A Systematic Review on Hidden Markov Models for Sentiment Analysis

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***Abstract*—This paper gives a review of the literature on the application of Hidden Markov Models in the field of sentiment analysis. This is done in relation to a research project on semantic representation and the use of probabilistic graphical models for the determination of sentiment in textual data. Relevant articles have been analyzed that correspond mainly to the certain variations of the implementation of HMM and a variety of use cases for the purpose of sentiment classification. Finally, this review presents the grounds for future works that seek to develop techniques for semantic text representations implemented with probabilistic graphical models (Hidden Markov Models) or that through a combination scheme allow for superior classification performance.**

Keywords— Hidden Markov Models, Markov Chain, Sentiment Analysis, Probabilistic Graphical Models, Review

I. Introduction

Sentiment analysis is a type of natural language processing technique whose main aim is to perform the task of classifying, extracting and detecting attitudes, sentiments and opinions of the different aspects or topics of an entity or product expressed in textual form. The usefulness of sentiment analysis includes but not limited to the level of consumer satisfaction [1], political movements [2], market intelligence [3], brand reputation [4], box office prediction [5], and many others [6], [7].

Access to people's opinions, sentiments and evaluations has increased in general and in a wide-variety of fields in e-commerce [8], tourism [9], and social networks [10], one of the major causes for this is the rise of Big Data. Consumers now read product reviews by previous customers, service providers improve their products and services by obtaining feedback from customers through various channels that employs textual data.

Despite the stated usefulness and advantages that comes with sentiment analysis, there are a lot of challenges. For instance, the users usage of sarcastic statements especially in social network platforms like Twitter, the same word may have negative connotations in some contexts, and positive in another; people also express their opinions is varied ways so a small change in the syntax of the message communicated can mean something different in the implied opinion. In addition, some of the opinions expressed cannot be categorized as a particular type of sentiment, since they may be composed of sentences that show positive opinion on a subject and maybe neutral in another perspective or even negative. Also issues like this could raise questions at what point can we classify a statement as being neutral or positive or negative. The aforementioned shows us how challenging performing sentiment analysis can be even for humans.

The problems of sentiment analysis can be approached through a variety of techniques amongst them probabilistic graphical models like Bayesian Networks, Hidden Markov Models and Conditional Random Fields. This review paper focuses on Hidden Markov Models (HMM), (also known as a variation of Dynamic Bayesian Network) a modelling technique that allows describing dependency relationships between different variables using an undirected graph structure that encodes conditional probability distributions [11].

The purpose of this work is to carry out a literature review regarding the application of HMM in the field of sentiment analysis. This review stems within the context of an ongoing research project interested in the investigation of the use of probabilistic graphical models to perform semantic sentiment analysis for textual information. The project is bent on finding if the semantic representations of textual data and the use of probabilistic models that can model dependencies can closely model the way humans classify sentiment.

In order to prepare adequate theoretical foundations that will provide answers to these questions there is a need to explore the existing connection between sentiment analysis, natural language processing and Hidden Markov Models of textual data.

In this review paper, previous works that have applied HMM to perform sentiment analysis are reviewed. In addition, close approximations to these models were considered. For each reviewed work, the variation of HMM employed, the text feature representations and their relative performance to existing models were discussed. To the best of our knowledge, this is the only review literature with a focus on Hidden Markov Models.

The remaining part of this document is structured as follows: in Section 2, a brief introduction to the fundamental concepts of HMM is provided with the purpose of providing the needed foundations to understand the rest of the work. In Section 3 a review of the literature made with different works on HMM discussing their peculiarities, text-feature representations and performance is presented.

Section 4 provides a discussion and recommendations for future research based on the findings of the previous section. Lastly, in Section 5 the conclusions of this work are presented.

II. Hidden Markov Models

This section focuses on a brief introduction to the Hidden Markov Models using as a foundation the exposition made by Jurafsky and Martin [11].

The HMM is based on amplifying the Markov Chain. A Markov Chain – the model that provides information about the probabilities of sequences of random variable states, each of which can take on values from some set. These sets can be words, or tags and even symbols that represent a variety of things. A Markov chain is useful when we need to compute a probability for a sequence of observable events. In several cases the events of interest are hidden - they are not observed directly. HMMs makes it possible to observe hidden and observable events. They are modelled as causal factors in our probabilistic model. HMM is a generative probabilistic model which consists of N not directly observable hidden states:

$$S = \{S_1, S_2, S_3 \ldots S_N\} \quad (1)$$

The emission alphabet i.e. M distinct observation symbols per state is given by:

$$V = \{V_1, V_2, V_3 \ldots V_M\} \quad (2)$$

Let the current state at time t, be denoted as $q^{(t)}$. Let the state transition probability distribution for the HMM be denoted as $A = \{a_{ij}\}$ and is given by

$$a_{ij} = P[q^{(t+1)} = S_j | q^{(t)} = S_i > 0] \, for 1 \leq i \leq N, 1 \leq j \leq N \quad (3)$$

Furthermore, an observation symbol probability distribution B $\{b_{jk}\}$ in state S_j is given by

$$b_{jk} = P[v_k | q^{(t)} = S_j \wedge v_k = O_t \, for 1 \leq j \leq N, 1 \leq k \leq M \quad (4)$$

Then an initial probability distribution over states $\pi = \{\pi_i\}$ with

$$\pi_i = P\left[q^{(1)} = S_i for 1 \leq i \leq N\right] \quad (5)$$

With all the above parameters, the Hidden Markov model can be written as a 3-tuple

$$\lambda = (A, B, \pi) \quad (6)$$

As a consequence, there is a bit of resemblance between a double stochastic process and an HMM where after each period, t the system can remain in its current state or make a transition. Given the state $S = \{S_1, S_2, S_3 \ldots S_N\}$, the system can get to another state in a single step implemented by $a_{ij} > 0$ in (3). In order to give a visual example, in Figure 1 a stochastic process with two states $S = \{S_1, S_2\}$ is shown. To integrate another stochastic process each of these states will now emit a symbol O_t of the emission symbol V at time t; then the model generates a sequence of observable states.

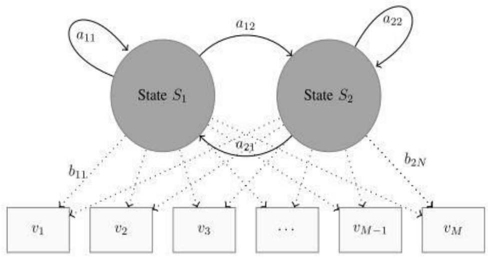

Figure 1: The emission probabilities for a Hidden Markov Model with two states and an emission of M symbols at time t

$$O(T) = [O_1, O_2, \ldots O_T] \quad (7)$$

Until a time, step T.

As stated by Rabiner [12] hidden Markov models should be marked by three fundamental tasks:

***Task 1* (*Evaluation*):** Estimating the probability of an observation sequence $O(T) = [O_1, O_2, \ldots O_T]$ for a model $\lambda = (A, B, \pi)$ this can be executed with the Forward algorithm.

Task 2: (Decoding): Estimation of the corresponding state sequence $Q = [q^{(1)}, q^{(2)} \ldots q^{(t)}]$ to an observation $O(T)$ and a model λ. This can be done with the Viterbi algorithm.

Task 3: (Learning): Fine tuning of the parameters $\lambda = (A, B, \pi)$ to maximize $P(O(T) \vee \lambda)$ via a method named Baum-Welch algorithm.

Table 1. Summary table of the reviewed articles by year

Year	Articles
2013	[13], [4], [14]
2014	[15], [16], [17]
2015	[18], [19], [20]
2016	[21]
2017	[22], [23]
2018	[24], [25]

III. literature review

In this section the details of the review carried out is discussed. Relevant examples of how the reviewed works have carried out sentiment analysis tasks will be discussed; we also demonstrate how these articles were selected.

