

PRACTICAL – 7

Aim: Perform the following Data Preparation task on any of the data

- Check the correlation between various columns
- Check the skewness and kurtosis of data

```
[1]: import pandas as pd
```

```
[2]: sample=pd.read_csv("Sample - Superstore - Sample - Superstore.csv")
```

```
[3]: sample.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 9994 entries, 0 to 9993  
Data columns (total 20 columns):  
#   Column                Non-Null Count  Dtype    
---  ---                  
0   Order ID              9994 non-null   object   
1   Order Date            9994 non-null   object   
2   Ship Date             9994 non-null   object   
3   Ship Mode             9994 non-null   object   
4   Customer ID           9994 non-null   object   
5   Customer Name         9994 non-null   object   
6   Segment               9994 non-null   object   
7   Country               9994 non-null   object   
8   City                  9994 non-null   object   
9   State                 9994 non-null   object   
10  Postal Code           9994 non-null   int64    
11  Region                9994 non-null   object   
12  Product ID            9994 non-null   object   
13  Category              9994 non-null   object   
14  Sub-Category          9994 non-null   object   
15  Product Name          9994 non-null   object   
16  Sales                 9994 non-null   float64  
17  Quantity              9994 non-null   int64    
18  Discount              9994 non-null   float64  
19  Profit                9994 non-null   float64  
dtypes: float64(3), int64(2), object(15)  
memory usage: 1.5+ MB
```

ANALYTICAL STATEMENT:

```
[4]: sample.columns
```

```
[4]: Index(['Order ID', 'Order Date', 'Ship Date', 'Ship Mode', 'Customer ID',  
         'Customer Name', 'Segment', 'Country', 'City', 'State', 'Postal Code',  
         'Region', 'Product ID', 'Category', 'Sub-Category', 'Product Name',  
         'Sales', 'Quantity', 'Discount', 'Profit'],  
        dtype='object')
```

ANALYTICAL STATEMENT:

```
[5]: sample['Sales'].corr(sample['Quantity'])
```

```
[5]: np.float64(0.2007947713738976)
```

ANALYTICAL STATEMENT:

```
[6]: sample['Quantity'].corr(sample['Profit'])
```

```
[6]: np.float64(0.06625318912428485)
```

ANALYTICAL STATEMENT:

```
[7]: sample[['Profit', 'Discount']].kurt()
```

```
[7]: Profit      397.188515  
     Discount    2.409546  
     dtype: float64
```

ANALYTICAL STATEMENT:

```
[8]: sample['Discount'].kurt()
```

```
[8]: np.float64(2.4095461225966774)
```

ANALYTICAL STATEMENT:

```
[9]: sample['Sales'].kurt()
```

```
[9]: np.float64(305.311753246823)
```

ANALYTICAL STATEMENT:

```
[10]: sample['Profit'].skew()
```

```
[10]: np.float64(7.561431562468343)
```

ANALYTICAL STATEMENT:

```
[11]: sample['Sales'].skew()
```

```
[11]: np.float64(12.97275234181623)
```

ANALYTICAL STATEMENT:

```
[12]: sample['Discount'].skew()
```

```
[12]: np.float64(1.6842947474238648)
```

ANALYTICAL STATEMENT:

PRACTICAL – 8

Aim: Perform the Data Transformation on date time and zip code feature.

```
import pandas as pd
data = pd.read_csv("Loan.csv")
```

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

	customer_id	disbursed_amount	interest	market	employment	time_employed	householder	income	date_issued	target	loan_purpose	number_open_accounts	d
0	0	23201.5	15.4840	C	Teacher	<=5 years	RENT	84600.0	2013-06-11	0	Debt consolidation	4	
1	1	7425.0	11.2032	B	Accountant	<=5 years	OWNER	102000.0	2014-05-08	0	Car purchase	13	
2	2	11150.0	8.5100	A	Statistician	<=5 years	RENT	69840.0	2013-10-26	0	Debt consolidation	8	
3	3	7600.0	5.8656	A	Other	<=5 years	RENT	100386.0	2015-08-20	0	Debt consolidation	20	
4	4	31960.0	18.7392	E	Bus driver	>5 years	RENT	95040.0	2014-07-22	0	Debt consolidation	14	

ANALYTICAL STATEMENT:

```
[4]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype  
---  -
 0   customer_id           10000 non-null  int64  
 1   disbursed_amount      10000 non-null  float64
 2   interest              10000 non-null  float64
 3   market                10000 non-null  object  
 4   employment            9389 non-null   object  
 5   time_employed         9471 non-null   object  
 6   householder           10000 non-null  object  
 7   income                10000 non-null  float64
 8   date_issued           10000 non-null  object  
 9   target                10000 non-null  int64  
10   loan_purpose            10000 non-null  object  
11   number_open_accounts  10000 non-null  int64  
12   date_last_payment     10000 non-null  object  
13   number_credit_lines_12 238 non-null    float64
dtypes: float64(4), int64(3), object(7)
memory usage: 1.1+ MB
```

ANALYTICAL STATEMENT:

```
data['Date'] = pd.to_datetime(data['date_issued'])  
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 10000 entries, 0 to 9999  
Data columns (total 15 columns):  
#   Column                Non-Null Count  Dtype  
---  ---  
0   customer_id           10000 non-null  int64  
1   disbursed_amount      10000 non-null  float64  
2   interest              10000 non-null  float64  
3   market                10000 non-null  object  
4   employment            9389 non-null   object  
5   time_employed         9471 non-null   object  
6   householder           10000 non-null  object  
7   income                 10000 non-null  float64  
8   date_issued           10000 non-null  object  
9   target                10000 non-null  int64  
10  loan_purpose            10000 non-null  object  
11  number_open_accounts  10000 non-null  int64  
12  date_last_payment     10000 non-null  object  
13  number_credit_lines_12 238 non-null    float64  
14  Date                  10000 non-null  datetime64[ns]  
dtypes: datetime64[ns](1), float64(4), int64(3), object(7)  
memory usage: 1.1+ MB
```

ANALYTICAL STATEMENT:

```
[6]: data['Month'] = data['Date'].dt.month  
data['Day'] = data['Date'].dt.day  
data['Year'] = data['Date'].dt.year  
data[['Month', 'Day', 'Year']].head()
```

```
[6]:
```

	Month	Day	Year
0	6	11	2013
1	5	8	2014
2	10	26	2013
3	8	20	2015
4	7	22	2014

ANALYTICAL STATEMENT:

```
[7]: data['day_of_week'] = data['Date'].dt.day_of_week  
data['day_of_year'] = data['Date'].dt.day_of_year
```

```
[8]: data[['Year', 'day_of_week', 'day_of_year']].head()
```

```
[8]:
```

	Year	day_of_week	day_of_year
0	2013	1	162
1	2014	3	128
2	2013	5	299
3	2015	3	232
4	2014	1	203

ANALYTICAL STATEMENT:

```
[9]: def week_part(day):  
    if day in [1,2,3,4,5,6,7]:  
        return "week 1"  
    elif day in [8,9,10,11,12,13,14]:  
        return "week 2"  
    elif day in [15,16,17,18,19,20,21]:  
        return "week 3"  
    elif day in [22,23,24,25,26,27,28]:  
        return "week 4"  
    elif day in [29,30,31]:  
        return "week 5"
```

ANALYTICAL STATEMENT:

```
[10]: data['Week_No'] = data['Day'].apply(week_part)  
data[['Day', 'Week_No']]
```

```
[10]:
```

	Day	Week_No
0	11	week 2
1	8	week 2
2	26	week 4
3	20	week 3
4	22	week 4
...
9995	14	week 2
9996	20	week 3
9997	3	week 1
9998	23	week 4
9999	19	week 3

10000 rows × 2 columns

ANALYTICAL STATEMENT:

```
[11]: data['Week_No'].value_counts()
```

```
[11]: week 1    2652  
      week 3    2591  
      week 2    2545  
      week 4    2212  
      Name: Week_No, dtype: int64
```

ANALYTICAL STATEMENT:

```
[12]: import numpy as np
data["date issued:is_weekend"] = np.where(data["day_of_week"].isin([5,6]),1,0)
data[["Date", 'day_of_week', 'date issued:is_weekend']].head()
```

```
[12]:
```

	Date	day_of_week	date issued:is_weekend
0	2013-06-11	1	0
1	2014-05-08	3	0
2	2013-10-26	5	1
3	2015-08-20	3	0
4	2014-07-22	1	0

ANALYTICAL STATEMENT:

```
[13]: data['is_leap_year'] = data['Date'].dt.is_leap_year
data[["Date", 'is_leap_year']]
```

```
[13]:
```

	Date	is_leap_year
0	2013-06-11	False
1	2014-05-08	False
2	2013-10-26	False
3	2015-08-20	False
4	2014-07-22	False
...
9995	2010-01-14	False
9996	2015-03-20	False
9997	2015-04-03	False
9998	2014-11-23	False
9999	2015-01-19	False

10000 rows × 2 columns

ANALYTICAL STATEMENT:


```
[14]: data['is_leap_year'].value_counts()
```

```
[14]: False    9385  
      True     615  
      Name: is_leap_year, dtype: int64
```

ANALYTICAL STATEMENT:

```
[15]: data['Date'].min(), data['Date'].max()
```

```
[15]: (Timestamp('2007-07-10 00:00:00'), Timestamp('2015-12-27 00:00:00'))
```

ANALYTICAL STATEMENT:

```
[16]: data['Date'].max() - data['Date'].min()
```

```
[16]: Timedelta('3092 days 00:00:00')
```

ANALYTICAL STATEMENT:

```
[17]: data['dt_period'] = data['Date'].dt.to_period('Y')  
      data.head()
```

```
[17]:
```

ic_employed	householder	income	date_issued	target	...	Date	Month	Day	Year	day_of_week	day_of_year	Week.No	date issued:is_weekend	is_leap_year	dt_period
<=5 years	RENT	84600.0	2013-06-11	0	...	2013-06-11	6	11	2013	1	162	week 2	0	False	2013
<=5 years	OWNER	102000.0	2014-05-08	0	...	2014-05-08	5	8	2014	3	128	week 2	0	False	2014
<=5 years	RENT	69840.0	2013-10-26	0	...	2013-10-26	10	26	2013	5	299	week 4	1	False	2013
<=5 years	RENT	100386.0	2015-08-20	0	...	2015-08-20	8	20	2015	3	232	week 3	0	False	2015
>5 years	RENT	95040.0	2014-07-22	0	...	2014-07-22	7	22	2014	1	203	week 4	0	False	2014

ANALYTICAL STATEMENT:

```
[18]: data['next_15_days'] = data['Date'] + pd.Timedelta(days=15)  
data[['Date', 'next_15_days']].head()
```

```
[18]:
```

	Date	next_15_days
0	2013-06-11	2013-06-26
1	2014-05-08	2014-05-23
2	2013-10-26	2013-11-10
3	2015-08-20	2015-09-04
4	2014-07-22	2014-08-06

ANALYTICAL STATEMENT:

```
[19]: data['date_issued:is_year_start'] = data['Date'].dt.is_year_start
data['date_issued:is_quarter_start'] = data['Date'].dt.is_quarter_start
data['date_issued:is_month_start'] = data['Date'].dt.is_month_start
data['date_issued:is_year_end'] = data['Date'].dt.is_year_end
data[['date_issued', 'date_issued:is_year_start', 'date_issued:is_quarter_start',
      'date_issued:is_month_start', 'date_issued:is_year_end']].head(15)
```

```
[19]:
```

	date_issued	date_issued:is_year_start	date_issued:is_quarter_start	date_issued:is_month_start	date_issued:is_year_end
0	2013-06-11	False	False	False	False
1	2014-05-08	False	False	False	False
2	2013-10-26	False	False	False	False
3	2015-08-20	False	False	False	False
4	2014-07-22	False	False	False	False
5	2013-08-21	False	False	False	False
6	2015-09-27	False	False	False	False
7	2015-03-20	False	False	False	False
8	2014-02-14	False	False	False	False
9	2013-12-25	False	False	False	False
10	2015-11-22	False	False	False	False
11	2014-04-04	False	False	False	False
12	2015-10-26	False	False	False	False
13	2015-11-13	False	False	False	False
14	2015-04-23	False	False	False	False

ANALYTICAL STATEMENT:

```
[21]: data['date_issued:is_year_start'].value_counts()
```

```
[21]: False    9973
      True      27
      Name: date_issued:is_year_start, dtype: int64
```

ANALYTICAL STATEMENT:

