notebook

April 13, 2024

0.0.1 E-commerce Store Analysis

Getting the data

[18]:
```
import pandas as pd

data = pd.read_csv("Ecommerce Customers")
data
```

[18]:

	Email	Address	Avatar	Avg. Session Length	Time on App	Time on Website	Length of Membership
0	mstephenson@fernandez.com	835 Frank Tunnel\nWrightmouth, MI 82180-9605	Violet	34.497268	12.655651	39.577668	4.082621
1	hduke@hotmail.com	4547 Archer Common\nDiazchester, CA 06566-8576	DarkGreen	31.926272	11.109461	37.268959	2.664034
2	pallen@yahoo.com	24645 Valerie Unions Suite 582\nCobbborough, D…	Bisque				
3	riverarebecca@gmail.com	1414 David Throughway\nPort Jason, OH 22070-1220	SaddleBrown				
4	mstephens@davidson-herman.com	14023 Rodriguez Passage\nPort Jacobville, PR 3…	MediumAquaMarine				
..	…	…	…				
495	lewisjessica@craig-evans.com	4483 Jones Motorway Suite 872\nLake Jamiefurt,…	Tan				
496	katrina56@gmail.com	172 Owen Divide Suite 497\nWest Richard, CA 19320	PaleVioletRed				
497	dale88@hotmail.com	0787 Andrews Ranch Apt. 633\nSouth Chadburgh, …	Cornsilk				
498	cwilson@hotmail.com	680 Jennifer Lodge Apt. 808\nBrendachester, TX…	Teal				
499	hannahwilson@davidson.com	49791 Rachel Heights Apt. 898\nEast Drewboroug…	DarkMagenta				

```
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
..                   …            …              …                     …
495            33.237660    13.566160        36.417985              3.746573
496            34.702529    11.695736        37.190268              3.576526
497            32.646777    11.499409        38.332576              4.958264
498            33.322501    12.391423        36.840086              2.336485
499            33.715981    12.418808        35.771016              2.735160

     Yearly Amount Spent
0             587.951054
1             392.204933
2             487.547505
3             581.852344
4             599.406092
..                   …
495           573.847438
496           529.049004
497           551.620145
498           456.469510
499           497.778642

[500 rows x 8 columns]
```

[19]:
```
# check for any null values
data.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
```

[20]:
```
# delete the email address and avatar columns
data = data.drop(["Email" , "Address" , "Avatar"] , axis=1)
```

[21]:
```
# Split the data into train and test data
train_data = data[:int(500*0.8)]
test_data = data[int(500*0.8):]
test_data
```

[21]:

	Avg. Session Length	Time on App	Time on Website	Length of Membership	Yearly Amount Spent
400	33.172331	13.078692	37.329819	5.405406	663.074818
401	33.247322	11.956426	36.517346	3.451751	506.375867
402	33.598913	13.252737	37.305961	2.935577	528.419330
403	33.085298	13.093537	38.315648	4.750360	632.123588
404	32.278443	12.527472	36.688367	3.531402	488.270298
..	…	…	…	…	…
495	33.237660	13.566160	36.417985	3.746573	573.847438
496	34.702529	11.695736	37.190268	3.576526	529.049004
497	32.646777	11.499409	38.332576	4.958264	551.620145
498	33.322501	12.391423	36.840086	2.336485	456.469510
499	33.715981	12.418808	35.771016	2.735160	497.778642

[100 rows x 5 columns]

