```
set.seed(10)
library(readxl)
creditcard <- read_excel("C:/Users/taeho/Documents/bankruptcy_data.xlsx")
# View(creditcard)

# number of predictors and observations
k=length(creditcard[1,])-2
n=nrow(creditcard)


crx = sapply(creditcard[,c(-1,-95)], function(x) (x - min(x, na.rm = T)) / (max(x, na.rm = T)
- min(x, na.rm=T)))
df = cbind(creditcard[,1], crx)
names(df) <- c("Class", paste("V", 1:94, sep=""))
attach(df)


#now feed it to glm:

attach(df)
```

```
## The following objects are masked from df (pos = 3):
##
##     Class, V1, V10, V11, V12, V13, V14, V15, V16, V17, V18, V19, V2,
##     V20, V21, V22, V23, V24, V25, V26, V27, V28, V29, V3, V30, V31,
##     V32, V33, V34, V35, V36, V37, V38, V39, V4, V40, V41, V42, V43,
##     V44, V45, V46, V47, V48, V49, V5, V50, V51, V52, V53, V54, V55,
##     V56, V57, V58, V59, V6, V60, V61, V62, V63, V64, V65, V66, V67,
##     V68, V69, V7, V70, V71, V72, V73, V74, V75, V76, V77, V78, V79, V8,
##     V80, V81, V82, V83, V84, V85, V86, V87, V88, V89, V9, V90, V91,
##     V92, V93, V94
```

```
glmAll =glm(Class~V1+V2+V3+V4+V5+V6+V7+V8+V9+V10+V11+V12+V13+V14+V15+
              V16+V17+V18+V19+V20+V21+V22+V23+V24+V25+V26+V27+V28+V29+
              V30+V31+V32+V33+V34+V35+V36+V37+V38+V39+V40+V41+V42+V43+
              V44+V45+V46+V47+V48+V49+V50+
              V51+V52+V53+V54+V55+V56+V57+V58+V59+V60+
              V61+V62+V63+V64+V65+V66+V67+V68+V69+V70+
              V71+V72+V73+V74+V75+V76+V77+V78+V79+V80+
              V81+V82+V83+V84+V85+V86+V87+V88+V89+V90+
              V91+V92+V93+V94
            ,data=df,family="binomial")
```

```
## Warning: glm.fit: 알고리즘이 수렴하지 않았습니다
```

```
## Warning: glm.fit: 적합된 확률값들이 0 또는 1 입니다
```

```
summary(glmAll)
```

```
##
## Call:
## glm(formula = Class ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 +
##     V9 + V10 + V11 + V12 + V13 + V14 + V15 + V16 + V17 + V18 +
##     V19 + V20 + V21 + V22 + V23 + V24 + V25 + V26 + V27 + V28 +
##     V29 + V30 + V31 + V32 + V33 + V34 + V35 + V36 + V37 + V38 +
##     V39 + V40 + V41 + V42 + V43 + V44 + V45 + V46 + V47 + V48 +
##     V49 + V50 + V51 + V52 + V53 + V54 + V55 + V56 + V57 + V58 +
##     V59 + V60 + V61 + V62 + V63 + V64 + V65 + V66 + V67 + V68 +
##     V69 + V70 + V71 + V72 + V73 + V74 + V75 + V76 + V77 + V78 +
##     V79 + V80 + V81 + V82 + V83 + V84 + V85 + V86 + V87 + V88 +
##     V89 + V90 + V91 + V92 + V93 + V94, family = "binomial", data = df)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
##  -8.49    0.00    0.00    0.00    8.49
##
## Coefficients: (3 not defined because of singularities)
##               Estimate Std. Error    z value Pr(>|z|)
## (Intercept) -1.700e+22  4.542e+15   -3741815   <2e-16 ***
## V1          -1.455e+16  1.114e+08 -130580970   <2e-16 ***
## V2          -2.153e+15  8.205e+07  -26241622   <2e-16 ***
## V3           1.540e+16  1.339e+08  115018310   <2e-16 ***
## V4           3.856e+18  3.942e+11    9782398   <2e-16 ***
## V5          -2.728e+16  1.577e+09  -17303753   <2e-16 ***
## V6          -8.283e+19  1.414e+13   -5858048   <2e-16 ***
## V7           6.936e+19  1.181e+13    5873020   <2e-16 ***
## V8          -1.391e+17  2.552e+09  -54528903   <2e-16 ***
## V9          -3.963e+19  6.760e+12   -5862490   <2e-16 ***
## V10         -2.619e+16  1.179e+09  -22209751   <2e-16 ***
## V11          1.249e+13  2.817e+06    4433459   <2e-16 ***
## V12          1.067e+14  3.263e+06   32703803   <2e-16 ***
## V13         -1.411e+16  1.316e+08 -107202662   <2e-16 ***
## V14         -1.035e+15  7.589e+06 -136408001   <2e-16 ***
## V15          3.224e+14  6.757e+06   47712956   <2e-16 ***
## V16         -3.141e+16  6.809e+08  -46132450   <2e-16 ***
## V17          1.057e+16  1.519e+09    6960400   <2e-16 ***
## V18          1.713e+16  1.358e+09   12618115   <2e-16 ***
## V19         -1.358e+16  1.384e+08  -98097662   <2e-16 ***
## V20         -2.011e+15  9.505e+07  -21159436   <2e-16 ***
## V21          5.409e+15  9.933e+07   54454447   <2e-16 ***
## V22          1.290e+16  7.349e+08   17549516   <2e-16 ***
## V23          7.131e+15  1.142e+08   62456578   <2e-16 ***
## V24         -1.546e+14  6.861e+07   -2253546   <2e-16 ***
## V25          1.564e+15  1.051e+08   14879447   <2e-16 ***
## V26          2.639e+16  6.781e+08   38924057   <2e-16 ***
## V27         -2.554e+16  6.733e+08  -37934978   <2e-16 ***
## V28         -1.578e+15  8.171e+07  -19317417   <2e-16 ***
## V29         -5.942e+13  2.973e+06  -19987750   <2e-16 ***
## V30          3.394e+15  7.668e+07   44266010   <2e-16 ***
## V31         -1.973e+15  1.141e+08  -17297161   <2e-16 ***
## V32          2.742e+15  7.586e+07   36148605   <2e-16 ***
## V33         -2.413e+15  7.828e+07  -30821996   <2e-16 ***
## V34         -5.340e+14  3.157e+07  -16915624   <2e-16 ***
## V35         -3.104e+15  7.267e+07  -42718912   <2e-16 ***
```

