# Assignment3

May 20, 2018

## 1 Assignment 3: Image Classification using CNNs

In this assignment you will learn about 1. The fundamental computations in neural networks for vision, including backpropagation 2. The basics of fitting a model for generalization 3. Nearest neighbor classifiers

**Note:** When you first load this colab webpage, it will be in read-only viewing mode. To edit and run code, you can either (a) download the Jupyter notebook ("File" -> "Download .ipynb") to run on your local computer or (b) copy to your Google Drive ("File" -> "Save a copy in Drive...") to work in the browser and run on a Google Cloud GPU. If you run locally, you will need to install Tensorflow and it is recommended that you use a GPU for problem 3.2. If you do not want to use Colab and do not have a local GPU, please let us know.

## 2 3.0 Nearest neighbor classification (20 points)

### 2.1 3.0.1 (20 points)

Given the following training set of labeled two-dimensional points for binary classification, draw a Voronoi diagram of the output of a 1-nearest neighbor classifier. Feel free to render the diagram using Python below (do not use scikit-learn or any machine learning libraries to do this) or submit a PDF along with your assignment.

```
Point (x,y)  | Label
-------------|-------
(1,3)        |   +
(-4,-2)      |   +
(-3,-1.5)    |   -
(3,3)        |   -
(0,-2)       |   +
(-2,0)       |   +
(-2,4)       |   -
```

```
In [4]: #Functions used to find the N-Nearest neighbors for assignment
        #The results for the Nearest Neighbor classification were created in Photoshop,
        #and can be found at the NN_Classification\1NN-Voronoi.jpg


        import matplotlib.pyplot as plt
```

```python
import numpy as np

"""
Function to calculate distance between two points

inputs: x1, y1 - datapoint 1
        x2, y2 - datapoint 2
"""
def distance(x1, x2, y1, y2):
    x_diff = x2 - x1
    y_diff = y2 - y1
    return np.sqrt((x_diff**2)+(y_diff**2))

"""
Function to find the nearest neighbor

inputs: x_idx,y_idx - the current datapoint to find the nearest neighbors for
        datapoints - the classified datapoints to consider as neighbors
        k - the count of nearest neighbors to consider
"""
def nearest_neighbors(x_idx, y_idx, datapoints, k):
    all_dist = []
    label = 0

    #Go through each datapoint
    for point in datapoints:

        #Calculate the distance and append to a list
        curr_distance = distance(x_idx, point[0], y_idx, point[1])
        all_dist.append((curr_distance, point[2]))

    #sort the list in order of closeness, and limit to the k-nearest neighbors
    sorted_dist = sorted(all_dist, key=lambda x:x[0])
    k_nn = sorted_dist[:k]

    #Go through each considered neighbor and impact the value depending on
    #whether the neighbor was a "+" or a "-", adding and subtracting respectively
    for neighbor in k_nn:
        if(neighbor[1] == "+"):
            label += 1
        else:
            label -= 1

    #Indicate label at the point, handling edge case of a tie by looking at the K-1 ne
    if(label > 0):
        return "+"
    elif(label < 0):
        return "-"
    else:
        return nearest_neighbors(x_idx, y_idx, datapoints, k-1)

"""
Function to print the indices at which the class changes, between positive and negativ

inputs: datapoints - the datapoints with their classes specified
        nn_cnt - the number of datapoints to consider when calculated class
"""
def print_switch_indices(datapoints, nn_cnt):
    #initialize the boundaries
    #Start with 50 and times by .1 to be able to iterate through pixel per tenth
    H = W = 50
    for i in range(-H,H):
        curr_class = ""
        i *= .1
        output = ""
        for j in range(-W,W):
            j *= .1

            label = nearest_neighbors(j, i, datapoints, nn_cnt)
            if(label != curr_class):
                output += " "+ str(j) + "," + str(i) + " switched to " + label
                curr_class = label
        print(output ,"\n")

#Initialize the datapoints
datapoints = [(1, 3, "+"), (-4, -2, "+"), (-3, -1.5, "-"), (3, 3, "-"), (0, -2, "+"),
#Find nearest neighbors
print_switch_indices(datapoints, 1)
```

## 2.2 3.0.2 (5 points, extra)

Render for 3-NN

```
In [5]: #The results for the Nearest Neighbor classification were created in Photoshop,
        #and can be found at the NN_Classification\3NN-Voronoi.jpg

        #Find nearest neighbors
        print_switch_indices(datapoints, 3)
```

# 3 3.1 Neural network operations (40 points)

In this section we provide a working example of a convolutional neural network written using basic numpy operations. Each neural network operation is represented by a Python class with methods *forward()* and *backward()*, which compute activations and gradients, respectively. Your task is to complete certain methods that are left blank.

1. 2D Convolution > * Forward > * **Backward (10 points)**
2. ReLU > * **Forward (5 points)** > * Backward
3. Average pooling > * Forward > * **Backward (5 points)**
4. Softmax cross-entropy > * **Forward (10 points)** > * Backward

When you complete an operation, you can check your work by executing its cell. We compare the outputs of your method to that of Tensorflow.

Finally, when you have all of the operations completed, you can run a small network for a few iterations of stochastic gradient descent and plot the loss.

```
In [1]: #@title (Hidden utility code: RUN ME FIRST) { display-mode: "form" }
        import tensorflow as tf
        import numpy as np

        class Variable:
          """Placeholder for labels and input images"""
          value = 0

        def cmp_ops(your_op, tf_op, tf_inputs, tf_weights=None):
          your_op.forward()
          your_op_f_out = your_op.value

          with tf.Session().as_default():
            tf_op_f_out = tf_op.eval()[0] # Remove the batch dimension

          print("Forward pass:")
          cmp_tensors(your_op_f_out, tf_op_f_out, verbose=False)

          your_op.inputs.dloss_dvalue = np.zeros(your_op.inputs.value.shape)
          your_op.dloss_dvalue = np.ones(your_op.value.shape)
          your_op.backward()
          your_op_g_inputs = your_op.inputs.dloss_dvalue

          if tf_weights is not None:
            your_op_g_weights = your_op.dloss_dweights
            g_inputs, g_weights = tf.gradients(tf.reduce_sum(tf_op), [tf_inputs, tf_weights])

            with tf.Session() as sess:
              tf_g_inputs_out, tf_g_weights_out = sess.run([g_inputs, g_weights])
              tf_g_weights_out = np.transpose(tf_g_weights_out, [3,0,1,2])

            print("Gradient wrt inputs:")
            cmp_tensors(your_op_g_inputs, tf_g_inputs_out[0])
            print("Gradient wrt weights:")
            cmp_tensors(your_op_g_weights, tf_g_weights_out)

          else:
            g_inputs = tf.gradients(tf.reduce_sum(tf_op), [tf_inputs])
```

```
    with tf.Session() as sess:
      tf_g_inputs_out = sess.run(g_inputs)

    print("Gradient wrt inputs:")
    cmp_tensors(your_op_g_inputs, tf_g_inputs_out[0], verbose=False)

def cmp_tensors(yours, tfs, verbose=False):
  print("  Your Op shape: " + str(yours.shape))
  print("  TensorFlow Op shape: " + str(tfs.shape))
  print("  Values equal: " + str(np.allclose(tfs, yours, atol=1e-6)))
  if verbose:
    print(tfs)
    print(yours)

inputs = Variable()
inputs.value = np.random.normal(size=(10, 10, 3)) # Input image is 10x10x3
tf_inputs = tf.constant(inputs.value[np.newaxis, ...], dtype=tf.float32)
```

