Computational Narrative Framing: Towards Identifying Frames through Contrasting the Evolution of Narrations

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Abstract
Our understanding of the world is fundamentally shaped by language, with narrations being a central point, and influenced by its framing. Recent advancements in language models gave rise to computational methods for both narrative understanding and framing analysis. Although given their overlap, these two strands are mostly researched independently. In this position paper, we argue for their consolidation in the form of narrative framing, i.e., the framing process driven by narrations. Herein, we outline similarities between both based on semantic elements. Besides, we discuss how different narratives might compete with each other, as well as evolve over time. Thereby, narratives inevitably change the framing, exemplarily depicted on the issue of climate change. We believe that the analysis of narrative frames will lead to a broader understanding of textual corpora as a whole rather than individual pieces of text.

Keywords
Framing Theory, Narrative Frames, Competing Narrations, Climate Change Framing, Semantic Graphs

1. Introduction

Experiences in the real-world and narrative perception are inextricably linked in humans, even on a neurological level [1]. In a similar vein, the framing of narratives can act as a device to blend fiction and reality [2], consequently suggesting certain solutions to specific problems [3] and affect the people's choices [4]. Unlike other types of frames, the pool of options concerning narratives for framing is essentially endless. Although some works on computationally extracting narrative framing have already been conducted [e.g., 5, 6, 7], the still sparse body of research tends to favor one strand of research, i.e., either narrative understanding or framing analysis, over the other.

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In this position paper, we present a basic theoretical framework for computational narrative framing analysis, effectively combining computational narrative understanding and computational framing analysis research. We identify the commonalities between the two strands to form an elementary understanding of the necessities for emerging approaches in this direction. Moreover, we explore how such a framework enables contrasting the evolution of different lines of narrative frames across important issues. Herein, we exemplarily discuss the narrative change regarding climate change, i.e., the evolution from *global warming* to the more urgent naming of *climate catastrophe* and similar [8].

As our main contribution, we want to provide an impulse towards further exploration of how narrations are being used to frame long-term discourses. We hope that our work bridges the gap between two similar but still distinct communities.

2. Background

The present work comprises two strands of computational research, based on narrations and frames, respectively. Specifically, we focus on the parts where computational narrative understanding and computational framing analysis mostly overlap.

Computational Narrative Understanding (CNU) Narrations, being defined by their content and structure, are used to study many topics, with the policy process in the narrative policy framework being a well-known example [9]. Herein, the elements of narrativity have first been fully formalized by Piper et al. [10], with the minimal definition being structured as *"Someone tells someone somewhere that || someone did something(s) [to someone] somewhere at some time for some reason"*. Here, the left part (before the ||) is the perspective of *narrating* the story, while the right part concerns the story itself (i.e., *diegesis*). In a similar vein, some strides have already been made towards analyzing narrative frames [5]. Overall, we observe that actors and events are central components of narrations, which provides overlap with some computational framing analysis approaches.

Computational Framing Analysis (CFA) Framing deals with salience in communication [3] and is concerned "how" a text is presented rather than "what" is apparent [11]. The analysis of framing can be seen as a task of natural language understanding (e.g., similar to tasks in the GLUE benchmark [12]). The notion of framing is very distinctively conceptualized in computational literature, comprising supervised and unsupervised, as well as mixed-method based approaches [11]. As supervised approaches depend on corpora and codebooks, unsupervised approaches are more in line with narrative understanding. For instance, DiMaggio et al. [13] use topic modeling for framing analysis and equate certain topics with frames. Besides, they define frames as comprising narratives among other cues, and also find narratives as being part of a particular topic. Other works consider semantic information, such as semantic role labels [6] and semantic graphs [7] to analyze narratives directly.

In the remainder of the paper, we use the theory presented by Piper et al. [10] for CNU and the survey by Ali and Hassan [11] for CFA as cornerstones in their respective areas. Also, when using the term *narrative framing*, we refer to the framing using narratives as device, thus compounding both CNU and CFA. Herein, we focus on framing through semantic structure (i.e., following Fillmore and Baker [14]) rather than other forms of framing.

