Problem #1

In [1]:

```
library(caretEnsemble)
library(RColorBrewer)
library(tm)
library(datarium)
library(leaps)
library(glmnet)
library(pls)
library(gam)
library(splines)
library(MVA)
library(nortest)
library(mvnormtest)
library(pastecs)
library(mvtnorm)
library(igraph)
library(dplyr)
library(ggplot2)
library(ggraph)
library(caret)
library(car)
library(mlbench)
library(tidyverse)
library(MASS)
library(ISLR)
library(psych)
library(faraway)
library(pls)
library(Matrix)
library(stats)
library(biotools)
library(ggpubr)
library(broom)
library(leaps)
library(tidyverse)
library(funModeling)
library(Hmisc)
```

```
Loading required package: NLP

Loading required package: Matrix

Loaded glmnet 4.1-2


Attaching package: ‘pls’


The following object is masked from ‘package:stats’:

    loadings


Loading required package: splines

Loading required package: foreach

Loaded gam 1.20
```

```
Loading required package: HSAUR2

Loading required package: tools


Attaching package: ‘igraph’


The following objects are masked from ‘package:stats’:

    decompose, spectrum


The following object is masked from ‘package:base’:

    union



Attaching package: ‘dplyr’


The following objects are masked from ‘package:igraph’:

    as_data_frame, groups, union


The following objects are masked from ‘package:pastecs’:

    first, last


The following objects are masked from ‘package:stats’:

    filter, lag


The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union



Attaching package: ‘ggplot2’


The following object is masked from ‘package:NLP’:

    annotate


The following object is masked from ‘package:caretEnsemble’:

    autoplot


Loading required package: lattice
```

```
Attaching package: ‘caret’


The following object is masked from ‘package:pls’:

    R2


Loading required package: carData


Attaching package: ‘car’


The following object is masked from ‘package:dplyr’:

    recode


── Attaching packages ─────────────────────────────────────── tidyverse 1.3.1 ──

✓ tibble  3.1.3     ✓ purrr   0.3.4
✓ tidyr   1.1.3     ✓ stringr 1.4.0
✓ readr   2.0.1     ✓ forcats 0.5.1

── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
x purrr::accumulate()     masks foreach::accumulate()
x ggplot2::annotate()     masks NLP::annotate()
x tibble::as_data_frame() masks dplyr::as_data_frame(), igraph::as_data_frame()
x ggplot2::autoplot()     masks caretEnsemble::autoplot()
x purrr::compose()        masks igraph::compose()
x tidyr::crossing()       masks igraph::crossing()
x tidyr::expand()         masks Matrix::expand()
x tidyr::extract()        masks pastecs::extract()
x dplyr::filter()         masks stats::filter()
x dplyr::first()          masks pastecs::first()
x dplyr::groups()         masks igraph::groups()
x dplyr::lag()            masks stats::lag()
x dplyr::last()           masks pastecs::last()
x purrr::lift()           masks caret::lift()
x tidyr::pack()           masks Matrix::pack()
x car::recode()           masks dplyr::recode()
x purrr::simplify()       masks igraph::simplify()
x purrr::some()           masks car::some()
x tidyr::unpack()         masks Matrix::unpack()
x purrr::when()           masks foreach::when()


Attaching package: ‘MASS’


The following object is masked from ‘package:dplyr’:

    select



Attaching package: ‘psych’


The following object is masked from ‘package:car’:
```

```
    logit


The following objects are masked from ‘package:ggplot2’:

    %+%, alpha



Attaching package: ‘faraway’


The following object is masked from ‘package:psych’:

    logit


The following objects are masked from ‘package:car’:

    logit, vif


The following object is masked from ‘package:lattice’:

    melanoma


The following objects are masked from ‘package:HSAUR2’:

    epilepsy, toenail


---
biotools version 4.2

Loading required package: Hmisc

Loading required package: survival


Attaching package: ‘survival’


The following objects are masked from ‘package:faraway’:

    rats, solder


The following object is masked from ‘package:caret’:

    cluster


Loading required package: Formula


Attaching package: ‘Hmisc’


The following object is masked from ‘package:psych’:
```

```
    describe


The following objects are masked from ‘package:dplyr’:

    src, summarize


The following objects are masked from ‘package:base’:

    format.pval, units


funModeling v.1.9.4 :)
Examples and tutorials at livebook.datascienceheroes.com
 / Now in Spanish: librovivodecienciadedatos.ai
```

In [2]:

```
data01 <- read.csv("https://stats.idre.ucla.edu/stat/data/binary.csv", header=TRUE, strin
```

In [3]:

```
head(data01)
```

A data.frame: 6 × 4

	admit	gre	gpa	rank
	<int>	<int>	<dbl>	<int>
1	0	380	3.61	3
2	1	660	3.67	3
3	1	800	4.00	1
4	1	640	3.19	4
5	0	520	2.93	4
6	1	760	3.00	2

In [4]:

```
str(data01)
```

```
'data.frame':	400 obs. of  4 variables:
 $ admit: int  0 1 1 1 0 1 1 0 1 0 ...
 $ gre  : int  380 660 800 640 520 760 560 400 540 700 ...
 $ gpa  : num  3.61 3.67 4 3.19 2.93 3 2.98 3.08 3.39 3.92 ...
 $ rank : int  3 3 1 4 4 2 1 2 3 2 ...
```

In [41]:

```
admit_f <- as.factor(data01$admit)
admit_f
```

0 · 1 · 1 · 1 · 0 · 1 · 1 · 0 · 1 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 1 · 1 · 1 · 1 · 1 · 0 · 0 · 0 · 0 · 1 ·
0 · 0 · 0 · 0 · 1 · 1 · 0 · 1 · 1 · 0 · 0 · 1 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 1 · 0 · 0 · 0 · 0 ·
0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 ·
0 · 0 · 1 · 1 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 1 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 ·
0 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 1 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 ·

0 · 0 · 0 · 1 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 1 · 0 · 0 · 1 · 0 · 0 · 0 · 1 · 1 · 0 ·
1 · 1 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 1 · 0 · 1 · 0 · 1 · 0 · 0 · 1 · 0 · 0 · 1 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 ·
0 · 0 · 0 · 1 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 1 · 1 · 0 · 1 · 1 · 0 · 0 · 0 · 0 · 1 · 1 · 1 · 0 · 0 · 1 · 1 · 0 · 1 · 0 ·
1 · 0 · 0 · 1 · 0 · 1 · 1 · 1 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 1 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 1 · 1 · 0 · 0 ·
1 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 1 · 1 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 1 · 0 · 0 · 0 · 1 ·
0 · 1 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 0 · 1 · 0 · 1 · 0 · 1 · 1 · 0 · 0 · 1 · 0 · 1 · 1 · 0 · 0 · 1 · 0 · 0 · 0 · 0 · 0 · 1 · 1 · 1 · 1 ·
0 · 0 · 0 · 1 · 0 · 0 · 0 · 1 · 0 · 0 · 1 · 0 · 1 · 0 · 0 · 0 · 1 · 1 · 1 · 1 · 1 · 0 · 0 · 0 · 0 · 0

▶ **Levels**:

In [49]:

```
# Subsetting the data and keeping the required variables
data01 <- data01[ ,c("admit", "gre", "gpa", "rank")]
```

In [45]:

```
# Checking the dim
dim(data01)
```

400 · 4

In [50]:

```
# Generating the frequency table
table(data01$admit)
```

```
  0   1 
273 127 
```

