Group 14

TEXAS The University of Texas at Austin

PREDICTING ALZHEIMER'S DISEASE

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Agenda

- Introduction and Exploratory Data Analysis
- KNN
- Logistic regression
- Trees (Bagging and boosting)
- Conclusion and reflection



Alzheimer's Disease Dataset

- From Kaggle
- 2,149 patient observations and 35 columns
- Target variable: Alzheimer's diagnosis (Yes/No)
- Data mildly imbalanced

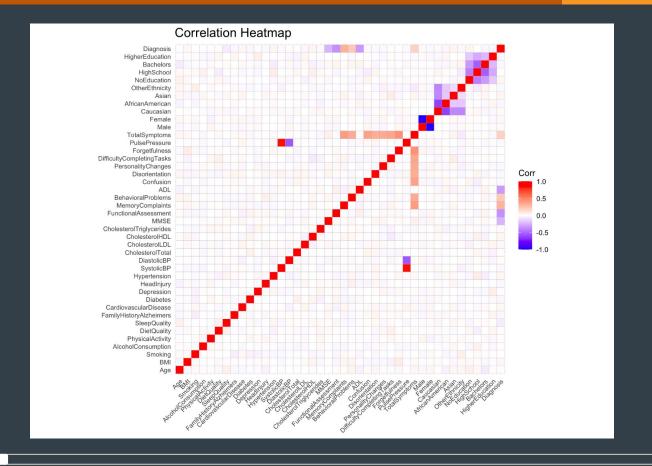




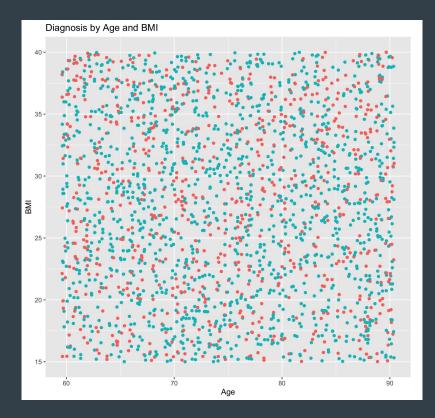
Feature Engineering

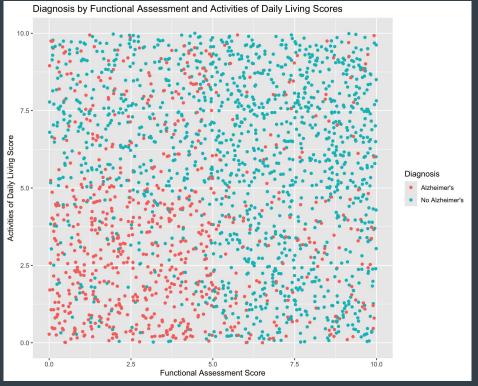
- Made two new predictor variables
 - Pulse Pressure
 - Total Symptoms
- One hot encoding
 - Gender
 - Ethnicity
 - Education Level



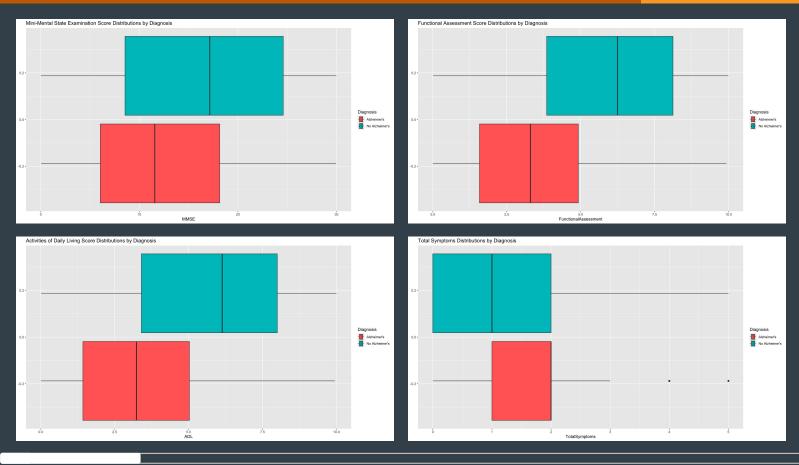








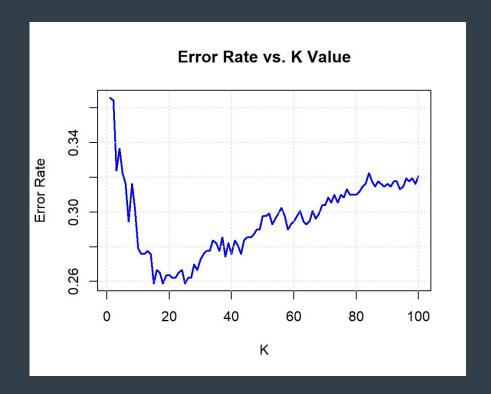






KNN

- Utilized all features
- Seed = 1k = 24





KNN Performance

Confusion Matrix

Accuracy: 73%

		Test Data	
		YES	No
Prediction	YES	262	112
	No	6	50



Logistic Regression

Methods

- All predictors
- All statistically significant predictors
- Lasso
- Ridge
- Stepwise



