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Characterizing and Predicting Early Reviewers for Effective Product Marketing on E-Commerce Websites

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ABSTRACT

Online reviews became a very important supply of knowledge for users before creating Associate in Nursing knowing purchase call. Early reviews of a product tend to own a high impact on the following product sales. during this paper, we have a tendency to take the initiative to check the behavior characteristics of early reviewers through their denote reviews on 2 real-world giant e-commerce platforms, i.e., Amazon and Yelp. In specific, we have a tendency to divide product life into 3 consecutive stages, particularly early, majority and laggards. A user World Health Organization has de note a review within the early stage is taken into account as Associate in Nursing early reviewer. we have a tendency to quantitatively characterize early reviewers supported their rating behaviors, the helpfulness scores received from others and also the correlation of their reviews with product quality. we've got found that (1) Associate in Nursing early reviewer tends to assign the next average rating score; Associate in Nursing (2) an early reviewer tends to post a lot of useful reviews. Our analysis of product reviews conjointly indicates that early reviewers' ratings and their received helpfulness scores area unit possible to influence product quality. By viewing review posting method as a multiplayer competition game, we have a tendency to propose a completely unique margin-based embedding model for early reviewer prediction. in depth experiments on 2 completely different e-commerce datasets have shown that our planned approach outperforms variety of competitive baseline.

Index Terms: Early reviewer, Early review, Embedding model.

INTRODUCTION

The emergence of e-commerce websites has enabled users to publish or share purchase experiences by posting the product reviews, that typically contain helpful pinions, comments and feedback towards a product. As such, a majority of shoppers can scan on-line reviews before creating associate hip to purchase call [1]. it's been reportable regarding seventy one of worldwide internet buyers scan on-line reviews before getting a product [2]. Product reviews, particularly the first reviews (i.e., the reviews denote within the early stage of a product), have a high impact on succeeding product sales [3]. we tend to decision the users UN agency denote the first reviews early reviewers. though early reviewers contribute solely a tiny low proportion of reviews, their opinions will verify the success or failure of recent merchandise and services [4], [5]. it's necessary for corporations to spot early reviewers since their feedbacks will facilitate corporations to regulate marketing methods and improve product styles, which may eventually cause the success of their new merchandise.

For this reason, early reviewers become the stress to monitor and attract at the first promotion stage of an organization. The important role of

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early reviews has attracted in depth attention from selling practitioners to induce client purchase intentions [6]. for instance, Amazon, one in all the biggest e-commerce company within the world, has advocated the first Reviewer Program1, that helps to ac- definite quantity early reviews on merchandise that have few or no reviews. With this program, Amazon shoppers will learn a lot of regarding merchandise and create smarter shopping for selections. As another connected program, Amazon Vine2 invitations the foremost sure reviewers on Amazon to post opinions regarding new and pre- unharness things to assist their fellow customers create hip to purchase selections.

Based on the on top of discussions, square measure able to} see that early reviewers are extraordinarily vital for product promoting. Thus, during this paper, we tend to take the initiative to review the behavior characteristics of early reviewers through their announce reviews on representative e-commerce platforms, e.g., Amazon and Yelp. we tend to aim to conduct effective analysis and build correct prediction on early reviewers. This prob- ballistic capsule is powerfully associated with the adoption of innovations. in a very generalized read, review posting method may be thought of as AN adoption of innovations3, that may be a theory that seeks to clarify however, why, and at what rate new ideas and technology unfold [8]. The analysis and detection of early adopters within the diffusion of innovations have attracted a lot of attention from the analysis community. 3 basic parts of a diffusion method are studied: attributes of AN innovation, communication channels, and social net- work structures [8]. However, most of those studies area.

- 1.https://www.amazon.com/gp/help/customer/show.html? node Id=202094910
- 2. https://www.amazon.com/gp/vine/help
- 3. Since users typically solely post reviews when they created product purchases, reviews on Amazon correspond to actual purchases most of the time [7]. Even if such correspondence doesn't exist typically, a announce review indicates AN interest on an exact product.

The critical analysis at the macro level and there's an absence of quantitative investigations. With the zoom of on-line social platforms and also the availableness of a high volume of social networking knowledge, studies of the diffusion of innovations

Have been wide conducted on social networks [9]–[12]. However, in several application domains, social networking links or channels are unobserved. Hence existing ways wishing on social network structures or communication channels aren't appropriate in our current problem of predicting early reviewers from on-line reviews.

To model the behaviors of early reviewers, we develop a principled thanks to characterize the adoption method in two real-world giant review datasets, i.e., Amazon and Yelp and more specially, given a product, the reviewers are sorted according to their timestamps for business their reviews. Following [8], we tend to divide the merchandise period into 3 consecutive stages, particularly early, majority and laggards. A user who has announce a review within the early stage is taken into account as an early reviewer. In our work here, we tend to chiefly concentrate on 2tasks, the primary task is to research the general characteristics of early reviewers compared with the bulk and laggard reviewers. we tend to characterize their rating behaviors and also the helpfulness scores received from others and also the correlation of their reviews with product quality. The second task is to learn a prediction model that predicts early reviewers given a product.

To analyze the characteristics of early reviewers, we take 2 vital metrics related to their reviews i.e., their review ratings and helpfulness scores allotted by others. we've got found that (1) associate degree early reviewer tends to assign the next average rating score to products; and (2) an early reviewer tends to post additional useful reviews. Our above not icings will find connection within the classic principles of personality variables theory from scientific discipline, that chiefly studies however innovation is a join time among the participants [8]: (1) earlier adopters have a additional favorable attitude toward changes than later adopters; and (2) earlier adopters have the next degree of opinion leadership than later adopters. we are able to relate our findings with the temperament variables theory as follows: higher average rating scores may be thought-about because the favorable angle towards the merchandise, and better helpfulness votes of early reviews given by others may be viewed as a proxy live of the opinion leadership. Our analysis additionally indicates that early reviewers' ratings and their received helpfulness scores are likely to influence product quality. we tend to more make a case for this finding with the herd behavior wide studied in economic science and social science [13]–[15]. Herd behavior refers to the fact that people are powerfully influenced by the choices of others. To predict early reviewers, we tend to propose a completely unique approach by viewing review posting method as a multiplayer competition game. solely the foremost competitive users will become the early reviewers to a product. The competition method can be more rotten into multiple pair wise comparisons between 2 players. in an exceedingly two-player competition the winner can beat the loser with associate degree earlier timestamp. Inspired by the recent progress in distributed illustration learning [16], [17], we tend to propose to use a margin-based embedding model by initial mapping each users and merchandise into constant embedding house, and so determinant the theoretical analysis at the macro level and there is a lack of quantitative investigations. With the rapid growth of online social platforms and the availability of a high volume of social networking data, studies of the diffusion of innovations have been widely conducted on social networks [9]–[12]. However, in many application domains, social networking links or communication channel are unobserved. Hence, existing methods relying on social network structures or communication channels are not suitable in our current problem of predicting early reviewers from online reviews.

To model the behaviors of early reviewers, we develop a principled way to characterize the adoption process in two real-world large review datasets, *i.e.*, Amazon and Yelp. More specially, given a product, the reviewers are sorted according to their timestamps for publishing their reviews. Following [8], we divide the product lifetime into three consecutive stages, namely *early*, *majority* and *laggards*. A user who has posted a review in the early stage is considered as an early reviewer. In our work here, we mainly focus on two tasks, the first task is to analyze the overall characteristics of early reviewers compared with the majority and laggard reviewers. We characterize their rating behaviors and the helpfulness scores received from others and the correlation of their reviews with product popularity. The second task is to learn a prediction model which predicts early reviewers given a product.

To analyze the characteristics of early reviewers, we take two important metrics associated with their reviews, i.e., their review ratings and helpfulness scores assigned by others. We have found that (1) an early reviewer tends to assign a higher average rating score to products; and (2) an early reviewer tends to post more helpful reviews. Our above findings can find relevance in the classic principles of personality variables theory from social science, which mainly studies how innovation is spread over time among the participants [8]: (1) earlier adopters have a more favorable attitude toward changes than later adopters; and (2) earlier adopters have a higher degree of opinion leadership than later adopters. We can relate our findings with the personality variables theory as follows: higher average rating scores can be considered as the favorable attitude towards the products, and higher helpfulness votes of early reviews given by others can be viewed as a proxy measure of the opinion leadership. Our analysis also indicates that early reviewers' ratings and their received helpfulness scores are likely to influence product popularity. We further explain this finding with the herd behavior widely studied in eco- nomics and sociology [13]–[15]. Herd behavior refers to the fact that individuals are strongly influenced by the decisions of others.To predict early reviewers, we propose a novel approach by viewing review posting process as a multiplayer competition game. Only the most competitive users can become the early reviewers to a product. The competition process can be further decomposed into multiple pair wise comparisons between two players. In a two-player competition, the winner will beat the loser with an earlier timestamp. Inspired by the recent progress in distributed representation learning [16], [17], we propose to use a margin-based embedding model by first mapping both users and products into the same embedding space, and then determining the order of a pair of users given a product based on their respective distance to the product representation.

Previous studies have highly emphasized the phenomenon that individuals are strongly influenced by the decisions of others, which can be explained by *herd behavior* [6], [13]–[15], [18]–[20]. The influence of early reviews on subsequent purchase can be understood as a special case of herding effect. Early reviews contain important product evaluations from previous adopters, which are valuable reference resources for subsequent purchase decisions. As shown in [19], when consumers use the product evaluations of others to estimate product quality on the Internet, herd behavior occurs in the online shopping process [19]. Different from existing studies on herd behavior, we focus on quantitatively analyzing the overall characteristics of early reviewers using large-scale real-world datasets. In addition, we formalize the early reviewer prediction task as a competition problem and propose a novel embedding based ranking approach to this task. To our knowledge, the task of early reviewer prediction itself has received very little attention in the literature. Our contributions are summarized as follows:

We present a first study to characterize early reviewers on an e-commerce website using two real-world large datasets.

We quantitatively analyze the characteristics of early reviewers and their impact on product popularity. Our empirical analysis provides support to a series of theoretical conclusions from the sociology and economics.

We view review posting process as a multiplayer competition game and develop a embedding-based ranking model for the prediction of early reviewers. Our model can deal with the cold-start problem by incorporating side information of products.

Extensive experiments on two real-world large datasets, *i.e.*, Amazon and Yelp have demonstrated the effectiveness of our approach for the prediction of early reviewers.

EXISTING SYSTEM

The emergence of e-commerce websites has enabled users to publish or share purchase experiences by posting product reviews, that typically contain helpful opinions, comments and feedback towards a product. As such, a majority of consumers can scan on-line reviews before creating associate degree knowledgeable purchase call. it's been reportable concerning seventy one of worldwide internet buyers scan on-line reviews before getting a product. Product reviews, particularly the first reviews (i.e., the reviews announce within the early stage of a product), have a high impact on enchant product sales. we have a tendency to decision the users UN agency announce the first reviews early reviewers. Though early reviewers contribute solely a tiny low proportion of reviews, their opinions will verify the success or failure of recent product and services. it's vital for firms to spot early reviewers since their feedbacks will facilitate firms to regulate promoting methods and improve product styles, which might eventually result in the success of their new product existing strategies counting on social network structures or communication channels aren't appropriate in our current downside of predicting early reviewers from on-line reviews. and sleuthing early reviewers, that is totally different from the present works on extracting opinions or distinctive opinion targets (or holders) from review knowledge. To our information, it's the first time that the task of early reviewer

PROPOSED SYSTEM

We take the initiative to check the behavioural characteristics of early reviewers through their denote reviews on representative e-commerce platforms, e.g., Amazon and Yelp. we have a tendency to aim to conduct effective analysis and create correct prediction on early reviewers. This drawback is powerfully associated with the adoption of innovations. during a generalized read, review posting method will be thought of as associate adoption of innovations, that could be a theory that seeks to clarify however, why, and at what rate new ideas and technology unfold. The analysis and detection of early adopters within the diffusion of innovations have attracted a lot of attention from the analysis community. 3 elementary components of a diffusion method are studied: attributes of associate innovation, communication channels, and social network structures.

Our empirical analysis provides support to a series of theoretical conclusions from the social science and social science.

Our model will contend with the cold-start drawback by incorporating aspect data of product. Quantitatively analyze the characteristics of early reviewers and their impact on product quality. We read review posting method as a multiplayer competition game and develop a embedding-based ranking model for the prediction of early reviewers .Early reviewers contribute a proportion of reviews, their opinions will confirm the success or failure of recent product and services.

SYSTEM DESIGN

System testing

The purpose of testing is to get errors. Testing is that the method of making an attempt to get each conceivable fault or weakness in a very work product. It provides the way to ascertain the practicality of elements, sub-assemblies, assemblies and/or a finished product. it's the method of physical exertion computer code with the intent of guaranteeing that the software package meets its needs associate degree user expectations and doesn't fail in an unacceptable manner. There are numerous sorts of check. every check sort addresses a selected testing demand

TYPES OF TESTS

Unit checking involves the planning of test cases that validate that the inner program logic is functioning properly, which program inputs turn out valid outputs. All call branches and internal code flow ought to be valid. it's the testing of individual code units of the applying .it is done once the completion of a personal unit before integration. this is often a structural testing, that depends on data of its construction and is invasive. Unit checks perform basic tests at element level and test a particular business method, application, and/or system configuration. Unit tests make sure that every distinctive path of a business method performs accurately to the documented specifications and contains clearly outlined inputs and expected results.

