Towards Sentiment-driven Maps Showing Touristic Attractiveness

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Abstract: User generated texts on tourism-related social network sites do not only contain factual information, but also valuable opinions and ratings of locations. Nevertheless, most maps on these sites only show markers where something described in a user generated text is located. In particular, no further information is derived from the text and displayed on the maps. Moreover, generalization operations are not employed, although in most cases aggregation and displacement of the user generated content would be necessary to achieve more readable maps. Therefore, we propose a method which automatically creates user-sentiment enriched maps. We use natural language processing tools in order to mine user sentiments for specific places from user generated texts and we propose specially designed point symbols which represent the corresponding mined user sentiment for each location. Additionally, we propose a heuristic, based on Voronoi diagrams, which slightly displaces the aforementioned symbols in case they are very close. This makes the provided map easier to read.

1 INTRODUCTION

A lot of user generated information accumulated in the web is related to a place. Because everything people do, they are doing it somewhere and most of the time it makes a difference where this is. This spatial reference is especially important on so-called travel social network sites. These sites do not only gather information about places and communicate information about where these places are actually located, they also offer travellers the opportunity to connect and share information. Especially these opinions and experiences of other users provide the additional benefit of those sites in comparison to traditional travel guides. Surprisingly, these sites are in their appearance very similar to other social network sites without an explicit spatial reference. Though maps are a very useful representation to describe the environment, there are rarely more maps on a travel social site than on a pure social site. Moreover, these maps often only show markers where something described in a text is, like it is shown in Figure 1. The rather simple information content of these maps is owed to the services, which are used for their creation. These services, like GoogleMaps, Bing or Yahoo Maps, enable their users to create layers containing any content that can then be viewed over the respective imagery base. But there is no aid in choosing appropriate markers for a special content. Furthermore, generalization

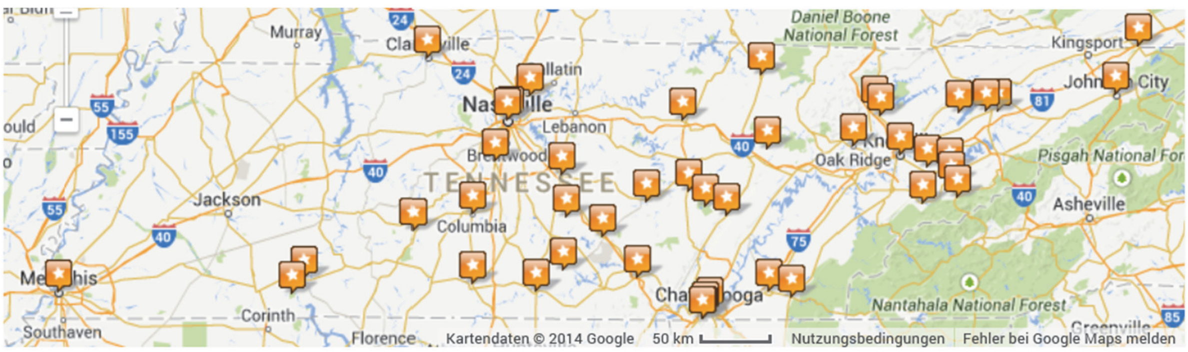

Figure 1: Popular locations in Tennessee, map extracted from virtualtourist.com.

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operations are not supported by these systems, although in most cases aggregation and displacement of the user generated content would be necessary to achieve more readable maps.

In this paper, we try to demonstrate that the already existing cartographic knowledge could be used to automatically create maps showing the sentiments towards places, which are more appealing and more expressive than the usual maps with markers. For this purpose we use well known natural language processing and opinion mining tools and generate maps of reviews for towns. These maps consist of a simple base map and specially designed point symbols, which represent for each location the corresponding sentiment values by their size and colour. If locations are too close to each other the map symbols will be minimized and slightly displaced. Thus, easily readable maps are produced, which enable the user to capture at a glance where attractive touristic locations are and how many reviews have contributed to their ratings.

The rest of the paper is organized as follows: In Section 2 the sentiment analysis method we utilized is described and evaluated. Section 3 addresses the design process for the map symbols representing sentiments. A method to displace point symbols is developed in Section 4. Afterwards, the map symbols and the displacement are applied to real world data and the results are presented in Section 5, before Section 6 concludes the paper.

2 SENTIMENT ANALYSIS

We considered three methods for sentiment analysis, namely SentiStrength (Thelwall et al., 2010), Lexicon-Based Classifier (Paltoglou and Thelwall, 2012) and SO-Cal (Taboada et al., 2011), which have been developed for informal web content. As the latter performs best in preliminary tests, we will only present and discuss its results.

We extracted 36,715 reviews about locations in the USA from a travel social network site, preprocessed them with the Brill Tagger (Brill, 1992) and classified them using SO-CAL. The majority of them, 24,367 were classified as positive, 8,659 as negative and 2,017 as neutral. In addition, 500 randomly selected reviews have been manually classified, in order to evaluate this analysis. The classification task was to assign to each review either a positive, a negative or a neutral value, depending on the sentiments expressed with respect to the location. Table 1 lists the resulting values for precision, recall and the f-measure of these 500 reviews.

Table 1: Evaluation results for 500 randomly selected reviews, considering only location specific sentiments.

	#	Precision	Recall	F-measure
Positive	304	0.86	0.90	0.88
Neutral	132	0.87	0.39	0.54
Negative	64	0.43	0.81	0.56

The result for positive reviews is satisfying, whereas neutral reviews have a rather low recall and negative reviews a low precision, resulting in a disappointing f-measure for both classes. One reason for this shortcoming of the method is that in a lot of reviews not only a location is described and rated, but also its historic background. Often the history is connected to a war or a natural disaster, consequently the text contains a lot of negative expressions, which are misjudged as a negative sentiment towards the corresponding location. Additionally, neutral reviews, which rather express facts then sentiments about a location, are seldom written completely in a factual diction. Instead, they quite often contain negative as well as positive judgments on the facts. If the manual classification task is modified, i.e., if the reviews should be classified by considering all sentiments expressed in the text, the results are significantly improved, as Table 2 shows. Still the recall for neutral and the precision for negative reviews are not as good as for positive ones, but they are in accordance to the results reported in (Taboada et al., 2011).

Table 2: Evaluation results for 500 randomly selected reviews, considering all sentiments.

	#	Precision	Recall	F-measure
Positive	315	0.92	0.92	0.92
Neutral	77	0.90	0.70	0.79
Negative	108	0.81	0.87	0.84

Hence, the method seems to be appropriate for our domain. Nevertheless, a preprocessing step, which filters background information out of reviews would be necessary, in order to get only the location specific sentiments.

3 MAP SYMBOLS FOR SENTIMENTS

According to the intended communication goal, the map symbols should fulfil the following requirements:

R1 Point signature representing two independent attributes

R2 Support quantitative perception between both attributes

R3 Support selective perception regarding one attribute

R4 Support ordered perception of the number of reviews that have been aggregated

First, we have to identify the components of the information we want to visualize. “Sentiment” can be considered either to be one component having values ranging from negative over indifferent to positive (from -1 to 1) or as two components: one nominal component having two values (positive and negative) and one quantitative component describing the strength of the sentiment. The latter approach is more suitable for our end as we want to distinguish if there are positive and negative sentiments towards a place or if there are only indifferent ones. As the number of reviews should also be represented, a third ordered component is added to our information “Sentiment”.

Consequently, we have to use three visual variables to visualize these three components. For the nominal component an unordered variable, i.e., form, color or orientation is appropriate (Bertin, 2011). As our goal is to represent two independent nominal attributes at the same place, it is necessary to use different forms that can be distinguished even if one is superimposed by the other. In order to fulfil requirement R3, also different colours are used as the form is not selective. As size is the only quantitative variable, it will be used for the sentiment value (R2). Finally, R4 leaves two choices for the number of reviews: texture and brightness. Due to the possibility of vibratory effects of textures we pick the latter. The change of the brightness of one object has the same visual effect as the change of its transparency, as long as the background is white. So we chose transparency, because it provides an additional benefit: the outlines of both forms are visible even if one covers the other completely.

Concerning the choice of the form, there are no formal guidelines, except not to use one that is already strongly associated with different information. So we chose as symbol for positive sentiments a turquoise six-pointed star and for negative ones a red circle. Green and red would be a more intuitive choice for colours to express positive and negative values (traffic light metaphor), though it is unfortunately not accessible for colour blind people. Stars are often used for ratings and have a positive connotation. On the one hand five-pointed stars are much more common and therefore suggest themselves, but on the other they might be easily misinterpreted. The sizes of the circle and the star are independent of each other as well as their opacity values. Figure 2 shows the map symbols for the positive as well as the negative values 0.1, 0.5 and 1 and all their possible combinations. The opacity for all symbols is 0.8, which is also defined as maximum value in order that both signatures are always cognizable. The minimum opacity value is set to 0.2, and in addition a maximum number of reviews is defined. The reason for this is that it is sufficient for the user to see, if the number of reviews exceeds a certain value, which indicates that the sentiment value is reliable.

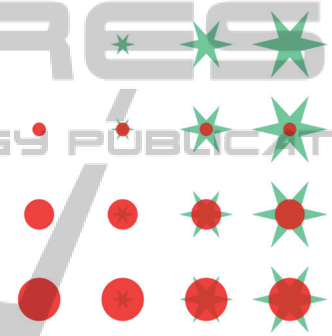

Figure 2: Map symbols for different combinations of sentiment values.

4 PLACEMENT OF MAP SYMBOLS

Ideally, map symbols should be placed at the exact coordinates of the object they symbolize. Furthermore, the map symbols should exceed the minimal graphical size (Keates, 1993) as well as map symbols should not overlap, in order to keep the map readable. Especially in small scale maps the map symbol often covers more space than the corresponding object, though increasing the probability for overlapping map symbols. Consequently, at least one of the following basic generalization operations, selection, aggregation and displacement should be used to resolve the overlap of map symbols. Selection would induce a complete loss of information, in our case the sentiment values of some locations, whereas displacement decreases the geographic accuracy and aggregation the “geographic” resolution. Consequently, displacement is the most appropriate choice for our application area.

Hence, we propose an iterative displacement method: The input parameters are the coordinates of the locations as well as the size of their map symbols and the output is a list of the displaced points. Furthermore, a threshold for the acceptable distance has to be defined. We use a Voronoi diagram of the input points as auxiliary structure, which is recalculated at the beginning of each iteration as the points are moved during the iteration steps.

For each iteration, the following conditions are checked one after the other and the corresponding instruction is executed. If the point symbol fits completely in the Voronoi cell of the corresponding point and the point is not marked as conflicting, the point is kept. If the point symbol actually overlaps any of its neighbours, it is checked if it is possible to place the signature anywhere within the Voronoi cell of its corresponding point. And if the distance between the original point and the new centre of the point symbol is less than the given threshold, the point is replaced. In this way the propagation of conflict, which arises when the displacement of one point symbol raises a conflict with a symbol that was not previously in conflict, is restricted, as Figure 3 illustrates.

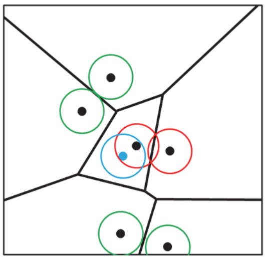

Figure 3: Displacement of single map symbol.

Otherwise the neighbours are marked as conflicting, they are checked again and the point is moved as far as acceptable towards the mass centre of the Voronoi cell. The reason for this is that the iterative calculation of centroidal Voronoi diagrams leads to a distribution of its points, where the “energy” between them complies with the global optimum (Du et al., 1999). Thus, we take the direction towards the mass centre as a hint for a promising displacement direction. In Figure 4 a rather dense set of randomly created points, which should be symbolized by grey discs is shown on the left side, and the result of the displacement method on the right.

The original points are drawn in black, the displaced points in blue. The threshold is set to the radius of the point symbols. The method stops if there are no more overlapping map symbols or if no point can be moved without exceeding the given threshold. Additionally, the number of iterations can be restricted, as the method delivers an intermediate solution after a few steps, which is at least considerably better than the initial placement, as empirical studies presented in the following Section indicate.

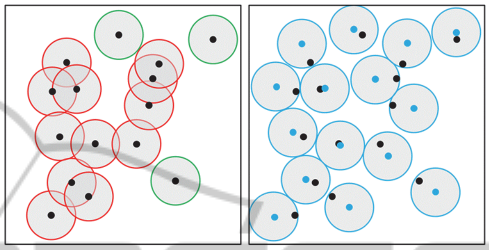

Figure 4: Point set before and after displacement.

5 APPLICATION TO REAL WOLRLD DATA

Our test set consists of sentiment values extracted from reviews for locations in the USA, as described in Section 2, which have been complemented by their coordinates taken from GeoNames. Additionally we extracted the borders of the single states from OpenStreetMap. For each state we created a map using the map symbols described in Section 3 and Esri’s world ocean base (MapServer) as a base map. The scale of the maps varies between 1:1,000,000 and 1: 5,000,000 in such a way as to enable us to present them true to scale within this paper. For 17 states the locations where wide spread, thus there were no, or less than ten easily solvable conflicts. Therefore, we only analysed the placement of map symbols for the remaining 3 states, whose results are listed in Table 3.

For each state the number of solved and unsolved conflicts as well as the number of displaced objects and the average distance by which they are displaced, are listed. The maximum number of iterations was set to 200, but for all except three states (IN, MA, OR) the method terminated earlier.

The threshold for the maximal acceptable displacement has been set to 5mm, nevertheless the average distance is about 2.6mm ± 1.3mm for the single states. As expected, not only the conflicting objects are displaced, but still the displacement is restricted to objects close to conflicting ones, as some objects always remain on their original location.

Table 3: Results of the displacement of point symbols.

State (Abbr.)	Area (km²)	# Sites	# Overlaps		Displacement	
			Solved	Not solved	# Objects	Ø Distance (mm)
Alaska (AK)	1,723,337	67	45	6	41	2.98
Alabama (AL)	135,767	72	23	1	35	2.31
Arizona (AZ)	295,233	88	15	1	33	1.85
California (CA)	423,968	100	116	26	79	3.02
Colorado (CO)	269,602	71	14	2	30	1.74
Connecticut (CT)	14,356	58	24	3	32	2.79
Florida (FL)	170,312	99	77	17	84	2.93
Georgia (GA)	153,910	78	15	7	26	1.68
Illinois (IL)	149,997	66	33	12	41	2.29
Indiana (IN)	94,327	76	38	5	43	2.44
Kansas (KS)	213,099	72	14	1	29	1.85
Kentucky (KY)	104,656	81	21	1	35	2.11
Louisiana (LA)	135,658	42	18	2	25	2.44
Massachusetts (MA)	27,335	72	134	44	57	3.96
Maryland (MD)	32,131	61	41	15	51	2.59
Maine (ME)	91,634	64	53	16	40	3.38
Michigan (MI)	250,488	87	18	5	37	1.98
Montana (MT)	380,832	53	9	3	23	2.04
North Carolina (NC)	139,391	95	71	8	69	2.68
Nebraska (NE)	200,330	52	10	1	20	1.78
New Hampshire (NH)	24,214	45	15	2	25	2.27
New Jersey (NJ)	22,592	90	44	6	57	2.70
Nevada (NV)	286,380	33	10	2	13	1.62
New York (NY)	141,297	89	77	17	63	3.07
Ohio (OH)	116,099	80	52	4	52	2.81
Oklahoma (OK)	181,038	74	10	2	22	1.80
Oregon (OR)	254,800	94	81	6	67	2.99
Pennsylvania (PA)	119,279	98	43	1	49	2.49
Tennessee (TN)	109,152	46	15	1	29	1.97
Texas (TX)	695,660	100	64	8	66	2.47
Virginia (VA)	110,787	89	82	14	60	2.90
Washington (WA)	184,661	94	74	20	63	2.76
West Virginia (WV)	62,755	59	10	1	24	2.00

The results also support the assumption that the resolvability of overlaps depends mainly on the distribution of points, as there is neither an interrelation between the number of conflicts and the number of objects, nor between the number of conflicts and the percentage of conflicts solved.

In Figure 5 the resulting map for Tennessee is shown, where all but one conflict at the southeast border could be resolved. The remaining overlap is due to the size and the closeness of the involved signatures not solvable, if the threshold of 5mm is kept.

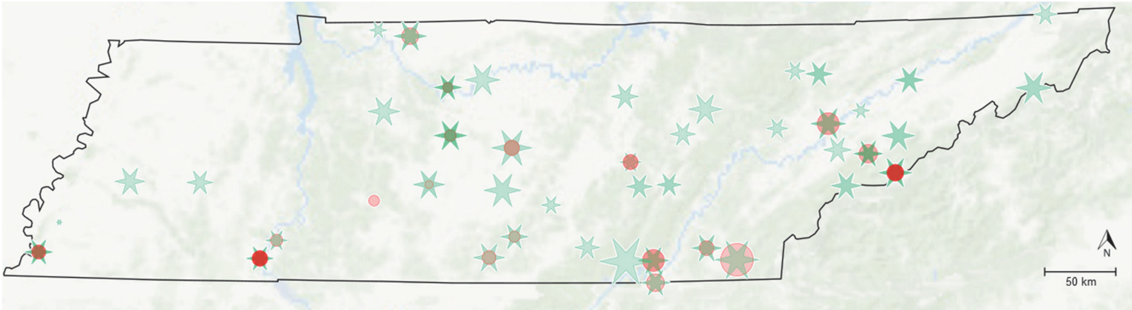

Figure 5: Sentiment map of Tennessee.

6 CONCLUSIONS

In this paper, we sketched out a method for generating maps for tourism-related social network sites that are more expressive than the usual pin maps shown on these websites. This was done via specific map symbols consisting of two separate parts, and by natural language processing including sentiment analysis. Furthermore, we proposed a heuristic method for point symbol displacement, which utilizes Voronoi diagrams.

It is obvious to use this kind of maps by embedding them in travel social network sites. In this case it would be adequate to show the names of the locations as tool tip texts. Moreover, a synthetic excerpt of the reviews as pop up after clicking on a location would be eligible. But though it is a well-treated issue (Pang and Lee, 2008), there is no ready to use solution available. Additionally, preferences of users, e.g., if they are more interested in adventure, family or wellness holidays, could be considered by analysing first the different aspects mentioned in a review and then the corresponding sentiments. The design of the presented sentiment maps has been optimized for small scale maps. As it is generally possible and desired to zoom into digital maps, the adaptability of this kind of maps to different scales is another aspect of future work.

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