

```

## 462    20.2  14.65  17.7      0
## 463    20.2  13.99  19.5      0
## 464    20.2  10.29  20.2      0
## 465    20.2  13.22  21.4      0
## 466    20.2  14.13  19.9      0
## 467    20.2  17.15  19.0      0
## 468    20.2  21.32  19.1      0
## 469    20.2  18.13  19.1      0
## 470    20.2  14.76  20.1      0
## 471    20.2  16.29  19.9      0
## 472    20.2  12.87  19.6      0
## 473    20.2  14.36  23.2      0
## 474    20.2  11.66  29.8      0
## 475    20.2  18.14  13.8      0
## 476    20.2  24.10  13.3      0
## 477    20.2  18.68  16.7      0
## 478    20.2  24.91  12.0      0
## 479    20.2  18.03  14.6      0
## 480    20.2  13.11  21.4      0
## 481    20.2  10.74  23.0      0
## 482    20.2   7.74  23.7      0
## 483    20.2   7.01  25.0      0
## 484    20.2  10.42  21.8      0
## 485    20.2  13.34  20.6      0
## 486    20.2  10.58  21.2      0
## 487    20.2  14.98  19.1      0
## 488    20.2  11.45  20.6      0
## 489    20.1  18.06  15.2      0
## 490    20.1  23.97   7.0      0
## 491    20.1  29.68   8.1      0
## 492    20.1  18.07  13.6      0
## 493    20.1  13.35  20.1      0
## 494    19.2  12.01  21.8      0
## 495    19.2  13.59  24.5      0
## 496    19.2  17.60  23.1      0
## 497    19.2  21.14  19.7      0
## 498    19.2  14.10  18.3      0
## 499    19.2  12.92  21.2      0
## 500    19.2  15.10  17.5      0
## 501    19.2  14.33  16.8      0
## 502    21.0   9.67  22.4      0
## 503    21.0   9.08  20.6      0
## 504    21.0   5.64  23.9      0
## 505    21.0   6.48  22.0      0
## 506    21.0   7.88  11.9      0

```

The following chunk will help you in creating Training/Validation/Testing Partitons in your Data.

```

set.seed(1)
train.rows <- sample(rownames(housing), dim(housing)[1]*0.6)
# The code above means -- sample(data,selecting column using dim() and then multiplying it by 0.6 which
train.data <- housing[train.rows, ] #This command is basically superposing the entire housing data on t

valid.rows <- setdiff(rownames(housing), train.rows) #The setdiff() command is a SETS command which cho

```

```
valid.data <- housing[valid.rows, ]

# alternative code for validation (works only when row names are numeric): # collect all the column.

# Just in case if you also want to add a TEST PARTITION in your data you would execute the following co
# test.rows <- setdiff(rownames(housing), union(train.rows, valid.rows))
# test.data <- housing[test.rows, ]
```

## #Chapter 3:- Data Visualization

### 1.Histograms 2.Box Plots 3.Bar Graphs 4.HeatMaps

```
{r} ## simple heatmap of correlations (without values) heatmap(cor(housing), Rowv = NA, Colv = NA)
```

```
install.packages("reshape") library(ggplot2) library(reshape) # to generate input for the plot cor.mat <-
round(cor(housing),2) # rounded correlation matrix melted.cor.mat <- melt(cor.mat) ggplot(melted.cor.mat,
aes(x = X1, y = X2, fill = value)) + geom_tile() + geom_text(aes(x = X1, y = X2, label = value))
```

```
#The command below gives you a heatmap of missing data heatmap(1 * is.na(housing), Rowv = NA, Colv
= NA)
```

“

#Full of Errors.....

```
{r} ## color plot par(xpd=TRUE) # allow legend to be displayed outside of plot area
plot(housing$NOX ~ housing$LSTAT, ylab = "NOX", xlab = "LSTAT", col = ifelse(housing$CAT..MEDV
== 1, "black", "gray")) # add legend outside of plotting area # In legend() use argument
inset = to control the location of the legend relative # to the plot. legend("topleft",
inset=c(0, -0.2), legend = c("CAT.MEDV = 1", "CAT.MEDV = 0"), col = c("black", "gray"), pch
= 1, cex = 0.5) # alternative plot with ggplot library(ggplot2) ggplot(housing, aes(y =
NOX, x = LSTAT, colour= CAT..MEDV)) + geom_point(alpha = 0.6) ## panel plots # compute
mean MEDV per RAD and CHAS # In aggregate() use argument drop = FALSE to include all
combinations # (existing and missing) of RAD X CHAS. data.for.plot <- aggregate(housing$MEDV,
by = list(housing$RAD, housing$CHAS), FUN = mean, drop = FALSE) names(data.for.plot)
<- c("RAD", "CHAS", "meanMEDV") # plot the data par(mfcol = c(2,1)) barplot(height =
data.for.plot$meanMEDV[data.for.plot$CHAS == 0], names.arg = data.for.plot$RAD[data.for.plot$CHAS
== 0], xlab = "RAD", ylab = "Avg. MEDV", main = "CHAS = 0") barplot(height = data.for.plot$meanMEDV[dat:
== 1], names.arg = data.for.plot$RAD[data.for.plot$CHAS == 1], xlab = "RAD", ylab =
"Avg. MEDV", main = "CHAS = 1") # alternative plot with ggplot ggplot(data.for.plot) +
geom_bar(aes(x = as.factor(RAD), y = `meanMEDV`), stat = "identity") + xlab("RAD") +
facet_grid(CHAS ~ .) NOX0.4 0.5 0.6 0.7 0.8
```

