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ARTICLE TYPE

Operation Room Personalized and Real-time Occupation Duration Prediction

Abstract
The challenge lies in predicting operation room occupation duration, crucial for healthcare providers' processes. Current pre-surgery predictions, aiming for average or worst-case scenarios, often underperform due to variances in surgeons, equipment, and patients. Our task is to enhance pre-surgery predictions and provide real-time improvements during surgery. Adopting a machine learning approach, we compile historical surgery data including surgeon profiles, equipment categories, patient states, and past durations. An ensemble of machine learning models, trained on this data, shows a 4% boost in pre-surgery predictions. Real-time adjustments further enhance predictions by 13% within the first 45 minutes of surgeries lasting three or more hours. This fosters optimized surgical scheduling and resource allocation, refining patient care.

The Problem

Predicting the duration of an operation room occupation is a central task for many other processes occurring in healthcare service providers' establishments. Commonly, this prediction is done before the operation even starts and aims to predict the average- or worse- case scenario. Both approaches shown to perform poorly in practice due to the large differences between surgeons, surgery equipment, and patient's clinical state. To this end, we are tasked to improve the current pre-surgery operation room occupation duration prediction and provide a real-time prediction improvement during the surgery itself.

The Solution

As expected, a machine learning-based approach is adopted. The process involves two main phases: offline prediction before surgery and real-time prediction during surgery. For offline prediction, historical data related to previous surgeries is collected by the client following our close guidance, encompassing various factors such as the surgeon's data (i.e., years of experience, surgery history, etc.), surgery equipment (represented by a category), patient clinical state, and past operation durations as the target variable. This dataset serves as the foundation for training machine learning models. Using this data, we train an ensemble of several machine-learning models including neighbor-based and tree-based ones. For real-time prediction during surgery, as the surgery progresses, data regarding the surgery's actual progression, surgeon decisions, and equipment utilization are recorded as part of the process. The model can then adjust its predictions in real-time, incorporating the evolving conditions. To enhance the model's performance, continuous retraining and updating with new surgery data are implemented.

The Outcome

The proposed solution was implemented and tested on 70 surgeries, showing 4% improvement over the pre-surgery prediction compared to the client's previous model. For real-time improvement, during the first 45 minutes of three or longer hours, the model's prediction is further improved by

13%. Importantly, this allows for enhanced surgical scheduling and resource allocation optimizing staff and equipment utilization.