Lab 7 : Implement Random Forest algorithm

Importing the required libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
df = pd.read_csv(r"C:\Users\Admin\Downloads\ecommerce.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	customer_age	gender	pages_viewed	time_on_site	device_type	made_pur
0	50	0	32	7.80	0	
1	50	0	45	13.79	1	
2	68	0	47	4.31	0	
3	60	0	21	28.64	0	
4	54	1	16	18.38	0	

In [4]:
```
df.shape
```

Out[4]:
```
(100, 6)
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['customer_age', 'gender', 'pages_viewed', 'time_on_site', 'device_ty
pe',
       'made_purchase'],
      dtype='object')
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   customer_age   100 non-null    int64  
 1   gender         100 non-null    int64  
 2   pages_viewed   100 non-null    int64  
 3   time_on_site   100 non-null    float64
 4   device_type    100 non-null    int64  
 5   made_purchase  100 non-null    int64  
dtypes: float64(1), int64(5)
memory usage: 4.8 KB
```

In [7]:

```python
df.describe()
```

Out[7]:

	customer_age	gender	pages_viewed	time_on_site	device_type	made
count	100.00000	100.00	100.000000	100.000000	100.000000	
mean	45.02000	0.45	24.320000	13.723600	0.520000	
std	14.28355	0.50	13.754617	8.090585	0.502117	
min	18.00000	0.00	1.000000	0.930000	0.000000	
25%	33.00000	0.00	12.750000	6.112500	0.000000	
50%	45.50000	0.00	24.500000	13.915000	1.000000	
75%	54.50000	1.00	35.000000	19.605000	1.000000	
max	69.00000	1.00	49.000000	29.410000	1.000000	

Putting Feature Variable to X and Target variable to y.

In [8]:

```python
# Putting feature variables into X
X = df.drop('made_purchase', axis=1)

# Putting response variable into y
y = df['made_purchase']
```

Train-Test-Split is performed

In [9]:

```python
# now lets split the data into train and test
from sklearn.model_selection import train_test_split
# Splitting the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, ra
X_train.shape, X_test.shape
```

Out[9]: ((70, 5), (30, 5))

Let’s import RandomForestClassifier and fit the data.

In [10]:
```
from sklearn.ensemble import RandomForestClassifier
classifier_rf = RandomForestClassifier(random_state=42, n_jobs=-1, max_depth
                                       n_estimators=100, oob_score=True)
#%%time
classifier_rf.fit(X_train, y_train)
```

Out[10]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=5, n_jobs=-1, oob_score=True, rand
om_state=42)
```

In [11]:
```
# checking the oob score
classifier_rf.oob_score_
```

Out[11]:
```
0.5714285714285714
```

Let’s do hyperparameter tuning for Random Forest using GridSearchCV and fit the data.

In [12]:
```
rf = RandomForestClassifier(random_state=42, n_jobs=-1)
params = {
    'max_depth': [2,3,5,10,20],
    'min_samples_leaf': [5,10,20,50,100,200],
    'n_estimators': [10,25,30,50,100,200]
}
from sklearn.model_selection import GridSearchCV
# Instantiate the grid search model
grid_search = GridSearchCV(estimator=rf,
                           param_grid=params,
                           cv = 4,
                           n_jobs=-1, verbose=1, scoring="accuracy")
#%%time
grid_search.fit(X_train, y_train)
```

```
Fitting 4 folds for each of 180 candidates, totalling 720 fits
```

Out[12]:
```
GridSearchCV
best_estimator_:
RandomForestClassifier
RandomForestClassifier
```

In [13]:
```
grid_search.best_score_
```

Out[13]:
```
np.float64(0.7001633986928105)
```

In [14]:
```
rf_best = grid_search.best_estimator_
rf_best
```

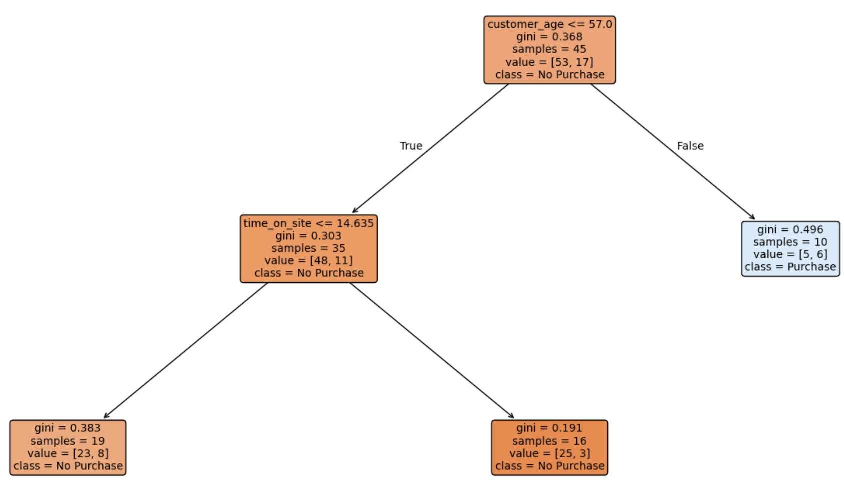
Out[14]:

RandomForestClassifier

```
RandomForestClassifier(max_depth=2, min_samples_leaf=10, n_estimators=10,
                       n_jobs=-1, random_state=42)
```

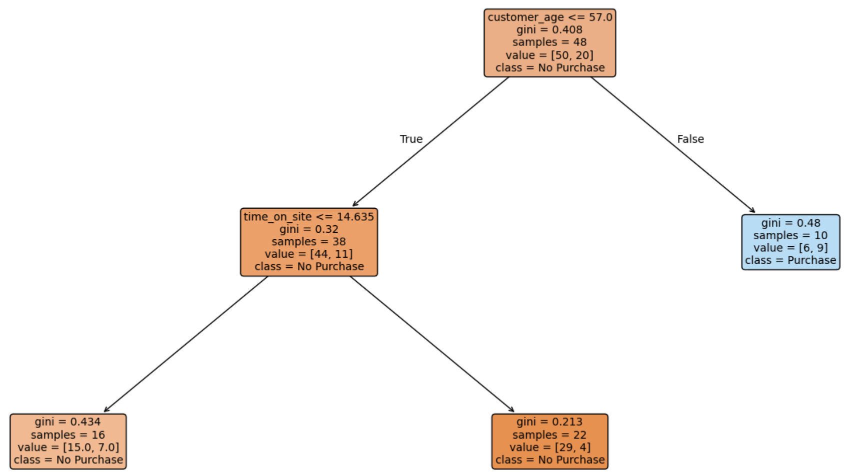
Now, let’s visualize

In [16]:
```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 10))
plot_tree(
    rf_best.estimators_[5],
    feature_names=X.columns,
    class_names=['No Purchase', 'Purchase'],
    filled=True,
    rounded=True,
    fontsize=10
)
plt.show()
```



In [18]:
```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 10))
```

```
plot_tree(
    rf_best.estimators_[7],
    feature_names=X.columns,
    class_names=['No Purchase', 'Purchase'],
    filled=True,
    rounded=True,
    fontsize=10
)
plt.show()
```



The trees created by estimators_[5] and estimators_[7] are different. Thus we can say that each tree is independent of the other.

Now let’s sort the data with the help of feature importance

In [19]:
```
rf_best.feature_importances_
```

Out[19]:
```
array([0.27572425, 0.3916449 , 0.00092586, 0.29102161, 0.04068338])
```

In [20]:
```
## feature importance

imp_df = pd.DataFrame({
    "Varname": X_train.columns,
    "Imp": rf_best.feature_importances_
})
```

In [21]:
```
imp_df.sort_values(by="Imp", ascending=False)
```

Out[21]:

	Varname	Imp
1	gender	0.391645
3	time_on_site	0.291022
0	customer_age	0.275724
4	device_type	0.040683
2	pages_viewed	0.000926