

8C_LR_Assignment

June 12, 2020

0.1 Task-C: Regression outlier effect.

Objective: Visualization best fit linear regression line for different scenarios

```
[1]: # 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

[2]: import numpy as np
import scipy as sp
import scipy.optimize

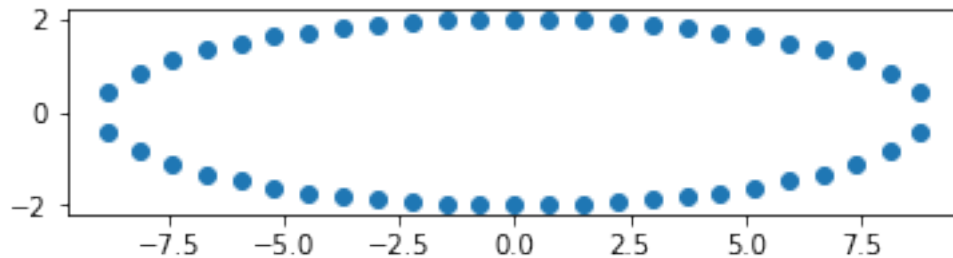
def angles_in_ellipse(num,a,b):
    assert(num > 0)
    assert(a < b)
    angles = 2 * np.pi * np.arange(num) / num
    if a != b:
        e = (1.0 - a ** 2.0 / b ** 2.0) ** 0.5
        tot_size = sp.special.ellipeinc(2.0 * np.pi, e)
        arc_size = tot_size / num
        arcs = np.arange(num) * arc_size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

[3]: 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()
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ax = fig.gca()
ax.axes.set_aspect('equal')
ax.scatter(b * np.sin(phi), a * np.cos(phi))
plt.show()
```



```
[4]: X= b * np.sin(phi)
      Y= a * np.cos(phi)
```

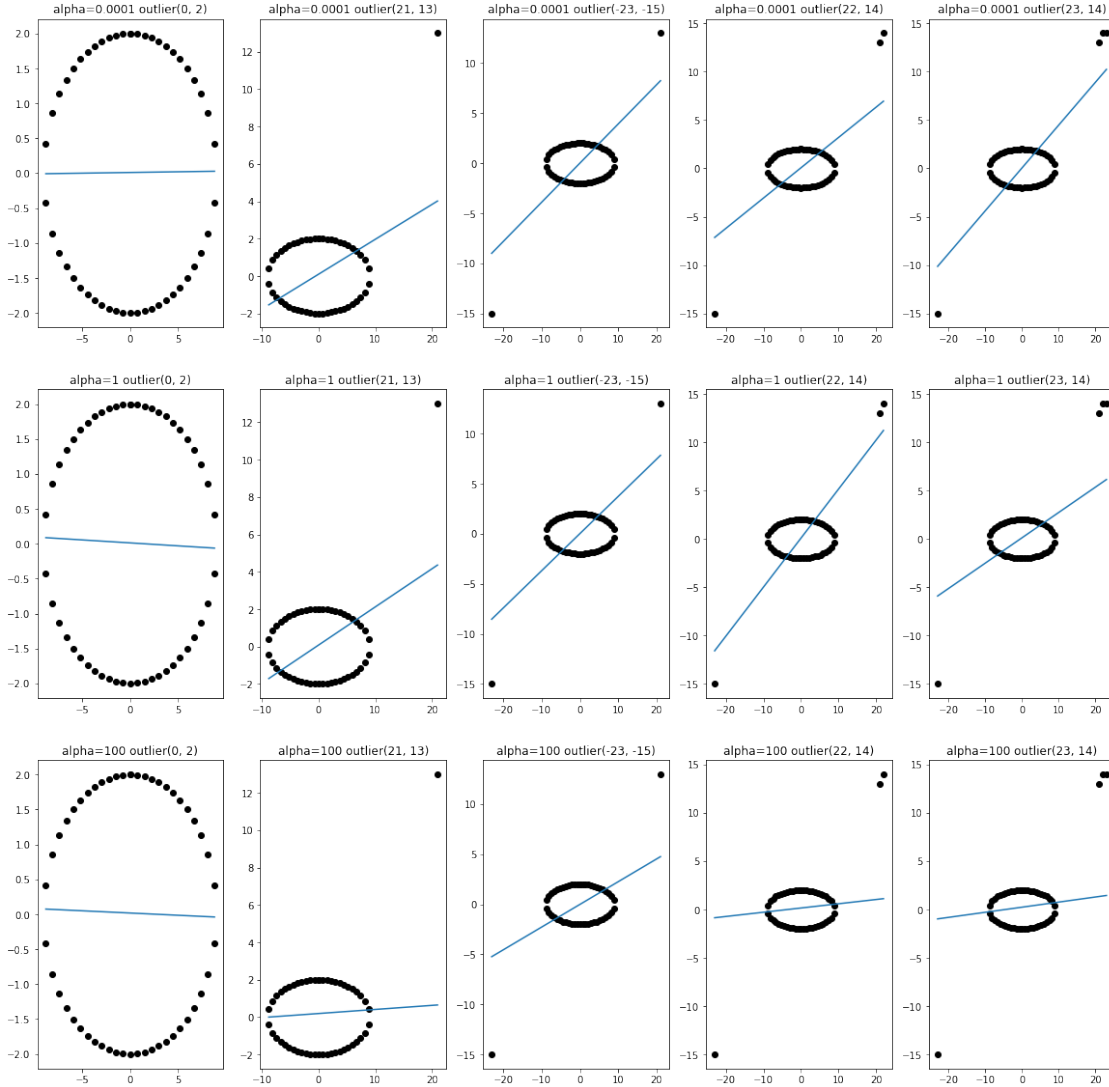
```
[5]: def draw_line(coef,intercept, mi, ma):
      #y=mx+c here c is intercept and slope(m) is coeff
      # to draw the hyper plane we are creating two points
      #1.(min,coeff*min+intercept) here min is minimum of x
      #2.(max,coeff*max+intercept) here max is maximum of x
      points=np.array([[mi,(coef*mi+intercept)],[ma,(coef*ma+intercept)]])
      plt.plot(points[:,0], points[:,1])
```

```
[6]: outliers=[(0,2),(21, 13),(-23, -15),(22,14), (23,14)]
      alpha=[0.0001,1,100]
      plt.figure(figsize=(20,20))
      grid=1
      for i in range(3):
          X= b * np.sin(phi)
          Y= a * np.cos(phi)
          for j in outliers:
              X=np.append(X,j[0]).reshape(-1,1)
              Y=np.append(Y,j[1]).reshape(-1,1)
              plt.subplot(3,5,grid)
              grid+=1
              clf=SGDRegressor(alpha=alpha[i],loss='squared_loss',eta0=0.
→001,learning_rate='constant')
              clf.fit(X,Y)
              coeff=clf.coef_
              intercept=clf.intercept_
              mi=np.min(X)
              ma=np.max(X)
              plt.scatter(X,Y,color='black')
```

```

draw_line(coeff[0],intercept,mi,ma)
plt.title('alpha='+str(alpha[i])+ ' outlier'+str(j))
plt.show()

```



Observations

1. when first (0,2) outlier is added , as alpha increases, the hyper plane postion changes slightly. so,hyper plane postion is slightly impacted by outlier. 2. when second (21,13) outlier is added , when alpha=0.0001 and 1, there is change in hyper plane position. hyper plane moves towards the outliers when alpha=100, hyper plane position moves away from outliers and its postion is almost return to normal. so, when alpha=100 hyper plane postion is not much impacted by outlier. 3. when third (-23,-15) outlier is added , when alpha=0.0001 and 1, there is change in hyper plane position. hyper plane moves towards the outliers when alpha=100 hyper plane postion slightly move away from ouliers. hyper plane postion is largely impacted by the outliers 4. when fourth (22,14)

outlier is added , when $\alpha=0.0001$ and 1 , there is change in hyper plane position.hyper plane moves towards the outliers when $\alpha=100$,hyper plane position moves away from outliers and its postion is some near to normal. 5.when fifth $(23,14)$ outlier is added , when $\alpha=0.0001$, there is change in hyper plane position.hyper plane moves towards the outliers when $\alpha=1$ hyper plane postion slightly move away from ouliers. when $\alpha=100$,hyper plane position moves away from outliers and its postion is some near to normal.

[]: