l4

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0.1 ML Assignmnet 4

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Year: Last year
Div: A
Subject: ML

Q. Write a program to implement bagging and boosting to solve classification problem on datasets.

1. Load and Preprocess the Data

[1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

[2]:
```
# Load the dataset
file_path = 'avocado.csv'
df = pd.read_csv(file_path)

# Display the first few rows
print(df.head())
```

```
   Unnamed: 0        Date  AveragePrice  Total Volume     4046       4225  \
0           0  27-12-2015          1.33      64236.62  1036.74   54454.85
1           1  20-12-2015          1.35      54876.98   674.28   44638.81
2           2  13-12-2015          0.93     118220.22   794.70  109149.67
3           3  06-12-2015          1.08      78992.15  1132.00   71976.41
4           4  29-11-2015          1.28      51039.60   941.48   43838.39

     4770  Total Bags  Small Bags  Large Bags  XLarge Bags          type  \
0   48.16     8696.87     8603.62       93.25          0.0  conventional
1   58.33     9505.56     9408.07       97.49          0.0  conventional
2  130.50     8145.35     8042.21      103.14          0.0  conventional
3   72.58     5811.16     5677.40      133.76          0.0  conventional
```

```
4   75.78     6183.95     5986.26      197.69           0.0  conventional

   year  region
0  2015  Albany
1  2015  Albany
2  2015  Albany
3  2015  Albany
4  2015  Albany
```

[3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18249 entries, 0 to 18248
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Unnamed: 0    18249 non-null  int64
 1   Date          18249 non-null  object
 2   AveragePrice  18249 non-null  float64
 3   Total Volume  18249 non-null  float64
 4   4046          18249 non-null  float64
 5   4225          18249 non-null  float64
 6   4770          18249 non-null  float64
 7   Total Bags    18249 non-null  float64
 8   Small Bags    18249 non-null  float64
 9   Large Bags    18249 non-null  float64
 10  XLarge Bags   18249 non-null  float64
 11  type          18249 non-null  object
 12  year          18249 non-null  int64
 13  region        18249 non-null  object
dtypes: float64(9), int64(2), object(3)
memory usage: 1.9+ MB
```

[4]:
```python
df.isnull().sum()
```

[4]:
```
Unnamed: 0      0
Date            0
AveragePrice    0
Total Volume    0
4046            0
4225            0
4770            0
Total Bags      0
Small Bags      0
Large Bags      0
XLarge Bags     0
type            0
```

```
year              0
region            0
dtype: int64
```

[5]:
```
# Preprocess the data
# Convert 'Date' to datetime format
df['Date'] = pd.to_datetime(df['Date'])

# Encode categorical variables
label_encoders = {}
for column in ['type', 'region']:
    le = LabelEncoder()
    df[column] = le.fit_transform(df[column])
    label_encoders[column] = le

# Drop any rows with missing values (if any)
df.dropna(inplace=True)

# Separate features and target variable
X = df.drop(['AveragePrice', 'Date'], axis=1)
y = df['AveragePrice']

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
C:\Users\iamim\AppData\Local\Temp\ipykernel_24820\810139836.py:3: UserWarning:
Parsing dates in %d-%m-%Y format when dayfirst=False (the default) was
specified. Pass `dayfirst=True` or specify a format to silence this warning.
  df['Date'] = pd.to_datetime(df['Date'])
```

2. Train-Test Split

3. Implement the KNN Classifier

[10]:
```
# Convert 'AveragePrice' to a binary classification target (1 if above median,␣
↪0 if below)
median_price = df['AveragePrice'].median()
df['PriceCategory'] = (df['AveragePrice'] > median_price).astype(int)

# Separate features and new target variable
X_classification = df.drop(['AveragePrice', 'Date', 'PriceCategory'], axis=1)
y_classification = df['PriceCategory']

# Scale the features
X_scaled_classification = scaler.fit_transform(X_classification)
```

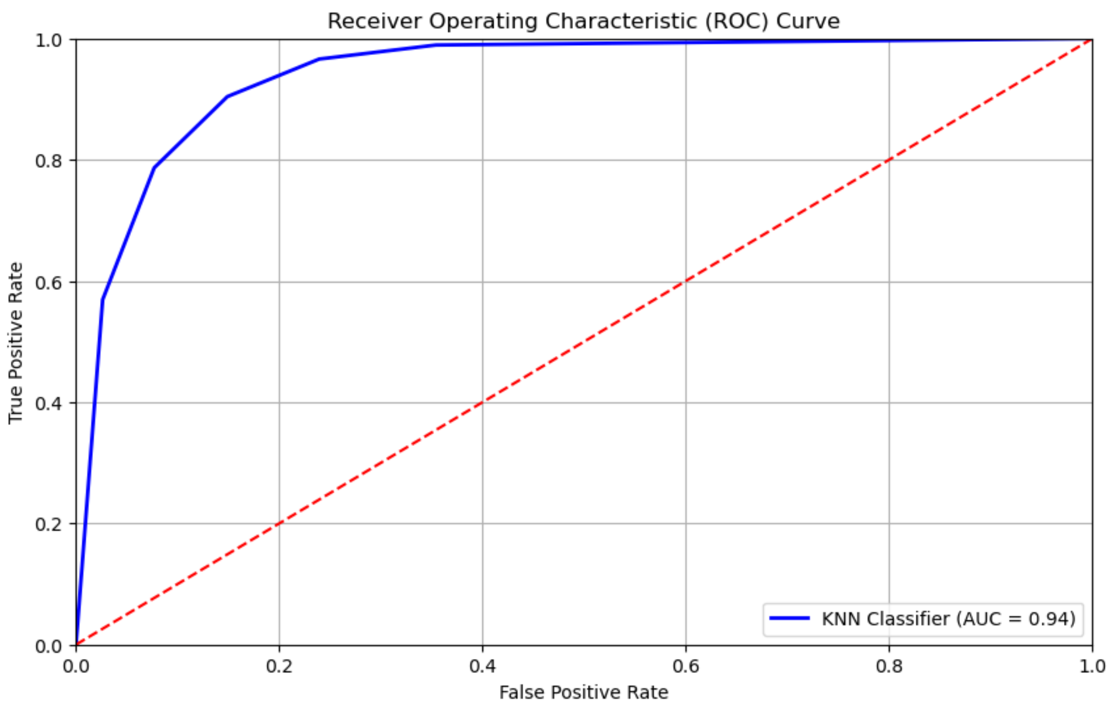
[11]:
```python
# Split the data into training and testing sets
X_train_clf, X_test_clf, y_train_clf, y_test_clf =␣
↪train_test_split(X_scaled_classification, y_classification, test_size=0.2,␣
↪random_state=42)
```

[12]:
```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, classification_report,␣
↪accuracy_score, roc_curve, auc

