

# Com Sci 146: Homework #5

## 704797256

Jingyue Shen

### Problem 1

#### Part A

We only model the word frequency in each class, but ignore the relation between current word and the words before and after it.

#### Part B

$$\log^{Pr(D_i, y_i)} = \log^{Pr(D_i | y_i)} + \log^{Pr(y_i)} = \log \frac{n!}{a_i! b_i! c_i!} \alpha_0^{a_i(1-y_i)} \alpha_1^{a_i y_i} \beta_0^{b_i(1-y_i)} \beta_1^{b_i y_i} \gamma_0^{c_i(1-y_i)} \gamma_1^{c_i y_i} + \log \theta^{y_i} (1-\theta)^{1-y_i}$$

#### Part C

$$\frac{\partial \log \prod_{i=1}^m P(D_i, y_i)}{\partial \alpha_1} = 0$$

$$\Rightarrow \frac{\partial \sum_{i=1}^m a_i y_i \log \alpha_1 + c_i y_i \log^{1-\alpha_1-\beta_1}}{\partial \alpha_1} = 0$$

$$\Rightarrow \frac{\sum_{i=1}^m a_i y_i}{\alpha_1} - \frac{\sum_{i=1}^m c_i y_i}{1-\alpha_1-\beta_1} = 0$$

$$\Rightarrow \alpha_1 (\sum a_i y_i + \sum c_i y_i) = (1 - \beta_1) \sum a_i y_i \quad (1)$$

Take partial derivative with respect to  $\beta_1$ , we can get

$$\beta_1 (\sum b_i y_i + \sum c_i y_i) = (1 - \alpha_1) \sum b_i y_i \quad (2)$$

Solve (1) and (2) together, we can get  $\alpha_1 = \frac{\sum a_i y_i}{\sum a_i y_i + \sum b_i y_i + \sum c_i y_i}$ ,  $\beta_1 = \frac{\sum b_i y_i}{\sum a_i y_i + \sum b_i y_i + \sum c_i y_i}$

Follow the same procedure, we can get  $\gamma_1 = \frac{\sum c_i y_i}{\sum a_i y_i + \sum b_i y_i + \sum c_i y_i}$ , and  $\alpha_0 = \frac{\sum a_i (1-y_i)}{\sum a_i (1-y_i) + \sum b_i (1-y_i) + \sum c_i (1-y_i)}$   
 $\beta_0 = \frac{\sum b_i (1-y_i)}{\sum a_i (1-y_i) + \sum b_i (1-y_i) + \sum c_i (1-y_i)}$ ,  $\gamma_0 = \frac{\sum c_i (1-y_i)}{\sum a_i (1-y_i) + \sum b_i (1-y_i) + \sum c_i (1-y_i)}$

### Problem 2

#### Part A

The missing transition probabilities are  $P(q_{t+1} = 1 | q_t = 2) = 1 - q_{11} = 0$  and  $P(q_{t+1} = 2 | q_t = 2) = 1 - q_{12} = 0$ , and the two missing probabilities are  $e_1(B) = P(O_t = B | q_t = 1) = 1 - e_1(A) = 0.01$  and  $e_2(A) = P(O_t = A | q_t = 2) = 1 - e_2(B) = 0.49$

#### Part B

$$P(\text{generate } A) = \pi_1 * e_1(A) + \pi_2 * e_2(A) = 0.49 \times 0.99 + 0.51 \times 0.49 = 0.735$$

$$P(\text{generate } B) = \pi_1 * e_1(B) + \pi_2 * e_2(B) = 0.49 \times 0.01 + 0.51 \times 0.51 = 0.265$$

So A is the most symbol appear in the first position of the sequence.

#### Part C

From the above we know that the most probable first symbol is A. Since  $q_{11} = q_{12} = 1$ , no matter the first state is 1 or 2, the second and third states must be 1. since  $e_1(A) = 0.99$ , so the most probable symbol in

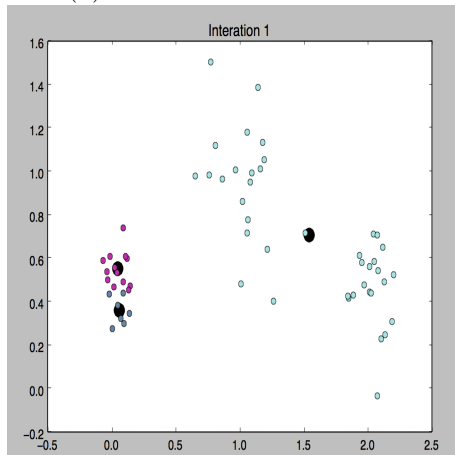
second and third positions are As. So the sequence of three output symbols that has the highest probability being generated is A A A.