Check relationship between Avg. Session Length and Yearly Amount Spent

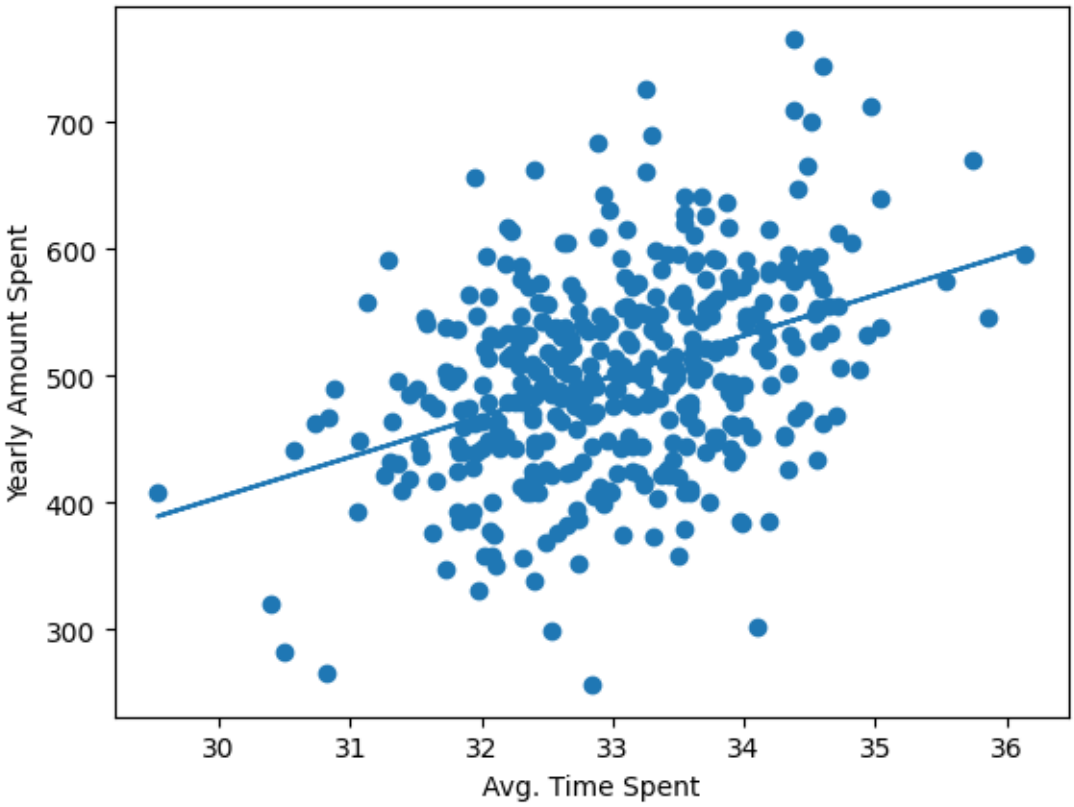
[22]:
```
import matplotlib.pyplot as plt
from scipy import stats

x = train_data["Avg. Session Length"]
y = train_data["Yearly Amount Spent"]
slope, intercept, r, p, std_err = stats.linregress(x,y)

def myfun(x):
    return slope*x + intercept

model = list(map(myfun , x))
plt.scatter(x , y)
plt.plot(x,model)
```

```
plt.xlabel("Avg. Time Spent")
plt.ylabel("Yearly Amount Spent")
plt.show()
print("The coefficient of correlation is: ", r)
```




```
The coefficient of correlation is:  0.39726338720882065
```

The coffiecient is only 0.39 showing that there is not good relationship between avg. time spent and yearly amount spent. Therefore, it is not a good indicator

