Ecommerce Analysis using Linear Regression

I will be analyzing an Ecommerce Company's (fictional) dataset to determine whether to focus their efforts on enhancing their mobile app experience or their website.

Retrieving the Data

First, I will import all relative python libraries and obtain our data

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:
```
customers = pd.read_csv('Ecommerce Customers')
```

Let's see what this data looks like.

In [4]:
```
customers.head()
```

Out[4]:

	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

Note that the time is given in minutes for all numerical columns except for Length of Membership (years) and Yearly Amount Spent (Dollars)

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

In [6]:
```
customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
Email                   500 non-null object
Address                 500 non-null object
Avatar                  500 non-null object
Avg. Session Length     500 non-null float64
Time on App             500 non-null float64
Time on Website         500 non-null float64
Length of Membership    500 non-null float64
Yearly Amount Spent     500 non-null float64
dtypes: float64(5), object(3)
memory usage: 31.3+ KB
```

Hypothesis: Time on App and Time on Website are the two factors that drive Yearly Amount Spent

To test this hypothesis, let's begin by exploring the data.

Exploratory Data Analysis (EDA)

I'll start with mapping the Empirical Cumulative Distribution Function (ECDF) for our target variable, Yearly amount spent

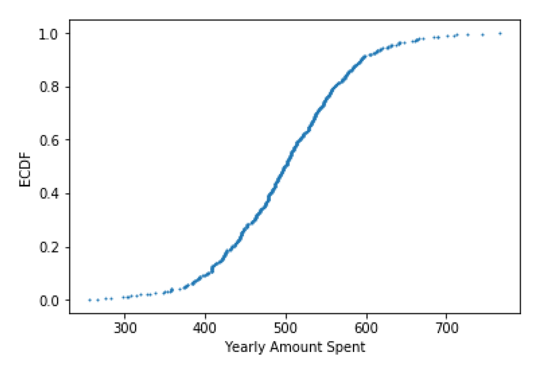
In [7]:
```
#creating a function to do perform Empirical Cumulative Distribution Function (ECDF)
def ecdf(data):
    '''Compute ECDF for a one-dimensional array of measurements.'''
    #Number of data points: n
    n = len(data)

    #x-data for the ECDF: x
    x = np.sort(data)

    #y-data for the ECDF: y
    y = np.arange(1,n+1)/n

    return x,y
```

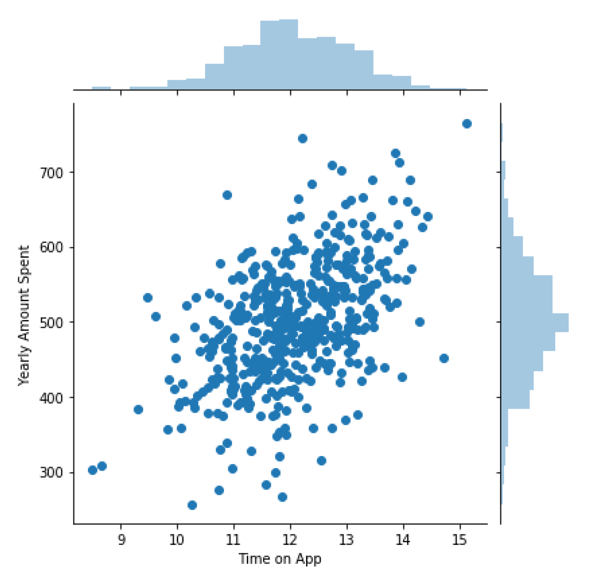
In [8]:
```
#plotting the ecdf
x, y = ecdf(customers['Yearly Amount Spent'])
_ = plt.plot(x,y, marker = '.',linestyle = 'none',markersize=2)
_ = plt.xlabel('Yearly Amount Spent')
_ = plt.ylabel('ECDF')
plt.show()
```



The ECDF gives us a sense for the probabilitistic distribution of the data.

In [10]:
```
#Let's see if Time on the app matters
fig = sns.jointplot(customers['Time on App'],customers['Yearly Amount Spent'])
np.corrcoef(customers['Time on App'],customers['Yearly Amount Spent'])[0,1]
```

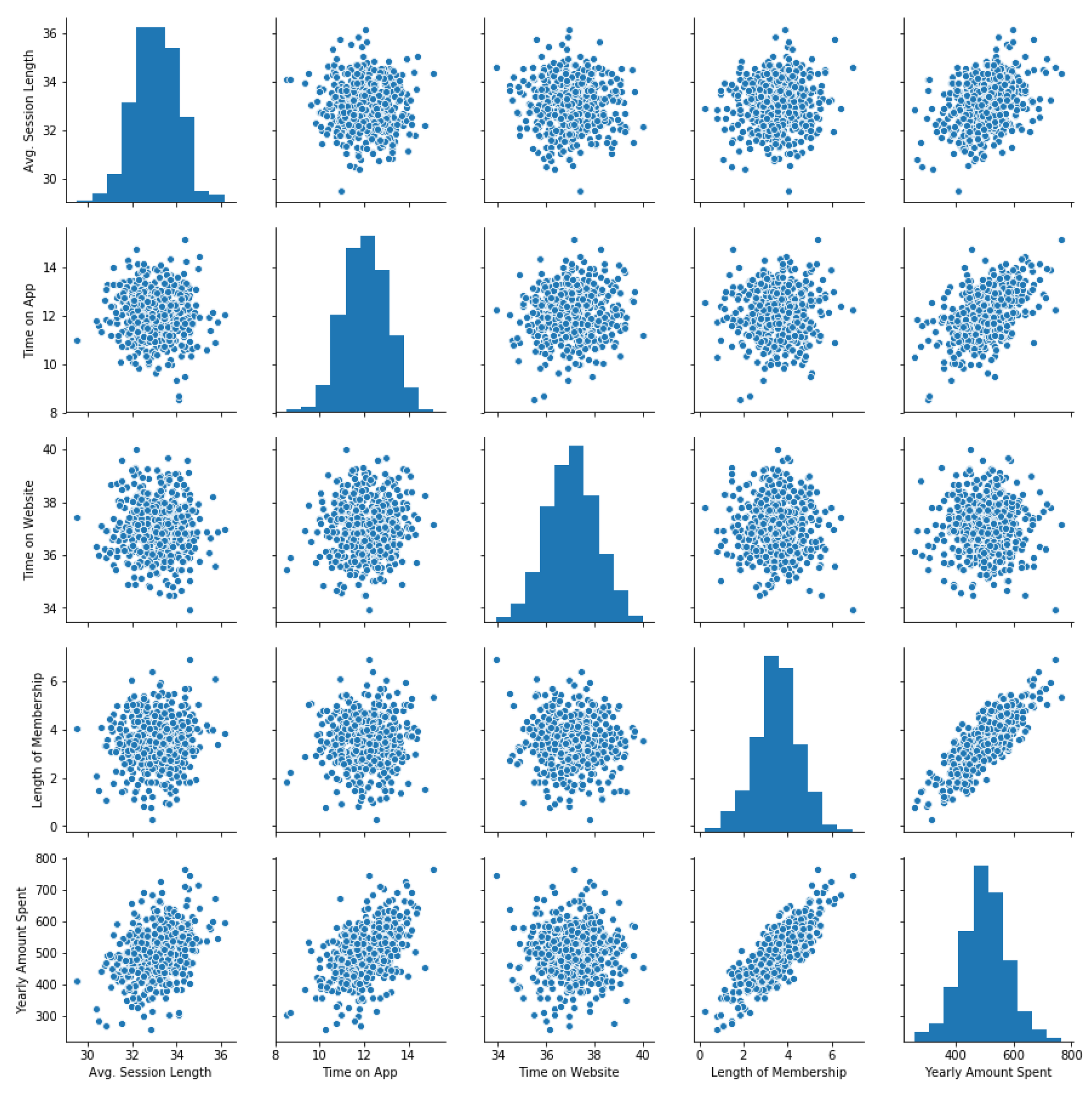
Out[10]: 0.4993277700534505



We see a larger correlation coefficient and the plot shows a more positive coorelation, especially in comparison to the Time on Website plot. Let's view all of our categories in comparison to each other through a pairplot.

In [11]:
```
sns.pairplot(customers)
```

Out[11]: <seaborn.axisgrid.PairGrid at 0x222e9bc6710>

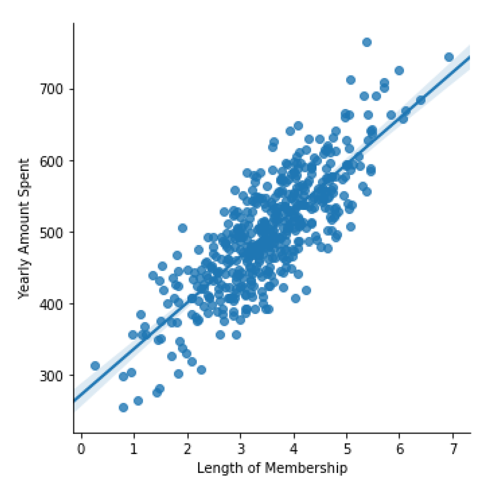


This pairplot shows that Avg. Session Length is slightly correlated and Length of Membership is heavily correlated with Yearly Amount Spent. It's also important to notice that all of our other categories do not appear obviously correlated with one another, making a regression analysis be a good candidate to try to predict Yearly Amount Spent.

Length of membership looks like a linear relationship, so Linear Regression looks to be like a good candidate for this analysis.

In [12]:
```
sns.lmplot(x = 'Length of Membership',y = 'Yearly Amount Spent', data = customers)
```

Out[12]: <seaborn.axisgrid.FacetGrid at 0x222ea9502b0>



We can already see that the error bars are very slim (telling us this is a good linear fit) which tells us that the longer you stay a member, the larger your Yearly Amount Spent

Training and Testing Data

Because we're interested in creating a model that can help us make prediction decisions, we are going to use the sklearn package to split our data into training and testing sets.

In [13]:
```
customers.columns
```

Out[13]:
```
Index(['Email', 'Address', 'Avatar', 'Avg. Session Length', 'Time on App',
       'Time on Website', 'Length of Membership', 'Yearly Amount Spent'],
      dtype='object')
```

In [28]:
```
#we will use all numerical columns for the linear regression input
X = customers[['Avg. Session Length', 'Time on App',
       'Time on Website', 'Length of Membership']]
```

In [17]:
```
y = customers['Yearly Amount Spent']
```

In [18]:
```
#importing sklearn's train/test split function
from sklearn.model_selection import train_test_split
```

In [38]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.3, random_state = 101)
```

Training the Model

Now to train the model with the training data

In [21]:
```
#importing Linear Regression functionality from sklearn
from sklearn.linear_model import LinearRegression
```

In [26]:
```
lm = LinearRegression()
```

In [39]:
```
lm.fit(X_train,y_train)
```

Out[39]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [40]:
```
#quick check of our coefficients to make sure the numbers look appropriate before evaluating our model
lm.coef_
```

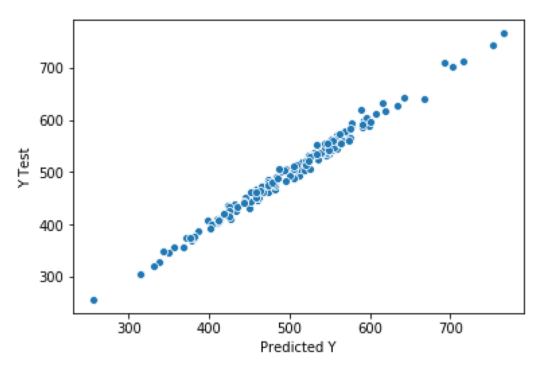
Out[40]:
```
array([25.98154972, 38.59015875,  0.19040528, 61.27909654])
```

Predicting Test Data

We want to evaluate our model before drawing any conclusions from the linear regression fit.

In [42]:
```
#predicting y values (Yearly Amount Spent) with our model using the data we reserved for testing
predictions = lm.predict(X_test)
```

In [45]:
```
#plotting the real values versus the predicted values
_ = sns.scatterplot(predictions,y_test)
_ = plt.xlabel('Predicted Y')
_ = plt.ylabel('Y Test')
```



With a perfect diagonal straight line being a perfect prediction, the 1:1 linear-looking relationship means that the model predicts our data well.

Evaluating the Model

Evaluating the model using common metrics is a good idea before drawing any conclusions. The explained variance score (R^2) is used to determine how much variance your model explains - the closer to 1, the better the model. Other common calculations to measure the performance of a regression model are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

In [46]:
```
#pulling metrics functionalities our of sklearn
from sklearn import metrics
```

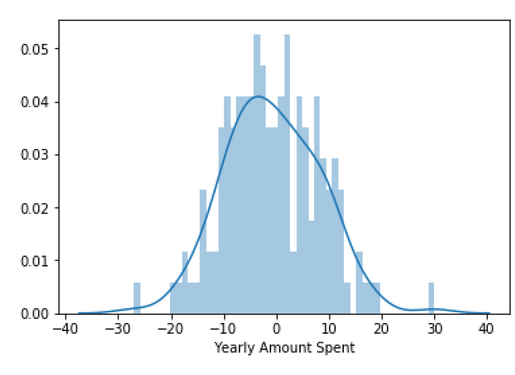
In [55]:
```
print('R^2:', metrics.explained_variance_score(y_test, predictions))
print('MAE:', metrics.mean_absolute_error(y_test,predictions))
print('MSE:', metrics.mean_squared_error(y_test,predictions))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, predictions)))
```

```
R^2: 0.9890771231889606
MAE: 7.228148653430838
MSE: 79.81305165097461
RMSE: 8.933815066978642
```

Our R^2 value is almost 99% which is very good, as our model describes almost 99% of the variance in the sample. Because the other values relate to the error, we want to see all of these values minimized as much as possible. The MAE is easiest to understand as it is the average error of the model, which is relatively low here.

In [51]:
```
#We want to explore the residuals and we're hoping to see something that is mostly normally distributed.
sns.distplot((y_test - predictions), bins=50)
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x222ecd8d710>



With a low average error compared to the magnitude of the values we are working with, and the residuals plot looking normally distributed, this can be considered a good model.

Drawing Insights

Now I'll return to the coefficients to draw insights about our model and what the company should do

In [56]:
```
#let's look at the coefficients of the model
cdf = pd.DataFrame(lm.coef_,X.columns,columns = ['Coeff'])
cdf
```

Out[56]:

	Coeff
Avg. Session Length	25.981550
Time on App	38.590159
Time on Website	0.190405
Length of Membership	61.279097

We can see that an increase in the Length of Membership would result in the biggest impact of the value of our customers for Yearly Amount Spent. It's good to remember that Length of Membership is measure in years. Second to Length of Membership is Time on the App.

With the question of what they should focus on between the website and the app, it depends on what the costs of developing the app vs. the website are. It's clear that the website needs more work compared to the time on the app, but it may be more cost effective to continue working on the App instead of bringing the website up to speed. Economic factors would determine which course of action to take, but at least we now have knowledge of the state of our website and our app in terms of yearly spend per customer. Above this, we also found that Length of Membership produced the most impact to a customer's Yearly Amount Spent and should be considered in the evaluation of whether to spend time on developing the app or the website.

Conclusion

A linear regression analysis was performed for an ecommerce company to help them decide between focusing on their app experience or their website. The model showed that the app currently has greater profitability for one more minute increase compared to the time on the website. An economical analysis would need to be done to further analyze which of the two would be more profitable: bringing the website up or developing the app further in efforts to increase time on either. Alongside this,however, Length of Membership was the greatest impacter in the amount a customer spent yearly, meaning that the longer the customers stay with the company, the more money the company will make in the long run. Length of Membership should be included in the economic consideration of what to focus on.

In [ ]: