2nd International Scientific Conference

1-3 June, 2017
Vrnjačka Banja, Serbia

2017

TOURISM IN FUNCTION OF DEVELOPMENT OF THE REPUBLIC OF SERBIA

Tourism product as a factor of competitiveness of the Serbian economy and experiences of other countries

THEMATIC PROCEEDINGS

I

UNIVERSITY OF KRAGUJEVAC

FACULTY OF HOTEL MANAGEMENT AND TOURISM IN VRNJAČKA BANJA

HOTEL GUEST REVIEWS AS A TOOL OF COMPETITIVE ADVANTAGE

Cvetko Andreeski[1]

Abstract

According to the research of many authors, guest reviews are important source of data used for different types of analysis which can support decision making process in hotel industry. Guest reviews are important for both tourists and hotel managers. The analyses of the reviews are main issue in detecting weaknesses in tourism offer. There are many questions before we can start the analysis of guest reviews and take data from these reviews. Text analysis such as text processing, text classification and sentiment analysis, metadata, statistical and econometric analysis can give good feedback of the quality of service in tourism. In this, paper we do the analysis of the relevance of guest reviews and propose a framework for sentiment analysis.

Key words: *review, analysis, tourism, online booking*
JEL classification: *Z31*

Introduction

Reservation systems give possibility of virtual visit of almost every tourism destination, as well as experience of other tourists that have already visited the destination. All the information of different types like text, photos, 360°-tours, visitor photos, etc., offer virtual tours for the potential tourists. Guest reviews play significant role in delivering first-hand experience for potential tourists. They rely on those reviews in choosing a hotel or even a destination. They are also very important for hotel managers. In some cases hotel ranking depends on guest review results but more important is the attractiveness and reputation of a hotel. Hotel managers can also follow the tendency of the review grades during years. However, we need to have tools for analysing guest reviews,

1 CvetkoAndreeski, PhD, Associate Professor, Faculty of Tourism and Hospitality – Ohrid, e-mail: cvetko.andreeski@yahoo.com

especially as text reviews are given in a non-structured form in different reservation systems.

At the beginning we need to know how relevant these reviews are. Do they play such an important role in choosing tourism destination? We made research on the literature dealing with these issues. In (Bogdanovych, et al., 2006) a qualitative research is conducted to give the answer to different aspects of online booking and tourist attitudes about online booking vs. booking via travel agencies. We have similar approach in (Стефановски, 2016) and (Јовиќ, 2016). The attitudes of guests are analyzed to get the relevant information about the influence of reservation systems and guest reviews on their decision concerning online reservation. Relevance of the reviews and grades from these reviews can be analyzed with quantitative methods also. We can find such a research in (Andreeski, Sentiment Analysis in Tourism, 2015) and (Sparks & Browning, 2011). In both references, besides the total grade of the reviews, the text sentiment is analyzed and several independent variables are taken into consideration to deliver conclusions. (Xiang, Du, Ma, & Fan, 2017) conduct big data analysis from diverse sources of data. They use data from three online review platforms TripAdvisor, Expedia and Yelp. They use metric tools to compare results of guest reviews from different review platform. They also point out some research that deals with platform biases, wich contributes to the validity of the results obtained by these researches (Ruths & Pfeffer, 2014). (Agheorghiesei & Ineson, 2011) conducted a survey on representatives of travel agencies in Romania and they focus on competitive impact of online bookings on customer loyalty, business and communication strategies.

Proserpio & Zevas (2016) have made analysis on management responses on consumer reviews in hotel industry and the outcomes of their response. Some papers (Diaz & Rodriguez, 2017) offer whole methodology of competitiveness on tourism destinations lodging offer based on online customer reviews. After the process of guest review analysis, management should make decisions about the results of the analysis. These results can also help the institutions to design the destination's strategy by identifying the advantages and disadvantages of the destination that can lead to making decisions about market segments, image, communication, branding, positioning, and promotion activities.

In the rest of the paper there is a qualitative research of the relevance of guest reviews and also comparison between different sources of results.

The qualitative analysis is followed by a quantitative one concerning relevance. Iterative Framework for Sentiment Analysis present some results about the sentiment analysis of guest reviews and methodology of natural language processing and text classification. At the end, some conclusions are given about using guest reviews as a tool for competitive advantage.

Research on the relevance of guest reviews

In this part of the paper, we present the results of two surveys conducted in the Republic of Macedonia and the Republic of Serbia about influence of ICT technology in hotel industry and tourism. The survey conducted in the Republic of Serbia included the population of 369 tourists and the survey conducted in the Republic of Macedonia was undertaken with the population of 318 tourists. Questions in both questionnaires are different, but there are common questions about guest attitudes towards getting information about tourist offer online, and also making online reservation. We will take into consideration next hypothesis.

