ConvEx: Conversation 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 a novel task of conversation exploration for users of online news platforms. Central to this task is that potential discussion participants get a quick overview of the course of the discussion so far and are not discouraged by an abundance of comments. To this end, we present a novel perspective on visualizations for user comments datasets and online discussions — a longtime neglected research area in academia and industry. We discuss strengths and weaknesses of our ideas in context of an exemplary news story that covers Brexit. Our research on this task is by no means complete and only outlines our envisioned future to support engaging online discussions.

CCS CONCEPTS

• Information systems → Recommender systems; **• Human-centered computing → Visualization theory, concepts and paradigms**; *Visual analytics*; *Information visualization*; **• Applied computing →** *Publishing*; *Document searching*; Evidence collection, storage and analysis.

KEYWORDS

Data Visualization, Online Discourse, Text Mining, Ranking

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1 INTRODUCTION

In the past, readers of a newspaper could only interact with and express their opinion on an article by writing a reader's 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 large effort of writing such letters, including sending them via mail, was a natural limiting factor for the number of interactions.

Since then, the situation has changed drastically. Online news platforms now provide comment sections, where readers can easily post comments and discuss article topics with others. Expressing ones opinion takes less effort than ever, it comes free of costs, and thanks to mobile devices it is available from anywhere at anytime.

Popular news articles receive thousands of user comments, with some of them even exceeding 30,000 comments.[1] While this development comes with many advantages and is sometimes termed as *democratization of opinion*, this mass of comments has also become infeasible to grasp. More and more people discuss online but also the number of troll comments and nonsense increases [23, 29]. As a result of the large number of comments, users sometimes cannot see the wood for the trees. The overload of comments hinders deeper discussions and while every user can express his or her opinion to a potential audience of ten-thousands of people, no dialogs emerge. Longer comment sections are split up into multiple webpages. The sheer number of such subpages discourages users from reading through more than the first page with the top ten to twenty comments. The opinions of the fastest users get a much larger exposure because of the chronological ranking of the comments. This ranking can create the impression of a bias of all comments.

In this paper, we envision online news platforms that put user conversations into their focus. Platforms that provide a space for detailed discussions and where users listen to and refer to each other's comments. To this end, the platforms' design needs to encourage users to read and to post comments. Certainly there is a gap between current platforms and the future ones that we envision. That is why we formulate a novel task at the intersection of human-computer interaction and information retrieval, which we call conversation exploration for users of online discussions. To address this task, we investigate on exploration and visualization methods that foster more engaging and in-depth discussions.

Four components are key to this goal:

(1) *More engagement:* more users who were passive in the past should become active in comment sections.
(2) *More in-depth:* more comments should refer to another and more dialogs should emerge.

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[1] https://www.theguardian.com/politics/live/2019/sep/26/boris-johnsons-brexit-rhetoric-condemned-as-mps-tell-of-death-threats-politics-live#comments

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(3) *More insights:* users who choose to read only (and not write) comments should read comments that are more relevant to them;
(4) *Faster insights:* users should not read multiple comments if they make the same or a very similar statement. Instead, such comments are clustered so that users can grasp their idea faster.

The first aspect aims to make more comment readers to comment writers. This conversion could reduce a potential bias in discussions because a broader group of people would contribute to it. For example, a small study among 1,000 people in the United States found some differences between comment readers and writers. Those leaving comments tend to be more male, have lower levels of education, and have lower incomes compared to those who read news comments, but do not comment [32]. More users who engage and interact are desirable for platforms also for another reason: an increased user retention rate. If a user becomes an integral part of a platform's community, he or she will also be more loyal to the platform and re-visit it more often or more likely.

The second aspect focuses on the *reply* feature in online discussions. Depending on the platform, only about one half of the comments indicates that they are a reply. This number also means that one half does not refer to any other comment. A larger number of replies in general and deeper threads, which means successive replies, are desirable. For example, 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. Referring to and dealing with the opinion of other users is also a sign for an open-minded discussion culture.

The third aspect is that readers of comments should be able to easily retrieve those comments that are most relevant to them. Reading through each and every comment below a particular news article in chronological order is infeasible for popular articles with many comments. Instead, we imagine that users read only a subset of the comments and an exploration tool helps them to decide which subset to read. Last but not least, comments in online discussions can be repetitive but users might want to read a summary of the discussions without redundant content. The idea is to condense long discussions to a form that allows getting a quick overview. This overview could also give information on majorities for different points of view, such as how many commentators share a particular point of view. Afterwards, users can decide whether such a generalization is enough for them or whether it aroused their curiosity. In the latter case, there should be an intuitive way to jump from the overview into the detailed, standard view and to start the interaction with other users. The remaining of this paper is organized as follows: Section 2 summarizes related work in the fields of conversation visualization and exploration. Section 3 is the main part of the paper and describes our perspective on an alternative comment section. It also explains what we envision as essential parts of conversation exploration for users and what methods of interaction are needed. We describe how this alternative works for an exemplary news story that covers Brexit in Section 4 and discuss the impact on online discussions in general in Section 5 before we close with conclusions and future work.

2 RELATED WORK

In the 90s and early 2000s, weblogs opened the ability for almost everyone to share their opinions. However, conversations on the blogosphere were hard to follow by others and were usually longer opinion pieces rather then short comments to recent news or other events [14]. As traditional news publishers moved to the Internet, the number of free journalistically moderated online news grew. With that, the ability for readers to interact and directly share their opinion was more accessible then ever. Gómez et al. [11] have shown, that the statistical analysis of user comments can be used to find communities in social networks and influential users similar to those in the blogosphere.

