In [1]:
```
# loading necessery packages #

using CSV
using DataFrames
using Clustering
using ElasticArrays
using DataStructures
using DecisionTree
using MLDataUtils
using FreqTables
using PyPlot
using StatsPlots
```

Data Import

Read a csv input (a filename given as a String, or any other IO source), returning a CSV.File object. Opens the file and uses passed arguments to detect the number of columns and column types. The returned CSV.File object supports the Tables.jl interface and can iterate CSV.Rows. CSV.Row supports propertynames and getproperty to access individual row values. Note that duplicate column names will be detected and adjusted to ensure uniqueness (duplicate column name a will become a_1).

CSV.read — Function: CSV.read(fullpath::Union{AbstractString,IO}, sink=DataFrame; kwargs...) => typeof(sink)

Parses a delimited file into a Julia structure (a DataFrame by default, but any valid Tables.jl sink function can be provided).

In [2]:
```
# reading dataset
dt = CSV.read("fraudData.csv")
```

Out[2]: 6,362,620 rows × 11 columns (omitted printing of 4 columns)

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDe
	Int64	String	Float64	String	Float64	Float64	String
1	1	PAYMENT	9839.64	C1231006815	170136.0	1.60296e5	M19797
2	1	PAYMENT	1864.28	C1666544295	21249.0	19384.7	M20442
3	1	TRANSFER	181.0	C1305486145	181.0	0.0	C55326
4	1	CASH_OUT	181.0	C840083671	181.0	0.0	C38997
5	1	PAYMENT	11668.1	C2048537720	41554.0	29885.9	M12307
6	1	PAYMENT	7817.71	C90045638	53860.0	46042.3	M57348
7	1	PAYMENT	7107.77	C154988899	183195.0	1.76087e5	M40806
8	1	PAYMENT	7861.64	C1912850431	1.76087e5	1.68226e5	M63332
9	1	PAYMENT	4024.36	C1265012928	2671.0	0.0	M11769
10	1	DEBIT	5337.77	C712410124	41720.0	36382.2	C19560
11	1	DEBIT	9644.94	C1900366749	4465.0	0.0	C99760
12	1	PAYMENT	3099.97	C249177573	20771.0	17671.0	M20965
13	1	PAYMENT	2560.74	C1648232591	5070.0	2509.26	M97286
14	1	PAYMENT	11633.8	C1716932897	10127.0	0.0	M80156
15	1	PAYMENT	4098.78	C1026483832	503264.0	4.99165e5	M16353
16	1	CASH_OUT	2.29134e5	C905080434	15325.0	0.0	C47640
17	1	PAYMENT	1563.82	C761750706	450.0	0.0	M17312
18	1	PAYMENT	1157.86	C1237762639	21156.0	19998.1	M18770
19	1	PAYMENT	671.64	C2033524545	15123.0	14451.4	M47305
20	1	TRANSFER	2.1531e5	C1670993182	705.0	0.0	C11004
21	1	PAYMENT	1373.43	C20804602	13854.0	12480.6	M13445
22	1	DEBIT	9302.79	C1566511282	11299.0	1996.21	C19735
23	1	DEBIT	1065.41	C1959239586	1817.0	751.59	C51513
24	1	PAYMENT	3876.41	C504336483	67852.0	63975.6	M14049
25	1	TRANSFER	3.11686e5	C1984094095	10835.0	0.0	C93258
26	1	PAYMENT	6061.13	C1043358826	443.0	0.0	M15580
27	1	PAYMENT	9478.39	C1671590089	116494.0	1.07016e5	M58488
28	1	PAYMENT	8009.09	C1053967012	10968.0	2958.91	M29530
29	1	PAYMENT	8901.99	C1632497828	2958.91	0.0	M33419
30	1	PAYMENT	9920.52	C764826684	0.0	0.0	M19400

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDe
	Int64	String	Float64	String	Float64	Float64	String
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

In [4]:
```
# here df is in DataFrame type and columnName is string type, call like the fo
llowing
# newdt = OneHotEncoding(dt,"type")
function OneHotEncoding(df,columnName)
    newdf = copy(df)
    for c in unique(df[Symbol(columnName)])
        newdf[Symbol(c)] = ifelse.(df[Symbol(columnName)] .== c, 1, 0)
    end
    deletecols!(newdf, Symbol(columnName))
    return newdf
end
```

Out[4]: OneHotEncoding (generic function with 1 method)

In [2]:
```
#Encoding the type column
dt = OneHotEncoding(dt,"type")
```

Out[2]: 6,362,620 rows × 15 columns

	step	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldl
	Int64?	Float64?	String?	Float64?	Float64?	String?	Flo
1	1	9839.64	C1231006815	170136.0	1.60296e5	M1979787155	0.0
2	1	1864.28	C1666544295	21249.0	19384.7	M2044282225	0.0
3	1	181.0	C1305486145	181.0	0.0	C553264065	0.0
4	1	181.0	C840083671	181.0	0.0	C38997010	211
5	1	11668.1	C2048537720	41554.0	29885.9	M1230701703	0.0
6	1	7817.71	C90045638	53860.0	46042.3	M573487274	0.0
7	1	7107.77	C154988899	183195.0	1.76087e5	M408069119	0.0
8	1	7861.64	C1912850431	1.76087e5	1.68226e5	M633326333	0.0
9	1	4024.36	C1265012928	2671.0	0.0	M1176932104	0.0
10	1	5337.77	C712410124	41720.0	36382.2	C195600860	418
11	1	9644.94	C1900366749	4465.0	0.0	C997608398	108
12	1	3099.97	C249177573	20771.0	17671.0	M2096539129	0.0
13	1	2560.74	C1648232591	5070.0	2509.26	M972865270	0.0
14	1	11633.8	C1716932897	10127.0	0.0	M801569151	0.0
15	1	4098.78	C1026483832	503264.0	4.99165e5	M1635378213	0.0
16	1	2.29134e5	C905080434	15325.0	0.0	C476402209	508
17	1	1563.82	C761750706	450.0	0.0	M1731217984	0.0
18	1	1157.86	C1237762639	21156.0	19998.1	M1877062907	0.0
19	1	671.64	C2033524545	15123.0	14451.4	M473053293	0.0
20	1	2.1531e5	C1670993182	705.0	0.0	C1100439041	224
21	1	1373.43	C20804602	13854.0	12480.6	M1344519051	0.0
22	1	9302.79	C1566511282	11299.0	1996.21	C1973538135	298
23	1	1065.41	C1959239586	1817.0	751.59	C515132998	103
24	1	3876.41	C504336483	67852.0	63975.6	M1404932042	0.0
25	1	3.11686e5	C1984094095	10835.0	0.0	C932583850	626
26	1	6061.13	C1043358826	443.0	0.0	M1558079303	0.0
27	1	9478.39	C1671590089	116494.0	1.07016e5	M58488213	0.0
28	1	8009.09	C1053967012	10968.0	2958.91	M295304806	0.0
29	1	8901.99	C1632497828	2958.91	0.0	M33419717	0.0
30	1	9920.52	C764826684	0.0	0.0	M1940055334	0.0

	step	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldl
	Int64⍰	Float64⍰	String⍰	Float64⍰	Float64⍰	String⍰	Flo
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Data Exploration

In this section, we explore the data

Pring Size of dataset

function size() returns the dimensionality of data, which shows that there are 6362620 Instances (or rows or records) and 15 Features (or columns).

In [3]:
```
# size function returns the number of row and columns of the dataset
row, col = size(dt)
println("Number of Instances: ", row)
println("Number of Features: ", col)
```

```
Number of Instances: 6362620
Number of Features: 15
```

List of features in training data

In [4]:
```
names(dt)
```

Out[4]:
```
15-element Array{Symbol,1}:
 :step
 :amount
 :nameOrig
 :oldbalanceOrg
 :newbalanceOrig
 :nameDest
 :oldbalanceDest
 :newbalanceDest
 :isFraud
 :isFlaggedFraud
 :CASH_IN
 :CASH_OUT
 :DEBIT
 :PAYMENT
 :TRANSFER
```

Showing first 10 example and last 10 example

In [5]:
```
# printing first 10 example

first(dt,10)
```

Out[5]: 10 rows × 15 columns

	step	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldb
	Int64⍰	Float64⍰	String⍰	Float64⍰	Float64⍰	String⍰	Floa
1	1	9839.64	C1231006815	170136.0	1.60296e5	M1979787155	0.0
2	1	1864.28	C1666544295	21249.0	19384.7	M2044282225	0.0
3	1	181.0	C1305486145	181.0	0.0	C553264065	0.0
4	1	181.0	C840083671	181.0	0.0	C38997010	211
5	1	11668.1	C2048537720	41554.0	29885.9	M1230701703	0.0
6	1	7817.71	C90045638	53860.0	46042.3	M573487274	0.0
7	1	7107.77	C154988899	183195.0	1.76087e5	M408069119	0.0
8	1	7861.64	C1912850431	1.76087e5	1.68226e5	M633326333	0.0
9	1	4024.36	C1265012928	2671.0	0.0	M1176932104	0.0
10	1	5337.77	C712410124	41720.0	36382.2	C195600860	418

In [6]:
```
# Printing last 10 examples

last(dt, 10)
```

Out[6]: 10 rows × 15 columns

	step	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldb
	Int64?	Float64?	String?	Float64?	Float64?	String?	Floa
1	742	63417.0	C778071008	63417.0	0.0	C1812552860	0.0
2	742	63417.0	C994950684	63417.0	0.0	C1662241365	2.76
3	743	1.25882e6	C1531301470	1.25882e6	0.0	C1470998563	0.0
4	743	1.25882e6	C1436118706	1.25882e6	0.0	C1240760502	5.03
5	743	3.39682e5	C2013999242	3.39682e5	0.0	C1850423904	0.0
6	743	3.39682e5	C786484425	3.39682e5	0.0	C776919290	0.0
7	743	6.31141e6	C1529008245	6.31141e6	0.0	C1881841831	0.0
8	743	6.31141e6	C1162922333	6.31141e6	0.0	C1365125890	684
9	743	8.50003e5	C1685995037	8.50003e5	0.0	C2080388513	0.0
10	743	8.50003e5	C1280323807	8.50003e5	0.0	C873221189	6.51

