Homework 9

Due Wednesday Nov 20, 2019 2019-11-17

```
#devtools::install_github("rstudio/keras")
#install_keras()
#install_tensorflow(gpu = FALSE)
mnist <- dataset_mnist()</pre>
x_train <- mnist$train$x</pre>
y_train <- mnist$train$y</pre>
x_test <- mnist$test$x</pre>
y_test <- mnist$test$y</pre>
# reshape
x_train <- array_reshape(x_train, c(nrow(x_train), 784))</pre>
x_test <- array_reshape(x_test, c(nrow(x_test), 784))</pre>
# rescale
x_train <- x_train / 255
x_test <- x_test / 255
y_train <- to_categorical(y_train, 10)</pre>
y_test <- to_categorical(y_test, 10)</pre>
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')
summary(model)
## Model: "sequential"
## ______## 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)
## Total params: 235,146
```

```
## Trainable params: 235,146
## Non-trainable params: 0
model %>% compile(
  loss = 'categorical_crossentropy',
  optimizer = optimizer_rmsprop(),
  metrics = c('accuracy')
history <- model %>% fit(
  x_train, y_train,
  epochs = 30, batch_size = 128,
  validation_split = 0.2
plot(history)
      0.4 -
      0.3 -
  loss
      0.2 -
      0.1 -
                                                                                  data
                                                                                   training
     0.99 -
                                                                                     validation
     0.96
  accuracy
     0.93 -
     0.90 -
     0.87 -
                               10
                                                                          30
                     5
                                          15
                                                     20
                                                               25
                                         epoch
table(model %>% evaluate(x_test, y_test))
##
                        accuracy
                         0.981000006198883
## loss
     0.107427766953344
table(model %>% predict_classes(x_test))
##
```

7

6

##

0

1

2

3

5

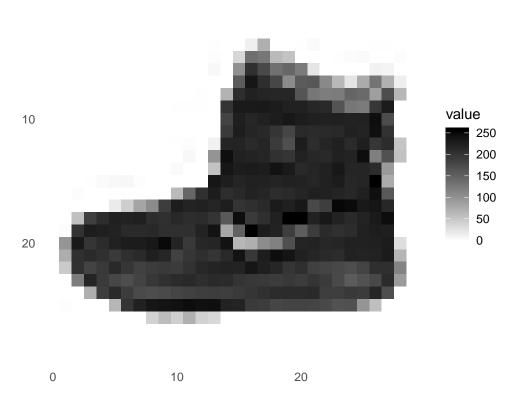
Example 1

Basic Classification

```
fashion_mnist <- dataset_fashion_mnist()</pre>
c(train_images, train_labels) %<-% fashion_mnist$train
c(test_images, test_labels) %<-% fashion_mnist$test
class_names = c('T-shirt/top',
                 'Trouser',
                 'Pullover',
                 'Dress',
                 'Coat',
                'Sandal',
                'Shirt',
                 'Sneaker',
                 'Bag',
                 'Ankle boot')
dim(train_images)
## [1] 60000
                28
                       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
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("")
```

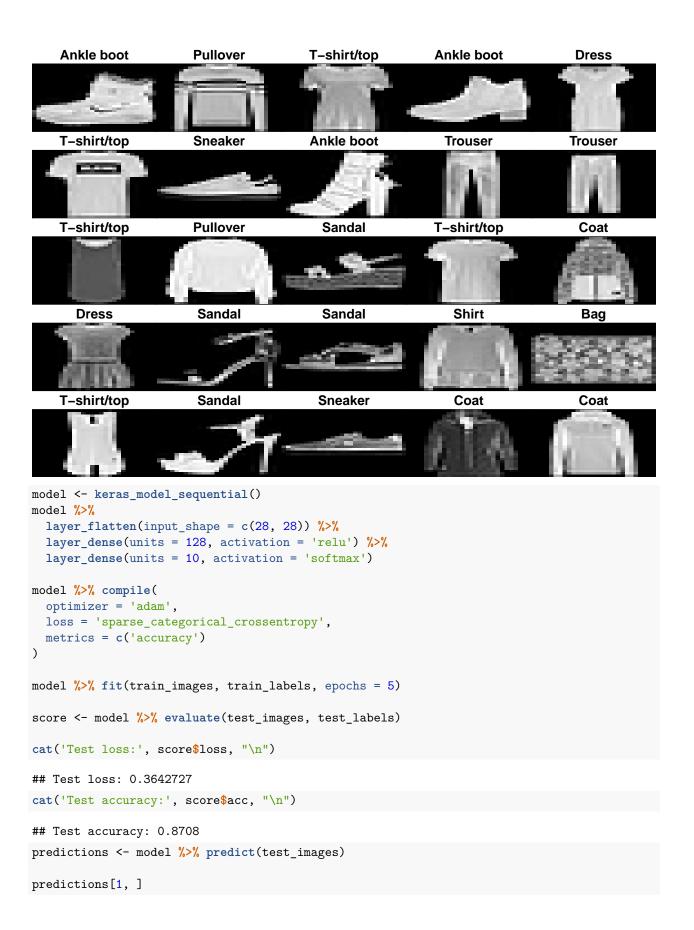
0



```
train_images <- train_images / 255

test_images <- test_images / 255

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>
```



```
## [1] 1.091267e-06 1.706949e-07 6.287783e-08 9.116476e-09 2.204292e-07
## [6] 2.915844e-03 3.226610e-07 8.017538e-02 5.035471e-05 9.168565e-01
which.max(predictions[1, ])
## [1] 10
class_pred <- model %>% predict_classes(test_images)
class_pred[1:20]
## [1] 9 2 1 1 6 1 4 6 5 7 4 5 5 3 4 1 2 2 8 0
test_labels[1]
## [1] 9
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 = pasteO(class_names[predicted_label + 1], " (",
                      class_names[true_label + 1], ")"),
        col.main = color)
```

```
nkle boot (Ankle boc Trouser (Trouser)
                                                          Trouser (Trouser) Pullover (Pullover)
                                          Coat (Coat)
                       Coat (Coat)
                                                         Pullover (Pullover)
Pullover (Pullover)
                                        Sandal (Sandal)
                                                                              Sandal (Sandal)
                                                           Pullover (Coat)
 Trouser (Trouser)
                       Shirt (Shirt)
                                       Sandal (Sneaker)
                                                                             Sneaker (Sneaker)
 Trouser (Trouser)
                    Sandal (Sandal)
                                         Dress (Dress)
                                                              Bag (Bag)
                                                                            Sandal (Ankle boot)
    Shirt (Shirt)
                                          Coat (Coat)
                    Sneaker (Sneaker)
                                                         -shirt/top (T-shirt/to Trouser (Trouser)
# Grab an image from the test dataset
# take care to keep the batch dimension, as this is expected by the model
img <- test_images[1, , , drop = FALSE]</pre>
dim(img)
## [1] 1 28 28
predictions <- model %>% predict(img)
predictions
##
                 [,1]
                               [,2]
                                             [,3]
                                                          [,4]
                                                                         [,5]
## [1,] 1.091267e-06 1.706949e-07 6.287807e-08 9.116476e-09 2.204288e-07
                [,6]
                             [,7]
                                        [,8]
                                                      [,9]
## [1,] 0.002915846 3.22661e-07 0.08017541 5.035471e-05 0.9168565
# subtract 1 as labels are O-based
prediction <- predictions[1, ] - 1</pre>
which.max(prediction)
## [1] 10
class_pred <- model %>% predict_classes(img)
class_pred
## [1] 9
```

Example 2

Text Classification

```
imdb <- dataset_imdb(num_words = 10000)</pre>
c(train_data, train_labels) %<-% imdb$train
c(test_data, test_labels) %<-% imdb$test</pre>
word_index <- dataset_imdb_word_index()</pre>
paste0("Training entries: ", length(train_data), ", labels: ", length(train_labels))
## [1] "Training entries: 25000, labels: 25000"
length(train_data[[1]])
## [1] 218
length(train_data[[2]])
## [1] 189
word_index_df <- data.frame(</pre>
  word = names(word index),
  idx = unlist(word_index, use.names = FALSE),
  stringsAsFactors = FALSE
# The first indices are reserved
word_index_df <- word_index_df %>% mutate(idx = idx + 3)
word_index_df <- word_index_df %>%
  add_row(word = "<PAD>", idx = 0)%>%
  add_row(word = "<START>", idx = 1)%>%
  add_row(word = "<UNK>", idx = 2)%>%
  add_row(word = "<UNUSED>", idx = 3)
word_index_df <- word_index_df %>% arrange(idx)
decode_review <- function(text){</pre>
  paste(map(text, function(number) word_index_df %>%
              filter(idx == number) %>%
              select(word) %>%
              pull()),
        collapse = " ")
}
decode_review(train_data[[1]])
## [1] "<START> this film was just brilliant casting location scenery story direction everyone's really
train_data <- pad_sequences(</pre>
 train_data,
  value = word_index_df %>% filter(word == "<PAD>") %>% select(idx) %>% pull(),
  padding = "post",
  maxlen = 256
)
```

```
test_data <- pad_sequences(</pre>
 test_data,
 value = word index df %% filter(word == "<PAD>") %>% select(idx) %>% pull(),
 padding = "post",
 maxlen = 256
length(train data[1, ])
## [1] 256
length(train data[2, ])
## [1] 256
# input shape is the vocabulary count used for the movie reviews (10,000 words)
vocab_size <- 10000</pre>
model <- keras_model_sequential()</pre>
model %>%
 layer_embedding(input_dim = vocab_size, output_dim = 16) %>%
 layer_global_average_pooling_1d() %>%
 layer_dense(units = 16, activation = "relu") %>%
 layer_dense(units = 1, activation = "sigmoid")
model %>% summary()
## Model: "sequential"
             ## Layer (type)
                      Output Shape
## -----
                      (None, None, 16)
## embedding (Embedding)
                                                    160000
## ______
## global_average_pooling1d (Global (None, 16)
## dense (Dense)
                            (None, 16)
## Total params: 160,289
## Trainable params: 160,289
## Non-trainable params: 0
## ______
model %>% compile(
 optimizer = 'adam',
loss = 'binary_crossentropy',
 metrics = list('accuracy')
)
x_val <- train_data[1:10000, ]</pre>
partial_x_train <- train_data[10001:nrow(train_data), ]</pre>
y_val <- train_labels[1:10000]</pre>
partial_y_train <- train_labels[10001:length(train_labels)]</pre>
```

```
history <- model %>% fit(
  partial_x_train,
  partial_y_train,
  epochs = 40,
  batch_size = 512,
  validation_data = list(x_val, y_val),
  verbose=1
)
results <- model %>% evaluate(test_data, test_labels)
results
## $loss
## [1] 0.3400047
##
## $accuracy
## [1] 0.8702
plot(history)
```

