

Marriage Proposal Acceptance or Rejection Prediction using Machine Learning



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

```
In [2]: import warnings
warnings.filterwarnings('ignore')
```

```
In [3]: df = pd.read_csv("marriage_proposal.csv")
```

```
In [4]: df
```

```
Out[4]:
```

| | Height | Age | Income | RomanticGestureScore | CompatibilityScore | CommunicationScore | DistanceKM | Response | AgeCategory |
|------|--------|-----|--------|----------------------|--------------------|--------------------|------------|----------|-------------|
| 0 | 156 | 59 | 7977 | 3 | 1 | 1 | 45 | 1 | Senior |
| 1 | 169 | 32 | 5842 | 0 | 1 | 5 | 46 | 1 | Middle-aged |
| 2 | 178 | 42 | 17638 | 2 | 5 | 5 | 13 | 0 | Middle-aged |
| 3 | 164 | 78 | 8793 | 0 | 0 | 7 | 52 | 0 | Senior |
| 4 | 160 | 35 | 15262 | 6 | 0 | 0 | 9 | 1 | Middle-aged |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 9995 | 162 | 76 | 12311 | 4 | 1 | 5 | 75 | 1 | Senior |
| 9996 | 162 | 75 | 6459 | 7 | 9 | 0 | 52 | 1 | Senior |
| 9997 | 166 | 70 | 9231 | 9 | 4 | 6 | 33 | 0 | Senior |
| 9998 | 176 | 78 | 12656 | 8 | 9 | 5 | 25 | 1 | Senior |
| 9999 | 156 | 68 | 5812 | 0 | 9 | 4 | 14 | 1 | Senior |

10000 rows × 9 columns

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

```
Out[5]: (10000, 9)
```

```
In [6]: df.columns
```

```
Out[6]: Index(['Height', 'Age', 'Income', 'RomanticGestureScore', 'CompatibilityScore',
              'CommunicationScore', 'DistanceKM', 'Response', 'AgeCategory'],
              dtype='object')
```

```
In [7]: df.duplicated().sum()
```

```
Out[7]: 0
```

```
In [8]: df.isnull().sum()
```

```
Out[8]: Height          0
Age                    0
Income                0
RomanticGestureScore  0
CompatibilityScore    0
CommunicationScore    0
DistanceKM            0
Response              0
AgeCategory          153
dtype: int64
```

```
In [9]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Height                10000 non-null  int64
1   Age                  10000 non-null  int64
2   Income               10000 non-null  int64
3   RomanticGestureScore 10000 non-null  int64
4   CompatibilityScore    10000 non-null  int64
5   CommunicationScore    10000 non-null  int64
6   DistanceKM           10000 non-null  int64
7   Response              10000 non-null  int64
8   AgeCategory           9847 non-null   object
dtypes: int64(8), object(1)
memory usage: 703.2+ KB
```

```
In [10]: df.describe()
```

| | Height | Age | Income | RomanticGestureScore | CompatibilityScore | CommunicationScore | DistanceKM |
|-------|--------------|--------------|--------------|----------------------|--------------------|--------------------|--------------|
| count | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 | 10000.000000 |
| mean | 165.170500 | 49.878300 | 12441.388000 | 4.965000 | 4.589000 | 4.543400 | 49.879600 |
| std | 8.907635 | 17.599059 | 4310.645672 | 3.140376 | 2.859702 | 2.870564 | 28.598155 |
| min | 150.000000 | 20.000000 | 5000.000000 | 0.000000 | 0.000000 | 0.000000 | 1.000000 |
| 25% | 157.000000 | 35.000000 | 8684.750000 | 2.000000 | 2.000000 | 2.000000 | 25.000000 |
| 50% | 165.000000 | 50.000000 | 12432.000000 | 5.000000 | 5.000000 | 5.000000 | 50.000000 |
| 75% | 173.000000 | 65.000000 | 16113.250000 | 8.000000 | 7.000000 | 7.000000 | 75.000000 |
| max | 180.000000 | 80.000000 | 19999.000000 | 10.000000 | 9.000000 | 9.000000 | 99.000000 |

```
In [11]: df.nunique()
```

```
Out[11]: Height          31
Age                    61
Income                7307
RomanticGestureScore  11
CompatibilityScore    10
CommunicationScore    10
DistanceKM            99
Response              2
AgeCategory           3
dtype: int64
```

```
In [12]: object_columns = df.select_dtypes(include=['object']).columns
print("Object type columns:")
print(object_columns)
```

```
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
print("\nNumerical type columns:")
print(numerical_columns)
```

```
Object type columns:
Index(['AgeCategory'], dtype='object')
```

```
Numerical type columns:
Index(['Height', 'Age', 'Income', 'RomanticGestureScore', 'CompatibilityScore',
      'CommunicationScore', 'DistanceKM', 'Response'],
      dtype='object')
```

```
In [13]: def classify_features(df):
    categorical_features = []
    non_categorical_features = []
    discrete_features = []
```

```

continuous_features = []

for column in df.columns:
    if df[column].dtype == 'object':
        if df[column].nunique() < 10:
            categorical_features.append(column)
        else:
            non_categorical_features.append(column)
    elif df[column].dtype in ['int64', 'float64']:
        if df[column].nunique() < 10:
            discrete_features.append(column)
        else:
            continuous_features.append(column)

return categorical_features, non_categorical_features, discrete_features, continuous_features

```

```
In [14]: categorical, non_categorical, discrete, continuous = classify_features(df)
```

```
In [15]: print("Categorical Features:", categorical)
print("Non-Categorical Features:", non_categorical)
print("Discrete Features:", discrete)
print("Continuous Features:", continuous)
```

```

Categorical Features: ['AgeCategory']
Non-Categorical Features: []
Discrete Features: ['Response']
Continuous Features: ['Height', 'Age', 'Income', 'RomanticGestureScore', 'CompatibilityScore', 'CommunicationScore', 'DistanceKM']

```

```
In [16]: null_counts = df.isnull().sum()
null_columns = null_counts[null_counts > 0].index.tolist()
```

```
In [17]: null_counts
```

```

Out[17]: Height                0
Age                0
Income             0
RomanticGestureScore  0
CompatibilityScore  0
CommunicationScore  0
DistanceKM         0
Response           0
AgeCategory       153
dtype: int64

```

```
In [18]: null_columns
```

```
Out[18]: ['AgeCategory']
```

```
In [19]: for column in null_columns:
    null_count = null_counts[column]
    print(f"Column '{column}' has {null_count} null values.")
```

```
Column 'AgeCategory' has 153 null values.
```

```
In [20]: total_rows = len(df)
null_percentage = (null_counts / total_rows) * 100
```

```
In [21]: null_df = pd.DataFrame({
    'Column': null_counts.index,
    'Null Count': null_counts.values,
    'Null Percentage': null_percentage.values
})
```

```
In [22]: null_df = null_df.sort_values(by='Null Count', ascending=False)
```

```
In [23]: null_df
```

| Out[23]: | Column | Null Count | Null Percentage |
|----------|----------------------|------------|-----------------|
| 8 | AgeCategory | 153 | 1.53 |
| 0 | Height | 0 | 0.00 |
| 1 | Age | 0 | 0.00 |
| 2 | Income | 0 | 0.00 |
| 3 | RomanticGestureScore | 0 | 0.00 |
| 4 | CompatibilityScore | 0 | 0.00 |
| 5 | CommunicationScore | 0 | 0.00 |
| 6 | DistanceKM | 0 | 0.00 |
| 7 | Response | 0 | 0.00 |

```
In [24]: df['AgeCategory'] = df['AgeCategory'].fillna('Not Available')
```

```
In [25]: df.isnull().sum()
```

```
Out[25]: Height          0
Age              0
Income          0
RomanticGestureScore  0
CompatibilityScore  0
CommunicationScore  0
DistanceKM       0
Response         0
AgeCategory      0
dtype: int64
```

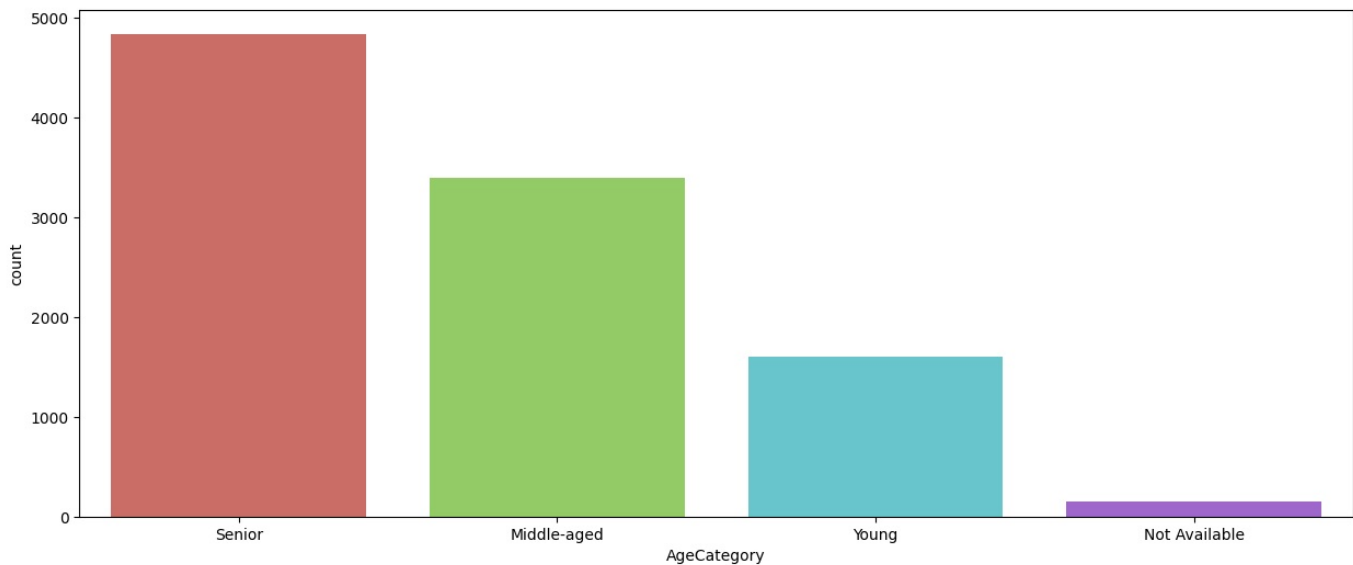
```
In [26]: df['AgeCategory'].unique()
```

```
Out[26]: array(['Senior', 'Middle-aged', 'Young', 'Not Available'], dtype=object)
```

```
In [27]: df['AgeCategory'].value_counts()
```

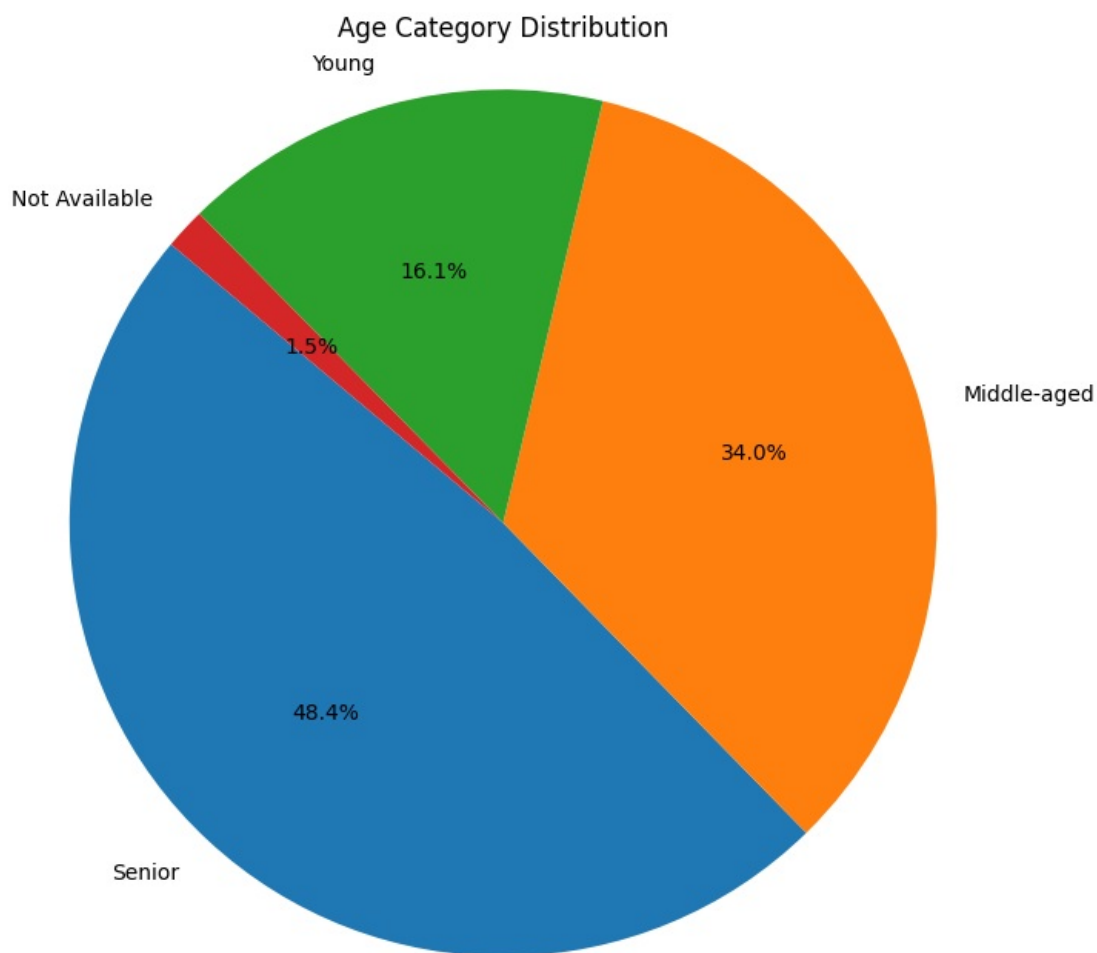
```
Out[27]: AgeCategory
Senior          4843
Middle-aged     3399
Young           1605
Not Available    153
Name: count, dtype: int64
```

```
In [28]: plt.figure(figsize=(15,6))
sns.countplot(x = 'AgeCategory', data = df, palette='hls')
plt.show()
```



```
In [29]: age_counts = df['AgeCategory'].value_counts()

plt.figure(figsize=(8, 8))
plt.pie(age_counts, labels=age_counts.index, autopct='%1.1f%%', startangle=140)
plt.axis('equal')
plt.title('Age Category Distribution')
plt.show()
```



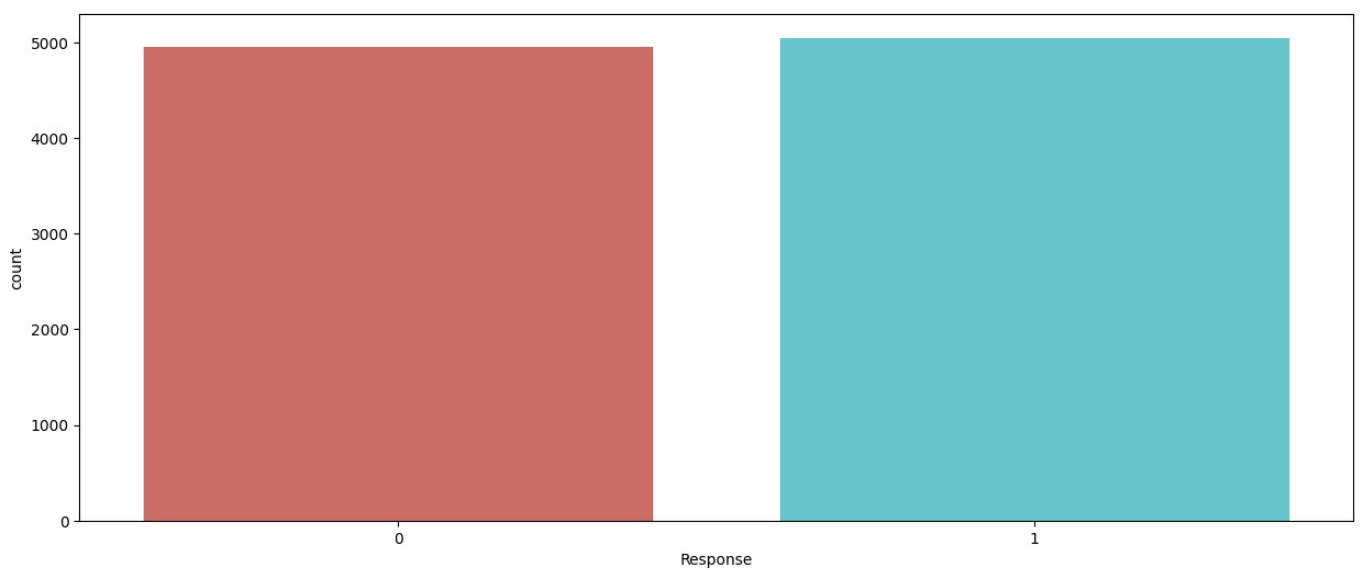
```
In [30]: df['Response'].unique()
```

```
Out[30]: array([1, 0], dtype=int64)
```

```
In [31]: df['Response'].value_counts()
```

```
Out[31]: Response
1      5047
0      4953
Name: count, dtype: int64
```

```
In [32]: plt.figure(figsize=(15,6))
sns.countplot(x = 'Response', data = df, palette='hls')
plt.show()
```