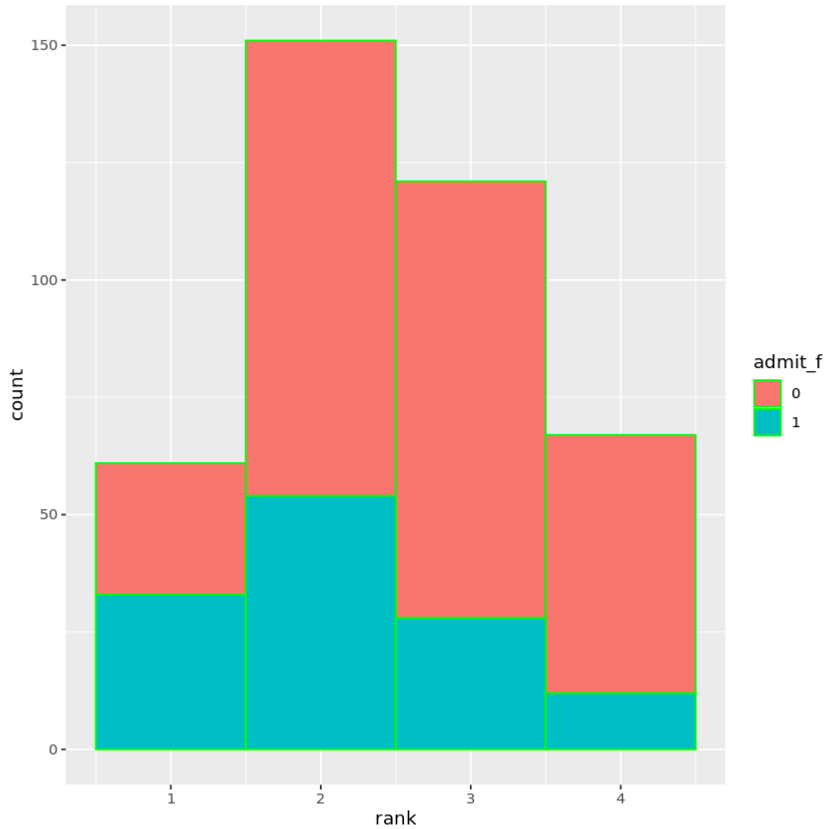
In [51]:

```
table(data01$rank)
```

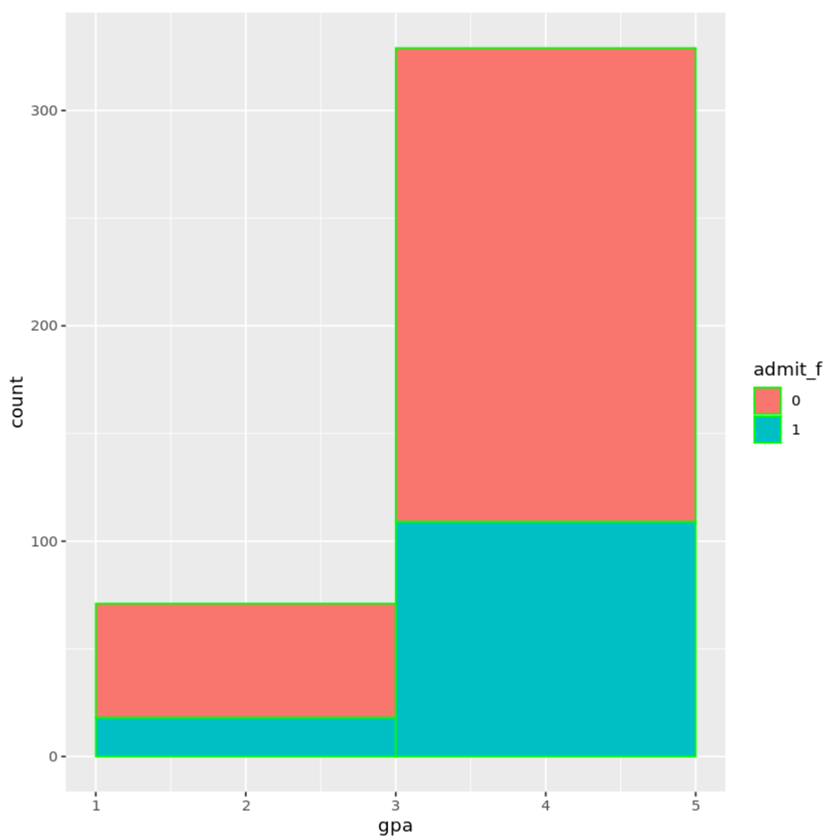
```
  1   2   3   4 
 61 151 121  67 
```

In [68]:

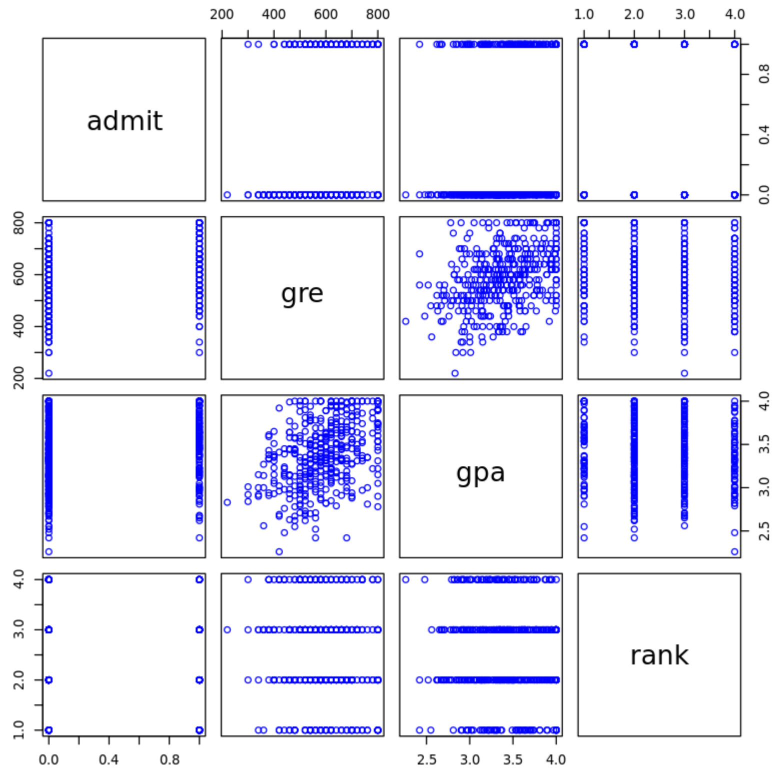
```
ggplot(data01, aes(rank)) +
  geom_histogram(aes(fill = admit_f), color = "green", binwidth = 1)
```



In [71]:
```
ggplot(data01, aes(gpa)) +
  geom_histogram(aes(fill = admit_f), color = "green", binwidth = 2)
```



In [72]:
```
pairs(data01, col = "blue")
```



In [73]:

```
round(stat.desc(cor(data01)),3)
```

A data.frame: 14 × 4

	admit	gre	gpa	rank
	<dbl>	<dbl>	<dbl>	<dbl>
nbr.val	4.000	4.000	4.000	4.000
nbr.null	0.000	0.000	0.000	0.000
nbr.na	0.000	0.000	0.000	0.000
min	-0.243	-0.123	-0.057	-0.243
max	1.000	1.000	1.000	1.000
range	1.243	1.123	1.057	1.243
sum	1.120	1.445	1.505	0.577
median	0.181	0.284	0.281	-0.090
mean	0.280	0.361	0.376	0.144
SE.mean	0.260	0.237	0.227	0.288
CI.mean.0.95	0.827	0.755	0.721	0.916
var	0.270	0.225	0.205	0.331
std.dev	0.520	0.474	0.453	0.576
coef.var	1.857	1.313	1.205	3.994

In [19]:

```
library(corrplot)
```

```
corrplot 0.90 loaded


Attaching package: ‘corrplot’


The following object is masked from ‘package:pls’:

    corrplot
```

In [12]:

```
data01c <- cor(data01)
```

In [13]:

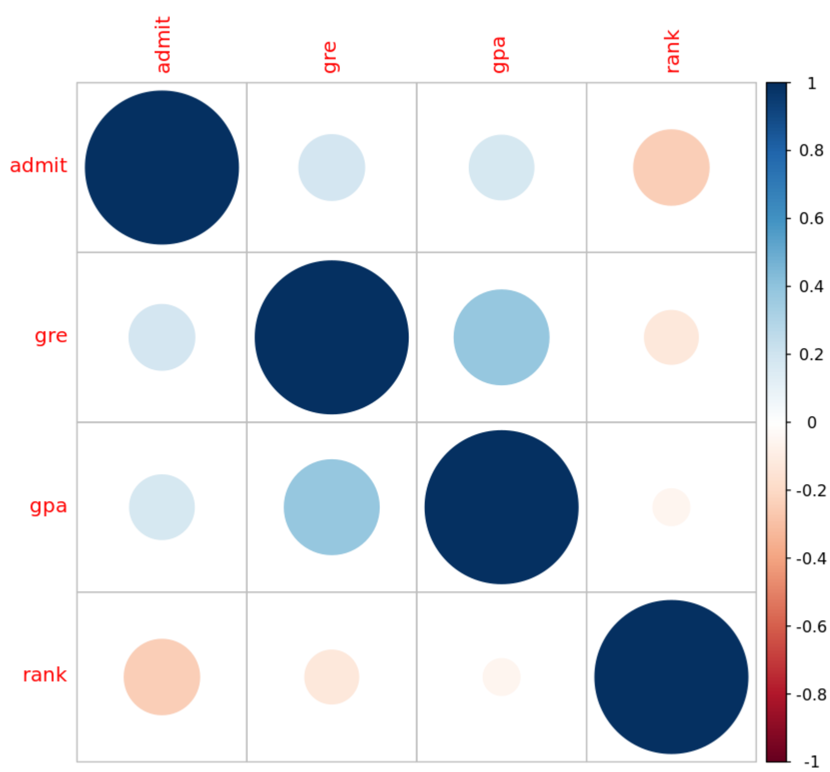
```
head(data01c)
```

A matrix: 4 × 4 of type dbl

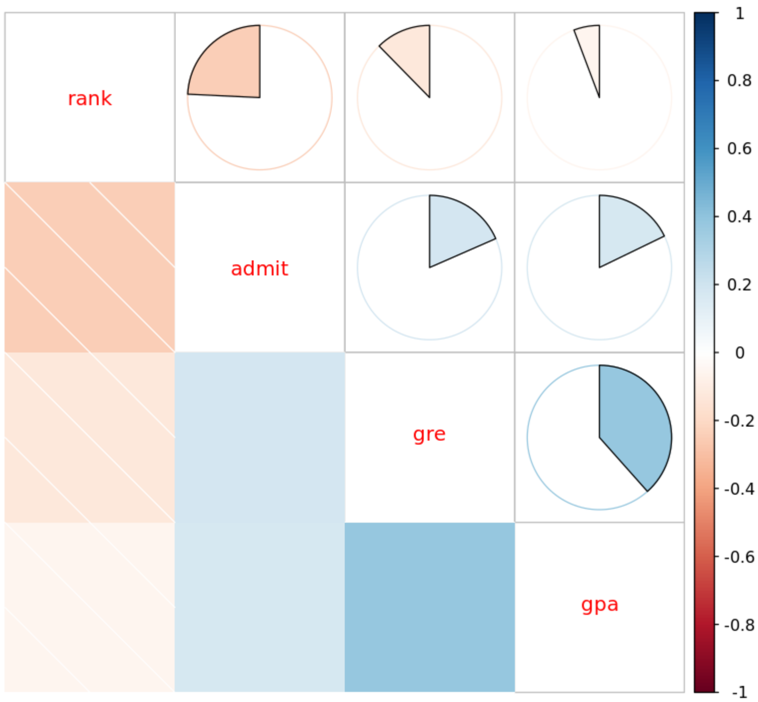
	admit	gre	gpa	rank
admit	1.0000000	0.1844343	0.17821225	-0.24251318
gre	0.1844343	1.0000000	0.38426588	-0.12344707
gpa	0.1782123	0.3842659	1.00000000	-0.05746077
rank	-0.2425132	-0.1234471	-0.05746077	1.00000000

In [20]:

```
corrplot(data01c)
```



In [21]:
```
corrplot.mixed(data01c, lower = 'shade', upper = 'pie', order = 'hclust')
```



In [6]:
```
# Exploratory data analysis
# Number of observations (rows) and variables
glimpse(data01)
```

```
Rows: 400
Columns: 4
$ admit <int> 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1…
$ gre   <int> 380, 660, 800, 640, 520, 760, 560, 400, 540, 700, 800, 440, 760,…
$ gpa   <dbl> 3.61, 3.67, 4.00, 3.19, 2.93, 3.00, 2.98, 3.08, 3.39, 3.92, 4.00…
$ rank  <int> 3, 3, 1, 4, 4, 2, 1, 2, 3, 2, 4, 1, 1, 2, 1, 3, 4, 3, 2, 1, 3, 2…
```

In [7]:
```
# Getting the metrics about data types, zeros, infinite numbers, and missing values
status(data01)
```

A data.frame: 4 × 9

	variable	q_zeros	p_zeros	q_na	p_na	q_inf	p_inf	type	unique
	<chr>	<int>	<dbl>	<int>	<dbl>	<int>	<dbl>	<chr>	<int>
admit	admit	273	0.6825	0	0	0	0	integer	2
gre	gre	0	0.0000	0	0	0	0	integer	26
gpa	gpa	0	0.0000	0	0	0	0	numeric	132
rank	rank	0	0.0000	0	0	0	0	integer	4

In [9]:
```
# Analyzing numerical variables
```

```
# # Quantitatively
profiling_num(data01)
```

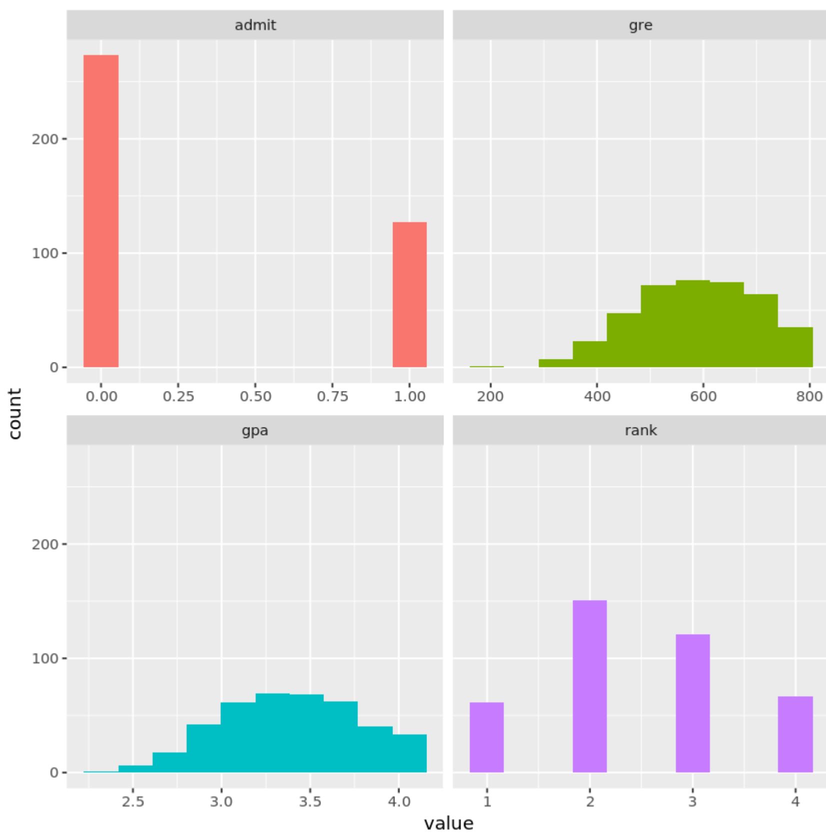
A data.frame: 4 × 16

variable	mean	std_dev	variation_coef	p_01	p_05	p_25	p_50	p_75	p_95	p_99
<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
admit	0.3175	0.4660867	1.4679897	0.0000	0.0000	0.00	0.000	1.00	1	1
gre	587.7000	115.5165364	0.1965570	339.6000	399.0000	520.00	580.000	660.00	800	800
gpa	3.3899	0.3805668	0.1122649	2.5196	2.7585	3.13	3.395	3.67	4	4
rank	2.4850	0.9444602	0.3800645	1.0000	1.0000	2.00	2.000	3.00	4	4

