Visualization of Swedish News Articles: A Design Study

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Abstract: The amount of available text data has increased rapidly in the past years, making it difficult for many users to find relevant information. To solve this, natural language processing (NLP) and text visualization methods have been developed, however, they typically focus on English texts only, while the support for low-resource languages is limited. The aim of this design study was to implement a visualization prototype for exploring a large number of Swedish news articles (made available by industrial collaborators), including the temporal and relational data aspects. Sketches of three visual representations were designed and evaluated through user tests involving both our collaborators and end-users (journalists). Next, an NLP pipeline was designed in order to support dynamic and hierarchical topic modeling. The final part of the study resulted in an interactive visualization prototype that uses a variation of area charts to represent topic evolution. The prototype was evaluated through an internal case study and user tests with two groups of participants with the background in journalism and NLP. The evaluation results reveal the participants' preference for the representation focusing on top topics rather than the topic hierarchy, while suggestions for future work relevant for Swedish text data visualization are also provided.

1 INTRODUCTION

In the modern digitised society, a large amount of text data is generated daily for different areas of applications such as product reviews, posts on social media, research papers and news articles. With such large-scale data come many challenges for the reader when exploring the underlying data at scale, such as finding and extracting relevant information, gaining insights, getting an overview, grasping the overall meaning of the data, as well as getting details on demand. To handle the large digitized text corpora, methods which involve *Natural Language Processing* (NLP) / *Text Mining*, and further *Artificial Intelligence* (AI), have been developed to extract valuable information automatically. The areas of *Visual Analytics* (VA) and *Visual Text Analytics* (VTA) have also grown larger in interest as *Information Visualization* (InfoVis), text visualization, and text analysis methods have been documented in an increasing number of papers over the years (Kucher and Kerren, 2015; Liu et al., 2019; Alharbi and Laramee, 2019). However, the majority of these papers have been based on English texts, and the research field of using NLP and visualization techniques for lower-resourced languages, such as Swedish, remains less explored, presenting challenges and opportunities for both academic research and industrial applications (for instance, the average word length in Swedish is greater than in English, affecting designs that rely heavily on text labels).

In this paper[1], we contribute to the less explored area of VTA for Swedish text data (more specifically, news articles as well as associated metadata) based on the data provided by our collaborators from iMatrics, a company located in Linköping, Sweden. As they explore the opportunities of using visualization for internal use as well as for products available for their clients (often with non-technical background, for in-

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[1]Based on a thesis project (Axelsson and Engström, 2023).

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stance, journalists), the design of our proposed solution takes the respective constraints and requirements into account. Our design study generally focuses on the challenges and necessary trade-offs of designing a temporal visualization, showing the relations between the topics of a large-scale text corpus, that is simple enough for a non-technical user to understand, while also considering the text genre aspect (e.g., articles focused on a specific story/event or a specific place/region) and target audience (e.g., the value of the interactive visualization prototype as perceived by the users with non-technical vs NLP background).

The rest of this paper is organized as follows: we discuss the related work as well as the methodology of this study in Sections 2 and 3. The first iteration of the study involving sketches and user feedback is described in Section 4. The backend and the frontend of our prototype are presented in Sections 5 and 6, respectively. Evaluation of the resulting prototype then follows in Section 7, and the discussion and conclusions are provided in Sections 8 and 9.

2 RELATED WORK

Both computational and visual/interactive perspectives are relevant to this study.

2.1 Natural Language Processing

NLP is a field that focuses on various text analysis techniques and methods used, among other tasks, to extract useful information such as keywords or topics (Chowdhary, 2020). *Topic modeling* is an unsupervised method used to uncover underlying topics, or themes, in a large collection of documents and group the documents according to these different topics (Tolegen et al., 2022). This is typically a soft clustering method, where each document belongs to each topic with a certain probability (Aggarwal and Zhai, 2012). Some of the more used topic modeling methods are *Latent Dirichlet Allocation* (LDA) and *Non-Negative Matrix Factorization* (NMF), for instance. There are also different extensions and applications of topic modeling, for example, *Dynamic Topic Modeling* (DTM) and *Hierarchical Topic Modeling* (HTM). DTM is a topic modeling approach which models the evolution of topics over time, with the ability to create a temporal overview of a large collection of documents (Blei and Lafferty, 2006). HTM focuses on hierarchical clustering/grouping of topics, including such methods as *hierarchical Latent Dirichlet Allocation* (hLDA) and *Pachinko Allocation Model* (PAM), for instance (Liu et al., 2016).

