Machine Learning Applied to Hepatocellular Carcinoma

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Section 1

Background HCC

HepatoCellular Carcinoma (HCC)

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- Data mining approach to tailor evaluation and treatment for HCC are limited in the literature.
- Using the HCC dataset, we undertook the data mining approach to evaluate the patient level factors to identify those who are at risk of one year mortality.

Section 2

Data Summary

Data Summary

- Clinical data of 165 pts with HCC (demographic, risk factors, lab data, and survival features)
- 49 features from HCC clinical practice guidelines (Table 1)
- About 80
- Missing data represents 10.22
- The target variable is the survival at 1 year, coded as 0 (dies) and 1 (lives).

Section 3

Data Summary

Data Summary

Table 1: Table 1. HCC Data Summary

	Overall (N=165)
gender	
female	32 (19.4%)
male	133 (80.6%)
symptom	
no	53 (36.1%)
yes	94 (63.9%)
N-Miss	18
alc	
no	43 (26.1%)
yes	122 (73.9%)

Section 4

Random Forest Model

Description

- Tree model

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- hyperparameters tuned by Bayesian Optimization
- KNN imputation

Estimated Performance

Calibration Plots

Variable Importance

Partial Dependence

Section 5

XGBoost Model

Description I

Input: training set $\{(x_i, y_i)\}_{i=1}^N$, a differentiable loss function $L(y, F(x))$, a number of weak learners M and a learning rate α.
Algorithm:

1. Initialize model with a constant value: $\hat{f}_{(0)}(x) = argmin_\theta \sum_{i=1}^N L(y_i, \theta)$.
2. For $m = 1, ..., M$:
   a. Compute gradients and hessians:
   $$\hat{g}_m(x_i) = \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=\hat{f}_{m-1}(x)}$$
   $$\hat{h}_m(x_i) = \left[\frac{\partial^2 L(y_i, f(x_i))}{\partial f(x_i)^2}\right]_{f(x)=\hat{f}_{m-1}(x)}.$$
   b. Fit a base leanrer using the training set $\left\{x_i, -\frac{\hat{g}_m(x_i)}{\hat{h}_m(x_i)}\right\}_{i=1}^N$ by solving the optimization problem below:
   $$\hat{\phi}_m = argmin_{\phi \in \Phi} \sum_{i=1}^N \frac{1}{2}\hat{h}_m(x_i)\left[-\frac{\hat{g}_m(x_i)}{\hat{h}_m(x_i)} - \phi(x_i)\right]^2.$$

Description II

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- put some advantages and disadvantages here

Estimated Performance I

Metric	KNN_none	KNN_corr	KNN_pca	MeanMode_none
Brier	0.2212310	0.2109347	0.2385479	0.2061546
Accuracy	0.7011029	0.7015114	0.6848039	0.6965686
Kappa	0.3566100	0.3636247	0.3306148	0.3405815
ROC AUC	0.7524242	0.7661255	0.7249567	0.7835931
Sensitivity	0.7736364	0.7736364	0.7427273	0.7827273
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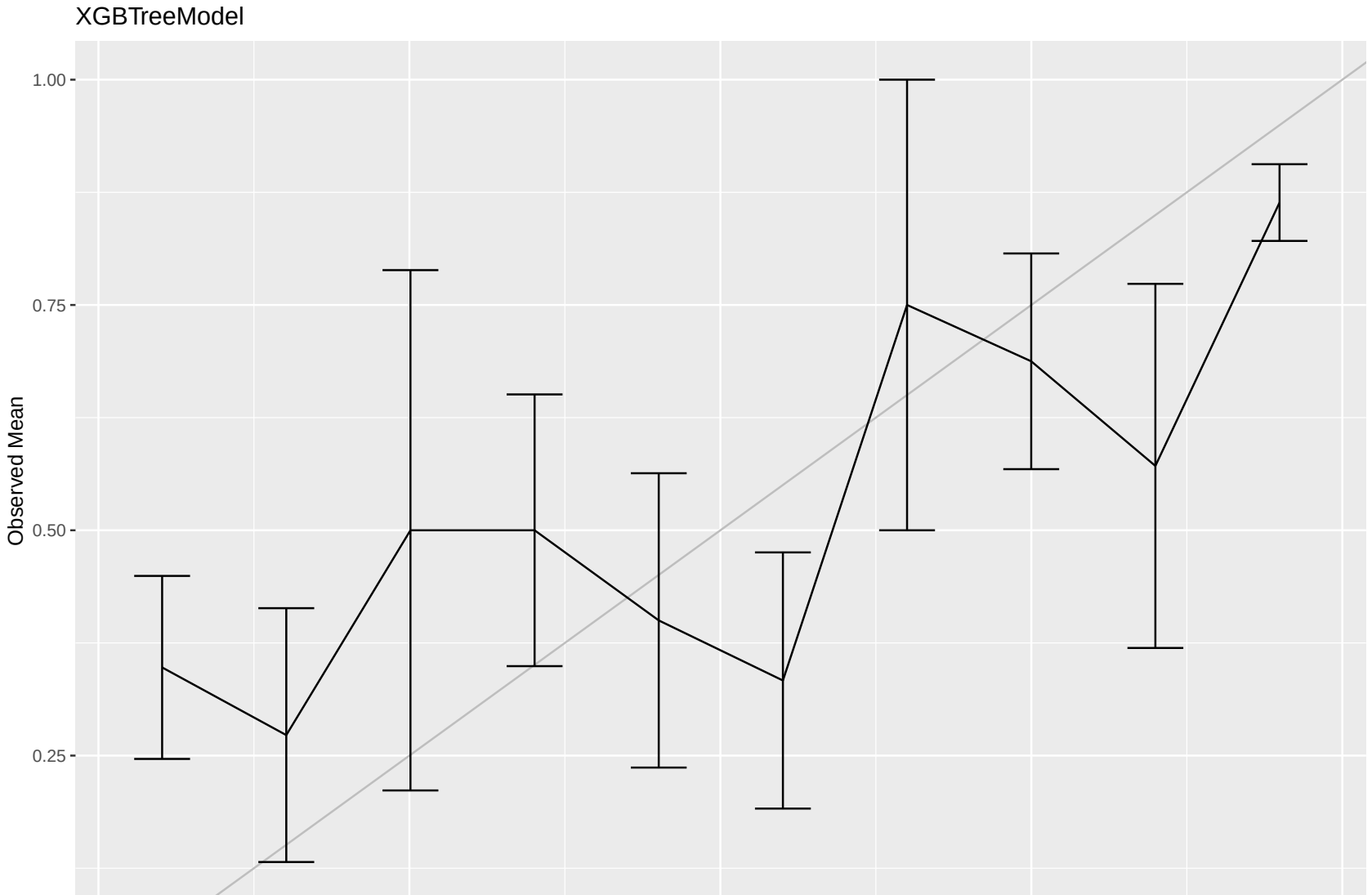
- KNN_corr appears to do better among these models for its highest accuracy, highest kappa, reasonable brier, roc auc, sensitivity and specificity.
- p-values are not significant.

