Impact of Social Media on Real Estate Sales

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Abstract. More and more businesses are using social media to promote services and increase sales. This paper explores the impact of Facebook on real estate sales. First, we examine how Facebook activities are associated with real estate sales. Then, we include time lags in our analysis, because a time lag can be expected between the activates on Facebook and a resulting real estate transaction. The results suggest that: (1) The total numbers of Facebook Likes, links, and stories are positively associated with real estate sales; (2) The sentiment score of Facebook posts is negatively associated with real estate sales; (3) Time lag affects the impact of Facebook activities on real estate sales. The results reveal the predicting value of social media and the power of selected Facebook variables on real estate sales. The research findings can be used to promote sale and forecasting.

Keywords: Decision making · Social media · e-Business · Sentiment analysis · Prediction

1 Introduction

Social media has profoundly changed our social lives and how we communicate with others [1]. Consumers from distinct backgrounds are rapidly adopting social media sites to communicate with friends and members of society and enhance their social lives [2]. Consumers who participate in social networks are feeling more empowered in their interactions with e-Businesses. After seeing the potential business value of social media platforms, many companies and e-Businesses have adopted social media sites to increase sales and revenues, increase customer loyalty and retention, create brand awareness and build reputation. For example, Ford Motor Company promoted the release of their new model Ford Focus via Facebook, Twitter and other social media sites [3].

Facebook, Twitter, YouTube, LinkedIn, Pinterest, Instagram and WhatsApp are often considered as most popular social media applications [4]. These social media applications rely mostly on user-generated contents including texts, photos, and videos. Companies can research the large amount, frequently updated social media data to mine useful knowledge, such as customer traffic, correlation between customer comments and sales. Such knowledge can be used in the decision making process later to improve customer satisfaction and increase sales [4, 5].

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Recent years, real estate companies and agents have adopted social media sites, such as Facebook business page for advertising. A Facebook business page is an excellent way to attract new clients, promote business, and get feedback from clients. However, to our best knowledge, we have not found any research on finding the impact of social media sites on real estate sales. Therefore, on one side, real estate companies and agents are uncertain about the impact of Facebook business page and Facebook activities on real estate sales. On the other side, homebuyers are uncertain about if they can use Facebook activities to predict the real estate sale trend. To this end, we are interested to address the following research questions:

(1) Is there a correlation between Facebook activities and real estate sales?
(2) To what extent are Facebook activities associated with real estate sales?
(3) To what extent can time lags affect the impact of Facebook activities on real estate sales?

The contributions of this paper are as follows: we investigate how different Facebook activities are associated with real estate sales; we examine how time lags affect the Facebook impact on the sales. This paper is organized as follows. In Sect. 2, we present an overview of relevant literature and theories, and discuss hypothesis development. We then describe research methodology including research model, data collection, and methods in Sect. 3. Subsequently, we analyze and discuss the results in Sect. 4. Finally, we discuss findings, implications and future research in Sect. 5.

2 Theories and Hypothesis Development

2.1 Using Social Media to Predict Sales

Forecasting sales is important in marketing and business. Social media is a form of collective wisdom. Asur and Huberman [6] demonstrate how to utilize sentiments extracted from Twitter to forecast box-office revenues for movies. Gruhl et al. [7] discuss how to use sales rank values and correlating postings in blogs, media and web pages to predict spikes in sales rank. Bollen, Mao and Zeng [8] first analyze the content of daily Twitter feeds by two mood tracking tool, track the changes in public mood state using large-scale Twitter feeds, and explore if public mood correlates to stock market. Bartov, Faurel and Mohanram [9] found that the aggregate opinion in individual tweets successfully predicts a firm's quarterly earnings and announcement returns after exploring a sample set from 2009 to 2012. Joshi and others [10] use the text of film reviews from different sources, movie metadata and linear regression to predict the opening weekend gross earnings. Wu and Brynjolfsson [11] report that a house search index, which is based on search activities from Google search engine, is strongly correlated with future home sales and prices. Schoen and others [12] classify forecasting models into three types: prediction marking models, survey models, and statistical models. And in practice, it is very common to apply statistical models to analyze social media data and make prediction.