A. Methodology

To gather related publications for this review, primary computer science, machine learning and natural language processing publication databases were considered: IEEE Xplore, Scopus, Advanced Computational Linguistics, (ACL) Digital Library and Google Scholar. A keyword search was performed to gather publications relevant to this review; examples of keywords used are “Hidden Markov Model”, “Sentiment Analysis”, “Probabilistic Graphical Models”, and “Semantic Sentiment Analysis”. The returned articles were narrowed down to fit the subject of discussion and relevant use cases. Each paper reviewed was based on the following criteria. (1) Does the paper presents an implementation of HMM to carry out sentiment analysis or text classification? (2) Does the work present evaluations that compares the performance of the proposed model with other algorithms. (3) Does the paper contains suggestions for future research? After examining the search results closely, a total of 14 publications were reviewed.

B. Reviewed Works

Kang et al. [25] focuses on the sequences of words to address some of the issues faced with the use of lexicons when performing sentiment analysis. They propose the use of model that will focus on word orders without the need of extracting sentiment lexicons. To achieve this an ensemble of text-based HMM is proposed. This model employed the boosting and clustering of words produced by latent semantic analysis.

With labeled input data and clustering of words in texts, the ensemble is used to create a classifier. The sentences were categorized into positive (Y=1) and negative (Y=−1) sentences. Based on the sentence orientation the corresponding labels were assigned using this equation

$$\hat{Y} = argmax \{f_{Y=1}(s), f_{Y=-1}\} \quad (8)$$

The above process known as TextHMMs when repeated over severally in different ways, an ensemble of TextHMMs is created – with this approach multiple and diverse patterns were reflected in the training data. To summarize, the authors were able to realize this approach in the following steps (1) Determine hidden states of words by clustering based on latent semantic analysis (2) Construct the HMM (3) Create an ensemble of TextHMMs by boosting.

The method of ensemble method used for the TextHMMs is known as Boosting. When tested on different datasets ranging from movie reviews to opinions of competing products on the web and compared with other state of the art machine learning algorithms used in SA such as Conditional Random Fields (CRF) -a dependency tree based method, a matrix vector recursive neural network (MV-RNN) model, a convolutional neural network using pre-trained vectors from Word2Vec and a multinomial naïve Bayes-Support Vector machines with uni-bigrams (NBSVM), the work shows that the accuracy of the Ensemble-HMM is generally higher than the compared methods in most of the cases. Further, this model was tested with real-life datasets; the results produced were relatively impressive.

Another implementation of HMMs was carried out by Zhao and Ohsawa in [24] but this time in a higher dimension. This work utilized a 2dHMM – HMMs which provides us with the ability to model sentiment analysis in higher dimensions. The SA experiments carried out in this research was not based on the subjectivity of the user alone it also considered the behavior of the user. This paper shows that the proposed model is able to capture the event where the sentiment of a user concerning a product is influenced by the observation of the last two reviews or top-rated review by the user. With this one could be able to model dependencies between the last two comments and a top-rated review and the words of a user to perform sentiment classification. This paper was able to demonstrate this by using a 2dHMM to model such situation given the web page of a product. Here the two latest reviews and a top-rated review of a Japanese Tea product was considered in the classification of the sentiment. It turns out that the 2dHMM produced better precision and F1 scores when compared to other conventional machine learning algorithms that performs classification based on user’s textual data alone. Reason for a better performance is based on the ability of the 2dHMM to model dependencies between recent reviews, top rated reviews and user’s sentiment.

Another approach of the use of HMM to perform SA is proposed in [23] this technique learns patterns of word sequences and sentimental word transitions. The HMM deployed was trained on constructed informative hidden states and transition patterns of words in sentimental sentences. Syntactic-sentimental (positive-adjectives) features were created by combining syntactic (adjectives, adverbs etc.) and sentimental (positive, negative, neutral) features. GMMs (Gaussian Mixture Models) were applied to the produced unigrams to get the SIGs (Similar syntactic and sentimental Information Groups). SIGs transitions between words were modeled. The SIGs are then used as hidden states of the HMMs, where they properly model transition patterns found in sentimental sentences. The performance evaluation carried out with Health Care Reform (HCR) dataset with about 839 tweets shows that HMMs with 4 states in most cases outperformed HMM algorithms with lower states, other conventional machine learning methods like the SVM, NB and algorithms implemented in [26]–[28].

In performing sentiment analysis for other languages other than English in [22], the review given by Suleiman et. al, it was observed that text classification tasks were possible. With a degree of modification and by further research the model can be adapted to sentiment analysis tasks. Also in [21] Wei and Yongxin demonstrates the use of HMM to perform network public sentiment analysis of Chinese text by using conventional methods. They pointed out that because of the robustness that HMM provides, it can be used to describe the probability model of stochastic process’s statistical properties. After carrying out performance evaluation using Chinese textual data, the work showed that the HMM outperformed the Naïve Bayes and Support Vector Machine algorithms.

Liu et al. [20] used a self-adaptive HMM to perform emotion classification on Weibo a microblogging website in China (similar to Tweeter). Due to the text mining challenges like word segmentation, arrival of new words on Weibo and ambiguity,a self-adaptive HMM was proposed. The application of HMMs facilitated the development of a more fine-grained emotional analysis, the creation of useful features to be trained on the HMM and a further improvement of HMM (self-adaptive HMM) to mine textual data from Sina-Weibo. The implementation of self-adaptive HMM required features extracted from textual data to be modelled as observed variables; in this approach states are considered to be a set of values that represent emotional category. The self-adaptive mechanism is obtained through the parameter estimation made by the Particle Swarm Optimization algorithm (PSO). The experimental result demonstrates that HMM outperforms SVM and NB, when classifying certain emotions.

Nicolas et al. in [19] demonstrated that sentiment analysis of financial news can be improved with the detection of negation scopes. To achieve this, both rule-based algorithms and the Hidden Markov Models were employed. First, data preprocessing tasks involving cleaning, tokenization, the removal of stop words, parts-of-speech tagging, and stemming were carried out. Afterwards, rule-based detection of negation scopes was carried out via the application of linguistic rules. In this work the HMM-Based Detection of Negation scope was employed to adapt to domain specific features and peculiarities of a chosen area. To utilize HMM for the prediction of negation scope directly observable states are given, the actual words are then chosen as emission symbols, then word stems acts as comparisons. The performance of the variants of HMMs (supervised and unsupervised) were then carried out. In the evaluation of the polarity of news announcements an approach known as the Net-optimism sentiment measure [29], [30], was applied. Using a manually labeled dataset that consists of 400 extracted sentences the HMM implementations were evaluated. The model when used to predict negation scope performed below baseline. In other words, the rule-based approach performed better with significant results in the negation scope forecast.

In another work [18], a variation of HMM known as selective HMMs were used to perform financial trend predictions with Twitter Moods; this was carried with the aim of achieving high prediction performance and gain good control over the financial trend prediction. First, the Twitter moods are evaluated and extracted by building a sentiment lexicon based on profile of mood states (POMS) Bipolar and WordNet to effectively extract a six-dimensional society moods from enormous tweets; in order to determine which of the Twitter Moods possess the most predictive power, the Granger causality analysis (GCA)[31] between the financial index and the Twitter mood is carried out to determine the most important mood that facilitates the prediction of the market trend. It was then discovered that the Twitter mood had the most predictive power. WordNet Synsets were used to expand the Bipolar POMS lexicon; Yifu et. al points out that selective HMMs are based on a concept known as selective prediction - a prediction framework that has the ability to characterize the results of its predictions. With selective HMM, financial index and Twitter moods are combined. Also, during the training of the selective HMM, MapReduce framework was employed for efficient evaluation. For the evaluation of the proposed algorithm, two Twitter datasets and two financial data were used in the experiments. The proposed model produced the least error margin when compared with other algorithms.

Kunpeng et al. [4] proposed a probabilistic graphical model that is able to represent relationships between social brands and users. The model is able to collectively measure reputations of entities in social networks; it not only captures network information but also includes the semantic information from users in terms of the comments they make. To achieve this the model adopts a block-based Markov Chain Monte Carlo (MCMC) sampling method to deduce the probability of hidden variables, user positives and brand reputations. This technique was used in order to avoid the computational complexity that comes with the direct calculation of the joint probability of the hidden variables due to large state space. One of the vital advantages of this model is its ability to reduce the biased effect from a single user and a single comment as this most times occur in other conventional methods used in performing sentiment analysis. Experiments were conducted using a large amount of data from Facebook taking into consideration relevant and unbiased features. This was compared with existing ranking systems - the IMDB movie ranking and top business school ranking by the US News and World report; the correlation between these ranking systems and the proposed algorithms were significant.

In another work done by Kunpeng et al. [17] a rather robust method of implementation was employed with conditional random fields (CRF). Factors which influence sentiment were considered, for instance the newly emerged internet language, emoticons, positive words, negative words, negation words and also useful information about the sentence structure like conjunction words and comparisons. Additionally, they also utilized context information to capture the relationship among sentences for the improvement of document-level sentiment classification; and incorporated human interaction to improve sentiment identification accuracy and construct a large training set.

The input of the algorithm includes specified subjects and a set of corresponding documents, while the output of the algorithm will assign a sentiment value to a particular sentence in a document. To capture context information among sentences in a document to predict their sentiment class; a form of sequence labeling is employed. The model is used to assign a label to each sentence as it corresponds to a certain sentence sequence. In this work the CRF employed provides a probabilistic framework for calculating the probability of a random variable or vector over corresponding label sequences (Y) conditioned on a random variable/vector over sequence data to be labeled (X). In this work a linear chain structure was employed (a structure similar to a Hidden Markov model). The document containing multiple sentences served as the observation sequence, this was used as the given condition for the label sequence tagged as a label. After which log-likelihood technique was used to perform parameter estimation, and then many iterative scaling algorithms were used to optimize the parameters. The Viterbi algorithm was employed to make inference with an approach very similar to the forward-backward algorithm of an HMM. Semantic features (number of positive/negative words, positive or negative emoticons, comparative sentences, type of conjunction words) and Syntactic features (sentence positions, simple or compound sentence, position of positive/negative words, position of negation words, comparison subject, similarity to neighboring sentences) were combined to form semantic-syntactic features and used with the CRF algorithm. The evaluation of the model shows that the CRF based model when compared with other methods - the compositional semantic rule (CSR)(a rule-based algorithm), Support Vector Machine (SVM), Logistic Regression (LR) and Hidden Markov Model (HMM) and tested on datasets collated from Amazon reviews, outperforms the other methods by 5-15%. However, the CSR performs best on the Facebook comments dataset and the rest of methods produce similar results.

In [14] the parameters of the HMM were estimated according to the corresponding classes and trained using the Baum-Welch algorithm; these estimations along with a scaled-forward algorithm was used to provide the probabilities associated with a given review and its corresponding class. After that, these calculated probabilities were passed through a decision-making block to perform the final classification task. It turns out that the HMM with three states gives the best results when compared with predictions made by the Fuzzy Control System (FCS), and Neuro-Fuzzy Models (ANFIS). In addition, this work proposed a hybrid-system that combines and HMMs and the other two algorithms to obtain better results.

Peculiar with most probabilistic graphical models, it can be observed that modelling dependencies between parameters can improve accuracy in sentiment classification. The authors of [16] demonstrates this further. With the Dependency-Sentiment-LDA, sentiment classification was carried out, however the text was modeled in the form of a Markov Chain [32] to facilitate this purpose. After evaluation it was observed that the introduction of topic dependencies and sentiment prior information increased the accuracy in sentiment classification.

