Programming Assignment 2 - CAINE, Wilbert (20584260)

Q1

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 64, 64]           9,408
       BatchNorm2d-2           [-1, 64, 64, 64]             128
              ReLU-3           [-1, 64, 64, 64]               0
         MaxPool2d-4           [-1, 64, 32, 32]               0
            Conv2d-5           [-1, 64, 32, 32]          36,864
       BatchNorm2d-6           [-1, 64, 32, 32]             128
              ReLU-7           [-1, 64, 32, 32]               0
            Conv2d-8           [-1, 64, 32, 32]          36,864
       BatchNorm2d-9           [-1, 64, 32, 32]             128
         Identity-10           [-1, 64, 32, 32]               0
             ReLU-11           [-1, 64, 32, 32]               0
         ResBlock-12           [-1, 64, 32, 32]               0
           Conv2d-13           [-1, 64, 32, 32]          36,864
      BatchNorm2d-14           [-1, 64, 32, 32]             128
             ReLU-15           [-1, 64, 32, 32]               0
           Conv2d-16           [-1, 64, 32, 32]          36,864
      BatchNorm2d-17           [-1, 64, 32, 32]             128
         Identity-18           [-1, 64, 32, 32]               0
             ReLU-19           [-1, 64, 32, 32]               0
         ResBlock-20           [-1, 64, 32, 32]               0
           Conv2d-21          [-1, 128, 16, 16]          73,728
      BatchNorm2d-22          [-1, 128, 16, 16]             256
             ReLU-23          [-1, 128, 16, 16]               0
           Conv2d-24          [-1, 128, 16, 16]         147,456
      BatchNorm2d-25          [-1, 128, 16, 16]             256
           Conv2d-26          [-1, 128, 16, 16]           8,192
      BatchNorm2d-27          [-1, 128, 16, 16]             256
             ReLU-28          [-1, 128, 16, 16]               0
         ResBlock-29          [-1, 128, 16, 16]               0
           Conv2d-30          [-1, 128, 16, 16]         147,456
      BatchNorm2d-31          [-1, 128, 16, 16]             256
             ReLU-32          [-1, 128, 16, 16]               0
           Conv2d-33          [-1, 128, 16, 16]         147,456
      BatchNorm2d-34          [-1, 128, 16, 16]             256
         Identity-35          [-1, 128, 16, 16]               0
             ReLU-36          [-1, 128, 16, 16]               0
         ResBlock-37          [-1, 128, 16, 16]               0
           Conv2d-38            [-1, 256, 8, 8]         294,912
      BatchNorm2d-39            [-1, 256, 8, 8]             512
             ReLU-40            [-1, 256, 8, 8]               0
           Conv2d-41            [-1, 256, 8, 8]         589,824
      BatchNorm2d-42            [-1, 256, 8, 8]             512
           Conv2d-43            [-1, 256, 8, 8]          32,768
      BatchNorm2d-44            [-1, 256, 8, 8]             512
             ReLU-45            [-1, 256, 8, 8]               0
         ResBlock-46            [-1, 256, 8, 8]               0
           Conv2d-47            [-1, 256, 8, 8]         589,824
      BatchNorm2d-48            [-1, 256, 8, 8]             512
             ReLU-49            [-1, 256, 8, 8]               0
           Conv2d-50            [-1, 256, 8, 8]         589,824
```

```
     BatchNorm2d-51              [-1, 256, 8, 8]             512
        Identity-52              [-1, 256, 8, 8]               0
            ReLU-53              [-1, 256, 8, 8]               0
        ResBlock-54              [-1, 256, 8, 8]               0
          Conv2d-55              [-1, 512, 8, 8]       1,179,648
     BatchNorm2d-56              [-1, 512, 8, 8]           1,024
            ReLU-57              [-1, 512, 8, 8]               0
