18BCS6033_Worksheet7and8

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1 Worksheet 7 & 8

1.1 Karan Trehan

1.1.1 18BCS6033

1.1.2 18AITAIML1 - Group B

[1]:
```
# To ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

1.2 Importing the Required Libraries

[2]:
```
# Importing the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

1.3 Reading and Understanding the Data

Let's start with the following steps:

1. Importing data using the pandas library
2. Understanding the structure of the data

[3]:
```
# Reading the csv file and putting it into 'train' object.
train = pd.read_csv('Training_set.csv')
valid = pd.read_csv('Validation_set.csv')
```

[4]:
```
# Let's understand the type of values in each column of our dataframe 'train'.
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
```

```
 0   Attribute 1 (a1)  30 non-null     int64
 1   Attribute 2 (a2)  30 non-null     int64
 2   Class Label       30 non-null     int64
dtypes: int64(3)
memory usage: 848.0 bytes
```

[5]:
```python
# Let's understand the type of values in each column of our dataframe 'valid'.
valid.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4 entries, 0 to 3
Data columns (total 7 columns):
 #   Column                                      Non-Null Count  Dtype
---  ------                                      --------------  -----
 0   Attribute 1 (a1)                            4 non-null      int64
 1   Attribute 2 (a2)                            4 non-null      int64
 2   True Class Label                            4 non-null      int64
 3   Class Label as predicted by the decision tree  4 non-null      int64
 4   Unnamed: 4                                  0 non-null      float64
 5   Unnamed: 5                                  0 non-null      float64
 6   Unnamed: 6                                  0 non-null      float64
dtypes: float64(3), int64(4)
memory usage: 352.0 bytes
```

[6]:
```python
# Let's understand the data, how it look like.
train.head()
```

[6]:

	Attribute 1 (a1)	Attribute 2 (a2)	Class Label
0	2	11	2
1	2	13	2
2	2	15	2
3	2	27	1
4	2	39	1

[7]:
```python
# Let's understand the data, how it look like.
valid.head()
```

[7]:

	Attribute 1 (a1)	Attribute 2 (a2)	True Class Label
0	2	35	1
1	12	13	2
2	-4	45	2
3	2	17	2

	Class Label as predicted by the decision tree	Unnamed: 4	Unnamed: 5
0	1	NaN	NaN
1	1	NaN	NaN
2	2	NaN	NaN
3	2	NaN	NaN

```
   Unnamed: 6
0         NaN
1         NaN
2         NaN
3         NaN
```

[8]:
```
valid = valid.iloc[:,:4]
valid.head()
```

[8]:
```
   Attribute 1 (a1)  Attribute 2 (a2)  True Class Label  \
0                 2                35                 1
1                12                13                 2
2                -4                45                 2
3                 2                17                 2

   Class Label as predicted by the decision tree
0                                              1
1                                              1
2                                              2
3                                              2
```

1.4 Checking for Missing and Duplicated Values

[9]:
```
#Checking for duplicacy in the DataFrame using '.duplicated()' method and then␣
↪checking the number of rows using
# '.shape[0]'
print("Number of Duplicate Rows in the Training DataFrame:" , train[train.
↪duplicated()].shape[0])
print("Number of Duplicate Rows in the Validation DataFrame:" , valid[valid.
↪duplicated()].shape[0])
```

```
Number of Duplicate Rows in the Training DataFrame: 0
Number of Duplicate Rows in the Validation DataFrame: 0
```

[10]:
```
#Checking the Percentage of Columns having Missing Values in both the DataFrames
print('-+-'*10)
print(round(train.isnull().sum()/len(train)*100,2))
print('-+-'*18)
print(round(valid.isnull().sum()/len(valid)*100,2))
print('-+-'*18)
```

```
-+--+--+--+--+--+--+--+--+--+-
Attribute 1 (a1)    0.0
Attribute 2 (a2)    0.0
Class Label         0.0
dtype: float64
-+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+-
```

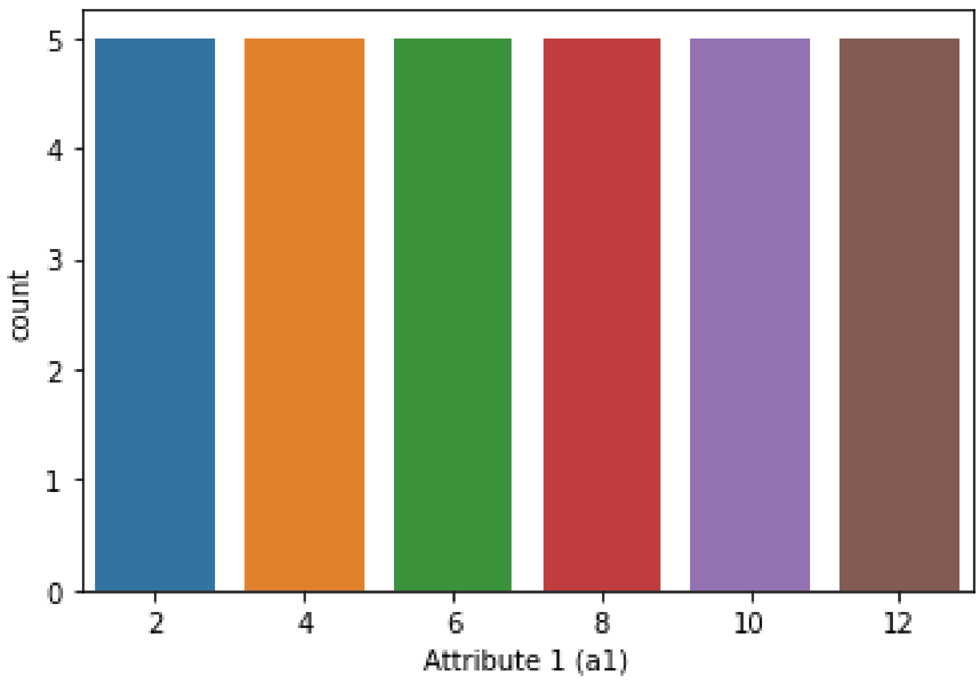
```
Attribute 1 (a1)                                0.0
Attribute 2 (a2)                                0.0
True Class Label                                0.0
Class Label as predicted by the decision tree   0.0
dtype: float64
-+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+-
```

- Explicitly checking the Missing Value Count.
- Inferring again that there are no Missing Values

1.5 Data Visualization

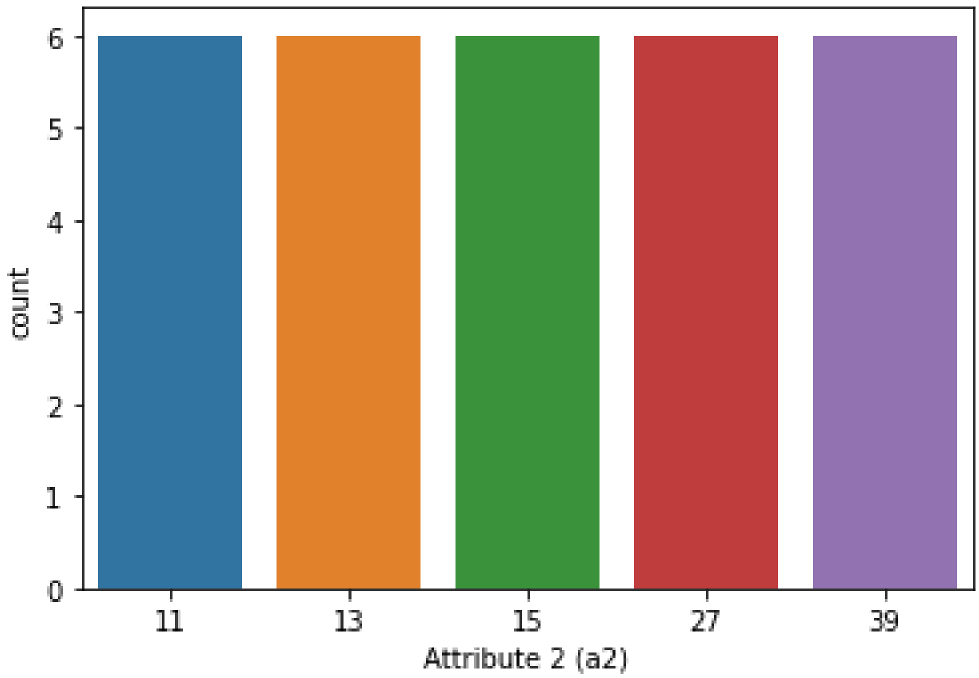
[11]:
```
sns.countplot(train['Attribute 1 (a1)'])
```

