Customer Segmentation using Classification

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Project Overview

In this practical, we will predict customer segments (A, B, C, or D) for potential new customers using machine learning classification models. An automobile company plans to expand into new markets with their existing products (P1-P5), and wants to classify 2,627 new potential customers into segments based on demographic and behavioral attributes.

Dataset Information

The dataset contains various customer attributes:

Variable	Definition
ID	Unique ID of the customer
Gender	Gender of the customer
Ever_Married	Marital status of the customer
Age	Age of the customer
Graduated	Whether the customer is a graduate
Profession	Profession of the customer
Work_Experience	Work experience in years
Spending_Score	Spending score of the customer
Family_Size	Number of family members (including customer)
Var_1	Anonymized category of the customer
Segmentation	Target Variable - Customer segment (A, B, C, or D)

Project Tasks

Task	Description
1. Data Exploration	• Load the dataset and display basic statistics • Identify the number of records, missing values, and data types • Visualize class distribution of Segmentation
2. Handling Missing Values	• Identify missing values and impute or drop them as required • Use appropriate strategies such as mean/median for numerical data and mode for categorical data

Task	Description
3. Exploratory Data Analysis	Perform at least 5 analyses: • Univariate Analysis (Distribution plots for numerical features) • Bivariate Analysis (Comparison between variables) • Correlation Heatmap • Bar plot for categorical variables • Outlier detection using box plots
4. Model Building	• Convert categorical variables into numerical representations • Perform train-test split (e.g., 80-20 split) • Train at least four classification models: 1. Logistic Regression 2. Random Forest Classifier 3. Support Vector Machine (SVM) 4. XGBoost
5. Model Evaluation	Compare models using performance metrics: • Accuracy • Precision, Recall, and F1-Score • Confusion Matrix
6. Model Saving	• Save the best-performing model
7. Prediction	• Load the saved model and make predictions on the new dataset • Display the predicted segments for new customers

Let's begin our analysis!

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1. Data Exploration

- Load the dataset and display basic statistics.
- Identify the number of records, missing values, and data types.
- Visualize class distribution of Segmentation.

..

In [1]:
```
# Import necessary libraries for data exploration
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Set display options for better visualization
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 1000)

# Load the datasets
train_df = pd.read_csv('Train.csv')
test_df = pd.read_csv('Test.csv')
```

..

Training Dataset Information

..

In [3]:
```python
# Display basic information about the training dataset
print("Training Dataset Information:")
print(" ")
print(f"Shape of training data: {train_df.shape}")
print("\nFirst 5 rows of training data:")
train_df
```

```
Training Dataset Information:

Shape of training data: (8068, 11)

First 5 rows of training data:
```

Out[3]:

	ID	Gender	Ever_Married	Age	Graduated	Profession	Work_Experience	Spending_Scor
0	462809	Male	No	22	No	Healthcare	1.0	Lov
1	462643	Female	Yes	38	Yes	Engineer	NaN	Averag
2	466315	Female	Yes	67	Yes	Engineer	1.0	Lov
3	461735	Male	Yes	67	Yes	Lawyer	0.0	Hig
4	462669	Female	Yes	40	Yes	Entertainment	NaN	Hig
...	...	...	...	...	...	...	...	.
8063	464018	Male	No	22	No	NaN	0.0	Lov
8064	464685	Male	No	35	No	Executive	3.0	Lov
8065	465406	Female	No	33	Yes	Healthcare	1.0	Lov
8066	467299	Female	No	27	Yes	Healthcare	1.0	Lov
8067	461879	Male	Yes	37	Yes	Executive	0.0	Averag

8068 rows × 11 columns

In [4]:
```python
# Display basic statistics of the training dataset
print("\nBasic statistics of training data:")
train_df.describe()
```

```
Basic statistics of training data:
```

Out[4]:

	ID	Age	Work_Experience	Family_Size
count	8068.000000	8068.000000	7239.000000	7733.000000
mean	463479.214551	43.466906	2.641663	2.850123
std	2595.381232	16.711696	3.406763	1.531413
min	458982.000000	18.000000	0.000000	1.000000
25%	461240.750000	30.000000	0.000000	2.000000
50%	463472.500000	40.000000	1.000000	3.000000
75%	465744.250000	53.000000	4.000000	4.000000
max	467974.000000	89.000000	14.000000	9.000000

In [5]:
```python
# Check data types and missing values in training data
print("\nData types in training data:")
train_df.info()
```

```
print("\nMissing values in training data:")

missing_values_table = pd.DataFrame({
    'Column': train_df.columns,
    'Missing Values': train_df.isnull().sum(),
    'Percentage': (train_df.isnull().sum() / len(train_df)) * 100
})

missing_values_table.style.hide_index()
```

```
Data types in training data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8068 entries, 0 to 8067
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ID               8068 non-null   int64  
 1   Gender           8068 non-null   object 
 2   Ever_Married     7928 non-null   object 
 3   Age              8068 non-null   int64  
 4   Graduated        7990 non-null   object 
 5   Profession       7944 non-null   object 
 6   Work_Experience  7239 non-null   float64
 7   Spending_Score   8068 non-null   object 
 8   Family_Size      7733 non-null   float64
 9   Var_1            7992 non-null   object 
 10  Segmentation     8068 non-null   object 
dtypes: float64(2), int64(2), object(7)
memory usage: 693.5+ KB

Missing values in training data:
```

```
C:\Users\KEVIN\AppData\Local\Temp\ipykernel_18604\302936981.py:13: FutureWarning: this method is deprecated in favour of `Styler.hide(axis="index")`
  missing_values_table.style.hide_index()
```

Out[5]:

Column	Missing Values	Percentage
ID	0	0.000000
Gender	0	0.000000
Ever_Married	140	1.735250
Age	0	0.000000
Graduated	78	0.966782
Profession	124	1.536936
Work_Experience	829	10.275161
Spending_Score	0	0.000000
Family_Size	335	4.152206
Var_1	76	0.941993
Segmentation	0	0.000000

In [6]:

```
# Display class distribution of the target variable
print("\nClass distribution of Segmentation (Target Variable):")
segmentation_counts = train_df['Segmentation'].value_counts()
segmentation_df = pd.DataFrame({
    'Count': segmentation_counts,
    'Percentage': (segmentation_counts / len(train_df) * 100)
```

```
})
segmentation_df.style.hide_index()
```

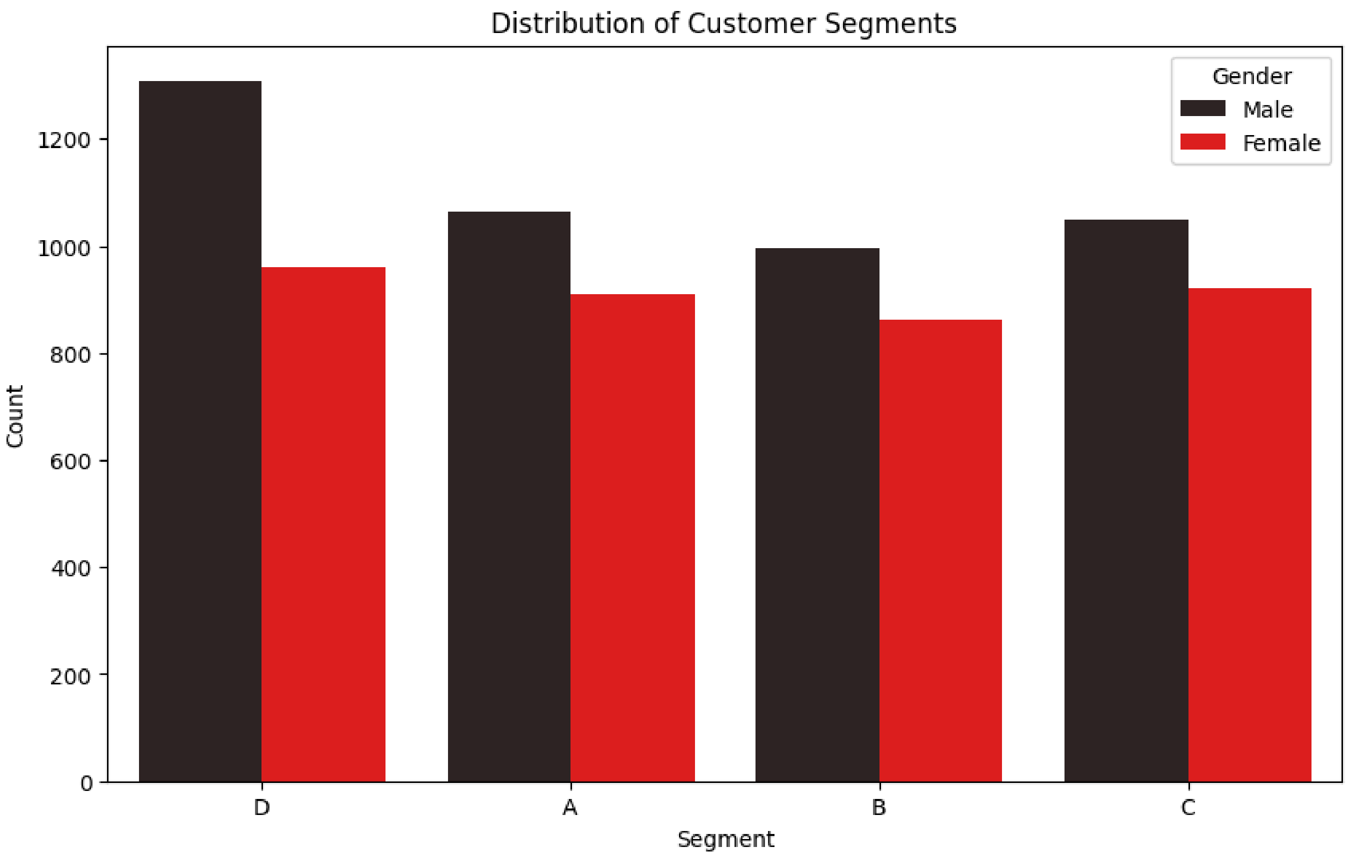
```
Class distribution of Segmentation (Target Variable):
C:\Users\KEVIN\AppData\Local\Temp\ipykernel_18604\686013384.py:8: FutureWarning: this method i
s deprecated in favour of `Styler.hide(axis="index")`
  segmentation_df.style.hide_index()
```

Out[6]:

Count	Percentage
2268	28.111056
1972	24.442241
1970	24.417452
1858	23.029251

In [7]:

```
# Visualize the class distribution
plt.figure(figsize=(10, 6))
sns.countplot(x='Segmentation', data=train_df , palette='dark:red' , hue= train_df['Gender'])
plt.title('Distribution of Customer Segments')
plt.xlabel('Segment')
plt.ylabel('Count')
plt.show()
```



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Testing Dataset Information

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In [8]:

```
# Display basic information about the testing dataset
print("\nTesting Dataset Information:")
print(f"Shape of testing data: {test_df.shape}")
```

```
print("\nFirst 5 rows of testing data:")
test_df.head()
```

```
Testing Dataset Information:
Shape of testing data: (2627, 11)

First 5 rows of testing data:
```

Out[8]:

	ID	Gender	Ever_Married	Age	Graduated	Profession	Work_Experience	Spending_Score	Fan
0	458989	Female	Yes	36	Yes	Engineer	0.0	Low	
1	458994	Male	Yes	37	Yes	Healthcare	8.0	Average	
2	458996	Female	Yes	69	No	NaN	0.0	Low	
3	459000	Male	Yes	59	No	Executive	11.0	High	
4	459001	Female	No	19	No	Marketing	NaN	Low	

In [9]:

```
# Check data types and missing values in Testinging data
print("\nData types in testing data:")


test_df.info()

print("\nMissing values in testing data:")

missing_values_table = pd.DataFrame({
    'Column': test_df.columns,
    'Missing Values': test_df.isnull().sum(),
    'Percentage': (test_df.isnull().sum() / len(test_df)) * 100
})

missing_values_table.style.hide_index()
```

```
Data types in testing data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2627 entries, 0 to 2626
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ID               2627 non-null   int64  
 1   Gender           2627 non-null   object 
 2   Ever_Married     2577 non-null   object 
 3   Age              2627 non-null   int64  
 4   Graduated        2603 non-null   object 
 5   Profession       2589 non-null   object 
 6   Work_Experience  2358 non-null   float64
 7   Spending_Score   2627 non-null   object 
 8   Family_Size      2514 non-null   float64
 9   Var_1            2595 non-null   object 
 10  Segmentation     2627 non-null   object 
dtypes: float64(2), int64(2), object(7)
memory usage: 225.9+ KB

Missing values in testing data:
```

```
C:\Users\KEVIN\AppData\Local\Temp\ipykernel_18604\1876749517.py:15: FutureWarning: this method is deprecated in favour of `Styler.hide(axis="index")`
  missing_values_table.style.hide_index()
```

Out[9]:

Column	Missing Values	Percentage
ID	0	0.000000
Gender	0	0.000000
Ever_Married	50	1.903312
Age	0	0.000000
Graduated	24	0.913590
Profession	38	1.446517
Work_Experience	269	10.239817
Spending_Score	0	0.000000
Family_Size	113	4.301485
Var_1	32	1.218120
Segmentation	0	0.000000

..

2. Handling Missing Values:

- Identify missing values and impute or drop them as required.
- Use appropriate strategies such as mean/median for numerical data and mode for categorical data.

..

In [10]:

```
# Function to handle missing values
def handle_missing_values(df):
    df_copy = df.copy()

    # For numerical columns, fill missing values with median
    numerical_cols = df_copy.select_dtypes(include=['int64', 'float64']).columns
    for col in numerical_cols:
        if df_copy[col].isnull().sum() > 0:
            median_value = df_copy[col].median()
            df_copy[col].fillna(median_value, inplace=True)
            print(f"Filled missing values in {col} with median: {median_value}")

    # For categorical columns, fill missing values with mode
    categorical_cols = df_copy.select_dtypes(include=['object']).columns
    for col in categorical_cols:
        if df_copy[col].isnull().sum() > 0:
            mode_value = df_copy[col].mode()[0]
            df_copy[col].fillna(mode_value, inplace=True)
            print(f"Filled missing values in {col} with mode: {mode_value}")

    return df_copy
```

In [11]:

```
# Apply the function to handle missing values in both datasets
train_df_clean = handle_missing_values(train_df)
test_df_clean = handle_missing_values(test_df)
```

```
Filled missing values in Work_Experience with median: 1.0
Filled missing values in Family_Size with median: 3.0
Filled missing values in Ever_Married with mode: Yes
Filled missing values in Graduated with mode: Yes
Filled missing values in Profession with mode: Artist
Filled missing values in Var_1 with mode: Cat_6
Filled missing values in Work_Experience with median: 1.0
Filled missing values in Family_Size with median: 2.0
Filled missing values in Ever_Married with mode: Yes
Filled missing values in Graduated with mode: Yes
Filled missing values in Profession with mode: Artist
Filled missing values in Var_1 with mode: Cat_6
```

