Analysing Social Media Marketing on Twitter using Sentiment Analysis

MAX MATTILA

HASSAN SALMAN
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Degree Programme in Computer Science and Engineering
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Supervisor: Richard Glassey
Examiner: Örjan Ekeberg
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School of Electrical Engineering and Computer Science
Abstract

Social media is an increasingly important marketing platform in today’s society, and many businesses use them in one way or another in their advertising. This report aimed to determine the effect of different factors on the sentiment in the response to a tweet posted on Twitter for advertising purposes by companies in the fast food sector in North America. The factors considered were the time of posting, the length and the sentiment of a tweet, along with the presence of media other than text in the tweet. Sentiment was extracted from samples of the response to the advertising tweets collected daily between the 27th of March and the 28th of April and plotted against the factors mentioned. The results indicate that the sentiment of the advertising tweet along with the time of posting had the biggest impact on the response, though no definitive conclusions on their effects could be drawn.
Sammanfattning

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Chapter 1

Introduction

In recent years the role of social media has expanded far beyond just dealing with our social lives. Social media platforms, such as Facebook and Twitter, now play an integral part in how we interact with politics and the world. Social media also play an important economic role, with many businesses using social media as integral parts of their marketing strategies, taking advantage of the direct interaction with consumers that social media allow. A report compiled by the Content Marketing Institute in North America[8] stated that 96% of business-to-consumer content marketers use social media for marketing purposes and some companies, such as Apple, even use social media as a part of their customer support.

The success of marketing campaigns is of great importance to the companies launching them. Social media management services, such as Sprinklr and Sprout, have already emerged with the rise of social media’s role in marketing, facilitating the planning and analysis of social media marketing campaigns. Additionally, many social media platforms provide their own research and consultation on marketing strategies for their platforms. The effectiveness of ad campaigns is often measured by brand and campaign awareness by looking at metrics such as increase in followers and mentions following the campaign, view rate and view time, as well as brand sentiment, meaning the general perception of the brand on social media, not to mention the actual sales figures of the companies in question.

Sentiment analysis and natural language processing are two additional tools that can be used in analyzing the response to and success of advertisements. They are both fields of computer science aimed
to make computers able to parse the sentiment or meaning behind language used by humans. Previous research in sentiment analysis has managed to find correlations between basketball players’ performances in games and the sentiment of the players posts on social media[17] and managed to predict stock market movements by analyzing the sentiment in social media[2]. It is therefore possible that performing sentiment analysis on the large amount of data generated daily by both consumers and businesses on social media, would grant important insight into the consumer market and the reception of marketing campaigns and the businesses behind them.

1.1 Research Question

The question this report aims to answer is in what way the following factors affect the success of a tweet posted on Twitter by a company in the fast food sector:

- Time of posting
- Length of tweet
- Sentiment of tweet
- Presence of other media (such as images or videos)

The success of a post is defined to be the sentiment of the response following the advertising tweet.

1.2 Hypothesis

The hypothesis is that the time of posting of tweets has an impact on the responses they garner. For example, a tweet posted early in the morning is expected to perform worse than a tweet posted later in the day, and a tweet posted during the weekend, when people are likely to be free from work and possibly in a better mood as a result of that, is expected to perform better than a tweet posted during the week. The presence of media is expected to have a positive impact on the success of a tweet, since fast food imagery tends to have a positive effect on our appetite.
1.3 Motivation

The results of this report could potentially grant further insight into social media marketing and the makings of a successful Twitter marketing campaign. This could impact how businesses model their advertising strategies and manage their social media, in turn having economic consequences. It is also possible that this report would grant better understanding of the relationship and interaction between businesses and consumers on social media.

1.4 Limitations

This report will only be looking at the posts of a select few fast food companies on Twitter shared between the 27\textsuperscript{th} of March and the 28\textsuperscript{th} of April. These companies are McDonald’s, Burger King, Subway, Pizza Hut, Papa Johns, Wendy’s, Taco Bell, KFC, Chick-fil-A and Domino’s Pizza. The tweets will be collected exclusively from the North American branches of the companies.
Chapter 2

Background

2.1 Social Media Marketing

Social media marketing is the use of social media to promote services and products. Big brands today use social media to a large extent in order to promote their services and products. Facebook, Twitter and Youtube are the most popular social media and are widely used by large companies for marketing purposes [15].

