OpinionBlocks: Visualizing Consumer Reviews

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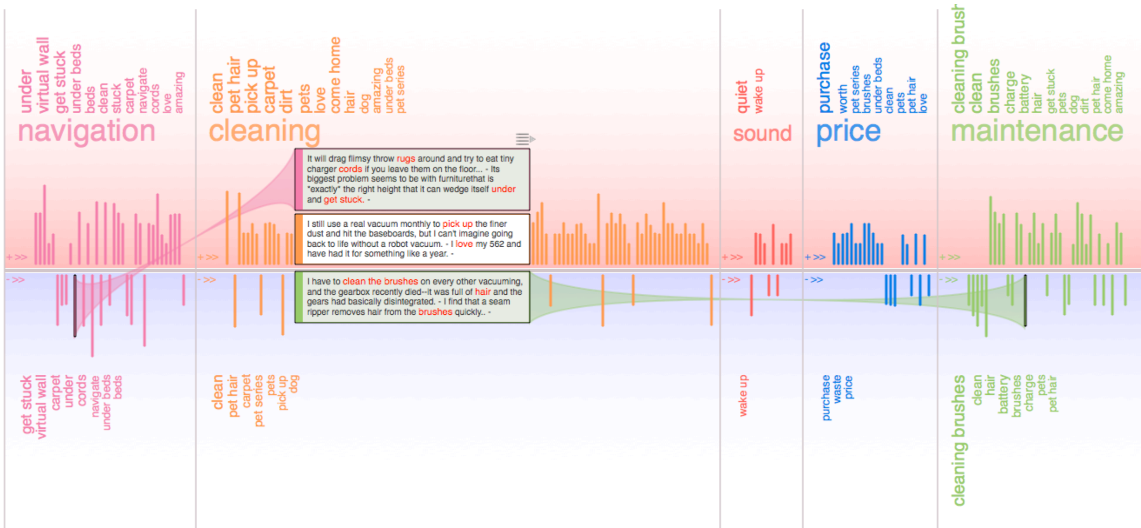

Fig. 1. OpinionBlocks: Overview of snippets from consumer reviews organized by major product features (color coded) that are discussed most frequently in the reviews and bi-polar sentiments(red region positive, blue negative). Keywords for each feature-sentiment group are shown in their corresponding region. A single snippet is expanded, so that it shows other snippets from the same review.

Abstract—Every day, vast numbers of customer reviews are accessed on retail or online services websites. Although valuable information can be gleaned from reviews, these sources are underutilized both by consumers and businesses due to their unstructured nature, serial presentation, limited search tools, and low ratio of useful information to the overall amount of data (high noise). *OpinionBlocks* is an interactive visualization tool to help people better understand customer reviews. It is designed to progressively disclose increasingly detailed textual information from various reviews while continuously providing visual graphical summaries. The visualization initially exposes text at the keyword level, and then exposes snippets that the keywords are used in, and finally shows the snippets within the context of an entire review. We provide interactive tools to let users navigate across different text granularities in an intuitive way and additionally, utilize smooth animations to preserve context across views.

Index Terms—Text visualization, visual analytics, consumer reviews, progressive disclosure.

1 Introduction

As the Internet has permeated everyday life, opinion text, such as customer reviews found on online retailers, increasingly plays a significant role in everyday decision making. These are largely uncurated, user created texts expressing opinions about products and services. Many studies suggest that these online reviews have a significant impact on what customers buy [5][7][8]. The large quantity of such unstructured text, serial presentation, and limited search tools present barriers for people trying to gain insights from the reviews, either consumers who want to choose the best product for their own needs, or businesses who want to effectively utilize such data in improving products and services. For example, the vast feature-space of products and the particular needs of each consumer can make it difficult for people to find reviews relevant to their needs. From the business side, sentiments expressed in reviews can dramatically change the opinion of customers, and if not handled appropriately could easily damage a company's reputation. Monitoring such content and addressing customers' complaints properly could build customer loyalty in the long term.

