The role of badges to spur frequent travelers to write online reviews

Abstract

Purpose

Online travel reviews platforms have become innovative information systems also due to the incorporation of sophisticated gamification elements such as visually appealing badges. This study aims to analyze three features of the review after leveling up a badge: review length (number of words), sentiment scoring, and period between two successive reviews (number of days until the next review is written).

Design/methodology/approach

A total of 77k online TripAdvisor reviews written by 100 frequent travelers and contributors are analyzed using a data mining approach. A data-based sensitivity analysis (DSA) is then conducted to provide an understanding of the data mining trained models.

Findings

The results show evidence that badges appealing for self-pride ("badge passport") and for peer-recognition ("badge helpful") have significant influence across the lifespan of online review, whereas badges simply awarded by counting the contributions have little effect.

Originality

This study provides the first analysis of how an experienced traveler is influenced as the badges and points are being awarded. Intrinsic motivational factor to award badges for standard contributions scarcely influence user behavior. Badges need to be designed to reward accomplishments that are not so trivial to be achieved and that do not depend entirely on the user.

Keywords

Gamification; badges; online reviews; data mining; user behavior.

1. Introduction

Social media has given voice to a large number of consumers throughout the world via online platforms, allowing to create, share, and exchange content using electronic word-of-mouth communication (eWOM), which empowers both consumers and providers (Hajli, 2015). International organizations worldwide soon recognized the power of such global platforms, so managers have devoted effort and resources to improve their brand image by increasingly interacting with e-consumers and improving the quality of their service organizations (Barreda *et al.*, 2020). Since the influence of online social media platforms on consumer behavior depends entirely on the number of remote access users, ongoing efforts are being made to create innovative features able to increase user engagement (Huang and Benyoucef, 2013). Gamification is the use of visually appealing features inspired in videogames in non-gaming contexts. As desirable achievements for users (Seaborn and Fels, 2015, Klock *et al.*, 2020), such features are designed to increase participation, being granted when a specific user accomplishes a certain level of contributions (Cook, 2013). One of the most adopted formats by online platforms is a badge system, which typically includes a set of different badges designed to accomplish different goals (Friedrich *et al.*, 2020).

The tourism industry was the first to embrace new communication paradigms provided by social media (Moro *et al.*, 2020). Initially, online platforms were developed to either sell services (e.g., Booking.com) or to share reviews posted by travelers during post-travel stage (e.g., TripAdvisor). However, the most successful platforms soon became the ones that adopted mixed strategies by selling services while incentivizing users to share their feelings and evaluations about the services bought. Nowadays platforms such as Expedia, Booking.com, TripAdvisor, and Airbnb enable reciprocal digital interactions between users and service providers (e.g., hotels, restaurants, and attractions). Such evolution led to the development of sophisticated platforms that compete for users' attention. Specifically, TripAdvisor has developed a complex badges system, which is a powerful tool to increase participation (Moro *et al.*, 2019). However, there is a paucity of literature on the influence of such system on user behavior. In fact, querying the Scopus database by ["gamification" AND "TripAdvisor"] only results in three hits. Sigala (2015) demonstrates by using an email survey that travelers are mostly motivated to write reviews because they earn points and badges. Moro *et al.* (2019) collect a large set of online reviews and demonstrate that both points and badges influence the review length and the sentiment scoring expressed by the reviewers. Specifically, reviews, reviewer points, and badges are analyzed at a single moment in time, yet how the traveler is influenced over time as the badges and points are being awarded (thus enriching user profile) has not been discussed so far in a consistent manner.

The present study addresses this gap by analyzing the behavior of 100 experienced travelers who have posted more than 77 thousand online reviews. Grounded on the broader Marketing literature on gamification, this study shows how different types of awarded badges are affecting the length of the next review to be written, the sentiment expressed, and when the next review will be written.

2. Background

2.1. Online reviews in tourism services

Online reviews play a significant role in tourism development within the social media landscape. As remote users can both express their own opinions using textual format and read other comments and ratings in real time, the impact of eWOM is amplified within online reviews platforms (Fine *et al.*, 2017). Online reviews have become of paramount importance in tourism and hospitality services since unit and brand managers encourage guests and visitors to write about their experiences. At the same time, managers promote their brand values by showing high review score of the accommodation to the guests (Yoo *et al.*, 2016). One of the most renowned platforms is TripAdvisor, where registered users can write reviews about their post-visits while managers and employees can reply to each visitor comment. Moreover, TripAdvisor is one of the largest databases of reviews (Ayeh *et al.*, 2013). Therefore, it has been adopted by many scholars to address a wide array of research themes, including studies aimed at exploring consumer perspective (e.g., Chang *et al.*, 2019).

