



**Department of Computer Science
American International University-Bangladesh
Mid Term Report**

Course Name: INTRODUCTION TO DATA SCIENCE

“Project on Data Pre-Processing”

Supervised By:

Dr. Akinul Islam Jony

Associate Professor, Computer Science -AIUB

Submitted By:

Sumaiya Malik

ID: 20-43688-2

Section: B

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Project Title: Applying Data Pre-processing on a Dataset.

Project Overview:

Text, photos, video, and other types of unprocessed, real-world data are disorganized. In addition to the possibility of faults and inconsistencies, it is frequently lacking and lacks a regular, consistent design. Machines prefer to process information that is neat and orderly; they can only read data as 1s and 0s. Hence, it is simple to calculate structured data like whole numbers and percentages. But unstructured data must first be cleaned and prepared in the form of text and graphics before analysis. Data preparation is the process of altering or encoding data so that a computer can quickly and easily understand it. For a model to provide accurate and precise predictions, the algorithm must be quick to decipher the characteristics of the data. Data preparation is therefore essential for raising the general level of data quality. Data cleaning, data integration, data transformation, data reduction, and data discretization are the four main stages of data preprocessing. Filling in missing values, reducing noise in the data, resolving discrepancies, and eliminating outliers are all steps in the data pretreatment process known as "data cleaning." A data preparation phase called data integration brings together data from several sources into one, more substantial data storage, like a data warehouse. By changing the value, structure, or format of data using methods like scaling, normalization, and others, data transformation is a methodology for turning high-quality data into various formats. In order to change the data into the right form, data transformation techniques also include data cleaning and data reduction. To produce patterns that are simpler to grasp, data transformation is a crucial data preprocessing technique that must be applied to the data before data mining. This method of pre-processing data is systematic.

The following dataset of the reports contains statistics in arrests per 100,000 residents for assault and murder, in each of the 50 US states, in 1973. Also given is the percentage of the population living in urban areas. In our given dataset initially, I have seen some missing value. After handle missing value it may occurs some noise like format problem. Then I use a defined format with my preferred methodology. I inserted a new column using a different column value from the one that was provided in our inquiry condition after adjusting the format. I tried to handle converting categorical values to numerical values, which is our discretization part, after adding the column. Finally, I attempted to compare the values of three columns using the normalizing technique.

Project Solution Design:

In this project, we are required to perform the techniques of Data pre-processing to obtain a clean dataset ready for Data Analysis. Here's a sequence of the project.

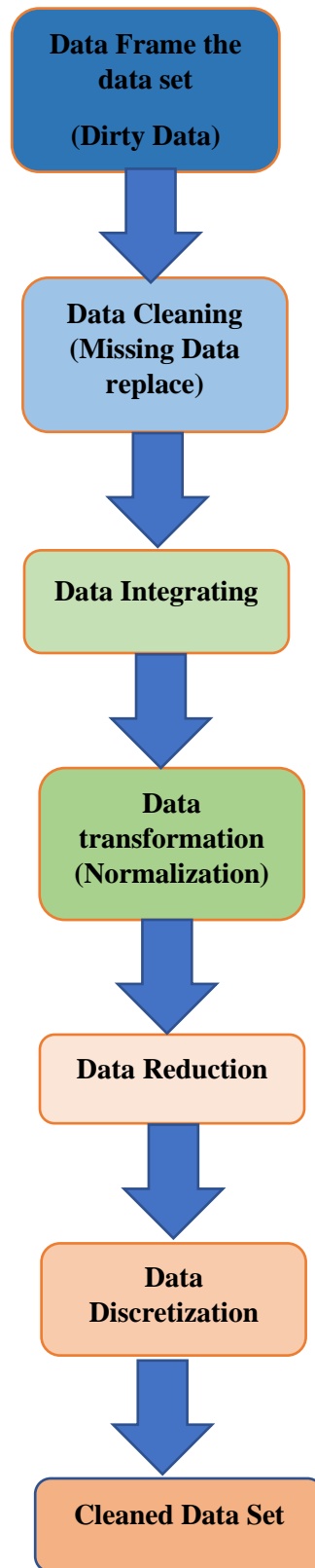


Figure 1: Block Diagram of the project Solution.

Software Used for This Project:

RStudio will be the program we employ to shape the data. A sophisticated and user-friendly Integrated Development Environment (IDE) that offers a one-stop shop for all statistical computing and graphics, RStudio is a powerful and simple method to engage with R programming. A more sophisticated version of R called The RStudio features a multi-pane window layout that gives users access to all essential features on a single screen (such as source, console, environment & history, files, photos, graphs, etc.). Then, we used a pdf to excel converter application to convert the data set to an excel file.

Data pre-processing:

1. **Data Frame dataset:** Before we start preprocessing our data, first we need to do data frame using the following code lines.

Code:

```
> X<-c("Alabama", "Alaska", "Arizona", "Arkansas", "California", "Colorado", "Connecticut", "Delaware", "Florida", "Georgia", "Hawaii", "Idaho", "Illinois", "Indiana", "Iowa", "Kansas", "Kentucky", "Louisiana", "Maine", "Maryland", "Massachusetts", "Michigan", "Minnesota", "Mississippi", "Missouri", "Montana", "Nebraska", "Nevada", "New_Hampshire", "New Jersey", "New Mexico", "New York", "North Carolina", "North Dakota", "Ohio", "Oklahoma", "Oregon", "Pennsylvania", "Rhode Island", "South Carolina", "South Dakota", "Tennessee", "Texas", "Utah", "Vermont", "Virginia", "Washington", "West Virginia", "Wisconsin", "Wyoming")
```

