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Patterns of Facial Expressions of Speakers in Banks' YouTube Videos

Predict Video's Popularity Over Time

Abstract

There has been little focus on nonverbal communication in social media advertising campaigns. We propose that specific patterns of facial expressions predict the popularity of YouTube's video among users of social media. To test that, we used a neuromarketing tool – FaceReader - to code facial videos of professional speakers who participated in social media campaign on YouTube of two big commercial banks. We analyzed more than 25,000 frames of 16 speakers' facial expressions of two big banks. We found that less of affiliative facial emotions (happiness and sadness) and more of non-emotional expressions (surprise) explained additional 25% of variance (from 61% to 86%) in the video's popularity (number of views on YouTube), after 8 months, in t2 in comparison to t1 as the only baseline predictor. We further showed that the disaffiliative facial emotions of the speakers (anger, fear and disgust) did not contribute as an indicator of the future performance of social media content. We provide speculation on possible mechanisms and practical implications.

Keywords: social media, YouTube, nonverbal communication, facial
expression, emotions

Submitted: 20 July 2015

Introduction

Nonverbal communication is an important aspect of presenting the message and transmitting information (Jones and LeBaron 2002). A specific type of social media that seems especially relevant for nonverbal communication is video-sharing websites, such as YouTube. This is because video communication allows social media users to see the source, which presents the message. When users can see people talking, users evaluate not only *what* is being said but also *how* people are saying it, which arguably constitutes what Singh and Sonneburg (2012) referred as an improvisation theater metaphor. In this paper, we literally (and only) focus on the *how* element of social media communication because arguably, such form of communication is understudied in corporate communication in social media, though it still constitutes an essential part of storytelling of brand in social media (Singh and Sonneburg, 2012, p. 17; the content vs. process).

We believe that by studying facial expressions of speakers who do not expect to have their expressions judged by an objective software, we tap more easily into, what Buck and VanLear (2006) call, *spontaneous communication*. This is “the nonintentional communication of motivational-emotional states based upon biologically shared

nonpropositional signal systems” (p.522). This is especially important aspect of nonverbal communication as compared to pseudo-spontaneous displays, which involve strategic and intentional manipulation of one’s nonverbal behavior which may try to “control the receiver’s response in accordance with the intended message or other social goals” (p. 526).

Importantly for the study of nonverbal communication, facial expressions are difficult to control spontaneously (see Gosselin, Perron, and Beaupré 2010 on the voluntary control of facial action units in adults). This therefore renders them more “truthful” source of information (Ekman 2003; Ekman and O’Sullivan 1991). We propose that paradoxically such spontaneous nonverbal communication as facial expression relate better to ever-cautious users of social media. For example, Labrecque, vor dem Esche, Mathwick, Novak and Hofacker (2013), show that such social media users have considerable power in the digital age. Consider as an example a number of video views on YouTube, next to a corporate video message of a particular company. We argue that this number of video views is a reflection of social media users’ interest and hence the video’s popularity. Therefore, popularity of the firm’s message is directly dependent on how many times people chose to watch it.

Another reason to focus on facial expressions is because the richest source of nonverbal behavior is human face. People can make up to 10,000 combinations of facial movements (Ekman and Rosenberg 1997) and the face is easily accessible for others to look at it (e.g. Carroll and Russell 1996). Face is often studied in context of facial emotions, which are not any random expressions but expressions, which have affective or emotional meaning (Ekman, Sorenson, and Friesen 1969; Ekman and Cordano 2011). Facial expressions are assumed to reflect the six basic emotions (happiness, sadness, anger, fear, disgust and surprise; Ekman & Friensen 1986).

