Argo: Argumentation Reasoning with Relational Concept Analysis for Online Debates Exploration

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Abstract

Online debates provide accessible platforms for individuals to engage in constructive dialogue, exchange diverse perspectives, and collectively tackle pressing issues, thereby democratizing the discourse and promoting inclusive decision-making in the digital era. The purpose of this paper is to structure the discourse of an online debate, aiming to facilitate the participation of the debaters. We use relational concept analysis to formalise the structure of online debates, using the relational part to model the succession of arguments. We then extract implications from the resulting relational context family to identify regularities in the terms used by debaters. We aim to use these implications to stimulate the debate by proposing terms and ideas to participants. We observe that RCA produces more trustworthy and novel rules compared to regular FCA, as relational modeling captures interactional and structural dependencies that go beyond simple attribute co-occurrence.

Keywords

Formal concept analysis, Relational concept analysis, Online debates, Argumentation reasoning

1. Introduction

In the dynamic landscape of the digital age, online platforms have emerged as vital arenas for discourse, offering accessible venues for individuals to engage in meaningful textual discussions, express their opinions, and collectively address pertinent societal issues. The advent of online debates has revolutionized the way individuals interact and deliberate on various topics, transcending geographical boundaries and facilitating the exchange of ideas on a global scale. Engaging in debates on specific issues can serve also as a valuable resource for journalists and politicians. It equips them with systematic summaries and key insights into argumentation trends, which can inform reporting, policy-making, and public communication.

In this paper, we use relational concept analysis (RCA) to formalise the structure of online debates. We start by indexing the debaters' arguments using key-terms to define a formal context and then using the relational part to model the succession of arguments. The resulting relational context family is used to extract implications to identify regularities in the terms used for indexing. We compare the RCA results to those obtained with formal concept analysis (FCA) to determine whether considering the sequence of arguments improves the quality of the generated implications (associations between terms). To do so, we use four datasets from two public social platforms, along with two interestingness metrics, i.e. the support to measure how much we trust the generated rule, to be added to the knowledge base *JeuxDeMots (JDM)*, and the novelty to measure whether the produced rule is considered new for *JDM*. Similarly, these metrics indicate if a rule is relevant to be proposed to participants to stimulate the debate.

The rest of the paper is organized as follows. We start by detailing, in Section 2, the preliminaries related to concept analysis. Next, we review the existing work for temporal data analysis with FCA

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and social platforms debate analysis in Section 3. Then, in Section 4, we justify the use of RCA in the context of debates modelling. Section 5 presents the experimental evaluation, based on two public social platforms, i.e. AREN and Reddit, aiming to study the effect of incorporating the temporal dimension in the quality of rules. Finally, Section 6 summarizes our work, with a discussion of the main limitations of our approach in Section 7.

2. Concept Analysis

This section briefly introduces the main notions of formal concept analysis (Section 2.1) and relational concept analysis (Section 2.2).

2.1. Formal Concept Analysis

Formal concept analysis (FCA) is a mathematical framework that allows structuring the information present in binary data [1]. Binary data take the form of *formal contexts*, i.e. triples $\mathcal{C} = (\mathcal{O}, \mathcal{A}, \mathcal{I})$ in which $\mathcal{O}$ is a set of *objects*, $\mathcal{A}$ is a set of *attributes* and $\mathcal{I} \subseteq \mathcal{O} \times \mathcal{A}$ is an *incidence relation* between objects and attributes. A formal context gives rise to two *derivation operators*, both denoted by $\cdot'$:

$$\cdot' : 2^{\mathcal{O}} \to 2^{\mathcal{A}}$$

$$O' = \{a \in \mathcal{A} \mid (o, a) \in \mathcal{I}, \forall o \in O\}$$

$$\cdot' : 2^{\mathcal{A}} \to 2^{\mathcal{O}}$$

$$A' = \{o \in \mathcal{O} \mid (o, a) \in \mathcal{I}, \forall a \in A\}$$

Both pairs of derivation operators, denoted as $(', ')$ form Galois connections and their compositions, both denoted as $''$ are thus closure operators on sets of objects and attributes, respectively.

The first pattern that can be found in a formal context is the *formal concept.* A formal concept is a pair $(E, I) \in 2^{\mathcal{O}} \times 2^{\mathcal{A}}$ such that $E = I'$ and $I = E'$. We then call E the *extent* and I the *intent* of the concept. Concepts can be ordered through the inclusion relation on their extents: $(E_1, I_1) \leq (E_2, I_2) \Leftrightarrow E_1 \subseteq E_2$. The set of all concepts in the formal context ordered in such a way forms a complete lattice called the *concept lattice* of the context. We use $\mathcal{L}(\mathcal{C})$ to denote the concept lattice of the formal context $\mathcal{C}$.

The second pattern that can be found in a formal context is the *implication.* An implication is a pair of attribute sets A and B, denoted as $A \to B$. It is said to *hold* in the context if and only if $B \subseteq A''$ i.e. all objects described by the attributes in A are also described by the attributes in B.

