# CSE 242 Assignment 4, Fall 2022

## 3 Questions, 100 pts, due: 23:59 pm, Nov 11th, 2022

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## Instruction

- Submit your assignments onto **Gradescope** by the due date. Upload a `zip` file containing:

  (1) The saved/latest `.ipynb` file, please **rename this file with your name included**.

  (2) Also save your file into a pdf version, if error appears, save an html version instead (easy to grade for written questions).

  **For assignment related questions, please reach TA or grader through Slack/Piazza/Email.**

- This is an **individual** assignment. All help from others (from the web, books other than text, or people other than the TA or instructor) must be clearly acknowledged.

## Objective

- **Task 1:** EM algorithm (Mathematical Derivation)
- **Task 2:** K-Means implementation (Coding)
- **Task 3:** Kernel Methods with Noisy Setting (Coding)

# Question 1. (EM algorithm, 20 pts)

Derive the E-step and M-step update equations of EM algorithm for estimating the Gaussian mixture model $p(X;\theta) = \sum_{k=1}^{K} \pi_k N(x; \mu_k, \sigma_k^2)$ where $\pi_k$ is the mixture weight with $\pi_k \geq 0$ and $\sum_{k=1}^{K} \pi_k = 1$, and $\mu_k$, $\sigma_k^2$ are the mean and variance of the gaussian distribution corresponding to cluster k.

For the E-step, first prove that $z_{ik} = P(z_i = k|X, \mu, \sigma, \pi) = \frac{\pi_k N(x_i; \mu_k, \sigma_k^2)}{\sum_{k=1}^{K} \pi_k N(x_i; \mu_k, \sigma_k^2)}$. Then, for the M-step, show the derivation to compute the updates for $(\mu_k, \pi_k)$. Note that, you don't need to show the derivation for $\sigma_k$. For each derivation step, mention the concept applied (e.g. just 2-3 keywords, e.g. formula for expectation, independence of datapoints, (f+g)' = f' + g', etc ... ).

**Hint:** For the M-step, you need to solve for $\mu_k^t = \underset{\mu_k}{argmax}\ E_{p(Z|X,\mu^{(t-1)},\sigma^{(t-1)},\pi^{(t-1)})}[\log p(X, Z|\mu, \sigma, \pi)]$ (and similarly for $\pi_k$) by applying the first order conditions for function optimization (take derivative and set it to zero). Note that the term $p(Z|X, \mu^{(t-1)}, \sigma^{(t-1)}, \pi^{(t-1)})$ is the one computed in the E-step, and uses fixed values for $\mu, \sigma, \pi$ from the previous iteration (t-1).

In [1]:
```
from IPython.display import Image
# Replace the figure name
Image(filename='1.1.jpg')
```

Out[1]:

1) Expectation Step:

The probability of assigning the $i^{th}$ data point to the cluster $k$ is given by:

$$Z_{ik} = P(Z_{i=k} \mid X = x_i, \mu_k, \sigma_k, \pi_k)$$

$$P(X|Y) = \frac{P(Y|X)\, P(X)}{P(Y)} \quad \text{— By Bayes Rule}$$

$$\text{Thus } Z_{ik} = \frac{P(Z_{i=k})\, P(x_i, \mu_k, \sigma_k, \pi_k \mid Z_i = k)}{P(x_i, \mu_k, \sigma_k, \pi_k)}$$

Since $P(Z_{i=k}) = \pi_k$ — (1) N-data points

and

$P(x_i, \mu_k, \sigma_k, \pi_k \mid z_i = k) = N(x_i \mid \mu_k, \sigma_k^2)$ — (2)

- likelihood of datapoint given the cluster $k$

$$P(X) = \sum_Y P(X,Y) = \sum_Y P(X|Y)\, P(Y)$$

$$P(x_i, \mu_k, \sigma_k, \pi_k) = \sum_{k=1}^{K} P(x_i, \mu_k, \sigma_k, \pi_k \mid Z_i = k) * P(Z_i = k)$$

$$\Rightarrow P(x_i, \mu_k, \sigma_k, \pi_k) = \sum_{k=1}^{K} N(x_i \mid \mu_k, \sigma_k^2) * \pi_k \quad \text{— (3)}$$

Hence: $$\boxed{z_{ik} = \frac{\pi_k * N(x_i \mid \mu_k, \sigma_k^2)}{\sum_{k=1}^{K} N(x_i \mid \mu_k, \sigma_k^2)}}$$ from (1), (2) & (3)

In [2]:
```
Image(filename='1.2.jpg')
```

Out[2]:

Maximization Step

$$\pi^{new}, \mu^{new}, \sigma^{new} = \underset{\pi,\mu,\sigma}{\operatorname{argmax}} \; \mathbb{E}_{P(Z|X,\pi^{t-1},\mu^{t-1},\sigma^{t-1})} \log(P(X,Z|\pi,\mu,\sigma)) \quad - (1)$$

