## Compulsory exercise 3

TMA4268 Statistical Learning V2019

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15 April, 2020

## Problem 1

```
library(ISLR)
library(keras)
set.seed(1)
College$Private = as.numeric(College$Private)
train.ind = sample(1:nrow(College), 0.5 * nrow(College))
college.train = College[train.ind, ]
college.test = College[-train.ind, ]
str(College)
```

```
## 'data.frame': 777 obs. of 18 variables:
## $ Private : num 2 2 2 2 2 2 2 2 2 2 ...
## $ Apps : num 1660 2186 1428 417 193 ...
## $ Accept
              : num 1232 1924 1097 349 146 ...
## $ Enroll : num 721 512 336 137 55 158 103 489 227 172 ...
## $ Top1Operc : num 23 16 22 60 16 38 17 37 30 21 ...
## $ Top25perc : num 52 29 50 89 44 62 45 68 63 44 ...
## $ F.Undergrad: num 2885 2683 1036 510 249 ...
## $ P.Undergrad: num 537 1227 99 63 869 ...
## $ Outstate : num 7440 12280 11250 12960 7560 ...
## $ Room.Board : num 3300 6450 3750 5450 4120 ...
## $ Books : num 450 750 400 450 800 500 500 450 300 660 ...
## $ Personal : num 2200 1500 1165 875 1500 ...
          : num 70 29 53 92 76 67 90 89 79 40 ...
## $ PhD
## $ Terminal : num 78 30 66 97 72 73 93 100 84 41 ...
## $ S.F.Ratio : num 18.1 12.2 12.9 7.7 11.9 9.4 11.5 13.7 11.3 11.5 ...
## $ perc.alumni: num 12 16 30 37 2 11 26 37 23 15 ...
## $ Expend
            : num 7041 10527 8735 19016 10922 ...
## $ Grad.Rate : num 60 56 54 59 15 55 63 73 80 52 ...
```

**a**)

Preprocessing the data by applying feature-wise normalization to the predictors.

```
#divide data into response and covariates
#training data

train_x <- college.train[,-9]

train_y <- college.train[,9]

#test data

test_x <- college.test[,-9]

test_y <- college.test[,9]

#we use the mean and std of the training data for both test and train set

mean <- apply(train_x , 2, mean)

std <- apply(train_x, 2, sd)

train_x <- scale(train_x, center = mean, scale = std)

test_x <- scale(test_x, center = mean, scale = std)</pre>
```

b)

The equation describing a network that predicts Outstate. The output layer has one node wich is numerical (the Out-of-state tuition), therefore we can choose betwenn ReLu and linear activation function for this layer, we choose the linear activation function.

$$\hat{y_1}(x) = \beta_{01} + \sum_{m=1}^{64} \beta_{m1} \max(\gamma_{0m} + \sum_{l=1}^{64} \gamma_{lm} \max(\alpha_{0l} + \sum_{j=1}^{17} \alpha_{jl} x_j, 0), 0)$$

skal det være med bias term eller ikke for hvert lag?

**c**)

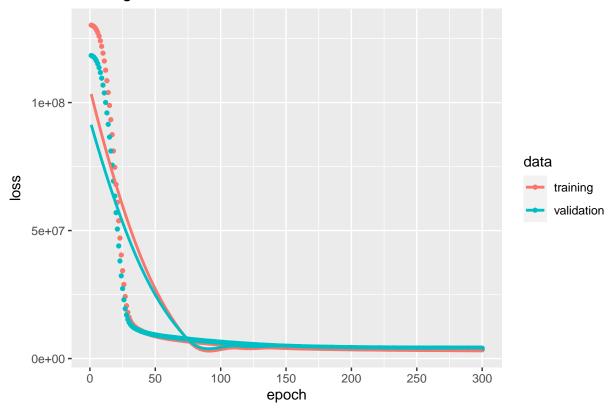
We will now train the network from b).

```
#define the model
model = keras_model_sequential() %>%
    layer_dense(units = 64, activation = 'relu', input_shape = dim(train_x)[2]) %>%
    layer_dense(units = 64, activation = 'relu') %>%
    layer_dense(units = 1)

#compile
model %>% compile(optimizer = "rmsprop", loss = "mse")

#train
history = model %>% fit(train_x, train_y, epochs = 300, batch_size = 8,
    validation_split = 0.2) #20% of the training set as validation set
plot(history)+ggtitle("Training and Validation Error")
```

## Training and Validation Error



```
#test MSE
mse <- model %>% evaluate(test_x, test_y)
```

The test MSE for this network is  $3.6865554 \times 10^6$ . From Compulsory 2, using the same dataset, the test MSE's for Forward selection is  $4.11268 \times 10^6$ , for Lasso is  $3.71702 \times 10^6$  and for Random Forest the MSE is  $2.607985 \times 10^6$ . The results

d)

set.seed(123)

e)	
Problem 2	
a)	
b)	
c)	
d)	
Problem 3	
a)	
b)	
c)	
Problem 4	
a)	
b)	
c)	
d)	
e)	
Problem 5	
a)	
b)	
c)	
d)	
e)	
f)	
References	

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. An Introduction to Statistical Learning with Applications in R. New York: Springer.  $_4$