In TripAdvisor and in other similar social media platforms, readers of reviews posted by other users can mark a review as being helpful, triggering an increased visibility and higher reputation of the reviewer as well as the perceived value (Guerreiro and Moro, 2017). Online reviewers can become powerful influencers since they participate actively by contributing to the platform. As a reader crawls through the reviews, TripAdvisor also shows indicators about the reviewers' activity on the platform, including the number of contributions and the number of helpful votes. Such indicators may denote a more experienced reviewer as more credible according to the e-reader (Filieri *et al.*, 2018). Also, as travelers become bloggers and attract followers, so thus an online reviewer profile of an experienced traveler can be subjected to scrutiny by many interested e-readers (Pirolli, 2018). Given these premises, managers are particularly aware and interested in what influencers are saying on TripAdvisor (Banerjee and Chua, 2016).

2.2. Gamification in tourism social media platforms

The competition among social media platforms has fostered innovation with the aim to attract users that take the role of producers and consumers of information across digital platforms (Quattrociocchi *et al.*, 2014). Gamification is one of the most common techniques to appeal users to participate in the platform. By rewarding participation with appealing awards, online platforms mimic video games and game players' desire to accomplish specific tasks and achieve an award (Zichermann and Cunningham, 2011). Gamified elements are already present in many platforms related to tourism and hospitality services at least for the past ten years, although just recently literature acknowledged their importance (Xu *et al.*, 2013). These elements often take the form of a simple system of points, which sums participation activities to grant visibility and peer-recognition to users (Friedrich *et al.*, 2020). As opposed to brand loyalty programs, which also adopt gamified elements using both physical and electronic loyalty cards (e.g., a frequent flyer card) to increase users' purchases, the goal of a social media gamified element is to increase users' engagement (Hamari, 2017). Afterall, the business model of social media platforms relies on users' interactions (Costa and da Cunha, 2010). Thus, platforms such as TripAdvisor have implemented visually appealing badges that extrinsically motivate users to participate for achieving a badge on their own profile (Figure 1).

Recently, there has been increasing interest in gamification in several domains, also considering services marking theory (Huotari and Hamari, 2017). Nevertheless, academics underlines the need of framing gamification and calling for innovative developments (Nacke and Deterding, 2017). As regards gamification applied to tourism, research is also still in its infancy. The literature analysis conducted by Koivisto and Hamari (2019) identified just two empirical studies in culture/tourism from a total of 462 gamification articles, in a database search performed in June 2015. Table 1 summarizes a total of seven studies on online reviews platforms in tourism. The results clearly confirm that research is missing and justify calls for papers on the subject.

This research aims to better understand the TripAdvisor user path, an online user is more easily get involved into the complex gamified system as he/she becomes a frequent reviewer. Thus, this study covers Marketing literature, specifically the impact of gamification upon consumers' path applied to the hospitality industry. Due to the lack of literature, novel hypotheses are drawn from the few studies shown in Table 1, and specifically focused on user behavior when are subject to gamified features as he/she publishes online reviews. The following set of hypotheses based on the four badges, shown in Figure 1, are detailed below:

H1: An online reviewer writes a lengthier review after:

> H1a: leveling up a badge directly computed from the number of reviews posted 100 frequent travelers and contributors (i.e., badge hotels; badge attractions, Figure 1).
>
> H1b: leveling up a badge related to the perceived helpfulness of online review by other reviews (i.e., badge helpful).
>
> H1c: leveling up a badge related to traveling (i.e., badge passport, which is awarded by the number of different places visited).

H2: An online reviewer writes a more positive review after:

> H2a: leveling up a badge directly computed from the number of reviews posted 100 frequent travelers and contributors.
>
> H2b: leveling up a badge related to the perceived helpfulness of online by other reviews.
>
> H2c: leveling up a badge related to traveling.

H3: An online reviewer writes more quickly a review (i.e., the time period between two reviews is shorter) after:

> H3a: leveling up a badge directly computed from the number of reviews posted 100 frequent travelers and contributors.
>
> H3b: leveling up a badge related to the perceived helpfulness of online review by other reviews.
>
> H3c: leveling up a badge related to traveling.

3. Data and approach

The experimental setup for this study is based on secondary data already available on TripAdvisor. Thus, instead of developing surveys to collect responses from TripAdvisor's users, the characteristics of online reviewers are collected to assess user behavior throughout their membership time. This approach has the advantages of benefiting from the massive amount of data, overcoming the limits of surveys and questionnaires (Moro *et al.*, 2020). To understand the behavior of influencers, we select a random sample of 100 frequent travelers that have written at least 100 reviews, each about their visits to many places during their TripAdvisor membership lifetime. Then, a web scraping script is specifically developed to crawl through each of the 100 users' profiles and collect all the reviews they have written, the date when those were posted, and the number of helpful votes received per review. The script is implemented using the open-source R statistical tool, which offers an intuitive scripting environment for data analysis, powered by a large enthusiastic community that contributes with packages for multiple tasks (Cortez, 2014). Specifically, we used the package "RSelenium" and the "rvest" for crawling through the webpages through a Selenium server and for retrieving data. As result, a dataset containing a total of 77,086 online reviews is collected. Then, the lifespan of each reviewer is simulated to compute both if each badge leveled up and the cumulative values that lead to rewards in the form of badges. The first allows to address the research questions, while the second reflects the influence of being an experienced user, exposed to many badges, which was deemed relevant within gamification in literature (Moro *et al.*, 2019). Thus, an R script is developed to perform the computations, whose details for review "n" are shown in Figure 2. The "sentimentr" package from R is chosen to develop a sentiment analysis. It computes a sentiment score with 0 meaning a neutral sentiment, while both polarities represent negative and positive sentiments (with a higher absolute value meaning a stronger sentiment). The "wordcount" function from the "ngram" package is used to compute the number of words per review, while a simple "difftime" is used to obtain the number of days between two reviews.

Although TripAdvisor has diverse types of badges, which each user can earn, since we are simulating the lifespan of users as online reviewers, we were able to compute only those badges for which TripAdvisor clearly provided the corresponding rules, i.e., how the badge was earned/leveled-up. As such, we adopted four badges highlighted in bold in Figure 2, with the rules detailed there.

To address the set of hypotheses previously defined, data mining approach is adopted following a similar procedure defined by Moro *et al.* (2020). Data mining enables to extract meaningful knowledge from patterns of data uncovered by machine learning-based algorithms. In other words, a dataset comprised of occurrences of a given problem characterized by a set of numerical or categorical variables is compiled and prepared to be given as input to an algorithm whose goal is to find non-trivial relations between the variables that may bring new insights to this question. Thus, a data understanding and preparation step are undertaken with the key goal of identifying the features that better address these hypotheses. Specifically, three main output features are identified for understanding user behavioral changes as gamification features are earned: i) review length (number of words); ii) sentiment scoring; and iii) period between two successive reviews (number of days until the next review is written). A data model is then trained for each gamification feature. As input features, eight of them stem directly from the simulation of the four badges lifecycle for each user, two per each badge (one feature that indicates if the badge leveled up due to a published review, and another one that shows the level of the badge). Additionally, three input features are included to compute for the current review the same as the three output features adopted (i-iii)(Figure 2). The total input and output features are described in Table 2.

All the three models are trained using multilayer perceptron, which is the most popular type of neural network, consisting in one hidden layer and N hidden nodes. The number of hidden nodes N defines the complexity of the network, which enables it to apprehend non-linear relations between features. The state of the *i*-th node is computed by:

$$s_i = f(w_{i.0} + \sum_{j \in P_i} w_{i,j} \times s_j)$$

where f is the logistic function, P_i is the set of nodes reaching node i, and $w_{i,j}$ is the weight between nodes i and j (Haykin, 2010). The k-fold cross validation is adopted to evaluate that each of the three models adequately modeled their target features. This technique divides the dataset into k folds and uses k-1 folds for training the model and the remaining fold for testing its performance on different data, rotating the fold used for testing until all folds have been used once for resting. K is set to ten following the recommendation by Refaeilzadeh *et al.* (2009). Two metrics are computed: the mean absolute error (MAE), which is the average of all the deviations between the real value and the output of the model, and the normalized MAE (NMAE), which divides the MAE by the amplitude of the target feature (i.e., the difference between maximum and minimum values) (Silva *et al.*, 2018). To corroborate the raised hypotheses, we need to understand how the input features (the badges) influence the outputs that translate user behavior when writing the next review. To this end, data-based sensitivity analysis (DSA) enables to apprehend how the input features affect the output of a given data mining model (Moro *et al.*, 2020). This procedure consists in selecting a random sample from the training dataset, varying each of the input features simultaneously through the range of possible values. If the output significantly changes, the input features varied are highly relevant for the output (Cortez and Embrechts, 2013). This aspect allows to assess which features mostly contribute to the modeled feature. All the data mining experiments are conducted using the “rminer” package, which is specifically suited for data mining tasks (Cortez, 2010).

4. Results and discussion

The first step required from a methodological standpoint is to assess the accuracy of the three models built using the input features previously described in Table 2.

Table 3 shows the performance evaluation metrics for the three models. While the MAE denotes average absolute deviations, the NMAE puts that metric into proportion to the amplitude of the scale for each of the three output targets. When compared to other studies, which also adopt NMAE (e.g., Silva *et al.*, 2018), the achieved values provide evidence that the input features model with low errors the three output features. When compared to the values obtained by Moro *et al.* (2019), the errors computed in this study are significantly lower (i.e., 13.89% versus 1.73% for review length in the cited study; 14.34% versus 3.91%). Such results show that (1) the same user tends to adopt similar behavior through his/her online review lifespan, and that (2) including the leveling up of badges (i.e., if a badge leveled up after a posted review) helped in increasing models’ accuracy. The next step after validating the robustness of the models is to apply DSA for extracting each feature relevance to the three target features. Figures 3, 4, and 5 show how each feature contributed to the modeling target. The labels for the input features are the same identified in Table 2. The first thing to note is that the input feature that reflects the same measure for the current review for each of the target features accounts for a large fraction of relevance (i.e., Figure 3: current review’s length - rev.nwords - versus next review’s length; Figure 4: current review’s sentiment score - rev.sentiment - versus next review’s sentiment score; Figure 5: number of days since the previous review was written - prev.rev.days.since - versus number of days to the next written review). This confirms the intrinsic influence of badge system on individual behavior, i.e., a reviewer that is used to write lengthier reviews is likely to continue writing lengthier reviews. Nevertheless, there is a predominance of the number of days have passed since the previous review as a highly influencing feature to all the three target features. In fact, it is also the most relevant feature to the length of reviews of the next posted review.

