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Prediction and modelling online reviews helpfulness using 1D Convolutional Neural Networks

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Latest research is showing as trending topic the identification of helpful reviews from a big volume of user-generated data. In this regard, this work puts forward a classification approach using an adaptive implementation of 1D Convolutional Neural Networks (CNNs), which early identifies if an online review is helpful, neutral, or not helpful with 66% of accuracy. Likewise, the neuronal encoding of CNNs allows us modelling online reviews helpfulness and having an automatic data classification using cluster analysis. Findings unveil that the most important words and documents for helpful reviews clusters in the product category 'Cars & Motorcycles' describe cars and their characteristics. While for not helpful reviews clusters is about details on car-related shops/companies in general. By demonstrating high performance on prediction and classification of review helpfulness with our proposed methodology, we are contributing to the research on business intelligence. Besides, we provide significant practical implications to marketers who can discriminate between the helpful and not helpful reviews and have an automatic data classification of different clusters.

Keywords: *Helpfulness, online reviews, Convolutional Neural Networks, classification*

1 Introduction

Before making any buying decision consumers would rather read online reviews. Online reviews also provide marketers and vendors and effective channel to reach consumers (Gu et al., 2013). Product related electronic world-of-mouth (eWOM) communities or some e-commerce websites enable consumers a space to exchange their opinions about products. These platforms allow consumers to make more informed decisions (Li et al., 2019). We chose the electronic word-of-mouth (eWOM) communities' context for this study because these websites are exclusively dedicated to the exchange of online reviews. Furthermore, the influence of word-of-mouth and its impact on consumer decision-making are well proven in previous literature (Engel et al., 1969; Herr et al., 1991; Bone, 1995). In fact, consumers tend to be gradually more online active when sharing their product experiences and throughout the eWOM communities many users are able to obtain knowledge from online reviews about products. However, it is challenging to discern the best online reviews because for some products there are a big volume of online reviews. Thus, it is important to ensure the quality of this user-generated content within online communities (Chen et al., 2011). In this regard, the helpfulness characteristic of online reviews works effectively to deal with information overload and supports the consumer within his/her decision-making process (Cao et al., 2011). Additionally, filtering out helpful reviews helps marketers and vendors to cut down costs related to business intelligence activities (Zhang and Lin, 2018). Typically, the helpfulness dimension of a review is the ratio of the number of helpful readers' votes to the number of total votes received by a review (Ngo-Ye et al., 2017). Nevertheless, not all online reviews get helpfulness votes, so the helpfulness voting procedure does not work successfully (Cao et al., 2011). Furthermore, the helpfulness functionality only displays a general voting score without taking into account the significant role of review content information (Ghose and Ipeirotis, 2011), which might worsen achieving a good performance on review helpfulness prediction. In this respect, some academic studies have mainly used text mining techniques to predict the helpfulness of reviews. For instance, Ngo-Ye and Sinha (2014) and Ngo-Ye et al. (2017) applied a text regression experiment using support vector regression (SVR) and Li et al. (2019) used support vector machine (SVM), which is a supervised learning machine for pattern classification and nonlinear regression. Other academics state that machine learning methods are needed to obtain valuable information on the online reviews helpfulness and that neural networks are those methods that capture intricate patterns of relationships between variables better than the statistical models (Lee and Choeh, 2014). As can be inferred, the analysis of helpfulness prediction using different machine learning methods has motivated much attention in the literature. However, little is still researched on predicting the helpfulness using convolutional neural networks. Actually, thus far, there are only two recent research works that present convolutional neural network models that aim at predicting the helpfulness value of online product reviews. The first work, by Saumya et al. (2019) does the prediction using a two-layered convolutional neural network model (2-CNN). The second study, by Mitra and Jenamani (2021) implements a dual CNN (D-CNN) model to capture lexical perspective of helpfulness. However, they focus only on the predictive model and not on the interpretation.

To the best of our knowledge, to date no study has simultaneously investigated the methodological point of view on review helpfulness using 1D Convolutional Neural Networks (1D-CNNs) and what exactly makes a review helpful to distinguish it from those reviews that are not helpful. Moreover, no study to date has deeply investigated the contextual characteristics of the helpful and not helpful reviews. It is only by studying these characteristics together that an appropriate conceptualization of review helpfulness can be assessed. Consequently, this study aims to propose an approach to assess the early prediction and modelling of online reviews helpfulness using an implementation of 1D-CNNs taking into account the textual characteristics of online reviews. Further contributions are the discovery of what makes a review helpful and the identification of clusters with the most meaningful words for helpful reviews and not helpful reviews. Accordingly, before even reading an online review, any user could acquire information about the helpfulness of the review for a given product without even looking at its helpful votes.

This paper is structured as follows. Section 2 presents the literature framework and our conceptual model with the proposed research questions. Section 5 explains the proposed methodology. Section 4 includes the experimental evaluation. Section 6 thereafter describes the obtained results. Finally, Section 7 concludes with the discussion and implications of the study.

2 Literature Background and Research Model

2.1 Analysis of online review helpfulness

Review helpfulness is the most significant feature among the many features related with consumers' online product reviews (Malik and Hussain, 2018). This could be argued because online reviews that have higher helpfulness votes also have higher correlations with sales (Chen et al., 2008). Especially, those helpful reviews that are exhibited on the product page show a positive impact on product sales (Kaushik et al., 2018). Because the helpfulness feature of an online product review is not a unique-faceted concept, several kinds of predictors are being investigated to determine the helpfulness of online reviews. Some academics have recognized the importance of the review features and its textual characteristics such as length or longevity (Chua & Banerjee, 2016; Salehan and Kim, 2016; Wu, 2017; Siering et al., 2018), others the reviewer expertise (Li et al., 2019; Malik and Hussain, 2018; Filieri et al., 2018; Huang et al., 2015; Zhou & Guo, 2017), and others the product features a well (Kaushik et al. 2018; Gao et al., 2017).

Mudambi and Schuff (2010) made an analysis of 1,587 reviews taken from Amazon.com and found that review depth, review extremity, and product type have an impact on the helpfulness of the online reviews. Later on, Filieri (2015) suggested that the helpfulness of an online review depends on the quality of information, the customer's ratings and other factors such as the length of the reviews (Qazi et al., 2016; Hong et al., 2017). In this regard, Huang et al. (2015) indicated that the number of words is a significant predictor of review helpfulness as long as reviews are short. Besides, the authors showed that longer reviews usually come from top reviewers. The authors Siering et al. (2018) and Gao et al. (2017) also stated that the reviews are more helpful whenever written by reviewers with more online experience. Moreover, according to Zhou and Guo (2017), when the reviewers provide their profile photo their reviews are perceived as more helpful. Contrariwise, Lee and Choeh (2016) suggested that top reviewers write less helpful reviews and that longer reviews are more helpful. Additionally, review helpfulness has been widely investigated assessing the content of reviews or its textual characteristics. In this regard, researchers have produced some important results in review mining. For instance, taking into account the semantic orientation of reviews and impact of stylistic (Cao et al., 2011) or sentiment analysis to show that review helpfulness varies across review sentiment (Salehan and Kim, 2016; Chua and Banerjee, 2016). In this regard, Huang et al. (2015) identified that the positive reviews were perceived as helpful by consumers. Likewise, Siering et al. (2018) confirmed the influence of review sentiment on review helpfulness. The authors specified that sentiment strength increases review helpfulness in the case of search goods, and it has a negative influence on review helpfulness for experience goods. Moreover, Kaushik et al. (2018) stated the positive impact that the positive reviews have on product sales and inversely, that the negative reviews negatively affect the product sales. Consequently, the content of the reviews could affect how users perceive and rate the helpfulness reviews (Yang et al., 2020). However, it is still left unexplored the importance of the content and context in reviews in predicting the helpfulness of online reviews. This approach also offers the possibility of interpreting the collected features in terms of the content that makes reviews helpful or not helpful.

2.2 Helpfulness prediction of online reviews using machine learning

Early research on the prediction of online reviews helpfulness includes various aspects such as descriptive features of reviews including date and time of the review, review rating, helpfulness score and the length of the review (Singh et al., 2017; Hu & Chen, 2016; Li et al., 2019; Ma et al., 2018). Other works have mainly focused on reviewer features (e.g., age, gender, nationality) (Lee et al., 2018; Liu et al., 2017; Zhang and Lin, 2018; Akbarabadi and Hosseini, 2020). Likewise, to analyze the online reviews there are other considered aspects such as the rating of the product or the product category (Krishnamoorthy, 2015; Malic, 2020). For performing the helpfulness prediction, several machine learning techniques are used, including support vector machines (Krishnamoorthy, 2015; Li et al., 2019; Zhang and Lin, 2018), neural networks (Ma et al., 2018; Eslami et al., 2018; Mitra and Jenamani, 2021) or decision trees (Akbarabadi and Hosseini, 2020; Lee et al., 2018) among others. Table 1 gathers an overview of all major latest works addressing helpfulness prediction using different machine learning techniques explicitly taking into account four helpfulness factors: (1) content review, (2) review features, (3) reviewer expertise, and (4) product features.

Some researchers affirm that sentiment analysis techniques are more efficient on online review helpfulness prediction (Zhang and Lin, 2018; Yang et al., 2020) while others support text (Ngo-Ye et al., 2017) or linear (Hu and Chen, 2016) regression models. Moreover, several authors, such as Eslami et al. (2018), claim that neural networks demonstrate better performance. In this regard, Ma et al. (2018) state that Recurrent Neural Network and Convolutional Neural Network are able to significantly improve the helpfulness prediction of online reviews. Likewise, the experiments by Saumya et al. (2019) show that their proposed Convolutional Neural Network model outperforms various state-of-art models. Similarly, in the experiments by Malik (2020) the Deep Neural Network method was proved as the best machine learning model. According to Lee et al. (2018), it is important to use several data mining techniques (random forest, support vector machine, logistic regression and decision tree) to improve review helpfulness classification performance.

Based on the analysis described in Table 1, the sentiment of the review has been popular in several studies with a demonstrated effect on review helpfulness prediction. For instance, Zhang and Lin (2018) state that sentiment analysis techniques show better performance on helpfulness prediction. Malik (2020) and Yang et al. (2020) emphasize the importance of the sentiment of the review title for helpfulness prediction. Moreover, Krishnamoorthy (2015) highlights the lower helpfulness predictive performance of negative reviews compared to the positive reviews. Contrariwise, Eslami et al. (2018) identify that the negative reviews are notably more helpful compared to the positives ones and the neutral reviews are only helpful for the services but not for the products. In this regard, the results by Malik (2020) show that the reviews with more helpful votes are those with high positive or negative sentiment scores. Among the popular aspects used in these existing studies, the length of a review is recognized to have a relationship with online review helpfulness (Eslami et al., 2018, Hu and Chen, 2016; Zhang and Lin, 2018). A longer review might include more useful information thus, it would be considered to be more helpful. Unmistakably, many authors in these studies consider the rating of the review as an essential parameter for helpfulness prediction (Akbarabadi and Hosseini, 2020; Eslami et al., 2018; Krishnamoorthy, 2015; Lee et al., 2018; Malik, 2020; Ngo-Ye et al., 2017; Yang et al., 2020). In this regard, Eslami et al. (2018) specify that the reviews with a lower review rating are more helpful. Besides, Singh et al. (2017) clarified that the review rating is even a more important parameter for experience goods than for search goods.

Additionally, Yang et al. (2020) indicate the significance of context awareness in online review helpfulness prediction. In this respect, some authors in Table 1 recognize that features such as readability (Li et al., 2019), polarity (Malik, 2020), subjectivity (Krishnamoorthy, 2015) or entropy (Singh et al., 2017) of an online review are important textual parameters for review helpfulness prediction. Akbarabadi and Hosseini (2020) study the same features adding the feature richness only for the title of the review and their conclusions were that those features within the title do not have a powerful influence on the review helpfulness prediction. Furthermore, Li et al. (2019) identify various types of context information that are correlated with better helpfulness reviewers prediction performance, such as using all capitals letters within the review or the linguistic style of reviewers' words. Inversely, using poor spelling, positive or negative social emotion, more past tense, and causation worsen helpfulness. Moreover, Zhang and Lin (2018) clarify that the reviews that describe each concept in more details are those receiving more helpfulness votes. Consequently, it is important to provide content context about reviews since the context features are perceived as important indicators in online review helpfulness prediction. Considering the discussion presented, it is only by evaluating the review content we can have a better understanding of review helpfulness, which would help choosing the most helpful online reviews in an appropriate order by the eWOM community itself.

Table 1. A qualitative overview of related works predicting the helpfulness of online reviews using machine learning techniques

Work	**Data source**	**Helpfulness factors analyzed**				**Prediction & classification ML technique applied**
		Content review	**Review features**	**Reviewer expertise**	**Product features & others**	
Eslami et al. (2018)	Amazon.com, Insureye.com	Length (# of words), sentiment (positive, neutral, negative)	Rating, helpfulness score	-	-	Artificial neural networks
Singh et al. (2017)	Amazon.com	Title, text, sentiment, # of sentences, # of words	Date and time, # helpfulness votes, % helpful	Reviewer ID, name	-	Ensemble learning technique (gradient boosting algorithm)
Akbarabadi & Hosseini (2020)	Amazon.com	Readability, length (# of words), linguistic features (# of adjectives, # of nouns, # of action verbs, # of state verbs), richness (# of concepts mentioned), sentiment subjectivity, sentiment polarity, title length, title richness, title sentiment subjectivity, title sentiment polarity	Helpfulness rating, review time (UNIX)	Reviewer ID, name, # of helpful votes obtained by a reviewer, ranking of a reviewer, country, Amazon badges	Rating, product ID (assigned by Amazon and its partners)	Decision trees and random forests
Hu & Chen (2016)	TripAdvisor.com	# of characters, # of syllables, # of words, # of sentences, average # of syllables per word, average # of words per sentence, strong positive/strong negative/weak positive/weak negative/strong/weak sentiment score, subjectivity per sentence	# of days the review was shown in TripAdvisor.com, # of days the review was shown on the first page of the hotel, # of reviews with the same rating at the time the review was posted, time (between the date a review has been posted and the date of its registration), # of users who voted a review helpful	Contribution level (top contributor, senior contributor, contributor, senior reviewer, reviewer, new reviewer, other)	Hotel # of stars	Linear regression, model tree (M5P), support vector regression (SVR)
Krishnamoorthy (2015)	Amazon.com	Linguistic categories (adjective, state verb, state action verb, interpretive action verb, descriptive action verb), readability, # of subjective words normalized by length (positive and negative opinion words)	Title, date, rating, helpfulness score, review extremity, review age (difference between date of review publication and date of product release)	Reviewer name	Product identifier, name, description, type, category, release date	Naive Bayes, Random forest, Support Vector Machine (SVM)
Lee et al. (2018)	TripAdvisor.com	Length (# of characters, # of syllables, # of words, # of sentences, # of syllables per word, # of words per sentence), readability, # of subjective sentences, # of sentences, review sentiment (strong positive/negative, ordinary positive/negative, strong, ordinary, overall, unsupervised/supervised)	Rating	Age, gender, level (contribution), nationality, join day (# of days since the registration of the reviewer until the review has been posted), # of reviews, rating for other reviews, # of votes received per post, # of traveled cities, distance traveled (miles)	Overall rating of a hotel	Random forest, decision tree, logistic regression, SVM
Li et al. (2019)	Epinion.com	Stop/stemming words, # of sentences starting with a capital, # of emoticons, # of all capital words, # of misspelled words, readability, attributive/modal adverbs, lexical/auxiliary verbs,	Helpfulness score	-	-	Logistic regression, SVM (LibSVM)

		epistemic adjectives, review length, LIWC factors				
Liu et al. (2017)	Aaqsiqauto.com.cn, Autohome.com.cn	# of words, # of characters, # of sentences, # of exclamatory sentences, # of interrogative/exclamatory sentences, # of verbs/adverbs/nouns, # of modal particles/mimetic words, # of positive/negative words, # of sentiment degree words 1/2/3/4/5/6, presence of key words	# of views, # of replies, # of posted reviews, # of review replies, whether the review contains pictures	Level of the reviewer, # of posts by the reviewer, # of replies by the reviewer	-	Multi-label classification HQRI model (Helpful Quality-related Review Identification)
Ma et al. (2018)	TripAdvisor.com, Yelp.com	Text review, review length	Image review, helpfulness label	-	-	Recurrent neural networks (RNN), deep residual network (ResNet), decision tree, SVM with linear kernel and logistic regression
Malic (2020)	Amazon.com	# of comments about a review, cosine similarity of product title and review text, sentiment, polarity, # of words in title, sentiment of title, polarity of title, % of nouns, % of verbs, % of adverbs, % of adjectives, readability, length (# of words, # of sentences), # of words in product title	Rating, days since the review was posted, sentiment of review in terms of rating, extremity, % of positive reviews, % of critical reviews	Time since the first review was posted, time between the first review and the latest review posted by a reviewer	# of questions answered about a product, potential score of a product	Multivariate adaptive regression (MAR), random forest (RandF), classification and regression tree (CART), neural network and deep neural network (Deep NN)
Mitra & Jenamani (2021)	Amazon.com	-	Helpfulness score, human scoring	-	-	SVM for non-linear regression, Dual CNN layer (D-CNN) for prediction
Ngo-Ye et al. (2017)	Amazon.com, Yelp.com	Length (# of words, # of characters, # of paragraphs, # of sentences), readability, review sentiment	Helpfulness score, rating (# of stars the reviewer assigned to the review), review extremity (difference between rating and average rating of all reviews), review age (time a review has been posted online)	-	-	Text regression models: Baseline, BOW-based and Script-based
Saumya et al. (2019)	Snapdeal.com, Amazon.com	Review text	# of helpful votes	-	-	Convolutional Neural Networks (1-CNN, 2-CNN)
Zhang & Lin (2018)	Yelp.com	Sentiment, # of concepts, # of concepts divided by # of words, # of characters	# of helpful votes	# of reviews written, # of helpful reviews written, # of compliments received, # of friends, # of fans	Stars of the restaurant (rating), # of reviews per restaurant, # of times a restaurant is visited and ‘‘checked-in” on phone	Text mining techniques (NLTK), sentiment analysis (SenticNet3), statistical modelling, SVMs
Yang et al. (2020)	Amazon.com	Length, sentiment, title length, title sentiment, sentiment consistency, review similarity (calculated with their own proposed measurement algorithm)	Rating, date, # of helpful votes, total votes of online reviews, time distance (days since the first review was posted)	-	-	Text mining techniques, sentiment analysis (TextBlob), regression analysis (Tobit model)
This study	Ciao.co.uk	Review text	# of helpful votes	-	-	Word2Vec to learn word embeddings, 1D Convolutional Neural Networks (1D CNNs) for early prediction, K-means clustering for representation

2.3 *Helpfulness prediction using 1D Convolutional Neural Networks*

As aforementioned, online product reviews are attracting much attention among academics, thus many works about how to cope with helpfulness of online reviews can also be found. Usually, academics focus either on reviewer-related features or on review-related ones, to analyze the helpfulness and most of the time using text mining techniques (Cao et al., 2011; Ngo-Ye et al., 2017; Yang et al., 2020; Zhang and Lin, 2018) and they do not usually contemplate more unconventional machine learning approaches. In this regard, "*the emergence of Deep Learning brings in a good insight that we do not have to manually design heuristic rules to extract domain-specific features for learning tasks"* (Fan et al., 2019). For instance, neural networks have revealed excellent success in natural language processing tasks (Li et al., 2020). Moreover, other deep learning methods, such as the convolutional neural networks (CNNs), are having a significant impact due to their performance in numerous tasks that are typically difficult, expensive, or inefficient when performed with other approaches (Kuang and Xu, 2018). For instance, the work by Chung and Sohn (2020) reported outstanding performance in natural language processing for early detection of valuable patents using CNNs. Originally, CNNs were used for image processing tasks since they perform very well on image classification and object detection. (He et al., 2016). Regarding helpfulness prediction using images the CNNs have been proven effective in Mat et al. (2018). The authors use data from two eWOM communities (Yelp and TripAdvisor) to compare two deep learning models, CNNs and RNNs, with other machine learning techniques to assess what is the influence of user-provided pictures on review helpfulness. Their findings show that CNNs and RNNs significantly improve the prediction of review helpfulness. In addition, the appearance of CNNs have brought many breakthroughs in several problems where traditional Artificial Neural Networks (ANNs) were not able solve or provide satisfactory solutions (Kuang and Xu, 2018). For instance, audio and music processing tasks (Lim et al., 2017) or detecting cyber-attacks (Kravchik and Shabtai, 2018).

