What, How and When: Patterns of Message Virality in Social Media Brand Communications

PHENOMENON AND RELEVANCE

The growing number of customers in social media has converted services such as Facebook and Twitter into the main channels for peer-to-peer content marketing distribution (McKinsey 2014). Success-proven, viral online content can drive up sales by 40% (Kumar et al. 2013), lead to 75% more online traffic (YouGov 2014) and increase brand awareness (Berger and Milkman 2012). However, 34 percent of customers believe they are spammed by social media content, and with a 600% expected increase in social media content by 2020, overwhelmed customers are expected to get into a *"content shock"* (NYTimes.com 2014). As a consequence it has become cumbersome for brands to develop effective strategies to deliver online content that is relevant for consumers. Not surprisingly, a top executives' survey reports online engagement as a strategic priority to drive growth, ranked in the top three digital trends (McKinsey 2014).

RESEARCH QUESTIONS

1. From a linguistics perspective, what types of intentions can brands and services pursue through social media?
2. Considering content marketing is a service, how can we use data analytics to automate the classification of content types in social media?
3. What is the most successful combination of social media content on a daily and weekly basis?
4. Why some message (e.g. posts or tweets) intentions and their combinations are more successful than others?

THEORETICAL FOUNDATIONS

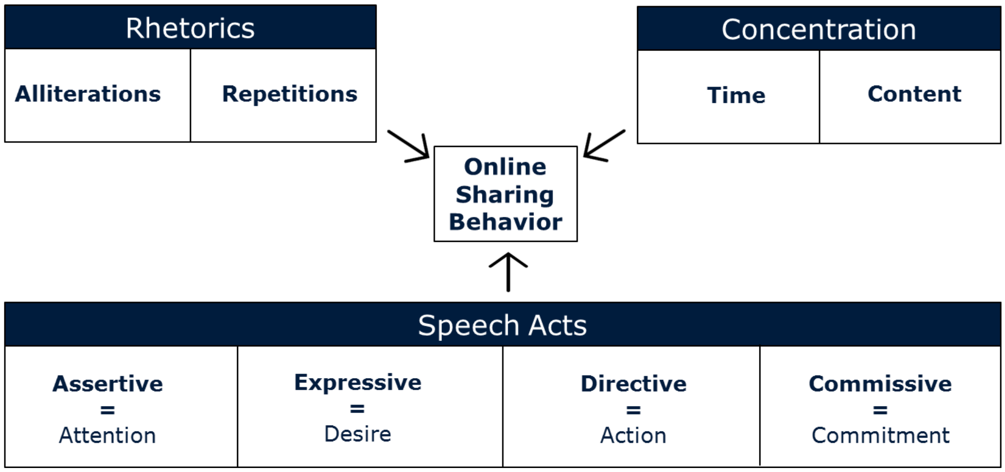
To sustain customer content sharing (virality), marketing research advises managers using varying word choices of content (e.g. positive emotion words) and arousal (e.g. awesome vs. good), together with interactivity pairs, such as videos and/or pictures (Berger and Milkman 2012; Lee, Hosanagar, and Nair 2013; de Vries, Gensler, and Leeflang 2012). However, research on Speech Acts indicates that not only word choices, but overall message intentions may inherently drive different reactions from customers.

By theorizing on speech acts, we suggest that brand posts in social media can be classified as varying marketing intentions, where directive language (e.g. "Act quick, last days of discount") can lead to spreading online content more widely than assertions (e.g. "last days of discount") or emotional expressions (e.g. "Best days of discount"). In addition to message intentions, research on Rhetoric suggests that stylistic schemes or word plays such as alliterations and repetitions may increase content sharing by customers (McQuarrie and Mick 2003). Furthermore, it remains unclear whether content concentration or specific speech act sequences within a day have an effect on content sharing. Considering the prevalence online communication, we draw on speech acts (Searle 1976) and rhetoric's (Nemesi 2013) to advance research into online brand communications and viral content.

CONCEPTUAL FRAMEWORK

Below it is presented our conceptual framework. It describes the causal relationships we are interested in. Hypotheses have not been finalized and that is why we have not included them.

FIGURE 1. Conceptual Framework



METHODOLOGY

Particularly, by using support vector machines and regular expressions codes, we identify speech acts and rhetorical figures in brand posts, and then assess their differential impacts on virality indicators such as retweet counts.

Based on an empirical assessment of a longitudinal dataset (eight months) of brand post in twitter (14.000 *brand tweets* across eight Fortune 100 brands). The accounts used for this study were Disney, McDonalds, Nike, Ford, Coca Cola, Walmart, Amazon and Tesco.

Models

Due to the nature of our datasets are mainly counts, we cannot assume a normal distribution. Consequently our three models use logarithmic transformations when a variable is based on count data.

Model 1: Dependent Variable: Number of Retweets per Brand Tweet. The unit of analysis in this model is single tweets posted by the eight firms. The objective was to understand with speech act will trigger more retweets (sharing behaviors).

$$\boldsymbol{RT_{ij}} = \alpha + \beta_1 D\_Desire_{ij} + \beta_2 D\_Action_{ij} + \beta_3 D\_Commitment_{ij} + \beta_4 Repetition_{ij} + \beta_5 Aliteration_{ij} + \beta_6 Wknd_{ij} + \beta_7 D\_Questions_{ij} + \beta_8 Picture_{ij} + \beta_9 URL_{ij} + \beta_{10} Follower\ Count_{ij} + \epsilon_{ij}$$

Model 2: Dependent Variable: Daily Number of Retweets per Brand Tweet. The unit of analysis in this model is an aggregated (sum) number of tweets posted by firms on each of the aforementioned speech acts and rhetorical forms. The objective was to understand in a daily basis whether content concentration (e.g. only twitting directives) and time concentration (twitting only in concentrated hours such as after work) will trigger more retweets daily.

$$\boldsymbol{RT_{ij}} = \alpha + \beta_1 Attention_{ij} + \beta_2 Desire_{ij} + \beta_3 Action_{ij} + \beta_4 Commitment_{ij} + \beta_5 Repetition_{ij} + \beta_6 Aliteration_{ij} + \beta_7 Content\ Concentration_{ij} + \beta_8 Time\ Concentration_{\ ij} + \beta_9 Number\ of\ Tweets_{ij} + \beta_{10} Wknd_{ij} + \beta_{11} Questions_{ij} + \beta_{12} Follower\ Count_{ij} + \epsilon_{ij}$$

Model 3: Dependent Variable: Number of Retweets per type of speech act (e.g. assertives). The units of analysis in this model are single tweets posted by firms on each of the aforementioned speech acts and rhetorical forms. The objective was to understand in which sequences of content (e.g. what is better to post a desire tweet followed by attention or vise-versa). The results for this model are still in progress therefore there are not reported here.

$$\boldsymbol{RTAttention_{ij}} = \alpha + \beta_1 Lag\_D\_Desire_{ij} + \beta_2 LagD\_Action_{ij} + \beta_3 LagD\_Commitment_{ij} + \beta_4 Repetition_{ij} + \beta_5 Aliteration_{ij} + \beta_6 Wknd_{ij} + \beta_7 LagD\_Questions_{ij} + \beta_8 Picture_{ij} + \beta_9 URL_{ij} + \beta_{10} Follower\ Count_{ij} + \epsilon_{ij}$$

FINDINGS

Descriptives:

- From a total of 14000 tweets 3920 (28%) are assertions (to drive attention), 980 (7%) questions, 700 (5%) expressives (to trigger desire), 280 (2%) commitments from the brand and 8120 (58%) directives (calls to action).
- 4% of tweets have a form of repetition (e.g. “come come this is your last day”)
- 35% of tweets use alliterations (e.g. “grown cheese for grown-ups”)
- Brands posts range from 1 to 127 tweets a day.
- In total 611 combinations of speech acts (attention, desire, action, commitment) per day.
- Brands post an average of 8 tweets per day.

