The Journal of Values-Based Leadership

Volume 8
Issue 2 *Summer/Fall 2015*

Article 7

July 2015

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Finding Truth in Cause-Related Advertising:
A Lexical Analysis of Brands' Health, Environment, and Social Justice Communications on Twitter

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Abstract

Consumers increasingly desire to make purchasing decisions based on factors such as health, the environment, and social justice. In response, there has been a commensurate rise in cause-related marketing to appeal to socially-conscious consumers. However, a lack of regulation and standardization makes it difficult for consumers to assess marketing claims; this is further complicated by social media, which firms use to cultivate a personality for their brand through frequent conversational messages. Yet, little empirical research has been done to explore the relationship between cause-related marketing messages on social media and the true cause alignment of brands. In this paper, we explore this by pairing the marketing messages from the Twitter accounts of over 1,000 brands with third-party ratings of each brand with respect to health, the environment, and social justice. Specifically, we perform text regression to predict each brand's true rating in each dimension based on the lexical content of its tweets, and find significant held-out correlation on each task, suggesting that a brand's alignment with a social cause can be somewhat reliably signaled through its Twitter communications — though the signal is weak in many cases. To aid in the identification of brands that engage in misleading cause-related communication as well as terms that more likely indicate insincerity, we propose a procedure to rank both brands and terms by their volume of "conflicting" communications (i.e., "greenwashing"). We further explore how cause-related terms are used differently by brands that are strong vs. weak in actual alignment with the cause. The results provide insight into current practices in cause-related marketing in social media, and provide a framework for identifying and monitoring misleading communications. Together, they can be used to promote transparency in cause-related marketing in social media, better enabling brands to communicate authentic values-based policy decisions, and consumers to make socially responsible purchase decisions.

Introduction

Consumers increasingly make purchasing decisions based on factors such as health, the environment, and social justice — a recent survey reports that 71% of Americans consider the environment when they shop. In response, there has been a commensurate rise in cause-related marketing to appeal to these socially-conscious consumers (Aaker, 1999; Sonnier & Ainslie, 2011). However, because there is little standardization of terminology used in marketing communications, vague and misleading terms (e.g., "greenwashing") can make it very difficult for consumers to make informed decisions (Kangun, et al., 1991; Laufer, 2003; Furlow, 2010).

This problem is amplified by the growth of social media, which provide a cost-effective platform for firms to cultivate brand personalities with frequent conversation-like messages, the volume of which complicates regulatory enforcement. The informal nature of Twitter makes it particularly easy to cultivate an association between a brand and a cause, without necessarily making concrete statements or claims.

Despite substantial theorizing on the prevalence and implications of such greenwashing, little empirical work has been done to broadly examine the nature of cause-related marketing messages in relation to a brand's true alignment with the cause. In this paper, we investigate the relationship between the lexical content of a brand's Twitter communications and the quality of that brand with respect to three cause-related dimensions: health, the environment, and social justice. We collect nearly three million tweets from over one thousand brands across two different sectors (Food & Beverage and Personal Care) and pair them with independent ratings from GoodGuide.com, which provides in-depth ratings of brands for social causes based on product contents, corporate policy, certifications, and awards. With these data, we explore several questions:

RQ1. *Can we estimate the health, environment, and social justice ratings of brands based on their Twitter communications?* We find that the lexical content of a brand's Twitter feed is significantly correlated with its rating, most strongly for health. A text regression model produces out-of-sample error rates between 1 and 2 points on a 10-point scale, suggesting that high-rated brands do indeed communicate differently than low-rated brands.

RQ2. *Can we detect brands that potentially engage in misleading Twitter marketing?* Selecting the brands for which the model overestimates the ratings quickly reveals instances of cause-related marketing that may conflict with the properties of the product. While explicit false advertising is uncommon, we instead find a concerted effort to cultivate a brand personality that suggests a stronger cause alignment than the ratings indicate.

RQ3. *Can we identify cause-related terms that are used most frequently by brands in misleading contexts?* We perform a variant of feature selection to identify terms that overall correlate with high ratings, but also appear often in tweets from low-rated brands. This analysis identifies cause-related marketing terms on Twitter that are most susceptible to "greenwashing" and may have reduced communication value.

RQ4. *Can we further classify misleading cause-related terms based on context?* We train a classifier to distinguish tweets containing terms like organic as originating from high-rated or low-rated brands, based on the context in which they are used. We find that retweets containing such salient terms are strong indicators of low-rated brands.