In [12]:

```python
# Verify that there are no missing values left
print("\nMissing values in training data after imputation:")

train_clean = pd.DataFrame({
    'Column': train_df_clean.columns,
    'Missing Values': train_df_clean.isnull().sum(),
    'Percentage': (train_df_clean.isnull().sum() / len(train_df_clean)) * 100
})

train_clean.style.hide_index()
```

```
Missing values in training data after imputation:
```

```
C:\Users\KEVIN\AppData\Local\Temp\ipykernel_18604\1011372368.py:10: FutureWarning: this method is deprecated in favour of `Styler.hide(axis="index")`
  train_clean.style.hide_index()
```

Out[12]:

Column	Missing Values	Percentage
ID	0	0.000000
Gender	0	0.000000
Ever_Married	0	0.000000
Age	0	0.000000
Graduated	0	0.000000
Profession	0	0.000000
Work_Experience	0	0.000000
Spending_Score	0	0.000000
Family_Size	0	0.000000
Var_1	0	0.000000
Segmentation	0	0.000000

In [73]:

```python
print("\nMissing values in testing data after imputation:")


test_clean = pd.DataFrame({
    'Column': test_df_clean.columns,
    'Missing Values': test_df_clean.isnull().sum(),
    'Percentage': (test_df_clean.isnull().sum() / len(test_df_clean)) * 100
})

test_clean.style.hide_index()
```

```
Missing values in testing data after imputation:
```

```
C:\Users\KEVIN\AppData\Local\Temp\ipykernel_18604\1547337592.py:10: FutureWarning: this method is deprecated in favour of `Styler.hide(axis="index")`
  test_clean.style.hide_index()
```

Out[73]:

Column	Missing Values	Percentage
ID	0	0.000000
Gender	0	0.000000
Ever_Married	0	0.000000
Age	0	0.000000
Graduated	0	0.000000
Profession	0	0.000000
Work_Experience	0	0.000000
Spending_Score	0	0.000000
Family_Size	0	0.000000
Var_1	0	0.000000
Segmentation	0	0.000000

In [71]:

```
train_df_clean.describe()
```

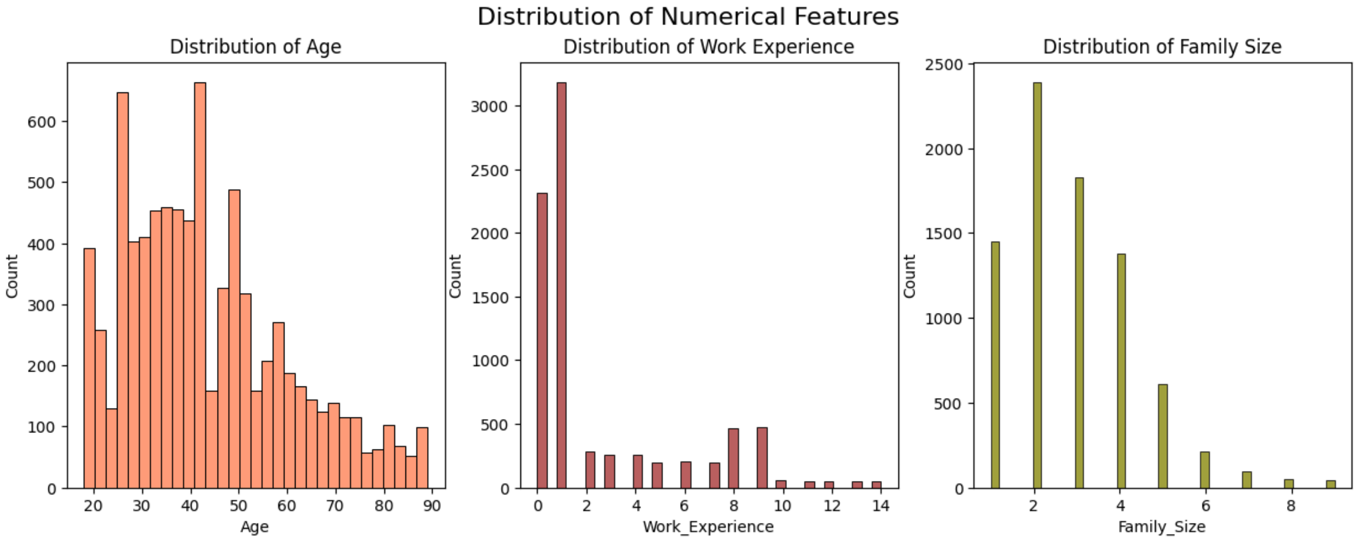
Out[71]:

	ID	Age	Work_Experience	Family_Size
count	8068.000000	8068.000000	8068.000000	8068.000000
mean	463479.214551	43.466906	2.472980	2.856346
std	2595.381232	16.711696	3.265248	1.499577
min	458982.000000	18.000000	0.000000	1.000000
25%	461240.750000	30.000000	0.000000	2.000000
50%	463472.500000	40.000000	1.000000	3.000000
75%	465744.250000	53.000000	4.000000	4.000000
max	467974.000000	89.000000	14.000000	9.000000

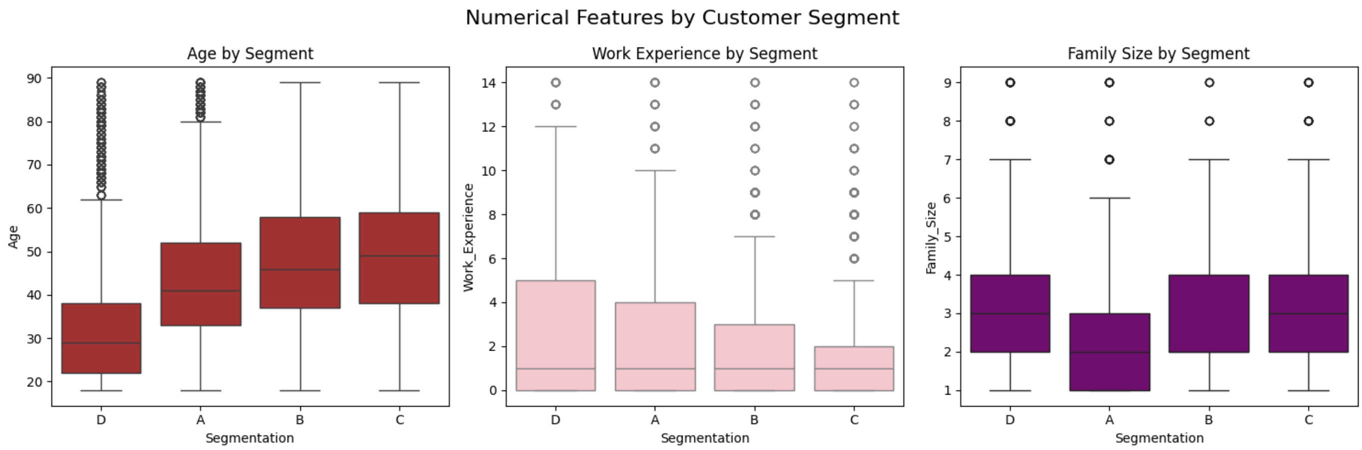
In [15]:

```
# Exploratory Data Analysis (EDA)

# Univariate Analysis for numerical features
plt.figure(figsize=(15, 5))

# Age distribution
plt.subplot(1, 3, 1)
sns.histplot(train_df_clean['Age'], color='coral')
plt.title('Distribution of Age')

# Work Experience distribution
plt.subplot(1, 3, 2)
sns.histplot(train_df_clean['Work_Experience'], color='brown')
plt.title('Distribution of Work Experience')

# Family Size distribution
plt.subplot(1, 3, 3)
sns.histplot(train_df_clean['Family_Size'],color='olive')
```

```
plt.title('Distribution of Family Size')


plt.suptitle('Distribution of Numerical Features', fontsize=16)
plt.show()
```



In [16]:
```
# Bivariate Analysis: Box plots for numerical features by segment
plt.figure(figsize=(15, 5))

# Age by Segment
plt.subplot(1, 3, 1)
sns.boxplot(x='Segmentation', y='Age', data=train_df_clean , color='firebrick')
plt.title('Age by Segment')


# Work Experience by Segment
plt.subplot(1, 3, 2)
sns.boxplot(x='Segmentation', y='Work_Experience', data=train_df_clean , color='pink')
plt.title('Work Experience by Segment')


# Family Size by Segment
plt.subplot(1, 3, 3)
sns.boxplot(x='Segmentation', y='Family_Size', data=train_df_clean , color='purple')
plt.title('Family Size by Segment')


plt.suptitle('Numerical Features by Customer Segment', fontsize=16)
plt.tight_layout()
plt.show()
```

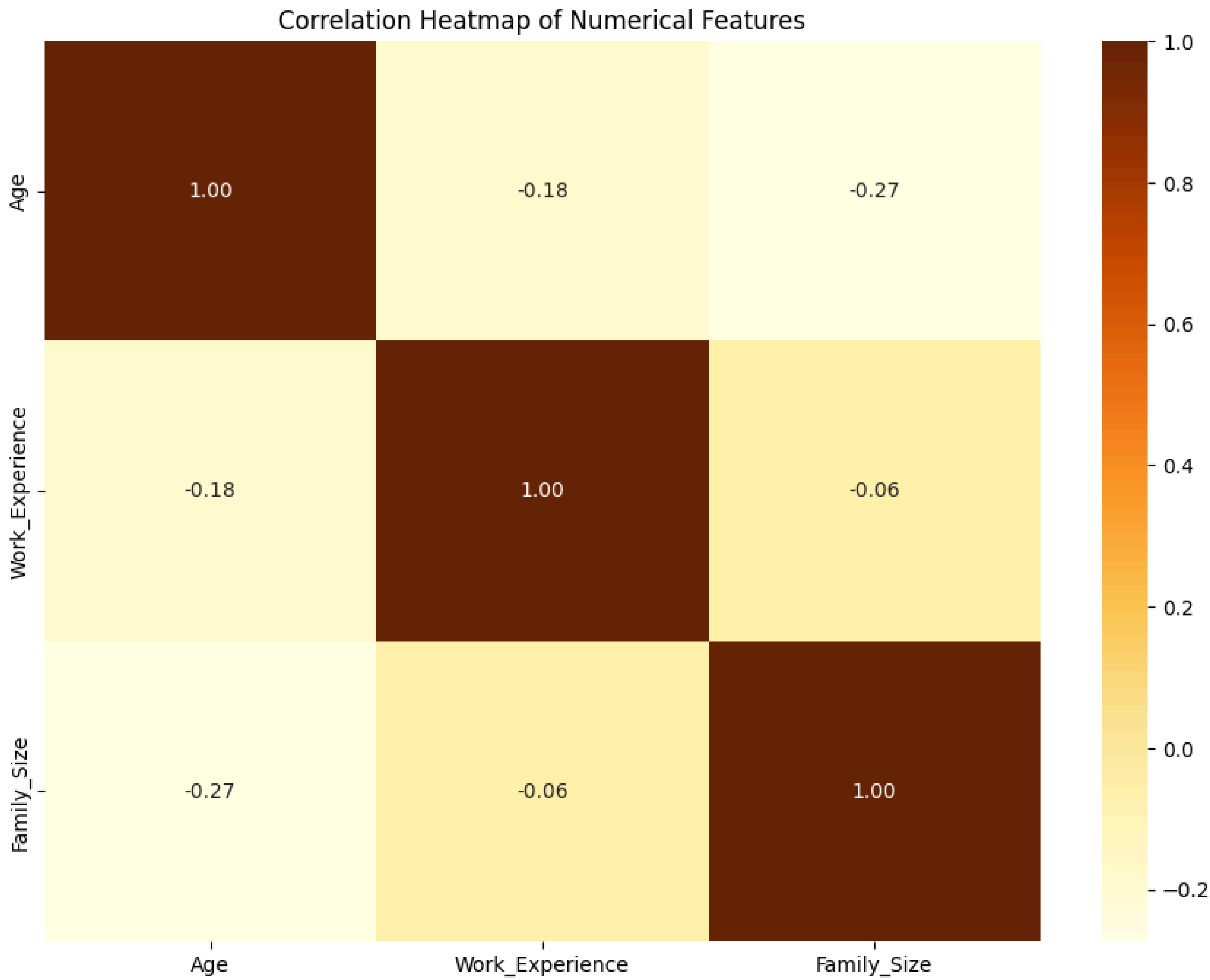


In [17]:

```python
numerical_features = train_df_clean.select_dtypes(include=['int64', 'float64']).columns.tolis
numerical_features = [f for f in numerical_features if f != 'ID']
```

In [18]:

