

Bikes rentals prediction

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Introduction

This study refers to a rental bikes system where the user rents a bike from any available position in the city for the period of his necessity and gives it back when finishing the using. The dataset of this study contains hourly counts of information between the years 2011 and 2012. The datasets were obtained from the UCI repository: <https://archive.ics.uci.edu/ml/datasets/bike+sharing+dataset>.

The subject of this study is to accomplish a data analysis by comparing graphically the behaviors between the casual and the registered cyclist for better understanding the differences between them and to visualize the influence that climatic conditions and times period exercises to each group. All of this analysis will be done in part I of the study.

In part II to predict the rentals by the hour we will elaborate machine learning model that better fits the rentals predictions against the actual rental values regardless of the climatic conditions or period of the year.

Attribute information

- instant: record index
- dteday: date
- season: season (1:springer, 2:summer, 3:fall, 4:winter)
- yr: year (0: 2011, 1:2012)
- mnth: month (1 to 12)
- hr: hour (0 to 23)
- holiday: weather day is holiday or not (extracted from [Web Link])
- weekday: day of the week
- workingday: if day is neither weekend nor holiday is 1, otherwise is 0.
- weathersit:
 - 1: Clear, Few clouds, Partly cloudy, Partly cloudy
 - 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
 - 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
 - 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp: Normalized temperature in Celsius. The values are derived via $(t-t_{\min})/(t_{\max}-t_{\min})$, $t_{\min}=-8$, $t_{\max}=+39$ (only in hourly scale)
- atemp: Normalized feeling temperature in Celsius. The values are derived via $(t-t_{\min})/(t_{\max}-t_{\min})$, $t_{\min}=-16$, $t_{\max}=+50$ (only in hourly scale)

- hum: Normalized humidity. The values are divided to 100 (max)
- windspeed: Normalized wind speed. The values are divided to 67 (max)
- casual: count of casual users
- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

Part I – Exploratory data analysis

1. Importing the data

```
data <- read.csv('hour.csv')
str(data)

## 'data.frame': 17379 obs. of 17 variables:
## $ instant : int 1 2 3 4 5 6 7 8 9 10 ...
## $ dteday : Factor w/ 731 levels "2011-01-01","2011-01-02",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ season : int 1 1 1 1 1 1 1 1 1 1 ...
## $ yr : int 0 0 0 0 0 0 0 0 0 0 ...
## $ mnth : int 1 1 1 1 1 1 1 1 1 1 ...
## $ hr : int 0 1 2 3 4 5 6 7 8 9 ...
## $ holiday : int 0 0 0 0 0 0 0 0 0 0 ...
## $ weekday : int 6 6 6 6 6 6 6 6 6 6 ...
## $ workingday: int 0 0 0 0 0 0 0 0 0 0 ...
## $ weathersit: int 1 1 1 1 1 2 1 1 1 1 ...
## $ temp : num 0.24 0.22 0.22 0.24 0.24 0.24 0.22 0.2 0.24 0.32 ...
## $ atemp : num 0.288 0.273 0.273 0.288 0.288 ...
## $ hum : num 0.81 0.8 0.8 0.75 0.75 0.75 0.8 0.86 0.75 0.76 ...
## $ windspeed : num 0 0 0 0 0 0.0896 0 0 0 0 ...
## $ casual : int 3 8 5 3 0 0 2 1 1 8 ...
## $ registered: int 13 32 27 10 1 1 0 2 7 6 ...
## $ cnt : int 16 40 32 13 1 1 2 3 8 14 ...
```