# Initialize the KNN Classifier
knn_clf = KNeighborsClassifier(n_neighbors=5)

# Train the model
knn_clf.fit(X_train_clf, y_train_clf)

# Make predictions
y_pred_clf = knn_clf.predict(X_test_clf)

# Evaluate the model
accuracy = accuracy_score(y_test_clf, y_pred_clf)
conf_matrix = confusion_matrix(y_test_clf, y_pred_clf)
class_report = classification_report(y_test_clf, y_pred_clf)

# Print the evaluation metrics
print(f'Accuracy: {accuracy}')
print('Confusion Matrix:')
print(conf_matrix)
print('Classification Report:')
print(class_report)
```

```
Accuracy: 0.8780821917808219
Confusion Matrix:
[[1526  267]
 [ 178 1679]]
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.85      0.87      1793
           1       0.86      0.90      0.88      1857

    accuracy                           0.88      3650
   macro avg       0.88      0.88      0.88      3650
weighted avg       0.88      0.88      0.88      3650
```

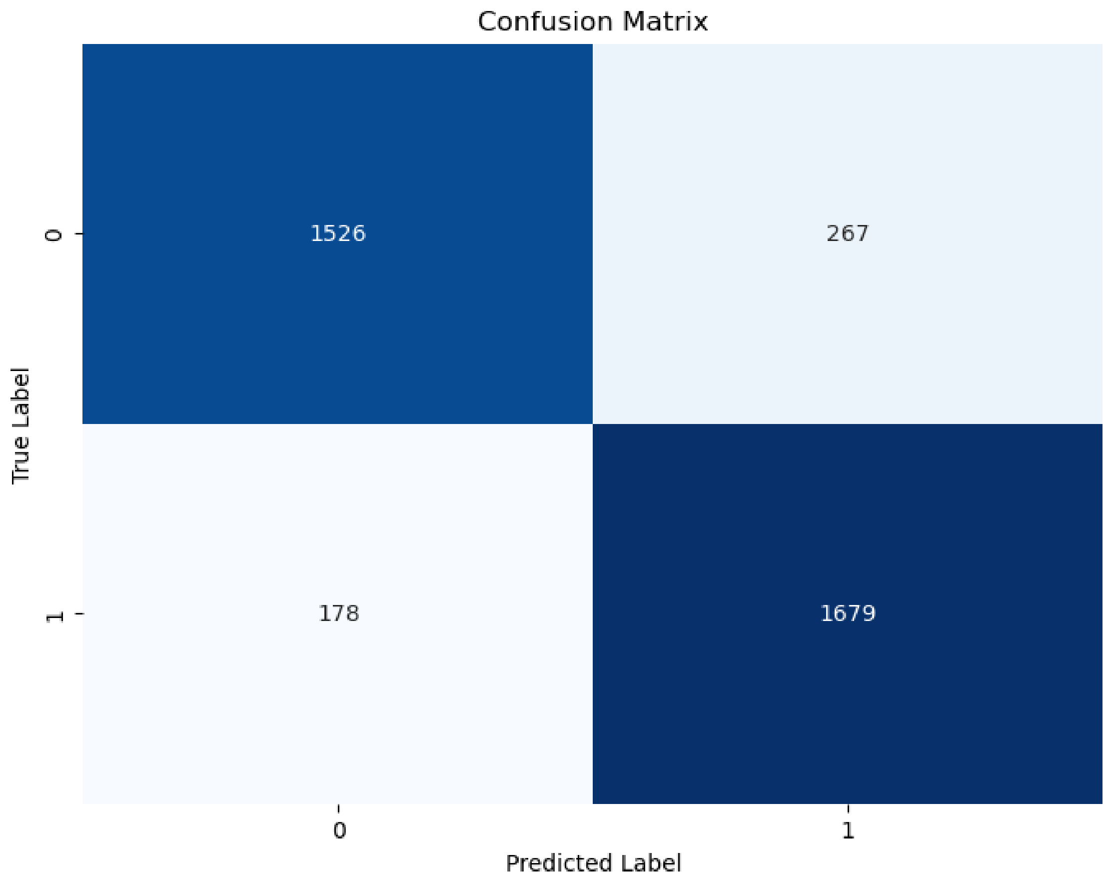
[16]:
```python
# Calculate the ROC curve and AUC
y_pred_prob = knn_clf.predict_proba(X_test_clf)[:, 1]
```

```
fpr, tpr, thresholds = roc_curve(y_test_clf, y_pred_prob)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'KNN Classifier (AUC = {roc_auc:.
↪2f})')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.grid(True)
plt.savefig('knn_roc_curve.png')
plt.show()
```

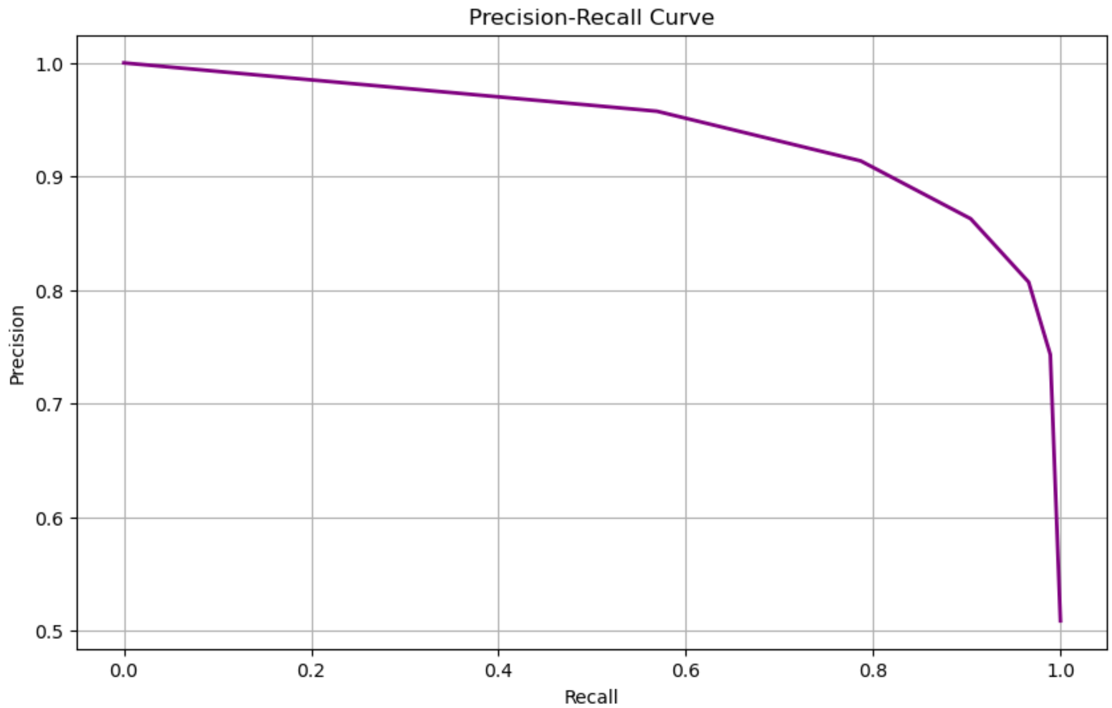


[18]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Confusion Matrix Plot
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
```

```
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.savefig('knn_confusion_matrix.png', dpi=300)
plt.show()
```



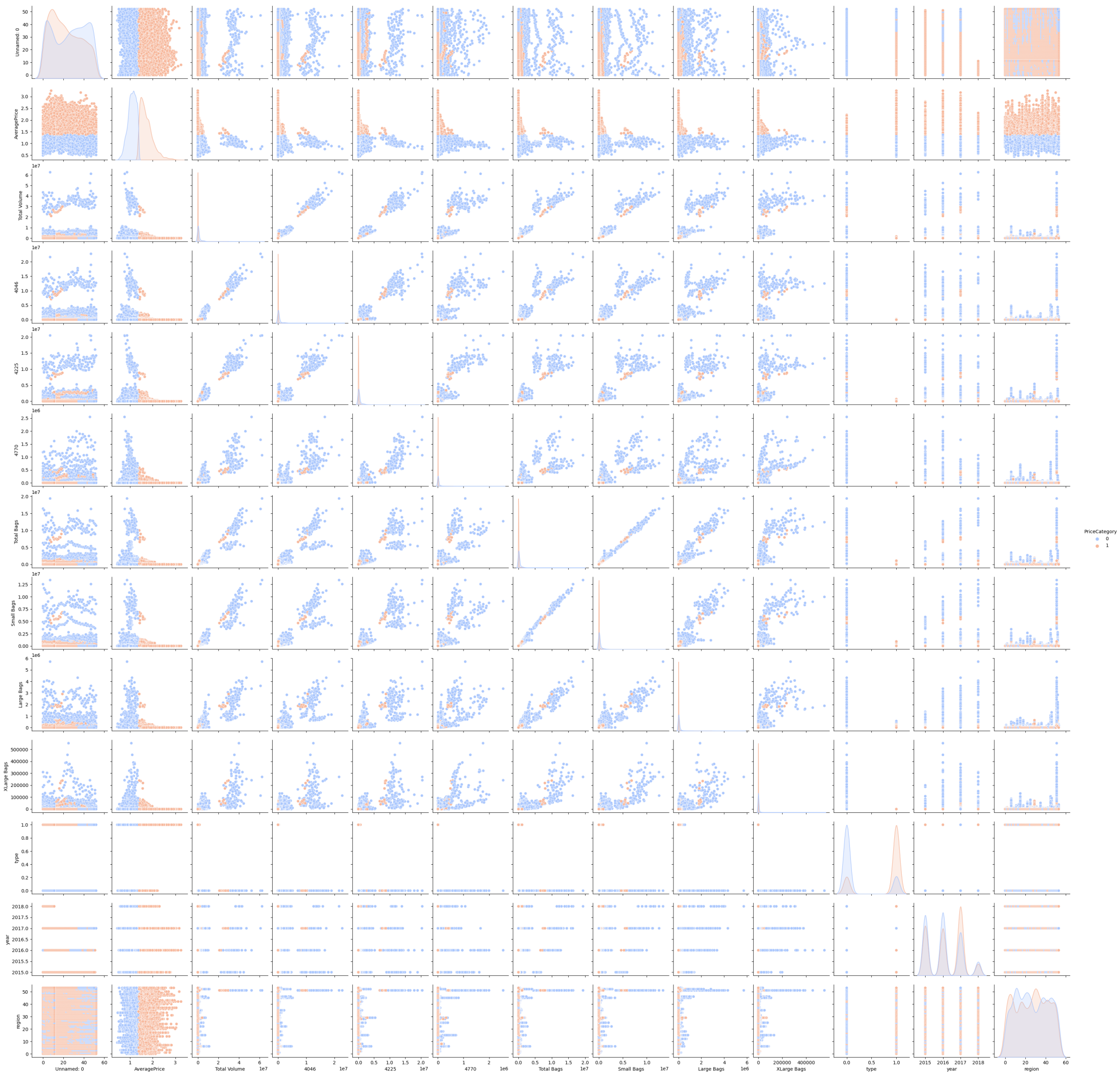
[20]:
```
from sklearn.metrics import precision_recall_curve

# Precision-Recall Curve
precision, recall, _ = precision_recall_curve(y_test_clf, y_pred_prob)

plt.figure(figsize=(10, 6))
plt.plot(recall, precision, color='purple', lw=2)
plt.title('Precision-Recall Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.grid(True)
plt.savefig('knn_precision_recall_curve.png', dpi=300)
plt.show()
```



Pairplot of Features

[21]:
```
sns.pairplot(df, hue='PriceCategory', palette='coolwarm', diag_kind='kde')
plt.savefig('knn_pairplot.png', dpi=300)
plt.show()
```

```
c:\Users\iamim\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning:

The figure layout has changed to tight
```

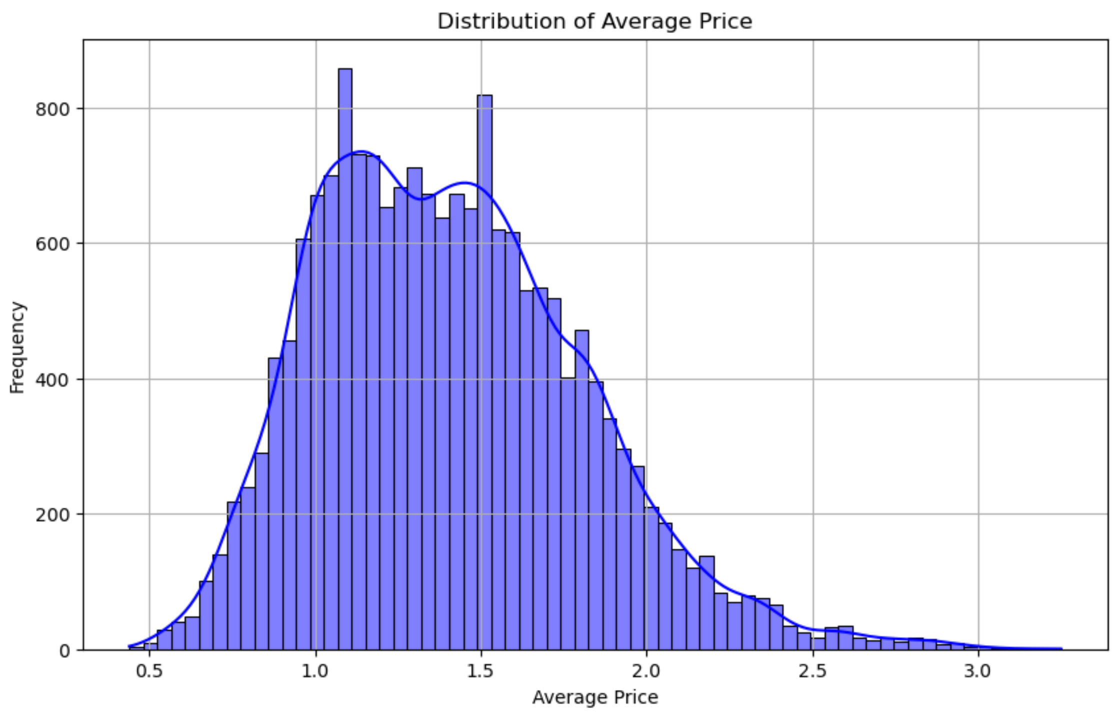


[22]:
```python
import plotly.express as px

# Confusion Matrix in Plotly
fig_conf_matrix = px.imshow(conf_matrix, text_auto=True, labels={'x':␣
↪'Predicted', 'y': 'True'}, title='Confusion Matrix')
fig_conf_matrix.write_html('knn_confusion_matrix.html')

# ROC Curve in Plotly
fig_roc = px.area(x=fpr, y=tpr, title=f'ROC Curve (AUC = {roc_auc:.2f})',
                  labels={'x': 'False Positive Rate', 'y': 'True Positive␣
↪Rate'},
                  hover_data={'False Positive Rate': fpr, 'True Positive Rate':␣
↪tpr})
fig_roc.add_shape(type='line', line=dict(dash='dash'), x0=0, x1=1, y0=0, y1=1)
```

```
fig_roc.write_html('knn_roc_curve.html')

# Precision-Recall Curve in Plotly
fig_pr = px.line(x=recall, y=precision, title='Precision-Recall Curve',
                 labels={'x': 'Recall', 'y': 'Precision'})
fig_pr.write_html('knn_precision_recall_curve.html')
```

