|  |  |  |
| --- | --- | --- |
| Model | Strategy for missing values | Best parameters tuned by 5-fold CV |
| XGBoost | To learn the splitting directions for samples with missing values based on the minimization of training loss [1] | max\_depth = 5  eta = 0.3  subsample = 1  colsample\_bytree = 0.8 |
| BART | To incorporate missingness by augmenting the nodes’ splitting rules to (a) use missingness itself as a variable to be considered in a splitting rule and (b) also handle sorting the missing data to the left or right [2] | k = 1  num\_trees = 150  prob\_rule\_class = 0.2 |
| Random Forest | To conduct split in a node, the algorithm imputes missing values by drawing randomly from the set of nonmissing in-bag data within the current node [3] | mtry = 2  nodesize = 5  splitrule = “gini”  sampprop = 0.8 |
| Conditional random forest | Splits are determined by only observed variables; then at one node, to pass down observations missing that variable, the algorithm considers surrogate splits. As an example, assume that the split (age < 40, age >= 40) has been chosen. The surrogate variables are found by re-applying the partitioning algorithm (without recursion) to predict the two categories “age <40” vs “age >=40” using the other independent variables. [4] | mtry = 5  maxsurrogate = 0 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | AUC | Sensitivity | Specificity | PPV | NPV |
| Training data (threshold) | | | | | |
| XGBoost  (0.312) | 1.000  (0.998,1.000) | 1.000  (0.877,1.000) | 0.989  (0.940,1.000) | 0.966  (0.822,0.999) | 1.000  (0.959,1.000) |
| BART  (0.312) | 0.983  (0.955,0.999) | 0.964  (0.817,0.999) | 0.944  (0.875,0.982) | 0.844  (0.672,0.947) | 0.988  (0.937,1.000) |
| Random Forest  (0.303) | 0.992  (0.979,1.000) | 1.000  (0.877,1.000) | 0.956  (0.890,0.988) | 0.875  (0.710,0.965) | 1.000  (0.958,1.000) |
| Conditional Random Forest  (0.230) | 0.914  (0.856,0.957) | 0.964  (0.817,0.999) | 0.722  (0.618,0.811) | 0.519  (0.376,0.660) | 0.985  (0.918,1.000) |
| Test data | | | | | |
| XGBoost | 0.767  (0.603,0.895) | 0.455  (0.167,0.766) | 0.789  (0.627,0.904) | 0.385  (0.139,0.684) | 0.833  (0.672,0.936) |
| BART | 0.746  (0.567,0.900) | 0.545  (0.234,0.833) | 0.842  (0.687,0.940) | 0.500  (0.211,0.789) | 0.865  (0.712, 0.955) |
| Random Forest | 0.847  (0.711,0.950) | 0.727  (0.390,0.940) | 0.763  (0.598,0.886) | 0.471  (0.230,0.722) | 0.906  (0.750,0.980) |
| Conditional Random Forest | 0.806  (0.639,0.947) | 0.818  (0.482,0.977) | 0.684  (0.513,0.825) | 0.429  (0.218,0.660) | 0.929  (0.765,0.991) |

An optimal threshold is determined based on the ROC curve estimated with the training data, such that the summation of sensitivity and specificity is the largest at the threshold [5]. This is because Youden Index = sensitivity + specificity – 1.

Reference

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