```
## V36          7.972e+15  6.018e+07  132470618   <2e-16 ***
## V37          7.680e+14  7.990e+07    9611885   <2e-16 ***
## V38                 NA         NA         NA       NA
## V39         -1.684e+15  3.503e+07  -48080453   <2e-16 ***
## V40          5.835e+14  3.055e+08    1909832   <2e-16 ***
## V41         -4.260e+15  2.097e+08  -20315806   <2e-16 ***
## V42         -9.165e+15  7.395e+08  -12393888   <2e-16 ***
## V43          3.335e+15  1.449e+08   23018514   <2e-16 ***
## V44          9.443e+15  3.677e+08   25682502   <2e-16 ***
## V45         -1.248e+15  1.973e+07  -63245489   <2e-16 ***
## V46         -6.615e+15  3.567e+07 -185421745   <2e-16 ***
## V47         -4.549e+15  3.529e+07 -128921985   <2e-16 ***
## V48          7.260e+13  2.671e+06   27182094   <2e-16 ***
## V49          2.394e+13  3.800e+06    6299205   <2e-16 ***
## V50         -3.959e+14  5.654e+07   -7001849   <2e-16 ***
## V51         -2.965e+15  9.582e+07  -30948164   <2e-16 ***
## V52          7.500e+14  3.143e+07   23861024   <2e-16 ***
## V53         -4.240e+14  2.834e+07  -14957937   <2e-16 ***
## V54          2.266e+22  6.041e+15    3750556   <2e-16 ***
## V55          5.106e+14  8.885e+06   57471881   <2e-16 ***
## V56         -6.205e+21  1.654e+15   -3750556   <2e-16 ***
## V57         -1.672e+15  1.034e+07 -161759353   <2e-16 ***
## V58         -1.932e+15  4.683e+07  -41252795   <2e-16 ***
## V59         -1.158e+14  1.587e+07   -7295806   <2e-16 ***
## V60          2.021e+22  5.388e+15    3750556   <2e-16 ***
## V61          4.249e+15  6.797e+07   62507804   <2e-16 ***
## V62          1.238e+15  8.107e+07   15265286   <2e-16 ***
## V63         -3.800e+14  1.434e+07  -26488072   <2e-16 ***
## V64          1.076e+14  1.155e+07    9314621   <2e-16 ***
## V65         -1.781e+16  4.566e+08  -39014723   <2e-16 ***
## V66          1.101e+16  1.030e+09   10683080   <2e-16 ***
## V67         -2.472e+14  1.380e+07  -17913905   <2e-16 ***
## V68          6.806e+13  6.200e+07    1097755   <2e-16 ***
## V69          1.476e+15  7.788e+07   18950230   <2e-16 ***
## V70         -6.024e+15  5.524e+07 -109044202   <2e-16 ***
## V71          3.521e+13  3.548e+06    9922468   <2e-16 ***
## V72          5.569e+13  2.891e+06   19263642   <2e-16 ***
## V73          2.030e+16  8.448e+08   24029406   <2e-16 ***
## V74         -1.948e+14  2.969e+06  -65630206   <2e-16 ***
## V75          2.433e+16  4.489e+08   54186768   <2e-16 ***
## V76          2.307e+15  7.403e+07   31162336   <2e-16 ***
## V77                 NA         NA         NA       NA
## V78                 NA         NA         NA       NA
## V79          7.854e+15  2.803e+08   28023378   <2e-16 ***
## V80          1.239e+14  3.716e+07    3335713   <2e-16 ***
## V81         -4.300e+15  4.561e+07  -94272748   <2e-16 ***
## V82         -1.430e+14  3.800e+07   -3763565   <2e-16 ***
## V83         -5.231e+14  1.155e+08   -4530376   <2e-16 ***
## V84         -6.571e+14  4.654e+07  -14118467   <2e-16 ***
## V85          1.965e+15  3.563e+07   55146713   <2e-16 ***
## V86         -3.767e+15  1.092e+08  -34494464   <2e-16 ***
## V87         -2.204e+14  2.216e+07   -9944961   <2e-16 ***
## V88         -1.253e+13  6.668e+07    -187881   <2e-16 ***
## V89         -3.823e+18  3.941e+11   -9700396   <2e-16 ***
## V90         -1.809e+15  1.665e+08  -10860941   <2e-16 ***
## V91         -3.106e+16  1.219e+09  -25475937   <2e-16 ***
```

```
## V92          1.630e+15  5.200e+07   31353485   <2e-16 ***
## V93          5.417e+15  6.176e+07   87701515   <2e-16 ***
## V94         -4.936e+15  2.885e+07 -171080270   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance:  1943.7  on 6818  degrees of freedom
## Residual deviance: 15498.8  on 6727  degrees of freedom
## AIC: 15683
##
## Number of Fisher Scoring iterations: 25
```

```
library(caret)
```

```
## 필요한 패키지를 로딩중입니다: ggplot2
```

```
## 필요한 패키지를 로딩중입니다: lattice
```

```
library(InformationValue)
```

```
##
## 다음의 패키지를 부착합니다: 'InformationValue'
```

```
## The following objects are masked from 'package:caret':
##
##     confusionMatrix, precision, sensitivity, specificity
```

```
library(ISLR)

confusionMatrix(predict(glmAll, type="response") >= 0.5, df$Class)->tt
(tt[1,1]+tt[2,2])/sum(tt)*100
```

```
## [1] 96.84705
```

```
tt[1,1]/(tt[1,1]+tt[1,2])*100
```

```
## [1] 99.78785
```

```
tt[2,2]/(tt[2,1]+tt[2,2])*100
```

```
## [1] 8.636364
```

```
if (tensorflow::tf$executing_eagerly())
  tensorflow::tf$compat$v1$disable_eager_execution()

library(keras)
K <- keras::backend()
# training parameters
vae_batch_size = 160L
fnn_batch_size = 160L
epochs = 1L
vae_ep = 1L
fnn_ep = 7L
vae_flag = 0L

sel_pr_up = 1.0 # upper bound probability for VAE
sel_pr_dw = 0.0 # lower bound probability for VAE
sel_rate = 0.6

vae_w1 = 0.0
vae_w2 = 0.0
vae_w3 = 1.0

# latent and intermediate dimension
latent_dim = 2L
intermediate_dim = 10L
epsilon_std <- 0.1




# input image dimensions
input_shape = c(k+1)
```

```
model1 <- keras_model_sequential() %>%
    layer_dense(units = 1, activation = "sigmoid", input_shape = c(94))
  # %>%     layer_dense(units = 1, activation = "sigmoid")

  model1 %>% compile(
    optimizer = "rmsprop",
    loss = "binary_crossentropy",
    metrics = c("accuracy")
  )
```

```
history2 <- model1 %>% fit(
    as.matrix(df[,-1]), as.matrix(df[,1]),
    shuffle = TRUE,
    epochs = fnn_ep, batch_size = fnn_batch_size,
    verbose = 0
  )



temp3<-predict(model1,as.matrix(df[,-1]))
confusionMatrix(temp3>=0.5, df[,1]) -> tt3
tt3
```

```
##   FALSE
## 0  6599
## 1   220
```

```
(tt3[1,1]+tt3[2,2])/(sum(tt3))*100
```

```
## numeric(0)
```

```
tt3[1,1]/(tt3[1,1]+tt3[1,2])*100
```

```
## numeric(0)
```

```
tt3[2,2]/(tt3[2,1]+tt3[2,2])*100
```

```
## numeric(0)
```

```
# 0의 범주를 갖는 행과 1의 범주를 갖는 행을 분리
df_class_0 <- df[df$Class == 0, ]
df_class_1 <- df[df$Class == 1, ]
nrow(df_class_0)
```

```
## [1] 6599
```

```
nrow(df_class_1)
```

```
## [1] 220
```

```
df_class_1 <- df_class_1[sample(nrow(df_class_1),nrow(df_class_0),replace=TRUE),]
oversample <- rbind(df_class_0, df_class_1)
oversample <- oversample[sample(nrow(oversample),nrow(oversample),replace=FALSE),]
```

```
glmOVER =glm(Class~V1+V2+V3+V4+V5+V6+V7+V8+V9+V10+V11+V12+V13+V14+V15+
               V16+V17+V18+V19+V20+V21+V22+V23+V24+V25+V26+V27+V28+V29+
               V30+V31+V32+V33+V34+V35+V36+V37+V38+V39+V40+V41+V42+V43+
               V44+V45+V46+V47+V48+V49+V50+
               V51+V52+V53+V54+V55+V56+V57+V58+V59+V60+
               V61+V62+V63+V64+V65+V66+V67+V68+V69+V70+
               V71+V72+V73+V74+V75+V76+V77+V78+V79+V80+
               V81+V82+V83+V84+V85+V86+V87+V88+V89+V90+
               V91+V92+V93+V94
             ,data=oversample,family="binomial")
```

```
## Warning: glm.fit: 알고리즘이 수렴하지 않았습니다
```

```
## Warning: glm.fit: 적합된 확률값들이 0 또는 1 입니다
```

```
summary(glmOVER)
```

```
##
## Call:
## glm(formula = Class ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 +
##     V9 + V10 + V11 + V12 + V13 + V14 + V15 + V16 + V17 + V18 +
##     V19 + V20 + V21 + V22 + V23 + V24 + V25 + V26 + V27 + V28 +
##     V29 + V30 + V31 + V32 + V33 + V34 + V35 + V36 + V37 + V38 +
##     V39 + V40 + V41 + V42 + V43 + V44 + V45 + V46 + V47 + V48 +
##     V49 + V50 + V51 + V52 + V53 + V54 + V55 + V56 + V57 + V58 +
##     V59 + V60 + V61 + V62 + V63 + V64 + V65 + V66 + V67 + V68 +
##     V69 + V70 + V71 + V72 + V73 + V74 + V75 + V76 + V77 + V78 +
##     V79 + V80 + V81 + V82 + V83 + V84 + V85 + V86 + V87 + V88 +
##     V89 + V90 + V91 + V92 + V93 + V94, family = "binomial", data = oversample)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
##  -8.49    0.00    0.00    0.00    8.49
##
## Coefficients: (3 not defined because of singularities)
##               Estimate Std. Error    z value Pr(>|z|)
## (Intercept)  6.047e+23  3.489e+15  173331495   <2e-16 ***
## V1          -9.288e+15  6.795e+07 -136692401   <2e-16 ***
## V2           6.341e+15  5.103e+07  124263426   <2e-16 ***
## V3           3.920e+15  8.849e+07   44306116   <2e-16 ***
## V4          -4.188e+19  2.943e+11 -142306838   <2e-16 ***
## V5           2.321e+17  1.261e+09  184145517   <2e-16 ***
## V6          -7.594e+20  1.080e+13  -70285695   <2e-16 ***
## V7           6.345e+20  9.024e+12   70314906   <2e-16 ***
## V8          -2.775e+17  2.348e+09 -118170277   <2e-16 ***
## V9          -3.630e+20  5.165e+12  -70289166   <2e-16 ***
## V10          2.211e+16  1.065e+09   20756937   <2e-16 ***
## V11          2.145e+14  2.057e+06  104299846   <2e-16 ***
## V12          1.762e+14  2.513e+06   70108015   <2e-16 ***
## V13         -5.326e+15  1.180e+08  -45141687   <2e-16 ***
## V14          9.124e+13  7.341e+06   12429049   <2e-16 ***
## V15          6.903e+14  5.194e+06  132919262   <2e-16 ***
## V16         -5.311e+16  5.204e+08 -102055800   <2e-16 ***
## V17          6.718e+16  8.160e+08   82326487   <2e-16 ***
## V18         -1.554e+16  6.282e+08  -24734550   <2e-16 ***
## V19         -2.340e+15  1.149e+08  -20355146   <2e-16 ***
## V20          8.233e+13  7.349e+07    1120194   <2e-16 ***
## V21         -4.926e+15  9.481e+07  -51954561   <2e-16 ***
## V22         -1.596e+15  6.130e+08   -2603746   <2e-16 ***
## V23         -8.935e+15  1.055e+08  -84677212   <2e-16 ***
## V24          1.285e+15  6.446e+07   19935639   <2e-16 ***
## V25         -4.018e+15  9.251e+07  -43433440   <2e-16 ***
## V26          2.571e+16  5.657e+08   45444773   <2e-16 ***
## V27         -1.865e+16  5.640e+08  -33068281   <2e-16 ***
## V28         -4.931e+14  7.751e+07   -6361911   <2e-16 ***
## V29          1.794e+14  2.418e+06   74206715   <2e-16 ***
## V30          2.420e+15  1.669e+07  145014924   <2e-16 ***
## V31         -9.874e+14  1.053e+08   -9376572   <2e-16 ***
## V32         -3.786e+14  2.498e+07  -15158243   <2e-16 ***
## V33         -1.015e+15  7.121e+07  -14253296   <2e-16 ***
## V34         -2.481e+15  1.768e+07 -140380411   <2e-16 ***
## V35          3.243e+15  4.600e+07   70510511   <2e-16 ***
```

```
## V36          4.668e+15  5.059e+07   92272468   <2e-16 ***
## V37          1.111e+16  4.311e+07  257770505   <2e-16 ***
## V38                 NA         NA         NA       NA
## V39          1.831e+14  3.022e+07    6057141   <2e-16 ***
## V40          3.255e+16  1.239e+08  262815124   <2e-16 ***
## V41          8.720e+15  8.906e+07   97912235   <2e-16 ***
## V42          1.375e+16  6.202e+08   22170860   <2e-16 ***
## V43         -1.334e+15  1.340e+08   -9956813   <2e-16 ***
## V44         -1.071e+16  2.034e+08  -52638098   <2e-16 ***
## V45         -9.725e+14  1.488e+07  -65356519   <2e-16 ***
## V46         -8.429e+15  3.403e+07 -247706063   <2e-16 ***
## V47         -3.705e+15  3.502e+07 -105784141   <2e-16 ***
## V48         -1.976e+14  2.007e+06  -98412020   <2e-16 ***
## V49         -1.703e+14  2.494e+06  -68266959   <2e-16 ***
## V50         -3.911e+15  3.965e+07  -98652910   <2e-16 ***
## V51         -3.925e+15  6.732e+07  -58302835   <2e-16 ***
## V52         -2.178e+15  2.633e+07  -82685507   <2e-16 ***
## V53         -1.777e+15  2.791e+07  -63670522   <2e-16 ***
## V54         -8.037e+23  4.639e+15 -173232412   <2e-16 ***
## V55         -4.168e+14  6.289e+06  -66278627   <2e-16 ***
## V56          2.201e+23  1.271e+15  173232413   <2e-16 ***
## V57         -2.632e+15  8.269e+06 -318347622   <2e-16 ***
## V58         -3.778e+15  4.421e+07  -85442843   <2e-16 ***
## V59         -6.706e+14  6.709e+06  -99965962   <2e-16 ***
## V60         -7.169e+23  4.138e+15 -173232413   <2e-16 ***
## V61          4.540e+15  5.635e+07   80565834   <2e-16 ***
## V62          1.381e+15  7.620e+07   18119174   <2e-16 ***
## V63         -1.345e+15  1.111e+07 -121090963   <2e-16 ***
## V64          1.036e+15  8.031e+06  129032044   <2e-16 ***
## V65          3.763e+15  2.522e+08   14920984   <2e-16 ***
## V66          5.262e+16  4.463e+08  117907972   <2e-16 ***
## V67         -4.981e+14  9.653e+06  -51600535   <2e-16 ***
## V68         -1.448e+15  4.377e+07  -33090259   <2e-16 ***
## V69          4.188e+15  7.676e+07   54561054   <2e-16 ***
## V70         -2.783e+15  3.596e+07  -77385726   <2e-16 ***
## V71          5.431e+14  2.535e+06  214220520   <2e-16 ***
## V72         -4.421e+14  2.097e+06 -210827850   <2e-16 ***
## V73          5.839e+16  7.926e+08   73673643   <2e-16 ***
## V74         -5.544e+14  2.349e+06 -235999462   <2e-16 ***
## V75          3.149e+16  4.329e+08   72747072   <2e-16 ***
## V76          3.063e+15  3.003e+07  101971947   <2e-16 ***
## V77                 NA         NA         NA       NA
## V78                 NA         NA         NA       NA
## V79          1.480e+16  1.378e+08  107406467   <2e-16 ***
## V80          2.671e+15  2.342e+07  114029537   <2e-16 ***
## V81         -5.589e+15  3.438e+07 -162564287   <2e-16 ***
## V82         -2.927e+15  2.391e+07 -122442674   <2e-16 ***
## V83         -3.556e+15  6.017e+07  -59101847   <2e-16 ***
## V84          2.504e+15  2.733e+07   91631349   <2e-16 ***
## V85          2.779e+14  1.098e+07   25301660   <2e-16 ***
## V86         -8.091e+15  5.392e+07 -150044073   <2e-16 ***
## V87          1.182e+15  1.113e+07  106241932   <2e-16 ***
## V88         -1.600e+14  6.247e+07   -2561270   <2e-16 ***
## V89          4.165e+19  2.943e+11  141532934   <2e-16 ***
## V90          9.163e+14  6.147e+07   14907418   <2e-16 ***
## V91         -9.331e+16  5.912e+08 -157831453   <2e-16 ***
```

```
## V92          1.857e+15  3.883e+07   47813605   <2e-16 ***
## V93         -3.101e+15  5.647e+07  -54906686   <2e-16 ***
## V94         -3.185e+15  2.548e+07 -124984168   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance:  18296  on 13197  degrees of freedom
## Residual deviance: 161115  on 13106  degrees of freedom
## AIC: 161299
##
## Number of Fisher Scoring iterations: 25
```

```
confusionMatrix(predict(glmOVER, type="response") >= 0.5, oversample$Class)->tt
(tt[1,1]+tt[2,2])/sum(tt)*100
```

```
## [1] 83.06562
```

```
tt[1,1]/(tt[1,1]+tt[1,2])*100
```

```
## [1] 78.05728
```

```
tt[2,2]/(tt[2,1]+tt[2,2])*100
```

```
## [1] 88.07395
```

```
model1 <- keras_model_sequential() %>%
    layer_dense(units = 1, activation = "sigmoid", input_shape = c(94))
  # %>%     layer_dense(units = 1, activation = "sigmoid")

  model1 %>% compile(
    optimizer = "rmsprop",
    loss = "binary_crossentropy",
    metrics = c("accuracy")
  )
```

```
history2 <- model1 %>% fit(
    as.matrix(oversample[,-1]), as.matrix(oversample[,1]),
    shuffle = TRUE,
    epochs = fnn_ep, batch_size = fnn_batch_size,
    verbose = 0
  )


temp3<-predict(model1,as.matrix(oversample[,-1]))
confusionMatrix(temp3>=0.5, oversample[,1]) -> tt3
tt3
```

```
##   FALSE TRUE
## 0  5219 1380
## 1  1339 5260
```

```
(tt3[1,1]+tt3[2,2])/(sum(tt3))*100
```

```
## [1] 79.39839
```

```
tt3[1,1]/(tt3[1,1]+tt3[1,2])*100
```

```
## [1] 79.08774
```

```
tt3[2,2]/(tt3[2,1]+tt3[2,2])*100
```

```
## [1] 79.70905
```

```
##data partition##
df = df[sample(nrow(df),nrow(df),replace=FALSE),]
# 0의 범주를 갖는 행과 1의 범주를 갖는 행을 분리
df_class_0 <- df[df$Class == 0, ]
df_class_1 <- df[df$Class == 1, ]

# 0의 범주를 8대2 비율로 train과 test로 나눔
train_class_0_rows <- round(0.8 * nrow(df_class_0))
train_class_0 <- df_class_0[1:train_class_0_rows, ]
test_class_0 <- df_class_0[(train_class_0_rows + 1):nrow(df_class_0), ]

nrow(train_class_0)
```

```
## [1] 5279
```

```
# 1의 범주를 8대2 비율로 train과 test로 나눔

train_class_1_rows <- round(0.8 * nrow(df_class_1))
train_class_1 <- df_class_1[1:train_class_1_rows, ]
train_class_1 <- train_class_1[sample(nrow(train_class_1),nrow(train_class_0),replace=TRUE),]
test_class_1 <- df_class_1[(train_class_1_rows + 1):nrow(df_class_1), ]

# train과 test를 합쳐 최종 train_df와 test_df 생성
df <- rbind(train_class_0, train_class_1)
dfTS <- rbind(test_class_0, test_class_1)
dfTR0 = df[df$Class==0,]
overDF1 = df[df$Class==1,]
table(df$Class)
```

```
##
##    0    1
## 5279 5279
```

```
table(dfTS$Class)
```

```
##
##    0    1
## 1320   44
```

```
glmOver =glm(Class~V1+V2+V3+V4+V5+V6+V7+V8+V9+V10+V11+V12+V13+V14+V15+
               V16+V17+V18+V19+V20+V21+V22+V23+V24+V25+V26+V27+V28+V29+
               V30+V31+V32+V33+V34+V35+V36+V37+V38+V39+V40+V41+V42+V43+
               V44+V45+V46+V47+V48+V49+V50+
               V51+V52+V53+V54+V55+V56+V57+V58+V59+V60+
               V61+V62+V63+V64+V65+V66+V67+V68+V69+V70+
               V71+V72+V73+V74+V75+V76+V77+V78+V79+V80+
               V81+V82+V83+V84+V85+V86+V87+V88+V89+V90+
               V91+V92+V93+V94
             ,data=df,family="binomial")
```

```
## Warning: glm.fit: 알고리즘이 수렴하지 않았습니다
```

```
## Warning: glm.fit: 적합된 확률값들이 0 또는 1 입니다
```

```
summary(glmOver)
```

```
##
## Call:
## glm(formula = Class ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 +
##     V9 + V10 + V11 + V12 + V13 + V14 + V15 + V16 + V17 + V18 +
##     V19 + V20 + V21 + V22 + V23 + V24 + V25 + V26 + V27 + V28 +
##     V29 + V30 + V31 + V32 + V33 + V34 + V35 + V36 + V37 + V38 +
##     V39 + V40 + V41 + V42 + V43 + V44 + V45 + V46 + V47 + V48 +
##     V49 + V50 + V51 + V52 + V53 + V54 + V55 + V56 + V57 + V58 +
##     V59 + V60 + V61 + V62 + V63 + V64 + V65 + V66 + V67 + V68 +
##     V69 + V70 + V71 + V72 + V73 + V74 + V75 + V76 + V77 + V78 +
##     V79 + V80 + V81 + V82 + V83 + V84 + V85 + V86 + V87 + V88 +
##     V89 + V90 + V91 + V92 + V93 + V94, family = "binomial", data = df)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
##  -8.49    0.00    0.00    0.00    8.49
##
## Coefficients: (3 not defined because of singularities)
##               Estimate Std. Error    z value Pr(>|z|)
## (Intercept)  3.280e+23  3.960e+15   82847592   <2e-16 ***
## V1          -2.153e+16  9.277e+07 -232069100   <2e-16 ***
## V2          -4.131e+15  6.016e+07  -68672975   <2e-16 ***
## V3           2.330e+16  1.153e+08  202051933   <2e-16 ***
## V4          -6.644e+19  3.337e+11 -199108656   <2e-16 ***
## V5           6.701e+16  1.361e+09   49252961   <2e-16 ***
## V6          -5.183e+18  1.247e+13    -415540   <2e-16 ***
## V7           3.742e+18  1.042e+13     359227   <2e-16 ***
## V8           7.207e+17  4.218e+09  170850125   <2e-16 ***
## V9          -2.299e+18  5.963e+12    -385508   <2e-16 ***
## V10         -1.465e+17  2.633e+09  -55661875   <2e-16 ***
## V11         -2.717e+14  2.340e+06 -116113008   <2e-16 ***
## V12          2.223e+13  2.827e+06    7865128   <2e-16 ***
## V13         -1.761e+16  1.302e+08 -135245835   <2e-16 ***
## V14          4.134e+13  8.333e+06    4961096   <2e-16 ***
## V15          5.502e+14  5.938e+06   92663752   <2e-16 ***
## V16         -4.785e+16  5.759e+08  -83090783   <2e-16 ***
## V17          1.338e+16  8.944e+08   14957805   <2e-16 ***
## V18          3.149e+16  6.904e+08   45610095   <2e-16 ***
## V19         -2.423e+16  1.298e+08 -186687542   <2e-16 ***
## V20          3.747e+15  8.133e+07   46065078   <2e-16 ***
## V21         -1.335e+16  1.599e+08  -83510934   <2e-16 ***
## V22          1.523e+16  6.533e+08   23308984   <2e-16 ***
## V23          5.546e+15  1.174e+08   47246580   <2e-16 ***
## V24          4.228e+15  6.570e+07   64359179   <2e-16 ***
## V25          1.968e+15  1.012e+08   19439548   <2e-16 ***
## V26          1.844e+14  6.131e+08     300757   <2e-16 ***
## V27          9.829e+14  6.118e+08    1606628   <2e-16 ***
## V28          1.143e+15  7.785e+07   14680346   <2e-16 ***
## V29          2.609e+14  2.710e+06   96255878   <2e-16 ***
## V30          3.152e+15  1.886e+07  167135802   <2e-16 ***
## V31         -1.504e+15  1.083e+08  -13885563   <2e-16 ***
## V32         -6.460e+15  5.774e+07 -111880424   <2e-16 ***
## V33         -6.996e+25  1.858e+17 -376596471   <2e-16 ***
## V34         -5.929e+15  3.674e+07 -161374512   <2e-16 ***
## V35          2.170e+13  6.255e+07     346850   <2e-16 ***
```

```
## V36          2.253e+16  5.522e+07  408062235   <2e-16 ***
## V37          5.771e+15  4.957e+07  116418980   <2e-16 ***
## V38                 NA         NA         NA       NA
## V39          4.138e+14  3.105e+07   13326495   <2e-16 ***
## V40          3.269e+16  1.573e+08  207841551   <2e-16 ***
## V41          1.586e+16  1.188e+08  133495829   <2e-16 ***
## V42         -2.889e+15  6.602e+08   -4376163   <2e-16 ***
## V43          9.165e+15  1.438e+08   63720140   <2e-16 ***
## V44         -1.898e+16  2.355e+08  -80578044   <2e-16 ***
## V45          2.503e+15  1.752e+07  142858336   <2e-16 ***
## V46         -1.398e+16  5.367e+07 -260375225   <2e-16 ***
## V47         -8.624e+15  3.945e+07 -218568478   <2e-16 ***
## V48          2.801e+14  2.271e+06  123346836   <2e-16 ***
## V49         -4.301e+14  2.877e+06 -149514517   <2e-16 ***
## V50         -1.402e+16  4.950e+07 -283200258   <2e-16 ***
## V51          6.753e+16  3.229e+08  209121370   <2e-16 ***
## V52         -1.741e+15  2.958e+07  -58864562   <2e-16 ***
## V53         -2.886e+15  3.498e+07  -82505235   <2e-16 ***
## V54         -4.362e+23  5.265e+15  -82849026   <2e-16 ***
## V55         -5.578e+14  7.142e+06  -78099309   <2e-16 ***
## V56          1.195e+23  1.442e+15   82849027   <2e-16 ***
## V57         -1.934e+15  9.260e+06 -208855016   <2e-16 ***
## V58         -4.882e+15  5.701e+07  -85627887   <2e-16 ***
## V59         -1.287e+14  8.280e+06  -15542987   <2e-16 ***
## V60         -3.891e+23  4.697e+15  -82849025   <2e-16 ***
## V61          1.763e+15  6.171e+07   28570440   <2e-16 ***
## V62         -2.706e+15  8.723e+07  -31024708   <2e-16 ***
## V63          8.392e+14  1.229e+07   68311031   <2e-16 ***
## V64         -6.013e+14  9.763e+06  -61586712   <2e-16 ***
## V65          1.899e+16  2.977e+08   63797095   <2e-16 ***
## V66          1.024e+17  5.481e+08  186771253   <2e-16 ***
## V67          4.829e+14  1.074e+07   44978539   <2e-16 ***
## V68         -1.354e+15  4.845e+07  -27941008   <2e-16 ***
## V69          8.528e+15  7.911e+07  107798492   <2e-16 ***
## V70         -6.024e+15  4.006e+07 -150365318   <2e-16 ***
## V71          2.303e+14  2.874e+06   80124621   <2e-16 ***
## V72         -4.041e+12  2.358e+06   -1713941   <2e-16 ***
## V73          1.388e+17  1.543e+09   89951856   <2e-16 ***
## V74         -7.375e+14  2.632e+06 -280223522   <2e-16 ***
## V75          6.118e+17  1.132e+09  540566411   <2e-16 ***
## V76         -1.140e+15  3.000e+07  -38002315   <2e-16 ***
## V77                 NA         NA         NA       NA
## V78                 NA         NA         NA       NA
## V79          2.592e+16  1.688e+08  153557057   <2e-16 ***
## V80          1.021e+15  2.653e+07   38500629   <2e-16 ***
## V81         -8.126e+15  3.785e+07 -214674854   <2e-16 ***
## V82          2.445e+15  3.166e+07   77235853   <2e-16 ***
## V83          7.969e+14  6.884e+07   11576676   <2e-16 ***
## V84         -1.745e+15  3.073e+07  -56773139   <2e-16 ***
## V85          1.088e+15  1.280e+07   85038937   <2e-16 ***
## V86         -6.677e+15  6.208e+07 -107566151   <2e-16 ***
## V87         -4.280e+14  1.559e+07  -27459868   <2e-16 ***
## V88          2.271e+15  7.029e+07   32306263   <2e-16 ***
## V89          6.637e+19  3.337e+11  198881841   <2e-16 ***
## V90         -4.711e+15  7.891e+07  -59696608   <2e-16 ***
## V91         -1.419e+17  7.359e+08 -192784647   <2e-16 ***
```

```
## V92         -1.742e+15  3.952e+07  -44075752   <2e-16 ***
## V93         -1.346e+15  7.622e+07  -17653604   <2e-16 ***
## V94         -3.582e+15  3.409e+07 -105074226   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance:  14636  on 10557  degrees of freedom
## Residual deviance: 124855  on 10466  degrees of freedom
## AIC: 125039
##
## Number of Fisher Scoring iterations: 25
```

```
confusionMatrix(predict(glmOver, type="response") >= 0.5, df[,1])->tt
tt
```

```
##   FALSE TRUE
## 0  3943 1336
## 1   396 4883
```

```
(tt[1,1]+tt[2,2])/sum(tt)*100
```

```
## [1] 83.59538
```

```
tt[1,1]/(tt[1,1]+tt[1,2])*100
```

```
## [1] 74.69218
```

```
tt[2,2]/(tt[2,1]+tt[2,2])*100
```

```
## [1] 92.49858
```

```
confusionMatrix(predict(glmOver, as.data.frame(dfTS),type="response") >= 0.5, dfTS[,1])->tt1
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
tt1
```

```
##   FALSE TRUE
## 0   970  350
## 1     8   36
```

```
(tt1[1,1]+tt1[2,2])/sum(tt1)*100
```

```
## [1] 73.75367
```

```
tt1[1,1]/(tt1[1,1]+tt1[1,2])*100
```

```
## [1] 73.48485
```

```
tt1[2,2]/(tt1[2,1]+tt1[2,2])*100
```

```
## [1] 81.81818
```

```
table(dfTS$Class)
```

```
##
##    0    1
## 1320   44
```

```
#####VAE fitting#######

if (tensorflow::tf$executing_eagerly())
  tensorflow::tf$compat$v1$disable_eager_execution()

library(keras)
K <- keras::backend()

# training parameters
vae_batch_size = 160L
fnn_batch_size = 160L
epochs = 1L
vae_ep = 1L
fnn_ep = 7L
vae_flag = 0L

sel_pr_up = 1.0 # upper bound probability for VAE
sel_pr_dw = 0.0 # lower bound probability for VAE
sel_rate = 1.0

vae_w1 = 0.0
vae_w2 = 0.0
vae_w3 = 1.0

# latent and intermediate dimension
latent_dim = 2L
intermediate_dim = 10L
epsilon_std <- 0.1




# input image dimensions
input_shape = c(k+1)

# encoder
original_input_size = c(k+1)
inp <- layer_input(shape = original_input_size)
x <- layer_lambda(inp, f=function(x) {x[,2:(k+1)]})
y <- layer_lambda(inp, f=function(x) {x[,1:1]})

hidden_1 <- layer_dense(x, units=intermediate_dim, activation="relu")
dropout_1 <- layer_dropout(hidden_1, rate = 0.5)
hidden_2 <- layer_dense(dropout_1, units=intermediate_dim, activation="relu")
dropout_2 <- layer_dropout(hidden_2, rate = 0.5)

z_mean = layer_dense(dropout_2, units = latent_dim)
z_log_var <- layer_dense(hidden_2, units = latent_dim)

# sampling part
sampling <- function(args) {
  z_mean <- args[, 1:(latent_dim)]
  z_log_var <- args[, (latent_dim + 1):(2 * latent_dim)]

  epsilon <- k_random_normal(
```

```
    shape = c(k_shape(z_mean)[[1]]),
    mean = 0.,
    stddev = epsilon_std
  )
  z_mean + k_exp(z_log_var) * epsilon
}

z <- layer_concatenate(list(z_mean, z_log_var)) %>% layer_lambda(sampling)

# decoder + prediction model
output_shape = c(vae_batch_size, k)

decoder_hidden = layer_dense(units=intermediate_dim, activation="relu")
decoder_upsample = layer_dense(units = intermediate_dim, activation="relu")
decoder_reshape <- layer_reshape(target_shape = intermediate_dim)
decoder_hidden1 = layer_dense(units=k, activation="sigmoid")

pred_layer = layer_dense(units = 1, activation = "sigmoid")

hidden_decoded  = decoder_hidden(z)
up_decoded = decoder_upsample(hidden_decoded)
reshape_decoded <- decoder_reshape(up_decoded)
hidden1_decoded = decoder_hidden1(reshape_decoded)

y_pred =pred_layer(hidden1_decoded)


vae_loss <- function(y, y_pred) {
  x <- k_flatten(x)
  x_decoded_mean_squash <- k_flatten(hidden1_decoded)
  xent_loss <- 1.0 * # initial weight = 1
    loss_mean_squared_error(x, x_decoded_mean_squash) # loss_categorical_crossentropy도 시도해
볼 것
  kl_loss <- -0.5 * k_mean(1 + z_log_var - k_square(z_mean) -  # initial weight = -0.5
                           k_exp(z_log_var), axis = -1L)
  p_loss <- 1.0 * loss_binary_crossentropy(y, y_pred) # initial weight = 0 * 12000

  k_mean(xent_loss*vae_w1 + kl_loss*vae_w2 + p_loss*vae_w3)
}

vae <- keras_model(inp, y_pred)
optimizers <- keras::keras$optimizers
vae %>% compile(optimizer = optimizers$legacy$RMSprop(learning_rate=0.0001), loss = vae_loss,
                metrics = c("accuracy"))
# summary(vae)

## encoder: model to project inputs on the latent space
# encoder <- keras_model(inp, list(z_mean, z_log_var))

## build a digit generator that can sample from the learned distribution
# gen_decoder_input <- layer_input(shape = latent_dim)
# gen_hidden_decoded <- decoder_hidden(gen_decoder_input)
# gen_up_decoded <- decoder_upsample(gen_hidden_decoded)
# gen_hidden1_decoded <- decoder_hidden1(gen_up_decoded)

# generator <- keras_model(gen_decoder_input, gen_hidden1_decoded)
```

```
vae1 <- keras_model(inp, hidden1_decoded) # can be used for generating synthetic samples for ca
se 0 and 1
```

```
model1 <- keras_model_sequential() %>%
    layer_dense(units = 1, activation = "sigmoid", input_shape = c(94))
  # %>%     layer_dense(units = 1, activation = "sigmoid")

  model1 %>% compile(
    optimizer = "rmsprop",
    loss = "binary_crossentropy",
    metrics = c("accuracy")
  )
```

```
history2 <- model1 %>% fit(
    as.matrix(df[,-1]), as.matrix(df[,1]),
    shuffle = TRUE,
    epochs = fnn_ep, batch_size = fnn_batch_size,
    validation_data = list(as.matrix(dfTS[,-1]), as.matrix(dfTS[,1]))
    , verbose = 0
  )

temp3<-predict(model1,as.matrix(df[,-1]))
confusionMatrix(temp3>=0.5, df[,1]) -> tt3
tt3
```

```
##   FALSE TRUE
## 0  4517  762
## 1  1643 3636
```

```
(tt3[1,1]+tt3[2,2])/(sum(tt3))*100
```

```
## [1] 77.22106
```

```
tt3[1,1]/(tt3[1,1]+tt3[1,2])*100
```

```
## [1] 85.56545
```

```
tt3[2,2]/(tt3[2,1]+tt3[2,2])*100
```

```
## [1] 68.87668
```

```
temp3 <- predict(model1, as.matrix(dfTS[,-1]))
confusionMatrix(temp3>=0.5, dfTS[,1]) -> tt3
tt3
```

```
##   FALSE TRUE
## 0  1127  193
## 1     8   36
```

```
(tt3[1,1]+tt3[2,2])/(sum(tt3))*100
```

```
## [1] 85.26393
```

```
tt3[1,1]/(tt3[1,1]+tt3[1,2])*100
```

```
## [1] 85.37879
```

```
tt3[2,2]/(tt3[2,1]+tt3[2,2])*100
```

```
## [1] 81.81818
```

```
# j : number of epoch
# i : number of batchs for one epoch

for (j in 1:epochs) {

# FNN MODEL FITTING

model1 <- keras_model_sequential() %>%
  layer_dense(units = 1, activation = "sigmoid", input_shape = c(94))
  # %>%     layer_dense(units = 1, activation = "sigmoid")

model1 %>% compile(
  optimizer = "rmsprop",
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Insert VAE part here if needed

if(vae_flag == 1){
history = vae %>% fit(
     as.matrix(df), as.matrix(df[,1]),
     shuffle = TRUE,
     epochs = vae_ep,
     batch_size = vae_batch_size,
     validation_data = list(as.matrix(dfTS), as.matrix(dfTS[,1])),
     verbose = 0
)
}


# whole train and test data preparation

 library(dplyr)

  temp0 <- predict(vae1, as.matrix(df))
  temp  <- predict(vae, as.matrix(df))
  temp1 <- as.data.frame(cbind(c(1), temp0[temp<=quantile(temp, sel_pr_up) &
temp>=quantile(temp, sel_pr_dw),]))
  names(temp1) = names(dfTR0)
  samp_ind = sample(1:nrow(temp), size = round(nrow(temp)*sel_rate))
  temp1 <- temp1[samp_ind,]

  temp2 <- dfTR0 %>% sample_frac(nrow(temp1)/nrow(dfTR0), replace = TRUE)
  train_df <-rbind(temp2, dfTR0, overDF1, temp1)
  train_df <- train_df[sample(1:nrow(train_df)),]

  # print(i)

  ## ---- Fitting -------------------------------------------------------

  history2 <- model1 %>% fit(
    as.matrix(train_df[,-1]), as.matrix(train_df[,1]),
    shuffle = TRUE,
    epochs = fnn_ep, batch_size = fnn_batch_size,
```

```
    validation_data = list(as.matrix(dfTS[,-1]), as.matrix(dfTS[,1]))
    , verbose = 0
  )

  print("FNN")
  print(history2)
 # plot(history2)
  print("VAE")
  if(vae_flag == 1){
  print(history)}
 #plot(history)
  print(j)
 ㅣ
```

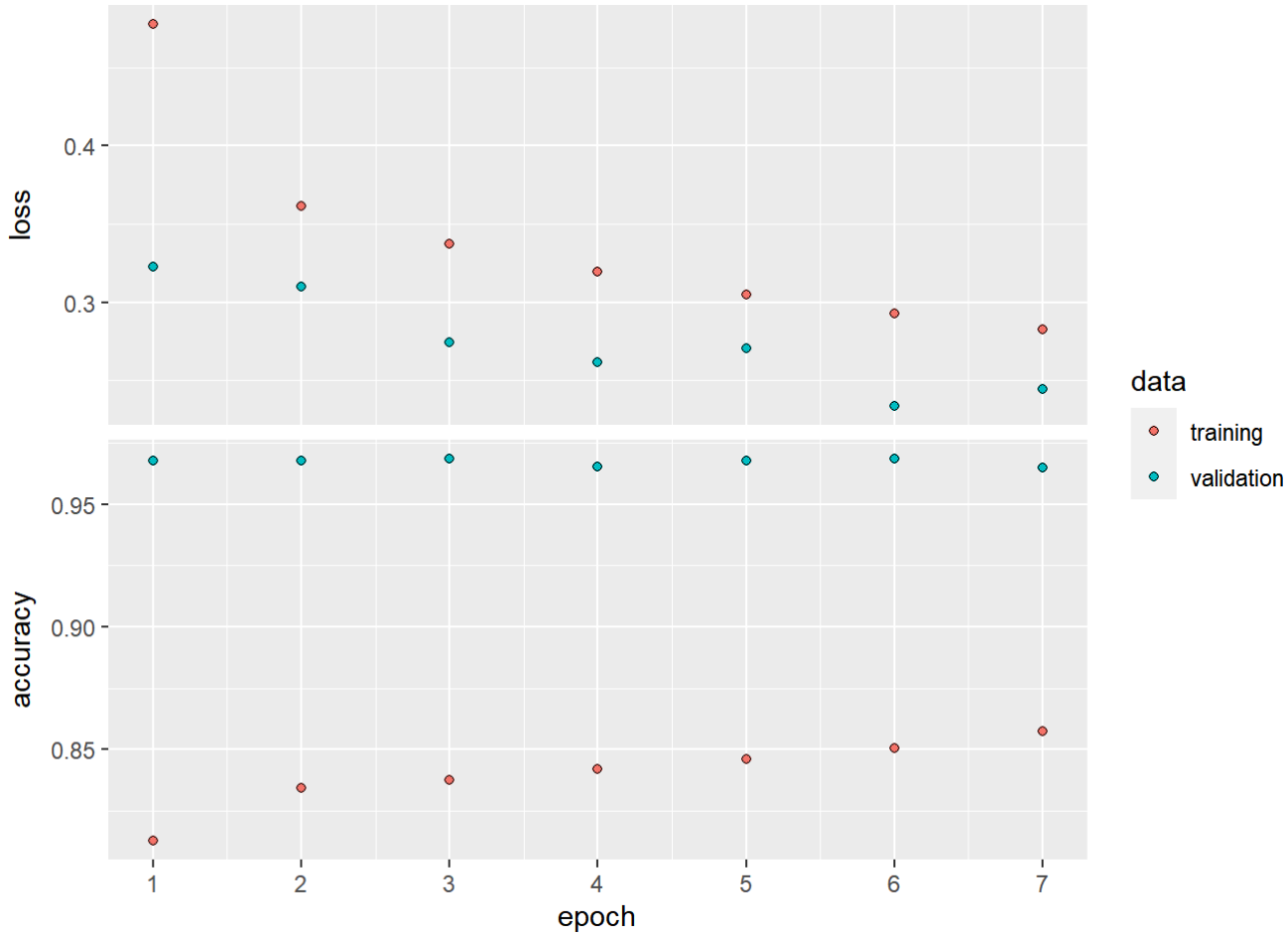
```
##
## 다음의 패키지를 부착합니다: 'dplyr'
```

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

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

```
## [1] "FNN"
## Trained on 31,674 samples (batch_size=160, epochs=7)
## Final epoch (plot to see history):
##         loss: 0.2829
##     accuracy: 0.8576
##     val_loss: 0.2446
## val_accuracy: 0.9648
## [1] "VAE"
## [1] 1
```

```
if(vae_flag == 1){
plot(history)
}
plot(history2)
```




```
temp3 <- predict(vae, as.matrix(dfTS))
confusionMatrix(temp3>=0.5, dfTS[,1]) -> tt
tt
```

```
##   FALSE
## 0  1320
## 1    44
```

```
(tt[1,1]+tt[2,2])/(sum(tt))*100
```

```
## numeric(0)
```

```
tt[1,1]/(tt[1,1]+tt[1,2])*100
```

```
## numeric(0)
```

```
tt[2,2]/(tt[2,1]+tt[2,2])*100
```

```
## numeric(0)
```

```
temp3 <- predict(model1, as.matrix(dfTS[,-1]))
confusionMatrix(temp3>=0.5, dfTS[,1]) -> tt3
tt3
```

```
##   FALSE TRUE
## 0  1308   12
## 1    36    8
```

```
(tt3[1,1]+tt3[2,2])/(sum(tt3))*100
```

```
## [1] 96.48094
```

accuracy for case 0

```
tt3[1,1]/(tt3[1,1]+tt3[1,2])*100
```

```
## [1] 99.09091
```

accuracy for case 1

```
tt3[2,2]/(tt3[2,1]+tt3[2,2])*100
```

```
## [1] 18.18182
```