## Problem 3

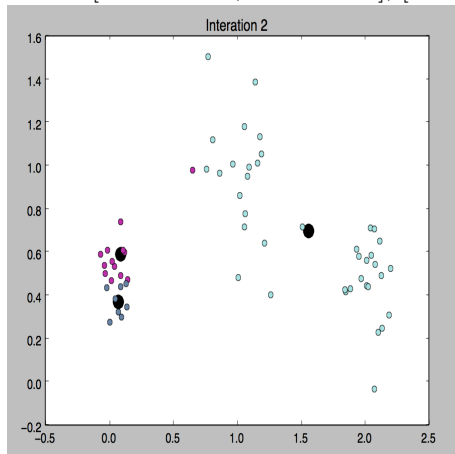
### Part A

It is a bad idea since if  $k$  is not fixed,  $J(c, \mu, k)$  can reach zero by having  $n$  centroids whose positions are the  $n$  datapoints. Under this case,  $k = n$ ,  $\mu_i = x^{(i)}$ ,  $c^{(i)} = i$

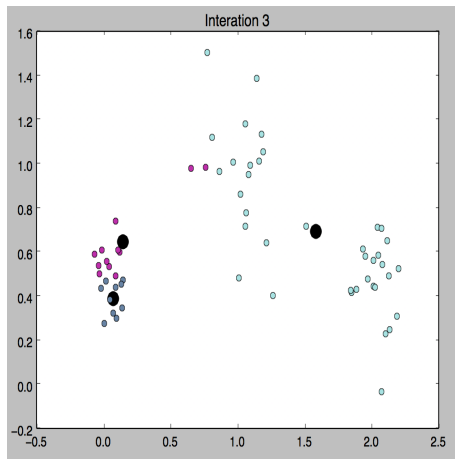
Part (d)



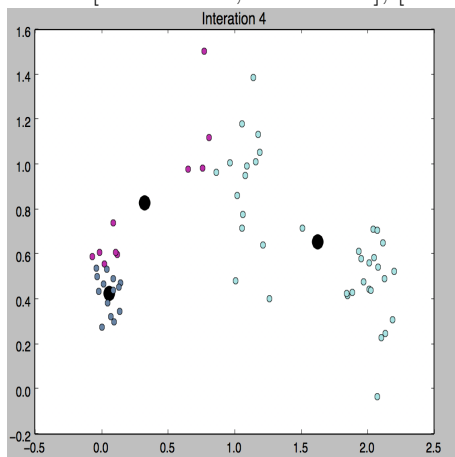
Center: [ 1.53574549, 0.70317209], [ 0.04416798, 0.548694 ], [ 0.05848729, 0.35555227]



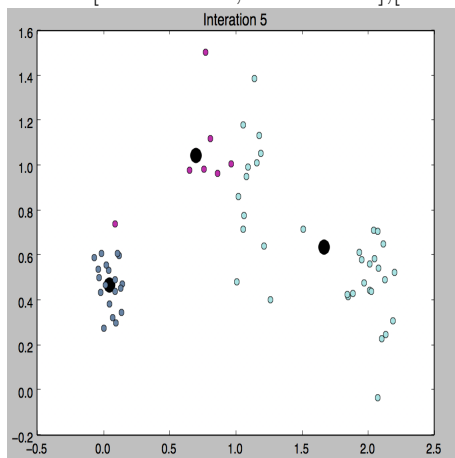
Center: [ 1.55846957, 0.69620803], [ 0.08399041, 0.58882485], [ 0.06765327, 0.36774192]



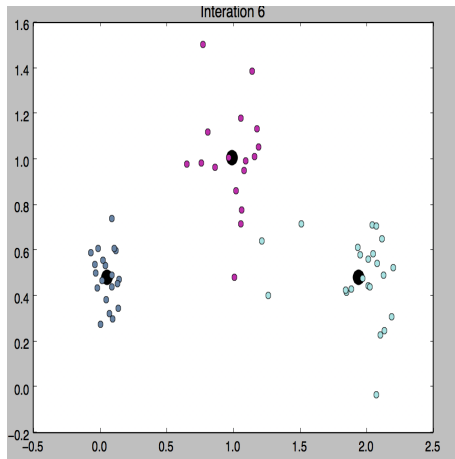
Center: [ 1.57957558, 0.6886763 ], [ 0.14104785, 0.64172345 ], [ 0.06969682, 0.38783907 ]



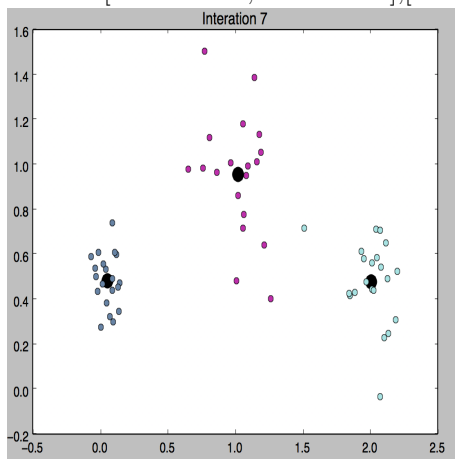
Center: [ 1.62366096, 0.65422844 ], [ 0.32109265, 0.82675015 ], [ 0.05362096, 0.42350331 ]



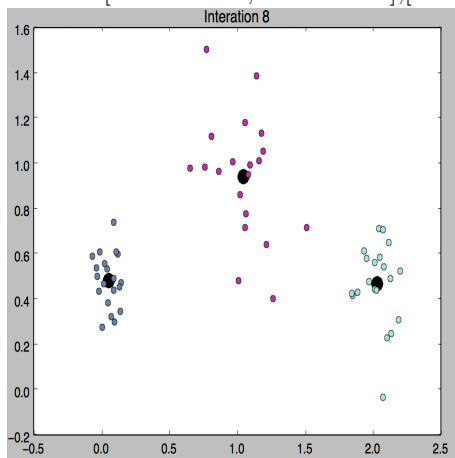
Center: [ 1.66538394, 0.63481783 ], [ 0.69870477, 1.04031048 ], [ 0.04733828, 0.46751536 ]



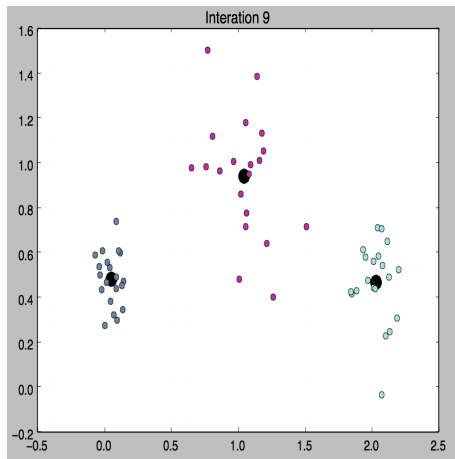
Center: [ 1.93884659, 0.48088921],[ 0.99037342, 1.00390775],[ 0.04917974, 0.4810944 ]



Center: [ 2.00594139, 0.47723895],[ 1.01605529, 0.95288767], [ 0.04917974, 0.4810944 ]

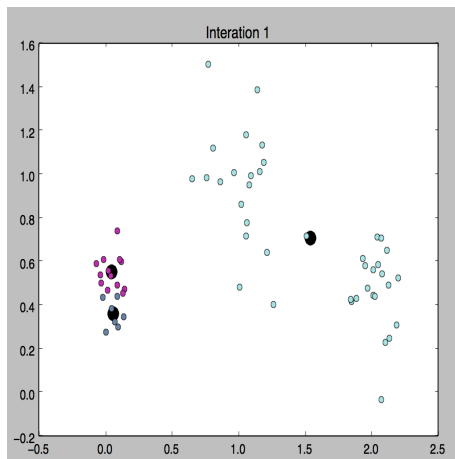


Center:[ 2.03085592, 0.46538378], [ 1.04063507, 0.9409604 ],[ 0.04917974, 0.4810944 ]

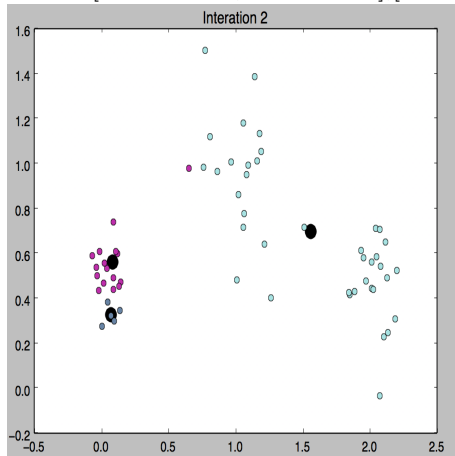


Center:[ 2.03085592, 0.46538378], [ 1.04063507,0.9409604 ],[ 0.04917974, 0.4810944 ]

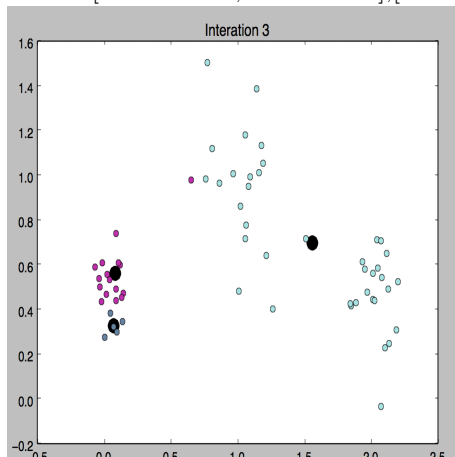
So k-mean converges in 9 iterations in this case.

