

CMSE 381, Fundamental Data Science Methods

November 9, 2025

Homework 7

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Question 1: ISLP § 8.4.4

This question relates to the plots in Figure 8.14 in ISLP. A copy of the figure is attached below.

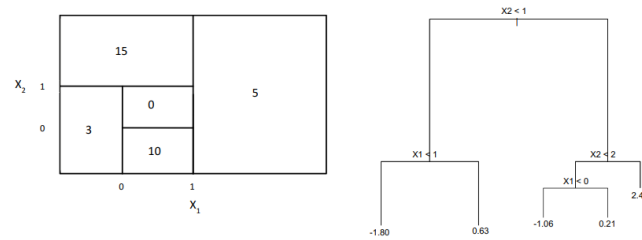
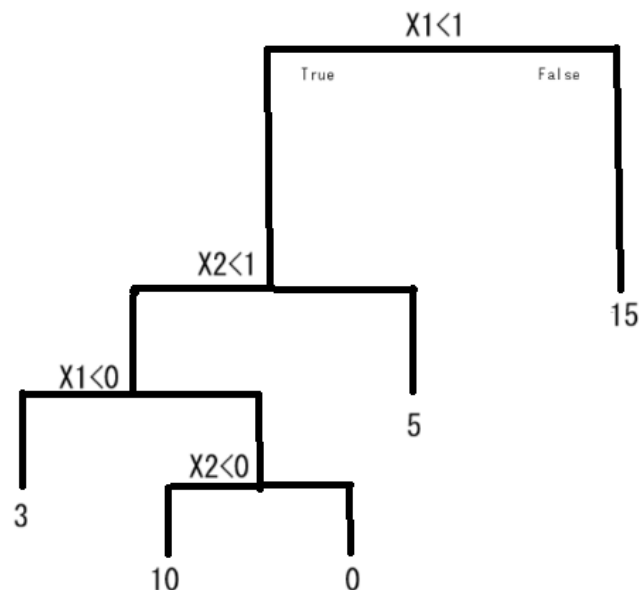


FIGURE 8.14. Left: A partition of the predictor space corresponding to Exercise 4a. Right: A tree corresponding to Exercise 4b.

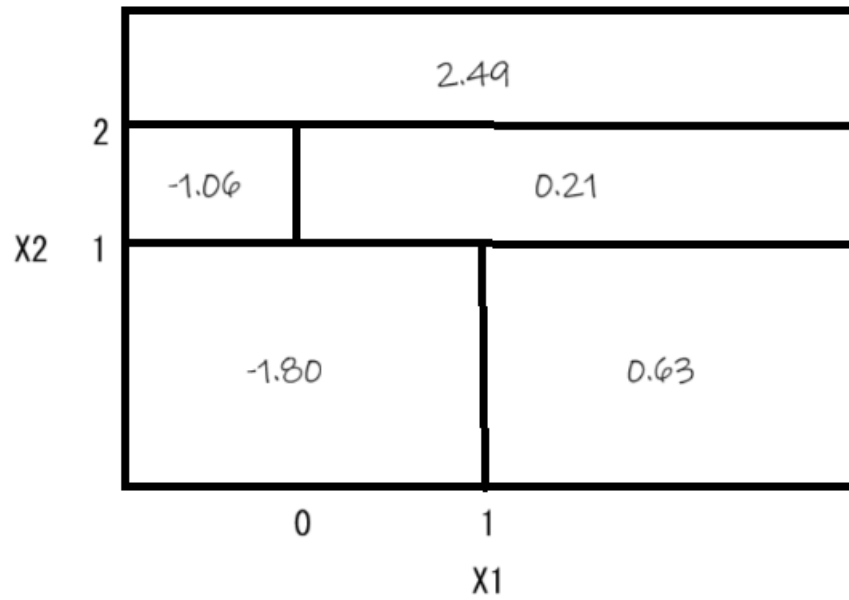
(a) Sketch the tree corresponding to the partition of the predictor space illustrated in the left-hand panel of Figure 8.14. The numbers inside the boxes indicate the mean of Y within each region. A text-based visualization of the corresponding tree for the given partitioned predictor space is as follows:

- If $X_1 \geq 1$, then $Y = 5$ (leaf node).
- If $X_1 < 1$, then:
 - If $X_2 \geq 1$, then $Y = 15$ (leaf node).
 - If $X_2 < 1$, then:
 - * If $X_1 < 0$, then $Y = 3$ (leaf node).
 - * If $X_1 \geq 0$, then:
 - If $X_2 \geq 0$, then $Y = 0$ (leaf node).
 - If $X_2 < 0$, then $Y = 10$ (leaf node).

The sketch I created is provided below:



(b) Create a diagram similar to the left-hand panel of Figure 8.14, using the tree illustrated in the right-hand panel of the same figure. You should divide up the predictor space into the correct regions, and indicate the mean for each region. The diagram is as follows.



Question 2: ISLP § 8.4.9

Only a subset of these problems are to be answered. An additional subproblem has been added to this question by the instructor.

This problem involves the OJ data set which is part of the ISLP package. First, I will be loading the data set as downloaded from the course website.

```
[2]: oj=pd.read_csv('../data/OJ.csv').rename({'Unnamed: 0': ''}, axis=1).set_index('')
oj.head()
```

```
[2]:
```

	Purchase	WeekofPurchase	StoreID	PriceCH	PriceMM	DiscCH	DiscMM	\
1	CH	237	1	1.75	1.99	0.00	0.0	
2	CH	239	1	1.75	1.99	0.00	0.3	
3	CH	245	1	1.86	2.09	0.17	0.0	
4	MM	227	1	1.69	1.69	0.00	0.0	
5	CH	228	7	1.69	1.69	0.00	0.0	

	SpecialCH	SpecialMM	LoyalCH	SalePriceMM	SalePriceCH	PriceDiff	Store7	\
1	0	0	0.500000	1.99	1.75	0.24	No	
2	0	1	0.600000	1.69	1.75	-0.06	No	
3	0	0	0.680000	2.09	1.69	0.40	No	
4	0	0	0.400000	1.69	1.69	0.00	No	
5	0	0	0.956535	1.69	1.69	0.00	Yes	

	PctDiscMM	PctDiscCH	ListPriceDiff	STORE
1	0.000000	0.000000	0.24	1
2	0.150754	0.000000	0.24	1
3	0.000000	0.091398	0.23	1
4	0.000000	0.000000	0.00	1
5	0.000000	0.000000	0.00	0

(a) Create a training set containing a random sample of 800 observations, and a test set containing the remaining observations. I will use the `train_test_split()` method from `sklearn.model_selection`, with the random seed state set at 381.

```
[3]: oj_train, oj_test = train_test_split(oj, train_size=800, random_state=381)
```

(b) Fit a tree to the training data, with Purchase as the response and the other variables as predictors. What is the training error rate? First, I will split the training and testing data to predictor-response format. I will also clean the data and encode the qualitative variables that are in the form of a string.

```
[4]: X_train = pd.get_dummies(oj_train.drop('Purchase', axis=1), drop_first=True)
X_test = pd.get_dummies(oj_test.drop('Purchase', axis=1), drop_first=True)
```

```
y_train = oj_train['Purchase']
y_test = oj_test['Purchase']
```

We can now train a classification decision tree to the training data.

```
[5]: clf = DecisionTreeClassifier(random_state=381)
      clf.fit(X_train,y_train)
```

```
[5]: DecisionTreeClassifier(random_state=381)
```

We can now calculate the training error.

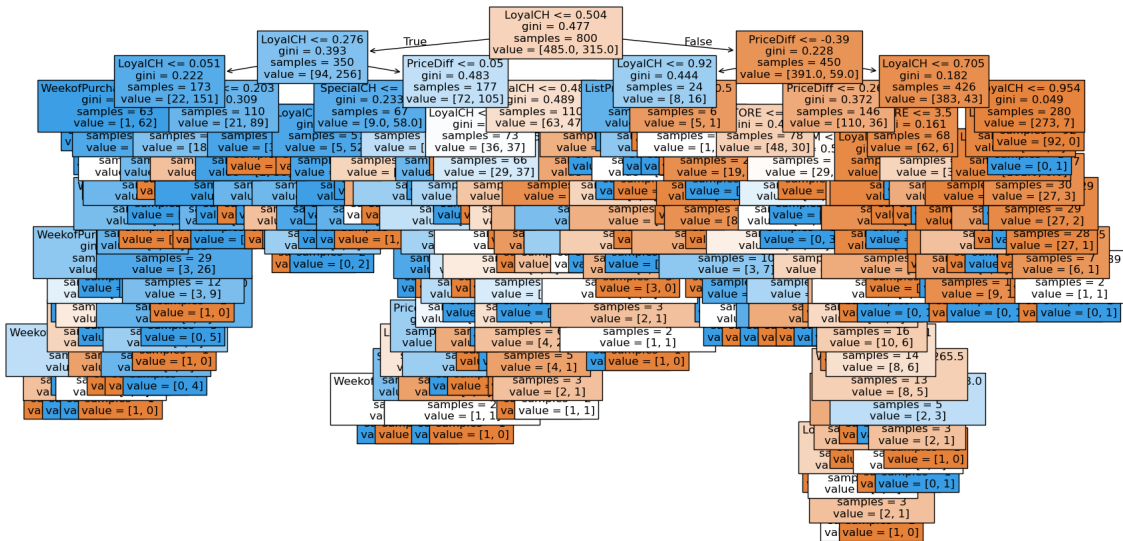
```
[6]: (1-accuracy_score(y_train, clf.predict(X_train)))
```

```
[6]: 0.0074999999999999951
```

The error rate is very low, at less than 0.75%. The tree is most likely overfit, so I expect the tree to be pretty bushy, and with significant depth, since I haven't constrained the maximum depth.

(c) Create a plot of the tree, and interpret the results. How many terminal nodes does the tree have? We can now use the `plot_tree()` method in `sklearn.tree` to visualize this tree.

```
[7]: fig = plt.figure(figsize = (20,10))
      _=tree.plot_tree(clf, feature_names = X_train.columns, filled = True, fontsize = 12)
      plt.show()
```



The plot agrees with my expectation that this will be a bushy tree. Since I cannot possibly count the number of terminal nodes, or leaves, I will query the tree object (`clf`) using `tree.n_leaves` as demonstrated in ISLP § 8.3.

```
[8]: clf.tree_.n_leaves
```

```
[8]: 151
```

There are 151 terminal nodes in the tree. This leads me to conclude that the tree generated is hardly interpretable.

(d) Use the `export_text()` function to produce a text summary of the fitted tree. Pick one of the terminal nodes, and interpret the information displayed.

```
[9]: print(tree.export_text(clf, feature_names = list(X_train.columns)))
```

```
|--- LoyalCH <= 0.50
|   |--- LoyalCH <= 0.28
|   |   |--- LoyalCH <= 0.05
|   |   |   |--- WeekofPurchase <= 268.50
|   |   |   |   |--- class: MM
|   |   |   |   |--- WeekofPurchase > 268.50
|   |   |   |   |--- PriceDiff <= 0.26
|   |   |   |   |   |--- class: MM
|   |   |   |   |   |--- PriceDiff > 0.26
|   |   |   |   |   |--- LoyalCH <= 0.00
|   |   |   |   |   |   |--- class: MM
|   |   |   |   |   |   |--- LoyalCH > 0.00
|   |   |   |   |   |   |   |--- class: CH
|   |   |--- LoyalCH > 0.05
|   |   |   |--- LoyalCH <= 0.20
|   |   |   |   |--- LoyalCH <= 0.18
|   |   |   |   |   |--- STORE <= 3.50
|   |   |   |   |   |   |--- WeekofPurchase <= 273.50
|   |   |   |   |   |   |   |--- WeekofPurchase <= 264.00
|   |   |   |   |   |   |   |   |--- STORE <= 1.50
|   |   |   |   |   |   |   |   |   |--- WeekofPurchase <= 243.00
|   |   |   |   |   |   |   |   |   |   |--- LoyalCH <= 0.07
|   |   |   |   |   |   |   |   |   |   |   |--- class: MM
|   |   |   |   |   |   |   |   |   |   |   |--- LoyalCH > 0.07
|   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |   |   |   |   |   |--- WeekofPurchase > 243.00
|   |   |   |   |   |   |   |   |   |   |   |   |   |--- class: MM
|   |   |   |   |   |   |   |   |   |   |   |   |   |--- STORE > 1.50
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- WeekofPurchase <= 236.50
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- class: MM
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- WeekofPurchase > 236.50
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- PctDiscCH <= 0.03
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- PctDiscCH > 0.03
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- class: CH
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- WeekofPurchase > 264.00
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |--- class: CH
```


[illegible]


```
| | | | | | | | --- LoyalCH <= 0.69  
| | | | | | | | |--- WeekofPurchase <= 236.50  
| | | | | | | | |   |-- WeekofPurchase <= 228.50  
| | | | | | | | |     |-- class: CH  
| | | | | | | | |       |-- WeekofPurchase > 228.50  
| | | | | | | | |         |-- STORE <= 3.50  
| | | | | | | | |           |-- class: MM  
| | | | | | | | |             |-- STORE > 3.50  
| | | | | | | | |               |-- truncated branch of depth 2  
| | | | | | | | |                 |-- WeekofPurchase > 236.50  
| | | | | | | | |                   |-- PriceDiff <= -0.06  
| | | | | | | | |                     |-- SalePriceCH <= 1.94  
| | | | | | | | |                       |-- truncated branch of depth 2  
| | | | | | | | |                         |-- SalePriceCH > 1.94  
| | | | | | | | |                           |-- truncated branch of depth 2  
| | | | | | | | |                             |-- PriceDiff > -0.06  
| | | | | | | | |                               |-- StoreID <= 1.50  
| | | | | | | | |                                 |-- class: CH  
| | | | | | | | |                                   |-- StoreID > 1.50  
| | | | | | | | |                                     |-- truncated branch of depth 10  
| | | | | | | | |                                       |-- LoyalCH > 0.69  
| | | | | | | | |                                         |-- class: MM  
| | | | | | | | |                                           |-- PctDiscMM > 0.20  
| | | | | | | | |                                             |-- class: MM  
| | | | | | | | |                                               |-- SalePriceMM > 2.15  
| | | | | | | | |                                                 |-- class: CH  
| | | | | | | | |--- PriceDiff > 0.27  
| | | | | | | | |   |-- STORE <= 3.50  
| | | | | | | | |     |-- LoyalCH <= 0.54  
| | | | | | | | |       |-- StoreID <= 2.50  
| | | | | | | | |         |-- class: MM  
| | | | | | | | |           |-- StoreID > 2.50  
| | | | | | | | |             |-- class: CH  
| | | | | | | | |               |-- LoyalCH > 0.54  
| | | | | | | | |                 |-- WeekofPurchase <= 251.50  
| | | | | | | | |                   |-- WeekofPurchase <= 248.00  
| | | | | | | | |                     |-- LoyalCH <= 0.68  
| | | | | | | | |                       |-- class: CH  
| | | | | | | | |                         |-- LoyalCH > 0.68  
| | | | | | | | |                           |-- WeekofPurchase <= 235.50  
| | | | | | | | |                             |-- WeekofPurchase <= 230.50  
| | | | | | | | |                               |-- class: CH  
| | | | | | | | |                                 |-- WeekofPurchase > 230.50  
| | | | | | | | |                                   |-- class: MM  
| | | | | | | | |                                     |-- WeekofPurchase > 235.50  
| | | | | | | | |                                       |-- class: CH  
| | | | | | | | |                                         |-- WeekofPurchase > 248.00  
| | | | | | | | |                                           |-- class: MM
```



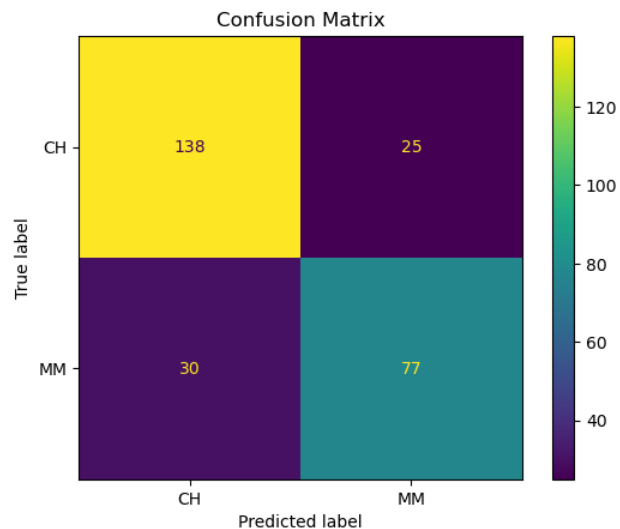
```
| | | | | | | | | | | | |--- DiscCH > 0.05
| | | | | | | | | | | | |--- LoyalCH <= 0.94
| | | | | | | | | | | | |--- class: CH
| | | | | | | | | | | | |--- LoyalCH > 0.94
| | | | | | | | | | | | |--- class: MM
| | | | | |--- LoyalCH > 0.95
| | | | | |--- class: MM
| | | |--- LoyalCH > 0.95
| | | |--- class: CH
```

I am choosing to interpret the first terminal node presented in the previous output.

The node was classified as Minute Maid (MM). The node can be interpreted as any customer who makes a purchase less than 268.5 weeks from the start of the data collection that has lesser than 5% of brand loyalty to Citrus Hill (with brand loyalty to Citrus Hill being split 3 distinct times at 50%, 28% and 5%) most likely purchases a Minute Maid orange juice bottle.

(e) Predict the response on the test data, and produce a confusion matrix comparing the test labels to the predicted test labels. What is the test error rate?

```
[10]: ConfusionMatrixDisplay(confusion_matrix=confusion_matrix(clf.
    ↪predict(X_test),y_test),
    display_labels=['CH', 'MM']).plot()
plt.title('Confusion Matrix')
plt.show()
```



```
[11]: (1-accuracy_score(y_test, clf.predict(X_test)))
```

```
[11]: 0.20370370370370372
```

The test error rate is a bit more than 21%, which is a massive increase from the training error rate.

(f) Use cross-validation on the training set in order to determine the optimal tree size. I first find the maximum tree depth of the current tree so I can create a range of candidate tree depth/size values.

```
[12]: clf.tree_.max_depth
```

```
[12]: 20
```

I can now conduct a 10-fold cross-validation accordingly to estimate the optimal tree size. We will be scoring the accuracy of the different depths.

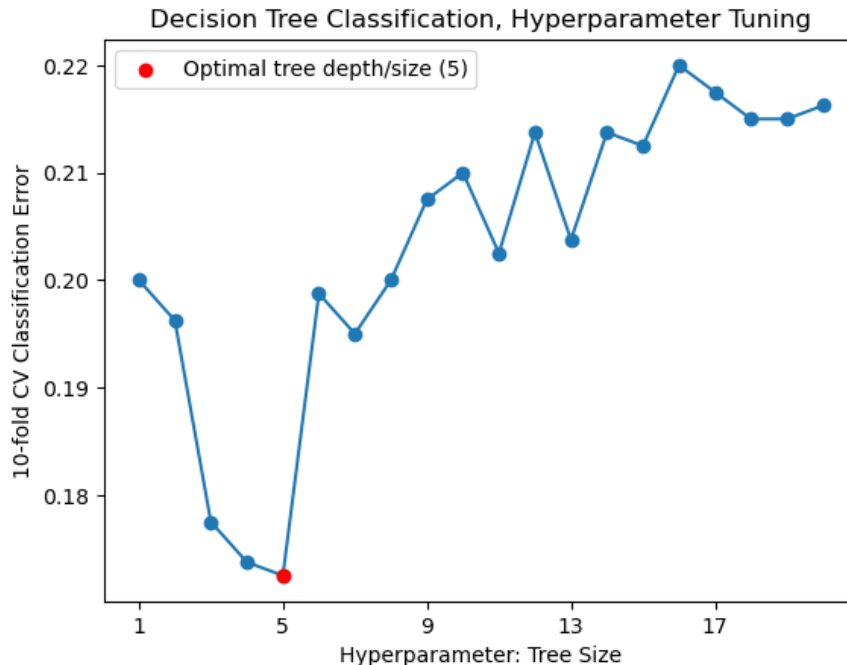
```
[13]: kf=KFold(n_splits=10, shuffle=True, random_state=381)
M=np.zeros(clf.tree_.max_depth)
for depth in range(1,len(M)+1):
    clf_cv=DecisionTreeClassifier(max_depth=depth, random_state=381)
    scores = cross_val_score(clf_cv, X_train, y_train, cv=kf)
    M[depth-1]=np.mean(scores)
depth_opt=np.argmax(M)+1
acc_opt=max(M)
print(depth_opt, acc_opt, sep=', ')
```

```
5, 0.8275
```

It looks like a maximum depth of 5 provides the highest cross-validation accuracy at 82.75% (lowest error rate at 17.25%).

(g) Produce a plot with tree size on the x -axis and cross-validated classification error rate on the y -axis.

```
[14]: plt.plot(range(1,clf.tree_.max_depth+1),1-M, '-o')
plt.title('Decision Tree Classification, Hyperparameter Tuning')
plt.scatter(depth_opt, 1-acc_opt, c='red', zorder=2, label=f'Optimal tree depth/
→size ({depth_opt})')
plt.xlabel('Hyperparameter: Tree Size')
plt.ylabel('10-fold CV Classification Error')
plt.legend()
plt.xticks(list(range(1,clf.tree_.max_depth+1,4)))
plt.show()
```



(h) Which tree size corresponds to the lowest cross-validated classification error rate? As determined in (f), the optimal tree size is 5, since it corresponds to the lowest cross-validated error rate of 17.25%.

(i) [Modified] Build a random forest model for the same classification task. Using the techniques from class, what choice of `n_estimators` and `max_features` would you choose for your model? I will be conducting a 10-fold cross-validation in a limited parameter grid that I will be creating. The number of estimators will be selected from a range of values, while the candidate values for the maximum number of features in terms of the total number of predictors p will be \sqrt{p} , $\frac{p}{3}$, $\frac{p}{2}$, and p . Ideally, I would use quarter the number of predictors too, i.e., $\frac{p}{4}$, but the integer type conversions of $\frac{p}{4}$ and \sqrt{p} are the same.

```
[15]: p=o.j.shape[1]
      param_grid = {
          'n_estimators': np.arange(10,501,10),
          'max_features': [int(np.sqrt(p)), int(p/3), int(p/2), p]
          # I initially used 'sqrt', but that complicated labeling in the plot.
      }
```

I will now conduct the cross-validation. I will be doing a grid search this time.

```
[16]: rf_clf = RandomForestClassifier(random_state=381, oob_score = True, max_depth=p)
      grid_search = GridSearchCV(
          estimator=rf_clf,
          param_grid=param_grid,
          scoring='accuracy',
          cv=10
      )
```

With that done, I will now proceed to train the classifier via the grid search to identify the optimal parameters. Cross-validating takes an immense amount of time with the number of parameters we are testing out.

```
[17]: grid_search.fit(X_train, y_train)
```

```
[17]: GridSearchCV(cv=10,
                  estimator=RandomForestClassifier(max_depth=18, oob_score=True,
                                                    random_state=381),
                  param_grid={'max_features': [4, 6, 9, 18],
                              'n_estimators': array([ 10,  20,  30,  40,  50,  60,
70,  80,  90, 100, 110, 120, 130,
140, 150, 160, 170, 180, 190, 200, 210, 220, 230, 240, 250, 260,
270, 280, 290, 300, 310, 320, 330, 340, 350, 360, 370, 380, 390,
400, 410, 420, 430, 440, 450, 460, 470, 480, 490, 500])},
                  scoring='accuracy')
```

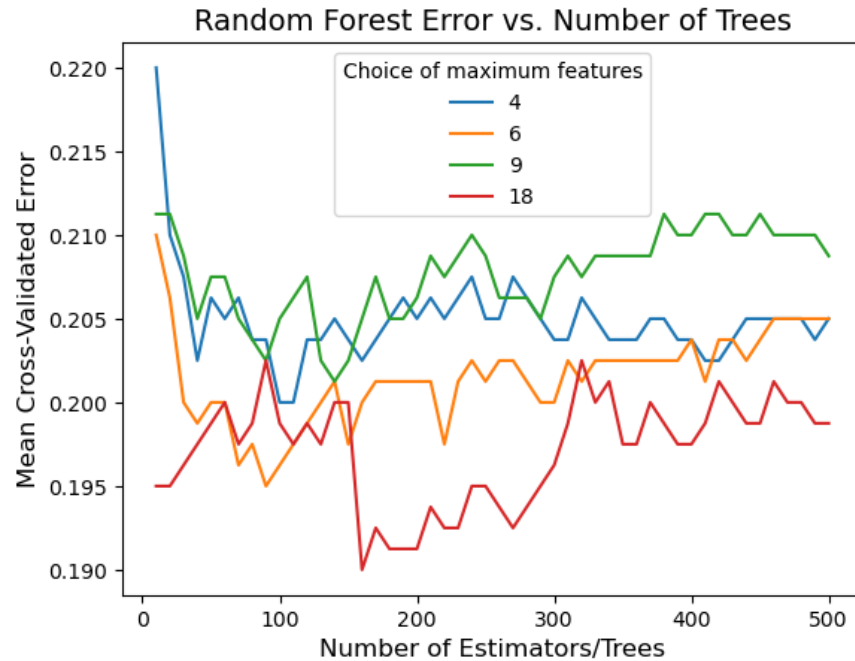
The optimal parameters are as follows:

```
[18]: opt_n = grid_search.best_params_['n_estimators']
      opt_m = grid_search.best_params_['max_features']
      opt_acc = grid_search.best_score_
      print(opt_n, opt_m, 1-opt_acc, sep=', ')
```

```
160, 18, 0.19000000000000006
```

We can conclude that the best parameters to conduct a Random Forest classification of this data would be 160 trees, using all 18 features, giving us an error of 19%. But since it is not advised to use all features, we can plot the error rates to find other optimal parameters.

```
[19]: results = pd.DataFrame(grid_search.cv_results_).loc[:, ['param_n_estimators',
    ↳ 'param_max_features', 'mean_test_score']]
      results.columns = ['n_estimators', 'max_features', 'mean_accuracy']
      for m in results['max_features'].unique():
          subset = results[results['max_features'] == m]
          plt.plot(subset['n_estimators'], 1-subset['mean_accuracy'],
                   label=m)
      plt.title('Random Forest Error vs. Number of Trees', fontsize=14)
      plt.xlabel('Number of Estimators/Trees', fontsize=12)
      plt.ylabel('Mean Cross-Validated Error', fontsize=12)
      plt.legend(title='Choice of maximum features')
      plt.show()
```

Disregarding the values for the full data set, it looks like an alternate value would be 40 trees when using half the predictors.

If I had a large amount of computing power, I would set `n_estimators=160` and `max_features=18`. If I had limited computing power, I would set `n_estimators=40` and `max_features=0.5` or `max_features=9`.

Acknowledgements

I adopted the `GridSearchCV()` method from `sklearn.model_selection` to conduct a grid search of the candidate optimal hyperparameters value instead of a regular nested loop structure.