

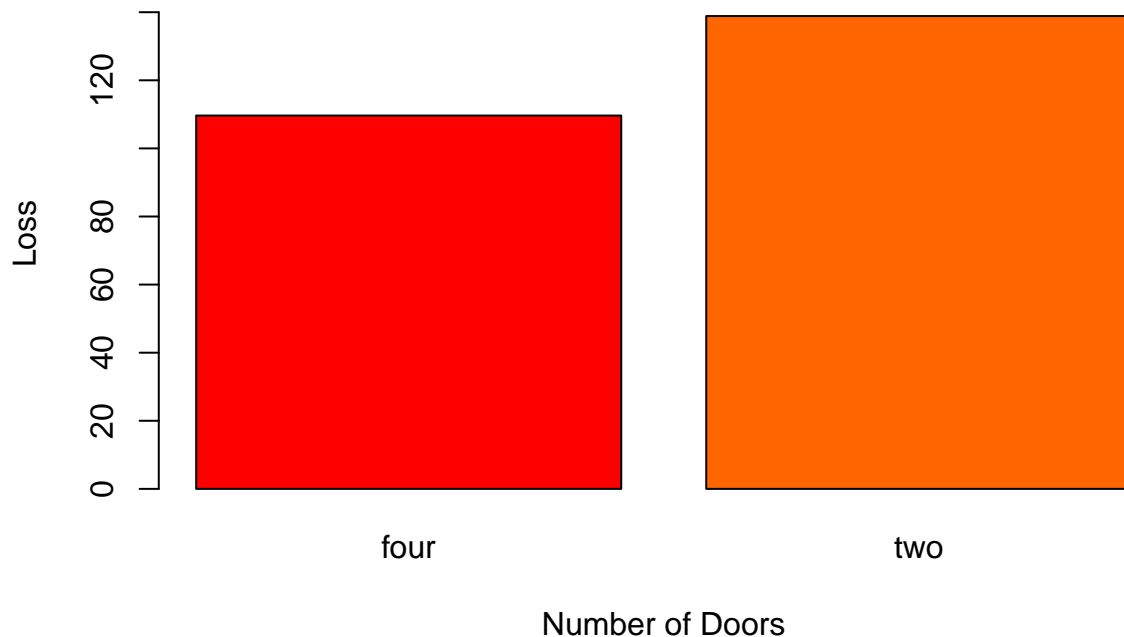
# Auto Losses and Bikeshare Analysis - Shahin Shakeri

I use R notebooks in RStudio cloud and the data is stored in the cloud on my google drive. I submitted this notebook in original format which can be simply be opened in R desktop and run.

## 1- Auto Losses

### 1.a) Two door cars are correlated with more losses

```
library('lattice')
Autoloss <- read.csv(url("https://drive.google.com/uc?export=download&id=1cbk_KGdo5sfY0c4_ALB5ULTeYQ87u"))
Autoloss <- na.omit (Autoloss)
ByDoors=taapply(Autoloss$Losses, Autoloss$NumDoors, mean)
barplot(ByDoors, col = rainbow(15),xlab="Number of Doors",ylab = "Loss",ylim=c(0,150))
```



### 1.b) Sedans have the lowest losses among the least costly losses. This doesn't mean the entire dataset follows this pattern.

```
Lowest<- Autoloss[order(Autoloss$Losses,decreasing=FALSE),][1:10,]
Lowest<-taapply(Lowest$Losses,Lowest$BodyStyle , mean)
Lowest
```

