Assignment No. 3

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Part 1 – Aim: ANN from Scratch

The following "compare changes" presents the changes that was made to add a 2nd layer to the supplied code.

Helper functions

Modification in *compute_mse_and_acc*

```
10   10          for i, (features, targets) in enumerate(minibatch_gen):
11        -          _, probas = nnet.forward(features)
     11   +          _, _, probas = nnet.forward(features)
12   12              predicted_labels = np.argmax(probas, axis=1)
```

Line 11. The _ variable represents the output layer (_, _ represents 2 layers).

Modification in *Train*

```
72        -          a_h, a_out = model.forward(X_train_mini)
     72   +          a_h, a_h2, a_out = model.forward(X_train_mini)
73   73
74   74              #### Compute gradients ####
75        -          d_loss__d_w_out, d_loss__d_b_out, d_loss__d_w_h, d_loss__d_b_h = \
76        -              model.backward(X_train_mini, a_h, a_out, y_train_mini)
     75   +          d_loss__d_w_out, d_loss__d_b_out, \
     76   +          d_loss__d_w_h, d_loss__d_b_h, \
     77   +          d_loss__d_w_h2, d_loss__d_b_h2 = \
     78   +              model.backward(X_train_mini, a_h, a_h2, a_out, y_train_mini)
77   79
78   80              #### Update weights ####
79   81              model.weight_h -= learning_rate * d_loss__d_w_h
80   82              model.bias_h -= learning_rate * d_loss__d_b_h
     83   +          model.weight_h2 -= learning_rate * d_loss__d_w_h2
     84   +          model.bias_h2 -= learning_rate * d_loss__d_b_h2
```

Line 72. The *ah* variable represents the output layer (*ah, ah* _ represents 2 layers).

Lines 75-78. The backward function returns the loss also for the 2nd layer.

Line 83-84. Adjust the weight and bias of the 2nd layer by using the 2nd layer loss value.

NeuralNetMLP Class

Modification in *class init*

```
     117 +        # 2nd layer weights (size * 2 than the first layer)
     118 +        rng = np.random.RandomState(random_seed)
     119 +
     120 +        self.weight_h2 = rng.normal(
     121 +            loc=0.0, scale=0.1, size=(num_hidden * 2, num_hidden))
     122 +        self.bias_h2 = np.zeros(num_hidden * 2)
112  123
113  124          # output
114  125          self.weight_out = rng.normal(
115      -            loc=0.0, scale=0.1, size=(num_classes, num_hidden))
     126 +            loc=0.0, scale=0.1, size=(num_classes, num_hidden * 2))
```

Line 117-122. Adding 2nd layer weight and bias initiate with random values, the 2nd layer size is twice the size of the 1st layer.

Line 126. Changing the output weight, the input of the last layer switched to the output of the 2nd layer. Thus, the input size is twice the size it was before.

Modification in *foward*

```
     135 +        # the second layer
     136 +        z_h2 = np.dot(a_h, self.weight_h2.T) + self.bias_h2
     137 +        a_h2 = sigmoid(z_h2)
124  138
125  139          # Output layer
126      -        # input dim: [n_examples, n_hidden] dot [n_classes, n_hidden].T
     140 +        # input dim: [n_examples, n_hidden * 2] dot [n_classes, n_hidden * 2].T
127  141          # output dim: [n_examples, n_classes]
128      -        z_out = np.dot(a_h, self.weight_out.T) + self.bias_out
     142 +        z_out = np.dot(a_h2, self.weight_out.T) + self.bias_out
     143 +        # z_out = np.dot(a_h, self.weight_out.T) + self.bias_out
129  144          a_out = sigmoid(z_out)
130      -        return a_h, a_out
     145 +        return a_h, a_h2, a_out
```

Lines 136-137. The output of the 1st layer goes through the 2nd layer.
Lines 140-142. The input of the output layer is the 2nd layer output.
Line 145. Return the output of the 2nd layer.

