# **EM-Algorithms**

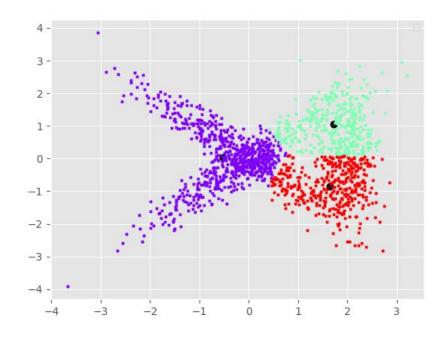
### 1. K-Means -

Using Python2.7 and the class slides, I fairly easily implemented the k-means algorithm from scratch. The only libraries I used for this was np.linagl.norm for calculating euclidean distance between data and centroids and matplotlib for drawing the clusters. I ran the algorithm for K=3, K=5, and K=10 as the number of clusters. I ran the algorithm 10 times for each of those numbers of clusters and choose the run with the lowest MSE. Below I've including the results of the 3 experiments.

## K = 3

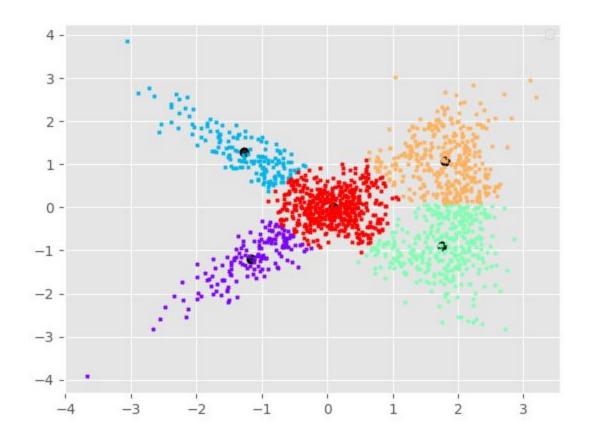
MSE: 582398.0295824544
Converged after 10 iterations.
Plotting...





MSE: 376387.2643944216 Converged after 10 iterations. Plotting...

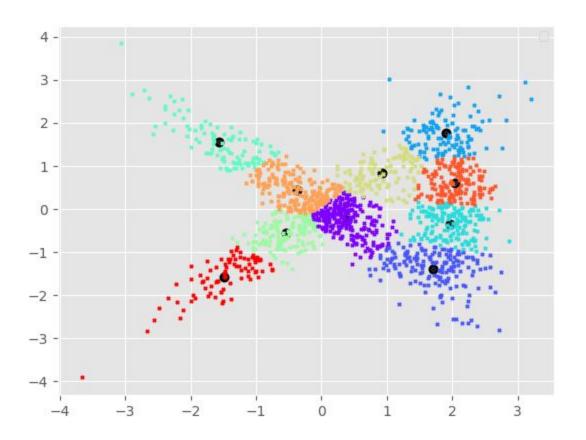
# 🔞 🖨 📵 Figure 1



## K=10

```
How many clusters would you like: 10
How many iterations of k-means would you like: 5
MSE: 172843.36282012748
Converged after 20 iterations.
Plotting...
```

## 🔞 🖨 📵 Figure 1



### 2. Gaussian Mixture Model

Programming the code for the Gaussian Mixture Model was a significantly harder task. After a little research and reviewing the class slides, I began my programming. The only library I needed for this part of the task was scipi.stats multivariate\_normal for calculating the covariance matrices and the responsibilities. I also used Python's math library for the constant pi, the exponential function and the log function. My initial experiments classified all points inside of one Gaussian bubble. After some debugging, I determined that I was incorrectly calculating my covariance matrices. After fixing that my algorithm converged correctly. When K=3, the number of classes in the data set, the algorithm classified the points almost to perfection. I also ran the algorithm with K=2, K=4, and K=5. See results below.

#### K=2

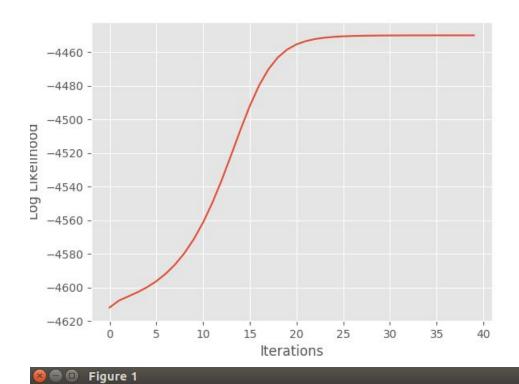
```
('log likelihood: ', -4449.919599518197)
Means-
[-0.11598922 -0.00684397]
[1.94054629 0.17000736]

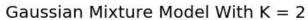
Covariance Matricies-
[ 0.96506927 -0.09561152]
[-0.09561152  0.87866293]
[ 0.12109816 -0.01151972]
[-0.01151972  1.40155003]

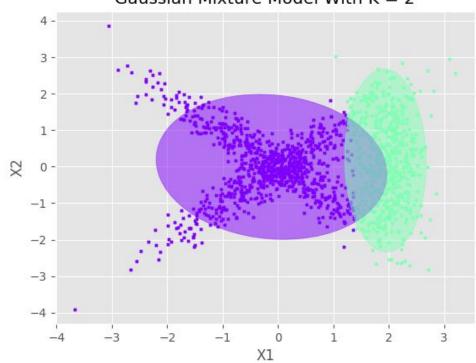
Priors-
0.6447907559490051
0.3552092440509949

Plotting...
```

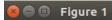


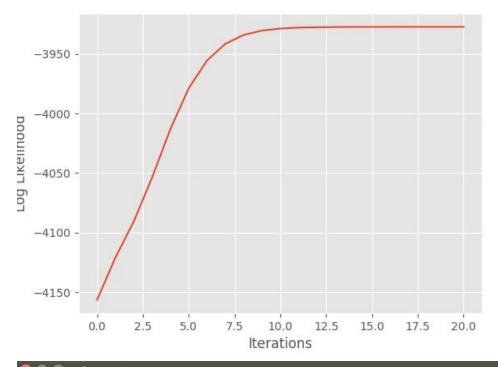


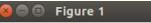


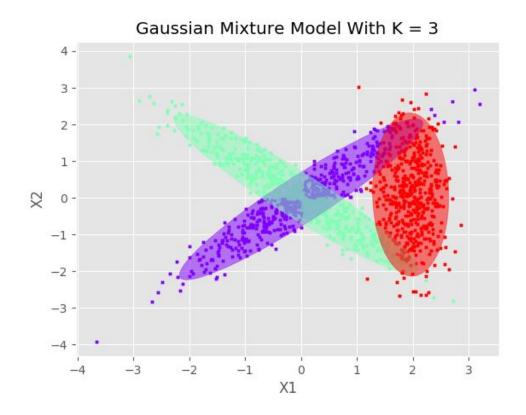


```
('log likelihood: ', -3927.3650764932295)
Means -
[ 0.00425201 -0.03969205]
[-0.09320913 0.11551842]
[1.96450773 0.09198051]
Covariance Matricies-
[1.05409804 0.99887186]
[0.99887186 1.06750198]
[ 1.05512966 -0.9869312 ]
[-0.9869312 1.03569525]
[ 0.10283618 -0.01077937]
[-0.01077937 1.0983756]
Priors-
0.33386836796317804
0.3380101325249987
0.3281214995118235
Plotting...
```

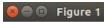


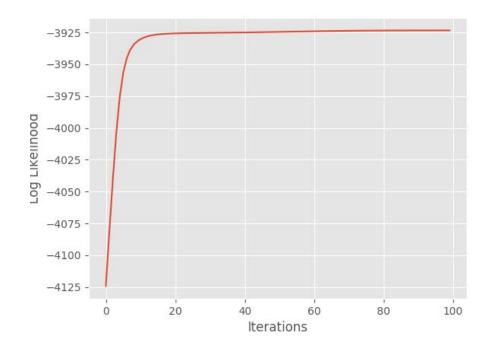




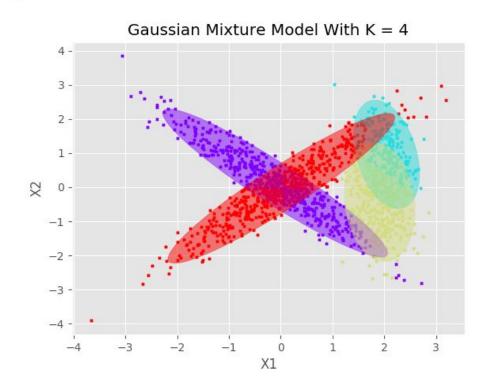


```
('log likelihood: ', -3923.333527010868)
Means -
[-0.10557344 0.12123675]
[2.04517193 0.96267517]
[ 1.91127569 -0.43871483]
[ 0.01368561 -0.03393161]
Covariance Matricies-
[ 1.04742846 -0.98805435]
[-0.98805435 1.04429006]
[ 0.08990954 -0.07909948]
[-0.07909948 0.56058257]
[ 0.10307781 -0.03901741]
[-0.03901741 0.67034965]
[1.0652867 1.00486085]
[1.00486085 1.0696691 ]
Priors-
0.33471622402929624
0.12213647846738546
0.20690714385985726
0.3362401536434612
Plotting...
```









```
('log likelihood: ', -3919.9792290408104)
(11, ' in a cluster, resetting!')
Means-
[-0.01012291 -0.04092371]
[ 0.17345901 -0.09615668]
[2.01739539 0.79534488]
[-0.12864707 0.13752146]
[ 1.9033811 -0.60894499]
Covariance Matricies-
[1.09885908 1.05856124]
[1.05856124 1.13631885]
[0.27520844 0.06604704]
[0.06604704 0.05479178]
[ 0.09559095 -0.05865564]
[-0.05865564 0.63122209]
[ 1.0655972 -1.0145897]
[-1.0145897 1.0764256]
[ 0.10386589 -0.03492633]
[-0.03492633 0.5837 ]
Priors-
0.3098522350273819
0.03666897953069773
0.16440167456964774
0.32050543291865446
0.16857167795361758
```