Assuming $\Omega = \mathbb{E}_{P(Z|X,\pi^{t-1},\mu^{t-1},\sigma^{t-1})} \log(P(X,Z|\pi,\mu,\sigma))$

since $E[f(x)] = \sum_x f(x)\, p(x)$

Hence $\Omega = \sum_Z \log(P(X,Z|\pi,\mu,\sigma))\, P(Z|X,\mu^{t-1},\sigma^{t-1},\pi^{t-1})$

$$\Omega = \sum_{z_1 \text{ to } z_N} P(z_1, z_2, \cdots, z_N | x_1, x_2, \cdots x_N, \mu^{t-1}, \sigma^{t-1}, \pi^{t-1}) \log(P(Z,X|\pi,\mu,\sigma))$$

$$= \sum_{z_{1 \text{ to } N}} P(z_1, z_2, \cdots z_N | x_1, x_2, \cdots x_N, \mu^{t-1}, \sigma^{t-1}, \pi^{t-1}) \times \log(P(Z|\pi) \times P(X|\sigma,\mu,Z))$$

If we consider data points to be independent

$$\Omega = \sum_{z_{1 \text{ to } N}} P(z_1 \cdots z_N | x_1 \cdots x_N, \mu^{t-1} \sigma^{t-1}, \pi^{t-1}) \log\left[\prod_{i=1}^{N} P(z_i|\pi) \times P(x|z_i,\mu,\sigma)\right]$$

$$= \sum_{z_{1 \text{ to } N}} P(z_1 \cdots z_N | x_1 \cdots x_N, \mu^{t-1} \sigma^{t-1} \pi^{t-1}) \left\{\sum_{i=1}^{N} \log[P(z_i|\pi) \times P(x|z_i,\mu,\sigma)]\right\}$$

In [3]:

```
Image(filename='1.3.jpg')
```

Out[3]:

$$\Omega = \sum_{i=1}^{N} \sum_{z_{1 \text{ to } N}} P(z_1 .. z_N \mid x_1 \cdots x_N, \mu^{t-1}, \sigma^{t-1}, \pi^{t-1}) \times \log[P(z_i \mid \pi) \times P(x \mid z_i, \mu, \sigma)]$$

$z_1, z_2 \cdots z_N$ are all independent

Thus : $\Omega =$

$$\sum_{i=1}^{N} \sum_{z_{1 \text{ to } N}} P(z_1 \mid x_1, \mu^{t-1} \sigma^{t-1} \pi^{t-1}) \times P(z_2 \mid x_2, \mu^{t-1} \sigma^{t-1} \pi^{t-1}) \times \cdots P(z_N \mid x_N, \mu^{t-1} \sigma^{t-1} \pi^{t-1}) \times \log[P(z_i \mid \pi) \times P(x \mid z_i, \mu, \sigma)]$$

$$\Omega = \sum_{i=1}^{N} \sum_{z_i} P(z_i \mid x_i, \mu, \sigma, \pi) \times \log[P(z_i \mid \pi) \cdot P(x_i \mid z_i, \mu, \sigma)] \times \underbrace{\sum_{z_{1 \text{ to } N}} P(z_1 \mid x_1, \mu^{t-1}, \sigma^{t-1}, \pi^{t-1}) \cdot P(z_2 \mid x_2, \mu, \sigma, \pi) \cdot P(z_N \mid x_N, \sigma, \mu, \pi)}_{=1}$$

$$\Omega = \sum_{i=1}^{N} \sum_{k} P(z_i \mid x_i, \mu^{t-1}, \sigma^{t-1}, \pi^{t-1}) \times \log[P(z_i \mid \pi) \cdot P(x_i \mid z_i, \mu, \sigma)] \quad - (2)$$

$$\mu^{new} = \text{argmax } \Omega(\mu)$$

$$= \underset{\mu}{\text{argmax}} \sum_{i=1}^{N} \sum_{k'} P(z_i \mid x_i, \mu^{t-1}) \times \log(P(z_i = k' \mid \pi) \cdot P(x_i \mid z_{i=k'}, \mu, \sigma, z_i)]$$

$$\frac{\partial \Omega(\mu)}{\partial \mu_k} = 0$$

In [4]:
```
Image(filename='1.4.jpg')
```

Out[4]:

Thus $\frac{\partial Q(\mu)}{\partial \mu_k} = \frac{\partial}{\partial \mu_k}\left[\sum_{i=1}^{N}\sum_{k'} P(z_i \mid x_i, \mu^{t-1}) \times \log(P(z_i = k' \mid \pi) \cdot P(x_i \mid \mu, \sigma, z_i)\right] = 0$

