Linear Regression - Project Exercise

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1 Linear Regression - Project Exercise

Congratulations! 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).

1.1 Imports

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

```
In [275]: import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          import seaborn as sns
          %matplotlib inline
```

1.2 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 [276]: customers = pd.read_csv("Ecommerce Customers")
```

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

In [277]: customers.head()

Out[277]:
```
                                 Email  \
0      mstephenson@fernandez.com
1              hduke@hotmail.com
2               pallen@yahoo.com
3        riverarebecca@gmail.com
4  mstephens@davidson-herman.com

                                             Address            Avatar  \
0       835 Frank Tunnel\nWrightmouth, MI 82180-9605            Violet
1     4547 Archer Common\nDiazchester, CA 06566-8576         DarkGreen
2  24645 Valerie Unions Suite 582\nCobbborough, D...            Bisque
3   1414 David Throughway\nPort Jason, OH 22070-1220       SaddleBrown
4  14023 Rodriguez Passage\nPort Jacobville, PR 3...  MediumAquaMarine

   Avg. Session Length  Time on App  Time on Website  Length of Membership  \
0            34.497268    12.655651        39.577668              4.082621
1            31.926272    11.109461        37.268959              2.664034
2            33.000915    11.330278        37.110597              4.104543
3            34.305557    13.717514        36.721283              3.120179
4            33.330673    12.795189        37.536653              4.446308

   Yearly Amount Spent
0           587.951054
1           392.204933
2           487.547505
3           581.852344
4           599.406092
```

In [278]: customers.describe()

Out[278]:
```
       Avg. Session Length  Time on App  Time on Website  \
count           500.000000   500.000000       500.000000
mean             33.053194    12.052488        37.060445
std               0.992563     0.994216         1.010489
min              29.532429     8.508152        33.913847
25%              32.341822    11.388153        36.349257
50%              33.082008    11.983231        37.069367
75%              33.711985    12.753850        37.716432
max              36.139662    15.126994        40.005182

       Length of Membership  Yearly Amount Spent
count            500.000000           500.000000
mean               3.533462           499.314038
std                0.999278            79.314782
min                0.269901           256.670582
25%                2.930450           445.038277
```

```
50%                  3.533975           498.887875
75%                  4.126502           549.313828
max                  6.922689           765.518462
```

In [279]:
```
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
```

1.3 Exploratory Data Analysis

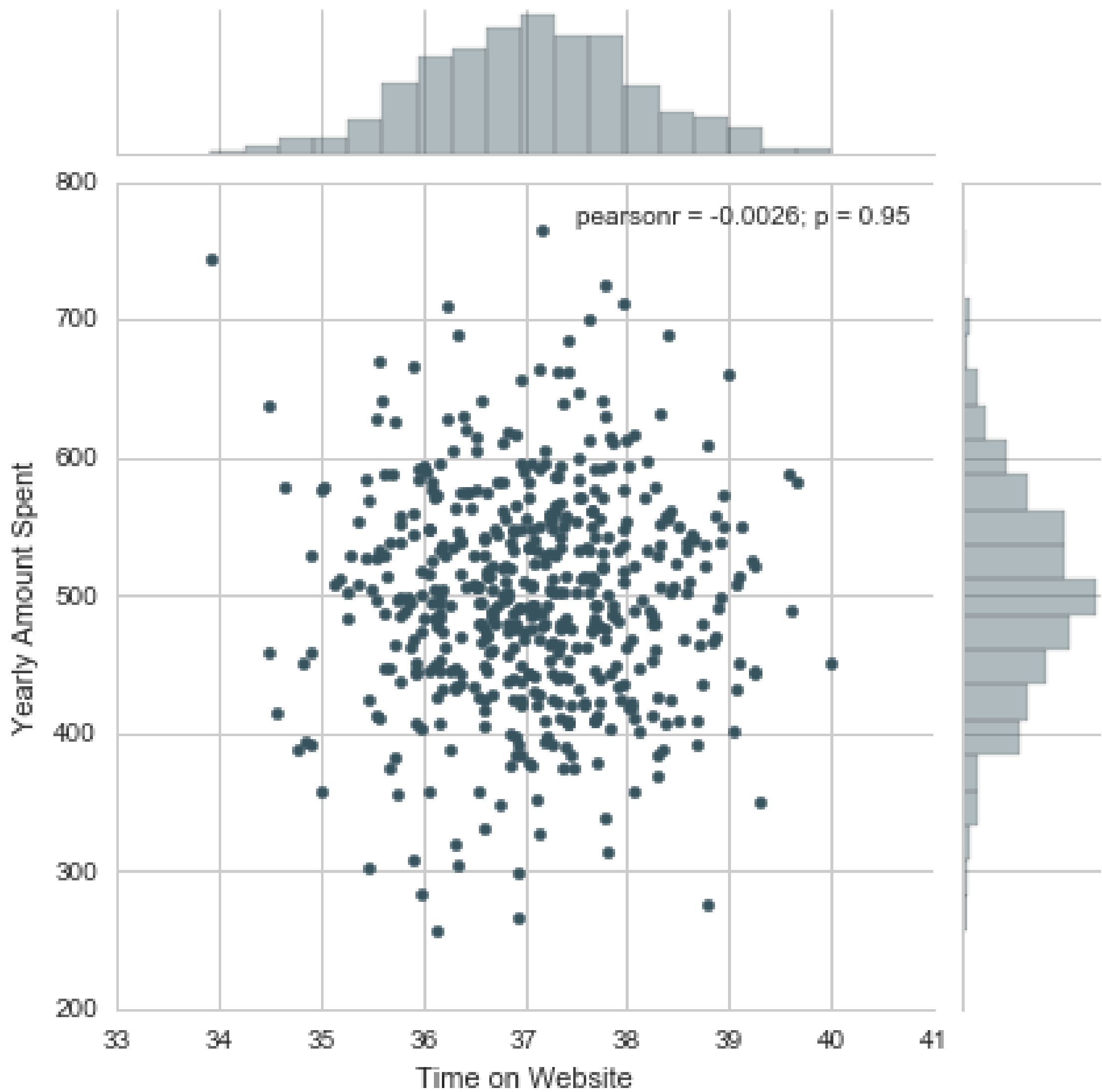
Let's explore the data!

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 [280]:
```
sns.set_palette("GnBu_d")
sns.set_style('whitegrid')
```

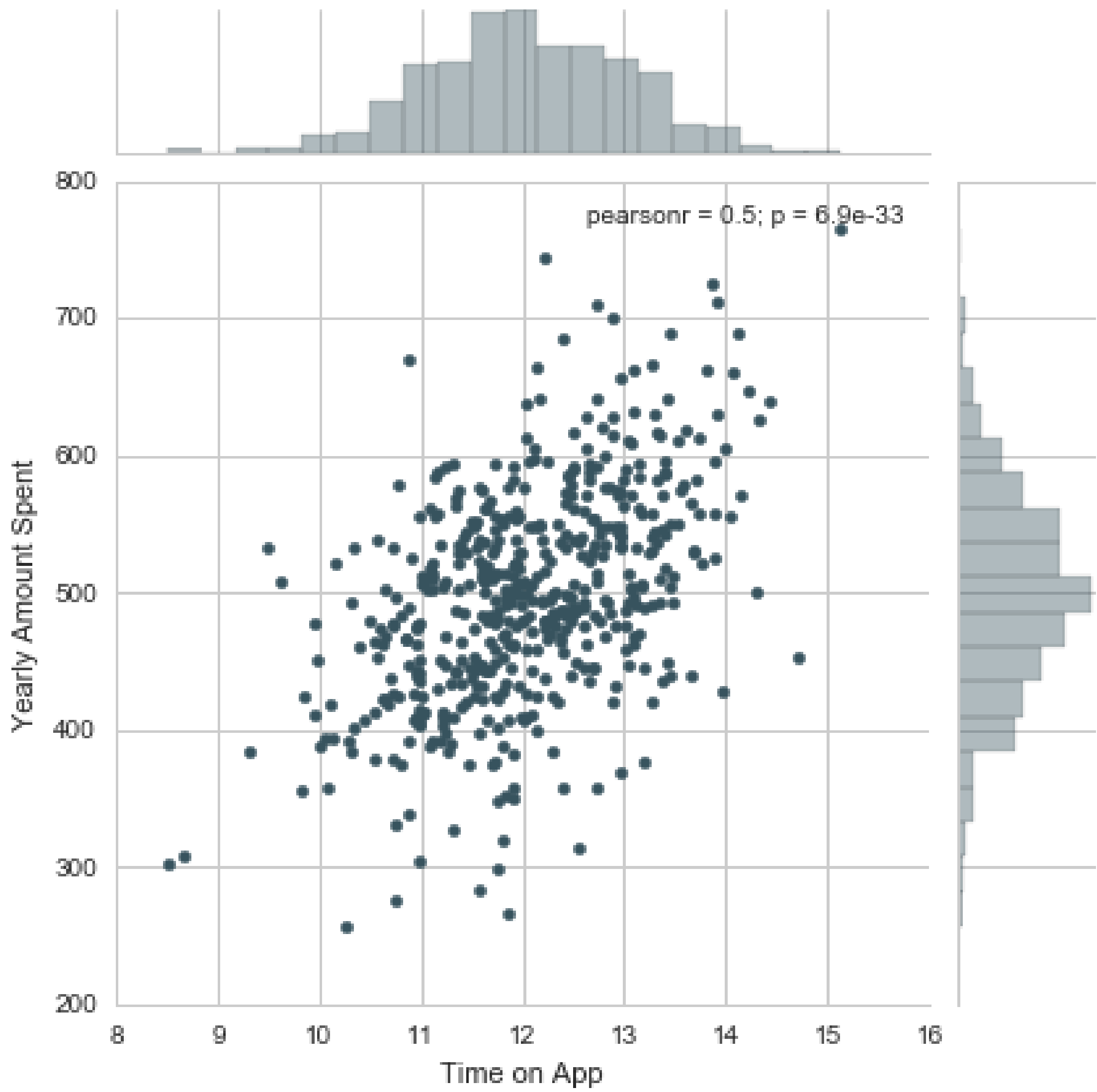
In [281]:
```
# More time on site, more money spent.
sns.jointplot(x='Time on Website',y='Yearly Amount Spent',data=customers)
```

Out[281]:
```
<seaborn.axisgrid.JointGrid at 0x120bfcc88>
```



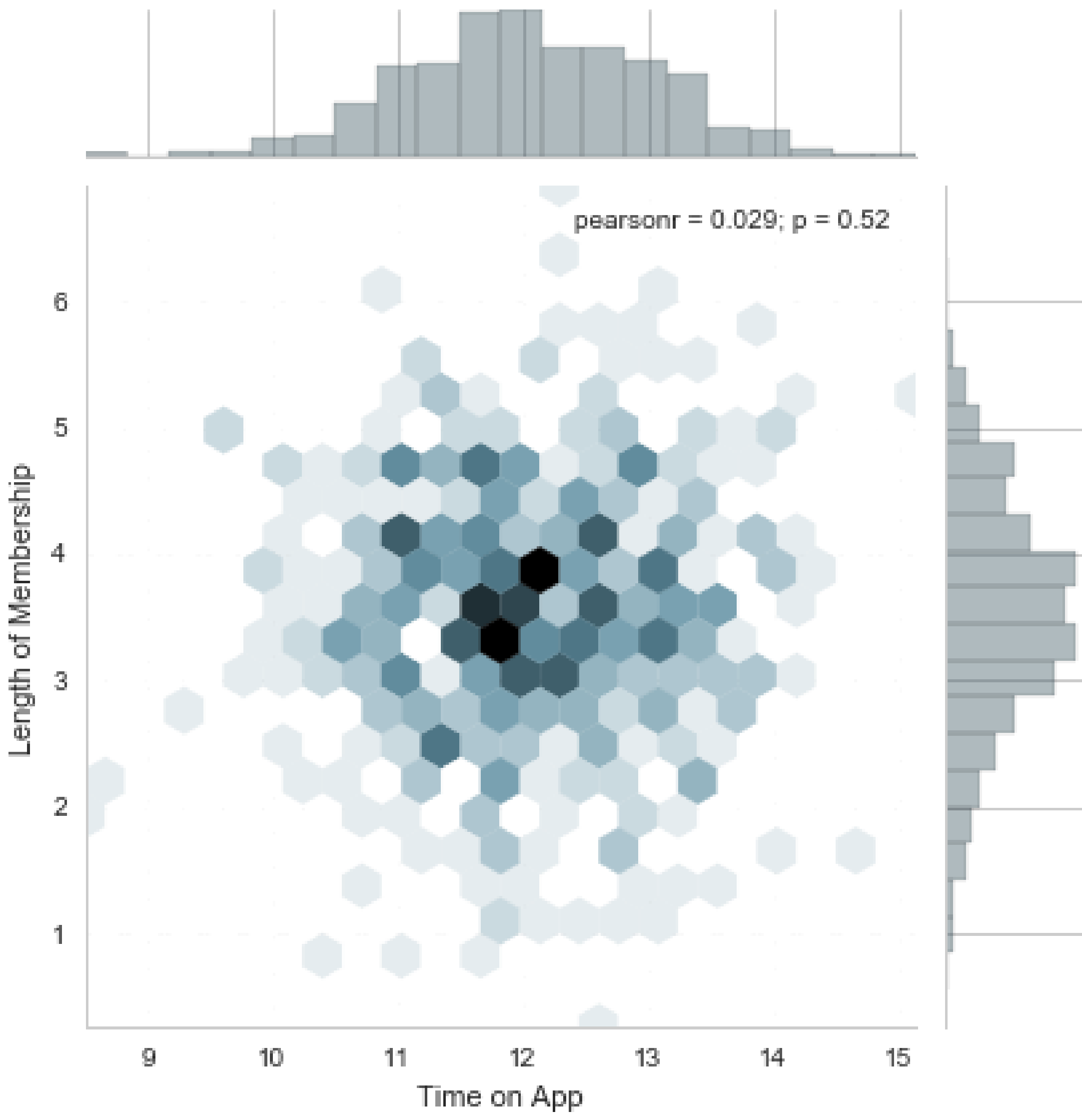
** Do the same but with the Time on App column instead. **

```
In [282]: sns.jointplot(x='Time on App',y='Yearly Amount Spent',data=customers)

Out[282]: <seaborn.axisgrid.JointGrid at 0x132db5908>
```



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

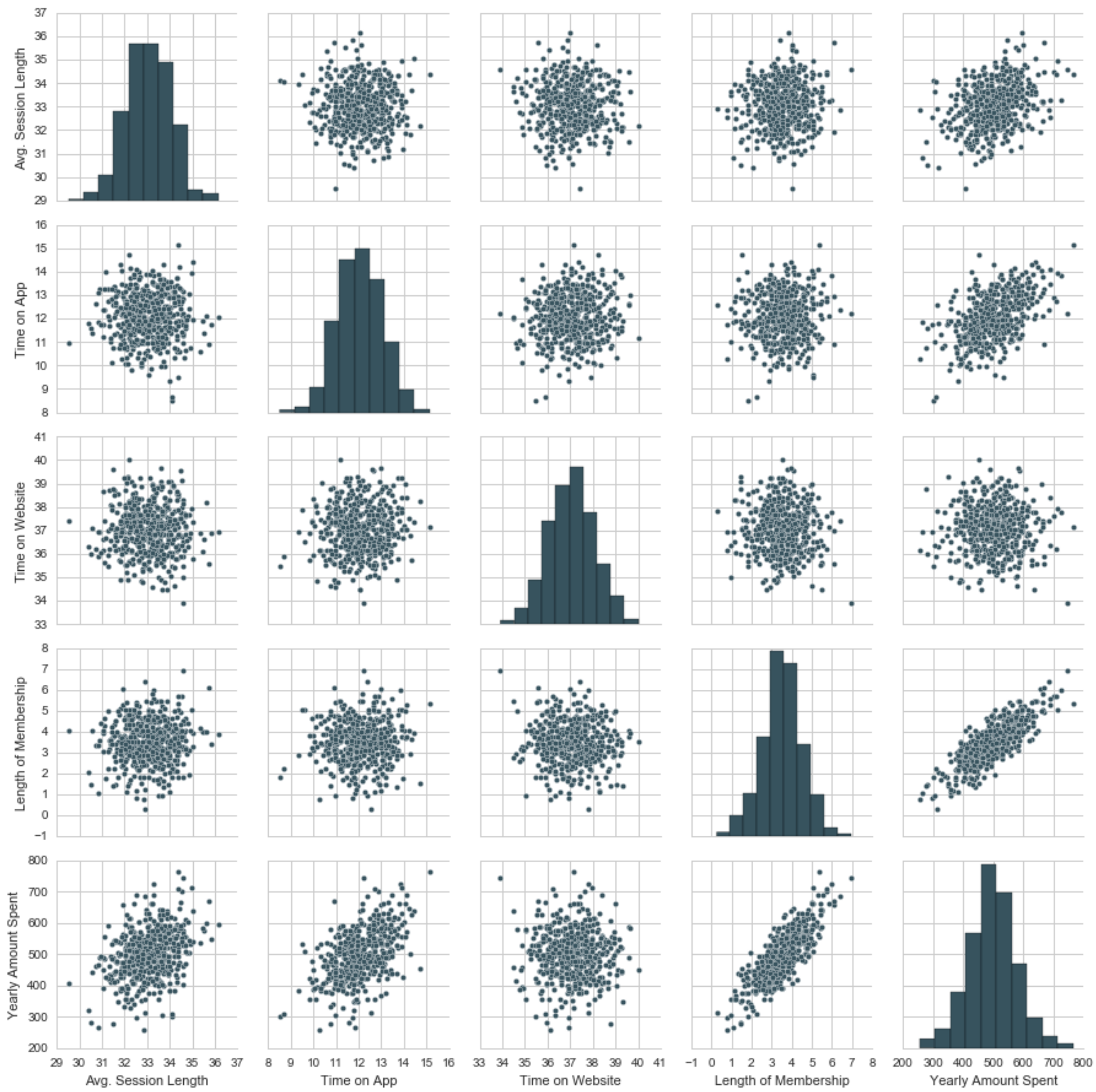
```
In [283]: sns.jointplot(x='Time on App',y='Length of Membership',kind='hex',data=customers)

Out[283]: <seaborn.axisgrid.JointGrid at 0x130edac88>
```



Let's explore these types of relationships across the entire data set. Use [pairplot](https://stanford.edu/~mwaskom/software/seaborn/tutorial/axis_grids.html#plotting-pairwise-relationships-with-pairgrid-and-pairplot) **to recreate the plot below.(Don't worry about the the colors)**

```
In [284]: sns.pairplot(customers)
```

```
Out[284]: <seaborn.axisgrid.PairGrid at 0x132fb3da0>
```

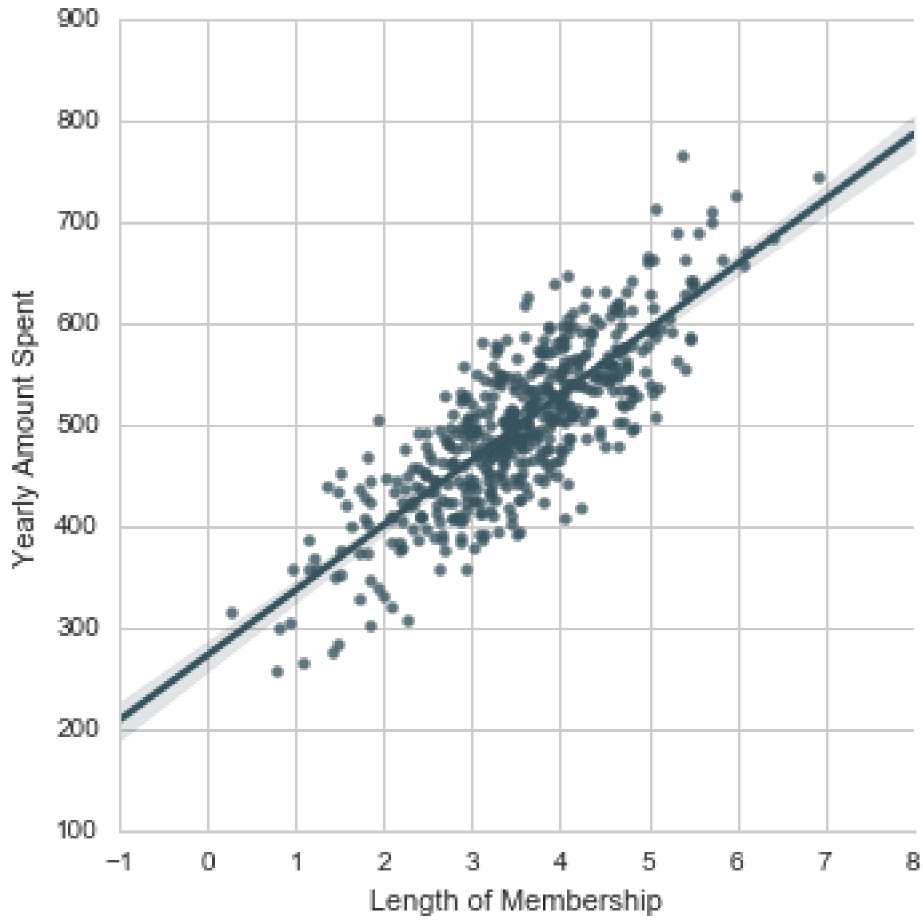


Based off this plot what looks to be the most correlated feature with Yearly Amount Spent?

```
In [285]: # Length of Membership
```

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

```
In [286]: sns.lmplot(x='Length of Membership',y='Yearly Amount Spent',data=customers)

Out[286]: <seaborn.axisgrid.FacetGrid at 0x13538d0b8>
```



1.4 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 [287]: y = customers['Yearly Amount Spent']
```

```
In [288]: X = customers[['Avg. Session Length', 'Time on App','Time on Website', 'Length of Mem
```

** 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 [289]: from sklearn.model_selection import train_test_split
```

```
In [290]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state
```

1.5 Training the Model

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

** Import LinearRegression from sklearn.linear_model **

```
In [291]: from sklearn.linear_model import LinearRegression
```

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

```
In [292]: lm = LinearRegression()
```

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

```
In [293]: lm.fit(X_train,y_train)

Out[293]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

Print out the coefficients of the model

```
In [294]: print('Coefficients: \n', lm.coef_)

Coefficients:
 [ 25.98154972  38.59015875   0.19040528  61.27909654]
```

1.6 Predicting Test Data

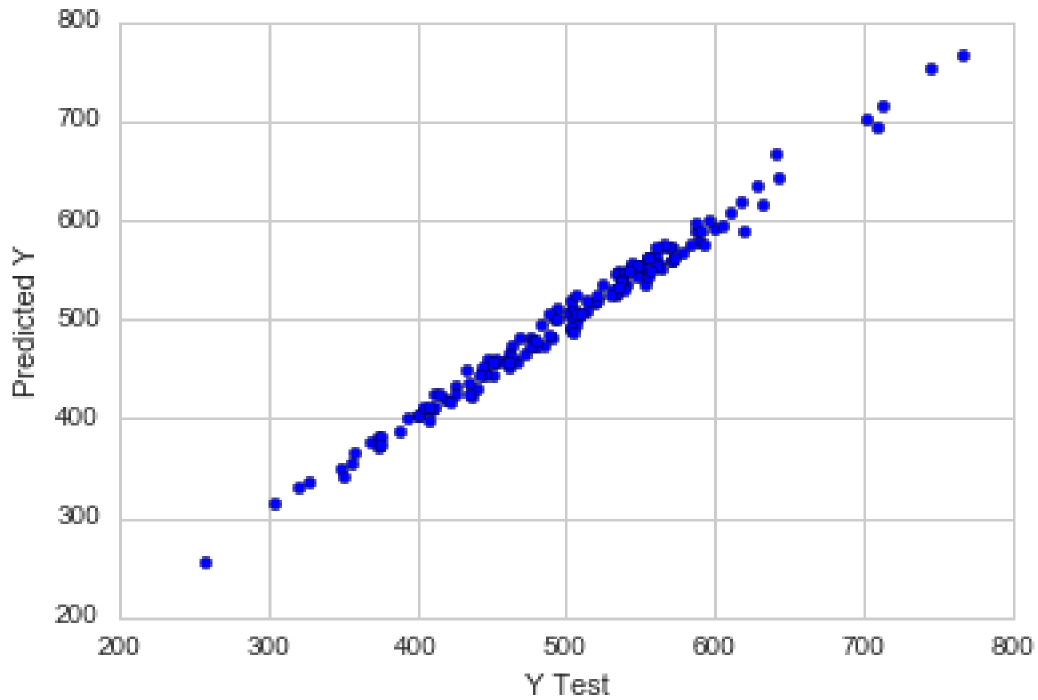
Now that we have fit our model, let's evaluate its performance by predicting off the test values!

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

```
In [295]: predictions = lm.predict( X_test)
```

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

```
In [296]: plt.scatter(y_test,predictions)
          plt.xlabel('Y Test')
          plt.ylabel('Predicted Y')

Out[296]: <matplotlib.text.Text at 0x135546320>
```



1.7 Evaluating the Model

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

** Calculate the Mean Absolute Error, Mean Squared Error, and the Root Mean Squared Error. Refer to the lecture or to Wikipedia for the formulas**

```
In [303]: # calculate these metrics by hand!
          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)))
```

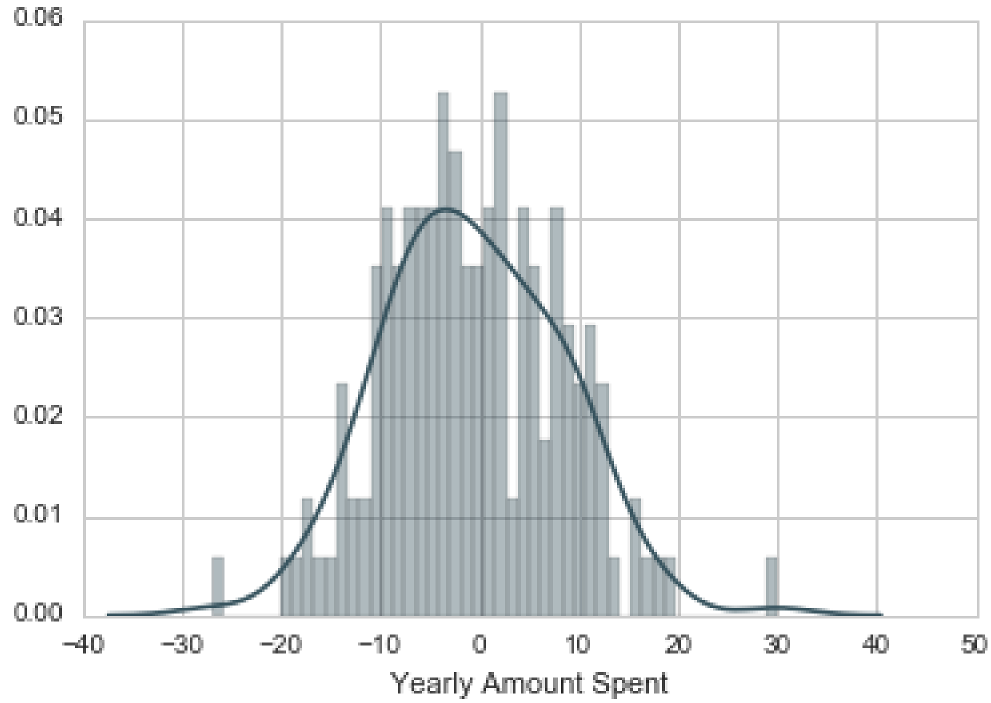
```
MAE: 7.22814865343
MSE: 79.813051651
RMSE: 8.93381506698
```

1.8 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 [317]:
```
sns.distplot((y_test-predictions),bins=50);
```



1.9 Conclusion

We still want to figure out the answer to the original question, do we focus our efforst 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 [298]:
```
coeffecients = pd.DataFrame(lm.coef_,X.columns)
coeffecients.columns = ['Coeffecient']
coeffecients
```

Out[298]:

	Coeffecient
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, you would probably want to explore the relationship between Length of Membership and the App or the Website before coming to a conclusion!

1.10 Great Job!

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