

Modeling heparin protocol dosing compliance using dynamic and static data to improve clinical outcomesAaron Noll, MD, MSCR^{1,2}, Bennett Lovejoy¹, Jeremy Foster, MBA¹, and J. Marc Overhage, MD, PHD¹¹Cerner Corporation, ²University Of Kansas Medical Center**Background.**

Healthcare organizations continuously strive to improve. Evidence based protocols are one recommended method for improving quality¹, safety², and reducing variation in care³. Although many hospitals have implemented protocols for activities such as medication administration or sepsis management in the hopes of improving outcomes, few have measured how well these protocols are followed. Hospitals often struggle to understand which factors influence compliance. Even if significant factors are identified, estimating the impact of interventions to modify such factors may be perceived as too resource intensive and is avoided. Multiple factors may influence protocol compliance and data about many of these factors exist in the EMR (electronic medical record). Such factors may include but are not limited to 1) the presence or absence and sequence of critical steps (dynamic data) in a given protocol process, and 2) information about the patient, provider, medication administration context and EMR interaction (static data). It has been shown that the modeling of static and dynamic features through machine learning may be useful in predicting the outcome of clinical processes.^{4,5} In this study we discuss preliminary results of leveraging both dynamic and static data to build a model for predicting compliance of a nurse driven protocol for heparin administration.

Methods.

Heparin administration dosing compliance was defined as administering the appropriate dose of heparin based on a patient's laboratory results (PTT or anti-FXa) and the sliding scale specified in their protocol. Heparin protocols were analyzed, and critical steps were identified to define the overall protocol process (dynamic data). Nine months of data were extracted from EMRs at two large and two moderate sized institutions where there was a desire to improve heparin administration. Levels of protocol compliance were presented to multidisciplinary teams including physicians, pharmacists, and patient safety staff. Teams were surveyed regarding what factors were likely to contribute to deviations from the protocol. Their feedback was organized into factors associated with either the patient, nurse, heparin administration, or nurse EMR interaction (static data). Static data were imputed for missing values and categorical variables were one hot encoded. Timestamps for process steps were obtained as dynamic data and associated with static data. Heparin protocol processes were mined for frequently occurring sequential sub-sequences using the prefix span algorithm and dummy variables for each discovered sub-sequence were generated. A dosing compliance classifier model using the XGBoost algorithm was created to compare the use of either the dynamic data, static data or the combination of both dynamic and static data. Training was performed on 65% of the entire dataset and a grid search with cross validation was used for optimization of model parameters. A weighted average of the micro and macro averages for precision, recall, and the F1 score on the remaining test data was used to judge model performance.

Results.

Of 83 static factors selected for model construction, 8 were associated with the patient, 14 with the administering nurse, 10 with heparin administration, and 51 with nurse EMR interaction. The average number of critical steps in a heparin process was 10. Features that were shared among the four institutions and appeared to influence protocol compliance the most were the patient's weight, age, administration time of day, and the hospital unit where the administration occurred. In general, using a combination of both sequence and static information resulted in a slightly higher weighted average for precision, recall and F1 score compared to only dynamic or static data alone (Table 1).

Institution	n	Precision			Recall			F1 Score		
		Dynamic	Static	Dynamic + Static	Dynamic	Static	Dynamic + Static	Dynamic	Static	Dynamic + Static
1	458	0.66	0.76	0.93	0.81	0.87	0.93	0.73	0.81	0.93
2	545	0.91	0.96	0.92	0.94	0.96	0.95	0.92	0.96	0.94
3	858	0.77	0.90	0.81	0.88	0.89	0.90	0.82	0.84	0.85
4	182	0.78	0.75	0.81	0.88	0.87	0.90	0.83	0.80	0.85

Table 1: Precision, Recall and F1 score using dynamic and static data from four different healthcare institutions**Conclusion.**

Preliminary results indicate that the combination of dynamic and static data may be used to predict protocol compliance. Low dynamic feature influence suggests an opportunity for process improvement such as introducing specific protocol checkpoints. Investigation of how hospital units differ may provide insights for improvement. Using machine learning to simulate interventions on modifiable factors may allow for a more rapid improvement in patient safety and quality. Further research is required to understand the applicability of findings to the clinical setting.

References:

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