CAP5610 HW2 - Yuan Du

Code stored at my Github: https://github.com/YuanEldaif/CAP5610

Task 1

1) Preprocess your Titanic training data

After data preprocessing based on HW1, there is no missing value. Additionally, categorical variable Embarked was converted to numeric. Name and PassengerId were dropped. Thus, the head of the train and test are listed as below:

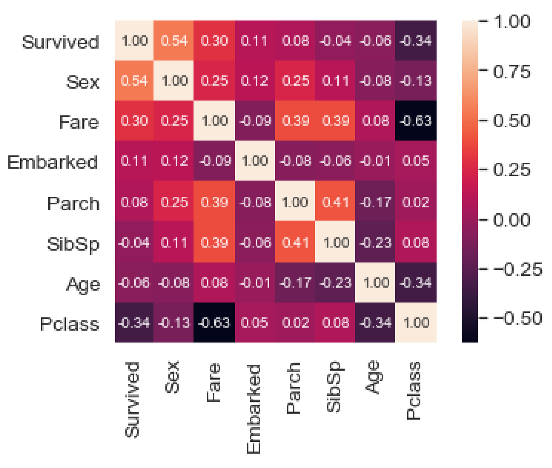
	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	0	3	0	22.0	1	0	0	0
1	1	1	1	38.0	1	0	3	1
2	1	3	1	26.0	0	0	1	0
3	1	1	1	35.0	1	0	3	0
4	0	3	0	35.0	0	0	1	0

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
0	3	0	34.5	0	0	0	2
1	3	1	47.0	1	0	0	0
2	2	0	62.0	0	0	1	2
3	3	0	27.0	0	0	1	0
4	3	1	22.0	1	1	1	0

2) Select a set of important features. Please show your selected features and explain how you perform feature selection.

Ticket feature has high ratio (22%) of duplicate values (unique=681). There may not be a correlation between Ticket and survival. We should drop the ticket feature. Cabin is highly incomplete with 687 null values in training dataset and 327 null values in test dataset. We should drop the Cabin feature. Name and PassengerId were dropped because they are identifiers. Thus, Pclass, Sex, Age, SibSp, Parch, Fare and Embarked were in the dataset after data preprocessing. Correlation matrix were presented as heatmap. All pearson correlation coefficients are less than 0.7. VIF was examined for multicolinearity detection. No variables were over 10. Recursive feature elimination (RFE) and univariate 4 highest scoring features (SelectKBest) was used to select the important features. RFE selected 3 features: Pclass, Sex, and Embarked. SelectKBest selected 4 hightest scoring features: Pclass, Sex, Age, and Fare.

Age is known as an important variable from HW1. Finally 4 features including Pclass, Sex, Age, Fare were selected for modeling.




```
((891, 7), (891,), (418, 6))
```

	VIF Factor	features
0	3.8	Pclass
1	1.7	Sex
2	5.1	Age
3	1.8	SibSp
4	1.7	Parch
5	4.1	Fare
6	1.4	Embarked

Output for Feature selection using RFE:

```
Num Features:  3
Selected Features:  [ True  True False False False False  True]
Feature Ranking:  [1 1 5 2 4 3 1]
   Pclass  Sex   Age  SibSp  Parch  Fare  Embarked
0       3    0  22.0      1      0     0         0
1       1    1  38.0      1      0     3         1
2       3    1  26.0      0      0     1         0
3       1    1  35.0      1      0     3         0
4       3    0  35.0      0      0     1         0
```

