Drug Prediction Model Interpretability One-Pager

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Background. Prescription drug abuse has been on the rise, and the prescription opioid epidemic has taken the lives of more than 14,000 people in 2019 in the US alone (CDC). Studies have investigated the increase in clinical usage of Black Box models used to predict addiction (Symons). However, clinical machine deep-learning systems need to have explanations for their outputs to gain trust from clinicians and to receive approval from the FDA. As such, interpretable models such as rule-based systems and parsimonious ML decision trees are the most useful in a clinical setting (Lee 2019).

Research Question. Which interpretable models are best for answering these questions in a **clinical** setting:

I. Opioid Abuse Prediction - Which groups of people are more likely to be addicted to illegal and legal opioids? What is the relationship between opioid prescriptions and opioid abuse?

II. Non-medical use (NMU) Prediction - Which patients are more likely to use prescription drugs outside of the doctors' prescription (i.e. prescription drug abuse)?

Methods. After cleaning the data and selecting relevant variables for our two research questions (variables are found in the appendix), we fit two interpretable models (decision tree classifier from sklearn and EBM from Microsoft's InterpretML) and one black box model (Random Forest from sklearn).

Results. Model Comparisons for one of Research Questions

Model Comparisons					
Question	Model	Accuracy	Sensitivty	Specificity	AUC
Opioid Abuse	DT	0.86	0.44	0.91	0.67
Opioid Abuse	EBM	0.91	0.36	0.98	0.67
Opioid Abuse	RF	0.90	0.32	0.98	0.65
NMU	DT	0.70	0.47	0.79	0.63
NMU	EBM	0.79	0.35	0.95	0.65
NMU	RF	0.79	0.35	0.95	0.65

Discussion. We've shown that interpretable models can be just as accurate as Black Box models in assessing and predicting both clinical and medical questions. However, we've found that these models are best used to answer questions about specific drug classes rather than drugs in general. One limitation to our data cleaning approach is that many variables were NaN because they were dependent on whether or not an earlier question was asked. For these questions, we imputed a "-1" for NaN. In the future, we plan on using a different method to dynamically impute these values, such as Multiple Imputation by Chained Equations or kNN (Păpăluță 2020). Next steps for this research is to try these methods on other countries and try other new interpretable models to predict, such as Additive Stumps and RiskSLIM.

Works Cited. Check out our appendix here: http://bit.ly/DataFestAppendix