Modelling the Role of Social Media in Hotel Selection Using Bayesian Networks

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***Abstract*— Consumers increasingly use social media to search for information, compare alternative products and services, and make decisions for activities, such as travel planning and hotel selection. In this context, social media have gathered the research interest as a major form of electronic Word-Of-Mouth (eWOM) to prospective travelers. Existing literature is rich on research works about the influence of travel-oriented online media, such as TripAdvisor, to consumers' decisions with several approaches for sentiment analysis. However, travelers are also widely affected by online comments posted on social media, such as Facebook, Twitter, etc. This paper proposes a methodology for modelling the role of social media in hotel selection using Bayesian Networks (BN). Specifically, it enables identifying the relationships between the way travelers use social media and the criteria for selecting hotels. The proposed approach is demonstrated on a dataset of 360 social media users.**

Keywords-belief network; data mining; e-tourism; tourism management.

I. INTRODUCTION

Consumers increasingly use online media to search for information, compare alternative products and services, and make decisions for activities, such as travel planning and hotel selection [1][2]. Not surprisingly, high ratings in social media have a direct impact on sales [3][4]. Due to the experiential nature of travel-related products and their instantaneous nature, online reviews have become an increasingly popular information source in travel planning and have a profound effect on consumers' buying decisions, particularly in hotel booking [5]. According to Travel Industry Association of America, the evidence shows that 64% of travelers use search engines for their travel planning [6][7].

In this context, social media have gathered the research interest as a major form of electronic Word-Of-Mouth (eWOM) to prospective travelers facilitating the sharing and seeking of experiences [5,8,9,10]. Hotel-related decision-making has fundamentally changed, as social media are used in every stage of the consumers' decision-making process. They play a key role before, during and after the trip [11]. Prospective tourists are influenced by social media, as content from other travellers can shape, guide and redirect their initial decisions [12][13].

In the business perspective, social media are perceived as effective tools and fruitful platforms for deepening customer engagement and enhancing customer–business interactions [14]. In fact, they have provided a new distribution channel for businesses to communicate with their customers [7]. In the consumer perspective, consumers use social media for a wide spectrum of scenarios, e.g., sharing their travel-related experiences, engaging with others, connecting with people from different destinations and buying travel-related products and services [15][16].

Existing literature is rich on research works about the influence of travel-oriented online media, such as TripAdvisor, to consumers' decisions. However, travelers are also widely affected by online comments posted on social media, such as Facebook, Twitter, etc. as well as by hotels' marketing campaigns [17]. Therefore, the identification of the relationships between the way travelers use social media and the criteria for selecting hotels is of outmost importance. This paper proposes a methodology for modelling the role of social media in hotel selection using Bayesian Networks (BN). To the best of our knowledge, despite their applicability in a wide range of problems and scenarios, BNs have not been used for identifying the influence of social media to the decisions of travelers about the hotel selection.

The rest of the paper is organized as follows: Section II presents the related work on methods and approaches for evaluating the effect of online reviews on social media on hotel booking. Section III describes the research methodology and the proposed approach for modelling the role of social media in hotel selection using BNs. Section IV presents the results from the adoption of the proposed methodology on a dataset of 360 users. Section V concludes the paper and outlines our plans for future work.

II. RELATED WORK

Online comment has become a popular and efficient way for sellers to acquire feedback from customers and improve their service quality [18]. These online reviews generate an eWOM effect, which influences future customer demand and hotels' financial performance [19]. However, apart from the hotels' websites and official social media pages, prospective travelers are increasingly interacting through social media in order to gather and share information about hotels and to select the one that matches their criteria. To this end, a vast

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amount of research has focused on travel-oriented platforms and social media, such as TripAdvisor, aiming at investigating their influence to hotel booking decisions [7][11][14][20][21]. Moreover, such works are conducted from a tourism management perspective resulting in the use of descriptive statistical methods instead of exploiting the advancements of data analytics and machine learning. On the other hand, the role of social media such as Facebook and Twitter on hotel selection is rarely investigated [8].

In [22], the authors examined the effects of traditional customer satisfaction relative magnitude and social media review ratings on hotel performance and explored which online travel intermediaries' review ratings serve as the most reliable and valid predictor for hotel performance. The results of this study indicate that social media review rating is a more significant predictor than traditional customer satisfaction for explaining hotel performance metrics. The research work in [23] assessed social media content produced by customers and related review-management strategies of domestic and international hotel chains with the use of descriptive statistics and multilevel regression.

