Classifying Movie Reviews with Deep Learning Neural Networks

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I. Introduction

The data set used for this project is the IMDB data set of movie reviews from Kaggle.com [7]. It will be used to train a natural language processing model to classify the sentiment of reviews in a binary fashion as either positive or negative. The movie reviews data set enables us to explore the capabilities of natural language processing models. Movie reviews are often written with emotional and opinionated expressions which are occasionally articulated using sarcasm or euphemisms. It would be interesting to see how well different machine learning methods can classify reviews despite the aforementioned nuances of human language. The goal of this project is to train a model sufficient enough to be implemented into the review section of a web page to automatically and accurately place submitted reviews into their respective categories.

II. Data set

The IMDB movie reviews data set contains 50 thousand total records, each consisting of two columns, one for the text in the review, and one for the binary classification of that review's sentiment (positive or negative). The data set will be split into a training and testing set, with an 80-20% ratio.

III. Literature Review

A. Is neuro-symbolic AI meeting its promises in natural language processing? A structured review [3]

This article is about Neuro symbolic (NeSy) AI and what exactly it is. In short, NeSy AI is the combination of deep learning and symbolic reasoning, aka human reasoning [1]. The goal of NeSy is to address the weaknesses of both symbolic and sub-symbolic approaches while preserving their strengths. There are two most fundamental aspects of intelligent cognitive behavior: the ability to learn from experience, and the ability to reason on what has been learned. There has been a lot of progress made on the learning side, especially in the area of Natural Language Processing (NLP) in particular with deep learning. This AI is still very much in its infancy, and researchers believe its weaknesses cannot be overcome through deep learning alone. Overall, the article provides an overview of the current state of Neuro Symbolic AI in NLP and stresses the lack of research that exists in order to make NeSy a viable intelligent agent to be used in nearly any industry.

B. Artificial intelligence approaches using natural language processing to advance EHR-based clinical research [4]

The article first highlights the issue of big data in the medical field; with so many hospitals converting their patient medical records to digital, leveraging the useful information of these records to assist clinical research is a top priority. This is where natural-language processing may have a part to play. An AI with sufficient training can examine millions of records in a matter of days if not hours and extract the relevant information. Such a model can drastically improve not only the accuracy but speed of new research for new medical breakthroughs, almost like an incredibly advanced ("Ctrl+F") function when reviewing a PDF. The article details some already existing NLP models utilized for both allergies and asthma, and a model for the asthma assessment shows how the EHR is broken down into structured data, such as patient information, and unstructured data, such as clinical notes by the physician. This is then put through the NLP model and is aggregated to give a summarized description of the asthma severity and possible treatments. As before, this article does mention that NLP of such a scale as to be used by the medical industry is still in its infancy, but strongly urges more and more industries to make use of automation via NLP to improve its viability.

C. A Survey of the State of Explainable AI for Natural Language Processing [2]

Explainable AI is any AI that can use natural language to explain its own processes and functions. This article serves to explain the capabilities and limitations of Explainable AI

(XAI) as of the time when it was written (2020). In brief, the article highlights three main obstacles in making NLP techniques for explainable AI more suitable for widespread use: Accuracy vs interpretability: If you want AI explanations to be more accurate, you run the risk of getting too confusing for the average viewer, and if you want explanations to be more interpretable, the user may not be given an accurate description. You have to train the NLP model to generalize and summarize, but not too much. Scalability: Large data sets become incredibly expensive to interpret (this can be said for any manner of data processing). And metrics: No standards for measuring an AI mode's ability to balance accuracy/interpretability with natural language have been developed, or have at least been widely adopted.

D. Learning Word Vectors for Sentiment Analysis [5]

This Stanford-published research paper attacked the challenge of analyzing the sentiment of movie reviews by combining the use of two natural language processing techniques: unsupervised word vector clustering and supervised sentiment classification. The word vector technique makes use of an unsupervised probabilistic approach in clustering words in a high-dimensional space, where the vectors between two words are determined by measuring the semantic similarity between them. This approach could group together words of similar strength in terms of expression, however, was unable to distinguish the sentimental difference between positive and negative expressions. To compensate for this, the polarity annotations (star ratings) that labeled each movie review enabled a supervised sentiment model to be implemented in tandem with the word vector clustering model to build a word vector model capable of realizing the nuances in sentiment, thus imbuing those realizations into the vectors themselves. A linear SVM was used to then classify vectors in the clusters.

IV. Methodology

The pipeline used for carrying out the research experiment consisted of initializing dependencies, data pre-processing, fine-tuning a pre-trained BERT model, evaluating and saving the model, and finally uploading the model to be used on a simple webpage for user interaction with the model in a real-world situation.

A. Initializing Dependencies

The dependencies for our project consisted of two modules useful for machine learning and natural language processing: pandas & transformers (Trainer, Tokenizer, model loader). The one most used for our project was the "transformers" module, which gave access to Huggingface's assortment of pre-trained transformers and NLP tokenizers.

B. Data Preprocessing

During the pre-processing stage, the IMDB data set downloaded from kaggle.com in CSV format was uploaded to the Python file into a pandas data frame for easier manipulation. Then, the data frame was separated into an 80-20 train-test split. The final training and evaluation data sets contained 40000 and 10000 records, respectively. For the BERT model to understand text input, the input must be tokenized into encoding that the model can understand. With that in mind, we tokenized the train and test data frames using the 'Auto-Tokenizer' from the transformers module.

C. Fine-tuning the model

Next, we loaded the pre-trained model called "bert-base-cased" from the transformers module. This model is a case-sensitive version of Google's BERT NLP model, whose structure can be seen in **Figure 1**. The model was then fine-tuned by calculating the model's loss and optimizing based on that loss using the AdamW optimizer for each of the five epochs. Once the fine-tuning training was completed, the model was evaluated using the tokenized test data set. The final training and validation loss percentages for the fine-tuned model were 2.26% and 29.67%, respectively. **Figure 2** displays the difference in training loss shown in blue and the validation loss shown in orange over the course of the five epochs.

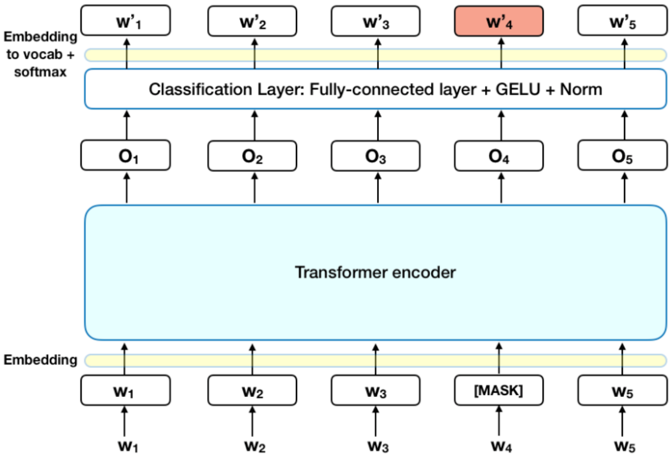


Fig. 1. Structure of BERT Model [Horev, 8]

V. Evaluation

After fine-tuning the BERT-base-uncased NLP model to the 40000 sample records from the IMDB data set, it was evaluated using the 10000 record test data set to find the model's accuracy, precision, and recall rate. The accuracy, a measurement of correctly classifying a review, was measured at 92.82 percent. The precision, a measurement of how much of the positively predicted sentiments actually were positive, was measured at 93.34 percent. Finally, the recall, a measurement of how many of the truly positive reviews were classified as positive, was measured at 92.23 percent. **Figure 3** displays a confusion matrix, an overview of the validation samples that were evaluated.

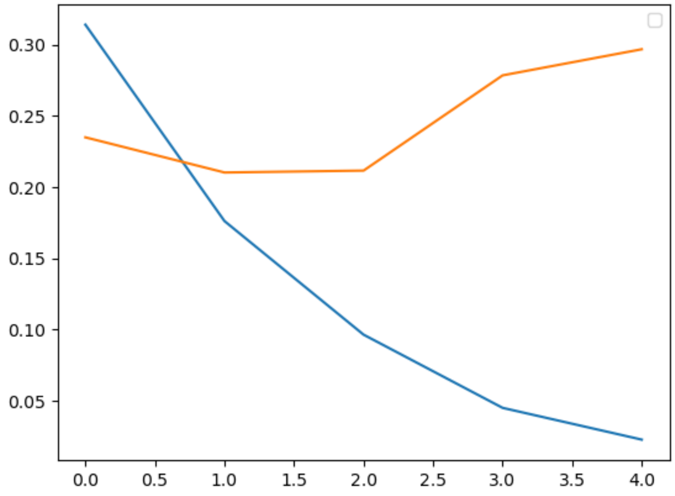


Fig. 2. Epoch training (blue) and validation (orange) loss

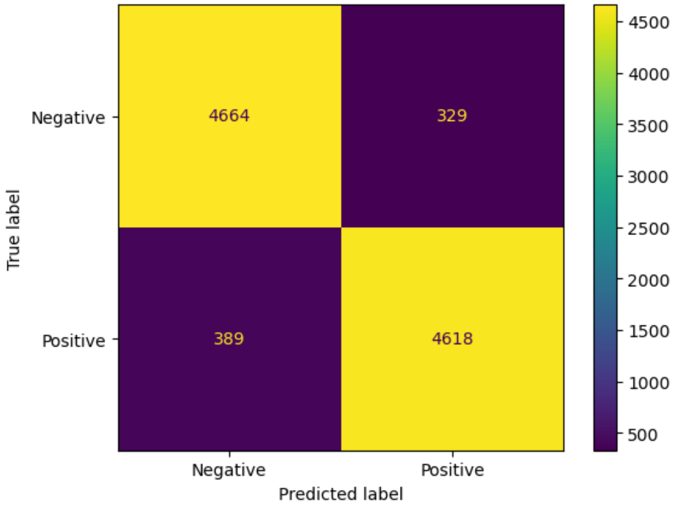


Fig. 3. Confusion matrix (10000 validation samples)

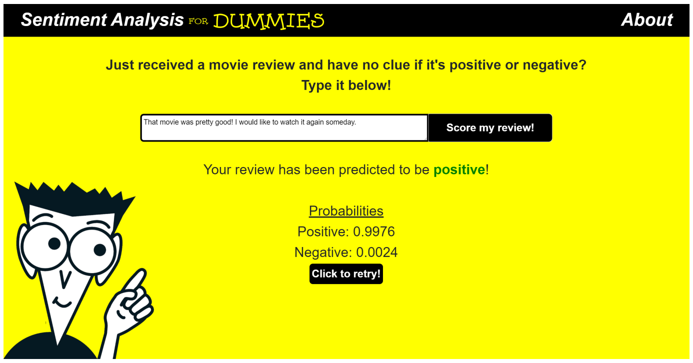
VI. Real-world Situation Simulation

The novel aspect of our project was in the user experience, as models are only useful when they are put to the test in real-world situations. Instead of training a machine learning model and only having it accessible through a jupyter notebook, we aimed to package our model and enable users to directly test it themselves.

We built a simple-to-use web page where the movie review sentiment analysis feedback from our model could be displayed both as ”positive” or ”negative” and as the percentages of positive or negative that the model predicts the review to be. This serves as a means of making the experience more user-friendly.

A. Implementation

To build this simulated user experience, we first had to save the model that we trained. This was done using the JobLib python module. Using JobLib, the model and accompanying tokenizer were both saved into a .sav file to be used in an external Python script from the one we initially used to fine-tune the model. Then, a Python script called ”RunFineTunedModel.py” was written to unpackage the model and tokenizer from the save file and use form data sent through the CGI python module to receive the review text and evaluate its sentiment. This Python file was stored in the CGI-bin of an Apache server, obi.kean.edu, where it could be accessed through POST requests sent by a client browser using the website. The website utilized JavaScript, jQuery, and AJAX to send asynchronous XML HTTP requests to the RunFineTunedModel python script so that predictions could be made and sent back to the page dynamically. **Figure 4** displays a screenshot of the working website, which is hosted at: https://obi.kean.edu/˜fisheral/movie_review_sentiment/.



Just received a movie review and have no clue if it's positive or negative?
Type it below!

That movie was pretty good! I would like to watch it again someday.

Your review has been predicted to be positive!

Probabilities
Positive: 0.9976
Negative: 0.0024

Fig. 4. Webpage User Interface

VII. Conclusion

All in all, our fine-tuned BERT model did a decent job at distinguishing reviews for being positive or negative. However, certain figures of speech such as sarcasm, euphemisms, and whatnot were usually taken literally by the model during manual evaluation through the UI, thus giving incorrect sentiment predictions. It should be noted that these figures of speech are difficult even for humans to pick out from text alone due to their reliance on the inflection of one’s voice when spoken. Nevertheless, the overarching goal of AI, to create a model that reflects human intelligence, was achieved through this project. In terms of understanding natural language and the sentiment of movie reviews specifically, our model did its job. Based on the implementation of the model into the UI we built, we have also learned how models we’ve trained ourselves could be exported and used in real-world, practical situations.

VIII. Future Work

A possible innovation for future work that may be implemented is distinguishing which sentences are relevant to the classification, (i.e., which sentences are relevant to the actual movie being reviewed).

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