

ECE521 Assignment #3 Example solutions

Due: March 2017

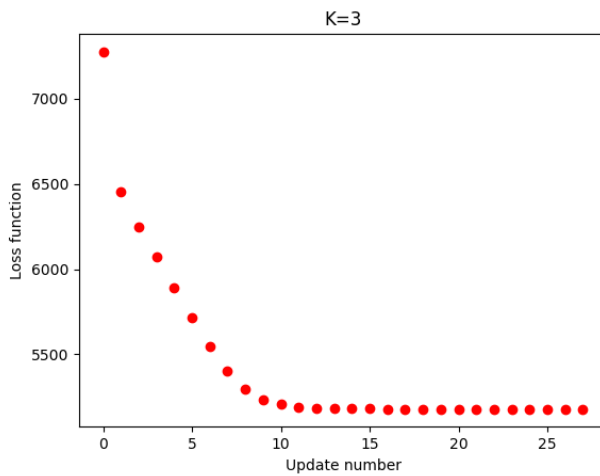
Question 1

- (a) $\mathcal{L}(\mu)$ is not convex, and this can most simply be seen through its multi-modality. Suppose μ_1 and μ_2 are two of many cluster centres positioned such that \mathcal{L} is at the global minimum. Switch any two cluster centres and the loss function is identical. When each of the cluster centres is in between switching, at point $x = \lambda\mu_1 + (1 - \lambda)\mu_2$, the loss function is higher. Thus Jensen's inequality does not hold, i.e. we cannot say that:

$$\mathcal{L}(\lambda\mu_1 + (1 - \lambda)\mu_2) \leq \lambda\mathcal{L}(\mu_1) + (1 - \lambda)\mathcal{L}(\mu_2).$$

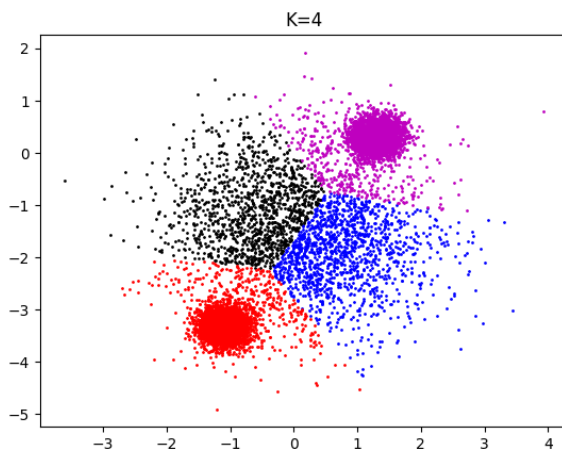
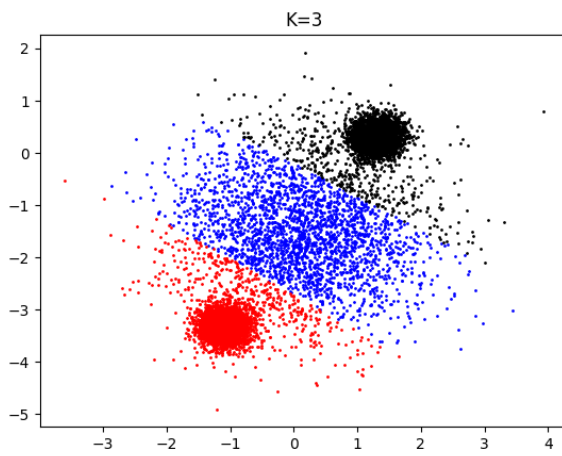
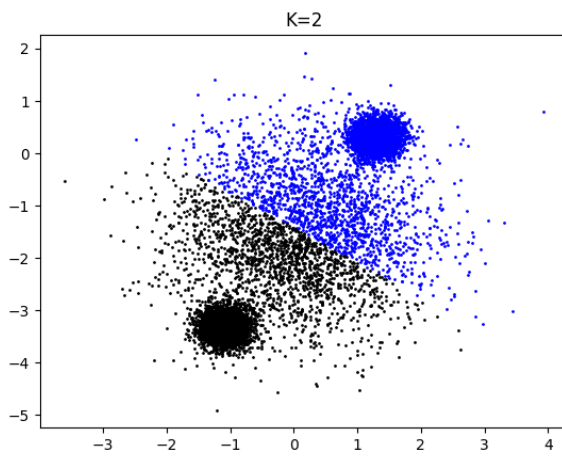
- (b) The estimated cluster centres were:

