tex2net: A Package for Storytelling using Network Models

Joao Tiago Aparicio
LNEC, INESC-ID, Instituto Superior Técnico, University of Lisbon, Portugal

Elisabete Arsenio
LNEC, Department of Transport, 1700-066 Lisbon, Portugal

Rui Henriques
INESC-ID, Instituto Superior Técnico, University of Lisbon, Portugal

ABSTRACT

As the volume of textual data grows at a fast pace, there is an increasing need for effective techniques to analyze and present this data meaningfully. Traditional methods of summarizing text data, such as word clouds or tag clouds may not provide a comprehensive narrative overview. In contrast, visual representations, such as graphs, arguably allow the visualization of more complex information. In this paper, we propose a text-to-graph conversion technique that allows the visualization of a story's main characters and relationships. Although visualizing text data through graphs is becoming increasingly popular, existing graph tools generally depend on structured data representations and are unable to comprehensively visualize a narrative and its entities (characters). Our proposed text-to-graph conversion technique addresses this gap, by providing a valuable tool for storytelling visualization, along with relevant guidelines. To this end, we propose a methodology to learn expressive graphs (stories) by extracting relevant relationships between focal entities (characters) from a text document. Graph representation is subsequently refined to communicate the flow of sample narratives. The methodology is provided as a software library, termed tex2net. The acquired results indicate that the proposed approach is able to summarize the story, complementing the use of traditional text summarization techniques. Additionally, we found the graphical summaries more engaging and easier to understand.

CCS CONCEPTS

• **Computing methodologiesArtificial intelligence**; • **Human-centered computingVisualization**;

KEYWORDS

text mining, storytelling, data visualization, network visualization, nlp, text to graph

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1 INTRODUCTION

Immerse yourself in the fascinating realm where literature intersects network analysis, unveiling a captivating exploration of words and ideas. This paper presents a foundational programming library (i.e. a collection of usable functions) for text visualization using networks, inspired by the intricate connections found within literary works and the visual representation of complex systems. This innovative tool enables the discovery of hidden relationships in textual data, allowing for the unraveling of narrative intricacies, exploration of semantic connections, and discovery of meaningful patterns. With its precision and creative approach, this library empowers researchers, linguists, and data enthusiasts to transform textual information into visually appealing representations. By facilitating deeper insights, fostering new discoveries, and enhancing our understanding of the intricate nature of language, this library brings a fresh perspective to the study and analysis of textual data.

Text network analysis has become increasingly popular due to its ability to identify and analyze the semantic relationships between words and phrases, and to represent social networks from exchanged messages and build recommender systems from content descriptions and text feedback. For example, a library can be used to convert a corpus of scientific papers into a network to identify clusters of related terms and topics. Popular libraries for text network analysis like the Natural Language Toolkit (NLTK) in Python [16] and the Stanford Network Analysis Platform (SNAP) [14] provide a range of functions for converting text into networks, as well as tools for network analysis and visualization. However, there are still significant gaps in the literature and available tools that remain to be addressed. One major issue is the lack of standardization in constructing text networks, leading to inconsistency in network representations and potential biases in the analysis [10]. Furthermore, the full richness of the underlying semantic relationships in a text document, as well as its expressive representation in networks, is still largely underexplored. As the volume of textual data continues to grow rapidly, there is an increasing need for effective techniques to analyze and present this data in a meaningful way [12]. Traditional methods of summarizing textual data such as word clouds or tag clouds may not provide a comprehensive overview of the narrative [5, 13]. In contrast, visual representations such as graphs or charts provide an effective way to visualize complex information [8] and is becoming increasingly popular [18]. However, existing techniques often focus on extracting simple trends from large amounts of data [3]. There is a lack of methods that allow the visualization of a narrative and its characters [20, 21].

