ShortFuse: Learning Time Series Representations in the Presence of Structured Information

In healthcare applications, temporal variables that encode movement, health status, and longitudinal patient evolution are often accompanied by rich structured information such as demographics, diagnostics and medical exam data. Current methods for analyzing these types of data rely on extensive feature engineering, often modeling the time-series and structured information independently. Traditionally, when methods such as PCA, Multiple Kernel Learning, Dynamic Time Warping, neural networks or other transformations are used to extract features from time series, the structured information in the datasets has no impact on the learned representations. However, in most biomedical applications, there are interactions and correlations between time series and covariates, which we aim to leverage.

We present ShortFuse, a method that boosts the accuracy of deep learning models for time series by explicitly modeling temporal interactions and dependencies with structured covariates, allowing the latter to guide feature learning. Our approach introduces specialized structures that we call 'hybrid layers', designed to incorporate structured information as distinct inputs used to parametrize, guide, and enrich the feature representations. First, we introduce the notion of 'hybrid convolution', operating on a multivariate time series x containing n signals sampled at t time points, together with its corresponding structured covariate vector s of size d. The output is a matrix z of m 'hybrid signals'. Each element $z_{i,j}$ of z is computed from $\bar{x}^{ij}$, a subset of signals from x in the time window centered at point j. We have $z_{i,j} = \mathbf{1}^T(\bar{x}^{ij} \circ \kappa)\mathbf{1} + \beta$, where κ is the hybrid filter kernel, β is a bias term, $\circ$ denotes the Hadamard product and $\mathbf{1}$ is a vector of ones. The structured covariates come into play in the kernel function, as each element from κ is a linear combination of a randomly-selected subset of the d structured covariates in s, where the weights are parameters of the hybrid convolutional layer. This formulation offers extreme flexibility, incorporating cross-terms between the signals and the covariates. Secondly, we introduce a Long-Term Short-Term Memory (LSTM) hybrid, which shares the covariates and their weights across the cells and uses them in the computation of the input gate, forget gate, state change, and output layer. The LSTM hybrid is thus able, for instance, to adjust the length of the forget window.

ShortFuse achieves state-of-the-art performance in the identification of candidates for surgical treatment of gait disorders associated with cerebral palsy as well as the prediction of cartilage degeneration in patients at risk for osteoarthritis. For the first application, we use joint angles from motion capture data collected from 236 subjects. The best time series representation model obtains an accuracy of 75%, bumped to 76% when appending the structured covariates. ShortFuse scores 80%, also outperforming the best previously-published result, a random forest model trained on clinical information as well as hand-engineered clinical features. We also applied the procedure to data from the Osteoarthritis (OA) Initiative. It includes activity counts collected from 1926 subjects over a monitoring period of 7 days, as well as 650 clinical features. The goal is to forecast whether a subject is at risk for fast OA progression. Previous studies on this data have applied simple transformations to the time series such as 3-bin histograms, with thresholds established by domain experts to represent light, moderate, and vigorous activity levels, resulting in an accuracy of 67%. ShortFuse obtains 75%, 3% more than the closest contender.