DATTA MEGHE COLLEGE OF ENGINEERING, AIROLI

PROJECT REPORT

"CREDIT CARD FRAUD ANALYSIS"

SUBMITTED BY

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UNDER THE GUIDANCE OF

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CREDIT CARD FRAUD ANALYSIS

Introduction

The aim of this R project is to build a classifier that can detect credit card fraudulent transactions. We will use a variety of machine learning algorithms that will be able to discern fraudulent from non-fraudulent one. By the end of this machine learning project, you will learn how to implement machine learning algorithms to perform classification.

SCOPE

The Data mining, best concept of machine learning algorithm is used for credit card fraud in this proposed system is proposed. Then, the number of standard models such as NB, SVM, and DL is used for evaluation terms. The credit card data is available in public ally, it is used for evaluation that is, use the standard models and hybrid models. The hybrid models such as AdaBoost and majority voting, this model are combination methods, also. The MCC metrics are only calculates the performance measures and it takes the account, and it predicts the true or false outcomes of credit card transaction. The best MCC score majority voting is used the majority voting.

PLATFORM: R STUDIO

R was specifically designed for statistical analysis, which makes it highly suitable for data science applications. Although the learning curve for programming with R can be steep, especially for people without prior programming experience, the tools now available for carrying out text analysis in R make it easy to perform powerful, cutting-edge text analytics using only a few simple commands. One of the keys to R's explosive growth has been its densely populated collection of extension software libraries, known in R terminology as packages, supplied and maintained by R's extensive user community. Each package extends the functionality of the base R language and core packages, and in addition to functions and data must include documentation and examples, often in the form of vignettes demonstrating the use of the package. The best-known package repository, the Comprehensive R Archive Network (CRAN), currently has over 10,000 packages that are published.

Text analysis in particular has become well established in R. There is a vast collection of dedicated text processing and text analysis packages, from low-level string operations to advanced text modelling techniques such as fitting Latent Dirichlet Allocation models, R provides it all. One of the main advantages of performing text analysis in R is that it is often possible, and relatively easy, to switch between different packages or to combine them. Recent efforts among the R text analysis developers' community are designed to promote this interoperability to maximize flexibility and choice among users. As a result, learning the basics for text analysis in R provides access to a wide range of advanced text analysis features.