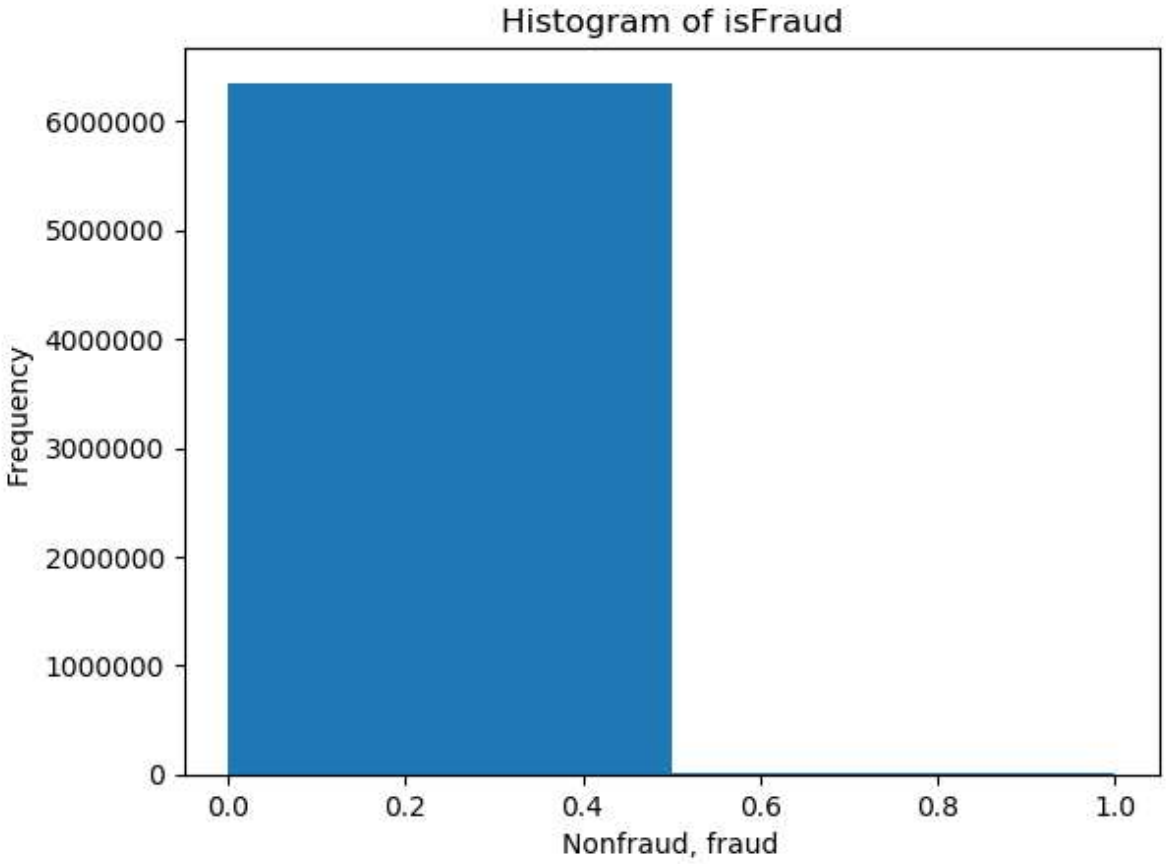
Distribution of every features in dataset.

In [7]:
```
println(describe(dt))
```

```
15×8 DataFrame
| Row | variable       | mean       | min          | median    | max          | nunique | nmissing | eltype   |
|     | Symbol         | Union…     | Any          | Union…    | Any          | Union…  | Int64    | DataType |
|-----|----------------|------------|--------------|-----------|--------------|---------|----------|----------|
| 1   | step           | 243.397    | 1            | 239.0     | 743          |         | 0        | Int64    |
| 2   | amount         | 1.79862e5  | 0.0          | 74871.9   | 9.24455e7    |         | 0        | Float64  |
| 3   | nameOrig       |            | C1000000639  |           | C999999784   | 6353307 | 0        | String   |
| 4   | oldbalanceOrg  | 8.33883e5  | 0.0          | 14208.0   | 5.9585e7     |         | 0        | Float64  |
| 5   | newbalanceOrig | 8.55114e5  | 0.0          | 0.0       | 4.9585e7     |         | 0        | Float64  |
| 6   | nameDest       |            | C1000004082  |           | M999999784   | 2722362 | 0        | String   |
| 7   | oldbalanceDest | 1.1007e6   | 0.0          | 1.32706e5 | 3.56016e8    |         | 0        | Float64  |
| 8   | newbalanceDest | 1.225e6    | 0.0          | 2.14661e5 | 3.56179e8    |         | 0        | Float64  |
| 9   | isFraud        | 0.00129082 | 0            | 0.0       | 1            |         | 0        | Int64    |
| 10  | isFlaggedFraud | 2.51469e-6 | 0            | 0.0       | 1            |         | 0        | Int64    |
| 11  | CASH_IN        | 0.219923   | 0            | 0.0       | 1            |         | 0        | Int64    |
| 12  | CASH_OUT       | 0.351663   | 0            | 0.0       | 1            |         | 0        | Int64    |
| 13  | DEBIT          | 0.00651178 | 0            | 0.0       | 1            |         | 0        | Int64    |
| 14  | PAYMENT        | 0.338146   | 0            | 0.0       | 1            |         | 0        | Int64    |
| 15  | TRANSFER       | 0.0837562  | 0            | 0.0       | 1            |         | 0        | Int64    |
```

Histogram showing frequency distribution of non-fraud and fraud instances

In [8]:
```
h = PyPlot.plt.hist(dt[:isFraud], 2)
plt.title("Histogram of isFraud")
plt.xlabel("Nonfraud, fraud")
plt.ylabel("Frequency")
```



Out[8]: PyObject Text(24.0, 0.5, 'Frequency')

Remove unnecessary column

As "nameOrig" and "nameDest" are not playing a vital role for a fraud transaction so we can delete these columns.

In [9]:
```
# Deleting String Type Feature 'nameOrig'
# Deleting String Type Feature 'nameDest'

dt = deletecols!(dt, :nameOrig)
dt = deletecols!(dt, :nameDest)
```

Out[9]: 6,362,620 rows × 13 columns

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Int64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰
1	1	9839.64	170136.0	1.60296e5	0.0	0.0
2	1	1864.28	21249.0	19384.7	0.0	0.0
3	1	181.0	181.0	0.0	0.0	0.0
4	1	181.0	181.0	0.0	21182.0	0.0
5	1	11668.1	41554.0	29885.9	0.0	0.0
6	1	7817.71	53860.0	46042.3	0.0	0.0
7	1	7107.77	183195.0	1.76087e5	0.0	0.0
8	1	7861.64	1.76087e5	1.68226e5	0.0	0.0
9	1	4024.36	2671.0	0.0	0.0	0.0
10	1	5337.77	41720.0	36382.2	41898.0	40348.8
11	1	9644.94	4465.0	0.0	10845.0	1.57982e5
12	1	3099.97	20771.0	17671.0	0.0	0.0
13	1	2560.74	5070.0	2509.26	0.0	0.0
14	1	11633.8	10127.0	0.0	0.0	0.0
15	1	4098.78	503264.0	4.99165e5	0.0	0.0
16	1	2.29134e5	15325.0	0.0	5083.0	51513.4
17	1	1563.82	450.0	0.0	0.0	0.0
18	1	1157.86	21156.0	19998.1	0.0	0.0
19	1	671.64	15123.0	14451.4	0.0	0.0
20	1	2.1531e5	705.0	0.0	22425.0	0.0
21	1	1373.43	13854.0	12480.6	0.0	0.0
22	1	9302.79	11299.0	1996.21	29832.0	16896.7
23	1	1065.41	1817.0	751.59	10330.0	0.0
24	1	3876.41	67852.0	63975.6	0.0	0.0
25	1	3.11686e5	10835.0	0.0	6267.0	2.71917e6
26	1	6061.13	443.0	0.0	0.0	0.0
27	1	9478.39	116494.0	1.07016e5	0.0	0.0
28	1	8009.09	10968.0	2958.91	0.0	0.0
29	1	8901.99	2958.91	0.0	0.0	0.0
30	1	9920.52	0.0	0.0	0.0	0.0

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Int64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Freqency distribution of isFraud column variables

0 represents non-fraudulant transaction 1 represents fraud transaction

In [10]:
```
frequency_isFraud = freqtable(dt[:isFraud])
```

Out[10]:
```
2-element Named Array{Int64,1}
Dim1 │
─────┼─────────
0    │ 6354407
1    │    8213
```

In [11]:
```
# Ration of non-fraud and fraud
ratio = prop(frequency_isFraud)
```

Out[11]:
```
2-element Named Array{Float64,1}
Dim1 │
─────┼─────────────
0    │   0.998709
1    │ 0.00129082
```

In [12]:
```
first(dt, 5)
```

Out[12]: 5 rows × 13 columns

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
	Int64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰
1	1	9839.64	170136.0	1.60296e5	0.0	0.0
2	1	1864.28	21249.0	19384.7	0.0	0.0
3	1	181.0	181.0	0.0	0.0	0.0
4	1	181.0	181.0	0.0	21182.0	0.0
5	1	11668.1	41554.0	29885.9	0.0	0.0

In [13]:
```
# Setting Random Seed
using Random
Random.seed!(1234)
```

Out[13]:
```
MersenneTwister(UInt32[0x000004d2], Random.DSFMT.DSFMT_state(Int32[-139324001
8, 1073611148, 45497681, 1072875908, 436273599, 1073674613, -2043716458, 1073
445557, -254908435, 1072827086  …  -599655111, 1073144102, 367655457, 1072985
259, -1278750689, 1018350124, -597141475, 249849711, 382, 0]), [0.0, 0.0, 0.
0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0], UInt128[0x00000000000000000000000000000000, 0x000000000000000
00000000000000000, 0x00000000000000000000000000000000, 0x000000000000000000
000000000000, 0x00000000000000000000000000000000, 0x000000000000000000000000
0000000, 0x00000000000000000000000000000000, 0x000000000000000000000000000000
00, 0x00000000000000000000000000000000, 0x00000000000000000000000000000000  …
0x00000000000000000000000000000000, 0x00000000000000000000000000000000, 0x000
00000000000000000000000000000, 0x00000000000000000000000000000000, 0x00000000
00000000000000000000, 0x00000000000000000000000000000000, 0x0000000000000000
00000000000000000, 0x00000000000000000000000000000000, 0x00000000000000000000
00000000000, 0x00000000000000000000000000000000], 1002, 0)
```

Spliting the dataset

We spliting the dataset using the Class column ("isFraud").

In "isFraud" there is two class value "0" & "1". We split the data into two part, those are

1. minorityData (class value "1")
2. majorityData (class value "0")

In [14]:
```
#=
Split dataset to minorityData where isFraud = 1
Split dataset to minorityData where isFraud = 0
=#
minorityData = dt[dt[:, 7] .== 1, :]
majorityData = dt[dt[:, 7] .== 0, :]
```

Out[14]: 6,354,407 rows × 13 columns

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Int64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰
1	1	9839.64	170136.0	1.60296e5	0.0	0.0
2	1	1864.28	21249.0	19384.7	0.0	0.0
3	1	11668.1	41554.0	29885.9	0.0	0.0
4	1	7817.71	53860.0	46042.3	0.0	0.0
5	1	7107.77	183195.0	1.76087e5	0.0	0.0
6	1	7861.64	1.76087e5	1.68226e5	0.0	0.0
7	1	4024.36	2671.0	0.0	0.0	0.0
8	1	5337.77	41720.0	36382.2	41898.0	40348.8
9	1	9644.94	4465.0	0.0	10845.0	1.57982e5
10	1	3099.97	20771.0	17671.0	0.0	0.0
11	1	2560.74	5070.0	2509.26	0.0	0.0
12	1	11633.8	10127.0	0.0	0.0	0.0
13	1	4098.78	503264.0	4.99165e5	0.0	0.0
14	1	2.29134e5	15325.0	0.0	5083.0	51513.4
15	1	1563.82	450.0	0.0	0.0	0.0
16	1	1157.86	21156.0	19998.1	0.0	0.0
17	1	671.64	15123.0	14451.4	0.0	0.0
18	1	2.1531e5	705.0	0.0	22425.0	0.0
19	1	1373.43	13854.0	12480.6	0.0	0.0
20	1	9302.79	11299.0	1996.21	29832.0	16896.7
21	1	1065.41	1817.0	751.59	10330.0	0.0
22	1	3876.41	67852.0	63975.6	0.0	0.0
23	1	3.11686e5	10835.0	0.0	6267.0	2.71917e6
24	1	6061.13	443.0	0.0	0.0	0.0
25	1	9478.39	116494.0	1.07016e5	0.0	0.0
26	1	8009.09	10968.0	2958.91	0.0	0.0
27	1	8901.99	2958.91	0.0	0.0	0.0
28	1	9920.52	0.0	0.0	0.0	0.0
29	1	3448.92	0.0	0.0	0.0	0.0
30	1	4206.84	0.0	0.0	0.0	0.0

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Int64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰	Float64⍰
⋮	⋮	⋮	⋮	⋮	⋮	⋮

In [15]:
```
# printing size of minorityData

println("Instances of Minority Data: ", nrow(minorityData))
println("Features of Minority Data: ", ncol(minorityData))
```

```
Instances of Minority Data: 8213
Features of Minority Data: 13
```

In [16]:
```
# printing size of majorityData
println("Instances of Majority Data: ", nrow(majorityData))
println("Features of Majority Data: ", ncol(majorityData))
```

```
Instances of Majority Data: 6354407
Features of Majority Data: 13
```

In [17]:
```
# This function splits minority data in given ratio
function split_MinorityData(min_data, ratio)
    minority_mat = convert(Array, min_data[1:13])
    min_trainShuf = shuffleobs(transpose(minority_mat))
    (min_train, min_test) = splitobs(min_trainShuf, at =ratio)
    min_train = Array(transpose(min_train))
    min_test = Array(transpose(min_test))
    return min_train, min_test
end
```

Out[17]: split_MinorityData (generic function with 1 method)

Split MinorityData

For bulid a independent test data we split the MinorityData into 70% and 30%.

We keep 70% for train and 30% for test dataset.

In [18]:
```
# Split minorityData for train an test
min_train, min_test = split_MinorityData(minorityData, .70)
println(size(min_train))
println(size(min_test))
```

```
┌ Warning: `convert(::Type{Array}, df::AbstractDataFrame)` is deprecated, use
`convert(Matrix, df)` instead.
│   caller = split_MinorityData(::DataFrame, ::Float64) at In[17]:3
└ @ Main ./In[17]:3

(5749, 13)
(2464, 13)
```

In [19]:
```
min_train
```

Out[19]:
```
5749×13 Array{Union{Missing, Float64},2}:
 326.0       4.24963e5       4.24963e5  …  1.0  0.0  0.0  0.0  0.0  0.0  1.0
 728.0       6.3224e6        6.3224e6      1.0  0.0  0.0  0.0  0.0  0.0  1.0
 641.0    2205.55         2205.55          1.0  0.0  0.0  0.0  0.0  0.0  1.0
 434.0   32671.9         32671.9           1.0  0.0  0.0  0.0  0.0  0.0  1.0
 531.0       8.34204e5       8.34204e5     1.0  0.0  0.0  1.0  0.0  0.0  0.0
 631.0       2.39161e6       2.39161e6  …  1.0  0.0  0.0  1.0  0.0  0.0  0.0
 373.0       4.29468e6       4.29468e6     1.0  0.0  0.0  0.0  0.0  0.0  1.0
 143.0       1.82275e6       1.82275e6     1.0  0.0  0.0  1.0  0.0  0.0  0.0
 291.0       2.32491e6       2.32491e6     1.0  0.0  0.0  1.0  0.0  0.0  0.0
 612.0       1.02319e6       1.02319e6     1.0  0.0  0.0  0.0  0.0  0.0  1.0
 324.0       3.62837e5       3.62837e5  …  1.0  0.0  0.0  1.0  0.0  0.0  0.0
 365.0   31315.5         31315.5           1.0  0.0  0.0  1.0  0.0  0.0  0.0
 496.0   30172.0         30172.0           1.0  0.0  0.0  1.0  0.0  0.0  0.0
   ⋮                                    ⋱                    ⋮
 319.0       4.89534e6       4.89534e6     1.0  0.0  0.0  0.0  0.0  0.0  1.0
  97.0    5624.02          5624.02          1.0  0.0  0.0  0.0  0.0  0.0  1.0
 303.0       4.4701e5        4.4701e5      1.0  0.0  0.0  0.0  0.0  0.0  1.0
 133.0       2.12131e5       2.12131e5  …  1.0  0.0  0.0  1.0  0.0  0.0  0.0
 261.0       1.96562e5       1.96562e5     1.0  0.0  0.0  1.0  0.0  0.0  0.0
 643.0       4.2226e6        4.2226e6      1.0  0.0  0.0  1.0  0.0  0.0  0.0
 232.0       5.70135e5       5.70135e5     1.0  0.0  0.0  1.0  0.0  0.0  0.0
 148.0       3.7331e6        3.7331e6      1.0  0.0  0.0  0.0  0.0  0.0  1.0
  59.0   44733.5         44733.5        …  1.0  0.0  0.0  1.0  0.0  0.0  0.0
 608.0  388172.0        388172.0           1.0  0.0  0.0  0.0  0.0  0.0  1.0
 674.0       9.32923e5       9.32923e5     1.0  0.0  0.0  1.0  0.0  0.0  0.0
 351.0       1.78344e5       1.78344e5     1.0  0.0  0.0  0.0  0.0  0.0  1.0
```

In [20]:
```
maj_mat = convert(Matrix{Float64}, majorityData[1:13])
```

Out[20]:
```
6354407×13 Array{Float64,2}:
   1.0   9839.64       170136.0        …  0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   1864.28        21249.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0  11668.1         41554.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   7817.71        53860.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   7107.77       183195.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   7861.64            1.76087e5  …  0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   4024.36         2671.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   5337.77        41720.0           0.0  0.0  0.0  0.0  1.0  0.0  0.0
   1.0   9644.94         4465.0           0.0  0.0  0.0  0.0  1.0  0.0  0.0
   1.0   3099.97        20771.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   2560.74         5070.0        …  0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0  11633.8         10127.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   1.0   4098.78       503264.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
   ⋮                                   ⋱                      ⋮
 718.0   8178.01        11742.0        …  0.0  0.0  0.0  0.0  0.0  1.0  0.0
 718.0      1.11964e5    4514.0           0.0  0.0  0.0  1.0  0.0  0.0  0.0
 718.0  17841.2         10182.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
 718.0  96239.7        101281.0           0.0  0.0  1.0  0.0  0.0  0.0  0.0
 718.0   1022.91           12.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
 718.0      3.17177e5    170.0        …  0.0  0.0  0.0  1.0  0.0  0.0  0.0
 718.0   4109.57         5521.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
 718.0   8634.29       518802.0           0.0  0.0  0.0  0.0  0.0  1.0  0.0
 718.0      1.59188e5    3859.0           0.0  0.0  0.0  1.0  0.0  0.0  0.0
 718.0      1.86274e5  168046.0           0.0  0.0  0.0  1.0  0.0  0.0  0.0
 718.0  82096.4         13492.0        …  0.0  0.0  0.0  0.0  0.0  0.0  1.0
 718.0   1864.24        20426.0           0.0  0.0  0.0  0.0  1.0  0.0  0.0
```

In [21]:
```
# converting DataFrame to Matrix and fliping dimension
# because Clustering.jl package takes in this form

majorityData_mat = permutedims(maj_mat, [2, 1])
```

Out[21]:
```
13×6354407 Array{Float64,2}:
      1.0           1.0       1.0      1.0   …    718.0     718.0
   9839.64       1864.28   11668.1   7817.71     82096.4    1864.24
 170136.0       21249.0    41554.0  53860.0      13492.0   20426.0
      1.60296e5  19384.7    29885.9  46042.3          0.0   18561.8
      0.0           0.0       0.0      0.0          0.0  188746.0
      0.0           0.0       0.0      0.0   …  82096.4       1.9061e5
      0.0           0.0       0.0      0.0          0.0       0.0
      0.0           0.0       0.0      0.0          0.0       0.0
      0.0           0.0       0.0      0.0          0.0       0.0
      0.0           0.0       0.0      0.0          0.0       0.0
      0.0           0.0       0.0      0.0   …      0.0       1.0
      1.0           1.0       1.0      1.0          0.0       0.0
      0.0           0.0       0.0      0.0          1.0       0.0
```

Clustering

Running k-means clustering using k = 5 and max iteration 1000.

In [22]:
```
# running kmeans clustering using k = 5
k = 5

result = kmeans(majorityData_mat, k; maxiter = 1000, display = :iter)
```

Iters	objv	objv-change	affected
0	7.931844e+19		
1	7.097583e+19	-8.342615e+18	5
2	6.989430e+19	-1.081531e+18	5
3	6.941902e+19	-4.752734e+17	5
4	6.912213e+19	-2.968918e+17	5
5	6.889818e+19	-2.239522e+17	5
6	6.869452e+19	-2.036567e+17	5
7	6.850030e+19	-1.942245e+17	5
8	6.830870e+19	-1.915946e+17	5
9	6.811035e+19	-1.983489e+17	5
10	6.792287e+19	-1.874876e+17	5
11	6.774288e+19	-1.799825e+17	5
12	6.757774e+19	-1.651443e+17	5
13	6.742832e+19	-1.494185e+17	5
14	6.730127e+19	-1.270530e+17	5
15	6.719190e+19	-1.093663e+17	5
16	6.710050e+19	-9.140463e+16	5
17	6.703486e+19	-6.563702e+16	5
18	6.698259e+19	-5.226961e+16	5
19	6.693656e+19	-4.603483e+16	5
20	6.689922e+19	-3.733421e+16	5
21	6.687130e+19	-2.792617e+16	5
22	6.684943e+19	-2.186492e+16	5
23	6.683319e+19	-1.624229e+16	5
24	6.681967e+19	-1.351972e+16	5
25	6.681053e+19	-9.141223e+15	5
26	6.680178e+19	-8.747182e+15	5
27	6.679651e+19	-5.274502e+15	5
28	6.679389e+19	-2.616778e+15	5
29	6.679202e+19	-1.872041e+15	5
30	6.679099e+19	-1.024141e+15	5
31	6.679043e+19	-5.638048e+14	5
32	6.679000e+19	-4.263360e+14	5
33	6.678981e+19	-1.910829e+14	4
34	6.678973e+19	-8.581677e+13	4
35	6.678965e+19	-7.092037e+13	5
36	6.678961e+19	-4.849664e+13	5
37	6.678957e+19	-3.895685e+13	5
38	6.678952e+19	-5.147563e+13	5
39	6.678949e+19	-2.467469e+13	4
40	6.678948e+19	-9.349956e+12	4
41	6.678947e+19	-8.678394e+12	4
42	6.678947e+19	-1.974778e+12	4
43	6.678947e+19	-9.096706e+11	4
44	6.678947e+19	-5.294806e+11	4
45	6.678947e+19	-2.289899e+11	3
46	6.678947e+19	-1.260516e+11	3
47	6.678947e+19	-8.561486e+10	3
48	6.678947e+19	-6.629869e+10	3
49	6.678947e+19	-2.214570e+11	4
50	6.678947e+19	-1.821142e+11	3
51	6.678947e+19	-1.981672e+11	4
52	6.678947e+19	-2.187288e+11	4
53	6.678947e+19	-8.856284e+10	2
54	6.678947e+19	-2.816212e+10	2

```
     55       6.678947e+19      -1.596413e+10 |        2
     56       6.678947e+19      -2.683658e+09 |        2
     57       6.678947e+19      -9.992520e+08 |        2
     58       6.678947e+19      -6.763315e+08 |        2
     59       6.678947e+19      -7.487078e+08 |        2
     60       6.678947e+19      -2.747761e+08 |        2
     61       6.678947e+19      -1.954120e+08 |        2
     62       6.678947e+19      -2.621604e+08 |        0
     63       6.678947e+19       0.000000e+00 |        0
K-means converged with 63 iterations (objv = 6.678946789396542e19)
```

Out[22]:
```
KmeansResult{Array{Float64,2},Float64,Int64}([242.808 237.652 … 249.015 290.2
37; 1.41196e5 1.60333e5 … 5.06892e5 2.18474e6; … ; 0.383817 0.000285857 … 0.0
0.0; 0.0743748 4.76429e-5 … 0.239177 0.33019], [1, 1, 1, 1, 1, 1, 1, 1, 1, 1
…  1, 1, 1, 1, 1, 1, 1, 1, 1, 1], [5.69408e11, 6.7804e11, 6.60296e11, 6.47895
e11, 5.64048e11, 5.66883e11, 6.97648e11, 5.78064e11, 5.34149e11, 6.78846e11
…  6.90104e11, 3.8873e11, 6.99904e11, 2.09735e11, 6.95314e11, 6.57836e11, 5.2
6504e11, 4.06876e11, 5.91948e11, 3.62782e11], [5605297, 293853, 1702, 423866,
29689], [5605297, 293853, 1702, 423866, 29689], 6.678946789396542e19, 63, tru
e)
```

In [23]:
```
size(majorityData_mat)
```

Out[23]:
```
(13, 6354407)
```

In [24]:
```
M = result.centers

#dmat = pairwise( SqEuclidean(), majorityData_mat) ## Equivalent to pairwise(d
istance, data_matrix, data_matrix)
#dmat = convert(Array{T} where T <: AbstractFloat, dmat)
#size(dmat)
```

Out[24]:
```
13×5 Array{Float64,2}:
    242.808       237.652        358.147       249.015       290.237
      1.41196e5     1.60333e5      8.26173e6     5.06892e5     2.18474e6
      2.69041e5     1.19105e7      9.88878e5     5.87292e5     1.12874e6
      2.84482e5     1.20707e7      1.01859e6     6.16509e5     1.16197e6
 465413.0           1.53007e6      1.12168e8     6.97442e6     2.67222e7
      5.57081e5     1.38626e6      1.21477e8     7.47361e6     2.9612e7
      0.0           0.0            0.0           0.0           0.0
      0.0           0.0            0.0           0.0           0.0
      0.176635      0.999585       0.23443       0.253207      0.260602
      0.35848       8.16735e-5     0.331375      0.498967      0.401226
      0.00669242    0.0            0.00940071    0.00864896    0.00798275
      0.383817      0.000285857    0.0           0.0           0.0
      0.0743748     4.76429e-5     0.424794      0.239177      0.33019
```

View the size of the each Cluster

In [25]:
```
# size of each cluster out of k

c = counts(result)
```

Out[25]:
```
5-element Array{Int64,1}:
 5605297
  293853
    1702
  423866
   29689
```

Clusters that only contines more than or equal 8213 instances

In [26]:
```
# we need clusters that only contines more than or equal 8213 instances

global j = 1
global cluster_list = []
global clusterNumber = 0
for i in c
    if i >= 8213
        println(j, "th Cluster Contains: ", i)
        clusterNumber = clusterNumber + 1
        push!(cluster_list, j)
    end
    j = j + 1
end
println("Usable Cluster: ", clusterNumber)
println(cluster_list)
```

```
1th Cluster Contains: 5605297
2th Cluster Contains: 293853
4th Cluster Contains: 423866
5th Cluster Contains: 29689
Usable Cluster: 4
Any[1, 2, 4, 5]
```

In [27]:
```
# obtain the resultant assignments
# a[i] indicates which cluster the i-th sample is assigned to

cluster_no = assignments(result)
```

Out[27]:
```
6354407-element Array{Int64,1}:
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
 ⋮
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
 1
```

In [28]:
```
# Number of row and column in features Matrix
global majority_sz = 6354407
row, col = size(majorityData_mat)
println(col)
```

```
6354407
```

In [29]:
```
# This function returns minoity instances in elastic array [ just a helper fun
ction ]
function collectMinority(min)

    row, col = size(min)

    temp = ElasticArray{Float64}(undef, 13, 0)

    for i = 1 : row
        r = min[i, :]
        append!(temp, r)
    end
    return temp
    #return reshape(temp, row, col)
end
```