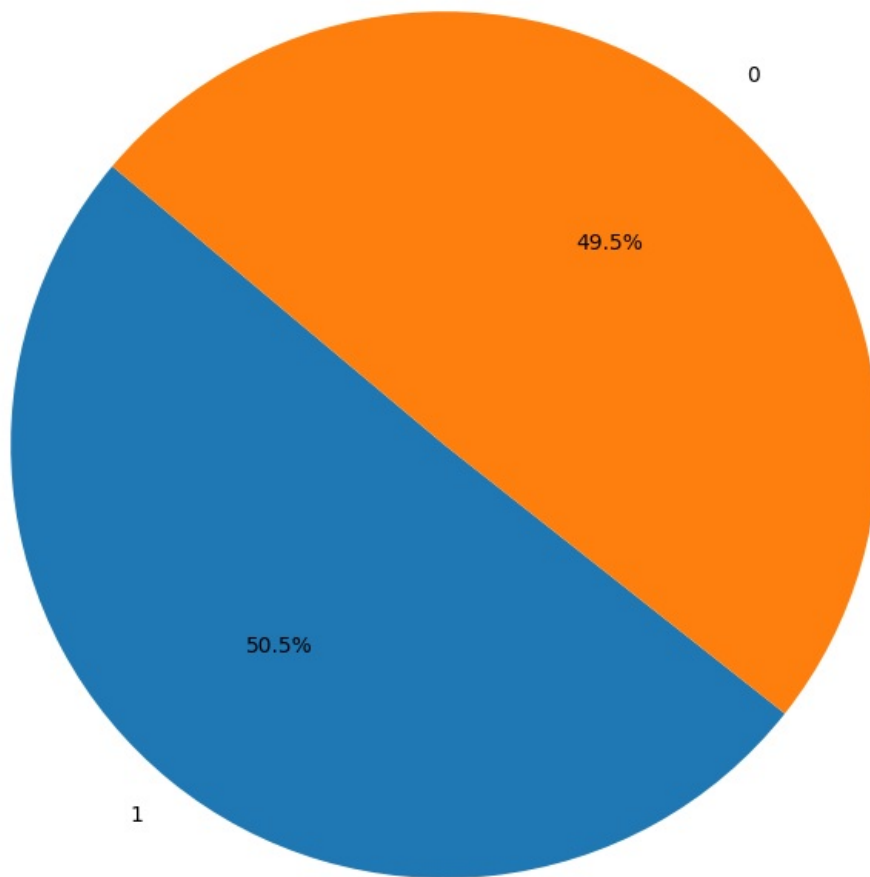


```
In [33]: response_counts = df['Response'].value_counts()

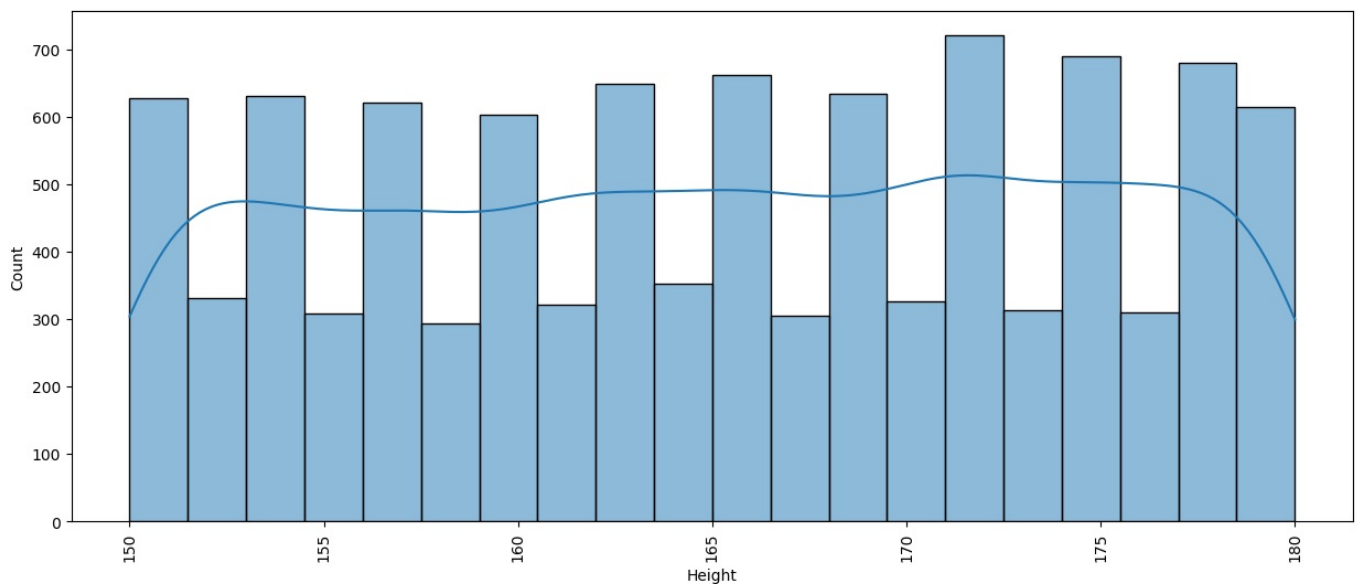
plt.figure(figsize=(8, 8))
plt.pie(response_counts, labels=response_counts.index, autopct='%1.1f%%', startangle=140)
plt.axis('equal')
plt.title('Response Category Distribution')
```

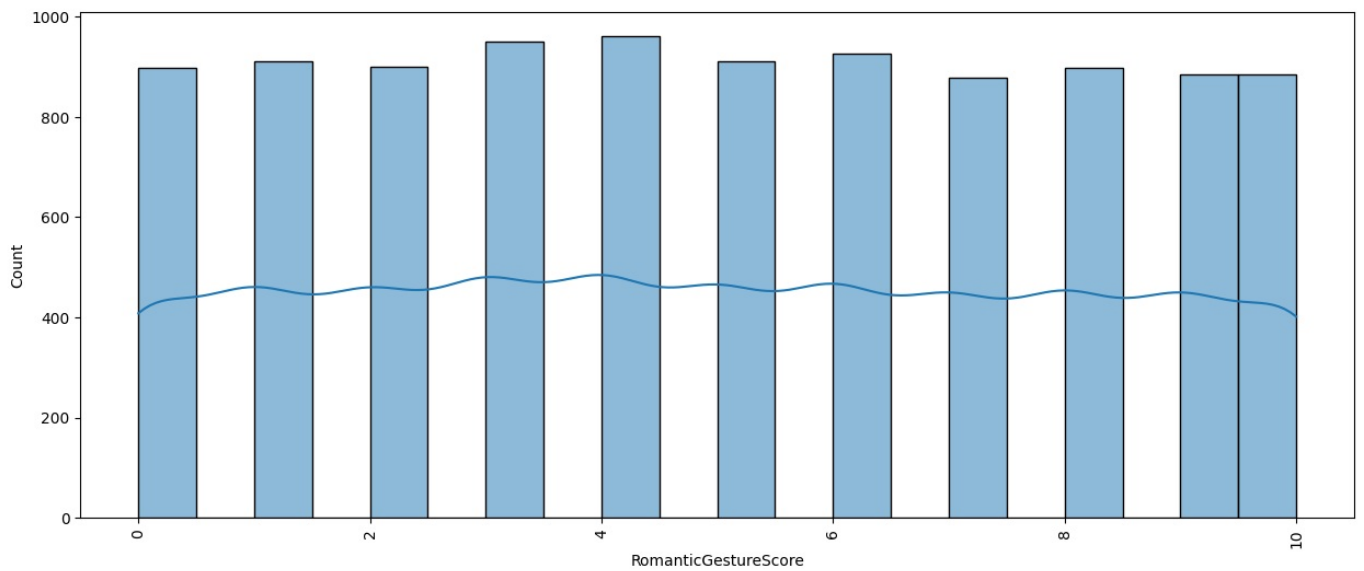
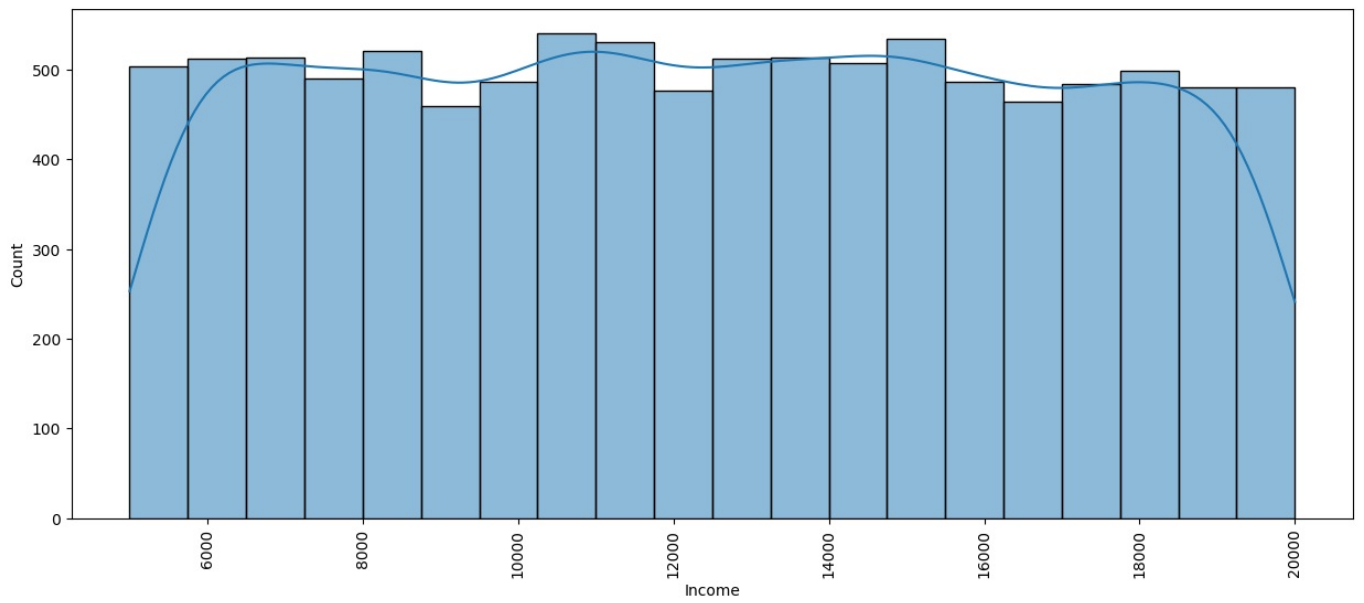
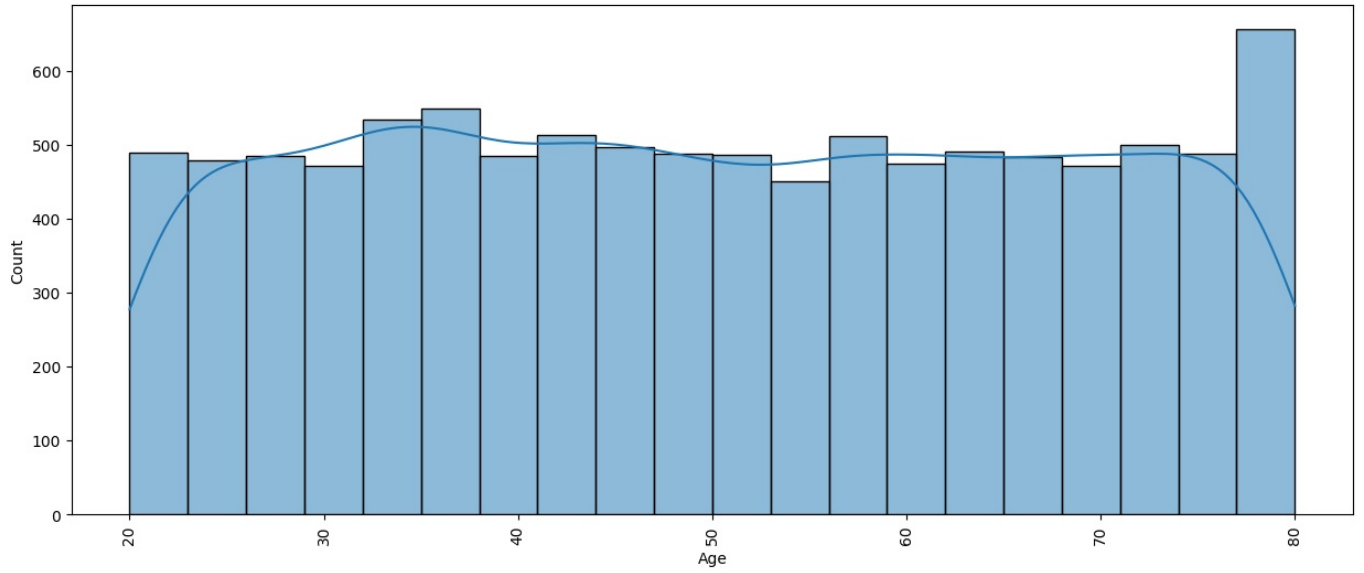
```
plt.show()
```

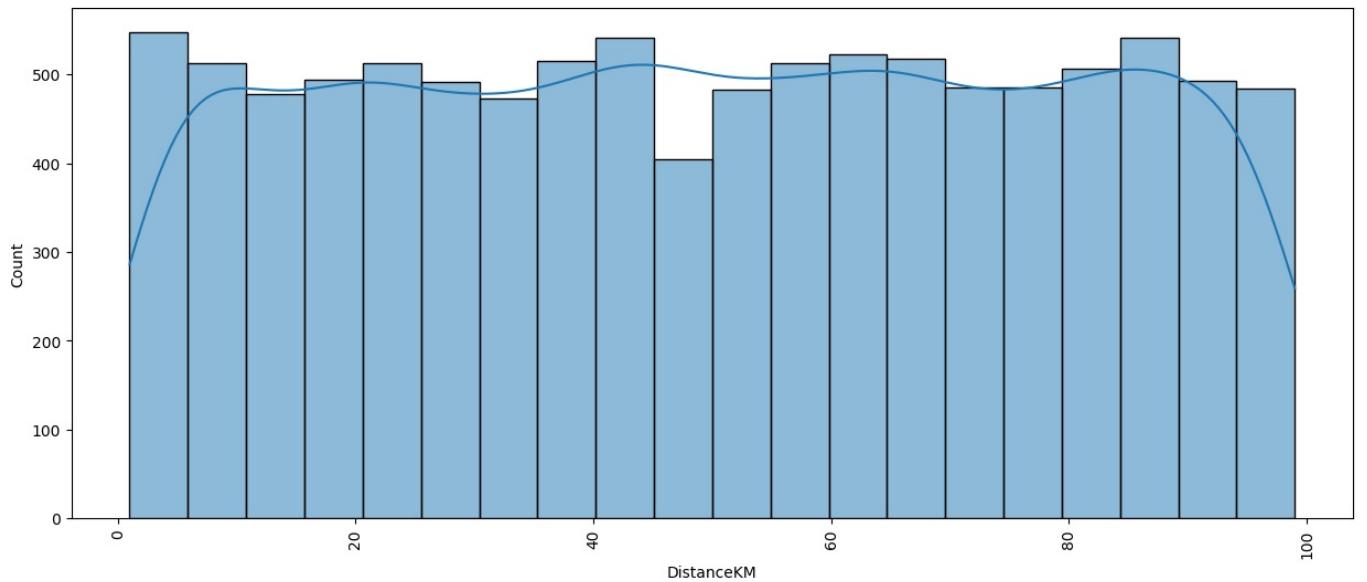
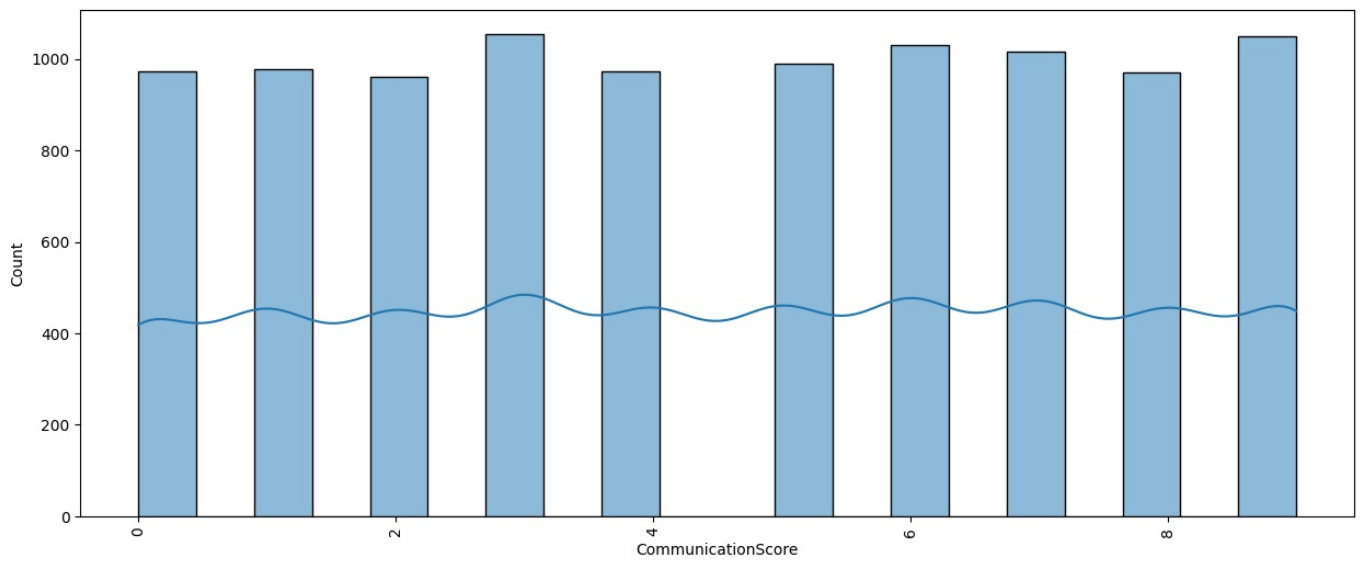
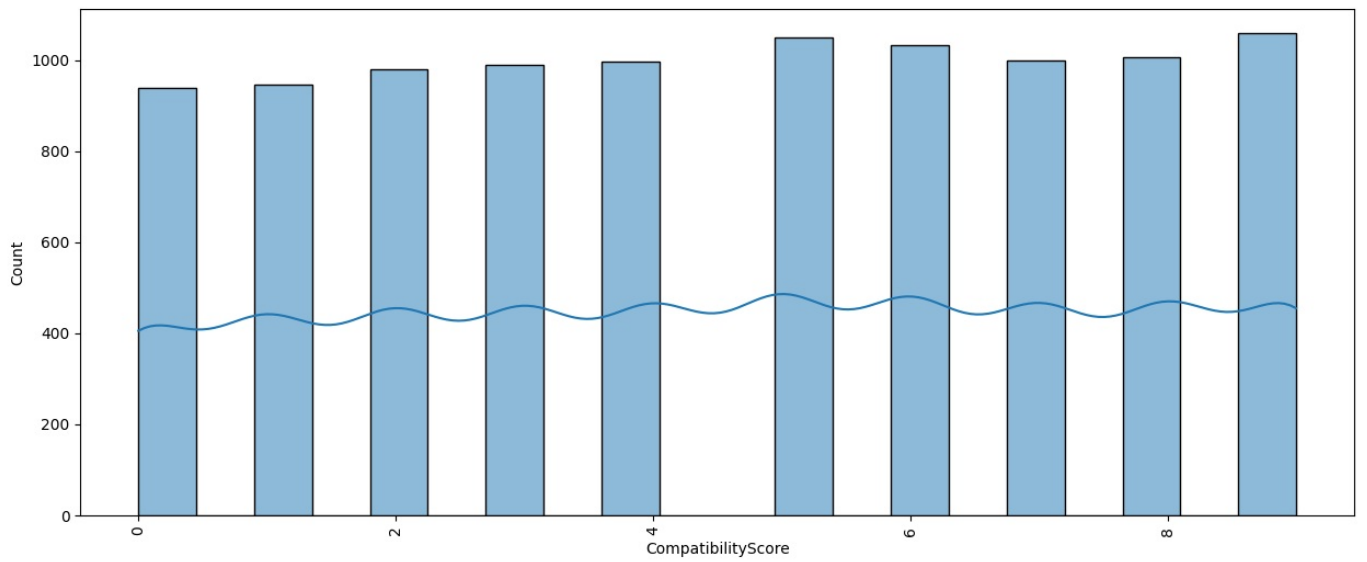
Response Category Distribution



