HarvardX - PH125.9x - DataScience: Capstone - ImageProcessing

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1. Introduction

This document summarizes the chosen project "Image Processing" for the Capstone Exam in course of the HardvardX Data Science Certificate.

The dataset used is the **Fashion-MNIST** dataset published by the company Zalando. It contains 28x28 pixel grayscale images of the articles which are associated with 10 classes. It is commonly used for benchmarking machine learning algorithms. Due to the fact that we already used the classical MNIST dataset with numbers, I'm really interested in the processing of pictures and this dataset is already tidy and proven, I decided to give it a go.

This project again will have the classical approach of machine learning projects, although I will put the focus on the machine learning part of things. The steps performed are as follows:

- 1. Download the raw data and import the files into R Studio
- 2. Process and explore the data, to find out more how to proceed during model creation
- 3. Build and optimize different models
- 4. Use the best model on the test set and evaluate the results
- 5. Conclution, limitations and comments

The ambition is to get a better understanding of which parameters and methods can be used for image processing problems.

The dataset

The original dataset can be found in different sources. I downloaded the data from **Kaggle** and reuploaded it into my dropbox so it can be automatically downloaded without having to register on the website.

In addition to the packages used during the MovieLens project I utilized the **downloader package**. The code for downloading and extracting the model looks as follows:

Afterwards we are loading the .csv files into R and storing them into our variables:

```
# Create the data set for model building and verification
verification = read.csv("fashion-mnist_test.csv", header = TRUE)
modelling = read.csv("fashion-mnist_train.csv", header = TRUE)
```

Now two datasets have been created one for modelling with 60,000 samples and one for the testing/verification of our final model with 10,000 samples. Let's take a look at the structure of the data:

```
modelling[1:5,1:10]
```

```
##
     label pixel1 pixel2 pixel3 pixel4 pixel5 pixel6 pixel7 pixel8 pixel9
## 1
          2
                  0
                          0
                                  0
                                          0
                                                   0
          9
                          0
                                                                           0
                                                                                   0
## 2
                  0
                                  0
                                          0
                                                   0
                                                           0
                                                                   0
## 3
          6
                  0
                          0
                                  0
                                          0
                                                   0
                                                           0
                                                                   0
                                                                           5
                                                                                   0
                          0
                                                   2
                                                           0
                                                                                   0
## 4
          0
                                  0
                                          1
                                                                   0
                                                                           0
## 5
          3
                  0
                          0
                                  0
                                          0
                                                   0
                                                           0
                                                                   0
                                                                           0
                                                                                   0
```

Each row contains the label in the first column and greyvalue for the 28 by 28 pixels of the image stored in the columns 2 to 785. Formulated differently, we have one picture plus label stored in each row of the matrix.

For easier processing we are also separating the labels from the images:

```
# Seperate labels and images
x <- modelling[,2:ncol(modelling)]
y <- factor(modelling[,1])
x_verification <- verification[,2:ncol(verification)]
y_verification <- factor(verification[,1])</pre>
```

The images are currently stored in a matrix as you can see here:

```
dim(x)
```

```
## [1] 60000 784
```

```
dim(x_verification)
```

```
## [1] 10000 784
```

For some kind of analysis it is easier to have arrays, so we create an additional dataset with reshaped data:

Now we have the data in the following format:

```
dim(x_images)
```

```
## [1] 60000 28 28
```

```
dim(x_verification_images)
```

```
## [1] 10000 28 28
```

To allow for faster computation we use a subset out of our training set, which we create as follows:

```
x_sub <- x_images[1:1000,,]
y_sub <- y[1:1000]
x_test_sub <- x_images[1001:1200,,]
y_test_sub <- y[1001:1200]</pre>
```

And as a last step in this section we will create the fashion categories according to the numbers which indicate the categories:

2. Analysing the data

In this section we will explore the data more in depth. How do the images acutally look like, do we see patterns between the categories or do we have some promising points for leveraging the most out of our method toolbox?

Let's take a look at the first 32 pictures of the dataset:

```
# Plot the first 16 images with labels to get an impression how they look
# Define a four by four grid for the plot
par(mfrow=c(4,4))
# Setting the margins around the pictures with "mar"
par(mar=c(0, 0, 1.5, 0))

# Plot every image (remember to reverse) on a gray scale with label
# Reverse the color scheme to get a white background
for (i in 1:16) {
   image(1:28, 1:28, as.matrix(x_images[i,,])[,28:1], col = gray((255:0)/255), xaxt = 'n',
        yaxt = 'n', xlab = "", ylab = "", asp = 1, main = paste(fashion_cat[y[i]]))
}
```

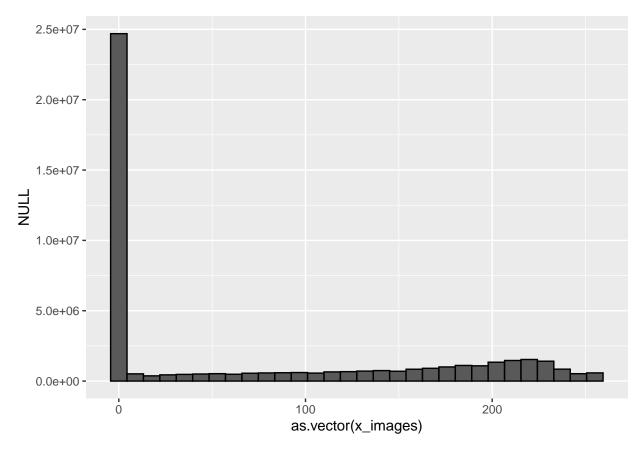




As we can see, we have some "low quality" pictures of several types of fashion, which can be relatively easily identified manually. But how can we do that with help of machine learning?

Let us start simple. First let us check whether we can set a threshold for making the pictures even simpler:

```
qplot(as.vector(x_images), bins = 30, color = I("black"))
```

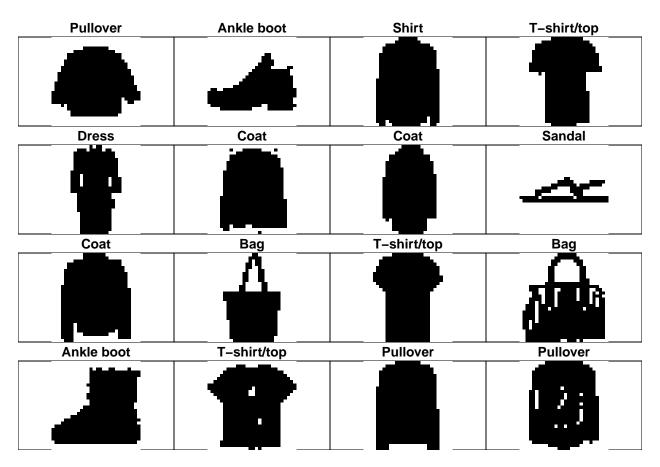


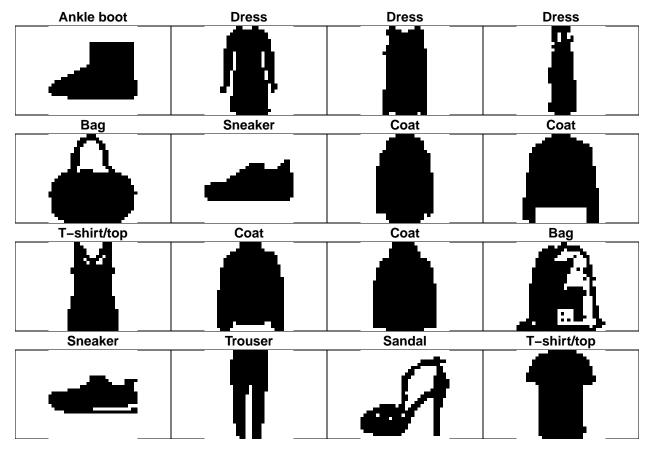
As we can see there is no clear cutoff, but we can try to set a low cutoff threshold, so we only have black and white left without anything in between. Here is the code we use on the subset (faster computation) for a cutoff below 10:

```
x_{sub_bw} \leftarrow ifelse(x_{sub_b} < 10, 0, 1)
```

Here are the same 32 pictures again

```
# Plot the first 16 images with labels to get an impression how they look
# Define a four by four grid for the plot
par(mfrow=c(4,4))
# Setting the margins around the pictures with "mar"
par(mar=c(0, 0, 1.5, 0))
# Plot every image (remember to reverse) on a gray scale with label
# Reverse the color scheme to get a white background
for (i in 1:16) {
   image(1:28, 1:28, as.matrix(x_sub_bw[i,,])[,28:1], col = gray(1:0), xaxt = 'n',
        yaxt = 'n', xlab = "", ylab = "", asp = 1, main = paste(fashion_cat[y[i]]))
}
```





As we can see, this does not help us. for example picture 3, 6 and 15 (shirt, coat and pullover) now look even more similar. So we will not pursue this approach any further.

Next, we can take a look at the intensity of the pictures, so the mean graycolor value for each picture. We exclude the first column, which contains the label, group by the label and add the fashion category vector so we have a better understanding:

```
cbind(modelling %>% mutate(row_mean = rowMeans(modelling[,-1])) %>%
    group_by(label) %>% summarize(avg_pic_int = mean(row_mean)),fashion_cat)
```

```
label avg_pic_int fashion_cat
##
                82.87926 T-shirt/top
## 1
          0
                56.74837
                              Trouser
## 2
          1
          2
                95.71933
                             Pullover
## 3
## 4
          3
                66.20149
                                Dress
## 5
          4
                98.15566
                                 Coat
## 6
          5
                34.87052
                               Sandal
## 7
          6
                85.11510
                                Shirt
## 8
          7
                42.83567
                              Sneaker
## 9
                90.03576
                                  Bag
## 10
          9
                77.00715
                          Ankle boot
```

Here is the standard deviation for the intensity by category:

```
cbind(modelling %>% mutate(row_sds = rowSds(as.matrix(modelling[,-1]))) %>%
    group_by(label) %>% summarize(avg_sds = mean(row_sds)),fashion_cat)
```

```
##
      label avg_sds fashion_cat
## 1
          0 81.42681 T-shirt/top
## 2
          1 85.02875
                          Trouser
## 3
          2 82.15846
                         Pullover
## 4
          3 85.63856
                            Dress
## 5
          4 90.36731
                             Coat
## 6
          5 63.28603
                           Sandal
## 7
          6 76.85188
                            Shirt
## 8
          7 72.85919
                          Sneaker
## 9
          8 87.32423
                              Bag
## 10
          9 91.94726
                       Ankle boot
```

Furthermore we look how many pixels are unequal to zero, and therefore used for the actual image excluding the background:

```
cbind(modelling %>% mutate(pixels = rowSums(modelling[,-1]>0)) %>%
    group_by(label) %>% summarize(avg_pixels_used = mean(pixels)),fashion_cat)
```

```
##
      label avg_pixels_used fashion_cat
## 1
                    466.3948 T-shirt/top
          0
## 2
          1
                    273.8315
                                  Trouser
          2
## 3
                    508.4588
                                  Pullover
## 4
          3
                    336.6065
                                     Dress
## 5
          4
                    471.9568
                                      Coat
## 6
          5
                    251.6750
                                    Sandal
## 7
          6
                    493.3368
                                     Shirt
## 8
          7
                    264.6172
                                  Sneaker
## 9
          8
                    458.3810
                                       Bag
## 10
                               Ankle boot
          9
                    380.6383
```

And last but not least we calculate the average pixel intensity by dividing the sum of the grayscale values divided by the number of pixels unequal to zero:

```
cbind(modelling %>% mutate(pixel_int = rowSums(modelling[,-1])/
    rowSums(modelling[,-1]>0)) %>% group_by(label) %>%
    summarize(avg_pixel_int = mean(pixel_int)),fashion_cat)
```

```
##
      label avg_pixel_int fashion_cat
                  139.5437 T-shirt/top
## 1
          0
## 2
          1
                  163.6052
                                Trouser
          2
## 3
                  147.7495
                               Pullover
                  155.0386
## 4
          3
                                  Dress
## 5
          4
                  163.0429
                                    Coat
          5
## 6
                  107.2801
                                  Sandal
## 7
          6
                  135.2090
                                  Shirt
## 8
          7
                                Sneaker
                  126.4115
## 9
          8
                  152.7075
                                     Bag
## 10
          9
                  158.2658
                             Ankle boot
```