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The Defining Features of Emotions in Online Stories

Online storytelling has become a powerful destination promotion strategy as it effectively conveys information and involves travellers emotionally through inspiring imagination. In this study, we use sentiment analyses to examine the emotion structures conveyed by 60 online stories related to various American destinations. We further examined the relationship between these key features and an important measure of story performance, the average length of time spent on the webpage reading the story. The results of these analyses demonstrate that emotion arousal levels at the start, peak and final stages of the story are significant predictors of reader involvement. The results of this research are consistent with the work by Kahneman and his colleagues and provide a valuable foundation for designing story-based online advertising.

Key words: Tourism advertising, Storytelling, Story structure, Sentiment analysis, Emotions

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Introduction

Destination websites are one of the main tools for destination promotion (Benckendorff et al., 2014). Indeed, online storytelling has become a powerful approach to destination promotion since it builds close emotional connections with tourists through narratives while delivering information (Tussyadiah and Fesenmaier, 2008; Tussyadiah et al., 2011). An essential element of an online story is the emotional structure, which supports the essence of the destination brand (Bagozzi et al., 1999). That is, stories generally follow a five-stage process (e.g., exposition, rising action, climax, falling action, and resolution) which, depending upon the plot, seeks to engender different emotions at different times and at different levels (Reagan, et al., 2016). Following from this literature, it is argued that the various strategies (i.e., plots, etc.) to evoke emotions in the story affect how readers evaluate the story, which in turn, affects perceptions of the destination. With the development of machine learning techniques, sentiment analysis has become a powerful tool with which to detect the emotional appeals within advertising stories (Höpken et al., 2017; Reagan et al., 2016). With this background, we first assessed the emotion structure of 60 online stories used to promote 12 different destinations in the United States using sentiment analysis; we then correlated the emotional structure of these stories with a key measure of performance - the extent to which the viewers actually read the story. The results of this study demonstrate that key features (e.g. emotion arousal levels at the beginning, peak and end of the story) significantly correlate with reader involvement in online stories.

Literature review

Destination websites are considered one of the main tools for destination promotion (Benckendorff et al., 2014). Further, storytelling has become a powerful strategy in destination marketing as it conveys not only informative contents but also emotional and attitudinal information which engages tourists mentally in a narrative world and "transports" them to the destination (Tussyadiah and Fesenmaier, 2008; Tussyadiah et al., 2011). Further, studies indicate that emotions substantially affect an individual's motivation, memory, attitude, interactions and behaviours (Bagozzi et al., 1999). Therefore, understanding the emotions conveyed in stories is essential to learning about how to design and incorporate stories into destination marketing campaigns (Izard, 2010; Moors et al., 2013).

Given the limitations of traditional self-report methods, researchers have begun to develop a series of more objective and unbiased approaches to assessing the emotions raised by the advertising including stories (Kim and Fesenmaier, 2015). Text-based sentiment analysis has been gaining a great deal of attention from industry and academia as a relatively inexpensive tool with which to assess emotions. Sentiment analysis is a text mining technique which can be used to assess the semantic expressions in a corpus of text and then classify them into different categories (i.e., positive and negative; or an n-point scale) based on the semantic orientation of the words (Höpken et al., 2017; Pang and Lee, 2008). Studies have shown that machine learning-based sentiment detection can help to understand how readers (i.e., potential travellers) respond emotionally to travel-related stories (Reagan et al., 2016). Studies comparing the results of emotional response to advertising using the traditional self-report methods and sentiment-based text analysis show that the latter approach (i.e., sentiment analysis) is resistant to subjective biases and is especially efficient when it comes to measuring emotions in large volumes of text (Mauss and Robinson, 2009; Liu, 2012; Xiang and Fesenmaier, 2017).

Further, research shows that the emotional structure of stories affects to a large extent how one experiences and therefore remembers the story. Indeed, the work of Kahneman and his colleagues (Baumgartner et al., 1997; Fredrickson and Kahneman, 1993; Kahneman, 2011) clearly demonstrate that these features of emotional response (often referred to as heuristics) correlate highly with viewer involvement, satisfaction, and happiness. Further, according to the narrative transportation theory, research indicates that the narratives of a story can create experiences that absorb the readers into it and 'transports' them into an imaginary world (Escalas, 1998). As such, readers lose a sense of time and self-awareness (Busselle and Bilandzic, 2008). Thus, based upon this research, this study used sentiment analysis to detect the text-based emotional cues in web-based destination marketing stories with the goal of linking the structure of these emotional cues to a key measure of story performance - the extent to which viewers actually read the story.

Methods

This study examined the emotional structure of 60 online stories which describe 12 states and cities located throughout the United States. The stories were designed and implemented during 2017 - 18 by a destination marketing company and vary in length, focus, logic, and story structure. This study adopts a two-stage analytic process where the first stage focuses on assessing the overall emotions raised in 60 online stories using sentiment analysis. Due to the variation in the length of the stories, the text comprising each story was broken into deciles (10 parts) based on the number of sentences and thus generated 10 sentiment scores to describe the overall emotional structure of a story (see Fig. 1). Sentiment analyses were first conducted at the sentence level and then aggregated into the deciles for each story. This process of deconstruction and analysis followed the procedures developed by Regan et al. (2016). This analysis used the dictionary developed by NRC (National Research Council Canada) Emotion Lexicon (referred to as EmoLex), which is a list of English words and their association with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy and disgust that identified by Plutchik) and two sentiments (positive and negative) (Mohammad and Turney, 2013). EmoLex was originally designed using responses obtained through Mechanical Turk wherein respondents were asked to assign emotions to a variety of words and has scores ranging on a continuous scale from -5 to 5.

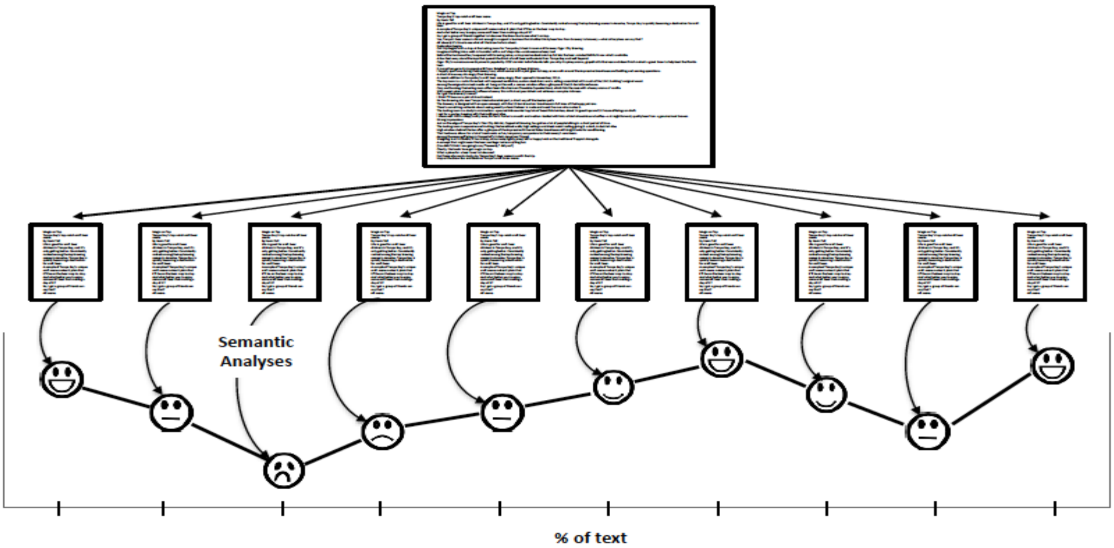

Figure 1. Schematic of how the stories were broken down for sentiment analyses

The first set of analyses was conducted using R where EmoLex has been implemented (Mohammad and Turney, 2013) so as to calculate various measures of story structure such as emotional level at the start, peak, end, trend and duration; further, the location of the "peak" was calculated as the distance from the peak sentiment to the beginning of the story. Further, the time readers spent reading the respective stories was obtained using Google Analytics. The second phase of the study used multiple regression analysis to estimate the relationship between the respective measures (e.g., start, peak, end, trend and duration) and the average time readers spent reading an online destination story. In this analysis, the average time spent reading an online story was transformed using a natural log transformation.

Results

The results of the first phase of this study are illustrated in Table 1 and indicate that the 60 destination stories differ significantly in terms of length, average time spent, emotions, the intensity of the emotional peak, and the location of the emotional peak. Specifically, the length of stories ranges from 19 sentences to 140 sentences. The average time spent on reading these stories ranges from 28 seconds to 735 seconds (M=212.75, SD=158.70). Each story shows diverse emotional patterns, especially at the final stage – 80% of the story (SD=4.57) and 100% of the story (SD=4.42). On average, the stories tend to have emotional peaks (maximum sentiment scores) at the beginning – 20% of the story (M=5.98) and the end – 100% of the story (M=6.18) (see Fig. 2); additionally, maximum sentiment intensity (M=6.07, SD=2.63) and its location within the story are different, indicating the emotional structure of online stories differ quite substantially.

