Multivariate Analisys Report

(MECD, Minor-CD, & MMAC, 1st Semester, 2023/2024)

2023-12-05

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Fitness Club Dataset for ML Classification

Introduction

Multivariate analysis is a pivotal statistical technique in the realm of data science, particularly when dealing with datasets encompassing multiple interrelated variables. It offers a sophisticated approach to understanding the nuanced relationships and patterns that emerge from complex data. This method is crucial for extracting meaningful insights from datasets where multiple factors interact in intricate ways, as is often the case in real-world scenarios.

Multivariate analysis includes a variety of techniques, each suited to different types of data and analysis objectives. Key methods such as logistic regression, decision trees, and cluster analysis are particularly relevant in scenarios where predicting outcomes or classifying data points are the main goals. These techniques allow for a comprehensive analysis, considering how various factors collectively influence outcomes.

Description of the problem under study

Our dataset was select from Kaggle. The dataset provided for this analysis originates from GoalZone, a well-known fitness club chain in Canada. GoalZone operates several fitness classes, with capacities of either 25 or 15 participants. A significant challenge they face is the discrepancy between class bookings and actual attendance. While some classes are consistently fully booked, the actual attendance rate often falls short of expectations. This scenario presents both a logistical challenge and an opportunity for optimization.

The primary challenge is predicting whether a member who has booked a class will actually attend. Accurately forecasting attendance allows GoalZone to optimize class capacities effectively, ensuring maximum utilization of resources and enhanced member satisfaction. This challenge involves analyzing various factors that might influence attendance, such as the time of the class, member demographics, previous attendance patterns, and class type.

Objectives

The analysis of the GoalZone dataset aims to achieve the following objectives:

Predictive Analysis: Develop a predictive model that can accurately forecast whether a member who has booked a class will attend. This involves identifying key variables that influence attendance and employing appropriate multivariate techniques. Optimization of Class Capacities: Use the insights gained from the predictive model to optimize class capacities, enabling GoalZone to allocate spaces more effectively and potentially increase the total number of spaces offered. Enhancing Member Experience: By improving the accuracy of attendance predictions, GoalZone can reduce overbooking and under-utilization issues, leading to a better overall experience for members. Data-Driven Decision Making: Provide GoalZone with data-driven strategies to manage class schedules and capacities, thereby improving operational efficiency.

You can also embed plots, for example:

```
fitdata <- read_csv("fitness_class_2212.csv", show_col_types = FALSE)
str(fitdata)
```

```
## spc_tbl_ [1,500 x 8] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ booking_id      : chr [1:1500] "0001" "0002" "0003" "0004" ...
##  $ months_as_member: num [1:1500] 17 10 16 5 15 7 11 9 23 7 ...
##  $ weight          : num [1:1500] 79.6 79 74.5 86.1 69.3 ...
##  $ days_before     : chr [1:1500] "8" "2" "14" "10" ...
##  $ day_of_week     : chr [1:1500] "Wed" "Mon" "Sun" "Fri" ...
##  $ time            : chr [1:1500] "PM" "AM" "AM" "AM" ...
##  $ category        : chr [1:1500] "Strength" "HIIT" "Strength" "Cycling" ...
##  $ attended        : num [1:1500] 0 0 0 0 0 0 0 0 1 0 ...
```

```
##  - attr(*, "spec")=
##   .. cols(
##   ..   booking_id = col_character(),
##   ..   months_as_member = col_double(),
##   ..   weight = col_double(),
##   ..   days_before = col_character(),
##   ..   day_of_week = col_character(),
##   ..   time = col_character(),
##   ..   category = col_character(),
##   ..   attended = col_double()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

```
summary(fitdata)
```

```
##   booking_id        months_as_member     weight       days_before
##  Length:1500        Min.   :  1.00   Min.   : 55.41   Length:1500
##  Class :character   1st Qu.:  8.00   1st Qu.: 73.49   Class :character
##  Mode  :character   Median : 12.00   Median : 80.76   Mode  :character
##                     Mean   : 15.63   Mean   : 82.61
##                     3rd Qu.: 19.00   3rd Qu.: 89.52
##                     Max.   :148.00   Max.   :170.52
##                                      NA's   :20
##  day_of_week            time            category            attended
##  Length:1500        Length:1500        Length:1500        Min.   :0.0000
##  Class :character   Class :character   Class :character   1st Qu.:0.0000
##  Mode  :character   Mode  :character   Mode  :character   Median :0.0000
##                                                           Mean   :0.3027
##                                                           3rd Qu.:1.0000
##                                                           Max.   :1.0000
##
```

```
sapply(fitdata, function(x) sum(is.na(x))) # check each column for NA values
```

```
##       booking_id months_as_member           weight      days_before
##                0                0               20                0
##      day_of_week             time         category         attended
##                0                0                0                0
```

Data Exploration and Cleaning

We noticed that some columns are not in the ideal format to work with our classification models. The column `days_before` should be a discrete (integer) number of days before the class the member registered, but in `fitdata` we got `class(fitdata$days_before)` as character. Here are the steps we used to convert to integer:

```
unique(fitdata$days_before)
```

```
##  [1] "8"       "2"       "14"      "10"      "6"       "4"       "9"
##  [8] "12"      "5"       "3"       "7"       "13"      "12 days" "20"
## [15] "1"       "15"      "6 days"  "11"      "13 days" "3 days"  "16"
## [22] "1 days"  "7 days"  "8 days"  "10 days" "14 days" "17"      "5 days"
## [29] "2 days"  "4 days"  "29"
```

```r
fitdata$days_before <- fitdata$days_before %>%
     strsplit(split = " ") %>% # split some strings that had more than the number of days
     sapply(function(x) x[1]) %>% # gets the 1st element of the split strings
     as.integer() # converts to integer

class(fitdata$days_before)
```

```
## [1] "integer"
```

For `day_of_week`, we needed to standardize to uniquely 7 values corresponding to the days of the week.

```r
unique(fitdata$day_of_week)
```

```
##  [1] "Wed"       "Mon"       "Sun"       "Fri"       "Thu"       "Wednesday"
##  [7] "Fri."      "Tue"       "Sat"       "Monday"
```

```r
fitdata$day_of_week <- fitdata$day_of_week %>%
     tolower() %>% # converts to lower case
     substr(1, 3) %>% # gets only the 3 first elements of each string
     factor() # Converts to factor to be used as categorical variable

table(fitdata$day_of_week)
```

```
##
## fri mon sat sun thu tue wed
## 305 228 202 213 241 195 116
```

`fitdata$time` is a ordinal variable which indicates if the booked fitness class is in the morning (AM) or afternoon (PM). This is also categorical so we encoded it to numerical representation ("AM" / "PM" to 0 / 1).

```r
table(fitdata$time)
```

```
##
##   AM   PM
## 1141  359
```

```r
fitdata$time <- ifelse(fitdata$time == "AM", 0, 1) %>%
     factor()

table(fitdata$time)
```

```
##
##    0    1
## 1141  359
```

`fitdata$category` correspond to the category of the fitness class. In this dataset only 6 categories are present and one of them is "-".

```r
table(fitdata$category)
```

```
##
##        -     Aqua  Cycling     HIIT Strength     Yoga
##       13       76      376      667      233      135
```

```r
fitdata <- fitdata %>%
     mutate(category = na_if(category, "-")) # Replace "-" with NA

fitdata$category <- factor(fitdata$category)
table(fitdata$category)
```

```
##
##     Aqua  Cycling     HIIT Strength     Yoga
##       76      376      667      233      135
```

Dealing with missing values is crucial in data analysis to ensure the integrity and validity of the results. Missing data can introduce bias, reduce the statistical power, and lead to invalid conclusions. By appropriately addressing these gaps, whether through imputation, removal, or analysis modifications, we can enhance the robustness of our findings and make more accurate inferences from the data. This process is essential for maintaining the quality and reliability of statistical analysis in any research or data-driven decision-making.

```r
get_na <- function(df) {
     na_rows <- lapply(df, function(x) which(is.na(x))) %>% # get indices of NA values in each column
          unlist() %>%
          unique() # get the unique indices of all columns
     return(df[na_rows, , drop = FALSE])
}

fit_na <- get_na(fitdata)

na_ratio <- dim(fit_na)[1] / dim(fitdata)[1]

fitdata <- na.omit(fitdata)
```

For `na_ratio` = 0.022 the removal of missing values (NAs) is acceptable since their proportion is very small, as it minimally affects the dataset's overall integrity and distribution.