2.2 Sentiment Analysis in Social Media

Sentiment Analysis is also known as Opinion Mining, referring to contextual mining of text which identifies and extracts subjective information in the text [13]. As the volume of social media data has been growing massively, mining user-generated content from social media has been a growing interest to obtain users' opinion. Although most of sentiments are simply classified into limited categories such as positive and negative, sentiment analysis is often used to understand the attitude of customers on specific topics or events [13, 14]

There is a large body of work on Sentiment Analysis. Generally, three techniques are used in Sentiment Analysis: machine learning method, lexicon-based method, and hybrid method [15]. The machine learning method applies the existing machine learning algorithms using linguistic features. The lexicon-based method employs a collection of known opinion words. The hybrid method combines the above two methods. Machine learning method includes supervised learning [16] and unsupervised learning [17]. With supervised learning methods, social posts (either document or sentences) can be classified into three categories, positive, negative, and neutral. Any existing supervised learning method can be applied to sentiment classification, such as, naive Bayesian classification [18], and support vector machines (SVM). Unsupervised learning is usually applied when there is no labeled training data.

Twitter and Facebook are common social media platforms used by many sentiment analysis applications [19]. Nakov et al. [20] discuss Sentiment Analysis in Twitter Task. This Task consists of five parts: (1) predicting if a tweet is positive, negative or neutral; (2) predicting whether a tweet conveys a sentiment towards a given topic; (3) estimating the tweet sentiment on a five-point scale from Highly Negative to Highly Positive; (4) estimating the distribution of a set of tweets in Positive and Negative classes; (5) estimating the distribution of a set of tweets in five classes. Severyn and Moschitti [21] apply deep learning in sentiment analysis of tweets. They propose a convolutional neural network for sentiment classification. Saif et al. [22] present SentiCircles, which is a lexicon based method for sentiment analysis on Twitter. SentiCircles can detect sentiment at both entity-level and tweet-level. A novel meta-heuristic clustering method based on K-means and cuckoo search is proposed by Pandey, Rajpoot, and Saraswat [23]. The proposed method finds the optimum cluster-heads from the sentimental contents of tweets. Ortigosa and his colleagues developed an application called SentBuk to extract sentiment from Facebook messages and support sentiment analysis in Facebook [24]. Meire and others [25] discuss the additional value of information available before (leading) and after (lagging) the focal post's creation time in Facebook sentiment analysis. Sentiment analysis has also been used to analyze other social media platforms such as YouTube [26, 27] and has often been used in application areas such as finance and product review [28, 29].

2.3 Hypothesis Development

The number of Facebook Likes increases when you click the "Like" below a post. It is a way to let people know that you enjoy it without leaving a comment. The Facebook Likes has been used in regression analysis to explore its impact on sales and also to forecast sales [30, 31]. According to prior literature, Facebook Likes can drive traffic, induce social selling, and increase sales. Many customers rely on Facebook Likes to decide if they buy a particular product [4, 31, 32]. Building upon the prior literature, we hypothesize that the Facebook Likes on a real estate firm's business page is positively associated with its real estate sales. In another word, if a real estate firm has more Facebook Likes, it tends to get more real estate transactions. This leads to the first hypothesis:

H1. The number of Facebook Likes has a positive influence on real estate sales.

As the volume of social media data has been growing massively, mining user-generated content from social media has been a growing interest to obtain users' opinions. Customer sentiment analysis is a process of gathering customer opinions [33, 34]. Sentiment analysis helps calculate emotions related to a business, product, or brand. For example, sentiment analysis can be used to analyze blog posts to provides useful insights towards a particular topic or product [35]. Sentiment analysis helps marketers to make future plans by analyzing customer reviews and monitors customer's dissatisfaction. On the basis of the prior literature, if a real estate firm's Facebook page has more positive posts, it tends to attract more home clients to work with it. In another word, if a real estate firm has more positive Facebook posts, it tends to have more real estate transactions. This leads to the second hypothesis:

H2. The sentiment of Facebook posts has a positive influence on real estate sales.

Seven other Facebook variables including the total number of posts, total number of photos, total number of videos, total number of comments made under posts, total number of sharers, total number of links, and total number of stories, have been employed in past research [4, 30–32]. The main purpose of a multiple regression is to explore more about the relationship between several independent variables (e.g., Facebook variables) and a dependent variable (e.g., real estate sales) [36]. Multiple regression can find out how different Facebook variables impact real estate sales [30]. Since more customers rely on social media to determine what product they want to purchase, social marketing is now the driving force behind brand awareness, customer engagement and sales. On the basis of prior literature, we assume a relationship between Facebook activities and real estate sales. This leads to the third hypothesis regarding a combinational impact of various Facebook activities:

H3. The activities on Facebook has a positive influence on real estate sales.

