Data Exploratory Analysis

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```
knitr::opts_chunk$set(message = FALSE, warning = FALSE, results = FALSE, fig.dim=c
(8,4))
```

The following section provides an **exploratory analysis of the data available** for this project. At first, a **generic analysis of the company** will be performed to observe the situation and address eventual trends. After that, **aggregate data will be created** in order to obtain the dependent variable of interest which is the ratio between deliveries and number of worked hours. Each dependent variable is referred to a driver, which is the statistical unit of this analysis. In conclusion, an **analysis of the relationship between the y - dependent variable - and each independent variable** will be performed in order to analyse the situation.

The following codes need a series of packages to be installed in order to perform the analysis:

```
library(tidyr)
library(dplyr)
library(chron)
library(ggmap)
library(ggplot2)
library(ggthemes)
library(tidyverse)
library(geosphere)
library(leaflet)
library(leaflet.extras)
load("Data_exploratory.RData")
```

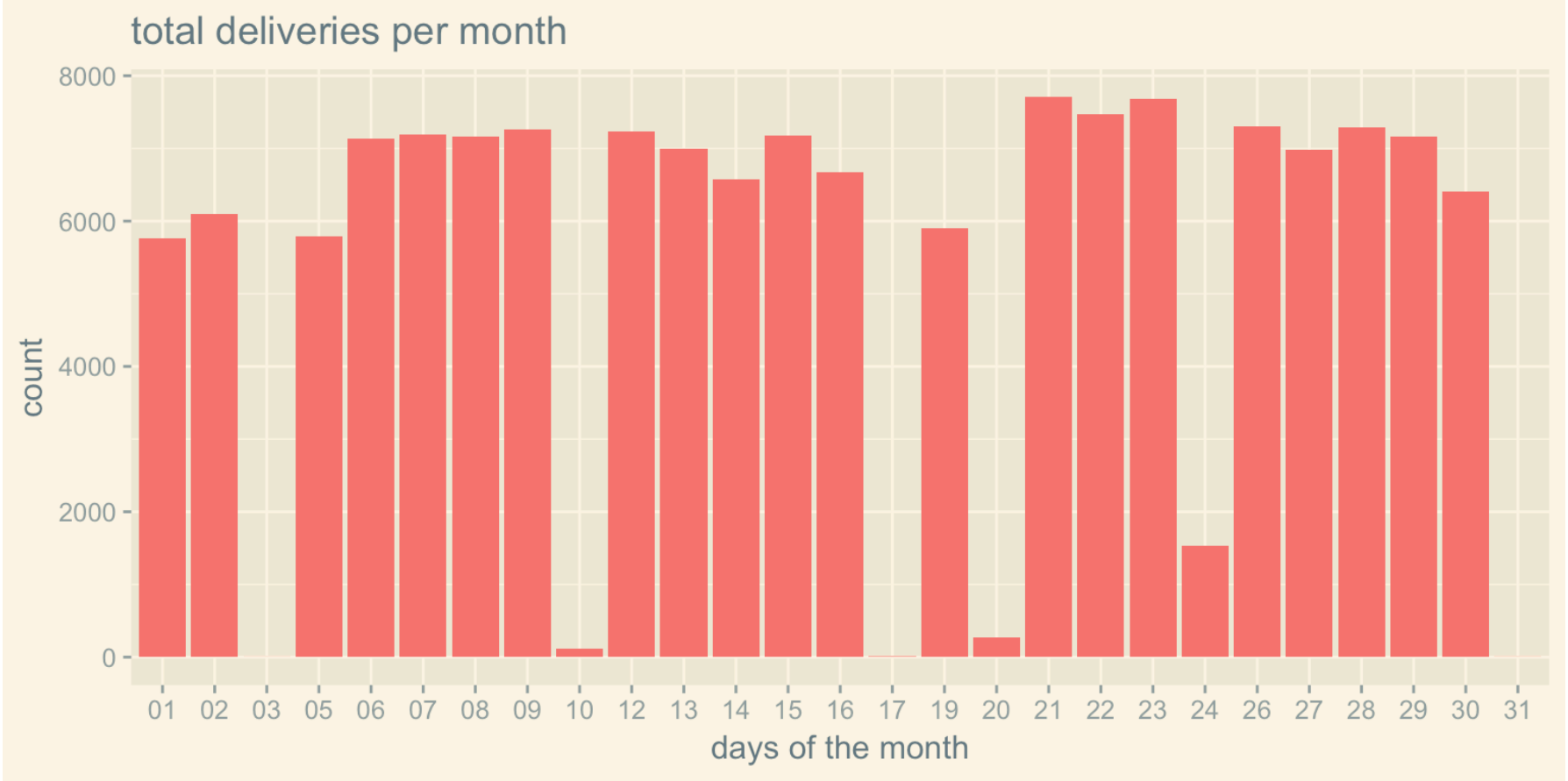
GENERICAL TREND OF THE COMPANY

DAYS OF THE MONTH

The data frame and the plot obtained by the codes below can be summarised as following:

```
data_exploratory$num_pack <- as.numeric(data_exploratory$num_pack)
deliveries_day_driver <- data_exploratory %>% group_by(driver_code,day_deliv) %>%
summarise(tot_deliveries = sum(delivery))
summary(deliveries_day_driver)
```

```
day_plot <- ggplot(data = data_exploratory, aes(x = day_deliv, fill = "indianred2"
)) +
  theme_solarized_2()
day_plot  + geom_bar() +  labs(title = "total deliveries per month", x = "days of
the month") + guides(fill = FALSE)
```



The bar chart shows two aspect of the analysis that need to be fixed: 1) For future analysis based on the day of the week there are a Tuesday, Friday and a Saturday more than any other weekday(1st,2nd and 3rd of March). 2) The Tuesday 20th corresponds to a strike that took place in Brescia. As a consequence, deliveries that day have been limited and apparently redistribuited in the following days causing an increase on the number of deliveries the following days.

This issue can cause problems in the moment where an analysis of the day of the week will be performed and as a consequence solutions will be provided in the following section.

```
stronger_day <- deliveries_day_driver %>% group_by(day_deliv) %>% summarise(tot_de
liveries = sum(tot_deliveries))
stronger_day <- stronger_day %>% arrange(desc(tot_deliveries))

head(stronger_day)
tail(stronger_day)
```

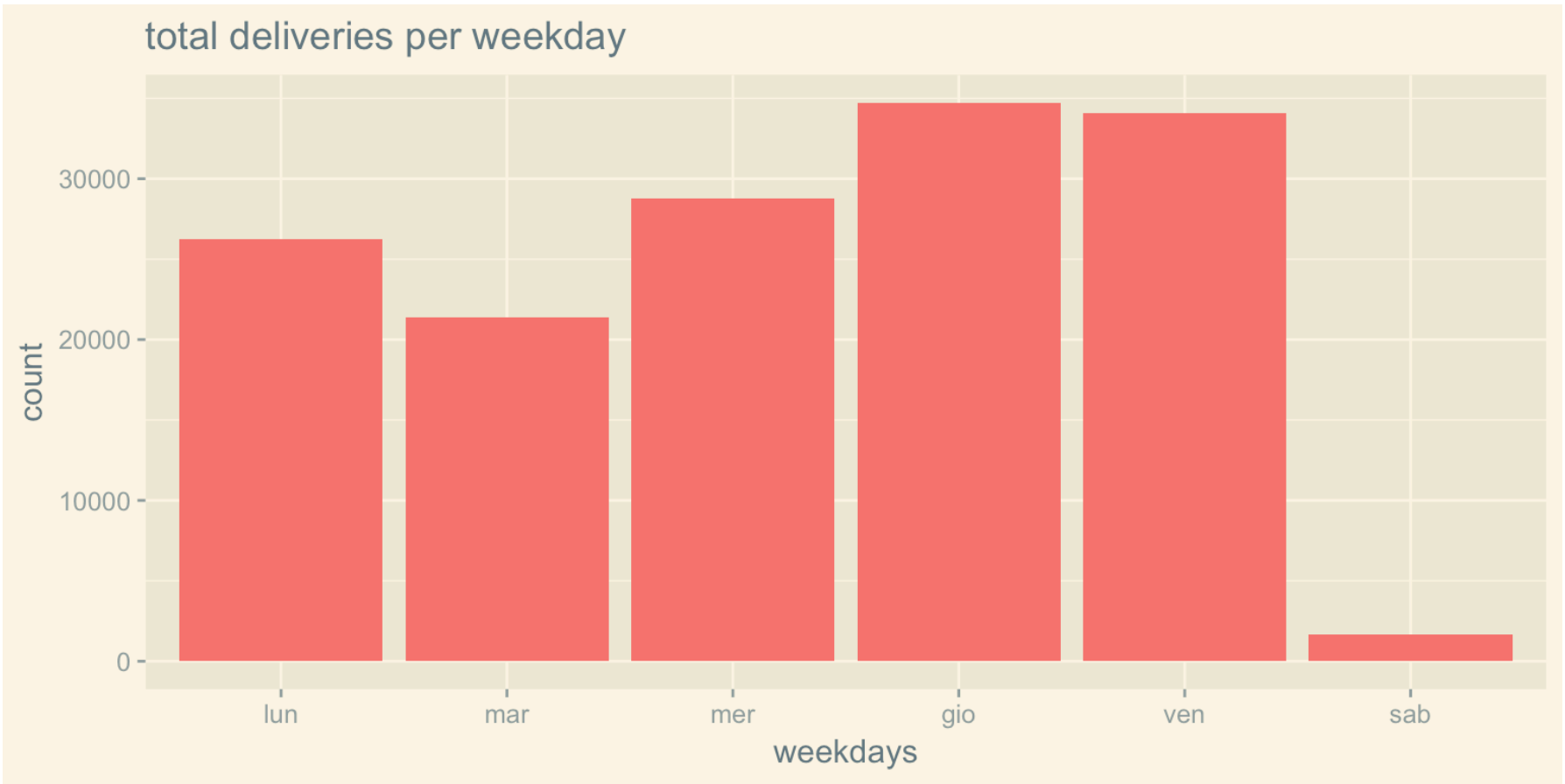
```
summary(stronger_day)
```

The chart shows the 21st, 23rd and 22nd to be the days with more deliveries and this is apparently coherent with the fact that the 20 March a strike paralized the normal activity of the company. The Mean of total deliveries per day is 5441 with a Median of 6984 suggesting a distribution skewed to the left.

ANALYSIS OF WEEKDAYS

```
data_exploratory$weekday_deliv <- factor(x = data_exploratory$weekday_deliv, level
s = c("lun","mar","mer","gio","ven","sab"))


stronger_weekday_driver <- data_exploratory %>% group_by(driver_code,weekday_deliv
) %>% summarise(tot_delivery = sum(delivery))

stronger_weekday <- data_exploratory %>% group_by(weekday_deliv) %>% summarise(tot
_delivery = sum(delivery))
```