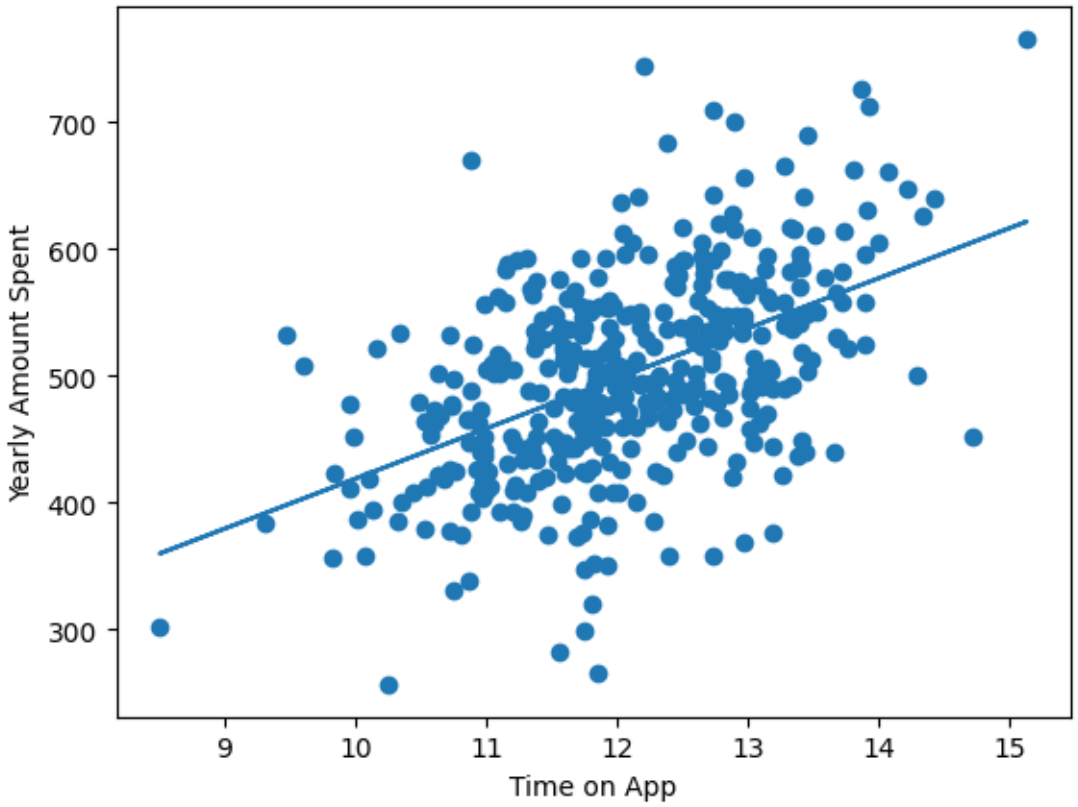
Check relationship between Time on App and Yearly Amount Spent

[23]:
```
x = train_data["Time on App"]
y = train_data["Yearly Amount Spent"]
slope, intercept, r, p, std_err = stats.linregress(x,y)

def myfun(x):
    return slope*x + intercept

model = list(map(myfun , x))
plt.scatter(x , y)
plt.plot(x,model)
```

```
plt.xlabel("Time on App")
plt.ylabel("Yearly Amount Spent")
plt.show()
print("The coefficient of correlation is: ", r)
```




```
The coefficient of correlation is:  0.5013178168518133
```

The coefficient is 0.5. Time on App is not a perfect indicator for predicting the Amount spent but it is certainly better indicator than Avg. Time Spent.

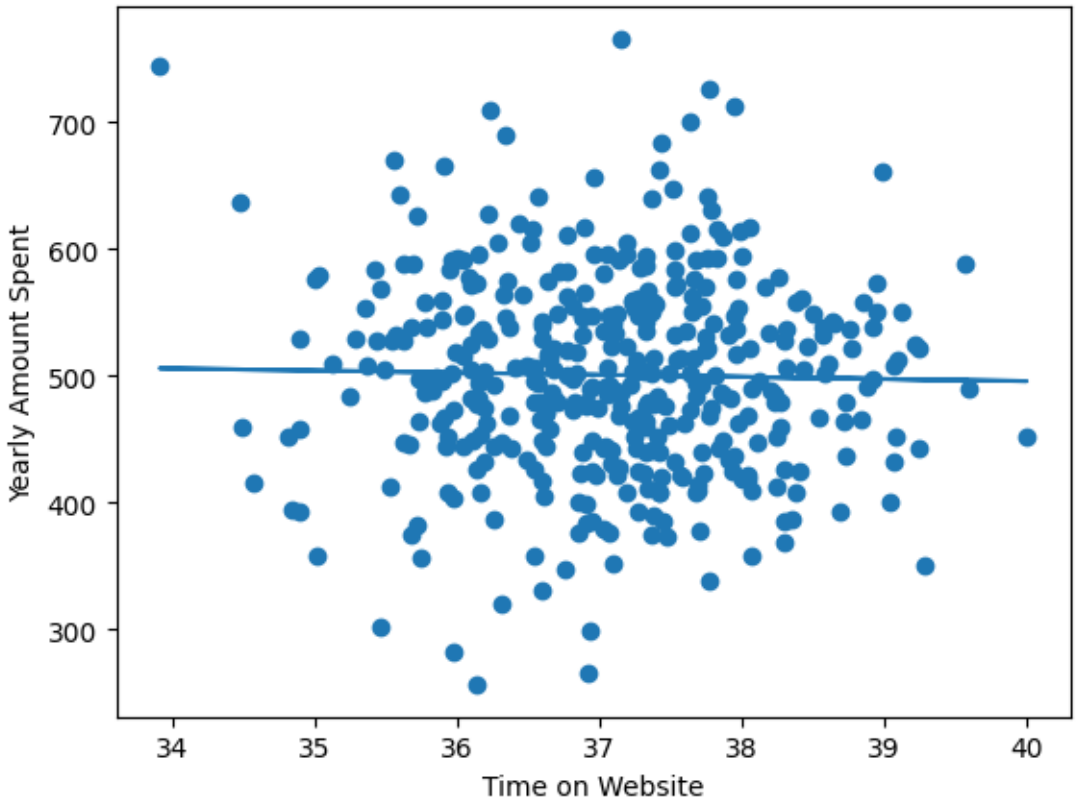
Check relationship between Time on Website and Yearly Amount Spent

[24]:
```
x = train_data["Time on Website"]
y = train_data["Yearly Amount Spent"]
slope, intercept, r, p, std_err = stats.linregress(x,y)

def myfun(x):
    return slope*x + intercept

model = list(map(myfun , x))
plt.scatter(x , y)
plt.plot(x,model)
```

```
plt.xlabel("Time on Website")
plt.ylabel("Yearly Amount Spent")
plt.show()
print("The coefficient of correlation is: ", r)
```




```
The coefficient of correlation is:  -0.021389301369613256
```

The coefficient of correlation is very low indicating that Time spent on websites by customers does not show any relation to how much the customers will spend money.

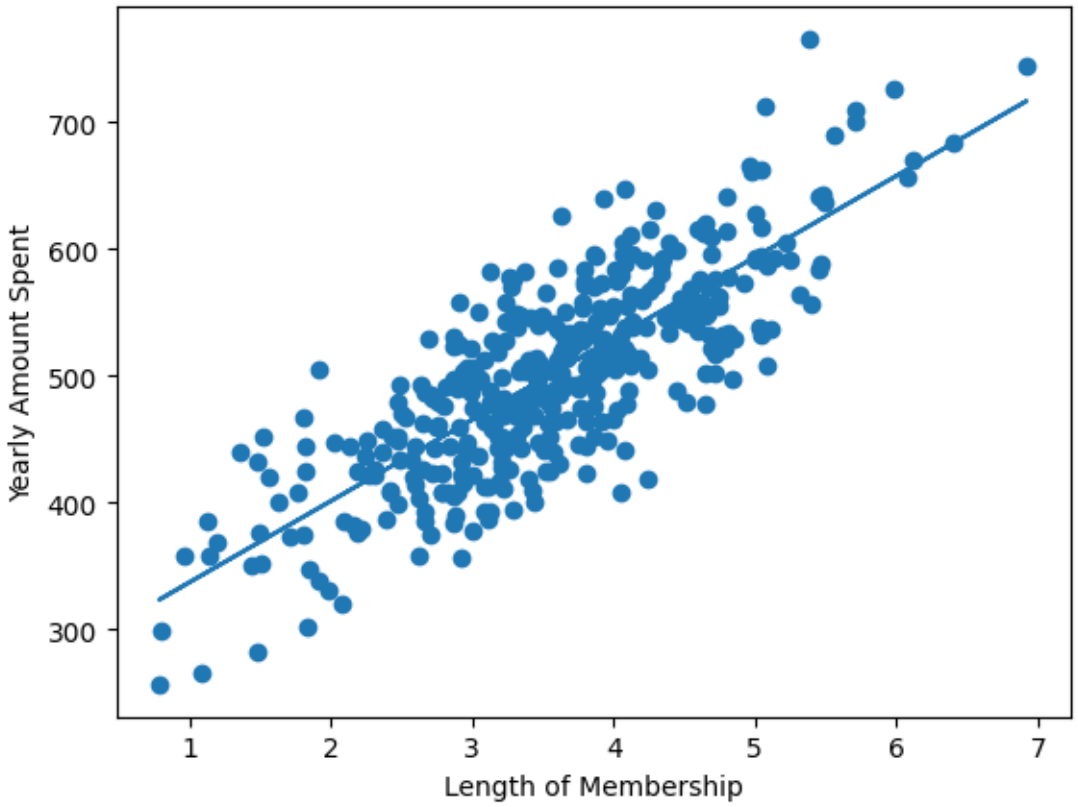
Check relationship between Length of Membership and Yearly Amount Spent

[25]:
```
x = train_data["Length of Membership"]
y = train_data["Yearly Amount Spent"]
slope, intercept, r, p, std_err = stats.linregress(x,y)

def myfun(x):
    return slope*x + intercept

model = list(map(myfun , x))
plt.scatter(x , y)
plt.plot(x,model)
```

```
plt.xlabel("Length of Membership")
plt.ylabel("Yearly Amount Spent")
plt.show()
print("The coefficient of correlation is: ", r)
```




```
The coefficient of correlation is:  0.8023014262910735
```

Length of Membership definetely shows a significant impact on how much a customer might spend money on products. The people who have been a member for a longer time are likely to spend more money than other people. Length of Membership is by far the best indicator for prediciting the customer's yearly expenditure.

[26]:
```
train_data
```

[26]:

	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	
..	…	…	…	…	
395	31.445972	12.846499	37.869217	3.420150	

```
396            35.742670    10.889828        35.565436              6.115199
397            34.012619    12.914570        36.046204              3.488030
398            34.140393    11.568527        38.918749              4.082855
399            32.377990    11.971751        37.199368              2.829700

     Yearly Amount Spent
0             587.951054
1             392.204933
2             487.547505
3             581.852344
4             599.406092
..                   …
395           484.876965
396           669.987141
397           547.709989
398           537.825282
399           408.216902

[400 rows x 5 columns]
```

Now let's train our model using multi-variable regression and try to predict the yearly amount spent

[27]:
```
from sklearn import linear_model

x = train_data[["Avg. Session Length","Time on App","Time on Website","Length␣
 ↪of Membership"]]
y = train_data['Yearly Amount Spent']

# train the model
regr = linear_model.LinearRegression()
regr.fit(x,y)

cdf = pd.DataFrame(regr.coef_ , x.columns , columns=["Coef" ])
cdf
```

[27]:
```
                         Coef
Avg. Session Length   25.576288
Time on App           38.345474
Time on Website        0.593094
Length of Membership  61.182253
```

0.0.2 We can say that Time on Website is the worst predictor and Length of Membership is the best predictor. And as Time on App seems to have more impact in whether a customer buys a product, the company should put more focus on making the app more user-friendly and improve the customer experience. They should also look at why website sells are not performing that well and try to solve and improve customer experience on the website as well to improve their sells. They should definitely focus on making their loyalty and membership programs more attractive to the customers.

Let's predict the Yearly Amount Spent using our test data

[28]:
```
test = test_data[["Avg. Session Length","Time on App","Time on Website","Length␣
↪of Membership"]]
result = regr.predict(test)

result
```

[28]:
```
array([656.53182746, 495.4050683 , 522.99217803, 615.38255148,
       497.4964396 , 500.76291281, 425.20749828, 419.01697905,
       481.74527484, 518.05632706, 607.90566062, 600.85210474,
       467.37139755, 497.76514136, 546.16417418, 282.28888056,
       507.2560816 , 446.14773139, 502.25581095, 478.31939136,
       647.96177913, 558.33921848, 626.93993035, 457.69487285,
       497.5062451 , 576.1633185 , 534.55273655, 578.18055091,
       557.70976655, 491.18624057, 547.92198686, 479.58620929,
       508.25807821, 434.88185925, 314.92189784, 572.89624926,
       582.96375103, 451.01628418, 399.60248079, 574.38149884,
       500.71533089, 486.93636324, 316.97439683, 548.08092536,
       427.67763992, 513.70459553, 531.20087059, 315.73232443,
       478.9900598 , 452.07978091, 473.89500771, 431.08579947,
       506.57803966, 480.19870705, 449.67654923, 447.94855878,
       394.69643466, 531.91841961, 542.55776388, 419.60224464,
       587.88989154, 495.69260639, 405.4429639 , 399.05990346,
       675.60293757, 535.06675011, 567.29218279, 422.36633758,
       562.92595229, 417.60859706, 433.40651325, 542.90160902,
       500.18327037, 427.85240271, 499.80484978, 532.2196441 ,
       414.31678871, 493.68025999, 487.64388829, 423.87117484,
       549.48063273, 480.78388867, 487.93878276, 481.44717085,
       457.80257012, 508.34325912, 579.67434799, 348.68598291,
       598.54585678, 338.48708318, 502.15572929, 513.24337263,
       402.28606038, 610.08871328, 512.64469285, 574.86288351,
       530.66070122, 555.76930236, 445.96493687, 480.83656462])
```

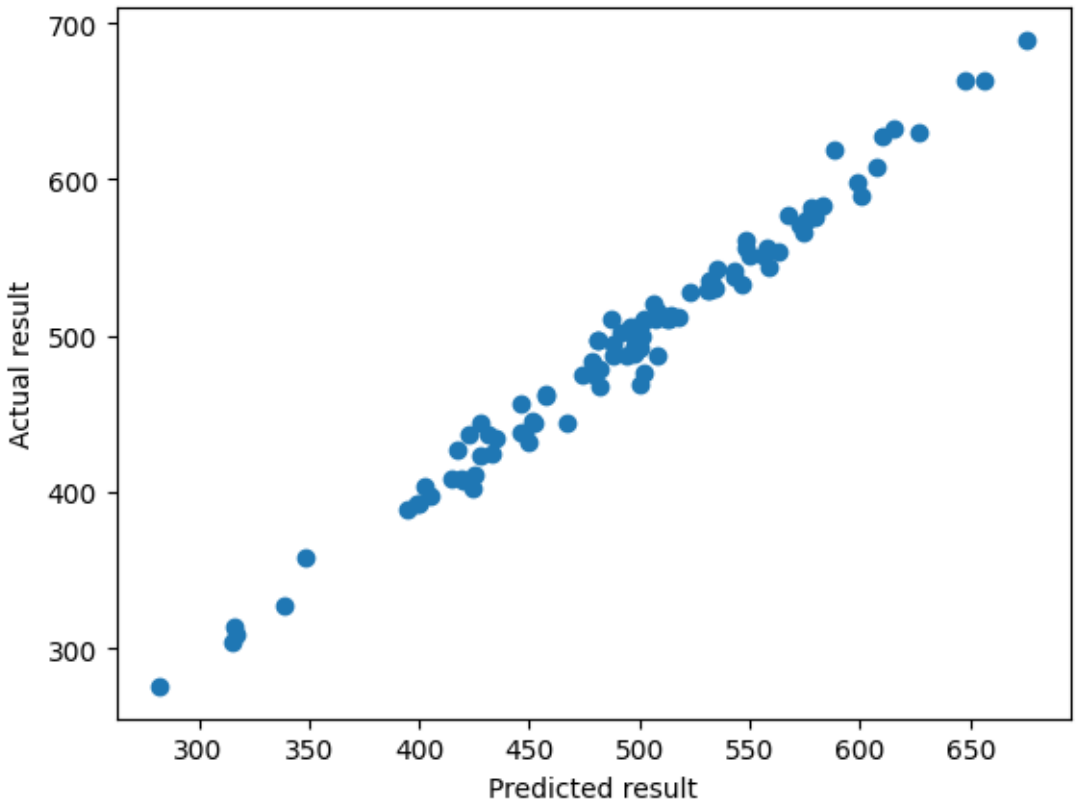
Let's compare our predicted data with the actual given data

[29]:
```
actual_result = test_data['Yearly Amount Spent']

plt.scatter(result , actual_result)
```

```
plt.xlabel("Predicted result")
plt.ylabel("Actual result")
```

[29]: `Text(0, 0.5, 'Actual result')`



[30]:
```
from sklearn.metrics import mean_absolute_error , mean_squared_error
import math

print("Mean absolute error: " , mean_absolute_error(result , actual_result))
print("Mean squared error: " , mean_squared_error(result , actual_result))
print("Root mean squared error: " , math.sqrt(mean_squared_error(result ,␣
 ↪actual_result)))
```

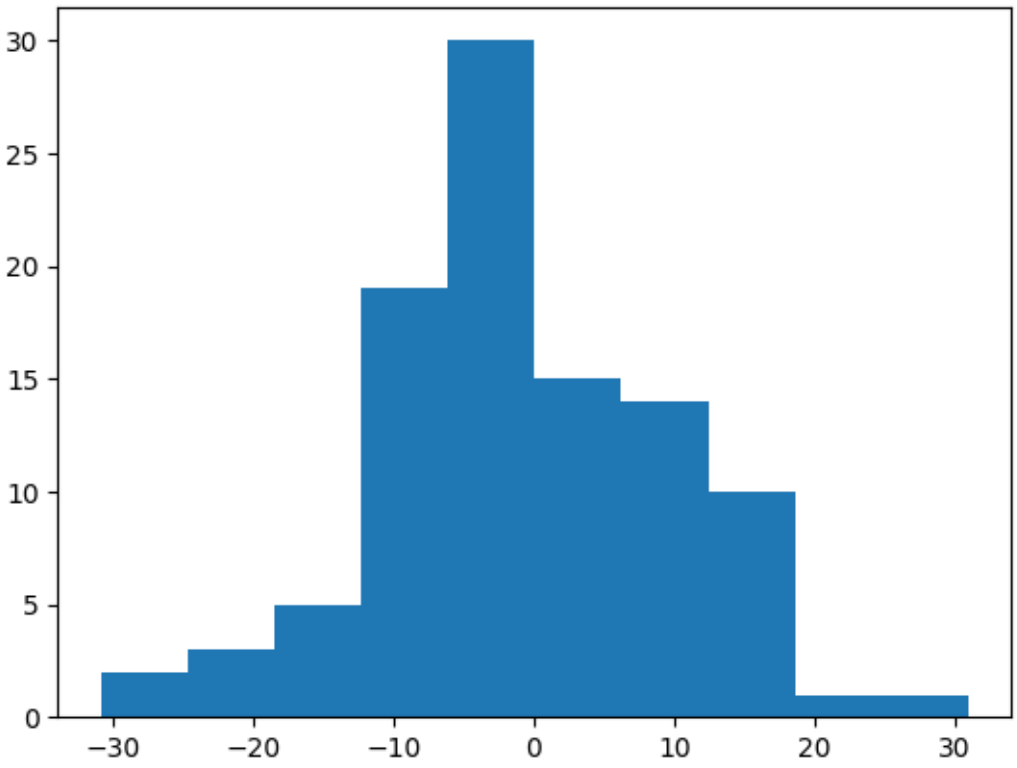
```
Mean absolute error:  8.222577352952001
Mean squared error:  112.51939038010785
Root mean squared error:  10.607515749698788
```

We can say that the model is very accurate in predicting the yearly spent amount with the error of just 10 dollars(max).

Residuals analysis

[31]:
```
residual = actual_result - result
plt.hist(residual , bins=10)
```

[31]:
```
(array([ 2.,  3.,  5., 19., 30., 15., 14., 10.,  1.,  1.]),
 array([-30.8001242 , -24.62450389, -18.44888358, -12.27326328,
         -6.09764297,   0.07797734,   6.25359765,  12.42921796,
         18.60483827,  24.78045858,  30.95607889]),
 <BarContainer object of 10 artists>)
```



[ ]: