Assignment Background

August 20, 2019

Healthcare operations have received growing interest from the operations management community over the past decade. Together with the trend in big data, healthcare data analytics has become an important topic not just in academia but also in practice. Critical care service provided by intensive care units (ICUs) is an important component for many health services provided by hospitals, like surgeries, and it is usually the most expensive service and bottleneck in patient flows. Given the special settings, it is critical to improving both patient outcome and operational efficiency for ICU management.

Over the past decade, the data collected in the intensive care units (ICUs) has grown exponentially and been used selectively in data mining studies (Ramon et al. 2007). However, the large amounts of data are still underutilized for the care of critically ill patients in the ICUs. Moreover, considering the unavailability and lack of human experts for various reasons, busy or novice physicians can overlook important details, while automated discovery tools built on various analytical models could analyze the raw data and extract high-level information for the decision maker enabling better decisions (Silva et al. 2006).

From the operational perspective, it has been recognized by the medical community the importance to consider operational efficiency in ICU management given the capacity limitations (Terwiesch et al. 2011). The research on ICU management is now an emerging area in operations management (Chan et al. 2012 2017, 2018, KC & Terwiesch 2012, Kim et al. 2015, Hu et al. 2018, Armony et al. 2018). These studies considered the operational decision making in the ICU environment, in particular, admission/discharge control, and pointed out the significant impact of operational efficiency on patient outcome. Therefore, having a set of analytical models that capture both medical condition of the patients and operational factors of the ICU is crucial to manage and improve the quality of critical care service.

The ICU setting is particularly well suited for an implementation of a data-driven system which acquires a large quantity of data to discover relationships for diagnostic, prognostic, and therapeutic factors using well-designed, predictive data mining models (Sierra et al. 2001). It is our goal in this series of assignments and competition to develop useful models using data collected in the ICU to predict various measures of patient outcome.

The assignment data was extracted from an open database for patients who stayed in an specialty IUC that offers intensive care service for cardiothoracic surgery patients. The data set includes information such as demographics, vital signs, laboratory test results, medications, caregiver notes, and outcome measures including mortality, readmission, and length of stay. Detailed description of the variables and samples will be released with each assignment.

References

- [1] Chan CW, Armony M, Zhu B (2018) Critical care in hospitals: When to introduce a Step Down Unit? Working paper.
- [2] Chan CW, Farias VF, Bambos N, Escobar GJ (2012) Optimizing ICU discharge decisions with patient readmissions. Operations Research 60(6): 1323–1341.
- [3] Chan CW, Farias VF, Escobar GJ (2017) The impact of delays on service times in the intensive care unit. Management Science 63(7): 2049–2072.
- [4] Hu W, Chan CW, Zubizerreta JR, Escobar GJ (2018) An examination of early transfers to the ICU based on a physiologic risk score. Manufacturing & Service Operations Management 20(3): 531–549.
- [5] KC DS, Terwiesch C (2012) An econometric analysis of patient flows in the cardiac intensive care unit. Manufacturing & Service Operations Management 14(1): 50–65.
- [6] Kim SH, Chan CW, Olivares M, Escobar GJ (2015) ICU admission control: an empirical study of capacity allocation and its implication on patient outcomes. Management Science 61(1): 19–38.
- [7] Ramon J, Fierens D, Guiza F, Meyfroidt G, Blockeel H, Bruynooghe M, van den Berghe G (2007) Mining data from intensive care patients. Advanced Engineering Informatics 21(3): 243–256.
- [8] Silva A, Cortez P, Santos MF, Gomes L, Neves J (2006) Mortality assessment in intensive care units via adverse events using artificial neural networks. Artificial Intelligence in Medicine 36(3): 223–234.
- [9] Terwiesch C, KC DS, Kahn JM (2011) Working with capacity limitations: operations management in critical care. Critical Care, 15(4): 308.