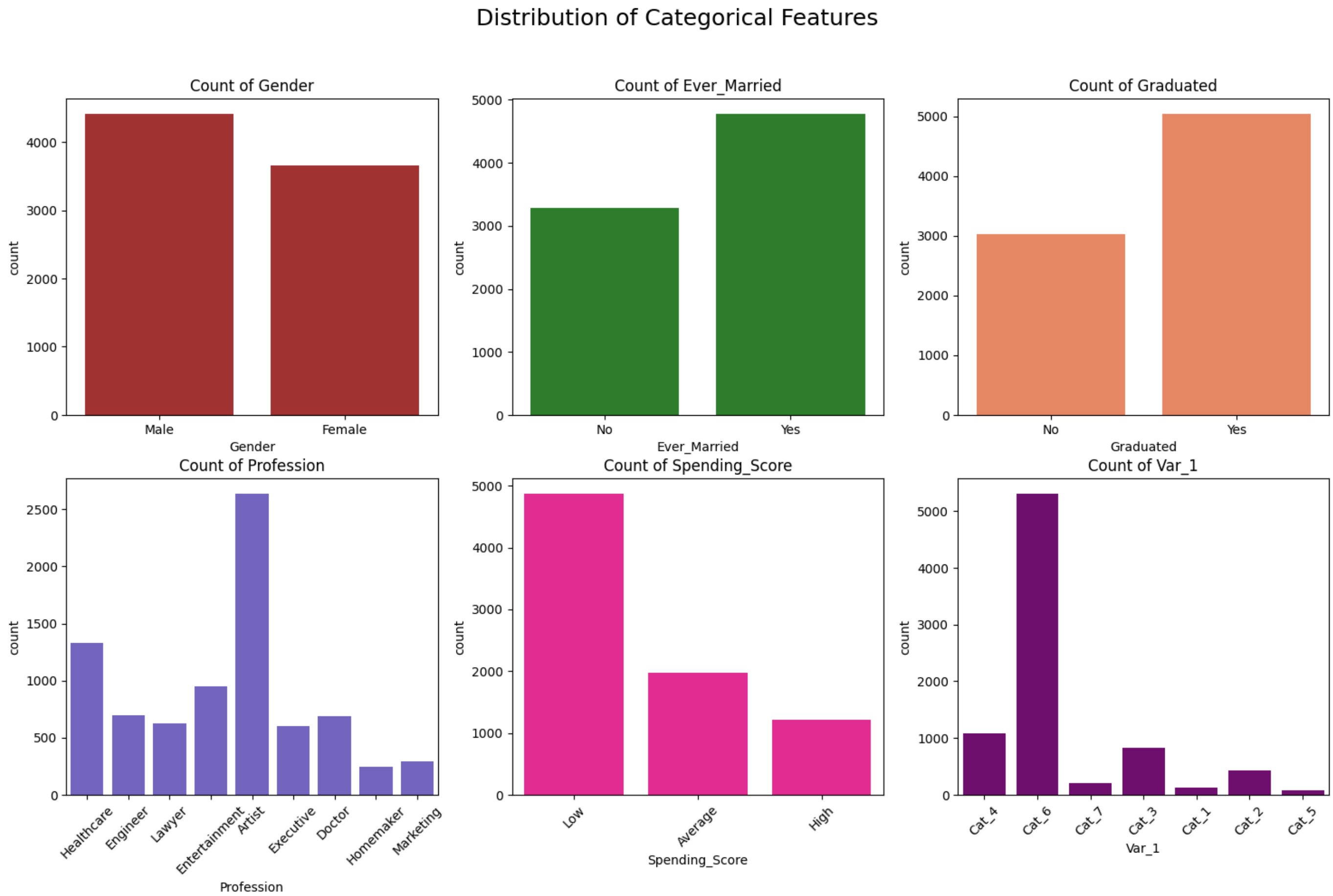
```python
# 3. Correlation Heatmap
plt.figure(figsize=(11, 8))
correlation_matrix = train_df_clean[numerical_features].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='YlOrBr', fmt='.2f')
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



In [19]:

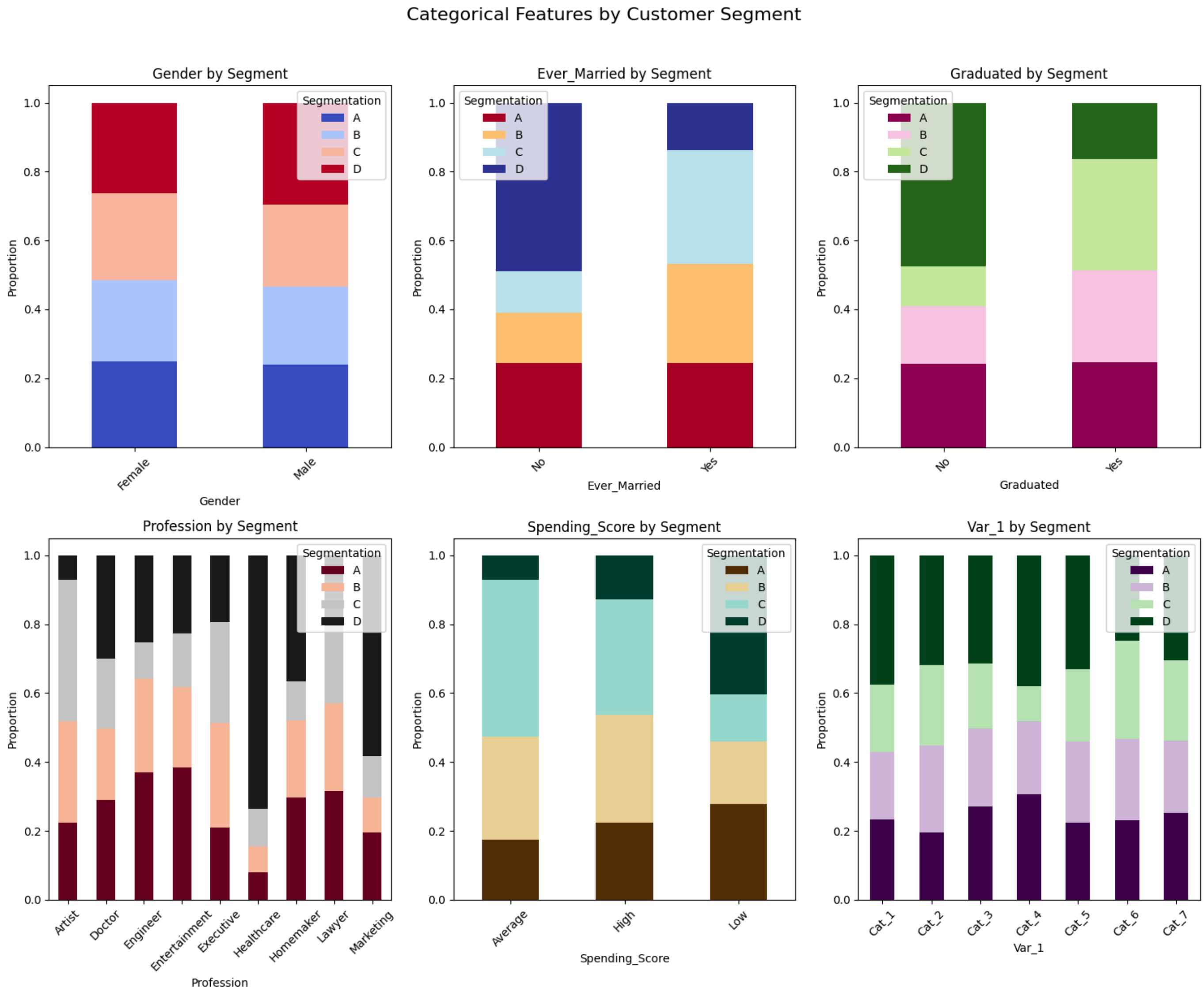
```python
# Bar plots for categorical variables
plt.figure(figsize=(18 , 10))

# Gender
plt.subplot(2, 3, 1)
sns.countplot(x='Gender', data=train_df_clean, color='firebrick')
plt.title('Count of Gender')


# Ever_Married
plt.subplot(2, 3, 2)
sns.countplot(x='Ever_Married', data=train_df_clean, color='forestgreen')
plt.title('Count of Ever_Married')


# Graduated
plt.subplot(2, 3, 3)
sns.countplot(x='Graduated', data=train_df_clean, color='coral')
plt.title('Count of Graduated')
```

```
# Profession
plt.subplot(2, 3, 4)
sns.countplot(x='Profession', data=train_df_clean, color='slateblue')
plt.title('Count of Profession')
plt.xticks(rotation=45)

# Spending_Score
plt.subplot(2, 3, 5)
sns.countplot(x='Spending_Score', data=train_df_clean, color='deeppink')
plt.title('Count of Spending_Score')
plt.xticks(rotation=45)