2. Variables transformations

```
data$dteday <- NULL

# Defining the categorical variables
categ_vars <- c('season', 'yr', 'mnth', 'hr', 'holiday', 'weekday', 'workingday',
'weathersit')

for (i in categ_vars) {
  data[, i] <- factor(data[, i])
}
```

```
# Renaming the categorical variables and their parameters
```

```
library(data.table)
```

```
library(plyr)
```

```
setnames(data, old = c('yr', 'mnth', 'hr', 'temp', 'atemp', 'hum', 'cnt'), new =  
c('year', 'month', 'hour', 'temperature', 'atemperature', 'humidity', 'count'),  
skip_absent = TRUE)
```

```
data$season <- mapvalues(data$season, from = c(1, 2, 3, 4), to = c('Spring',  
'Summer', 'Fall', 'Winter'))
```

```
data$year <- mapvalues(data$year, from = c(0, 1), to = c(2011,2012))
```

```
data$holiday <- mapvalues(data$holiday, c(0, 1), to = c('No_holiday',  
'Yes_holiday'))
```

```
data$weekday <- mapvalues(data$weekday, from = c(0,1,2,3,4,5,6), to = c("Sun",  
"Mon", "Tue", "Wed", "Thu", "Fri", "Sat"))
```

```
data$workingday <- mapvalues(data$workingday, from = c(0 ,1), to = c('No_workday',  
'Yes_workday'))
```

```
data$weathersit <- mapvalues(data$weathersit, from = c(1,2,3,4), to = c("Clear",  
"Cloudy", "Light Rain/Snow", "Heavy Rain/Snow"))
```

```
str(data)
```

```
## 'data.frame': 17379 obs. of 16 variables:
```

```
## $ instant : int 1 2 3 4 5 6 7 8 9 10 ...
```

```
## $ season : Factor w/ 4 levels "Spring","Summer",...: 1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ year : Factor w/ 2 levels "2011","2012": 1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ month : Factor w/ 12 levels "1","2","3","4",...: 1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ hour : Factor w/ 24 levels "0","1","2","3",...: 1 2 3 4 5 6 7 8 9 10 ...
```

```
## $ holiday : Factor w/ 2 levels "No_holiday","Yes_holiday": 1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ weekday : Factor w/ 7 levels "Sun","Mon","Tue",...: 7 7 7 7 7 7 7 7 7 7 ...
```

```
## $ workingday : Factor w/ 2 levels "No_workday","Yes_workday": 1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ weathersit : Factor w/ 4 levels "Clear","Cloudy",...: 1 1 1 1 1 2 1 1 1 1 ...
```

```
## $ temperature : num 0.24 0.22 0.22 0.24 0.24 0.24 0.22 0.2 0.24 0.32 ...
```

```
## $ atemperature: num 0.288 0.273 0.273 0.288 0.288 ...
```

```
## $ humidity : num 0.81 0.8 0.8 0.75 0.75 0.75 0.8 0.86 0.75 0.76 ...
```

```
## $ windspeed : num 0 0 0 0 0 0.0896 0 0 0 0 ...
```

```
## $ casual : int 3 8 5 3 0 0 2 1 1 8 ...
```

```
## $ registered : int 13 32 27 10 1 1 0 2 7 6 ...
```

```
## $ count : int 16 40 32 13 1 1 2 3 8 14 ...
```

```
summary(data)
```

```
##      instant      season      year      month      hour
## Min.      :    1  Spring:4242  2011:8645    5      :1488   16      : 730
## 1st Qu.: 4346  Summer:4409  2012:8734    7      :1488   17      : 730
## Median : 8690   Fall :4496           12      :1483   13      : 729
## Mean    : 8690  Winter:4232           8      :1475   14      : 729
## 3rd Qu.:13034           3      :1473   15      : 729
## Max.    :17379           10     :1451   12      : 728
##                                     (Other):8521 (Other):13004
##      holiday      weekday      workingday
## No_holiday :16879  Sun:2502  No_workday : 5514
## Yes_holiday: 500  Mon:2479  Yes_workday:11865
##                                     Tue:2453
##                                     Wed:2475
##                                     Thu:2471
##                                     Fri:2487
##                                     Sat:2512
##      weathersit      temperature      atemperature      humidity
## Clear      :11413  Min.      :0.020  Min.      :0.0000  Min.      :0.0000
## Cloudy      : 4544  1st Qu.:0.340  1st Qu.:0.3333  1st Qu.:0.4800
## Light Rain/Snow: 1419  Median :0.500  Median :0.4848  Median :0.6300
## Heavy Rain/Snow: 3    Mean      :0.497  Mean      :0.4758  Mean      :0.6272
##                                     3rd Qu.:0.660  3rd Qu.:0.6212  3rd Qu.:0.7800
##                                     Max.      :1.000  Max.      :1.0000  Max.      :1.0000
##
##      windspeed      casual      registered      count
## Min.      :0.0000  Min.      : 0.00  Min.      : 0.0  Min.      : 1.0
## 1st Qu.:0.1045  1st Qu.: 4.00  1st Qu.: 34.0  1st Qu.: 40.0
## Median :0.1940  Median : 17.00  Median :115.0  Median :142.0
## Mean      :0.1901  Mean      : 35.68  Mean      :153.8  Mean      :189.5
## 3rd Qu.:0.2537  3rd Qu.: 48.00  3rd Qu.:220.0  3rd Qu.:281.0
## Max.      :0.8507  Max.      :367.00  Max.      :886.0  Max.      :977.0
##
```

3. Data analysis

In this section, it will be displayed some graphs comparing the behaviors of the casual and registered users in the way that they rent the bikes according to climatic conditions, weekday, month or hour of the day. It is observable that the casual users are basically composed by the tourists, eventual users or the people that don't utilize regularly the bikes for the working destination. Otherwise, the use proposal of the registered cyclists is essentially for the work locomotion.

