MNIST Dataset Overview

This example is using MNIST handwritten digits. The dataset contains 60,000 examples for training and 10,000 examples for testing. The digits have been size-normalized and centered in a fixed-size image (28x28 pixels) with values from 0 to 255.

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In [1]:
from future import absolute import, division, print function
import tensorflow as tf
from tensorflow.keras import Model, layers
import numpy as np
In [2]:
# MNIST dataset parameters.
num classes = 10 \# total classes (0-9 digits).
# Training parameters.
learning rate = 0.001
training steps = 25
batch size = 64
display step = 10
# Network parameters.
conv1 filters = 32 # number of filters for 1st conv layer.
conv2 filters = 64 # number of filters for 2nd conv layer.
fc1 units = 1024 # number of neurons for 1st fully-connected layer.
In [3]:
# Prepare MNIST data.
from tensorflow.keras.datasets import mnist
(x train, y train), (x test, y test) = mnist.load data()
# Convert to float32.
x train, x test = np.array(x train, np.float32), np.array(x test, np.float3
# Normalize images value from [0, 255] to [0, 1].
x_{train}, x_{test} = x_{train} / 255., x_{test} / 255.
In [4]:
# Use tf.data API to shuffle and batch data.
train data = tf.data.Dataset.from tensor slices((x train, y train))
train data = train data.repeat().shuffle(5000).batch(batch size).prefetch(1
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In [5]:
# Create TF Model.
class ConvNet (Model):
    # Set layers.
   def init (self):
        super(ConvNet, self). init ()
        # Convolution Layer with 32 filters and a kernel size of 5.
        self.conv1 = layers.Conv2D(32, kernel size=5, activation=tf.nn.relu
)
        # Max Pooling (down-sampling) with kernel size of 2 and strides of
2.
        self.maxpool1 = layers.MaxPool2D(2, strides=2)
        # Convolution Layer with 64 filters and a kernel size of 3.
        self.conv2 = layers.Conv2D(64, kernel size=3, activation=tf.nn.relu
)
        # Max Pooling (down-sampling) with kernel size of 2 and strides of
2.
        self.maxpool2 = layers.MaxPool2D(2, strides=2)
        # Flatten the data to a 1-D vector for the fully connected layer.
        self.flatten = layers.Flatten()
        # Fully connected layer.
        self.fc1 = layers.Dense(1024)
        # Apply Dropout (if is training is False, dropout is not applied).
        self.dropout = layers.Dropout(rate=0.5)
        # Output layer, class prediction.
        self.out = layers.Dense(num classes)
    # Set forward pass.
    def call(self, x, is training=False):
        x = tf.reshape(x, [-1, 28, 28, 1])
        x = self.conv1(x)
       x = self.maxpool1(x)
        x = self.conv2(x)
        x = self.maxpool2(x)
        x = self.flatten(x)
        x = self.fcl(x)
        x = self.dropout(x, training=is training)
        x = self.out(x)
        if not is training:
            # tf cross entropy expect logits without softmax, so only
            # apply softmax when not training.
            x = tf.nn.softmax(x)
        return x
```

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# Build neural network model.
conv net = ConvNet()
In [6]:
# Cross-Entropy Loss.
# Note that this will apply 'softmax' to the logits.
def cross entropy loss(x, y):
    # Convert labels to int 64 for tf cross-entropy function.
    y = tf.cast(y, tf.int64)
    # Apply softmax to logits and compute cross-entropy.
    loss = tf.nn.sparse softmax cross entropy with logits(labels=y, logits=
\times)
    # Average loss across the batch.
    return tf.reduce mean(loss)
# Accuracy metric.
def accuracy(y_pred, y_true):
    # Predicted class is the index of highest score in prediction vector (i
.e. argmax).
    correct prediction = tf.equal(tf.argmax(y pred, 1), tf.cast(y true, tf.
    return tf.reduce mean(tf.cast(correct prediction, tf.float32), axis=-1)
# Stochastic gradient descent optimizer.
optimizer = tf.optimizers.Adam(learning rate)
In [7]:
# Optimization process.
def run optimization(x, y):
    # Wrap computation inside a GradientTape for automatic differentiation.
    with tf.GradientTape() as q:
        # Forward pass.
        pred = conv net(x, is training=True)
        # Compute loss.
        loss = cross_entropy_loss(pred, y)
    # Variables to update, i.e. trainable variables.
    trainable_variables = conv_net.trainable_variables
    # Compute gradients.
    gradients = g.gradient(loss, trainable variables)
```

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# Update W and b following gradients.
    optimizer.apply gradients(zip(gradients, trainable variables))
In [8]:
# Run training for the given number of steps.
for step, (batch_x, batch_y) in enumerate(train_data.take(training_steps),
    \# Run the optimization to update W and b values.
    run optimization(batch x, batch y)
    if step % display step == 0:
        pred = conv net(batch x)
        loss = cross_entropy_loss(pred, batch_y)
        acc = accuracy(pred, batch y)
        print("step: %i, loss: %f, accuracy: %f" % (step, loss, acc))
In [9]:
# Test model on validation set.
pred = conv net(x test)
print("Test Accuracy: %f" % accuracy(pred, y test))
In [10]:
# Visualize predictions.
import matplotlib.pyplot as plt
In [11]:
# Predict 5 images from validation set.
n images = 5
test images = x test[:n images]
predictions = conv_net(test_images)
# Display image and model prediction.
for i in range(n_images):
    plt.imshow(np.reshape(test images[i], [28, 28]), cmap='gray')
    plt.show()
    print("Model prediction: %i" % np.argmax(predictions.numpy()[i]))
```