

Deep Neural Networks - Fashion Mnist



Set up - load libraries and data set

```
# Load libraries
library(keras)
library(ggplot2)
library(dplyr)

# Load data set
fashion_mnist <- dataset_fashion_mnist()
```

Data

Fashion-MNIST is a data set of Zalando's article images - it consists 60000 pictures for training and 10000 pictures for testing purposes.

Each image is 28px in width and 28px in height, each pixel is represented by a greyscale value from 0 to 255 (where 0 means white and 255 - black).

Column 1 (train_labels / test_labels) is the class label, where numbers 0-9 represent one from 10 categories:

- 0 T-shirt/top
- 1 Trouser
- 2 Pullover
- 3 Dress
- 4 Coat
- 5 Sandal
- 6 Shirt
- 7 Sneaker
- 8 Bag
- 9 Ankle boot.

Data set preparation

```
# Train data set
c(train_images, train_labels) %<-% fashion_mnist$train

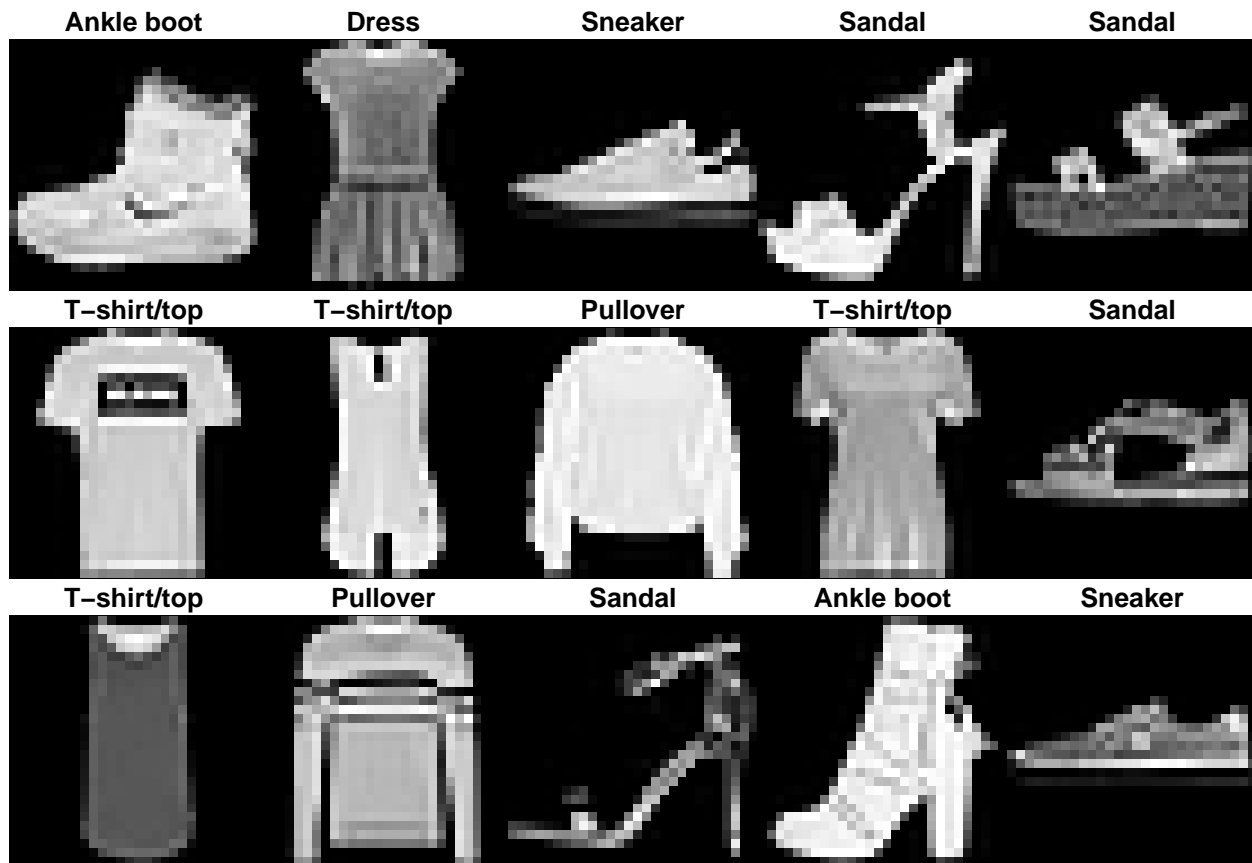
# Test data set
c(test_images, test_labels) %<-% fashion_mnist$test

# Rescale data set
train_images <- train_images / 255
test_images <- test_images / 255

# Create classes vector
class_names = c('T-shirt/top',
                'Trouser',
                'Pullover',
                'Dress',
                'Coat',
                'Sandal',
                'Shirt',
                'Sneaker',
                'Bag',
                'Ankle boot')

# Show examples from data set
par(mfcol = c(3, 5))
par(mar = c(0, 0, 1.5, 0), xaxs = 'i', yaxs = 'i')

for (i in 1:15) {
  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]))
}
```



```
# Reshape each image from 28 x 28 to 1 x 28 (single-line array)
train_images <- array_reshape(train_images, c(nrow(train_images), 28 * 28))
test_images <- array_reshape(test_images, c(nrow(test_images), 28 * 28))

# Change to categorical
train_labels <- to_categorical(train_labels, 10)
test_labels <- to_categorical(test_labels, 10)
```

DNN models

```
# Model 1: 3 dense layers with dropout, big batch size (480)
model_1 <- keras_model_sequential() %>%
  layer_dense(units = 512, activation = 'relu', input_shape = 28 * 28) %>%
  layer_dropout(rate = 0.4) %>%
  layer_dense(units = 256, activation = 'relu') %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 10, activation = 'softmax')

summary(model_1)
```

```
## Model: "sequential"
## -----
## Layer (type)                Output Shape                Param #
## =====
## dense_3 (Dense)              (None, 512)                 401920
## dropout_2 (Dropout)          (None, 512)                 0
## dense_2 (Dense)              (None, 256)                 131328
## dropout_1 (Dropout)          (None, 256)                 0
## dense_1 (Dense)              (None, 128)                 32896
## dropout (Dropout)            (None, 128)                 0
## dense (Dense)                (None, 10)                  1290
## =====
## Total params: 567,434
## Trainable params: 567,434
## Non-trainable params: 0
## -----
```

```
model_1 %>% compile(
  loss = 'categorical_crossentropy',
  optimizer = optimizer_adam(),
  metrics = 'accuracy')

model_1 %>% fit(train_images,
  train_labels,
  epochs = 50,
  validation_split = 0.2,
  batch_size = 480, ) -> model_1_dnn

# Model 2: 2 dense layers w/o dropout, smaller batch size (128)
model_2 <- keras_model_sequential() %>%
  layer_dense(units = 256, activation = 'relu', input_shape = 28 * 28) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dense(units = 10, activation = 'softmax')

summary(model_2)
```

```
## Model: "sequential_1"
## -----
## Layer (type)                Output Shape                Param #
## =====
## dense_6 (Dense)              (None, 256)                 200960
## dense_5 (Dense)              (None, 128)                 32896
## dense_4 (Dense)              (None, 10)                  1290
## =====
## Total params: 235,146
## Trainable params: 235,146
## Non-trainable params: 0
## -----
```

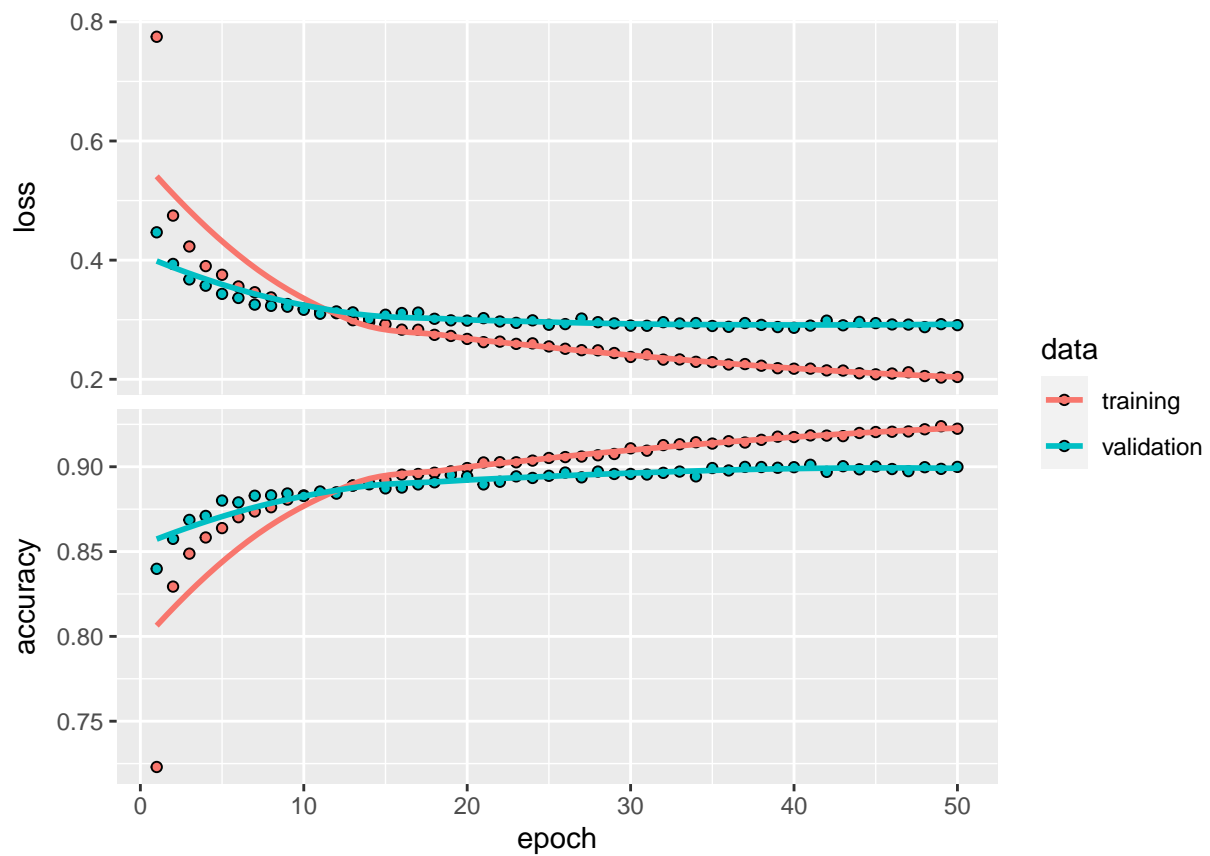
```
model_2 %>% compile(
  loss = 'categorical_crossentropy',
  optimizer = optimizer_adam(),
  metrics = 'accuracy')
```

```
model_2 %>% fit(train_images,
               train_labels,
               epochs = 50,
               validation_split = 0.2,
               batch_size = 96, ) -> model_2_dnn
```

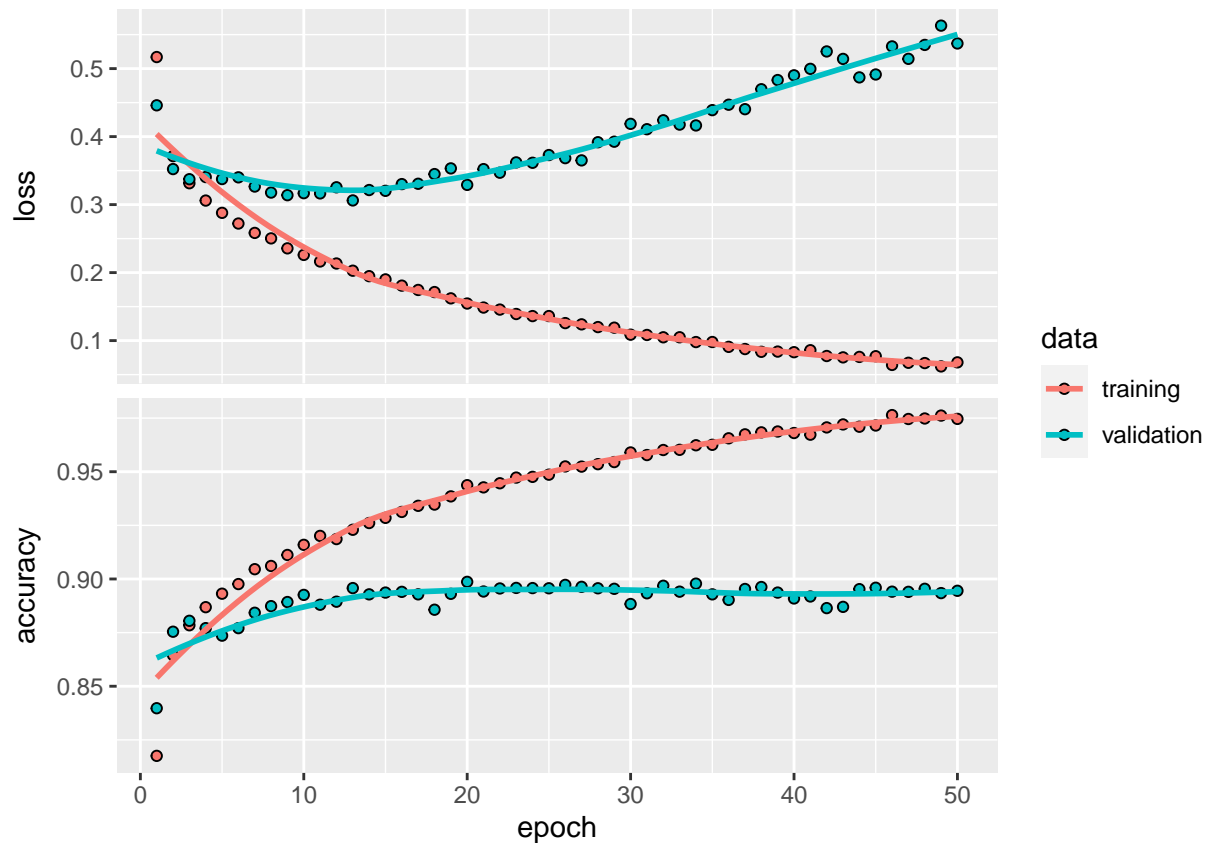
Models summary

Training and validation performance

```
plot(model_1_dnn)
```



```
plot(model_2_dnn)
```



Models evaluation

```
# Model 1 - train data set
model_1 %>% evaluate(train_images, train_labels)
```

```
##      loss  accuracy
## 0.1784874 0.9346167
```

```
# Model 1 - test data set
model_1 %>% evaluate(test_images, test_labels)
```

```
##      loss  accuracy
## 0.3120304 0.8940000
```

```
# Model 2 - train data set
model_2 %>% evaluate(train_images, train_labels)
```

```
##      loss  accuracy
## 0.1472071 0.9644000
```

```
# Model 2 - test data set
model_2 %>% evaluate(test_images, test_labels)
```

```
##      loss  accuracy
## 0.5950837 0.8935000
```

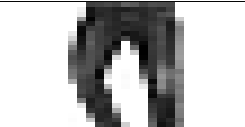

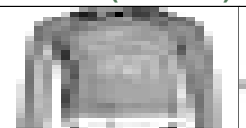







Accuracy and loss are better for **model_1**.

Prediction

```
# Predicted probabilities on test data
model_1 %>% predict(test_images) -> predictions

# Predicted classes on test data
model_1 %>% predict(test_images) %>%
  k_argmax() %>%
  as.numeric() -> predicted_clothes

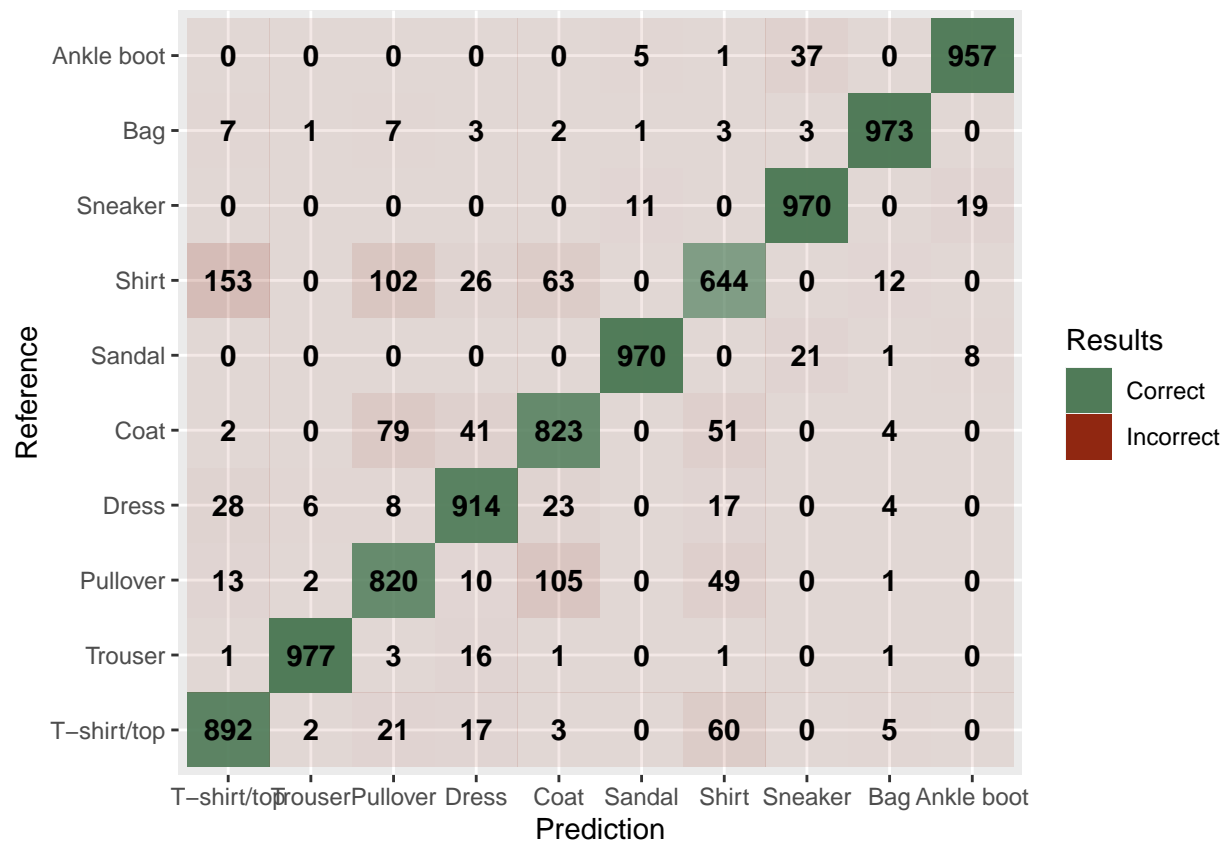
# See prediction results: prediction (real)
par(mfcol = c(5, 5))
par(mar = c(0, 0, 1.5, 0), xaxs = 'i', yaxs = 'i')
for (i in 1:25) {
  img <- fashion_mnist$test$x[i, , ]
  img <- t(apply(img, 2, rev))
  if (predicted_clothes[i] == fashion_mnist$test$y[i]) {
    color <- '#507B58'
  } else {
    color <- '#902711'
  }
  image(1:28, 1:28, img, col = gray((255:0) / 255), xaxt = 'n', yaxt = 'n',
        # prediction
        main = paste0(class_names[predicted_clothes[i]+1], ' (',
        # (real)
        class_names[fashion_mnist$test$y[i]+1], ')'),
        col.main = color)
}
```

ankle boot (Ankle boot)	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)
				
Trouser (Trouser)	Sandal (Sandal)	Dress (Dress)	Bag (Bag)	Sandal (Ankle boot)
				
Shirt (Shirt)	Sneaker (Sneaker)	Coat (Coat)	-shirt/top (T-shirt/top)	Trouser (Trouser)
				

Confusion matrix

```
data.frame(table(predicted_clothes, fashion_mnist$test$y)) %>%
  setNames(c('Prediction', 'Reference', 'Freq')) %>%
  mutate(Results = ifelse(Prediction == Reference, 'Correct', 'Incorrect')) -> conf_table

conf_table %>%
  ggplot(aes(y = Reference, x = Prediction, fill = Results, alpha = Freq)) +
  geom_tile() +
  geom_text(aes(label = Freq), vjust = 0.5, fontface = 'bold', alpha = 1) +
  scale_fill_manual(values = c(Correct = '#507B58', Incorrect = '#902711')) +
  ylim(rev(levels(conf_table$Reference))) +
  guides(alpha = FALSE) +
  scale_x_discrete(labels=class_names) +
  scale_y_discrete(labels=class_names)
```

References

1. **Data set:** <https://www.kaggle.com/datasets/zalando-research/fashionmnist>