a. temperature vs count

As observed, the general behavior between casual and registered cyclists is the same. When the temperature conditions are nice the bikes utilization increases, and on the other hand, in extreme conditions the usage drops accentually.

```
library(dplyr)
library(ggplot2)
library(tidyr)

# Creating a new dataframe
casual <- data[, 'casual']
registered <- data[, 'registered']
temperature <- data[, 'temperature']
weekday <- data[, 'weekday']
weathersit <- data[, 'weathersit']
season <- data[, 'season']
hour <- data[, 'hour']
month <- data[, 'month']

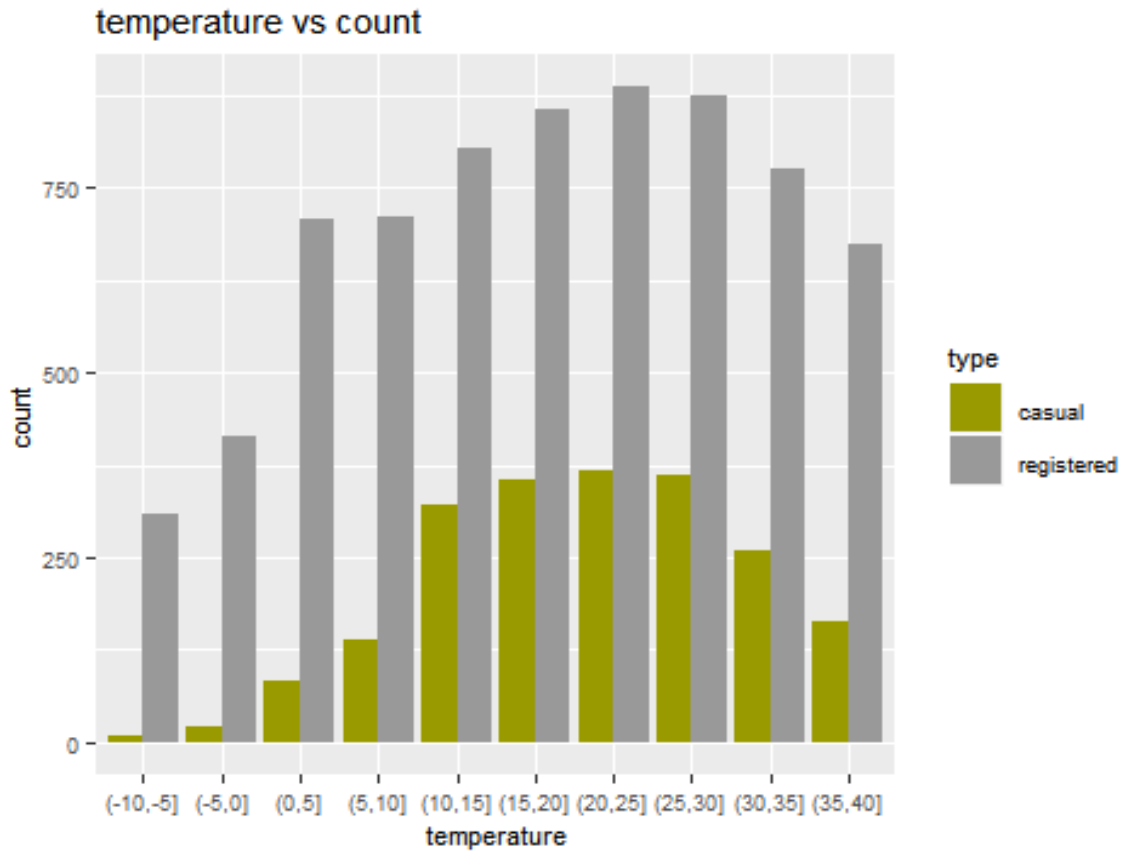
data1 <- data.frame(casual, registered, temperature, weekday, weathersit, season,
hour, month)

# Converting the temperaute data to Celsius
data1$temperature <- data1$temperature*(max(data1$temperature)-
min(data1$temperature))+min(data1$temperature)
data1$temperature <- round(data1$temperature*(39-(-8))+(-8),1)

# Plotting the graph
data2 <- data1 %>%
  gather(type, count, -c(temperature, weekday, weathersit, season, hour, month))

data3 <- data2 %>%
  mutate(temperature = cut(temperature, breaks= c(-10, -5, 0, 5, 10, 15, 20, 25,
30, 35, 40)))

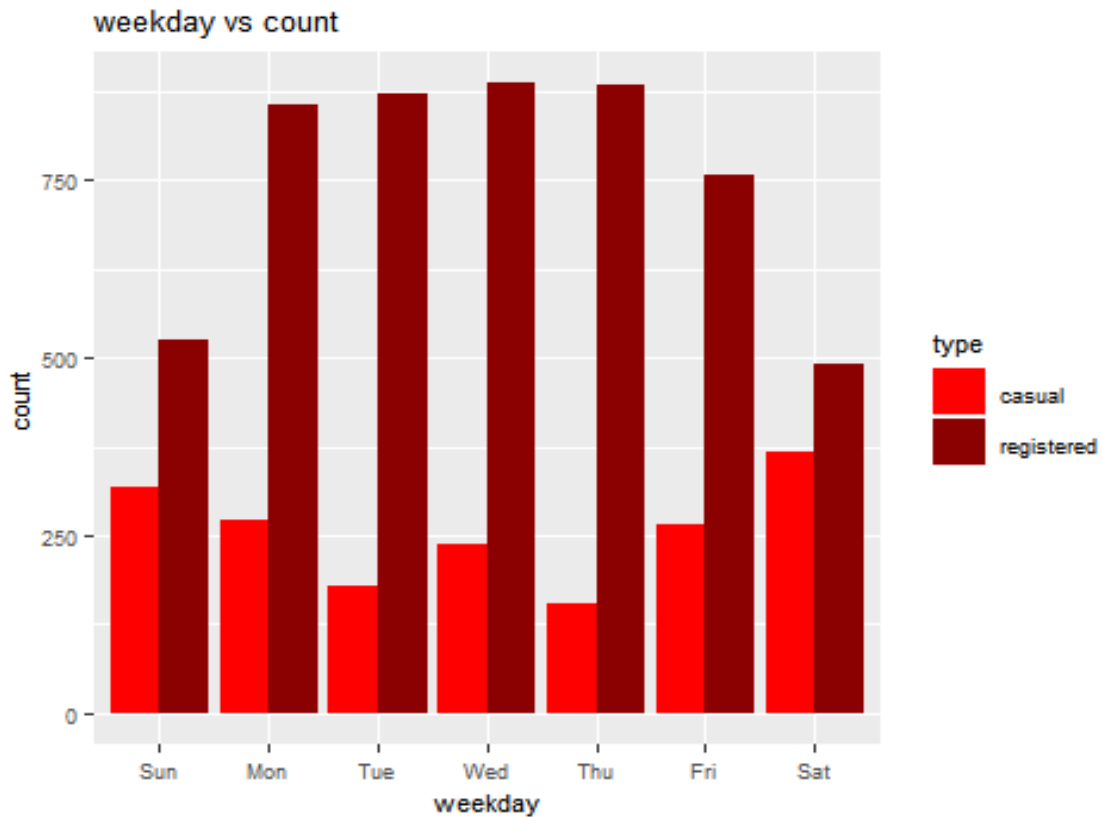
ggplot(data = data3, aes(x = temperature, y = count, fill = type)) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  scale_fill_manual(values = c("#999900", "#999999")) +
  ggtitle("temperature vs count") +
  theme(text = element_text(size=8.5),
        axis.text.x = element_text(angle=0))
```



b. weekday vs count

As predicted, the main utilization of the bikes for the registered users is for working, seen during the rentals of the week. In the opposite, on the weekend the rental proportion of casual users increases compared to a weekday, denoting the recreational use adopted by most of the casual users.