2.2. Relational Concept Analysis

Relational concept analysis (RCA) [2] is an extension of the FCA framework that aims to deal with more complex data, aka multi-relational data. They are formalised as a *relational context family* (RCF). An RCF is a pair $(\mathbb{C}, \mathbb{R})$ such that:

- $\mathbb{C} = \{\mathcal{C}_i = (\mathcal{O}_i, \mathcal{A}_i, \mathcal{I}_i)\}$ is a set of formal contexts (object-attribute relations).
- $\mathbb{R} = \{r \mid r \subseteq \mathcal{O}_i \times \mathcal{O}_j\}$ is a set of relations r between objects of a *source context* $\mathcal{C}_i$ and those of a *target context* $\mathcal{C}_j$ (object-object relations).

We use $src(r)$ and $tar(r)$ to denote, respectively, the source and target context of a relation r. Fig. 1 depicts a relational context family with two 4×4 formal contexts $\mathcal{C}_1$ and $\mathcal{C}_2$, and a relation r between the objects of these two contexts. Additionally, we use $r(o)$ to denote the *image* of an object $o \in \mathcal{O}_i$ by a relation $r \subseteq \mathcal{O}_i \times \mathcal{O}_j$.

In the same fashion as FCA, RCA aims at structuring the information present in the description of objects of the RCF in the form of patterns and structures. Contrary to FCA, concepts in an RCF are

$\mathcal{C}_1$	a_1	a_2	a_3	a_4
o_1	×	×		
o_2			×	
o_3				×
o_4			×	×

$\mathcal{C}_2$	a_5	a_6	a_7	a_8
o_5	×			
o_6		×		
o_7		×	×	
o_8				×

r	o_5	o_6	o_7	o_8
o_1			×	
o_2	×	×		
o_3				×
o_4				

Figure 1: A relational context family containing two contexts $\mathcal{C}_1 = (\{o_1, o_2, o_3, o_4\}, \{a_1, a_2, a_3, a_4\}, \mathcal{I}_1)$ and $\mathcal{C}_2 = (\{o_5, o_6, o_7, o_8\}, \{a_5, a_6, a_7, a_8\}, \mathcal{I}_2)$, and a relation r between their objects.

$\mathcal{C}_1^1$	a_1	a_2	a_3	a_4	$\exists r.(\emptyset)$	$\exists r.(\{a_5\})$	$\exists r.(\{a_6\})$	$\exists r.(\{a_6, a_7\})$	$\exists r.(\{a_8\})$
o_1	×	×			×		×	×	
o_2			×		×	×	×		
o_3				×	×				×
o_4			×	×	×				

Figure 2: The result of one step of relational scaling applied to the context $\mathcal{C}_1$ depicted in Fig. 1. Concepts in relational attributes are represented only by their intents to save space.

described not only by attributes but also by relations with other objects. In order to take this additional information into account, RCA transforms it into attributes by using *relational scaling*. Let us consider $(\mathbb{C}, \mathbb{R})$ be an RCF, $\mathcal{C}_i = (\mathcal{O}_i, \mathcal{A}_i, \mathcal{I}_i)$ be a context in $\mathbb{C}$, R be the set of relations in $\mathbb{R}$ for which $\mathcal{C}_i$ is the source and $\mathcal{Q}$ a set of scaling operators (i.e. quantifiers) associated with the relations of R. The formal context $\mathcal{C}_i^+ = (\mathcal{O}_i, \mathcal{A}_i^+, \mathcal{I}_i^+)$ is then defined by extension of C_i such that:

$\mathcal{A}_i^+ = \mathcal{A}_i \cup \{qr.X \mid q \in \mathcal{Q}, r \in R, q$ is associated with r and $X \in \mathcal{L}(tar(r))\}$

$\mathcal{I}_i^+ = \mathcal{I}_i \cup \{(o, qr.X) \mid X = (E, I)$ and E respects q w.r.t. $r(o)\}$

Here, we only consider the existential quantifier $\exists$. E respects $q = \exists$ w.r.t. $r(o)$ when $E \cap r(o) \neq \emptyset$, meaning that o is connected by r to at least one element in E. The set of all extended formal contexts is $\mathbb{C}^+ = \{\mathcal{C}_i^+ \mid \mathcal{C}_i \in \mathbb{C}\}$.

The computation of $\mathcal{A}_i^+$ and $\mathcal{I}_i^+$, and thus that of $\mathbb{C}^+$, requires the knowledge of all the formal concepts in the target contexts of the various relations r. For this reason, RCA uses an iterative process, where each step i is divided into first computing the concepts of the contexts in the RCF (extended when $i \geq 1$), and then constructing a new RCF $(\mathbb{C}^+, \mathbb{R})$ using these concepts to generate new attributes encapsulating the information brought by the relations.

We use $\mathbb{C}^0 = \mathbb{C}$ and $\mathbb{C}^n = \mathbb{C}^{(n-1)+}$ to denote the state of the contexts at step 0 and n, respectively. The iterative process stops either when a user-defined number of iterations has been reached or when the concept lattices of all formal contexts reach a fixed point, which always happens [2].

