Narrative Analysis, an Introduction of Federated Learning to Text Based Emotional Analysis

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CSCE 585: Machine Learning Systems

GitHub Repository: https://github.com/csce585-mlsystems/Narrative-Analysis

Presentation: Narrative_Analysis.pdf

Video Presentation: Narrative Analysis Presententation

Abstract

Due to the nature of behavioral therapy and the required observation period, diagnostic times for mental health disorders can be lengthy. A real time emotional analysis tool has been proven to be helpful in recognizing symptoms of certain mental health disorders, like post-traumatic stress disorder and depression. This possible clinical use could help decrease diagnostic times by allowing providers a deeper understanding of patient's day-to-day emotional states. One limitation holding this technology back is the required security of health data, limiting training material for past emotional analysis machine learning systems. With the introduction of federated learning to a language model trained to identify emotions, this limitation can be bypassed. User data would only be stored locally, with iterations of the model learning from the new user data and only sending those weight changes back to the global model. This, along with differential privacy techniques, keeps user data private enough to help increase the availability of training data for real time emotional analysis models.

Introduction

Although mental health treatment has become as available and well understood as ever, mental health disorders are still widespread and impair millions [1]. The availability of treatment options [2] as well as the long diagnostic periods required compared to other ailments [3] are barriers to mental health treatment. These barriers cause many to go without treatment, with most people who suffer from mental health disorders never receiving treatment [4]. If providers were able to remotely analyze their patient's moods and emotions in between appointments, diagnostic times could be improved, and more patients could have access to mental health resources.

This need for a real time emotional analysis tool is real, and with recent improvements it is viable in the clinical space. Machine learning has allowed for accurate emotional analysis using facial, auditory, and textual analysis [5,6,7]. Given these advancements emotional analysis models have already been used to recognize clinically validated psychiatric symptoms of certain mood disorders [8].

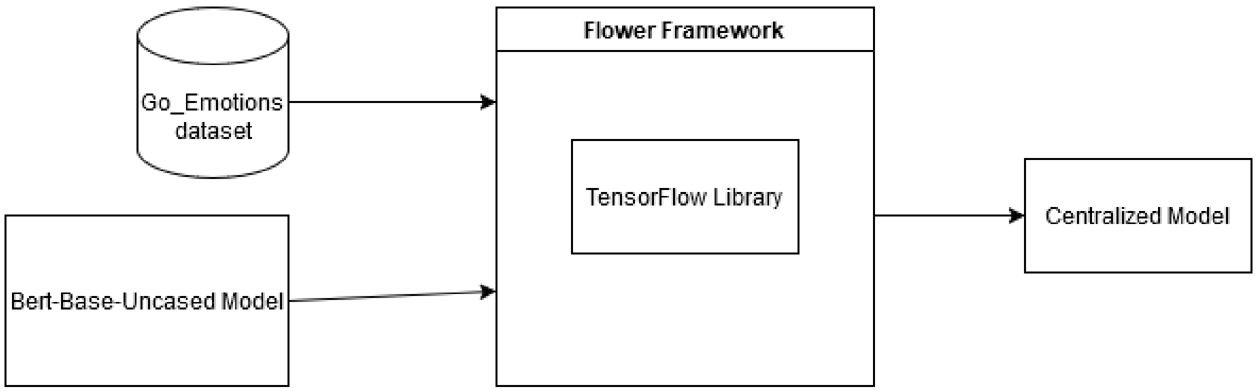
One limitation in this field is the fact that personal health data is required to make the models as accurate as possible. Health data needs to comply with HIPPA as well as consumer privacy laws like the GLBA [9], and these restrictions make it difficult to compile datasets to train emotional analysis models. Most datasets that include health data are composed of specific cases patients have consented for use or artificial cases [10]. By introducing federated learning to an emotional analysis model, this limitation can be bypassed.

Federated learning works using a global shared model, where individual user data only impacts a local iteration of the model. The changes in weights of this iteration are then used to update the global model. Since no user data is stored anywhere other than locally, the updates to the global model will follow necessary data privacy laws [11]. Federated learning is already being used in different sectors of healthcare for this very reason [12].