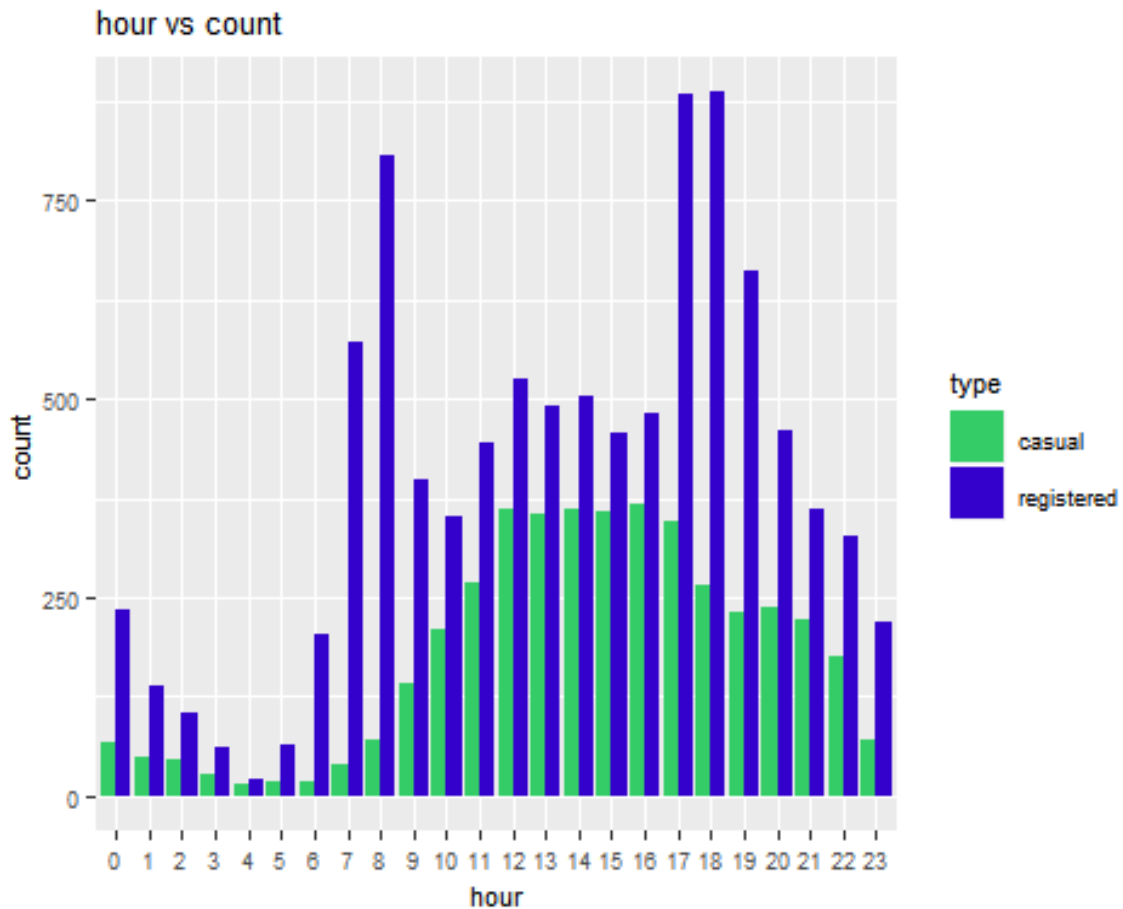
```
ggplot(data = data2, aes(x = weekday, y = count, fill = type)) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  scale_fill_manual(values = c("red", "darkred")) +
  ggtitle("weekday vs count") +
  theme(text = element_text(size=8),
        axis.text.x = element_text(angle=0))
```



c. hour vs count

To corroborate the working utilization of the bikes by the registered users, the demand peaks can be clearly observed on the entrance and the exit regular working times, not noted for the casual cyclists that use the bikes in more affordable times.

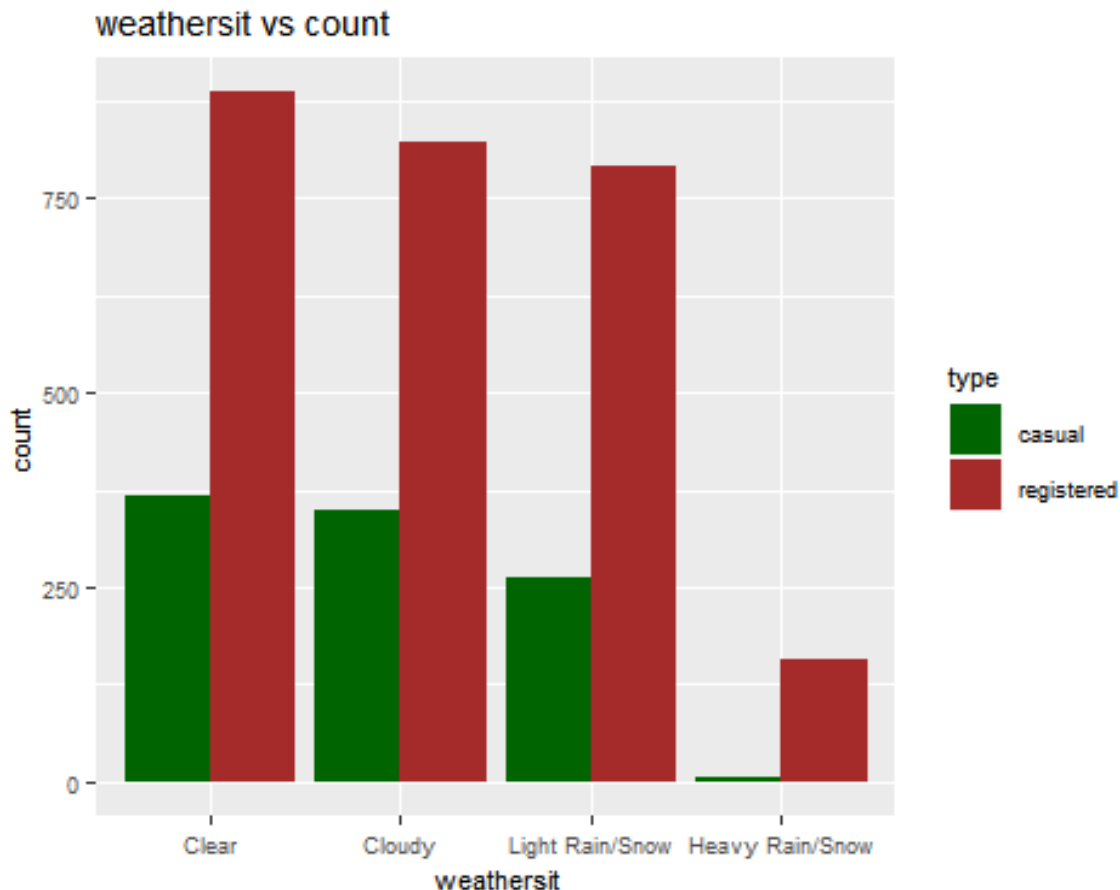
```
ggplot(data = data2, aes(x = hour, y = count, fill = type)) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  scale_fill_manual(values = c("#33cc66", "#3300cc")) +
  ggtitle("hour vs count") +
  theme(text = element_text(size=8),
        axis.text.x = element_text(angle=0))
```



d. weathersit vs count

The weather conditions like the temperature have correlations for even casual and registered users to utilize or not the bikes due to climatic conditions. How worse it is, less they will rent it. Proportionally in the heavy rain/snow, the use by the casual cyclists drops more radically.

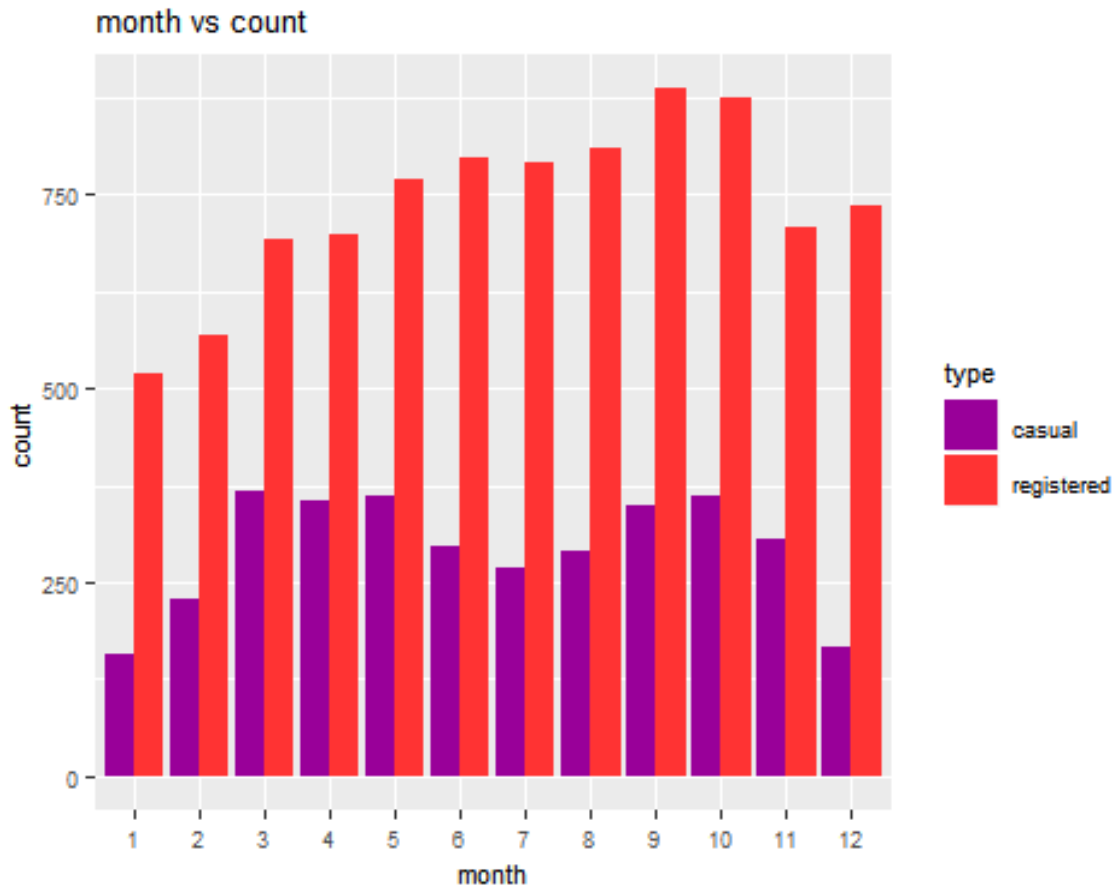
```
ggplot(data = data2, aes(x = weathersit, y = count, fill = type)) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  scale_fill_manual(values = c("darkgreen", "brown")) +
  ggtitle("weathersit vs count") +
  theme(text = element_text(size=8.5),
        axis.text.x = element_text(angle=0))
```

e. month vs count

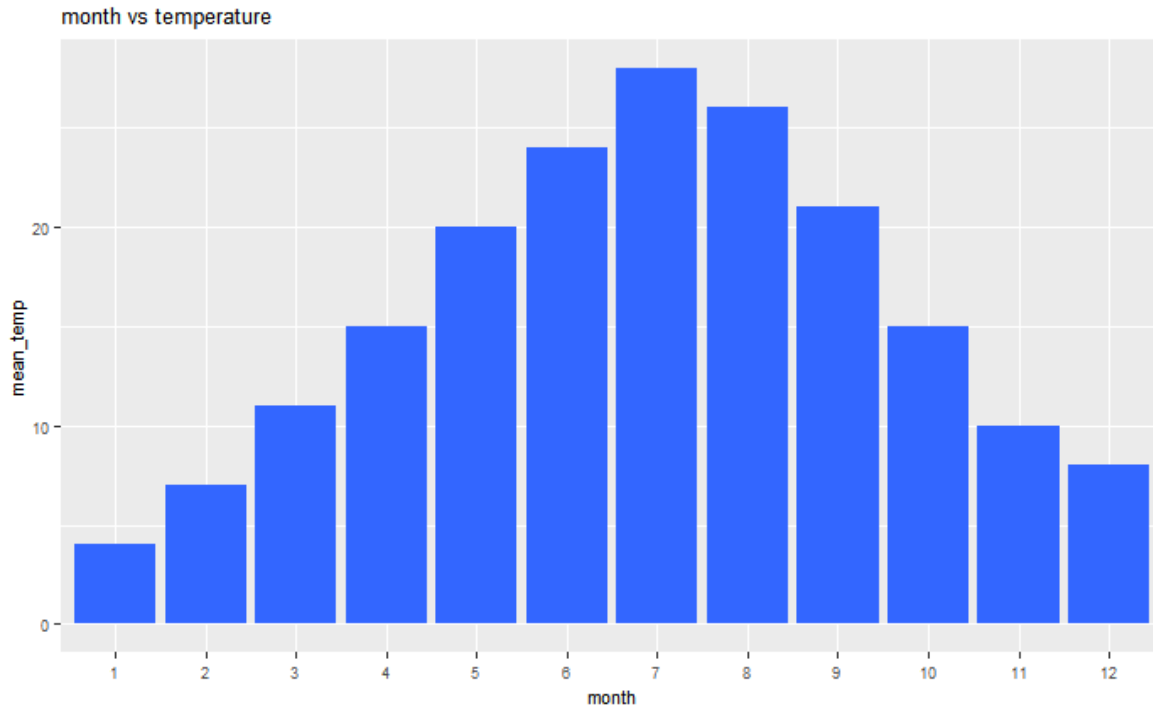
As mentioned previously, the bikes utilization is highly related to the temperature values (graph a). And the temperature is highly correlated with each respective month (graph e). On the extreme temperatures measured in the winter and summer, it can be noticed a natural decrease of the usage of the bikes, mainly detected on the casual cyclists during the months June through August, probably due to high summer temperatures in these months (see below month vs mean temperature graph) that can justify the casual cyclist to avoid the rental of the bikes. But there is no similar descent behavior on these months to the registered cyclists, once the employment is concentrated on the entrance and the exit regular working times, where the temperatures are normally lower (graph c).

```
ggplot(data = data2, aes(x = month, y = count, fill = type)) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  scale_fill_manual(values = c("#990099", "#FF3333")) +
  ggtitle("month vs count") +
  theme(text = element_text(size=8),
        axis.text.x = element_text(angle=0))
```



Month vs temperature

```
data4 <- data2 %>%  
  select(month, temperature) %>%  
  group_by(month) %>%  
  summarise(mean_temp = round(mean(temperature)))  
  
ggplot(data = data4, aes(x = month, y = mean_temp)) +  
  geom_bar(stat = "identity", fill = "#FF6699") +  
  ggtitle("month vs temperature") +  
  theme(text = element_text(size=8),  
        axis.text.x = element_text(angle=0))
```



Part II - Prediction model

According to the analysis in the previous section, it was demonstrated based on the graphics that there is a reasonable difference among the **casual** and the **registered** cyclists, which for the proposal of this part II on the development of the predictive model to each group, to distinct both of them for a better analytical solution where the peculiarities of each group does not influence the another one.

Targeting the simplification of this study, despite for the selecting the best model that better adjusts to the dataset is necessary to test many models, as were did, it will be only mentioned the best model that presented the best results with the lower root mean squared error (RMSE). The model that was chosen is the Extreme Gradient Boosting (XGBoost), which properly performed the model construction taking into account the tradeoff between willing results and computational needs.

1. Casual cyclists

1.1 Feature Selection

Through the testing of many machine models for the feature selection, all of them basically resumed similar results, where it was defined, which are the most and least important variables as shown below on the list of the importance of the variables. The result demonstrates that the holiday variable is not significative to predictive modeling. And besides, due to the high correlation between the temperature

and atemperature variables, next calculated, the temperature variable was chosen to be removed to prevent the collinearity and for being a little less significative compared to the atemperature. As a reference to the importance of the variables, follows the demonstration by using the linear regression model and this methodology is valid for both, to casual and registered cyclists, by giving similar results.

1.2 Variables correlation

Correlation between the temperature and the atemperature variables.

```
cor(data$temperature, data$atemperature)
## [1] 0.9876721
```

1.3 Feature selection model

Constructing the model based on the linear regression algorithm for the determination of the most important variables.

```
library(caret)

trainIndex <- createDataPartition(data$casual,
                                   p = 0.7,
                                   list = FALSE,
                                   times = 1)

train_data <- data[trainIndex, ]
test_data <- data[-trainIndex, ]

control <- trainControl(savePredictions = TRUE)

model_lm <- train(log10(casual + 1) ~ season + year + workingday + month + hour +
                  holiday + weekday +
                    weathersit + atemperature + temperature + humidity + windspeed,
                  data = train_data,
                  method = 'lm',
                  trControl = control
                  )

var_imp <- as.matrix(varImp(model_lm)$importance)
apply(var_imp, 2, sort)

##                                Overall
## holidayYes_holiday              0.0000000
## `weathersitHeavy Rain/Snow`      0.5856824
## weekdaySat                      6.3749277
## month2                          8.3440858
## weathersitCloudy                 9.3390970
## month7                         10.7360121
```

## month12	11.0189204
## temperature	14.3338940
## month8	14.5333773
## seasonFall	14.7344802
## month6	15.5555542
## atemperature	16.5017123
## hour7	17.8057545
## weekdayMon	17.8870968
## windspeed	18.1255701
## month11	18.9248888
## seasonWinter	19.4652048
## month4	22.1161728
## hour23	22.4189548
## month9	22.5077173
## seasonSummer	24.2105851
## hour1	25.2154517
## month5	26.0657955
## weekdayThu	26.8243072
## month10	28.5656517
## weekdayTue	30.1671879
## hour6	30.8737872
## humidity	32.0901420
## weekdayWed	34.5713867
## month3	40.4584366
## hour22	40.9549333
## hour2	42.4563236
## workingdayYes_workday	50.3697675
## hour21	52.4758202
## hour8	56.4770643
## year2012	61.3792994
## hour20	62.2761512
## `weathersitLight Rain/Snow`	67.2097087
## hour3	67.8580033
## hour9	68.9819392
## hour5	74.8768907
## hour19	76.7345243
## hour10	81.8841268
## hour4	82.4202365
## hour11	89.6797475
## hour18	89.8933836
## hour15	91.1183775
## hour12	92.5529811
## hour14	92.7542905
## hour13	92.9429975
## hour16	94.8637583
## hour17	100.0000000

1.4 Predicting model

Elaborating the predictive model to the casual cyclists using the Xgboost algorithm.

```
library(parallel)
library(iterators)
library(caret)
library(foreach)
library(doParallel)

cluster <- makeCluster(detectCores())
registerDoParallel(cluster)

control <- trainControl(savePredictions = TRUE, allowParallel = TRUE)
model_casual <- train(log10(casual + 1) ~ season + year + workingday + month + hour
+ weekday +
                        weathersit + atemperature + humidity + windspeed,
                      data = train_data,
                      method = 'xgbLinear',
                      trControl = control
                      )

stopCluster(cluster)
registerDoSEQ()

model_casual$results

##      lambda alpha nrounds eta      RMSE Rsquared      MAE      RMSESD
## 27  1e-01 1e-01      150 0.3 0.2459743 0.8566191 0.1846733 0.003143472

##      RsquaredSD      MAESD
## 27 0.004209250 0.002135967

RMSE <- min(model_casual$results$RMSE)
RMSE
## [1] 0.2449309
```

1.5 Relative error calculation

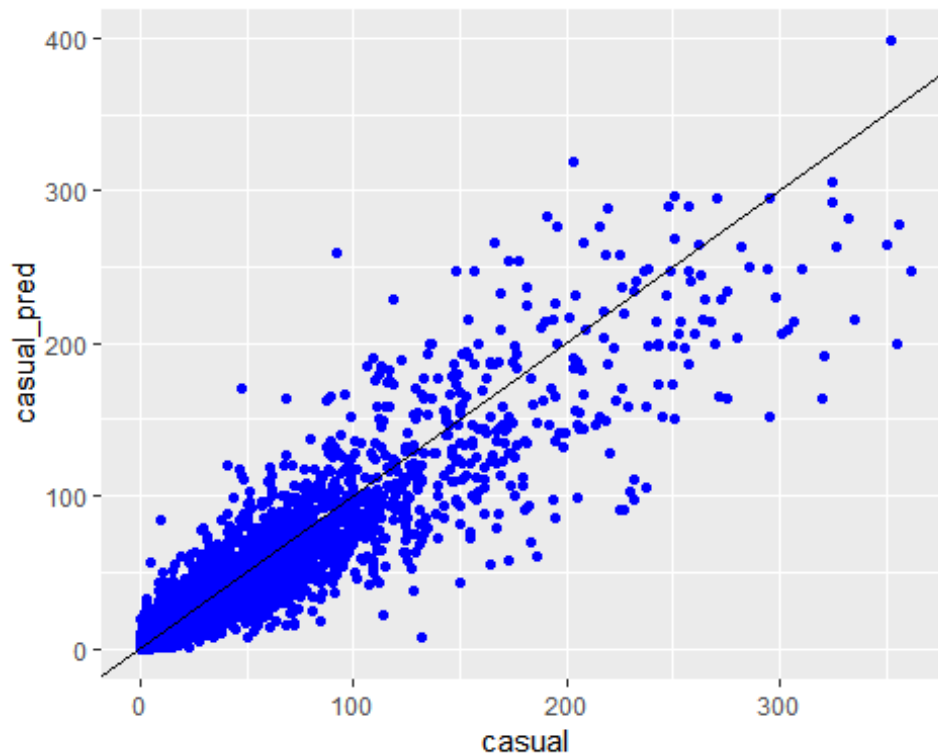
Relative error calculation between the actual and the predictive values.

```
library(dplyr)
pred <- predict(model_casual, test_data)
test_data$casual_pred <- 10^(pred) - 1

test_data %>%
  select(casual, casual_pred) %>%
  summarise(error = round(mean((abs(sum(casual) -
sum(casual_pred))/sum(casual))*100),2))
```

```
## error
## 1 5.71

library(ggplot2)
ggplot(test_data, aes(x = casual, y = casual_pred)) +
  geom_point(color = 'blue') +
  geom_abline()
```



2. Registered cyclists

2.1 Predicting model

Elaborating the predictive model to the registered cyclists using the Xgboost algorithm.

```
library(caret)

trainIndex <- createDataPartition(data$registered,
                                   p = 0.7,
                                   list = FALSE,
                                   times = 1)
```

```

train_data <- data[trainIndex, ]
test_data <- data[-trainIndex, ]

library(parallel)
library(iterators)
library(caret)
library(foreach)
library(doParallel)

cluster <- makeCluster(detectCores())
registerDoParallel(cluster)

control <- trainControl(savePredictions = TRUE, allowParallel = TRUE)
model_registered <- train(log10(registered + 1) ~ season + year + workingday +
month + hour + weekday +
                        weathersit + atemperature + humidity + windspeed,
                        data = train_data,
                        method = 'xgbLinear',
                        trControl = control
                        )
stopCluster(cluster)
registerDoSEQ()

model_registered$results

##      lambda alpha nrounds eta      RMSE Rsquared      MAE      RMSESD
## 27  1e-01 1e-01      150 0.3 0.1675581 0.9239825 0.1146977 0.002583555

##      RsquaredSD      MAESD
## 27 0.002525471 0.001512846

RMSE <- min(model_registered$results$RMSE)
RMSE
## [1] 0.1675581

```

2.2 Relative error calculation

Relative error calculation between the actual and the predictive values.

```

library(dplyr)
pred <- predict(model_registered, test_data)
test_data$registered_pred <- 10^(pred) - 1

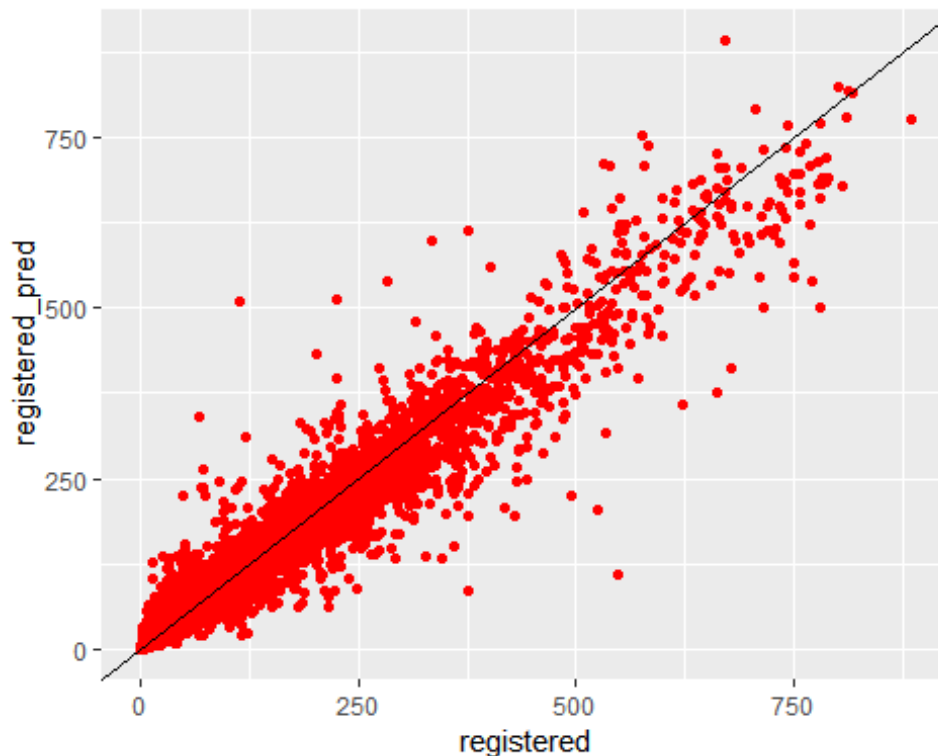
test_data %>%
  select(registered, registered_pred) %>%
  summarise(error = round(mean((abs(sum(registered) -
sum(registered_pred))/sum(registered))*100), 2))

```



```
## error
## 1 3.84

library(ggplot2)
ggplot(test_data, aes(x = registered, y = registered_pred)) +
  geom_point(color = 'red') +
  geom_abline()
```



Conclusion

By the data analysis, it was observed the main differences of the bikes employment between the casual and the registered users, the first one using occasionally and on the better climatic conditions, and the second group focusing as a vehicle to the working destination.

These characteristics can be confirmed when examining the RMSE and the relative error results and comparing the dispersion of the points on the casual and registered graphs. It can be seen respectively the lower error values and the bigger precision on graphs for the registered cyclists, denoting a more regular behavior of this group.

Thinking one step further for future analysis regarding the discrepancies found among the predictive and actual values, it would be to analyze them, why they occurred, try to group them and discover if

there is a noticeable pattern of this manifestation, that is more prominent on the high values of casual and registered counts where is visible on the graphs.