ChronCN: Visualizing Topic Model Output with Chronological Chain Networks

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***Abstract*—This paper presents Chronological Chain Network (ChronCN), a network-based visualization framework designed to enhance the presentation and interpretation of topic model outputs. ChronCN addresses two challenges: (1) effectively visualizing essential informational dimensions of topic models, including temporal variations in topic prevalence, and (2) capturing the sequential dynamics of user engagement with different topics. To assess ChronCN, we employ a twofold evaluation strategy. First, we conduct a comparative analysis of existing visualization methods for topic modeling and position ChronCN within the current landscape. Second, we perform a preliminary user study to examine the users' ability to identify and comprehend the informational elements depicted in various visualizations. Our findings indicate that users recognize the richness of informational content conveyed by ChronCN and are generally successful in accurately interpreting the visualization. Furthermore, ChronCN's network-based design facilitates the visualization and simulation of potential user engagement paths across topics.**

***Index Terms*—Network, Topic Evolution, Topic Model, User Engagement, User Paths, Visualization**

I. Introduction

Topic modeling techniques use a range of different methods, including probabilistic frameworks, matrix factorization approaches, and word embedding-based models, to address a wide array of applications. However, visualization tools that facilitate the analysis and interpretation of topic model output are comparatively scarce. Typically, each topic modeling approach provides its own tailored visualization tools that are customized for one output format. A limited number of specialized approaches exist that support visualizations across multiple types of topic modeling algorithms (e.g., LDAvis [1]). Moreover, visualizations often represent only a selected subset of the output of a topic model. For example, topic content in the form of keyword lists, document-topic distributions, inter-topic similarities, or associated metadata such as user or temporal attributes. As these elements are typically visualized in separate plots, conducting visual analyses across multiple dimensions remains a significant challenge. To address these limitations, this work contributes to the field by introducing a framework that

(i) is applicable to the output of a broad range of topic models,
(ii) visualizes basic topic characteristics (e.g., topic prevalence) and temporal aspects, such as sequential user engagement in a single plot, and
(iv) supports the computation of temporal network metrics.

We present *Chronological Chain Network* (ChronCN), a network-based framework that comprehensively visualizes the temporal interconnectedness of user engagement across different topics. Although, ChronCN can be used for any topic or clustering model that assigns cluster labels and contains some sort of chronological indicator for each document, we see ChronCN's main contribution in the context of narrative analysis.

Building on previous work [2], [3], we conceptualize a narrative as: "*a set of topic-wise interconnected messages posted on social media platforms*" (see also [4], [5]). However, this perspective requires the use of models that incorporate contextual features into topic assignments, which is not the case for all topic modeling approaches. To maintain a broad applicability of ChronCN, we therefore adopt the more general terms *topic* and *cluster*, which we will use interchangeably when referring to the output of a topic model. We present ChronCN as a visualization approach compatible with a wide range of topic modeling results. We also evaluate our approach with data from a preliminary user study, and provide a comprehensive overview of ChronCN's capabilities.

The remainder of this paper is structured as follows: section II reviews relevant literature. Section III outlines the research questions, the evaluation, and the design of ChronCN (section III-A). Our evaluation results are presented in section IV, followed by a discussion in section V. Finally, section VI summarizes the main findings and suggests directions for future research.

II. Related Work

In one of the few comprehensive reviews on the visualization of topic model outputs [6], the authors categorized existing visualization approaches into five main types: (i) map-based, (ii) network-based, (iii) evolution-based, (iv) chart-based, and (v) other methods. Maps typically rely on geolocation data. In contrast, network-based visualizations represent either the semantic relationships among topics or words (semantic graphs) or social structures and interactions (sociograms). Evolution-based visualization techniques include Streamgraphs, evolutionary paths, and line charts. This group typically illustrates the temporal dynamics of topics by showing their prevalence over time. Unlike network-based approaches, they do not incorporate or display user metadata. Visualizations that do not rely on geolocation data, relational structures, or temporal information were classified as chart-based approaches. The remaining methods, grouped under 'other methods', include graphs or plots tailored to meet the specific requirements of particular application domains. In another study [7], present a review of topic model visualizations in the context of bibliometric studies. They categorize various visualization techniques into groups based on their focus on topic content, inter-topic relationships, or (temporal) topic evolution.

