A Comparative Study Of Document Clustering

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Abstract: Data mining or knowledge discovery means extracting the knowledge or data from large amount of knowledge or data and summarising it into useful information. Data mining software has many tools for analysing data and summarising it. One of the tool is weka. It contains many machine learning algorithms. In this paper we are studying various clustering algorithms for the documents by using weka. Clustering means collecting a set of documents into group called clusters so that the documents in the same cluster are more similar than to other clusters.

Key-Words: Data mining algorithms, Weka tools, clustering algorithm .

1. Introduction:

Knowledge discovering process consists of different steps: Data Cleaning, Data Integration, Data Selection, Data Transformation, Data Mining, Pattern Evaluation and Knowledge Presentation. Data mining is a process in which many methods are applied to find out the data which are stored in database or data ware house. Data mining functionalities are: characterisation and discrimination, mining frequent pattern, association, correlation, classification and prediction, cluster analysis, outlier analysis and evolution analysis [1].

Three types of Data Mining techniques are Regression, Classification and Clustering. Clustering means, taking the similar documents into a cluster and other into another cluster. Clustering is an important technique for statistical data analysis including machine learning, pattern recognition, information retrial and bioinformatics. Here we are using weka data mining tool for clustering the documents. Then we are applying the stemming process to each clustering algorithm and finding out the difference between all algorithms that means how the documents are changing their cluster or group by applying the stemming algorithm.

2. Weka

Weka is one of the open source data mining software tool developed by University of Wail Kato in New Zealand that provides solution to many algorithms. Weka or Wooden (Gallirallus australis) is an endemic bird of New Zealand. It is a collection of machine learning algorithms for data mining tasks and only a tool kit such wide spread adaption and survive for an extended period of time [2]. WEKA is open source software issued under the GNU General Public License [3]. It is platform independent.



Figure1. View of weka tool

The GUI Chooser consists of four buttons:

- Explorer: It is an environment to explore the data with WEKA.
- Experimenter: It is an environment to perform experiments and conduct statistical tests between learning schemes.
- Knowledge Flow: The function of this environment is same as the Explorer but with a dragand-drop interface with an advantage of incremental learning support.
- Simple CLI: It provides a simple command-line interface which allows direct execution of WEKA commands for operating systems in which own command line interface is not provided.

When we click the "explorer button" we find Weka Explorer pre-processing, classification, clustering, association, attribute selection and visualisation tools. We have open the files which are must be in ".arff" format. Then we apply the clustering algorithms to all the documents.

3. Clustering Methods

- a) Cobweb Clustering.
- b) Expectation Maximization Clustering.
- c) Farthest Fast Clustering.
- d) Filtered Clustering.
- e) Hierarchical Clustering.
- f) Make Density Based Clustering.
- g) Simple K-Means Clustering.

3.1 Cobweb Clustering

This algorithm is developed by machine learning researchers in 1980[4]. It provides cluster without any predefined number of clusters. Here each cluster is represented by probabilistically with a conditional probability. It uses an evaluation function called category utility to guide the construction of the tree.

- a. This algorithm starts with an empty root node.
- b. Instances are added one after another.
- c. For each instance following options are taken.
 - The instance is classified into an existing class
 - A new class is created and the instance is placed into it
 - Two classes are combined into a single class (merging) and the new instance is placed in the resulting hierarchy;
 - A class is divided into two classes (splitting) and the new instance is placed in the resulting hierarchy.

reprocess Classify Cluster Associate Select attribut	es Visualize
Clusterer	
Choose Cobweb -A 1.0 -C 0.00282094791773878	15 -5 42
Cluster mode	Clusterer output
 Use training set 	Run information
Supplied test set Set	
Percentage split % 66	Scheme: Weka.clusterers.codweb -A 1.0 -C 0.00282094/91/
Classes to clusters evaluation	Instances: 300
	Attributes: 1017
(rum) - +	[list of attributes omitted]
Store dusters for visualization	Test mode: evaluate on training data
Ignore attributes	
	=== Clustering model (full training set) ===
Start Stop	
Result list (right-click for options)	Number of merges: 0
14:44:24 - HierarchicalClusterer	Number of splits: 0
14:46:58 - MakeDensityBasedClusterer	Number of clusters: 304
14:48:59 - SimpleKMeans	node 0 [300]
19(52:28 - COOWED	leaf 1 [1]
	node 0 [300]
	leaf 2 [1]
	node 0 [300]
	1 1ear 3 [1]
	100e 0 [300]
Status	

Figure 2: Cobweb clustering algorithm

3.2 Expectation Maximization Clustering

Expectation means computing the probability that each datum (attribute) is a member of each class (cluster), Maximisation means altering the parameters of each class (cluster) to maximise the probabilities [5]. It is convergence but not necessarily correct.



Figure 3: EM clustering algorithm

3.3 farthest Fast Clustering

This algorithm is developed by Hochbaum and Shomoy in 1985: A best possible heuristic for K-centre problem [6]. It is a variant of K means that places each cluster centre in turn at the point farthest from existing cluster centre.

By taking the TF and IDF the following analysis of the documents are shown below:-

eprocess Classify Cluster Associate Select attributes 1	fisualize
Choose FarthestFirst -N 5 -5 1	
luster mode	Clusterer output
Use training set Suppled test set Set Percentage splt % 66 Gasses to dusters evaluation (Num) - *	122 0.0
Ignore abites for wavesteen Ignore abiteutes Start Stop easilt ist (right-clock for options) 1:45:07 - PM 1:45:07 = Fath testStrat	Time taken to build model (full training data) : 0.1 seconds === Model and evaluation on training set === Clustered Instances
	0 264 (888) 1 15 (54) 2 1 (04) 3 17 (64) 4 3 (13) 4

Figure 4: Farthest fast clustering algorithm

To find out the result of the algorithm we right click on the visualise cluster assignment, a new window is opened and show the result in the form of a graph. By clicking the "save button" we can save the result in the form of "arff." Format.



Figure 5: Result of Farthest fast in form of graph

3.4 Hierarchical Clustering

Here the cluster is generated hierarchically that means a tree of clusters called as dendrograms[7]. It is of two types.

a) Agglomerative (bottom up)

- Start with 1 point (singleton).
- Recursively add two or more appropriate clusters.
- Stop the process when k number of clusters is achieved.
- b) Divisive (top down)
 - •Start with a big cluster.
 - •Recursively divided into smaller clusters.
 - Stop the process when k number of clusters is achieved.

🗿 Weka Explorer	
Preprocess Classify Cluster Associate Select attributes V	isualize
Clusterer	
Choose HierarchicalClusterer -N 5 -L SINGLE -P -A "w	eka.core.EuclideanDistance -R first-last"
Cluster mode	Clusterer output
Output Use training set	Test mode: evaluate on training data ^
O Supplied test set Set	
Percentage split % 66	Clustering model (full training set)
Classes to clusters evaluation	Cluster 0
(Num) - •	
Store clusters for visualization	
Innore attributes	
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Start Stop	=== Model and evaluation on training set ===
Result list (right-dick for options)	
14:44:24 - HierarchicalOlusterer	Clustered Instances
	0 296 (99%)
	1 1 (0%)
	2 1 (0%)
	3 1 (0%)
	4 1 (0%)
	()
Status	
OK	Log 🛷 x0

Figure 6: Hierarchical clustering algorithm

3.5 Make Density Based Clustering

This algorithm is proposed by Martin Ester, Hans-Peter Kriegel, Jorge Sander and Xiaowei Xu in 1996.In this algorithm we try to find the cluster according to the density of data point in a region. The main idea of this clustering is for each of cluster the neighbourhood of given radius has contain at least minimum number of instances. DBSCAN [8] is the most common clustering algorithm and also most cited scientific literature.

eprocess Classify Cluster Associate Select attribut	ves Visualize
lusterer	
Choose MakeDensityBasedClusterer -M 1.0E-	6 -W weka.clusterers.SimpleKMeansN 5 -A "weka.core.EuclideanDistance -R first-last" -I 500
luster mode	Clusterer output
Use training set	Normal Distribution. Mean = 0.0485 StdDev = 0.3069
Supplied test set	Attribute: your
	Normal Distribution. Mean = 0.2648 StdDev = 1.1068
9 Percentage spit % 65	Attribute: -
Classes to clusters evaluation	Normal Discribución, Mean - 0.0101 Scabey - 0.2004
(Num)	
Store dusters for visualization	Time taken to build model (full training data) : 1.39 seconds
Ignore attributes	=== Model and evaluation on training set ===
Start Stop	Clustered Instances
Start Stop	
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<i>.</i>	2 1 (08)
	4 118 (39%)
	Log likelihood: -615.17049
atus	

Figure 7: Make density based clustering algorithm

3.6 Filtered Clusterer

It is a class for running an arbitrary cluster on data that has been passed through an arbitrary filter. Filtering is the process of removing special characters and punctuation that are not required for providing the result.

reprocess Classify Cluster Associate Select attribute	es Visualize				
Justerer					
Choose FilteredClusterer -F weka.filters.AllFilter	-W weka.clusterers.SimpleK	MeansN 5 -A "weka.c	ore.EuclideanDi	stance -R first-la	st" -I 500 -nu
Cluster mode	Clusterer output				
 Use training set 	year	0.2797	0.5274	0.1586	c
Supplied test set	years	0.2692	0.1379	0.3505	1.8439
	you	0.1777	0.1509	0	C
Percentage split % 66	young	0.1128	0.1396	0	C
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Figure 8: Filtered clusterer algorithm

3.7 Simple K-Means Clustering

The term "k means" was first used by James Macqueen in 1967 [9] is the one of the unsupervised learning algorithm and it was developed by Stuart Lloyd in 1957 based on the technique of pulse-code modulation. The aim of the algorithm is partitioning n documents [10] into k clusters in which each document belongs to the cluster with the nearest means. It provides an output which is most efficient in terms of execution time.

The algorithm is worked in the following steps [11]:

- 1. Arbitrarily choose k points from data set D as initial cluster. These points represent the initial group of centroids.
- 2. Assign the object to the cluster or group which has closest centroid.
- 3. Recalculate the position of the k-centroids.
- 4. Repeat step 2 and 3 until the centroids are no longer change.

reprocess Classify Cluster Associate Select attribut	es Visualize				
Clusterer					
Choose SimpleKMeans -N 5 -A "weka.core.Euclid	leanDistance -R first-last" -I	500 -num-slots 1 -S 10			
Cluster mode	Clusterer output				
Our Use training set	year	0.2797	0.5274	0.1586	۲ م
Supplied text cat	years	0.2692	0.1379	0.3505	1.8439
	you	0.1777	0.1509	0	C
Percentage split % 66	young	0.1128	0.1396	0	c
Classes to clusters evaluation	your	0.1214	0.0676	0	(
(1)		0.1128	0.2969	0	C
Start Stop	Time taken to	build model (full evaluation on tra	training d	ata) : 0.95 ==	seconds
Start Stop	Time taken to	build model (full evaluation on tra	training d ining set =	ata) : 0.95 ==	seconds
Start Stop Start Stop 4:44:24 - HerarchicalOusterer 4:46:58 - MakeDensityBasedOusterer	Time taken to === Model and Clustered Inst	build model (full evaluation on tra tances	training d ining set =	ata) : 0.95 ==	seconds
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Start Stop Start Stop Real: tat (right-dak for options) 44-44:23 - Herard vicia/Clusterer 44-46:35 - ValaeDenstySeare/Clusterer 44-46:55 - SimpletMeans	Time taken to Model and Clustered Inst 0 57 (1 1 60 (2 2 1 (3 59 (2 4 123 (4	build model (full evaluation on tra sances 19%) 0%) 0%) 0%) 0%) 1%)	training d	ata) : 0.95	seconds
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Figure 9: Simple k-means clustering algorithm

Figure10: Result of Simple k-means in form of graph

4. Comparison

The above section involves all the clustering algorithms using weka tool. We are taking 300 numbers of documents which are from five domains like Pollution, Entertainment, Constitution of India, Festivals of India and Indian History. Then we make a comparative study of the documents by taking all clustering algorithms using weka tool.

This comparative study involves three cases:

- 1. By taking both term frequency transform (TF) and inverse document frequency transform (IDF)
- 2. By taking only term frequency transform (TF)
- 3. By taking Stemmer(Lovins Stemmer & Snowball Stemmer) with term frequency transform (TF) and inverse document frequency transform (IDF)

The results of the clustering algorithms are shown in four different tables:

Name	No. of clus ters	Cluster instances	Time taken to build model	Un- clust ered Insta nces	
EM	5	0:58(19%) 1:63(21%) 2:60(20%) 3:59(20%) 4:60(20%)	13.64 second s	0	
Farthest Fast	5	0:264(88%) 1:15(5%) 2:1(0%) 3:17(6%) 4:3(1%)	0.05 second s	0	
Filtered Cluster	5	0:57(19%) 1:60(20%) 2:1(0%) 3:59(20%) 4:123(41%)	1 second s	0	
Hierarc hical Clusteri ng	5	0:296(99%) 1:1(0%) 2: 1(0%) 3: 1(0%) 4: 1(0%)	0.91 second s	0	
Density based Clusteri ng	5	0:60(20%) 1: 60(20%) 2:1(0%) 3:61(20%) 4:118(39%)	1.2 second s	0	
K- Means	5	0:57(19%) 1:60(20%) 2:1(0%) 3:59(20%) 4:123(41%)	0.95 second s	0	

Table -1(Comparison result by taking both TF and IDF):

Table 2 (Comparison	result by	taking	only	TF):
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Name	No.	Cluster	Time	Un-
	of	instances	taken	clust
	clus		to	ered
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			model	nces
		0:58(19%)		
		1:60(20%)	15.18	
EM	5	2:63(21%)	second	0
		3:60(20%)	S	
		4:59(20%)		
		0:263(88%)		
Farth		1:16(5%)	0.06	
est	5	2:1(0%)	second	0
Fast		3:17(6%)	S	
		4:3(1%)		
Filtor		0:57(19%)		
ed		1:60(20%)	1.12	
Cluste	5	2:1(0%)	second	0
r		3:59(20%)	S	
1		4:123(41%)		
Hiera		0:296(99%)		
rchica		1:1(0%)	0.73	
1	5	2:1(0%)	second	0
Cluste		3: 1(0%)	S	
ring		4:1(0%)		
Densit		0:59(20%)		
У		1:60(20%)	1.36	
based	5	2:1 (0%)	second	0
Cluste		3:61(20%)	S	
ring		4:119(40%)		
		0:58(19%)		
K-		1:63(21%)	1.3	
Mean	5	2:60(20%)	second	0
S		3:59(20%)	S	
		4:60(20%)		

Table 3 Comparison result by taking snowball stemmer with TF and IDF:

Table 4 comparison result by taking lovins stemmer with TF and IDF:

Name	No.	Cluster	Time	Un-		Name
	of	instances	taken	clus		1 vuine
	clus		to	tere		
	ters		build	d		
			model	Inst		
				anc		
-				es		
		0:58(19%)	10.05			EM
	_	1:63(21%)	13.95	0		
EM	5	2:60(20%)	second	0		
		3:59(20%)	S			Farth
		4:60(20%)				1 11 11
		0:264(88%)	0.02			est
Farth	_	1:15(5%)	0.03	0		Fast
est	5	2:1(0%)	second	0		
Fast		3:1/(6%)	S			Filter
		4:3(1%)				bo
Filter		0.5/(19%)				cu
ed	5	1:60(20%)	0.97se	0		Cluste
Cluste	3	2:1(0%)	conds	0		r
r		5.39(20%)				•
Uiono		4.123(41%)				Hiera
rehico		1.290(99%)				rchica
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cluste		3:61(20%)	S	, J		
ring		4:118(39%)				У
		0:57(19%)			1	based
К-		1:60(20%)	0.98			Clust
Mean	5	2:1(0%)	second	0		Clust
S		3:59(20%)	S			ring
		4:123(41%)				V

Name	No.	Cluster	Time	Un-
	of	instances	taken	clust
	clust		to build	ered
	ers		model	Insta nces
		0:58(19%)		nees
	_	1:63(21%)	13.96	
EM	5	2: 60(20%)	seconds	0
		3: 59(20%)	seconds	
		4:60(20%)		
Farth		0.239(80%) 1.2(1%)	0.09	
est	5	2:21(7%)	0.09	0
Fast		3: 32(11%)	seconds	
rast		4: 6(2%)		
Filter		0:114(38%)		
ed		1:60(20%)	0.97	
Clusto	5	2: 3(1%)	seconds	0
Cluste		3: 59(20%)	seconds	
r		4: 4(2%)		
Hiera				
rchica		0:296(99%)		
1	5	1:1(0%)	0.48	0
1	3	2:1(0%)	seconds	0
Cluste		3: 1(0%)		
ring		4. 1(070)		
Densit				
v		0:111(37%)		
basad	5	1:60(20%)	1.12	0
Dascu	5	2:4(1%)	seconds	0
Cluste		3:00(20%) 4:65(22%)		
ring		ч. 0 <i>3</i> (2270)		
K-		0:114(38%)		
Moon	5	1:60(20%)	0.89	0
wicali	5	2:3(1%)	seconds	U
S		5: 59(20%) 4: 64(21%)		
		T. 04(21/0)		

4. Conclusion

In this paper we have projected various clustering algorithms in document clustering using weka. We do not require deep knowledge about algorithms when working with weka. So weka is more suitable data mining tool. We found that the k-means clustering algorithm is simplest and provide better performance as compared to other algorithms while taking the above three cases. But when the time factor is concerned, the farthest fast clustering algorithm executes faster & EM clustering algorithm takes more time than all other algorithms. Hierarchical clustering algorithm is more sensitive for noisy data than other algorithms. We also found that density based clustering algorithm is not suitable for data with high variance in density.

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