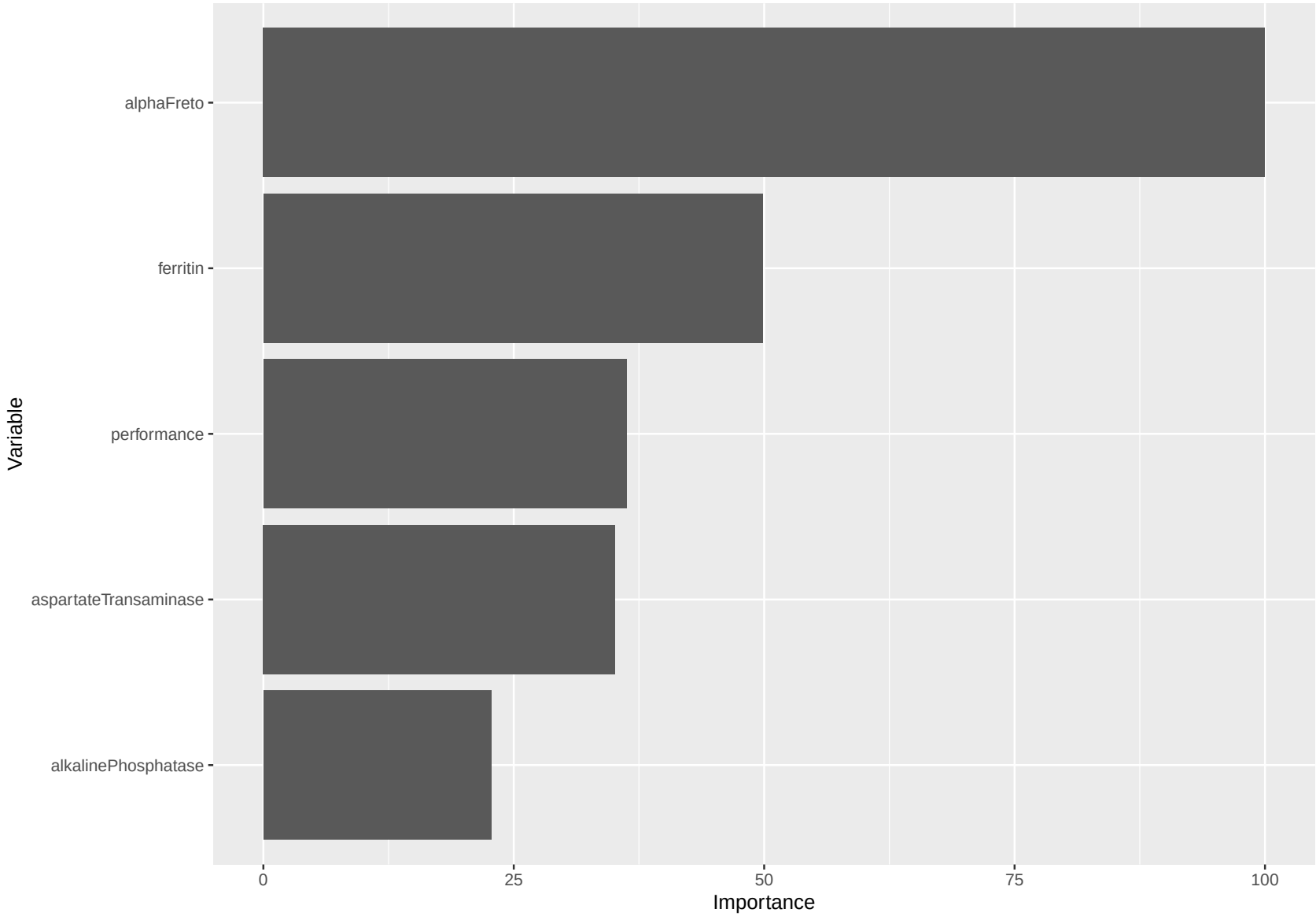
Estimated Performance II

Calibration Plots

```
## $XGBTreeModel
```



Variable Importance



Partial Dependence