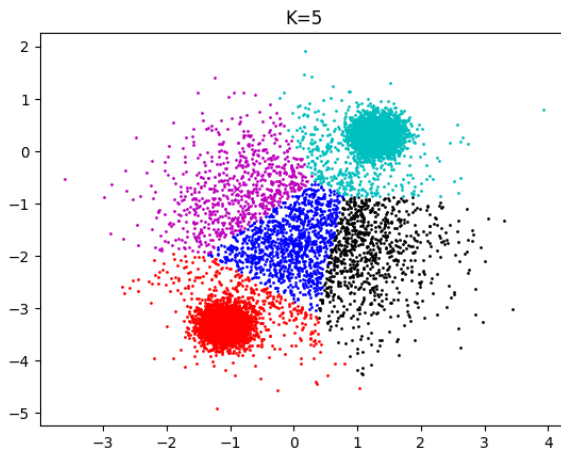
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1.253296  0.246562
0.121239 -1.51951
-1.055331 -3.242612
```



- (c) The percentage breakdown was:

K	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
1	100%				
2	50.5%	49.5%			
3	38.2%	38.0%	23.8%		
4	37.3%	37.1%	13.5%	12.0%	
5	36.3%	35.9%	11.3%	9.0%	7.5%





From the figures, the dataset is comprised of a roughly Gaussian component with high variance, plus two dense circular areas (lower left and upper right). A good value for K is 3. Two is the minimum to capture the two dense areas, three is the minimum to model these plus the region in between separately, and going above 3 is mainly a matter of subdividing the latter.

(d) The loss function values were:

K	Validation loss
1	6724
2	2639
3	1705
4	1465
5	1370

Creating a third component drops the validation loss by about 35% which is significant. Adding a fourth lowers the validation loss by about 14%, which may be important in some applications. Adding a fifth lowers the loss by only about 6%. The best K is 3 or 4.

Python code for Question 1:

```
import numpy as np
import math
import random

# Initializations
K = 2
Xall = np.load('data2D.npy')
D = int(Xall.shape[1])
B = int(Xall.shape[0])
#B=int(round(B*2/3)) # For part 4
X = Xall[:B,:]
mu = np.random.randn(K,D)

# Distance function from Assignment 1:
def getD(X,Z): #KxD - BxD -> BxK
```

```

diff=X[np.newaxis, :, :]-Z[:, np.newaxis, :]
return np.sqrt(np.sum(diff**2,axis=-1))

def gradL(mu,X):
    K = int(mu.shape[0])
    D = int(X.shape[1])
    B = int(X.shape[0])
    myD = getD(mu,X) # BxK
    minMu = np.argmin(myD,axis=1)
    gradMu = np.zeros((K,D))
    for n in range(B):
        gradMu[minMu[n],:] -= 2*(X[n,:]-mu[minMu[n],:])
    for k in range(K):
        if not any(minMu==k):
            gradMu[k,0] = -99
    return gradMu

def L(mu,X):
    K = int(mu.shape[0])
    D = int(X.shape[1])
    B = int(X.shape[0])
    myD = getD(mu,X)
    minMu = np.argmin(myD,axis=1)
    Lmu = myD[range(B),minMu]
    return np.sum(Lmu)

# Optimize
V = 1000
t = 0
losses = np.zeros(V)
if K==1:
    alpha = .1/B
else:
    alpha = 1/B
while t < V:
    t += 1
    oldMu = mu
    g = gradL(mu,X)
    for k in range(K):
        if (g[k,0] == -99): # lost sheep
            mu[k,:] = np.random.randn(D)
    mu = mu - alpha*g # Gradient descent
    losses[t-1] = L(mu,X)
    theChange = np.sum(np.sum(np.power(oldMu-mu,2)))
    if theChange < 1e-8:
        V = t
print(t, theChange, L(mu,X))

# Part 2: The centres
print(mu)

```

```

# Part 3: Plotting and percentages
import matplotlib.pyplot as plt
col = ['bo', 'ko', 'ro', 'mo', 'co']
myD = getD(mu, X)
minMu = np.argmin(myD, axis=1)
plt.clf()
for k in range(K):
    u = np.where(minMu==k)
    ul = len(np.transpose(u))/B*100
    print('Points in cluster %d: %.1f'%(k, ul))
    plt.plot (X[u, 0], X[u, 1], col[k], markersize=1)
    plt.plot (mu[k, 0], mu[k, 1], 'gx')
plt.title('K=%d'%(K))
plt.show()

if (K==3 and B==10000):
    plt.clf()
    plt.plot (range(V), losses[:V], 'ro')
    plt.xlabel ('Update number')
    plt.ylabel ('Loss function')
    plt.title('K=3')
    plt.show()

# Part 4: Loss on validation data
if (B==6667):
    s1 = int(X.shape[0])
    X = Xall[B:, :]
    s2 = int(X.shape[0])
    print ('Training on %d points, the loss on %d validation points was %.1f'
          % (s1, s2, L(mu, X)))

```