Figure 2 depicts the result of the first step of the iteration on our example RCF. One interesting result of RCA is highlighting more relationships between objects. E.g. In our example, o_1 and o_2 do not share attributes (they respectively own $\{a_1, a_2\}$ and $\{a_3\}$) and they have links by r to distinct objects (respectively $\{o_7\}$ and $\{o_5, o_6\}$). But as o_6 and o_7 share the attribute a_6, they are grouped in a concept C_{a_6} introducing a_6 in its intent, and it can be established that o_1 and o_2 have at least one link by r to one object of the extent of this concept C_{a_6}. In other words, o_1 and o_2 share the relational attribute $\exists r.(C_{a_6})$, denoted, by abuse of notation, $\exists r.(\{a_6\})$, as an intent reduced to the introduced attributes uniquely identifies the corresponding concept, if this simplified intent is not empty. Another way to consider this is to see it as the propagation of groups by going back along the links: (1) o_6 and o_7 are grouped because they share the attribute a_6, then (2) o_1 and o_2 are grouped because they are linked to at least one object owning a_6.

3. Related Work

In this section, we scrutinize the research work related to FCA, RCA, and online debates analysis.

3.1. Formal and Relational Concept Analysis

In this paper, we compare FCA and RCA specifically in terms of the support and novelty of the extracted rules, which to our knowledge has not been the focus of prior comparisons. As for prior work, the existing comparisons address different dimensions. Wajnberg et al. show that RCA is more than a standard FCA encoding of relational data, in that it may produce additional relational concepts not obtained from standard FCA encodings [3]. Euzenat provides the theoretical grounding for this difference: RCA computes families of mutually constrained lattices rather than a single lattice built from a fixed context. In his fixed-point semantics, acceptable RCA solutions are characterised as common fixed points of an expansive and a contractive function over well-formed lattice families. The standard RCA algorithm returns the least such solution, while circular dependencies may give rise to other acceptable solutions [4]. Atencia et al. show in practice that FCA can account for simple link key candidates, while RCA becomes necessary when properties are object-valued or keys are interdependent [5]. Dolques et al. compare RCA with propositionalisation for handling relational data: in the acyclic case, applying FCA to a propositionalised representation and applying RCA directly can yield comparable structures, though the resulting descriptions differ in their construction and interpretation [6]. None of these works evaluate the two approaches in terms of rule quality metrics such as support or novelty. This is the specific contribution of our comparison.

Integrating temporal information with FCA is not a new problem and several propositions have been made over the years. Temporal concept analysis [7, 8, 9] and temporal sequence mining [10, 11] aim to represent and analyze changing objects, continuous, discrete or hybrid space and time, with FCA. In our case, we do not have changing objects, but rather observations that are made over time. In this perspective, triadic rules have been used in longitudinal studies in health sciences [12, 13]. This approach does not suit our needs either as we need to separate the indexing of comments from the *respondTo* relation (which determines whether a comment responds to another), which cannot be done in a triadic setting. RCA has already been used for modeling such temporality, for instance in the analysis of hydrology sequential data [14, 15]. In the latter work, the extracted patterns are directed acyclic graphs, in which information extracted from the concepts is used to label the vertices. They do not aim to extract rules.

3.2. Online Social Platforms Debate Analysis

The goal of argument mining is to automatically identify theoretically established argumentative structures within discourse and their interconnections [16]. This section provides a brief overview of research on argument mining and structure focused on social media text. Cabrio and Villata have made significant contributions to this field, particularly with their work on extracting and analyzing arguments in online debates [17]. They have also focused on the task of predicting relationships between arguments in a corpus of online debates sourced from Debatepedia in [18, 19]. Their model uses textual entailment techniques to identify support and attack relationships between arguments. The authors in [20] studied the problem of measuring the properties of online argumentation around a topic of interest. They proposed a framework for understanding arguments in Reddit, which detects argument structure within threads using argument similarity and clustering algorithms. In [21], the authors presented a system for analyzing discussions in Twitter based on valued abstract argumentation. They developed an automatic labeling system to discover the semantic relation between tweets in a discussion and then associated weights with tweets from its social relevance. The authors in [22] studied the problem of uncertainty in public argumentation. They found out that argumentative threads are more likely to be successful if they focus on idea articulation, coherence, and semantic diversity.

In terms of debate structure mining, a bipartite debate graph was constructed in [23], where nodes are posts that agree or disagree with the root comment, and edges are the disagree edges between comments of the two different groups. Next, a graph neural network was used to compute the measure of interest defined from the set of accepted arguments. The dynamic structure of a comment thread has been studied in [24] to determine if the discussion gradually diversifies over time or immediately branches out and remains topically disjoint.

More recently, [25] introduced a novel approach to evaluating argument quality using large language models (LLMs) designed to follow instructions, so-called *instruct* models. Instead of merely fine-tuning LLMs on specific evaluation tasks, the proposal was to systematically instruct them with argumentation theories, argumentative scenarios, and methods to address problems related to arguments. In [26], a new approach is proposed to enhance the explainability and contestability of decisions made by LLMs. The proposed concept of *argumentative LLMs* is a method that leverages LLMs to construct argumentation frameworks as a basis for formal reasoning in decision-making. This approach aims to combine the extensive knowledge of LLMs with the ability to provide explanations that are interpretable by humans.

In summary, no prior research has focused on extracting associations between debate terms to gain deeper insights into debaters' arguments. Besides, the approach we propose does not involve deep neural networks or LLMs, as we aim for an explanatory architecture that is relatively frugal and under our full control from end to end. Additionally, the model must adapt continuously as debates evolve, and therefore it does not include any additional training or fine-tuning phases.