#Simple Plot

```
# use plot() to generate a matrix of 4X4 panels with variable name on the diagonal,
# and scatter plots in the remaining panels.
```

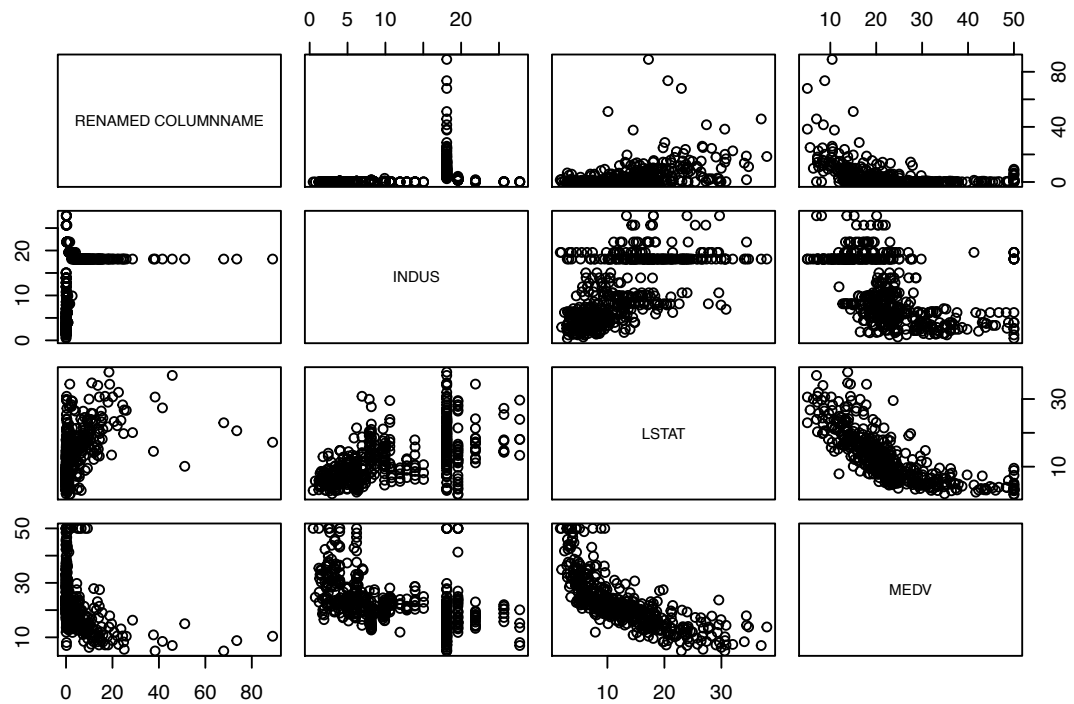
```
plot(housing[, c(1, 3, 12, 13)])
```

```
# ALTERNATIVE, nicer plot (displayed)
```

