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# Cluster Analysis of Cyber Crime Data using R

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***Abstract- Cluster analysis divides the data into groups that are meaningful, useful or both. It is also used as a starting point for other purposes of data summarization. This paper discuss some very basic algorithms like K-means, Fuzzy C-means, Hierarchical clustering to come up with clusters, and use R data mining tool. The results are tested on the datasets namely Online News Popularity, Cyber Crime Data Set data analysis. All datasets was analyzed with different clustering algorithms and the figures we are showing is the working of them in R data mining tool. Every algorithm has its uniqueness and antithetical behavior.***

***Keywords: k-means algorithm, fuzzy c-means algorithm, hierarchical clustering algorithm, R tool.***

## I. INTRODUCTION

Cluster analysis divides data into meaning full groups (clusters) which share common characteristics i.e. same cluster are similar to each other than those in other clusters. It is the study of automatically finding classes. A web page especially news articles which are flooded in the internet have to be grouped. The clustering of these different groups is a step forward towards the automation process, which requires many fields, including web search engines, web robots and data analysis.

Any new web page goes through numerous phases including data acquisition, preprocessing, Feature extraction, classification and post processing into the database. Cluster analysis can be regarded as a form of the classification which creates a labeling of objects with class labels. However it derives these labels only from the data. Data mining functionalities are the Characterization and discrimination, mining frequent patterns, association, correlation, classification and prediction, cluster analysis, outlier analysis and evolution analysis [1].

Clustering is a vivid method. The solution is not exclusive and it firmly depends upon the analysts' choices. Clustering always provides groups or clusters, even if there is no predefined structure. While applying cluster analysis we are contemplating that the groups exist. But this speculation may be false. The outcome of clustering should never be generalized. [9].

## II. R TOOL

R is a free software environment for statistical computing and graphics. It compiles and runs on a wide variety of UNIX platforms, Windows and Mac OS [12]

R is public domain software primarily used for statistical analysis and graphic techniques [10]. A core set of packages is included with the installation of R, with more than 7,801 additional packages (as of January 2016[update]) available at the Comprehensive R Archive Network (CRAN), Bio conductor, Omegahat, Git Hub, and other repositories.[14] R tool provides a wide class of statistical that includes classical statistical tests, linear and nonlinear modeling, classification, time-series analysis, clustering and various graphical functions.[13]R uses collections of packages to perform different functions [11]. CRAN project views provide numerous packages to different users according to their taste. R package contain different functions for data mining approaches. This paper compares various clustering algorithms on datasets using R which will be useful for researchers working on medical data and biological data as well. For this IDE, R Studio is used refer the below Figure 1.

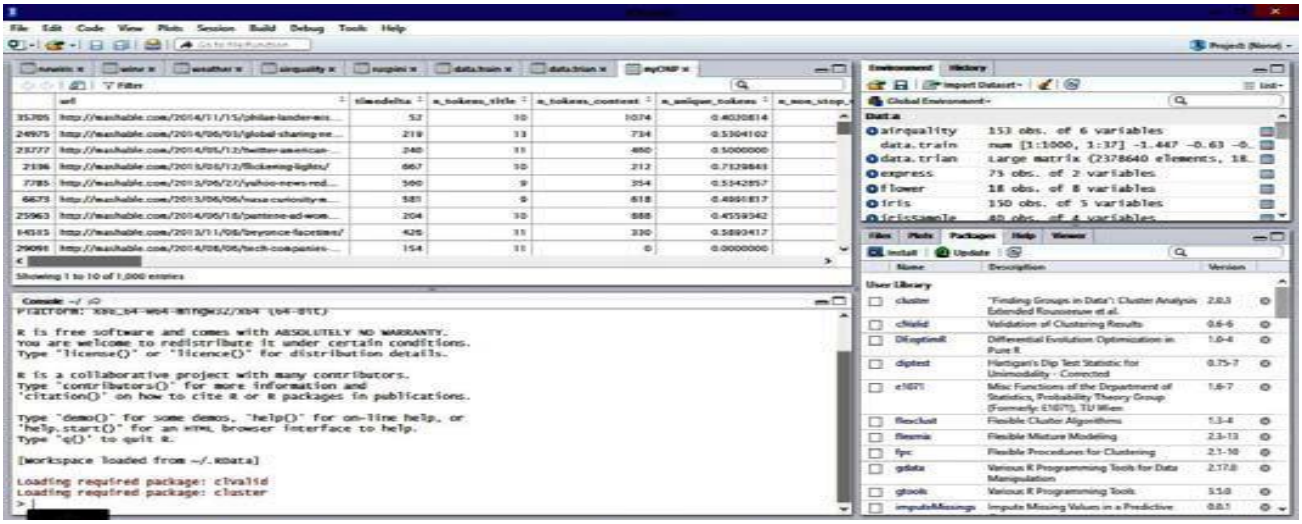


*Fig 1:* R tool Studio

## III. Literature Survey

Arit Thammano [1] describes the most popular clustering algorithm because of its efficiency and superior performance. However, the performance of K-means algorithm depends heavily on the selection of initial centroids. This paper proposes an extension to the original K-means algorithm enabling it to solve classification problems. First, the entropy concept is employed to adapt the traditional K-means algorithm to be used as a classification technique. Then, to improve the performance of K-means algorithm, a new scheme to select the initial cluster centers is proposed. The proposed models are tested on seven benchmark data sets from the UCI machine learning repository. Data classification is one of the fundamental problems in data mining. Classification, as described, is a process of finding a model that describes and distinguishes data classes, for the purpose of being able to use the model to predict the class of objects which class label is unknown. There are many classification techniques that have been used thus far such as Decision tree, Neural networks, Support vector

machines, and Bayesian networks. This paper focuses on a type of classification model that is based on K-means clustering algorithm. K-means is the most popular clustering algorithm. It is very efficient and very easy to implement. Besides being used as a clustering technique, K-means has also been adapted for data classification.

Ying zhao, George karypis [2] describe a fast and high-quality document clustering algorithms play an important role in providing intuitive navigation and browsing mechanisms by organizing large amounts of information into a small number of meaningful clusters. In particular, clustering algorithms that build meaningful hierarchies out of large document collections are ideal tools for their interactive visualization and exploration as they provide data-views that are consistent, predictable, and at different levels of granularity. This paper focuses on document clustering algorithms that build such hierarchical solutions and (i) presents a comprehensive study of partition and agglomerative algorithms that use different criterion functions and merging schemes. (ii) presents a new class of clustering algorithms called constrained agglomerative algorithms, which combine features from both partition and agglomerative approaches that allows them to reduce the early-stage errors made by agglomerative methods and hence improve the quality of clustering solutions.

Chun-Nan Hsu, Han-Shen Huang , Bo-Hou Yang [3] describe the Expectation-Maximization (EM) algorithm is one of the most popular algorithms for data mining from incomplete data. However, when applied to large data sets with a large proportion of missing data, the EM algorithm may converge slowly. The triple jump extrapolation method can effectively accelerate the EM algorithm by substantially reducing the number of iterations required for EM to converge.

# IV. Related Work

## DATA PREPARATION

### DATA PRE-PROCESSING

Data pre-processing [20] is a data mining technique that involves transforming raw data into an understandable format. Often the data is unstructured, inconsistent, has missing values, and lack in certain behaviour or trends that gives many errors. Therefore, it needs to be cleaned, integrated, transformed, and hence reduced. Cleaning fills in the missing values and removes noise.

Integration take the data cubes or chunks together using multiple databases. Transformation uses normalization and aggregates the data and Reduction helps in decreasing the volume of data keeping similar analytical results.

The data set as mentioned above is taken from a UCI Repository: Communities and Crime dataset. It has total 1994 instances and 128 attributes like population, race, and age.The attributes are real and of multivariate characteristics. This data was first converted into CSV file using JSON file from the website using Python. For naming convention, original data was assumed as ‘dirty data’ and the data with no missing values as ‘cleaned data’.

For clean data, removal of missing values was needed to get an appropriate crime data set. Initially, columns that had these missing values or sparse values were deleted as undefined values would have a negative impact on the accuracy of the model. For dirty data, the missing data of a feature were converted into median value of that feature. For predicting feature, 'Per Capita Violent Crimes', a new column called 'High Crime' was created that had a value '1' for Per Capita Violent Crime' greater than 0.1 and '0' otherwise. The threshold of 0.1 was decided upon manual analysis of data by view-through process. All the features had to be predicted using this target feature 'High crime'.

### Crime pattern Analysis

The data mining is data analyzing techniques that used to analyze crime data beforehand stored from various resources to find patterns and trends in crimes. In additional, it can be applied to enlarge efficiency in solving the crimes quicker and also can be applied to automatically advise the crimes. Crime preclusion and revealing become an important trend in crime and a very challenging to solve crimes. Several studies have discovered various techniques to solve the crimes that used too many applications. Such studies can help to speed up the process of solving crime and help the huge data are very difficult and complex.

**Objective**

I. Crime prevention and detection become an important trend in crime and a very challenging to solve crimes.
II. The data used for analysis require the accuracy and sufficiency.
III. This proposed system focuses on Traffic Violation and Border Control, Violent Crime, the Narcotics, Cyber Crime.
IV. Issues and challenges on crime are Data Collection and Integration, Crime Pattern, Performance, Visualization.

## V. Proposed Work

After preprocessing we can use various clustering algorithms

**K-NEAREST NEIGHBORS ALGORITHM**

The k-Nearest Neighbors algorithm (k-NN) is a non-parametric technique utilized for classification and regression. In both cases, the input consists of the k closest training exemplar in the characteristic space.

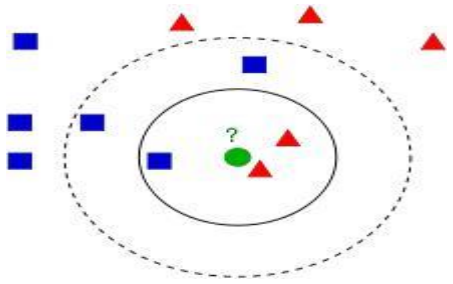



**Fig 4.1** *k*-NN classification

In *k*-NN regression, the *k*-NN algorithm is used for estimating continuous variables. One such algorithm uses a weighted average of the *k* nearest neighbors, weighted by the inverse of their distance. This algorithm works as follows:

1. Compute the Euclidean distance from the query example to the labeled examples.
2. Order the labeled examples by increasing distance.

**K-NN Algorithm**

**Input: Crime Data, Watermark Data**

**Output: Modified Crime Observation Data**

1. Add the Crime Profiles (P).
2. Add the Crime Observation Data (O).
3. Enter watermark content (W).
4. Convert the watermark data to bytes and find the length of watermark data (L).

5. Sort the Crime Observation Data (O) Crime wise.
6. I=0
7. For Each Crime's Observation Set in (O)
8. Alter the Observation Data's third value such that OD(3) = 301 + W(I)
9. Change the OD(1) position = OD(1) position + W(I)
10. I=I+1

11. If I>=L Then
12. Break
13. End If
14. Next
15. Output the New Crime Data Set.

**Input: Modified Crime Observation Data**

**Output: Crime Observation Data, Extracted Watermarked Data**

1. Select the Crime Data Set (where Watermark Data Embedded) (P).
2. I=0;

3. For Each Crime's Observation Set in (O)
4. W(I) = Observation Data's third value - 301
5. Change the OD(3) value= OD(3) value -301
6. If I=0 Then

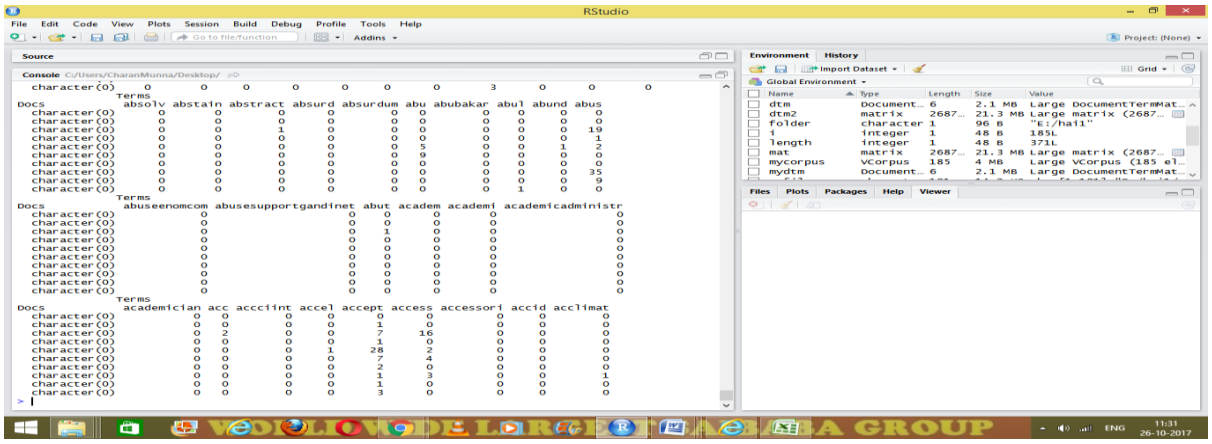
7. L= W(I)
8. End If

9. I=I+1
10. If I >L Then
11. Break
12. End If
13. Next
14. Convert the watermark bytes to data.
15. Check the KNN Property.
16. Output Watermark Data.

