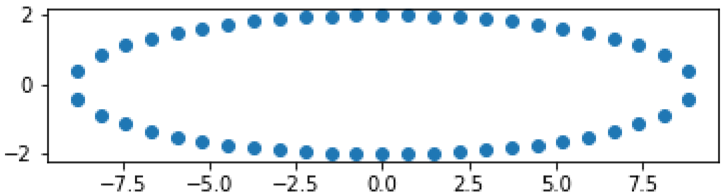
Task-C: Regression outlier effect.

Objective:Visualization best fit linear regression line for different scenarios

```
# you should not import any other packages
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
import numpy as np
from sklearn.linear_model import SGDRegressor
```

```
import numpy as np
import scipy as sp
import scipy.optimize

def angles_in_ellipse(num,a,b):
    assert(num > 0)
    assert(a < b)
    angles = 2 * np.pi * np.arange(num) / num
    if a != b:
        e = (1.0 - a ** 2.0 / b ** 2.0) ** 0.5
        tot_size = sp.special.ellipeinc(2.0 * np.pi, e)
        arc_size = tot_size / num
        arcs = np.arange(num) * arc_size
        res = sp.optimize.root(
            lambda x: (sp.special.ellipeinc(x, e) - arcs), angles)
        angles = res.x
    return angles


a = 2
b = 9
n = 50

phi = angles_in_ellipse(n, a, b)
e = (1.0 - a ** 2.0 / b ** 2.0) ** 0.5
arcs = sp.special.ellipeinc(phi, e)

fig = plt.figure()
ax = fig.gca()
ax.axes.set_aspect('equal')
ax.scatter(b * np.sin(phi), a * np.cos(phi))
plt.show()
```



```
X= b * np.sin(phi)
Y= a * np.cos(phi)
```

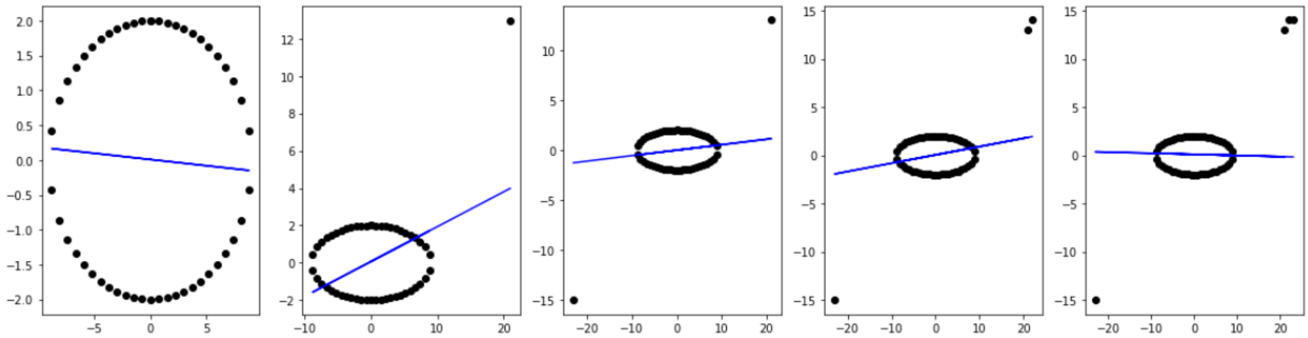
1. As a part of this assignment you will be working the regression problem and how regularization helps to g

2. Use the above created X, Y for this experiment.

3. to do this task you can either implement your own SGDRegression(prefered) excatly similar to "SGD assig you can use the SGDRegression of sklearn, for example "SGDRegressor(alpha=0.001, eta0=0.001, learning_ note that you have to use the constant learning rate and learning rate ***eta0*** *initialized.*

4. as a part of this experiment you will train your linear regression on the data (X, Y) with different regular observe how prediction hyper plan moves with respect to the outliers

5. This the results of one of the experiment we did (title of the plot was not metioned intentionally)



in each iteration we were adding single outlier and observed the movement of the hyper plane.

6. please consider this list of outliers: [(0,2),(21, 13), (-23, -15), (22,14), (23, 14)] in each of tuple the first elem is the input feature(X) and the second element is the output(Y)

7. for each regularizer, you need to add these outliers one at time to data and then train your model again on the updated data.

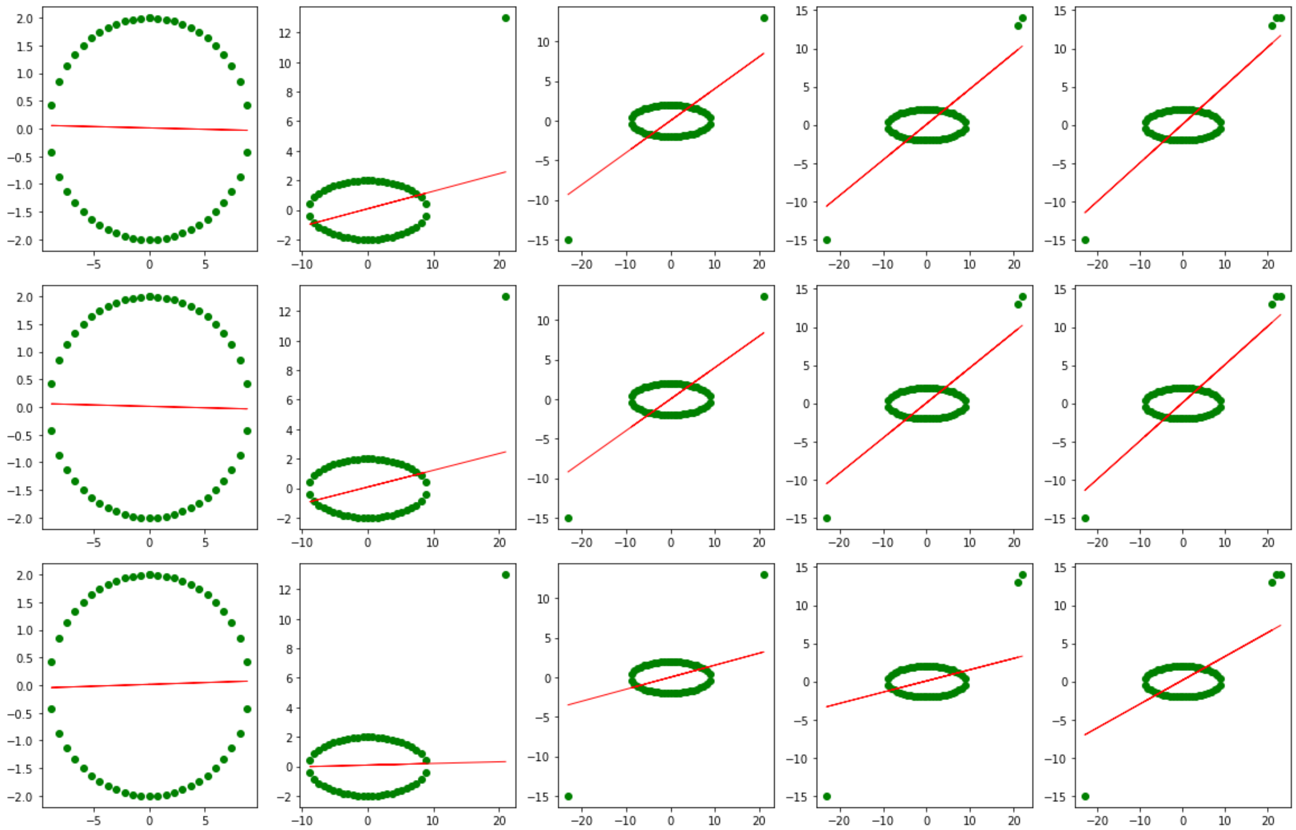
*8. you should plot a 3*5 grid of subplots,*
where each row corresponds to results of model with a single regularizer.

9. Algorithm:

for each regularizer:
  for each outlier:
    #add the outlier to the data
    #fit the linear regression to the updated data
    #get the hyper plane
    #plot the hyperplane along with the data points

10. MAKE SURE YOU WRITE THE DETAILED OBSERVATIONS, PLEASE CHECK THE LOSS FUNCTION I (please do search for it).

```
#as a part of this experiment you will train your linear regression on the data (X, Y) wit
#and observe how prediction hyper plan moves with respect to the outliers
alpha = [0.0001, 1, 100]

# please consider this list of outliers: [(0,2),(21, 13), (-23, -15), (22,14), (23, 14)]
#in each of tuple the first element is the input feature(X) and the second element is the
outliers = [(0,2),(21, 13), (-23, -15), (22,14), (23, 14)]

#9. Algorithm:
#for each regularizer:
#   for each outlier:
        #add the outlier to the data
        #fit the linear regression to the updated data
        #get the hyper plane
        #plot the hyperplane along with the data points

for alp in alpha:
  plt.figure (figsize = (20,4))
  X= b * np.sin(phi)
  Y= a * np.cos(phi)


  for idx, out in enumerate(outliers):
    plt.subplot(1,5, idx + 1)

    X = np.append(X, np.array(out[0]))
    Y = np.append(Y, np.array(out[1]))

    X =X.reshape(-1,1)

    mod = SGDRegressor(alpha=alp, eta0=0.001, learning_rate='constant', random_state=0)
    mod.fit(X,Y)
    pred = mod.predict(X)

    plt.scatter(X,Y, color='green')
    plt.plot(X, pred, color='red', linewidth=1)

plt.show()
```



Observations:

1. Linear Regression is known as "Ordinary Least Square" or Linear Least Square Method. Our Aim should be minimizing that squared loss by finding best possible line. And it has been done by optimising the loss function, particulary by balancing L2 Regularization term.
2. From that visualization, we can state that, high alpha value leads to better regularization term, and thats why we can find best fit line.

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