Derivative of sum is the sum of derivatives

$$\sum_{i=1}^{N}\sum_{k'} P(z_{i=k} \mid x_i, \mu^{t-1}) \frac{\partial}{\partial \mu_k} \log[\underbrace{P(z_i = k' \mid \pi) \cdot P(x_i \mid z_{i=k'}, \mu, \sigma, z_i)}_{N(x_i \mid \mu_{k'}, \sigma_{k'}, \pi_{k'})}]$$

$$\Rightarrow \sum_{i=1}^{N} P(z_{i=k} \mid x_i, \mu^{t-1}) \frac{\partial}{\partial \mu_k}\left[\log(N(x_i \mid \mu_{k'}, \sigma_{k'}))\right] = 0$$

$$\Rightarrow \sum_{i=1}^{N} P(z_{i=k} \mid x_i, \mu^{t-1}) \frac{\partial}{\partial \mu_k}\left[\log\left(\frac{1}{\sqrt{2\pi\sigma_k^2}} \times e^{-\frac{(x_i - \mu_k)^2}{2\sigma^2}}\right)\right] = 0$$

$$\sum_{i=1}^{N} P(z_{i=k} \mid x_i, \mu^{t-1}) \frac{\partial}{\partial \mu_k}\left[\log\left(\frac{1}{\sqrt{2\pi\sigma_k^2}}\right) - \frac{(x_i - \mu_k)^2}{2\sigma^2} \times \log e\right] = 0$$

$$\sum_{i=1}^{N} P(z_{i=k} \mid x_i, \mu^{t-1}) \frac{\partial}{\partial \mu_k}\left[-\frac{(x_i - \mu_k)^2}{2\sigma^2}\right] = 0$$

$$\sum_{i=1}^{N} z_{i=k}\left(\frac{-\cancel{2} \times (x_i - \mu_k)}{\cancel{2}\sigma^2} \times -1\right) = 0$$

$$\sum_{i=1}^{N} z_{ik}(x_i - \mu_k) = 0$$

In [5]:
```
Image(filename='1.5.jpg')
```

Out[5]:

$$\Rightarrow \sum_{i=1}^{N} z_{ik} x_i - \sum_{i=1}^{N} z_{ik} \mu_k = 0$$

or $$\boxed{\mu_k = \frac{\sum_{i=1}^{N} z_{ik} x_i}{\sum_{i=1}^{N} z_{ik}}}$$

$$\pi_k^{new} = \arg\max \mathbb{E}_{P(Z|X, \pi^{t-1}, \mu^{t-1}, \sigma^{t-1})} \ln(P(X, Z|\pi, \mu, \sigma)) \quad - (3)$$

From Lagrange's condition

$$L(\pi, \lambda) = \Omega(\pi) + \lambda\left(1 - \sum_{k'=1}^{K} \pi_{k'}\right) \quad - (4)$$

$$\frac{\partial}{\partial \pi_k} L(\pi, \lambda) = 0$$

$$\frac{\partial}{\partial \pi_k} \Omega(\pi) + \frac{\partial}{\partial \pi_k}\left(\lambda\left(1 - \sum_{k'=1}^{K} \pi_{k'}\right)\right) = 0$$

from (3) $$\frac{\partial}{\partial \pi_k}\left(\mathbb{E}_{P(Z|X, \pi, \mu, \sigma)} \ln(P(Z, X|\pi, \mu, \sigma))\right) + \frac{\partial}{\partial \pi_k}\left(\lambda\left(1 - \sum_{k'=1}^{K} \pi_{k'}\right)\right) = 0$$

In [6]:
```
Image(filename='1.6.jpg')
```

Out[6]:

$$\frac{\partial}{\partial \pi_k}\left[\sum_{i=1}^{N} P(Z_{i=k} \mid x_i, \pi^{t-1}) \log\left(P(Z_i \mid \pi)\, P(x_i \mid \mu, \sigma, Z_i)\right)\right] + \lambda \frac{\partial}{\partial \pi_k}\left[1 - \sum_{k'=1}^{K} \pi_{k'}\right] = 0$$

or $$\frac{\partial}{\partial \pi_k}\left[\sum_{i=1}^{N} z_{ik}\left(\log\left[\pi_k \times N(x_i \mid \mu, \sigma, Z_i)\right]\right)\right] - \lambda \times \frac{\partial}{\partial \pi_k}\left[1 + \cdots + k\right] = 0$$

$$\frac{\partial}{\partial \pi_k}\left[\sum_{i=1}^{N} z_{ik}\left(\log \pi_k + \log\left(N(x_i \mid \mu, \sigma, Z_i)\right)\right)\right] - \lambda = 0$$

$$\sum_{i=1}^{N} z_{ik} \frac{\partial}{\partial \pi_k}\left(\log \pi_k + \log\left(N(x_i \mid \mu, \sigma, Z_i)\right)\right) = \lambda$$

$$\Rightarrow \sum_{i=1}^{N} z_{ik}\left(\frac{1}{\pi_k} + 0\right) = \lambda$$

or $$\boxed{\lambda = \frac{\sum_{i=1}^{N} z_{ik}}{\pi_k}} \quad — \quad (5)$$

We know that: $\sum_{k'=1}^{K} P(Z_i = k') = \sum_{k'=1}^{K} \pi_{k'} = 1$

Thus $\lambda = \lambda \times 1$ or

$$\lambda = \sum_{i=1}^{K} \lambda \times \pi_{k'}$$

In [7]:

```
Image(filename='1.7.jpeg')
```

Out[7]:

Substituting the value of $\lambda$ from 5

$$\lambda = \sum_{k'=1}^{K} \left( \frac{\sum_{i=1}^{N} z_{ik'}}{\cancel{\pi_{k'}}} \right) \times \cancel{\pi_{k'}}$$

$$\lambda = \sum_{i=1}^{N} \sum_{k'} z_{ik}$$

$\therefore \sum_{k'} z_{ik} = 1$ because we are adding all the probabilities of ith datapoint belonging to all the clusters.

$$\Rightarrow \lambda = \sum_{i=1}^{N} 1 = N \quad - 6$$

From 5 & 6 :

$$\boxed{\pi_k = \frac{\sum_{i=1}^{N} z_{ik}}{N}}$$

References:

https://www.youtube.com/watch?v=XGRXH9Fcc-w

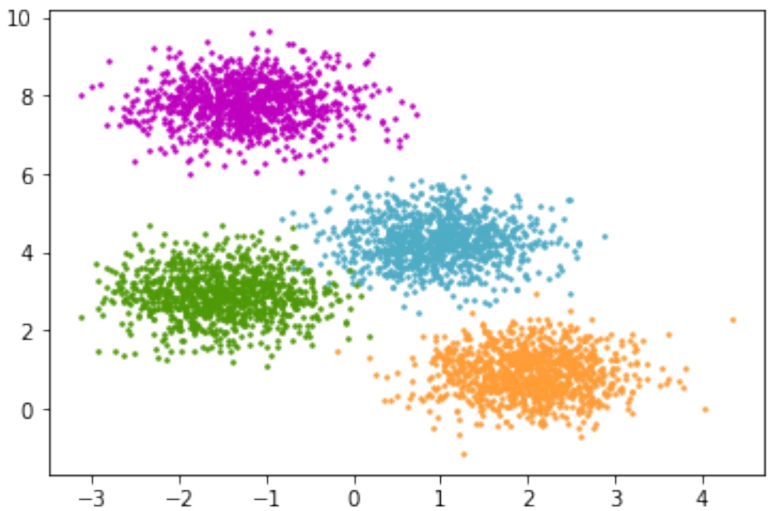
# Question 2. (K-Means implementation, 20 pts)

**Question 2.1.** Implement K-means in Python from scratch. Complete following sub-functions `update_centroids` and `update_assignments`.

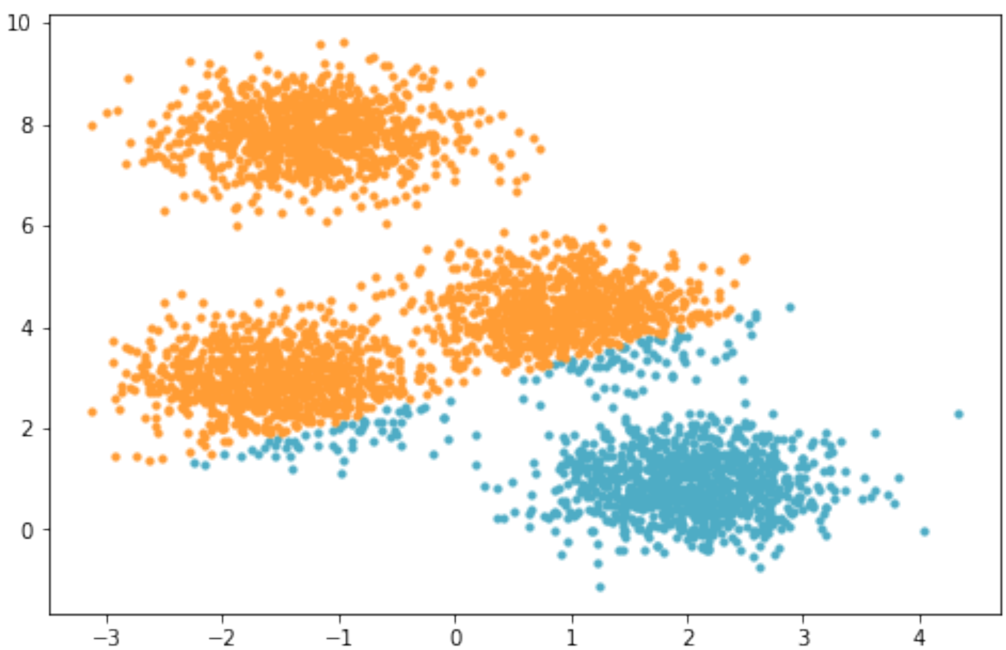
In [8]:
```
import numpy as np
from scipy.spatial.distance import cdist
def update_assignments(data, centroids):

  ########################
  #### YOUR CODE HERE ####
  row, col = data.shape
  assignments = np.empty([row])
  distances = cdist(data, centroids)
  assignments=np.argmin(distances,axis=1)


  ## you will get cluster#
  ##assignments here #####
  ########################

  return assignments

def update_centroids(data,centroids,assignments):

  ########################
  #### YOUR CODE HERE ####
  ########################
  K = centroids.shape[0]
  centroids=np.empty(centroids.shape)
  for i in range(K):
    centroids[i]=np.mean(data[assignments ==i], axis=0)

  return centroids


def kmeans(data, centroids, max_iterations):

    for j in range(max_iterations):
        # update cluter assignments
        assignments = update_assignments(data,centroids)     # WRITE CODE FOR

        # update centroid locations
        centroids = update_centroids(data,centroids,assignments)  # WRITE CO

    # final assignment update
    assignments = update_assignments(data,centroids)
    return centroids, assignments
```

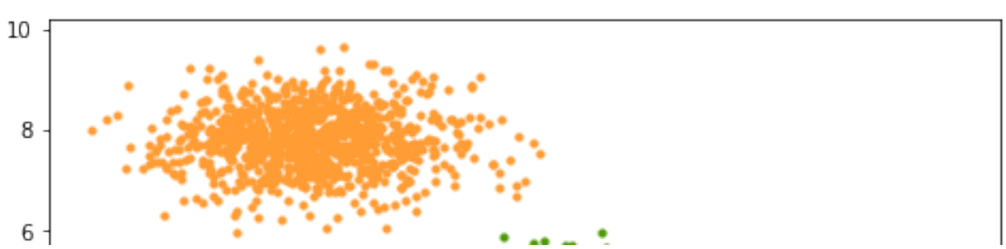
**Question 2.2.** Run your code on following toy dataset for different k-values, where k = {2, 3, 4, 6, 10} and plot the cluster assignments for different k's as shown in following diagram.

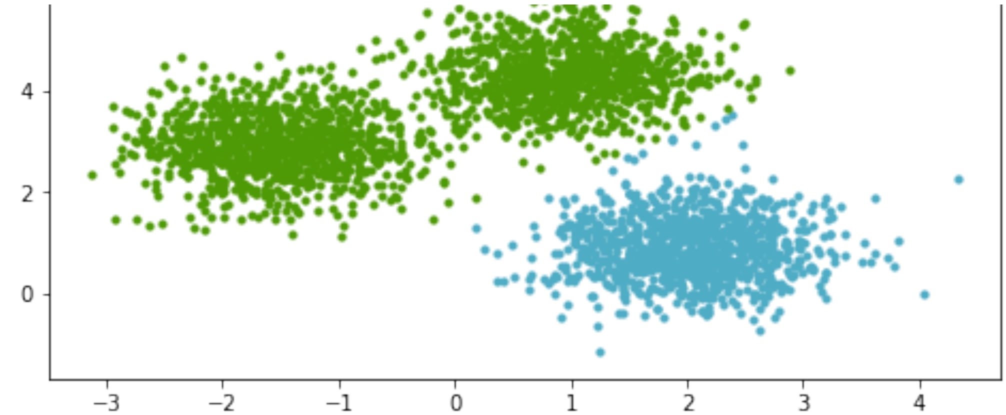
In [9]:
```
from sklearn.datasets import make_blobs
import matplotlib.pyplot as plt

# Generate sample data
n_samples = 4000
n_components = 4

X, y_true = make_blobs(
    n_samples=n_samples, centers=n_components, cluster_std=0.60, random_stat
)

colors = ["#4EACC5", "#FF9C34", "#4E9A06", "m"]

for k, col in enumerate(colors):
    cluster_data = y_true == k
    plt.scatter(X[cluster_data, 0], X[cluster_data, 1], c=col, marker=".", s
```

