

Data Mining and Modeling Methods for Site Inspection Selection

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Disclaimer

This presentation reflects the views of the presenter and should not be construed to represent the United States Food and Drug Administration's views or policies.



Outline

- Motivation
- Objectives and background
- Data sets and structures
- Challenges
- Methods and their performance
- Other considerations



Motivation

- In a clinical trial setting, data reliability can be jeopardized by:
- Poorly Collected data
- \circ Poorly Processed data
- Poorly Reported data
- Tampered or Fraudulent data

The number and complexity of clinical trials have risen dramatically making it difficult for regulators to choose clinical sites for inspection



Objectives

To determine whether

- supervised data mining methods can be used to predict site inspection results
- unsupervised statistical monitoring

can be used to identify 'unusual' clinical sites for inspection (*ongoing work*)



Objectives

Onsite inspections help ensure the integrity of the clinical trials via source data verification

Due to limited resources only less than 1% of the sites can be inspected annually. It is therefore crucial to select the appropriate clinical sites



Data sets

Site inspection results can be classified into:

- NAI (No Action Indicated)
- VAI (Voluntary Action Indicated)
- OAI (Official Action Indicated)



Data sets

Clinical trial data and the results from clinical site Inspections

- Response
- can be:
- Ordinal with three distinct classes
 (OAI, VAI, NAI)

 Binary: 2 of 3 ordinal classes are suppressed to 1 (VAI, OAI) vs. NAI

Challenges (ordinal response)

Missing data

Assumptions: missing values are MAR and can be predicted by observed values

Random Forest (RF) imputation

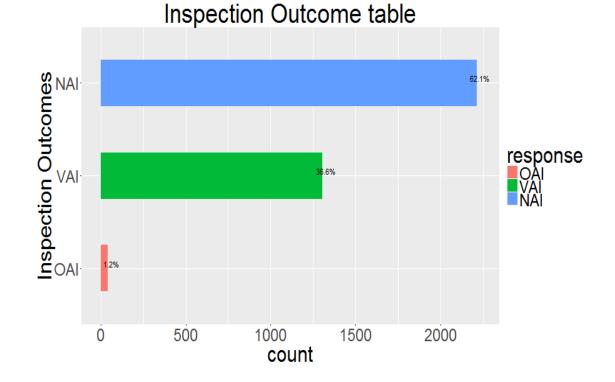
- Replace missing values with sample median
- Use RF to compute proximity between missing and non-missing samples
- o Repeat

Variable	Туре	% missing
Enrollment	continuous	
Site Specific Efficacy	continuous	27.7%
Protocol deviation	continuous	
NS adverse event	continuous	
% subject death	continuous	
Enroll/Screen %	continuous	
Subject discontinuation	continuous	
Number of INDs	continuous	
Financial disclosure	continuous	29.9%
Complaint history	Binary	
Time since last inspection	continuous	4.32%
OAI history	Binary	



Challenges (ordinal response)

Imbalanced outcomes-OAI classification is a rare event with only 1% of sites being classified as OAI





Challenges (ordinal response)

Synthetic Minority Over-Sampling Technique-SMOTE

- Generate synthetic samples for the minority class
- Input the number of nearest neighbors, k, T minority class samples and size of SMOTE, N
- Output is the synthetic minority class samples

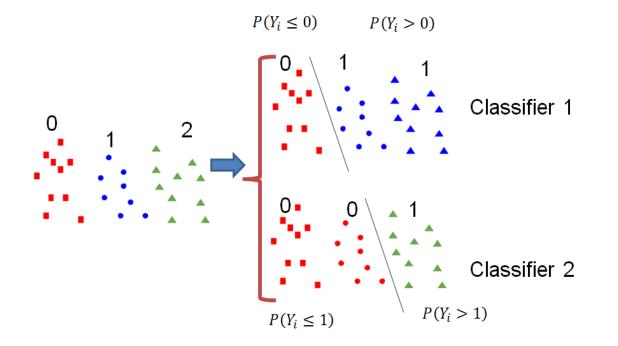


Statistical methods (ordinal response)

- Ordinal regression
- Combined binary classifiers
- Random forests
- \odot Boosted trees

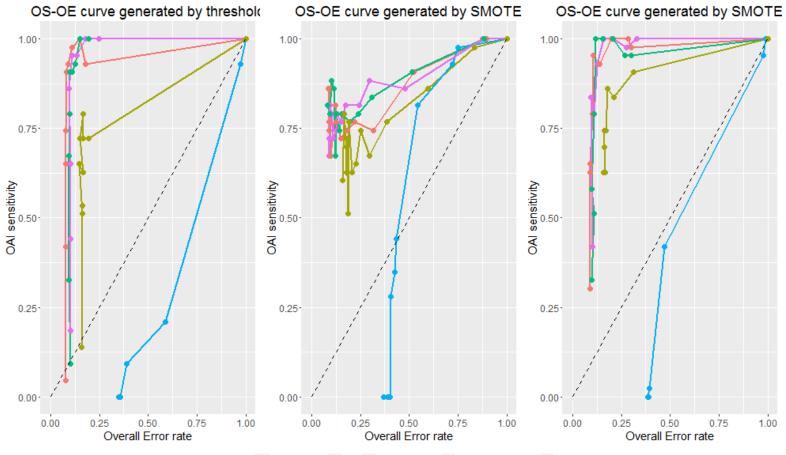
Combined binary classifier

Convert an ordinal regression problem into nested binary classification problems by splitting the data into groups $Y_i \leq j$ and $Y_i > j$ and a binary probability classifier to estimate the probabilities $P(Y_i \leq j)$ and $P(Y_i > j)$





Classifier performance



method 🔸 Boosted tree 🔸 C50 🔸 Combined-RF 🔸 Ordinal regression 🔸 RF



Statistical methods (binary response)

- Random Forest
- Boosted Tree
- Boosted Dropout

(As boosting is susceptible to overfitting-high bias, low variance)

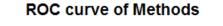


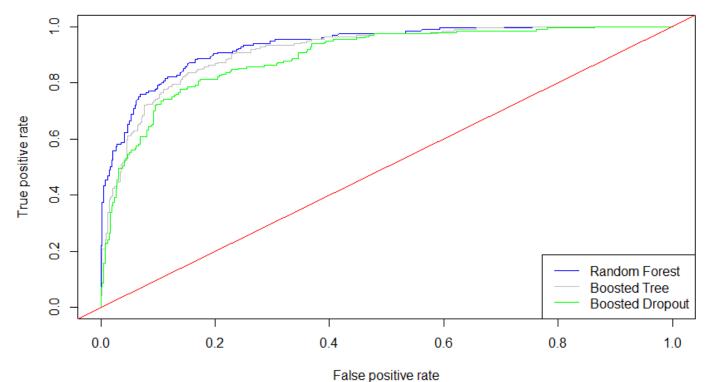
Challenges (binary response)

- Studying the sensitivity of each variable to predict the outcome
- \odot Using the EM-algorithm to impute missing data
- Using 5-fold cross-validation to assess model performance



Classifier Performance





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Model performance

Method	CV error	Misclassification
RF	13.5%	14.0%
Boosted Tree	15.9%	14.9%
Boosted Tree with Dropout	16.9%	16.4%



Outcome

R-Shiny application that uses the supervised learning methods and

- Predicts the potentially fraudulent cases from different clinical sites
- \odot Validates the parameter that gives the best fit
- Detects the covariates that are most predictive of the outcomes





Cooperative Research and Development Agreement with CluePoints

The main objective is to detect atypical sites in a multicenter study

Method tests the distribution of data in one center with data in other centers and produces a p-value demonstrating how unlikely the outcomes from one clinical center are (unsupervised approach)

Approaching the end of 2nd year is a 3 year agreement



References

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, *16*, 321-357.

Rashmi, K. V., & Gilad-Bachrach, R. (2015, May). Dart: Dropouts meet multiple additive regression trees. In *International Conference on Artificial Intelligence and Statistics*(pp. 489-497).



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Thank you!