H1. Tourists use the Internet as the main source of information for tourism destination and accommodation facilities

H2. Online booking is acceptable choice for most of the tourists

   a. Attitudes of tourists about online booking differ for different ages and levels of education

Table 1: *Gender distribution of tourists in Serbia and Macedonia*

Gender	**Serbia**	**Macedonia**
Male	58%	53.46%
Female	42%	46.54%

There are questions in both questionnaires about the source of information for tourism destination. In the survey conducted in the Republic of Serbia, the question is “How did you get the information about tourism offer of the destination”. Results are given in table 2.

Table 2: *Results of the question “How did you get the information about tourism offer of the destination”*

How did you get the information about tourism offer of the destination	
By recommendation of a travel agent	3.5%
In a travel agency	20.6%
In TV commercial	2.7%

On the Internet	52.3%
By recommendation of a friend	20.9%

In the survey conducted in the Republic of Macedonia, we have the question “Do you use the Internet for getting information about tourism offer of destinations”. Results are given in Table 3.

Table 3: *Results of the question “Do you use the Internet for getting information about tourism offer of a destination or a hotel”*

Do you use the Internet for getting information about tourism offer of a destination or a hotel	
Yes, always	86%
Sometimes when I go for a private arrangement	10%
Never, I get information from travel agencies	4%

Despite the fact that the questions are different in both questionnaires, we can see the differences in attitudes of the respondents. In the Republic of Serbia 52.3% of the respondents prefer the Internet as a source of information about the destination, and in Macedonia that percentage is much higher 86%. It is obvious in both surveys that more than 50% of the respondents use the Internet as a basic source of information about the tourism offer of the preferred destination. We made crosstab analysis on both surveys. Crossed variables are age of respondents and attitude towards choosing source of information about tourism offer of the destination. Results are given in Table 4 and Table 5.

Table 4: *Crosstab analysis for survey conducted in the Republic of Macedonia*

		Do you use the Internet for getting information about tourism offer of a destination or a hotel			**Total**
		Yes, always	Sometimes when I go for a private arrangement	Never, I get information from tourist agencies	
Which is your age group	18-30	126	5	0	131
	31-40	87	7	0	94
	41-50	10	9	8	27
	50+	51	11	4	66
Total		274	32	12	318

Young people till the age of 40, use the Internet as the main source of information in almost 95%. Older people use the Internet as the main source of information in more than 77%. In total, only about 4% use only information from tourism agencies for tourism offer of a destination or a hotel.

Table 5: *Crosstab analysis for the survey conducted in the Republic of Serbia*

		How did you get information about tourism offer of the destination					Total
		By recommendation of travel agent	In travel agency	In TV commercial	On the Internet	By recommendation of friend	
Which is your age group	18-30	2	2	0	18	7	29
	31-40	5	37	1	103	26	172
	41-50	4	28	5	63	26	126
	50+	2	9	4	9	18	42
Total		13	76	10	193	77	369

In this survey, young people till the age of 40 use the Internet as the main source of information in more than 60%. Older people use the Internet as the main source of information for tourism offer in only 21%. In this survey travel agencies were the main source of information in 20.5%.

Next interesting question is the attitude of respondents about online booking of accommodation. We have the results on this question from both surveys: in the Republic of Macedonia, and also in the Republic of Serbia. The results are given in Table 6 and Table 7.

Table 6: *Do you make online reservations? (Survey conducted in the Republic of Macedonia)*

	Frequency	Percent	Valid Percent	Cumulative Percent
Yes, always	219	68.9	68.9	68.9
Sometimes when I go for a private arrangement	60	18.9	18.9	87.7

Never, I get information from tourist agencies	39	12.3	12.3	100.0
Total	318	100.0	100.0	

On this question, almost 70% of the respondents give answer that they prefer online booking of accommodation. About 12% use services from travel agencies for reservations of accommodation.

Table 7: What is your attitude about making online reservations of accommodation? (Survey conducted in the Republic of Serbia)

	Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Negative	20	5,4	5,4	5,4
Neutral	119	32,2	32,2	37,7
Positive	230	62,3	62,3	100,0
Total	369	100,0	100,0	

Results given in Table 7 are presented in short Likert scale. More than 62% of the respondents have positive attitude towards making online reservations of accommodation. Only 5.4% of the respondents have negative attitude towards this question. We can find another qualitative analysis on guest review attitudes of the respondents on www.statista.com. Results are given in Table 8.

Table 8: *Results of the survey of respondent attitudes towards guest reviews*

	IMPORTANCE OF GUEST REVIEWS TO HOTEL BOOKING DECISIONS WORLDWIDE			**IMPORTANCE OF HOTEL CLASSIFICATION WHEN SELECTING HOTELS WORLDWIDE**		
	Very important	Important	Not important	Very important	Important	Not important
AUSTRALIA	69%	23%	8%	67%	21%	12%
UNITED STATES	69%	17%	14%	64%	21%	15%
GREAT BRITAIN	61%	21%	18%	55%	20%	25%
GERMANY	51%	21%	28%	51%	21%	28%
FRANCE	39%	31%	30%	45%	24%	31%

In this survey five countries are involved: Australia, the United States, Great Britain, Germany and France. From the results of the survey, we can conclude that only in France guest reviews are not “very important” for the potential tourists. In this country, 30% of the respondents find that guest reviews are not important for making a decision. Another question in this survey is Importance of the Hotel Classification when selecting Hotels Worldwide. The answer is similar to the answer of the previous question.

Quantitative analysis on relevance

Guests give their opinion on quality of service after the end of the visit of some accommodation or tourism destination. They give numeric grades for some aspects of the facilities (in TripAdvisor there are six of them: sleep quality, location, rooms, service, value, cleanliness), but also guests have the opportunity to give written review on many aspects about the quality of service. We can make statistical analysis on the grades about different aspects of the accommodation, but we can also make sentiment analysis on written reviews and compare results with the given grades. If the managers take into consideration grades of the guests, they should be aware of the relevance of the reviews.

Sentiment Analysis Approach

In the sentiment analysis, one guest review is one document, and every document can have one or more sentences. Each sentence is analysed and the sentiment orientation is calculated. We have chosen hotels with enough guest reviews to have a valid analysis. As a base for calculation of semantic orientation we use the phrase patterns with predefined semantic value. These phrases are measured from highly negative like “poor” to highly positive like “perfect”.

Many different approaches for sentiment analysis are used in many researches. (Pang & Lee, 2008) made survey about techniques and methods of sentiment and opinion analysis of product reviews. Some of them are based on Information Extraction - IE text processing tools from tokenizers, sentence splitters, part of speech analyses and annotations (Dietmar, Markus, Gunther, & Matthias, 2012), (Kasper & Vela, 2011). This approach is mostly semi-automatic approach of sentiment analysis. Besides the fact that this approach is simple, it is effective due to manual (human) analysis of the contents. Sometimes it is hard to detect the semantic orientation of the sentence. If we just follow the n-gram identification approach, we can calculate some value of semantic orientation which can lead to wrong conclusions. Calculations of a real positive or negative orientation of the sentence can be very challenging, unless we fully understand the content of the sentence. Even in the negative aspects of review, we can find some positive aspects like in the following part of the review "*food was good and quite reasonably priced but the better wines were very over-priced*". Remarks in the reviews could be also found in positive contents. In some cases, content can be followed in several sentences. This is one of the most challenging tasks.

For the machine learning approaches, in most cases support vector machine and Naïve Bayes classification method are used.

Data and Analysis

Hotels are categorized with stars (1 to 5), according to their offer and services included in the offer. On the Ohrid Lake coast we can find hotels with 3, 4 and 5 stars, as well as private accommodation categorized in private Villas, apartments and rooms for rent. This categorization is legally based and accepted by the institutions. There is a difference in the guest perception of each accommodation facility. If one wants to measure the difference, the review analysis of the guest reviews is needed and according to the obtained opinion, the classification of the accommodation facilities in the frames of the same category can be made, as well as the level of guest satisfaction for each category. Table 9 presents data for the accommodation facilities analysed in this paper.

Table 9: *Analysed accommodation facilities*

	3 stars	4 stars	Villas
Number of analysed facilities	4	6	6
Number of reviews (documents)	122	296	375
Number of separated phrases	339	855	1145

For the analysis, data are collected for the 3- and 4-star Hotels, because most of the hotels on Ohrid Lake Coast are categorized in these two categories (there are only two 5-star hotels, the second one operating for one year). Data are taken from the beginning of the existence on TripAdvisor till the end of June 2015. Three-star hotels chosen for the analysis are: the Desaret, the Riviera, the Garden and the Denarius; fourstar hotels are: the Alexander Villa, the Tino, the Aleksandrija, the Belvedere, the Sileks, the Metropol; the analyzed reviews concern the following villas: Villa Dea, Villa Germanoff, Villa Veron, Villa St. Sofia, Villa Kale and Villa St. Clement The Lesser. In order to compare the results, we have made data acquisition for villas as the best offer of the private accommodation. Besides the fact that we have guest reviews for different Hotel categories, the main focus is put on the analyses of the guest level of satisfaction. The reviews are taken from the most relevant guest review web site tripadvisor.com. For the analysis, only the written reviews are taken for different aspects of the accommodation, while the numeric values are not considered. On the TripAdvisor web site, grades are separated in several aspects, such as: sleep quality, rooms, service, etc. However, for the selection of the accommodation facilities, concurrent facilities are taken into account according to their location, placement and the price level.

As a tool for Information Extraction for the text pre-processing we have chosen General Architecture for Text Engineering – GATE application. Syntactic and semantic analysis is taken for semi-automatic sentiment analysis. For the syntactic analysis we have applied the following Processing Resources – PRs from GATE PRs: ANNIE English Tokenizer, ANNIE Sentence Splitter, ANNIE POS Tagger and ANNIE Gazetteer. At the end of this preparation for further analysis we got POS tags and annotation files in GATE structured for semantic analysis. Some of the annotations important for our analysis are not defined in Gate gazetteer, so there was a need for adding some of our local annotations to the existing ones (like Ohrid, Ohrid Lake, Skopje, some other specific words from the destination like Galicica, Plaosnik, etc.). In order to find relations between phrases and important annotation, we made some grammar rules in Jape Transducer. We have made a group of "Positive" and "Negative" annotations where we have put words which suggest positive and negative attitude towards the accommodation like: good, excellent, exceptional, best, superior, bad, mediocre, etc. So, we needed to introduce these annotations to the jape code of the grammar rules. We can implement unlimited number of grammar rules on the stack.

For the calculation of the sentiment orientation for every sentence, phrases are used with the predefined sentiment value in the interval (-1, 1). On average, for the reviews of the 3-star hotels we have 2.7 phrases per sentence and for the villas there are 3.05 phrases. The phrases could be some words that express positive or negative aspects like: bad, worse, inconvenient, good, great, best, incredible, perfect, etc. Basically, the n-gram approach is taken into account and for the classification we use the support vector machine algorithm. Phrases are analysed in the context with annotations (nouns) such as: room, food, location, hotel, staff, etc. For every phrase potential negations are searched like not, n't, unlike. In that case, the negative sentiment value is calculated for the phrase. We also take into account the intensifiers such as: very, perfectly, little, much, etc. They can increase or decrease the sentiment value of the phrases.

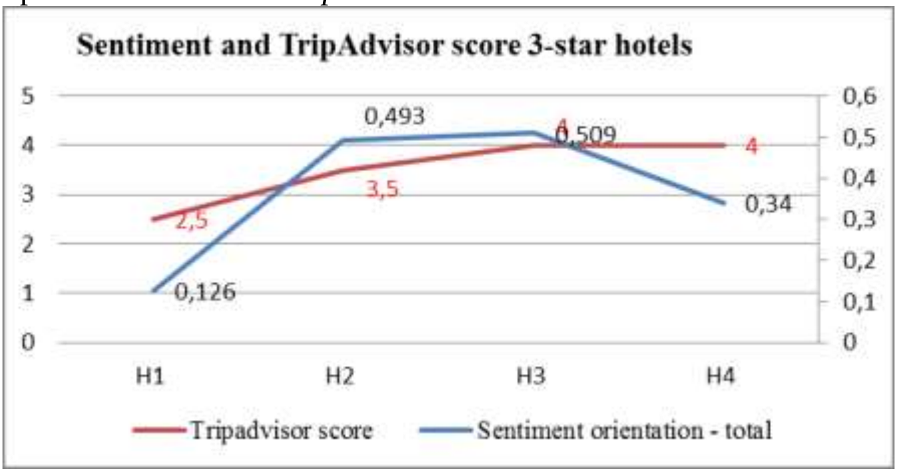
For every accommodation facility, we calculated sentiment orientation, and we have compared it with the score on tripadvisor.com. We also compared the scores for some annotations important for hotels such as: comfort, location, staff, and cleanliness. The results are given in Table 10.

Table 10: *Results of sentiment analysis for accommodations*

Accommodation	**Unit**	**Sentiment orientation - total**	**TripAdvisor score**
3-star hotels	H1	0.126	2.5
	H2	0.493	3.5
	H3	0.509	4.0
	H4	0.340	4.0
4-star hotels	H1	0.439	4.5
	H2	0.245	3.0
	H3	0.581	4.0
	H4	0.186	3.5
	H5	0.226	3.5
	H6	0.265	3.0
Villas	V1	0.544	4.5
	V2	0.484	4.5
	V3	0.455	4.5
	V4	0.471	4.5
	V5	0.573	5.0
	V6	0.505	4.5

Graphs 1 and 2, respectively, present values of sentiment orientation for the analysed 3-star hotels and their TripAdvisor score. It is obvious that there are differences between these two scores. Parts of the differences are present because of the number of annotations taken for the total score. While TripAdvisor takes six annotations (sleep quality, location, rooms, service, value, cleanliness) which are essential for total score, sentiment analysis takes into consideration much more. The scale on TripAdvisor is for 0.5 units, and it gives approximate value of the score. There are also different texts in the review and the value for some annotations. For instance, we can find text like “very good location” but the numeric value for the location is low on the scale. There is a lower discrepancy between the sentiment and TripAdvisor score for the analysed villas. They are also highly ranked than the hotels. Probably it is for the expectations according to the prices of the accommodation in these facilities and less things to be maintained. We have calculated the percent of accuracy of the analysis by the information extraction approach. The average accuracy of the analysis is 75.3%. Results are given in Table 11.

Graph 1: *Sentiment and TripAdvisor Score*



Graph 2: *Sentiment and TripAdvisor Score*

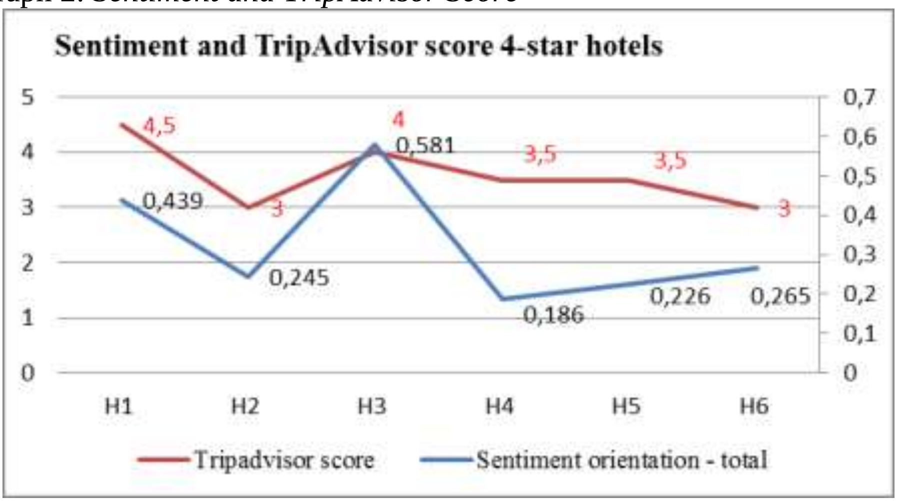


Table 11: *Accuracy of semantic analysis*

Accommodation	Unit	Accuracy
3-star hotels	H1	76.9%
	H2	83.3%
	H3	70.2%
	H4	69.23%
4-star hotels	H1	80.1%
	H2	83.3%
	H3	62.2%
	H4	78.6%
	H5	77.3%
	H6	74.3%
Villas	V1	79.8%
	V2	71.7%
	V3	76.9%
	V4	76.7%
	V5	73.5%
	V6	78.3%

There are some challenges of semantic analysis at our research. The known problems are already solved, e.g. negation is taken with different sign (positive or negative).

Reservation systems make own surveys on relevance of guest reviews and attitudes of the guests. They have the largest collection of guest reviews with all information (text, guest info, metadata, responses from managers). In the research conducted by one of the most relevant reservation systems TripAdvisor[2], we have the following results:

- 53% of the respondents would not book a hotel that does not have reviews
- 65 percent of respondents are more likely to book hotels that win awards from TripAdvisor
- 73 percent of respondents said that submitted photos help them to make the decision.

2 http://hotelmarketing.com

Iterative Framework for Sentiment Analysis

We can use several different models for sentiment analysis like Support Vector Machines, Naïve Bayes, LDA, MaxEnt and many variants and modification on these models. In the last years, the hot topic on sentiment analysis is differentiation of sentences into segments (logical segments) and tracing the change of aspect and polarity between the segments, as well as creating rules on how to detect the changes in polarity and aspect. Many unsupervised and semi-supervised approaches are presented in many papers on sentiment analysis. Aspect extraction of the text can be found in many papers like (Zhiyuan, Arjun, & Bing, 2014) or (Chang, Boyd-Graber, Chong, Gerrish, & Blei, 2009), (Chen, Mukherjee, & Liu, 2014). The unsupervised models of aspect extraction are important tools for testing reviews. (Lazaridou, Titov, & Sporleder, 2013) present the discourse model based on discourse-agnostic approach. The work with elementary discourse units – EDUs which lead them to the model extracting the information about changes in polarity and aspect in different EDUs. The LDA model is the base of their research. (Zhang & Singh, 2014) propose the semi-supervised framework – ReNew for a domain-specific sentiment lexicon. They have worked on segments of words, extracted from sentences. They employ the Conditional Random Fields-CRF model for sentiment prediction. They also use the forward and backward learner for improving the polarity check of the segments. (Dietmar, Markus, Gunther, & Matthias, 2012) worked on domain specific lexicon for customer reviews. Many fields of work have their own specific lexicon, so we need to have such a lexicon for guest reviews, as well.

Guest reviews are good examples of segments in sentences. Guest reviews in most cases are presented with short segments about some specific subject connected to guest experience. For example, the review "*Very clean and stylish room, great location, friendly owners*.[3]" is review with three different segments about positive aspects of the hotel, one aspect for the room (very clean and stylish), one for location (great) and one for the owners or the staff (friendly). But segments, even in one sentence, can have different polarity. In many cases we have distinctive words that separate or announce different polarity among the segments in one sentence.

3 www.booking.com

Pre-processing of the documents

In order to have plain text, easier for learning and parsing we made some pre-processing of the documents. At the beginning we separated sentences as individual documents (sentence splitting). We removed some information that is not important for the analysis like: the names of the employees are changed with receptionist, staff etc., the number of spent minutes are replaced with few, several or many, money amounts are also changed with appropriate words like money, cheap, expensive, etc. Some misspellings and grammatical rules are also applied to the text to have better text for sentiment analysis. Some special characters are removed from the sentences like emoticons, question marks, etc. The names of the properties are removed from the sentences or replaced with general names like hotel(s), apartment(s), etc. The same was dome with the names of the places; they are replaced with city, town, resort, etc.

The starting lexicon for learning was 500 documents of domain-specific text. Half of the documents are with positive and other half with negative sentiment. The testing data are 50 sentences with positive reviews and 50 sentences with negative gust reviews. The testing set is the fold of the training set, and those folds change for making multiple tests. The performance of the model is measured by well-known measurements: Precision, Recall, and F measure (results are given in Table 13).

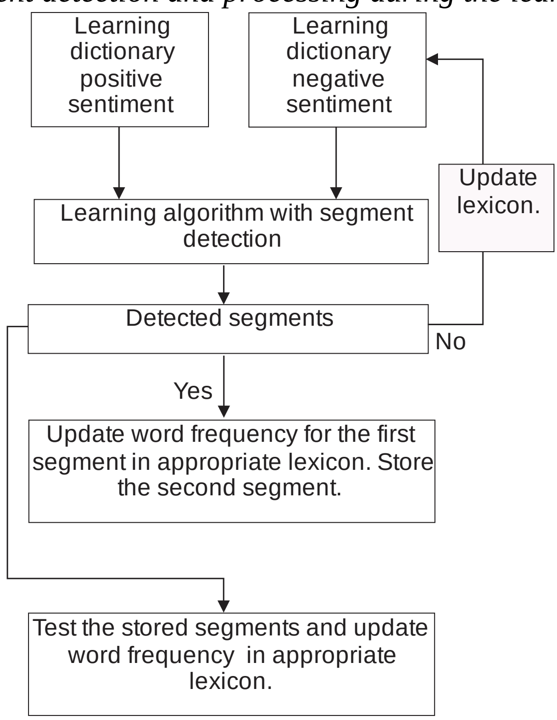
During the testing, we found that some combinations of words (couples) can affect the overall sentiment of the sentence. For instance "Hotel is close to the *old town*". The term old is usually more present in the negative lexicon, so the final calculation of the sentiment for the sentence could be negative. The same issue can be found for the couple of words "*old wine*", "*old bazaar*", etc. These couples of words can be found in many guest reviews for Macedonian tourism places. For these combinations of words we have created rule of dependence on two connected words in one like "old_town", "old_wine", etc. After the process of re-learning, the lexicon was updated with new terms. It is quite opposite than the no-pattern proposed by (Zhang & Singh, 2014), which is useful for enhancement of the polarity of the sentence.

Other sentences difficult to classify properly were sentences expressing reviewers expectations. For instance, "*I would expect a better quality and a fresh coffee possibility*" sentence have a lot of positive words like

“better quality”, “fresh coffee”, but the overall sentiment of the sentence is negative.
As far as the segmentation of the text is concerned, we searched for key words that indicate the same sentiment for next segment (and) or changes in polarity for the next segment (keywords “but”, “although” and “however”). There are several examples of polarity changes in the following sentences:
“*The heating is on* ***but*** *the big glass windows have bad isolation.*”… “***Although*** *the site says that payment by credit card is available, it is actually not.*”… “*Check-in was really quick,* ***however*** *the checkout guy was terrible.*”

In some cases the word “but” does not change the polarity of the next segment. For example, the sentence “*Room was small but there's not much you can do about that*.” is the sentence with two segments, and both of them are negative. Semi-supervised learning is the best approach for this kind of learning where we cannot define certain rules for polarity detection. We did not assume that the other segment of the sentence separated by the word “but” should have another polarity.

Graph 3: *Segment detection and processing during the learning phase*



The words “but” and “however” split a sentence into two easily recognizable segments, but the word “although” announces the change in polarity which should be traced in the sentence. In some cases, words “but” and “however” are found in the following sentence. In this case no special pre-processing of the sentences is needed. During the phase of learning we also trace the existence of segments. In this phase first segment is taken as appropriate for the lexicons where it is originally located, but the second segment is stored for including in the lexicon at the end of the learning process. In many cases, there are changes in polarity, so if we do not separate the segments we can produce wrong model of polarity (Graph 3).

Retraining of the model

During the process of preprocessing the text, the learner marks the sentences with the included segments. Also, for every sentence, the learner marks words that are not in both lexicons. After the identification of segments and missing words for the lexicon, those segments are added in the appropriate sentiment class. Words that are checked for splitting the sentences into segments (but, however, although) are deleted. After the process of retraining, the refreshing of the lexicons and vectors is initiated, in order to have ready upgraded lexicons for the next polarity check of the testing set. The algorithm for the update of lexicons is presented by Algorithm 1 in the following text.

Algorithm 1: Lexicon update with new segments

do the preprocessing of the text;
change couple of words into the appropriate word present in the lexicon;
for all sentences s in d do
 detect transition in the sentence
if the first segment sg1 is classified right
 {check if the second segment sg2 is classified right
if second segment is classified wrong or new words for lexicon
 add segment sg2 into lexicon with appropriate sentiment}
else
 add segment sg1 into lexicon with appropriate sentiment
end for
refresh the lexicon
check the test documents

Graph 4 presents the processes of testing and upgrading. Testing data are the source of retraining of the domain-specific lexicons. After the process of segmentation and lexicon check, there is the main process of testing and supervision. If the segmentation is correct and there are no errors in polarity check, the process can go further for new data. If there are segments in the text and there is wrong polarity check for the segments we have proposals for the improvement of the lexicon. After the update of the lexicon and frequencies in the lexicon, new data are taken for segmentation and lexicon check.

For the review results we have also created the table of frequencies for the mainly used nouns in the guest reviews like: cleanliness, location, staff, recommendation, etc. Those aspects are very important for the managers and owners of accommodation facilities. They want to know which keyword is listed in negative aspects, and what the frequency in each aspect is. Results are given in Table 12.

Graph 4: *The processes of the lexicon testing and upgrading*

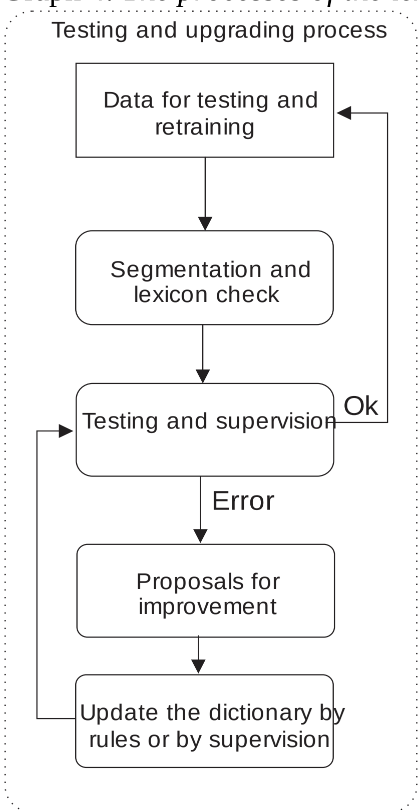


Table 12: *Frequencies of the most used nouns in the reviews*

	Positive	**Negative**
cleanliness	1	4
location	9	1
staff	3	1
recommendation	1	1
parking	4	2
room	13	21
hotel	9	7

Another issue that very important for the guest reviews is Multilanguage classification. As we have already mentioned, Naïve Bayes is a high bias classifier. Once established and tested, training lexicon can be translated in several languages. The process of retraining is fast, so we can switch languages. Even if we have reviews in different languages in one testing set, we can make classification by applying different training set for every language. This classifier is fast enough to switch to another lexicon, or to update the lexicons. However, it is better to have testing sets in one language, not to have additional switching on languages during the test phase.

Testing the model

For the process of testing we have compared our results with the results given by WEKA application for classification. We use the same method for classification (Multinomial Naïve Bayes) as well as original Naïve Bayes method. On the other side, we tested the results either for the sentences or for the segments of sentences.

At the beginning, we prepared the reviews in separate text files with negative and positive polarity. For our testing, we had documents as plain text separated in two different files, one for positive and one for negative. We converted them to arff WEKA file by using command interpreter. In the preprocessing step, we used some features which can preprocess the strings in appropriate manner to have similar preprocessed text as the one we used for our classification. By using StringToVector filter we chose the WordTokenizer and lowerCaseTokens to true. In order to have common conditions for testing, we made cross-validation of the test set with five folds. In our application, we used the test sets of 50 documents from different position in the set. For the test options of the classifier in WEKA application, we chose the cross validation with five folds. Results are given in Table 13.

Table 13: *Results of the testing*

	Precision	**Recall**	**F-measure**
Weka Naïve Bayes	0.803	0.803	0.803
Weka Multinomial Naïve Bayes	0.892	0.815	0.852
Sentences Multinomial Naïve Bayes	0.9375	0.938	0.939
Segment Multinomial Naïve Bayes	0.94	0.94	0.94

In the test sequence, we had five sentences with segment, so we can see that the results for the sentences and segments are not very different. If we had more segments, we could expect bigger gap in the results.

Conclusion

Guest reviews are important and they should be taken into consideration in the process of analysis on the quality of service. In every survey presented in this paper, guest reviews are relevant for more than 50% of the respondents. Even if the guest grades do not always represent the real opinion of the guests, they are very important for new potential guests. Hotel managers should take into consideration every aspect of the guest review. By making analysis on written reviews they can follow many aspects of the hotel's quality of service. Sentiment analysis is a tool for conducting such an analysis. Even if we have great amount of reviews for analysis, this tool can make valid analysis on many aspects.

References

1. Agheorghiesei, D. T., Ineson, E. (2011). The Impact of Online Booking Systems on Customer Loyalty in Romania. *Journal of Tourism*, 45-54.

2. Andreeski, C. (2015). Sentiment Analysis in Tourism. *ETAI 2015* (p. A2), ETAI Organization, Ohrid.

3. Andreeski, C. (2015). Steps towards statistical and sentiment analysis on guest reviews. *MiPro*, MiPro Croatian Society, Opatijia.

4. Andreeski, C. (2016). Iterative Framework on upgrading Lexicons for Sentiment Analysis. *ETAI* (pp. AM-1), ETAI Association, Struga.

5. Bogdanovych, A., Berger, H., Simoff, S., Sierra, C., Hitz, M., Sigala, M., Murphy, J. (2006). Travel agents vs. online booking: tackling the shortcomings of nowadays online tourism portals. *International Conference on Information and Communication Technologies in Tourism,* Springer, Lausanne, 418-428.

6. Chang, J., Boyd-Graber, J., Chong, W., Gerrish, S., Blei, D. (2009). Reading Tea Leaves: How Humans Interpret Topic Models. *Proceedings of Neural Information Processing Systems*, Vancouver, 288-296.

7. Chen, Z., Mukherjee, A., Liu, B. (2014). Aspect Extraction with Automated Prior Knowledge Learning. *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics* Association for Computational Linguistics, Baltimore, 347-358.

8. Diaz, M. R., Rodriguez, T. E. (2017). A methodology for a comparative analysis of the lodging offer of tourism destinations based on online customer reviews. *Journal of Destination Marketing & Management*, http://dx.doi.org/10.1016/j.jdmm.2017.02.006.

9. Dietmar, G., Markus, Z., Gunther, F., Matthias, F. (2012). Classification of Customer Reviews based on Sentiment Analysis. *19th Conference on Information and Communication Technologies in Tourism.* Helsingborg.

10. Kasper, W., Vela, M. (2011). Sentiment Analysis for Hotel Reviews. *Proceedings of the Computational Linguistics-Applications Conference*, Katowice, 45-52.

11. Lazaridou, A., Titov, I., Sporleder, C. (2013). A Bayesian Model for Joint Unsupervised Induction of Sentiment, Aspect and Discourse Representations. *Annual Meeting of the Assiciation for Computational Linguistics*, 1630-1639.

12. Pang, B., Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, Vol. 2, No. 1, 1-135.

13. Proserpio, D., Zevas, G. (2016). Online reputation management: Estimating the impact of management responses on consumer reviews. *Marketing Science*, 1-43.

14. Ruths, D., Pfeffer, J. (2014). Social media for large studies of behavior. *Science 346*, 1063-1064.

15. Sparks, B., Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, Vol. 32, No. 6, 1310-1323.

16. Xiang, Z., Du, Q., Ma, Y., Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, Vol. 58, 51-65.

17. Zhang, Z., Singh, M. (2014). A Semi-Supervised Framework for Generating Domain-Specific Lexicons and Sentiment Analysis. *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, 542-551.

18. Zhiyuan, C., Arjun, M., Bing, L. (2014). Aspect Extraction with Automated Prior Knowledge Learning. *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, Association for Computational Linguistics, Baltimore, 347-358.

19. Јовиќ, Ј. (2016). Утицај информационе технологије на рад туристичких агенција. In J. Јовиќ. Охрид: ФТУ-Охрид.

20. Стефановски, С. (2016). Улогата и влијанието на информатичко-комуникациските технологии во охридските хотели. In С. Стефановски. Охрид: ФТУ - Охрид.