In [11], the authors proposed the use of multi-criteria ratings provided by the travelers in social media networking sites for developing a new recommender system for hotel recommendations in e-tourism platforms. Reference [3] applied multilevel regression analysis in order to quantify the extent to which differences in client satisfaction with hotels can be attributed to the destination in which the hotels are located. They measured this through ratings provided through social media outlets. In [24], the authors also investigated the influence of social media on destination choice. In [5], the presented work is based upon homophily and similarity-attraction theory in order to prove that review valence significantly affects hotel booking intention, and that reader-reviewer demographic similarity moderates this effect. This three-way interaction reveals a substituting moderation effect between demographic similarity and preference similarity.

In [12], the authors explored how social media influence the way consumers search, evaluate and select a hotel within the 'evaluation stage' of the wider hotel decision-making process, i.e., in the pre-travel stage during which social media unfold their most critical role. In [6], the authors examined tourists' knowledge sharing behavior in social media for two different types of social media: Facebook and TripAdvisor. They proposed a structural model that connects homophily and knowledge sharing through posting. Finally, the research work in [13] investigated the influencing role of social media in the consumer's hotel decision-making process and identified the advantages and disadvantages. They concluded that the advantages of utilizing social media in hotel selection outperform the disadvantages.

III. RESEARCH METHODOLOGY

A. Data Collection and Structuring

The data was collected in the form of a questionnaire completed by 360 social media users. The questions lay on three categories: generic questions, questions related to the reasons of searching information on social media, and questions related to the criteria according to which the users select a hotel for vacation. The first category of questions was in the form of multiple choice, while the last two were in the form of Likert scale.

B. Modelling the Relationships between Social Media and Hotel Selection Criteria Using Bayesian Networks

In order to model the relationships between the reasons of searching information on social media and the criteria according to which the users select a hotel for vacation, we applied BNs. A Bayesian Network (BN) [25], also known as belief network, is defined as a pair $B = (G, \Theta)$. $G = (V, E)$ is a Directed Acyclic Graph (DAG) where $V = \{v_1, \ldots, v_n\}$ is a collection of n nodes, $E \subset V \times V$ a collection of edges and a set of parameters Θ containing all the Conditional Probabilities (CP) of the network.

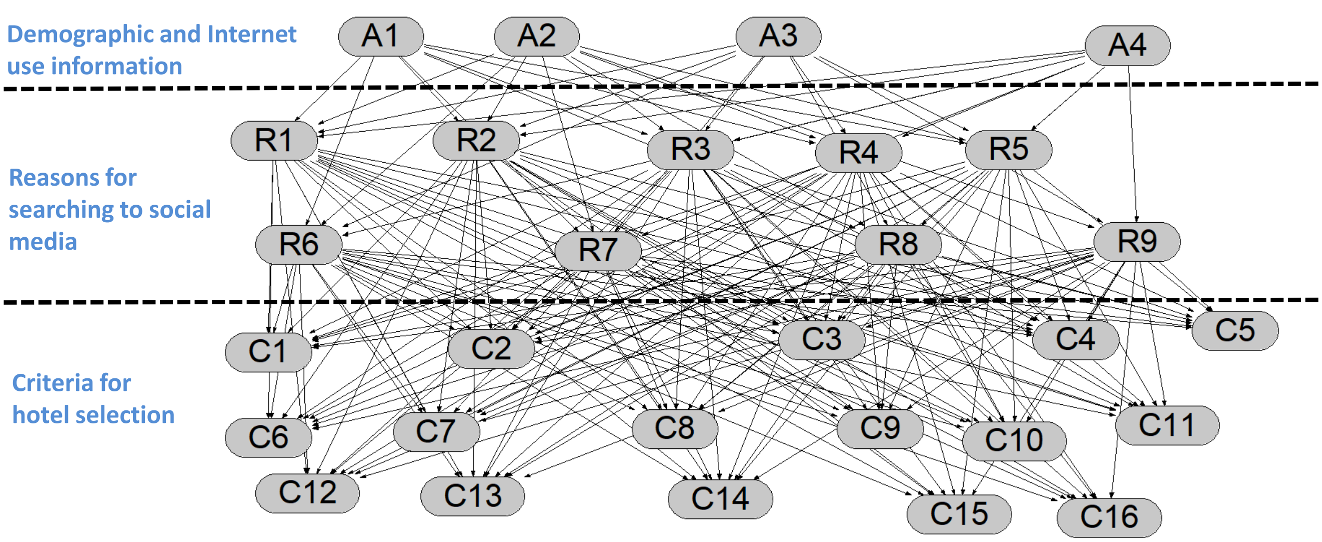

Figure 1. The Bayesian Network structure for modelling the role of social media in hotel selection.