Distribution Plot of AveragePrice

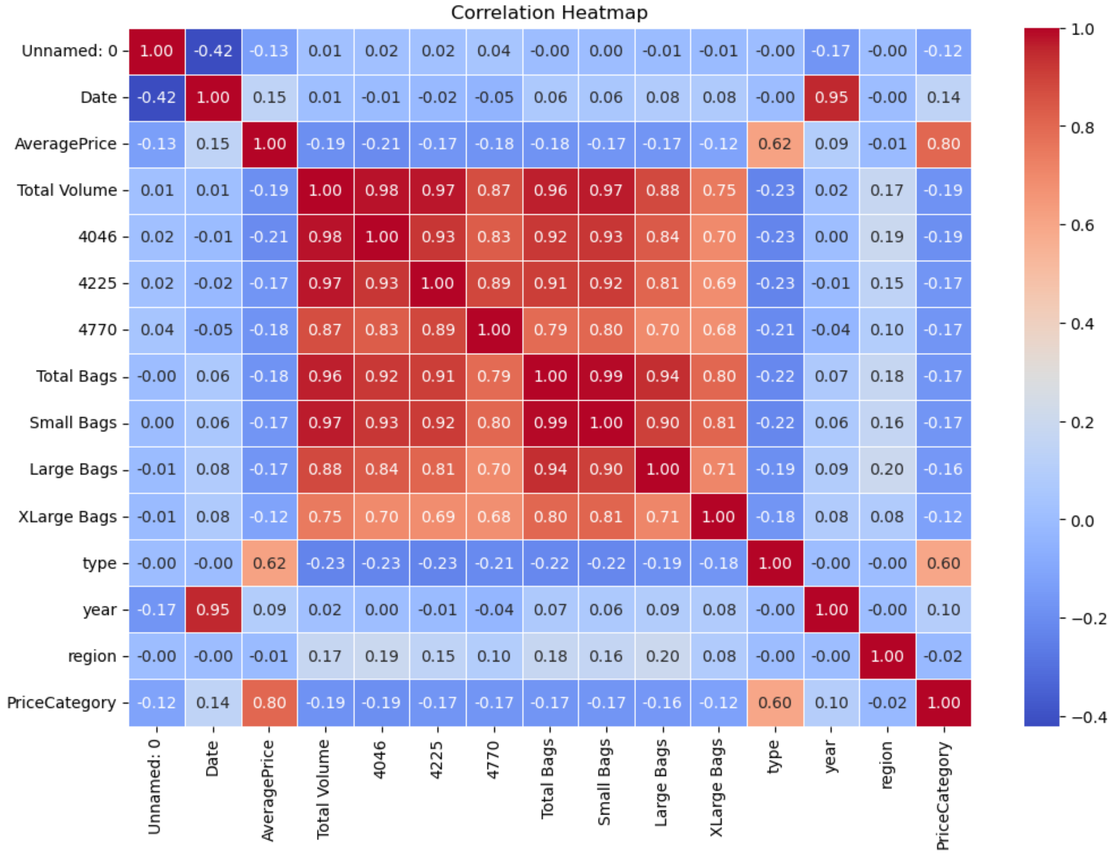
[23]:
```
plt.figure(figsize=(10, 6))
sns.histplot(df['AveragePrice'], kde=True, color='blue')
plt.title('Distribution of Average Price')
plt.xlabel('Average Price')
plt.ylabel('Frequency')
plt.grid(True)
plt.savefig('average_price_distribution.png', dpi=300)
plt.show()
```



Correlation Heatmap

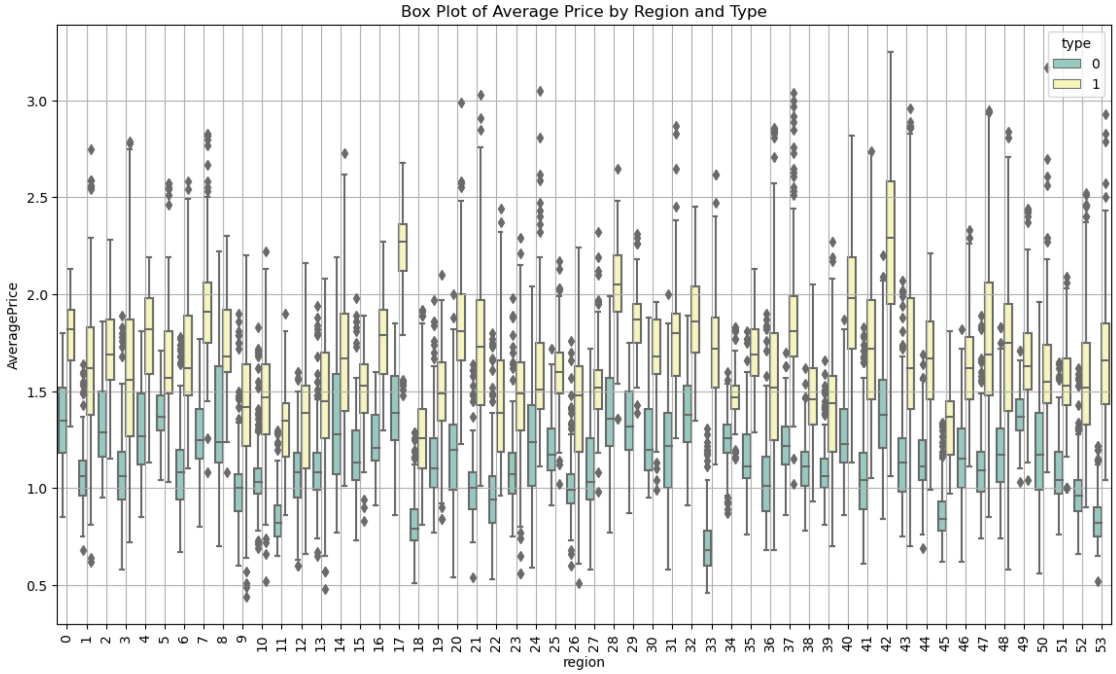
[24]:
```
plt.figure(figsize=(12, 8))
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f',␣
 ↪linewidths=0.5)
```

```
plt.title('Correlation Heatmap')
plt.savefig('correlation_heatmap.png', dpi=300)
plt.show()
```