2 LITERATURE REVIEW

Text network analysis (TNA) has emerged as a powerful tool for understanding the relationships between words and phrases in various domains. TNA offers a unique lens to probe the intricate webs of relationships and patterns embedded within textual data. Through TNA, researchers can unravel which concepts frequently co-occur, decipher the underlying structure of discourses, and map the inter-relations among different entities or ideas within the text [6]. Particularly valuable for large datasets, TNA can identify distinct topical clusters, revealing overarching themes and segregated topic communities [17] or even robustness of connections [2]. The research in this field spans across multiple disciplines, including computer science, linguistics, and social sciences. One of the earliest works in this field is the study by Leydesdorff and Vaughan [15] where they used cooccurrence analysis to identify the core concepts and themes in scientific papers. Since then, the application of text network analysis has expanded to various domains, including social networks, recommender systems, and information retrieval. In the domain of social networks, Wasserman and Faust's book [19] provides a comprehensive overview of the theoretical foundations and applications of network analysis in social sciences. They underscore the importance of network structure components, such as centrality measures and clustering coefficients, in comprehending the dynamics of social networks. Kadushin's work [11] extends this understanding, offering a profound analysis of the role of networks in various social spheres, from friendships to politics. Building on this theme of understanding human interactions and experiences, narrative inquiry comes into play. As Jones [9] elucidates, narrative inquiry delves into understanding human experiences using storytelling. In this sense, text visualization methods can be powerful tools for Story Mapping, comparison of narratives and pattern recognition on story structure. Several studies have highlighted the challenges of text network analysis, including issues with standardization, scalability, and interpretation. In particular, Leskovec et al. [14] developed the Stanford Network Analysis Platform (SNAP), a powerful tool for network analysis that includes several functions for building and analyzing large-scale networks. Among complementary tools used to analyze text, it is especially relevant the Voyant software. This software is specially user friendly and is very successful in the context of humanities. However, it suffers from lack of flexibility as it does not rely on machine learning techniques to process text and annotate the retrieved content. Despite the relevant progress, the scalability of text network analysis remains a challenge, and several studies have proposed efficient algorithms for handling large-scale text networks, such as the study by Gleich et al. [7] that proposed an adapted PageRank algorithm for text networks. Interpretation of text network analysis results is also a critical issue, and several studies have proposed novel visualization techniques for representing and exploring text networks. For example, Boyack and Klavans [4] proposed a method for generating maps of scientific fields based on cooccurrence analysis, which provides an intuitive representation of the structure of a field and the relationships between its components. Text network analysis has become a powerful tool for understanding the relationships between words and phrases in various domains. However, the field still faces several challenges, including issues of standardization, scalability, and interpretation. Nevertheless, the potential applications of text network analysis are vast and diverse, ranging from social networks to finance and healthcare. As the research in this field continues to grow, we can expect to see new and innovative methods for analyzing text networks and new applications in previously unexplored domains. Future research can focus on developing visualization techniques and other tools that can help users interpret the results of text network analysis and derive actionable insights.

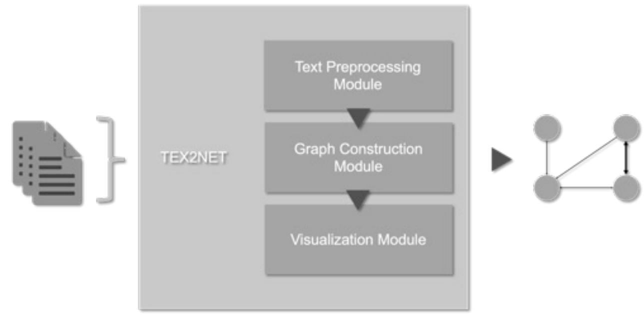

Figure 1: Modular view of tex2net processing and analytical facilities.