# Var_1
plt.subplot(2, 3, 6)
sns.countplot(x='Var_1', data=train_df_clean, color='purple')
plt.title('Count of Var_1')
plt.xticks(rotation=45)


plt.suptitle('Distribution of Categorical Features',  fontsize=18)
plt.show()
```



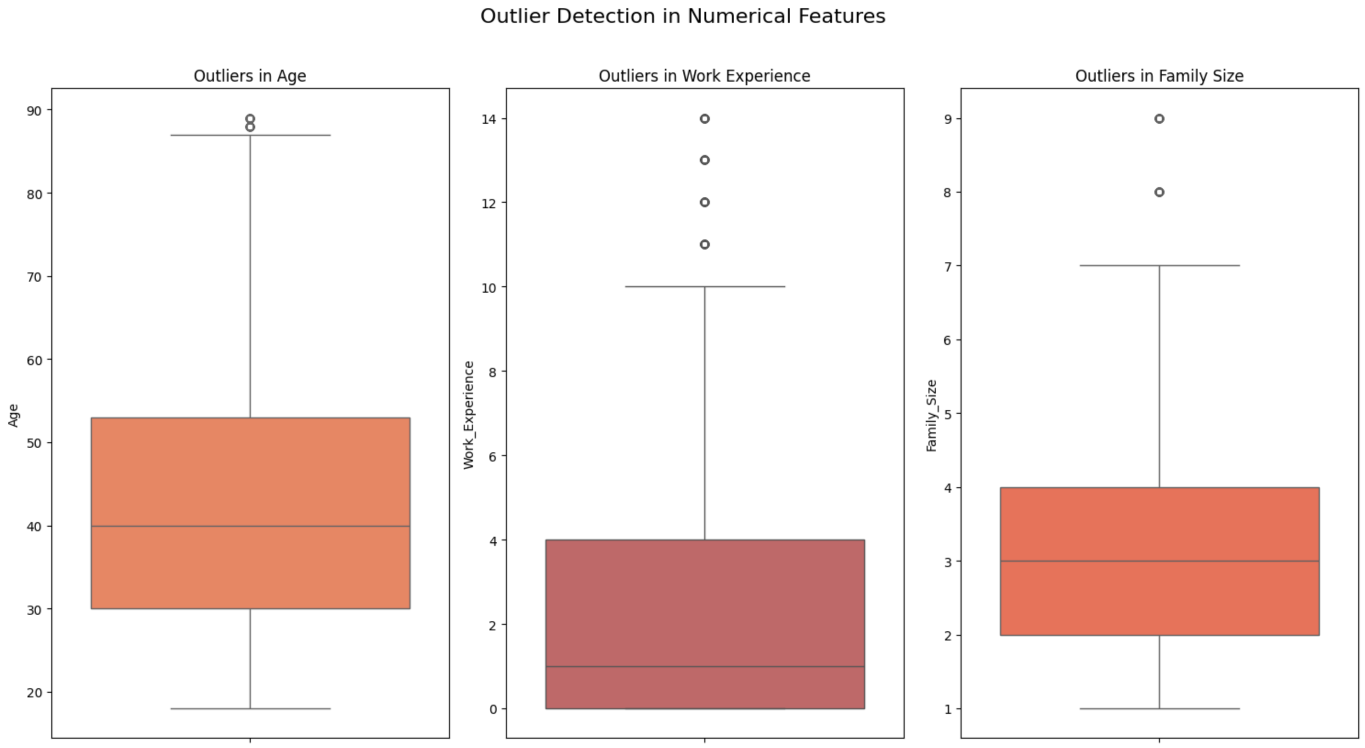
In [20]:
```
# 5. Stacked bar plots for categorical variables by segment
fig = plt.figure(figsize=(15, 12))
plt.clf()  # Clear the current figure

# Gender
ax1 = plt.subplot(2, 3, 1)
pd.crosstab(train_df_clean['Gender'], train_df_clean['Segmentation'], normalize='index').plot
    kind='bar', stacked=True, colormap='coolwarm', ax=ax1)
plt.title('Gender by Segment')
plt.xticks(rotation=45)
plt.ylabel('Proportion')
```

```
# Ever_Married
ax2 = plt.subplot(2, 3, 2)
pd.crosstab(train_df_clean['Ever_Married'], train_df_clean['Segmentation'], normalize='index'
    kind='bar', stacked=True, colormap='RdYlBu', ax=ax2)
plt.title('Ever_Married by Segment')
plt.xticks(rotation=45)
plt.ylabel('Proportion')

# Graduated
ax3 = plt.subplot(2, 3, 3)
pd.crosstab(train_df_clean['Graduated'], train_df_clean['Segmentation'], normalize='index').p
    kind='bar', stacked=True, colormap='PiYG', ax=ax3)
plt.title('Graduated by Segment')
plt.xticks(rotation=45)
plt.ylabel('Proportion')

# Profession
ax4 = plt.subplot(2, 3, 4)
pd.crosstab(train_df_clean['Profession'], train_df_clean['Segmentation'], normalize='index').
    kind='bar', stacked=True, colormap='RdGy', ax=ax4)
plt.title('Profession by Segment')
plt.xticks(rotation=45)
plt.ylabel('Proportion')

# Spending_Score
ax5 = plt.subplot(2, 3, 5)
pd.crosstab(train_df_clean['Spending_Score'], train_df_clean['Segmentation'], normalize='inde
    kind='bar', stacked=True, colormap='BrBG', ax=ax5)
plt.title('Spending_Score by Segment')
plt.xticks(rotation=45)
plt.ylabel('Proportion')

# Var_1
ax6 = plt.subplot(2, 3, 6)
pd.crosstab(train_df_clean['Var_1'], train_df_clean['Segmentation'], normalize='index').plot(
    kind='bar', stacked=True, colormap='PRGn', ax=ax6)
plt.title('Var_1 by Segment')
plt.xticks(rotation=45)
plt.ylabel('Proportion')

plt.suptitle('Categorical Features by Customer Segment', y=1.02, fontsize=16)
plt.tight_layout()
plt.show()
```

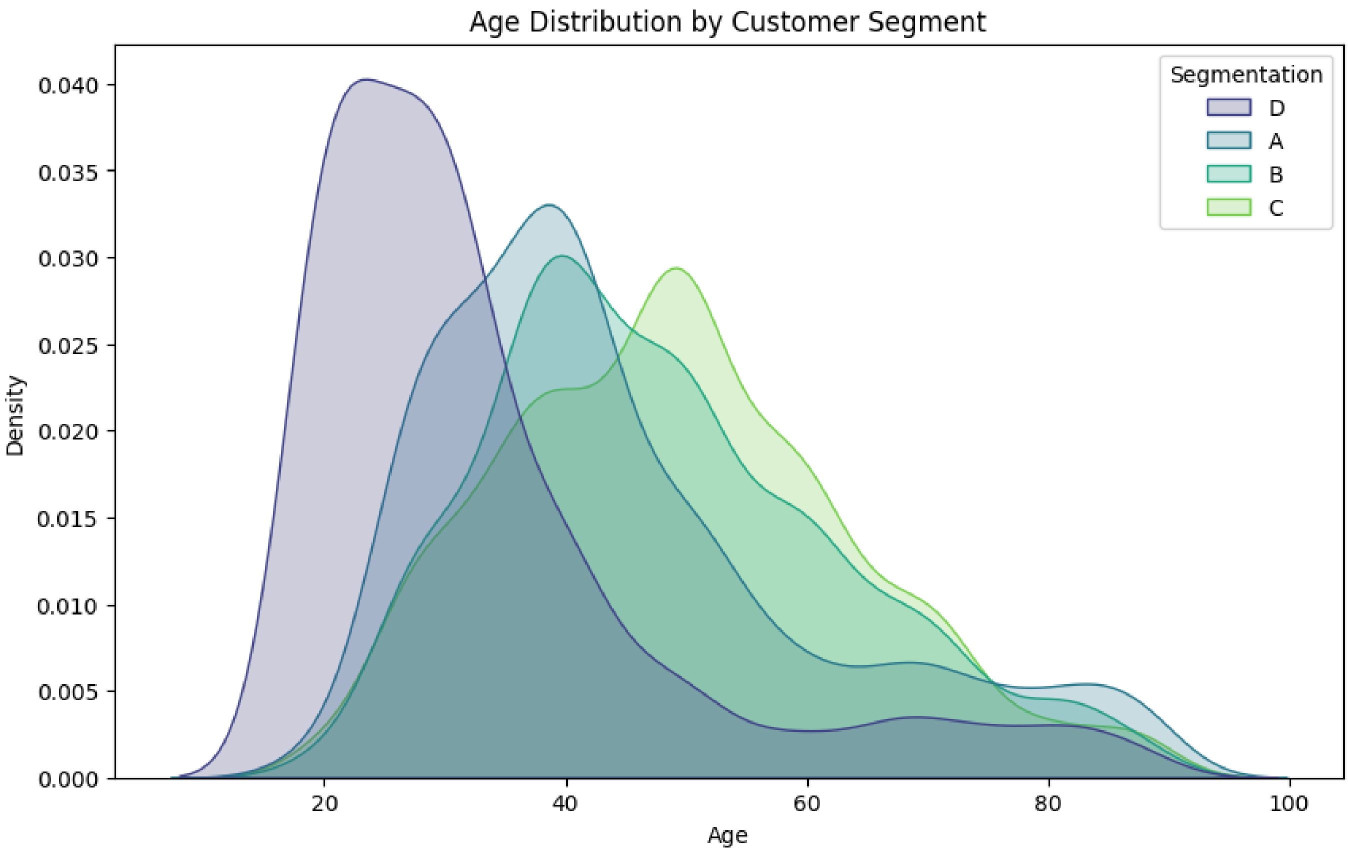


In [21]:

