HW9 Chen Han

Han Chen 11/20/2019

Example 1

```
# install
# install.packages("devtools")
# devtools::install_github("rstudio/keras")
library(keras)
install_keras()
```

Prapare Data

```
library(keras)
mnist <- dataset_mnist()
x_train <- mnist$train$x
y_train <- mnist$train$y
x_test <- mnist$test$x
y_test <- mnist$test$y

# reshape
x_train <- array_reshape(x_train, c(nrow(x_train), 784))
x_test <- array_reshape(x_test, c(nrow(x_test), 784))
# rescale
x_train <- x_train / 255
x_test <- x_test / 255

y_train <- to_categorical(y_train, 10)
y_test <- to_categorical(y_test, 10)</pre>
```

Defining the Model

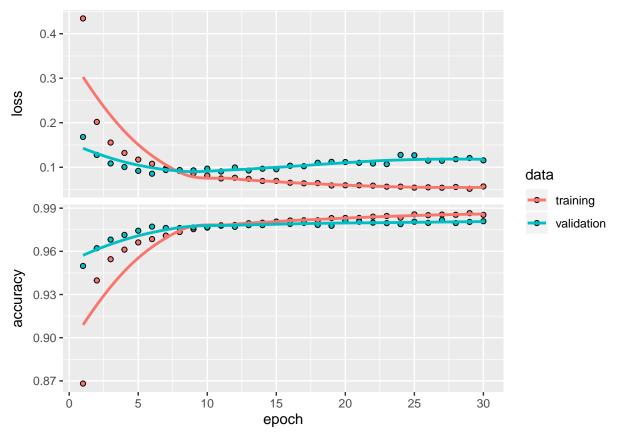
```
model <- keras_model_sequential()
model %>%
  layer_dense(units = 256, activation = 'relu', input_shape = c(784)) %>%
  layer_dropout(rate = 0.4) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dropout(rate = 0.3) %>%
  layer_dense(units = 10, activation = 'softmax')

summary(model)
```

```
## 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
## _____
model %>% compile(
 loss = 'categorical_crossentropy',
 optimizer = optimizer_rmsprop(),
 metrics = c('accuracy')
)
```

Training and Evaluation

```
history <- model %>% fit(
  x_train, y_train,
  epochs = 30, batch_size = 128,
  validation_split = 0.2
)
plot(history)
```



```
## $loss
## [1] 0.1063325
##
## $accuracy
## [1] 0.9826
model %>% predict_classes(x_test)
       [1] 7 2 1 0 4 1 4 9 6 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 4 6 4
##
      [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 2 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} \begin{smallmatrix} 1 & 3 & 9 & 5 & 2 & 9 & 4 & 5 & 9 & 3 & 9 & 0 & 3 & 6 & 5 & 5 & 7 & 2 & 2 & 7 & 1 & 2 & 8 & 4 & 1 & 7 & 3 & 3 & 8 & 8 & 7 & 9 & 2 & 2 \\ \end{smallmatrix} 
##
     [239] 4 1 5 9 8 7 2 3 0 6 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 2 9 3 0 4 2 0 7 1 1 2 1 5 3 3 9 7 8 6
##
##
     [341] 5 6 1 3 8 1 0 5 1 3 1 5 5 6 1 8 5 1 7 4 4 6 2 2 5 0 6 5 6 3 7 2 0 8
##
     [375] 8 5 4 1 1 4 0 3 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
##
     [443] 3 0 2 0 6 4 9 3 3 3 2 3 9 1 2 6 8 0 5 6 6 6 3 8 8 2 7 5 8 9 6 1 8 4
##
     [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
##
     [545] 4 0 0 2 3 2 7 7 0 8 7 4 4 7 9 6 9 0 9 8 0 4 6 0 6 3 5 4 8 3 3 9 3 3
     [579] 3 7 8 0 2 2 1 7 0 6 5 4 3 8 0 9 6 3 8 0 9 9 6 8 6 8 5 7 8 6 0 2 4 0
##
##
     ##
     [647] 2 1 3 7 6 7 1 2 5 8 0 3 7 1 4 0 9 1 8 6 7 7 4 3 4 9 1 9 3 1 7 3 9 7
     [681] 6 9 1 3 3 8 3 3 6 7 2 4 5 8 5 1 1 4 4 3 1 0 7 7 0 7 9 4 4 8 5 5 4 0
##
##
     [715] 8 2 1 6 8 4 8 0 4 0 6 1 7 3 2 6 7 2 6 9 3 1 4 6 2 5 9 2 0 6 2 1 7 3
     [749] 4 1 0 5 4 3 1 1 7 4 9 9 4 8 4 0 2 4 5 1 1 6 4 7 1 9 4 2 4 1 5 5 3 8
##
##
     [783] 3 1 4 5 6 8 9 4 1 5 3 8 0 3 2 5 1 2 8 3 4 4 0 8 8 3 3 1 7 3 5 9 6 3
     [817] \ 2 \ 6 \ 1 \ 3 \ 6 \ 0 \ 7 \ 2 \ 1 \ 7 \ 1 \ 4 \ 2 \ 4 \ 2 \ 1 \ 7 \ 9 \ 6 \ 1 \ 1 \ 2 \ 4 \ 8 \ 1 \ 7 \ 7 \ 4 \ 8 \ 0 \ 7 \ 3 \ 1 \ 3
##
##
     [851] 1 0 7 7 0 3 5 5 2 7 6 6 9 2 8 3 5 2 2 5 6 0 8 2 9 2 8 8 8 8 7 4 4 3
##
     [885] 0 6 6 3 2 1 3 2 2 9 3 0 0 5 7 8 5 4 4 6 0 2 9 1 4 7 4 7 3 9 8 8 4 7
##
     ##
     [953] \ 6 \ 4 \ 9 \ 5 \ 1 \ 3 \ 3 \ 4 \ 7 \ 8 \ 9 \ 1 \ 1 \ 6 \ 9 \ 1 \ 4 \ 4 \ 5 \ 4 \ 0 \ 6 \ 2 \ 2 \ 3 \ 1 \ 5 \ 1 \ 2 \ 0 \ 3 \ 8 \ 1 \ 2
##
     [987] 6 7 1 6 2 3 9 0 1 2 2 0 8 9 9 0 2 5 1 9 7 8 1 0 4 1 7 9 5 4 2 6 8 1
    [1021] 3 7 5 4 4 1 8 1 3 8 1 2 5 8 0 6 2 1 1 7 1 5 3 4 6 9 5 0 9 2 2 4 8 2
##
    [1055] 1 7 2 4 9 4 4 0 3 9 2 2 3 3 8 3 5 7 3 5 8 1 2 4 4 6 4 9 5 1 0 6 9 5
##
##
    [1089] 9 5 9 7 3 8 0 3 7 1 3 6 7 8 5 9 7 9 6 9 6 3 7 4 6 5 3 5 4 7 8 7 8 0
    [1123] \ 7 \ 6 \ 8 \ 8 \ 7 \ 3 \ 3 \ 1 \ 9 \ 5 \ 2 \ 7 \ 3 \ 5 \ 1 \ 1 \ 2 \ 1 \ 4 \ 7 \ 4 \ 7 \ 5 \ 4 \ 5 \ 4 \ 0 \ 8 \ 3 \ 6 \ 9 \ 6 \ 0 \ 2
##
##
    [1157] 7 4 4 4 4 6 6 4 7 9 3 4 5 5 8 7 3 7 2 7 0 2 4 1 1 6 8 9 2 8 7 2 0 1
    ##
##
    [1225] 2 8 2 2 9 8 4 0 4 5 8 5 1 2 1 3 1 7 4 5 7 2 0 5 8 8 6 2 5 4 1 9 2 1
    [1259] 5 8 7 0 2 4 4 3 6 8 8 2 4 0 5 0 4 4 7 9 3 4 1 5 9 7 3 5 8 8 0 5 3 3
##
##
    [1293] 6 6 0 1 6 0 3 5 4 4 1 2 9 1 4 6 9 9 3 9 8 4 4 3 1 3 1 3 8 7 9 4 8 8
##
    [1327] 7 9 9 1 4 5 6 0 5 2 2 2 1 5 5 2 4 9 6 2 7 7 2 2 1 1 2 8 3 7 2 4 1 7
##
    [1361] 1 7 6 7 2 2 7 3 1 7 5 8 2 6 2 2 5 6 5 0 9 2 4 3 3 9 7 6 6 8 0 4 1 3
    [1395] \ 8 \ 2 \ 9 \ 1 \ 8 \ 0 \ 6 \ 7 \ 2 \ 1 \ 0 \ 5 \ 5 \ 2 \ 0 \ 2 \ 2 \ 0 \ 2 \ 4 \ 9 \ 8 \ 0 \ 9 \ 9 \ 4 \ 6 \ 5 \ 4 \ 9 \ 1 \ 8 \ 3 \ 4
##
    [1429] 9 9 1 2 2 8 1 9 6 4 0 9 4 8 3 8 6 0 2 5 1 9 6 2 9 4 0 9 6 0 6 2 5 4
    [1463] 2 3 8 4 5 5 0 3 8 5 3 5 8 6 5 7 6 3 3 9 6 1 1 2 9 0 4 3 3 6 9 5 0 3
##
```

model %>% evaluate(x_test, y_test)

```
##
        [8841] 3 9 3 8 2 0 9 5 6 0 1 0 6 5 3 5 3 8 0 0 3 4 1 5 3 0 8 3 0 6 2 7 8 1
##
        [8875] 7 1 3 8 5 4 2 0 9 7 6 7 4 1 6 2 6 7 1 9 8 0 6 9 4 9 9 6 2 3 7 1 9 2
##
         [8909] \ 2\ 5\ 3\ 7\ 8\ 0\ 1\ 2\ 3\ 4\ 7\ 8\ 9\ 0\ 1\ 2\ 3\ 4\ 7\ 8\ 9\ 0\ 1\ 7\ 8\ 9\ 8\ 9\ 2\ 6\ 1\ 3\ 5\ 4 
        [8943] 8 2 6 4 3 4 5 9 2 0 3 9 4 9 7 3 8 7 4 4 9 8 5 8 2 6 6 2 3 1 3 2 7 3
##
##
        [9011] 2 3 4 5 6 2 0 1 2 2 8 6 3 9 2 1 9 3 9 6 1 7 2 4 4 5 7 0 0 1 6 6 8 2
##
        [9045] 7 7 2 4 2 1 6 1 0 6 9 8 3 9 6 3 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7
        [9079] 8 9 0 1 2 3 4 5 6 7 8 9 1 6 8 9 9 0 1 2 4 4 3 7 4 4 4 0 3 8 7 5 8 2
##
##
        [9113] 1 7 5 3 8 5 2 5 1 1 6 2 1 3 8 6 4 2 6 2 5 5 0 2 8 0 6 8 1 7 9 1 9 2
         [9147] \ \ 6 \ \ 7 \ \ 6 \ \ 6 \ \ 8 \ \ 7 \ \ 4 \ \ 9 \ \ 2 \ \ 1 \ \ 3 \ \ 0 \ \ 5 \ \ 5 \ \ 8 \ \ 0 \ \ 3 \ \ 7 \ \ 9 \ \ 7 \ \ 0 \ \ 2 \ \ 7 \ \ 9 \ \ 1 \ \ 7 \ \ 8 \ \ 0 \ \ 3 \ \ 5 \ \ 3 \ \ 6 \ \ 0 
##
         [9181] \ 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 0 \ 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 0 \ 1 \ 2 \ 3 \ 4 \ 7 \ 8 \ 9 \ 6 \ 4 \ 2 \ 6 \ 4 \ 7 \ 8 
        [9215] 9 2 9 3 9 3 0 0 1 0 4 2 6 3 5 3 0 3 4 1 5 3 0 8 3 0 6 1 7 8 0 9 2 6
##
##
        [9249] 7 1 9 6 9 4 9 9 6 7 1 2 5 3 7 8 0 1 2 4 5 6 7 8 9 0 1 3 4 5 6 7 5 0
       [9283] 1 3 4 7 8 9 7 5 5 1 9 9 7 1 0 0 5 9 7 1 7 2 2 3 6 8 3 2 0 0 6 1 7 5
##
##
         [9317] \  \, 8 \  \, 6 \  \, 2 \  \, 9 \  \, 4 \  \, 8 \  \, 8 \  \, 7 \  \, 1 \  \, 0 \  \, 8 \  \, 7 \  \, 7 \  \, 5 \  \, 8 \  \, 5 \  \, 3 \  \, 4 \  \, 6 \  \, 1 \  \, 1 \  \, 5 \  \, 5 \  \, 0 \  \, 7 \  \, 2 \  \, 3 \  \, 6 \  \, 4 \  \, 1 \  \, 2 \  \, 4 \  \, 1 \  \, 5 \  \, 5 \  \, 0 \  \, 7 \  \, 2 \  \, 3 \  \, 6 \  \, 4 \  \, 1 \  \, 2 \  \, 4 \  \, 1 \  \, 5 \  \, 1 \  \, 1 \  \, 5 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1 \  \, 1
##
        [9351] 4 2 0 4 8 6 1 9 0 2 5 6 9 3 6 3 6 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6
         [9385] \ 7 \ 8 \ 9 \ 0 \ 1 \ 2 \ 3 \ 5 \ 6 \ 7 \ 8 \ 1 \ 0 \ 9 \ 5 \ 7 \ 5 \ 1 \ 8 \ 6 \ 9 \ 0 \ 4 \ 1 \ 9 \ 3 \ 8 \ 4 \ 4 \ 7 \ 0 \ 1 \ 9 \ 2 
##
##
        [9419] 8 7 8 2 3 9 6 0 6 5 5 3 3 3 9 8 1 1 0 6 1 0 0 6 2 1 1 3 2 7 7 8 8 7
       [9453] 8 4 6 0 2 0 7 0 3 6 8 7 1 5 9 9 3 7 2 4 9 4 3 6 2 2 5 3 2 5 5 9 4 1
##
        [9487] 7 2 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 1 0
##
        [9521] 1 2 7 5 3 4 4 0 0 6 9 6 6 5 7 2 3 4 4 9 1 4 0 7 9 5 7 2 3 1 4 4 0 9
        [9555] 9 6 1 8 3 3 7 3 9 8 8 4 7 7 6 2 1 9 8 7 8 8 7 2 2 3 9 3 3 5 5 0 7 4
##
##
        [9589] 5 6 5 1 4 1 1 2 8 2 6 1 5 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9 0
        [9623] 1 2 3 4 5 6 7 8 8 0 6 0 1 2 3 7 9 4 7 1 9 1 7 1 4 0 0 1 7 5 7 1 3 3
        [9657] 3 1 6 9 7 1 3 0 7 6 0 8 9 4 3 5 4 8 1 5 9 0 6 3 3 8 1 4 7 5 2 0 0 1
##
       [9691] 7 8 9 6 8 8 2 3 6 1 2 9 5 2 0 1 2 3 4 5 6 7 8 9 0 1 2 3 4 5 6 7 8 9
##
         [9725] \ 0 \ 1 \ 2 \ 3 \ 4 \ 6 \ 6 \ 7 \ 8 \ 9 \ 7 \ 4 \ 6 \ 1 \ 4 \ 0 \ 9 \ 9 \ 3 \ 7 \ 8 \ 0 \ 7 \ 5 \ 8 \ 5 \ 3 \ 2 \ 2 \ 0 \ 5 \ 5 \ 6 \ 0 
        [9759] 3 8 1 0 3 0 4 7 4 9 2 9 0 7 1 7 1 6 6 0 6 2 8 7 6 4 9 9 5 3 7 4 3 0
       [9793] 4 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
##
##
       [9827] 0 8 3 9 5 5 2 6 8 4 1 7 1 2 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 2 8 1 5 1 0 2 3 3 5 7 0 6 8 6 3 9 9 5 2
##
         [9895] \ 7 \ 7 \ 1 \ 0 \ 1 \ 7 \ 8 \ 9 \ 0 \ 1 \ 0 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 0 \ 1 \ 2 \ 3 \ 4 \ 7 \ 8 \ 9 \ 7 \ 8 \ 6 \ 4 \ 1 \ 9 \ 3 \ 8 \ 4 
##
       [9929] 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 2 6 6 0 1 2 3 4 5 6 7 8 9 0 1 2
##
        [9997] 3 4 5 6
```

Example 2

Import the Fashion MNIST dataset

```
'Bag',
'Ankle boot')
```

Explore the data

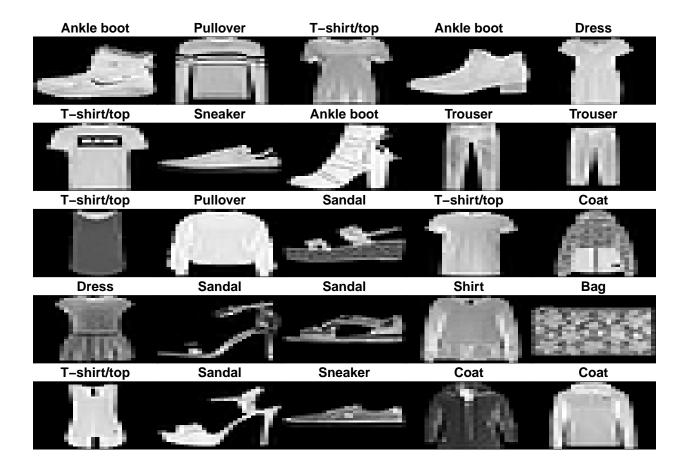
Preprocess the data

```
library(tidyr)
library(ggplot2)
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("")
```



```
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>
```



Build the model

```
model <- keras_model_sequential()
model %>%
  layer_flatten(input_shape = c(28, 28)) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dense(units = 10, activation = 'softmax')

model %>% compile(
  optimizer = 'adam',
  loss = 'sparse_categorical_crossentropy',
  metrics = c('accuracy')
)

model %>% fit(train_images, train_labels, epochs = 5)

score <- model %>% evaluate(test_images, test_labels)

cat('Test loss:', score$loss, "\n")

## Test loss: 0.3479988

cat('Test accuracy:', score$acc, "\n")

## Test accuracy: 0.8768
```

```
predictions <- model %>% predict(test_images)
predictions[1, ]
## [1] 8.431207e-06 1.438180e-08 1.167668e-08 5.673658e-08 7.317357e-07
## [6] 1.520386e-02 6.743840e-06 8.637270e-02 6.766369e-04 8.977308e-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 7 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 = paste0(class_names[predicted_label + 1], " (",
                       class_names[true_label + 1], ")"),
        col.main = color)
}
```

```
nkle boot (Ankle boc Trouser (Trouser)
                                          Coat (Coat)
                                                           Trouser (Trouser) Pullover (Pullover)
                                                                              Sandal (Sandal)
Pullover (Pullover)
                       Coat (Coat)
                                        Sandal (Sandal) Pullover (Pullover)
 Trouser (Trouser)
                       Shirt (Shirt)
                                       Sneaker (Sneaker)
                                                           Pullover (Coat)
                                                                             Sneaker (Sneaker)
 Trouser (Trouser)
                     Sandal (Sandal)
                                         Dress (Dress)
                                                              Bag (Bag)
                                                                            nkle boot (Ankle boo
                                          Coat (Coat)
    Shirt (Shirt)
                    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
                              [,2]
                                            [,3]
                                                          [,4]
                                                                        [,5]
##
                 [,1]
## [1,] 8.431225e-06 1.43818e-08 1.167663e-08 5.673649e-08 7.317352e-07
               [,6]
                                         [,8]
                                                      [,9]
                             [,7]
## [1,] 0.01520382 6.743841e-06 0.08637261 0.000676637 0.8977309
# subtract 1 as labels are 0-based
prediction <- predictions[1, ] - 1</pre>
which.max(prediction)
## [1] 10
class_pred <- model %>% predict_classes(img)
class_pred
## [1] 9
```