Assignment 2: Experiment 6

Team 10

Apply fine tuning for your team's network to the CIFAR 10 dataset.

Team's network: DenseNet169

Fine tuning is a technique to use pre-trained models and how to extract features from

them for training a model for a different task.

In fine tuning we freeze the initial layers and retain the later layers for our task. As

explained here, the initial layers learn very general features and as we go higher up the

network, the layers tend to learn patterns more specific to the task it is being trained on.

In addition to the base DenseNet169 a dense layer and a softmax were added to

classify the output.

Experiments performed:

1. Training only the last convolutional layer:

Results: Best test accuracy and test loss obtained in this method (using various

dropouts) was 0.4408 and 2.7471.

2. Training the last two convolutional layers:

Results: Best test accuracy and test loss obtained were 0.4672 and 2.8262

respectively.

3. Training the last three convolutional layers:

Results: An accuracy of 0.4296 and a loss of 2.8412 were observed.

Results from other experiments were listed below.

Experiments:

Base Model: Trainable layers: base model.layers[:-4]

Unfreeze the last conv layer, pooling and norm layers.

Base model: model.compile(loss='categorical crossentropy',

optimizer = optimizers.Adam(Ir=1e-4), metrics=['acc'])

Model 1:

Added: ##Add new Dense layer and a softmax to classify.

model.add(layers.Flatten())

model.add(layers.Dense(1024, activation = 'relu'))

model.add(layers.Dense(10,activation='softmax'))

Result after 10 epochs:

Model 2:

model.add(layers.Flatten())

model.add(layers.Dense(1024, activation = 'relu'))

model.add(layers.Dropout(0.2)) ##Added a dropout to base model

model.add(layers.Dense(10,activation='softmax'))

Model 3: All same as model 2 but changed Adam to RMSprop

Model 4: All same as base but learning rate is 1e-5, base_model.layers[:-8] ##Unfreeze the last 2 conv2D layers of base model

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Model 5: Same as 3 with dropout 0.3

Epoch 8/10											
50000/50000 [======] -	245	482us/step -	loss:	1.0490	- acc:	0.6379	- val_loss:	2.7414	- val_acc:	0.4468
Epoch 9/10											
50000/50000 [======		245	483us/step -	loss:	1.0240	- acc:	0.6465	- val_loss:	2.8056	- val_acc:	0.4366
Epoch 10/10											
50000/50000 [======		245	483us/step -	loss:	0.9961	- acc:	0.6527	- val loss:	2.7466	- val acc:	0.4352

Model 6: All same as base but learning rate is 1e-5, base_model.layers[:-7] and 30 epochs

Epoch 26/30	153	7.30	150	
50000/50000 [======		159us/step - loss: 1	.0234 - acc: 0.6388 - val_lo	ss: 2.7690 - val_acc: 0.4678
Epoch 27/30				
50000/50000 [======] - 23s 4	160us/step - loss: 1	.0160 - acc: 0.6431 - val_lo	ss: 2.8146 - val_acc: 0.4657
Epoch 28/30				
50000/50000 [=======] - 235	159us/step - loss: 1	.0064 - acc: 0.6454 - val_lo	ss: 2.8397 - val_acc: 0.4651
Epoch 29/30				
50000/50000 [======] - 23s 4	159us/step - loss: 0	.9969 - acc: 0.6520 - val_lo	ss: 2.8170 - val_acc: 0.4670
Epoch 30/30				
50000/50000 [======] - 23s 4	60us/step - loss: 0	.9905 - acc: 0.6520 - val_lo	ss: 2.8262 - val_acc: 0.4672

Model 7: All same as base with unfreeze the last 3 conv layers:

Epoch 28/30												
50000/50000	[======================================] -	23s	465us/step -	loss:	1.0826	- acc:	0.6219	- val_loss	2.8498	- val_acc:	0.4282
Epoch 29/30												
50000/50000	[:] -	23s	466us/step -	loss:	1.0724	- acc:	0.6266	- val_loss	2.8935	- val_acc:	0.4253
Epoch 30/30												
50000/50000	[======================================	- 1	23s	465us/step -	loss:	1.0579	- acc:	0.6315	- val loss:	2.8412	- val acc:	0.4296