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An Intelligent Method for Understanding Consumers' Perception of Luxury Hotel Brands Using Convolutional Neural Networks

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Abstract

Branding is an effective tool for companies to identify and differentiate products or services in consumers' minds. Branding is a marketing strategy widely used to improve firm performance. There is considerable ambivalence in how different societies and cultures relate to the consumption of luxury goods. The aim of this paper is to understand consumers' perception of luxury hotel brands. For this purpose, this research investigates consumers' "big" visual data on TripAdvisor through a Convolutional Neural Networks (CNN). The CNN is one of the most accurate machine learning algorithms that can detect and capture hidden relationships between different variables. To this end, this article explores visual data emerged from 7105 pictures posted in March 2019 by unique users, related to six different luxury hotels in Florida, Unites States. The obtained results showed the significance of non-textual elements of the hotel experience such as pictures, which cannot be examined within conventional schemes as content analysis. The analysis of 7105 consumers' pictures using CNN leads to the identification of the features that had the higher impact on their experience. These features emerged as specific characteristics of interior elements of the hotels (rooms and restaurant). The obtained results indicate how big data analytics and CNN can help monitoring social media and understand consumer's perception of luxury hotels through the new analysis of visual data, as well as turn into better brand management strategies for luxury hotel managers.

1. Introduction

In a world where everything has to be documented on social media, customers are increasingly looking for experience-related services. It is not enough anymore to wear luxury products such as a purse or shoes, customers now want to pair their products to an overall experience. Luxury travelers are craving experiences that go beyond simple products, and this is why fashion brands have found the perfect combination to satisfy both their growth and customers' demand by projecting a whole lifestyle [1]. Many of them now own their own hotels, which are located in either strategic locations, i.e. big cities such as Tokyo, Dubai, or London… or in exotic locations, attracting luxury guests. These expansion approaches are key to the success of luxury brands. In fact, the former allows them to be closer to their target segment whereas the latter helps them to elevate their brand even further [2].

The increasing demand of luxury brands is adding complexity to the luxury marketplace, by positing new challenges for brand managers. Success in brand management results from the right understanding of consumers' expectations and the ability of managers to reply accordingly to generate profitability. Specifically, luxury hotel management is acquiring the interest of scholars and practitioners in both brand management and tourism management literature. Indeed, past studies made some attempts to understand the source of consumers' satisfaction with hotel brands through questionnaires, online rating and sentiment analysis, and social media interactions [3]. Especially systematic social media monitor would allow understanding consumers' behavior and engagement with the brand [4].

In this vein, big data analytics and machine learning techniques would support to gather online insights on consumers, with emphasis on social media sources. However, big data analytical tools are still scarcely explored in branding and luxury branding studies. Therefore, finding new approaches to monitor social media would help in understanding the unique characteristics of luxury brands

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shared through social media, while machine-learning algorithms would make this monitor happen. Hence, two questions arise in this new competitive scenario. The first one is 'How can big data analytics and machine learning algorithms help monitoring social media and understand consumers' perception of luxury hotels?' and the second one is 'How can big data analytics turn into better brand management strategies for luxury hotel managers?'.

The aim of this study is to understand consumers' perception of luxury hotel brands through systematically monitoring social media, resulting in better brand management strategies. To this end, the present study explored visual data emerged from 7105 pictures posted in January 2019 by unique users, related to six different luxury hotels in Florida, Unites States. Results allow understanding the different hotel attributes, with implications for scholars in tourism and brand management, and practitioners in hotel management.

A class of machine learning techniques named deep learning was developed mainly since 2006, where many layers of non-linear information processing stages or hierarchical architectures are exploited. Deep learning performance is better than the existing classification methods [5]. In this context, the convolutional neural network (CNN) is able to learn the feature vector directly from the training data without using any handcrafting techniques to determine the feature vector. In the proposed method, CNN is used to analyze the picture and detect the hidden relationships and patterns between different attributes and luxury items.

The rest of paper is structured as follows. Section 2 investigates the recent studies on brand management with emphasis on luxury brands and luxury hotel brands. Section 3 introduce CNN briefly and picture analysis procedure. Section 4 introduces the proposed method. Section five presents the obtained results and finally section six concludes the paper.