One of the most popular approaches for visualizing topics is LDAvis [1]. The idea behind LDAvis is to provide an overview of a large amount of topics and documents through interactivity. The main informative components of this approach are (i) topic content, (ii) topic prevalence and (iii) topic relation (i.e., how do topics relate to each other?). LDAvis can be applied to the output of various topic models and across different domains, such as the conceptualization of public discourse during the COVID-19 pandemic [8] or the analysis of future directions in blockchain technology [9].

A more recent and increasingly prominent approach to topic modeling is BERTopic [10] which utilizes a modular framework that combines word embeddings, dimensionality reduction, and clustering techniques. BERTopic offers different visualization tools. Similar to LDAvis, it includes an interactive plot that illustrates topic similarities. Furthermore, it provides a visualization of topic prevalence over time, based on the number of associated documents. When class-based metadata is available in the input corpus, BERTopic also supports class-based topic representations through a dedicated plot. Additional methods are provided for visualizing the more fine-grained structure of topics, encompassing both document- and term-level information. Another topic modeling approach offering a comprehensive suite of visualization tools is the Structural Topic Model (STM) [11]. STM enables visualization of topic content through representative keywords, temporal trends in topic prevalence, topic content conditioned on model-included covariates, and correlations between topics.

III. Research Procedure

Our work is guided by the following research questions:

RQ 1: *What visualization techniques can be employed to represent the output of a topic model in a manner that simultaneously captures temporal dynamics, topic prevalence, and patterns of user engagement within a single integrated plot?*

For this research question, we examined different visualization techniques for topic model outputs and the types of insights they offer. Building on the limitations we identified, we introduce ChronCN, an approach designed to provide comprehensive insights into sequential user engagement patterns over time, the temporal prevalence of topics, and the evolution of topic prevalence, all within a single visualization. In order to provide a comparative analysis of information included in different types of visualizations, we use the following guiding questions as criteria:

- **Topic prevalence**: How many documents are associated with a given topic?
- **Temporal topic prevalence**: How many documents are associated with a given topic at a specific timestamp?
- **Topic relatedness**: How similar are the semantic representations of different topics?
- **User engagement**: How many different users engage in a topic?
- **Sequential user engagement**: What sequences of user interaction across different topics can be observed in the topic model output?

Note that in this study, we do not consider the visualization of topical content, as it is highly dependent on the specific output of the underlying topic model. The criteria outlined above will be applied in both the comparative analysis and the preliminary user study.

RQ 2: *How does Chronological Chain Network (ChronCN) enhance users' understanding of the temporal aspects in cluster analysis and topic modeling?*

This research question focuses on the user-centric evaluation of ChronCN. The goal of the visualization is to expand the range of analyses that are possible with topic model outputs. Therefore, we consider it crucial for our visualization to be easily interpretable. To this end, we conducted a preliminary user study, which included the output of two different topic models and two different datasets. The user study consisted of a criterion-based usability rating of ChronCN and performance-based tasks.

The criterion-based evaluation was guided by the question "What informational components do users identify in the visualization?" and the performance-based tasks focused on "How do users interpret the visualized informational components?". Our evaluation procedure is inspired by the User Performance Evaluation Paradigm (UP) [12] and the evaluation of other graph based visualizations (see, e.g., [13]). The visualizations for our study were generated from topic model output provided by BERTopic [10] and LDA [14]. The selection of these models was guided by the objective of showcasing the broad

Dataset	Tweets	Users	Days
Santa Fe shooting	967,674	113,146	8
Las Vegas shooting	3,436,187	505,850	13

TABLE I
SUMMARY OF DATASETS RELATED TO THE 2018 SCHOOL SHOOTING IN SANTA FE (TX), AND THE 2017 CONCERT SHOOTING IN LAS VEGAS (NV) INCLUDING TWEET COUNTS, UNIQUE USERS, AND COLLECTION TIME SPAN IN DAYS.

applicability of ChronCN, using both a probabilistic, traditional topic model (LDA) and an embedding-based modular topic model (BERTopic).