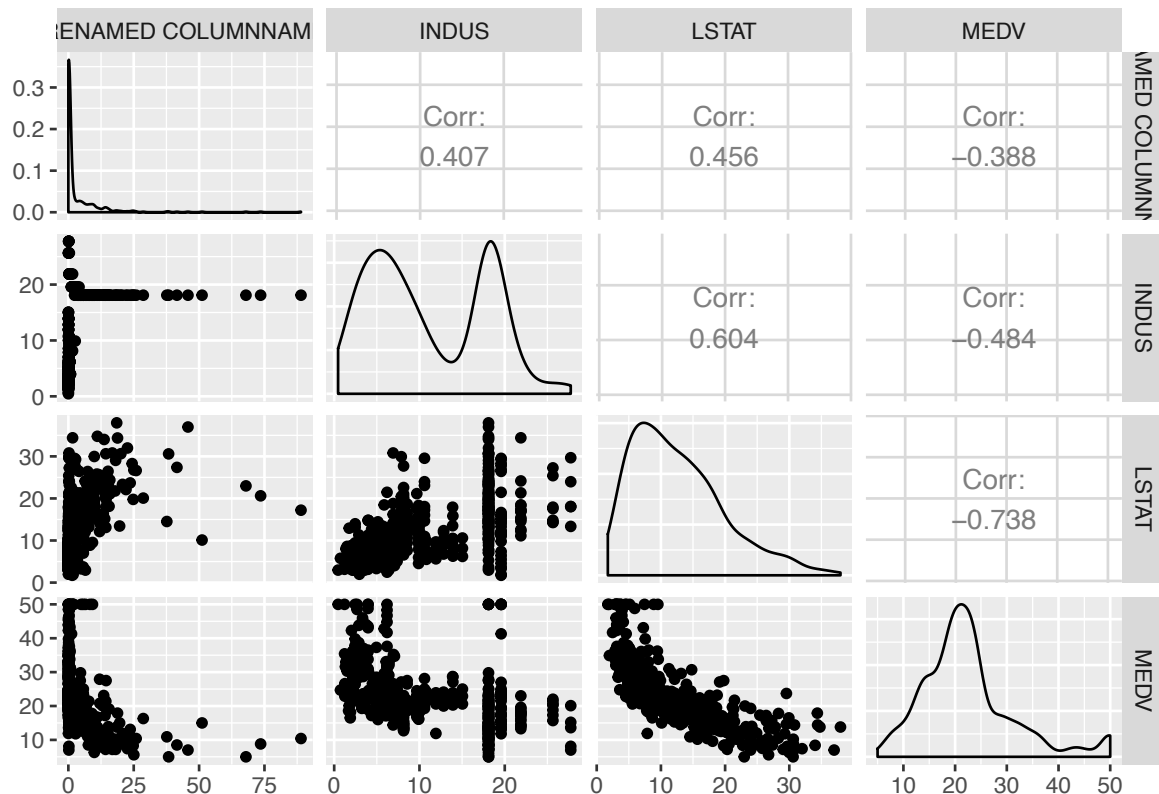
```
#install.packages("GGally")
library(GGally)
```

```
## Loading required package: ggplot2
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg      ggplot2
```



```
ggpairs(housing[, c(1, 3, 12, 13)])
```



#RESCALING to view the visualization in a better way.

“{r}”

## scatter plot: regular and log scale

```
plot(housingMEDV housingCRIM, xlab = "CRIM", ylab = "MEDV") # to use logarithmic scale set
argument log = to either 'x', 'y', or 'xy'. plot(housingMEDV housingCRIM,xlab = "CRIM", ylab =
"MEDV", log = 'xy')
```

## ALTERNATIVE log-scale plot with ggplot

```
library(ggplot2) ggplot(housing) + geom_point(aes(x = CRIM, y = MEDV)) + scale_x_log10(breaks =
10^(-2:2), labels = format(10^(-2:2), scientific = FALSE, drop0trailing = TRUE)) + scale_y_log10(breaks
= c(5, 10, 20, 40)) “
```

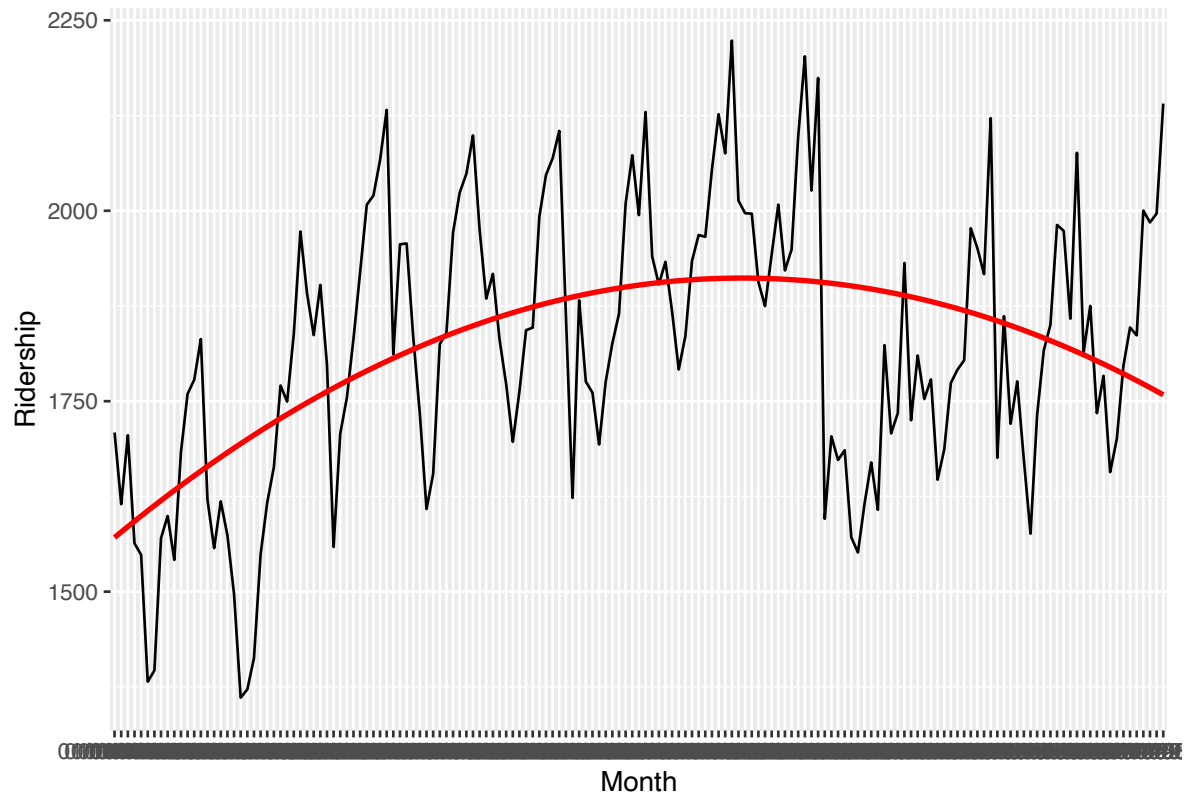
#See and learn how to draw this graph

Read about:- 1. aes 2. geom\_line() 3. geom\_smooth()

#GGPLOT IS CERTAINLY ONE OF THE MOST IMPORTANT LIBRARIES IN R.

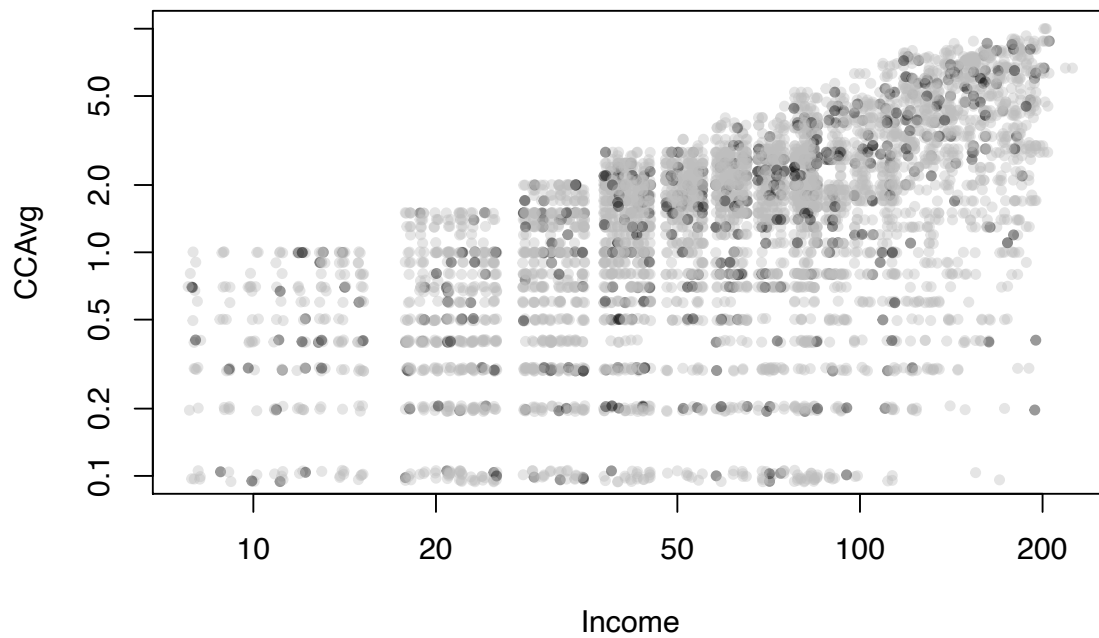
```
# alternative plot with ggplot
library(ggplot2)
Amtrak.df <- read.csv("Amtrak.csv")
```

```
ggplot(Amtrak.df, aes(y = Ridership, x = Month, group = 12)) +
  geom_line() + geom_smooth(formula = y ~ poly(x, 2), method= "lm", colour = "red", se = FALSE, na.rm = T)
```



```
#install.packages("scales")
library(scales)
universal.df <- read.csv("UniversalBank.csv")
plot(jitter(universal.df$CCAvg, 1) ~ jitter(universal.df$Income, 1),
  col = alpha(ifelse(universal.df$Securities.Account == 0, "gray", "black"), 0.4), pch = 20, log = 'xy',
  xlab = "Income", ylab = "CCAvg")
```

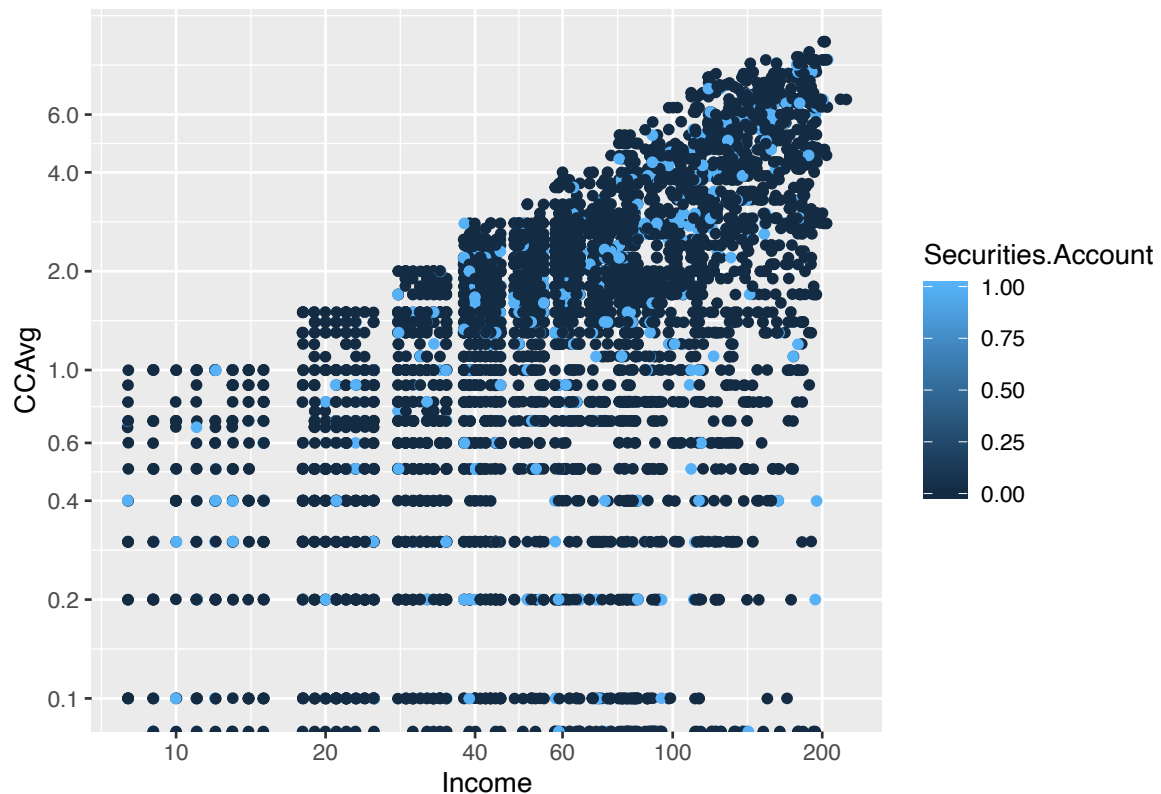
```
## Warning in xy.coords(x, y, xlabel, ylabel, log): 53 y values <= 0 omitted
## from logarithmic plot
```



```
# ALTERNATIVE with ggplot
```

```
library(ggplot2)
ggplot(universal.df) +
  geom_jitter(aes(x = Income, y = CCAvg, colour = Securities.Account)) + scale_x_log10(breaks = c(10, 20,
```

```
## Warning: Transformation introduced infinite values in continuous y-axis
```



#NETWORK GRAPH

Understand the Graph properly EACH and every line of code

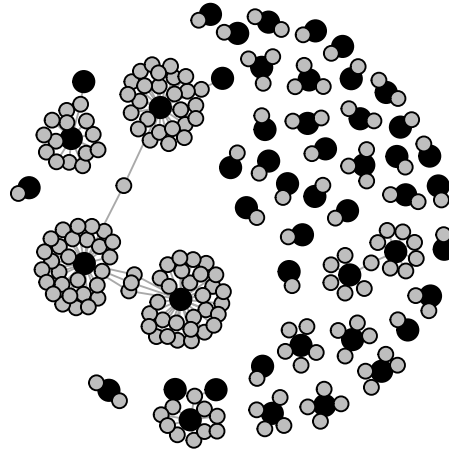
```
#install.packages("igraph")
library(igraph)
```

```
##
## Attaching package: 'igraph'
```

```
## The following objects are masked from 'package:stats':
##
##   decompose, spectrum
```

```
## The following object is masked from 'package:base':
##
##   union
```

```
ebay.df <- read.csv("eBayNetwork.csv")
# transform node ids to factors
ebay.df[,1] <- as.factor(ebay.df[,1])
ebay.df[,2] <- as.factor(ebay.df[,2])
graph.edges <- as.matrix(ebay.df[,1:2])
g <- graph.edgelist(graph.edges, directed = FALSE)
isBuyer <- V(g)$name %in% graph.edges[,2]
plot(g, vertex.label = NA, vertex.color = ifelse(isBuyer, "gray", "black"), vertex.size = ifelse(isBuyer,
```



```
#TreeMaps
```

```
{r} install.packages("treemap") library(treemap) tree.df <- read.csv("EbayTreemap.csv") #
add column for negative feedback tree.df$negative.feedback <- 1* (tree.df$Seller.Feedback
< 0) # draw treemap treemap(tree.df, index = c("Category","Sub.Category", "Brand"),
vSize = "High.Bid", vColor = "negative.feedback", fun.aggregate = "mean", align.labels =
list(c("left", "top"), c("right", "bottom"), c("center", "center")), palette = rev(gray.colors(3)),
type = "manual", title = "")
```

```
{r} library(ggmap) SCstudents <- read.csv("SC-US-students-GPS-data-2016.csv")
```

#In your GCP Console the API Key that you need to use for Google Maps in R is “Maps Static API”. . . .Make sure you disable it once done using because it is NOT for FREE.

```
register_google(key = “AIzaSyDDLm-37lvXKv2ItpvPJDMm5tETM9tkOPo”, write = TRUE)
```

```
Map <- get_map(“Oklahoma City,OK”, zoom = 4) ggmap(Map) + geom_point(aes(x = longitude, y =
latitude), data = SCstudents,alpha = 0.5, colour = “red”, size = 0.8) “
```

```
library(mosaic)
```

```
## Loading required package: dplyr
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:igraph':
```

```
##
```

```
## as_data_frame, groups, union
```



```

## The following object is masked from 'package:GGally':
##
##      nasa

## The following objects are masked from 'package:stats':
##
##      filter, lag

## The following objects are masked from 'package:base':
##
##      intersect, setdiff, setequal, union

## Loading required package: lattice

## Loading required package: ggformula

## Loading required package: ggstance

##
## Attaching package: 'ggstance'

## The following objects are masked from 'package:ggplot2':
##
##      geom_errorbarh, GeomErrorbarh

##
## New to ggformula? Try the tutorials:
##   learnr::run_tutorial("introduction", package = "ggformula")
##   learnr::run_tutorial("refining", package = "ggformula")

## Loading required package: mosaicData

## Loading required package: Matrix

## Registered S3 method overwritten by 'mosaic':
##   method                from
##   fortify.SpatialPolygonsDataFrame ggplot2

##
## The 'mosaic' package masks several functions from core packages in order to add
## additional features. The original behavior of these functions should not be affected by this.
##
## Note: If you use the Matrix package, be sure to load it BEFORE loading mosaic.

##
## Attaching package: 'mosaic'

## The following object is masked from 'package:Matrix':
##
##      mean

```

```
## The following objects are masked from 'package:dplyr':  
##  
##     count, do, tally
```

```
## The following object is masked from 'package:scales':  
##  
##     rescale
```

```
## The following object is masked from 'package:ggplot2':  
##  
##     stat
```

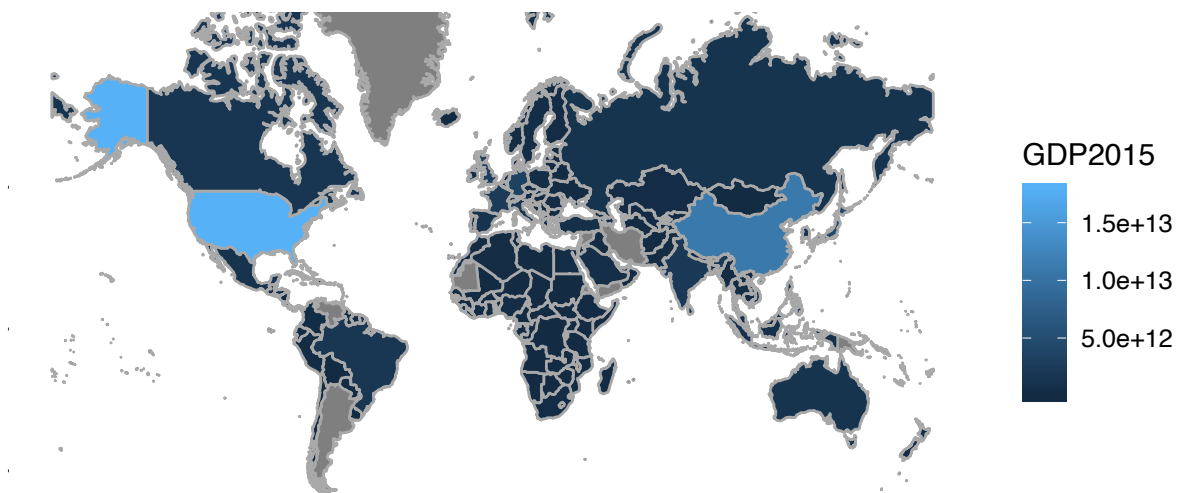
```
## The following objects are masked from 'package:stats':  
##  
##     binom.test, cor, cor.test, cov, fivenum, IQR, median,  
##     prop.test, quantile, sd, t.test, var
```

```
## The following objects are masked from 'package:base':  
##  
##     max, mean, min, prod, range, sample, sum
```

```
#install.packages("lattice")  
#install.packages("ggformula")  
#install.packages("ggstance")  
#install.packages("mapproj")  
  
gdp.df <- read.csv("gdp.csv", skip = 4, stringsAsFactors = FALSE)  
names(gdp.df)[5] <- "GDP2015"  
happiness.df <- read.csv("Veerhoven.csv")  
# gdp map  
mWorldMap(gdp.df, key = "Country.Name", fill = "GDP2015") + coord_map()
```

```
## Mapping API still under development and may change in future releases.
```

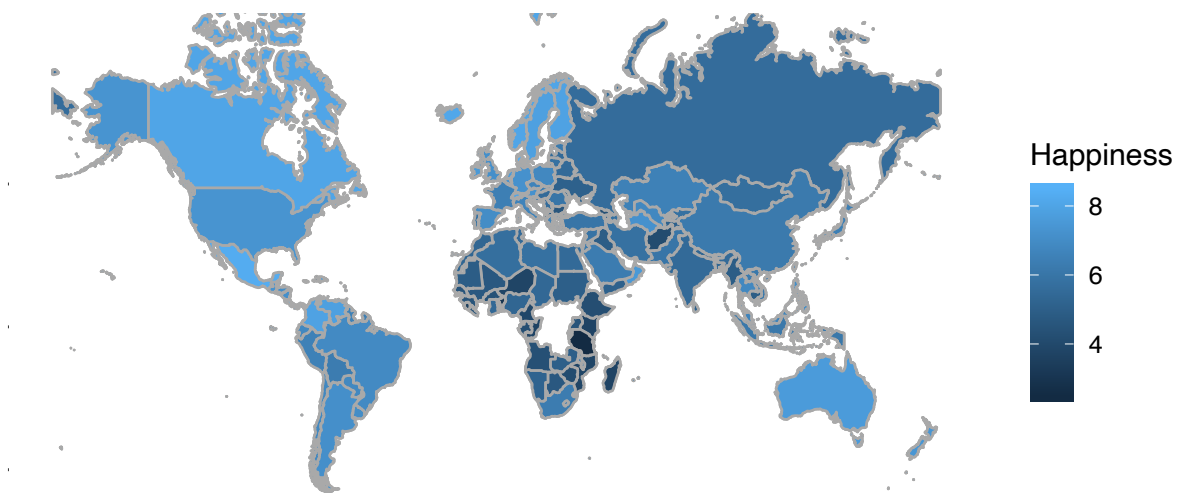
```
## Warning in standardName(x, countryAlternatives, ignore.case =  
## ignore.case, : 52 items were not translated
```



```
# eell-being map  
mWorldMap(happiness.df, key = "Nation", fill = "Score") + coord_map() +  
scale_fill_continuous(name = "Happiness")
```

```
## Mapping API still under development and may change in future releases.
```

```
## Warning in standardName(x, countryAlternatives, ignore.case =  
## ignore.case, : 9 items were not translated
```



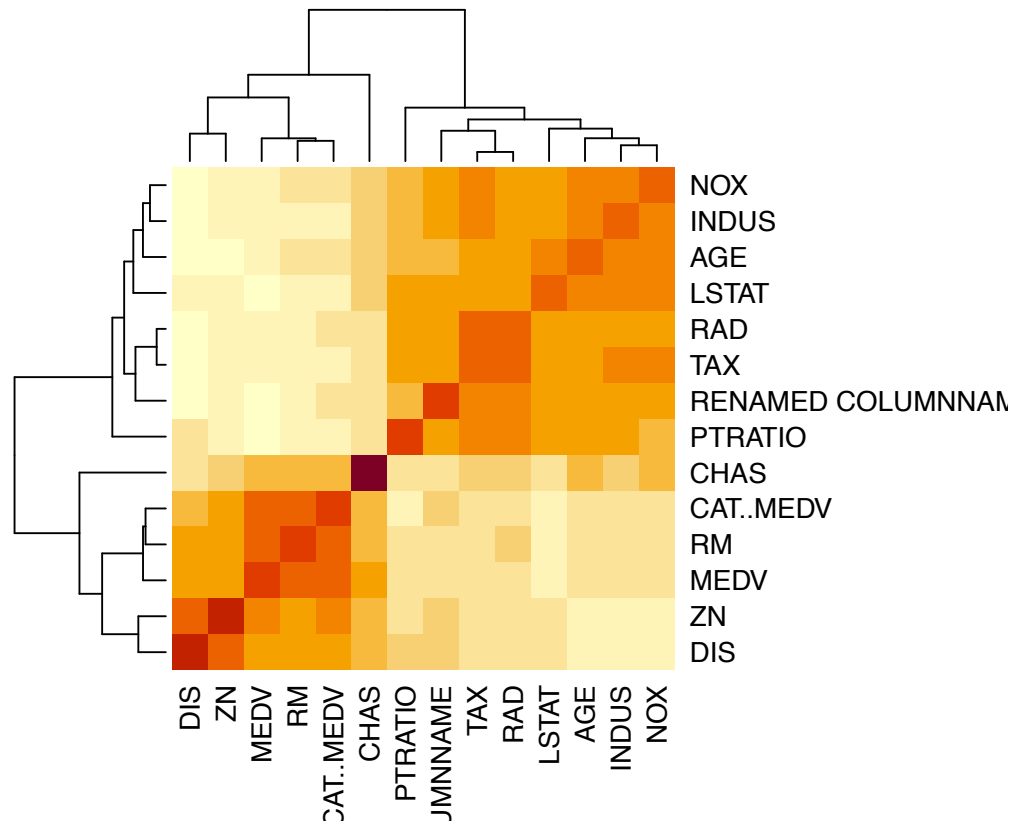
Prediction • Plot outcome on the y-axis of boxplots, bar charts, and scatter plots. • Study relation of outcome to categorical predictors via side-by-side box- plots, bar charts, and multiple panels. • Study relation of outcome to numerical predictors via scatter plots. • Use distribution plots (boxplot, histogram) for determining needed trans- formations of the outcome variable (and/or numerical predictors). • Examine scatter plots with added color/panels/size to determine the need for interaction terms. • Use various aggregation levels and zooming to determine areas of the data with different behavior, and to evaluate the level of global vs. local patterns.

Classification • Study relation of outcome to categorical predictors using bar charts with the outcome on the y-axis. • Study relation of outcome to pairsof numerical predictors via color-coded scatter plots (color denotes the outcome). • Study relation of outcome to numerical predictors via side-by-side box- plots: Plot boxplots of a numerical variable by outcome. Create similar displays for each numerical predictor. The most separable boxes indicate potentially useful predictors. • Use color to represent the outcome variable on a parallel coordinate plot. • Use distribution plots (boxplot, histogram) for determining needed trans- formations of numerical predictor variables. • Examine scatter plots with added color/panels/size to determine the need for interaction terms. • Use various aggregation levels and zooming to determine areas of the data with different behavior, and to evaluate the level of global vs. local patterns.

Time Series Forecasting • Create line graphs at different temporal aggregations to determine types of patterns. • Use zooming and panning to examine various shorter periods of the series to determine areas of the data with different behavior. • Use various aggregation levels to identify global and local patterns. • Identify missing values in the series (that will require handling). • Overlay trend lines of different types to determine adequate modeling choices.

Unsupervised Learning • Create scatter plot matrices to identify pairwise relationships and cluster- ing of observations. • Use heatmaps to examine the correlation table. • Use various aggregation levels and zooming to determine areas of the data with different behavior. • Generate a parallel coordinates plot to identify clusters of observations.

```
heatmap(cor(housing))
```



```
#Principal Component Analysis
```

```
cereals.df <- read.csv("Cereals.csv")
# compute PCs on two dimensions
pcs <- prcomp(data.frame(cereals.df$calories, cereals.df$rating))
summary(pcs)
```

```
## Importance of components:
##                PC1    PC2
## Standard deviation  22.3165  8.8844
## Proportion of Variance  0.8632  0.1368
## Cumulative Proportion  0.8632  1.0000
```

```
pcs$rot
```

```
##                PC1    PC2
## cereals.df.calories  0.8470535  0.5315077
## cereals.df.rating   -0.5315077  0.8470535
```

```
scores <- pcs$x
head(scores, 5)
```

```
##           PC1           PC2
## [1,] -44.921528  2.1971833
## [2,]  15.725265 -0.3824165
## [3,] -40.149935 -5.4072123
## [4,] -75.310772 12.9991256
## [5,]   7.041508 -5.3576857
```

#Evaluating Predictive Performance In this chapter we will evaluate how data mining methods can be assessed on the basis of the following Prediction Accuracy Measures:- 1. Avreage Error 2. MAPE 3. RMSE 4. MPE 5. RMSE

Shown below is how to do Performance Evaluation:-

```
# package forecast is required to evaluate performance
library(forecast)
```

```
## Registered S3 method overwritten by 'xts':
##   method      from
##   as.zoo.xts zoo
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
## Registered S3 methods overwritten by 'forecast':
##   method      from
##   fitted.fracdiff fracdiff
##   residuals.fracdiff fracdiff
```

```
# load file
toyota.corolla.df <- read.csv("ToyotaCorolla.csv")

# randomly generate training and validation sets
training <- sample(toyota.corolla.df$Id, 600)
validation <- sample(setdiff(toyota.corolla.df$Id, training), 400)

# run linear regression model
reg <- lm(Price~., data=toyota.corolla.df[, -c(1,2,8,11)], subset=training, na.action=na.exclude)
pred_t <- predict(reg, na.action=na.pass)
pred_v <- predict(reg, newdata=toyota.corolla.df[validation, -c(1,2,8,11)], na.action=na.pass)
```

```
## Warning in predict.lm(reg, newdata = toyota.corolla.df[validation, -c(1, :
## prediction from a rank-deficient fit may be misleading
```

```
# Performance Evaluation
```

```
# training
accuracy(pred_t, toyota.corolla.df[training,]$Price)
```

```
##           ME      RMSE      MAE      MPE      MAPE
## Test set -1.177212e-10 1051.666 797.3029 -1.006025 8.15141
```

```
# validation
accuracy(pred_v, toyota.corolla.df[validation,]$Price)
```

```
##           ME    RMSE    MAE    MPE    MAPE
## Test set 100.5568 2646.66 944.7535 -0.1726984 8.758258
```