Clustering Anesthesiology Case Data for Machine Learning

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Background. Anesthesiology is a field of medicine requiring equal parts early preparation and real-time decision making. Anesthesiology services cover all surgical procedures spanning both inpatient and outpatient practice, and with recent implementation of electronic medical records throughout most institutions, there is a vast amount of data collected. While standard procedures exist for some anesthetic procedures, there is tremendous variation in executed anesthetic techniques. We hypothesize that there exists variation in anesthetic outcomes based on practice variation both across and within individual medical institutions. The goal of this work is to cluster and characterize anesthesiology practice data, and implement machine learning techniques, to create tools to understand and improve anesthesiology clinical practice.

Methods. We collected data from all patients undergoing procedures from the Multicenter Perioperative Group (MPOG) registry. We identified over 10 million unique cases across 50 hospitals, spanning 18 states. We clustered cases on procedural text using natural language processing (NLP) techniques including stemming, edit-distance, n-gram, and topic segmentation. Patient-specific data included age, sex, American Society of Anesthesiologists physical status (ASA), and emergent status. Intraoperative data included administered medications, venous access, perioperative nerve blocks, airway management, and over 18 billion case-specific physiologic observations. Features were further created using the evolving list of established MPOG phenotypes. Cases were grouped by institution. Perioperative practice decisions were identified trialing different clustering techniques including k-means, GMM, DBSCAN, Agglomerative Clustering, and Spectral Clustering. Visualization was attempted through the following dimension reduction methods: PCA, t-SNE, LLE, Spectral Embedding, and MDS. We used BIC, Silhouette Coefficient, and the Calinski-Harabaz Index for the quantitative analysis of clusters. A user-interface was created for interactive display of the data, which was separated into unique treatment "paths". Outcomes were defined by institution and anesthetic path. These outcomes include 30-day in-hospital mortality, intraoperative medication use (including oral morphine equivalency (OME) and vasopressors), intraoperative complications (including myocardial infarction, respiratory failure, pulmonary embolism, AKI), estimated blood loss, urine output, fluid and blood product administration, and provider-specific information (staffing ratios and provider quality assessments). Machine learning models were then applied to create additional tools for automated characterization for billing, research, and quality including Current Procedure Terminology (CPT) prediction.

Results. The results from clustering allowed for differentiation and grouping of perioperative anesthetic decisions. These groupings defined the characterization of treatment paths used in perioperative care. With this organization we were able to gain valuable understanding of clinical practice variation. Using knee arthroplasty as an example procedure, there were 137 unique anesthetic paths across all institutions. The frequency of the top path ranged from 14.5 - 72.6% by institution. There were 15 distinct top paths among 50 institutions. Using OME as an example outcome for this procedure, OME ranged from 21.5 to 146.5, with an average OME per institution of 55.1 (+/- 23.3). Another tool was created to aid billing. This tool used machine learning to automate anesthesiology CPT assignment and resulted in ~60% of cases automatically assigned with >96% accuracy. Overall, 99.9% of all cases had their CPT code predicted within the top 3 choices.

Conclusion. There is considerable variation in anesthesiology practice both between and within institutions for given procedures. Using clustering techniques and feature engineering to design appropriate phenotypes, we have created an analytical tool for understanding and analyzing variation in anesthesia practice. With this tool, we have begun to investigate clinical practice variation including opioid use and billing applications. Our next steps are to utilize supervised machine learning models to identify potentially optimal or detrimental paths in anesthetic care. As several decisions within the anesthetic paths are chronological, and the real-time anesthesiology decision making relies heavily upon chronological physiologic data, we believe reinforcement learning techniques can be applied and offer insight to anesthesiology decision making. Overall, the results of medical treatment path clustering and ML implementation can be utilized within any field of medicine and/or across complete patient care paths encompassing multiple medical fields.