Functional check

Functional tests give systematic demonstrations that functions tested are on the market as such as by the business and technical necessities, system documentation, and user manuals.

Functional testing is targeted on the subsequent items:

- Valid Input : identified categories of valid input should be accepted.
- Invalid Input : identified categories of invalid input should be rejected.
- Functions : identified functions should be exercised.
- Output : identified categories of application outputs.
- Systems/Procedures : interfacing systems or procedures should be invoked.

Organization and preparation of practical tests is concentrated on necessities, key functions, or special check cases. additionally, systematic coverage bearing on determine Business method flows; knowledge fields, predefined processes, and consecutive processes should be thought of for testing. Before practical testing is complete, extra tests are known and also the effective price of current tests is decided.

System check

System testing ensures that the whole integrated software meets demand. It tests a configuration to confirm notable and inevitable results. associate example of system checking is that the configuration familiarized system integration test. System testing is predicated on method descriptions and flows, accenting pre-driven method links and integration points.

White Box Testing

White Box Testing could be a testing during which during which the code tester has data of the inner workings, structure and language of the code, or a minimum of its purpose. it's purpose. it's accustomed check areas that can't be reached from a recorder level.

Black Box Testing

Black Box Testing is testing the code with none data of the inner workings, structure or language of the module being tested. recorder tests, as most different kinds of tests, should be written from a definitive supply document, like specification or necessities document, like specification or necessities document.

Test objectives

- All field entries should work properly.
- Pages should be activated from the known link.
- The entry screen, messages and responses should not be delayed.

Integration Testing

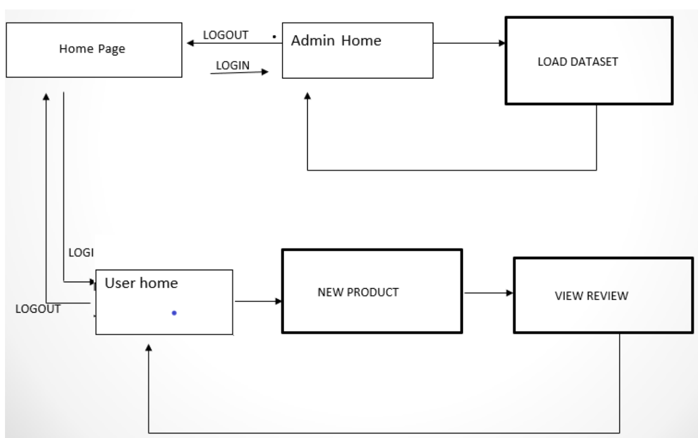
Code integration testing is that the progressive integration testing of 2 or additional integrated code elements on one platform to provide failures caused by interface defects. The task of the mixing check is to envision that elements or code applications, e.g. elements in a very software or – one intensify – code applications at the corporate level – move while not error.

Acceptance Testing

User Acceptance Testing could be a vital part of any project and needs important participation by the top user. It conjointly ensures that the system meets the practical necessities.

V.7. Test Results: All the check cases mentioned higher than passed with success.
No defects encountered.

DATA FLOW DIAGRAM



LITERATURE SURVEY

Our current study is especially associated with the subsequent 3 lines of analysis. Early parent Detection The term of early parent originates from the classic theory for Diffusion of Innovations. AN early parent may seek advice from a trendsetter, e.g., AN early client of a given company, product and technology. The importance of early adopters has been wide studied in social science and political economy. it's been shown that early adopters square measure vital in trend prediction, infective agent selling, product promotion, and so on. Moreover, the influence of early adopters is closely associated with the studies of herd behaviour that describes that people square measure powerfully influenced by the choices of others, like available market bubbles, decision-making, social selling and products success. As for product selling, customers oftentimes choose in style brands as a result of they believe that quality indicates higher quality. as an example, in digital auctions, patrons tend to bid for listings that others have already bid for, whereas ignoring similar or additional enticing un-bid-for listings. Similarly, AN experimental study shows that the social influence of early adopters' decisions of songs ends up in each difference and unpredictability of the songs in terms of transfer counts. Some additional investigations additionally reveal that product evaluations from previous adopters, like star ratings and sales volume, influence customers' on-line product decisions. The analysis and detection of early adopters within the diffusion of innovations have attracted a lot of attention from the analysis community. typically speaking, 3 parts of a diffusion method are studied: attributes of AN innovation, communication channels, and social network structures. Early studies square measure in the main theoretical analysis at the macro level. With the rising of on-line social platforms and also the accessibility of a high volume of social networking information, studies of the diffusion of innovations are mostly conducted on social networks, together with resource-constrained networks, following or re tweet networks, user-click graphs and text-based innovation networks.

Modelling Comparison-based preference Comparison-based preference has been studied for many decades and a survey of the classic approaches and strategies was given. By modelling comparison based mostly preference, we will basically perform any ranking task. as an example, in data retrieval (IR), learning to rank aims to be told the ranking for a listing of candidate things with manually designated options. 3 classes of wide used learning to rank approaches embrace purpose wise, pair wise and list wise strategies. excluding IR, the competition-based ranking strategies have additionally been wide studied in games and matches, wherever the aim is to gauge the talent level of every concerned player. These studies usually solely use a scalar price because the live of the talent rating of a private player. as an example, supported the two-player model, True talent ranking system developed by Microsoft uses a uni variate distribution to model every player's talent and uncertainty. There are studies that aim at inferring every player's strength through learning from cluster competition. These strategies represent the properties of every item or player as one variety, that cannot well adapt several complicated real-world settings. to handle this downside, many studies projected to use additional communicatory ways in which of modelling players, like generalized Bradley-Terry model with vectorized representations for the preference ranking task. additional recently, Chen et al. have projected to use multidimensional representations to capture each grammatical relation and context data for modelling pair wise comparison relations. In social science, it's a standard sense that competition is sometimes correlate expertly. Following this, several studies try and model the experience level of a user employing a competition-based ranking approach, e.g., community question and responsive platforms and generalized crowd sourcing systems.

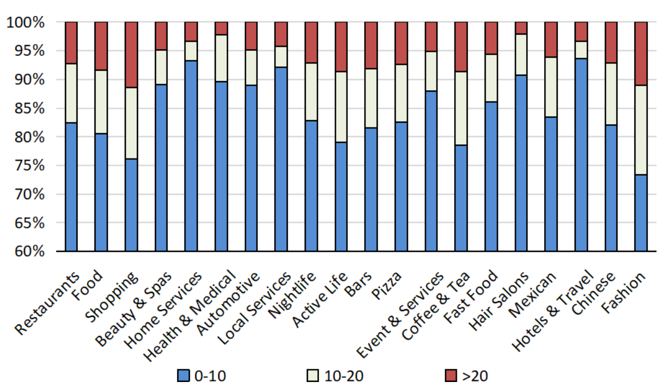
Distributed illustration Learning Since its seminal work, distributed illustration learning has been with success utilized in numerous application areas together with tongue process (NLP), speech recognition and laptop vision. the most plan of distributed representations is to utilize low-dimensional dense vectors to represent data entities. as an example, in NLP, many linguistics embedding models are projected, together with word embedding, phrase embedding, and sentence embedding. Word embedding models like word2vec, have generalized the classic n-gram language models by exploitation continuous variables to represent words during a vector area and are with success applied to capture latent linguistics for human language technology tasks. Specially, word2vec has given 2 major model architectures, particularly skip-gram (SG) and continuous bag-of-words (CBOW). SG predicts the encompassing words supported the present word, whereas CBOW predicts the present word exploitation the encompassing words as contexts. In CBOW, the discourse data is sculpture as embedding vector exploitation a mean pooling over the embedding of encompassing words. supported word2vec, doc2vec additional incorporates the document specific embedding into the word2vec model. the same as word, it additionally provides 2 model architectures: distributed bag-of-words model and distributed memory model. Additional recently, the thought of distributed representations has been extended on the far side pure language modelling to numerous text connected tasks, like data graph completion text-based attribute illustration and multimodal modelling. Additionally to model text information, the distributed illustration approach has been wide applied to numerous applications in different fields, like network analysis and recommendation.

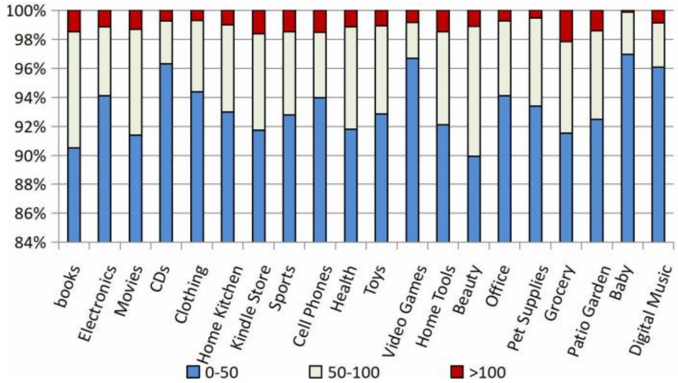
QUANTITATIVELY ANALYZING THE CHARACTERISTICS OF EARLY REVIEWERS

It has been reportable that early adopters are necessary to the diffusion of innovations [8]. Hence, we have a tendency to expect that early reviewers play a key role in future product adoptions. There has been a scarcity of measure of the correlations between the first reviewers and merchandise adoptions on massive datasets, i.e., Amazon and Yelp. during this section, we study however early reviewers are totally different from others and how they impact product quality.

Characteristics of Early Reviewers

To understand however early reviewers are totally different from others, we begin with Associate in Nursing analysis of their announce early reviews by looking into average ratings of the reviews and helpfulness scores voted by others. Exploitation the categorization technique discussed in Section a pair of, we have a tendency to assign every review into one among the three classes outlined in Figure a pair of. Recall that every review is related to a rating score and votes on its helpfulness. The rating score is during a five-star scale. For helpfulness, in Amazon dataset, we have a tendency to count the quantity of affirmative and No votes respectively so normalize them to the vary of [0; 1]. While in Yelp dataset, users vote on the helpfulness of a review by clicking the helpful button. we have a tendency to count the quantity of Useful because the review's helpfulness score. Given the 3 categories of reviews, we have a tendency to cipher the common ratings and helpfulness scores in every review class. Early reviewers tend to assign a better average rating score. we have a tendency to compare the common rating ample reviews by the 3 classes in Figure half-dozen. it's discovered that early reviews are additional doubtless to keep company with a better rating score than those from the opposite 2 classes. Note that we have removed spam reviews since their ratings tend to be extreme, either too high or too low .Early reviewers tend to post additional useful reviews. We compare the common helpfulness ample reviews by the three classes in Figure seven. Note that Amazon dataset contains each affirmative and No votes of reviews, we use the percentage of affirmative votes to represent the helpfulness scores of a review. whereas in Yelp dataset, we use the number of Useful votes as the helpfulness score.





PREDICTING EARLY REVIEWERS

We have so far shown that early reviews are indeed important to product popularity. Next a practical question is: given a product, can we predict who will become its reviewers at the early stage of its release to market? Such a prediction can have the following potential benefits. First, identifying early reviewers is helpful to monitor and manage early promotion. Second, early reviewers are very likely to be the actual adopters of a product, leading to direct purchase. In what follows, we first formally define the early reviewer prediction task, and then propose a novel embedding-based ranking approach for predictive modelling.

Problem Formulation

Given a product p and a candidate user set Up :fu1; u2; :::; u N the task of predicting early reviewers aims to produce a top-K list of users from Up, who would post reviews on p at the early stage of product p in market .Producing a top-K list can be formulated as a ranking problem. We propose to use a ranking function S(p; u) to select users, which measures the likelihood that user u becomes an early reviewer of product p. To learn such a function, we assume that a training set of past early adoption records is available, i.e., fhpi;Liig. Each training instance consists of a product pi with a complete lifetime, and Li : hu(I)1 ; s(I)1 I ! hu(I)2 ; s(I)2 i::: ! hu(I)Np ; s(I) Npi I is an ordered list of reviewers fu(I) j g on pi by the timestamps fs(I) j g when publishing the reviews .A major challenge is that our task is a cold-start ranking problem. Since we are interested in the early reviewers of a product, the predictions should be made when a new product is just released. We will have very little and sometimes even no observed user behaviour data at the early stage of a new product. Inspired by previous cold-start information to assist with this ranking drawback. We assume that a product p is with a class label cp and a title description tp and use the 2 kinds of aspect info to learn product representations or embeddings as are going to be discussed in Section five.2. A competition-based viewpoint to the ranking task. To address the ranking drawback, we have a tendency to draw our inspiration from multiplayer competition to develop our approach. Generally speaking, given a product p and 2 candidate users u and u0, we have a tendency to request to model the partial order between them. We consider the review posting method as multiplayer competition [26]: solely the foremost competitive users will become the early reviewers a product. The competition method will be more rotten into multiple pairwise comparisons between 2 player. a contest is meted out between two users given a product. in a very two-player competition ,the winner can beat the loser with associate degree earlier timestamp .Formally, we have a tendency to use u p u0 denote that user u has associate degree earlier review timestamp than u0 for product p. Competition-based ranking has been an explored for community question answering [27] and player ranking [26]. However, to the best of our information, it's ne'er been explored for early reviewer or early adoptive parent prediction.

Margin-based Embedding Model for Predicting

Early Reviewers

The essence of this task is to model the partial order between two candidate users u and u0 given a product p. Hence, we can forged the overall order ranking drawback into a pair wise comparison drawback. impressed by the recent progress in distributed illustration learning [16], [17], we propose to use associate degree embedding model for this task. we have a tendency to assume that both users and product are mapped into a latent area .In this means, a user u is sculptural with a low-dimensional representation vector vu, and a product p is sculptural with a low-dimensional dense illustration vector up. Within the embedding space, we will reconstruct the partial order relations in the coaching set and learn the model parameters.

Modelling the Pair wise Comparison

Based on the embedding illustration, we will outline the objective operate S(p; u) as associate degree real between user and product embeddings, i.e.,

S(p; u) = v> p vu: (1) In the embedding area, it's expected that v> p vu > v>
p vu0 once u p u0. Given the initial coaching set A =fhpi;Liig, we have a tendency to 1st remodel them into a group of partial order pairs T = fu p u0ju; u0 a pair of Lpg, wherever phonograph recording is that the reviewer
list of product p. To learn such embeddings, we have a tendency to minimize a margin-based ranking criterion [17] over the coaching set T :`(T) =X upu02T [m + S(p; u0) □ S(p; u)]+; (2) = X upu02T [m + v> u0 vp □ v> u vp]+;

EXPERIMENTSON EARLY REVIEWER PREDICTION

In this section, we have a tendency to conduct experiments to gauge our projected margin-based embedding model for early reviewer prediction. TABLE 3 Statistics of the analysis sets in early reviewer prediction. ANRU and ANRP area unit the abbreviations of Average range of Reviews announce by each User and Average range of Reviews received by every Product. Dataset #Product #User #Pairs ANRU ANRP Amazon 12,814 16,355 3,122,797 18 23 Yelp 2,545 3,912 282,718 14 22

Datasets

Since it's unreliable to incorporate users or merchandise with terribly few reviews for analysis, we have a tendency to take away the merchandise that are related to but fifty reviews in Amazon dataset and ten reviews in Yelp dataset, and users WHO announce less than fifty reviews in Amazon dataset and ten reviews in Yelp dataset. The statistics of the information sets employed in our experiment are shown in Table three. Note that "#Pairs" indicates the entire number of comparison pairs that may be generated in our evaluation set following the tactic mentioned in Section 5.2. Given a product, though its associated reviews in our evaluation set area unit solely a set of all reviews found regarding this product within the original dataset, the temporal arrangement of these reviews (and the corresponding reviewers) remains the same. we have a tendency to assign the class labels to reviewers based mostly on the initial dataset and use them as our ground truth. 6.2 analysis metrics Given a product, every candidate methodology can turn out AN ordered list of users. Hence, we have a tendency to adopt 3 ranking-based metrics for analysis of predicting results.

Over lapping magnitude relation at rank k (OR@k). Given the anticipated ordered list of users for a product, OR@k is outlined as:OR@k =jL(k) \ G(k)j k ; (3) where L(k) and G(k) denote the sets of users came back by a candidate methodology and obtained by sorting in step with actual timestamps for the primary k reviewers severally. Note that once k is larger than the particular range of early reviewers given a product, G(k) would contain users WHO are not early reviewers. Hit magnitude relation at rank k (Hit@k). Given the anticipated ordered list of users for a product ,Hit@k is define dp as :Hit@k =Pk I=1 I(p; ui) N(E) p ; (4)where I(p; ui) returns one if i was AN early reviewer for product p in original dataset, and zero otherwise; and N(E) p is the actual range of early reviewers for product p.

Ratio of Correct Comparison Pairs (RCCP). Since our model is trained from comparison pairs, we have a tendency to additionally use RCCP to measure the standard of pair wise ranking, that is outlined as :RCCP = #correctly foretold pairs #test pairs :(5) Note that we have a tendency to don't adopt ranking-based correlation coefficient as analysis metrics (e.g., Spearman or biochemist Tau). For our task, the standard of prime predictions for early reviewers are more important to consider. Hence, we mainly use the aforementioned metrics for top-k ranking.

RELATED WORK

Our current study is mainly related to the following three lines of research.

Early Adopter Detection

The term of *early adopter* originates from the classic theory for Diffusion of Innovations [8]. An early adopter could refer to a trendsetter, *e.g.*, an early customer of a given company, product and technology. The importance of early adopters has been widely studied in sociology and economics. It has been shown that early adopters are important in trend pre- diction, viral marketing, product promotion, and so on [4]. Moreover, the influence of early adopters is closely related Fig. 11. Early reviewer prediction performance with different sizes of training set or embedding dimensions in Amazon dataset.

To the studies of herd behavior [6], [13]–[15], [18]–[20], that describes that people square measure powerfully influenced by the selections of others, like available market bubbles, decision-making, social promoting and merchandise success. As for product promoting, shoppers oftentimes choose fashionable brands as a result of they believe that quality indicates higher quality [13]. for instance, in digital auctions, consumers tend to bid for listings that others have already bid for, whereas ignoring similar or additional enticing un bid for listings [33]. Similarly, AN experimental study shows that the social influence of early adopters' decisions of songs ends up in each difference and unpredictability of the songs in terms of transfer counts [3]. Some additional investigations additionally reveal that product evaluations from previous adopters, like star ratings and sales volume, influence customers' on-line product decisions [13]. The analysis and detection of early adopters within the diffusion of innovations have attracted abundant attention from the analysis community typically speaking, 3 parts of a diffusion method are studied: attributes of AN innovation, communication channels, and social network structures [8]. Early studies square measure chiefly theoretical analysis at the macro level [5], [34]. With the rapid climb of on-line social platforms and the convenience of a high volume of social networking information, studies of the diffusion of innovations are mostly conducted on social networks, together with resource-constrained networks [9], following or retweet networks [10], user-click graphs [12] and text-based innovation networks [11]. Following this, several studies try and model the experience level of a user employing a competition-based ranking approach, e.g., community question and respondent platforms [27], [51] and generalized crowd sourcing systems [50], [52].

Distributed illustration Learning

Since its seminal work [53], distributed illustration learning has been with success employed in varied application areas as well as linguistic communication process (NLP), speech recognition and laptop vision. the most plan of distributed representations is to utilize low-dimensional dense vectors to represent data entities. for instance, in NLP, many linguistics embedding models are planned, as well as word embedding [16], phrase embedding [54], and sentence embedding [55]. Word embedding models like word2vec [16], have generalized the classic n-gram language models by mistreatment continuous variables to represent words in a very vector house and are with success applied to capture latent linguistics for NLP tasks. Specially, word2vec has given 2 major model architectures, specifically skip-gram (SG) and continuous bag-of-words (CBOW). SG predicts the encompassing words supported this word, whereas CBOW predicts this word mistreatment the surrounding words as contexts. In CBOW, the discourse data is shapely as associate degree embedding vector mistreatment a median pooling over the embedding's of close words. supported word2vec, doc2vec [55] additional incorporates the document- specific embedding's into the word2vec model. Almost like word2vec, it additionally provides 2 model architecture: distribute dysfunction bag-of-words model and distributed memory model. additional recently, the construct of distributed representations has been extended on the far side pure language modeling to numerous text connected tasks, like information graph completion [17], [56], text-based attribute illustration [57] and multimodal modeling [58]. Additionally to model text information, the distributed illustration approach has been wide applied to numerous applications in different fields, like network analysis [59] and recommendation [60] [61] [62].

Summary

Our work is additionally associated with the studies on mining review information [63], [64]. However, we have a tendency to specialize in characterizing early reviews and police investigation early reviewers, that is completely different from the present works on extracting opinions or identifying opinion targets (or holders) from review information. To our information, it's the primary time that the task of early reviewer analysis and detection has been investigated on the real- world e-commerce review datasets, i.e., Amazon and Yelp. we have a tendency to propose a unique margin-based embedding ranking mod- el in a very competition-based framework, that has ne'er been adopted in early adoptive parent detection additionally, we have a tendency to extend the first competition-based framework by incorporating vital facet data concerning merchandise. we have a tendency to additionally use a distributed illustration approach to handle the cold- begin downside. Our empirical analysis has confirmed a series of theoretical conclusions from the social science and economic- s.

CONCLUSION

In this paper, we've got studied the novel task of early reviewer characterization and prediction on 2 real-world on-line review datasets. Our empirical analysis strengthens a series of theoretical conclusions from social science and social science. we tend to found that (1) Associate in Nursing early reviewer tends to assign the next average rating score; Associate in Nursing (2) an early reviewer tends to post a lot of useful reviews. Our experiments additionally indicate those early reviewers' ratings and their received helpfulness scores area unit doubtless to influence product quality at a later stage. we've got adopted a competition-based viewpoint to model the review posting method, and developed a margin- primarily based embedding ranking model (MERM) for predicting early reviewers in a very cold-start setting.

In our current work, the review content isn't considered. With in the future, we are going to explore effective ways in which in incorporating review content into our early reviewer pre- diction model. Also, we've got not studied the communication channel and social network structure in diffusion of innovations partially because of the problem in getting the relevant info from our review knowledge. we are going to look into alternative sources of information like fluster during which social networks are often extracted and perform a lot of perceptive analysis. Currently, we tend to concentrate on the analysis and prediction of early reviewers, whereas there remains a crucial issue to deal with, i.e., a way to improve product promoting with the known early reviewers. We are going to investigate this task with real e-commerce cases unitedly with e-commerce corporations within the future.

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