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Comparative Visual Analysis of Large Customer Feedback Based on Self-Organizing Sentiment Maps

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***Abstract*—Textual customer feedback data, e.g., received by surveys or incoming customer email notifications, can be a rich source of information with many applications in Customer Relationship Management (CRM). Nevertheless, to date this valuable source of information is often neglected in practice, as service managers would have to read manually through potentially large amounts of feedback text documents to extract actionable information. As in many cases, a purely manual approach is not feasible, we propose an automatic visualization technique to enable the geospatial-aware visual comparison of customer feedback. Our approach is based on integrating geospatial significance calculations, textual sentiment analysis, and visual clustering and aggregation based on Self-Organzing Maps in an interactive analysis application. Showing significant location dependencies of key concepts and sentiments expressed by the customer feedback, our approach helps to deal with large unstructured customer feedback data. We apply our technique to real-world customer feedback data in a case-study, showing the capabilities of our method by highlighting interesting findings.**

***Keywords*—customer relationship management, review analysis, self-organizing maps, sentiment analysis.**

I. INTRODUCTION

Many companies with business in the world wide web collect reviews and customer feedback of their products and services. One common way of assessing customer satisfaction are grading schemes (e.g., one to five stars) and free text forms allowing more detailed customer comments. But aside from showing the average rating or the distribution of ratings, more sophisticated and consequently also more expressive analyses are performed very rarely. This is surprising, as the free text provided by customers is a valuable source of hints with respect to customer needs and satisfaction levels, but a manual inspection is often not feasible. Modern approaches of text processing and visualization can help at this end, by summarizing important themes and sentiments in large amounts of text.

An effective analysis of textual customer feedback should involve and examine different aspects of the text content. The most obvious one is the *frequency of statements or terms*. Simple statistics and visualization methods like word clouds may help to get a first impression of most important keywords. But simple statistics do not help to analyze, whether the customers liked or disliked these points. The next important aspect is the *sentiment* extracted from the context of the addressed keywords occurring in the text. E.g., customers may complain or praise products or services, and by using sentiment analysis, we aim at capturing this notion. From a company's point of view, negative statements are in many cases more important to analyze than the positive ones, to improve customer satisfaction. But the computation of one single sentiment score is not very expressive as customers might review more than one aspect, and different customers may have different opinions. Therefore, the challenge is to arrive at a fine-grained analysis in this complex data. The sentiment analysis should assign sentiment scores with respect to the attributes of the product or service, instead of computing one value. Customers, for instance, could like a certain bought product, at the same time complain about a too complicated ordering process. Yet another key aspect holding valuable information in customer feedback data is the *geospatial location*. Customer feedback can be geolocated by several ways, including having the customer address in a corporate database, or by geo-resolving the IP address an anonymous web feedback was provided. From that we can derive the geospatial distribution of customer feedback, which is important for two reasons. First, for global companies, cultural differences may influence the customers' conception and country specific products or services should be offered. Second, besides cultural differences there is another aspect which may change customer's needs. The geographic location determines for instance the climate and may also impose delivery obstacles resulting from the geographic topology. In very dry areas, for example, it may be reasonable to leave a parcel outside the customer's housing, but in rainy areas the customer may complain about a soaked product. Concerning the topology, hard to reach customers (e.g., islands or exclaves) may complain about long delivery times, but there may be nothing the company could do about it.

Our main motivation for this work was the following starting hypothesis, to be explored on a real-world CRM data set: "The geographic position of reviewing customers correlates to their satisfaction levels and needs." We wanted to see, whether there are differences in customer preferences caused by the geospatial location. The result of this analysis could help to improve the customer satisfaction by detecting differences in customer needs. Companies can therefore differentiate better among their customers and can easily focus and channel their efforts.

In this paper, we perform customer feedback analysis based on *sentiment maps*. Sentiment maps are the result of preceding opinion mining steps, where the occurrence of a term is drawn on a geographic map. The color used hereby depicts the sentiment and the sentiment map consequently shows not only the geospatial distribution of the term but simultaneously also

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Fig. 1. Visualization of customer feedback data using sentiment analysis and self organizing maps. Term groups with different sentiment scores are visible and additionally the geospatial distribution of the terms is displayed. The brightness of the background represents the coherence of the geographic distribution for each SOM node.

the sentiment distribution. Following this approach leads to one sentiment map for each term. Further details of this approach can be found in the beginning of the analysis results section of this paper. A result of our technique is depicted in Figure 1.

We present in this paper our methodology analyzing customer feedback with respect to sentiment and geospatial customer location. Our contributions are the combined text and geospatial analysis of customer feedback data and the visual representation allowing a comparative analysis. Furthermore, we show that there are indeed frequent feedback terms (concepts) with a high geospatial dependency. The paper is structured as follows. First, we will give an overview to existing and related work in section II, and then detail our approach in section III. Findings from an application to a real-world data set will be discussed in section IV. We will conclude with an outlook to future work.

II. Related Work

Our work relates to a number of areas, which we briefly review in the next paragraphs.

Self-Organizing Maps for Visual Data Analysis. Many problems in visual data analysis require the reduction of data to perform meaningful analysis on a reduced version of data. Clustering reduces the data to a smaller number of groups to more easily analyze and compare; and dimensionality reduction reduces the number of dimensions of data items to consider, and to project data to 2D displays. The Self-Organizing Map (SOM) algorithm [1] is a well-known method, which provides both data reduction and projection in an integrated framework. As a neural-network type method it learns a set of prototype vectors arranged on a regular grid, typically embedded in 2D. The method typically provides robust results in both data clustering and 2D layouting. Using regular 2D grids as neural structures for the SOM training, visualization in form of heatmaps, component planes, and distance distributions comprise basic methods for visual exploration of data using SOM processing [2]. SOM-based Visual Analysis to date has considered different application domains, including financial data analysis based on multivariate data models [3], analysis of web clickstream data using Markov Chain models [4], trajectory-oriented data [5], or time-oriented data [6]. Image Sorter [7] proposed to visually analyze collections of images by training a SOM over color features extracted from the images. We here follow that idea, in that we analyze geospatial heatmaps of sentiment scores using SOM of respective color features as well.

SOM-Based Visual Analysis of Geospatial Data. Many application problems involve georeferenced data items, and visual analysis approaches have been identified as very helpful also for geospatial data analysis processes [8]. Choropleth (or thematic) maps are a basic, popular technique to show the distribution of a scalar value over a land-covering map [9]. Also, SOM-based approaches have been studied in context of geospatial data analysis, and proven useful to this end. When considering georeferenced data with SOM, basically two approaches exist. First, in the *joint data model*, one single data representation is formed by combining spatial and other multivariate data into a single vector representation which is input to the SOM method. Examples include [10], where a joint vector representation for both geolocation and demographic data was formed for census data analysis. More methods can be found in [11]. As a second approach, *linked views* integrate visual data analysis of each data aspect (geolocation, time, multivariate measures, etc.) in separate views combined by linking and brushing. One example system is [12], where a linked view system proposed the joint visual analysis of geospatial and multivariate data. Also, in [13], we proposed to jointly analyze geospatial and temporal phenomena by a linked view. There, SOM clusters can be computed for either data perspective, and the correspondence of clusters to the other perspective is shown by an auxiliary view. In our approach we do not consider geolocation data explicit for the SOM generation, but implicitly by the spatial-sensitive color features extracted from sentiment heatmaps generated from text data (cf. also Section III for details).

Feature-based Text Visualization. Finally, we relate to a body of work in visual document analysis. In general, *feature-based document analysis* abstracts a document (or collection, or stream) by a set of features which are more easy to visualize, as compared to the content of the documents. Numerous document features for different applications have been studied

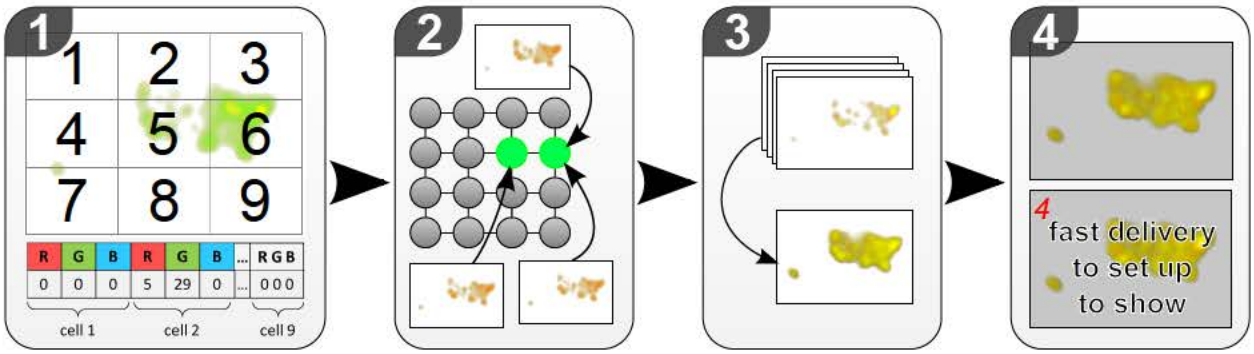

Fig. 2. Process pipeline to create self-organizing sentiment maps. The self-organizing sentiment map is determined by (1) extracting corresponding feature vectors, (2) calculating the best matching unit, (3) aggregating similar images according to the SOM, and finally (4) mapping the coherence and the additional information like the used terms to the images.

to date. For example, features scoring the readability of documents have been proposed in [14], and features applicable to classify authorship of documents have been surveyed in [15]. Sentiment features rate the polarity (in terms of positiveness of negativeness of statements) in a given text. In combination with time-series analysis, sentiment features can be used, e.g., to detect critical customer opinions in near real time, as possibly arising from some feedback channel [16]. In [17], we applied sentiment analysis to customer feedback data and analyzed it by means of geospatial heatmaps generated for the sentiments. While in [17], we considered only small sets of such heatmaps which we sequentially inspected, the focus of our work here is the comparative analysis of large numbers of sentiment maps, based on the SOM method.

III. Technique

Our approach enables the geospatial visual comparison of customer feedback sentiments by using a Self-Organizing overview display. Figure 2 shows the overall process that is divided into four steps: (1) First, we extract a color feature vector for each sentiment map. (2) Second, we train the SOM and assign every sentiment map exactly one node. In step (3) we aggregate all sentiment maps that are located on the same map node. (4) Finally, we calculate the coherence and enhance the aggregated sentiment map with the content terms from the represented customer review texts. We next detail these steps.

Feature Vector Extraction. The feature vector we use as input to the SOM computation consists of localized RGB color values. We create a grid overlay for each sentiment map and calculate the color mean value for each cell. The mean value is determined by the color value of each single pixel contained in the corresponding grid cell. The representative feature vector for any sentiment map is created using the RGB color model. All RGB mean values are forming the feature vector:

$$\text{Picture1} = (R_{1,1}\, G_{1,1}\, B_{1,1}\, R_{1,2}\, G_{1,2}\, B_{1,2}\, R_{1,3}\, G_{1,3}\, B_{1,3} \ldots)$$

$R_{i,j}$ represents the value of R for picture i and cell j. This format is used as feature vector representing one sentiment map; each picture is assigned exactly one vector. Then, the extracted feature vectors are used to train the SOM using the SOMPAK implementation [18] (see also Figure 2 (1)).

Sentiment Map Classification. We apply a standard SOM training process following best practices suggested in [18]. Based on the defined SOM grid resolution, the prototype vectors are linearly initialized. Then, two learning phases are applied. First, a coarse learning is performed with a larger training radius, so that every considered node has a wide impact factor. Then, a fine-tuning training step is performed with a smaller training radius. Once the SOM-training has finished, the best matching prototype vector on the SOM grid (best matching unit, or bmu) is determined for each sentiment map by finding the node with the minimal distance (1).

$$bmu(SM) = \min_{k=1}^{M} \left(\sqrt{\sum_{i=1}^{N} (v(SM).i - v(node_k).i)^2} \right) \quad (1)$$

We iterate all sentiment maps and calculate the best matching unit for each sentiment map SM. Then, we iterate all M trained SOM nodes and calculate the minimal Euclidean distance between the sentiment map and the trained SOM node. Therefore, the feature vector of the sentiment map and the vector of the SOM node are used. The corresponding vector is determined via the function $v()$ with size N. The control variable i addresses every single vector entry. Finally, the sentiment map is assigned to the SOM node with the minimal distance (see also Figure 2 (2)). The grid size can be chosen individually for each application.

Similarity-based Sentiment Map Aggregation. As the outcome of the SOM and bmu mapping, multiple sentiment images may share the same SOM node. Therefore, we need to provide aggregation of such sets of maps. To find a representative image for those sentiment maps different approaches are possible. We here chose to apply visual aggregation and merge all similar images into one. Therefore, every sentiment map is assigned a transparency value, so that we are able to create one image by lying one sentiment map upon each other. The resulting image visualizes all aggregated sentiment areas. By adding multiple pictures on top of each other, the last added picture on top has the highest impact according to the process of alpha composition in terms of occlusion [19]. For that reason, we calculate the intersection of sentiment maps on our own based on the color, shown in Figure 2 (3).

Coherence Mapping and Map Enhancement. The last step of the pipeline is twofold: First, we map the background

of the aggregated sentiment map to its coherence. Second, we enhance the aggregated sentiment map with additional information.

Aggregating multiple sentiment maps may result in an image showing a constant distribution. But the single pictures might be very diverse regarding the positions where the identified sentiment was mapped to. In order to understand the composition of those aggregated sentiment clusters it is important to define a quality criterion: the coherence of the sentiment maps. Thus, we make use of the background and define a coherence measure. The coherence measure (2) expresses how similar two sentiment maps are according to its feature vector. The coherence is mapped to the color range from black (high coherence) to white (very low coherence).

$$coherence(SMS) = \frac{\sum_{i=1}^{N}\sum_{j=i}^{N} dist(SMS_i, SMS_j)}{\frac{N \cdot (N+1)}{2}} \quad (2)$$

The $coherence$ is calculated for N sentiment maps (SMS) addressing the same SOM node. Summarizing, we build the average of all pictures including a distance function. We then sum the distance value of each sentiment map to all other sentiment maps. The distance function $dist$ between two sentiment maps is defined in equation (3).

$$dist(p,q) = \frac{\sqrt{\sum_{k=1}^{M}(v(p).k - v(q).k)^2}}{|\{i \in 1..M : \neg(v(p).i = v(q).i = 0)\}|} \quad (3)$$

The distance function requires two sentiment maps as parameters with dimension M. The Euclidean distance is normalized by the number of vector dimensions M excluding all dimensions with zero values in both dimensions. The problem of a possible low coherence raises with the algorithm of the SOM: To calculate the similarity in the second step the Euclidean distance combines sentiment maps that are very sparse, as the exact locations do not matter.

Sentiment Keyword Visualization. Every sentiment map corresponds to one term. As a consequence, if multiple sentiment maps are aggregated, the resulting image corresponds to multiple terms. Hence, we combine the aggregated sentiment maps with a simple but effective text representation: All terms are drawn semi-transparent with a gray border on top of the aggregated image. Also, the amount of sentiment maps that have been aggregated is indicated by a red number on the top left corner. Using an intelligent text layout algorithm, the analyst can easily identify the terms corresponding to the image; the text uses the full width and height to be easy to read. Figure 2 (4) illustrates the automatic labeling result.

Depending on the chosen grid size in the first step (feature vector extraction), the final result may differ. To allow data abstraction and overview large data sets, we typically chose a relatively small grid size, where the amounts of nodes is significantly smaller than the amount of considered sentiment maps.

IV. Analysis Results

We applied our methods described above to sentiment maps of a real-world data set of collected customer reviews. The reviews were collected after online purchases via an online survey. The data set consists out of 86.812 customer reviews with an average of 18.4 words per review (the median is 12 words per review). In this section, we will first describe the input images resulting from a technique called sentiment maps more in detail. Afterwards, we will discuss interesting findings with respect to the geographic distribution of frequently reported review terms.

Sentiment Maps. Sentiment maps allow the user to inspect the geospatial sentiment distribution of individual terms and are introduced in [17]. After collecting all terms of all reviews excluding stop words one visualization for each of these terms is created. More specifically, first all occurrences of the respective term are determined and the sentiment value for these occurrences are retrieved. The data is then used to generate the sentiment map as illustrated in Figure 3. The data is first partitioned into two subsets: the occurrences with positive sentiment in Figure 3(a) and occurrences with negative sentiment in Figure 3(c). The two partitions are processed separately. A Gaussian blurring function is applied in order to spatially extend the occurrences and increase the visual salience of the geospatial distribution patterns. The result is a blurred representation for both sentiments showing the respective geospatial occurrences as depicted in Figures 3(b) and 3(d). Finally, a combined image is created by using the RGB channels of the RGB color model. The blurred image of the negative occurrences is put in the red channel and the green channel is used for the positive occurrences. Consequently, locations with both positive and negative sentiments will result in yellow colors, while pure positive sentiments will result in green colors. We did not differentiate between within negative sentiments or positive sentiments respectively as this differentiation is highly user and application dependent. But sentiment maps could be extended by this possibility. The final result of this technique can be seen in Figure 3(e).

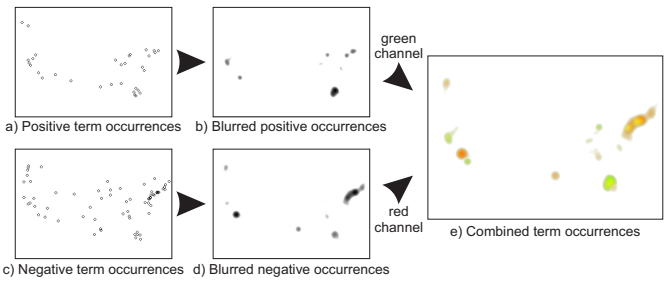

Fig. 3. The location maps of positive (a) and negative (c) review terms are blurred to increase the visual saliency and to give a visual aggregation (b,d). Both blurred location maps are then combined (e) by using the RGB channels and show the distribution of positive (green), neutral (yellow) and negative (red) term occurrences.

Discussion of Findings. We applied the technique described in section III to a dataset consisting of 327 sentiment maps. These terms were found in preceding document mining steps and contains the words being nouns, verbs, and adjectives. Note that some of these terms are even compound nouns like ”phone call“ or negated verbs like ”not to send“. The resulting overview visualization can be seen in Figure 4.

On an abstract level there is a clear grouping and ordering of the sentiment maps visible. Terms with only negative

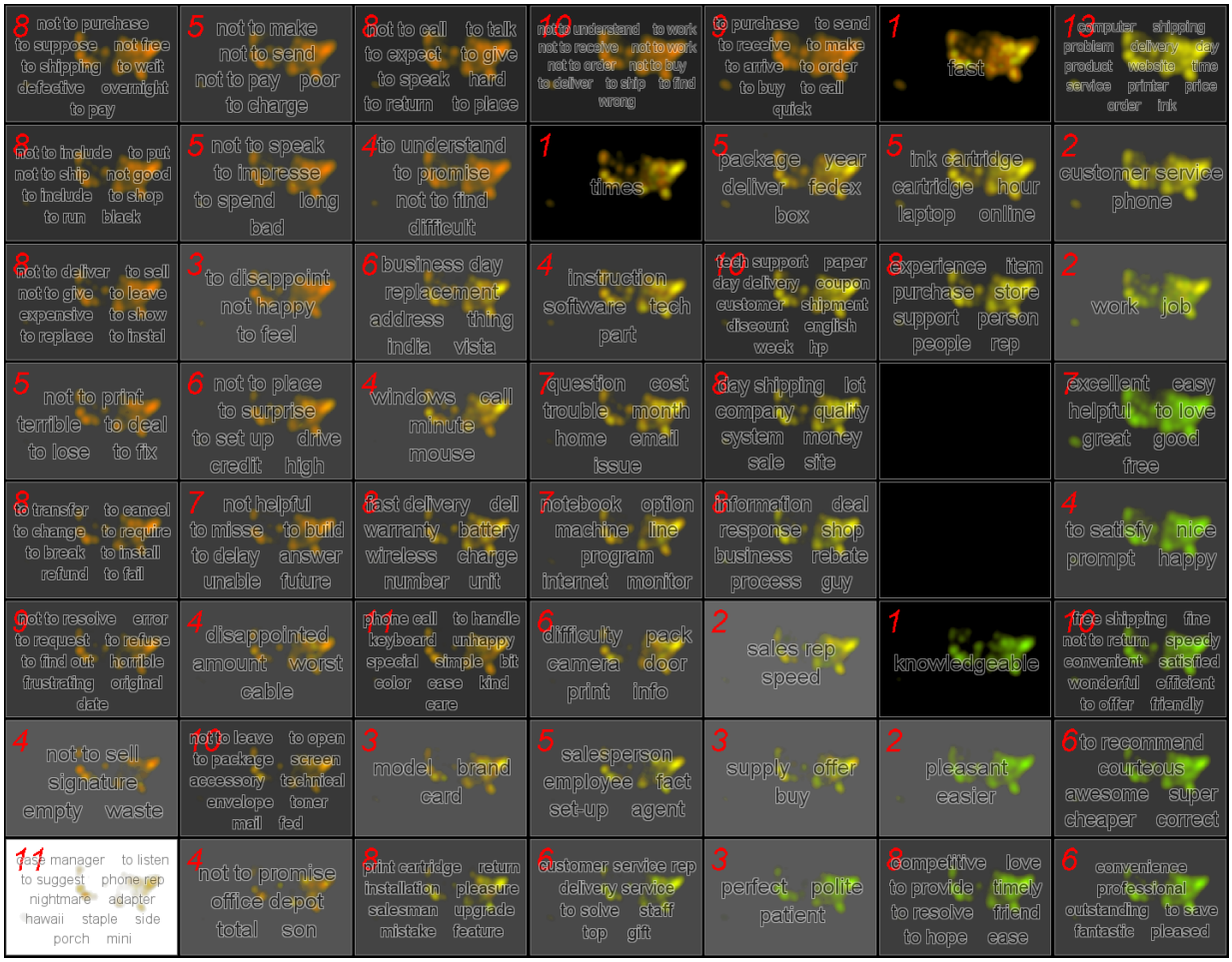

Fig. 4. Resulting overview visualization of the SOM analysis process. There are SOM nodes like the one in the lower left being highlighted with a bright background showing a high internal diversity.

occurrences (reddish images) are located in the upper left while positive terms (greenish sentiment maps) are located in the lower right. The first diagonal consists of terms being either mentioned negatively and positively equally often (upper right) and terms with a geospatial, diverse distribution (lower left). The SOM analysis enables the analyst to get a fast overview over terms being mentioned always positive or negative.

The strongly highlighted, white node of Figure 4 in the lower left contains eleven terms showing a very diverse geospatial distribution. As this is the node being highlighted most we will investigate this node in the following paragraphs. Detailed analysis via drill-down techniques are possible in our system and reveal the geospatial distribution for each single term. The visualization of all eleven contained terms is depicted in Figure 5.

Inspecting the sentiment maps more in detail reveals that this node mainly contains sentiment maps with sparse and diverse geospatial distributions.

The most obvious sentiment map contained in this SOM node is the term ”hawaii“. It is occurring mostly positively and collocated with the geospatial position of the Hawaiian islands. Inspecting the customer comments in detail, we found that customers liked the free shipping possibilities to Hawaii,

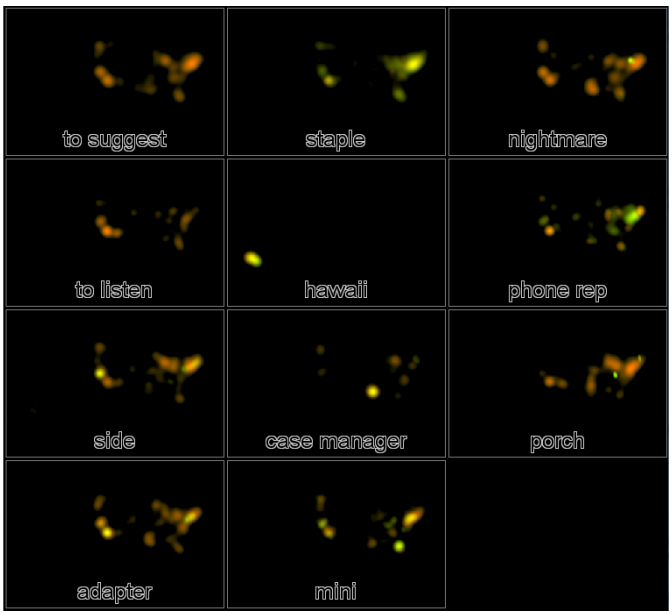

Fig. 5. Visual representation of all sentiment maps contained in the lower left node of Figure 4.

which seems not to be taken for granted. Service managers can learn from this information that (Hawaiian) customers do care about the shipping procedure and that free shipping might be an advantage over competitors.

Also, the term "case manager" (third row, second column in Figure 5) shows an interesting pattern. Although mostly mentioned negatively because of language issues – the customer support was hard to understand because of foreign accents – there are many positive occurrences in Houston, Texas where customers liked the support regarding their printers. Service managers should now investigate further what the characteristics about the problems in Houston were.

Two further interesting sentiment maps are the ones of "nightmare" and "porch". Investigating the underlying reviews shows that the preceding sentiment analysis did not work correctly as all the reviews were purely negative. This is not a drawback of the method per se, but exemplifies the uncertainty of any sentiment analysis and the sensitivity of our method to the input data. The comments regarding the term "porch" were mentioning that the parcel was left unattended on the porch. The term "nightmare" was used in cases where the process of ordering and returning products did not go smoothly.

V. Conclusion

We presented our approach to visually compare and inspect large sets of textual customer feedback with respect to sentiment expressed regarding key concepts, and geographic distribution. For each concept, a sentiment map was rendered, and set of all maps was visually clustered and aggregated by the SOM approach. Interaction methods allow to navigate the overview visualizations and drill down for detailed inspection and relation of feedback topics in geospatial context. Application findings presented indicate that key concepts and their sentiment scores being highly dependent on geographic position. Such findings can be very helpful in analyzing service levels across locations, products, and customers, and similar applications in CRM.

We have several ideas to extend our work in future for improved analysis. One possibility improving the visual representation is the integration of semantic zoom approaches. Semantic zoom can allow to merge neighboring SOM nodes to reduce the level of detail. Additionally, semantic zoom can be applied to the shown terms by using an ontology grouping terms, showing only the common parent of a set of related concepts. The ontology also leads to another extension possibility we are going to integrate in future. We plan to show the hierarchic relationships between terms directly on the SOM representation. Last but not least, we want to consider more detailed map visualizations concerning production facilities and income distributions among different cities correlating geospatial dependent properties with the text features.

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