Figures 3, 4, and 5 show another important finding: the features indicating if a badge leveled up or not account for different amounts of relevance. While “leveledup.bpassport” and “leveledup.bhelpful” account for at least around 10% or more in the three models, the remaining, i.e., "leveledup.hotel" and "leveledup.attraction" account for as little as 2.5% to 5% of relevance, implying their contribution as influencing features is reduced. To answer H1(a,b,c), we plot the variable effect characteristic (VEC) graphic, which is drawn from the output of the DAS. It enables to understand how an input feature influences the output (Cortez and Embrechts, 2013).

In regard to the four analyzed badges, Figure 6 shows how being awarded with each badge influences next review length. The obtained results refute hypothesis H1a, since there is not a clear trend that indicates that leveling up a badge for hotels/attractions leads to a lengthier review. Such results also indicate the smaller relevance of these two badges in comparison to the remaining features shown in Figure *3*. Both H1b and H1c are confirmed, i.e., there is a trend suggesting that remote users that become frequent contributors in TripAdvisor platform tend to write lengthier reviews, after leveling up a badge passport or a helpful badge.

Figure 7 shows the influence of leveling up each of the four badges on the sentiment score (H2 hypotheses). The trends for both badge hotels and badge attractions confirm H2a, i.e., users leveling up each of these two badges write more positive reviews afterwards. However, the difference between leveling up or not those two badges is small, also due to the little relevance of these two features, which are the two least relevant, as shown in Figure *4*. Interestingly, H2b is refuted, i.e., leveling up a badge helpful result in a next review being less positive. It confirms the finding of previous studies (Filieri, 2015), i.e., negative reviews tend to be considered more helpful to readers. The effect is the most remarkable from the four badges, showing an inverse influence when compared to what H2b postulated. As for H2c, it is confirmed, i.e., leveling up the badge passport results in a next review more positive. Such fact may derive from the satisfaction of an accomplished desire to add another location to the list of visited places, which is acknowledged by TripAdvisor and, in turn, the user feels pleased and reflects it in the next written review.

Figure 8 enables to address H3. The badge passport mostly influences the number of days until the next review is written, confirming H3c. Thus, a traveler who is writing about a new place he/she never visited before (or at least, never wrote about it on TripAdvisor), when awarded with a badge passport, is motivated to write faster another review. In regard to H3b, the results also show that a reviewer, whose review was previously awarded with a badge helpful level up, results in a more motivated user to write faster another review. On the opposite, the lesser relevant badges attraction/hotel, when awarded, show little difference in the number of days until next review.

5. Conclusions and implications

5.1.Conclusions

Research on gamification in tourism appeared to be still in its infancy until very recently (Xu *et al.*, 2017), while practitioners have taken the lead several years ago. However, progress has been made in just a few years to understand how to motivate users and how to co-design personalized services, in treasure hunts and multiple applications in cultural heritage and tourism marketing (Klock *et al.*, 2020, Xu and Buhalis, 2021, Xu *et al.*, 2016). Pasca *et al*. (2021) identified the need to gain insight into *service provider-generated content* theme, namely by exploring how reviewers' behavior with different levels of badges changes. Our research shows that those online users, who usually write lengthier reviews, continue writing lengthier reviews. Negative reviews tend to be considered more helpful to readers. When considering a traveler who earns a badge passport after writing about a place he/she never visited before, he/she tends to write other reviews faster.

5.2.Theoretical implications

To gain insight into gamification in tourism, this study focuses on how leveling up badges influences user's participation within online reviews platform. Three types of badges awarded by TripAdvisor to accomplish different goals are analyzed using data mining approach. First, the badge hotel and the badge attraction are leveled up by writing reviews about hotels and attractions. Thus, these badge systems serve as counters of reviews. Both were found to be the least relevant of the features influencing the next written review, considering three variables: length of review in words, sentiment score of review, and the number of days until the next review. Second, the badge helpful rewards public recognition by others. This was found to influence the three variables, although the sentiment score decreases after an awarded level up to the badge. Third, the badge passport, which appeals to pride and smugness, by rewarding the individual accomplishment of visiting a new location and being granted visibility for such achievement. Significantly, the badges are not all the same and their appeal and influence differ according to what is being rewarded.

5.3.Practical implications

Focusing on potential managerial implications, given the proven influence of badge system on remote user's behavior and the need of developing a user-centric approach (Klock *et al.*, 2020, Pasca *et al.*, 2021), service providers, destination marketers, and travel managers should develop and personalize new badges to understand the impact these may have on users depending on user profile. Specifically, badges appealing to individual vanity as well as badges recognizing the visibility of a user by their peers and fans have a deeper impact on users' behavior, when compared to simple counters awarding participation.

5.4.Limitations and future research

This study has some limitations that should be highlighted. First, this analysis regards only those reviews posted by frequent travelers. A larger number of users could be analyzed in future research to compare and validate the results obtained in this study. Additionally, TripAdvisor offers many badges that should be further investigated (e.g., badges that account for contributing with photos). One possibility could be to analyze a set of users for a certain period, to fully understand the process of badges as they are rewarded.

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Table 1 - Studies on gamification in online reviews of tourism services.

Reference	Platform	Data	Method	Major findings
Sigala (2015)	TripAdvisor	E-mail questionnaire conducted in August-September 2013, with 463 valid responses	Exploratory factor analyses	Impacts of the TripAdvisor’s funware design: experiential values gained by using TripAdvisor; impacts of TripAdvisor on travelers’ trip planning processes; impacts of Tripadvisor on trip experiences.
Schuckert *et al.* (2016)	TripAdvisor	Web scraping of 1,181,935 reviews in August 2013 from 1 to 5 star hotels in Hong Kong	Correlation analysis between contributor badge level and review score and helpfulness	Reviewers with high-level badges tend to post moderate ratings and avoid extreme ratings.
Liang *et al.* (2017)	Airbnb	Web scraping in August 2015 of 3830 accommodations belonging to 1872 hosts	Multivariate econometric models	Accommodations with the “Superhost” badge are more likely to receive reviews and higher ratings. In addition, guests are willing to spend more on “Superhost” accommodations.
van Nuenen (2019)	TripAdvisor	Critical discussion of the user as a reviewer in the context of an algorithmic culture, giving TripAdvisor as an example of a gamified platform		TripAdvisor's gamified system puts the user in a state of immersion through playful systems by mimicking other’s stories of unicity and authenticity.
Moro *et al.* (2019)	TripAdvisor	Web scraping of 67,685 reviews published in 2016 and 2017, written by different users about Las Vegas hotels	Data mining	There is an influence of gamification features on both sentiment score and review length.

Xu *et al.* (2016)		Four focus groups, 26 students in Nanjing University, China	Exploratory study. Focus group	Multi-dimensional factors influence tourists as mobile gamers
Pasca *et al.* (2021)	Online platforms (including TripAdvisor, Airbnb)	36 papers in the Scopus database published between 2011 and 2019.	Systematic literature review	T&H services generate value for both users and service providers. A research agenda is identified.

Table 2 - Features used for the developed models.

Features		**Description**
input	prev.rev.days.since	Days since last review was written
	rev.sentiment	Sentiment score of review
	rev.nwords	Review length in words
	badge.rev.hotel	Badge hotel (levels up for each 3 reviews)
	badge.rev.attraction	Badge attraction (levels up for each 3 reviews)
	badge.helpful.nr	Badge helpful (levels up for the following sequence of helpful votes: 1, 5, 10, 25, 50, and for each 100 helpful votes reached)
	badge.passport.level	Badge passport (levels up for each new city visited)
	leveledup.bhotel	If badge hotel leveled up (Y; N otherwise)
	leveledup.battraction	If badge attraction leveled up (Y; N otherwise)
	leveledup.bhelpful	If badge helpful leveled up (Y; N otherwise)
	leveledup.bpassport	If badge passport leveled up (Y; N otherwise)
output	next.rev.sentiment	Sentiment score of the next written review
	next.rev.nwords	Next review length in words
	next.rev.days	Days until the next review is written

Table 3 - Modeling results

Model	**Evaluation metrics**	
	MAE	**NMAE**
Days for next review	7.71	0.09%
Sentiment score of next review	0.131	3.91%
Nr. words of next review	32.62	1.73%

Figure 1 - Examples of TripAdvisor badges.

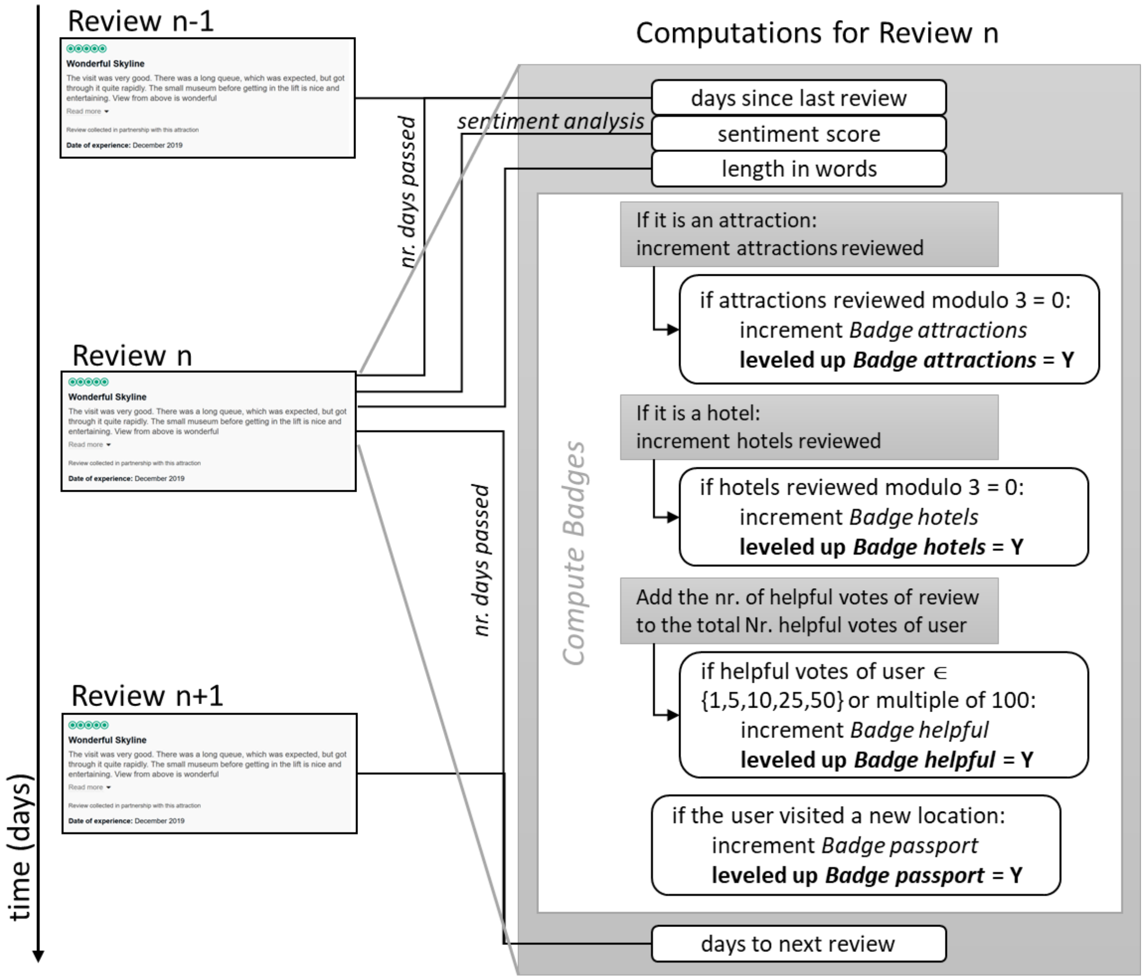

Figure 2 - Simulation procedure for computing badges.

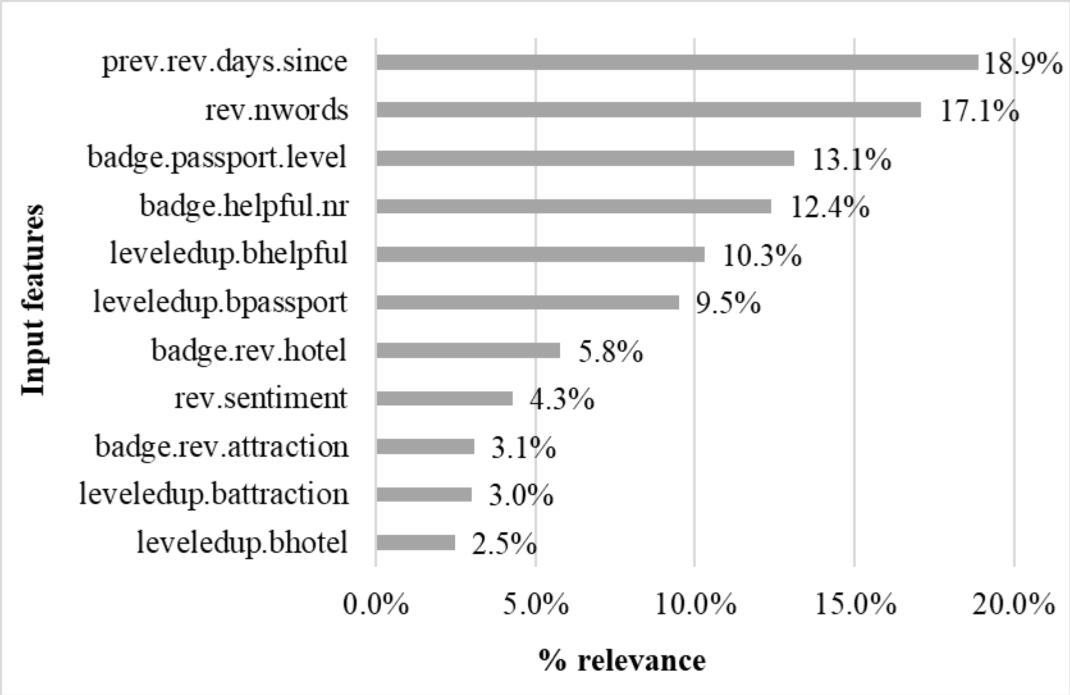

Figure 3 - Importance of features to modeling the next review length (number in words).

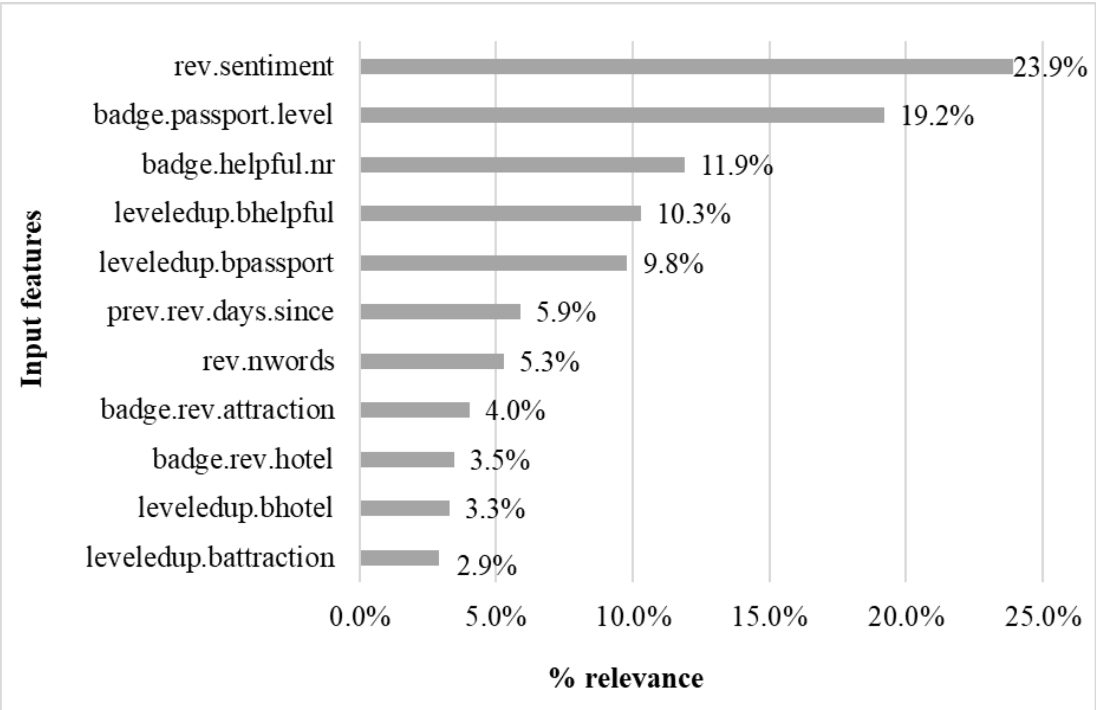

Figure 4 - Importance of features to modeling the next review sentiment score.

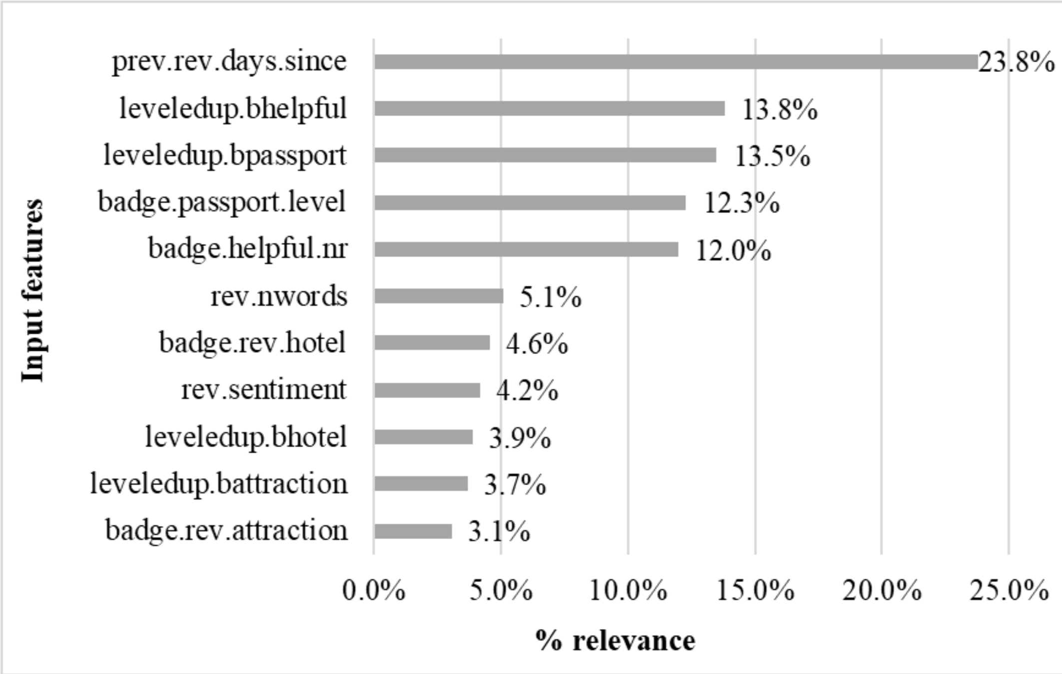

Figure 5 - Importance of features to modeling the number of days to the next review.

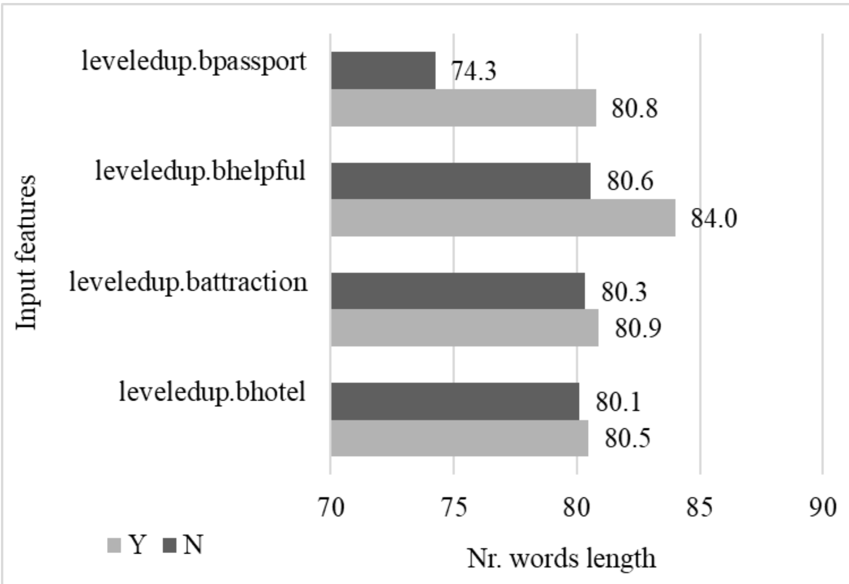

Figure 6 - Influence of leveling badges to the next review word length.

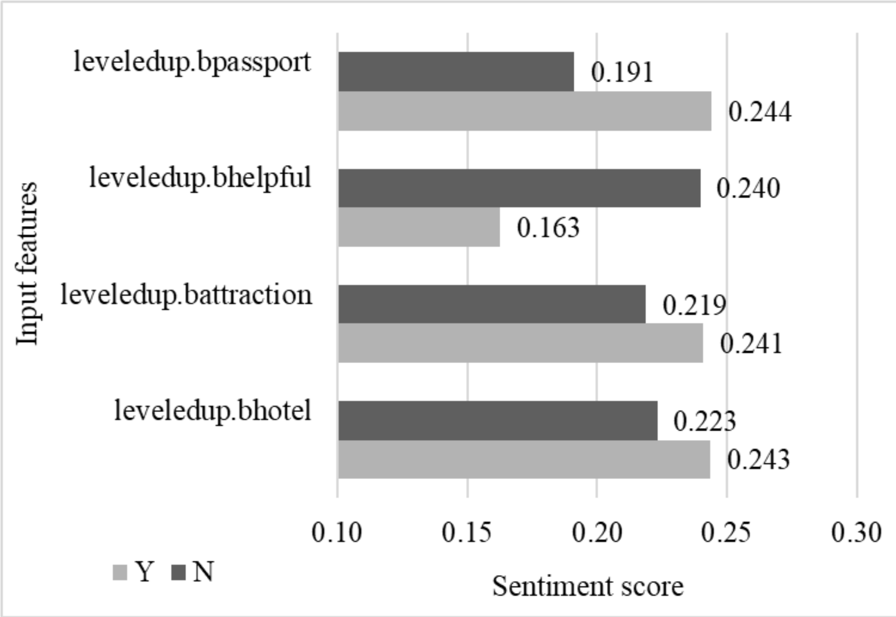

Figure 7 - Influence of badges to the next review sentiment score.

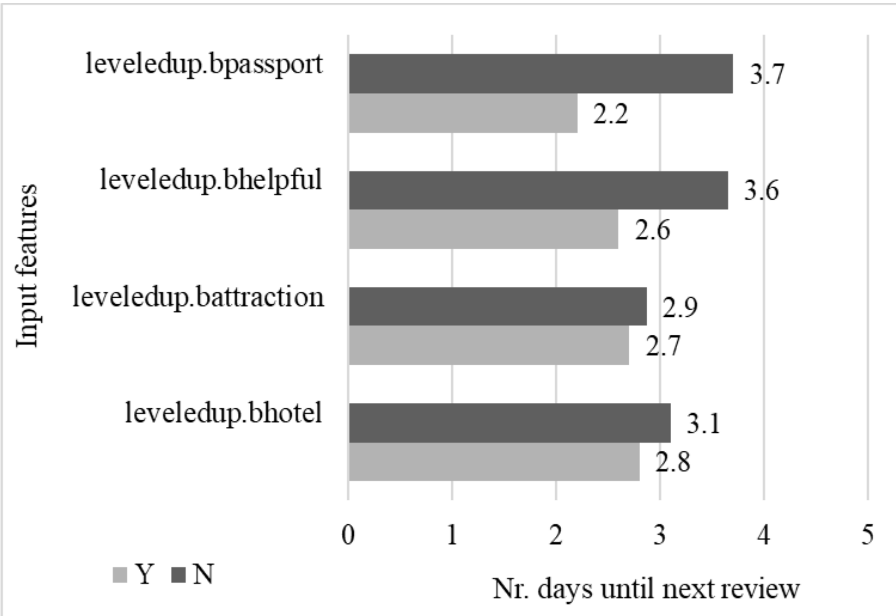

Figure 8 - Influence of badges to the number of days until the next review is written.