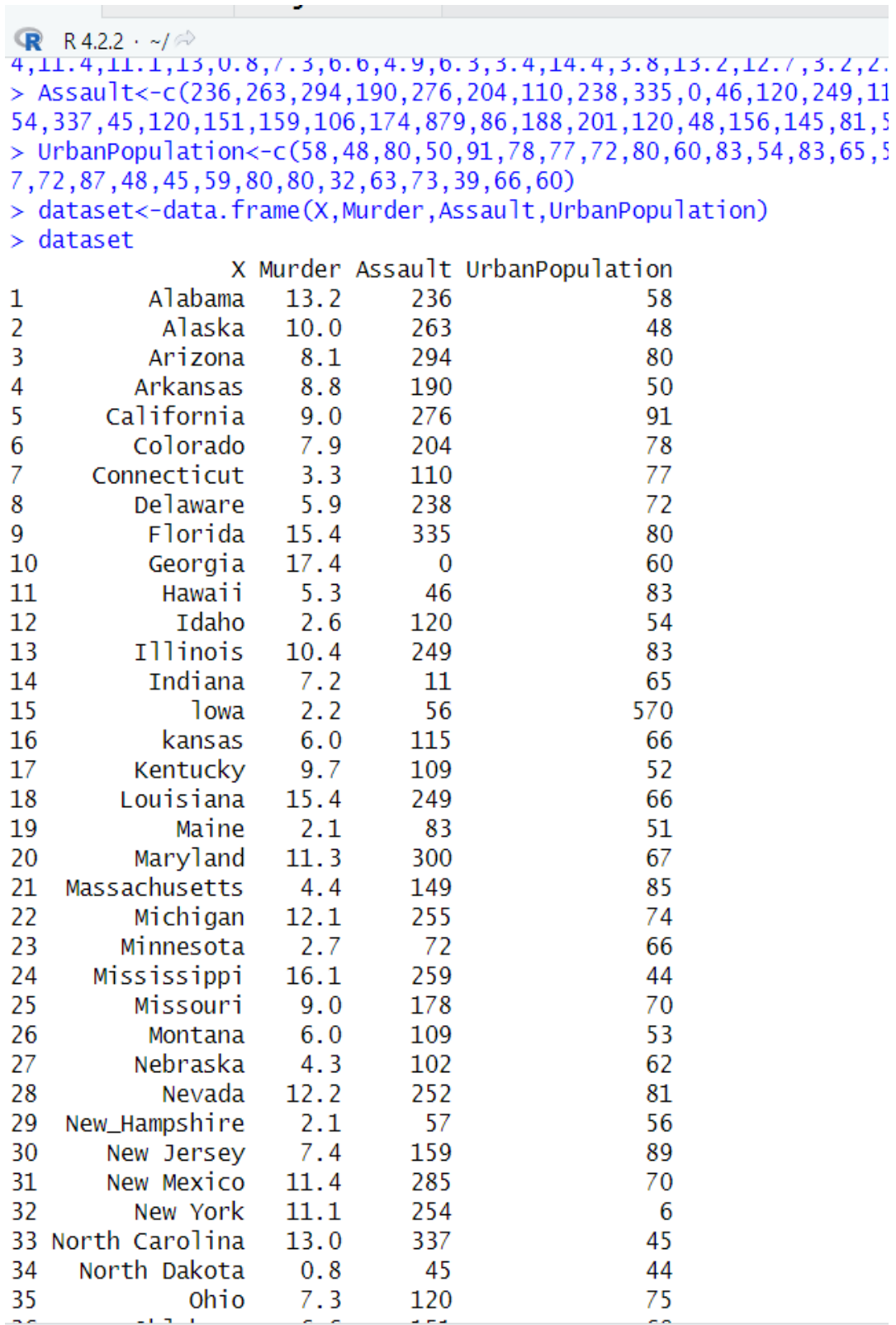
```
> Murder<-c(13.2,10,8.1,8.8,9,7.9,3.3,5.9,15.4,17.4,5.3,2.6,10.4,7.2,2.2,6,9.7,15.4,2.1,11.3,4.4,12.1,2.7,16.1,9,6,4.3,12.2,2.1,7.4,11.4,11.1,13,0.8,7.3,6.6,4.9,6.3,3.4,14.4,3.8,13.2,12.7,3.2,2.2,8.5,4,5.7,2.6,6.8)
```

```
> Assault<-c(236,263,294,190,276,204,110,238,335,0,46,120,249,11,56,115,109,249,83,300,149,255,72,259,178,109,102,252,57,159,285,254,337,45,120,151,159,106,174,879,86,188,201,120,48,156,145,81,53,161)
```

```
> Urban.Population<-c(58,48,80,50,91,78,77,72,80,60,83,54,83,65,570,66,52,66,51,67,85,74,66,44,70,53,62,81,56,89,70,6,45,44,75,68,67,72,87,48,45,59,80,80,32,63,73,39,66,60)
```

```
> dataset<-data.frame(X,Murder,Assault,Urban.Population)
```

```
> dataset
```



```

R 4.2.2 · ~/
4,11.4,11.1,13,0.8,7.3,6.6,4.9,6.3,3.4,14.4,3.8,13.2,12.7,3.2,2.
> Assault<-c(236,263,294,190,276,204,110,238,335,0,46,120,249,11
54,337,45,120,151,159,106,174,879,86,188,201,120,48,156,145,81,5
> UrbanPopulation<-c(58,48,80,50,91,78,77,72,80,60,83,54,83,65,5
7,72,87,48,45,59,80,80,32,63,73,39,66,60)
> dataset<-data.frame(X,Murder,Assault,UrbanPopulation)
> dataset

```

	X	Murder	Assault	UrbanPopulation
1	Alabama	13.2	236	58
2	Alaska	10.0	263	48
3	Arizona	8.1	294	80
4	Arkansas	8.8	190	50
5	California	9.0	276	91
6	Colorado	7.9	204	78
7	Connecticut	3.3	110	77
8	Delaware	5.9	238	72
9	Florida	15.4	335	80
10	Georgia	17.4	0	60
11	Hawaii	5.3	46	83
12	Idaho	2.6	120	54
13	Illinois	10.4	249	83
14	Indiana	7.2	11	65
15	Iowa	2.2	56	570
16	kansas	6.0	115	66
17	Kentucky	9.7	109	52
18	Louisiana	15.4	249	66
19	Maine	2.1	83	51
20	Maryland	11.3	300	67
21	Massachusetts	4.4	149	85
22	Michigan	12.1	255	74
23	Minnesota	2.7	72	66
24	Mississippi	16.1	259	44
25	Missouri	9.0	178	70
26	Montana	6.0	109	53
27	Nebraska	4.3	102	62
28	Nevada	12.2	252	81
29	New_Hampshire	2.1	57	56
30	New Jersey	7.4	159	89
31	New Mexico	11.4	285	70
32	New York	11.1	254	6
33	North Carolina	13.0	337	45
34	North Dakota	0.8	45	44
35	Ohio	7.3	120	75

Figure 2: After performing the Data Frame.