Robert et al.[15] developed a graphical model that is able to synthesize network and linguistic information to make better predictions about these parameters. This also demonstrates the ability for graphical models to perform multidimensional sentiment analysis. The idea employed in this work was to predict A's sentiment of B using the synthesis of the structural context around A and B inside a social network and sentiment analysis of the evaluative texts relating A to B. Although an NP hard problem, the authors point out an approach that can relax the problem to an efficiently solvable hinge-loss Markov Random field (a variation of HMM). In this paper they further demonstrated how joint models of text and network structure can excel where their components part cannot.

In the bid to analyze and quantify to what extent joint probabilistic models outperform pipeline probabilistic models in terms of extraction of aspects, subjective phrases and the relation between them, Roman and Philipp [13] discovered that the use of a joint inference model made way for the yielding of a deeper and fine grained analysis of sentiments by modelling the relation between aspects and subjective phrases; and also outperforms the pipeline model in the prediction of aspects. However, in the prediction of subjective phrases and relations, the pipeline model outperforms the joint model. The inference on the imperatively-defined factor graphs (the employed probabilistic graphical model) are carried out by the Markov Chain Monte Carlo Technique. The data representation employed possess peculiar similarities with the data model of a Hidden Markov Model; templates were used to define the sets of variables that form the graphical structure of the probabilistic model, the features that lead to the factor's score and the parameters associated with them. Then effective sampling strategies were employed for the joint and pipeline models coupled with adequate objective functions and training.

IV. Discussion and Recommendations

The varied implementations of HMMs to perform sentiment classification occur where other machine learning algorithms can be used – algorithms like the Naïve Bayes, Support Vector Machines, Maximum Entropy, and Recurrent Neural networks. However, we have seen that as with most probabilistic graphical models, HMMs can be used to model a multidimensional sentiment analysis where the classification of a sentiment may not only be dependent on the textual data alone but on some other latent events surrounding the sentiment classification. This ability gives HMMs a degree of prospect and advantage over non-probabilistic graphical models. One of the issues facing the task of sentiment analysis has been that other machine learning algorithms are only able to learn patterns from a single domain. However, from the reviewed literature we see how the HMM was used to combine different domains and used to improve accuracy in sentiment classification. Even though there are challenges, this does not contradict the fact that there have been successes. However, there is a need to delve deeper to create more efficiency in this area.

In addition, there is a need for the creation of novel and innovative text feature representations for Hidden Markov Models. HMMs take as input varied forms of sequential data. It is able to discover patterns in sequential data and perform text classifications. Recently, there has been an increase in the amount of text feature representations ranging from weighted words to contextualized word representations [33]. Although some of these features are tailored for certain kinds of algorithms is it possible to create a degree of imitation for implementations with HMMs and possibly other probabilistic graphical models? Doing this can facilitate research in the representation and use of semantics to perform sentiment analysis as some of these features possess a form of semantic representation. With this there is a possibility for breakthrough; this is because in use cases where other machine learning algorithms may fail, probabilistic graphical models like the HMM may come to the rescue.

Focusing on the reviewed literature, other ensemble methods like Bagging and Stacking calls for investigation. TextHMMs has shown promising results and there is potential for greater accuracy. One of the reviewed literature showed how a 2dHMM was able to combine two domains to achieve sentiment analysis. Can this model be taken a step higher? Another key area to note is the ability for HMMs to deploy genetic algorithms like the particle swarm optimization algorithm. Investigating the application of its variations can be a key area for research as this may provide some promising results.

V. ConcLusion

In this work, a literature review on the application of Hidden Markov Models in the field of sentiment analysis has been conducted. In this situation, the goals of this work have been attained. It is important to reiterate that the applications of Hidden Markov Models are varied, although the main ones are used as a sequence prediction technique by modelling hidden and observable states, states obtained by varied amount of feature extraction methods. As part of future work, we seek to construct text feature representations based on the fundamental concepts to the ones pointed out above. An adequate representation is key to the improvement of probabilistic graphical models. In addition, later studies can be carried out to find models additional to neural networks that can be consolidated with Hidden Markov Models in such a way that performance of sentiment classification is improved while maintaining a reasonable balance.

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