3 PROPOSAL

3.1 Design and Architecture

In terms of Architectural Design, the current proposal is composed of three main modules that allow the user to turn a narrative into a network visualization with annotations. It follows a modular design that allows for flexibility and extensibility (as seen in Figure 1). It consists of several key components:

- **Text Preprocessing Module**: This module handles the initial processing of raw text data, including tasks such as tokenization, stemming, stop word removal, and entity extraction. It uses well-established algorithms and techniques to clean and standardize the text, preparing it for further analysis and visualization.
- **Graph/Network Construction Module**: After preprocessing, the extracted entities and relationships are transformed into a graph representation. This module constructs the graph using appropriate data structures and algorithms, with entities as nodes and relationships as edges. The graph captures the narrative structure and character interactions, forming the basis for visualization.
- **Visualization Module**: The visualization module in tex2net is responsible for generating various visual representations of the text data. It offers a wide range of visualization techniques, including word clouds, treemaps, scatter plots, and network visualizations. These techniques provide different perspectives and insights into the text data, enabling users to explore and analyze the narrative and its components effectively.

To ensure further understandability of the data representation, Figure 2 provides a view of the network models produced by the Graph Construction Module. The design of this tool is based on Design Science Research [1].

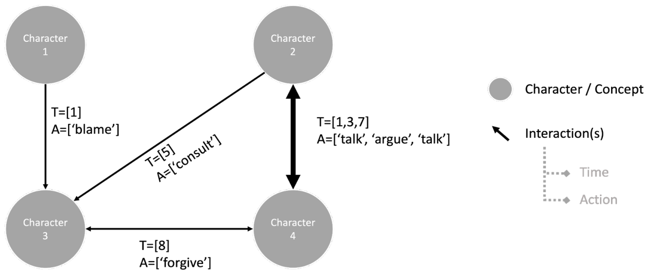

Figure 2: Illustrative network model for narrative visualization and inquiry.

3.2 Features and Functionality

Given a text, we may generate a social network of relevant entities (characters) with annotated relationships. Figure X offers a visualization of a narrative where we have 4 characters that interact with one another with directed actions (A) at specific time points (T), both represented as lists in the annotated edges of the network. We can perform social network analysis in different texts in accordance with this prototype visualization. In addition, we can further inquiry specific aspects of the generated narrative. For instance, we may ask what is the main character in the text and answer this through different centrality types. We may also perform community finding to understand sub characters that are presented together. Finally, we can also quantify the strength of a set of characters through the number of interactions and semantic meaning of each interaction type.

Social Network Analysis (SNA) applied to a network representation with character nodes and directed edges, incorporating temporal and action information, allows for insightful analysis of complex narrative structures and character relationships. This approach unveils hidden patterns, dynamics, and interactions within a story, providing a unique perspective on the characters' roles, influence, and connections. Here are some examples of the type of analyses that can be conducted using this framework:

- **Character Centrality and Influence**: By analyzing the graph's topology, we can identify the most central characters within the narrative. Centrality measures, such as degree centrality or betweenness centrality, can be employed to quantify a character's influence over the storyline. For instance, a character with high betweenness centrality acts as a bridge between different groups of characters or drives pivotal events, shaping the overall narrative arc.
- **Character Interactions Over Time**: The temporal information associated with directed edges provides an opportunity to explore the evolution of character interactions throughout the story. By analyzing the frequency and timing of interactions, we can identify key turning points, conflicts, or alliances. Visualizing this temporal network can reveal the dynamics of relationships, showing how characters' interactions change over time and influence the storyline's development.
- **Community Detection and Group Dynamics**: Community detection algorithms can unveil natural clusters or groups of characters within the graph. This analysis can shed light on the social dynamics and power structures within the narrative. For instance, detecting distinct communities may reveal subplots or factions within the story, showcasing character alliances, rivalries, or shared motivations that are not immediately apparent from the surface-level plot.
- **Character Action Patterns**: The inclusion of action information in the graph allows for the exploration of character behaviors and the identification of recurring action patterns. By analyzing the directed edges' labels, we can detect patterns such as characters consistently cooperating, betraying, or influencing one another. This analysis provides insights into the underlying motives and strategies employed by the characters, unraveling their intentions and impact on the storyline.
- **Influence Diffusion and Propagation**: Using the graph's directed edges, we can investigate how actions or influence spread through the network over time. By modeling influence diffusion processes, such as information cascades or contagion effects, we can explore how a character's actions or decisions propagate through the network, affecting other characters' behaviors and shaping the narrative's trajectory.
- **Character Evolution and Arcs**: Analyzing the temporal and action information in the graph allows for character trajectory analysis. By tracking a character's interactions, relationships, and actions over time, we can observe their growth, development, and transformation throughout the story. This analysis can reveal character arcs, narrative arcs, and how individual characters contribute to the overall plot progression.

