24MDT0184_AML_DA_1

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Course code:	PMDS602P
Course:	Advanced Machine Learning Lab
Slot:	L7+L8
Assignment:	1

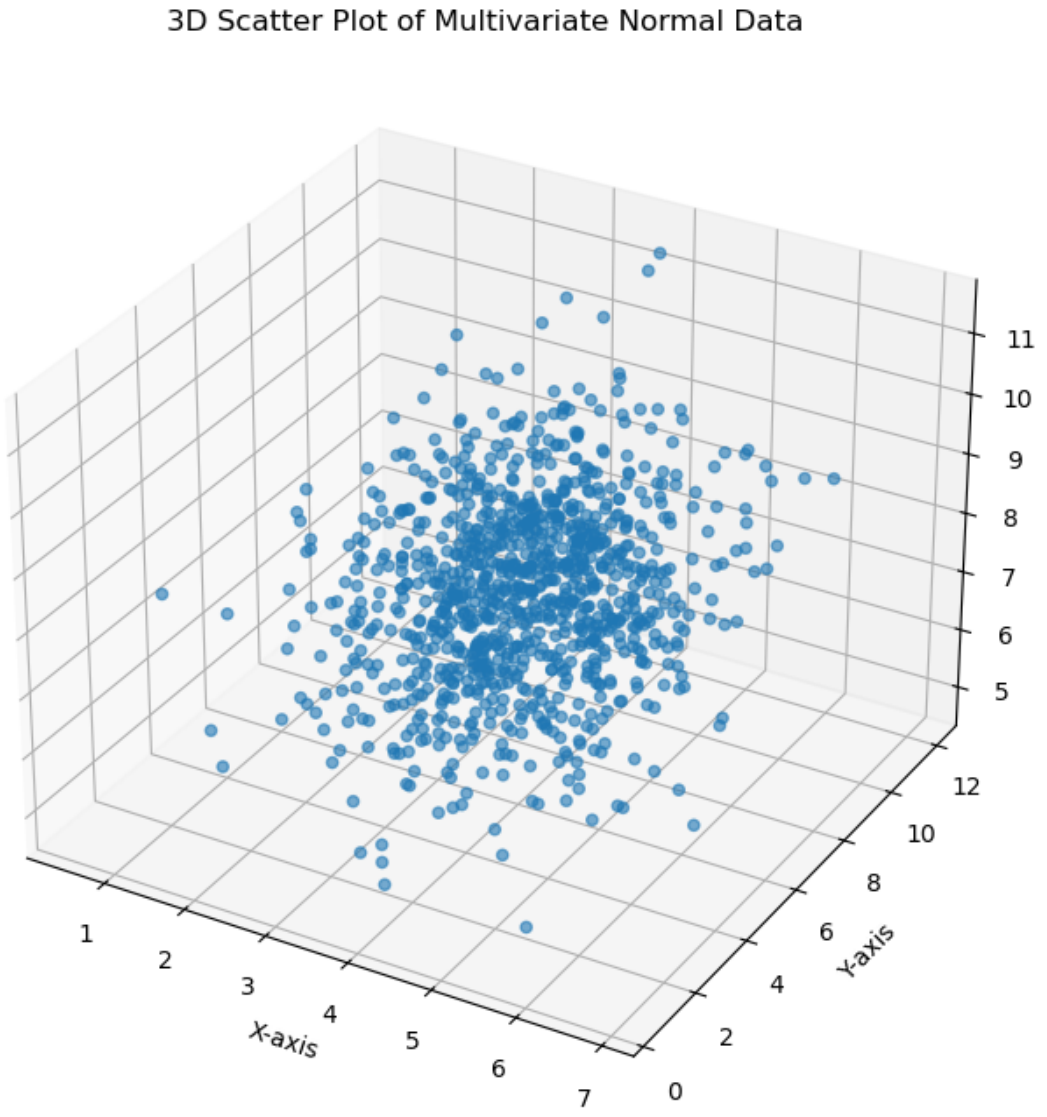
0.1 1. Generate a set of multivariate three-dimensional data following normal distribution with mean μ = [4, 6, 8]T and covariance matrix Σ =[[1 0 0],[0 3 1],[0 1 1]] having size 1000. Plot the generated points in a 3d plot.Further, generate a dataset of two-dimensional points following normal distribution, forming a circle with radius 5 centred around [1, 0]T. Plot the generated points.

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

mean_3d = np.array([4,6,8])
cov_3d = np.array([[1,0,0],[0,3,1],[0,1,1]])

dist_3d = np.random.multivariate_normal(mean_3d, cov_3d, size = 1000)
dist_3d
```

[1]:
```
array([[3.5555288 , 8.55785764, 9.36095131],
       [5.14653856, 1.81712041, 5.71402274],
       [5.29963451, 4.73259657, 6.68603442],
       …,
       [4.06979998, 7.02388986, 8.43001364],
       [3.38897145, 8.44096368, 9.12522204],
       [4.18667825, 8.19602467, 7.77445661]])
```

0.1.1 Plotting the points

[3]:
```
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(dist_3d[:, 0], dist_3d[:, 1], dist_3d[:, 2], alpha=0.6)
ax.set_title('3D Scatter Plot of Multivariate Normal Data')
ax.set_xlabel('X-axis')
ax.set_ylabel('Y-axis')
ax.set_zlabel('Z-axis')
plt.show()
```



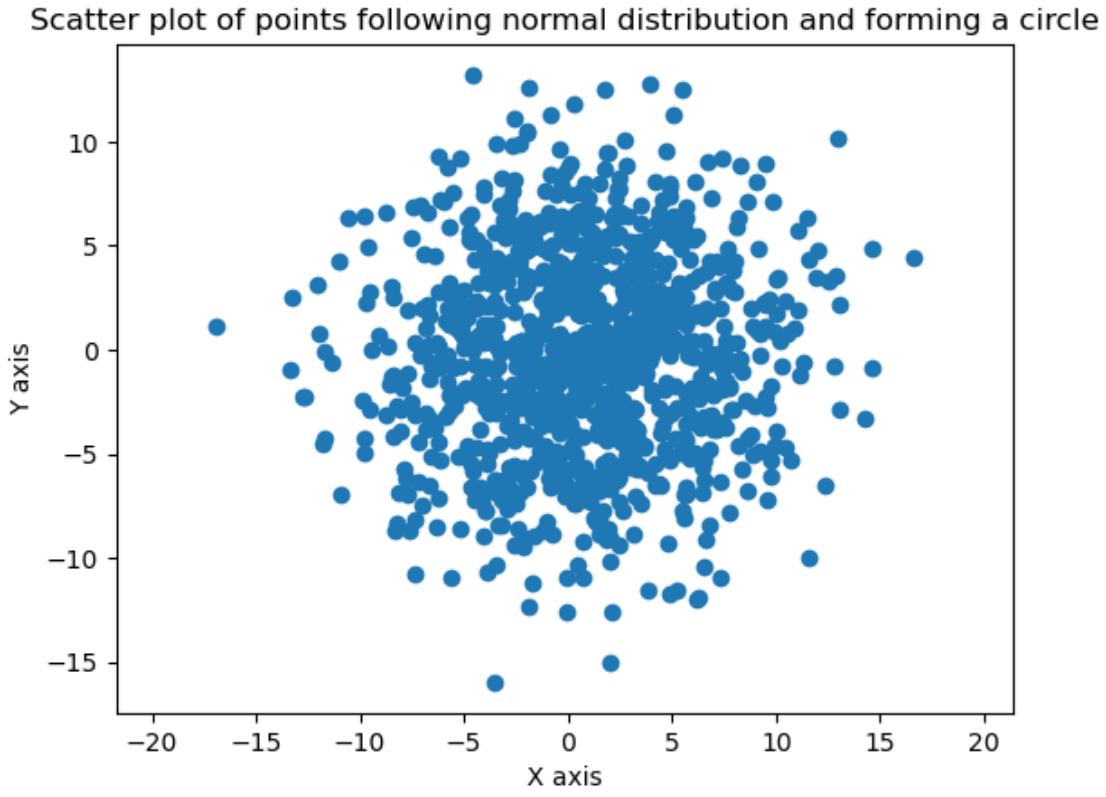
0.1.2 2d distribution

[11]:
```
mean_2d = np.array([1,0])
cov_2d = np.array([[25,0],[0,25]])
dist_2d = np.random.multivariate_normal(mean_2d,cov_2d, size = 1000)
dist_2d
```

[11]:
```
array([[ 2.42821174,  0.9296129 ],
       [ 1.94033871,  9.47491359],
       [ 2.0798545 , -0.67072333],
       …,
       [-1.94561314,  4.77939021],
       [ 3.06701875, -5.65779277],
       [ 7.8776851 ,  2.83813679]])
```

0.1.3 plot

[20]:
```
plt.scatter(dist_2d[:,0],dist_2d[:,1])
plt.xlabel("X axis")
plt.ylabel("Y axis")
plt.title("Scatter plot of points following normal distribution and forming a␣
 ↪circle")
plt.axis("equal")
plt.show()
```



0.2 2. Identify (with justification) the outlier(s) amongst the data A = {[1, 0]T , [0, 1]T ,[1, 1]T, [1, 1.5]T, [1.5, 1]T, , [1.5, 1.5]T , [2, 1.5]T , [1.5, 2]T , [1, 2]T , [10000, 15000]T , [20000, 15000]T , [1, 15000]T }. Consider the level of significance to be 5%. If you modify the level of significance to be 10% how would your answer change? If it were 15%?

[19]:
```
## Finding outlier by mahalanobis method

from scipy.spatial.distance import mahalanobis
from scipy.stats import chi2

data = np.array([[1,0],[0,1],[1,1],[1,1.5],[1.5,1],[1.5,1.5],[2,1.5],[1.
 ↪5,2],[1,2],
                 [10000,15000],[20000,15000],[1,15000]])

mean_vector = np.mean(data, axis=0)
cov_matrix = np.cov(data.T)
inv_cov_mat = np.linalg.inv(cov_matrix)

# Mahalanobis distance
distances = [mahalanobis(d, mean_vector, inv_cov_mat) for d in data]

# thresholds

## 5% level of significance
threshold_5 = np.sqrt(chi2.ppf(0.95, 2))

## 10% level of significance
threshold_10 = np.sqrt(chi2.ppf(0.90, 2))

## 15% level of significance
threshold_15 = np.sqrt(chi2.ppf(0.85, 2))

df = pd.DataFrame(data, columns=['X','Y'])
df['Mahalanobis_Distance'] = distances
df['outlier_5%'] = df['Mahalanobis_Distance'] > threshold_5
df['outlier_10%'] = df['Mahalanobis_Distance'] > threshold_10
df['outlier_15%'] = df['Mahalanobis_Distance'] > threshold_15

df
```

[19]:

	X	Y	Mahalanobis_Distance	outlier_5%	outlier_10%	\
0	1.0	0.0	0.552959	False	False	
1	0.0	1.0	0.552812	False	False	

```
2       1.0      1.0              0.552812       False        False
3       1.0      1.5              0.552738       False        False
4       1.5      1.0              0.552812       False        False
5       1.5      1.5              0.552738       False        False
6       2.0      1.5              0.552738       False        False
7       1.5      2.0              0.552664       False        False
8       1.0      2.0              0.552664       False        False
9   10000.0  15000.0              1.658312       False        False
10  20000.0  15000.0              2.872313        True         True
11      1.0  15000.0              2.872249        True         True

    outlier_15%
0         False
1         False
2         False
3         False
4         False
5         False
6         False
7         False
8         False
9         False
10         True
11         True
```

0.3 inference:

- in all the three level of significance we get the same outliers i.e [20000,15000] and [1,15000]