Bike Buyers Prediction

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Importing Libraries

In [ ]:
```
import pandas as pd
import numpy as np
from IPython.display import display
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn import metrics
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.feature_selection import SelectKBest, f_regression, RFE, SelectFromModel
from sklearn.ensemble import RandomForestRegressor
from sklearn.decomposition import PCA

import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
import seaborn as sb
import plotly.express as px
plt.style.use('default')
import warnings
warnings.filterwarnings('ignore')
```

Import Data

In [ ]:
```
dfa = pd.read_csv("D:\\PROGRAMMING\\DATASETS\\G\\LogReg\\bike_buyers.csv")
print(dfa.shape)
dfa.head()
```

```
(1000, 13)
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
0	12496	Married	Female	40000.0	1.0	Bachelors	Skilled Manual	Yes	0.0	0-1 Miles	Europe	42.0	No
1	24107	Married	Male	30000.0	3.0	Partial College	Clerical	Yes	1.0	0-1 Miles	Europe	43.0	No
2	14177	Married	Male	80000.0	5.0	Partial College	Professional	No	2.0	2-5 Miles	Europe	60.0	No
3	24381	Single	NaN	70000.0	0.0	Bachelors	Professional	Yes	1.0	5-10 Miles	Pacific	41.0	Yes
4	25597	Single	Male	30000.0	0.0	Bachelors	Clerical	No	0.0	0-1 Miles	Europe	36.0	Yes

Data Exploration

In [ ]:
```
print(dfa['Gender'].value_counts())
```

```
Gender
Male      500
Female    489
Name: count, dtype: int64
```

In [ ]:
```
print(dfa['Education'].value_counts())
```

```
Education
Bachelors              306
Partial College        265
High School            179
Graduate Degree        174
Partial High School     76
Name: count, dtype: int64
```

In [ ]:
```
print(dfa['Occupation'].value_counts())
```

```
Occupation
Professional      276
Skilled Manual    255
Clerical          177
Management        173
Manual            119
Name: count, dtype: int64
```

In [ ]:
```
print(dfa["Marital Status"].value_counts())
```

```
Marital Status
Married    535
Single     458
Name: count, dtype: int64
```

In [ ]:
```
print(dfa["Region"].value_counts())
```

```
Region
North America    508
Europe           300
Pacific          192
Name: count, dtype: int64
```

In [ ]:
```
print(dfa["Purchased Bike"].value_counts())
```

```
Purchased Bike
No     519
Yes    481
Name: count, dtype: int64
```

- Here, we don't have class imbalance problem

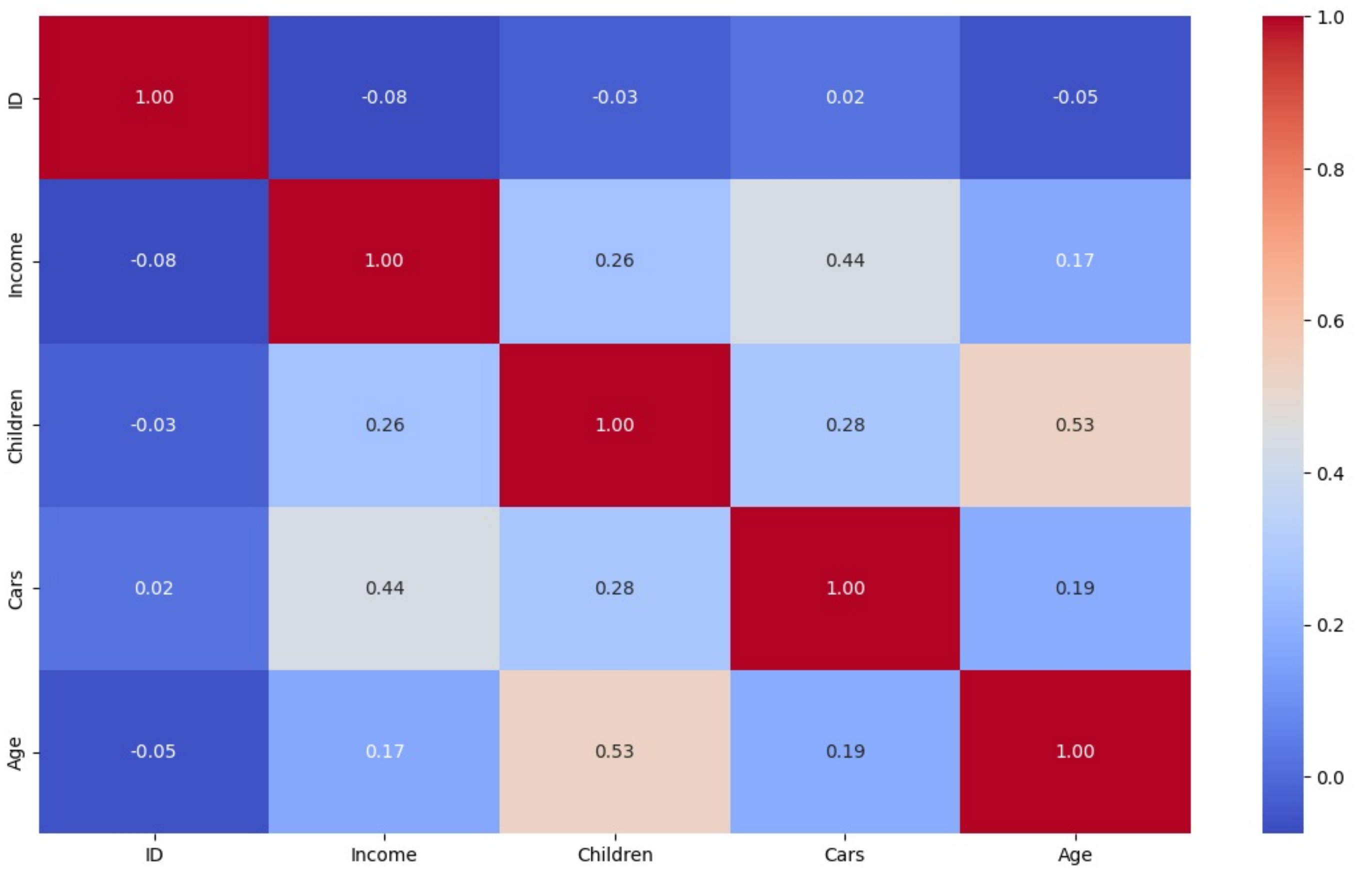
In [ ]:
```
dfa.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   ID                1000 non-null   int64  
 1   Marital Status    993 non-null    object 
 2   Gender            989 non-null    object 
 3   Income            994 non-null    float64
 4   Children          992 non-null    float64
 5   Education         1000 non-null   object 
 6   Occupation        1000 non-null   object 
 7   Home Owner        996 non-null    object 
 8   Cars              991 non-null    float64
 9   Commute Distance  1000 non-null   object 
 10  Region            1000 non-null   object 
 11  Age               992 non-null    float64
 12  Purchased Bike    1000 non-null   object 
dtypes: float64(4), int64(1), object(8)
memory usage: 101.7+ KB
```

In [ ]:
```
numeric_attribute = dfa.select_dtypes(include = ['int64', 'float64'])
```

In [ ]:
```
plt.figure(figsize=(14, 8))
sb.heatmap(numeric_attribute.corr(), annot=True, cmap='coolwarm', fmt='.2f')
```

Out[ ]: <Axes: >



In [ ]:
```
## Finding out correlation of each attribute with each other
cor_data = numeric_attribute.corr().round(4)
for k in numeric_attribute:
    print(f"\n-------{k}:")
    print(cor_data[k].sort_values(ascending=False))
```

```
-------ID:
ID          1.0000
Cars        0.0221
Children   -0.0287
Age        -0.0542
Income     -0.0751
Name: ID, dtype: float64

-------Income:
Income      1.0000
Cars        0.4400
Children    0.2611
Age         0.1708
ID         -0.0751
Name: Income, dtype: float64

-------Children:
Children    1.0000
Age         0.5317
Cars        0.2802
Income      0.2611
ID         -0.0287
Name: Children, dtype: float64

-------Cars:
Cars        1.0000
Income      0.4400
Children    0.2802
Age         0.1864
ID          0.0221
Name: Cars, dtype: float64

-------Age:
Age         1.0000
Children    0.5317
Cars        0.1864
Income      0.1708
ID         -0.0542
Name: Age, dtype: float64
```

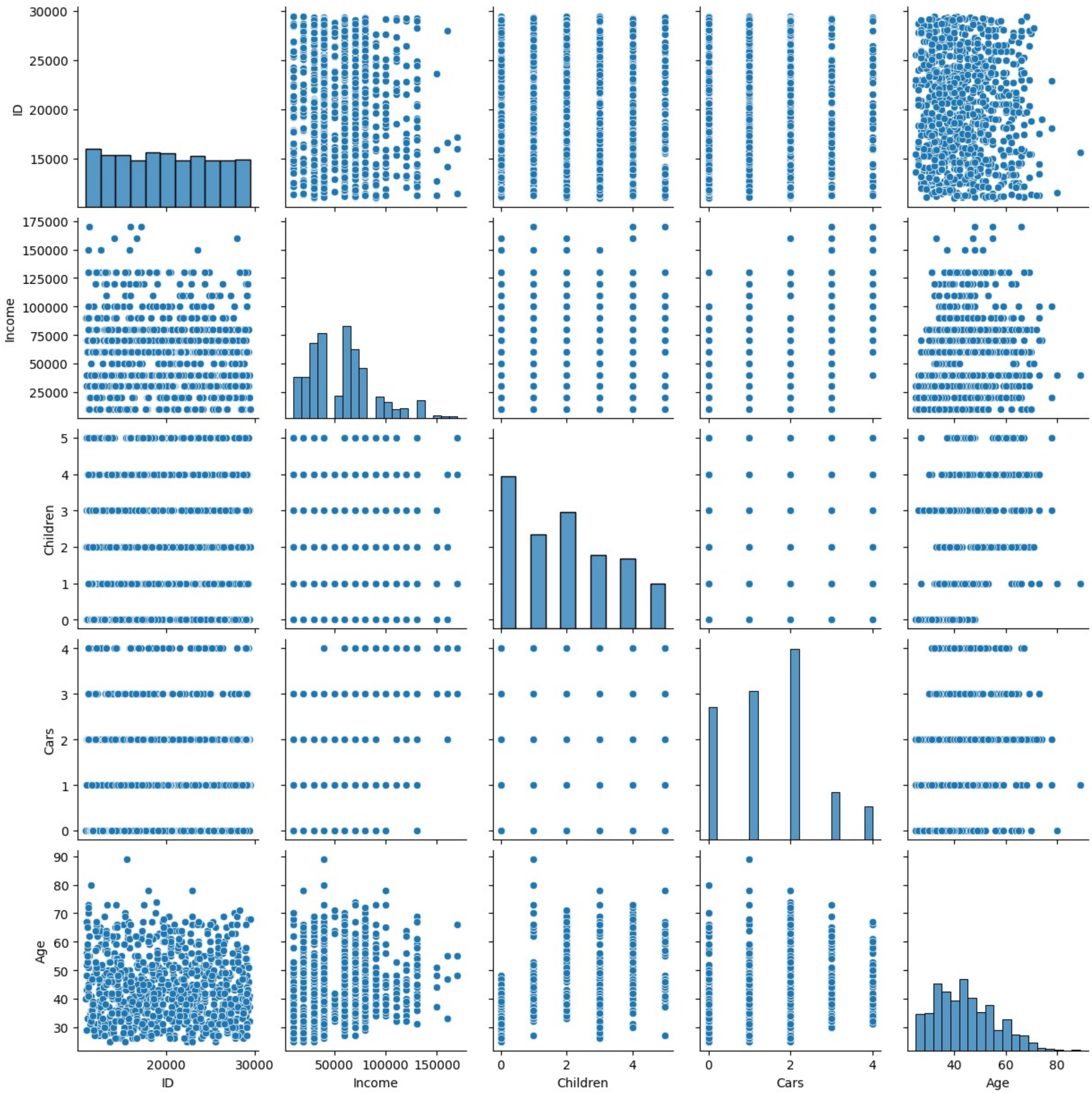
- There is no multicollinearity

In [ ]:

```
sb.pairplot(dfa)
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x22d61f1a170>
```



Data Wrangling

In [ ]:
```
## Checking For Duplicate Values
dfa.duplicated().sum()
```

Out[ ]: 0

In [ ]:
```
## Checing for missing values
dfa.isnull().sum()
```

Out[ ]:
```
ID                  0
Marital Status      7
Gender             11
Income              6
Children            8
Education           0
Occupation          0
Home Owner          4
Cars                9
Commute Distance    0
Region              0
Age                 8
Purchased Bike      0
dtype: int64
```

In [ ]:
```
# Drop rows with missing values in the numeric_attribute DataFrame
numeric_attribute_cleaned = numeric_attribute.dropna()
```

In [ ]:
```
numeric_attribute_cleaned.isnull().sum()
```

Out[ ]:
```
ID          0
Income      0
Children    0
Cars        0
Age         0
dtype: int64
```

In [ ]:
```
dfb = dfa.copy()
```

In [ ]:
```
dfb.isnull().sum()
```

Out[ ]:
```
ID                   0
Marital Status       7
Gender              11
Income               6
Children             8
Education            0
Occupation           0
Home Owner           4
Cars                 9
Commute Distance     0
Region               0
Age                  8
Purchased Bike       0
dtype: int64
```

In [ ]:
```
# Assuming 'numeric_attribute' contains the column names of numeric attributes
numeric_attribute = numeric_attribute_cleaned.columns.tolist()
# Add imputed numeric attributes to dfb
dfb[numeric_attribute] = numeric_attribute_cleaned
```

In [ ]:
```
dfb.isnull().sum()
```

Out[ ]:
```
ID                  29
Marital Status       7
Gender              11
Income              29
Children            29
Education            0
Occupation           0
Home Owner           4
Cars                29
Commute Distance     0
Region               0
Age                 29
Purchased Bike       0
dtype: int64
```

In [ ]:
```
for col in ['Marital Status', 'Gender', 'Home Owner']:
    mode_val = dfb[col].mode()[0]
    dfb[col].fillna(mode_val, inplace=True)

# Weighted random sampling for Region
region_counts = dfb['Region'].value_counts(normalize=True)
missing_indices = dfb[dfb['Region'].isnull()].index
imputed_values = np.random.choice(region_counts.index, size=len(missing_indices), p=region_counts.values)
dfb.loc[missing_indices, 'Region'] = imputed_values
```

In [ ]:
```
dfb.isnull().sum()
```

Out[ ]:
```
ID                  29
Marital Status       0
Gender               0
Income              29
Children            29
Education            0
Occupation           0
Home Owner           0
Cars                29
Commute Distance     0
Region               0
Age                 29
Purchased Bike       0
dtype: int64
```

In [ ]:
```
dfb = dfb.dropna()
```

- Here we dealt with missing vals

In [ ]:
```
dfb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 971 entries, 0 to 999
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   ID                971 non-null    float64
 1   Marital Status    971 non-null    object 
 2   Gender            971 non-null    object 
 3   Income            971 non-null    float64
 4   Children          971 non-null    float64
 5   Education         971 non-null    object 
 6   Occupation        971 non-null    object 
 7   Home Owner        971 non-null    object 
 8   Cars              971 non-null    float64
 9   Commute Distance  971 non-null    object 
 10  Region            971 non-null    object 
 11  Age               971 non-null    float64
 12  Purchased Bike    971 non-null    object 
dtypes: float64(5), object(8)
memory usage: 106.2+ KB
```

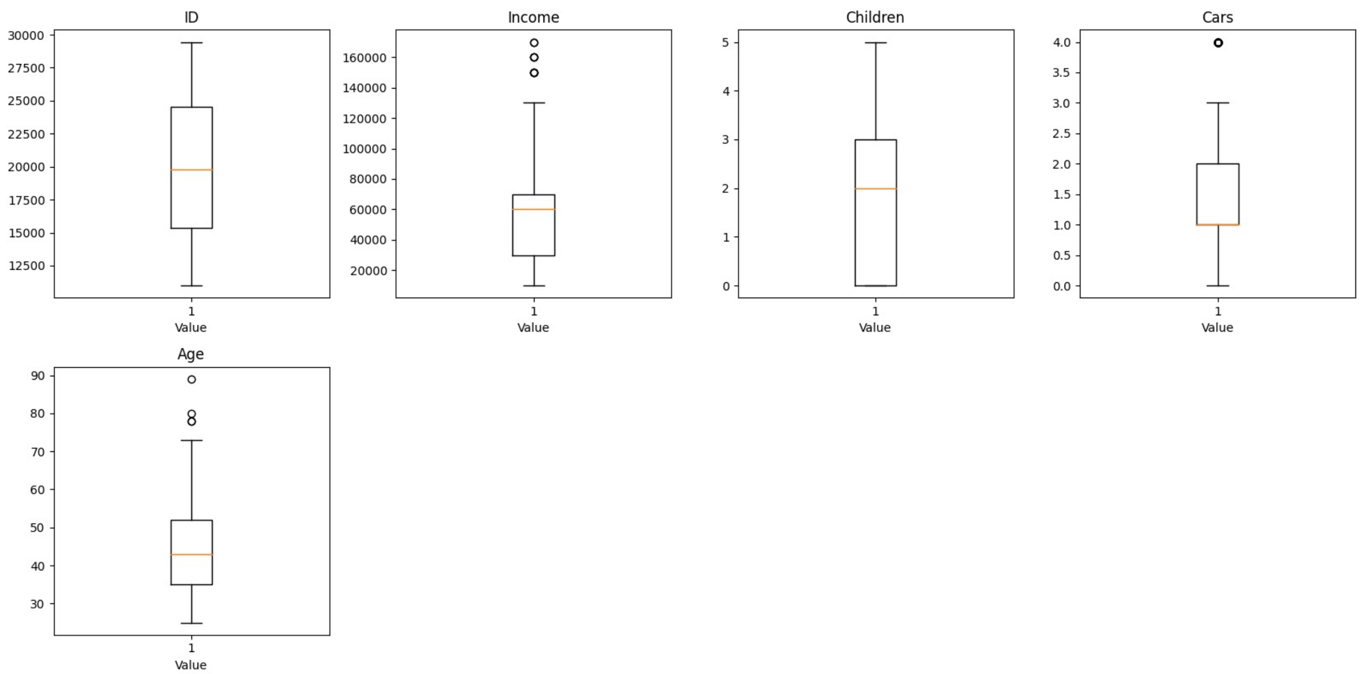
In [ ]:
```
categorical_attribute = dfa.select_dtypes(include = ['object'])
```

Outliers

In [ ]:
```
numeric_attribute
```

Out[ ]:
```
['ID', 'Income', 'Children', 'Cars', 'Age']
```

In [ ]:
```
import math
nc = dfb.select_dtypes(include = ['int64', 'float64'])
# Calculate the number of rows and columns for subplots
num_cols = len(nc.columns)
num_rows = math.ceil(num_cols / 4)  # Adjust the number of columns per row as needed

plt.figure(figsize=(16, 4 * num_rows))

for i, column in enumerate(nc.columns):
    plt.subplot(num_rows, 4, i+1)

    plt.boxplot(nc[column])

    plt.title(column)

    plt.xlabel('Value')
    plt.ylabel('')

plt.tight_layout()
plt.show()
```



In [ ]:
```
from scipy import stats
z_scores = stats.zscore(dfb[['Income', 'Age']])
threshold = 3
outliers = (abs(z_scores) > threshold).any(axis=1)
```

```
rows_with_outliers = dfb[outliers]
print("Rows with outliers:")
rows_with_outliers
```

Rows with outliers:

Out[ ]:

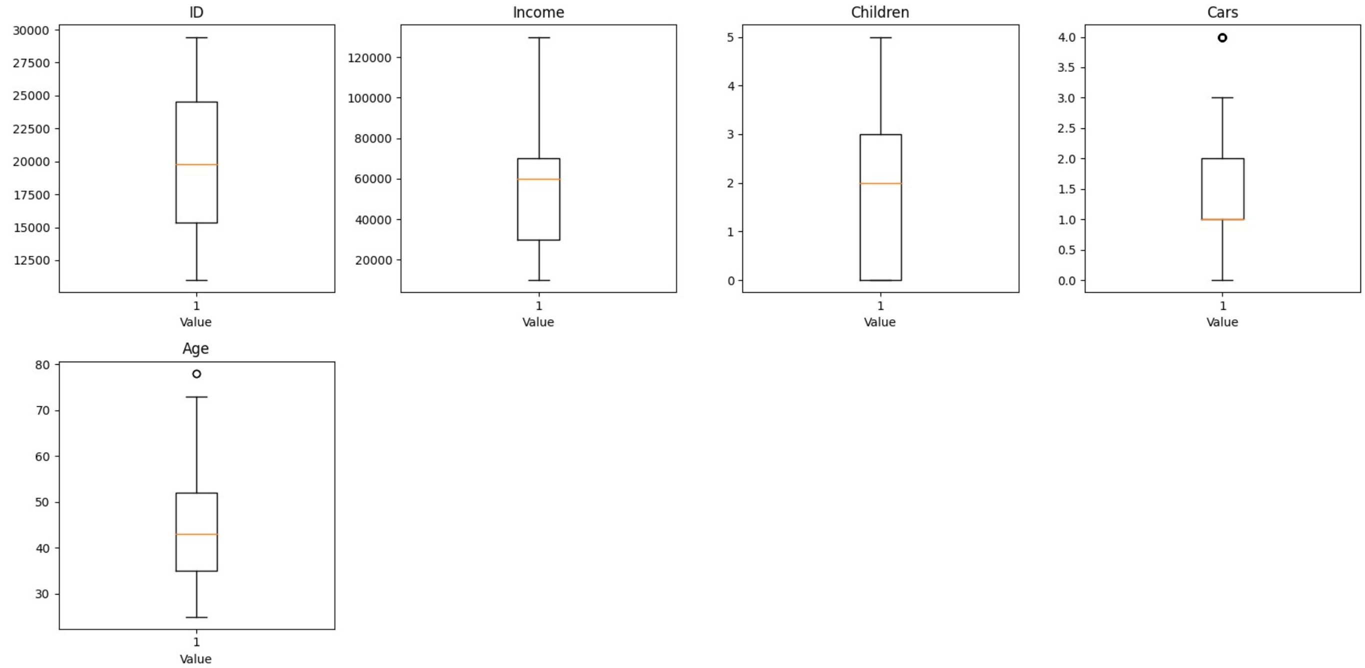
	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
6	27974.0	Single	Male	160000.0	2.0	High School	Management	Yes	4.0	0-1 Miles	Pacific	33.0	Yes
43	17185.0	Married	Female	170000.0	4.0	Partial College	Professional	No	3.0	5-10 Miles	Europe	48.0	Yes
121	15922.0	Married	Male	150000.0	2.0	High School	Professional	Yes	4.0	0-1 Miles	Europe	48.0	No
178	14191.0	Married	Male	160000.0	4.0	Partial College	Professional	No	2.0	10+ Miles	Europe	55.0	Yes
259	12705.0	Married	Male	150000.0	0.0	Bachelors	Management	Yes	4.0	0-1 Miles	Pacific	37.0	Yes
321	16675.0	Single	Female	160000.0	0.0	Graduate Degree	Management	No	3.0	0-1 Miles	Pacific	47.0	Yes
356	23608.0	Married	Female	150000.0	3.0	High School	Professional	Yes	3.0	0-1 Miles	Europe	51.0	Yes
375	15628.0	Married	Female	40000.0	1.0	Bachelors	Skilled Manual	Yes	1.0	0-1 Miles	Europe	89.0	No
401	11555.0	Married	Female	40000.0	1.0	Bachelors	Clerical	Yes	0.0	0-1 Miles	Europe	80.0	No
829	16009.0	Single	Male	170000.0	1.0	Graduate Degree	Management	No	4.0	0-1 Miles	North America	66.0	No
993	11292.0	Single	Male	150000.0	1.0	Partial College	Professional	No	3.0	0-1 Miles	North America	44.0	Yes

In [ ]:

```
z_scores = stats.zscore(dfb[['Income', 'Age']])
threshold = 3
outliers = (abs(z_scores) > threshold).any(axis=1)
average_income = dfb['Income'].mean()
average_age = dfb['Age'].mean()
dfb.loc[outliers, 'Income'] = average_income
dfb.loc[outliers, 'Age'] = average_age
```

In [ ]:

```
import math

nc = dfb.select_dtypes(include = ['int64', 'float64'])
# Calculate the number of rows and columns for subplots
num_cols = len(nc.columns)
num_rows = math.ceil(num_cols / 4)  # Adjust the number of columns per row as needed

# Set the figure size
plt.figure(figsize=(16, 4 * num_rows))

# Iterate through each numerical column
for i, column in enumerate(nc.columns):
    plt.subplot(num_rows, 4, i+1)
    plt.boxplot(nc[column])
    plt.title(column)
    plt.xlabel('Value')
    plt.ylabel('')

plt.tight_layout()
plt.show()
```

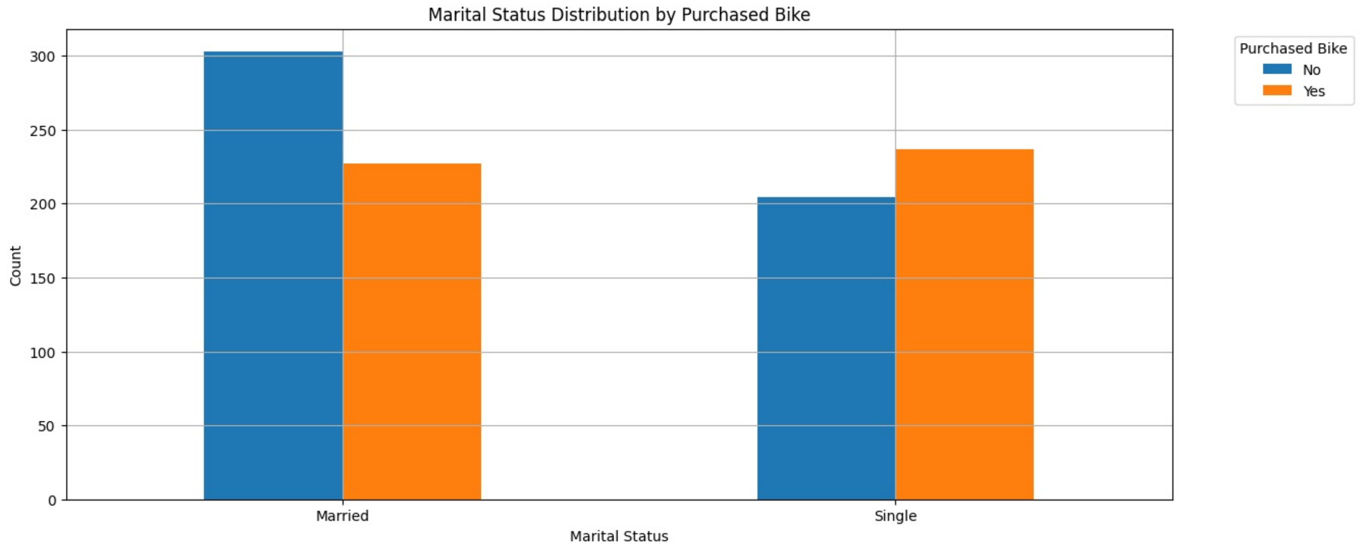


Exploratory Data Analysis (EDA)

--> How many people with what marital status purchased bike

```
In [ ]: plt.figure(figsize=(14, 7))

        # Grouping data by 'Marital Status' and 'Purchased Bike'
        grouped_data = dfb.groupby(['Marital Status', 'Purchased Bike']).size().unstack(fill_value=0)

        # Plotting grouped bar plot
        grouped_data.plot(kind='bar', stacked=False, figsize=(14, 6))

        plt.title('Marital Status Distribution by Purchased Bike')
        plt.xlabel('Marital Status')
        plt.ylabel('Count')
        plt.grid()
        plt.xticks(rotation=0)
        plt.legend(title='Purchased Bike', bbox_to_anchor=(1.05, 1), loc='upper left')
        plt.show()
```

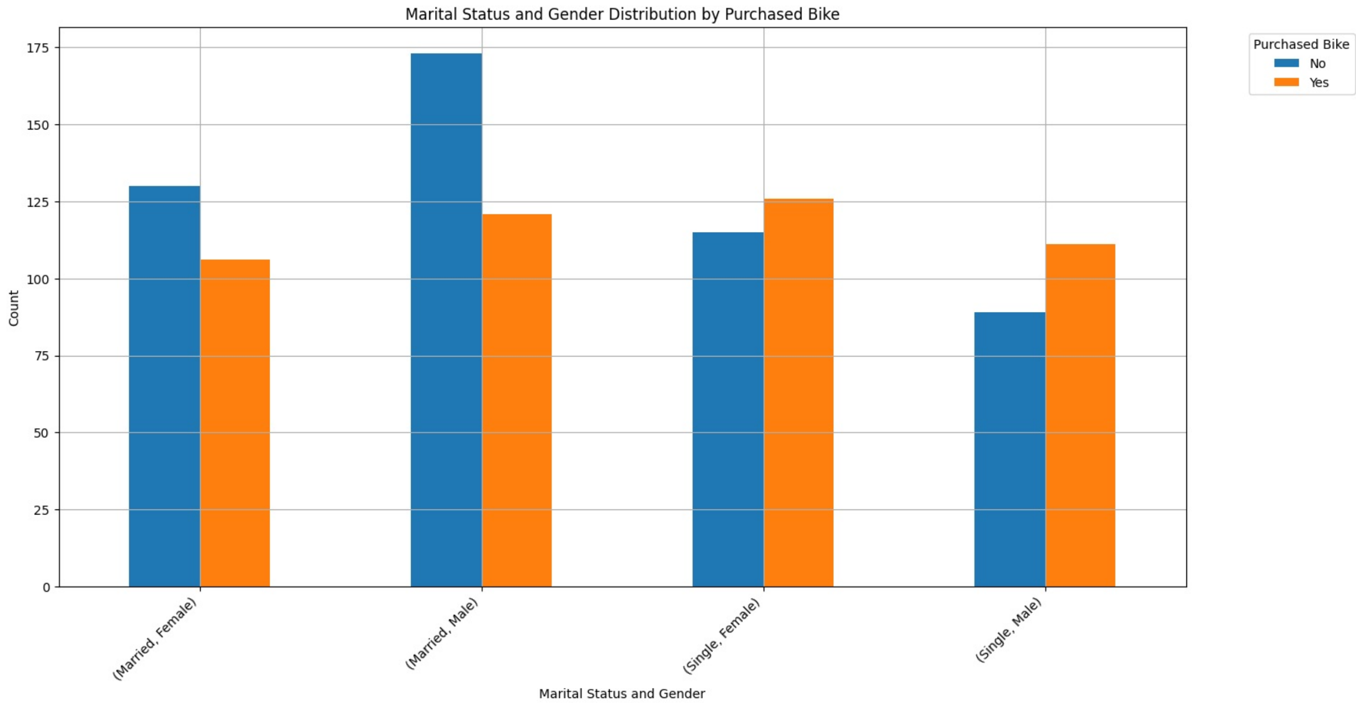
<Figure size 1400x700 with 0 Axes>



--> People with gender and marital status purchaed bike or not

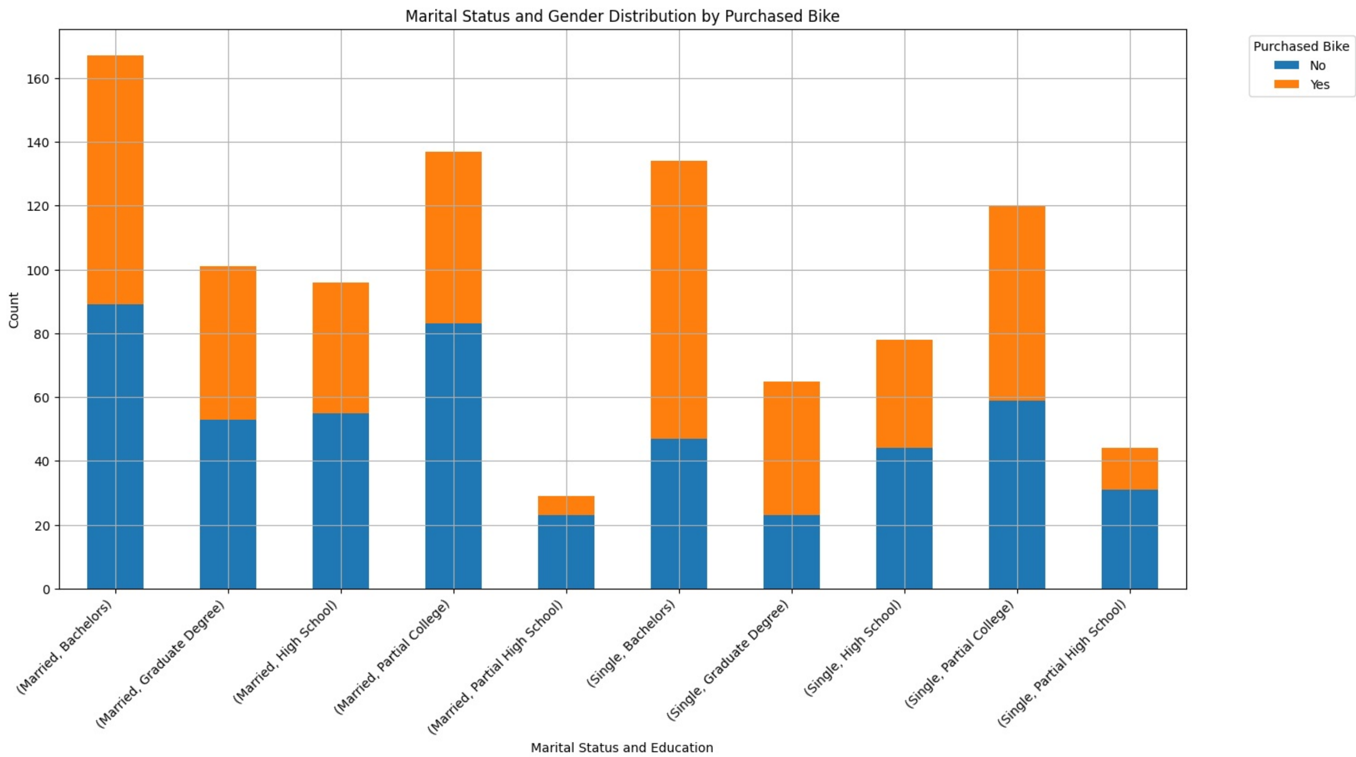
```
In [ ]: # Grouping data by 'Marital Status', 'Gender', and 'Purchased Bike'
        grouped_data = dfb.groupby(['Marital Status', 'Gender', 'Purchased Bike']).size().unstack(fill_value=0)