The democratization of comments required automated and crowd-moderated mechanisms to process the large amount of user-generated content. With hundreds or sometimes thousands of comments on one article, the discourse can get lost, arguments are repeated by different users and it is infeasible to get an overview. Some platforms offer users the ability to vote on comments, so they can be ranked by their popularity [15] or automatically by their contribution to the discussion [36]. On other platforms, editors can pick their favorite comments that are prominently shown near the top. Kolhatkar and Taboada [19] even tried to automatically discover such constructive comments. Although ranking can be useful, it is traditionally only limited to changing the order of a simple list. Interactive visualizations open a number of possibilities, where a ranking score is only an input feature of many. El-Assady et al. [6] extracted entities mentioned in political debates and used this now structured data to visualize the discourse in different ways such as a highlighted miniature version of the text, an entity view over the transcription including sentiment, or a node-link graph to show how the entities were connected in the discussion.

The extracted structured data has the advantage that it can be used in many different forms. However, the temporal aspect of when something was mentioned might get lost, furthermore the scope is limited to a fixed domain. Topic models can be used to find the various aspects mentioned in a comment section and provide meaningful keywords to describe these in a short but abstract way. TextDNA [33] forms a high resolution abstraction of a text by translating text fragments (token, sentence, or paragraph) into colored pixels. The color of pixels can be determined using a number of features, such as length, topic, sentiment, or other linguistic metrics. When concatenated, the blocks form patterns. Gold et al. [10] also use colored blocks to show the development of topics, sentiment, and mentioned entities over the course of transcribed debates. In ThemeDelta [9], the authors apply dynamic topic models on historical newspapers and display keywords for each time-slice along a vertical axis. Related topics across time are connected to see constant and evolving topics. Dou et al. [4] take a different approach with Leadline and use a stream graph like visualization where the width of a topic stream indicates its popularity. Some sections are highlighted and enhanced with additional keywords for previously detected events and respectively matching topics. CommentSpace is an expert system for analysts for tagging and commenting websites in a collaborative fashion using a similar visualization with connected parallel coordinates [37].

The previously mentioned approaches mostly focus on preserving the temporal evolution of a text corpus and visualizing it using descriptive keywords or visual cues. However, if applied to user comments, they completely neglect connections of the underlying social network. Viégas et al. [34] visualize the email exchange for selected inboxes with a calendar view and a social network view. These views are connected and both focus on the time of interactions. Other approaches use the visualization to depict the evolution of a social network in a single static image. Sallaberry et al. [28] therefore use the analogy of a growing tree that branches with new communities from the perspective of a single node in the network. The actual interactions are leaf nodes on the smallest branches of the tree, thus directly showing the popularity of certain connections. They used this later in a case study on bibliographic data and compared the evolving tree visualization with traditional node-link diagrams and visualizations of adjacency matrices [8]. Although the branching structure provides some cues to how the connections form communities, other visualizations depict this aspect more clearly. For example, Gronemann and Jünger [12] use the analogy of topological maps to show the inherent network structure. Nodes of the network are positioned using a force-layout based on hierarchical clusters. The density map of the layout is translated to the topological structure. A threshold-based water level is added enhance the visibility of clusters.

In this work, we use this analogy of a clustered map to visualize comments. A more abstract description of this setting is a two-dimensional canvas onto which comments are projected and enriched with other features, such as glyphs, overlays, or responsive interactions. Rappaz et al. [26] for example propose dynamic embeddings for news over time and use dimensionality reduction to draw point clouds. Their main focus is the clear visualization of the density map with abstract contour lines and their changing shape over time. In earlier work, they use this technique to find and correct selection biases in news coverage [2]. Although they offer some level of user interaction with the model, others put more focus on the exploration of the data. Information retrieval systems, as comment sections, usually display results as a ranked list. On a two-dimensional canvas, users can interactively refine their results by selecting regions on the canvas and specify multiple aspects to find relevant documents more easily [18]. All approaches mentioned above require the user to inspect some examples more closely to understand the semantics of the canvas. Topicassembly, one of the visualizations in [27] places word clouds around a rectangle and represents documents as glyphs with beams towards these point clouds. The topic affinity determines the position of glyphs and their beam lengths. In this way, the underlying model is inherently explainable by the visualization. El-Assady et al. [5] use a similar approach with ConToVi. They demonstrate a number of ways to show utterances from political debates based on a force-layout within that circle with surrounding topics. For example, utterances appear over time and form sediment piles at the circumference of the circle or stakeholders are shown as the sum of their utterances and thus leave a trace on the canvas as arguments and topics change. Similarly, Wang et al. [35] use a hierarchy of topics and manual groups to explore such a space they call TopicPanorama. It links news articles based on mentioned entities, clusters that naturally form within the circle are overlaid with descriptive keyphrases.

Cho et al. [3] demonstrated a dashboard with coordinated multiple views (CMV) to explore and filter social media comments for event discovery including maps, wordclouds, follower graphs, and a calendar view. Although this work mostly focuses on the integration of multiple views, most of the previously presented contributions utilize them in one way or another. The advantage of CMVs is, that a visualization does not have to include every aspect of the data but relates it to a different specialized view. However, that also adds to the complexity of a system. We have seen, that authors of related work achieve abstraction of underlying data through networks, topic models, or embeddings and have to balance trade-offs to their descriptiveness, including temporal aspects, and interactivity. For expert systems, the level of configurability and complexity is required for in-depth analyses. The interactive visualization of online news comments, however, needs to be easily understood by everyone.

3 THE ALTERNATIVE COMMENT SECTION

Comment sections on online news platforms lead to the democratization of opinion by allowing almost anyone to share their thoughts. In this paper, we propose a concept for alternate ways to interact with the growing number of comments that became impractical to read and get an overview of the discourse. This section discusses the challenges of creating a visualization for users of online news platforms for an interactive overview of all comments. By abstracting the data, users can gain the same information and insights much quicker without having to read all comments. Some commercial platforms, such as Perspective[2] try to achieve that by only showing a small ranked subset. Here, we use the analogy from databases to produce a local and a global view on the data. Instead of only visualizing the comment section for an article on one platform (local view), we can integrate the data on the same story and embed them into a single (global) view. The data is virtually integrated, meaning it remains unchanged with the news platforms. Thus, it only provides an enriched view on the data without being a competitive platform.

In this section, we systematically review each step of the integration pipeline from the raw input to a visualization and new paradigms for interaction to express opinions. Our decisions are derived from a number of specifications that are discussed in Section 3.2. We further identify open challenges for the aggregations of our visualization in the area of natural language processing (Section 3.4). The inferred concept is described by paradigms for each aspect of the integrated global view (Sections 3.3 & 3.5). The local view allows fundamentally new ways for responses and interactions beyond just writing comments as discussed in Section 3.7. Section 3.6 puts special focus on the time aspect of the conversation. It is our goal to demonstrate an alternative comment section that provides an aggregated overview without loosing information of the discussion.

3.1 Aspects of Comment Data

In order to better understand the problem at hand, we describe the raw data as schematically depicted in Figure 1. Although every

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

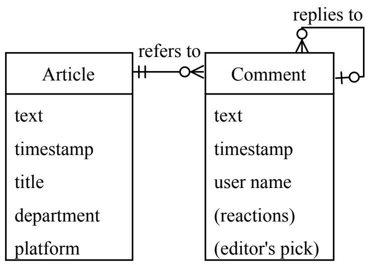


Figure 1: General schema of news comment data.

news platform has their distinctive feature, the underlying schema is generally the same.

Each news article has a title, one or more authors, a timestamp, optionally a timestamp of an update, and the actual content text. Based on the platform, an article may have a teaser or abstract, sometimes even bullet points with key aspects. Articles are labeled with keywords and categories or departments (e.g. politics, sports, ...) and might refer to related reports. Some of these features are useful for navigating the platform, others are added by the publisher to promote content.

Several platforms allow users to respond to their articles with comments. A comment always refers to an article, has a timestamp, and the actual comment text. Most platforms require comment writers to be registered, so that the comments can be linked to one account. Only a few platforms allow commenting without an account. There is a variety of additional features that we group into three aspects. Users may *react* to the article or a comment by liking, up/downvoting, flagging, or otherwise acknowledging contributions without having to write a comment. Users may *respond* to a comment by writing a direct reply or mentioning another user. Replies can be nested to a certain depth and refer to a parent comment. Comments can be *featured* as editor's picks, which means they are selected and prominently placed at the top of the comment section. We compare supported features of popular online news outlets in our study of the current news landscape in Section 4.

3.2 Identifying Relevant Aspects

The raw data has many attributes already. On top of that, there are many additional aspects that can be derived through text mining or by otherwise enriching the data. The number of possibilities is sheer endless, thus we discuss our assumptions for a faithful representation of a comment section. Apart from assumptions of the data, we identify aspects of the discussion that are actually relevant to gain an overview and understand the core arguments and their relation. By aggregating the data users are enabled to actually comprehend the entire dataset in one compact view and gain information. However, this aggregation comes with the loss of details. The core challenge is to balance this loss with the benefits of the overview.

First of all, most comments are relatively short and usually consider only one perspective on one aspect of the article. We also assume that comments actually refer to the article or discuss matters in the same topical domain. If the latter is not the case, they can be grouped into an outlier class or removed completely. Furthermore, we limit the scope to comment sections with at least 50 and at most 1500 comments. The comments sections of articles with fewer than 50 comments can be read in a reasonable amount of time and are hard to aggregate automatically. Sections longer than 1500 comments are topically too broad to provide a meaningful overview. We choose these limits because presumably, they include a large number of articles. For example, 63 percent of articles from the Guardian and 40 percent of articles from the Daily Mail fall into this category in 2017. These numbers of course vary for other timeframes (for the Guardian 44 percent since 2006 and for the Daily Mail 37 percent since 2009).

Although we refer to a comment section as a discussion or discourse, a lot of statements and arguments are frequently repeated by different users without referring to an already existing thread. An abstracted view on the data should group such comments into a cluster. This abstraction yields two advantages. First, users do not have to read the essentially same statements repeatedly. Second, the size of a cluster of comments indicates the popularity of the underlying statement, whereas in traditional comment sections each comment on its own would only receive reactions.

There are several open challenges with this kind of summary or clustering. Even though two comments might be very similar and have the same core statement, one might add a new perspective. For most existing language models this nuanced difference is hard to accurately identify. A discussion can be hierarchically clustered. Comments are grouped by article topics or aspects on the top level and by arguments or statements on subsequent levels. Sub-clusters have to properly reflect the sentiment, partisanship, and their relations. These prerequisites for a language model and clustering algorithm are already hard to fulfill. Additionally, most existing approaches perform better on longer, well structured text but have problems with short social media posts such as tweets. Furthermore, these models require a large amount of training data, which is not not always available. Pre-training on a larger amount of data by using comments beyond an article is not applicable due to the dynamics of news and our requirement to distinguish fine grained nuances.

Our main focus is to identify the inherent semantic clusters of comments. The aggregation should still allow to follow data provenance. We cover the aspect of time in the discussion separately in Section 3.6. Although it is only possible in the local view, users should still be able to react and respond to comments. In Section 3.7 we discuss principles of interacting with groups of comments.

3.3 Particles on a 2D Canvas

Derived from our discussion of requirements and assumptions, we propose to visualize comments as particles on a two-dimensional canvas, otherwise also known as a point cloud or scatter-plot. We choose this underlying concept as it is intuitive to understand by many users and it can be integrated into all platforms as a basic version does not need much space. Furthermore, it offers many opportunities to flexibly depict different aspects of the underlying data. The comment positions, for example, should reflect similarity and cluster affiliation. This can be enriched by overlays of cluster contours or heat maps. The particles can be drawn as glyphs and thus contain a lot of additional information or at least vary in size or color. Particles can also be animated by mapping aspects of changes over time to translation, transformation, or opacity. We refrain from introducing animations because they require uninterrupted attention and users might need to watch the animation loop several times to comprehend the overview. Interacting with moving particles is harder and there is now view of the entirety of the data. A mostly static is therefore preferred. We do however visually emphasize comments within a selected interval that can be animated. Size and opacity of comment particles however will never drop below a threshold where they are not visible any more. As stated before in the context of aggregations, it should always be possible to trace a particle on the canvas back to the original data.

In the previous section we suggested clustering comments. The particle analogy has the advantage, that their position is continuous and is not strictly assigned. Following this analogy, an article emits particles, which represent comments. Language models and clustering algorithms are used to model forces between particles and towards regions on the canvas. The final layout results after finding a state where all forces are balanced. In the following section we go into more detail on how these forces can be modeled. This approach only represents the inherent semantic structure of the comment data, which is one of our previously defined goals. However, it comes at the cost of loosing all textual content and with that a way to directly interpret the canvas. A simple tooltip containing the comment when hovering a particle would be more tedious then reading a selected few comments. We show ways to make the canvas more intuitive and explainable in later sections.

3.4 Positioning Particles

The goal of positioning comments as particles on a two-dimensional canvas is to get visual clusters to better comprehend the semantic structure of the comments. The structure should reflect the key topics and arguments made. As we discussed before, there are existing approaches to achieve baseline results. However, the specific requirements in the domain of visualizing news comments are not met. Especially appropriately mapping the nuances of a discussion, the size of the dataset, and the text lengths pose as hard problems. Here, we review possible baseline approaches.

Mapping features to axes. The naïve baseline for visualizing comments as particles on a two-dimensional canvas is to use features that can be projected onto the axes. For example, plotting time versus sentiment provides indicators to the development of the discussion. Also other examples outside the scope of time series can be used to gain quick insights into the dataset. However, the options are limited and results are more useful for specific analyses of a discourse rather than single visualization to show all aspects of a comment section.

Topic Models. Others have already demonstrated approaches to visualize text using topic models. El-Assady et al. [5] proposed *Topic Spaces* in ConToVi for transcribed parliamentary debates. With the Dust & Magnet metaphor [31], they place topics as magnets in a circle and the speech acts as dust particles are positioned on the canvas in the middle according to their topical distribution. They also presented a sediment view in which the particles accumulate around a topic magnet and form small piles. Riehmann et al. [27] use a similar approach but extend the metaphor by using word clouds around the canvas that the text particles are attracted based on their respective term overlap. These are promising approaches, however they do not consider aspects of topics and cannot be used directly for hierarchical clusters or hyperbolic zooming to focus on one aspect of the discussion.

Embeddings and tSNE. Many research articles on language models use scatter-plots based on tSNE projections [21] of embedding vectors to show inherent characteristics. With Cartograph, Sen et al. [30] demonstrate a system for a map-like interactive visualization of Wikipedia articles and "countries" based on categories. Embedding-based solutions work best with large datasets. Our use-case requires pre-training an embedding on a larger set of comments beyond those on the news story at hand.

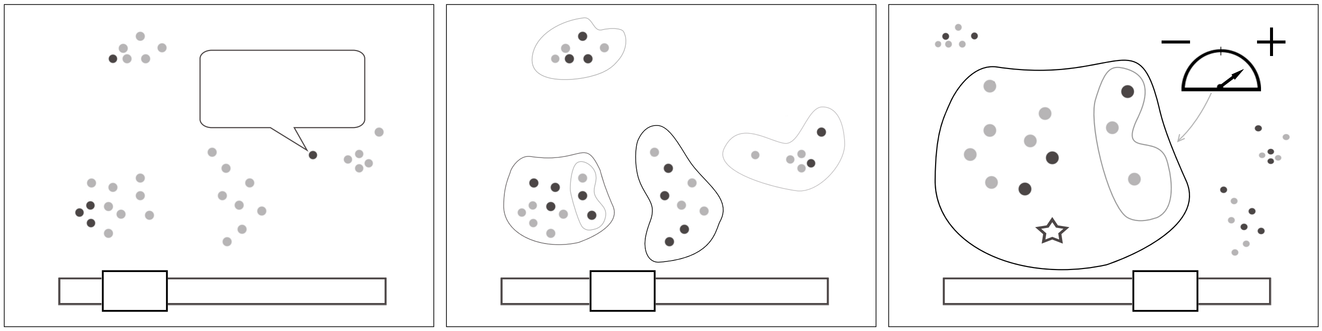
Positioning Discussion Particles. Using features directly comes with the downside of loosing semantic information. Topic models and embeddings require large training datasets or pre-trained models. Further, they have problems to reflect multiple aspects and the different opinions on a very narrow topic.

Thus, we propose a combination of the baselines presented above. A globally trained topic model is trained on all available comment data within a given time frame or category and updated regularly. Given a comment section, the most relevant topics are selected and used for a rough layout similar to that used by Riehmann et al. [27]. Comments are then clustered into the key discussion points with a density-based approach. Clusters form pseudo-documents that are allowed to drift apart, all comments within a cluster however are forced together. The layout within a cluster is done using attracting and repelling forces between particles based on sentiment or keywords. Alternatively, automatically extracted keywords within a cluster could be placed on a virtual axis and the sentiment on another virtual axis to put comments in relation to one another. This way we benefit from topic models to get a global layout and force layouts using mined meta-data (clusters, keywords, sentiment, ...) for a nuanced local layout.

Figure 2 offers schematic drafts of our proposed visualization at different time intervals. We will discuss the influence of time in more detail in a later section. The first view (Figure 2a) shows the canvas where one specific comment is focused. Figures 2b and 2c show the interaction between a global view and the detail view of one cluster that is hyperbolically zoomed.

3.5 Explaining the Canvas

Previous sections mostly focused on the general layout of comments on a two-dimensional canvas to visually reflect the intrinsic structure of an online discussion. However, the resulting scatter-plots lack an inherent explanation of the semantics. Word-cloud overlays are typically used in related work to provide a general description of the plot. This works for large datasets with a broad topical range but not to reflect the subtle distinctions within a comment section. Furthermore, single keywords do not express the context of the argument, which might be important to understand the point someone made.



(a) Detail view of a comment at time t_0 **(b) Overview of all comments at time t_1** **(c) Detail view of a cluster at time t_2**

Figure 2: Schematic sketches of our proposed view on comments and interaction paradigms at different time steps. All comments are always visible, depending on the selected time slot and focus some comments are emphasized in different ways.

To circumvent the missed context, representative comments could be selected for each cluster. This way, a user gets a broad overview of opinions and aspects of the discussion in relation to one another, which a traditional ranked list of comments could not provide. The selection of representative comments however is difficult. A single comment might touch all major points of an aspect of the comment section but it might not include other views or opinions on that matter and thus might not faithfully represent the respective cluster. Furthermore, the number of representative comments to show is very limited due to space constraints. Automatically extracting keyphrases might be more promising. Zooming or focusing on one cluster reveals more keyphrases. They should always relate to specific comments, which can be indicated by visual cues. On clicking or hovering, the user should always be able to read the underlying comment or jump directly to the original comment section for transparency of data provenance. Colors, shapes, or glyphs can be used to reflect relevant meta-data.

As Merrouni et al. [22] have shown in their recent survey of state-of-the-art automatic keyphrase extraction algorithms, there is only little work on short texts or small datasets. Most notably, the approach by Huang et al. [16] produces very good results also on small datasets, however, due to the lack of phrase redundancy in short documents their solution is not applicable here. Zhang et al. [38] on the other hand focus especially on summarizing social media posts from Twitter and Waibo to provide aggregates of all reposts and replies in a conversation. To do so, they form pseudo-documents as context used in an encoder of a recurrent neural network from which the summary is generated. This seems promising, however the applicability to significantly smaller datasets is not evaluated.

3.6 Visualizing Evolving Discussions

Time is an integral piece of information in online news comment sections. In current systems, time is almost the most important factor as comments are usually ordered by time. If newest comments are shown first, older comments quickly become irrelevant to the discussion, as users are less likely to read though multiple pages of comments, so only the latest posts are considered. If the oldest comments are shown first, there is very limited motivation to post additional comments because most users will not notice them. If the platform allows additional ranking options, ordering by popularity or recommendation is often used. As a result, new comments with no feedback do not get to the top even though they might add new insights or an otherwise relevant contribution. Even though some platforms offer a mechanism for direct replies, similar issues arise as threads are nested too deep or long. In addition, commentators might use the reply functionality when they wish to post a general comment due to unclear interface design.

Time indicates latent references between comments and a topical focus at a given time even though a reply function might not be available or is not used. Liu et al. [20] use stacked stream graphs of topic strengths over time to visualize the thematic changes of document collections. They extend the idea of ThemeRiver [13] by adding keywords onto the graph for better interpretability and easier exploration. A similar approach is great for visualizing the temporal dependencies and evolution of an online discussion. However, this concept does not consider direct references between comments. ThreadArcs [17] are used to visualize the reply structure of email threads. The considered scope of related emails is relatively small compared to our use-case with many comments referring to one another. El-Assady et al. [7] provide a similar visualization for discussion in reddit threads with 100-200 messages. They use mentions of named entities, substring matching, speech acts, and meta-features to reconstruct references in the threads. Statically visualizing the time aspect of hundreds of comments shared over multiple days comes with additional challenges compared to the examples discussed. The added complexity when integrating references, time, and topics could be distracting and makes it difficult to interpret. Alternatively, animations can be used to visualize time, however, this requires users to loop the animation sequence repeatedly until they can comprehend the full picture. Our proposed solution focuses primarily on the semantic aspect of the data. Although temporal development of the data is undeniably important, we argue that opinions and key statements are timeless. Our primary focus is to convey the semantic structure so users are able to get an overview and quickly gain insights into the most relevant aspects of available comments.

However, we also do not want to neglect temporal aspects completely. As depicted in the schematic drawings in Figure 2, we provide users with a slider of an adjustable time window. While the points on the canvas remain static, they are emphasized if their respective comments are contained in the selected time interval. This emphasis can be achieved through changing opacity or size of particles or fading a density based heat map, whereas the density is determined by user activity at different times. Particles should not move at all or only a little upon changing the selected time interval to make it easy to follow. Movement would also hinder the interaction with particles. Following our argument that opinions and statements are time-independent in a discussion, the overlaid keyphrases should also stay static. We do however acknowledge the fact that the focus of the comments changes over time. Thus, we suggest to keep a number of most notable keyphrases constant and supplement them with additional time-dependent keyphrases or keywords that are faded in and out as the user changes the selected time window.

3.7 Interacting with ConvEx

Our novel approach to represent news comment sections gives users new ways to express their opinion or view on an already existing discussion beyond just replying or upvoting a single comment. As initially stated, these new ways are limited to the local view on one platform and are not applicable to the global view on multiple integrated platforms. It is unclear how reactions would be propagated down to the original source.

In the following, we assume that our visualization is embedded in the comment section of an online news outlet. This way the global context is lost, but the overview of hundreds of comments on one article is still beneficial. Furthermore, global data could be included as an opaque background without the possibility to react to it.

New Paradigms for Reactions and Responses. Generally, instead of only appending a response to an existing list, users are now able to interact with groups of comments at once or more fine grained to single keyphrases instead of longer comments with multiple statements. Additionally, their interaction could be to rearrange content or place their reaction directly onto the canvas to introduce new clusters or forces within the layout. Traditionally, platforms allow users to vote on comments in one way or another. As depicted in Figure 2c, we allow users to agree or disagree with clusters or place their sentiment onto a point on the canvas without having to write a comment. This way, the layout algorithm can include the feedback as the discussion evolves. It also means, that users interact with concepts, statements, or opinions instead of single comments. Where applicable, a lasso tool could be used to make custom selections. Reactions made through such selections effectively influence the layout as comments are attracted or repelled by additional meta-cluster assignments.

Another way of providing feedback is to draw a separating line into a cluster. For example, if an existing cluster of comments on one aspect only contains one view, the user could indicate disagreement so that this cluster splits into two views. A more direct, but possibly too intricate interaction could be to move existing comments. This would be aggregated over all interactions and eventually rearrange the particles on the canvas. Newly written comments can also be placed into the landscape as a reply to an abstract statement, a comment, or a cluster. This new comment can be marked as an opposing view or an added argument supporting a view. Obviously, users will always be able to simply write their comments as usual directly below the visualization. It is important to choose only a subset of interaction methods discussed above to keep the interface as intuitive and simple-to-use as possible. Feature-overloading not only makes the layout algorithm more complex but also distracts from our goal to improve and encourage user engagement in online discussions. Future work needs to evaluate interaction patterns to identify those that are most intuitive and inviting to use. Such evaluations could use the framework by O'Brien and McCay-Peet [24].

Exploration of the Comment Sphere. Beyond interacting with our proposed visualization to leave reactions or responses, users can also choose just to explore the data. Apart from the aforementioned ability to highlight details within a given time window and hyperbolic zooming to focus on a cluster of comments, our system allows a number of alternative interaction patterns. Using the comment data or user reactions, a model can identify *interesting* points in the discussion. A point in the discussion is defined by a time window and an area on the canvas, whereas the interestingness is defined by the model and has to be evaluated in a user study. Clear examples of interesting points are a spike in comments at certain times or comments with noteworthy numbers of reactions. We hypothesize that bursts and apparently polarizing comments influenced user engagement in the past, so it might be interesting to point them out in the overview. In their analysis of millions of comments, Ambroselli et al. [1] have identified three main causes for increased user engagement. Comments containing hate speech or very controversial statements lead to a number of responses by users pointing out the violation of community standards. Also personal stories by users related to the story or comments by the article's author with polls increase engagement of focused discussion or spontaneous question and answering sessions. The main contributing factor to changing user engagement is the time of day and time since the last article update. Highlighting areas in the canvas based on these indicators can be a useful tool to focus a user's attention. It could also be used to propose bookmarks that show and highlight these distinguished parts of the conversation. Simply using these bookmarks to jump to selected comments or the underlying indicators to rank comments in a traditional list view would miss the context of comments. Our proposed canvas model is able to retain the context while subtly changing the focus by adding details or highlighting points but never completely hiding data.

4 PRACTICAL EXAMPLE

After the previous theoretical considerations, we now discuss the practical application of the proposed concepts. We start with an overview of the status quo of comment sections on different platforms. After that, an example describes how conversation exploration could work in the context of a particular news story.

4.1 English-Language Comment Sections

Table 1 gives an overview of the comment sections on seven English-language online news platforms. Most of the analyzed platforms make use of reaction systems, in which a comment can receive votes (column *Reaction*). While upvotes are widespread and used by every platform that utilizes reaction systems, downvotes can only be found in the platforms of The Independent and Daily Mail. A reason for this might be that the platforms only want to encourage positive feedback, but not the option to consciously downgrade others, for example to prevent aggressive behavior. Keeping trolls off the platform might be the reason why The Telegraph neglects any reaction system. Provoking any positive or negative reaction from other users is essential for the motivation of trolls. Most platforms only allow comments for a selection of news articles (column *Selective*). The New York Times allows comments only during a 24 hours time frame after article publication. Presumably, these selections are due to the high costs for comment moderation.

All platforms that allow voting on comments also allow to rank by the number of votes as an alternative to chronological ranking (column *Ranking*). Both ranking criteria, timestamps and number of votes, are intuitive for users. In practice, ranking by the number of votes is susceptible to manipulation by malicious users. For example, pushing a favored comment up by creating multiple fake accounts gives an immediate reward to manipulators. On the platforms of Washington Post and Los Angeles Times, users also can rank comments by the number of replies they received. This ranking criterion is based on the assumption that comments evoking many other comments or inviting many other users to the discussion are of particular interest. The majority of analyzed platforms highlight a special comment selection, mostly consisting of comments handpicked by the platform's Editors (column *Featured Posts*). The Independent further has a highlighting feature for comments of its premium users. Daily Mail and Washington Post do not have any featured posts, probably because also this feature increases the workload for the comment moderation team significantly. Figure 3 shows an exemplary comment section from the Guardian[3]. There are the editor's picks called *Guardian Picks* at the top and the comments are ranked by *Recommendations*, which is the number of upvotes. The example also shows that the comment section is split into twelve pages with at least 100 comments per page. Finally the indentation of the second comment indicates that it is a reply to the first comment. In summary, all the different platforms extended their comment sections by additional features to make them more engaging for users. However, none of the features really addresses the problem that users do not start in-depth discussions. The platforms provide no way to grasp a discussions main topics and respective opinions by other users — except for reading through all the comments.

4.2 The Media Coverage of Brexit

As a concrete example, we consider the media coverage of Brexit. In a UK-wide referendum in June 2016, the British people voted on whether the UK should leave or remain a member of the European Union. Starting from months before the referendum until today, it was a daily news topic. Especially the British news platforms Guardian, Independent, Telegraph, and Daily Mail cover Brexit extensively. We estimate that the number of online articles published by these four news platforms on this topic between January 2016

[3]https://www.theguardian.com/commentisfree/2019/oct/03/northern-ireland-border-brexit-boris-johnson

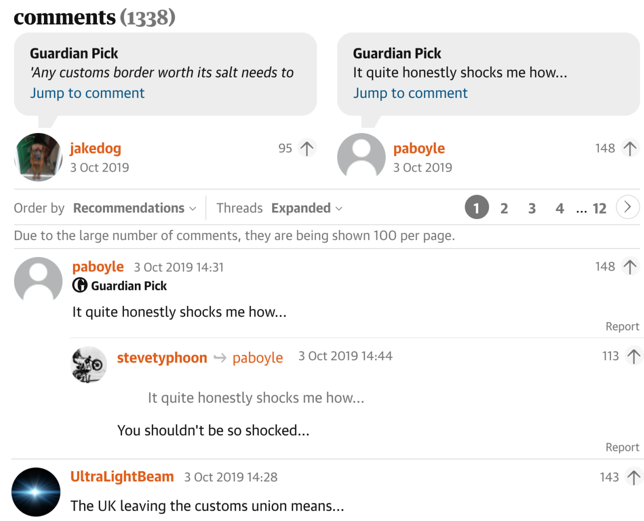


Figure 3: An exemplary comment section on the platform of the Guardian.

and October 2019 amounts to roughly 100,000 articles. This estimation is based on a keyword-based search for the words *Brexit* and *referendum* on the platforms, filtered by articles in the section UK-news or politics. The large-scale coverage is beyond the scope of the system for conversation exploration that we envision. However, smaller news stories or events with a daily or weekly importance to a general audience are suitable. This finer granularity allows to consider all news articles that cover a story while still having a clear dataset.

To calculate the average number of user comments on articles about Brexit, we consider the most recent ten news articles on this topic per platform. If a recent article does not allow comments, the article is skipped. The time of data collection is the 4th of October, 2019 and we consider only articles that were published before this day. Thereby, users had at least one day to post their comments. Because the New York Times and Washington Post does not allow comments for large amounts of recent articles the average was calculated with less than ten articles. In case of Los Angeles Times, the most recent 20 articles about Brexit do not allow comments. Further, live-articles that accumulate comments over multiple updated article versions are skipped because the number of received comments there is a clear outlier. This method leads to the following average comment numbers for the different news platforms: The Guardian: 1220, The Telegraph: 144, The Independent: 118, Daily Mail: 2452, New York Times: 52, Washington Post: 454, Los Angeles Times: 0. One of the main topics in the articles and the respective user comments in early October, 2019 is the Irish border. Users propose and discuss different options how the border could be handled after Brexit. With the help of our envisioned conversation exploration tool, readers could identify the options mentioned in the comments quickly. This overview would enable them to easily find an option that they want to support. Users also frequently express agreement and disagreement with government policy. Therefore, the conversation exploration tool could sort the comments into two clusters and

Table 1: Features in comment sections of English-language online news platforms.

Platform	Reaction	Selective	Ranking	Featured Posts
The Guardian	👍	Yes	Time, upvotes	Editor's Picks
The Telegraph	–	–	Time	Editor's Picks
The Independent	👎👍	Yes	Time, up/down-votes	Editor's Picks, Premium
Daily Mail	👎👍	Yes	Time, up/down-votes	–
New York Times	👍	24 hours	Time, upvotes	Editor's Picks
Washington Post	👍	–	Time, upvotes, most replied	–
Los Angeles Times	👍	Yes	Time, upvotes, most replied	Editor's Picks

visualize how the size of the clusters changes overtime. In a more detailed view, the clustering could focus on comments that discuss the popularity of particular politicians, such as the prime minister Boris Johnson. Or the view could cluster all comments that hypothesize about the future, such as "The only good outcome is that this fiasco will lead finally to a united Ireland." or "Anything short of a no-deal Brexit will see huge numbers of Tory members defecting.". Other users can then add their own hypothesis or vote on what they believe will come true. A good candidate for showing the text of some selected comments in the exploration tool are comments that received many replies. Especially short comments that start a longer conversation might be interesting for users of the tool. For example, the comment "Get Brexit Gone" as an alteration of the slogan "Get Brexit Done" summarizes a thread with fifteen replies. Brexit is a very broad and complex topic that affects almost every reader of the British news platforms. A strength of the conversation exploration tool is its ability to provide an overview in this context. It gives insights into the different points of view. Our tool makes a contribution to a more dialog-oriented dispute. One weakness of the exploration tool is that it highlights controversial statements and emphasizes polarizing views. On the one hand, this is desirable because there would be no discussions without different opinions and opposing views. On the other hand, discussion could also escalate more quickly and more easily due to the tool. Thus, it could harden the fronts of pro- and anti-Brexiteers. The integration of the tool into the news platforms and enforcing its responsible use by users will be a challenge for comment moderation.

5 IMPACT ON ONLINE DISCUSSIONS

Online news platforms offer a place to exercise one's right to freedom of speech. As such, they complement professional journalism in forming a public opinion in western democracies. This is a very important process that needs to be protected from manipulation and at the same time should be open for all citizens of a society to participate in discussions. Currently many users hesitate to take part in the discussions for various reasons: they feel their voice will not be heard, they are worried of negative feedback or worse, or they feel it is pointless to post a comment. This leaves the field to trolls and loud extroverts distorting the perceived public opinion.

With our proposed visualizations we hope to encourage more people to contribute. We want to achieve this by fostering more interaction among users and the uttered opinions. Further, we want to facilitate or enable fruitful discussions by making it easier to join an ongoing discussion thread, to make sure one's opinion counts, and to reward well-formulated arguments by more visibility.

Besides encouraging engagement, we believe that our aggregated views and interactive visualizations can also provide a superior overview of opinions and discussion status. This leads in the best case to an unbiased view and conveys the public opinion much better than current lists of individual statements. The proposed novel interaction not only with single user comments but with clusters of opinions will allow for specific references and context for one's own comment. And last but not least, singular, loud opinions, e.g. stated over and over again by power users or trolls, will be perceived as exactly this: repetitive, individual statements. In addition, our visualizations can help to step out of the filter bubble [25] by presenting not only the majority opinion but explicitly showing diverse views and multiple aspects of a topic. We purposely refrained from personalization to prevent echo chamber effects as known from social media. This effect exposes users more and more with their own opinion in a self-reinforcing vicious circle. By exposing online news readers to diverse opinions in a respectful and engaging fashion we hope to not only alleviate the exchange of ideas and opinions online but also to learn again to listen and respect what other people have to say. In some sense intuitive interactions and visualizations can lead to people discussing with each other and finding common ground instead of shouting at each other and building metaphorical walls.

6 CONCLUSIONS AND FUTURE WORK

Discussion sections of online news platforms have become a pool of ten-thousands of comments that only loosely refer to a news article and other user's comments. To improve the way people exchange ideas online and to foster in-depth discussions, we studied the novel task of conversation exploration for users of such platforms. In contrast to previous work on conversation or discourse exploration that developed analytics tools for experts, we focus on letting comment readers and comment writers interact with the exploration tool. To this end, we propose different methodologies for the visualization of comments in online conversations and discuss their application and impact in context of an exemplary news story. We envision a system that encourages more in-depth discussions by letting users explore conversations. This system makes it easier for users to find relevant content in comment sections and thereby fosters user engagement. We hope that future research on the presented novel task can build on our perspective of how comment sections can become more explorable for users. In particular, a promising path for future work are visualization methods for online comments and the intuitive exploration of such visualizations. One exemplary question is how visualizations could help to establish a higher conversion rate of comment readers into comment writers. Potential next steps are to implement baselines for conversation exploration and to conduct user studies to identify interaction patterns.

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