Classification (Decision Tree)

This code imports the necessary libraries for data manipulation, model training, evaluation, and visualization in a decision tree classification task. It includes pandas for data handling, scikit-learn for model-related functions, and matplotlib for plotting the decision tree.

In [1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import matplotlib.pyplot as plt
from sklearn import tree
```

Data Preparation

In [2]:
```
# Load the dataset
df = pd.read_csv('Starbucks satisfactory survey_modified.csv')
df = df.drop(columns=['Timestamp','Gender', 'Age'])
```

In [3]:
```
# Separate the dataset into features and target variable
x = df.drop(columns=['Continue to buy?'])
y = df['Continue to buy?']
```

In [4]:
```
# Encode the categorical variables
le_x = LabelEncoder()
x = x.apply(le_x.fit_transform)
```

This code initializes a LabelEncoder and applies it to the target variable y to convert its categorical labels into numerical values for model training.

In [5]:
```
le_y = LabelEncoder()
y = le_y.fit_transform(y)
```

Modeling

In [6]:
```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [7]:
```
# Define the classifiers
clf_gini = DecisionTreeClassifier(max_depth=3, random_state=0)
clf_entropy = DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
```

In [8]:
```
# Fit the models
clf_gini.fit(X_train, y_train)
clf_entropy.fit(X_train, y_train)
```

Out[8]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
```

Model Evaluation

In [9]:
```
# Predict using the models
y_pred_gini = clf_gini.predict(X_test)
y_pred_entropy = clf_entropy.predict(X_test)
```

In [13]:
```
# Evaluate the models
print('Accuracy score for Gini criterion:', accuracy_score(y_test, y_pred_gini))
print('Accuracy score for Entropy criterion:', accuracy_score(y_test, y_pred_entropy))

print('\nGini criterion')
print('Training set score: {:.4f}'.format(clf_gini.score(X_train, y_train)))
print('Test set score: {:.4f}'.format(clf_gini.score(X_test, y_test)))

print('\nEntropy criterion')
print('Training set score: {:.4f}'.format(clf_entropy.score(X_train, y_train)))
print('Test set score: {:.4f}'.format(clf_entropy.score(X_test, y_test)))
```

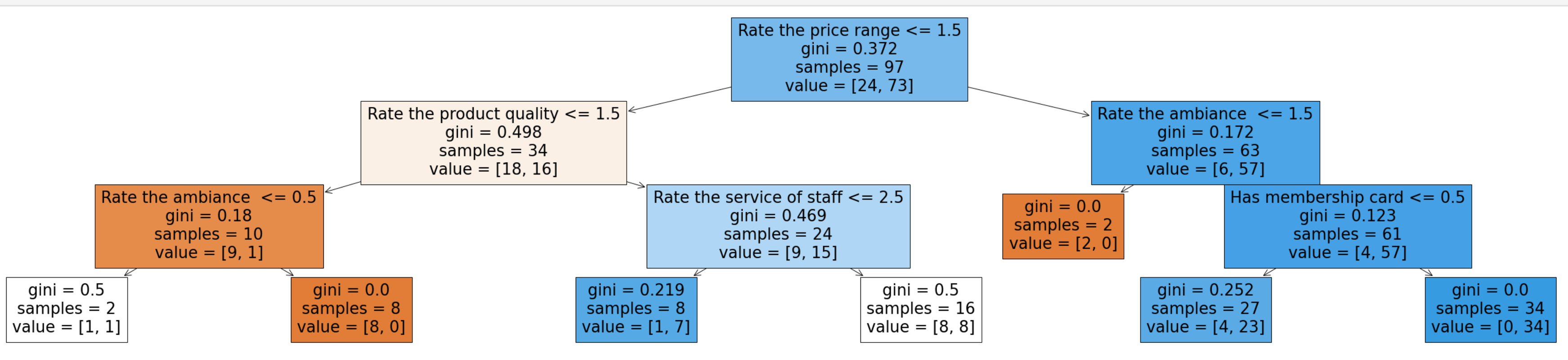
```
Accuracy score for Gini criterion: 0.84
Accuracy score for Entropy criterion: 0.84

