





PRIN 2022 Project EPICA

Deliverable 4.2 Measuring Effectiveness of Public Interest Communication with the EPICA Tool

Stefano Bistarelli¹, Francesco Santini¹, and Carlo Taticchi¹

¹Dipartimento di Matematica e Informatica - Universitá degli Studi di Perugia

Abstract

This report presents a web-based tool for analysing public interest communication through computational argumentation. Arguments are modelled as value-oriented vectors, enabling the evaluation of their impact across different audiences and supporting structured campaign analysis.

System Description

The EPICA tool is implemented as a web-based platform¹, designed to support the modelling and evaluation of public interest communication through computational argumentation. Each argument is represented by a value vector that encodes its degree of alignment with a set of values influencing public perception. By analysing these value vectors, the tool provides insights into how alternative argumentative strategies may appeal to different audience segments.

User interaction is structured into three main stages: (i) campaign definition, (ii) visualisation of computed measures, and (iii) analytical evaluation based on goal-oriented criteria.

¹Tool webpage: https://epica.dmi.unipg.it/tool.







Campaign Definition

Campaigns are modelled using a Vector-based extension [1] of Value-based Argumentation Frameworks $\langle A, \rightarrow, A^{\mathsf{pos}} \rangle$ originally introduced in [2]. Here, A denotes a finite set of arguments, \rightarrow is a binary attack relation, and $A^{\mathsf{pos}} \subseteq A$ represents the core arguments directly supporting the campaign's objectives.

To increase expressive power, the framework additionally incorporates values and audiences [1]. Arguments may support multiple values simultaneously, with different intensities. This is modelled through a value space $V=[0,1]^n$, where each dimension corresponds to a specific value. A mapping function val $A \to V$ associates each argument $A \in A$ with a vector indicating its degree of support for each value.

The set of audiences is denoted by $I = \{1, 2, \dots, k\}$, where k is the number of distinct audiences considered. Each audience $i \in I$ is assigned a weight p_i representing the proportion of the overall population that shares similar value preferences. These weights satisfy:

$$\sum_{i=1}^k p_i = 1 \quad \text{and} \quad p_i \ge 0 \ \forall i \le k.$$

Audience-specific value preferences are encoded by a function as $v:I\to V$, where the j-th entry of $\operatorname{asv}(i)$ quantifies the relative importance of value j for audience i.

Within the tool, campaign structures are specified through a JSON schema², which formalises the framework $\langle A, \rightarrow, A^{\mathsf{pos}} \rangle$ enriched with values and audiences. The schema requires seven core components: positiveArguments, arguments, attacks, values, audiences, argumentValues, and audienceValues.

Arguments are separated into core (positiveArguments, corresponding to A^{pos}) and non-core (arguments, corresponding to $A \setminus A^{\text{pos}}$). Each argument is defined by a unique identifier and a set of textual representations. The attacks component encodes the binary relation \rightarrow , with each attack represented by a source—target pair. Values are enumerated in values and associated with arguments through argumentValues, which assigns weights in [0,1] analogous to the val function. Audiences are specified in audiences, each with a label and weight p_i , while audienceValues captures the preference function asv by assigning weights to reflect audience priorities.

Campaigns can be defined by uploading or pasting a JSON file, or through an interactive input form.

²Schema available at: https://epica.dmi.unipg.it/tool/script/schema.js.







Visualisation

In the second stage, users may explore the campaign through tabular visualisations of measures proposed in [1]. The following components are generated after computation.

Impact measure. For each $a \in A$ and $i \in I$, the tool computes the impact function

$$\|a\|_i = \frac{1}{\sqrt{n}} \|\operatorname{asv}(i) \odot \operatorname{val}(a)\|,$$

which quantifies the influence of a on i as the degree of alignment between the values expressed by a and the priorities of i.

Defeat relation. To integrate values and audience preferences, the framework computes a defeat relation \twoheadrightarrow_i for each audience $i \in I$. Given $a, b \in A$, defeat is defined as

$$a \rightarrow_i b \iff (a \rightarrow b \land ||a||_i \ge ||b||_i),$$

ensuring that an argument may only defeat another if it both attacks it and has at least equal impact on i.

Acceptability. The system evaluates argument acceptance with respect to each audience by applying grounded semantics [3] on $\langle A, \twoheadrightarrow_i \rangle$. The result, denoted $\operatorname{con}_i(a)$, is true if and only if a is included in the grounded extension for audience i.

Campaign graph. An interactive graph is provided to facilitate the interpretation of results. The graph is rendered from the perspective of a selected audience, chosen via a dropdown menu. Nodes represent arguments (positiveArguments or arguments), edges represent both \rightarrow and \twoheadrightarrow_i , and visual cues distinguish arguments accepted under $\operatorname{con}_i(a)$.

The interface supports interactive editing, including the addition of arguments, creation of attacks, and repositioning of nodes. Each modification triggers recomputation of the measures above, ensuring consistency between the graph and the underlying framework. For example, when a new attack is introduced, the system verifies whether it constitutes a defeat and updates the corresponding edge style. When a new argument is added, users specify its







identifier, type, textual content, and value weights, ensuring full integration into the framework. Tooltips provide additional information such as the computed impact of an argument for the selected audience.

Analysis

The final stage supports campaign analysis through two goal functions. The Overall Effectiveness goal selects the argument $a \in A^{pos}$ maximising impact across all audiences, weighted by their proportions:

$$\sum_{i=1}^k p_i \cdot ||a||_i.$$

The Convinced People goal selects the argument $a \in A^{pos}$ that convinces the largest weighted proportion of the population:

$$\sum_{i=1}^{k} p_i \cdot [\mathsf{con}_i(a)],$$

where $[\varphi] = 1$ if φ is true and 0 otherwise.

Results for both goal functions are presented in a comparative table listing the weighted scores of all positive arguments.

References

- [1] Pietro Baroni, Giulio Fellin, Massimiliano Giacomin, and Carlo Proietti. A vector-based extension of value-based argumentation for public interest communication. In Carlo Proietti and Carlo Taticchi, editors, *Proceedings of the 8th Workshop on Advances in Argumentation in Artificial Intelligence 2024 co-located with the 23rd International Conference of the Italian Association for Artificial Intelligence (AlxIA 2024), Bozen, Italy, November 28, 2024*, volume 3871 of *CEUR Workshop Proceedings*. CEUR-WS.org, 2024.
- [2] Trevor J. M. Bench-Capon. Persuasion in practical argument using value-based argumentation frameworks. *J. Log. Comput.*, 13(3):429–448, 2003.
- [3] Phan Minh Dung. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning and logic programming. In Ruzena Bajcsy,







editor, *Proceedings of the 13th International Joint Conference on Artificial Intelligence. Chambéry, France, August 28 - September 3, 1993*, pages 852–859. Morgan Kaufmann, 1993.