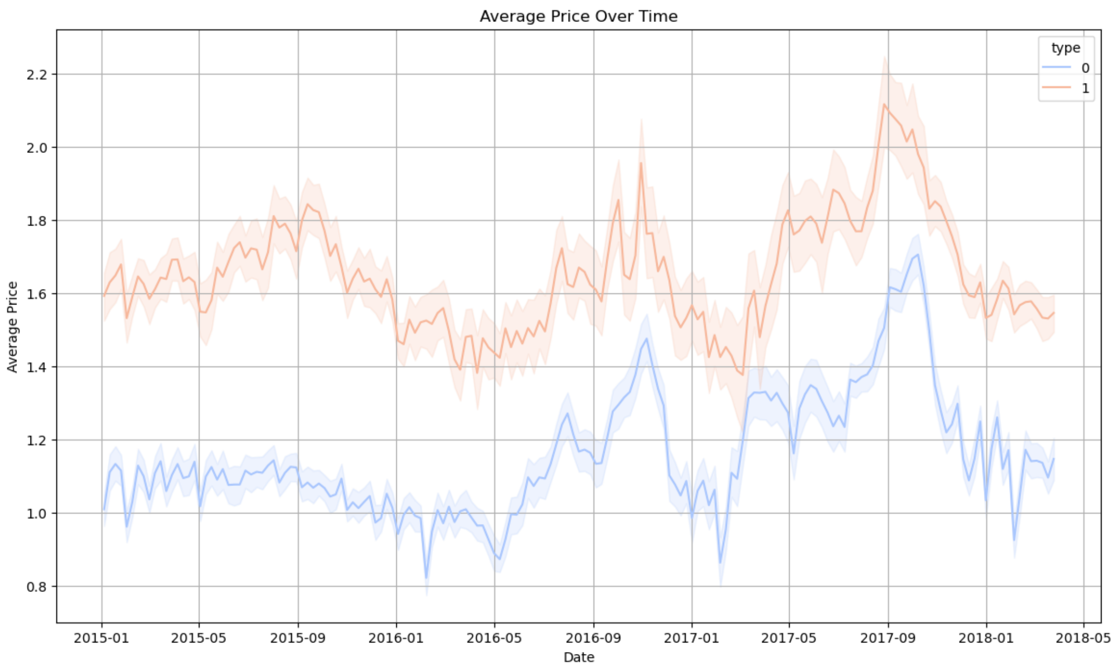
Box Plot of AveragePrice by Region and Type

[25]:
```
plt.figure(figsize=(14, 8))
sns.boxplot(x='region', y='AveragePrice', hue='type', data=df, palette='Set3')
plt.title('Box Plot of Average Price by Region and Type')
plt.xticks(rotation=90)
plt.grid(True)
plt.savefig('boxplot_average_price_region_type.png', dpi=300)
plt.show()
```



Time Series Plot of AveragePrice

[26]:
```
plt.figure(figsize=(14, 8))
sns.lineplot(x='Date', y='AveragePrice', hue='type', data=df,␣
↪palette='coolwarm')
plt.title('Average Price Over Time')
plt.xlabel('Date')
plt.ylabel('Average Price')
plt.grid(True)
plt.savefig('average_price_over_time.png', dpi=300)
plt.show()
```



[27]:
```python
# Distribution Plot using Plotly
fig_dist = px.histogram(df, x='AveragePrice', nbins=50, marginal='box',␣
↪title='Distribution of Average Price')
fig_dist.write_html('average_price_distribution.html')

# Correlation Heatmap using Plotly
fig_corr = px.imshow(correlation_matrix, text_auto=True, aspect='auto',␣
↪title='Correlation Heatmap')
fig_corr.write_html('correlation_heatmap.html')

# Box Plot using Plotly
fig_box = px.box(df, x='region', y='AveragePrice', color='type', title='Box␣
↪Plot of Average Price by Region and Type')
fig_box.update_layout(xaxis_tickangle=-90)
fig_box.write_html('boxplot_average_price_region_type.html')

# Time Series Plot using Plotly
fig_time = px.line(df, x='Date', y='AveragePrice', color='type', title='Average␣
↪Price Over Time')
fig_time.write_html('average_price_over_time.html')
```

Implementation of Ada boost, Gradient boosting & Random Forest, Bagging classifiers

[28]:
```python
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier,␣
↪RandomForestClassifier, BaggingClassifier
from sklearn.metrics import accuracy_score, classification_report
import matplotlib.pyplot as plt
import seaborn as sns

# Initialize a dictionary to store the accuracy of each model
model_accuracies = {}
```

AdaBoost Classifier

[29]:
```python
# AdaBoost Classifier
ada_clf = AdaBoostClassifier(n_estimators=50, random_state=42)
ada_clf.fit(X_train_clf, y_train_clf)
y_pred_ada = ada_clf.predict(X_test_clf)

# Accuracy and classification report
ada_accuracy = accuracy_score(y_test_clf, y_pred_ada)
model_accuracies['AdaBoost'] = ada_accuracy
print(f"AdaBoost Accuracy: {ada_accuracy:.2f}")
print(classification_report(y_test_clf, y_pred_ada))
```

```
AdaBoost Accuracy: 0.83
              precision    recall  f1-score   support

           0       0.81      0.84      0.83      1793
           1       0.84      0.81      0.83      1857

    accuracy                           0.83      3650
   macro avg       0.83      0.83      0.83      3650
weighted avg       0.83      0.83      0.83      3650
```

Gradient Boosting Classifier

[30]:
```python
# Gradient Boosting Classifier
gb_clf = GradientBoostingClassifier(n_estimators=100, random_state=42)
gb_clf.fit(X_train_clf, y_train_clf)
y_pred_gb = gb_clf.predict(X_test_clf)

# Accuracy and classification report
gb_accuracy = accuracy_score(y_test_clf, y_pred_gb)
model_accuracies['Gradient Boosting'] = gb_accuracy
print(f"Gradient Boosting Accuracy: {gb_accuracy:.2f}")
print(classification_report(y_test_clf, y_pred_gb))
```

```
Gradient Boosting Accuracy: 0.87
              precision    recall  f1-score   support
```

```
           0       0.87      0.87      0.87      1793
           1       0.87      0.87      0.87      1857

    accuracy                           0.87      3650
   macro avg       0.87      0.87      0.87      3650
weighted avg       0.87      0.87      0.87      3650
```