## Result Analysis

Now we can take input data set

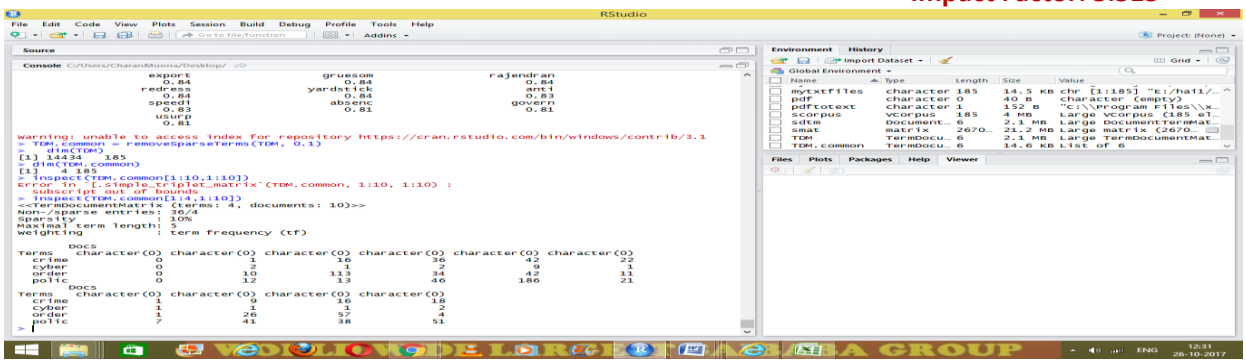
We can take 200 papers charters details dataset



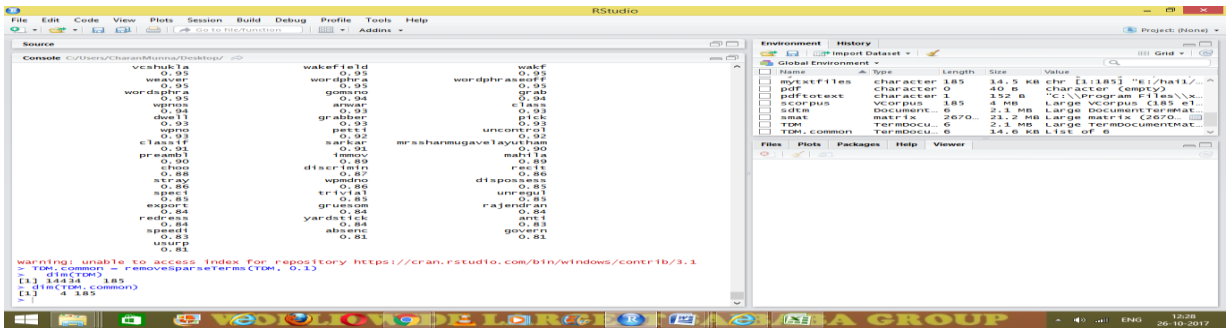

After data preprocessing

Each of these words occurred more than 150 times.

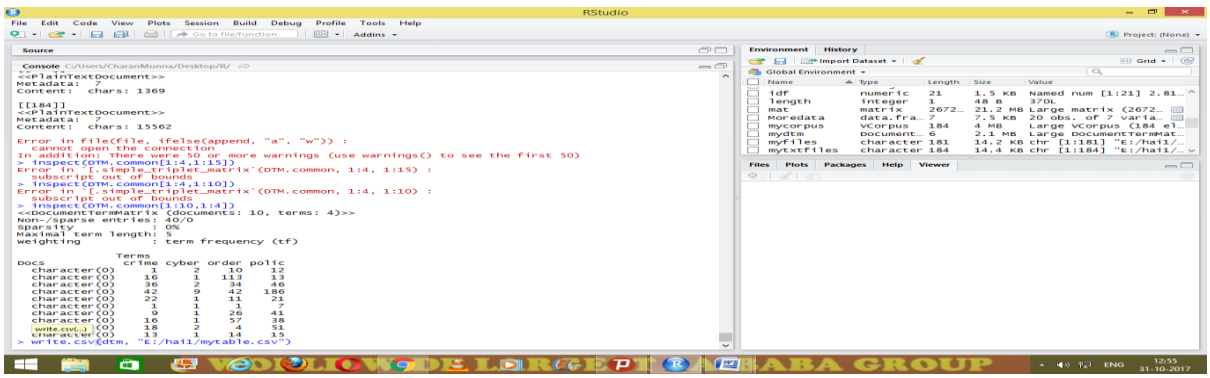
 



From the 14434 terms that we started with, we are now left with a TDM which considers on 4 commonly occurring terms.

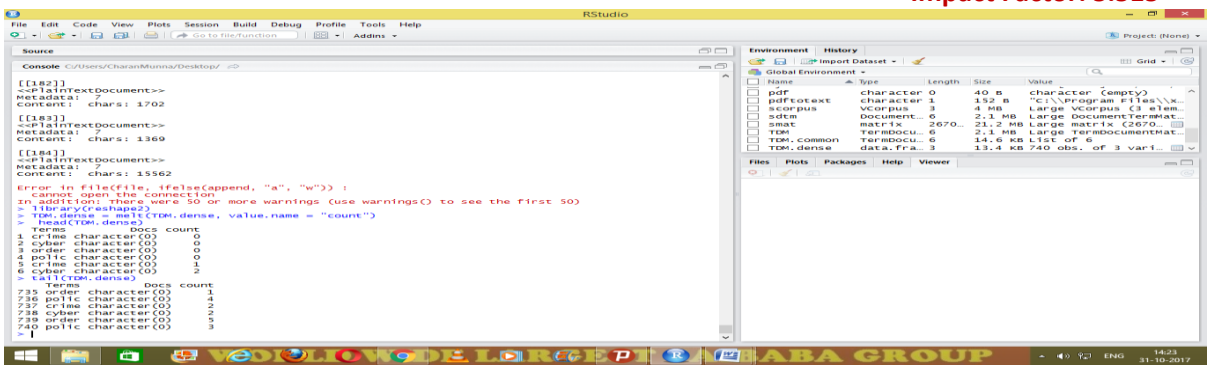


Term frequency

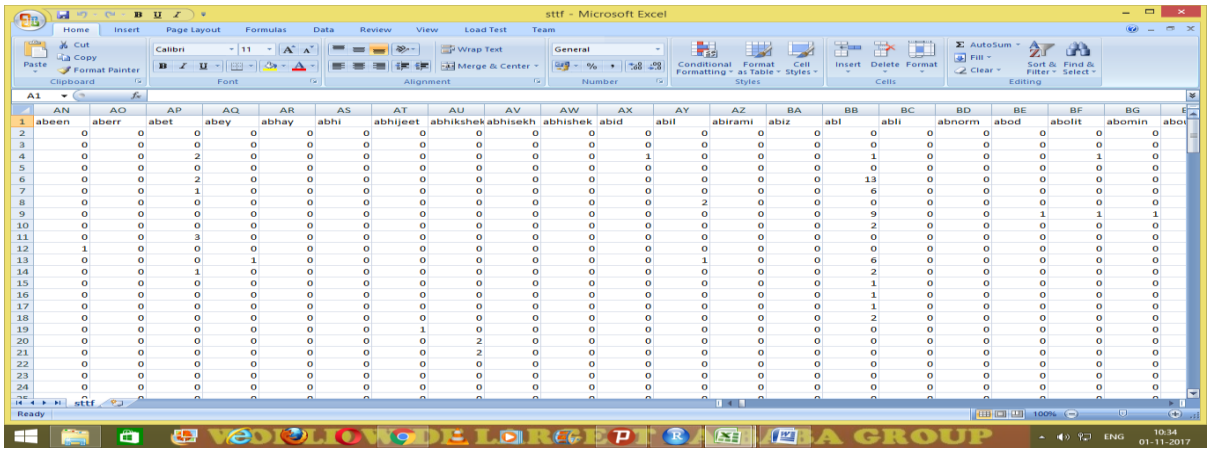


So, as it turns out the sparse representation was actually wasting space! (This will generally not be true though: it will only apply for a matrix consisting of just the common terms). Anyway, we need the data as a normal matrix in order to produce the visualisation. The next step is to convert it into a tidy format.




Sttf with 186 documents and terms




## Conclusion

Crime are characterized which change over time and increase continuously. The changing and increasing of crime lead to the issues of understanding the crime behavior, crime predicting, precise detection, and managing large volumes of data obtained from various sources. Research interests have tried to solve these issues. In the crime investigation procedures, input data is very essential to use in training process and testing process. The training process is used to accomplish the crime model and the testing process is used to validate the algorithm. The issues of crime pattern are concerning with finding and predicting the hidden crime. The proposed methodology provides security for the crime data during outsourcing. Clustering and classification is made on the crime information. While classifying the crime data, watermark content is added for the purpose of defense. The watermark content is used for verifying the classification data. Based on clustering and classification, the data can be classified and kept secured manner. Also the crime data is been split as per the crime ratio.

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