Assignment 2.1

University of San Diego

ADS 502

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Introduction to Data Mining: Exercises 3.11 – Page 186: Question #3

3. Consider the training examples shown in Table 3.6 for a binary classification problem.

Table 3.6. Data set for Exercise 3.

Instance	a1	a2	a3	Target Class
1	T	T	1.0	+
2	T	T	6.0	+
3	T	F	5.0	−
4	F	F	4.0	+
5	F	T	7.0	−
6	F	T	3.0	−
7	F	F	8.0	−
8	T	F	7.0	+
9	F	T	5.0	−

a. **What is the entropy of this collection of training examples with respect to the class attribute?**

$P(\text{positive}) = \frac{4}{9}$.

$P(\text{negative}) = \frac{5}{9}$

Entropy for positive class

$$= -\left(\frac{4}{9}\log_2\left(\frac{4}{9}\right) + \frac{5}{9}\log_2\left(\frac{5}{9}\right)\right)$$

$$= \boxed{0.991}$$

b. What are the information gains of a1 and a2 relative to these training examples?

a_1	+	-
T	3	1
F	1	4

entropy for a1 : $\frac{4}{9}\left[-\frac{3}{4}\log_2\left(\frac{3}{4}\right)-\frac{1}{4}\log_2\left(\frac{1}{4}\right)\right]+\frac{5}{9}\left[-\frac{1}{5}\log_2\left(\frac{1}{5}\right)-\frac{4}{5}\log_2\left(\frac{4}{5}\right)\right]$

$= 0.762$

Information gain : $0.991 - 0.762$

$= \boxed{0.229}$

a_2	+	-
T	2	3
F	2	2

entropy for a2 : $\frac{5}{9}\left[-\frac{2}{5}\log_2\left(\frac{2}{5}\right)-\frac{3}{5}\log_2\left(\frac{3}{5}\right)\right]+\frac{4}{9}\left[-\frac{2}{4}\log_2\left(\frac{2}{4}\right)-\frac{2}{4}\log_2\left(\frac{2}{4}\right)\right]$

$= 0.984$

Information gain : $0.991 - 0.984$

$= \boxed{0.007}$

DP

c. **For a3, which is a continuous attribute, compute the information gain for every possible split.**

a3:	1		3		4		5		6		7		8.			
split pos.	0.5		2		3.5		4.5		5.5		6.5		7.5		8.5	
	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>		
+	0	4	1	3	1	3	2	2	2	2	3	1	4	0	4	0
-	0	5	0	5	1	4	1	4	3	2	3	2	4	1	5	0

Split 1:

$$\text{Entropy} = -\left[\left(\frac{4}{9}\log_2\left(\frac{4}{9}\right) + \frac{5}{9}\log_2\left(\frac{5}{9}\right)\right)\right]$$

$$= 0.991$$

$$\text{Infor. gain} = 0.991 - 0.991 = \boxed{0}$$

split 2:

$$<= \ \text{Entropy} = -\left[1 \cdot \log_2(1) + 0 \cdot \log_2(0)\right] = 0.$$

$$> \ \text{Entropy} = -\left[\frac{3}{8} \cdot \log_2\frac{3}{8} + \frac{5}{8} \cdot \log_2\frac{5}{8}\right] = 0.954$$

~~Infor. gain =~~

$$\text{Info. gain} = 0.991 - \left(\frac{1}{9} \cdot 0 + \frac{8}{9} \cdot 0.954\right) = \boxed{0.143}$$

Split 3:

$$<= \text{Entropy} = -\left[\frac{1}{2}\cdot\log_2\frac{1}{2} + \frac{1}{2}\cdot\log_2\frac{1}{2}\right] = 1$$

$$> \text{Entropy} = -\left(\frac{3}{7}\cdot\log_2\frac{3}{7} + \frac{4}{7}\cdot\log_2\frac{4}{7}\right) = 0{,}985.$$

$$\text{Info gain} = 0{,}991 - \left(\frac{2}{9}\cdot 1 + \frac{7}{9}\cdot 0{,}985\right) = \boxed{0{,}00249}$$

Split 4:

$$<= \text{Entropy} = -\left(\frac{2}{3}\cdot\log_2\frac{2}{3} + \frac{1}{3}\cdot\log_2\frac{1}{3}\right) = 0{,}918$$

$$> \text{Entropy} = -\left(\frac{2}{6}\cdot\log_2\frac{2}{6} + \frac{4}{6}\cdot\log_2\frac{4}{6}\right) = 0{,}918.$$

$$\text{Info gain} = 0{,}991 - \left(\frac{3}{9}\cdot 0{,}918 + \frac{6}{9}\cdot 0{,}918\right) = \boxed{0{,}0727}$$

Split 5:

$$<= \text{Entropy} = -\left(\frac{2}{5}\cdot\log_2\frac{2}{5} + \frac{3}{5}\cdot\log_2\frac{3}{5}\right) = 0{,}971$$

$$> \text{Entropy} = -\left(\frac{2}{4}\cdot\log_2\frac{2}{4} + \frac{2}{4}\cdot\log_2\frac{2}{4}\right) = 1$$

$$\text{Info. gain} = 0.991 - \left(\frac{5}{9}\cdot 0.971 + \frac{4}{9}\cdot 1\right) = \boxed{0.00714}$$

Split 6 :

<= Entropy $= -\left(\frac{3}{6}\cdot\log_2\frac{3}{6} + \frac{3}{6}\cdot\log_2\frac{3}{6}\right) = 1$

> Entropy $= -\left(\frac{1}{3}\cdot\log_2\frac{1}{3} + \frac{2}{3}\cdot\log_2\frac{2}{3}\right) = 0.918$.

Info. gain $= 0.991 - \left(\frac{6}{9}\cdot 1 + \frac{3}{9}\cdot 0.918\right) = \boxed{0.0182}$

Split 7 :

<= Entropy $= -\left(\frac{4}{8}\cdot\log_2\frac{4}{8} + \frac{4}{8}\cdot\log_2\frac{4}{8}\right) = 1$

> Entropy $= -\left(0\cdot\log_2 0 + 1\cdot\log_2 1\right) = 0$.

Info. gain $= 0.991 - \left(\frac{8}{9}\cdot 1 + \frac{1}{9}\cdot 0\right) = \boxed{0.102}$

Split 8 :

<= Entropy $= -\left(\frac{4}{9}\cdot\log_2\frac{4}{9} + \frac{5}{9}\cdot\log_2\frac{5}{9}\right) = 0.992$.

> Entropy $= -\left(0\cdot\log_2 0 + 0\cdot\log_2 0\right) = 0$.

Info. gain $= \boxed{0.}$

DP

d. **What is the best split (among a1, a2 and a3) according to the information gain?**

$\boxed{a_1,}$ due to its higher gain of 0,229

e. **What is the best split (between a1 and a2) according to the misclassification error rate?**

Classification Error Rate :

$a_1 = 1 - (\frac{7}{9}, \frac{2}{9}) = 1 - \frac{7}{9} = \frac{2}{9}$. ✓

$a_2 = 1 - (\frac{5}{9}, \frac{4}{9}) = 1 - \frac{5}{9} = \frac{4}{9}$.

$\boxed{a_1}$ is the better split for its lower MER

of $\frac{2}{9} \approx 0.222$

DP

f. **What is the best split (between a1 and a2) according to the Gini index?**

Gini Index :

$$a_1 = 1 - \left[\left(\frac{7}{9}\right)^2 + \left(\frac{2}{9}\right)^2\right] = 0{,}346 .$$ ✓

$$a_2 = 1 - \left[\left(\frac{4}{9}\right)^2 + \left(\frac{5}{9}\right)^2\right] = 0{,}494$$

$\boxed{a_1}$ is the best split for its lower GI.

of 0,346 .

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Assignment 2.1 [Python]

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Dingyi Duan

For Exercises 21–30, continue working with the bank_marketing_training data set. Use

either Python or R to solve each problem.

21. Produce the following graphs. What is the strength of each graph? Weakness?

a. Bar graph of marital.

In [1]:
```
ort pandas as pd
ort numpy as np
ort matplotlib.pyplot as plt
k_train = pd.read_csv("C:/Users/DDY/Desktop/2021-Spring-textbooks/ADS-502/Module2/
set_option('display.max_columns', None)
```

In [2]:
```
bank_train.head()
```

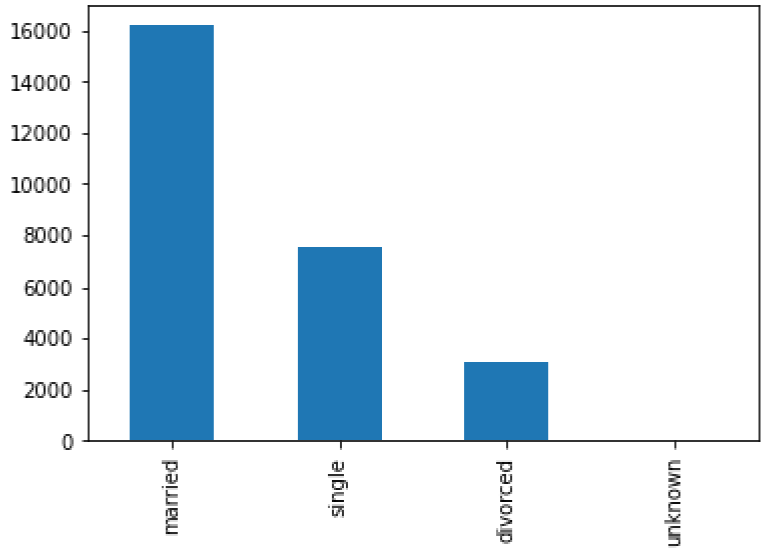
Out[2]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	d
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	
2	41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon	
3	25	services	single	high.school	no	yes	no	telephone	may	mon	
4	29	blue-collar	single	high.school	no	no	yes	telephone	may	mon	

In [3]:
```
# Use df.plot(kind = 'bar') for barplot; use value_count() for non-numeric values
```

In [4]:
```
bank_train['marital'].value_counts().plot(kind = 'bar')
```

Out[4]: <AxesSubplot:>



Strenghth: Easy to see which the number difference;

Weakness: values are not normalized thus can't see the exact number of the category with minimal value

b. Bar graph of marital, with overlay of response.