[11]: <matplotlib.axes._subplots.AxesSubplot at 0x2135f6fde50>



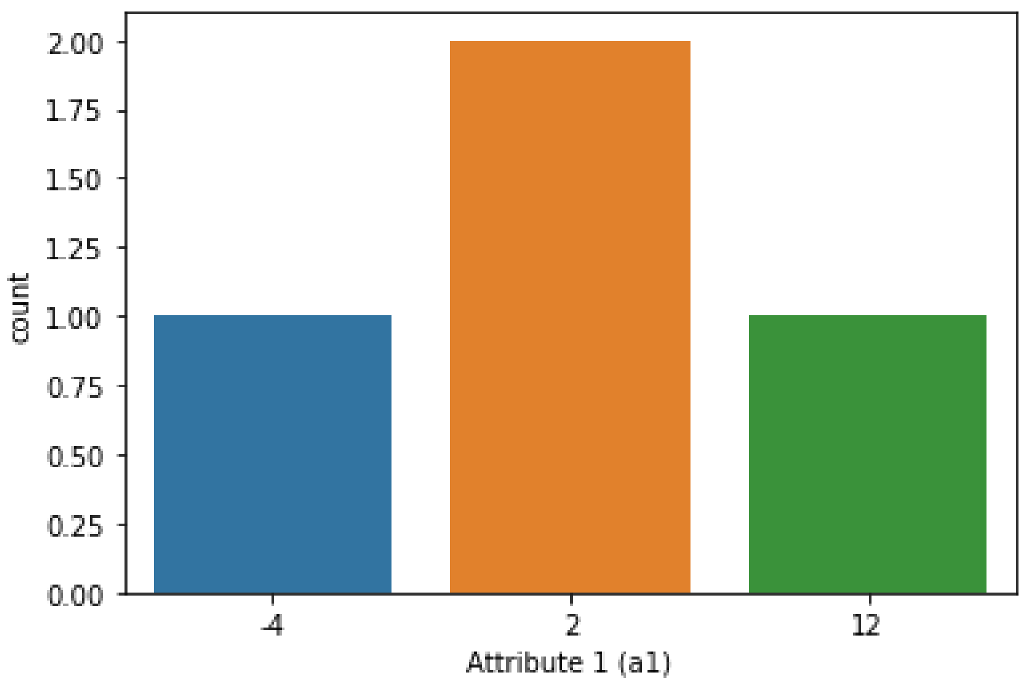
[12]:
```
sns.countplot(train['Attribute 2 (a2)'])
```

