Machine Learning (ML): ML is an application of Artificial Intelligence (AI) that provides systems the ability to automatically learn themselves and improve from the experience without being explicitly programmed. ML focuses on the development of computer programs that can access data and use it to learn themselves.

Data Set: A collection of related sets of information that is composed of separate elements but can be manipulated as a unit by a computer.

Data Visualisation: It is a representation of data or information in a graph, chart, or other visual formats which is helpful to conduct analyses such as predictive analysis which can serve as helpful Visualisation to present.

Data Cleaning: It is the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data within a dataset.

Supervised Learning: The model is trained using 'labeled data'. Datasets are said to contain labels that contain both input and output parameters. To simplify – 'Data is already tagged with the correct answer'.

Simple Linear Regression: It is a Regression Model that estimates the relationship between the independent variable and the dependent variable using a straight line .
[y = mx + c]
where both the variables should be quantitative.

Models: Those are output by algorithms and are comprised of model data and a prediction algorithm.

Training Model: In supervised learning, an ML Algorithm builds a model by examining many examples and attempting to find a model that minimizes loss and improves prediction accuracy.

These are the few terms used in machine learning while creating a model and to get familiar with. Now let's get started with the analysis and prediction of the model.
This is about a fictional e-commerce company based in New York City that sells clothing online but they also have in-store style and clothing advice sessions. Customers come in to the store, have sessions/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.
Data is fictional, including Email id's data and other personally identifiable information.
In this mini-project, I am going to use supervised data and simple linear regression for analysis and prediction. The Ultimate goal is the predict the company whether it has to focus on application or website development using the trained model to the highest achievable accuracy using available data.
This is an pratical application project to generalize them any one can change data set and some parameters to get the desired output
The steps involved are:

1. Loading the dataset.
2. Visualising the Data or exploring the data
3. Build the Model and Train it.

4. Evaluating the model.
5. Making a decision on the given data.

==========Importing libraries==========

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

==========Loading the dataset==========

The 'Ecommerce Customers' dataset has Customer info, suchas Email, Address, and their color Avatar. Then it also has numerical value columns:

Avg. Session Time **Length:** Average session of in-store style advice sessions.
Time on App: Average time spent on App in minutes
Time on Website: Average time spent on Website in minutes
Length of Membership: How many years the customer has been a member.

In [ ]:

```
df=pd.read_csv("/content/Ecommerce Customers.txt",sep=",")
print("Data frame created successfuly")
```

Data frame created successfuly

In [ ]:

```
print("top 5 rows\n")
df.head()
```

top 5 rows

Out[ ]:

	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

In [ ]:

```
print("bottom 5 rows \n")
df.tail()
```

bottom 5 rows

Out[ ]:

	Email	Address	Avatar	Avg. Session Length	Time on App	Time on Website	Length of Membership	Yearly Amount Spent
495	lewisjessica@craig-evans.com	4483 Jones Motorway Suite 872\nLake Jamiefurt,...	Tan	33.237660	13.566160	36.417985	3.746573	573.847438
496	katrina56@gmail.com	172 Owen Divide Suite 497\nWest Richard, CA 19320	PaleVioletRed	34.702529	11.695736	37.190268	3.576526	529.049004
497	dale88@hotmail.com	0787 Andrews Ranch Apt. 633\nSouth Chadburgh, ...	Cornsilk	32.646777	11.499409	38.332576	4.958264	551.620145
498	cwilson@hotmail.com	680 Jennifer Lodge Apt. 808\nBrendachester, TX...	Teal	33.322501	12.391423	36.840086	2.336485	456.469510
499	hannahwilson@davidson.com	49791 Rachel Heights Apt. 898\nEast Drewboroug...	DarkMagenta	33.715981	12.418808	35.771016	2.735160	497.778642

In [ ]:

```
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
```

In [ ]:

```
df.columns
```

Out[ ]:

```
Index(['Email', 'Address', 'Avatar', 'Avg. Session Length', 'Time on App',
       'Time on Website', 'Length of Membership', 'Yearly Amount Spent'],
      dtype='object')
```

In [ ]:

```
df.describe()
```

Out[ ]:

	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

==========Exploratory Data Analysis==========

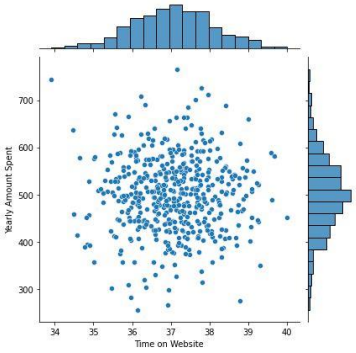
Here we are comparing different parameters to find the strong relationship between parameters.

In [ ]:

```
sns.jointplot(x='Time on Website', y='Yearly Amount Spent', data=df)
```

Out[ ]:

<seaborn.axisgrid.JointGrid at 0x7f7a33500f90>

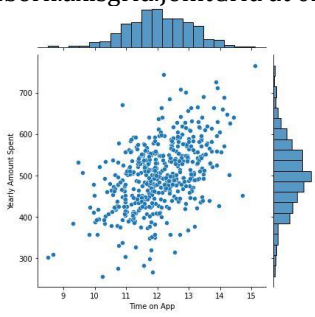


In [ ]:

```
sns.jointplot(x='Time on App', y='Yearly Amount Spent', data=df)
```

Out[ ]:

<seaborn.axisgrid.JointGrid at 0x7f7a2a022190>



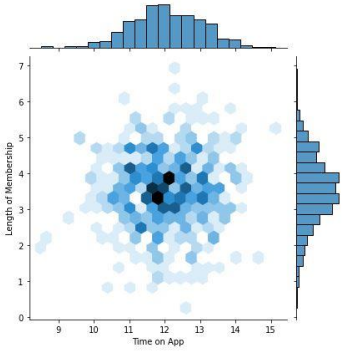
From the plot,it seems like that there is some relationship between Yearly Amount Spent and Time on App as most of points are some how near to each other

In [ ]:

```
sns.jointplot(x='Time on App', y='Length of Membership', data=df, kind='hex')
```

Out[ ]:

<seaborn.axisgrid.JointGrid at 0x7f7a29a5f890>



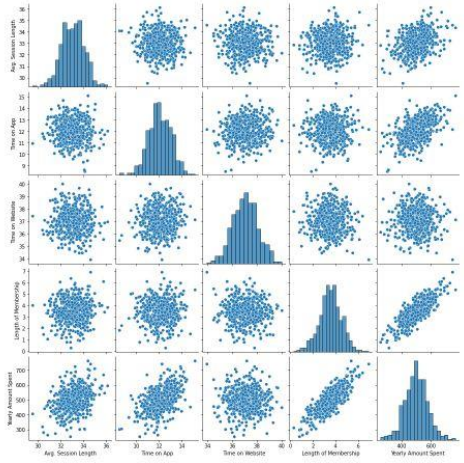
From the plot,it seems like that there is some relationship between Yearly Amount Spent and Time on App as most of points are some how near to each other

In [ ]:

```
sns.jointplot(x='Time on App', y='Length of Membership', data=df, kind='hex')
```

Out[ ]:

<seaborn.axisgrid.JointGrid at 0x7f7a29a5f890>



from the above graphs we can say that there is a close relationship between Length of Membership and Yearly Amount spent

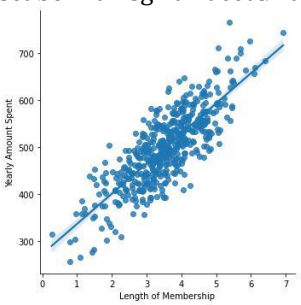
Checking the relationship of Yearly Amount Spent vs. Length of Membership using a linear model plot.

In [ ]:

```
sns.lmplot(x='Length of Membership', y='Yearly Amount Spent', data=df)
```

Out[ ]:

<seaborn.axisgrid.FacetGrid at 0x7f7a28c7db90>



==========Training and Testing Data==========

Let's split the data into training and testing sets.

Setting a variable X equal to the numerical features of the customers and a variable y equal to the "Yearly Amount Spent" column.

Note: omitted categorical values as they have no impact on model

In [ ]:

```
df.columns
```

Out[ ]:

```
Index(['Email', 'Address', 'Avatar', 'Avg. Session Length', 'Time on App',
       'Time on Website', 'Length of Membership', 'Yearly Amount Spent'],
      dtype='object')
```

In [ ]:

```
X = df[['Avg. Session Length', 'Time on App',
       'Time on Website', 'Length of Membership']]
```

In [ ]:

```
y = df['Yearly Amount Spent']
```

==========Building a model==========

In [ ]:

```
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=0)
```

==========Traning model==========

In [ ]:

```
from sklearn.linear_model import LinearRegression
```

In [ ]:

```
lm = LinearRegression()
```

In [ ]:

```
lm.fit(X_train, y_train)
```

Out[ ]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

==========Printing out the coefficients of the model==========

In [ ]:

```
lm.intercept_
```

Out[ ]:

```
-1060.5508096198853
```

In [ ]:

```
lm.coef_
```

Out[ ]:

```
array([25.88815047, 38.87046474,  0.47066154, 61.78369022])
```

In [ ]:

```
cdf = pd.DataFrame(lm.coef_, X_train.columns, columns=['Coefficients'])
```

In [ ]:

Cdf

Out[ ]:

	Coefficients
Avg. Session Length	25.888150
Time on App	38.870465
Time on Website	0.470662
Length of Membership	61.783690

==========Predicting Test Data==========

Now that we have fit our model, let's evaluate its performance by predicting off the test values.

In [ ]:

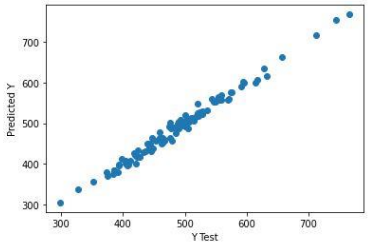
predictions = lm.predict(X_test)

In [ ]:

plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
plt.scatter(y_test, predictions)

Out[ ]:

<matplotlib.collections.PathCollection at 0x7f7a222f47d0>



==========Evaluating the Model==========

Let's evaluate our model performance by calculating the residual sum of squares and the explained variance score (R^2).

In [ ]:

```
from sklearn import metrics
```

In [ ]:

```
print('MAE:', metrics.mean_absolute_error(y_test, predictions))
print('MSE:', metrics.mean_squared_error(y_test, predictions))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, predictions)))
```

MAE: 7.645674798915295
MSE: 92.89010304498562
RMSE: 9.637951185028156

In [ ]:

metrics.explained_variance_score(y_test, predictions)

Out[ ]:

0.9862059058088554

In [ ]:

cdf = pd.DataFrame(lm.coef_, X_train.columns, columns=['Coefficient'])

cdf

Out[ ]:

	Coefficient
Avg. Session Length	25.888150
Time on App	38.870465
Time on Website	0.470662
Length of Membership	61.783690

==========CONCLUSION==========

Given that the coefficients are all positive, for every unit change in the features, the average yearly spend increases by the coefficient holding all other features fixed. In this case, the most important factor seems to be the length of membership of a customer.

Should the company focus more on their mobile app or on their website?

If the company really needs to choose now between the two, they should focus more on their mobile app as it has a bigger influence on yearly spend based on the length of time the customers spend on it. It would be also good to explore the relationship between how long a customer has been a member (length of membership) and the time they spend on the app and website. That might yield some better conclusions and action plans for the company.