A Review on Bayesian Networks for Sentiment Analysis

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Abstract. This article presents a review of the literature on the application of Bayesian networks in the field of sentiment analysis. This is done in the context of a research project on text representation and use of Bayesian networks for the determination of emotions in the text. We have analyzed relevant articles that correspond mainly to two types, some in which Bayesian networks are used directly as classification methods and others in which they are used as a support tool for classification, by extracting features and relationships between variables. Finally, this review presents the bases for later works that seek to develop techniques for representing texts that use Bayesian networks or that, through an assembly scheme, allow for superior classification performance.

Keywords: Bayesian Networks, Sentiment Analysis, Literature Review, Opinion Mining

1 Introduction

Sentiment analysis, also known as opinion mining, is a type of natural language processing whose purpose is to perform the task of detecting, extracting, and classifying opinions, sentiments, and attitudes concerning different topics expressed in a text. Sentiment analysis helps in observing the attitudes of a population towards political movements [1], market intelligence [2], the level of consumer satisfaction with a product or service [3], box office prediction for feature films [4], among others [5, 6].

The availability of opinions and evaluations, in general, has increased in several fields, such as e-commerce [7], tourism [8] and the analysis of social networks such as Twitter [9], this has occurred together with the rise of Big Data. As an example, e-commerce consumers currently read product reviews published by previous consumers before purchasing, while producers and service providers improve their products and services by obtaining feedback from consumers.

Furthermore, there are numerous challenges that sentiment analysis must face [10]; for example, the same word may have negative connotations in some contexts, and positive in others; on the other hand, there is a great variety of ways in which people express their opinions, this means that small changes in syntax of the messages communicated can cause an important difference in the underlying opinions; this can be seen in the phrases "the movie was good" and "the movie was not good". Furthermore, the opinions expressed are not purely composed of a particular type of judgment, since they may be composed of sentences that show a positive opinion on the subject, and others a negative one. All the above conditions, taken together, allow seeing the inherent difficulty in the task of sentiment analysis since this is challenging even for human beings [11].

The problems of sentiment analysis can be approached through various techniques, among them Bayesian networks. Bayesian networks are a modeling technique that allows describing dependency relationships between different variables by using a directed graph structure that encodes conditional probability distributions [12].

The aim of this work is to carry out a literature review regarding the application of Bayesian networks in the field of sentiment analysis. This review emerges within the context of an ongoing research project interested in providing, among other things, the development of adequate representation techniques for the modeling of emotions in text. In particular, this project contemplates the application of Bayesian probabilistic graphical models to perform or support classification tasks, by storing expert knowledge in the structure of these models. Thus, in order to prepare adequate theoretical foundations to do this, we need to explore the existing connection between sentiment analysis, natural language processing and Bayesian networks in the context of emotion determination in texts.

It should be noted that even though Naïve Bayes corresponds to the simplest Bayesian network model (a simple Bayesian network with a single root node) [13]. A large number of works in the field apply this technique to perform the classification task [6], thus, this technique has been extensively used and well-studied within the sentiment analysis literature. Considering this, for the purposes of this work Naïve Bayes has not been considered in the search, because the intention of this review is to analyze the more complex Bayesian Network structures and approaches that have been applied in sentiment analysis, in order to obtain better models than the simple Naïve Bayes approach. In this context, we have reviewed the sentiment analysis literature in order to find works that apply Bayesian approaches, from these works we have removed those that do not refer to any kind of Bayesian Network, which are the focus of our work, and we have removed those that are purely based on Naïve Bayes, since we decided to exclude it for the aforementioned reasons.

The rest of this document is structured as follows, in Section 2 a brief introduction to the basic concepts of Bayesian networks is given with the purpose of providing the necessary foundations to understand the rest of the work. Section 3 presents a review of the literature made with the different works found and their implications. Then, in Section 4 a discussion is made summarizing the main results that can be extracted from the review conducted. Finally, in Section 5 the conclusions of this work are provided.

2 Bayesian Networks

In this section, a brief introduction to Bayesian networks is given, using as a basis the exposition made by Crina and Ajith [12] among other references.

