Step 2: Clustering testing data vectors
a-Ntest **y**
While (Iter < Max_Iteration)
Load (Aw-m, m = 1,…, mem-max , ya)
for all ant-Worker Aw, (w = 1,……., Aw-max) **do**
Find Minimum Average Distance (ya, Ci)
Compute Neighbour Function *f* (ya, Ci) Equation 3
if Pd (ya) >= t **then** Equation 2
Drop(ya, Ci);
Update Threshold (ti, tnew) **end-for** Equation 6&7
end-while

Step 3: Merging the most similar and neighboring Clusters
for all Ci, (i = 1,……., C-max) **do**
Compute Clusters Minimum Equation5
Average Distance MAD (Ci, Cj)
Compute Cluster Neighbour Function *f* (Ci, Cj) Equation 3
if f(ya, Cj) ³ t || f(yb, Ci) ³ t **then**
Merge Clusters (Ci, Cj); **end-for**

Step 4: Cluster Refinement: Detecting Small Clusters and Checking Boundaries Rule 1-3
Find Clusters mean points (Cm) R. 1
for all Cmi& Cmj , (i &j = 1,……,Cm-max) **do**
Compute Neighbour Function Equation 3
for Close Clusters *f* (Cmi , Cmj)
if Pp (Cmi) >= t **then** Equation 1
Merge Clusters (Ci, Cj); **end-for**
Find Intersection Vectors for Close Clusters (Ci, Cj) R. 2
for all ya, (a = 1,……., y-max) **do**
Compute Neighbour Function *f* (ya ,Ci) &*f* (ya, Cj) Equation 3
if Pp (ya , Ci) > Pp (ya , Cj) && R. 3
Pd (ya , Cj) >= t **then**
Add(ya , Cj); **end-for**
Hybrid Agglomerative Clustering and Ant Colony Optimization (ACO) provide high efficiency and high quality data clustering.

5. Results

This method is used to achieve high efficiency and high-quality data clustering. The method is also beneficial to be used in textual document clustering algorithms for many text domain applications. To enhance this work, we are proposing a new hybrid clustering algorithm using agglomerative clustering with ACO algorithm. In this we have done pre-processing from new document by document clustering and using agglomerative & ACO algorithms then after we evaluate the performance. By using these algorithms we can achieve high efficiency and high quality.

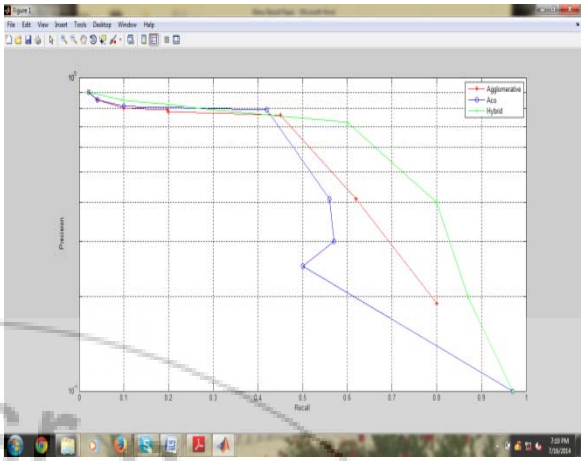

Figure 4.1: Showing Agglomerative Clustering Hybrid with ACO

Our algorithm allow for two input parameters: Precision and Recall. As in Text Mining in Clustering, Hybrid algorithms Agglomerative and ACO for high efficiency and high quality. Recall set for Hybrid is 0.9 and precision 0.2. Hybrid algorithm accurate from another is value around 20%.

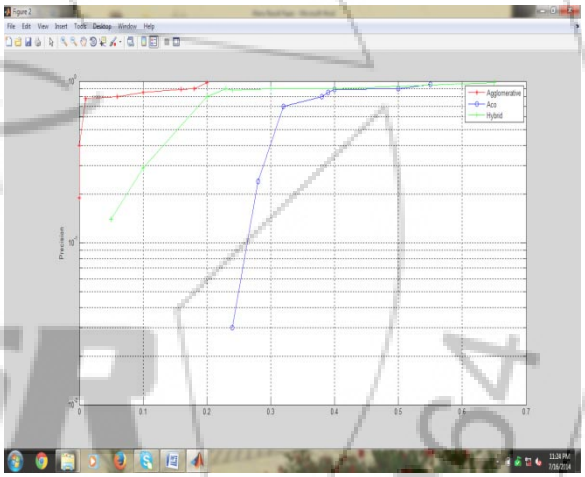

Figure 4.2: Showing Agglomerative Clustering Hybrid with ACO.

Our algorithm allow for two input parameters: Precision and Recall. As in Text Mining in Clustering, Hybrid algorithms Agglomerative and ACO for high efficiency and high quality. Recall set for Hybrid is 0.7 and precision 0.2. Hybrid algorithm accurate from another is value around 25%.

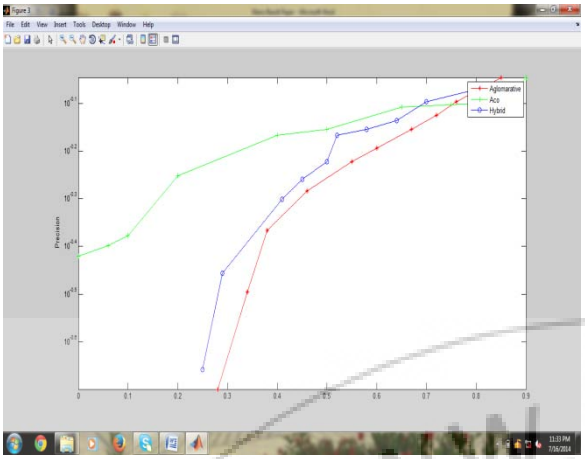

Figure 4.3: Showing Agglomerative Clustering Hybrid with ACO.