4. Modelling Debates

An online debate revolves around a supporting text (or a multimedia content) that brings together a group of users. These users participate by providing comments expressing their opinions, arguments, or points of view on a segment of the supporting text or of a previously published comment, thereby creating branches in the general tree of the debate. In order to capture the temporal dynamics and the interrelations among debate comments, we employ RCA. This approach considers the relationships between the comments and their indexing terms (Section 4.1), as the formal context, and the hierarchical structure of comments, determining which comment responds to the another (Section 4.2), as the relational context.

4.1. Thematic Indexation of Comments

The various arguments put forth by participants in the debate are contained in raw and unstructured texts. The thematic indexing of comments aims to produce a structured representation of them, facilitating the synthesis of comments via sets of key-terms. The indexing terms may refer to concepts mentioned in the text or lexical units deemed salient within the comment. This keyword extraction step relies on external knowledge from the lexico-semantic network *JDM* [27], and is carried out by the *IDÉFIX*[1] service. *IDÉFIX* is an overlayer of the *JDM* network, enabling the selection of relevant terms for a given input text. This selection occurs locally within the comment, mimicking examples learned from previous interactions with the user (validation, invalidation, and proposal of key-terms).

For example, based on the text "*It is a known historical phenomenon that to resolve a financial crisis, local currencies were used MLCCs, for example in 1929 in Basel*"[2], the obtained indexing terms are as follow: *crisis resolution complementary currency • historical phenomenon • exchange • local economy • short circuit • famous for • being flexible • communicating effectively • fair exchange.*

To achieve its result, *IDÉFIX* calculates three sets of weighted terms and combines them in the proportions of 1/6, 2/6, and 3/6.

– The first set of *extracted terms* involves the direct extraction of terms from the text with lemmatization and identification of compound terms.

In the same example, we obtain: *historical being • to be known • a phenomenon • historical phenomenon • to resolve a crisis • historical for • known for • to resolve • a financial crisis • having been • local currencies • local currency • MLCC • to use • used • example • 1929 • Basel • basel • phenomenon • to solve • currency.* This initial set of extracted terms undergoes lexical disambiguation through the *Bellérophon*[3] service. The meanings selected for polysemous terms are then added to this set, i.e. *currency>money.*

[1]https://www.jeuxdemots.org/intern_extract.php
[2]The original French comments, indexing terms, and association rules have been translated into English for clarity.
[3]https://www.jeuxdemots.org/intern_desamb.php

– The second set of *associated terms* encompasses all associations (relation *r_associated* in *JDM*) positively linked to the extracted terms.

Following the previous example, we get, where the character | separates the term from its weight: *complementary currency | 10 • exchange | 3.41 • local economy | 3.17 • short circuit | 2.67 • famous for | 2.66 • being flexible | 2.66 • communicating effectively | 2.66 • fair exchange | 2.41 • solidarity currency | 1.34 • alternative currency | 1.24 • citizen currency | 1.17 • local exchange | 1.13 • responsible consumption | 0.97 • specialized in | 0.88 • circular economy | 0.86 • exchange of goods and services | 0.81 • territorial enhancement | 0.60 • service exchange | 0.59 • local purchasing power | 0.58 • archaeological discovery | 0.33 • being creative | 0.26 • ecological transition | 0.24 • economy | 0.23 • local services | 0.21 • MLC | 0.20.*

– The third set of *activated terms* corresponds to the output activations in a discrete neural network constructed within *JDM*, that associates a set of input terms (the extracted terms) with a set of output terms. In the previous example, after thresholding, we obtain: *crisis resolution • historical phenomenon • MLCC • financial crisis • local currencies • Basel • 1929.*

To clarify the integration and the proportion of the different sets within the IDÉFIX service, we should point out the proportions $1/6$, $2/6$, and $3/6$ do not represent a strict constraint on the number of terms extracted from each set, but rather a weighting factor applied to the internal activation scores of the terms during the merging and filtering phase.

Specifically, the weights of the second set (the 'r_associated' relations in JeuxDeMots) are used as follows: 1. Initial Score Retrieval: Each term in the second set comes with an intrinsic association weight from JDM (e.g., complementary currency: 10, exchange: 3.41). 2. Normalisation & Weighting: These weights are normalised and then multiplied by their respective set coefficient (here, $2/6$). 3. Merging: If a term appears in multiple sets (for instance, complementary currency appears via different activation paths), its scores are combined. 4. Threshold Filtering: Finally, a global filtering threshold is applied to the aggregated scores to retain only the most salient keywords.

In the provided example, the second set generates a high concentration of terms whose aggregated and weighted scores pass the selection threshold. Conversely, the discrete neural network (the third set) yields highly specific terms, but only a few of them (crisis resolution and historical phenomenon) emerge above the threshold after applying the $3/6$ weighting factor. This explains why the final selection displays seven terms from the second set and only two from the third set, while fully respecting the architectural proportions of the algorithm.

4.2. "Respond to" Relations Between Comments

A discussion begins when a user submits an initial piece of content, i.e. a piece of text or media, referred to as a submission. Other users can then comment on this submission, while also receiving replies to their comments. As users engage in back-and-forth responses, the conversation expands in a branching, tree-like structure.

The tree structure of the debate reflects the temporal aspect of the comments. Based on this structure, we consider the "respond to" relationship between comments to define the relational context.

For example, considering two comments $C1$ *"The local currency has already served as a tool in times of crisis"*, and $C2$ *"It is a known historical phenomenon that to resolve a financial crisis, local currencies were used MLCCs, for example in 1929 in Basel"*. In the debate, $C2$ comes as a response to agree with $C1$.

Knowing that $C1$ is indexed by the list of terms $T1$ = {*sustainable local currency, complementary local exchange systems, local cooperative, free local currency, local neighborhood currency, fair exchange, complementary currency, dematerialized local currency, local currency complementary and sustainable, shared currency, short circuit, crisis period, community bank, various bootmaker tools, quarter inch, local project, Wir, system of reciprocal exchange of knowledge, participatory local currency*}, and $C2$ by the list of terms $T2$ = {*crisis resolution, complementary currency, historical phenomenon, exchange, local economy, short circuit, famous for, being flexible, communicating effectively, fair exchange*}, the relation between $C1$ and $C2$ is then represented by adding to the indexation of $C2$ new "terms" of the form $\exists respondTo.(X, Y)$ where (X, Y) is a formal concept such that $C1 \in X$. For instance, $C2$ could be described by $\exists respondTo.(\{sustainable\ local\ currency\})$[4], meaning it groups comments that are a response to at least one comment about *sustainable local currency*.

5. Case Study

In this section, we describe our datasets (Section 5.1), then the metrics used to assess the research questions (Section 5.2). The section ends with the presentation and the discussion of the results (Section 5.3). We use the thematic indexation of comments as input to FCA and add the "Respond to" relations between comments to produce relation context families for the RCA process.

5.1. Datasets Description

In this paper, we use two online social platforms as source of data: AREN and Reddit.

5.1.1. AREN datasets

AREN[5] is a web application that provides a platform for debate, bringing together a community of users. The discussions revolve around a supporting text published on the platform. Users participate by commenting to express their arguments on specific segments of the text or on previously published comments. This interaction creates branching threads in the overall debate structure. The debaters also contribute to the construction of the term sets used to index comments by reviewing and validating the terms generated with *IDÉFIX*. Their feedback is incorporated into subsequent thematic indexing processes, leading to progressively higher-quality indexing.

We use two datasets related to two debates on the AREN platform. The first dataset is about local currencies[6]. The second one turns about Egyptology[7]. The main characteristics of our datasets are presented in Table 1.

Table 1
Statistics of the datasets

Debate	Platform	Subject	Debaters	Arguments	Keywords	Period
D1	AREN	Local currencies	8	48	675	2020 – 2023
D2		Egyptology	2	54	1,065	Mar. 2024
D3	Reddit	Democracy	211	527	4,243	Feb. 2023
D4		Drought	115	271	2,298	Feb. 2023

The depth of the discourse tree (or the length of the maximal chain of comments) in the debate on Local currencies D1 (respectively Egyptology D2) is 5 (respectively 3), with the support text being regarded as level 0. Each argument of a debater is associated with an initial text of the debate, we call selection, and described by a reformulation, a sentence which reflects their understanding of the argued text, and an opinion. In the case of D1, 83.33% of the arguments are "*rather agree*" and 16.67% are "*rather disagree*". In total, 675 distinct keywords were used to index the arguments. However, for D2, $79,63\%$ were "*rather agree*" and 20.37% were "*rather disagree*", using $1,065$ distinct keywords for indexing.

5.1.2. Reddit datasets

Reddit is an online discussion platform where users engage in communities organized around specific topics, known as "*subreddits*". These subreddits cover a vast range of subjects, fostering discussions

[4]with the notation abuse consisting in denoting the concept by its simplified intent if non empty
[5]https://portail-aren.lirmm.fr/aren2023
[6]Are local currencies a tool to save the local economy?
[7]Egeektologue

that reflect diverse language styles, cultural backgrounds, and education levels, leading to a wide array of perspectives and language styles. A discussion begins with a submission, which can be a piece of media or text that invites responses from users. Comments can also receive replies, forming chains of responses, which create a "*posts tree*".

We use two datasets related to two debates from the "r/france" subreddit with $2M$ registered members. The first dataset is about democracy[8] and the second about drought[9]. Table 1 shows the main characteristics of the Reddit datasets. The depth of the discourse tree in the debate on democracy D3 (respectively drought D4) is 20 (respectively 9), with the support text being regarded as level 0. The number of upvotes of D3 (respectively D4) is about 763 upvotes (respectively 1, 046). Besides, D3 was shared 541 times, compared to D4 with 261 shares.

5.2. Evaluation Metrics

Our objective is to extract regularities to stimulate the debates. This requires "relevant" implications. In this paper, we want to know whether taking the sequence of arguments into account using RCA produces even more relevant implications than FCA. To evaluate this, we use the following interestingness measures.

5.2.1. Support

The support of an implication is the number of objects (or comments) described by the terms involved in the rule. It is defined as:

$$Support(r) = |(T_r^p \cup T_r^c)'|$$

where T_r^p and T_r^c are respectively the terms of the premise and conclusion of a rule r. The support is useful to determine whether the elements involved in the rule are frequent in the dataset, and therefore it allows us to differentiate noise and real patterns in the debate.

5.2.2. Novelty

A rule is considered novel if its premise and conclusion are not statistically independent [28]. The novelty is given by:

$$Novelty(r) = p(T_r^p \cup T_r^c) - p(T_r^p)\,p(T_r^c)$$

where T_r^p and T_r^c denote respectively the sets of terms forming the premise and the conclusion of a rule r, and $p(T) = \frac{|T'|}{|\mathcal{O}|}$ denotes the empirical probability of observing the set of terms T in the dataset, where $\mathcal{O}$ is the set of objects, i.e. the comments in the debate. The novelty is useful to determine whether an implication between terms is new to *JDM* and can be used to enrich its knowledge base, or to suggest new terms and topics to debaters to stimulate the debate.

5.3. Experimental Results

In these experiments, we restricted ourselves to the computation of unitary implications – implications whose premises are singletons – as they better lend themselves to the completion of a knowledge base with relations between single terms. We extracted these implications from the contexts resulting from a single step of the RCA process, focusing only on the immediate responses between comments.

5.3.1. Quantitative results

We begin by providing a quantitative view of the results of FCA and RCA. In Table 2, we report the number of attributes and rules obtained for all datasets. As we can see, for all four datasets the number of attributes and rules is higher with RCA. This is expected since RCA adds attributes that represent the relations between the objects, which produces rules involving those attributes.

[8] France, a "full" democracy according to The Economist
[9] Risk of multiyear drought in France - climate emergency

Table 2
Number of implications with FCA and RCA

	D1		D2		D3		D4	
	FCA	**RCA**	**FCA**	**RCA**	**FCA**	**RCA**	**FCA**	**RCA**
$\|attributes\|$	675	1,020	1,065	1,215	4,243	5,524	2,298	2,790
$\|rules\|$	645	956	1,011	1,121	3,944	5,114	2,161	2,568

5.3.2. Examples of computed implications

This section presents some of the implications computed with RCA. An interpretation and a potential usage of these implications are also proposed.

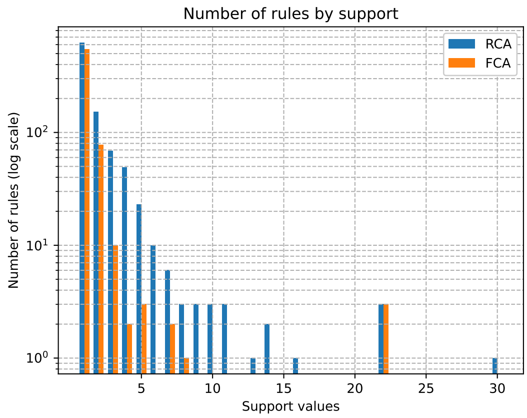
- $local\ exchange\ systems \rightarrow pooling, \exists.respondTo.(\{exchange\})$
  - Interpretation: All comments about local exchange systems talk about pooling and respond to a comment about exchange.
  - Usage: A new association (*local exchange systems, r_associated, pooling*) would be added to *JDM*. As *local exchange systems* is a hyponym of *exchange*, we could suggest other hyponyms of *exchange* to respond to comments about *exchange*.
- $\exists.respondTo.(\{currency\ >\ money\}) \rightarrow economy, \exists.respondTo.(\{money\ refunded, social\ organisation, exchange\})$
  - Interpretation: All comments that respond to a comment about currency talk about economy and respond to a comment about social organisation and exchange.
  - Usage: We can stimulate the debate by informing the debaters that others who comment on the topic of currency usually talk about economy as opposed to numismatic, for example.

5.3.3. Qualitative results

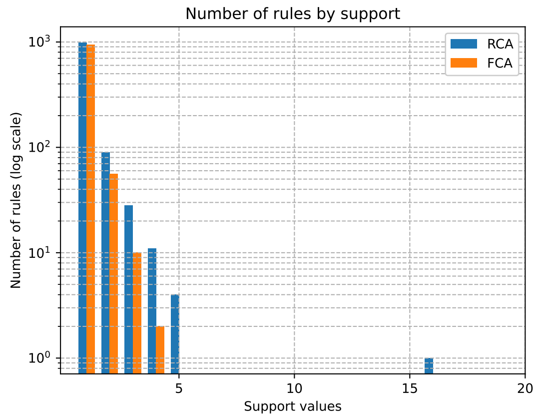
To assess the impact of incorporating the temporal aspect, we compare the rules obtained with FCA versus those of RCA. We compute the supports of the rules (Fig. 3) and their novelties (Fig. 4).

As we can notice in both Fig. 3a and 3b, related respectively to debates D1 and D2, we get more interesting rules with RCA, that produces more rules with higher supports. For example, in debate D2 (Fig. 3b), we obtained with RCA $1,121$ rules with support values varying from 1 to 16, whereas with FCA we obtained $1,011$ rules with supports between 1 and 4. In addition, for a given support value, for instance 2, RCA produces 90 rules, with only 56 rules for FCA. The same conclusions are applicable for Reddit debates D3 and D4, when we got more interesting rules with RCA than FCA (Fig. 3c and 3d). More precisely, FCA produced $3,944$ rules in total with supports lower than 8, however the rule supports reached 99 with RCA with a total number of $5,114$ rules. From that, we deduce that implications generated by RCA are more trustworthy and can be used as potential new associations to stimulate the debate.