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## $alphaFreto
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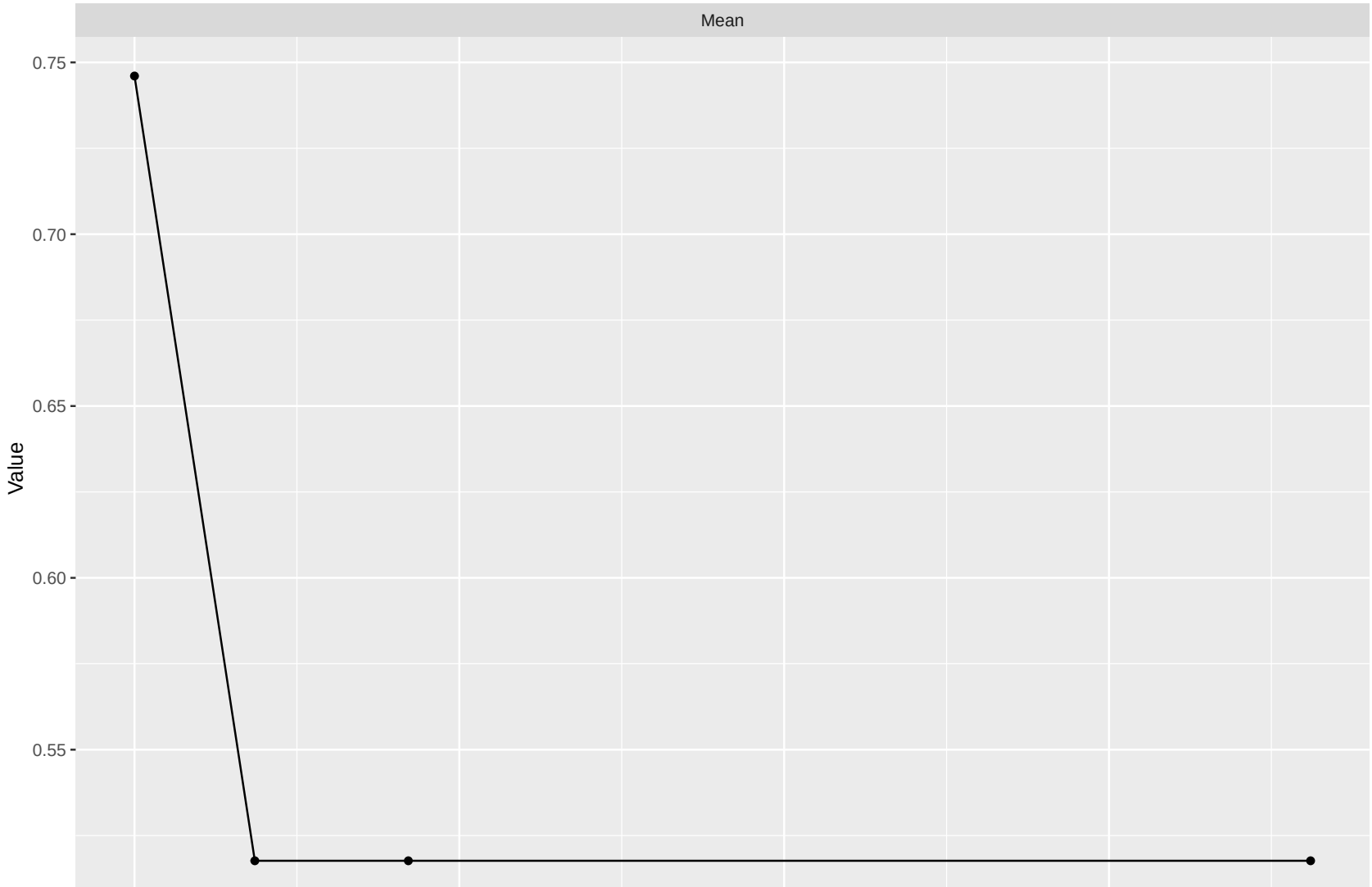

Section 6

Support Vector Machine Model

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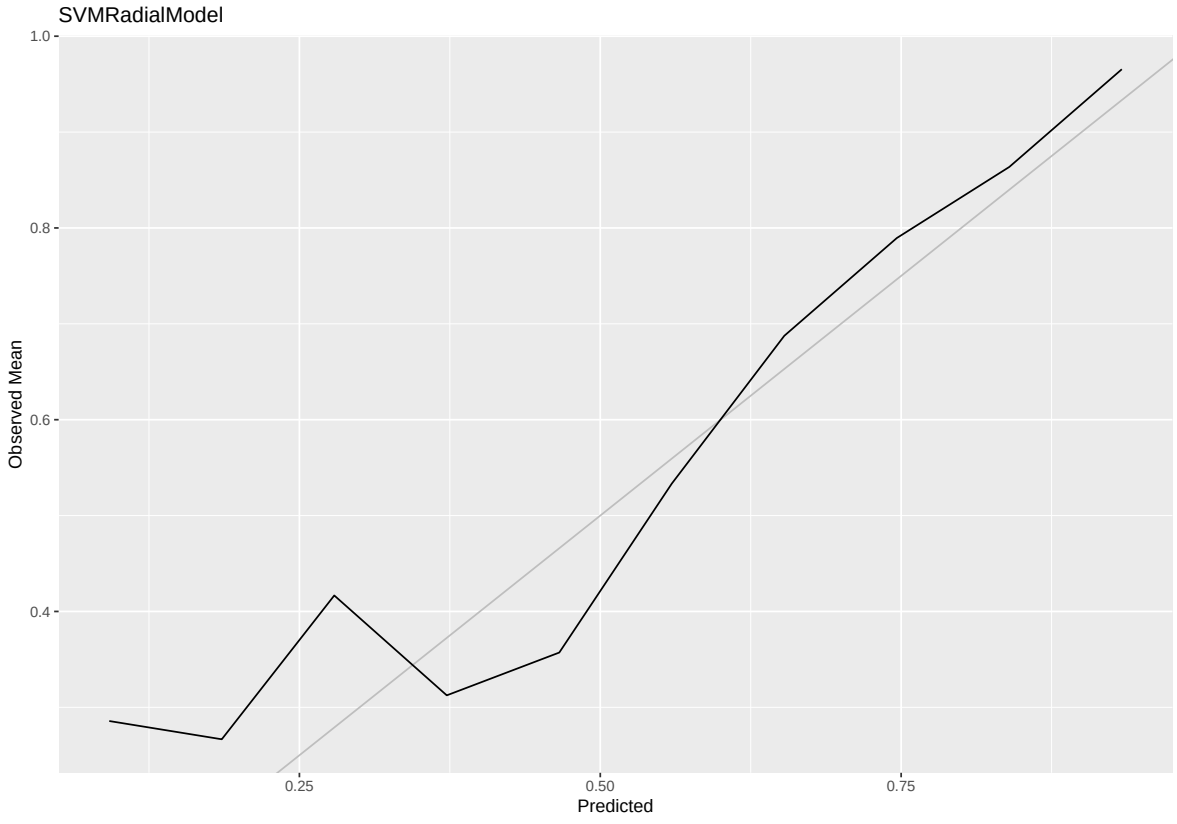
- Cost of misclassification C =0.8956493
- imputation using knn with neighbors = 4

Estimated Performance

Table 2: SVMRad results with knn imputation

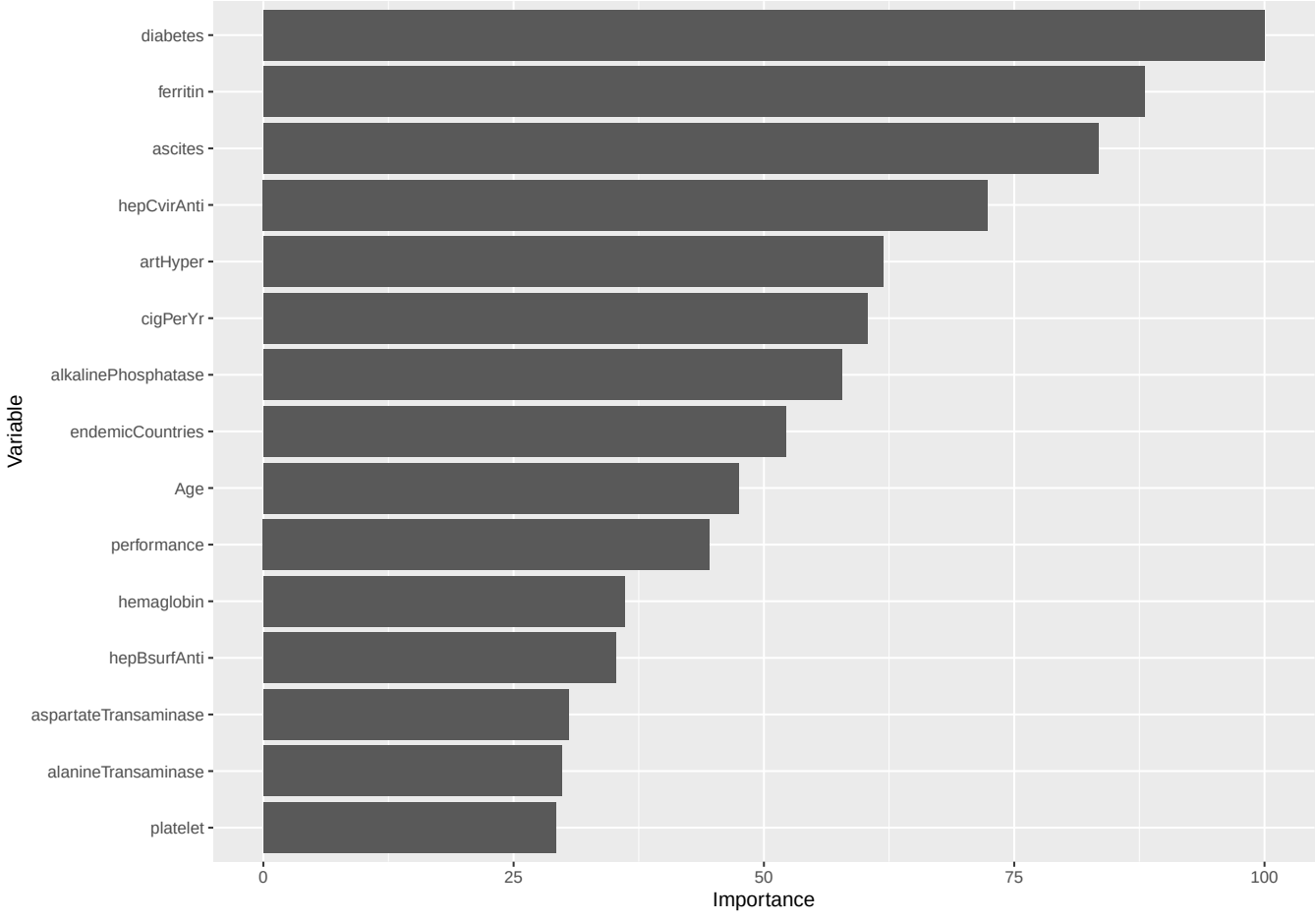
Metric	Mean	Median	SD	Min	Max	NA
Brier	0.176	0.166	0.057	0.101	0.287	0
Accuracy	0.756	0.764	0.119	0.562	0.938	0
Kappa	0.482	0.503	0.254	0.097	0.871	0
ROC AUC	0.818	0.829	0.101	0.600	0.967	0
Sensitivity	0.803	0.809	0.107	0.600	0.909	0
Specificity	0.681	0.643	0.190	0.500	1.000	0

