Multivariate Analysis Report

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

2023-12-05

Professor: M. Rosário Oliveira

Group Members:

Antonio Villas Bôas	Darlan Nascimento	Emma Dennis-Knieriem	Leonardo Aikawa	Tunahan Güneş
ist1105429	ist1108076	ist1105545	ist1104694	ist1108108

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 [1].

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:

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

```
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.

```
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 [2].

```
get_na <- function(df) { # get indices of NA values in each column
     na_rows <- lapply(df, function(x) which(is.na(x))) %>%
          unlist() %>% unique() # get the unique indices of all columns
     return(na_rows)
}
na_rows <- get_na(fitdata)
na_ratio <- length(na_rows) / dim(fitdata)[1]

fitdata <- fitdata[-na_rows, ]
```

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.

Estimation and validation methods

Unsupervised Learning Models

1. K-means clustering

The K-means clustering algorithm, crucial in high-dimensional data analysis, is detailed in classics like John Hartigan's "Clustering Algorithms." This iterative, algorithmic method identifies centroids of pre-specified clusters in multi-dimensional spaces, a task challenging in higher dimensions. K-means partitions data into clusters, requiring an initial guess of cluster numbers. Adjusting this number in subsequent runs helps in fine-tuning the clustering outcome, essential for analyzing complex data structures. [3]

As an unsupervised learning algorithm, K-means does not work with a target variable (in our case, `fitdata$attended`), but it can segment data into clusters, which can then potentially be analyzed to infer patterns that might be relevant for prediction.

Two unsupervised learning techniques were used to compare the results: k-means clustering and agglomerative nesting (Hierarchical Clustering). Although is not directly correlated, we used 2 centroids to try to see if each model would classify the fitness club attendance into 0 or 1 and then compare with `fitdata$attended`.

The metric used to compare models was a simple proportion of matching attendance and cluster assignments given by:

$$\frac{\sum(\text{fitdata.attended} == \text{prediction})}{\text{length}(\text{fitdataattended})}$$

2. Agglomerative Nesting (Hierarchical Clustering)

For the agglomerative nesting (agnes) we tried an algorithm that tested every combination of `metrics` and `methods` such:

```
metrics <- c('euclidean', 'manhattan')
methods <- c('single', 'complete', 'average')
```

The best AgNes combination was: {metric: manhattan, method: complete}. And the accuracy results are shown below:

Model	Accuracy
K-means	0.49488
AgNes	0.72392

The image below shows plots of the actual fitness club attendance, the attendance prediction of the K-means models, and the attendance of the best AgNes model, respectively. For more details about the algorithm used to create the models and plots, please check the `kmeans.R` file.

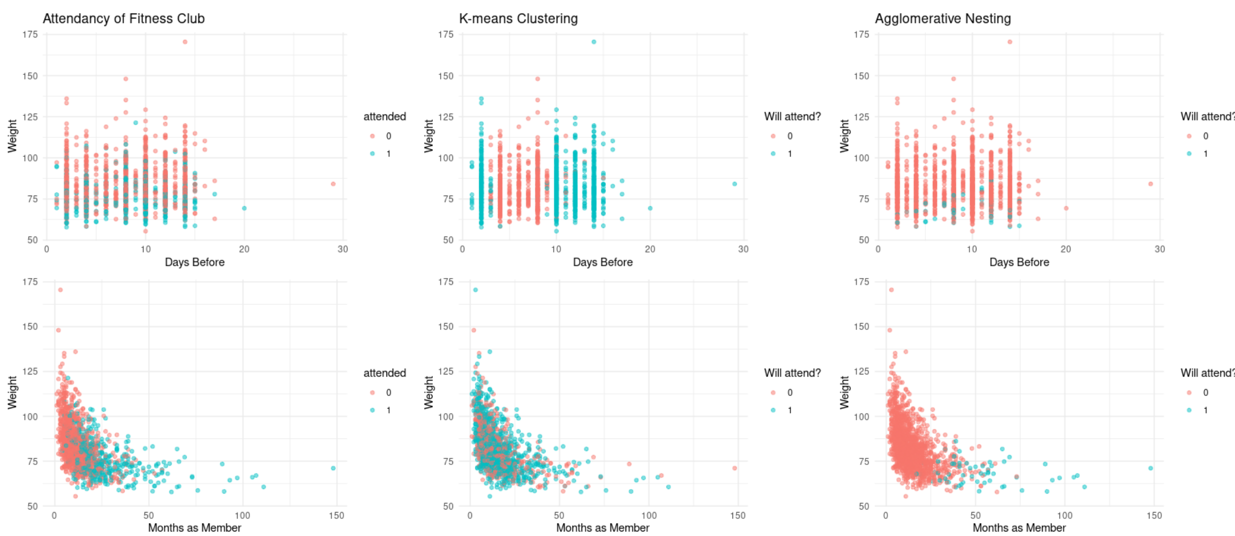


Figure 1: Attendance Comparison

According to the plots above, there doesn't appear to be a clear boundary separating the attended and not-attended groups in either plot, suggesting that these features alone may not strongly predict attendance.

Supervised Learning Models

To train and test our supervised models, we applied a 80-20 split for our data. And, all the models we applied are then trained and tested on the same sets such that:

```
source('tidydata.R')

library(caret)
library(dplyr)
library(MLmetrics)

fitdata_prepared <- fitdata %>%
      select(-booking_id) %>%
      mutate_at(
            vars(months_as_member,weight,days_before),
            scale) %>%  # Scale numerical variables
      mutate(
            day_of_week = as.numeric(day_of_week),  # Convert factors to numeric
```

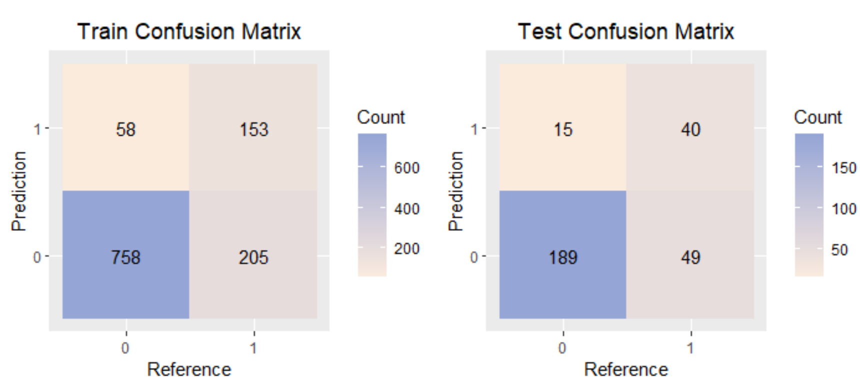
```
        time = as.numeric(time),
        category = as.numeric(category)
    )

set.seed(42)
training_indices <- createDataPartition(fitdata_prepared$attended, p = 0.8, list = FALSE)

train_data <- fitdata_prepared[training_indices, ]
test_data <- fitdata_prepared[-training_indices, ]
```

1. Logistic Regression

Logistic regression is a statistical model used for predicting the probability of a binary outcome based on one or more predictor variables. Unlike linear regression, which predicts a continuous outcome, logistic regression is used when the dependent variable is categorical and specifically binary, meaning it has only two possible outcomes (like yes/no, true/false, 1/0). The model estimates the probability that a given input point belongs to a certain class. The output of logistic regression is a probability score (between 0 and 1), and it employs a logistic function, often called the sigmoid function, to model the data. This function has an 'S'-shaped curve that can take any real-valued number and map it into a value between 0 and 1, making it useful for models where the output is a probability.

Applying logistic regression to this dataset is appropriate because the target variable, 'attended', is binary, indicating whether a fitness club member attended a class (1) or not (0). This fits perfectly with the nature of logistic regression, which is designed to handle binary outcome variables. Additionally, the dataset contains a mix of continuous, discrete, and categorical variables (like weight, days_before, day_of_week, time, etc.), which logistic regression can effectively incorporate to predict the probability of attendance. The model can thus help in understanding the relationship between these features and the likelihood of a member attending a class, providing valuable insights that could be used for decision-making or strategy development in the context of the fitness club. For instance, it can identify patterns or key factors influencing attendance, aiding in resource planning, personalized member engagement, or targeted marketing strategies.

```
model <- glm(attended ~ ., data = train_data, family = "binomial")
```



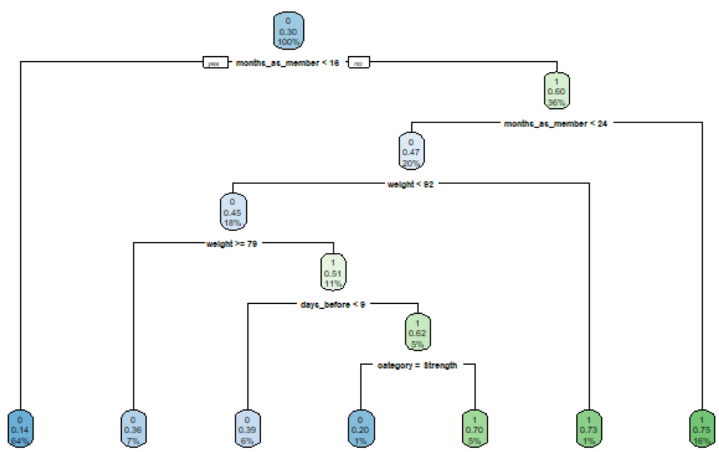
Data	Accuracy	Balanced Accuracy	F-1 Score
Train	0.776	0.6781	0.8521641
Test	0.7816	0.6880	0.8552036

2. Decision Tree

The Decision Tree is a supervised classification model known for its simplicity and interpretability. It handles categorical variables well and is not affected much by irrelevant features. However, it can overfit and is sensitive to training data variability. For our categorical-heavy data, a decision tree could be advantageous. To avoid overfitting, we can limit tree growth by setting constraints or prune the tree after full growth, though care must be taken to prevent underfitting with too much restriction.

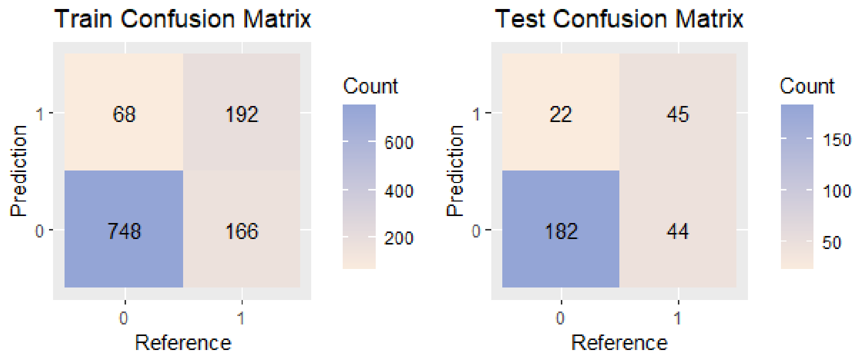
In this project, both of the approaches are applied and tested with a large number of different parameters. At their best settings of both approaches by looking at the test data performance, the resulting trees were identical. Therefore, we kept the model with the first approach with minsplit=20, and minbucket=7 for simplicity:

```r
library(rpart)

dt_model <- rpart(attended ~ ., data = train_data, method = "class", minsplit=20, minbucket=7)
```



As it can be seen by the tree our target variable is too dependent on the "months_before" and "weight" features. So that, majority of our data can be classified by just splitting the "months_before" feature.

The following results and confusion matrices are gathered by this tree:



Data	Accuracy	Balanced Accuracy	F-1 Score
Train	0.8007	0.7265	0.8647399
Test	0.7747	0.6989	0.8465116

Although the accuracies are relatively better, having significantly lower balanced accuracies is worrisome. This means that the model is not effectively dealing the class imbalance. Even with experiements with different settings, and models such as SVMs, Neural Networks we were not able to get significantly better results. Therefore, we can conclude that the classes in our data are not easily seperable, and in order to have better classification, it is required to have more features that can explain our classes better.

Discussion of the results and interpretation of the findings

Results in the real world can be messier and less satisfying than conclusions that we reach in theoretical problems or learning models, as is the case here. The combination of features in this dataset are not enough to predict our target, actual class attendance. This was surprising, since it's logical that current weight, days before commitment, and fitness category all seem relevant factors in how much a member would want to attend their session. In our case, there was no such straightforward or satisfactory answer.

To a researcher doing further investigation, we would advise less directly related variables, and for them to think more outside the box. Perhaps we made an incorrect assumption, that the features in our dataset had to do with motivation to attend classes, when in actuality, attendance motivation was not as high a factor as outside circumstances; things the fitness group member could not control and had to forfeit the class they signed up for. Some reasons may include a young child temper tantrum, a family member's sickness, a traffic jam, or unpredictable weather conditions, which could be measured in features as number of young children, number of adults who depend on them, distance from their home to the gym, and temperature/precipitation, respectively.

Another feature that would be helpful is the member ID. While the booking ID is already a feature, member ID would be a valued additional feature. It is reasonable to assume that individual members would be pretty consistent about how committed they were to their bookings. For example, a member who has previously skipped several of their booked classes is less likely to attend than a member who has a nearly perfect attendance record.

Regarding the apparent inseparability, some boundary regions might be teased out by adding more features not currently expressed by the data. Age, payment method, job satisfaction, and reason for membership may illuminate separation boundaries.

It is also possible that broader temporal trends have an effect across groups. For example, perhaps people skip the Saturday class they booked during week, or in the summer they're already getting outdoor recreation and feel little need for indoor fitness classes, or people decide to sleep in rather than waking up for an early class. A time series analysis could determine whether certain times of day/week/year have any more bearing on class absences.

If the combination of these new features together made some patterns clear, we might also be able to determine outliers. Identifying and taking into account outliers would strengthen our models.

In the dataset, the “attended” binary variable could be balanced. As is, there are more absents (0) than addends (1), by a ratio of approximately 70% to 30%, respectively. If this class imbalance were dealt with by oversampling the 1’s, then perhaps a more assured conclusion could be drawn.

Conclusions

Our objective was to predict and optimize actual attendance, given the risks and costs of having overbooked or under-attended classes. Before applying any multivariate analysis techniques, the data had to be cleaned and formatted for us to work with. The missing values were discarded to ensure uniformity, which did not compromise the dataset'92s integrity due to the small proportion of these values. After preprocessing, the remaining dataset was ready for us to begin analyzing.

Unsupervised learning methods K-means clustering and agglomerative nesting (AgNes) were used to identify potential patterns across variables. Supervised learning models logistic regression and decision tree classification were used to predict the target, actual class attendance, from the features at our disposal in the dataset.

The accuracy results the the unsupervised learning methods were not high, suggesting the the models struggled to effectively classify attendance based on the input features. The accuracy of the decision tree model was higher on the training set than on the test set, where it struggled with class imbalance. This may imply that the classes in the data are not easily and clearly separable, and that additional features not already included in the dataset may be needed for more accurate classification. If this is the case, GoalZone would be advised to include less obvious information that may reveal hidden or confounding variables not already included in the dataset we analyzed.

References

[1] R. A. Johnson and D. W. Wichern, *Applied multivariate statistical analysis*, 6th ed. New Jersey: Prentice-Hall, 2007.

[2] R. J. A. Little and D. B. Rubin, *Statistical analysis with missing data.* John Wiley & Sons, 2002.

[3] R. D. Peng, *Exploratory data analysis with r.* lulu.com, 2016. Available: https://bookdown.org/rdpeng/exdata/