Congratulations! You passed!

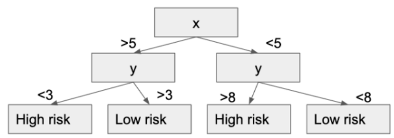
Grade received 100% To pass 80% or higher

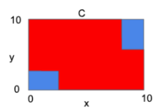
Go to next item

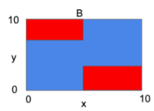
1. Which decision boundary corresponds to the following decision tree?

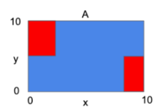
1 / 1 point

In the options, red indicates high risk, blue indicates low risk.









Correct

One way to approach this is to work your way back up from the leaves to see the regions that are classified as high risk. Doing this, we see that one high risk area is where x > 5 and y > 3, and where x < 5 and y > 8. This corresponds to the two rectangles shown here.

2. True or False: A tree of depth 1 is more expressive than a classical linear model.

1 / 1 point

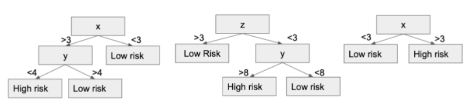
- False
- True

Correct

Most of the time, a tree has a more flexible decision boundary. However, a tree of depth one can just threshold on one of the features, which a linear model can do as well by making the coefficients of all other features zero. The linear model can also get non-axis aligned boundaries by using combinations of covariates, so in this case, the linear model has a larger hypothesis space.

3. One way to aggregate predictions from multiple trees is by a majority vote. Using this aggregation rule, select the prediction of the following trees on the data point (x=4, y=7, z=2):

1 / 1 point



- High risk
- Low risk

Correct

The hardest part of this is just keeping track of the coordinates. Following the tree from the root down, we get low risk from the first tree, low risk from the second tree, and high risk from the third tree. Therefore the majority vote is low risk.

4. You've fit a random forest of 10 trees with max depth 20. Your training ROC is 0.99 and test ROC is 0.54. Which of the following is NOT a reasonable thing to try?

1 / 1 point

- (●) Increasing the max depth
- ( ) Decreasing max depth
- ( ) Trying a linear model
- ( ) Increasing the number of trees

Correct
The model is overfitting, since it's performing poorly on the test set compared to the training set.

Increasing the depth INCREASES the variance of the trees, which you would do if the model was UNDER-fitting. Since the model is already OVER-fitting, increasing the model's variance would make it under-fit even more.

Therefore, increasing max depth is NOT a reasonable thing to try in this case.

5. When is complete case analysis least likely to bias your model?

1 / 1 point

- ( ) Data is missing not at random
- (●) Data is missing completely at random
- ( ) Dropping data will bias your model in all of the above cases
- ( ) Data is missing at random

Correct
If data is missing completely at random, then there is no difference in the distribution of your data with and without the rows with missing data, so as long as you have enough complete data, dropping those rows should not bias your model.

6. You have created a model using mean imputation. At test time, you should fill in missing values with:

1 / 1 point

- ( ) None of the above
- ( ) 0.0
- (●) Mean from the train data
- ( ) Mean from the test data

Correct
Explanation: When testing your model, you should use the mean from your training data. Otherwise, your test statistics will not be reflective of your training procedure and how they will perform in the real world, since in the real world you will not have access to the entire collection of test examples beforehand.

7. Let's say blood pressure (BP) measurements are more likely to be missing among young people, who generally have lower blood pressure. You use mean imputation to train your model. Which option correctly characterizes the mean BP (after imputation) in your training dataset?

1 / 1 point

- ( ) It is lower than the true mean
- (●) It is higher than the true mean
- ( ) It is the same as the true mean
- ( ) None of the above

Correct
The BP measurements which will be present in your dataset will be higher than average, since many of the lower BP values from the younger people in the dataset will be missing.

Therefore the mean which you impute will be higher than average, so the overall mean will be higher. This is an example of bias introduced in your dataset through imputation.

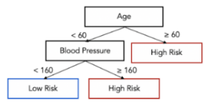
8. You have trained the following tree and want to make a prediction on someone, but all you know is they are 40 years old, and do not have their blood pressure.

1 / 1 point

From you dataset, you learn the linear relationship between blood pressure and age is:

$BP = 1.7 \times Age + 60.$

Using regression imputation, and the decision tree shown here, what is your prediction for this person's risk of heart attack?



- ( ) High Risk
- (●) Low Risk

Correct
First let's get our imputed BP value. Following the formula, we get BP = 1.7*40 + 60 = 128.

The person is less than 60 and has BP less than 160, so we can categorize them as low risk.

9. Assume you have missing data on one of your features, and are considering two options:

1 / 1 point

Option 1: Drop the feature that has missing values and fit a linear regression on the remaining features.

Option 2: Use imputation on the feature that has missing values, and fit a linear regression on all features.

True or False: "Both options have the same performance".

- (•) False
- ( ) True

Correct

It seems like this might be true because you could plug in your imputation equation into the linear regression to get a linear regression based on all features but the imputed one.

However, since the imputed feature is not exactly a linear combination of the other features, the model that is learned will not be the same, since the model will still be able to take into account the variation in the feature when it is not missing. Recall that for some patients, the data of the feature is still measured, and not missing for all patients.

To convince yourself, think of a dataset with 1000 points where only one example is missing a measurement. Fitting a model on the whole dataset will not be the same as fitting it on a dataset that drops that entire column.