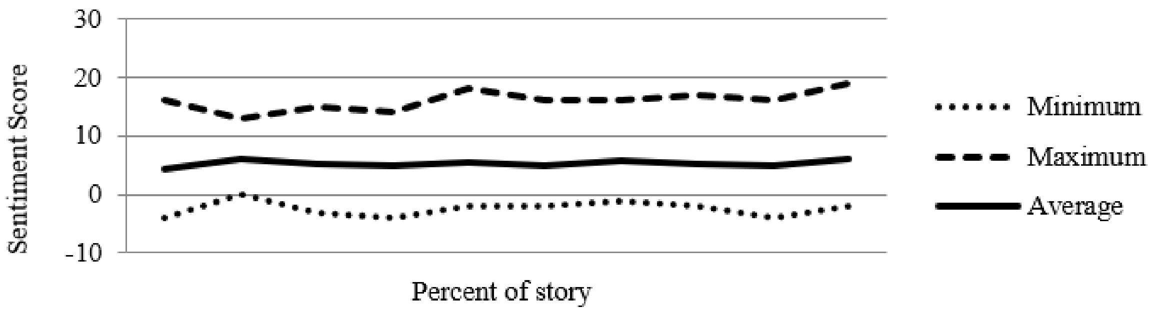

Figure 2. Variation in Emotions across the stories

Multivariate regression analysis was then used to assess the relationship between key characteristics of online stories (e.g., start, peak, end, duration, and variation) and the log average time spent reading the destination stories. The results are presented in Table 1 show that the various measures of structure explain 97% of the variation in the average time spent (R^2 =.97, Adjusted R^2 =.96, df=11, f=89.22, p=.000). It is noted that the relatively high explanation power (R^2) is, in part, due to the *exclusion* of a constant based upon the assumption that the average time spent reading the story would be near 0 if all independent variables have a value of 0. The results of the regression analysis indicate the variation of emotions at 20% (β=0.10, *p*=0.04), 30% (β=0.09, *p*=0.02) and 80% (β=0.09, *p*=0.03), and maximum sentiment intensity (β=0.26, *p*=0.00) are significant predictors of time spent reading the story. These results generally confirm the importance of some key components (start, end and peak) within the story, which is consistent with studies by Fredrickson (2000) and Kahneman et al. (1993). Interestingly, the length of the story is not a significant predictor.

Table 1: Descriptive statistics and regression results

Variable	Min.	Max.	Mean	SD	Estimate	Std. Error	t value	p value
Total Sentence	19	140	64.47	20.13	0.00	0.01	0.40	0.69
Sentiment 10%	-4	16	4.25	3.85	-0.02	0.07	-0.27	0.79
Sentiment 20%	0	13	5.98	3.06	0.10	0.05	2.08	0.04 *
Sentiment 30%	-3	15	5.23	3.97	0.09	0.04	2.33	0.02 *
Sentiment 40%	-4	14	4.90	4.13	0.01	0.04	0.28	0.78
Sentiment 50%	-2	18	5.47	4.16	0.03	0.04	0.78	0.44
Sentiment 60%	-2	16	4.80	4.10	0.01	0.04	0.21	0.83
Sentiment 70%	-1	16	5.90	3.86	0.07	0.05	1.26	0.21
Sentiment 80%	-2	17	5.25	4.57	0.09	0.04	2.22	0.03 *
Sentiment 90%	-4	16	4.77	3.62	0.01	0.05	0.18	0.86
Sentiment 100%	-2	19	6.18	4.42	0.01	0.05	0.30	0.77
Max. intensity	2.76	15.29	6.07	2.63	0.26	0.08	3.24	0.00 **
Max. location	.04	1.00	.38	.28	-0.12	0.63	-0.20	0.85
Min. intensity	-13.46	0.00	-2.55	2.43	-0.06	0.09	-0.74	0.47
Min. location	.02	1.00	.349	.26	0.82	0.56	1.46	0.15
SD of sentiment	.84	6.42	3.39	1.09	0.14	0.16	0.86	0.39

Note: DV: ln (average time spent) – Mean: 212.75, SD: 158.70, Min.: 28, Max.: 735
Maximum (minimum) intensity: Maximum (minimum) score / average score
Maximum (minimum) location: location of peak/lowest point from 1st sentence
R^2=.9701, Adjusted R^2=.9592, df=11, f=89.22, p=.000; *$p < 0.05$, **$p < 0.01$

Discussion

The results of this study confirm that the emotional levels of the beginning, peak, and the end of online story are significantly correlated with to the extent which readers actually read the story. Specifically, the stories with high overall emotional scores at the key points (start, end and peak) tend to be read more completely. However, duration showed a non-significant relationship with reading time, which is consistent with the duration neglect theory proposed by previous studies (Baumgartner et al., 1997; Fredrickson and Kahneman, 1993). This finding is important in that it enables tourism marketers to design much better online tourism advertising. Further, it is argued that sentiment analysis can be used to assess the sentiments of online text automatically and efficiently, especially when using large volumes of text. Thus, sentiment analysis appears to be a very useful tool for guiding the design of destination advertising based on storytelling; and, indeed, advanced machine learning techniques can be used, for example, to automatically generate online stories related to the optimal travel experience, which, in turn, can be very useful for the development of more persuasive recommender systems.

Several limitations exist in this study and should be addressed in future studies. This study considered only the emotions conveyed by text; thus, future studies should examine the influence of the various design elements of the website (e.g., pictures, videos, colour scheme, or etc.) on reader's response. Further, future research should combine various self-reported and/or physiological data to better capture the effect of story components on the reader's navigation behaviours. Lastly, this study considered online stories as a unit of analysis; but, if data is available, individual-level analysis could provide additional insights on how the structure of stories influences on the readers' response to online stories.

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