**EEG Event Detection on the TUH EEG Corpus**

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BigData resources are critical to the application of state of the art machine learning algorithms to signal and text data in biomedical informatics. The Neural Engineering Data Consortium (NEDC: *www.nedcdata.org*) has recently released the Temple University Hospital EEG Corpus, which consists of over 28,000 EEG studies from over 15,000 patients. This corpus represents 14 years of clinical EEGs performed at Temple Hospital – a large urban public hospital. The data is extremely diverse and includes numerous artifacts expected in clinical data (e.g., patient movement). Each record includes the signal data and an EEG report containing the neurologist’s findings.. Ideally, the correlations of the automatic processing of the signal data with the information extracted from the EEG report will bootstrap the quality of signal processing.

We present pilot results of experiments on the prediction of some basic attributes of an EEG signal using a manually labeled subset of the corpus that was developed to allow small scale experiments to be run that give good indicators of overall performance. We define a 6-way classification task that involves detection of: (1) spike and/or sharp waves (SPSW), (2) periodic lateralized epileptiform discharges (PLED), (3) generalized periodic epileptiform discharges (GPED), (4) artifacts (ARTF) (recorded electrical activity that is not of cerebral origin, such as those due to the equipment, patient behavior or the environment); (5) eye movement (EYEM) (common events that can often be confused with a spike); and (6) background (BCKG) (used for all other signals). A baseline machine learning approach based on time-frequency analysis, hidden Markov models and deep learning are shown to be capable of predicting commonly occurring events with an 89% detection accuracy and a 4% false alarm rate. Maintaining a low false alarm rate is important to the success of this technology in clinical settings.

Submitting Author’s Career Stage: Professor