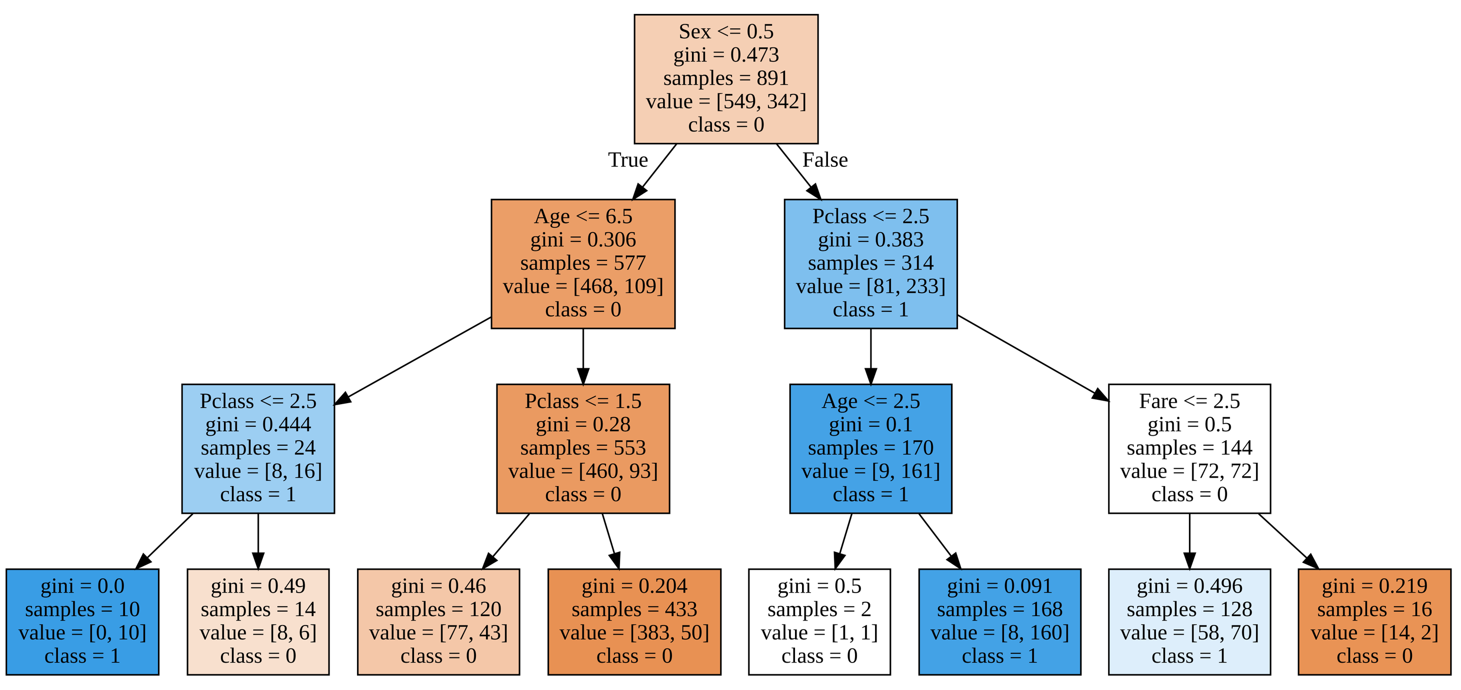
Output for Feature selection using SelectKBest:

```
[ 30.874 170.348  21.649   2.582  10.097  64.722  11.353]
[[ 3.  0. 22.  0.]
 [ 1.  1. 38.  3.]
 [ 3.  1. 26.  1.]
 [ 1.  1. 35.  3.]
 [ 3.  0. 35.  1.]]
   Pclass  Sex   Age  SibSp  Parch  Fare  Embarked
0       3    0  22.0      1      0     0         0
1       1    1  38.0      1      0     3         1
2       3    1  26.0      0      0     1         0
3       1    1  35.0      1      0     3         0
4       3    0  35.0      0      0     1         0
```

```
((891, 4), (891,), (418, 4))
```

3) Learn a decision tree model with the Titanic training data using Gini index, plot your decision tree;

Decision tree with depth=3 is presented as below:



4) Apply the five-fold cross validation of the decision tree learning algorithm to the Titanic training data to extract average classification accuracy;

```
5K CV Decision tree classification accuracy: [0.765 0.809 0.798 0.775 0.843]
5K CV Decision tree average classification accuracy:  0.7980164459230431
=== Mean AUC Score ===
Training Mean AUC Score - Decision tree:  0.8351005597873191
```

5) Apply the five-fold cross validation of the random forest learning algorithm to the Titanic training data to extract average classification accuracy;

```
5K CV Random Forest classification accuracy: [0.754 0.792 0.837 0.815 0.826]
5K CV Random Forest average classification accuracy:  0.8047705730964786
=== Mean AUC Score ===
Training Mean AUC Score - Random Forest:  0.844975220896641
```

6) Which algorithm is better, Decision Tree or Random Forest?

Random Forest is better with higher average accuracy (0.805>0.798) and mean AUC of ROC (0.845>0.835). Also, after data partition into 80% vs 20% training and validation. F1-scores for training and validation were presented as below: Random forest has a higher F1 score for both training and validation. Overall random forest is better.

```
DT Training Set Evaluation F1-Score=> 0.8879999999999999
DT Validation Set Evaluation F1-Score=> 0.7248322147651007
RF Training Set Evaluation F1-Score=> 0.8910505836575876
RF Validation Set Evaluation F1-Score=> 0.7631578947368421
```

7) What can you learn from the algorithm comparison and analysis?

Random forest is a bagging method by combining week classifers into a stronger prediction model and also de-correlated variables, thus reduce variance and overffiting. It generally has better performance than decision tree.

Task 2

(a)

Training error = Number of wrong predictions / Total number of predictions = (5+6+2+6+5+5)/(14+5+6+7+2+10+8+6+5+17+15+5) =0.29

(b)

T will be assign to +. The results will be decided by the probability of class = "+" compared with class = "-". There are three weighted probabilities (3 branches) need to be combined.

1. A=0 -->B & B=1 -->E & E =0 --> p(+)=2/12 =1/6 & p(-)=10/12=5/6 ;
2. C=1 --> p(+)=15/20=3/4 & p(-)=5/20=1/4;
3. D=1 --> p(+)=6/13 & p(-)=7/13; three weights for 123 branches are (2+10)/(2+10+6+7+15+5);(15+5)/(2+10+6+7+15+5);(6+7)/(2+10+6+7+15+5) so the sum of weighted probability of "+" is 0.51 over 0.5. so T will be assigned to +.

Task 3

Q1: What is the overall entropy before splitting?

Entropy(p)= -(4/10)log((4/10) - (6/10)log(6/10) = 0.971

Q2: What is the gain in entropy after splitting on A?

T (7/10) entropy: -(4/7)log(4/7)-(3/7)log(3/7) = 0.985;

F (3/10) entropy: -0log0-(3/3)log(3/3) = 0

Gain on A: Entropy(p)- (T (7/10) entropy + F (3/10) entropy) = -(4/10)log((4/10) - (6/10)log(6/10) -[(7/10)*(-(4/7)log(4/7)-(3/7)log(3/7))* + *(3/10)*0] = 0.281

Q3: What is the gain in entropy after splitting on B:

T (4/10) entropy: -(3/4)log(3/4)-(1/4)log(1/4) = 0.811;

F (6/10) entropy: -(1/6)log(1/6)-(5/6)log(5/6) = 0.65

Gain on A: Entropy(p)- (T (4/10) entropy + F (6/10) entropy) = -(4/10)log((4/10) - (6/10)log(6/10) -[(4/10) *(-(3/4)log(3/4)-(1/4)log(1/4))* + *(6/10)*(-(1/6)log(1/6)-(5/6)log(5/6))] = -0.065

Q4: Which attribute would the decision tree choose?

Choose A which has higher information gain 0.281 > -0.065

Q5: Draw the full decision tree that would be learned for this dataset. You do not need to show any calculations. (We want to split first on the variable which maximizes the information gain until there are no nodes with two class labels.)

Please see the attached picture with the submission or find it under my github folder.

Task 4

Q1: Are decision trees a linear classifier?

Decision trees are non-linear classifer.

Q2: What are the weaknesses of decision trees?

They are unstable. A small change in the data can lead to a large change in the structure of the optimal decision tree. Decision trees are biased for categorical variables with different number of levels. Information gain in decision trees is in favor of those attributes with more levels.

Q3: Is Misclassification errors better than Gini index as the splitting criteria for decision trees?

No. Gini index is better than misclassificatin errors as the splitting criteria. Gini index is more sensitive to changes in the node probabilities than the misclassification errors.