The usage guide provides a step-by-step approach to utilizing tex2net for text visualization tasks. It includes code examples and sample datasets to demonstrate the library's capabilities. The recommended workflow enables users to:

- **Preprocess Text**: Raw text data is first profiled using tex2net's text preprocessing facilities. This includes tokenization, stemming, and removing stop words to clean and standardize the text.
- **Extract Entities and Relationships**: tex2net's entity extraction module identifies the main characters or entities in the text. This module uses techniques like named entity recognition and dependency parsing to extract relevant entities and their relationships.
- **Create a Network Representation**: Once the entities and relationships are extracted, tex2net converts them into a graph representation. Each entity becomes a node in the graph, and the relationships between entities become edges connecting the nodes. The graph visually represents the narrative structure and character interactions.
- **Visualize the Network**: tex2net offers various visualization techniques to represent the graph. Users can choose from options like network visualizations, where nodes and edges are displayed, or other visualizations like word clouds, treemaps, or scatter plots. The choice of visualization depends on the specific storytelling requirements and desired visual impact.

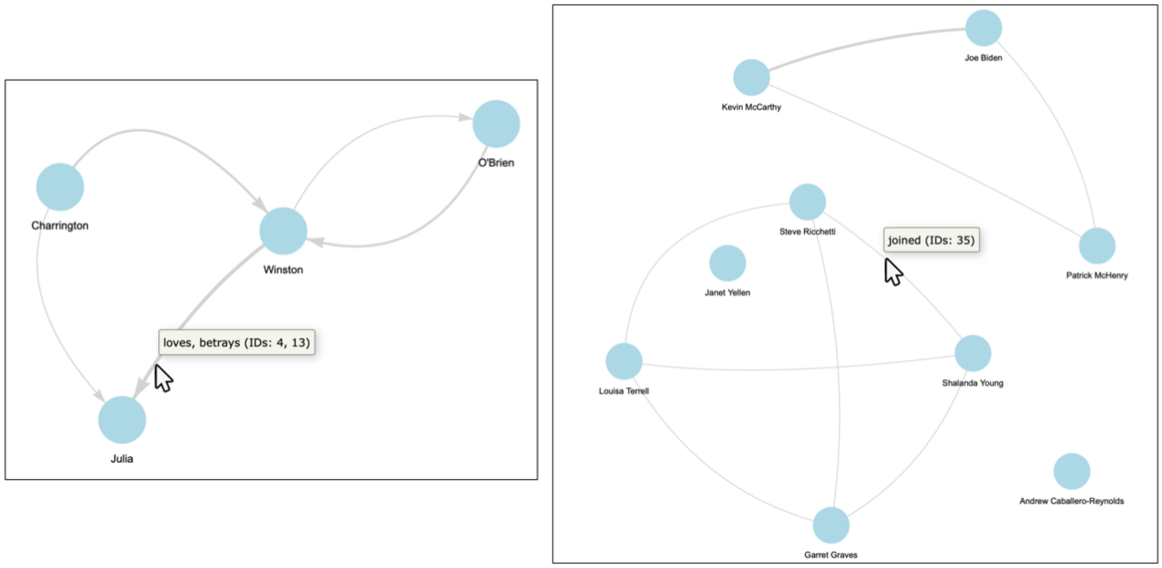

Figure 3: Illustrative network model produced from 1984 book summary (on the left) and CNBC's article (on the right) using tex2net. Although static in structure, nodes (characters) and their relationships (edges) yield temporal information (based on feature localization along a text document) that can be inquired.