2.2 Visualization

InfoVis focuses on gaining insights of the (abstract) data with the use of various (interactive) visualization techniques (Spence, 2014). The prior works have established the basic stages of creating a visualization (Ware, 2021) as well as workflows for supporting user tasks from overview to details (Shneiderman, 1996) and design study methodology (Sedlmair et al., 2012). Visual Analytics is a related field, wherein interactive visualizations are designed based on computational data analysis methods, with the aim to explore and understand especially large and complex data sets (Keim et al., 2010), including the concerns such as the data characteristics, the users, and their tasks (Miksch and Aigner, 2014) into account.

Regarding the special data types that have strong implications for the visualization design process, **text** is one prominent example (Cao and Cui, 2016). As of today, there are many respective techniques to choose from, depending on the specific data and task at hand (Kucher and Kerren, 2015; Liu et al., 2019; Alharbi and Laramee, 2019). When designing a visualization for **temporal** data, multiple design choices must also be made. A type of stacked graph, named a *Streamgraph*, has been a prominent example of a visual representation for time series (Byron and Wattenberg, 2008). This graph comprises individual layers, stacked upon each other, with different colours and labels to reflect separate data series. The thickness of the stack is then set to represent the total sum of the layers' corresponding time series. Furthermore, there can be a need of visualizing data which contains many different **distributions** at once. A few viable options for this are ridgeline plots, violin plots, and boxplots (Wilke, 2019). For example, the ridgeline plot is especially useful when visualizing overall trends in distributions. Each distribution in the ridgeline plot is displayed in the form of an area chart, where the area chart is represented through a density estimate.

There have been many previous implementations of VA tools that include visualizations of topics over time, or relationships between topics, based on results from topic modeling. For example, *ThemeRiver* is a visualization using the river-based-flow / stacked graph metaphor to present, e.g., themes and patterns of a large document corpus over time (Havre et al., 2002). *Visual Backchannel* is a multi-faceted interface that visualizes events over time through providing the user with three types of visualizations: a stacked graph, a spiral, and an image cloud (Dörk et al., 2010). *StoryFlow* is a storyline visualization system developed for visualizing the evolution of stories over time and hierarchical relationships between

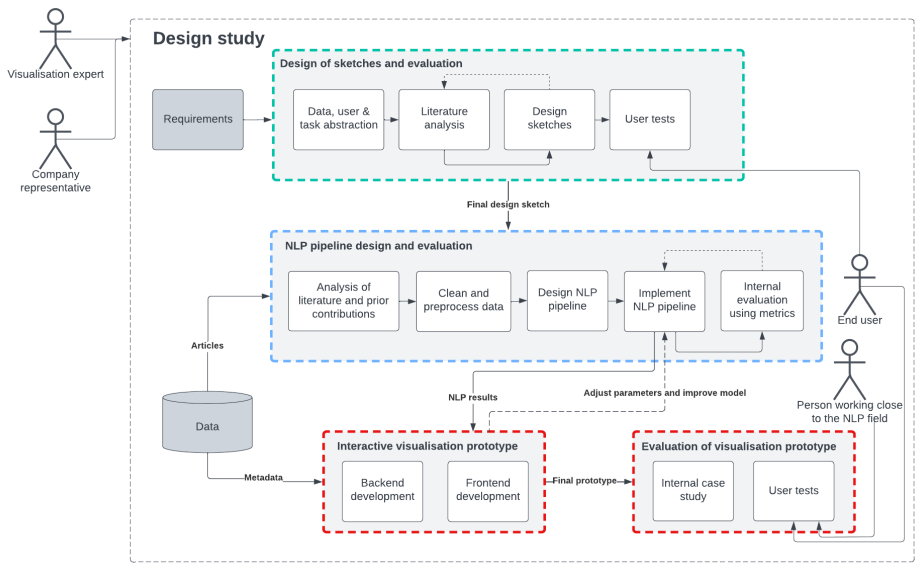


Figure 1: Workflow explaining the different parts and actors of the study and how these relate to each other.

a large set of entities (Liu et al., 2013). It should be mentioned that **evaluation** of such approaches is considered a difficult challenge (Lam et al., 2012; Elmqvist and Yi, 2015). This is due to visualizations being designed to solve activity tasks, such as gaining insights or making conclusions from the data visualized, which are generally complex and context-dependent tasks, also often limited to a particular target user audience. There are also several challenges with evaluating VTAs specifically, due to their complexity of combining NLP and visualization, which themselves can consist of systems that are not perfect (Kucher et al., 2022). Still, the methods such as semi-structured interviews as well as heuristic evaluation (Stasko, 2014) can be applied to get a glimpse, if not conclusive evidence, about the validity of the proposed approach and potential improvements.