Gini criterion
Training set score: 0.8557
Test set score: 0.8400

Entropy criterion
Training set score: 0.8557
Test set score: 0.8400
```

In [14]:
```
# Confusion matrix and classification report
cm_gini = confusion_matrix(y_test, y_pred_gini)
cm_entropy = confusion_matrix(y_test, y_pred_entropy)
```

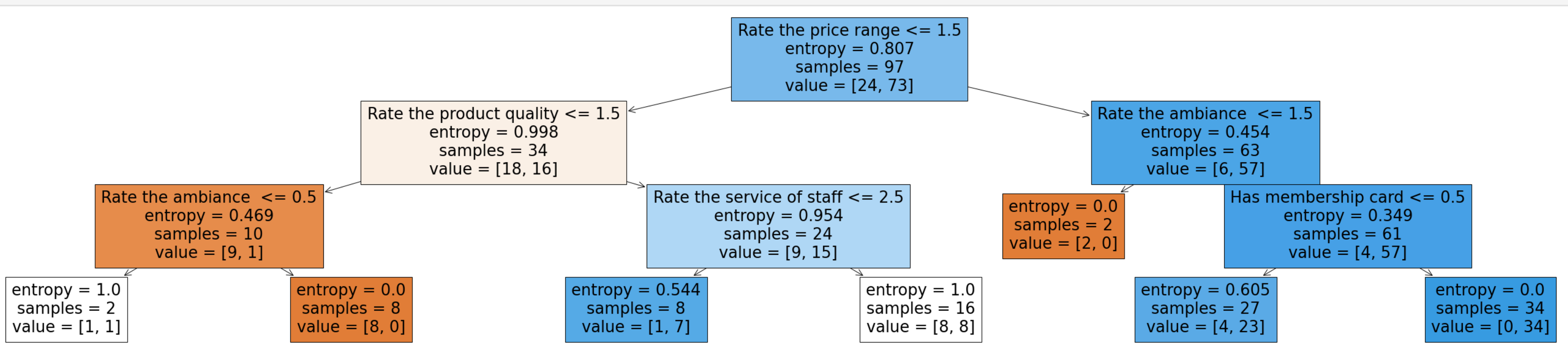
In [15]:
```
print('Confusion matrix with criterion gini index: \n', cm_gini)
print('Confusion matrix with criterion entropy: \n', cm_entropy)

print('Classification report with criterion gini index: \n', classification_report(y_test, y_pred_gini, zero_division=1))
print('Classification report with criterion entropy: \n', classification_report(y_test, y_pred_entropy, zero_division=1))
```

```
Confusion matrix with criterion gini index:
 [[ 2  2]
 [ 2 19]]
Confusion matrix with criterion entropy:
 [[ 2  2]
 [ 2 19]]
Classification report with criterion gini index:
               precision    recall  f1-score   support

           0       0.50      0.50      0.50         4
           1       0.90      0.90      0.90        21

    accuracy                           0.84        25
   macro avg       0.70      0.70      0.70        25
weighted avg       0.84      0.84      0.84        25

Classification report with criterion entropy:
               precision    recall  f1-score   support

           0       0.50      0.50      0.50         4
           1       0.90      0.90      0.90        21

    accuracy                           0.84        25
   macro avg       0.70      0.70      0.70        25
weighted avg       0.84      0.84      0.84        25
```

In [17]:
```
# Visualize the decision trees
plt.figure(figsize=(50,10))
tree.plot_tree(clf_gini, feature_names=x.columns, filled=True)
plt.show()
```



In [18]:
```
plt.figure(figsize=(50,10))
tree.plot_tree(clf_entropy, feature_names=x.columns, filled=True)
plt.show()
```



Data Preparation

In [19]:
```
# Load the dataset again for balancing
df = pd.read_csv('Starbucks satisfactory survey_modified.csv')
df = df.drop(columns=['Timestamp','Gender', 'Age'])
```

In [20]:
```
#Separate the dataset into two DataFrames based on the class label
df_majority = df[df['Continue to buy?'] == "No"]
df_minority = df[df['Continue to buy?'] == "Yes"]
```

In [21]:
```
# Randomly sample the minority class with replacement to match the majority class size
df_minority_oversampled = df_minority.sample(n=len(df_majority), replace=True)
```

In [22]:
```
# Concatenate the oversampled minority class DataFrame with the majority class DataFrame
df_balanced = pd.concat([df_majority, df_minority_oversampled], ignore_index=True)
```

In [23]:
```
# Shuffle the DataFrame
df_balanced = df_balanced.sample(frac=1).reset_index(drop=True)
```

In [24]:
```
# Separate the balanced dataset into features and target variable
x_balanced = df_balanced.drop(columns=['Continue to buy?'])
y_balanced = df_balanced['Continue to buy?']
```

In [25]:
```
# Encode the categorical variables in balanced data
x_balanced = x_balanced.apply(le_x.fit_transform)
y_balanced = le_y.fit_transform(y_balanced)
```

Modeling

In [26]:
```
# Split the balanced dataset into training and testing sets
X_train_balanced, X_test_balanced, y_train_balanced, y_test_balanced = train_test_split(x_balanced, y_balanced, test_size=0.2, random_state=42)
```

In [27]:
```
# Train the models with the balanced dataset
clf_gini.fit(X_train_balanced, y_train_balanced)
clf_entropy.fit(X_train_balanced, y_train_balanced)
```

Out[27]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
```

Model Evaluation

In [28]:
```
# Make predictions
y_pred_gini_balanced = clf_gini.predict(X_test_balanced)
y_pred_entropy_balanced = clf_entropy.predict(X_test_balanced)
```

In [29]:
```
print('Gini criterion with balanced data')
print('Training set score: {:.4f}'.format(clf_gini.score(X_train_balanced, y_train_balanced)))
print('Test set score: {:.4f}'.format(clf_gini.score(X_test_balanced, y_test_balanced)))

print('\nEntropy criterion with balanced data')
print('Training set score: {:.4f}'.format(clf_entropy.score(X_train_balanced, y_train_balanced)))
print('Test set score: {:.4f}'.format(clf_entropy.score(X_test_balanced, y_test_balanced)))
```

```
Gini criterion with balanced data
Training set score: 0.8409
Test set score: 0.8333

Entropy criterion with balanced data
Training set score: 0.8409
Test set score: 0.8333
```

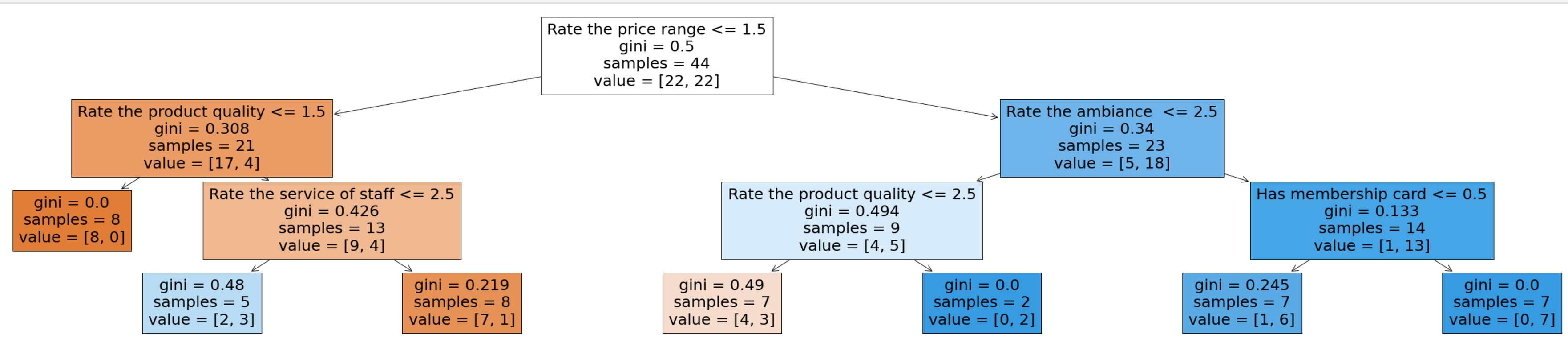
In [32]:
```
# Confusion matrix and classification report for balanced data
cm_gini_balanced = confusion_matrix(y_test_balanced, y_pred_gini_balanced)
cm_entropy_balanced = confusion_matrix(y_test_balanced, y_pred_entropy_balanced)

print('Confusion matrix with criterion gini index on balanced data: \n', cm_gini_balanced)
print('Confusion matrix with criterion entropy on balanced data: \n', cm_entropy_balanced)
```

```
Confusion matrix with criterion gini index on balanced data:
 [[5 1]
 [1 5]]
Confusion matrix with criterion entropy on balanced data:
 [[5 1]
 [1 5]]
```

