code for machine learning

Zheng Pan

7/5/2021

Contents

Introduction	2
Workflow	3
code	4
prerequisites	 . 4
machine learning	 . 5

Introduction

This is a slide which demonstrates the a workflow using R programming language. The dependent value is continuous in this case.

Workflow

- 1. modeling
- 2. performance assessment
- 3. model optimization

code

prerequisites

• load requried libraries

```
library('tidyverse')
library('mlr3')
library('mlr3verse')
library("mlr3viz")
library('reshape2')
library('GenSA')
```

• function that generates pearson heat map

```
options(width=80)
pearson_heat <- function(df, corm = -1){</pre>
  defaultW <- getOption("warn")</pre>
  options(warn = -1)
  if(corm == -1){
    corm = cor(df)
  }
  options(warn = defaultW)
  res <- melt(corm) %>%
    ggplot(aes(Var1,Var2,fill = value)) +
    geom tile(color = "black",alpha = 0.8) +
    theme(axis.text.x = element_text(angle = 90,
                                      hjust = 0.5, vjust = 0.5)) +
    scale_fill_gradient2() +
    theme(panel.border = element_blank(),
          panel.grid.major = element_blank(),
          panel.grid.minor = element_blank(),
          axis.line = element_line(colour = "black")) +
    xlab(NULL) +
    ylab(NULL)
  return(res)
```

• feature selecting by pearson correlation coefficient

```
fea_slc_bycor <- function(df, corr = 0.8){
  corm <- cor(df)
  name_of_features <- colnames(df)
  name_of_features_d <- name_of_features
  origin_fea_length <- length(name_of_features)
  for(q in 1:(origin_fea_length - 1)){
    fea_t <- name_of_features_d[q]
    other_fea_t <- name_of_features_d[(q+1):length(name_of_features_d)]
    de_fea <- names(corm[fea_t, other_fea_t][abs(corm[fea_t, other_fea_t]) >= corr])
```

```
name_of_features <- name_of_features[!(name_of_features %in% de_fea)]
}
res <- df[, colnames(df) %in% name_of_features]
return(res)
}</pre>
```

- import data
- prepare the prediction set

```
tsk_df1 <- lapply(unique(st1$X), function(s){</pre>
  df1 \leftarrow st1[st1$X == s, ][1, ][, c(-length(st1[st1$X == s, ][1, ]),
      -length(st1[st1$X == s, ][1, ]) + 1,
      -length(st1[st1$X == s, ][1, ]) + 2, -length(st1[st1$X == s, ][1, ])
      + 3)]
  df2 <- cbind(df1, Manufacture.Method = c(1,2,3))</pre>
  res1 <- lapply(1:nrow(df2), function(q){
    df t \leftarrow df2[q,]
    (cbind(df_t, Material.Ratio.PbI2.Cation = seq(0,2,0.1)))
  df3 <- do.call(rbind, res1)</pre>
  res2 <- lapply(1:nrow(df3), function(q){</pre>
    \# q = 1
    df_t \leftarrow df3[q,]
    (cbind(df_t, Time.s. = seq(0,500,5)))
  })
  df4 <- do.call(rbind, res2)</pre>
  df4 <- as.data.frame(df4)</pre>
  df4$Current.A. <- NA
  df4
})
```

• feature engineering

```
features <- st[, -ncol(st)]
pearson_heat(features, corm = cor(features))
fea_new <- fea_slc_bycor(features, corr = 0.8)
pearson_heat(fea_new)</pre>
```

machine learning

• Task construction

```
tsk_df <- cbind(st_t[, colnames(fea_new)], current = st_t[, ncol(st_t)])
task <- TaskRegr$new(id = "task", backend = tsk_df, target = "current")</pre>
```

• pick up a learner

```
cl <- mlr_learners$keys()[35:44]
qq = 9
learner <- mlr_learners$get(cl[qq])</pre>
```

In this case, the learner name is regr.svm

train and test

```
train_set <- sample(NN, 0.8 * NN)
test_set <- setdiff(seq_len(NN), train_set)
learner$train(task, row_ids = train_set)
prediction <- learner$predict(task, row_ids = test_set)</pre>
```

• performance assessment

• output predictions

```
learner$predict(task, row_ids = 361: 500)$response
ind_seq <- c(seq(NN + 1, nrow(st_t), 500000), nrow(st_t))
ind_seq_1 <- lapply(1:(length(ind_seq) - 1), function(q){
    if(q != 1){
        return((ind_seq[q] + 1):ind_seq[q+1])
    }else{
        ind_seq[q]:ind_seq[q+1]
    }
})
pred <- lapply(1:length(ind_seq_l), function(q){
    prediction2 <- learner$predict(task, row_ids = ind_seq_l[[q]])
    data.frame(prediction2$response)
})
preds <- do.call(rbind, pred)

to_w <- st2[(NN+1): nrow(st2),]
to_w[, ncol(to_w)] <- preds

write_csv(to_w, file = paths)</pre>
```