Labsheet - 4

Decision Trees

Machine Learning

BITS F464
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Decision Trees

Decision tree is a supervised learning algorithm which is used for both classification and regression. As the name goes, it uses a tree-like model of decisions, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.
It consists of a set of rules for dividing large heterogeneous population into smaller groups with respect to the target label, the algorithm used for this tree construction is recursive partitioning. It follows top- down approach.

Decision tree Terminology:
Root node: Represents entire population (entire training data - impure)
Splitting: Process of dividing the population into child nodes (2 or more). Purpose of splitting is to reduce impurity in the child nodes and to eventually get pure leaf nodes.
Leaf Nodes: Pure node containing data from only 1 class
Intermediate Nodes: Nodes that are neither root nor leaf nodes (any node between root & leaf nodes)
Pruning: Reducing the size of the tree (post/pre pruning)

The following are some of the popular algorithms to build a decision tree:

1. CART :- uses Gini Index (Classification) as metric.
2. ID3:- uses Entropy function and Information gain as metrics.
3. C4.5
4. Hunt's algorithm

In order to grow decision tree please load the Carseats dataset using the rpart package in R. Mind that you need to install the ISLR and rpart packages in your R Studio environment first. Let's first load the Carseats dataframe from the ISLR package.

```
library(ISLR)
```

Let's also load the rpart package.

```
library(rpart)
```

The Carseats dataset is a dataframe with 400 observations on the following 11 variables:

- Sales: unit sales in thousands
- CompPrice: price charged by competitor at each location
- Income: community income level in 1000s of dollars
- Advertising: local ad budget at each location in 1000s of dollars
- Population: regional pop in thousands
- Price: price for car seats at each site
- ShelveLoc: Bad, Good or Medium indicates quality of shelving location
- Age: age level of the population
- Education: ed level at location
- Urban: Yes/No
- US: Yes/No

Let's take a look at the histogram of car sales:

```
hist(carseats$Sales)
```

Observe that Sales is a quantitative variable. You want to demonstrate it using trees with a binary response. To do so, you turn Sales into a binary variable, which will be called High. If the sales is less than 8, it will be not high. Otherwise, it will be high. Then you can put that new variable High back into the dataframe

```
High = ifelse(carseats$Sales<=8, "No", "Yes")
carseats = data.frame(carseats, High)
```

Now let's fill a model using decision trees. Of course, you can't have the Sales variable here because your response variable High was created from Sales. Thus, let's exclude it and fit the tree.

```
tree.carseats = rpart(High~.-Sales, data=carseats)
```

Let's see the summary of your classification tree:

```
summary(tree.carseats)
```

You can see the variables involved, the number of terminal nodes, the residual mean deviance, as well as the misclassification error rate. To make it more visual, let's plot the tree as well, then annotate it using the handy text function:

```
plot(tree.carseats, uniform = TRUE)
text(tree.carseats, pretty=1)
# Examine the complexity plot
printcp(tree.carseats)
plotcp(tree.carseats)
```

There are so many variables, making it very complicated to look at the tree. At least, you can see that at each of the terminal nodes, they're labeled Yes or No. At each splitting node, the variables and the value of the splitting choice are shown (for example, Price < 92.5 or Advertising < 13.5). For a detailed summary of the tree, simply print it. It'll be handy if you want to extact details from the tree for other purposes:

```
tree.carseats
```

There are two types of pruning: pre-pruning and post-pruning.

1. **Pre-pruning**

   Prepruning is also known as early stopping criteria. As the name suggests, the criteria are set as parameter values while building the rpart model. Below are some of the pre-pruning criteria that can be used. The tree stops growing when it meets any of these pre-pruning criteria, or it discovers the pure classes.

   - **maxdepth**: This parameter is used to set the maximum depth of a tree. Depth is the length of the longest path from a Root node to a Leaf node. Setting this parameter will stop growing the tree when the depth is equal the value set for maxdepth.
   - **minsplit**: It is the minimum number of records that must exist in a node for a split to happen or be attempted. For example, we set minimum records in a split to be 5; then, a node can be further split for achieving purity when the number of records in each split node is more than 5.

```
Preprune_tree.carseatss = rpart(High~.-Sales, data=carseats, method=”class”, control
= rpart.control(cp = 0, maxdepth = 8,minsplit = 100))
```

2. **Post-pruning**

The idea here is to allow the decision tree to grow fully and observe the CP value. Next, we prune/cut the tree with the optimal CP value as the parameter as shown in below code:

```
Postprune_tree.carseats <- prune(tree.carseats, cp = 0.0026 )
```

Exercises

- What are the reasons for overfitting in decision tree?
- How do you deal with continuous attribute in terms of splitting?
- What is the accuracy of decision tree by randomly selecting 70% data for testing and 30% for training?