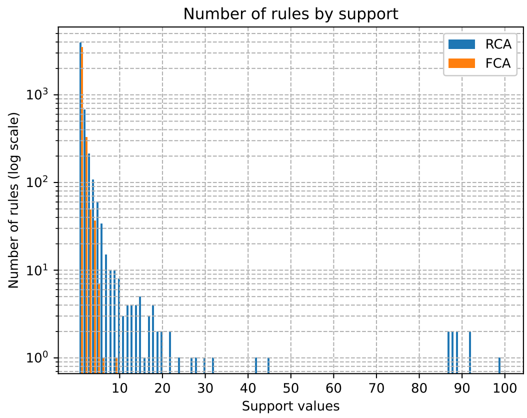
As for the novelty related respectively to debates D1 and D2, depicted in both Fig. 4a and 4b, RCA also produced more rules with higher novelties compared to FCA. For instance, in debate D1 (Fig. 4a), RCA generated 27 rules with novelty values higher than 0.15, when FCA produced only 9 rules. RCA generated also more rules with highest novelties than FCA for the Reddit debates D3 and D4 (Fig. 4c and 4d). For example for the democracy dataset, all the FCA rules novelties are lower than 0.02, when the RCA rules novelties reached 0.152. These results prove that we can find more new associations that do not exist in *JDM* with RCA than with FCA. This observation demonstrates the importance of the succession of comments to generate new associations between terms.



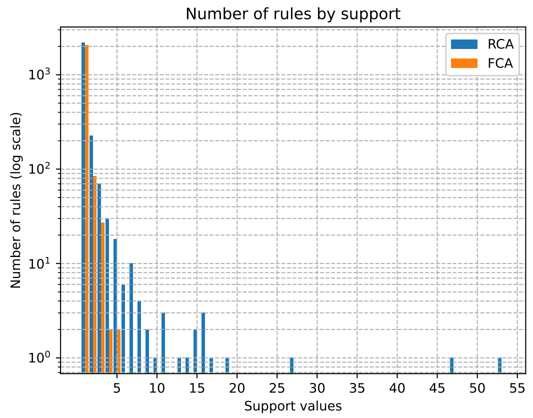
(a) Local currencies dataset



(b) Egyptology dataset



(c) Democracy dataset



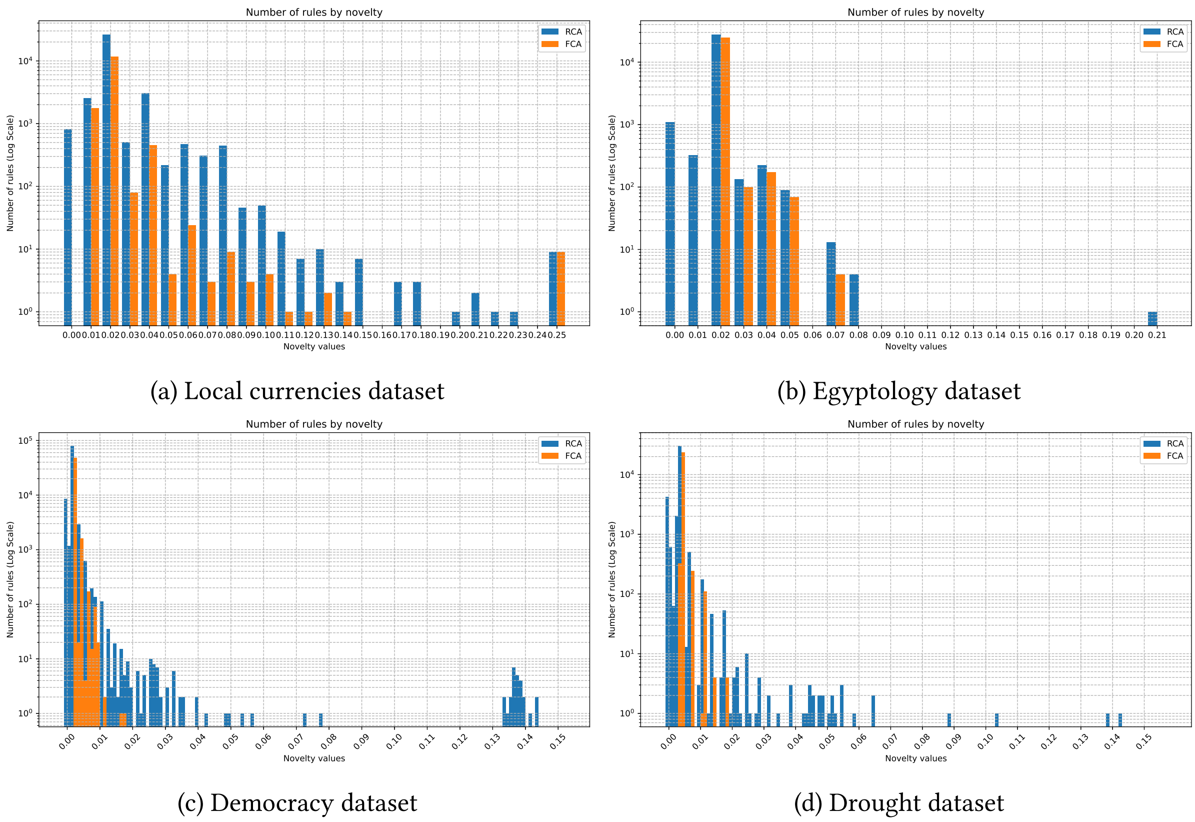
(d) Drought dataset

Figure 3: Number of rules per support using FCA (orange) and RCA (blue) for AREN (first row) and Reddit (second row) datasets.

5.4. Discussion on Operational Deployment

To address how these extracted implications can concretely achieve the goal of stimulating online debates without causing cognitive overload, we adopted the following workflow:

- User Interface Integration: We do not display raw or textualized implications directly to the debaters. Instead, the implications serve as a background filtering mechanism within the platform (e.g., AREN). When a participant writes a comment, the system dynamically monitors their active vocabulary, matches it against the premises of highly-ranked RCA implications, and subtly suggests related target concepts or alternative viewpoints (e.g., suggesting pooling when a user is replying to a comment about exchange) as "ideas to explore".
- Filtering Useful Implications: To separate noise from meaningful knowledge, the dual-metric system detailed in Section 5.2 is fully leveraged. Support ensures that suggestions are rooted in frequent, shared structural patterns of the active community, while Novelty prioritizes emerging conceptual shifts specific to the debate that are not yet registered in the JDM baseline. Restricting the system to unitary implications further reduces computational complexity and ensures direct term-to-term recommendation mappings.
- Live Evolution and Scalability: Because our architecture deliberately avoids heavy deep neural networks or LLM fine-tuning phases, it remains highly frugal and adaptable. In a live setting where the debate continuously evolves, the RCA fixed-point calculation does not need to run synchronously for every single comment. Instead, the Relational Context Family (RCF) can be



(a) Local currencies dataset

(b) Egyptology dataset

(c) Democracy dataset

(d) Drought dataset

Figure 4: Number of rules per novelty value using FCA (orange) and RCA (blue).

updated asynchronously at periodic intervals (e.g., every few minutes) or incrementally, allowing local rule approximations to guide users while global structural recalculations are queued.

6. Conclusion

In conclusion, our approach provides a fresh perspective to enrich debate by identifying valuable insights that evade traditional FCA. Specifically, our exploration of temporality modeling through relations raises intriguing questions such as symmetry and transitivity. These aspects warrant further investigation to better comprehend how they influence conceptual dynamics. Moreover, the forthcoming integration of polyadic relational concept analysis [29] holds promise in opening new research avenues and understanding within this domain. Ultimately, our work establishes a robust foundation for future studies aiming to explore and extend the possibilities of conceptual analysis in debate structuring.

7. Limitations

While our approach demonstrates promising results, it also has certain limitations that affect its scalability and accuracy. Below, we outline key challenges related to scalability constraints, knowledge base reliability, the impact of misinformation, and the lack of comparative study with LLMs.

One of the primary limitations of our work is the scalability of FCA and RCA. As dataset size increases (like debate D3 with $4,243$ keywords), the exponential growth of concept lattices and the computational complexity of generating and managing these structures become a significant challenge.

Another limitation of our approach, which relies on the knowledge base *JDM*, is its inherent incompleteness, potential outdatedness, and occasional inconsistencies, like any other knowledge base. These issues impact the reliability of inferences drawn from the data, particularly affecting the indexing task in our case, and may introduce biases into the analysis. Furthermore, our approach struggles to accommodate emerging and domain-specific knowledge that is not yet well-represented, limiting its applicability in dynamic and specialized contexts.

A significant limitation of our approach is the challenge posed by trolls and misinformation in online debates. Trolls often introduce false, misleading, or deliberately provocative statements that can distort the extracted implications. As a result, the automatic integration of associations between terms risks incorporating biased or incorrect information into the knowledge base *JDM*. To mitigate this, a validation step is necessary before integrating extracted implications, requiring expert review to ensure accuracy and relevance. However, this introduces an additional problem, as domain-specific experts are needed to assess the validity of the information, which can be time-consuming and resource-intensive. This dependency on expert validation limits the scalability and automation of the approach, particularly in rapidly evolving or highly specialized domains.

The last limitation of our work is the absence of a comparison between our RCA-based approach, for extracting implications from debate-indexing keywords, and LLMs. LLMs, with their advanced natural language understanding and contextual reasoning capabilities, have shown strong performance in extracting semantic relationships from text. Comparing RCA with LLMs could provide valuable insights into their respective strengths and weaknesses, like the explainability and formal structure offered by RCA versus the flexibility and adaptability of LLMs. Additionally, such a comparison could highlight potential hybrid approaches, where RCA's formalised conceptual structures could complement LLMs' ability to process nuanced language and infer implicit meanings. Future work should explore this comparison to assess how both methods can contribute to improving implications extraction between terms of online debates.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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