PRACTICAL – 9

Aim: Perform Logistics Regression on Diabetic dataset and evaluate the model performance

```
[13]: import numpy as np
import pandas as pd
from sklearn.datasets import load_diabetes
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_curve, auc
import matplotlib.pyplot as plt
```

```
[14]: # Load dataset from url
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
column_names = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
                'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome']

df = pd.read_csv(url, names=column_names)
df.head()
```

```
[14]:
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

ANALYTICAL STATEMENT:

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

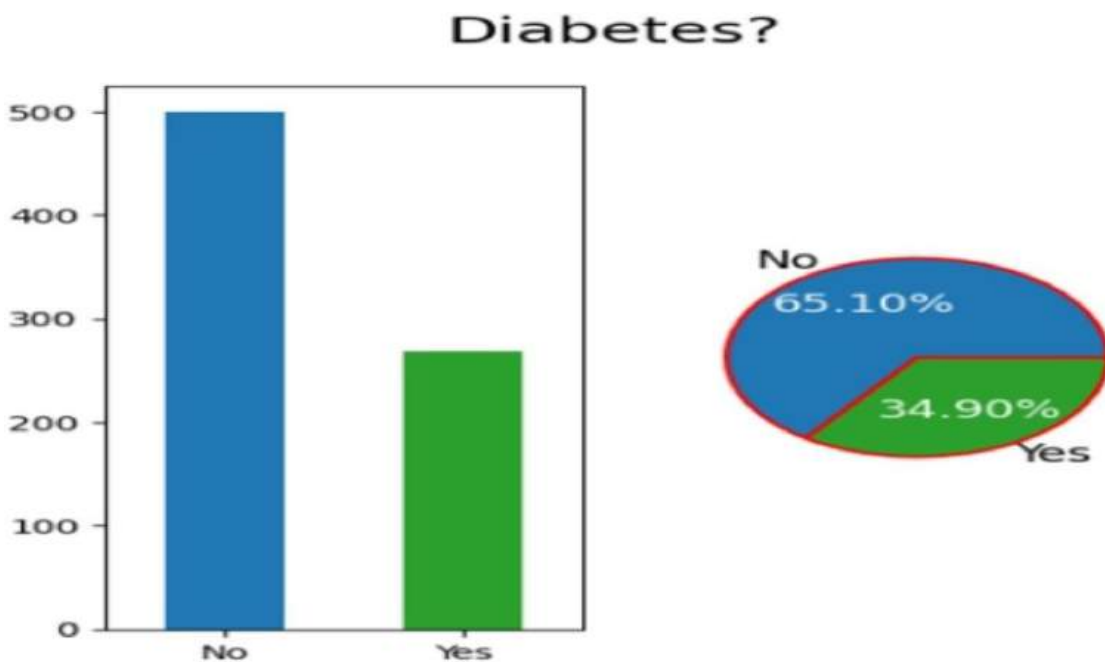
f, ax = plt.subplots(1, 2, figsize=(5, 5))
f.suptitle('Diabetes?', fontsize=18)

# Bar plot
_ = df.Outcome.value_counts().plot.bar(
    ax=ax,
    rot=0,
    color=(sns.color_palette(), sns.color_palette()[2])
)
ax.set_xticklabels(["No", "Yes"])

# Pie chart
_ = df.Outcome.value_counts().plot.pie(
    labels=("No", "Yes"),
    autopct="%.2f%%",
    label="",
    fontsize=13,
    ax=ax[1],
    colors=(sns.color_palette(), sns.color_palette()[2]),
    wedgeprops={"linewidth": 1.5, "edgecolor": "r"}
)

# Set pie chart text color for percentage values
ax[1].texts[1].set_color("#F7F7F7")
ax[1].texts[3].set_color("#F7F7F7")

plt.tight_layout(rect=[0, 0.03, 1, 0.93])
plt.show()
```

