

**NANYANG  
TECHNOLOGICAL  
UNIVERSITY**  

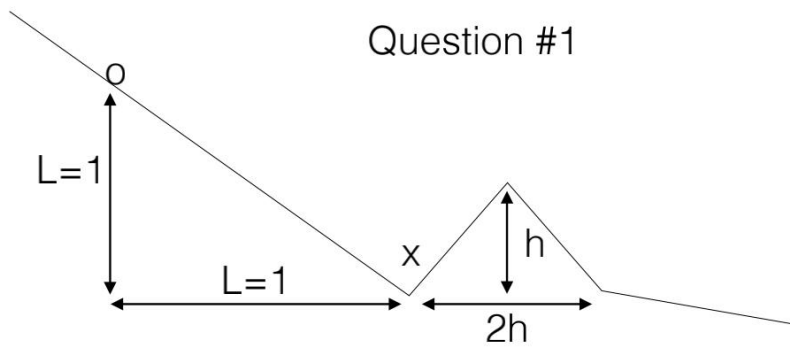
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**SINGAPORE**

## BS6207 Assignment 2

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## Question #1



The diagram above shows a plot of a 1D function and gradient descent is applied to minimise the function at the point 'o'. there is a bump a distance  $L$  away with bump dimensions given as  $h \times 2h$ . Let  $L = 1$ ,  $a = 0.3$  and  $h > a$  where  $a$  is the learning rate

(a) If we apply standard gradient descent to minimize the function at the point 'o':

$$\frac{\partial \text{Loss}}{\partial y} = -1, x < 1$$

$$\frac{\partial \text{Loss}}{\partial y} = 1, 1 < x < 1 + h$$

$$\frac{\partial \text{Loss}}{\partial y} = -1, 1 + h < x < 1 + 2h$$

Assume that  $y = 1$  with learning rate  $a = 0.3$ ,

$$y = y - a * \frac{\partial \text{Loss}}{\partial y} = 1 - 0.3 * (-1) = 0.7$$

$$y = y - a * \frac{\partial \text{Loss}}{\partial y} = 0.7 - 0.3 * (-1) = 0.4$$

$$y = y - a * \frac{\partial \text{Loss}}{\partial y} = 0.4 - 0.3 * (-1) = 0.1$$

$$y = y - a * \frac{\partial \text{Loss}}{\partial y} = 0.1 - 0.3 * (-1) = 0.4$$

$$y = y - a * \frac{\partial \text{Loss}}{\partial y} = 0.4 - 0.3 * (1) = 0.1$$

.....

$$y = y - a * \frac{\partial \text{Loss}}{\partial y} = 0.4 - 0.3 * (1) = 0.1$$

At the point (0.9, 0.1) with the learning rate  $a = 0.3$ .

```

# Based on the Qa's formula to get x
def grad(x, h):
    if x<1:
        return -1
    elif 1<x< (1+h):
        return 1
    elif (1+h)< x<(1+2*h):
        return -1
    else:
        return -0.3
# Adam Optimizer
def max_h( deri, n_iter, alpha, betal, beta2, eps=0):
    for h in np.arange(0.3,1,0.0001):
        x = 0
        m = 0.0
        v = 0.0
        for t in range(1,n_iter):
            g = grad(x,h)
            m = betal * m + (1 - betal) * g
            v = beta2 * v + (1 - beta2) * g**2
            mhat = m / (1.0 - betal**t)
            vhat = v / (1.0 - beta2**t)
            x = x - alpha * mhat / (vhat**0.5 )
            if x>(1+h):
                break
        if x<(1+h):
            print("The maximum h=", h)
            break
#generate the parameters of Adam.
N_iter = 1000
alpha = 0.3
betal = 0.9
beta2 = 0.999
max_h( grad, N_iter, alpha, betal, beta2)

```

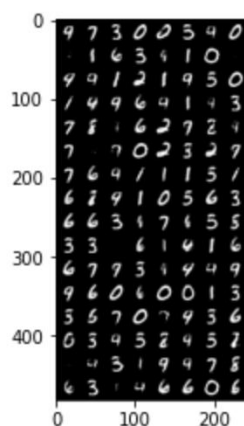
The maximum h= 0.41019999999998785

The maximum h= 0.41019999999998785

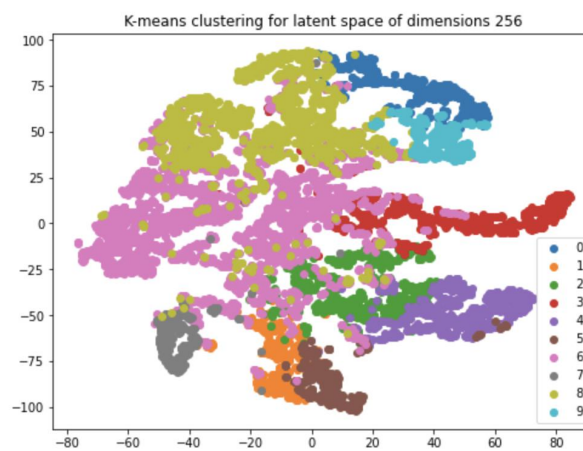
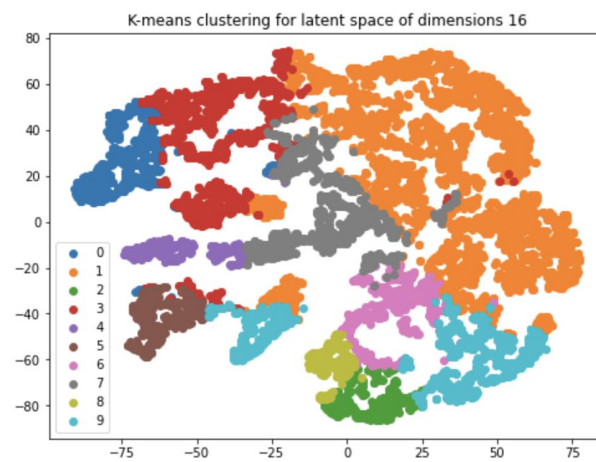
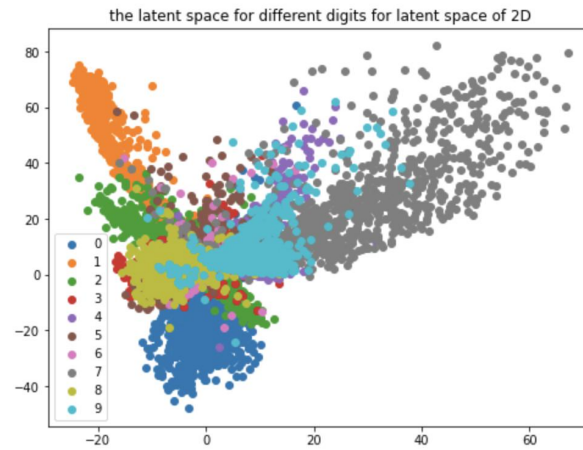
Oscqrgrn ! 0

&' Bcqqel \_l \_srmcl anbcprmr\_i c g KLGRk \_ecq ugf j\_rcl rqn\_ac  
 bdk cl qgrn md0\*/ 4\*034, Rp\_d \_srmcl anbcpu gf J/ + mpk pcam qpsargn  
 jmqq ,

epoch: 50, loss is 0.16591624915599823



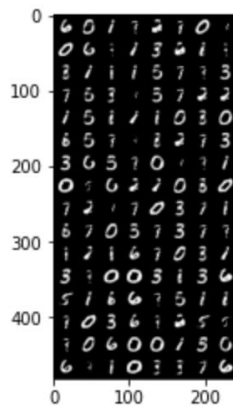
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 I k c\_l q ajsqr p e dnp j\_rcl r qn\_ac m b g cl q m q / 4\*034, Sqc m c anj p  
 dpc\_af bgr, Pcnmr \_jj pqsjr q,



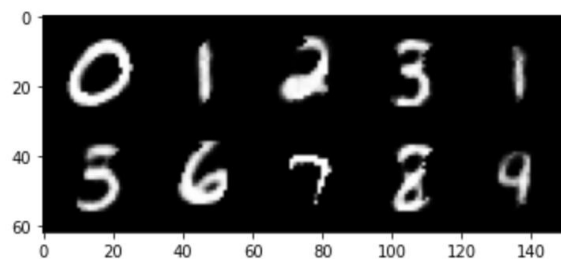
I think K-means clustering for latent space of dimensions 16 present most well.

&' Bcqqel \_l mf cpl csp\_j l cru mp ábq] l crī mbqap k g \_rc ` cru ccl ` jsp  
 g \_ecq \_l b ajc \_p k \_ecq, @sp k \_ecq a \_l ` c ecl cp\_rcb ` wr\_i g e rf c  
 m p g \_j KL QR b \_r \_l b bmqrk c e\_sqqg l ` jsp

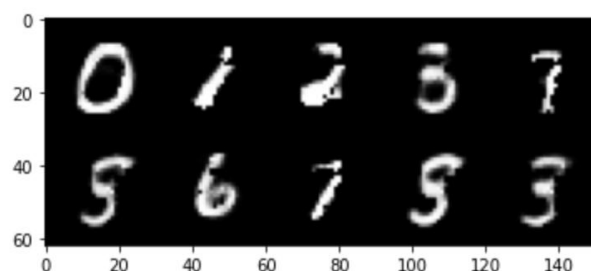
epoch: 50, loss is 0.18306782841682434



Rp\_g \_srmcl ambcpu gf J/ + mp k pcaml qpsargm jmq ) bqap k g \_mpjmq,  
 K\_i c pcaml qpsarc b g \_ecq \_q ajc \_p \_q nmqqg jc\* rf \_r g \* rf c \_srm  
 cl ambcpu g j l ccb rm ` c rp\_g cb qmrf \_r ábq] l crī qamp g \_q \_ ajc \_p k \_ec,



&'



&'

Maybe the reconstructed image of (a) is closer to the original image of (b) because the blurring image is used as the input and there is a gap with the original image.