Using Decision Trees for Determining Anesthetic Technique Using Only Data from Multiparameter Patient Monitors

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Background: When leveraging data from large vital signs databanks, such as the Multicenter Perioperative Outcomes Group registry [1], or the BC Children's Hospital local databank, certain characteristics might not be (immediately) available for case classification. In the absence of an Anesthesia Information Management System (AIMS), we are forced to make decisions based on vital signs only, without being able to mine medication records. One possible problem is determining the type of anesthetic, such as total intravenous anesthesia (TIVA), inhalational anesthesia (IHA), or mostly intravenous anesthesia (MIVA), defined as an inhalational induction followed by intravenous maintenance.

In determining the effect of anesthetic technique on blood pressure in children [2], a key challenge was how to distinguish cases by anesthesia regimen (TIVA, IHA, or MIVA). One possible solution is to manually define a set of rules based on minimum alveolar concentration (MAC). The drawback of this approach is that, to avoid misclassification, it discards many potentially useful cases, and also requires manual tuning of identification parameters to achieve a trade-off between cases being discarded and cases being mislabeled.

Another approach is to employ human-augmented machine learning. Decision trees are preferred over other machine learning methods, since their decision process can be visualized, which aids validation [3]. Such an approach eliminates the need for manual optimization and enables automated creation of complex rules accounting for variability in the data. The aim of this work is to explore the feasibility of using decision trees to classify anesthetic technique.

Methods: With REB approval, data for 24,457 cases were extracted from a de-identified vital signs database [4]. A decision tree classifier was created to distinguish between IHA, MIVA and non-identifiable cases; classifying TIVA is straightforward (cumulative sum of MAC = 0). An interactive incremental approach was used to train the classifier on a sequence of cases:

1. A case is first classified by a manual set of conservative rules [4]. If TIVA, the case is not used for classifier training.
2. Next, the case is classified by the decision tree classifier, based on the following features: mean, variance, and maximum value of MAC, maximum value of MAC in the 2nd half of the case, and time spent with MAC < 0.55.
3. If the labels produced by the rules and the tree differ, the program plots the case and prompts the user to label it.
4. The resulting label and feature vector are added to a training database; the tree is retrained from scratch on the database.
5. The decision rules are visualized, and the training continues iteratively until the user is satisfied with the performance.

Results: A decision tree was trained on 490 cases, which took <5 minutes of user interaction. This tree classifier was subsequently applied to the full cohort. The number of discarded cases was lower compared to the rule-based approach [3,218 vs. 3,775]. The tree produced appropriate labels for most cases identified by the original conservative rules (Table 1).

Conclusions: We tested a machine learning method for inferring anesthetic technique from MAC, which can be generalized to classification of other parameters from vital sign recordings. This method may simplify real-world classification tasks by using a data-driven interactive approach, which iteratively refines a classification model starting from a set of roughly defined rules. Opportunities to improve classification performance include increasing the size of the manually labeled training dataset, and engineering more features for classification. Further investigation is necessary to determine the method's full potential.

References: [1] https://mpog.org; [2] Anesth Analg. 2019;128(4S):63-4; [3] IEEE Trans Sys Man Cybern. 1991;21(3): 660-674; [4] Abstract submitted to the Proc Soc Tech Anesth. 2020

Table 1: Confusion matrix for the resulting decision tree classifier vs. labels obtained from the conservative rule set

Prediction / **Label**	TIVA	IHA	MIVA	Non-identified
TIVA	11,862			
IHA		4,728	1	41
MIVA		44	3,711	295
Non-identified		506	387	2,882