2. Literature Review

Recent studies demonstrated the extent to which the image of a certain destination influences tourists' behavior prior to, during, and after visiting a certain place. Indeed, pictures are among the preferred contents included in online posts, able to enhance the attractiveness, by providing a virtual access to the hotel features [6, 7]. To this end, social media like Instagram, Myspace and Facebook are also used for branding places. This usage does not imply the generation of new images, but the set of a certain choreography according to the functionalities of the medium (i.e., the choice of particular filters to improve the quality of the image or to add appealing digital effects) [8]. Therefore, the presence on social media as part of marketing campaign has become a consolidated practice for brand managers [9]. For instance, this presence allows firm to both find new customers (also exploiting the electronic word of mouth communication- eWOM), and to maintain and retain the existing ones, who can consider this digital tool as a direct channel to interact with the brand [10, 11].

From a brand management perspective, the exploitation of fan pages on social media like Facebook further allows brand to increase reputation [12] and awareness [13], as well as to develop and disseminate corporate identity [14]. More specifically, specialized tourism platforms like TripAdvisor or Booking provide travelers with the access to a massive amount of online reviews to support their choice when planning holidays. Indeed, TripAdvisor is considered the largest travel platform with more than 455 million average monthly unique visitors and over 630 million reviews of hotels, restaurants, and attractions related businesses [15]. In particular, the platform collects consumers' rating, ranking, and pictures that are freely accessible without registration or login. Since taking pictures allows tourists to share with other the meaningful tourism experience lived in a certain place, sharing pictures online allows tourists to get the appreciation of others including strangers, by improving the experience in a sort of "hermeneutic circle" [16].

For this reason, an increasing number of studies in tourism considers pictures taken by tourists as rich data sources for tourism research [17, 18], able to support the deeper understanding of consumers' perception of hotel brand image [19], destination attractiveness, and quality of tourism experience. To this end, images based on their manifest content can be directly observed and quantitatively summarized with acceptable reliability [20].

To date, studies on luxury hotel brand management mainly focus on the evaluation of the hotel brand experience and perceived service quality, price promotions, drivers of customer loyalty, and website performances through traditional research methods such as interviews and surveys. However, how luxury hotel might benefit from the exploitation of social media and related analytics, with emphasis on big and visual data, to support brand management is still at an early stage. Accordingly, recent studies highlight the importance of digital and social media analytics to understand how exploiting social media presence to generate positive trust, and to investigate consumers' evaluations through online reviews analytics, suggesting for future research in this sense.

3. Analysis Tool

In recent years, machine learning algorithm and meth-heaurestic population based optimization algorithms have been applied in different medical, engineering, signal processing and other applications [21- 27]. The CNNs can detect hidden pattern between input-output pairs using several convolution and pooling layers. These convolution and pooling layers can capture the most effective and informative features automatically. In CCN structure, hyper-parameters and parameters such as learning rate, number of convolution layers, kernel size and number of filters have huge impact on its performance.

CNNs are special type of Multi-layer perceptron (MLP). They are similar to neural networks in the following aspects. They are made of neurons with weights and biases which should be learned. Some inputs are given to each neuron. Then, an operation of dot product is performed followed by an optional function of nonlinearity. Basically, CNN is made of three types of main layers namely, Convolutional layer, Pooling layer and a Fully connected layer with a rectified linear activation function (ReLU).

The convolution layer performs feature extraction, and also to decrease the computation cost it is usually interspersed with sub-sampling layers. Each layer includes multiple neurons and each of them has their own weights. Feature extraction can be obtained by multiple roll over convolution layers and pooling layers. This is the most significant part of the convolutional neural network, and the classification can be obtained by the last layer. The convolution layer has a local receptive structure, which can be obtained by a sparse connection, where a neuron with only one part of the input is connected. The training difficulty can be decreased by sub pooling layer. Furthermore, for each convolution layer neuron, their connection weight is the same, so the computation cost can be significantly reduced. In the convolutional neural network, the pooling layer usually follows the roll accumulation layer, and the pooling layer and the convolution layer may alternately appear many times, thus forming a multi-layer convolutional neural network. The main structure of CNN is shown in Figure 1. The CNN network can be expanded by adding more convolution and pooling layers. Here, CNN has two layers namely, convolution and pooling.

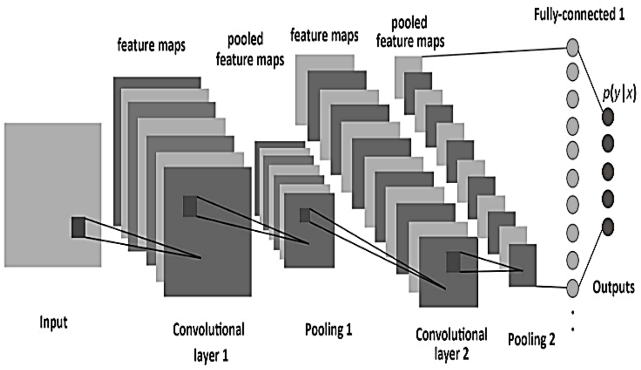

Figure 1. CNN structure [28]

CNNs were initially used in the area of image processing where it receives raw image pixels on the input end, transform it through a series of hidden layers and finally give the class scores at the other end. Our application is on analyzing signals which are one dimensional, so we use Convolution 1D layers, pooling 1D layers and fully connected layer. Here CNN takes the time series data in one dimensional form where in the data are arranged in the order of sequential time instants. In our case, the input one dimensional data vector is $x = (x_1, x_2, \dots, x_n)$ where $x_n \in R^d$ denotes features (here time series CCP data). Convolution 1D constructs a feature map fm by applying the convolution operation on the input data with a filter $w \in R^{fd}$ where f denotes the features inherent in the input data producing at its output, new set of features which is fed to input of the next block in line. A new feature map fm is obtained from a set of features f as Eq. (1)

$$hl_i^{fm} = tan\left(w^{fm} x_{i:i+f-1} + b\right) \quad (1)$$

The filter hl is employed to each set of features f in the input data defined by $\{x_{1:f}, x_{2:f+1}, \dots, x_{n-f+1}\}$ so as to generate a feature map as $hl = [hl_1, hl_2, \dots, hl_{n-f+1}]$ where $b \in R$ denotes a bias term and $hl \in R^{n-f+1}$.

The output of the convolutional layer is given to the pooling (POOL) layer. Convolutional layer uses ReLU activation function that apply $\max(0, \mathrm{x})$ to each of the inputs to the ReLU represented by x. The next layer (POOL) performs a down sampling operation. Here, the max-pooling operation is applied on each feature map $\overrightarrow{hl} = max\{hl\}$. This produces the most significant features. These selected features are fed to fully connected layer, containing the Softmax function that gives the probability distribution over each class. Thus, the fully connected layer (FC) will compute the classes which form the final output of the CNN network. Thus the CNN has the architecture of INPUT-CONV-POOL-FC.

4. Proposed Method

Tourists' photographs posted online have been largely considered a rich data sets to support the deep understanding of behaviors and preferences. Accordingly, machine-learning algorithms can be successfully employed to mine information from unstructured data like images to explore lacks and assets of hotel services. In the present study, the analysis consists of the identification of objects included in pictures posted online by consumers. To this goal, the research used CNN, allowing to extract models and predictions on big data.

We selected six luxury hotels in Florida, United States, and collected all the pictures posted by unique TripAdvisor users. In particular, the six hotels have the similar characteristics, including:

- being in the same area
- providing between 85 and 100 rooms (including suites) at comparable room rates, facilities (i.e., swimming pool, Spa, airport transportation, etc.),
- having more than 500 reviews on TripAdvisor.

A total of 7105 images were collected from consumers' reviews posted in March 2019. More information about dataset is listed in Table 1.

Table 1. Number of photographs collected per each hotel in TripAdvisor.

Hotel	Consumers' photos on TripAdvisor
A	1052
B	1529
C	962
D	1021
E	1769
F	772

The CNN provides the function Image Identify (supervised machine learning algorithm), which allows recognizing each object present in a certain picture, and assigns to each object the reference category, creating a classification. In this way, given the set of photos taken by tourists in the six hotels, the algorithm identifies the main object in each image returning the result into a specific category (Figure 1). While manual categories have been developed to classify pictures on previous studies, CNN provides more than 10,000 categories to classify objects. The adopted algorithm is based on deep learning, aimed at stimulating the human learning process in order to make the system able to self-improve as soon as new information are available. Image Identify provides a classification label, associating the recognition probability. The probability describes the identification degree of the object appearance using a value range from 0 to 1.

To test the software and the probability of the right identification of the object, we provided to software some pictures taken by tourists in the luxury hotels suggesting a specific category (“bed” and “table”). The output shows the degree of accuracy with which the software achieves required goals. Figure 2 shows the code adopted to test the performance and functioning of the algorithm. From a mathematical perspective, the software adopts the mathematical function with the highest probability of response on the dataset.

```
aa = thumbnails = Table[Import[M1[[a]], "Image"],
   {a, Length[M1]}]
```

```
bb = ImageIdentify[aa]
{reception desk, tiramisu, double bed, restaurant}
```

Figure 2. Part of code and output for CNN

```
bb = ImageIdentify[ , "bed", 6, "Probability"]
```

```
<|double bed → 0.596806, trundle bed → 0.39566, single bed → 0.0050244,
hospital bed → 0.0050244, Murphy bed → 0.0010193, bed → 1.|>

ImageIdentify[ , "table", 6, "Probability"]
```

```
<|table → 0.201171, counter → 0.195422, work table → 0.00387889,
vanity → 0.00116796, bar → 0.194936, drafting table → 0.00387889|>
```

Fig. 2. Probability of right identification of the objects in pictures in *Wolfram Mathematica*.

Figure 3. Probability of right identification of the objects in pictures in CNN

5. Results

Each object included in a certain image per hotel has been classified in a specific category. Figure 3 summarizes the results related to the ten most photographed objects per hotel, with the related number of pictures they appear. Although consumers took different pictures in the hotels, giving attention to different objects, there are some recurrent elements in the pictures of the six hotels. Indeed, bedroom and dinner table are the most photographed ones, appearing as the first or the second element for each hotel. Subsequently, the top hotels attractions are the bathroom, double bed (appearing in five out of six hotel), and washbasin, living room, person and restaurant (appearing in four out of the six hotels related pictures) (Table 2).

Hotel1	
living room	51
bedroom	48
bathroom	31
seat	11
washbasin	11
double bed	9
dinner table	9
window seat	7
room	7
love seat	7

Hotel2	
bedroom	67
washbasin	47
airport terminal	47
bathroom	41
shower	36
office building	35
dinner table	32
coast	30
oil refinery	30
home theater	29

Hotel3	
living room	42
bedroom	37
dinner table	34
buffet car	20
double bed	17
restaurant	16
bathroom	16
window seat	13
person	12
washbasin	11

Hotel4	
home theater	10
restaurant	9
double bed	9
bedroom	8
airport terminal	8
conference room	7
washbasin	6
dinner table	6
bathroom	5
person	4

Hotel5	
bedroom	171
bathroom	95
dinner table	91
antechamber	88
living room	74
double bed	66
restaurant	61
person	44
revolving door	37
airport terminal	33

Hotel6	
dinner table	152
bedroom	128
restaurant	106
antechamber	91
living room	63
person	46
double bed	38
bathroom	36
shopping center	34
staircase	25

Figure 4. The ten most photographed elements in luxury hotels.

Findings show that consumers are very attentive to the services quality of the private areas such as bedroom and bathroom, with emphasis in particular details such as the washbasin or the bed, this might imply a particular attention to both the cleanness and care of these elements. Taking pictures of these elements would also indicate attention to design and architecture, and comfort of the spaces where relaxing.

Table 2. The most recurrent elements in the pictures taken in the six luxury hotels.

	bedroom	dinner table	bathroom	double bed	living room	restaurant	washbasin	person
Hotel 1	48	9	31	9	51	0	11	0
Hotel 2	67	32	41	0	0	0	47	0
Hotel 3	37	34	16	17	42	16	11	12
Hotel 4	8	6	5	9	0	9	6	4
Hotel 5	171	91	95	66	74	61	0	44
Hotel 6	128	152	36	38	63	106	0	46
Mean	75.5	54.0	37.3	23.1	38.3	32	12.5	17.6
SD	55.88	51.9	28.5	22.4	28.5	39	16	19.7

6. Conclusion

Results allow understanding the different hotel attributes, with implications for scholars in tourism and brand management, and practitioners in hotel management. First, results highlight the extent to which big data analytics and machine learning algorithms support luxury hotel managers to more carefully and systematically monitor social media, with emphasis on visual data. Secondly, they allow understanding the different hotel attributes influencing consumers' evaluation of a certain luxury hotel through the analysis of consumer-generated pictures. Finally, the adopted methodology might be considered as a technique for a "dimensionality-reduction" of the volume of "big" visual data, while opening up the potential for new research methods in consumer behavior as never exploited before. Results also provide compelling evidence on the specific luxury hotel attributes able to influence consumers' perception at the most.

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