In [5]:
```
# Create the contingency table first in order to create an overlaid bar chart
```

In [6]:
```
crosstab_01 = pd.crosstab(bank_train['marital'], bank_train['response'])
```

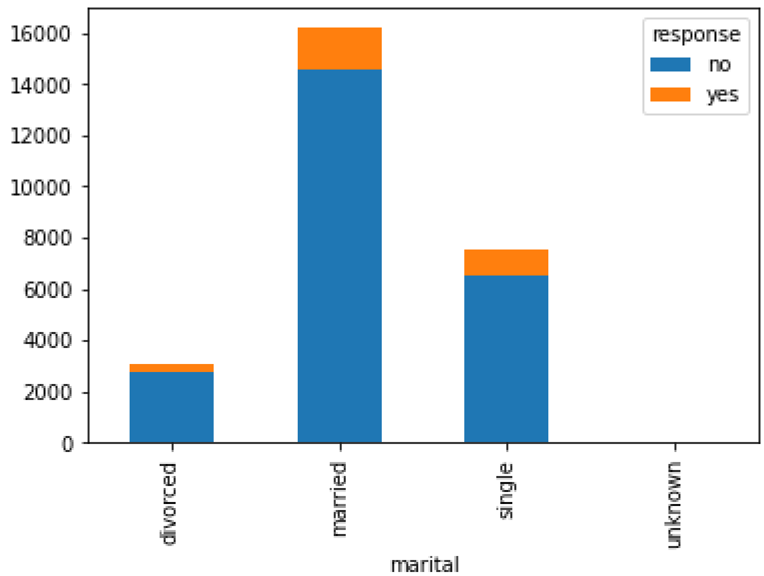
In [7]:
```
crosstab_01
```

Out[7]:

response	no	yes
marital		
divorced	2743	312
married	14579	1608
single	6514	1061
unknown	50	7

In [8]:
```
crosstab_01.plot(kind='bar', stacked = True)
```

Out[8]: <AxesSubplot:xlabel='marital'>



Strength: can clearly see which category has more values;

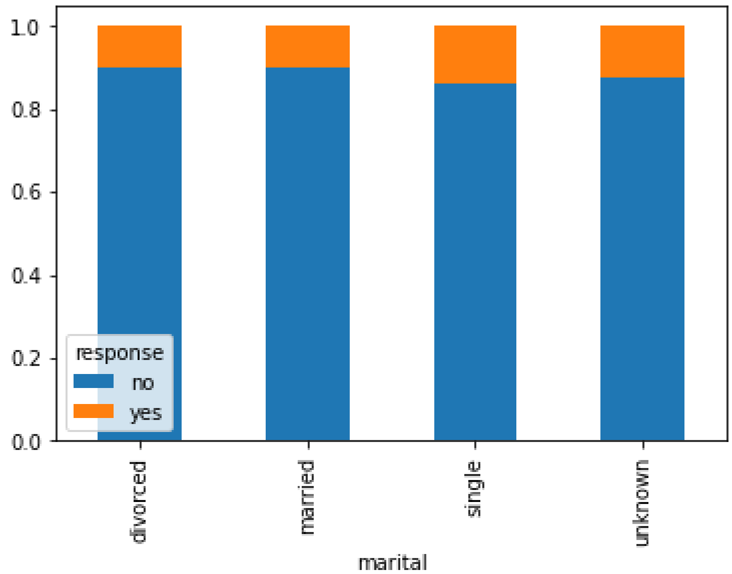
Weakness: it is hard to tell the ratio of response of yes and no

c. Normalized bar graph of marital, with overlay of response.

In [9]:
```
# Normalize the contingency table using table.div(table.sum(axis=1),axis=0);
# divide each value in the row by the sum of the columns
```

In [10]:
```
crosstab_01_norm = crosstab_01.div(crosstab_01.sum(axis=1), axis = 0)
crosstab_01_norm.plot(kind='bar', stacked = True)
```

Out[10]: <AxesSubplot:xlabel='marital'>



Strength: can have a better understanding of the ratio of yes and no;

Weakness: cannot see the numeric difference between each category

22. Using the graph from Exercise 21c, describe the relationship between marital and response.

In divorced and married status, the response of "yes" rate is the same and the lowest among all;

For unknown status, the response of "yes" rate is in between single and divorced/married;

Response rate of "yes" is the highest for single marital status

23. Do the following with the variables marital and response.

a. Build a contingency table, being careful to have the correct variables representing

the rows and columns. Report the counts and the column percentages.

In [11]:
```
crosstab_02 = pd.crosstab(bank_train['response'], bank_train['marital'])
```

In [12]:
```
crosstab_02_percent_col = (round(crosstab_02.div((crosstab_02.sum(axis=0))/100,ax
```

In [13]:
```
crosstab_02_percent_col
```

Out[13]:

marital	divorced	married	single	unknown
response				
no	89.79%	90.07%	85.99%	87.72%
yes	10.21%	9.93%	14.01%	12.28%

b. Describe what the contingency table is telling you.

For response of "no", 'married' has the most percentage;

For response of "yes", 'single' has the most percentage.

24. Repeat the previous exercise, this time reporting the row percentages. Explain the

difference between the interpretation of this table and the previous contingency table.

In [14]:
```
crosstab_01_percent_row = (round(crosstab_01.div((crosstab_01.sum(axis=1))/100,ax
```

In [15]:
```
crosstab_01_percent_row
```

Out[15]:

response	no	yes
marital		
divorced	89.79%	10.21%
married	90.07%	9.93%
single	85.99%	14.01%
unknown	87.72%	12.28%

This time the row percentage shows the ratio in each marital status of response of "yes" and "no";

In "divorced", 89.79% responded "no" and 10.21% responded "yes";

In "married", 90.07% responded "no" and 9.93% responded "yes";

In "single", 85.99% responded "no" and 14.01% responded "yes";

In "unknown", 87.72% responded "no" and 12.38% responded "yes";

Overall, more people repsonded "no" than "yes".

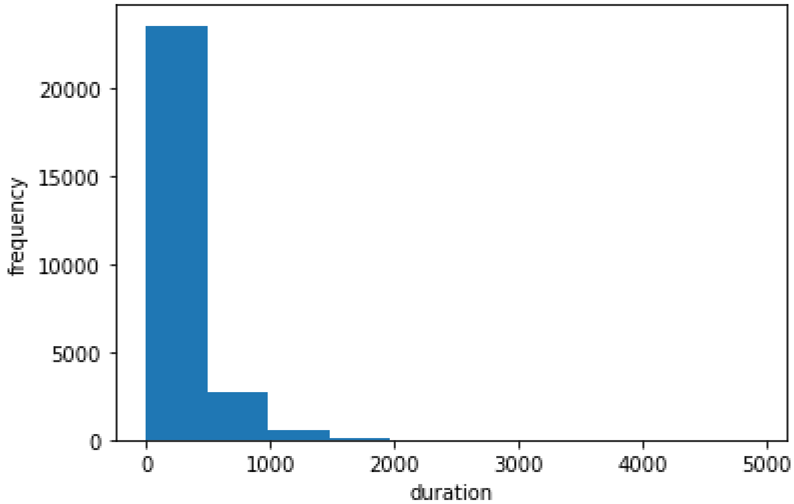
The difference between this two tables is one is from the perspective of response while the other is

from the perspective of marital status.

25. Produce the following graphs. What is the strength of each graph? Weakness?

a. Histogram of duration.

In [16]:
```
plt.hist(bank_train['duration'])
plt.xlabel('duration');
plt.ylabel('frequency');
```



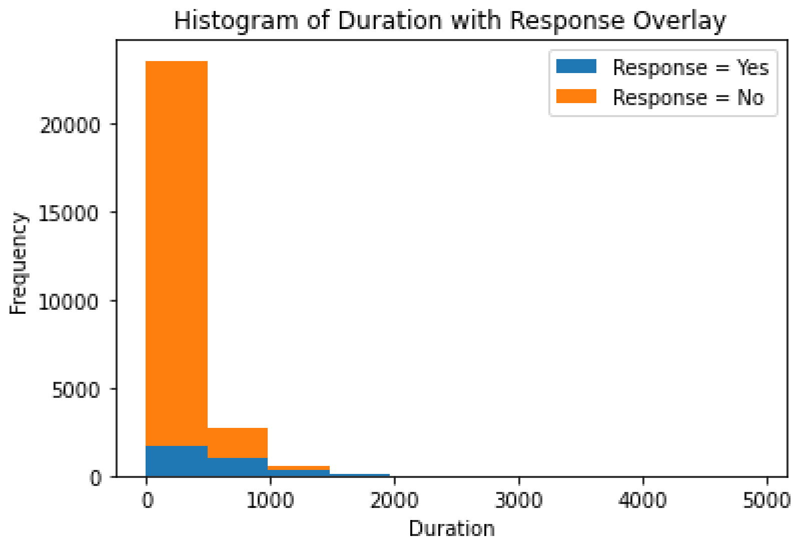
Strength: easy to see the general range of the mode

Weakness: hard to get the clear idea of more detailed bin range

b. Histogram of duration, with overlay of response.

In [17]:
```
duration_y = bank_train[bank_train.response == "yes"]['duration']
duration_n = bank_train[bank_train.response == "no"]['duration']
```

In [18]:
```
plt.hist([duration_y, duration_n], bins = 10,stacked = True)
plt.legend(['Response = Yes', 'Response = No'])
plt.title('Histogram of Duration with Response Overlay')
plt.xlabel('Duration'); plt.ylabel('Frequency'); plt.show()
```

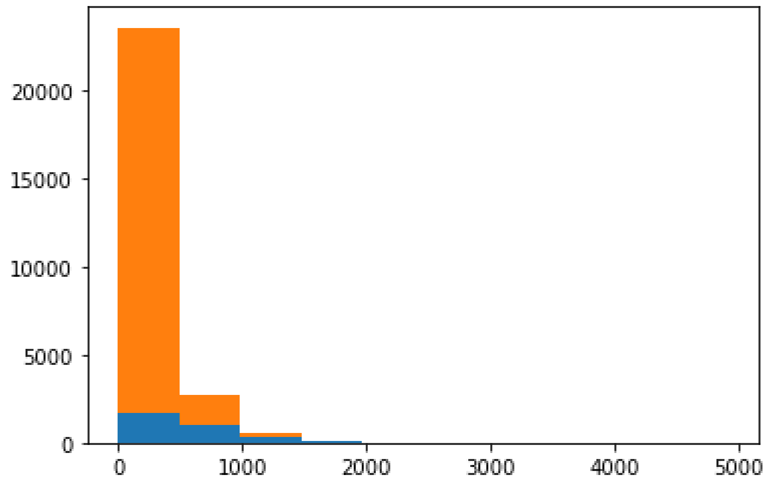


Strength: Can see frequency of duration with overlay of response with each bin (hardly)

Weakness: hard to tell the ratio comparison between the durations

c. Normalized histogram of duration, with overlay of response.

In [19]:
```
(n, bins, patches) = plt.hist([duration_y, duration_n], bins =
10, stacked = True)
```

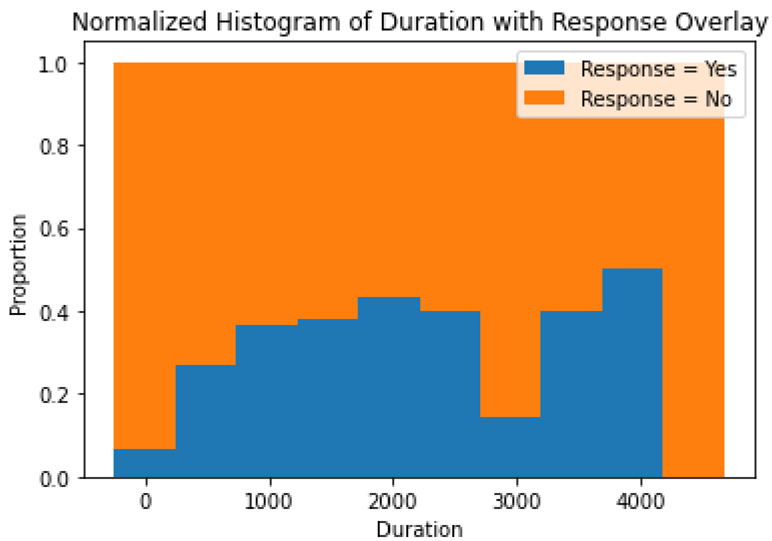


In [20]:
```
n_table = np.column_stack((n[0], n[1]))
```

In [21]:
```
n_norm = n_table / n_table.sum(axis=1)[:, None]
```

In [22]:
```
ourbins = np.column_stack((bins[0:10], bins[1:11]))
```

In [23]:
```
p1 = plt.bar(x = ourbins[:,0], height = n_norm[:,0],
width = ourbins[:, 1] - ourbins[:, 0])
p2 = plt.bar(x = ourbins[:,0], height = n_norm[:,1],
width = ourbins[:, 1] - ourbins[:, 0],
bottom = n_norm[:,0])
plt.legend(['Response = Yes', 'Response = No'])
plt.title('Normalized Histogram of Duration with Response Overlay')
plt.xlabel('Duration'); plt.ylabel('Proportion'); plt.show()
```



Strength: Can clearly see the ratio of yes and no for each bin

Weakness: hard to tell the which bin contains higher frequency of duration

For Exercises 14–20, work with the adult_ch6_training and adult_ch6_test data sets. Use either Python or R to solve each problem.

14. Create a CART model using the training data set that predicts income using marital status and capital gains and losses. Visualize the decision tree (that is, provide the decision tree output). Describe the first few splits in the decision tree.

In [24]:
```
from sklearn.tree import DecisionTreeClassifier, export_graphviz
adult_training = pd.read_csv("C:/Users/DDY/Desktop/2021-Spring-textbooks/ADS-502/
```

In [25]:
```
adult_training.head()
```

Out[25]:

	Marital status	Income	Cap_Gains_Losses
0	Never-married	<=50K	0.02174
1	Divorced	<=50K	0.00000
2	Married	<=50K	0.00000
3	Married	<=50K	0.00000
4	Married	<=50K	0.00000

In [26]:
```
y = adult_training[['Income']]
```

In [27]:
```
y
```

Out[27]:

	Income
0	<=50K
1	<=50K
2	<=50K
3	<=50K
4	<=50K
...	...
18756	<=50K
18757	<=50K
18758	<=50K
18759	<=50K
18760	<=50K

18761 rows × 1 columns

In [28]:
```
X = adult_training[['Marital status', 'Cap_Gains_Losses']]
```

In [29]:
```
X
```

Out[29]:

	Marital status	Cap_Gains_Losses
0	Never-married	0.02174
1	Divorced	0.00000
2	Married	0.00000
3	Married	0.00000
4	Married	0.00000
...	...	...
18756	Divorced	0.00000
18757	Married	0.00000
18758	Married	0.00000
18759	Divorced	0.00000
18760	Married	0.00000

18761 rows × 2 columns

In [30]:
```
marital_dummy = pd.get_dummies(X['Marital status'])
```

In [31]:
```
marital_dummy
```

Out[31]:

	Divorced	Married	Never-married	Separated	Widowed
0	0	0	1	0	0
1	1	0	0	0	0
2	0	1	0	0	0
3	0	1	0	0	0
4	0	1	0	0	0
...	...	...	...	...	...
18756	1	0	0	0	0
18757	0	1	0	0	0
18758	0	1	0	0	0
18759	1	0	0	0	0
18760	0	1	0	0	0

18761 rows × 5 columns

In [32]:
```
# Concatenate by cols
```

In [33]:
```
X = pd.concat((X[['Cap_Gains_Losses']], marital_dummy), axis = 1)
```

In [34]:
```
X
```

Out[34]:

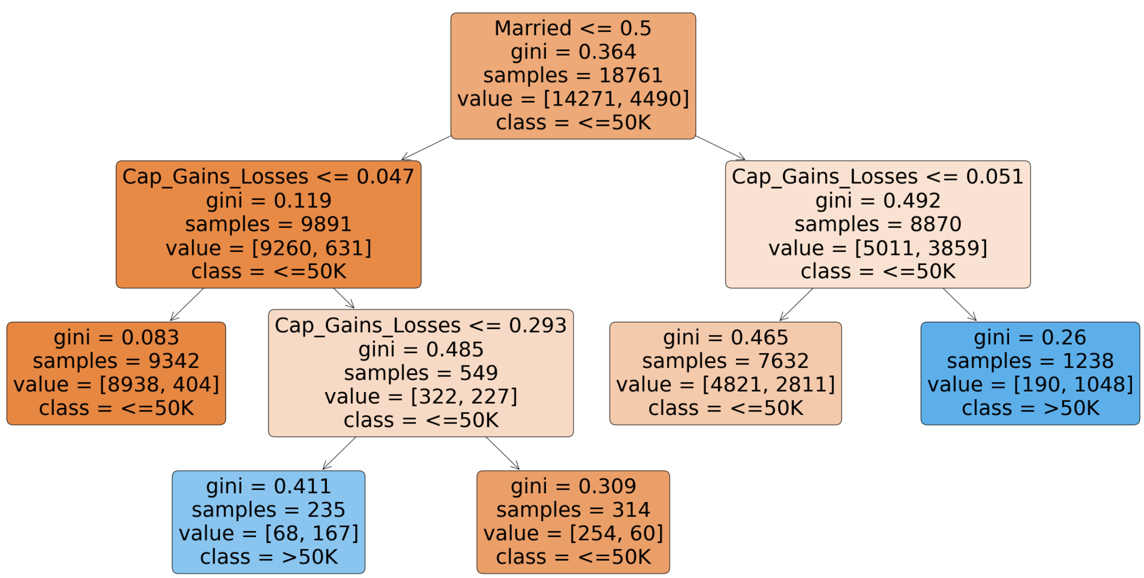
	Cap_Gains_Losses	Divorced	Married	Never-married	Separated	Widowed
0	0.02174	0	0	1	0	0
1	0.00000	1	0	0	0	0
2	0.00000	0	1	0	0	0
3	0.00000	0	1	0	0	0
4	0.00000	0	1	0	0	0
...	...	...	...	...	...	...
18756	0.00000	1	0	0	0	0
18757	0.00000	0	1	0	0	0
18758	0.00000	0	1	0	0	0
18759	0.00000	1	0	0	0	0
18760	0.00000	0	1	0	0	0

18761 rows × 6 columns

In [35]:
```
DT_CART = DecisionTreeClassifier(criterion='gini', max_leaf_nodes=5).fit(X, y)
```

In [36]:
```python
from sklearn.tree import plot_tree

plt.figure(figsize=(40,20))
plot_tree(DT_CART,
          feature_names = X.columns,
          class_names=y['Income'].unique(),
          filled=True,
          rounded = True)
```

Out[36]:
```
[Text(1116.0, 951.3000000000001, 'Married <= 0.5\ngini = 0.364\nsamples = 18761
\nvalue = [14271, 4490]\nclass = <=50K'),
 Text(558.0, 679.5, 'Cap_Gains_Losses <= 0.047\ngini = 0.119\nsamples = 9891\nv
alue = [9260, 631]\nclass = <=50K'),
 Text(279.0, 407.70000000000005, 'gini = 0.083\nsamples = 9342\nvalue = [8938,
404]\nclass = <=50K'),
 Text(837.0, 407.70000000000005, 'Cap_Gains_Losses <= 0.293\ngini = 0.485\nsamp
les = 549\nvalue = [322, 227]\nclass = <=50K'),
 Text(558.0, 135.89999999999998, 'gini = 0.411\nsamples = 235\nvalue = [68, 16
7]\nclass = >50K'),
 Text(1116.0, 135.89999999999998, 'gini = 0.309\nsamples = 314\nvalue = [254, 6
0]\nclass = <=50K'),
 Text(1674.0, 679.5, 'Cap_Gains_Losses <= 0.051\ngini = 0.492\nsamples = 8870\n
value = [5011, 3859]\nclass = <=50K'),
 Text(1395.0, 407.70000000000005, 'gini = 0.465\nsamples = 7632\nvalue = [4821,
2811]\nclass = <=50K'),
 Text(1953.0, 407.70000000000005, 'gini = 0.26\nsamples = 1238\nvalue = [190, 1
048]\nclass = >50K')]
```



In [37]:
```python
predIncomeCART = DT_CART.predict(X)
predIncomeCART
```

Out[37]:
```
array(['<=50K', '<=50K', '<=50K', ..., '<=50K', '<=50K', '<=50K'],
      dtype=object)
```

From the top: total sample is 18761; there are 9891 samples that are not married with income <=50k; there are 9342 samples that have Capital gain and losses <=0.047 and income <= 50k; there are 235 samples that have capital gains and losses <= 0.293 and

income <= 50k; there are 7632 samples that have capital gains and losses <= 0.051 and income <= 50k.

15. Develop a CART model using the test data set that utilizes the same target and predictor variables. Visualize the decision tree. Compare the decision trees. Does the test data result match the training data result?

In [38]:
```
adult_test = pd.read_csv("C:/Users/DDY\Desktop/2021-Spring-textbooks/ADS-502/Modu
```

In [39]:
```
y2 = adult_test[['Income']]
```

In [40]:
```
X2 = adult_test[['Marital status', 'Cap_Gains_Losses']]
```

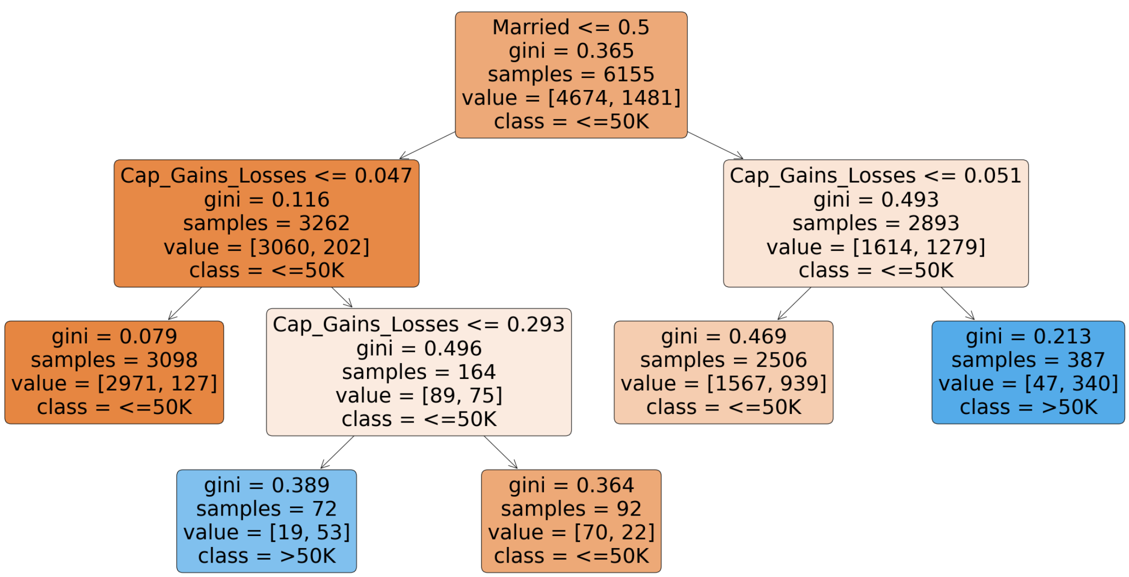
In [41]:
```
marital_dummy_test = pd.get_dummies(X2['Marital status'])
```

In [42]:
```
X2 = pd.concat((X2[['Cap_Gains_Losses']], marital_dummy_test), axis = 1)
```

In [43]:
```
DT2_CART = DecisionTreeClassifier(criterion='gini', max_leaf_nodes=5).fit(X2, y2)
```

In [44]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(40,20))
plot_tree(DT2_CART,
          feature_names = X2.columns,
          class_names=y2['Income'].unique(),
          filled=True,
          rounded = True)
```

Out[44]:
```
[Text(1116.0, 951.3000000000001, 'Married <= 0.5\ngini = 0.365\nsamples = 6155
\nvalue = [4674, 1481]\nclass = <=50K'),
 Text(558.0, 679.5, 'Cap_Gains_Losses <= 0.047\ngini = 0.116\nsamples = 3262\nv
alue = [3060, 202]\nclass = <=50K'),
 Text(279.0, 407.70000000000005, 'gini = 0.079\nsamples = 3098\nvalue = [2971,
127]\nclass = <=50K'),
 Text(837.0, 407.70000000000005, 'Cap_Gains_Losses <= 0.293\ngini = 0.496\nsamp
les = 164\nvalue = [89, 75]\nclass = <=50K'),
 Text(558.0, 135.89999999999998, 'gini = 0.389\nsamples = 72\nvalue = [19, 53]
\nclass = >50K'),
 Text(1116.0, 135.89999999999998, 'gini = 0.364\nsamples = 92\nvalue = [70, 22]
\nclass = <=50K'),
 Text(1674.0, 679.5, 'Cap_Gains_Losses <= 0.051\ngini = 0.493\nsamples = 2893\n
value = [1614, 1279]\nclass = <=50K'),
 Text(1395.0, 407.70000000000005, 'gini = 0.469\nsamples = 2506\nvalue = [1567,
939]\nclass = <=50K'),
 Text(1953.0, 407.70000000000005, 'gini = 0.213\nsamples = 387\nvalue = [47, 34
0]\nclass = >50K')]
```



In [45]:
```
predIncomeCART2 = DT2_CART.predict(X)
predIncomeCART2
```

Out[45]:
```
array(['<=50K', '<=50K', '<=50K', ..., '<=50K', '<=50K', '<=50K'],
      dtype=object)
```

The decision tree of test dataset matches the one with training dataset

16. Use the training data set to build a C5.0 model to predict income using marital status and capital gains and losses. Specify a minimum of 75 cases per terminal node. Visualize the decision tree. Describe the first few splits in the decision tree.

Since Python packages do not directly implement C5.0, this will be done using R.

17. How does your C5.0 model compare to the CART model? Describe the similarities and differences.

For the following exercises, work with the bank_reg_training and the bank_reg_test data sets. Use either Python or R to solve each problem.

34. Use the training set to run a regression predicting Credit Score, based on Debt-to-Income Ratio and Request Amount. Obtain a summary of the model. Do both predictors belong in the model?

In [46]:
```
import statsmodels.api as sm
```

In [47]:
```
bank_reg_train = pd.read_csv('C:/Users/DDY/Desktop/2021-Spring-textbooks/ADS-502/
bank_reg_test = pd.read_csv('C:/Users/DDY/Desktop/2021-Spring-textbooks/ADS-502/N
```

In [48]:
```
bank_reg_train.head()
```

Out[48]:

	Approval	Credit Score	Debt-to-Income Ratio	Interest	Request Amount
0	F	695.0	0.47	2700.0	6000.0
1	F	775.0	0.03	6300.0	14000.0
2	T	703.0	0.21	3600.0	8000.0
3	T	738.0	0.18	8100.0	18000.0
4	T	685.0	0.16	7650.0	17000.0

In [49]:
```
X = pd.DataFrame(bank_reg_train[['Debt-to-Income Ratio','Request Amount']]) #Prec
```

In [50]:
```
y = pd.DataFrame(bank_reg_train[['Credit Score']]) #Target
```

In [51]:
```
X = sm.add_constant(X) #Adding constant
```

In [52]:
```
model = sm.OLS(y, X).fit() #Multiple Regression Model
```

In [53]:
```
model.summary()
```

Out[53]:

OLS Regression Results

Dep. Variable:	Credit Score	**R-squared:**	0.028
Model:	OLS	**Adj. R-squared:**	0.028
Method:	Least Squares	**F-statistic:**	156.2
Date:	Sun, 11 Jul 2021	**Prob (F-statistic):**	1.37e-67
Time:	20:49:52	**Log-Likelihood:**	-59972.
No. Observations:	10693	**AIC:**	1.199e+05
Df Residuals:	10690	**BIC:**	1.200e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	668.4562	1.336	500.275	0.000	665.837	671.075
Debt-to-Income Ratio	-48.1262	4.785	-10.058	0.000	-57.505	-38.747
Request Amount	0.0011	6.84e-05	15.727	0.000	0.001	0.001

Omnibus:	1658.575	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2844.250
Skew:	-1.021	**Prob(JB):**	0.00
Kurtosis:	4.487	**Cond. No.**	1.24e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.24e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Since p values are small < 0.005, so all predictors are statistically significant. We need to see if they are correlated.

In [54]:
```
print(np.corrcoef(bank_reg_train['Debt-to-Income Ratio'], bank_reg_train['Request
```

```
[[1.         0.13118806]
 [0.13118806 1.        ]]
```

Correlation between the predictors is small (0.131), no multicollinearity, so they both can belong to the model.

35. Validate the model from the previous exercise.

In [55]:
```
# Use test dataset to validate the model
```

In [56]:
```
X_test = pd.DataFrame(bank_reg_test[['Debt-to-Income Ratio','Request Amount']])
y_test = pd.DataFrame(bank_reg_test[['Credit Score']])
X_test = sm.add_constant(X_test)
model = sm.OLS(y_test, X_test).fit()
model.summary()
```

Out[56]:

OLS Regression Results

Dep. Variable:	Credit Score	**R-squared:**	0.038
Model:	OLS	**Adj. R-squared:**	0.038
Method:	Least Squares	**F-statistic:**	215.4
Date:	Sun, 11 Jul 2021	**Prob (F-statistic):**	1.94e-92
Time:	20:49:52	**Log-Likelihood:**	-60395.
No. Observations:	10775	**AIC:**	1.208e+05
Df Residuals:	10772	**BIC:**	1.208e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	665.4987	1.328	501.265	0.000	662.896	668.101
Debt-to-Income Ratio	-52.1374	4.826	-10.803	0.000	-61.597	-42.677
Request Amount	0.0013	6.85e-05	19.013	0.000	0.001	0.001

Omnibus:	1792.693	**Durbin-Watson:**	1.985
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3194.120
Skew:	-1.067	**Prob(JB):**	0.00
Kurtosis:	4.600	**Cond. No.**	1.25e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.25e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Validation complete

36. Use the regression equation to complete this sentence: “The estimated Credit Score equals....”

The estimated Credit Score equals y = 668.4562 - 48.1262* Debt-to-Income Ratio + 0.0011* Request Amount

37. Interpret the coefficient for Debt-to-Income Ratio.

The coefficient for Debt-to-Income Ratio is negative which means the lower the Debt-to-Income Ratio, the higher the credit score.

38. Interpret the coefficient for Request Amount.

The coefficient for Request Amount is positive which means the higher the Request Amount, the higher the credit score.

39. Find and interpret the value of s.

In [57]:
```
s = np.sqrt(model.scale) #Standard error for the model
s
```

Out[57]:
```
65.77845809176674
```

The size of model prediction error is 65.8 (66), that is the difference between the actual credit score and of which predicated from the model.

40. Find and interpret Radj2 . Comment.

The adjusted R squared value is modified version of R-squared that has been adjusted for the number of predictors in the model. It increases when the new term improves the model more than would be expected by chance. It decreases when a predictor improves the model by less than expected. The R-adj^2 is 0.028 from the model. This means that 2.8% of the variability in Credit Score is accounted for by the predictors Debt-to-Income Ratio and Request Amount.

41. Find MAE_Baseline and MAE_Regression, and determine whether the regression model outperformed its baseline model.

In [58]:
```
from sklearn.metrics import mean_absolute_error as MAE
```

In [59]:
```
predictions = model.predict(X_test)
MAE(y_true=y_test, y_pred=predictions)
```

Out[59]:
```
48.01625111759975
```

In [60]:
```
y_bar = sum(bank_reg_test['Credit Score'])/y_test.shape[0]
y_bar
```

Out[60]:
```
673.3147099767981
```

In [61]:
```
MAE_Baseline = (abs((y_test - y_bar)['Credit Score']).sum())/y_test.shape[0]
MAE_Baseline
```

Out[61]:
```
48.60024069637869
```

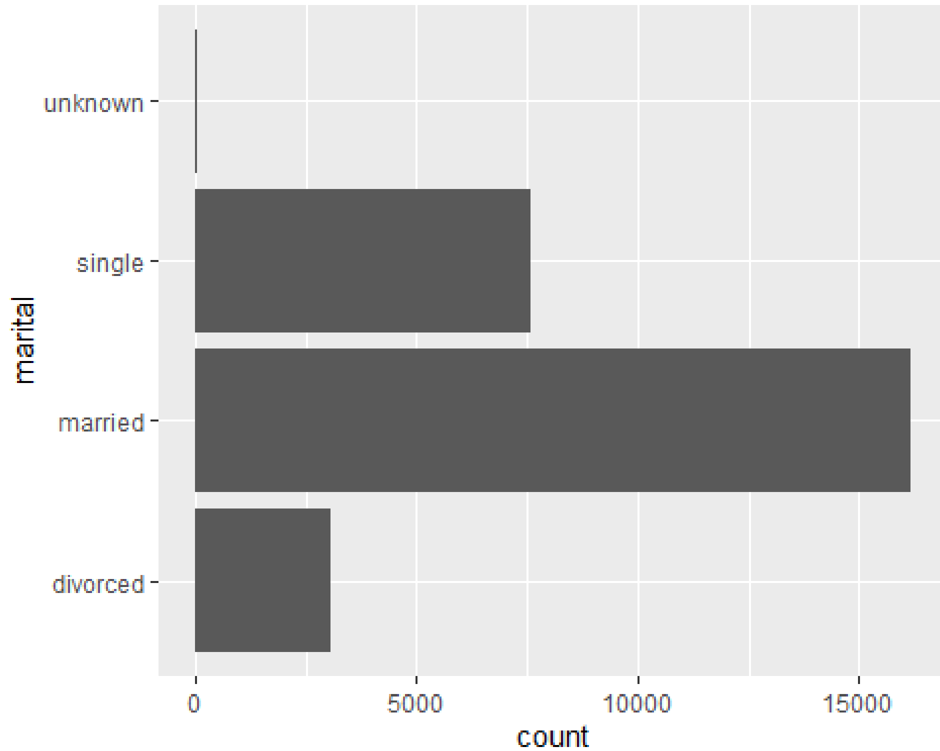
So the MAE_Regression is 48.02 and the MAE_Baseline is 48.60. Since MAE_Regression < MAE_Baseline, thus, our regression model outperformed its baseline model.

ADS502-Assignment-2.1-R.R

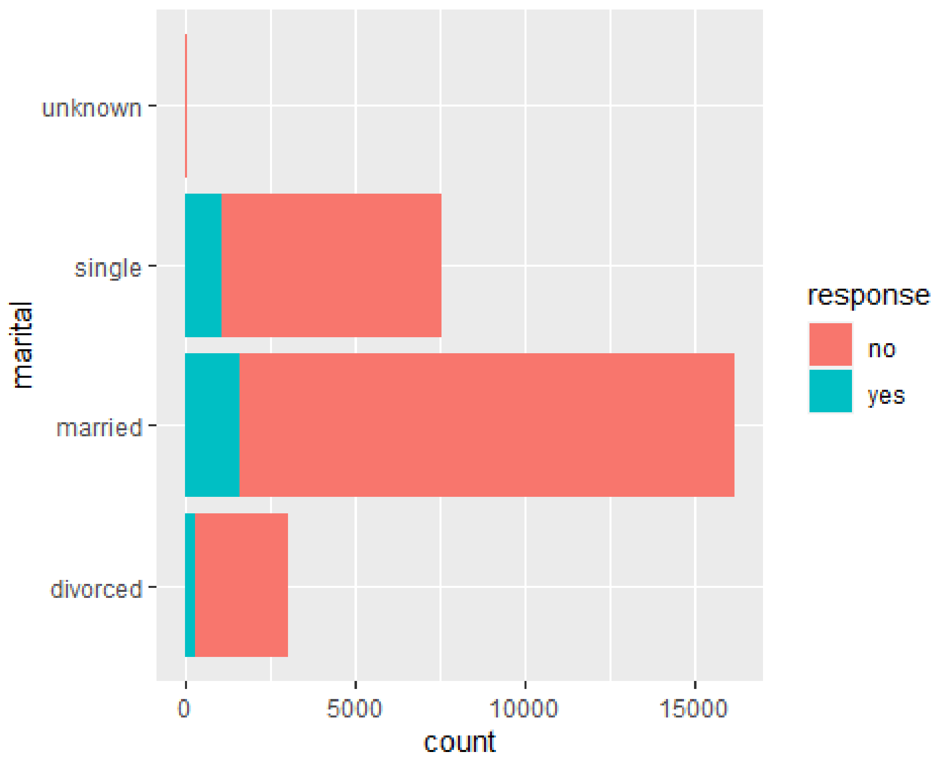
DDY

2021-07-11

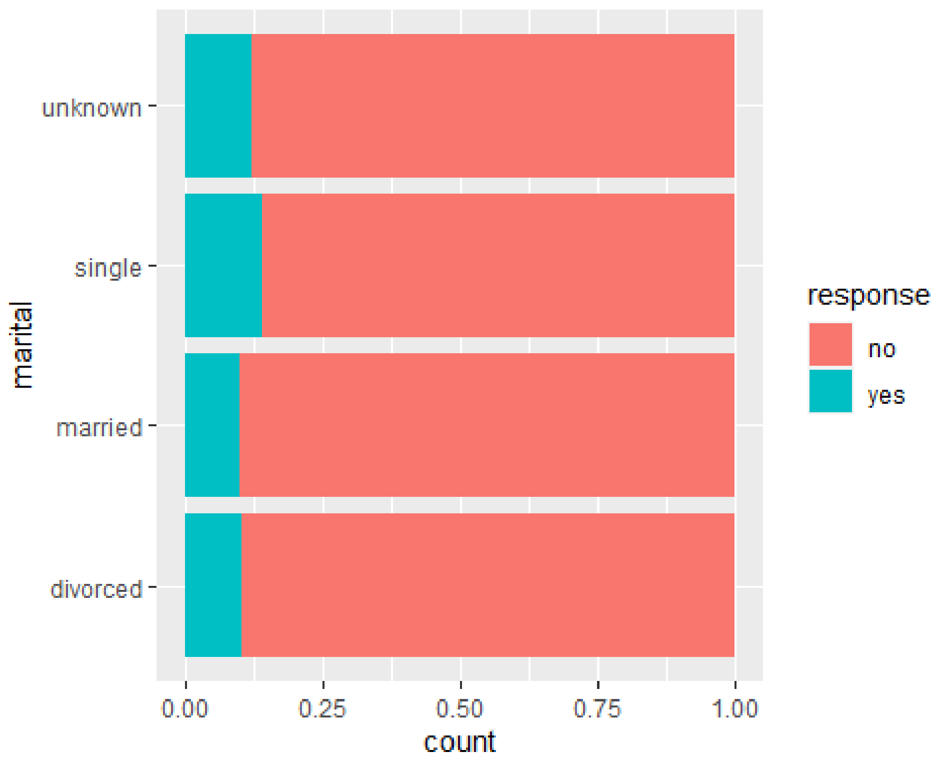
```
# Assignment 2.1 [R]

# University of San Diego

# ADS 502

# Dingyi Duan


# For Exercises 21-30, continue working with the
bank_marketing_training
# data set. Use either Python or R to solve each problem.

# 21. Produce the following graphs. What is the strength of each graph?
Weakness?

# a. Bar graph of marital.

library(ggplot2)

bank_train <- read.csv(file = "C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data
Sets/bank_marketing_training.csv")

ggplot(bank_train, aes(marital)) + geom_bar() + coord_flip()
```




```
# b. Bar graph of marital, with overlay of response.

ggplot(bank_train, aes(marital)) + geom_bar(aes(fill = response)) +
coord_flip()
```



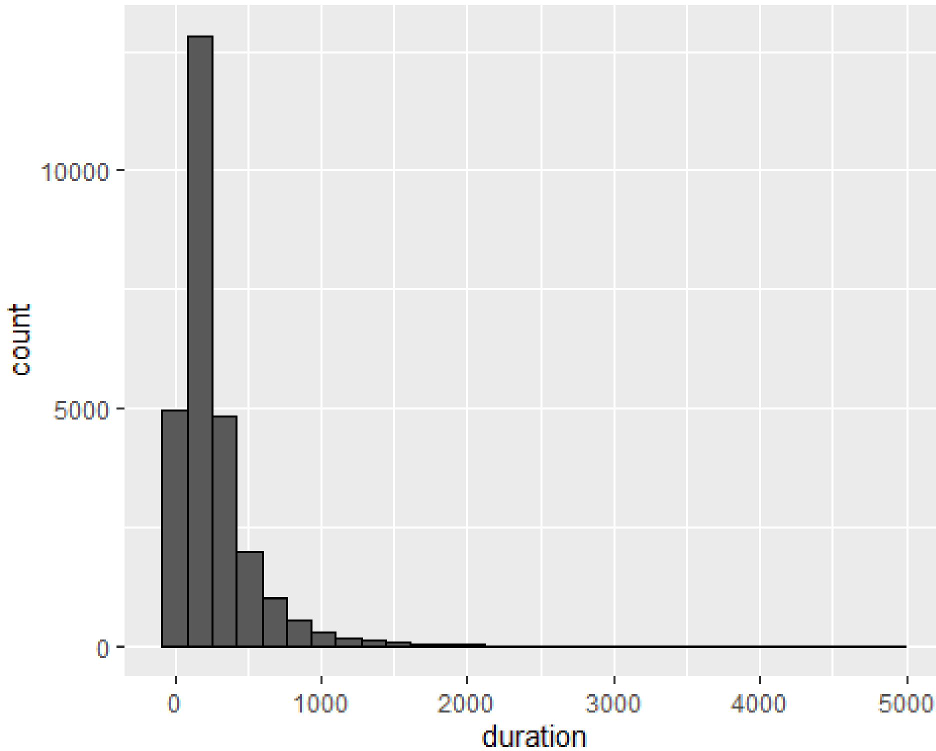

```
# c. Normalized bar graph of marital, with overlay of response.

ggplot(bank_train, aes(marital)) + geom_bar(aes(fill = response),
                                            position = "fill") +
coord_flip()
```



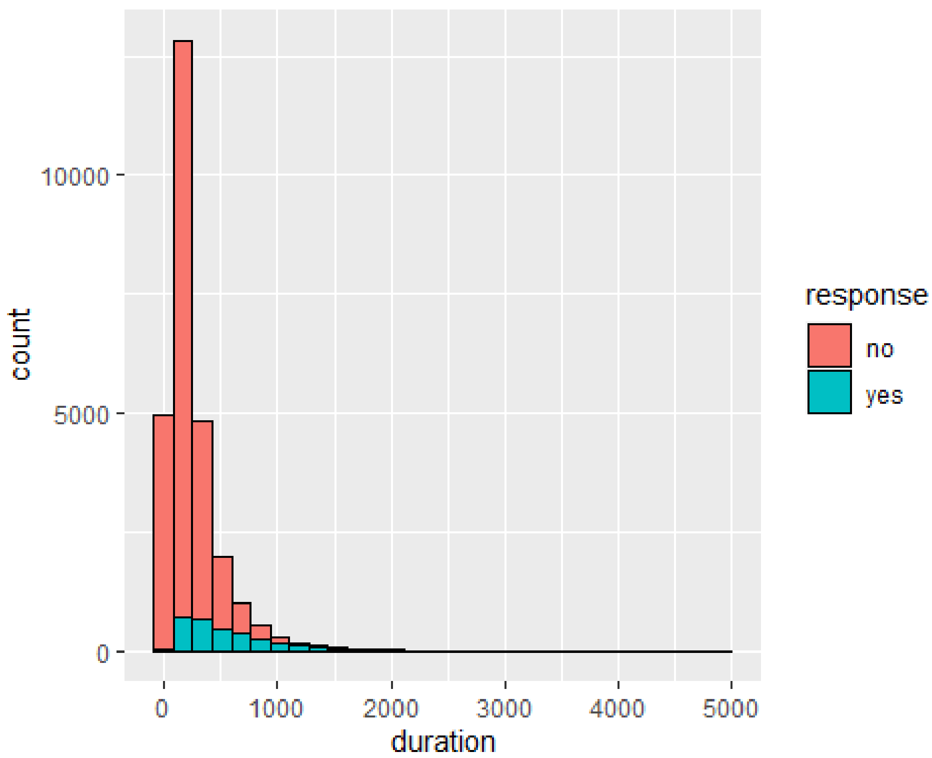

```
# 22. Using the graph from Exercise 21c, describe the relationship
between marital and response.
# In divorced and married status, the response of "yes" rate is the
same and the lowest among all;
# For unknown status, the response of "yes" rate is in between single
and divorced/married;
# Response rate of "yes" is the highest for single marital status


## 23. Do the following with the variables marital and response.

# a. Build a contingency table, being careful to have the correct
variables
# representing the rows and columns. Report the counts and the column
percentages.

t.v1 <- table(bank_train$response, bank_train$marital)
t.v2 <- addmargins(A = t.v1, FUN = list(total = sum),quiet = TRUE)

# table without total
t.v1

##
##        divorced married single unknown
##   no       2743   14579   6514      50
##   yes       312    1608   1061       7
```

```r
# table with total
t.v2

##
##          divorced married single unknown total
##   no        2743   14579   6514      50 23886
##   yes        312    1608   1061       7  2988
##   total     3055   16187   7575      57 26874

t.v1_pct <- round(prop.table(t.v1, margin = 2)*100, 1)
t.v2_pct <- addmargins(A = t.v1_pct, FUN = list(total = sum),quiet =
TRUE)

# percentage table
t.v1_pct

##
##        divorced married single unknown
##   no       89.8    90.1   86.0    87.7
##   yes      10.2     9.9   14.0    12.3

# b. Describe what the contingency table is telling you.
# For response of "no", 'married' has the most percentage;
# For response of "yes", 'single' has the most percentage.

# 24. Repeat the previous exercise, this time reporting the row
percentages. Explain the
# difference between the interpretation of this table and the previous
contingency table.

# swap cols and rows
t.v1_r <- table(bank_train$marital, bank_train$response)
t.v2_r <- addmargins(A = t.v1_r, FUN = list(total = sum),quiet = TRUE)

t.v1_r

##
##                no   yes
##   divorced  2743   312
##   married  14579  1608
##   single    6514  1061
##   unknown     50     7

t.v2_r

##
##                no   yes total
##   divorced  2743   312  3055
##   married  14579  1608 16187
##   single    6514  1061  7575
```

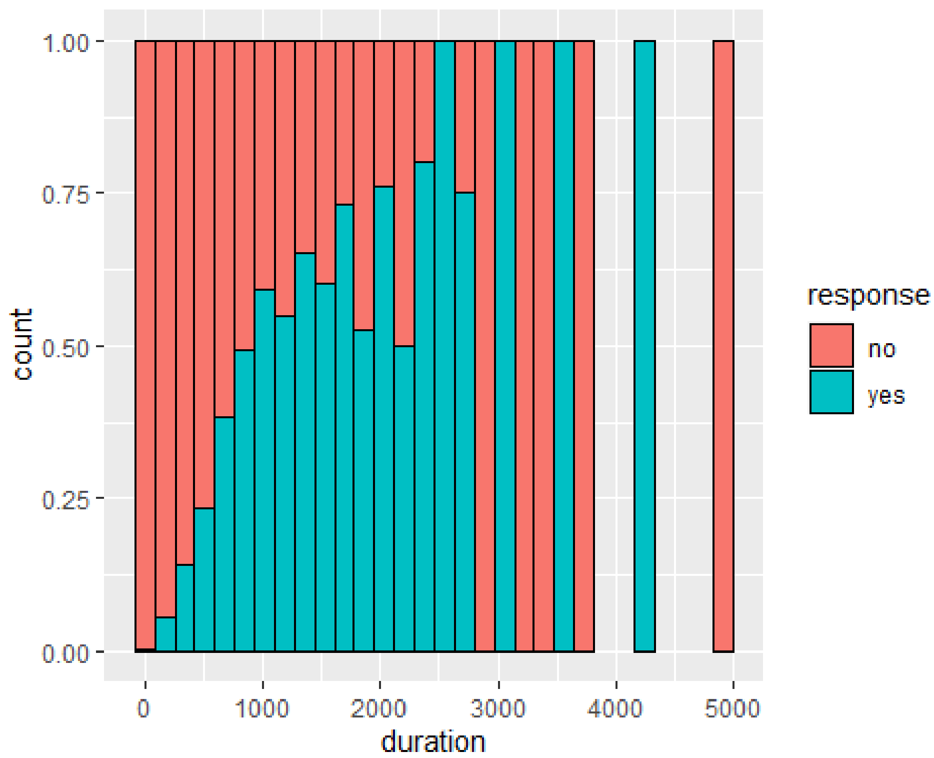
```
##   unknown     50     7    57
##   total    23886  2988 26874

t.v1_r_pct <- round(prop.table(t.v1_r, margin = 1)*100, 1)
t.v2_r_pct <- addmargins(A = t.v1_r_pct, FUN = list(total = sum),quiet
= TRUE)

t.v1_r_pct

##
##              no  yes
##   divorced 89.8 10.2
##   married  90.1  9.9
##   single   86.0 14.0
##   unknown  87.7 12.3

# This time the row percentage shows the ratio in each marital status
of response of "yes" and "no";
# In "divorced", 89.79% responded "no" and 10.21% responded "yes";
# In "married", 90.07% responded "no" and 9.93% responded "yes";
# In "single", 85.99% responded "no" and 14.01% responded "yes";
# In "unknown", 87.72% responded "no" and 12.38% responded "yes";
# Overall, more people recompensed "no" than "yes".

# The difference between this two tables is one is from the perspective
of
# response while the other is
# from the perspective of marital status.


### 25. Produce the following graphs. What is the strength of each
graph? Weakness?

# a. Histogram of duration.

ggplot(bank_train, aes(duration)) + geom_histogram(color="black")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



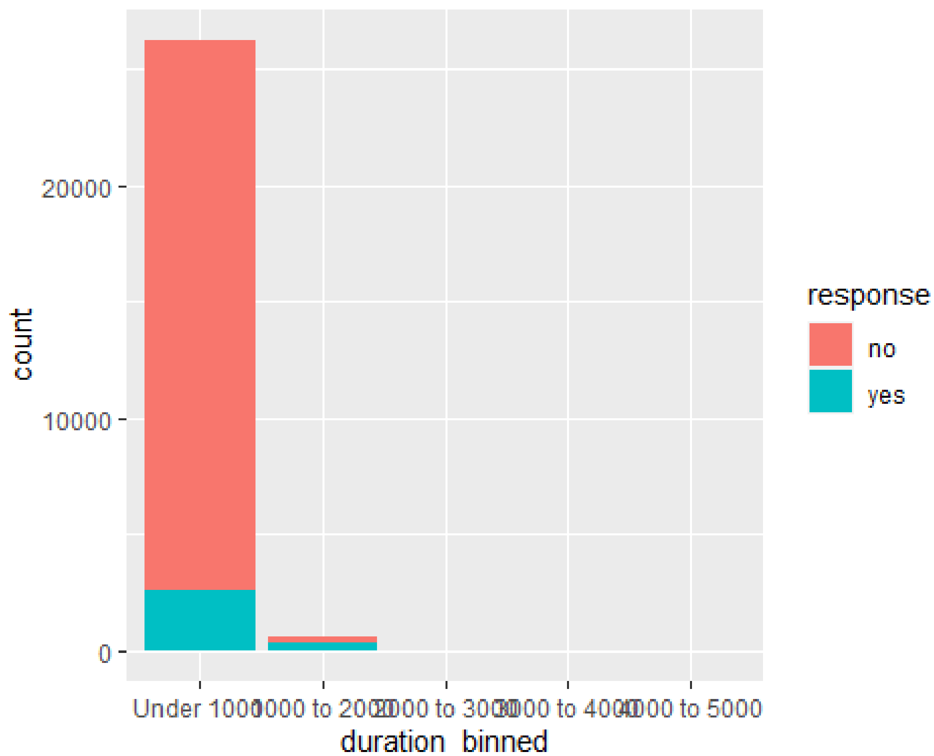

```
# b. Histogram of duration, with overlay of response.

ggplot(bank_train, aes(duration)) + geom_histogram(aes(fill =
response), color="black")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



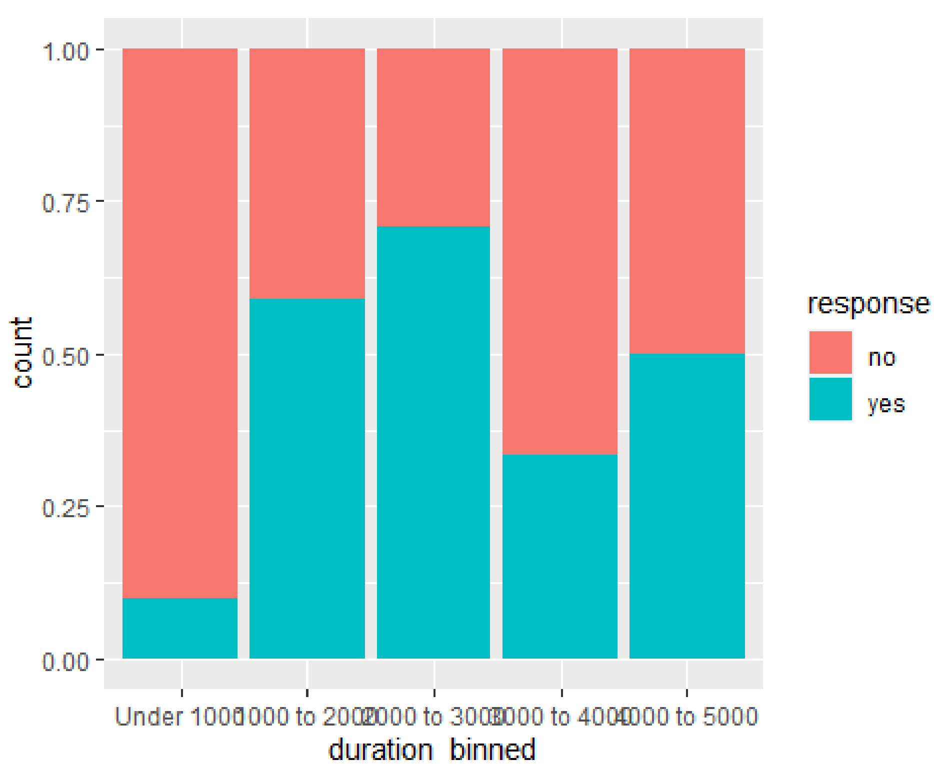

```
# c. Normalized histogram of duration, with overlay of response.

ggplot(bank_train, aes(duration)) + geom_histogram(aes(fill =
response), color="black",
                 position = "fill")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Warning: Removed 10 rows containing missing values (geom_bar).
```



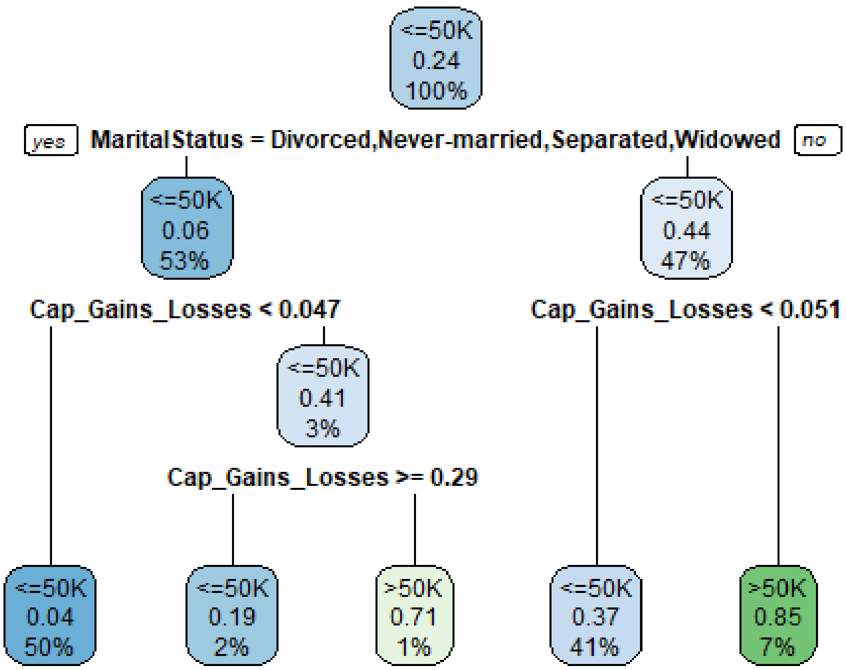

```
# binned barchart

bank_train$duration_binned <- cut(x = bank_train$duration, breaks =
c(0, 1000, 2000, 3000,4000,5000),
                              right = FALSE,
                              labels = c("Under 1000", "1000 to 2000",
"2000 to 3000",
                                          "3000 to 4000", "4000 to
5000"))
ggplot(bank_train, aes(duration_binned)) + geom_bar(aes(fill =
response))
```



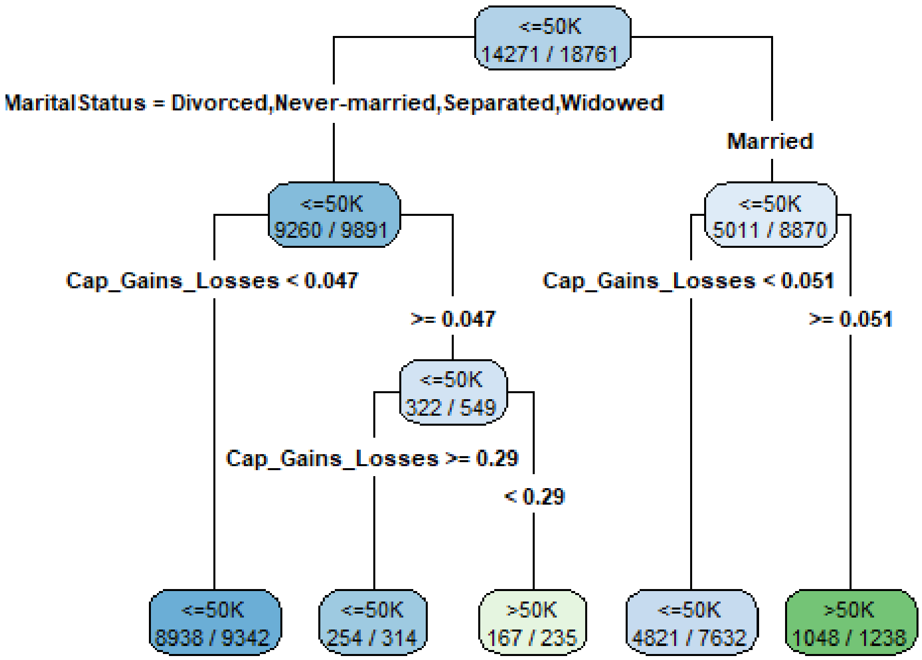

```
ggplot(bank_train, aes(duration_binned)) + geom_bar(aes(fill =
response), position = 'fill')
```



```r
# For Exercises 14-20, work with the adult_ch6_training and
adult_ch6_test data
# sets. Use either Python or R to solve each problem.

# 14. Create a CART model using the training data set that predicts
income using
# marital status and capital  gains and losses. Visualize the decision
tree
# (that is, provide the decision tree output). Describe the first few
splits in the decision tree.

adult_training <- read.csv(file = "C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/adult_ch6_training")

colnames(adult_training)[1] <- "MaritalStatus"

# change income and marital status to factors
adult_training$Income <- factor(adult_training$Income)
adult_training$MaritalStatus <- factor(adult_training$MaritalStatus)


library(rpart); library(rpart.plot)

# build decision tree
DT_CART <- rpart(formula = Income ~ MaritalStatus +
Cap_Gains_Losses,data =
                   adult_training, method = "class")

rpart.plot(DT_CART)
```

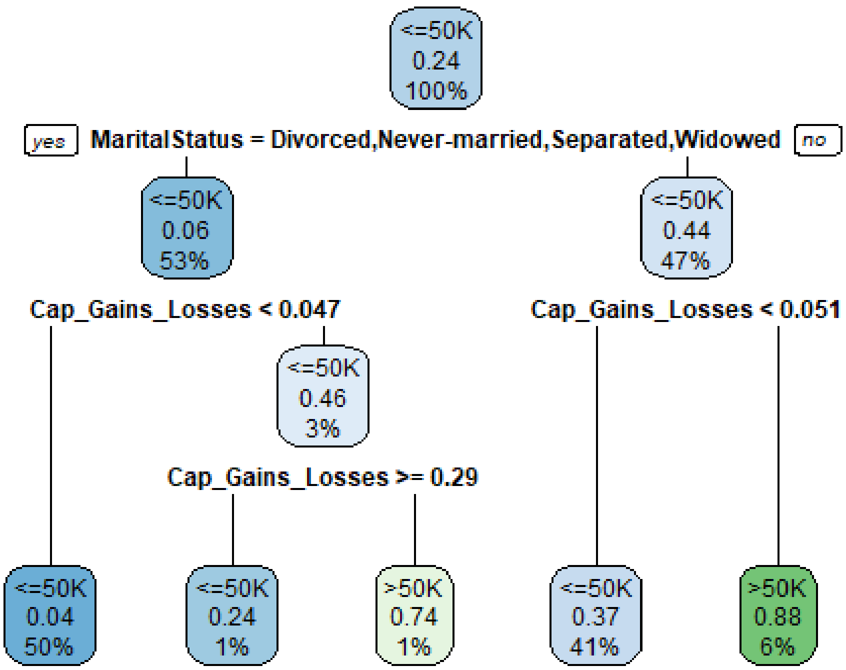



```
?rpart.plot

## starting httpd help server ...

##   done

# using type = 4 to label each branch with its specific value, instead
of a
# yes/no at the top of the split

#extra = 2 to add the correct classification proportion to each node.

rpart.plot(DT_CART, type = 4, extra = 2)
```

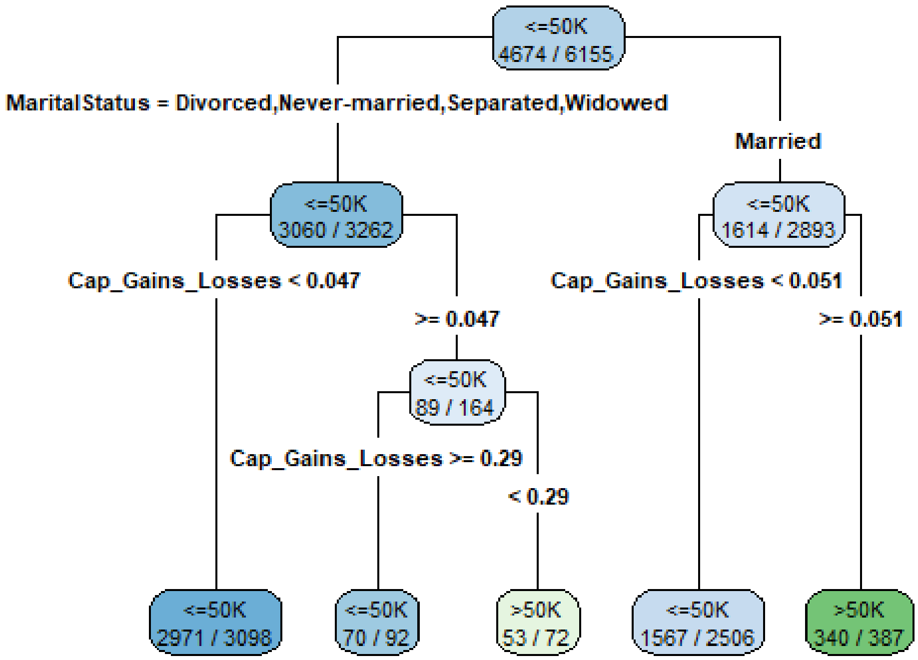



```
# create a data frame that includes the predictor variables of the
records you
# wish to classify
X = data.frame(MaritalStatus = adult_training$MaritalStatus,
               Cap_Gains_Losses =
                 adult_training$Cap_Gains_Losses)

# Once you have the predictor variables you wish to classify, use the
predict()
# command.
predIncomeCART = predict(object = DT_CART, newdata = X,type = "class")


# 15. Develop a CART model using the test data set that utilizes the
same target
# and predictor variables. Visualize the decision tree. Compare the
decision trees.
# Does the test data result match the training data result?

adult_test <- read.csv(file = "C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/adult_ch6_test")

# run through the same process using test dataset
colnames(adult_test)[1] <- "MaritalStatus"
adult_test$Income <- factor(adult_test$Income)
adult_test$MaritalStatus <- factor(adult_test$MaritalStatus)
```

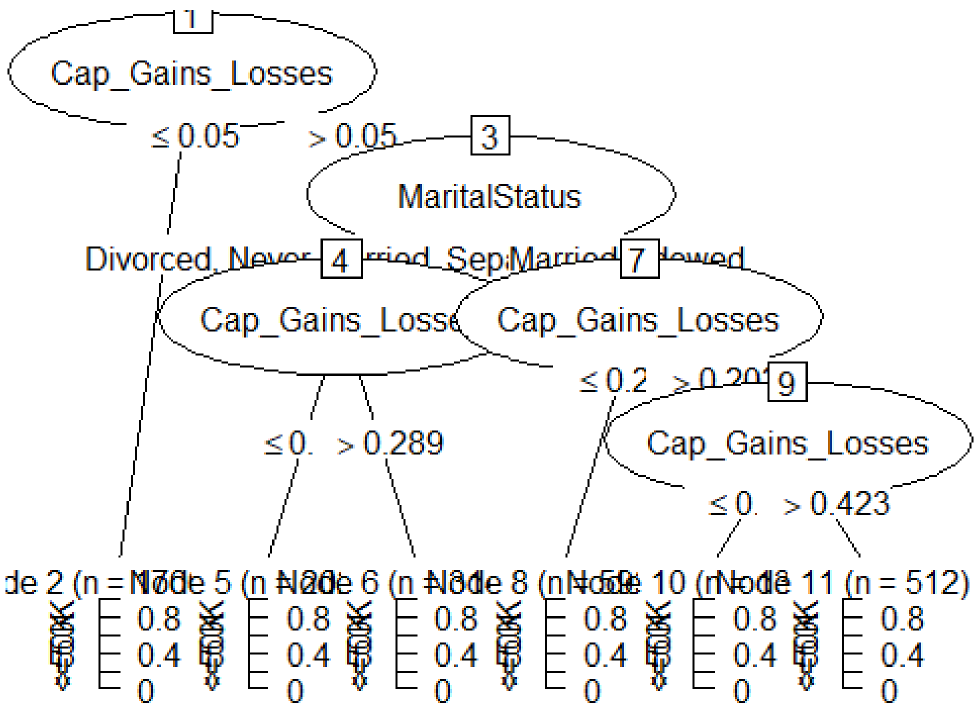
```
DT_CART_test <- rpart(formula = Income ~ MaritalStatus +
Cap_Gains_Losses,data =
                   adult_test, method = "class")

rpart.plot(DT_CART_test)
```




```
rpart.plot(DT_CART_test, type = 4, extra = 2)
```




```
X_test = data.frame(MaritalStatus = adult_test$MaritalStatus,
                    Cap_Gains_Losses =
                      adult_test$Cap_Gains_Losses)

predIncomeCART_test = predict(object = DT_CART_test, newdata = X_test,
                              type = "class")

# The decision tree of test dataset matches the one with training
dataset.


# 16. Use the training data set to build a C5.0 model to predict income
using
# marital status and capital gains and losses. Specify a minimum of 75
cases per
# terminal node. Visualize the decision tree. Describe the first few
splits in the decision tree.

library(C50)

# run c5.0 algo
C5 <- C5.0(formula = Income ~ MaritalStatus + Cap_Gains_Losses,
           data = adult_training, control = C5.0Control(minCases=75))
plot(C5)
```




```
#predict(object = C5, newdata = X)

# 17. How does your C5.0 model compare to the CART model? Describe the
similarities and differences.

# Similarities: Both CART and C50 follow the similar logic of test
conditions;
# Differences: CART starts the split with marital status and goes on
with Cap_Gains_Losses
# while c50 starts with Cap_Gains_Losses and goes on with marital
status; Different
# number of nodes and different ways of displaying classes for the leaf
nodes.


# For the following exercises, work with the bank_reg_training and the
# bank_reg_test data sets. Use either Python or R to solve each
problem.

# 34. Use the training set to run a regression predicting Credit Score,
# based on Debt-to-Income Ratio and Request Amount. Obtain a summary of
the model.
# Do both predictors belong in the model?

bank_reg_train = read.csv(file ='C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/bank_reg_training')
```

```
bank_reg_test = read.csv(file ='C:/Users/DDY/Desktop/2021-Spring-
textbooks/ADS-502/Module2/Website Data Sets/bank_reg_test')

# run the model
model01 <- lm(formula = Credit.Score ~ Debt.to.Income.Ratio
+Request.Amount,
              data = bank_reg_train)

# display the summary table
summary(model01)

##
## Call:
## lm(formula = Credit.Score ~ Debt.to.Income.Ratio + Request.Amount,
##     data = bank_reg_train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -279.13  -25.11   10.87   39.93  175.32
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           6.685e+02  1.336e+00  500.27   <2e-16 ***
## Debt.to.Income.Ratio -4.813e+01  4.785e+00  -10.06   <2e-16 ***
## Request.Amount        1.075e-03  6.838e-05   15.73   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 66 on 10690 degrees of freedom
## Multiple R-squared:  0.02839,    Adjusted R-squared:  0.02821
## F-statistic: 156.2 on 2 and 10690 DF,  p-value: < 2.2e-16

# 35. Validate the model from the previous exercise.

model02 <- lm(formula = Credit.Score ~ Debt.to.Income.Ratio +
Request.Amount,
              data = bank_reg_test)

summary(model02)

##
## Call:
## lm(formula = Credit.Score ~ Debt.to.Income.Ratio + Request.Amount,
##     data = bank_reg_test)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -288.16  -24.49   11.08   39.47  199.84
##
## Coefficients:
```

```
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             6.655e+02  1.328e+00  501.26   <2e-16 ***
## Debt.to.Income.Ratio -5.214e+01  4.826e+00  -10.80   <2e-16 ***
## Request.Amount        1.302e-03  6.849e-05   19.01   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 65.78 on 10772 degrees of freedom
## Multiple R-squared:  0.03845,    Adjusted R-squared:  0.03827
## F-statistic: 215.4 on 2 and 10772 DF,  p-value: < 2.2e-16

# Validation complete.

# 36. Use the regression equation to complete this sentence: "The
estimated Credit Score equals.."
# The estimated Credit Score equals y = 668.4562 - 48.1262* Debt-to-
Income Ratio + 0.0011* Request Amount

# 37. Interpret the coefficient for Debt-to-Income Ratio.
# The coefficient for Debt-to-Income Ratio is negative which means the
lower the
# Debt-to-Income Ratio, the higher the credit score.

# 38. Interpret the coefficient for Request Amount.
# The coefficient for Request Amount is positive which means the higher
the
# Request Amount, the higher the credit score.

# 39. Find and interpret the value of s.
# Residual standard error: 65.78 on 10772 degrees of freedom. The size
of model
# prediction error is 65.8 (66), that is the difference between the
actual
# credit score and of which predicated from the model.

# 40. Find and interpret Radj2 . Comment.
# The adjusted R squared value is modified version of R-squared that
has been
# adjusted for the number of predictors in the model. It increases when
the new
# term improves the model more than would be expected by chance. It
decreases
# when a predictor improves the model by less than expected. The R-
adj^2 is 0.028
# from the model. This means that 2.8% of the variability in Credit
Score is
# accounted for by the predictors Debt-to-Income Ratio and Request
Amount.
```

```r
# 41. Find MAE_Baseline and MAE_Regression, and determine whether the
regression
# model outperformed its baseline model.

# use the predicators from the test dataset to predict
X_test <- data.frame(Debt.to.Income.Ratio =
bank_reg_test$Debt.to.Income.Ratio,
                     Request.Amount = bank_reg_test$Request.Amount)

# y predicated using the model from the test dataset
ypred <- predict(object = model02, newdata = X_test)

# compare to the actual targets from the test dataset
ytrue <- bank_reg_test$Credit.Score

library(MLmetrics)

##
## Attaching package: 'MLmetrics'

## The following object is masked from 'package:base':
##
##     Recall

# mean absolute error for regression
MAE_Regression = MAE(y_pred = ypred, y_true = ytrue)

# mean absolute error for baseline using the formula
```

Compute the MAE for the baseline model, as follows:

$$MAE_{Baseline} = \frac{\sum |y - \bar{y}|}{n}$$

```r
y_y_bar = abs(bank_reg_test$Credit.Score -
mean(bank_reg_test$Credit.Score))
MAE_Baseline = sum(y_y_bar)/length(y_y_bar)

MAE_Regression

## [1] 48.01625

MAE_Baseline

## [1] 48.60024

# So the MAE_Regression is 48.02 and the MAE_Baseline is 48.60.
# Since MAE_Regression < MAE_Baseline, thus, our regression model
outperformed its baseline model.
```