Social media sentiments affect sales with a delay, which is named as time lag [37]. Kotler states that consumers go through five stages when buying a product: (1) consumer's recognition of a need or problem; (2) information search; (3) evaluation of alternatives; (4) actual purchase decision; and (5) post purchase behavior [38].The time lag between an increase in positive/negative comments and an increase/decrease in sales is a variable since social media may influence the consumer at any stage (early or late) of the buying process [3]. Similarly, the time lag between activities on Facebook and an increase/decrease in real estate sales should be considered as well. This leads to the fourth hypothesis:

H4. The time lag affects the impact of Facebook activities on real estate sales.

3 Methodology

In order to test the research hypotheses and answer the research questions, we need to explore how the opinions on social media impact real estate sales. In this section, we discuss how we collected data and built the data model.

Figure 1 displays the research model. Buyer agency commission is selected as the dependent variable. This is the commission received by the real estate firm that represents the buyer. This commission is typically 2–3% of the real estate sale amount and is finally shared between the buyer agent and his/her firm. Several Facebook activities are used as independent variables, in which an average sentiment score is derived from Facebook posts.

3.1 Data Collection

We collected all the real estate transaction records from MLS (Multiple Listing Service) between January 2016 and June 2018 for the Orange county, California. We used list office phone number, list office name, and buyer agent office name to identify real estate firms on Facebook. We calculated the commission paid to the buyer agency for each sale. In order to analyze commissions by month and by year, the closing date (the date the purchase agreement was fulfilled) is included.

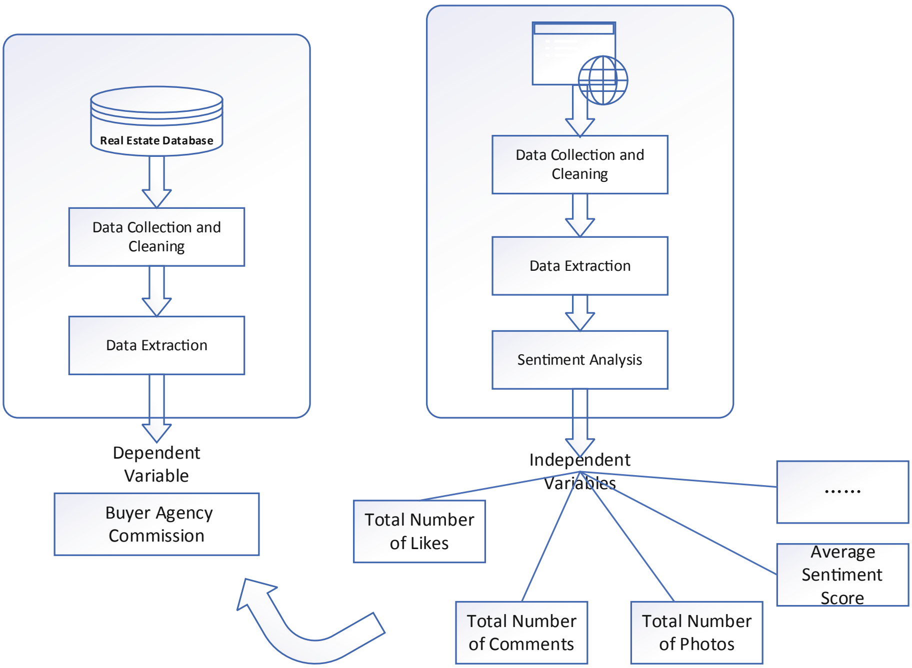

Fig. 1. Research model

Based on our datasets, there are about 400 real estate firms in Orange county. About 63% of those real estate firms have used Facebook regularly as part of their real estate marketing practice. Table 1 presents a sample list of real estate firms that have an active Facebook business page since 2016.