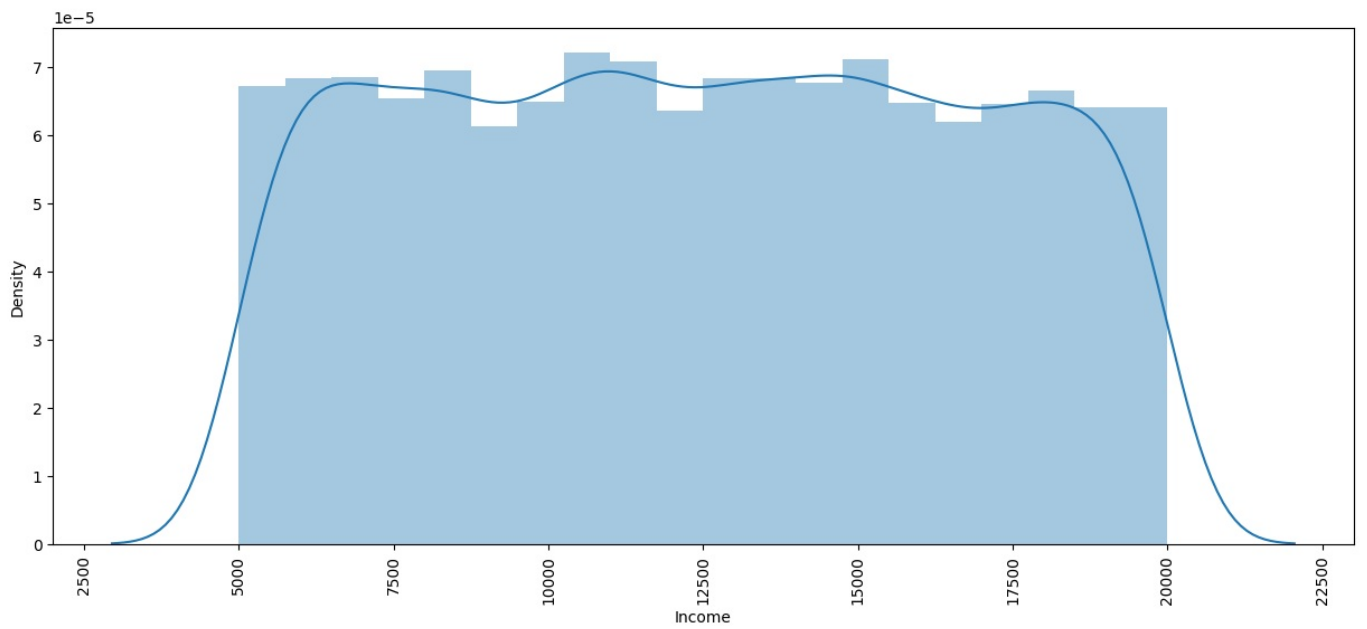
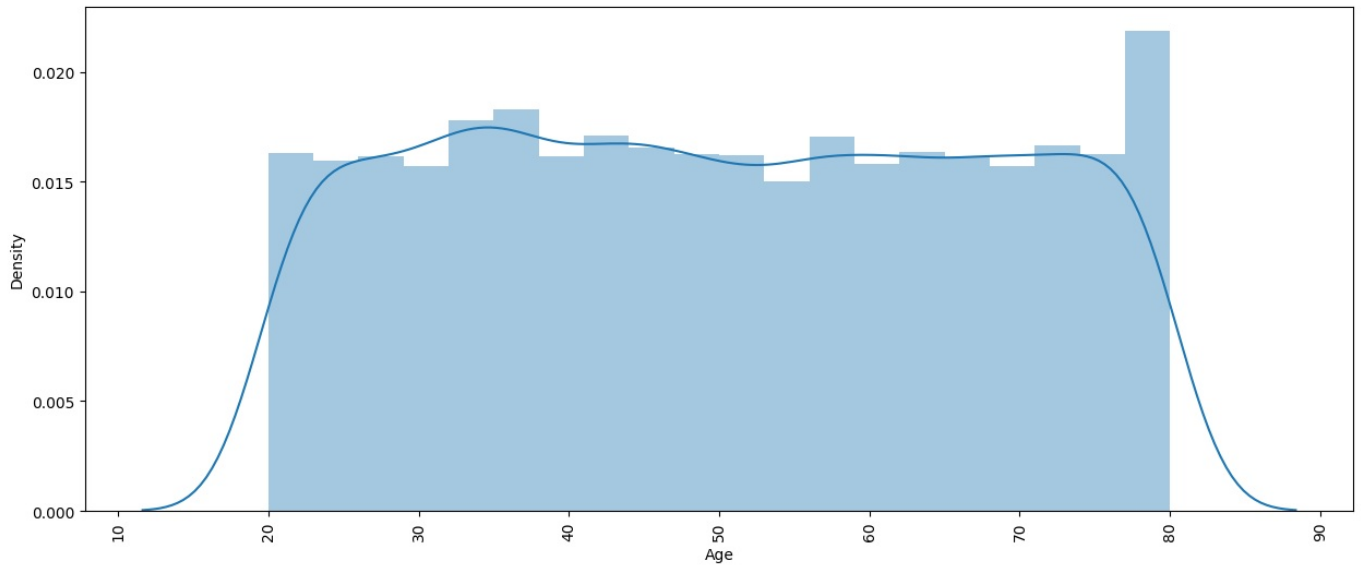
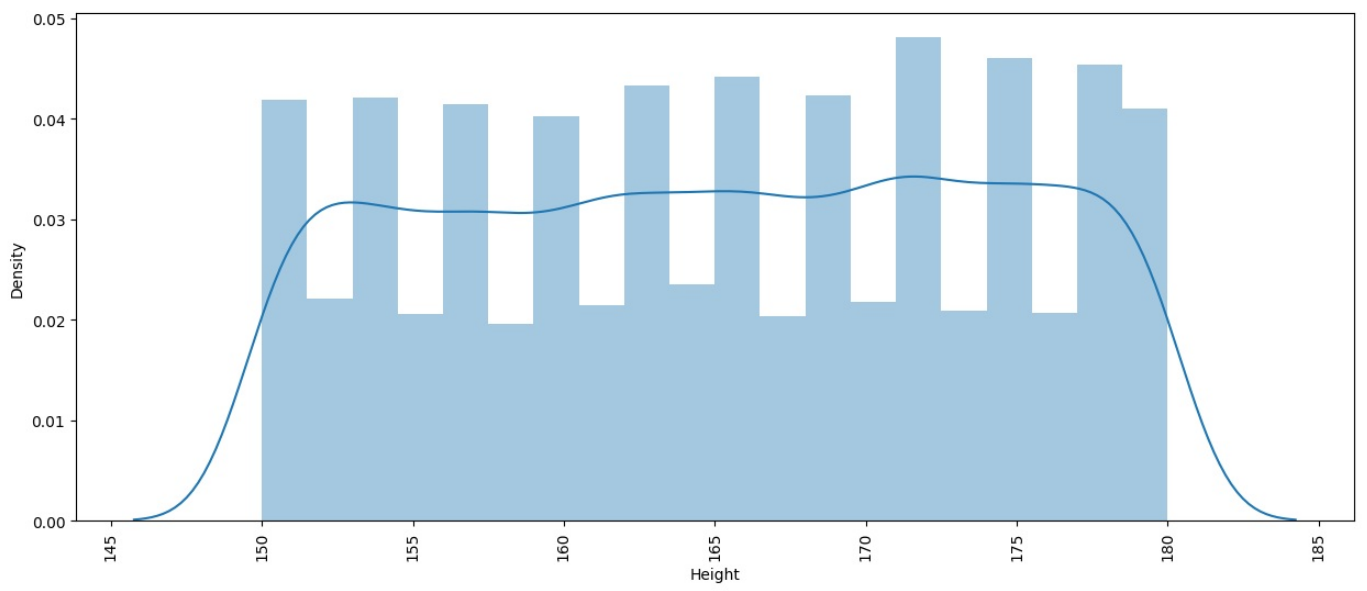
```
In [34]: for i in continuous:
plt.figure(figsize=(15,6))
sns.histplot(df[i], bins = 20, kde = True, palette='hls')
plt.xticks(rotation = 90)
plt.show()
```

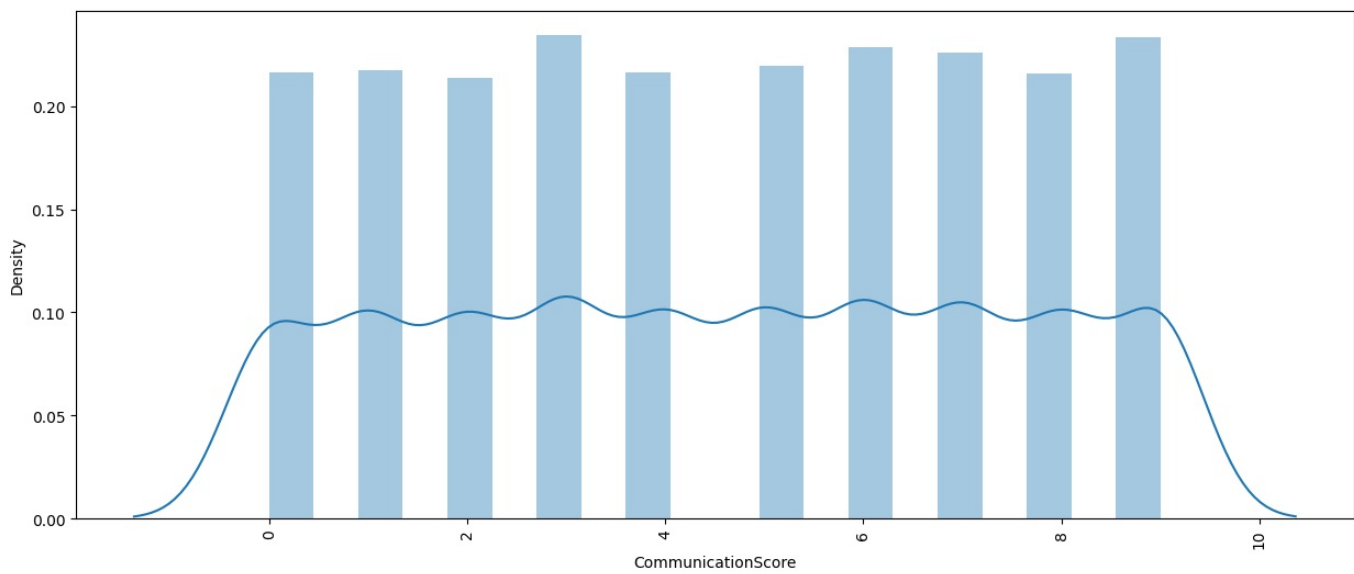
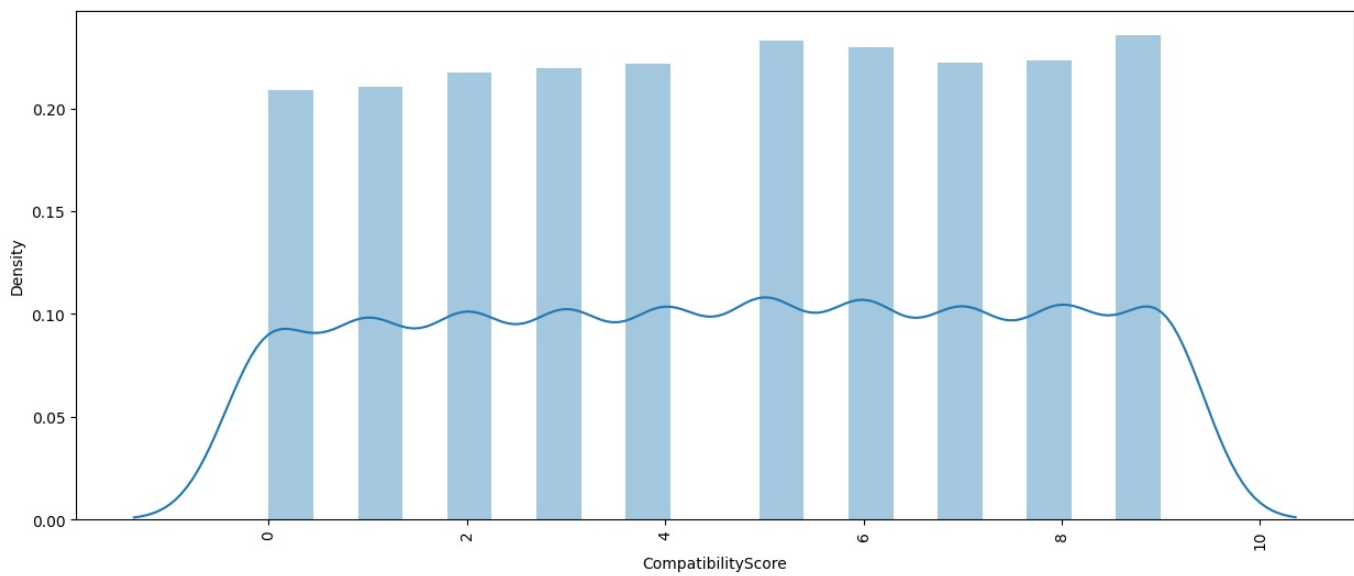
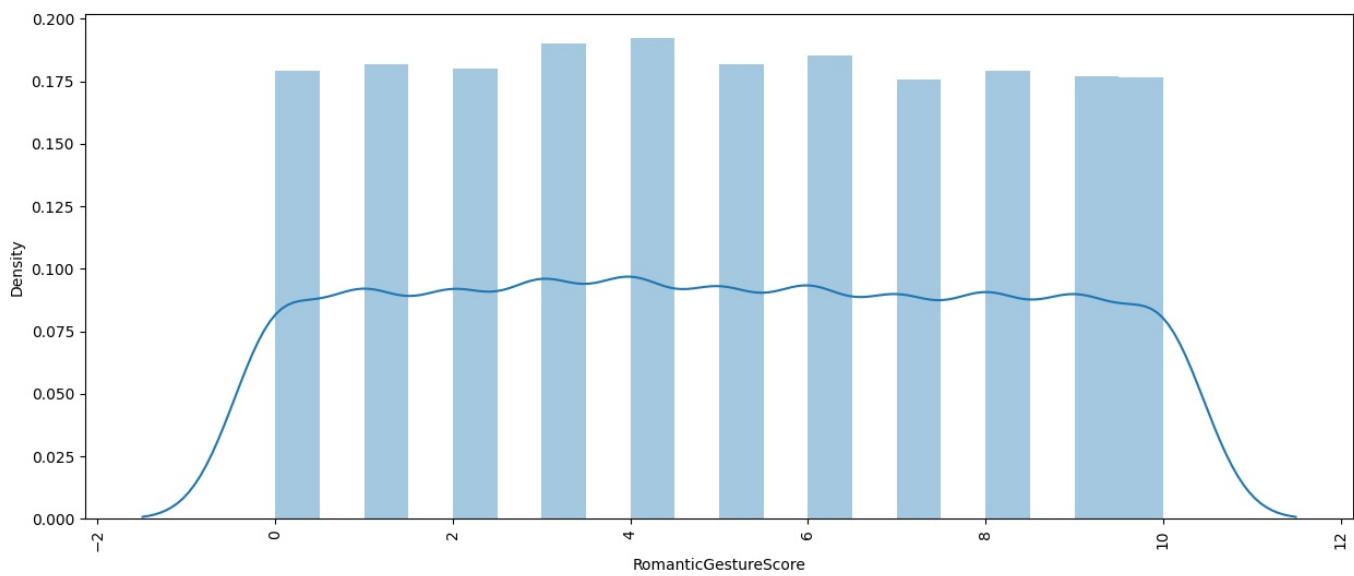


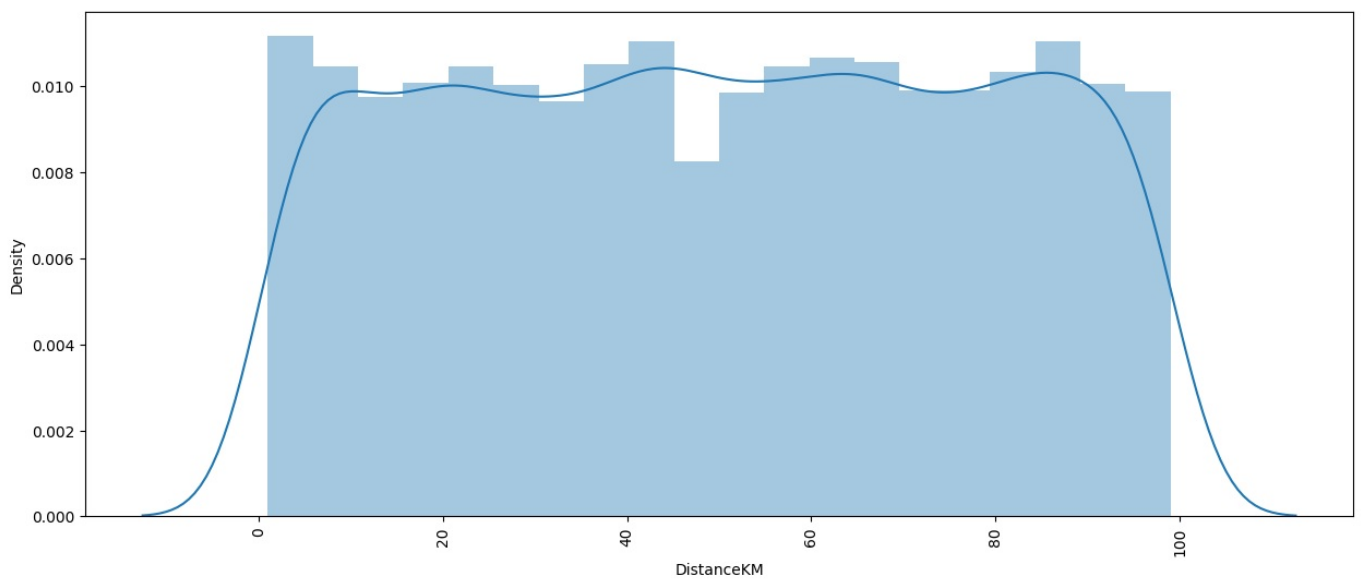




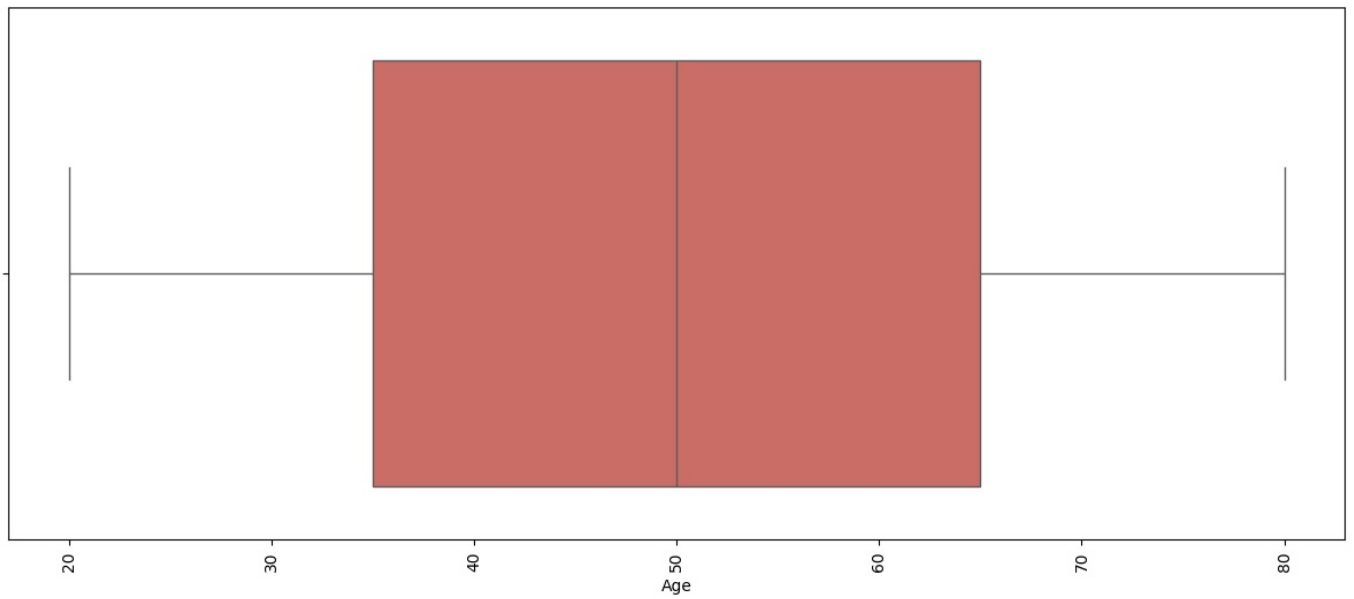
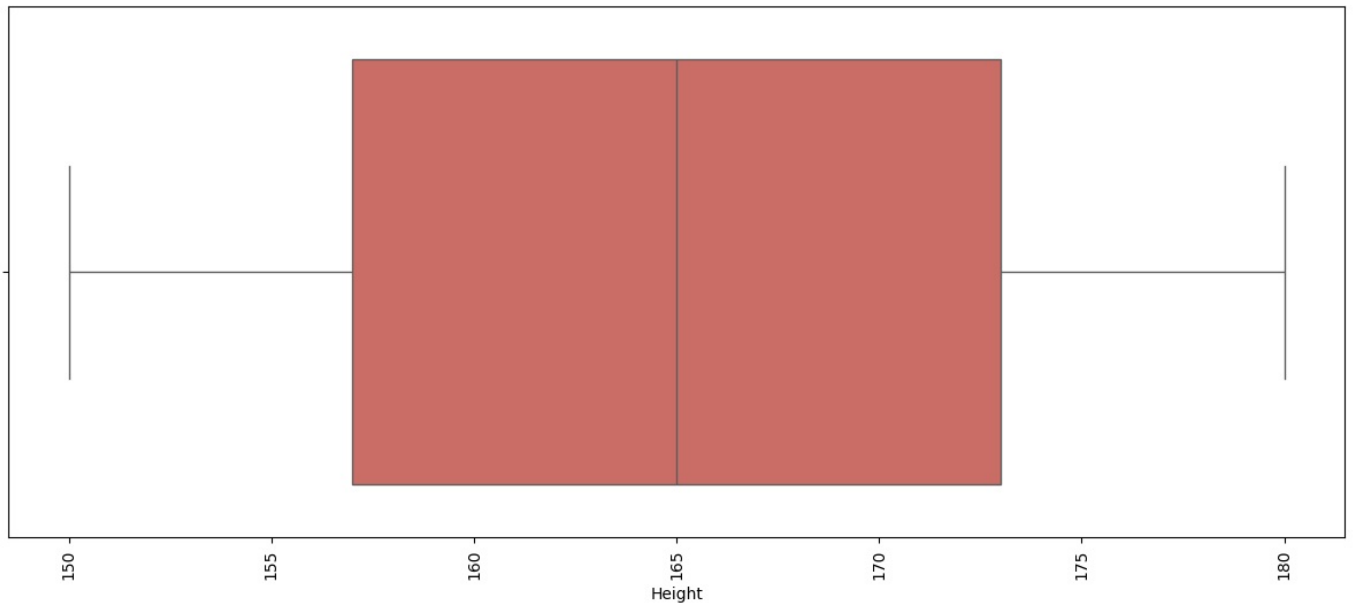
```
In [35]: for i in continuous:
plt.figure(figsize=(15,6))
sns.distplot(df[i], bins = 20, kde = True)
plt.xticks(rotation = 90)
plt.show()
```

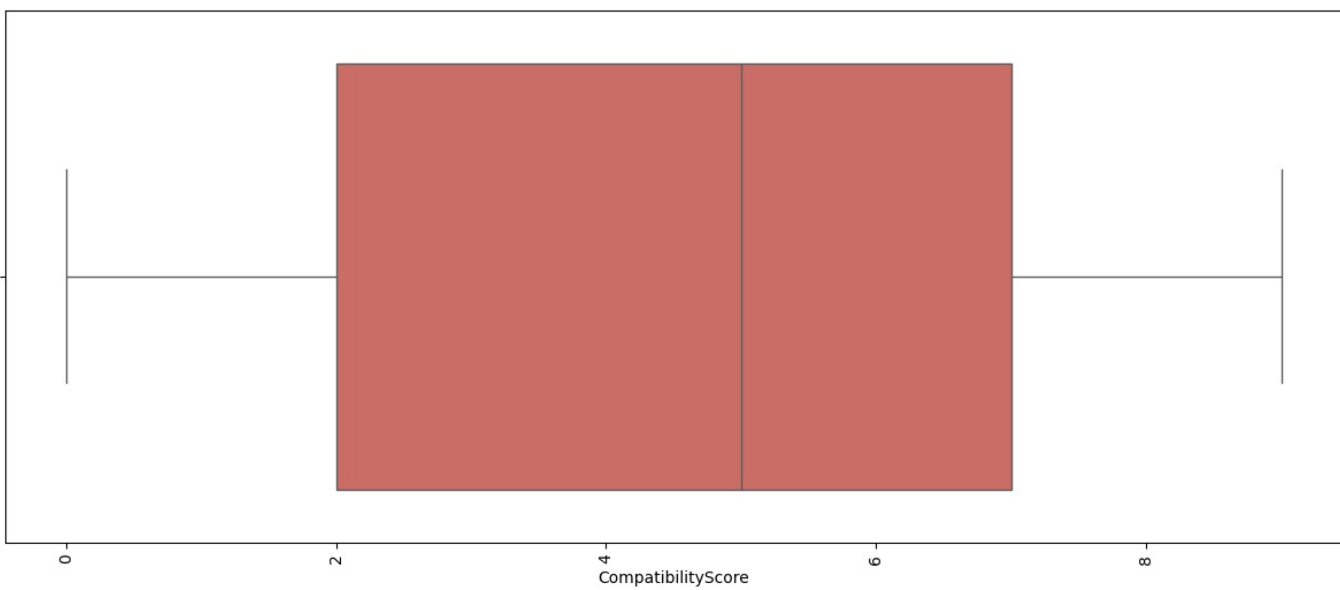
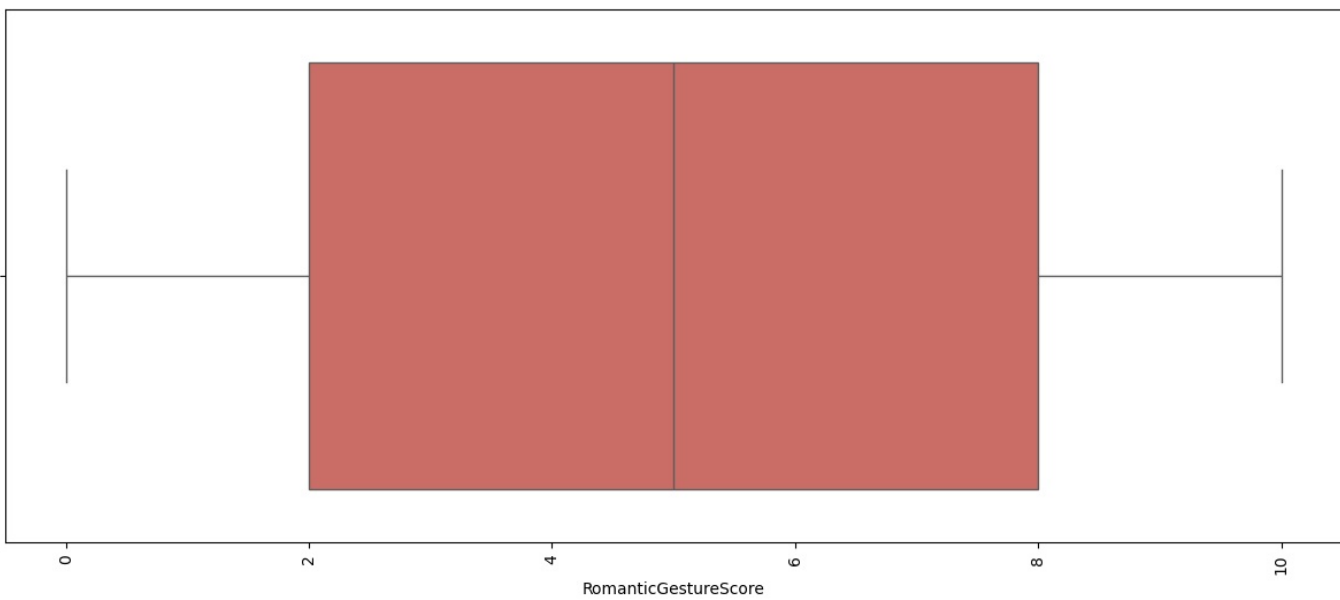
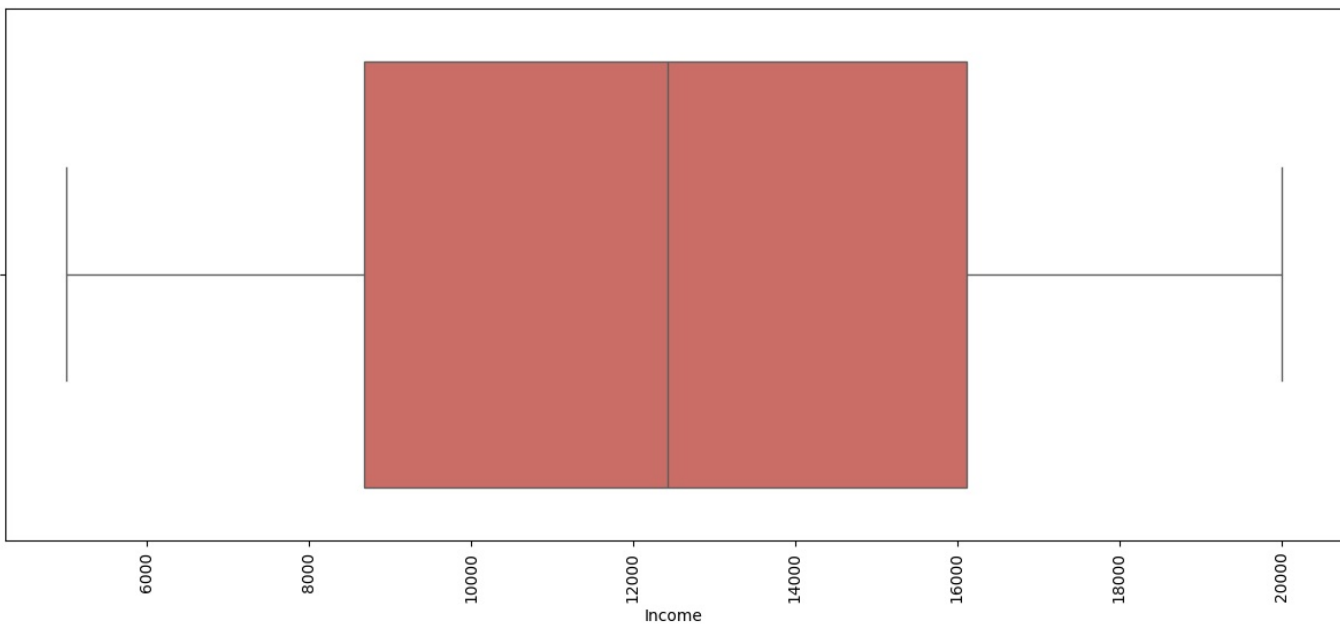