Random Forest Classifier

[31]:
```
# Random Forest Classifier
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_train_clf, y_train_clf)
y_pred_rf = rf_clf.predict(X_test_clf)

# Accuracy and classification report
rf_accuracy = accuracy_score(y_test_clf, y_pred_rf)
model_accuracies['Random Forest'] = rf_accuracy
print(f"Random Forest Accuracy: {rf_accuracy:.2f}")
print(classification_report(y_test_clf, y_pred_rf))
```

```
Random Forest Accuracy: 0.93
              precision    recall  f1-score   support

           0       0.93      0.92      0.92      1793
           1       0.92      0.94      0.93      1857

    accuracy                           0.93      3650
   macro avg       0.93      0.93      0.93      3650
weighted avg       0.93      0.93      0.93      3650
```

Bagging Classifier

[32]:
```
# Bagging Classifier
bagging_clf = BaggingClassifier(base_estimator=KNeighborsClassifier(),␣
 ↪n_estimators=50, random_state=42)
bagging_clf.fit(X_train_clf, y_train_clf)
y_pred_bagging = bagging_clf.predict(X_test_clf)

# Accuracy and classification report
bagging_accuracy = accuracy_score(y_test_clf, y_pred_bagging)
model_accuracies['Bagging'] = bagging_accuracy
print(f"Bagging Classifier Accuracy: {bagging_accuracy:.2f}")
print(classification_report(y_test_clf, y_pred_bagging))
```

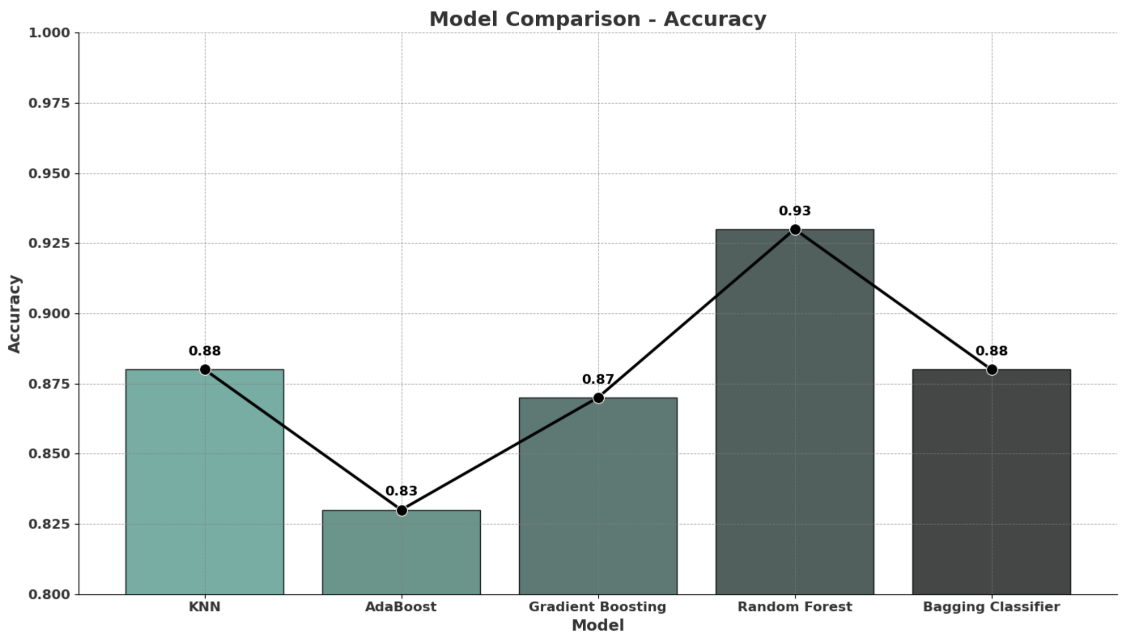
```
c:\Users\iamim\anaconda3\Lib\site-packages\sklearn\ensemble\_base.py:156:
FutureWarning:
```

```
`base_estimator` was renamed to `estimator` in version 1.2 and will be removed
in 1.4.


Bagging Classifier Accuracy: 0.88
              precision    recall  f1-score   support

           0       0.90      0.85      0.88      1793
           1       0.86      0.91      0.89      1857

    accuracy                           0.88      3650
   macro avg       0.88      0.88      0.88      3650
weighted avg       0.88      0.88      0.88      3650
```

Plot the Accuracies Together

[42]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Example model accuracies (replace with your actual data)
model_accuracies = {
    'KNN': 0.88,
    'AdaBoost': 0.83,
    'Gradient Boosting': 0.87,
    'Random Forest': 0.93,
    'Bagging Classifier': 0.88
}

# Professional Plot for Model Comparison
plt.figure(figsize=(14, 8))

# Bar plot for model accuracies
sns.barplot(x=list(model_accuracies.keys()), y=list(model_accuracies.values()),
            palette='dark:#5A9_r', alpha=0.85, edgecolor='black')

# Line plot for model accuracies
sns.lineplot(x=list(model_accuracies.keys()), y=list(model_accuracies.values()),
             marker='o', color='black', linewidth=2.5, markersize=10)

# Adding text annotations for each bar
for i, v in enumerate(model_accuracies.values()):
    plt.text(i, v + 0.005, f"{v:.2f}", ha='center', fontsize=12,␣
 ↪fontweight='bold', color='black')

plt.title('Model Comparison - Accuracy', fontsize=18, fontweight='bold',␣
 ↪color='#333333')
plt.ylabel('Accuracy', fontsize=14, fontweight='bold', color='#333333')
```

```
plt.xlabel('Model', fontsize=14, fontweight='bold', color='#333333')

# Adjusting y-axis limits to ensure all values are visible
plt.ylim(0.80, 1.0)  # Increased lower limit to 0.80

plt.xticks(fontsize=12, fontweight='bold', color='#333333')
plt.yticks(fontsize=12, fontweight='bold', color='#333333')

# Adding subtle grid lines
plt.grid(True, which='major', linestyle='--', linewidth=0.6, color='grey',␣
 ↪alpha=0.7)

# Remove top and right borders
sns.despine()

plt.tight_layout()

