Practice Questions for Mid-Semester Test

COMP3010 Machine Learning

Question 1 – Machine learning methods and problem formulation

You are developing a machine learning system to classify the images into two different classes: red images and green images.

- **Name a suitable method for this task and justify your answer.**
  Since we are developing an algorithm to classify images, we are dealing with a classification problem. Therefore, a suitable method is softmax regression as it allows us to train models for multiclass classification.

- **Use this example with the named method to describe the four important key components of a machine learning algorithm.**
  The four key features of a machine learning algorithm are:
  1. The *data* which we seek to learn from. In this case, the data is images.
  2. A *model* to transform the data. In this case, the model is softmax.
  3. An *objective function* which quantifies the performance of the model. In this case, the objective function is cross-entropy loss.
  4. An *algorithm* to adjust the model's parameters to optimise the objective function. In this case, the algorithm is stochastic gradient descent (SGD).

Question 2: Multilayer Perception (MLP)

Suppose you are implementing an MLP network with two hidden layers which share both their weights and biases, and a linear output layer, for image classification with 5 classes, and the input image size is 20x20.

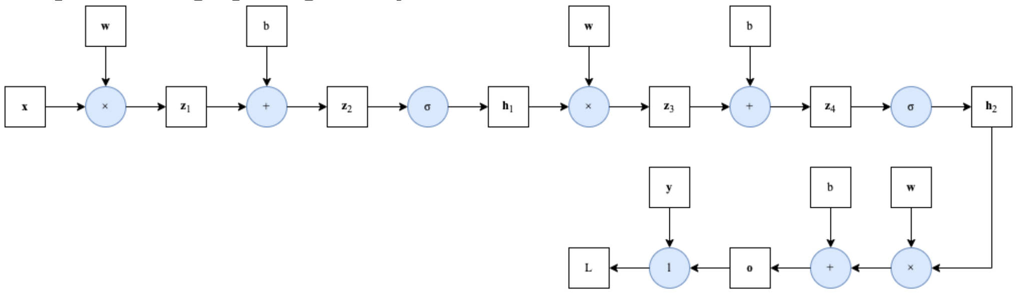
2.1. Define the MLP model with `nn.Sequential()`**.**

```
shared = nn.Linear(400, 256)
net = nn.Sequential(nn.Flatten(),
                    shared,
                    nn.ReLU(),
                    shared,
                    nn.ReLU()
                    nn.Linear(256, 5))
```

2.2. Write the encoding of the class labels.
Using one-hot encoding, the encoding of the class labels is given by y ∈ {(1, 0, 0, 0, 0), (1, 0, 0, 0, 0), (1, 0, 0, 0, 0), (1, 0, 0, 0, 0), (1, 0, 0, 0, 0)}.

2.3. Name the loss function.
The loss function is SGD.

2.4. Draw the computational graph of the forward propagation path.
The computational graph is given by:



Computational Graph of an MLP Network

Question 3. Regularisation

3.1. Explain why regularization methods are required in training neural networks.
They are required as, often, neural networks are prone to *overfitting*–the phenomenon of fitting our training data more closely than fitting the underlying distribution. When we train neural networks, due to resource constraints we must learn from only a fraction of data examples. However, when working with limited data sets, we are in danger of discovering apparent associations that eventually turn out to not hold up when we collect more data.

3.2. Name two regularisation methods and briefly explain how to use them in training of neural networks.
One regularisation method is *weight decay*. With this method, we compute the norm of the weight vector and add it as a penalty term in the loss function. Therefore, rather than minimising the prediction loss on the training labels, we opt to minimise the sum of the prediction loss and the penalty term. Now, if the norm of the weight vector is too large, our learning algorithm might focus on minimising the weight norm rather than the training error, reducing the likelihood of overfitting.

Another such method is *dropout*. With this method, we inject noise while computing each hidden layer during training by literally dropping out some neurons. Throughout training, on each iteration, standard dropout consists of zeroing out some fraction of the nodes in each layer before calculating the subsequent layer. Moreover, we ensure to dropout neurons in an unbiased manner so that the expected value of each layer–while fixing the others–equals the value it would have taken without dropout.

Question 4. **Hyper-parameters**

With an example to explain what hyper-parameters are in training of neural networks and how they should be selected.
Hyperparameters are parameters which are tunable but tuned outside of the training loop. These parameters should be selected through the process of *hyperparameter tuning*, which typically requires that we adjust them based on the results of the training loop as assessed on a separate validation dataset. For example, the number of epochs–which is defined as the number of times the training loop iterates–is considered a hyperparameter as it is tuned after training our model.

Question 5 – Convolutional Neural networks

5.1. Suppose 3x3 convolution kernels are used in a convolutional neural network with three convolutional layers, what is the receptive field of the element in the last convolutional layer? How many layers do we need if a receptive field of 21x21 is required?

The receptive field RF is given by:

$$\begin{aligned} RF &= \left(k_h l - (l-1)\right) \times \left(k_w l - (l-1)\right) \\ &= \left((3)(3) - (3-1)\right) \times \left((3)(3) - (3-1)\right) \\ &= (9-2) \times (9-2) \\ &= 7 \times 7 \end{aligned}$$

where:

- k_h and k_w denote the height and width dimensions, respectively, of kernel k
- l denotes the number of convolutional layers

Therefore, the receptive field RF of the elements in the last convolutional layer is 7 × 7.

The number of layers needed l is given by:

$$\begin{aligned} RF &= \left(k_h l - (l-1)\right) \times \left(k_w l - (l-1)\right) \\ 21 \times 21 &= \left(3l - (l-1)\right) \times \left(3l - (l-1)\right) \\ 441 &= (3l - l + 1) \times (3l - l + 1) \\ 441 &= (2l+1) \times (2l+1) \\ 21 &= 2l + 1 \\ 20 &= 2l \\ 10 &= l \\ l &= 10 \end{aligned}$$

where:

- k_h and k_w denote the height and width dimensions, respectively, of kernel k
- l denotes the number of convolutional layers

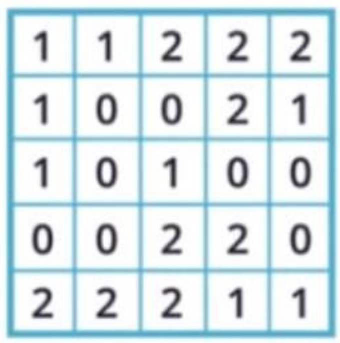
Therefore, the number of layers needed l if a receptive field of 21 × 21 is required is 10.

5.2. Describe how the neurons of convolutional neural networks and multilayer network are designed differently and why convolutional neural networks are more suitable for image classification tasks.

In multi-layer networks, at each subsequent layer, neurons are designed to receive, as inputs, the output of every neuron in the previous layer. In convolutional neural networks, however, neurons are designed to receive only a window of outputs from the previous layer.

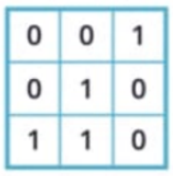
Unlike multilayer networks, which are invariant to the order of the features, convolutional neural networks enable us to leverage the knowledge that nearby pixels are typically related to each other, which can encourage the construction of more efficient models for learning from images.

5.3. Consider the following image



1	1	2	2	2
1	0	0	2	1
1	0	1	0	0
0	0	2	2	0
2	2	2	1	1

and a convolution kernel below with stride 2 and zero padding (2,2).



0	0	1
0	1	0
1	1	0

What is the output of the convolution?

The output O of the convolution is given by:

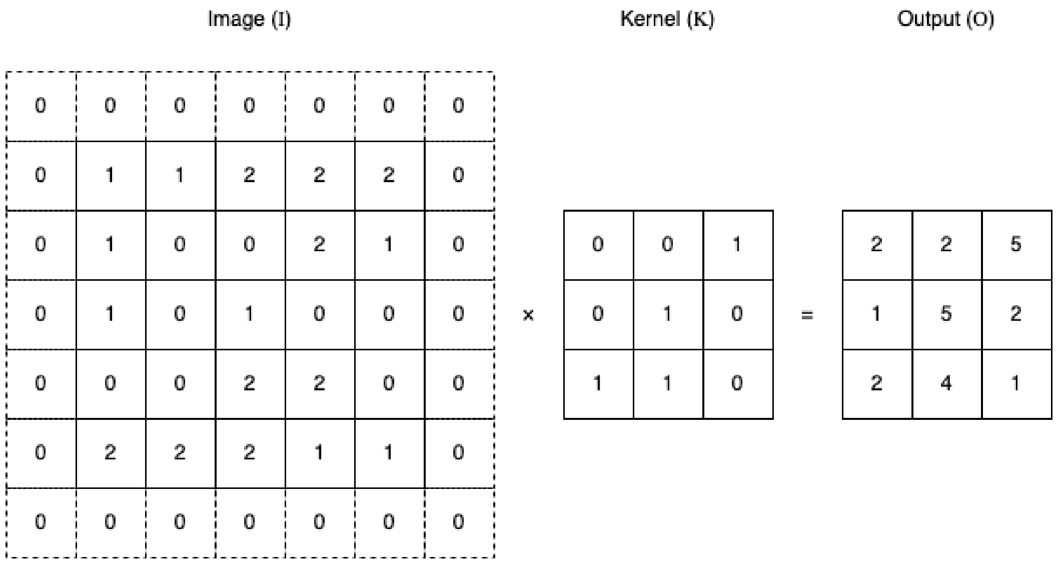


Image (I)

0	0	0	0	0	0	0
0	1	1	2	2	2	0
0	1	0	0	2	1	0
0	1	0	1	0	0	0
0	0	0	2	2	0	0
0	2	2	2	1	1	0
0	0	0	0	0	0	0

×

Kernel (K)

0	0	1
0	1	0
1	1	0

=

Output (O)

2	2	5
1	5	2
2	4	1

Cross-correlation with Zero-padding and Stride (2, 2)

END OF TEST