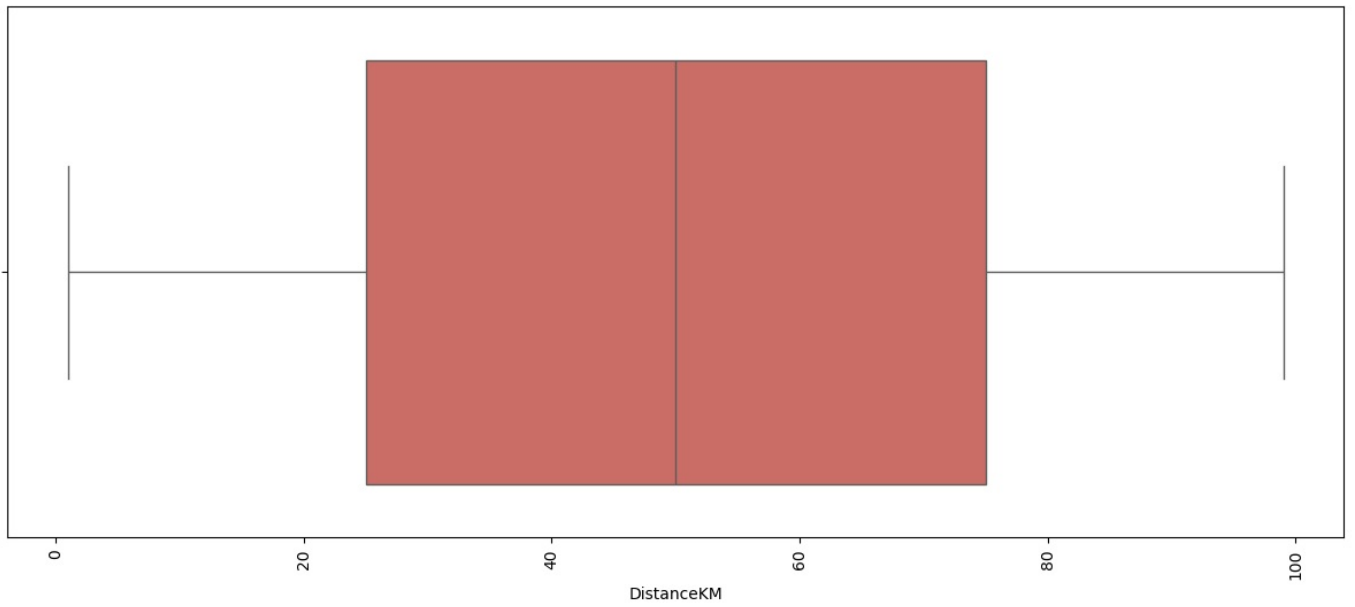
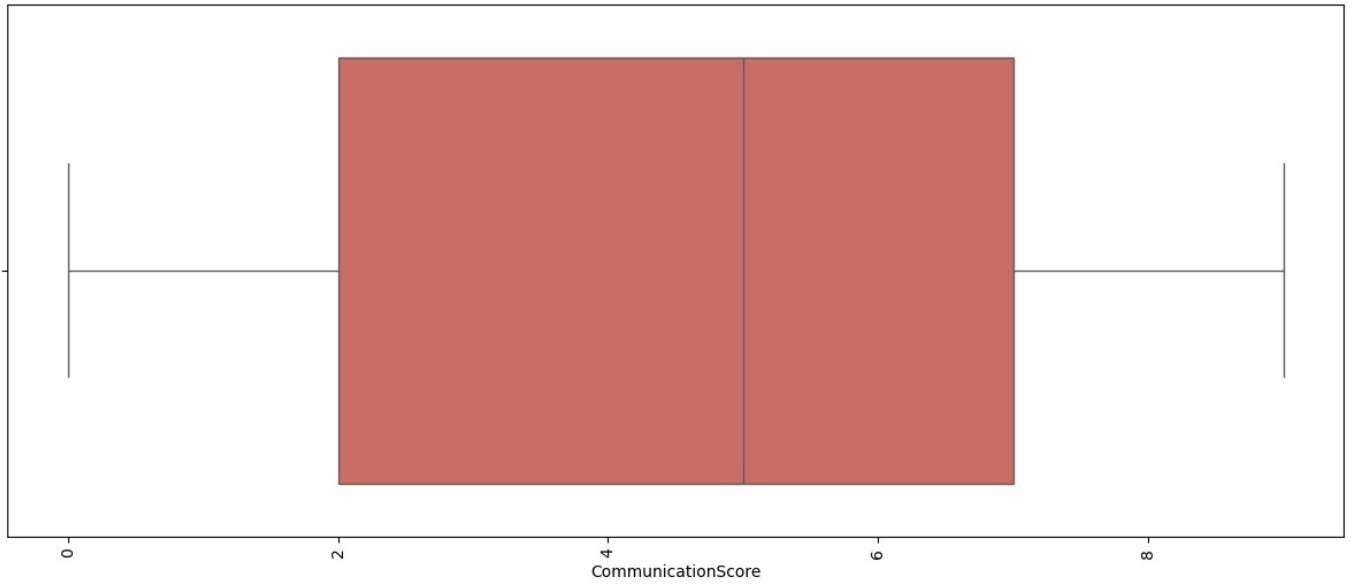




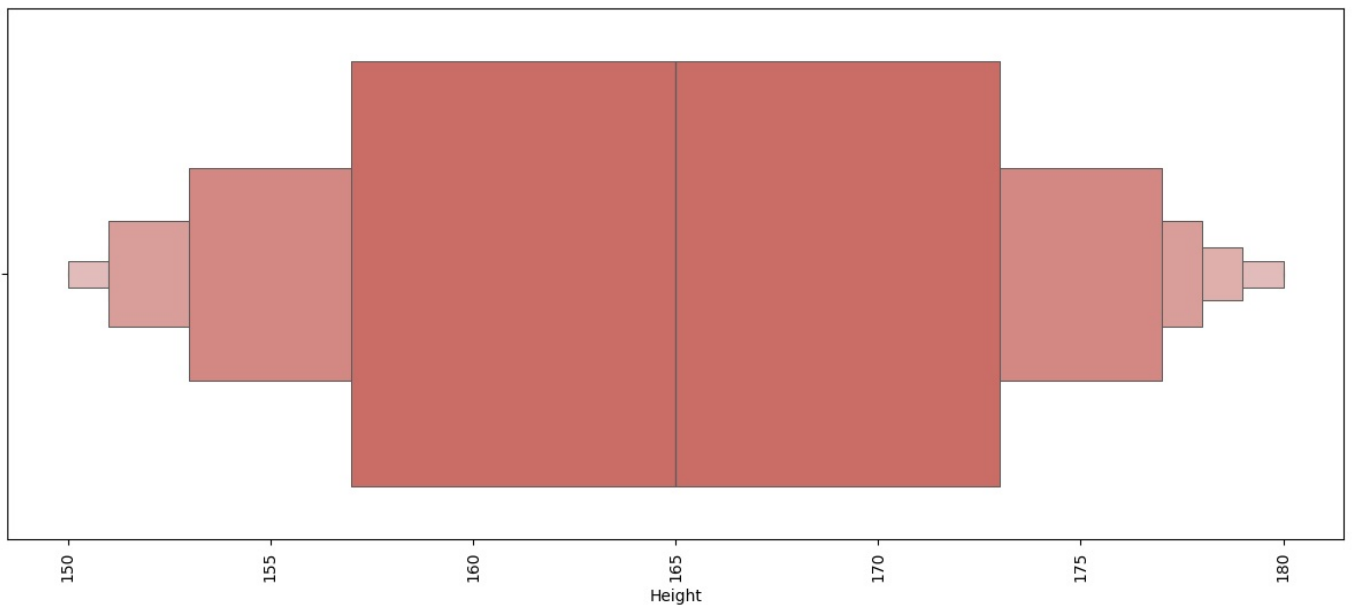
```
In [36]: for i in continuous:  
    plt.figure(figsize=(15, 6))  
    sns.boxplot(x=i, data=df, palette='hls')  
    plt.xticks(rotation=90)  
    plt.show()
```

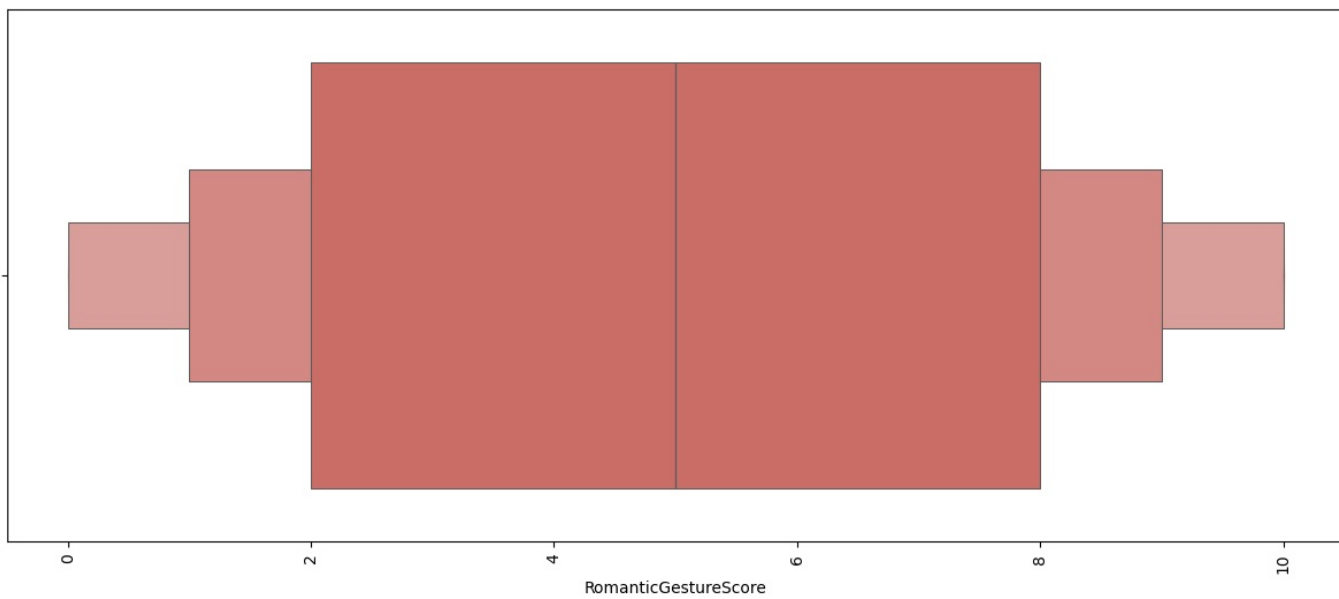
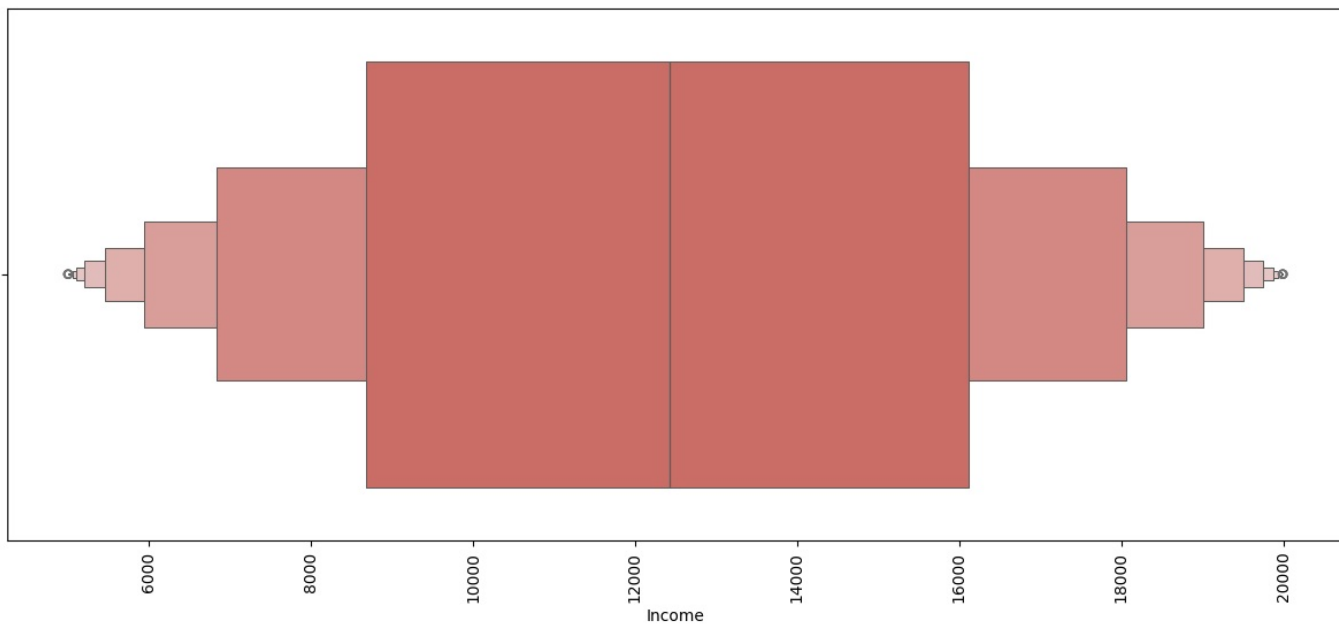
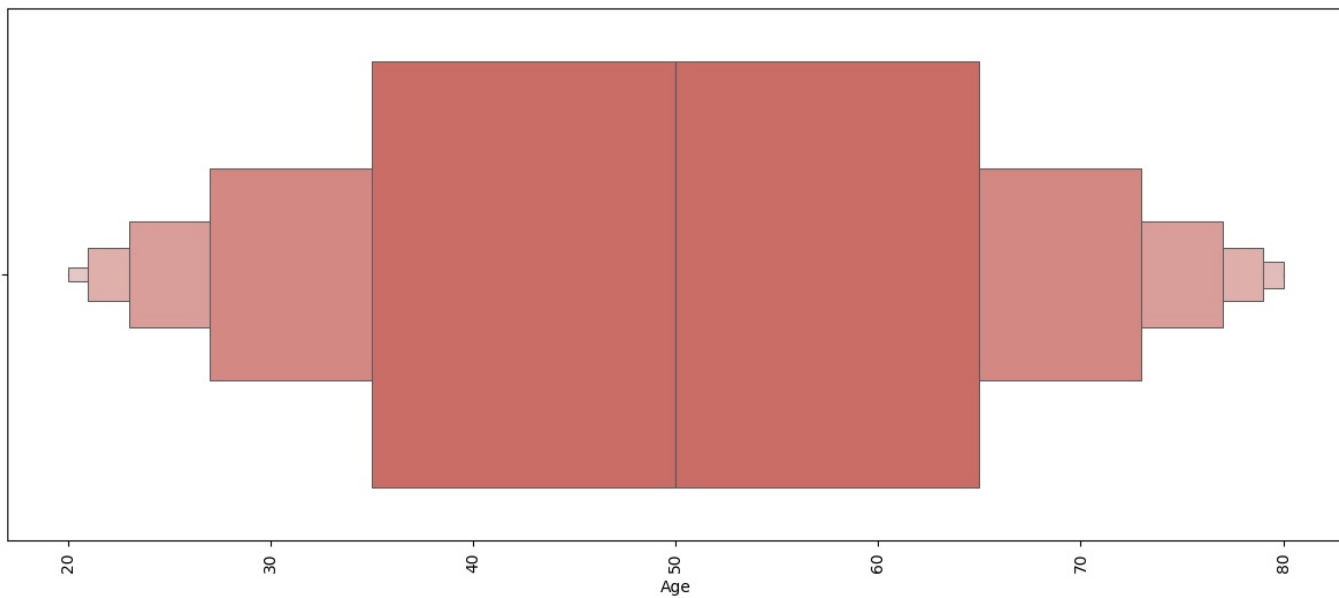