Background and Related Work

It is well established that brand image and personality associations constitute an important component of brand equity (Aaker, 1999; Sonnier & Ainslie, 2011). Brands serve not only to signal functional product attributes, but also to provide consumers with an identity association they can use for self-congruence and social signaling (Aaker, 1999). Marketing activities designed to cultivate such image and personality associations have been referred to as brand image advertising (Kuksov, et al., 2013) and cause-related marketing (Varadarajan & Menon, 1988) when the desired association is with a social cause. Because consumers often project human personality characteristics onto brands (Aaker, 1999), firms can benefit from cultivating a general personality around social responsibility or causes of interest, even without making specific claims about their products or policies (for example, by enthusiastically recognizing Earth Day or retweeting news about the environment) (Etter & Plotkowiak, 2011; Banerjee, et al., 1995). This type of cause-related brand personality cultivation is often seen on Twitter, which provides a means of frequent conversation-like communications with their network (Etter & Plotkowiak, 2011). Such indirect tactics are low-cost to implement and can influence consumers who seek relationships with brands based on perceived humanlike characteristics that match their own values (Sen & Bhattacharya, 2001). However, because there is little regulation or standardization of terminology used in related marketing communications, vague and misleading terms are often used to imply socially responsible practices that are not in place (Kangun, et al., 1991).

Numerous researchers have expressed concern over the potential implications of such practices (e.g., Kangun, et al., 1991; Laufer 2003; Bhattacharya & Sen, 2004; Marciniak, 2009; Mark-Herbert & von Schantz, 2007). Some researchers have hypothesized, for example, that an abundance of misleading advertisements may desensitize consumers to sincere communications of cause-related initiatives, thus reducing firms' incentives to adopt socially responsible practices (Furlow, 2010). Others have suggested that consumers will identify insincere marketing communications and penalize such firms for hypocrisy (Bhattacharya & Sen, 2004; Mark-Herbert & von Schantz, 2007; Wagner, et al., 2009). Popoli (2011) provides a review of literature on the link between corporate social responsibility (CSR) practice and brand image, but discusses little about the potentially moderating role of topic-relevant marketing communications. Brown and Dacin (1997) show that increasing consumer awareness about a firm's CSR activities can affect brand evaluations, but the role of marketer generated content (MGC) as a vehicle for awareness is not explored. Du, et al. (2010) and Varadarajan and Menon (1988) present conceptual frameworks for the role of MGC in realizing the value of legitimate CSR initiatives, but do not consider the effects of greenwashing practices or examine large empirical samples.

Despite the importance of this issue and the confusion surrounding it, the literature does not yet offer broad empirically-grounded insights on truthfulness in cause-related marketing practices — i.e., on understanding the overall relationship between cause-related communication and commitment to the cause; on ways to detect brands and terms that may signal greenwash; and on identifying they ways in which sincere and insincere cause-related marketing communications differ. We expect that this is likely because empirically exploring this question requires collecting and labeling an extensive data set of categorized marketing communications, which can be prohibitively difficult and costly to obtain for large numbers of brands through traditional techniques (e.g., manual content coding) (Netzer, et al., 2012; Godes & Mayzlin, 2004; Liu, 2006).

The recent explosion of social media use by marketers offers an unprecedented data trail of such communications, though new methods must be developed in order to effectively leverage this tremendous volume of unstructured data. We introduce an approach that uses text regression to build a model to predict a brand's third-party ratings along different dimensions of social responsibility from the textual content of their Tweets. This technique has been used in the past to predict movie revenues from online reviews (Joshi et al., 2010), stock volatility from financial reports (Kogan, et al., 2009), and legislative roll calls from legislative text (Gerrish & Blei, 2011). In doing this, we can discover, over a wide range of brands, the extent to which truth can be predicted from Twitter communications; identify brands and terms that may be using or used in greenwashing practices; and glean insight into how cause-related terms are used differently in sincere vs. misleading contexts.

Data

GoodGuide

Several organizations have attempted to objectively rate different aspects of a brand or product, including the impact on health, environment, and society. While there is considerable debate on how to most usefully measure this (Delmas & Blass, 2010), for this study we rely on data from GoodGuide.com, one of the most ambitious efforts in this area. Founded in 2007 by a professor of environmental and labor policy at the University of California, Berkeley, GoodGuide applies a highly rigorous and well-documented scientific methodology to rate the health, environmental, and social impact of thousands of companies and brands across a range of sectors.

Beyond its rigor, the GoodGuide ratings are uniquely suited for our research purposes as they provide ratings at the brand as well as company level, while most rating systems provide assessments only of corporate-level policies, and many only for Fortune 500 firms (e.g., TruCost, *Newsweek*, *Fortune*). For large companies, sub-brands may vary dramatically in both the environmental friendliness of the product line, and the brand personality/image. Corporate images can have highly variable influence on brand images (Berens, et al., 2005; Brown & Dacin, 1997) and in many cases consumers are more likely to form the relationship-like connections we aim to explore at the brand level.

GoodGuide considers over 1,000 different indicators to rate performance, including greenhouse gas emissions, environmental certifications and awards, third-party ratings, company policy statements, amount of recycled content in products, types of chemicals used, and fair trade status. These are compiled into three scores between 1 and 10, for health, environment, and social impact. Higher scores indicate better performance.

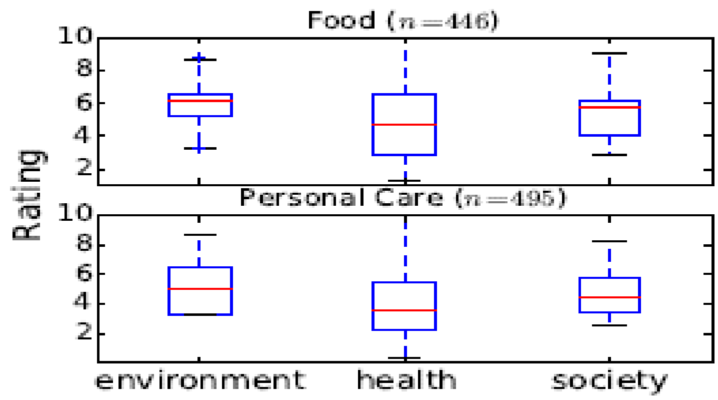
We collect brand-level information from GoodGuide for the two sectors with the most ratings: Food & Beverage (1,644 brands) and Personal Care (1,377 brands). These sectors contain many brands that have been rated along all three dimensions (unlike Cars or Apparel, which lack a Health rating).

Twitter

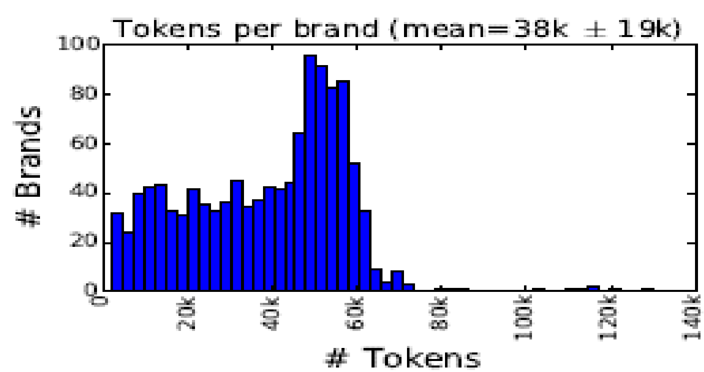
For each brand, we searched for its official Twitter account using a semi-automated method. First, we executed a script to query the Twitter API for user profiles containing the name of the brand or its parent company. To focus on brands with an active Twitter presence, we removed accounts with fewer than 1,000 followers or 100 tweets or 1,000 tokens. We also removed accounts that appeared to be personal, rather than company accounts (i.e., those containing "I" or "me" in the description field or containing only first names in the name field). Finally, we manually checked each account to ensure it was correctly matched to the brand. This resulted in a final list of 941 brands in the two categories of Food & Beverage (446) and Personal Care (495). The GoodGuide scores for these final brands are summarized in Figure 1(a).

We note that roughly 65% of the original brands collected from GoodGuide were removed from analysis because of a lack of Twitter presence (either no account found, or insufficient tweets or followers). An obvious limitation of our approach is that it is only applicable to brands that are active on Twitter (recently, it was estimated that 77% of Fortune 500 companies maintain active Twitter accounts (Barnes, et al., 2013)). We leave for future work extensions to other social media outlets (e.g., Facebook).

The Twitter Search API allows us to collect up to 3,200 tweets per account. Doing so results in 2.95M tweets containing 49.7M word tokens, or 38k tokens per brand on average (Figure 1(b)).



(a)



(b)

***Figure 1*: Descriptive statistics of the collected data: (a) the ratings distribution from GoodGuide.com for the two product categories and three dimensions considered; (b) the number of tokens collected from each brand's Twitter account.**

Analysis

Predicting Ratings from Text

To explore RQ1, in this section we perform text regression to predict the GoodGuide rating of each brand based on the lexical content of its tweets.

Preprocessing

We created one term vector per brand, summarizing the content of all of that brand's tweets. We tokenized each tweet by converting to lower case, collapsing URLs and mentions into identifier tokens, and collapsing characters repeated more than twice. Punctuation is retained, as are indicators for hashtags and retweets. For example, a tweet *http://www.foo.com fast-forward hi :) how?? U.S.A. @you whaaaaaaat? #awesome*. is transformed into the tokens: *URL fast-forward hi :) how ?? u.s.a. MENTION what ? #awesome*. A retweet *RT hi there* is transformed into *rt-hi rt-there*. The motivation here is to retain the distinction between hashtags and regular tokens, and between retweeted text and regular text. This allows us to identify Twitter-specific distinctions in brand marketing strategy.

Next, these tokens were converted into a binary representation, where 1 indicates that a term is used by a brand, 0 otherwise. We removed from the vocabulary terms not used by at least 10 different brands, to help identify terms that are generalizable across brands. This resulted in 54,958 unique terms. Finally, to downweight common terms, we transformed these into tf-idf vectors by dividing by one plus the number of brands that use each term.

Regression

Given the list of brand vectors paired with three ratings from GoodGuide, we fit six separate ridge regression models (one for each category/rating pair). We performed 10-fold cross-validation to assess the out-of-sample error rate of the model, reporting two quality metrics:

- Pearson's r: We collect all the predicted values from the held-out data in each fold and compute the correlation with the true values; $r \in [-1, 1]$; larger is better.
- nrmsd: Normalized root-mean-square deviation computes the square root of the mean square error, normalized by the range of true values:

$$\mathrm{nrmsd}(\mathbf{y}, \hat{\mathbf{y}}) = \frac{\sqrt{\frac{\sum_i (\hat{y}_i - y_i)^2}{|\mathbf{y}|}}}{\max(\mathbf{y}) - \min(\mathbf{y})}$$

where y is the vector of true ratings and ŷ is the vector of predicted ratings. $\mathrm{nrmsd} \in [0, 1]$; smaller is better.

Results

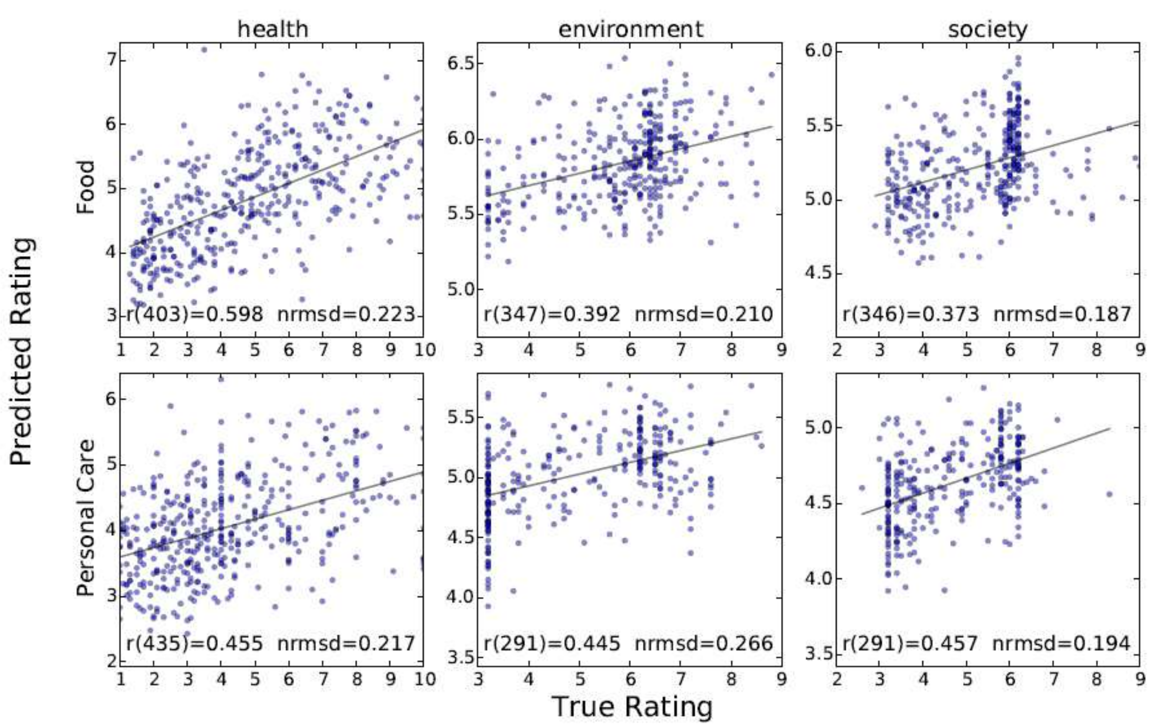


Figure 2**: Scatter plots of the true rating (from GoodGuide) and that predicted from the tweets from each brand, along with the held-out correlation (r) and normalized root-mean-square deviation (nrmsd).**

Figure 2 shows the scatter plots for each category/rating pair. The out-of-sample correlation ranges from .598 (Food/Health) to .373 (Food/Society). All correlations are statistically significant at the .001 significance level using a two-tailed t-test. To interpret the nrmsd values, on a scale from 1-10, a value of .2 means that, on average, the predicted rating is within 1.8 points of the true rating (.2 * (10-1)).

These results suggest that high-rated brands do indeed tweet differently than low-rated brands. It is perhaps unsurprising that the Food/Health results are the most accurate — the health of food is a widely discussed issue, and this rating is most tied to the contents of the actual product. Additionally, Figure 1(a) shows that the Health category has the largest dispersion of scores, which may provide a more useful signal for training. What is more surprising is the extent to which environment and society issues are discussed, and how predictive the related terms are of the brand rating.

To further investigate these results, Table 1 shows the top six coefficients for each of the six models. We find a number of intuitive results, including terms like *organic*, *fair trade*, *sustainable*, and *chemicals*. Other terms require more context. While some may be a result of model over-fitting, others have plausible explanations once we examine the matching tweets: *m-f* is used when providing customer service phone number and hours to customers with complaints or queries. These correspond to brands with a very engaged customer support operation, which appears to correlate with high ratings. The term "mom's" refers in part to the *Mom's Best Award*, a website that recommends products safe for expectant mothers; a similar website mentioned is *Mom's Best Bets*. Highly-rated products promote the fact that they have been awarded a high rating from such websites. The term "87" comes from a popular retweet of a poll indicating that 87% of Americans want genetically-modified organisms (GMOs) to be labeled. Thus, while richer language analysis may uncover more complex linguistic patterns, it appears that a simple bag-of-words approach quickly identifies salient terms used by highly-rated brands.

Sector	Health	Environment	Society
Food	nutritious (0.72) cereals (0.70) rt-cereals (0.69) #organic (0.68) rt-organic (0.63) grains (0.63)	#organic (0.40) sustainable (0.38) rt-film (0.37) farming (0.36) rt-#fairtrade (0.35) chalk (0.33)	rt-#fairtrade (0.52) #fairtrade (0.36) m-f (0.30) philly (0.30) peeps (0.29) farming (0.28)
Personal Care	mom's (0.75) chemical (0.75) #organic (0.71) toxic (0.65) rt-#eco (0.63) chemicals (0.62)	rt-#ad (0.39) reco (0.36) incl (0.36) simone (0.36) photographs (0.36) ss14 (0.35)	rt-#ad (0.32) feed (0.30) collaboration (0.30) 87 (0.28) core (0.28) reco (0.27)

***Table 1*: The top weighted coefficients for each category.**

Identifying Potentially Misleading Brands

In RQ2, we explore whether the model from the previous section can be used to identify instances of low-rated brands using terms that are indicative of high-rated brands, and whether we can identify patterns in these potentially misleading accounts to better understand greenwashing practices in social media.

A natural way to investigate this question is to examine brands for which the model over-estimates the true rating. While some of these errors are simply due to inaccuracies of the model, many may be indicative of attempts to position a brand as higher rated than it is. For each brand, we compute the predicted rating minus the true rating, and sort the brands in decreasing order.

Table 2 displays a sample of the top brands according to this measure. For each brand, we identified the terms that had the largest contribution to a high predicted rating (based on the corresponding coefficient), then we searched for tweets containing those terms.

Brand	GoodGuide	Predicted	Sample Tweet
The Ginger People	1.6	5.4	#EarthDay every day. Partnership with Non-GMO Project. Expanding organic production. Focus on complete sustainable and ethical supply chain.
Daisy Brand	3.5	6.9	Top 5 Myths About the Diabetes Diet via @TodaysDietitian by @nutritionjill
Pamela's Products	2.4	5.6	PP Tasting 10/4 @ Organics & More in Wyoming, Ontario Canada
Stretch Island	2.9	6.1	Try a healthier option for trick-or-treating this year with #StretchIsland FruitaBu Fruit Rolls! They're naturally sweet and nutritious!
Wholly Wholesome	2.4	5.2	Did you know our cookie doughs are 70% organic?! http://t.co/zEGIic7iD8 #Organic #Baking #Cookies
Chobani	3.3	6.3	@JWright99 We are actively exploring an organic option for consumers who prefer having that choice.
Guiltless Gourmet	3.2	6.0	Check out this amazing vid, and stop drinking bottled water! #green #reuse #greenisgood #waste #eco #earthtweet
Philip Kingsley	0.5	4.1	Our top 8 holiday season foods high in iron -a mineral essential for healthy, beautiful hair growth & wellbeing.
Herbacin	1.1	4.6	Hi everyone! Welcome to Herbacins Twitter page. Herbacin is a European skincare line that contains organic and natural ingredients.

***Table 2*: A sample of the brands for which the model over-predicts the true rating by the largest amount.**

Examining these results, a few patterns emerge:

1. Brand Personality: The most common pattern found is where a brand uses Twitter to cultivate an informal personality consistent with support of a cause. For example, Guiltless Gourmet discusses the environmental damage of water bottles, which is tangential to its product line. Similarly, Pamela's Products mentions that its products are available at a store called "Organics and More," even though its products are not necessarily organic. Finally, Philip Kingsley has a very low health rating, in large part because of hair products containing Cocamide Dea, which GoodGuide labels as a health concern. While its tweets do not make direct claims about the health of its products, the brand personality promotes health and well-being.

2. Product Labeling. A second common case arises when low-ranked brands attempt to label their products with terms popularly associated with a cause, most notably for health and the environment. For example, some brands with low GoodGuide ratings have advocated for voluntary labeling of genetically-modified organisms (GMOs) or have advertised their products as GMO-free. Similarly, many brands highlight that their products are gluten-free or vegan. For example, in Table 2, Wholly Wholesome, which makes organic desserts, receives a low health rating from GoodGuide (due to high sugar content), but the model predicts a high score due to the term "organic." Additionally, Herbacin, which makes skincare products, highlights its organic ingredients, though GoodGuide assigns a low health rating due to the presence of Propyl Paraben in some of its products, which GoodGuide views as a health risk.

3. Explicit Health Marketing: A third category contains direct attempts to promote the health of a line of products. For example, Daisy Brand, known most for sour cream and cottage cheese, often posts tweets promoting the health value of its products, e.g.: "Our mission is to make the highest-quality & healthiest cottage cheese on the planet." The sample tweet in Table 2 cites an article clarifying that not all white foods are unhealthy (in response to the guidance to encourage people to eat more whole grains).

This analysis provides insight into the most common ways in which brands may be engaging in greenwashing practices on Twitter and cultivating a brand image that is more in line with a social cause than independent ratings suggest.

Identifying Potentially Misleading Terms

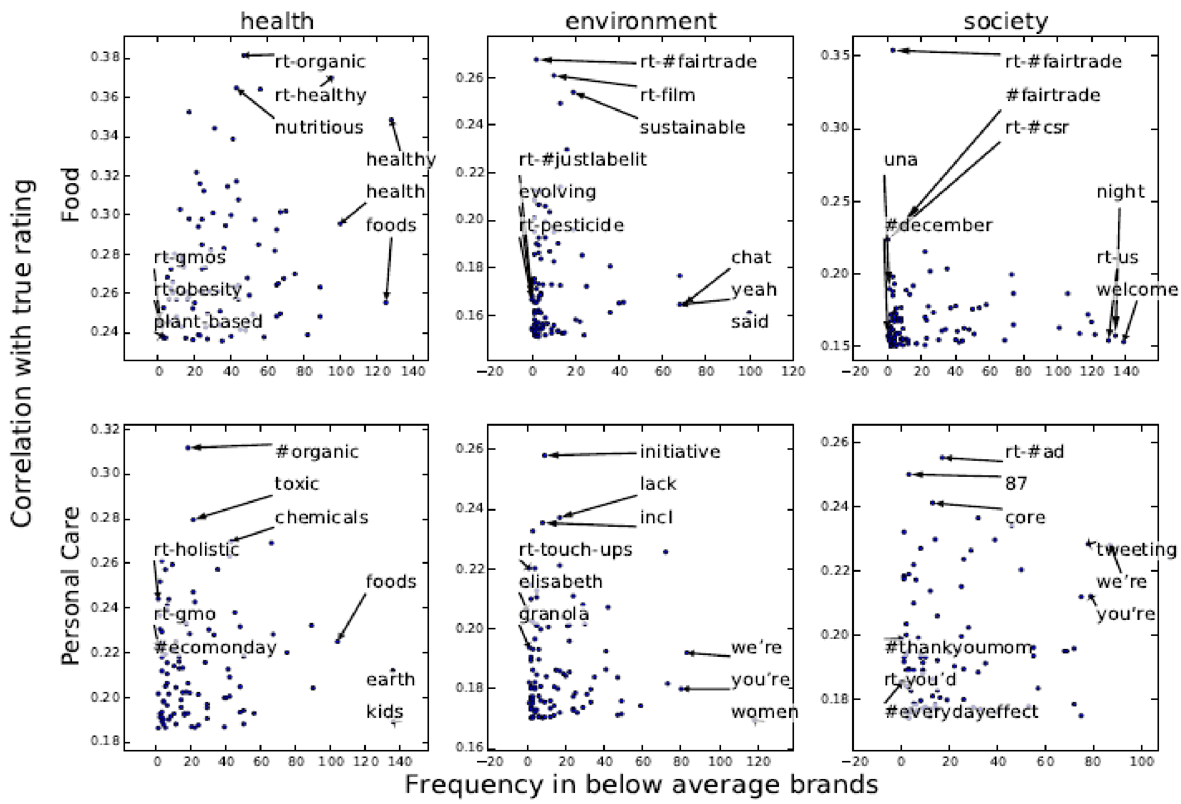


***Figure 3*: The 100 most highly correlated terms for each rating. We have labeled the three terms with the highest correlation, as well as the three terms with the lowest and highest usage among below average brands. Terms with high usage by below average brands may indicate attempts to enhance the perception of a brand.**

Given that brands with very different ratings may use similar terminology, in this section we investigate how to identify terms that might be used most in misleading contexts. In doing so, we aim to provide insight to marketers and consumers alike regarding the true communication value of common cause-related marketing terms (and to provide a method for monitoring trends therein). The problem can be understood as follows: identify terms that are generally predictive of high ratings, but are also occasionally used by low-rated brands.

We build on traditional feature selection approaches to identify such terms. A common approach is to rank features by their correlation with the output variable. While this will provide us with terms correlated with health and the environment, terms with similar correlation values may have very different usage among low-rated brands. To distinguish between these cases, for each term we also compute the number of brands with a below average rating that have used it.

Figure 3 plots these results for the 100 terms with the strongest positive correlation with each category. We include a label for 9 terms per plot: the three with the highest correlation, the three with the lowest usage by below average brands (smallest x value), and the three with the highest usage by below average brands (largest x value).

Term	Category	Rating	No. Tweets	Accuracy
organic	food	health	15988	0.880 ±0.02
gmo	food	health	3109	0.858 ±0.03
health	food	health	15099	0.812 ±0.03
fairtrade	food	society	990	0.810 ±0.06

nutritious	food	health	897	0.704 ±0.03
foods	food	health	10204	0.656 ±0.02
healthy	food	health	22507	0.652 ±0.02
chemicals	personal care	health	999	0.549 ±0.04
organic	personal care	health	15988	0.483 ±0.04
toxic	personal care	health	858	0.457 ±0.07
			Avg.	0.686

***Table 3*: Binary classification results distinguishing different contexts of salient terms.**

Examining these plots can provide some insight into the state of lexical usage in a category. For example, the term "healthy" has a strong correlation with foods with high health ratings; however, it is also used by nearly 130 below average brands. This reinforces the observation from the previous section concerning explicit health marketing (e.g., Daisy Brand), which dilutes the predictive power of the term "healthy." In contrast, the term "rt-#fairtrade" appears to be a reliable indicator of environmental and social justice ratings — it has both a strong correlation and is used by very few below average brands.

We also investigated the context in which high- and low-rated brands used predictive terms. For example, the terms "vegan," "#organic," and "healthy" are commonly used by healthy brands in the context of farming practices, specific vegetables, or grains (e.g., quinoa, tofu); in contrast, brands rated as less healthy tend to use these terms to modify foods that are typically not healthy (e.g., pie, baking, desserts).

"Sustainable" is used by environmentally-friendly food brands along with words such as "petition" and "policy," suggesting a more engaged, activist approach to environmentalism. Low-rated personal care brands tend to use the word "sustainable" with terms like "#ecomonday" and "#earthmonth," suggesting that these brands typically discuss sustainability issues in the context of re-occurring events that focus on the environment.

Disambiguating Terms Based on Context

The preceding analysis presumes the presence of third-party ratings to detect potentially misleading uses of terms – we find, for example, that a salient term like "organic" is used by brands with very different ratings. However, this approach can only be applied given some rated brands. That is, we can use the approach in the preceding section to identify potentially misleading terms, but given a new tweet from a new brand, how can we assess whether it is misaligned with the rating of the brand?

In this section, we next consider whether the context in which these terms are used can be analyzed to infer whether they are being used by high- or low-rated brands. For example, consider these four (real) tweets:

- **T1.** ***#FillInTheBlank! My favorite healthy lunch to make is ______.***
- **T2.** ***RT @Qalisto26: @aveda My new year's resolution is to use more environmentally conscious, natural, organic, non-gmo, & sustainable products.***
- **T3.** ***We believe children should be fed from pure ingredients, which is why we provide high quality certified #organic foods that do not use GMOs!***
- **T4.** ***Resolve to avoid toxic beauty and skin care products. Do something good for you and let Aubrey Organics help! http://t.co/HVHjbk3K***

Each tweet contains one or more terms correlated with a high rating. However, the usage and context is quite different. T1 asks users to respond with healthy lunch items, but does not make any claims about a specific product. T2 is a retweet of a user who has mentioned a personal care product (Aveda), listing many desirable properties of the brand. This is an interesting and common case of a brand retweeting a customer's tweet to promote a product. These differ from T3 and T4, which provide direct statements about the health of a product. Indeed, the GoodGuide ratings for the brands of T1 and T2 are lower than those for T3 and T4.