Results Model 1:

Variables	M1	M2
(Intercept)	-16,54***	-1,63***
Desire	0,09	0,10
Action	-0,43***	-0,57***
Commitment	-0,08	-0,07
Word Repetition	0,12'	0,07
Alliteration	0,09**	-0,10*
Action_Repetition		0,16
Action_Alliteration		0,34***
Weekend	-0,14***	-0,13***
Questions	-0,21***	-0,19***
Picture	0,26***	0,27***
URL	-0,47***	-0,46***
LN_FollowersCount	1,47***	1,46***
LN_HashtagCount	0,38***	0,38***
LN_AttCount	0,37***	0,36***
D_Coke	0,16'	0,15'
D_Tesco	0,97***	0,96***
D_Walmart	-0,65***	-0,67***
D_Amazon	-2,24***	-2,23***
D_McDonalds	-0,08	-0,10
D_Ford	0,02	0,02
D_Nike	-0,07	-0,09
RSquared	**0,60**	**0,61**

0'***'0.001'**'0.01'*'0.05’

Results Model 2:

Variables	M1	M2	M3
(Intercept)	5,02***	5,75***	4,02***
LN(Attention_Count)	0,09	-0,08	-0,08
LN(Desire_Count)	0,47***	0,24*	0,27*
LN(Action_Count)	-0,29**	-0,45***	-0,46***
LN(Commitment_Count)	-0,09	-0,25’	-0,20
LN(Repetition_Count)	0,23***	0,24***	0,24***
LN(Alliteration_Count)	0,00	0,01	0,01
Content Concentration		-1,31***	1,6
Time Concentration			0,13**
LN_NumbTweets	1,04***	1,04***	1,04***
Weekend	-0,21**	-0,21**	-0,21**
LN(Question_Count)	-0,22**	-0,43***	-0,40***
RSquared	**0.6109**	**0.616**	0.6178

0'***'0.001'**'0.01'*'0.05’

DISCUSSION AND RESEARCH IMPLICATIONS

Considering the prevalence conversational channels in social media, we theorize on speech acts and rhetoric’s to advance research into brand communications and online virality in three ways.

First, by classifying online brand messages into attention, desire, action and commitment (Searle 1976) we provide clarity in terms of what marketing communicational intentions drive more virality in social media. Although marketing research has shown that high arousal emotional content is more viral, no previous study has elaborated on what marketing intentions more effective in online platforms. We proceed to this analysis by using text-preprocessing and supervised machine learning algorithms to detect multiple classes of speech acts (Zhang, Gao, and Li 2011). Interestingly we found that when companies explicitly seek to drive behavior through calls to action (directive acts) consumers are less prone to share. Contrary we found that tweet designed to trigger attention (assertive acts) are preferred by consumers.

Second, we contribute to research in online brand communications by looking at how rhetorical figures (e.g. word plays) can enhance virality. Current literature claims that virality changes are explained due to differences on psychological properties of literal language (Chung and Pennebaker 2007), relaying heavily in the use of word dictionaries but disregarding other communicational devices such as language structure (Berger and Milkman 2012; de Vries, Gensler, and Leeflang 2012). We address these shortcomings by assessing the presence of rhetorical figures in schematic form (e.g. Alliteration: “grown cheese for grownups”) (McQuarrie and Mick 2003), using regular expression codes (Villarroel O. et al. 2014). Then by assessing their presence (absence) in brands’ original tweets and posts, we evaluate their influence on virality. In particular we find using rhetorical figures can enhance the performance calls to action (directive acts). This has strong implications

Third, by analyzing content concentration and sequences, we advance research on social media communication. We found that concentration is a key element that content manager specialist should pay attention to. Our study shows that consumers seek for content variety and as soon as they see that a company provides monothematic intentions (only posts calls to action such as “please share”, “follow us”, “buy this”) then consumers tend to not share their content.

Conclusion

Our research contributes to the literature on virality by extending the understanding how varying marketing intentions affect content sharing behaviors. Furthermore, we extend findings in advertising research by demonstrating the persuasive effects of rhetorical repetitions in online brand communications. Finally, by analyzing content concentration and sequences, we advance research on social media communication. For marketing managers we provide an actionable framework to organize social media content suggesting tactics about what, how and when social media content should be posted.

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