Modification in *backward*

```
156      -        # [n_examples, n_hidden]
157      -        d_z_out__dw_out = a_h
     171 +        # [n_examples, n_hidden * 2]
     172 +        # the last layer before out is now layer 2 (size = n_hidden * 2)
     173 +        d_z_out__dw_out = a_h2
```

Line 173. The input of the output layer is the 2nd layer output. (Set variable to 2nd layer output)

```
168      -        # [n_classes, n_hidden]
169      -        d_z_out__a_h = self.weight_out
     184 +        # [n_classes, n_hidden * 2]
     185 +        d_z_out__a_h2 = self.weight_out
170  186
171      -        # output dim: [n_examples, n_hidden]
172      -        d_loss__a_h = np.dot(delta_out, d_z_out__a_h)
     187 +        # output dim: [n_examples, n_hidden * 2]
     188 +        # delta_out is for the final layer loss, d_z_out__a_h are the final layer weights
     189 +        d_loss__a_h2 = np.dot(delta_out, d_z_out__a_h2)
     190 +
     191 +        # [n_examples, n_hidden * 2]
     192 +        d_a_h__d_z_h2 = a_h2 * (1. - a_h2)  # sigmoid derivative
     193 +
     194 +        # [n_examples, n_hidden]
     195 +        d_z_h__d_w_h2 = a_h1
```

Line 185. The input of the output layer is the 2nd layer output. (Set variable to output weight).
Line 189. Calculates the loss result from the 2nd layer.
Line 192. Calculate the sigmoid on the 2nd layer.
Line 195. Set variable to 1st layer output

```
     197 +        # output dim: [n_hidden * 2, n_features]
     198 +        delta_out_h2 = d_loss__a_h2 * d_a_h__d_z_h2
     199 +        d_loss__d_w_h2 = np.dot(delta_out_h2.T, d_z_h__d_w_h2)
     200 +        d_loss__d_b_h2 = np.sum(delta_out_h2, axis=0)
     201 +
     202 +        # [n_classes, n_hidden * 2]
     203 +        d_z_out__a_h = self.weight_h2
     204 +
     205 +        # output dim: [n_examples, n_hidden * 2]
     206 +        # delta_out is for the final layer loss, d_z_out__a_h are the final layer weights
     207 +        d_loss__a_h = np.dot(delta_out_h2, d_z_out__a_h)
```

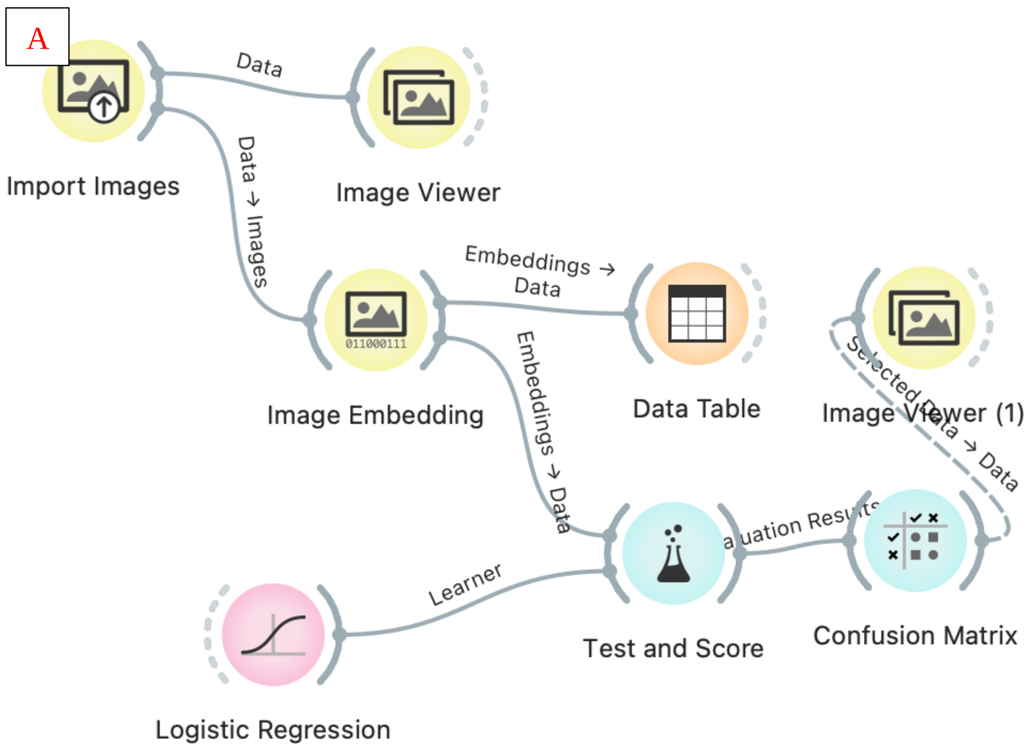
Lines 198-200. Calculates the loss for the 2nd layer.
Line 203. Set variable to the weight of the 2nd layer (The layer after the 1st layer)
Line 207. Calculate the loss result from the 1st layer.

```diff
175       -         d_a_h__d_z_h = a_h * (1. - a_h)  # sigmoid derivative
     210  +         d_a_h__d_z_h = a_h1 * (1. - a_h1)
176  211
177  212            # [n_examples, n_features]
178  213            d_z_h__d_w_h = x
          @@ -182,4 +217,5 @@ def backward(self, x, a_h, a_out, y):
182  217            d_loss__d_b_h = np.sum((d_loss__a_h * d_a_h__d_z_h), axis=0)
183  218
184  219            return (d_loss__dw_out, d_loss__db_out,
185       -                 d_loss__d_w_h, d_loss__d_b_h)
     220  +                 d_loss__d_w_h, d_loss__d_b_h,
     221  +                 d_loss__d_w_h2, d_loss__d_b_h2)
```

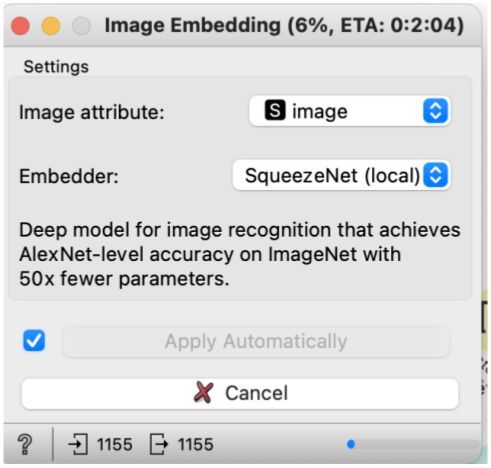
Line 210. Calculates the sigmoid on the 1st layer.
Lines 220-221. Returns the loss for the 2nd layer.

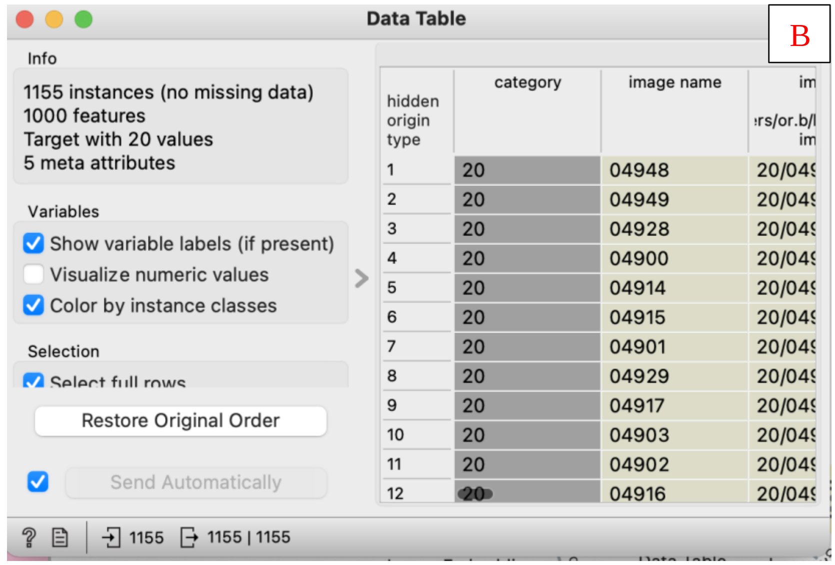
Part 2- Aim: Practice the usage of CNN (Convolutional Neural Network).