In the context of modeling and machine learning problems, Bayesian networks are typically used to find relationships among a large number of words. In this context, Bayesian networks provide an adequate tool to represent these relationships. These models are a type of probabilistic graphical model and in some cases, they are known as Bayesian belief networks. A Bayesian network consists of a directed acyclic graph where each node represents a random variable and the edges between the nodes represent an influence relationship (i.e., as the parent node influences the child node). These influences are modeled using conditional probability distributions [14–17].

A Bayesian network for a set of variables consists of a network structure that encodes conditional independence assertions about the variables, and a set of local probability distributions associated with each variable. Together, these two components allow defining a joint probability distribution for the set of all the problem variables. This conditional independence allows building a compact representation [12].

In order to define the conditional probability distributions, a table is defined (Conditional Probability Table or CPT). This table assigns probabilities to the variable of a node depending on the values of its parents in the graph. If a node does not have parents, the table assigns a probability distribution to that random variable [12]. An example of a Bayesian network is shown in Figure 1. In this example, the variable of interest corresponds to an indicator of whether the text expresses a positive or negative sentiment, while the factors that determine this are given by the content of the text (variables indicating if the text contains ”dog” and ”love”). Note that if it is known a priori that event A is true, then the probability of event B changes, for this particular example the probability of occurrence of B increases from 0.3 to 0.6. Finally, in this example, the variable S depends both on events A and B as it can be seen in its CPT.

The construction of a classifier using Bayesian networks requires first learning the structure of the network and their respective CPTs [18]. The concept of conditional probability tables can be extended to the continuous case in which variables can be based on other laws of probability such as a Gaussian distribution or solved by discretization [19–21].

One of the applications of Bayesian networks is that it is possible to make inferences about them using available information. In this context, there are several types of inference [22–26], such as diagnostic inference, causal inference, inter-causal inference, and mixed inferences. While inference in any Bayesian Network is an NP-hard problem [27], there are efficient alternatives that exploit conditional independence restrictions for certain kinds of networks [28, 12]. On the other hand, one of the benefits of Bayesian networks is that they can directly handle incomplete data sets (i.e., if one of their entries is missing) [12].

Bayesian networks have been applied successfully to solve different machine learning problems, even outperforming other popular machine learning approaches [29]. It should be noted that the simple Bayes classifier (Naïve Bayes) is a special case of a Bayesian network [30]and is one of the most used algorithms in the literature, especially in the context of sentiment analysis [6].

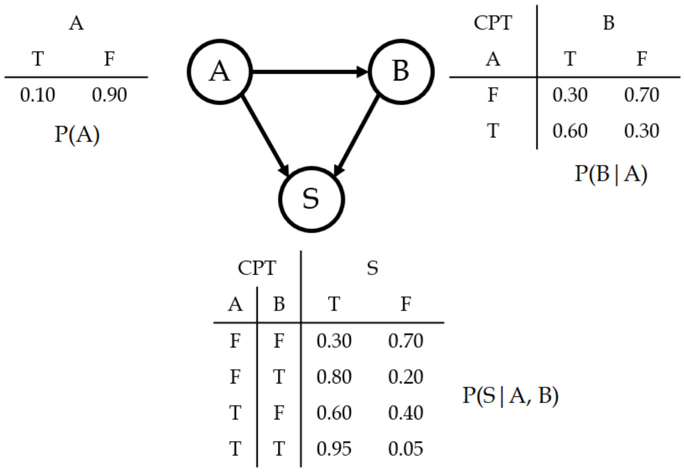

Fig. 1. Example of a simple Bayesian network (A: The text contains the word "dog"; B: The text contains the word "love"; S: The text expresses a positive sentiment).

3 Literature review

In the review carried out, two main tasks have been found in which Bayesian networks are used in sentiment analysis, specifically, these can be used to perform classification tasks directly or for the extraction of characteristics to support the classification task with another method. A brief description of the reviewed works is presented below, followed by a series of relevant observations extracted from them in the context of the project. The articles found are summarized in Table 1.