Out[29]: collectMinority (generic function with 1 method)

In [30]:
```
# It's a helper function that takes cluster number as parameter
# and returns all the instances belongs to this cluster

function collectClusteredData(cl_no)

    temp = ElasticArray{Float64}(undef, 13, 0)

    for i = 1 : majority_sz
        if cluster_no[i] == cl_no
            append!(temp, majorityData_mat[:, i])
        end
    end

    return temp
end
```

Out[30]: collectClusteredData (generic function with 1 method)

In [31]:
```
# It's a helper function that returns cluster member of a perticular cluster

function getElem(cluster, i)
    st_idx = (i - 1) * 13 + 1
    en_idx = st_idx + 13 - 1
    return cluster[st_idx : en_idx]
end
```

Out[31]: getElem (generic function with 1 method)

In [32]:
```
# this function takes cluster number and sample size as parameter
# and returns n-random sample from that cluster

function randSample(cluster, sample_sz)
    row, col = size(cluster)
    idxs = rand(1:col, sample_sz)

    rnd_sample = ElasticArray{Float64}(undef, 13, 0)

    for i = 1 : sample_sz
        sample = getElem(cluster, idxs[i])
        append!(rnd_sample, sample)
    end

    return  rnd_sample#reshape(rnd_sample,sample_sz, row)
end
```

Out[32]:
```
randSample (generic function with 1 method)
```

In [33]:
```
# This function merge both minoirty and majority sub data in given sample size
function mergeMajorityMinority(majority, minority, sample_sz)
    return hcat(majority, minority)
end
```

Out[33]:
```
mergeMajorityMinority (generic function with 1 method)
```

In [34]:
```
# cluster_list array has the usable cluster indexes
println(cluster_list)
```

```
Any[1, 2, 4, 5]
```

Collecting cluster members

In [35]:
```
# Usable clusters, decided in the previousStep

c1 = collectClusteredData(cluster_list[1])
c2 = collectClusteredData(cluster_list[2])
c3 = collectClusteredData(cluster_list[3])
c4 = collectClusteredData(cluster_list[4])
```

Out[35]:
```
13×29689 ElasticArray{Float64,2,1}:
 1.0        1.0             1.0        …  718.0         718.0
 3.49506e5  2.22711e5  227478.0             1.73137e5     1.39144e5
 7.33024e6  2.41907e6   25743.8            95.0        7075.0
 7.67974e6  2.64178e6       0.0             0.0           0.0
 1.7001e7   1.66515e7       1.64288e7       2.96365e7     4.90402e7
 1.91692e7  1.91692e7       1.91692e7  …    2.98096e7     4.91793e7
 0.0        0.0             0.0             0.0           0.0
 0.0        0.0             0.0             0.0           0.0
 1.0        1.0             0.0             0.0           0.0
 0.0        0.0             1.0             0.0           0.0
 0.0        0.0             0.0        …    0.0           0.0
 0.0        0.0             0.0             0.0           0.0
 0.0        0.0             0.0             1.0           1.0
```

In [36]:
```
# min_train and min_test are converted to elastic array.
min_trains =  collectMinority(min_train)
min_tests =  collectMinority(min_test)
```

Out[36]:
```
13×2464 ElasticArray{Float64,2,1}:
   496.0    530.0          184.0  646.0    …  259.0          74.0
 30172.0  19577.0        73486.8    1.0e7       1.95037e6     2.45142e6
 30172.0  19577.0        73486.8    1.0e7       1.95037e6     2.45142e6
     0.0      0.0            0.0    0.0         0.0           0.0
     0.0      7.62609e5      0.0    0.0         3.3131e5   4870.65
     0.0      7.82186e5      0.0    1.0e7  …    2.28168e6     2.45629e6
     1.0      1.0            1.0    1.0         1.0           1.0
     0.0      0.0            0.0    0.0         0.0           0.0
     0.0      0.0            0.0    0.0         0.0           0.0
     0.0      1.0            0.0    1.0         1.0           1.0
     0.0      0.0            0.0    0.0    …    0.0           0.0
     0.0      0.0            0.0    0.0         0.0           0.0
     1.0      0.0            1.0    0.0         0.0           0.0
```

In [37]:
```
print("Size of minority_train: ", size(min_train))
print("Size of minority_test: ", size(min_test))
```

```
Size of minority_train: (5749, 13)Size of minority_test: (2464, 13)
```

In [38]:
```
# This function rename given dataframe
function renameDf(df)

col_name = [:step,
 :amount,
 :oldbalanceOrg,
 :newbalanceOrig,
 :oldbalanceDest,
 :newbalanceDest,
 :isFraud,
 :isFlaggedFraud,
 :CASH_IN,
 :CASH_OUT,
 :DEBIT,
 :PAYMENT,
 :TRANSFER]
 return names!(df, col_name)

end
```

Out[38]: renameDf (generic function with 1 method)

In [39]:
```
function PrepareSampledDataset(cluster, minority_sample, sample_sz)

    picked_sample = randSample(cluster, sample_sz)
    temp_dataset  = mergeMajorityMinority(picked_sample, minority_sample, samp
le_sz)

    features_sz, msamples_sz = size(temp_dataset)

    to_dataframe   = convert(DataFrame, temp_dataset)
    transposed_mat = permutedims(convert(Matrix{Float64}, to_dataframe[1:msamp
les_sz]), [2, 1])


    to_dataframe   = convert(DataFrame, transposed_mat)
    #df = to_dataframe.sample(frac=1).reset_index(drop=True)
    dataframe_shuffle = to_dataframe[StatsBase.sample(1:size(to_dataframe,1),
size(to_dataframe,1), replace=false),:]

    return renameDf(dataframe_shuffle)

end
```

Out[39]: PrepareSampledDataset (generic function with 1 method)

Declare sample size of majority sample for train and test

In [40]:
```
majority_sample_train = 8623
majority_sample_test = 5749
```

Out[40]: 5749

Merging Cluster data, minoirty sub data for creating samples for train and test

In [41]:
```
# 7 sample for training

using StatsBase

sample1_c1 = PrepareSampledDataset(c1, min_trains, majority_sample_train)
sample2_c1 = PrepareSampledDataset(c1, min_trains, majority_sample_train)
sample3_c1 = PrepareSampledDataset(c1, min_trains, majority_sample_train)


sample1_c2 = PrepareSampledDataset(c2, min_trains, majority_sample_train)
sample2_c2 = PrepareSampledDataset(c2, min_trains, majority_sample_train)

sample1_c3 = PrepareSampledDataset(c3, min_trains, majority_sample_train)
sample2_c3 = PrepareSampledDataset(c3, min_trains, majority_sample_train)
```

Out[41]: 14,372 rows × 13 columns

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Float64	Float64	Float64	Float64	Float64	Float64
1	69.0	2.96025e6	2.96025e6	0.0	0.0	0.0
2	274.0	3.14112e5	0.0	0.0	4.11372e6	4.42783e6
3	652.0	80397.9	80397.9	0.0	0.0	0.0
4	380.0	2.27907e5	0.0	0.0	3.88945e6	4.11736e6
5	230.0	2.14692e5	0.0	0.0	1.17875e7	1.20022e7
6	402.0	1.27156e5	1.27156e5	0.0	0.0	0.0
7	520.0	1.45918e6	1.45918e6	0.0	1.1206e6	2.57978e6
8	333.0	5735.9	7215.0	1479.1	1.35661e7	1.35718e7
9	651.0	1.30777e5	1.30777e5	0.0	0.0	1.30777e5
10	233.0	1.7555e6	0.0	0.0	4.49912e6	6.25462e6
11	326.0	3.87374e5	0.0	0.0	6.45928e6	6.84665e6
12	133.0	69573.7	0.0	0.0	6.94273e6	9.99489e6
13	16.0	31074.0	31074.0	0.0	0.0	0.0
14	12.0	1.49669e5	0.0	0.0	44170.1	1.93839e5
15	257.0	1.43537e6	229804.0	0.0	1.03321e7	1.17675e7
16	388.0	2.36388e5	2.36388e5	0.0	0.0	0.0
17	235.0	1.70557e5	0.0	0.0	5.46753e6	5.63809e6
18	640.0	46974.0	46974.0	0.0	0.0	46974.0
19	250.0	54109.5	1.59228e6	1.64639e6	4.71455e6	4.66044e6
20	296.0	2.61875e5	2.61875e5	0.0	0.0	2.61875e5
21	307.0	1.44173e5	0.0	0.0	1.2517e7	1.26612e7
22	74.0	85637.1	85637.1	0.0	0.0	0.0
23	715.0	2.12028e5	2.12028e5	0.0	0.0	0.0
24	279.0	1.89778e5	3.15086e5	1.25307e5	7.04858e6	7.23836e6
25	544.0	4.12668e5	4.12668e5	0.0	1.44505e6	1.85772e6
26	192.0	8783.42	8783.42	0.0	0.0	0.0
27	326.0	8.01264e6	74163.7	0.0	1.12537e7	1.92664e7
28	137.0	5.22166e5	159156.0	6.81322e5	5.16213e6	4.63996e6
29	358.0	64781.2	0.0	0.0	1.54892e7	1.55539e7
30	380.0	2.22672e5	46251.0	2.68923e5	6.43914e6	6.21646e6

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Float64	Float64	Float64	Float64	Float64	Float64
⋮	⋮	⋮	⋮	⋮	⋮	⋮

In [42]:
```
# sample for test
sample1_c4_test = PrepareSampledDataset(c4, min_tests, majority_sample_test)
```

Out[42]: 8,213 rows × 13 columns

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Float64	Float64	Float64	Float64	Float64	Float64
1	324.0	3.60408e6	0.0	0.0	1.90715e7	2.26756e7
2	297.0	1.00385e7	0.0	0.0	1.48123e7	2.48508e7
3	164.0	48899.4	5.9452e5	6.43419e5	2.06202e7	2.05713e7
4	228.0	63463.8	0.0	0.0	2.04009e7	2.04644e7
5	372.0	2.16955e5	51689.0	0.0	3.38761e7	3.40931e7
6	148.0	3.94886e5	3.94886e5	0.0	0.0	0.0
7	397.0	3.43814e5	7.46364e6	7.80745e6	1.80353e7	1.76915e7
8	359.0	86974.3	2.0978e7	2.10649e7	5.56062e7	5.55192e7
9	371.0	7.98773e6	0.0	0.0	3.10661e7	3.90538e7
10	304.0	4.73295e5	3.36654e6	3.83984e6	1.81947e7	1.77214e7
11	569.0	1.77991e5	0.0	0.0	1.78874e7	1.80654e7
12	43.0	6305.71	5.13931e5	5.20237e5	1.88137e7	1.88012e7
13	524.0	91911.4	0.0	0.0	4.53971e7	4.5489e7
14	308.0	3.42536e5	2.53545e5	5.96081e5	2.94772e7	2.91347e7
15	304.0	1.0e7	0.0	0.0	1.06027e7	3.05019e7
16	522.0	1.78131e5	1.65483e7	1.67264e7	2.18782e7	2.17e7
17	402.0	34473.5	1.65267e7	1.65612e7	5.04361e7	5.04017e7
18	357.0	178002.0	0.0	0.0	2.24875e7	2.26655e7
19	303.0	2.07501e7	34596.6	0.0	2.92139e7	4.9964e7
20	308.0	1.40711e5	20985.0	0.0	4.39965e7	4.41372e7
21	307.0	102782.0	0.0	0.0	1.89146e7	1.90174e7
22	491.0	1.26503e6	1.26503e6	0.0	0.0	0.0
23	304.0	1.46191e7	0.0	0.0	3.03413e7	4.49604e7
24	323.0	87034.4	2.63771e6	2.72474e6	1.99828e7	1.98958e7
25	396.0	26359.9	1.05288e7	1.05551e7	2.2359e7	2.23327e7
26	161.0	1.74818e5	7.92805e5	9.67623e5	1.85517e7	1.83769e7
27	345.0	2.50516e5	0.0	0.0	1.86527e7	1.89032e7
28	380.0	2.46753e5	5.29739e6	5.54414e6	3.1439e7	3.11923e7
29	644.0	9.55467e5	1.29089e5	0.0	2.114e7	2.20955e7
30	375.0	23294.1	0.0	0.0	5.812e7	5.81433e7

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDes
	Float64	Float64	Float64	Float64	Float64	Float64
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Writing all the created samples for train and test as csv using CSV.write function

In [43]:
```
CSV.write("sample1_c1.csv", sample1_c1)
CSV.write("sample2_c1.csv", sample2_c1)
CSV.write("sample3_c1.csv", sample3_c1)

CSV.write("sample1_c2.csv", sample1_c2)
CSV.write("sample2_c2.csv", sample2_c2)

CSV.write("sample1_c3.csv", sample1_c3)
CSV.write("sample2_c3.csv", sample2_c3)
```

Out[43]: "sample2_c3.csv"

In [44]:
```
CSV.write("sample1_c4_test.csv", sample1_c4_test)
```

Out[44]: "sample1_c4_test.csv"

ScikitLearn

ScikitLearn.jl provides a uniform interface for training and using models, as well as a set of tools for chaining (pipelines), evaluating, and tuning model hyperparameters.

To install ScikitLearn.jl, type]add ScikitLearn at the REPL.

To import Python models (optional), ScikitLearn.jl requires the scikit-learn Python library, which will be installed automatically when needed. Most of the examples use PyPlot.jl

In [45]:
```
IJulia.installkernel("Julia nodeps", "--depwarn=no")
```

```
┌ Info: Installing Julia nodeps kernelspec in /home/tarik/.local/share/jupyte
r/kernels/julia-nodeps-1.1
└ @ IJulia /home/tarik/.julia/packages/IJulia/4UizY/deps/kspec.jl:72
```

Out[45]: "/home/tarik/.local/share/jupyter/kernels/julia-nodeps-1.1"

In [46]:
```
using ScikitLearn: fit!, predict, @sk_import, fit_transform!
 import ScikitLearn: CrossValidation
 @sk_import metrics: accuracy_score
 @sk_import ensemble: RandomForestClassifier
 @sk_import metrics: (confusion_matrix, f1_score, classification_report, preci
sion_score, recall_score)
```

```
┌ Info: Recompiling stale cache file /home/tarik/.julia/compiled/v1.1/ScikitL
earn/tbUuI.ji for ScikitLearn [3646fa90-6ef7-5e7e-9f22-8aca16db6324]
└ @ Base loading.jl:1184
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = import_sklearn() at Skcore.jl:120
└ @ ScikitLearn.Skcore /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skco
re.jl:120
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
┌ Warning: `getindex(o::PyObject, s::Symbol)` is deprecated in favor of dot o
verloading (`getproperty`) so elements should now be accessed as e.g. `o.s` i
nstead of `o[:s]`.
│   caller = top-level scope at Skcore.jl:158
└ @ Core /home/tarik/.julia/packages/ScikitLearn/HK6Vs/src/Skcore.jl:158
```

Out[46]:
```
PyObject <function recall_score at 0x7fb3bde23840>
```

Import the train and test sample

In [47]:
```
sample1_c1 = CSV.read("sample1_c1.csv")
sample2_c1 = CSV.read("sample2_c1.csv")
sample3_c1 = CSV.read("sample3_c1.csv")

sample1_c2 = CSV.read("sample1_c2.csv")
sample2_c2 = CSV.read("sample2_c2.csv")

sample1_c3 = CSV.read("sample1_c3.csv")
sample2_c3 = CSV.read("sample2_c3.csv")

sample1_c4_test = CSV.read("sample1_c4_test.csv")
```

Out[47]: 8,213 rows × 13 columns

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceD
	Float64?	Float64?	Float64?	Float64?	Float64?	Float64?
1	324.0	3.60408e6	0.0	0.0	1.90715e7	2.26756e7
2	297.0	1.00385e7	0.0	0.0	1.48123e7	2.48508e7
3	164.0	48899.4	5.9452e5	6.43419e5	2.06202e7	2.05713e7
4	228.0	63463.8	0.0	0.0	2.04009e7	2.04644e7
5	372.0	2.16955e5	51689.0	0.0	3.38761e7	3.40931e7
6	148.0	3.94886e5	3.94886e5	0.0	0.0	0.0
7	397.0	3.43814e5	7.46364e6	7.80745e6	1.80353e7	1.76915e7
8	359.0	86974.3	2.0978e7	2.10649e7	5.56062e7	5.55192e7
9	371.0	7.98773e6	0.0	0.0	3.10661e7	3.90538e7
10	304.0	4.73295e5	3.36654e6	3.83984e6	1.81947e7	1.77214e7
11	569.0	1.77991e5	0.0	0.0	1.78874e7	1.80654e7
12	43.0	6305.71	5.13931e5	5.20237e5	1.88137e7	1.88012e7
13	524.0	91911.4	0.0	0.0	4.53971e7	4.5489e7
14	308.0	3.42536e5	2.53545e5	5.96081e5	2.94772e7	2.91347e7
15	304.0	1.0e7	0.0	0.0	1.06027e7	3.05019e7
16	522.0	1.78131e5	1.65483e7	1.67264e7	2.18782e7	2.17e7
17	402.0	34473.5	1.65267e7	1.65612e7	5.04361e7	5.04017e7
18	357.0	178002.0	0.0	0.0	2.24875e7	2.26655e7
19	303.0	2.07501e7	34596.6	0.0	2.92139e7	4.9964e7
20	308.0	1.40711e5	20985.0	0.0	4.39965e7	4.41372e7
21	307.0	102782.0	0.0	0.0	1.89146e7	1.90174e7
22	491.0	1.26503e6	1.26503e6	0.0	0.0	0.0
23	304.0	1.46191e7	0.0	0.0	3.03413e7	4.49604e7
24	323.0	87034.4	2.63771e6	2.72474e6	1.99828e7	1.98958e7
25	396.0	26359.9	1.05288e7	1.05551e7	2.2359e7	2.23327e7
26	161.0	1.74818e5	7.92805e5	9.67623e5	1.85517e7	1.83769e7
27	345.0	2.50516e5	0.0	0.0	1.86527e7	1.89032e7
28	380.0	2.46753e5	5.29739e6	5.54414e6	3.1439e7	3.11923e7
29	644.0	9.55467e5	1.29089e5	0.0	2.114e7	2.20955e7
30	375.0	23294.1	0.0	0.0	5.812e7	5.81433e7

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceD
	Float64?	Float64?	Float64?	Float64?	Float64?	Float64?
⋮	⋮	⋮	⋮	⋮	⋮	⋮

In [48]:
```
frequency_isFraud = freqtable(sample1_c1[:isFraud])
```

Out[48]:
```
2-element Named Array{Int64,1}
Dim1 │
─────┼─────
0.0  │ 8623
1.0  │ 5749
```

Size of a sample for train

In [49]:
```
row, col = size(sample1_c1)
println("Number of Instances in training sub-sample: ", row)
println("Number of features  in training sub-sample: ", col)
```

```
Number of Instances in training sub-sample: 14372
Number of features  in training sub-sample: 13
```

Freqency distribution of isFraud column variables

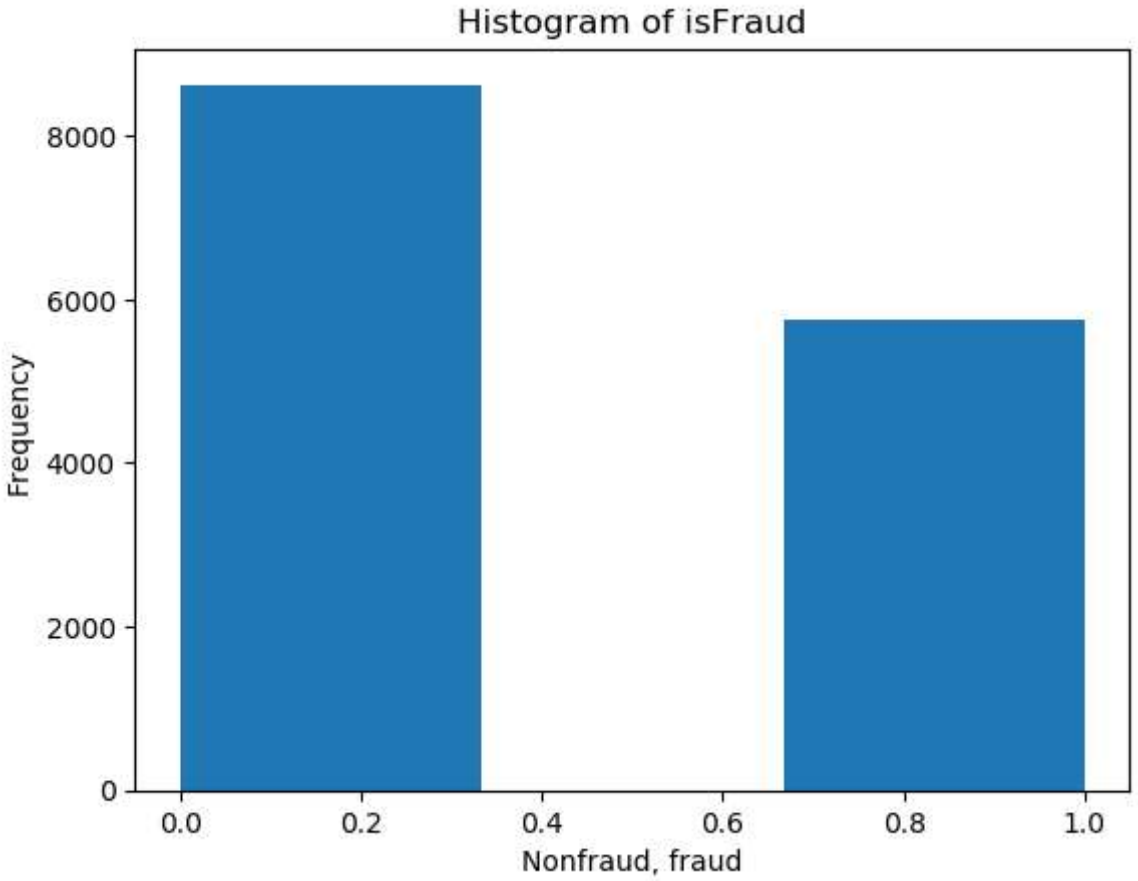
0 represents non-fraudulant transaction 1 represents fraud transaction

In [50]:
```
frequency_isFraud = freqtable(sample1_c1[:isFraud])
```

Out[50]:
```
2-element Named Array{Int64,1}
Dim1 │
─────┼─────
0.0  │ 8623
1.0  │ 5749
```

Histogram showing frequency distribution of non-fraud and fraud instances in Training

In [51]:
```
h = PyPlot.plt.hist(sample1_c1[:isFraud], 3)
plt.title("Histogram of isFraud")
plt.xlabel("Nonfraud, fraud")
plt.ylabel("Frequency")
```



Out[51]: PyObject Text(24.0, 0.5, 'Frequency')

In [52]:
```
# Ratio of non-fraud and fraud in training
ratio = prop(frequency_isFraud)
println("Non-Fraud and Fraud ratio in training sub-sample: ", round(ratio[1]*1
000)," : ", round(ratio[2]*1000))
```

```
Non-Fraud and Fraud ratio in training sub-sample: 600.0 : 400.0
```

In [53]:
```
# Size of a sample for test set
row, col = size(sample1_c4_test)
println("Number of Instances in test sub-sample: ", row)
println("Number of features  in test sub-sample: ", col)
```

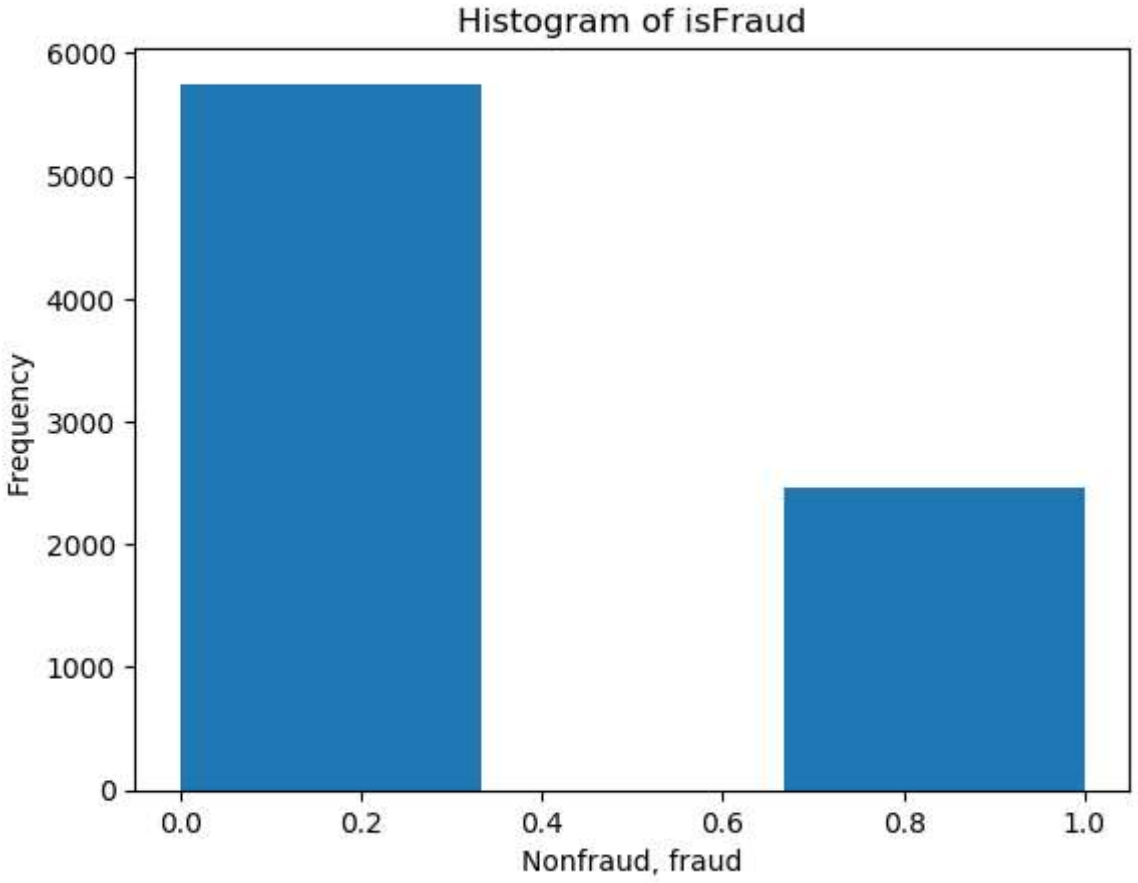
```
Number of Instances in test sub-sample: 8213
Number of features  in test sub-sample: 13
```

In [54]:
```
frequency_isFraud = freqtable(sample1_c4_test[:isFraud])
```

Out[54]:
```
2-element Named Array{Int64,1}
Dim1 │
─────┼─────
0.0  │ 5749
1.0  │ 2464
```

Histogram showing frequency distribution of non-fraud and fraud instances in Training

In [55]:
```
h = PyPlot.plt.hist(sample1_c4_test[:isFraud], 3)
plt.title("Histogram of isFraud")
plt.xlabel("Nonfraud, fraud")
plt.ylabel("Frequency")
```



Out[55]:
```
PyObject Text(24.0, 0.5, 'Frequency')
```

In [56]:
```
# Ratio of non-fraud and fraud in testing

ratio = prop(frequency_isFraud)
println("Non-Fraud and Fraud ratio in training sub-sample: ", round(ratio[1]*1
000)," : ", round(ratio[2]*1000))
```

```
Non-Fraud and Fraud ratio in training sub-sample: 700.0 : 300.0
```

Preparing samples for Classifiers

1. Seperate features from and target class
2. Convert dataframes into Matrix

In [57]:
```
# Features for Training
features = [:step,:amount,:oldbalanceOrg,:newbalanceOrig,:oldbalanceDest,:newb
alanceDest,
:isFlaggedFraud,:CASH_IN,:CASH_OUT,:DEBIT,:PAYMENT, :TRANSFER,]

Xfeat_samp1_c1 = convert(Matrix, sample1_c1[features])
Xfeat_samp2_c1 = convert(Matrix, sample2_c1[features])
Xfeat_samp3_c1 = convert(Matrix, sample3_c1[features])
Xfeat_samp1_c2 = convert(Matrix,sample1_c2[features])
Xfeat_samp2_c2 = convert(Matrix,sample2_c2[features])
Xfeat_samp1_c3 = convert(Matrix, sample1_c3[features])
Xfeat_samp2_c3 = convert(Matrix, sample2_c3[features])

Xfeat_samp1_c4_test = convert(Matrix, sample1_c4_test[features])
```

Out[57]:
```
8213×12 Array{Union{Missing, Float64},2}:
 324.0      3.60408e6      0.0         …  0.0  0.0  0.0  0.0  0.0  1.0
 297.0      1.00385e7      0.0            0.0  0.0  0.0  0.0  0.0  1.0
 164.0  48899.4            5.9452e5       0.0  1.0  0.0  0.0  0.0  0.0
 228.0  63463.8            0.0            0.0  0.0  1.0  0.0  0.0  0.0
 372.0      2.16955e5  51689.0            0.0  0.0  1.0  0.0  0.0  0.0
 148.0      3.94886e5      3.94886e5   …  0.0  0.0  0.0  0.0  0.0  1.0
 397.0      3.43814e5      7.46364e6      0.0  1.0  0.0  0.0  0.0  0.0
 359.0  86974.3            2.0978e7       0.0  1.0  0.0  0.0  0.0  0.0
 371.0      7.98773e6      0.0            0.0  0.0  0.0  0.0  0.0  1.0
 304.0      4.73295e5      3.36654e6      0.0  1.0  0.0  0.0  0.0  0.0
 569.0      1.77991e5      0.0         …  0.0  0.0  0.0  0.0  0.0  1.0
  43.0   6305.71           5.13931e5      0.0  1.0  0.0  0.0  0.0  0.0
 524.0  91911.4            0.0            0.0  0.0  1.0  0.0  0.0  0.0
   ⋮                                  ⋱                          ⋮
 615.0      3.68973e5      3.68973e5      0.0  0.0  0.0  0.0  0.0  1.0
 554.0      9.42186e6      9.42186e6      0.0  0.0  1.0  0.0  0.0  0.0
 304.0      1.39968e7      0.0            0.0  0.0  0.0  0.0  0.0  1.0
 394.0      5.49504e5      0.0            0.0  0.0  1.0  0.0  0.0  0.0
 354.0      2.08688e5      0.0         …  0.0  0.0  1.0  0.0  0.0  0.0
 408.0      5.6711e6       0.0            0.0  0.0  0.0  0.0  0.0  1.0
 304.0      7.7123e5       0.0            0.0  0.0  0.0  0.0  0.0  1.0
 666.0      1.45945e5      1.45945e5      0.0  0.0  0.0  0.0  0.0  1.0
 211.0      9.66964e5      0.0            0.0  0.0  0.0  0.0  0.0  1.0
 327.0      2.84791e6      0.0         …  0.0  0.0  0.0  0.0  0.0  1.0
 205.0      1.50015e5      0.0            0.0  0.0  1.0  0.0  0.0  0.0
 600.0      5.40155e5      5.40155e5      0.0  0.0  1.0  0.0  0.0  0.0
```

In [58]:
```
Ylabel_samp1_c1 = convert(Array, sample1_c1[:isFraud])
Ylabel_samp2_c1 = convert(Array, sample2_c1[:isFraud])
Ylabel_samp3_c1 = convert(Array, sample3_c1[:isFraud])
Ylabel_samp1_c2  = convert(Array, sample1_c2[:isFraud])
Ylabel_samp2_c2  = convert(Array, sample2_c2[:isFraud])
Ylabel_samp1_c3 = convert(Array, sample1_c3[:isFraud])
Ylabel_samp2_c3 = convert(Array, sample2_c3[:isFraud])

Ylabel_samp1_c4_test = convert(Array, sample1_c4_test[:isFraud])
```

Out[58]:
```
8213-element Array{Union{Missing, Float64},1}:
 0.0
 0.0
 0.0
 0.0
 0.0
 1.0
 0.0
 0.0
 0.0
 0.0
 0.0
 0.0
 0.0
 0.0
 ⋮
 1.0
 1.0
 0.0
 0.0
 0.0
 0.0
 0.0
 0.0
 1.0
 0.0
 0.0
 0.0
 1.0
```

Building 7 Random Forest classifiers with 7 sample data

model = build_forest(labels, features, n_subfeatures, n_trees, partial_sampling, max_depth, min_samples_leaf, min_samples_split, min_purity_increase)

In [59]:
```
model1 = build_forest(Ylabel_samp1_c1, Xfeat_samp1_c1, 5, 100, 0.5, 10)
model2 = build_forest(Ylabel_samp2_c1, Xfeat_samp2_c1, 5, 100, 0.5, 10)
model3 = build_forest(Ylabel_samp3_c1, Xfeat_samp3_c1, 5, 100, 0.5, 10)
model4 = build_forest(Ylabel_samp1_c2, Xfeat_samp1_c2, 5, 100, 0.5, 10)
model5 = build_forest(Ylabel_samp2_c2, Xfeat_samp2_c2, 5, 100, 0.5, 10)
model6 = build_forest(Ylabel_samp1_c3, Xfeat_samp1_c3, 5, 100, 0.5, 10)
model7 = build_forest(Ylabel_samp2_c3, Xfeat_samp1_c3, 5, 100, 0.5, 10)
```

Out[59]:
```
Ensemble of Decision Trees
Trees:      100
Avg Leaves: 111.02
Avg Depth:  10.0
```

In [60]:
```
# packing all the models into a tuple
all_models = (model1, model2, model3, model4, model5, model6, model7)
```

Out[60]:
```
(Ensemble of Decision Trees
Trees:      100
Avg Leaves: 65.19
Avg Depth:  10.0, Ensemble of Decision Trees
Trees:      100
Avg Leaves: 66.87
Avg Depth:  10.0, Ensemble of Decision Trees
Trees:      100
Avg Leaves: 65.87
Avg Depth:  10.0, Ensemble of Decision Trees
Trees:      100
Avg Leaves: 3.58
Avg Depth:  2.37, Ensemble of Decision Trees
Trees:      100
Avg Leaves: 4.38
Avg Depth:  2.98, Ensemble of Decision Trees
Trees:      100
Avg Leaves: 35.05
Avg Depth:  10.0, Ensemble of Decision Trees
Trees:      100
Avg Leaves: 111.02
Avg Depth:  10.0)
```

Function for ensembler classifier, that applies 7 random forest on test data

In [61]:
```
function ensemblerClassifier(Xfeatures_test, models)

    model1, model2, model3, model4, model5, model6, model7 = models
    predictions1 = apply_forest(model1, Xfeatures_test)
    predictions2 = apply_forest(model2, Xfeatures_test)
    predictions3 = apply_forest(model3, Xfeatures_test)
    predictions4 = apply_forest(model4, Xfeatures_test)
    predictions5 = apply_forest(model5, Xfeatures_test)
    predictions6 = apply_forest(model6, Xfeatures_test)
    predictions7 = apply_forest(model7, Xfeatures_test)


    predictions = (predictions1, predictions2, predictions3, predictions4, pre
dictions5, predictions6, predictions7)

    sz = size(predictions7)
    prediction_rwo_sz = sz[1]

    majorityVoted_predictions = calcualteMajorityVote(predictions, prediction_
rwo_sz)

    return majorityVoted_predictions
end
```

Out[61]: ensemblerClassifier (generic function with 1 method)

Function that clalucate majority vote for ensembler

In [62]:
```
function calcualteMajorityVote(predictions, len)
    majority_prediction = Float64[]
    predictions1, predictions2, predictions3, predictions4, predictions5,predi
ctions6, predictions7  = predictions
    for i = 1 : len
       temp = predictions1[i] + predictions2[i] + predictions3[i] + prediction
s4[i] + predictions5[i] + predictions6[i]+ predictions7[i]
        if temp > 3
            push!(majority_prediction, 1.0)
        else
            push!(majority_prediction, 0.0)
        end
        temp = 0
    end
    return majority_prediction
end
```

Out[62]: calcualteMajorityVote (generic function with 1 method)

In [63]:
```
# ensemblerClassifier function takes test data, and traning models as argument
and return votted prediction set.

votted_prediction = ensemblerClassifier(Xfeat_samp1_c4_test, all_models)
```

Out[63]:
```
8213-element Array{Float64,1}:
 0.0
 0.0
 0.0
 0.0
 0.0
 1.0
 0.0
 0.0
 0.0
 0.0
 0.0
 0.0
 0.0
 ⋮
 1.0
 1.0
 0.0
 0.0
 0.0
 0.0
 0.0
 1.0
 0.0
 0.0
 0.0
 1.0
```

In [64]:
```
function ensembler_result(votted_prediction, Ylabel_samp1_c4_test)
    acc = accuracy_score(votted_prediction, Ylabel_samp1_c4_test)
    p_score  = precision_score( Ylabel_samp1_c4_test, votted_prediction)
    r_score = recall_score(Ylabel_samp1_c4_test, votted_prediction)
    f_score = f1_score( Ylabel_samp1_c4_test, votted_prediction)

    return acc, p_score, r_score, f_score
end
```

Out[64]:
```
ensembler_result (generic function with 1 method)
```

Classification Report

In [65]:
```
all_result =  ensembler_result(votted_prediction, Ylabel_samp1_c4_test)
```

Out[65]:
```
(0.9755266041641301, 0.9274650547789951, 0.9963474025974026, 0.96067305810995
9)
```

In [66]:
```
println("Accuracy: ",  all_result[1] * 100)
println("Precision: ", all_result[2] * 100)
println("Recall: ", all_result[3] * 100)
println("f1-Score: ", all_result[4] * 100)
```

```
Accuracy: 97.552660416413
Precision: 92.7465054778995
Recall: 99.63474025974025
f1-Score: 96.06730581099589
```

Confusion Matrix

In [67]:
```
confusion_matrix(Ylabel_samp1_c4_test, votted_prediction)
```

Out[67]:
```
2×2 Array{Int64,2}:
 5557   192
    9  2455
```