Social media constitute a very cheap and cost-effective marketing platform, since the usage of social media is free in most cases. The main cost for businesses is the time employees spend on planning and executing the social media marketing, as opposed to traditional media such as TV and news media, where advertising slots can be pricy. Additionally, using social media for marketing purposes means that any advertising is made available to the consumers immediately and grants the business the possibility of receiving instant feedback to the marketing efforts. [10]

While using social media for marketing has been identified as being crucial for the growth of a company, it does imply some risks for the companies and their public image. If the social media marketing is not carried out with a clearly defined plan that is in line with the existing business goals and is instead carried out in an arbitrary fashion, the potential risks are much harder to predict, and the company’s revenue can be negatively affected. [13].

So, while the cost of social media marketing is very low in comparison to the existing alternatives, its effectiveness and potential can be both an asset and a risk. It is therefore of great importance that social
media campaigns are carefully planned and that its goals are clearly identified before it is realized, in order to minimize risks and optimize the reception of the campaign and the profits accordingly.

2.2 Natural Language Processing

Natural Language Processing (NLP) is a research area that includes the development of computer programs and algorithms to analyse, understand or generate natural human language. It also includes modelling and simulation of human linguistic behaviour using computers [4]. NLP is considered as a field in Artificial Intelligence, along with computer and information science, linguistics, mathematics, electronic engineering and psychology [11]. The most commonly used methods for NLP today are based on machine learning (ML) [3].

2.3 Sentiment Analysis

Sentiment Analysis (SA) extracts the sentiment out of a text and then analyses it. By analysing the sentiment it can be determined whether a text expresses an opinion or value and, if so, which one. There are several methods in which this can be done and the most commonly used methods today are based on ML and lexicon-based methods [12].

<table>
<thead>
<tr>
<th>Sentence</th>
<th>Sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentiment analysis is fun and easy!</td>
<td>Positive</td>
</tr>
<tr>
<td>I do not like sentiment analysis at all!</td>
<td>Negative</td>
</tr>
<tr>
<td>This is a study.</td>
<td>Neutral</td>
</tr>
</tbody>
</table>

Table 2.1: Examples of sentiment in sentences

2.3.1 Methods

Sentiment classification

Classification is to allocate data into different classes. The purpose is to structure the input data into a model that can be analysed. Each piece of data is analysed and evaluated on certain attributes in order to be placed in a class. A common approach is to class data by giving it
scores on a scale from negative to positive where a more neutral score is closer to the middle.

**Lexicon-based**

To classify data into different classes, one can use a lexicon-based approach. This approach is more primitive and research indicates that it can be more effective than other more complex approaches [9]. It uses a special lexicon based on certain data where each word has a score depending on its value. The lexicon is then used to give different scores depending on words in the text and the text as a whole.

**Machine Learning-based**

The ML based approach to classify data requires training to train the classifier on a certain data set. There are several algorithms to solve this problem, but three are considered as standard algorithms; Naive Bayes, maximum entropy classification, and support vector machines[14]. The trained classifier is then used to classify text similar to the lexicon approach by giving scores to the input data.

### 2.4 Tools

#### 2.4.1 Twitter Developer API

The Twitter Developer API consists of a number of different endpoints, but the most central one to this report is the Search endpoint. Twitter offers three tiers of search APIs: standard, premium and enterprise. Out of these, only the standard API is available to all, but an application can be made to access a free sandbox version of the premium API, which is what was used in this report. When querying for tweets from the last 30 days, the query length can be up to 265 characters long and a maximum of 100 tweets will be returned per request. Furthermore, these tweets can be filtered by specifying certain parameters in the API call, such as sender, recipient or date of posting.[16]

#### 2.4.2 Vader Sentiment

Vader Sentiment (VS) is an open-source toolkit written in Python for extracting sentiment out of a text. This is a lexicon-based toolkit that
is specifically attuned to sentiment expressed in social media. The lexicon used in this toolkit is based on raw human rating scores on tokens and words and is especially attuned to microblog contexts. The scores are used together with the VS-engine algorithm’s grammatical and syntactical rules to extract the sentiments out of a text. The VS-engine gives a normalized and weighted composite score to texts on a scale from -1 to 1, where -1 is the most negative score, 1 is the most positive score and 0 is a neutral score. [7].

<table>
<thead>
<tr>
<th>Sentence</th>
<th>Sentiment score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bob is smart, handsome, and funny.</td>
<td>0.8316</td>
</tr>
<tr>
<td>Bob is very smart, handsome, and funny.</td>
<td>0.8545</td>
</tr>
<tr>
<td>Bob is VERY SMART, handsome, and FUNNY.</td>
<td>0.9227</td>
</tr>
<tr>
<td>Im very disappointed</td>
<td>-0.5256</td>
</tr>
<tr>
<td>At least it isn’t a horrible book.</td>
<td>0.431</td>
</tr>
<tr>
<td>Today SUX!</td>
<td>-0.5461</td>
</tr>
<tr>
<td>Today only kinda sux! But I’ll get by, lol</td>
<td>0.2228</td>
</tr>
<tr>
<td>Oh great.. another rainy day.. I love rainy and sad days..</td>
<td>0.128</td>
</tr>
<tr>
<td>lol, im stealing that meme</td>
<td>-0.2263</td>
</tr>
</tbody>
</table>

Table 2.2: Examples of sentiment in sentences analysed by VS

The examples from table 2.2 shows what score VS extracted from the sentences. It is shown that it manages to extract the appropriate score very well for sentences and is caps sensitive, so it will give a higher score where the positive words are upper case and vice versa. Also, it handles negated sentences and words very well. However, it does not handle humor, sarcasm and jokes so well.

### 2.4.3 Linear Regression

Linear regression is a linear approach to investigate and model the relationship between a scalar dependent variable $Y$ and independent variables $X$. In cases where there are only one independent variable $X$, the approach is called Simple Linear Regression [6]. With Simple Linear Regression, one assumes that a straight line can be adapted to the data, thus the linear model is typically stated in the following form:

$$ y = \beta_0 + \beta_1 x + \epsilon $$

(2.1)
In this form \( y \) is the dependent variable, \( \beta_1 \) is the \( y \) intercept and is calculated through this following formula:

\[
\beta_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}
\]  

(2.2)

\( \beta_0 \) is the slope of the line and is obtained through this following formula:

\[
\beta_0 = \bar{y} - \bar{x}\beta_1
\]  

(2.3)

\( x \) is the independent variable and \( \epsilon \) is the random error [18].

### 2.5 Related Work

In 2016, Ogbuji and Papazafeiropoulou [13] analysed frameworks used for social media marketing to suggest which one provides the necessary alignment between social media goals with business objectives. The frameworks are guidelines and strategies on how a business should use social media for marketing purposes and are based on different factors. Effing and Spiel [5], for example, stress that marketing campaigns need to be modeled after target audience, marketing platform and business goals and policies, and that regular contribution on the platform along with monitoring of the response is essential in developing social media strategies. The study by Ogbuji and Papazafeiropoulou found that the best way for companies was to first identify areas within the business that needs improvement and then evaluate which social media platform that should be used for marketing.

Asur & Huberman managed to predict box-office revenues of movies using sentiment analysis on Twitter. By looking at the number of tweets mentioning the individual movies and the sentiment in the tweets, the authors fit a linear regression model to the data to make their predictions, outperforming extant models such as a news-based predictor and the Hollywood Stock Exchange, which is a simulated stock market for movies that has previously been proven to serve as a good indicator for the performance of movies in the box-office. The polarity or sentiment of the tweets was noticed to have a larger impact after the movie had been released and the authors noted that “social media expresses a collective wisdom which, when properly tapped, can yield and extremely powerful and accurate indicator of future outcomes”. [1]
Chapter 3

Methods

3.1 Data Gathering

The data used in this report is comprised of tweets collected between March 27th - April 28th 2018 from the official Twitter accounts of the following companies:

- McDonald’s
- Subway
- KFC
- Wendy’s
- Pizza Hut
- Papa John’s
- Burger King
- Domino’s Pizza

Any tweet posted by the listed companies was regarded as an instance of advertising, if it was not posted in reply to another tweet. This is because most of the original tweets posted by these accounts contain at the very least some allusion to their products, while the replies are oftentimes posted for the sake of consumer interaction, either expressing gratitude for their patronage, or concern in the case that a problem has been brought up. As the focus of this report lies on social media marketing, only the original tweets of the companies (i.e. non-reply tweets) have been used in the analysis.
The tweets were collected through the Twitter Developer API. The API provides an endpoint to access the feed or timeline of specific accounts, returning only the non-reply tweets of that account. The timelines of each company were accessed daily in order to save the most recent tweet of each company for later use in the analysis of the data.

In addition to the company tweets, the response to each tweet was stored. The Twitter API does not allow direct access to the replies of a specific tweet at the free sandbox level, but it is possible to search for any tweets sent to a specific account through the Search endpoint of the API. However, a maximum of 100 tweets can be returned per request, and the number of requests that can be made is also limited. Therefore, the response to each original tweet posted by the companies mentioned above was considered to be the sample of up to 100 tweets directed at the specific company, posted within 24 hours of the original advertising tweet.

These tweets were collected through the aforementioned Search feature of the Twitter API, using the query parameter “to:[account name]”. Twitter offers the possibility to return either the most recent tweets, the most popular tweets (measured by a metric of their own) or a mix of the two. In this report the most recent tweets have been collected at each point of sampling, since the popular tweets were oftentimes posted by other business accounts and not consumers, in our experience.

3.2 Sentiment Analysis

3.2.1 Lexicon-based

Previous studies indicate that a lexicon-based approach often performs better than a ML approach on smaller texts [9]. Since the data-set used in this thesis is of the same character, a lexicon approach and the VS toolkit was used over a ML approach to extract the sentiments out of the data. As mentioned, this toolkit is specifically attuned to texts in social media contexts, which is another reason why this toolkit was chosen.

Every single tweet collected from companies was run on the VS-engine along with its replies and related tweets. A score for the company tweet was extracted as well as a mean of all scores from the replies and related tweets. This data along with data related to the
company tweet was stored for further analysis. Since this thesis aims to measure the sentiment in the response to advertising tweets, any response lacking a clear sentiment (i.e. having a neutral score) was disregarded in the analysis.

3.3 Data Analysis

The sentiment scores along with related data are analysed based on factors mentioned, in order to find correlations. Scattered plots on the sentiment scores were made based on the time and the day of posting along with the mean and standard deviation. A simple linear regression analysis was made on sentiment scores for the corporate tweets and the sentiment scores on the replies. The length of advertising tweets was also analysed with corresponding plots.
Chapter 4

Results

Figure 4.1: Distribution of advertising tweets over the week

Figure 4.2: Mean sentiment scores on weekdays, with standard deviation

<table>
<thead>
<tr>
<th>Day</th>
<th>Amt. of tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>58</td>
</tr>
<tr>
<td>Tuesday</td>
<td>46</td>
</tr>
<tr>
<td>Wednesday</td>
<td>40</td>
</tr>
<tr>
<td>Thursday</td>
<td>44</td>
</tr>
<tr>
<td>Friday</td>
<td>70</td>
</tr>
<tr>
<td>Saturday</td>
<td>29</td>
</tr>
<tr>
<td>Sunday</td>
<td>27</td>
</tr>
<tr>
<td>Total</td>
<td>314</td>
</tr>
</tbody>
</table>

Table 4.1: Distribution of advertising tweets over the week
Figure 4.1 shows the distribution of company tweets over the days of the week, starting with Monday, as well as the sentiment score of each tweet. Table 4.1 shows the total amount of tweets posted by the companies on each day of the week during the period of data gathering. Figure 4.2 shows the mean sentiment score of the response to the tweets posted on each weekday, with the red triangles marking the standard deviations. The results show that advertising tweets tend to be unsuccessful on Sundays and less successful on Saturdays and Mondays. The figure suggests that advertising tweets posted on Tuesdays and Fridays tend to have a better success rate than other days. The response to tweets posted on Fridays seems to be more volatile than others based on the fact that the standard deviation of their sentiment scores is the largest, though one should note that Friday is also the day with the most data points, as shown in table 4.1.