# Save the plot with higher DPI for better quality
plt.savefig('professional_model_comparison_accuracy.png', dpi=300,␣
 ↪bbox_inches='tight')
plt.show()
```



Displaying Classification Reports

[44]:
```
import pandas as pd
from sklearn.metrics import classification_report, accuracy_score
```

```python
# Example predictions and true labels (replace with your actual data)
# y_test_clf, y_pred_clf, y_pred_ada, y_pred_gb, y_pred_rf, y_pred_bagging␣
↪should be defined

# Store the classification reports and accuracies in dictionaries
classification_reports = {
    'KNN': classification_report(y_test_clf, y_pred_clf, output_dict=True),
    'AdaBoost': classification_report(y_test_clf, y_pred_ada, output_dict=True),
    'Gradient Boosting': classification_report(y_test_clf, y_pred_gb,␣
↪output_dict=True),
    'Random Forest': classification_report(y_test_clf, y_pred_rf,␣
↪output_dict=True),
    'Bagging': classification_report(y_test_clf, y_pred_bagging,␣
↪output_dict=True)
}

accuracies = {
    'KNN': accuracy_score(y_test_clf, y_pred_clf),
    'AdaBoost': accuracy_score(y_test_clf, y_pred_ada),
    'Gradient Boosting': accuracy_score(y_test_clf, y_pred_gb),
    'Random Forest': accuracy_score(y_test_clf, y_pred_rf),
    'Bagging': accuracy_score(y_test_clf, y_pred_bagging)
}

# Convert the reports into DataFrames
reports_df = {model: pd.DataFrame(report).transpose() for model, report in␣
↪classification_reports.items()}

# Add accuracy as a new row to each DataFrame
for model, df in reports_df.items():
    df.loc['accuracy', :] = pd.Series(accuracies[model], index=df.columns)

# Add accuracy to the classification report for clarity
for model, df in reports_df.items():
    df.loc['accuracy', :] = pd.Series(accuracies[model], index=df.columns)

# Create a DataFrame for accuracies
accuracy_df = pd.DataFrame(list(accuracies.items()), columns=['Model',␣
↪'Accuracy']).set_index('Model')

# Combine the DataFrames into a single DataFrame for better visualization
combined_report_df = pd.concat(reports_df, axis=1)

# Append the accuracies DataFrame to the combined report DataFrame
combined_report_df = pd.concat([combined_report_df, accuracy_df.T], axis=0)
```

```python
# Display the combined classification report
with pd.option_context('display.max_columns', None):  # to display all columns
    print(combined_report_df)
```

```
              (KNN, precision)  (KNN, recall)  (KNN, f1-score)  \
0                     0.895540       0.851088         0.872748
1                     0.862795       0.904146         0.882987
accuracy              0.878082       0.878082         0.878082
macro avg             0.879168       0.877617         0.877868
weighted avg          0.878881       0.878082         0.877957
Accuracy                   NaN            NaN              NaN

              (KNN, support)  (AdaBoost, precision)  (AdaBoost, recall)  \
0                1793.000000               0.813678            0.842722
1                1857.000000               0.842722            0.813678
accuracy            0.878082               0.827945            0.827945
macro avg        3650.000000               0.828200            0.828200
weighted avg     3650.000000               0.828454            0.827945
Accuracy                 NaN                    NaN                 NaN

              (AdaBoost, f1-score)  (AdaBoost, support)  \
0                         0.827945          1793.000000
1                         0.827945          1857.000000
accuracy                  0.827945             0.827945
macro avg                 0.827945          3650.000000
weighted avg              0.827945          3650.000000
Accuracy                       NaN                  NaN

              (Gradient Boosting, precision)  (Gradient Boosting, recall)  \
0                                   0.868083                     0.866146
1                                   0.871037                     0.872913
accuracy                            0.869589                     0.869589
macro avg                           0.869560                     0.869530
weighted avg                        0.869586                     0.869589
Accuracy                                 NaN                          NaN

              (Gradient Boosting, f1-score)  (Gradient Boosting, support)  \
0                                  0.867113                   1793.000000
1                                  0.871974                   1857.000000
accuracy                           0.869589                      0.869589
macro avg                          0.869544                   3650.000000
weighted avg                       0.869586                   3650.000000
Accuracy                                NaN                           NaN

              (Random Forest, precision)  (Random Forest, recall)  \
0                               0.932955                 0.915784
```

```
1                              0.920106                 0.936457
accuracy                       0.926301                 0.926301
macro avg                      0.926530                 0.926120
weighted avg                   0.926418                 0.926301
Accuracy                            NaN                      NaN

              (Random Forest, f1-score)  (Random Forest, support)  \
0                              0.924289               1793.000000
1                              0.928209               1857.000000
accuracy                       0.926301                  0.926301
macro avg                      0.926249               3650.000000
weighted avg                   0.926284               3650.000000
Accuracy                            NaN                       NaN

              (Bagging, precision)  (Bagging, recall)  (Bagging, f1-score)  \
0                         0.900885           0.851645             0.875573
1                         0.863939           0.909532             0.886149
accuracy                  0.881096           0.881096             0.881096
macro avg                 0.882412           0.880588             0.880861
weighted avg              0.882088           0.881096             0.880954
Accuracy                       NaN                NaN                  NaN

              (Bagging, support)       KNN  AdaBoost  Gradient Boosting  \
0                    1793.000000       NaN       NaN                NaN
1                    1857.000000       NaN       NaN                NaN
accuracy                0.881096       NaN       NaN                NaN
macro avg            3650.000000       NaN       NaN                NaN
weighted avg         3650.000000       NaN       NaN                NaN
Accuracy                     NaN  0.878082  0.827945           0.869589

              Random Forest   Bagging
0                       NaN       NaN
1                       NaN       NaN
accuracy                NaN       NaN
macro avg               NaN       NaN
weighted avg            NaN       NaN
Accuracy           0.926301  0.881096
```