Unfolding the drivers for sentiments generated by Airbnb Experiences

Abstract

Purpose

Airbnb Experiences is a new type of service launched by Airbnb in November 2016 where users can offer travellers a wide range of activities. This study devotes attention to analysing customer feedback expressed in online reviews published in Airbnb to evaluate those experiences.

Design/methodology/approach

A total of 1,110 reviews were collected from twelve categories, including 111 experiences, thus ten reviews per experience. First, the sentiment score was computed based on the text of the reviews. Second, seventeen quantitative features encompassing user, experience, and review information were used to model the score through a support vector machine. Third, a sensitivity analysis was performed to extract knowledge on the most relevant features influencing the sentiment score.

Findings

Tourists writing online reviews are not only influenced by their tourist experience, but also by their own online experience with the booking and online review platform. The number of reviews made by the user accounted for more than 20% of relevance, while users with more reviews tend to grant more positive reviews.

Originality/value

Current literature is enhanced with a conceptual model grounded on existing studies that assess tourist satisfaction with tour services. Both services online visibility and user characteristics have shown significant importance to tourist satisfaction, adding to the existing body of knowledge.

Keywords

Tourist experience; Airbnb; sentiment analysis; data mining.

1. Introduction

The innovative Internet-based environment has been a stepping-stone to new types of businesses in the tourism industry. Accordingly, Airbnb has flourished by offering a previously unforeseen service at a global scale: to provide every user with the possibility to rent its own real estate at a lower cost than using a traditional intermediary and with worldwide visibility (Guttentag, 2015). Airbnb's expansion strategy beyond lodging has led them to offer a new service they named "Experiences" based on immersive travel experiences such as gastronomy tours and nature activities (Kokalitcheva, 2016; Meltzer, 2016). While this is a recent service, it benefits from the general features of the Airbnb platform, namely the mandatory online reviews system where users can provide valuable feedback on the booked services.

The present study is focused on modelling the sentiment score from the textual reviews of Airbnb Experiences offered throughout the globe using the remaining features that characterise the experience and the tourist who wrote the review. Therefore, we aim to unfold tourist feedback into its main available dimensions in the post-purchase experience based on online reviews. The emotional load computed through sentiment analysis is used as a proxy of customer satisfaction. We expect the diversity of services provided through Airbnb and the large number of online reviews available to provide additional insights to existing literature.

2. Literature review

Tourist experience is at the core of tourism services since tourist satisfaction derived from each experience leads to intention to return in the future and post-purchase word-of-mouth (Dmitrović *et al.*, 2009). Thus, it is of chief importance to assess travellers' feelings about each experience. Social media has emerged to empower consumers on a worldwide scale by offering online platforms where users can share their thoughts about products and services (Costa *et al.*, 2019; Nave *et al.*, 2018). These platforms also enable service providers to read consumers' opinions. Specifically, online reviews play a relevant role in the tourism industry through sophisticated platforms such as TripAdvisor (Brochado *et al.*, 2018; Moro *et al.*, 2019). Therefore, traditional e-commerce platforms such as Booking.com have been developed to include online reviews (Moro *et al.*, 2018a; Xiang *et al.*, 2017). By applying data, text mining and sentiment analysis (a subdomain within text mining) to online reviews, several researchers have claimed interesting findings to tourism (Calheiros *et al.*, 2017).

Tourist experiences encompass all activities that a tourist may seek for pleasure and self-fulfilment (Cole and Scott, 2004). These include food and beverage, nature, sports, or cultural activities, among others (Volo, 2010). Airbnb's new service enables the categorisation of experiences into twelve categories: Arts and Design, Entertainment, Fashion, Gastronomy, History, Lifestyle, Music, Nature, Nightlife, Social Impact, Sports, and Wellness.