- **Customize and Enhance**: tex2net provides customization options to fine-tune the visualizations. Users can adjust the layout, color scheme, node size, and edge thickness to emphasize specific aspects of the story. Additionally, interactive visual analytics' tools can be integrated to enable dynamic exploration and filtering of the text data.
- **Iterate and Refine**: The iterative process allows users to refine the visualization by incorporating feedback and adjusting based on the desired storytelling goals. Users can experiment with different visualization techniques and settings to find the most effective representation of the narrative.

4 IMPLEMENTATION AND USAGE

To apply the tex2net graph representation and analysis, we leverage on name entity recognition advances using opensource spacy software. Initially, we identify the proper nouns present in the text. Next, we may employ a modularity maximization method to construct network communities of characters within the text. This facilitates understanding of the main characters, their interactions, grouping patterns, prominent groups, and influential characters connecting different character sets. By following this systematic approach, we effectively generate a character social network based on any written text in Portuguese. To showcase the functionality of the library, we use two text samples that exude different textual properties: a summarized version of the novel 1984 by George Orwell (to maintain simplicity and understandability) and a publicly available article from CNBC entitled: "McCarthy calls Biden meeting 'productive' and 'professional,' but no debt ceiling deal yet"[1], that was chosen to showcase robustness of the tool to real world text data. Using the create_character_graph function that receives the raw text, the graph is generated. Then, using the visualize_graph, we access an interactive graph representation (as a generated html) of the characters and their interactions, represented in figure 3.

We may use the function detect_communities to find sets of characters that are highly related with each other. For instance, we may answer questions like how frequently are interactions between this set of characters reported together?

```
2: ['Kevin McCarthy', 'Joe Biden', 'Patrick McHenry'], 3: ['Janet Yellen'], 0: ['Andrew Caballero-Reynolds'], 1: ['Garret Graves', 'Steve Ricchetti', 'Shalanda Young', 'Louisa Terrell']
```

We may also use native networkx functions such as nx.degree_centrality to calculate information regarding character importance in the report. We can measure several temporal indexes on the graph to understand the flow of the story. Using the analyze_temporal_relationships function. This is useful to understand if for instance a text is in fact describing interactions between characters. It displays: Average Temporal Distance: 11.5 Density of Temporal Interactions: 0.1388889 Reciprocity of the Graph: 0.2

To understand the variables of the temporal analysis we describe them and explain what they mean in this context:

- **Average Temporal Distance:** This variable represents the average number of sentences that separate the interactions between characters in the text. In this case, the average temporal distance is 1.0, which means that, on average, there is only one sentence between the interactions of the characters. It indicates a relatively close temporal proximity of the character interactions.
- **Density of Temporal Interactions**: The density of temporal interactions measures the proportion of possible interactions that actually occur in the text. It is calculated by dividing the number of observed interactions by the total

[1] available at: https://www.cnbc.com/2023/05/22/debt-ceiling-joe-biden-kevin-mccarthy-meet.html

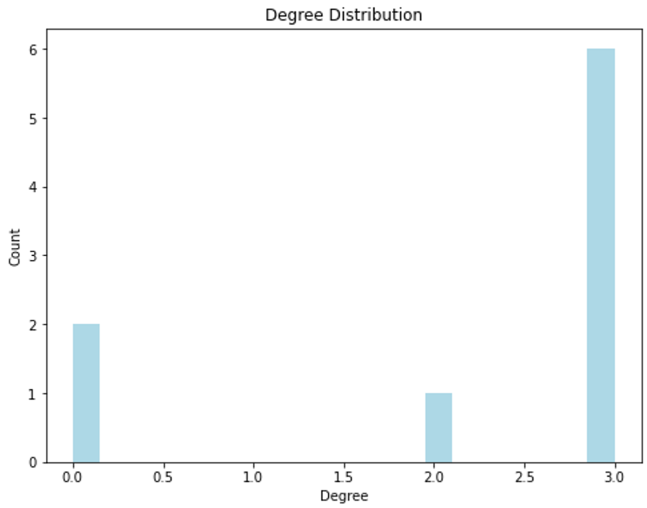

Figure 4: Distribution of character interactions along a plot. In the given example, bars can be inspected to assess whose characters show unlikely interactions (left bar) and those how yield multiple relationships (right bars).