Table 1. Summary table of the reviewed articles by year.

Year	Articles
2004	[31]
2011	[32]
2012	[33, 34]
2013	[35, 36]
2015	[37]
2018	[42]

Classification is one of the most recurrent uses of Bayesian networks. In this context, in Wan's work [37] and the article by Al-Smadi et al. [42] Bayesian networks are used directly as a sentiment classifier, obtaining competitive results and in some cases higher, when compared with other approaches.

In the work proposed by Chen et al. [43], the authors develop a parallel algorithm for Bayesian networks structure learning from large-scale text datasets. This algorithm is implemented by using a MapReduce cluster and is applied to capture dependencies among words. In particular, this approach allows us to obtain a vocabulary for extracting sentiments. The analysis of the experimental results obtained on a blogs dataset shows that the method is able to extract features with fewer predictor variables compared to the complete data set (i.e., a more parsimonious model), resulting finally in better predictions than the usual methods found in the literature.

The article by Lane et al. [34] addresses the problems of choice of models, feature extraction and unbalanced data in the field of sentiment analysis. The particular task that the authors address is classification, although they consider two different approaches, the first corresponds to classification of subjectivity (i.e., determining whether the text indicates something objective or subjective) and the second corresponds to determination of polarity (i.e., determining if the opinion of the text is positive or negative). In this paper, several classifiers and approaches to extracting features are evaluated, as well as the effect of balancing the data set before training. In some cases of the studied data sets, Bayesian networks showed a decrease in their performance when applying data balancing techniques, in contrast to the behavior of the other classifiers.

In the article by Ortigosa et al. [33] the authors address a multidimensional problem, in which they use three related dimensions for sentiment analysis. Most traditional approaches are focused on a one-dimensional case and are inappropriate, whereas multilabel approaches cannot be applied directly. Given this, the authors propose the use of a network of multidimensional Bayesian classifiers [44, 45]. In addition, applying semi-supervised techniques avoid the hard work of manually labeling the examples.

The work carried out by Airoldi et al. [31] and Bai [32] proposes a two-stage Markov Blanket Classifier to perform the task of extracting sentiments from unstructured text, such as film reviews, using Bayesian networks. This approach also uses the Tabu Search algorithm [46] to prune the resulting network and obtain better classification results. While this has proved useful in preventing the overfitting of models, their work does not fully exploit the dependencies among sentiments. In this context, the work carried out by Olubulu et al. [38] proposes an improvement in considering dependencies among different sentiments.

Another work by Olubolu [35] proposes an improvement for the Bayesian network model that includes sentiment-dependent penalties for the scoring functions of Bayesian networks (e.g., K2, Entropy, MDL and BDeu). The authors call this approach Sentiment Augmented Bayesian Network, which was evaluated and contrasted with the techniques used in the literature, obtaining competitive results and in some cases higher than the baseline. The proposed modification also derives the dependency structure of sentiments using conditional mutual information between each pair of variables in the data set. In a later work [29] this proposal is continued evaluating it in another domain (product reviews), here the knowledge contained in SentiWordNet [47]. The empirical results in the evaluated data sets suggest that this sentiment-dependent model could improve the classification results in some specific domains.

In the paper by Ren and Kang [36] a hierarchical approach is proposed for the modeling of simple and complex emotions in text. While most of the work focuses on the modeling of simple emotions in each document, the reality is that many documents are associated with complex human emotions that are a mixture of simple emotions difficult to model. The hierarchical model is superior to the traditional machine learning techniques used in the baseline (such as Naïve Bayes and Support Vector Machines) for the task of classifying simple emotions, while for complex emotions it shows promising results. The analysis of results also indicates that there is a relationship between the topics of the documents and the emotions contained in them.

The study of complex emotions is also addressed in the article by Wang et al. [39]. The authors evaluate multilabel sentiment analysis techniques on a set of data obtained from Chinese weblogs (Ren-CECps). Using the theory of probabilistic graphical models and Bayesian networks, the latent variables that represent emotions and topics are used to determine complex emotions from the sentences of weblogs. The analysis of the experimental results demonstrates the effectiveness of the model in recognizing the polarity of emotions in this domain.

In the work proposed by Chaturvedi et al. [40], a Bayesian network is used in conjunction with convolutional networks for the detection of subjectivity, this work is continued in [41]. The authors introduce a Bayesian Deep Convolutional Neural Network that has the ability to model higher-order features through several sentences in a document. One of the differences with other works is that they use Gaussian Bayesian networks to learn the features that are fed to the convolutional neural network. Their proposal delivers superior results to those of the different approaches used in the baseline.

4 Discussion

The tasks in which Bayesian networks are used are also recurrent in articles where machine learning techniques, such as Naïve Bayes and Support Vector Machines, are used. For this reason, it is expected that the performance of models based on Bayesian networks are also subject to, at least, some drawbacks that normally arise in environments where machine learning techniques are used. For example, the problem of high dimensionality in the domain is identified (e.g., sentiment analysis) and solutions are proposed, such as the extraction of a reduced vocabulary to perform classification tasks.

According to the reviewed literature, overfitting of the model poses another problem, which the reviewed articles solve by pruning the Bayesian network. On the other hand, the segmentation of the data set and its correct balancing also appears as a challenge, whose solution reports positive or negative variations depending on the specific domain in which Bayesian networks are applied.

Furthermore, another recurrent and relevant topic is sentiment analysis carried out on complex emotions; among these articles, the work of Chaturvedi et al. [40, 41] which approaches the problem through ensemble learning relying on the main technique of Bayesian networks and convolutional neural networks (CNN).

The applications proposed in the articles together with their respective scopes are varied, ranging from the use of simple Bayesian networks as direct classifiers to the incorporation of this model with other more complex deep learning ones [48]. Such versatility provides a perspective that is taken into account in the research project, since the range of application possibilities of Bayesian networks in sentiment analysis not only is broad but also is presented as a still extensible field.

One of the challenges of sentiment analysis is correctly addressing how context affects the semantic orientation of the words [11]. In this context, it should be noted that the approaches previously discussed do not directly address this challenge, but rather focus on either classification or feature extraction. Those centered on classification could benefit from using an adequate representation that addresses this issue, while those that are centered on feature extraction could possibly be modified to partially address this issue, through the addition of contextual information into the extracted features."

In the context of the project addressed, one of the work dimensions consists of the development of an encoding of the texts to obtain an adequate representation. In particular, the construction of a highly discriminating features space for the text is sought with the purpose of determining the emotions present in it (i.e., a sentiment analysis task). Following this line of work, the development of classifiers that have more than one output (multidimensional [49] or multilabel [50, 51] as appropriate) has been considered to obtain the different emotions of the text. To achieve this, the line of work of multidimensional Bayesian classifiers is considered, these methods based on graphical models allow to support the multidimensional classification by storing expert knowledge in its structure. The literature review indicates that Bayesian networks have been used with varying levels of success, but that there are still several challenges regarding their application [52–54].

In particular, with regards to the objective of finding an adequate representation of text for the task of determining emotion, the works by Chen et al. [43], Ortigosa et al. [33] and Chaturvedi et al. [40] are the most interesting in the context of this project. The first work due to its focus on feature extraction using fewer prediction variables, the second article because of its focus on multidimensional sentiment analysis, which is well-aligned with the objectives of the project, and finally the third paper because of its use of deep learning in order to model higher-order features, which could be useful in our search of an adequate representation.

5 Conclusions

In this work, a literature review on the application of Bayesian networks in the field of sentiment analysis has been conducted. In this context, the work's objectives are considered accomplished. It should be noted again that the applications of Bayesian networks are varied, although the main ones are as a classification method or as a support tool, by extracting features and relationships between variables. As part of future work, we seek to develop text representation techniques based on the concepts shown above. As mentioned above, sentiment analysis, and in particular the modeling of emotions, has a wide range of applications, so that an adequate representation could benefit them. In addition, subsequent studies can be conducted to find models, additional to CNN, that can be assembled with Bayesian networks in such a way that classification performance improves maintaining a favorable trade-off.

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