Chan *et al.* (2015) identified both core (i.e., accommodation, transport) and supporting (e.g., recreation and entertainment activities) services within a tour. Additionally, Moro *et al.* (2017a) found that the service visibility in terms of user online feedback, i.e. the user experience as a member of the online platform where (s)he is writing the review, and the review date have an impact on the expressed satisfaction. Thus, the proposed conceptual model by Chan *et al.* (2015) was complemented with the findings of Moro *et al.* (2017a). Such theoretical model, composed by six dimensions, is exhibited in Figure 1 and is validated through the online reviews collected from Airbnb.

3. Materials and methods

The data used for the experimental procedure consisted in gathering reviews from ten experiences containing at least ten reviews each, thus encompassing a total of a hundred reviews per category. However, some of the fourteen categories offered by Airbnb are underrepresented. Most notably, "business" and "technology" are two categories without experiences containing at least ten reviews when the data collection procedure took place (July 2017). Table 1 contains the number of experiences and the total number of reviews gathered from each of the twelve categories (excluding the two aforementioned ones). Figure 2 displays the adopted method. First, information encompassing three dimensions (experience, user, and review) was collected, including the review comment. Table 2 discriminates the individual features used to train the model, categorising them according to the proposed conceptual model (Figure 1). The sentiment score was computed through sentiment analysis of the textual comment of the review. The procedure used the seventeen features highlighted in Table 2 to model the sentiment score using a support vector machine (SVM). SVM is an advanced data mining technique that finds hidden patterns of knowledge by transforming the high dimensional feature space using a nonlinear mapping depending on a Gaussian kernel to identify the best linear separating hyperplane based on a set of support vector points (Moro *et al.*, 2017a). After assuring a proper evaluation of the model's accuracy, a knowledge extraction step occurs using the data-based sensitivity analysis (DSA). The DSA technique tests the sensitivity of the model, regardless of the modelling technique used, by assessing output variation to varying multiple input features through their range of possible values (Cortez and Embrechts, 2013). DSA uses a random sample collected from the dataset used to train the model. By applying DSA, it is possible to understand each feature's contribution to the model, enabling the obtention of the percentage relevance per feature.

All experiments were executed using the R statistical tool (https://cran.r-project.org/), which is an open source platform offering a large number of data analysis packages implemented by an enthusiastic community (Cortez, 2014). Specifically, the packages "sentimentr" and "rminer" were chosen, with the former implementing sentiment score computation, while the latter implements functions for data mining modelling and DSA (Cortez, 2010).

4. Results and discussion

Table 3 shows the statistics on the sentiment score computed from the comments' text. While the amplitude (the difference between maximum and minimum) is above 1.6, the standard deviation and both first and third quartiles denote the general sentiments expressed hold a relatively low variation. Nevertheless, the apparent homogeneity in the score hides the sentiments' oscillation worthy of being analysed, given the impact that a slightly more positive review may have in electronic word-of-mouth (Hu *et al.*, 2014).

The SVM model's performance was assessed by two metrics: the mean absolute error (MAE), which measures the average deviation of the score computed by the model against the real score; and the normalised area under the regression error characteristic curve (NAREC), which measures the error tolerance versus the percentage of points predicted within the tolerance, with 0.5 representing a random guess model, and 1.0 a perfect model (Hyndman *et al.*, 2016; Huntsinger, 2017). For the trained model, the

MAE achieved was 0.126, and the NAREC was 0.874, providing accurate metrics for validating the model as appropriate for knowledge extraction (e.g., Moro *et al.*, 2018b).

Figure 3 shows the contributions of each of the proposed dimensions of our conceptual model (Figure 1) to tourist satisfaction, measured by the sentiment score expressed in the textual content of the reviews. The features were categorised into the dimensions according to Table 2. It is clear that the user characteristics play a key role when compared to the remaining dimensions. Thus, our extension of the previous model proposed by Chan *et al.* (2015) has proven fruitful. Since online platforms often gather user-related information, we propose that such information should be used when evaluating tourist satisfaction. Such finding is aligned with customer feedback theory, which suggests that individual characteristics must be considered to meet users' expectations (O'Neill *et al*., 2003).