As input data, we chose two distinct Twitter datasets related to gun shooting events in the United States, which varied with respect to the duration of the data collection and the overall number of extracted messages. More detailed information on the datasets is shown in Table I. The hyperparameter k (i.e., the number of topics) was determined based on topic coherence and topic diversity metrics, following the evaluation methodology proposed in [10]. For LDA, this resulted in six topics for the first (Santa Fe) and five for the second (Las Vegas) dataset. BERTopic identified 30 topics for the first and the second dataset, respectively.

Below, we introduce ChronCN and compare it to LDAvis and selected BERTopic visualizations, as including a broader range would introduce redundancy.

A. Chronological Chain Network

This section describes the network formation process of ChronCN. By employing general terms, such as "cluster" instead of "topic", we want to emphasize that ChronCN is not restricted to topic models but can be applied to any type of clustering results that incorporate metadata about classes and a temporal or sequential dimension for each observation.

Using sequential messages with topic labels (Table II), we derive the *Chronological Chain Network* (ChronCN), a directed, multipartite network (Figure 1). Each node represents a unique cluster-day combination (e.g., C1D1 denotes cluster 1 on day 1), and each edge represents an inter-day user message (e.g., if user 1 posts in cluster 1 on day one and subsequently in cluster 2 on day two, an edge is formed from C1D1 to C2D2). For users posting once or multiple times per day within the same cluster, no edge is added to the network. The edge formation is illustrated in the last column of Table II. User 1 posts a message in cluster 1 on day one, a message in cluster 2 on day two and again in cluster 1 on day three. Therefore, two edges are created in the network graph. Since user 2 only posted once, no edge will be added.

In order to quantify the dominance of a given cluster, we assign a *Cluster Importance Score* (CIS) to each node. This score is determined as the weighted average of two components: 1) the proportion of daily messages associated with the cluster and 2) the total number of forwards (e.g. retweets) it received, with both components given equal weight. To mitigate potential distortions in the analysis that might be caused by bots or highly active users (see also [2], [15], [16]), the edges are weighted by the respective user's average number of messages and transformed by a sigmoid function. For the analysis, we combine all edges by summing up their weights.

User	Day 1	Day 2	Day 3	Edges
1	1	2	1	C1D1-C2D2, C2D2-C1D3
2	1	-	-	no Edges
3	-	1	2	C1D2-C2D3
4	1	-	2	C1D1-C2D3

TABLE II
GRAPH CONSTRUCTION TABLE OF MESSAGES.

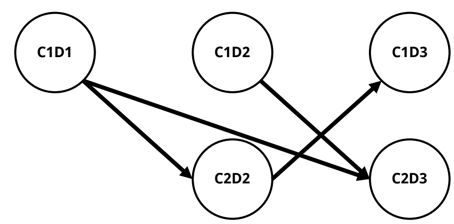

Fig. 1. Example ChronCN Graph.

In our approach, we draw on a similar concept as presented in [17]. The authors presented a time-ordered network which is a chronologically ordered directed graph that consists of concatenated temporal snapshots. ChronCN differs from the time-ordered network in terms of edge formation. In particular, we do not assume adjacent edges between the same clusters on different day partitions, if there is no corresponding message. The idea of representing streams of messages via edges was initially presented in [18].

B. Comparative Analysis

For the comparative analysis, we first present the examined visualizations generated by BERTopic, LDAvis and ChronCN. We then evaluate the informational visualization components outlined in Section III across the two Twitter datasets and each visualization tool. A summary of our comparison is provided in Table IV in Section IV.

Figure 2 was created with BERTopic, each topic is represented by a circle. The size of each circle corresponds to the number of documents associated with the respective topic. The spatial proximity of topics reflects their semantic similarity, such that topics positioned closer together share more common terms. The horizontal (D1) and vertical (D2) axes represent latent dimensions of topic similarity. The figure includes an interactive feature that allows individual topic selection, with distinct coloring to enhance clarity.

Figure 3 displays BERTopic's per class topic representation. Depending on the type of class-based metadata in the input corpus, different aspects can be visualized using this feature. This analysis employed user identifiers as class labels. The frequency metric indicates the number of documents contributed by each user that are associated with a given topic.

