

Algorithm for Ranking Consumer Reviews on E-commerce Websites

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Abstract— With the rise in the number of reviews available online there is an increasing need for classifying and extracting authentic and better quality reviews. In this paper we propose an efficient method for ranking user reviews on online portals (primarily consumer service websites) to enrich user experience and enable efficient decision making through experiences of other users. The algorithm ranks user reviews using content analysis and credibility of the content author. We have introduced author credibility as a factor to take into account the authenticity of the review content. Using scores as outputs from factors mentioned above, we generate a cumulative weighted score and assign it to each review. The scores are then used to rank reviews that would be displayed to users. We correct for weighted averages using feedback from the user-base on the online portal. The algorithm dynamically keeps improving itself using user feedback, making it self aware.

Keywords— E-commerce, Consumer Reviews, Ranking, Content analysis, Backpropagation.

I. INTRODUCTION

E-commerce websites have proliferated at a steep rate over the last decade. The number of consumers shifting to online platforms has also increased significantly. With the ever-increasing competition in e-commerce consumers have numerous options to choose from. This gives rise to the need of providing an enriched shopping experience to the consumer. The primary drawback of online shopping is the inability to provide consumers with an alternate for the physical look-and-feel experience of a product. Without this physical experience, prospective consumers are left with no alternate but to rely on the feedback from past consumers to make the final decision of buying the product. Therefore, reviews have a huge impact on the sales of e-commerce websites^[1]. Consumers try to find out how other consumers have recommended the product based on its quality, usefulness and many other parameters. This makes the role of consumer reviews regarding a product highly critical^[2]. Reviews in itself are not sufficient. The entire content posted by users online is not relevant and useful. We need to display the content that is most relevant and is useful. Filtering out high quality reviews out of this plethora of content is a task that requires critical analysis. This paper explicates an efficient algorithm to rank user reviews. The algorithm bases itself on content analysis from a grammatical, sentimental and relevance point of view. In addition to content analysis, author credibility and authenticity are also scrutinised. Finally, the outcome of

each analysis is fed into a Neural Network which corrects for the weights for each analysis using back propagation.

II. METHODOLOGY

In our approach, we first compute score for each type of analysis of the review text. The content analysis generates three types of scores based on - Grammar, Sentiment and Relevance. The author credibility analysis, on the other hand, generates two scores based on- Credibility and Authenticity. After computing all of these scores, a cumulative rank score is calculated using neural network.

1. Content and Credibility Analysis

1.1 Grammar Analysis

Clear communication is nearly impossible without correct grammar. Proper grammar usage ensures that the author expresses his/her views clearly without being misunderstood. Moreover, this gives the reader a sense of credibility about the author. To analyze grammar, we have used LanguageTool^[3], an Open Source proof-reading program which detects various errors that a simple spell checker cannot detect and several grammatical errors. LanguageTool has a python wrapper - *language_check*^[4] which takes the review content and returns the number of spelling and grammatical errors (n_{errors}). The grammar score of the review can thus be calculated in the range of [0, 1] using the following equation:

$$\mu_{grammar-score} = 1 - \frac{n_{errors}}{n_{words}}$$

where, n_{words} is the total number of words in the review.

1.2 Sentiment Analysis

The overall sentiment of the review conveys the author's final judgment about the product. It is the conclusive opinion which the author has formed about the product after considering all the experiences - pros and cons. The sentiment can be positive, negative or mixed. The degree to which the review sentiment concurs with the collective sentiment of all the earlier reviews about the product can be a factor adding to the review's popularity. The review's chances of being accurate are boosted by the fact that large number of consumers agree with the author's sentiment. Alchemy API^[5] generates text sentiment ($\mu_{alchemy}$) in the range of [-1,1]. Negative values imply negative sentiment and positive values imply positive sentiment in the text. Deviation of sentiment values from 0 conveys the strength of the emotion. For example, a value of 0.8 conveys

stronger positive emotion than the value 0.4. The collective sentiment of earlier reviews can be obtained in the range of [0,1] by taking rated average of total number of ratings (n) available for the product.

$$\mu_{collective-sentiment} = \frac{\sum_{i=0}^n rating_i}{n \times maximum\ possible\ rating}$$

For conversion of sentiment obtained from API into [0,1] scale:

$$\mu_{review-sentiment} = 0.5 + \frac{\mu_{alchemy}}{2}$$

Now the sentiment score can be calculated by taking the complement of the deviation of review sentiment from the collective sentiment of previous reviews.

$$\mu_{sentiment-score} = 1 - |\mu_{collective-sentiment} - \mu_{review-sentiment}|$$

Note: The sentiment score will only be effective if we have significant amount of ratings present for the product.

1.3 Relevance Analysis

Relevance of a review takes into account the fact that a good review covers most number of aspects about a product. When computing relevance score for a review we enumerate the key aspects that have been taken into account by the author of the review. Each class of product is assigned a set of keywords, for instance, mobile phones will have a set of keywords like {"display", "battery", "camera", "flash", "memory"}. The occurrences of these keywords is accounted for if they occur at least once.

n_{ki} denotes number of occurrence of i^{th} keyword from a set of n keywords

μ_{ki} denotes score for each keyword

$$\mu_{ki} = \begin{cases} 1, & \text{if } n_{ki} \geq 1 \\ 0, & \text{otherwise} \end{cases}$$

Once we have generated score for each keyword we calculate the cumulative score,

$$\mu_{relevance-score} = \frac{\sum_{i=0}^n \mu_{ki}}{n}, \mu_{relevance-score} \in [0,1]$$

1.4 Credibility Analysis

A reviewer, who has reviews of other products to his name which have received good feedback from other consumers, is more likely to write a similar review beneficial for other consumers in the future too. On the other hand, a reviewer who has written reviews disliked by other consumers in the past is likely to write a bad one in the future too. We base our credibility score on this premise. For each earlier review posted by the user we calculate its likeability based on the number of likes and dislikes that review has received.

$$\mu_{likeability} = \frac{Total\ likes - Total\ dislikes}{Total\ likes + Total\ dislikes}, \mu_{likeability} \in [-1,1]$$

Now we generate the credibility score using the likeability values of each review:

$$\mu_{credibility-score} = \frac{\sum_{i=0}^n \mu_{likeability_i}}{n}$$

where, $\mu_{likeability_i}$ is likeability value for i^{th} review
n is the total number of earlier reviews posted by the user,
and $\mu_{credibility-score} \in [-1,1]$

1.5 Authenticity Analysis

Authenticity of a review is reflected by the fact that the author has in fact used the product (or service). Being a certified buyer of a product affirms that the author is sharing his opinion based on personal experience with the product. This makes the certified buyer tag an even more important contributor to the authenticity of the review.

$$\mu_{authenticity-score} = \begin{cases} 1, & \text{if user has bought the product} \\ 0, & \text{otherwise} \end{cases}$$

2. Backpropagation Neural Network

The final step of the approach involves the use of a backpropagation neural network^[6] that takes as input the scores that we have computed in the earlier steps. The choice of backpropagation neural network as a means of computing final score is in accordance with the capability of backpropagation algorithm to train our feed-forward neural network for a given set of input pattern.

Initially the set of weights for each score are not decided and are rather assumed. When each entry of the sample set is presented to the network, the network examines its output response to the sample input pattern. The output response is then compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted.

This corrective procedure is applied continuously and repetitively for each set of inputs and the corresponding set of outputs until the error value is minimized.

Fig. 1 illustrates a Single Layer Neural Network that computes the final output. The input layer consists of the scores that were computed in the previous steps. Weights (w_1, w_2, \dots, w_5) are then associated with each input variable. We also take into account the bias factor in the neural network which is denoted by, w_0 .

The hidden layer consists of a single neuron that is basically a sigma function and computes weighted sum of all the input parameters.

$$\vartheta = \sum (\mu_i \times w_i)$$

Output from the hidden layer is then passed through the activation function (φ), in this case the Sigmoid function which scales down the output to [0,1] range, which is in fact the final score associated with the review (Y).

$$Y = \varphi(\vartheta + b)$$

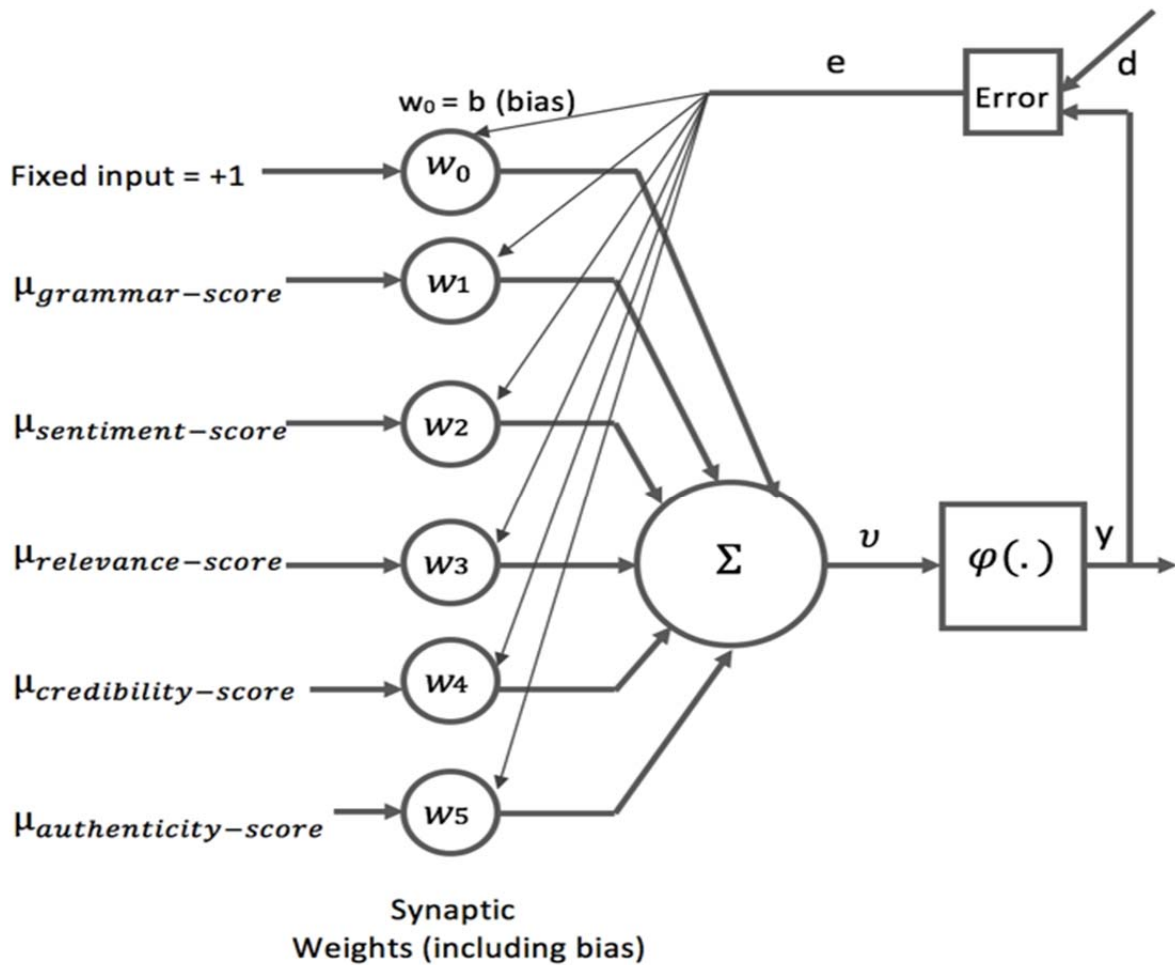


Fig. 1 Backpropagation Neural Network

3. Feedback Mechanism (Backpropagation)

The above method clarifies the output computation part of the neural network. Once we have the output, we need to correct the weights so as to make the computation part more accurate. The feedback to the network is provided by calculating the correct score for the review. The correct score is computed using user response on the review. For a given review, we calculate the correct rank score using following equation:

$$d(\text{desired output}) = \frac{\text{Number of upvotes}}{\text{Total number of votes}}, d \in [0,1]$$

The total number of votes have to clear a minimum threshold so as to become significant as a learning example. Once we have the corrected score, calculated using above methodology, we can feed it back into the neural network. The Backpropagation algorithm starts at the output layer and corrects the weights using following equations^[7]:

$$w_i = w'_i + LR * e * \mu_i$$

where,

$$e = Y * (1 - Y) * (d - Y)$$

For the i^{th} input of the neuron in the output layer, the weight w_i is adjusted by adding to the previous weight value, w'_i , a term determined by the product of a learning rate, LR , an error term, e , and the value of the i^{th} input, μ_i . The error term, e , for the neuron is determined by the product of the actual output, Y , its complement, $1 - Y$, and the difference between the desired output, d , and the actual output.

As we train the network, the total error, that is the sum of the errors over all the training sets, becomes smaller and smaller. The final score associated with each review is used to generate the rankings. Reviews are displayed in the decreasing order of their final scores. This is because showing high quality reviews on top improves the overall buying experience as users have to spend less time searching for reviews which are technically correct and answer most of their queries regarding the product.

Besides, showing reviews with high scores on top increases the amount of user feedback these reviews receive which in turn helps in perfecting the weights associated with each score.

III. RESULTS AND CONCLUSION

The ranking algorithm is a systematic approach towards providing a better experience to the consumers. The algorithm critically analyses all the important factors that are necessary for determining the quality of reviews. The learning network for calculating the weights of each factor makes sure that the algorithm adjusts itself to the changing priorities of users. The weights reflect importance of each factor in ranking and the user response provides us with the priorities of users - what factors they look for in a useful review. By providing feedback to the network through user response we enable the algorithm to improve its efficiency. This provides us with an intelligent ranking system that leads to an enhanced and enriched user experience.

IV. FUTURE SCOPE

As per the current algorithm, scores generated from various factors is used to generate a cumulative weighted score for each review. This score is then used to rank reviews to obtain the order in which these reviews are displayed to the user. The algorithm can be further extended to detect fake reviews using the final score generated. In case a review fails to attain a minimum threshold score or reviews submitted by a particular user are regularly

assigned low scores, then the likelihood that those reviews are fake is very high. Also if large number of reviews are submitted for a product in a small period of time, there is a very high chance that all of those reviews are fake. In such cases a check for similarity (closeness in cumulative weighted score) between those reviews can be done to generate originality score.

Besides the five scores generated in our approach, a score based on the age of the review can also be calculated. This is based on the premise that users generally give more importance to latest reviews in comparison to reviews which were submitted few months or years back.

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