Furthermore, our results show that the online features proposed by Moro *et al*. (2017a) are more relevant to tourist satisfaction than the dimensions suggested by Chan *et al.* (2015). This element leads us to hypothesise that the tourist experience in itself is highly influenced by the online platform where the tourist booked and wrote the review. Previous studies have demonstrated the power of such platforms in the written reviews through appealing gamification features (Moro *et al.*, 2019). The present study contributes to current state-of-the-art research by unveiling how difficult it is for users to separate the tourist experience from their own online experience. This aspect is a subject requiring further development in future research.

Next, we develop on the five most influential features (names according to Table 2) to modelling sentiment score (Figure 4). The relevance of the remaining features (each of them with individual relevance below 5.5%) is aggregated in the column labelled "others".

The most influential feature by far (the second most relevant feature has almost half of the relevance) has nothing to do with the experience offered neither with the review; rather, it reflects the subjectivity inherent of users when rating experiences, confirming our previous claims. When users also have other reviews on their own offers (experiences or others), they tend to express more positive sentiments toward the experiences they comment (Figure 5). Such a result contradicts the finding by Moro *et al.* (2017a), who discovered that users having reviewed more hotels on TripAdvisor tend to be more demanding, granting lower quantitative scores. However, it should be highlighted that Airbnb is a bi-profile platform, as users may interchangeably switch from hospitality buyer to service/product seller. This different perspective of Airbnb as a tourism and hospitality marketplace providing bidirectional reviews for both seller and buyer was highlighted by Zervas *et al.* (2017). Fradkin *et al.* (2015) corroborate such a perspective by unveiling that non-reviewers tend to have worse experiences than reviewers.

Nevertheless, given the recent emergence of these kinds of marketplaces in tourism, further studies are in demand to confirm or refute the results presented. In the opposite direction, a higher number of reviews already granted to the experience translate into a lesser positive sentiment (Figure 6). Several hypotheses may justify such behaviour. Tourists are highly positive toward new offers, while as the experience loses this novelty aura and competition occurs, tourists may reflect such sentiment into the reviews they write (Wu, 2013). Also, tourists who are highly motivated toward a certain experience may be more prone to express enthusiastic feelings; on the other side, as the experience gets recognised by the online community through electronic word-of-mouth, other lesser enthusiastic tourists regarding the experience may adhere to it, although at a higher risk to miss meeting their higher expectations created through word-of-mouth (Mauri and Minazzi, 2013). Finally, the third most relevant feature is the category to which the experience belongs to, according to the Airbnb categorisation system.

Figure 7 shows that arts and design experiences translate into more positive sentiments, followed by gastronomy, music, and social impact. It is interesting to note that these top four rated experiences regarding sentiment score are all associated with cultural aspects, which is a key characteristic to attract and please tourists, a highly mature market in Europe and North America, where the largest number of experiences is currently being offered (Moro et al., 2017b). At the other end are wellness experiences, which may be justified by the more demanding tourists when the subject is related to healthcare (Dimitrovski and Todorović, 2015).

5. Conclusions

This study represents the first attempt to analyse tourists' feedback on the innovative new service of Airbnb Experiences launched in November 2016. As tourists gradually embrace the experiences offered, their perceptions get carved onto the comments they make, enabling to uncover both positive and negative sentiments about the experiences. Yet, tourists are not only influenced by their tourist experiences, but also by their own experience using the online platform where they booked and wrote their reviews. Therefore, using online reviews as a proxy for tourist satisfaction has this important drawback that researchers should account for, especially when data and text analysis using online reviews is becoming a common trend in tourism research. Additionally, we found that hosts offering experiences tend to be more positive when writing reviews about their own travelling experiences, perhaps because they are more condescending due to playing both roles (not only as tourists but also as hosts). It is as if the tourists intend to reward the experiences offered by other hosts for the impact of the services they provide through Airbnb.