Some other prior studies have also made several attempts and generated diverse results using CNN to research helpfulness prediction of online reviews. Lee and Choeh (2014) proposed a model for predicting helpfulness using a neural network. It used a back propagation multilayer perceptron neural network to predict the level of review helpfulness using the determinants of product data, the reviews characteristics, and the textual characteristics. The authors achieved a better prediction accuracy than that of a linear regression analysis. Also in this line, Kim (2014) completed experiments with CNNs trained on top of pre-trained word vectors for sentence-level classification tasks that performed remarkably well. Additionally, Chen et al. (2018) addressed review helpfulness prediction using two techniques: embedding-gated CNN and cross domain relationship learning. Their model was built on CNN with word-, character- and topic-based representations and was also able to extract multi-granularity text features from reviews. The authors affirmed that their model significantly outperformed the state of the art.

This work employs a 1D Convolutional Neural Network (1D-CNN) classifier for prediction and modelling of the online review helpfulness. 1D-CNNs are also used on text data as it is possible to represent texts as a time series data (Abdoli et al., 2019). 1D-CNNs are quite easy to train and offer the minimal computational complexity whereas achieving high performance levels (Kiranyaz et al., 2019). The benefits of using a 1D-CNN are: (1) its compact architecture configuration, (2) its practical and cost-effective real-time hardware implementation, (3) its capability to work without any pre-determined transformation, and (4) its ability to offer efficient training of the classifier having a reduced amount of training data (Eren et al., 2019). There is a recent study by Saumya et al. (2019) illustrates the success of including two layers of convolution (2-CNN) in review representation. The authors created a model that predicts the helpfulness score of a review using only the text of the review. Their experiments showed that the CNNs are capable of preserving complex semantic information of the reviews. A more recent work by Mitra and Jenamani (2021) has also implemented a deep neural network-based Dual-CNN model to predict helpfulness from lexical perspective. The authors explore the semantic text similarity among words using n-grams. The D-CNN model works on word vectors that represent the semantics of words. The authors state that the textual content can be understood when going through the words and recognizing what are the semantics involved.

As can be observed, the works by Saumya et al. (2019) and by Mitra and Jenamani (2021) use CNN to predict review helpfulness. However, these works do not interpret what makes a review helpful, but rather remain only in the predictive capacity. To this end, we propose a review helpfulness system that not only can early identify whether an online review is helpful or not, but also the review content is evaluated. Consequently, in this work we take advantage of the neuronal encoding to identify different types of clusters of helpful and not helpful reviews distinguished by the most significant contextual characteristics.

3 Research questions

Based on the theoretical discussion for predicting the helpfulness of online reviews, we now propose an overview of our research model in Figure 1 to address the research objectives of this study.

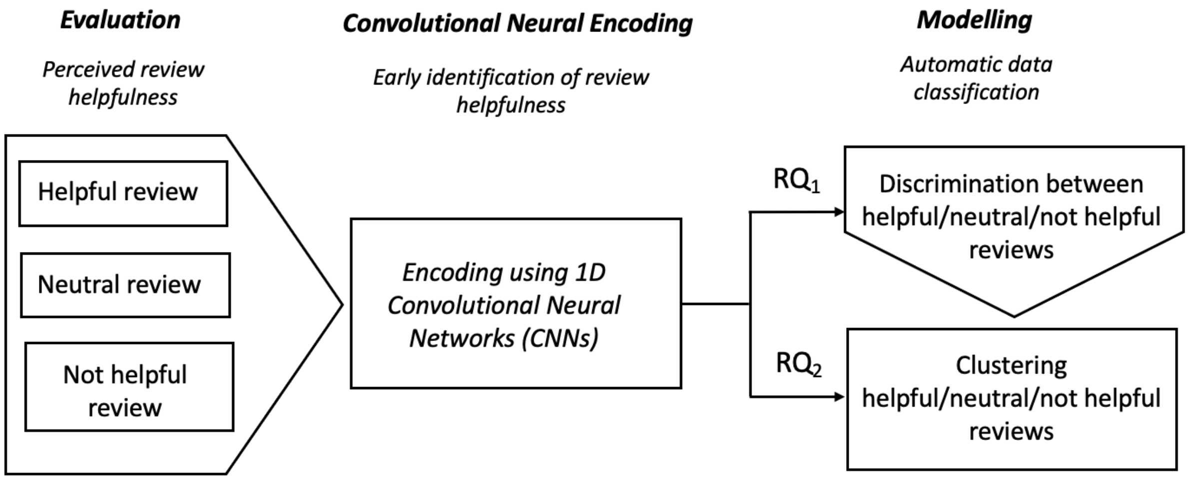


Figure 1. Outline of the proposed research model

Earlier research mostly develops conventional machine learning techniques such as regressions (Hu & Chen, 2016; Ngo-Ye et al., 2017), support vector machines (Krishnamoorthy, 2015; Ma et al., 2018), or decision trees (Akbarabadi and Hosseini, 2020; Lee et al., 2018) to predict online review helpfulness. Likewise, several authors have made used of deep learning techniques such as Artificial Neural Networks (Eslami et al., 2018), Deep Neural Networks (Malik, 2020) or CNN (Saumya et al., 2019; Mitra and Jenamani, 2021) for helpfulness prediction. However, as aforementioned, most of these studies typically make use of helpfulness factors such as content review, review features, reviewer expertise, and product features. In this regard, Mitra and Jenamani (2021) stated that using only on the textual content of online reviews makes a model simpler in terms of implementation. Besides, the authors assured that information is revealed through the semantics of words, which is very useful when representing the perception of helpfulness. Accordingly, although conventional machine learning techniques are useful for text content understanding, they are limited for comprehending the semantic meanings of the texts. Therefore, the benefit of using CNNs is that it is possible to understand textual data from a holistic approach. Moreover, CNNs provide a mathematically dense representation of documents in a n-dimensional space obtained due to the training process of the neural network.

Consequently, this representation tends to discriminate documents that belong to different classes, so it is expected that they will be far away in the resulting n-dimensional space. As a result, using CNNs will be not only useful for prediction but also for modelling online reviews helpfulness since it also provides with content-awareness of the review. In a combination of these ideas with the existing gaps in the literature, the following research questions are formed:

RQ_1: Does convolutional encoding discriminate between documents by separating them into the pre-assigned classes?

RQ_2: After an encoding using CNNs, is it possible to identify clusters of a review helpfulness with its most significant characteristics?

In this research, we consider both the predictive accuracy of the model and the interpretation of the review content. Moreover, with this model the eWOM community itself would be able to present the initial evaluation of the review helpfulness without the aid of the user voting mechanism at first. This would help in highlighting what are the most helpful reviews suitably, so that they can be displayed in the front page of the eWOM community or viewed by other users.

4 Methodology

The aim of the proposed methodology is to find a document encoding that differentiates the three considered classes. Hence, and using the resulting encoding, the specific topics that determine the helpfulness of shared reviews can be identified. Figure 3 depicts the procedure to obtain the document encoding using a combination of word embedding and neural networks.

Collected reviews are treated and analyzed using text mining techniques. Therefore, there is a first pre-processing stage consisting of removing stop words, punctuations and lower-case conversion, so the body of reviews is transformed into a homogeneous and clean text. However, the text still contains plurals and derivations of words that are accounted as different words. To solve this issue, a stemming process is also conducted. Stemming consists of reducing words to their root form by removing affixes. This way, words that differ in their affixes are accounted as the same word. Next, the collected dataset is split into the training set, used for fitting the weighs of the classifier, and the test set, used for reporting the accuracy of the classifier. Figure 2 details the proposed classifier, which starts with the word encoding. Traditionally, text mining techniques have used the "Bag of Word" scheme to build a word encoding given by the number of occurrences of words in documents (TF, Term Frequency) or a normalized value considering how frequent the term is along the set of documents (TF-IDF, Term Frequency- Inverse Document Frequency). However, both representations lead to sparse vectorization of words of high dimensionality (the dimensionality is given by the number of documents). More recently, word embedding techniques provide a dense vectorization of words able to capture more efficiently the semantic relations of words (Tien et al., 2019). The Word2Vec model is a word embedding algorithm that is able to achieve the best performance in natural language processing by similar grouping words, i.e., similar words have the same vector (Nawangsari et al., 2019). The Gensim library (Řehuřek and Sojka, 2010) in Python was used for the implementation of Word2Vec with a vector dimensionality of 100.

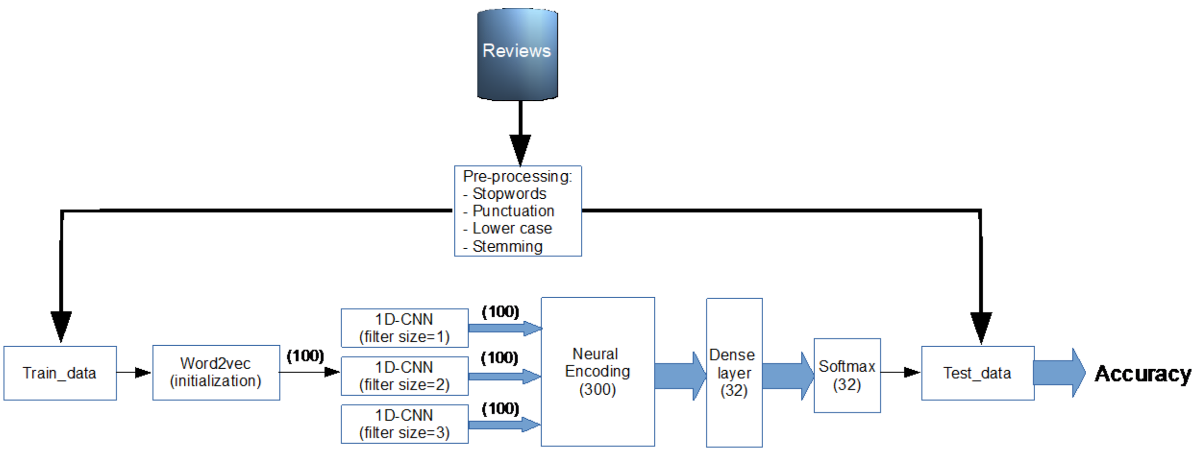


Figure 2. Block diagram for the documents neural encoding.

The document encoding is performed as part of the neural classifier. It is based on the concatenation of three 1D-CNNs. The first 1D-CNN consists of 100 filters of size 1, which means that documents are analyzed on the basis of unigrams; the second 1D-CNN consists of

100 filters of size 2, which refers to bigrams; and finally, the last 1D-CNN are 100 filters of size 3, that is, trigrams. The concatenation of the three previous layers lead to the final encoding of size 300, which is the document encoding. Finally, a dense layer of size 32 and a SoftMax layer complete the classifier, which is tested using the test data set.

The main advantage of the proposed encoding is that the vector representation is fitted as part of the classification problem. This means that the document encoding not only shows the semantic similarities among classes but also emphasize the differences among documents belonging to different classes. Such encoding will be used to extract the specific topics related to helpful and not helpful reviews using the k-means clustering algorithm.

5 Experimental evaluation

Ciao UK was selected as the research context. Data was gathered from this eWOM community with more than 1.3 million registered users and more than 7 million online reviews on 1.4 millions of products (Olmedilla et al., 2016a). In February 2018 Ciao was closed down and acquired by Kelkoo. Ciao UK was organized through 28 categories of products that contain all the reviews written by the users. For this paper, data was collected by scrapping all the posted reviews (title and body) on the category 'Cars & Motorcycles' as well the associated helpfulness score of the reviews using a web crawler in Python detailed in (Olmedilla, et al., 2016b).

Only registered users in Ciao with at least one "helpful" review can rate other reviews and also write comments on them. To rate a review, users must choose one of the six choices that are listed underneath the review to define how useful they considered it: exceptional, very helpful, helpful, somewhat unhelpful, not helpful, not rated (see Figure 3).

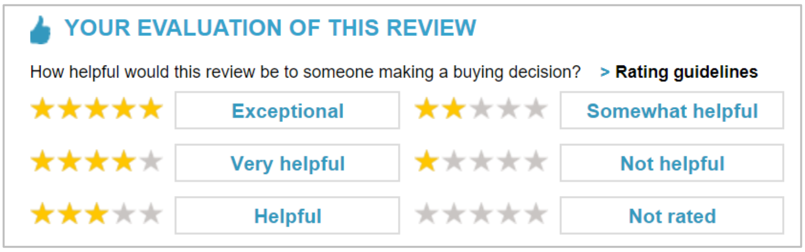


Figure 3. Different options of ratings to describe how helpful an online review is in Ciao UK

The overall rating given by a user for a review is determined by translating the rating into a number of stars. Then, for each review an average rating is calculated from all the ratings received. Figure 4 shows a typical review page at Ciao, containing three reviews. They belong to the category ‘Cars & Motorcycles’. Each review shows the score given by the reviewer (stars at the left side of the title of the review), the title of the review, a brief summary of its content and the helpfulness score highlighted with a red square.

