Statistical Packages

HW9

Mohamed Salem

```
# we begin by loading our required libraries
library(reticulate)
library(tensorflow)
library(keras)
```

Due to issues and incompatibilities faced when attempting to install the latest version of Anaconda on a windows 8 machine, and incompatibilities between the latest version of Python (3.7) and Tensorflow, we have manually installed an older version of Anaconda (3.5.1) which comes with Python 3.6. We've also manually installed tensorflow through Anaconda via the pip commands:

pip install tensorflow conda create -n tensorflow_env tensorflow

Next we load both keras and tensorflow through the set up conda environment:

```
# Note, we've excluded this chunk from being evaluated to avoid
# running an installation every time we knit
install_tensorflow(method = "conda", conda = "C:/ProgramData/Anaconda3/Scripts/conda.exe",
    envname = "tensorflow_env")
install_keras(method = "conda", conda = "C:/ProgramData/Anaconda3/Scripts/conda.exe")
Sys.setenv(TENSORFLOW_PYTHON = "C:/ProgramData/Anaconda3/envs/tensorflow_env/python.exe")
Sys.setenv(KERAS PYTHON = "C:/ProgramData/Anaconda3/envs/tensorflow env/python.exe")
tensorflow::use condaenv("tensorflow env")
keras::use_condaenv("tensorflow_env")
use python("C:/ProgramData/Anaconda3/envs/tensorflow env/python.exe")
use_condaenv(conda = "C:/ProgramData/Anaconda3/Scripts/conda.exe")
is_keras_available()
## [1] TRUE
use_condaenv(conda = "C:/ProgramData/Anaconda3/Scripts/conda.exe")
# Finally, we check if keras is available for use
is_keras_available()
## [1] TRUE
# and we check that Tensorflow is active and visible to our system
reticulate::py_config()
## python:
                   C:/ProgramData/Anaconda3/envs/tensorflow_env/python.exe
                   C:/ProgramData/Anaconda3/envs/tensorflow_env/python36.dll
## libpython:
                   C:\PROGRA~3\ANACON~1\envs\TENSOR~1
## pythonhome:
                   3.6.9 | Anaconda, Inc. | (default, Jul 30 2019, 14:00:49) [MSC v.1915 64 bit (AMD64)]
## version:
## Architecture:
                  64bit
## numpy:
                   C:\PROGRA~3\ANACON~1\envs\TENSOR~1\lib\site-packages\numpy
## numpy_version: 1.17.4
                   C:\PROGRA~3\ANACON~1\envs\TENSOR~1\lib\site-packages\tensorflow\__init__.p
## tensorflow:
## NOTE: Python version was forced by RETICULATE PYTHON
```

We've also faced issues loading the MNIST dataset directly from keras. So, we've opted for importing the

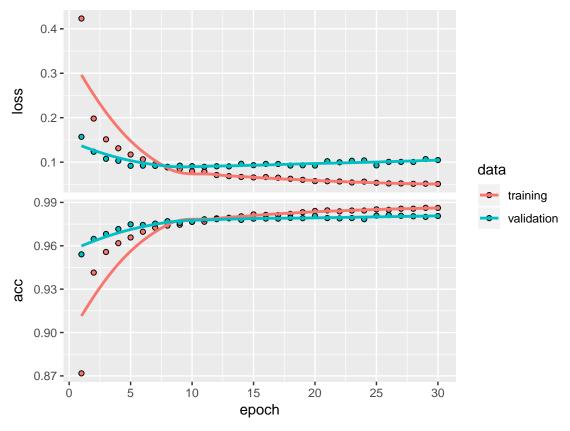
same dataset from another package as displayed below:

```
library(dslabs)
mnist <- read_mnist()</pre>
```

Now that we have our MNIST dataset loaded and functional, we begin by fitting our neural networks:

```
# Splitting the data into training and testing sets
x train <- mnist$train$images</pre>
y_train <- mnist$train$labels</pre>
x_test <- mnist$test$images</pre>
y_test <- mnist$test$labels</pre>
# Converting the data from 3D arrays into matrices
x train <- array reshape(x train, c(nrow(x train), 784))
x_test <- array_reshape(x_test, c(nrow(x_test), 784))</pre>
# converting grayscale values into integers
x_train <- x_train/255</pre>
x_{test} <- x_{test/255}
# Creating dummy variables for the response
y_train <- to_categorical(y_train, 10)</pre>
y_test <- to_categorical(y_test, 10)</pre>
# Setting up the keras Sequential model
model <- keras_model_sequential()</pre>
model %>% layer_dense(units = 256, activation = "relu", input_shape = c(784)) %>%
    layer_dropout(rate = 0.4) %>% layer_dense(units = 128, activation = "relu") %>%
    layer_dropout(rate = 0.3) %>% layer_dense(units = 10, activation = "softmax")
# A summary of the model
summary(model)
```

```
## Layer (type)
                   Output Shape
                                           Param #
## dense (Dense)
                       (None, 256)
                                            200960
## dropout (Dropout)
                       (None, 256)
## _____
## dense_1 (Dense)
                        (None, 128)
                                            32896
## dropout_1 (Dropout)
                       (None, 128)
## dense_2 (Dense) (None, 10)
                                           1290
## Total params: 235,146
## Trainable params: 235,146
## Non-trainable params: 0
## ______
# Compiling the model with a loss function and other metrics
model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
  metrics = c("accuracy"))
# Training the model 30 times using 128 images per trial
history <- model %>% fit(x_train, y_train, epochs = 30, batch_size = 128,
  validation_split = 0.2)
# A plot of the model's development and improvement
plot(history)
```



Evaluating the model's performance on the test set
model %>% evaluate(x_test, y_test)

```
## $loss
## [1] 0.1040854
##
## $acc
## [1] 0.9811
```

Generating predictions model %>% predict_classes(x_test)

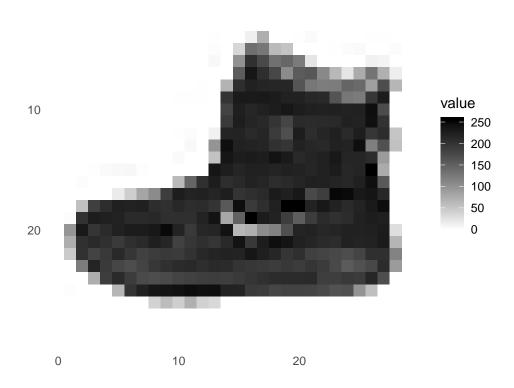
$[1] \ 7 \ 2 \ 1 \ 0 \ 4 \ 1 \ 4 \ 9 \ 5 \ 9 \ 0 \ 6 \ 9 \ 0 \ 1 \ 5 \ 9 \ 7 \ 3 \ 4 \ 9 \ 6 \ 6 \ 5 \ 4 \ 0 \ 7 \ 4 \ 0 \ 1 \ 3 \ 1 \ 3 \ 4$ ## [35] 7 2 7 1 2 1 1 7 4 2 3 5 1 2 4 4 6 3 5 5 6 0 4 1 9 5 7 8 9 3 7 $[69] \ 3 \ 0 \ 7 \ 0 \ 2 \ 9 \ 1 \ 7 \ 3 \ 2 \ 9 \ 7 \ 7 \ 6 \ 2 \ 7 \ 8 \ 4 \ 7 \ 3 \ 6 \ 1 \ 3 \ 6 \ 9 \ 3 \ 1 \ 4 \ 1 \ 7 \ 6 \ 9 \ 6 \ 0$ ## [103] 5 4 9 9 2 1 9 4 8 7 3 9 7 4 4 4 9 2 5 4 7 6 7 9 0 5 8 5 6 6 5 7 8 1 ## ## [137] 0 1 6 4 6 7 3 1 7 1 8 2 0 3 9 9 5 5 1 5 6 0 3 4 4 6 5 4 6 5 4 5 1 4 ## [171] 4 7 2 3 2 7 1 8 1 8 1 8 5 0 8 9 2 5 0 1 1 1 0 9 0 3 1 6 4 2 3 6 1 1 ## $\begin{smallmatrix} 205 \end{smallmatrix}] \ 1 \ 3 \ 9 \ 5 \ 2 \ 9 \ 4 \ 5 \ 9 \ 3 \ 9 \ 0 \ 3 \ 5 \ 5 \ 7 \ 2 \ 2 \ 7 \ 1 \ 2 \ 8 \ 4 \ 1 \ 7 \ 3 \ 3 \ 8 \ 8 \ 7 \ 9 \ 2 \ 2$ [239] 4 1 5 9 8 7 2 3 0 2 4 2 4 1 9 5 7 7 2 8 2 6 8 5 7 7 9 1 8 1 8 0 3 0 ## ## [273] 1 9 9 4 1 8 2 1 2 9 7 5 9 2 6 4 1 5 8 2 9 2 0 4 0 0 2 8 4 7 1 2 4 0 [307] 2 7 4 3 3 0 0 3 1 9 6 5 2 5 9 7 9 3 0 4 2 0 7 1 1 2 1 5 3 3 9 7 8 6 ## [341] 3 6 1 3 8 1 0 5 1 3 1 5 5 6 1 8 5 1 7 9 4 6 2 2 5 0 6 5 6 3 7 2 0 8 ## ## [375] 8 5 4 1 1 4 0 7 3 7 6 1 6 2 1 9 2 8 6 1 9 5 2 5 4 4 2 8 3 8 2 4 5 0 [409] 3 1 7 7 5 7 9 7 1 9 2 1 4 2 9 2 0 4 9 1 4 8 1 8 4 5 9 8 8 3 7 6 0 0 ## ## ## [477] 1 2 5 9 1 9 7 5 4 0 8 9 9 1 0 5 2 3 7 0 9 4 0 6 3 9 5 2 1 3 1 3 6 5 [511] 7 4 2 2 6 3 2 6 5 4 8 9 7 1 3 0 3 8 3 1 9 3 4 4 6 4 2 1 8 2 5 4 8 8

```
## [9725] 0 1 2 3 4 6 6 7 8 9 7 4 6 1 4 0 4 9 3 7 8 0 7 5 8 5 3 2 2 0 5 8 6 0 ## [9759] 3 8 1 0 3 0 4 7 4 9 0 9 0 7 1 7 1 6 6 5 6 2 8 7 6 4 9 9 5 3 7 4 3 0 ## [9793] 7 6 6 1 1 3 2 1 0 0 1 2 3 4 7 8 9 0 1 2 3 4 5 6 7 8 0 1 2 3 4 7 8 9 8 6 7 ## [9827] 0 8 3 9 5 5 2 6 8 4 1 7 1 7 1 7 3 5 6 9 1 1 1 2 1 2 0 7 7 5 8 2 9 8 6 7 ## [9861] 3 4 6 8 7 0 4 2 7 7 5 4 3 4 5 6 7 8 0 1 2 3 4 5 6 7 8 0 1 2 3 4 7 8 9 9 8 2 ## [9829] 4 7 0 1 9 2 8 7 8 2 6 0 6 5 3 3 3 9 1 4 0 6 1 0 0 6 2 1 1 7 7 8 4 6 ## [9963] 0 7 0 3 6 8 7 1 5 2 4 9 4 3 6 4 1 7 3 6 6 0 1 2 3 4 5 6 7 8 9 0 1 2 ## [9997] 3 4 5 6
```

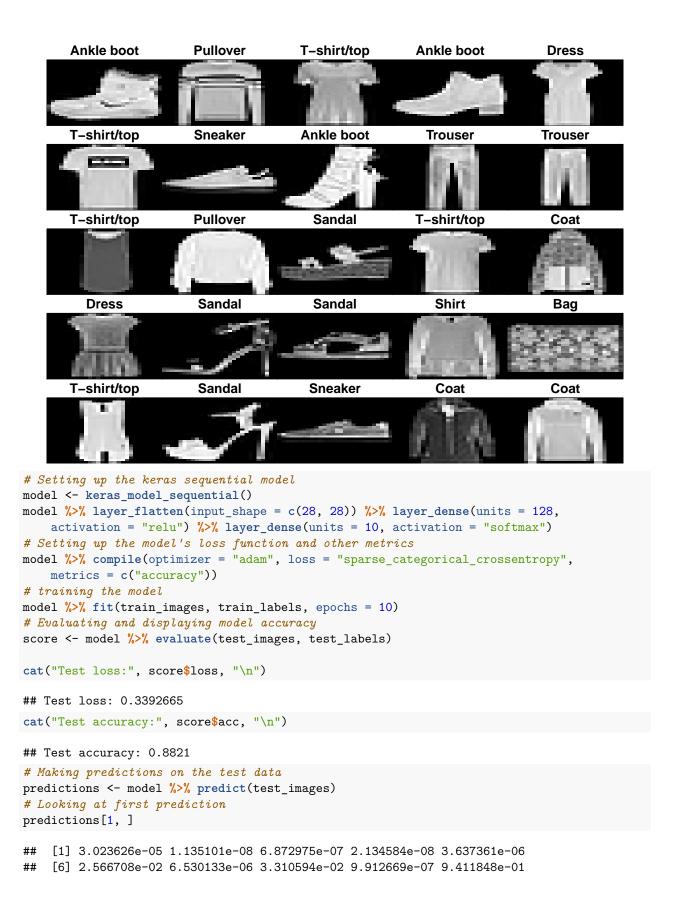
Now that we've got our tools up and running on the MNIST dataset, we'll move on to the more interesting Fashion MNIST dataset.

```
# Importing the Fashion MNIST dataset
fashion_mnist <- dataset_fashion_mnist()</pre>
# Splitting the data into testing and training sets
c(train_images, train_labels) %<-% fashion_mnist$train
c(test_images, test_labels) %<-% fashion_mnist$test
# Creating a vector of class names
class_names = c("T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
    "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot")
# Exploring the dimensions and characteristics of the data
dim(train images)
## [1] 60000
                       28
dim(train labels)
## [1] 60000
train_labels[1:20]
## [1] 9 0 0 3 0 2 7 2 5 5 0 9 5 5 7 9 1 0 6 4
dim(test_images)
## [1] 10000
                28
                      28
dim(test_labels)
## [1] 10000
# Examining a sample of the data
image_1 <- as.data.frame(train_images[1, , ])</pre>
colnames(image_1) <- seq_len(ncol(image_1))</pre>
image_1$y <- seq_len(nrow(image_1))</pre>
image_1 <- gather(image_1, "x", "value", -y)</pre>
image_1$x <- as.integer(image_1$x)</pre>
ggplot(image_1, aes(x = x, y = y, fill = value)) + geom_tile() + scale_fill_gradient(low = "white",
    high = "black", na.value = NA) + scale y reverse() + theme minimal() +
    theme(panel.grid = element_blank()) + theme(aspect.ratio = 1) +
    xlab("") + ylab("")
```





```
# Converting grayscale into integer values
train_images <- train_images/255
test_images <- test_images/255
# Visually examining the training set images
par(mfcol = c(5, 5))
par(mar = c(0, 0, 1.5, 0), xaxs = "i", yaxs = "i")
for (i in 1:25) {
   img <- train_images[i, , ]
   img <- t(apply(img, 2, rev))
   image(1:28, 1:28, img, col = gray((0:255)/255), xaxt = "n", yaxt = "n",
        main = paste(class_names[train_labels[i] + 1]))
}</pre>
```



```
# the label associated with the previous prediction (1-10 scale)
which.max(predictions[1, ])
## [1] 10
# Another way to retrieve the first twenty predictions
class pred <- model %>% predict classes(test images)
class_pred[1:20]
## [1] 9 2 1 1 6 1 4 6 5 7 4 5 7 3 4 1 2 2 8 0
# Retrieving first prediction label again (0-9) scale
test_labels[1]
## [1] 9
# Plotting sample of first 25 predictions
par(mfcol = c(5, 5))
par(mar = c(0, 0, 1.5, 0), xaxs = "i", yaxs = "i")
for (i in 1:25) {
    img <- test_images[i, , ]</pre>
    img <- t(apply(img, 2, rev))</pre>
    \# subtract 1 as labels go from 0 to 9
    predicted_label <- which.max(predictions[i, ]) - 1</pre>
    true_label <- test_labels[i]</pre>
    if (predicted_label == true_label) {
        color <- "#008800"
    } else {
        color <- "#bb0000"
    image(1:28, 1:28, img, col = gray((0:255)/255), xaxt = "n", yaxt = "n",
        main = paste0(class_names[predicted_label + 1], " (", class_names[true_label +
            1], ")"), col.main = color)
}
```

```
kle boot (Ankle bo Trouser (Trouser)
                                          Coat (Coat)
                                                         Trouser (Trouser) Pullover (Pullover)
   Pullover (Pullover)
                        Coat (Coat)
                                        Sandal (Sandal) Pullover (Pullover) Sandal (Sandal)
    Trouser (Trouser)
                        Shirt (Shirt)
                                       Sneaker (Sneaker) Pullover (Coat) Sneaker (Sneaker)
                                         Dress (Dress)
    Trouser (Trouser) Sandal (Sandal)
                                                                          Sandal (Ankle boot
                                                             Bag (Bag)
                                                        shirt/top (T-shirt/tcTrouser (Trouser)
       Shirt (Shirt)
                     Sneaker (Sneaker)
                                          Coat (Coat)
# Making a single prediction
img <- test_images[1, , , drop = FALSE]</pre>
dim(img)
## [1] 1 28 28
predictions <- model %>% predict(img)
predictions
##
                 [,1]
                               [,2]
                                             [,3]
                                                           [,4]
                                                                         [,5]
## [1,] 3.023629e-05 1.135103e-08 6.872995e-07 2.134576e-08 3.637361e-06
                             [,7]
                                         [,8]
                                                      [,9]
                                                                [,10]
## [1,] 0.02566708 6.530126e-06 0.03310595 9.912669e-07 0.9411848
# Prediction label (1-10 scale)
prediction <- predictions[1, ] - 1</pre>
which.max(prediction)
## [1] 10
# Prediction label (0-9 scale)
class_pred <- model %>% predict_classes(img)
class_pred
## [1] 9
```