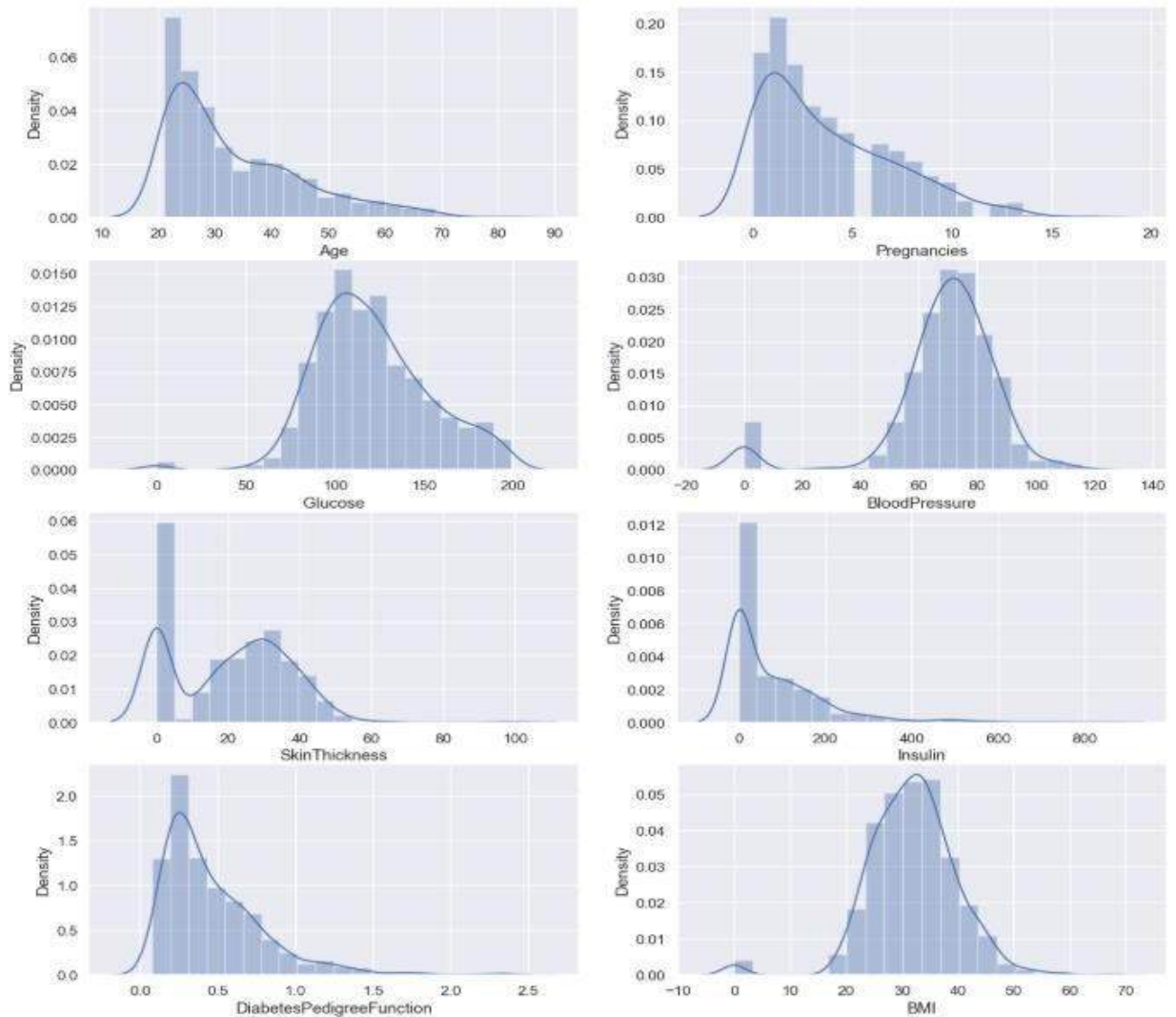


ANALYTICAL STATEMENT:

```
[24]: fig, ax = plt.subplots(4, 2, figsize=(16, 16))

# Each line plots the distribution of a DataFrame column
sns.distplot(df.Age, bins=20, ax=ax[0, 0])
sns.distplot(df.Pregnancies, bins=20, ax=ax[0, 1])
sns.distplot(df.Glucose, bins=20, ax=ax[1, 0])
sns.distplot(df.BloodPressure, bins=20, ax=ax[1, 1])
sns.distplot(df.SkinThickness, bins=20, ax=ax[2, 0])
sns.distplot(df.Insulin, bins=20, ax=ax[2, 1])
sns.distplot(df.DiabetesPedigreeFunction, bins=20, ax=ax[3, 0])
sns.distplot(df.BMI, bins=20, ax=ax[3, 1])
```

[24]: <Axes: xlabel='BMI', ylabel='Density'>

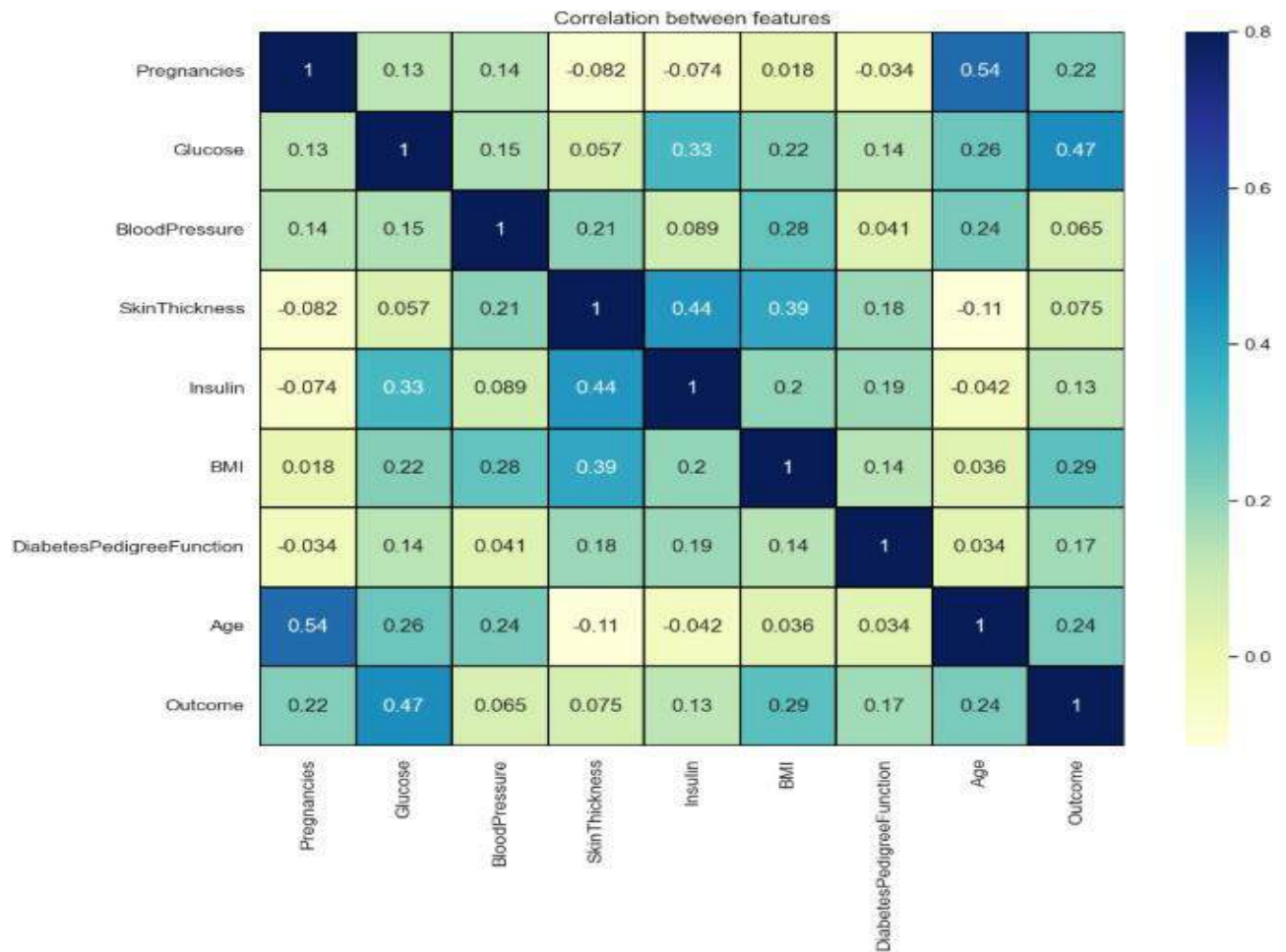


ANALYTICAL STATEMENT:

```
[23]: corr = df.corr() # Compute correlation matrix

sns.set(font_scale=1.15)
plt.figure(figsize=(14, 10))

sns.heatmap(
    corr,
    vmax=0.8,
    linewidths=0.01,
    square=True,
    annot=True,
    cmap='YlGnBu',
    linecolor="black"
)
plt.title('Correlation between features');
```