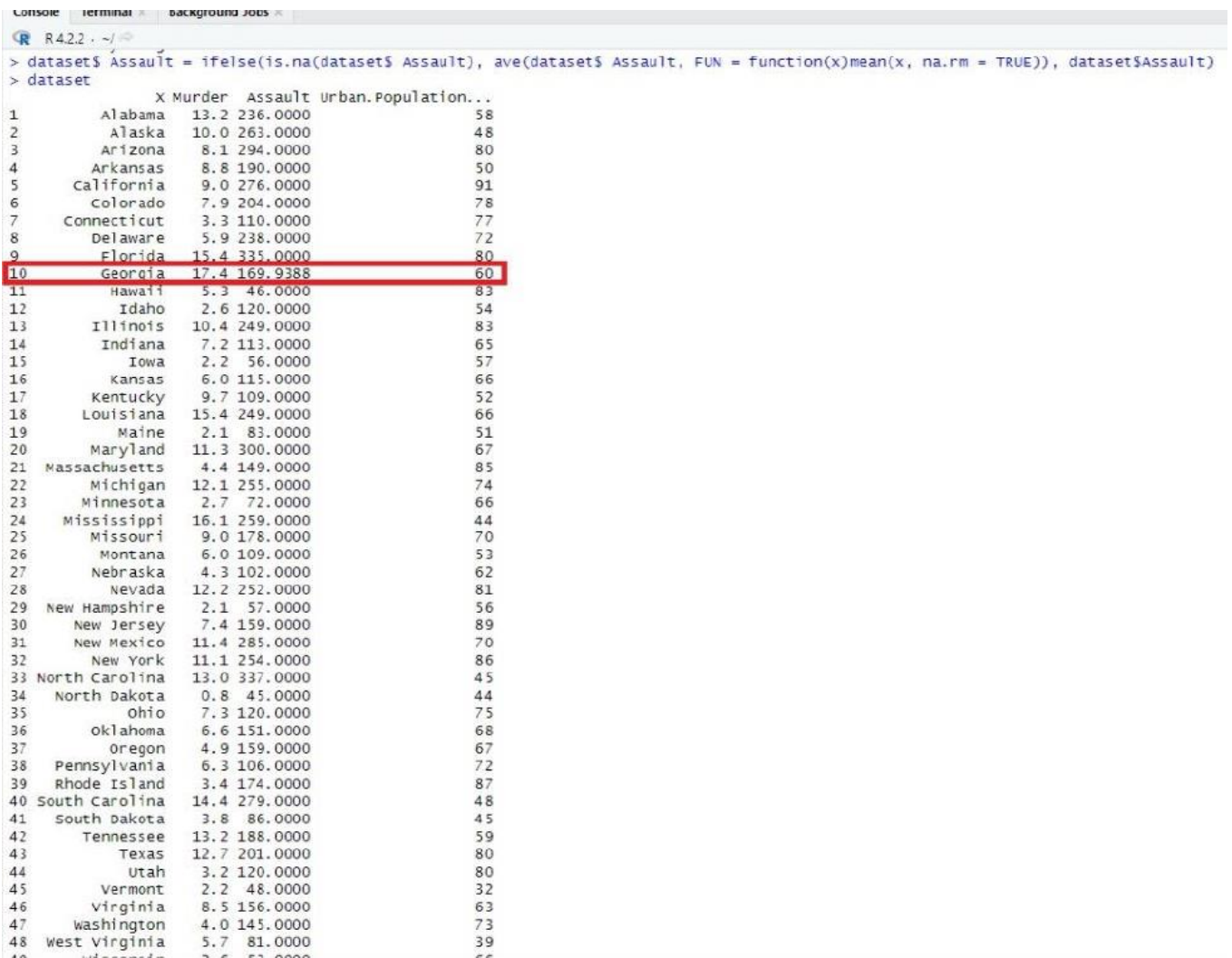
2.Data Cleaning:

2.1 Data Munging: Since in this dataset all the data are per 100,000 residents, there are no data munging steps in the data set.

2.2 Handling the missing data: The Assault column value in the dataset has missing data. This issue must be resolved before to incorporating a data set into a model; otherwise, it will seriously impact that model. So, we should handle this data set. we can handle 2 ways either replace the data or Discard. As it has only 50 data so we couldn't remove any data. so, we can replace using average function as a numerical data.

Code:

```
> dataset$ Assault = ifelse(is.na(dataset$ Assault), ave(dataset$ Assault, FUN=
function(x)mean(x, na.rm = TRUE)), dataset$Assault)
> dataset
```



```
R42.2. ~/
> dataset$ Assault = ifelse(is.na(dataset$ Assault), ave(dataset$ Assault, FUN = function(x)mean(x, na.rm = TRUE)), dataset$Assault)
> dataset
```

	X	Murder	Assault	Urban.Population...
1	Alabama	13.2	236.0000	58
2	Alaska	10.0	263.0000	48
3	Arizona	8.1	294.0000	80
4	Arkansas	8.8	190.0000	50
5	California	9.0	276.0000	91
6	Colorado	7.9	204.0000	78
7	Connecticut	3.3	110.0000	77
8	Delaware	5.9	238.0000	72
9	Florida	15.4	335.0000	80
10	Georgia	17.4	169.9388	60
11	Hawaii	5.3	46.0000	83
12	Idaho	2.6	120.0000	54
13	Illinois	10.4	249.0000	83
14	Indiana	7.2	113.0000	65
15	Iowa	2.2	56.0000	57
16	Kansas	6.0	115.0000	66
17	Kentucky	9.7	109.0000	52
18	Louisiana	15.4	249.0000	66
19	Maine	2.1	83.0000	51
20	Maryland	11.3	300.0000	67
21	Massachusetts	4.4	149.0000	85
22	Michigan	12.1	255.0000	74
23	Minnesota	2.7	72.0000	66
24	Mississippi	16.1	259.0000	44
25	Missouri	9.0	178.0000	70
26	Montana	6.0	109.0000	53
27	Nebraska	4.3	102.0000	62
28	Nevada	12.2	252.0000	81
29	New Hampshire	2.1	57.0000	56
30	New Jersey	7.4	159.0000	89
31	New Mexico	11.4	285.0000	70
32	New York	11.1	254.0000	86
33	North Carolina	13.0	337.0000	45
34	North Dakota	0.8	45.0000	44
35	Ohio	7.3	120.0000	75
36	Oklahoma	6.6	151.0000	68
37	Oregon	4.9	159.0000	67
38	Pennsylvania	6.3	106.0000	72
39	Rhode Island	3.4	174.0000	87
40	South Carolina	14.4	279.0000	48
41	South Dakota	3.8	86.0000	45
42	Tennessee	13.2	188.0000	59
43	Texas	12.7	201.0000	80
44	Utah	3.2	120.0000	80
45	Vermont	2.2	48.0000	32
46	Virginia	8.5	156.0000	63
47	Washington	4.0	145.0000	73
48	West Virginia	5.7	81.0000	39
49	Wisconsin	3.6	115.0000	66

Figure 3: After replace missing value.

2.3 Smooth Noisy Data: Here we first search for any outliers in the data set. Now we run the codes.

Code:

```
> outMurder <- dataset[(dataset$Murder > 20 | dataset$Murder < 1),]  
> outMurder
```

```
10 Georgia      17.4    182.                60  
# ... with 40 more rows  
# i Use 'print(n = ...)' to see more rows  
> outMurder <- dataset[(dataset$Murder > 20 | dataset$Murder < 1),]  
> outMurder  
# A tibble: 1 x 4  
  States      Murder Assault `Urban population (%)`  
  <chr>      <dbl>  <dbl>          <dbl>  
1 North Dakota  0.8    45             44  
> |
```

Code:

```
> outAssault <- dataset[(dataset$Assault > 400 | dataset$Assault < 45),]  
> outAssault
```

```
# A tibble: 1 x 4  
  States      Murder Assault `Urban population (%)`  
  <chr>      <dbl>  <dbl>          <dbl>  
1 South Carolina  14.4    879             48  
> |
```

Code:

```
> outUP <- dataset[(dataset$`Urban.Population (%)` < 32 | dataset$`Urban.population (%)` > 91),]  
> outUP
```

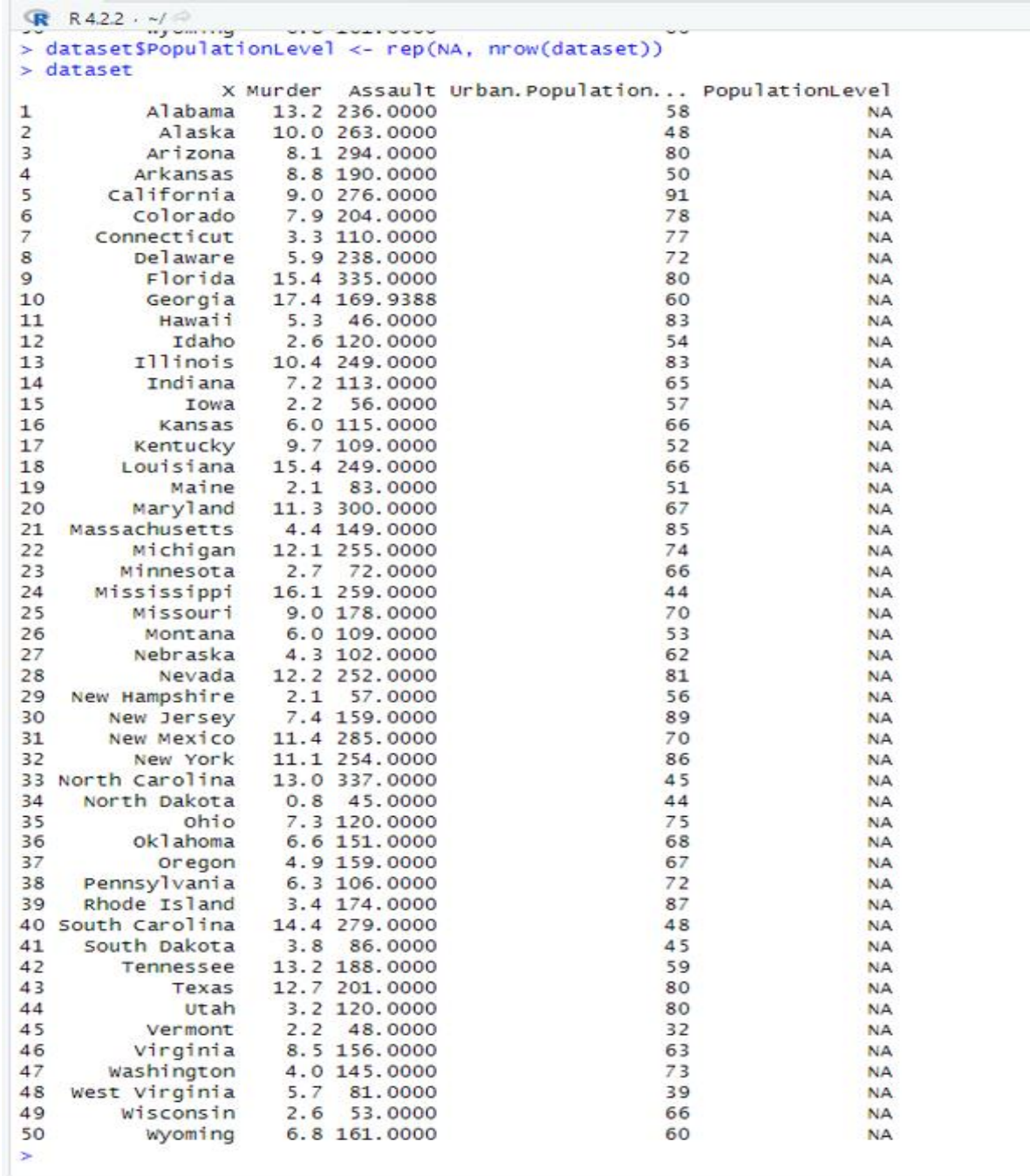
```
> outUP <- dataset[(dataset$ Urban population (%) < 32 | dataset$ Urban population (%) > 91),]  
> outUP  
# A tibble: 2 x 4  
  States      Murder Assault `Urban population (%)`  
  <chr>      <dbl>  <dbl>          <dbl>  
1 Iowa        2.2    56             570  
2 New York   11.1   254              6  
> |
```

Figure 4: After smoothing noisy data values.

3.Data Integration: Data integration is a process where we need to integrate new data from different source or table Let's now imagine that we must add a new column of data to our data table based on estimates of the urban population.

