

FEATURE-LEVEL RATING SYSTEM USING CUSTOMER REVIEWS AND REVIEW VOTES

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ABSTRACT

Online reviews have become an important source of information for users before making an informed purchase decision. Early reviews of a product tend to have a high impact on the subsequent product sales. In this paper, we take the initiative to study the behavior characteristics of early reviewers through their posted reviews on two real-world large e-commerce platforms, i.e., Amazon and Yelp. In specific, we divide 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. We quantitatively characterize early reviewers based on their rating behaviors, the helpfulness scores received from others and the correlation of their reviews with product popularity. We have found that (1) an early reviewer tends to assign a higher average rating score; and (2) an early reviewer tends to post more helpful reviews. Our analysis of product reviews also indicates that early reviewers' ratings and their received helpfulness scores are likely to influence product popularity. By viewing review posting process as a multiplayer competition game, we propose a novel margin-based embedding model for early reviewer prediction. Extensive experiments on two different e-commerce datasets have shown that our proposed approach outperforms a number of competitive baselines.

1 INTRODUCTION

Online reviews have become an important source of information for users before making an informed purchase decision. Online reviews are often our first port of call when considering products and purchases online. When evaluating a potential purchase, we may have a specific query in mind. Early reviews of a product tend to have a high impact on the subsequent product sales. In this paper, we take the initiative to study the behavior characteristics of early reviewers through their posted reviews on two real-world large e-commerce platforms, i.e., Amazon and Yelp. In specific, we divide 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. We quantitatively characterize early reviewers based on their rating behaviors, the helpfulness scores received from others and the correlation of their reviews with product popularity. We have found that an early reviewer tends to assign a higher average rating score; and an early reviewer tends to post more helpful reviews. Our analysis of product reviews also indicates that early reviewers' ratings and their received helpfulness scores are likely to influence product popularity. By viewing review posting process as a multiplayer competition game, we propose a novel margin-based embedding model for early reviewer prediction. Extensive experiments on two different e-commerce datasets have shown that our proposed approach outperforms a number of competitive baselines.

2. LITERATURE SURVEY AND RELATED WORK

TITLE: “Addressing complex and subjective product-related queries with customer reviews,

AUTHOR: “J. McAuley and A. Yang,

CONTENT:

Online reviews are often our first port of call when considering products and purchases online. When evaluating a potential purchase, we may have a specific query in mind, e.g. ‘will this baby seat fit in the overhead compartment of a 747?’ or ‘will I like this album if I liked Taylor Swift’s 1989?’. To answer such questions we must either wade through huge volumes of consumer reviews hoping to find one that is relevant, or otherwise pose our question directly to the community via a Q/A system. In this paper we hope to fuse these two paradigms: given a large volume of previously answered queries about products, we hope to automatically learn whether a review of a product is relevant to a given query. We formulate this as a machine learning problem using a mixture-of-experts-type framework—here each review is an ‘expert’ that gets to vote on the response to a particular query; simultaneously we learn a relevance function such that ‘relevant’ reviews are those that vote correctly. At test time this learned relevance function allows us to surface reviews that are relevant to new queries on-demand. We evaluate our system, Moqa, on a novel corpus of 1.4 million questions (and answers) and 13 million reviews. We show quantitatively that it is effective at addressing both binary and open-ended queries, and qualitatively that it surfaces reviews that human evaluators consider to be relevant.

TITLE: N. V. Nielsen,

AUTHOR: “E-commerce: Evolution or revolution in the fastmoving consumer goods world,”

CONTENT:

Across the globe, shoppers are increasingly turning to the web to buy the things they need. Online shopping offers certain conveniences—from delivering your order right to your door to broad selection and low prices—that brick-and-mortar stores can’t. But for certain categories, traditional retail stores still hold the cards. The most popular e-commerce categories, not surprisingly, are non-consumable—durables and entertainment-related products. Almost half of global respondents in an online survey intend to purchase clothing or make airline or hotel reservations using an online device in the next six months. On the other hand the online market for buying groceries and other consumable products is comparatively smaller. The hands-on buying nature and perishability of these goods limits the usefulness and practicality of buying online.

Nevertheless, the global audience is willing and eager to shop the web. Online purchase intention rates have doubled in three years for 12 of 22 measured categories. While consumable categories will continue to trail non-consumable ones, the frequency of purchasing these products is increasing e-commerce’s appeal. And beyond buying, digital is an increasingly important research and engagement platform.

3 EXISTING SYSTEM

Previous studies have highly emphasized the phenomenon that individuals are strongly influenced by the decisions of others, which can be explained by herd behavior. 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, when consumers use the product evaluations of others to estimate product quality on the Internet, herd behavior occurs in the online shopping process. 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 an 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.

Proposed system:

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 reviewer’s w.r.t. to a product. The competition process can be further decomposed into multiple pairwise 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, 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.

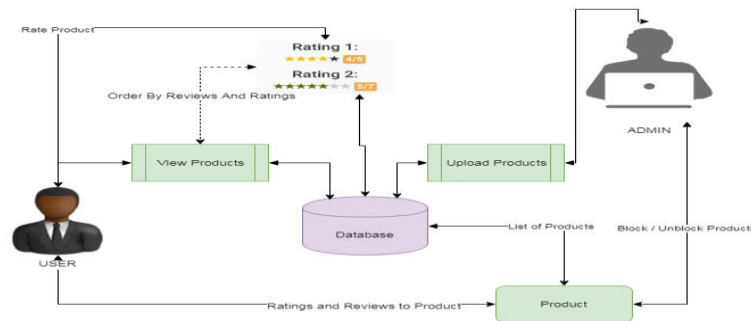


FIG 1: SYSTEM ARCHITECTURE

4 METHODOLOGIES

implementation

1.UPLOAD PRODUCTS:

Uploading the products is done by admin. Authorized person is uploading the new arrivals to system that are listed to users. Product can be uploaded with its attributes such as brand, color, and all other details of warranty. The uploaded products are

able to block or unblock by users.

2.PRODUCT REVIEW BASED ORDER:

The suggestion to user’s view of products is listed based on the review by user and rating to particular item. Naïve bayesalgorithm is used in this project to develop the whether the sentiment of given review is positive or negative. Based on the output of algorithm suggestion to users is given. The algorithm is applied and lists the products in user side based on the positive and negative.

3.RATINGS AND REVIEWS:

Ratings and reviews are main concept of the project in order to find effective product marketing. The main aim of the project is to get the user reviews based on how they purchased or whether they purchased or not. The major find out of the project is when they give the ratings and how effective it is. And this will helpful for the users who are willing to buy the same kind of product.

4.DATA ANALYSIS

The main part of the project is to analysis the ratings and reviews that are given by the user. The products can be analysis based on the numbers which are given by user. The user data analysis of the data can be done by charts format. The graphs may vary like pie chart, bar chart or some other charts.

5 RESULTS AND DISCUSSION SCREENSHOTS

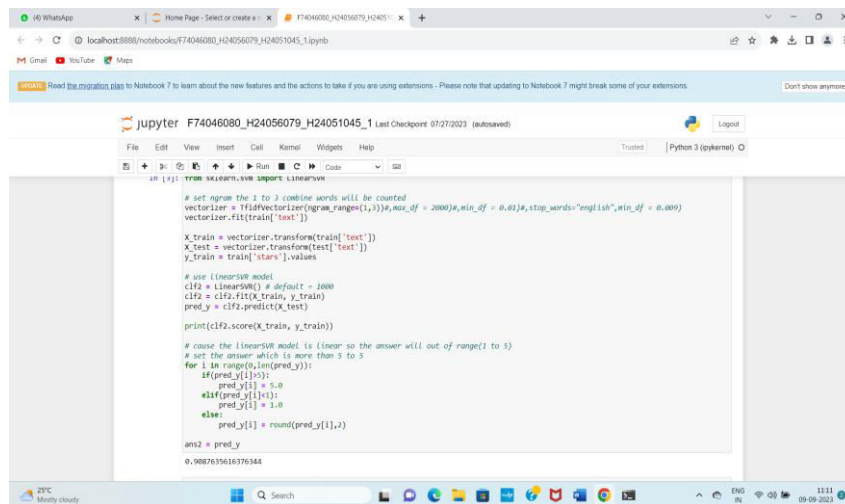


Fig 2: - tfidfvectorisztion accuracy

```

In [2]: from sklearn.svm import LinearSVC
...
x_train = df.drop(["review_id", "business_id", "user_id", "date"], axis=1)
...
vectorizer = CountVecorizer()
vectorizer.fit(train["text"])
...
vectorizer = TfidfVectorizer(stop_words='english', min_df = 0.03)
vectorizer.fit(train["text"])
x_train = vectorizer.transform(train["text"])
x_test = vectorizer.transform(test["text"])
y_train = train["stars"].values
clf = LinearSVC() # default = 2000
clf = TfidfVectorizer
pred_y = clf.predict(x_test)
print(clf.score(x_train, y_train))
output = np.vstack((out1f, pred_y)).T
output = pd.DataFrame(output, columns=["user_id", "stars"])
np.savetxt("L_SVC.csv", output, fmt="%s", delimiter=",")
0.9770821351257
    
```

Fig 3: - tfidfvectorisztion After training accuracy achieved 97.07%

```

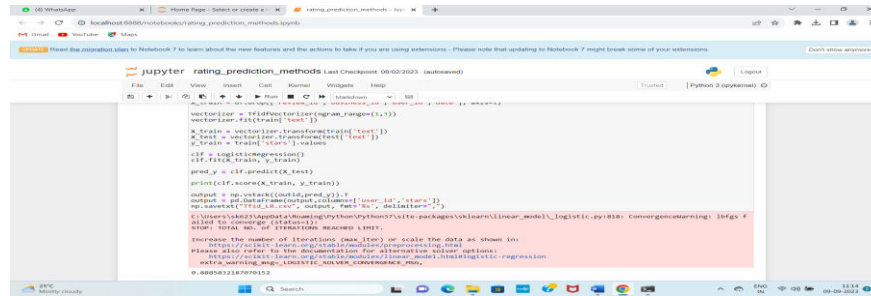
In [1]: import pandas as pd
import numpy as np
df = pd.read_csv("training_data.csv")
text = pd.read_csv("test_data.csv")
print(df.head())
out1f = text["review_id"].values a dataframe to numpy
print(out1f)
print(len(out1f))
train = df
...
review_id business_id user_id \
0 4223 2055 2533
1 4928 4355 4373
2 7123 869 4920
3 5083 1083 2789
4 3948 2347 1285
...
text date stars
1 I know kerrie through my networking and we ben... 2010-12-28 5
2 Love their pizza!! Every fresh. Their cannoli... 2012-09-29 5
3 Being from MI, I'm always on the prowl for my ... 2009-08-07 4
4 We have tried this spot a few times and each v... 2011-02-29 4
    
```

Fig 4: - using linear SVC

```

In [1]: from sklearn.svm import LinearSVC
...
x_train = df.drop(["review_id", "business_id", "user_id", "date"], axis=1)
...
vectorizer = CountVecorizer()
vectorizer.fit(train["text"])
...
vectorizer = TfidfVectorizer(stop_words='english', min_df = 0.03)
vectorizer.fit(train["text"])
x_train = vectorizer.transform(train["text"])
x_test = vectorizer.transform(test["text"])
y_train = train["stars"].values
clf = LinearSVC() # default = 2000
clf = TfidfVectorizer
pred_y = clf.predict(x_test)
print(clf.score(x_train, y_train))
for i in range(0, len(pred_y)):
    if pred_y[i] != y_train[i]:
        print("Error at %d" % i)
        print("Actual: %d, Predicted: %d" % (y_train[i], pred_y[i]))
output = np.vstack((out1f, pred_y)).T
output = pd.DataFrame(output, columns=["user_id", "stars"])
np.savetxt("L_SVC.csv", output, fmt="%s", delimiter=",")
0.907280247864755
    
```

Fig 5: - using linear SVC achieved accuracy 90.77%



```

vectorize = Vectorizer(ngram_range=(1,3))
vectorizer.fit(train['text'])
X_train = vectorizer.transform(train['text'])
X_test = vectorizer.transform(test['text'])
y_train = train['score']
clf = LogisticRegression()
clf.fit(X_train, y_train)
pred_y = clf.predict(X_test)
print(clf.score(X_train, y_train))
output = pd.DataFrame({'text': X_test, 'score': pred_y})
accuracy = sum(output['score'] == output['score']).sum() / output['score'].sum()
print('Accuracy: %f' % accuracy)

```

packages\sklearn\linear_model_logistic.py:1318: ConvergenceWarning: lbfgs failed to converge (50 iterations).

Increase the number of iterations (max_iter) or scale the data as shown in: https://scikit-learn.org/stable/tutorial/basic/parameter_tuning.html

Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

Fig 6: - using linear logistic achieved accuracy 88.85%

6. CONCLUSION AND FUTURE SCOPE

In this paper, we have studied the novel task of early reviewer characterization and prediction on two real-world online review datasets. Our empirical analysis strengthens a series of theoretical conclusions from sociology and economics. We found that (1) an early reviewer tends to assign a higher average rating score; and (2) an early reviewer tends to post more helpful reviews. Our experiments also indicate that early reviewers' ratings and their received helpfulness scores are likely to influence product popularity at a later stage. We have adopted a competition-based viewpoint to model the review posting process, and developed a margin based embedding ranking model (MERM) for predicting early reviewers in a cold-start setting.

FUTURE SCOPE:

In our current work, the review content is not considered. In the future, we will explore effective ways in incorporating review content into our early reviewer prediction model. Also, we have not studied the communication channel and social network structure in diffusion of innovations partly due to the difficulty in obtaining the relevant information from our review data. We will look into other sources of data such as Flixster in which social networks can be extracted and carry out more insightful analysis. Currently, we focus on the analysis and prediction of early reviewers, while there remains an important issue to address, i.e., how to improve product marketing with the identified early reviewers. We will investigate this task with real e-commerce cases in collaboration with e-commerce companies in the future.

7 REFERENCES

- [1] J. McAuley and A. Yang, "Addressing complex and subjective product-related queries with customer reviews," in WWW, 2016, pp. 625–635.
- [2] N. V. Nielsen, "E-commerce: Evolution or revolution in the fastmoving consumer goods world," nngroup. com, 2014.
- [3] W. D. J. Salganik M J, Dodds P S, "Experimental study of inequality and unpredictability in an artificial cultural market," in ASONAM, 2016, pp. 529–532.
- [4] R. Peres, E. Muller, and V. Mahajan, "Innovation diffusion and new product growth models: A critical review and research directions," International Journal of Research in Marketing, vol. 27, no. 2, pp. 91 – 106, 2010.

- [5] L. A. Fourt and J. W. Woodlock, "Early prediction of market success for new grocery products." *Journal of Marketing*, vol. 25, no. 2, pp. 31 – 38, 1960.
- [6] B. W. O, "Reference group influence on product and brand purchase decisions," *Journal of Consumer Research*, vol. 9, pp. 183–194, 1982.
- [7] J. J. McAuley, C. Targett, Q. Shi, and A. van den Hengel, "Imagebased recommendations on styles and substitutes," in *SIGIR*, 2015, pp. 43–52.
- [8] E. M. Rogers, *Diffusion of Innovations*. New York: The Rise of HighTechnology Culture, 1983.
- [9] K. Sarkar and H. Sundaram, "How do we find early adopters who will guide a resource constrained network towards a desired distribution of behaviors?" in *CoRR*, 2013, p. 1303.
- [10] D. Imamori and K. Tajima, "Predicting popularity of twitter accounts through the discovery of link-propagating early adopters," in *CoRR*, 2015, p. 1512.