**Part E**

Center: [ 1.50765091, 0.71434218], [ 0.04054534, 0.52890919], [ 0.06755541, 0.31829728]



Center: [ 1.50765091, 0.71434218], [ 0.04054534, 0.52890919], [ 0.06755541, 0.31829728]

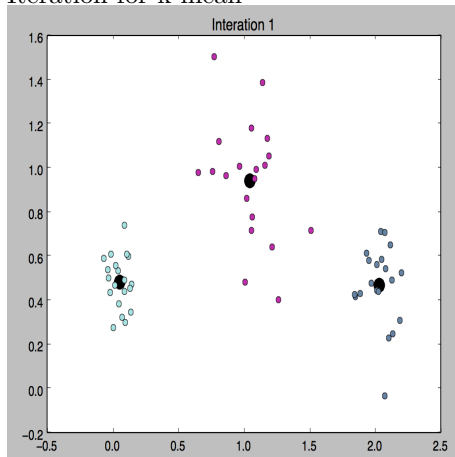


Center: [ 1.50765091, 0.71434218], [ 0.04054534, 0.52890919], [ 0.06755541, 0.31829728]

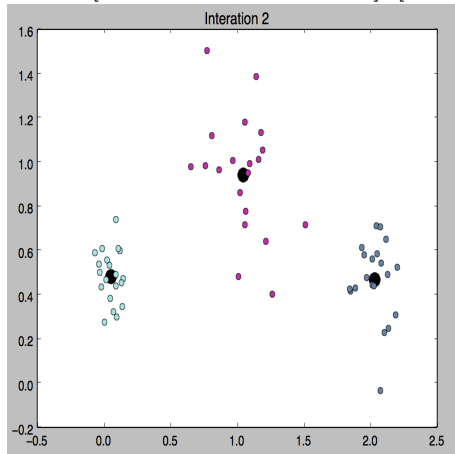
So k-medoids converges in 3 iterations , but I think it does not cluster as well as k-means in this case

**Part F**

Iteration for k-mean

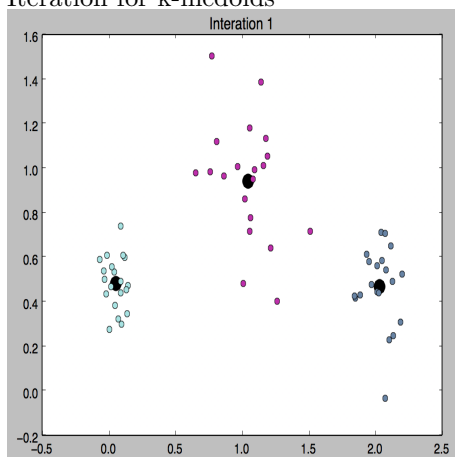


Center: [ 0.04917974, 0.4810944 ], [ 1.04063507, 0.9409604 ], [ 2.03085592, 0.46538378]

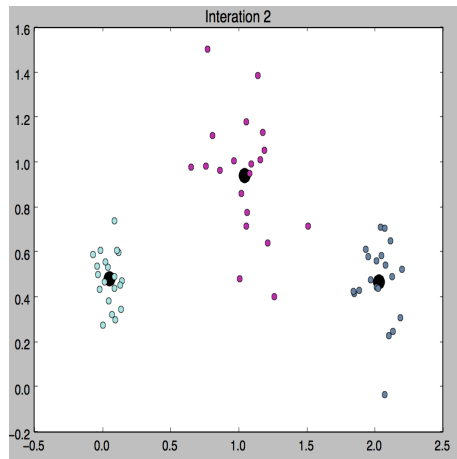


Center: [ 0.04917974, 0.4810944 ], [ 1.04063507, 0.9409604 ], [ 2.03085592, 0.46538378]

Iteration for k-medoids



Center: [ 0.0124713 , 0.46772052], [ 1.07699221, 0.94787531], [ 2.01197635, 0.44000531]



Center:[ 0.0124713 , 0.46772052], [ 1.07699221, 0.94787531], [ 2.01197635, 0.44000531]

When using cheat initialization, both k-means and k-medoids converges in 2 iterations and both generalize well.