Interestingly, a limitation of this study is that tourists are simultaneously influenced by their tour experience and their experience using the online platform where they booked the tour and wrote the review. Thus, other in-loco instruments such as surveys conducted when the tour takes place can provide a complementary means to measure tourist satisfaction about the tour itself. Also, since online reviews are written after the experience happened, we did not consider pre-purchase influence in this study.

References

Brochado, A., Oliveira, C., Rita, P., and Oliveira, F. (2018), "Shopping centers beyond purchasing of luxury goods: a tourism perspective", *Annals of Leisure Research*, DOI:10.1080/11745398.2018.1522594.

Calheiros, A.C., Moro, S., and Rita, P. (2017), "Sentiment Classification of Consumer-Generated Online Reviews Using Topic Modeling", *Journal of Hospitality Marketing & Management*, Vol.26 No.7, pp.675-693.

Chan, A., Hsu, C.H., and Baum, T. (2015), "The impact of tour service performance on tourist satisfaction and behavioral intentions: A study of Chinese tourists in Hong Kong", *Journal of Travel & Tourism Marketing*, Vol.32 No.1-2, pp.18-33.

Cole, S.T. and Scott, D. (2004), "Examining the mediating role of experience quality in a model of tourist experiences", *Journal of Travel & Tourism Marketing*, Vol.16 No.1, pp.79-90.

Cortez, P. (2010), "Data mining with neural networks and support vector machines using the R/rminer tool", *Advances in data mining*. Applications and theoretical aspects, pp.572-583.

Cortez, P. (2014), *Modern optimization with R*, Springer.

Cortez, P. and Embrechts, M.J. (2013), "Using sensitivity analysis and visualization techniques to open black box data mining models", *Information Sciences*, Vol.225, pp.1-17.

Costa, A., Guerreiro, J., Moro, S., and Henriques, R. (2019), "Unfolding the characteristics of incentivized online reviews", *Journal of Retailing and Consumer Services*, Vol.47, pp.272-281.

Dmitrović, T., Knežević Cvelbar, L., Kolar, T., Makovec Brenčič, M., Ograjenšek, I., and Žabkar, V. (2009), "Conceptualizing tourist satisfaction at the destination level", *International Journal of Culture, Tourism and Hospitality Research*, Vol.3 No.2, pp.116-126.

Dimitrovski, D., and Todorović, A. (2015), "Tourism Management Perspectives", *Tourism Management*, Vol.16, pp.259-265.

Fradkin, A., Grewal, E., Holtz, D., and Pearson, M. (2015), "Bias and reciprocity in online reviews: Evidence from field experiments on Airbnb", in *Proceedings of the Sixteenth ACM Conference on Economics and Computation* (pp.641-641). ACM.

Guttentag, D. (2015), "Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector", *Current issues in Tourism*, Vol.18 No.12, pp.1192-1217.

Hu, N., Koh, N.S., and Reddy, S.K. (2014), "Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales", *Decision Support Systems*, Vol.57, No.42-53.

Huntsinger, R.A. (2017), *Evaluating Forecasting Performance in the Context of Process-Level Decisions: Methods, Computation Platform, and Studies in Residential Electricity Demand Estimation* (Doctoral dissertation, Carnegie Mellon University).

Hyndman, R.J. and Koehler, A.B. (2006), "Another look at measures of forecast accuracy", *International Journal of Forecasting*, Vol.22 No.4, pp.679-688.

Kokalitcheva, K. (2016), *Airbnb Wants to Go Beyond Home-Sharing With Debut of "Experiences"*. Fortune Tech. Retrieved from http://fortune.com/2016/11/17/airbnb-experiences-trips/.

Mauri, A.G. and Minazzi, R. (2013), "Web reviews influence on expectations and purchasing intentions of hotel potential customers", *International Journal of Hospitality Management*, Vol.34, pp.99-107.

