```python
# This jupyter notebook is prepared by Nawras Rawas Qalaji

import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import missingno as msno
import scipy.stats as st
from sklearn import ensemble, tree, linear_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.linear_model import LinearRegression, SGDRegressor,
Ridge, ElasticNet, Lasso
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.pipeline import Pipeline


#import hrdata.csv to hrdata dataframe
hrdata = pd.read_csv("/content/drive/MyDrive/Colab
Notebooks/ecommarce.csv")

#count columns and rows
print("Count Columns and rows")
print("columns " + str(hrdata.shape[1]))
print("rows " + str(hrdata.shape[0]) + "\n")

#describe datafram
print("\nDescribe")
print(hrdata.describe())
```

```
Count Columns and rows
columns 9
rows 500



Describe
       Unnamed: 0   Credit Card  Avg. Session Length  Time on App  \
count  500.000000  5.000000e+02           500.000000   500.000000
mean   249.500000  3.706324e+17            34.053194    13.052488
std    144.481833  1.235588e+18             0.992563     0.994216
min      0.000000  5.018057e+11            30.532429     9.508152
25%    124.750000  3.683275e+13            33.341822    12.388153
50%    249.500000  3.513612e+15            34.082008    12.983231
75%    374.250000  4.777131e+15            34.711985    13.753850
max    499.000000  4.959148e+18            37.139662    16.126994

       Time on Website  Length of Membership  Yearly Amount Spent
```

```
count       500.000000            500.000000           500.000000
mean         38.060445              4.033462           500.314038
std           1.010489              0.999278            79.314782
min          34.913847              0.769901           257.670582
25%          37.349257              3.430450           446.038277
50%          38.069367              4.033975           499.887875
75%          38.716432              4.626502           550.313828
max          41.005182              7.422689           766.518462
```

Explain in words about the description of any two variables

- The data collected on the credit card is not really useable since its just the credit card number instead of any actual data related to it
- The data on unnamed is also useless since its just the index of the array

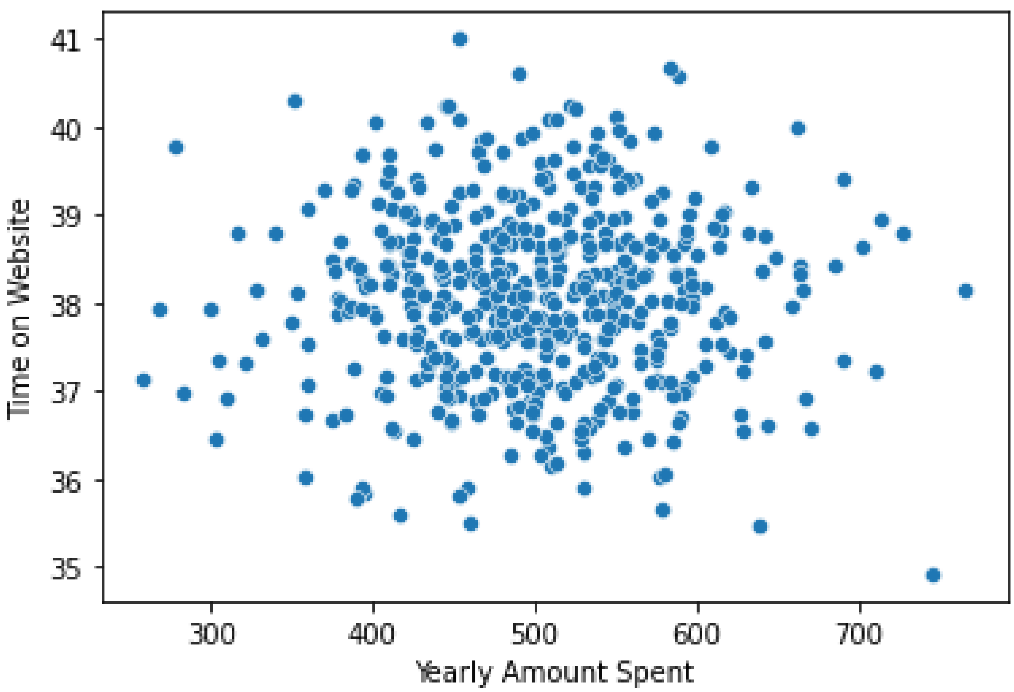
```
#top and bottom 5 rows
print("\nTop Five Rows")
print(hrdata.loc[[0,1,2,3,4]])
print("\nBottom Five Rows")
print(hrdata.iloc[[-1,-2,-3,-4,-5]])

#numerical columns
print("\nNumerical Columns")
print(hrdata.select_dtypes(include = [np.number]).columns)

#categorical columns
print("\nCategorical Columns")
print(hrdata.select_dtypes(include = [np.object]).columns)

#missing values
print("\nMissing Values Numerically")
missingValues = hrdata.isnull().sum().sort_values(ascending = False)
print(missingValues)

print("\nMissing Values Percentage")
print(missingValues/len(hrdata)*100)
```

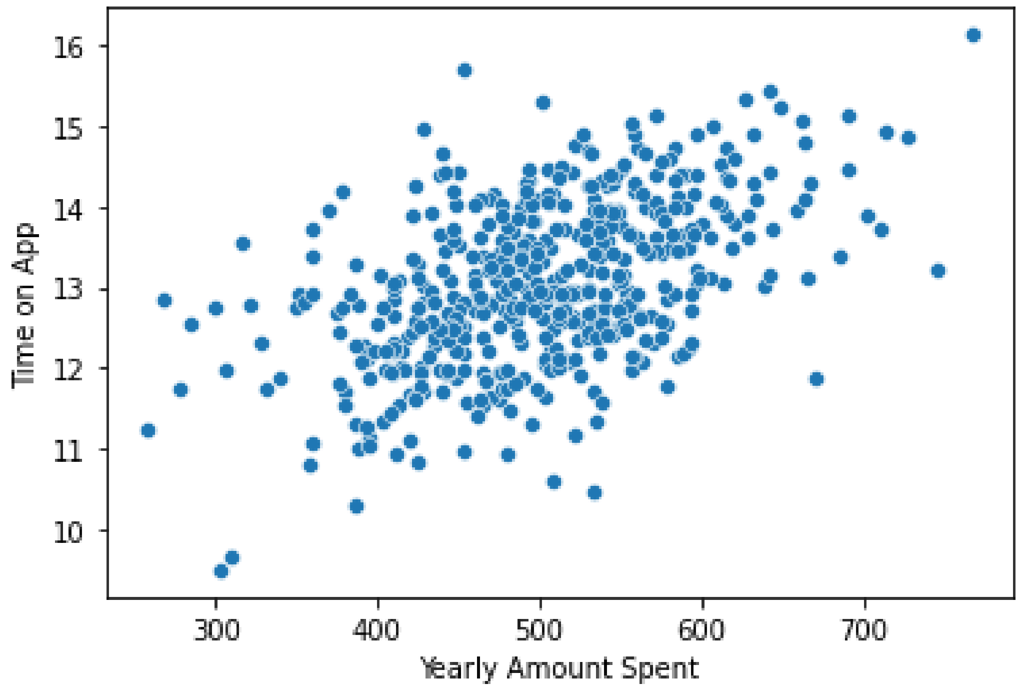
```
Top Five Rows
   Unnamed: 0         Email
Address  \
0           0  adkv@ota.com              89280 Mark Lane\nNew John,
MN 16131
1           1  gjun@syj.com  363 Amanda Cliff Apt. 638\nWest Angela,
KS 31437
2           2  qjyr@pkk.com          62008 Adam Lodge\nLake Pamela,
NY 30677
3           3  jkiu@xsb.com        950 Tami Island\nLake Aimeeview,
MT 93614
4           4  stvb@niy.com       08254 Kelly Squares\nNorth Lauren,
```

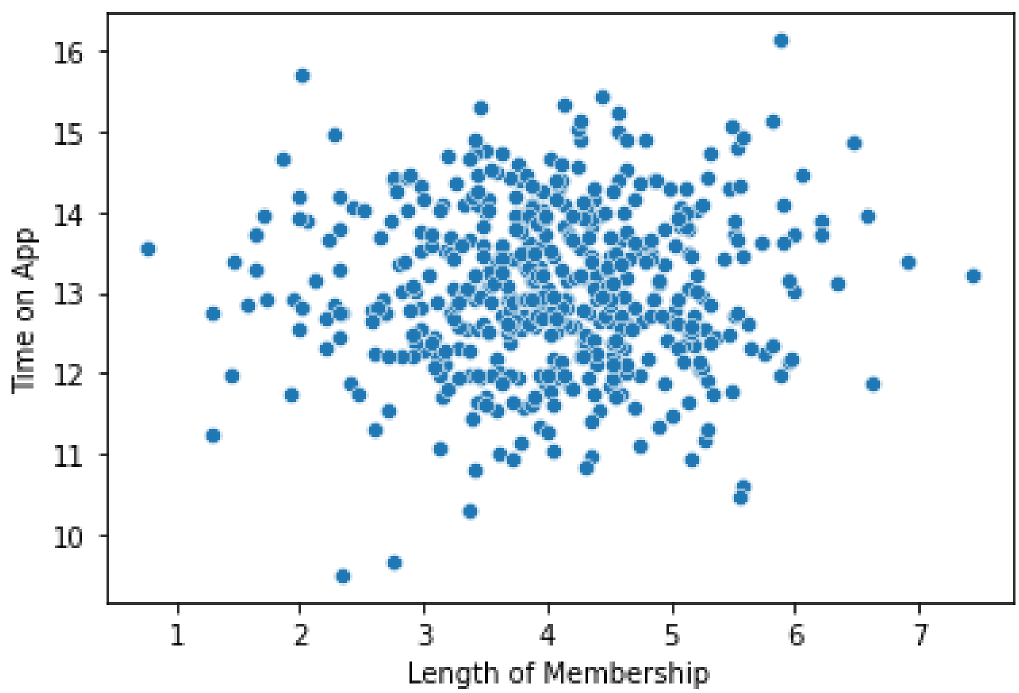
```
AR 78382

           Credit Card  Avg. Session Length  Time on App  Time on
Website  \
0     3544288738428794            35.497268    13.655651
40.577668
1     6546228325389133            32.926272    12.109461
38.268959
2  4406395951712628314            34.000915    12.330278
38.110597
3       30334036663133            35.305557    14.717514
37.721283
4     3582080469154498            34.330673    13.795189
38.536653

   Length of Membership  Yearly Amount Spent
0              4.582621           588.951054
1              3.164034           393.204933
2              4.604543           488.547505
3              3.620179           582.852344
4              4.946308           600.406092

Bottom Five Rows
     Unnamed: 0         Email  \
499         499  phqb@nlg.com
498         498  zvtz@onj.com
497         497  pndt@jyr.com
496         496  awrc@iok.com
495         495  xskz@gwj.com

                                               Address          Credit
Card  \
499       424 Mark Junctions\nDarrellchester, TX 09088
5427200269739116
498  5568 Robert Station Apt. 030\nTurnerstad, GA 9...
36218092488069
497            1555 Chen Road\nBergerchester, NH 46418
4086276267550896697
496  663 Christopher Garden\nLake Carrieberg, PA 70796
6011536844623717
495            7083 Wallace Rest\nNew Trevor, NM 70240
30206742023085

     Avg. Session Length  Time on App  Time on Website  Length of
Membership  \
499            34.715981    13.418808        36.771016
3.235160
498            34.322501    13.391423        37.840086
2.836485
497            33.646777    12.499409        39.332576
```

```
5.458264
496            35.702529    12.695736        38.190268
4.076526
495            34.237660    14.566160        37.417985
4.246573

     Yearly Amount Spent
499           498.778642
498           457.469510
497           552.620145
496           530.049004
495           574.847438

Numerical Columns
Index(['Unnamed: 0', 'Credit Card', 'Avg. Session Length', 'Time on
App',
       'Time on Website', 'Length of Membership', 'Yearly Amount
Spent'],
      dtype='object')

Categorical Columns
Index(['Email', 'Address'], dtype='object')

Missing Values Numerically
Unnamed: 0              0
Email                   0
Address                 0
Credit Card             0
Avg. Session Length     0
Time on App             0
Time on Website         0
Length of Membership    0
Yearly Amount Spent     0
dtype: int64

Missing Values Percentage
Unnamed: 0              0.0
Email                   0.0
Address                 0.0
Credit Card             0.0
Avg. Session Length     0.0
Time on App             0.0
Time on Website         0.0
Length of Membership    0.0
Yearly Amount Spent     0.0
dtype: float64

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:13:
DeprecationWarning: `np.object` is a deprecated alias for the builtin
`object`. To silence this warning, use `object` by itself. Doing this
```

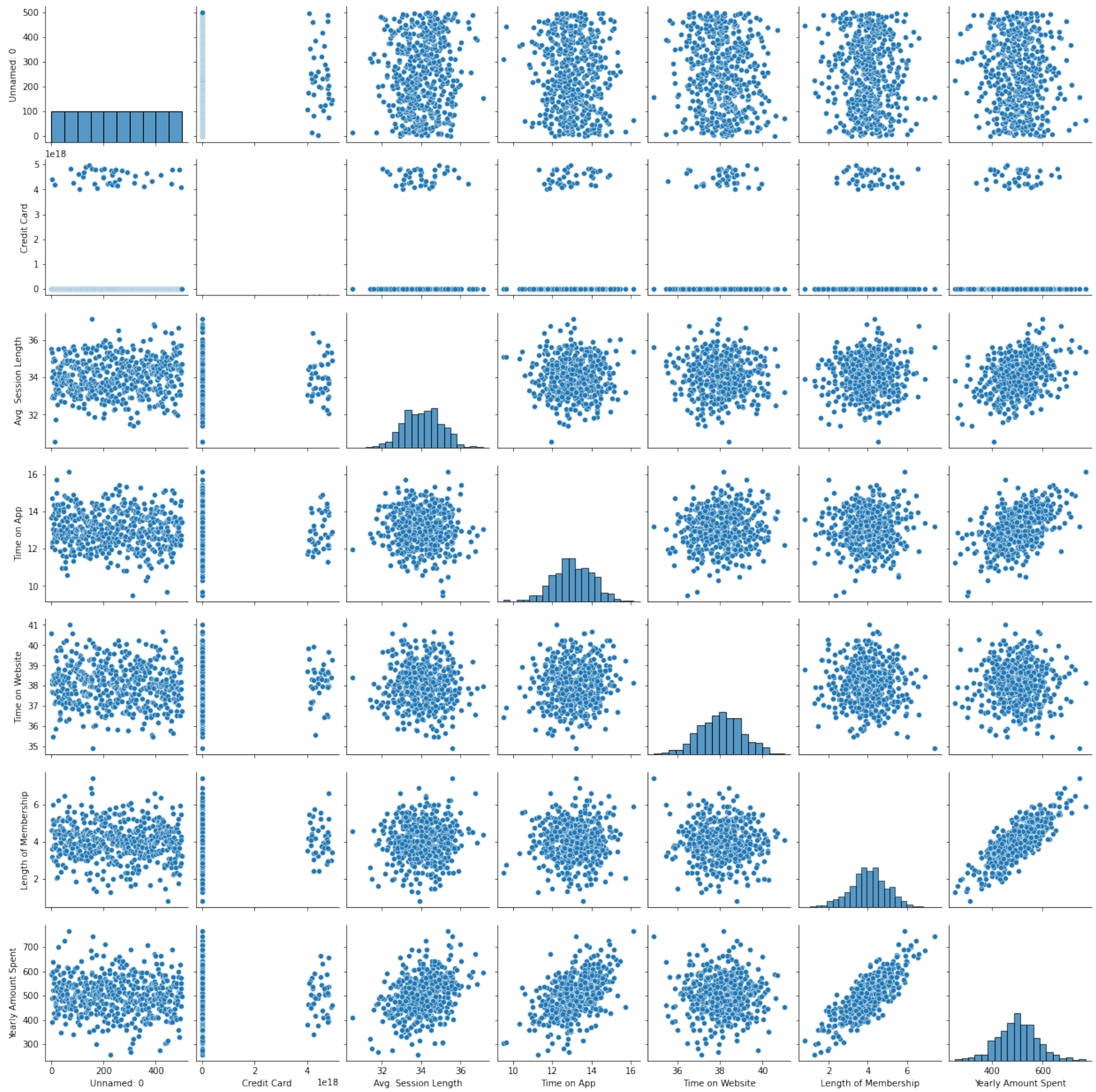
```
will not modify any behavior and is safe.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  del sys.path[0]

#scatterplots
plt.figure()
sns.scatterplot(x = "Yearly Amount Spent", y = "Time on Website", data
= hrdata)
plt.show()

plt.figure()
sns.scatterplot(x = "Yearly Amount Spent", y = "Time on App", data =
hrdata)
plt.show()

plt.figure()
sns.scatterplot(x = "Length of Membership", y = "Time on App", data =
hrdata)
plt.show()
```





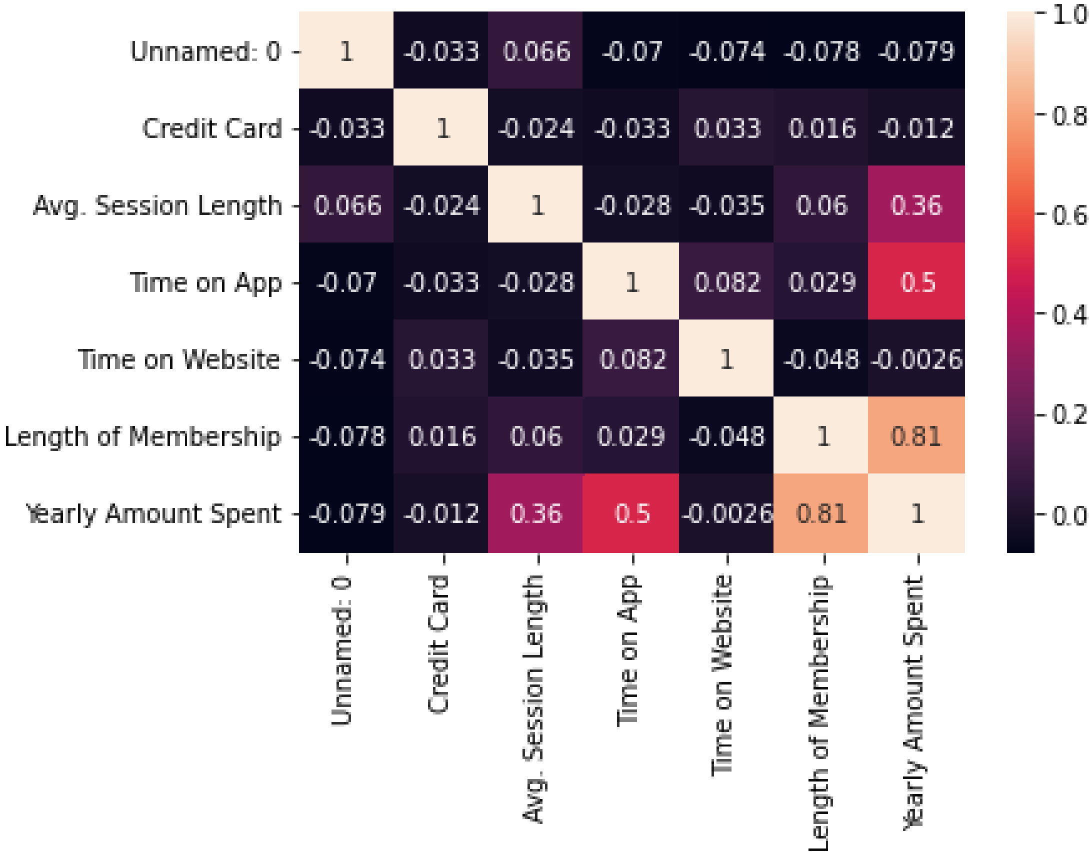



```
sns.pairplot(data = hrdata)
plt.figure()
plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

```
correlationNums = hrdata.select_dtypes(include = [np.number])
sns.heatmap(data = correlationNums.corr(), annot = True)
plt.figure()
plt.show()
```

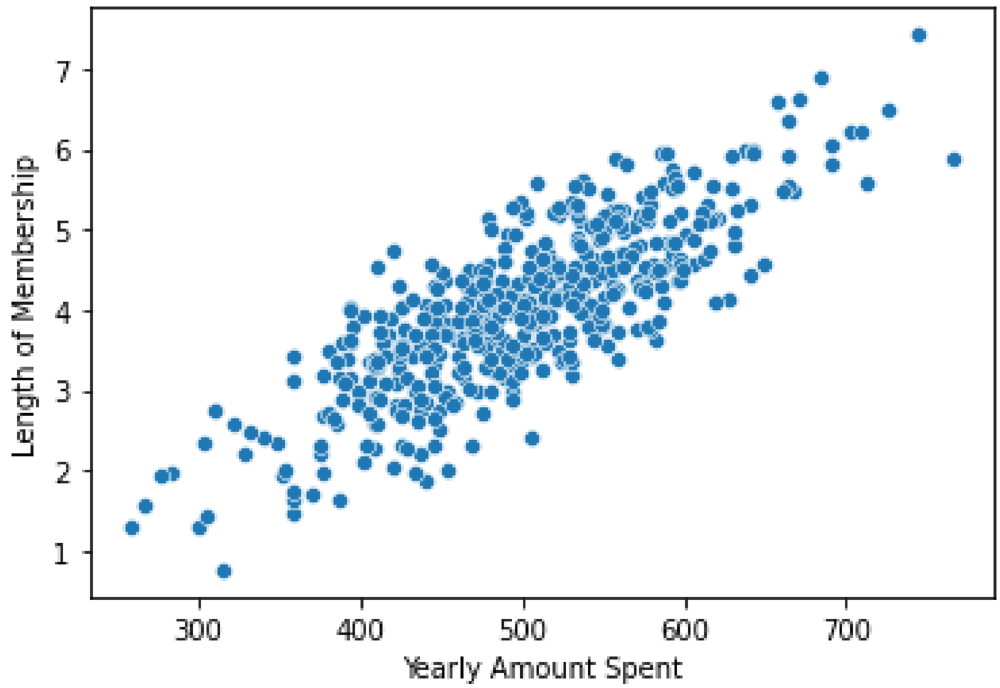



```
<Figure size 432x288 with 0 Axes>
```

discuss which columns must be removed based on that and which column is mostly interesting and related to Yearly Amount Spent?

- You would probably drop Unnamed: 0, credit card, and time on website because they have a negative corralation. Length of membership is most interesting and related to yearly amount spent.

```
plt.figure()
sns.scatterplot(x = "Yearly Amount Spent", y = "Length of Membership",
data = hrdata)
plt.show()
```




```
#drop uneccessary columns
hrdata.drop(["Unnamed: 0","Credit Card", "Email", "Address"], axis =
1)
```

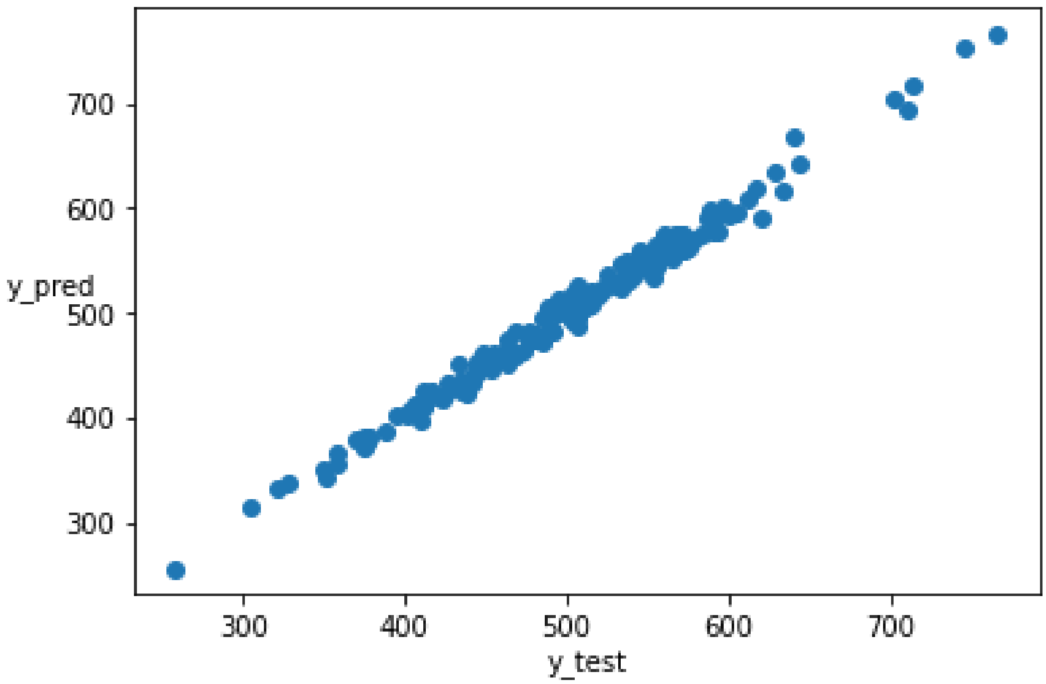
```
     Avg. Session Length  Time on App  Time on Website  Length of
Membership  \
0              35.497268    13.655651        40.577668
4.582621
1              32.926272    12.109461        38.268959
3.164034
2              34.000915    12.330278        38.110597
4.604543
3              35.305557    14.717514        37.721283
3.620179
4              34.330673    13.795189        38.536653
4.946308
..                   ...          ...              ...
...
495            34.237660    14.566160        37.417985
4.246573
496            35.702529    12.695736        38.190268
4.076526
497            33.646777    12.499409        39.332576
5.458264
498            34.322501    13.391423        37.840086
2.836485
499            34.715981    13.418808        36.771016
3.235160
```

```
     Yearly Amount Spent
0             588.951054
1             393.204933
2             488.547505
3             582.852344
4             600.406092
..                   ...
495           574.847438
496           530.049004
497           552.620145
498           457.469510
499           498.778642

[500 rows x 5 columns]
```

```
X = hrdata[["Avg. Session Length", "Time on App", "Time on Website",
"Length of Membership"]]
y = hrdata["Yearly Amount Spent"]

scaler = StandardScaler()
scaler.fit(X)
X = scaler.transform(X)

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size =
.3, random_state = 101)

#Linear regression
lr = LinearRegression()

#train
lr.fit(X_train, y_train)

#predict
y_pred = lr.predict(X_test)

#print coeffecients and intercepts
print("Coefficients " + str(lr.coef_))
print("Intercept " + str(lr.intercept_))

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
```

```
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```

```
Coefficients [25.76252659 38.32855202  0.19220992 61.17355707]
Intercept 500.5316677457304
```




```
R^2: 0.9890046246741234
Mean Squared Error: 79.8130516509746
Mean Absolute Error: 7.228148653430835
Root Mean Squared Error: 8.933815066978642
```

Interpret the coefficient and which coefficient belongs to which feature and based on that explain any strategy that should help the business

- 25.7625 belongs to Avg session length, 38.3285 belongs to time on app, 0.1922 belongs to time on website and 61.1735 belongs to length of membership.
- A higher coeffecient means a stronger corralation so its expected that those with a longer membership will have a larger yearly amount spent and the business should focus on those with a longer membership.

```
#Normal Equation

#add 1s
X_b = np.c_[np.ones((350,1)), X_train]
```

```
#change y to numpy and reshape
y_new = y_train.to_numpy()
y_new = y_new.reshape(-1,1)

#normal equation
theta_best_values=np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y_new)
print("theta values\n" + str(theta_best_values))
```

```
theta values
[[5.00531668e+02]
 [2.57625266e+01]
 [3.83285520e+01]
 [1.92209922e-01]
 [6.11735571e+01]]
```

Are they very close to the sklearn's linear regression

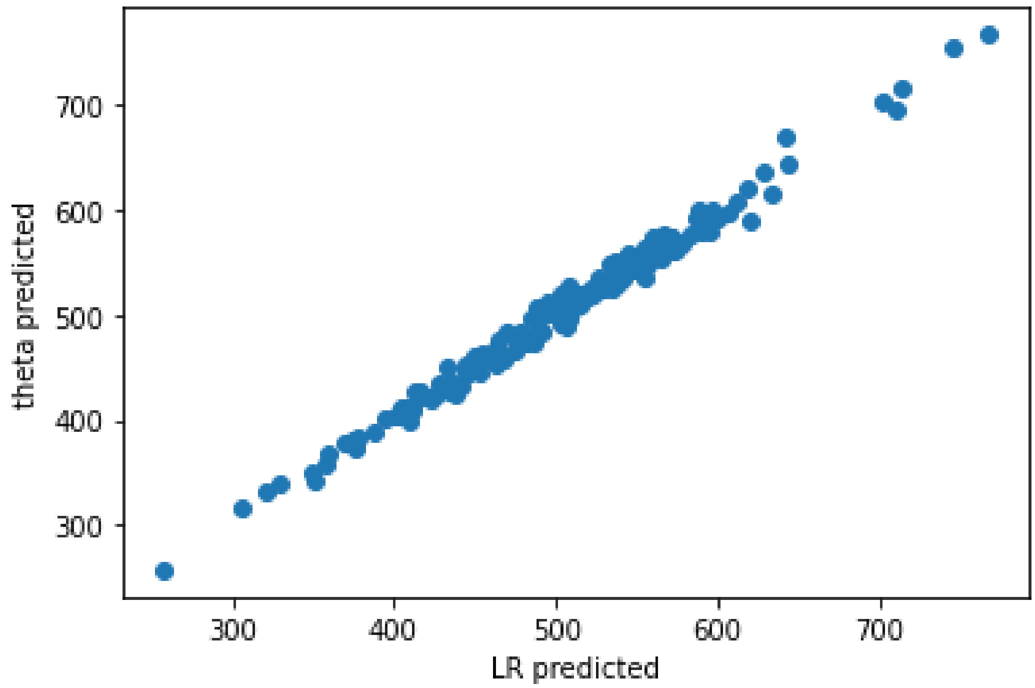
- Theta best values are very close to the intercept and coeffecients of the linear regression

LR Intercept 500.53620759592945

LR Coefficients [25.76851649 38.34767562 61.16352344]

Theta [[500.5362076] [25.76851649] [38.34767562] [61.16352344]]

```
#Normal equation Linear Regression
X_test_new = np.c_[np.ones((len(X_test),1)), X_test]

theta_prediction = X_test_new.dot(theta_best_values)

#generate scatterplot
plt.xlabel("LR predicted")
plt.ylabel("theta predicted")
plt.scatter(y_test, theta_prediction)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
theta_prediction)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
theta_prediction)))

rmse = np.sqrt(mean_squared_error(y_test, theta_prediction))
print("Root Mean Squared Error: {}".format(rmse))
```




```
R^2: 0.9890046246741234
Mean Squared Error: 79.81305165097464
Mean Absolute Error: 7.228148653430841
Root Mean Squared Error: 8.933815066978644
```

What is the limitation of using the Normal equation for regression?

- Using the normal equation can become very slow for larger data sets and for larger number of features

```
#Gradient descent
cost_list = []
epoch_list = []
predicted_list = []

eta = 0.1  # learning rate
n_iterations = 1000
m = 350

theta = np.random.randn(5,1)  # random initialization

for iteration in range(n_iterations):
    gradients = 2/m * X_b.T.dot(X_b.dot(theta) - y_new)
    theta = theta - eta * gradients

    y_predicted = np.dot(theta.T, X_b.T)

    cost = np.mean(np.square(y_new - y_predicted)) # MSE (Mean Squared
Error)
```

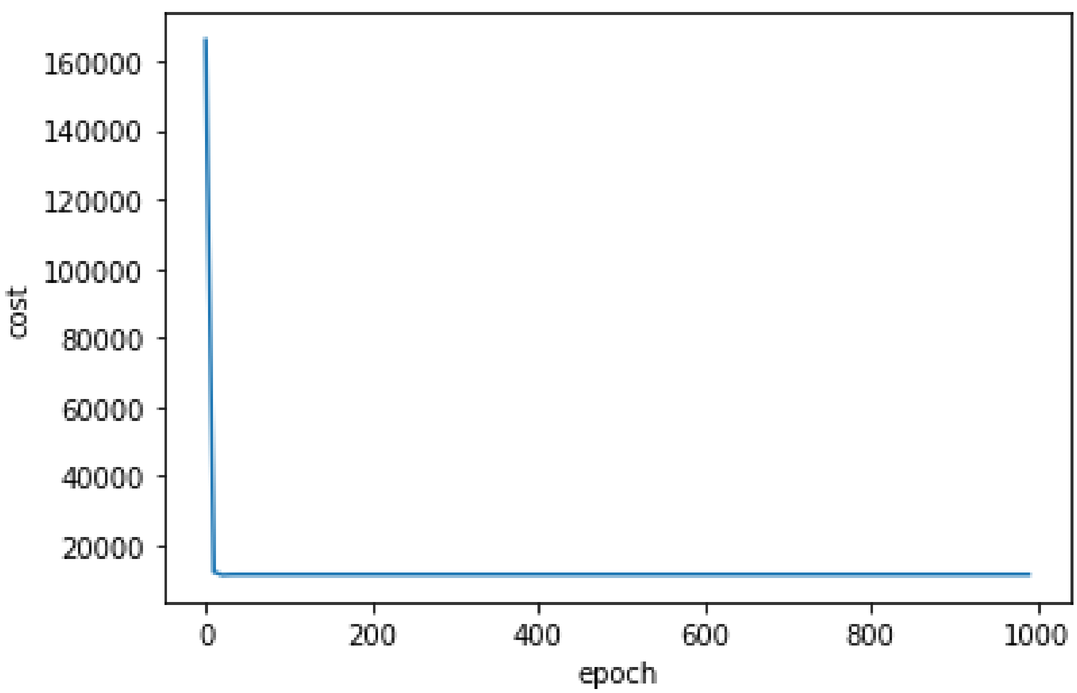
```
    if iteration%10==0:
      cost_list.append(cost)
      epoch_list.append(iteration)

print("Gradient theta\n" + str(theta))
```

```
Gradient theta
[[5.00531668e+02]
 [2.57625266e+01]
 [3.83285520e+01]
 [1.92209922e-01]
 [6.11735571e+01]]
```

Are they very close to the sklearn's linear regression?

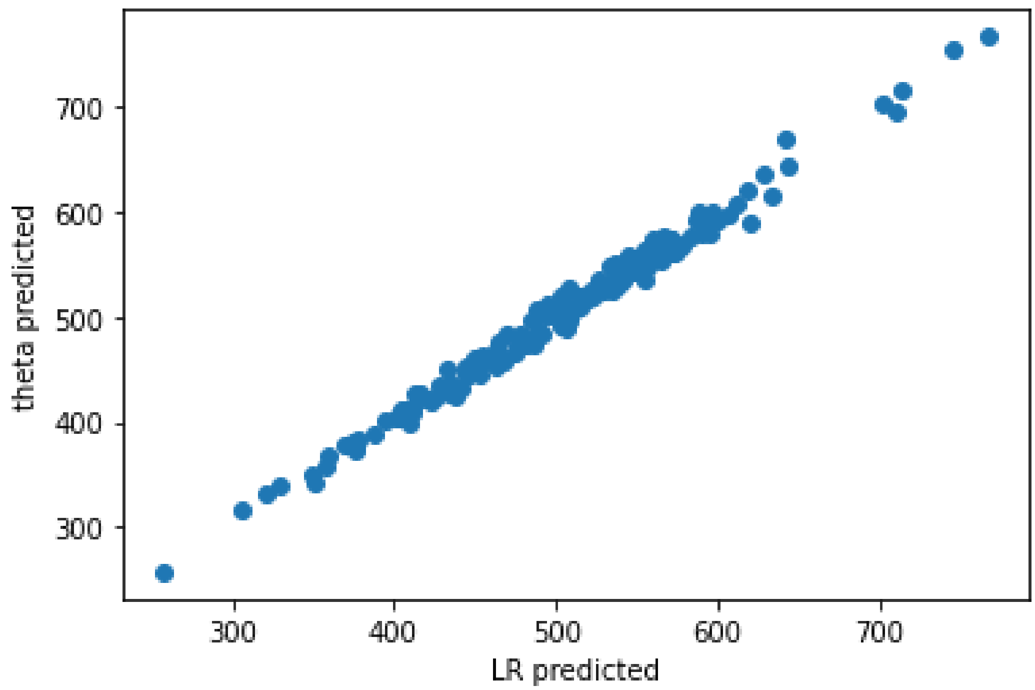
- Yes theta values are extremely close

```
#plot step number against cost
plt.xlabel("epoch")
plt.ylabel("cost")
plt.plot(epoch_list, cost_list)
plt.show()
```




```
#generate prediction based on gradient thetas
gradient_theta_prediction = X_test_new.dot(theta)

#generate scatterplot
plt.xlabel("LR predicted")
plt.ylabel("theta predicted")
```

```
plt.scatter(y_test, gradient_theta_prediction)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
gradient_theta_prediction)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
gradient_theta_prediction)))

rmse = np.sqrt(mean_squared_error(y_test, gradient_theta_prediction))
print("Root Mean Squared Error: {}".format(rmse))
```




```
R^2: 0.9890046246741234
Mean Squared Error: 79.81305165097444
Mean Absolute Error: 7.2281486534308295
Root Mean Squared Error: 8.933815066978633
```

Short Question: How do derivatives help in the process of gradient descent?

- If the slope decreases the alpha derivative will also decrease which reduces the step size automatically

Short Question: What are the benefits and the limitations of using batch gradient descent?

- Batch gradient descent is guaranteed to approch the global minimum, or the solution, assuming enough time and a good learning rate

- Batch gradient descent can become very slow with large amounts of data since it uses the whole data set while training, though it scales better with the number of features unlike the normal equation.
- Should preform a hyper parameter optimization to find a good learning rate hyperparameter or the BGD will either take too long to find the solution or constantly over shoot

- If there are multiple features you need to ensure all features have a similar scale or convergence will take much longer
- Irregular data can have local minimums which can slow down the process

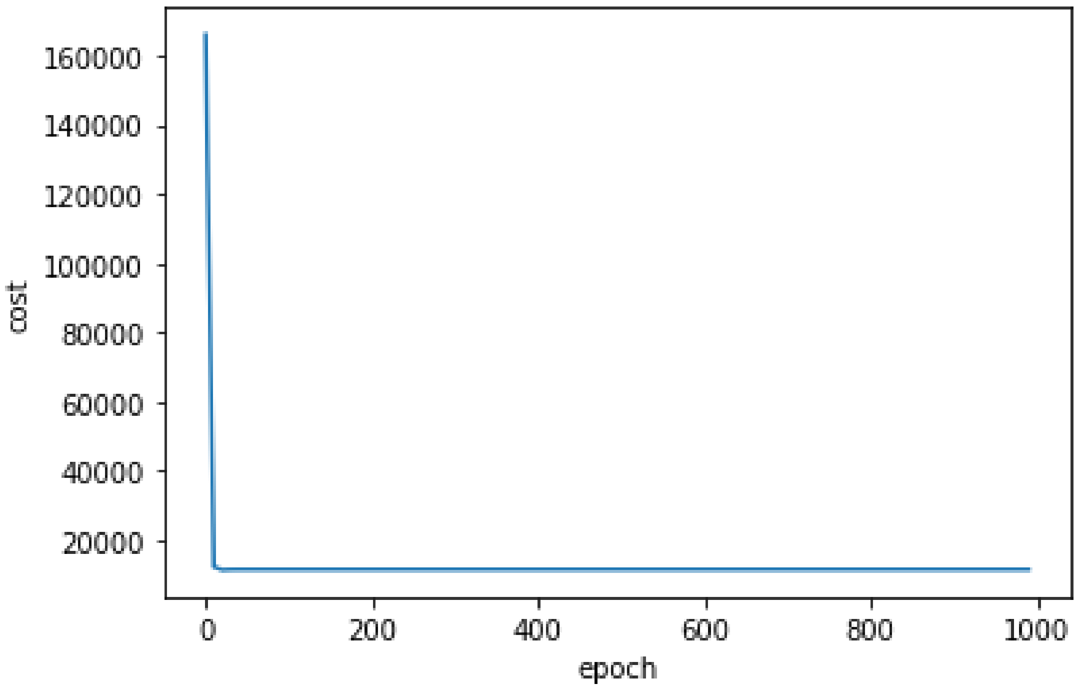
```
#Stochastic Gradient Descent
n_epochs = 50
t0, t1 = 5, 50 # learning schedule hyperparameters

def learning_schedule(t):
  return t0 / (t + t1)

theta = np.random.randn(5,1) # random initialization

for epoch in range(n_epochs):
  for i in range(m):
    random_index = np.random.randint(m)
    xi = X_b[random_index:random_index+1]
    yi = y_new[random_index:random_index+1]
    gradients = 2 * xi.T.dot(xi.dot(theta) - yi)
    eta = learning_schedule(epoch * m + i)
    theta = theta - eta * gradients
theta_first = theta
print("Stochastic Gradient theta\n" + str(theta_first))
```

```
Stochastic Gradient theta
[[5.00554695e+02]
 [2.57827596e+01]
 [3.83005549e+01]
 [2.56321105e-02]
 [6.13485039e+01]]
```

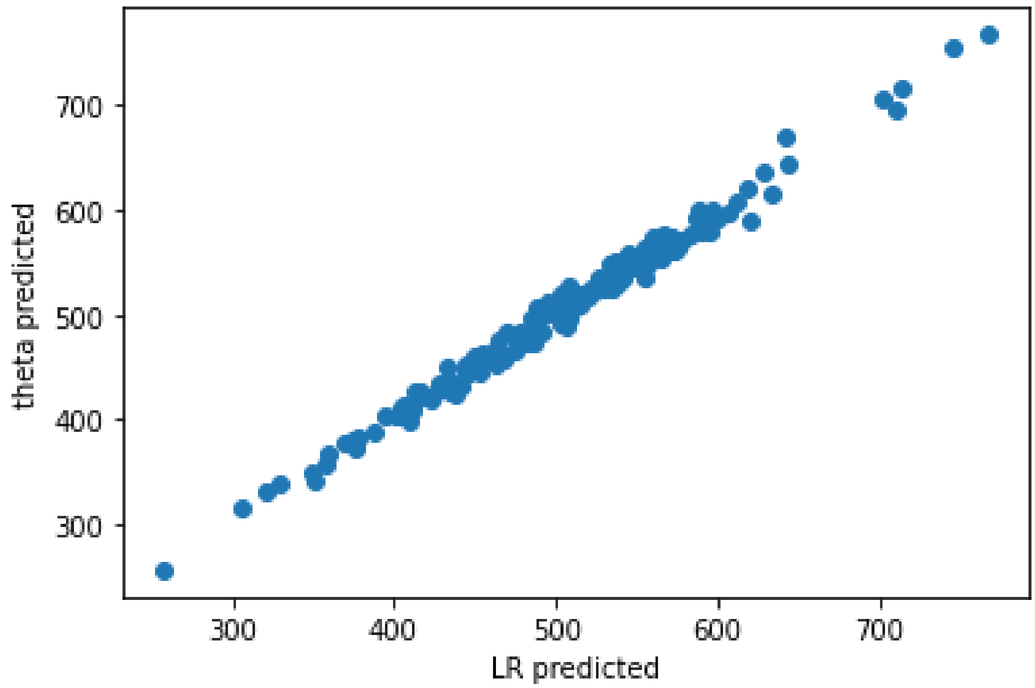
Are they very close to the sklearn's linear regression

- Yes theta values are extremely close

```
#plot step number against cost
plt.xlabel("epoch")
plt.ylabel("cost")
plt.plot(epoch_list, cost_list)
plt.show()
```




```
#generate prediction based on Stochastic gradient thetas
Stochastic_gradient_theta_prediction = X_test_new.dot(theta_first)

#generate scatterplot
plt.xlabel("LR predicted")
plt.ylabel("theta predicted")
plt.scatter(y_test, Stochastic_gradient_theta_prediction)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
Stochastic_gradient_theta_prediction)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
Stochastic_gradient_theta_prediction)))

rmse = np.sqrt(mean_squared_error(y_test,
Stochastic_gradient_theta_prediction))
print("Root Mean Squared Error: {}".format(rmse))
```



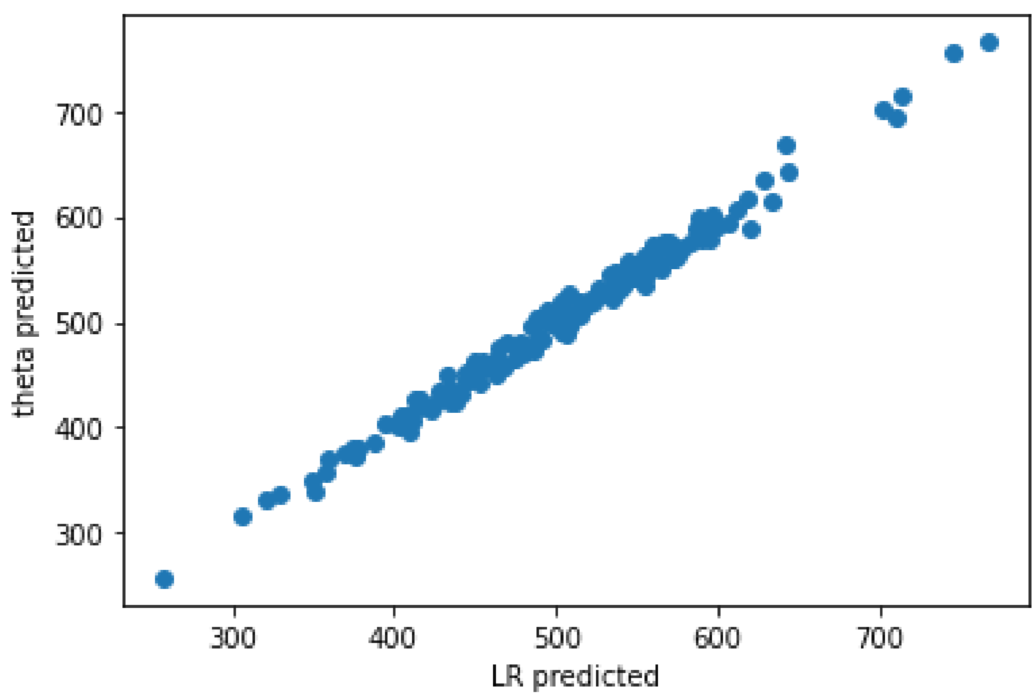

```
R^2: 0.9890046246741234
Mean Squared Error: 79.94079056737529
Mean Absolute Error: 7.2326289910661306
Root Mean Squared Error: 8.940961389435438
```

Short Question: What are the benefits and the limitations of using Stochastic gradient descent?

- Possible to train on huge amounts of data sets since it randomly picks only one instance in the training set for each step, much faster and less memory used
- However this also means that it will converge to the minimum via average instead of gently decreasing, once arriving it won't stop making the final values not optimal.
- SGD is actually better for irregular data since it has a better chance of leaving a local minima and instead finding the global minimum

```
#SGDRegressor
sgd_reg = SGDRegressor(max_iter=1000, tol=1e-3, penalty=None,
eta0=0.1)
sgd_reg.fit(X_train, y_train)

print("SGD intercept\n" + str(sgd_reg.intercept_))
print("SGD coeff\n" + str(sgd_reg.coef_))

SGD intercept
[499.3792388]
SGD coeff
[26.44472664 38.19148203 -0.50325016 60.99652463]
```

```
#generate prediction based on gradient thetas
SGDRegressor_theta_prediction = sgd_reg.predict(X_test)

#generate scatterplot
plt.xlabel("LR predicted")
plt.ylabel("theta predicted")
plt.scatter(y_test, SGDRegressor_theta_prediction)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
SGDRegressor_theta_prediction)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
SGDRegressor_theta_prediction)))

rmse = np.sqrt(mean_squared_error(y_test,
SGDRegressor_theta_prediction))
print("Root Mean Squared Error: {}".format(rmse))
```



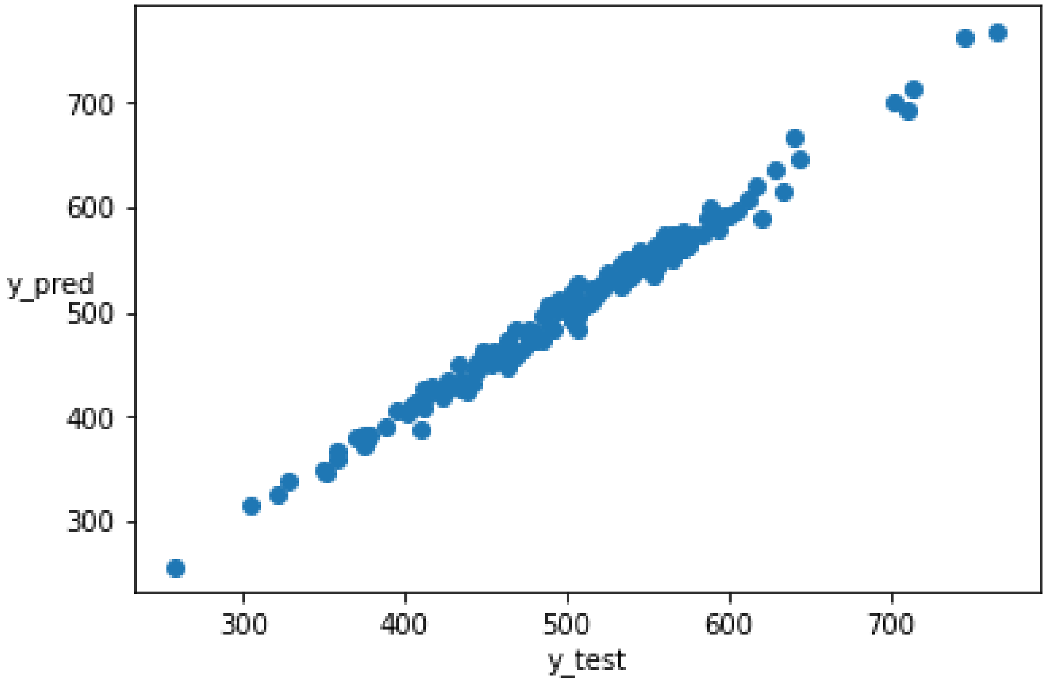

```
R^2: 0.9890046246741234
Mean Squared Error: 83.2206157055982
Mean Absolute Error: 7.329839552591657
Root Mean Squared Error: 9.122533403917917
```

Briefly explain how mini-batch can overcome the limitations of Batch gradient descent and SGD.

- For each step computing based on small random sets instead of entire set or random instances of one in the set makes it faster than BGD but more accurate than SGD

```
#polynomial of degree 2
poly_features = PolynomialFeatures(degree=2, include_bias=False)

X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.fit_transform(X_test)

#train and predict
lr.fit(X_train_poly, y_train)
y_pred = lr.predict(X_test_poly)

#print coeffecients and intercepts
print("Coefficients\n" + str(lr.coef_))
print("Intercept " + str(lr.intercept_))

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test_poly, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```

```
Coefficients
[ 2.56324041e+01  3.83930621e+01  1.40993709e-01  6.12010238e+01
 -8.38261559e-01 -1.61454843e-01 -6.96974957e-02  1.53178741e-01
  4.04112605e-01 -2.24521389e-01  4.19382892e-02  5.97272276e-01
 -3.66429892e-01 -4.27833581e-02]
Intercept 500.49414369135536
```

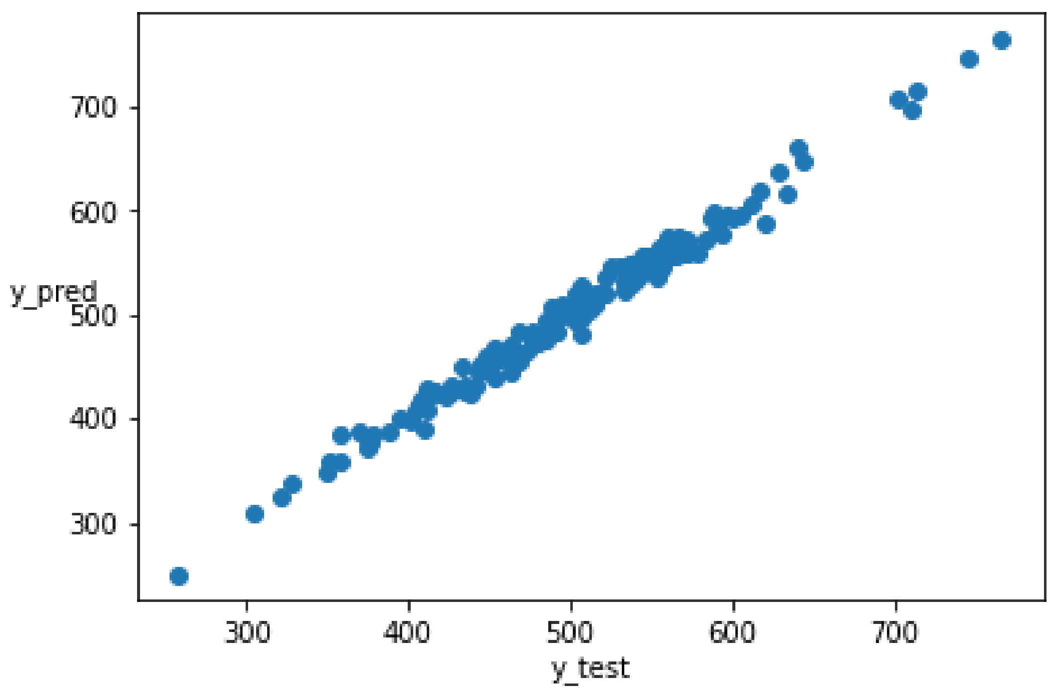



```
R^2: 0.9882421824247092
Mean Squared Error: 85.34745505511978
Mean Absolute Error: 7.432195703827265
Root Mean Squared Error: 9.238368636026589
```

```
#polynomial of degree 3
poly_features = PolynomialFeatures(degree=3, include_bias=False)

X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.fit_transform(X_test)

#train and predict
lr.fit(X_train_poly, y_train)
y_pred = lr.predict(X_test_poly)

#print coeffecients and intercepts
print("Coefficients\n" + str(lr.coef_))
print("Intercept " + str(lr.intercept_))

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test_poly, y_test)))
```

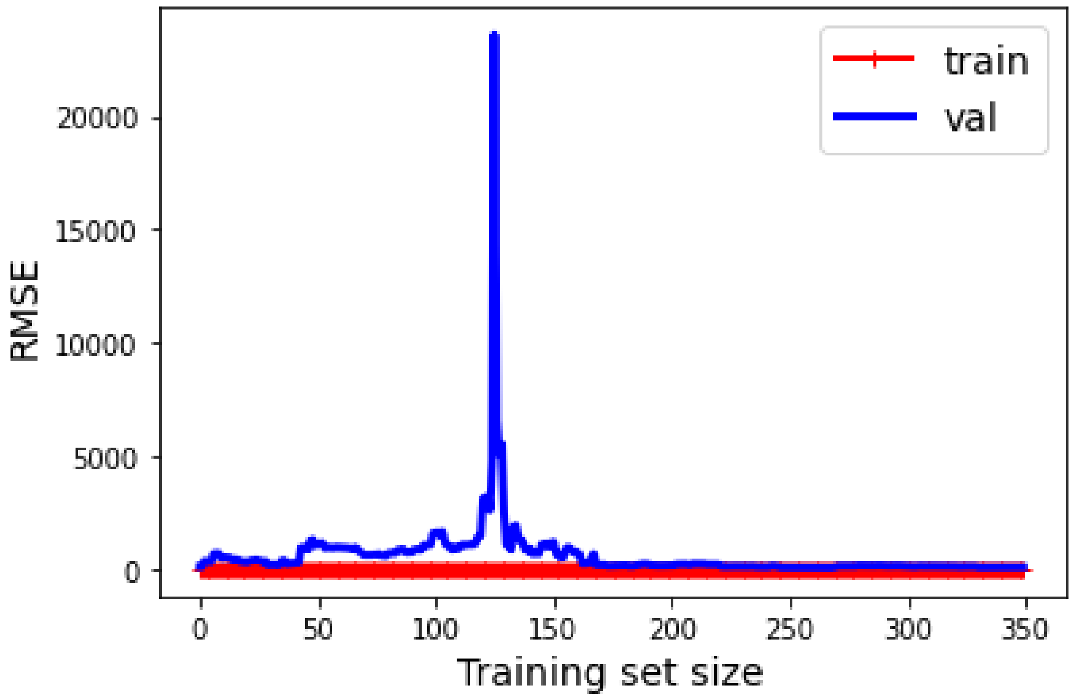
```
print("Mean Squared Error: {}".format(mean_squared_error(y_test,
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```

```
Coefficients
[25.66180088 37.73817386  1.71438477 61.53147374 -0.9027249  -
0.18506912
  0.13999095  0.62340699  0.22250795 -0.35852515 -0.23855601
0.65188939
 -0.62388113  0.0795928   0.08363636 -0.35101308 -0.10954996
0.40875869
  0.13211318 -0.64021488  0.28780793 -0.28538261  0.66323145 -
0.36183884
 -0.09354415 -0.48873914 -0.28292754  1.1650947   0.55789041
0.47209095
 -0.34630194 -1.07106588 -0.41258377  0.15717302]
Intercept 500.5258833779942
```

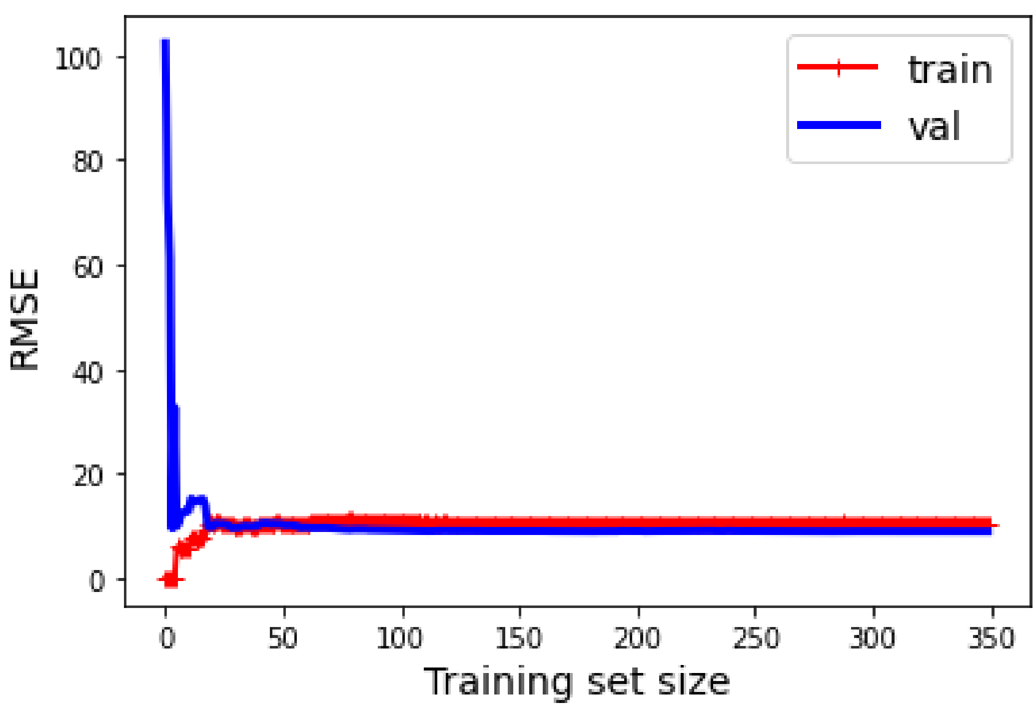



```
R^2: 0.986916696696579
Mean Squared Error: 94.96886930852037
Mean Absolute Error: 7.6958010080256205
Root Mean Squared Error: 9.745197243181913
```

```
#learning curve
def plot_learning_curves(model, X, y):
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size
= .3, random_state = 101)

    train_errors, val_errors = [], []

    for m in range(1, len(X_train) + 1):
        model.fit(X_train[:m], y_train[:m])
        y_train_predict = model.predict(X_train[:m])
        y_val_predict = model.predict(X_val)
        train_errors.append(mean_squared_error(y_train[:m],
y_train_predict))
        val_errors.append(mean_squared_error(y_val, y_val_predict))

    plt.plot(np.sqrt(train_errors), "r-+", linewidth=2, label="train")
    plt.plot(np.sqrt(val_errors), "b-", linewidth=3, label="val")
    plt.legend(loc="upper right", fontsize=14)
    plt.xlabel("Training set size", fontsize=14)
    plt.ylabel("RMSE", fontsize=14)

#plotting linear regression with learning curve
polynomial_regression = Pipeline([
        ("poly_features", PolynomialFeatures(degree=5,
include_bias=False)),
        ("lin_reg", LinearRegression()),
    ])

plot_learning_curves(polynomial_regression, X, y)

plt.show()
```




```
poly_features = PolynomialFeatures(degree=3, include_bias=False)

lin_reg = LinearRegression()
plot_learning_curves(lin_reg, X, y)

plt.show()
```



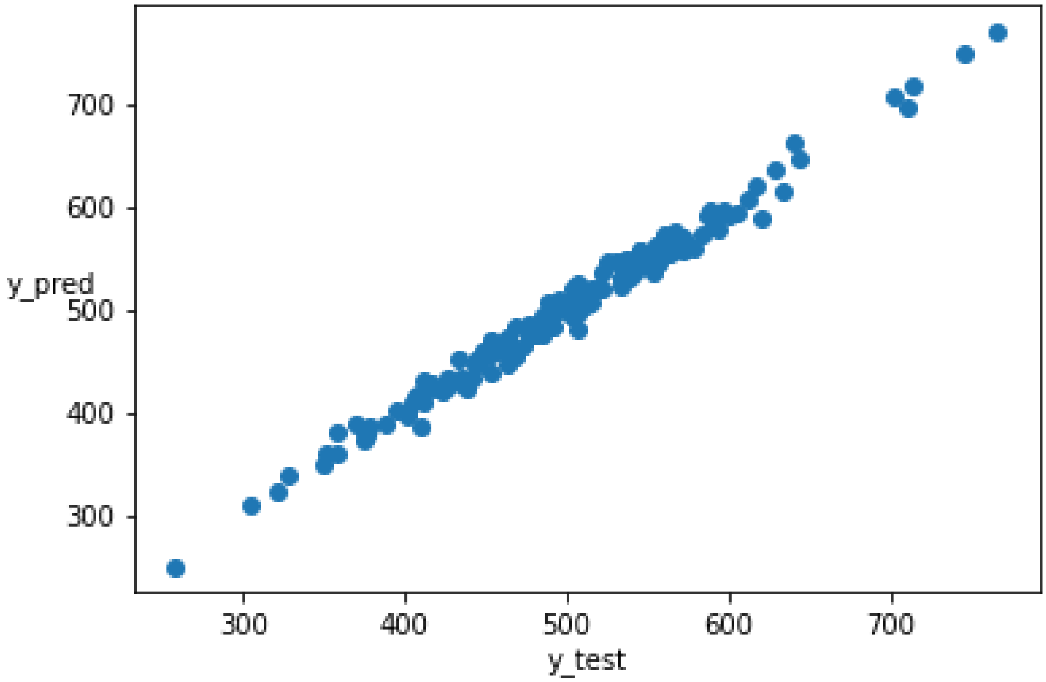
Interpret the result

- Function of the learning curves of degree 10 and degree 3 polynomials
- For degree 3 as more instances are added it becomes harder to fit the data perfectly so the train's RMSE increases until it eventually levels out similarly to the val line.

Explain the purpose of regularization

- To constrain a model and make it simpler and reduce the risk of overfitting; less degrees of freedom means harder to overfit data

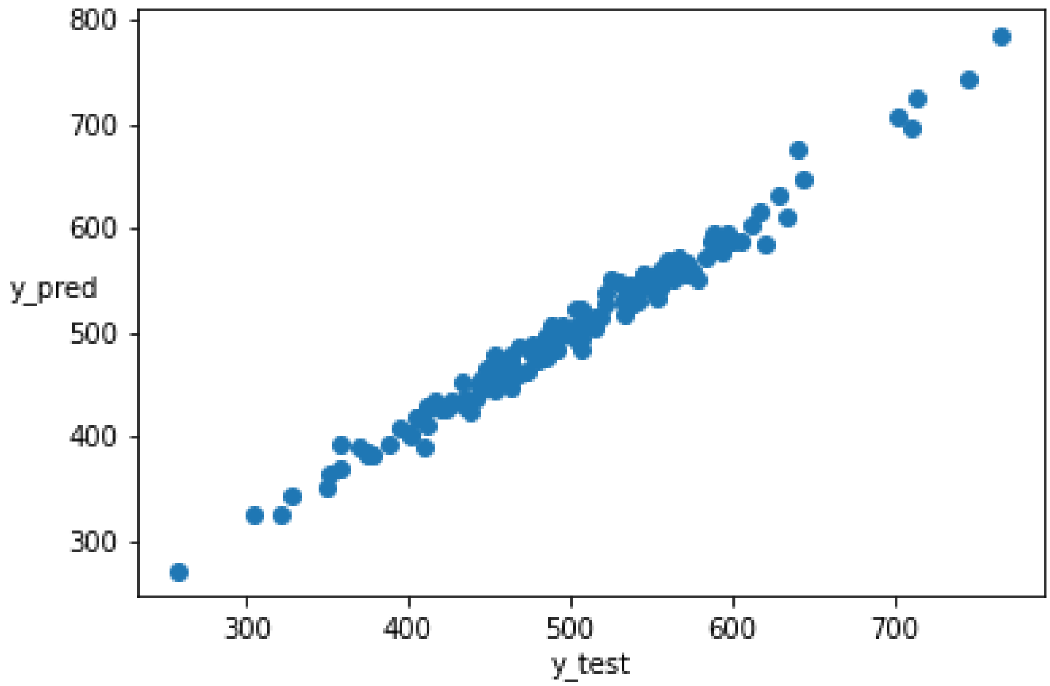
```
#polynomial of degree 3 Regularization
poly_features = PolynomialFeatures(degree=3, include_bias=False)

X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.fit_transform(X_test)

#ridge Regression
ridge_reg = Ridge(alpha=1, solver="cholesky", random_state=42)

#train and predict
ridge_reg.fit(X_train_poly, y_train)
y_pred = ridge_reg.predict(X_test_poly)

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test_poly, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```




```
R^2: 0.986916696696579
Mean Squared Error: 97.65959147337
Mean Absolute Error: 7.855335064312333
Root Mean Squared Error: 9.882286753245424
```

```
#SGDregressor for ridge
sgd_reg = SGDRegressor(penalty="l2") #L2

#train and predict
sgd_reg.fit(X_train_poly, y_train)
y_pred = sgd_reg.predict(X_test_poly)

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test_poly, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))
```

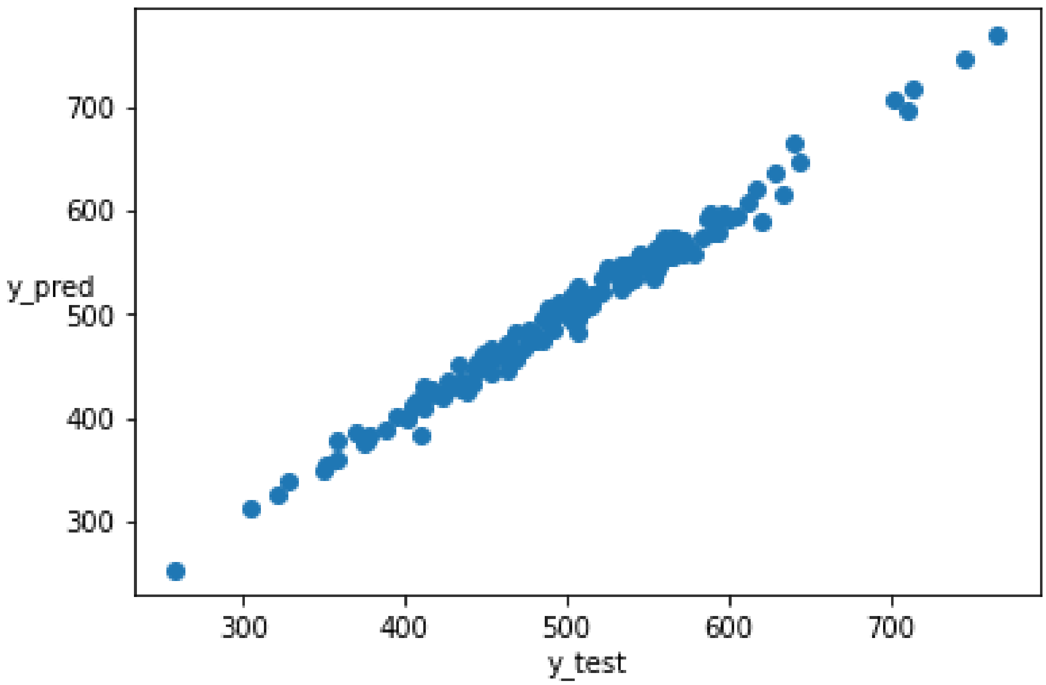
```
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```




```
R^2: 0.986916696696579
Mean Squared Error: 138.16301767995463
Mean Absolute Error: 9.487205443326394
Root Mean Squared Error: 11.754276569825752
```

```
#Lasso regression
lasso_reg = Lasso(alpha=0.1)

#train and predict
lasso_reg.fit(X_train_poly, y_train)
y_pred = lasso_reg.predict(X_test_poly)

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
print("R^2: {}".format(lr.score(X_test_poly, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))
```

```
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```



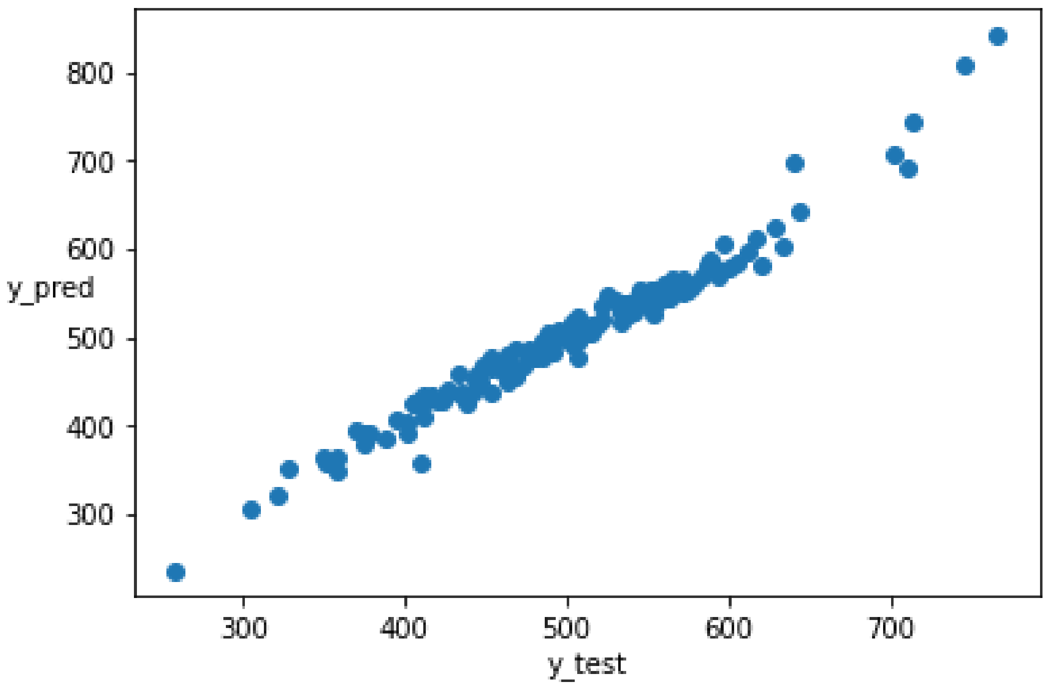

```
R^2: 0.986916696696579
Mean Squared Error: 93.21215816943548
Mean Absolute Error: 7.679627716794205
Root Mean Squared Error: 9.654644383375054
```

How Lasso perform the regularization and how does that affect the thetas?

- adds regularization term to cost function using the norm of the weight vector
- automatically eliminates the weights of the least important features by setting them to 0

```
#Elastic net regression
elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5, random_state=42)

#train and predict
elastic_net.fit(X_train_poly, y_train)
y_pred = elastic_net.predict(X_test_poly)

#generate scatterplot
plt.xlabel("y_test")
plt.ylabel("y_pred", rotation = 0)
plt.scatter(y_test, y_pred)
plt.show()

# Compute and print R^2, RMSE, MAE and MSE
```

```
print("R^2: {}".format(lr.score(X_test_poly, y_test)))

print("Mean Squared Error: {}".format(mean_squared_error(y_test,
y_pred)))

print("Mean Absolute Error: {}".format(mean_absolute_error(y_test,
y_pred)))

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```




```
R^2: 0.986916696696579
Mean Squared Error: 261.69175128224043
Mean Absolute Error: 11.378641625545779
Root Mean Squared Error: 16.17688941923757
```

How ElasticNet different compared to Lasso and RIDGE perform the regularization and how does that affect the thetas?

- Is a mix of both ridge and lasso via a ratio r, when r=0 then equivalent to ridge, while r=1 then equivalent to lasso. Behaves less erratically when their are more features than training instances or when features are strongly correlated
- Also automatically reduces the weights of useless features