Review texts are often high dimensional (e.g. discussions on many different features of a product) yet unstructured (e.g. ambiguous natural language text). Reviews vary dramatically in terms of quality or length, and conflicting views may exist on the same subject. Reviews may be carefully written or carelessly penned, objective or extremely emotional, right to the point or vague, and so on. All these characteristics pose significant consumability problems for opinion text. For instance, it is desirable to read enough reviews to understand common issues and the preponderance of opinions, yet the sheer volume means that it is usually impractical (or at least tiresome) to try to read every review. On the other hand, there may not be a single review or a summary of reviews that satisfies all the reader's information needs. In fact, the usefulness of a review also

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depends on the reader and her decision making task at hand, which are often unclear *a priori*.

With the goal of alleviating the above text consumability problems, we have created the *OpinionBlocks* text visualization system. This system aims to let users gain useful information for decision making as quickly and as effortlessly as possible, by transforming large collections of opinion text into interactive visualizations that provide the same conceptual understanding that would otherwise require the reading through the whole text collection.

Technologies such as information extraction and data mining often derive a multitude of information from text [9][13][14] . However, the challenge of making such information consumable by end-users has yet to be successfully tackled [1][17]. Existing approaches range from utilizing simple representations [10] that do not necessarily support interactive exploration, to powerful yet complex visualizations that are not suitable for end-users [17]. While some approaches consider complete reviews as the unit of opinion, others break down reviews into smaller units for different features of a product [2][3][6][11][12]. However, most of these visualizations rely overly on automatically extracted structural information and their visual representations, and by doing so overlook the actual text in reviews. Since users are more often than not, better judges of the meanings of text and their own information needs, we believe it is imperative for any system to focus on presenting the actual text in order to help users making their own decisions.

Our approach aims to strike a balance between automatically organizing text into meaningful structures and providing a clear reading experience for users. Since our ultimate goal is to help decision making, the design of the *OpinionBlocks* must be considered in such a context. To this end, this paper first describes a set of design goals, followed by the details of an interactive visualization that we created to meet these goals. The paper concludes with a discussion on future work.

2 Design Goals for OpinionBlocks

We conducted a few informal interviews in order to understand user needs and goals while they are trying to glean information from online reviews before committing to a product. Based on existing practices and commonly faced issues we identified the following as what our tool should support:

Provide concise summaries about user sentiment: Users avoid long reviews, which mostly give a detailed description of the product. Whereas they would like to read about how other users feel about the product rather than about what the product is.

Help identify key issues: Users generally skim through negative reviews [15] in order to find out commonly faced problems, which would deter them from this particular product. Our tool should help them identify the salient factors and features of the product and the general areas of concern.

Enable assessing feature-specific opinions: Users would like to be able to search for opinions about features that are important to them. They also often want to avoid reviews that are not about the product but rather about sellers, shipment, or customer services, which is irrelevant for their purposes most of the time.

Show the text source for the quantitative rating: Users often find numerical ratings (e.g., “5 stars”) inconsistent with the textual content. For instance, people who like a product to a great extent can give a one star based on a single feature that they didn’t like. Users want to be able to judge fairness of the rating, or trustworthiness of the review by examining the content.

3 Opinion Blocks

The *OpinionBlocks* visualization relies upon a conceptual space model [4] of opinion text that we are developing. For the purposes of this paper, we manually extracted review information; future work includes automating this process. First, all reviews of a product are analyzed so that the most frequently discussed features of a product are identified. Within each review, snippets discussing these features are assigned a positive or negative sentiment polarity, using methods similar to those used in a commercial sentiment analysis tool [18]. Key words in these snippets are indexed and sorted according to their frequency of occurrence as well.

Our main design goal for the *OpinionBlocks* was to use a conventional visual language that users could familiarize themselves with easily, while communicating as many different facets of data and metadata as possible. Although the design of OpinionBlocks generally follows the accepted principles of graphical user interface design [16], embedding actual text source into the graphical representation introduces unique challenges; such as differences between the significance of the content and the amount of text.

OpinionBlocks aims to achieve a high level of cognitive economy in information gains vs. efforts by progressively disclosing information as needed. The visualization starts with aggregated graphical representations of sentiments per feature (Fig. 2), and key phrases associated with each feature-specific sentiment. The users can then drill-down to snippets of text containing the key phrases, and explore all the way back to the full text view of individual reviews (Fig. 5) in a gradual manner. In all of the visualizations, the text themselves, albeit in different levels of granularity, are the focal points of the visualization.

3.1 Overview first

To support the task of identifying key issues, visualization in *OpinionBlocks* starts with the summary view of the reviews (Figure 2), where the screen is divided on the horizontal axis among features that are most commonly discussed in the reviews. On the vertical axis, the screen is divided into negative (bottom, blue) and positive (up, red) sentiment regions. Each rectangular block represents a

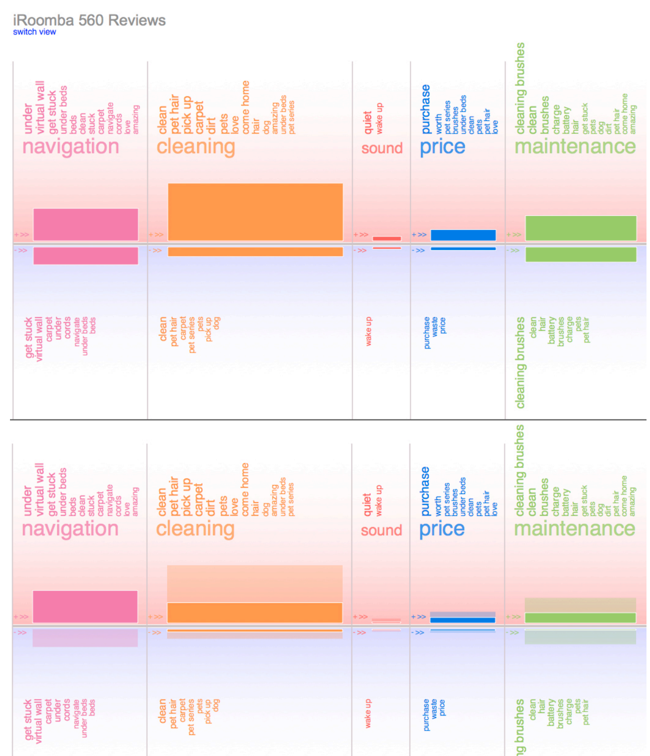


Fig. 2. Overview visualization showing general distribution of text frequency and quantity distributed among feature-sentiment duals (top). Below image shows user hovering on the rectangle representing reviews mentioning navigation positively (top-pink). Other rectangles shrink to show what portion of the feature-sentiment dual they represent is mentioned in the same reviews.

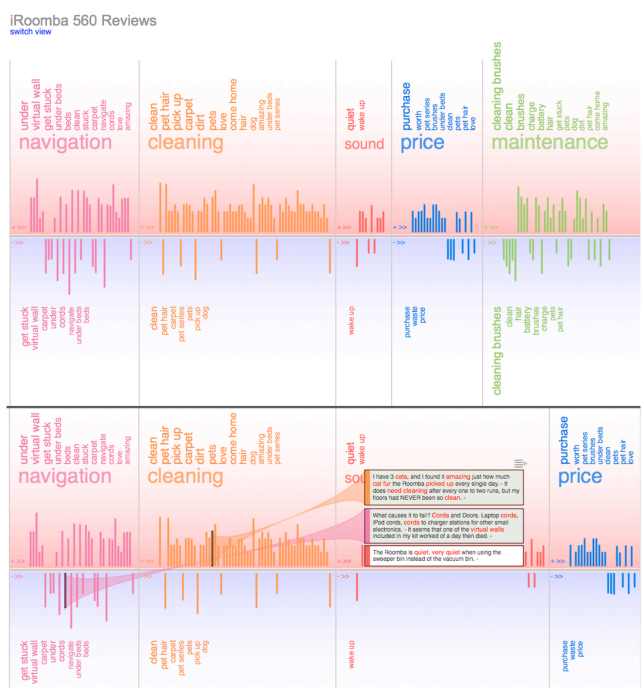
feature-sentiment dual, color coded per feature. The width of the rectangle is proportional to the number of reviews discussing the feature (both positive and negative), and the height of the rectangle is proportional to the amount of text in the snippets that carry positive (above) or negative (below) sentiment about the feature.

In a single image, the overview visualization communicates important features, how much each of these features is discussed (the width of each rectangle block), and the quantity of sentiment: the number of positive or negative snippets related to the topic (the height of the rectangle above the horizontal bar versus the height of the rectangle below). The visualization also displays keywords for each feature-sentiment dual scaled proportional to their frequency. At this level, users are able to see that people who made negative comments related to "maintenance" most frequently mentioned "cleaning brushes", whereas people who made positive comments related to "cleaning" frequently talked about "pet hair".

The overview visualization also supports assessing relations among feature-sentiment duals. When the user hovers on a feature-sentiment rectangle, the other rectangles highlight the portion of the reviews they represent, which mention the same feature with the same sentiment as the hovered rectangle. Figure 2 bottom shows the user hovering on the rectangle for reviews that discussed navigation with positive sentiment. Very few of these reviews were negative about cleaning and price, and they were consistently positive about maintenance.

3.2 Individual Snippets View

Clicking the overview visualization, switches the view to the next granularity level, where the individual snippets from the reviews per feature-sentiment can be viewed (Fig. 3). Each snippet is shown as a column, where the height of the column is proportional to the amount of text. The user can view the text content by hovering on the columns, and expanding the object horizontally. During the hover, the other snippets from the same review are highlighted with a black border so that the user can view which other features are discussed in the same review and with what sentiment. When



Fig, 3. Next level of granularity: the snippets view. Snippets are sorted across positive and negative sentiments per feature. Bottom image shows a single snippet expanded via mouse click. Other snippets from the same review are shown with a light gray background. Their duplicates are highlighted and connected with transparent geometries.

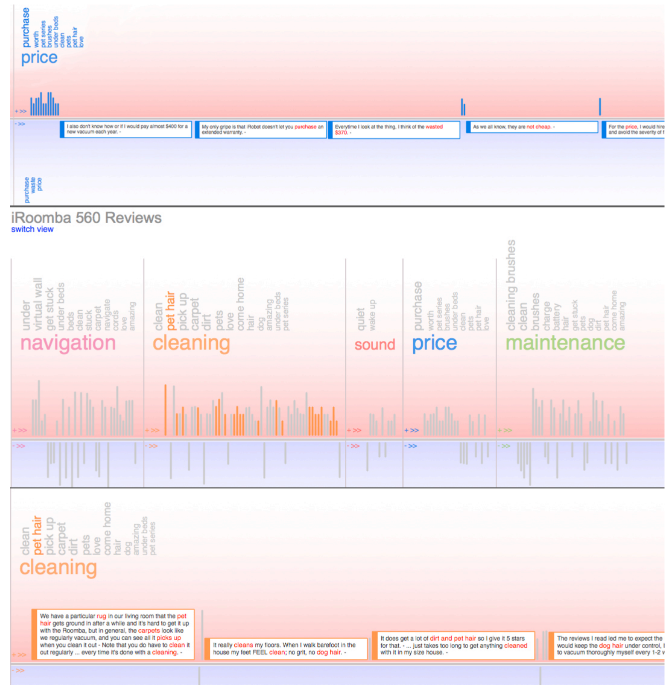


Fig. 4. Top figure shows snippets negative about price are being expanded by clicking a button in that region. Snippets can be expanded per keyword. Hovering on a keyword highlights only the snippets that include the selected keyword (middle). Clicking on the keyword expands all such snippets, so the user can view their contents (bottom).

clicked, the snippet further expands vertically, showing other snippets from the same review above or below it, in order of appearance in the original text. Note that these snippets are discussing other features, thus they are replications of other snippet objects in different feature regions. We show this duplication by highlighting their aliases and connecting them with transparent geometries. This highlighting also helps to assess quickly whether other snippets are positive or negative. When switched to the individual snippets view, a small replication of the overview visualization (without keywords) is shown in the upper right corner of the visualization. This serves as a reminder of the overview, as well as a button to switch back to the overview visualization.

3.3 Filtering by Visual Queries

The visualization lets users expand and view contents of all snippets from a feature-sentiment dual by clicking a button placed in that feature-sentiment region. As shown in Figure 4 (top), users can filter and read all snippets that were negative about price.

The snippets can be filtered further by keywords. Hovering on a keyword highlights all snippets that contain the keyword (Fig. 4. middle). Clicking on the keyword expands all such snippets so that the viewer can see their text contents (Fig. 4. bottom). Following these steps, the user can form complex queries like "Show me the snippets that were positive about cleaning and mentioned *pet hair*."

When a category of snippets is expanded, the view expands beyond the available screen space. Users need to scroll in order to view and read all snippets.

When expanding and collapsing snippets we utilize smooth animations in order to preserve context across views. Similarly, when a snippet is expanded we slide all snippets to the right of the expanded one further away. We are also investigating different interaction metaphors that would help users move between detailed filtered summaries and actual source in a continuous smooth fashion.

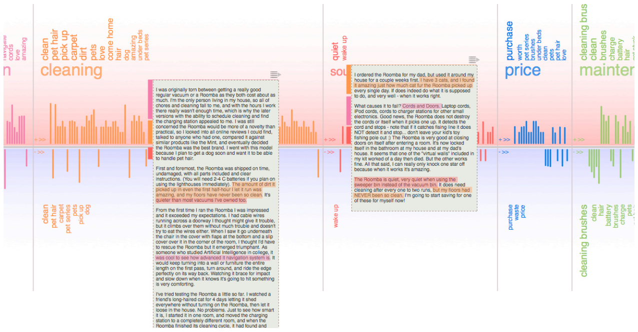


Fig. 5. By clicking a button on the top of an expanded snippet, the user can view the full review text, where snippets used in the previous visualization is highlighted with their respective colors.

3.4 Zoom In to Source

Our visualization provides access to the full review text from a snippet. When expanded, a button appears on top of the snippet box. Clicking this button shows full review text in place of the snippets. Snippets discussing the main features within this text are highlighted with color-coded backgrounds (Fig. 5.).

Providing the actual source is significant for two reasons: i) details provide critical evidence on trustworthiness or reasoning behind the outcome sentiment summarized in the snippet form, ii) viewing snippets within their larger context enables user to verify accuracy of automatic text categorization. Automatic text analysis methods often mis-classify text at different error rates. Our visualization aims to mitigate this problem by enabling users to view snippets in their larger context, hence be able to judge the accuracy of the automatic analysis. We will be adding interactive features that will enable users to annotate and re-classify snippets when needed.

4 Conclusion and Future work

The design of *OpinionBlocks* emphasizes enhancing users' experience of reading unorganized folksonomic texts. To this end, we developed two different visualization modes by presenting text at varying granularities categorized across frequently discussed features and postive-negative sentiments. The initial view presents graphical representations for aggregated feature-sentiment duals along with key phrases for each category. When switched to the snippets view, users can view keywords more in the context by viewing them within snippets, or in the full context of whole review text.

We are planning a series of formal user studies to evaluate the effectiveness of our progressive text disclosure approach to conventional full text displays. Designing such an experiment will be a challenge, considering the fact that users read or make use of reviews in a very chaotic manner. In further studies, we will investigate how to progress the text disclosure, i.e. how much more to reveal at every stage.

In future iterations of *OpinionBlocks* we hope to utilize the compact representation that visualization affords to let users perform side-by-side comparison of multiple products. We hope to integrate more user input at different stages, by enabling users to annotate and re-classify existing reviews. We also want to add tools to let users save full reviews or portions of them, in other words, create their own summary, for future reference and sharing with other users.

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