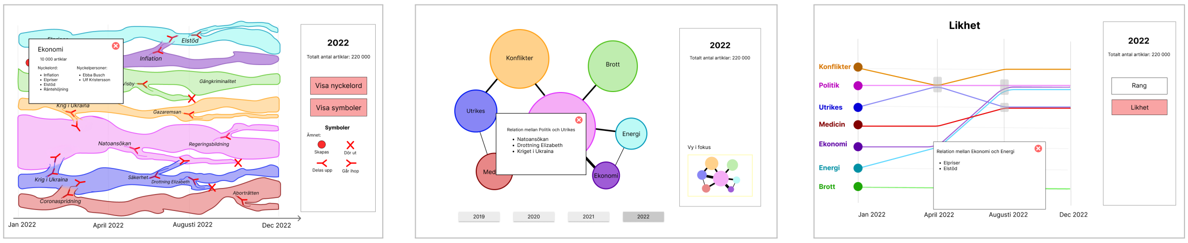
3 DESIGN STUDY METHODOLOGY

The main steps and actors of this study are presented in Figure 1. During the initial phase, the general **requirements** were discussed with the collaborating company representative, namely, developing a visualization prototype for the **tasks** of representing and exploring interesting data aspects (including temporal and relational) from a large number of news articles in Swedish. The **end-users** were not strictly defined, however, as such a prototype could be interesting for various audiences, including non-technical ones.

The first major step consisted of a visualization sketch design and evaluation process (the green block in Figure 1). Here, it was important to consider the requirements mentioned in the earlier stage, which was partially done by defining the data, users, and tasks (Miksch and Aigner, 2014) in the abstraction step. Besides the preliminary exploration of the available data and review of the prior work, sketches of the entire visualization prototype were prepared and evaluated through user tests using the think-aloud method, in order to gain feedback from possible end-users and decide on which design should be further developed.

The second major step (the blue block in Figure 1) was to design and implement the NLP pipeline, while internally evaluating it. The next steps (the two red blocks) were to implement the visualization prototype and evaluate it. The visualization front-end was developed in an iterative manner along with the NLP pipeline. Evaluations were then performed on the visualization prototype, which would test how the participants perceived the final visualization, while taking their background (non-technical vs NLP) into account. Additionally, a smaller case study was performed by visualizing two use cases through the prototype and comparing these to see if there were any noticeable visual differences for articles of different types, e.g., articles related to a certain place or event.

The **data** used in this project was based on a larger collection of news articles from the years 2019–2022—in total, ≈200,000 articles. However, due to the performance concerns, each year was initially handled separately and only the articles and features interesting for the scope of this design study were extracted, including the headline, text, timestamps, and



(a) (b) (c)

Figure 2: The initial visualization interface sketches: (a) the streamgraph sketch with glyphs, keywords, and an info box shown; (b) the network graph sketch with an info box for an edge shown; and (c) the storyline sketch with an info box describing the similarities between two topics.

article tags. The tags had been automatically generated by iMatrics and manually approved by their clients, i.e., journalists. All of the data described above was cleaned and preprocessed, with only articles containing texts in Swedish kept for further analyses. In order to extract two use cases for the case study performed later and to reduce the computation time, two smaller (sub)sets of data were extracted. These two data sets, one with the story tag “COVID-19” and another with the city tag “Kalmar”, contained around 10,000 and 38,000 articles, respectively.

4 INITIAL DESIGN

Based on the initial analyses and discussions, three concepts were chosen as the basis for interactive sketches created with *Figma*[2] in order to make the user tests more time efficient and provide the participants with interactions (such as hovering and clicking for details on demand) to test as well.

4.1 Initial Sketches Design

The decision was made to explore the visualization possibilities (and to get the initial user feedback) before implementing any NLP methods, since the choice of visual representations and interactions—and the required underlying information—highly affects the NLP pipeline design. Thus, the initial sketches relied on a combination of data from two fixed time intervals with more general mock-up topics such as “Crime” or “Politics”, while the participants were instead asked to imagine that the visualization prototype could eventually display both general and more specific news topics. Overview of the resulting interactive Figma sketches is provided in Figure 2.

