A2WriteUp_part2

March 6, 2020

0 Setup

[0]:
```
# ignore all future warnings
from warnings import simplefilter
simplefilter(action='ignore', category=FutureWarning)
```

[0]:
```
# importing tensorflow
try:
    import google.colab
    import tensorflow as tf
    %tensorflow_version 1.13
except:
    import tensorflow as tf
    assert tf.__version__ == "1.13.1"

    # ignore tensorflow depreciation warnings
    import tensorflow.python.util.deprecation as deprecation
    deprecation._PRINT_DEPRECATION_WARNINGS = False
```

[0]:
```
# imports
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models
```

[4]:
```
print(tf.__version__)
```

```
1.15.0
```

0.1 Visualizing the Dataset

[0]:
```
# given by the assignment
def loadData():
    with np.load("notMNIST.npz") as data:
        Data, Target = data ["images"], data["labels"]
        np.random.seed(521)
        randIndx = np.arange(len(Data))
        np.random.shuffle(randIndx)
        Data = Data[randIndx]/255.
        Target = Target[randIndx]
        trainData, trainTarget = Data[:15000], Target[:15000]
        validData, validTarget = Data[15000:16000], Target[15000:16000]
        testData, testTarget = Data[16000:], Target[16000:]
    return trainData, validData, testData, trainTarget, validTarget, testTarget
```

[6]:

```
trainData, validData, testData, trainTarget, validTarget, testTarget =␣
 ↪loadData()
print(f"Training Data: {trainData.shape}\tTraining tagets: {trainTarget.shape}")
print(f"Validation Data: {validData.shape}\tValidation tagets: {validTarget.
 ↪shape}")
print(f"Testing Data: {testData.shape}\tTesting tagets:{testTarget.shape}")
```

```
     ␣
↪---------------------------------------------------------------------------

    FileNotFoundError                         Traceback (most recent call␣
↪last)

    <ipython-input-6-bd37811a1dc2> in <module>()
  ----> 1 trainData, validData, testData, trainTarget, validTarget, testTarget␣
↪= loadData()
      2 print(f"Training Data: {trainData.shape}\tTraining tagets:␣
↪{trainTarget.shape}")
      3 print(f"Validation Data: {validData.shape}\tValidation tagets:␣
↪{validTarget.shape}")
      4 print(f"Testing Data: {testData.shape}\tTesting tagets:{testTarget.
↪shape}")


    <ipython-input-5-8c04b2024273> in loadData()
      1 def loadData():
  ----> 2     with np.load("notMNIST.npz") as data:
      3         Data, Target = data ["images"], data["labels"]
      4         np.random.seed(521)
      5         randIndx = np.arange(len(Data))


    /usr/local/lib/python3.6/dist-packages/numpy/lib/npyio.py in load(file,␣
↪mmap_mode, allow_pickle, fix_imports, encoding)
    426         own_fid = False
    427     else:
  --> 428         fid = open(os_fspath(file), "rb")
    429         own_fid = True
    430


    FileNotFoundError: [Errno 2] No such file or directory: 'notMNIST.npz'
```

[0]:
```
def plot(image, target, ax=None):
    ax = plt.gca() if ax == None else ax
    ax.imshow(image, cmap=plt.cm.gray)
    target_names = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J']
    ax.set_title(target_names[target])
    # targets interger encoded from 0 to 9 corresponding to 'A' to 'J',␣
 ↪respectively
```

[0]:
```
fig, axis = plt.subplots(2, 5, figsize=(16, 5))
for ax in axis.reshape(-1):
    r = np.random.randint(trainData.shape[0])
    plot(trainData[r], trainTarget[r], ax=ax)
plt.show()
```

0.2 Useful Functions

Some useful functions that will be used throughout the assignment such as getting random weights, getting the accuracy of a batch, making the loss and accuracy plots look nice, and global variables used throughout the code

[0]:
```
# given by the assignment
def convertOneHot(trainTarget, validTarget, testTarget):
    newtrain = np.zeros((trainTarget.shape[0], 10))
    newvalid = np.zeros((validTarget.shape[0], 10))
    newtest = np.zeros((testTarget.shape[0], 10))
    for item in range(0, trainTarget.shape[0]):
        newtrain[item][trainTarget[item]] = 1
    for item in range(0, validTarget.shape[0]):
        newvalid[item][validTarget[item]] = 1
    for item in range(0, testTarget.shape[0]):
        newtest[item][testTarget[item]] = 1
    return newtrain, newvalid, newtest
```

[0]:
```
def accuracy(y_pred, y):
    if y_pred.shape != y.shape:
        raise ValueError(f"prediction dimension {y_pred.shape} and label␣
↪dimensions {y.shape} don't match")
    return np.sum(y_pred.argmax(axis=1) == y.argmax(axis=1)) / y.shape[0]
```

[0]:
```
def plot_loss(x, train_loss=None, valid_loss=None, test_loss=None, title=None,␣
↪ax=None):
    ax = plt.gca() if ax == None else ax
    if train_loss != None:
        ax.plot(x, train_loss, label="Training Loss")
    if valid_loss != None:
        ax.plot(x, valid_loss, label="Validation Loss")
    if test_loss != None:
        ax.plot(x, test_loss, label="Testing Loss")

    ax.set_title("Loss" if title == None else title)

    ax.set_xlabel("Iterations")
    ax.set_xlim(left=0)
    ax.set_ylabel("Loss")
    ax.set_ylim(bottom=0)
    ax.legend(loc="upper right")

def plot_accuracy(x, train_accuracy=None, valid_accuracy=None,␣
↪test_accuracy=None, title=None, ax=None):
    ax = plt.gca() if ax == None else ax
    if train_accuracy != None:
```

```
        ax.plot(x, train_accuracy, label="Training Accuracy")
    if valid_accuracy != None:
        ax.plot(x, valid_accuracy, label="Validation Accuracy")
    if test_accuracy != None:
        ax.plot(x, test_accuracy, label="Testing Accuracy")

    ax.set_title("Accuracy" if title == None else title)

    ax.set_xlabel("Iterations")
    ax.set_xlim(left=0)
    ax.set_ylabel("Accuracy")
    ax.set_yticks(np.arange(0, 1.1, step=0.1))
    ax.grid(linestyle='-', axis='y')
    ax.legend(loc="lower right")


def display_statistics(train_loss=None, train_acc=None, valid_loss=None,␣
 ↪valid_acc=None,
                       test_loss=None, test_acc=None, y_loss_min=0,␣
 ↪y_acc_min=0):

    tl = "-" if train_loss is None else round(train_loss[-1], 4)
    ta = "-" if train_acc is None else round(train_acc[-1]*100, 2)
    vl = "-\t" if valid_loss is None else round(valid_loss[-1], 4)
    va = "-" if valid_acc is None else round(valid_acc[-1]*100, 2)
    sl = "-\t\t" if test_loss is None else round(test_loss[-1], 4)
    sa = "-" if test_acc is None else round(test_acc[-1]*100, 2)

    print(f"Training loss: {tl}{'':.20s}\t\tTraining acc: {ta}{'%' if ta != '-'␣
 ↪else ''}")
    print(f"Validation loss: {vl}{'':.20s}\tValidation acc: {va}{'%' if va !=␣
 ↪'-' else ''}")
    print(f"Testing loss: {sl}{'':.20s}\tTesting acc: {sa}{'%' if sa != '-'␣
 ↪else ''}")

    fig, ax = plt.subplots(1, 2, figsize=(18, 6))
    plot_loss(np.arange(0, len(train_loss), 1), train_loss, valid_loss,␣
 ↪test_loss, ax=ax[0])
    plot_accuracy(np.arange(0, len(train_loss), 1), train_acc, valid_acc,␣
 ↪test_acc, ax=ax[1])
    plt.show()
    plt.close()
```

[0]:
```
TINY = 1e-20
VTDatasets = {"validData" : validData, "validTarget" : validTarget,
              "testData" : testData, "testTarget" : testTarget}
```

```
N = trainData.shape[0]
d = trainData.shape[1] * trainData.shape[2]
K = 10
```

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2 Neural Networks in Tensorflow

2.1 Model implementation

[0]:
```
# load + reshape data
trainData, validData, testData, trainTarget, validTarget, testTarget =␣
 ↪loadData()
trainData = trainData.reshape(15000,28,28,1)
validData = validData.reshape(1000,28,28,1)
testData = testData.reshape(2724,28,28,1)

# one-hot encode
train_labels, valid_labels, test_labels = convertOneHot(trainTarget,␣
 ↪validTarget, testTarget)
```

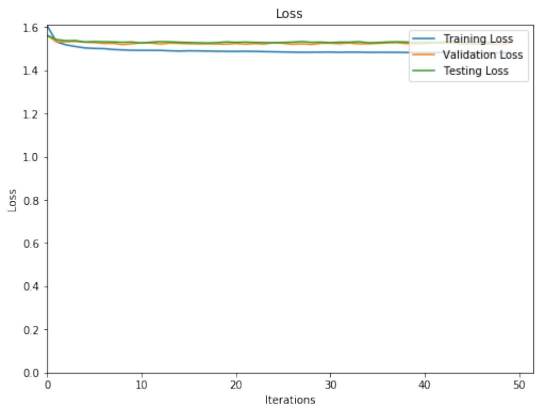
[0]:
```
# training params
learning_rate = 0.0001
epochs = 50
batch_size = 32

# create model
model = models.Sequential()
model.add(layers.InputLayer(input_shape=(28, 28,1)))     # input layer
model.add(layers.Conv2D(                                  # conv layer
        filters=32,
        strides=(1,1),
        kernel_size=[3, 3],
        padding="same",
        activation='relu',
        kernel_initializer=tf.contrib.layers.xavier_initializer(uniform=False)))
model.add(layers.BatchNormalization())                    # batch norm
model.add(layers.MaxPooling2D((2, 2)))                    # max pooling
model.add(layers.Flatten())                               # flatten
model.add(layers.Dense(784, activation='relu'))           # fully-connected 784
model.add(layers.Dense(10))                               # fully-connected 10
model.add(layers.Softmax())                               # softmax output

# compile model w/ Adam optimizer + cross entropy loss
model.compile(optimizer=tf.keras.optimizers.Adam(lr=learning_rate),
              loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

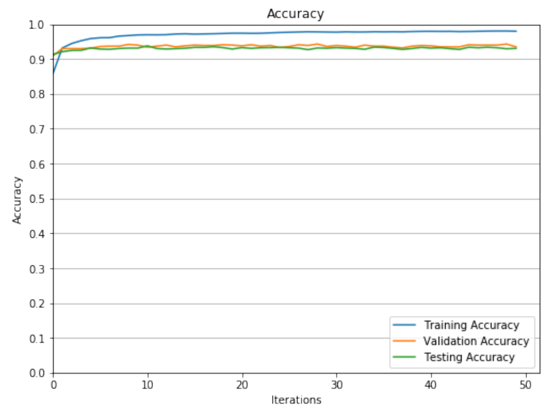
2.2 Model Training

[ ]:
```
# callback to test after each epoch
class TestCallback(tf.keras.callbacks.Callback):
    def __init__(self, test_data):
        self.test_data = test_data
        self.test_acc = []
        self.test_loss = []

    def on_epoch_end(self, epoch, logs=None):
        # perform a test per epoch
        x, y = self.test_data
        loss, acc = self.model.evaluate(x, y, verbose=0, batch_size=32)
        self.test_loss.append(loss)
        self.test_acc.append(acc)
        # append to returned dictionary
        logs["test_loss"] = self.test_loss
        logs["test_acc"] = self.test_acc
```

[0]:
```
# training
history = model.fit(trainData, train_labels,
                    validation_data = (validData, valid_labels),
                    epochs=epochs,
                    batch_size=batch_size,
                    callbacks=[TestCallback((testData, test_labels))],
                    verbose=0,  # 0 = silent, 1 = per epoch
                    shuffle=True)

# display statistics
train_acc, train_loss = history.history["acc"], history.history["loss"]
val_acc, val_loss = history.history["val_acc"], history.history["val_loss"]
test_acc, test_loss = history.history["test_acc"][0], history.
 ↪history["test_loss"][0]

display_statistics(train_loss=train_loss, train_acc=train_acc,
                   valid_loss=val_loss, valid_acc=val_acc,
                   test_loss=test_loss, test_acc=test_acc)
```

```
Training loss: 1.4814           Training acc: 97.97%
Validation loss: 1.5248 Validation acc: 93.5%
Testing loss: 1.5293    Testing acc: 93.06%
```


Loss
Training Loss
Validation Loss
Testing Loss
Loss
Iterations


Accuracy
Training Accuracy
Validation Accuracy
Testing Accuracy
Accuracy
Iterations

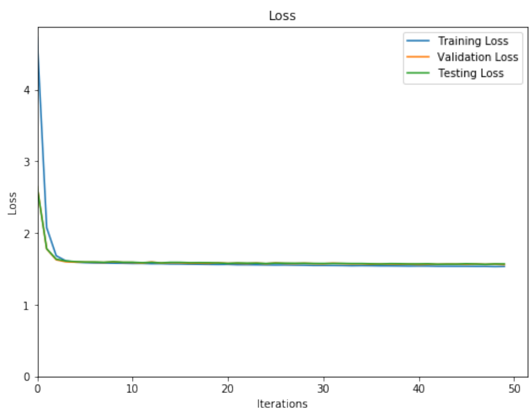
2.3 Hyperparameter Investigation

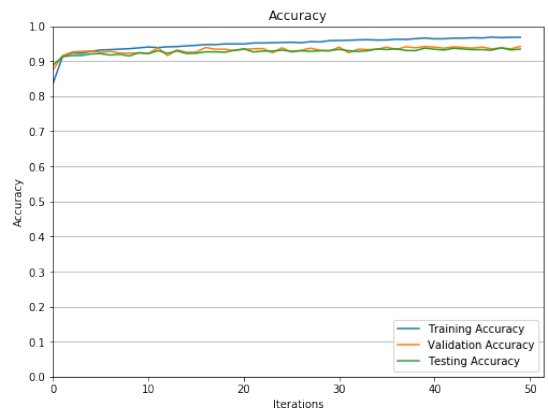
2.3.1 L2 Regularization

[0]:
```
# training params
learning_rate = 0.0001
epochs = 50
batch_size = 32

# test all weight decays [0.01, 0.1, 0.5]
for scale in [0.01, 0.1, 0.5]:
    print("\nL2 Normalization with {}\n".format(scale))

    # create model
    model = models.Sequential()
    model.add(layers.InputLayer(input_shape=(28, 28,1)))    # input layer
    model.add(layers.Conv2D(                                # conv layer
          filters=32,
          strides=(1,1),
          kernel_size=[3, 3],
          padding="same",
          activation='relu',
          kernel_initializer=tf.contrib.layers.
↪xavier_initializer(uniform=False)))
    model.add(layers.BatchNormalization())                  # batch norm
    model.add(layers.MaxPooling2D((2, 2)))                  # max pooling
    model.add(layers.Flatten())                             # flatten
    model.add(layers.Dense(784,
                        activation='relu',
                        kernel_regularizer=tf.contrib.layers.
↪l2_regularizer(scale=scale)))                                  #␣
↪fully-connected 784 w/ ReLu
    model.add(layers.Dense(10))                             # fully-connected 10
    model.add(layers.Softmax())                             # softmax output

    # compile model w/ Adam optimizer + cross entropy loss
    model.compile(optimizer=tf.keras.optimizers.Adam(lr=learning_rate),
                loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True),
                metrics=['accuracy'])

    # train
    history_1 = model.fit(trainData, train_labels,
                        validation_data = (validData, valid_labels),
                        epochs=epochs,
                        batch_size=batch_size,
                        callbacks=[TestCallback((testData, test_labels))],
                        verbose=0,  # 0 = silent, 1 = per epoch
```

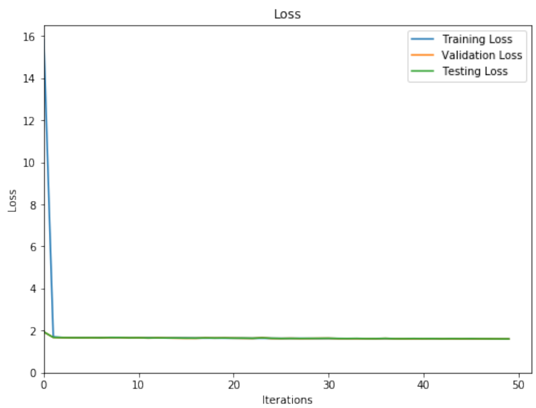
```
                        shuffle=True)
    # display statistics
    train_acc, train_loss = history.history["acc"], history.history["loss"]
    val_acc, val_loss = history.history["val_acc"], history.history["val_loss"]
    test_acc, test_loss = history.history["test_acc"][0], history.
↪history["test_loss"][0]

    display_statistics(train_loss=train_loss, train_acc=train_acc,
                        valid_loss=val_loss, valid_acc=val_acc,
                        test_loss=test_loss, test_acc=test_acc)
```

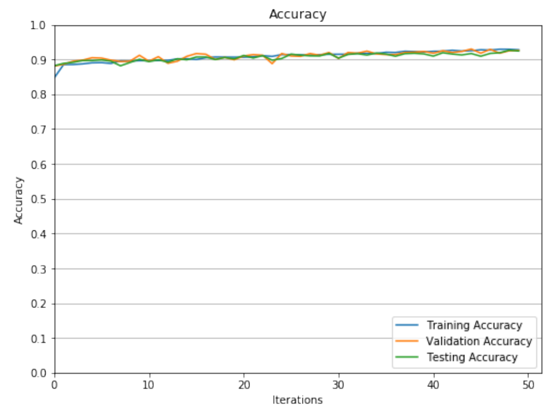
```
L2 Normalization with 0.01

Training loss: 1.5349           Training acc: 96.81%
Validation loss: 1.5601 Validation acc: 94.2%
Testing loss: 1.5696    Testing acc: 93.43%
```



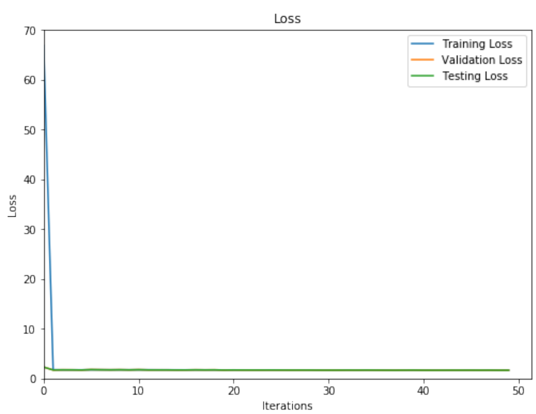


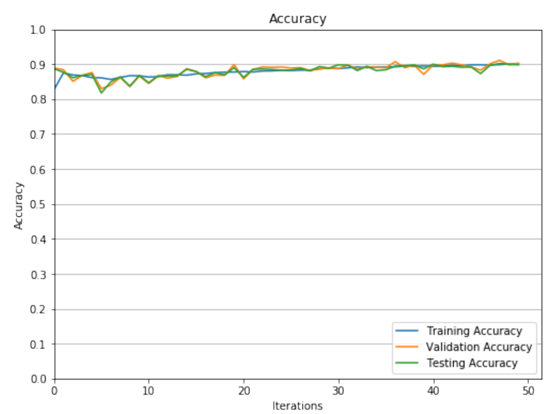

```
L2 Normalization with 0.1

Training loss: 1.6037           Training acc: 92.77%
Validation loss: 1.6033 Validation acc: 92.6%
Testing loss: 1.6058    Testing acc: 92.44%
```






```
L2 Normalization with 0.5

Training loss: 1.6729           Training acc: 90.07%
Validation loss: 1.6705 Validation acc: 90.3%
Testing loss: 1.6746    Testing acc: 89.83%
```





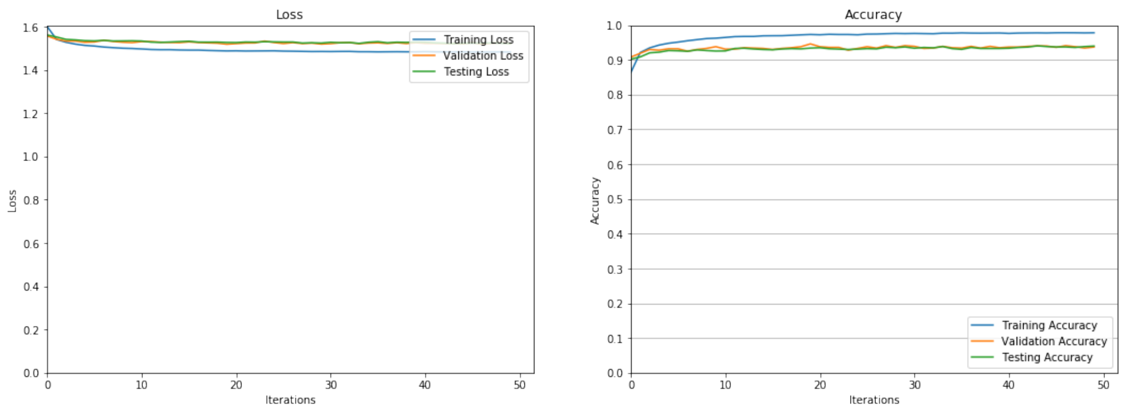
General Comments: L2 regularization is a technique to reduce overfitting. For small values of λ, we expect a slight improvement in model performance and a reduced discrepancy between training and validation/test accuracies. This is exactly what we observe here. For $\lambda = 0.01$, we observe validation and testing accuracy both improve slightly while training accuracy decreases by $\sim 1.5\%$. So, the model performance improves slightly and the model overfits less as expected. For values of λ that are too large, we expect the model to start underfitting as we are harshly penalizing parameter vectors which are large in magnitude. As λ increases, we see the discrepancy between training and validation/test accuracies decrease dramatically (the model is no longer overfitting). However, this change is accompanied by a reduction in overall accuracy (by $\sim 2\%$) as the model is now underfitting.

2.3.2 Dropout

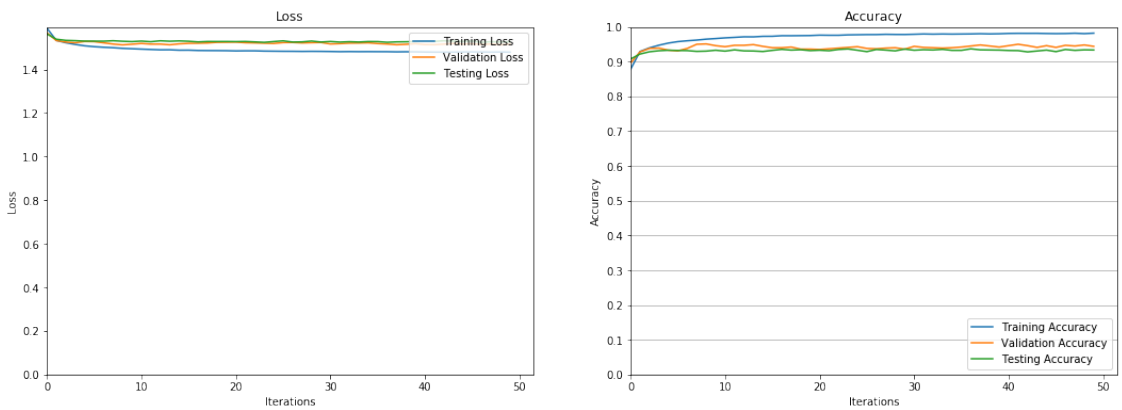
[0]:
```
# training params
learning_rate = 0.0001
epochs = 50
batch_size = 32

# for rate in [0.9, 0.75, 0.5]:
for rate in [0.1, 0.25, 0.5]:
    print("\nDropout with probability {}\n".format(rate))

    # create model
    model = models.Sequential()
    model.add(layers.InputLayer(input_shape=(28, 28,1)))    # input layer
    model.add(layers.Conv2D(                                # conv layer
          filters=32,
          strides=(1,1),
          kernel_size=[3, 3],
          padding="same",
          activation='relu',
          kernel_initializer=tf.contrib.layers.
 ↪xavier_initializer(uniform=False)))
    model.add(layers.BatchNormalization())                  # batch norm
    model.add(layers.MaxPooling2D((2, 2)))                  # max pooling
    model.add(layers.Flatten())                             # flatten
    model.add(layers.Dense(784))                            # fully-connected 784
    model.add(layers.Dropout(rate=rate))                    # dropout
    model.add(layers.ReLU())                                # Relu activation
    model.add(layers.Dense(10))                             # fully-connected 10
    model.add(layers.Softmax())                             # softmax output

    # compile model w/ Adam optimizer + cross entropy loss
    model.compile(optimizer=tf.keras.optimizers.Adam(lr=learning_rate),
                loss=tf.keras.losses.CategoricalCrossentropy(from_logits=True),
                metrics=['accuracy'])

    # train
    history_2 = model.fit(trainData, train_labels,
                      validation_data = (validData, valid_labels),
                      epochs=epochs,
                      batch_size=batch_size,
                      callbacks=[TestCallback((testData, test_labels))],
                      verbose=0,  # 0 = silent, 1 = per epoch
                      shuffle=True)
    # display stats
    train_acc, train_loss = history.history["acc"], history.history["loss"]
    val_acc, val_loss = history.history["val_acc"], history.history["val_loss"]
```

```
    test_acc, test_loss = history.history["test_acc"][0], history.
↪history["test_loss"][0]

    display_statistics(train_loss=train_loss, train_acc=train_acc,
                       valid_loss=val_loss, valid_acc=val_acc,
                       test_loss=test_loss, test_acc=test_acc)
```

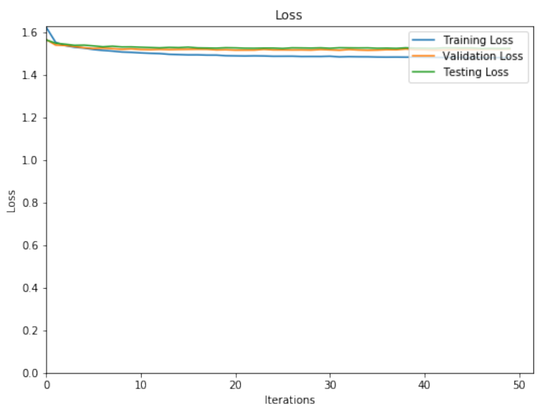
```
Dropout with probability 0.1

Training loss: 1.4831           Training acc: 97.81%
Validation loss: 1.5229 Validation acc: 93.7%
Testing loss: 1.5219    Testing acc: 93.98%
```

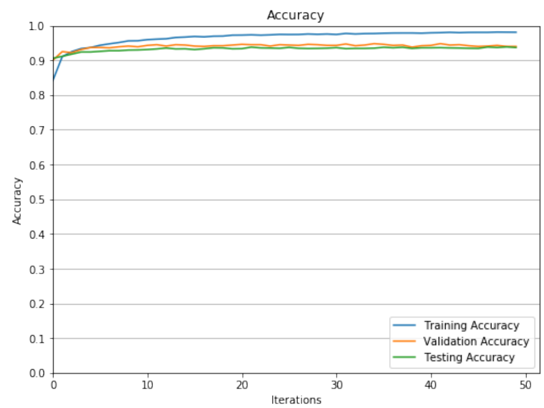



```
Dropout with probability 0.25

Training loss: 1.4794           Training acc: 98.19%
Validation loss: 1.5156 Validation acc: 94.4%
Testing loss: 1.527     Testing acc: 93.36%
```



```
Dropout with probability 0.5

Training loss: 1.4803           Training acc: 98.09%
Validation loss: 1.5206 Validation acc: 94.0%
Testing loss: 1.5238    Testing acc: 93.69%
```





General Comments: Dropout is a technique which aims to decrease overfitting in our model. We expect see this in the form of improved accuracy and loss statistics. Indeed, this is exactly observed. As the amount of dropout increases (keeping the rate within reason), the validation and testing accuracies both improve. Note that we also see training accuracy improve. So, it seems that the model as an increased capacity to learn overall. With dropout, it is able to learn the training data better, but it is also able to generalize better.