Each node $v \epsilon V$ of the graph represents a random variable X_V with a state space $\boldsymbol{X_V}$ which can be either discrete or continuous. An edge $(v_i, v_j) \epsilon E$ represents the conditional dependence between two nodes v_i, $v_j \epsilon V$ where v_i is the parent of child v_j. If two nodes are not connected by an edge, they are conditional independent. Because a node can have more than one parent, let π_v the set of parents for a node $v \epsilon V$.

Therefore each random variable is independent of all nodes $V \setminus \pi_v$. For each node, a Conditional Probability Table (CPT) contains the CP distribution with parameters $\theta_{xi|\pi i} := P(x_i|\pi_i) \epsilon \Theta$ for each realization x_i of X_i conditioned on π_i. The joint probability distribution over V is visualized by the BN and can be defined as

$$P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i|\pi_i) \tag{1}$$

With BN, inference for what-if analysis can be supported, either top-down (predictive support) or bottom-up (diagnostic support). If a random variable which is represented by a node is observed, the node is called an evidence node; otherwise, it is a hidden node [26]. Based on the categories of the questions included in the questionnaire, a BN with three layers was developed, as shown in Figure 1. The nodes per each layer of the BN are presented in Table I.

The top layer of the BN includes 4 nodes related to generic information (A1-A4). These nodes along with their alternative values are: the respondent's age group = {*15-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, >50*), the frequency of vacations = {*once per 2 years, once per year, twice per year, three times per year, more than three times per year*}, the frequency of staying at hotel in vacations = {*always, very often, often, rarely, never*}, and the frequency of using social media for hotel information = {*always, very often, often, rarely, never*}.

The intermediate layer includes nodes related the reasons of searching information on social media in general and consists of 9 nodes (R1-R9). In other words, it indicates the behaviour and the attitude of the users with respect to the use of social media.

The bottom layer includes nodes related to the criteria according to which the users select a hotel for vacation and consists of 14 nodes (C1-C16). Their candidate values are {*Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree*}.

Based upon this structure, the BN is subject to reasoning in order to compute all the CPTs. The BN was constructed in a way that all the nodes of the intermediate and the bottom layer are potentially affected by all the nodes of the top and the intermediate layer respectively. Therefore, the CPTs are calculated accordingly.

The outcome of the proposed methodology indicates the probability assigned to each selection criterion (bottom layer) given the reasons a user searches for information in social media (intermediate layer) and some generic information (top layer).

TABLE I. BAYESIAN NETWORK NODES PER LAYER

Layers	Nodes		Node Values
Top Layer *(General Information)*	**A1**	Age group	{15-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, >50}
	A2	Frequency of vacations	{once per 2 years, once per year, twice per year, three times per year, more than three times per year}
	A3	Frequency of staying at hotel in vacations	{always, very often, often, rarely, never}
	A4	Frequency of using social media for hotel information	{always, very often, often, rarely, never}
Intermediate Layer *(Reasons of searching to social media)*	**R1**	Trust the social media users	{Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree}
	R2	Possibility of asking opinions	
	R3	Search engines are not helpful	
	R4	Socializing	
	R5	Quick responses	
	R6	Easy procedure	
	R7	Better quality of responses	
	R8	Costless	
	R9	Funny	
Bottom Layer *(Criteria for hotel selection)*	**C1**	Personnel	{Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree}
	C2	Reliable booking procedure	
	C3	Fast check-in / check-out	
	C4	Immediate service and problem solving	
	C5	Hotel security and privacy assurance	
	C6	Cleanliness	
	C7	Reasonable price	
	C8	Convenient parking	
	C9	Comfortable bed	
	C10	Comfortable public spaces	
	C11	Interior design	
	C12	Location	
	C13	External environment	
	C14	Quality of hotel restaurant	
	C15	Availability of mini bar in the rooms	
	C16	Belonging to a reputable hotel chain	

Therefore, the model can answer questions such as: "What is the probability that a user will select a hotel according to the criteria of the reliable booking procedure

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(C2) and the cleanliness (C6) given that he/she uses the social media for socializing (R4) (referring to node values *"Strongly Agree"* and *"Agree"*) and for receiving better quality of responses (R7), while he/she belongs to the age group *31-35* (A1), he/she goes for vacations *once per year* (A2), he/she stays at a hotel *often* (A3) and he/she *often* uses social media for hotel information (A4)?". In order to answer such questions, the model computes all the CPTs for all its nodes and for all their alternative values.

The model is able to identify, represent and store in the database complex relationships aiming at supporting marketing and hotel operations in response to different customers' profiles. Upon request, the model can compute the CPTs of every possible relationship based upon the resulting CPT in order to provide insights on the hotel selection criteria. In this way, the hotels can focus on specific target groups according to their strengths as well as to improve their operations that result in lower rating of certain criteria. Moreover, it is able to serve as a model for predicting the criteria according to which a social media user will select a hotel among various alternatives. The model is extensible to additional nodes per each layer in case more information needs to be incorporated.

IV. RESULTS

The proposed approach was applied on a dataset of 360 social media users. The implementation and execution of the experiments were performed using the BN functionalities of the pgmpy (Probabilistic Graphical Models using Python) package in Python [27]. We developed the associated BN and we calculated the CPTs for all the nodes.

Table II presents the criteria (C_i) and their associated values with the highest CPs, given the values of the reasons of searching information in social media (R_i) and the generic information (A_i). Table III presents the criteria (C_i) and their associated values with the lowest CPs, given the values of the reasons of searching information in social media (R_i) and the generic information (A_i).

For this specific analysis, we have grouped the values *Strongly Agree* and *Agree* in order to identify the most probable criteria in the first columns of the aforementioned Tables. The results show that the criterion C6 given the values of the R_i and A_i nodes that are shown in the first row of Table II is the one with the highest CP, which is equal to 39.5%. The criterion C15 given the values of the R_i and A_i nodes that are shown in the first row of Table III is the one with the lowest CP, which is equal to 1.2%.

Based upon these results, the hotels are able to identify the most important criteria according to which a social media user selects a hotel given some generic information, such as the age group, the frequency of vacations, etc., and their attitude towards the use of social media for searching information. In this way, the hotels may design more specialized marketing strategies, e.g., focusing on specific target groups, and to improve their operations in order to achieve higher service quality and increased customer satisfaction with respect to certain criteria.

TABLE II. CRITERIA C_I WITH THE HIGHEST CPS GIVEN R_I AND A_I

Criteria (Child Nodes)	**Parent Nodes**		***CP***
C_i	R_i	A_i	
C6	R1={Neutral}, R2={Agree}, R3={Disagree}, R4={Agree}, R5={Strongly Agree}, R6={Neutral}, R7={Disagree}, R8={Neutral}, R9={Strongly Disagree}	A1={36-40}, A2={once per year}, A3={very often}, A4={often}	0.395
C1	R1={Disagree}, R2={Agree}, R3={Strongly Disagree}, R4={Strongly Disagree}, R5={Agree}, R6={Neutral}, R7={Neutral}, R8={Agree}, R9={Strongly Disagree}	A1={46-50}, A2={twice per year}, A3={very often}, A4={rarely}	0.362
C7	R1={Agree}, R2={Strongly Agree}, R3={Disagree}, R4={Agree}, R5={Agree}, R6={Strongly Agree}, R7={Neutral}, R8={Neutral}, R9={Agree}	A1={31-35}, A2={once per 2 years}, A3={often}, A4={very often}	0.294
C12	R1={Strongly Agree}, R2={Strongly Agree}, R3={Neutral}, R4={Strongly Agree}, R5={Neutral}, R6={Neutral}, R7={Neutral}, R8={Neutral}, R9={Agree}	A1={26-30}, A2={once per year}, A3={rarely}, A4={always}	0.285
C11	R1={Neutral}, R2={Agree}, R3={Disagree}, R4={Neutral}, R5={Agree}, R6={Agree}, R7={Disagree}, R8={Agree}, R9={Neutral}	A1={41-45}, A2={twice per year}, A3={very often}, A4={often}	0.239
C2	R1={Neutral}, R2={Strongly Agree}, R3={Neutral}, R4={Agree}, R5={Strongly Agree}, R6={Neutral}, R7={Disagree}, R8={Neutral}, R9={Neutral}	A1={36-40}, A2={once per year}, A3={very often}, A4={often}	0.217
C4	R1={Disagree}, R2={Agree}, R3={Neutral}, R4={Agree}, R5={Strongly Agree}, R6={Agree}, R7={Neutral}, R8={Agree}, R9={Neutral}	A1={36-40}, A2={twice per year}, A3={very often}, A4={very often}	0.208

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TABLE III. CRITERIA C_i WITH THE LOWEST CPS GIVEN R_i AND A_i

Criteria (Child Nodes)	Parent Nodes		CP
C_i	R_i	A_i	
C15	R1={Strongly Agree}, R2={Neutral}, R3={neutral}, R4={Strongly Disagree}, R5={Agree}, R6={Neutral}, R7={Neutral}, R8={Disagree}, R9={Agree}	A1={21-25}, A2={three times per year}, A3={never}, A4={very often}	0.012
C14	R1={Strongly Agree}, R2={Strongly Disagree}, R3={Neutral}, R4={Agree}, R5={Neutral}, R6={Strongly Disagree}, R7={Disagree}, R8={Neutral}, R9={Strongly Disagree}	A1={26-30}, A2={once per year}, A3={rarely}, A4={always}	0.023
C3	R1={Strongly Agree}, R2={Strongly Agree}, R3={Neutral}, R4={Agree}, R5={Agree}, R6={Agree}, R7={Disagree}, R8={Strongly Agree}, R9={Neutral}	A1={21-25}, A2={once per 2 years}, A3={rarely}, A4={rarely}	0.025
C10	R1={Agree}, R2={Agree}, R3={Strongly Disagree}, R4={Neutral}, R5={Neutral}, R6={Strongly Agree}, R7={Disagree}, R8={Agree}, R9={Agree}	A1={31-35}, A2={once per 2 years}, A3={rarely}, A4={often}	0.031
C16	R1={Strongly Agree}, R2={Agree}, R3={Neutral}, R4={Strongly Agree}, R5={Agree}, R6={Agree}, R7={Neutral}, R8={Agree}, R9={Strongly Agree}	A1={21-25}, A2={once per 2 years}, A3={rarely}, A4={very often}	0.044
C8	R1={Disagree}, R2={Neutral}, R3={Disagree}, R4={Neutral}, R5={Agree}, R6={Strongly Agree}, R7={Strongly Agree}, R8={Agree}, R9={Neutral}	A1={21-25}, A2={once per year}, A3={very often}, A4={often}	0.046
C5	R1={Agree}, R2={Neutral}, R3={Strongly Disagree}, R4={Neutral}, R5={Strongly Agree}, R6={Agree}, R7={Strongly Agree}, R8={Agree}, R9={Neutral}	A1={36-40}, A2={three times per year}, A3={rarely}, A4={always}	0.052

TABLE IV. CONFUSION MATRIX

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP) = 41	False Negative (FN) = 9
Actual Negative	False Positive (FP) = 3	True Negative (TN) = 32

As already mentioned, the model can also serve as a classifier for predicting the class attribute of criteria (C_i) as soon as new records of R_i and A_i are inserted into the database. In order to evaluate its classification effectiveness, we inserted additional records, derived from more questionnaires addressed to social media users, and we created the confusion matrix according to Table IV in order to estimate the precision and the recall of the classifier using the (2) and (3) [28].

$$Precision = \frac{TP}{TP + FP} = \frac{41}{41 + 3} = 93.1\% \quad (2)$$

$$Recall = \frac{TP}{TP + FN} = \frac{41}{41 + 9} = 82\% \quad (3)$$

The Precision results are quite satisfactory, while the Recall results can be further improved. The BN model sticks to the initially identified relationships, i.e., the ones that have been mined during the model training. Therefore, when new relationships, not previously identified, are added, they are not classified correctly. These records include values that are not frequent (e.g., A1={>50} and A4={always}), so they are not critical for decision making.

V. CONCLUSIONS AND FUTURE WORK

Consumers increasingly use social media to search for information, compare alternative products and services, and make decisions for activities such as travel planning and hotel selection. In this context, social media have gathered the research interest as a major form of eWOM to prospective travelers. In this paper, we proposed a BN model for modelling the role of social media in hotel selection. More specifically, we developed a 3-layered BN corresponding to generic information, reasons for searching information to social media, and criteria for hotel selection respectively. In this way, the model is able to mine relationships and to compute the CPTs in order to reveal meaningful insights and predictions about the criteria of hotel selection given the use of social media and other information.

The BN model was applied to a dataset of 360 social media users, derived from an associated questionnaire. According to the defined BN structure, all the CPTs were computed. We presented indicative examples of the outcome, i.e., the criteria with the highest and the lowest CPs. We also validated the model in terms of its precision and recall in predicting the most important hotel selection criteria when new records are inserted into the database.

Regarding our future work, we plan to use more data analytics and machine learning methods and algorithms in order to mine hidden relationships among various attributes.

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Moreover, we aim to use fuzzy pattern matching methods for mining also online review comments, as well as clustering and fuzzy sets qualitative analytics algorithms for extracting user profiling insights of hotel customers. These directions have the potential to further enhance decision making process in hotel management from both a marketing (e.g., revealing key groups of customers and target groups) and an operations management (e.g., for improving service quality if it receives negative review rating) perspective.

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