## 3.1 3.1.1 2D Convolution (10 pts)

```
In [2]: import numpy as np

        """rows x cols x filters"""

        class OpConv2D:
          """Two-dimensional convolutional layer"""

          def __init__(self, filters, kernel_size, inputs):
            # Shape of the input feature map
            input_height = inputs.value.shape[0]
            input_width = inputs.value.shape[1]
            input_filters = inputs.value.shape[2]

            # Shape of this layer's feature map
            self.height = input_height - kernel_size + 1
            self.width = input_width - kernel_size + 1
            self.filters = filters

            self.inputs = inputs
            #Attempted extra credit function implementation here
            #self.inputs = self.pad_inputs(inputs)
            self.kernel_size = kernel_size
            self.weights = np.random.normal(size=(filters, kernel_size, kernel_size, input_fil
            self.reset_values()

          def reset_values(self):
            self.value = np.zeros((self.height, self.width, self.filters))
```

```
    self.dloss_dvalue = np.zeros(self.value.shape)
    self.dloss_dweights = np.zeros(self.weights.shape)

  def forward(self):
    # Reset value and gradient at start of forward pass
    self.reset_values()

    for y in range(self.height):
      for x in range(self.width):
        for f in range(self.filters):
          z = 0.0

          for ky in range(self.kernel_size):
            for kx in range(self.kernel_size):
              for kf in range(self.weights.shape[3]):
                z += self.inputs.value[y+ky, x+kx, kf] * self.weights[f, ky, kx, kf]

          self.value[y, x, f] = z

  def backward(self):
    ## Complete this method, which sets:
    ## 1. Partial derivative of the loss with respect to the values of the inputs
    ## self.inputs.dloss_dvalue, which is a `height x width x input_filters` tensor
    ## 2. Partial derivative of the loss with respect to the weights
    ## self.dloss_dweights, which is a `filters x kernel_size x kernel_size x input_fi
    ##
    ## This will utilize tensors:
    ## 1. The partial with respect to the value of this layer
    ## self.dloss_dvalue, a `height x width x filter` tensor
    ## 2. The weights of this layer
    ## self.weights, a `filters x kernel_size x kernel_size x input_filters` tensor
    ## 3. The value of the input layer
    ## self.inputs.value, a `height x width x input_filters` tensor
    pass

    for y in range(self.height):
      for x in range(self.width):
        for f in range(self.filters):

          for ky in range(self.kernel_size):
            for kx in range(self.kernel_size):
              for kf in range(self.weights.shape[3]):
                self.inputs.dloss_dvalue[y+ky, x+kx, kf] += self.weights[f, ky, kx, kf
                self.dloss_dweights[f, ky, kx, kf] += self.inputs.value[y+ky, x+kx, kf

    """
    Attempted function to pad the input image with 0s for extra credit
    Intention was to replace line in __init__ "self.inputs = inputs"
```

```
          with "self.inputs = self.pad_inputs(inputs)"
          However, when in use, result turned false so not used

          inputs: inputs - input shape to be padded with 0s

          """
        def pad_inputs(self, inputs):
          #Add half kernel size to both ends of the image
          self.half_k_size = int((kernel_size-1)/2)

          # Shape of the input feature map with paddinf
          input_height = inputs.value.shape[0] + (2*self.half_k_size)
          input_width = inputs.value.shape[1] + (2*self.half_k_size)

          #Initialize padded input to be returned
          padded_inputs = Variable()
          padded_inputs.value = np.zeros((input_height, input_width, self.filters))

          for y in range(0, inputs.value.shape[0]):
            for x in range(0, inputs.value.shape[1]):
              for f in range(0, inputs.value.shape[2]):
                #Copy each input into the padded output
                padded_inputs.value[x+self.half_k_size][y+self.half_k_size][f] = inputs.valu

          # Update feature map
          self.height = input_height - kernel_size + 1
          self.width = input_width - kernel_size + 1

          return padded_inputs

        def gradient_step(self, step_size):
          self.weights -= step_size * self.dloss_dweights

    # Double check that op matches tensorflow
    print("Testing Conv2D...")
    op1 = OpConv2D(4, 3, inputs)

    tf_weights = tf.constant(np.transpose(op1.weights, [1,2,3,0]), dtype=tf.float32)
    tf_op1 = tf.nn.conv2d(tf_inputs,
                          tf_weights,
                          [1,1,1,1],
                          'VALID')
    cmp_ops(op1, tf_op1, tf_inputs, tf_weights)
```

```
Testing Conv2D...
Forward pass:
  Your Op shape: (8, 8, 4)
  TensorFlow Op shape: (8, 8, 4)
  Values equal: True
Gradient wrt inputs:
  Your Op shape: (10, 10, 3)
  TensorFlow Op shape: (10, 10, 3)
  Values equal: True
Gradient wrt weights:
  Your Op shape: (4, 3, 3, 3)
  TensorFlow Op shape: (4, 3, 3, 3)
  Values equal: True
```

## 3.2 3.1.2 ReLU (5 pts)

```
In [3]: class OpRelu:
          """Elementwise relu operator"""

          def __init__(self, inputs):
            # Shape of the input feature map
            self.input_shape = inputs.value.shape
            self.inputs = inputs
            self.reset_values()

          def reset_values(self):
            self.value = np.zeros(self.inputs.value.shape)
            self.dloss_dvalue = np.zeros(self.inputs.value.shape)

          def forward(self):
            # Reset value and gradient at start of forward pass
            self.reset_values()
            height, width, filters = inputs.value.shape
            for y in range(self.input_shape[0]):
              for x in range(self.input_shape[1]):
                for f in range(self.input_shape[2]):
                  self.value[y, x, f] = max(self.inputs.value[y, x, f], 0)


            ## Complete this code by setting self.value using self.inputs.value
            #self.value = self.inputs.value > 0 ? self.inputs.value : 0

          def backward(self):
            self.inputs.dloss_dvalue = self.dloss_dvalue * np.greater(self.value, 0.0)

          def gradient_step(self, step_size):
            pass

        # Double check that each op matches tensorflow
        print("\nTesting Relu...")
        op2 = OpRelu(inputs)
        tf_op2 = tf.nn.relu(tf_inputs)
        cmp_ops(op2, tf_op2, tf_inputs)
```

```
Testing Relu...
Forward pass:
  Your Op shape: (10, 10, 3)
  TensorFlow Op shape: (10, 10, 3)
  Values equal: True
Gradient wrt inputs:
  Your Op shape: (10, 10, 3)
  TensorFlow Op shape: (1, 10, 10, 3)
  Values equal: True
```

## 3.3 3.1.3 Average Pooling (5 pts)

```
In [4]: class OpAvgPool:
          """Average pooling layer. Non-overlapping cells."""

          def __init__(self, cell_size, inputs):
            # Shape of the input feature map
            self.input_height = inputs.value.shape[0]
            self.input_width = inputs.value.shape[1]
            self.input_filters = inputs.value.shape[2]

            # Shape of this layer's feature map
            self.height = int((self.input_height + cell_size - 1) / cell_size)
            self.width = int((self.input_width + cell_size - 1) / cell_size)
            self.filters = self.input_filters

            self.inputs = inputs
            self.cell_size = cell_size
            self.reset_values()

          def reset_values(self):
            self.value = np.zeros((self.height, self.width, self.filters))
            self.dloss_dvalue = np.zeros(self.value.shape)

          def forward(self):
            # Reset value and gradient at start of forward pass
            self.reset_values()

            for y in range(self.height):
              for x in range(self.width):
                for f in range(self.filters):
                  z = 0.0
                  for ky in range(min(self.cell_size, self.input_height - y*self.cell_size)):
                    for kx in range(min(self.cell_size, self.input_width - x*self.cell_size)):
                      z += self.inputs.value[self.cell_size*y+ky, self.cell_size*x+kx, f]

                  self.value[y, x, f] = z / (self.cell_size * self.cell_size)

          def backward(self):
            ## Complete this method by setting the partial with repect to the values of the in
            ## self.inputs.dloss_dvalue, an `input_height x input_width x filters` tensor
            ## This will use the partial with respect to the value of this layer
            ## self.dloss_dvalue, a `height x width x filters` tensor
            d_xsq = float(1)/((self.cell_size * self.cell_size))

            for y in range(self.input_height):
              for x in range(self.input_width):
                for f in range(self.input_filters):
                  curr_x = int(x/2)
                  curr_y = int(y/2)
                  self.inputs.dloss_dvalue[y, x, f] = self.dloss_dvalue[curr_y, curr_x, f] * d

          def gradient_step(self, step_size):
            pass

        # Double check that each op matches tensorflow
        print("\nTesting AvgPool...")
        op3 = OpAvgPool(2, inputs)
        tf_op3 = tf.nn.avg_pool(tf_inputs, [1, 2, 2, 1], [1,2,2,1], "VALID")
        cmp_ops(op3, tf_op3, tf_inputs)
```

```
Testing AvgPool...
Forward pass:
  Your Op shape: (5, 5, 3)
  TensorFlow Op shape: (5, 5, 3)
  Values equal: True
Gradient wrt inputs:
  Your Op shape: (10, 10, 3)
  TensorFlow Op shape: (1, 10, 10, 3)
  Values equal: True
```

## 3.4 3.1.4 Softmax Cross-entropy Loss (10 pts)

```
In [5]: import math

        class OpSoftmaxCrossEntropyLoss:
          """Cross-entropy loss."""
```

```
  def __init__(self, logits, true_label):
    """
    inputs:
      logits: shape [1,1,num_classes]
      true_label: scalar in range [0, num_classes-1]
    """

    # Shape of the input feature map
    self.num_classes = logits.value.shape[2]
    self.inputs = logits
    self.true_label = true_label

  def reset_values(self):
    self.max_label = 0
    self.value = np.zeros((1,))
    self.softmax_prob = np.zeros((self.num_classes,))

  def forward(self):
    # Reset value and gradient at start of forward pass
    self.reset_values()
    ## Complete this method by:
    ## (1) setting self.value to the scalar value of the
    ##     negative log probability of the true class under a Softmax distribution.
    ##     Loss = -ln(exp(y_true) / sum_j (exp(y_j))), where y_j is the logits
    ##     value for class j.
    ## (2) setting self.softmax_prob to the vector representing the probability
    ##     of each class according to the Softmax distribution
    ##     softmax_prob[j] = exp(y_i) / sum_j (exp(y_j)), where y_j is the logits
    ##     value for class j.
    ## This will use
    ## self.inputs.value, a `1 x 1 x num_classes` tensor containing the logits
    sum_exp_logits = 0

    for i in range(self.num_classes):
        sum_exp_logits += math.exp(self.inputs.value[0,0, i])
    for i in range(self.num_classes):
        self.softmax_prob[i] = math.exp(self.inputs.value[0,0,i]) / sum_exp_logits

    self.value[0] = - math.log(math.exp(self.inputs.value[0, 0, self.true_label.value]

  def backward(self):
    # Loss = -ln(exp(y_true) / sum_j (exp(y_j)))
    # dLoss/dYk = exp(y_k) / sum_j (exp(y_j))
    # dLoss/dYtrue = exp(y_true) / sum_j (exp(y_j)) - 1
    self.inputs.dloss_dvalue[0, 0, :] += self.softmax_prob
    self.inputs.dloss_dvalue[0, 0, self.true_label.value] += -1

  def gradient_step(self, step_size):
    pass

# Double check that each op matches tensorflow
print("\nTesting Cross Entropy Loss...")
pooled = OpAvgPool(10, inputs)
pooled.forward()
tf_pooled = tf.nn.avg_pool(tf_inputs, [1, 10, 10, 1], [1,10,10,1], "VALID")

true_label = Variable()
op4 = OpSoftmaxCrossEntropyLoss(pooled, true_label)
tf_op4 = tf.nn.softmax_cross_entropy_with_logits_v2(logits=tf_pooled,
                                                    labels=tf.one_hot(tf.constant(0),
cmp_ops(op4, tf_op4, tf_pooled)
```

```
Testing Cross Entropy Loss...
Forward pass:
  Your Op shape: (1,)
  TensorFlow Op shape: (1, 1)
  Values equal: True
Gradient wrt inputs:
  Your Op shape: (1, 1, 3)
  TensorFlow Op shape: (1, 1, 1, 3)
  Values equal: True
```

## 3.5 3.1.5 Run for a few iterations (10 pts)

Here we assemble all of our operations into a full convolutional neural network. We then run stochastic gradient descent on a small collection of ten images to ensure that the loss is decreasing.

Run this cell to plot 100 iterations of training. **(5 pts)**

Why is this plot jagged? What is it about our architecture or training procedure that causes this, and how might adjusting these factors change the shape of this curve? **(5 pts)**

## 3.6 3.1.5 Answers

1 - Cell is run with 100 iterations, reaching < .1 loss at iteration 21

2 - The plot is jagged in several locations because of an over-adjustment from the learning rate. In certain cases, the learning rate can overshoot the minimum value, causing a spike in the amount of loss. One modification that can be made is to use a smaller learning rate, so the steps are less likely to miss the minimum. This can also have its own issues, such as taking more iterations to find the minimum, wasting time and resources. Another modification could be, rather than just reducing the learning rate totally, but reduce the learning rate every couple of iterations. This could even be improved on by automatically adjusting the learning rate, depending on the current loss value and whether or not it is improving the loss.

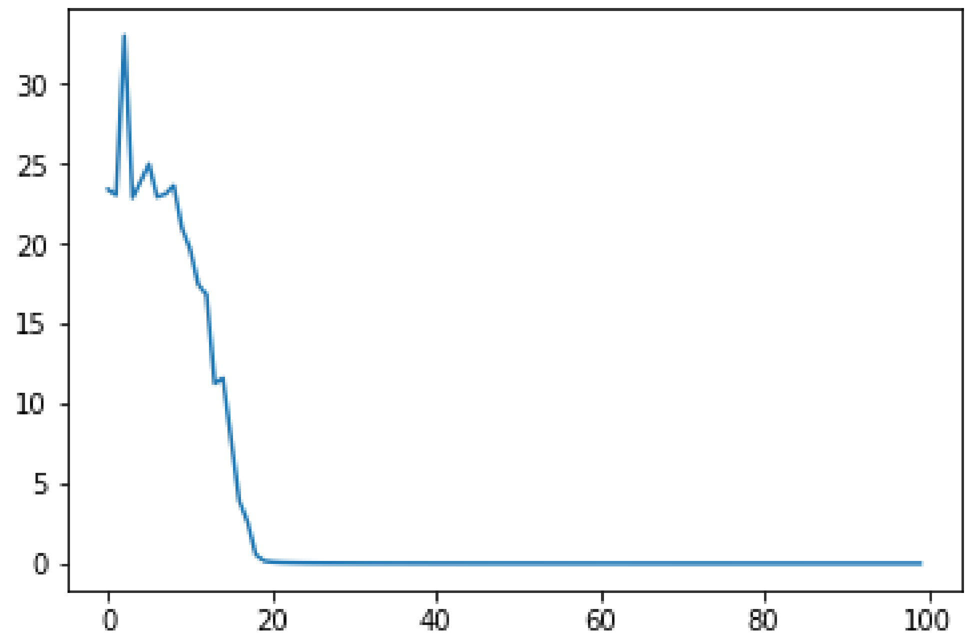
```
In [12]: from tensorflow.examples.tutorials.mnist import input_data
```

```python
# Construct a mini network for MNIST
inputs = Variable()
true_label = Variable()
inputs.value = np.random.normal(size=(28, 28, 1))
inputs.dloss_dvalue = np.random.normal(size=(28, 28, 1))

op1 = OpConv2D(16, 5, inputs) # Output is 28-5+1=24
op2 = OpAvgPool(2, op1)      # Output is 24/2=12
op3 = OpRelu(op2)

op4 = OpConv2D(16, 5, op3) # Output is 12-5+1=8
op5 = OpAvgPool(2, op4)      # Output is 8/2=4
op6 = OpRelu(op5)

op7 = OpConv2D(10, 3, op6) # Output is 4-3+1=2
op8 = OpAvgPool(2, op7)      # Output is 2/2=1

op9 = OpSoftmaxCrossEntropyLoss(op8, true_label)
ops_list = [op1,op2,op3,op4,op5,op6,op7,op8,op9]

# Run for a few iterations, make sure loss is going down
learning_rate = 0.2
inputs.value = np.random.normal(size=(28, 28, 1))

mnist = input_data.read_data_sets('MNIST_data', one_hot=False)

num_its = 100
batch_size = 10
batch_x, batch_y = mnist.train.next_batch(batch_size)

loss_list = []

for it in range(num_its):
  loss_of_batch = 0.0

  for im in range(batch_size):
    inputs.value = np.reshape(batch_x[im], (28,28,1))
    true_label.value = batch_y[im]

    for op in ops_list:
      op.forward()

    loss_of_batch += ops_list[-1].value

    for op in reversed(ops_list):
      op.backward()
      op.gradient_step(learning_rate)
```

```
          loss_list.append(loss_of_batch)

          print("Iteration " + str(it) + " Loss: "+str(loss_of_batch))


        plt.plot(range(num_its), loss_list)
```

```
Extracting MNIST_data\train-images-idx3-ubyte.gz
Extracting MNIST_data\train-labels-idx1-ubyte.gz
Extracting MNIST_data\t10k-images-idx3-ubyte.gz
Extracting MNIST_data\t10k-labels-idx1-ubyte.gz
Iteration 0 Loss: [23.41012041]
Iteration 1 Loss: [23.04136509]
Iteration 2 Loss: [33.02728799]
Iteration 3 Loss: [22.87526167]
Iteration 4 Loss: [23.91612511]
Iteration 5 Loss: [24.99470937]
Iteration 6 Loss: [22.92684561]
Iteration 7 Loss: [23.12011341]
Iteration 8 Loss: [23.6434794]
Iteration 9 Loss: [20.99400669]
Iteration 10 Loss: [19.65962341]
Iteration 11 Loss: [17.43971532]
Iteration 12 Loss: [16.81324139]
Iteration 13 Loss: [11.25986187]
Iteration 14 Loss: [11.60630934]
Iteration 15 Loss: [7.75956445]
Iteration 16 Loss: [3.91766387]
Iteration 17 Loss: [2.61136097]
Iteration 18 Loss: [0.56996349]
Iteration 19 Loss: [0.17073335]
Iteration 20 Loss: [0.10324958]
Iteration 21 Loss: [0.07379704]
Iteration 22 Loss: [0.05912035]
Iteration 23 Loss: [0.04928768]
Iteration 24 Loss: [0.04206357]
Iteration 25 Loss: [0.03675321]
Iteration 26 Loss: [0.03248868]
Iteration 27 Loss: [0.02912694]
Iteration 28 Loss: [0.02635941]
Iteration 29 Loss: [0.02407387]
Iteration 30 Loss: [0.02211561]
Iteration 31 Loss: [0.02045481]
Iteration 32 Loss: [0.01902443]
Iteration 33 Loss: [0.01776665]
Iteration 34 Loss: [0.01665903]
Iteration 35 Loss: [0.01567942]
Iteration 36 Loss: [0.01480166]
Iteration 37 Loss: [0.01400921]
Iteration 38 Loss: [0.01328856]
Iteration 39 Loss: [0.01263496]
Iteration 40 Loss: [0.012043]
Iteration 41 Loss: [0.01149989]
Iteration 42 Loss: [0.01100061]
Iteration 43 Loss: [0.01054451]
Iteration 44 Loss: [0.01012262]
Iteration 45 Loss: [0.00973088]
Iteration 46 Loss: [0.00936687]
Iteration 47 Loss: [0.00902727]
Iteration 48 Loss: [0.00871002]
Iteration 49 Loss: [0.00841282]
Iteration 50 Loss: [0.00813405]
Iteration 51 Loss: [0.00787185]
Iteration 52 Loss: [0.00762462]
Iteration 53 Loss: [0.00739158]
Iteration 54 Loss: [0.00717145]
Iteration 55 Loss: [0.00696317]
Iteration 56 Loss: [0.00676585]
Iteration 57 Loss: [0.00657882]
Iteration 58 Loss: [0.0064013]
Iteration 59 Loss: [0.00623373]
Iteration 60 Loss: [0.00607424]
Iteration 61 Loss: [0.00592191]
Iteration 62 Loss: [0.00577619]
Iteration 63 Loss: [0.00563655]
Iteration 64 Loss: [0.0055016]
Iteration 65 Loss: [0.00537266]
Iteration 66 Loss: [0.00524915]
Iteration 67 Loss: [0.00513098]
Iteration 68 Loss: [0.00501779]
Iteration 69 Loss: [0.00490931]
Iteration 70 Loss: [0.00480489]
Iteration 71 Loss: [0.00470461]
Iteration 72 Loss: [0.00460806]
Iteration 73 Loss: [0.00451522]
Iteration 74 Loss: [0.00442572]
Iteration 75 Loss: [0.00433952]
Iteration 76 Loss: [0.00425634]
Iteration 77 Loss: [0.00417612]
Iteration 78 Loss: [0.00409893]
Iteration 79 Loss: [0.00402436]
Iteration 80 Loss: [0.00395226]
Iteration 81 Loss: [0.00388254]
Iteration 82 Loss: [0.00381505]
Iteration 83 Loss: [0.00374958]
Iteration 84 Loss: [0.00368617]
Iteration 85 Loss: [0.00362475]
Iteration 86 Loss: [0.00356524]
Iteration 87 Loss: [0.00350752]
Iteration 88 Loss: [0.00345152]
Iteration 89 Loss: [0.00339719]
Iteration 90 Loss: [0.00334455]
Iteration 91 Loss: [0.00329337]
Iteration 92 Loss: [0.00324365]
Iteration 93 Loss: [0.00319529]
Iteration 94 Loss: [0.00314828]
Iteration 95 Loss: [0.00310284]
Iteration 96 Loss: [0.00305856]
Iteration 97 Loss: [0.00301541]
Iteration 98 Loss: [0.0029735]
Iteration 99 Loss: [0.0029327]
```

```
Out[12]: [<matplotlib.lines.Line2D at 0x520bb70>]
```



## 3.7 3.1.6 Extra credit (5 points)

Extend the functionality of one of these operations (e.g. add stride, dilation, or padding to the 2D Convolution) or implement a new one (e.g. fully-connected layer).

### 3.8 3.1.6 Extra Credit Attempt

An attempt was made at padding the 2D Convolution (see funtion pad_inputs()). However, this was not completed in time for the assignment

## 4 3.2 Training an image classifier (40 points)

```
In [1]: #@title (Hidden utility code: RUN ME FIRST) { display-mode: "form" }
        #!git clone https://github.com/tensorflow/models.git /content >/dev/null
        import sys
        import math
        sys.path.append('C:\\content\\tutorials\\image\\cifar10')
        from datetime import datetime
        import matplotlib.pyplot as plt
        import numpy as np

        plt.rcParams['axes.facecolor'] = 'white'

        import tensorflow as tf
        tf.reset_default_graph()
        try:
          tf.app.flags.FLAGS.f
        except Exception:
          tf.app.flags.DEFINE_string('f', '', """Placeholder.""")
        import cifar10
        tf.app.flags.FLAGS.batch_size = 100
        #from tensorflow.examples.models.tutorials.image.cifar10 import cifar10

        def plot_filters(filters, xlabel=None, ylabel=None):
          print(filters.shape)
          # filters: height x width x channels x num_filters
          num_filters = filters.shape[3]
          filter_height = filters.shape[0]
          filter_width = filters.shape[1]
          filter_channels = filters.shape[2]
          spacing = 1
          rows = int(math.ceil(math.sqrt(num_filters)))
          cols = int(math.ceil(math.sqrt(num_filters)))
          plot = np.zeros((rows*(filter_height+spacing), cols*(filter_width+spacing), min(filte

          min_value = np.min(filters)
          max_value = np.max(filters)
          filters = (filters - min_value) / (max_value - min_value)

          for f in range(num_filters):
            r = int(f/cols)
            c = f - r*cols
            plot[r*(filter_height+spacing):r*(filter_height+spacing)+filter_height,
                c*(filter_width+spacing):c*(filter_width+spacing)+filter_width,:] = filters[:,

          plt.grid(False)
          plt.imshow(np.squeeze(plot))
          if xlabel is not None:
            plt.xlabel(xlabel)
          if ylabel is not None:
            plt.ylabel(ylabel)
          plt.show()

        cifar10.maybe_download_and_extract()
        images, labels = cifar10.inputs(False)
        test_images, test_labels = cifar10.inputs(True)
```

### 4.1 3.2.1 Early stopping (15 points)

We have specified a very simple convolutional neural network to classify images from the Cifar-10 dataset. We then provide a training loop to optimize the weights of the network. Your task is to add Early Stopping (ES) to this training loop. Validation accuracy should be measured periodically, and training should stop if the validation accuracy does not reach a new absolute maximum after some number of measurements (this is called the "patience"). After training, we then measure the test accuracy. Before implementing ES, run the following cell to see a plot of the training loss and validation accuracy. Report the test accuracy you have found with ES.

### 4.2 Early Stopping Implementation

Early stopping is implemented by continually checking the value of the current accuracy within a certain incremental window. At each increment, the current accuracy is compared to the greatest accuracy found in the testing iterations, saving the current session if it is the greatest. The implementation includes a patience paramenter, to indicate how many increments it will search for a new maximum until quitting.

For this implementation, an approach was used to find the best validation increment and patience value similar to hyperparameter tuning. A large set of combinations was tested (see Early_Stopping_Parameter_Tuning PDF in directory Early_Stopping), finally resulting in the parameters chosen - a validation increment of 15 with a maximum patience of 25. While the values were recorded, none of the .ipynb notebooks with the results were saved (although there are several screenshots from results present in the directory).

### 4.3 3.2.2 Tuning hyperparameters (25 points)

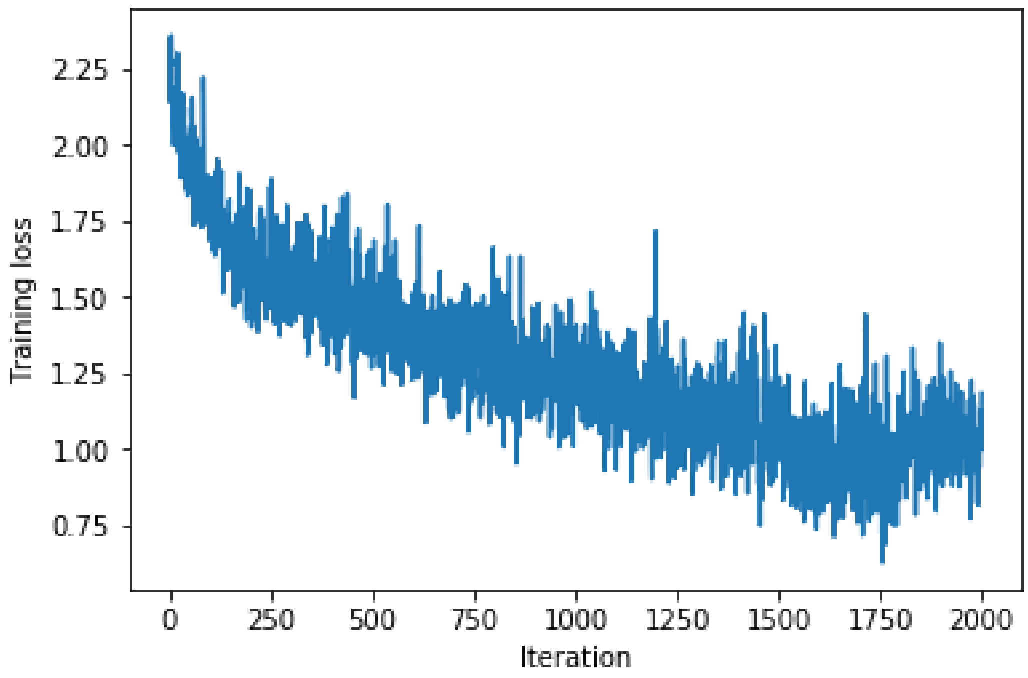
The hyperparameters we have chosen are not necessarily optimal. Pick two factors to search over (e.g. number of layers, filters per layer, learning rate, convolutional kernel size, etc.). Then write a procedure that uses grid search to find the combination of these hyperparameters that yields the highest validation accuracy. Finally, report the test accuracy achieved by this model.

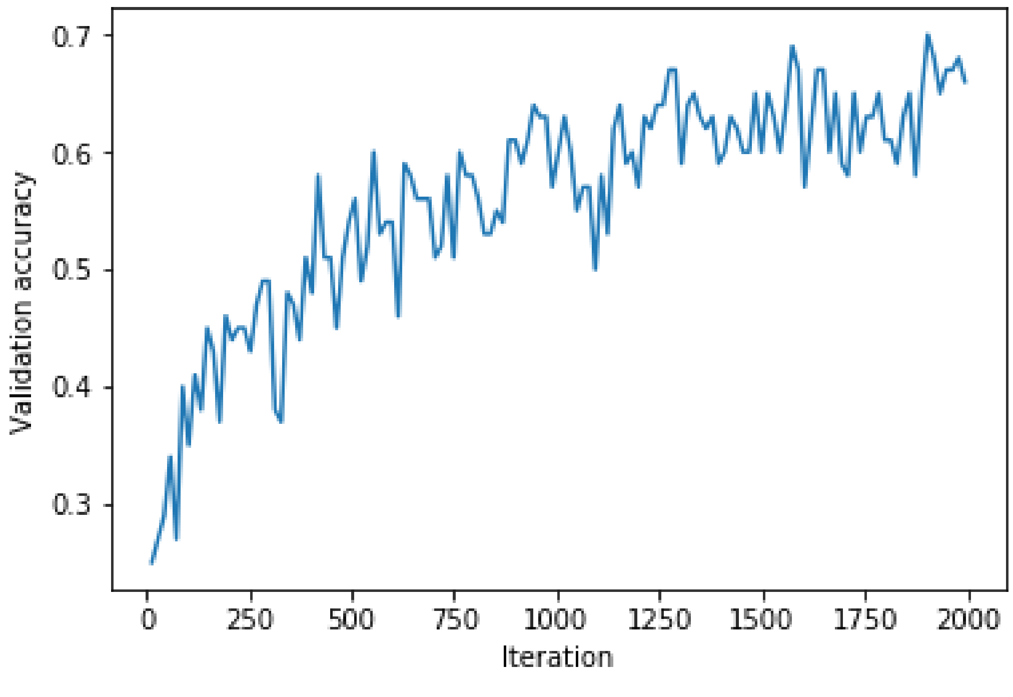
### 4.4 Tuning Hyperparameters Implementation

The two hyperparameters chosen for tuning in this implementation were learning rate and filter size. A large set of combinations was tested (see Hyperparameter_Tuning_Results PDF in directory Tuning_Hyperparameters), with the learning rate ranging from .001 to .5 and the filter size ranging from 32 to 128 (actual tested values can be seen below in lists or in the pdf). Unfortunately, there was a significant degredation of run time when attempting to calculate multiple hyperparameter combinations together. Therefore, the corresponding runs that led to each values are split into multiple notebooks, found in the Tuning_Hyperparameters directory. Each notebook is run over multiple filter sizes, keeping the learning rate values limited to one or two. The different notebooks can be found in files with the following format "Assignment3_learningrate_p#.ipynb", mostly split between 2 notebooks, with an exception of .2 being in three. In the end, the best parameters found in this testing were a learning rate of .06 and a filter size of 128.

```
In [2]: #Thweid: Added garbage collector in the attempt to speed up performance
        import gc

        #Thweid: Parameters included for hyperparameter tuning
        #        Lists were used to batch process different learning rates with different filt
        #all_learning_rates = [.001, .005, .01, .02, .025, .05, .06 , .075, .1, .2, .5 ]
        #all_filter_sizes = [ 32, 48, 64, 80, 96, 112, 128]
        best_learning_rate = [.06]
        best_filter_size = [128]

        #Parameters to keep track of the best total session through hyperparameter tuning
        best_valid_acc = -1
        best_sess_path = "/tmp/best-model.ckpt"

        sess = tf.Session()
        with sess.as_default():
          for lr in best_learning_rate:
            for f in best_filter_size:

              tf.train.start_queue_runners()
              im_width = 24

              # Define placeholders for image and label
              y_ = tf.placeholder(tf.float32, [None, 10])
              x = tf.placeholder(tf.float32, [None, im_width, im_width, 3])

              # Define a convolutional neural network (CNN)
              cnnL1 = tf.layers.conv2d(x, f, 5, strides=(2,2), activation=tf.nn.relu)
              cnnL2 = tf.layers.conv2d(cnnL1, f, 5, activation=tf.nn.relu)
              cnnL3 = tf.layers.conv2d(cnnL2, f, 5, activation=tf.nn.relu)
              cnn = tf.reduce_sum(tf.reduce_sum(cnnL3, axis=1), axis=1)
              cnn = tf.contrib.layers.flatten(cnn)
              y_cnn = tf.layers.dense(cnn, 10)

              cross_entropy_cnn = tf.reduce_mean(
                  tf.nn.softmax_cross_entropy_with_logits_v2(labels=y_, logits=y_cnn))
              train_step_cnn = tf.train.GradientDescentOptimizer(lr).minimize(cross_entropy_cn
              correct_prediction_cnn = tf.equal(tf.argmax(y_cnn, 1), tf.argmax(y_, 1))
              accuracy_cnn = tf.reduce_mean(tf.cast(correct_prediction_cnn, tf.float32))

              tf.global_variables_initializer().run(session=sess)

              #Thweid: Additional values added for Early Stopping
              #        Patience values from parameter tuning mentioned above
              #Use saver to save the current session with the best results from the validatio
              saver = tf.train.Saver()
              best_sess_path = "/tmp/model.ckpt"
              curr_max_accuracy = -1
              curr_patience = 0
              max_patience = 25
              validation_increment = 15
              quit_flag = False

              # Train
              print('Training... '+str(datetime.now()))
              valid_batch_xs, valid_batch_ys = sess.run([test_images, tf.one_hot(test_labels, 1
              train_losses = []
              test_accuracies = []
              valid_its = []
              valid_accuracies = []
                #Thweid: Iterations increased as patience and increment intervals requires 375
              num_its = 2000
              for it in range(num_its):
                if (it+1) % validation_increment == 0:
                  print('Iteration %d/%d ...' % (it, num_its))

                  # Validation accuracy
                  valid_acc_cnn = sess.run(accuracy_cnn, feed_dict={x: valid_batch_xs, y_: vali
                  valid_accuracies.append(valid_acc_cnn)
                  valid_its.append(it)

                  #Thweid:Increase patience
                  #       Check to see if a new max validity is found, reseting the max patien
                  #       Verify patience hasn't been exhausted, exiting if so
                  curr_patience += 1
                  if (valid_acc_cnn > curr_max_accuracy):
                    saver.save(sess, best_sess_path)
                    curr_max_accuracy = valid_acc_cnn
                    curr_patience = 0
                  if(curr_patience > max_patience):
                    quit_flag = True


                batch_xs, batch_ys = sess.run([images, tf.one_hot(labels, 10)])
                loss_cnn_out, _ = sess.run([cross_entropy_cnn, train_step_cnn], feed_dict={x: b
                train_losses.append(loss_cnn_out)

                #Thweid: If flag set to quit, then stop going through validation set
                if(quit_flag):
                  break

              #Thweid: Add Check to see if this was the best accuracy, updating if so
              #         call garbage collector for attempted speedup
              if(curr_max_accuracy > best_valid_acc):
                best_valid_acc = curr_max_accuracy
                saver.save(sess, best_sess_path)
              gc.collect()

          #Restore saved session
          saver.restore(sess, best_sess_path)

          print('Testing... '+str(datetime.now()))
          # # Test trained model
          test_batch_xs, test_batch_ys = sess.run([test_images, tf.one_hot(test_labels, 10)])

          true_label = tf.argmax(y_, 1)
          cnn_label = tf.argmax(y_cnn, 1)
          acc_cnn_out, true_label_out, cnn_label_out = sess.run([accuracy_cnn, true_label, cnn
                                                  y_: test_batch_ys})

        # Plot train loss and validation accuracy
        plt.plot(range(it+1), train_losses)
        plt.ylabel('Training loss')
        plt.xlabel('Iteration')
        plt.show()
        plt.plot(valid_its, valid_accuracies)
        plt.ylabel('Validation accuracy')
        plt.xlabel('Iteration')
        plt.show()

        print('Test accuracy: ' + str(acc_cnn_out*100)+ '%')
```

```
Training... 2018-05-20 23:17:42.975054
Iteration 14/2000 ...
Iteration 29/2000 ...
Iteration 44/2000 ...
Iteration 59/2000 ...
Iteration 74/2000 ...
Iteration 89/2000 ...
Iteration 104/2000 ...
Iteration 119/2000 ...
Iteration 134/2000 ...
Iteration 149/2000 ...
Iteration 164/2000 ...
Iteration 179/2000 ...
Iteration 194/2000 ...
Iteration 209/2000 ...
Iteration 224/2000 ...
Iteration 239/2000 ...
Iteration 254/2000 ...
Iteration 269/2000 ...
Iteration 284/2000 ...
Iteration 299/2000 ...
Iteration 314/2000 ...
Iteration 329/2000 ...
Iteration 344/2000 ...
Iteration 359/2000 ...
Iteration 374/2000 ...
Iteration 389/2000 ...
Iteration 404/2000 ...
Iteration 419/2000 ...
Iteration 434/2000 ...
Iteration 449/2000 ...
Iteration 464/2000 ...
Iteration 479/2000 ...
Iteration 494/2000 ...
Iteration 509/2000 ...
Iteration 524/2000 ...
Iteration 539/2000 ...
Iteration 554/2000 ...
Iteration 569/2000 ...
Iteration 584/2000 ...
Iteration 599/2000 ...
Iteration 614/2000 ...
Iteration 629/2000 ...
Iteration 644/2000 ...
Iteration 659/2000 ...
Iteration 674/2000 ...
Iteration 689/2000 ...
Iteration 704/2000 ...
Iteration 719/2000 ...
Iteration 734/2000 ...
Iteration 749/2000 ...
Iteration 764/2000 ...
Iteration 779/2000 ...
Iteration 794/2000 ...
Iteration 809/2000 ...
Iteration 824/2000 ...
Iteration 839/2000 ...
Iteration 854/2000 ...
Iteration 869/2000 ...
Iteration 884/2000 ...
Iteration 899/2000 ...
Iteration 914/2000 ...
Iteration 929/2000 ...
Iteration 944/2000 ...
Iteration 959/2000 ...
Iteration 974/2000 ...
Iteration 989/2000 ...
Iteration 1004/2000 ...
Iteration 1019/2000 ...
Iteration 1034/2000 ...
Iteration 1049/2000 ...
Iteration 1064/2000 ...
Iteration 1079/2000 ...
Iteration 1094/2000 ...
Iteration 1109/2000 ...
Iteration 1124/2000 ...
Iteration 1139/2000 ...
Iteration 1154/2000 ...
Iteration 1169/2000 ...
Iteration 1184/2000 ...
Iteration 1199/2000 ...
Iteration 1214/2000 ...
Iteration 1229/2000 ...
Iteration 1244/2000 ...
Iteration 1259/2000 ...
Iteration 1274/2000 ...
Iteration 1289/2000 ...
Iteration 1304/2000 ...
Iteration 1319/2000 ...
Iteration 1334/2000 ...
Iteration 1349/2000 ...
Iteration 1364/2000 ...
Iteration 1379/2000 ...
Iteration 1394/2000 ...
Iteration 1409/2000 ...
Iteration 1424/2000 ...
Iteration 1439/2000 ...
Iteration 1454/2000 ...
Iteration 1469/2000 ...
Iteration 1484/2000 ...
Iteration 1499/2000 ...
Iteration 1514/2000 ...
Iteration 1529/2000 ...
Iteration 1544/2000 ...
Iteration 1559/2000 ...
Iteration 1574/2000 ...
Iteration 1589/2000 ...
Iteration 1604/2000 ...
Iteration 1619/2000 ...
Iteration 1634/2000 ...
Iteration 1649/2000 ...
Iteration 1664/2000 ...
Iteration 1679/2000 ...
Iteration 1694/2000 ...
Iteration 1709/2000 ...
Iteration 1724/2000 ...
Iteration 1739/2000 ...
Iteration 1754/2000 ...
Iteration 1769/2000 ...
Iteration 1784/2000 ...
Iteration 1799/2000 ...
Iteration 1814/2000 ...
Iteration 1829/2000 ...
Iteration 1844/2000 ...
Iteration 1859/2000 ...
Iteration 1874/2000 ...
Iteration 1889/2000 ...
Iteration 1904/2000 ...
Iteration 1919/2000 ...
Iteration 1934/2000 ...
Iteration 1949/2000 ...
Iteration 1964/2000 ...
Iteration 1979/2000 ...
Iteration 1994/2000 ...
INFO:tensorflow:Restoring parameters from /tmp/model.ckpt
Testing... 2018-05-20 23:26:43.559973
```





```
Test accuracy: 55.000001192092896%%
```

If you are curious what the weights, activations, or confused images look like, we visualize them below. Feel free to modify this code to inspect other aspects of your trained model.

with sess.as_default(): # Show weights from the first layer print('Weights from the first layer') with tf.variable_scope("conv2d_1", reuse=True): weights = tf.get_variable('kernel') plot_filters(weights.eval())

# Show activations from the first feature map print('Activations from the first feature map.') fmap = cnnL1.eval(feed_dict={x: test_batch_xs, y_: test_batch_ys}) plot_filters(np.transpose(fmap[0:1,...], (1,2,0,3)))

# Show images in a confusion matrix confusion = np.zeros((24,24,3,100)) for b in range(true_label_out.shape[0]): confusion[:,:,:,true_label_out[b]*10 + cnn_label_out[b]] = test_batch_xs[b]

plot_filters(confusion, ylabel='True label', xlabel='Guessed label')