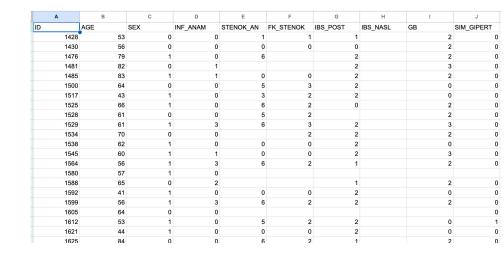
Predicting Lethal Outcome for Myocardial Infarction Patients

Jacob Weissman

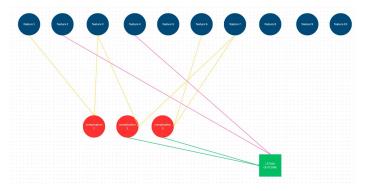
About the Dataset

- Myocardial infarction
- Features + Complications
- Lethal outcome: was cause of death myocardial infarction?
- Imbalance: 84.06% alive
 - stratified split



Project Goals

- Predict lethal outcome on day 3
 - o medical specialists can craft care plans and appropriately monitor patients to mitigate risk of death
- Scoring: **F1**
- Model type: random forest
- Incorporate complications data available during training ONLY



Preprocessing

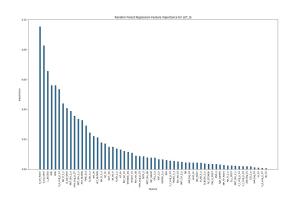
- Avoid data leakage!
- Convert lethal outcome to **binary** dead/alive



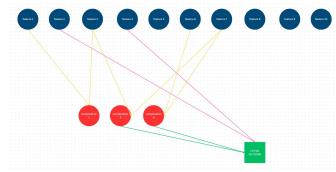
- Missing: compare single-median and KNN imputation
- Robust scaling for continuous numerical features

Feature Selection

- Perform separately for KNN and single-median imputations
- Perform for target 'lethal outcome' variable (pink arrows)
- Perform for each complication (yellow arrows)

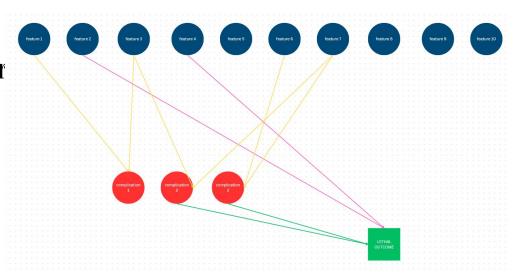


example model's random forest feature importance - elbow method was then used for each target/complication model



Complication Feature Selection

- Perform complication features
 selection (green arrows)
 - select only models with strong performance on holdout dataset

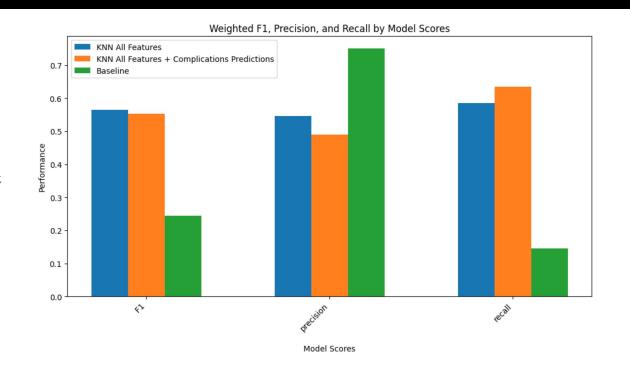


Final Results: Lethal Outcome

KNN All Features: highest performing on a validation dataset, without predictions

KNN All Features + Complications: highest performing on a validation dataset, with complication predictions

Baseline: single median imputation, no other preprocessing



(test dataset, full training)

Conclusions

- Feature selection unsuccessful
 - highest performing on validation and used for testing -> all features
 - o too few samples -> too much noise?
 - o small amounts of information?
- KNN > single-median
 - missing at random?
- Poor complication performance
 - o too few samples? ambiguous diagnoses?
- Predicting complications improved recall, is useful

Thank You!

Jacob Weissman