ANALYTICAL STATEMENT:

```
[25]: from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
      from sklearn.model_selection import train_test_split
      from sklearn.linear_model import LogisticRegression
      from sklearn.tree import DecisionTreeClassifier
      from sklearn.ensemble import GradientBoostingClassifier

      # Prepare feature matrix X and label vector y
      X = df.iloc[:, :-1] # all rows, all columns except the last (features)
      y = df.iloc[:, -1] # all rows, last column (target)

      # Split into train and test sets (75% train, 25% test)
      X_train, X_test, y_train, y_test = train_test_split(
          X, y, test_size=0.25, random_state=0
      )

      # Create and train Logistic Regression model
      LR = LogisticRegression()
      LR.fit(X_train, y_train)
```

```
[25]: • LogisticRegression
      LogisticRegression()
```

ANALYTICAL STATEMENT:

```
[26]: # Prediction on test set
      y_pred = LR.predict(X_test)

      # Calculate and print accuracy (%)
      print("Accuracy", LR.score(X_test, y_test) * 100)

      Accuracy 79.16666666666666
```

ANALYTICAL STATEMENT:


```
[27]: # Plot the confusion matrix
sns.set(font_scale=1.5)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, fmt="g")
plt.show()
```



ANALYTICAL STATEMENT:

```
[28]: print("Classification Report :\n", classification_report(y_test, y_pred))
```

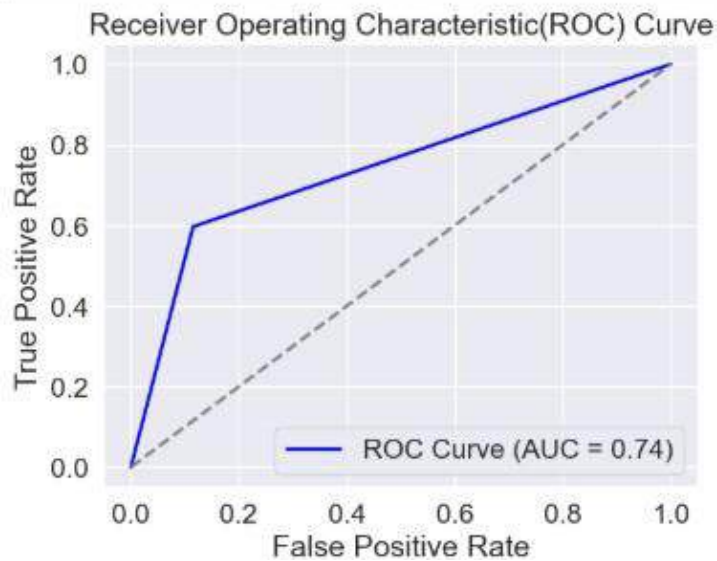
```
Classification Report :
              precision    recall  f1-score   support

     0       0.82        0.88        0.85        130
     1       0.71        0.60        0.65         62

 accuracy          0.79
 macro avg         0.77        0.74        0.75        192
 weighted avg      0.79        0.79        0.79        192
```

ANALYTICAL STATEMENT:

```
[29]: fpr, tpr, thresholds = roc_curve(y_test, y_pred)
      roc_auc = auc(fpr, tpr)
      plt.figure()
      plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {roc_auc:.2f})')
      plt.plot([0, 1], [0, 1], color='grey', lw=2, linestyle='--')
      plt.xlabel('False Positive Rate')
      plt.ylabel('True Positive Rate')
      plt.title('Receiver Operating Characteristic(ROC) Curve')
      plt.legend(loc='lower right')
      plt.show()
```



ANALYTICAL STATEMENT:

PRACTICAL – 10

Aim: Case Study: Amazon clothes sell clothes online. Customers come into the store, have meetings with a personal stylist, then they can go home and order either on a mobile app or website for the clothes they want. The company is trying to decide whether to focus their efforts on their mobile app experience or their website. Following is predictive analysis for this company

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

```
[2]: df = pd.read_csv('Ecommerce Customers.csv')
```

```
[3]: df.head()
```

	Email	Address	Avatar	Avg. Session Length	Time on App	Time on Website	Length of Membership	Yearly Amount Spent
0	mstephenson@fernandez.com	835 Frank Tunnel\nWrightmouth, MI 82180-9605	Violet	34.497268	12.655651	39.577668	4.082621	587.951054
1	hduke@hotmail.com	4547 Archer Common\nDiazchester, CA 06566-8576	DarkGreen	31.926272	11.109461	37.268959	2.664034	392.204933
2	pallen@yahoo.com	24645 Valerie Unions Suite 582\nCobbborough, D...	Bisque	33.000915	11.330278	37.110597	4.104543	487.547505
3	riverarebecca@gmail.com	1414 David Throughway\nPort Jason, OH 22070-1220	SaddleBrown	34.305557	13.717514	36.721283	3.120179	581.852344
4	mstephens@davidson-herman.com	14023 Rodriguez Passage\nPort Jacobville, PR 3...	MediumAquaMarine	33.330673	12.795189	37.536653	4.446308	599.406092

ANALYTICAL STATEMENT:

```
[4]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype  
---  --
 0   Email                 500 non-null    object  
 1   Address               500 non-null    object  
 2   Avatar                500 non-null    object  
 3   Avg. Session Length   500 non-null    float64  
 4   Time on App           500 non-null    float64  
 5   Time on Website       500 non-null    float64  
 6   Length of Membership  500 non-null    float64  
 7   Yearly Amount Spent   500 non-null    float64  
dtypes: float64(5), object(3)
memory usage: 31.4+ KB
```

```
[5]: df.describe()
```

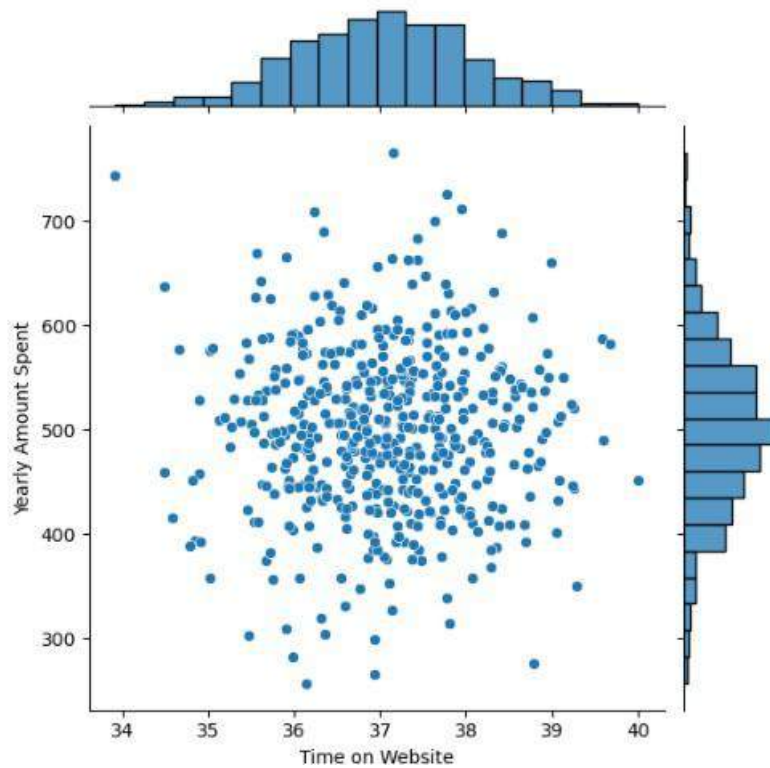
```
[5]:
```

	Avg. Session Length	Time on App	Time on Website	Length of Membership	Yearly Amount Spent
count	500.000000	500.000000	500.000000	500.000000	500.000000
mean	33.053194	12.052488	37.060445	3.533462	499.314038
std	0.992563	0.994216	1.010489	0.999278	79.314782
min	29.532429	8.508152	33.913847	0.269901	256.670582
25%	32.341822	11.388153	36.349257	2.930450	445.038277
50%	33.082008	11.983231	37.069367	3.533975	498.887875
75%	33.711985	12.753850	37.716432	4.126502	549.313828
max	36.139662	15.126994	40.005182	6.922689	765.518462

ANALYTICAL STATEMENT:

```
[6]: sns.jointplot(x=df['Time on Website'], y=df['Yearly Amount Spent'])
```

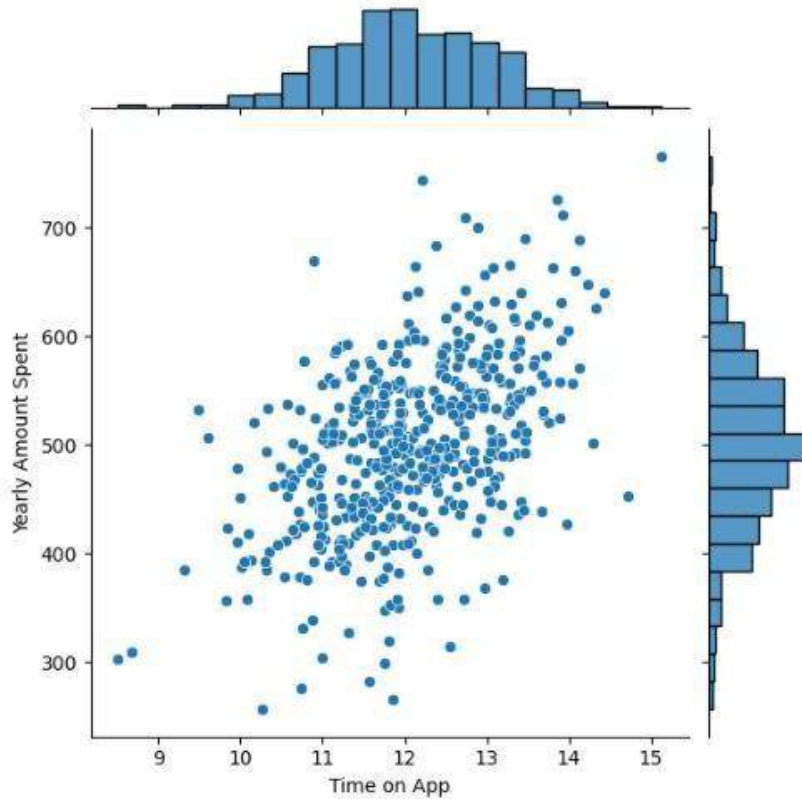
```
[6]: <seaborn.axisgrid.JointGrid at 0x2699b410ec0>
```



ANALYTICAL STATEMENT:

```
[7]: sns.jointplot(x=df['Time on App'], y=df['Yearly Amount Spent'])
```

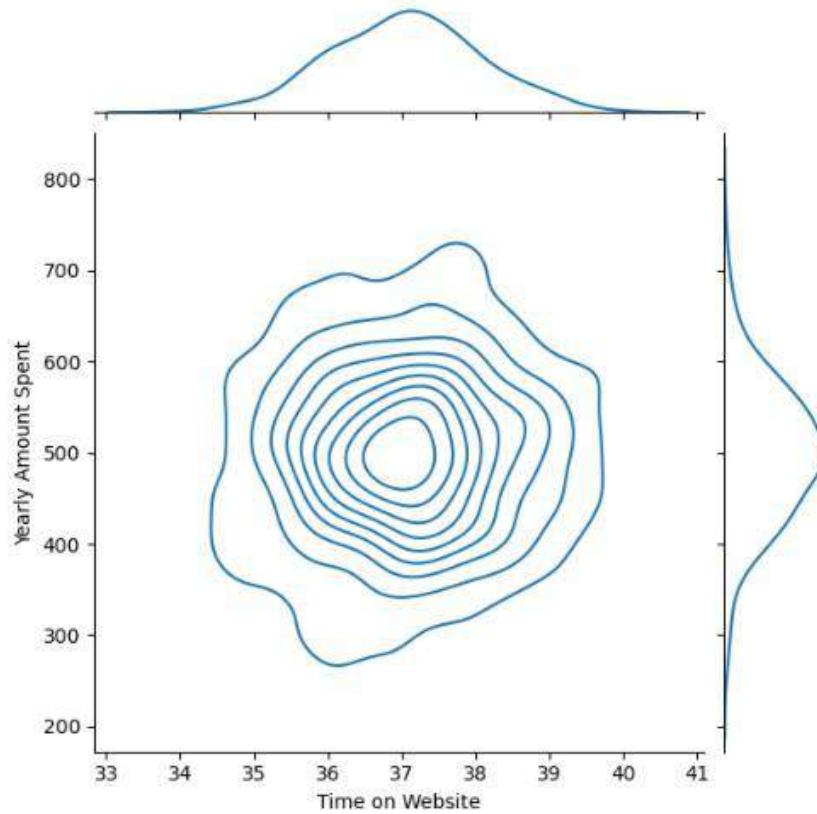
```
[7]: <seaborn.axisgrid.JointGrid at 0x2699b669f90>
```



ANALYTICAL STATEMENT:

```
[8]: sns.jointplot(x=df['Time on Website'], y=df['Yearly Amount Spent'], kind='kde')
```

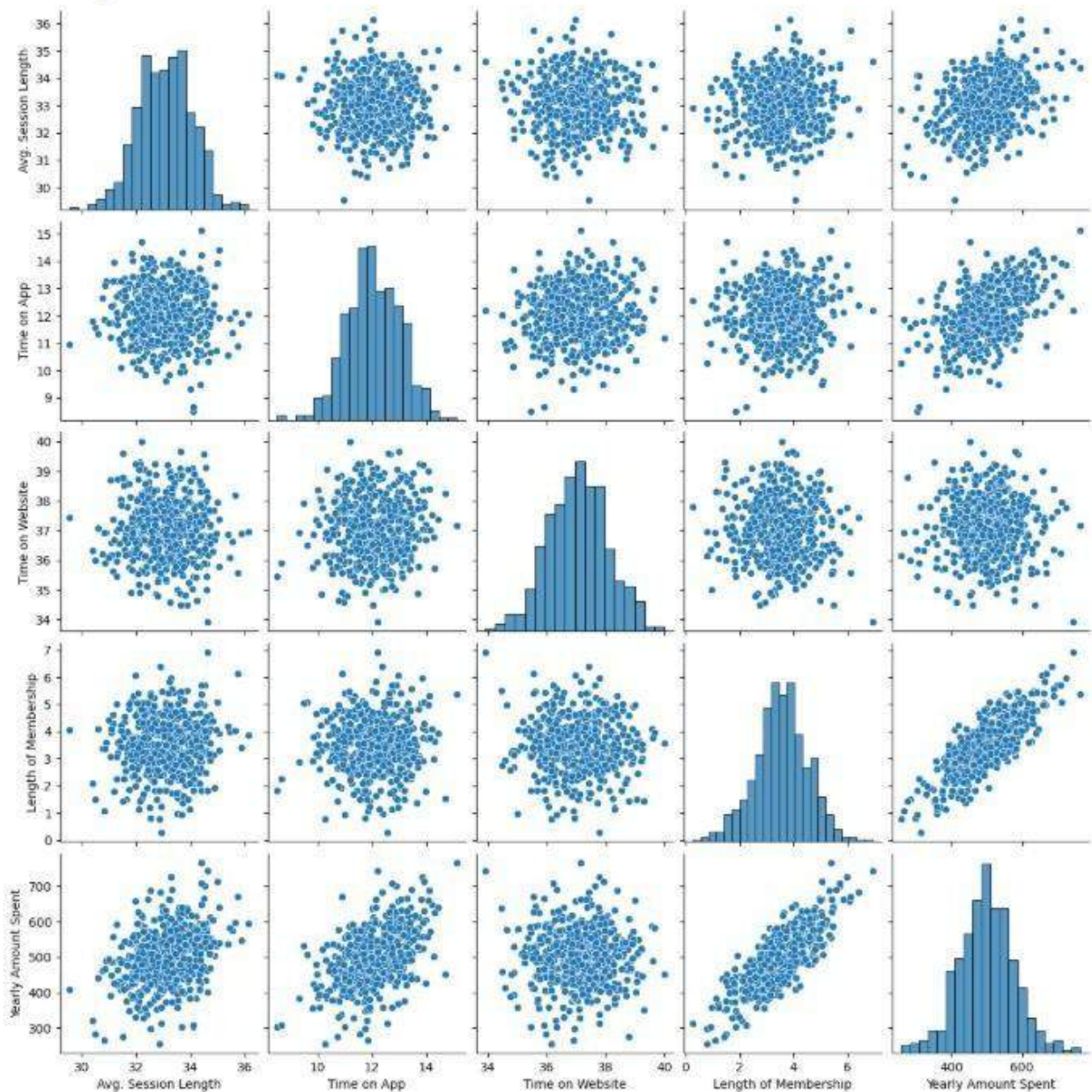
```
[8]: <seaborn.axisgrid.JointGrid at 0x2699c29a5d0>
```



ANALYTICAL STATEMENT:


```
[9]: sns.pairplot(df)
```

```
[9]: <seaborn.axisgrid.PairGrid at 0x2699b58a270>
```



ANALYTICAL STATEMENT:


```
[10]: # Select target and features.
y = df['Yearly Amount Spent']
X = df[['Avg. Session Length', 'Time on App', 'Time on Website', 'Length of Membership']]

# Split into train and test sets (78% train, 22% test)
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=466
)
```

```
[11]: x_train
```

	Avg. Session Length	Time on App	Time on Website	Length of Membership
110	31.853075	12.149375	37.325334	3.361815
100	32.498393	13.410759	35.990489	3.184619
189	32.200799	12.276962	38.232606	3.316465
328	33.369517	10.627949	38.040314	3.002957
122	33.268330	11.113330	37.387946	4.018727
...
95	32.461212	13.291143	38.633626	3.871003
495	33.237660	13.566160	36.417985	3.746573
164	33.154255	11.795887	37.658617	4.520353
369	34.357196	9.477778	37.906015	5.047023
330	30.574364	11.351049	37.088847	4.078308

350 rows × 4 columns

```
[12]: x_test
```

	Avg. Session Length	Time on App	Time on Website	Length of Membership
277	32.192499	13.325412	36.897295	5.049927
7	32.739143	12.351959	37.373359	4.434273
392	33.258238	11.514949	37.128039	4.662845
9	31.936549	11.814128	37.145168	3.202806
476	34.336677	11.246813	38.682584	2.094762
...
339	32.997459	12.589241	37.332241	2.804014
176	32.332637	11.548761	38.576516	4.773503
384	33.593964	11.520567	36.189132	3.561215
373	31.366212	11.163160	37.088319	3.620355
455	33.421212	10.706642	35.766154	3.393975

150 rows × 4 columns

ANALYTICAL STATEMENT:

```
[13]: y_train  
  
[13]: 110    459.285123  
      100    518.064558  
      189    478.885391  
      328    422.368737  
      122    514.239521  
      ...  
      95     543.340166  
      495    573.847438  
      164    550.047581  
      369    531.961551  
      330    442.064414  
      Name: Yearly Amount Spent, Length: 350, dtype: float64  
  
[14]: y_test  
  
[14]: 277    616.660286  
      7     549.904146  
      392    549.131573  
      9     427.199385  
      476    488.958336  
      ...  
      339    476.139247  
      176    532.717486  
      384    474.532329  
      373    430.588883  
      455    438.303708  
      Name: Yearly Amount Spent, Length: 150, dtype: float64
```

ANALYTICAL STATEMENT:

```
[15]: from sklearn.linear_model import LinearRegression  
  
      lm = LinearRegression()  
      lm.fit(x_train, y_train)  
  
[15]: LinearRegression  
      LinearRegression()
```

ANALYTICAL STATEMENT:

```
[16]: # Print the coefficients for each feature  
      print("coefficients : \n", lm.coef_)  
  
      coefficients :  
      [25.80332726 38.51709286  0.25895459 61.31108629]
```

ANALYTICAL STATEMENT:

```
[17]: # Print the model intercept  
print(lm.intercept_)  
  
-1044.5036020011362
```

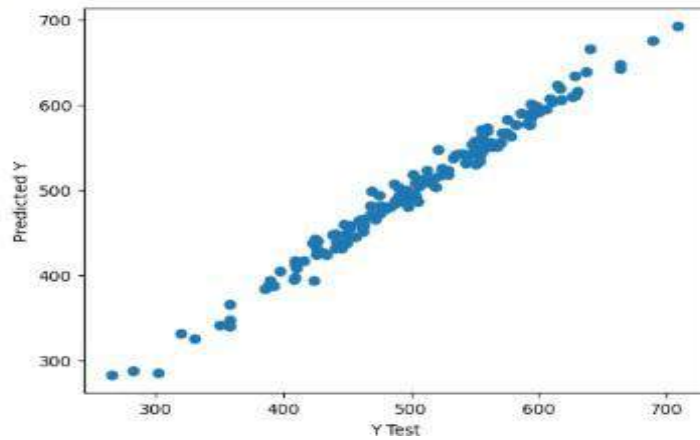
ANALYTICAL STATEMENT:

```
[18]: # Make predictions on the test set  
pred = lm.predict(x_test)  
  
[19]: pred  
  
[19]: array([618.59738219, 557.58489234, 552.69054252, 440.59792148,  
413.14058911, 340.28200231, 417.05076117, 567.14512987,  
486.39861505, 512.55353338, 605.29708886, 562.95628446,  
607.08443312, 460.13846164, 576.35649482, 444.91206259,  
424.23448484, 541.48186139, 553.75608221, 568.86829905,  
499.10455935, 456.93287659, 542.81573022, 417.49577921,  
366.04769894, 603.43045993, 590.70039625, 692.29665547,  
431.78681007, 500.34768221, 547.00973557, 517.81598481,  
566.28447227, 438.13950331, 491.37880007, 394.21075412,  
555.31484354, 331.52342984, 424.69870138, 285.04378446,  
325.61851113, 588.15883309, 638.46491303, 387.39050509,  
609.13717179, 450.60014251, 493.18836125, 386.62876645,  
587.74165284, 513.5439275 , 601.10754812, 341.94674184,  
404.59612411, 580.26830959, 547.50152258, 426.83924916,  
384.02457468, 445.40171027, 562.73546791, 523.01747242,  
480.87160424, 471.15971056, 518.07824072, 409.0043681 ,  
446.88904424, 484.40816565, 592.76916447, 465.9794765 ,  
455.72937994, 511.21739216, 572.54515976, 610.11018863,  
395.53832715, 487.05595184, 556.07747141, 488.59518707,  
394.50055902, 472.93228755, 480.77595416, 495.57527412,  
397.50941223, 531.5911328 , 348.06423309, 534.67898031,  
492.73232369, 550.64560032, 455.99795499, 481.04415785,  
598.69087795, 437.59311244, 552.22190717, 465.47724338,  
589.50022185, 622.24323315, 503.16112831, 589.0955597 ,  
478.07535762, 435.34662831, 442.52444787, 530.48062232,  
459.6123008 , 542.60349929, 486.07411577, 455.85960052,  
487.2535891 , 499.50230338, 516.43794831, 431.38320758,  
542.38014362, 432.01744695, 287.83181211, 571.01047393,  
457.12136611, 582.61188067, 508.95211349, 642.28039777,  
598.22751992, 647.68078398, 448.80808719, 533.45179723,  
283.19734675, 551.16954995, 525.20597843, 550.42009754,  
481.20571627, 552.55237583, 439.44568918, 504.61300804,  
490.54504007, 458.21853804, 675.01852482, 542.63614686,  
480.56015115, 577.2105439 , 594.81658673, 577.05241883,  
464.06446285, 633.59356482, 523.42199249, 615.41761635,  
508.06676416, 513.4365391 , 507.3196324 , 503.34480176,  
665.96149325, 473.42605979, 537.26895335, 493.78449287,  
426.39355141, 447.61368551])
```

ANALYTICAL STATEMENT:

```
[20]: plt.scatter(y_test, pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

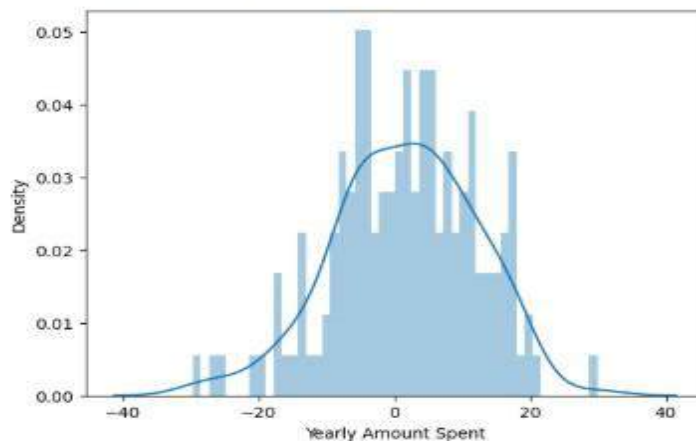
```
[20]: Text(0, 0.5, 'Predicted Y')
```



ANALYTICAL STATEMENT:

```
[21]: sns.distplot((y_test - pred), bins=50)
```

```
[21]: <Axes: xlabel='Yearly Amount Spent', ylabel='Density'>
```



ANALYTICAL STATEMENT:

```
[22]: from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, pred))           # Mean Absolute Error
print('MSE:', metrics.mean_squared_error(y_test, pred))           # Mean Squared Error
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, pred))) # Root Mean Squared Error

MAE: 8.515783988090931
MSE: 111.46467736774434
RMSE: 10.55768333371216
```

ANALYTICAL STATEMENT:

```
[25]: coefficients = pd.DataFrame(lm.coef_, X.columns)
coefficients.columns = ['Coefficient']
coefficients
```

```
[25]:
```

	Coefficient
Avg. Session Length	25.803327
Time on App	38.517093
Time on Website	0.258955
Length of Membership	61.311086

ANALYTICAL STATEMENT: