IMPLICIT REVIEWS VIA FINANCIAL INTERACTIONS

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Implicit Reviews via Financial Interactions

Abstract

A review/rating (hereinafter “review”) system models the satisfaction of a group of consumers with a product, service, or business (hereinafter “product”) based on objective transaction information, such as transaction amounts, transaction type, transaction frequency, and gratuity characteristics. Such an approach can mitigate the effect of selection bias, inauthentic reviews, and infrequent reviews. The approach also can mitigate the effect of review standards that may vary among reviewers. The models can be used to cluster and rank products, and to respond to a specific consumer’s query in a fashion tailored to that specific consumer.

Keywords

Business review, business rating, product review, product rating, consumer satisfaction, objective transaction information, selection bias, authenticity, low sample rate, and review calibration.

Description

Typical review systems, whether for restaurants, movies, service providers, retail merchants, or individual products, may be susceptible to factors that may skew review system results. Among these factors are selection bias, inauthenticity, low sample rate, and poor calibration of review standards across reviewers.

“Selection bias” in consumer reviews can refer to the difference between the distribution of opinion in the reviewing population and the distribution of opinion in the total consumer population. It is common for only those consumers who are either greatly dissatisfied with a product, or who are greatly satisfied with the product, to make their opinions known. Review summaries or numerical ratings, informed primarily by the upper and lower tails of the distribution of consumer sentiment, may be less useful than review summaries or numerical ratings that represent the complete population of consumers.
“Inauthenticity” in consumer reviews can take several forms. For example, a business owner can create (or have created by others) false positive reviews for his business, or false negative reviews for competitors. Consumers have been known to threaten businesses with false negative reviews to obtain discounts.

Review data for new businesses, or businesses where infrequent purchases are the norm, can suffer from a “low sample rate” that may negatively impact the signal-to-noise ratio of the review statistics and that may make potential customers reluctant to risk a transaction with a business that has not received a meaningful number of reviews.

“Poor calibration” across reviewers can result, for example, when one reviewer’s “average” rating on a scale of 1-10 is “5,” while another reviewer’s “average” rating on the same scale is “7.” This discrepancy can lead to spreading of the distribution of numerical ratings in a way that does not accurately reflect the sentiment of the entire population of consumers. In extreme cases, poor calibration can result in a multimodal distribution of consumer sentiment where such distribution does not actually exist.

As a result, many review systems may be less than reliable. However, consumers still may use unreliable review systems, since under-sampled, noisy, or biased data often is preferable to not having any data when making a purchase decision.

Some existing review systems apply machine learning and other algorithms to detect fake reviews, while seeking to retain and show only the most valuable reviews. Other review systems try to reduce noise and manipulation by using a curated roster of reviewers, or by curating the reviews themselves. Whether through algorithms or through using a human in the loop, such systems still rely on subjective, and possibly biased, human reporting for input rather than relying on objective metrics.

The present review technology models consumer satisfaction based on objective transaction information related to the product. Systems that manage electronic payments, loyalty accounts, technical support accounts, and the like can gather the transaction information as objective transaction information related to the product. The model of consumer satisfaction can be used to 1) derive reviews/ratings for a product, 2) customize rankings for a specific user, 3)
cluster/filter reviews to form “apples-to-apples” comparisons between products, and 4) respond to consumer queries regarding products.

Referring to Figure 1, when a consumer uses a consumer device (such as a smartphone or a personal computer over a communications network) or a payment card to interact with a business (such as through a point-of-sale (POS) device, an online technical support system, or any other business server), the transaction data server collects data on the interaction. A business’s own systems can serve as the transaction data server, as can the systems of credit card companies, third-party payment services, and review services providers.

Transaction data includes an identification of the consumer (which typically is anonymized), an identification of the business, the location of the business, the time and date of the transaction, the nature of the transaction (for example, payment, registration, product return, enrollment for recurring purchase), the amount of the transaction (including the amount of gratuity, if any), and repair requests.

Each of these types of transaction data is less susceptible to selection bias, inauthenticity, and calibration issues compared to conventional methods of review data collection. By definition, every paying customer, not just those having opinions in the upper and lower tails of the distribution of consumer sentiment, engages in a transaction with a business. Further, it is unlikely that someone would conduct a transaction, especially involving payment, merely to influence the review process. Since each interaction between each consumer and a business, and not just a small sample of interactions, can contribute to transaction data, the technology is less susceptible than other review technologies to low sample rate issues. Since the amount paid for identical products, while not always identical, is at least typically uniform across a group of customers, calibration issues are mitigated.

The transaction data server communicates collected transaction data to a review server, which uses the transaction data to model consumer satisfaction and to derive reviews and ratings.

Consider a consumer that visits a particular restaurant roughly monthly and pays with a physical credit card. The frequency of the consumer’s visits, as reflected in transaction data collected by the restaurant’s business server and supplied to the review server by a transaction
data server, can be used to infer a steady state level of satisfaction with the restaurant on the part of that particular consumer. If the restaurant changes ownership and the frequency of the consumer’s visits declines, that change is an objective measure of the consumer’s satisfaction with the restaurant regardless of whether the consumer participates in customer satisfaction surveys. The review server can consider transaction frequency when determining a rating attributable to the particular consumer. Even without a change in ownership, changes in transaction frequency and changes in the period that transactions span over time can be used by the review server to determine a rating for the restaurant. For example, if a particular hairdresser’s average client has been patronizing the hairdresser for 4 years, while a typical hairdresser’s clients are loyal for an average of about 1 year, the review server can infer that customer satisfaction of the particular client is much higher than average for that particular hairdresser.

In addition to considering transactional data for a single business to determine a rating for that business, the review server considers transactional data collected across businesses by the transaction data server. Continuing with the restaurant example, the review server can compare the frequency, proportion, and actual amount of gratuities that a given consumer includes across restaurants, as both a comparison between restaurants and to normalize such data.

Comparisons across businesses by the review server, such as the comparison across restaurants described above, can benefit from clustering businesses by one or more characteristics of the business, or, more specifically, characteristics of the transactions. For example, a consumer might dine at a fast casual restaurant several times per month, but only visit a fine dining restaurant annually or less. Similarly, tips are likely to vary greatly by class of restaurant. Therefore, the review server can cluster businesses by various factors including type (for example, restaurant, auto repair), subtype (for example, fast casual, food truck, fine dining), pricing tier, etc. As further examples, the review server can cluster transaction data by customer demographics and by geography. In general, the review server can cluster transaction data to seek more “apples-to-apples” comparisons.
For larger transactions and for transactions involving products with longer lifecycles such as furniture and appliances, the review server can use transaction data such as percentage of returns, payment disputes, number of follow-up repairs, and brand loyalty.

Because every implicit review requires a financial interaction, this technology can reduce the problems presented by review inauthenticity. For example, while a business owner could still ask friends and family to shop at their business to manipulate results, such an approach is more difficult to coordinate, and far more costly to the manipulators. Since the review server can track most every transaction between a business and its consumers, the risk of selection bias is reduced. Likewise, an abundance of implicit reviews will exist even for new businesses, so the review server will obtain sufficient data points much faster compared to traditional review approaches.

The review server can determine a variety of derived metrics, such as statistical parameters, that can be used to review/rate a business. Such metrics include mean and median spend, mean and median tip, mean and median loyalty points accumulated, and mean and median visit frequency. The review server can determine changes over time of such metrics.

The review server can customize rankings for a specific user based on clustering/filtering data to similar users. For example, the review server can use the data from users with similar spending habits and tastes when giving a user recommendations/rankings.

Basing reviews on objective information as described herein facilitates construction of a model of consumer sentiment that is less susceptible to selection bias, inauthenticity, low sample rate, and calibration issues. Statistics derived from such objective information enable grouping and filtering that facilitates “apples-to-apples” comparisons between products and filtering tailored to an individual consumer.

As depicted in the Fig. 1, an architecture for the present technology includes network devices; each of which may be configured to communicate with one another via a communications network, such as the Internet. A user associated with a device may have to install an application and/or make a feature selection to obtain the benefits of the technology described herein.
In situations in which the technology discussed herein collects personal information about users, or may make use of personal information, the users may be provided with an opportunity or option to control whether programs or features collect user information (e.g., information about a user’s social network, social actions or activities, profession, a user’s preferences, or a user’s current location), or to control whether and/or how to receive content from the content server that may be more relevant to the user. In addition, certain data may be treated in one or more ways before it is stored or used, so that personally identifiable information is removed. For example, a user’s identity may be treated so that personally identifiable information cannot be determined for the user, or a user’s geographic location may be generalized where location information is obtained (such as to a city, ZIP code, or state level), so that a particular location of a user cannot be determined. Thus, the user may have control over how the technology collects and uses information about the user.