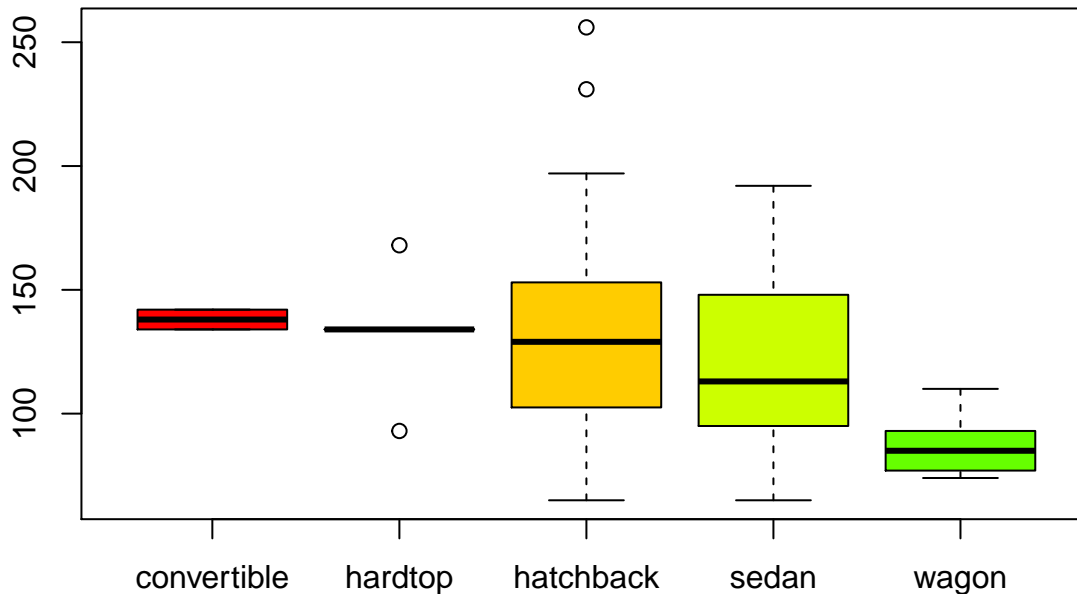
## convertible	hardtop	hatchback	sedan	wagon
## NA	NA	68	65	74

1.c) Sedans and Hatchbacks have the widest spread of losses. The losses in sedan are skewed towards the lower end where in the other styles are more or less evenly distributed.

```
ByWheels<-tapply(AutoLoss$Losses,AutoLoss$BodyStyle,mean)
ByWheels
```

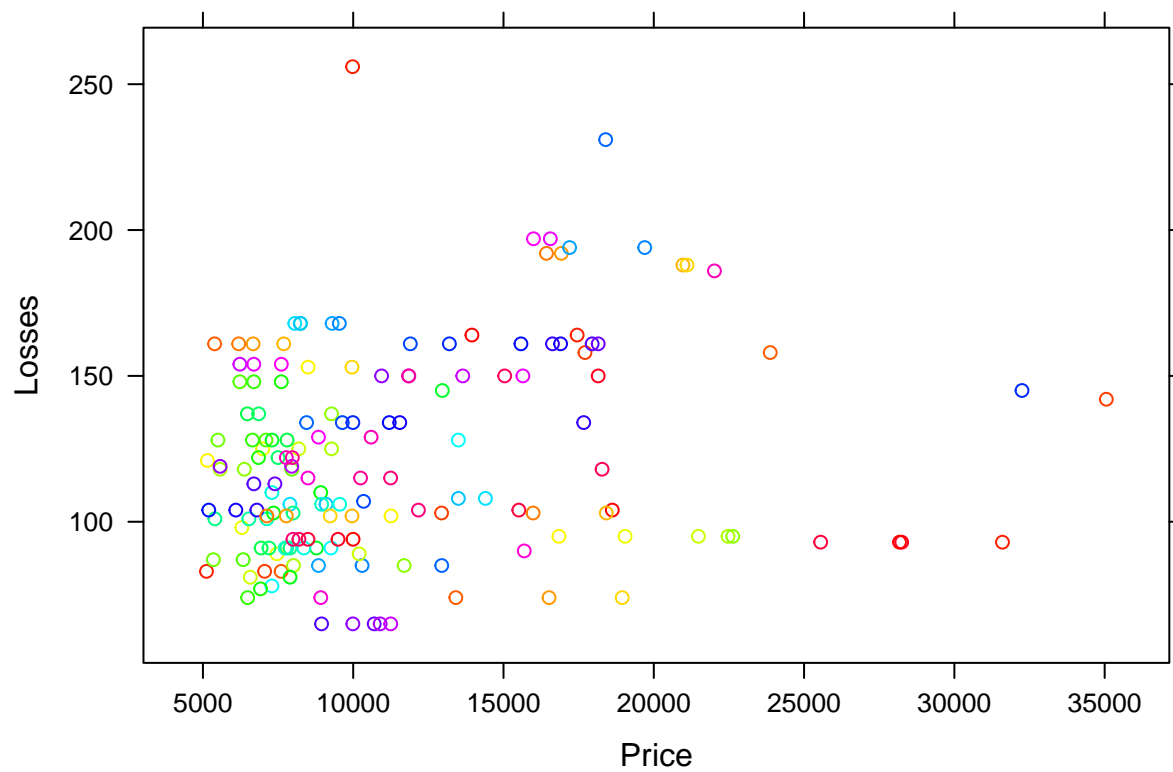
```
## convertible      hardtop    hatchback      sedan      wagon
##   138.00000    132.60000    132.08333    120.35443    87.52941
```

```
boxplot(Losses~BodyStyle,data=AutoLoss ,col = rainbow(15))
```



1.d) Lower priced car have costlier losses than higher priced cars on average

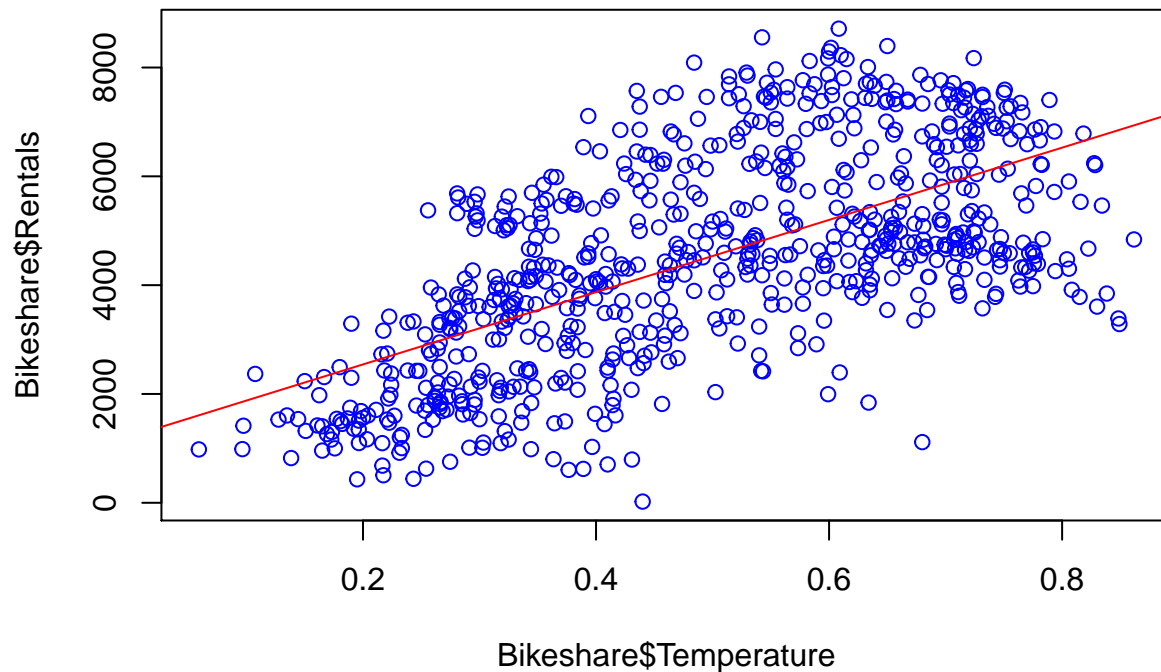
```
xyplot(Losses~Price,data=AutoLoss, col = rainbow(50))
```



## 2 -Bikeshare

2.a) We run a simple regression for  $\text{Rentals} \sim \text{Temperature}$

```
Bikeshare <- read.csv(url("https://drive.google.com/uc?export=download&id=1jtfh-qmyDM3l_nU3AkPP_ZsepL-j"))
LModel=lm(Rentals~Temperature,data=Bikeshare)
{plot(Bikeshare$Temperature,Bikeshare$Rentals,col='blue')
abline(LModel,col="red" )}
```



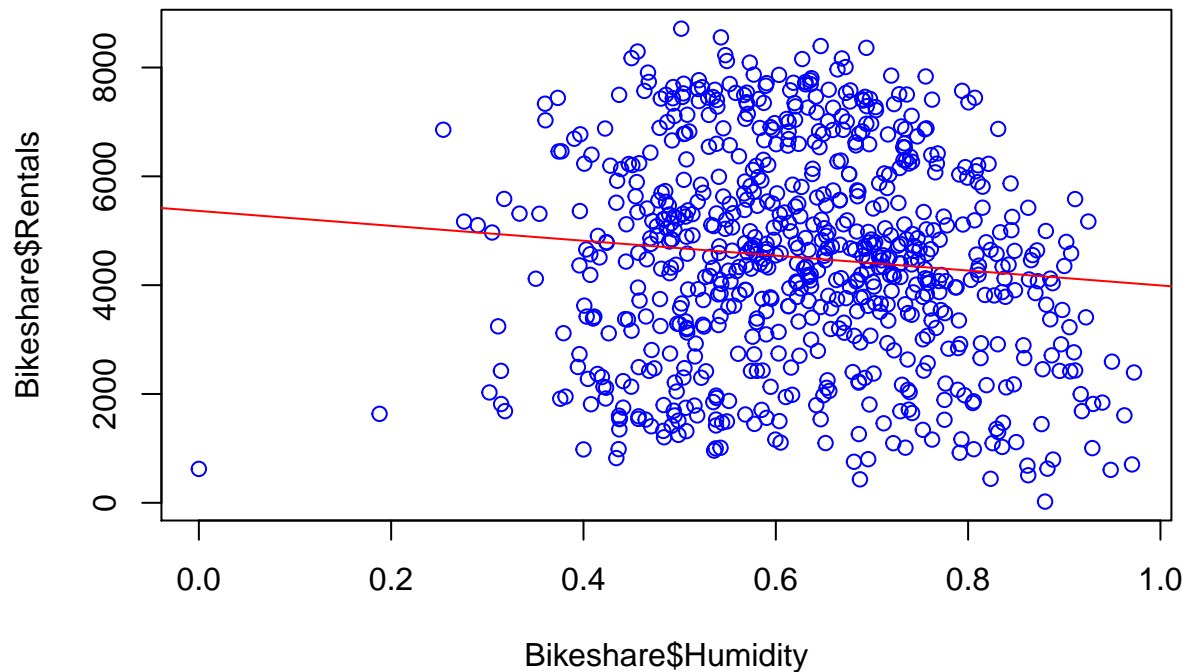
```
summary(LModel)
```

```
##
## Call:
## lm(formula = Rentals ~ Temperature, data = Bikeshare)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4615.3 -1134.9  -104.4   1044.3   3737.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1214.6      161.2    7.537 1.43e-13 ***
## Temperature   6640.7      305.2   21.759 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1509 on 729 degrees of freedom
## Multiple R-squared:  0.3937, Adjusted R-squared:  0.3929
## F-statistic: 473.5 on 1 and 729 DF,  p-value: < 2.2e-16
```

For every 1 change to normalized Temperature, Rentals change by 6640.7. According to small  $p < .05$  this is significant

2.b) We run a simple regression for Rentals~Humidity

```
LModel=lm(Rentals~Humidity,data=Bikeshare)
{plot(Bikeshare$Humidity,Bikeshare$Rentals,col='blue')
abline(LModel,col="red" )}
```



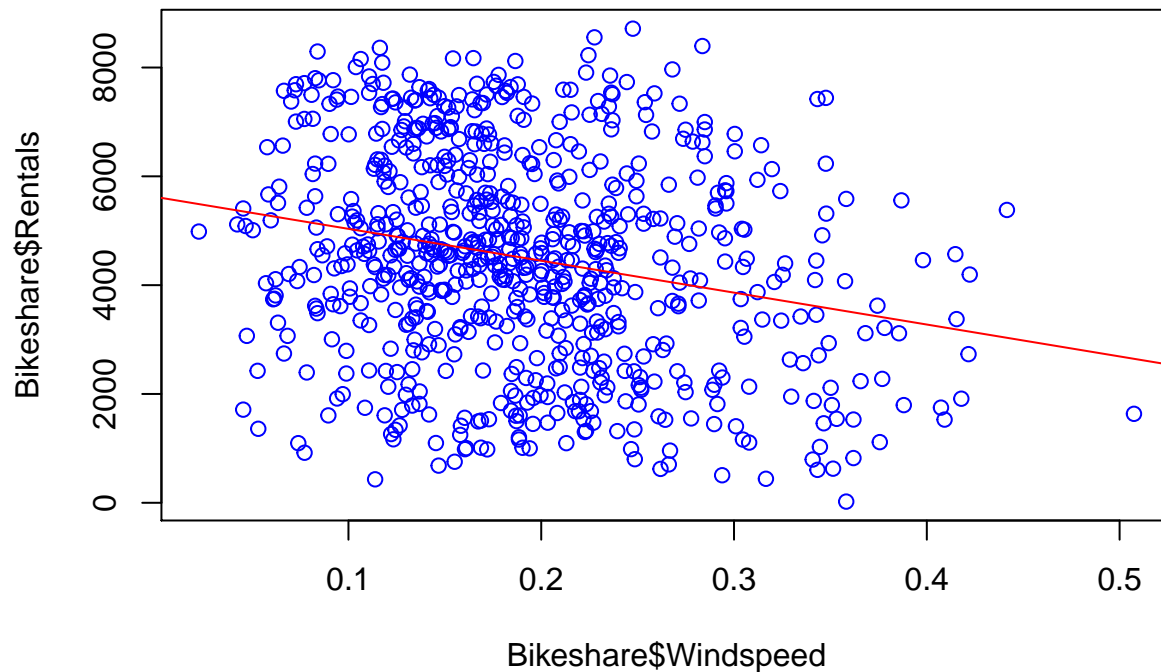
```
summary(LModel)
```

```
##
## Call:
## lm(formula = Rentals ~ Humidity, data = Bikeshare)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4741.0 -1386.9   50.3  1439.3  4036.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5364.0      322.7  16.623 < 2e-16 ***
## Humidity     -1369.1      501.2  -2.732  0.00645 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1929 on 729 degrees of freedom
## Multiple R-squared:  0.01013,    Adjusted R-squared:  0.008774
## F-statistic: 7.462 on 1 and 729 DF,  p-value: 0.006454
```

For every 1 increase to normalized Humidity, Rentals change by -1369.1/100 . According to small  $p < .05$  this is significant but the R-squared: 0.01013 shows this is not a good model

2.c) We run a simple regression for Rentals~Windspeed

```
LModel=lm(Rentals~Windspeed,data=Bikeshare)
{plot(Bikeshare$Windspeed,Bikeshare$Rentals,col='blue')
abline(LModel,col="red" )}
```



```
summary(LModel)
```

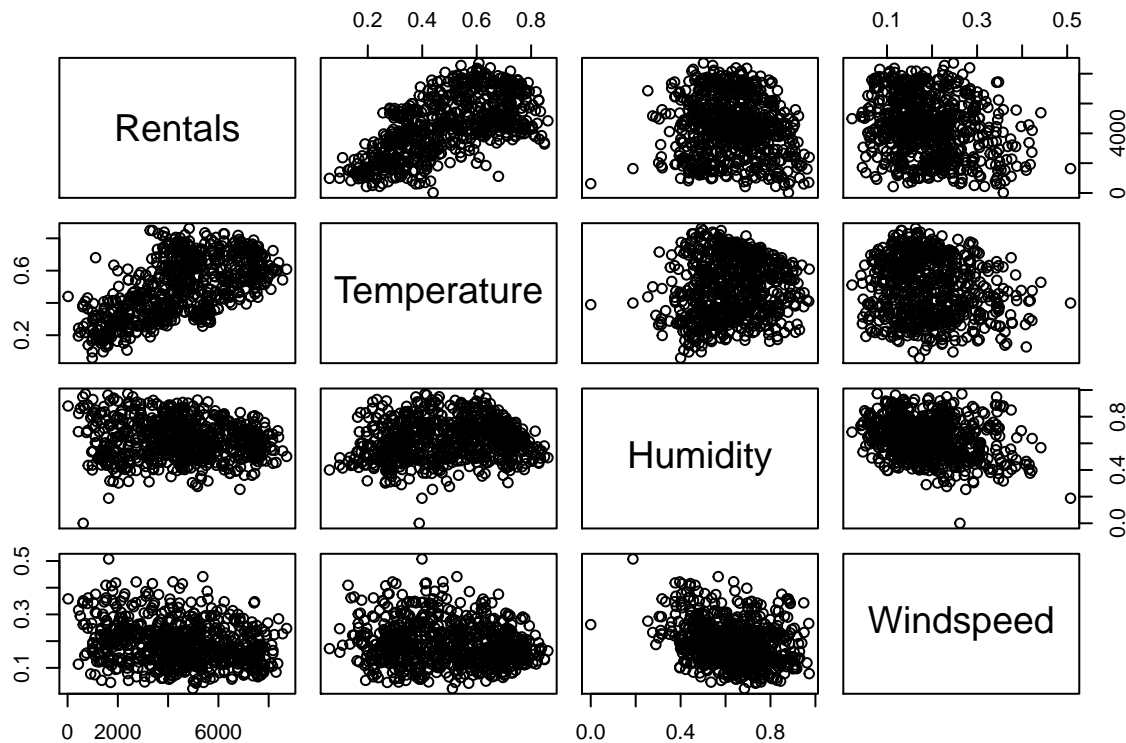
```
##
## Call:
## lm(formula = Rentals ~ Windspeed, data = Bikeshare)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4522.7 -1374.7   -74.6  1461.8  4544.0
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5621.2      185.1  30.374 < 2e-16 ***
## Windspeed    -5862.9      900.0  -6.514 1.36e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1884 on 729 degrees of freedom
## Multiple R-squared:  0.05501,    Adjusted R-squared:  0.05372
## F-statistic: 42.44 on 1 and 729 DF,  p-value: 1.36e-10
```

For every 1 increase to Windspeed, Rentals change by -5862.9/69. According to small  $p < .05$  this is significant but R-squared: 0.05501 shows this is not significant

#3 Multiple Linear Regression

3.a)

```
pairs(Rentals~Temperature+ Humidity +Windspeed ,data=Bikeshare)
```



3.b) We use a multivar regression model

```
model <- lm(Rentals~Temperature+ Humidity +Windspeed ,data=Bikeshare)
```

```
summary(model)
```

```
##
## Call:
## lm(formula = Rentals ~ Temperature + Humidity + Windspeed, data = Bikeshare)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4780.5 -1082.6   -62.2  1056.5  3653.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4084.4      337.9  12.089 < 2e-16 ***
## Temperature   6625.5      293.1  22.606 < 2e-16 ***
## Humidity     -3100.1      384.0  -8.073 2.83e-15 ***
## Windspeed    -4806.9      708.9  -6.781 2.48e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1425 on 727 degrees of freedom
## Multiple R-squared:  0.4609, Adjusted R-squared:  0.4587
```

```
## F-statistic: 207.2 on 3 and 727 DF,  p-value: < 2.2e-16
```

In the order of p value Temperature, Humidity and Windspeed have the highest impact/

3.c)

```
new_day<-data.frame(Temperature=(15-(-8))/39, Humidity=50/100,Windspeed=5/67)  
predict(model,new_day,interval='confidence')
```

```
##          fit      lwr      upr  
## 1 6082.941 5848.711 6317.171
```