PROJECT SPECIFICATION

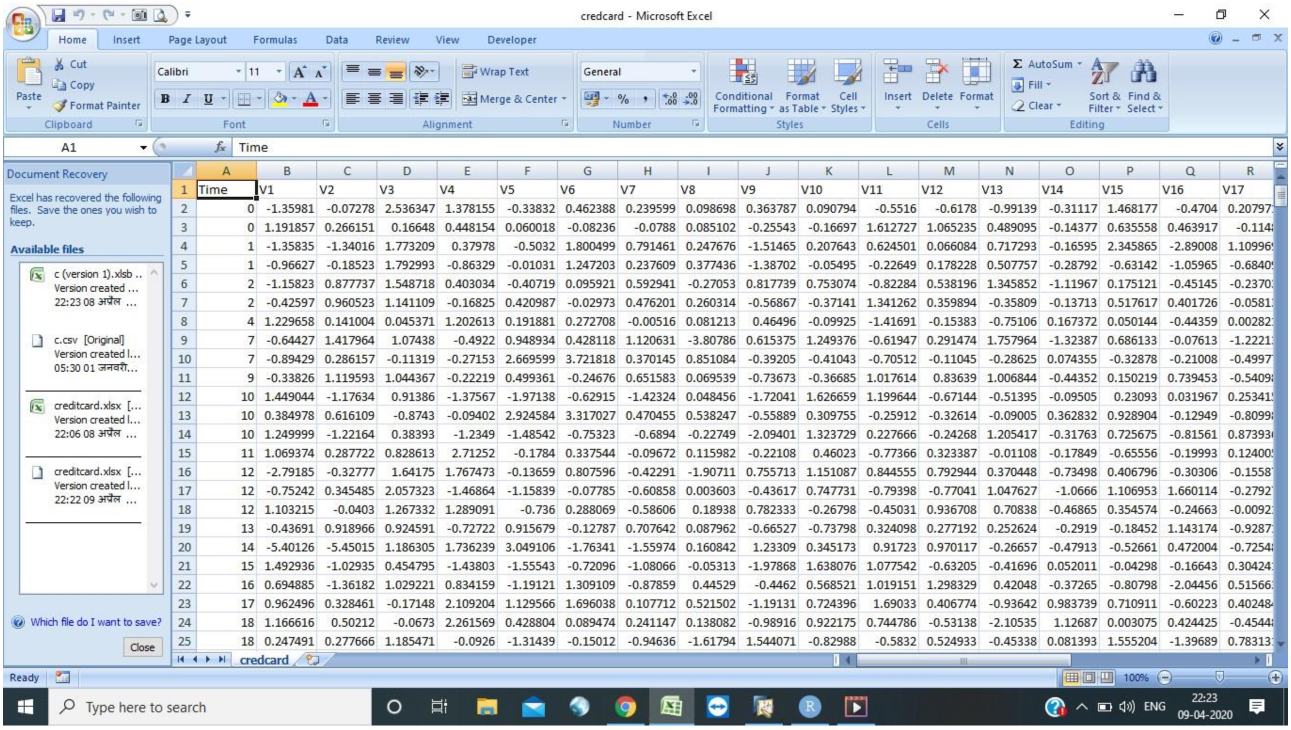
- R Studio version 1.2.5033

HARDWARE SPECIFICATIONS

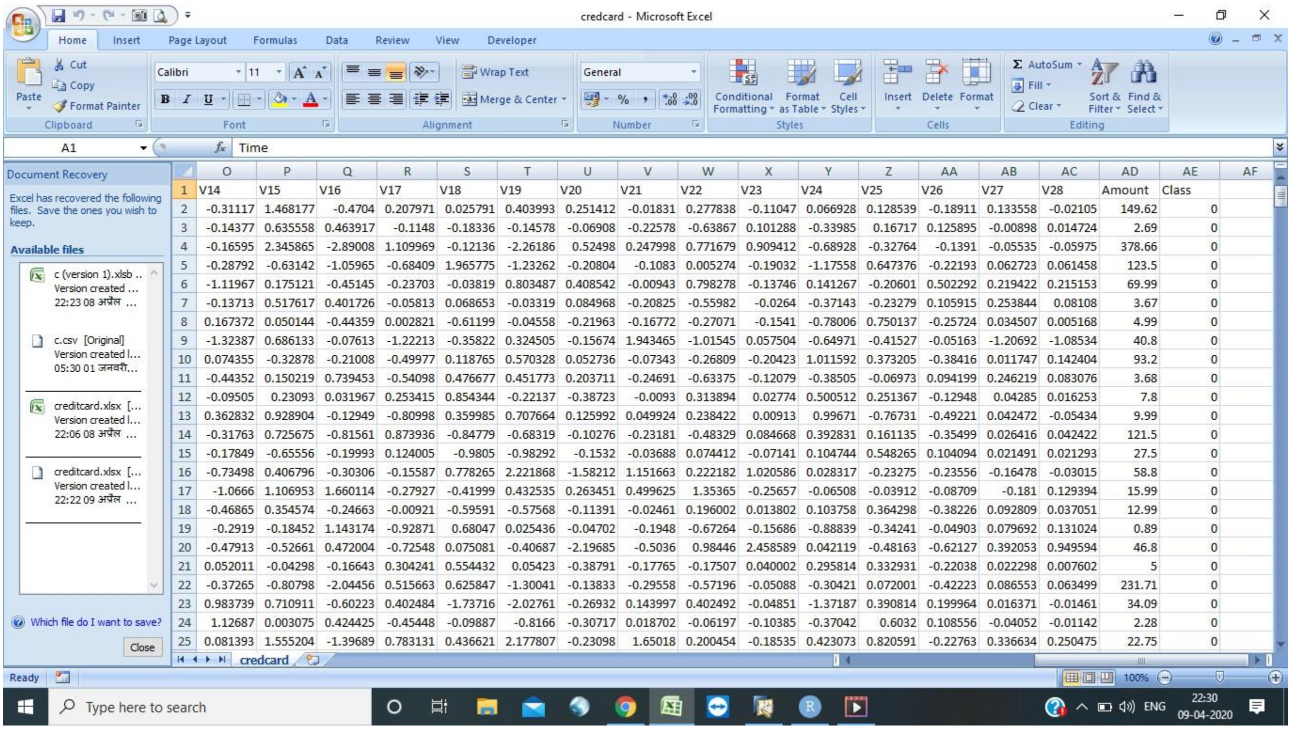
- Microsoft® Windows® 7/8/10 (32- or 64-bit)
- 3 GB RAM minimum, 8 GB RAM recommended;
- 2 GB of available disk space minimum
- core processor of i3 minimum or above.

DATASET

- creditcard.xml



Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17
0	-1.35981	-0.07278	2.536347	1.378155	-0.33832	0.462388	0.239599	0.098698	0.363787	0.090794	-0.5516	-0.6178	-0.99139	-0.31117	1.468177	-0.4704	0.20797
0	1.191857	0.266151	0.16648	0.448154	0.060018	-0.08236	-0.0788	0.085102	-0.25543	-0.16697	1.612727	1.065235	0.489095	-0.14377	0.635558	0.463917	-0.114
1	-1.35835	-1.34016	1.773209	0.37978	-0.5032	1.800499	0.791461	0.247676	-1.51465	0.207643	0.624501	0.066084	0.717293	-0.16595	2.345865	-2.89008	1.10996
1	-0.96627	-0.18523	1.792993	-0.86329	-0.01031	1.247203	0.237609	0.377436	-1.38702	-0.05495	-0.22649	0.178228	0.507757	-0.28792	-0.63142	-1.05965	-0.6840
2	-1.15823	0.877737	1.548718	0.403034	-0.40719	0.095921	0.592941	-0.27053	0.817739	0.753074	-0.82284	0.538196	1.345852	-1.11967	0.175121	-0.45145	-0.2370
2	-0.42597	0.960523	1.141109	-0.16825	0.420987	-0.02973	0.476201	0.260314	-0.56867	-0.37141	1.341262	0.359894	-0.35809	-0.13713	0.517617	0.401726	-0.0581
4	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.00516	0.081213	0.46496	-0.09925	-1.41691	-0.15383	-0.75106	0.167372	0.050144	-0.44359	0.00282
7	-0.64427	1.417964	1.07438	-0.4922	0.948934	0.428118	1.120631	-3.80786	0.615375	1.249376	-0.61947	0.291474	1.757964	-1.32387	0.686133	-0.07613	-1.2221
7	-0.89429	0.286157	-0.11319	-0.27153	2.669599	3.721818	0.370145	0.851084	-0.39205	-0.41043	-0.70512	-0.11045	-0.28625	0.074355	-0.32878	-0.21008	-0.4997
9	-0.33826	1.119593	1.044367	-0.22219	0.499361	-0.24676	0.651583	0.069539	-0.73673	-0.36685	1.017614	0.83639	1.006844	-0.44352	0.150219	0.739453	-0.5409
10	1.449044	-1.17634	0.91386	-1.37567	-1.97138	-0.62915	-1.42324	0.048456	-1.72041	1.626659	1.199644	-0.67144	-0.51395	-0.09505	0.23093	0.031967	0.25341
10	0.384978	0.616109	-0.8743	-0.09402	2.924584	3.317027	0.470455	0.538247	-0.55889	0.309755	-0.25912	-0.32614	-0.09005	0.362832	0.928904	-0.12949	-0.8099
10	1.249999	-1.22164	0.38393	-1.2349	-1.48542	-0.75323	-0.6894	-0.22749	-2.09401	1.323729	0.227666	-0.24268	1.205417	-0.31763	0.725675	-0.81561	0.87393
11	1.069374	0.287722	0.828613	2.71252	-0.1784	0.337544	-0.09672	0.115982	-0.22108	0.46023	-0.77366	0.323387	-0.01108	-0.17849	-0.65556	-0.19993	0.12400
12	-2.79185	-0.32777	1.64175	1.767473	-0.13659	0.807596	-0.42291	-1.90711	0.755713	1.151087	0.844555	0.792944	0.370448	-0.73498	0.406796	-0.30306	-0.1558
12	-0.75242	0.345485	2.057323	-1.46864	-1.15839	-0.07785	-0.60858	0.003603	-0.43617	0.747731	-0.79398	-0.77041	1.047627	-1.0666	1.106953	1.660114	-0.2792
12	1.103215	-0.0403	1.267332	1.289091	-0.736	0.288069	-0.58606	0.18938	0.782333	-0.26798	-0.45031	0.936708	0.70838	-0.46865	0.354574	-0.24663	-0.0092
13	-0.43691	0.918966	0.924591	-0.72722	0.915679	-0.12787	0.707642	0.087962	-0.66527	-0.73798	0.324098	0.277192	0.252624	-0.2919	-0.18452	1.143174	-0.9287
14	-5.40126	-5.45015	1.186305	1.736239	3.049106	-1.76341	-1.55974	0.160842	1.23309	0.345173	0.91723	0.970117	-0.26657	-0.47913	-0.52661	0.472004	-0.7254
15	1.492936	-1.02935	0.454795	-1.43803	-1.55543	-0.72096	-1.08066	-0.05313	-1.97868	1.638076	1.077542	-0.63205	-0.41696	0.052011	-0.04298	-0.16643	0.30424
16	0.694885	-1.36182	1.029221	0.834159	-1.19121	1.309109	-0.87859	0.44529	-0.4462	0.568521	1.019151	1.298329	0.42048	-0.37265	-0.80798	-2.04456	0.51566
17	0.962496	0.328461	-0.17148	2.109204	1.129566	1.696038	0.107712	0.521502	-1.19131	0.724396	1.69033	0.406774	-0.93642	0.983739	0.710911	-0.60223	0.40248
18	1.166616	0.50212	-0.0673	2.261569	0.428804	0.089474	0.241147	0.138082	-0.98916	0.922175	0.744786	-0.53138	-2.10535	1.12687	0.003075	0.424425	-0.4544
18	0.247491	0.277666	1.185471	-0.0926	-1.31439	-0.15012	-0.94636	-1.61794	1.544071	-0.82988	-0.5832	0.524933	-0.45338	0.081393	1.555204	-1.39689	0.78313



V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
-0.31117	1.468177	-0.4704	0.207971	0.025791	0.403993	0.251412	-0.01831	0.277838	-0.11047	0.066928	0.128539	-0.18911	0.133558	-0.02105	149.62	0
-0.14377	0.635558	0.463917	-0.1148	-0.18336	-0.14578	-0.06908	-0.22578	-0.63867	0.101288	-0.33985	0.16717	0.125895	-0.00898	0.014724	2.69	0
-0.16595	2.345865	-2.89008	1.109969	-0.12136	-2.26186	0.52498	0.247998	0.771679	0.909412	-0.68928	-0.32764	-0.1391	-0.05535	-0.05975	378.66	0
-0.28792	-0.63142	-1.05965	-0.68409	1.965775	-1.23262	-0.20804	-0.1083	0.005274	-0.19032	-1.17558	0.647376	-0.22193	0.062723	0.061458	123.5	0
-1.11967	0.175121	-0.45145	-0.23703	-0.03819	0.803487	0.408542	-0.00943	0.798278	-0.13746	0.141267	-0.20601	0.502292	0.219422	0.215153	69.99	0
-0.13713	0.517617	0.401726	-0.05813	0.068653	-0.03319	0.084968	-0.20825	-0.55982	-0.0264	-0.37143	-0.23279	0.105915	0.253844	0.08108	3.67	0
0.167372	0.050144	-0.44359	0.002821	-0.61199	-0.04558	-0.21963	-0.16772	-0.27071	-0.1541	-0.78006	0.750137	-0.25724	0.034507	0.005168	4.99	0
-1.32387	0.686133	-0.07613	-1.22213	-0.35822	0.324505	-0.15674	1.943465	-1.01545	0.057504	-0.64971	-0.41527	-0.05163	-1.20692	-1.08534	40.8	0
0.074355	-0.32878	-0.21008	-0.49977	0.118765	0.570328	0.052736	-0.07343	-0.26809	-0.20423	1.011592	0.373205	-0.38416	0.011747	0.142404	93.2	0
-0.44352	0.150219	0.739453	-0.54098	0.476677	0.451773	0.203711	-0.24691	-0.63375	-0.12079	-0.38505	-0.06973	0.094199	0.246219	0.083076	3.68	0
-0.09505	0.23093	0.031967	0.253415	0.854344	-0.22137	-0.38723	-0.0093	0.313894	0.02774	0.500512	0.251367	-0.12948	0.04285	0.016253	7.8	0
0.362832	0.928904	-0.12949	-0.80998	0.359985	0.707664	0.125992	0.049924	0.238422	0.00913	0.99671	-0.76731	-0.49221	0.042472	-0.05434	9.99	0
-0.31763	0.725675	-0.81561	0.873936	-0.84779	-0.68319	-0.10276	-0.23181	-0.48329	0.084668	0.392831	0.161135	-0.35499	0.026416	0.042422	121.5	0
-0.17849	-0.65556	-0.19993	0.124005	-0.9805	-0.98292	-0.1532	-0.03688	0.074412	-0.07141	0.104744	0.548265	0.104094	0.021491	0.021293	27.5	0
-0.73498	0.406796	-0.30306	-0.15587	0.778265	2.221868	-1.58212	1.151663	0.222182	1.020586	0.028317	-0.23275	-0.23556	-0.16478	-0.03015	58.8	0
-1.0666	1.106953	1.660114	-0.27927	-0.41999	0.432535	0.263451	0.499625	1.35365	-0.25657	-0.06508	-0.03912	-0.08709	-0.181	0.129394	15.99	0
-0.46865	0.354574	-0.24663	-0.00921	-0.59591	-0.57568	-0.11391	-0.02461	0.196002	0.013802	0.103758	0.364298	-0.38226	0.092809	0.037051	12.99	0
-0.2919	-0.18452	1.143174	-0.92871	0.68047	0.025436	-0.04702	-0.1948	-0.67264	-0.15686	-0.88839	-0.34241	-0.04903	0.079692	0.131024	0.89	0
-0.47913	-0.52661	0.472004	-0.72548	0.075081	-0.40687	-2.19685	-0.5036	0.98446	2.458589	0.042119	-0.48163	-0.62127	0.392053	0.949594	46.8	0
0.052011	-0.04298	-0.16643	0.304241	0.554432	0.05423	-0.38791	-0.17765	-0.17507	0.040002	0.295814	0.332931	-0.22038	0.022298	0.007602	5	0
-0.37265	-0.80798	-2.04456	0.515663	0.625847	-1.30041	-0.13833	-0.29558	-0.57196	-0.05088	-0.30421	0.072001	-0.42223	0.086553	0.063499	231.71	0
0.983739	0.710911	-0.60223	0.402484	-1.73716	-2.02761	-0.26932	0.143997	0.402492	-0.04851	-1.37187	0.390814	0.199964	0.016371	-0.01461	34.09	0
1.12687	0.003075	0.424425	-0.45448	-0.09887	-0.8166	-0.30717	0.018702	-0.06197	-0.10385	-0.37042	0.6032	0.108556	-0.04052	-0.01142	2.28	0
0.081393	1.555204	-1.39689	0.783131	0.436621	2.177807	-0.23098	1.65018	0.200454	-0.18535	0.423073	0.820591	-0.22763	0.336634	0.250475	22.75	0

CHAPTER 1

Importing the Essential Packages

In the first step of our R project, we will import the essential packages that we will use in this uber data analysis project. Some of the **important libraries of R** that we will use are –

- ggplot2

This is the backbone of this project. ggplot2 is the most popular data visualization library that is most widely used for creating aesthetic visualization plots.

- Ggthemes

This is more of an add-on to our main ggplot2 library. With this, we can create better create extra themes and scales with the mainstream ggplot2 package.

- Lubridate

Our dataset involves various time-frames. In order to understand our data in separate time categories, we will make use of the lubridate package.

- Dplyr

This package is the lingua franca of *data manipulation in R*.

- Tidyr

This package will help you to tidy your data. The basic principle of tidyr is to tidy the columns where each variable is present in a column, each observation is represented by a row and each value depicts a cell.

- DT

With the help of this package, we will be able to interface with the *JavaScript* Library called – Datatables.

- scales

With the help of graphical scales, we can automatically map the data to the correct scales with well-placed axes and legends.

We are importing the datasets that contain transactions made by credit cards-

Code:

```
library(ranger)
library(caret)
```

```
## Loading required package: lattice
```

```
library(data.table)
creditcard_data <- read.csv("/home/dataflair/data/Credit Card/creditcard.csv")
```

CHAPTER 2

Data Exploration

In this section of the fraud detection project, we will explore the data that is contained in the creditcard_data dataframe. We will proceed by displaying the creditcard_data using the head () function as well as the tail () function. We will then proceed to explore the other components of this dataframe.

```
dim(creditcard_data)
```

```
## [1] 284807     31
```

```
head(creditcard_data,6)
```

```
##   Time         V1          V2        V3         V4          V5          V6
## 1    0 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778
## 2    0  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081
## 3    1 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938
## 4    1 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317
## 5    2 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146
## 6    2 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755
##            V7          V8         V9         V10        V11         V12
## 1  0.23959855  0.09869790  0.3637870  0.09079417 -0.5515995 -0.61780086
## 2 -0.07880298  0.08510165 -0.2554251 -0.16697441  1.6127267  1.06523531
## 3  0.79146096  0.24767579 -1.5146543  0.20764287  0.6245015  0.06608369
## 4  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823
## 5  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555
## 6  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384
##          V13        V14        V15        V16         V17         V18
## 1 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058
## 2  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127
## 3  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931
## 4  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500
## 5  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479
## 6 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315
```

```r
tail(creditcard_data,6)
```

```
##          Time          V1          V2         V3         V4          V5
## 284802 172785   0.1203164  0.93100513 -0.5460121 -0.7450968  1.13031398
## 284803 172786 -11.8811179 10.07178497 -9.8347835 -2.0666557 -5.36447278
## 284804 172787  -0.7327887 -0.05508049  2.0350297 -0.7385886  0.86822940
## 284805 172788   1.9195650 -0.30125385 -3.2496398 -0.5578281  2.63051512
## 284806 172788  -0.2404400  0.53048251  0.7025102  0.6897992 -0.37796113
## 284807 172792  -0.5334125 -0.18973334  0.7033374 -0.5062712 -0.01254568
##                V6         V7         V8         V9        V10        V11
## 284802 -0.2359732  0.8127221  0.1150929 -0.2040635 -0.6574221  0.6448373
## 284803 -2.6068373 -4.9182154  7.3053340  1.9144283  4.3561704 -1.5931053
## 284804  1.0584153  0.0243297  0.2948687  0.5848000 -0.9759261 -0.1501888
## 284805  3.0312601 -0.2968265  0.7084172  0.4324540 -0.4847818  0.4116137
## 284806  0.6237077 -0.6861800  0.6791455  0.3920867 -0.3991257 -1.9338488
## 284807 -0.6496167  1.5770063 -0.4146504  0.4861795 -0.9154266 -1.0404583
##                V12        V13         V14         V15        V16
## 284802  0.19091623 -0.5463289 -0.73170658 -0.80803553  0.5996281
## 284803  2.71194079 -0.6892556  4.62694203 -0.92445871  1.1076406
## 284804  0.91580191  1.2147558 -0.67514296  1.16493091 -0.7117573
## 284805  0.06311886 -0.1836987 -0.51060184  1.32928351  0.1407160
## 284806 -0.96288614 -1.0420817  0.44962444  1.96256312 -0.6085771
## 284807 -0.03151305 -0.1880929 -0.08431647  0.04133346 -0.3026201
```

CHAPTER 3

Data Manipulation

In this section of the R data science project, we will scale our data using the scale () function. We will apply this to the amount component of our creditcard_data amount. Scaling is also known as feature standardization. With the help of scaling, the data is structured according to a specified range. Therefore, there are no extreme values in our dataset that might interfere with the functioning of our model. We will carry this out as follows:

```
head(creditcard_data)
```

```
##   Time         V1          V2        V3         V4          V5          V6
## 1    0 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778
## 2    0  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081
## 3    1 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938
## 4    1 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317
## 5    2 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146
## 6    2 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755
##            V7          V8         V9         V10        V11         V12
## 1  0.23959855  0.09869790  0.3637870  0.09079417 -0.5515995 -0.61780086
## 2 -0.07880298  0.08510165 -0.2554251 -0.16697441  1.6127267  1.06523531
## 3  0.79146096  0.24767579 -1.5146543  0.20764287  0.6245015  0.06608369
## 4  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823
## 5  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555
## 6  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384
##           V13        V14        V15        V16         V17         V18
## 1 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058
## 2  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127
## 3  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931
## 4  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500
## 5  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479
## 6 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315
##            V19         V20          V21          V22         V23
## 1  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391
## 2 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802
## 3 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226
## 4 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052
## 5  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808
## 6 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767
```

```
creditcard_data$Amount=scale(creditcard_data$Amount)
NewData=creditcard_data[,-c(1)]
head(NewData)
```

```
##           V1          V2        V3         V4          V5          V6
## 1 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778
## 2  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081
## 3 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938
## 4 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317
## 5 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146
## 6 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755
##            V7          V8         V9         V10        V11         V12
## 1  0.23959855  0.09869790  0.3637870  0.09079417 -0.5515995 -0.61780086
## 2 -0.07880298  0.08510165 -0.2554251 -0.16697441  1.6127267  1.06523531
## 3  0.79146096  0.24767579 -1.5146543  0.20764287  0.6245015  0.06608369
## 4  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823
## 5  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555
## 6  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384
##          V13        V14        V15        V16         V17         V18
## 1 -0.9913898 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058
## 2  0.4890950 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127
## 3  0.7172927 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931
## 4  0.5077569 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500
## 5  1.3458516 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479
## 6 -0.3580907 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315
##           V19         V20          V21          V22         V23
## 1  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391
## 2 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802
## 3 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226
## 4 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052
## 5  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808
## 6 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767
```

CHAPTER 4

Data Modeling

After we have standardized our entire dataset, we will split our dataset into training set as well as test set with a split ratio of 0.80. This means that 80% of our data will be attributed to the train_data whereas 20% will be attributed to the test data. We will then find the dimensions using the dim () function

```
library(caTools)
set.seed(123)
data_sample = sample.split(NewData$Class,SplitRatio=0.80)
train_data = subset(NewData,data_sample==TRUE)
test_data = subset(NewData,data_sample==FALSE)
dim(train_data)
```

```
## [1] 227846     30
```

```
dim(test_data)
```

```
## [1] 56961    30
```

```
  Logistic_Model=glm(Class~.,test_data,family=binomial())
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
  summary(Logistic_Model)
```

```
##
## Call:
## glm(formula = Class ~ ., family = binomial(), data = test_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.9019  -0.0254  -0.0156  -0.0078   4.0877
```

CHAPTER 5

Fitting Logistic Regression Model

In this section of credit card fraud detection project, we will fit our first model. We will begin with logistic regression. A logistic regression is used for modelling the outcome probability of a class such as pass/fail, positive/negative and in our case – fraud/not fraud. We proceed to implement this model on our test data as follows –

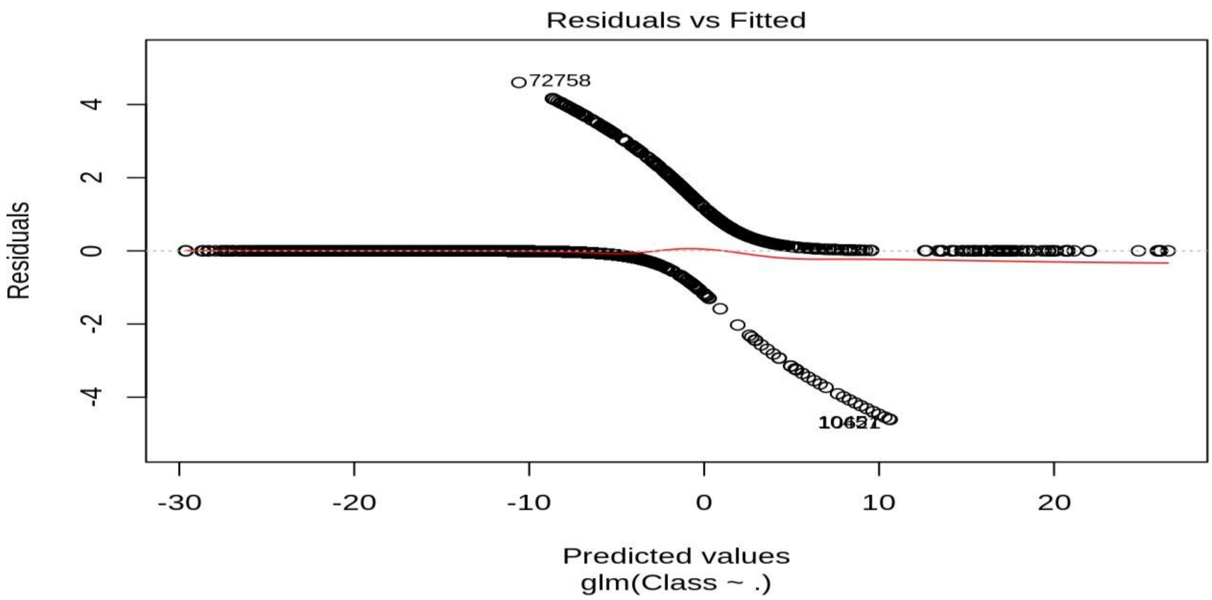
```
Logistic_Model=glm(Class~.,test_data,family=binomial())
```

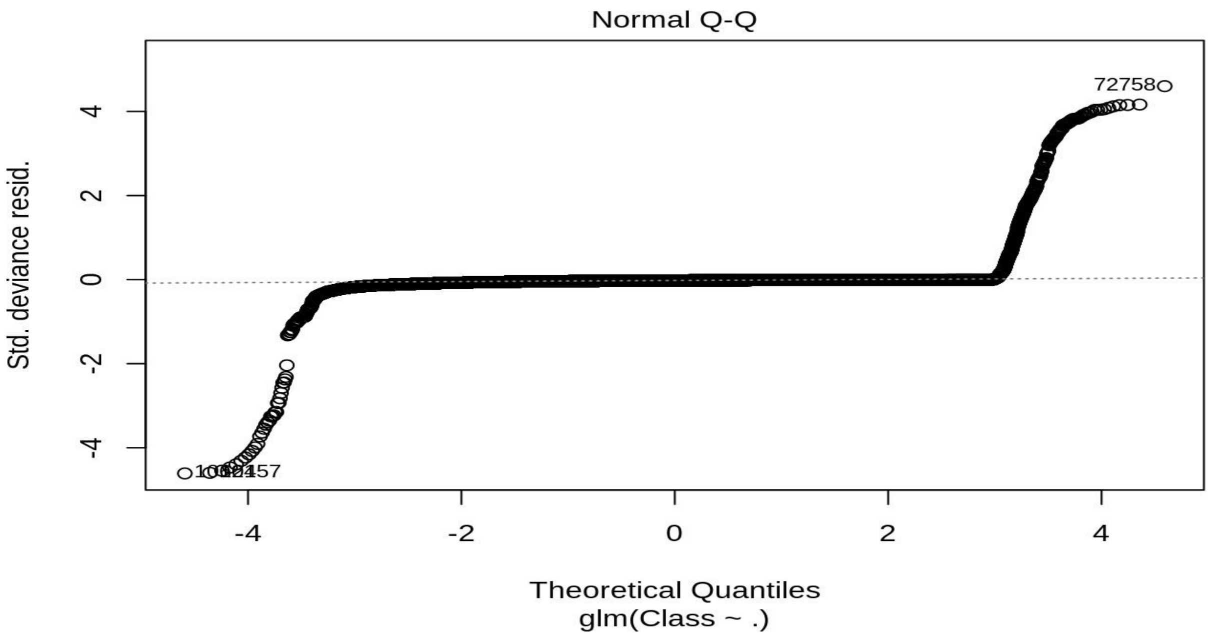
```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

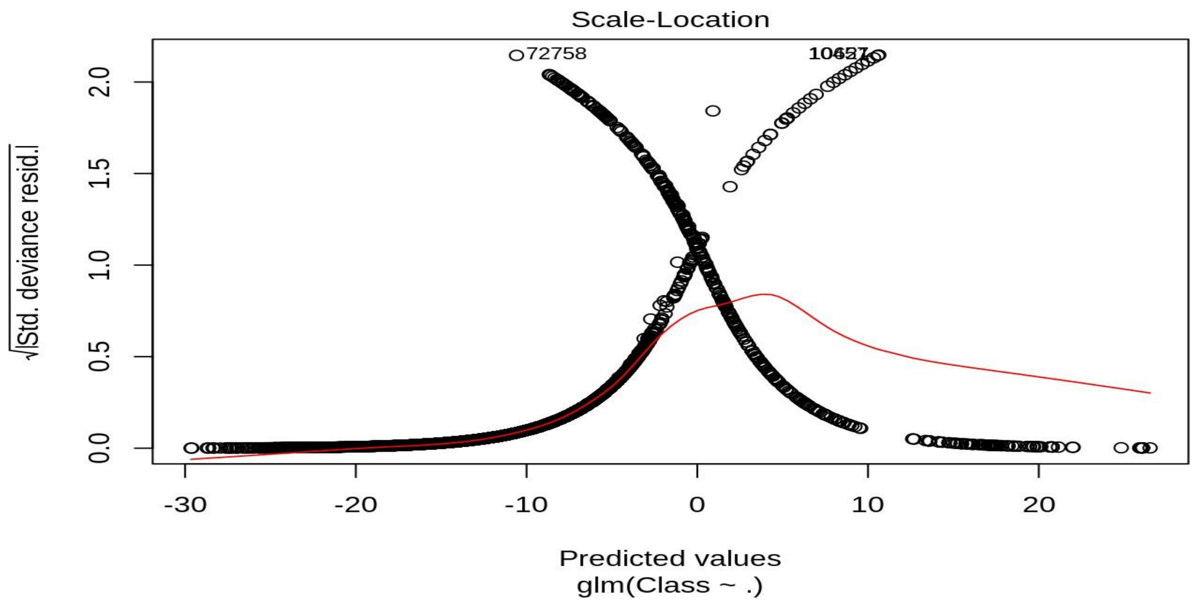
```
summary(Logistic_Model)
```

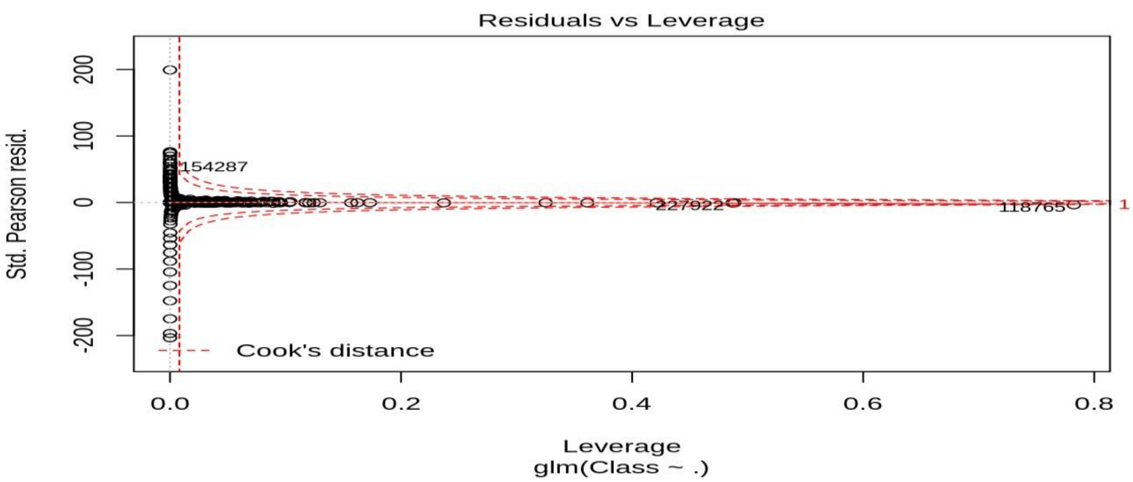
```
##
## Call:
## glm(formula = Class ~ ., family = binomial(), data = test_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.9019  -0.0254  -0.0156  -0.0078   4.0877
```

```
plot(Logistic_Model)
```




Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
glm(Class ~ .)
72758
-4
-2
0
2
4

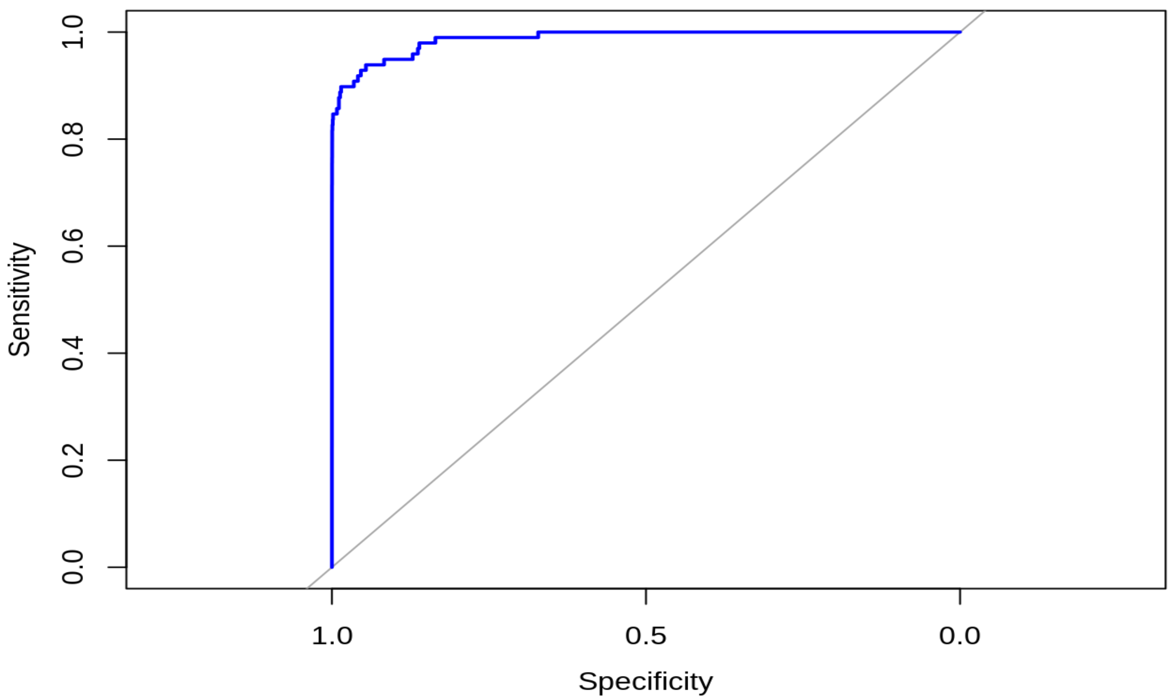

Scale-Location
√|Std. deviance resid.|
Predicted values
glm(Class ~ .)
72758
0.0
0.5
1.0
1.5
2.0
-30
-20
-10
0
10
20

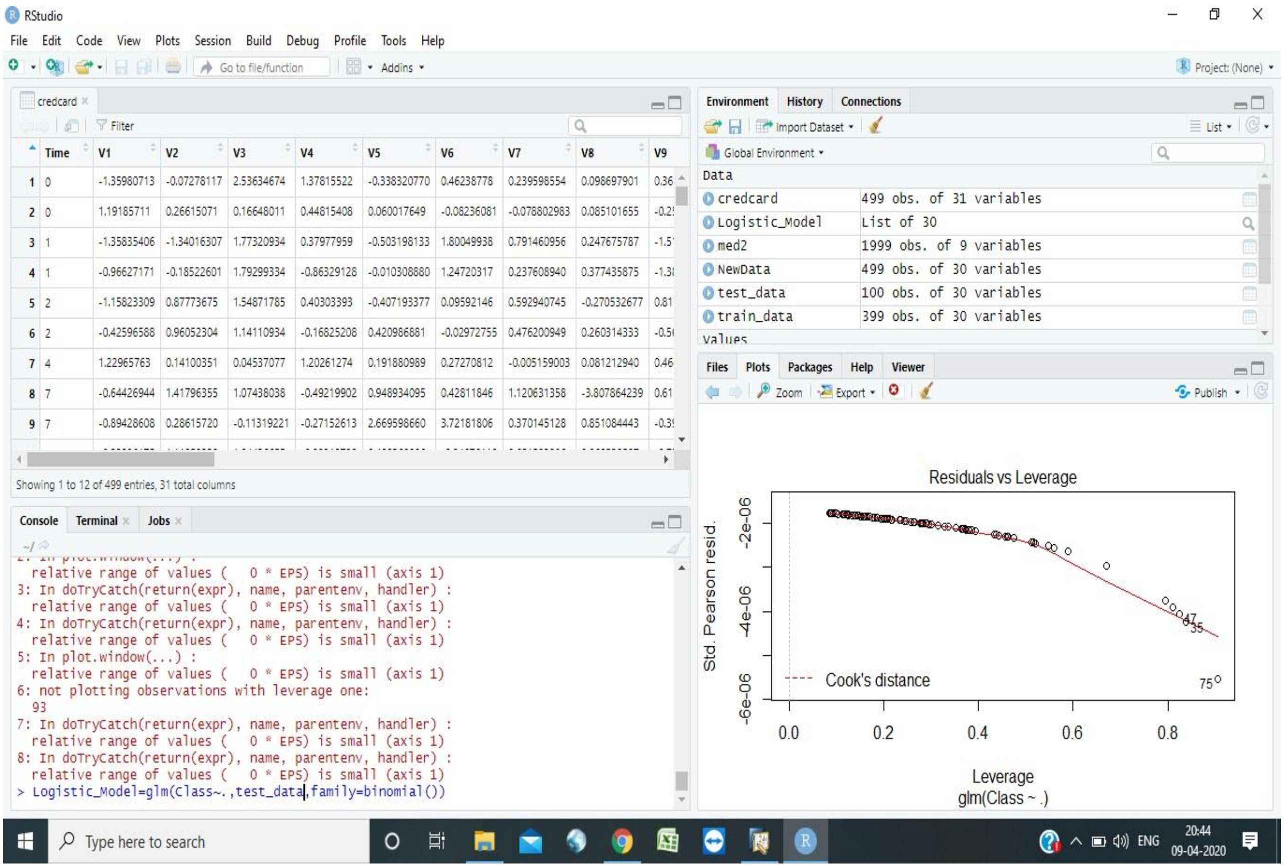

Residuals vs Leverage
Std. Pearson resid.
Leverage
glm(Class ~ .)
154287
227922
118765
1
Cook's distance
-200
-100
0
100
200
0.0
0.2
0.4
0.6
0.8

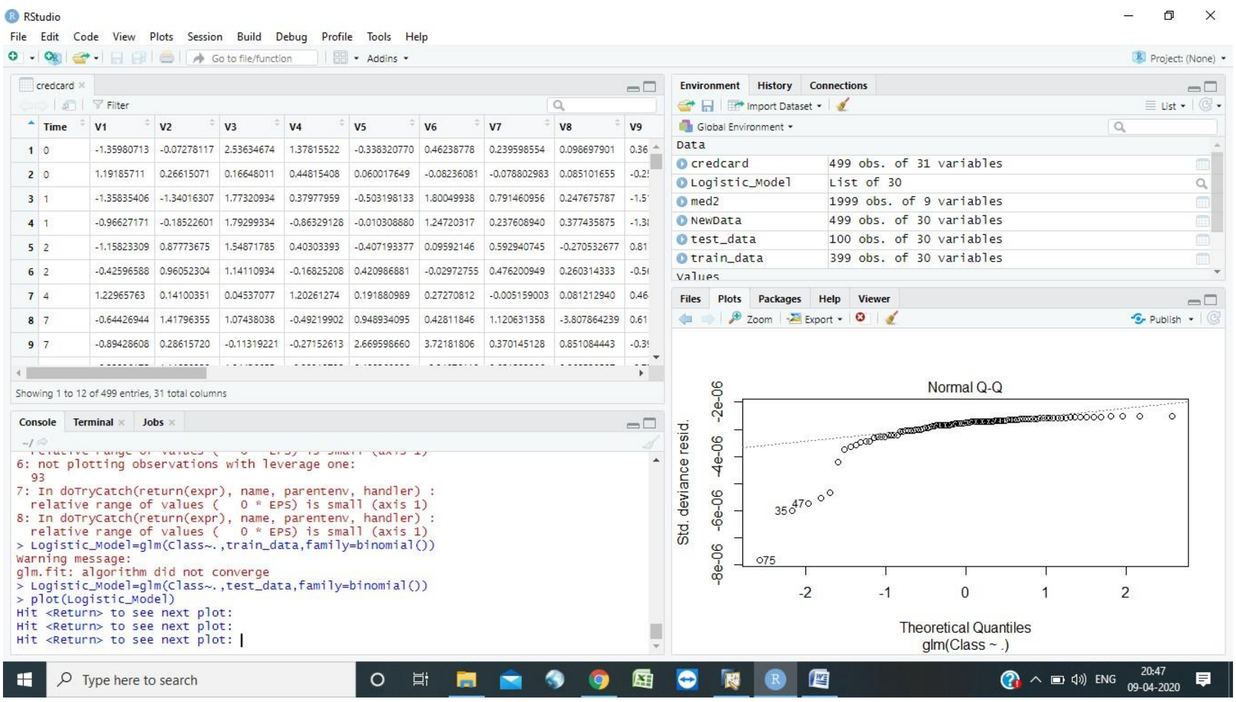
In order to assess the performance of our model, we will delineate the ROC curve. ROC is also known as Receiver Optimistic Characteristics. For this, we will first import the ROC package and then plot our ROC curve to analyze its performance.

```
Logistic_Model=glm(Class~.,train_data,family=binomial())
summary(Logistic_Model)
```

```
##
## Call:
## glm(formula = Class ~ ., family = binomial(), data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.6108  -0.0292  -0.0194  -0.0125   4.6021
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -8.651305   0.160212 -53.999  < 2e-16 ***
## V1           0.072540   0.044144   1.643 0.100332
## V2           0.014818   0.059777   0.248 0.804220
```




RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function
Addins
Project: (None)
credcard
Filter
Showing 1 to 12 of 499 entries, 31 total columns
Console Terminal Jobs
relative range of values (0 * EPS) is small (axis 1)
3: In doTryCatch(return(expr), name, parentenv, handler) :
relative range of values (0 * EPS) is small (axis 1)
4: In doTryCatch(return(expr), name, parentenv, handler) :
relative range of values (0 * EPS) is small (axis 1)
5: In plot.window(...) :
relative range of values (0 * EPS) is small (axis 1)
6: not plotting observations with leverage one:
93
7: In doTryCatch(return(expr), name, parentenv, handler) :
relative range of values (0 * EPS) is small (axis 1)
8: In doTryCatch(return(expr), name, parentenv, handler) :
relative range of values (0 * EPS) is small (axis 1)
> Logistic_Model=glm(Class~.,test_data,family=binomial())
Environment History Connections
Import Dataset
Global Environment
Data
credcard 499 obs. of 31 variables
Logistic_Model List of 30
med2 1999 obs. of 9 variables
NewData 499 obs. of 30 variables
test_data 100 obs. of 30 variables
train_data 399 obs. of 30 variables
Values
Files Plots Packages Help Viewer
Zoom Export Publish
Residuals vs Leverage
Std. Pearson resid.
Cook's distance
Leverage
glm(Class ~ .)
Type here to search
ENG
20:44
09-04-2020


RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function
Addins
Project: (None)
credcard
Filter
Showing 1 to 12 of 499 entries, 31 total columns
Console Terminal Jobs
6: not plotting observations with leverage one:
93
7: In doTryCatch(return(expr), name, parentenv, handler) :
relative range of values (0 * EPS) is small (axis 1)
8: In doTryCatch(return(expr), name, parentenv, handler) :
relative range of values (0 * EPS) is small (axis 1)
> Logistic_Model=glm(Class~.,train_data,family=binomial())
Warning message:
glm.fit: algorithm did not converge
> Logistic_Model=glm(Class~.,test_data,family=binomial())
> plot(Logistic_Model)
Hit <Return> to see next plot:
Hit <Return> to see next plot:
Hit <Return> to see next plot:
Environment History Connections
Global Environment
Data
credcard 499 obs. of 31 variables
Logistic_Model List of 30
med2 1999 obs. of 9 variables
NewData 499 obs. of 30 variables
test_data 100 obs. of 30 variables
train_data 399 obs. of 30 variables
Values
Files Plots Packages Help Viewer
Normal Q-Q
Std. deviance resid.
Theoretical Quantiles
glm(Class ~ .)
Type here to search
ENG
20:47
09-04-2020

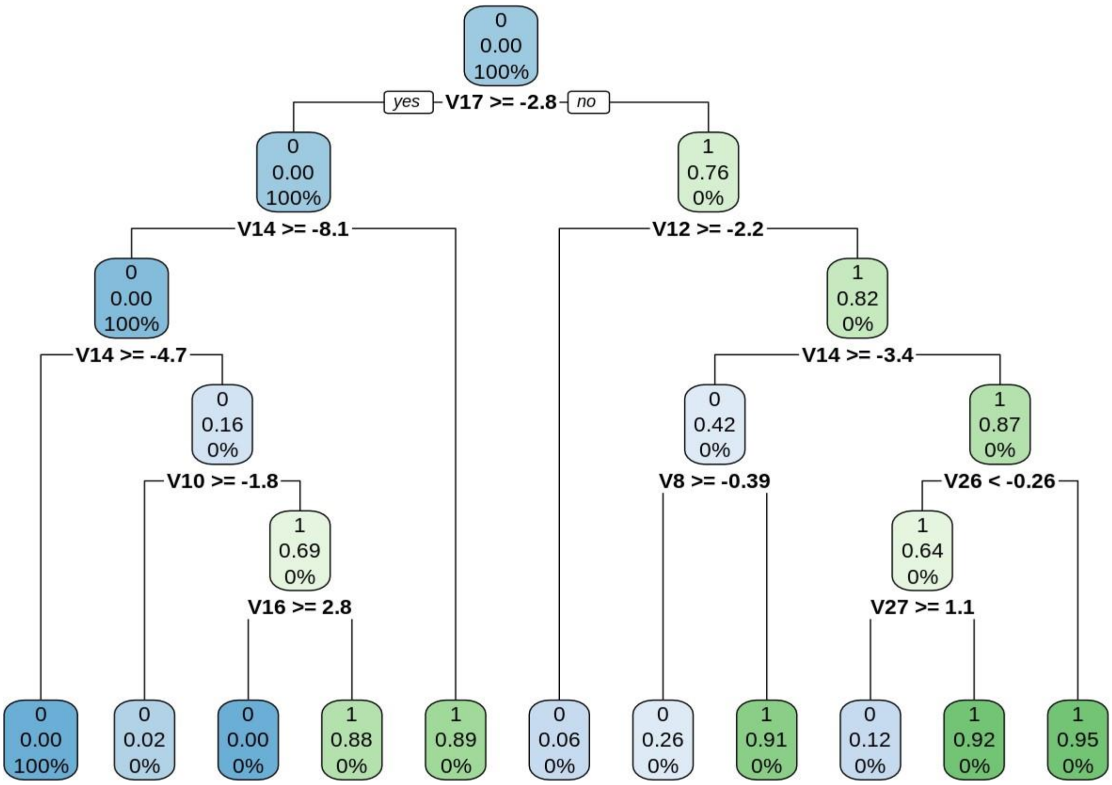
CHAPTER 6

Fitting a Decision Tree Model

In this section, we will implement a decision tree algorithm. *Decision Trees* to plot the outcomes of a decision. These outcomes are basically a consequence through which we can conclude as to what class the object belongs to. We will now implement our decision tree model and will plot it using the rpart.plot() function. We will specifically use the recursive parting to plot the decision tree.

```
library(rpart)
library(rpart.plot)
decisionTree_model <- rpart(Class ~ . , creditcard_data, method = 'class')
predicted_val <- predict(decisionTree_model, creditcard_data, type = 'class')
probability <- predict(decisionTree_model, creditcard_data, type = 'prob')

rpart.plot(decisionTree_model)
```



CONCLUSION

At the end of the Credit Card Fraud Detection R project, we observed how to create data visualizations. We made use of packages like ggplot2, ranger that allowed us to plot various types of visualizations that pertained to several time-frames of the year. With this, we could conclude how time affected customer trips. We learnt how data can be analyzed and visualized to discern fraudulent transactions from other types of data.

BIBLIOGRAPHY

1) https://gtd.crdit-card-fraud.com/files/gtd-1970-2018/
2) https://cran.r-project.org
3) https://susanli2016.github.io/Credit-card-DataAnalysis/
4) https://cran.r-project.org/web/packages/xlsx/xlsx.pdf