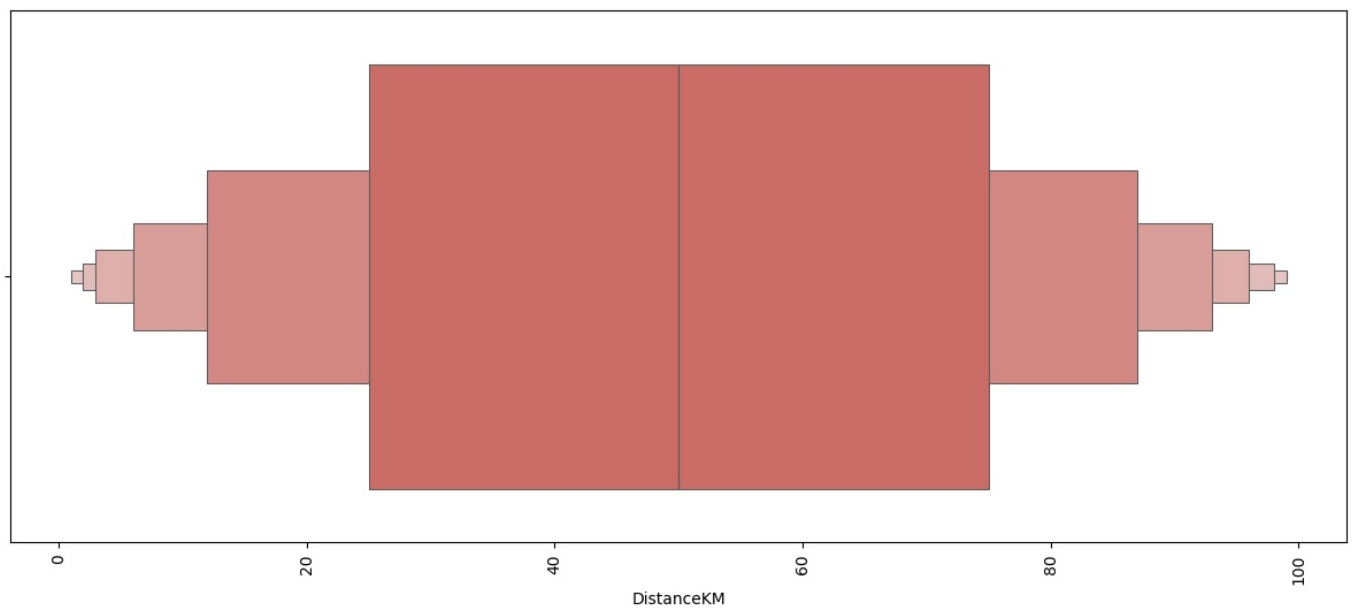
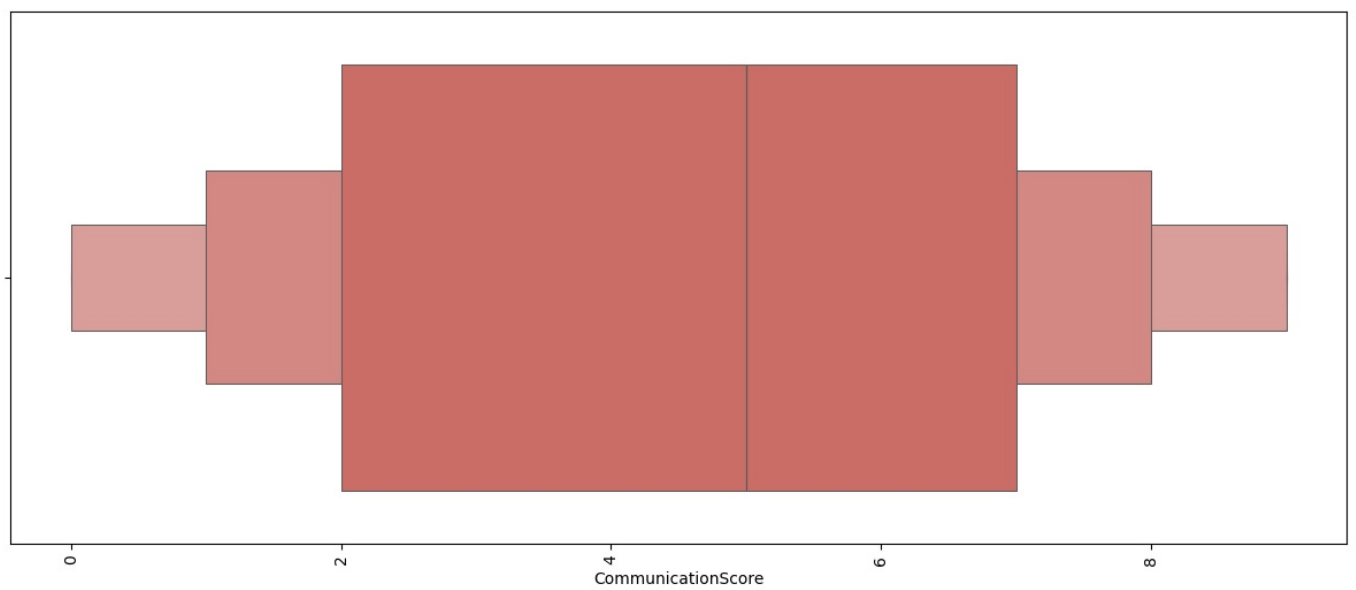
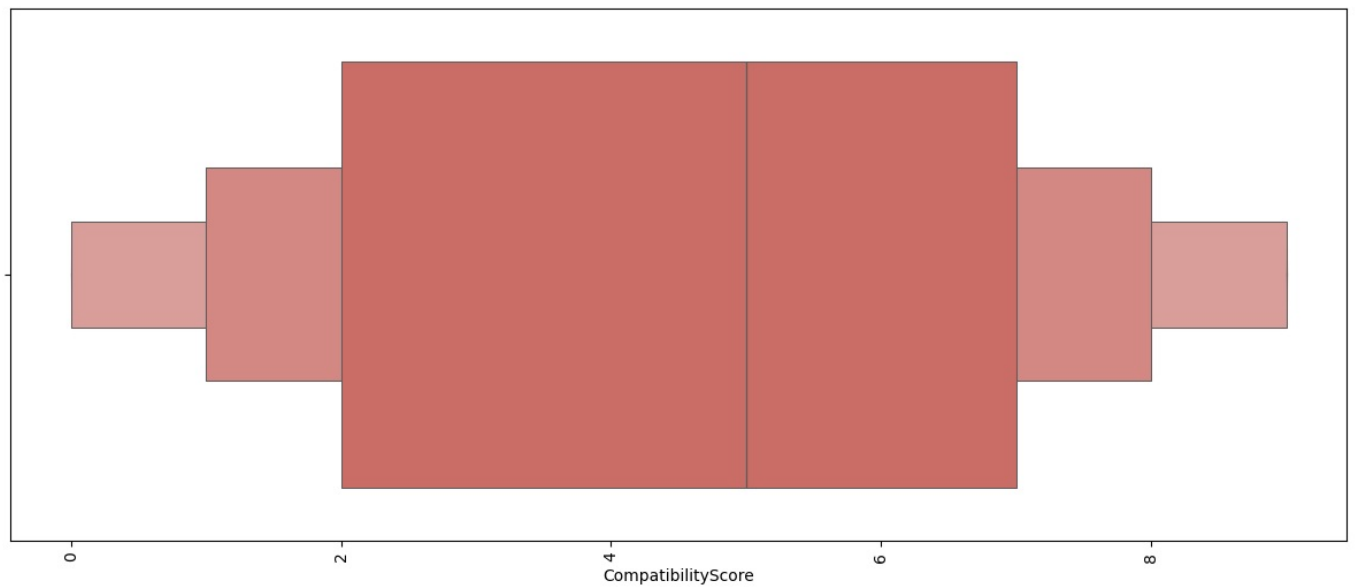




```
In [37]: for i in continuous:
plt.figure(figsize=(15, 6))
sns.boxplot(x=i, data=df, palette='hls')
plt.xticks(rotation=90)
plt.show()
```

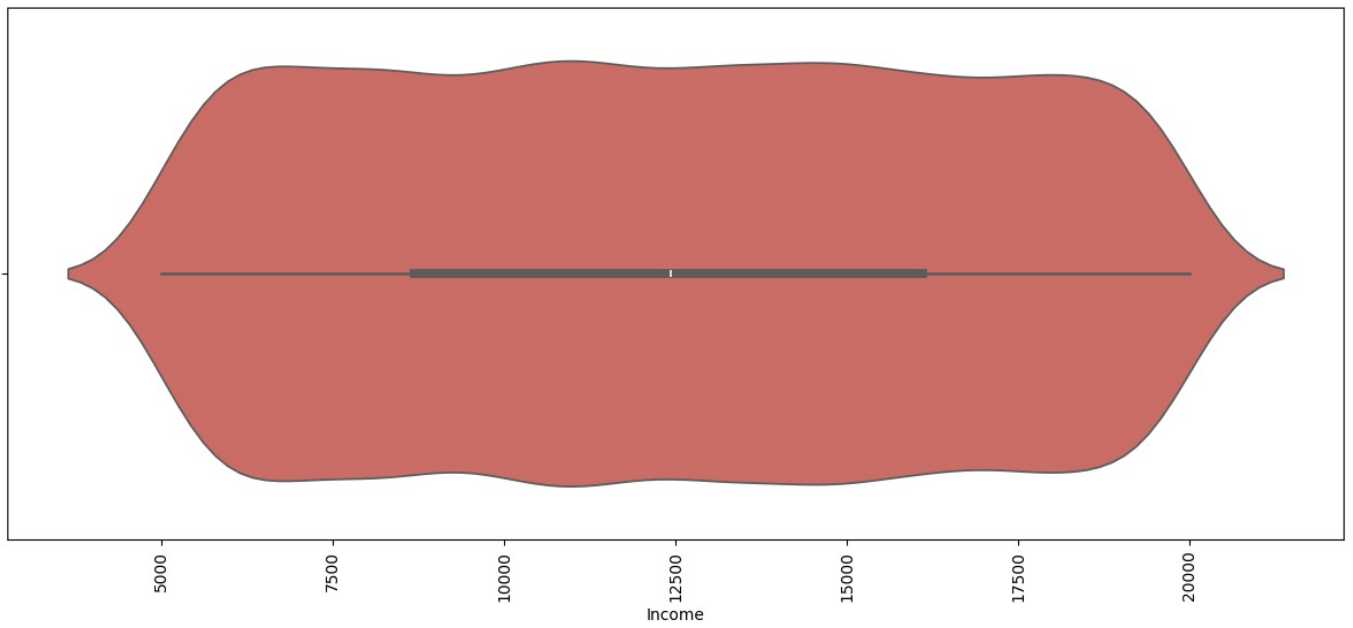
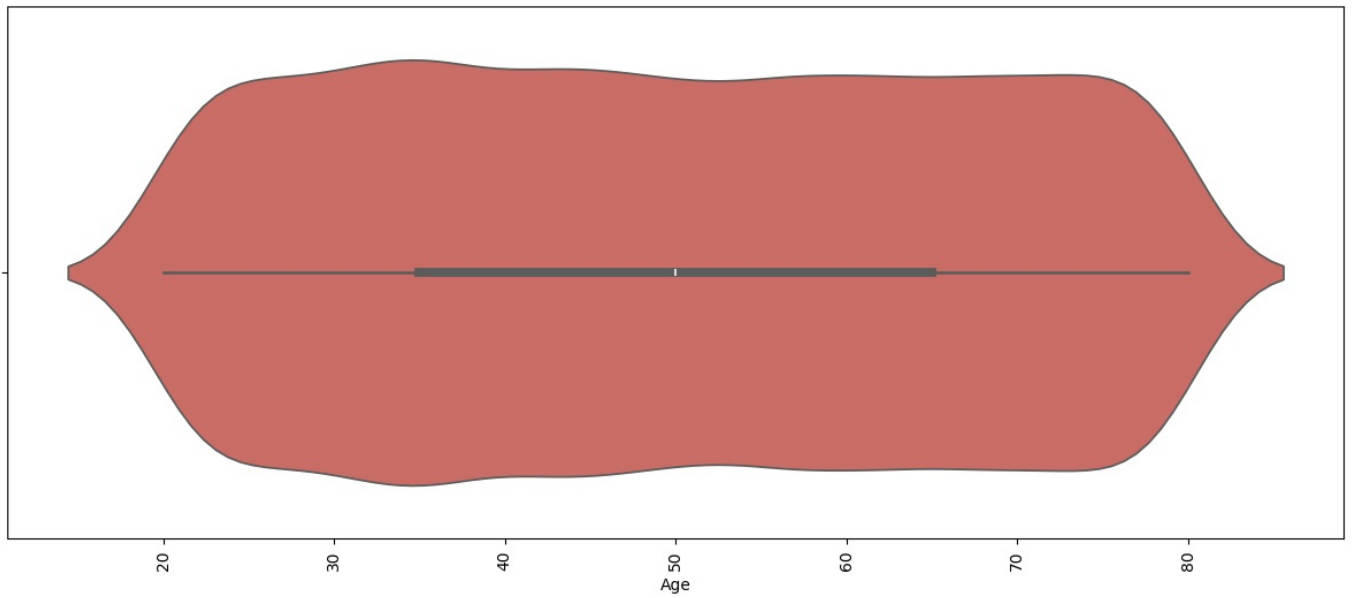
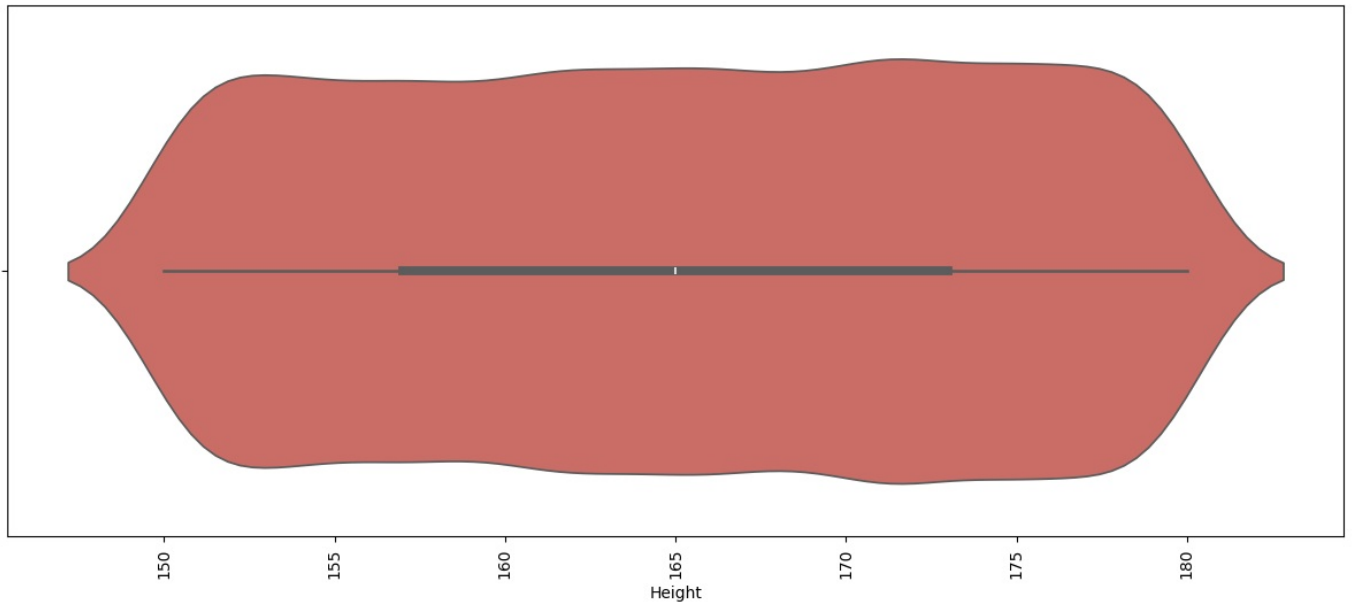