Logistic Regression

- Use the following predictors:
 - MMSE
 - Functional Assessment
 - Memory Complaints
 - Behavioral Problems
 - ADL
- Threshold = 0.5



```
Deviance Residuals:
##
       Min
                 10 Median
                                   3Q
                                           Max
  -0.95553 -0.27230 -0.04281 0.26716 1.14373
##
  Coefficients:
##
                       Estimate Std. Error t value Pr(>|t|)
                    0.9694298  0.0267783  36.20  <2e-16 ***
  (Intercept)
  MMSE
                     -0.0142408 0.0009952 -14.31 <2e-16 ***
## FunctionalAssessment -0.0536886
                                 0.0029883 -17.97 <2e-16 ***
## MemoryComplaints 0.3343039
                                 0.0214397 15.59 <2e-16 ***
  BehavioralProblems 0.3368824
                                 0.0235439 14.31 <2e-16 ***
                     -0.0523070 0.0029245 -17.89 <2e-16 ***
## ADL
##
  Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

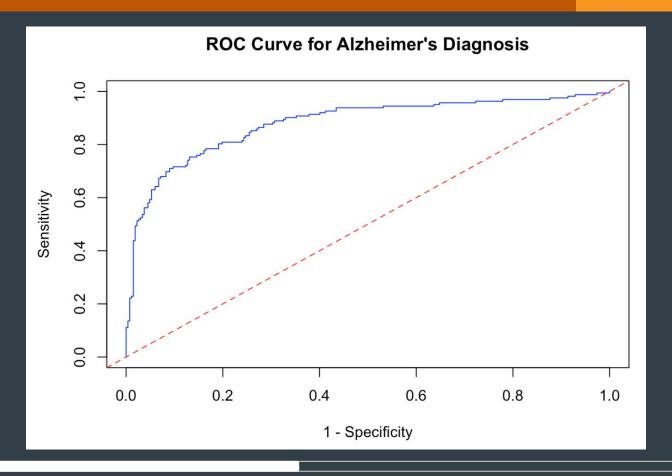


Logistic Performance

Accuracy = ~83%

		Test Data	
		YES	No
Prediction	YES	110	21
	No	52	246





AUC = 87.89%



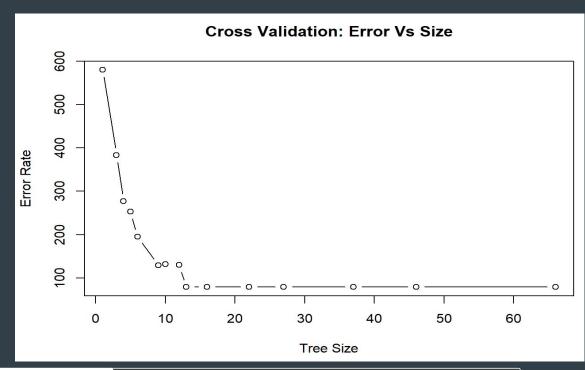
Trees

- A Classification Tree
- Random Forest
- Bagging
- Boosting

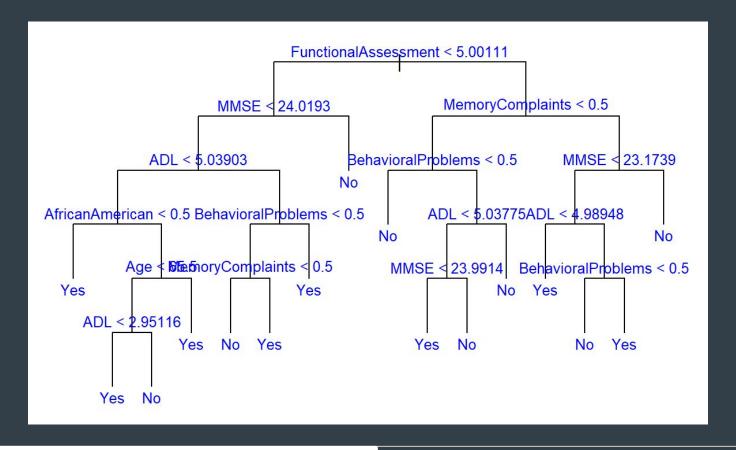


Classification Tree

Grow & Prune method









Tree Performance

Accuracy = ~94%

Pruned Tree		Test Data	
		YES	No
Prediction	YES	145	9
	No	17	259

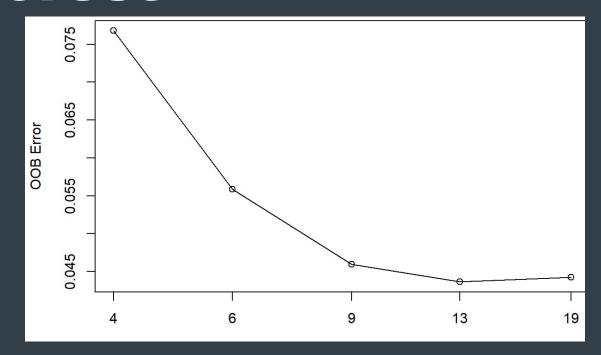


Random Forest

