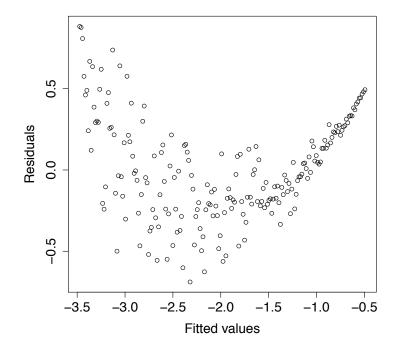
Sample Exam Questions

Instruction: Check the boxes next to the right answers. There can be **zero to four** correct answers to each question.

- 1. For linear regression, the residual plot below indicates that
 - \square The errors have non-constant variance but the linear assumption is correct.
 - ☐ The errors have non-constant variance and the linear assumption is wrong.
 - \square The linear assumption is correct and the errors have constant variance.
 - \square The linear assumption is wrong and the errors have constant variance.



- 2. Interaction/synergy effect of two predictors x_1 and x_2 in regression
 - \square May be incorporated by including a term of the form βx_1^2 .
 - \square May be incorporated by including a term of the form $\beta x_1 x_2$.
 - \square May be incorporated by including a term of the form $\beta(x_1 + x_2)$.
 - ☐ May be incorporated by using a Generalized Additive Model (GAM) of the form

$$y = \beta_0 + f_1(x_1) + f_2(x_2)$$

.

3. Running a linear regression in **R** and applying the summary function we get the following output

Call:

 $lm(formula = y ~ x + I(x^2))$

Residuals:

Min 1Q Median 30 Max -2.31384 -0.67054 0.01942 0.62198 2.35304

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.01030 0.06014 -0.171 0.864
        I(x^2)
       0.07300 0.08409 0.868 0.387
```

Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 '' 1

Residual standard error: 0.3079 on 97 degrees of freedom Multiple R-squared: 0.8892, Adjusted R-squared: 0.8881 F-statistic: 790.8 on 2 and 97 DF, p-value: < 2.2e-16

Based on this output we can say that

- \Box The predictor x can be dropped from the linear model since it does not help to predict the response in the presence of the second predictor.
- \Box The predictor x^2 can be dropped from the linear model since it does not help to predict the response in the presence of the first predictor.
- \Box Both the predictors x and x^2 can be dropped from the linear model since they have no relationship with the response.
- 4. The logistic regression model

$$Prob(Y = 1 | X_1, \dots, X_p) = \frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}},$$

- □ always produces a linear decision boundary.
- \square can be applied to a classification problem with two classes.
- \square cannot be fitted to a dataset in which the observations in different classes are not linearly separable.
- \square will become less flexible if some coefficients β_i are forced to be zero.
- 5. Which of the following are true for the k Nearest Neighbor approach to classification?
 - \square If we increase k, then it is more likely to overfit.
 - \square We should choose k to minimize the training error.
 - \square It does not apply to a 3-class problem if k < 3.
- **6.** Which of the following are true for cross-validation?
 - \square It produces an estimate of the test error.
 - ☐ It can be used to choose the value of a tuning parameter for a classification method.

| ☐ For supervised learning problems, it can be used to select a model from several candidate models with different degrees of flexibility. |
|--|
| \square It can be used to choose the degrees of freedom of a cubic spline in a regression problem. |
| 7. Using k -fold cross validation with a dataset of size $n = 100$ to select the value of the budget parameter C in a support vector classifier |
| \Box does not make sense since we should always set $C=0$ to obtain a separating hyperplane. |
| \square might give different answers depending on the random splitting. \square is equivalent to Leave-One-Out Cross Validation when $k=1$. |
| \square is equivalent to be ave-one-out cross validation when $n-1$. |
| 8. Comparing the subset S_1 of predictors selected by Lasso and the subset S_2 selected by Best Subser Selection using AIC (on the same dataset), |
| \square We always have \mathcal{S}_1 being a subset of \mathcal{S}_2 . |
| \square We always have $\mathcal{S}_1 = \mathcal{S}_2$. |
| \square A linear model fitted using the predictors in \mathcal{S}_1 will always have higher (or equal) training error than \mathcal{S}_2 . |
| \square A linear model fitted using the predictors in \mathcal{S}_1 will always have higher (or equal) test error than \mathcal{S}_2 . |
| 9. Consider Lasso and Ridge Regression. |
| We should use Ridge Regression if we want to select a subset of predictors. They always produce the same coefficient estimates if the same tuning parameter λ are used. If λ > 0, then they correspond to less flexible models compared to the model fitted using the least squares approach. |
| |
| 10. Which of the following oparations will typically increase the flexibility of a model? |
| \Box Increasing the parameter λ in a smoothing spline. |
| ☐ Increasing the number of knots in a cubic spline. |
| ☐ Using a regression tree with more leafs. |
| ☐ Pruning a classification tree. |
| 11. Which of the following are true for the Generalized Additive Models (GAMs)? |
| \square It applies to regression problems. |
| ☐ It applies to classification problems. |
| □ The regression model $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$ is a special case of a GAM with predictors (X_1, X_2) |
| \square The logistic regression model |
| $Prob(Y = 1 X_1) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_1^2}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_1^2}}$ |

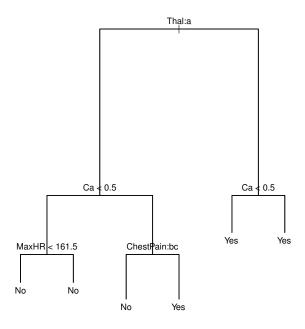
is a special case of a GAM with the predictor X_1 .

| 12. Which of the following are true for regression trees? | |
|---|--------------|
| $\hfill\Box$ The bias typically increases when the number of leafs increases. | |
| \Box The bagging approach typically leads to lower variance than a single tree. | |
| \Box The number of leafs of a tree will not matter too much as long as it is large enough. | |
| \square A regression tree typically corresponds to a linear model of the response and predictors. | |
| | |
| 13. Random Forests | |
| | |
| □ cannot be applied if some of the predictors are categorical. | |
| □ cannot be applied if the response variable is categorical. | |
| \square with $m = p$ are equivalent to the bagging approach (p is the total number of predictors and m is the number of predictors considered in each split). | \mathbf{S} |
| □ cannot be applied to a classification problem with more than 2 classes. | |
| a cannot be applied to a classification problem with more than 2 classes. | |
| 14. In the K NN electification election algorithm, using a larger K typically | |
| 14. In the K -NN classification algorithm, using a larger K typically | |
| \Box increases the bias. | |
| \Box increases the variance. | |
| \square leads to a more flexible model. | |
| \Box leads to a lower training error. | |
| | |
| 15. A Support Vector Machine | |
| \square produces a linear decision boundary if a linear kernel is used. | |
| ☐ may produce a nonlinear decision boundary is a radial kernel is used. | |
| ☐ can be applied to a classification problem with more than two classes via the One-Versus-On | e |
| approach. | _ |
| \square leads to more flexible models if the value of the budget parameter C is increased. | |
| | |
| 16. Logistic regression | |
| \Box has higher variance than random forests. | |
| □ should always be fitted using all the predictors. | |
| □ produces a classifier with the same number of false positives and false negatives on the trainin | g |
| data. | 0 |
| has good performance on the training data if the corresponding Area Under the Curve (AUC) | İS |
| close to one. | |
| | |
| 17. Using a Generalized Additive Model with smoothing splines when there are p predictors | |
| \square Is always better than using a linear model. | |
| \square Is always better than a regression tree. | |
| \square Is problematic when $p > 3$ since smoothing splines are piecewise cubic curves. | |
| | |

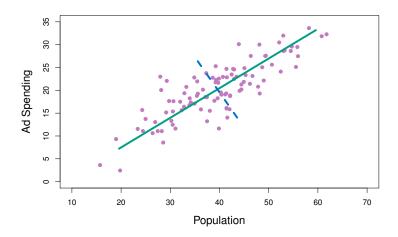
18. Compared to a linear model, a random forest with B=500 trees

| Is usually easier to interpret. |
|---|
| Is usually more difficult to interpret. |
| Is usually more flexible. |

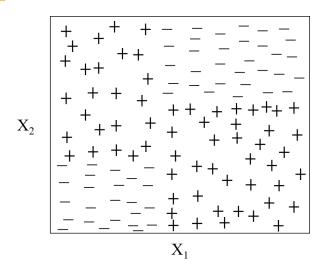
- 19. Consider a classification tree depicted in the plot below. Based on that tree, the predicted value \hat{y} for a new observation with predictors Ca=1.2, ChestPain=b, MaxHR=150 and Thal=a will be given by
 - \square No.
 - \square Yes.
 - \square Yes or No depending on the values of the other predictors.



- 20. Which is/are true for the plot below?
 - \square The solid line corresponds to the first principal component of the data.
 - \square The dashed line corresponds to the first principal component of the data.
 - ☐ Among all straight lines, the solid line has the lowest total squared distance to the observations.



- 21. Consider a two-dimensional training dataset shown in the plot below, which contains observations in two classes ("+" and "-"). Which of the following methods would you expect to perform best in terms of classification accuracy on a test set generated in the same way?
 - \square Lasso.
 - $\hfill\square$ Logistic Regression Generalized Additive Models with step functions.
 - \square Support Vector Machines with linear kernels.
 - ☐ Classification trees.



- 22. Which of the following is true for clustering?
 - \square The value of k in k-means clustering needs to be chosen by cross-validation.
 - \square We should choose k in k-means clustering to minimize the total within-cluster variation.
 - \square The clustering results are usualy not affected by the choice of the distance metric.
 - □ One may obtain a specific number of clusters by cutting the dendrogram produced by hierarchical clustering.
- 23. Which of the following are appropriate for selecting a subset of predictors?

| ☐ Principal Component Analysis (PCA). |
|---|
| \square The <i>p</i> -values of the coefficient estimates of a linear regression model. |
| \square Ridge regression. |
| ☐ Lasso. |
| |
| 24. Which of the following can be used to fit a nonliear classifier? |
| ☐ Support Vector Machines with appropriate kernels. |
| ☐ Logistic Regression Generalized Additive Model. |
| \square Random Forests. |
| \square The K Nearest Neighbor algorithm. |