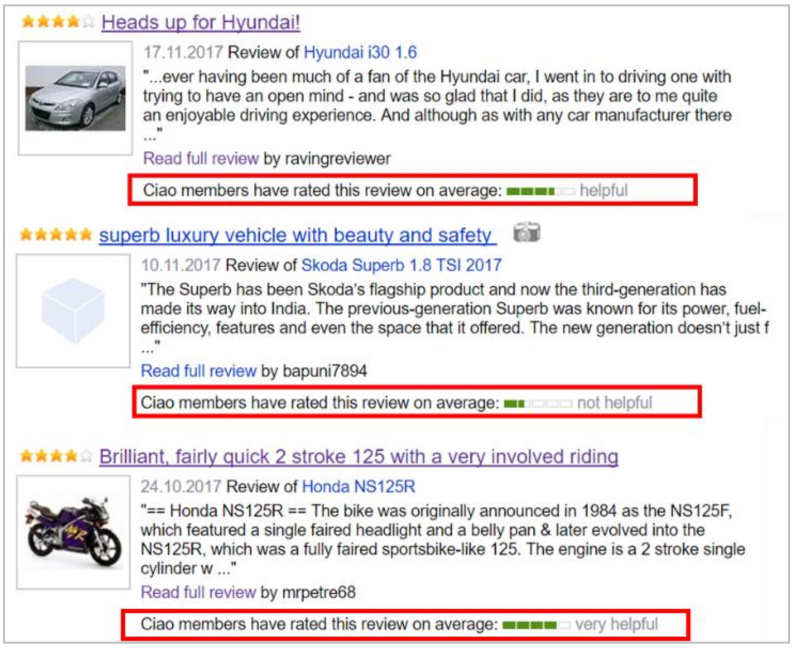
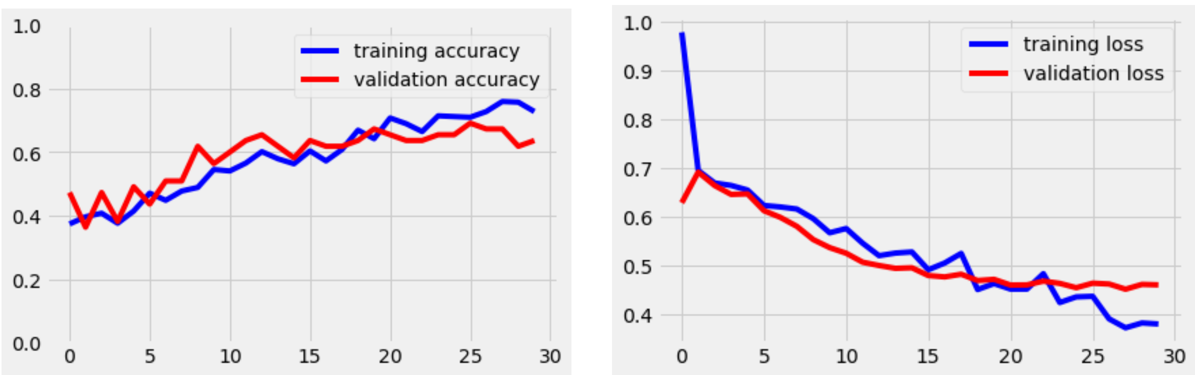


Figure 4. Options to rate a review in Ciao UK

6 Results

The original collected data set consists of 1,164 online reviews belonging to the product category “Cars & Motorcycles”. To perform this study, we used 180 online reviews with the rating “exceptional” that have been classified as “helpful”, 200 online reviews with “somewhat helpful” classified as “neutral” and 175 online reviews with “not helpful” classified as so.

Each document has been encoded in a space of dimension 300 given by the concatenation of 1D-CNN layers with filters of size 1, 2 and 3, so the convolutions are applied to individual words, sets of 2 words and sets of 3 words, respectively. Therefore, the first 100 elements of the vector of size 300 correspond to the analysis of isolated words made by the neural network, the next 100 elements correspond to the analysis of sets of 2 words and the last 100 elements correspond to the analysis of sets of 3 words. A Word2Vec word embedding model has been used, so the sequentially of the text and the context of the words are considered when the neural network searches for meaningful features. Figure 6 depicts the evolution of accuracy and loss during training. The final accuracy given by the test set is 0.66, being the majority of misclassified elements those reviews not helpful that are misclassified as neutral reviews. On the contrary, there is no misclassified elements between help and not helpful reviews. This result is explained because neutral reviews represent a midpoint between helpful and not helpful reviews, so they can easily resemble reviews belonging to the other two classes.



(a) Training and validation accuracy (b) Training and validation loss

Figure 5. Convergence of the proposed 1D CNN classifier.

To facilitate the interpretation of results, a correspondence analysis using the neuronal encoding was conducted to visualize the difference between the three types of classes. Figure 6 illustrates the obtained bi-plot that projects the 300-dimensional space into two dimensions.

Answering to RQ_1, the x-axis represents clearly the difference between the three pre-assigned classes (online reviews) from left to right: not helpful (color red), neutral (color yellow) and helpful (color blue). On the one hand, the x-axis, Dim1, is the main dimension that represents the helpfulness of the reviews and also means that the projection retains 77.7% of the original data, hence it has more importance and has more weight.

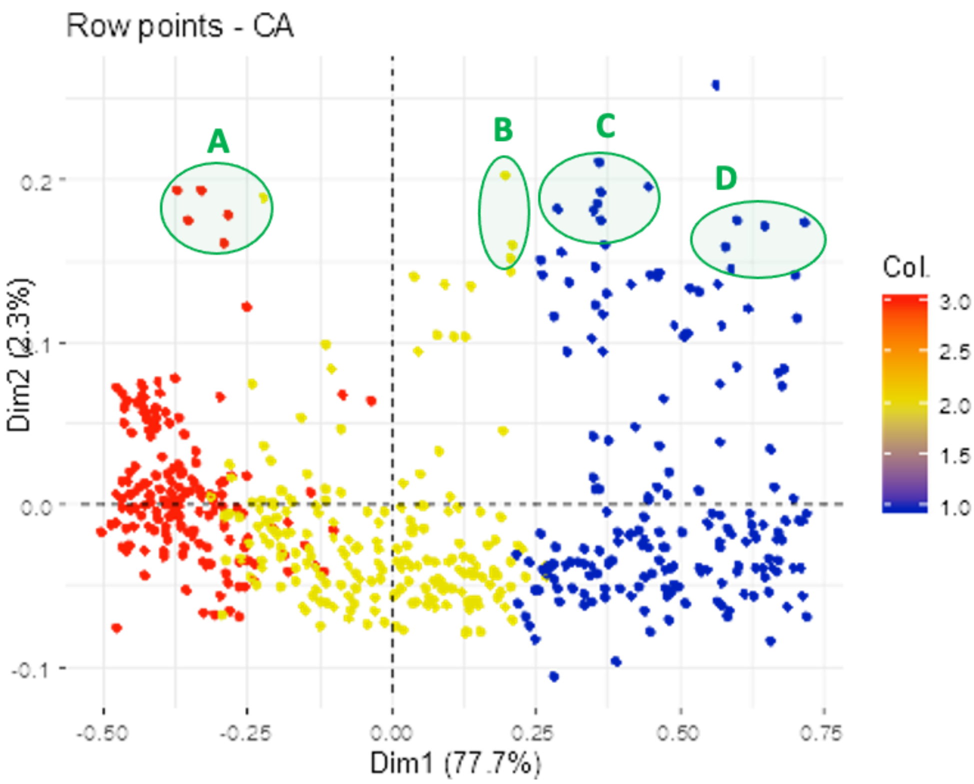
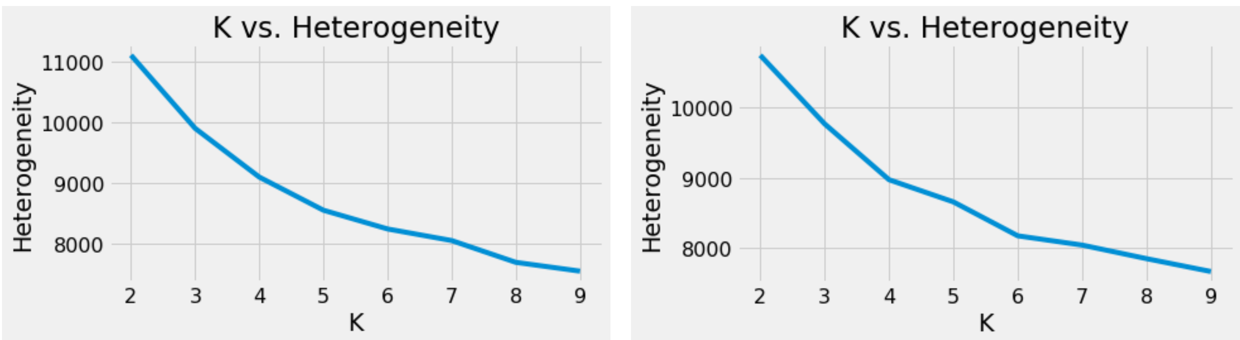


Figure 6. Map of online reviews corresponding to the three classes helpful, neutral and not helpful

On the other hand, the y-axis, Dim2, is a vertical dimension that contributes very little since it retains only a 2.3% of the original data. To understand the meaning of this dimension we analyzed and interpreted the documents. Indeed, after going through the online reviews we discovered another feature collaterally. Although most online reviews placed in the middle of the y-axis focus on cars or motorbikes specific brands, when taking a look at the points that are high above (a few minorities) we found that they focus on more general topics about vehicles. Those points, in turn, are grouped in 4 subsets where each of them has a common topic as well.

- Subset A: car establishments (e.g., repair shop, auto windscreens shop, cars insurance company, etc.).
- Subset B: car search web portal.
- Subset C: car oil (engine oil, changing gear oil, etc.).
- Subset D: common-structured text within the review (introduction of issue, description of personal case with technical data, and recommendation).

Although from a more methodological point of view, the classifier is very interesting to predict the helpfulness of an online review, it is also important to understand the review content for the interpretation of results. Thus, to facilitate a deeper interpretability of results, studying the contextual characteristics together can assess a proper conceptualization of review helpfulness. To this end, by using neural encoding we have made a cluster analysis (clustering) of the helpful and not helpful online reviews. As observed in Figure 7, we have plotted the heterogeneity as a function of the number of clusters and chosen the elbow of the curve as the number of clusters to use, which is 4.



(a) Helpful reviews (b) Not helpful reviews

Figure 7. Number of clusters vs heterogeneity

As shown in Figure 8, when doing the clustering it is appreciated what are the most relevant words in each cluster (keeping in mind that the words are with the stemmer) and also which are the most representative documents, meaning the 5 documents that are closest to the centroid of the cluster. The clustering has been done with the representation of 300 and to find the relevance of the words we have calculated the TF / IDF.

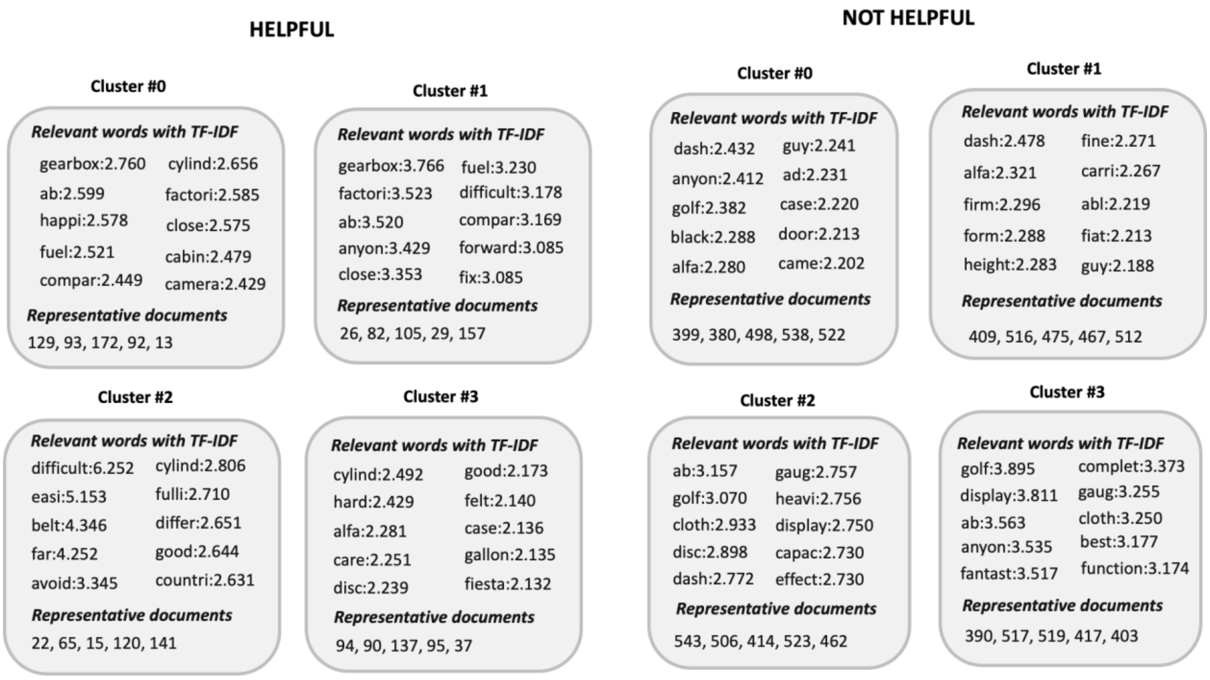


Figure 8. Cluster analysis for helpful and not helpful reviews using neural encoding

Consequently, with the neural encoding using CNNs, we have identified clusters of helpful reviews and not helpful reviews with its most significant characteristics, which answers our RQ_2.

The clusters in Figure 7 and Figure 8 that represent the helpful reviews focus on describing cars and their characteristics.

- Cluster #0 focuses on payments car-related (e.g., driving test, cleaning the car, buying a new car, etc.).
- Cluster #1 describes in detail new cars comparing with previous cars models.

- Cluster #2 focuses on large family cars describing precisely the space, pricing or fuel consumption.
- Cluster #3 has to do with a well-structured description of recently acquired cars with common points such as performance/driving, safety, design and technical specifications.

The clusters in Figure 7 and Figure 8 representing the not helpful reviews detail car-related shops/companies in general.

- Cluster #0 focuses on car repair shops.
- Cluster #1 has to do with insurance providers.
- Cluster #2 describes malfunction of car parts (e.g., dashboard, windscreen, etc.) and problems having with the refunding policy
- Cluster #3 focuses on experiences driving cars (e.g., test driving or driving on the roads).

7 Discussion and implications

In this research work we have addressed the subject of predicting the helpfulness of online reviews and interpret what makes an online review helpful. To our knowledge, no research has aimed to address these matters at once using CNNs encoding to discriminate between helpful and not helpful reviews and identify their most significant characteristics. Indeed, prior research has used approaches consisting in building methods to only predict the helpfulness of reviews using CNNs (Saumya et al., 2019; Mitra and Jenamani, 2021) but no evaluation or interpretation of the content of the helpful reviews has been considered. It is only by studying the helpful reviews characteristics together that an appropriate conceptualization of review helpfulness can be assessed.

7.1 Theoretical implications

In online reviews, information about the helpfulness is not simply revealed through the analysis of all the factors studied in previous research such as review length (Huang et al., 2015;

Lee and Choeh, 2016; Zhou & Guo, 2017), review rating (Gao et al., 2017; Eslami et al., 2018; Filieri et al., 2018) or product rating (Huang et al., 2015; Karimi and Wang, 2017) among others. Semantics of words and sequence are also useful when characterizing the perception of review helpfulness (Mitra and Jenamani, 2021). The results of this study have several implications for research in this field. In this regard, the proposed approach using 1D-CNNs - as in line with Saumya et al. (2019 and Mitra and Jenamani (2021) - can not only early identify if a review might be helpful, or not helpful, which allows us to predict with high accuracy how consumers are likely to evaluate an online review. But also, with the 1D-CNN encoding it is possible to separate documents into helpful and not helpful reviews and create clusters that reveal the most significant words and documents. The results unveil that information contained in the clusters of helpful reviews explain cars and their characteristics, while information in the clusters of not helpful reviews define details on car-related shops/companies in general.

Consequently, this study participates in the emerging research on helpfulness prediction of online product reviews. Indeed, D-CNNs use encoding not only to obtain better predictive performance but also further contributions are the discovery of what makes a review helpful and the identification of clusters with the most meaningful words for helpful reviews and not helpful reviews. Accordingly, before reading a review, a user could obtain information about the helpfulness of the review for a given product without even looking at its helpful votes.

7.2 Practical and managerial implications

As eWOM websites are still developing and user-generated content, such as online reviews, is becoming more varied and significant, our ability to understand managerial problems, will likely be defined by techniques that do not only process but also analyze and interpret these new data. In this regard, this study shows the capability of 1D-CNNs when using online reviews to predict and model online reviews helpfulness. Furthermore, due to the importance of review helpfulness on consumer buying behavior, the early prediction of review helpfulness can be interesting for eWOM community managers, to highlight helpful and new reviews before waiting for the evaluation of the community, and for manufacturers, who can monitor the quality of their products more effectively. To further make the contribution stronger, the approach deals with interpretation of the content review helpfulness, this would help in listing and recommending the reviews, so that they can be viewed by users searching for buying similar products or being informed about them. Besides, with the CNNs encoding that identifies clusters of helpful reviews with its most significant characteristics, it is also possible to recognize which of the reviews are informative or which are not to maximize information processing. A previous work by Olmedilla et al. (2019) also captured and identified unique attributes and ideas of a set of pre-defined classes in an open innovation community using text mining techniques. However, focusing on the importance and the developments in deep learning applications in marketing, managers could use this CNNs technique for modelling online reviews helpfulness and automatic data classification in other fields to get insights and value from the user-generated content of online reviews. Helpful reviews deserve managerial attention, for instance, managers can also improve the strategy of review systems by suggesting topics or issues that a reviewer should comment about to make the review more comprehensive and informative at the same time, so the reviews could have a better impact on buying decisions.

Finally, in consumers' product evaluation and buying decision the helpfulness of online reviews play an important role. Thereby, for decision sellers and/or buyers to better comprehend and manage review helpfulness, it is essential to have a framework in which review helpfulness can be defined and understand. We posit that review helpfulness is an important element that not only needs to be early predicted but also contextualized and interpreted to identify the possible impact of social influence in the users rating behavior on review helpfulness.

7.3 Research limitations and future work

This paper assesses the helpfulness dimension of online reviews from different perspectives: the early identification of review helpfulness, the discrimination between helpful and not helpful reviews and the creation of clusters for the helpful and not helpful reviews. Despite the novel dimension of this paper, it has some limitations that could lead to an improvement of the model in future research. Firstly, data has been gathered from one eWOM community and online reviews used are contextualized only for one product category. Thus, it can be extended to other product categories reviews for different eWOM communities. Secondly, there are many word embeddings and other techniques for documents representation. Apart from Word2Vec, other word embeddings techniques worth to be implemented are GloVe, FastText or Swivel. Moreover, they also have the possibility of using pretrained models with large corpuses of text, so the word embedding layer can remain frozen during the training time. Finally, different architectures of the neural network could be explored. Although CNNs works effectively with natural language processing, LSTM (Long Short-Term Memory) networks are also suitable for discovering long and short-term dependencies over text.

8 Conclusions

The objective of this research is to investigate the helpfulness prediction of online reviews and its characteristics. Based on our literature review, we claim that we are introducing new research questions of how convolutional encoding can not only early identify review helpfulness but also exploring how is possible to identify clusters of a review helpfulness with its most significant characteristics. We have observed that there exists a visible gap that review helpfulness using machine learning techniques is usually only predicted but the review content is not evaluated, nor is it interpreted. We believe that what is really important when using techniques such as CNNs is to take advantage of the encoding to interpret what makes a review helpful and understand the importance of the content and context in reviews in predicting the helpfulness.

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