• RFM1: mtry = 6

mtry tuning

• ntrees = 500





Feature Importance

Mean Decrease Accuracy

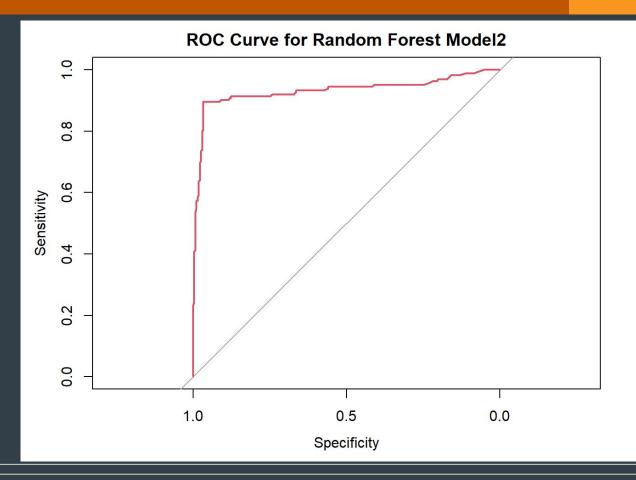
Mean Decrease Gini



RF Performance Accuracy = 95.6%*

RF		Test Data	
		YES	No
Prediction	YES	549	49
	No	27	1094







Bagging

- Cross-validation
- folds = 5



Bagging Feature Importance

ADL

FunctionalAssessment

MMSE

MemoryComplaints

BehavioralProblems

SleepQuality

MMSE

FunctionalAssessment

ADL

MemoryComplaints

MemoryComplaints

BehavioralProblems

O

DietQuality

ChalacteralUDL

O

ChalacteralUD

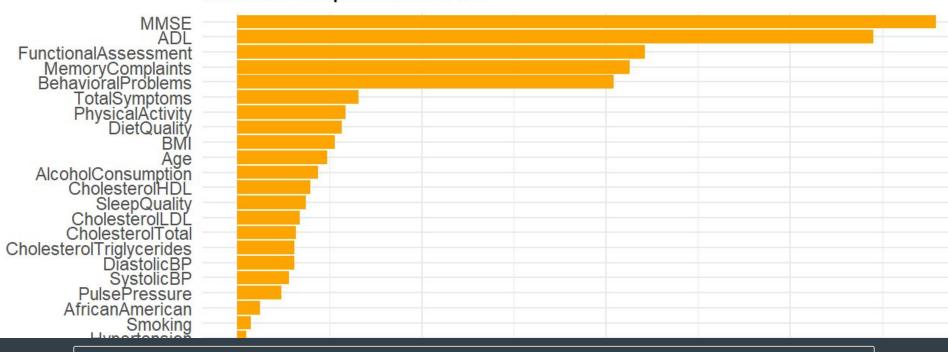
Mean Decrease Accuracy

Mean Decrease Gini



Bagging

Variable Importance Plot



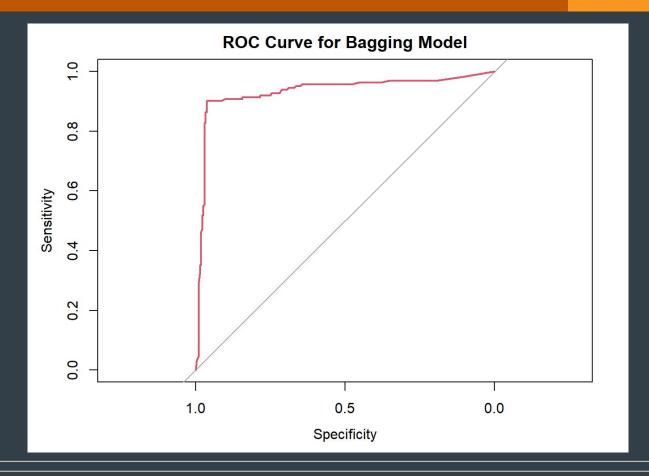


Bagging Performance

Accuracy = 92.6%

Bagging with CV		Test Data	
		YES	No
Prediction	YES	141	11
	No	21	257

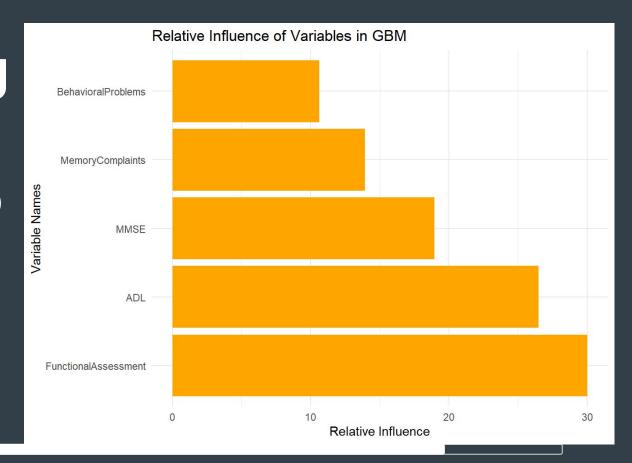






Boosting

- cv =10
- n.trees = 500



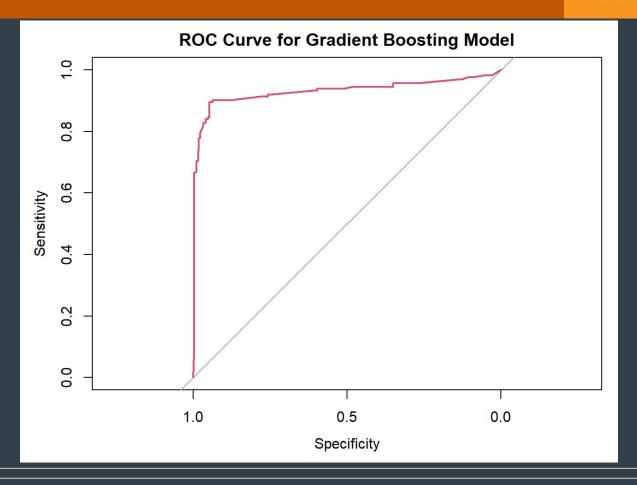


Boosting

Accuracy = 91.2%

Boosting with CV		Test Data	
		YES	No
Prediction	YES	133	29
	No	9	259







Conclusion

- Best model: Random Forest
- High accuracy (95.6%)
- Robustness
 - Sensitivity: 95.31%
 - Specificity: 95.71%
 - Good for imbalanced data



Reflection

- Identifying causes/outcome relationships
 - Feature engineering
 - Correlation analysis
- Evaluation metrics
 - Opportunity cost for 'False positive' vs 'False negative'

Descriptive
Analysis

Diagnostics
Analysis

Predictive
Analysis

Prescriptive
Analysis

Analysis



Questions?