Code:

```
> dataset$PopulationLevel <- rep(NA, nrow(dataset))
> dataset
```



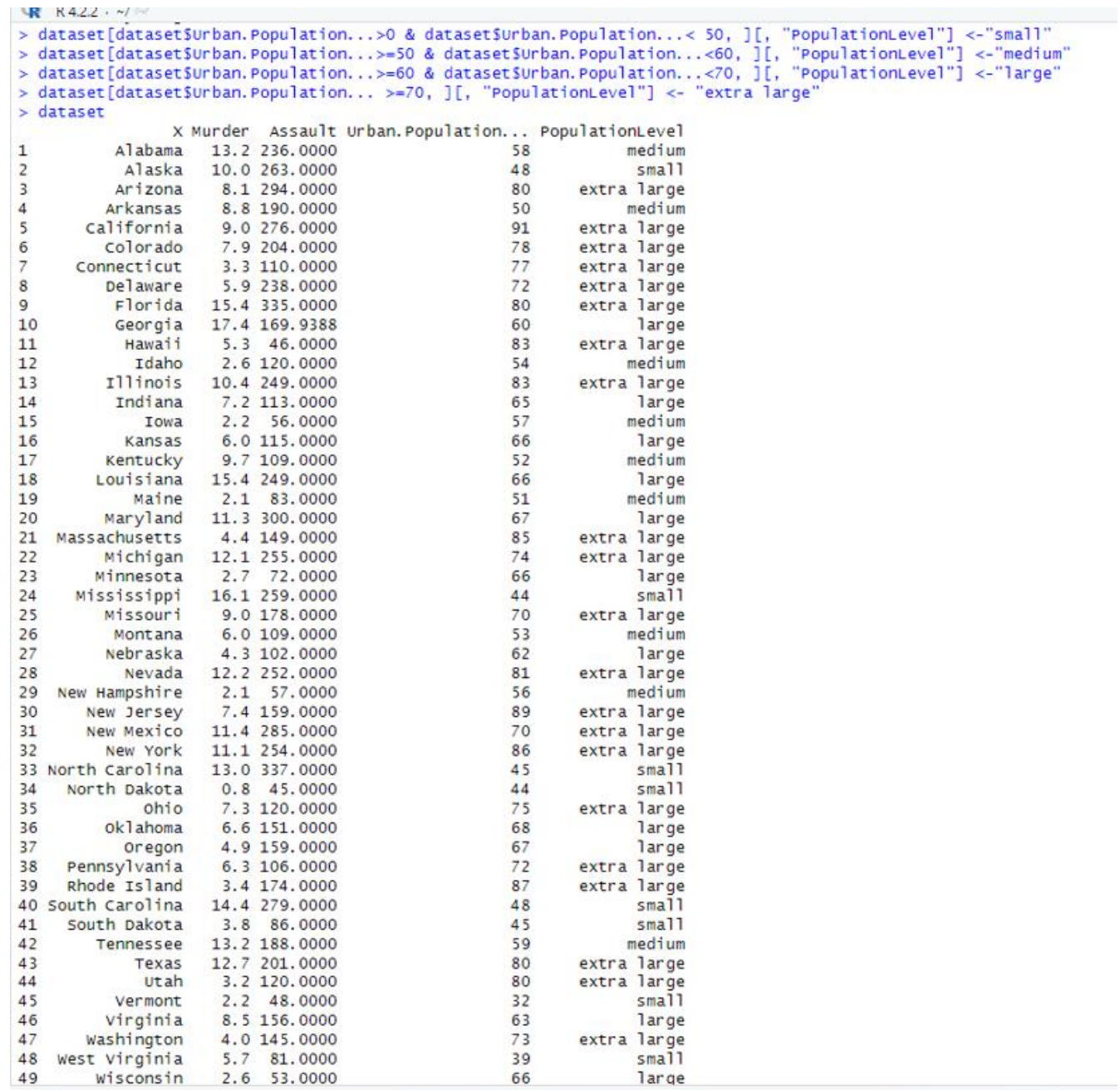
	X	Murder	Assault	Urban.Population...	PopulationLevel
1	Alabama	13.2	236.0000	58	NA
2	Alaska	10.0	263.0000	48	NA
3	Arizona	8.1	294.0000	80	NA
4	Arkansas	8.8	190.0000	50	NA
5	California	9.0	276.0000	91	NA
6	Colorado	7.9	204.0000	78	NA
7	Connecticut	3.3	110.0000	77	NA
8	Delaware	5.9	238.0000	72	NA
9	Florida	15.4	335.0000	80	NA
10	Georgia	17.4	169.9388	60	NA
11	Hawaii	5.3	46.0000	83	NA
12	Idaho	2.6	120.0000	54	NA
13	Illinois	10.4	249.0000	83	NA
14	Indiana	7.2	113.0000	65	NA
15	Iowa	2.2	56.0000	57	NA
16	Kansas	6.0	115.0000	66	NA
17	Kentucky	9.7	109.0000	52	NA
18	Louisiana	15.4	249.0000	66	NA
19	Maine	2.1	83.0000	51	NA
20	Maryland	11.3	300.0000	67	NA
21	Massachusetts	4.4	149.0000	85	NA
22	Michigan	12.1	255.0000	74	NA
23	Minnesota	2.7	72.0000	66	NA
24	Mississippi	16.1	259.0000	44	NA
25	Missouri	9.0	178.0000	70	NA
26	Montana	6.0	109.0000	53	NA
27	Nebraska	4.3	102.0000	62	NA
28	Nevada	12.2	252.0000	81	NA
29	New Hampshire	2.1	57.0000	56	NA
30	New Jersey	7.4	159.0000	89	NA
31	New Mexico	11.4	285.0000	70	NA
32	New York	11.1	254.0000	86	NA
33	North Carolina	13.0	337.0000	45	NA
34	North Dakota	0.8	45.0000	44	NA
35	Ohio	7.3	120.0000	75	NA
36	Oklahoma	6.6	151.0000	68	NA
37	Oregon	4.9	159.0000	67	NA
38	Pennsylvania	6.3	106.0000	72	NA
39	Rhode Island	3.4	174.0000	87	NA
40	South Carolina	14.4	279.0000	48	NA
41	South Dakota	3.8	86.0000	45	NA
42	Tennessee	13.2	188.0000	59	NA
43	Texas	12.7	201.0000	80	NA
44	Utah	3.2	120.0000	80	NA
45	Vermont	2.2	48.0000	32	NA
46	Virginia	8.5	156.0000	63	NA
47	Washington	4.0	145.0000	73	NA
48	West Virginia	5.7	81.0000	39	NA
49	Wisconsin	2.6	53.0000	66	NA
50	Wyoming	6.8	161.0000	60	NA

Figure 5: Adding a new column for Population Level.

Code:

```
> dataset[dataset$Urban.Population...>0 & dataset$Urban.Population...< 50, ][, "PopulationLevel"] <- "small"
> dataset[dataset$Urban.Population...>=50 & dataset$Urban.Population...<60, ][, "PopulationLevel"] <-
"medium"
> dataset[dataset$Urban.Population...>=60 & dataset$Urban.Population...<70, ][, "PopulationLevel"] <-
"large"
> dataset[dataset$Urban.Population... >=70, ][, "PopulationLevel"] <- "extra large"

>dataset
```



The screenshot shows an R console window with the following code and output:

```
> dataset[dataset$Urban.Population...>0 & dataset$Urban.Population...< 50, ][, "PopulationLevel"] <- "small"
> dataset[dataset$Urban.Population...>=50 & dataset$Urban.Population...<60, ][, "PopulationLevel"] <- "medium"
> dataset[dataset$Urban.Population...>=60 & dataset$Urban.Population...<70, ][, "PopulationLevel"] <- "large"
> dataset[dataset$Urban.Population... >=70, ][, "PopulationLevel"] <- "extra large"
> dataset
```

		X Murder	Assault	Urban.Population...	PopulationLevel
1	Alabama	13.2	236.0000	58	medium
2	Alaska	10.0	263.0000	48	small
3	Arizona	8.1	294.0000	80	extra large
4	Arkansas	8.8	190.0000	50	medium
5	California	9.0	276.0000	91	extra large
6	Colorado	7.9	204.0000	78	extra large
7	Connecticut	3.3	110.0000	77	extra large
8	Delaware	5.9	238.0000	72	extra large
9	Florida	15.4	335.0000	80	extra large
10	Georgia	17.4	169.9388	60	large
11	Hawaii	5.3	46.0000	83	extra large
12	Idaho	2.6	120.0000	54	medium
13	Illinois	10.4	249.0000	83	extra large
14	Indiana	7.2	113.0000	65	large
15	Iowa	2.2	56.0000	57	medium
16	Kansas	6.0	115.0000	66	large
17	Kentucky	9.7	109.0000	52	medium
18	Louisiana	15.4	249.0000	66	large
19	Maine	2.1	83.0000	51	medium
20	Maryland	11.3	300.0000	67	large
21	Massachusetts	4.4	149.0000	85	extra large
22	Michigan	12.1	255.0000	74	extra large
23	Minnesota	2.7	72.0000	66	large
24	Mississippi	16.1	259.0000	44	small
25	Missouri	9.0	178.0000	70	extra large
26	Montana	6.0	109.0000	53	medium
27	Nebraska	4.3	102.0000	62	large
28	Nevada	12.2	252.0000	81	extra large
29	New Hampshire	2.1	57.0000	56	medium
30	New Jersey	7.4	159.0000	89	extra large
31	New Mexico	11.4	285.0000	70	extra large
32	New York	11.1	254.0000	86	extra large
33	North Carolina	13.0	337.0000	45	small
34	North Dakota	0.8	45.0000	44	small
35	Ohio	7.3	120.0000	75	extra large
36	Oklahoma	6.6	151.0000	68	large
37	Oregon	4.9	159.0000	67	large
38	Pennsylvania	6.3	106.0000	72	extra large
39	Rhode Island	3.4	174.0000	87	extra large
40	South Carolina	14.4	279.0000	48	small
41	South Dakota	3.8	86.0000	45	small
42	Tennessee	13.2	188.0000	59	medium
43	Texas	12.7	201.0000	80	extra large
44	Utah	3.2	120.0000	80	extra large
45	Vermont	2.2	48.0000	32	small
46	Virginia	8.5	156.0000	63	large
47	Washington	4.0	145.0000	73	extra large
48	West Virginia	5.7	81.0000	39	small
49	Wisconsin	2.6	53.0000	66	large

Figure 6: After Integration of a new column (Population Level).

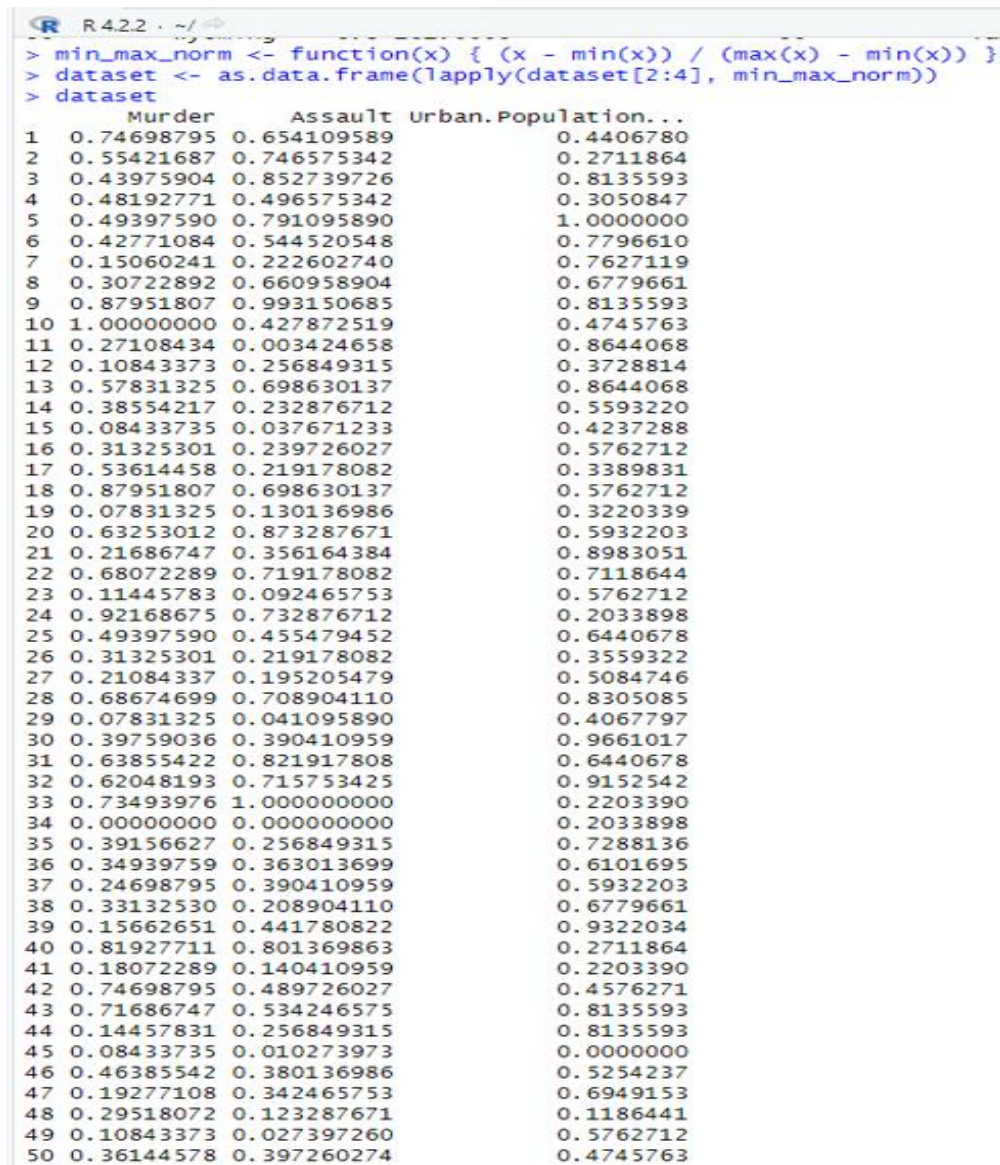
4. Data Transformation: As has already been known, the data transformation process includes one or more of the following steps: normalization, summarization, noise removal, smoothing, and summarizing of the data. for our data set I used normalization.

4.1 Normalization:

The statistical distribution of the data is positively impacted by normalization procedures since they allow us to minimize the magnitude of the variables.in this data set I have normalized column between 2 to 4.