Happiness is clearly a positive emotion and sadness is clearly a negative emotion (Russell, 1980). Surprise is ambiguous in terms of emotional valence (Russell, 1980), however it is most “cognitive” of basic emotions (Lorini & Castelfranchi, 2009) and often considered *not* to be a (basic) emotion (Ortony & Tuner, 1990) and more of a cognitive appraisal (Frijda , Kuipers, & Ter Schure, 1989), indicating heightened attention (Smith & Ellsworth, 1985). Thus, in this paper, we assume that surprise is not an emotion. Furthermore, happiness and sadness are affiliative emotions generating approach tendencies towards the person expressing them, by person who is watching (Frijda & Tcherkassof, 1997; Frijda, 2010). For example, when a people smile or are sad, they invite an

approach to either share the joy or be consoled. Expression of happiness and sadness are defined to correspond mainly to FACS's (Ekman, Friesen & Hager, 2002) Action Unit 12 (lip corner puller) and Action Unit 15 (lip corner depressor), which are two antagonistic muscle movements as the names indicate (EMFACS-7, Friesen & Ekman, 1983). This means that it is extremely difficult to show the two emotions at the same time, as the muscles are working in opposite directions. This adds further support that happiness and sadness, even though affiliative emotions, can explain unique variance in other behavioral measures (e.g. popularity as in this study). Anger, fear and disgust are clearly negative emotion (Russell, 1980), with dis-affiliative tendencies (Frijda & Tcherkassof, 1997; Frijda, 2010). Surprise is judged to be ambiguous as to expression of (dis)affiliation.

In nonverbal behavior, not only presence and intensity of a facial emotion is important but also lack of emotion is also very informative and even expected (see Fernández-Dols, Carrera, Barchard, & Gacitua 2008), i.e. sometimes, less of emotions can be more. However, the face should also not be simply blank as very neutral faces because it can look threatening (e.g. see Lee, Kang, Park, Kim, & An, 2008). Therefore, in certain context (e.g. in corporate communication of banking industry), a certain "tension" is created, a people who communicates the company's

message should not show emotions in their faces but they also should not have a blank face. This a proposition we set to test in this paper. We make a critical distinction between specific facial expressions that indicate antagonist emotions yet are similar in terms of affiliation (happiness and sadness), non-emotional facial expression (surprise) and dis-affiliative emotional expressions (anger, fear and disgust) as explained above.

We believe this proposition might be especially important in the case of corporate communication. Likely social media users do not expect certain facial expressions (especially emotional expressions) to be present in professional actors (or speakers) display who present the firm's *informative* message. We also assume that certain professional groups such as bankers are not really expected to show happiness or sadness while presenting firm's message or information (Percy, 2014). Banking industry is assumed to cultivate a "serious" image (at least the two banks, we selected – ING and ABN AMRO) (Percy, 2014). There is no reason to show *emotions* while taking in a professional and only informative context (as in contrast in advertising or sales context) but there is *no* reason to *not* show anything in the face neither. Therefore, we hypothesize and test in this study if less of expression of happiness and sadness in the facial emotions of bankers leads to higher popularity of a video message while presence of non-emotional facial expression has a positive effect. In other

words, the less emotional facial expression (happiness and fear) and the more non-emotional facial expressions (surprise) the less popular the video is.

Study

Method

Video selection. First author went through YouTube channel playlist that featured campaigns of big banks with front-up, forward facing, talking speakers and had good lighting. The author identified 10 out of 28 available videos from the same campaign – “ING Private Banking” and 6 videos from ABN AMRO campaign targeted at English-speaking expats living in the Netherlands, which met such criteria. Such criteria was necessary to use our automatic facial coding software. In the ING campaign, the speakers were talking in Dutch over topics related to private banking, such as purchasing power, testaments or spending patterns. In ABN AMRO campaign, the speakers were talking in English about banking issues especially important to expatriates living in the Netherlands (e.g. opening a bank account, applying for a mortgage or using a credit card). On average the video lasted 91.25 seconds ($SD = 9.20$), i.e. 2281.18 frames ($SD = 221.89$). In total, the videos contained 36499 frames.

Facial expressions. In order to measure facial expressions of the speakers, we used FaceReader, version 6.0 (Noldus 2014), which is a software that automatically codes six basic facial emotions. For each emotion, it assigns a value from 0 to 1, which indicates intensity and probability of that emotion. FaceReader works in three steps; first, it detects the face. Second, through the Active Appearance Model it creates a 3D superimposed model of a face with 500 hyperconnected tracking points. In the last, most important stage, FaceReader uses 3-layer feed-forward hidden neural network, trained on more than 10,000 of images depicting basic emotions, to recognize an emotional expression of the person. For detailed algorithmic description of the software analysis process, see van Kuilenburg, Wiering and den Uyl (2005). Importantly, accuracy rate of recognizing basic emotions of 89% for FaceReader 1.0 (den Uyl and van Kuilenberg 2005) and 88% for FaceReader 6.0 has been reported (Lewinski, den Uyl, & Butler, 2014). This neuromarketing tool has been successfully used in consumer (de Wijk, He, Mensink, Verhoeven, & de Graaf, 2014), marketing (Lewinski et al., 2014) or psychology research (He, Boesveldt, de Graaf, Wijk, 2014).

We used a measure of facial expressions, which took into account the most intense periods of showing an expression. The most intense periods of facial expressions were defined as an average of 10% of the

highest values of probability and intensity of facial expressions per frame. This measure has been validated by Lewinski, Fransen and Tan (2014).

The software was not able to analyze 10074 out of 36499 frames (27.6%). This was due to different technical reasons mostly because the software could not detect the face or model it properly - the actors were moving their heads or the face was shown from angle higher than 45°. See Figure 1 for visualization of the FaceReader analysis of a facial emotion of a speaker.

--- Figure 1 about here ---

Number of video views. On YouTube channel, the number of video views is reported for each video. We accessed this number of video views on two points in time, first on 31 October 2014 (t1) and then on 14 July 2015 (t2). The number of video views is assumed to be an objective and behavioral measure of video's popularity and possibly virality. Eight months of difference between t1 and t2 was judged as sufficiently large period to predict popularity of the video from a baseline at t1. There was a high positive correlation between the t1 and t2, $r(10) = .82, p < .01$ (two-tailed), indicating that number of views is a stable measure of popularity.

Results

Table 1 provides mean, standard deviations and minimum and maximum values of all dependent (video views in t2) and independent variables (video views in t1, happiness, sadness, surprise, anger, fear and disgust).

.--- Table 1 about here---

A linear regression was run to predict number of video views in t2 from number of video views in t1. This variable statistically significantly predicted number of video views in t2, $F(1, 14) = 24.50$, $p < .0005$, $\text{adj. } R^2 = .61$. Number of video views in t1 accounted for 61% of the explained variability in number of video views in t2. We assume this to be a baseline prediction.

A multiple regression was run to predict number of video views in t2 from number of video views in t1, and facial expressions of happiness, sadness and surprise. These variables statistically significantly predicted number of video views in t2, $F(4, 11) = 24.46$, $p < .0005$, $\text{adj. } R^2 = .86$. All four variables added statistically significantly to the prediction, $p < .05$. Number of video views in t1, facial expression of happiness, sadness and surprise accounted for 86% of the explained variability in number of video views in t2. Therefore, we explained additional 25% in variance from the baseline prediction.

Regression coefficients and standard errors can be found in Table

2. The values from the Table 2 indicate that for each 1 unit decrease in happiness, there is an increase in video views in t2 by 252.52. Similarly, for sadness, an decrease of 1 unit equates to a 742.65 increase in video views in t2. However, for each 1 unit increase in surprise, there is an increase in video views in t2 by 198.75.

.--- Table 2 about here---

As a check, a multiple regression was run to predict number of video views in t2 from number of video views in t1, and facial expressions of happiness, sadness, surprise as well as anger, fear and disgust (i.e. all basic emotions). These variables statistically significantly predicted number of video views in t2, $F(4, 11) = 24.46$, $p < .0005$, adj. $R^2 = .84$. However, only first four variables (i.e. the same variables as in previous regression) added statistically significantly to the prediction, $p < .06$. Therefore, anger, fear and disgust did not explain any additional variance ($p > .32$). Regression coefficients and standard errors for this additional analysis can be found in Table 3.

.--- Table 3 about here---

Discussion

We found that the *lack* of facial emotions and the *presence* of facial non-emotions were important indicators of video's popularity. The less of affiliative emotions (happiness and sadness), the more popular the video was. The more of non-emotions (surprise), the more popular the video was. We ran the study and we confirmed the hypothesis in a novel way. We used two objective measures of behavior: automatically coded facial expressions and a number of views of YouTube videos. We strategically did not use any self-reported measures in order to demonstrate automatic and unobtrusive method of predicting video's popularity.

We found that less of affiliative facial emotions (happiness and sadness) and more of non-emotional expressions (surprise) explained additional 25% of variance (from 61% to 86%) in the video's popularity (number of views on YouTube), after 8 months, in t2 in comparison to t1 as the only baseline predictor. We further showed that the disaffiliative facial emotions of the speakers (anger, fear and disgust) did not contribute as an indicator of the future performance of social media content. As a speculation on possible mechanism, we note that this could be because people do not expect from banker to show affiliative emotions. On the

other hand, disaffiliative emotions are simply not acceptable in any company-consumer interaction and are simply ignored by social media users as atypical instances or simple artefacts of spontaneous facial behavior. This plausible process needs though further testing.

Theoretical Implications

Theoretically, our findings are novel because they show that the less of certain emotional expressions is an important indicator of the performance of social media videos. As Singh and Sonneburg (2012) indicated the difference between the content (what) vs. process (how) in performance of brand in social media, we successfully predicted most of variance just from *how* the content was shown. From this study, we cannot yet conclude what is the precise mechanism behind this finding. We may only speculate about this further, as we partially did in the introduction.

However, one important theoretical insight is that facial expressions lead to lower popularity and not that lower popularity changes facial expressions. Because the facial videos were recorded *before*, we can now prove a causal link of facial expressions *leading to* a change in video popularity in time t2. Our finding relates to similar finding in advertising research where facial expression also predicted liking for a video stimuli and *not* liking predicting the facial expression (Lewinski et al. 2014). This

all adds further support to the idea of Buck and VanLear (2006) that spontaneous nonverbal communication of a people (such as facial expressions) is a “true” indicator of their internal emotional-affective states. This is why *their* facial expressions are predictive of *other* people’s motivational responses such as popularity or liking. This is presumably because such expressions do not try “control the receiver’s response” (p. 526) and hence they may resonate with people easier than controlled forms of nonverbal expressions. However, this is just a speculation.

Further, we hypothesized that speakers should show as little as possible of affiliative emotions (happiness and sadness), while still being expressive (surprise) because we assumed that this is what the social media users expected. Another possible explanation is assumption made by social media users who watched the videos. It could be that some of the users assumed the speakers to be employee of the bank while others thought they were just actors. However, these proposed explanations, even though reasonable, were not tested in this paper and should be tested in the future.

Limitations

One of the limitations of our findings lays in a small sample of YouTube videos, as only 16 videos were available and eligible for this

analysis. However, what must be taken into account is that it is difficult to find appropriate facial videos for analyzes with facial coding software as the videos must meet specific criteria (see Method section). This limitation has been somehow mitigated by relatively many data points analyzed in the data set (more than 25,000 frames successfully analyzed). Noteworthy, our method saves time considerably if compared with manual coding. Assuming that a human coder would take 1 minute to code seven basic for each frame it would take more than 300 hours of manual coding to code our material and therefore a substantial money and time investment. In any case, we suggest replicating our findings with a bigger sample of videos in more diverse settings (e.g. different banks, markets and countries).

Another limitation stems from the applied methodology. The number of video views could have been influenced by number of factors, which we did not control for. The videos differed in terms of content, the order in the playlist, release date as well as different actors present and such factors could have influence the results. For example, Gorn, Jiang and Johar (2008) showed that “babyfaces” of actors, lead to inference of different traits of the speakers and hence change people’s response to public relations communications. Further, even with ignoring the qualitative content of the messages, we managed to achieve a high explanatory power by using the facial expressions of the speakers.

However, we did not control for those and many other possible explanatory factors, we successfully showed a model that explained up to 86% of variance in video's future popularity and only 14% of variance was left unexplained, which we judge to be a relative small value.

Further, only videos from banking industry were analyzed and the hypothesis were matched to that context. This means that possibility of generalization beyond this specific context might be limited.

Practical Implications

Importantly, to our knowledge this is the first time ever that this technique has been applied to YouTube videos in corporate channels of big firms. This method opens up a new and exciting avenue of studying nonverbal communication in corporate settings. Further, it is easy to imagine analyzing nonverbal behavior in different contexts (e.g. presidential debate or news presenter). With our method, we show the first proof-of-concept at work, its possible applications and interpretations. Such analysis of emotional face behavior of actors in company's message or advertisement could be for example used to build and measure brand value, an added to social media metrics guidelines (e.g. Peters, Chen, Kaplan, Ognibeni & Pauwels, 2013). In fact, first steps are taken into that direction, e.g. by a start-up called Media Distillery (see

www.mediadistillery.tv). In principle, such analysis could be automated and applied to all video-material around internet (e.g. YouTube, Vimeo) but also to monitoring of TV channels 24 hours a day, 7 days a week. The basic applied idea stemming from this proof-of-concept study, would be combine such analysis with a system, which would automatically detect the appearance of specific people on TV (politicians in general, government, famous people, etc), emotional expression (basic emotions, arousal, valence, confusion, etc) of the speakers (both specific people but also everyone appearing on TV) and statistics on the demographics of people appearing on TV (average age, gender, etc). Next step would be to correlate such statistics with other metrics. (e.g., popularity, awareness, likeability, etc.) such as we report in this study.

Further, we contribute to practice of corporate communication. Firms must pay attention to not only what is verbally expressed in the video communication but also how the speakers behave with their body. To our understanding, practice of teaching “proper” nonverbal behavior to key representatives is rather rudimentary. We show convincing evidence that patterns of facial expressions are important to consider during social media campaign and when company speakers are “out in the public” as much as what they say (Riff, Lacy, & Fico, 2014) and what cloths they are wearing (Shao, Baker & Wagner, 2004). To sum up, our findings are

intuitively easy to understand. In the case of professional institutions such as banks, simple and non-emotional message is what potential customers, such as social media users, find most noteworthy to watch.

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Figures

Figure 1. Visualization of the FaceReader analysis of a facial emotion of three speakers. To see FaceReader video visualization see - youtu.be/cvjHHD_qgEU

Tables

Table 1. Descriptive statistics

Valid cases = 16; cases with missing value(s) = 0.

<i>Variable</i>	<i>N</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Minimum</i>	<i>Maximum</i>
Video Views - t2	16	362.25	179.14	128.00	716.00
Video Views - t1	16	157.31	115.53	53.00	479.00
Happiness	16	.44	.20	.06	.74
Sadness	16	.06	.15	.00	.51
Surprise	16	.65	.30	.13	.99
Anger	16	.38	.23	.05	.87
Fear	16	.04	.06	.00	.17
Disgust	16	.47	.20	.20	.86

Table 2. Summary of Multiple Regression Analysis with Hypothesized Predictors

Coefficients (Video Views - t2)

	<i>Unstandardized Coefficients</i>		<i>Standardized Coefficients</i>	<i>t</i>	<i>Sig.</i>
	<i>B</i>	<i>Std. Error</i>	<i>Beta</i>		
(Constant)	87.19	72.84	.00	1.20	.254
Video Views - t1	1.92	.21	1.24	9.18	.000
Happiness	-252.52	90.88	-.29	-2.78	.018
Sadness	-742.65	170.06	-.61	-4.37	.001
Surprise	198.74	62.94	.34	3.16	.009

Table 3. Summary of Multiple Regression Analysis with All Basic Emotions

Coefficients (Video Views - t2)

	<i>Unstandardized Coefficients</i>		<i>Standardized Coefficients</i>	<i>t</i>	<i>Sig.</i>
	<i>B</i>	<i>Std. Error</i>	<i>Beta</i>		
(Constant)	46.94	142.04	.00	.33	.749
Video Views - t1	2.06	.25	1.33	8.14	.000
Happiness	-316.88	150.21	-.36	-2.11	.068
Sadness	-1043.57	315.51	-.85	-3.31	.011
Surprise	265.60	95.89	.45	2.77	.024
Anger	-152.56	145.19	-.19	-1.05	.324
Fear	553.86	665.42	.19	.83	.429
Disgust	114.99	109.68	.13	1.05	.325