BERTopic also offers functionality to visualize the temporal evolution of topic prevalence (Figure 4). In this context,

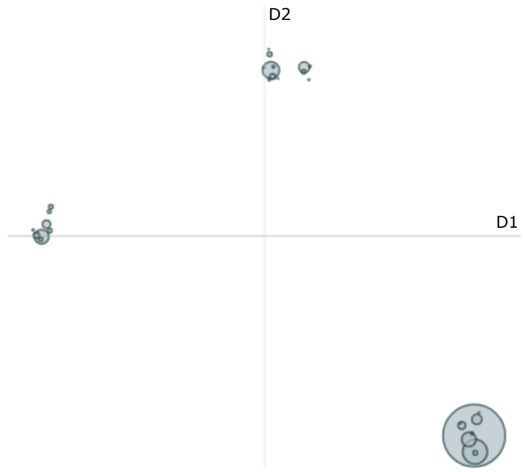

Fig. 2. BERTopic Intertopic Distance.

frequency denotes the daily count of documents attributed to each topic. In the comparative analysis, the topic prevalence component was categorized as either present or absent, depending on the data and its visibility in the visualization.

As described in Section II, LDAvis mainly builds on the interactivity of its plot to enhance the analytical understanding of topic model output. Figure 5 presents a screenshot of that interactive visualization. Unlike BERTopic and ChronCN, this approach displays the topical content (i.e., keywords) alongside the topic distance map, enabling the simultaneous examination of topic prevalence and inter-topic similarity.

Figure 6 presents a ChronCN visualization with user data for all topics. As outlined in Section III-A, each node represents a day-topic combination and its size reflects the topic prevalence for that day. For clarity, node labels in the visualizations display only the topic number (e.g., C1) rather than the full identifier (e.g., C1D1). An edge between two nodes indicates that at least one user transitioned between the corresponding topics (e.g., from C0 on day 1 to C0 on day 2, reflecting continued engagement with topic 0). Edge color reflects usage frequency, with a continuous scale from blue representing many users and yellow indicating few users. Table III displays network details for each dataset's ChronCN.

Dataset	Model	Nodes	Edges
Santa Fe	BERTopic	197	1,108
Santa Fe	LDA	48	961
Las Vegas	BERTopic	311	3,427
Las Vegas	LDA	65	1,947

TABLE III
CHRONCN DETAILS FOR EACH DATASET AND EACH MODEL. EDGES DENOTE UNIQUE EDGES IN EACH NETWORK.

As with the BERTopic temporal visualization, the informational component topic prevalence is dependent on the underlying data provided to ChronCN.

Our comparison showed that ChronCN offers higher information density within a single visualization, enabling simultaneous analysis of temporal dynamics, user behavior, and topic prevalence. However, compared to other visualizations, it may be more challenging to interpret. Supplementary views, such as topic-specific ChronCN plots (see Figure 7), can help improve interpretability.

C. Preliminary User Study

The preliminary user study was designed to investigate the effect of ChronCN on user understanding of the temporal aspects in cluster analysis and topic modeling. We employed the same visualization types used in the comparative analysis, varying only the data input. The study was divided into two parts. In the first part, participants were asked to identify the types of information they could infer from each visualization by selecting one or more relevant informational components. The second part involved performance-based tasks with single-choice questions, where participants were presented with statements about the visualized information and asked to select the correct one.[1] The preliminary user study was conducted with eleven participants, all of whom had experience with data visualizations across various domains, though not necessarily with topic modeling. This aligns with our goal of developing a visualization approach accessible to a broad and diverse target audience.

IV. RESULTS

Comparative analysis. We found that ChronCN provides more information than other visualizations in terms of temporal topic evolution and additional user engagement sequences. While LDAvis enhances topic content analysis by presenting prominent keywords associated with each topic, it is inherently dependent on an interactive interface. In contrast, BERTopic offers a broader array of visualizations, covering not only topics but also topic hierarchies and the distribution of documents across topics—features that were beyond the scope of the our study.[2] However, each informational component within BERTopic requires a separate visualization, and none provide a depiction of sequential user engagement. A summary of the comparative results is presented in Table IV.

Visualization	TP	TTP	TR	UE	SUE
BERTopic Intertopic	Yes	No	Yes	No	No
BERTopic Classes	No	No	No	Yes	No
BERTopic Temporal	Yes/No	Yes	No	No	No
LDAvis Standard	Yes	No	Yes	No	No
ChronCN Standard	Yes/No	Yes	No	Yes	Yes

TABLE IV
COMPARATIVE ANALYSIS OF INFORMATIONAL COMPONENTS ACROSS TOPIC MODEL VISUALIZATIONS. TP = TOPIC PREVALENCE, TTP = TEMPORAL TOPIC PREVALENCE, TR = TOPIC RELATEDNESS, UE = USER ENGAGEMENT, SUE = SEQUENTIAL USER ENGAGEMENT.

Preliminary user study. The preliminary user study included an almost equal distribution of gender, with six female

[1]The complete user study is available from the authors upon request.
[2]For a comprehensive overview of BERTopic visualizations, see https://maartengr.github.io/BERTopic/getting_started/visualization/visualization.html

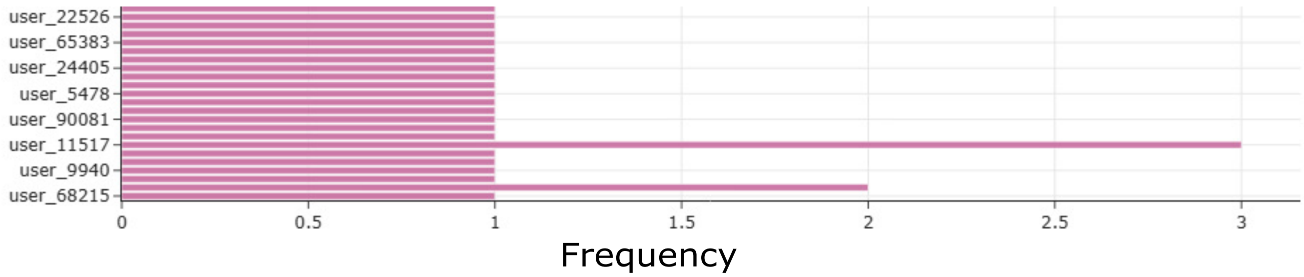

Fig. 3. BERTopic User Engagement within topic 6.

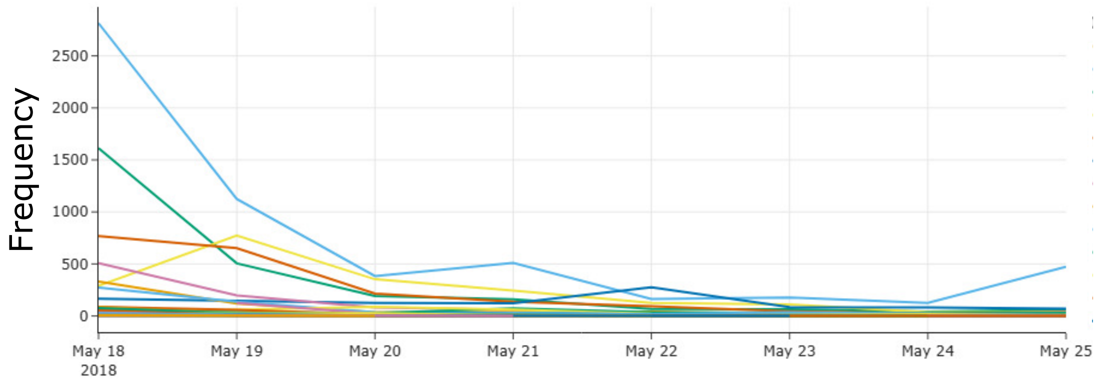

Fig. 4. BERTopic Temporal Topic Prevalence Evolution. Each colored line presents one topic with Frequency denoting the number of Documents assigned to that topic on a specific day.