[2]https://www.figma.com/

4.2 Initial Sketches Evaluation

To evaluate the sketches, user tests were performed with a focus on how easy or difficult the sketches were to interpret, the usefulness of the proposed representations/interfaces, and what information the participants were interested in seeing in such a potential future tool. Each participant of the user test was tested individually, in person at their respective workplaces, and each user test took around 40–60 minutes.

The user test was performed with two different groups of participants: one group consisted of three journalists (two investigative reporters with 8 and 14 years of experience + a journalist/photographer with 27 years of experience), while the other group consisted of two iMatrics staff members (one entrepreneur with around 6–7 years of experience + a head of marketing with around half a year of experience in that role). This group included two investigative reporters had worked as reporters for 8 and 14 years, respectively, while the third participant, a journalist/photographer, had worked for 27 years. The journalists all confirmed being in general used to visualizations such as line graphs and pie charts; and the staff members also come in contact with visualizations often or daily, while their attitude towards using technical aids was either neutral or positive.

To summarize the outcomes briefly, the **network graph** was considered as the best alternative with respect to simplicity and representation of relations (but not over time)—however, it was also considered the worst in showing *valuable* information, and it lacked the support for temporal aspects. The **storyline graph** was overall considered quite simple to understand and the most useful on average, while being the best in showing relations over time. However, it was considered difficult to interpret by the participants. The **streamgraph** was overall considered valuable, yet difficult to understand at a first glance; however, one participant commented that the difficulty may be caused by the lack of familiarity.

As the result, we made the decision to focus on a streamgraph for the rest of this design study, however, several changes would be made in order to simplify the visualization (e.g., the participants had a hard time understanding what the streamgraph "branches" represented) and to better match the expected NLP pipeline results. Overall, features such as visualizing coverage of topics, details in the form of access to original articles, and more visual clarity of the relations between topics were considered important to support, as well as the scalability.

5 NLP PIPELINE

Based on the chosen streamgraph sketch, the NLP pipeline and eventually the visualization frontend could then be designed. In order to analyze and represent the evolution of topics, we intended to apply Dynamic Topic Modeling; to address the relations between topics, while being able to scale to a larger number of topics, we also decided to support Hierarchical Topic Modeling, as inspired by the HierarchicalTopics tool (Dou et al., 2013), for instance. Due to the performance, but also support for HTM and flexibility in customization, we chose BERTopic[3] (Grootendorst, 2022) for our implementation. To set the different parameters or model options used by BERTopic, e.g., the sentence transformer used to generate document representations (embeddings), evaluations were carried out to compare different choices. For these comparisons, the COVID-19 use case data was used. The metric used to evaluate the results from the NLP pipeline in an unsupervised fashion was the silhouette score (Rousseeuw, 1987). For this project, two different sentence transformers were tested: a multilingual one[4] (Reimers and Gurevych, 2019) and a Swedish sentence transformer[5] from KB Lab (Rekathati, 2021). When using the former, the training of the model took 8 minutes and 54 seconds and 131 topics were generated. Meanwhile, the latter took 63 minutes and 182 topics were generated. The generated silhouette score for the multilingual sentence transformer was around 0.565, while the Swedish sentence transformer received a slightly higher silhouette score of 0.648. Based on these results, we can see that the multilingual transformer was considerably faster, but it also gave slightly worse clustering results. Other than the time and the silhouette scores, a third important aspect to take in regard was the more subjective quality of the topics. The quality was investigated for topics from both transformers, and one typical example is how the multilingual sentence transformer produced a topic with representative words chosen such as "worst", "increases", and "most", while the Swedish sentence transformer led a topic with more descriptive words such as "elderly homes" or "the public health authority"[6]. Based on all of these results, it was decided that the Swedish sentence transformer would be used for the final pipeline and any further evaluations.

[3]https://maartengr.github.io/BERTopic/

[4]https://huggingface.co/sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2

[5]https://huggingface.co/KBLab/sentence-bert-swedish-cased

6 VISUALIZATION PROTOTYPE

The resulting interactive visualization prototype is implemented using *D3.js*[7]. As Figure 3 demonstrates, the main visual representation is a stack of area charts resembling a ridgeline plot, which typically visualizes the distribution of multiple groups over time or space (however, we avoid the overdrawing applied in typical ridgeline plots for vertical space compression and specific aesthetics, even though this design decision leads to increased vertical space usage and vertical scrolling within the user interface). This representation was deemed to contain multiple similarities with the Figma sketch, e.g., in the forms of visualizing distribution of each topic over time and showing multiple topics at once, while avoiding the issues related to interpretation of streamgraph "branches", as reported in Section 4.2. The height scale is the same for all topics and is determined by the topic with the highest frequency peak (i.e., the values are normalized against the global maximum count). Each graph also uses a separate categorical color for a more distinct representation and supports a magic lens for exploring the topical keywords over time, as well as an additional pop-up dialog with details on demand. The user can adjust the displayed time range by using a range slider at the bottom of the interface (divided into 15 temporal bins as a trade-off between a cluttered x-axis and an overly coarse level of detail). Furthermore, the user can toggle the representation of locally- (as opposed to globally-) normalized topic counts over time (as a dotted outline) in order to observe trends easier, especially for less prominent topics. The prototype is showcased through two different views/perspectives (chosen by the user): a top 10 topics view (based on DTM only) and a hierarchical topics view (with an option to navigate to the nested child topics).

[6]These examples are translated from Swedish.

[7]https://d3js.org/

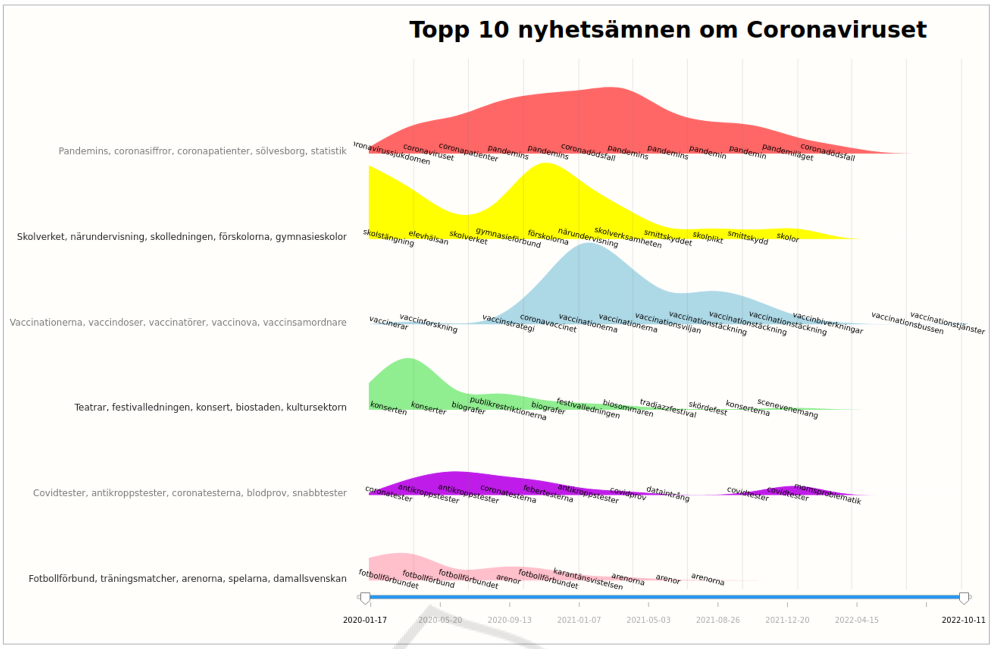


Figure 3: The resulting visualization prototype showing the top topics for the COVID-19 use case.

7 EVALUATION

Finally, with the implementation complete, a smaller case study and user tests were performed.

7.1 Case Study

The case study consisted of visualizing and analyzing the two use cases defined earlier, i.e., articles tagged with either a story tag “COVID-19” or a place tag “Kalmar”. These two data sets were both separately processed through the NLP pipeline with the same parameters. The prototype was used internally with the available data, leading to some interesting observations: for example, some of the hierarchical topic groups were quite peculiar, such as one group for the COVID-19 data that was described by the top keywords “rehabilitation”, “funerals”, “fever”, “patients”, and “long-term covid”—by drilling down into the details, we found out that this group contained a mixture of topics related to both COVID-19-related aspects and *crime*. The use cases were then compared in order to discover if there are any visual differences, with only the top 10 topics compared. As demonstrated in Figure 4, there were more visible changes in the COVID-19 use case, i.e., there were clear ups and downs regarding how much each topic had been written about (further details in Figure 3), including the “School” and “Vaccinations” topics, for instance, while the Kalmar use case demonstrated more stable behavior. There was also a smaller difference regarding the time periods of the use cases, as the Kalmar data stretched over a wider period (2019–2022) than the COVID-19 use case data (2020–2022).

7.2 User Tests

The user tests were performed to evaluate the prototype in its final state. Each user test took in total around 40–60 minutes and consisted of an introduction, demo, two introductory mini tasks (identifying peaks and navigating & exploring the respective topical keywords), and multiple interview questions focusing on the users’ interpretation of the prototype, which were inspired by ICE-T questions (Stasko, 2014; Wall et al., 2019). Similar to the sketch evaluation sessions described in Section 4.2, the user tests were divided into two groups of participants (and the questions adapted accordingly): (1) participants with journalistic experience (conducted remotely due to different locations; four participants in total with 7, 20, 35, and 14 years of journalistic work experience, respectively, and weekly exposure to visualizations), and (2) participants with technical roles/experience (conducted in person; five participants in total with 2, 28, and between 2–5 years of experience with NLP, and daily or weekly exposure to visualizations). To summarize the outcomes of these evaluation sessions briefly, both groups were able to succeed in the mini tasks with ease. Both groups were interested in in-

(a) (b)

Figure 4: Topic trend differences from (a) the COVID-19 use case and (b) the Kalmar use case.

vestigating somewhat similar questions regarding the data set of articles, such as the topic evolution over time; and both groups mentioned that the prototype supports this task, which in itself fulfills one of the main purposes of the prototype. The visualisation was stated to convey a visual overview of the articles written, compared to the archive search otherwise used. The prototype could also be useful in some other contexts, e.g., making sure to not miss follow-ups from previous years. Regarding the hierarchical topic view, the results were considered somewhat confusing by both groups, and thus the value of this functionality considered lower than the top 10 topics view.

8 DISCUSSION

One of the interesting observations related to the initial sketches' evaluation is that the streamgraph was considered difficult to understand, e.g., through the branches showcasing the relations, but it was also found most useful by a majority of the participants. An impression was also that the same participants took a longer time to investigate the sketch and that resulted in a deeper discussion, e.g., regarding the graph's potential and improvement possibilities; however, raising the level of complexity of the solution too high also has a risk of discouraging the users.

With respect to the final prototype, the results of the evaluation show that the prototype is promising in its current state, as it provides the user with insights through, e.g., showing trends and helping the user to draw conclusions from a larger set of articles over a longer period of time. There were, however, many improvements mentioned by the user participants such as including: real-time data, the articles' full text, a search function, a map showing the extent of the topics, etc., some of which are beyond the scope of a prototype as opposed to a full-fledged tool/product. The overall feedback of the participants was positive with respect to the top 10 topics view—the participants from the field of journalism mentioned that it could, with some improvements, aid them in their work. The hierarchical topics view had, however, in general lower value and quality for both groups, while the group of people working closely to NLP understood why some unexpected hierarchical topics appeared. This shows that including hierarchies of topics can be difficult for an end-user to perceive.

While the design space of all possible representations, interactions, and NLP methods potentially applicable for news articles data is enormous, only a part of that design space was considered due to the limited scope of this project; thus, this study cannot claim to provide definitive answers and design guidelines, but rather contribute to the existing body of knowledge, especially with respect to the user feedback for various visual representations that can be considered well-known and trivial within the visualization research community, while being unfamiliar to the end-users. Additionally, some questions about the scalability of the approach as well as its generalizability towards other languages could be part of future work. Finally, the number of participants involved in evaluations was limited and some additional concerns could be considered (e.g., remote vs on-site participation), which could be addressed to some extent by further evaluation efforts.

9 CONCLUSIONS

The aim to develop a web-based visualization prototype, which can be used to explore a large set of Swedish news articles, was fulfilled through this project. In this project, it was of interest to include both temporal and relational data, which challenged the design and choice of visual representations, especially when considering non-technical end-users. Therefore, there is a challenge in trying to adapt the visualizations, yet include as much valuable information as possible while still not overwhelming the user. Secondly, an important trade-off when designing a visualization for a large-scale text corpus is that it is not possible to show all of the data at once, yet the data visualized should fulfill the user's needs. The end-users saw value in the prototype as it gave a visual aspect of the articles and could be helpful when, e.g., doing research or writing follow-up stories. Meanwhile, people working closely to the NLP field did perceive some value in the features of the prototype, but did not relate it as clearly to areas of application.

To develop a visualization prototype for low-resource language such as Swedish (in comparison to English) can be considered a positive contribution as it makes such tools accessible to further audiences. Thus, the lessons learned from this design study as well as its limitations and identified suggestions for improvements could lead to the future work in that direction from the perspective of visual text analytics, within and beyond the academic community.

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