Proceedings of Machine Learning Research 1–4, 2023

Exploring a Hybrid Approach of Hidden Markov Model and Gaussian Mixture Model: Simplifying Models and Enhancing Interpretability

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Abstract

The aim of this study is to explore the feasibility of a hybrid approach that combines Hidden Markov Model (HMM) and Gaussian Mixture Model (GMM) for estimating automata. The process involves fitting the HMM to latent values, obtaining cluster centroids, and processing the hidden states of the pre-trained model. The study suggests that simplifying models and using surrogate models can facilitate the extraction of simpler and better interpretable models from pre-trained neural networks. Furthermore, the study presents also the prior researches that demonstrates the potential applications of this hybrid approach in various areas of machine learning, highlighting how other researchers have incorporated the combination of Hidden Markov Models and Gaussian Mixture Models within their methodologies.

Keywords: Hybrid approach, Hidden Markov Model (HMM), Gaussian Mixture Model (GMM), Natural Language Processing (NLP), Recurrent Neural Networks (RNNs), Automatic Translation, DFA (Deterministic Finite Automata).

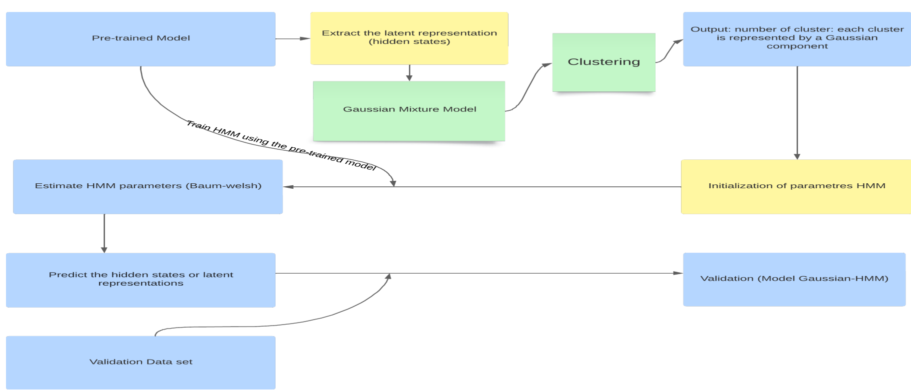
1. Introduction

Natural Language Processing (NLP) is an AI field focused on enabling machines to understand and manipulate human language for various tasks including automatic translation, speech recognition and text classification. Recurrent Neural Networks (RNN) have recently been used for processing sequential data in NLP. It's has proven to be an efficient and an accurate model for building language models. However, RNN suffers from some limitations such as the slow and complex training procedures for processing the long sequences. To overcome this challenge, a combination of models, namely Gaussian Mixture Model and Hidden Markov Model, along with pre-trained Recurrent Neural Network models, is employed to improve overall performance and reduce prediction errors. This study explores the application of these integrated techniques to develop a more precise and efficient model based on pre-trained RNN models, with the objective of achieving advancements. Hidden Markov Model combined with Gaussian Mixture Models has made impressive achievement in speech recognition, handwriting, signature verification, engineering and many other fields. In recent years, the hybrid approach was applied for reliability assessment of Integrated Energy Systems (IESs) and was compared to the probabilistic deep learning: Chi et al. (2021). Thomas et al. (2013) explored the use of HMM and DNN models for keyword extraction in handwriting documents. To capture the dependency between successive feature vectors in speech emotion recognition, El Ayadi et al. (2007) proposed an efficient system based on the Gaussian mixture vector auto regressive (GMVAR) model. Guorong Xuan et al. (2001) investigated the use of GMMs for on-line signature verification for modeling intra-variability in signatures. Yao et al. (2020) proposes a new traffic classification model called MGHMM, which combines Gaussian mixture models and hidden Markov models to accurately classify encrypted traffic. Xing et al. (2023) enunciate a method for dynamic texture classification using a bag-of-models approach with a mixture of student's t-hidden Markov models (MixSHMM). In a recent work, Benyacoub et al. (2022) proposed an HMM classifier for credit scoring, and the experiment showed the effectiveness of the modeling approach.

2. Methodology

The hybrid model merges GMM and HMM to exploit their strengths, improving modeling and prediction capabilities. It involves extracting latent representations, applying GMM for distribution capture and clustering, training HMM with transition probabilities, and predicting hidden states. Combining predictions optimally utilizes the models' strengths, unveiling latent patterns and temporal dependencies for predictions in new data. In this

Figure 1: Enhancing Modeling and Prediction with a Hybrid GMM and HMM for Pre-trained Models



study, the building process of the hybrid model, which is shown in Figure 1, is starts from the number of clusters N find using Gaussian-mixture model, and then the estimation of HMM parameters is obtained using the Baum-Welch procedure. This process can be presented as follows:

- Use the pre-trained model.
- Application of Gaussian-Mixture model to obtain the number of clusters N.
- Initialization of HMM parameters λ^0=(π^0,$\boldsymbol{A}^0$,$\boldsymbol{B}^0$), where π^0 is a vector of dimension N, $\boldsymbol{A}^0$ is a $N \times N$ matrix and $\boldsymbol{B}^0$ is $N \times M$ matrix, wich M is the number of alphabets (output information).
- Re-estimation of HMM parameters using the Baum-Welch procedure.

- Validation of the Gaussian-HMM model using validation data set.

3. Data sets and numerical results

3.1. Data set and Performance Evaluation

In this study, only symbolic sequential data have been used to train RNN, presented as sequences of integer. Our approach is trained and validated using the available data set representing 10 % from each eleven data set used in the competition. The evaluation is based on three main criteria: score, memory usage and CPU time. The goal should be to reach the lowest possible score across all of these criteria.

3.2. Results

Table 1 shows the results obtained for different data sets demonstrating that substitution models have been successful in reproducing the behavior of the original neural network while being simpler and more easily interpretable. However, some data sets were more difficult than others. It should also be noted that some data sets presented memory issues, indicated by the "-" symbol in the table. This highlights the importance of considering hardware limitations when creating surrogate models. Overall, the findings suggest that simplifying the model and utilizing substitution models offer an effective approach to extract simpler and more interpretable models from pre-trained neural networks.

Table 1: Performance results of classification using Gaussian mixture model and HMM.

Data sets	Error rate	Memory Usage(MiB)	CPU time(ms)	Score
1.1	0.4478500	159.00	0,2	0.3582396
1.2	0.5001800	158.00	0.202	0.3837155
1.3	0.5000000	148.00	0.158	0.3517917
1.4	-	-	-	-
1.5	0.5207700	149.00	0.152	0.3652613
1.6	-	-	-	-
1.7	-	-	-	-
1.8	-	-	-	-
1.9	0.9274160	156.00	0.160	0.5912362
1.10	0.9319784	156.00	0.162	0.5868875
1.11	0.7100964	162.00	0.153	0.4548389

3.3. Comparison

During the competition we were ranked fifth or fourth. Table 2 shows a list of datasets and their respective ranks.

Table 2: Rankings in the competition.

Data sets	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11
Rank	5	5	4	-	4	-	-	-	5	5	5

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