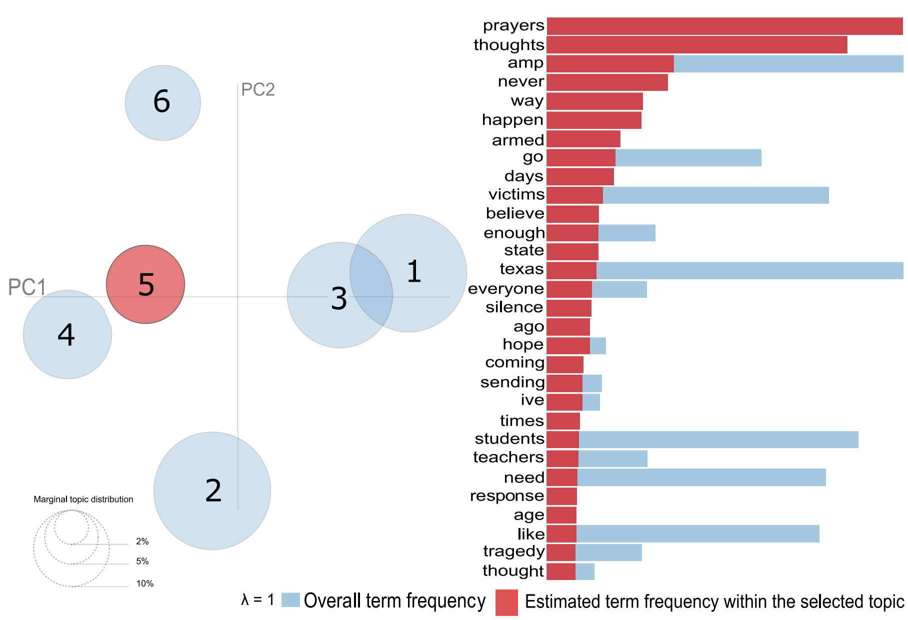

Fig. 5. Example of an LDAvis visualization with topic 5 highlighted in red. Topics are displayed as circles on the left panel, where circle size indicates the relative proportion of documents assigned to each topic, and spatial proximity reflects semantic similarity between topics. The right panel presents the most representative terms for the selected topic 5.

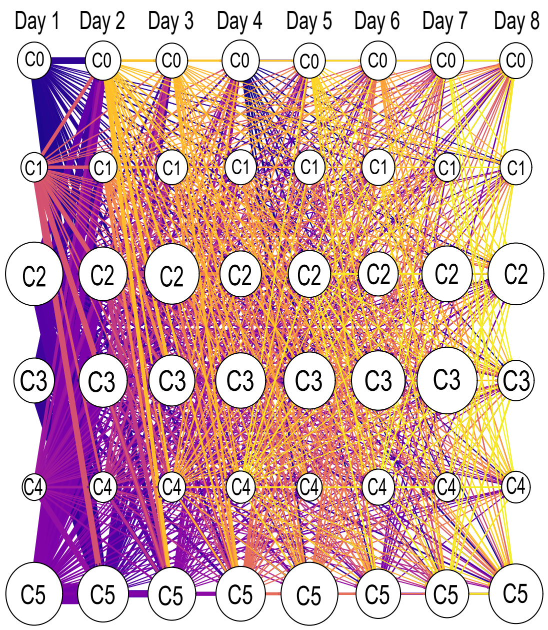

Fig. 6. ChronCN with connections involving all topics. Color scale from blue (strongly connected) to yellow (weakly connected) indicates connection frequency.

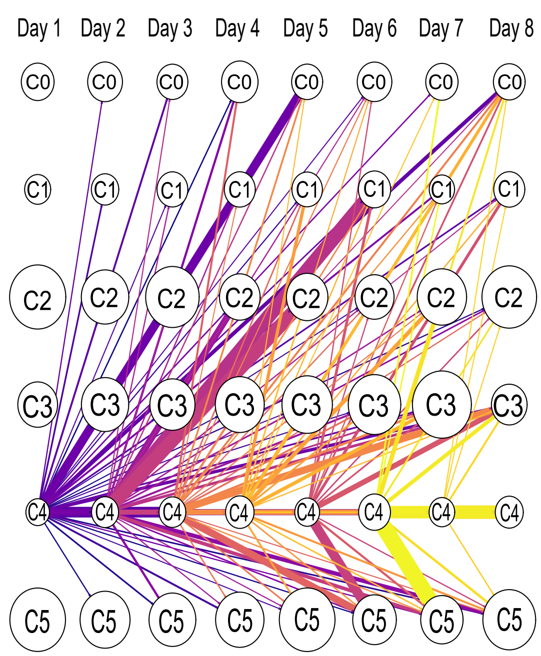

Fig. 7. ChronCN only connections involving Topic 4. Color scale from blue (strongly connected) to yellow (weakly connected) indicates connection frequency.

and five male participants. The majority of participants were aged 25-44 years (n = 5 for 25-34 years, n = 5 for 35-44 years), followed by those aged 45–54 years (n = 1). A total of 36.36% of participants (n = 4) affirmed familiarity with topic modeling, although only 27.27% (n = 3) reported being more than "somewhat familiar". 81.82% (n = 9) declared to use data visualization at least "occasionally" to "frequently", while only 18.18% use it "rarely".

The first part of the study covered the informational components in each visualization, it reached an overall Fleiss' Kappa of 0.464 (p=0). This indicates a moderate level of agreement among participants [19]. In this phase, the five informational components (TP, TTP, TR, UE, SUE, see Table V) relevant to the comparative analysis were listed for each visualization, and participants were instructed to identify which components were present in the respective visualization.

Inter-rater Agreement (Fleiss' Kappa) was very high (0.745, p = 0) for the temporal topic prevalence (TTP) component and even better for the topic relatedness (TR) component (0.824, p = 0). The remaining components, topic prevalence (TP), user engagement (UE) and sequential user engagement (SUE) yielded Fleiss' Kappa scores between 0.214 (p = 0.00038) (sequential user engagement) and 0.298 (p = 0.000000804) (topic prevalence).

Tool	Visualization	TP	TTP	TR	UE	SUE
BERTopic	Intertopic	0.81	0	1	0.09	0
BERTopic	Classes	0.18	0	0	0.82	0.18
BERTopic	Temporal	0.74	1	0	0.18	0
LDAvis	Standard	0.91	0	1	0.09	0
ChronCN	Standard	0.28	0.46	0.23	0.46	0.46

TABLE V

PROPORTION OF USER STUDY PARTICIPANTS WHO IDENTIFIED EACH INFORMATIONAL COMPONENT IN THE VISUALIZATIONS. TP = TOPIC PREVALENCE, TTP = TEMPORAL TOPIC PREVALENCE, TR = TOPIC RELATEDNESS, UE = USER ENGAGEMENT, SUE = SEQUENTIAL USER ENGAGEMENT.

Table V displays the relative agreement of participants to the presence of the specific informational component for each visualization. The highest dispersion of agreement exists for ChronCN. Nevertheless, informational components overlapped with comparative analysis results.

In the performance-based section of the survey, participants responded to multiple single-choice questions assessing their ability to extract informational components from the visualizations. These questions included statements such as, "Topic 3 and 4 are more similar than Topic 1 and 2", or "More users contribute to Topic 2 than to Topic 5". Across all questions, Fleiss' Kappa was 0.466 (p = 0), indicating a moderate level of inter-rater agreement. Over 90% of participants correctly answered the question related to the BERTopic Intertopic Distance visualization, while all other questions yielded an accuracy rate of 81.82%. The lowest accuracy was observed for a single ChronCN-related question, with 63.64% of participants selecting the correct response. Despite the complex structure, especially for users not regularly working with topic model output, ChronCN yielded competitive results.

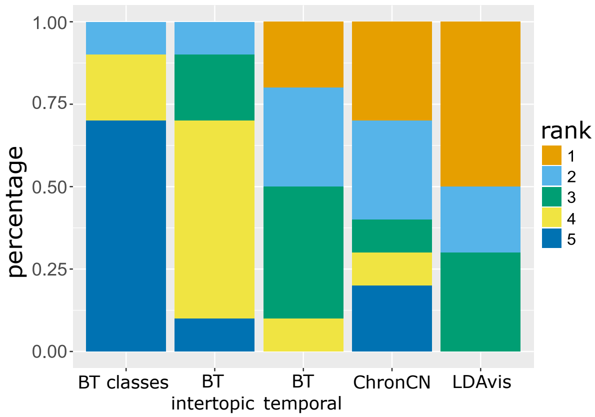

Fig. 8. Rankings of all visualizations based on perceived informational content (1 = highest, 5 = lowest).

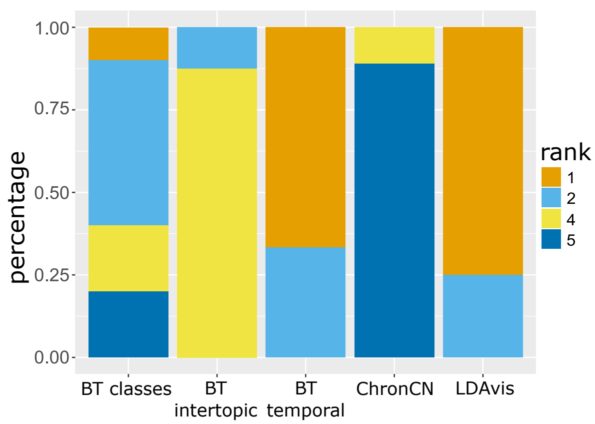

Fig. 9. Rankings of all visualizations based on perceived ease of understanding the presented information (1 = highest, 5 = lowest).

The last part of our survey included two ranking tasks. Participants had to rank the previously presented visualizations according to 1) their perceived information content according to your personal impression of how informative they are ("Please rank the the visualizations presented by how much useful information you can get from each one. 1 is best, 5 is worst") and 2) on the perceived ease of understanding the presented information ("Please rank the visualizations presented by how easy they are to interpret, according to your personal impression of how easy they are to understand. 1 is best, 5 is worst"). Figures 8 and 9 display the results. LDAvis ranked best in both questions. While the degree of information for ChronCN was perceived as high by most users it was outperformed by the other visualizations in terms of ease of interpretation.

V. Discussion

In this study, we presented the Chronological Chain Network (ChronCN), a novel network-based visualization technique for representing topic model output. Following a comparative analysis of commonly used topic model visualizations, we conducted a user study to evaluate their effectiveness. The results indicate that users recognized the high density of informational components conveyed within a single ChronCN plot. In the performance-based evaluation, the majority of participants (63.64% and 81.82%) were able to accurately interpret the information presented by ChronCN. Additionally, 6 out of 10 participants ranked ChronCN first or second in terms of informational content. However, regarding the ease of interpretation, ChronCN was ranked last or second-to-last by all participants. This result highlights the need to either supplement the visualization with additional explanatory information or limit its use to audiences with prior experience in topic modeling.

While ChronCN is computationally efficient in generating networks, the interpretability may diminish when the resulting networks contain a large number of clusters (i.e., rows of nodes). However, we do not assume that longer time spans or larger user sets inherently reduce interpretability. ChronCN integrates multiple informational components—including sequential user engagement, topic prevalence, temporal topic prevalence, and overall user engagement. In contrast to other visualizations that require interactive interfaces to convey comparable information, ChronCN achieves this goal through a static network-based representation. To enable this functionality, the input dataset must include chronological information, such as a document timestamp or a sequential index.

It is important to note that ChronCN is not intended for evaluating topic model quality but rather for analyzing and interpreting the output of an existing model. Furthermore, due to its network-based structure, ChronCN supports additional analytical applications, such as computing the shortest weighted path across topics and timestamps or conducting Markov chain simulations to identify temporal topic dynamics.

VI. Conclusion

ChronCN offers a versatile approach to visualizing topic model output, with its network-based structure presenting a notable advantage over most existing methods. Both, our comparative analysis and user study indicate that ChronCN is capable of conveying a wide range of informational components within a single static plot, without requiring interactive elements. However, its unconventional design may pose a barrier to initial interpretation, necessitating explanatory support and careful examination of the underlying data, ideally accompanied by illustrative examples. Once understood, the visualization facilitates efficient comparison of topic model outputs and enables deeper analyses of sequential user engagement, a perspective that can significantly advance the investigation of topic dynamics. Moreover, ChronCN supports basic network analytics that we will further investigate in our future work. Examples include calculating the weighted shortest path between topics across the temporal span of a dataset, or simulating topic transitions using Markov chains to explore probabilistic patterns of topic evolution.

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