Our algorithm allow for two input parameters: Precision and Recall. As in Text Mining in Clustering, Hybrid algorithms Agglomerative and ACO for high efficiency and high quality. Recall set for Hybrid is 0.7 and precision 0.2. Hybrid algorithm accurate from another is value around 32%.

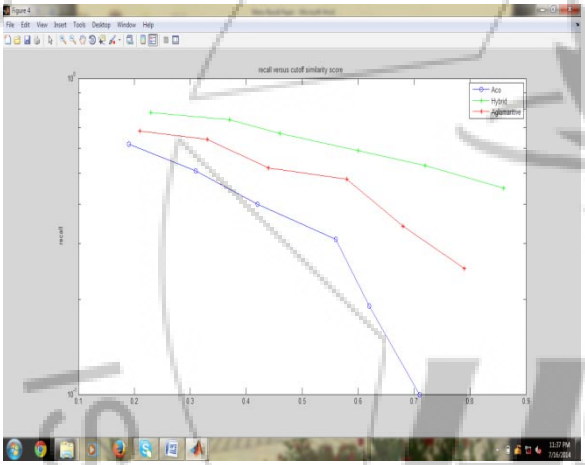

Figure 4.4: Showing Agglomerative Clustering Hybrid with ACO for Recall and Recall cut off Similarity Score.

Our algorithm allow for two input parameters: Recall and Recall cut off Similarity Score. As in Text Mining in Clustering, Hybrid algorithms Agglomerative and ACO for high efficiency and high quality. Recall set for Hybrid is 0.2 and Recall cut off Similarity Score 0.9. Hybrid algorithm accurate from another is value around 20%.

Table 1: Showing Clustering Performance Evaluation of Precision and Recall.

Partition	Cluster	Precision	Recall	F-measure
P1	C1	0.82	0.566	0.649
	C2	0.32	0.5865	0.4049
P2	C3	1	0.4255	0.6086
	C4	0.94	0.2876	0.3533
P3	C5	1	0.5	0.6543
	C6	0.4987	1	0.9765
P4	C7	1	0.3233	0.456
	C8	1	0.3211	0.52345
P5	C9	0.775	0.2356	0.28764
P6	C10	1	0.3567	0.4876
	C11	0.8	0.45	0.396
P7	C12	1	0.3567	0.4676
	C13	0.65	0.0975	0.1834
P8	C14	1	0.3032	0.453
	C15	0.3876	0.0975	0.17543
P9	C16	1	0.06756	0.13654
P10	C17	0.82	0.3	0.35678
P11	C18	0.55	0.07532	0.18765
P12	C19	1	0.27	0.45643
	C20	0.7	0.27	0.37875
P13	C21	1	0.6	0.687643
	C22	0.56	0.3	0.33333
P14	C23	1	0.71	0.16543

We have used the metrics precision, recall and F- measure shown in table 1 for evaluating the performance of the proposed approach. The evaluation metrics used in the proposed approach is given below:

F(i, j)= 2 * Recall (i, j) * Precision (i, j) / Precision (i, j) + Recall (i, j)

For each cluster, we compute the Precision, Recall and F – measure with the help of the above mentioned equation. The obtained results are shown in table 1.

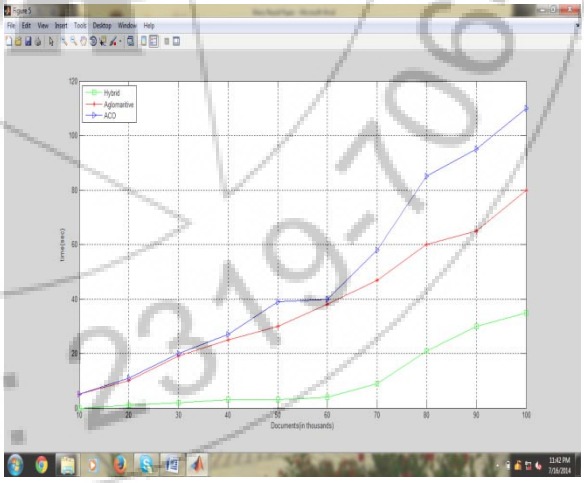

Figure 4.5: Showing Agglomerative Clustering Hybrid with ACO For Time and Document.

Our algorithm allow for two input parameters: Time and Document. As in Text Mining in Clustering, Hybrid algorithms Agglomerative and ACO for high efficiency and high quality. Time set for Hybrid is 30 and Document 100. Hybrid algorithm accurate from another is value around 30%.

6. Conclusion and Future Work

Data mining process is to extract information from a data set and transform it into an understandable structure for further use. In our work, we load a dataset on which preprocessing will be performed. Document clustering will be performed on the dataset using hybrid agglomerative clustering algorithm and ACO (Ant colony optimization) to get higher efficiency and higher quality rate. Performance will be evaluated on the basis of four parameters named as recall, precision, time and document. For future, we can enhance the performance of our work by using better optimization algorithm to get more efficiency in results.

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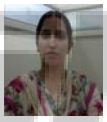

Sukhpreet Kaur received the B. Tech degree in Computer Science and Engineering from Punjab Technical University, Punjab, India in 2007 and M.Tech Degree in Computer Engineering from Punjabi University, Patiala, India in 2010. She worked as an Assistant Professor at Department of Computer Science and Engineering in Baba Farid College of Engineering and Technology,Punjab, India till 2012. She is working as Assistant Professor at Department of Computer Science and Engineering, Shri Guru Granth Sahib World University Fatehgarh Sahib, Punjab, India since July 2012. She has published more than 30 research papers in different international journals and conferences. Her research areas include Software Engineering and Data mining.