number of possible interactions. In this case, the density is 0.3333, indicating that approximately one-third of the possible interactions between characters are present in the text. A higher density value suggests a more interconnected set of characters in terms of temporal relationships.

- **Reciprocity of the Graph**: Reciprocity refers to the extent to which character interactions in the graph are bidirectional or mutual. It is calculated by dividing the number of bidirectional edges (where actions occur between characters in both directions) by the total number of edges in the graph. A reciprocity value of 0.0 indicates that none of the interactions between characters are reciprocated. It means that the relationships are predominantly one-sided or unilateral in nature, with no mutual actions between the characters.

Using the describe_degee function, the degree distribution can be inspected (example Figure 3) to understand the number of interactions all characters have on a plot (see Figure 4).
Finally we may even use the 'analyze_graph_characteristics' to compare overall character graph characteristics, yielding:

> Number of Nodes: 9; Number of Edges: 10 Average Degree: 2.2222223; Average Clustering Coefficient: 0.4444444

Using these indexes may allow us to compare graphs between different narratives and answer questions like: How does the number of nodes in the character graph differ between Narrative A and Narrative B? Does the variation in the number of nodes reflect the complexity or richness of the character interactions in each narrative? Does a higher average degree suggest a more extensive network of character interactions? How does the average degree relate to the depth and complexity of the narrative in each case?

5 DISCUSSION

The described solution can be effectively utilized in various forms of text narratives, opening up exciting possibilities. Social Network Analysis (SNA) offers a powerful approach that goes beyond traditional written novels or stories when applied to a graph representation featuring character nodes and directed edges with rich features. Consider the world of film and TV series, where characters interact and evolve over time, much like in written narratives. By delving into the character network within these visual narratives, we gain valuable insights into the dynamics, relationships, and influence among the characters. This analysis enables us to uncover central characters, community structures, and understand how character interactions shape the plot, enriching our appreciation of these visual storytelling mediums. Moving to the realm of plays and theater productions, the social network perspective can be seamlessly applied. Here, by representing characters as nodes and their interactions as directed edges, we unlock a deeper understanding of the relationships, alliances, and conflicts that unfold on stage. This analysis grants us insights into the social dynamics and power structures within the theatrical narrative, unraveling the intricate webs woven by the characters.

Video games offer yet another exciting avenue for applying SNA techniques. With their complex narratives boasting multiple characters and branching storylines, analyzing the character network within these games becomes highly rewarding. Through this analysis, we gain an understanding of pivotal characters, their impact on the narrative, and the consequences of player choices. Ultimately, this analysis enhances game design, character development, and the art of storytelling in the gaming industry.

In the realm of social media, where dynamic and interactive narratives manifest through conversations and discussions, SNA proves invaluable. By representing individuals as nodes and their interactions as directed edges, we gain insights into the social dynamics, influence, and spread of information within these online narratives. This analysis unveils influential users, communities, and the evolution of conversations over time, illuminating the underlying social fabric of these digital platforms.

Beyond entertainment, SNA techniques extend their reach to textual narratives documenting historical events or biographies. By representing historical figures or individuals as nodes and their interactions as directed edges, we embark on a journey to explore the relationships, collaborations, and power dynamics that shaped historical events. This analysis reveals insights into social movements, political alliances, and the impact of individuals on historical outcomes, offering a fresh perspective on the past.

Even in the realm of news articles and reports, SNA proves its mettle. By analyzing the network of individuals and organizations mentioned in these texts, we uncover hidden connections, influence networks, and social structures across various domains. This analysis aids in identifying key actors, understanding their roles, and assessing their impact on specific events or issues discussed in the news, deepening our understanding of contemporary affairs.