3. Computational Narrative Framing

As a starting point for better understanding narrative framing, we analyze how their research directions are entangled. Both, Piper et al. [10] and Ali and Hassan [11], identify a set of future research endeavors by stating core challenges and open questions, respectively. We provide an overview of these future directions in Table 1. Comparing them, we observe remarkable overlap between the two strands that we summarize as key requirements.

First (*R1*), there is the improvement of methods by considering fine-grained nuanced features, e.g., latent features (CNU) and semantic relations (CFA). Herein, CNU focuses on understanding deep stories via narrative structuring of higher-order organizing principles, while CFA focuses on semantic relations going beyond words with the aim to better explore frames. Here, we identify *narrative structure* as a key direction for future research.

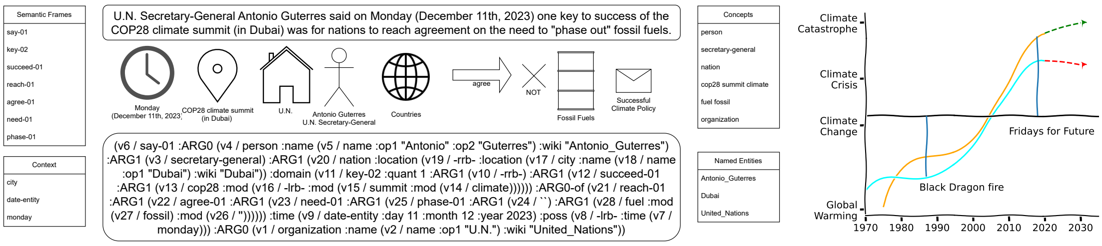
Second (*R2*), the relation between multiple documents (potentially even for distinct types) for a broader understanding are established. CNU aims to understand narrative discourse by studying the interaction of narrative features, even between different narrative products (e.g., movies vs. books). CFA questions how different documents can be connected or inform each other. We reason that the understanding of narratives must go beyond individual narratives and shift towards a focus on *competing narratives*.

Third (*R3*), both emphasize the incorporation of more nuanced knowledge sources, e.g., past events like wars (CNU), culture, and omission (CFA). CNU argues for more robust classification of narrative types via interdisciplinary large-scale registers. CFA calls for a computational model to construct frames via salience through various framing devices. We see the modeling of the *temporal evolution* as a good starting point to capture more nuances.

Based on these suggestions, we reason that computational narrative framing approaches must go beyond simple feature analysis (e.g., on the word-level) of individual documents, but rather analyze the corpus as a whole considering the nuances within. Specifically, we argue that narrative frames emerge from the temporal evolution of collections of documents comprising structural elements. In the following, we aim to synthesize these requirements from the bottom-up.

Table 1
Overview of core challenges in CNU [10] and open question in CFA [11].

	CNU core challenges	CFA open questions (abbreviated)	Synthesized requirements
R1	Narrative beliefs	Capture all relevant semantic relations?	Narrative Structure
R2	Narrative responses	Frames across multiple documents?	Competing Narratives
R3	Narrative economies	Salience through framing devices?	Temporal Evolution



(a) Narrative Framing Representation

(b) Temporal Evolution

Figure 1: Exemplary plot on how narratives on climate change could be depicted.

3.1. Narrative Structure

To start, we establish narrative frames that go beyond word frequency, with structure being a focal point. We base the analysis on our prior work [7] using semantic graphs based on abstract meaning representations [15].

In Figure 1a, we depict an example that shows how complex such representations can be, even for short sentences. Specifically, we used a sentence from a recent news article on the COP28[1]:

> U.N. Secretary-General Antonio Guterres said on Monday (December 11th, 2023) one key to success of the COP28 climate summit (in Dubai) was for nations to reach agreement on the need to "phase out" fossil fuels.

We transformed the text to a graph using [16][2] and present its linearized form for brevity. While a detailed explanation is beyond the scope of this paper[3], the key elements that such model extracts are semantic frames (comprising verbs and senses) [14], concepts (nouns), contextual information (time and location), as well as named entities. We want to highlight that the model implicitly performs both simplifications (e.g., singularization of nations to nation) and generalizations (e.g., wikification of U.N. to United Nations), potentially in unison (e.g., stemming and verbification of agreement to agree-01), to improve the resulting representations.

Therefore, this or similar representations are necessary to fulfill the first requirement for computational narrative framing (R1). Note that, we used a straightforward parser here for demonstration, but more recent language models, e.g., BART [17], might be better suited for the task at hand.

3.2. Competing Narratives

After having extracted the narratives of individual documents, we might compare them. In most scenarios, narratives will cluster together and compete with each other, with narratives

[1]Taken from: https://www.reuters.com/business/environment/phasing-out-fossil-fuels-is-key-cop28-success%2Dsays-uns-guterres-2023-12-11/ where we enhanced the text with meta-data from the article, i.e., time and location, which we put in parentheses.
[2]Available as open tool at: https://bollin.inf.ed.ac.uk/amreager.html
[3]The guidelines are available at: https://github.com/amrisi/amr-guidelines/blob/master/amr.md

of conspiracy theories being an obvious instance. Especially regarding the topic of climate change, conspiracy thinking seems larger than anticipated [18]. Even for COP28, conspiracy narratives are spreading, such as relating to the fear of keeping the population captive[4]. Besides considering conspiracies, many intra- and inter-corpus dependencies should also be considered, with polarization [19] being another noteworthy example.

To identify such competing narratives, we can rely on established methods for corpus analysis (e.g., [20]). However, beyond applying them on lexical features (e.g., words), considering the semantic level as established in 3.1 is important for the second requirement (R2).

3.3. Temporal Evolution

While the third requirement (R3) contains many distinct points, we focus on the temporal aspects that we see as the most common factor. Hence, the present should depend on the past, while also account for irregularities like notable omissions of specific narratives. Furthermore, the evolution will depend on the competing narratives established in 3.2. For example, the overall narrative framing might show a similar trend but at a different pace depending on the cultural context, which we visually illustrate using an artificial example in Figure 1b. Notably, certain events could lead to sudden shifts in trajectories that need to be accounted for.

While methods like time-series analyses seems sound at first glance, we believe that due to discreteness of narrative frames, sequential modeling approaches [21] are a better fit. In such models, side-information such as relevant events could be utilized as well.

3.4. Challenges in Narrative Framing Analysis

Foremost, we acknowledge that the main challenges identified still remain unsolved. Beyond that, detecting narrative frames is even more difficult to achieve than both CNU and CFA individually. While data is sparse in both domains, there is a complete lack of ground truth data to train algorithms for predicting the narrative framing. Moreover, classical machine learning setups like classification would not work at all, as there is no complete set of narrative frames due to their emergent properties. Finally, the validation, especially quantitatively, is unsolved as the evolving nature of narrative frames hinders most (static) measures.

4. Learning from Evolving Narratives: The Case of Global Warming to Climate Catastrophe

Following up on the topic of the example provided in Figure 1, we now briefly discuss how considering computational narrative framing would support understanding the discourse on climate change. The framing of climate change has gradually shifted from *global warming* to *climate change*, and more recently towards *climate crisis* or even *climate catastrophe* [8]. While anecdotally obvious, such patterns are notoriously challenging to detect computationally when they are not known in advance. Climate change, in particular, is a long-term issue where changes are noticeable even for laymen. Besides the reframing of the scientific consensus

[4]https://phys.org/news/2023-11-climate-conspiracy-theories-flourish-cop28.html

towards increasing urgency, even the framing of climate change denial shifted their narrations from outright denying climate change to denying human-made climate change. Supporting such discourse analysis with computational methods would be very beneficial for identifying narrative patterns for preemptive counteraction, as well as future predictions.

5. Conclusion

In this paper, we introduced *computational narrative framing* that combines the research of *computational narrative understanding* with *computational framing analysis*. Herein, we identified that both of their pressing future research directions overlap, which coincidentally situate the main requirements for the task at hand. Specifically, (i) narrative structure, (ii) competing narratives, and the (iii) temporal evolution are fundamental for a thorough understanding. We exemplarily support our reasoning concerning the evolution of competing narrations in climate change discourse. Our hope is that this paper serves as a starting point for mutual benefit between two distinct research strands that enables a broader understanding of important societal topics.

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