You Are Not You When You Are Hungry: Machine Learning Investigation of Impact of Ratings on Ratee Decision Making

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Abstract. We leverage machine learning methods to investigate the role of online ratings on ratee decision making on an online food delivery platform in India. Findings reveal that in the emerging economies, ratings are not likely to have a strong bearing on certain ratee decisions on the online platform. Research on the platform economy in the emerging markets is likely to enable us to broaden our knowledge on the overall impact of online ratings.

Keywords: Platforms · Ratings · Decision tree induction · Machine learning · Emerging markets · India

1 Introduction

This past decade has witnessed rapid transformations in various industries due to the emergence of digital marketplaces and online platforms. User generated content, in the form of reviews, ratings, and comments, is a critical common characteristic across many of these marketplaces and platforms. Production of user generated content usually does not impose an explicit cost on consumers [5, 11, 24]. Instead, user generated content affects the decision-making processes of other consumers and hence many marketplaces and platforms encourage the production and curation of user generated content. Consequently, generation of content has become the primary purpose of many online platforms, such as review and rating websites like Yelp and TripAdvisor.

A substantive literature examines issues related to user generated content, its antecedents, and consequences in digital marketplaces and online platforms. Ratings, a specific type of aggregated user generated content, have been determined to especially impact strategic behavior and decision-making of other consumers. While reviews, comments and user interactions capture many nuances [24], ratings reflect all these together in a single indicator. Thus, the rating of a ratee aggregates the overall sentiment of raters and can be viewed as a codified assessment on a standardized scale [11].

Do ratings matter? This is a fundamental question that has been explored extensively. Researchers have examined the effect of three aspects of ratings: valence (e.g., [5]), variance (e.g., [3]) and volume (e.g., [5]). However, we observe a key inadequacy in the literature. Though effects of ratings on the strategic behavior and choices of raters have received extensive attention (e.g., [23]), how ratings influence the decision

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making of ratees has not been given equal consideration (e.g., [34]). Prior research suggest that ratings influence the decision making of ratees in the context of brand building, customer acquisition, and product development [4]. For example, research using panel data shows that sellers (ratees) with low ratings are more likely to exit eBay [2]. However, it is not necessary that ratings matter for all types of strategic decisions by ratees. Further, prior work may suffer from sample selection biases, false positives due to overfitting of data and idiosyncrasies of the marketplace being investigated. Furthermore, the influence of ratings on ratees may differ in different economic and national contexts. The combination of these factors gives rise to a gap in our understanding regarding the efficacy of ratings on ratee decision making under specific combination of attributes. Specifically, our understanding of how ratings influence financial decisions of ratees in the context of a growing platform, in a non-western, less educated, unindustrialized, impoverished, emerging economy is limited. Formally, we aim to address the following research question:

Do ratings on an online marketplace affect the decision of the ratee to participate in financial transactions on the marketplace?

To address this research gap, we apply a machine learning classification technique on a population level dataset of restaurants, their features, ratings, and financial participation decision from a major food marketplace in India. India is one of the most diverse nations in the world, with 22 official languages, dozens of cultures and a complex gastronomic palate. It is home to over a hundred thousand restaurants in the organized sector, which serve diverse, rich, and mature cuisines. Availability of large datasets from India, combined with big data analytical techniques have contributed extensively to the emerging field of computational gastronomy (e.g., [13]). India has also been studied extensively in the management, operations management and information systems literatures (e.g., [15, 16, 37]). This paper is another step in this direction.

Our initial dataset consists of the population of nearly ninety-six thousand restaurants across 37 cities in India. After dropping restaurants without ratings, we analyzed the flow of the decision-making process of over sixty thousand restaurants by applying decision tree induction. This enabled us to model the cumulative decision experiences of the ratees and ascertain the role of ratings as the ratees go through the decision of participating in financial transactions on the marketplace [19]. Though this methodology has been used sparingly in the past (e.g., [25, 33, 35], there has been an increase in recent applications due to methodological advancements and the availability of large datasets. Decision tree induction has several advantages, including a lack of distributional assumptions and the ability to discover underlying patterns in the data and decision-making attributes [1, 17, 21]. It is especially optimal for our research question and theory development [14] due to its low rate of false positive predictions [32].

Our decision trees were grown using the C4.5 decision tree classification algorithm [29, 30]. A series of computational experiments were conducted across varied levels of pruning to uncover the role of ratings in the underlying structure of the data. We find that ratings on a platform are not part of the decision-making attributes for the rated (restaurants) when they decide whether to participate in financial transactions on the digital marketplace. In other words, we show that under specific conditions, ratings do not matter to the rated.

2 Related Literature

Related literature has demonstrated that consumers reduce their cognitive effort and resort to simplifying strategies and heuristics for decision making as a response to two issues: complexity and abundance of information; and, cognitive limitations to processing this information in limited time [11, 36]. Information that can be easily aligned or can interpreted through numeric values along a standard scale [10] is considered more accessible and less effortful to process. Thus, numerical ratings require are used by consumers to simplify (reduce) the amount of effort that they expend on making decisions regarding product selection and purchase. Formally, ratings reduce information asymmetry in digital marketplaces by soliciting and displaying information about transaction quality to market participants. Hence ratings are considered to improve market efficiency and overcome market failure [23].

There is significant related literature has examined the effect of valence [5], variance [3] and volume [5] of ratings on the decision-making process of raters with respect to product sales. A few common themes emerge from this literature. First, ratings matter, but not always: empirical results have been mixed [5, 18]. While some studies find no effect of rating variance and volume on sales, others find negative and significant effects [5]. Second, the nature of the product or service being rated and the nature of the rating system (one-sided versus two-sided ratings) matter: they influence the distribution and consequences of ratings. For example, 31% of ratings on TripAdvisor and 44% on Expedia are five-star ratings as compared to compared to 75% on Airbnb [22]. Also, some researchers have found no significant impact of ratings on box-office of movies (e.g., [5]), whereas others have found positive (e.g., [3]) and even long-term impacts (e.g., [18]). On the other hand, the positive effect of ratings on sales of electronic products has been established in several studies. Third, ratings alone are not enough: other aspects of reviews are required to explain all nuances of raters' decision-making behavior with regards to sales [24] because numeric ratings do not fully capture the polarity information in the review [6]. Thus, the effect of ratings on sales rank is mostly indirect, through sentiments, while sentiments' effect on sales rank is mostly direct [11]. Finally, on the few occasions that the effect of ratings on ratees has been examined, ratings matter. Ratees with lower ratings witness drop in sales, and more frequent subsequent lower ratings [2]. Also, low ratings increase the chance of market exits of ratees [2]. Considering these broad thematic contours of the related literature, it is plausible that ratings should affect the decision of ratees to participate in subsequent financial transactions on a digital marketplace.

3 Model Formulation

3.1 Machine Learning

Classification with machine learning, e.g., tree induction, is a data-driven methodology for discovering patterns from data [29, 30]. Induction yields easy-to-interpret, rules which shed light on tacit decision rationale to make informed inferences about decision making [1, 20]. Trees are accessible to a variety of stakeholders including top management executives and policy makers (e.g., [14, 17]) as they represent the discovered patterns in the form of a tree of if-then rules. Often, articulating business logic can be difficult for stakeholders as the underlying logic tends to be tacit.

Classification via tree induction opens the black box of the tacit business logic and represents interrelationships between various decision attributes and outcomes. Machine learning techniques for classification are effective for discovering combinations of attributes often not known ex ante, and compactly representing their cumulative influence on outcomes [17, 21]. Trees shine the light on emergent interconnections between attributes that are deemed informative (the only attributes included in the tree) [17, 21]. Thus, trees weed out features that are not informative for explaining outcomes. Moreover, tree induction makes few distributional assumptions about the data making this methodology more generalizable.

Building on the idea of partitioning, is a testing mode called n-fold validation where the data is divided into n partitions and n-1 partitions are used as the training sample and one partition (or fold) is used for validation. 10-fold validation, used in this investigation, is a popular testing mode for induction. A pitfall with analytics is that data scientists over-fit their models and explain noise in their data (as opposed to underlying relationships of interest). We take necessary precautions and not fall into the overfitting trap by using data partitioning. We assess generalizability of the knowledge discovered on training data by testing its prediction accuracy on unseen data from the validation data partition.

3.2 Inductive Model

Post data partitioning, two steps define classification via machine learning. Firstly, the C4.5 algorithm is used to grow the tree on training data [29, 30]. Secondly, tree grown in step 1 is pruned by validating it with unseen data from the validation partition. By employing high levels of pruning, we are able to discover the tacit structure of the data and demonstrate robustness of the discovered knowledge. The Weka platform, a popular, open-source platform is used for data partitioning, and for growing and pruning trees [8].

Tree induction iteratively groups together observations (i.e., restaurants) such that they are similar not only in certain information attributes, but also similar in terms of their participation in financial transactions outcomes. There are two inputs to tree induction: (1) restaurants described by all information attributes, and (2) financial transactions participation decisions. The objective of tree induction is to discover tacit combinations of information attributes associated with similar final outcomes (i.e., similar decisions regarding financial transaction participation) [29]. Trees only retain the most pertinent decision attributes for explaining decisions and organize decision attributes in a context-dependent manner; certain questions are only raised depending on answers obtained to other questions [30].

Using prediction accuracy of the decision tree as the sole criterion when choosing the best representative tree (among alternative models) can be misleading and would be akin to falling into the overfitting trap. We avoid the overreliance on the prediction accuracy by considering two other heuristics, namely communicability and consistency of the discovered knowledge. In summary, three heuristics, (i) prediction accuracy, (2) communicability, and (3) stability of the discovered knowledge guide the choice of the best representative tree.

Trees discovered by induction are not reflective of the exact rules or “scripts” used by the decision makers, but rather represent credible approximations of the decision rationale [1]. Instead of the correlations between attributes, induction relies on the amount of information an attribute conveys about the decision outcome.

3.3 Context and Data

Our research context is a large, comprehensive review and rating website based in India. This website has a pan-India presence and has been in operation for more than 2 years in all large cities in India. This website also provides a digital marketplace for food ordering. All registered restaurants in India are listed on website, irrespective of whether they participate in financial transactions in the marketplace. Thus, all restaurants receive ratings (subject to a few conditions). This effectively addresses concerns stemming from sample selection bias as we are able to observe ratees, irrespective of whether they participate in the marketplace or not. The marketplace does not levy fees from customers and thus does not cross-subsidize restaurant participation in financial transactions. Restaurants’ financial transaction participation choices are therefore not influenced by dynamics of the underlying fee / payment structure. Finally, in our setting, multi-homing costs are low and a restaurant can choose to affiliate with any number of marketplaces. Research suggests that winner-take-all outcomes are unlikely in such contexts [7].

A population sample of 95,735 restaurants, serving a total of 135 different cuisines, located in the 37 cities of India form our dataset. Restaurants across India are part of the sample if they are listed on the digital marketplace. Any consumer can list a restaurant on the website; listed restaurants can garner reviews and ratings from other consumers. A strategic choice that restaurant owners must make is to choose if they wish to participate in financial transactions through the marketplace. *Mere listing does not imply participation.*

This decision is a nontrivial decision that can have different outcomes. Participating in financial transactions on the marketplace may increase demand for the restaurant’s products among customers who use the marketplace. A positive outcome can be increased sales for the restaurant. However, this decision carries with it an increased risk that the restaurant may not be able to fulfill demand arising from the digital marketplace, adversely impacting its rating, and, its sales [12]. Specifically, there are three reasons for this risk. First, restaurants pay the digital marketplace a fee inversely proportional to the transaction value as per a multi-tier structure. Second, restaurants might not be able to cope with high spikes and unforeseen growth in demand. Third, adverse reputational affects can accrue owing to a mismatch in service levels at the restaurant and the stakeholders on the platform (e.g., delivery personnel).

3.4 Outcome of Interest

We investigate an individual restaurant's decision to *participate in financial transactions on the online marketplace* and thus digitize a certain proportion of their business transactions. The outcome variable, *Participation*, is coded as Yes if the restaurant participates in the financial transactions and coded as No if it does not. Next, we describe the attributes included in our theory.

3.5 Decision Attributes

We included several decision attributes. The *Cost* of a meal for two persons at the restaurant reflects the strategic positioning of the restaurant (e.g., cost leadership [26–28]). Specifically, cost for a restaurant that offers a meal for two persons for 1000 Indian Rupees (INR) and above was assigned a value of high, less than or equal to 300 INR assigned a value of low, and medium otherwise. *Number of Cuisines* was assigned a value of low if the restaurant offered a single cuisine, medium if two or three cuisines were offered. A value of high was assigned if the restaurant offered more than three cuisines. If the restaurant is a vegetarian only restaurant or not is captured by using a dummy called *Vegetarian*. Similarly, if the restaurant provides only Indian food (vs. world cuisines) is captured using a dummy called *Only Indian*. If the restaurant serves alcohol is captured using a dummy called *Alcohol*. If the restaurant provides any form of parking services is captured using a dummy called *Offers Parking*. If the restaurant provides any features that can encourage customers to dine in, such as live entertainment or music, (as opposed to ordering in) is captured using a dummy called *Go-In*. Two attributes captured a restaurant's technology readiness. First, if restaurants accept electronic payments through digital wallets was captured using a dummy called *Digi-Pay*. Second, if the restaurant provides free wi-fi internet access to its customers is captured using a dummy called *Wi-fi*.

A key institutional attribute that we captured corresponds to whether a restaurant is part of a group of restaurants with the same name. These restaurants may be part of a chain or might share a common name that reflects a well-established identity [9]. Institutional norms and processes are likely to be common across restaurants that belong to the same chain or group [31] and hence similar with regards to their propensity to participate in financial transaction on platforms. Thus, we capture this attribute by assigning *Chain* a value of high if nine or more other restaurants had the same name as the focal restaurant, medium if at least one other restaurant, and less than nine other restaurants, shared their names with the focal restaurant, and low if the restaurant's name was unique.

We also captured a key environmental attribute corresponding to the unique context of India. Restaurants located in metropolitan cities of India (Mumbai, Delhi, Chennai and Kolkata and now Pune, Hyderabad and Bangalore) are likely to be systematically different in their propensity to participate in financial transaction on online platforms compared to restaurants in the rest of India. We capture these differences using an attribute called *Metro India*.

Finally, the focal variable of our analysis, a restaurant's online *Rating* was captured. A restaurant's online rating represents its reputation or social capital in the digital world. A restaurant's offline reputation migrates to the digital marketplace as more and more customers review and rate the restaurant. Overall, since information contained in the reviews is distilled to one final online rating, we only included the overall online rating in our analysis. This website recorded a restaurant's rating on a 5-point scale. We transformed ratings from their numeric value to three categories of high, medium and low (high when greater than or equal to 4, low when less than 3, medium otherwise). Certain restaurants did not have ratings and such restaurants were excluded from our analysis.

3.6 Model Setup

To ensure that decision rationale is comprehensively discovered, a process of drawing, mutually exclusive, training and testing subsamples is repeated multiple times. An iteration of tree induction is described next. In each iteration, we draw random, mutually exclusive subsamples of restaurants from the original data; one set, known as the training set, from which the tacit decision rationale is discovered by the C4.5 induction algorithm [29], and another disjoint set of initiatives, known as the testing set, which is used to test the predictive accuracy of this discovered rationale. We used 10-fold validation where the full sample is divided into 10 partitions of which 9 partitions are used for building the tree and the last partition is used for validation. Prediction accuracy of the tree discovered from training set is assessed by predicting decisions for restaurants from unseen data from the validation set.

4 Computational Experiments

4.1 Attribute Selection and Model Identification

Multiple approximations of the tacit rationale are derived by iterating experiments where the 10-fold validation process is repeated at varying levels of pruning. These experiments are integral to induction to ensure that multiple approximations of the underlying decision process are available to the researchers. We rely on three heuristics to select the best representative, a credible approximation, of the tacit decision process: high predictive accuracy, high parsimony, and high reliability.

All twelve information attributes characterizing restaurants in conjunction with the final financial transaction participation decision, are inputs to induction. All information attributes deemed informative for explaining participation decisions are included in the trees as decision attributes and the induction algorithm excludes all the non-informative attributes from the tree. The most informative decision attribute is the top-most attribute in the tree. Importance of attributes decreases as we move away from the top of the tree to its leaves. Trees organize attributes in a context-dependent manner; certain questions are only raised depending on answers obtained to questions answered previously [30].

Table 1. Computational experiments

No.	Degree of pruning	Min instances at leaves	Number of leaves	Top two levels of decision attributes	Prediction error	Ratings
1	Low	100	25	1: Urban India 2: Digi-Pay, Cost	31.80%	Not in the tree
2	Low	200	21	1: Urban India 2: Digi-Pay, Cost	31.77%	Not in the tree
3	Low	500	24	1: Urban India 2: Digi-Pay, Cost	31.91%	Lowest in the tree
4	Medium	100	28	1: Urban India 2: Digi-Pay, Cost	27.72%	Not in the tree
5	Medium	200	21	1: Urban India 2: Digi-Pay, Cost	31.75%	Not in the tree
6	Medium	500	24	1: Urban India 2: Digi-Pay, Cost	28.12%	Lowest in the tree
7	High	100	21	1: Urban India 2: Digi-Pay, Cost	31.83%	Not in the tree
8	High	200	21	1: Urban India 2: Digi-Pay, Cost	31.83%	Not in the tree
9	High	500	19	1: Urban India 2: Digi-Pay, Cost	32.00%	Not in the tree
10	Aggressive	100	19	1: Urban India 2: Digi-Pay, Cost	31.97%	Not in the tree
11	Aggressive	200	20	1: Urban India 2: Digi-Pay, Cost	32.05%	Not in the tree
12	Aggressive	500	20	1: Urban India 2: Digi-Pay, Cost	32.04%	Not in the tree

4.2 Experimental Setup

We generated alternative models by changing the degree of pruning and the minimum number of instances at leaves in the trees. The entire comprehensive collection of twelve attribute was used to model platform participation decisions. Across all our computational experiments, metro was consistently the top most classification attribute and the ratings attribute was absent from the decision tree.

Given our counterintuitive findings and importance of ratings in the extant literature, we explored additional combinations of the degree of pruning and the minimum number of instances (i.e., restaurants) on the leaves (see Table 1). In some scenarios, we were indeed able to induce trees which included ratings as a predictor. In all such instances, ratings were consistently the least important predictor. These findings represent strong evidence to suggest that, in this case, ratings are not critical for influencing financial participation decisions of the ratee.

4.3 Key Finding

The counter intuitive finding is that ratings is not included in the decision tree. This is a key finding from our research. Given the importance of ratings in the prior literature, this finding deserved more exploration. To accomplish this goal, we computationally modified our experimental parameters - degree of pruning and minimum number of instances at the leaves, with the purpose of further exploring the role of ratings into the decision tree. At times, though ratings did indeed appear in the decision trees, it always appeared as the lower most decision attribute. This suggests that ratings do not substantively influence the ratee to participate in financial transactions on the platform. This finding empowers us to qualify the explanatory power of ratings. Ratings are key for guiding the actions of other users on digital platforms. In some cases, ratings also guide the behavior of the ratees. In this case, user-generated ratings do not explain the financial transaction participation decisions of ratees on the food delivery platform.

5 Conclusion

In this paper, we have studied how ratings affect the strategic choices and decision making of the ratee. While the effect of ratings on the behavior of raters (e.g., consumers), has been extensively examined, to our knowledge, there have been few attempts in the literature to address this perspective [4]. Our analysis aimed to answer an important question within a specific context: do ratings on a platform affect the decision of the rated (restaurants) to participate in financial transactions on the platform? To address this research gap, we applied a machine learning classification technique on a population level dataset of restaurants, features, and ratings from a major food platform in India.

We used the C4.5 decision tree algorithm to initialize a solution on training data. We then conducted a series of computational experiments, wherein we used unseen data to repeatedly apply a 10-fold validation process at varying levels of pruning. A key advantage of this approach is while we avoid the common overfitting trap, decision trees themselves have a low rate of false positive predictions. Thus, our empirical choices enable us to qualify our key findings with high confidence. We have shown that ratings do not matter to the rated. Specifically, ratings on a digital marketplace are not part of the decision-making attributes for the rated (restaurants) when they decide whether to participate in financial transactions on the marketplace.

The findings from this study have implications for both practice and research. For practice, the implications of our findings study are two-fold. First, while ratings have been demonstrated to have a significant impact on the strategic behaviour of raters, it may not be a salient feature of the decision-making process for the ratee. Thus, for owners of digital marketplaces and online platforms, features other than ratings should be form the organizing principles for increasing participation in financial transactions and thus growing their installed base of ratees. Second, follow-up analyses can offer a nuanced view into the decision-making process of ratees regarding participation in financial transactions on non-exclusive marketplaces. Our practice implications can also extend to other contexts of non-exclusive digital marketplace participation.

For research, our work makes a key theoretical contribution. Ratings are considered a critical decision feature when studying decision making of participants of online platforms and digital marketplaces. Our study shows that ratings do not matter for specific stakeholders (the ratee), for specific decisions (participating in financial transactions), under specific contexts (growing marketplace in a non-western economy). Similar ideas should and need to be tested in other contexts and on other strategic choices made by the ratee, such as change in level of engagement, change in scope of participation, and platform abandonment. Methodologically, our use of the C4.5 decision tree algorithm, which has low rate of false positives, serves as a sample context where machine learning classification techniques can be applied [32].

Despite providing valuable insights, our results must be interpreted within the boundaries of the study. As noted, an interesting extension of this research would be to incorporate different types of strategic choices as the consequence of ratings. Another limitation is the generalizability of our results to other contexts (online platforms and digital marketplaces) may be limited. This is an interesting scope for future research studies.

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