In the context of technical communication, the use of narratives aids in effectively conveying complex details. Tex2net's visualization capability presents an opportunity to further enhance the comprehension and interactivity of such narratives. Here's how:

- **Organizing Technical Information**: For instance, by visualizing a software manual's structure using tex2net, for instance, users can easily understand the relationships between different software modules or functionalities. It provides a bird's-eye view, enabling easier navigation and comprehension.
- **Visualizing Interconnections**: Consider a technical document detailing a complex machinery's working, such as a car engine. Using tex2net, one can visualize the relationships between different engine components, how they interact, and their dependencies. Such a graph can assist both novice and expert users in quickly grasping the intricacies of the machinery.
- **Highlighting Temporal Relationships**: For tutorials or guides that involve step-by-step procedures, like assembling a computer, tex2net can showcase the sequence of actions, helping users visualize and follow the correct order of steps.
- **Supporting User-Centered Design**: This is paramount in any technical communication. By using tex2net, a technical writer can draft documentation tailored to a user's perspective, emphasizing the narrative structure that most aligns with a user's needs and journey. However, it's crucial to understand that while tex2net helps in organizing and representing the information, the feedback loop with real users is irreplaceable. A writer should always validate if the drafted content resonates with its audience, and tex2net can serve as an intermediary tool to refine and adjust the narrative based on user feedback.
- **Comparative Analysis**: Consider different versions of a software's user guide. Tex2net can be employed to compare them, visualizing the evolution of the software's features, detecting newly added or removed components, and helping technical writers ensure that the most recent documentation is comprehensive and coherent.

By translating text into a network representation with tex2net, the tool not only aids in dissecting the narrative but also fosters a comprehensive understanding. Nevertheless, it's worth noting that while tex2net provides valuable insights, the end goal is to ensure that the narrative effectively communicates with the reader. Hence, integrating tex2net's analysis with user feedback methods, like usability testing or reader surveys, can offer a more holistic approach to crafting compelling and user-friendly technical narratives.

6 CONCLUSIONS

In this paper, we have presented tex2 net, a powerful library that leverages natural language processing and graph analysis techniques to extract and visualize character networks from textual narratives. Our research makes several significant contributions to the field of computational narrative analysis and provides valuable insights for various domains, including social media analysis, news sentiment analysis, and academic research.

One of the key contributions of tex2 net is its ability to transform unstructured textual data into structured graph representations, enabling researchers and analysts to gain a deeper understanding of the intricate relationships between characters within a narrative. By employing techniques such as named entity recognition and relationship extraction, tex2 net accurately identifies main characters and their interactions, facilitating the exploration of social networks and dynamics within a story.

Moreover, tex2 net offers a wide range of graph analysis capabilities that empower users to extract meaningful insights from character networks. The library provides functionality for measuring centrality metrics, identifying communities, and analyzing temporal patterns, among other graph-based analyses. These features allow researchers to uncover key characters, influential relationships, and temporal dynamics that shape the narrative, leading to a richer and more comprehensive understanding of the underlying story structure.

Furthermore, tex2net demonstrates its effectiveness through case studies across diverse domains. From social media analysis to news sentiment analysis and academic research, the library showcases its versatility and applicability in different contexts. The evaluation of tex2net's performance in these application scenarios highlights its ability to extract accurate character networks and provide valuable analytical capabilities for narrative inquiry.

Tex2net serves as a valuable tool for researchers, analysts, and practitioners seeking to delve into the intricate webs of characters within textual narratives. By providing a comprehensive set of functionalities for character network extraction, visualization, and analysis, tex2net empowers users to uncover hidden insights, identify narrative patterns, and gain a deeper appreciation of the storytelling dynamics. In the future, simulating information propagation in a character network with rich context features can be considered for understanding influence dynamics, predicting story development in incomplete texts, and evaluating narrative coherence.

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