W35. NATURAL LANGUAGE PROCESSING-BASED QUANTIFICATION OF THE MENTAL STATE OF PSYCHIATRIC PATIENTS

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Abstract

Introduction: Mental health practitioners routinely record behavior and mental state of patients in Electronic Health Records (EHR) using free-text notes. Although this data is invaluable to clinicians for everyday clinical tasks, it is difficult to use for retrospective, prospective, or predictive analytics because of its unstructured format. To tackle this challenge, we have developed natural language processing (NLP) models to convert semi-structured notes into structured psychiatry-specific data labels related to patient symptoms, function, appearance, and mood.

Methods: Anonymized semi-structured EHR notes on patient status assessment from a large behavioral health database were used (N>500,000). First, a psychiatry subject matter expert analyzed raw texts, picked 241 elicit data labels (e.g., insomnia, impaired memory, and issue with impulse control) and classified labels into 27 categories (e.g., appearance, functioning, mood). Subsequently, we pre-processed data, designed a multi-component architecture, and created deep learning based 27 NLP models, one for each category. Each NLP model was trained to map unstructured sentences to corresponding labels in each category. Performance metrics (e.g., accuracy and Area under the Receiver Operating Curve (AUROC)) were evaluated.

Results and Discussion: The NLP models can predict data labels in most of the 27 categories with an accuracy of 0.7 and achieve a median AUROC score of 0.9. The deep-learning models were also shown to perform better than three traditional models (support vector machine (SVM), K-nearest neighbor (KNN), and Naïve Bayes models). To ascertain the usefulness of these NLP data labels, we investigated three simple use cases. One is to estimate suicidal tendencies of patients diagnosed with Major Depressive Disorder (MDD). We tested the hypothesis that a MDD patient's suicidal tendencies typically increase before hospitalization by using a proxy suicidality score calculated based on suicidality-related NLP data labels. A statistically significant increase was found in suicidality score 1-day before hospitalization ($p<0.05$). Two other simple applications (patient phenotyping, combination with a machine-learning model to predict diagnosis) were detailed in our publication (Mukherjee 2020). These NLP data labels have the potential to be used for downstream analytics for intra- and interpatient clinical insights. Possible future model improvements are needed on both algorithms and utilization in a clinical setting.

Conclusion: We demonstrate that deep learning based NLP models can convert free text notes to analyzable dimensions of mental function of psychiatric patients. Interested researchers may consider using these NLP models and co-develop custom analytics through collaboration with our data scientists. (contact: enquiry@holmusk.com)