Calibration Plots



- Decently calibrated. Low probabilities have many false negatives.

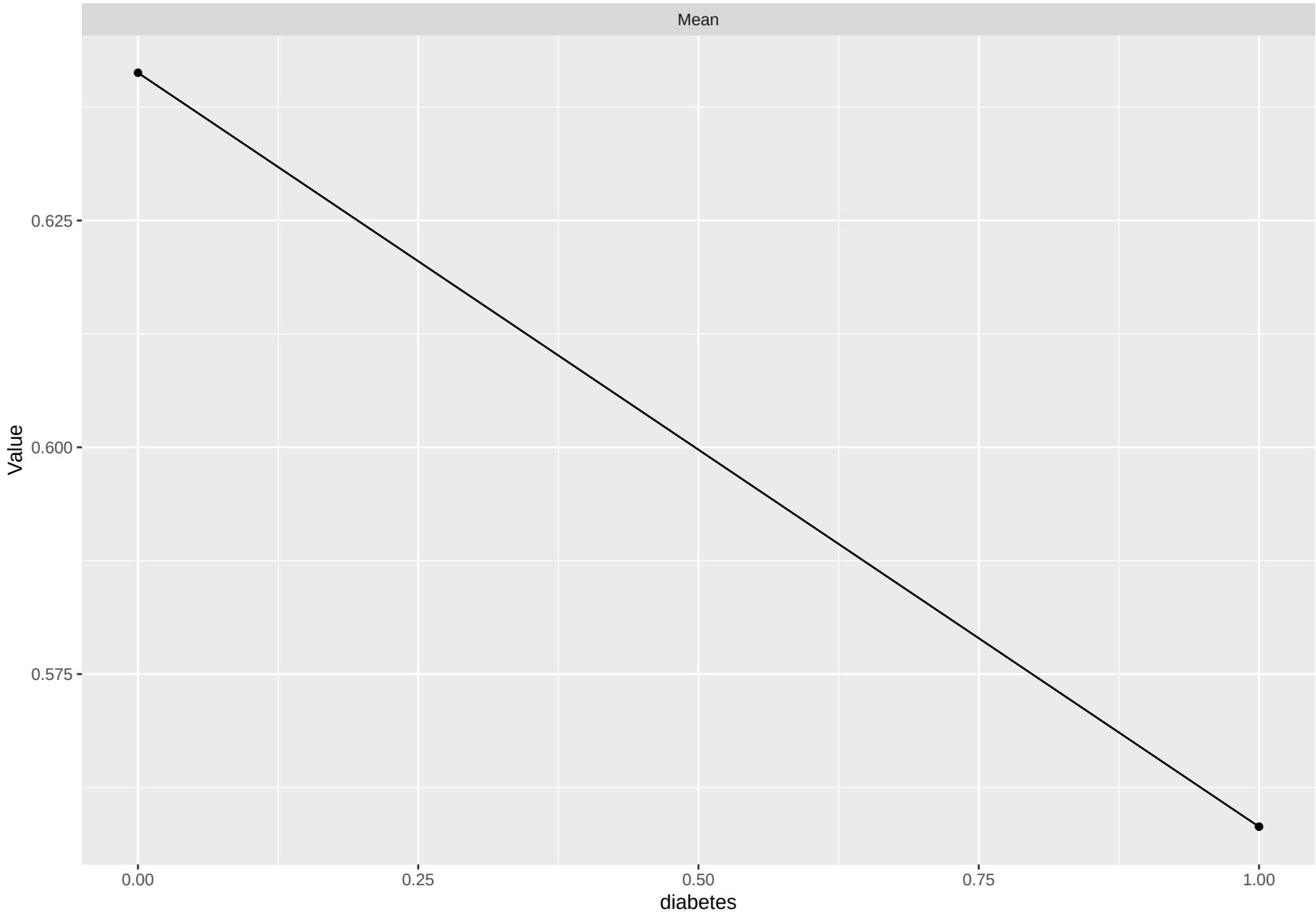
Variable Importance



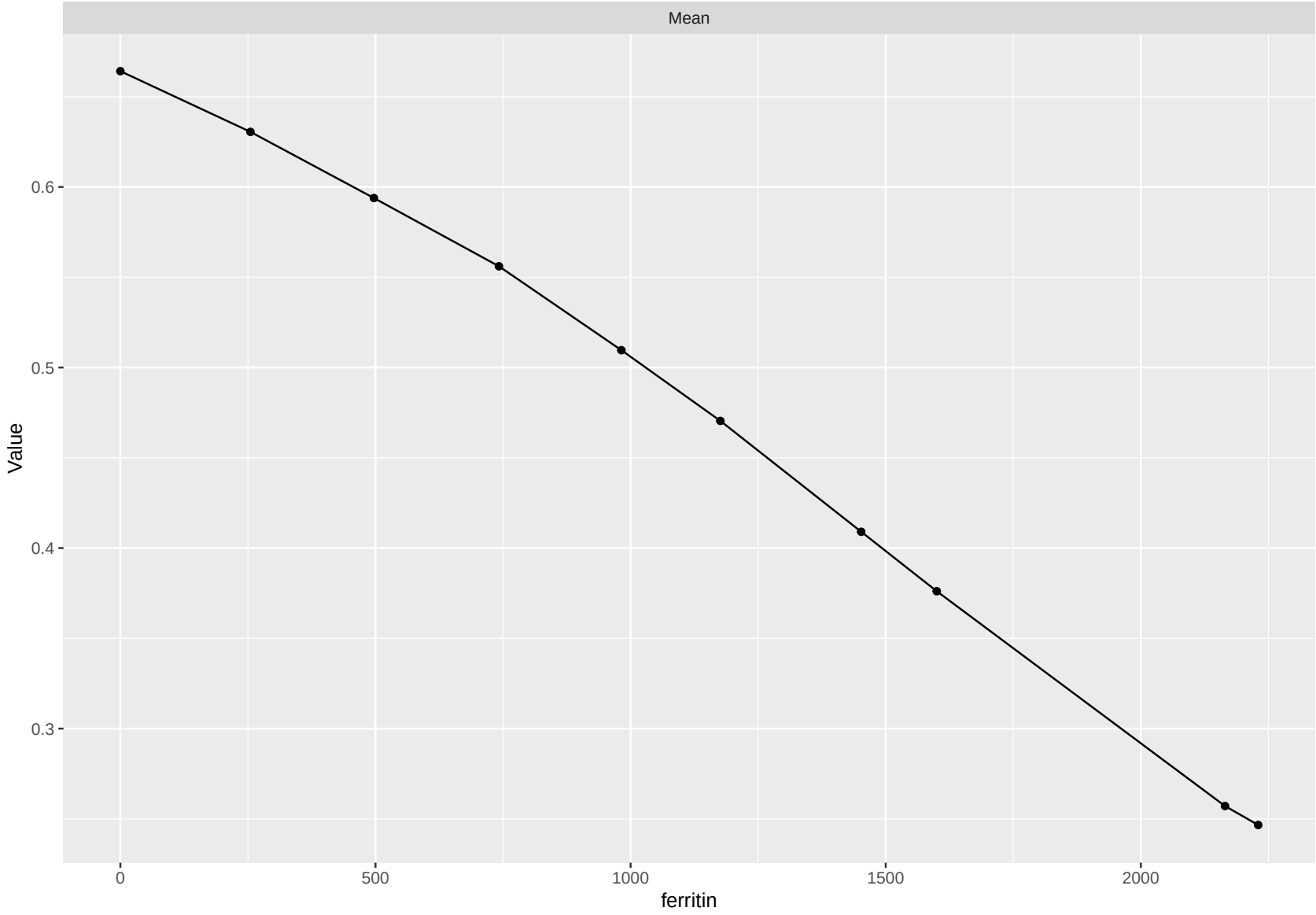
Variable Importance

- Symptoms (performance)
- Indicators of liver injury/disease/infection (hepBsurfAnti, hepCvirAnti,aspartateTransaminase, alkalinePhosphatase, ferritin, totalProteins, ascites, hemoglobin)
- Biological Characteristics (age, portalVeinThromb)
- Risk factors (diabetes, artHyper)
- behavioral/demographic (endemicCountries, cigPerYr)

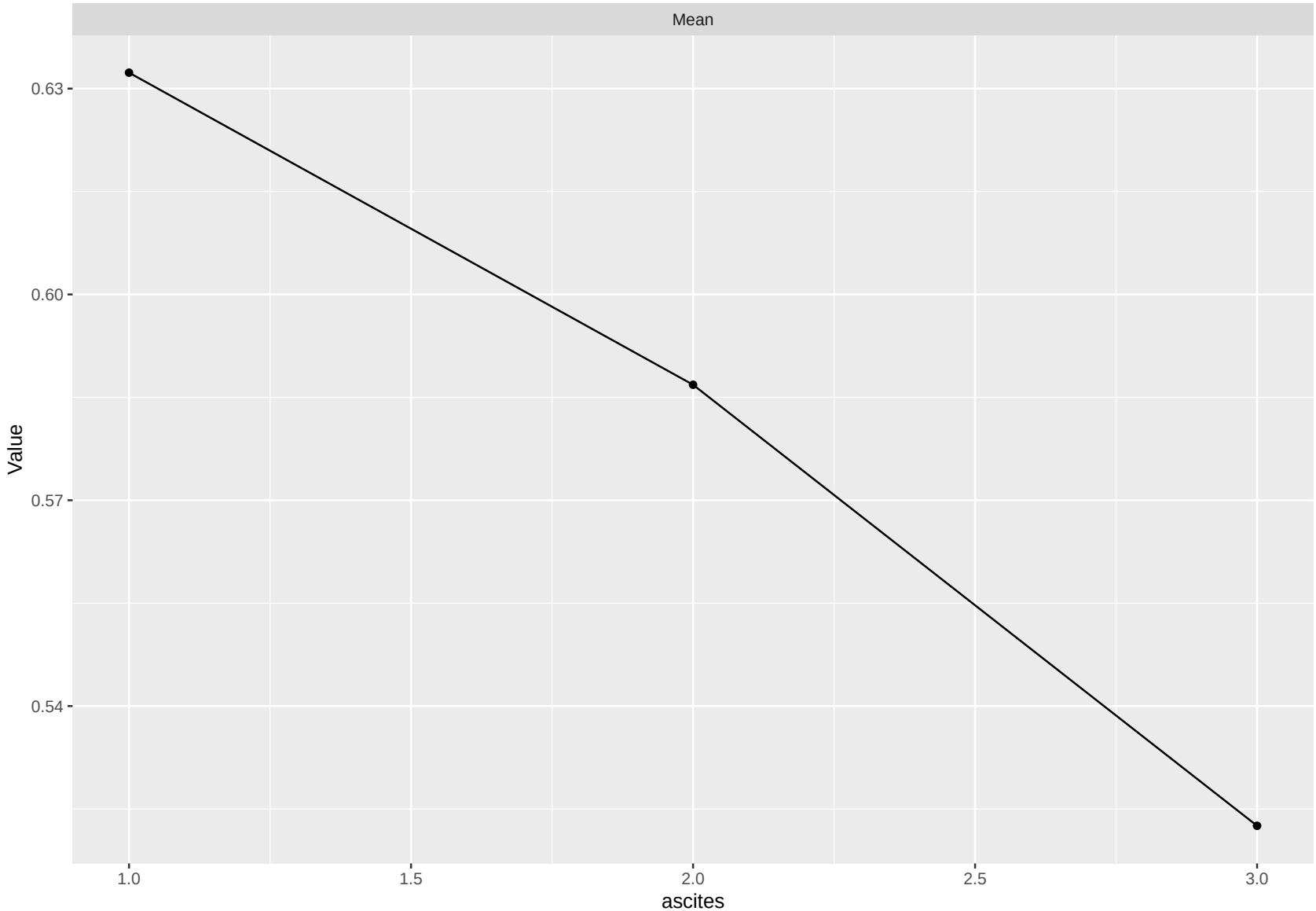
Partial Dependence: diabetes



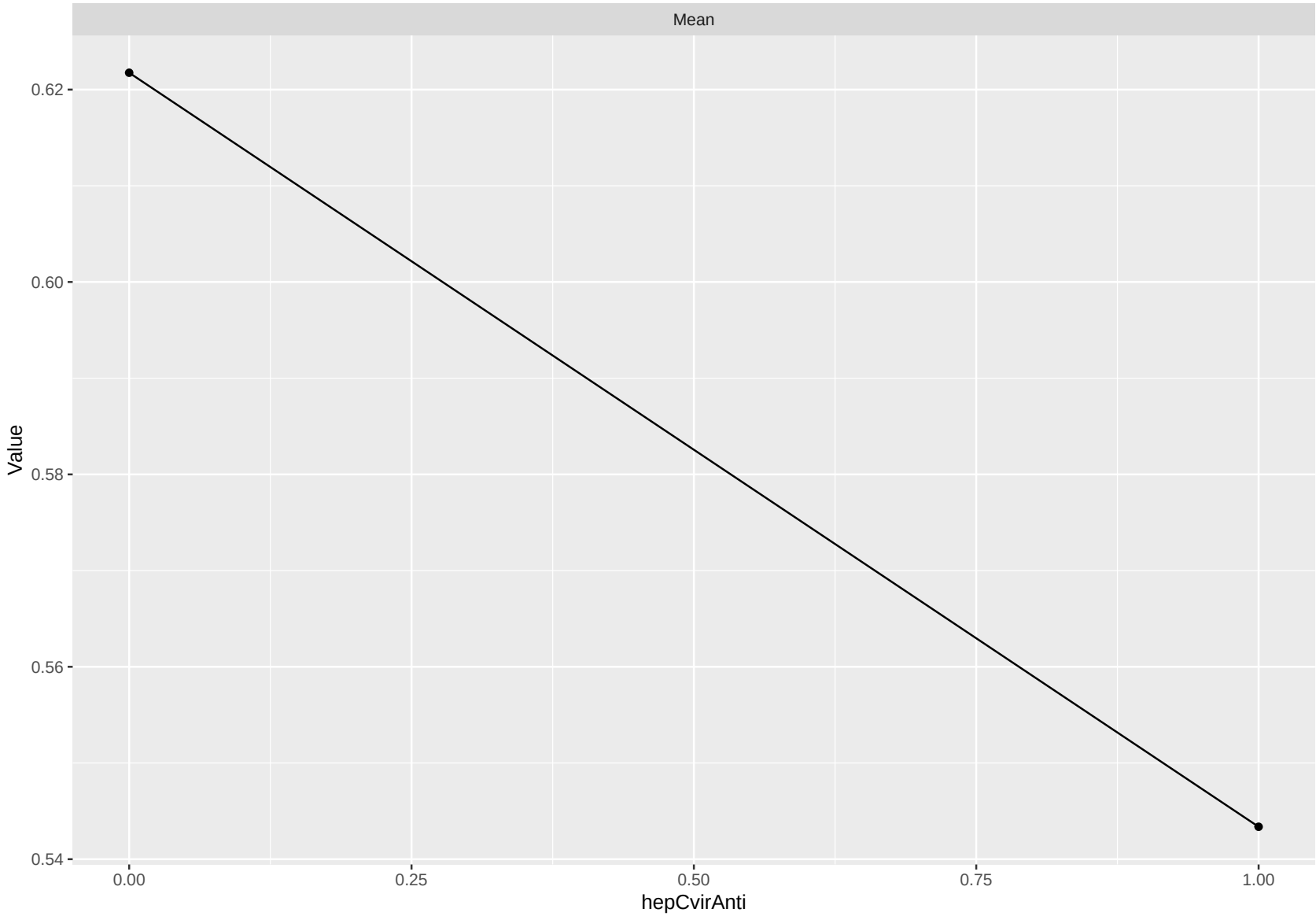
Partial Dependence: ferritin



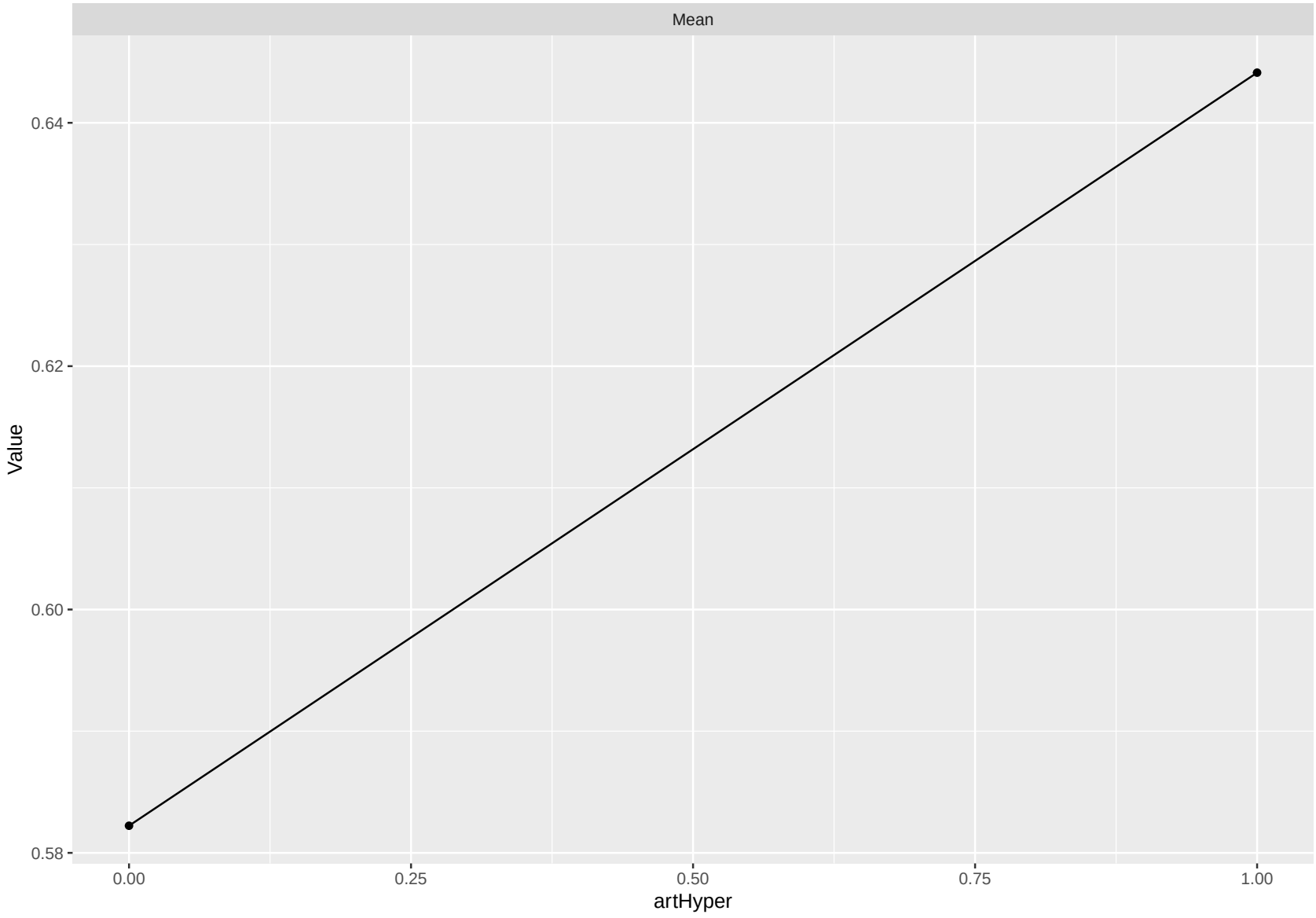
Partial Dependence ascites



Partial Dependence: artHyper



Partial Dependence: symptom



Section 7

Final Model

Final Model

- Final model was chosen by the model with the highest Sensitivity - 2SD

Section 8

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