

GMM

EM algorith

$$\pi_k^{\text{new}} = \frac{N_k}{N}$$

$$\boldsymbol{\mu}_k^{\text{new}} = \frac{1}{N_k} \sum_{n=1}^N \gamma_{nk} \mathbf{x}_n$$

$$\boldsymbol{\Lambda}_k^{-1\text{new}} = \frac{1}{N_k} \sum_{n=1}^N \gamma_{nk} \mathbf{x}_n \mathbf{x}_n^T - \boldsymbol{\mu}_k^{\text{new}} \boldsymbol{\mu}_k^{\text{new}T}$$

where,

$$N_k = \sum_{n=1}^N \gamma_{nk}$$

$$\gamma_{nk} = \frac{\pi_k N \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Lambda}_k^{-1})}{\sum_{k'=1}^K \pi_{k'} N(\mathbf{x}_n | \boldsymbol{\mu}_{k'}, \boldsymbol{\Lambda}_{k'}^{-1})}$$

In [1]:

```
1 import matplotlib.pyplot as plt
2 import numpy as np
3 import math
4 from scipy.stats import multivariate_normal as multi_gauss
5 from mpl_toolkits.mplot3d import Axes3D
```

In [2]:

```

1 class EM_GMM:
2     def __init__(self,K):
3         self.K=K
4
5     def E_step(self,X,pi,mu,Sigma):
6         gamma=np.zeros((self.N,self.K))
7
8         for n in range(self.N):
9             for k in range(self.K):
10                 gamma[n,k]= pi[k]*self.gauss(X[n].reshape(self.D, 1), mu[k].reshape(self.D, 1), Sigma[k])
11
12
13         gamma=gamma/np.sum(gamma, axis=1, keepdims=True)
14
15         return gamma
16
17     def M_step(self,X,gamma):
18         Nk=np.sum(gamma,axis=0)
19         pi=Nk/self.N
20         mu=np.zeros((self.K,self.D))
21         Sigma=np.zeros((self.K,self.D,self.D))
22         temp=np.zeros((self.N,self.D,self.D))
23         for n in range(self.N):
24             temp[n]=np.dot(X[n].reshape(self.D,1),X[n].reshape(1,self.D))
25         for k in range(self.K):
26             mu[k]=np.average(X,axis=0,weights=gamma[:,k])
27             Sigma[k]=np.average(temp,axis=0,weights=gamma[:,k])-np.dot(mu[k].reshape(self.D,1),mu[k].reshape(1,self.D))
28
29         return pi,mu,Sigma
30
31     def gauss(self, x, mu, Sigma):
32         x=x.reshape(self.D,1)
33         mu=mu.reshape(self.D,1)
34         return np.exp(-0.5*(x-mu).T @ np.linalg.inv(Sigma)@(x-mu))/(np.linalg.det(Sigma) * np.sqrt(2*np.pi))
35
36     def loglikelihood(self, X,pi,mu,Sigma):
37         # compute log likelihood
38         logL = 0
39         for n in range(self.N):
40             L = 0
41             for k in range(self.K):
42                 L += pi[k] * self.gauss(X[n].reshape(self.D, 1), mu[k].reshape(self.D, 1), Sigma[k])
43             logL += np.log(L)
44         return logL
45
46     def classify(self, X,pi,mu,Sigma):
47         gamma = np.zeros((self.N,self.K))
48         for n in range(self.N):
49             for k in range(self.K):
50                 gamma[n, k] = pi[k] * self.gauss(X[n].reshape(self.D, 1), self.mu[k].reshape(self.D, 1), self.Sigma[k])
51         gamma=gamma/np.sum(gamma, axis=1, keepdims=True)
52
53         return gamma, np.argmax(gamma, axis=1)
54
55     def fit(self,X,T=100):
56         #initialize
57         self.D = len(X[0])
58         self.N=X.shape[0]
59         pi=np.ones(self.K)/self.K

```

```

60 mu0 = np.mean(X,axis=0)
61 mu=np.random.uniform(X.min(), X.max(), (self.K, self.D))
62 Sigma=np.zeros((self.K,self.D,self.D))
63 temp=np.dot(X.T,X)/self.N
64 for k in range(self.K):
65     Sigma[k]=temp
66
67 #EM algorythm
68 record=[]
69 for step in range(T):
70     gamma = self.E_step(X,pi,mu,Sigma)
71     pi,mu,Sigma=self.M_step(X,gamma)
72
73     logL = self.loglikelihood(X,pi,mu,Sigma)
74     print("iter: %d, log likelihood: %f" % (step, logL))
75     record.append([step, logL])
76     if step == 0:
77         oldL = logL
78     else:
79         if logL - oldL < 1e-5:
80             print("breaked")
81             break
82         else:
83             oldL = logL
84
85     self.pi=pi
86     self.mu=mu
87     self.Sigma=Sigma
88
89     return np.array(record)

```

In [3]:

```

1 X = np.loadtxt("x.csv", delimiter=",")
2 gmm = EM_GMM(4)
3 record = gmm.fit(X, 100)
4 gamma, labels = gmm.classify(X,gmm.pi,gmm.mu,gmm.Sigma)

```

```

iter: 0, log likelihood: -89842.850601
iter: 1, log likelihood: -89100.863614
iter: 2, log likelihood: -84373.313521
iter: 3, log likelihood: -75787.685201
iter: 4, log likelihood: -70841.695423
iter: 5, log likelihood: -69020.953043
iter: 6, log likelihood: -67539.371575
iter: 7, log likelihood: -64994.921849
iter: 8, log likelihood: -61990.960767
iter: 9, log likelihood: -60560.098923
iter: 10, log likelihood: -59971.336261
iter: 11, log likelihood: -59434.089810
iter: 12, log likelihood: -58671.070596
iter: 13, log likelihood: -58000.545772
iter: 14, log likelihood: -57878.212356
iter: 15, log likelihood: -57875.581612
iter: 16, log likelihood: -57875.561716
iter: 17, log likelihood: -57875.561128
iter: 18, log likelihood: -57875.561105
iter: 19, log likelihood: -57875.561105
breaked

```

In [4]:

```

1  # save data
2  np.savetxt("z.csv", gamma, delimiter=",")
3  with open("params.dat", "w") as f:
4      f.write("pi:\n")
5      for k in range(gmm.K):
6          f.write("cluster %d: %f\n" % (k, gmm.pi[k]))
7      f.write("\nmeans:\n")
8      for k in range(gmm.K):
9          f.write("cluster %d: %s\n" % (k, gmm.mu[k]))
10     f.write("\nprecision matrix:\n")
11     for k in range(gmm.K):
12         f.write("cluster %d\n" % k)
13         f.write("%s\n" % np.linalg.inv(gmm.Sigma[k]))
14 with open("em_likelihood.txt", "w") as f:
15     f.write("step\tlog-likelihood\n")
16     for i in range(len(record)):
17         f.write("%d\t%f\n" % (record[i, 0], record[i, 1]))
18 # plot
19 colors = ["red", "lightblue", "lightgreen", "orange"]
20 label_color = [colors[int(label)] for label in labels]
21 fig = plt.figure()
22 ax = Axes3D(fig)
23 for i in range(X.shape[0]):
24     ax.plot([X[i, 0]], [X[i, 1]], [X[i, 2]], "o", color=label_color[i])
25 ax.set_xlim(-10, 10)
26 ax.set_ylim(-10, 10)
27 ax.set_zlim(-10, 10)
28 plt.savefig("em.png")
29 plt.show()
30 plt.close()

```