```
# 6. Outlier detection using box plots
plt.figure(figsize=(15, 8))

# Age boxplot
plt.subplot(1, 3, 1)
sns.boxplot(y='Age', data=train_df_clean, color='coral')
plt.title('Outliers in Age')

# Work Experience boxplot
plt.subplot(1, 3, 2)
sns.boxplot(y='Work_Experience', data=train_df_clean, color='indianred')
plt.title('Outliers in Work Experience')

# Family Size boxplot
plt.subplot(1, 3, 3)
sns.boxplot(y='Family_Size', data=train_df_clean, color='tomato')
plt.title('Outliers in Family Size')

plt.suptitle('Outlier Detection in Numerical Features', y=1.02, fontsize=16)
plt.tight_layout()
plt.show()
```



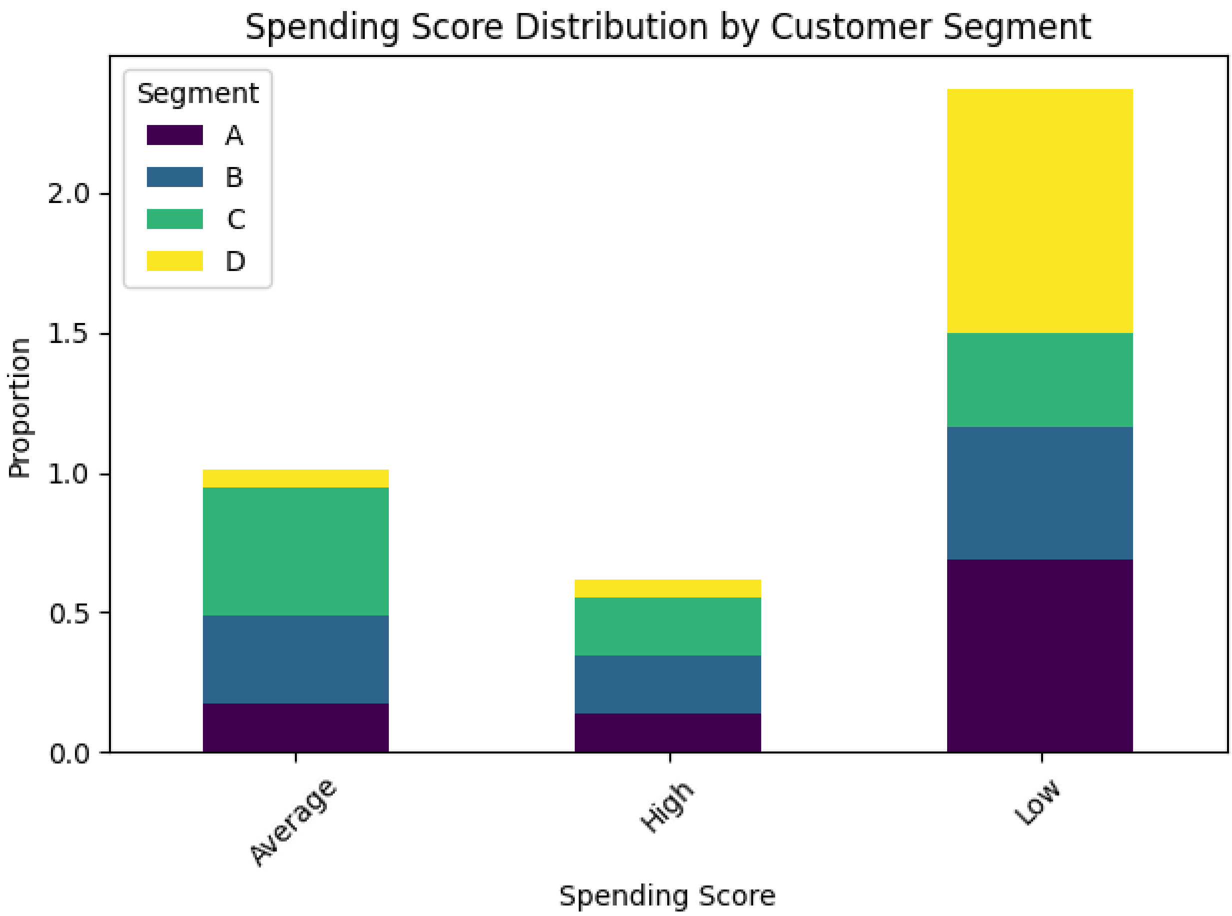
In [22]:
```
# 7. Additional analysis: Age distribution by segment
plt.figure(figsize=(10, 6))
sns.kdeplot(data=train_df_clean, x='Age', hue='Segmentation', fill=True, common_norm=False, p
plt.title('Age Distribution by Customer Segment')
plt.xlabel('Age')
plt.ylabel('Density')
plt.show()
```



In [23]:
```
# 8. Additional analysis: Spending score distribution by segment
plt.figure(figsize=(10, 6))
spending_seg = pd.crosstab(train_df_clean['Spending_Score'], train_df_clean['Segmentation'],
spending_seg.plot(kind='bar', stacked=True, colormap='viridis')
plt.title('Spending Score Distribution by Customer Segment')
plt.xlabel('Spending Score')
```

```
plt.ylabel('Proportion')
plt.legend(title='Segment')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

<Figure size 1000x600 with 0 Axes>



..

4. Model Building:

- Convert categorical variables into numerical representations.
- Perform train-test split (e.g., 80-20 split).
- Train at least four classification models:
    1. Logistic Regression
    2. Random Forest Classifier
    3. Support Vector Machine (SVM)
    4. Xgboost

..

In [145…

```
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, recall_score, precisi
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import numpy
```

```
classifier = {
    'Logistic Regression': LogisticRegression(),
    'Random Forest': RandomForestClassifier(),
    'SVM': SVC(),
    'XGBoost': XGBClassifier()
}
```

In [133…

```
A = train_df_clean.drop(['ID', 'Segmentation'], axis=1)
B = train_df_clean['Segmentation']


C = test_df_clean.drop(['ID', 'Segmentation'], axis=1)
D = test_df_clean['Segmentation']
```

In [ ]:

```
numerical_features = ['Age', 'Work_Experience', 'Family_Size']
categorical_features = ['Gender', 'Ever_Married', 'Graduated', 'Profession', 'Spending_Score'


numeric_transformer = StandardScaler()
categorical_transformer = LabelEncoder()


def transform_data(df):
    df_transformed = df.copy()

    df_transformed[numerical_features] = numeric_transformer.fit_transform(df_transformed[num

    for feature in categorical_features:
        df_transformed[feature] = categorical_transformer.fit_transform(df_transformed[featur

    return df_transformed


A_train_processed = transform_data(A)
#B_train_processed = LabelEncoder().fit_transform(B)

C_test_processed = transform_data(C)
#D_test_processed = LabelEncoder().fit_transform(D)
```

In [122…

```
X = pd.concat([A_train_processed, C_test_processed], ignore_index=True)
```

In [135…

```
Y = pd.concat([B,D], ignore_index=True)
Y = LabelEncoder().fit_transform(Y)
```

..

5. Model Evaluation:

- Compare models using performance metrics such as:
    - o Accuracy
    - o Precision, Recall, and F1-Score
    - o Confusion Matrix

..

In [153…

```
model_scores = {}
for name, clf in classifier.items():
    print("\n" + "="*30)
    print(f"Classifier: {name}")
```

```python
    print("="*30)
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    model_scores[name] = {
        "accuracy": accuracy,
        "precision": precision,
        "recall": recall,
        "f1_score": f1
    }

    print(f"\n🔷 Accuracy: {accuracy:.4f}")
    print("\n📊 Performance Metrics:")
    print("-" * 60)
    print(f"{'Average Type':<15} {'Precision':<20} {'Recall':<20} {'F1 Score':<20}")
    print("-" * 60)

    for avg in ['macro', 'micro', 'weighted']:
        p = precision_score(y_test, y_pred, average=avg)
        r = recall_score(y_test, y_pred, average=avg)
        f = f1_score(y_test, y_pred, average=avg)
        print(f"{str(avg):<15} {p:.4f}            {r:.4f}            {f:.4f}")

    print("-" * 60)
    print("\n📌 Confusion Matrix:")
    print(confusion_matrix(y_test, y_pred))
    print("\n" + "="*30 + "\n")
```

```
==============================
Classifier: Logistic Regression
==============================

🔷 Accuracy: 0.4549

📊 Performance Metrics:
------------------------------------------------------------
Average Type    Precision            Recall               F1 Score
------------------------------------------------------------
macro           0.4246            0.4450            0.4066
micro           0.4549            0.4549            0.4549
weighted        0.4293            0.4549            0.4160
------------------------------------------------------------

📌 Confusion Matrix:
[[256  24 136 168]
 [185  30 189  86]
 [ 96  25 282  69]
 [123  13  52 405]]

==============================


==============================
Classifier: Random Forest
==============================

🔷 Accuracy: 0.4474

📊 Performance Metrics:
------------------------------------------------------------
Average Type    Precision            Recall               F1 Score
------------------------------------------------------------
macro           0.4373            0.4409            0.4382
micro           0.4474            0.4474            0.4474
weighted        0.4409            0.4474            0.4432
------------------------------------------------------------

📌 Confusion Matrix:
[[236 107  93 148]
 [136 145 118  91]
 [ 84 112 213  63]
 [130  58  42 363]]

==============================


==============================
Classifier: SVM
==============================

🔷 Accuracy: 0.4815

📊 Performance Metrics:
------------------------------------------------------------
Average Type    Precision            Recall               F1 Score
------------------------------------------------------------
macro           0.4828            0.4728            0.4706
micro           0.4815            0.4815            0.4815
weighted        0.4847            0.4815            0.4761
------------------------------------------------------------
```

```
📌 Confusion Matrix:
[[306  69  91 118]
 [182 132 109  67]
 [118  69 230  55]
 [165  31  35 362]]

==============================



==============================
Classifier: XGBoost
==============================

🔷 Accuracy: 0.4750

📊 Performance Metrics:
------------------------------------------------------------
Average Type    Precision            Recall               F1 Score
------------------------------------------------------------
macro           0.4655           0.4701           0.4663
micro           0.4750           0.4750           0.4750
weighted        0.4678           0.4750           0.4699
------------------------------------------------------------

📌 Confusion Matrix:
[[242 107  92 143]
 [124 154 125  87]
 [ 67  95 246  64]
 [143  44  32 374]]

==============================
```

In [156…

```python
best_model = max(model_scores, key=lambda x: model_scores[x]["precision"])

print("\n" + "="*40)
print(f"🏆 Best Model: {best_model}")
print(f"🔷 Accuracy: {model_scores[best_model]['accuracy']:.4f}")
print(f"🔷 Precision: {model_scores[best_model]['precision']:.4f}")
print(f"🔷 Recall: {model_scores[best_model]['recall']:.4f}")
print(f"🔷 F1 Score: {model_scores[best_model]['f1_score']:.4f}")
print("="*40)
```

```
========================================
🏆 Best Model: SVM
🔷 Accuracy: 0.4815
🔷 Precision: 0.4847
🔷 Recall: 0.4815
🔷 F1 Score: 0.4761
========================================
```

..

6. Model Saving:

- Save the best-performing model.

..

In [171…

```python
import joblib
```

```
joblib.dump(classifier[best_model], 'best_model.pkl')
```

Out[171…

```
['best_model.pkl']
```

..

7. Prediction:

- Load the saved model and make predictions on the new dataset.
- Display the predicted segments for new customers.

..

In [179…

```
import joblib
import pandas as pd
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer

model = joblib.load('best_model.pkl')

new_data_path = 'Test.csv'
df_new = pd.read_csv(new_data_path)
```

In [180…

```
if 'ID' in df_new.columns:
    df_ids = df_new[['ID']]
    df_new = df_new.drop(columns=['ID'])
else:
    df_ids = None

unused_columns = ['Segmentation']
df_new = df_new.drop(columns=[col for col in unused_columns if col in df_new.columns])
```

In [181…

```
numerical_features = ['Age', 'Work_Experience', 'Family_Size']
categorical_features = ['Gender', 'Ever_Married', 'Graduated', 'Profession', 'Spending_Score'

imputer_num = SimpleImputer(strategy='mean')
imputer_cat = SimpleImputer(strategy='most_frequent')
scaler = StandardScaler()
label_encoders = {feature: LabelEncoder() for feature in categorical_features}

def transform_data(df):
    df_transformed = df.copy()

    df_transformed[numerical_features] = imputer_num.fit_transform(df_transformed[numerical_f
    df_transformed[categorical_features] = imputer_cat.fit_transform(df_transformed[categoric

    df_transformed[numerical_features] = scaler.fit_transform(df_transformed[numerical_featur
    for feature in categorical_features:
        df_transformed[feature] = label_encoders[feature].fit_transform(df_transformed[featur

    return df_transformed

df_processed = transform_data(df_new)

if df_processed.isnull().values.any():
    print("Warning: NaN values still present after transformation!")
```

In [183…

```
predictions = model.predict(df_processed)

prediction_mapping = {0: 'A', 1: 'B', 2: 'C', 3: 'D'}
```

```python
predictions_mapped = [prediction_mapping[pred] for pred in predictions]

output_df = pd.DataFrame({'Prediction': predictions_mapped})
if df_ids is not None:
    output_df = pd.concat([df_ids, output_df], axis=1)
output_df.to_csv('Predictions.csv', index=False)

print("Predictions:")
print(output_df)
print("Predictions saved to Predictions.csv")
```

```
Predictions:
          ID Prediction
0     458989          A
1     458994          C
2     458996          B
3     459000          C
4     459001          D
...      ...        ...
2622  467954          D
2623  467958          A
2624  467960          A
2625  467961          B
2626  467968          D

[2627 rows x 2 columns]
Predictions saved to Predictions.csv
```