Meltzer, H. (2016), *Airbnb launches tailor-made city tours and exclusive experiences with local experts*. The Telegraph (Travel News). Retrieved from http://www.telegraph.co.uk/travel/news/airbnb-launches-trips-tours-and-experiences-with-local-experts/.

Moro, S., Ramos, P., Esmerado, J., and Jalali, S.M.J. (2019), "Can we trace back hotel online reviews' characteristics using gamification features?", *International Journal of Information Management*, Vol.44, pp.88-95.

Moro, S., Rita, P., and Coelho, J. (2017a), "Stripping customers' feedback on hotels through data mining: the case of Las Vegas Strip", *Tourism Management Perspectives*, Vol.23, pp.41-52.

Moro, S., Rita, P., and Cortez, P. (2017b), "A text mining approach to analyzing Annals literature", *Annals of Tourism Research*, Vol.66, pp.208-210.

Moro, S., Rita, P., and Oliveira, C. (2018a), "Factors influencing hotels' online prices", *Journal of Hospitality Marketing & Management*, Vol.27 No.4, pp.443-464.

Moro, S., Rita, P., Oliveira, C., Batista, F., and Ribeiro, R. (2018b), "Leveraging national tourist offices through data analytics", *International Journal of Culture, Tourism, and Hospitality Research*, Vol.12 No.4, pp.420-426.

Nave, M., Rita, P., and Guerreiro, J. (2018), "A decision support system framework to track consumer sentiments in social media", *Journal of Hospitality Marketing & Management*, Vol.27 No.6, pp.693-710.

O'Neill, M., Wright, C., and Palmer, A. (2003), "Disconfirming user expectations of the online service experience: inferred versus direct disconfirmation modeling", *Internet Research*, Vol.13 No.4, pp.281-296.

Volo, S. (2010), "Bloggers' reported tourist experiences: Their utility as a tourism data source and their effect on prospective tourists", *Journal of Vacation Marketing*, Vol.16 No.4, pp.297-311.

Wu, P.F. (2013), "In search of negativity bias: An empirical study of perceived helpfulness of online reviews", *Psychology & Marketing*, Vol.30 No.11, pp.971-984.

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

Zervas, G., Proserpio, D., and Byers, J.W. (2017), "The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry", *Journal of Marketing Research*, Vol.54 No.5, pp.687-705.

Tables

Table 1 - Reviews collected per experience category.

Category	Nr. of experiences	Total nr. reviews
Arts and Design	10	100
Entertainment	10	100
Fashion	10	100
Gastronomy	10	100
History	9	90
Lifestyle	10	100
Music	10	100
Nature	10	100
Nightlife	6	60
Social Impact	8	80
Sports	10	100
Wellness	8	80
	111 experiences	**1110 reviews**

Table 2 - Features used.

Feature	**Dimensions**	**Description**
category	Tour guiding service	See Table 1
cont.exp		Continent where it occurs: {America; Asia; Europe} Note: only experiences in these 3 continents were analysed.
duration		Duration of the experience in hours.
incl.drink	Core services	If the experience included drinks.
incl.snack		If the experience included snacks.
incl.meal		If the experience included meals.
incl.transp		If the experience included transportation.
incl.equip	Support services	If the experience included equipment.
incl.ticket		If the experience included tickets.
lang.nat		If the guide speaks native language.
nr.rev.exp	Service visibility	Nr. reviews the experience has.
facebook		If the user was connected to Airbnb through their Facebook account.
cont.origin	User characteristics	Continent corresponding to the nationality country of the user.
nr.rev.usr		Nr. reviews the user has in his/her own offers on Airbnb.
airbnb.memb		How long the user is an Airbnb member (in months).
month	Review date	Month the review was written.
weekday		Weekday the review was written.
sentiment	**Customer satisfaction**	***Sentiment score computed based on the review text.***

Table 3 - Statistics on the sentiment score.

Average	0.381
Std. dev.	0.170

Minimum	1st quartile	Median	3rd quartile	Maximum
-0.362	0.276	0.355	0.471	1.387

Figures

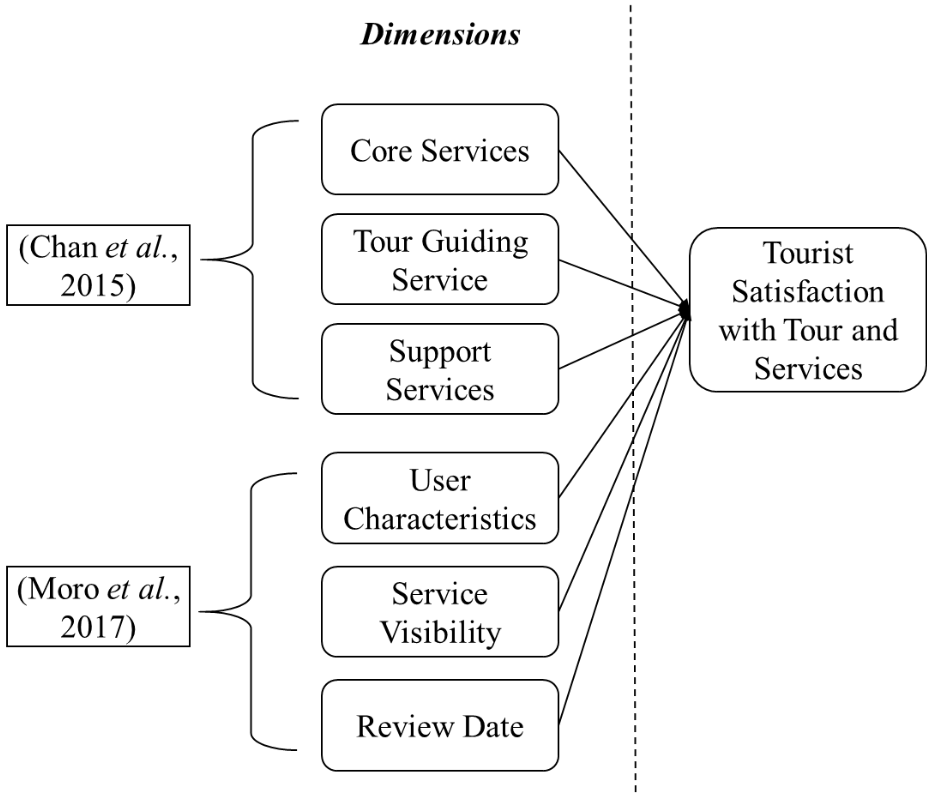

Figure 1 - Conceptual model.

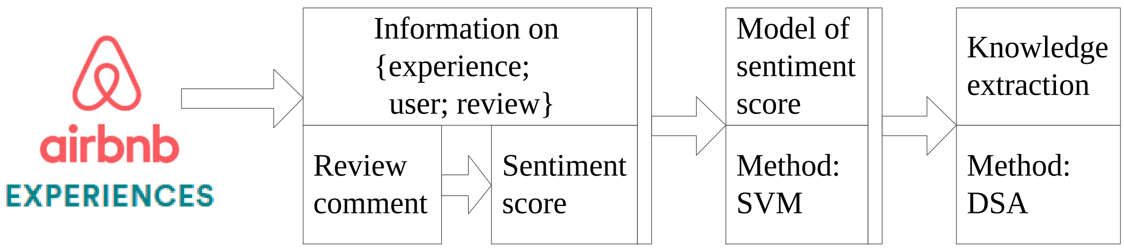

Figure 2 - Experimental procedure.

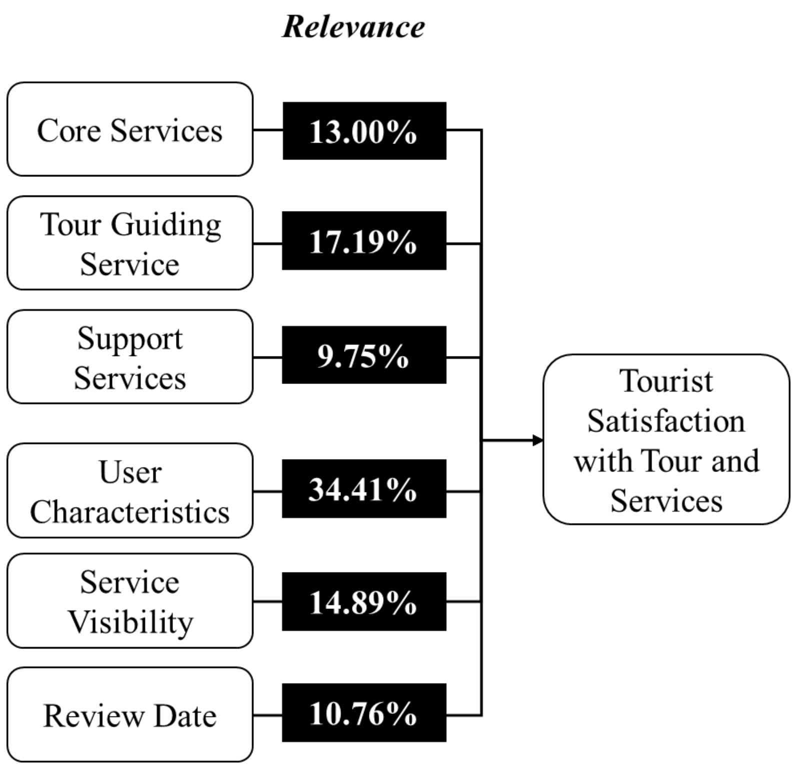

Figure 3 – Relevance of the dimensions of the proposed model.

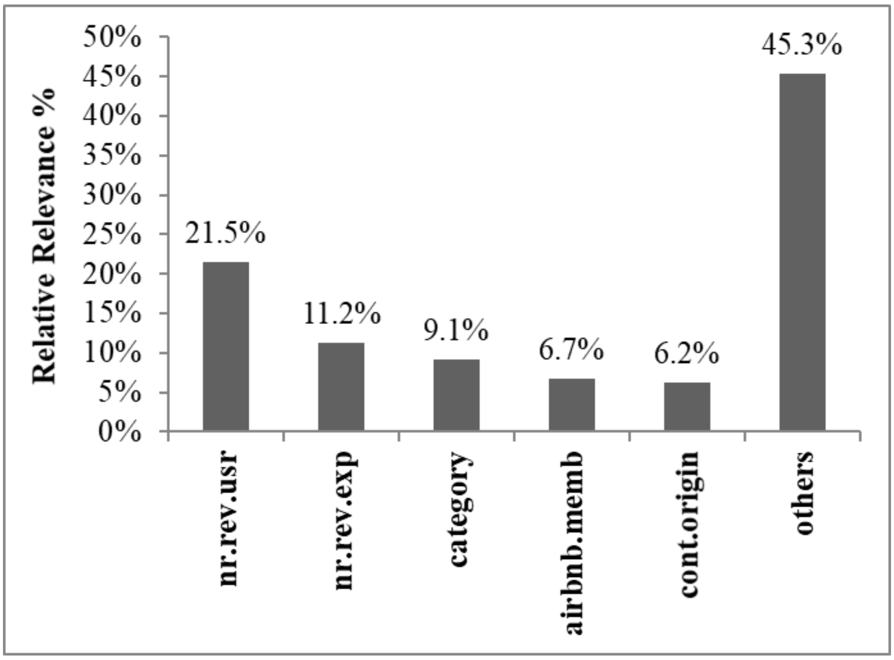

Figure 4 - Features' relevance to model sentiment score.

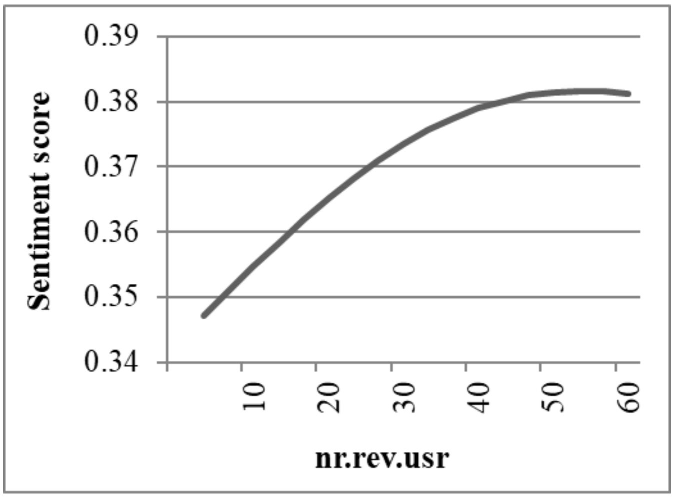

Figure 5 - Influence of the nr. reviews the user has in his/her own offers on sentiment score.

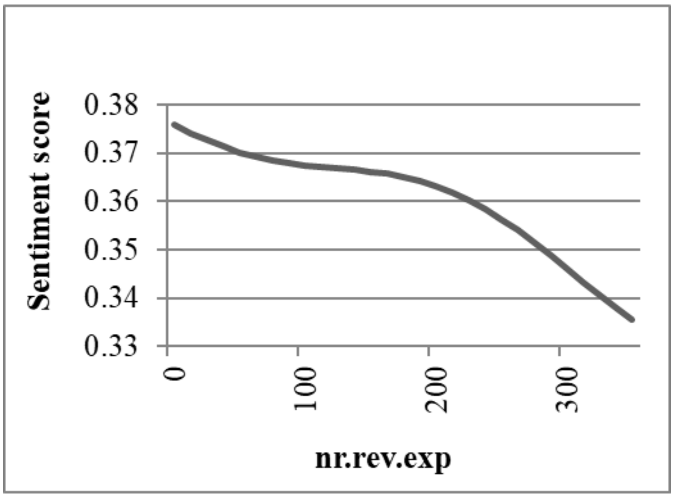

Figure 6 - Influence of the nr. reviews of the experience on sentiment score.

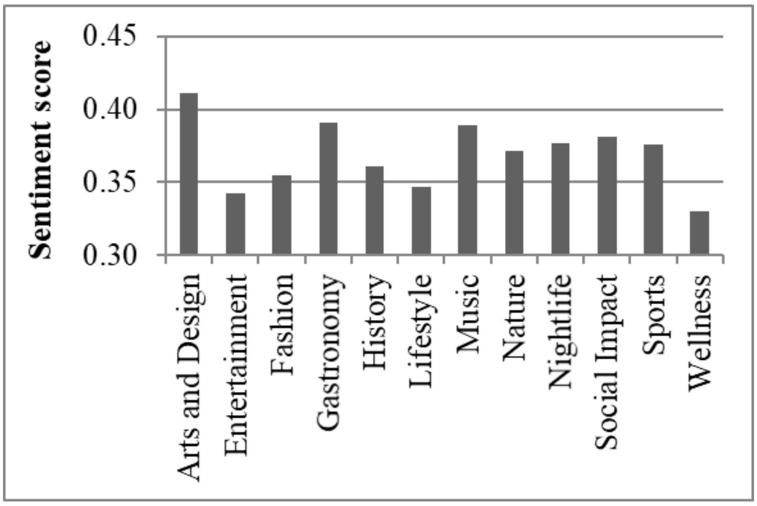

Figure 7 - Influence of the category of the experience on sentiment score.