ECON 425 HW4

January 30, 2024

Problem 2 (survival on the *Titanic*)

The titanic.xls dataset contains information on each of the 1309 passengers of RMS *Titanic*. The goal is to predict passenger survival. Use the first 1100 rows as the training sample and the remaining rows as the test sample.

- (i) Fit a decision tree of maximal depth $d \in \{1, 2, 3, 4, 5, 6, 7, 8\}$ with the information gain as the splitting criterion.
- (ii) Plot the decision trees corresponding to d=1 and d=2 (in Python, use sklearn.tree.plot_tree). Interpret the results.
- (iii) Calculate the test error (misclassification rate) on the test sample and plot it as a function of depth d. Does the test error change much? Which value of d would you choose?

ML HW 4

February 7, 2024

0.1 Problem 2

```
[118]: import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, f1_score
import numpy as np
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, auc
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, roc_auc_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import accuracy_score
```

```
[119]: df=pd.read_csv("/Users/sandinatatu/Desktop/titanic.csv") df=df[:-1]
```

0.1.1 i)

Prior to fitting decision trees to my dataset, I transform the dataset by obtaining dummies for all of the non-numerical variables.

```
[124]: X = df.drop(['survived', 'name'], axis=1)
y=df[["survived"]].copy()

cols = X.columns[X.dtypes=="object"]

for col in cols:
    X[col] = X[col].fillna('missing')

for col in cols:
    X[col] = pd.Categorical(X[col])

X=pd.get_dummies(X, columns= cols, prefix=cols, drop_first = True, dtype=int)
```

```
[125]: x_train = X.iloc[:1100]
x_test = X.iloc[1100:]

y_train = y.iloc[:1100]
y_test = y.iloc[1100:]
```

Below I fit decision tree of maximal depth {1, 2, 3, 4, 5, 6, 7, 8} to my dataset. I use the information gain (or entropy) as the splitting criterion. The best out-of-sample accuracy is 0.98, obtained for d {2, 3, 4, 8}. The best in-sample accuracy is 0.98, obtained for d=8.

```
stored_models={}
misclassification_rates={}

np.random.seed(15)

for d in range(1,9):
    clf =tree.DecisionTreeClassifier(max_depth = d, criterion = "entropy")
    clf.fit(x_train, y_train)
    y_pred = clf.predict(x_train)
    acc=accuracy_score(y_train, y_pred)

print(f"In sample accuracy for max_depth = {d} is {round(acc,2)}")

y_pred = clf.predict(x_test)
    acc=accuracy_score(y_test,y_pred)
    misclassification_rates[d] = 1-acc

print(f"Out of Sample accuracy for max_depth = {d} is {round(acc,2)}")

if d in[1,2]:
    stored_models[d] = clf
```

In sample accuracy for max_depth = 1 is 0.58 Out of Sample accuracy for max_depth = 1 is 0.83 In sample accuracy for max_depth = 2 is 0.97 Out of Sample accuracy for max_depth = 2 is 0.98 In sample accuracy for max_depth = 3 is 0.97 Out of Sample accuracy for max_depth = 3 is 0.98 In sample accuracy for max_depth = 4 is 0.97 Out of Sample accuracy for max_depth = 4 is 0.98 In sample accuracy for max_depth = 5 is 0.91 Out of Sample accuracy for max_depth = 5 is 0.84 In sample accuracy for max_depth = 6 is 0.78 Out of Sample accuracy for max_depth = 6 is 0.78 In sample accuracy for max_depth = 7 is 0.9 Out of Sample accuracy for max_depth = 7 is 0.79 In sample accuracy for max_depth = 8 is 0.98 Out of Sample accuracy for max_depth = 8 is 0.98

0.1.2 ii)

Below I plot the decision trees with max_depths 1 and 2. For max_depth 1, the tree will always predict that someone did not survive, hence the low in-sample accuracy. For max_depth of 2, the accuracy is much higher. This is because this tree initially uses the boat_missing criterion, which allows it to identify passengers who had boats and categorize them as survivors. It then does another split for those who had boat boat missing = 1, and splits the further based on their sex.

Decision Tree with max_depth = 1

body <= inf entropy = 0.982 samples = 1100 value = [636, 464] class = Not Survived

entropy = 0.0 samples = 102 value = [102, 0] class = Not Survived

entropy = 0.996 samples = 998 value = [534, 464] class = Not Survived

```
Decision Tree with max_depth = 2
             boat missing \leq 0.5
               entropy = 0.982
               samples = 1100
              value = [636, 464]
             class = Not Survived
                              sex male \leq 0.5
 entropy = 0.0
                              entropy = 0.996
samples = 452
                               samples = 648
value = [8, 444]
                              value = [628, 20]
class = Survived
                            class = Not Survived
               entropy = 0.636
                                              entropy = 0.035
                samples = 112
                                              samples = 536
               value = [94, 18]
                                              value = [534, 2]
             class = Not Survived
                                            class = Not Survived
```

0.1.3 iii)

```
[145]: keys = list(misclassification_rates.keys())
values = list(misclassification_rates.values())
```

Below I plot the misclassification rates for each max_depth. The lowes misclassification rates are obtained for d {2, 3, 4, 8}. The test error does indeed change a lot, with it being much higher for d=1 or when d {5,6,7}. Overall, I would choose d=1 for the purpose of parsimony.

```
[148]: plt.figure(figsize=(10,6))
  plt.plot(keys, values)
  plt.title("Misclassification rates by max_depth")
  plt.xlabel("Max_depth")
  plt.ylabel("Misclassification rate")
  plt.show()
```

