# Linear Regression Project

You just got some contract work with an Ecommerce 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. They've hired you on contract to help them figure it out! Let's get started!

Just follow the steps below to analyze the customer data (it's fake, don't worry I didn't give you real credit card numbers or emails).

## Imports

**Import pandas, numpy, matplotlib,and seaborn. Then set %matplotlib inline (You'll import sklearn as you need it.)**

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

## Get the Data

We'll work with the Ecommerce Customers csv file from the company. It has Customer info, suchas Email, Address, and their color Avatar. Then it also has numerical value columns:

- Avg. Session 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.

**Read in the Ecommerce Customers csv file as a DataFrame called customers.**

In [2]:
```
customers = pd.read_csv("12 Linear Regression (E-Commerce).csv")
```

**Check the head of customers, and check out its info() and describe() methods.**

In [3]:
```
customers.head()
```

Out[3]:

| | 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 [4]:
```
customers.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 [5]:
```
customers.describe()
```

Out[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 |

## Exploratory Data Analysis

**Let's explore the data!**

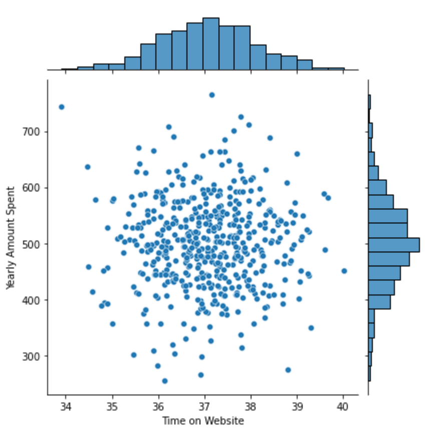
For the rest of the exercise we'll only be using the numerical data of the csv file.

---

**Use seaborn to create a jointplot to compare the Time on Website and Yearly Amount Spent columns. Does the correlation make sense?**

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

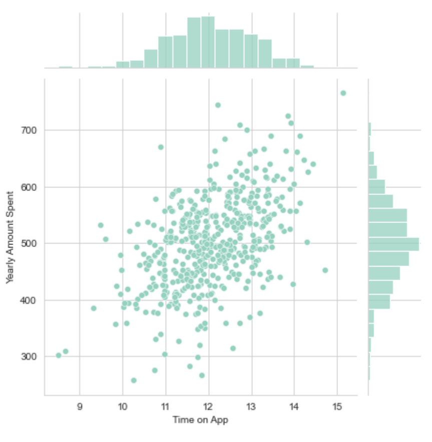
Out[6]: <seaborn.axisgrid.JointGrid at 0x22a271f85e0>




**Do the same but with the Time on App column instead.**

In [7]:
```
sns.set_palette("GnBu_d")
sns.set_style('whitegrid')
sns.jointplot(x='Time on App',y='Yearly Amount Spent',data=customers)
```

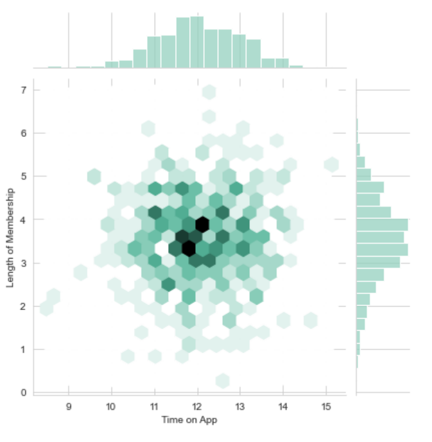
Out[7]: <seaborn.axisgrid.JointGrid at 0x22a271f8bb0>




**Use jointplot to create a 2D hex bin plot comparing Time on App and Length of Membership.**

In [8]:
```
sns.jointplot(x='Time on App',y='Length of Membership',kind='hex',data=customers)
```

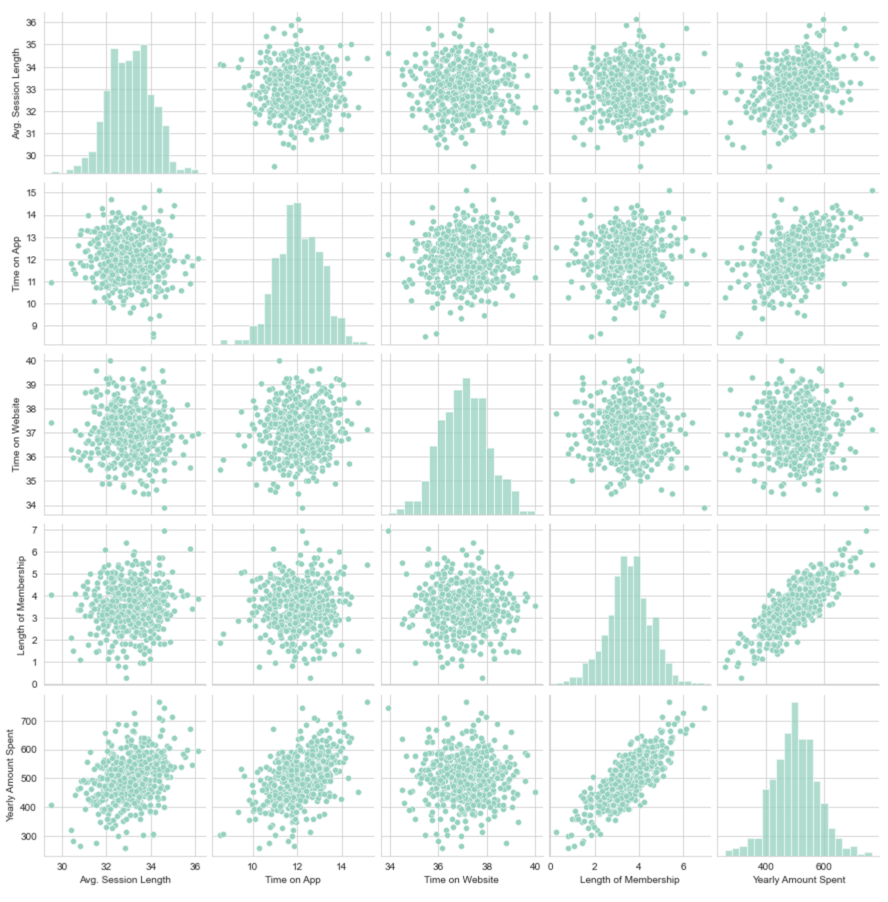
Out[8]: <seaborn.axisgrid.JointGrid at 0x22a271f8c70>




**Let's explore these types of relationships across the entire data set. Use pairplot to recreate the plot below.**

In [9]:
```
sns.pairplot(customers)
```

Out[9]: <seaborn.axisgrid.PairGrid at 0x22a27677070>



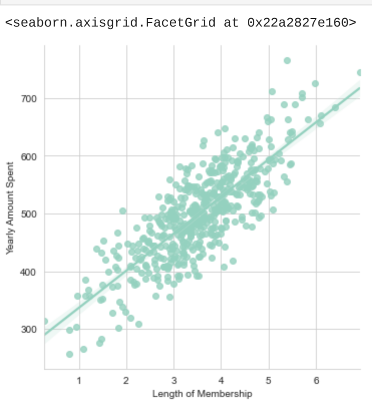

**Based off this plot what looks to be the most correlated feature with Yearly Amount Spent?**

In [10]:
```
# Length of Membership
```

**Create a linear model plot (using seaborn's lmplot) of Yearly Amount Spent vs. Length of Membership.**

In [11]:
```
sns.lmplot(x='Length of Membership',y='Yearly Amount Spent',data=customers)
```

Out[11]: <seaborn.axisgrid.FacetGrid at 0x22a2827e160>




## Training and Testing Data

Now that we've explored the data a bit, let's go ahead and split the data into training and testing sets. **Set a variable X equal to the numerical features of the customers and a variable y equal to the "Yearly Amount Spent" column.**

In [12]:
```
y = customers['Yearly Amount Spent']
```

In [13]:
```
X = customers[['Avg. Session Length', 'Time on App','Time on Website', 'Length of Membership']]
```

**Use model_selection.train_test_split from sklearn to split the data into training and testing sets. Set test_size=0.3 and random_state=101**

In [14]:
```
from sklearn.model_selection import train_test_split
```

In [15]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)
```

## Training the Model

Now its time to train our model on our training data!

**Import LinearRegression from sklearn.linear_model**

In [16]:
```
from sklearn.linear_model import LinearRegression
```

**Create an instance of a LinearRegression() model named lm.**

In [17]:
```
lm = LinearRegression()
```

**Train/fit lm on the training data.**

In [18]:
```
lm.fit(X_train,y_train)
```

Out[18]: LinearRegression()

**Print out the coefficients of the model**

The coefficient tells you how much the dependent variable is expected to increase when that independent variable increases by one

In [19]:
```
# The coefficients
print('Coefficients: \n', lm.coef_)
```

```
Coefficients: 
 [25.98154972 38.59015875  0.19040528 61.27909654]
```

## Predicting Test Data

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

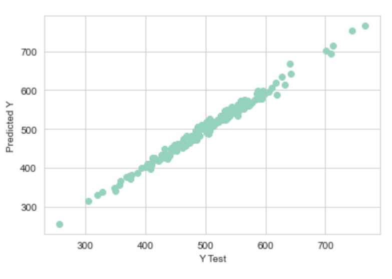
**Use lm.predict() to predict off the X_test set of the data.**

In [20]:
```
predictions = lm.predict( X_test)
```

**Create a scatterplot of the real test values versus the predicted values.**

In [21]:
```
plt.scatter(y_test,predictions)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

Out[21]: Text(0, 0.5, 'Predicted Y')




## Evaluating the Model

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

In [22]:
```
from sklearn import metrics

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: 7.2281486534308215
MSE: 79.81305165097433
RMSE: 8.933815066978626
```

## Residuals

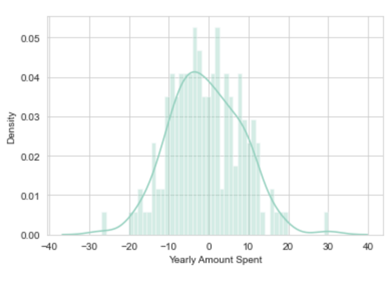
You should have gotten a very good model with a good fit. Let's quickly explore the residuals to make sure everything was okay with our data.

**Plot a histogram of the residuals and make sure it looks normally distributed. Use either seaborn distplot, or just plt.hist().**

In [23]:
```
sns.distplot((y_test-predictions),bins=50)
```

```
C:\Users\Yasin\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```

Out[23]: <AxesSubplot:xlabel='Yearly Amount Spent', ylabel='Density'>




## Conclusion

We still want to figure out the answer to the original question, do we focus our effort on mobile app or website development? Or maybe that doesn't even really matter, and Membership Time is what is really important. Let's see if we can interpret the coefficients at all to get an idea.

**Recreate the dataframe below.**

In [24]:
```
coeffecients = pd.DataFrame(lm.coef_, index = X.columns, columns=['Coefficient'])
coeffecients
```

Out[24]:

| | Coefficient |
|---|---|
| Avg. Session Length | 25.981550 |
| Time on App | 38.590159 |
| Time on Website | 0.190405 |
| Length of Membership | 61.279097 |

**How can you interpret these coefficients?**

Interpreting the coefficients:

- Holding all other features fixed, a 1 unit increase in **Avg. Session Length** is associated with an **increase of 25.98 total dollars spent**.
- Holding all other features fixed, a 1 unit increase in **Time on App** is associated with an **increase of 38.59 total dollars spent**.
- Holding all other features fixed, a 1 unit increase in **Time on Website** is associated with an **increase of 0.19 total dollars spent**.
- Holding all other features fixed, a 1 unit increase in **Length of Membership** is associated with an **increase of 61.27 total dollars spent**.

**Do you think the company should focus more on their mobile app or on their website?**

This is tricky, there are two ways to think about this: Develop the Website to catch up to the performance of the mobile app, or develop the app more since that is what is working better. This sort of answer really depends on the other factors going on at the company

## Great Job!

Congrats on your contract work! The company loved the insights! Let's move on.