In this section, we build a classifier to distinguish between these two types of contexts. We borrow ideas from word-sense disambiguation (Stevenson and Wilks, 2003), a common natural language processing task to identify the sense of a term (e.g., bass the fish or bass the musical instrument). While here the terms are not expected to have different senses in the NLP sense, we do expect the contexts to differ based on the rating of the brand.

Thus, we can view this as a supervised learning task: the training data consist of a list of (term, context) pairs; each point is assigned a label that is positive if the term is used by a high-rated brand, and negative if the term is used by a low-rated brand. Once we fit a classifier, we can then apply it to new tweets (with unknown ratings) in order to determine whether the author is a brand with a high or low rating.

To binarize the ratings, we consider brands with ratings above 5.5 to be positive, and those below 4.5 to be negative (to filter neutral ratings). We then fit a logistic regression classifier[7] using the same term list use in the previous regression analysis. The primary difference is that here we are classifying individual tweets containing a specific keyword, rather than estimating the rating of a brand based on all of that brand's tweets.

Table 3 displays the average accuracy of 10-fold cross-validation. To better estimate generalization accuracy, we have ensured that a tweet from the same brand cannot occur in both a training and testing split in the same fold. (This is to confirm the classifier is not simply learning to associate brand-identifying terms with the class label.)

We can see that the difficulty of this classification task varies by keyword, ranging from 88% accuracy for tweets containing the word "organic," to only 46% accuracy for tweets containing the term "toxic." Averaged over all terms, the classifier is 68.6% accurate at determining whether a tweet originated from a high- or low-rated brand, given that the tweet contains a keyword known to correlate with high ratings. This indicates that there exist contextual clues that may sometimes reveal the rating of a brand.

We also examined how Twitter-specific behavior differs between the two contexts. Specifically, we investigate whether usage of retweets, hashtags, urls, and mentions differs between high- and low-rated brands. Table 4 displays how often each Twitter feature was among the top 10 most highly-correlated features for high- and low-rated brands. We can see that the behavior varies considerably depending on the term. For example, the use of hashtags is strongly correlated with high-rated food brands mentioning the term "organic," but the use of hashtags is correlated with low-rated food brands mentioning the term "health." We can see that the feature that displays the most consistent signal is retweeting — for 7 of 10 terms, it is strongly correlated with low-rated brands. For example, if the term "organic" appears in a retweet, it is more likely to be from a low-rated brand. This suggests that retweets may be a way for low-rated brands to align themselves with a particular cause.

Examining other highly weighted terms reveals another interesting insight: for the term

"GMO," the highest weighted term is certified. This labeling carries a stronger, official meaning ("certified GMO-free") and so is likely to be used by high-rated brands to distinguish their products.

Feature	High Rating	Low rating
hashtag	5	4
retweet	2	7
mention	3	3
url	5	4

Table 4: **The number of terms in Table 3 for which each feature was among the top 10 most highly correlated features for a high or low rating. While hashtags, mentions, and urls are strongly predictive of class, which class that is varies depending on the term. On the other hand, retweets containing salient terms are a fairly reliable indicator of low-rated brands.**

Conclusion and Future Work

Using text regression, we have found that the textual content of brands' tweet can, to some extent, predict their ratings with respect to three different concerns (health, environment, social justice). Furthermore, we have found that such a model can then be applied to identify patterns that might suggest misleading or conflicting messages. Finally, we have provided a method to explore terms that are used in conflicting contexts. We expect the presented findings and approaches can be useful towards promoting transparency in online, cause-related marketing. Such transparency and accountability is necessary for values-based leadership to flourish, enabling values-based decisions to be effectively communicated to consumers, empowering consumers to make more informed decisions, and enabling marketing researchers and policy-makers to track trends cause-related advertising practices.

There are a number of limitations with this work: a brand must have an active social media presence and the model requires ratings from third-party sources for training. In future work, we will explore: (1) adapting this methodology to other social media platforms; (2) more sophisticated linguistic analysis beyond unigrams; and (3) improved monitoring of the marketplace for greenwashing brands and terms that have weakened messaging value.

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