In [10]:

```
# Graphically
plot_num(data01)
```

```
Warning message:
“`guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> = "none")` instead.”
```



In [11]:

```
# Analyzing numerical and categorical at the same time
describe(data01)
```

```
data01

 4  Variables      400  Observations
--------------------------------------------------------------------------------
admit
```

```
       n  missing distinct     Info      Sum     Mean      Gmd 
     400        0        2     0.65      127   0.3175   0.4345 

--------------------------------------------------------------------------------
gre 
       n  missing distinct     Info     Mean      Gmd      .05      .10 
     400        0       26    0.997    587.7    131.2      399      440 
     .25      .50      .75      .90      .95 
     520      580      660      740      800 

lowest : 220 300 340 360 380, highest: 720 740 760 780 800
--------------------------------------------------------------------------------
gpa 
       n  missing distinct     Info     Mean      Gmd      .05      .10 
     400        0      132        1     3.39   0.4351    2.758    2.900 
     .25      .50      .75      .90      .95 
   3.130    3.395    3.670    3.940    4.000 

lowest : 2.26 2.42 2.48 2.52 2.55, highest: 3.95 3.97 3.98 3.99 4.00
--------------------------------------------------------------------------------
rank 
       n  missing distinct     Info     Mean      Gmd 
     400        0        4     0.91    2.485    1.038 

Value          1     2     3     4
Frequency     61   151   121    67
Proportion 0.152 0.378 0.302 0.168
--------------------------------------------------------------------------------
```

In [75]:

```
# Splitting the data into train and test
index <- createDataPartition(data01$admit, p = .70, list = FALSE)
train <- data01[index, ]
test <- data01[-index, ]
```

In [28]:

```
# Training the model
model01 <- glm(admit ~ ., family = binomial(), train)
```

In [29]:

```
# Checking the model
summary(model01)
```

```
Call:
glm(formula = admit ~ ., family = binomial(), data = train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-1.6215  -0.9049  -0.6054   1.1610   2.1185  

Coefficients:
             Estimate Std. Error z value Pr(>|z|)    
(Intercept) -3.062512   1.366750  -2.241   0.0250 *  
gre          0.002386   0.001287   1.854   0.0637 .  
gpa          0.697089   0.393053   1.774   0.0761 .  
rank        -0.611697   0.153179  -3.993 6.51e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 355.98  on 279  degrees of freedom
Residual deviance: 325.11  on 276  degrees of freedom
AIC: 333.11

Number of Fisher Scoring iterations: 3
```

In [32]:
```
exp(-0.611697)
```

0.542429584580667

In [38]:
```
p = exp(-0.611697)
p
```

0.542429584580667

In [39]:
```
k = 1- p
k
```

0.457570415419333

There is only one statistically significant variable - rank. Null deviance suggests the response by the model if we only consider the intercept. Lower the value better is the model. The Residual deviance indicates the response by the model when all the variables are included, again, lower the value, better is the model. The beta coefficient of the rank variable is -0.611697, which is in the logit of odds terms. When convert this to odds by taking exp(-0.611697) the result is 0.542429584580667 < 1. The value indicates that the odds of an individual with lower rank to get admited decreases by 46% than the one in with higher rank.

In [30]:
```
# Predicting in the test dataset
model01_pred <- predict(model01, test, type = "response")
```

In [148]:
```
summary(model01_pred)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.06118 0.19618 0.31002 0.31508 0.40660 0.69290 
```

In [78]:
```
# Converting from probability to actual output
model01_pred_conv <- ifelse(model01$fitted.values >= 0.5, "0", "1")
```

In [79]:
```
# Generating the classification table - train
model01_clstab_train <- table(train$admit, model01_pred_conv)
model01_clstab_train
```

```
   model01_pred_conv
      0   1
  0  28 164
  1  13  75
```

In [82]:
```
# Converting from probability to actual output
model01_test_pred <- ifelse(model01_pred >= 0.5, "0", "1")
```

In [83]:
```
# Generating the classification table - test
```

```
model01_clstab_test <- table(test$admit, model01_test_pred)
model01_clstab_test
```

```
   model01_test_pred
     0  1
  0 13 68
  1  1 38
```

In [80]:

```
# Accuracy in Training dataset
accuracy_model01_train <- sum(diag(model01_clstab_train))/sum(model01_clstab_train)*100
accuracy_model01_train
```

36.7857142857143

The logistics model is able to classify 36.8% of all the observations correctly in the training dataset.

In [85]:

```
# Accuracy in Test dataset
accuracy_model01__test <- sum(diag(model01_clstab_test))/sum(model01_clstab_test)*100
accuracy_model01__test
```

42.5

The logistics model is able to classify 42.5% of all the observations correctly in the testing dataset.

In [94]:

```
# Recall in Train dataset(also known as True Positive Rate): indicates how often does the
Recall <- (model01_clstab_train[2, 2]/sum(model01_clstab_train[ , 2]))*100
Recall
```

31.3807531380753

In [95]:

```
# True Negative Rate in Train dataset: indicates how often does the model predicts actual
TNR <- (model01_clstab_train[1, 1]/sum(model01_clstab_train[1, ]))*100
TNR
```

14.5833333333333

In [96]:

```
# Precision in Train dataset
Precision <- (model01_clstab_train[2, 2]/sum(model01_clstab_train[ , 2]))*100
Precision
```

31.3807531380753

In [97]:

```
# F-Score is a harmonic mean of recall and precision. The score value lies between 0 and
F_Score <- (2 * Precision * Recall / (Precision + Recall))/100
F_Score
```

0.313807531380753

The result shows moderate precision and recall.

In [98]:

```
library(pROC)
```

```
Type 'citation("pROC")' for a citation.


Attaching package: ‘pROC’
```

```
The following objects are masked from ‘package:stats’:

    cov, smooth, var
```

In [99]:

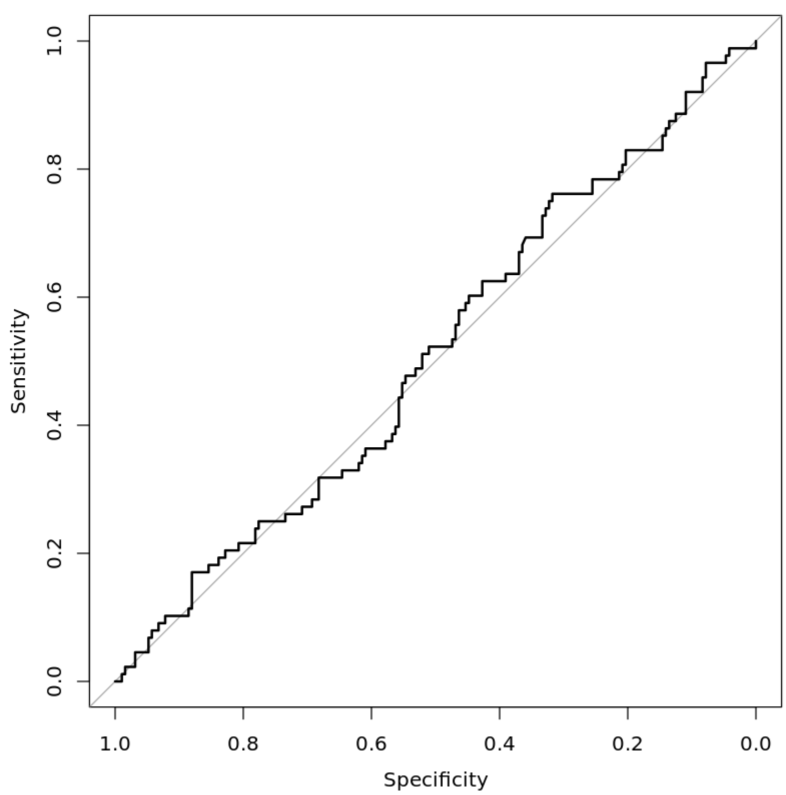
```
roc <- roc(train$admit, model01$fitted.values)
auc(roc)
```

```
Setting levels: control = 0, case = 1

Setting direction: controls > cases
```

0.510919744318182

In [101]:

```
plot(roc)
```



The area under the curve(AUC) is the measure that represents ROC(Receiver Operating Characteristic) curve. This ROC curve is a line plot that is drawn between the Sensitivity and (1 – Specificity) Or between True Positive Rate and True Negative Rate. This graph is then used to generate the AUC value. An AUC value of greater than .70 indicates a good model. Since the AUC value for this model is 0.51092 that model is far from perfect, but is still useful. Problem #2

In [102]:

```
data02 <- read.csv('UtilityFailure-2.csv')
head(data02)
```

A data.frame: 6 × 10

SN	Status	Age	Failure	Light_OutageCount	MVA	PM_Count	RM_Count	UM_Count	Total_P

	SN	Status	Age	Failure	Light_OutageCount	MVA	PM_Count	RM_Count	UM_Count	Total_P
	<int>	<chr>	<dbl>	<chr>	<int>	<dbl>	<int>	<int>	<int>	
1	1	In-Service	45.66185	NO	4	25	27	0	7	
2	2	In-Service	45.66185	NO	4	25	25	0	3	
3	3	Retired	44.63708	NO	12	10	26	0	0	
4	4	In-Service	26.27281	YES	1	5	26	0	1	
5	5	In-Service	42.43172	NO	1	5	21	0	1	
6	6	Retired	0.00000	NO	25	10	24	0	0	

In [103]:

```
str(data02)
```

```
'data.frame':	678 obs. of  10 variables:
 $ SN               : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Status           : chr  "In-Service" "In-Service" "Retired" "In-Service" ...
 $ Age              : num  45.7 45.7 44.6 26.3 42.4 ...
 $ Failure          : chr  "NO" "NO" "NO" "YES" ...
 $ Light_OutageCount: int  4 4 12 1 1 25 20 20 16 16 ...
 $ MVA              : num  25 25 10 5 5 10 10 10 10 10 ...
 $ PM_Count         : int  27 25 26 26 21 24 23 25 25 22 ...
 $ RM_Count         : int  0 0 0 0 0 0 0 0 0 0 ...
 $ UM_Count         : int  7 3 0 1 1 0 0 0 1 0 ...
 $ Total_PMCount    : int  34 28 26 27 22 24 23 25 26 22 ...
```

In [104]:

```
summary(data02)
```

```
       SN           Status               Age           Failure         
 Min.   :  1.0   Length:678         Min.   : 0.00   Length:678        
 1st Qu.:178.2   Class :character   1st Qu.:14.40   Class :character  
 Median :350.5   Mode  :character   Median :30.22   Mode  :character  
 Mean   :351.2                      Mean   :28.80                     
 3rd Qu.:525.8                      3rd Qu.:42.60                     
 Max.   :702.0                      Max.   :58.79                     
                                    NA's   :1                         
 Light_OutageCount       MVA          PM_Count        RM_Count     
 Min.   :  0.000   Min.   : 1.5   Min.   : 0.00   Min.   :0.0000  
 1st Qu.:  0.000   1st Qu.:10.0   1st Qu.:17.00   1st Qu.:0.0000  
 Median :  0.000   Median :20.0   Median :23.00   Median :0.0000  
 Mean   :  7.213   Mean   :17.9   Mean   :23.11   Mean   :0.3997  
 3rd Qu.:  6.000   3rd Qu.:25.0   3rd Qu.:30.00   3rd Qu.:1.0000  
 Max.   :171.000   Max.   :35.0   Max.   :94.00   Max.   :5.0000  
 NA's   :8                                                         
    UM_Count      Total_PMCount  
 Min.   : 0.000   Min.   :  0.00  
 1st Qu.: 0.000   1st Qu.: 18.00  
 Median : 1.000   Median : 25.50  
 Mean   : 1.842   Mean   : 25.35  
 3rd Qu.: 2.750   3rd Qu.: 33.00  
```

```
 Max.   :41.000   Max.   :101.00
```

In [106]:

```
# Converting to factor variables
data02$Status <- as.factor(data02$Status)
data02$Failure <- as.factor(data02$Failure)
```

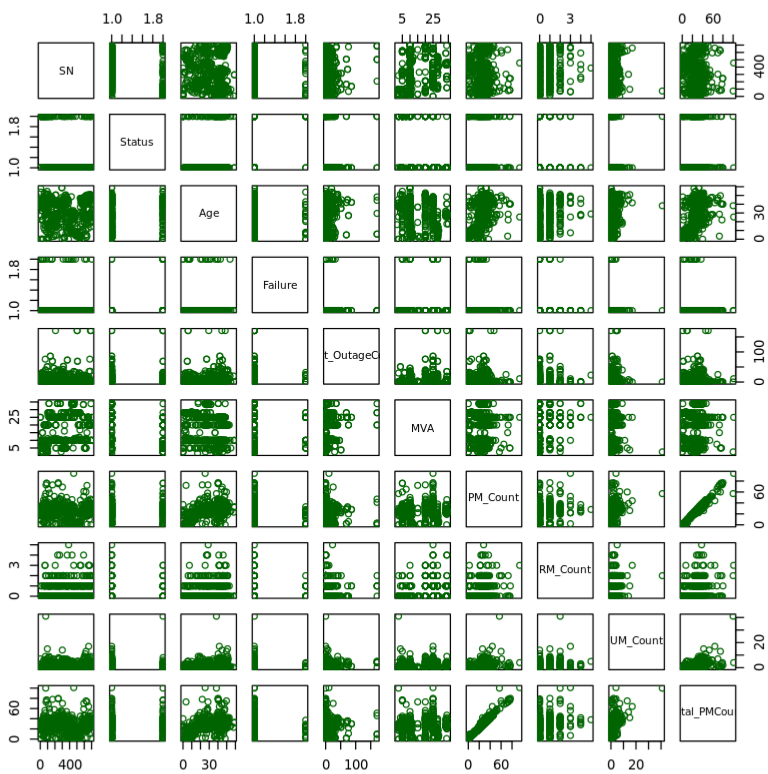
In [107]:

```
str(data02)
```

```
'data.frame':	678 obs. of  10 variables:
 $ SN               : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Status           : Factor w/ 2 levels "In-Service","Retired": 1 1 2 1 1 2 2 2 2 2 ...
 $ Age              : num  45.7 45.7 44.6 26.3 42.4 ...
 $ Failure          : Factor w/ 2 levels "NO","YES": 1 1 1 2 1 1 1 2 1 1 ...
 $ Light_OutageCount: int  4 4 12 1 1 25 20 20 16 16 ...
 $ MVA              : num  25 25 10 5 5 10 10 10 10 10 ...
 $ PM_Count         : int  27 25 26 26 21 24 23 25 25 22 ...
 $ RM_Count         : int  0 0 0 0 0 0 0 0 0 0 ...
 $ UM_Count         : int  7 3 0 1 1 0 0 0 1 0 ...
 $ Total_PMCount    : int  34 28 26 27 22 24 23 25 26 22 ...
```

In [108]:

```
pairs(data02, col = "darkgreen")
```



In [111]:

```
round(stat.desc(cor(data02[, 5:10])),2)
```

```
Warning message in qt((0.5 + p/2), (Nbrval - 1)):
“NaNs produced”
```

A data.frame: 14 × 6

Light_OutageCount	MVA	PM_Count	RM_Count	UM_Count	Total_PMCount

	Light_OutageCount	MVA	PM_Count	RM_Count	UM_Count	Total_PMCount
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
nbr.val	1	5.00	5.00	5.00	5.00	5.00
nbr.null	0	0.00	0.00	0.00	0.00	0.00
nbr.na	5	1.00	1.00	1.00	1.00	1.00
min	1	-0.07	-0.07	0.17	0.08	-0.04
max	1	1.00	1.00	1.00	1.00	1.00
range	0	1.07	1.07	0.83	0.92	1.04
sum	1	1.19	2.41	1.89	2.13	2.69
median	1	0.08	0.32	0.24	0.32	0.49
mean	1	0.24	0.48	0.38	0.43	0.54
SE.mean	NA	0.20	0.22	0.16	0.16	0.20
CI.mean.0.95	NaN	0.55	0.60	0.43	0.44	0.56
var	NA	0.19	0.24	0.12	0.13	0.21
std.dev	NA	0.44	0.49	0.35	0.35	0.45
coef.var	NA	1.86	1.01	0.92	0.83	0.85

In [112]:

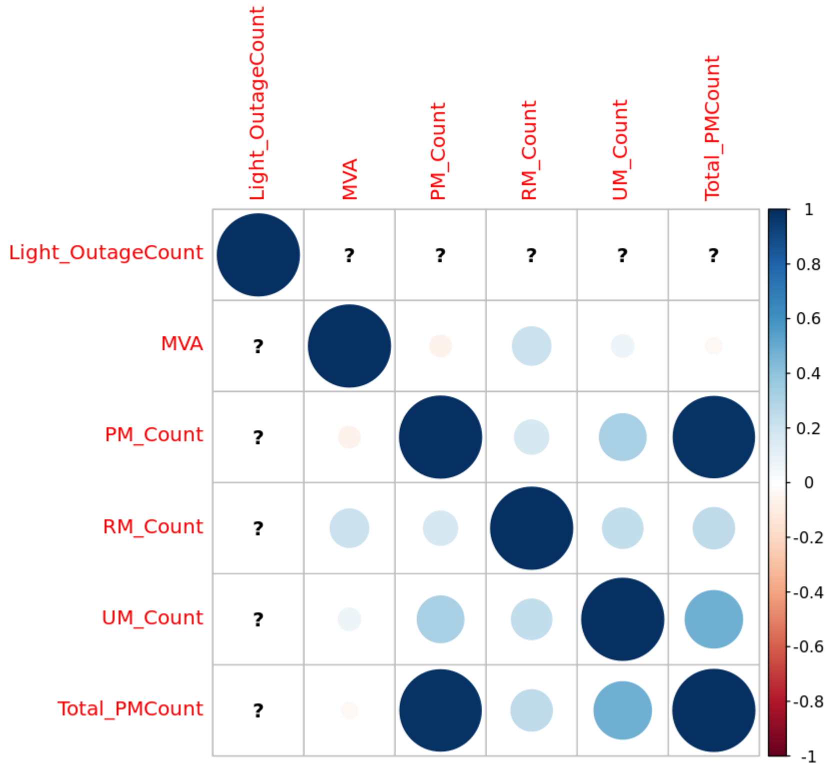
```
CM <- cor(data02[, 5:10])
CM
```

A matrix: 6 × 6 of type dbl

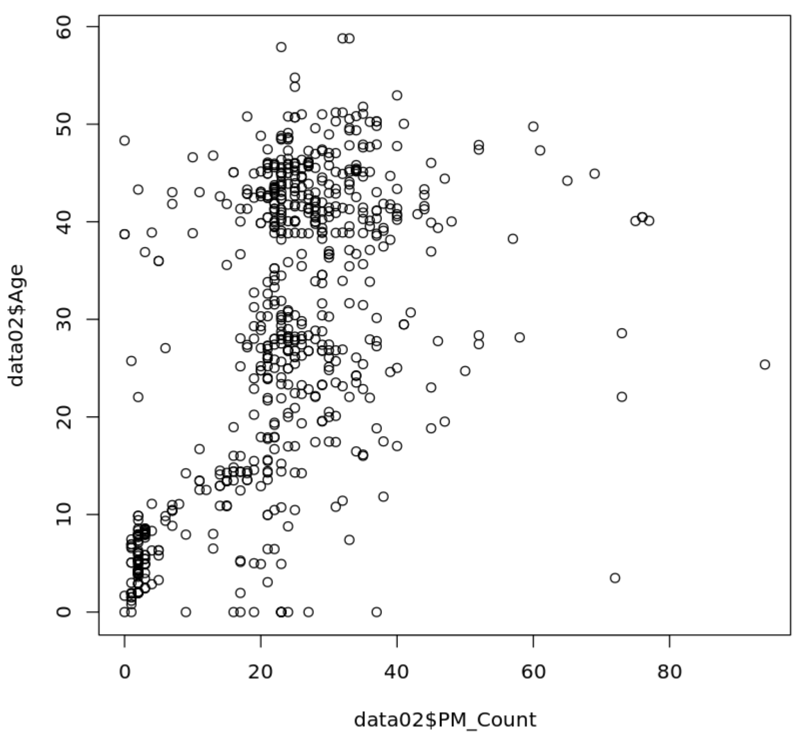
	Light_OutageCount	MVA	PM_Count	RM_Count	UM_Count	Total_PMCount
Light_OutageCount	1	NA	NA	NA	NA	NA
MVA	NA	1.00000000	-0.06992971	0.2194637	0.0751832	-0.0392208
PM_Count	NA	-0.06992971	1.00000000	0.1735181	0.3230318	0.9821974
RM_Count	NA	0.21946370	0.17351813	1.0000000	0.2423843	0.2534218
UM_Count	NA	0.07518320	0.32303176	0.2423843	1.0000000	0.4889054
Total_PMCount	NA	-0.03922080	0.98219744	0.2534218	0.4889054	1.0000000

In [113]:

```
corrplot(CM)
```

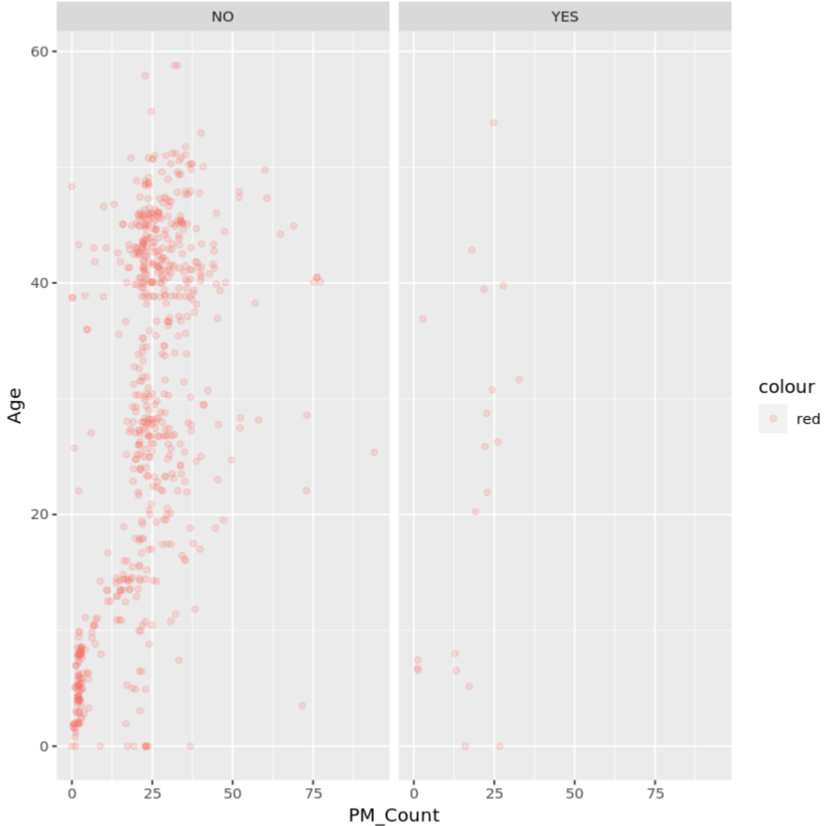


In [121]:
```
plot(data02$Age ~ data02$PM_Count)
```



In [125]:
```
ggplot(data02, aes(x=PM_Count, y=Age, col = 'red')) + geom_point(alpha=0.2, position=posi
```

```
Warning message:
“Removed 1 rows containing missing values (geom_point).”
```



In [126]:
```
status(data02)
```

A data.frame: 10 × 9

	variable	q_zeros	p_zeros	q_na	p_na	q_inf	p_inf	type
	<chr>	<int>	<dbl>	<int>	<dbl>	<int>	<dbl>	<chr>
SN	SN	0	0.000000000	0	0.000000000	0	0	integer
Status	Status	0	0.000000000	0	0.000000000	0	0	factor
Age	Age	13	0.019174041	1	0.001474926	0	0	numeric
Failure	Failure	0	0.000000000	0	0.000000000	0	0	factor
Light_OutageCount	Light_OutageCount	430	0.634218289	8	0.011799410	0	0	integer
MVA	MVA	0	0.000000000	0	0.000000000	0	0	numeric
PM_Count	PM_Count	5	0.007374631	0	0.000000000	0	0	integer
RM_Count	RM_Count	483	0.712389381	0	0.000000000	0	0	integer
UM_Count	UM_Count	221	0.325958702	0	0.000000000	0	0	integer
Total_PMCount	Total_PMCount	4	0.005899705	0	0.000000000	0	0	integer

In [127]:
```
sum(is.na(data02))
```

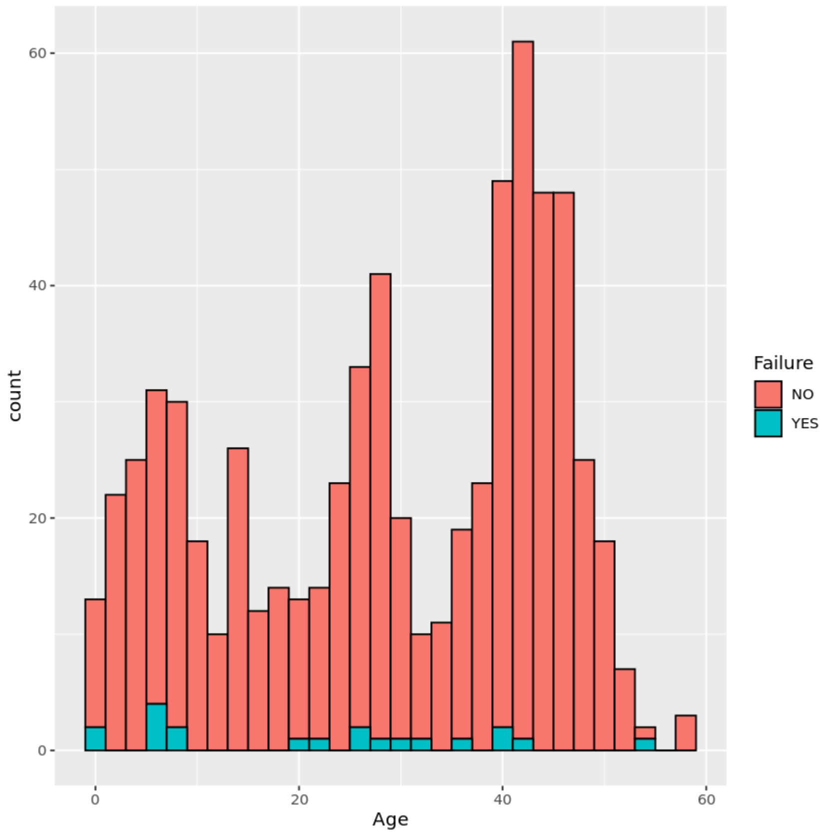
9

In [128]:
```
# Keeping only the na.omit() function
data02 <- na.omit(data02)
```

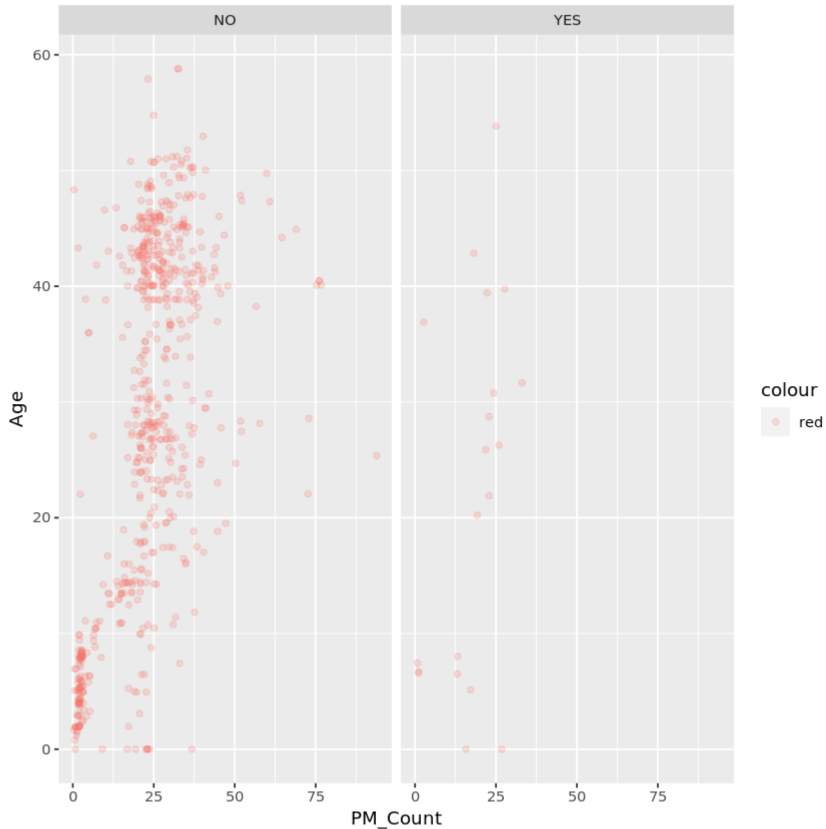
In [129]:
```
sum(is.na(data02))
```

0

In [131]:
```
ggplot(data02, aes(Age)) +
  geom_histogram(aes(fill = Failure), color = "black", binwidth = 2)
```

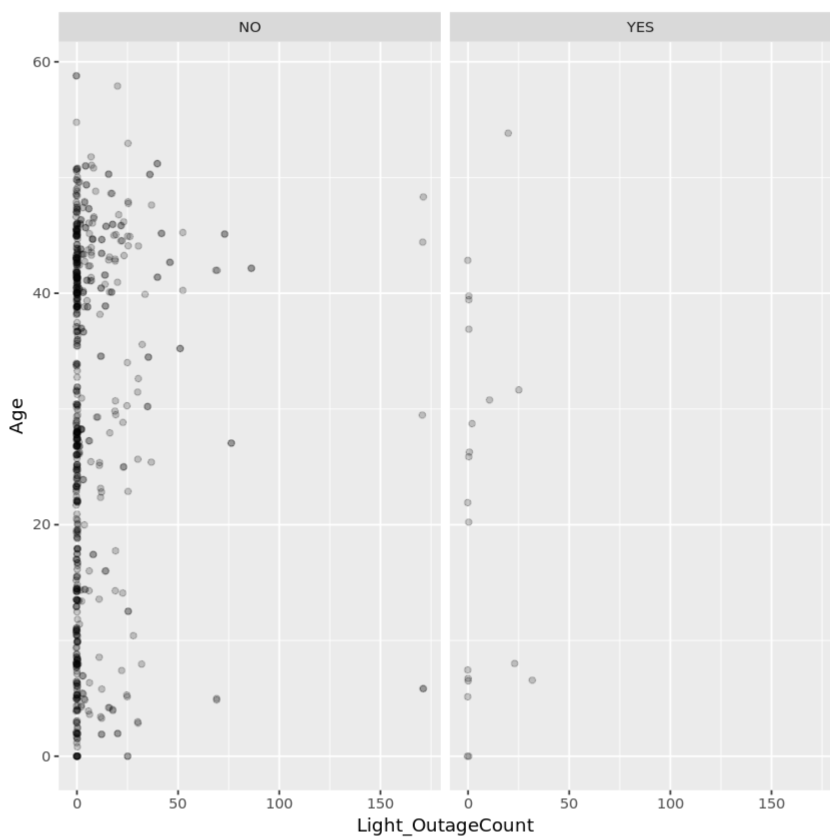


In [132]:
```
ggplot(data02, aes(x=PM_Count, y=Age, col = 'red')) + geom_point(alpha=0.2, position=posi
```



In [137]:

```
ggplot(data02, aes(x=Light_OutageCount, y=Age)) + geom_point(alpha=0.2, position=position
```



In [138]:

```
# Splitting the data into train and test
index1 <- createDataPartition(data02$Failure, p = .70, list = FALSE)
```

```
train1 <- data02[index1, ]
test1 <- data02[-index1, ]
```

In [140]:

```
# Training the model
model02 <- glm(Failure ~ ., family = binomial(), train1)
```

In [141]:

```
summary(model02)
```

```
Call:
glm(formula = Failure ~ ., family = binomial(), data = train1)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1414  -0.1003  -0.0380  -0.0212   4.1845

Coefficients: (1 not defined because of singularities)
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)       -6.588e+00  1.604e+00  -4.107 4.01e-05 ***
SN                -5.715e-05  1.514e-03  -0.038   0.9699
StatusRetired      6.657e+00  1.491e+00   4.466 7.96e-06 ***
Age               -2.555e-02  2.169e-02  -1.178   0.2387
Light_OutageCount -1.256e-02  3.219e-02  -0.390   0.6963
MVA                9.767e-02  5.249e-02   1.861   0.0628 .
PM_Count          -7.782e-02  3.887e-02  -2.002   0.0453 *
RM_Count          -1.011e-01  6.933e-01  -0.146   0.8840
UM_Count           5.271e-02  1.293e-01   0.408   0.6835
Total_PMCount             NA         NA      NA       NA
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 125.901  on 468  degrees of freedom
Residual deviance:  69.262  on 460  degrees of freedom
AIC: 87.262

Number of Fisher Scoring iterations: 9
```

Only two of the variables in the above output have turned out to be significant(p values are less than 0.05 for all the variables). Null deviance suggests the response by the model if only the intercept is under consideration:lower the value better is the model. The Residual deviance indicates the response by the model when all the variables are included. Again, lower the value, better is the model. Intercept(β0) indicates the log of odds of the whole population of interest to be on higher-income class with no predictor variables in the model.

In [142]:

```
simple_odds_intercept <- exp(-6.588e+00)
```

In [143]:

```
simple_odds_intercept
```

0.00137679079346135

In [144]:

```
odds_value_i <- 1 - simple_odds_intercept
odds_value_i
```

0.998623209206539

In [145]:
```
simple_odds_sts_rtrd <- exp(6.657e+00)
simple_odds_sts_rtrd
```

778.212793284794

AIC: 87.262

In [147]:
```
# Predicting in the test dataset
model02_pred_test <- predict(model02, test1, type = "response")
summary(model02_pred_test)
```

```
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
“prediction from a rank-deficient fit may be misleading”
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
0.0000291 0.0002616 0.0011117 0.0519300 0.0139128 0.9176618
```

In [149]:
```
# Converting from probability to actual output: train1
model02_train1_pred <- ifelse(model02$fitted.values >= 0.5, "Yes", "No")
```

In [150]:
```
# Generating the classification table
clstab_train1 <- table(train1$Failure, model02_train1_pred)
clstab_train1
```

```
     model02_train1_pred
       No Yes
  NO  455   0
  YES  12   2
```

In [151]:
```
# Converting from probability to actual output: test1
model02_test1_pred <- ifelse(model02_pred_test >= 0.5, "Yes", "No")
```

In [155]:
```
# Generating the classification table
clstab_test1 <- table(test1$Failure, model02_test1_pred)
clstab_test1
```

```
     model02_test1_pred
       No Yes
  NO  193   1
  YES   3   3
```

In [156]:
```
# Accuracy in Training dataset
accuracy_train1 <- sum(diag(clstab_train1))/sum(clstab_train1)*100
accuracy_train1
```

97.4413646055437

This logistics model is able to classify 97.44% of all the observations correctly in the training dataset. A model is considered fairly good if the model accuracy is greater than 70%.

In [157]:
```
# Recall in Train dataset(True Positive Rate)
Recall1 <- (clstab_train1[2, 2]/sum(clstab_train1[2, ]))*100
Recall1
```

14.2857142857143

In [158]:

```
# True Negative Rate in Train dataset
TNR1 <- (clstab_train1[1, 1]/sum(clstab_train1[1, ]))*100
TNR1
```

100

In [159]:

```
# Precision in Train dataset
Precision1 <- (clstab_train1[2, 2]/sum(clstab_train1[, 2]))*100
Precision1
```

100

In [160]:

```
# F-Score is a harmonic mean of recall and precision.
F_Score1 <- (2 * Precision1 * Recall1 / (Precision1 + Recall1))/100
F_Score1
```

0.25

In [161]:

```
# ROC Curve
roc1 <- roc(train1$Failure, model02$fitted.values)
auc(roc1)
```

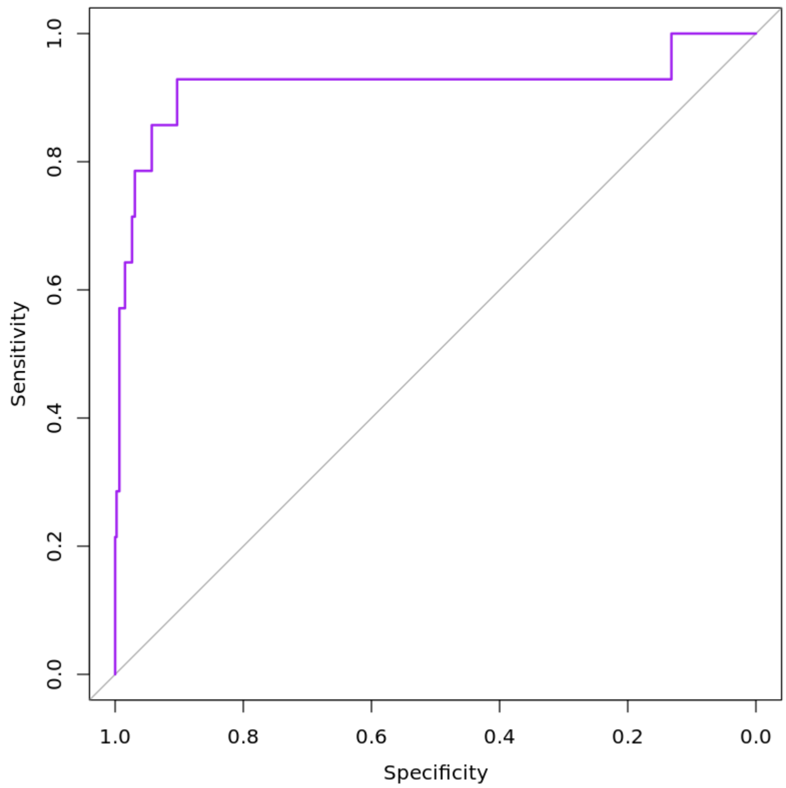
```
Setting levels: control = NO, case = YES

Setting direction: controls < cases
```

0.91978021978022

An AUC value of greater than .70 indicates a good model. In this case: 0.91978021978022 => model is good!

In [163]:

```
plot(roc1, col = 'purple')
```



In [ ]: