

Homework 1

Adam Shelton

5/8/2019

Getting Data

```
fashion_mnist = keras::dataset_fashion_mnist()

x_train = fashion_mnist$train$x
y_train = fashion_mnist$train$y

x_test = fashion_mnist$test$x
y_test = fashion_mnist$test$y

rm(fashion_mnist)

x_train = array_reshape(x_train, c(nrow(x_train), 28 * 28))/255
x_test = array_reshape(x_test, c(nrow(x_test), 28 * 28))/255

y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

Initial test

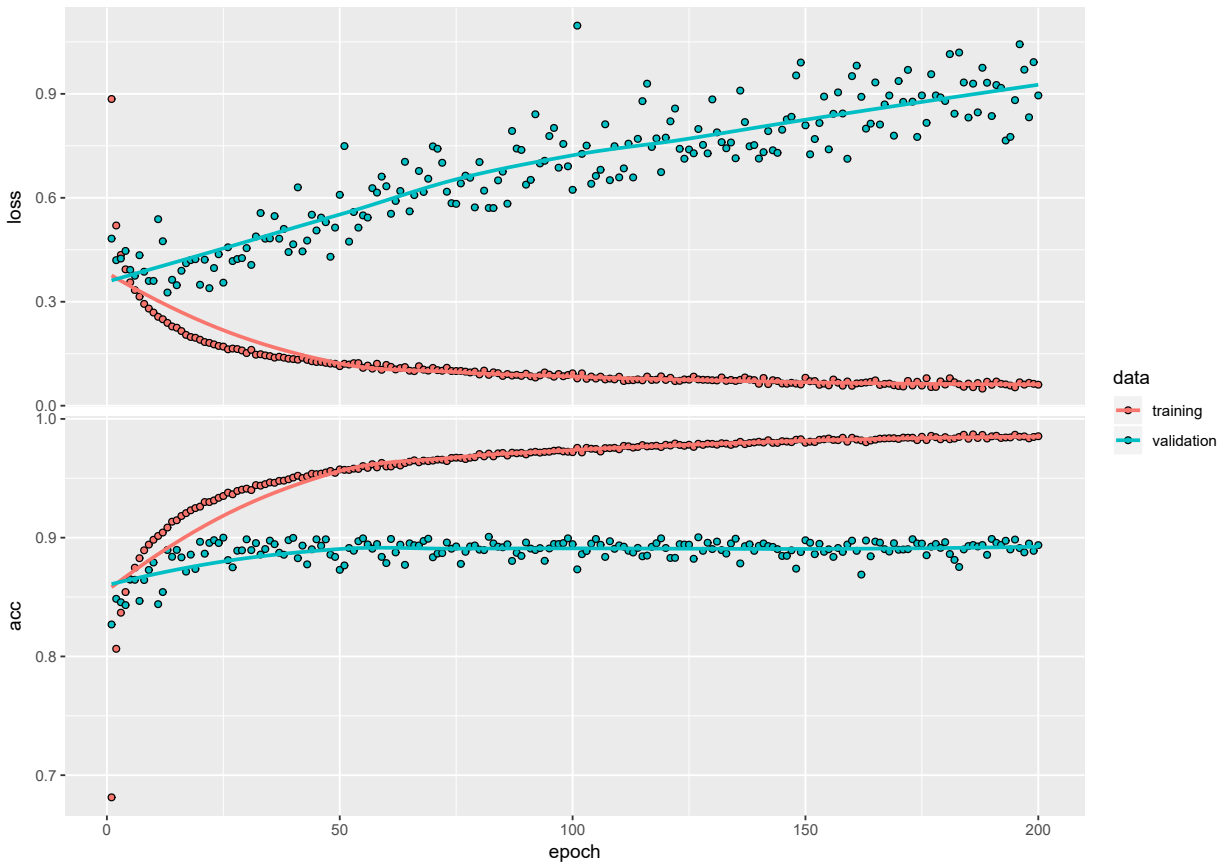
```
model = keras_model_sequential()

model %>% layer_dense(units = 512, activation = "relu", input_shape = c(784)) %>%
  layer_dense(units = 512, activation = "relu") %>% layer_dense(units = 512,
  activation = "relu") %>% layer_dense(units = 512, activation = "relu") %>%
  layer_dense(units = 10, activation = "softmax")

model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
  metrics = c("accuracy"))

history_init = model %>% fit(x_train, y_train, epochs = 200,
  batch_size = 512, validation_split = 0.166666666666667)

plot(history_init)
```



```
model %>% evaluate(x_test, y_test)
```

```
## $loss
## [1] 0.9614517
##
## $acc
## [1] 0.8927
```

The validation performance does not improve any further after 50 epochs.

Implementing Dropout

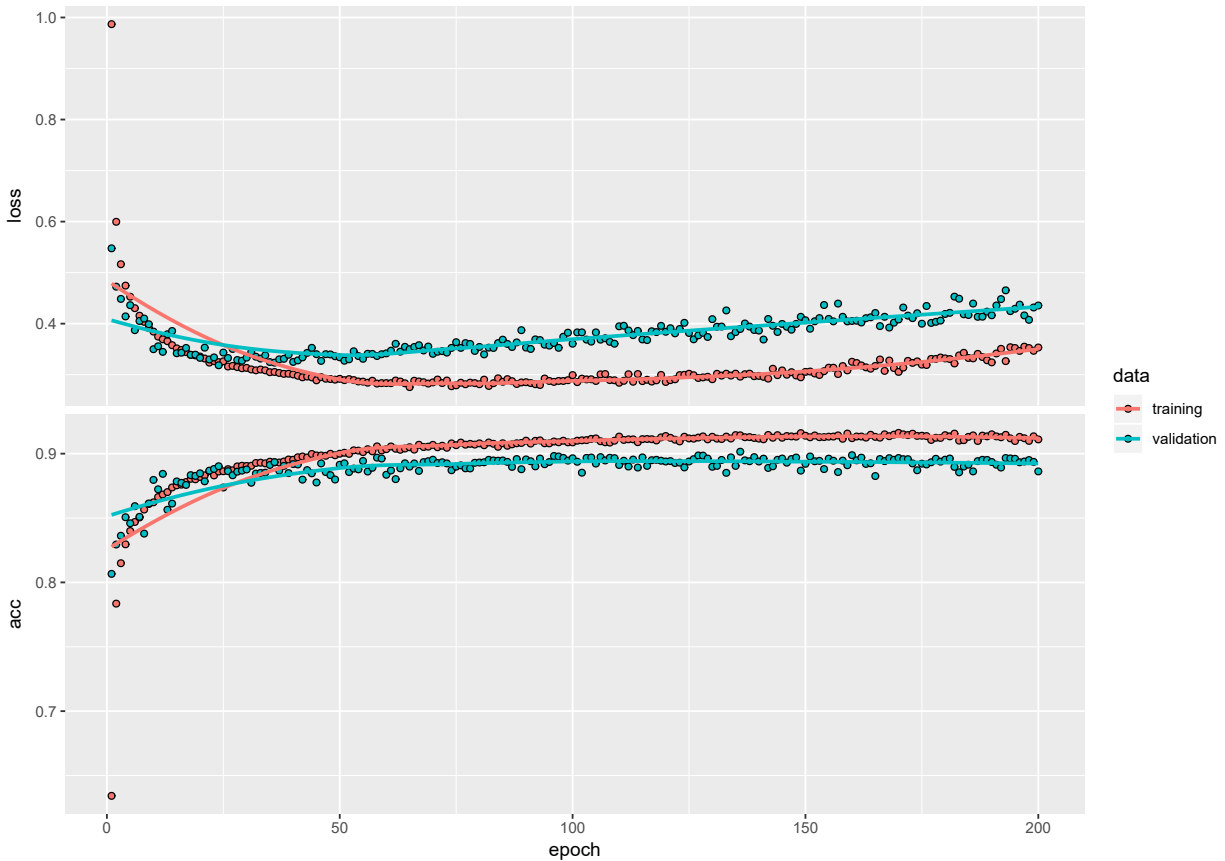
```
model = keras_model_sequential()

model %>% layer_dense(units = 512, activation = "relu", input_shape = c(784)) %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 512, activation = "relu") %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 512, activation = "relu") %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 10, activation = "softmax")

model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
  metrics = c("accuracy"))

history_do = model %>% fit(x_train, y_train, epochs = 200, batch_size = 512,
  validation_split = 0.1666666666666667)
```

```
plot(history_do)
```



```
model %>% evaluate(x_test, y_test)
```

```
## $loss
## [1] 0.4862465
##
## $acc
## [1] 0.8835
```

The validation accuracy, while still leveling off around epoch 50, is considerably higher, with validation losses being less as well.

Weight Regularization

```
model = keras_model_sequential()

model %>% layer_dense(units = 512, activation = "relu", input_shape = c(784),
  kernel_regularizer = regularizer_l1(0.001)) %>% layer_dropout(rate = 0.5) %>%
  layer_dense(units = 512, activation = "relu", kernel_regularizer = regularizer_l1(0.001)) %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 512, activation = "relu",
  kernel_regularizer = regularizer_l1(0.001)) %>% layer_dropout(rate = 0.5) %>%
  layer_dense(units = 512, activation = "relu", kernel_regularizer = regularizer_l1(0.001)) %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 10, activation = "softmax")

model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
```

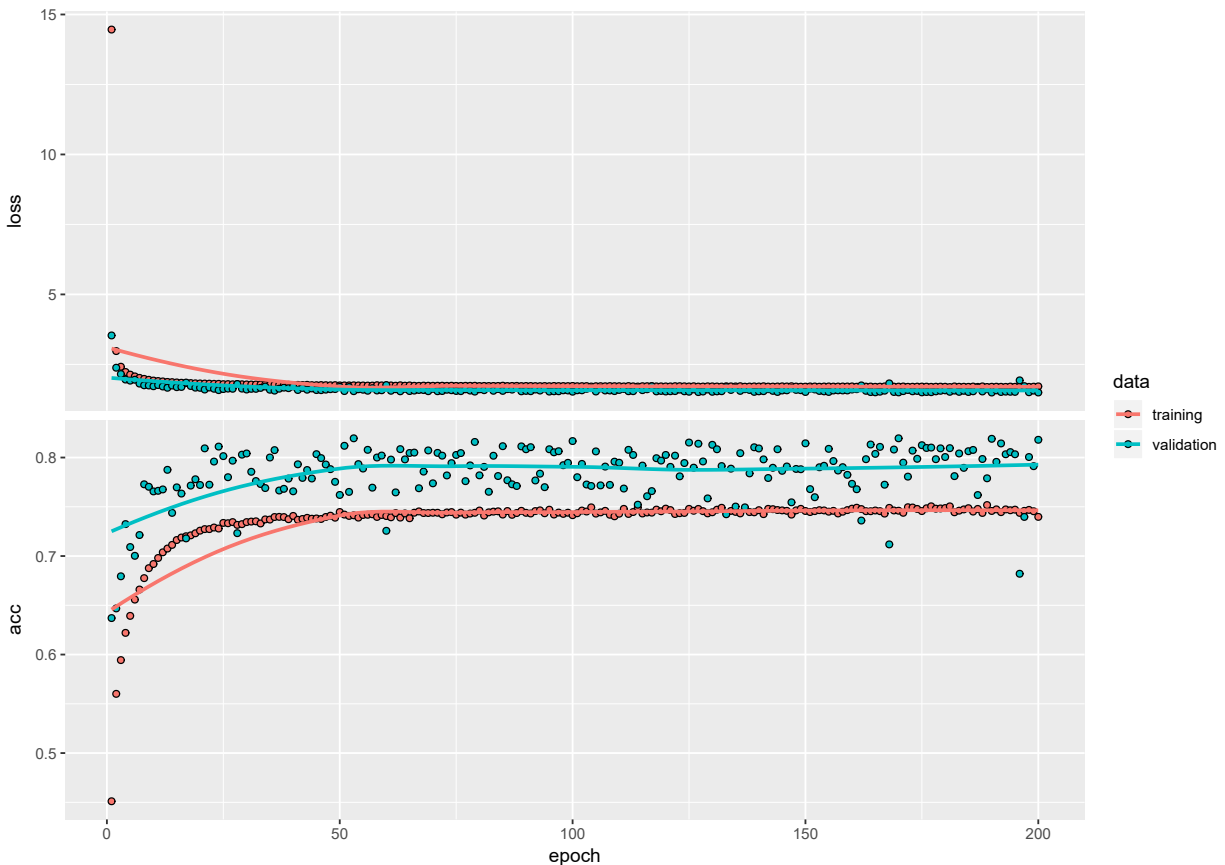
```

metrics = c("accuracy"))

history_l1 = model %>% fit(x_train, y_train, epochs = 200, batch_size = 512,
  validation_split = 0.1666666666666667)

plot(history_l1)

```



```

model %>% evaluate(x_test, y_test)

```

```

## $loss
## [1] 1.517587
##
## $acc
## [1] 0.8071

```

With L1 regularization at 0.001, training accuracy drops to be lower than validation accuracy. Both accuracies are lower than previous models.

```

model = keras_model_sequential()

model %>% layer_dense(units = 512, activation = "relu", input_shape = c(784),
  kernel_regularizer = regularizer_l2(0.001)) %>% layer_dropout(rate = 0.5) %>%
  layer_dense(units = 512, activation = "relu", kernel_regularizer = regularizer_l2(0.001)) %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 512, activation = "relu",
  kernel_regularizer = regularizer_l2(0.001)) %>% layer_dropout(rate = 0.5) %>%
  layer_dense(units = 512, activation = "relu", kernel_regularizer = regularizer_l2(0.001)) %>%
  layer_dropout(rate = 0.5) %>% layer_dense(units = 10, activation = "softmax")

```

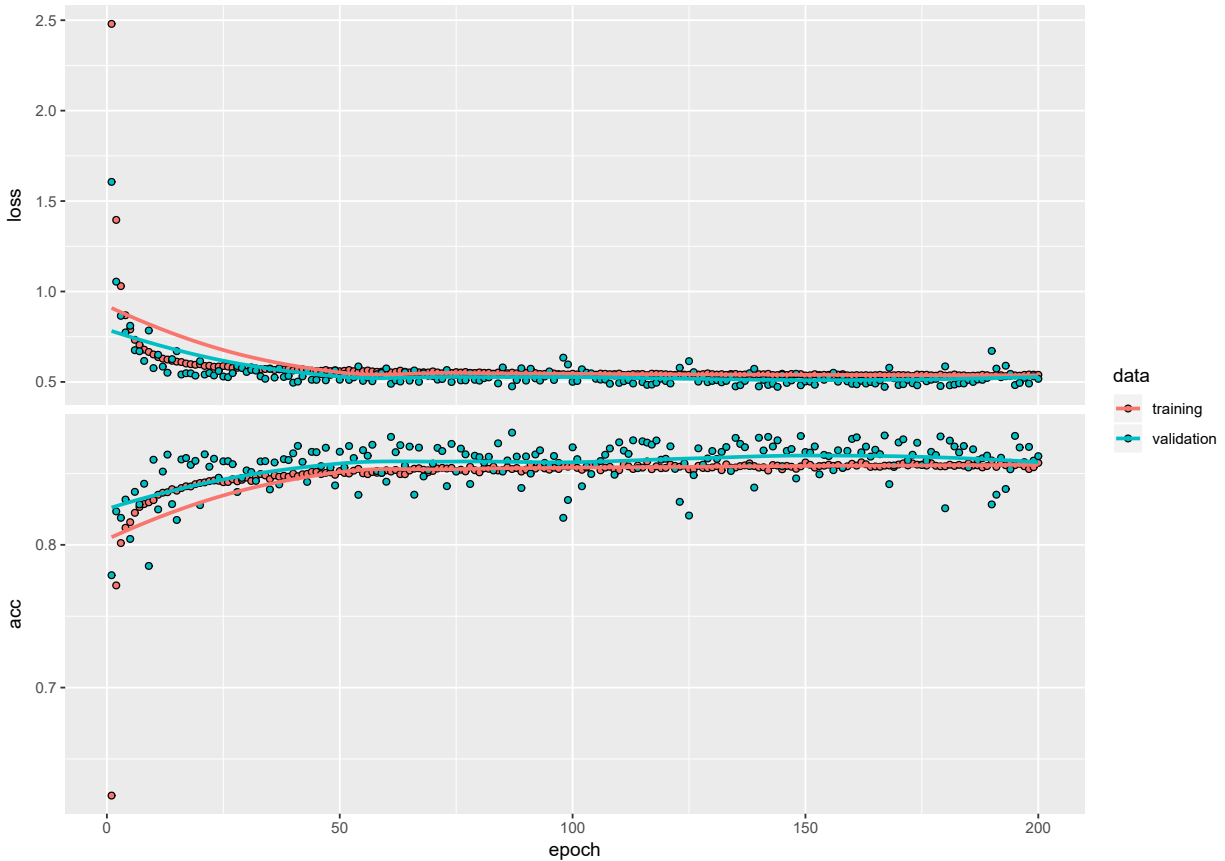
```

model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
  metrics = c("accuracy"))

history_l2 = model %>% fit(x_train, y_train, epochs = 200, batch_size = 512,
  validation_split = 0.1666666666666667)

plot(history_l2)

```



```
model %>% evaluate(x_test, y_test)
```

```

## $loss
## [1] 0.5407895
##
## $acc
## [1] 0.8559

```

The L2 regularization results in training and validation accuracy which are much more similar than with L1 regularization. The accuracy is also higher at about 0.9.

Other Options

```

tune_grid = expand_grid(num_units = c(256, 512), bat_size = c(512),
  epochs = c(50, 200), do_ratio = c(0.25, 0.5), weight_pen = c(0.001),
  weight_method = c(1, 2)) %>% as_tibble()

hyper_param_tune = function(index, t_grid, model) {

```

```

params = t_grid[index, ]

model = keras_model_sequential()

if (params$weight_method == 2) {
  model %>% layer_dense(units = params$num_units, activation = "relu",
    input_shape = c(784), kernel_regularizer = regularizer_l2(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = params$num_units,
    activation = "relu", kernel_regularizer = regularizer_l2(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = params$num_units,
    activation = "relu", kernel_regularizer = regularizer_l2(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = params$num_units,
    activation = "relu", kernel_regularizer = regularizer_l2(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = 10,
    activation = "softmax")
} else {
  model %>% layer_dense(units = params$num_units, activation = "relu",
    input_shape = c(784), kernel_regularizer = regularizer_l2(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = params$num_units,
    activation = "relu", kernel_regularizer = regularizer_l1(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = params$num_units,
    activation = "relu", kernel_regularizer = regularizer_l1(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = params$num_units,
    activation = "relu", kernel_regularizer = regularizer_l1(params$weight_pen)) %>%
    layer_dropout(rate = params$do_ratio) %>% layer_dense(units = 10,
    activation = "softmax")
}

model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
  metrics = c("accuracy"))

history_l2 = model %>% fit(x_train, y_train, epochs = params$epochs,
  batch_size = params$bat_size, validation_split = 0.166666666666667)

model %>% evaluate(x_test, y_test) %>% as_tibble() %>% bind_cols(params) %>%
  return()
}

results = sapply(1:length(tune_grid$num_units), hyper_param_tune,
  tune_grid, model)

results %>% as.matrix() %>% t() %>% as_tibble() %>% kable()

```

| loss | acc | num_units | bat_size | epochs | do_ratio | weight_pen | weight_method |
|-------------------|-------------------|-----------|----------|--------|----------|------------|---------------|
| 0.725365580463409 | 0.85860002040863 | 256 | 512 | 50 | 0.25 | 0.001 | 1 |
| 1.04473942184448 | 0.849200010299683 | 512 | 512 | 50 | 0.25 | 0.001 | 1 |
| 0.698598344993591 | 0.853600025177002 | 256 | 512 | 200 | 0.25 | 0.001 | 1 |
| 0.988663054084778 | 0.860899984836578 | 512 | 512 | 200 | 0.25 | 0.001 | 1 |
| 0.871824821281433 | 0.831300020217896 | 256 | 512 | 50 | 0.5 | 0.001 | 1 |
| 1.16336769018173 | 0.839399993419647 | 512 | 512 | 50 | 0.5 | 0.001 | 1 |
| 0.843302340316772 | 0.831799983978271 | 256 | 512 | 200 | 0.5 | 0.001 | 1 |
| 1.11139794340134 | 0.83050000667572 | 512 | 512 | 200 | 0.5 | 0.001 | 1 |

| loss | acc | num_units | bat_size | epochs | do_ratio | weight_pen | weight_method |
|-------------------|-------------------|-----------|----------|--------|----------|------------|---------------|
| 0.594045415210724 | 0.834699988365173 | 256 | 512 | 50 | 0.25 | 0.001 | 2 |
| 0.553289919757843 | 0.842899978160858 | 512 | 512 | 50 | 0.25 | 0.001 | 2 |
| 0.489982923412323 | 0.867200016975403 | 256 | 512 | 200 | 0.25 | 0.001 | 2 |
| 0.488590700721741 | 0.863499999046326 | 512 | 512 | 200 | 0.25 | 0.001 | 2 |
| 0.532943052577972 | 0.852299988269806 | 256 | 512 | 50 | 0.5 | 0.001 | 2 |
| 0.633132949542999 | 0.819199979305267 | 512 | 512 | 50 | 0.5 | 0.001 | 2 |
| 0.52707149374485 | 0.857900023460388 | 256 | 512 | 200 | 0.5 | 0.001 | 2 |
| 0.517564965677261 | 0.860400021076202 | 512 | 512 | 200 | 0.5 | 0.001 | 2 |

The best model appears to be a model using L2 weight regularization, with 256 units, a batch size of 512, a dropout ratio of 0.25, running at 200 epochs. However, while the gains in accuracy are minimal from a model that runs for 50 epochs, a model running for 200 epochs runs for significantly more time. As the previous models all improved very little past 50 epochs, I will use a model with 50 epochs instead to sacrifice a little accuracy to gain back a significant amount of time.

Final Model

```
final_model = keras_model_sequential()

final_model %>% layer_dense(units = 256, activation = "relu",
  input_shape = c(784), kernel_regularizer = regularizer_l2(0.001)) %>%
  layer_dropout(rate = 0.25) %>% layer_dense(units = 256, activation = "relu",
  kernel_regularizer = regularizer_l2(0.001)) %>% layer_dropout(rate = 0.25) %>%
  layer_dense(units = 512, activation = "relu", kernel_regularizer = regularizer_l2(0.001)) %>%
  layer_dropout(rate = 0.25) %>% layer_dense(units = 256, activation = "relu",
  kernel_regularizer = regularizer_l2(0.001)) %>% layer_dropout(rate = 0.25) %>%
  layer_dense(units = 10, activation = "softmax")
4

## [1] 4

final_model %>% compile(loss = "categorical_crossentropy", optimizer = optimizer_rmsprop(),
  metrics = c("accuracy"))
history_final = final_model %>% fit(x_train, y_train, epochs = 50,
  batch_size = 512, validation_split = 0)

plot(history_final)
```

