GNR638: Assignment 2

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Qn 1

For the given specifications, the gradients obtained using Analytical method and backpropagation are as follows:

```
Analytical gradients are
[[-0.01637912 -0.01637912]
 [-0.02355449 -0.02355449]]
[-0.16504242 -0.16504242]
============================================

Backpropagated gradient are
[[-0.01638029 -0.01638029]
 [-0.02355442 -0.02355442]]
[[-0.16096605 -0.16504206]]
```

Qn 2

The input dimension is $12 \times 12 \times 3$ and output dimension is $8 \times 8 \times 256$.

Normal Convolution :

In normal convolution, convolution is applied across all spatial dimension/channels. So a there will be 256 kernels of size $5 \times 5 \times 3$. So total multiplications will be $5 \times 5 \times 3 \times 8 \times 8 \times 256$ which is equal to $12, 28, 800$.

Depthwise Convolution :

In depthwise convolution, first we apply convolution along channels and then we do pointwise convolution. So first we for each channel of size 12×12 we have a kernel of size 5×5, after convolution we get $8 \times 8 \times 3$ dimension. Then for each $1 \times 1 \times 3$ column we apply pointwise convolution by using 256 kernels to get final output with dimension $8 \times 8 \times 256$. So total multiplication are $5 \times 5 \times 8 \times 8 \times 3 + 8 \times 8 \times 3 \times 256 = 53952$.

Qn 3

We are given that the relation between input and output variables is defined by poisson distribution, So we have:

$$P(y_i|x_i, \theta) = \frac{e^{-\theta^T x_i}(\theta^T x_i)^{y_i}}{y_i!}$$

Hence, the likelihood function will be:

$$L(\theta) = \prod_{i=1}^{i=n} \frac{e^{-\theta^T x_i}(\theta^T x_i)^{y_i}}{y_i!}$$

Taking log on both side:

$$log(L(\theta)) = -\sum \theta^T x_i + \sum y_i \log(\theta^T x_i) - \sum \log y_i!$$

Maximizing this likelihood is same as minimizing $\sum \theta^T x_i - \sum y_i \log(\theta^T x_i) + \sum \log y_i!$ wrt to $theta$, hence

$$Poissonloss = \sum \theta^T x_i - \sum y_i \log(\theta^T x_i) + \sum \log y_i!$$