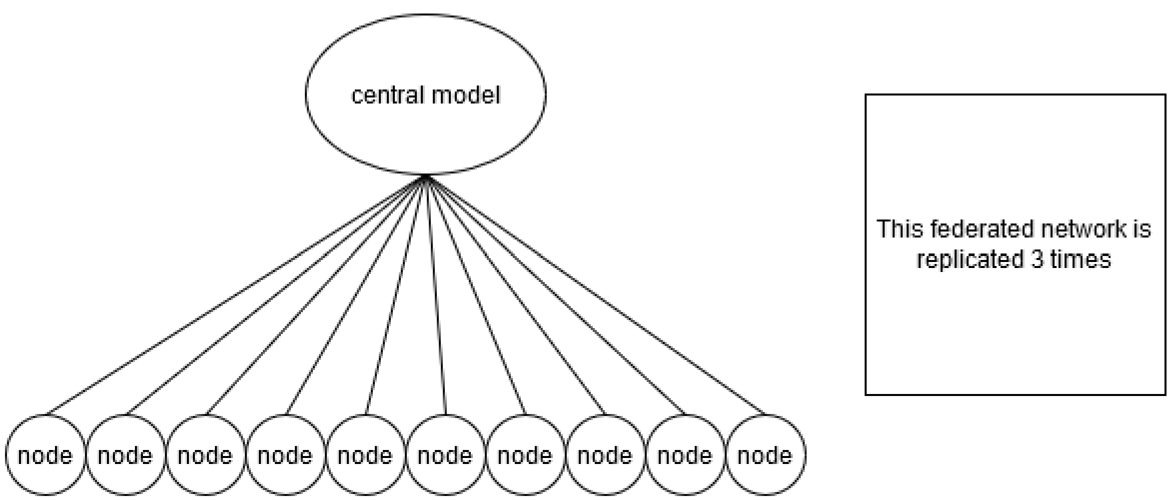
To introduce federated learning to our emotional analysis tools, we will use a TensorFlow library within the Flower framework. The Flower framework is a crucial component of this project for a few key reasons. It is scalable across edge devices, which is necessary for future development of an applicable real time analysis tool. It also allows for language and ML framework-agnostic implementation of a federated learning system. Finally, flower allows for the transition of existing ML systems into a federated learning setup, which allows for the evaluation of its convergence properties [13].

METHODOLOGIES

To set up our experiment, we created a federated learning system and tested multiple times to evaluate model convergence. The federated learning framework itself utilizes the Flower framework, which allows for the testing of a federated learning environment on a single device rather than having to set up multiple devices like an actual federated learning system would do in practice. We then pulled from the pre-existing bert-base-uncased model which excels in identifying nuances in language which can be highly effective for sentiment analysis. Finally, we utilized the go_emotions dataset from google-research-datasets [15].



The setup we used for the federated learning system with Flower consisted of running 10 partitions, which act like nodes in a federated learning environment and training them on the dataset. These 10 partitions are then used to train one central node using their training data. We would repeat this process 3 separate times and then compare the convergence of all 3 central models to check for the accuracy of the federated learning environment.



ANALYSIS

We unfortunately were not able to get our experimental setup to run due to several issues regarding framework compatibility with OS versions and the dataset we were using. The best form of analysis we could do at the moment would be to compare our setup to similar federated learning systems. Based on other research, these systems often end up converging if trained on other health datasets [15]. So, although we do not have any hard results, we can at best assume that the model is likely to converge

CONCLUSION

In this paper we studied the problem of training an AI model using personal health data while simultaneously keeping that data secure. We introduced the use of federated learning, a system which manages to train models on patient data while also maintaining privacy for personal information. Our federated learning system with the flower framework utilized the pre-existing bert-base-uncased which we then trained on the go_emotions dataset across 10 nodes which all fed training information to a central model. We were unable to run the experiment and instead had to assume based on similar experiments what our result may be. If the assumption were to be held true, we would find this to be a good starting point to show that a federated learning setup can work when it comes to utilizing personal health data to train AI models. The use of federated learning also ensures that no personal health data is being sent across models, rather only training data is being changed. As a result, personal data privacy is ensured, and the AI models are still able to be effectively and consistently trained.

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