ProcedureView (ProView): Analyzing and Presenting Anesthesiology Case Data for Providers using Machine Learning

Presenting Author: Michael L Burns, MD PhD, Department of Anesthesiology – University of Michigan
Co-Authors: Anik Sinha, MS[1], Yuwei Bao[1], Sean Meyer, BS[2], John Vandervest, MS[1], Sachin Kheterpal, MD MBA[1]
University of Michigan: [1]Department of Anesthesiology [2]Department of Integrated Systems and Design

Introduction: As an anesthesiologist you realize there is tremendous variation in executed anesthetic techniques. Practicing anesthesia providers can rely on personal experience, institution guidelines, training, and continuing education – but pertinent case examples may be lacking for specific cases of interest in published case series and review articles. Through wide spread adoption of electronic medical record systems, we now have access to vast amounts of electronic anesthesiology clinical data. **The objective of our study** is to create an organized system to identify and understand anesthesiology practice variation and potentially associated outcomes with the intent of improving anesthesiology education and clinical practice.

Methods: We used unsupervised machine learning (ML) techniques to develop key path anesthetic decision points. Using data from the Multicenter Perioperative Group (MPOG) registry, we identified over 10 million unique cases across 18 states and over 50 hospitals. We developed clusters of case/patient combinations in an attempt to organize data. 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, case-specific physiologic observations, and existing MPOG phenotypes. Cases were grouped by institution and displayed in a web-interface (Figure 1) in which a "user" can login and interact with the data. Data is organized by institution (with de-identified comparison between institutions) and displayed with analysis of patient demographics, executed anesthetic treatment plans separated into unique treatment "paths", and associated outcomes defined by institution and anesthetic path. Outcomes currently include 30-day in-hospital mortality, intraoperative complications (including myocardial infarction, respiratory failure, pulmonary embolism, AKI), estimated blood loss, urine output, fluid and blood product administration, intraoperative medication use (including oral morphine equivalency (OME) and vasopressors), and provider-specific information including staffing ratios and provider quality assessments.

Results and Conclusions: In grouping procedure data with institutions we were able to gain valuable understanding of clinical practice variation. As an example, there were 137 unique anesthetic paths across all institutions for knee arthroplasty with the frequency of the top path ranging from 14.5 - 72.6% by institution. Among 50 distinct hospitals there were 15 distinct top paths. 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). A procedure with considerably less variability is liver transplant where the top path was chosen 77% of the time across all MPOG sites. The ProView tool we have created illustrates the considerable variation in anesthesiology practice both between and within institutions for given procedures. We envision 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. This information could be useful for providers at various levels of training and continuing medical education. Additionally, we are currently utilizing 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 also 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.

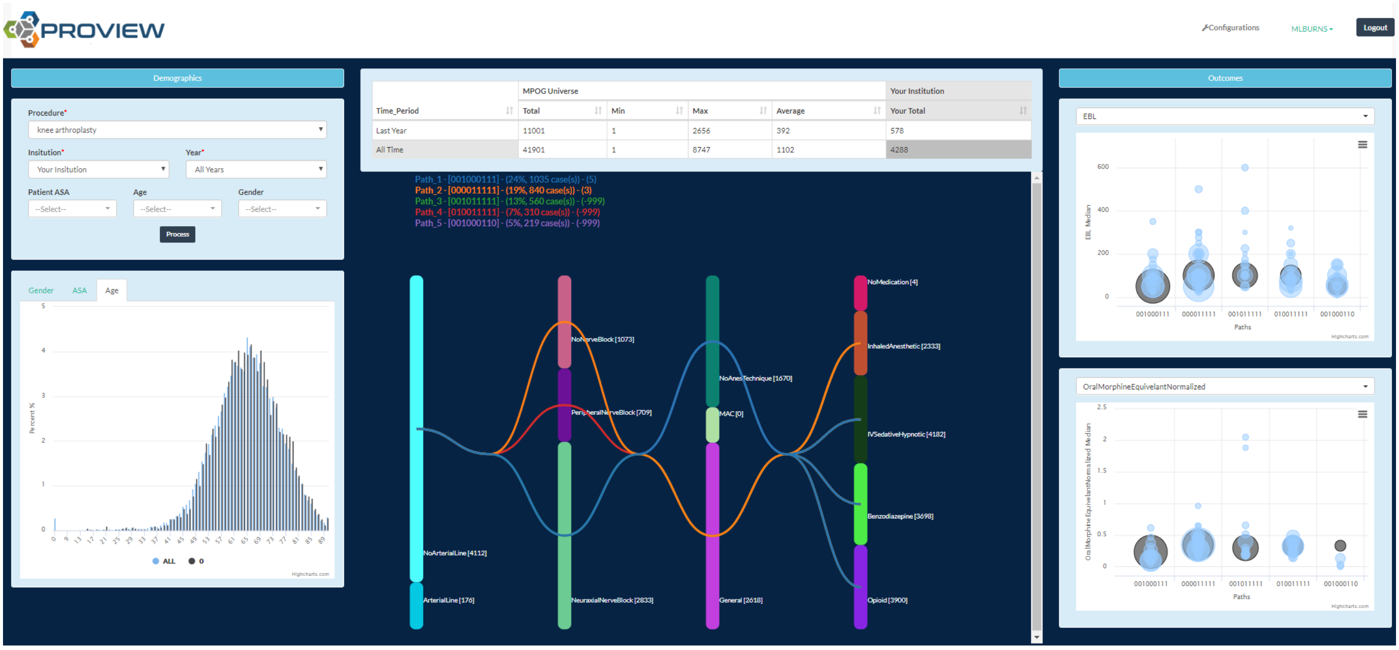

Figure 1: Web version of ProcedureView (ProView), a practice variation tool for anesthesia providers. Paths are shown as lines through specified anesthetic decisions (bars). Demographic (age) histogram is shown on the left, while estimated blood loss (EBL) and oral morphine equivalent (OME) are shown on the right.