Branty: a social media ranking tool for brands

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Abstract. In the competitive world of popular brands, strong presence in social media is of major importance for customer engagement and products advertising. Up to now, many such tools and applications enable end-users to observe and monitor their company's web profile, their statistics, as well as their market outreach and competition status. This work goes beyond the individual brands statistics since it automates a brand ranking process based on opinions emerging in social media users' posts. Twitter streaming API is exploited to track micro-blogging activity for a number of famous brands with emphasis on users' opinions and interactions. The social impact is captured from 3 different perspectives (objective counts, opinion reckoning, influence analysis), which estimate a score assigned to each brand via a multi-criteria algorithm. The results are then exposed in a Web application as a list of the most social brands on Twitter. But, are conventional metrics, such as followers, enough in order to measure the social impact of a brand? Different usage scenarios of our application reveal that the social presence of a brand is more complex than current social impact frameworks care to admit.

Keywords: social media analytics \cdot brand ranking \cdot multiple criteria decision analysis \cdot sentiment classification \cdot visualization

1 Introduction

Twitter has become a valuable tool for extracting public opinion. Indeed, a trend towards replacing conventional surveys by opinion mining over popular social media has already been highlighted in the literature [1]. Large scale vendors have always spent a lot of money to gain information about their products and services. Exploiting social media statistics, sentiment analysis and further metrics is today gaining a momentum and significantly impacting brands' marketing strategy. Such tools exist, a popular one being *Sysomos* [2], which started as a research project and is now a large commercial company that comes with a price, whereas free-of-charge platforms provide nearly enough data for someone to recognize what he has to change for his brand to improve its social web profile.

BRANTY¹ is a partly open-source social media monitoring platform that analyzes, ranks and visualizes the social presence of brands on Twitter. BRANTY

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¹ Branty web application http://branty.org/

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ranks brands based on social media analytics. Users can specify their preferences via an easy Web interface which is facilitating users adjustments and results summarizations. BRANTY is characterized by its openness with an aim to provide the BRANTY rating as an external service, which would be pluggable by other social media tools, product review sites and e-shops.

2 Ranking Brands with Branty

BRANTY formulates the problem of brand ranking as a multiple criteria decision analysis (MCDA) problem. Each brand is characterized with respect to the 16 criteria summarized in Table 1. BRANTY employs the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [3] for ranking the monitored brands. TOPSIS assumes two extra brands which have the best and worst possible score in each criterion and assigns the best rate to the brand closest to the optimal and furthermost to the worst one. It proceeds to ranking by receiving input weights by the user, showing the relative importance of each criterion.

Table 1. Criteria each	ı brand is	characterized	with.
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Objective Counts Criteria						
Overall time	Current week					
Number of brand followers	Number of tweets by users					
Friends-Followers ratio	Number of tweets by the brand					
Verified Twitter page or not	Appearances of the brand's website					
Twitter lists the brand is member of	Times the brand has been mentioned					
Average number of brand's posts per month,	Sum of re-tweets of the brand's tweet					
since its registration						
	Sum of favorites of the brand's tweets					
Opinion Reckoning Criteria						
Overall time	Current week					
-	Number of users' positive tweets					
	Number of users' negative tweets					
	Number of users' neutral tweets					
Influence Analysis Criteria						
Overall time	Current week					
Klout Score	Positive tweets on trending topics					

These criteria assess three different views of brands' social impact on Twitter and span either a small recent time period (e.g. week) or a more archival time period (the whole dataset). *Objective Counts Criteria* are statistics which assess the social presence of a brand on Twitter while *Opinion Reckoning Criteria* assess the current opinion Twitter users have for this brand. Positive tweets on trending topics show the strength a brand has among popular topics, meaning that a @brand is met along with at least one of the most popular hashtags. We track the other Influence Analysis Criterion in a comparative to our score manner, using Klout service².

MongoDB³ was used to store the data, while the implementation was based on the Java Twitter $4J^4$ library in order to utilize Twitter API. The current version of BRANTY is outlined with data for approximately 400 brands in 4 distinct categories: Auto, Fashion, Food/Beverages, Technology, collected from December 2013 until today.

2.1 Classifying Tweets by Sentiment

Opinion Reckoning Criteria require the classification of tweets by sentiment as positive, negative or neutral. This is achieved via a linear support vector machine classifier, trained on a number of tweets (approximately 1000 tweets manually annotated in this case study). Particular pre-processing has cleaned text by removing URLs, references, punctuation, hash-tag symbols and all other nonalphanumeric characters, while question and exclamation marks were converted to words. We then used a standard tf-idf representation for the pre-processed tweets. Also, SentiWordNet (SWN) [4] was utilized to derive 4 additional features corresponding to the fraction of positive, negative and neutral words within a sentence (tweet text in our case), as well as to the overall sentiment score of the sentence (the result of the SWN lexicon). The inclusion of these SWN attributes increased the accuracy of our approach by 5%. We managed to achieve a prediction accuracy of around 80%, similarly to [5,6].

3 Visualizing Data on a Web Application

Figure 3 shows the interface of BRANTY. On the left, a folding tab hosts horizontal sliders that allow users to weigh each of the criteria according to their preferences. The calculate button at the bottom of this tab refreshes the brand ranking according to the current weight settings. Brands are ranked in descending order according to their score, which is displayed as both a number and a horizontal bar. At the top right, clickable icons can be used to filter the ranking by brand category. At the same time, the top 10 hash-tags within the tweets of the selected category's brands are displayed above the ranking.

Experimenting with BRANTY, we noticed its functionality since differentiating weights in partial or all criteria has resulted in deviating brand ranking results. Its innovative contribution is that it enables tunable weighting for the end-users, using criteria which have different emphasis on the brands' ranking. Utilizing Twitter is justified by the fact that its presence is dominant, which is why it is used by BRANTY, integrating all of its features into a user-friendly interface. Via BRANTY's fine grained tunable and automated brand ranking,

² Klout Service, an external framework which ranks its users after measuring their social influence http://klout.com/

³ http://www.mongodb.org/

⁴ http://twitter4j.org/

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SELECT WEIGHTS		Set al .	Calculate	br	00	P nn	Technology	- O
Objective Counts Criteria	Opinion Recko		ysis Criteria 0.2				I	. 🚓 🗟
OVERALL TIME		CURRENT WEEK		#android #gar	meinsight #	indroidgames #tecl	h #job #apple #technology #iphone #gadgets #wordpress	▼ ▲
Number of brand followers		Number of tweets by users		1.	6	Instagram		46
Eriande Enlloware ratio			- 0.8	2.	NDRIA	GIDITRAFFIC		35
Verified Twitter page				3.	ዩ	Vine		25
T			0.8	4.		WhatsApp		19
•		•	0.8	5.	6	Disney Pixar		16
Average number of brand's posts/month		Sum of re-tweets of the brand's tweets		6.	Ü	UberSocial		15
		Sum of favorites of the brand's tweets		7.	æ	PlayStation		15
				8.	Testine	TWT.FM	-	14

Fig. 1. BRANTY's interface. The top 8 Technology brands ranking snaphot.

companies can monitor their social presence relative to that of their competitors with respect to different criteria, discover their weak points and adopt strategies for improvements and effective decision making.

4 Conclusion and Future Work

We have developed a ranking framework based on social media for evaluating brands in a comparative manner. Our first hypothesis was that a ranking analysis is defined by many factors and demands a deeper analysis. On our framework, a parameterized view of the current picture in social media can be created, giving brands a powerful tool to play with and analyze the results near real-time.

In the future we plan to extend BRANTY with criteria coming from other social media, such as Facebook, Google+ and LinkedIn. We also plan to increase the number of monitored brands by replacing our single server system with a distributed infrastructure solution.

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