          Conv2d-58              [-1, 512, 8, 8]       2,359,296
     BatchNorm2d-59              [-1, 512, 8, 8]           1,024
          Conv2d-60              [-1, 512, 8, 8]         131,072
     BatchNorm2d-61              [-1, 512, 8, 8]           1,024
            ReLU-62              [-1, 512, 8, 8]               0
        ResBlock-63              [-1, 512, 8, 8]               0
          Conv2d-64              [-1, 512, 8, 8]       2,359,296
     BatchNorm2d-65              [-1, 512, 8, 8]           1,024
            ReLU-66              [-1, 512, 8, 8]               0
          Conv2d-67              [-1, 512, 8, 8]       2,359,296
     BatchNorm2d-68              [-1, 512, 8, 8]           1,024
        Identity-69              [-1, 512, 8, 8]               0
            ReLU-70              [-1, 512, 8, 8]               0
        ResBlock-71              [-1, 512, 8, 8]               0
       AvgPool2d-72              [-1, 512, 1, 1]               0
```

Input
Conv+BN+ReLU = 64 x 64 x 64
Max pooling = 64 x 32 x 32
ResBlock = 64 x 32 x 32
ResBlock = 64 x 32 x 32
ResBlock-D = 128 x 16 x 16
ResBlock = 128 x 16 x 16
ResBlock-D = 256 x 8 x 8
ResBlock = 256 x 8 x 8
ResBlock = 512 x 8 x 8
ResBlock = 512 x 8 x 8
Average pooling = 512 x 1 x 1
Output

Q2

Kernel size = 8 x 8
Stride = 1

Q3

Convolution is a possible alternative to the pooling layer. By applying convolutional layer with the certain settings, such as the number of output channels equals to the number of input channels and the stride equals to the kernel size, we will obtain a 1D vector out of the output feature map. In the case of average pooling, we could define a convolutional layer where the weights would compute the average of the receptive field with the same kernel size and stride and without bias. More specifically, the weights are all equal to one another with sum of one. Thus, we obtain that the weights equal 1/kernel_side_length^2. This process would mimic the process of average pooling. With this understanding, we could view the average pooling layer as a special case of convolutional layer. One thing to note is that average pooling layer do not have trainable parameter unlike convolutional layer.

Q4

The first ResBlock consists of:

```
            Conv2d-5           [-1, 64, 32, 32]          36,864
       BatchNorm2d-6           [-1, 64, 32, 32]             128
              ReLU-7           [-1, 64, 32, 32]               0
            Conv2d-8           [-1, 64, 32, 32]          36,864
       BatchNorm2d-9           [-1, 64, 32, 32]             128
         Identity-10           [-1, 64, 32, 32]               0
             ReLU-11           [-1, 64, 32, 32]               0
```

with a total of 73984 trainable parameters.

Q5

None of the layers of the modified ResNet-18 model cannot load the pretrained weights
The following layers of the pretrained weights are discarded: fc

- `fc.weight param cannot be found in our model`
- `fc.bias param cannot be found in our model`

Q6

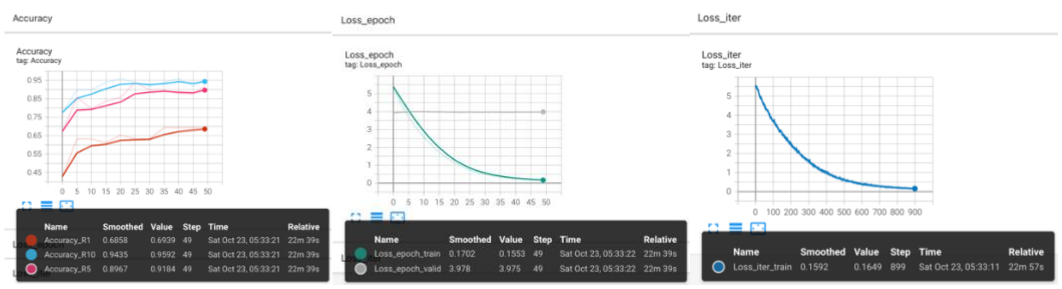
The output dimensionality of the last FC layer depends on the number of candidates, i.e. 230 and 49 for training and validation stage respectively.

Q7

Using dropout layer, we randomly set neurons to zero with the pre-specified probability during the forward pass. So, there is a factor of randomness during the training of the neurons. Another way to interpret the model with dropout in training mode is that we are training a large ensemble of models that share parameters.

Dropout is useful because it prevents co-adaptation of features, and it forces the network to have redundant representation. Thus, we could prevent overfitting the model.

Q8



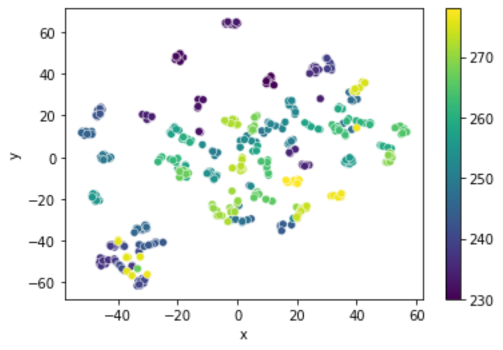
	Name	Smoothed	Value	Step	Time	Relative
●	Accuracy_R1	0.6858	0.6939	49	Sat Oct 23, 05:33:21	22m 39s
●	Accuracy_R10	0.9435	0.9592	49	Sat Oct 23, 05:33:21	22m 39s
●	Accuracy_R5	0.8967	0.9184	49	Sat Oct 23, 05:33:21	22m 39s

	Name	Smoothed	Value	Step	Time	Relative
●	Loss_epoch_train	0.1702	0.1553	49	Sat Oct 23, 05:33:22	22m 39s
●	Loss_epoch_valid	3.978	3.975	49	Sat Oct 23, 05:33:22	22m 39s

	Name	Smoothed	Value	Step	Time	Relative
●	Loss_iter_train	0.1592	0.1649	899	Sat Oct 23, 05:33:11	22m 57s

In the above plots, we observe that the accuracy increases overall while the training and the training loss per iteration decreases overtime as we train for larger epoch number. The validation loss per epoch is not affected as mentioned in the project guideline. The accuracy order from highest to lowest is R10, R5, and R1 which is expected considering the way they are measured where it is generally more difficult to predict correctly given fewer prediction candidates. The training losses are already considerably close to zero at the later epochs. Further hyperparameter tuning and training epochs could potentially yield better results.

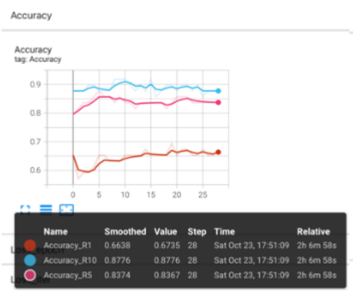
Q9



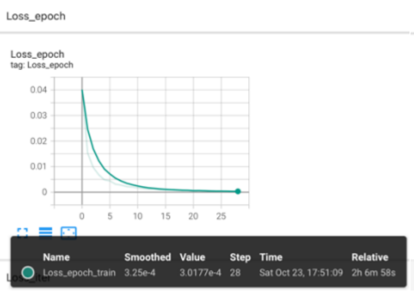
Q10

There are 230 * (10 * 9) * 229 * 10 = 47403000 possible triplets in the training dataset

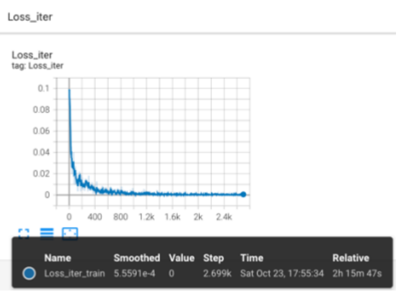
Q11



	Name	Smoothed	Value	Step	Time	Relative
🔴	Accuracy_R1	0.6638	0.6735	28	Sat Oct 23, 17:51:09	2h 6m 58s
🔵	Accuracy_R10	0.8776	0.8776	28	Sat Oct 23, 17:51:09	2h 6m 58s
🔴	Accuracy_R5	0.8374	0.8367	28	Sat Oct 23, 17:51:09	2h 6m 58s



	Name	Smoothed	Value	Step	Time	Relative
🟢	Loss_epoch_train	3.25e-4	3.0177e-4	28	Sat Oct 23, 17:51:09	2h 6m 58s



	Name	Smoothed	Value	Step	Time	Relative
🔵	Loss_iter_train	5.5591e-4	0	2.699k	Sat Oct 23, 17:55:34	2h 15m 47s

In the above plots, we observe that the accuracy for R1 drops considerably in the beginning before increasing and stabilizes around 0.67, R5 increases significantly in the beginning and remains around 0.83, and R10 overall could not increase as the training process continues further. As in the previous model, the accuracy order from highest to lowest is R10, R5, and R1. The training loss per epoch and the training loss per epoch decreases overtime as we train for larger epoch number. The losses are already considerably close to zero at the later epochs.