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Helpfulness Prediction of multimodal reviews considering customer confirmation bias

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1. INTRODUCTION AND RESEARCH QUESTIONS

Useful online reviews on e-commence is beneficial to consumers, merchants, and platforms. Previous research has investigated that consumers exhibit a confirmation bias when assessing the usefulness of online reviews (Yin et al., 2016). Consumers tend to perceive the reviews aligning with their initial beliefs helpful for their purchase decisions. The confirmation bias primarily arises from consumers' initial beliefs about a product after reading the review statistical information displayed on the platform. However, previous studies on predicting the helpfulness of reviews have typically assumed that customers perceive a review's helpfulness in an unbiased manner, solely relying on the information provided within the review itself (Ren et al., 2024). Few research focus on this information processing bias when predicting the usefulness of reviews. Moreover, consumers intend to present product reviews with texts and images now. The multimodal reviews maybe change the initial beliefs of consumers in some extent. Therefore, it is essential to investigate the impact of confirmation bias on the perceived helpfulness in the context of multimodal reviews.

This study will investigate how the consumers' initial beliefs are calibrated by the multimodal information of reviews when predicting the helpfulness of multimodal reviews. Our research questions are as follows: (1) How to formulate the consumers' initial beliefs about the product? (2) How the initial beliefs are calibrated by the texts and images of individual reviews? (3) How to aggregate the initial beliefs and multimodal deep semantic information of both texts and images for predicting review helpfulness?

2. THEORY AND RESEARCH MODEL

Based on confirmation bias theory and elaboration likelihood model (ELM), this study proposes a hierarchically-trusted multi-view deep learning model for predicting review helpfulness. The model consists of four components including initial-belief view construction, central-route view construction, peripheral-route view construction, and hierarchically-trusted multi-view fusion (Figure 1).

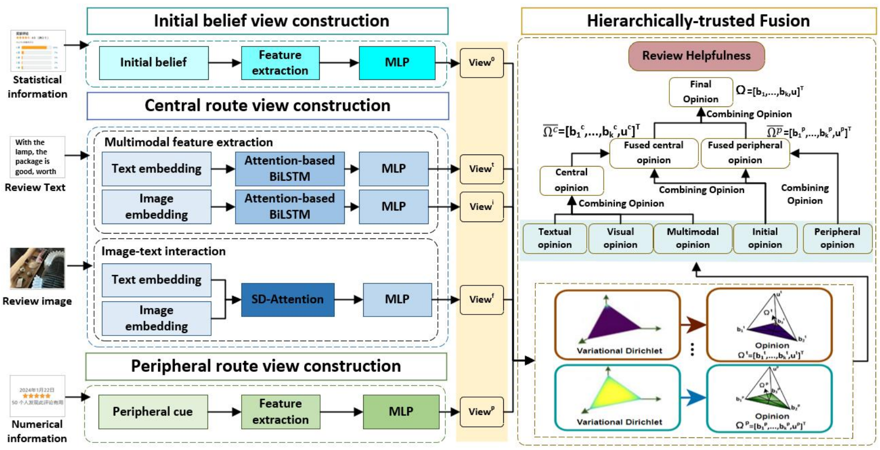

Figure 1. The hierarchically-trusted multi-view deep learning model

Firstly, we designed the initial belief feature, which consists of two components including group recommendation and confidence. The average rating of the product and the dispersion of ratings were used to measure these components (Yin et al., 2016). Then, a central-route view is constructed. Three indicators are used to describe the central cues of reviews including quality, consistency and visual complexity. Meanwhile, in peripheral-route view construction, we designed three indicators including popularity, satisfaction and timelines. They were measured by the number of votes, star ratings, and publication time, respectively. Thirdly, a hierarchically-trusted multi-view fusion strategy is designed to fuse the central and peripheral views with the initial beliefs, simulating the confirmation bias phenomenon of consumers. Finally, a Kullback-Leibler (KL) divergence-based learning strategy is proposed to model the interaction among the initial beliefs, the central cues and peripheral cues of reviews.

3. MATERIALS, RESULTS AND MAJOR FINDINGS

Experiments are conducted using a collection of Amazon reviews for home category products. We map the number of review votes into five intervals (i.e., [1,2], [2, 4], [4, 8], [8, 16], [16, ∞]), corresponding to five categories of helpfulness scores {0, 1, 2, 3, 4}. The mean average precision (MAP) and normalized discounted cumulative gain (NDCG@N) are the evaluation metrics for assessing the performance of the prediction model. Specifically, we considered N = 3 and N = 5 for NDCG。

Table 1. Values of MAP, N@3, N@5 for all tested models

Data	Method	MAP	N@5	N@3
Text reviews	Bi-GRU	0.8252	0.8305	0.7402
	PRH-Net	0.8267	0.8285	0.7376
Image reviews	CNN	0.8185	0.8273	0.7311
Multimodal data	CLSTM	0.8372	0.8492	0.7660
	CSIMD	0.8387	0.8498	0.7700
	MFRHP	0.8499	0.8578	0.7866
The proposed model	TRHPM	0.8548	0.8620	0.7902

Table 2. Results of ablation experiments

Method	MAP	N@5	N@3
-w/o central cue module	0.7898	0.8218	0.7124
-w/o initial belief module	0.8455	0.8565	0.7792
-w/o peripheral cue module	0.8499	0.8605	0.7894
-w/o hierarchically-trusted fusion module	0.8499	0.8607	0.7891
Our	0.8548	0.8620	0.7902

The experimental results show some valuable and interesting findings: (1) Considering the feature extraction of multimodal deep semantic information of reviews, the proposed model outperformed the current multimodal prediction model including CLSTM (Ma et al.,2018), CSIMD (Xiao et al.,2022) and MFRHP (Ren et al., 2024), as shown in Table1; (2) The initial-belief view and the central-route view play significant roles in the overall usefulness assessment. we conducted ablation experiments by gradually removing different parts of the model to validate the importance of each component. The experimental results indicate the necessity of considering consumers' initial perceptions when evaluating the usefulness of reviews, as shown in Table 2. (3) The similarity between texts and images play more important roles than the difference between them in predicting review helpfulness. It is evident that the model achieves its best performance when the parameter alpha is set to 0.9, as shown in Figure 2. (4) The interaction among the initial beliefs, the central cues and the peripheral cues contributes 30% for predicting review helpfulness. As shown in Figure 3, the parameter beta is set to 0.3 when the proposed model achieves best performance.

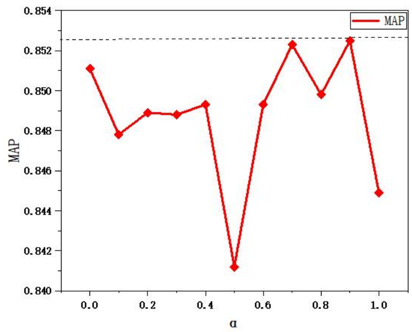

Figure 2. Sensitivity analysis of similarity and difference balance factors of images and texts

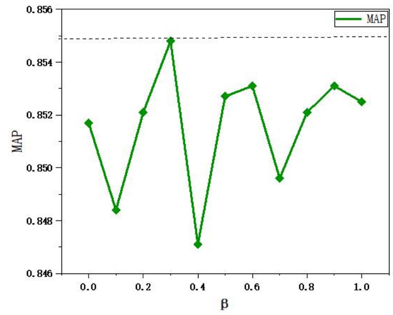

Figure 7. Balance factor sensitivity analysis of KL divergence

4. MAIN CONTRIBUTIONS

From a methodological perspective, we propose a hierarchically-trusted multi-view learning approach based on the theory of confirmation bias and ELM. We investigate the role of initial beliefs in evaluating the usefulness of multimodal reviews and its interaction with multimodal deep semantic information of reviews. From a managerial perspective, accurately predicting the usefulness of reviews can enhance user experience and reputation on platforms. Consumers can make more informed decisions, and businesses can gain insights to improve their products and services, strengthening their relationships with customers. Furthermore, it is necessary for platforms to display statistical information about reviews.

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