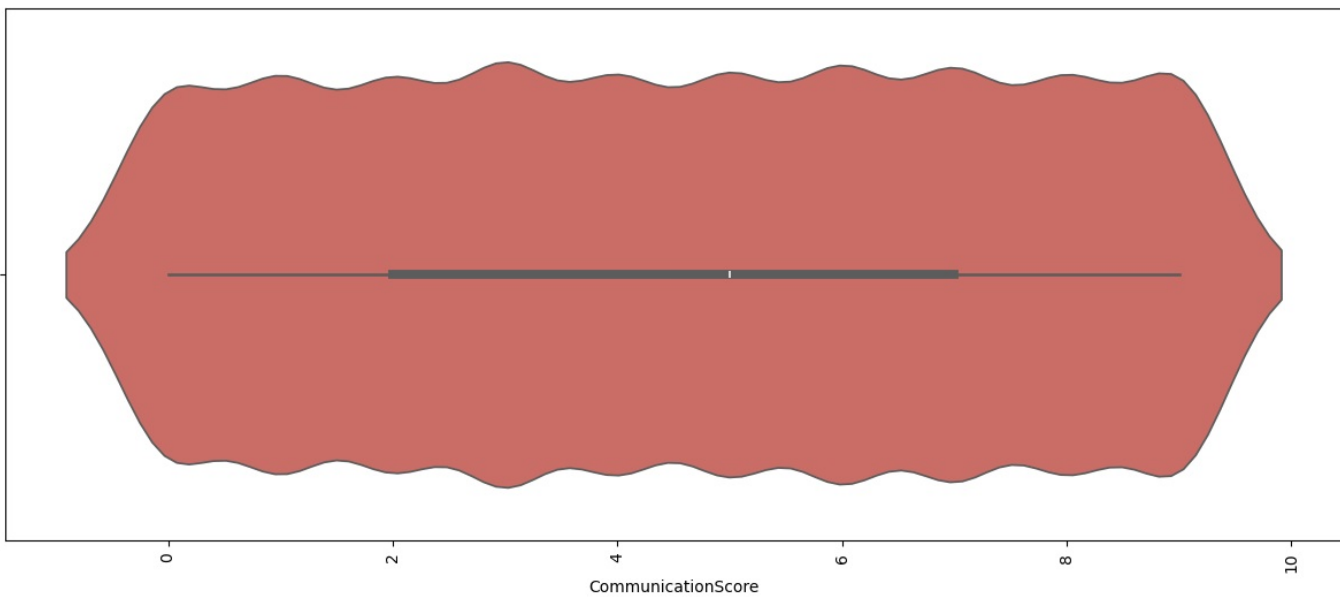
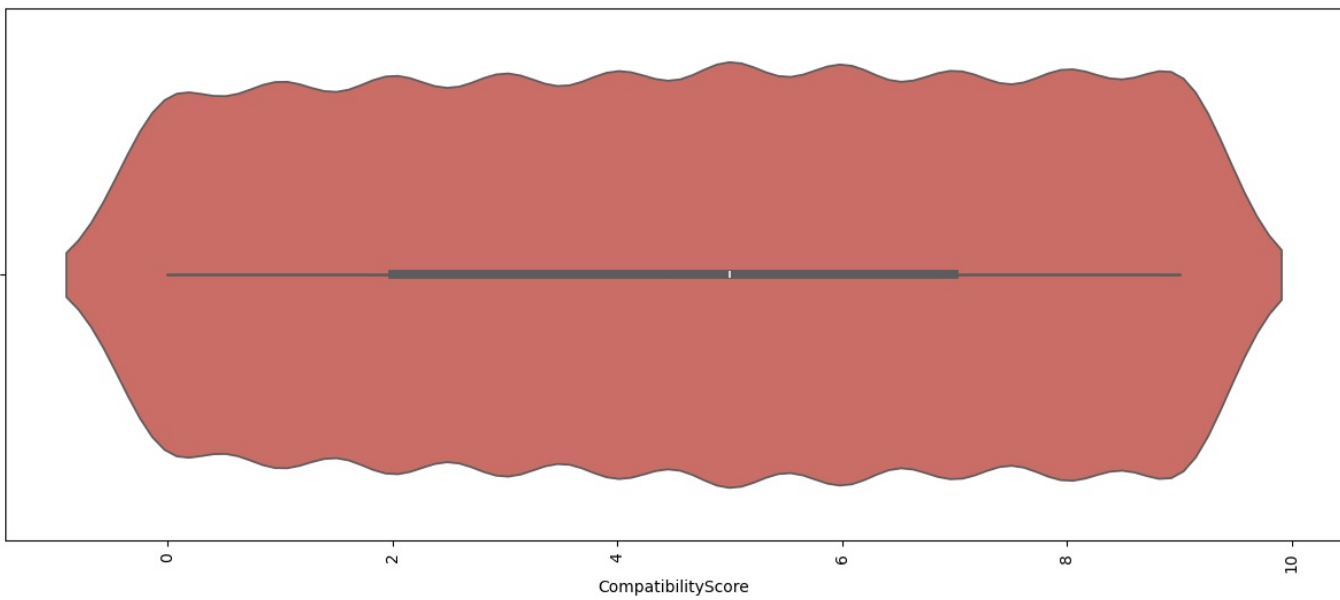
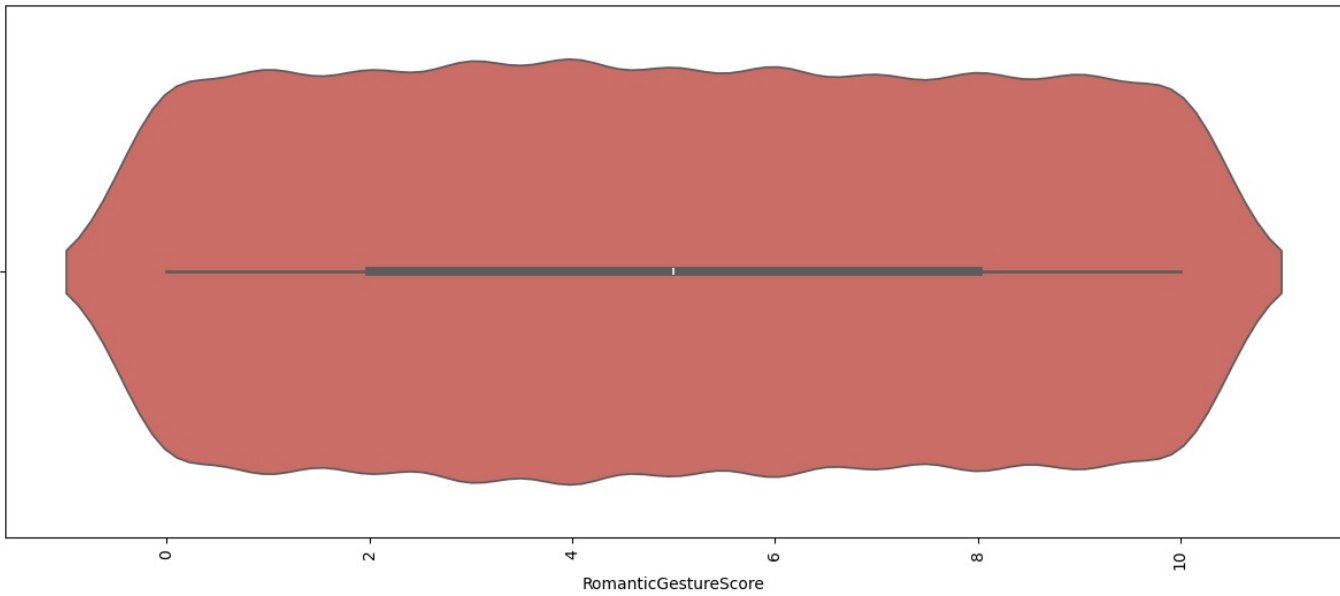


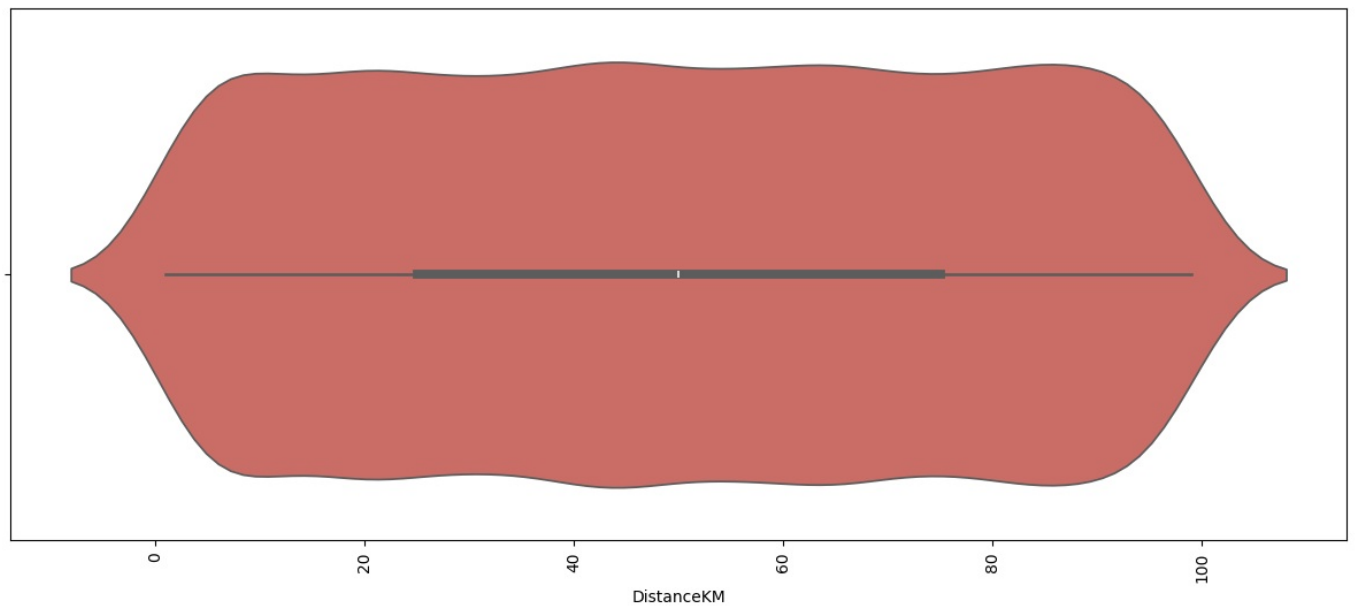


```
In [38]: for i in continuous:
```

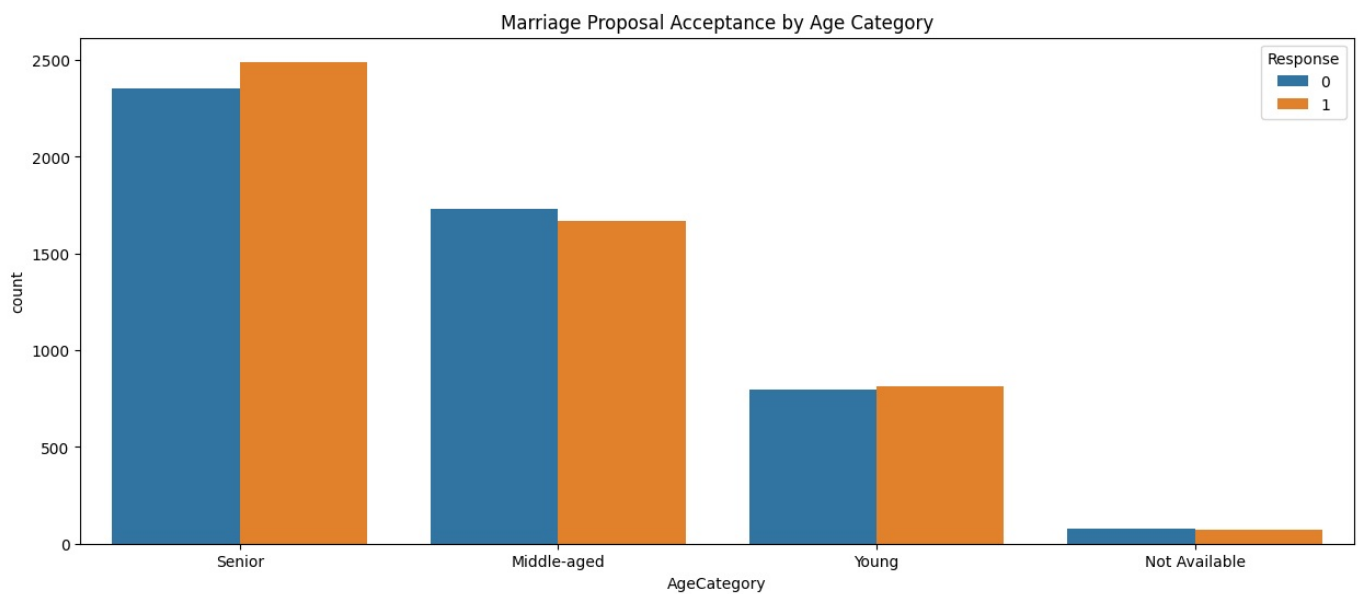
```
plt.figure(figsize=(15, 6))
sns.violinplot(x=i, data=df, palette='hls')
plt.xticks(rotation=90)
plt.show()
```



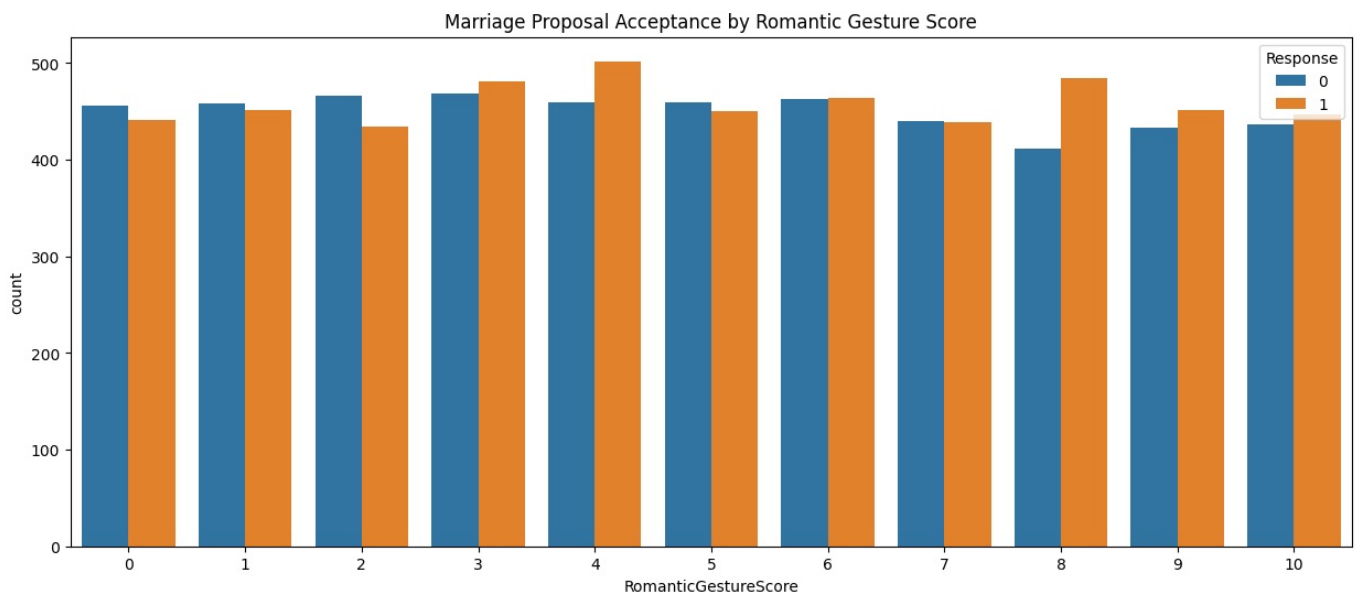




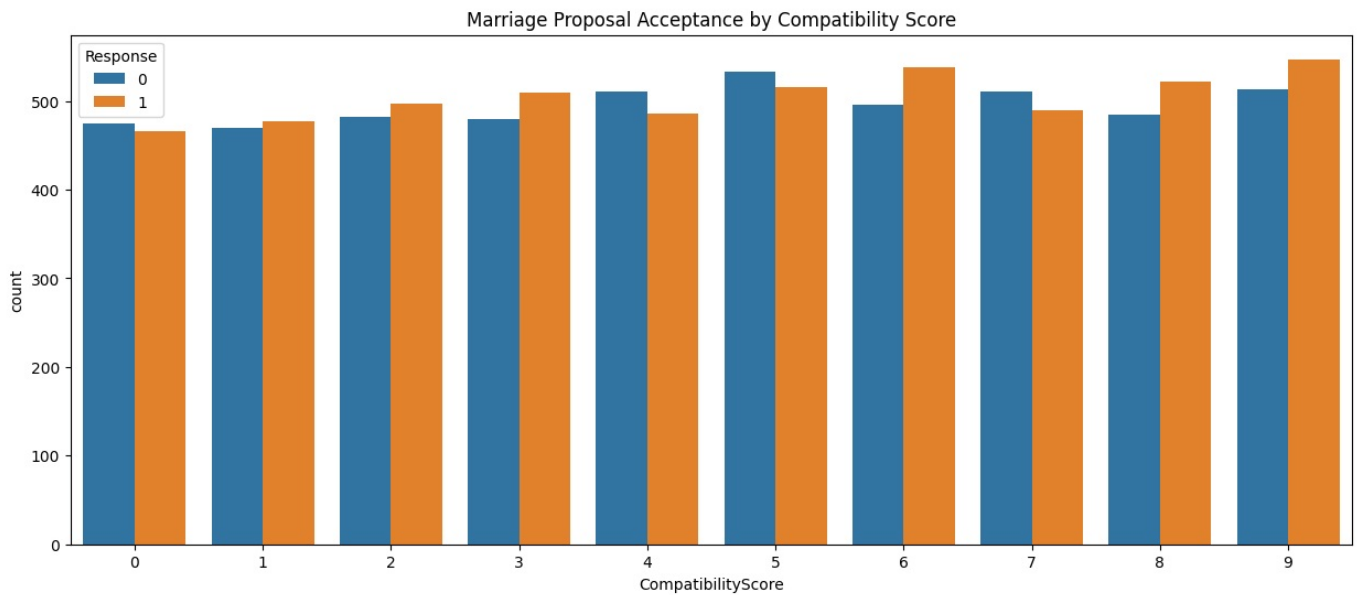
```
In [39]: plt.figure(figsize=(15, 6))
sns.countplot(x='AgeCategory', hue='Response', data=df)
plt.title('Marriage Proposal Acceptance by Age Category')
plt.show()
```



```
In [40]: plt.figure(figsize=(15, 6))
sns.countplot(x = 'RomanticGestureScore', hue='Response', data=df)
plt.title('Marriage Proposal Acceptance by Romantic Gesture Score')
plt.show()
```



```
In [41]: plt.figure(figsize=(15, 6))
sns.countplot(x = 'CompatibilityScore', hue='Response', data=df)
plt.title('Marriage Proposal Acceptance by Compatibility Score')
plt.show()
```



```
In [42]: pivot_table = pd.pivot_table(df, values='Income', index='AgeCategory', columns='Response', aggfunc='mean')
```

```
In [43]: pivot_table
```

```
Out[43]:
```

| | Response 0 | Response 1 |
|---------------|--------------|--------------|
| AgeCategory | | |
| Middle-aged | 12470.907407 | 12440.625374 |
| Not Available | 12060.632911 | 11876.189189 |
| Senior | 12397.293367 | 12465.092734 |
| Young | 12375.469773 | 12588.330456 |

```
In [44]: pivot_table = pd.pivot_table(df, values='Income', index='AgeCategory', columns='Response', aggfunc='max')
```

```
In [45]: pivot_table
```

```
Out[45]:
```

| | Response 0 | Response 1 |
|---------------|------------|------------|
| AgeCategory | | |
| Middle-aged | 19992 | 19999 |
| Not Available | 19656 | 19906 |
| Senior | 19985 | 19991 |
| Young | 19990 | 19963 |

In [46]: `pivot_table = pd.pivot_table(df, values='Income', index='AgeCategory', columns='Response', aggfunc='min')`

In [47]: `pivot_table`

Out[47]:

| | Response | 0 | 1 |
|---------------|----------|------|---|
| AgeCategory | | | |
| <hr/> | | | |
| Middle-aged | 5012 | 5018 | |
| Not Available | 5068 | 5098 | |
| Senior | 5000 | 5008 | |
| Young | 5019 | 5004 | |

In [48]: `cross_tab = pd.crosstab(df['AgeCategory'], df['Response'])`

In [49]: `cross_tab`

Out[49]:

| | Response | 0 | 1 |
|---------------|----------|------|---|
| AgeCategory | | | |
| <hr/> | | | |
| Middle-aged | 1728 | 1671 | |
| Not Available | 79 | 74 | |
| Senior | 2352 | 2491 | |
| Young | 794 | 811 | |

In [50]: `pivot_table = pd.pivot_table(df, values=['RomanticGestureScore', 'CompatibilityScore'], index='AgeCategory', columns='Response', aggfunc='mean', margins=True, fill_value=0)`

In [51]: `pivot_table`

Out[51]:

| | CompatibilityScore | | | RomanticGestureScore | | |
|---------------|--------------------|----------|----------|----------------------|----------|----------|
| Response | 0 | 1 | All | 0 | 1 | All |
| AgeCategory | | | | | | |
| Middle-aged | 4.552662 | 4.675643 | 4.613122 | 4.968171 | 5.081388 | 5.023831 |
| Not Available | 4.126582 | 4.891892 | 4.496732 | 4.670886 | 4.810811 | 4.738562 |
| Senior | 4.575255 | 4.606985 | 4.591575 | 4.861395 | 4.999599 | 4.932480 |
| Young | 4.614610 | 4.464858 | 4.538941 | 4.994962 | 4.926017 | 4.960125 |
| All | 4.566525 | 4.611056 | 4.589000 | 4.917020 | 5.012086 | 4.965000 |

In [52]: `cross_tab = pd.crosstab(df['AgeCategory'], [df['Response'], df['RomanticGestureScore'], df['CompatibilityScore']], normalize='index', margins=True)`

In [53]: `cross_tab`

Out[53]:

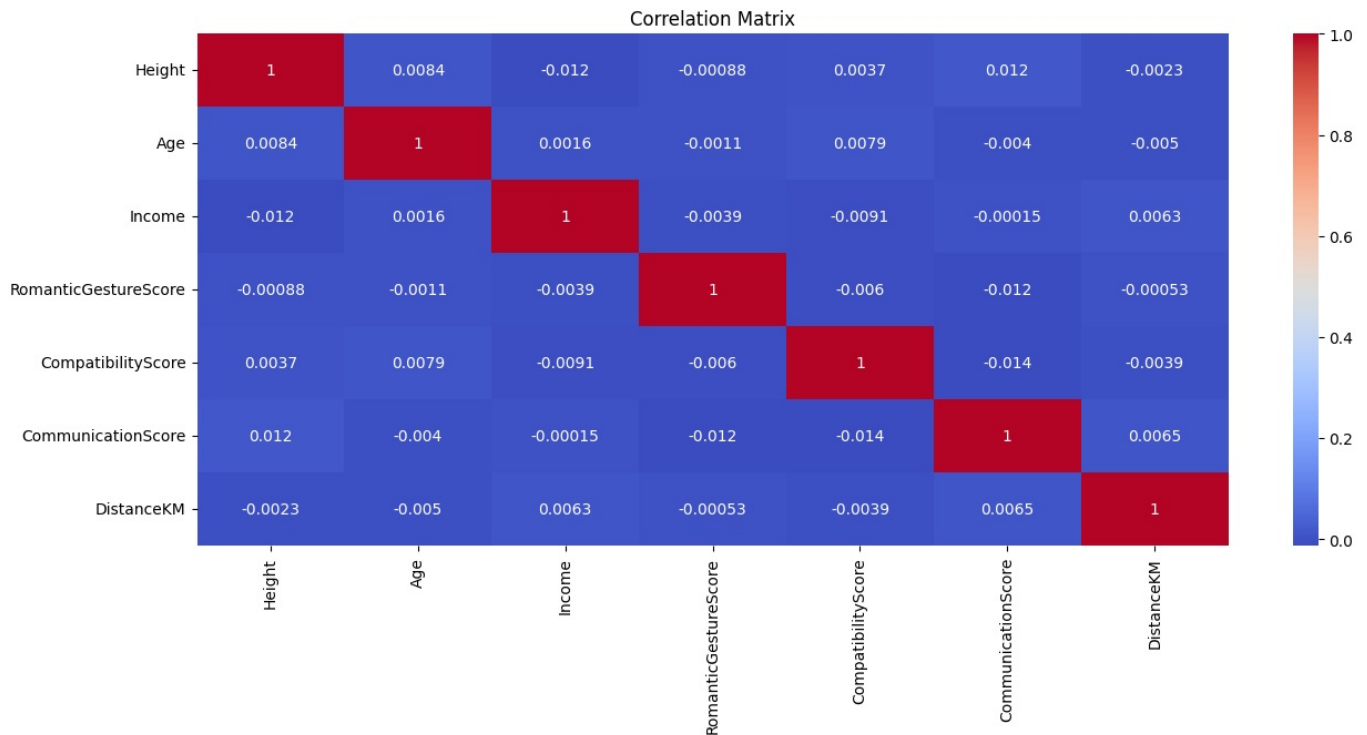
| | Response | | | | | | | | | | | 0 | ... |
|--|----------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-----|-----|
| | RomanticGestureScore | | | | | | | | | | | 0 | ... |
| | CompatibilityScore | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | |
| | AgeCategory | | | | | | | | | | | | |
| | Middle-aged | 0.002059 | 0.004413 | 0.005296 | 0.002942 | 0.004119 | 0.004413 | 0.005296 | 0.004413 | 0.003825 | 0.004707 | ... | 0.0 |
| | Not Available | 0.013072 | 0.006536 | 0.000000 | 0.000000 | 0.013072 | 0.006536 | 0.000000 | 0.006536 | 0.000000 | 0.000000 | ... | 0.0 |
| | Senior | 0.005988 | 0.003510 | 0.004336 | 0.007020 | 0.004749 | 0.004543 | 0.004336 | 0.005162 | 0.004956 | 0.005369 | ... | 0.0 |
| | Young | 0.003738 | 0.003115 | 0.002492 | 0.003115 | 0.006231 | 0.003738 | 0.003738 | 0.005607 | 0.006231 | 0.003115 | ... | 0.0 |
| | All | 0.004400 | 0.003800 | 0.004300 | 0.004900 | 0.004900 | 0.004400 | 0.004500 | 0.005000 | 0.004700 | 0.004700 | ... | 0.0 |

5 rows × 220 columns



In [54]: `plt.figure(figsize=(15, 6)) correlation_matrix = df[['Height', 'Age', 'Income', 'RomanticGestureScore', 'CompatibilityScore', 'Communication']].corr() sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')`

```
plt.title('Correlation Matrix')
plt.show()
```



```
In [55]: df['AgeCategory'] = df['AgeCategory'].astype('category')
df_new = pd.get_dummies(df, columns=['AgeCategory'], drop_first=True)
```

```
In [56]: df_new = df_new.astype(int)
```

```
In [57]: df_new
```

```
Out[57]:
```

| | Height | Age | Income | RomanticGestureScore | CompatibilityScore | CommunicationScore | DistanceKM | Response | AgeCategory Avai |
|------|--------|-----|--------|----------------------|--------------------|--------------------|------------|----------|---------------------|
| 0 | 156 | 59 | 7977 | 3 | 1 | 1 | 45 | 1 | |
| 1 | 169 | 32 | 5842 | 0 | 1 | 5 | 46 | 1 | |
| 2 | 178 | 42 | 17638 | 2 | 5 | 5 | 13 | 0 | |
| 3 | 164 | 78 | 8793 | 0 | 0 | 7 | 52 | 0 | |
| 4 | 160 | 35 | 15262 | 6 | 0 | 0 | 9 | 1 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 9995 | 162 | 76 | 12311 | 4 | 1 | 5 | 75 | 1 | |
| 9996 | 162 | 75 | 6459 | 7 | 9 | 0 | 52 | 1 | |
| 9997 | 166 | 70 | 9231 | 9 | 4 | 6 | 33 | 0 | |
| 9998 | 176 | 78 | 12656 | 8 | 9 | 5 | 25 | 1 | |
| 9999 | 156 | 68 | 5812 | 0 | 9 | 4 | 14 | 1 | |

10000 rows × 11 columns

```
In [58]: from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

```
In [59]: X = df_new.drop('Response', axis=1)
y = df_new['Response']
```

```
In [60]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify = y, random_state=42)
```

```
In [61]: log_reg_model = LogisticRegression()
log_reg_model.fit(X_train, y_train)
log_reg_pred = log_reg_model.predict(X_test)
log_reg_accuracy = accuracy_score(y_test, log_reg_pred)
print("Logistic Regression Accuracy:", log_reg_accuracy)
```

Logistic Regression Accuracy: 0.488

```
In [62]: rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)
rf_pred = rf_model.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_pred)
print("Random Forest Accuracy:", rf_accuracy)
```

Random Forest Accuracy: 0.5245

```
In [63]: svm_model = SVC()
svm_model.fit(X_train, y_train)
svm_pred = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_pred)
print("SVM Accuracy:", svm_accuracy)
```

SVM Accuracy: 0.4825

```
In [64]: from sklearn.preprocessing import StandardScaler
```

```
In [65]: non_discrete_features = ['Height', 'Age', 'Income', 'RomanticGestureScore', 'CompatibilityScore', 'CommunicationScore']
```

```
In [66]: scaler = StandardScaler()

df_new[non_discrete_features] = scaler.fit_transform(df_new[non_discrete_features])
```

```
In [67]: X = df_new.drop('Response', axis=1)
y = df_new['Response']
```

```
In [68]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify = y, random_state=42)
```

```
In [69]: svm_model = SVC()
svm_model.fit(X_train, y_train)
svm_pred = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_pred)
print("SVM Accuracy:", svm_accuracy)
```

SVM Accuracy: 0.486

```
In [70]: from sklearn.tree import DecisionTreeClassifier
```

```
In [71]: dt_classifier = DecisionTreeClassifier(random_state=42)
```

```
In [72]: dt_classifier.fit(X_train, y_train)
```

```
Out[72]: ▼      DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

```
In [73]: dt_pred = dt_classifier.predict(X_test)

dt_accuracy = accuracy_score(y_test, dt_pred)
print("Decision Tree Accuracy:", dt_accuracy)
```

Decision Tree Accuracy: 0.514

```
In [74]: from sklearn.preprocessing import PolynomialFeatures
```

```
In [75]: degree = 2

selected_features = ['Height', 'Age', 'Income', 'RomanticGestureScore',
                    'CompatibilityScore', 'CommunicationScore', 'DistanceKM']
```

```
In [76]: X_selected = df[selected_features]
```

```
In [77]: poly = PolynomialFeatures(degree=degree, include_bias=False)
```

```
In [78]: poly_features = poly.fit_transform(X_selected)
```

```
In [79]: poly_feature_names = poly.get_feature_names_out(input_features=selected_features)

df_poly = pd.DataFrame(poly_features, columns=poly_feature_names)

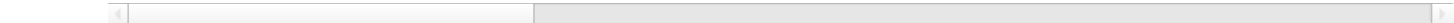
df_poly = pd.concat([df[['Response']], df_poly], axis=1)
```

```
In [80]: df_poly
```

Out[80]:

| | Response | Height | Age | Income | RomanticGestureScore | CompatibilityScore | CommunicationScore | DistanceKM | Height^2 | |
|------|----------|--------|------|---------|----------------------|--------------------|--------------------|------------|----------|----|
| 0 | 1 | 156.0 | 59.0 | 7977.0 | 3.0 | 1.0 | 1.0 | 45.0 | 24336.0 | |
| 1 | 1 | 169.0 | 32.0 | 5842.0 | 0.0 | 1.0 | 5.0 | 46.0 | 28561.0 | |
| 2 | 0 | 178.0 | 42.0 | 17638.0 | 2.0 | 5.0 | 5.0 | 13.0 | 31684.0 | |
| 3 | 0 | 164.0 | 78.0 | 8793.0 | 0.0 | 0.0 | 7.0 | 52.0 | 26896.0 | 1: |
| 4 | 1 | 160.0 | 35.0 | 15262.0 | 6.0 | 0.0 | 0.0 | 9.0 | 25600.0 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 9995 | 1 | 162.0 | 76.0 | 12311.0 | 4.0 | 1.0 | 5.0 | 75.0 | 26244.0 | 1: |
| 9996 | 1 | 162.0 | 75.0 | 6459.0 | 7.0 | 9.0 | 0.0 | 52.0 | 26244.0 | 1: |
| 9997 | 0 | 166.0 | 70.0 | 9231.0 | 9.0 | 4.0 | 6.0 | 33.0 | 27556.0 | 1: |
| 9998 | 1 | 176.0 | 78.0 | 12656.0 | 8.0 | 9.0 | 5.0 | 25.0 | 30976.0 | 1: |
| 9999 | 1 | 156.0 | 68.0 | 5812.0 | 0.0 | 9.0 | 4.0 | 14.0 | 24336.0 | 1: |

10000 rows × 36 columns



```
In [81]: df_poly.columns
```

```
Out[81]: Index(['Response', 'Height', 'Age', 'Income', 'RomanticGestureScore',
              'CompatibilityScore', 'CommunicationScore', 'DistanceKM', 'Height^2',
              'Height Age', 'Height Income', 'Height RomanticGestureScore',
              'Height CompatibilityScore', 'Height CommunicationScore',
              'Height DistanceKM', 'Age^2', 'Age Income', 'Age RomanticGestureScore',
              'Age CompatibilityScore', 'Age CommunicationScore', 'Age DistanceKM',
              'Income^2', 'Income RomanticGestureScore', 'Income CompatibilityScore',
              'Income CommunicationScore', 'Income DistanceKM',
              'RomanticGestureScore^2', 'RomanticGestureScore CompatibilityScore',
              'RomanticGestureScore CommunicationScore',
              'RomanticGestureScore DistanceKM', 'CompatibilityScore^2',
              'CompatibilityScore CommunicationScore',
              'CompatibilityScore DistanceKM', 'CommunicationScore^2',
              'CommunicationScore DistanceKM', 'DistanceKM^2'],
              dtype='object')
```

```
In [82]: from sklearn.feature_selection import SelectFromModel
```

```
In [83]: X = df_poly.drop(columns=['Response'])
         y = df_poly['Response']
```

```
In [84]: clf = RandomForestClassifier(n_estimators=100, random_state=42)
```

```
In [85]: selector = SelectFromModel(clf)
         selector.fit(X, y)
```

Out[85]:

▶ SelectFromModel

▶ estimator: RandomForestClassifier

▶ RandomForestClassifier

```
In [86]: selected_feature_indices = selector.get_support(indices=True)
```

```
In [87]: selected_features = X.columns[selected_feature_indices]
```

```
In [88]: X_selected = X[selected_features]
         X_train, X_test, y_train, y_test = train_test_split(X_selected, y, test_size=0.2, random_state=42)
```

```
In [89]: X_selected = X[selected_features]
         X_train, X_test, y_train, y_test = train_test_split(X_selected, y, test_size=0.2, random_state=42)

         model = LogisticRegression()
         model.fit(X_train, y_train)
```

Out[89]:

▼ LogisticRegression

LogisticRegression()

```
In [90]: y_pred = model.predict(X_test)
         accuracy = accuracy_score(y_test, y_pred)
         print("Accuracy:", accuracy)
```

Accuracy: 0.4965

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