```
weekday_plot <- ggplot(data = data_exploratory, aes(x = weekday_deliv, fill = "ind
ianred2")) +
  theme_solarized_2()+ labs(title = "total deliveries per weekday", x = "weekdays"
) + guides(fill = FALSE)
weekday_plot + geom_bar()
```

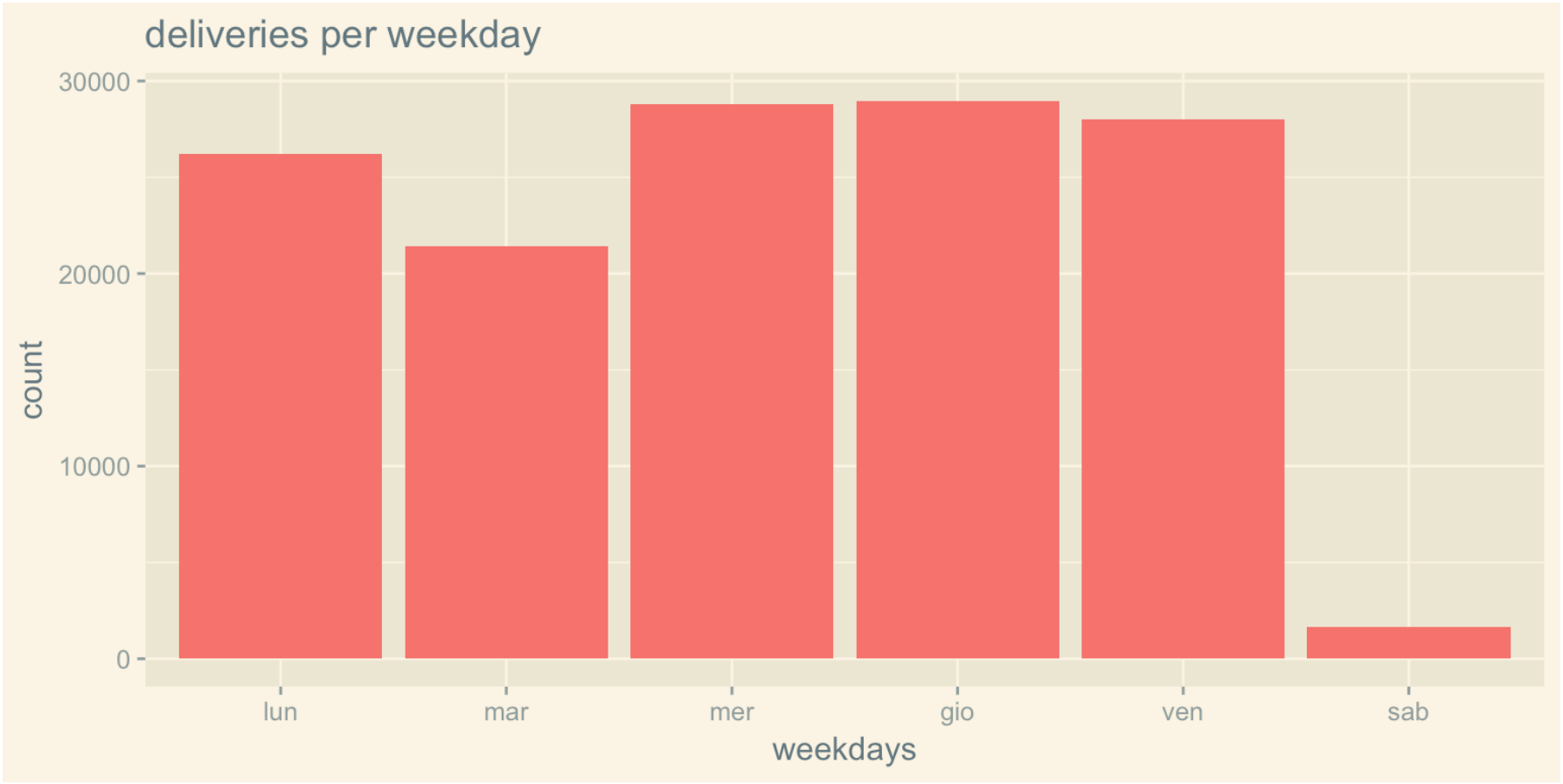


As aforementioned described, these data can be misleading due to the reasons previously described. To overcome this it could be possible to:

1. Divide the month in weeks, aggregating each weekday by the number of the week (e.g. Week_1, Week2, etc.) and perform the Mean of weekdays. However, having just one month of observation makes this operation not so significant. Point number 2 will be adopted.
2. Erasing the first three days of the month in order to obtain and work with complete weeks only, from Monday to Saturday.

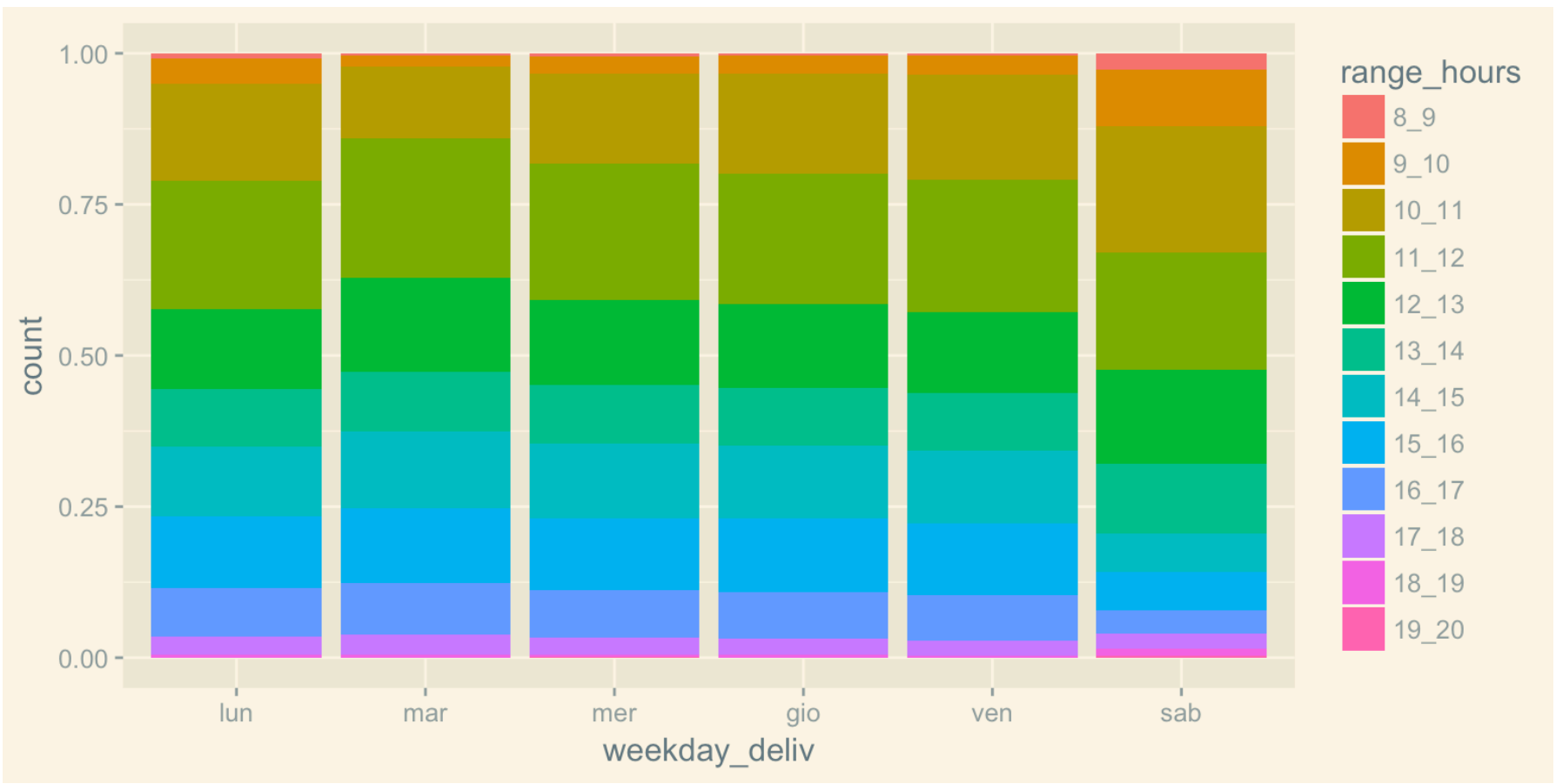
```
data_strongerweekdays <- data_exploratory %>% filter(data_exploratory$day_deliv !=
"01",
                                                     data_exploratory$day_deliv !=
"02",
                                                     data_exploratory$day_deliv !=
"03")
```

```
weekday2_plot <- ggplot(data = data_strongerweekdays, aes(x = weekday_deliv, fill
= "indianred2")) +
  theme_solarized_2()
weekday2_plot + geom_bar()+ labs(title = "deliveries per weekday", x = "weekdays")
+ guides(fill = FALSE)
```



The plot shows Tuesday to be the weakest day of the week, but this situation can be due to the abovementioned strike. The following codes aim to deepen the analysis to observe if weekdays can be significantly influenced by other variables such as the range of hour.

```
weekday2_plot + aes(fill = range_hours) + geom_bar(position = "fill")
```



The plot shows an interesting insight which will be deepened in the following section related to the analysis of range hours.

ANALYSIS OF THE TIME OF DELIVERY

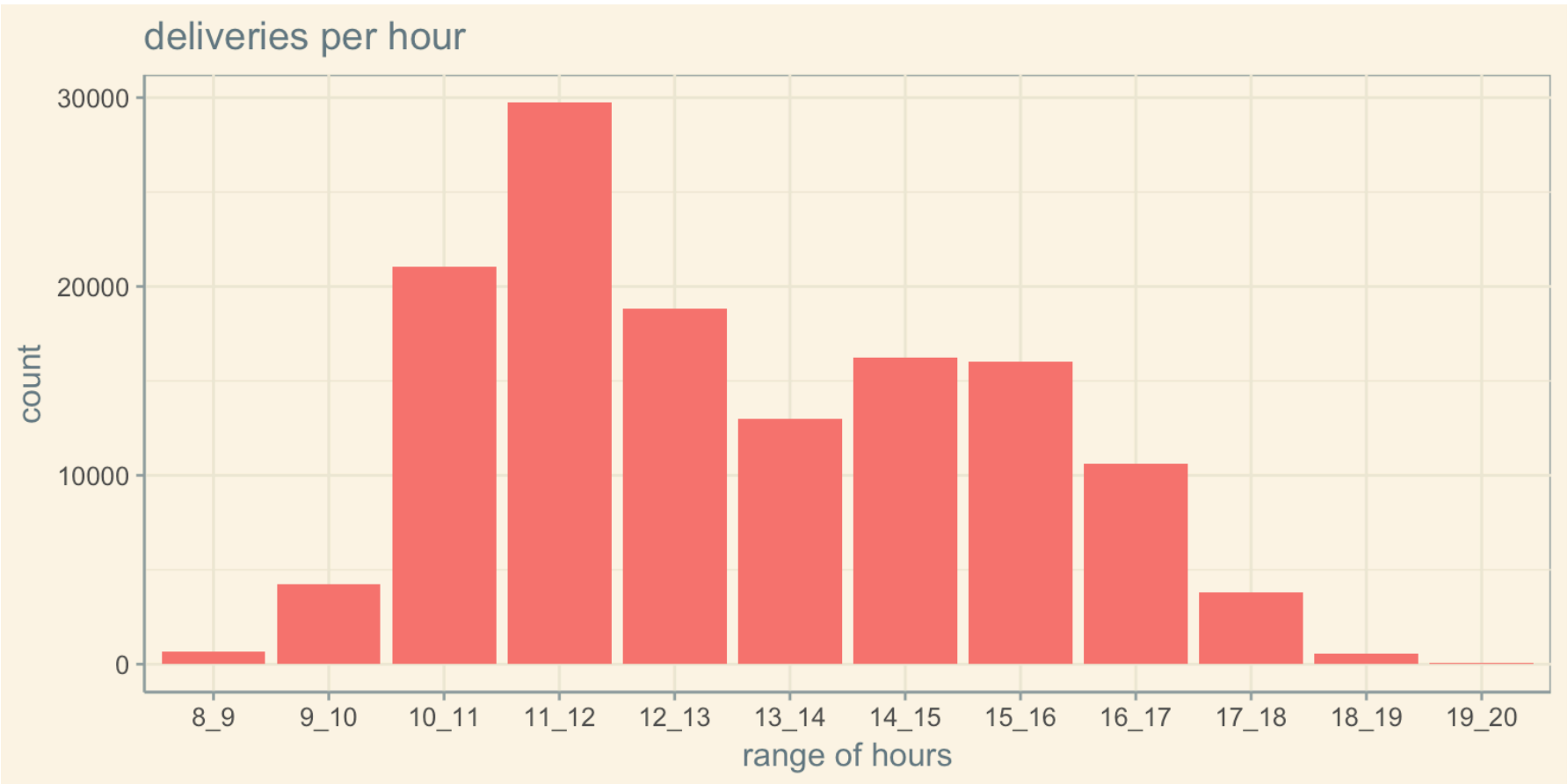
Creating of Range Hours from the variable pickedup_time

```
data_exploratory = data_exploratory %>% mutate(range_hours = sub(pattern = "^08.*"
, replacement = "8_9",x = pickup_time),
                                               range_hours = sub(pattern = "^09.*"
, replacement = "9_10",x = range_hours),
                                               range_hours = sub(pattern = "^10.*"
, replacement = "10_11",x = range_hours),
                                               range_hours = sub(pattern = "^11.*"
, replacement = "11_12",x = range_hours),
                                               range_hours = sub(pattern = "^12.*"
, replacement = "12_13",x = range_hours),
                                               range_hours = sub(pattern = "^13.*"
, replacement = "13_14",x = range_hours),
                                               range_hours = sub(pattern = "^14.*"
, replacement = "14_15",x = range_hours),
                                               range_hours = sub(pattern = "^15.*"
, replacement = "15_16",x = range_hours),
                                               range_hours = sub(pattern = "^16.*"
, replacement = "16_17",x = range_hours),
                                               range_hours = sub(pattern = "^17.*"
, replacement = "17_18",x = range_hours),
                                               range_hours = sub(pattern = "^18.*"
, replacement = "18_19",x = range_hours),
                                               range_hours = sub(pattern = "^19.*"
, replacement = "19_20",x = range_hours),
                                               range_hours = sub(pattern = "^20.*"
, replacement = "20_21",x = range_hours))




unique(data_exploratory$range_hours)

data_exploratory = data_exploratory %>% filter(range_hours != "20_21" & range_hour
s != "06:51:00")

data_exploratory$range_hours <- factor(x = data_exploratory$range_hours, levels =
c("8_9","9_10","10_11","11_12","12_13","13_14","14_15","15_16","16_17","17_18","18
_19", "19_20"))
```

```
stronger_hour <- data_exploratory %>% group_by(driver_code,range_hours) %>% summar
ise(tot_deliveries = sum(delivery))

data_strongerhours <- data_exploratory %>% filter(data_exploratory$day_deliv != "0
1",
                                                  data_exploratory$day_deliv != "0
2",
                                                  data_exploratory$day_deliv != "0
3",
                                                  data_exploratory$day_deliv != "2
0")
```

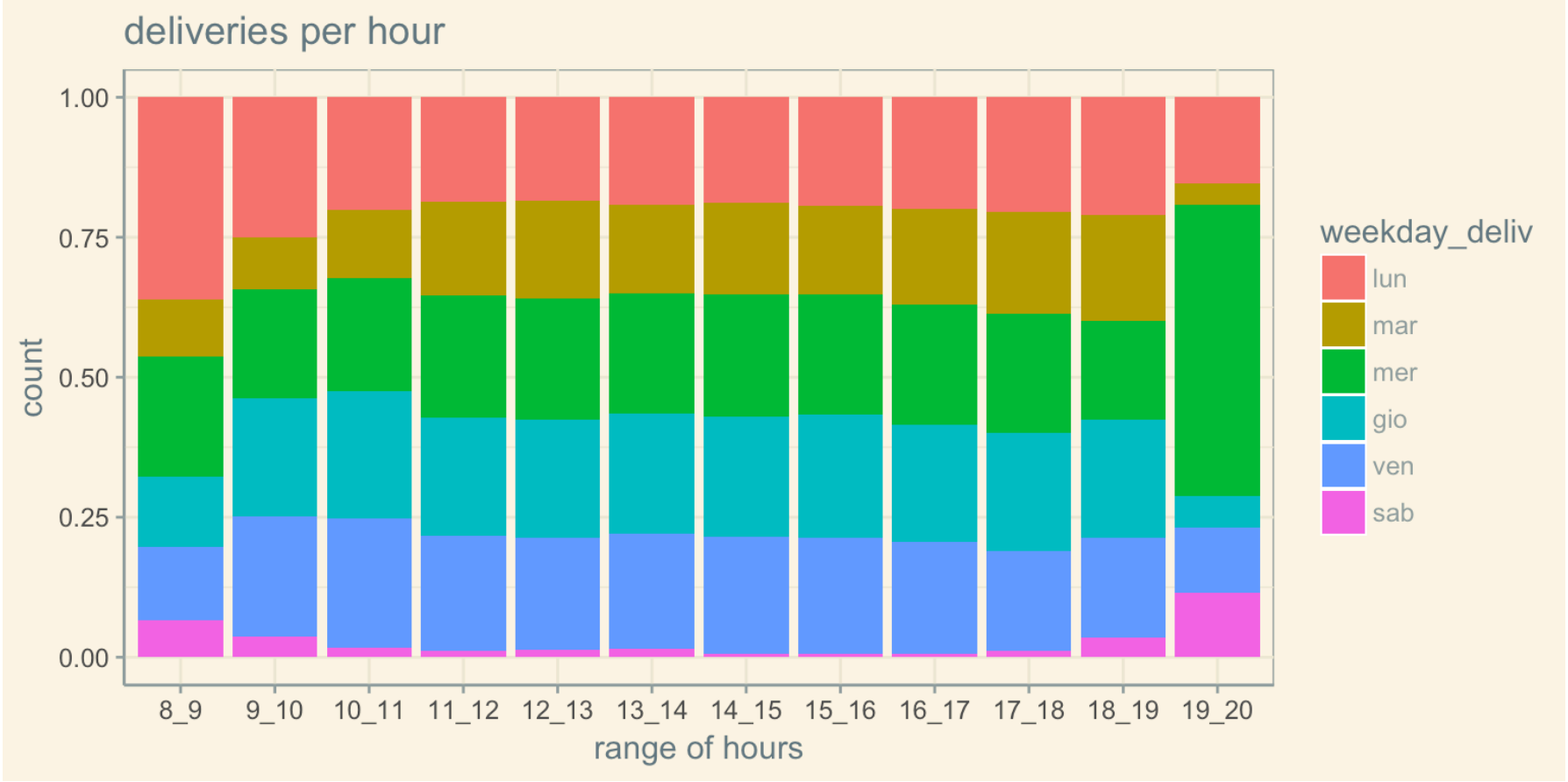
The following graph is based on complete weeks only. In fact, the first three days of the month have been deleted as well as the Tuesday 20, which represents the aforementioned strike.

```
strongerhour_plot <- ggplot(data = data_strongerhours, aes(x = range_hours, fill=
"indianared2")) + theme_solarized()+
  labs(title = "deliveries per hour", x = "range of hours")

strongerhour_plot + geom_bar() +  guides(fill = FALSE)
```



The plot shows a peak of deliveries on the range between 11 am and 12 pm. After that pick, the curve regularly decreases until the end of the day with the exception of the range between 13 and 14, where the number of deliveries first decreases before to increase again on the following hour range. From this point of view, it is possible to observe that the morning between 10 and 13 the majority of the deliveres are done.

```
strongerhour_plot + aes(fill = weekday_deliv) + geom_bar(position = "fill")
```

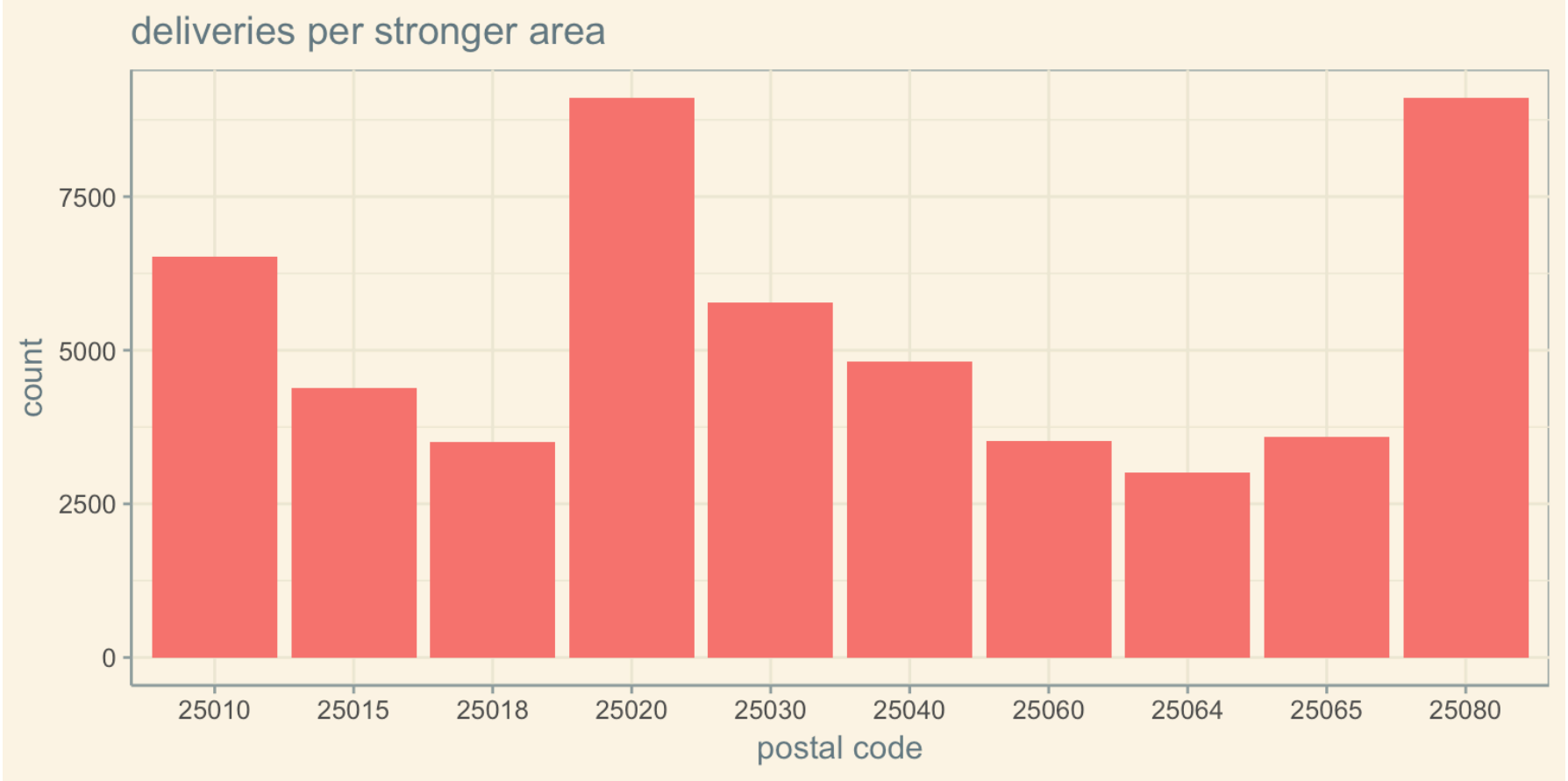


The plot shows Monday to be the day where the majority of deliveries are done in the range between 8 and 9. Moreover, Wednesday is apparently the day when the majority of deliveries are done between 19 and 20. This could be due to the strike of the 20 which led to the necessity to work more in the following days.

ANALYSIS OF THE AREA OF DELIVERY

```
stronger_area <- data_exploratory %>% group_by(postal_code) %>% summarise(cnt = n(
)) %>%
                arrange(desc(cnt))

summary(stronger_area)
tail(stronger_area)
```

```
stronger_area_NOBS <- stronger_area[-1,]
stronger_area10<- head(stronger_area_NOBS,n = 10)
stronger_area10

stronger_area10_plot <- ggplot(data = stronger_area10, aes(x = postal_code, fill=
"indianared2")) + theme_solarized()+
  labs(title = "deliveries per stronger area", x = "postal code")+ guides(fill = F
ALSE) + geom_bar(aes(weight = cnt))
stronger_area10_plot
```



metti in ordine, esplicita i nomi dei comuni principali e spiega perche hai tolto il primo.

Due to the fact that for the center of Brescia it was not possible to obtain one postal code, it has been identified with the observation “25121/25136”. This represents an important outlier of this distribution. For this observation, the number of monthly deliveries is 31846, with the second postal code with maximum number of deliveries which is 9111. This postal code is 25020 which is an area south of Brescia which includes several important district of the city. Third postal code is 25080 which is an area close to the Lake Garda, where commercial activities and tourism are really frequent. This postal code is right adjacent to the fourth most frequently delivered postal code, which is 25010 and it represents the northern part of the Garda Lake.

```
leaflet(stronger_area10) %>%
  addProviderTiles(providers$CartoDB.Positron) %>%
  addHeatmap(lng=~lon, lat=~lat,blur = 20, max = 1.2, radius = 30)
```

SPLIT AREA

The aim of this paragraph is to split postal codes into 3 different areas based on the distance between them and the center of Brescia. As imaginable, one of the factor that can really influence the performance of the drivers is the presence of traffic, and the distance of the points of delivery between each others. From this point of view, it will be expected to have more traffic and points of delivery closer to each other in the center of Brescia and the opposite further from the city center.

At first, I will have to obtain the coordinates of each postal code.

```
experiment <- data_exploratory %>% group_by(postal_code) %>% summarise()
experiment$city <- "Brescia"
experiment <- unite(data = experiment, c(experiment$postal_code, experiment$city),
sep = "-")
experiment <- experiment %>% rename("postal_code" = `c(experiment$postal_code, exp
eriment$city)`)
latlong <- geocode(experiment$postal_code)
experiment <- cbind(experiment, latlong)
```

```
experimentNA1 <- filter(experiment, is.na(experiment$lon))
experimentNA1 <- experimentNA1 %>% select(postal_code)
latlong1 <- geocode(experimentNA1$postal_code)
experimentNA1 <- cbind(experimentNA1, latlong1)

experimentNA2 <- filter(experimentNA1, is.na(experimentNA1$lon))
experimentNA2 <- experimentNA2 %>% select(postal_code)
latlong2 <- geocode(experimentNA2$postal_code)
experimentNA2 <- cbind(experimentNA2, latlong2)

experimentNA3 <- filter(experimentNA2, is.na(experimentNA2$lon))
experimentNA3 <- experimentNA3 %>% select(postal_code)
latlong3 <- geocode(experimentNA3$postal_code)
experimentNA3 <- cbind(experimentNA3, latlong3)

# Very often geocode function gives NA value, so that you have to evaluate the fun
ction again in order to work
# For this reason I have created several dataframe in order to have the possibilit
y to evaluate the rows where geocode previously returned NA.

experimentNA4 <- filter(experimentNA3, is.na(experimentNA3$lon))
experimentNA4 <- experimentNA4%>% select(postal_code)
latlong4 <- geocode(experimentNA4$postal_code)
experimentNA4 <- cbind(experimentNA4, latlong4)

experimentNA5 <- filter(experimentNA4, is.na(experimentNA4$lon))
experimentNA5 <- experimentNA5%>% select(postal_code)
latlong5 <- geocode(experimentNA5$postal_code)
experimentNA5 <- cbind(experimentNA5, latlong5)

experimentNA6 <- filter(experimentNA5, is.na(experimentNA5$lon))
experimentNA6 <- experimentNA6%>% select(postal_code)
latlong6 <- geocode(experimentNA6$postal_code)
experimentNA6 <- cbind(experimentNA6, latlong6)

experiment <- experiment %>% filter(!is.na(experiment$lat))
experimentNA1 <- experimentNA1 %>% filter(!is.na(experimentNA1$lat))
experimentNA2 <- experimentNA2 %>% filter(!is.na(experimentNA2$lat))
experimentNA3 <- experimentNA3 %>% filter(!is.na(experimentNA3$lat))
experimentNA4 <- experimentNA4 %>% filter(!is.na(experimentNA4$lat))

postalcode_latlong <- rbind(experiment,experimentNA1,experimentNA2)

# postalcode_latlong1 <- postalcode_latlong %>%
#                       mutate(postal_code = gsub(pattern = "Brescia", "", postalcod
e_latlong))

postalcode_latlong <- separate(postalcode_latlong, col = postal_code, into= c("pos
tal_code","city"),sep = "-")
postalcode_latlong$city <- NULL
data_exploratory <- left_join(x = data_exploratory, y = postalcode_latlong, by = "
postal_code" )
data_exploratory1 <- NULL
```

Secondly, I will obtain the distances between the points and the center of Brescia.

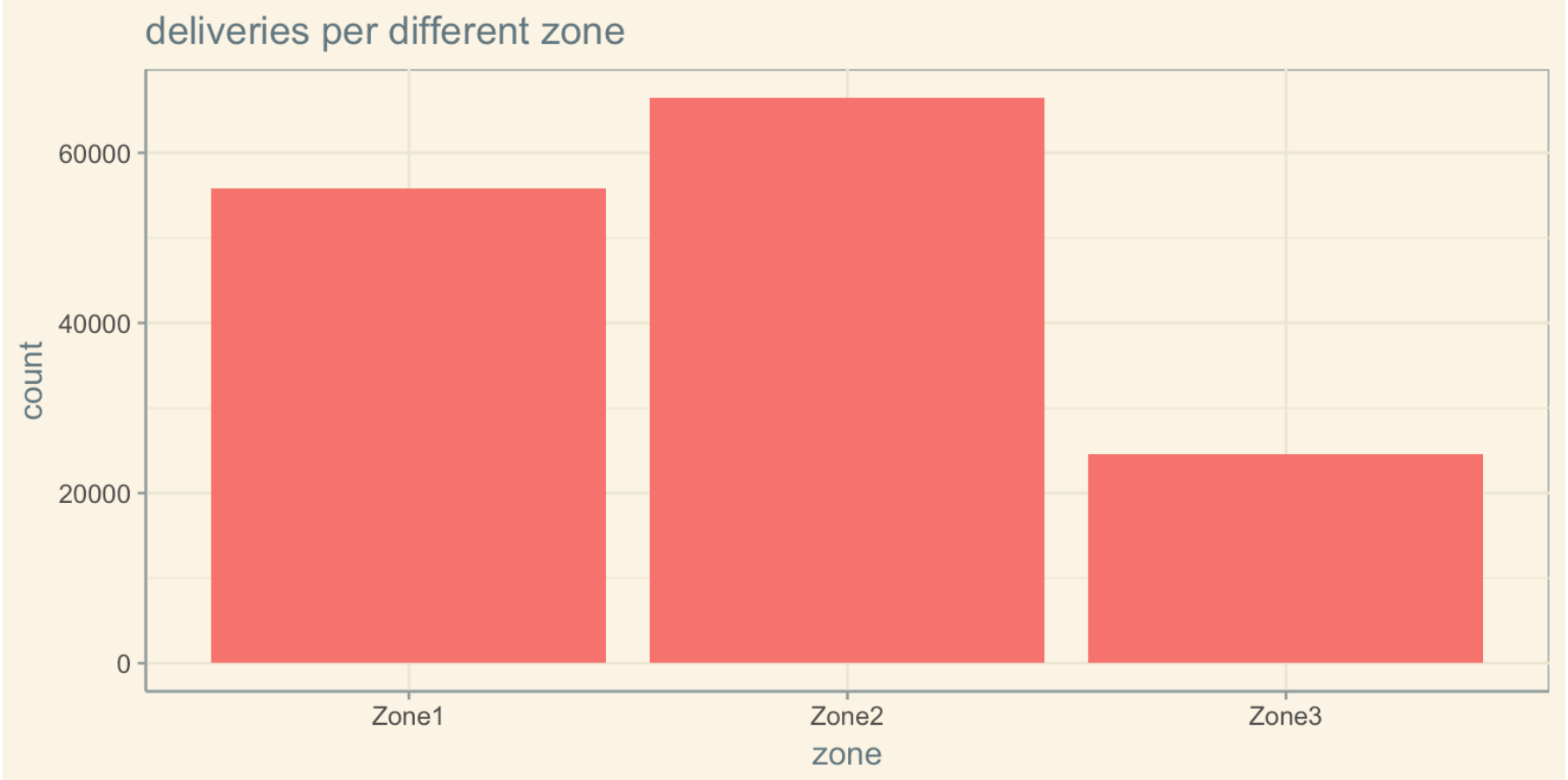
```
postalcode_latlong <- load("postalcode_latlong.RData")
```

```
postalCodes <- postalcode_latlong

#Find co-ordinates of center of Brescia
Brescia <- geocode("Corso Zanardelli, Brescia")

#In case you go over the limit, you can hard code it
Brescia$lon <- 10.220992
Brescia$lat <- 45.5366031

#Calculate Distance between Center and other points
#First create an empty vector to store the results

Distance <- vector("numeric",length = nrow(postalCodes))

#Now claculate the distance using a for loop
for(i in 1:nrow(postalCodes)){
  Distance[i] <- distm(c(Brescia$lon,Brescia$lat),
                       c(postalCodes$lon[i], postalCodes$lat[i]),
                       fun = distHaversine)
}

#Combine it with postalCodes
postalCodes$Distance <- Distance
```

Finally, I will obtain the three different areas of the city storing them in the variable “area”

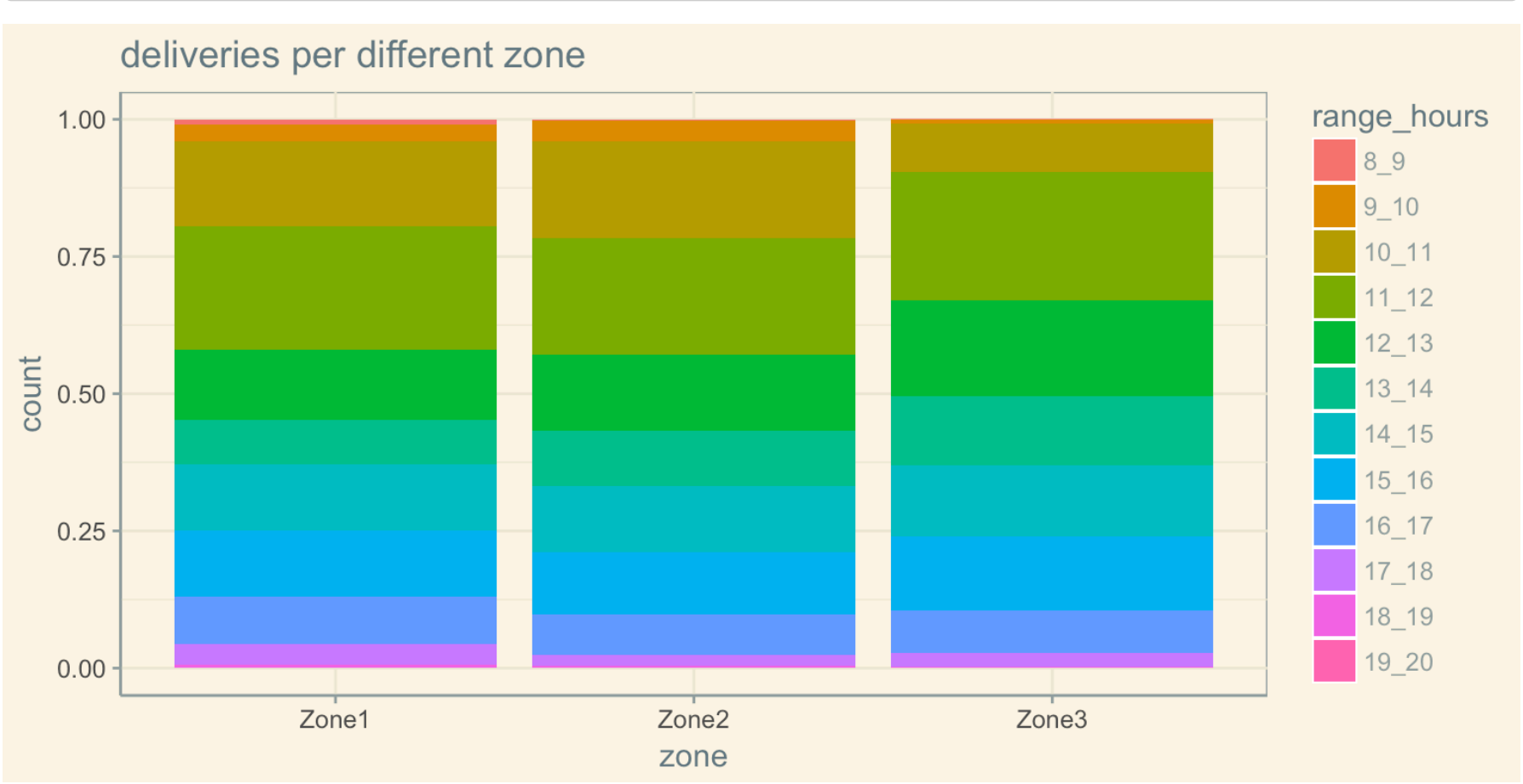
```
# Calculating the distance using a for loop

area <- vector("character",length = nrow(postalCodes))

for(i in 1:nrow(postalCodes)){
  if(postalCodes$Distance[i] <= 15000)
  {area[i] = "Zone1"}
  else if(postalCodes$Distance[i] > 15000 & postalCodes$Distance[i] <= 30000 )
  {area[i] = "Zone2"}
  else
  {area[i] = "Zone3"}
}

postalCodes$area <- area

table(data_exploratory$area)

data_exploratory <- left_join(x = data_exploratory, y = postalCodes, by = "postal_
code" )

data_exploratory <- data_exploratory %>% select(-lat.y,-lon.y, Distance.y) %>% ren
ame("lon" = lon.x, "lat" = lat.x, "distance" = Distance.x)



data_exploratory <- data_exploratory %>% mutate(zone1 = ifelse(data_exploratory$ar
ea == "Zone1",1,0),
                                                zone2 = ifelse(data_exploratory$area =
= "Zone2",1,0),
                                                zone3 = ifelse(data_exploratory$area =
= "Zone3",1,0))
zone_split <- data_exploratory %>% group_by(driver_code) %>% summarise(del_zone1 =
sum(zone1),del_zone2 = sum(zone2),del_zone3 = sum(zone3))
```

```
area_analysis <- data_exploratory %>% group_by(area,driver_code)

ggplot(data_exploratory, aes(x = area,fill= "indianared2")) + theme_solarized()+
  labs(title = "deliveries per different zone", x = "zone")+ guides(fill = FALSE)+
geom_bar()
```



The plot shows that the majority of the deliveries are done in the area between 15 and 30 km to the centre. However, it is more significant to observe that the minority of the deliveries are done in the area further 30 km from the centre, which is the zone3.

```
ggplot(data_exploratory, aes(x = area, fill= range_hours)) + theme_solarized()+
  labs(title = "deliveries per different zone", x = "zone")+ geom_bar(position = "
fill")
```



The plot above illustrated aims to deepen the analysis of the three different area in which the city has been split. In particular, for each area is observed the delivery behave on the different range hours. From this point of view, it is possibile to observe that the zone 3 seems to have a different attitude than the other. The majority of the deliveries in that area start in the range between 11 and 12, while in the other two a big portion of deliveries can be observed starting from 10 to 11. Despite this situation, it does not seem to

result a situation where deliveries in zone3 are performed later than the ones in the other. This seems to suggest that the activity in the Zone1 is more active, with possibility to start earlier and to finish later, probably due to the closeness to the area from the field office.

```
leaflet(data_exploratory) %>%
  addProviderTiles(providers$CartoDB.Positron) %>%
  addHeatmap(lng=~lon, lat=~lat,blur = 20, max = 0.5, radius = 15)
```

The plot shows the area of delivery. In this way it is possible to observe where the majority of deliveries are performed (indicated with red colour). This map seems to be coherent with the analysis previously performed of the strongest area of activity of the company.

ANALYSIS OF DEPENDENT VARIABLE Y

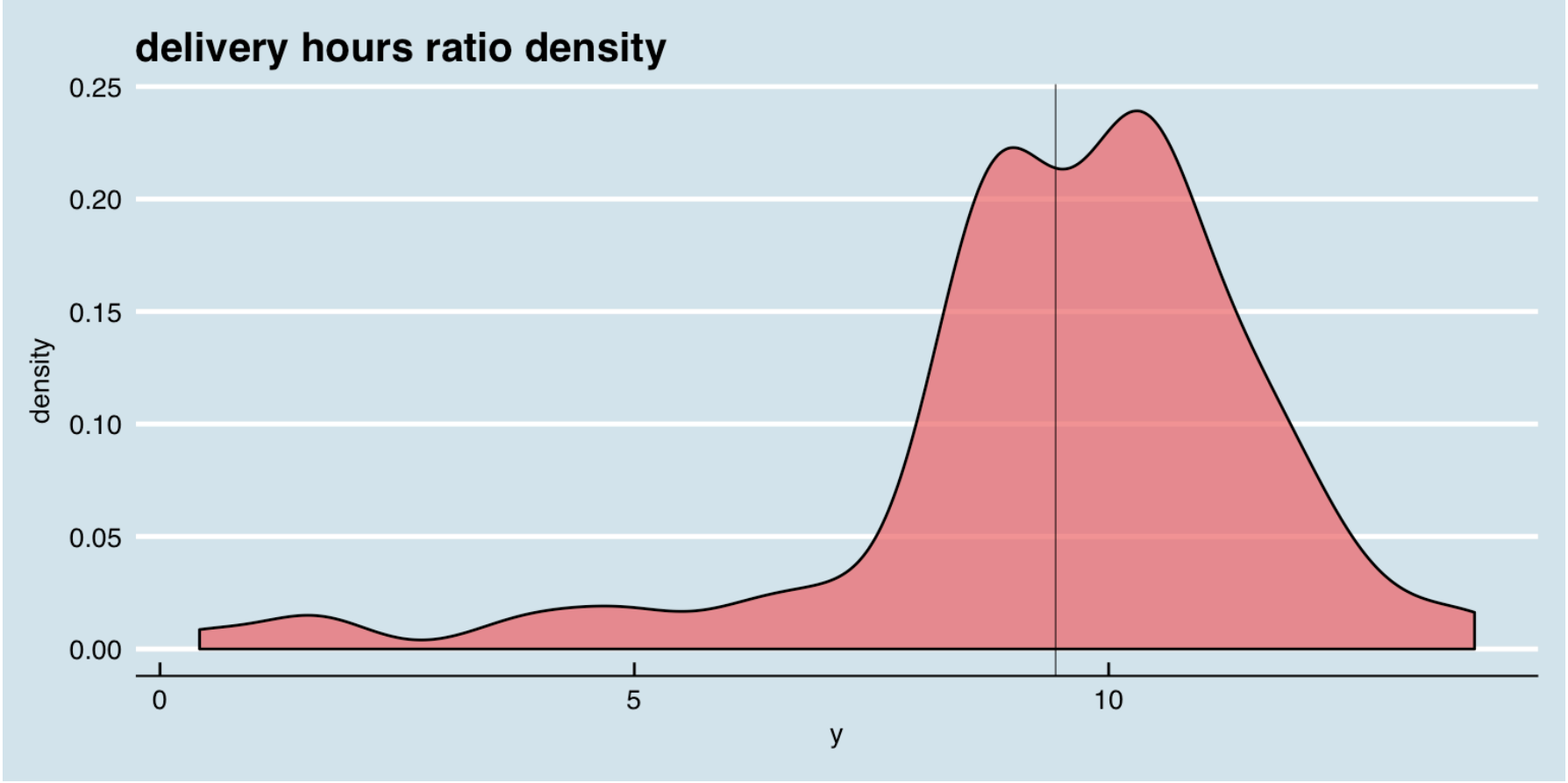
In the following section I will aggregate data in order to obtain the independent variable of this analysis, which is the relationship between deliveries and hours worked for each driver, which represent my statistical unit. By the end of this paragraph a data frame named aggregate_data_last will be obtained in order to later estimate different models whose predictive capacity will be tested.

OBTAIN THE HOURS WORKED FOR EACH DRIVER AND RATIO DELIVERIES PER DAY WORKED

```
data_exploratory <- na.omit(data_exploratory)
data_exploratory <- data_exploratory %>% filter(driver_code != "208" & driver_code
!= "234"& driver_code != "260" & driver_code != "336" & driver_code != "404" & dri
ver_code != "534" & driver_code != "535" & driver_code != "623"  & driver_code !=
"132")
aggregate_data <- data_exploratory %>% group_by(driver_code, day_deliv, pickup_tim
e, delivery) %>% summarise()

# aggregate_data <- aggregate_data %>% filter(driver_code != "208" & driver_code !
= "234"& driver_code != "260" & driver_code != "336" & driver_code != "404" & driv
er_code != "534" & driver_code != "535" & driver_code != "623"  & driver_code != "
132")

aggregate_data$pickup_time <- as.character(aggregate_data$pickup_time)
aggregate_data$pickup_time = as.POSIXlt(aggregate_data$pickup_time, format = "%H:%
M:%S")

class(aggregate_data$pickup_time)


time_delivery <- rep(0,nrow(aggregate_data))

# Turning time into the difference of minutes between every point of delivery for
every driver

for (i in 1:(nrow(aggregate_data)-1)) {
```

```
  if(aggregate_data$driver_code[i] == aggregate_data$driver_code[i+1])
  {time_delivery[i] = difftime(aggregate_data$pickup_time[i], aggregate_data$picku
p_time[i+1], units = "mins" ) }
}

time_delivery=ifelse(time_delivery>0,0,time_delivery)
aggregate_data=aggregate_data[,-3]
aggregate_data=cbind(aggregate_data,time_delivery)
aggregate_data$time_delivery <- abs(aggregate_data$time_delivery)


# sum the worked minutes per driver(minutes worked) and create a new variable base
d on hours (hours worked per driver)

aggregate_data2 <- aggregate_data %>% group_by(driver_code) %>% summarise(tot_deli
veries = sum(delivery), tot_minutes = sum(time_delivery))
hours_delivery <- aggregate_data2$tot_minutes/60
aggregate_data2 <- cbind(aggregate_data2, hours_delivery)

y = aggregate_data2$tot_deliveries / aggregate_data2$hours_delivery
aggregate_data2 <- cbind(aggregate_data2, y)

# aggregate_data2 <- aggregate_data2 %>% filter(driver_code != "208" & driver_code
!= "234"& driver_code != "260" & driver_code != "336" & driver_code != "404" & dri
ver_code != "534" & driver_code != "535" & driver_code != "623"  & driver_code !=
"132")

# Now that I have the total of deliveries per driver and the Independent variable
I can plot them to analyse the trend.
```

```
summary(aggregate_data2$y)
y_plot <- ggplot(data = aggregate_data2, aes(x = y))
y_plot + geom_density(fill = "indianred2", alpha = 0.7) + theme_economist() + labs
(title = "delivery hours ratio density")+ geom_vline(xintercept = 9.4412, size = 0
.2)
```



The dependent variable y is represented by a left tailed distribution, with a mean of 9.4412 deliveries per hours. It is important to observe that the dependent variable chosen for this analysis cannot assume negative values. As a consequence, this situation will influence the future approach on the predictive analysis.

```
aggregate_data$day_deliv <- as.numeric(aggregate_data$day_deliv)
aggregate_data3 <- data_exploratory %>% group_by(driver_code) %>% summarise(day_wo
rked = n_distinct(day_deliv))
# aggregate_data3 <- aggregate_data3 %>% filter(driver_code != "208" & driver_code
!= "234"& driver_code != "260" & driver_code != "336" & driver_code != "404" & dri
ver_code != "534" & driver_code != "535" & driver_code != "623"  & driver_code !=
"132")
aggregate_data2 <- cbind(aggregate_data2, aggregate_data3$day_worked)
```

TOTAL PACK LOADED PER DRIVER

```
load("aggregate_data4.Rdata") # Load a dataset previously cleaned during the wrang
ling phase. Dataset provided by the client later on

# clean the data for the needs of this analysis
aggregate_data4 <- aggregate_data4 %>% filter(driver_code != "208" & driver_code !
= "234"& driver_code != "260" & driver_code != "336" & driver_code != "404" & driv
er_code != "534" & driver_code != "535" & driver_code != "623"  & driver_code != "
132",
                                              driver_code != "1000", driver_code !
= "101", driver_code != "402")
aggregate_data4 <- aggregate_data4 %>% mutate(driver_code = gsub(pattern = "8421",
replacement = "421",x = driver_code),
                                              driver_code = gsub(pattern = "8618",
replacement = "618", x = driver_code),
                                              driver_code = gsub(pattern = "8678",
replacement = "678", x = driver_code),
                                              driver_code = gsub(pattern = "8679",
replacement = "679", x = driver_code),
                                              driver_code = gsub(pattern = "8531",
replacement = "531", x = driver_code))
```

```
aggregate_data5 <- aggregate_data4 %>% group_by(driver_code ) %>% summarise(tot_pa
ckloaded = sum(pack_loaded))
setdiff(aggregate_data5$driver_code, aggregate_data2$driver_code)
aggregate_data5 <- aggregate_data5 %>% filter(tot_packloaded > 0, driver_code != "
851", driver_code != "805")
```

TOTAL PICKED UP PACKS PER DRIVER

```
aggregate_data6 <- aggregate_data4 %>% group_by(driver_code) %>% summarise(pickedu
p_total = sum(pickup_services))
aggregate_data6 <- aggregate_data6 %>% filter( driver_code != "851", driver_code !
= "805")
```

TOTAL ARRIVED PACKS PER DRIVER

```
aggregate_data7 <- aggregate_data4 %>% group_by(driver_code) %>% summarise(packarr
ived_total = sum(pack_arrived))
setdiff(aggregate_data7$driver_code, aggregate_data2$driver_code)
aggregate_data7 <- aggregate_data7 %>% filter( driver_code != "851", driver_code !
= "805")
```

TOTAL WEIGHT OF PACKS DELIVERED BY DRIVER

```
data_exploratory <- data_exploratory %>% mutate(weight_pack = gsub(pattern = ",",r
eplacement = ".", x = weight_pack))
data_exploratory$weight_pack <- as.double(data_exploratory$weight_pack)
aggregate_data8 <- data_exploratory %>% group_by(driver_code, day_deliv) %>% summa
rise(sum(weight_pack))
aggregate_data9 <- data_exploratory %>% group_by(driver_code) %>% summarise(tot_we
ight_pack = sum(weight_pack))
```

TOTAL PACKS NOT DELIVERED PER DRIVER

```
aggregate_data10 <- aggregate_data4 %>% group_by(driver_code) %>% summarise(packno
tdelivered_total = sum(not_delivered))
setdiff(aggregate_data10$driver_code, aggregate_data2$driver_code)
aggregate_data10 <- aggregate_data10 %>% filter( driver_code != "851", driver_code
!= "805")
```

TOTAL SERVICES PER DRIVER

This variable summarise the total amount of services performed by each driver (pack_delivered, pickedup_pack and failed deliveries or pick up).

```
aggregate_data11 <- aggregate_data4 %>% group_by(driver_code) %>% summarise(tot_se
rvices = sum(tot_serv))
setdiff(aggregate_data11$driver_code, aggregate_data2$driver_code)
aggregate_data11 <- aggregate_data11 %>% filter( driver_code != "851", driver_code
!= "805")
```

The lack of precise data regarding the amount of picked up kg represents the reason why this variable will not be taken in consideration. A lot more from this point of view will have to be done in order to obtain the necessary variables to solve this problem.

OBTAINING AN AGGREGATE DATA FRAME WITH ALL THE NECESSARY VALUES

```
aggregate_data_last <- left_join(aggregate_data2,aggregate_data3)
aggregate_data_last <- left_join(aggregate_data_last, aggregate_data3)
aggregate_data_last <- left_join(aggregate_data_last, aggregate_data5)
aggregate_data_last <- left_join(aggregate_data_last, aggregate_data6)
aggregate_data_last <- left_join(aggregate_data_last, aggregate_data7)
aggregate_data_last <- left_join(aggregate_data_last, aggregate_data9)
aggregate_data_last <- cbind(aggregate_data_last, zone_split$del_zone1,zone_split$
del_zone2,zone_split$del_zone3)
aggregate_data_last <- aggregate_data_last %>% rename("del_zone1"
=`zone_split$del_zone1`,
                                                      "del_zone2" = `zone_split$de
l_zone2`,
                                                      "del_zone3" = `zone_split$de
l_zone3`)

aggregate_data_last$`aggregate_data3$day_worked` <- NULL

aggregate_data_last <-cbind(aggregate_data_last, tot_services = aggregate_data11$t
ot_services)
```

```
summary(aggregate_data_last)
```

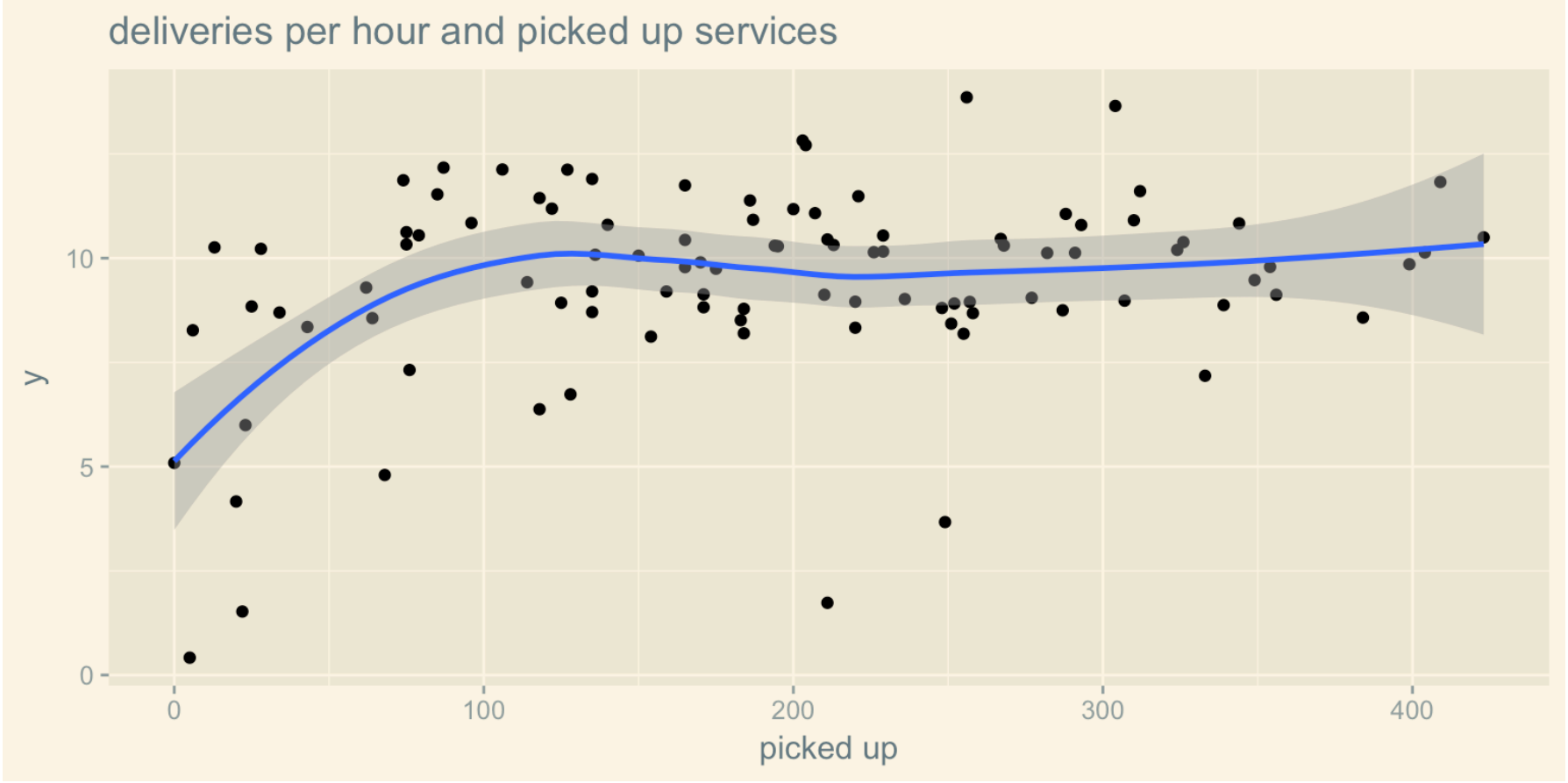
1_ It is important to notice that the variable “packarrived_total” contains 26 NA’s value. As a consequence, this element will be taken in consideration for the application of the different predictive models.

2_ The summary function shows that every variable obtained on this dataset contains outliers in the lower tale of their distribution. In particular, the Min represented by del_zone1,del_zone2, del_zone3 is due to the fact that some of the drivers have never performed a delivery in that specific area and the observation of those drivers for that variable takes value 0.

ANALYSIS OF THE DEPENDENT VARIABLE COMPARED TO THE INDEPENTENT VARIABLES

Y AND PICKED UP PACKS

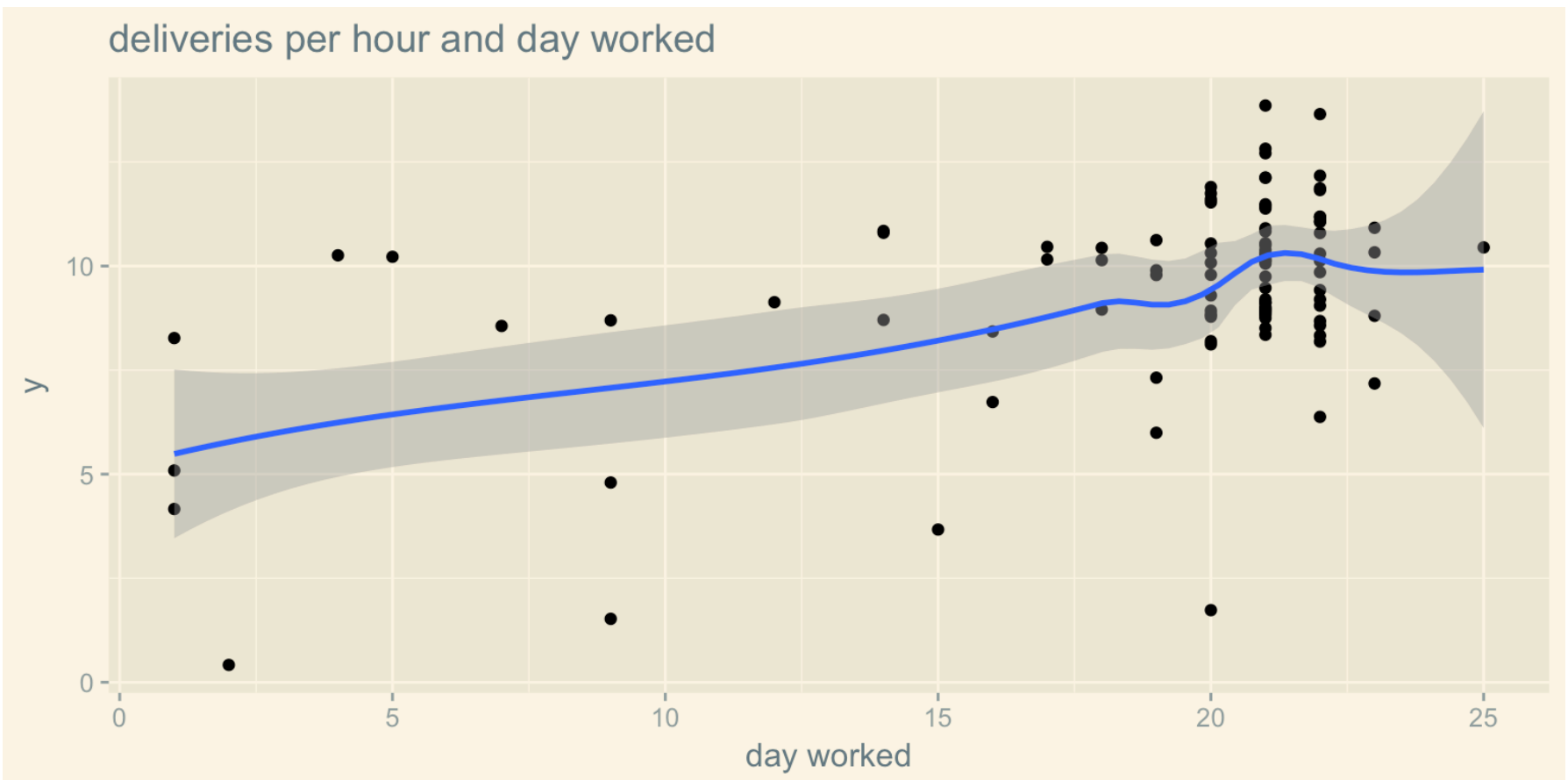
```
y_pickedup_plot<- ggplot(data = aggregate_data_last, aes(x = pickedup_total,y = y)
)+ theme_solarized_2()+
  labs(title = "deliveries per hour and picked up services", x =  "picked up" )

#

y_pickedup_plot + geom_point()+ geom_smooth()
```



The graph shows a relationship which is stronger until number of picked up packages around 200. After this threshold the relation does not seem to be as relevant as before.

Y AND DAY WORKED

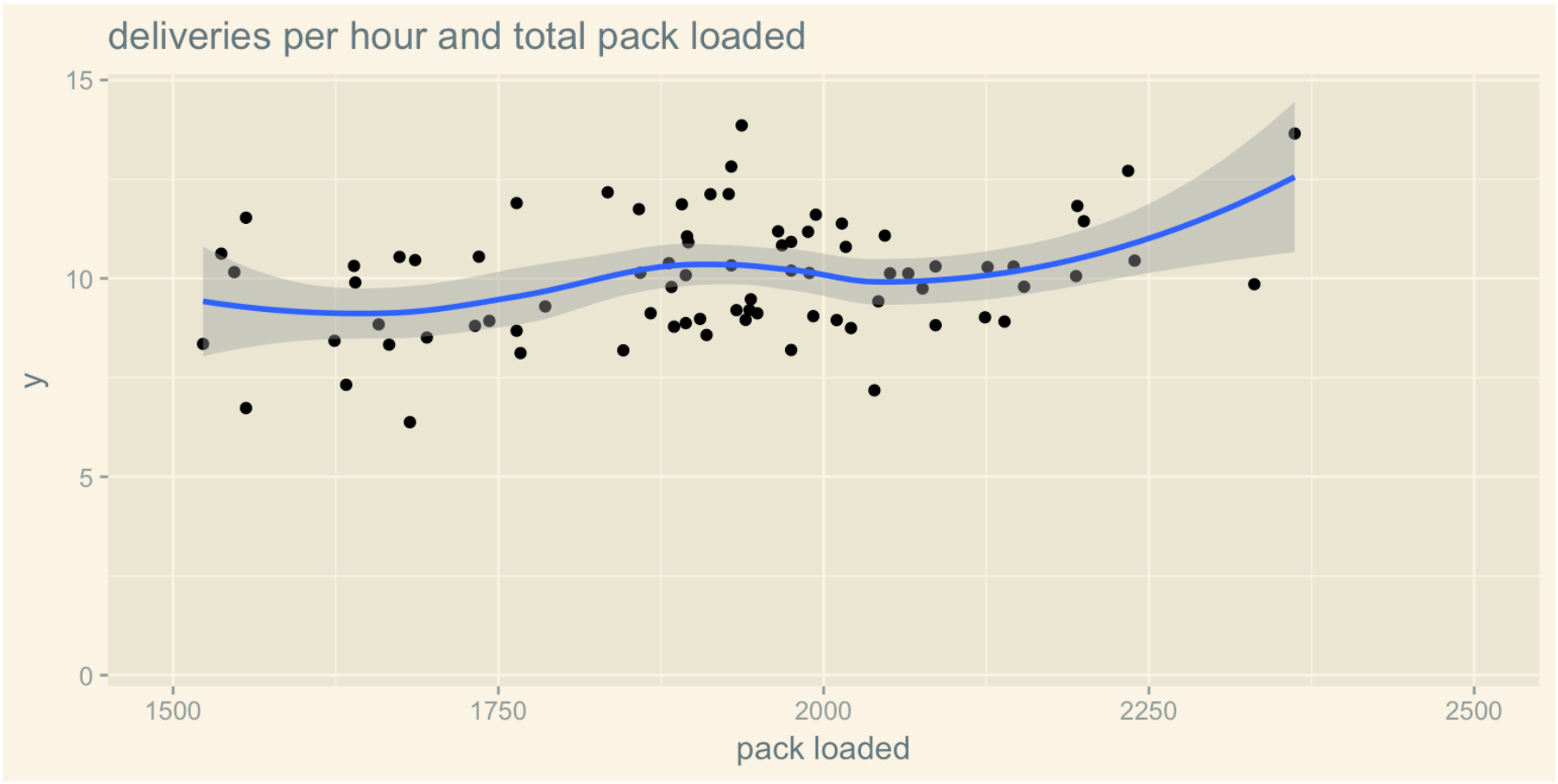
```
y_dayworked_plot<- ggplot(data = aggregate_data_last, aes(x = day_worked,y = y))+
theme_solarized_2()+
  labs(title = "deliveries per hour and day worked", x =  "day worked" )

y_dayworked_plot + geom_point() + geom_smooth()
```



The graph shows a weak positive relationship between the deliveries per hour and the amount of worked day. There are few observations, which can be found at the bottom of the graph, which seem to show a strange behaviour, which will be taken in consideration after.

Y AND TOT PACK LOADED

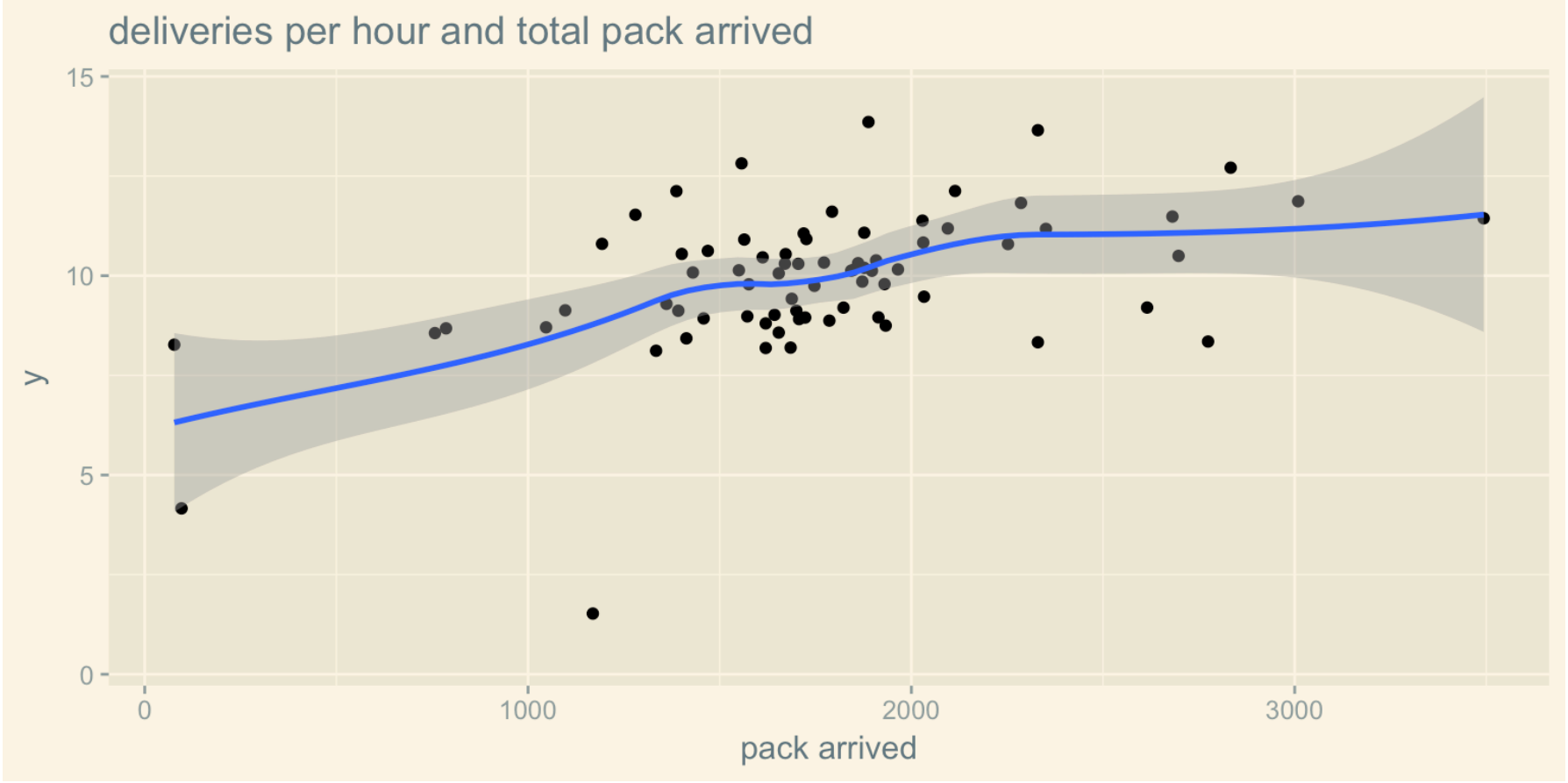
```
y_packloaded_plot<- ggplot(data = aggregate_data_last, aes(x = tot_packloaded,y =
y))+ theme_solarized_2()+
  labs(title = "deliveries per hour and total pack loaded", x =  "pack loaded" )

y_packloaded_plot + geom_point() + geom_smooth()+ scale_x_continuous(limits = c(15
00, 2500))
```



The graph showed has been zoomed since only few observation where outside of this section. However, it does not seem to show any strong relationship.

Y AND PACK ARRIVED TOTAL

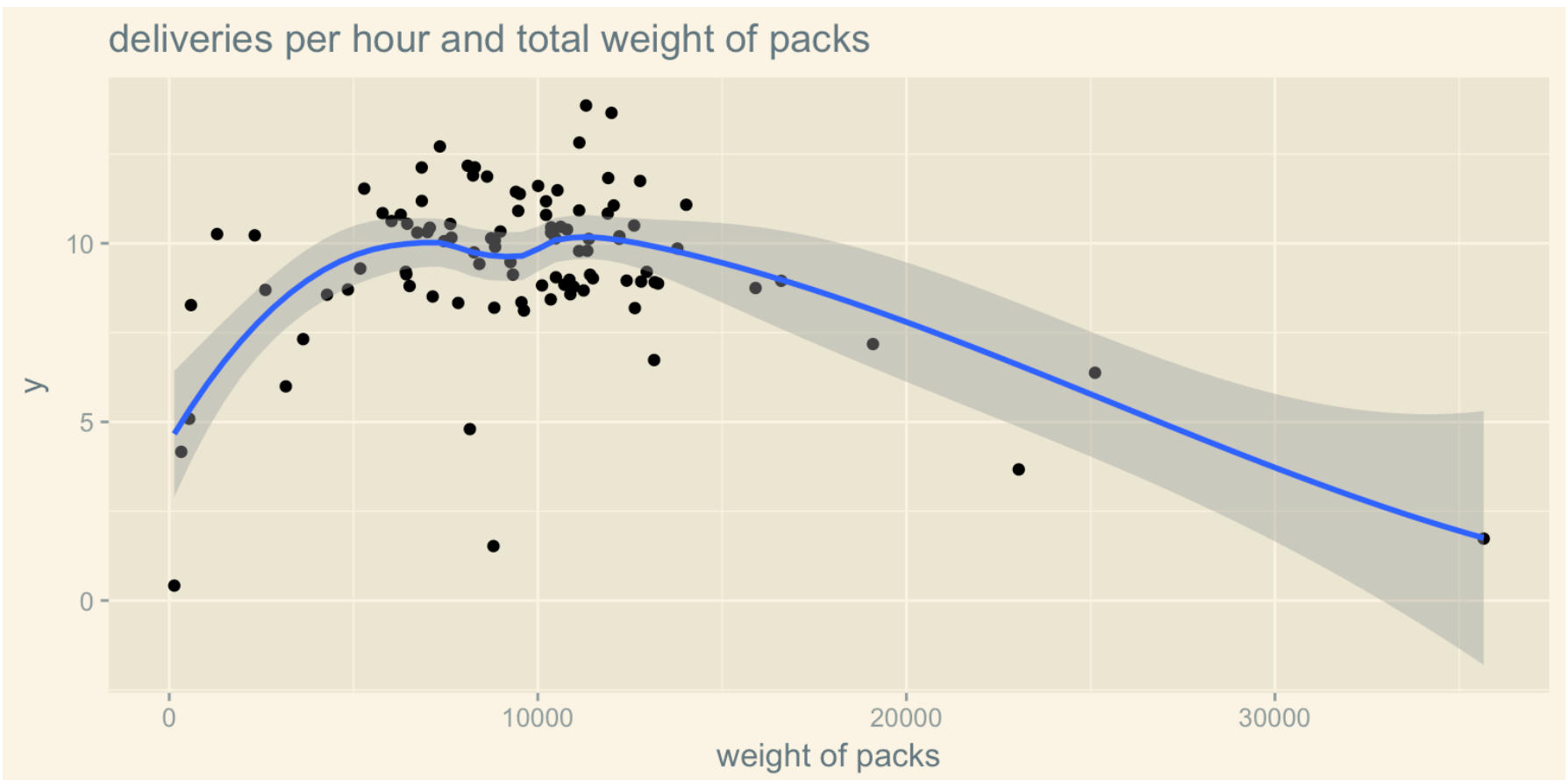
```
y_packarrived_plot<- ggplot(data = aggregate_data_last, aes(x = packarrived_total,
y = y))+ theme_solarized_2()+
  labs(title = "deliveries per hour and total pack arrived", x =  "pack arrived" )

y_packarrived_plot + geom_point() + geom_smooth()
```



The graph shows a weak positive relationship between pack arrived and the dependent variable. However, this situation can be due to the presence of few observations with a lower pack arrived value.

Y AND WEIGHT TOTAL

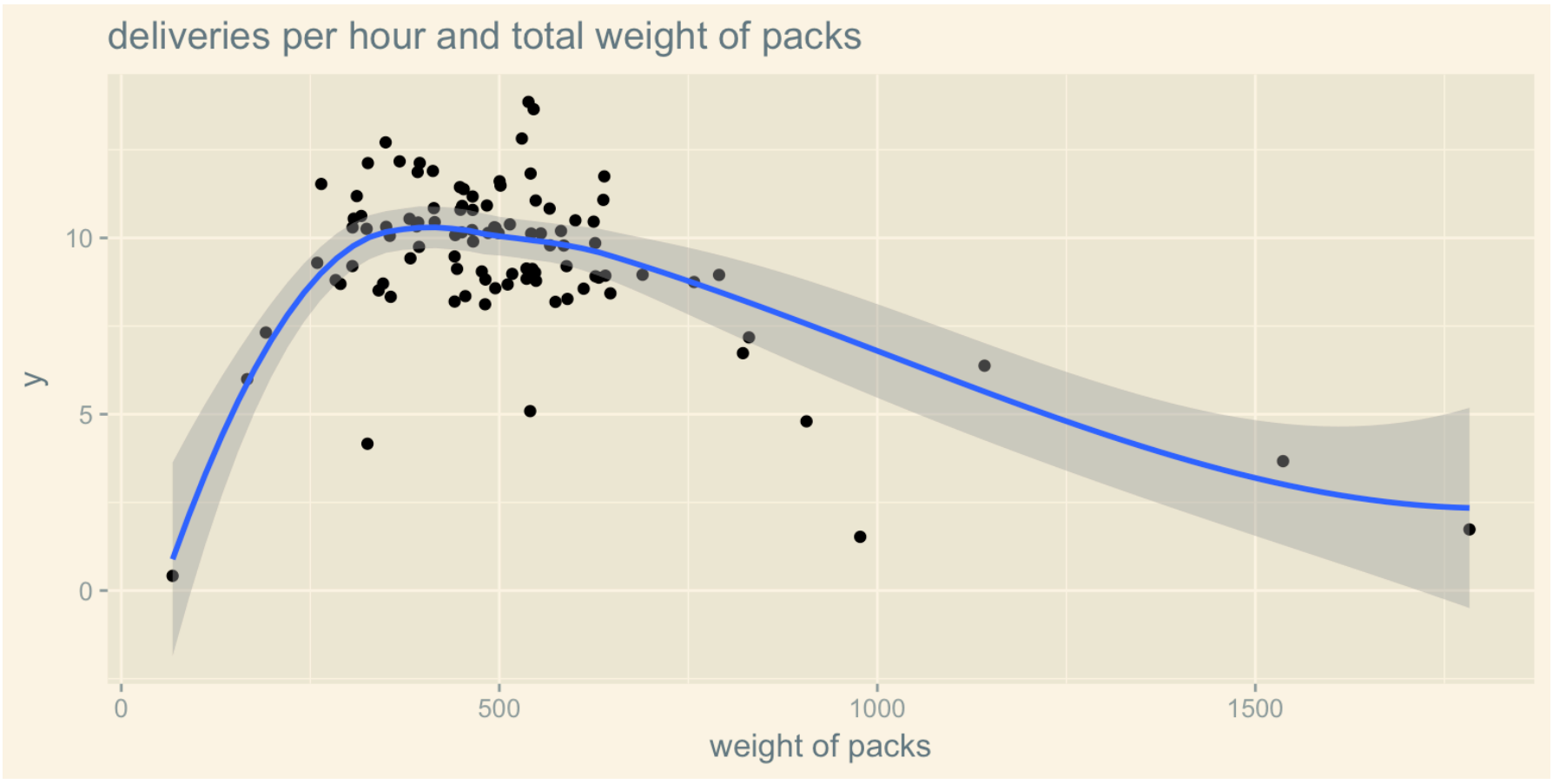
```
y_weight_plot<- ggplot(data = aggregate_data_last, aes(x = tot_weight_pack,y = y))
+ theme_solarized_2()+
  labs(title = "deliveries per hour and total weight of packs", x =  "weight of pa
cks" )

y_weight_plot + geom_point() + geom_smooth()
```



Some driver result in a lower weight due to a lower amount of worked day. As a consequence, it is opportune to divide the weight for the number of day worked.

```
y_weight_dayworked_plot<- ggplot(data = aggregate_data_last, aes(x = tot_weight_pa
ck/day_worked,y = y))+ theme_solarized_2()+
  labs(title = "deliveries per hour and total weight of packs", x =  "weight of pa
cks" )
```

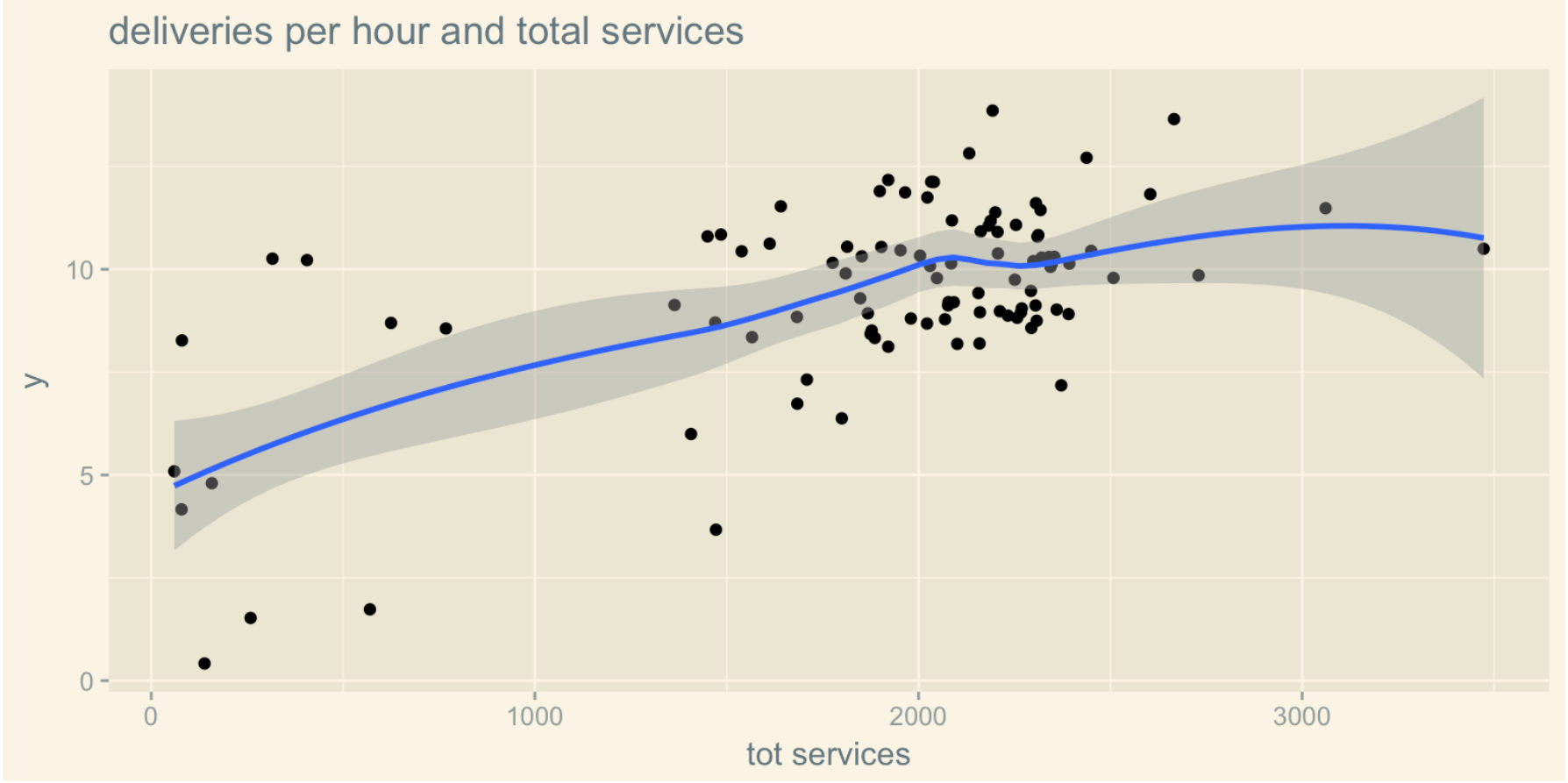
```
y_weight_dayworked_plot + geom_point() + geom_smooth()
```



The relationship seems to identify a general trend where the increase of the weight of packs leads to a decrease of the relationship between deliveries and worked hours.

Y AND TOT SERVICES

```
y_totservices_plot<- ggplot(data = aggregate_data_last, aes(x = tot_services,y = y
))+ theme_solarized_2()+
  labs(title = "deliveries per hour and total services", x =  "tot services" )
y_totservices_plot + geom_point() + geom_smooth()
```

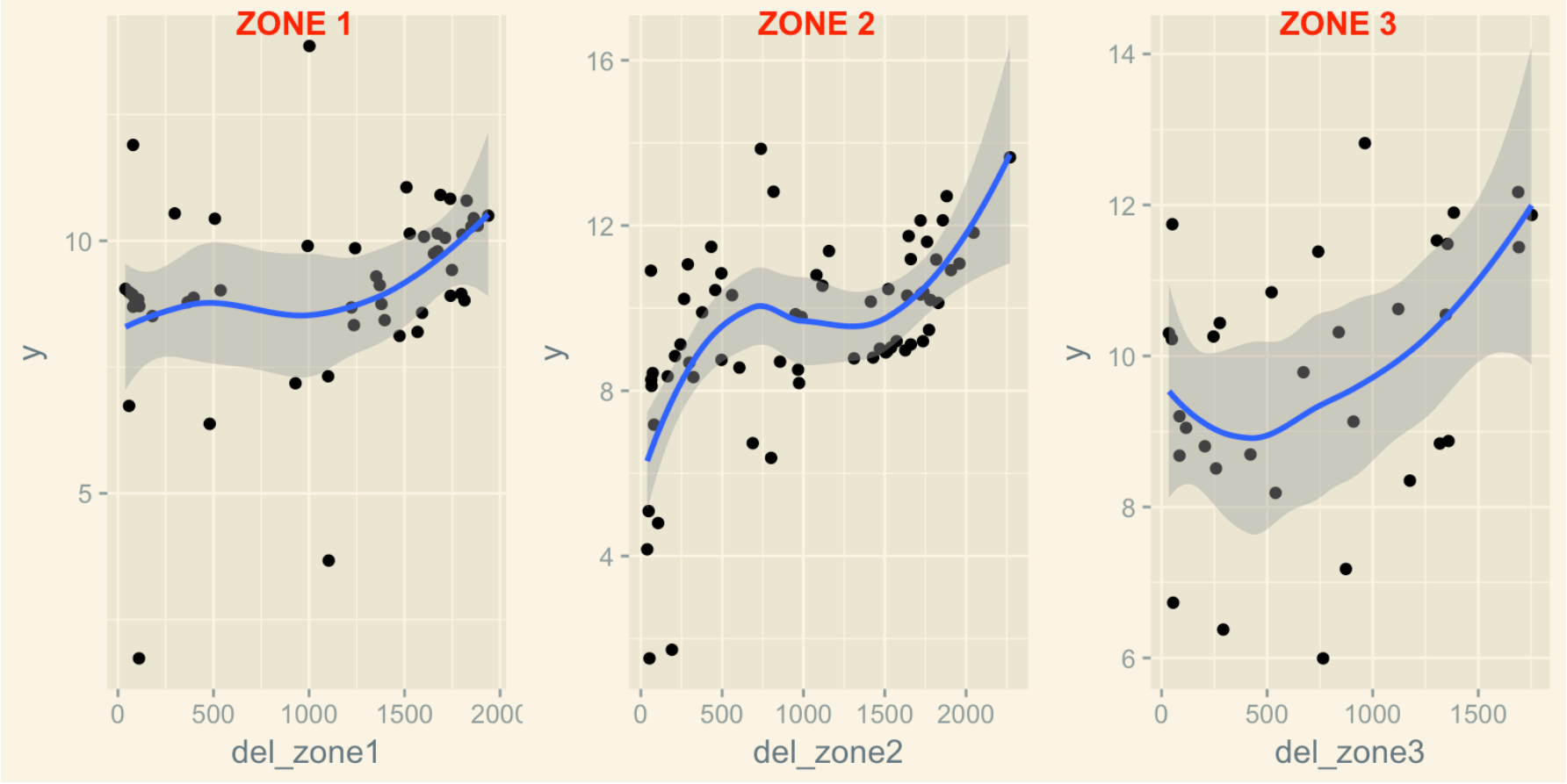


The graph shows a positive relationship between the y analysed and the total amount of services done.

Y AND AREA OF DELIVERY

```
aggregate_data_last_zone1 <- aggregate_data_last %>% filter(aggregate_data_last$de
l_zone1>30)
zone1_plot <- ggplot(data = aggregate_data_last_zone1, aes(x = del_zone1, y = y))+
geom_point()+ geom_smooth()+ theme_solarized_2()

aggregate_data_last_zone2 <- aggregate_data_last %>% filter(aggregate_data_last$de
l_zone2>30)
zone2_plot <- ggplot(data = aggregate_data_last_zone2, aes(x = del_zone2, y = y))+
geom_point()+ geom_smooth()+ theme_solarized_2()

aggregate_data_last_zone3 <- aggregate_data_last %>% filter(aggregate_data_last$de
l_zone3>30)
zone3_plot <-ggplot(data = aggregate_data_last_zone3, aes(x = del_zone3, y = y))+
geom_point()+ geom_smooth()+ theme_solarized_2()
```

```
library(ggpubr)

ggarrange(zone1_plot, zone2_plot, zone3_plot ,
          labels = c("ZONE 1", "ZONE 2", "ZONE 3"),
          ncol = 3, nrow = 1, font.label = list(size = 12, face = "bold", color ="
red"),hjust = -2)
```



Zone 1 seems to be the area where the ratio between deliveries and worked area is more constant. Opposite situation regards the zone 2.