MODEL 2 NEURAL NETWORK-BASED CLASSIFICATION MODEL

REY P. PENDANG

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```r
# Helper packages

library(dplyr)         # for data wrangling
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(tidyverse)     # for filtering
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.2 --

## v ggplot2 3.4.0     v purrr   0.3.5
## v tibble  3.1.8     v stringr 1.4.1
## v tidyr   1.2.1     v forcats 0.5.2
## v readr   2.1.3
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
library(readr)          # load dataset
library(rsample)        # for creating validation splits
library(bestNormalize) # for normalizing the dataset
library(keras)          # for fitting DNNs
library(tfruns)         # for additional grid search
library(tfestimators)  # provides grid search & model training interface
```

```
## tfestimators is not recomended for new code. It is only compatible with Tensorflow version 1, and is
```

```r
library(tensorflow)
```

Load the data set

The data frame output of data reprocessing converted into to "csv", which will be used for entire project.

```r
dt <- read_csv("normalRad.CSV")
```

```
## Rows: 197 Columns: 431
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (1): Institution
## dbl (430): Failure.binary, Failure, Entropy_cooc.W.ADC, GLNU_align.H.PET, Mi...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
View(dt)

head(dt)
```

```
## # A tibble: 6 x 431
##   Institution Failure.~1 Failure Entro~2 GLNU_~3 Min_h~4 Max_h~5 Mean_~6 Varia~7
##   <chr>            <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 A                    0   1.15     12.9  -0.433  -0.270 -0.257   -0.192  0.0509
## 2 A                    1  -0.533    12.2  -1.02    0.671  0.405    0.490  0.687
## 3 A                    0   2.24     12.8   0.179  -1.41  -1.57    -1.53  -1.57
## 4 A                    1  -0.140    13.5   2.00   -0.218  0.0764  -0.153  0.0127
## 5 A                    0   0.787    12.6   0.153  -1.06  -1.15    -1.45  -1.91
## 6 A                    1  -2.80     13.2   0.391  -1.57  -1.91    -1.72  -1.84
## # ... with 422 more variables: Standard_Deviation_hist.PET <dbl>,
## #   Skewness_hist.PET <dbl>, Kurtosis_hist.PET <dbl>, Energy_hist.PET <dbl>,
## #   Entropy_hist.PET <dbl>, AUC_hist.PET <dbl>, H_suv.PET <dbl>,
## #   Volume.PET <dbl>, X3D_surface.PET <dbl>, ratio_3ds_vol.PET <dbl>,
## #   ratio_3ds_vol_norm.PET <dbl>, irregularity.PET <dbl>,
## #   tumor_length.PET <dbl>, Compactness_v1.PET <dbl>, Compactness_v2.PET <dbl>,
## #   Spherical_disproportion.PET <dbl>, Sphericity.PET <dbl>, ...
```

Check for null and missing values

Using *sum(is.n())*.function, We can determine if any missing values in our data.

#The result shows either *True* or *False*. If True, omit the missing values using *na.omit()*

#[1] FALSE

#Thus, our data has no missing values.

```
sum(is.na(dt))
```

```
## [1] 0
```

Split the data into training (80%) and testing (20%)

```
dt<-dt %>%
  mutate(Failure.binary=ifelse(Failure.binary== "No",0,1))
dt=dt[,-1]

set.seed(123) # for reproducibility

split = initial_split(dt,prop = 0.8 ,strata = "Failure.binary")
churn_train <- training(split)
churn_test  <- testing(split)
```

```
X_train <- churn_train[,-c(1,2)]%>%as.matrix.data.frame()
X_test <- churn_test[,-c(1,2)]%>%as.matrix.data.frame()
y_train <- churn_train$Failure.binary
y_test <- churn_test$Failure.binary
```

Reshape the data set

```
X_train <- array_reshape(X_train, c(nrow(X_train), ncol(X_train)))
X_train <- X_train

X_test <- array_reshape(X_test, c(nrow(X_test), ncol(X_test)))
X_test <- X_test

y_train <- to_categorical(y_train, num_classes = 2)
```

```
## Loaded Tensorflow version 2.9.3
```

```
y_test <- to_categorical(y_test, num_classes = 2)
```

Run the model

with the R function **keras_mod_sequential()** of keras package, allows us to create our network with a layering approach.First, we initiated our sequential feedforward DNN architecture with *keras_model_sequential()* and then added some dense layers.Hence, we created five hidden layers with 256, 128, 128, 64 and 64 neurons, we added the *sigmoid* activation function. Followed by an output layer with 2 nodes and specified activation = *softmax*.

```
model <- keras_model_sequential() %>%
  layer_dense(units = 256, activation = "sigmoid", input_shape = c(ncol(X_train))) %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 128, activation = "sigmoid") %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 128, activation = "sigmoid") %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 64, activation = "sigmoid") %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 64, activation = "sigmoid") %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 2, activation = "softmax")%>%
 compile(
    loss = "categorical_crossentropy",
    optimizer = optimizer_rmsprop(),
    metrics = c("accuracy")
  )
```

Model compile approach

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

```
  metrics = c("accuracy")
)
```

Training the model

Already built a fundamental mod; all that remains is to feed it some data to train on. To achieve this, we input our training data and mod into a **fit()** function.

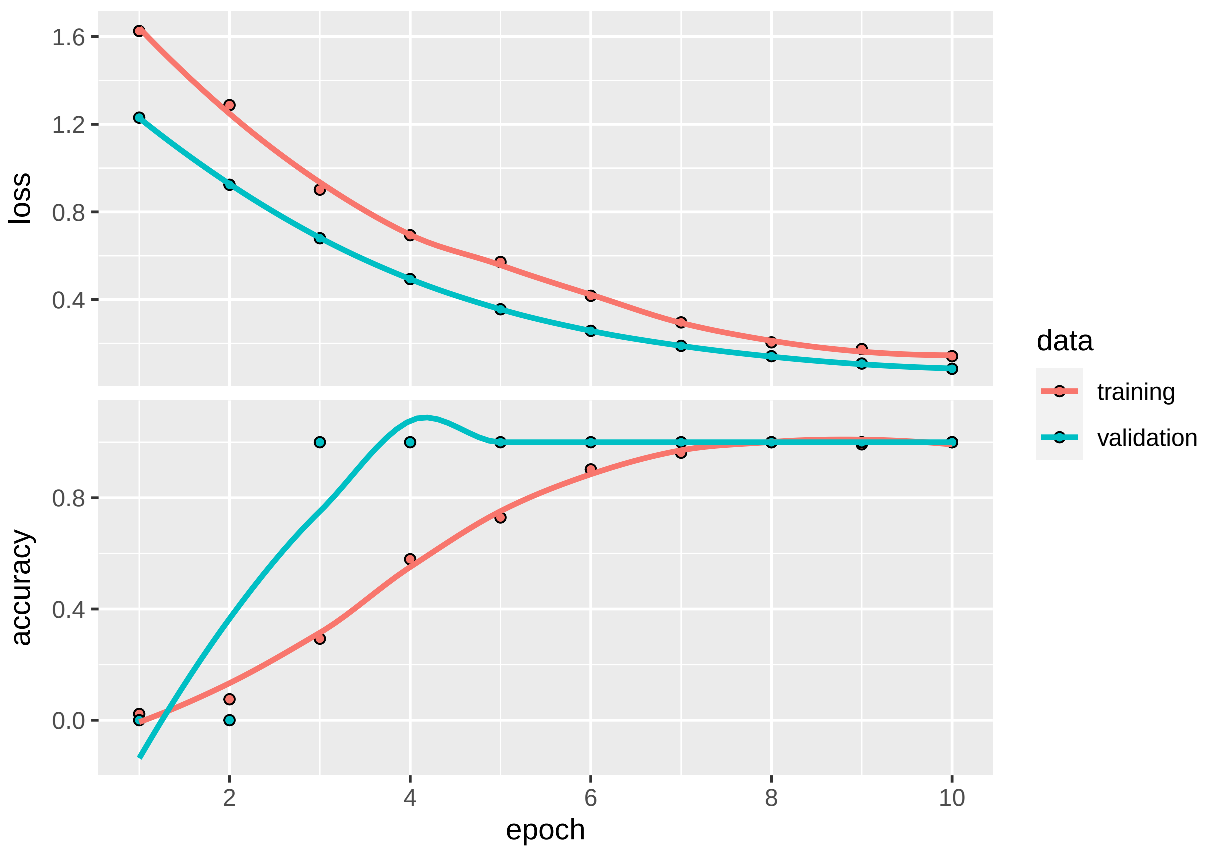
An epoch indicates how many times the algorithm views the entire dataset. Therefore, an epoch has ended whenever the algorithm has viewed all of the samples in the data set. Since a single epoch would be too large to transmit to the computer all at once, we divide it in several smaller batches.

```
trainm <- model %>%
  fit(X_train, y_train, epochs = 10, batch_size = 128, validation_split = 0.15)

trainm
```

```
##
## Final epoch (plot to see history):
##         loss: 0.1416
##     accuracy: 1
##     val_loss: 0.08408
## val_accuracy: 1
```

```
plot(trainm)
```



Evaluate the trained model using testing dataset

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

```
##       loss   accuracy
## 0.08298509 1.00000000
```

```
dim(X_test)
```

```
## [1]  40 428
```

```
dim(y_test)
```

```
## [1] 40  2
```

Model prediction using testing dataset

```
model   %>% predict(X_test) %>% `>`(0.8) %>% k_cast("int32")
```

```
## tf.Tensor(
## [[0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
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##  [0 1]
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##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
##  [0 1]
```

```
## [0 1]
## [0 1]
## [0 1]
## [0 1]
## [0 1]
## [0 1]], shape=(40, 2), dtype=int32)
```