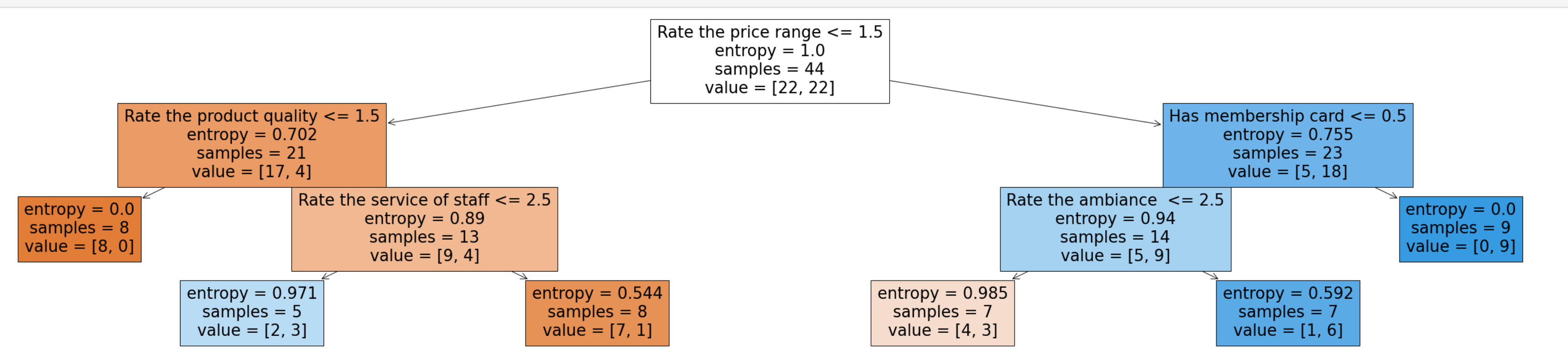
In [33]:
```
print('\nClassification report with criterion gini index on balanced data: \n', classification_report(y_test_balanced, y_pred_gini_balanced, zero_division=1))
print('Classification report with criterion entropy on balanced data: \n', classification_report(y_test_balanced, y_pred_entropy_balanced, zero_division=1))
```

```
Classification report with criterion gini index on balanced data:
               precision    recall  f1-score   support

           0       0.83      0.83      0.83         6
           1       0.83      0.83      0.83         6

    accuracy                           0.83        12
   macro avg       0.83      0.83      0.83        12
weighted avg       0.83      0.83      0.83        12

Classification report with criterion entropy on balanced data:
               precision    recall  f1-score   support

           0       0.83      0.83      0.83         6
           1       0.83      0.83      0.83         6

    accuracy                           0.83        12
   macro avg       0.83      0.83      0.83        12
weighted avg       0.83      0.83      0.83        12
```

In [36]:
```
# Visualize the decision trees with balanced data
plt.figure(figsize=(50,10))
tree.plot_tree(clf_gini, feature_names=x.columns, filled=True)
plt.show()
```



In [35]:
```
plt.figure(figsize=(50,10))
tree.plot_tree(clf_entropy, feature_names=x.columns, filled=True)
plt.show()
```



Learning Reflection

Implementing Decision Trees

I learned that implementing the decision tree algorithm provides valuable insights into the machine learning process. From data preparation to model evaluation, each step contributed to a deeper understanding of the algorithm's mechanics and its application in real-world scenarios.

Data Preparation

The journey began with loading and cleaning the dataset, ensuring that it was free from irrelevant information. This step emphasized the importance of data quality and its direct impact on model performance. Removing unnecessary columns and handling missing values laid a solid foundation for subsequent analysis.

Feature Engineering

While the code primarily focused on label encoding for categorical variables, it underscored the significance of transforming raw data into meaningful features. Feature engineering is a creative process that can enhance model performance by capturing relevant patterns and relationships within the data. Although basic in this implementation, it laid the groundwork for more advanced feature transformations in future projects.

Modeling

Creating decision tree classifiers using both Gini impurity and entropy criteria showcased the flexibility of the algorithm. Understanding the parameters and their effects on the model allowed for fine-tuning and optimization. Decision trees' interpretability made them an ideal choice for initial classification tasks, providing insights into the decision-making process behind the model's predictions.

Model Evaluation

Evaluating model performance involved metrics such as accuracy, confusion matrices, and classification reports. These metrics provided a comprehensive assessment of the model's strengths and weaknesses. Beyond accuracy, considering additional metrics like precision, recall, and F1-score offered a more nuanced understanding of the model's behavior, especially in handling imbalanced datasets.

Handling Imbalanced Data

The code addressed the challenge of imbalanced data by employing oversampling techniques to balance the dataset. This step ensured that the model remained unbiased and could generalize well to unseen data. Handling imbalanced data is crucial for building fair and accurate models, preventing biases that may skew predictions towards the majority class.

Visualization

Visualizing decision trees provided insights into the model's decision-making process. Interpreting the tree's structure and feature importance enhanced understanding and trust in the model's predictions. Visualization played a vital role in model interpretation, facilitating communication of results to stakeholders.

Summary

In conclusion, implementing the decision tree algorithm was a rewarding learning experience that highlighted the importance of data quality, feature engineering, model selection, evaluation metrics, handling imbalanced data, and visualization. Each step contributed to a deeper understanding of the machine learning workflow and its practical applications. Moving forward, these insights will inform future projects, guiding the development of robust and reliable machine learning solutions.