Machine Learning for Healthcare 2020 - Clinical Abstract Track

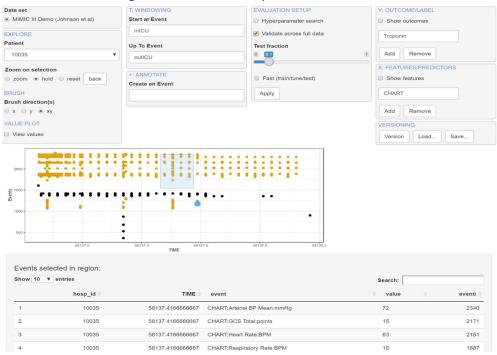
TL-Lite: Temporal Visualization for Clinical Supervised Learning

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Abstract.

Clinical data extraction is a necessary step for quantitative analysis in clinical research. Whereas most machine learning algorithms learn on fixed length or regularly-collected panel data, health records data are neither. To facilitate working and developing intuition with such data, we built a data transformation and ingestion process for temporal machine learning frameworks. TL-Lite, a temporal visualization tool assists analysts and researchers in the extraction process. The central principle behind of TL-Lite is to provide visual responsiveness at the individual level alongside management of the desired transformations behind the scenes that go on to be applied throughout the cohort.

While other temporal clinical visualizations and extraction tools exist [Wang (2009), Ledesma (2019)], our work focuses on facilitating extraction by providing a reactive environment that shows visual consequences of these extraction design choices. To provide responsive reactivity, our contribution provides two data views: the reactive, individual-level view, and the staged, cohort-level view. The individual-level view provides useful indicators at the level of the unit of analysis, while the cohort-level processing is central to statistical characterization and generalizability beyond the individual, both of which are informative in the design of the derivative cohort. We use MIMIC III Demo data, which is a public, deceased-only subset to illustrate our method [Johnson (2019)]. We provide a screenshot in Figure 1 and will provide an interactive demonstration of the tool.



TLLite: a modeling framework for temporal clinical data

Figure 1. TL-Lite, an interactive clinical timeline. The user views the exemplar, and the exemplar updates as the user makes post- data collection design decisions. With confirmation the changes are applied to the full data set to create a downloadable derivative. Outcomes: large and blue; outcomes: tan; unused features: black. Demo at: https://bit.ly/3hqpdzA.

References.

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