AML_HW1_S2024_Questions-2

February 15, 2024

0.1 Homework 1: Applied Machine Learning

[2]:
```
from google.colab import drive
drive.mount('/content/drive')

import os
os.chdir("/content/drive/MyDrive/1")
```

```
Mounted at /content/drive
```

This assignment covers contents of the first three lectures.

The emphasis for this assignment would be on the following: 1. Data Visualization and Analysis 2. Linear Models for Regression and Classification 3. Support Vector Machines

[3]:
```
import warnings

def fxn():
    warnings.warn("deprecated", DeprecationWarning)

with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()
```

[5]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from numpy.linalg import inv
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
 ↪OrdinalEncoder, LabelEncoder
from sklearn.metrics import r2_score, accuracy_score
from sklearn.svm import LinearSVC, SVC
```

0.2 Part 1: Data Visualization and Analysis

Data visualization comes in handy when we want to understand data characteristics and read patterns in datasets with thousands of samples and features.

Note: Remember to label plot axes while plotting.

0.2.1 The dataset to be used for this section is data / AdultIncome.csv

[4]:
```
# Load the dataset
adult_income_df = pd.read_csv("/content/drive/MyDrive/1/adult_income.csv")
adult_income_df
```

[4]:
```
       age workclass     education      marital status         occupation  \
0       90       NaN       HS-grad             Widowed                NaN
1       82   Private       HS-grad             Widowed    Exec-managerial
2       66       NaN  Some-college             Widowed                NaN
3       54   Private       7th-8th            Divorced  Machine-op-inspct
4       41   Private  Some-college           Separated     Prof-specialty
…     …         …           …                   …                …
32556   22   Private  Some-college       Never-married    Protective-serv
32557   27   Private    Assoc-acdm  Married-civ-spouse       Tech-support
32558   40   Private       HS-grad  Married-civ-spouse  Machine-op-inspct
32559   58   Private       HS-grad             Widowed       Adm-clerical
32560   22   Private       HS-grad       Never-married       Adm-clerical

        relationship   race  gender  capital gain  capital loss  \
0      Not-in-family  White  Female             0          4356
1      Not-in-family  White  Female             0          4356
2          Unmarried  Black  Female             0          4356
3          Unmarried  White  Female             0          3900
4          Own-child  White  Female             0          3900
…              …      …       …            …             …
32556  Not-in-family  White    Male             0             0
32557           Wife  White  Female             0             0
32558        Husband  White    Male             0             0
32559      Unmarried  White  Female             0             0
32560      Own-child  White    Male             0             0

       hours per week income  income_value
0                  40  <=50K         47710
1                  18  <=50K         40375
2                  40  <=50K         43369
3                  40  <=50K         32399
4                  40  <=50K         39642
…                …     …           …
32556              40  <=50K         41979
32557              38  <=50K         48434
```

```
32558                40   >50K       1247500
32559                40  <=50K         38473
32560                20  <=50K         35115

[32561 rows x 13 columns]
```

1.1 Handle the missing values of the data and Create a bar chart to compare the average income for Females and Males from Income Dataset. Are there differences in income ?

[5]:
```python
### Code here
adult_income_df.head()
```

[5]:
```
   age workclass     education marital status         occupation  \
0   90       NaN       HS-grad        Widowed                NaN
1   82   Private       HS-grad        Widowed    Exec-managerial
2   66       NaN  Some-college        Widowed                NaN
3   54   Private       7th-8th       Divorced  Machine-op-inspct
4   41   Private  Some-college      Separated     Prof-specialty

    relationship   race  gender  capital gain  capital loss  hours per week  \
0  Not-in-family  White  Female             0          4356              40
1  Not-in-family  White  Female             0          4356              18
2      Unmarried  Black  Female             0          4356              40
3      Unmarried  White  Female             0          3900              40
4      Own-child  White  Female             0          3900              40

  income  income_value
0  <=50K         47710
1  <=50K         40375
2  <=50K         43369
3  <=50K         32399
4  <=50K         39642
```

[6]:
```python
data = adult_income_df
data.dropna(inplace=True)
data
#data.head()
```

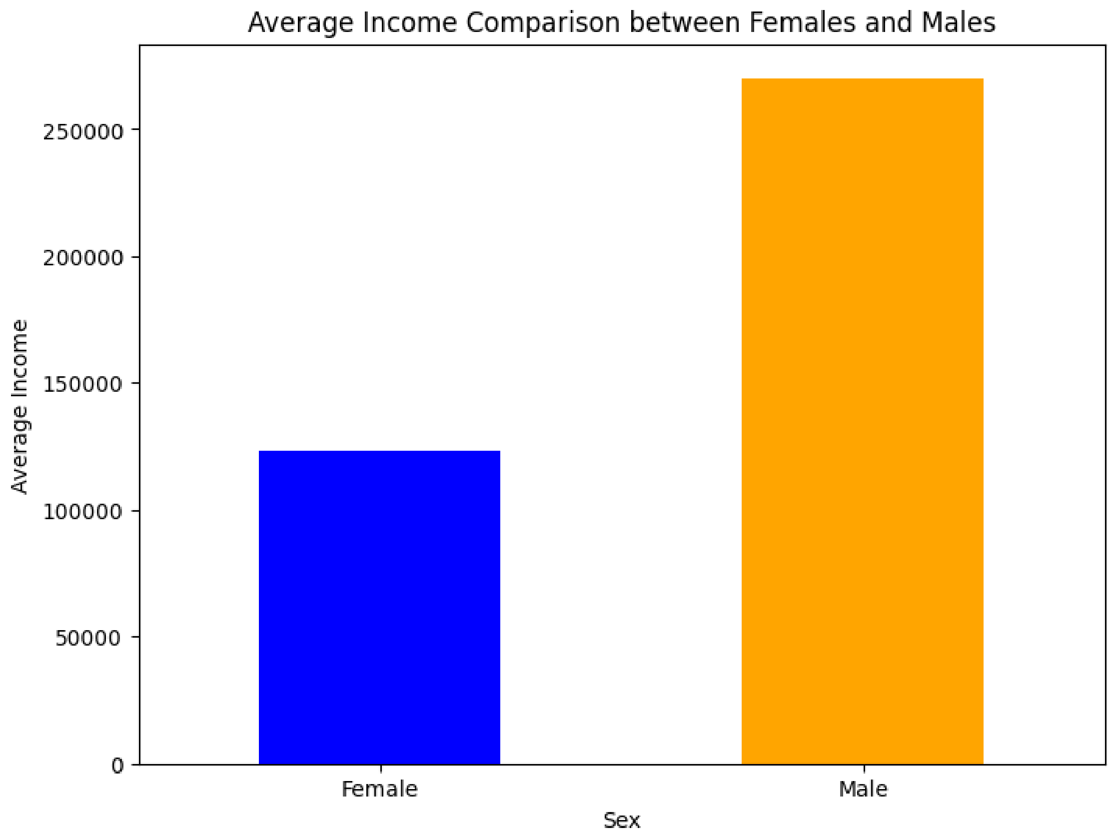
[6]:
```
       age workclass     education      marital status         occupation  \
1       82   Private       HS-grad             Widowed    Exec-managerial
3       54   Private       7th-8th            Divorced  Machine-op-inspct
4       41   Private  Some-college           Separated     Prof-specialty
5       34   Private       HS-grad            Divorced      Other-service
6       38   Private          10th           Separated       Adm-clerical
…     …       …            …                   …                …
32556   22   Private  Some-college       Never-married    Protective-serv
32557   27   Private    Assoc-acdm  Married-civ-spouse       Tech-support
```

```
32558   40   Private       HS-grad  Married-civ-spouse  Machine-op-inspct
32559   58   Private       HS-grad             Widowed       Adm-clerical
32560   22   Private       HS-grad       Never-married       Adm-clerical

        relationship   race  gender  capital gain  capital loss  \
1      Not-in-family  White  Female             0          4356
3          Unmarried  White  Female             0          3900
4          Own-child  White  Female             0          3900
5          Unmarried  White  Female             0          3770
6          Unmarried  White    Male             0          3770
…                …     …      …           …             …
32556  Not-in-family  White    Male             0             0
32557           Wife  White  Female             0             0
32558        Husband  White    Male             0             0
32559      Unmarried  White  Female             0             0
32560      Own-child  White    Male             0             0

       hours per week income  income_value
1                  18  <=50K         40375
3                  40  <=50K         32399
4                  40  <=50K         39642
5                  45  <=50K         49615
6                  40  <=50K         31855
…                 …     …           …
32556              40  <=50K         41979
32557              38  <=50K         48434
32558              40   >50K       1247500
32559              40  <=50K         38473
32560              20  <=50K         35115

[30718 rows x 13 columns]
```

[7]:

```
# Calculate average income for females and males
avg_income = data.groupby('gender')['income_value'].mean()

# Create a bar chart
plt.figure(figsize=(8, 6))
avg_income.plot(kind='bar', color=['blue', 'orange'])
plt.title('Average Income Comparison between Females and Males')
plt.xlabel('Sex')
plt.ylabel('Average Income')
plt.xticks(rotation=0)
plt.show()

# Checking if there are differences in income
income_difference = avg_income['Male'] - avg_income['Female']
if income_difference > 0:
```

```
    print("Males have higher average income than females.")
elif income_difference < 0:
    print("Females have higher average income than males.")
else:
    print("There is no difference in average income between females and males.")
```




```
Males have higher average income than females.
```

COMMENT HERE

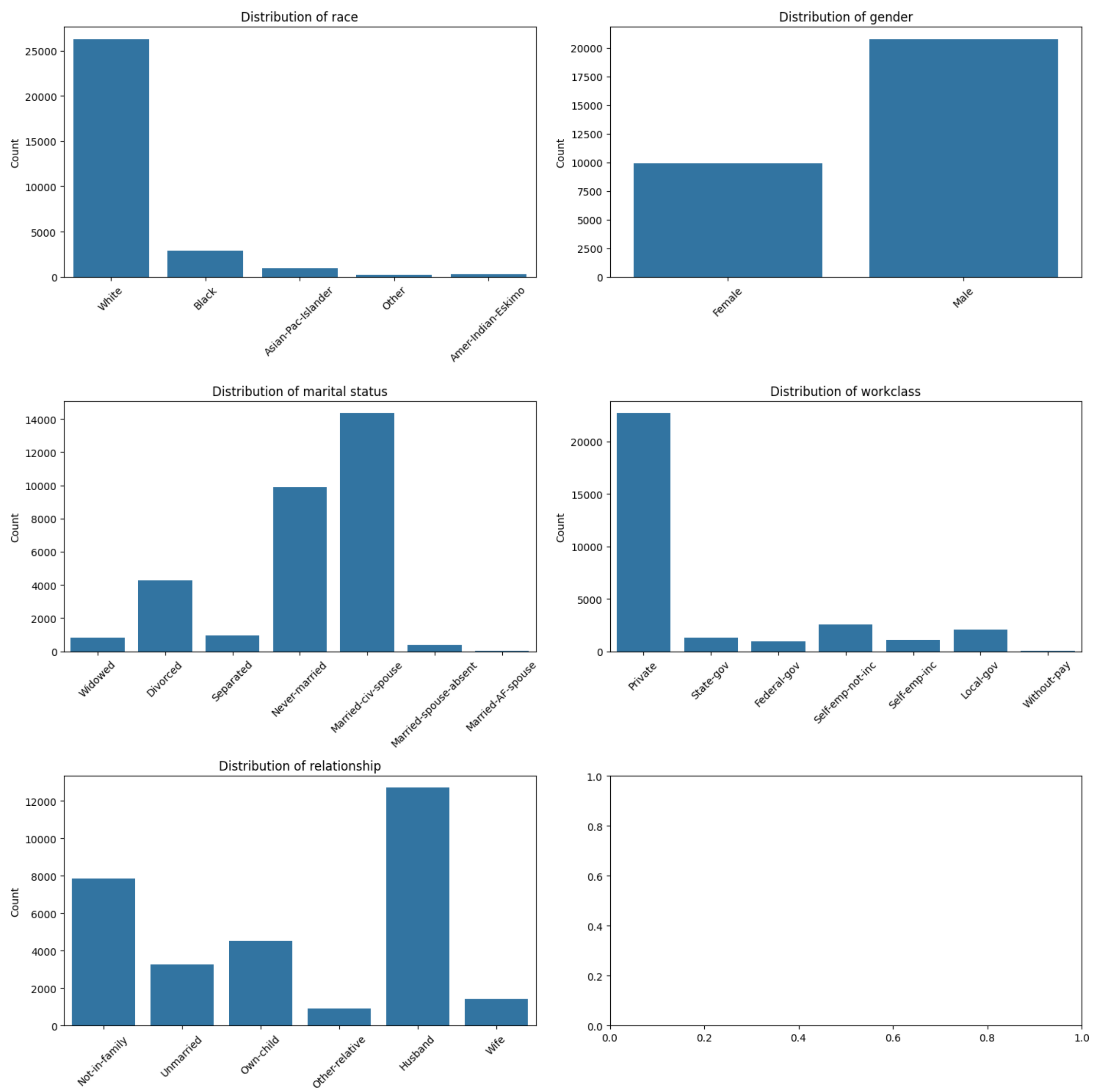
We dropped the entries where the value is NIL and then we calculated the mean value of the income for males and females. Upon plotting we find there is a difference income and average male income is more than average female income.

[8]:
```
# We dropped the entries where the value is NIL and then we calculated the mean␣
↪value of the income for males and females.
# Upon plotting we find there is a difference income and average male income is␣
↪more than average female income.
```

1.2 Plot a small multiple of bar charts to understand data distribution of the following categorical variables Income Dataset. 1. race 2. gender 3. maritial_status 4. working class 5. relation

[9]:

```python
category = ['race', 'gender', 'marital status', 'workclass', 'relationship']
fig, axes = plt.subplots(3, 2, figsize=(15, 15))

for i, variable in enumerate(category):
    row = i // 2
    col = i % 2
    sns.countplot(x=variable, data=data, ax=axes[row, col])
    axes[row, col].set_title(f'Distribution of {variable}')
    axes[row, col].set_xlabel('')
    axes[row, col].set_ylabel('Count')
    axes[row, col].tick_params(axis='x', rotation=45)

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



1.3 Compare the income of based on Education Qualification in Income Data Set

[10]:
```
### Code here
income_median = data.groupby('education')['income_value'].median().sort_values()
income_mean = data.groupby('education')['income_value'].mean().sort_values()
# income = income.sort_values()
display(income_median,'\n')
display(income_mean)
```

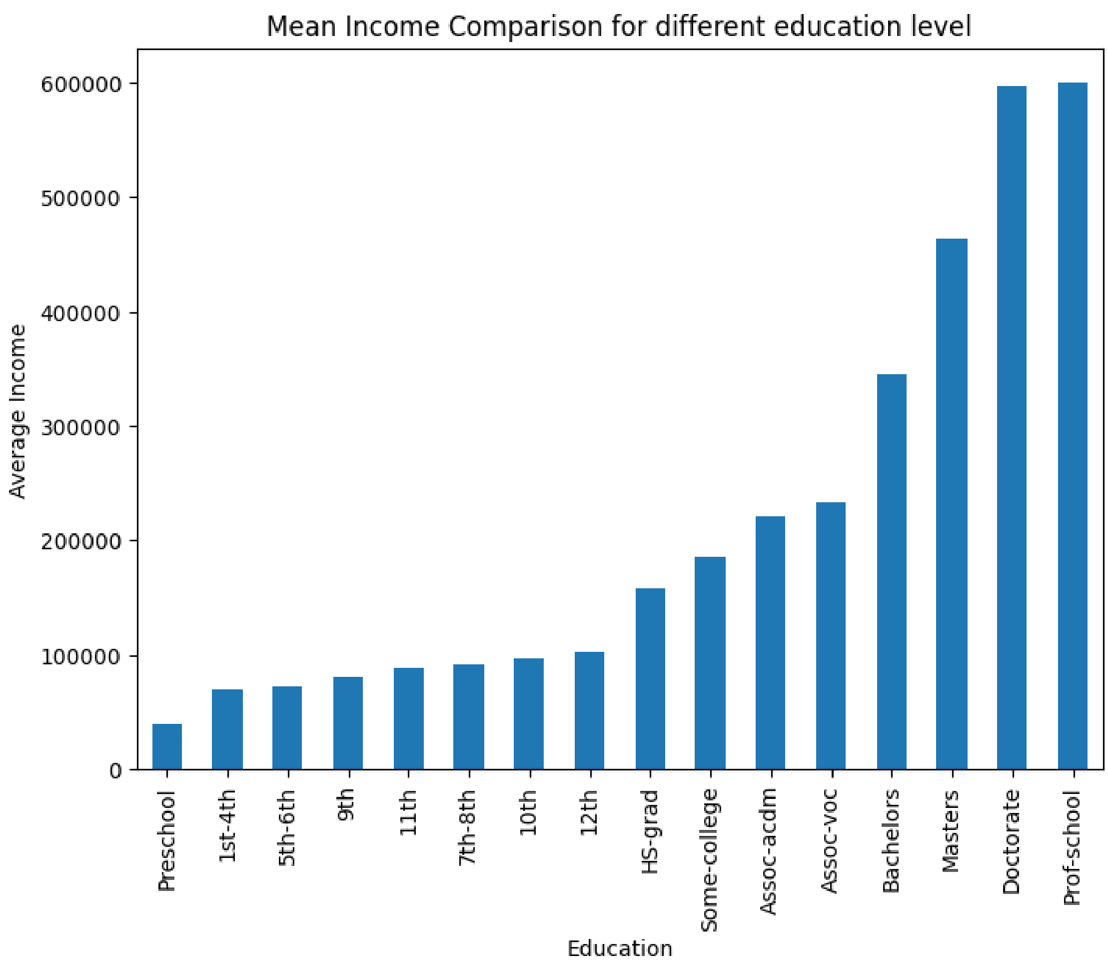
```
education
Preschool        39128.5
1st-4th          39351.0
12th             40231.0
10th             40257.0
9th              40335.0
7th-8th          40546.0
11th             40638.5
5th-6th          41364.0
HS-grad          41720.0
Some-college     42590.0
Assoc-acdm       43573.0
Assoc-voc        43839.0
Bachelors        47296.0
Masters         203428.0
Doctorate       509154.5
Prof-school     598596.0
Name: income_value, dtype: float64
```

```
'\n'
```

```
education
Preschool        38704.391304
1st-4th          70010.698718
5th-6th          72042.874587
9th              79790.887689
11th             88148.429924
7th-8th          91692.450262
10th             96189.226233
12th            101429.974555
HS-grad         157977.590891
Some-college    185226.003690
Assoc-acdm      221132.912745
Assoc-voc       233339.690386
Bachelors       344291.819182
Masters         464266.980896
Doctorate       597935.195980
Prof-school     600250.152330
```

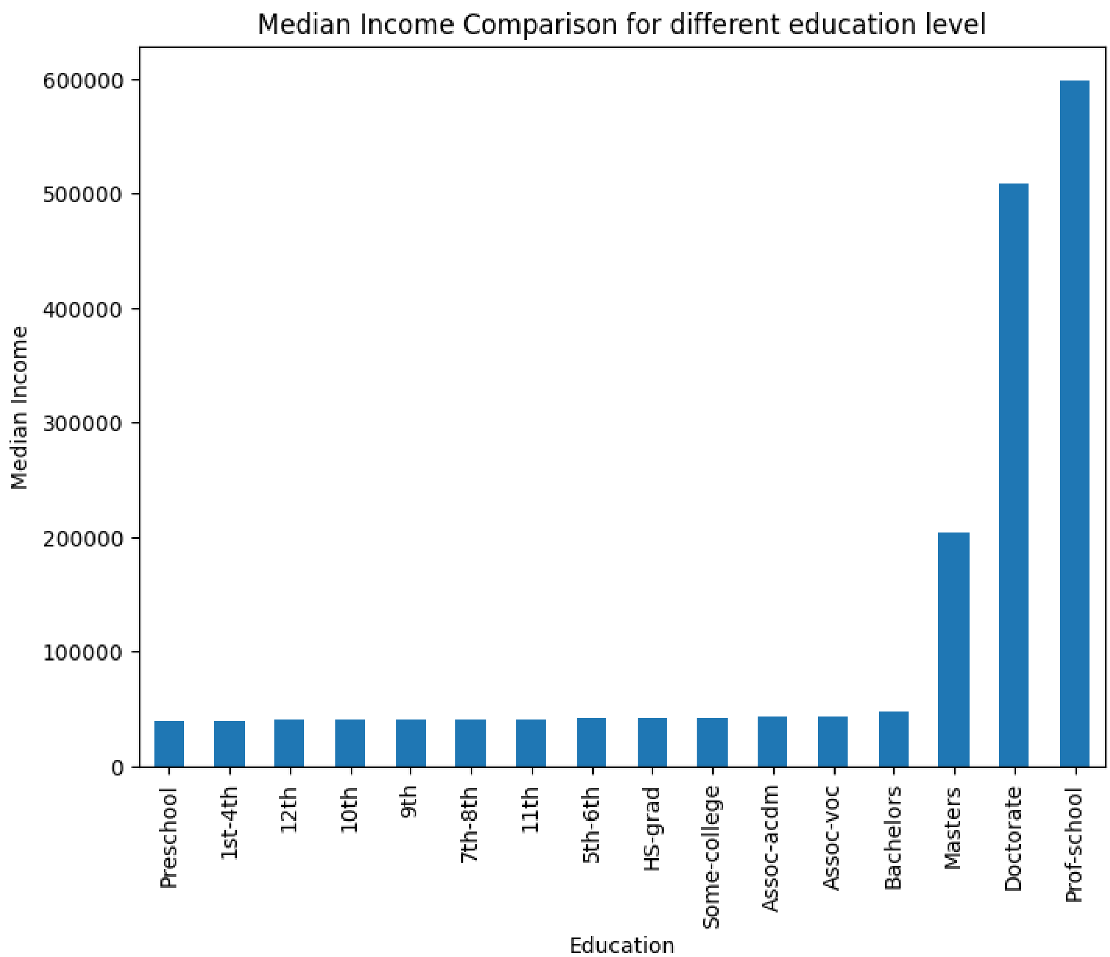
```
Name: income_value, dtype: float64
```

[11]:
```python
# Creating a bar chart of the sorted mean income data
plt.figure(figsize=(8, 6))
income_mean.plot(kind='bar')
plt.title('Mean Income Comparison for different education level')
plt.xlabel('Education')
plt.ylabel('Average Income')
plt.xticks(rotation=90)
plt.show()
```



[12]:
```python
# Creating a bar chart of the sorted median income data
plt.figure(figsize=(8, 6))
income_median.plot(kind='bar')
plt.title('Median Income Comparison for different education level')
plt.xlabel('Education')
plt.ylabel('Median Income')
```

```
plt.xticks(rotation=90)
plt.show()
```



1.4 Plot relationships between the following features and the target variable Income_value as a small multiple of scatter plots, is there any relation between them ? Is it possible to perform Regression on it ?

1. age
2. capital gain
3. capital loss
4. hours per week

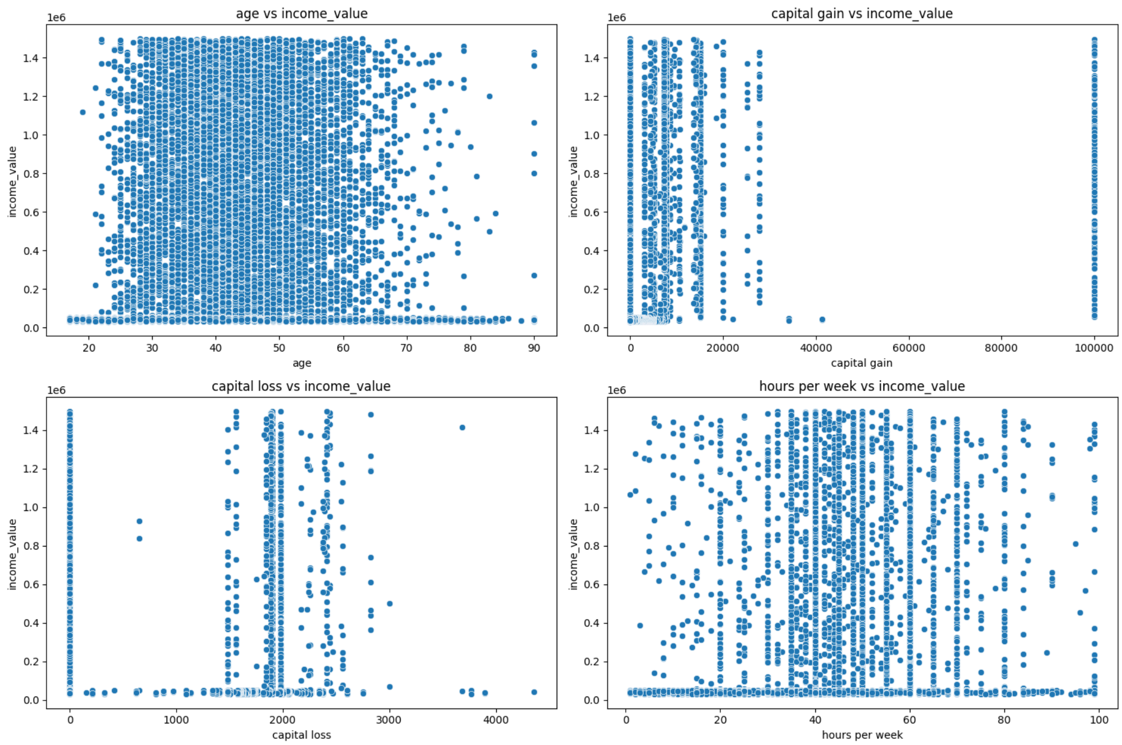
[13]:
```
data.head()
```

[13]:
```
   age workclass     education marital status         occupation  \
1   82   Private       HS-grad        Widowed    Exec-managerial
3   54   Private       7th-8th       Divorced  Machine-op-inspct
4   41   Private  Some-college      Separated     Prof-specialty
```

```
5   34    Private       HS-grad       Divorced      Other-service
6   38    Private          10th      Separated       Adm-clerical

    relationship   race  gender  capital gain  capital loss  hours per week  \
1  Not-in-family  White  Female             0          4356              18
3      Unmarried  White  Female             0          3900              40
4      Own-child  White  Female             0          3900              40
5      Unmarried  White  Female             0          3770              45
6      Unmarried  White    Male             0          3770              40

  income  income_value
1  <=50K         40375
3  <=50K         32399
4  <=50K         39642
5  <=50K         49615
6  <=50K         31855
```

[14]:

```
# relevant features and target variable
features = ['age', 'capital gain', 'capital loss', 'hours per week']
target_variable = 'income_value'

# small subplots of scatter plots
plt.figure(figsize=(15, 10))
for i, feature in enumerate(features):
    plt.subplot(2, 2, i+1)
    sns.scatterplot(x=feature, y=target_variable, data=data)
    plt.title(f'{feature} vs {target_variable}')
    plt.xlabel(feature)
    plt.ylabel(target_variable)

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



It is not possible to perform Regression on this data because Linear and Logistic regression will have a lot of variance & errors.

1.5 Load the Car Rental Data Set , handle missing values and Create a bar chart to compare the average car rental count on holiday and non-holiday weekdays. Are there differences in rental patterns?

0.2.2 The dataset to be used for this section is data / car_rental.csv

[15]:
```
# Load the dataset
car_rental_df = pd.read_csv('/content/drive/MyDrive/1/car_rental.csv')
car_rental_df
```

[15]:
```
        month  season holiday    weekday working_day weather      temp  \
0     January  winter      No   Saturday          No  cloudy  0.344167
1     January  winter      No     Sunday          No  cloudy  0.363478
2     January  winter      No     Monday         Yes   clear  0.196364
3     January  winter      No    Tuesday         Yes   clear  0.200000
4     January  winter      No  Wednesday         Yes   clear  0.226957
..        …       …       …         …           …       …         …
726  December  winter      No   Thursday         Yes  cloudy  0.254167
727  December  winter      No     Friday         Yes  cloudy  0.253333
728  December  winter      No   Saturday          No  cloudy  0.253333
729  December  winter      No     Sunday          No   clear  0.255833
```

```
730  December  winter      No     Monday         Yes  cloudy  0.215833

     feels_temp  humidity  windspeed  casual  registered  count_value
0      0.363625  0.805833   0.160446     331         654          985
1      0.353739  0.696087   0.248539     131         670          801
2      0.189405  0.437273   0.248309     120        1229         1349
3      0.212122  0.590435   0.160296     108        1454         1562
4      0.229270  0.436957   0.186900      82        1518         1600
..          …         …         …      …           …           …
726    0.226642  0.652917   0.350133     247        1867         2114
727    0.255046  0.590000   0.155471     644        2451         3095
728    0.242400  0.752917   0.124383     159        1182         1341
729    0.231700  0.483333   0.350754     364        1432         1796
730    0.223487  0.577500   0.154846     439        2290         2729

[731 rows x 13 columns]
```

[16]:

```python
### Code here
cardata = car_rental_df
cardata.dropna(inplace=True)
cardata
```

[16]:

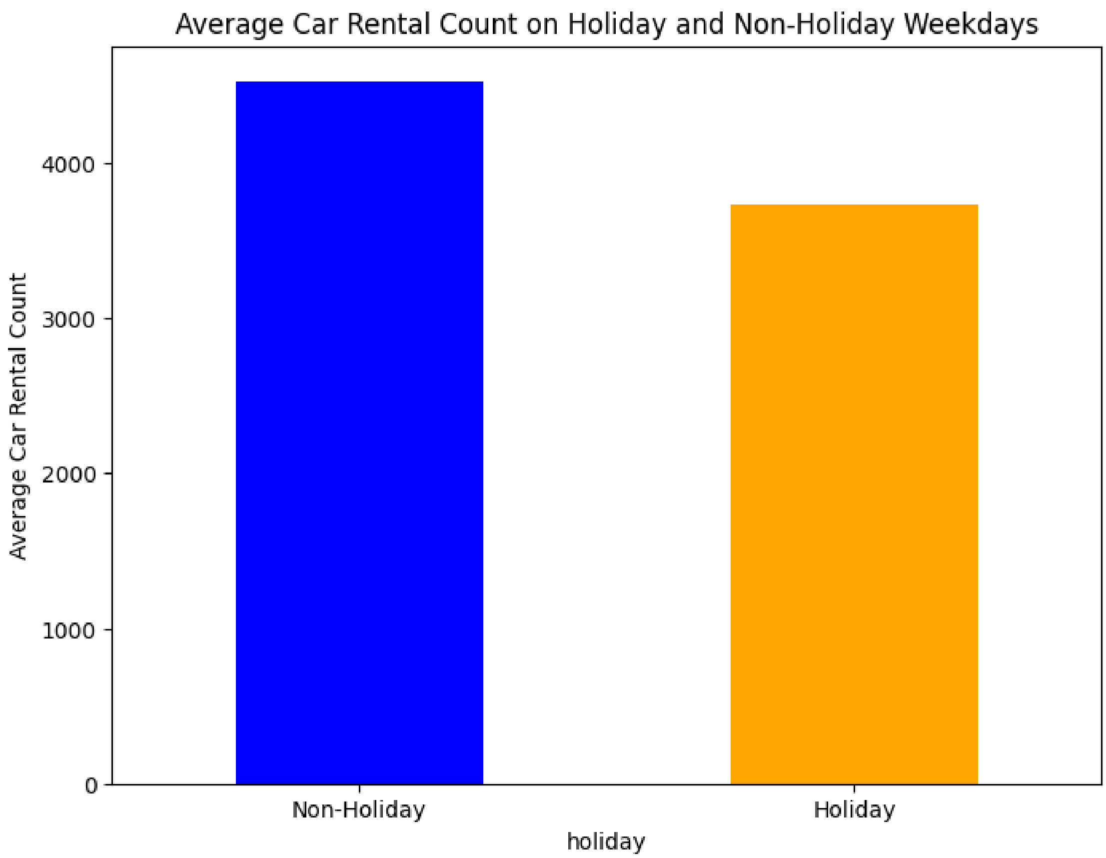
```
        month   season holiday    weekday working_day weather      temp  \
0     January   winter      No   Saturday          No  cloudy  0.344167
1     January   winter      No     Sunday          No  cloudy  0.363478
2     January   winter      No     Monday         Yes   clear  0.196364
3     January   winter      No    Tuesday         Yes   clear  0.200000
4     January   winter      No  Wednesday         Yes   clear  0.226957
..        …       …      …          …          …       …         …
726  December  winter      No   Thursday         Yes  cloudy  0.254167
727  December  winter      No     Friday         Yes  cloudy  0.253333
728  December  winter      No   Saturday          No  cloudy  0.253333
729  December  winter      No     Sunday          No   clear  0.255833
730  December  winter      No     Monday         Yes  cloudy  0.215833

     feels_temp  humidity  windspeed  casual  registered  count_value
0      0.363625  0.805833   0.160446     331         654          985
1      0.353739  0.696087   0.248539     131         670          801
2      0.189405  0.437273   0.248309     120        1229         1349
3      0.212122  0.590435   0.160296     108        1454         1562
4      0.229270  0.436957   0.186900      82        1518         1600
..          …         …         …      …           …           …
726    0.226642  0.652917   0.350133     247        1867         2114
727    0.255046  0.590000   0.155471     644        2451         3095
728    0.242400  0.752917   0.124383     159        1182         1341
729    0.231700  0.483333   0.350754     364        1432         1796
730    0.223487  0.577500   0.154846     439        2290         2729
```

```
[731 rows x 13 columns]
```

[17]:
```
cardata.head()
```

[17]:
```
     month  season holiday    weekday working_day weather      temp  \
0  January  winter      No   Saturday          No  cloudy  0.344167
1  January  winter      No     Sunday          No  cloudy  0.363478
2  January  winter      No     Monday         Yes   clear  0.196364
3  January  winter      No    Tuesday         Yes   clear  0.200000
4  January  winter      No  Wednesday         Yes   clear  0.226957

   feels_temp  humidity  windspeed  casual  registered  count_value
0    0.363625  0.805833   0.160446     331         654          985
1    0.353739  0.696087   0.248539     131         670          801
2    0.189405  0.437273   0.248309     120        1229         1349
3    0.212122  0.590435   0.160296     108        1454         1562
4    0.229270  0.436957   0.186900      82        1518         1600
```

[18]:
```
avg_rental_count = cardata.groupby('holiday')['count_value'].mean()

plt.figure(figsize=(8, 6))
avg_rental_count.plot(kind='bar', color=['blue', 'orange'])
plt.title('Average Car Rental Count on Holiday and Non-Holiday Weekdays')
plt.ylabel('Average Car Rental Count')
plt.xticks(rotation=0, ticks=[0, 1], labels=['Non-Holiday', 'Holiday'])
plt.show()

if avg_rental_count['Yes'] > avg_rental_count['No']:
    print("There are more rentals on holidays compared to non-holiday weekdays.
 ↪")
elif avg_rental_count['Yes'] < avg_rental_count['No']:
    print("There are more rentals on non-holiday weekdays compared to holidays.
 ↪")
else:
    print("There is no significant difference in rental patterns between␣
 ↪holiday and non-holiday weekdays.")
```

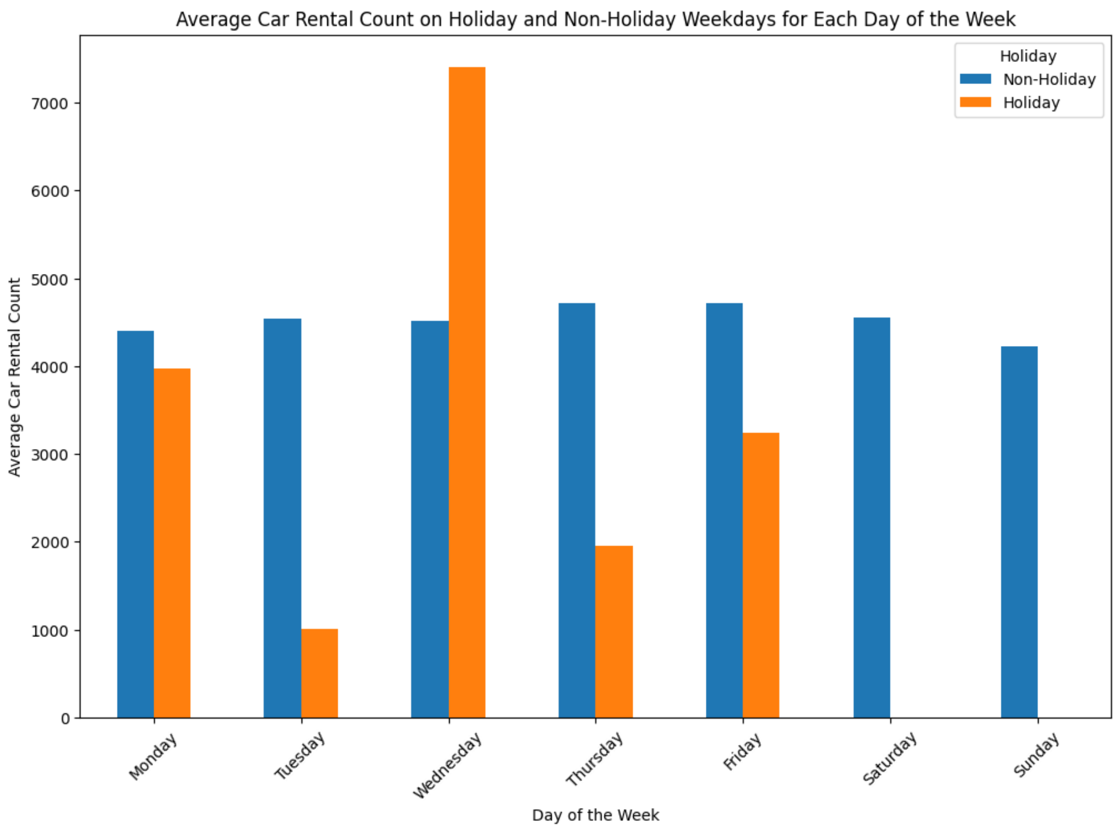



```
There are more rentals on non-holiday weekdays compared to holidays.
```

Surprisingly the count of car rentals on holidays is less than that on Non-holiday weekdays. This analogy can be becuase that people don't rent cars to go to work on holidays and there is a dip in rentals.

[19]:
```
# Calculate average car rental count for each day of the week, separated by
↪holiday and non-holiday weekdays
avg_rental_count2 = cardata.groupby(['weekday', 'holiday'])['count_value'].
↪mean().unstack()

# Re-order weekdays for better visualization
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
↪'Saturday', 'Sunday']
avg_rental_count2 = avg_rental_count2.reindex(weekday_order)

# Create a bar chart for each day of the week
fig, ax = plt.subplots(figsize=(12, 8))
avg_rental_count2.plot(kind='bar', ax=ax)
plt.title('Average Car Rental Count on Holiday and Non-Holiday Weekdays for
↪Each Day of the Week')
```

```python
plt.xlabel('Day of the Week')
plt.ylabel('Average Car Rental Count')
plt.xticks(rotation=45)
plt.legend(title='Holiday', labels=['Non-Holiday', 'Holiday'])
plt.show()
```

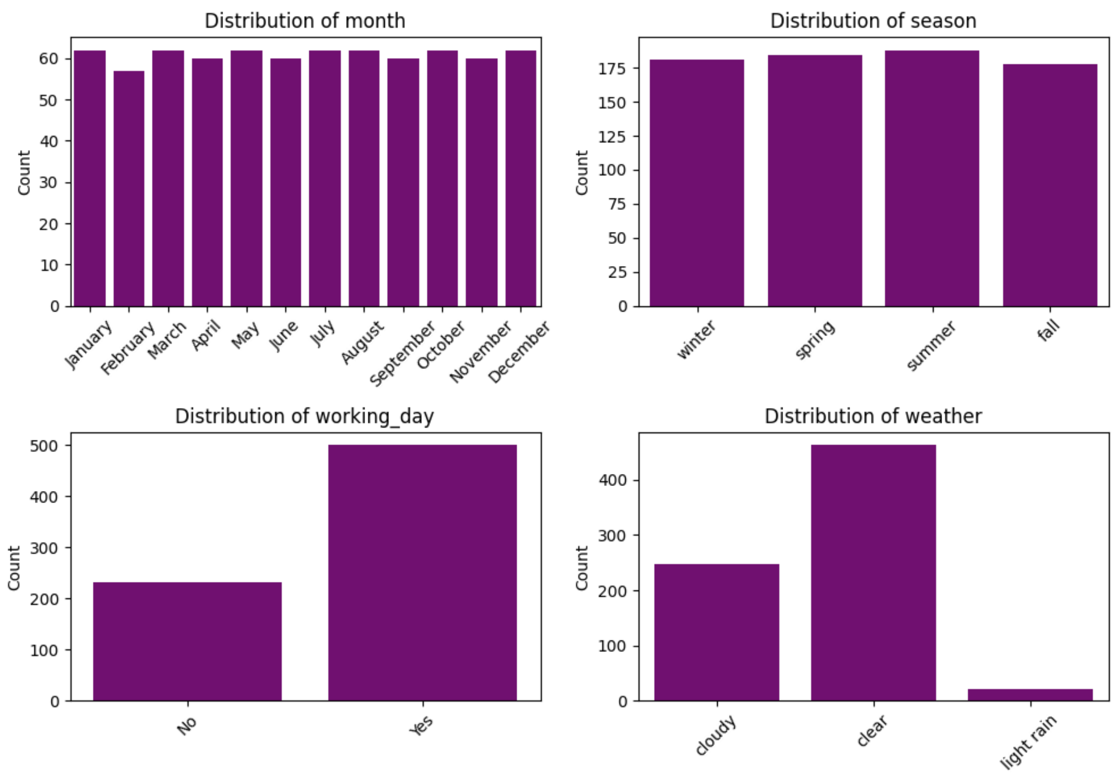


[20]:
```python
### Comment here: Generally the car rental sales is high but an anomaly is seen␣
↪on wednesday where the holiday sales > non-holiday sales.
# Also we have no reported holiday data for weekends, so no plot for holiday␣
↪rentals on weekend.
```

1.6 Plot a small multiple of bar charts to understand data distribution of the following categorical variables. 1. month 2. season 3. working_day 4. weather

[21]:
```python
### Code Here
# Define categorical variables
categorical_variables = ['month', 'season', 'working_day', 'weather']

# Create small multiples of bar charts
fig, axes = plt.subplots(2, 2, figsize=(10, 7))
```

```
for i, variable in enumerate(categorical_variables):
    row = i // 2
    col = i % 2
    sns.countplot(x=variable, data=cardata, ax=axes[row, col], color='purple')
    axes[row, col].set_title(f'Distribution of {variable}')
    axes[row, col].set_xlabel('')
    axes[row, col].set_ylabel('Count')
    axes[row, col].tick_params(axis='x', rotation=45)

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



1.7 Compare the number of registered and casual car rentals over time by month. Create a stacked bar chart to show the contributions of each user type.

[22]:
```
cardata.head()
```

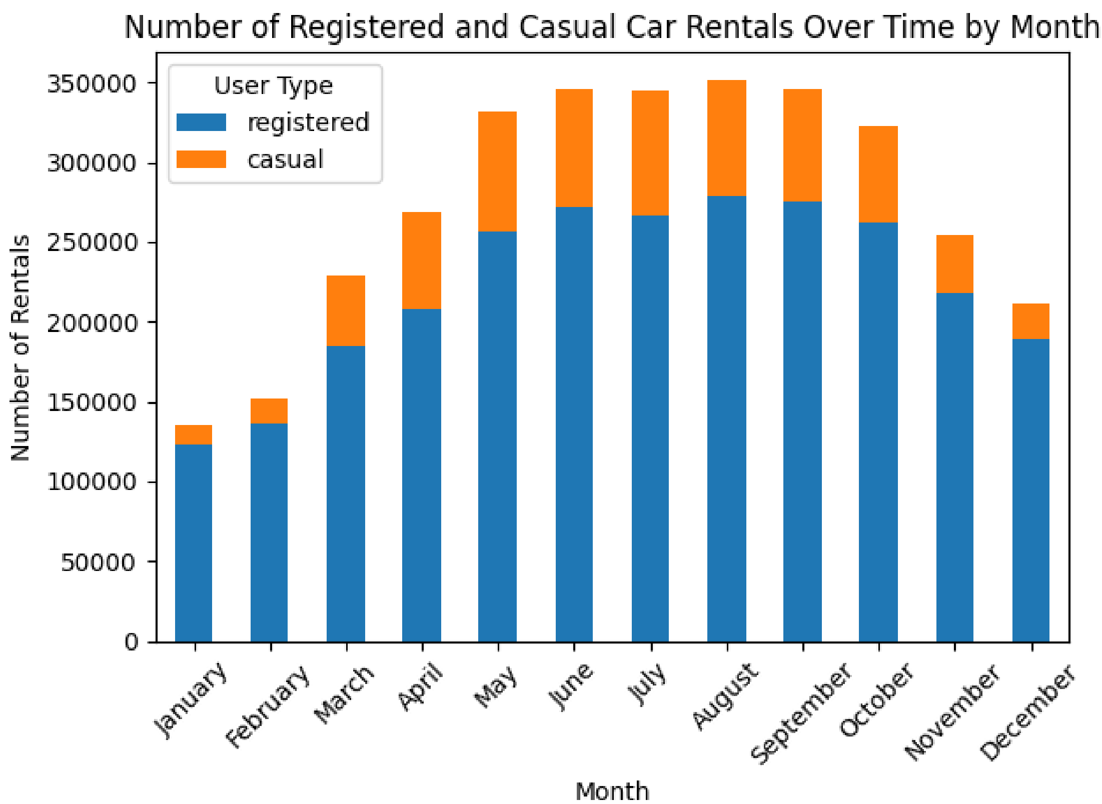
[22]:
```
     month  season holiday    weekday working_day weather      temp  \
0  January  winter      No   Saturday          No  cloudy  0.344167
1  January  winter      No     Sunday          No  cloudy  0.363478
2  January  winter      No     Monday         Yes   clear  0.196364
3  January  winter      No    Tuesday         Yes   clear  0.200000
```

```
4  January  winter      No  Wednesday         Yes   clear  0.226957

   feels_temp  humidity  windspeed  casual  registered  count_value
0    0.363625  0.805833   0.160446     331         654          985
1    0.353739  0.696087   0.248539     131         670          801
2    0.189405  0.437273   0.248309     120        1229         1349
3    0.212122  0.590435   0.160296     108        1454         1562
4    0.229270  0.436957   0.186900      82        1518         1600
```

[23]:

```python
rentals_by_month = cardata.groupby('month')[['registered', 'casual']].sum()

months_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
 ↪'August', 'September', 'October', 'November', 'December']
rentals_by_month = rentals_by_month.reindex(months_order)

plt.figure(figsize=(10, 6))
rentals_by_month.plot(kind='bar', stacked=True)
plt.title('Number of Registered and Casual Car Rentals Over Time by Month')
plt.xlabel('Month')
plt.ylabel('Number of Rentals')
plt.xticks(rotation=45)
plt.legend(title='User Type')
plt.tight_layout()
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```

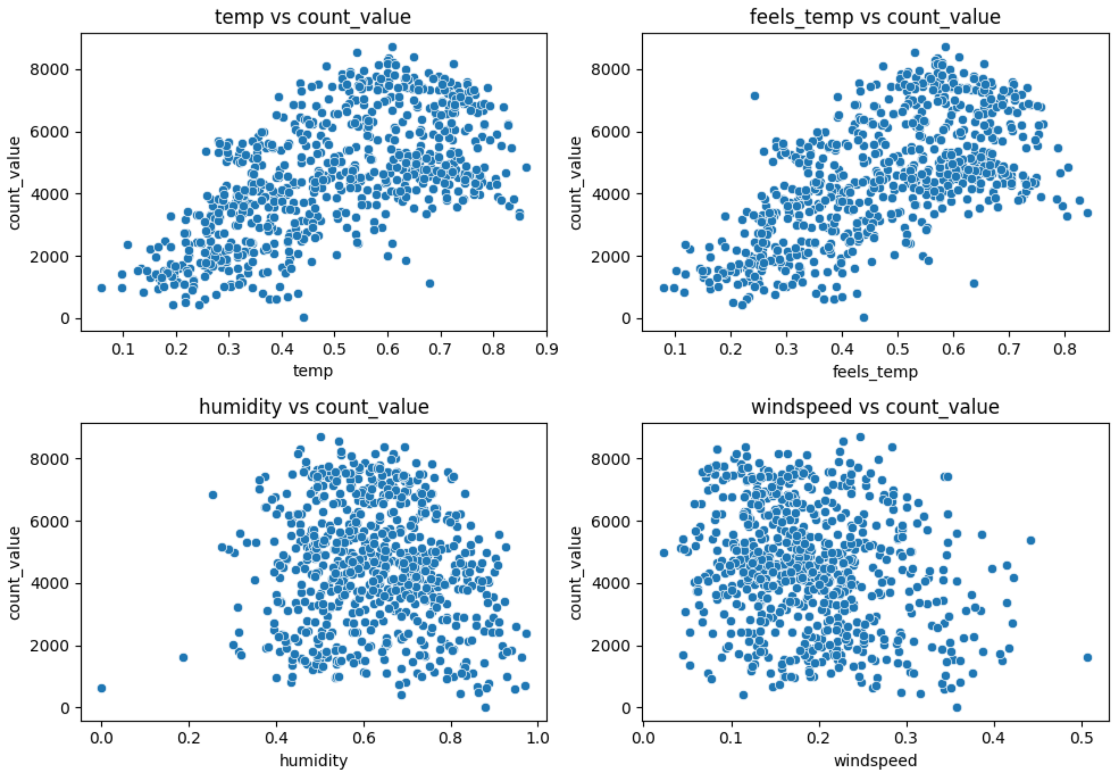


1.8 Plot relationships between the following features and the target variable count as a small multiple of scatter plots.is there any relationship between them ?

1. temp
2. feels_temp
3. humidity
4. windspeed

[24]:
```
### Code here
# relevant features and target variable
features = ['temp', 'feels_temp', 'humidity', 'windspeed']
target_variable = 'count_value'

# small subplots of scatter plots
plt.figure(figsize=(10, 7))
for i, feature in enumerate(features):
    plt.subplot(2, 2, i+1)
    sns.scatterplot(x=feature, y=target_variable, data=cardata)
    plt.title(f'{feature} vs {target_variable}')
    plt.xlabel(feature)
    plt.ylabel(target_variable)
```

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



[25]:
```
### Comment here: For temp and feels_temp the count value generally increases␣
↪upon increasing the value of temp & feels_tmep.
# But nothing linear can be said about the humidity & windspeed vs count_value,␣
↪but we can say that majority care sales (count_value) is observed only
# after & before a certain threshold respectively.
```

0.3 Part 2: Linear Models for Regression and Classification

In this section, we will be implementing three linear models **linear regression, logistic regression, and SVM**. We will see that despite some of their differences at the surface, these linear models (and many machine learning models in general) are fundamentally doing the same thing - that is, optimizing model parameters to minimize a loss function on data.

0.3.1 2.1 Linear Regression

The objective of this dataset is to predict the count of car rentals based on weather and time. We will use linear regression to predict the count using weather and time.

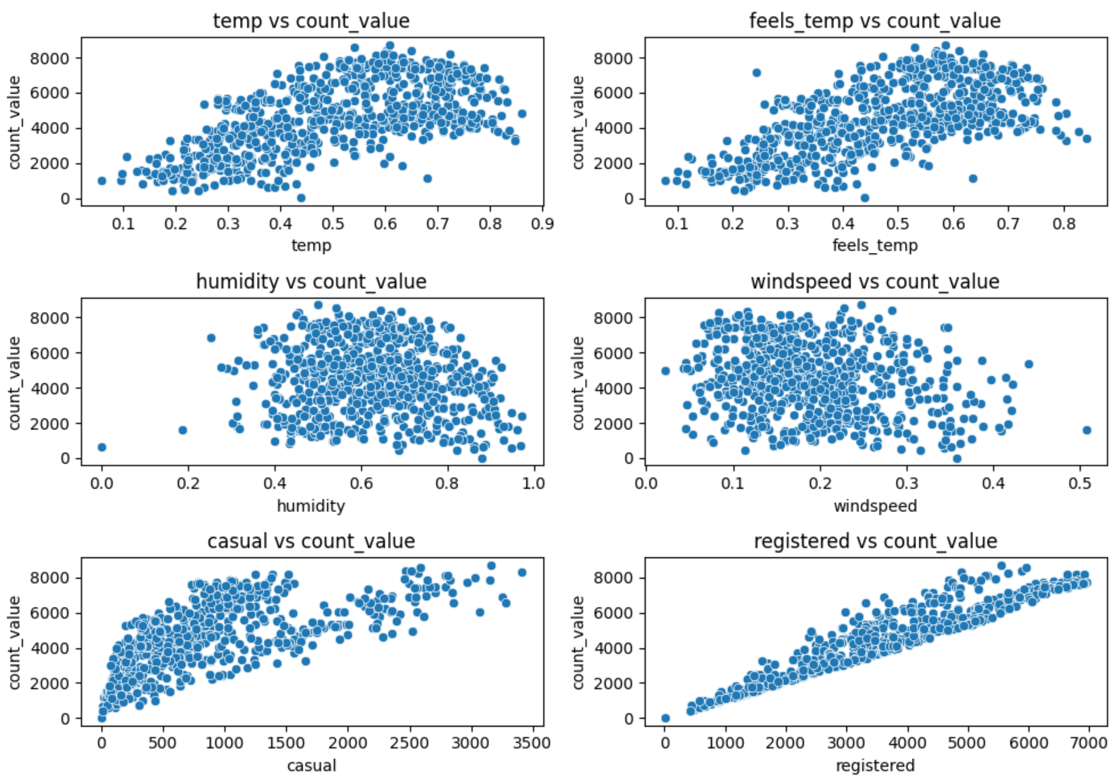
[26]:
```
# split data into features and labels
# I am creating 2 new variables with changed suffix so as to avoid running the␣
↪code again if any error faced in future

car_rental_df2 = car_rental_df
cardata2 = cardata

car_rental_X = car_rental_df2.drop(columns=['count_value'])
car_rental_y = car_rental_df2['count_value']
```

[27]:
```
cardata2.head()
```

[27]:
```
     month  season holiday    weekday working_day weather      temp  \
0  January  winter      No   Saturday          No  cloudy  0.344167
1  January  winter      No     Sunday          No  cloudy  0.363478
2  January  winter      No     Monday         Yes   clear  0.196364
3  January  winter      No    Tuesday         Yes   clear  0.200000
4  January  winter      No  Wednesday         Yes   clear  0.226957

   feels_temp  humidity  windspeed  casual  registered  count_value
0    0.363625  0.805833   0.160446     331         654          985
1    0.353739  0.696087   0.248539     131         670          801
2    0.189405  0.437273   0.248309     120        1229         1349
3    0.212122  0.590435   0.160296     108        1454         1562
4    0.229270  0.436957   0.186900      82        1518         1600
```

2.1.1 Plot the relationships between the label (count_value) and the continuous features (temp, feels_temp, humidity, windspeed, casual, registered) using a small multiple of scatter plots. Make sure to label the axes.

[28]:
```
### Code here
ct_features = ['temp', 'feels_temp', 'humidity', 'windspeed', 'casual',␣
↪'registered']
label = 'count_value'

# small subplots of scatter plots
plt.figure(figsize=(10, 7))
for i, feature in enumerate(ct_features):
    plt.subplot(3, 2, i+1)
    sns.scatterplot(x=feature, y=label, data=cardata2)
    plt.title(f'{feature} vs {label}')
    plt.xlabel(feature)
    plt.ylabel(label)

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



2.1.2 From the visualizations above, do you think linear regression is a good model for this problem? Why and/or why not? Please explain.

[29]:
```
### Comment here
# I feel that linear regression can be used to predict count value but␣
↪variables like humidity and windspeed shouldn't
# be relied upon as much as others and overall the count value is linear with␣
↪the desired parameters with some nominal confidence interval as expected.
```

0.3.2 Data Preprocessing

Before we can fit a linear regression model, there are several pre-processing steps we should apply to the datasets:

1. Encode categorial features appropriately.
2. Remove highly collinear features by reading the correlation plot.
3. Split the dataset into training (60%), validation (20%), and test (20%) sets.
4. Standardize the columns in the feature matrices X_train, X_val, and X_test to have zero mean and unit variance. To avoid information leakage, learn the standardization parameters (mean, variance) from X_train, and apply it to X_train, X_val, and X_test.
5. Add a column of ones to the feature matrices X_train, X_val, and X_test. This is a common trick so that we can learn a coefficient for the bias term of a linear model.

2.1.3 Encode the categorical variables of the dataset.

[30]:
```
cardata2.head()
```

[30]:
```
     month  season holiday    weekday working_day weather      temp  \
0  January  winter      No   Saturday          No  cloudy  0.344167
1  January  winter      No     Sunday          No  cloudy  0.363478
2  January  winter      No     Monday         Yes   clear  0.196364
3  January  winter      No    Tuesday         Yes   clear  0.200000
4  January  winter      No  Wednesday         Yes   clear  0.226957

   feels_temp  humidity  windspeed  casual  registered  count_value
0    0.363625  0.805833   0.160446     331         654          985
1    0.353739  0.696087   0.248539     131         670          801
2    0.189405  0.437273   0.248309     120        1229         1349
3    0.212122  0.590435   0.160296     108        1454         1562
4    0.229270  0.436957   0.186900      82        1518         1600
```

[31]:
```
columns = ['month', 'season', 'holiday', 'weekday', 'working_day', 'weather']

for column_name in columns:
    counts = cardata2[column_name].value_counts()
    print(f"Unique values and their frequencies for column '{column_name}':")
    print(counts)
    print()
```

```
Unique values and their frequencies for column 'month':
January      62
March        62
May          62
July         62
August       62
October      62
December     62
April        60
June         60
September    60
November     60
February     57
Name: month, dtype: int64

Unique values and their frequencies for column 'season':
summer    188
spring    184
winter    181
fall      178
Name: season, dtype: int64

Unique values and their frequencies for column 'holiday':
```

```
No     710
Yes     21
Name: holiday, dtype: int64

Unique values and their frequencies for column 'weekday':
Saturday     105
Sunday       105
Monday       105
Tuesday      104
Wednesday    104
Thursday     104
Friday       104
Name: weekday, dtype: int64

Unique values and their frequencies for column 'working_day':
Yes    500
No     231
Name: working_day, dtype: int64

Unique values and their frequencies for column 'weather':
clear         463
cloudy        247
light rain     21
Name: weather, dtype: int64
```

Month –> 12 values –> Ordinal encoding

Season –> 4 values –> One-hot encoding

Holiday –> 2 values –> Binary encoding (~ label encoding if 2 values)

Weekday –> 7 values –> Ordinal encoding

Working day –> 2 values –> Binary encoding (~ label encoding if 2 values)

weather –> 3 values –> One-hot encoding

[32]:
```
cardata2
```

[32]:
```
        month  season holiday    weekday working_day weather      temp  \
0     January  winter      No   Saturday          No  cloudy  0.344167
1     January  winter      No     Sunday          No  cloudy  0.363478
2     January  winter      No     Monday         Yes   clear  0.196364
3     January  winter      No    Tuesday         Yes   clear  0.200000
4     January  winter      No  Wednesday         Yes   clear  0.226957
..        …       …      …          …           …       …         …
726  December  winter      No   Thursday         Yes  cloudy  0.254167
727  December  winter      No     Friday         Yes  cloudy  0.253333
728  December  winter      No   Saturday          No  cloudy  0.253333
```

```
729  December  winter      No     Sunday         No   clear  0.255833
730  December  winter      No     Monday        Yes  cloudy  0.215833

     feels_temp  humidity  windspeed  casual  registered  count_value
0      0.363625  0.805833   0.160446     331         654          985
1      0.353739  0.696087   0.248539     131         670          801
2      0.189405  0.437273   0.248309     120        1229         1349
3      0.212122  0.590435   0.160296     108        1454         1562
4      0.229270  0.436957   0.186900      82        1518         1600
..          …         …          …       …          …           …
726    0.226642  0.652917   0.350133     247        1867         2114
727    0.255046  0.590000   0.155471     644        2451         3095
728    0.242400  0.752917   0.124383     159        1182         1341
729    0.231700  0.483333   0.350754     364        1432         1796
730    0.223487  0.577500   0.154846     439        2290         2729

[731 rows x 13 columns]
```

[33]:

```python
### Code here

# Ordinal encoding for 'month' & 'weekday'
month_mapping = {'January': 1, 'February': 2, 'March': 3, 'April': 4, 'May': 5,␣
↪'June': 6,
                 'July': 7, 'August': 8, 'September': 9, 'October': 10,␣
↪'November': 11, 'December': 12}
cardata2['month_encoded'] = cardata2['month'].map(month_mapping)

weekday_mapping = {'Sunday': 0, 'Monday': 1, 'Tuesday': 2, 'Wednesday': 3,␣
↪'Thursday': 4, 'Friday': 5, 'Saturday': 6}
cardata2['weekday_encoded'] = cardata2['weekday'].map(weekday_mapping)

# One-hot encoding for 'season' and 'weather'
cardata2 = pd.get_dummies(cardata2, columns=['season', 'weather'],␣
↪drop_first=True)

# Binary encoding for 'holiday' and 'working_day'
cardata2['holiday_encoded'] = (cardata2['holiday'] == 'Yes').astype(int)
cardata2['working_day_encoded'] = (cardata2['working_day'] == 'Yes').astype(int)

# Drop the original categorical columns
cardata2.drop(['month', 'holiday', 'weekday', 'working_day'], axis=1,␣
↪inplace=True)
```

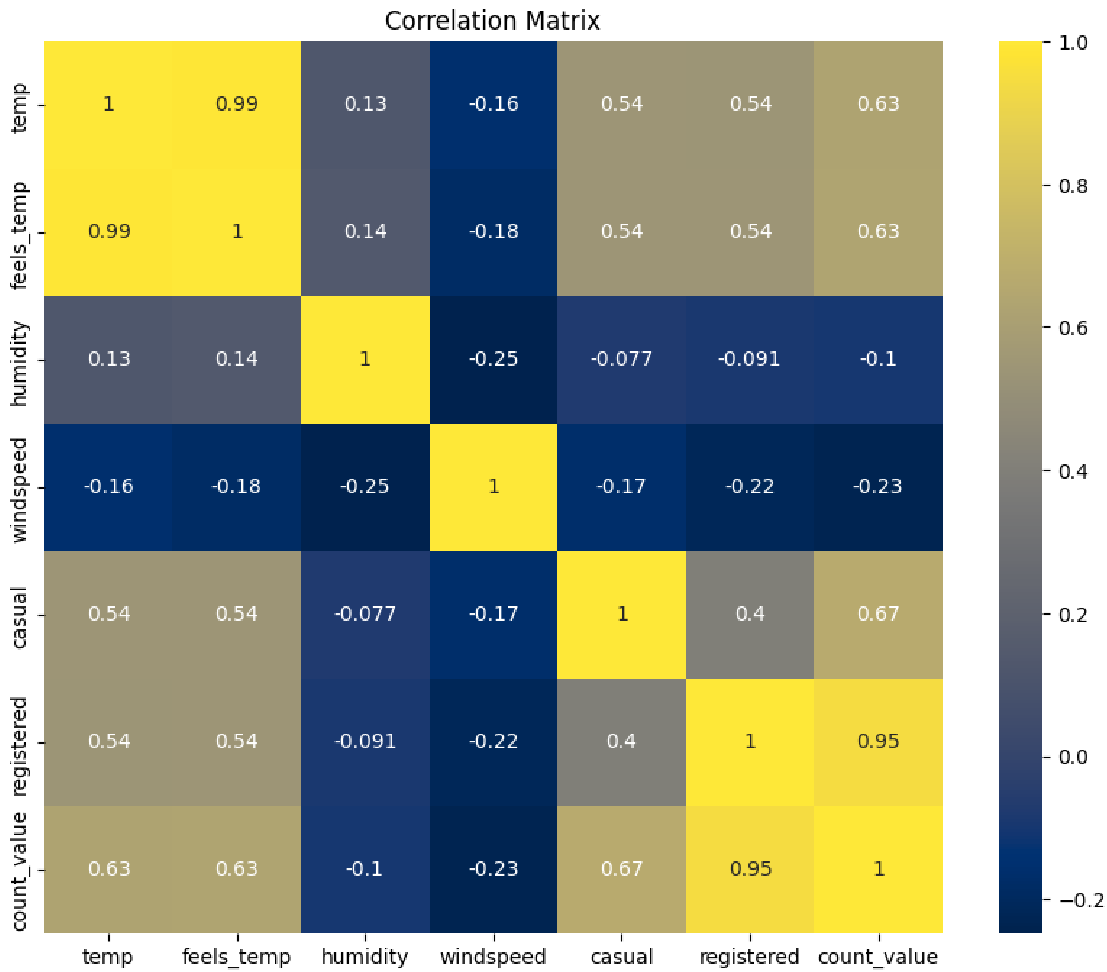
[34]:

```python
### Code here
cardata2.head()
```

[34]:
```
       temp  feels_temp  humidity  windspeed  casual  registered  count_value  \
0  0.344167    0.363625  0.805833   0.160446     331         654          985
1  0.363478    0.353739  0.696087   0.248539     131         670          801
2  0.196364    0.189405  0.437273   0.248309     120        1229         1349
3  0.200000    0.212122  0.590435   0.160296     108        1454         1562
4  0.226957    0.229270  0.436957   0.186900      82        1518         1600

   month_encoded  weekday_encoded  season_spring  season_summer  \
0              1                6              0              0
1              1                0              0              0
2              1                1              0              0
3              1                2              0              0
4              1                3              0              0

   season_winter  weather_cloudy  weather_light rain  holiday_encoded  \
0              1               1                   0                0
1              1               1                   0                0
2              1               0                   0                0
3              1               0                   0                0
4              1               0                   0                0

   working_day_encoded
0                    0
1                    0
2                    1
3                    1
4                    1
```

2.1.4 Plot the correlation matrix, and check if there is high correlation between the given numerical features (Threshold >=0.9). If yes, drop one from each pair of highly correlated features from the dataframe. Why is necessary to drop those columns before proceeding further?

[35]:
```python
### Code here
variables = ['temp', 'feels_temp', 'humidity', 'windspeed', 'casual',␣
 ↪'registered', 'count_value']

# correlation matrix
corr = cardata2[variables].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap='cividis')
# sns.heatmap(corr, annot=True, cmap='RdBu')
plt.title('Correlation Matrix')
plt.show()
```



[36]:
```
### Code here
cardata2 = cardata2.drop(columns = ['registered', 'feels_temp'])
```

Why we need to dorp these columns?

Multicollinearity: Highly correlated features provide redundant information to the process, leading to multicollinearity. This can destabilize the model's coefficient estimates and make them sensitive to small changes in the data.

Overfitting: Including highly correlated features in the model can lead to overfitting, where the model performs well on the training data but poorly on unseen data. By removing redundant features, we reduce the risk of overfitting and improve the generalization performance of the model.

Computational Efficiency: Removing highly correlated features can improve computational efficiency during model training and prediction, as the model has fewer features to process.

[37]:
```
### Comment here: Answered in the markdown above
```

[38]:

```
cardata2
```

[38]:

```
         temp  humidity  windspeed  casual  count_value  month_encoded  \
0    0.344167  0.805833   0.160446     331          985              1
1    0.363478  0.696087   0.248539     131          801              1
2    0.196364  0.437273   0.248309     120         1349              1
3    0.200000  0.590435   0.160296     108         1562              1
4    0.226957  0.436957   0.186900      82         1600              1
..        …         …          …       …           …              …
726  0.254167  0.652917   0.350133     247         2114             12
727  0.253333  0.590000   0.155471     644         3095             12
728  0.253333  0.752917   0.124383     159         1341             12
729  0.255833  0.483333   0.350754     364         1796             12
730  0.215833  0.577500   0.154846     439         2729             12

     weekday_encoded  season_spring  season_summer  season_winter  \
0                  6              0              0              1
1                  0              0              0              1
2                  1              0              0              1
3                  2              0              0              1
4                  3              0              0              1
..               …              …              …              …
726                4              0              0              1
727                5              0              0              1
728                6              0              0              1
729                0              0              0              1
730                1              0              0              1

     weather_cloudy  weather_light rain  holiday_encoded  working_day_encoded
0                 1                   0                0                    0
1                 1                   0                0                    0
2                 0                   0                0                    1
3                 0                   0                0                    1
4                 0                   0                0                    1
..              …                   …                …                    …
726               1                   0                0                    1
727               1                   0                0                    1
728               1                   0                0                    0
729               0                   0                0                    0
730               1                   0                0                    1

[731 rows x 14 columns]
```

2.1.5 Split the dataset into training (60%), validation (20%), and test (20%) sets.

[39]:

```
### Code here
```

```
car_rental_X = cardata2.drop(columns=['count_value'])
car_rental_y = cardata2['count_value']

car_rental_X_dev, car_rental_X_test, car_rental_y_dev, car_rental_y_test =␣
↪train_test_split(car_rental_X, car_rental_y, test_size=0.2, random_state=42)
car_rental_X_train, car_rental_X_val, car_rental_y_train, car_rental_y_val =␣
↪train_test_split(car_rental_X_dev, car_rental_y_dev, test_size=0.25,␣
↪random_state=84)

print("Training set:", car_rental_X_train.shape, car_rental_y_train.shape)
print("Validation set:", car_rental_X_val.shape, car_rental_y_val.shape)
print("Testing set:", car_rental_X_test.shape, car_rental_y_test.shape)
```

```
Training set: (438, 13) (438,)
Validation set: (146, 13) (146,)
Testing set: (147, 13) (147,)
```

2.1.6 Standardize the columns in the feature matrices.

[40]:
```
### Code here

scalar = StandardScaler()

car_rental_X_train = scalar.fit_transform(car_rental_X_train)
car_rental_X_val = scalar.transform(car_rental_X_val)
car_rental_X_test = scalar.transform(car_rental_X_test)
```

[41]:
```
mean_train = np.mean(car_rental_X_train, axis=0)
std_train = np.std(car_rental_X_train, axis=0)
print("Mean of scaled training data:", mean_train)
print("Standard deviation of scaled training data:", std_train,'\n')

mean_val = np.mean(car_rental_X_val, axis=0)
std_val = np.std(car_rental_X_val, axis=0)
print("Mean of scaled validation data:", mean_val)
print("Standard deviation of scaled validation data:", std_val,'\n')

mean_test = np.mean(car_rental_X_test, axis=0)
std_test = np.std(car_rental_X_test, axis=0)
print("Mean of scaled training data:", mean_test)
print("Standard deviation of scaled training data:", std_test,'\n')
```

```
Mean of scaled training data: [ 3.24448738e-17  9.14539880e-16 -1.01390231e-17
-3.34587761e-17
 -1.22682179e-16  1.15584863e-16 -1.82502415e-17  9.73346213e-17
  1.17612667e-16  5.27229199e-17  2.83892646e-17  8.31399891e-17
 -1.50057541e-16]
Standard deviation of scaled training data: [1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
```

```
1.]

Mean of scaled validation data: [ 0.12333931 -0.09349533 -0.0750898   0.30660114
-0.00847874 -0.22253312
  0.2430764  -0.01560976 -0.1717074   0.06296156 -0.07532436  0.07642723
 -0.15265751]
Standard deviation of scaled validation data: [0.95585769 1.10286613 0.93736754
1.11914276 0.91200294 1.04959886
 1.1172116  0.99131216 0.88481339 1.02007666 0.78007092 1.21756997
 1.04880076]

Mean of scaled training data: [-0.09913622 -0.14158677 -0.03114188 -0.06929798
0.07227562 -0.0196876
 -0.01984297 -0.01953875  0.02697197 -0.01443075 -0.07609297  0.12041188
  0.11708097]
Standard deviation of scaled training data: [1.02486781 1.03231937 0.99159948
0.92764765 1.00933482 0.96256507
 0.98718022 0.9890746  1.01427035 0.99478021 0.77746856 1.32470774
 0.94431805]
```

[42]:
```python
#Adding a column of ones to the feature matrices for the bias term.

car_rental_X_train = np.hstack([np.ones((car_rental_X_train.shape[0], 1)),
 ↪car_rental_X_train])
car_rental_X_val = np.hstack([np.ones((car_rental_X_val.shape[0], 1)),
 ↪car_rental_X_val])
car_rental_X_test = np.hstack([np.ones((car_rental_X_test.shape[0], 1)),
 ↪car_rental_X_test])
```

At the end of this pre-processing, you should have the following vectors and matrices: - Car_Rental Prediction dataset: car_rental_X_train, car_rental_X_val, car_rental_X_test, car_rental_y_train, car_rental_y_val, car_rental_y_test

0.3.3 Implement Linear Regression

Now, we can implement our linear regression model! Specifically, we will be implementing ridge regression, which is linear regression with L2 regularization. Given an (m x n) feature matrix X, an (m x 1) label vector y, and an (n x 1) weight vector w, the hypothesis function for linear regression is:

$$y = Xw$$

Note that we can omit the bias term here because we have included a column of ones in our X matrix, so the bias term is learned implicitly as a part of w. This will make our implementation easier.

Our objective in linear regression is to learn the weights w which best fit the data. This notion can be formalized as finding the optimal w which minimizes the following loss function:

$$\min_w \|Xw - y\|_2^2 + \alpha\|w\|_2^2$$

This is the ridge regression loss function. The $\|Xw - y\|_2^2$ term penalizes predictions Xw which are not close to the label y. And the $\alpha\|w\|_2^2$ penalizes large weight values, to favor a simpler, more generalizable model. The α hyperparameter, known as the regularization parameter, is used to tune the complexity of the model - a higher α results in smaller weights and lower complexity, and vice versa. Setting $\alpha = 0$ gives us vanilla linear regression.

Conveniently, ridge regression has a closed-form solution which gives us the optimal w without having to do iterative methods such as gradient descent. The closed-form solution, known as the Normal Equations, is given by:

$$w = (X^T X + \alpha I)^{-1} X^T y$$

2.1.7 Implement a `LinearRegression` class with two methods: `train` and `predict`.

Note: You may NOT use sklearn for this implementation. You may, however, use `np.linalg.solve` to find the closed-form solution. It is highly recommended that you vectorize your code.

[43]:
```
class LinearRegression():
    '''
    Linear regression model with L2-regularization (i.e. ridge regression).

    Attributes
    ----------
    alpha: regularization parameter
    w: (n x 1) weight vector
    '''

    def __init__(self, alpha=0):
        self.alpha = alpha
        self.w = None

    def train(self, X, y):
        '''Trains model using ridge regression closed-form solution
        (sets w to its optimal value).

        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
```

```
        None
        '''
        ### Your code here

        n = X.shape[1]
        self.w = np.linalg.inv(X.T @ X + self.alpha * np.identity(n)) @ X.T @ y



        return None

    def predict(self, X):
        '''Predicts on X using trained model.

        Parameters
        ----------
        X : (m x n) feature matrix

        Returns
        -------
        y_pred: (m x 1) prediction vector
        '''
        ### Your code here
        y_pred = X @ self.w
        return y_pred
```

0.3.4 Train, Evaluate, and Interpret LR Model

2.1.8 Train a linear regression model ($\alpha = 0$) on the training data. Make predictions and report the R^2 score on the training, validation, and test sets. Report the first 3 and last 3 predictions on the test set, along with the actual labels.

[44]:
```
def get_report(y_pred, y_test):
    """
    function to Report the first 3 and last 3 predictions on X_test,
    along with the actual labels in y_test.

    Returns a dataframe with 6 rows.
    """
    preds = np.concatenate([y_pred[:3], y_pred[-3:]])
    actuals = np.concatenate([y_test[:3], y_test[-3:]])
    df_compare = pd.DataFrame({'Prediction': preds,
                               'Actual':actuals})
    df_compare['Position'] = [1, 2, 3, len(y_pred) - 2, len(y_pred) - 1,␣
 ↪len(y_pred)]
    df_compare = df_compare.set_index('Position')
    return df_compare
```

[45]:

```
### Code here

lr_model = LinearRegression(alpha=0)
lr_model.train(car_rental_X_train, car_rental_y_train)

y_train_pred = lr_model.predict(car_rental_X_train)
y_val_pred = lr_model.predict(car_rental_X_val)
y_test_pred = lr_model.predict(car_rental_X_test)

r2_train = r2_score(car_rental_y_train, y_train_pred)
r2_val = r2_score(car_rental_y_val, y_val_pred)
r2_test = r2_score(car_rental_y_test, y_test_pred)

print("R2 score on training set:", r2_train)
print("R2 score on validation set:", r2_val)
print("R2 score on test set:", r2_test)

report_df = get_report(y_test_pred, car_rental_y_test)
print("\nPredictions for test set vs Actual labelds:")
print(report_df)
```

```
R2 score on training set: 0.758701065251997
R2 score on validation set: 0.7342074285364513
R2 score on test set: 0.7180929946660735

Predictions for test set vs Actual labelds:
           Prediction  Actual
Position
1         5121.532889    6606
2         2740.480997    1550
3         4655.839353    3747
145       6145.228240    2792
146       5490.724268    5180
147       4896.430445    3958
```

2.1.9 As a baseline model, use the mean of the training labels (car_rental_y_train) as the prediction for all instances. Report the R^2 on the training, validation, and test sets using this baseline.

This is a common baseline used in regression problems and tells you if your model is any good. Your linear regression R^2 should be much higher than these baseline R^2.

[46]:

```
### Code here
y_train_mean = car_rental_y_train.mean()
y_val_mean = car_rental_y_val.mean()
y_test_mean = car_rental_y_test.mean()
```

```
r2_train_base = r2_score(car_rental_y_train, np.full_like(car_rental_y_train,␣
  ↪y_train_mean))
r2_val_base = r2_score(car_rental_y_val, np.full_like(car_rental_y_val,␣
  ↪y_val_mean))
r2_test_base = r2_score(car_rental_y_test, np.full_like(car_rental_y_test,␣
  ↪y_test_mean))

print("Baseline R2 score on training set:", r2_train_base)
print("Baseline R2 score on validation set:", r2_val_base)
print("Baseline R2 score on test set:", r2_test_base)
```

```
Baseline R2 score on training set: -6.435502197810195e-08
Baseline R2 score on validation set: -5.715014217422265e-08
Baseline R2 score on test set: -3.491074251904536e-08
```

2.1.10 Interpret your model trained on the car rental dataset using a bar chart of the model weights. Make sure to label the bars (x-axis) and don't forget the bias term!

[47]:
```
### Code here

feature_names = ['bias'] + ['feature_' + str(i) for i in range(1, len(lr_model.
  ↪w))]

weights_df = pd.DataFrame({'Features': feature_names, 'Weights': lr_model.w})

weights_df
```

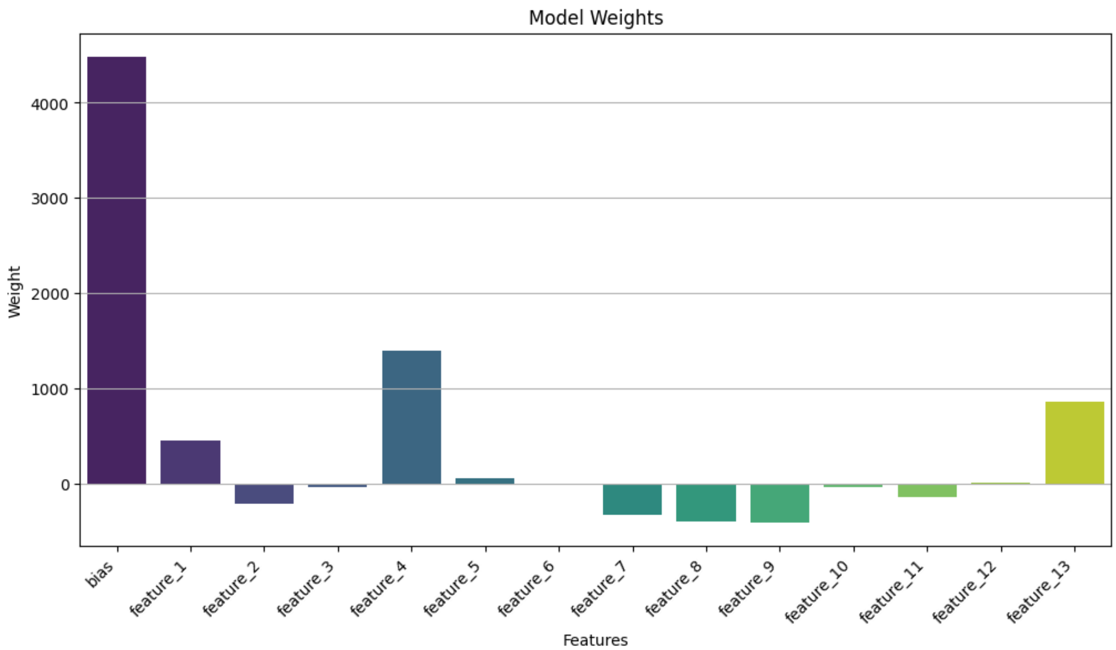
[47]:

	Features	Weights
0	bias	4486.488584
1	feature_1	443.978079
2	feature_2	-219.833155
3	feature_3	-39.220857
4	feature_4	1388.141817
5	feature_5	50.777229
6	feature_6	-13.480006
7	feature_7	-326.423734
8	feature_8	-403.800204
9	feature_9	-408.057979
10	feature_10	-36.005110
11	feature_11	-143.262614
12	feature_12	11.452388
13	feature_13	855.383611

[48]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='Features', y='Weights', data=weights_df, palette='viridis')
# RdBu cividis viridis
plt.xlabel('Features')
```

```
plt.ylabel('Weight')
plt.title('Model Weights')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='-')
plt.show()
```

```
<ipython-input-48-139b795ab4b1>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='Features', y='Weights', data=weights_df, palette='viridis')
```



[49]:
```
weights_df_sorted = weights_df.sort_values(by = ['Weights'], ascending=False)
weights_df_sorted
```

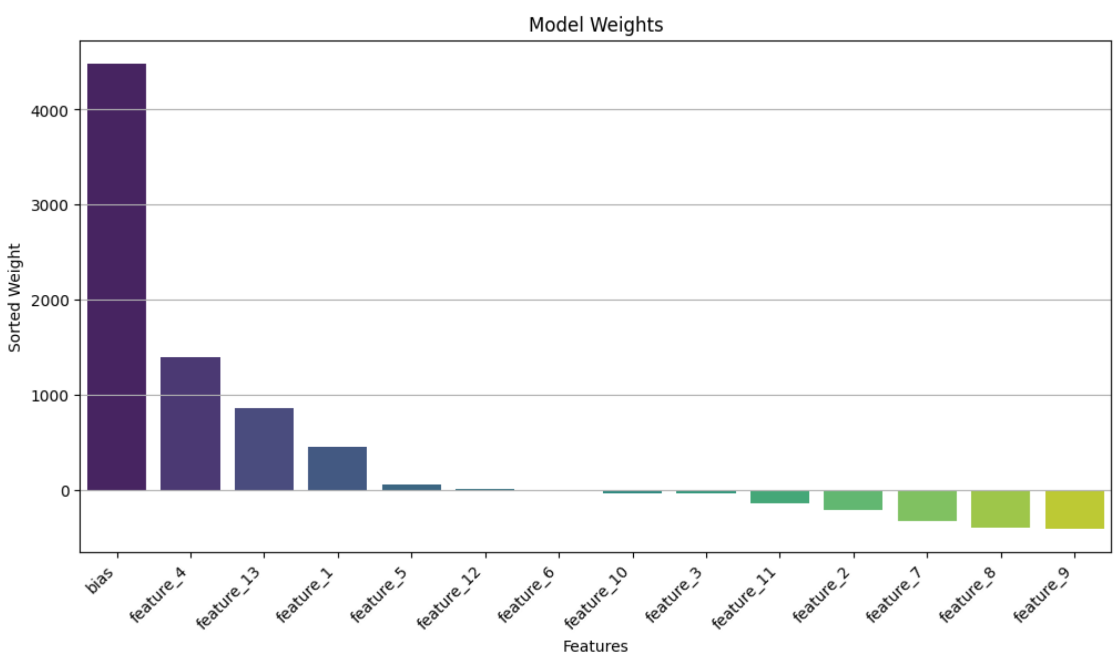
[49]:

	Features	Weights
0	bias	4486.488584
4	feature_4	1388.141817
13	feature_13	855.383611
1	feature_1	443.978079
5	feature_5	50.777229
12	feature_12	11.452388
6	feature_6	-13.480006
10	feature_10	-36.005110

```
3    feature_3   -39.220857
11  feature_11  -143.262614
2    feature_2  -219.833155
7    feature_7  -326.423734
8    feature_8  -403.800204
9    feature_9  -408.057979
```

[50]:
```python
plt.figure(figsize=(12, 6))
sns.barplot(x='Features', y='Weights', data=weights_df_sorted, palette='viridis')
# RdBu cividis viridis
plt.xlabel('Features')
plt.ylabel('Sorted Weight')
plt.title('Model Weights')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='-')
plt.show()
```

```
<ipython-input-50-9877f1a6bb7e>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x='Features', y='Weights', data=weights_df_sorted,
palette='viridis')
```



2.1.11 According to your model, which features are the greatest contributors to the income?

[51]:
```
### Comment here
# According to the model I trained bias is the greatest contributor tothe␣
 ↪income variable.
# If we exclude bias variable feature 4 > 13 > 1 > 5 > 12 > 6 > 10 > 3 > 11 > 2␣
 ↪> 7 > 8 > 9 is the order of contribution
# where 4 being the higghest and 9 being the lowest in all the weights category
```

0.3.5 Hyperparameter Tuning (α)

Now, let's do ridge regression and tune the α regularization parameter on the car rental dataset.

2.1.12 Sweep out values for α using alphas = np.logspace(-5, 1, 20). Perform a grid search over these α values, recording the training and validation R^2 for each α. A simple grid search is fine, no need for k-fold cross validation. Plot the training and validation R^2 as a function of α on a single figure. Make sure to label the axes and the training and validation R^2 curves. Use a log scale for the x-axis.

[52]:
```
alphas = np.logspace(-5, 1, 20)
alphas
```

[52]:
```
array([1.00000000e-05, 2.06913808e-05, 4.28133240e-05, 8.85866790e-05,
       1.83298071e-04, 3.79269019e-04, 7.84759970e-04, 1.62377674e-03,
       3.35981829e-03, 6.95192796e-03, 1.43844989e-02, 2.97635144e-02,
       6.15848211e-02, 1.27427499e-01, 2.63665090e-01, 5.45559478e-01,
       1.12883789e+00, 2.33572147e+00, 4.83293024e+00, 1.00000000e+01])
```

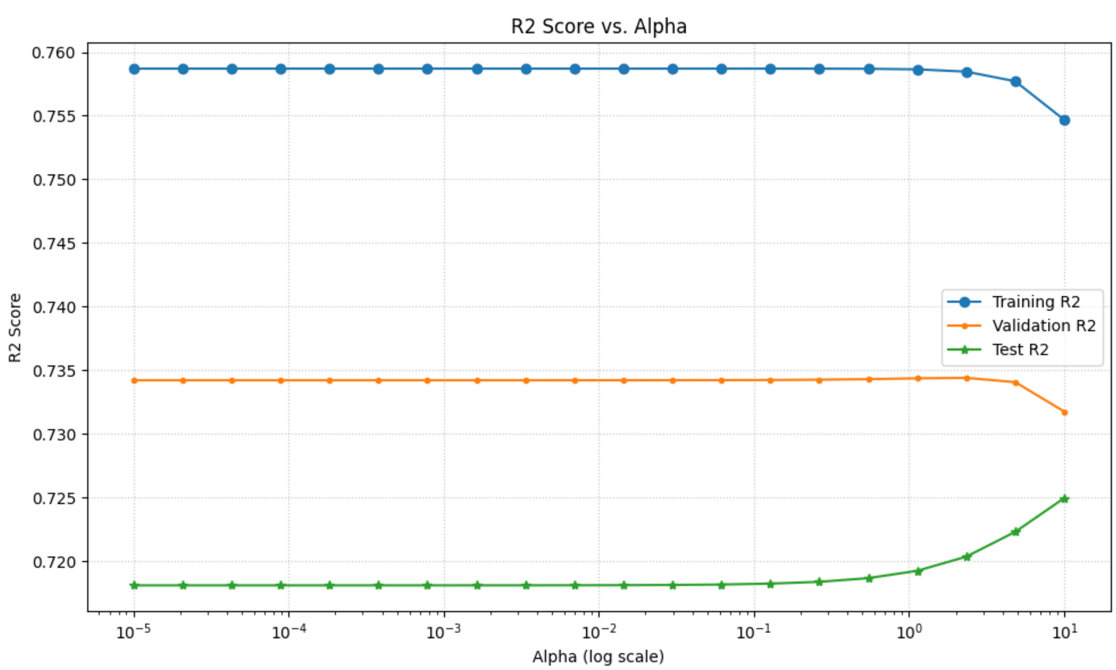
[53]:
```
### Code here
alphas = np.logspace(-5, 1, 20)

train_r2_scores = []
val_r2_scores = []
test_r2_scores = []

for alpha in alphas:
    model = LinearRegression(alpha=alpha)
    model.train(car_rental_X_train, car_rental_y_train)

    y_train_pred = model.predict(car_rental_X_train)
    y_val_pred = model.predict(car_rental_X_val)
    y_test_pred = model.predict(car_rental_X_test)

    train_r2 = r2_score(car_rental_y_train, y_train_pred)
    val_r2 = r2_score(car_rental_y_val, y_val_pred)
    test_r2 = r2_score(car_rental_y_test, y_test_pred)
```

```
    print("alpha = ", alpha)
    print("Training R2 value = ",train_r2)
    print("Validation R2 value = ",val_r2)
    print("Testing R2 value = ",test_r2,'\n')


    train_r2_scores.append(train_r2)
    val_r2_scores.append(val_r2)
    test_r2_scores.append(test_r2)

plt.figure(figsize=(10, 6))
plt.plot(alphas, train_r2_scores, label='Training R2', marker='o')
plt.plot(alphas, val_r2_scores, label='Validation R2', marker='.')
plt.plot(alphas, test_r2_scores, label='Test R2', marker='*')
plt.xlabel('Alpha (log scale)')
plt.ylabel('R2 Score')
plt.title('R2 Score vs. Alpha')
plt.xscale('log')  # Set x-axis to log scale
plt.legend()
plt.grid(True, linestyle=':', alpha=0.7)
plt.tight_layout()
plt.show()
```

```
alpha =  1e-05
Training R2 value =  0.7587010652519924
Validation R2 value =  0.73420743043499
Testing R2 value =  0.7180930052484915

alpha =  2.06913808111479e-05
Training R2 value =  0.7587010652519777
Validation R2 value =  0.7342074324647796
Testing R2 value =  0.718093016562549

alpha =  4.281332398719396e-05
Training R2 value =  0.7587010652519146
Validation R2 value =  0.7342074366646605
Testing R2 value =  0.7180930399728661

alpha =  8.858667904100833e-05
Training R2 value =  0.7587010652516444
Validation R2 value =  0.7342074453546448
Testing R2 value =  0.7180930884119181

alpha =  0.00018329807108324357
Training R2 value =  0.7587010652504875
Validation R2 value =  0.734207463334789
Testing R2 value =  0.718093188638461
```

```
alpha =  0.000379269019073225
Training R2 value =  0.7587010652455346
Validation R2 value =  0.7342075005354758
Testing R2 value =  0.7180933960186919

alpha =  0.0007847599703514606
Training R2 value =  0.7587010652243295
Validation R2 value =  0.7342075774972106
Testing R2 value =  0.7180938251070637

alpha =  0.001623776739188721
Training R2 value =  0.7587010651335444
Validation R2 value =  0.73420773669191
Testing R2 value =  0.7180947129075103

alpha =  0.003359818286283781
Training R2 value =  0.7587010647448733
Validation R2 value =  0.734208065874705
Testing R2 value =  0.7180965497066547

alpha =  0.0069519279617756054
Training R2 value =  0.7587010630809284
Validation R2 value =  0.7342087460874083
Testing R2 value =  0.7181003495161282

alpha =  0.01438449888287663
Training R2 value =  0.7587010559577887
Validation R2 value =  0.7342101496375446
Testing R2 value =  0.7181082085008363

alpha =  0.029763514416313162
Training R2 value =  0.7587010254679951
Validation R2 value =  0.7342130370672546
Testing R2 value =  0.718124455504964

alpha =  0.06158482110660261
Training R2 value =  0.7587008949906581
Validation R2 value =  0.7342189400592011
Testing R2 value =  0.7181580115244742

alpha =  0.1274274985703132
Training R2 value =  0.7587003369006802
Validation R2 value =  0.734230848402274
Testing R2 value =  0.7182271815311165

alpha =  0.26366508987303555
Training R2 value =  0.7586979521785666
```

```
Validation R2 value =  0.7342541824061265
Testing R2 value =  0.7183691847090847

alpha =  0.5455594781168515
Training R2 value =  0.758687783177184
Validation R2 value =  0.7342968991834324
Testing R2 value =  0.7186582414662832

alpha =  1.1288378916846884
Training R2 value =  0.7586446009185033
Validation R2 value =  0.7343616968031852
Testing R2 value =  0.7192361358400543

alpha =  2.3357214690901213
Training R2 value =  0.7584627487617622
Validation R2 value =  0.7343967770222932
Testing R2 value =  0.7203471334005782

alpha =  4.832930238571752
Training R2 value =  0.7577090812899584
Validation R2 value =  0.734062000583835
Testing R2 value =  0.7222973867580884

alpha =  10.0
Training R2 value =  0.7546748471474571
Validation R2 value =  0.7317529603425801
Testing R2 value =  0.7249488090037539
```



2.1.13 Explain your plot above. How do training and validation R^2 behave with decreasing model complexity (increasing α)?

From the provided data, we can observe the behavior of the training and validation R^2 scores with decreasing model complexity (increasing α) as follows:

1. For very small values of α (close to 0), both the training and validation R^2 scores are high. This indicates that the model is fitting the training data well and generalizing well to unseen validation data. This is typical behavior when the model has low complexity and is not regularized much.

2. As α increases, the model complexity decreases, leading to a decrease in the training R^2 score. This is because higher values of α result in stronger regularization, which penalizes complex models and leads to a simpler model with potentially lower training performance.

3. The validation R^2 score initially increases with increasing α, reaching a peak value at an optimal α value. This indicates that some level of regularization improves the model's ability to generalize to unseen data. However, beyond this optimal α value, further increasing α leads to a decrease in the validation R^2 score. This is because excessive regularization causes the model to underfit the data, leading to poor performance on both the training and validation sets.

Overall, the plot illustrates the trade-off between model complexity and generalization performance. The goal is to select an optimal α value that achieves a balance between fitting the training data well and generalizing well to unseen data.

[54]:
```
### Comment here: commented above in text markdown cell
```

0.3.6 2.2 Logistic Regression

[116]:
```
%reset -f
```

[117]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from numpy.linalg import inv
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder
from sklearn.metrics import r2_score, accuracy_score
from sklearn.svm import LinearSVC, SVC
```

2.2.1 Load the dataset, the dataset to be used is loan_data.csv

[118]:
```
### Code here
loan_data = pd.read_csv('/content/drive/MyDrive/1/loan_data.csv')
```

```
loan_data_df = loan_data
loan_data_df
```

[118]:

```
      Loan_ID  Gender Married Dependents     Education Self_Employed  \
0    LP001002    Male      No          0      Graduate            No
1    LP001003    Male     Yes          1      Graduate            No
2    LP001005    Male     Yes          0      Graduate           Yes
3    LP001006    Male     Yes          0  Not Graduate            No
4    LP001008    Male      No          0      Graduate            No
..        …       …       …          …           …             …
609  LP002978  Female      No          0      Graduate            No
610  LP002979    Male     Yes         3+      Graduate            No
611  LP002983    Male     Yes          1      Graduate            No
612  LP002984    Male     Yes          2      Graduate            No
613  LP002990  Female      No          0      Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
..               …                  …          …                …
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
0               1.0         Urban           Y
1               1.0         Rural           N
2               1.0         Urban           Y
3               1.0         Urban           Y
4               1.0         Urban           Y
..              …           …          …
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

[614 rows x 13 columns]
```

[119]:

```
loan_data_df = loan_data_df.drop(columns=['Loan_ID'])
loan_data_df
```

[119]:
```
     Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0      Male      No          0      Graduate            No             5849
1      Male     Yes          1      Graduate            No             4583
2      Male     Yes          0      Graduate           Yes             3000
3      Male     Yes          0  Not Graduate            No             2583
4      Male      No          0      Graduate            No             6000
..      ...     ...        ...           ...           ...              ...
609  Female      No          0      Graduate            No             2900
610    Male     Yes         3+      Graduate            No             4106
611    Male     Yes          1      Graduate            No             8072
612    Male     Yes          2      Graduate            No             7583
613  Female      No          0      Graduate           Yes             4583

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                  0.0         NaN             360.0             1.0
1               1508.0       128.0             360.0             1.0
2                  0.0        66.0             360.0             1.0
3               2358.0       120.0             360.0             1.0
4                  0.0       141.0             360.0             1.0
..                 ...         ...               ...             ...
609                0.0        71.0             360.0             1.0
610                0.0        40.0             180.0             1.0
611              240.0       253.0             360.0             1.0
612                0.0       187.0             360.0             1.0
613                0.0       133.0             360.0             0.0

    Property_Area Loan_Status
0           Urban           Y
1           Rural           N
2           Urban           Y
3           Urban           Y
4           Urban           Y
..            ...         ...
609         Rural           Y
610         Rural           Y
611         Urban           Y
612         Urban           Y
613     Semiurban           N

[614 rows x 12 columns]
```

2.2.2 Are there any missing values in the dataset? If so, what is the best way to deal with it and why?

[120]:
```
### Code here
missing_values = loan_data_df.isnull().sum()
```

```python
print("Missing values in each column:")
print(missing_values)
```

```
Missing values in each column:
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

[121]:
```python
loan_data_df.dropna(inplace=True)
# loan_data = loan_data_df
```

[122]:
```python
loan_data_df
```

[122]:
```
     Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
1      Male     Yes          1      Graduate            No             4583
2      Male     Yes          0      Graduate           Yes             3000
3      Male     Yes          0  Not Graduate            No             2583
4      Male      No          0      Graduate            No             6000
5      Male     Yes          2      Graduate           Yes             5417
..      …       …          …           …             …                …
609  Female      No          0      Graduate            No             2900
610    Male     Yes         3+      Graduate            No             4106
611    Male     Yes          1      Graduate            No             8072
612    Male     Yes          2      Graduate            No             7583
613  Female      No          0      Graduate           Yes             4583

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
1               1508.0       128.0             360.0             1.0
2                  0.0        66.0             360.0             1.0
3               2358.0       120.0             360.0             1.0
4                  0.0       141.0             360.0             1.0
5               4196.0       267.0             360.0             1.0
..                 …          …               …              …
609                0.0        71.0             360.0             1.0
610                0.0        40.0             180.0             1.0
611              240.0       253.0             360.0             1.0
612                0.0       187.0             360.0             1.0
```

```
613                 0.0       133.0             360.0             0.0

    Property_Area Loan_Status
1           Rural           N
2           Urban           Y
3           Urban           Y
4           Urban           Y
5           Urban           Y
..            …           …
609         Rural           Y
610         Rural           Y
611         Urban           Y
612         Urban           Y
613     Semiurban           N

[480 rows x 12 columns]
```

From the notes I see 2 ways in which we can handle missing values if performing logistic regression.

1. **Imputation:** *Impute missing values with a suitable statistic value such as the mean, median, or mode of the column or row. However, for categorical variables, imputing with the mode or a separate category for missing values may be more appropriate.*
2. **Dropping rows or columns:** *We can consider dropping rows with missing values or dropping entire columns with a high proportion of missing values.*

I dropped the corrsponding rows & columns because I didn't want to add any values that would shift the true threshold while performing activation.

[124]:
```
### Comment here: Wrote in markdown above.
```

2.2.3 Encode the categorical variables.

[125]:
```
cols = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',␣
 ↪'Property_Area']

for col_name in cols:
    freqs = loan_data_df[col_name].value_counts()
    print(f"Unique values and their frequencies for column '{col_name}':")
    print(freqs)
    print()
```

```
Unique values and their frequencies for column 'Gender':
Male      394
Female     86
Name: Gender, dtype: int64

Unique values and their frequencies for column 'Married':
Yes    311
```

```
No     169
Name: Married, dtype: int64

Unique values and their frequencies for column 'Dependents':
0     274
2      85
1      80
3+     41
Name: Dependents, dtype: int64

Unique values and their frequencies for column 'Education':
Graduate        383
Not Graduate     97
Name: Education, dtype: int64

Unique values and their frequencies for column 'Self_Employed':
No     414
Yes     66
Name: Self_Employed, dtype: int64

Unique values and their frequencies for column 'Property_Area':
Semiurban    191
Urban        150
Rural        139
Name: Property_Area, dtype: int64
```

[128]:
```
## Code here

# Binary/Label encoding for Gender, Married and Self employed
loan_data_df['Gender'] = loan_data_df['Gender'].map({'Male': 1, 'Female': 0})
loan_data_df['Married'] = loan_data_df['Married'].map({'Yes': 1, 'No': 0})
loan_data_df['Self_Employed'] = loan_data_df['Self_Employed'].map({'No': 0,␣
↪'Yes': 1})

# OH encoding for dpendnets, Education & Property area
loan_data_df = pd.get_dummies(loan_data_df, columns=['Dependents'],␣
↪prefix='Dependents')
loan_data_df = pd.get_dummies(loan_data_df, columns=['Education',␣
↪'Property_Area'])
```

[130]:
```
loan_data_df
```

[130]:
```
     Gender  Married  Self_Employed  ApplicantIncome  CoapplicantIncome  \
1         1        1              0             4583             1508.0
2         1        1              1             3000                0.0
3         1        1              0             2583             2358.0
```

```
4         1       0             0            6000              0.0
5         1       1             1            5417           4196.0
..      …      …            …             …                …
609       0       0             0            2900              0.0
610       1       1             0            4106              0.0
611       1       1             0            8072            240.0
612       1       1             0            7583              0.0
613       0       0             1            4583              0.0

     LoanAmount  Loan_Amount_Term  Credit_History Loan_Status  Dependents_0  \
1         128.0             360.0             1.0           N             0
2          66.0             360.0             1.0           Y             1
3         120.0             360.0             1.0           Y             1
4         141.0             360.0             1.0           Y             1
5         267.0             360.0             1.0           Y             0
..          …               …             …         …           …
609        71.0             360.0             1.0           Y             1
610        40.0             180.0             1.0           Y             0
611       253.0             360.0             1.0           Y             0
612       187.0             360.0             1.0           Y             0
613       133.0             360.0             0.0           N             1

     Dependents_1  Dependents_2  Dependents_3+  Education_Graduate  \
1               1             0              0                   1
2               0             0              0                   1
3               0             0              0                   0
4               0             0              0                   1
5               0             1              0                   1
..            …           …            …                 …
609             0             0              0                   1
610             0             0              1                   1
611             1             0              0                   1
612             0             1              0                   1
613             0             0              0                   1

     Education_Not Graduate  Property_Area_Rural  Property_Area_Semiurban  \
1                         0                    1                        0
2                         0                    0                        0
3                         1                    0                        0
4                         0                    0                        0
5                         0                    0                        0
..                     …                  …                      …
609                       0                    1                        0
610                       0                    1                        0
611                       0                    0                        0
612                       0                    0                        0
613                       0                    0                        1
```

```
     Property_Area_Urban
1                      0
2                      1
3                      1
4                      1
5                      1
..                   ...
609                    0
610                    0
611                    1
612                    1
613                    0

[480 rows x 18 columns]
```

[129]:
```python
loan_data_df.columns
```

[129]:
```
Index(['Gender', 'Married', 'Self_Employed', 'ApplicantIncome',
       'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History',
       'Loan_Status', 'Dependents_0', 'Dependents_1', 'Dependents_2',
       'Dependents_3+', 'Education_Graduate', 'Education_Not Graduate',
       'Property_Area_Rural', 'Property_Area_Semiurban',
       'Property_Area_Urban'],
      dtype='object')
```

2.2.4 Do you think that the distribution of labels is balanced? Why/why not? Hint: Find the probability of the different categories.

[131]:
```python
loan_data_df.head()
```

[131]:
```
   Gender  Married  Self_Employed  ApplicantIncome  CoapplicantIncome  \
1       1        1              0             4583             1508.0
2       1        1              1             3000                0.0
3       1        1              0             2583             2358.0
4       1        0              0             6000                0.0
5       1        1              1             5417             4196.0

   LoanAmount  Loan_Amount_Term  Credit_History Loan_Status  Dependents_0  \
1       128.0             360.0             1.0           N             0
2        66.0             360.0             1.0           Y             1
3       120.0             360.0             1.0           Y             1
4       141.0             360.0             1.0           Y             1
5       267.0             360.0             1.0           Y             0

   Dependents_1  Dependents_2  Dependents_3+  Education_Graduate  \
1             1             0              0                   1
```

```
2                0             0              0                    1
3                0             0              0                    0
4                0             0              0                    1
5                0             1              0                    1

   Education_Not Graduate  Property_Area_Rural  Property_Area_Semiurban  \
1                       0                    1                        0
2                       0                    0                        0
3                       1                    0                        0
4                       0                    0                        0
5                       0                    0                        0

   Property_Area_Urban
1                    0
2                    1
3                    1
4                    1
5                    1
```

[133]:
```
### Code here
prob_Y = (loan_data_df['Loan_Status'] == 'Y').mean()
prob_N = (loan_data_df['Loan_Status'] == 'N').mean()

print("Probability of approval (Y):", prob_Y)
print("Probability of rejection (N):", prob_N)
```

```
Probability of approval (Y): 0.6916666666666667
Probability of rejection (N): 0.30833333333333335
```

Labels balanced or not?

- Probability of approval (Y): ~ 0.692
- Probability of rejection (N): ~ 0.308

We can observe that the probability of approval (Y) is significantly higher than the probability of rejection (N).

This indicates that the distribution of labels is imbalanced, with a larger proportion of loans being approved ('Y') compared to loans being rejected ('N').

[20]:
```
### Comment here: Typed in markdown cell abobe
```

2.2.5 Plot the correlation matrix (first separate features and Y variable), and check if there is high correlation between the given numerical features (Threshold >=0.9). If yes, drop those highly correlated features from the dataframe.

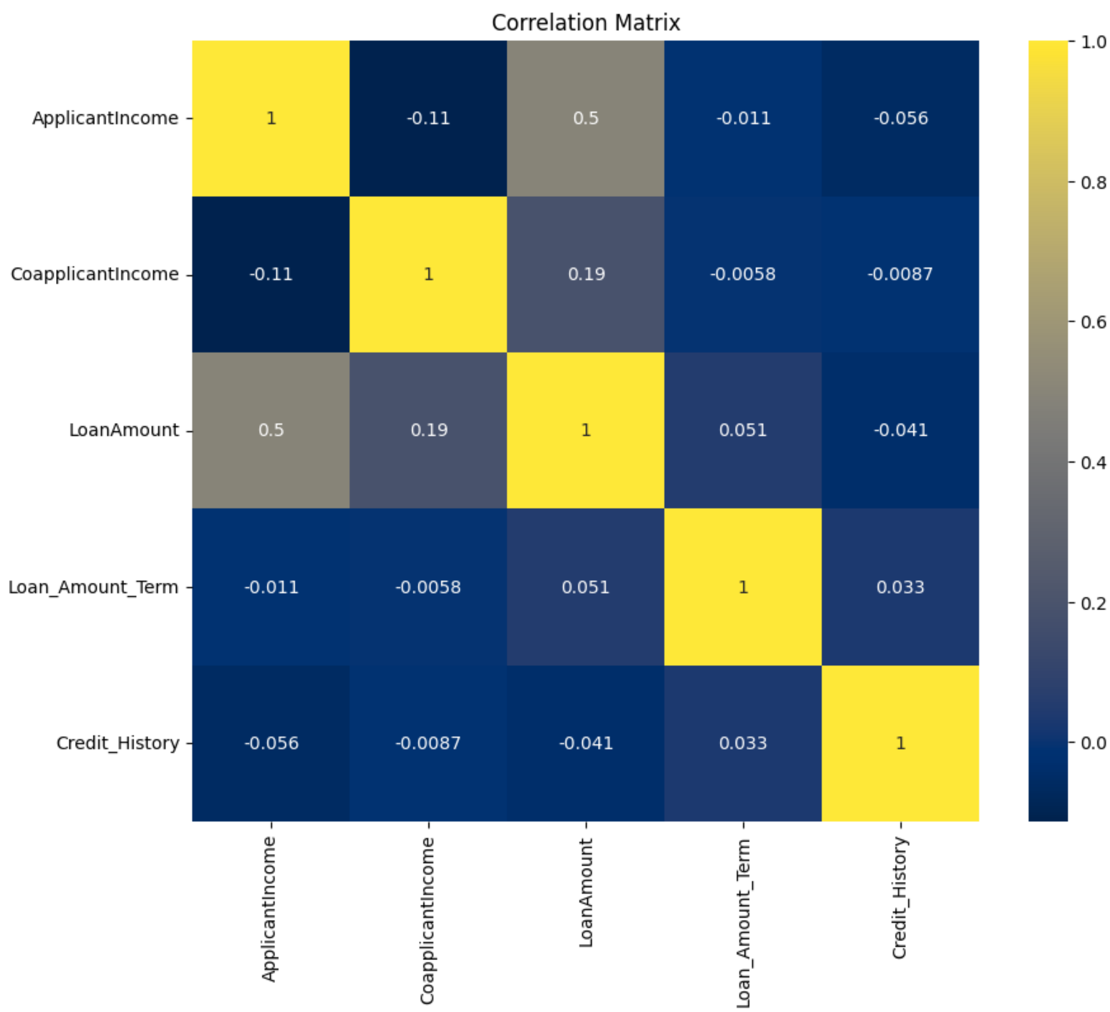
[134]:
```
loan_data_df.columns
```

[134]:

```
Index(['Gender', 'Married', 'Self_Employed', 'ApplicantIncome',
       'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History',
       'Loan_Status', 'Dependents_0', 'Dependents_1', 'Dependents_2',
       'Dependents_3+', 'Education_Graduate', 'Education_Not Graduate',
       'Property_Area_Rural', 'Property_Area_Semiurban',
       'Property_Area_Urban'],
      dtype='object')
```

[135]:

```
### Code here
vars = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',␣
 ↪'Loan_Amount_Term', 'Credit_History']

corr2 = loan_data_df[vars].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr2, annot=True, cmap='cividis')
# sns.heatmap(corr2, annot=True, cmap='RdBu')
plt.title('Correlation Matrix')
plt.show()
```



[136]:
```
### Comments
#  No columns had corr >= 0.9 so nothing was dropped
```

2.2.6 Apply the following pre-processing steps:

1. Convert the label from a Pandas series to a Numpy (m x 1) vector. If you don't do this, it may cause problems when implementing the logistic regression model.
2. Split the dataset into training (60%), validation (20%), and test (20%) sets.
3. Standardize the columns in the feature matrices. To avoid information leakage, learn the standardization parameters from training, and then apply training, validation and test dataset.
4. Add a column of ones to the feature matrices of train, validation and test dataset. This is a common trick so that we can learn a coefficient for the bias term of a linear model.

[138]:
```
loan_data_X = loan_data_df.drop(columns=['Loan_Status'])
loan_data_y = loan_data_df['Loan_Status']
```

[139]:
```
loan_data_y = loan_data_y.map({'Y': 1, 'N': 0})

loan_data_y_array = loan_data_y.to_numpy()

# Reshape the numpy array to a 2D array with shape (480, 1)
loan_data_y = loan_data_y_array.reshape(-1, 1)

# Now, y_train_2d is a 2D numpy array with shape (480, 1)
print(loan_data_y.shape)



X_dev, X_test, y_dev, y_test = train_test_split(loan_data_X, loan_data_y,␣
↪test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_dev, y_dev, test_size=0.25,␣
↪random_state=42)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

X_train_scaled = np.column_stack((np.ones((X_train_scaled.shape[0], 1)),␣
↪X_train_scaled))
X_val_scaled = np.column_stack((np.ones((X_val_scaled.shape[0], 1)),␣
↪X_val_scaled))
X_test_scaled = np.column_stack((np.ones((X_test_scaled.shape[0], 1)),␣
↪X_test_scaled))
```

```
(480, 1)
```

[140]:
```
print("Training set shape:", X_train_scaled.shape, y_train.shape)
print("Validation set shape:", X_val_scaled.shape, y_val.shape)
print("Testing set shape:", X_test_scaled.shape, y_test.shape)
```

```
Training set shape: (288, 18) (288, 1)
Validation set shape: (96, 18) (96, 1)
Testing set shape: (96, 18) (96, 1)
```

[ ]:
```
# ### Code here

# y = np.array(loan_data['Loan_Status'])
# # label_encoder = LabelEncoder()
# # y = label_encoder.fit_transform(y)

# # X = loan_data_df.drop(columns=['Loan_Status'])
```

```
# X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.
↪2, random_state=42)
# X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val,␣
↪test_size=0.25, random_state=42)

# scaler = StandardScaler()
# X_train_scaled = scaler.fit_transform(X_train)
# X_val_scaled = scaler.transform(X_val)
# X_test_scaled = scaler.transform(X_test)

# X_train_final = np.hstack([np.ones((X_train_scaled.shape[0], 1)),␣
↪X_train_scaled])
# X_val_final = np.hstack([np.ones((X_val_scaled.shape[0], 1)), X_val_scaled])
# X_test_final = np.hstack([np.ones((X_test_scaled.shape[0], 1)),␣
↪X_test_scaled])

# print("Training set shape:", X_train_final.shape, y_train.shape)
# print("Validation set shape:", X_val_final.shape, y_val.shape)
# print("Testing set shape:", X_test_final.shape, y_test.shape)
```

[141]:
```
mean_train2 = np.mean(X_train_scaled, axis=0)
std_train2 = np.std(X_train_scaled, axis=0)
print("Mean of scaled training data:", mean_train2)
print("Standard deviation of scaled training data:", std_train2,'\n')

mean_val2 = np.mean(X_val_scaled, axis=0)
std_val2 = np.std(X_val_scaled, axis=0)
print("Mean of scaled validation data:", mean_val2)
print("Standard deviation of scaled validation data:", std_val2,'\n')

mean_test2 = np.mean(X_test_scaled, axis=0)
std_test2 = np.std(X_test_scaled, axis=0)
print("Mean of scaled testing data:", mean_test2)
print("Standard deviation of scaled testing data:", std_test2,'\n')
```

```
Mean of scaled training data: [ 1.00000000e+00  2.77555756e-17 -2.46716228e-17
3.08395285e-17
 -3.08395285e-18  6.16790569e-18 -1.23358114e-16  2.89891568e-16
 -1.35693925e-16  6.78469626e-17  4.31753398e-17  2.77555756e-17
  3.08395285e-17  1.23358114e-17 -1.23358114e-17 -4.31753398e-17
  3.70074342e-17 -4.31753398e-17]
Standard deviation of scaled training data: [0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
1. 1. 1. 1. 1. 1.]

Mean of scaled validation data: [ 1.00000000e+00  5.33760513e-02  1.49820476e-01
-2.86887655e-02
 -8.48852732e-02  7.47244083e-02 -1.00764388e-01 -4.89665072e-02
```

```
  1.39754249e-01 -7.02693669e-03 -6.31888377e-02  2.31296463e-17
  1.04577397e-01 -1.43366643e-01  1.43366643e-01 -4.58349249e-02
  1.00227817e-01 -5.90812302e-02]
Standard deviation of scaled validation data: [0.         0.95481983 0.95237005
0.97203702 0.49182901 1.53238674
 0.69919577 1.09903708 0.85467465 1.00106106 0.94395593 1.
 1.15005424 1.10147523 1.10147523 0.97769236 1.01989336 0.97660107]

Mean of scaled testing data: [ 1.          0.05337605  0.19262633 -0.22951012
-0.05626652 -0.09481478
  0.04194318  0.05596172  0.13975425 -0.04918856 -0.1173507   0.13975425
  0.06536087 -0.08960415  0.08960415  0.02291746  0.10022782 -0.12554761]
Standard deviation of scaled testing data: [0.         0.95481983 0.93391339
0.71607067 0.51465576 0.76917125
 1.10832124 0.85398732 0.85467465 1.00637412 0.88955807 1.10926496
 1.09736215 1.06681636 1.06681636 1.01018968 1.01989336 0.94518428]
```

0.3.7 Implement Logisitc Regression

We will now implement logistic regression with L2 regularization. Given an (m x n) feature matrix X, an (m x 1) label vector y, and an (n x 1) weight vector w, the hypothesis function for logistic regression is:

$$y = \sigma(Xw)$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$, i.e. the sigmoid function. This function scales the prediction to be a probability between 0 and 1, and can then be thresholded to get a discrete class prediction.

Just as with linear regression, our objective in logistic regression is to learn the weights w which best fit the data. For L2-regularized logistic regression, we find an optimal w to minimize the following loss function:

$$\min_{w} \ -y^T \ \log(\sigma(Xw)) \ - \ (\mathbf{1} - y)^T \ \log(\mathbf{1} - \sigma(Xw)) \ + \ \alpha\|w\|_2^2$$

Unlike linear regression, however, logistic regression has no closed-form solution for the optimal w. So, we will use gradient descent to find the optimal w. The (n x 1) gradient vector g for the loss function above is:

$$g = X^T\Big(\sigma(Xw) - y\Big) + 2\alpha w$$

Below is pseudocode for gradient descent to find the optimal w. You should first initialize w (e.g. to a (n x 1) zero vector). Then, for some number of epochs t, you should update w with $w - g $, where η is the learning rate and g is the gradient. You can learn more about gradient descent here.

$w = \mathbf{0}$

for $i = 1, 2, ..., t$

$ w = w - g $

A LogisticRegression class with five methods: train, predict, calculate_loss, calculate_gradient, and calculate_sigmoid has been implemented for you below.

[142]:
```python
class LogisticRegression():
    '''
    Logistic regression model with L2 regularization.

    Attributes
    ----------
    alpha: regularization parameter
    t: number of epochs to run gradient descent
    eta: learning rate for gradient descent
    w: (n x 1) weight vector
    '''

    def __init__(self, alpha=0, t=100, eta=1e-3):
        self.alpha = alpha
        self.t = t
        self.eta = eta
        self.w = None

    def train(self, X, y):
        '''Trains logistic regression model using gradient descent
        (sets w to its optimal value).

        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
        losses: (t x 1) vector of losses at each epoch of gradient descent
        '''

        loss = list()
        self.w = np.zeros((X.shape[1],1))
        for i in range(self.t):
            self.w = self.w - (self.eta * self.calculate_gradient(X, y))
            loss.append(self.calculate_loss(X, y))
        return loss

    def predict(self, X):
        '''Predicts on X using trained model. Make sure to threshold
        the predicted probability to return a 0 or 1 prediction.
```

```
        Parameters
        ----------
        X : (m x n) feature matrix

        Returns
        -------
        y_pred: (m x 1) 0/1 prediction vector
        '''
        y_pred = self.calculate_sigmoid(X.dot(self.w))
        y_pred[y_pred >= 0.5] = 1
        y_pred[y_pred < 0.5] = 0
        return y_pred

    def calculate_loss(self, X, y):
        '''Calculates the logistic regression loss using X, y, w,
        and alpha. Useful as a helper function for train().

        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
        loss: (scalar) logistic regression loss
        '''
        return -y.T.dot(np.log(self.calculate_sigmoid(X.dot(self.w)))) - (1-y).
↪T.dot(np.log(1-self.calculate_sigmoid(X.dot(self.w)))) + self.alpha*np.
↪linalg.norm(self.w, ord=2)**2

    def calculate_gradient(self, X, y):
        '''Calculates the gradient of the logistic regression loss
        using X, y, w, and alpha. Useful as a helper function
        for train().

        Parameters
        ----------
        X : (m x n) feature matrix
        y: (m x 1) label vector

        Returns
        -------
        gradient: (n x 1) gradient vector for logistic regression loss
        '''
        return X.T.dot(self.calculate_sigmoid( X.dot(self.w)) - y) + 2*self.
↪alpha*self.w
```

```
    def calculate_sigmoid(self, x):
        '''Calculates the sigmoid function on each element in vector x.
        Useful as a helper function for predict(), calculate_loss(),
        and calculate_gradient().

        Parameters
        ----------
        x: (m x 1) vector

        Returns
        -------
        sigmoid_x: (m x 1) vector of sigmoid on each element in x
        '''
        return (1)/(1 + np.exp(-x.astype('float')))
```

2.2.7 Plot Loss over Epoch and Search the space randomly to find best hyperparameters.

i) Using your implementation above, train a logistic regression model **(alpha=0, t=100, eta=1e-3)** on the loan training data. Plot the training loss over epochs. Make sure to label your axes. You should see the loss decreasing and start to converge.

ii) Using **alpha between (0,1), eta between(0, 0.001) and t between (0, 100)**, find the best hyperparameters for LogisticRegression. You can randomly search the space 20 times to find the best hyperparameters.

iii) Compare accuracy on the test dataset for both the scenarios.

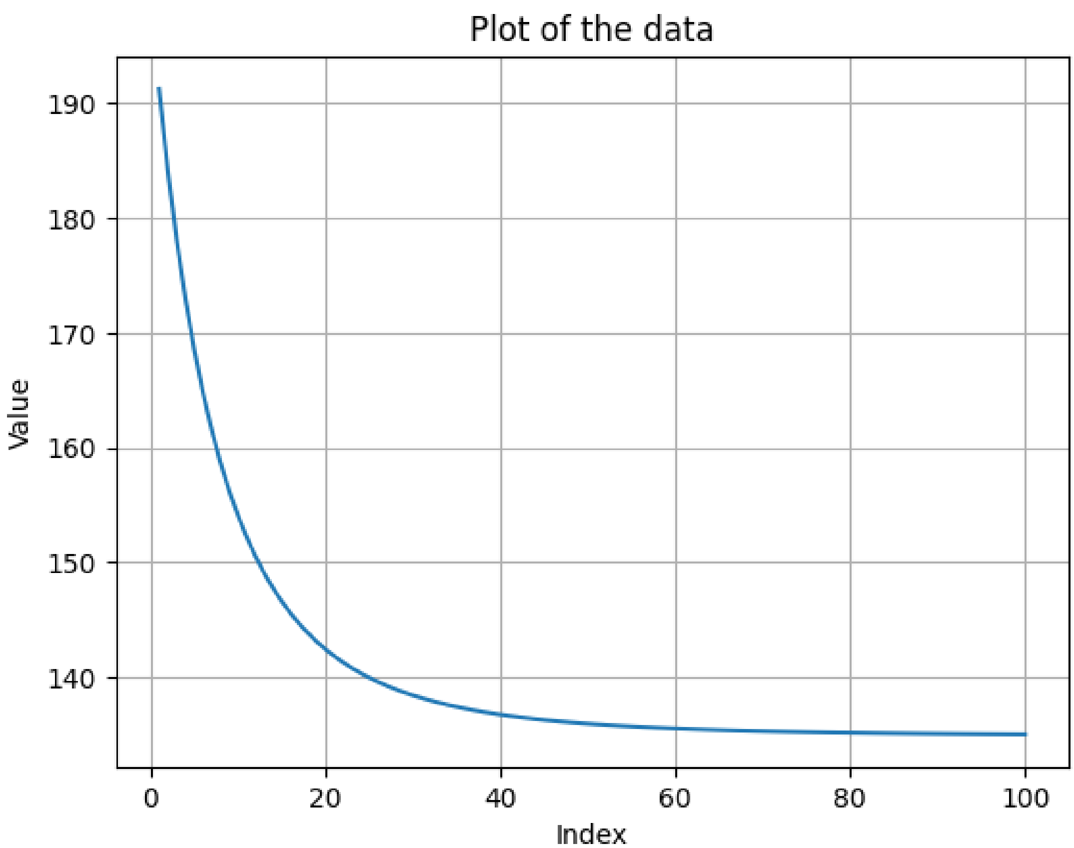
[ ]:
```
print(loan_data_y.shape)
```

[ ]:
```
# y_train_array = y_train.to_numpy()

# # Reshape the numpy array to a 2D array with shape (480, 1)
# y_train_2d = y_train_array.reshape(-1, 1)

# # Now, y_train_2d is a 2D numpy array with shape (480, 1)
# print(y_train_2d.shape)
```

[143]:
```
### Code here

log_reg = LogisticRegression(alpha=0, t=100, eta=1e-3)
losses = log_reg.train(X_train_scaled, y_train)
```

[144]:
```
values = [arr[0][0] for arr in losses]

# Creating x values (assuming it starts from 1 and increments by 1)
x_values = np.arange(1, len(values) + 1)
```

```python
# Plotting
plt.plot(x_values, values)
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Plot of the data')
plt.grid(True)
plt.show()
```



[146]:
```python
## Code for random parmaters on validation set

alphas = np.random.uniform(0, 1, size=20)
etas = np.random.uniform(0, 0.001, size=20)
ts = np.random.randint(1, 100, size=20)

best_loss = float('inf')
best_hyperparameters = None

for alpha, eta, t in zip(alphas, etas, ts):
    model = LogisticRegression(alpha=alpha, eta=eta, t=t)
```

```
    losses = model.train(X_val_scaled, y_val)

    final_loss = losses[-1]

    if final_loss < best_loss:
        best_loss = final_loss
        best_hyperparameters = {'alpha': alpha, 'eta': eta, 't': t}

print("Best hyperparameters:", best_hyperparameters)
print("Best validation loss:", best_loss)
```

```
Best hyperparameters: {'alpha': 0.3286983380426536, 'eta':
0.0005929875474338326, 't': 92}
Best validation loss: [[41.80604499]]
```

[ ]:
```
best_hyperparameters
```

[147]:
```
from sklearn.metrics import accuracy_score

# log_reg_initial = LogisticRegression(alpha=0, t=100, eta=1e-3)
# log_reg_initial.train(X_train_scaled, y_train)
y_pred_initial = log_reg.predict(X_test_scaled)
accuracy_initial = accuracy_score(y_test, y_pred_initial)
print("Accuracy with initial hyperparameters:", accuracy_initial)


# log_reg_best = LogisticRegression(alpha=best_hyperparameters['alpha'],
#                                   t=best_hyperparameters['t'],
#                                   eta=best_hyperparameters['eta'])
# log_reg_best.train(X_train_scaled, y_train)
y_pred_best = model.predict(X_test_scaled)
accuracy_best = accuracy_score(y_test, y_pred_best)
print("Accuracy with best hyperparameters:", accuracy_best)
```

```
Accuracy with initial hyperparameters: 0.8125
Accuracy with best hyperparameters: 0.8229166666666666
```

0.3.8 Feature Importance

2.2.8 Interpret your trained model using a bar chart of the model weights. Make sure to label the bars (x-axis) and don't forget the bias term!

[148]:
```
log_reg.w
```

[148]:
```
array([[ 0.80013321],
       [ 0.19176587],
       [ 0.16580628],
       [ 0.00458451],
```

```
       [ 0.05847558],
       [-0.10387606],
       [-0.2066172 ],
       [-0.36167444],
       [ 1.23556606],
       [ 0.02776434],
       [-0.12566237],
       [ 0.08766333],
       [ 0.00732844],
       [ 0.0521606 ],
       [-0.0521606 ],
       [-0.16232888],
       [ 0.2929875 ],
       [-0.14530606]])
```

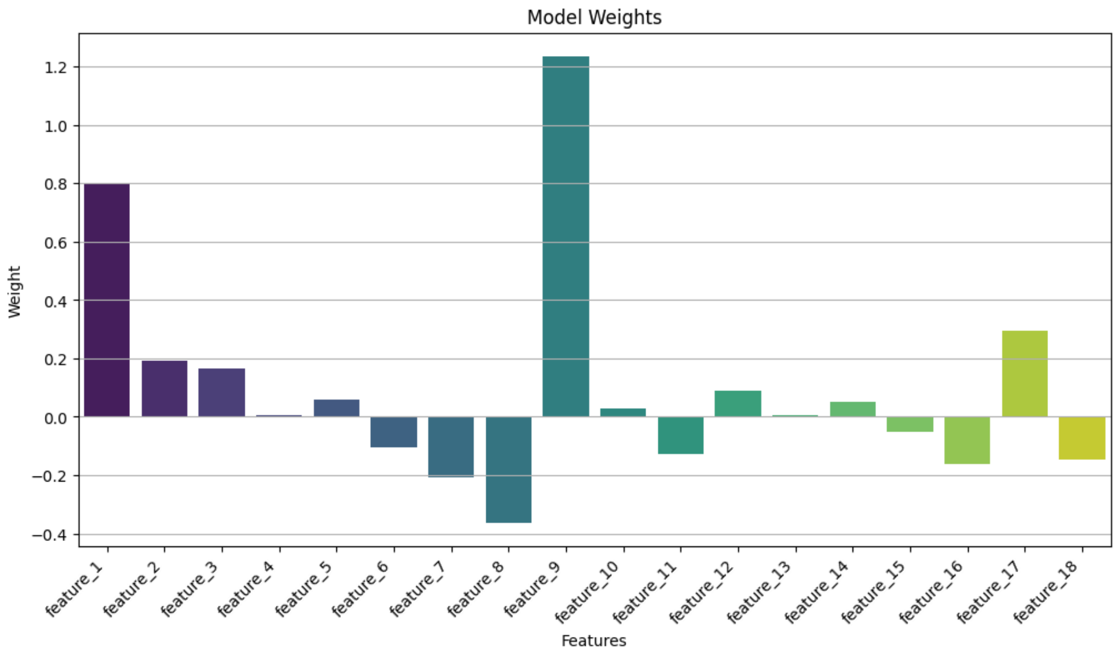
[149]:
```python
### Code here
import pandas as pd

weights = log_reg.w
feat_names =  [f'feature_{i}' for i in range(1, len(weights) + 1)]
wt_df = pd.DataFrame({'Features': feat_names, 'Weights': weights.flatten()})
wt_df
```

[149]:

	Features	Weights
0	feature_1	0.800133
1	feature_2	0.191766
2	feature_3	0.165806
3	feature_4	0.004585
4	feature_5	0.058476
5	feature_6	-0.103876
6	feature_7	-0.206617
7	feature_8	-0.361674
8	feature_9	1.235566
9	feature_10	0.027764
10	feature_11	-0.125662
11	feature_12	0.087663
12	feature_13	0.007328
13	feature_14	0.052161
14	feature_15	-0.052161
15	feature_16	-0.162329
16	feature_17	0.292988
17	feature_18	-0.145306

[150]:
```python
plt.figure(figsize=(12, 6))
sns.barplot(x='Features', y='Weights', data=wt_df, palette='viridis')
# RdBu cividis viridis
plt.xlabel('Features')
```

```
plt.ylabel('Weight')
plt.title('Model Weights')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='-')
plt.show()
```



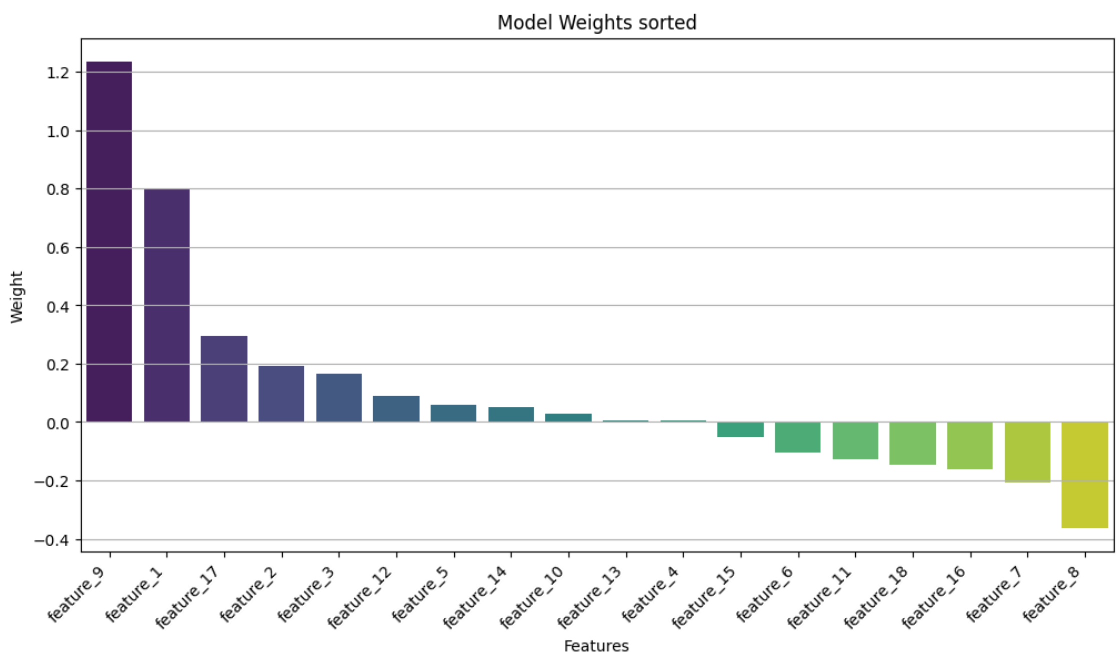
[151]:
```
wt_df_sorted = wt_df.sort_values(by = ['Weights'], ascending=False)
wt_df_sorted
```

[151]:

	Features	Weights
8	feature_9	1.235566
0	feature_1	0.800133
16	feature_17	0.292988
1	feature_2	0.191766
2	feature_3	0.165806
11	feature_12	0.087663
4	feature_5	0.058476
13	feature_14	0.052161
9	feature_10	0.027764
12	feature_13	0.007328
3	feature_4	0.004585
14	feature_15	-0.052161
5	feature_6	-0.103876
10	feature_11	-0.125662
17	feature_18	-0.145306
15	feature_16	-0.162329

```
6     feature_7 -0.206617
7     feature_8 -0.361674
```

[152]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x='Features', y='Weights', data=wt_df_sorted, palette='viridis')
# RdBu cividis viridis
plt.xlabel('Features')
plt.ylabel('Weight')
plt.title('Model Weights sorted')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='-')
plt.show()
```



Based on the obtained wts, some inferences:

1. Bias (Feature 1): The positive weight indicates a baseline prediction or bias towards positive outcomes.
2. Positive Influencers (Features 17, 2, 3, 12, 5, 14): These features have small positive weights, suggesting they contribute positively to the predictions, albeit to a lesser extent compared to other features.
3. Negative Influencers (Features 6, 11, 18, 16, 7, 8): Features 6, 7, and 8 have negative weights, indicating they negatively influence the predictions. Feature 8 has the strongest negative influence.
4. Strong Positive Influencer (Feature 9): Feature 9 has a very strong positive weight, indicating it has a significant positive impact on the predictions.

5. Negligible Impact (Feature 10, 13, 4, 15): Feature 4 has an almost negligible positive weight, suggesting it has minimal impact on the predictions.
6. Mixed Impact (Features 10-18): These features have weights close to zero, indicating they have relatively minor influences on the predictions compared to other features.

In summary, Feature 9 appears to be the most influential in predicting positive outcomes, while Features 6, 7, and 8 have the strongest negative influences. Other features have varying degrees of influence, with some contributing positively, some negatively, and others having negligible impact.

[ ]:
```
### Comment here: Typed in markdown abve
```

0.3.9 2.3 Support Vector Machines

In this part, we will be using support vector machines for classification on the loan dataset.

0.3.10 Train Primal SVM

2.3.1 Train a primal SVM (with default parameters) on the loan dataset. Make predictions and report the accuracy on the training, validation, and test sets.

[154]:
```
### Code here
svm = SVC(kernel='linear')
svm.fit(X_train_scaled, y_train.ravel())

y_train_pred = svm.predict(X_train_scaled)
y_val_pred = svm.predict(X_val_scaled)
y_test_pred = svm.predict(X_test_scaled)

train_accuracy = accuracy_score(y_train, y_train_pred)
val_accuracy = accuracy_score(y_val, y_val_pred)
test_accuracy = accuracy_score(y_test, y_test_pred)

print("Accuracy on training set:", train_accuracy)
print("Accuracy on validation set:", val_accuracy)
print("Accuracy on test set:", test_accuracy)
```

```
Accuracy on training set: 0.7951388888888888
Accuracy on validation set: 0.8333333333333334
Accuracy on test set: 0.8229166666666666
```

0.3.11 Train Dual SVM

2.3.2 Train a dual SVM (with default parameters) on the loan dataset. Make predictions and report the accuracy on the training, validation, and test sets.

[155]:
```
### Code here
svm2 = SVC(kernel='rbf')
svm2.fit(X_train_scaled, y_train.ravel())
```

```python
y_train_pred = svm2.predict(X_train_scaled)
y_val_pred = svm2.predict(X_val_scaled)
y_test_pred = svm2.predict(X_test_scaled)

train_accuracy = accuracy_score(y_train, y_train_pred)
val_accuracy = accuracy_score(y_val, y_val_pred)
test_accuracy = accuracy_score(y_test, y_test_pred)

print("Accuracy on training set:", train_accuracy)
print("Accuracy on validation set:", val_accuracy)
print("Accuracy on test set:", test_accuracy)
```

```
Accuracy on training set: 0.8194444444444444
Accuracy on validation set: 0.8333333333333334
Accuracy on test set: 0.8125
```

[165]:
```
!jupyter nbconvert --to PDF "W4995_HW1_amp2365.ipynb"
```

```
[NbConvertApp] WARNING | pattern 'W4995_HW1_amp2365.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
```

```
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and
include the error message in the cell output (the default behaviour is to abort
conversion). This flag is only relevant if '--execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with
default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=
--ClearOutputPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True
--TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True
--TemplateExporter.exclude_input=True
--TemplateExporter.exclude_input_prompt=True]
--allow-chromium-download
    Whether to allow downloading chromium if no suitable version is found on the
system.
    Equivalent to: [--WebPDFExporter.allow_chromium_download=True]
--disable-chromium-sandbox
    Disable chromium security sandbox when converting to PDF..
    Equivalent to: [--WebPDFExporter.disable_sandbox=True]
--show-input
    Shows code input. This flag is only useful for dejavu users.
    Equivalent to: [--TemplateExporter.exclude_input=False]
--embed-images
    Embed the images as base64 dataurls in the output. This flag is only useful
for the HTML/WebPDF/Slides exports.
    Equivalent to: [--HTMLExporter.embed_images=True]
```

```
--sanitize-html
    Whether the HTML in Markdown cells and cell outputs should be sanitized..
    Equivalent to: [--HTMLExporter.sanitize_html=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN', 'ERROR',
'CRITICAL']
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown', 'notebook',
'pdf', 'python', 'rst', 'script', 'slides', 'webpdf']
            or a dotted object name that represents the import path for an
            ``Exporter`` class
    Default: ''
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_name]
--template-file=<Unicode>
    Name of the template file to use
    Default: None
    Equivalent to: [--TemplateExporter.template_file]
--theme=<Unicode>
    Template specific theme(e.g. the name of a JupyterLab CSS theme distributed
    as prebuilt extension for the lab template)
    Default: 'light'
    Equivalent to: [--HTMLExporter.theme]
--sanitize_html=<Bool>
    Whether the HTML in Markdown cells and cell outputs should be sanitized.This
    should be set to True by nbviewer or similar tools.
    Default: False
    Equivalent to: [--HTMLExporter.sanitize_html]
--writer=<DottedObjectName>
    Writer class used to write the
                                    results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                    results of the conversion
    Default: ''
```

```
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    overwrite base name use for output files.
                can only be used when converting one notebook at a time.
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each notebook.
To recover
                                  previous default behaviour (outputting to the
current
                                  working directory) use . as the flag value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url pointing to a
copy
            of reveal.js.
            For speaker notes to work, this must be a relative path to a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of the
            current directory (from which the server is run).
            See the usage documentation
            (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-
html-slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb --to html

            Options include ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides', 'webpdf'].

            > jupyter nbconvert --to latex mynotebook.ipynb
```

```
            Both HTML and LaTeX support multiple output templates. LaTeX
includes
            'base', 'article' and 'report'.  HTML includes 'basic', 'lab' and
            'classic'. You can specify the flavor of the format used.

            > jupyter nbconvert --to html --template lab mynotebook.ipynb

            You can also pipe the output to stdout, rather than a file

            > jupyter nbconvert mynotebook.ipynb --stdout

            PDF is generated via latex

            > jupyter nbconvert mynotebook.ipynb --to pdf

            You can get (and serve) a Reveal.js-powered slideshow

            > jupyter nbconvert myslides.ipynb --to slides --post serve

            Multiple notebooks can be given at the command line in a couple of
            different ways:

            > jupyter nbconvert notebook*.ipynb
            > jupyter nbconvert notebook1.ipynb notebook2.ipynb

            or you can specify the notebooks list in a config file, containing::

                c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

            > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.
```