Grammar Detection for Sentiment Analysis through Improved Viterbi Algorithm

Surya Teja Chavali1, Charan Tej Kandavalli1, Sugash T M1, Subramani R2

1Department of Computer Science and Engineering, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India.
2Department of Mathematics, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India.
E-mail: bl.en.u4aie19014@bl.students.amrita.edu, bl.en.u4aie19013@bl.students.amrita.edu, bl.en.u4aie19062@bl.students.amrita.edu, r_subramani@blr.amrita.edu

Abstract—Grammar Detection, also referred to as Parts of Speech Tagging of raw text, is considered an underlying building block of the various Natural Language Processing pipelines like named entity recognition, question answering, and sentiment analysis. In short, forgiven a sentence, Parts of Speech tagging is the task of specifying and tagging each word of a sentence with nouns, verbs, adjectives, adverbs, and more. Sentiment Analysis may well be a procedure accustomed to determining if a given sentence’s emotional tone is neutral, positive or negative. To assign polarity scores to the thesis or entities within phrase, in-text analysis and analytics, machine learning (ML) and natural language processing (NLP), approaches are incorporated. This Sentiment Analysis using POS tagger helps us urge a summary of the broader public over a specific topic. For this, we are using the Viterbi algorithm, Hidden Markov Model (HMM), Constraint-based Viterbi algorithm for POS tagging. By comparing the accuracies, we select the foremost accurate model’s result for Sentiment Analysis for determining the character of the sentence.

Keywords—POS, Natural Language Processing, Viterbi, Hidden Markov Model, Sentiment Analysis

I. INTRODUCTION

In NLP, we need to pre-process the text to do the remaining work efficiently on the processed text. Word classes for a word in a sentence are automatically labelled using parts of speech tagging (POS)[1]. Sentiment analysis, parsing, question answering, and machine translations are among applications that require POS tagging. Each word must be tagged in order to do sentiment analysis.

We Humans can tag it quickly for a sentence, but it becomes complicated to tag the text when the length and number of sentences increase. So, we train our machine to do that work for us. Sentiment analysis, also known as opinion mining, aims to learn about the attitudes, opinions, and feelings expressed about a product or issue by regulating the emotional tone behind a collection of words[2]. Companies can save time and money by using sentiment analysis to tag customer data such as survey replies, reviews, and support tickets, social media comments, and many others.

There are a variety of approaches that can be utilized for Parts of Speech tagging:
• POS Tagging using Constraint-based Viterbi
• Transformation Based POS Tagging
• Deep Learning Models
• Stochastic or Probabilistic tagging

We have used both Constraint-based and Stochastic methods of tagging. By comparing the accuracies, we proceeded with the best accuracy producing technique[3-4]. We implement POS tagging for pre-processing the text to split up the sentence and tags each word. We use the classical Viterbi technique, HMM technique from the inbuilt library, and Viterbi with some pre-defined constraints for this tagging. By comparing the accuracies of all considered models, we select the model with the highest accuracy and use that to tag our sentence[5]. The Viterbi algorithm determines the most likely sequence, a sequence with the largest probability of POS tags. The tagged text is then used for analysing the text’s nature by using Sentiment Analysis. Most of the previous works used three main approaches. Those are K – order generative, PGM’s, Sequence labelling for the classification problem, Conditional Random Fields (CRFs). But we have used Viterbi with some pre-defined constraints. Most of the POS Tagging works are done in regional native languages. In our paper, we have done it on the English language[6]. Many research has been happen in analysis of components such as image, tagging, etc [11—14].

The structuring of this paper is as follows: The second section talks about the basic mathematics involving in our application, which includes Markov models, HMM, Viterbi Algorithm and CRFs.
Moving on to the section three, we describe various methods on implementation of our paper in Python. Following this is the results and analysis part, discussed in section four.

II. PRELIMINARIES

We need to understand the background mathematical theory before we apply our model in the implementation section. The following three sections will brief about HMMs and the Viterbi algorithm. With the help of this knowledge, anyone can understand how we executed the Sentiment Analysis part in the latter part.

A. Markov Models

Markov Chains are generally referred to represent probabilistic graphical models which symbolize active processes, i.e., processes that change over time and are rather not static. A state is any particular situation that is possible in the system. Any system with a specified number of states and the probability that the system will change from one state to another is a Markov chain [7]. The main theme of a Markov process tells us that a future state relies only on the previous state and not on any other states before it.

Mathematically, we can represent Markov chains as follows:

\[ P(X_{n+1} = x | X_n = x) \]

Here, \( X = \{ \text{set of defined states} \} \)
\( n = \text{state position} \)
\( x = \text{probability that state will occur.} \)

Here, we can infer that the possibility that the \( n+1 \) can occur depends only on the \( n \)th and not on any other state.

The simplest Markov model is a Markov chain, in which all states are observable and probabilities converge over time.

B. Hidden Markov Model (HMM)

HMMs can be mainly used in areas of NLP, a few of which are:

- Speech Recognition
- Pattern Recognition
- Bioinformatics
- Signal Processing

An HMM can be considered as a stochastic process. Essentially, in an HMM, the shift between states is usually hidden. We can simply visualize HMMs as a combination of Hidden Markov Chains plus Observed variables. A detailed understanding of the above is explained in the next section.

Figure 1. Graphical model of Hidden Markov model

The above figure (Fig. 1) illustrates a graphical representation of an HMM. Here, the first set of states (\( S_t \)) are a set of states which are discrete random variables and are termed as “Hidden” states. The states below them (\( Y_t \)) are either discrete or continuous random variables showing the observable data with respect to time \( t \).

With the help of this given relation between Hidden and observable states, we can easily predict the future states associated with Hidden states, as they are dependent on the observed states. Also, here vertical dependencies represent that the observed states are dependent on the Hidden states.

The working of an HMM is described as follows:

STEP – 1: The probability distribution of the states is defined as \( \pi = (\pi_1, \ldots, \pi_n) \), which is a stationary distribution and \( \pi^\top A = \pi \), where ‘A’ represents the transition probability matrix which contains probabilities of likely the states are followed immediately by the previous states.

STEP – 2: This symbolizes the very famous eigenvector equation, \( Av = \lambda v \). And thus, we can conclude that \( \pi \) is nothing but a left eigenvector with eigenvalue 1.

STEP – 3: Recalling our equation described above for Markov chains, it can be reframed for the representation of HMMs as:

\[ \arg \max \ A = A_1, A_2, \ldots, A_n | B = B_1, B_2, \ldots, B_n \]

From the above equation, we can have a clear picture that we have to find that particular sequence of \( X \), for which \( (X | Y) \) is maximum. A point to be noted here is that, in a HMM, we observe the sequences of \( Y \). Here, if we follow closely, there is...
no direct way to find this probability\[8\]. Therefore, we bring in the Bayes theorem, which transforms the equation as:

$$
\text{arg max } \frac{P(B|A) \cdot P(A)}{P(B)}
$$

where the numerator is nothing but the joint probability distribution of X and Y, i.e.,

$$
P(Y|X) = \prod P(X_i | Y_i)
$$

C. Viterbi Algorithm

Unlike the classical Forward and Backward algorithms, The Viterbi algorithm is an optimized backward induction technique, i.e., a dynamic programming algorithm that helps us find the most probable sequence of hidden states with the highest probability\[9\].

This statement can be visualized as the following formula:

$$
X_{0:T}^* = \text{arg max } P(X_{0:T} | Y_{0:T})
$$

The following recursive formula is used to visualize the probability distribution:

$$
\mu(X_k) = \max_{X_{0:k-1}} P [X_{0:k}, Y_{0:k}]
= \max_{X_{k-1}} \mu(X_{k-1}) = P [X_k | X_{k-1}] P[Y_k | X_k]
$$

The recursive formula above represents the optimum initial state that maximizes the product of the elements on the right-hand side while leaving the primary state as a free parameter to be determined in the second calculation.

The advantage of Viterbi over other algorithms is that it is much more efficient and is best picturized using a framework (a diagram) to find out how the path is selected from a time step to the next one. We later optimize this Viterbi algorithm to improve our model's accuracy, which is further discussed in the implementation section of this paper.

D. Conditional Random Fields (CRF)

The conditional random field is a probabilistic paradigm for data segmentation and labelling. It's a form of undirected graphical model in which for each observation sequence, a single log-linear distribution over label sequences is defined. \( P(Y|X) \) conditional probability distributions of label sequences for the given input sequences are defined by CRFs.

Lafferty et al consider the probability of label sequence to be \( Y \) for the given observation sequence \( X \) for which the normalized product is considered for each of the potential functions \[10\]. The following description is defined as follows:

$$
\exp \left( \sum \theta_i f_i (Y_{j-1}, Y_j, X, j) + \sum \mu_k S_k (Y_j, X, j) \right)
$$

where, \( \theta_i \) is nothing but the feature function of the transition happening inside the entire observation sequence as well as the positions of the labels at \( j \) and \( j - 1 \). \( \theta_i \) and \( \mu_k \) are parameters to be estimated from training data, and \( S_k (Y_j, X, j) \) is a state characteristic function of the label at position \( i \) and the observation sequence.

$$
F_i (Y, X) = \sum f_i (Y_{j-1}, Y_j, X, j),
$$

where each \( f_i (Y_{j-1}, Y_j, X, j) \) is either a state function \( S(Y_{j-1}, Y_j, X, j) \) or a transition function \( t(Y_{j-1}, Y_j, X, j) \). As a result, if we have an observation sequence \( X \), then the probability of a label sequence \( Y \) can be written as:

$$
P(Y|X, \theta) = \left( \frac{1}{Z(X)} \right) \exp \left( \sum \theta_i F_i (Y, X) \right).
$$

where \( Z(X) \) is a normalization factor.

III. IMPLEMENTATION

We should always make sure that a computer executes the methodologies we prepare to manipulate, analyze, etc., and make sure that our approaches are suitable. Therefore, we have implemented all of the ideation discussed above in Python.

We have used the Natural Language Tool kit present in Python, then carried out the Viterbi algorithm and later improved it. Later we have also developed an application out of it to perform Sentiment Analysis.

Following is the briefing about it.

A. Natural Language Tool Kit

NLP is the automatic modification of natural language by software programs, such as speech and text. The Natural Language Toolkit (NLTK) is a module present in Python for Natural Language Processing (NLP). It is a programming framework for working with linguistic data. Around 50 corpora, lexical resources, n-gram collections, parts of speech tagger, tree models and text chunks for collecting, and named entity identification resources are included.

In implementing POS tagger for sentimental Analysis, Treebank corpora have been used. It is
accessible under a liberal use license to demonstrate how to use the NLTK tools for parsing, tokenizing (splitting), tagging, and chunking. It contains 1650 sentences of raw, tagged, processed, and merged data from the Wall Street Journal.

B. Computing Transition Matrices

The transition probability in POS tagging indicates the possibility of a specific sequence, such as how likely it is for a noun to be followed by a verb. To have a clear idea, let's consider some example sentences to understand our problem better.

The sentences have been chosen in such a way, that some set of words have different parts of speech, provided word being the same at both places.

Four sentences are manually tagged in Fig 2. Now we will build the transition matrix by considering these tagged sentences.

| Tags | N | M | V | End |
|------|---|---|---|-----|
| Start | 3/4 | 1/4 | 0 | 0 |
| N | 1/9 | 3/9 | 1/9 | 4/9 |
| M | 1/4 | 0 | 3/4 | 0 |
| V | 4/4 = 1 | 0 | 0 | 0 |

Fig – 2 Example of the above explanation.

The table's indexes in Table I are the transition probabilities for the given sample sentences. In Table I, we can see that the Noun tag is followed by the Model verb three times. Thus, the numerator in the second row, the third column, is 3. Similarly, the rest of the table is filled. Now, we divide each phrase in a row of the table by the total number of co-occurrences of the tag in question to get the probability. For example, a Noun tag is followed by any other tag is nine times, as shown in Fig. 2. Thus, we divide each element in the second row by nine.

C. Computing Emission Matrices

In POS tagging, the emission probability gives how likely the particular word has specific, for example, how likely Mary is a noun. To show how to compute these probabilities, let's consider the same sample sentences in Fig. 2.

| Words | Noun | Model | Verb |
|-------|------|-------|------|
| Mary  | 4/9  | 0     | 0    |
| Jane  | 2/9  | 0     | 0    |
| Will  | 1/9  | 3/4   | 0    |
| Spot  | 2/9  | 0     | 1/4  |
| Can   | 0    | 1/4   | 0    |
| See   | 0    | 0     | 2/4  |
| Pat   | 0    | 0     | 1    |

The table's indexes in Table II are the emission probabilities for the given sample sentences. In Table II we can see that Mary, tagged as Noun, occurred four times. Thus, the numerator of the second row, the second column, is 4. Similarly, the rest of the table is filled. Now, we calculate the probability by dividing each term in a table row by the total number of occurrences of a particular tag. For example, the Noun tag has occurred nine times for a different set of words. Thus, we divide each element in the second column by nine. Now we have computed transition and emission probabilities. Note that these calculations are only for the particular set of sentences, but while implementing the program, the functions calculate these parameters for a massive collection of datasets.

D. Applications of Viterbi

Further proceeding with the implementation, the Viterbi algorithm has been executed. The Viterbi technique is used in POS tagging to determine the most likely or maximum state probability for a sequence of POS taggers for a given set of words. To boost up the accuracy, we have enhanced our Viterbi algorithm by defining some pre-defined constraints for tagging. To showcase the difference between Viterbi and HMM, we have also implemented HMM. In addition to that, we have also ensured that our improved Viterbi algorithm works for compound noun phrases.
In this paper, we have implemented one of the essential applications of POS tagging, i.e., Sentimental Analysis. For implementing this application, we have used our improvised Viterbi algorithm to assign the tags to the words, which will be used as an input for one of the steps in the Sentiment Analysis part. The output for the application is the polarity or the score of the given sentences. In the final part of the implementation.

The float value of Polarity lies between [-1,1], with 1 signifying a positive statement and -1 implying a negative statement. Subjective statements are often used to express personal feelings, emotions, or judgments, whereas objective words are used to express facts.

IV. RESULT AND ANALYSIS

For assessing the performance of our algorithm, we have some of the outputs in console window which showcases our results as follows:

| Algorithm       | Accuracy achieved (in %) |
|-----------------|--------------------------|
| Improved Viterbi| 97.12918                 |
| Viterbi         | 93.77990                 |
| HMM             | 94.25837                 |
| CRF             | 79.17                    |

We have a considered a reference paper “Part-Of-Speech Tagging and Chunking using Conditional Random Fields and Transformation Based Learning” in order to compare our work to their algorithm’s performance. They have used CRFs to perform POS tagging and achieved a decent accuracy. As, we can observe in the above table III. Our model also clearly identifies different compound nouns as well as phrasal sentences.

This is because some of the words in our input sentence were nouns, but only our enhanced version of the Viterbi algorithm could detect that, and the rest two algorithms tagged those words as pronouns. Moreover, we carried out sentiment analysis as an application, based on the above algorithm. We have considered a sample sentence for testing our model, which is: “You have done a really good project!”

We can infer from the above figure Table IV that when we pass in that sentence, we get the emotional tone, saying it is a ‘Positive’ statement. Furthermore, we even calculated the polarity score, indicating that the sentence is 87.5% positive.

V. CONCLUSION AND FUTURE WORK

In this paper, we have presented how Markov models and the Viterbi algorithm can be used to carry out Sentiment Analysis. To showcase the novelty in this work, we have even enhanced our Viterbi algorithm to outperform some of the other NLP models for POS tagging.

The current model is still under development, i.e., as a part of future enhancement, one can extend this paper to implement some of the advanced techniques such as Maximum localization, Baum Welsh Algorithm, etc.