<u>To understand the data, I used the Orange3™</u>



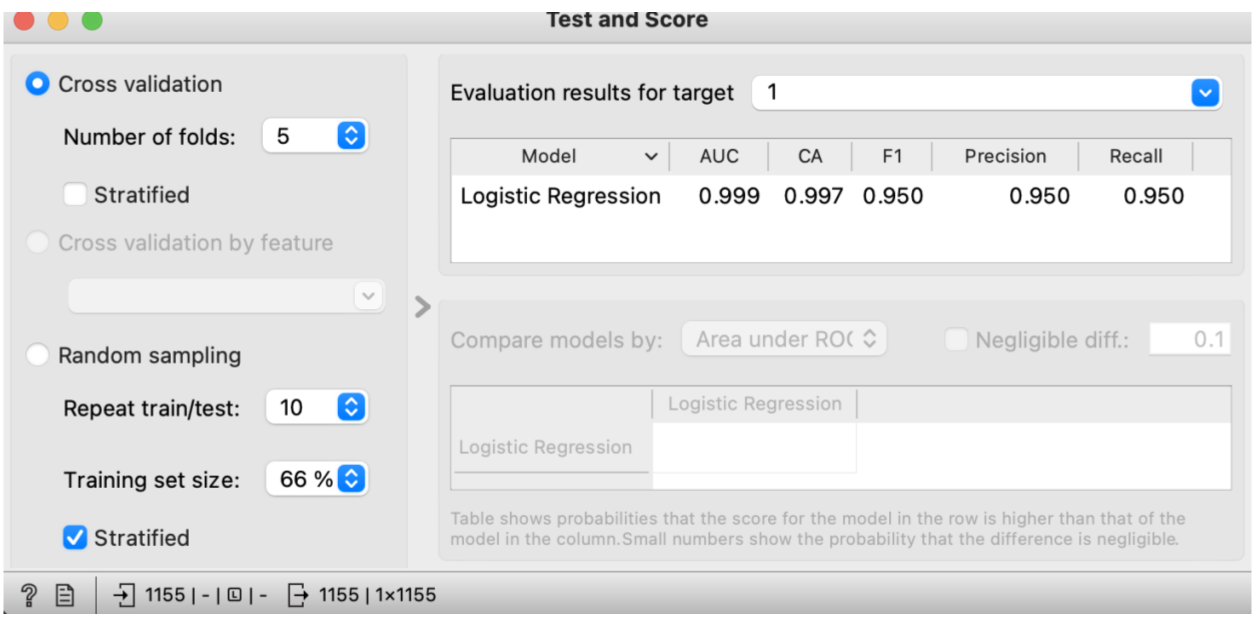
Orange Embedding





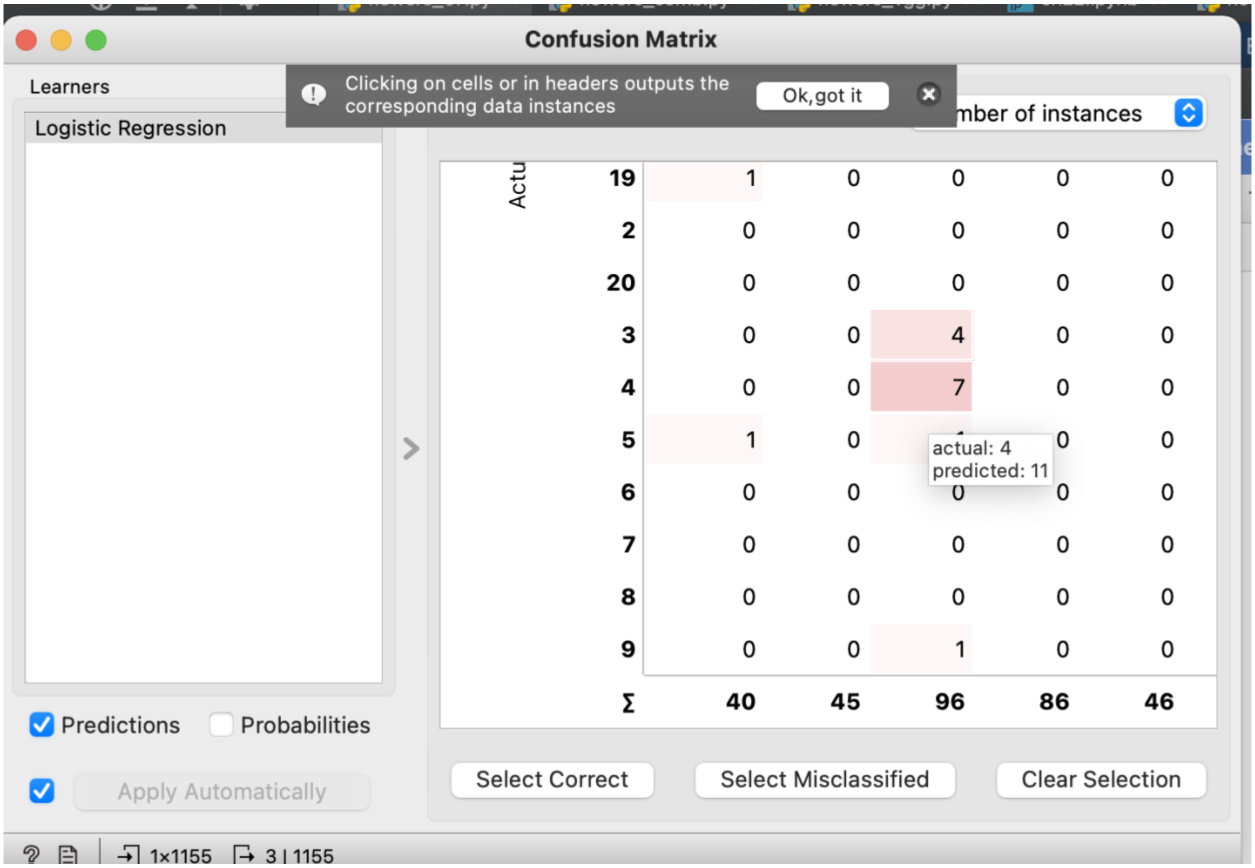
Block A is an import images block that reads the images into the orange framework.
Orange default emending is a pre-trained network, SqueezeNet.
The emending block converts the images into a table containing 1000 features (B). Each feature receives a probability that affiliates to a particular group of images.

Test and Score



The results are quite high since I used a small number of Images (1155 images). Yet, it provides a good indication of the SqueezeNet.

Confusion Matrix

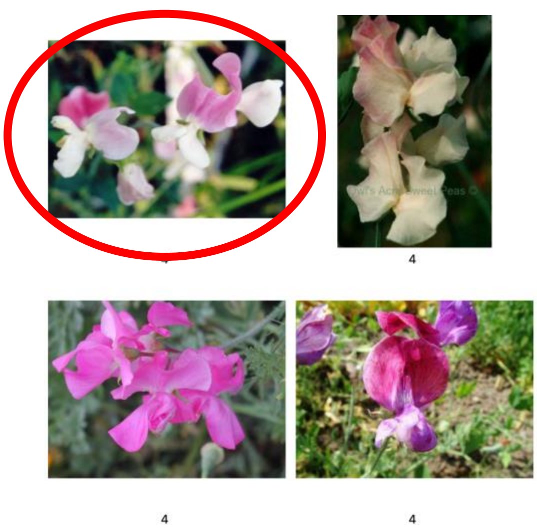


The following example shows that a group of 7 flowers mistakenly belong to category 11, although they belong to category 4.

Category 4 flowers

Category 11 flowers

Confused Flowers (4 -> 11)



Confusion Analysis

For example, the circled flower (in red) is a bit blur. Applying a blur augmentation on the dataset might deal with this issue.

Train, validate and test the whole dataset (102 oxford flowers)

Two pre-trained network were selected – SqueezeNet and MobileNet.
The pre-trained layer were set to non-trainable.

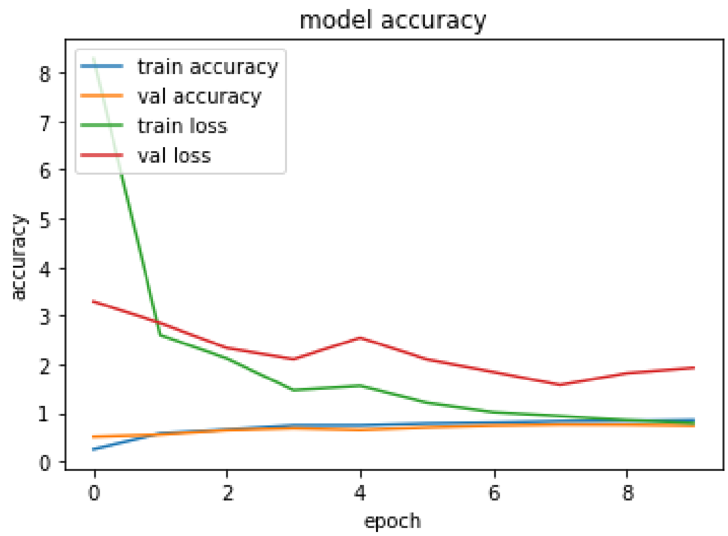
All images were imported and preprocessed using Keras image processing.

The dataset was randomly divided into training (50%), validation (25%) for hyperparameter tuning, and test sets (25%). This random split was repeated twice.

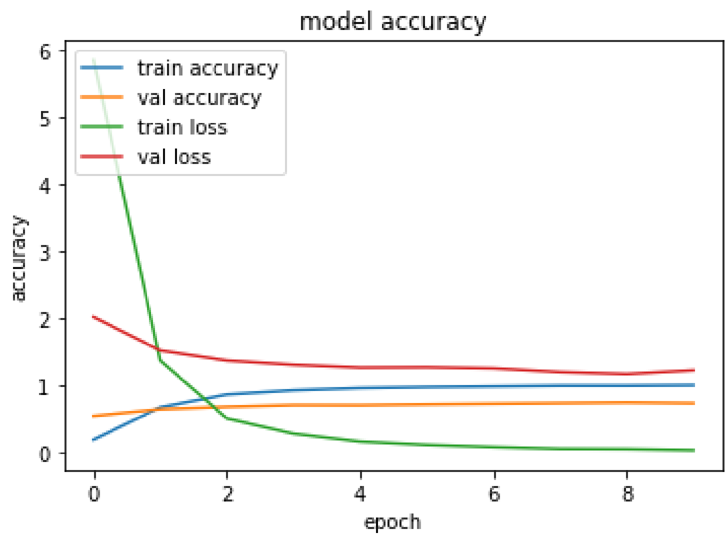
The last layer of each model is a Dense layer at a size of 102 (number of categories in the dataset)

Each fitting set consists of 10 epochs.

SqueezeNet Learning Graph



MobileNet Learning Graph



Results

SqueezeNet

1st run - accuracy of 73.4%

2nd run - - accuracy of 78.6%

MobileNet

1st run - - accuracy of 73.09%

2nd run - - accuracy of 74.46%