[12]: <matplotlib.axes._subplots.AxesSubplot at 0x2135fe69c10>



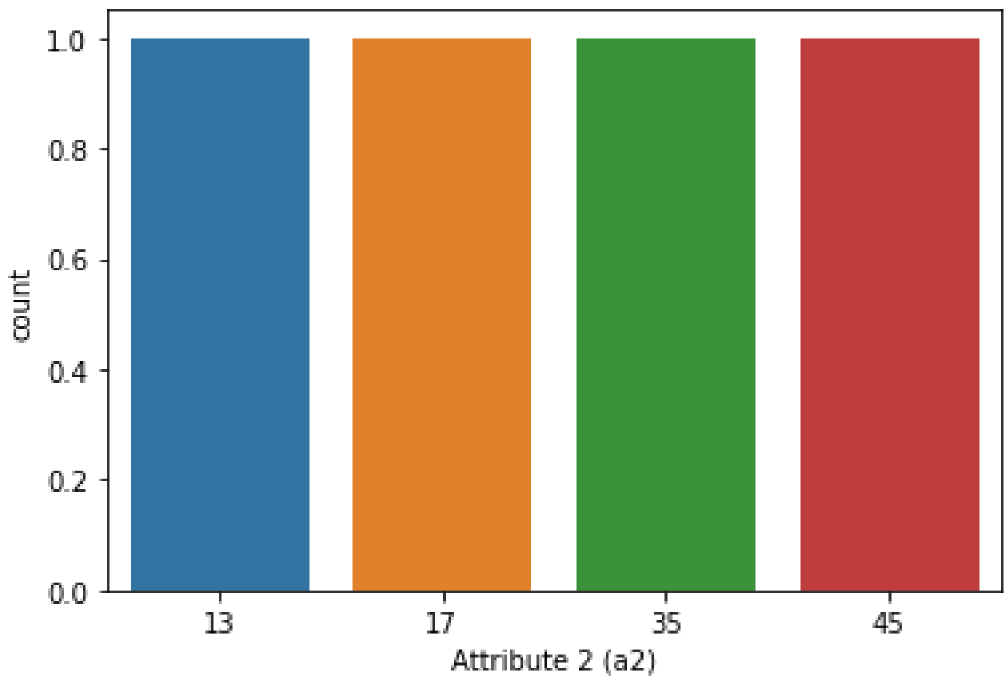
[13]:
```
sns.countplot(valid['Attribute 1 (a1)'])
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x2135fee9220>



[14]:
```
sns.countplot(valid['Attribute 2 (a2)'])
```

[14]: <matplotlib.axes._subplots.AxesSubplot at 0x2135ff350a0>



1.6 Separating the Features and the Label columns

[15]:
```
# Putting feature variable to X
X_train = train.drop('Class Label',axis=1)

# Putting response variable to y
y_train = train['Class Label']
```

[16]:
```
# Putting feature variable to X
X_valid = valid.iloc[:,:2]

# Putting response variable to y
y_valid = valid['True Class Label']
```

1.7 Fitting a Decision Tree Classifier Model

Use the following hyperparameters to solve the following questions:

- max_depth = 20

- min_samples_split = 10
- min_samples_leaf = 5
- Homogeneity measure = gini

[17]:
```
# Importing decision tree classifier from sklearn library
from sklearn.tree import DecisionTreeClassifier

# Fitting the decision tree with default hyperparameters, apart from
# max_depth which is 5 so that we can plot and read the tree.
# model with optimal hyperparameters
dtc = DecisionTreeClassifier(criterion = "gini",
                             random_state = 100,
                             max_depth=20,
                             min_samples_leaf=5,
                             min_samples_split=10)
dtc.fit(X_train, y_train)
```

[17]:
```
DecisionTreeClassifier(max_depth=20, min_samples_leaf=5, min_samples_split=10,
                       random_state=100)
```

1.8 Evaluating the Model

[18]:
```
# Let's check the evaluation metrics of our default model

# Importing classification report and confusion matrix from sklearn metrics
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score

# Making predictions
y_pred = dtc.predict(X_valid)

# Printing classification report
print(classification_report(y_valid, y_pred))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00         1
           2       0.50      0.33      0.40         3

    accuracy                           0.25         4
   macro avg       0.25      0.17      0.20         4
weighted avg       0.38      0.25      0.30         4
```

[19]:
```
# Confusion matrix and accuracy
print(confusion_matrix(y_valid,y_pred))
print(accuracy_score(y_valid,y_pred))
```

```
[[0 1]
 [2 1]]
0.25
```

1.9 Visualizing the Decision Tree

[20]:
```python
# Importing required packages for visualization
from IPython.display import Image
from six import StringIO
from sklearn.tree import export_graphviz
import pydotplus, graphviz

# Putting features
features = list(train.columns[:2])
features
```

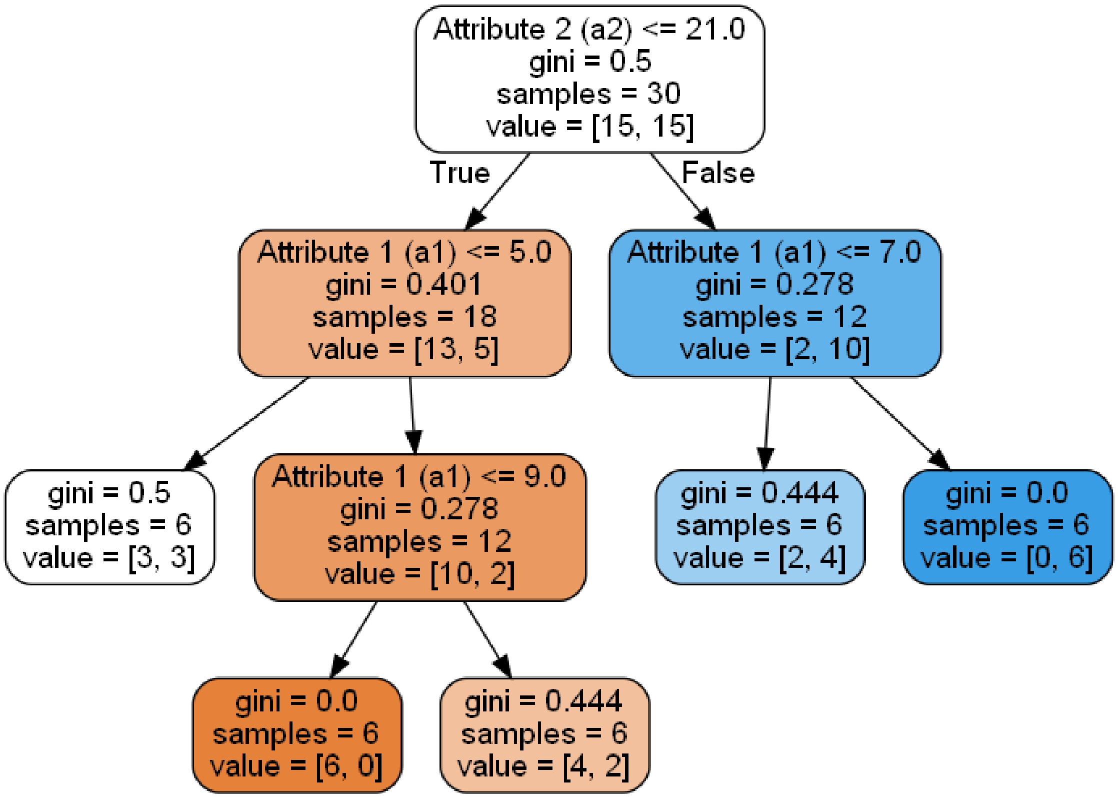
[20]:
```
['Attribute 1 (a1)', 'Attribute 2 (a2)']
```

[21]:
```python
# If you're on windows:
# Specifing path for dot file.
import os
os.environ["PATH"] += os.pathsep + 'C:/Program Files/Graphviz 2.44.1/bin'
```

[22]:
```python
dot_data = StringIO()
export_graphviz(dtc,␣
 ↪out_file=dot_data,feature_names=features,filled=True,rounded=True)

graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

[22]:


Attribute 2 (a2) <= 21.0
gini = 0.5
samples = 30
value = [15, 15]
True
False
Attribute 1 (a1) <= 5.0
gini = 0.401
samples = 18
value = [13, 5]
Attribute 1 (a1) <= 7.0
gini = 0.278
samples = 12
value = [2, 10]
gini = 0.5
samples = 6
value = [3, 3]
Attribute 1 (a1) <= 9.0
gini = 0.278
samples = 12
value = [10, 2]
gini = 0.444
samples = 6
value = [2, 4]
gini = 0.0
samples = 6
value = [0, 6]
gini = 0.0
samples = 6
value = [6, 0]
gini = 0.444
samples = 6
value = [4, 2]

Thank you!