Title: CSE469 Project

Date: Dec.6 – 2020

Name: Hon Ching Li, Yinuo Chen

UBIT: 50185646, 50220710

Introduction: We are trying to predict whether an individual income exceeds \$50K per year based on census data. Our model is able to predict whether a person's income exceeds \$50K per year based on age, workclass, fnlwgt, education, maritial-status, occupation, relationship, race, sex, capital-gain/loss, hours-per-week and native-country. Whenever there is a new census data come in but without their income's status, our model is able to predict whether each person within the census data earn more than \$50K per year or not. Our correctness score is at least 83%.

Formulation: The data mining task can be formulated it into Decision Tree Classification. The inputs are age, workclass, education, maritial-status, occupation, relationship, race, sex, capital-gain/loss, hours-per-week and native-country of the adults. The expected output contains of 2 types of class label. Whether the person income <=\$50K or >\$50K.

Datasets: We got the dataset adult.data from https://archive.ics.uci.edu/ml/datasets/Adult. For example, the feature age, capital gain, capital lose, hours per week are the continuous data type, workclass, education, marital status, occupation, relationship, race, sex are the categorical type.

For preprocessing the data we had these tasks:

Pre-task: dummy up the class label.

Task1: Check to see how many categories within each feature and decide whether to 'dummy' the feature (convert to numeric).

Task2: If the categories within a feature not too much, then dive into the feature to see how 'convincing' of all the categories, if majority amount is within one category. Then we can ignore the rest categories by grouping them into one value/category.

Task3: If majority observations within a feature belong to one value/category, combine the other values/categories as one.

Task4: Create a dummy list, make all categorical features 'dummy', mean convert str to numeric. s.t. Machine Model can use. Need to drop the original column. It's redundant.

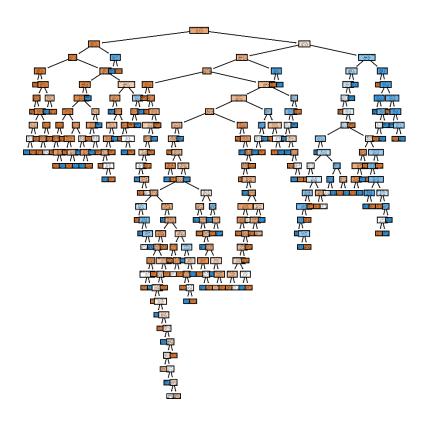
Task5: Handle with the missing value, replacing all the missing values with mean.

Algorithm: We applied decision tree classification algorithm to predict whether each person within the census data earn <=\$50K or >\$50K per year.

Experiments: Within 32562 observations of census dataset, we split 80% of all the observations as our training set and 20% as our testing set. We evaluate the output using sklearn.metrics import confusion_matrix, accuracy_score. We use supervised learning, we put in the actual test set with ground truth and the prediction from our model into the accurancy_score class. That will compute the correctness score for us, we also print out both as np array to visually compare the actual truth with our predictions.

```
confusion Matrix:
[[4444 475]
[ 661 933]]
accurancy score: 0.8255796100107478
```

Decision Tree:



Challenge: our data type consists of various data types, in order to use the methods within sklearn library, we had to convert the types of our dataset to appropriate types that the classes of sklearn library can accept.

Code:

```
import matplotlib.pyplot as plt
def decisionTreeClassification():
```

```
X = pd.DataFrame(data=impute.transform(X), columns= X.columns)
```

```
print(np.concatenate([y test.reshape(len(y test), 1),
y_pred.reshape(len(y pred), 1)], axis=1))
```