

AN EFFICIENT CLUSTER SYSTEM FOR BIO-INFORMATICS DATA USING AMALGAM OF CLUSTERING METHODS

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Abstract:

At this pandemic Covid-19 situation, Machine learning is inspired to develop an automated drug evaluation system for the patients suffering with routine illness conditions from the existing valid drug bank using a blend of clustering methods. To get effective win over the corona virus we have to use technological advances to prevent the pandemic disease by avoiding physical contacts as well as use Artificial Intelligence like Chest Scan image processing to predict covid-19 virus in lungs by using proper algorithm to differentiate Corona lobes with other disease lobes. In this scenario I would like to use computer science knowledge based on the physio chemical properties and enzyme inhibition properties of drug dataset provided by standard drug bank repository i.e., www.drugs.com, www.drugbank.ca [2] and www.malacards.org[4]. Here I applied existing clustering techniques as a blend of k-means, k-medoids, hierarchical methods and Fuzzy k-means[9] to determine an appropriate set of drugs from the given drugbank for different illness conditions of thyroid patients[10]. In this research work data preparation for drug evaluation is playing a crucial role, we used Correspondence Analysis (CA) method to make our Cluster system is efficient and effective. We have shown the analysis as a blend of cluster methods successful for this cluster system using graphical presentation and derived best hybrid cluster system as final outcome.

Keywords: *Machine Learning, Covid-19, Artificial Intelligence, CA, Clustering, Thyroid.*

1.0 Introduction

Clustering algorithms has been categorized as Exclusive, Overlapping, Hierarchical and Probabilistic Clustering. In exclusive method, data assembled in an elite manner, and if a datum has a place with a clear bunch then it couldn't be incorporated into another group [1]. The clustering by overlapping method utilizes fuzzy sets to group information, so each point may have a place with at least two groups with various degrees of participation. The most for the most part announced and regularly used isolating methods are k-implies, k-medoids, and different assortments.

For K-medoids, a medoid speaks to the most delegate purpose of a gathering of focuses. K-Means clustering [2] is also an iterative clustering procedure, but it predefines the number of clusters that will be in the dataset. PAM stands for “partition around medoids” [3]. The method intends to discover an arrangement of items called medoids that are halfway situated in groups. The objective of the algorithmic method is to reduce the object dissimilarities with respect to their nearby selected datum. The structure of k-medoids is nearly similar to that of k-means [4]. The cluster representative is the one data point which is located central in the cluster. Any two objects distance is calculated and the one having minimum dissimilarity when compared to all other objects is chosen as the center. PAM is susceptible but tough to noise as well as outliers than kmeans because medoids contemplates marginal distance which isolates it from alternate objects [5].

The observation being classified into groups necessitates few methods for measuring the distance between observations, which means no unsupervised machine learning algorithms can take place without some notion of distances. The selection of distance measure is crucial step in clustering [6]. It characterizes how the likeness of two components (x, y) is computed and it will impact the state of the groups. The most generally utilized and acknowledged technique is Euclidean separation measure. The estimation of separation measures is personally identified with the scale on which estimations are made. Therefore, factors are frequently scaled (i.e. standardized) before estimating the dissimilarities [7]. Generally variables are scaled to have standard deviation one and mean zero. The goal is to make the variables comparable and they will have equal importance in the clustering algorithm. This is especially prescribed when factors are estimated

in various scales. The standardized data is a methodology broadly utilized with regards to gene examination before grouping [8]. In this work, we present a hybridized program encompassing both k means and medoids algorithm to cluster a dataset of thyroid disease drugs and the program is run to generate data groups based on the algorithm, thereby refining the outcome based on fuzzy kmeans.

2.0 Materials and Methods

2.1 Dataset

Nearly 189 drugs as dataset was utilized where they are reported as thyroid inhibitors, downloaded from Malady cards database [9]. It was observed that few drugs come under other disease conditions; however, involved in the dataset because they are known to representation several other diseases including thyroid disease.

2.2 R: Result of information in science understood the criticalness of information mining in the structure of convolution of bio frameworks [11]. R program is uninhibitedly accessible programming accessible in a domain utilizing object arranged programming for the most part focused for factual figuring just as designs.

2.3 Hybrid clustering

K-suggests pack technique is least requesting and the most exhaustively utilized parceling framework for segment a dataset into an arrangement of k groups. The system utilizes Euclidean separation evaluates between server farms to pick within and the between-bundle tantamount characteristics [12]. The PAM estimation depends upon the quest for k administrator objects or medoids among the perspective on the dataset.

These acknowledgments should address the structure of the information. In the wake of finding a strategy of k medoids, k bundles are made by assigning every wisdom to the closest medoid.

3.0 Results and Discussion

3.1 Cluster Validity

In this work, NbClust was engaged which was integrated with 30 validity indices to examine the numbers of groups in a given dataset. Therefore, from this analysis, the outcome signified that about 13 different index programs suggested three clusters as optimum whereas eleven index

programs suggested two groups and 4 indices reported four clusters. As per the majority ruling method, the best output referred to three groups [8].

Hence, it can be established that the optimum numbers of clustering groups, k for the given dataset comprised of various drugs involved in thyroid disease was three cluster results. So, an initial $k=3$ value was utilized to achieve k-means, PAM as well as hybrid algorithm on the thyroid dataset [13].

3.2 k-means algorithm

The k-means approach is an apportioning issue, wherein the information isolated as gatherings with each redundancy of the calculation [10]. Since the assignments were begun aimlessly, n start = 25 is indicated, which implies that the program will endeavor 25 different arbitrary beginning stages and afterward picked the outcome with lowermost inside bunch disparity (Figure 1). A better group will bring about qualities with least withinss and greater betweenness which further depends on the whole of k groups chose initially. From this time forward, low withinss and high betweenness for $k=3$ was gotten

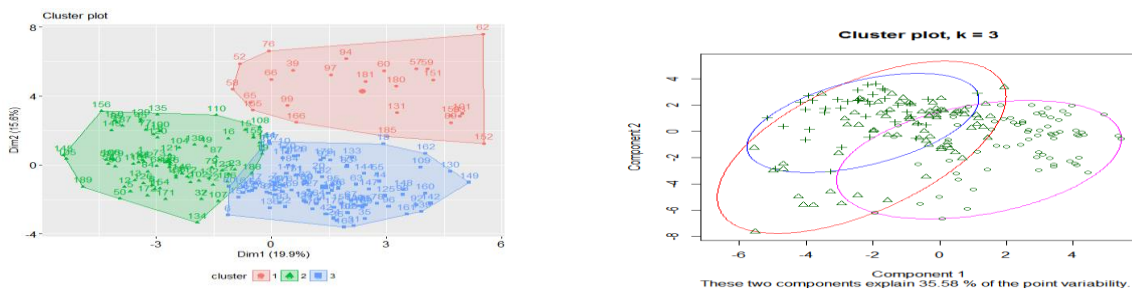


Figure 1: Output of 3 clusters and cluster centers obtained from kmeans program and K-medoids.

3.3 Partitioning Around Medoids

It was reported that outliers influence the outcome of k-means cluster result which would otherwise influence the task of cluster annotations. Hence, anew, strong algorithm is presented by PAM algorithm, also referred as k-medoids [14].

From both methods, it was observed that some samples have a negative silhouette. This means that they are not in the right cluster. On contrast between k-means versus PAM, k-means ensued around 13 which are negative whereas PAM resulted in 27, respectively.

3.4 Hybrid kmeans-PAM Clustering Algorithm

Before long, these two standard gathering methods have their own one of a kind inclinations and imprisonments. In this manner, a novel hybrid methodology is executed to mix the best of k-means and PAM grouping. proceeds in three stages. First it figures k beginning medoids as k-bunches on the hidden dataset. By then the PAM bunch centers are determined trailed by handling k-implies by using group focuses as the underlying k [10]. The 3 grouping came about gatherings procured using k=cluster focuses, which are the three gatherings of PAM computation, achieved absolutely three different bundle sizes 77, 25 and 87 independently. Inquisitively, the negative blueprints got from blend system are 11 against 13 from k-suggests alone and 27 by PAM procedure, which prescribes the way that crossbreed method is valuable in expelling information from groups (Table 1).

Table 1: Three cluster groups appeared from kmeans and PAM methods.

	Group 1	Group2	Group3	Size of Hybrid cluster
Group1	59	18	0	77
Group2	9	14	2	25
Group3	4	44	39	87
Size of PAM cluster	72	76	41	

It is worth to take note of that the individual k-means calculation could group dataset as 25, 70 and 94 gatherings while the hybrid kmeans-kmedoids brought about comparable cluster of size 25 and remaining being 87 and 77. This data can be seen graphically (Figure 2).

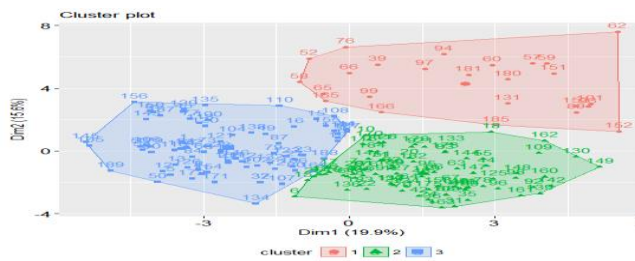


Figure 2: Visual representation of 3 clusters and centers resulted from hybrid kmeans-kmedoids method

It was observed from the plots of hybrid clustering algorithm that the data points at the edge of clusters 2 and 3 were found to be overlapped and efficient clustering was not possible when plots are visualized. Hence, work was initiated to introduce k-means procedure coupled with fuzzy

algorithm [8]. Fuzzy being soft clustering procedure mixed with hard clustering k-means, reported as fuzzy k-means (FKM) algorithm in order to produce meaningful clusters.

3.5 Fuzzy k-means algorithm

A subset including 25 information focuses from the 189 thyroid medication parameter dataset was exposed to fkm calculation and the yield chart is accounted for in Figure 3. It is confirm that the program can bunch 3 sets with clear division.

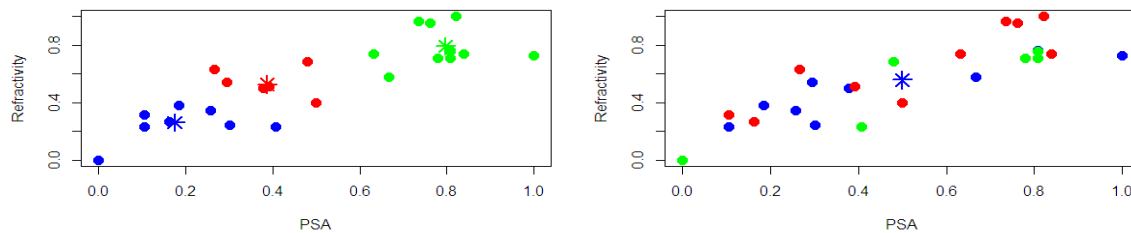


Figure 3: Dataset clusters via FKM algorithm with Entropy regularization

3.6 Fuzzy k-means via entropy regularization

An energizing stuff in regards to the fluffy k-implies by means of entropy regularization is that the models are gotten as weighted methods with loads proportionate to the enlistment degrees (rather than to the cooperation degrees at the force of m as is for the fluffy k-implies). It is seen from Figure 4 that couple of articles from one bunch showed up in other bunch gatherings.

3.7 Fuzzy k-means via entropy regularization plus noise cluster

The entropy regularization abstained from utilizing the fake fluffiness parameter m . The clamor group is an extra bunch (concerning the k standard groups) to such an extent that items perceived to be anomalies are allotted to it with high enrollment degrees [8].

3.8 Gustafson and Kessel-like fuzzy k-means

The program plays out the Gustafson and Kessel-like soft k-suggests packing computation and is worthwhile to choose gatherings.

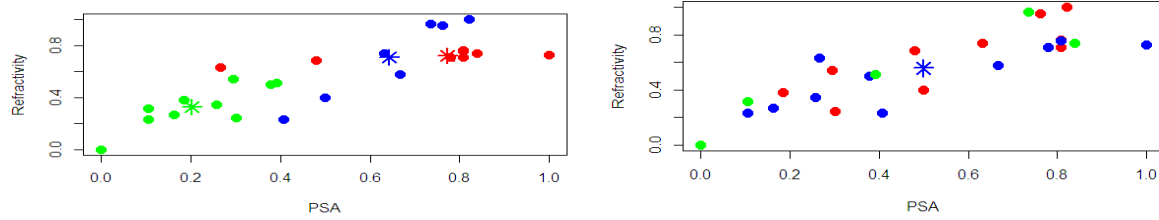


Figure 4: Gustafson and Kessel - like fuzzy k-means clustering algorithm with Entropy Regularization.

3.9 Gustafson and Kessel-like fuzzy k-means via entropy regularization

The program performs the Gustafson and Kessel - like fuzzy k-means clustering algorithm with entropy regularization [21]. The method permits to evade utilizing the artificial fuzziness parameter m . If standardization is set to $stand=1$, the algorithm runs based on standard data. Figure 5 suggested that the data was discrete and the program unable to identify and cluster better possibilities.

3.10 Gustafson and Kessel-like fuzzy k-means using entropy regularization plus noise cluster

The program runs the Gustafson and Kessel-like fuzzy k-means clusters using entropy regularization and noise cluster which is different from fuzzy k-means, and the method identifies non-spherical clusters.

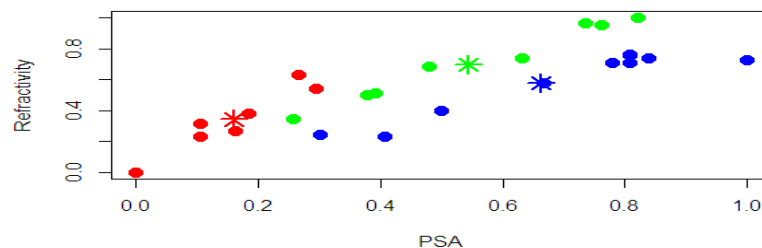


Figure 5: Gustafson and Kessel - like fuzzy k-means clustering algorithm with entropy regularization and noise cluster resulted in better clusters.

Of all variations in FKM algorithms presented here, only natural FKM algorithm is able to produce estimated three better cluster solutions. Hence, it should be noted that testing all possibilities should be made before proceeding with allied variations of algorithms.

4.0 Conclusion

From both individual k-means and k-medoids strategies, it was seen that a few examples announced negative outlines. On correlation between k-means and PAM, the previous brought about 13 negative outlines though PAM technique brought about 27 negative outlines and comparable is the perception with bunch size. In addition, covering of bunches was seen for each situation just as in half breed strategy. Consequently, a lot of six fluffy calculation variations concentrated on a subset of thyroid dataset brought about 3 unmistakable groups by fluffy k-implies followed by Gustafson and Kessel - like fluffy k-implies with entropy regularization and commotion bunch calculation[8]. Table 2 shows the drugs suitable for Hyper Thyroid and Hypo Thyroid patients derived from the mappings of this novel cluster system [10][16].

Table 2: Cluster System Output – Drugs data set divided into 3 Cluster groups as shown below (Hybrid K-Means K-Medoids Algorithm)

Sl. No	Drug_ ID	Cluster 1 DRUGS	S.No	Drug_ ID	Cluster 2 Drugs	S.No	Drug_ ID	Cluster 3 Drugs
1	1	Nitroprusside	1	39	Methotrexate	1	6	Sevoflurane
2	2	Propylthiouracil	2	52	Folic Acid	2	7	Etoricoxib
3	3	Hydrocortisone	3	57	Paclitaxel	3	9	Remifentanyl
4	4	Prednisone	4	58	Pemetrexed	4	10	Methylprednisolone
5	5	Nitric Oxide	5	59	Everolimus	5	17	Diclofenac
6	8	Propofol	6	60	Sirolimus	6	18	Travoprost
7	11	Menthol	7	62	Octreotide	7	20	Bimatoprost
8	12	Acetylcholine	8	65	Doxycycline	8	21	Latanoprost
9	13	Benzocaine	9	66	Oxytetracycline	9	22	Dexmedetomidin

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10	14	Dexamethasone	10	76	Leucovorin	10	24	Tizanidine
11	15	Triamcinolone	11	89	Indinavir	11	25	Clonidine
12	16	Dinoprost Tromethamine	12	93	Ritonavir	12	26	Methyltestosterone
13	19	Timolol	13	94	Azithromycin	13	29	Bupivacaine
14	23	Metoprolol	14	97	Doxorubicin	14	30	Celecoxib
15	27	Estradiol	15	99	Minocycline	15	31	Sertraline
16	28	Guaifenesin	16	101	Vincristine	16	33	Morphine
17	32	Pseudoephedrine	17	131	Etoposide	17	35	Fentanyl
18	34	Metformin	18	151	Docetaxel	18	36	Diazepam
19	37	Ephedrine	19	152	Vinorelbine	19	38	Xylometazoline
20	41	Betamethasone	20	165	Cefazolin	20	40	Donepezil
21	45	Ribavirin	21	166	Piperacillin	21	42	Citalopram
22	47	Dopamine	22	180	Pimecrolimus	22	43	Exemestane
23	49	Entecavir	23	181	Tacrolimus	23	44	Amiodarone
24	50	Cysteamine	24	185	Bromocriptin	24	46	Olanzapine

					ine			
25	53	Niacin	25	153	Vinblastine	25	48	Risperidone
26	54	Nicotinamide				26	51	Droperidol
27	68	Carboplatin				27	55	Imatinib Mesylate
28	72	Carbimazole				28	56	Chlorphenirami ne
29	73	Epinephrine				29	61	Miconazole
30	77	Alendronate				30	63	Sorafenib
31	79	Lacosamide				31	64	Bexarotene
32	80	Carbamazepi ne				32	67	Vildagliptin
33	84	Caffeine				33	69	Levonorgestrel
34	85	Vitamin C				34	70	Ropivacaine
35	87	Genistein				35	71	Topiramate
36	90	Acetaminophe n				36	74	Esomeprazole
37	100	Carbidopa				37	75	Norgestimate
38	102	Cyclophospha mide				38	78	Ezogabine
39	104	Vorinostat				39	81	Melatonin
40	105	Hydroxyurea				40	82	Ergocalciferol
41	106	Fluorouracil				41	83	Vitamin E
42	107	Histamine				42	86	Cholecalciferol
43	108	Bortezomib				43	88	Midazolam

44	110	Fludarabine				44	91	Lansoprazole
45	112	Chlorpropamide				45	92	Sunitinib
46	113	Salicylic acid				46	95	Loperamide
47	114	Glipizide				47	96	Rosiglitazone
48	116	Tolbutamide				48	98	Ezetimibe
49	118	Zoledronic acid				49	103	Nitisinone
50	120	Decitabine				50	109	Dabrafenib
51	121	Dacarbazine				51	111	Glimepiride
52	122	Temozolomide				52	115	Glyburide
53	123	Melphalan				53	117	Desogestrel
54	126	Valproic Acid				54	119	Pioglitazone
55	129	Azacitidine				55	124	Tamoxifen
56	132	Ifosfamide				56	125	Gefitinib
57	134	Mechlorethamine				57	127	Drospirenone
58	135	Vidarabine				58	128	Capecitabine
59	138	Gemcitabine				59	130	Irinotecan
60	143	Levodopa				60	133	Trametinib
61	145	Glycine				61	136	Diphenhydramine
62	146	Tretinoin				62	137	Promethazine
63	150	Tagatose				63	139	Crizotinib

64	154	Metronidazole				64	140	Rabeprazole
65	155	Famotidine				65	141	Lenalidomide
66	156	Mannitol				66	142	Ponatinib
67	164	Cocaine				67	144	Calcitriol
68	167	Ursodeoxycho lic acid				68	147	Alfacalcidol
69	168	Ketorolac				69	148	Tipifarnib
70	171	Isoflurane				70	149	Lapatinib
71	172	Desflurane				71	157	Vitamin A
72	174	Aspirin				72	158	Vatalanib
73	179	Vigabatrin				73	159	Veliparib
74	186	Pentoxifylline				74	160	Erlotinib
75	187	Glucosamine				75	161	Hydroxychloroq uine
76	188	Thiamine				76	162	Bosentan
77	189	Choline				77	163	Ketamine
						78	169	Reboxetine
						79	170	Cortisone acetate
						80	173	Rocuronium
						81	175	Anastrozole
						82	176	Letrozole
						83	177	Tropicamide
						84	178	Tauroursodeoxy

							cholic acid
					85	182	Cyproterone Acetate
					86	183	Doxepin
					87	184	Lovastatin

5.0 References

1. Hastie T, Tibshirani R, Friedman J. Unsupervised learning. In The elements of statistical learning 2009 (pp. 485-585).Springer New York
2. Halkidi M, Batistakis Y, Vazirgiannis M. On clustering validation techniques. Journal of intelligent information systems. 2001 Dec 1;17(2):107-45
3. <http://www.malacards.org/>
4. Banerjee, A. (2004). "Validating clusters using the Hopkins statistic". IEEE International Conference on Fuzzy Systems: 149–153
5. Ferraro M.B., Giordani P., 2013. A new fuzzy clustering algorithm with entropy regularization. Proceedings of the meeting on Classification and Data Analysis (CLADAG)
6. Katikireddy Srinivas, Dr K V D Kiran, “Computational Approach to Overcome Overlapping of Clusters by Fuzzy k-Means” International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-4S2, December 2018.”
7. Katikireddy Srinivas, Dr K V D Kiran, Performance Analysis of Hybrid Hierarchical K-Means Algorithm Using Correspondence Analysis for Thyroid Drug Data” in Journal of Advanced Research in Dynamical and Control Systems, Volume 10, 12-Special Issue, August 2018.
8. Katikireddy Srinivas, Dr K V D Kiran “A Novel Hybrid Clustering System using k-means, k-medoids, hierarchical, Fuzzy C Means Algorithms on Thyroid Drug Data using

R, International Journal of Advanced Science and Technology Vol. 29, No. 5, (2020), pp. 9480-9492.”

9. Katikireddy Srinivas, Dr K V D Kiran “Performance Analysis of Clustering of Thyroid Drug data using Fuzzy and M-Clust”, Journal of Critical Reviews, Vol.7, Issue 11, July 2020, pp. 2128-2141.
10. Katikireddy Srinivas, Dr K V D Kiran “A novel hybrid k-means-k-medoids algorithm as an efficient method of Clustering for Thyroid disease drug database using R “in International Journal of Sciences and Research(IJSR),Volume no:73 and Issue no 8, August 2017(Doi:10.21506/j.ponte.2017.8.51),Ponte Publishers, Italy
11. Ferraro M.B., Giordani P., 2013.”A new fuzzy clustering algorithm with entropy regularization”, Proceedings of the meeting on Classification and Data Analysis (CLADAG)
12. “The art of R Programming”, Norman Matloff, William Pollack, 2013,I edition .
13. Data mining Concepts and Techniques, Han & Kamber, Morgan Kaufmann(Elsevier)
14. www.sthda.com
15. www.datanovia.com
16. www.drugs.com.