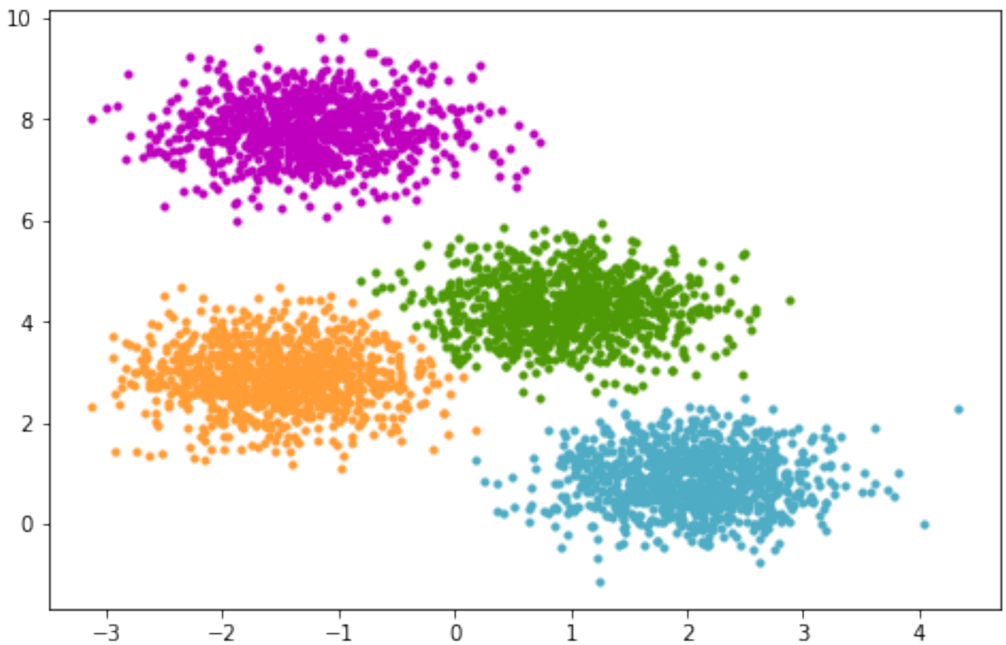


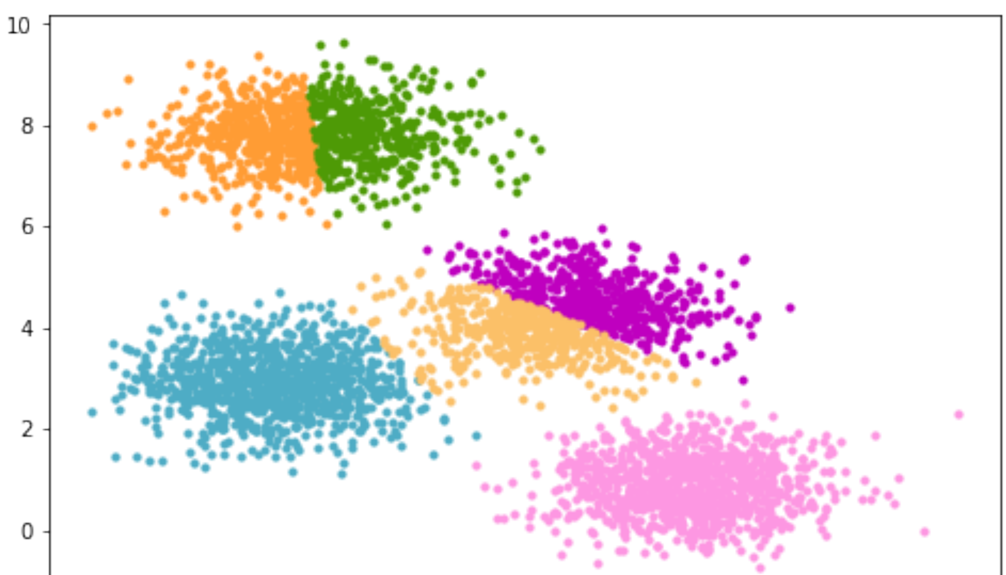
In [10]:
```
import numpy as np

# function to get initial cluster centroids; we randomly choose k points fro
def get_initial_clusters(k, X):
  random_indices = np.random.randint(0, X.shape[0], k)
  initial_centroids = X[random_indices]

  return initial_centroids

# your code here.
clusters=[2,3,4,6,10]
colors = ["#4EACC5", "#FF9C34", "#4E9A06", "m",
          "#fbc068", "#fd97e2", "#b8c2aa", "#7c5858",
          "#3b6f05", "#001b58"]
fig, axs = plt.subplots(len(clusters), figsize=[8,30])
for idx, i in enumerate(clusters):
    centroids=get_initial_clusters(i, X)
    centroids,assignments=kmeans(X,centroids,100)
    #print(assignments.shape)
    for k in range(i):
        cluster_data = assignments == k
        axs[idx].scatter(X[cluster_data, 0], X[cluster_data, 1], color=color
```

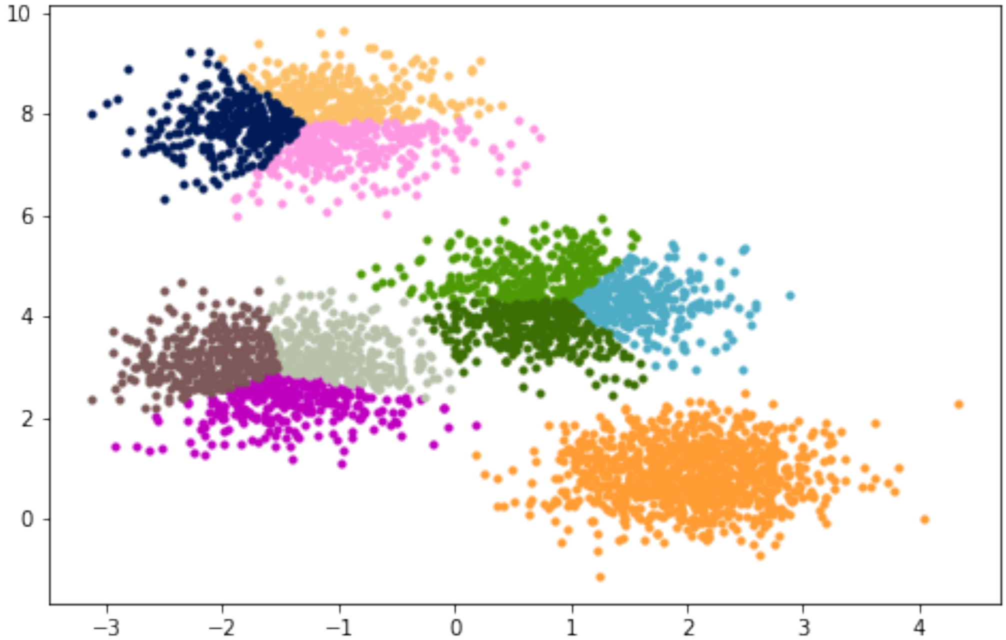









# Question 3. (Kernel Methods with Noisy Setting, 60 pts)

**SVM on synthetic dataset generated as follows:**

- Draw $1000$ $(x_0, x_1)$ feature vectors from the 2-D Gaussian distribution with mean $\mu_+ = (1, 1)$ and $\Sigma_+ = [1, 0; 0, 1]$ and label them as $+1$.
- Draw $1000$ $(x_0, x_1)$ feature vectors from the 2-D Gaussian distribution with mean $\mu_- = (-1, -1)$ and $\Sigma_- = [3, 0; 0, 3]$ and label them as $-1$.
- This gives you a $2000$ example training set. Repeat the above to draw a test set the same way.

Use a SVM package ( scikit-learn svm.SVC class) to learn SVMs with a variety of parameter settings.

In [11]:
```
# Your code here
import numpy as np
import pandas as pd
from sklearn.utils import shuffle
np.random.seed(220)
mean1= (1,1)
cov1=[[1,0],[0,1]]
mean2=(-1,-1)
cov2=[[3,0],[0,3]]
df1 = pd.DataFrame(np.random.multivariate_normal(mean1,cov1,1000),columns=['
df1['label']=+1
df2 = pd.DataFrame(np.random.multivariate_normal(mean2,cov2,1000),columns=['
df2['label']=-1
df_train = pd.concat([df1,df2], ignore_index=True)
#Shuffling to avoid consistency
# df_train = shuffle(df_train)
df_train = df_train.reset_index(drop=True)
df_train
```

Out[11]:

| | x | y | label |
|---|---|---|---|
| **0** | -0.324352 | -0.465870 | 1 |
| **1** | -0.249991 | 1.654616 | 1 |
| **2** | 2.235651 | -0.122390 | 1 |
| **3** | 1.414549 | 0.806798 | 1 |
| **4** | -0.747681 | 2.687990 | 1 |
| **...** | ... | ... | ... |
| **1995** | -2.454008 | -3.098631 | -1 |
| **1996** | -5.584851 | -0.248678 | -1 |
| **1997** | 2.095982 | 0.153912 | -1 |
| **1998** | 1.639896 | -3.109557 | -1 |
| **1999** | 0.186215 | -2.850072 | -1 |

2000 rows × 3 columns

In [12]:
```
df1 = pd.DataFrame(np.random.multivariate_normal(mean1,cov1,1000),columns=['
df1['label'] = +1
df2 = pd.DataFrame(np.random.multivariate_normal(mean2,cov2,1000),columns=['
df2['label'] = -1
df_test = pd.concat([df1,df2], ignore_index=True)
df_test
```

Out[12]:

| | x | y | label |
|---|---|---|---|
| **0** | -1.898160 | 1.556240 | 1 |
| **1** | 1.784113 | -0.436965 | 1 |
| **2** | 1.986831 | 2.236635 | 1 |
| **3** | -0.213913 | 1.240479 | 1 |
| **4** | 2.431783 | 0.760874 | 1 |
| **...** | ... | ... | ... |
| **1995** | -1.012130 | 0.737504 | -1 |
| **1996** | 0.199889 | 1.865863 | -1 |
| **1997** | -2.578212 | 1.371016 | -1 |
| **1998** | -0.800268 | -1.951012 | -1 |
| **1999** | -2.646145 | -1.403640 | -1 |

2000 rows × 3 columns

# (a -- 20 pts)

- Use an RBF kernel with parameters $C = 1$, $\gamma = 0.01$.
- For each training data with +1 label, randomly flip their label to -1 with probability $\mathbf{0.35}$.
- For each training data with -1 label, randomly flip their label to +1 with probability $\mathbf{0.20}$.
- Train with the above noisy training examples.
- Random flipping introduces the randomness. You can repeat multiple times (e.g. 20) and then report the average accuracy on the testing dataset (clean) in the noise parameter setting.

In [13]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
import random
X_train =df_train[['x', 'y']]
y_train =df_train['label'].values
X_test = df_test[['x', 'y']]
y_test = df_test['label'].values


model = SVC(kernel='rbf',C=1, gamma=0.01, random_state = 21)
model = model.fit(X_train, y_train)


y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy score before flip: ",accuracy)
```

```
Accuracy score before flip:  0.8585
```

In [14]:
```
def flip_labels(pos,neg,prob_pos=0.35,prob_neg=0.20):
    pos_prob=np.random.random(size=pos.shape[0])
    flip_pos=np.where(pos_prob<prob_pos,-1,pos)

    neg_prob=np.random.random(size=neg.shape[0])
    flip_neg=np.where(neg_prob<prob_neg,1,neg)

    return np.hstack([flip_pos,flip_neg])

y_train_flipped= flip_labels(y_train[:1000],y_train[1000:])
```

In [15]:
```
model1 = SVC(kernel='rbf', probability=True, C=1, gamma=0.01)
model1 = model1.fit(X_train, y_train_flipped)


y_pred = model1.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy score after flip: ",accuracy)
```

```
Accuracy score after flip:  0.7895
```

# (b -- 20 pts) Open question

- Try using **K-Nearst Neighbors** to correct wrong labels before training.
- Then train the model with the newly processed training dataset.
- Report the accuracy on the testing dataset in the noise parameter setting. Do you observe performance improvement?

In [16]:
```
# Your code here
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
best_knn_svm=0
best_k_svm=0

best_knn=0
best_k=0
best_knn_model=None

for k in range(1,100):
    knn_neigh=KNeighborsClassifier(n_neighbors=k)
    knn_neigh.fit(X_train,y_train_flipped)

    y_neigh_predict_test=knn_neigh.predict(X_train)
    if(accuracy_score(y_test,y_neigh_predict_test)*100>best_knn):
        best_knn=accuracy_score(y_test,y_neigh_predict_test)*100
        best_k=k
        best_knn_model=knn_neigh

#print(best_k)
svm_knn=SVC(kernel='rbf',random_state=0,gamma=.01,C=1)

y_train_knn=best_knn_model.predict(X_train)
svm_knn.fit(X_train,y_train_knn)

y_svm_knn_predict_test=svm_knn.predict(X_test)

best_knn_svm=accuracy_score(y_test,y_svm_knn_predict_test)*100

    #if(accuracy_score(y_test,y_svm_knn_predict_test)*100>best_knn_svm):
    #    best_knn_svm=accuracy_score(y_test,y_svm_knn_predict_test)*100
    #    best_k_svm=k

print(f"Accuracy with knn+svm: {best_knn_svm}")
#print(f"Accuracy with just knn: {best_knn},k neighbors:{best_k}")
```

```
Accuracy with knn+svm: 83.89999999999999
```

After correcting the noisy labels using knn, and then running svm on that- the accuracy has improved

# (c -- 20 pts) Open question

- Try using **clustering (i.e., K-means, EM-clustering)** to correct wrong labels before training.
- Then train the model with the newly processed training dataset.
- Report the accuracy on the testing dataset in the noise parameter setting. Do you observe performance improvement?

In [17]:

```
# Your code here
from sklearn.cluster import KMeans
kmeans_cluster=KMeans(n_clusters=2,random_state=0).fit(X_train)
Y_kmeans=kmeans_cluster.labels_
#print(Y_kmeans)
for i,ele in enumerate(Y_kmeans):
    if Y_kmeans[i] ==1:
        Y_kmeans[i]=-1
    elif Y_kmeans[i]==0:
        Y_kmeans[i]=1
#print(Y_kmeans)
svm_kmeans=SVC(kernel='rbf', random_state=0,gamma=.01,C=1)
svm_kmeans.fit(X_train,Y_kmeans)

y_svm_kmeans_predict_test=svm_kmeans.predict(X_train)

print(f"Accuracy with kmeans+svm: {accuracy_score(y_test,y_svm_kmeans_predic
```

```
Accuracy with kmeans+svm: 82.25
```

The accuracy after k-means is comparitively less as it is unsupervised and the labels are labelled based on the cluster. But the accuracy has still improved a little.

In [18]:

```
from sklearn.mixture import GaussianMixture
EM_cluster= GaussianMixture(n_components=2,random_state=0).fit(X_train)
Y_EM=EM_cluster.predict(X_train)
#print(Y_EM)

for i,ele in enumerate(Y_EM):
    if Y_EM[i] ==1:
        Y_EM[i]=-1
    elif Y_EM[i]==0:
        Y_EM[i]=1
#print(Y_EM)
svm_EM=SVC(kernel='rbf', random_state=0,gamma=.01,C=1)
svm_EM.fit(X_train,Y_EM)

y_svm_EM_predict_test=svm_EM.predict(X_train)

print(f"Accuracy with EM+svm: {accuracy_score(y_test,y_svm_EM_predict_test)*
```

```
Accuracy with EM+svm: 83.35000000000001
```

The accuracy has improved compared to the one with noisy labels. Still its less than knn because EM is again unsupervised.