ComEx: Comment Exploration on Online News Platforms

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Abstract

The comment sections of online news platforms have shaped the way in which people express their opinion online. However, due to the overwhelming number of comments, no in-depth discussions emerge. To foster more interactive and engaging discussions, we propose our *ComEx* interface for the exploration of reader comments on online news platforms. Potential discussion participants can get a quick overview and are not discouraged by an abundance of comments. It is our goal to represent the discussion in a graph of comments that can be used in an interactive user interface for exploration. To this end, a processing pipeline fetches comments from several different platforms and adds edges in the graph based on topical similarity or meta-data and ranks nodes on metrics such as controversy or toxicity. By interacting with the graph, users can explore and react to single comments or entire threads they are interested in.

Keywords

Online Discussions, Discourse Mining, Corpus Visualization

1. Introduction

In the past, newspaper readers could only interact with and express their opinion on an article by writing a letter to the editor. The editor could then decide to publish and/or to reply to the letter in the next issue of the newspaper. The considerable effort of writing and mailing such letters, was a natural limiting factor for the number of interactions. Now, users of online news platforms can easily post comments and discuss article topics with others. The simplicity and ubiquity of expressing one's opinion online was therefore termed as *democratization of opinion*. On the downside, readers can be overwhelmed by the volume of comments. Repeated arguments, Troll comments, or attention-seeking unrelated opinions hinder the emergence of meaningful discussions. Long discussions across multiple pages may discourage readers from scrolling through more than the top ten comments.

We envision a platform that focuses on providing a space for discussions where people listen to and refer to each other's comments. To this end, we part from a traditional "linear" list to a two-dimensional canvas that groups comments using different features for a better overview. This allows for new interaction paradigms that could inspire readers of news comments to engage in an already ongoing discussion.

In this paper, we present *ComEx*, a platform for visualizing of and interacting with online discussions. We present a novel concept of stipulating engagement through improved information visualization. In this regard, we identified three components that are crucial to reach this goal:

1. *More engagement:* more users who were passive in the past should become active contributors in discussions.
2. *More in-depth:* more comments should refer to one another and more dialogues should emerge.
3. *More insights:* users should read more relevant and less redundant or off-topic comments.

Besides these user-centered aspects, technical aspects are also currently preventing a better user experience. Online discussion spaces are fragmented across various individual platforms. Although the topics discussed are typically similar, e.g. daily news events. We are the first to introduce the idea of a common, shared discussion platform with the goal of increasing engagement of discussion participants and facilitating interaction. To this end, we present a novel interface for exploring large amounts of reader comments across different news platforms. The core of the visualization is based on a graph representation of comments, where nodes are sentences and edges describe how they relate to one another. This graph allows us to incorporate several views on the data and enrich the comments with syntactic and semantic features, such as topical similarity or temporal proximity. It is

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our goal, to find a graph representation that captures arguments and the evolution of the discourse. By clustering, filtering, and merging, the interface enables users to reduce the complexity by exploring the comments at different levels or granularity.

The following sections provide an overview of the system architecture of *ComEx* and describe the visualization paradigms behind it. Furthermore, we discuss our work in progress towards a meaningful graph representation and showcase initial results applied in a case study on reader comments about bushfires in Australia.[1]

2. Related Work

In this section, we discuss related work on visualizations of written discourse and relevant text mining methods. The goal for our interactive visualization is to form visual clusters of comments that make it easy to comprehend the inherent semantic structure of a large set of comments. To achieve this goal, the underlying layout model reflects not only the structural information, e.g., sentences belonging to the same comment, but also the key topics and arguments made. Appropriately mapping the nuances of a discussion, the size of the dataset, and the text lengths pose as hard problems for language models. Attempts using topic models have been made to visualize political speeches [1] as moving particles or text collections as glyphs symbolizing topic distributions [2]. Others use document embeddings and dimensionality reduction to create a partial map of Wikipedia articles [3] or scatterplots of forum posts [4]. Both examples are not applicable here, as they rely on a large, manually labeled dataset. We propose to use pre-trained sentence embeddings. All comments of one story are clustered into key discussion points. The layout within each cluster is done using attracting and repelling forces between particles based on sentiment or keywords. Thereby, we benefit from sentence embeddings to get a global layout and achieve a nuanced local layout by using mined meta-data (clusters, keywords, sentiment, etc.).

Related work in the area of text mining forms clusters of comments mentioning the same entities [5] or and visualizes discussions with pie charts [6] or topic-model-based graphs [7]. Zhang et al. [8] focus on summarizing social media posts to provide aggregates of all reposts and replies in a conversation. They form pseudo-documents as context used in an encoder

[1]Interactive demo and code available at https://hpi.de/naumann/s/comex

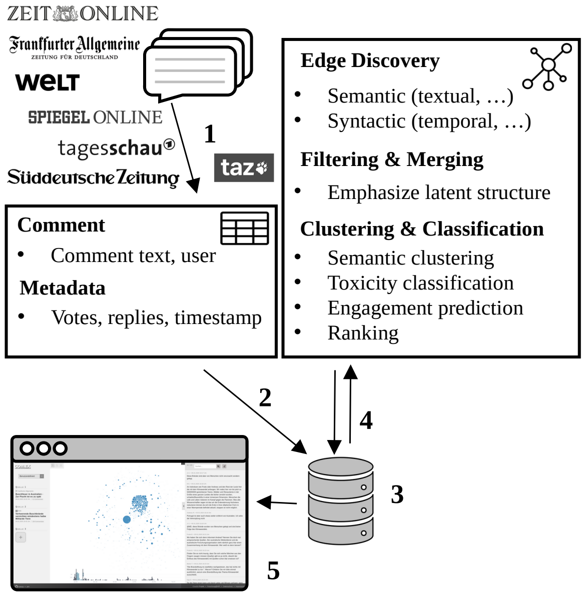

Figure 1: The *ComEx* system transforms comments into a graph structure and allows their exploration through a web interface.

of a recurrent neural network from which the summary is generated. Leveraging sentiment analysis and stance detection, there is also related work on allowing users to search for diverse perspectives on the same topic [9, 10]. In their analysis of millions of comments, Ambroselli et al. [11] identified three main causes for increased user engagement: reactions to personal stories, hate speech, or comments by the article's author. Our system allows integrating such additional functionality in the form of data processing modules. As an example, we incorporate a comment classification approach that identifies main causes for increased user engagement based on comment texts [12]. Thereby, *ComEx* can highlight engaging points of a discussion that are likely to trigger many user reactions. More distantly related is work that supports exploratory search through scientific articles [13]. A comprehensive overview of the characteristics of exploratory search has been published by Palagi et al. [14].

3. System Overview and Paradigms

The *ComEx* system implements a novel concept of interacting with and getting an overview of the growing number of reader comments in online news discussions. Figure 1 shows the system architecture. The data ingestion pipeline scrapes comments from different news platforms (1). The comment texts and their metadata, such as upvotes, references to other comments, or timestamps are then stored in a relational format (2), which is cached (3) to reduce the load on the news platforms. This data is transformed into a graph structure, where the nodes (sentences of comments) and edges (relations between sentences) are processed with text mining and graph analysis algorithms, such as semantic clustering, TextRank [15], and toxic comment classification (4). The results are sent back to the cache. A web-based user interface allows exploring the enriched graph at different levels of detail (5). The architecture of the system is designed in such a way, that text and graph processing modules are interchangeable and can easily be configured. More details on that are highlighted in the following section. The representation model and pipeline can be used programmatically for experiments or other applications. In the scope of our system, the data is accessed through a highly customizable API by our interactive frontend.

We enrich our graph representation through text mining and graph analysis beyond the comment metadata. These steps of analysis and aggregation come with loss of details, which has to be balanced with the benefits of a better overview. Although we refer to the comments on online news platforms as a discussion or discourse, many statements and arguments are frequently repeated by different users without referring to an already existing comment. Our graph representation helps to identify and visualize these inherent semantic clusters of comments.

In the most simplified view, the graph representation is used to draw particles on a two-dimensional canvas.Hereby, the comment positions reflect semantic similarity and cluster affiliation. To convey more additional information, particles can be drawn as glyphs or vary in size or color. The canvas can be enriched by overlays of cluster contours, heat maps, and explanatory keyphrases.

We embed comment threads originating from multiple news platforms in the same space, thus merging topically related discussions from various articles. In this way, we provide a global view and increase the diversity of represented opinions following our three key goals. The summarizing visualization aims for *more engagement*, reducing potential bias in discussions by having a broader group of contributors and novel playful ways of interaction, such as reacting to clusters of comments. We anticipate a larger number of replies in general and deeper threads, which means *more in-depth* replies. If a user receives a reply to his or her comment, this reply is an acknowledgment for the user and demonstrates that the comment is relevant to others. Readers should be able to easily navigate to comments that are most interesting to them, as reading every single comment becomes infeasible for popular articles. Our interactive visualization condenses long discussions into groups of similar comments for *more insights*. In this way, we are still able to show all contributed comments, while users can make an informed decision on which subset of comments to actually read. This overview could also give information on different viewpoints, such as how many commentators share a particular point of view. By retaining data provenance information, users are able to switch back and forth between the generalized overview and the underlying data for more details. Further, the system includes a full-text search and time or lasso selection in the interface to filter the list of comments. Afterwards, users can jump back to the original platform to comment, or react to a selection of comments directly in the visualization.

4. Graph Representation of Reader Comments

The processing pipeline transforms the tabular comment data retrieved by the scrapers into a graph and further enriches the information it contains. Each comment may contain more than one main semantic aspect, such as different arguments or responses to other comments. Thus, we heuristically assume sentences to be the smallest "atomic" semantic unit of a comment. Each sentence is added as a node in the graph representation of a discussion. By adding edges between sentences of the same comment, we are able to maintain data provenance along with metadata about the original content. In this section, we discuss possible data mining methods to enrich the graph representation.

The first step is the discovery of relations between sentences and adding edges to represent these relations. Second, we assign class labels and scores to the nodes and edges. This allows us to rank and cluster them based on these assignments. Finally, the number of nodes and edges is reduced by filtering or merging them to provide a comprehensible entry point. Note, that edges of the graph are only the basis to internally represent reader comments and the layout. Edges won't be directly visible in the interface to reduce visual clutter.

Edge Discovery. Our approach builds on ideas by Barker and Gaizauskas [16], who represent arguments in comments (assertions or viewpoints) in a graph. Given this graph, they generate textual summaries of an entire discussion. In contrast to their laborious process of manually constructing the nodes and edges, we generate them automatically and present them in an interactive visualization. To this end, we construct a network of sentences as nodes adding edges if their pairwise semantic similarity is above a certain threshold. This similarity is the cosine similarity of the sentence embedding vectors calculated with fastText [17]. Syntactic edges are added between all sentences that belong to the same comment and also to its replies. Thereby, structural information of the comments and the discourse is incorporated. The resulting network is drawn using a force-based layout algorithm. Edges are hidden for the user, so that the comment landscape only shows clusters of points representing sentences. Since we include both semantic and syntactic edges, the layout can provide an overview of the key topics of the discussion, while prevailing its overall structure.

Clustering and Classification. On the node level, the TextRank algorithm [15] ranks sentences and assigns weights to identify key statements, which we assume to be strongly connected and to form similarity communities. The clustering progressively removes edges and thereby conforms to our idea of reducing the discussion to its most essential statements for a comprehensible overview. Further, a neural network model detects *toxic* comments, such as insults or threats, which are comments that make other users leave a discussion [18]. Another neural network model from related work [12] detects *engaging* comments, such as questions or factual statements, which are likely to receive many reactions by other users.

Filtering and Merging. The class labels generated by the two neural networks are used to put more visual emphasis on the engaging comments than on the toxic comments. Nodes with a small number of edges represent sentences that are only loosely connected. In a simplified view, these nodes are either filtered completely or merged with a neighbored node. Nodes for sentences with almost similar embeddings are grouped together.

