Computer Science
Defense

Predicting Time-to-Event and Clinical Outcomes from High-Dimensional Unstructured Data

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Abstract: This dissertation addresses challenges in learning to predict time-to-event outcomes such as survival and treatment response from high dimension data including whole slide images and genomic profiles that are being produced in modern pathology labs. Learning from these data requires integration of disparate data types, and the ability to attend to important signals within vast amounts of irrelevant data present in each sample. Furthermore, clinical translation of machine learning models for prognostication requires communicating the degree and types of uncertainty to clinical end users who will rely on inferences from these models. ¡br¿ This dissertation has addressed these challenges. To validate our developed data fusion technique, we have selected cancer histology data as it reflects underlying molecular processes and disease progression and contains rich phenotypic information predictive of patient outcomes. This study shows a computational approach for learning patient outcomes from digital pathology images using deep learning to combine the power of adaptive machine learning algorithms with survival models. We illustrate how these survival convolutional neural networks (SCNNs) can integrate information from both histology images and genomic biomarkers into a single unified framework to predict time-to-event outcomes and show prediction accuracy that surpasses the current clinical paradigm for predicting the overall survival of patients diagnosed with glioma. Next, to capture the volume of data and manage heterogeneity within the histology images, we have developed GestAltNet, which emulates human attention to high-yield areas and aggregation across regions. GestAltNet points toward a future of genuinely whole slide digital pathology by incorporating human-like behaviors of attention and gestalt formation process across massive whole slide images. We have used GestAltNet to estimate the gestational age from whole slide images of placental tissues and compared this to networks lacking attention and aggregation capabilities. To address the challenge of representing uncertainty during inference, we have developed a Bayesian survival neural network that captures the aleatoric and epistemic uncertainties when predicting clinical outcomes. These networks are the next generation of machine learning models for predicting time-to-event outcomes, where the degree and source of uncertainty are communicated to clinical end users

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