and M. Thimm, Using graph convolutional networks for approximate reasoning with abstract argumentation frameworks: A feasibility study, in: *Scalable Uncertainty Management – 13th International Conference, SUM 2019, Proceedings*, Compiègne, France, December 16–18, 2019, N.B. Amor, B. Quost and M. Theobald, eds, Lecture Notes in Computer Science, Vol. 11940, Springer, 2019, pp. 24–37. doi:10.1007/978-3-030-35514-2_3.

[53] J. Lagniez, E. Lonca and J. Mailly, CoQuiAAS: A constraint-based quick abstract argumentation solver, in: *27th IEEE International Conference on Tools with Artificial Intelligence, ICTAI 2015, Vietri Sul Mare*, Italy, November 9–11, 2015, IEEE Computer Society, 2015, pp. 928–935. doi:10.1109/ICTAI.2015.134.

[54] J. Lagniez, E. Lonca, J. Mailly and J. Rossit, Introducing the fourth international competition on computational models of argumentation, in: *Proceedings of the Third International Workshop on Systems and Algorithms for Formal Argumentation Co-Located with the 8th International Conference on Computational Models of Argument (COMMA 2020)*, September 8, 2020, S.A. Gaggl, M. Thimm and M. Vallati, eds, CEUR Workshop Proceedings, Vol. 2672, CEUR-WS.org, 2020, pp. 80–85, https://ceur-ws.org/Vol-2672/paper_9.pdf.

[55] J. Lagniez, E. Lonca, J. Mailly and J. Rossit, *Design and Results of ICCMA 2021*, *CoRR*, (2021), arXiv:2109.08884. https://arxiv.org/abs/2109.08884.

[56] J. Lagniez, E. Lonca, J. Mailly and J. Rossit, A new evolutive generator for graphs with communities and its application to abstract argumentation, in: *Proceedings of the First International Workshop on Argumentation and Applications Co-Located with 20th International Conference on Principles of Knowledge Representation and Reasoning (KR 2023)*, Rhodes, Greece, September 2–8, 2023, O. Cocarascu, S. Doutre, J. Mailly and A. Rago, eds, CEUR Workshop Proceedings, Vol. 3472, CEUR-WS.org 2023, pp. 52–64, https://ceur-ws.org/Vol-3472/paper4.pdf.

[57] B. Liao, Toward incremental computation of argumentation semantics: A decomposition-based approach, *Ann. Math. Artif. Intell.* **67**(3–4) (2013), 319–358, https://doi.org/10.1007/s10472-013-9364-8. doi:10.1007/s10472-013-9364-8.

[58] L. Longo and L. Hederman, Argumentation theory for decision support in health-care: A comparison with machine learning, in: *Brain and Health Informatics – International Conference, BHI 2013, Proceedings*, Maebashi, Japan, October 29–31, 2013, K. Imamura, S. Usui, T. Shirao, T. Kasamatsu, L. Schwabe and N. Zhong, eds, Lecture Notes in Computer Science, Vol. 8211, Springer, 2013, pp. 168–180. doi:10.1007/978-3-319-02753-1_17.

[59] J. Mailly and J. Rossit, Stability in Abstract Argumentation, *CoRR*, (2020), https://arxiv.org/abs/2012.12588 arXiv:2012.12588.

[60] L. Malmqvist, T. Yuan, P. Nightingale and S. Manandhar, Determining the acceptability of abstract arguments with graph convolutional networks, in: *Proceedings of the Third International Workshop on Systems and Algorithms for Formal Argumentation Co-Located with the 8th International Conference on Computational Models of Argument (COMMA 2020)*, September 8, 2020, S.A. Gaggl, M. Thimm and M. Vallati, eds, CEUR Workshop Proceedings, Vol. 2672, CEUR-WS.org 2020, pp. 47–56, https://ceur-ws.org/Vol-2672/paper_5.pdf.

[61] Z. Newsham, V. Ganesh, S. Fischmeister, G. Audemard and L. Simon, Impact of community structure on SAT solver performance, in: *Theory and Applications of Satisfiability Testing – SAT 2014–17th International Conference, Held as Part of the Vienna Summer of Logic, VSL 2014, Proceedings*, Vienna, Austria, July 14–17, 2014, C. Sinz and U. Egly, eds, Lecture Notes in Computer Science, Vol. 8561, Springer, 2014, pp. 252–268. doi:10.1007/978-3-319-09284-3_20.

[62] A. Niskanen and M. Järvisalo, Algorithms for dynamic argumentation frameworks: An incremental SAT-based approach, in: *ECAI 2020–24th European Conference on Artificial Intelligence, 29 August-8 September 2020 – Including 10th Conference on Prestigious Applications of Artificial Intelligence (PAIS 2020)*, Santiago de Compostela, Spain, August 29 – September 8, 2020, G.D. Giacomo, A. Catalá, B. Dilkina, M. Milano, S. Barro, A. Bugarín and J. Lang, eds, Frontiers in Artificial Intelligence and Applications, Vol. 325, IOS Press, 2020, pp. 849–856. doi:10.3233/FAIA200175.

[63] A. Niskanen and M. Järvisalo, μ-Toksia: An efficient abstract argumentation reasoner, in: *Proceedings of the 17th International Conference on Principles of Knowledge Representation and Reasoning, KR 2020*, Rhodes, Greece, September 12–18, 2020, D. Calvanese, E. Erdem and M. Thielscher, eds, 2020, pp. 800–804. doi:10.24963/kr.2020/82.

[64] D. Odekerken, A. Borg and F. Bex, Estimating stability for efficient argument-based inquiry, in: *Computational Models of Argument – Proceedings of COMMA 2020*, Perugia, Italy, September 4–11, 2020, H. Prakken, S. Bistarelli, F. Santini and C. Taticchi, eds, Frontiers in Artificial Intelligence and Applications, Vol. 326, IOS Press, 2020, pp. 307–318. doi:10.3233/FAIA200514.

[65] S.H.P. Oo, N.D. Hung and T. Theeramunkong, Justifying convolutional neural network with argumentation for explainability, *Informatica (Slovenia)* **46**(9) (2023), https://doi.org/10.31449/inf.v46i9.4359. doi:10.31449/INF.V46I9.4359.

[66] A. Previti and M. Järvisalo, A preference-based approach to backbone computation with application to argumentation, in: *Proceedings of the 33rd Annual ACM Symposium on Applied Computing, SAC 2018*, Pau, France, April 09–13, 2018, H.M. Haddad, R.L. Wainwright and R. Chbeir, eds, ACM, 2018, pp. 896–902. doi:10.1145/3167132.3167230.

[67] I. Rahwan and L. Amgoud, An argumentation based approach for practical reasoning, in: *5th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2006)*, Hakodate, Japan, May 8–12, 2006, H. Nakashima, M.P. Wellman, G. Weiss and P. Stone, eds, ACM, 2006, pp. 347–354. doi:10.1145/1160633.1160696.

[68] O. Rodrigues, EqArgSolver – system description, in: *Theory and Applications of Formal Argumentation – 4th International Workshop, TAFA 2017, Revised Selected Papers*, Melbourne, VIC, Australia, August 19–20, 2017, E. Black, S. Modgil and N. Oren, eds, Lecture Notes in Computer Science, Vol. 10757, Springer, 2017, pp. 150–158. doi:10.1007/978-3-319-75553-3_11.

[69] O. Rodrigues, E. Black, M. Luck and J. Murphy, On structural properties of argumentation frameworks: Lessons from ICCMA, in: *Proceedings of the Second International Workshop on Systems and Algorithms for Formal Argumentation (SAFA 2018) Co-Located with the 7th International Conference on Computational Models of Argument (COMMA 2018)*, Warsaw, Poland, September 11, 2018, M. Thimm, F. Cerutti and M. Vallati, eds, CEUR Workshop Proceedings, Vol. 2171, CEUR-WS.org 2018, pp. 22–35, http://ceur-ws.org/Vol-2171/paper_3.pdf.

[70] M. Soos, K. Nohl and C. Castelluccia, Extending SAT solvers to cryptographic problems, in: *Theory and Applications of Satisfiability Testing – SAT 2009, 12th International Conference, SAT 2009, Proceedings*, Swansea, UK, June 30 – July 3, 2009, O. Kullmann, ed., Lecture Notes in Computer Science, Vol. 5584, Springer, 2009, pp. 244–257. doi:10.1007/978-3-642-02777-2_24.

[71] M. Thimm, The tweety library collection for logical aspects of artificial intelligence and knowledge representation, *Künstliche Intell.* **31**(1) (2017), 93–97, https://doi.org/10.1007/s13218-016-0458-4. doi:10.1007/s13218-016-0458-4.

[72] M. Thimm, F. Cerutti and M. Vallati, Fudge: A light-weight solver for abstract argumentation based on SAT reductions, *CoRR*, (2021), https://arxiv.org/abs/2109.03106 arXiv:2109.03106.

[73] M. Thimm, F. Cerutti and M. Vallati, Skeptical reasoning with preferred semantics in abstract argumentation without computing preferred extensions, in: *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI 2021, Virtual Event /*, Montreal, Canada, 19–27 August 2021, Z. Zhou, ed., ijcai.org, 2021, pp. 2069–2075, https://doi.org/10.24963/ijcai.2021/285. doi:10.24963/IJCAI.2021/285.

[74] M. Thimm and T. Rienstra, Approximate reasoning with ASPIC+ by argument sampling, in: *Proceedings of the Third International Workshop on Systems and Algorithms for Formal Argumentation Co-Located with the 8th International Conference on Computational Models of Argument (COMMA 2020)*, September 8, 2020, S.A. Gaggl, M. Thimm and M. Vallati, eds, CEUR Workshop Proceedings, Vol. 2672, CEUR-WS.org, 2020, pp. 22–33, https://ceur-ws.org/Vol-2672/paper_3.pdf.

[75] M. Thimm and S. Villata, The first international competition on computational models of argumentation: Results and analysis, *Artif. Intell.* **252** (2017), 267–294, https://doi.org/10.1016/j.artint.2017.08.006. doi:10.1016/j.artint.2017.08.006.
[76] F. Toni, A tutorial on assumption-based argumentation, *Argument Comput.* **5**(1) (2014), 89–117. doi:10.1080/19462166.2013.869878.
[77] B. Verheij, Two approaches to dialectical argumentation: Admissible sets and argumentation stages, in: *Proceedings of the 8th Dutch Conference on Artificial Intelligence (NAIC'96)*, 1996, pp. 357–368.
[78] F. Wilcoxon, Individual comparisons by ranking methods, *Biometrics Bulletin* **1**(6) (1945), 80–83, http://www.jstor.org/stable/3001968. doi:10.2307/3001968.
[79] Y. Xu and C. Cayrol, The matrix approach for abstract argumentation frameworks, in: *Theory and Applications of Formal Argumentation – Third International Workshop, TAFA 2015, Revised Selected Papers*, Buenos Aires, Argentina, July 25–26, 2015, E. Black, S. Modgil and N. Oren, eds, Lecture Notes in Computer Science, Vol. 9524, Springer, 2015, pp. 243–259. doi:10.1007/978-3-319-28460-6_15.
[80] Q. Zhong, X. Fan, X. Luo and F. Toni, An explainable multi-attribute decision model based on argumentation, *Expert Syst. Appl.* **117** (2019), 42–61, https://doi.org/10.1016/j.eswa.2018.09.038. doi:10.1016/j.eswa.2018.09.038.