Calculation of Parameters and Details Discussion of Neural Network Model

Md. Istiak Ahammed

Example: Feed Forward Neural Network Architecture including

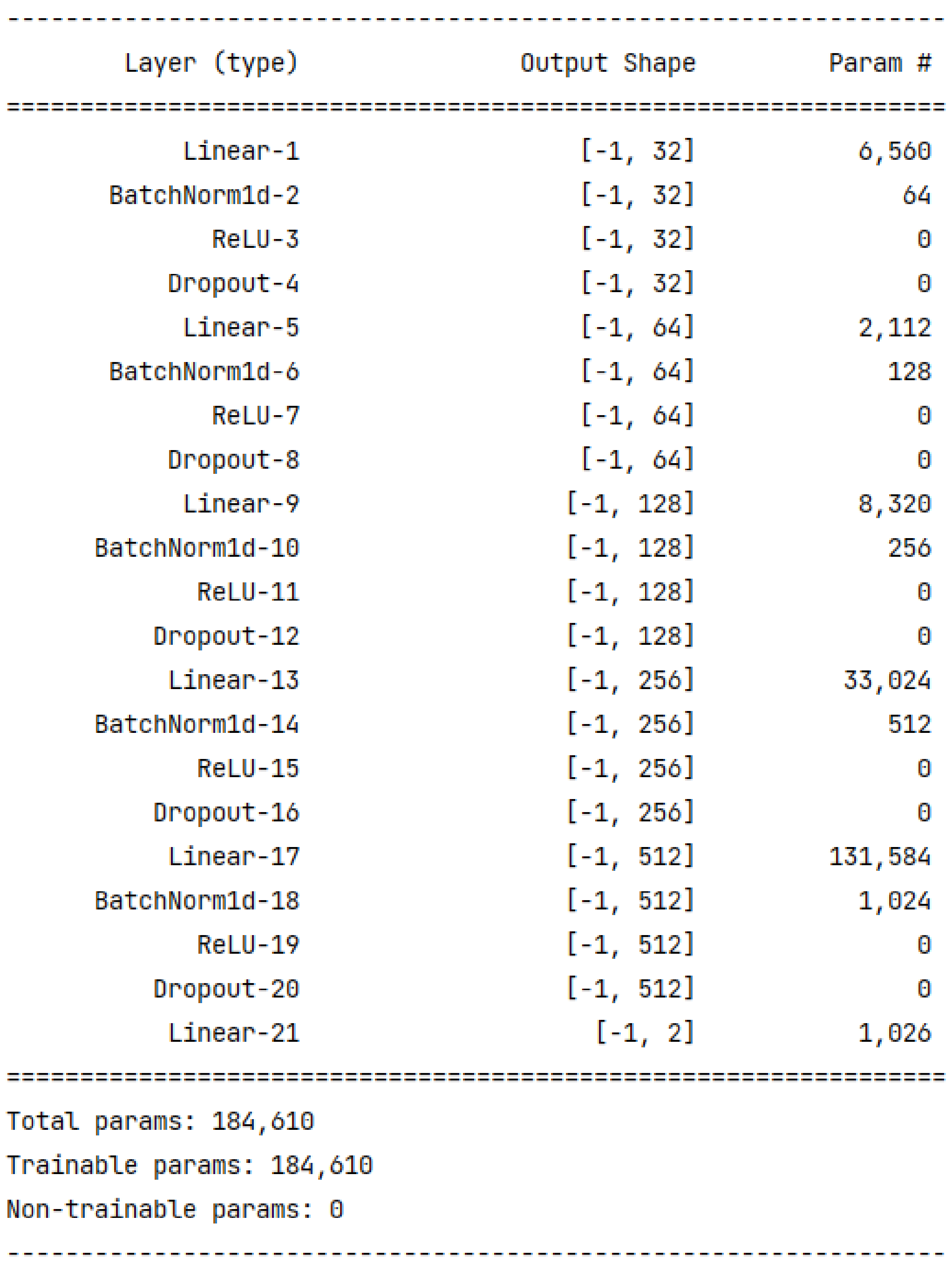
1. Fully connected layer/Dense layer/Linear layer
2. 1D Batch Normalization layer
3. ReLU activation function layer
4. Dropout layer

Model's Code: Dimensionality increasing custom model

```
class CustomFFNv5(nn.Module):
  def __init__(self, input_dim, hidden_dim, output_dim, l2_lambda):
    super(CustomFFNv5, self).__init__()

    self.fc1 = nn.Linear(input_dim, hidden_dim) # 32
    self.bn1 = nn.BatchNorm1d(hidden_dim) # Apply Batch Normalization
    self.relu1 = nn.ReLU()
    self.dropout1 = nn.Dropout(0.2)

    self.fc2 = nn.Linear(hidden_dim, 2 * hidden_dim) # (32, 64)
    self.bn2 = nn.BatchNorm1d(2 * hidden_dim) # Apply Batch Normalization # 64
    self.relu2 = nn.ReLU()
    self.dropout2 = nn.Dropout(0.2)

    self.fc3 = nn.Linear(2 * hidden_dim, 4 * hidden_dim) # (64, 128)
    self.bn3 = nn.BatchNorm1d(4 * hidden_dim) # Apply Batch Normalization
    self.relu3 = nn.ReLU()
    self.dropout3 = nn.Dropout(0.2)

    self.fc4 = nn.Linear(4 * hidden_dim, 8 * hidden_dim) # (128, 256)
    self.bn4 = nn.BatchNorm1d(8 * hidden_dim) # Apply Batch Normalization
    self.relu4 = nn.ReLU()
    self.dropout4 = nn.Dropout(0.2)

    self.fc5 = nn.Linear(8 * hidden_dim, 16 * hidden_dim) # (256, 512)
    self.bn5 = nn.BatchNorm1d(16 * hidden_dim) # Apply Batch Normalization
```

```
        self.relu5 = nn.ReLU()
        self.dropout5 = nn.Dropout(0.2)

        self.fc6 = nn.Linear(16 * hidden_dim, output_dim)  # (512, 2=Two Class)
        self.l2_lambda = l2_lambda

    def forward(self, x):
        x = self.fc1(x)
        x = self.bn1(x)  # Apply Batch Normalization
        x = self.relu1(x)
        x = self.dropout1(x)

        x = self.fc2(x)
        x = self.bn2(x)  # Apply Batch Normalization
        x = self.relu2(x)
        x = self.dropout2(x)

        x = self.fc3(x)
        x = self.bn3(x)  # Apply Batch Normalization
        x = self.relu3(x)
        x = self.dropout3(x)

        x = self.fc4(x)
        x = self.bn4(x)  # Apply Batch Normalization
        x = self.relu4(x)
        x = self.dropout4(x)

        x = self.fc5(x)
        x = self.bn5(x)  # Apply Batch Normalization
        x = self.relu5(x)
        x = self.dropout5(x)

        x = self.fc6(x)
        return x

    def l2_regularization_loss(self):
        l2_loss = 0.0
        for param in self.parameters():
            l2_loss += torch.sum(torch.square(param))

        return self.l2_lambda * l2_loss
```

Model’s Summary:



```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                   [-1, 32]           6,560
       BatchNorm1d-2                   [-1, 32]              64
              ReLU-3                   [-1, 32]               0
           Dropout-4                   [-1, 32]               0
            Linear-5                   [-1, 64]           2,112
       BatchNorm1d-6                   [-1, 64]             128
              ReLU-7                   [-1, 64]               0
           Dropout-8                   [-1, 64]               0
            Linear-9                  [-1, 128]           8,320
      BatchNorm1d-10                  [-1, 128]             256
             ReLU-11                  [-1, 128]               0
          Dropout-12                  [-1, 128]               0
           Linear-13                  [-1, 256]          33,024
      BatchNorm1d-14                  [-1, 256]             512
             ReLU-15                  [-1, 256]               0
          Dropout-16                  [-1, 256]               0
           Linear-17                  [-1, 512]         131,584
      BatchNorm1d-18                  [-1, 512]           1,024
             ReLU-19                  [-1, 512]               0
          Dropout-20                  [-1, 512]               0
           Linear-21                    [-1, 2]           1,026
================================================================
Total params: 184,610
Trainable params: 184,610
Non-trainable params: 0
----------------------------------------------------------------
```

Explanation of Parameters calculation in each layer

Linear-1: This is a fully connected layer with an input dimension of input_dim (204) and an output dimension of hidden_dim (32). The number of parameters in this layer is calculated as (input_dim + 1) * hidden_dim = (204 + 1) * 32 = 6,560.

BatchNorm1d-1: This is a batch normalization layer for 1-dimensional input with hidden_dim (32) features. It has 2 * hidden_dim parameters, consisting of mean and variance for each feature. So the number of parameters in this layer is 2 * hidden_dim = 2 * 32 = 64.

Batch Normalization is typically applied after the linear transformation in a neural network layer and before the non-linear activation function. This helps to normalize the inputs to the activation function, stabilizing the training process and improving the network's ability to learn.

ReLU-1: This is the activation function layer and doesn't have any parameters.

Dropout-1: This is the dropout layer with a dropout rate of 0.2. It doesn't have any parameters.

Linear-2: This is a fully connected layer with an input dimension of hidden_dim (32) and an output dimension of 2 * hidden_dim (64). The number of parameters in this layer is (hidden_dim + 1) * (2 * hidden_dim) = (32 + 1) * 64 = 2,112.

BatchNorm1d-2: Batch normalization layer for 1-dimensional input with 2 * hidden_dim (64) features. It has 2 * (2 * hidden_dim) = 2 * 64 = 128 parameters.

ReLU-2: Activation function layer.

Dropout-2: Dropout layer with a dropout rate of 0.2.

Linear-3: Fully connected layer with an input dimension of 2 * hidden_dim (64) and an output dimension of 4 * hidden_dim (128). The number of parameters in this layer is (2 * hidden_dim + 1) * (4 * hidden_dim) = (2 * 32 + 1) * 128 = 8,320.

BatchNorm1d-3: Batch normalization layer for 1-dimensional input with 4 * hidden_dim (128) features. It has 2 * (4 * hidden_dim) = 2 * 128 = 256 parameters.

ReLU-3: Activation function layer.

Dropout-3: Dropout layer with a dropout rate of 0.2.

Linear-4: Fully connected layer with an input dimension of 4 * hidden_dim (128) and an output dimension of 8 * hidden_dim (256). The number of parameters in this layer is (4 * hidden_dim + 1) * (8 * hidden_dim) = (4 * 32 + 1) * 256 = 33,024.

BatchNorm1d-4: Batch normalization layer for 1-dimensional input with 8 * hidden_dim (256) features. It has 2 * (8 * hidden_dim) = 2 * 256 = 512 parameters.

ReLU-4: Activation function layer.

Dropout-4: Dropout layer with a dropout rate of 0.2.

Linear-5: Fully connected layer with an input dimension of 8 * hidden_dim (256) and an output dimension of 16 * hidden_dim (512). The number of parameters in this layer is (8 * hidden_dim + 1) * (16 * hidden_dim) = (8 * 32 + 1) * 512 = 131,584.

BatchNorm1d-5: Batch normalization layer for 1-dimensional input with 16 * hidden_dim (512) features. It has 2 * (16 * hidden_dim) = 2 * 512 = 1,024 parameters.

ReLU-5: Activation function layer.

Dropout-5: Dropout layer with a dropout rate of 0.2.

Linear-6: Fully connected layer with an input dimension of 16 * hidden_dim (512) and an output dimension of output_dim (2). The number of parameters in this layer is (16 * hidden_dim + 1) * output_dim = (16 * 32 + 1) * 2 = 1,026.

To calculate the total number of parameters, you sum up the parameters from all the layers. In this case, you sum up the parameters from all the Linear layers.

Let's calculate the total parameters for your model using input_dim = 204, hidden_dim = 32, and output_dim = 2

Total parameters = 6,560 + 64 + 2,112 + 128 + 8,320 + 256 + 33,024 + 512 + 131,584 + 1,024 + 1,026

= 184,610