        # Plotting grouped bar plot
        grouped_data.plot(kind='bar', stacked=False, figsize=(16, 8))

        plt.title('Marital Status and Gender Distribution by Purchased Bike')
        plt.xlabel('Marital Status and Gender')
```

```
plt.ylabel('Count')
plt.grid()
plt.xticks(rotation=45, ha='right')
plt.legend(title='Purchased Bike', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



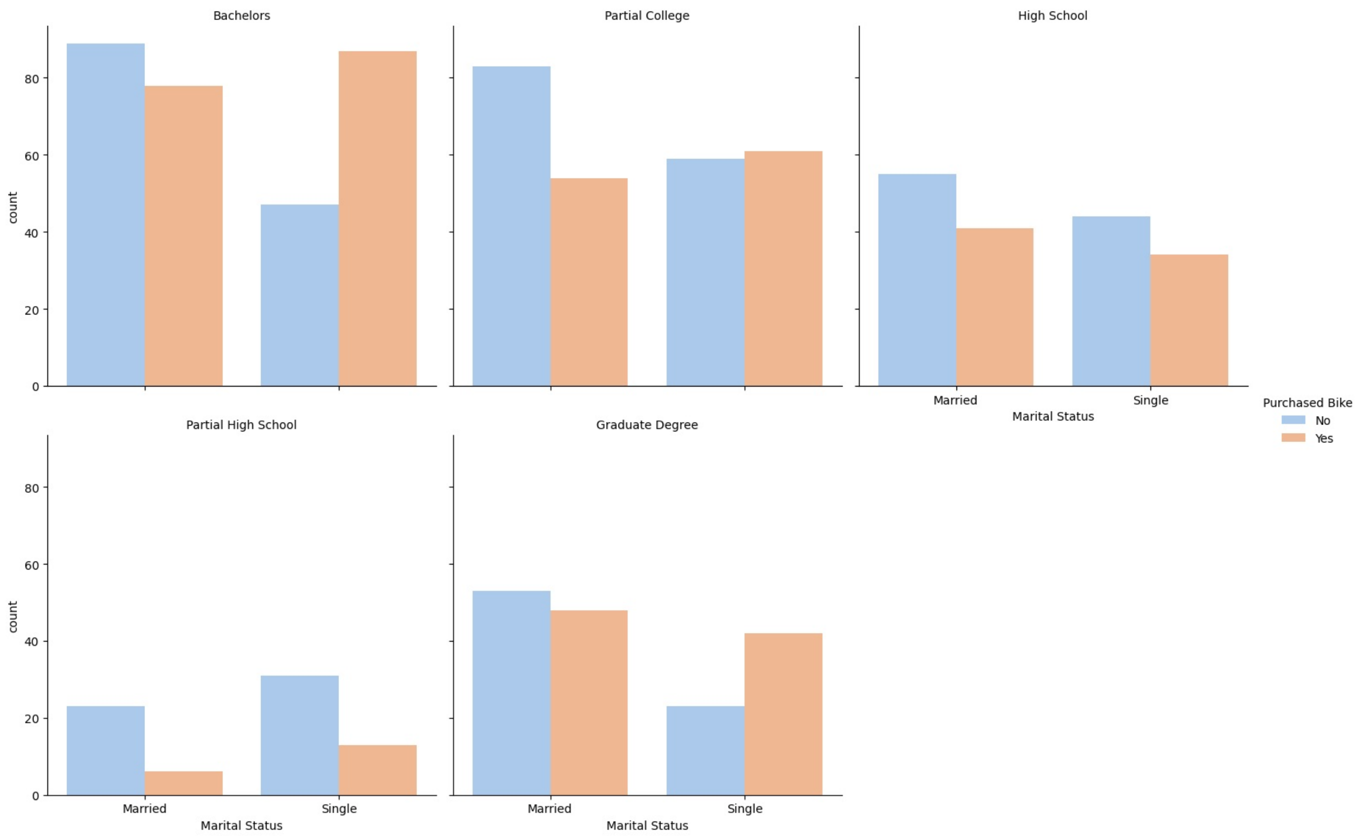
In [ ]:

```
# Stacked Bar Plot
stacked_data = dfb.groupby(['Marital Status', 'Education', 'Purchased Bike']).size().unstack(fill_value=0)
stacked_data.plot(kind='bar', stacked=True, figsize=(16, 8))
plt.title('Marital Status and Gender Distribution by Purchased Bike')
plt.xlabel('Marital Status and Education')
plt.ylabel('Count')
plt.grid()
plt.xticks(rotation=45, ha='right')
plt.legend(title='Purchased Bike', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



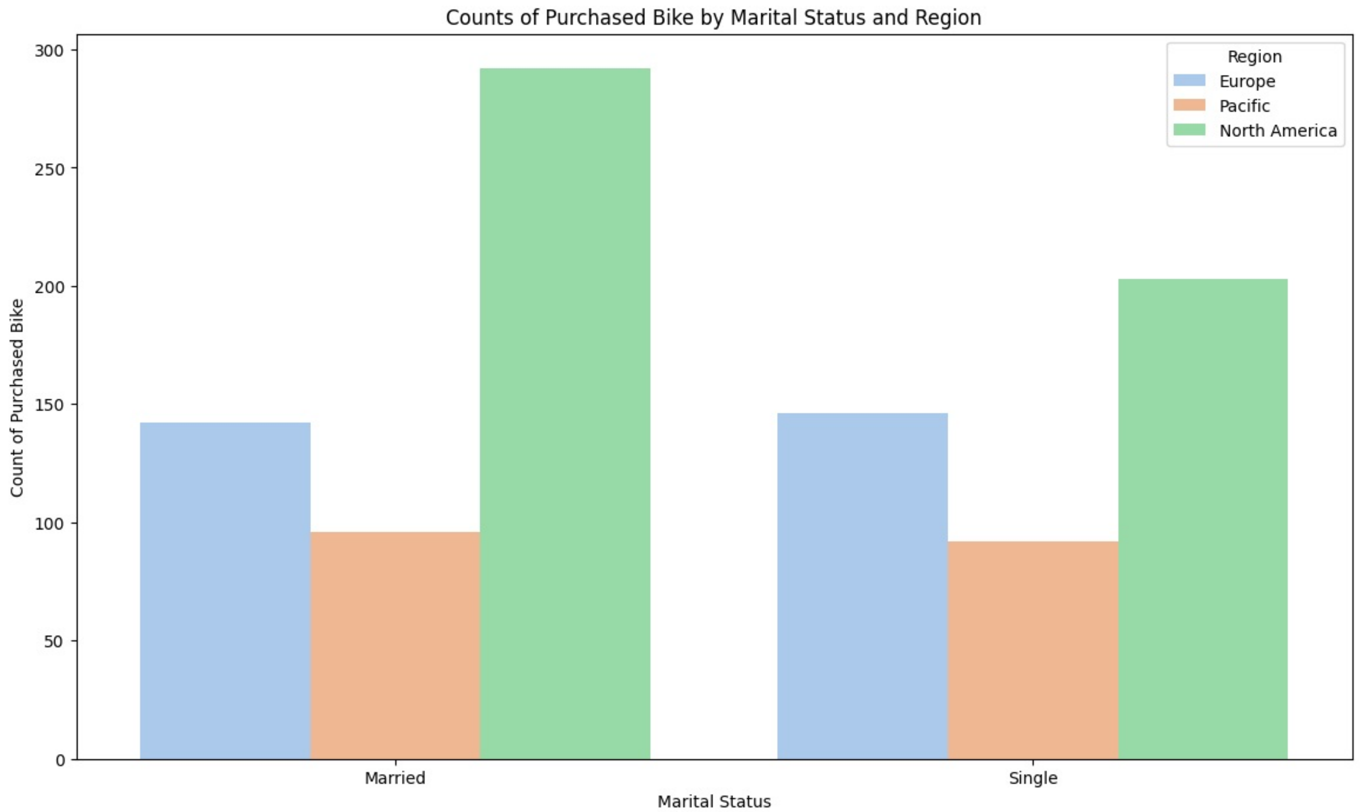
In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt

# Faceted Bar Plot
g = sns.catplot(data=dfb, kind='count', x='Marital Status', col='Education', hue='Purchased Bike', palette='pas
g.set_titles('{col_name}')
plt.show()
```



Married persons in each region

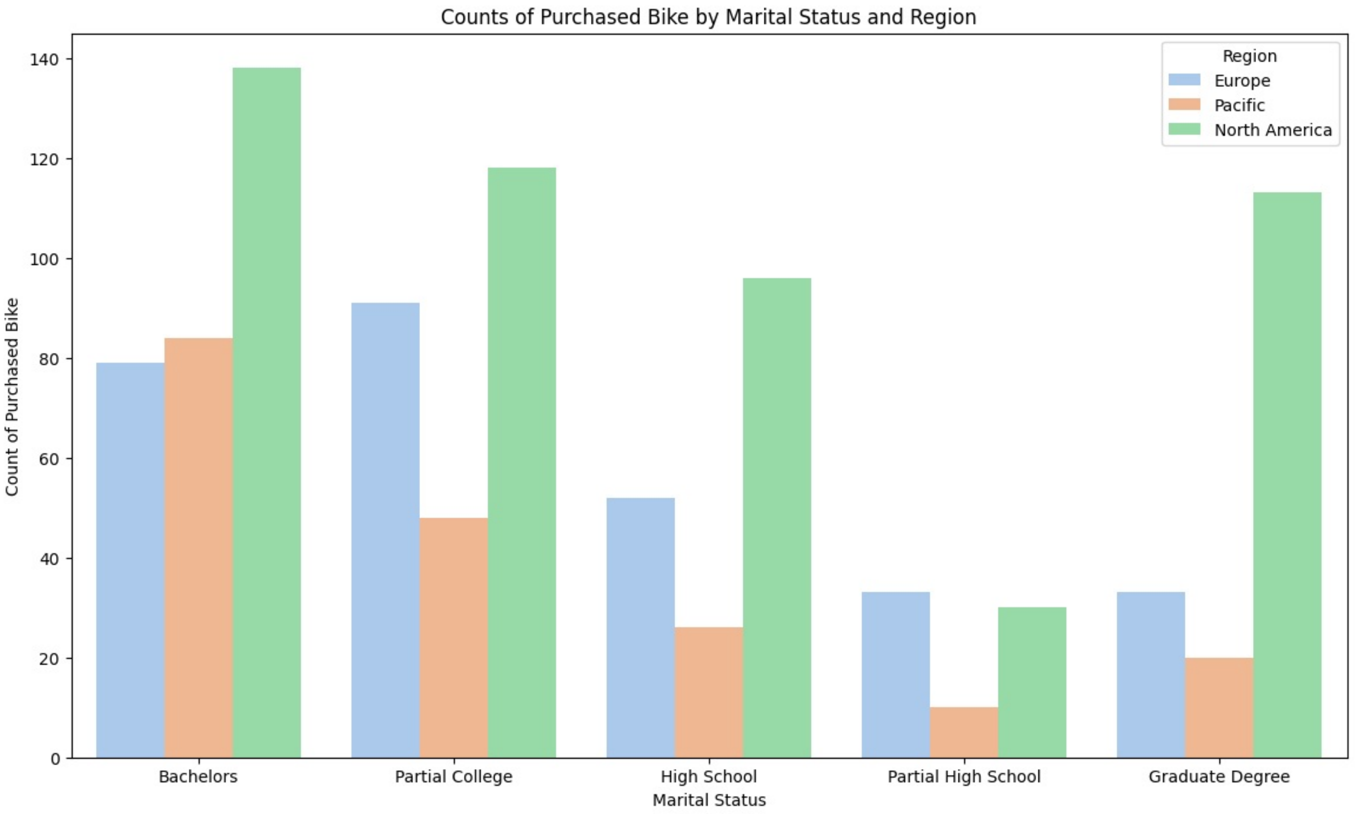
In [ ]:
```
# Create a clustered bar chart
plt.figure(figsize=(14, 8))
sns.countplot(data=dfb, x='Marital Status', hue='Region', palette='pastel')
plt.title('Counts of Purchased Bike by Marital Status and Region')
plt.xlabel('Marital Status')
plt.ylabel('Count of Purchased Bike')
plt.legend(title='Region', loc='upper right')
plt.show()
```



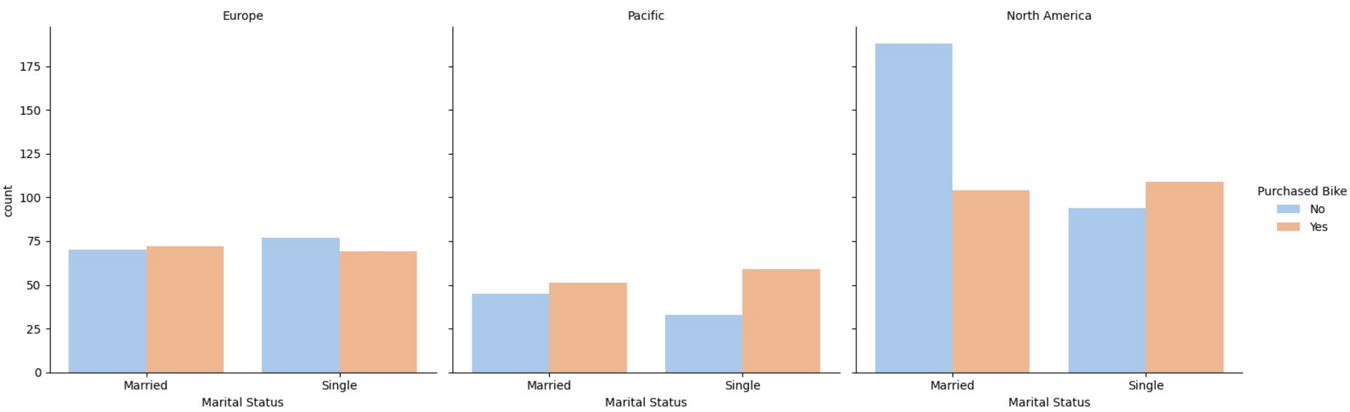
Education in each region

In [ ]:
```
# Create a clustered bar chart
plt.figure(figsize=(14, 8))
sns.countplot(data=dfb, x='Education', hue='Region', palette='pastel')
plt.title('Counts of Purchased Bike by Marital Status and Region')
```

```
plt.xlabel('Marital Status')
plt.ylabel('Count of Purchased Bike')
plt.legend(title='Region', loc='upper right')
plt.show()
```



In [ ]:
```
# Faceted Bar Plot
g = sb.catplot(data=dfb, kind='count', x='Marital Status', col='Region', hue='Purchased Bike', palette='pastel'
g.set_titles('{col_name}')
plt.show()
```



Feature Engineering

In [ ]:
```
dfb['ID'] = dfb['ID'].astype(int)
dfb['Income'] = dfb['Income'].astype(int)
dfb['Children'] = dfb['Children'].astype(int)
dfb['Cars'] = dfb['Cars'].astype(int)
dfb['Age'] = dfb['Age'].astype(int)
```

In [ ]:
```
dfc = dfb.copy()
```

In [ ]:
```
dfc.head()
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
0	12496	Married	Female	40000	1	Bachelors	Skilled Manual	Yes	0	0-1 Miles	Europe	42	No
1	24107	Married	Male	30000	3	Partial College	Clerical	Yes	1	0-1 Miles	Europe	43	No
2	14177	Married	Male	80000	5	Partial College	Professional	No	2	2-5 Miles	Europe	60	No
3	24381	Single	Male	70000	0	Bachelors	Professional	Yes	1	5-10 Miles	Pacific	41	Yes
4	25597	Single	Male	30000	0	Bachelors	Clerical	No	0	0-1 Miles	Europe	36	Yes

In [ ]:
```
from sklearn.preprocessing import OneHotEncoder
```

Label Encoding

In [ ]:
```
dfc['Gender'] = dfc['Gender'].map({'Male':1, 'Female':0})
dfc['Home Owner'] = dfc['Home Owner'].map({'Yes':1, 'No':0})
dfc['Purchased Bike'] = dfc['Purchased Bike'].map({'Yes':1, 'No':0})
dfc['Marital Status'] = dfc['Marital Status'].map({'Married':1, 'Single':0})
```

In [ ]:
```
dfc.head()
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
0	12496	1	0	40000	1	Bachelors	Skilled Manual	1	0	0-1 Miles	Europe	42	0
1	24107	1	1	30000	3	Partial College	Clerical	1	1	0-1 Miles	Europe	43	0
2	14177	1	1	80000	5	Partial College	Professional	0	2	2-5 Miles	Europe	60	0
3	24381	0	1	70000	0	Bachelors	Professional	1	1	5-10 Miles	Pacific	41	1
4	25597	0	1	30000	0	Bachelors	Clerical	0	0	0-1 Miles	Europe	36	1

In [ ]:
```
dfd = dfc.copy()
```

In [ ]:
```
# Define the custom rank mapping
education_mapping = {
    'Partial High School': 0,
    'High School': 1,
    'Partial College': 2,
    'Bachelors': 3,
    'Graduate Degree': 4
}


dfd['Education'] = dfd['Education'].map(education_mapping)
```

In [ ]:
```
dfd.head()
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
0	12496	1	0	40000	1	3	Skilled Manual	1	0	0-1 Miles	Europe	42	0
1	24107	1	1	30000	3	2	Clerical	1	1	0-1 Miles	Europe	43	0
2	14177	1	1	80000	5	2	Professional	0	2	2-5 Miles	Europe	60	0
3	24381	0	1	70000	0	3	Professional	1	1	5-10 Miles	Pacific	41	1
4	25597	0	1	30000	0	3	Clerical	0	0	0-1 Miles	Europe	36	1

Random Sampling

In [ ]:
```
# Random sampling
random_sample = dfd.sample(n=3, random_state=42)
```

In [ ]:
```
random_sample
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
173	17907	1	0	10000	0	2	Manual	1	1	2-5 Miles	Pacific	27	0
862	22330	1	1	50000	0	4	Skilled Manual	1	0	1-2 Miles	North America	32	1
78	15752	1	1	80000	2	1	Skilled Manual	0	2	1-2 Miles	Pacific	50	1

Stratified Sampling

In [ ]:
```
# Stratified sampling
stratified_sample, _ = train_test_split(dfd, test_size=0.4,
                                        stratify=dfd['Purchased Bike'], random_state=42)
```

In [ ]:
```
stratified_sample.head()
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
566	18847	1	0	60000	2	4	Management	1	2	5-10 Miles	North America	70	0
903	14432	0	1	90000	4	4	Management	1	1	5-10 Miles	North America	73	0
813	25899	1	0	70000	2	1	Professional	1	2	10+ Miles	North America	53	0
73	26956	0	0	20000	0	2	Manual	0	1	2-5 Miles	Europe	36	1
782	16112	0	1	70000	4	3	Professional	1	2	2-5 Miles	North America	43	1

Systematic Sampling

In [ ]:
```
# Systematic sampling
k = 2
indices = np.arange(0, len(dfd), k)
systematic_sample = dfd.iloc[indices]
```

In [ ]:
```
systematic_sample.head()
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike
0	12496	1	0	40000	1	3	Skilled Manual	1	0	0-1 Miles	Europe	42	0
2	14177	1	1	80000	5	2	Professional	0	2	2-5 Miles	Europe	60	0
4	25597	0	1	30000	0	3	Clerical	0	0	0-1 Miles	Europe	36	1
6	27974	0	1	56179	2	1	Management	1	4	0-1 Miles	Pacific	44	1
8	22155	1	1	20000	2	0	Clerical	1	2	5-10 Miles	Pacific	58	0

Dissimilarity Matrix

- Nominal Attributes: For this example, let's use 'Occupation' and 'Region'.
- Ordinal Attributes: We'll use 'Education' and 'Commute Distance'.
- Binary Attributes: We'll use 'Marital Status' and 'Gender'.
- Numeric Attributes: We'll use 'Income' and 'Age'.

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
from scipy.spatial.distance import pdist, squareform

label_encoders = {}
for column in ['Occupation', 'Region', 'Education', 'Commute Distance']:
    le = LabelEncoder()
    dfd[column] = le.fit_transform(dfd[column])
    label_encoders[column] = le

# Dissimilarity matrix for Nominal attributes: 'Occupation' and 'Region'
nominal_dissimilarity_matrix = squareform(pdist(dfd[['Occupation', 'Region']], metric='euclidean'))
```

```
# Dissimilarity matrix for Ordinal attributes: 'Education' and 'Commute Distance'
ordinal_dissimilarity_matrix = squareform(pdist(dfd[['Education', 'Commute Distance']], metric='euclidean'))
```

In [ ]:
```
import numpy as np

# Dissimilarity matrix for Binary attributes: 'Marital Status' and 'Gender'
binary_dissimilarity_matrix = np.zeros((len(dfd), len(dfd)))
marital_status = dfd['Marital Status'].values
gender = dfd['Gender'].values

for i in range(len(dfd)):
    for j in range(len(dfd)):
        if marital_status[i] == marital_status[j] and gender[i] == gender[j]:
            binary_dissimilarity_matrix[i][j] = 0
        else:
            binary_dissimilarity_matrix[i][j] = 1
```

In [ ]:
```
# Dissimilarity matrix for Numeric attributes: 'Income' and 'Age'
numeric_dissimilarity_matrix = squareform(pdist(dfd[['Income', 'Age']], metric='euclidean'))
```

In [ ]:
```
print("Dissimilarity Matrix for Nominal Attributes (Occupation, Region):\n\n", nominal_dissimilarity_matrix)
print("\n\nDissimilarity Matrix for Ordinal Attributes (Education, Commute Distance):\n\n", ordinal_dissimilari
print("\n\nDissimilarity Matrix for Binary Attributes (Marital Status, Gender):\n\n", binary_dissimilarity_matr
print("\n\nDissimilarity Matrix for Numeric Attributes (Income, Age):\n", numeric_dissimilarity_matrix)
```

```
Dissimilarity Matrix for Nominal Attributes (Occupation, Region):

 [[0.         4.         1.         ... 1.         3.16227766 1.41421356]
 [4.         0.         3.         ... 4.12310563 1.41421356 3.16227766]
 [1.         3.         0.         ... 1.41421356 2.23606798 1.        ]
 ...
 [1.         4.12310563 1.41421356 ... 0.         3.         1.        ]
 [3.16227766 1.41421356 2.23606798 ... 3.         0.         2.        ]
 [1.41421356 3.16227766 1.         ... 1.         2.         0.        ]]


Dissimilarity Matrix for Ordinal Attributes (Education, Commute Distance):

 [[0.         1.         3.16227766 ... 0.         1.         2.82842712]
 [1.         0.         3.         ... 1.         1.41421356 2.23606798]
 [3.16227766 3.         0.         ... 3.16227766 2.23606798 1.41421356]
 ...
 [0.         1.         3.16227766 ... 0.         1.         2.82842712]
 [1.         1.41421356 2.23606798 ... 1.         0.         2.23606798]
 [2.82842712 2.23606798 1.41421356 ... 2.82842712 2.23606798 0.        ]]


Dissimilarity Matrix for Binary Attributes (Marital Status, Gender):

 [[0. 1. 1. ... 1. 1. 1.]
 [1. 0. 0. ... 0. 1. 1.]
 [1. 0. 0. ... 0. 1. 1.]
 ...
 [1. 0. 0. ... 0. 1. 1.]
 [1. 1. 1. ... 1. 0. 0.]
 [1. 1. 1. ... 1. 0. 0.]]


Dissimilarity Matrix for Numeric Attributes (Income, Age):
 [[0.00000000e+00 1.00000001e+04 4.00000040e+04 ... 2.00000004e+04
  6.00000001e+04 2.00000030e+04]
 [1.00000001e+04 0.00000000e+00 5.00000029e+04 ... 3.00000004e+04
  7.00000002e+04 3.00000017e+04]
 [4.00000040e+04 5.00000029e+04 0.00000000e+00 ... 2.00000121e+04
  2.00000121e+04 2.00000012e+04]
 ...
 [2.00000004e+04 3.00000004e+04 2.00000121e+04 ... 0.00000000e+00
  4.00000000e+04 1.50000000e+01]
 [6.00000001e+04 7.00000002e+04 2.00000121e+04 ... 4.00000000e+04
  0.00000000e+00 4.00000028e+04]
 [2.00000030e+04 3.00000017e+04 2.00000012e+04 ... 1.50000000e+01
  4.00000028e+04 0.00000000e+00]]
```

Hunt's Algorithm

In [ ]:
```
df_encoded = dfd.copy()
```

In [ ]:
```
import numpy as np

class Node:
```

```python
    def __init__(self, attribute=None, value=None, leaf_class=None):
        self.attribute = attribute  # Attribute to split on
        self.value = value  # Value of the attribute for splitting
        self.leaf_class = leaf_class  # Class label for leaf nodes
        self.children = {}  # Dictionary to store child nodes {value: child_node}

def entropy(y):
    _, counts = np.unique(y, return_counts=True)
    probabilities = counts / len(y)
    return -np.sum(probabilities * np.log2(probabilities))

def information_gain(X, y, attribute, value):
    # Split dataset based on the given attribute and value
    left_indices = X[:, attribute] == value
    right_indices = ~left_indices

    # Calculate entropy before splitting
    entropy_before = entropy(y)

    # Calculate entropy after splitting
    entropy_left = entropy(y[left_indices])
    entropy_right = entropy(y[right_indices])

    # Calculate information gain
    num_left = np.sum(left_indices)
    num_right = np.sum(right_indices)
    total_instances = len(y)
    information_gain = entropy_before - ((num_left / total_instances) * entropy_left + (num_right / total_insta

    return information_gain

def hunt(X, y, attributes):
    if len(np.unique(y)) == 1:  # If all instances have the same class label
        return Node(leaf_class=y[0])

    if len(attributes) == 0:  # If there are no more attributes to split on
        return Node(leaf_class=np.argmax(np.bincount(y)))  # Return the class with the majority vote

    best_attribute = None
    best_value = None
    best_information_gain = -np.inf

    for attribute in attributes:
        unique_values = np.unique(X[:, attribute])
        for value in unique_values:
            gain = information_gain(X, y, attribute, value)
            if gain > best_information_gain:
                best_information_gain = gain
                best_attribute = attribute
                best_value = value

    if best_information_gain <= 0:  # If no attribute provides information gain
        return Node(leaf_class=np.argmax(np.bincount(y)))  # Return the class with the majority vote

    node = Node(attribute=best_attribute, value=best_value)
    remaining_attributes = [a for a in attributes if a != best_attribute]
    for value in np.unique(X[:, best_attribute]):
        indices = X[:, best_attribute] == value
        child_node = hunt(X[indices], y[indices], remaining_attributes)
        node.children[value] = child_node

    return node

# Prepare data
X = df_encoded.drop(columns=['ID', 'Purchased Bike']).values
y = df_encoded['Purchased Bike'].values
attributes = list(range(X.shape[1]))

# Build decision tree using Hunt's algorithm
root_node = hunt(X, y, attributes)

# Print decision tree
def print_tree(node, depth=0):
    if node.leaf_class is not None:
        print(depth * '  ', 'Predict:', node.leaf_class)
    else:
        print(depth * '  ', 'Attribute:', node.attribute, 'Value:', node.value)
        for value, child_node in node.children.items():
            print(depth * '  ', '  ', 'Value:', value)
            print_tree(child_node, depth + 1)

print_tree(root_node)
```

```
Attribute: 7 Value: 2
```

```
    Value: 0
  Attribute: 10 Value: 38
      Value: 25
    Predict: 1
      Value: 26
    Predict: 1
      Value: 27
    Predict: 1
      Value: 28
    Predict: 1
      Value: 29
    Attribute: 1 Value: 0
        Value: 0
      Predict: 1
        Value: 1
      Predict: 0
      Value: 30
```

In [ ]:
```python
dfe = dfc.copy()
```

In [ ]:
```python
dfe['Commute Distance'].value_counts()
```

Out[ ]:
```
Commute Distance
0-1 Miles     350
5-10 Miles    187
1-2 Miles     165
2-5 Miles     160
10+ Miles     109
Name: count, dtype: int64
```

In [ ]:
```python
# Remove 'Miles' from 'Commute Distance'
dfe['Commute Distance'] = dfe['Commute Distance'].str.replace(' Miles', '')
dfe['Commute Distance'] = dfe['Commute Distance'].str.replace('10+', '10-10')
```

In [ ]:
```python
# Split 'Commute Distance' into 'minimum_miles' and 'maximum_miles'
dfe[['minimum_miles', 'maximum_miles']] = dfe['Commute Distance'].str.split('-', expand=True)
dfe['minimum_miles'] = dfe['minimum_miles'].astype(int)
dfe['maximum_miles'] = dfe['maximum_miles'].astype(int)
```

In [ ]:
```python
dfe.head()
```

Out[ ]:

	ID	Marital Status	Gender	Income	Children	Education	Occupation	Home Owner	Cars	Commute Distance	Region	Age	Purchased Bike	minimum_
0	12496	1	0	40000	1	Bachelors	Skilled Manual	1	0	0-1	Europe	42	0	
1	24107	1	1	30000	3	Partial College	Clerical	1	1	0-1	Europe	43	0	
2	14177	1	1	80000	5	Partial College	Professional	0	2	2-5	Europe	60	0	
3	24381	0	1	70000	0	Bachelors	Professional	1	1	5-10	Pacific	41	1	
4	25597	0	1	30000	0	Bachelors	Clerical	0	0	0-1	Europe	36	1	

Decision Tree

In [ ]:
```python
df_encoded = dfd.copy()
```

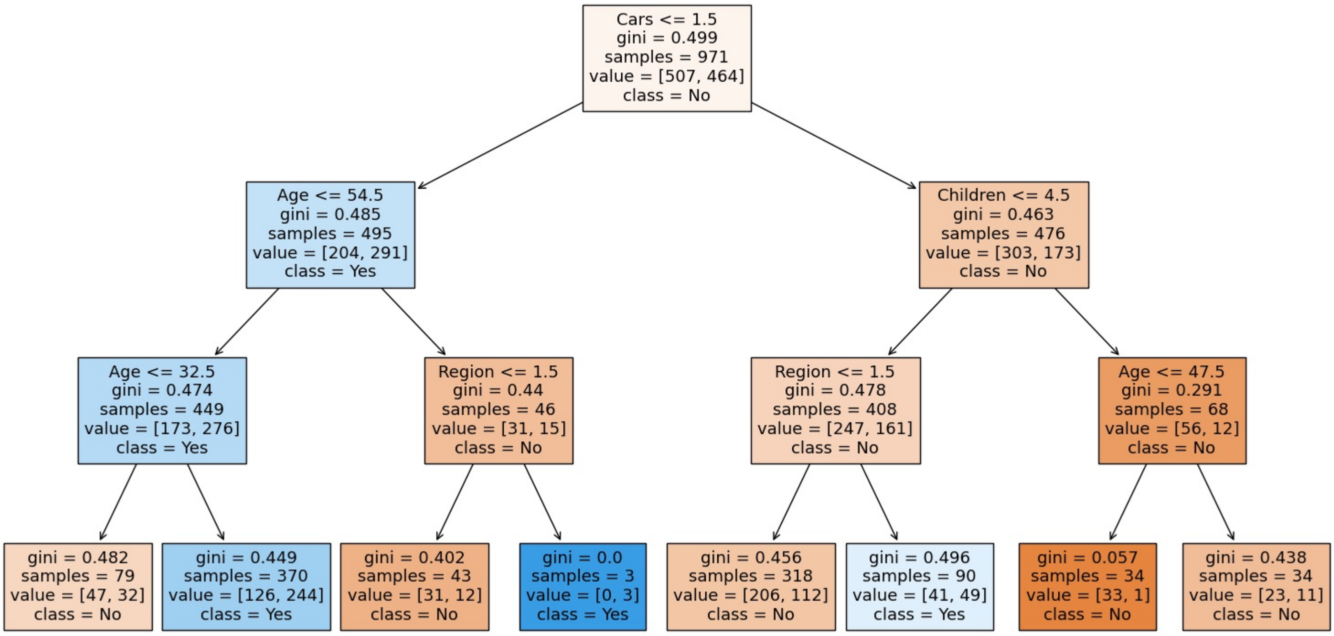
In [ ]:
```python
from sklearn.tree import DecisionTreeClassifier

# Prepare data
X = df_encoded.drop(columns=['ID', 'Purchased Bike'])
y = df_encoded['Purchased Bike']

# Initialize and fit Decision Tree
decision_tree = DecisionTreeClassifier(random_state=42)
decision_tree.fit(X, y)
```

Out[ ]: DecisionTreeClassifier

```
DecisionTreeClassifier(random_state=42)
```

In [ ]:

```python
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Initialize and fit Decision Tree with limited depth
decision_tree = DecisionTreeClassifier(max_depth=3, random_state=42)
decision_tree.fit(X, y)

# Plot decision tree with limited depth
plt.figure(figsize=(19, 10))
plot_tree(decision_tree, feature_names=X.columns, class_names=['No', 'Yes'], filled=True)
plt.show()
```



Classification

In [ ]:

```python
from sklearn.metrics import classification_report

# Predict using the decision tree
y_pred = decision_tree.predict(X)

# Classification report
classification_report = classification_report(y, y_pred, target_names=['No', 'Yes'])
print("Classification Report:\n", classification_report)
```

```
Classification Report:
               precision    recall  f1-score   support

          No       0.67      0.67      0.67       507
         Yes       0.64      0.64      0.64       464

    accuracy                           0.65       971
   macro avg       0.65      0.65      0.65       971
weighted avg       0.65      0.65      0.65       971
```