Code:

```
> min_max_norm <- function(x) { (x - min(x)) / (max(x) - min(x)) }
> dataset <- as.data.frame(lapply(dataset[2:4], min_max_norm))
> dataset
```



The screenshot shows an R console window with the following content:

```
R 4.2.2 ~ /
> min_max_norm <- function(x) { (x - min(x)) / (max(x) - min(x)) }
> dataset <- as.data.frame(lapply(dataset[2:4], min_max_norm))
> dataset
```

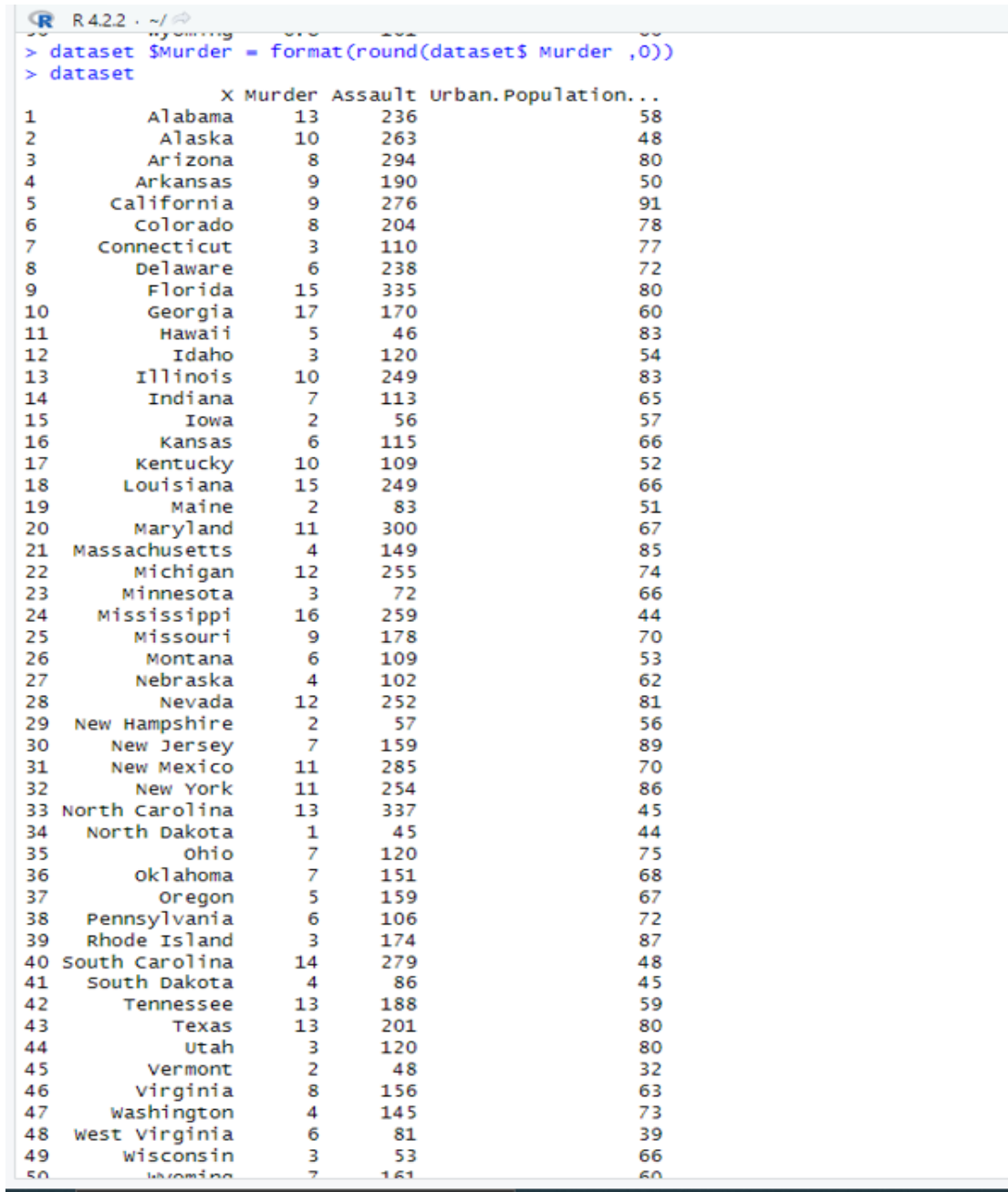
	Murder	Assault	Urban.Population...
1	0.74698795	0.654109589	0.4406780
2	0.55421687	0.746575342	0.2711864
3	0.43975904	0.852739726	0.8135593
4	0.48192771	0.496575342	0.3050847
5	0.49397590	0.791095890	1.0000000
6	0.42771084	0.544520548	0.7796610
7	0.15060241	0.222602740	0.7627119
8	0.30722892	0.660958904	0.6779661
9	0.87951807	0.993150685	0.8135593
10	1.00000000	0.427872519	0.4745763
11	0.27108434	0.003424658	0.8644068
12	0.10843373	0.256849315	0.3728814
13	0.57831325	0.698630137	0.8644068
14	0.38554217	0.232876712	0.5593220
15	0.08433735	0.037671233	0.4237288
16	0.31325301	0.239726027	0.5762712
17	0.53614458	0.219178082	0.3389831
18	0.87951807	0.698630137	0.5762712
19	0.07831325	0.130136986	0.3220339
20	0.63253012	0.873287671	0.5932203
21	0.21686747	0.356164384	0.8983051
22	0.68072289	0.719178082	0.7118644
23	0.11445783	0.092465753	0.5762712
24	0.92168675	0.732876712	0.2033898
25	0.49397590	0.455479452	0.6440678
26	0.31325301	0.219178082	0.3559322
27	0.21084337	0.195205479	0.5084746
28	0.68674699	0.708904110	0.8305085
29	0.07831325	0.041095890	0.4067797
30	0.39759036	0.390410959	0.9661017
31	0.63855422	0.821917808	0.6440678
32	0.62048193	0.715753425	0.9152542
33	0.73493976	1.000000000	0.2203390
34	0.00000000	0.000000000	0.2033898
35	0.39156627	0.256849315	0.7288136
36	0.34939759	0.363013699	0.6101695
37	0.24698795	0.390410959	0.5932203
38	0.33132530	0.208904110	0.6779661
39	0.15662651	0.441780822	0.9322034
40	0.81927711	0.801369863	0.2711864
41	0.18072289	0.140410959	0.2203390
42	0.74698795	0.489726027	0.4576271
43	0.71686747	0.534246575	0.8135593
44	0.14457831	0.256849315	0.8135593
45	0.08433735	0.010273973	0.0000000
46	0.46385542	0.380136986	0.5254237
47	0.19277108	0.342465753	0.6949153
48	0.29518072	0.123287671	0.1186441
49	0.10843373	0.027397260	0.5762712
50	0.36144578	0.397260274	0.4745763

Figure 7: After Normalized Data table.

5.Data Reduction: Given the enormous number of rows in this dataset, it could be more logical to round the murder and assault rates per capita to the nearest zero decimal places, depending on the processing and storage resources we have available.

Code;

```
> dataset $Murder = format(round(dataset$ Murder ,0))
> dataset $Assault = format(round(dataset$ Assault ,0))
> dataset
```



```
R 4.2.2 ~ / ...
> dataset $Murder = format(round(dataset$ Murder ,0))
> dataset
```

		X Murder	Assault	Urban. Population...
1	Alabama	13	236	58
2	Alaska	10	263	48
3	Arizona	8	294	80
4	Arkansas	9	190	50
5	California	9	276	91
6	Colorado	8	204	78
7	Connecticut	3	110	77
8	Delaware	6	238	72
9	Florida	15	335	80
10	Georgia	17	170	60
11	Hawaii	5	46	83
12	Idaho	3	120	54
13	Illinois	10	249	83
14	Indiana	7	113	65
15	Iowa	2	56	57
16	Kansas	6	115	66
17	Kentucky	10	109	52
18	Louisiana	15	249	66
19	Maine	2	83	51
20	Maryland	11	300	67
21	Massachusetts	4	149	85
22	Michigan	12	255	74
23	Minnesota	3	72	66
24	Mississippi	16	259	44
25	Missouri	9	178	70
26	Montana	6	109	53
27	Nebraska	4	102	62
28	Nevada	12	252	81
29	New Hampshire	2	57	56
30	New Jersey	7	159	89
31	New Mexico	11	285	70
32	New York	11	254	86
33	North Carolina	13	337	45
34	North Dakota	1	45	44
35	Ohio	7	120	75
36	Oklahoma	7	151	68
37	Oregon	5	159	67
38	Pennsylvania	6	106	72
39	Rhode Island	3	174	87
40	South Carolina	14	279	48
41	South Dakota	4	86	45
42	Tennessee	13	188	59
43	Texas	13	201	80
44	Utah	3	120	80
45	Vermont	2	48	32
46	Virginia	8	156	63
47	Washington	4	145	73
48	West Virginia	6	81	39
49	Wisconsin	3	53	66
50	Wyoming	7	161	60

Figure 8: After Reducing value size.

6. Data Discretization: Data discretization is a one kind of reducing process.in can be categorical to numerical. In our dataset ‘type’ column had four categorical values. which I have replaced by 4 numerical values: “small” replace by 0. “medium” replace by 1. “large” replaced by 2 “extra large” replaced by 3.

Code:

```
>dataset$PopulationLevel=factor(dataset$OrderedFactorPopulation,levels=c('small',
'medium','large','extra large'), labels = c(1,2,3,4))
```

```
> dataset
```

```
> dataset$OrderedFactorPopulation = factor(dataset$OrderedFactorPopulation,levels = c('small', 'medium','large','extra large'), labels = c(1,2,3,4))
```

```
> dataset
```

		X Murder	Assault	Urban.Population...	OrderedFactorPopulation
1	Alabama	13.2	236	58	2
2	Alaska	10.0	263	48	1
3	Arizona	8.1	294	80	4
4	Arkansas	8.8	190	50	2
5	California	9.0	276	91	4
6	Colorado	7.9	204	78	4
7	Connecticut	3.3	110	77	4
8	Delaware	5.9	238	72	4
9	Florida	15.4	335	80	4
10	Georgia	17.4	NA	60	3
11	Hawaii	5.3	46	83	4
12	Idaho	2.6	120	54	2
13	Illinois	10.4	249	83	4
14	Indiana	7.2	113	65	3
15	Iowa	2.2	56	57	2
16	Kansas	6.0	115	66	3
17	Kentucky	9.7	109	52	2
18	Louisiana	15.4	249	66	3
19	Maine	2.1	83	51	2
20	Maryland	11.3	300	67	3
21	Massachusetts	4.4	149	85	4
22	Michigan	12.1	255	74	4
23	Minnesota	2.7	72	66	3
24	Mississippi	16.1	259	44	1
25	Missouri	9.0	178	70	4
26	Montana	6.0	109	53	2
27	Nebraska	4.3	102	62	3
28	Nevada	12.2	252	81	4
29	New Hampshire	2.1	57	56	2
30	New Jersey	7.4	159	89	4
31	New Mexico	11.4	285	70	4
32	New York	11.1	254	86	4
33	North Carolina	13.0	337	45	1
34	North Dakota	0.8	45	44	1
35	Ohio	7.3	120	75	4
36	Oklahoma	6.6	151	68	3
37	Oregon	4.9	159	67	3

Figure 9: After discretization.

Lastly, after completing all the steps finally we have obtained the full cleaned data set.

		X Murder	Assault	Urban.Population...	PopulationLevel	OrderedFactorPopulation
1	Alabama	13.2	236.0000	58	medium	2
2	Alaska	10.0	263.0000	48	small	1
3	Arizona	8.1	294.0000	80	extra large	4
4	Arkansas	8.8	190.0000	50	medium	2
5	California	9.0	276.0000	91	extra large	4
6	Colorado	7.9	204.0000	78	extra large	4
7	Connecticut	3.3	110.0000	77	extra large	4
8	Delaware	5.9	238.0000	72	extra large	4
9	Florida	15.4	335.0000	80	extra large	4
10	Georgia	17.4	169.9388	60	large	3
11	Hawaii	5.3	46.0000	83	extra large	4
12	Idaho	2.6	120.0000	54	medium	2
13	Illinois	10.4	249.0000	83	extra large	4
14	Indiana	7.2	113.0000	65	large	3
15	Iowa	2.2	56.0000	57	medium	2
16	Kansas	6.0	115.0000	66	large	3
17	Kentucky	9.7	109.0000	52	medium	2
18	Louisiana	15.4	249.0000	66	large	3
19	Maine	2.1	83.0000	51	medium	2
20	Maryland	11.3	300.0000	67	large	3
21	Massachusetts	4.4	149.0000	85	extra large	4
22	Michigan	12.1	255.0000	74	extra large	4
23	Minnesota	2.7	72.0000	66	large	3
24	Mississippi	16.1	259.0000	44	small	1
25	Missouri	9.0	178.0000	70	extra large	4
26	Montana	6.0	109.0000	53	medium	2
27	Nebraska	4.3	102.0000	62	large	3
28	Nevada	12.2	252.0000	81	extra large	4
29	New Hampshire	2.1	57.0000	56	medium	2
30	New Jersey	7.4	159.0000	89	extra large	4
31	New Mexico	11.4	285.0000	70	extra large	4
32	New York	11.1	254.0000	86	extra large	4
33	North Carolina	13.0	337.0000	45	small	1
34	North Dakota	0.8	45.0000	44	small	1
35	Ohio	7.3	120.0000	75	extra large	4
36	Oklahoma	6.6	151.0000	68	large	3
37	Oregon	4.9	159.0000	67	large	3
38	Pennsylvania	6.3	106.0000	72	extra large	4
39	Rhode Island	3.4	174.0000	87	extra large	4

Figure 10: Full Clean Dataset.

Discussion & Conclusion:

We used R language structures and approaches to gradually improve the data during data processing. After all the data pre-processing procedures were successfully used, the data set was made cleaner and better. Nonetheless, not every technique's step required to be employed for this job. We gained knowledge of the sector's pre-processing of data as well as real data. expanding our toolkit with more knowledge. Data pre-processing helps us increase the dataset's correctness. Any values that are incorrect or missing due to human error or issues are removed. The consistency had increased.