

Hw5

$$1. (a) \textcircled{1} \text{ feature map (size) } = \frac{W-k+p}{s} + 1 = \frac{64-3+2 \times 1}{1} + 1$$

and \therefore there are 4 output channels = 64

$$\therefore \text{output size} = 4 \times 64 \times 64$$

$\textcircled{2}$ For one ^{unit} kernel, there are $3 \times 3 \times 4$ parameters

and \therefore there are 4 output channels every layer and 10 kernel (layers)

$$\therefore \text{we have } 10 \times (3 \times 3 \times 4 + 4 \times 1) = 1480 \text{ parameters in total}$$

bias

$$(b) \textcircled{1} \text{ we can also use } \left(\frac{W-k+p}{s} + 1 \right) \text{ to calculate the result with}$$

$$= \frac{64-2}{2} + 1 = 32$$

But pooling layer doesn't influence the depth of input

\therefore output depth is also 4

$$\therefore \text{output size} = 4 \times 32 \times 32$$

$\textcircled{2}$ Because max pooling is a rule / formula

\therefore it doesn't need other parameters

\therefore In pooling layer, we need 0 parameter.



2. (a) Kmeans ++

① The first centroid $X^{(1)} = (2.8)$

(2.5) $X^{(1)}$	9	$\frac{9}{194}$	the first random number is 0.6 \therefore we will choose $X^{(6)}$ as the next centroid.
(1.2) $X^{(3)}$	37	$\frac{37}{194}$	
(5.8) $X^{(4)}$	9	$\frac{9}{194}$	
(7.3) $X^{(5)}$	50	$\frac{50}{194}$	
(6.4) $X^{(6)}$	32	$\frac{32}{194} \Rightarrow [0.54, 0.706]$	
(8.4) $X^{(7)}$	52	$\frac{52}{194}$	
(4.7) $X^{(8)}$	5	$\frac{5}{194}$	

▷ Normalized

② The second centroid $X^{(6)} = (6.4)$

(2.5) $X^{(2)}$	17	9	$\frac{9}{58} [0, 0.55]$ the second random number
(1.2) $X^{(3)}$	29	29	$\frac{29}{58} [0.55, 0.5]$ is 0.2
(5.8) $X^{(4)}$	17	9	$\frac{9}{58} \therefore$ we will choose $X^{(3)}$ as
(7.3) $X^{(5)}$	2	2	$\frac{2}{58}$ the third centroid.
(6.4) $X^{(7)}$	4	4	$\frac{4}{58}$
(4.7) $X^{(8)}$	13	5	$\frac{5}{58}$

 $D^2 \Rightarrow \min(D^2)$ Normalized

\therefore Finally } $C_1 : X^{(1)} = (2.8)$ three centroids
 $C_2 : X^{(6)} = (6.4)$
 $C_3 : X^{(3)} = (1.2)$



No.

Date. / /

Iteration 1

(b)	C_1	C_2	C_3	$Q(c, c) = \frac{1}{8} \cdot [0+9+0+9+2+4+0+5]$ $= \frac{29}{8}$
$x^{(1)}$	(0)	$\sqrt{32}$	$\sqrt{37}$	
$x^{(2)}$	(3)	$\sqrt{17}$	$\sqrt{10}$	
$x^{(3)}$	$\sqrt{37}$	$\sqrt{29}$	(0)	At the same time new $C_1 = (\frac{13}{4}, 7)$
$x^{(4)}$	(3)	$\sqrt{17}$	$\sqrt{52}$	new $C_2 = (7, \frac{11}{3})$
$x^{(5)}$	$\sqrt{50}$	($\sqrt{2}$)	$\sqrt{37}$	new $C_3 = (1, 2)$
$x^{(6)}$	$\sqrt{32}$	(0)	$\sqrt{29}$	
$x^{(7)}$	$\sqrt{52}$	(2)	$\sqrt{53}$	
$x^{(8)}$	($\sqrt{5}$)	$\sqrt{13}$	$\sqrt{34}$	

(c) iteration 2	$C_1 (\frac{13}{4}, 7)$	$C_2 (7, \frac{11}{3})$	$C_3 (1, 2)$
$x^{(1)} (2.8)$	($\sqrt{\frac{41}{16}}$)	$\sqrt{\frac{394}{9}}$	$\sqrt{37}$
$x^{(2)} (2.5)$	($\sqrt{\frac{89}{16}}$)	$\sqrt{\frac{241}{9}}$	$\sqrt{10}$
$x^{(3)} (1.2)$	($\sqrt{\frac{431}{16}}$)	$\sqrt{\frac{349}{9}}$	(0)
$x^{(4)} (5.8)$	($\sqrt{\frac{65}{16}}$)	$\sqrt{\frac{205}{9}}$	$\sqrt{52}$
$x^{(5)} (7.3)$	($\sqrt{\frac{431}{16}}$)	($\sqrt{\frac{4}{9}}$)	$\sqrt{37}$
$x^{(6)} (6.4)$	($\sqrt{\frac{245}{16}}$)	($\sqrt{\frac{10}{9}}$)	$\sqrt{29}$
$x^{(7)} (8.4)$	($\sqrt{\frac{505}{16}}$)	($\sqrt{\frac{10}{9}}$)	$\sqrt{53}$
$x^{(8)} (4.7)$	($\sqrt{\frac{9}{16}}$)	$\sqrt{\frac{181}{9}}$	$\sqrt{34}$

\therefore Just need two iteration, the algorithm can converge.

(2)

$$Q(c, c) = \frac{1}{8} \left(\frac{41}{16} + \frac{89}{16} + \frac{65}{16} + 0 + \frac{4}{9} + \frac{10}{9} + \frac{10}{9} + \frac{9}{16} \right)$$

$$= \frac{185}{96}$$



3. ① VAE: Variational Autoencoder

GAN: Generative Adversarial Network \Rightarrow cycle GAN / stack GAN / conditional GAN

Here, p_{data} is the distribution of real data, and z is a random noise sampled from prior distribution $p(z)$. And then $G(z)$ is the generated data, and D is the discriminator.

② A: minimax objective function

Explanation

$$\min_{D_g} \max_{D_d} [E_{x \sim p_{data}} \log D_d(x) + E_{z \sim p(z)} \log (1 - D_d(G(z)))]$$

B: How to update parameters

a. we update the discriminator at first by using gradient ascent

$$\max_{D_d} [E_{x \sim p_{data}} \log D_d(x) + E_{z \sim p(z)} \log (1 - D_d(G(z)))]$$

using backprop on the classification objective

b. Then we update the generator by using gradient descent

$$\min_{D_g} E_{z \sim p(z)} \log (1 - D_d(G(z)))$$

using backprop