5. User Interface

The *ComEx* user interface is structured into three main components: the news outlet selection, the interactive graph, and the detailed comment view (Figure 2).

News Outlet Selection. The panel on the left-hand side of the interface allows selecting a set of reader discussions on articles from different news outlets. There are presets of news stories that were covered by many platforms but users are free to select (the comments of) any news article that is published on one of the seven platforms currently supported. Users can add an article by simply pasting its URL. Comments on this article are then retrieved by our server and merged with previously selected comments to construct a graph representation. Mckay et al. [19] suggested to build systems that support users in reflecting on their own view by comparing it with diverse views of others. By incorporating comments from many different news outlets, we implement this design idea in the context of online discussions.

Interactive Graph. In the center of the interface is the graph layout of all the comments. Note that the edges of the underlying graph are used only by the force-layout and are not shown for simplicity. This visualization enables users to interact with single keyphrases of longer comments or with multiple comments at once — instead of only appending a reply to an existing list.[2] Additionally, they can rearrange or filter the nodes and navigate the canvas by zooming and panning. When using a lasso to select nodes, comments on the right panel are automatically filtered. By selecting an interval on the time histogram at the bottom, additional filters are applied. As stated before, nodes in the graph are individual sentences of comments. By clicking a node, all other nodes belonging to the comment are highlighted and the comment is shown in the right panel. Once a lasso selection is active, users can vote up or down on multiple comments to signal their agreement or disagreement. The fill color of the nodes is updated to convey areas of predominantly positive or negative sentiment. The size of nodes can be determined by multiple factors. In Figure 2 the TextRank score is used, but the votes or number of replies on the originating platform has similar effects. Sliding a selection window over the time histogram shows how the discussion evolves over time. For example, it reveals which topics came up early in the course of the discussion.

[2] In the context of our demo, the effects of voting on or replying to one or multiple comments are not transmitted back to the news platforms.

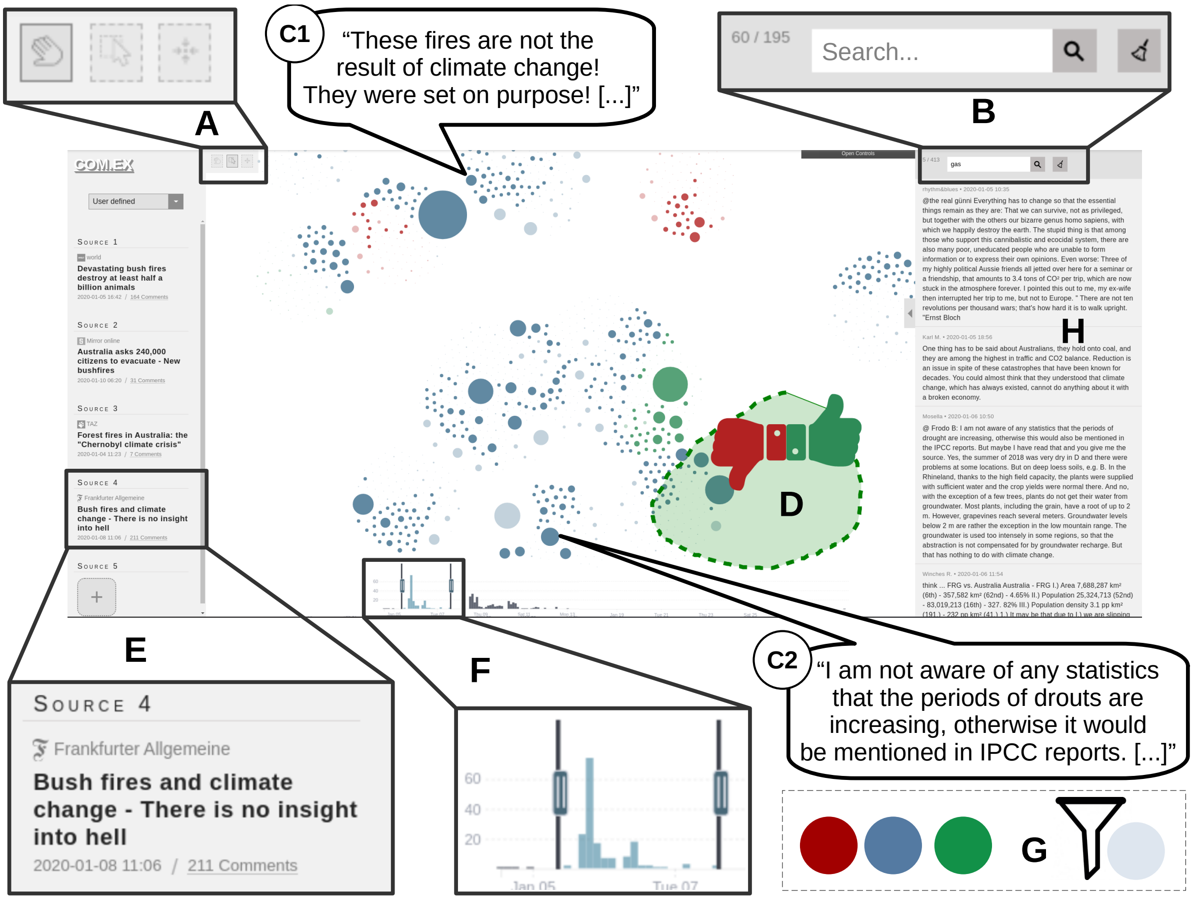

Figure 2: *ComEx* user interface; Users select news articles (E), comments are visualized in the center and can be filtered by time (F) or search terms (B); different modes are available (A), such as exploration by zooming, panning and reading a selected comment (H) by clicking nodes, or users can lasso-select and express their sentiment on groups of comments (D), nodes are colored based on average sentiment and greyed out when filtered (G). Two example comments (C1, C2) are shown.

Detailed Comment View. The panel on the right-hand side lists the comment texts where the text of the currently selected comment is highlighted. With a search bar, users can quickly find comments that mention keywords they are interested in. At the top of the panel are also parameter controls to adjust the number of nodes and edges displayed. This view is also updated by filters applied to the interactive graph.

Additional Possibilities. In this section, we described features of the interface we thought to be essential for exploring the comment landscape. All these features are implemented in a prototype system. Further features could be added to enable users to analyze the data in more depth. The underlying graph representation of reader comments provides the basis for additional capabilities. As the graph implicitly maintains data provenance, tools for filtering comments based on meta-data is possible at all times. Furthermore, the information could also be used to control the shape, color, or size of the visualized nodes. For example, a user might want to color all nodes based on the news outlet the respective comments were extracted from.

6. Case Study

A meaningful, thorough evaluation of the proposed concepts and platform requires many active users and a sophisticated experimental setup. Such an evaluation is beyond the scope of this paper and deferred to future work. Nevertheless, we conducted a small-scale case study to validate the presented ideas.

The system described in this paper was designed for the purpose of visualizing comments from different

Table 1
The interaction features of comment sections of online news platforms in our study are limited to upvotes, downvotes, and replies as well as ranking comments by time or popularity with regard to the number of received upvotes or replies. These limitations motivate our research on an interactive user interface for comment exploration.

				Ranking by		
Platform	Upvotes	Downvotes	Replies	Time	Votes	Replies
Frankfurter Allg. Zeitung	✓	–	✓	✓	✓	–
Spiegel Online	✓	✓	✓	✓	✓	✓
Süddeutsche Zeitung	✓	✓	✓	✓	✓	–
Tagesschau	–	–	✓	✓	–	–
Die Welt	✓	–	✓	✓	✓	–
Die Tageszeitung	–	–	✓	✓	–	–
Zeit Online	✓	–	✓	✓	✓	–

platforms on a single topic. We therefore use the notion of a *news story*, which is covered by several *news articles* on the same emerging news event.

Our initial findings are based on hand-selected news stories of seven different German news platforms: faz.net, tagesschau.de, spiegel.de, sz.de, taz.de, welt.de and zeit.de. Each day between November 2019 and February 2020, we manually selected the most prevalent news stories. For each story, the annotators manually collected respective articles from the previously mentioned news platforms. The resulting dataset comprises 150 news stories and 1,350 news articles. Only 570 of these articles have publicly available reader comments, which we retrieved programmatically. In total, we retrieved 111,000 comments and the average comment length is 45 tokens. To give an example, one of the most discussed stories in this dataset contains 4,696 comments and is covered by 4 news platforms. It is about the UN Climate Change Conference held in Madrid, 2019.

The interaction features of the seven popular German-language news outlets we selected are limited to comment replies, upvotes, and downvotes as well as ranking by time or number of votes or replies (summarized in Table 1). *ComEx*, on the other hand, could drastically change how users interact with online comments. It provides a feature-rich exploration interface for a global overview of comments from across multiple online news platforms. Going through the processing pipeline by hand, the annotators printed all comments of two exemplary stories and collaboratively assigned semantic groups similar to the argument graph described by Barker and Gaizauskas [16]. Our manual results in general confirmed the graph layout automatically generated by *ComEx.*

Figure 2 shows the interface for four articles on Australian wildfires in 2020 with 413 reader comments. If a user wants to add additional news articles, she can add a URL on the left pane (E). The *ComEx* system will then extract comments from the website in the background, update the comment graph and the visualization in the center pane. In the displayed use case, we opted to visualize topical similarity leading to clusters of topically similar comments. The cluster at the top contains comments (C1) discussing climate change, while another cluster of comments (C2) on the bottom primarily concerns droughts. The timeline at the bottom indicates the date the comments were published. By selecting a time-window (F), comments can be filtered. Comment outside the selected window are greyed out in the visualization and removed from the comment pane (H). Users may also filter comments using full-text search (B). There are two modes (A) in which the user can interact with the data displayed in the center pane. The first mode supports *exploration*, including zooming and panning the visualization. Furthermore, clicking a node in the visualization highlights the corresponding comment in the comment pane (H) and vice versa. The second mode supports *engagement*, by providing a lasso tool to select several comments at once. Users can then express their sentiment by voting up or down. We store this information and use color (G) to indicate the average sentiment of all votes from negative (red), neutral (blue), to positive (green).

With this case study we have shown the novel way our *ComEx* system enables users to interact with reader comments. More evaluation is necessary to validate the user-centered aspects of being *more engaging* and *more in-depth*, and providing *more insights.*

7. Conclusions and Future Work

To improve the way people exchange ideas online and to foster in-depth discussions, we studied the novel task of comment exploration for users of online news platforms. Previous work on conversation or discourse exploration developed analytics tools for experts. In contrast, we focused on letting comment readers and comment writers interact with the exploration tool. To this end, we presented *ComEx*, a comment exploration system that implements different methodologies for the interactive analysis and visualization of comments in online discussions.

A promising path for future work is to study the impact of novel visualization and exploration methods on online discussions. One exemplary research question in this context would be how visualizations could help to establish a higher conversion rate of comment readers into comment writers. Potential next steps are to conduct user studies to evaluate our prototype and identify interaction patterns. The presented system is not limited to the news comments use case, but can be employed in all kinds of scenarios where user-generated content can be linked to each other.

Although some examples we looked at in depth showed initially promising results, we see room for improvement and potential for future work in the construction and filtering of the underlying graph representation. Our modular architecture for node enrichment and edge generation and filtering allows for a simple configuration of the pipeline. One of the major challenges is to limit the number of generated edges, e.g., by introducing locality-sensitive thresholds for similarity-based edges, such as those based on sentence embedding distances. The visualization uses a force-based layout algorithm. We experimented with several approaches to incorporate weighted aggregates of edge weights produced from different sources, i.e., for combining cluster assignment, embedding similarity, temporal proximity, and reply structure. Finding a robust and ideally self-adjusting approach remains a task for future work. Furthermore, we found, that a keyword overlay to briefly describe the "meaning" of a visual neighborhood could be a useful addition to the interface.

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