Figure 4.3: Distribution of advertising tweets by hour of posting  
Figure 4.4: Mean sentiment score of response by hour of posting

<table>
<thead>
<tr>
<th>Time</th>
<th>Tweets</th>
<th>Time</th>
<th>Tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>8 a.m.</td>
<td>38</td>
<td>3 p.m.</td>
<td>32</td>
</tr>
<tr>
<td>9 a.m.</td>
<td>3</td>
<td>4 p.m.</td>
<td>21</td>
</tr>
<tr>
<td>10 a.m.</td>
<td>17</td>
<td>5 p.m.</td>
<td>16</td>
</tr>
<tr>
<td>11 a.m.</td>
<td>36</td>
<td>6 p.m.</td>
<td>14</td>
</tr>
<tr>
<td>12 p.m.</td>
<td>45</td>
<td>7 p.m.</td>
<td>13</td>
</tr>
<tr>
<td>1 p.m.</td>
<td>31</td>
<td>8 p.m.</td>
<td>6</td>
</tr>
<tr>
<td>2 p.m.</td>
<td>31</td>
<td>Total</td>
<td>304</td>
</tr>
</tbody>
</table>

Table 4.2: Distribution of advertising tweets over the day
Figure 4.3 shows the distribution of advertising tweets over the day, with the X-axis marking time in UTC - 4, which is the time zone of New York, chosen because it is the biggest city by population in the USA. It is clear that most advertising tweets are posted roughly between 8:00 a.m. and 8:00 p.m. Very few tweets were posted around 9:00 a.m. during the data gathering for this report and thus the results may be less reliable. In figure 4.4, which shows the average sentiment score of the responses to tweets posted between 8:00 a.m. and 8:00 p.m. along with the corresponding standard deviations, it is shown that advertising tweets that were posted between 10:00 a.m. and 4:00 p.m. were generally more successful than tweets posted at other times.

Figure 4.5: Linear regression on company tweet sentiment score

Figure 4.5 shows the sentiment of the response to company tweets on the Y-axis and the sentiment of the advertising tweets on the X-axis.
A line has been fitted to the curve through linear regression, showing a positive correlation between the sentiment score of the response and the original tweet. The majority of company tweets are neutral or positive in sentiment, with only a handful of tweets scoring below zero.

![Graph showing mean sentiment score based on presence of media]

Figure 4.6: Mean sentiment score based on presence of media

<table>
<thead>
<tr>
<th>Amt. of tweets containing media</th>
<th>Amt. of tweets containing text alone</th>
</tr>
</thead>
<tbody>
<tr>
<td>209</td>
<td>105</td>
</tr>
</tbody>
</table>

Table 4.3: Distribution of tweets based on presence of media

Figure 4.6 shows the average sentiment scores of the response to tweets containing media such as images or videos on the right and tweets containing text alone on the left. The squares mark the mean sentiment score.
sentiment score in the response to all company tweets of either category and the triangles mark the standard deviation. As seen in the figure, the presence of media in an advertising tweet does not seem to have a noticeable impact on the success rate of advertising tweets. There are some extreme cases where the sentiment score is above normal, but generally the presence of media does not seem to have an impact on the success rate. As shown in table 4.3, about two thirds of the gathered advertising tweets contain media.

Figure 4.7 shows the response sentiment on the Y-axis and tweet length in characters on the X-axis. A line has been fitted to the data points using linear regression, suggesting that the length of the advertising tweet has a very small impact on its success.
Chapter 5
Discussion

5.1 Analysis of Results

The results indicate that the time of posting does seem to have an influence on the sentiment of the response to the advertising tweets sent out by companies in the fast food sector. Tweets posted early in the morning do perform worse than tweets posted later on in the day, partially supporting the hypothesis that was presented in section 1.3. Tweets posted in the evening also seem to perform worse than tweets posted during the day, which was unexpected. It should be noted that the differences in sentiment scores are rather small, and may not carry any significant meaning. However, even a small difference in sentiment may be relevant in proportion to the overall range in sentiment score, which is quite small. This can be seen clearly in figure 4.6, where the majority of tweets are shown to lie between -0.2 and 0.3 in sentiment value.

Another observation that can be made from the results is that the response sentiment does vary slightly over the days of the week. Interestingly, tweets posted on Tuesdays garnered the most positive response on average, though Friday was the most popular day for advertising. The sentiment scores of the responses do seem to indicate that fast food adverts are well received on Fridays as well, as was predicted in the hypothesis. The reason for this could be that people are looking forward to the weekend and are happy to find ways to enjoy themselves and spend time with friends and family, though this line of reasoning is somewhat contradicted by the decline in positivity of the response on Saturdays and Sundays.
A positive correlation could be found between the sentiment score of the advertising tweet and the sentiment of the response that it garnered. While the correlation is not very strong, it could be expected that a positive message is more likely positive response than a negative message is. With that being said, even the advertising tweets that have been categorized as negative often have a positive or humorous message. An example of this is the following tweet by Domino’s Pizza, which contains the word “steal” and has therefore been classified as negative by the sentiment classification algorithm.

“Reply with a [emoji wearing sunglasses] if you always manage to steal the last slice”

While stealing generally has a negative connotation, the concept of stealing the last slice of pizza is presented as a positive thing for the sake of humor, meaning that most people would probably interpret it positively.

The working hypothesis was that tweets containing media would receive a more positive response, but the data suggests that the presence of media does not have a noteworthy impact on the sentiment of the response. That is not to say that the presence of media in food advertising especially does not have an effect on the overall success of social media marketing, response sentiment aside.

The length of advertising tweets could not be shown to have a significant impact on the response in this report. A weak correlation was found when fitting a curve to the data through linear regression, but it is natural to assume that the length of the advertisement does have an impact on its success. Short advertisements may be limited in their content, while lengthy ones may lose the consumers’ attention prematurely. This is not something that can be measured by sentiment analysis alone, so future research may want to include likes and retweets as a measure of engagement with the advertisement. In addition to that, Twitter limits users to 280 characters, meaning that the difference in length tends to be small and its impact not as apparent.

### 5.2 Considerations

There are several factors that may have affected the results of this report, that have not been accounted for in the analysis of the data. One
such factor is the occurrence of special events during the gathering of the data, which may affect either the content of the advertising or the consumer base. Examples of events that occurred between March 27th and April 28th are March Madness (a big sporting event), the Easter holidays and April Fool’s day. Additionally, a maximum of 100 tweets were collected for each company per day and as mentioned before, the tweets were not direct replies to the original advertisement, but tweets mentioning the company after the posting of the advertisement. This means that the observed response is technically a sample of the general response to the company after the tweet, and not a response to the advertisement itself.

Furthermore, the analysis in this report only looks at the sentiment of the advertising and not the actual content or character of the tweets. It is probable that humoristic tweets would garner a more positive response than more generic tweets, which is something that is difficult to capture through sentiment analysis alone. Another consideration regarding sentiment analysis is that sarcasm, negators and humor are not picked up on in the analysis, meaning that tweets containing such things are easily misclassified.

5.3 Future Work

It would be interesting to see if similar results could be found in other sectors than the fast food sector. Would tweets posted on Fridays, for example, still see an increase in the positivity of the response? Furthermore, one could consider metrics such as likes and retweets in addition to sentiment in the analysis of the success of the advertising tweets. Using a different method of data gathering may give different and possibly more reliable results. Another interesting approach would be to apply machine learning to analyse the content of the tweets, as well as the sentiment, to get a more extensive view of social media marketing.
Chapter 6

Conclusions

The results suggest that posting positive advertising tweets during the day on Tuesdays or Fridays may increase the chances of a slightly more positive response, but no definitive conclusions can be drawn as of to what factors lead to a successful advertisement on Twitter for fast food restaurants. The presence of media in the tweet is determined to be insignificant to the sentiment of the response and the length of the tweet has only a small, albeit positive, influence on it, with data suggesting that longer tweets perform slightly better. Future research could incorporate likes and retweets into the analysis and possibly make use of machine learning to form a better understanding of business-to-consumer interaction in social media marketing.
Bibliography