Table 1. Sample list of real estate agents and Facebook links

No	Real estate firm name	Facebook link
1	Allison james estates & homes	https://www.facebook.com/AJEliteHomes/#
2	Beach cities real estate	https://www.facebook.com/beachcitiesrealty/#
3	EHM real estate, inc	https://www.facebook.com/EHMRealEstate/
4	Engel & voelkers newport beach	https://www.facebook.com/EngelVolkersNewportBeach/
5	Frontier realty	https://www.facebook.com/findhomedeals/#
6	Intero real estate services	https://www.facebook.com/InteroSC/?ref=br_rs#
7	K. Hovnanian companies of California	https://www.facebook.com/khov.nocal/#
8	Pacific sterling realty	https://www.facebook.com/Pacific-Sterling-Realty-1377515665814381/
9	Pinpoint properties	https://www.facebook.com/PinpointProperties/
10	re/max prestige properties	https://www.facebook.com/RemaxPrestigePropertiesCA

To explore the opinions on Facebook, the following eight variables were collected from each real estate firm's Facebook page: total number of posts, total number of photos, total number of videos, total number of likes, total number of comments made under posts, total number of sharers, total number of links, and total number of stories. In addition, two other variables were derived to test the research hypotheses. One is the average length of posts and the other is the average sentiment score of posts. The length of a post may decide the impact of social media content on its viewers because the length shows how much effort and time that a real estate firm spent to maintain its Facebook page. Standford CoreNLP [39] was employed to calculate a sentiment score for each post. The average sentiment score was added to the Facebook dataset as a variable. The sentiment score can be used to determine the sentiment of posts. We are curious of the question: If posts sound more positive, do they tend to have more impact on sales?

3.2 Why Linear Regression?

The residuals histogram and the normal Probability Plot (PP) plot were examined to ensure that the linear regression analysis criteria were satisfied. We conducted multiple regressions. It might take months for the Facebook activities to catch up people's attention, and to finally fulfill purchase agreement. Thus, there can be a time lag between Facebook activities and a resulting real estate transaction. To account for the lagging effect, different time lags were considered in the regression analysis.

4 Results and Discussion

Multiple regressions were conducted to find out how different Facebook variables correlate with real estate sales. As explained in the prior data collection section, we collected 10 Facebook variables. Backward elimination method [40] was adopted to determine which variables should be excluded. We started with all 10 Facebook variables, then tested the deletion of each variable using criterion, which are theoretical considerations for relevance, p-values and adj. R^2 [41].

We examined the residuals histogram and the PP plot to make sure that that the linear regression analysis criteria were satisfied. After backward elimination, seven Facebook variables were included in multiple regressions. The multiple regression equation is presented as follows:

$$\text{real estate sale} = \beta_0 + \beta_1 \textit{total likes} + \beta_2 \textit{total comments} + \beta_3 \textit{total sharers} + \beta_4 \textit{total links} + \beta_5 \textit{total stories} + \beta_6 \textit{post length} + \beta_7 \textit{sentiment score} + \varepsilon \tag{1}$$

The regression results from year 2016 to year 2018 are presented in Tables 2a–2c. An asterisk marks whether this relationship is significant at p <=0.05.

Table 2a. Multiple regression results for year 2016

	Coefficient	Standard error
Total likes	0.163	0.182
Total comments	−0.198	0.220
Total sharers	0.097	0.107
Total links	0.338(*)	0.111
Total stories	0.170(*)	0.088
Average message length	−0.041	0.071
Average sentiment score	−0.193	0.138
R^2	0.087	
Significance F	0.008	

Table 2b. Multiple regression results for year 2017

	Coefficient	Standard error
Total likes	0.651 (*)	0.083
Total comments	−0.214	0.114
Total sharers	−0.147	0.095
Total links	0.313 (*)	0.094
Total stories	0.245 (*)	0.068
Average message length	−0.057	0.059
Average sentiment score	−0.262(*)	0.103
R^2	0.314	
Significance F	3.85E-14	

Table 2c. Multiple regression results for first six months of 2018

	Coefficient	Standard error
Total likes	0.324(*)	0.083
Total comments	−0.062	0.107
Total sharers	−0.068	0.095
Total links	0.229(*)	0.115
Total stories	0.335(*)	0.082
Average message length	−0.039	0.069
Average sentiment score	−0.200	0.139
R^2	0.170	
Significance F	1.72E-05	

As postulated by hypothesis H1, the total Facebook Likes is assumed to positively influence the real estate sales. The regression results support this hypothesis. The results in Tables 2b and 2c show the significant positive impact of total Facebook Likes on real estate sales from 2017 to 2018. Therefore, the number of Facebook Likes is positively associated with the firm's sales, probably because a higher number of Likes is a sign of the client base of this firm. The result for Facebook Likes in Table 2a (for year 2016) is not significant. One explanation is that, more recently home buyers/sellers started using Facebook Likes to help them make purchasing decisions (from 2016). Tables 2a–2c show that the sentiment is negatively associated with real estate sales, the correlation is significant in Table 2b for year 2017. Therefore, H2 is not supported. Tables 2a–2c show that the total links and total stories have strong, positive and significant correlations with real estate sales from 2016 to 2018. Thus, H3 is supported.

Time Lag. There may be a time lag between the activates on Facebook and a resulting real estate transaction, time lags were included in the following experiments and analysis. The month was used as the unit of time. First, the impact of Facebook variables on real estate sales was examined month by month. For example, Facebook variables from January 2016 were used as independent variables and the commission in January 2016 was used as dependent variable. Second, time lags were explored by choosing one-month, two-month, three-month, four-month and five-month intervals. For example, for two-month interval, if Facebook variables are from February and March 2016, then the commission in April 2016 was used as dependent variable. The regression results with and without time lags are compared in Fig. 2. The Y-axis represents a significant rate in one year. The significant rate is defined as follow.

$$\text{significant rate in one year} = \frac{\text{number of months that has significant result}}{\text{number of months in one year}} \quad (2)$$

Where a month has a significant result if the relationship in this month is significant at p <=0.05.

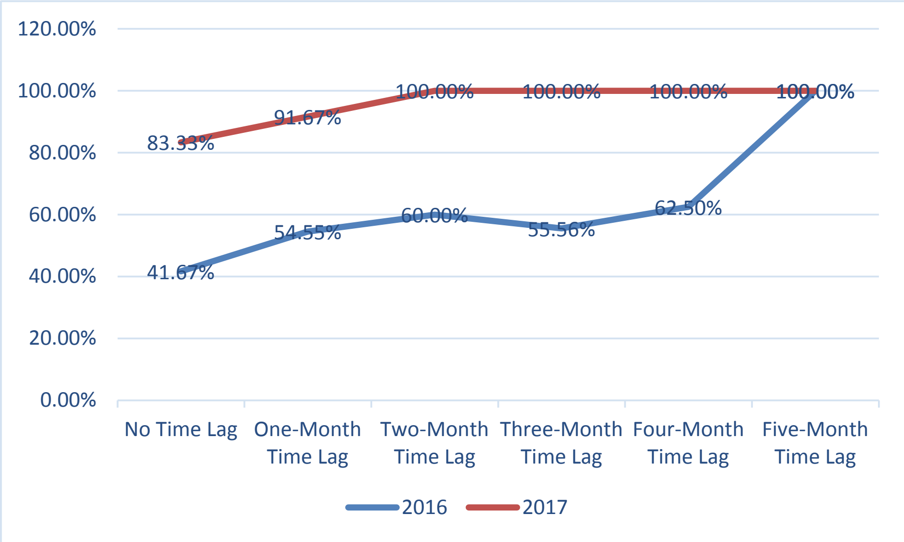

Fig. 2. Significant rates in 2016 and 2017

As shown in Fig. 2, for both 2016 and 2017, if time lag is not considered, the significant rate is the lowest. For both years, the significant rate is the highest when the time lag is at five-month. Based on the results, no matter for prediction or decision making, time lag is an important factor affecting accuracy and precision. The results in Fig. 2 support the assumption made in hypothesis H4, which is that time lag affects the impact of Facebook activities on real estate sales.

5 Conclusions and Future Research

Social media has a broad influence on businesses, and it has been used to collect customer feedback, promote brand awareness, and predict sales. In this research, we study how Facebook activities are associated with real estate sales. Using two and half years of real estate sales records for the Orange county, California and Facebook business pages of about 250 real estate firms, we find that the total numbers of Facebook Likes, links, and stories are positively associated with real estate sales; the sentiment score of Facebook posts is negatively associated with sales; when considering a time lag between Facebook activities and real estate sales, a five-month time lag leads to the highest significant rate.

As for future research, we plan to interview buyers and agents to get their further input and perception on social media's influence on real estate business. We will explore different form of social media including Twitter and YouTube and consider more attributes with a bigger real estate data set from different states to study how social media impacts real estate business.

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