REFERENCES

[1] Kumar, S., Kumar, M. Anand and Soman, K.P., "Deep Learning Based Part-of-Speech Tagging for Malayalam Twitter Data (Special Issue: Deep Learning Techniques for Natural Language Processing)" Journal of Intelligent Systems, vol. 28, no. 3, 2019, pp. 423-435. https://doi.org/10.1515/jisys-2017-0520
[2] Shraddha Suratkar , Faruk Kazi Rohan Gaikwad “Multi Hidden Markov Models for Improved Anomaly Detection Using System Call Analysis”, 2019 IEEE Bombay Section Signature Conference, D OI: 10.1109/IBSSC47189.2019.8973098
[3] Huang M., Haralick R.M. (2009) A Probabilistic Graphical Model for Recognizing NP Chunks in Texts. In: Li W., Mollá-Aliod D. (eds) Computer Processing of Oriental Languages. Language Technology for the Knowledge-based Economy. ICCPOL 2009. Lecture Notes in Computer Science, vol 5459. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-00831-3_3
[4] Antony P.J, Santhanu P. Mohan, Soman, “SVM Based Part of Speech Tagger for Malayalam”, IEEE International Test Conference (TC), DOI: 10.1109/ITC.2010.18
[5] Nisheeth Joshi , Hemant Darbari and Iti Mathur, “HMM Based POS Tagger for Hindi”, Computer Science & Information Technology . pp. 341–349, 2013
[6] S. Lakshminar Pandian, T.V Geetha, “CRF Models for Tamil Parts of Speech Tagging and Chunking”, Computer Processing of Oriental Languages. Language Technology for the Knowledge-based Economy, 22nd International Conference, ICCPOL 2009, Hong Kong, March 26–27, 2009. Proceeding
[7] Bharathi Raja Chakravarthi, KP Soman, Rahul Ponnumusy, Prasanna Kumar Kumaresan, Kingston Pal Thamburaj, John P McCrae, DravidianMultiModality: A Dataset for Multi-modal Sentiment Analysis in Tamil and Malayalam, arXiv:2106.04853v1 [cs.CL] 9 Jun 2021
[8] X. Zhao, and Y. Ohsawa, “Sentiment Analysis on the Online Reviews Based on Hidden Markov Model”, Journal of Advances in Information Technology, vol 9(2), pp. 33–38, 2018.
[9] Jun Li, Yanhui Li and Shuangqing Chen, “The fast Viterbi algorithm caching Profile Hidden Markov Models on graphic processing units,” 2011 IEEE International Conference on Computer Science and Automation Engineering, 2011, pp. 567-570, doi: 10.1109/CSAE.2011.5952535.

[10] John Lafferty, Andrew McCallum, and Fernando C.N. Pereira, “Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data”, June 2001.

[11] S. S. Teja Gontumukkala, Y. S. Varun Godavarthi, B. R. Ravi Teja Gonugunta, R. Subramani and K. Murali, "Analysis of Image Classification using SVM," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2021, pp. 01-06, doi: 10.1109/ICCCNT51525.2021.9579803.

[12] Y. L. Prasanna, Y. Tarakaram, Y. Mounika and R. Subramani, “Comparison of Different Lossy Image Compression Techniques,” 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), 2021, pp. 1-7, doi: 10.1109/ICSES52305.2021.9633800.

[13] M. Tanuj, A. Virigineni, A. Mani and R. Subramani, "Comparative Study of Gradient Domain Based Image Blending Approaches," 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), 2021, pp. 1-5, doi: 10.1109/ICSES52305.2021.9633858.

[14] B. Murugadoss, S. N. R. Karna, J. S. Kode and R. Subramani, "Blind Digital Image Watermarking using Henon Chaotic Map and Elliptic Curve Cryptography in Discrete Wavelets with Singular Value Decomposition," 2021 International Symposium of Asian Control Association on Intelligent Robotics and Industrial Automation (IRIA), 2021, pp. 203-208, doi: 10.1109/IRIA53009.2021.9588744.